FROM OBSERVATIONS TO PREDICTIONS AND PROJECTIONS: OPPORTUNITIES AND CHALLENGES FOR CLIMATE RISK ASSESSMENT AND MANAGEMENT IN SUB-SAHARAN AFRICA

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METHODS
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ENACTS: Advancing Climate Services Across Africa

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Despite recent and mostly global efforts to promote climate services in developing countries, Africa still faces significant limitations in its institutional infrastructure and capacity to develop, access, and use decision-relevant climate data and information products at multiple levels of governance. The Enhancing National Climate Services (ENACTS) initiative, led by Columbia University's International Research Institute for Climate and Society (IRI), strives to overcome these challenges by co-developing tailored, actionable, and decision-relevant climate information with and for a wide variety of users at the local, regional, and national levels. This is accomplished through an approach emphasizing direct engagement with the National Meteorological and Hydrological Services (NMHS) and users of their products, and investments in both technological and human capacities for improving the availability, access, and use of quality climate data and information products at decision-relevant spatial and temporal scales. In doing so, the ENACTS approach has been shown to be an effective means of transforming decision-making surrounding vulnerabilities and risks at multiple scales, through implementation in over a dozen countries at national level as well as at the regional levels in both East and West Africa. Through the ENACTS approach, challenges to availability of climate data are alleviated by combining quality-controlled station observations with global proxies to generate spatially and temporally complete climate datasets. Access to climate information is enhanced by developing an online mapping service that provides a user-friendly interface for analyzing and visualizing climate information products. Use of the generated climate data and the derived information products is promoted through raising awareness in relevant communities, training users, and co-production processes.

Keywords: ENACTS, climate services, climate data, data gaps, data quality, Africa, coproduction

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INTRODUCTION

Building resilience is vital if countries and communities are to cope with the challenges of climate variability and change. This is particularly important in those parts of the world, like Africa, which are the most affected by climatic changes but possess the least adaptive capacity to manage the associated risks (African Development Bank, 2019). As such, solutions to mitigate the negative effects of climate change and variability, and adapt to anticipated changes are in particular and dire need (Conway and Vincent, 2021).

Climate information is one such solution with an enormous role to play in improving resilience and decision-making in the face of increasingly erratic precipitation and temperature patterns. From shorter-term decisions such as planning for, managing, and responding to climate hazards such as droughts or floods associated with climate variability to longer-term decisions to inform strategic or policy planning around climate risk management and climate change, climate information is the bedrock of climate-smart decision-making for governments, organizations, communities, and individuals (Cooper et al., 2008; Hansen et al., 2011, 2019a,b; Sheffield et al., 2014; Vaughan and Dessai, 2014; Stern and Cooper, 2017).

This reality has been increasingly recognized by the international community, which has developed resources and materials to promote its use at multiple levels. The United Nations Framework Convention on Climate Change (UNFCCC) Least Developed Countries Expert Group (LEG), for example, has developed guidelines, which emphasize the need for using climate information in the design and implementation of adaptation to climate change (Burton et al., 2002). Similarly, in the academic and practitioner communities, there is a growing body of research on the need to support adaptation through the provision of climate information that is salient, accessible, legitimate, credible, equitable, and integrated (Hewitt et al., 2012; Hansen et al., 2014; Daron et al., 2015; Harold et al., 2016; Buontempo and Hewitt, 2018; Buontempo et al., 2018; Christel et al., 2018; Vaughan et al., 2018; Clifford et al., 2020). However, there are still major practical challenges to ensuring that climate information is actually useful, usable, and used by those who need it most, and climate services approaches aim to address them (Hansen et al., 2011, 2019a; Vaughan and Dessai, 2014).

The World Meteorological Organization (WMO) defines climate services as "the provision of one or more climate products or advice in such a way as to assist decision-making by individuals or organizations," (WMO, 2014), while the Climate Services Partnership (CSP) describes climate services as "the production, translation, transfer, and use of climate knowledge and information in climate-informed decision making and climate-smart policy and planning," (Climate Services Partnership, 2011). The common thread between these two definitions is that climate services involve the provision of specific climate information products or services for a specific decision-making process. In other words, it is not the mere presence of climate information, but how this information is developed, tailored, communicated, and used in climate-sensitive decisions that ultimately determines its efficacy toward its stated goals in supporting adaptation.

Before information, however, there is the data that underlies it. Climate data is the foundation for providing climate services. However, due to the limitations surrounding the availability of and access to climate data and information products in Africa, the use of climate information in plans to manage risks from current climate variability or adapting to climate change has been limited. While many reasons for this exist, most limitations are related to climatic infrastructure and investment. In many parts of Africa, weather stations are sparse and their number has been declining (Washington et al., 2006; Dinku et al., 2014; Dinku, 2019). Moreover, where weather stations do exist, their distribution is uneven, with most stations located in towns along major roads. Thus, useful climate information is often not available purely because of data constraints. And when data does exist, it is often inaccessible to those who need it most.

However, data constraints or even accessibility issues are not always at fault for climate information not being useful. Even when high-resolution data exist, the information derived from such data may not be at a scale—temporally or spatially—or presented in a format that is relevant for decision-makers. A map showing precipitation patterns and likely areas of malaria incidence for the health sector, for example, may prove meaningless for those in the agriculture sector who would prefer to have information relating to rain onset or amounts to inform planting and seed choice visualized, or even entirely unusable for farmers who can only receive such information via radio or text. A shared collection of climate information can be applicable to more than one sector and provide a robust system for managing risks and shocks (Goddard et al., 2020; Conway and Vincent, 2021), but it is not inevitable that this will come about.

To ensure usefulness, usability, and actual use of climate information, intentional investments need to be made in the translation of this information for a wide array of users and sectors, in communication systems and strategies for sharing this information for different audiences, and in capacity building approaches promoting awareness and understanding of the information itself (Christel et al., 2018; Vincent et al., 2020) And, perhaps most importantly, norms, policies, programs, and practices need to be established to ensure an ongoing, iterative dialogue—also known as "coproduction"—between those who ultimately produce climate information products and those whom it is intended to serve (Meadow et al., 2015; Kruk et al., 2017; Vincent et al., 2018, 2020; Conway and Vincent, 2021).

The accompaniment of efforts to improve data availability and quality with kinds of capacity building and investments just described is especially salient and needed in Africa, where there is limited manpower capacity and National Meteorological and Hydrological Services (NHMS) culture that tends to see its responsibility in the realm of information generation, rather than shepherds or stewards of its use as just described. In contrast to the holistic vision of climate services just laid forth, most NMHS were historically established and mandated with the purpose of simply providing weather forecasts for aviation and other similar activities. As such, they have very limited manpower and experience in climate services, which requires engagement with users in a co-production framework (Vincent et al., 2018; Bremer et al., 2019). And as a result, these NMHS have been slow to transition from issuing weather and climate forecast to providing the kind of climate services needed for climate risk management and climate change adaptation by a variety of sectors.

The Enhancing National Climate Services (ENACTS) initiative led by Columbia University's International Research Institute for Climate and Society (IRI) has been making efforts to alleviate the challenges described above (Dinku et al., 2014, 2018). Working closely with NMHS of various countries, particularly in Africa, this initiative aims to improve the availability and quality of climate data, facilitate access to data and derived climate

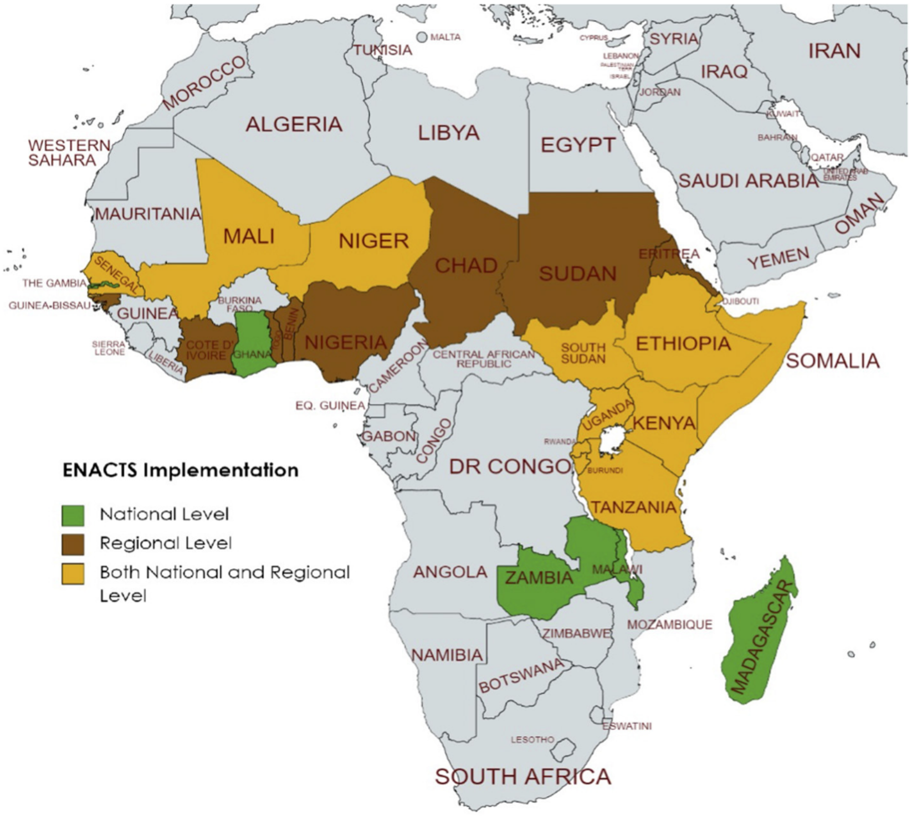

FIGURE 1 | Countries and regions where ENACTS has been implemented or is in the process of being implemented. The brown color shows where ENACTS has been implemented at the regional level, while the green color shows where ENACTS has been implemented only at the national level. Countries in orange are those in which ENACTS has been implemented both at the regional and the national levels.

information products, and promote the use of the data and climate information products for improved decision-making in different climate-sensitive sectors. Engagement with the NMHS has been critical to the ENACTS approach, as the NMHS are the nationally mandated organizations for the collection, management, and dissemination of meteorological observations. Enhancing National Climate Services improves the availability of climate data by blending the best available national meteorological observations with global climate and environmental products. Access to climate data and information products is enhanced by working with NMHS and climate services users in order to generate information products needed for climate resilient decision-making in key development sectors and then making those products freely available through a user-friendly dynamic web interface. This system enables the NMHS to generate and deliver targeted climate information products relevant to the needs of decision makers from local to national levels. The use of information products is facilitated by supporting the NMHS to engage their users at the different levels. The IRI is able to provide this support because the institution itself is comprised of a multidisciplinary team of climate scientists as well as sectoral specialists (e.g., agriculture, health, and water) that works at the nexus of science, development practice, and policy.

Enhancing National Climate Services was first launched in Ethiopia in 2012, and has now been implemented in about 16 countries at national level and at regional level in East and West Africa (**Figure 1**). This has been accomplished by fostering collaborations at national, regional, and global levels. The national level engagement with NMHS as well as experts from the climate-sensitive sectors such as agriculture has been instrumental in enhancing the national capacity to provide and use climate information. The engagement with Regional Climate Centers (RCC) has been critical in building ENACTS-related capacity in the region and making implementation of ENACTS sustainable and cost-erective. At the global level, ENACTS has been supported through funding by a number of organizations that include the United States Agency for International Development (USAID), the UK Department or International Development (DFID), the World Bank and the African Climate Policy Center (ACPC). It has also received input from relevant global institutions such as the WMO, and the Global Framework for Climate Services (GFCS), including some funding.

The general philosophy and approach of ENACTS has been discussed in detail by Dinku et al. (2018). The next sections will summarize the approach, and then focus on how ENACTS is actually implemented in practice, by presenting the main steps and activities.

THE ENACTS APPROACH

The goal of the ENACTS initiative is to transform how decision makers make climate-sensitive decisions at the local, regional, and national levels. This is accomplished through the following three objectives (Dinku et al., 2018):

1. Improve the availability and quality of climate data and information products at the local, national, and regional levels.
2. Enhance access to climate data, information products, and services relevant to the needs of the public, national, and local practitioners in climate-sensitive sectors, as well as policy makers, those in the private sector, and researchers.
3. Promote the widespread use of climate information and services by pursuing effective stakeholder engagement and tapping into existing demand for climate information.

The following sections provide the details of these three objectives.

Improve the Availability and Quality of Climate Data

This objective involves assessing available climate observations, executing quality-control of all rainfall and temperature observations from any given country's meteorological network, and then combining the quality-controlled station observations with satellite estimates for rainfall. For temperature, the quality-controlled observations are combined with digital elevation models and climate reanalysis products. During this activity, station observations undergo a comprehensive quality check procedure. While this procedure for checking and, whenever possible, fixing erroneous observations and coordinates is challenging and time-consuming, it is essential to ensure the quality of the datasets.

In order to create temporally and spatially complete climate data sets, the quality-controlled ground observations are blended with satellite rainfall estimates and reanalysis proxies (for temperature). The strengths of the satellite rainfall estimate and climate model reanalysis temperature products include the following:

(i) complete spatial coverage over most of the globe;
(ii) available free of charge from many global centers; and
(iii) long time series, which is close to 40 years for satellite precipitation products and over 50 years of time series for reanalysis products.

The proixies also suffer from some weaknesses, the main one being low accuracy compared to station observations. The ENACTS approach thus strives to overcome the weaknesses of both station observations (limited coverage) and satellite and reanalysis products (accuracy) by combing the better spatial coverage of the proxies with the better accuracy of the ground observations. These blended datasets provide 40-year time series of rainfall and 50 years of temperature time series at high (4 or 5 km) spatial resolutions. These datasets represent a significant improvement over the station-only or proxy-only datasets, depending on the application.

Enhance Access to Climate Data, Information Products, and Services

Access to climate information products is made easier by developing and making available on online climate information portals (maprooms) with visualizations of this information (Nsengiyumva et al., 2021). The first step to accomplish this is the installation of the IRI Data Library (DL) at the NMHS. The DL is a very powerful platform for hosting, analyzing, visualizing, and disseminating multidisciplinary data and information products (Blumenthal et al., 2014). It supports Geographic Information System (GIS) capability, is highly interoperable across major data formats and protocols, and is portable to remote sites. The DL is then used to develop online climate information products called Maprooms. A Maproom is an online platform where a collection of select information products can be developed and presented for specific user audiences. Beyond Maprooms, the DL is used to develop and make available an array of other climate information products for different applications as well.

Promote the Widespread Use of Climate Information and Services

Availability of climate information products on the web may not automatically lead to understanding and uptake of these products. A number of efforts are needed to ensure the uptake and use of these products. To start with, potential users would need to know that these products exist. Then, users need to be trained on how to navigate, understand, and use the different climate information products. Above all, users need to be engaged, through a co-production process, so that generated information products respond to specific user needs. This co-design and co-production process, which requires constant dialogue and iterative interactions, is in line with the implementation of National Framework for Climate Services (NFCS) being led through the GFCS (WMO, 2014). Thus, ENACTS lays the foundation for the implementation of the NFCS.

IMPLEMENTATION OF ENACTS

The ENACTS approach incorporates several innovations to overcome the data and human capacity constraints of NMHS for providing climate information and services that are relevant to local user needs. These constraints are addressed by supporting NMHS with methods, tools, and training to: (a) spatially and temporally complete, gridded, historical climate datasets; (b) generate suites of derived decision-relevant climate information products; and (c) disseminate climate information products through an interactive online visualization platform (Maprooms). The ENACTS team visits each NMHS and works directly with NMHS staff in implementing the different

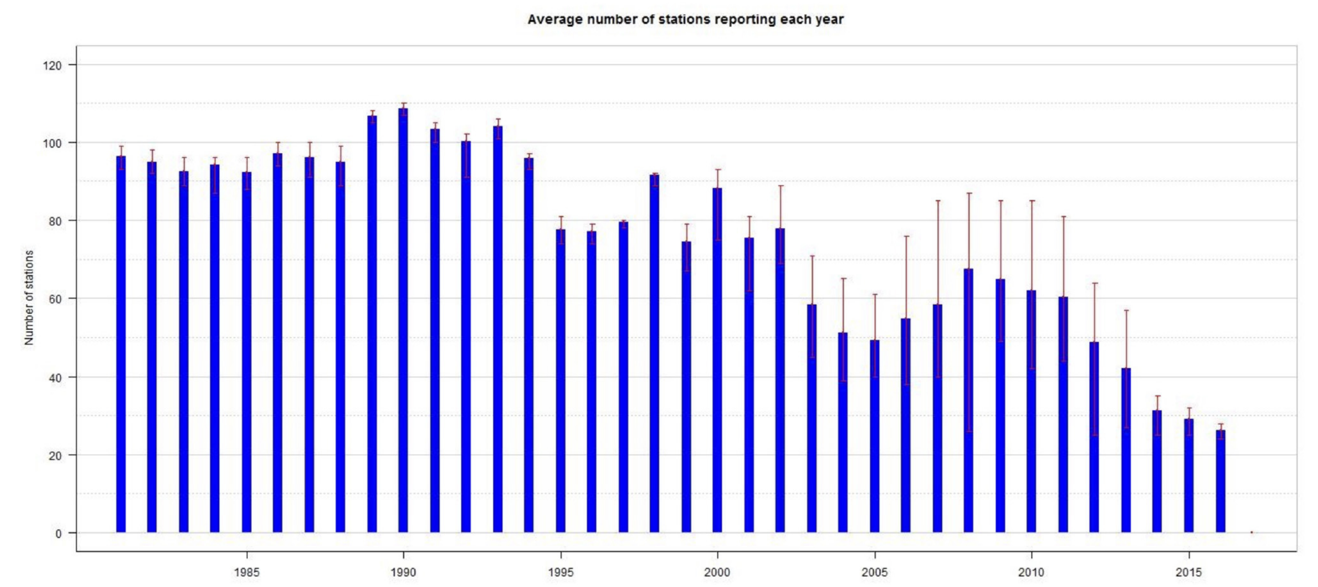

FIGURE 2 | Average number of stations that reported data for each month.

components of ENACTS. While this support is costly, it is necessary for making use of all available climate data and ensuring ownership and sustainability. Nonetheless, there are ways to reduce the cost while still promoting sustainability.

The implementation of ENACTS is a well-structured process according to the three objectives described above and is thus straightforward, though it may need to be adapted to the specific needs of each target country. Implementation is initiated with the first visit of the ENACTS team member to the NMHS to discuss and agree on the plan of execution. The implementation of each component is described in more detail below.

Improve the Availability and Quality of Climate Data

This component involves four steps: (i) install the Climate Data Tool (CDT) and train NMHS staff to use it; (ii) organize and assess availability of station observations; (iii) assess and fixing the quality of station observations; and (iv) fill spatial and temporal gaps in the observations.

Installation of CDT and Training of NMHS Staff

The CDT software is a free, open-source R package created specifically for NHMS in Africa, which generally do not have access to data organization and analytical tools for climate data. The CDT has been evolving for over 5 years and has become a powerful and easy to use tool. The main functionalities of CDT include:

- Organization of station and proxy data;
- Assessment of data availability;
- Assessment and correction of data quality;
- Combination of station observation with proxies (satellite rainfall and climate model reanalysis products) to fill temporal and spatial gaps in station observations;
- Evaluation of gridded products, including satellite, reanalysis, and combined data products;
- Extraction of data from gridded products, including satellite, reanalysis, and combined data products, at any point, for a selected box, and for any administrative boundary; and
- Analysis and visualization of station and gridded datasets.

The CDT training starts with theoretical basics covering quality control of station data, satellite rainfall estimation, climate model reanalysis products, combining station data with proxies, and evaluation of the generated products.

Organization and Assessment Station Observations

Rainfall and minimum and maximum temperature observations in the NMHS database are first organized and converted into a format that can be used in CDT. Then CDT is used to assess which data are available and which are missing. Climate Data Tool presents this assessment in tabular and graphic formats. **Figures 2**, **3** are examples of CDT outputs in graphics format. **Figure 2** shows the number of stations that were reporting each year, while **Figure 3** shows the percentage of data available from each station across the country. This was an eye-opening exercise for NMHS in many countries, as this was the first time they could visualize and analyze their data in this way.

Assessing and Fixing the Quality of Observations

Data quality control is a critical component of ENACTS. Station observations undergo a comprehensive quality check procedure. The quality check process involves identifying, and whenever possible fixing, erroneous observations, and erroneous station locations (coordinates). This is the most time-consuming and challenging task in the process, but it is crucial for ensuring data quality. The CDT is used to perform this quality control task. Climate Data Tool checks for a multitude of station observation error types and presents the outputs in different formats (e.g., **Figure 4**). This helps the NMHS staff to easily identify the errors and fix or remove the data from their databases.

Filling Spatial and Temporal Gaps in the Observations

Spatial and temporal gaps in the historical climate datasets are filled by combining the quality-controlled station observations with satellite rainfall estimates or climate model reanalysis temperature products (**Figure 5**). Reanalysis products are climate data generated by systematically combining climate observations (analyses) with climate model forecasts using data assimilation schemes and climate models. For rainfall, the Climate Hazards Group Infrared Precipitation (CHIRP, Funk et al., 2015) or Tropical Applications of Meteorology using Satellite data (TAMSAT; Maidment et al., 2014) satellite rainfall estimates are used depending on the performance of those products relative to station observations over the particular country. These two satellite products have been chosen because of their long time series (starting from 1981/1983), high spatial resolution (about 5/4 km), and use of consistent satellite sensor (infrared) data throughout the time series. The Japanese 55-year climate model reanalysis (JRA55; Kobayashi et al., 2015) is used for temperature mainly because of its long time series (since 1958) and regular update. However, this product has a coarse spatial resolution of about 50 km. Thus, the reanalysis data are downscaled to 4 or 5 km spatial resolution using station observations and elevation maps (digital elevation model).

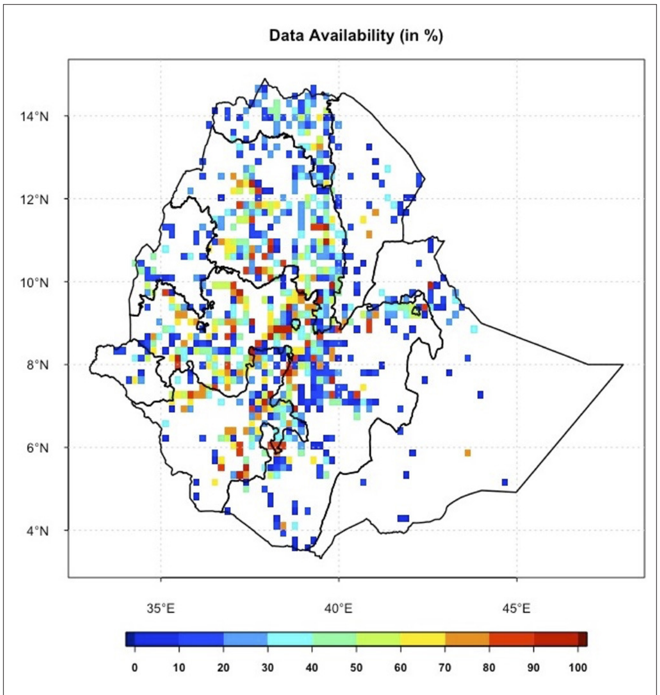

FIGURE 3 | An example data availability assessment showing what percent of data is available for each station.

Steps for Creating ENACTS Datasets

The approach adopted for generating rainfall and temperature time series, performed using CDT, involves the following steps:

- Downscale proxy data (only reanalysis for temperature);
- Use historical station data to calculate climatological adjustments factors;
- Apply the adjustment factors to all proxy data;
- Merge the output from the previous step with available station data for each dekad (10-day period) or each day of each year.

One of the main strengths of ENACTS is that by working directly with NMHS, it is able to make use of all local observational data, which significantly enhances the quality of the generated data relative to similar globally produced products. **Figure 6** compares three different station networks from Senegal. The data from the few synoptic station networks are shared with the world everyday through the WMO's Global Telecommunication System (GTS). These are the stations used in most of the global merged station-satellite products, which means they form the backbone of data available to decision makers. Some or all of the stations from the climate network are used in gridded products

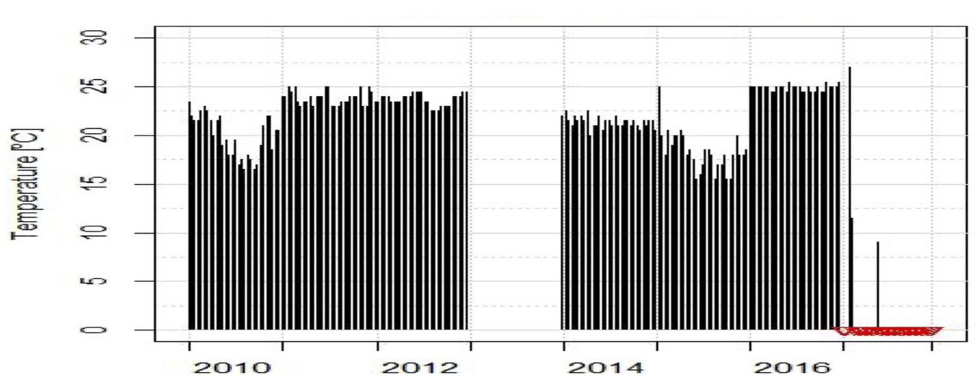

FIGURE 4 | An output from the quality check procedure showing (in red) rainfall data mixed up with temperature measurements.

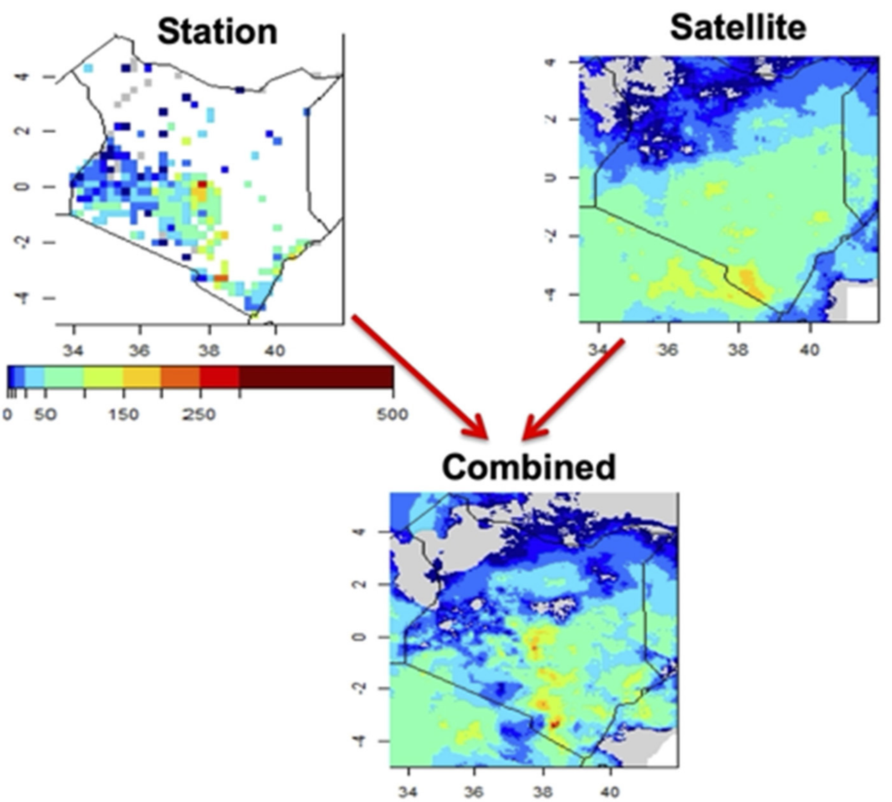

FIGURE 5 | Ten-day total rainfall as observed by station (top left), estimated by satellite (top right), and the optimal combination of the two (bottom). The color bar shows rainfall amounts in mm.

such as those from the Global Precipitation Climatology Center (GPCC, Becker et al., 2013). The ENACTS product uses all the stations in **Figure 6**, which are about 100.

Enhance Access to Climate Data and Information Products

Enhancing access to climate data and information products involves developing online mapping services (Maprooms) that provide user-friendly tools for the analysis, visualization, and download of climate information products, as well as basic explanations of main climate phenomena (Nsengiyumva et al., 2021). This process starts with the customization and installation of the IRI DL tool at NMHS. The DL is a powerful tool that facilitates access to a number of climate datasets, and enables analyses, visualization, and download of data and results in a variety of commonly used data formats (Blumenthal et al., 2014). The climate data developed in Section Improve the Availability and Quality of Climate Data above and the DL are then used to create automated interactive tools for data analysis and display. These tools are called "Maprooms" because the main displays are maps; however, the visualizations also include different graphs and tables.

Critical for sustainability and scale-up, the NMHS are trained on installation and management of the DL, as well as development and maintenance of the Maprooms. The trainees are shown all the steps needed to install the DL while it is installed on their computers.

Maproom training requires two steps: The first step is to train NMHS staff on how to navigate the DL Internet interface. This training is given to potential users for simple navigation of the DL, but can also be scaled to include more advanced training which introduces users to the programming language, which affords them the ability to perform data analysis and disseminate the information generated by such analysis. The second stem would be to train NMHS staff on how to use the DL to develop climate information products (maprooms).

The current version of the Maproom includes three "generic" Climate Maprooms as well as three application-specific Maprooms (**Figure 7**). However, different countries may develop a different number of products depending on needs or availability of funds. The Climate Maprooms include Climate Analysis, Climate Monitoring, and Climate Forecast.

The Climate Analysis Maproom (**Figure 8**) provides information on the past climate (in terms of rainfall and temperature) at any point or at national or sub-national levels. Products in this Maproom include the following:

- Daily statistics (mean intensity, number wet/dry dais, probability dry/wet spells, and more);

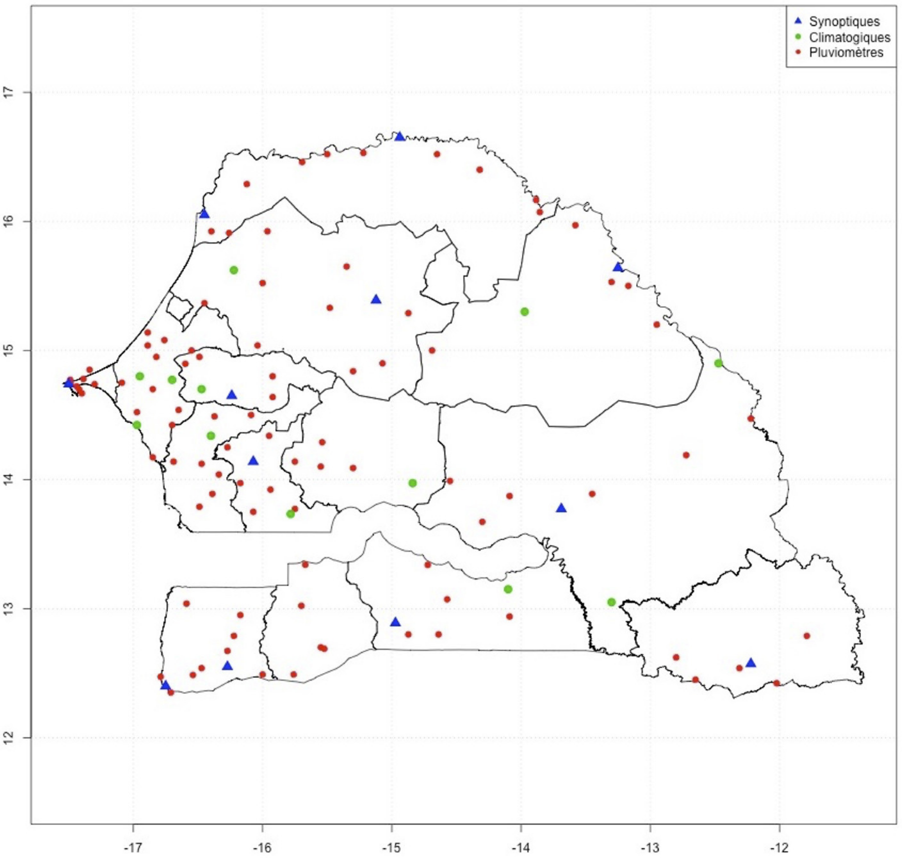

FIGURE 6 | Different classes of meteorological stations over Senegal: synoptic (blue), climate (green), and raingauge only (red).

- Monthly climatology and seasonality,
- Seasonal climatology, trends, and probability of extremes;
- El Nino Southern Oscillation/Indian Ocean Dipole (ENSO/IOD) analysis.

The ENSO and IOD product offers analysis of the impact that different ENSO and IOD phases would have over different parts of the country or region.

The Climate Monitoring Maproom enables monitoring of the current season. Different maps and graphs compare the current season with the expected or with recent years. This information can be extracted at any point or for any administrative boundary. The capability to extract and present summary information for any administrative level enables a user to focus on a specific area of interest.

The Climate Forecast Maproom translates the seasonal forecasts to flexible information that can be easily understood by users. It has thus been dubbed the "Flexible Seasonal Forecast Maproom." Here it should be noted that this Maproom does not actually generate forecasts. It just presents forecasts generated by the country in a more decision-relevant format, The Flexible Forecast Maproom has transformed how seasonal rainfall forecasts are presented. Instead of the usual terciles (below normal, normal, above normal) presentation, the new forecast Maproom allows users to choose a threshold in which they are interested either as percentiles or rainfall amounts. For instance, one can explore the probability that the total rainfall for the coming season will be above or below a given amount (**Figure 9**). The forecasts are also provided at each 4 or 5 km grid, making the forecast locally relevant (**Figure 10**).

The application-specific Maprooms currently include the Climate and Agriculture, Climate and Water, and Climate and Health Maprooms (**Figure 7**). These Maprooms have been developed/improved through a co-production process with sectoral experts at IRI as well as relevant in-country stakeholders.

The Climate and Agriculture Maproom provides climate information that is important for agricultural activities. This includes dry spell frequencies that influence the soil water balance, onset and duration of the growing season, and growing degree-days that influence the timing of crop maturity. The Climate and Water Maproom provides climate information (past, monitoring, and forecast) at the watershed and sub-watershed level. This would be very useful for water resources assessment, risk analysis, and monitoring. The current version of the Climate and Health Maproom enables one to analyze

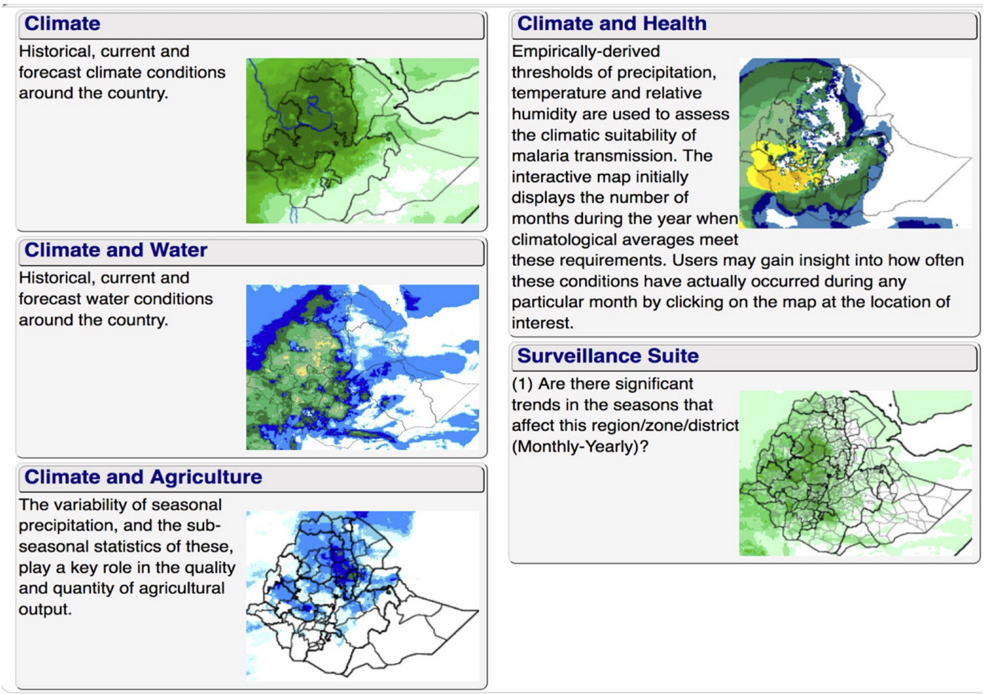

FIGURE 7 | The current version of ENACTS maprooms for one of the advanced ENACTS countries.

the impact of different climate variables on malaria occurrence. Empirically-derived thresholds of rainfall, temperature, and humidity are used to assess the climatic suitability of malaria transmission. The interactive map initially displays the number of months during the year when climatological averages meet these requirements. Users may gain insight into how often these conditions have actually occurred during any particular month by clicking on the map at the location of interest.

All of these aforementioned Maprooms are integrated directly into the NMHS web pages for each country. The "uptime" of these sites is monitored to help identify constraints to continuous delivery of climate information (most commonly down time is associated with interrupted energy supply to the server). An analytical capability has also been established at the NMHS so that they can better understand the traffic to their Maprooms, learn from their users and respond accordingly.

The above Maprooms are just a few examples of what can be done with the data and the DL tools. The main limitations to what could be generated are mastery of the tool and understanding what users need. Thus, there is much potential to develop additional products to help meet various user needs. Enhancing National Climate Services efforts include training the staff of the NMHS in the creation of Maprooms so they can develop further information products to satisfy user-specific needs.

Promote the Widespread Use of Climate Information and Services

While generating climate information products and making them available online makes it easier for people to access these information products, it may not necessarily lead to uptake and use. To bridge the gap between information access and use, potential users need to be made aware of these products, their value, and their applications. At a minimum, people (ranging from policymakers to technical experts, students, and members of the public) need to be aware of current ENACTS products and services and potential future services. Awareness is important for those who may positively (or negatively) influence the enabling environment for ENACTS uptake, funding, and institutional support. Awareness may also engage potential users of ENACTS products and services. In particular, widespread awareness may allow a broad community of "autonomous users" to be created at no additional cost to the NMHS in terms of time and resources, and ENACTS Maproom services have the potential to inform a very wide user base. Creating awareness of the work going on through the ENACTS initiatives will help the "word of mouth"-type dissemination, as well as build an identity and profile for the NMHS within a broad stakeholder community. In this respect, one component of ENACTS implementation is a 1-day "ENACTS launch" workshop to introduce the new ENACTS data and products to stakeholders, including policy and decision makers, experts from different sectors, academia, media, etc.

Users also need to be trained on how to navigate the products, understand them, and ultimately use them. There is a very high number of people with the potential to utilize the ENACTS data and information products. Thus, supporting the NMHS in various countries to train their users has been another important component of the ENACTS approach to date. This is usually done

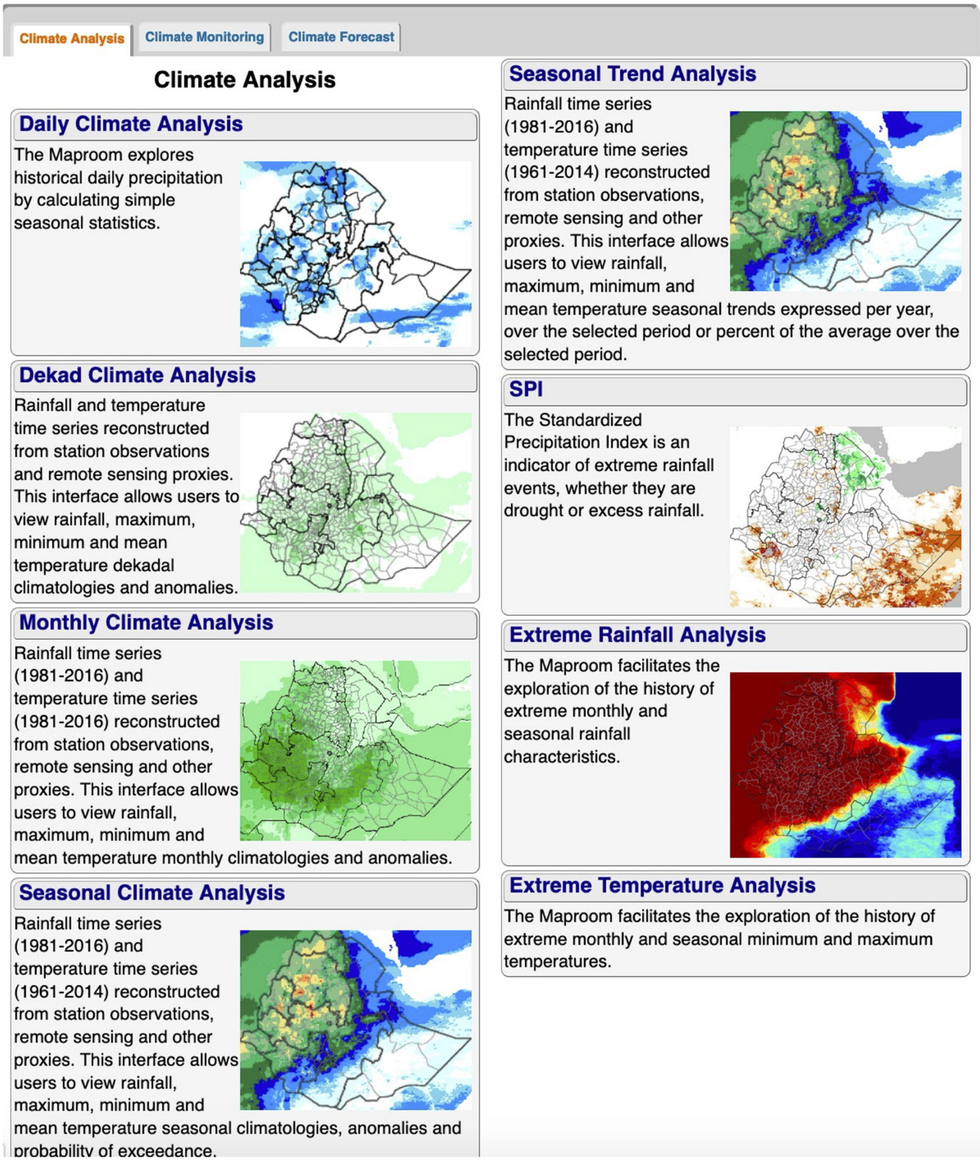

FIGURE 8 | Different products in the Climate Analysis Maproom.

by holding workshops for the training of trainers (ToT), and then teaching them how to navigate and use the Maprooms so they may train others to do the same. However, this component has not been as strong as it should be because the trainings typically require significant time and resource commitments in institutional environments where NMHS manpower and funding is already spread thin.

It is also important to engage users in co-development of information products that would serve and be tailored to their specific needs. Enhancing National Climate Services promotes the use of climate information by encouraging, and sometimes supporting, the NMHS to engage and collaborate with users. This includes engaging with policy makers, humanitarians, or development practitioners to discuss climate impacts on their activities and building their capacity to understand basic climate science. It also requires identifying what information they need based on the constraints, needs, and limitations in their own field. It is important to maintain constant dialogue and iterative interactions with different user groups.

USE CASE

The ENACTS data and product are being used for enhancing climate services in the different countries. The level of use varies widely among the different countries. The reasons for these differences include availability of following up activities (projects) after first implementation, the strength of the NMHS

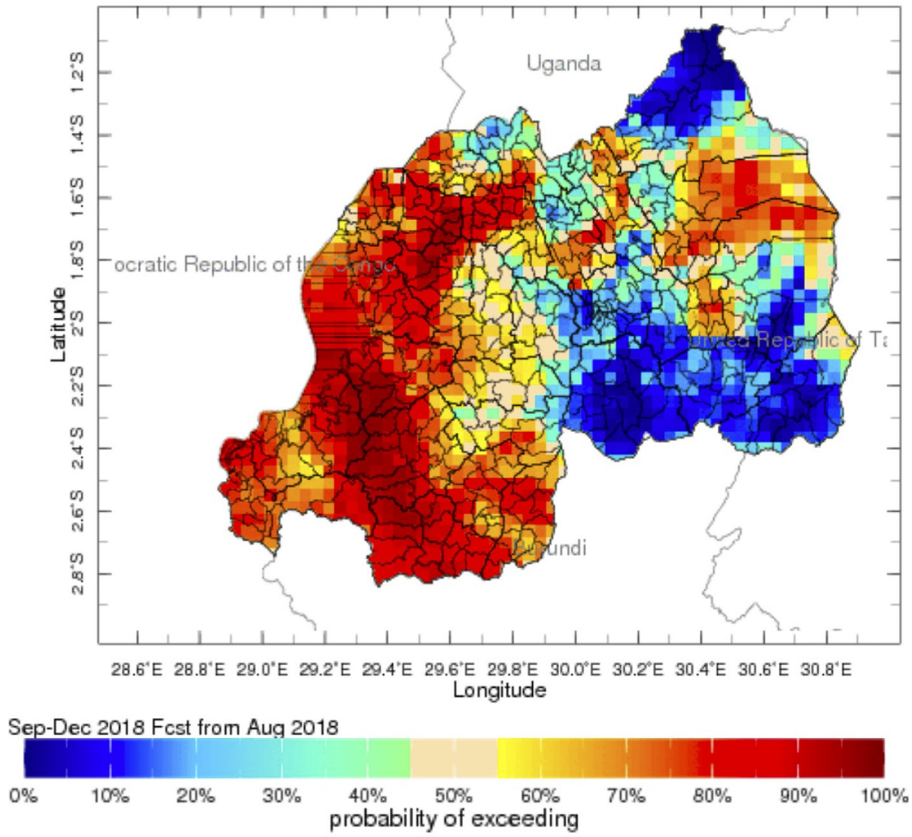

FIGURE 9 | The Flexible Forecast Maproom showing the probability of receiving over 500 mm of rainfall during the forecasted season (Sep–Dec in this case).

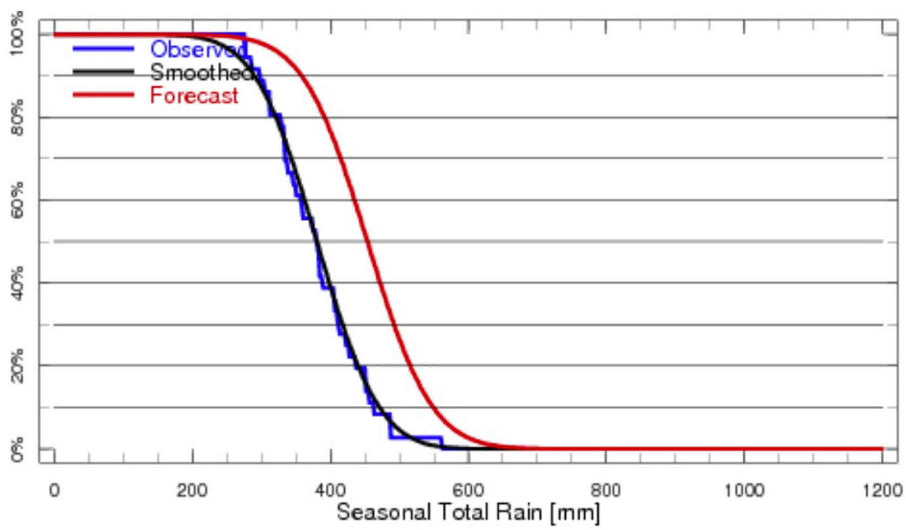

FIGURE 10 | Drilling down to a specific location: the probability that next season's rainfall total will exceed a range of values (exceedance probability), comparing the forecasted (red) with what is normally expected for that location (blue).

and its understanding of ENACTS, awareness of sectoral users about ENACTS, and the relationship between NMHS and users. Two examples are presented here. The first is Rwanda with focus on a specific application, and the second is Ethiopia where ENACTS has been supporting climate more systematically.

Implementation of the Participatory Integrated Climate Services in Rwanda

In Rwanda, a USAID-funded Rwanda Climate Services for Agriculture project (https://ccafs.cgiar.org/research/projects/building-climate-services-capacity-rwanda) worked with the country's national agricultural extension service to scale up the delivery of climate services using the Participatory Integrated Climate Services (PICSA). Participatory Integrated Climate Service is an approach designed to help agricultural extensionists work with farmers to make climate-informed decisions in their agricultural planning with the use of participatory tools to aid their decision making (Walker Institute, 2018). This is accomplished by combining the use of timely location-specific historical climate information with participatory decision-making tools that help farmers make decisions that fit their local and individual contexts. Through the PICSA approach, agricultural extension staff, non-governmental development agents as well as other intermediaries in Rwanda were trained to integrate climate services into their ongoing work with farming communities across Rwanda's 30 districts (Clarkson et al., 2017; Hansen et al., 2019a; Birachi et al., 2020). This is made possible because ENACTS ensures availability of spatially complete (available 4 km across Rwanda) historical climate data, which enables implementation of PICSA at any location. Location-specific historical climate information produces (graphs) allow those in the agriculture sector to visualize things like frequency of wet and dry events as well as the onset and duration of the rainy season, while downscaled seasonal rainfall forecasts at high resolution also provide locally-relevant information to facilitate agricultural planning. On the other hand, the expanded suite of ENACTS Maproom products (Nsengiyumva et al., 2021) support PICSA requirements for providing climate information (as graphs) to farming communities The ENACTS Maprooms provide an efficient way for the trained intermediaries to access location-specific data and graphs as they work with farmers and other local decision makers within the PICSA process. The Rwanda Climate Services for Agriculture project was won the "Climate-Smart Agriculture Project of the Year Award 2018" (http://www.aidforum.org/Topics/health-and-wash/rwanda-climate-services-for-agriculture-wins-project-of-the-year-award/).

Adapting Ethiopia's Agriculture to Climate

Ethiopia was the first country to implement ENACTS and it is also where ENACTS has been exploited the most. This has been accomplished through a number of following up projects that included engagement with the user community. One of these projects is ACToday (Adapting Agriculture to Climate Today for Tomorrow), which aims to develop climate service solutions through enhancement of the availability and effectiveness of climate information in national policy, planning, management, and other decision-making processes (Pattni and Ward, 2018; Goddard et al., 2020). This project, being implemented in Ethiopia and five other countries (IRI, 2020), has as a goal improving food security, nutrition, environmental sustainability, and economic outcomes. Adapting Agriculture to Climate Today for Tomorrow promotes the use of climate information and services to manage current climate risks while laying the grounds for adopting to the changing climatic conditions.

Adapting Agriculture to Climate Today for Tomorrow-Ethiopia works to strengthen the four pillars of climate services (Generation, Translation, Transfer, and Use; Goddard et al., 2020) by working with the most relevant institutions. The main institution for the "generation" of climate information is the National Meteorological Agency (NMA). Generation, Translation, Transfer has been strengthening NMA's capacity mainly around data and products and improving seasonal and sub-seasonal forecasts. The outputs from NMA are inputs into activities undertaken by the Ethiopian Institute Agricultural Research (EIAR), which plays the role of "translation" and "transfer." Adapting Agriculture to Climate Today support to EIAR includes ENACTS maproom products, development decision support systems and of an agro-weather advisory system. Products and tools from EIAR will is used by the Ministry of Agriculture (MoA) at different levels (from the minister all the way to the farmers) for climate risk management. Disaster, mainly in the form of droughts, has been a major challenge to food security and development in Ethiopia. Thus, ACToday is also supporting disaster risk management by working with the relevant institutions, which include the National Disaster Risk Management Commission (NDRMC) with effective use of climate information for early warning and action, and working with the Word Food Program (WFP) on index insurance and Forecast-based Financing.

All these efforts would be in vain if users do not understand and use climate information. Thus, an important component of ACToday has been the development and piloting of a skilled-based modular training course on Climate Risk Management *at* different levels in collaboration with MoA, EIAR, and NMA. These curricula include graduate-certificate at university level, a semester course for students attending vocational training, 2-week professional development training for district agricultural experts and extension officers, and PICSA for extension officers and farmers. These capacity building activities are designed in such a way to strengthen and reinforce capacities, and maximize synergies amongst different decision-makers and institutions. Those trained in climate risk management at the university level, for example, may go on to work within the extension system as subject matter specialists guiding the development agents who work most closely with farmers at the local level.

Agriculture to Climate Today-Ethiopia has also been supporting the implementation of the NFCS in Ethiopia. This is an institutional mechanism to coordinate, facilitate, and strengthen collaboration among national institutions to improve the co-production, tailoring, delivery, and use of science-based climate predictions and services (WMO, 2018). This is accomplished by focusing on the five pillars of the GFCS (WMO, 2014). This would be a very important planform/process for developing strategies to foster the access and use of climate knowledge and services by national and/or international organizations. Supporting this process will ensure that the achievements of ENACTS and ACToday are sustainably embedded in national-level processes.

WHAT IS NEXT FOR ENACTS?

Enhancing National Climate Services has been demonstrated to be an effective approach to transforming national climate services. The ENACTS products have generated a great deal of interest in the meteorological, humanitarian, and development communities. However, there is still room for further improvement of the different components of ENACTS. This means a lot of work is still needed to strengthen ENACTS where it has already been implemented, as well as in future implementation countries. The countries in which it is currently implemented represent only a fraction of Africa. The initiative would thus need to expand to the rest of the continent, and beyond. Finally, there is also a need to ensure the sustainability of ENACTS. These three areas are further discussed below.

Strengthening ENACTS

Strengthening ENACTS in the countries where it has already been implemented will entail:

- ***Increasing the number of climate variables used***: Variables such as relative humidity, evapotranspiration, and sunshine hours are all important for applications such as agriculture, water resource management, and renewable energy. Integrating them into ENACTS would empower those seeking to improve yields while managing scarce resources.
- ***Developing more climate information products***: The current Maprooms include both generic climate products, as well as some sector-specific products for the health, agriculture, water, and disaster risk management sectors. At climate product level, there have been request for analysis of climate change projections. Climate change projections have not been the focus ENACTS, but this will change going forward. There are already a couple of ENACTS Maprooms that include some climate change products, but these were not developed by IRI (see section Expanding ENACTS below) On the other hand, beyond contextualizing ENACTS on a sectoral level, users have been asking for more products relevant to the specific decisions they have to make. In addition, the health and water Maprooms have limited products. Thus, more work is needed to add more products. Some of these will require incorporating new climate variables such as those described above. There have also been requests from other sectors, such as aquaculture and energy for sectoral-specific products. Thus, in addition to developing more decision-relevant products, there is also a need to expand to other sectors.
- ***Creating decision support systems for specific decision-making processes*****:** Creating specific decision support tools for decision-makers would allow for more efficient management of a number of processes, services, and programs, including hydropower dams, improved and expanded crop yield forecasting, malaria monitoring, and early warning systems.
- ***Promoting effective use of climate data and information products***: The return on investment of ENACTS data and its products can only be realized through its effective use. Efforts are being made to promote the use of ENACTS. However, this is still the area most in need of further development within the ENACTS approach. Initial plans depended on the NMHS themselves promoting the use of ENACTS. However, it has become clear that many NHMS are not able to do so quickly enough. The main challenge has been the fact that the ENACTS approach is new to the NMHS themselves who are used to providing only limited climate information products such as weather and seasonal forecasts. Thus, the ENACTS approach must be reshaped to involve sectoral experts, as well as other relevant actors in its use and promotion. This has already started in some countries through the aforementioned ToT sessions, but it is still very limited. Implementation of the NFCS could be an opportunity for expanding the use of ENACTS products. The co-development of services with users (involvement of the different stakeholders in the development of the products) will contribute to the endorsement and wider use of ENACTS products.
- ***Targeting high-impact decision-makers with capacity building:*** While ENACTS Maprooms have been used as a climate tool by NMHS for many years, use of such Maprooms remains limited amongst development and humanitarian organizations, despite the high potential for impact amongst decision-makers in this space. In Ethiopia, for example, where ENACTS was first launched and the NMA has been implementing the approach for almost 9 years as it rippled across more than a dozen countries in Africa, use of the tool still remains limited. Especially in sectors related to disaster risk reduction and management (DRR/M) where there is a high potential for use of ENACTS tools and approaches (such as Maprooms) in saving lives, promoting food and nutrition security, and managing multi-hazard risks inclusive of climate, awareness of the initiative, and its services is low. Targeted capacity building and sensitization on the ENACTS approach is therefore necessary to realize its full potential.

Expanding ENACTS

Most African countries, if not all, will greatly benefit from the innovative approach of ENACTS. By its nature, ENACTS can lay the foundation for the NFCS, which some countries have already started implementing. However, so far only 16 countries have benefited from ENACTS at a national level (though there some more covered at regional level implementation). There is clearly still room for expansion. While the efforts of the IRI, NMHS, and development partners offer a strong practical example of climate services development in Africa, substantial funding and collaboration with national, regional, and global organizations will be needed to expand ENACTS across the continent. There are many potential opportunities for synergy among current initiatives including the NFCS process, RCC, African Meteorological Conference on Meteorology (AMCOMET), GFCS, UNDP, World Bank efforts, and others. All could benefit greatly from better basic information for their evidence-based priority setting and evaluation processes. Enhancing National Climate Services aligns tightly with AMCOMET objectives (AMCOMET, 2015), the five pillars of the GFCS (WMO, 2014), and World Bank and UNDP investments in strengthening NMHS.

The expansion could be made cost-effective and efficient by building technical capacity within the continent. An approach ENACTS has adapted to ensure cost-effectiveness is building ENACTS–related expertise at the RCC in Africa. This is accomplished by training and working with regional and continental climate institutions. This has already started at the IGAD Climate Prediction and Application Center (ICPAC) in East Africa and, and at the Agrometeorology, Hydrology and Meteorology (AGRHYMET) Regional Center in West Africa. IGAD Climate Prediction and Application Center has already started developing Maprooms, and providing training and technical support for ENACTS countries in the region. IGAD Climate Prediction and Application Center has even implemented ENACTS in some countries in the region with Maprooms that include climate change projections.

Ensuring Sustainability of ENACTS

Enhancing National Climate Services is not a one-time project. It is an ongoing process that enhances climate services incrementally and continuously. The existing ENACTS countries need to be supported to make the best use of the existing ENACTS platforms as it expands to other countries. At the same time, ENACTS data and climate information products will keep improving and expanding based on user requirements. Thus, the NMHS may need sustained support to continue providing the ENACTS-generated products and also to add new ones and engage their users. This would be a daunting task for one institution alone and can only be achieved and sustained through broad partnership. As mentioned earlier, ENACTS attempts to ensure sustainability and cost-effectiveness by building ENACTS-related expertise at the RCC in Africa. The ultimate goal is to transfer all operational ENACTS activities to RCC and limit ENACTS team's role to technical support to the regional centers, developing and refining tools and products, supporting innovations, and facilitating engagements with users.

SUMMARY

Building resilience against the negative effects of climate variability and change requires reliable climate data and information products. Climate services can provide climate information to help decision-makers, including those at the highest levels (such as policymakers or government officials) all the way down to those at the grassroots levels (such as farmers or pastoralists), manage current climate extremes, and adapt to the changing climate. Climate data is the foundation for any climate services. However, lack of available climate data and information products has posed serious challenges to the use of climate information and services in Africa and many other parts of the world. The ENACTS initiative is designed to alleviate these problems by enabling the integration of climate information in national and local decision-making processes through the improvements in the availability, access, and use of climate data and information products. The main strengths of ENACTS include the following:

- It creates high-resolution and reliable climate data by directly working with NMHS. Working with NMHS is critical because it provides access to climate observations that are not available elsewhere. This will also help in building trust and ensuring sustainability.
- Worked with sectoral experts to develop climate information products that are relevant to different sectors and make them available online. This has helped create a web portal (Maprooms) with rich and dynamic climate information products that are not available anywhere else.
- Build the capacity of NMHS staff to generate the required climate information products and the capacity of users to understand and apply those products.

The main weakness of ENACTS has been effective exploitation of the developed products.

While it was initially hoped that the NHMS would be able to lead on promotion of climate information products, in reality, progress has been slow due to inertia surrounding long-standing norm of NMHS only providing limited products such as weather and seasonal forecasts.

Though efforts have been made to train NMHS staff and sectoral experts on how to navigate, understand, and use the maprooms, it has been found not to be sufficient. The other challenge is that this component requires more resources and time. Addressing this challenge requires evolving the approach to involve more sectoral experts besides the NMHS in the promotion of ENACTS. This will broaden the conversation and support national and international dialogue and momentum for the incorporation of effective climate services in all corners and sectors affected by climate.

Since its launch in Ethiopia in 2012, ENACTS has been implemented at the national level in 16 countries, as well as at the broader regional level in East and West Africa. Over that time, ENACTS has proven to be effective in strengthening climate services at the national level. However, more work is needed to strengthen ENACTS where it has already been implemented, expand it to other countries in Africa and elsewhere. Strengthening ENACTS will involve expanding several different aspects of the initiative, including adding g more climate variables, such as humidity and daily hours of sunshine. Finally, the area most in need of development is the expansion of ENACTS data and information products into new geographies and sectors. While the efforts of the IRI, NMHS, and development partners offer a strong practical example of climate services development in Africa, substantial funding and collaboration with national, regional, and global organizations will be needed to expand ENACTS across Africa, and beyond. The strengthening and expansion can be made cost effective and more sustainable by building technical capacity within the continent. This has already started at the IGAD ICPAC in East Africa and at the AGRHYMET Regional Center in West Africa.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

TD: lead the team. RF: CDT development and training. RC and AV: Maproom development and training. IK: data library installation and training. JH: Maproom development and user engagement advisor. AG: coordinator and manuscript editor. All authors contributed to the article and approved the submitted version.

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Adaptation Planning: An Integrated Approach to Understanding Vulnerability in the Lake Victoria Basin

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Decision makers need actionable information on the factors that inhibit household adaptation to climate variability and other changes, especially those changes reinforcing environmentally unsustainable livelihood strategies. In this paper, we show how a combination of quantitative and qualitative data can help assess current livelihood vulnerability and the social and institutional obstacles facing specific population groups that lock in risk and undermine opportunities. Detailed analysis of current household economies in two case study communities (one in Uganda and one in Kenya) in the Lake Victoria Basin, East Africa, was combined with a qualitative, intersectional exploration of constraints on income adaptation and diversification. Quantitative household economy analysis showed low levels of household disposable income overall and additionally, poor returns on investment from enterprises typically controlled by women. Qualitative research highlighted changes in gender roles driven by women's entrepreneurial responses to reduced household income from traditional agricultural and natural resource-based activities. However, due to unequal access to finance and culturally mediated norms and expectations, many women's enterprises were small scale and insecure. The broader political economy context is one of limited national investment in education and infrastructure, further constraining local opportunities for human and economic development. The approach described here was directed by the need to understand and quantify economic vulnerability, along with the cultural and institutional constraints on adaptation, as a basis for making better adaptation policies and interventions to build resilience over the longer term.

Keywords: climate, adaptation, resilience, quantitative, qualitative, HEA, IHM

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INTRODUCTION

Adaptive capacity is influenced by actors' abilities to capitalize on available opportunities that ease the planning and implementation of adaptation as well as constraints that make adaptation processes more difficult for both human and natural systems (Klein et al., 2014).

In the past decade, many discipline-based guidelines, frameworks and indices have addressed environmental and social aspects of adaptation and resilience (Patel et al., 2017; Tanner et al., 2017).

Miller et al. (2010) have called for the conceptual insights that have emerged from these discipline-based approaches to adaptation, to be "translated into operational assessment methodologies, guidelines, and procedures that are easily accessible to practitioners and decision makers."

The approach described in this study was directed by the need to understand and quantify the economic, as well as the cultural and institutional constraints on adaptation, as a basis for actionable policies and interventions and was designed to address the immediate problem: "*What information do local policy and decision makers need now, to reduce vulnerability and enhance resilience?*" To ensure that these measures are timely, proportionate, and well-targeted we show how a combination of disaggregated quantitative and qualitative data can be assembled by local teams to assess current vulnerability and adaptive capability. This information can be used to identify those social and economic obstacles that lock in risk and undermine opportunities among specific population groups, providing the robust, policy relevant evidence required for building resilience over the longer term.

The wealth of research driven by the climate emergency has produced new understandings of the nature and limits of resilience and adaptive capability in poor rural communities (e.g., Tanner et al., 2014; Clay, 2017; Ford et al., 2018; Hallegatte et al., 2018; Singh et al., 2019); these have highlighted the incremental drivers of vulnerability, with an increasing focus on the role of gender and intersectional issues in shaping responses (Nyantakyi-Frimpong and Bezner-Kerr, 2015; Call and Sellers, 2019). This work has also shown the importance of collaboration across disciplines (e.g., Furberg et al., 2018) as a key element in both scenario development work (Birkmann et al., 2015) and the exploration of adaptation pathways (Wise et al., 2014). Adaptation pathways research has also opened new avenues for better integration and dialogue between disciplines (Werners et al., 2021).

Despite this high level of activity, policy makers still face the practical dilemma: "*How can these insights be put to work, to address immediate and compelling problems of marginality and poverty?*" Quantitative climate and livelihoods data, combined with local testimony and deliberation, are needed to guide short term interventions and populate the "what if" models that are increasingly used to explore livelihood and environmental tipping points (Haasnoot et al., 2013; Young et al., 2020).

This study was undertaken as part of the multi-disciplinary HyCRISTAL project (http://www.walker.ac.uk/research/projects/hycristal-integrating-hydro-climate-science-into-policy-decisions-for-climate-resilient-infrastructure-and-livelihoods/), within the FCDO/NERC Future Climate for Africa programme (FCFA) (https://futureclimateafrica.org). FCFA aims to generate "*fundamentally new climate science focused on Africa, and to ensure that this science has an impact on human development across the continent*." Case study material draws on data from field research conducted in the Lake Victoria Basin which used both quantitative and qualitative methods to explore different dimensions of livelihood resilience and vulnerability, in populations where climate change was just one of many factors impacting on the ability of households to adapt to contemporary challenges. The methods used are replicable, bridge the "quantitative-qualitative" divide (Onwuegbuzie and Leech, 2005) and are designed to provide policy and decision makers with a comprehensive, evidence-based understanding of the boundaries of resilience and adaptation, from local to national and international levels.

The Individual Household Method (IHM; Seaman et al., 2014) was selected for the quantitative livelihood analysis, based on its rigorous approach to data collection and the empirical insight it provides into the sensitivity of households to different shocks or changes affecting their livelihoods. This includes:

- A measure of disposable Income (**Figure 4A**).
- Detailed analysis of the main sources of cash income (**Figure 4B**).
- Analysis of the main sources of food (**Figure 4C**).
- A detailed breakdown of the main crops grown (**Figure 6**).
- Asset holdings including land, livestock (**Figure 4D**)

The quantitative IHM data was complemented by a series of age- and gender-differentiated focus group interviews at each site, conducted by experienced social scientists and using a common protocol. Discussions focused on current livelihood options, changes that had taken place in recent decades, investment opportunities and other factors that influenced livelihood choices.

THE HOUSEHOLD ECONOMY APPROACH (HEA) AND THE INDIVIDUAL HOUSEHOLD METHOD (IHM): BACKGROUND AND EXTENT OF USE.

The Household Economy Approach (HEA) was developed in the 1990's as a method of famine prediction that could be applied at scale, to predict the impact of a defined shock e.g., crop failure, on the income and food access of defined population groups, and provide governments and donors with relevant information e.g., to determine the amount of food aid or cash required to avoid the forced sale of assets (Seaman et al., 2014). The HEA is well-established and used by USAID FEWSNET and governments, UN agencies and others across Africa and in parts of the Middle East, the Caribbean, and South Asia, to assess food security at national level (see www.fews.net). The Individual Household Method (IHM) is an extension of the Household Economy Approach.

HEA arose from Amartya Sen's entitlement theory of famine (Sen, 1981), with its key insight that famine was caused by people's inability to access food, rather than the absence of food. Understanding how a crop failure or some other "shock" will affect people's food access requires knowledge of the way in which people normally acquire food and cash income, how this varies from place to place and between poorer and better off households, and the ability of households to "cope." The HEA was designed to collect this data set quickly and at scale (Seaman et al., 2014), and is now widely and successfully used by governments and donors and NGOs across sub-Saharan Africa.

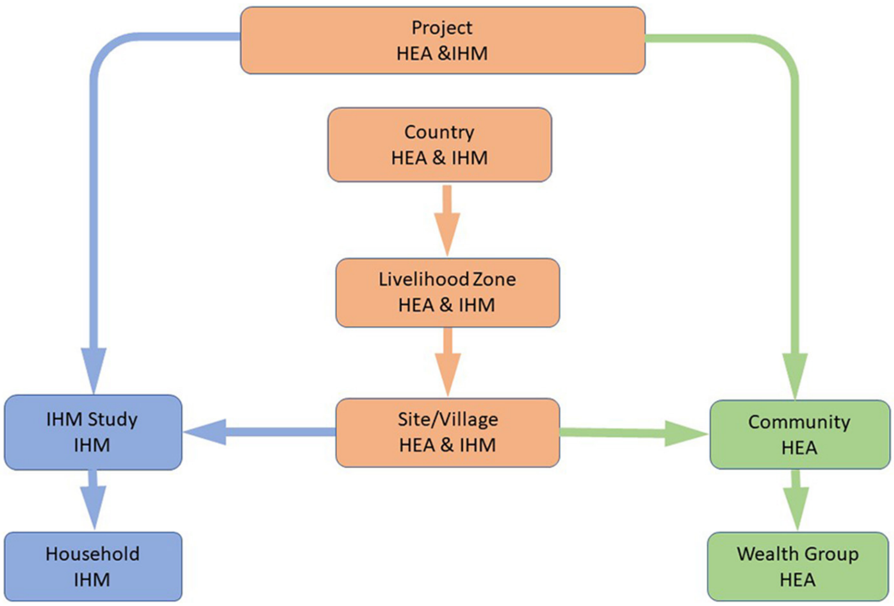

FIGURE 1 | The HEA and IHM: levels of data collection. Source: own elaboration based on images with "no copyright reserved" (Creative Commons Attribution Non Commercial No Derivatives 4.0 International license).

The extensive HEA experience of gathering income data suggested that a similar method based on individual household measurements would be useful where a more detailed understanding of poverty and the variation in poverty within populations is needed. The IHM was developed for this purpose and has proved to be a valuable research tool. It has been used by researchers and non-government agencies for project baseline and impact studies and for longitudinal monitoring in FCDO and Irish Aid funded programmes (Petty and Savage, 2007; Petty and Ellis, 2015a).

The IHM provides a measure of household disposable income (i.e., cash remaining after the household has met its basic food energy requirements) and a "standard of living threshold," indicating a level of income sufficient to meet social inclusion norms in the study sites. This data is crucial in understanding the potential capability of households to invest, pay interest on loans and cope with natural disasters, price shocks, and adverse life events. Resilience and adaptive capability are indicated by levels of disposable income and by asset holdings, which are documented in the household interview. Customized software (OpenIHM)[1] is used to analyse the IHM survey data This allows users to explore the impact of different shocks on all sources of household income, which are comprehensively documented in household interviews, and hence to identify the characteristics of specific threats or risks in relation to different population groups. Users can generate reports on income sources, land, livestock and other assets, and can compare households with different demographic characteristics (e.g., female headed/non female headed).

Figure 1 shows levels of data collection in HEA and IHM studies, and the greater level of disaggregation possible in IHM studies. Data is collected at an individual household level in IHM studies, and at "Wealth Group" level in HEA studies.

This methodology allowed us to explore current year income levels in the case study assessments (these were the most recent full agricultural years and were described by local residents as "*neither particularly good nor bad, compared with other recent years*"). Further analysis of income allowed us to identify specific sensitivities to shock at household level. Finally, by looking at the current investment costs associated with different local enterprises, we were able to assess the potential for income diversification and adaptation across the population. Whilst recognizing that this study is only a snapshot of recent case study years, findings are indicative of the scale to which households at different levels of income are "trapped" in current patterns of economic activity, and help to answer questions such as, "*What level of income is needed to invest and diversify income streams?*" Follow on qualitative interviews allowed us to explore the options and opportunities that are available to different groups within the population, and in this process, to link up quantitative and qualitative aspects of the study, generating policy-relevant findings (see Section Implications for Policy).

The IHM uses a semi-structured interview framework to record the household's productive assets (land, labor, livestock, etc) and the way in which these are used to generate food, food stocks, and cash income. A preliminary survey is conducted by the assessment team before individual interviews begin. This includes locating the survey site within a wider "livelihood zone" i.e., an agro-ecological area within which households have access to a similar range of markets and economic opportunities [see Seaman et al. (2014) and examples of livelihood zones

[1] https://code.google.com/archive/p/open-ihm/downloads

at https://fews.net/fews-data/335], and mapping the village and its immediate locality, to show land use, main infrastructure and physical features. Information is also collected from focus groups and key informants on crops grown and livestock kept, seasonality of labor, pay rates, crop returns, government and NGO programmes implemented locally, as well as the essential items of expenditure required by people in that community to meet the norms for "social inclusion." Information from the various focus groups is shared before individual household interviews begin. This means that interviewers have a good initial grasp of the local economy, can identify inconsistencies in responses, and can probe further and cross question where appropriate, e.g., if a crop yield seems implausible or unlikely.

The interview framework is designed to avoid known sources of error, including a tendency to underestimate or omit sources of income (Kasprzyk, 2005). Data checking is an essential part of the interviewer training process and takes place at all stages of field work and analysis. Data is consolidated, checked, and entered in the OIHM database on the day of collection. Where there is no plausible explanation for apparent inconsistencies, or where there appear to be gaps in the information, households are re-visited the following day. It has been found that, in nearly all cases, the information gap can be filled if households are given a clear explanation for the return visit.

Depending on the purpose of the research, additional focus groups are conducted, for example on water sources and costs, access to credit, use of fertilizer, etc. The approach is fundamentally different from the standard questionnaire approach, where the interviewer records answers (generally yes/no or a number) designed for automated processing. Interviews are held at a time that is convenient to the interviewee, and fatigue that can affect both the interviewer and interviewee is avoided by keeping interviews relatively short (most interviews are completed within an hour). At the end of the conversation, the interviewee, as well as the interviewer, will have an overview of his or her household's individual livelihood system and comments from the interviewee on the value of the interaction are not uncommon.

Whilst other methods of income measurement, for example the extrapolation of income from consumption data (Lipton and Ravallion, 1995; Baulch, 1996) may be useful for macro-economic accounting, these methods cannot be used with the same accuracy and specificity to assess livelihood vulnerability and resilience at household level. For this purpose, details of income sources are needed. Cognisant of known sources of error in the collection of household data (Moore et al., 2000; Kasprzyk, 2005), rigorous quality control checks and the use of analytical software in the field allows error sources to be quickly identified and corrected, for example, by re-visiting interviewees or by further contextual enquiry.

STANDARDIZED INCOME METRIC

A reliable measure of income is an essential, although not sufficient, in answering our research question "*What information do local policy and decision makers need now, to reduce vulnerability and enhance resilience*." To better understand the financial limitations on adaptation in our study communities, we use the standardized measure of "Disposable Income." In IHM studies, this is defined as the amount of money available to the household after its food energy requirements have been met, based on World Health Organisation (1985) reference values.

In rural areas in many developing countries, household income is made up of food produced or otherwise obtained by the household and consumed ("food income") and income in other forms—for practical purposes this means income as cash. A measure of household income requires a method of combining "food income" and "cash income" into a single result. This could be done by imputing a cash value for all food income and adding this to cash income. However, not all food produced in rural areas is traded so it can be difficult to price (e.g., wild foods, or in some places perishable foods such as milk). The alternative is to calculate the money left to the household after it has met its food energy needs, considering the kilocalorie (Kcal) value of food produced and consumed by the household. This is the approach used in IHM studies and is referred to as "disposable income."

$$\begin{aligned} &\textit{Disposable income} \\ &= \sum \textit{all household cash income} \\ &- \big[(\textit{household food energy requirement}, \textit{kcal} \\ &\quad - \sum \textit{all household food income},\ \textit{kcal}) \\ &\times \textit{price per kcal of staple diet}\big] \end{aligned} \tag{1}$$

The IHM data structure is shown in **Figure 2**.

Households that do not have sufficient income to meet their WHO reference standard food energy requirement are considered to be below the food poverty line. To allow for comparison between households of different size and demography, income is further standardized by "adult equivalent" (AE), giving disposable income (DI) per adult equivalent (DI per AE). Finally, a "standard of living threshold" (SoLT) is set. This represents the cost of a locally defined basket of essential items required to meet the community's norms for social inclusion. According to context, this generally includes items such as water, soap, fuel, sanitation, primary education, clothes, shelter, etc. Households that cannot afford the full set of items in the study year are described as being below the standard of living threshold. Information is generally collected for a twelve-month period covering the most recent "agricultural year," which is established in consultation with the study community at the start of the assessment. In longitudinal studies, the project baseline year is compared with subsequent years (e.g., Martin et al., 2009; Petty and Ellis, 2015b). This approach provides an easily understood indicator of a household's capacity to meet on-going costs, absorb the year on year impact of climate and other shocks, or invest in new enterprises.

The Study Context: Lake Victoria Basin

In line with the objectives of the HyCRISTAL project, the IHM studies were conducted as part of rural pilot studies in lakeshore

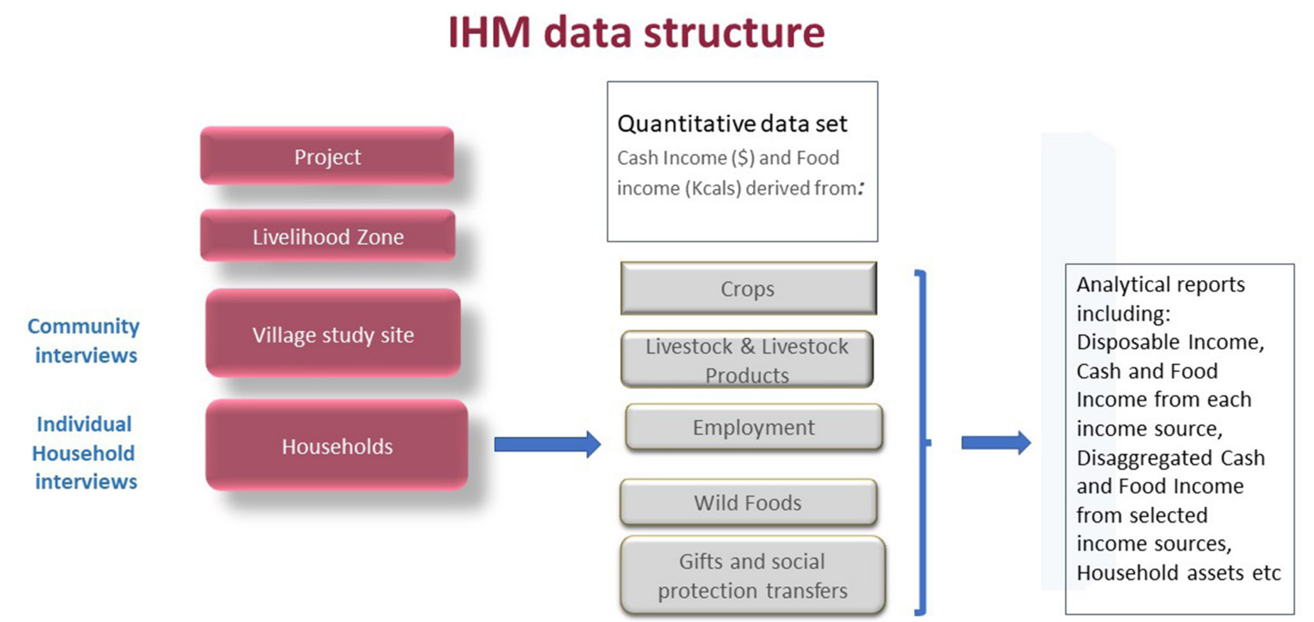

FIGURE 2 | The IHM data structure. Source: own elaboration based on images with "no copyright reserved" (Creative Commons Attribution Non Commercial No Derivatives 4.0 International license).

communities within the Lake Victoria Basin (LVB), between 2015 and 2018. The LVB covers an area of 194,200 km^2 and includes Kenya, Tanzania, Uganda, Burundi, and Rwanda. It has a population of around 45 million (World Bank, 2018) which is growing rapidly-for example, at around 3.2% per annum in Uganda (Worldometers, 2018). The area has been designated by the East African Community as an "area of common economic interest" and a "*regional economic growth zone to be developed jointly by the Partner States*" (Lake Victoria Basin Commission).[2]

Fisheries provide an important source of revenue for both national governments through fish exports and for local communities bordering the lake in Tanzania, Kenya, and Uganda. Between 2011 and 2014, estimated total fish landings from the lake was around 1 million metric tons, with a beach value in 2014 of around US $ 840 Million (Lake Victoria Fisheries Organisation Secretariat, 2016). Loss of habitat, the introduction of the invasive Nile Perch species and overfishing have all contributed to a decline in the fisheries industry in recent decades (Njiru et al., 2018). Policies and regulations introduced to address these issues and manage the fisheries sustainably are described by Njiru et al. as "*sectorial, disjointed and unharmonized and have not reduced the declining fish catch rates.*"[3]

Study sites within the basin are subject to different rainfall regimes and different dependencies on fishing and agriculture. With advice from colleagues leading the HyCRISTAL climate science work (Finney et al., 2019) and from local NGO partners, the search was narrowed down to Mukono District in Uganda and Homa Bay in Kenya. Mukono rainfall is more uniform during the year than Homa Bay, which experiences much larger contrasts.

National statistics indicate "average" poverty levels in Mukono (15–30% below the national poverty line) and a young population, with 52% of the population under 18 years (World Resources Institute, 2005; World Bank, 2016). Unicef data for Kenya show child poverty rates in Homa Bay, measured by "average deprivation intensity," slightly above the national average (UNICEF Child Poverty in Kenya, 2017). The proportion of the population under 18 years (59%) is also higher than the national average of 49% (Unicef, op.cit.). Rainfall at both sites is bimodal, with the peak rainy season from March to May ("Long Rains") and a second shorter season in October/November ("Short Rains"), although historically, rainfall has been more evenly distributed in Mukono than in Homa Bay. Average annual rainfall in Mukono is 1,390 mm and average annual temperature 21.5 degrees C (Mukono, World weather online).[4] Homa Bay has a slightly lower average annual rainfall of 1,200 mm with peaks in April/May and October/November. Average temperatures are around 22.5°C (Homa Bay, World weather online).[5]

The selected village sites were identified in scoping studies carried out in advance of field work (Acidri, 2015; Machuki and Owuor, 2017). The Uganda study was conducted in

[2]www.lvbcom.org/

[3]Our local studies, carried out in 2016 and 2018 corroborate this view. However, a clampdown on illegal fishing by the Ugandan government appears to be having an impact, and increased catches have been reported more recently, in both Uganda and Tanzania [Seafoodsource.com. (2021). https://www.seafoodsource.com/news/supply-trade/uganda-tanzania-report-increased-fish-production retrieved 16.7.2021].

[4]Worldweather online, Mukono: https://us.worldweatheronline.com/v2/weather-averages.aspx?locid=2534011androot_id=2529715andwc=local_weatherandmap=/mukono-weather-averages/mpigi/ug.aspx.

[5]World weather online Homa Bay: https://us.worldweatheronline.com/v2/weather-averages.aspx?locid=1312804androot_id=1312150andwc=local_weatherandmap=/homa-bay-weather-averages/nyanza/ke.aspx.

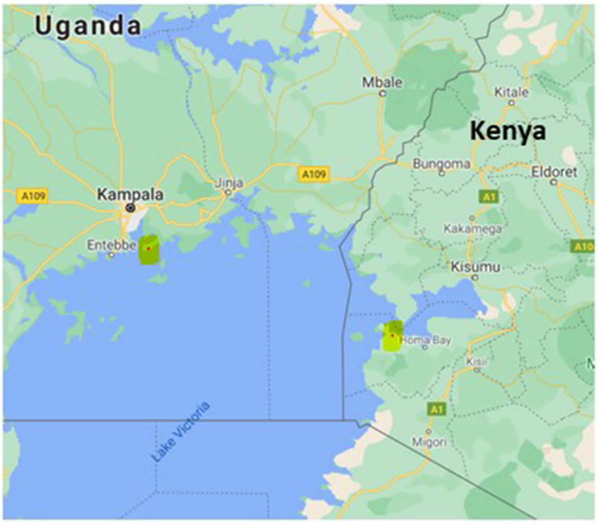

FIGURE 3 | BS (Uganda) and NB (Kenya). Source: Google maps. Authors' own based on images with "no copyright reserved" (Creative Commons Attribution Non Commercial No Derivatives 4.0 International license).

the "Fishing-forestry-sandmining" livelihood zone of Mukono District (Seaman et al., 2016) and the Kenya study in the "Lake Shore Fishing, Sandmining and Stone Quarry" livelihood zone of Homa Bay (Acidri et al., 2018). Criteria for selection included distance to Mukono town on Homa Bay (maximum 90 min drive) and rural rather than urban or peri-urban communities. We also wanted to study communities with a mix of both agriculture and fishing to include a wider range of potential climate-related impacts.

IHM Survey Implementation

Field research was carried out in two villages, shown in **Figure 3**. The Uganda site had over 200 households, so it was necessary to carry out a sample survey, rather than a whole village assessment.

A total of 105 households were interviewed and all were included in the final analysis. The Kenya site was a smaller community with just 53 households, so it was possible to include all available households in the survey. Due to the absence of some households, 41 households were included in the final analysis. The "absent" households were all identified as having their main residence and businesses in urban centers including Homa Bay town.[6] The survey teams were led by Evidence for Development (EfD) local associates, who are highly experienced practitioners with between 10 and 15 years in household economy survey work. They were supported by local partners from Gulu university and Maseno University who received additional on-site training as part of an on-going capacity building process.

The studies provide a contemporaneous, cross-sectional view of current socio-economic status in the 12 months agricultural year for which data was collected.

[6]Whilst they retained property in the village, resources were not available to establish further details of their interactions with the community.

Within the study populations, and in the study year, the main sources of income were recorded. Customized software was used to analyse how this income was distributed across the population, the disposable income available to households after their basic survival needs had been met, and the assets and natural resources to which households had access. This provided an indication of the potential impact of defined shocks (e.g., a fall in price or production of a main food crop; a pest infestation destroying an important cash crop) on population sub-groups.

Analysis of income source was also used to identify the specific sensitivities to, and potential vulnerabilities of, groups within the two sites which are exposed to a range of climatic and economic hazards. The agricultural years in both sites (2014–2015 in BS; 2016–2017 in NB) were described as "normal"—neither exceptionally good nor exceptionally bad—compared with recent years.

OVERVIEW AND DISCUSSION OF HOUSEHOLD ECONOMY FINDINGS FROM BS (UGANDA) AND HB (KENYA)

In this section, we look at the way in which disaggregated baseline household economy data can be used to assess the nature of economic vulnerability facing different sections of the population and the economic constraints on adaptation. We also show how this information can contribute to future climate risk scenarios or climate storylines [see Burgin et al. (2019)], and inform climate sensitive social protection interventions. We draw on the following analyses from more extensive case study working papers (Petty et al., 2016; Ngoleka et al., 2018) to address our key research questions:

- Disposable Income. This shows the cash available to households after food energy needs have been met, providing an indication of *the capability of households at different levels of income to adapt to changing conditions and invest in new activities*. Data is standardized per adult equivalent to enable a fair comparison between households of different size (**Figure 4A**).
- Detailed analysis of the main sources of cash income. This is an indicator of *household sensitivity to specific changes* (positive or negative) e.g., in market prices, fish catches, and lakeshore business revenues etc. (**Figure 4B**).
- Analysis of the main sources of food income i.e., food produced by the household and retained for its own consumption. This is an *indicator of market dependence and exposure to crop failure, market price increases etc*. (**Figure 4C**).
- Detailed breakdown of the main crops grown, used to identify *specific sensitivities to different shocks at different times of the year* (**Figure 6**).
- Asset holdings including land, livestock (**Figure 4D**), and major productive assets such as boats, motor bikes, agricultural equipment.

Whilst this is only a snapshot, the results for both communities indicate very low levels of disposable income in the bottom half of the distribution at both sites, with households

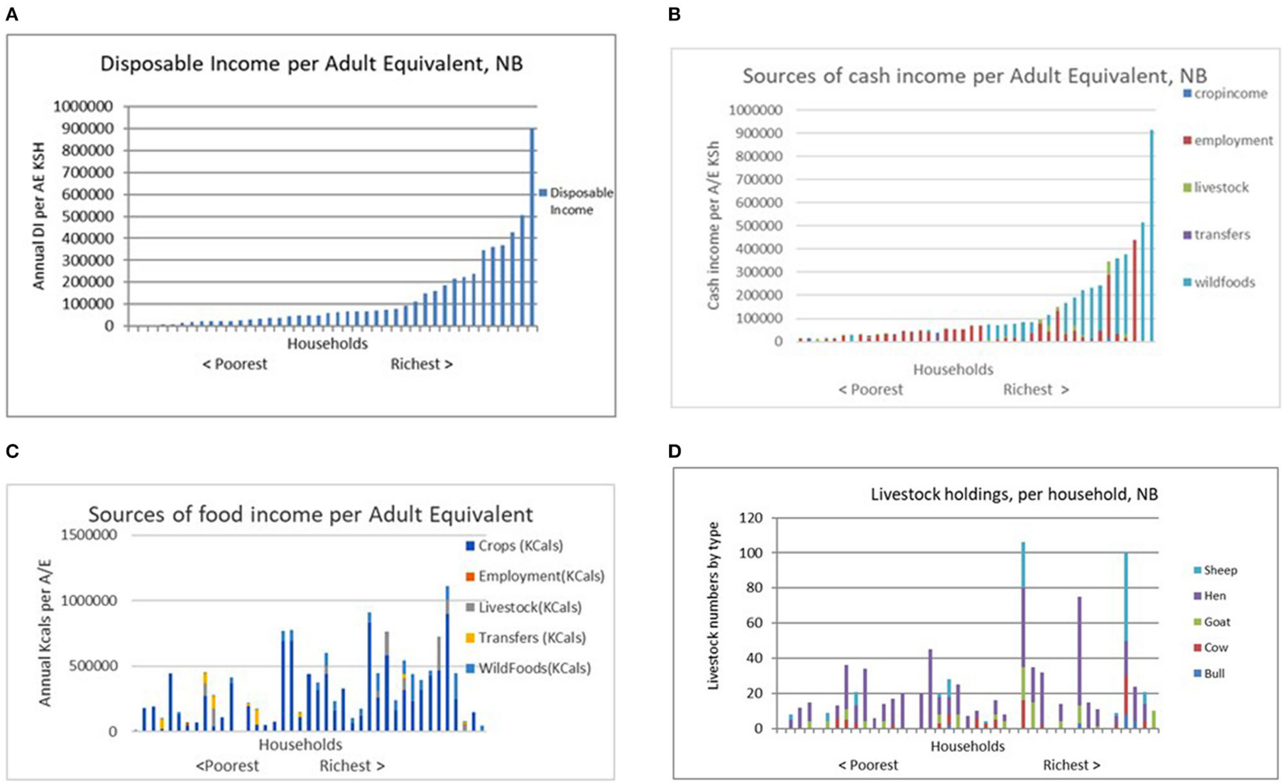

FIGURE 4 | Disposable Income, Cash Income, Food Income and Livestock holdings: Analysis from IHM reports, NB Village, Homa Bay. **(A)** Indicator: cash available for investment. **(B)** Indicator: sensitivity to cash income loss in different sectors. **(C)** Indicator: dependence on market purchase for food security. Annual food energy requirement per adult equivalent is just under 1 million kcals. **(D)** Indicator: assets, livestock holdings.

holding few assets: only those households at the top end of the distribution had significant discretionary income available for saving and investment. This finding is broadly in line with national poverty statistics outlined above.

Main Economic Activities, Assets, and Basic Needs: Summary of Results

Analysis showed that both study communities include mixed populations of fishers, farmers and households that combined both activities, along with others specializing in activities such as boat making and lakeshore enterprises, providing services such as cooked food, bars and restaurants. In both communities, higher levels of income from fishing were concentrated at the top end of the income distribution among boat owners. Poorer households derived their income from activities including day labor in agriculture or fishing, selling cooked food, petty trade, or small shops. In our study samples, professionals (teachers, government officials, health workers, etc) did not feature. The overall pattern of income distribution was similar in both sites, with a high level of income inequality.

Land and livestock assets were fairly evenly distributed in both lakeshore communities, and at both sites, plots were generally small (around 1.5 acres). This has limited the scope for investment in agriculture in the immediate lakeshore area, although two of the wealthier households at BS had landholdings outside their village. Population pressure was cited as a problem at both sites, which had resulted in division of land and smaller plots and, due to poor sanitation, was associated with increased lake pollution. In both communities, high levels of youth unemployment were also reported.

All households at both sites could meet food energy needs to WHO recommended standards (World Health Organisation, 1985) but in BS around 11% of households fell below the locally defined "standard of living threshold." These households did not have sufficient income, after meeting their food energy needs to cover the cost of all items needed to meet locally acceptable norms for "social inclusion." In NB, all were able to meet their basic food and non-food needs, according to the locally defined minimum standard of living, in the study year. This represents the minimum required for basic "social inclusion" and is not an aspirational level.

None of the study households were entirely "self-sufficient" in food and at both sites, households were dependent on market purchase for most of their food energy needs. In NB, households were able to produce, on average, around 46% of their food energy needs from their own crop production, supplemented in some cases by their fishing and livestock production. Around 20% of households produced vegetables for sale but only one household gained significant income from agriculture. Figures on market dependency were similar in BS. Low-income households

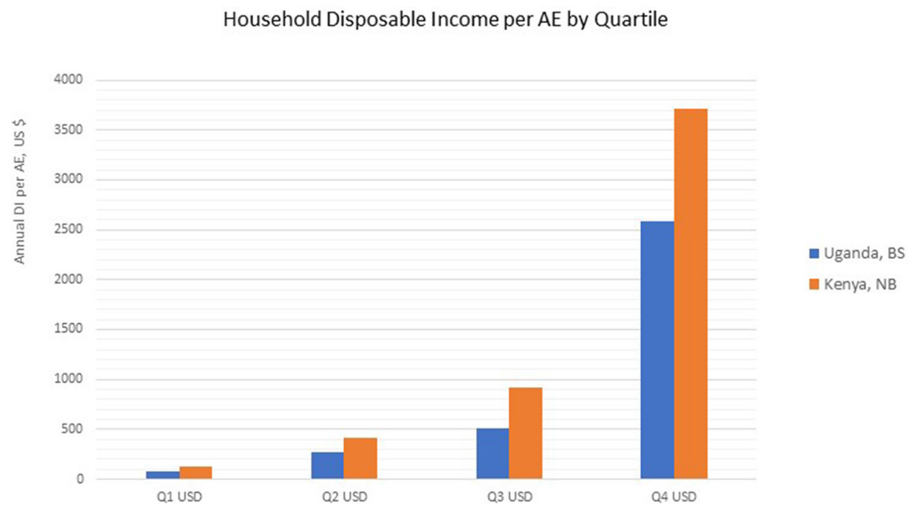

FIGURE 5 | Disposable incomes per Adult Equivalent (AE) by Quartile (Q) at the two study sites, BS and NB (Jan 2016 USD exchange rate).

at both sites would therefore be exposed to hardship if the price of staples were to rise, without additional cash from social protection programmes or other sources.

Demography

No single demographic characteristic typified poorer or better off households at either site.

Both communities have been badly affected by HIV/AIDS and there was a high number of female-headed households (10% BS and 20% NB), including households headed by grandmothers. Female-headed households were found across the income distribution, but there was a higher proportion of female-headed households in the lowest quartile, underlining the importance of gender disaggregation in policy focussed research. With its relatively high population of migrant fishers, single male households (mainly although not exclusively fishermen) were over-represented in the top quartile in BS. There were no single male households in NB.

At both sites, people under 25 years of age made up most of the population (74% in BS and 65% in NB). These figures reflect the extremely young populations of both countries.

Income Distribution

The shape of the income distribution curve is similar at both sites, with a substantial level of inequality between the disposable income of the poorest 50% and the richest households (see **Figure 5**).

Whilst average disposable incomes per adult equivalent are almost twice as high in NB compared with BS in all but the richest quartile, the cost of living was also higher in NB and it would therefore be wrong to assume that this community is better able to cope with shocks.

Data from both sites provides strong evidence of the income constraints that limit adaptation options for most households. At low levels of disposable income, the cost of investing in new enterprises, even with the lowest entry levels, was unaffordable. Contextual information indicates that start-up capital for enterprises requiring the lowest level of investment, such as petty trade in fish, was around US$95. The investment costs of enterprises with higher returns, such as bars or kiosks, was between US$500 and US$800. With start-up costs requiring either external support or years of saving, finding new income sources was limited to potentially negative coping strategies such as removing children from school, sand mining (which was an option at both sites), non-licensed brewing, etc.

Risk and Exposure

There is an extensive climatological and social science literature documenting the range of hazards to which communities in the Lake Victoria Basin are exposed: these include climatic and weather extremes resulting in drought, storms, and flooding, as well as crop pests and diseases. Environmental pollution and poor standards of regulation and governance add to these risks (Hammond and Xie, 2020). However, not all households are equally exposed to every hazard. Sensitivity to a specific event depends on its timing in the agricultural or fishing calendar, and the household's capacity to make up losses from other economic activities by selling assets or by calling on social networks to provide cash, food or loans. Government social protection programmes may be triggered in extreme circumstances, but their effectiveness depends on the type of assistance provided, and the accuracy of targeting. This in turn relies on reliable, location-specific livelihoods information.

To understand the nature of vulnerability and potential to adapt and diversify economic activities in the face of these and other threats, we looked at data on all sources of cash income and food income (food produced and retained for household consumption) at the two sites.

Sources of Food and Cash Income

The same pattern of cash and food income shown in the **Figures 4A–D** for NB (Kenya) was also found in BS (Uganda).

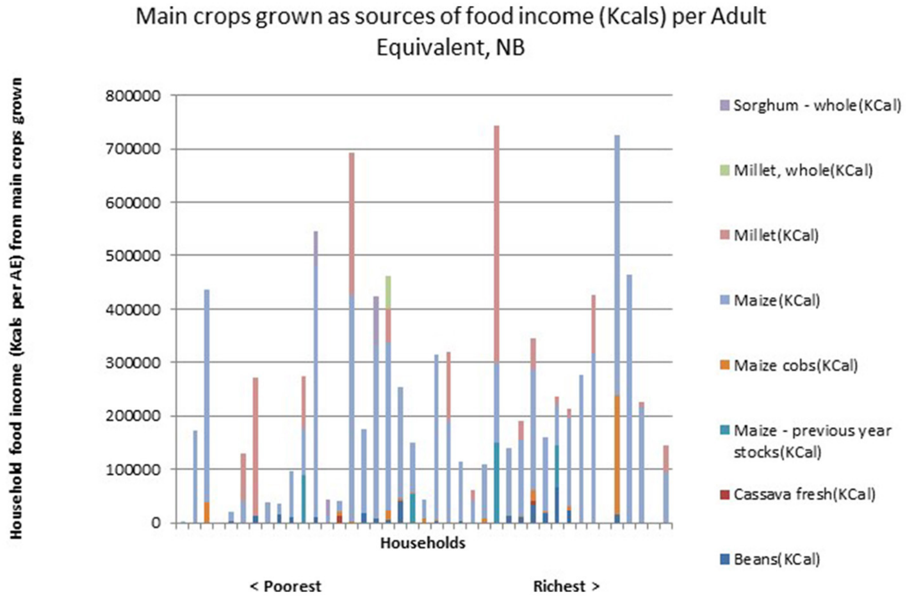

FIGURE 6 | Breakdown of main crops grown and retained for household consumption.

In common with many communities across the continent, household livelihoods and food security in BS and NB typically depend on multiple sources of income, including food crops grown for both the household's own consumption and for cash, and a range of on farm and off farm employment. The specific mix of income streams varies across the wealth distribution. For example, in BS, fishing (classified as "wild foods" in the IHM database) was the predominant source of income in the richest quartile. Many households in the middle of the distribution derived their income from a combination of employment (bars, kiosks, and restaurants) and farming, and poorer households were more reliant on day labor in fishing and agriculture, although most also grew some crops. In NB, better off households gained most of their cash income from fishing, whilst poorer households were largely reliant on employment in fishing and associated activities. In relation to resilience and exposure to hazards, specialization among better off households enabled them to accumulate wealth and invest in additional boats, fishing gear and labor. To understand the risks of specialization, additional work would be needed into how this groups invests its surplus cash, current debt levels, etc.

The risks facing households in the poorest quartiles are less ambiguous. The poorest households in NB were almost exclusively dependent on fishery-related employment and linked petty trade for their cash income, with small amounts of additional cash from transfers and sale of livestock products (mainly poultry). The main sources of employment were gender differentiated: for men, it was day labor in fishing, whilst for women, petty trade in fish, selling food and work in other lakeshore businesses. The poor, as a group, were therefore highly dependent, both directly and indirectly, on the success of the fishing industry. Poorer households in BS had more diversified sources of income, including more agricultural and off farm work. In this group, transfers (cash gifts from relatives) were also important for some households. However, at both sites, earnings among the poorest quartile were extremely low, leaving very little cash for investment in alternative livelihood activities.

Disaggregated, household level data on income of this kind can be used to model the immediate impact of defined shocks on current income levels across the population as a whole and indicate the level of social protection interventions that would be needed to mitigate the impact among poorer households lacking access to alternative sources of income. It can also be used for planning purposes, specifically in relation to climate adaptation. For example, cassava and tomatoes are both important cash crops in BS and tomato production has emerged as a local response to volatile global coffee prices and coffee wilt disease. However, tomatoes are drought intolerant and farmers in BS complained that without irrigation, increasingly erratic rainfall meant that the tomato harvest had become unreliable. Similarly, whilst cassava is more drought tolerant than crops such as maize, it is susceptible to waterlogging, so if climate change were to result in hotter, wetter conditions, this would make it a less viable option. This illustrates the dangers of "expert-led" adaptation where decisions require not only planning and investment, but also discussion led by community members who are aware of multiple factors impacting on adaptation pathways. This long-standing issue is discussed at length by Eriksen et al. (2021).

Food Income

Whilst the crops and livestock produced in the study sites are not a major source of cash income, staple foods are widely grown to provide some protection against potentially volatile market prices. A household's resilience and ability to mitigate losses will depend on it's capacity to replant, it's access to and ability to pay for alternative seeds, and it's access to labor, information and experience.

For example, **Figure 6** shows that in the study year, maize was the crop most widely grown as a staple food for household consumption in NB. However, this provides only a relatively small proportion (<40%) of the annual household food energy requirements of around 1 million kcals/adult equivalent for most households.

As households in NB are already highly dependent on the market to access their staple food needs, a fall in maize yields and/or any increase in the price of maize, would be felt sharply by households at the lower end of the income distribution.

A similar analysis of food income from the BS study showed that sweet potatoes were the most important staple crop among poorer households, whereas maize was more important among households in the top half of the distribution. Both staples are grown to reduce market dependence and have different climate sensitivities, resulting in different levels of exposure to climate related hazards.

These examples illustrate the need for greater integration of climate information and livelihood data for climate adaptation and resilience planning and for greater awareness of the factors affecting crop choice among different groups within the population. Understanding these factors requires complementary enquiries, using a range of different social science research methods.

Land and Livestock Assets

Access to land is limited in both BS and NB (around 1.5 acres on average) and availability of land for grazing was highlighted in BS as a major constraint in developing the livestock sector. In addition, very poor road transport infrastructure adds to both the time and cost of reaching markets from BS. The number of sheep, goats and cattle held per household are similar in NB and BS. Better off households do not have substantially larger landholdings than poorer households, although they are more likely to have cattle. In NB poultry are widely held and in larger numbers than BS, suggesting potential for commercial exploitation that could provide an important additional income source. However, poor market links and high interest rates are currently holding back local investment. At both sites, there are households in the wealthiest income quartile that do not have any landholdings; they derive their income entirely from fishing or from business enterprises. However, the opportunities for making significant returns on livestock investments for most people are negligible.

The story of changes in land ownership in BS is an interesting one, which illustrates an earlier period of "adaptation." Faced with falling fish catches, many landowners sold up in the 1990's, left BS and started transport and other business, mainly in Kampala, where new opportunities were opening up (focus group comms.). With a growing population, and migration from other parts of Uganda, the remaining plots have been divided into smaller units, with only small areas available for rental and little opportunity for business expansion.

Drivers of Adaptation and Diversification

Quantitative data of the kind we have described is needed to better understand current constraints on adaptation and income diversification, and to model potential future climate impacts on human populations (Enenkel et al., 2020), as well as the short term implications of natural disasters and other hazards. It also provides evidence of risk exposure among different sections of the population, potentially reducing opportunities for "elite annexation" of adaptation policies by wealthier groups, that may result in an increased gap between poor and rich (Eriksen et al., 2021). These studies have also shown the financial limits constraining poorer households' exercise of choice, in line with the findings of other micro-level studies of adaptation in Africa (e.g., Hisali et al., 2011).

Building on this work, we were able to incorporate approaches from the constructivist social science tradition to gain a deeper understanding of responses to changing economic and environmental conditions, mindful that income is a necessary but not always a sufficient explanation for these responses. We therefore asked older community members in the two study communities to look back and describe the main changes that had occurred during their lifetime, and we listened to younger women and men explain how they dealt with the challenges they faced in improving their economic circumstances. Finally, we heard from youth, many of whom were considering migration as the best route out of poverty.

A series of focus group discussions, differentiated by age and gender was led by local researchers (Achiro and Acidri in BS, Uganda, and Owuor with Ngoleka in NB, Kenya). The same protocol was followed at both sites. The issues raised in these discussions reflected local social, cultural and behavioral norms that had impacted on "adaptive" decisions, along with issues of governance, particularly in relation to the use of natural resources (overfishing and pollution). To put these in perspective, we set responses alongside quantitative data relating to the affordability of potential adaptation and diversification strategies (Petty et al., 2017; Ngoleka et al., 2018).

Key Findings of Focus Group Discussions

The discussions provided insight into the process of locally driven, endogenous change that had led to some shifts in both social and gender norms and inter-generational relations. The most notable change was in the economic activity of women outside the domestic sphere.

Older focus groups were asked to describe changes that had taken place in their communities in recent decades. As yields from traditional income sources had collapsed women described how they had become increasingly involved in petty trade and other enterprises. However, despite greater economic independence, younger female discussants described how legal and social constraints continued to limit their options, particularly in access to financial services. Participants in all focus groups referred to underlying problems including poor returns on investment, weak governance, and absence of infrastructure. In particular, young people felt their education had been neglected, leaving them ill equipped for the modern workforce and with poor chances of employment in their communities where there was no immediate prospect of investment or renewal.

Comments From Participants

In both communities, income from agriculture and fisheries had fallen dramatically due to crop disease, over-fishing, and changes in the global economy. This included the collapse of coffee prices in the late 1990's in BS, and in both study communities, pressures to meet fish export targets.

Older men focused on changes in traditional sources of livelihood security:

"*Fishing and farming have become less reliable sources of livelihoods due to lower stock of fish, more regulation of fishing and less land for agricultural activities, with unpredictable weather conditions.*" *BS*

"*Unpredictable weather patterns have also affected farmers in the village because of prolonged dry periods and sometime too much rain, hence farmers not knowing what to do.*" *NB*

"*Cash income is still derived from the same activities namely coffee and banana production. However there are attempts for diversification into intensive vegetable and other crop farming such as tomatoes, cabbages, beans, ...and cassava.... all this is on small scale due to limited capital for investment.*" *BS*

Women's perspectives were markedly different. They described how they had responded to the loss of income from fisheries and cash crops and how some traditional gender defined roles had changed as a result.

"*More women ... are involved in various business ventures that facilitate the family welfare not like 20 years ago when women relied only on the man as a bread winner.*" *BS*

"*Women start their own enterprises other than waiting for everything from the man.*" *BS*

Women also spoke of the empowerment that came with taking on economic roles outside their traditional spheres:

"*The women can now finance family activities including paying school fees. This is because they now are able to operate their own enterprises*" *BS*

"More businesses have come up in the present like hotel, saloon of which women can earn money from. All women can take advantage of this opportunities so as to be able to earn a living and not to depend on men as it was in the past." NB

However, using the IHM database, when we calculated for each income quartile the average income from the small business enterprises in which women were mainly involved, it was clear that returns from enterprises typically run by women were low, and would not finance business growth or diversification. **Tables 1**, **2** show start-up capital costs and average household incomes from the Uganda study site (BS).

Intersectional issues also became clear as groups discussed the legal and social norms that held back adaptation and entrepreneurship, restricting women's choices and limiting their options in seeking loans to finance new businesses. Comments from women included:

"Most women fear applying for these (Uwezo) funds due to fear of defaulting and government grabbing of assets like land, livestock, house items on failure to pay in time, strict rules and regulations on borrowing, high interest rates, 12%." NB

TABLE 1 | Enterprise start-up capital, BS.

Activities	Startup capital requirement	USD
Kiosk	2 million UGX	$540
Bar	3 million UGX	$810
Restaurant	2 million UGX	$540
Fish preservation	2 million UGX	$540

TABLE 2 | Average household disposable income by quartile, BS.[a]

Q1 UGX	Q2 UGX	Q3 UGX	Q4 UGX
949,692	3,168,807	6,796,452	20,899,304
($255)	($ 854)	($1,830)	($5,630)

[a] *These are absolute values/not standardized per Adult Equivalent (AE).*
Data from NB (Kenya) showed a similar pattern.

"Women's business doing well can easily be possessed by their husbands." NB

Pressures within the household also created problems for many women.

"Confiscation of household items sometimes leads to separation in the family particularly if the husband was unaware of the loan. It has led in occasional suicide due to frustrations and depression." NB

"The new challenges include among others overwhelming home responsibilities since they [women] can operate enterprises, and domestic violence when they fail to reach a consensus." BS

Women also cited fear of failure and social ridicule if enterprises were unsuccessful, and malicious gossip in relations to the financing of a new business.

Finally, with high levels of local unemployment, migration was seen as the only option by many young people. However young rural migrants were also at a disadvantage. In NB they spoke of lack of skills to exploit emerging opportunities in town, due to high levels of illiteracy and corrupt practices that allowed under-aged children to drop out of school and take up work in fishing. In BS the problem was that *"local people from places like [this] lack capital"*—and there was *"little industrial or agricultural development to provide jobs."* They also suffered from educational disadvantage, as English to at least secondary level is now necessary for jobs *"as low as a house help."*

Qualitative insights gained through these discussions highlight the importance of integrated analysis that gives weight to the lived experiences of individuals negotiating change and confronting socially constructed as well as natural hazards. By cross referencing data from the quantitative IHM study and providing space for local voices, we were able show how policy makers might access more precise information on the immediate, local factors that stand in the way of enterprise and adaptation. For wider civil society organizations the approach also provides hard evidence for advocacy and engagement with local political debate (Cornforth et al., 2021a).

IMPLICATIONS FOR POLICY

The focus of this paper has been on operational assessment methodologies that are designed to provide decision makers at local and national level with more granular insight into the structure of local livelihood systems. This information is critical in circumstances where many priorities are competing for limited budgets.

Here, we look at some of the underlying development issues that are impacting on the depleted livelihoods described in the previous sections and how policy relevant information generated in the case studies might inform future policy responses. Some of these involve multiple stakeholders working at different levels, others require decisions at national and international levels. For example, the consequences of government and donor under investment in education and rural infrastructure is illustrated by (i) the testimony of young people, whose life chances have been severely limited by the poor education they have received and (ii) by the low levels of household disposable income due to the absence of investment in sectors such as rural food processing. Investment in both these sectors would raise levels of household income in the short and long term. Green climate funds may offer new possibilities in relation to climate adaptation, particularly in providing sources of renewable energy and with this new employment opportunities and better connectivity. However, improvements in children's education will only follow if there is commensurate investment in teacher skills and IT equipment. The approach must be cross sectoral and interdisciplinary.

Evidence of the continuing undermining of development through gender discrimination in access to financial services is also a feature of both the quantitative and qualitative elements of this research. Removing these inequalities requires further action at national policy level, but also by local institutions implementing programmes and designing new, inclusive services. Failure to address this problem will continue to constrain women's entrepreneurship and their households' resilience.

The research highlighted underlying environmental problems requiring policy action. Specific issues were generally within the remit of local policy oversight but need cross-sectoral support from national and sub-national authorities to mitigate them. Examples included: illegal sand mining resulting in increased flooding of lakeshore communities; lack of sanitation and management of human waste; and overfishing. Quantitative income information is needed in the context of a systemic response to each of these environmental issues. For example, to "build back better," budget holders need to know the proportion of households that will need support to relocate or to better protect their homes from future flooding. It is needed to assess the economic cost of income lost due to water borne disease, strengthening the case budgetary case for public health improvements. Lastly, where illegal fishing is better regulated, those fishers who cannot afford the correct gear will be without an income. Household economy data can be used assess the cost and design appropriate social protection policies to support households in this situation.

In relation to increasing smallholder resilience at household level, an immediate dilemma facing many central and local policy makers in the global south, concerns the adoption by farmers of new climate-adapted seed varieties (Cacho et al., 2020). There are numerous reasons why farmers may choose not to take on the risk of planting unfamiliar varieties (Acevedo et al., 2020), or adopting an entirely new crop. However, a common problem relates to the cost of both seeds and/or inputs. The information in our case studies includes data, that could be used, on the basis of disposable income levels and distribution, to assess the proportion of households that could afford to purchase a new seed variety if they chose to, and the proportion that could not, even if they wanted to.

This has budget implications—should new seed varieties be subsidized? It also has implications for private sector seed distributors and for public-private partnerships in this area.

CONCLUSION

Our focus in this paper has been on the immediate question: "*What information do local policy makers need now to reduce vulnerability and enhance resilience?*" We have shown how quantitative household economy analysis can be combined with qualitative information generated through participatory social science methods, to provide policy relevant information on adaptation and resilience. For the first time, within the same study populations, quantitative IHM analysis highlighting sensitivities to specific shocks at household level has been complemented by qualitative analysis signposting ways in which mitigation measures might be more equitably targeted, gender and generational inequalities reduced, and policies to strengthen resilience more effectively implemented.

Policy makers need a far clearer map of the "vulnerability and resilience landscape" than siloed studies typically provide. We have shown how key findings of quantitative analysis, combined with insight into local norms and legal and institutional barriers, throws a very specific spotlight on areas where action could remove immediate obstacles to adaptation and change. Underlying issues of chronic poverty, however, require long term investment and commitment from local to national, and international public and private sector institutions. Green development funds offer opportunities to address this problem, although implementation continues to be slow and problematic (Caldwell and Larsen, 2021).

The two study communities have faced multiple stresses over the past three decades, with some, but by no means all, attributable to climate change. In BS, conflict, and post conflict migration in the 1990's coincided with the collapse of global coffee prices, market liberalization and widespread plant disease, which removed the main source of income and economic security from many households. Returns from fishing were also falling, leading some households to "adapt" by selling their main asset (land) to migrants and moving to urban areas. Those who remained have faced further decades of decline in both fishing and agriculture. Female-led small enterprise has gone some way to bridging the gap in household income, but returns for most activities are extremely low, and prospects for the rising generation are poor. NB has also experienced challenges, many of which relate to environmental degradation, rapid population growth and a lack of investment in the infrastructure needed to connect rural enterprises in this community with the wider economy. Here too, female entrepreneurship has softened the economic impact of change. However, without external assistance or unforeseen innovation, adaptation to climate and other shocks appears to be reaching its limits. Whilst greater female involvement in small business has contributed to a shift in gender dynamics at household level, overall income and returns on investment across the commercial and agricultural sectors are low and fisheries have been depleted. For the younger generation, options are particularly bleak. Given the extremely high proportion of the population under 25 years, youth unemployment is likely to dominate the political agenda in the coming decade and require targeted youth-focused economic investment.

The framework we have described shows how established research tools rooted in both the positivist and constructivist traditions can combine to provide a deeper, policy relevant understanding of fundamental questions relating to the boundaries and opportunities of adaptation. These studies provide detailed socio-economic data which is contributing to inter-disciplinary storyline work (Young et al., 2020), on-going policy and advocacy work in Uganda (Cornforth et al., 2021a) and finally, to modeling the livelihood impact of climate change in the Lake Victoria Basin and beyond (Cornforth et al., 2021b; Hinkel et al., 2021). Most importantly, they also provide evidence of community readiness to adopt new livelihood strategies where these are practical, affordable, and contribute to the household's social and economic well-being.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by SAPD Ethics Committee University of Reading. The Ethics Committee waived the requirement of written informed consent for participation.

AUTHOR CONTRIBUTIONS

CP led research design, analysis, writing, and directed quantitative field work in Uganda. SN led quantitative field work in Kenya. EA and JA led qualitative work in Uganda and contributed to quantitative field research at all sites. JO contributed to qualitative research at all sites. RC supported research design and implementation and contributed to the text. AA and GW contributed to qualitative research design and structuring of the paper. All authors contributed to the article and approved the submitted version.

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Contributions to the Improvement of Climate Data Availability and Quality for Sub-Saharan Africa

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Reliable weather observations are the basis to assess climate change and variability. Compared to other regions of the world, long time series of weather observations are sparse in many countries of Sub-Saharan Africa. Various activities at national or international level are ongoing to improve the availability and quality of climate databases. Here, we present ongoing international contributions with a focus on representative examples hosted at Germany's national meteorological service DWD (Deutscher Wetterdienst). The international exchange of monthly climate reports (CLIMAT) is monitored within the Monitoring Centre of the GCOS Surface Network (Global Climate Observing System). In that context also quality control is performed and data are made publicly available. Recent climate observations can be complemented by digitization of historical hand-written weather observations which are available in distributed archives. International data centers, such as the Global Precipitation Climatology Centre (GPCC), collect international data. They perform quality-control of these observations and provide derived products in support of global and regional climate assessments. These activities can also contribute to the improvement of national climate databases, as e.g., demonstrated in a cooperation among selected countries with the SASSCAL initiative (Southern African Science Service Centre for Climate Change and Adaptive Land Management). Satellite-based observations are an additional source that can provide climatological information for selected parameters. In particular, the METEOSAT satellite series provides valuable data for the African continent. The Satellite Application Facility on Climate Monitoring (CM SAF) provides high resolution climate data covering the last decades derived from observations of such meteorological satellites. Based on these examples the paper illustrates the variety of ongoing international efforts in support of regional observation-based climate information, but also identifies the needs for further activities.

Keywords: climatology, climate data, climate monitoring, weather observation, Africa, precipitation, data rescue, satellite climatology

INTRODUCTION

In recent decades the mean temperature of the African continent has increased at a rate comparable to that of most other continents (WMO, 2020). Ground-based meteorological observations are relevant for reliable assessments of regional climate change and a wide range of other applications. Such observations are typically performed by national meteorological and hydrological services (NMHSs) that are responsible for the operation of the national observation networks. Providing long-term statistics and assessing long-term climate change requires availability of long time series of appropriate quality. Several meteorological tasks rely on international data exchange, e.g., to be used for data assimilation in numerical models or for global climate monitoring. Exchange of climate data from surface stations is organized within the Global Climate Observing System (GCOS: Karl et al., 2010).

The GCOS Surface Network Monitoring Centre (GSNMC) monitors the exchange of monthly climate reports ("CLIMAT"). These data are collected, quality-controlled, archived and published through international data centers. However, the length and completeness of the time series depends on the region. Another option to compile long-time series of station data are historical observations in hand-written form that are available in the archives of meteorological agencies. Such documents from various countries are also available in archives of DWD and efforts are ongoing to digitize these data. Additionally, historical observations taken from ships can provide climatological information over oceanic areas. Several international data centers collect recent observations and historic time series of meteorological data and use them to derive assessments of climate and climate change at the regional and global scale. One example is the Global Precipitation Climatology Centre, operated under the auspices of the World Meteorological Organization (WMO) and hosted at DWD. It has a collection of historic precipitation series that allows it to generate monthly fields of global precipitation back to 1891. It receives current observations and performs quality-control of these precipitation series. The series are finally used to provide various gridded products with global coverage. In addition to ground-based observations, satellite observations can also provide climatological information for selected parameters. Meteorological satellites have now been in operation for several decades. The Satellite Application Facility on Climate Monitoring uses data from meteorological satellites to derive climatological data products of various meteorological parameters. In particular the series of METEOSAT satellites provides good coverage and resolution also for Africa. Among those parameters, especially surface radiation is of high relevance for practical applications, e.g., in the context of renewable energy assessments or for estimating evaporation in applications in the water or agricultural sectors.

Here, we provide an insight into activities at DWD that contribute to an improvement of meteorological data availability and quality in Sub-Saharan Africa. These examples cover a wide spectrum from data rescue of historical observations to reprocessing of satellite data and are therefore representative examples for international activities in support of climate data availability and quality in Sub-Saharan Africa.

The Section "International Availability of Regional Climate Observations" provides information on the status of regional data availability based on the monitoring activities of the Global Climate Observing System (GCOS) Surface Network Monitoring Centre (GSNMC). The Section "Data Rescue and Digitization of Historical Observations" illustrates how data rescue activities contribute to complementing historical time series. The Section "Activities and Regional Products of the Global Precipitation Climatology Centre" describes how such collections of weather observations are used by the Global Precipitation Climatology Centre to derive information on regional precipitation. The Section "Cooperation Among Meteorological Services" provides examples on the use of these data sources to improve the data availability within national meteorological services within the region and provides some additional examples of international cooperation. The Section "Satellite-Based Climate Datasets" illustrates how satellite-based information can complement the ground-based observations. Conclusions are drawn in Section "Summary and Conclusions".

INTERNATIONAL AVAILABILITY OF REGIONAL CLIMATE OBSERVATIONS

International exchange of climate data from surface stations is organized within the so-called "Global Climate Observing System (GCOS)." One element is the GCOS Surface Network (GSN), which is a global baseline network comprising a set of about 1,000 selected weather stations. The selection aims at a fairly uniform spatial coverage in all regions, preferably based on stations with appropriate data record length and quality.

A particular product of these stations are the so-called monthly CLIMAT messages that include monthly averages, extremes and threshold exceedances of meteorological observations of the previous month from a weather station (WMO, 2009). A CLIMAT message starts with the date (month and year) of the included climatological data and comprises several meteorological parameters. Some are mandatory such as the monthly mean of air pressure and temperature, precipitation total and sunshine duration. Others are optional, for example the days with values beyond certain thresholds as well as the maxima of different parameters. Additionally, the climatological normals of the reference period shall be included.

CLIMAT messages are disseminated by weather stations which belong to different observation networks (acronyms of the specific networks are: GSN, RBCN, AntON or CLIMAT) and are distributed on a monthly basis by NMHSs in bulletins *via* the Global Telecommunication System (GTS). In 2019 WMO started a trial phase to exchange monthly reports of daily climate data (DAYCLI). This data will complement the CLIMAT messages and it is foreseen that the operational exchange of DAYCLI *via* the GTS will begin in 2023.

The GCOS Surface Network Monitoring Centers (GSNMC, operated by DWD and the Japan Meteorological Agency JMA) monitors the global exchange of CLIMAT reports. Transmission,

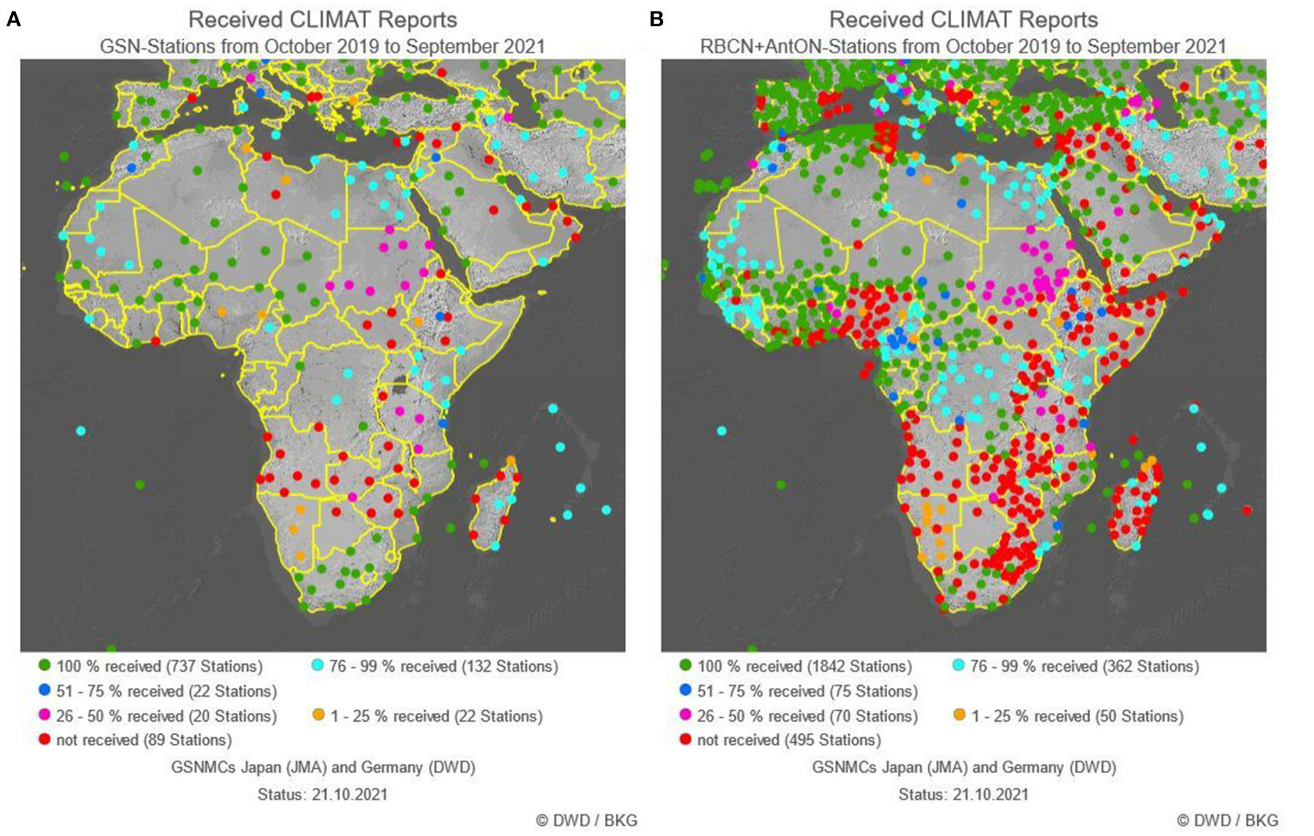

FIGURE 1 | Percentage of monthly CLIMAT reports that have been received by one of the monitoring centers (at DWD and JMA) for the period October 2019 to September 2021 (i.e., a 24 months period). Percentage refers to the expected number of reports from each station. **(A)** Percentage of GSN-stations, **(B)** percentage for the RBCN- and AntON-stations. Both figures produced via the interactive website of the GSNMC: https://www.dwd.de/DWD-GCOS/EN/nationalcontributions/servicesforgcos/centresforqualityassurance/gsmnc/gsnmc_monitoring_produkte/gsnmc/climat_avail_new/climat_avail_node.html.

completeness and quality of CLIMAT data are monitored, and coding corrections made where possible. After such quality-control procedures, these data are consolidated and archived. The time series of these data are available at international data centers, but length and network density depend on the region.

Alongside the GSN, the nearly 3,000 stations in the Regional Basic Synoptic Network (RBCN) are also expected to produce monthly CLIMAT reports.

The **Figures 1A,B** show the availability of monthly CLIMAT reports that have been received by one of the monitoring centers (at DWD and JMA) for the period October 2019 to September 2021 (i.e., 24 months period). The Figures show the percentage of the received reports (relative to the expected number of reports from each station). **Figure 1A** shows the percentage for the GSN, whereas **Figure 1B** shows the percentage for the RBCN- and AntON-stations. The Figures indicate significant differences in the amount of data received from different countries in Sub-Saharan Africa. For some countries no data is received, but for several countries data from several national stations have been received and are therefore available at the international level. Quality-controlled data sets from the GSNMC are made publicly available e.g., *via* the open data server of DWD's Climate Data Center (https://opendata.dwd.de/climate_environment/CDC/observations_global/CLIMAT/).

In order to feedback monitoring results from the GSNMC to the local network operators, regional CBS Lead Centers for GCOS have been designated by WMO to liaise with National Focal Points for GCOS, and other responsible officials, to improve data and metadata availability and quality. For Africa, two CBS Lead Centers were established, one in Morocco for northern Africa and a second one in Mozambique for southern Africa.

The need for improvement of local capacities for data handling and transmission has already been identified and initial steps have been undertaken (see section "International Cooperation").

DATA RESCUE AND DIGITIZATION OF HISTORICAL OBSERVATIONS

Background

For assessments of long-term climate change, the observational time series should be as long as possible. Early observations are available for many regions in the world, but are often not yet available in digital form and the original documents from various countries might be archived at different places and in some cases even not yet identified (Brönnimann et al., 2018). The portal of the "International Data Rescue (I-DARE)" project provides an overview on the status of past and present

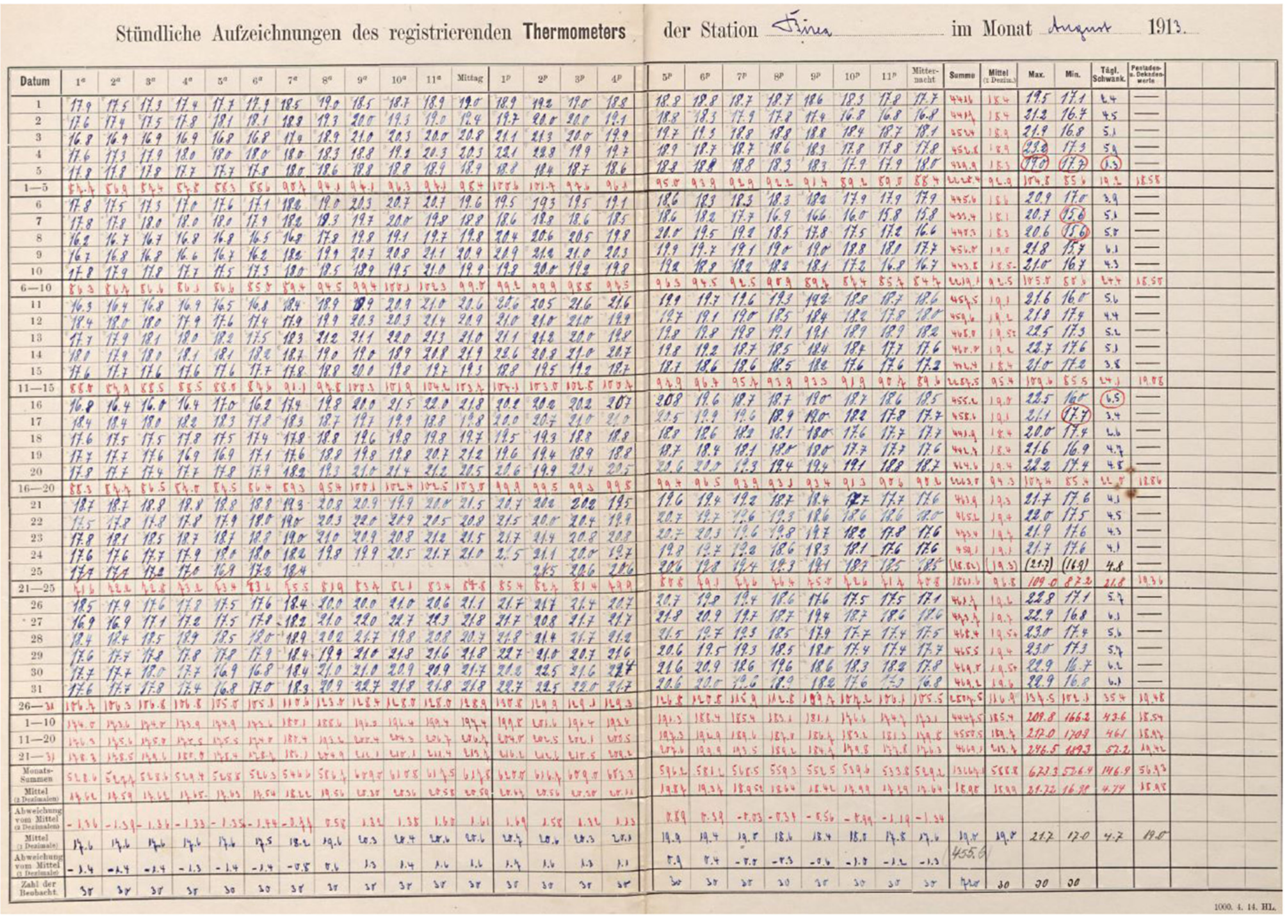
Stündliche Aufzeichnungen des registrierenden Thermometers der Station Buea im Monat August 1913.

FIGURE 2 | Hourly observations of the recording thermometer (thermograph) at station Buea (Cameroon) in August 1913.

worldwide data rescue projects and on known archives with historic weather data that are valuable to be rescued (https://www.idare-portal.org/). DWD houses huge archives of historical handwritten journals of weather observations originating also from the activities of his predecessor organizations. These archives do not only comprise observations from Germany, but also of the oceans and land stations in many parts of the world. Similarly, such historic observations can be found in archives of other national meteorological services. Some efforts to digitize the observations have been ongoing for decades and in recent years these activities were extended to previously untouched archive collections. An overview of DWD's data rescue activities was presented in (Kaspar et al., 2015a). International observations are part of the marine archive (located in DWD's branch office in Hamburg) which contains (among others) the collections of the German Naval Observatory, "Deutsche Seewarte," a predecessor of DWD that existed from 1868 to 1945 in Hamburg. It includes meteorological data records from ships, as well as from land stations in many parts of the world (e.g., from former German colonies). The archives therefore also contain observations taken in Sub-Saharan African countries and also from the adjacent oceanic areas. The following sections provide further details on the specific collections.

The digitization process is a labor-intensive and therefore time-consuming activity, as at the current stage it can only be realized by manual key entry. To illustrate the typical appearance of such handwritten documents, **Figure 2** shows an example from Cameroon (hourly temperature, taken in August 1913).

Observations of Historic Land Stations

The archive of the German Naval Observatory contains a collection of weather observations from more than 2,000 so-called "overseas" stations in many parts of the world, mainly in the former German colonies, including several countries in Sub-Saharan African. The "Deutsche Seewarte" equipped those stations with calibrated instruments and the meteorological observations were performed according to standardized rules. The archive contains climate data from the period 1830 to 1945, mainly from 1890 to 1945. Until now, more than 2,000 stations have been identified in the archive and data from 764 stations has been digitized in total (status: August 2021). About 1,700 of these stations are located in Africa and more than 400 are currently in the process of digitization or have been completed. The majority

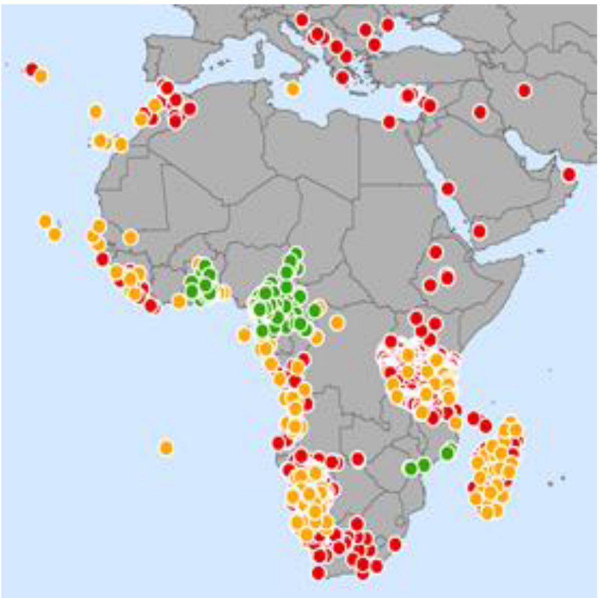

FIGURE 3 | Station location and status of digitization effort for historical stations in the archive of DWD. Colors indicated the status as of 8/2021: Green, digitized and quality controlled; yellow, in progress; red, not yet digitized.

of the stations were located in Cameroon, Namibia and Tanzania. The stations were either set up as permanent stations measuring for several years, but also as interim or scientific stations for shorter periods of <1 year. Depending on the station type, either only precipitation was observed or a set of parameters including precipitation, temperature and weather data. **Figure 3** illustrates the locations of the stations and the current status of the digitization process. **Figure 4** shows the data availability over time in the major regions of Africa.

Meteorological Ship Logbooks

The archive of historical ship logbooks consists of several ship logbook collections from 1828 to 1945. As well as the overseas stations, the archive originates from the Deutsche Seewarte. With a stock of more than 37,000 meteorological ship logbooks, it is one of the world's largest archives of this kind. The first observations are from regular nautical logbooks. Similar to the standardized meteorological logbooks that were introduced by Maury (1840–1860), the German Marine Observatory started in 1868 to provide their own meteorological journals to German merchant ships. The majority of journals had been provided starting around 1870. After World War II, the marine-meteorological observations were continued by DWD.

The total number of marine observations in the historical archive of the Seewarte is estimated to be at least 23 million observations, and likely to be considerably more. Efforts to digitize the logbooks started in the early 1940s by transferring the data to punch cards. Since then, the digitization effort has been continued at DWD in several phases. Until now, about 15 million observations have been digitized and are collected in a digital data base. **Figure 3** shows the geographical distribution of the digitized data. In particular, along the shipping routes around the Cape and to the former German colonies a substantial amount of historic marine meteorological observations provides important information about the climate and weather conditions for Africa.

A sophisticated workflow has been established to digitize the contents of the ship journals, consisting of several steps: gathering all metadata for a specific logbook, optical scanning of the logbooks and finally transcription (keying) of the contents. All digitized data from each step are stored in a database system. Finally, quality-controlled data are included in the DWD's marine meteorological archive as well as provided to the International Comprehensive Ocean-Atmosphere Data Set (ICOADS, see: Freeman et al., 2017).

Challenges in Digitization and International Cooperation

Digitization efforts, not only at DWD, have been ongoing for decades in different projects (Allan et al., 2021). Consequently, the different data archive contents are fragmented, e.g., some documents were only partly digitized, or the database entries originate from different phases of digitization activities. For other datasets, the links to the respective metadata records have been lost over time. In the course of data exchange programs, some data has been duplicated in several archives. Hence, a further challenge, in addition to the integration of newly digitized data, is the consolidation and homogenization of these existing data archives.

The digitization effort of DWD still relies mostly on keying the observations by hand. Old German handwriting and varying data sheet layouts are still a challenge for automatic text recognition systems, which may be overcome by new techniques in the future, with the potential to significantly speed up the transcription process. However, the (meta)data management of the rescued data, as well as the handling and scanning of the old and fragile documents will continue to require a lot of careful work to create modern data sets of high quality from these valuable historical data sources (see also Allan et al., 2021 for further examples).

ACTIVITIES AND REGIONAL PRODUCTS OF THE GLOBAL PRECIPITATION CLIMATOLOGY CENTRE

International data centers do not only collect and control weather observation; some of them also derive products in support of global and regional climate monitoring. One example is the Global Precipitation Climatology Centre (GPCC), which is operated by DWD under the auspices of the World Meteorological Organization (WMO). As final products, the GPCC provides global precipitation analyses for monitoring of the Earth's climate and related research. To achieve this aim, station-based precipitation observations are obtained from different sources, primarily from national meteorological services. The GPCC data archive is by far the largest worldwide for precipitation. The observations are quality-controlled,

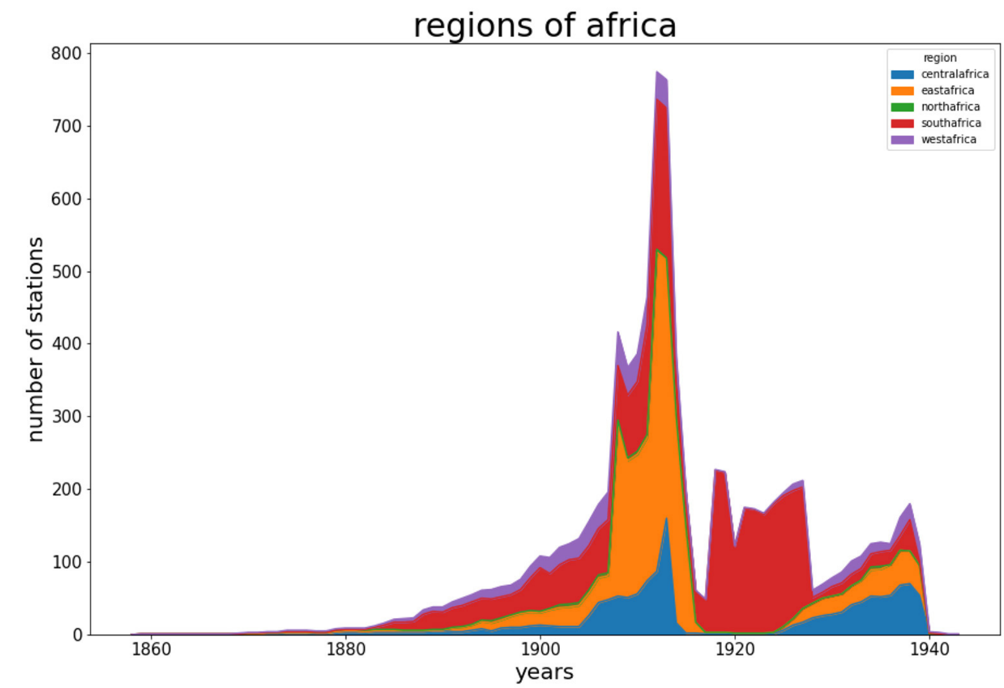

FIGURE 4 | Availability of hand-written observations in the archive of the German Naval Observatory per year. The graph shows the number of stations in specific regions of Africa. The archive contains data from the following countries which are summarized by regions (stacked in the following order); (blue: Central Africa): Angola, Cameroon, Congo, Gabon; (orange: Eastern Africa): Ethiopia, Kenya, Tanzania; (green: Northern Africa): Egypt, Morocco; (red: Southern Africa): Madagascar, Mozambique, Namibia, South Africa, St. Helena; (purple: Western Africa): Benin, Cape Verde, Equatorial Guinea, Ivory Coast, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Senegal, Sierra Leone, Togo.

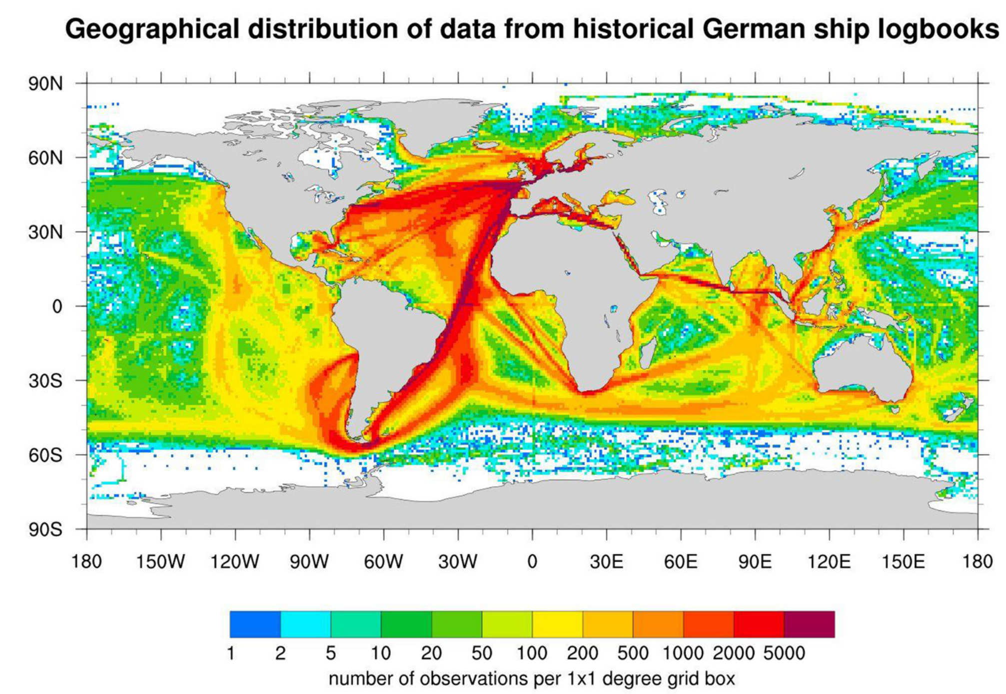

FIGURE 5 | Geographical distribution of observations from historical ship logbooks digitized by Deutscher Wetterdienst (Status: 2021).

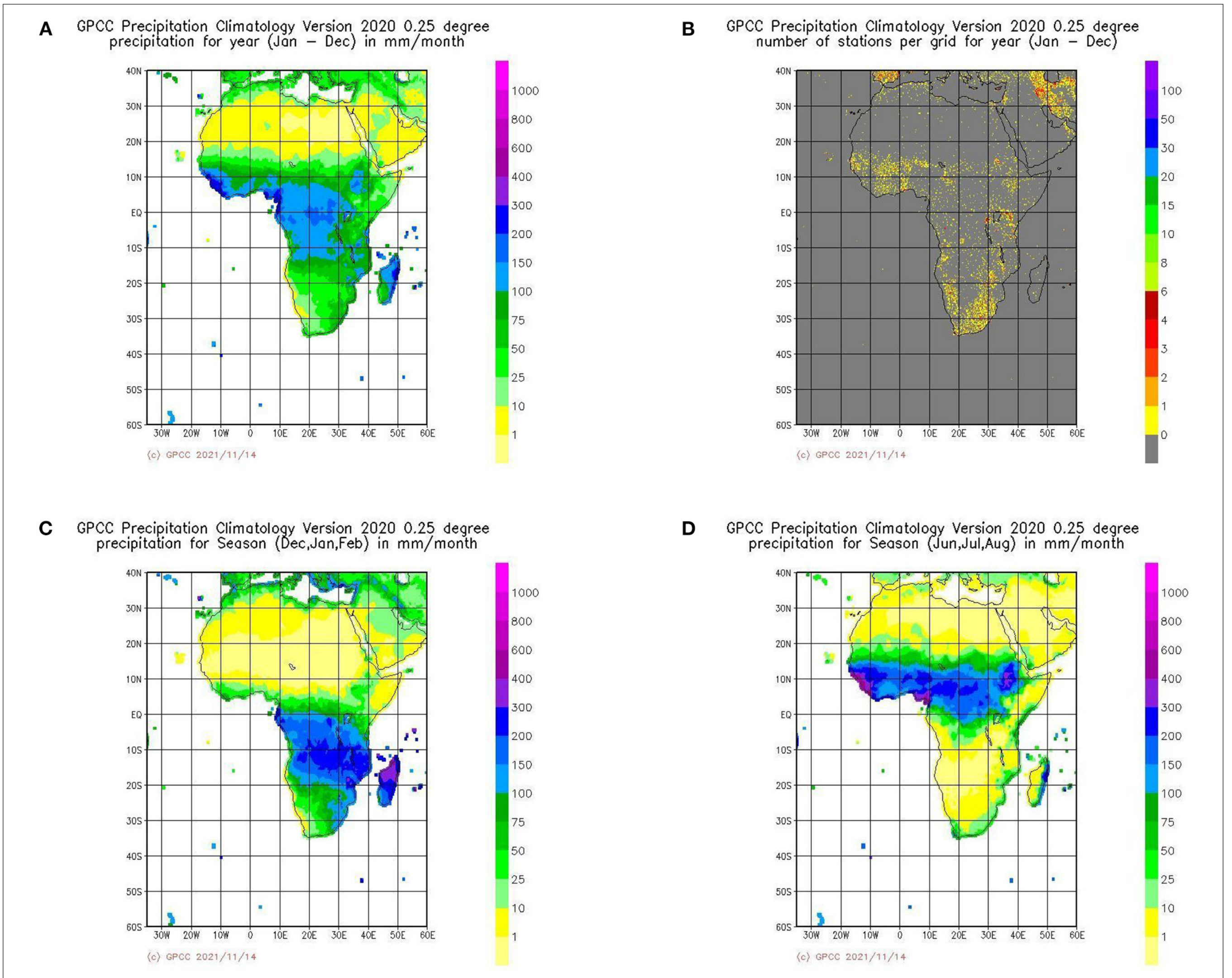

FIGURE 6 | (A) Long term annual mean precipitation in Africa according to GPCC climatology - version 2020. **(B)** Number of stations per 0.25° grid cell used for the production of the climatology - **(C)** Long term mean precipitation for the season December, January, February. **(D)** Long term mean precipitation for the season June, July, August in Africa (https://kunden.dwd.de/GPCC/Visualizer).

eventually corrected, archived and used to derive various gridded precipitation products for the Earth's land-surface, as e.g., monthly means. As an example, **Figure 6A** shows the long-term annual average precipitation in Africa on a spatial grid with 0.25° resolution. **Figures 6C,D** show the long-term average precipitation for two seasons (December, January, February and June, July, August) and illustrate, for example, the regionally pronounced change between dry and rainy seasons. **Figure 6B** shows the stations that were used for the production of the gridded dataset.

The products of the GPCC are disseminated under an open data policy. However, the original station data are not published, as the GPCC does not claim copyrights on acquired data. GPCC applies a general policy not to pass any original station data but is in the position to provide data back to the original suppliers or country of origin, if requested (Becker et al., 2013). GPCC can thus support the development or improvement of national climate databases, as was already the case for Angola, for instance (Posada et al., 2016). In such cases, the national archives also benefit from the quality improvements implemented by GPCC.

The main steps performed at GPCC are:

1. Acquisition of precipitation data from meteorological and climate observation networks.
2. Quality-control and assessment of the collected data and correction of errors.
3. Estimation of a correction with respect to systematic gauge measuring errors.
4. Calculation of various gridded precipitation products for the Earth's land-surface, as e.g., monthly means; including error assessments at the gridcell level for some products.
5. Dissemination of the products under an open data license.

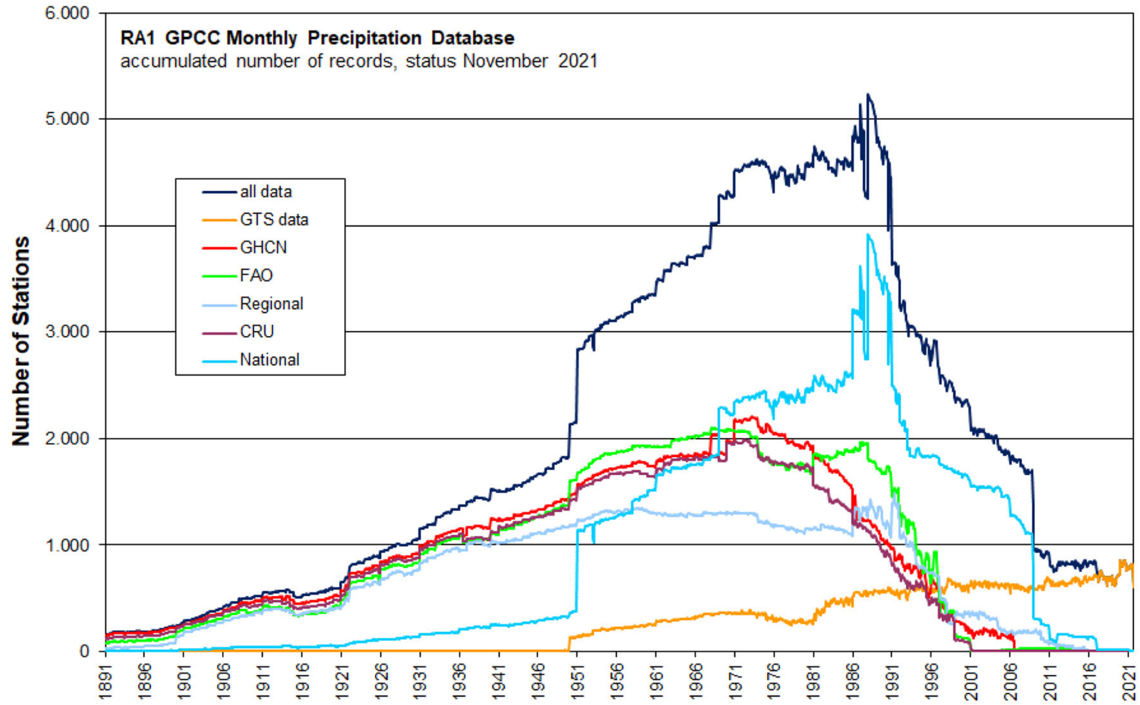

FIGURE 7 | Number of stations per year in the GPCC data base per data source for WMO-region "RA 1" (Africa) and accumulated amount (dark blue). GTS, Global Telecommunication System; GHCN, Global Historical Climatology Network; FAO, Food and Agriculture Organization; CRU, Climatic Research Unit.

A variety of products are available that differ with regard to the underlying data, the temporal and spatial resolution and the intended application purpose. For near-real time products only a reduced amount of data is available with sufficient timeliness. They are therefore also produced at reduced spatial resolution. The full product portfolio is described in Schneider et al. (2016) and Becker et al. (2013) or on the website of GPCC (https://gpcc.dwd.de). Products with high relevance for Africa (but typically covering all inhabited continents) are:

- The "GPCC Climatology" provides gridded fields of monthly long-term climatological means with a spatial resolution up to 0.25°. It is based on monthly means focusing on the period 1951–2000 for ∼85,000 stations worldwide (see Schneider et al., 2014 for a detailed description of an earlier version). Beyond its application as a reference climatology the dataset is also used as background fields for the anomaly interpolation of other GPCC products. **Figures 6A,C,D** shows the climatology for Africa for the annual mean and two seasons. **Figure 6B** illustrates the underlying density of stations.
- The "GPCC First Guess" products (daily and monthly) are based on synoptic weather reports (SYNOP messages) of ∼7,000 stations (worldwide) arriving at DWD via WMO's Global Telecommunication System (GTS) in near-real time after observation. Maps and data products in a resolution of 1° are available within 5 days after the observation month and can therefore be used for applications that require high timeliness, e.g., drought monitoring (Schamm et al., 2014).
- The "GPCC Full Data Monthly" product provides monthly fields in a resolution of up to 0.25° for the period from 1891 onwards and is based on quality-controlled data from all stations in GPCC's database (with a maximum number of more than 53,000 stations in 1986/1987). The product is thereby optimized for applications that require best spatial coverage, e.g., verification of models or for analysis of historic global precipitation or research concerning the global water cycle.
- The "GPCC Full Data Daily" product provides daily information of global land-surface precipitation in a resolution of 1° and is based on data provided by national meteorological and hydrological services, global and regional data collections as well as WMO GTS-data. The temporal coverage of the dataset currently starts with January 1982.
- The "GPCC Drought Index" is a standardized anomaly of precipitation and potential evapotranspiration relative to long term means to be applied for, e.g., drought monitoring (Ziese et al., 2014). It is available in a version with high timeliness and a version regarding long term means for the period from 1952 onwards. Aggregation periods of 1, 3, 6, 9, 12, 24, and 48 months are calculated.

Figure 7 shows the number of stations in Africa per year that are available for the generation of these products. Near-real time products ("first guess") are based on observations received via WMO's Global Telecommunication System (GTS data). For the "Full Data" products, additional stations are available, which have been integrated into the archive based on national contributions and by integrating data from international databases. The contributions of the National Meteorological and Hydrological Services are an essential part of the database. Overall, GPCC received monthly data from about 4,500 stations in Africa for the period 1971–1990 and from a maximum of over 5,000 stations. In earlier and later years, the number of stations is smaller.

COOPERATION AMONG METEOROLOGICAL SERVICES

The previous section illustrated activities at the international level in support of data quality and the availability of ground-based observations and derived products. However, for provision of climate services at the national level, it is also important to improve the local capacity to operate stations networks and to build up climate databases to support local applications ranging from analysis of climate trends to data provision for all types of applications in support of adaptation measures. Such tasks are typically under the responsibility of national meteorological services. Some initiatives in recent years have demonstrated how international cooperation can contribute to an improvement of local capacities, partly also linked to the above-mentioned activities.

It is generally accepted that relevant gaps in observing networks persist and results of projects aiming at a strengthening of these networks have often been suboptimal (Santamaria et al., 2021). The need for capacity enhancements in developing countries is therefore also addressed in the WMO Strategic Plan 2020–2023 (WMO, 2019), but technical and financial support is needed to achieve significant improvements (Kijazi et al., 2021). A questionnaire of WMO (2012) on Climate Data Management Systems led to the conclusion that several NMHSs in developing countries do not operate database management systems (DMS) for their climate data management systems (CDMSs).

An example of an initiative with focus on both, observation networks and climate data bases, are the activities which have been jointly performed within the framework of the "Southern African Science Service Centre for Climate Change and Adaptive Land Management" (SASSCAL; https://www.sasscal.org). Within SASSCAL, the national weather authorities of Angola, Botswana, Germany and Zambia as well as further partner institutions in Germany, Namibia and South Africa, cooperated to support the extension of the regional meteorological observation network and the improvement of the climate archives at national level in the respective countries (Kaspar et al., 2015b). To improve the low density of climate stations in the SASSCAL region the establishment of a network of weather stations was started in 2009/2010 and a total of 154 weather stations were reached. Important strategic and technical steps of this activity are discussed by Muche et al. (2018). This extension of the network was complemented by activities to improve the climate data management concepts at the national weather authorities. In addition to training activities, a focus was also on the extension of the data bases with historical climate data. Those were partly obtained by digitization efforts in the countries, but also by identifying additional sources in international archives, as e.g., the above-mentioned archive of precipitation data of the GPCC. It was found that some of these data were no longer available in some national databases. Details of the activities are described in Posada et al. (2016, 2018) and (Kaspar et al., 2015b). The CDMS used in the participating countries is Climsoft, a system frequently used in developing countries. In the meantime, efforts were ongoing to develop this system toward a free Open Source Climate Data Management System (https://climsoft.org).

The national and regional data archives can also be complemented by integrating the historic observations from the above-mentioned digitization efforts of DWD or other NHMSs. The provision of historic weather observations from the overseas archive to the countries where the stations were originally located is therefore an important initiative that is currently supported on a case-by-case basis, depending on progress in digitization. For example, a complete digital copy and data package of the documents contained in the archive of the former colonial stations in Cameroon were officially handed over by DWD to the diplomatic representation of Cameroon and is forwarded to the "Direction de la Météorologie Nationale du Cameroun" (CMR). Similar data transfers have already been made for other stations, e.g., in Canada, China and Korea, and will be continued for other countries, when the respective data has been digitized, documented and quality controlled.

SATELLITE-BASED CLIMATE DATASETS

In addition to ground-based observations, satellite data can also provide climatological information, but the feasibility depends on the meteorological parameter. For example, cloudiness and surface radiation can be derived from observations of meteorological satellites. Meteorological satellites have now been in operation for some decades and therefore can provide data of appropriate length for climatological analyses. The METEOSAT satellites are located at a position over the equator from where they are in an optimal position to provide information for Africa (see **Figure 8**). The first METEOSAT satellite was launched in 1977. However, the satellites were originally not intended to provide long term climate information and therefore the data need careful processing and inter-calibration between satellites to provide reliable products for climatological applications. Such work is done at the Satellite Application Facility on Climate Monitoring (CM SAF, https://www.cmsaf.eu), a EUMETSAT activity organized as a network with contributions from several national meteorological services in Europe and led by DWD. The derived data products are available with a spatial resolution of a few kilometers and therefore at much higher resolution than the typical density of ground-based observations of radiation

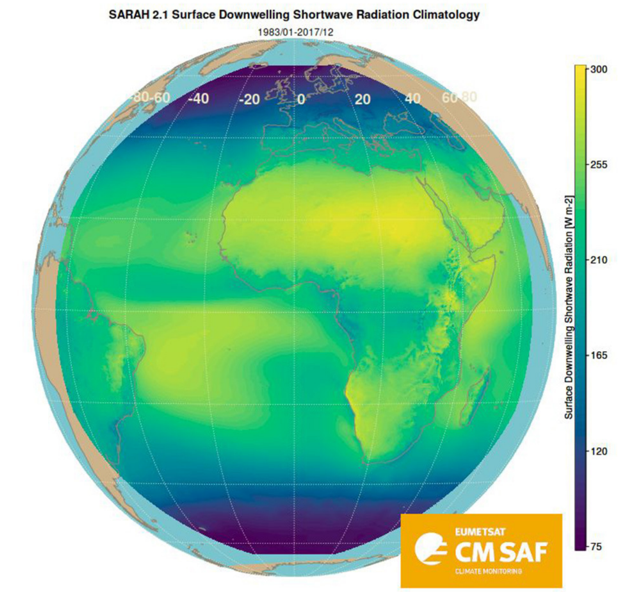

FIGURE 8 | Spatial distribution of mean surface solar radiation (global radiation) in the period 1983–2017 based on the CM SAF SARAH-2.1 data set.

or cloudiness. Especially surface radiation, but also cloudiness, are important parameters for applications in the energy sector or for modeling evaporation in applications related to water or vegetation. A relevant example of such datasets is the surface solar radiation data set SARAH-2. The "second edition of the Surface Solar Radiation Data Set - Heliosat" (SARAH-2, together with the update to SARAH-2.1) is a satellite-based climate data record of a set of radiation parameters: solar surface irradiance, surface direct irradiance (direct horizontal and direct normalized), sunshine duration, spectral information, and the effective cloud albedo. They are derived from satellite-observations of the visible channels of the MVIRI and the SEVIRI instruments onboard the geostationary METEOSAT satellites (Kothe et al., 2017; Pfeifroth et al., 2017, 2018, 2019). The data are available from 1983 to 2017 and cover the region $\pm 65°$ longitude and $\pm 65°$ latitude (**Figure 8**; $\pm 60°$ longitude and $\pm 60°$ latitude for the spectral information), thereby providing information for all of Africa. The products are available as monthly and daily means, and as 30-min instantaneous data (sunshine duration is available as monthly and daily sum) on a regular latitude/longitude grid with a spatial resolution of $0.05° \times 0.05°$ degrees. In addition to the SARAH-2.1 data set, CM SAF provides a day-to-day continuation of the data records. A completely new update of the SARAH-2.1 is currently being produced in the CM SAF and will be made available in 2022 as SARAH-3, then covering the years 1982–2020. Similar to other products of CM SAF, the data set is freely available and complemented with a comprehensive documentation of the algorithms, a validation report and user guidance.

Similarly, datasets for cloud parameters are available covering the same region and time period (e.g., Benas et al., 2017). Such satellite products can therefore complement ground-based observations, but only for selected parameters. For instance, deriving near-surface temperature or near-surface wind is currently not possible in a comparable quality at the global or continental scale.

SUMMARY AND CONCLUSIONS

There continue to be relevant gaps in the availability of meteorological data in Sub-Saharan Africa. The monitoring of data availability as implemented within the GCOS Surface Network Monitoring Centre provides an overview of data that have been received and are available for climate analysis at the international level. The results reveal gaps especially in Southern and Eastern Africa. Although Africa is considered a vulnerability "hot spot" for climate variability and change impacts (WMO, 2020), the gaps in the data availability hinder detailed assessments of the climate change that has already taken place. The need for improvements and financial support is discussed at the international level (e.g., Santamaria et al., 2021). Cooperation between national meteorological agencies can support capacity building at the national level and some initiatives of the last few years can provide some lessons learned, as e.g., the activities within SASSCAL where cooperations between Germany and countries in Southern Africa were established. Establishing climate data bases at the national level in developing countries can also benefit from the digitization of historical data in archives of European meteorological agencies. Such additional data will be especially valuable for assessment of long-term climate change. However, this digitization continues to be a labor-intensive process.

Some parameters can also be derived from satellite observations. Datasets covering some decades have been produced, e.g., at EUMETSAT's Satellite Application Facility on Climate Monitoring and provide information for Africa at high spatial and temporal resolution. In particular, radiation, sunshine duration or cloudiness are relevant parameters for a wide range of applications and are available from this activity.

For precipitation, a portfolio of datasets is provided by the Global Precipitation Climatology Centre (GPCC). They are based on station-based observations. Gridded products are openly available. The original station data can be handed over to the country of origin to be included in national climate databases. Improving the international data exchange will also improve the quality of such products from global data centers.

These activities of Germany's national meteorological service (Deutscher Wetterdienst, DWD) are examples for international contributions to the improvement of climate data availability and quality in Sub-Saharan Africa. They illustrate that a variety of activities are needed to achieve a comprehensive understanding of climate variability and change. Improving data availability and exchange will not only support the understanding of climate trends, but will also support applications as especially numerical weather forecasting (Meque et al., 2021). The combination of observations and numerical models also allows to generate long-term climate reanalysis datasets that provide realistic three-dimensional fields of past weather and are therefore used in a wide range of applications. These activities also benefit from digitized historic observations which are used in the data assimilation of these models. Such datasets exist as products with global coverage (e.g., produced within the European Copernicus Climate Change Service; Hersbach et al., 2020) or as regional products with higher resolution for some continents (e.g., Kaspar et al., 2020), but not yet for the African continent.

AUTHOR CONTRIBUTIONS

FK drafted the manuscript with input from all co-authors. All authors contributed to the article and approved the submitted version.

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The Climate Data Tool: Enhancing Climate Services Across Africa

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Climate services can contribute to alleviating a range of climate-sensitive development challenges, including those of agricultural production and food security. However, the use of climate data for research and applications in Africa has been scanty, mainly due to poor availability of and access to quality climate data. Weather stations are sparse, and their number has been declining. Access to existing climate data is a challenge mainly because of national data policies, low financial investment, lack of dissemination capacity and tools, and high access costs. The ENACTS (Enhancing National Climate Services) initiative led by the International Research Institute for Climate and Society (IRI) at Columbia University has been tackling this problem by working with National Meteorological Services (NMS) in Africa and in other developing countries. This initiative helps NMS to improve data availability and quality, by combining quality-controlled data from national observation networks with satellite estimates for rainfall and climate model reanalysis products for temperature. This requires access to an easy-to-use and freely available tool for preforming the tasks required to generate the data, as well as using the generated data. Most NMS in Africa do not have access to such a tool. To meet this significant need, the IRI developed such a tool in-house. This is the Climate Data Tool (CDT), which is an open-source, R-based software with an easy-to-use a graphical user interface (GUI). It can be used for data organization, quality control, combining station data with satellite and reanalysis data, evaluating merged and inputs datasets, performing an array of analyses, and visualization. The CDT software has been evolving over that last seven years with inputs from the NMS themselves. Now, it has become a powerful and user-friendly tool, and has been installed in over 20 countries in Africa alone.

Keywords: climate, climate data, data quality, data errors, climate services, CDT, data tool

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INTRODUCTION

There has always been a close relationship between socio-economic development, human wellbeing, and a varying and changing climate. However, climate change is expected to impede and undo development gains by increasing the frequency and severity of extreme weather events, shifting suitability zones for crops and diseases, and endangering coastal areas with sea-level rise (IPCC, 2014). These changes threaten many essential sectors such agriculture, forestry, water resources, tourism, transportation, energy, and health. However, because about 80% of the world's cultivated land is rain-fed (UNESCO, 2009), agriculture is widely regarded as the most climate-sensitive human activity and sector of all. Climate variability in agriculture not only affects the availability, access, and consumption of food, but also the income of smallholder farmers (Shumetie and Yismaw, 2018).

In the face of these challenges, "effective" use of climate information offers a way for agricultural practitioners to make better informed decisions at different levels, ultimately aiding them on their quest to make agriculture more resilient to increasingly erratic precipitation and temperature patterns. For example, it might inform which types of seed varieties, such as those that are drought or flood-resistant, an extension system promotes, or when a farmer chooses to plant.

No matter the decision at hand, the information should be useful, usable, and used to achieve the goals of climate risk management and adaptation. Climate services, defined by the Climate Services Partnership (2011) as "production, translation, transfer, and use of climate knowledge and information in climate-informed decision making and climate-smart policy and planning," play a pivotal role in making this happen. However, even when researchers or meteorological agencies strive to produce information that users need, significant barriers may still remain that inhibit that potentially "useful" information from actually being "usable" (McNie, 2013; Vincent et al., 2018). Some of these barriers include the relevance of the information itself, which can be limited by problems with the underlying data—the spatial scale at which data is available, the quality of the data, or even the presence at all data observations.

As a result, information and products that are sorely needed for anticipating, managing, and responding to agriculture or food security risks triggered by climate extremes, as well as adapting to longer-term risks associated with climate change, can simply be limited (De Leeuw et al., 2014; Hansen et al., 2014; WMO, 2014).

This is the case in many places around the world, including most African countries. It is here that collection of climate data has been seriously inadequate, and even when available, poorly accessible (Dinku, 2019). Where data does exist, it is often of poor or inconsistent quality, limiting decision-makers at all levels from taking appropriate adaptive actions in the face of a changing and varying climate.

The Enhancing National Climate Services (ENACTS) initiative of the International Research Institute for Climate and Society (IRI), Columbia University, has been helping countries to address such gaps in data quantity and quality, as well as access to and use of climate information products by working closely with National Meteorological Services (NMS) in Africa and beyond (Dinku et al., 2014, 2018). These NMS have the primary responsibility to provide observed and forecast weather information, climate information, and warnings of impending hydro-climatic threats to a variety of users, and any limitations in their data are thus felt widely.

To ensure such limitations are addressed and the data upon which information is based is robust, the ENACTS approach works directly with NMS in Africa and other developing countries on data quality and availability issues. One of the core ways this is done is by combining quality-controlled data from national observation networks with satellite estimates for rainfall and climate model reanalysis products for temperature (Dinku et al., 2013, 2018).

This data blending process involves the organization of station and proxy data, quality control and check of station and proxy data, combination of quality-controlled station data with proxies, evaluation of the combined data, and further analysis and visualization of station and combined data.

However, many NMS do not have access to an easy-to-use and freely available tool for performing these and other tasks. To meet this need, the Climate Data Tool (CDT), was developed in-house by the IRI, and is now used by 24 countries in primarily in Africa, but also Asia and Latin America. CDT is an open-source, R-based software package with an easy-to-use a graphical user interface (GUI), which can be run under multiple operating systems, including Windows and Linux. The only system requirement is the installation of the latest version of R. After 5 years of evolution and thanks to the iterative feedback from NMS around Africa, CDT has now become a powerful, dynamic, intuitive, and user-friendly tool. The main functionalities of CDT include (see **Figure 1**):

- Organization of station and proxy data;
- Assessment of data availability;
- Assessment and correction of data quality;
- Merging station observation with proxies;
- Extraction of data from gridded products, including satellite, reanalysis and combined data products, at any point, for a selected box, and for any administrative boundary; and
- Analysis and visualization of station and gridded datasets.

Though it has a graphical user interface (GUI), CDT can also be run at script level for advanced users who need more flexibility. As any R-package, there are manuals for the different modules.

Implementation of CDT at NMS includes installation of the tool, as well as training. In other words, beyond just a technology or software package, implementation CDT also includes a standard training package. Technological and human resources are addressed in tandem. The training package is generally comprised of three steps:

- Theoretical background on the basics of climate data quality control, remote sensing of rainfall, climate reanalysis products, interpolation of climate data, and combination of climate data from different sources;
- Practical, hands-on training starting with installation of the system;
- Actual use of CDT for data quality control and generation of merged rainfall and temperature data for those who implement ENACTS.

The CDT has so far been installed in 15 ENACTS countries, nine non-ENACTS countries, and two Regional Climate Centers (RCCs) shown in **Figure 2**. Installation and training in the ENACTS countries and the two RCCs was done mostly by the IRI, while most of the installation and training in the non-ENACTS countries has been done by the RCCs.

FIGURE 1 | CDT graphical user interface.

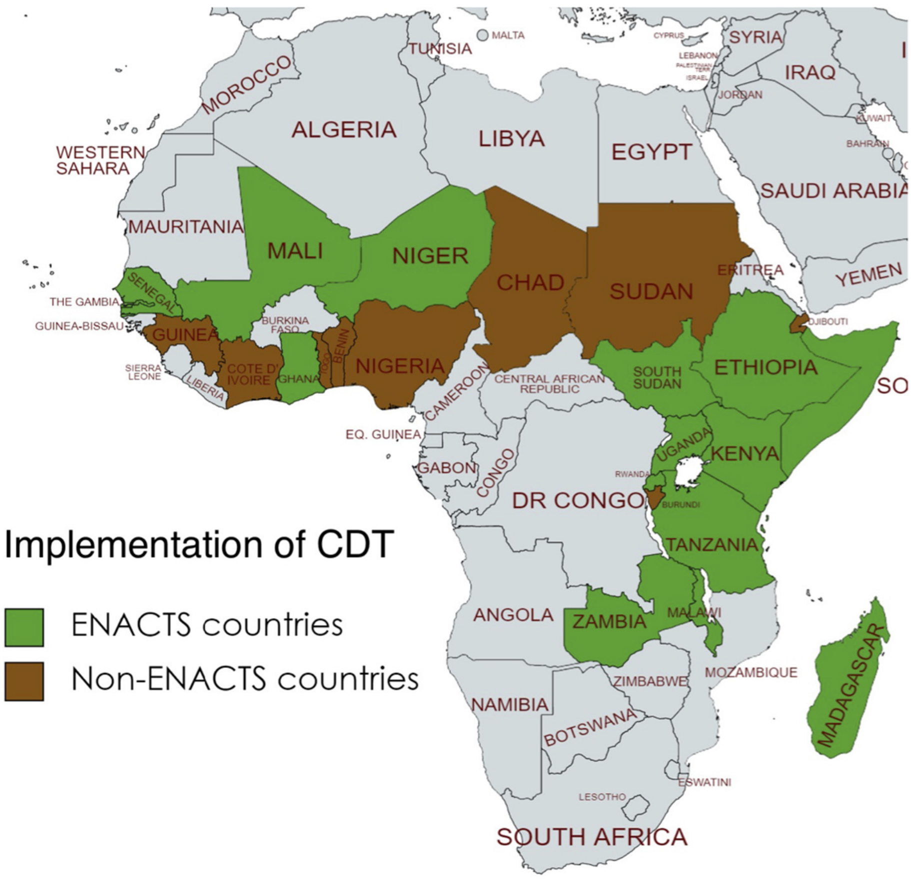

FIGURE 2 | Countries where CDT has been implemented (installation and training) either as part of ENACTS implementation or independent of ENACTS (implemented by Regional Climate Centers).

The next section, Methodology, provides summary descriptions of the different CDT functionalities, while Section Results presents some results. The paper concludes with discussion in Section Discussion.

METHODOLOGY

The CDT allows users, particularly NMS staff, to perform an array of tasks, from data preparation to extensive analyses and

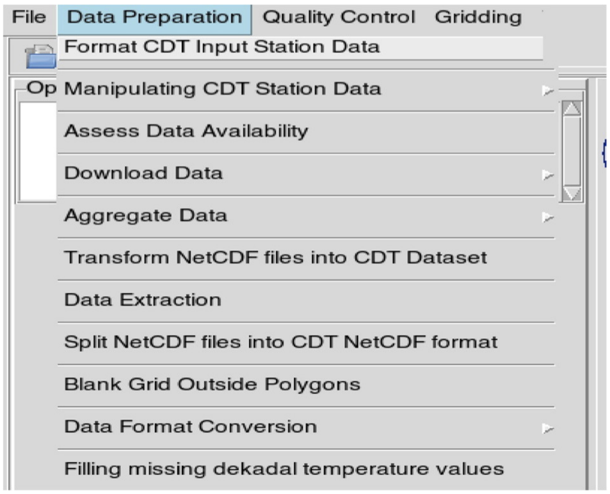

FIGURE 3 | CDT data preparation menu.

visualizations. This is accomplished through an interactive GUI as well as command line execution within the R environment. The main modules that are accessed through the GUI include the following (**Figure 1**):

- Data preparation
- Quality control of station observations;
- Interpolation of station observations and merging data from different sources
- Validation of merged and other data
- Various analytical tools
- Visualization of stations and gridded data as well as analyses results

An overview of these different modules is presented below.

Data Preparation

The CDT offers a suite of operations dedicated to data preparation (**Figure 3**), which include organizing observations from meteorological stations, assessing availability of observations, downloading, and processing proxy data (satellite rainfall estimates and climate model reanalysis products). This can also be used for obtaining some ancillary data such as digital elevation models (DEM) and shape files for country administrative boundaries.

Users can upload station data into CDT in text and comma-separated-values (CSV) formats. CDT can also use data from the WMO-supported climate data management systems (CDMS) used by NMS in Africa. It can directly access data from the CLINMSOFT database while data from other databases such CLISYS and CLIDAT have to be converted to text or CSV format firs. These input are converted into a format used by CDT for further analyses. This is a text file format, and CDT allows users to convert data into this format. The converted data can then be aggregated to different temporal scales, including pentad (5-day), dekadal (10-day), monthly and seasonal. CDT also lets the user explore availability of data in the NMS database (what is available and what is missing) using various formats including, tables, graphs of average number of stations reporting each year, graphs showing number of non-missing data per year for each station over the years, and percentage of data available for all stations plotted on a map. These offer a full picture of the available data, which is important information for both the NMS and their users.

Downloading and Processing Proxy and Ancillary Data

The CDT also allows users to download and process various proxy and ancillary data used in meteorological and climatological analysis. These include six different satellite rainfall estimates:

- ARC (Africa Rainfall Climatology; Novella and Thiaw, 2013);
- CHIRP/S (the Climate Hazards Group Infrared Precipitation and combined with station data; Funk et al., 2015).
- CMORPH [Climate Prediction Center (CPC) Morphing Techniques; Joyce et al., 2004],
- GPM (Global Precipitation Measurement Mission; Hou et al., 2014)
- PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks; Nguyen et al., 2018)
- RFE [Famine Early Warning System NETwork (FEWS NET) satellite rainfall estimate; Xie et al., 2017],
- TAMSAT [Tropical Applications of Meteorology using SATellite and ground-based observations (TAMSAT); Grimes et al., 1999; Thorne et al., 2001]
- TMPA (TRMM Multi- Satellite Precipitation Analysis; Huffman et al., 2010).

There are also three climate reanalysis products that can be downloaded through CDT for generating merged temperature data:

- Japanese 55-year Reanalysis (JRA55);
- Modern-Era Retrospective Analysis 2 (MERRA2); and
- European Center for Medium-Range Weather Forecasts (ECMWF-ERA5).

The main advantage of CDT here is that the users can specify the spatial and temporal domain and time resolution of interest and download only the data they actually need. Most of these products can be downloaded either from the IRI Data Library (Blumenthal et al., 2014) or from the original data source for that particular data product. CDT can also be used to download ancillary data such as digital elevation models country administrative boundaries.

Once downloaded, the satellite and reanalysis data can be processed further using some simple aggregation functions such as sum, average, minimum, maximum, count, etc. These datasets could also be aggregated to coarser spatial resolutions. CDT uses NetCDF as a native gridded data format, but can also export data to other formats such as Climate Predictability Tool (CPT), GeoTiff, and GrADS.

Quality Control

Quality of climate data is a serious challenge for many countries in Africa (e.g., Dinku, 2019). This includes poor accuracy or precision of observations, as well as missing data. These errors can stem from multiple sources that include instrument error, observer error, digitization, summarization, etc. (reference). These errors need to be identified and fixed. However, many NMS lack appropriate tools to perform quality control or the capacity to use existing tools.

The CDT offers a robust quality check process for identifying and, when possible, fixing erroneous observations. The tool enables checking for a multitude of error types and presents the outputs in different formats that enables the NMS staff to easily identify the errors and fix or remove the data from the database. These could be done at different temporal scales including daily, dekadal, and monthly. The NMS staff have the options to replace suspicious values by a missing data code, replace the suspected values with correct observations, or leave the data as it is.

The quality check process implemented in CDT includes the following:

(i) checking for station coordinates;
(ii) checking for false zero values (for rainfall);
(iii) checking for suspicious observations (outliers); and
(iv) checking for homogeneity of climate time series.

Coordinate Check

It would be difficult to automatically check for the accuracy of the coordinates of a given station. Thus, CDT simply checks whether a station is located within the country boundary. It also displays the location of the stations on Google Map. The display enables the NMS staff to check whether the station is located where it is supposed to be. CDT can also check for duplicate and missing coordinates, which happen frequently.

False Zero Check

In many instances, observers may not enter zero values in the data register when there is no rainfall; instead, they may leave the specific dates on the register blank. The data register could also be blank for the days when observations were not taken (missing data). However, during data transfer to computers, data entry staff may enter both (zero observation and missing data) as zero, leading to false zeros. To check for false zeros, CDT compares the percentage of zero values for each month at the target station and the average of the neighboring stations. If the ratio of the stations zero count for that month is greater than a user-defined threshold, that month is flagged as suspicious. Then the NMS staff can choose to investigate or replace the suspicious month with missing data.

Checking for Outliers

There are different ways to check for outliers or suspicious observations. The methods implanted in CDT include, limit check, internal consistency check, temporal check, and spatial check. Limit check involves comparing an observation to previously defined upper and lower limits of the specific element for the specific climate. For instance, no negative values are expected for maximum temperature over locations in Africa, and there could also be upper limits for daily rainfall amounts.

In internal consistency checks, an observation is compared with other parameter values to see if they are physically or climatologically consistent, either instantly or for time series according to adopted observation procedures. Normally, more than one meteorological parameter is measured at an observing station at the same time. Some of these parameters are physically related and the internal consistency check tests if values of related parameters are free of contradictions. The only internal consistency check implemented in CDT is making sure minimum temperature is less than maximum temperature, and vice versa.

Temporal consistency checks if an observation of a given station for a given month is significantly different compared to the long time series for that particular month. This test is based on the fact that many climatological variables show significant serial correlation. In CDT, this comparison is done for each of the 12 months separately in order to make sure data from climatological periods (e.g., cold months vs. warm months) are not compared. The outputs are presented both in tabular and graphical formats, which will be shown in the next section. These presentations allow easy inspection of suspected values, and one can either keep or change these outlier values just by making changes directly on the table.

The spatial check compares the observation to be checked with the observations from nearby stations or the expected value at the station that is estimated using the observations from neighboring stations. This may be accomplished either by interpolation between observations, by checking against numeric prognostic values (on the basis of values from many different stations), or by comparing statistics. Those data for which there is a significant difference between the expected and actual observations are flagged as suspect. The following conditions are checked in CDT: isolated rainfall (rainfall observed at station of interest but surrounding stations reported zero), isolated zero (opposite of the previous one), and outlier (observation too high or too low compared to nearby observations). These suspected values can be viewed both in graphical and tabular formats. Values can be viewed on map with the options of adding administrative boundaries, digital elevation model as well as gridded proxy data. This enables use of background data (e.g., DEM for temperature and satellite estimates for rainfall) that provides additional information to decide whether the observation is actually an outlier. For instance, nearby station could report significantly different temperature observation because of the altitude at which they are located. A DEM background could be used to check if this is the case.

The user can correct the suspicious values in different ways. The easiest one would be replacing all suspected values with missing code. A better way would be consulting paper records to confirm whether the suspicious values is a wrong observation or just wrong entry, and in the latter case replace the suspicious value with the correct one. CDT offers both options. For the second option, the user just needs to enter the correct value to the table presenting the errors (**Table 1**), and then CDT will replace the value in the original data

TABLE 1 | Example table of errors in CDT.

STN.ID	DATE	STN.VAL	OUT.SPATIAL	NOT.REPLACE	REPLACE.VAL
01001DAM	19810430	24.7	isolated.precipitation	1	NA
01001DAM	19810707	28.4	too.large.deviation.above	1	NA
01001DAM	19810711	56	too.large.deviation.above	1	NA
01001DAM	19810730	36.9	too.large.deviation.above	1	NA
01001DAM	19810828	39	too.large.deviation.above	1	NA
01001DAM	19820320	13	too.large.deviation.above	1	NA
01001DAM	19820326	7.6	isolated.precipitation	1	NA
01001DAM	19820409	38.5	too.large.deviation.above	1	NA
01001DAM	19820608	23.7	too.large.deviation.above	1	NA
01001DAM	19820725	8.4	isolated.precipitation	1	NA
01001DAM	19830214	12	isolated.precipitation	1	NA

file. This is very convenient and saves NMS staff a lot of time.

Homogeneity Check

Homogeneity checks are used to determine if a climate time series is homogeneous over a period of time. Data inhomogeneity can affect the quality of climate studies, particularly the domain of climate trends, variability and climate extreme analysis. Inhomogeneity can stem from many factors such as changes in observational routine (Hansel et al., 2016), changes in instruments, observation methods, station relocation, etc. (Li-Juan and Zhong-Wei, 2012). Homogenization of climate data consists of two main parts: detecting breaks and adjusting the specific segment for inhomogeneity (Squintu et al., 2020). The CDT offers four approaches for detecting breaks in a climate time series. The first approach is Pettit test, which is a non-parametric rank-based method used for detecting shift in the mean value of the distribution of the variable under study (Mallakpour and Villarini, 2016). The other approach adapted in CDT is the normal standard test (SNHT) (Alexandersson and Moberg, 1997). The other two approaches use cumulative sum (CUMSUM) approach with and without trends (Gallagher et al., 2013). For adjusting inhomogeneities, CDT offers two methods: mean and quantile matching. Mean method compares the mean before and after the break and quantile matching compares quantiles before and after the break (Squintu et al., 2020).

Gridding

CDT's Gridding menu offers options for simple spatial interpolation using different methods, as well as combining station observations with gridded proxies such as satellite rainfall estimate and temperature reanalysis products. The latter option is a critical component of the ENACTS approach described earlier. The merging process can also be done in a cross-validation mode, which enables evaluation of the merged product.

Spatial Interpolation

CDT offers for spatial interpolation, which include nearest neighbor (Shope and Maharjan, 2015), nearest neighbor with elevation, inverse distance weighted average, modified Shephard (Renka, 1988), spheremap (Kluver et al., 2016), ordinary kriging, and universal kriging (Bargaoui and Chebbi, 2009). The tool enables users explore different methods as well as different parameters (grid seize and resolution, interpolation radius, minimum/maximum number of neighbors, variogram type, …etc.) for the different interpolation methods. Thus, users can choose the most suitable method and parameter for their specific needs. Interpolation can be done at multiple time steps (days, dekads, months, seasons, etc.). One can display and examine the outputs or can perform validation using independent datasets as described later in this section.

Merging Station Observations and Proxy Data

Combining observations from meteorological stations and proxies such as satellite rainfall estimates or climate model reanalysis products can help alleviate challenges with evaluability of data owing to sparse distributions of meteorological observations. In CDT, satellite rainfall estimates are combined with rain gauge measurements while reanalysis products are used for minimum and maximum temperature. CDT uses NetCDF data format both input and output gridded data. The approach adopted in CDT involves the following steps:

- Downscale proxy data (only for reanalysis for temperature);
- Use historical station data to calculate climatological adjustments factors;
- Apply the adjustment factors to all proxy data;
- Merge the output from the previous step with contemporaneous observations for each time step (day, pentad, dekad, month, etc.).

The reanalysis data would need to downscale the reanalysis data from its coarse resolution to a higher resolution (4 km ENACTS data). We can utilize lapse rate for each month to downscale reanalysis data. This involves using digital elevation model (DEM) and station temperature observations to *Compute Downscaling Coefficients* which are then applied to time series of reanalysis data.

Bias correction aims to remove the bias from proxy data using station data. CDT offers four approaches for mean bias correction: multiplicative bias with variable time step, or for each month, and quantile mapping with fitted distribution and quantile method with empirical distribution. First the correction factors are computed using any one of the four methods. This will create a file with bias coefficients associated with the method selected by the user. The next step would be applying the corrections to the time series of the satellite and reanalysis data.

Next, the bias-corrected time series of proxy data is merged with contemporaneous stations observations. CDT offers four different methods for merging proxy data with station data, which are, simple bias adjustment, Cressman scheme (Mateus et al., 2016), Barnes scheme (Rozante and Demerval, 2010), and regression kriging (Hengl et al., 2007).

Validation

The CDT tool offers a robust validation scheme both to assess the input proxy data, as well as the merged output data. There are several statistics that can be used for doing this comparison, and CDT offers an array of validation statistics, which include correlation coefficient, mean error, Nash-Sutcliffe efficiency coefficient, percent bias, probability of detection and false alarm ratio. The merged data could be validated either using independent data that was not used in the merging or using cross validation. Calculated validation statistics could be displayed as tables or could be visualized on maps.

Analysis and Visualization

Analysis

The CDT tool can perform number of data analyses that are pertinent to climate data analysis. The "Analysis" Menu bar offers different functionalities that include computing summary statistics (minimum, maximum, mean, median, number of missing values, 1st quartile, 3rd quartile and standard deviation), calculating some derived climate variables (e.g., calculating potential evapotranspiration), computing climatologies and anomalies, daily rainfall analysis (rainfall intensity, number of dry days, number of wet days, number of dry spells, and number

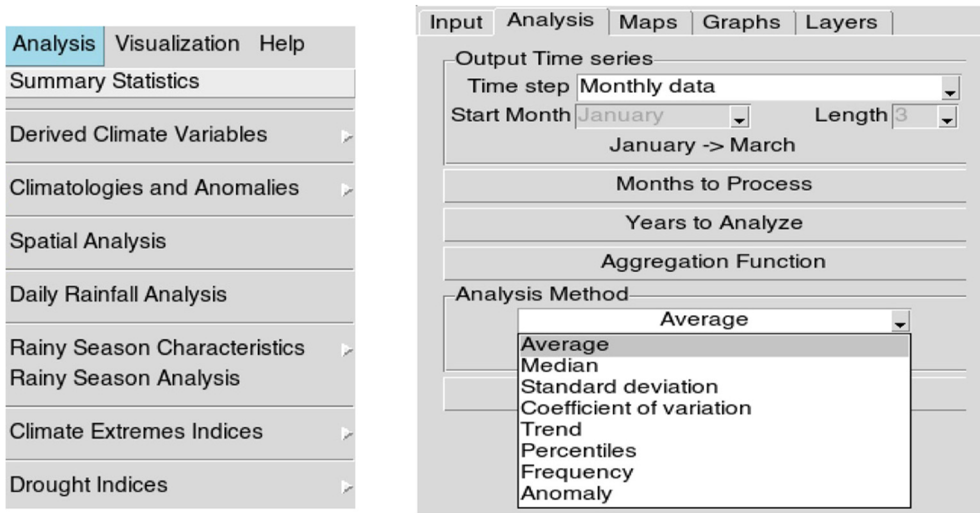

FIGURE 4 | CDT analysis menu.

TABLE 2 | Number of reported data for each year and month for a given station.

STN.ID	DATE	STN.VAL	OUT.TEMPORAL	OUT.SPATIAL	NOT.REPLACE	REPLACE.VAL
ARABOM11	19891209	18.2	lower.outliers	spatial.not.outliers	1	NA
ARABOM11	19891218	19	lower.outliers	spatial.not.outliers	1	NA
ARABOM11	19930127	16.5	lower.outliers	spatial.not.outliers	1	NA
ARABOM11	19930207	15.4	lower.outliers	spatial.not.outliers	1	NA
ARABOM11	19930208	15.7	lower.outliers	spatial.not.outliers	1	NA
ARABOM11	19930417	17.5	lower.outliers	spatial.not.outliers	1	NA
ARABOM11	19961118	19	lower.outliers	spatial.not.outliers	1	NA
ARABOM11	19961119	18.5	lower.outliers	spatial.not.outliers	1	NA
ARABOM11	19980501	10.3	TMIN >= TMAX	spatial.low.value	NA	NA
ARABOM11	20010108	16.5	lower.outliers	spatial.low.value	1	NA
ARABOM11	20110101	45.5	upper.outliers	spatial.high.value	1	NA
ARABOM11	20120811	33.5	upper.outliers	spatial.high.value	1	NA

of wet spells), rainy season characteristics (rainy season onset, rainy season cessation and rainy season length), climate extremes, and various spatial analyses. The results are presented in maps and different graphs such as line chart, bar plot, probability of exceeding for El Nino, La Nina or neutral years, anomaly bar plot, etc. These indices climate extremes are similar to those offered by CLIMDEX from this address: https://www.climdex.org/learn/indices/. Drought indices such as standardized precipitation index (SPI) and standardized precipitation evapotranspiration index can also be calculated using CDT. **Figure 4** shows the CDT Analysis menu.

Visualization

The CDT tools offer an extensive visualization feature for presenting input data and the outputs of the different analyses performed. Many of these visualization tools are part of the

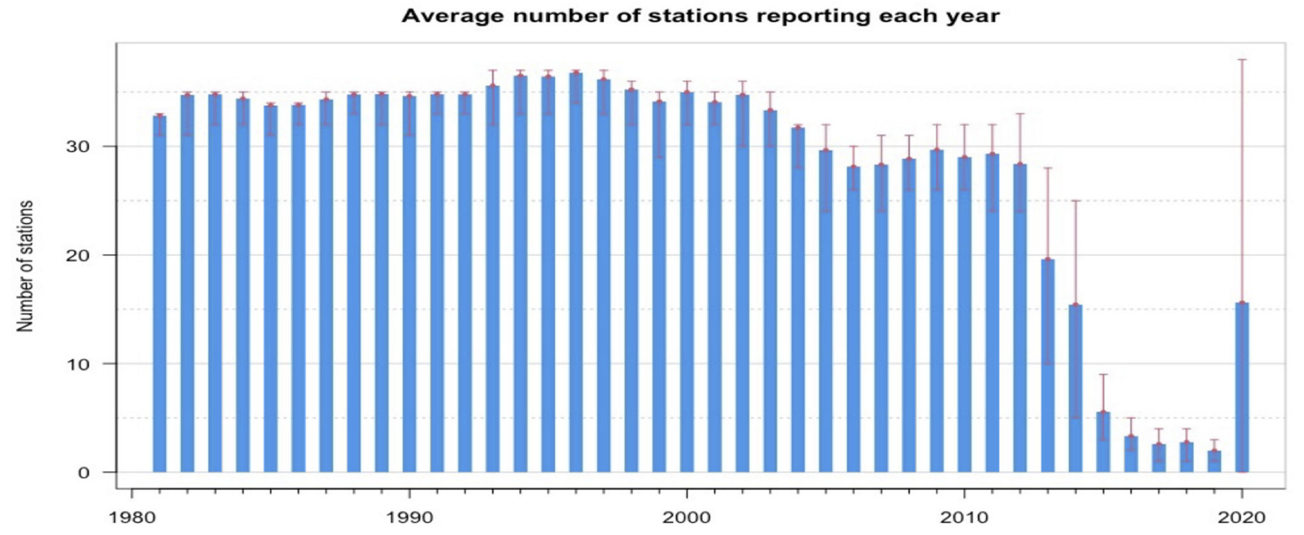

FIGURE 5 | Average number of stations reporting observations for each year for precipitation. The red bar represents the minimum and maximum number of days with observations for each year.

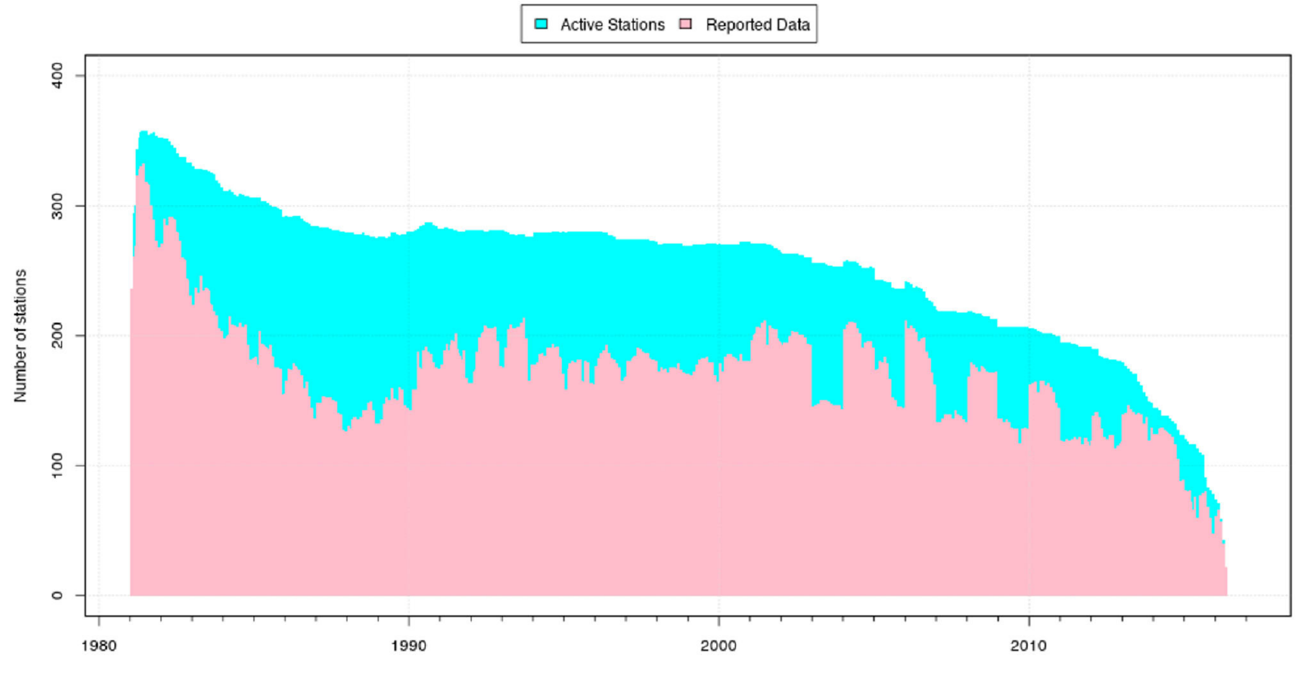

FIGURE 6 | Active stations and reported data from the same stations.

specific analysis menu and include tables, graphs, and maps. However, CDT also has a separate Menu bar for visualizing different data types such as CDT stations data, CDT gridded data and NetCDF data. One can plot either a single NetCDF files, time sequence of NetCDF files (such as a time series), NetCDF files with multiple variables and even a combination of different data types such as station data and NetCDF data. The later allows users to compare data from different sources (e.g., station, satellite, and merged) as required.

RESULTS

This section will illustrate the varied usage and multiple applications of the CDT tool presented above with examples. As the functionality of CDT is very extensive, only the salient features are covered here. The examples presented in this section are actual outputs from the relevant activities at the different NMS as part of the implementation of ENACTS.

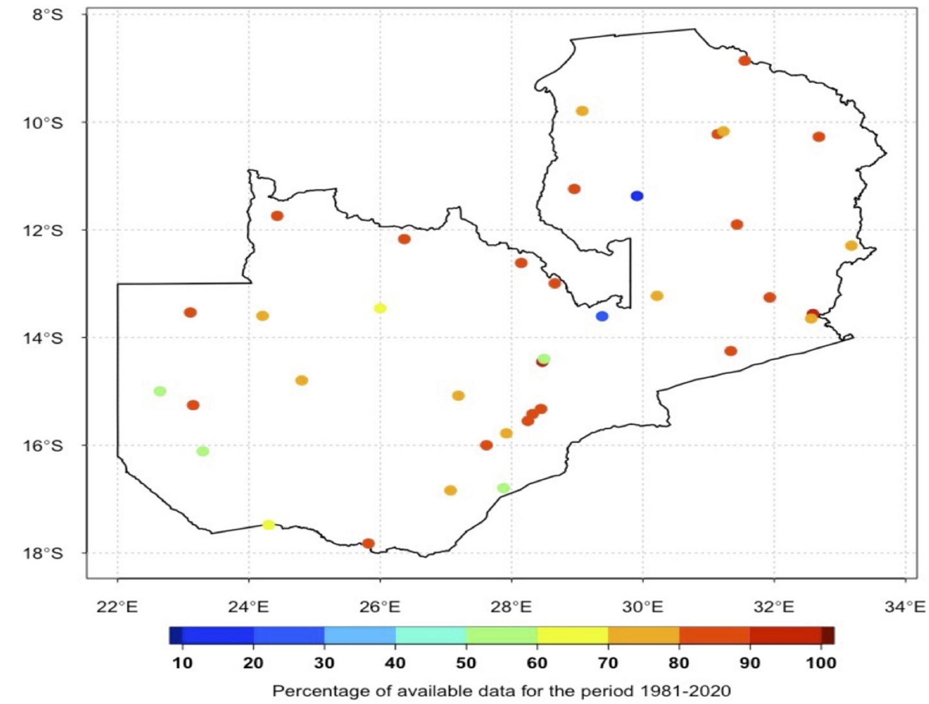

FIGURE 7 | Percentage of available daily rainfall data from each station over Zambia during the period 1981–2020. This shows the completeness of the data for each station.

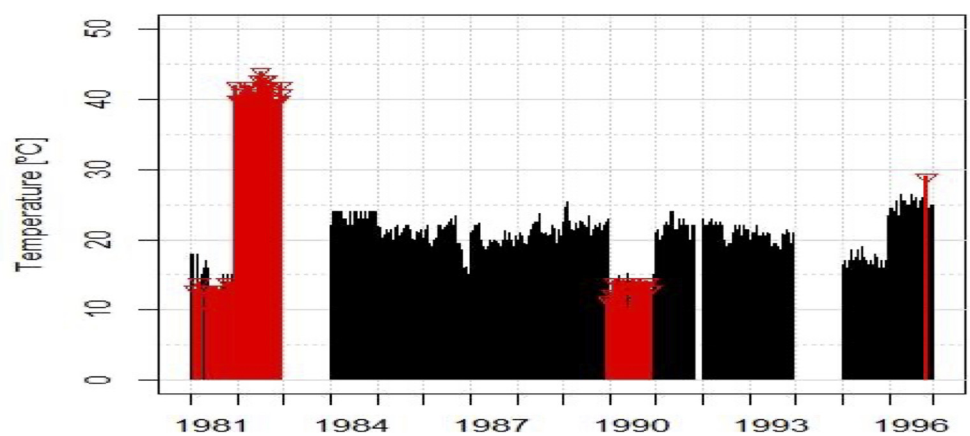

FIGURE 8 | CDT output of temporal check for minimum temperature for the month of May. The red bars show what CDT identifies as outliers (values that are too large or too small compared to what is expected for that month). The blank spaces show missing data.

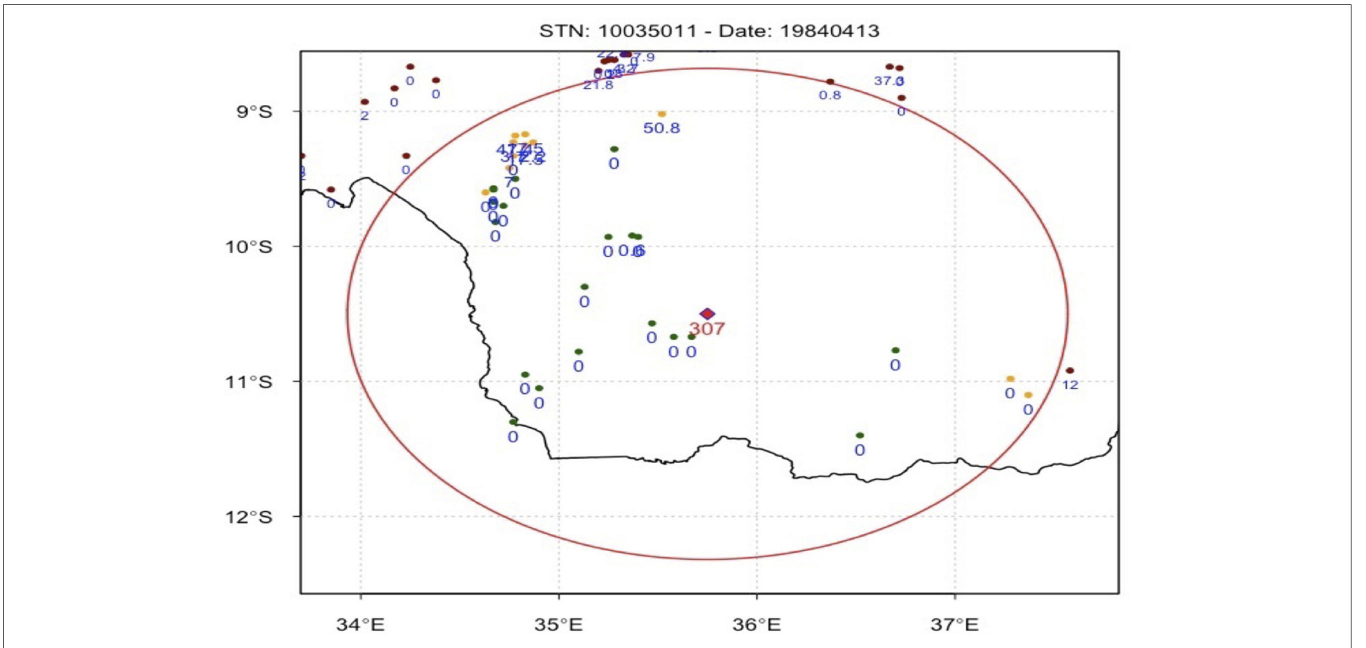

FIGURE 9 | Result of CDT spatial check for daily rainfall, station ID: 10035011 on April 13, 1984. A value of 307 mm (red) is shown as an outlier comparted to the neighboring stations (all reporting zero rainfall).

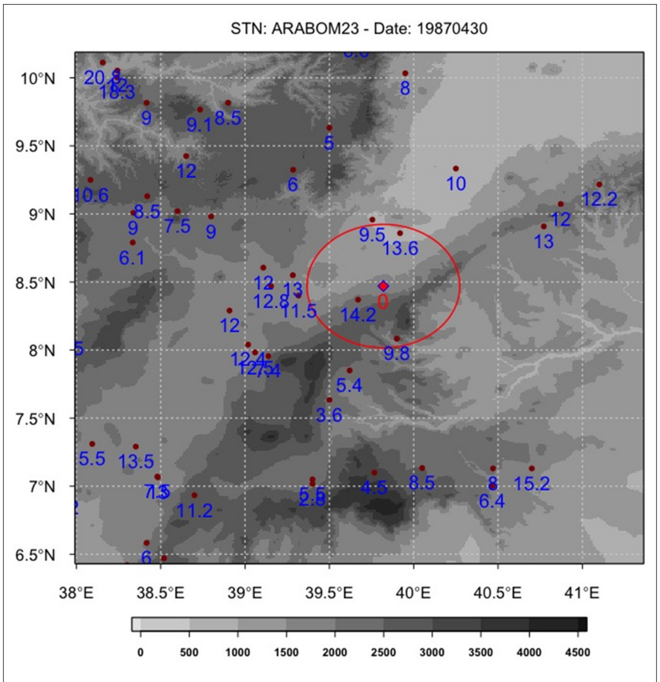

FIGURE 10 | Comparison of temperature observations for neighboring stations with elevation as a background.

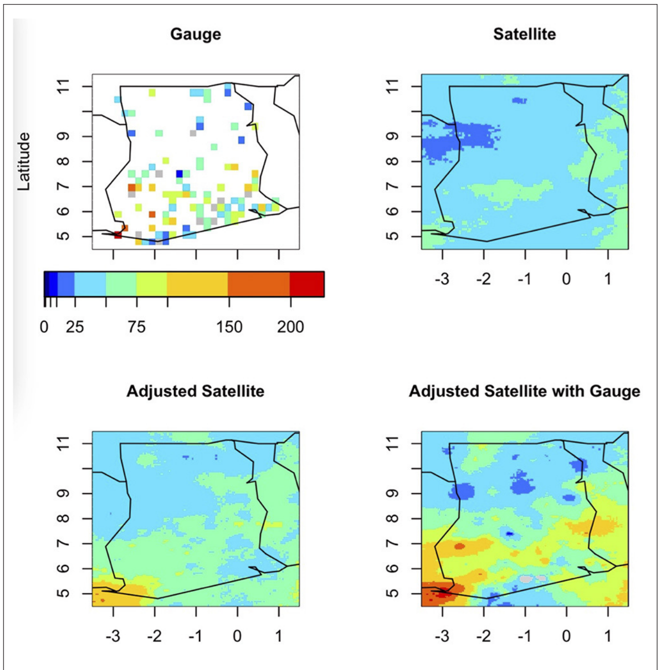

FIGURE 11 | Station observation, satellite rainfall estimates, bias adjusted satellite output and final merged product (1983, June 2nd dekad).

Assessing Data Availability

This functionality offers NMS different options to look at the rainfall and temperature data available in their climate data base. This may sound trivial, but many NMS in Africa, and elsewhere, do not have an easy-to-use tool that enables them to clearly see what data are available, where and when these data are available, and what is missing. CDT presents data availability in tabular (**Table 2**), graph (**Figures 5**, **6**), and map (**Figure 7**) formats.

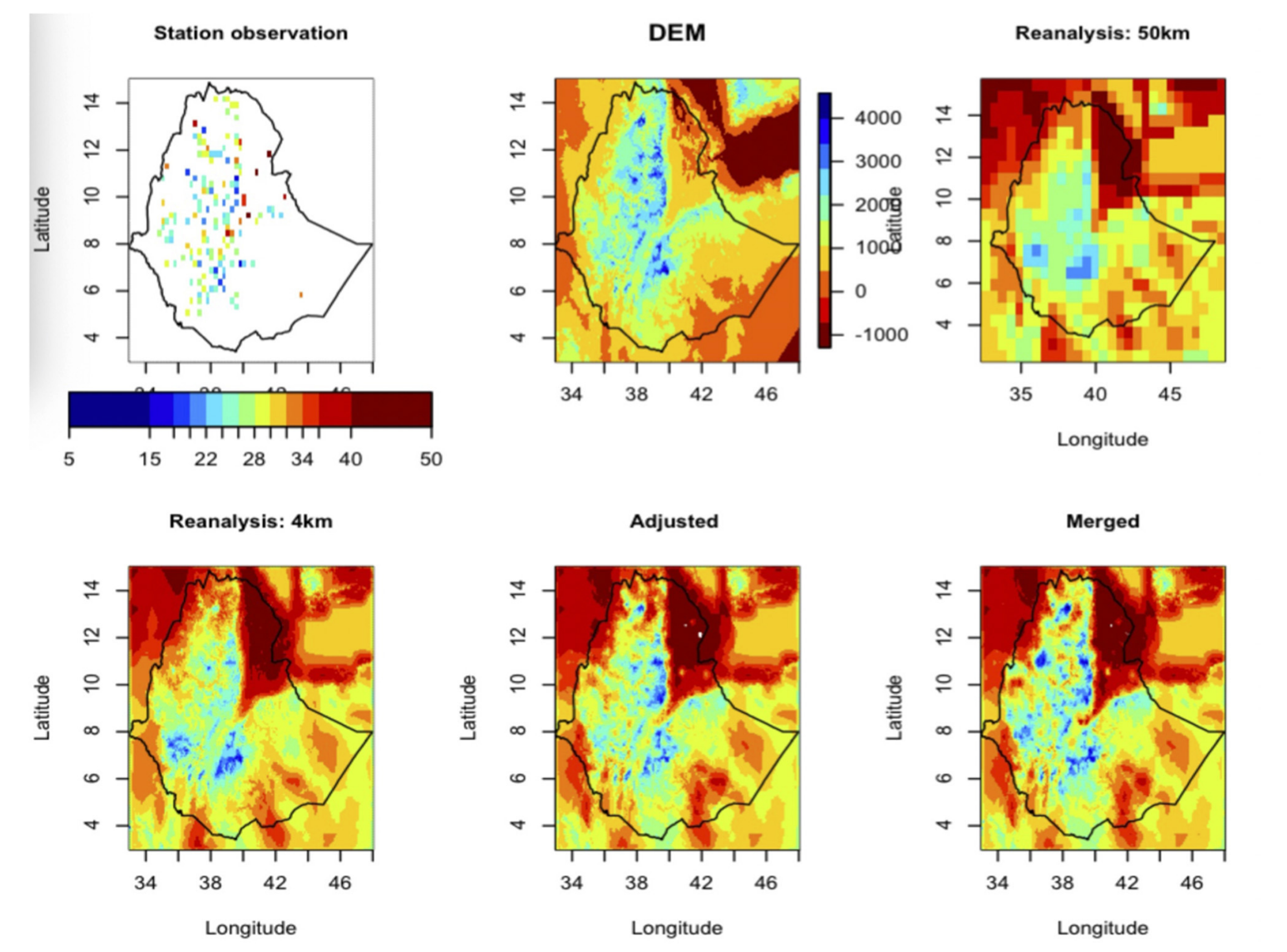

FIGURE 12 | Similar as **Figure 11** but for temperature, along with elevation map (DEM) (2000, May 15th).

Table 2 summarizes the number of reported data for each year and month for a given station. **Figure 5** shows the average number of stations that reported each year (in this case for rainfall), while **Figure 6** compares how many stations were active and how any of the active stations were reporting for each year. The map in **Figure 7** presents the percentage of data (relative to what is expected) available for each station over Zambia.

Quality Control

Quality control of station observation (rainfall and temperature) is one of the most useful functionalities of CDT. These involve checking station coordinates, as well as suspicious data outliers. The outliers are detected using both temporal and spatial checks. A temporal check is performed for each month to ensure that each observed value is consistent with the expected climatology of each station. Suspicious values detected by the quality test are flagged as outliers and would need to be checked by NMS staff. **Figure 8** shows an example of CDT output from a temporal check for minimum temperature for the given station during the month of May. The red bars represent suspicious values identified by the quality check procedure. This figure shows both low and high extremes in consecutive years (1981–1983). The high extreme could be maximum temperature entered as minimum temperature, while the lower values could be data from another station. Sometimes, particularly for rainfall, it is possible that a station could revive a higher than usual rainfall amount. However, this may not happen just at one station. In such cases, would be good to compare the suspicions observation with values from the surrounding stations. This is part of the spatial check, which is demonstrated in **Figure 9**. In this figure, the extreme value (shown in red) is compared to observations from the neighboring stations (shown in blue). In this case, it is very unlikely that one station receives a daily rainfall amount of 307mm, while the neighboring station records zero rainfall. However, one may need to be careful when comparing temperature observations from nearby stations as nearby stations could have significantly different values because of elevations. The CDT enables comparison of neighboring stations with elevation as a background (**Figure 10**). Satellite rainfall estimates could also be used as a background when comparing rainfall observations from nearby stations.

TABLE 3 | Validation outputs.

Stat	Value	Full name
CORR	0.801	Correlation
NSE	0.634	Nash-Sutcliffe Efficiency
BIAS	0.95	Bias
MAE	41.279	Mean Absolute Error
ME	–5.082	Mean Error
RMSE	71.026	Root Mean Square Error
POD	0.902	Probability of Detection
FAR	0.057	False Alarm Ratio
FBS	0.957	Frequency Bias
CSI	0.855	Critical Success Index
HSS	0.544	Heidke Skill Score
VHI	0.983	Volumetric Hit Index
QPOD	0.902	Quantile Probability of Detection
VFAR	0.01	Volumetric False Alarm Ratio
QFAR	0.057	Quantile False Alarm Ratio
VMI	0.017	Volumetric Miss Index
VCSI	0.974	Volumetric Critical Success Index
QCSI	0.855	Quantile Critical Success Index

Merging Data

The next step after quality control is combining station observations with satellite or reanalysis proxies. This a very important step in implementing ENACTS, and it corresponds to the "Improving Availability" component of ENACTS. As described in the previous section, CDT provides different options for merging station observations and proxy data, starting with simple mean bias adjustment and then combining the bias adjusted proxy with contemporaneous station observations. **Figure 11** presents the two inputs (station observation and satellite rainfall estimates), the intermediate output (bias adjusted satellite) and the final merged product. The approach for temperature is similar, except that the reanalysis data need to be downscaled. **Figure 12** shows the different input and output products along with elevation map (DEM) used for downscaling.

Validation

In the implementation of ENACTS, validation is needed to evaluate the different satellite rainfall estimates and reanalysis products for a specific country as well as assess the accuracy merged products. However, the tool can also be used to evaluate any gridded climate data in NetCDF format. Thus, it could be used for research purposes as well. The evaluation of the merged data could be done either in a cross-validation approach or using different training and validation datasets. The validation uses different validation statics, including both categorical (mainly

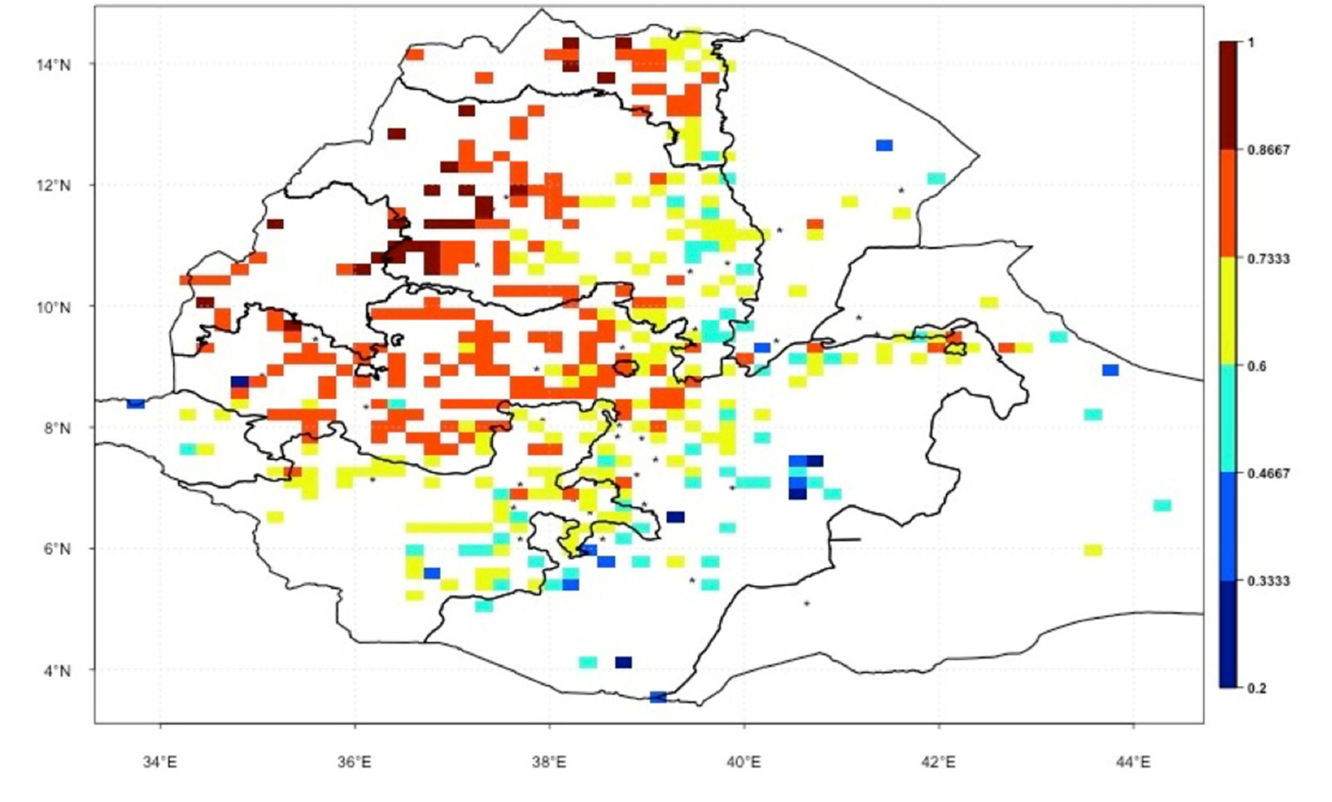

FIGURE 13 | Probability of detection for daily rainfall over Ethiopia.

used for daily rainfall) and continuous variables. The output could be presented as a table (**Table 3**), graphs (e.g., scatter plots), and maps (**Figures 13**, **14**). For instance, **Figure 13**, shows a plot of the probability of detection (POD) statics at station locations over Ethiopia. The main advantage of this kind of presentation would be to understand the spatial distributions of the errors. As shown in **Figure 14**, a background variable (such as DEM) could also be used to see the dependence of the errors on elevation or other factors.

Analysis

As described in Section Methodology above, the Analysis menu offers an array of option for data analysis, ranging from summary statistics for station observations to more involved computations in spatial analysis. Outputs are presented in tabular and graphic formats. **Figure 15** is an example of graphic output for onsets dates over Ethiopia. One strength of CDT in computing onset, cessation and length season is that different parts of the country could be treated separately with different onsets/cessation criteria. This enables definition of onsets/cessation that fits different agroclimatic zones.

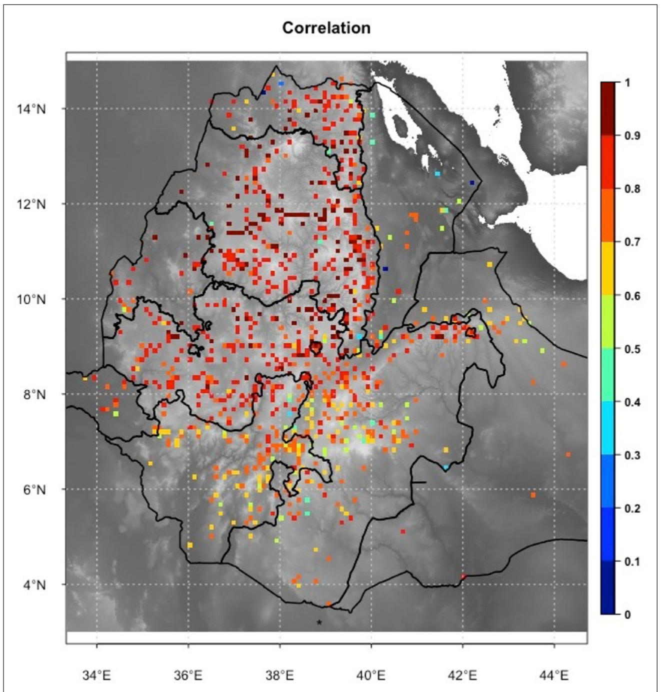

FIGURE 14 | Correlation Coefficients from cross-validation of monthly RR plotted with DEM as background.

DISCUSSION

The Climate Data Tool (CDT) has been developed to address specific needs of National Meteorological Services (NMS), particularly in Africa. The understanding of the need of NMS comes from over two decades of International Research Institute for Climate and Society (IRI) engagement with NMS in Africa. The CDT is now being used by many NMS for organizing station and other proxy (e.g., satellite rainfall estimates and climate model reanalysis products) data, performing rigorous quality control of station data, combining station observations with relevant proxies, evaluating proxy and combined gridded datasets, preforming specific analyses and visualizing the results. The tool has undergone significant improvements over the last seven years, mainly in response to feedback from the NMS. This feedback is collected in three different ways: (i) while training the NMS staff; (ii) while working with NMS to generate ENACTS (Enhancing National Climate Services) datasets; and (iii) feedback sent by email either reporting issues or suggesting additional functionalities. As a result, CDT has now become an indispensable tool for the 24 NMS and the two RCCs in Africa and five NMS outside Africa that have implemented it. CDT has also started attracting the attention of universities as a tool for climate data analyses, and the IRI has been receiving requests for training. For instance, 28 teachers and graduate students were trained at Arba Minch University in Ethiopia during August 2021.

This is a tool designed to address specific challenges faced specifically by NMS, and it has been developed in consultation with NMS. This consolation process has helped in addressing most of the initial limitations of the tool. However, there are still some limitations that users need to be aware of. The first limitation is the fact that the tool is based on another tool (R), and users need to install the system before installing and running CDT. This could be an inconvenience for some users. Another limitation is that users cannot add their own statistical methods or replace the graphical software to improve visualization.

Limited input and outputs data formats could also be another inconvenience. For instance, many NMS wish to use CDT for organizing and processing data from Automatic Weather Stations (AWS), which come from different AWS systems, are in different formats, and may sit on different servers. We have come to understand that this is a serious problem many NMS, and we have started developing a separate tool to address this issue. The new tool, AWS Data Tool (ADT), has been implemented in two countries and there are already requests from many other NMS.

Training is a critical component in implementing CDT. The standard training (implemented as part of ENACTS) lasts about 2 weeks and includes theoretical training on basic concepts used in CDT; hands on training using NMS's own data; and on-the-job training for selected NMS staff.

Though developed with the needs of NMS mind, CDT can also be used by anyone interested in quality-control, analyses and visualization of climate data. For instance, we have recently trained students and staff from Arbamich University in Ethiopia. Availability of climate data outside the NMS, such as the SASSACAL (Muche et al., 2018) and TAHMO (van de Giensen et al., 2014), would also increase the use of CDT.

Going forward, CDT would need to be updated (both the software and training) where it has been implemented. NMS using CDT may also need technical support including trouble shouting. CDT would also need to expand to other countries in Africa. This would be a daunting task for the IRI alone.

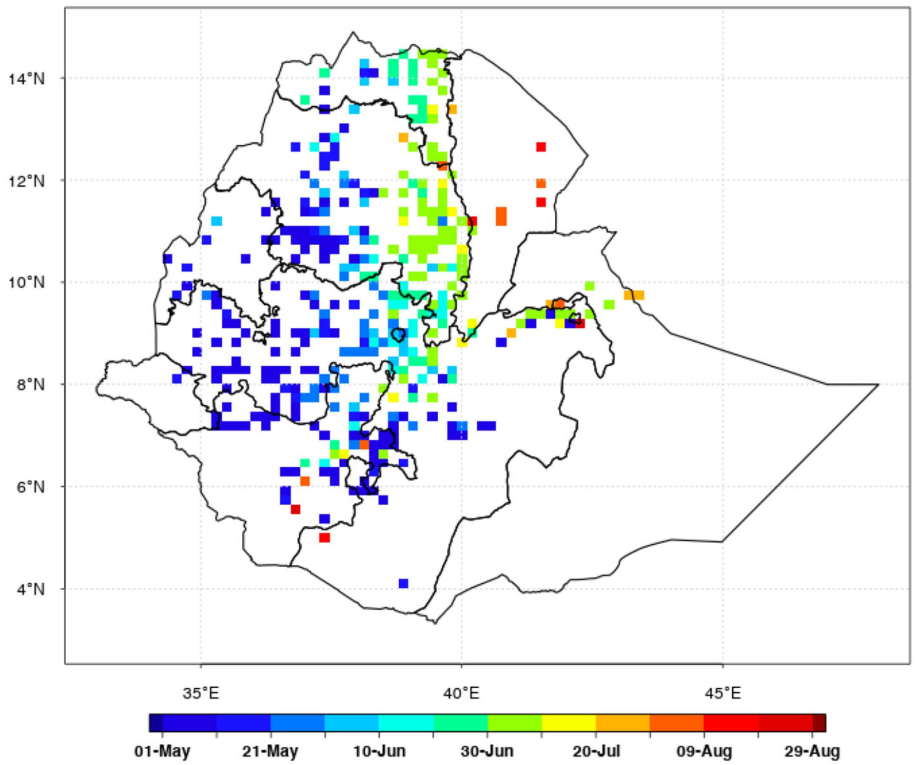

FIGURE 15 | Example of map output for onsets dates over Ethiopia. Onset seems to start in May for the southwestern part of the country (blue color), and in August for the northeastern part of the country (red color).

Implementation of CDT would be sustainable only if relevant capacity is built within the continent, preferably at regional level. The ultimate goal is to transfer CDT implementation to regional climate centers and limit IRI's role to technical support to the regional centers and keep on improving the tool. This would ensure sustainability as well as cost-effectiveness. The IRI has been building CDT–related expertise at two Regional Climate Centers (RCCs) in Africa. This capacity building and strategic partnership has been undertaken with the Intergovernmental Authority on Development (IGAD) Climate Prediction and Application Center (ICPAC) in East Africa, and the Agrometeorology, Hydrology, Meteorology (AGRHYMET) Regional Center in West Africa. These two RCCs have already started exploiting this capacity to strengthen and expand CDT in their respective regions. The AGRHYMET Regional Center has supported expansion of CDT to nine countries in the region with little or no support from the IRI, an encouraging demonstration of sustainable capacity building. ICPAC has also been supporting expansion of CDT to three new countries and has strengthened existing CDT installation (through tool update and more training) in many of the ENACTS countries in the East African region. This shows that capacity building at regional level is critical for sustainability as well as expanding the use of CDT. The RCCs provide much needed technical support and training to the NMS, which would have been both difficult and inefficient for the IRI alone to do. In many cases, there is a need to repeat the trainings either because of updated CDT version or owing to NMS staff turnover. The RCCs have been very helpful in this respect, re-training NMS where ENACTS has already been implemented and expanding it to non-ENACTS countries. In most cases, the RCCs have done the majority of these activities without the IRI's involvement and using their own funds and resources.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

TD: tool co-developer, implementer, and lead author. RF: tool developer, implementer, and also contributed to manuscript writing. SI and GN: contributed to manuscript writing. AG: contributed to manuscript writing (final editing). All authors contributed to the article and approved the submitted version.

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Using a Climate Change Risk Perceptions Framing to Identify Gaps in Climate Services

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Given the rise in climate services for decision-making, it is important to understand whether these services are meeting the context-specific needs of decision-makers, including identifying any gaps in current climate services. This study sets out to investigate the efficacy of current climate services provision in east Africa through the lens of climate change risk perceptions. Risk perceptions have established relationships with important aspects of the decision context and have been shown to influence the kinds of information people use in making decisions, therefore, an understanding of how elements of risk perceptions relate to climate services use can provide valuable insights for enhancing climate services. Using this premise, the relationships between determinants of climate change risk perceptions and the use of climate services information are explored through a combination of statistical survey analysis and qualitative interview analysis. The analysis revealed three main gaps in climate services in east Africa. These gaps include the lack of long-term climate change projections disseminated through National Meteorological Services (NMS), limited locally ground-truthed delivery of impact-based forecasts and the requirement for specialist capacity to use some complex climate services. Filling these gaps will require enhanced collaboration between the NMS, other providers of climate-related information (such as research institutes) and the practitioner and user communities in order to facilitate the coordinated delivery of locally ground-truthed impact-based forecasts, facilitate capacity development across the user-producer spectrum and augment the role of the NMS as conduits of climate change information.

Keywords: climate services, climate change risk perceptions, Africa, evaluation, climate risk

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INTRODUCTION

Climate variability and change represent a significant threat to developing countries, disproportionally more so than to developed countries (IPCC, 2014). Given this threat, there is a growing need to plan for climate change. This need has resulted in the rapidly growing field of climate services (Hewitson et al., 2017; Vogel et al., 2019) that, at the fundamental level, seek to provide weather and climate information that is useful for informed planning.

Alongside this escalation in climate services is a burgeoning literature base that attempts to evaluate the quality and effectiveness of currently-available climate services for Africa (e.g., Vaughan and Dessai, 2014; Vaughan et al., 2016, 2018; Carr and Onzere, 2018; Tall et al., 2018). Evaluating current climate services has two main purposes. First, it allows for the design and delivery of currently-available climate services to be improved so that they are better aligned to the individual user decision context (Steynor and Pasquini, 2019). Second, evaluations allow for the identification of pitfalls or gaps in the currently available climate services in relation to the specific user needs (the focus of this present study).

Evaluations of climate services have been useful in informing recommended changes to climate services in the past. For instance, at the continental scale, a comprehensive evaluation of the offerings from selected National Meteorological Services (NMSs) in Africa informed a set of recommended interventions for strengthened climate services provision (Winrock International, 2018). The evaluation framework developed as a result of this work forms the basis for regular World Meteorological Organisation evaluations for international reporting purposes (Dinku et al., 2018a; Cullmann et al., 2019). At the country level, an evaluation of climate services in Malawi revealed that major barriers to the use of climate information (particularly the use of climate change projections) was the incomprehensibility of the climate information and the lack of consensus amongst different climate information sources (Vincent et al., 2017). The evaluation recommended the development of a national set of climate change scenarios to make long-term information more accessible to policy users. This recommendation led to the development of a national climate brief which outlined historical climate trends and future climate projections (Mittal et al., 2017).

While these examples provide a snap-shot of the utility of evaluations in informing climate services, the evaluations literature, to date, has been largely focused on evaluating individual project offerings through user consultations, surveys, independent audits or website statistics of use (Vaughan et al., 2018). In augmenting these traditional techniques, new methods for evaluating climate services are needed, especially if they have the potential to identify gaps in climate services that may not be uncovered by these traditional evaluations.

On this basis, this study (i) demonstrates the efficacy of an evaluation approach based on statistical (quantitative) analysis, supported through qualitative interpretation, as a methodology for evaluating current east African climate services and (ii) identifies gaps in the current east African climate services landscape. While mixed qualitative/quantitative methods are already recommended in the evaluations literature (Tall et al., 2018), the approach presented here is novel because it utilises individual climate change risks perceptions as a conceptual framing.

Climate change presents a significant risk at both an individual and societal level. There is preliminary evidence to suggest that the perceptions of climate change risk are heightened in the African context, where climate change is considered to be impacting society already (Selormey et al., 2019; Steynor and Pasquini, 2019; Steynor et al., 2020b, 2021; Simpson et al., 2021). Climate change risk perceptions have established relationships with important aspects of the decision context that influence the use of climate services. For instance, climate change risk perceptions have been shown to influence both willingness to act on climate change (Spence et al., 2012; Lo and Chan, 2017; Smith and Mayer, 2018; Xie et al., 2019) and actual action on climate change (Blennow et al., 2012; Fahad and Wang, 2018; van Valkengoed and Steg, 2019). Heightened risk perceptions have been shown to increase an individual's information seeking behaviour (Kahlor, 2007) and the desire for climate information amongst natural resource planners when acting on climate change risk in the workplace (Peters et al., 2018). The perceived proximity of a risk has also been shown to influence the kinds of information people use in making decisions (Brügger et al., 2016). For instance, if climate change is perceived to be happening already then decision-makers may focus less on long-term climate information. Instead they may focus on trying to address climate change with short-term climate information that offers them concrete information such as potential short-term impacts (Steynor and Pasquini, 2019). Therefore, climate change risk perceptions are a useful conceptual framing with which to evaluate the fit of currently available climate services, because the types and timescales of information used within the decision context vary depending on perceptions of climate change risk.

Climate change risk perceptions are influenced by several underlying determinants (van der Linden, 2015; Steynor et al., 2021), for example social norms and experience of extreme weather events (amongst others). Given the role that climate change risk perceptions play in influencing the use of climate information in decision making, each of these risk perception determinants should also be considered when utilising a risk perceptions framing because they may also be reasonably expected to have an influence on the types of climate information used in addressing climate change-related risks. Therefore, exploring how each of the determinants of climate change risk perceptions relate to climate information use is proposed as a way of gaining insight into the climate services information use landscape and, in turn, what is currently missing from the landscape.

To this end, this paper begins with an introduction to the existing landscape of climate services in east Africa, as the region of study (Section The Existing Landscape of Climate Services Provision in East Africa). This presentation of the existing landscape is followed by the methodological approach for exploring the relationship between determinants of climate change risk perceptions and the current landscape of climate services information use (Section Methods). Section Results and Discussion presents the statistical results and qualitative analysis. Finally, Section Filling the Gaps in Climate Services for East African utilises the insight gained to identify current gaps in east African climate services and offer potential solutions for filling these gaps.

THE EXISTING LANDSCAPE OF CLIMATE SERVICES PROVISION IN EAST AFRICA

Climate services encompass a wide range of activities associated with the production, tailored delivery and uptake of weather and climate information into decision-making (Vaughan and Dessai, 2014) as well as the associated user engagement and capacity development (Vincent et al., 2018). In the present study we focus principally on the information provision component of climate services.

While it is important to draw a distinction between weather and climate information, the line between the two is somewhat blurred in the climate services space, primarily because, in order to provide a seamless information product for decision-making, it is important that information on both weather and climate timescales operate together (Tall, 2013). Further, products such as historical observations and trends of weather are essential for informing the production of numerical weather prediction models as well as climate models. This interconnectivity has led the World Meteorological Organisation to adopt a framing of climate services that includes consideration of all timescales of information from historical observations through to climate projections data (e.g., Cullmann et al., 2019, 2020). For the purposes of this study, therefore, we have adopted this comprehensive framing of climate services.

We focus this section on the current actors in the climate services provision space, and the types and timescales of available information, for the Greater Horn of Africa (hereafter referred to as east Africa) with particular focus on the countries of Ethiopia, Kenya, Rwanda, Tanzania and Uganda (as our study's focus countries). This section draws on review of the literature and on review of each country's online offerings through their NMS (**Table 1**).

Climate Services in East Africa

The provision of climate services in east Africa are supported by several internationally-funded research and implementation programmes. These programmes range from short-term research and practise-based interventions (such as the Weather and Climate Information Services for Africa programme) to sustained development solutions (such as the Famine Early Warning Systems Network). In addition, the World Meteorological Organisation-affiliated regional centres, namely the African Centre of Meteorological Applications for Development and the Intergovernmental Authority on Development Climate Predictions and Application Centre (ICPAC) provide focused regional support (Ngari et al., 2016). The latter (ICPAC) has a specific mandate to focus on addressing the east African regional challenges associated with climate risks (Percy et al., 2021). To this end, ICPAC disseminates weekly, monthly and seasonal forecasts at the region scale as well as rainfall and crop monitoring products[1]. ICPAC also has regional climate modelling capacity allowing for modelling of longer-term climate change projections (Percy et al., 2021). ICPAC is instrumental in convening the Greater Horn of Africa Climate Outlook Forums (GHACOFs) which allows for collaboration between regional, national and international climate experts in developing national seasonal forecasts (Cullmann et al., 2019; Percy et al., 2021). The GHACOFs are attended by representatives from each of the NMSs in the region as well as sectoral representatives and users.

[1]https://www.icpac.net/

Climate Services at the National Level

The primary mechanism for delivery of climate services at a national level is through each country's respective NMS (Singh et al., 2018), who are the mandated national authorities for provision of climate services (Hansen et al., 2019). While we recognise that each NMS is complemented by various public and private (both non-profit and profit) sources of climate services, these sources are too numerous to document here. Examples of these additional sources include private sources such as a Where (Ngari et al., 2016) or tailored climate services provided through ministerial bodies, such as the Ministry of Health or Agriculture (Kadi et al., 2011). Given the complexity of the national landscape, our country-level review is focused on the online climate service offerings provided by each of the five country's NMSs (**Table 1**). This focus is justified given the prominent position occupied by the NMSs as the authoritative climate services provider in each country.

The sale of observational data (**Table 1**) is a common financial model replicated by NMSs across Africa (Hansen et al., 2019). It a vital mechanism for supplementing the income of the NMSs and, in turn, supporting their sustainability as a national service (Hansen et al., 2019). A recent initiative that sought to improve the availability and equitable access to historical information was the Enhancing National Climate Services initiative (Dinku et al., 2018b). Through a collaborative approach between the International Research Institute for Climate and Society at Columbia University with each NMS, the project enabled access to satellite-derived reanalysis products through map rooms hosted by each NMS (Dinku et al., 2018b). This satellite-derived data can act as proxies for observational data for some applications (Dinku et al., 2018b) providing a potential alternative to station observation data. The map rooms hosted at each NMS (**Table 1**) and at the ICPAC regional centre are a legacy of this initiative and provide a foundation for the addition of further services based on the emerging user need (Dinku et al., 2018b). To this end, training was provided to NMS staff on how to create and maintain the map rooms (Dinku et al., 2018b).

Beyond observational data, the main focus of east African NMSs is on short-term forecasts (daily to seasonal forecasts) (**Table 1**). African NMSs work closely with each country's respective disaster management authorities in leveraging these short-term forecasts to provide early warning advisories of extreme weather events, where possible (Cullmann et al., 2020). In addition, when compared to other regions in Africa, east Africa has a reasonably strong base of impact-based forecast information on the daily to seasonal timescales (Nkiaka et al., 2020). It should be noted, though, that impact-based forecasts currently focus, primarily, on the national or regional level and at daily, weekly to seasonal timescales (**Table 1**).

While the literature documents ready access to longer term information in the region (including climate change projections) (Singh et al., 2018) these are not provided by any of the five country's NMSs and are, almost exclusively, provided by international sources such as the Intergovernmental Panel on Climate Change (IPCC) and the Coordinated Regional Downscaling Experiment (CORDEX), amongst others (Hansen et al., 2019). Ethiopia is an exception in this regard, with

TABLE 1 | Climate services offered to the public by each country's National Meteorological Service (NMS) (collated through an online review of each NMS's website, undertaken in May 2021).

	Ethiopia national meteorological agency	Kenya meteorological department	Rwanda meteorological agency	Tanzania meteorological authority	Uganda national meteorological agency	Synthesis commentary
Observed data	✓ Daily data available for purchase. Map room containing historical climate analyses	✓ Daily data available for purchase. Map room not operational	✓ Daily data available for purchase (with exceptions for research and government contractors). Map room containing gridded reanalysis/satellite datasets as well as climatological averages	✓ Daily data available for purchase. Map room containing gridded reanalysis/satellite datasets as well as climatological averages	✓ Daily data available for purchase. Map room not operational	All NMSs facilitate the purchase of daily observational (station) data. This data is not freely available, with the exception of Rwanda where free access to observational daily data can be obtained for use in research or for civil infrastructure. All NMSs host "map rooms", however, at the time of the review, two of these map rooms were not operational. The map rooms provide access to gridded reanalysis data and satellite data in Rwanda and Tanzania. The map rooms also offer access to additional historical climate analyses, such as Malaria risk in Ethiopia, Rwanda and Tanzania.
Daily to weekly forecasts	✓	✓	✓	✓	✓	The focus of the NMSs is on short-term forecasts from days to seasons. Most of the seasonal forecast bulletins also provide high-level advisories for chosen sectors within each country
Monthly forecasts	✓	✓	✓	✓	✓	
Seasonal forecasts	✓ Includes sectoral impact advisories for health, agriculture and water	✓ Includes sectoral impact advisories for: agriculture, food security and livestock; environment and natural resources; disaster management; health; transport; water and energy	✓ Includes broad-scale impact advisory (not sector specific)	✓ Includes sectoral impact advisories for: agriculture and food security; livestock and fishery; tourism and wildlife, transport; energy, water and mineral; local authorities; health; disaster management; media	✓ Includes sectoral impact advisories for a selection of: agriculture; livestock; fisheries; forestry; health, water and energy; works and infrastructure	
Separate sectoral advisories (including impacts information)	✓ Health, agrometeorological and hydrometeorological bulletins. Map room: Historical Malaria risk, historical and future water conditions and historical analysis of climate variables relevant to agriculture	✓ Bio and agrometeorological bulletins. Map room not operational	✓ Agrometeorological bulletin. Other sectoral services for purchase Map room: Historical Malaria risk, historical analysis of climate variables relevant to agriculture, climate summaries for local governments	✓ Agro - and Hydrometeorological bulletin. Restricted access aviation forecasts. Other sectoral services for purchase Map room: Historical Malaria risk.	✓ Restricted access aviation forecasts Map room not operational	All NMSs provide some broad sectoral advisories as stand-alone bulletins, with the level of detail dependent on the individual NMS.
1–5 year projections	X Not available	X Not available	X Not available	X Not available	X Not available	None of the NMSs provide climate information beyond the seasonal timescale
Climate change projections (5 years or further into the future)	X Not available	X Not available	X Not available	X Not available	X Not available	

The final column presents a synthesis interpretation of the similarities across each of the NMS offerings.

an in-country dedicated Ethiopian Panel on Climate Change established by the Ethiopian Academy of Science to provide a country level interpretation of the IPCC fifth assessment report (Ethiopian Panel on Climate Change, 2015).

It is within the context described above that we position our current study. We seek to understand how well this landscape of climate services actors and provision of information matches the current needs of climate services users at the policy level.

METHODS

The study employed an explanatory sequential mixed-methods approach (Creswell and Creswell, 2017). This approach starts with quantitative analysis and then builds on the results of the quantitative analysis to explore and explain them through qualitative research. This mixture of quantitative and qualitative approaches recognises their complementarity but also their differential explanatory power for answering specific research questions.

As a framing, our study uses the model introduced by Steynor et al. (2021), which offers an east African framework for identifying and prioritising the various determinants of climate change risk perceptions that motivate action on climate change in the workplace of policy decision influencers. The Steynor et al. (2021) model includes the following climate change risk perceptions determinants: observance of social norms, the psychological distance of climate change, experience of extreme weather events, personal values (both self-enhancing and self-transcending values) and the socio-demographic variables of age, gender and education. Each of these risk perception determinants are further explained in Section Survey Measures.

Design and Participants in the Survey

Following the target community defined by Steynor et al. (2021), we focused our research on policy decision influencers in east Africa, as the frequently targeted recipients and users of climate services. Policy decision influencers, in this context, were defined as individuals who are able to influence natural resource policy and would be expected to use climate services in this regard. For instance, policy decision influencers included national and local government officials (71% of the sample), academic researchers, non-governmental organisations (NGOs), private enterprise, international development agencies and parastatals (organisations owned by the government). An evaluation of climate services amongst this group is important because it is comprised of individuals who have the authority to influence local and national planning around climate variability and change.

Data to inform the study were collected through 474 surveys (a participant response rate of 77%) with policy decision influencers in the five east African countries of Ethiopia, Kenya, Rwanda, Tanzania and Uganda (hereafter referred to together as "east Africa") between September 2018 and January 2019. The minimum number of country surveys collected was 49 (Uganda) and the maximum number was 138 (Kenya). Relevant policy decision influencer organisations in the region were identified through a consultative exercise with stakeholders at an earlier project workshop and specific respondents at each organisation were identified based on the criterion that they would be expected to use or benefit from the use of climate services in their role.

The surveys were administered in English by trained enumerators in each country. Each survey was conducted in-person, with the exception of the section on individual values, because of its potential to be subject to social desirability bias. The values section was completed by the respondent themselves, independent of the enumerator, in order to minimise this potential bias. Participants took part in the survey on a voluntary basis and were granted anonymity through a consent form. The final sample consisted of 29.7% females and 70.3% males with an average educational attainment of an undergraduate university degree and an average age of 30–39 years.

Survey Measures

Brief descriptions of each of the survey measures are included here. More detailed descriptions of each of the risk perception determinant survey measures are included in Steynor et al. (2021).

Observance of Social Norms

Social norms refer to the external expectations on an individual to behave in a certain way and are generally understood to be unwritten rules or standards set by a social group (Popenoe, 1983). Social norms have been shown to have a strong influence on human behaviour at home and in the workplace (Inoue and Alfaro-Barrantes, 2015), including influencing pro-environmental behaviour (Doherty and Webler, 2016).

Six survey items were included to measure the observance of social norms for action on climate change and use of weather and climate information at work amongst this group. Three questions measured descriptive norms (what most people around them do) and three measured prescriptive norms (what most people around them approve of). The responses to the survey were measured on a five-point Likert scale from "strongly agree" to "strongly disagree".

Psychological Distance of Climate Change

Psychological distance is a measure of the perception of a threat as either far away or near (Pahl et al., 2014). It is measured on four dimensions, namely how close a threat is socially (the threat to oneself or ones social group), spatially (the geographical proximity of the threat), temporally (whether the threat is happening now or in the future), and hypothetically (the certainty of the threat) (Trope and Liberman, 2011). Previous studies have demonstrated a relationship between the psychological distance (closeness) of climate change and perceptions of climate change risk, i.e., the more psychologically close climate change is, the more it is perceived as a risk of concern (Spence et al., 2012).

The psychological distance of climate change was measured using seven survey items covering each of the four dimensions of psychological distance. These survey items were based largely on those proposed by Spence et al. (2012) and included two questions on social distance, two questions on spatial distance, two questions on hypothetical distance and one question on temporal distance. Responses were recorded on a five-point Likert scale from "strongly agree" to "strongly disagree", apart from the question related to temporal distance which was measured on a five-point Likert scale of "never" to "the effects are already being felt".

Experience of Extreme Weather Events

Previous experience of extreme weather events have been shown to increase climate change risk perceptions because experience renders the potential impacts of climate change more real or tangible (Akerlof et al., 2013; Demski et al., 2017). Experience of extreme weather events were measured through four items in the survey, namely how often, in the past 5 years, participants had experienced (i) floods, (ii) droughts, (iii) high temperatures/heat events, and (iv) changes to the rainy season pattern. Responses were captured on a five-point Likert scale from "very often" (more than ten times) to "never".

Values

Values are defined as core beliefs or standards that guide ones attitude, priorities and behaviour (Rokeach, 2008). Broadly, values can be grouped into four higher-order categories including self-transcending values (a focus outside of oneself for the greater humanitarian good), self-enhancing values (a focus on the prosperity and achievement of oneself), conservation (a focus on maintaining the current situation and traditions) and openness to change. In this study, we focussed on self-transcending and self-enhancing values, which have both been shown to have a relationship with perceptions of climate change risk. Self-transcending values have been linked to higher climate change risk perceptions (Poortinga et al., 2011, 2019), whereas self-enhancing values have been linked to lower climate change risk perceptions (Smith and Leiserowitz, 2012).

Values were assessed in the survey by using the Schwartz (2003a) 21-item Portrait Values Questionnaire and responses were recorded on a seven-point Likert scale from "very much like me" to "not like me at all". Using guidance from Schwartz (2003b), the responses were converted to centred scores and the two higher-order values of self-transcending values and self-enhancing values were extracted for use in the analysis.

Demographics

Demographics such as age, gender and education have all been shown to have a relationship with climate change risk perceptions (van der Linden, 2015). Therefore, demographic data including age range (in 10-year bands from 20 to 29 onwards), educational attainment (highest qualification) and gender were collected in the survey.

Types of Climate Services Information Used

One survey item was included with respect to what climate services information types are currently being used for decision-making. Survey participants were asked to select all weather and/or climate and/or impact information they currently use for their job. Choices included observed weather data (i.e., historical records), daily to weekly weather forecasts, seasonal forecasts (3 months), 1–5 year projections of climate, projections of climate 5 years or further into the future and impact-based forecasts. Impact-based forecasts were described as including, for example, forecasts of dam levels, of crop yields, of river levels, of climate-related disease outbreaks, etc. Responses were coded as a binary variable of use vs. non-use for each information type.

Trust in Sources of Information

In order to assess the participant's most trusted source of climate services, participants were asked to rank their top three most trusted sources for receiving climate services information. Choices included: university scientists/other research scientists, government scientists, representatives of national government, representatives of local/regional government, politicians, the country's NMSs, independent companies that provide weather and climate information (for example AccuWeather), friends and family, environmental consultants, non-governmental organisations (NGOs), community leaders, television, radio, newspapers or other. Responses were recorded on a ranking schedule from first to third trusted source.

Interview Design and Participants

In order to further explore the findings from the survey, a set of in-depth semi-structured interviews were conducted in two countries in the region. While interviews are an effective way of gaining a deeper understanding of quantitative findings (Baxter and Jack, 2008), it was only possible to conduct interviews in two countries, due to resource and time constraints. Therefore, although there are many socio-cultural and political similarities across the region, it should be acknowledged that the interviews would not have captured subtle nuances from the other three countries. The interviews took place in the countries of Kenya and Ethiopia during August and September 2019, respectively. Interviews were conducted with 20 participants in Kenya and 16 participants in Ethiopia (a total of 36) with eight participants from national government, three from local government, three from the private sector, seven from NGOs, two from international development agencies, five from parastatals and eight academics/researchers. No incentive was offered for participation and each interview lasted ∼1 h. The interview cohort consisted of a range of respondents that spanned the same sectors and similar organisational affiliations as the survey respondents and were identified through introductions or by approaching relevant organisations. Care was taken to ensure an equitable gender balance in interview respondents and all interviewees were assured of confidentiality.

The interviews covered a range of topics of relevance for further understanding the survey findings. Of importance to the present study, the interviews sought to gain an understanding of what climate services information types were being used, what facilitated or hindered their use, from where that information was obtained and what it was used for. All interviews were recorded and transcribed.

Analyses

For the purposes of analysing and presenting the quantitative regional survey results, the data from each of the five countries were aggregated together to represent the "east African region". This decision was justified due to the homogeneity in the types of climate services information used across all the countries. These similarities were likely a result of the region experiencing similar climate risks, having similar products available from their respective NMSs (**Table 1**) and receiving joint regional support from mechanisms such as ICPAC and the GHACOFs.

The quantitative data from the survey was statistically analysed in SPSS Statistics 26 to ascertain the relationship between each climate change risk perception determinant and the current use of each climate services information type in decision-making (described in Section Survey Measures above). Robust statistical analysis requires 10 participants for each included parameter (Schreiber et al., 2006), therefore the sample size of 474 more than adequately met the minimum criteria of 140 participants.

The non-parametric Mann Whitney U-test was chosen for the analysis because of the Likert scale nature and non-normal distributions present in the risk perceptions data. As the only categorical variable, the relationship between gender and climate services information use was analysed with Chi-Square analysis.

The qualitative data from the interviews were coded through a multi-step process in NVivo. First, the data were deductively coded into broad pre-defined categories of interest related to climate services information access and use, such as the use of the different types and timescales of climate information, barriers to the access and use of climate information, source of climate information, etc. Through repeated subsequent coding processes, these categories were then further sub-divided into sub-categories representing repeated ideas or patterns in the responses arising from the data. These sub-categories were used to detect consistent overarching themes in the data, providing further understanding and explanation of the statistical findings.

RESULTS AND DISCUSSION

Results of the Statistical Analyses

For the purposes of this study, only statistically significant results (ρ-value < 0.05) were taken as relevant for identifying the relationship between risk perception determinants and the current use of climate services information types. Therefore, while tests were performed for all combinations of risk perception determinants and information types (**Table 2**), only statistically significant results (presented in bold) are further interpreted in the final column of the table. The Chi-Square analysis revealed no statistically significant differences in types of climate services information used between the two genders.

Qualitative Results and Discussion

The semi-structured interviews allowed for further exploration, in two countries, of the statistically significant relationships between individual drivers of climate change risk perceptions and the use of climate services information types in the regional survey. The qualitative results and discussion are presented per climate change risk perception determinant.

The Relationship Between Observance of Social Norms and the Use of Climate Services

The statistical analysis of the regional survey revealed that observance of social norms for climate change action and use of climate services information at work was higher amongst those who used seasonal forecast information than those who did not (**Table 2**). The interviews provided insight into the reasons why this relationship between observance of social norms for climate change action and the use of seasonal forecast information may have existed. The interviews revealed that planning along seasonal timescales was considered to be part of taking action on climate change, thereby encouraging the use of seasonal forecast information in acting on climate change. This understanding was revealed when respondents were asked to provide examples of how they were planning for climate change: 13 respondents provided examples of addressing climate change through interventions aimed at coping with climate risk on a seasonal basis, a proportion greater than the number providing examples of taking action on climate change on any other timescale. For instance, when asked about expectations to prepare for climate change in job activities, one national government respondent provided an example of climate change action by saying they needed to provide advice to farmers on how to deal with inadequate rainy seasons.

> *"Yes* [there is a strong expectation on us to prepare for the impacts of climate change] *because most of our farmers out there are relying on rain-fed agriculture. So, they need directions from the specialists, that is like our ministry here, to give them the best way forward, in the event that the rain is short, it's not adequate to see the crops through the season."* Respondent K9, national government, Kenya

If taking action on climate change is conflated with taking action on the seasonal timescale then it would make sense that those who have a higher observance of social norms for action on climate change would also report the use of seasonal forecasts in taking action.

Despite this focus on the seasonal timescale, a few respondents ($n = 5$) acknowledged that this type of seasonal response mode was not a holistic approach to adaptation planning, and it meant that there was limited consideration of longer-term climate change information in climate change planning/action. This was demonstrated by a respondent from local government who stated that they had not used longer-term climate information, but he believed that it would be good to use it for resilience planning.

> *"The nature of our activity has not taken us there. But I want to believe that it will be good if we can see what the weather is going to be in the future, so that we, as a county, are able to do long-term planning... so that you can be able to prepare for the city to be resilient."* Respondent K14, local government, Kenya

One respondent explained the focus on the seasonal timescale by saying it resulted from agriculture being a sector of priority economic importance.

> *"Of course we know the government should be planning with the long-term climate information, but if you look at the priority areas*

TABLE 2 | *r*-values (bold where ρ-value < 0.05) of the Mann Whitney *U*-tests between risk perception determinants and current use of climate services information types.

***N* = 474**	**Observed data**	**Daily to weekly forecasts**	**Seasonal forecast**	**1–5 years projections**	**>5 years projections**	**Impact-based forecasts**	**Interpretation of statistically significant relationships**
Observance of social norms for action on climate change and using weather and climate information at work	0.08	0.08	**0.14****	0.07	0.08	0.04	Observance of social norms was greater for those who used seasonal forecasts (Mdn = 23; Mean rank = 251) than for those who did not (Mdn = 22; Mean rank = 211), $\rho = 0.003$.
Psychological distance	0.02	0.01	0	0	0.05	0	
Experience of extreme weather events	0.04	0.05	0.01	0.02	0.01	**0.11***	Reported experience of extreme events was higher amongst those who used impact-based forecasts (Mdn = 13; Mean rank = 257) than those who did not (Mdn = 12; Mean rank = 227), $\rho = 0.022$.
Self-enhancing values	0.07	0.05	0.01	0.05	**0.11***	**0.22****	Self-enhancing values were lower amongst those who used projections further than 5 years into the future (Mdn = −0.58; Mean rank = 209) than those who did not (Mdn = −0.38; Mean rank = 246), $\rho = 0.013$ and lower for those who used impact-based forecasts (Mdn = −0.62; Mean rank = 197) than those who did not (Mdn = −0.31; Mean rank = 260), $\rho = 0.000$.
Self-transcending values	0.09	0.06	0.01	0.02	0.07	**0.13****	Self-transcending values were higher amongst those who used impact-based forecasts (Mdn = 0.58; Mean rank = 261) than those who did not (Mdn = 0.43, Mean rank = 224), $\rho = 0.005$.
Education	**0.11***	0.06	0.06	**0.14****	**0.19****	**0.14****	Level of educational attainment was higher amongst those who used observational data (Mdn = 3, Mean rank = 250) than those who did not (Mdn = 3, Mean rank = 222), $\rho = 0.018$, amongst those who used 1–5 year projections (Mdn = 4; Mean rank = 264) than for those who did not (Mdn = 3; Mean rank = 226), $\rho = 0.002$, amongst those who used projections of further than 5 years into the future (Mdn = 4; Mean rank = 283) than those who did not (Mdn = 3; Mean rank = 224), $\rho = 0.000$, and amongst those who used impact-based forecasts (Mdn = 4; Mean rank = 262) than those who did not (Mdn = 3; Mean rank = 224), $\rho = 0.002$.
Age	0.06	0.09	0.02	0.01	**0.11***	**0.10***	Those who used projections of further than 5 years into the future (Mdn = 2; Mean rank = 265) were older than those who did not (Mdn = 2; Mean rank = 229), $\rho = 0.013$, and those who used impact-based forecasts were older (Mdn = 2; Mean rank = 254) than those who did not (Mdn = 2; Mean rank = 228), $\rho = 0.035$.

$^*p < 0.05$, $^{**}p < 0.01$.

> *like agriculture, then they tend to look for seasonal forecasts."*
> Respondent K1, NGO, Kenya

Agriculture is of high economic importance in many African countries (Nkiaka et al., 2019; Carr et al., 2020) and, as such, is a primary focus for policy decision influencers. This importance was demonstrated through the interviews in which 26 respondents cited impacts on agriculture or farming when providing examples of climate change impacts. Agriculture is particularly sensitive to seasonal climatic patterns such as variations in the onset and cessation of rainfall, droughts and prolonged heat events (Adhikari et al., 2015). For instance, heat stress during development and flowering of a crop can cause poor crop quality and yield (ibid) and planting during a false onset of the rainy season can result in lower yields or the need to replant the entire crop (Lala et al., 2021).

With agriculture as a primary economic focus, it is likely that the seasonal planning timescale became the predominant planning timescale because, as explained below by the same NGO respondent as above, planning on the seasonal timescale enables interventions in the agricultural sector, providing tangible economic outcomes and benefits to policy decision-makers within their typically short-term policy planning cycles.

> *"A season is very small and if I am told rains will come then you take action, and you will reduce certain losses or increase the yields then it is short term and the outcome is likely to be realised in the foreseeable future. But when you start talking of long term, then some people will not be keen, especially from the political level... they are interested in the next five years, when they are sure of being in the office, so they want to do things within that time frame."*
> Respondent K1, NGO, Kenya

This focus on short-term policy planning cycles was a factor noted by 9 interview respondents, therefore it is likely that the focus on agriculture, together with the need to demonstrate tangible impacts within policy planning cycles, is an influential factor behind the focus on seasonal planning as the predominant planning horizon. However, as the policy planning cycles can be anything up to 5 years, the policy cycles do not fully explain why projections longer than seasonal are not used more in planning. The interview results suggest that there may be a further reason for the predominant use of seasonal information in climate change planning.

When asked about their main sources of climate services information, 28 respondents said they obtained this information primarily from the NMS, with 13 stating that the NMS was the mandated or authoritative source of climate services information for the country. This finding aligned with the results from the regional survey which found that the NMS was the most trusted (first rank) source of climate services information by 59.5% of participants (**Supplementary Figure 2**). However, the longest timescale of forecasts currently provided by the NMSs in the region are seasonal forecasts (**Table 1**), meaning that those receiving their information from the NMS would not have access to projections longer than the seasonal timescale.

Lack of accessibility to longer-term climate projections was cited as a barrier to use of this information by 8 respondents, suggesting that despite the scientific literature documenting ready access to longer-term climate information outside of the NMS (Singh et al., 2018), its use is limited because of the prevalent role that the NMS plays in information dissemination at the national level. For instance, one respondent stated that he did not use longer-term projections because he didn't know where to get them, despite demonstrating that he believed he ought to know where to get them as a specialist in his field.

> "*We are not using that* [long term projections]. *We don't have the access, even I don't know where to get that kind of information.*"
> Respondent E13, NGO, Ethiopia

Additional barriers to the use of longer-term climate information also emerged from the interviews. These included difficulty in understanding the longer-term projections and/or how to use them ($n = 9$) and a distrust of longer-term climate information because of its inherent uncertainty or the evolving nature of the science ($n = 7$).

This section's analysis of the relationship between social norms and the use of climate services suggests that the lack of longer-term climate projections provided by the NMSs, together with limited trust and capacity to use longer-term information, are potentially posing structural barriers to the uptake of longer-term climate information into planning, thus potentially further reinforcing the seasonal timescale as the predominant planning time horizon. This highlights a potential gap in the provision of accessible climate services, particularly if the climate services community wish to promote the use of longer-term climate information in planning.

The Relationship Between Experience of Extreme Weather Events, Values, and the Use of Climate Services

The statistical analysis of the regional survey found reported experience of extreme weather events to be higher amongst those who used impact-based forecasts when compared to those who did not use impact-based forecasts (**Table 2**). Experience of extreme events can evoke strong emotions, making the events memorable and concrete, often associated with vivid negative consequences (Loewenstein et al., 2001; Weber, 2006). Furthermore, experiences of extreme weather events have been shown to play a role in bringing climate change psychologically closer (Steynor et al., 2021) thereby influencing how individuals mentally construe climate risk (Reser et al., 2014) and, in turn, the types of information they use to act on the risk (Trope and Liberman, 2011; Brügger et al., 2016). When in a mental processing mode associated with a risk that is construed as psychologically close, individuals seek out concrete, actionable information (Brügger et al., 2016).

Considering all interview respondents ($n = 36$) recalled at least one recent extreme weather event that impacted negatively on the region, it makes sense that greater experience of extreme weather events might lead them to use impact-based forecasts, which are likely to provide the kind of concrete, actionable information required in this mental processing mode. A local government official explicitly linked his experience of specific past extreme weather events to the desire for future impacts information to support planning, particularly around similar events, by saying:

> "[W]*e usually look at what kind of impacts we anticipate; what kind of losses will occur. And when we are seeking information, we also start thinking what kind of information is necessary so that we are able to avert such events, that is in terms of preparedness. Some of these areas where we have previous experiences, for example, flood-prone zones, we also start thinking this has been a problem for us, but moving in the future, what we want to do so that it doesn't happen* [again]." Respondent K14, local government, Kenya

The regional survey results also revealed self-transcending values to be higher, and self-enhancing values to be lower, amongst those who used impact-based forecasts. As these values lie in opposition to each other, their relationship with the use of impact-based forecasts is not surprising and can also be explained through the different ways these groups may construe climate risks. Those with predominantly self-transcending values (the majority of this cohort), who, by definition, have a more outward-facing awareness of the world around them, being motivated to help others and the environment, might therefore be more aware of climate risks and the associated impacts experienced by communities and ecological systems. This awareness might translate to a state of construal that leads them to seek concrete, impact-based information to mitigate the potential for future impacts. The hypothesised link between the use of impact-based forecasts and this cohort's outward-facing desire to help wider society was found in 10 of the interviews. For instance, a national government official linked the use of impact-based forecasts to the need to provide government assistance during periods of drought.

> "*If it was a drought, and we need to get maybe livestock feed or we need to know how to take care of people in those areas... part of the information that we prepare is possible impacts of that weather forecast.*" Respondent K9, national government, Kenya

While the survey revealed that impact-based forecasts were used by 36% of policy decision influencers (**Supplementary Figure 1**), the interviews revealed a mismatch between the readily available impact-based forecasts and those suitable for local application by the user community, with 15 respondents reporting that they generated their own impact-based forecasts based on the information received from the NMS. For instance, a national government official in Ethiopia noted that, while the NMS did provide impact-based forecasts, this information required further strengthening through ground-truthing with local information in order to be applicable to the local decision context. This ground-truthed information was produced in-house.

> "*The met*[eorological] *people are trying to give that* [impacts] *forecast. But the detailed one is prepared here, with ground information. So, we are using that ground information, so we can strengthen the information that we get from the met*[eorological] *office.*" Respondent E14, national government, Ethiopia

Given the prominence of the NMS as a source of climate services information (Section The Relationship Between Observance of Social Norms and the Use of Climate Services), this mismatch between the readily available impact-based forecasts from the NMS and what is required for on-the-ground decision-making revealed a potential shortcoming in the current delivery of impact-based forecasts.

Finally, the regional survey analysis found that self-enhancing values were lower amongst those respondents who used long-term projections (projections of climate further than 5 years into the future) than among those who did not. This relationship was more difficult to explain through the interviews, especially as respondents did not openly report self-enhancing tendencies (which may be perceived as undesirable). However, speculative reasons for this relationship can be drawn from the literature. Those with higher self-enhancing tendencies tend to have a lower engagement with climate change and are less concerned about it (Corner et al., 2014). On this basis, it can be hypothesised that those with high self-enhancing values would be less likely to engage with long-term projections of changing climate, primarily because of their lower engagement with climate change. Therefore, this may then explain why the respondents using long-term projections of climate change have lower self-enhancing values.

This section's analysis of the relationship between experience of extreme weather events and the use of climate services revealed a gap in the provision of climate services with regards to the delivery of decision-relevant, locally ground-truthed impact-based forecasts. As decision makers are likely to continue to seek concrete, actionable information to address the impacts of climate change going forward, the enhanced provision of impact-based forecasts is likely an important area of focus for climate services improvement.

The Relationship Between Education, Age, and the Use of Climate Services

The statistical analysis of the regional survey revealed that the level of educational attainment was higher amongst those who used observational data, 1–5 year projections, projections of further than 5 years into the future and impact-based forecasts (**Table 2**). All of these information types were used less than daily/weekly forecasts or seasonal forecasts by the regional survey respondents (**Supplementary Figure 1**). An understanding of the reasons behind their lower use provides insight into their relationship with educational attainment.

Starting with the use of longer-term information (1–5 year projections and projections 5 years or further into the future), the interviews revealed that reasons for not using longer-term information included: difficulty in understanding the longer-term projections and/or how to use them ($n = 9$), lack of accessibility ($n = 8$), and a lack of trust in the longer-term climate information ($n = 7$) (Section The Relationship Between Observance of Social Norms and the Use of Climate Services). Of these reasons, the difficulty in understanding longer-term projections and their use would seem to be the reason that best explains why respondents who use these types of information are the most educated respondents. It seems reasonable to suppose that the relationship between the use of longer-term information and higher educational attainment would be explained by the potential for education to provide the required capacity to access, understand and interpret this information.

With regards to observational data, the interviews highlighted a requirement for specialist capacity for pre-processing or filling incomplete datasets before they could be useful. The skills required to pre-process incomplete data are often acquired through higher educational attainment. For instance, a senior hydrologist with a Masters degree noted that he had to pre-process observational data from the NMS before he was able to use it:

> "*This climate information we got from the National Meteorological Agency, there is a lot of data gaps... so, we have to prepare it, we have to fill it. It is difficult to fill the data gaps.*" Respondent E4, private sector, Ethiopia

The same requirement for specialist capacity can be applied to explain the relationship between the use of impact-based forecasts and educational attainment. As evidenced in Section The Relationship Between Experience of Extreme Weather Events, Values, and the Use of Climate Services, many of the impact-based forecasts were produced in-house in response to specific user needs. As noted by a respondent from Kenya, the ability to generate these in-house forecasts or advisories requires specialist knowledge.

> "*When you look at the seasonal forecast, they* [the NMS] *will give you some* [impact] *advisories, but I find that these advisories could apply in any season, anytime, anywhere... So, a lot of people have to interpret the forecast for themselves. The extent that is possible also depends upon capacity, knowledge.*" Respondent K5, NGO, Kenya

The statistical analysis also revealed that those who used climate projections of further than 5 years into the future and those who used impact-based forecasts were older than those who did not. Unfortunately, the age of the interview respondents was not recorded, so it is not possible to explain the relationship between age and the use long-term climate information and impact-based forecasts through the interviews. However, a speculative reason for the existence of these relationships may be that older policy decision influencers have, through experience, come to appreciate the limitations of planning based on short-term information alone and have also come to understand the added value that impact-based forecasts might provide them for planning.

This section's analysis of the relationship between education and the use of climate services revealed that the specialist knowledge required to use some climate services is potential posing a barrier to their uptake.

FILLING THE GAPS IN CLIMATE SERVICES FOR EAST AFRICAN

The analysis of the intersection between climate change risk perception determinants and the use of climate services provided useful information in understanding and explaining current climate services use. The analysis also allowed for the identification of potential gaps in the services supply landscape. These gaps are noted below, alongside recommendations for responding to them.

The Need for Provision of Longer-term Climate Projections Alongside Short-term Forecasts

The extent to which short-term information is used by policy decision influencers emphasises the need to continue providing short-term information for decision-making. However, it was revealed that there was limited use of longer-term information among policy decision influencers, despite some recognition that they should be using it. One reason for this limited use seems likely to be due to the gap in provision of longer-term climate information from the NMSs, who are the mandated and trusted information source in each country.

To support the uptake of longer-term, particularly climate change information, into planning, the NMSs could be encouraged to act as conduits for climate change projections while continuing to provide shorter-term information. This provision of longer-term climate information may begin with simple messages around the direction of change of future climate (for example from the United Nations Framework Convention on Climate Change national communication documents) and move towards developing an approach that integrates both short-term weather forecasting and longer-term climate change projections into a continuous forecast of the future (Singh et al., 2018), also known as seamless forecasting.

While integrating longer-term information into the NMS offerings seems a straightforward recommendation, it is acknowledged that anything beyond very simple messages, such as the direction of change of future climate, requires additional staffing resources and capacity (Winrock International, 2018). NMSs in the region are already notoriously underfunded and understaffed and lack the institutional legacy of capacity that some of the NMSs in developed countries have (Winrock International, 2018). Therefore, to achieve this seamless forecasting approach, opportunities lie in strengthening the international and in-country collaborations between, for instance, universities, the private sector and the NMSs, in order to draw on a range of national and international expertise in tailoring longer-term information for specific users, as well as providing guidance to ensure their robust use. However, while this kind of collaborative approach has been widely supported in the literature (e.g., Winrock International, 2018; Cullmann et al., 2019), the siloed culture of national institutions at present (Winrock International, 2018) is a hindrance to this type of collaboration, presenting a barrier that would need careful consideration in overcoming. An initial step towards overcoming this barrier may be to embark on developing memorandums of understanding between institutions for data sharing and collaborative working or to leverage the burgeoning development of the National Climate Services Frameworks (under the Global Framework for Climate Services) to establish sustained collaborative engagement platforms.

The Need for Enhanced Delivery of Impact-Based Forecasts

While it is evident that east Africa is more advanced in the delivery of impact-based forecasts than some other parts of Africa (Nkiaka et al., 2020), there is still scope to improve the delivery of impact-based forecasts so that they incorporate more locally-specific detail. Through enhanced collaboration and coordination between, for instance, the NMS, other suppliers of climate-related information (such as research institutes and regional bodies), sectoral experts and indigenous knowledge holders there is scope to enhance the delivery of these impact-based forecasts so that they are locally ground-truthed, providing information that is more relevant for local decision-making.

Building on the mandate and authority of the NMS, as the central source of climate services information, the NMS and ICPAC map rooms provide potential for hosting these impact-based forecasts, as is currently the case for historical Malaria risk in Rwanda and Tanzania (**Table 1**). However, at the time of this review, the map rooms of the Ethiopian National Meteorological Agency and the Kenyan Meteorological Department were not functioning, which confirms the need to carefully consider the sustainability of any suggested intervention at each NMS. The establishment of a strategic oversight group within each NMS to both coordinate donor funding and lobby government for sustainability funding would likely assist in this process.

The Need for Building Capacity, Trust, and User-Focused Climate Services

The analysis revealed that specialist knowledge is required to use some climate services such as observational data, impact-based forecasts and longer-term information. With particular respect to longer-term information, limited trust in the information was also cited as a barrier.

Previous literature has commonly offered user capacity development as a solution to increase the use of complex climate information (e.g., Jones et al., 2015; Vincent et al., 2017; Singh et al., 2018; Hansen et al., 2019; Nkiaka et al., 2019), because, as highlighted in this research, higher educational attainment has a relationship with the use of some of the more specialist climate services information types. The push towards capacity development has led to a growing number of tailored and targeted short courses to enhance the use of climate services in Africa. As an additional form of capacity development, the current research suggests that mentorship between senior (older), more qualified, and junior (younger), less qualified members of staff may encourage the use of climate change projections, as it was found that older respondents were also more likely to use longer-term information.

However, while user capacity development is undoubtedly one part of the solution, the onus should not be placed solely on the users of climate services to increase their ability to use complex information. There is a reciprocal need for capacity building amongst the providers of climate services to enable them to produce usable information. This requires that the climate services producers gain a better understanding of the complexities of the user decision context (Jones et al., 2017; Müller et al., 2020), understanding what constitutes usable as opposed to useful information (Lemos et al., 2012) and how to effectively communicate climate services information in a way that maximises uptake and use (Daron et al., 2021).

Similar to the recommendations for further collaboration made in Section The Need for Enhanced Delivery of Impact-Based Forecasts, enhanced collaboration and knowledge exchange between climate services providers, intermediaries and the users of climate services are an increasingly recognised way of enhancing the utility and use of climate services information (Steynor et al., 2016, 2020a; Jones et al., 2017; Done et al., 2021; Vincent et al., 2021). These transdisciplinary collaborations have also proved to be effective ways of building trust relationships which, in turn, create trust in the resulting climate information (Vincent et al., 2018).

CONCLUSION

This study introduced a climate change risk perceptions approach for identifying the current gaps in climate services information available in east Africa. Three main gaps have been elucidated, namely the lack of longer-term climate information disseminated through NMSs, the limited delivery of ground-truthed impact-based forecasts and the limited capacity to understand, trust and use complex longer-term climate projections. While none of these gaps are surprising, the seemingly central role played by the NMSs in driving information use is important to note and could provide a valuable leverage point for increasing the use of climate services.

In addressing these gaps, a future vision for climate services in east Africa may include an approach that is premised on the enhanced collaboration between the NMS, research institutes and the practitioner communities in developing a community of practise that would facilitate the ready access to longer-term climate projections and locally-relevant impacts information. This enhanced collaboration would also provide the framework required to build capacity across the climate services community (between producers, practitioners and users) in the robust supply and uptake of climate services into decision-making. Under the auspices of each country's National Framework for Climate Services, the NMS could act as a central point or champion for this community, thereby providing a critical role in connecting the community and acting as a conduit for the dissemination of decision-relevant information, including longer-term climate change information.

While this vision appears a simple suggestion, a collaboration such as the one described above would require significant changes in the current operating culture in the region. While some partnerships do exist, enhanced collaboration on the scale recommended here would likely be constrained due to lack of financial or personnel resources (Winrock International, 2018). Therefore, there is a need for further research to understand the cost-benefit trade-offs between focusing limited funding resources primarily on the advancement of decision-relevant products or focusing resources on the enhancement of networks and collaborative arrangements that underpin the development of these products. Given the growing need to adapt to a changing climate, this is a question that needs careful consideration within the current funding landscape.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because much of the data includes identifiable information that would invalidate the anonymity granted to the participants. Requests to access the datasets should be directed to AS, asteynor@csag.uct.ac.za.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by University of Cape Town Faculty of Science Research Ethics Committee. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

AS conceptualised, executed the research, and drafted the paper. LP intellectually contributed to the execution of the study as well as reviewed and contributed to the draft paper. Both authors contributed to the article and approved the submitted version.

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Profiling User Needs for Weather and Climate Information in Fostering Drought Risk Preparedness in Central-Southern Nigeria

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Weather and climate information trigger early action and facilitate better disaster preparedness. Decision-driven and people-centered weather and climate information are pivotal for the effective uptake. The challenge of early responses in preparing for drought hazard is growing in the dry savannah of tropical sub-Saharan African countries. This paper analyzed user needs for weather and climate information in fostering drought risk preparedness in Central-Southern Nigeria. Stratified, snowball, and simple random samplings were used to obtain a sample of 397 respondents across the agro-ecological zones of Edo State. Structured questionnaire was used to collect farm-level household data across communities. Eight focus group discussions and 11 key informants' interviews were conducted, targeting contact farmers and other agricultural stakeholders in selected key economic sectors of Edo State, Central-Southern Nigeria. Results show that non-users of weather and climate information are more than users in the savannah area. Heckman probit results explained that male gender, farmers' experience, income, and persistent incidence of erratic rainfall have more propensity to facilitate use of WCI in taking critical decisions while group membership or associations and distance of meteorological station prevent stakeholders from developing interest in using WCI for drought preparedness and response. Multi-criteria decision-making indicated that rainfall amount, onset and cessation rainfall dates, and rainfall distributions are the most useful WCI needed by end users in their decision response plan in agriculture; rainfall intensity, rainfall cessation date, rainfall distributions, and length of dry season are ranked as the most useful WCI for water resource management while heat intensity, rainstorms, and drought alerts were ranked as most appropriate for users in the disaster risk reduction in fostering resilience toward anticipated future drought hazard. Subseasonal-to-seasonal (S2S) and medium (4–10 days) timescales information are the most highly rated to facilitate resource planning for efficient utilization and management in all the economic sectors. The users' most preferred delivery method of receiving WCI are mobile telephone, radio, agricultural extension officers, farmers' groups, and contact farmers/specialist for efficiency and convenient criteria in enhancing users' decision capacity to uptake WCI. There is a need for a policy drive to build synergy that will make WCI forecasting systems include impact-based forecast estimates and response advisory across a wide range of natural hazards. A seamless collaborative effort in bringing scientific outputs and users' needs together will increase the utility of WCI through systematic efforts. NiMet should improve on its engagement with the stakeholders, the agricultural extension and planning office, water management authorities, and disaster risk reduction and emergency response personnel as partner institutions. These policy actions would provide a robust collaborative framework for co-producing useable WCI based on user needs in managing decision points against extreme events and mainstream preparedness into existing decision-making apparatus of rural communities in Central-Southern Nigeria.

Keywords: drought hazard, weather and climate information, multi-criteria decision, Nigeria, hazard preparedness

INTRODUCTION

Scientific evidence suggests that extreme weather events and climate variability, either under present or future climate conditions, will have severe consequences for development, and pose risks to food security and disaster risk management apparatus. Climate change is already modifying the frequency and intensity of many weather-related hazards as well as steadily increasing the vulnerability and eroding the resilience of exposed populations that depend on arable land, access to water, and stable mean temperatures and rainfall. Risk to weather-related hazards is concentrated in low- and middle-income countries (IPCC, 2014; UNDRR, 2020). Climate change is expected to exacerbate prolonged drought periods, shifts in rainfall patterns, flooding, and extreme heat conditions. Social, ecological, and economic vulnerabilities to such weather extremes currently exist, and will exacerbate existing vulnerabilities, creating new risks (IDB, 2015; TWB, 2015; FAO, 2016; Cho, 2019; World Bank, 2020; Awolala et al., 2021). These severe weather changes may increase both the frequency and intensity of disasters and the likelihood of mega disasters. The projected impacts of climate change that will drive disaster risk include decreasing agricultural yields in warmer environments due to heat stress with serious implications for rural livelihoods, long droughts aggravating poor availability of water resources for agricultural and domestic utilizations, and more severe and frequent extreme rainfall intensifying existing patterns of extensive risk in view of population growth (FAO, 2015; UNDRR, 2020).

The risk associated with weather-related hazards is disproportionately concentrated in developing countries and within these countries in poorer sectors of the population, thus rural livelihoods that depend on agriculture and other natural resources are vulnerable to even slight variations in weather and seasonality (Ziervogel et al., 2006; UNDRR, 2020). Agriculture is critical to the growth and development of Africa, responsible for over one-fifth of sub-Saharan Africa's economic output, hence extreme climate events could make it more challenging, especially in the arid and semi-arid regions (McKinsey Global Institute, 2020). The sector is increasingly showing a high level of vulnerability because its weather patterns are becoming less favorable, the frequency and/or severity of extreme events is increasing as projected rise in temperatures continue rising, and rainfall patterns are expected to shift more than they have already (Antwi-Agyei et al., 2012; Wood et al., 2014; Nwanze and Fan, 2016).

Africa is disproportionately affected by prolonged droughts given that most of its economies are climate dependent with poor infrastructural base. Drought is one of the critical extreme events facing the tropical savannah region of sub-Saharan Africa. In Africa, during the last decade (2010–2019), a significant increase of 52% in economic losses was recorded mainly due to floods, drought, and storms compared with the period 1970–2009 (Vicente-Serrano et al., 2012; CRED and UNISDR, 2020; WMO, 2020a). Drought has accounted for 95% of hydro-meteorological hazard-related deaths over the past 50 years. Between 1970 and 2019, disasters have accounted for US$ 38 billion in economic damages (WMO, 2020a). Over the last 50 years, 35% of deaths related to weather, climate, and water extremes have occurred in Africa. Vulnerable people in countries with weaker disaster preparedness systems are facing the greatest risks. Smallholder farmers in West Africa rely on rain-fed agriculture for their daily subsistence, making these farmers extremely vulnerable to the adverse impacts of climate fluctuations (Coulibaly et al., 2015). Consequently, food security and rural livelihoods, water availability, or per-capita renewable water resources are declining due to multi-prolonged destruction of rural irrigation systems, which pose an additional threat to freshwater resources for agricultural use and domestic purposes (FAO, 2018; Haider, 2019). In recent years, impacts of droughts are increasing in magnitude and complexity in Nigeria, particularly pronounced in increasing aridity and challenging traditional farming systems in the savannah areas (Abdullahi et al., 2016; Elijah et al., 2017; Hassan and Fullen, 2019).

Given that climate change is so closely linked to many underlying risk drivers, it must be addressed within the same context of reducing these drivers of risk. If these drivers are not addressed, disaster risk will continue to increase even if climate change is successfully mitigated (UNDRR, 2020). As extreme climate events continue to threaten human lives, ecosystems, and economies, climate information and early warning system is increasingly observed as a key strategy for reducing impacts of these hazards. The key strategy to minimize current disaster risks implies improving the disaster preparedness efforts and integrating disaster risk reduction into development strategies. Disaster preparedness contains the activities and measures taken in advance to ensure an effective response to the impact of hazards, including timely and effective early warning systems (ISDR, 2001; Lavell et al., 2012; WMO, 2020b).

The National Center for Disaster Preparedness (2016) observed a growing recognition linking climate change and disaster preparedness is on the premise that the understanding will assist to prioritize efforts in preventing, preparing, and responding through planning prevention interventions (IFRC, 2003; Petkova, 2021). Disaster preparedness measures, including early warning, serves as a bridge between disaster risk reduction and disaster management. Preparedness attempts to assist vulnerable communities in eliminating adverse effects that could be experienced once a physical event(s) occurs (Cutter et al., 2012). Early Warning System (EWS) is a top adaptation priority in the Nationally Determined Contributions (NDCs) of the majority of Parties to the United Nations Framework Convention on Climate Change (UNFCCC), including Nigeria. EWS is a key proven measure for effective disaster risk reduction and adaptation (UNFCCC, 2017). Access to useful and quality-controlled climate information is inevitable for better informed decisions aimed at addressing existing and future weather and climate-related hazards (Nkiaka, 2019; Antwi-Agyei et al., 2021). Weather and Climate Services (WCS) can provide decision support information in facilitating both climate change adaptation efforts and disaster risk reduction practices (Street et al., 2019).

Given this perspective, the focus on agriculture, water resources, and disaster management sectors is justified by their climate sensitivities (Vaughan et al., 2016; FAO, IFAD, UNICEF, WFP, and WHO, 2018), and the overall significance as priority areas within the Global Framework for Climate Services (GFCS) that provide a worldwide mechanism for coordinated actions toward enhancing the quality, quantity, and use of WCS. Effective climate services will facilitate climate-smart decisions that will address the impacts of climate-related disasters, improve food security, enhance water resources management, and improve outcomes in disaster risk reduction (World Meteorological Organization, WMO, 2013; Nkiaka, 2019).

CONTEXT OF CLIMATE INFORMATION IN MANAGING EXTREME EVENTS

WMO (2020b) defines Weather and Climate Services (WCS) as the transformation of climate-related data and other information into customized products such as projections, trends, economic analysis, advice on best practices, and any other useful services. This stressed the importance of a user-driven approach rather than the supply-driven Global Framework for Climate Services (GFCS) definition merely as to strengthen the production, availability, delivery, and application of science-based climate prediction and service. WCS provide science-based and user-specific information relating to past, present, and potential future climates helping countries make better and informed decisions in climate-sensitive sectors, thereby generating substantial economic benefits and sustainable development (Snow et al., 2010). The Global Framework for Climate Services (GFCS) defines climate services as climate information prepared and delivered to meet users' needs (WMO, 2011).

Climate services have been identified as adaptation measure that could assist on local scale by enhancing disaster preparedness actions against droughts and dry spells, especially in the savannah drylands (Jones et al., 2014). Climate services are regarded as generation, provision, and contextualization of information and knowledge obtained from climate research for decision-making in all climate-sensitive sectors. It helps develop and disseminate climate relevant information for decision-making (Mjelde et al., 2000; Vaughan and Dessai, 2014; Brasseur and Gallardo, 2016). In Africa, addressing impacts of extreme events through access to weather information, early warnings, and other adaptive mechanisms are foremost in climate policy dialogues and development agendas of many countries (Oyekale, 2015b; Awolala, 2018; Vogel et al., 2019). The overarching goal of the GFCS Adaptation and Disaster Risk Reduction in Africa program is to provide timely and accurate climate and weather services for disaster risk reduction and increased resilience in agriculture (WMO, 2021a). Climate information has played a significant role in improving the management of water resources and making the agriculture sector in the arid areas more resilient. The establishment of a warning system to cope with climate uncertainties helps to provide advice to farmers on sustainable agricultural practices (Britz, 2021). Nevertheless, despite improved capacities in disaster risk knowledge and forecasting that are relatively well advanced in Africa, there is a need to make this information actionable and accessible so as to better link information to action (UNDRR, 2020; WMO, 2020b). There has never been a more critical time to work on improving adaptation to climate-sensitive disasters by applying scientific approach on how people prepare and respond to future disasters (Petkova, 2021).

Nigeria is classified as one of the 10 most vulnerable countries to the impacts of climate change and natural hazards (Climate Scorecard, 2019) and ranked 160 out of 181 countries in the 2020 ND-GAIN Index, which emphasized serious attention to set the goal of readiness to improve resilience by prioritizing decisions for more efficient responses (University of Notre Dame, 2020). An estimated 24% of Nigeria's population (about 41 million people) are living in high climate exposure areas (GFDRR, 2019). The high vulnerability to seasonal variations and long-term climate changes has cumulative impacts (Olagunju, 2015; Ayanlade et al., 2018). The trends in extreme events especially are threatening its overall economic structures, notably the regular multiple hazards such as increased aridity and drought, increased duration of dry spells, and rising temperatures, among others

(World Bank, 2021). The high levels of poverty, low degree of development, and dependence on rain-fed agriculture limit the capacity of rural households and constrain communities to manage climate risk, increasing their vulnerability to climate-related shocks (UNFCCC, 2016). Significant consequences are expected for the country's water resources (UNFCCC, 2020), agriculture (UNFCCC, 2018, 2021), and disaster risk prone areas (USAID, 2019). Nigeria is working to advance its disaster risk management (DRM) agenda through resilience efforts to share data from climate information and early warnings, develop plans for disaster preparedness, and planning the agricultural and allied sectors at community levels (GFDRR, 2019).

Climate services are primarily available through the Nigerian meteorological and hydrological agencies, aimed at generating climate-smart decisions across all socio-economic sectors (NiMet, 2021; The Cable, 2021). The agency helps the grassroots understand its application in the agricultural value chain (WMO, 2021b) and transform climate information systems into relevant warnings useful for end users. Despite recent improvements in the operational weather and climate forecasting with the development of Numerical Weather Prediction (NWP) models and partnerships with the WMO for operational activities (NiMet, 2021), there are serious challenges limiting uptake of WCI. Underutilization of available WCI at the grassroots for climate risk management and preparedness decisions is limited because of low education and inadequate financial support that result in limited ability to adopt innovative communication technologies to access WCI (Baumüller, 2016; Tall et al., 2018; Krell et al., 2021), lack of relevance and misalignment between the climate information provided and actual information needs of users (Dilling and Lemos, 2011; Ekstrom et al., 2011; Li et al., 2012; Awolala, 2018; Nkiaka, 2019; Muita et al., 2021), and disconnection between service providers and user institutions (Antwi-Agyei et al., 2020; Hansen et al., 2019; Naab et al., 2019; Sultan et al., 2020). Furthermore, the inability to provide precise site-specific WCI due to sparse and poor weather observation network (Guthiga and Newsham, 2011; Kusangaya et al., 2014; Karuma et al., 2016), uncertainty in various types of climate information constraining decision-making, unsuitability to inform decision-making required by communities (Silvestri et al., 2012; Apgar et al., 2017), ineffective dissemination of climate services reaching the most vulnerable and poor understanding by vulnerable communities (Onwuemele, 2014; Vaughan and Dessai, 2014; Jones et al., 2015; Adenle et al., 2017; Awolala, 2018; Nkiaka, 2019; Antwi-Agyei et al., 2021), and poor capacity of agencies providing hydrological information and warning services to provide climate services for water, and emergency preparedness (Ziervogel et al., 2008; Kumi et al., 2020; Britz, 2021), have been recognized as barriers that have made WCI credibility doubtful and limiting the uptake on climate information in making smart decisions on risk preparedness by communities.

In recent times, sharing of information on weather and climate has improved by the Nigerian Meteorological Agency (NiMet) and the Nigerian Hydrological Services Agency (NIHSA). There have been more use of online and news media as medium of dissemination. Some partnering public institutions have also increased their efforts in climate communication by incorporating advisory services, although the size of the coverage is still low due to the very large population. Past studies on impacts of climate change in Nigeria have mainly addressed response patterns with resultant implications for environment and livelihoods (Adeaga, 2011; Garba et al., 2013a,b; Ifaniyi, 2013; Haider, 2019; Ogunrinde et al., 2019; Ohiomu and Ozor, 2021; World Bank, 2021); nevertheless, the extent at which households' decision-making capacity are enhanced for taking actions in drought risk preparedness with WCI has never been articulated in these studies. Rural communities do not often use WCI on a regular basis, hence the specific influence of weather parameters on local scale decision-making is not well known, thus there is an urgent need to better integrate weather and climate information into societal decision-making processes. Ensuring the relevance and appropriateness of tailored information in facilitating risk management decisions remains the persistent challenge for the service provider community. The extent to which the WCI are shared primarily for the purpose of local decision-making remains unclear.

The overall goal of this study is to provide a deeper understanding of the specific climate information needs of end users as they plan their resilience and adaptive capacity to drought hazard. The key questions remain: What are the gaps in the packaging, dissemination, access, and utilization of WCI? What are the appropriate WCI that could best equip communities to develop drought hazard preparedness plan? What drives individual decisions to use WCI in drought hazard preparedness as a climate-smart strategy? This study attempts to answer these questions by assessing the climate information needs in the agriculture, water resources, and disaster management sectors. The study will guide the development of synergies between forecasters and end users as stakeholders in co-producing and communicating decision-driven climate information for response effectiveness and preparedness planning by rural households in managing the risks associated with extreme climate events.

FARM-LEVEL DECISION-MAKING: CONCEPTUAL AND THEORETICAL FRAMEWORK

The study analyzed determinants of decisions for using weather and climate information as a drought hazard preparedness strategy. The framework begins by emphasizing that farmers can be irrational thereby unable to optimize returns from their decision-making processes (Clark and Marshall, 2002; Ziervogel, 2004). Ziervogel (2004) described this premise upon which such decisions are based as "bounded rationality" due to non-existence of perfect knowledge. It is based on the theory of technology adoption theory, which posits that social, economic, ecological, and institutional systems as well as individuals can drive adaptation to changing environment. The level of sustainable adaptation depends on the adaptive capacity, information, knowledge, social networks, assets, infrastructure, and institutions accessible to enable undertaking effective adaptation (IPCC, 2007).

Technology innovation utilization has been guided mainly by innovation-diffusion, economic constraint, and adopter perception paradigms. Innovation-diffusion paradigm identifies information dissemination as a key factor in influencing adoption decisions while the economic constraint paradigm argues that technology adoption is influenced by utility maximization behavior and economic constraints due to asymmetric distribution of resources. On the other hand, the adopter perceptions paradigm posits that the adoption process starts with the adopters' perception of the problem and technology proposed. The adopter perception paradigm argues that perceptions of adopters are important in influencing adoption decisions (Kalinda, 2011).

The decision to participate in implementing an intervention is based on perceived utility expected by a farmer but is also influenced by individual and socio-economic characteristics, as well as market, institutional, and environmental factors influencing the decision-making processes. Farmers' overall objective is to improve the household welfare, thus to participate in an intervention, a farmer has an expected utility of the intervention associated with the influencing factors. Agricultural objectives in addition to public infrastructure contribute as basic conditions that influence a farmer to participate or not in the intervention. The basic conditions, expected utility, and the factors influencing the participation decision will all lead to impact, improved welfare.

This study used the random utility theory approach, which posits that a farmer's decision to participate in a drought hazard preparedness strategy depends on the level of utility expected to derive from that participation (U_p). Therefore, a farmer will only participate in a strategy i if the expected utility of participation (U_{ip}) is greater than the utility without participation (U_{in}) (Ali and Abdulai, 2010). Therefore, the decision to participate in the strategy is a discrete choice in which a farmer can decide to use the strategy or not based on idiosyncratic preferences, farm characteristics, and institutional and environmental factors, among others. The level of integrating WCI into the overall household decision-making framework, hence use of WCI, depends on each farmer's self-selection behavior rather than on a random assignment to the strategy. Denoting the difference between the net utility of usage and non-usage for each farmer i gives

$$I_i^* = \left(U_{ip}\right) - (U_{in}) > 0 \tag{1}$$

Equation (1) means that farmer i will use the strategy if the perceived utility of usage exceeds that of non-usage, *ceteris paribus.*

THE ANALYTICAL FRAMEWORK

Heckman probit selection model was used to analyze factors influencing use of weather and climate information (WCI) for drought hazard preparedness decisions as a climate-smart strategy. In many studies where the decision to uptake a new technology involves a decision process requiring more than one stage, models with two-step regressions are commonly used to correct for the sample selection bias generated in such decision-making processes. William and Stan (2003) used Heckman's two-step procedure to analyze factors affecting the awareness and adoption of new agricultural technologies in the USA. The first stage was the analysis of factors affecting awareness of new agricultural technologies, and the second stage is the adoption of the new agricultural technologies. Yirga (2007) and Kaliba et al. (2000) used Heckman's selection model to analyze the two-step processes of agricultural technology adoption and intensity of agricultural input use in Ethiopia. Maddison (2006) analyzed farmers' adaptation to climate change in South Africa and found farmers' adaptation is a two-step process which first involves perceiving a changing climate and then second, responding to changes through adaptation. Deressa et al. (2008) used Heckman's two-step procedure to analyze farmers' perceptions of climate change, and next, farmers' adaptations to climate change. Gbetibouo (2009) used Heckman's model to analyze farmers' perceptions and adaptations to climate change and variability in the Limpopo basin, South Africa. In the first stage, farmers' perceptions were analyzed followed by farmers' adaptations in the second stage.

Following Maddison (2006), this study applied Heckman's probit selection model to analyze the access and use of WCI by farmers in study area. Heckman' model has two equations of interest, the selection (access) equation and the outcome (use) equation. The selection equation was used to model farmers' access to WCI services for hazard preparedness while the response equation was used to model application of WCI as a strategy in preventing losses to drought shocks. In their studies, Maddison (2006), Deressa et al. (2008), and Gbetibouo (2009) specified Heckman's sample selectivity model based on two latent variables as follows:

$$y_1 = \left(w_i{}' \phi\right) + \mu_i \tag{2}$$

$$y_2 = \left(y_i{}' \beta\right) + \varepsilon_i \tag{3}$$

where ϕ is a k-vector of regressors; β is an m-vector of regressors, possibly including 1's for the intercepts; and the error terms μ_i and ε_i are jointly normally distributed, independently of ϕ andβ , with zero expectations. $y_1$and$y_2$are the regressands denoting use and access of weather and climate information. While this study is primarily interested in the first model, the latent variable is only observed if$y_2 > 0$. Then, the actual dependent variable is

$$y = y_1 \text{ if } y_2 > 0,\ y \text{ is a missing value if } y_2 \leq 0 \tag{4}$$

y_2 is taken as a latent variable, which is not observable, but only its sign. It is concluded that $y_2 > 0$ if y is observable and that $y_2 \leq 0$if y is unobservable. Therefore, without any loss of generality,$\varepsilon_i$can be normalized so that it has a variance of 1. Suppose the self-selection problem is disregarded and y regressed on ϕ based on the observed y values, then the resulting ordinary least squares (OLS) estimator of $w_i^{'}$ would be biased, since

$$E\left[y_1 \left|y_2 > 0, \phi, \beta\right.\right] = w_i^{'}\phi + rs\frac{f(y_1{}'\beta)}{F(y_1{}'\beta)} \tag{5}$$

where F is the cumulative distribution function of the standard normal distribution, f is the corresponding density, s^2 is the variance of μ_i, and r is the correlation between $\mu_i$andε_i. Therefore:

$$E\left[y_1 \left|y_2 > 0, \phi\right.\right] = w_i^{'}\phi + rsE\left[\frac{f(y_1{}'\beta)}{F(y_1{}'\beta)}\,|x\right] \tag{6}$$

The final term gives rise to self-selection bias when r is non-zero. To avoid the self-selection bias and obtain asymptotically efficient estimators, the maximum likelihood estimation (MLE) was used to estimate the model parameters.

METHODOLOGY AND DATA

Description of the Study Area

The study was carried out in Edo State, Central-Southern Nigeria. The inland state lies in the tropical rainforest zone of Nigeria with a total land surface area of 19,281.93 km^2 with population of over 5 million persons (Emeribe et al., 2017). It possesses a humid tropical climate based on Köppen climatic classification, typical of the tropical rainforest zone vegetation. The average annual rainfall in the north of the State ranges between 127 and 152 cm but in the range of 252 and 254 cm in the south (Koyenikan and Anozie, 2017). The basis of the economy is livelihood activities in smallholding farming, fishing, aquaculture, poultry, and livestock in many communities. The state derives an estimated 40% of its revenue from proceeds from agriculture. The rural population of about 200,000 largely depends on subsistent agriculture, which is responsible for about 80% of the total agricultural production in Edo State (www.edostate.gov.ng/commercialagriculture). The urban economy is dominated by government in the formal sector and trade in the informal. Government is the main employer for the wage-earning part of the population because about 50% of the urban work force is in clerical and sales-and-service professions. Other livelihoods involve services and trading by both men and women. Edo State consists of eighteen (18) Local Government three agro-ecological zones with the guinea savannah, derived savannah, and mangrove forest describing the agricultural regions of Edo North, Edo Central, and Edo South, respectively. Edo North agro-ecological zone has a sub-humid climate, characterized by light rainfall and semi-savannah vegetation. Edo Central zone is characterized by derived savannah vegetation while the climate is humid tropical in the Edo South (Oladipupo et al., 2014). **Figure 1** shows the map of Edo State in Central-Southern Nigeria showing the study sites. Edo State is experiencing a fast-disappearing vegetation and increasing aridity, which characterized the savannah area in recent times.

Sampling Techniques, Sample Size, and Data

This study focused on households from rural communities drawn from three agricultural zones of Edo State. Edo North has an estimated population of 1,252,100, Edo Central has 775,000 people, and the projection is 2,208,700 in Edo South (Brinkhoff, 2016). The State was purposively selected because of its fast-disappearing vegetation due to its increasing aridity, characterized by the dry savannah with negative consequences for the teeming rural population. The agricultural zones were stratified by Agro-Ecological Zones, Blocks, and Cells. Household data for the study were collected through field survey conducted during the 2019 farming season using a multi-stage sampling technique. The study area was stratified into three agro-ecological zones, namely Edo North, Edo Central, and Edo South zones, to allow for characteristics that may affect responses across different zones shaped by biophysical, socio-economic, and environmental context of the areas (Lema and Majule, 2009), and based on the Edo State Agricultural Development Programme delineation.

Edo North is made up of six Local Government Areas (LGAs), Edo Central has five LGAs and Edo South zone has seven, making a total of eighteen LGAs, which formed the Blocks. At the Zonal Level, the sampling process involved purposive selection of the three Edo North, Edo Central, and Edo South agroecological zones. At the Block level, one block each was randomly selected from a total of 6, 5, and 7 blocks in the North, Central, and South Zones, respectively. These blocks were Etsako East in Edo North, Esan South East in Edo Central, and Ovia Southwest in the Edo South Zone. At the Cell level, each block consists of 8 cells. A random selection of 6 cells were made from blocks one and three but 4 cells from block two, for a total of 16 cells that made up the rural communities. At the Farmers' level, both snowballing and simple random sampling techniques were then used in selecting 25 farmers from each community. Of the 400 respondents interviewed, the data from 3 copies of respondents' interview schedule were invalid due to some exaggerations; therefore, a total of 397 respondents were used for analysis. The distribution of final samples across the study sites are presented in **Table 1**.

Reconnaissance visits to the study area were facilitated by the extension workers from the Edo State Agricultural Development Programme (EDADP). The outcome of this reconnaissance also informed the selection of key stakeholders who were engaged in the inception meeting that was later held with the local farmers, community members, community heads, EDADP contact farmers, and the key informants. The outcome from the deliberations was used to develop the structured questionnaire used for the survey. The researcher personally administered the structured questionnaire prepared in English Language and interviewed respondents with six trained field assistants from the agricultural extension personnel of EDADP and Department of Agricultural Economics, University of Benin, Edo State. The Pre-testing of the questionnaire was conducted and checked through an iterative process for 5 days prior to the actual survey.

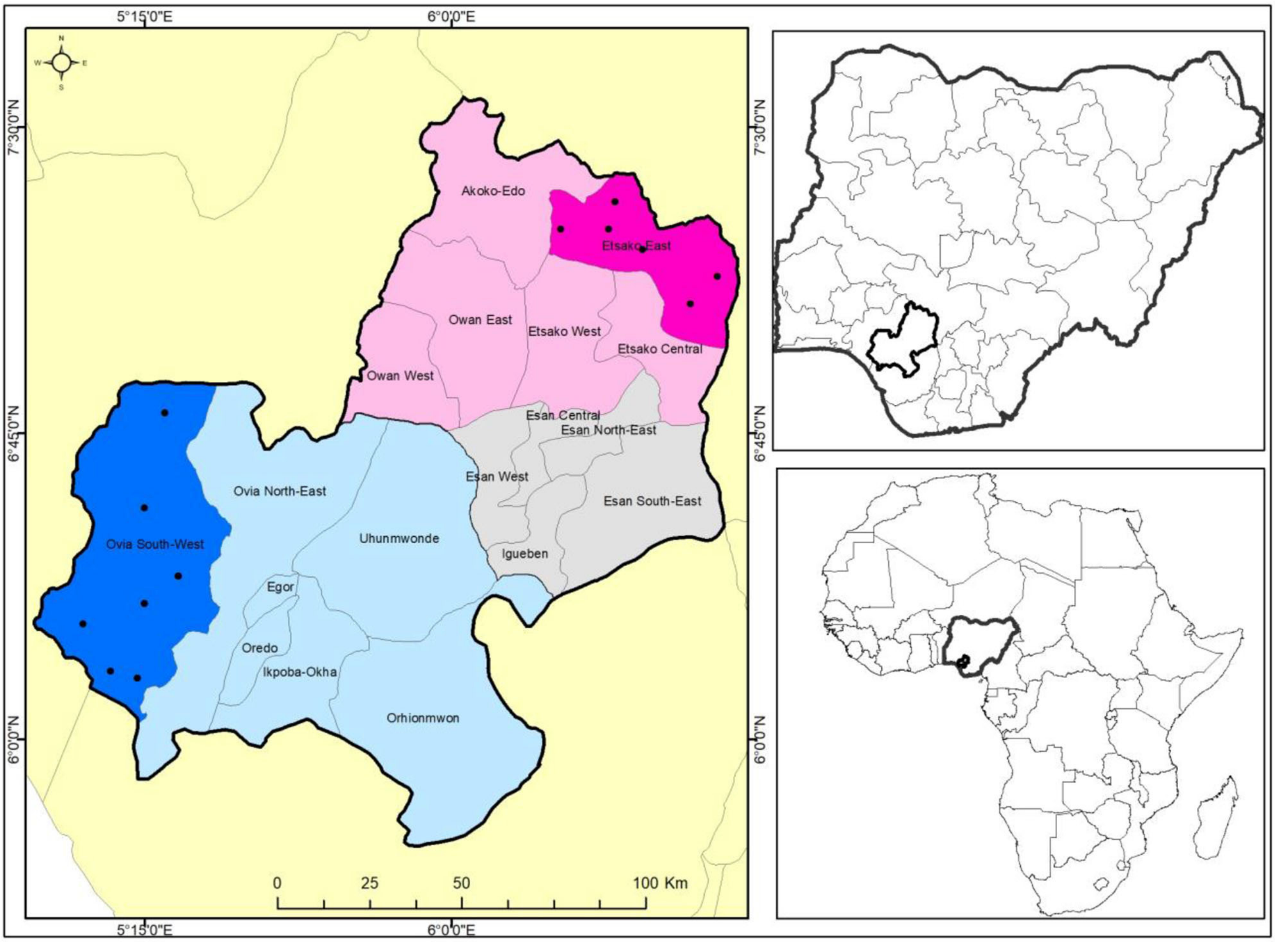

FIGURE 1 | Map of study area in Edo State of Central-Southern Nigeria.

The researcher acquired approval from the village heads before embarking on the study after providing explanations on the study objectives to the community leaders.

Given the permission, the first phase in the data collection, the researcher proceeded onto the participants for the survey enumeration. In each community, the household head was interviewed, or anyone with authority to speak. The questionnaire was administered in local languages with the assistance of field assistants who translated the questionnaire into Edo, Igarra, Etsako/Afemai, and Esan dialects for proper decoding during enumeration. The structured questionnaire elicited information on socio-economic profile of the respondents, and questions on what existing gaps in the packaging, dissemination, access, and extent of utilization of WCI in taking preparedness decisions? What appropriate WCI that could best equip communities to develop drought hazard preparedness plan? What drive individual decisions to use WCI in drought hazard preparedness as a climate-smart strategy? What types of information time scale required for end users to make adjustment plans indicating that they value information available to them? The questionnaire was developed to assess climate information needs in the target economic sectors of agriculture, water resources, and disaster management, rather than scientific forecast products and services produced by the meteorological agency. In the second phase, individuals who were recognized during the survey with sufficient agro-ecological and environmental knowledge were selected for focus group discussions (FGDs). In all, 8 FGDs (2 family heads, 2 women groups, 3 farmers' groups, and 1 water user association) were held in the study communities with participants ranging from 10 to 12 persons. Focus groups were conducted to validate responses obtained during survey enumeration based on life's experiences from the respondents.

The researcher also made appointments with key informants selected based on their understanding of local environmental changes, agricultural systems, and households' vulnerability to extreme climate events within the 16 communities. In the agricultural sector, key informant interviews (KIIs) were planned with officers of the Edo State Agricultural Development Project (EDADP), Federal Ministry of Agriculture and Natural

TABLE 1 | Sampling distribution of the respondents in the survey.

Zone	Block	Cell
Edo North	Etsako East	Ikhideu
		Likpoke
		Idumebo
		Ekpoma
		Isokwi
		Weppa
Edo Central	Esan South East	Agenebode
		Ilushi
		Ekpoma
		Irua
Edo South	Ovia Southwest	Obarenren
		Udo
		Ighoriaikhi
		Ofunama
		Ugbogue
		Umaza

Source: Field survey (2019).

TABLE 2 | Distribution of the respondents used for the study.

Targeted respondents	Number of respondents		Response rate
	Targeted	Actual	(%)
Family heads (interviews)	2	2	100.00
Villagers (questionnaire)	400	397	99.30
Farmers' groups (focus group discussions)	3	3	100.00
Women groups (focus group discussions)	2	2	100.00
Water user associations (focus group discussions)	2	2	100.00
Key informant (interviews)	14	11	78.57
Total	423	417	98.50

Resources (FMANR), and All Farmers Association of Nigeria (AFAN). In the water sector, KIIs were planned with Edo Fadama Water User Association (EFWUA) and Benin-Owena River Basin Development Authority (BORBDA) officers; in the disaster management, the National Emergency Management Agency (NEMA) and Edo State Emergency Management Agency (ESEMA) officers. The climate service provider, the Nigerian Meteorological Agency (NiMet), officers were also interviewed. These key informants have been offering climate-related technical assistances to the local communities. At a designated time, the researcher conducted face-to-face interviews with the key informants. In the third phase, 14 key informants were targeted but 11 KIIs conducted comprise 2 officers from EDADP, 1 from FMANR, 2 from AFAN, 2 from EFWUA, 1 officer from BORBDA, 1 from NEMA, 1 from ESEMA, which are rendering disaster risk reduction program, and 1 from the NiMet.

These interviews were conducted to validate responses on the use of climate information in decision-making, most useful WCI and time scale that are decision driven to end users, and the most required delivery methods or effective communication pathways across agriculture, water, and disaster risk management sectors in the study communities. These sectors have been identified by stakeholders as sectors with great potential for optimal impact from the improved decision-driven climate information and services, if well utilized. These key informants were selected based on their proximity and in-depth knowledge on the research problems in the communities. These interviews were conducted to investigate the status and extent to which climate information is capable of informing preparedness plans of local communities. They explained some periodic government's activities through their offices on the uptake of climate information services in facilitating preparedness plan to extreme hazards. The distribution of the respondents is presented in **Table 2**.

Table 3 presents the summary of data requirement, collection methods, and sample used in analyzing research problems for the study.

DATA ANALYSIS

Descriptive Statistics

Descriptive statistics such as frequency distributions, means, percentages, standard deviations, and minimum and maximum values were used to describe socio-economic and demographic characteristics of the respondents, analyze the distribution of users and non-users of WCI in operational decision-making, existing gaps in the packaging, dissemination, access, and the extent at which farmers utilize WCI in taking preparedness decisions, actual climate information needs which are sufficiently useful in taking drought hazard preparedness decisions in the agriculture, water resources and disaster risk management sectors, and types of information time scale required for end users to make adjustment plans in the study area.

Multi-Criteria Analysis

Multi-criteria analysis was performed to determine the appropriate WCI that could best equip communities to develop drought hazard preparedness plan and response action. Decision-making problems often involve a complex decision-making process by which multiple requirements and uncertain conditions have to be taken into consideration simultaneously (Haque, 2016). Effectiveness of multi-criteria decision-aiding system as well as accuracy of decisions is based on an application of a proper multi-criteria decision-making method (MCDM) method (Zavadskas and Turskis, 2011; Alinezhad and Khalili, 2019).

The Weighted Aggregated Sum Product Assessment

Weighted aggregated sum product assessment (WASPAS) method was applied in this study, which involved an increase in the ranking accuracy of various WCI that users can use to take drought preparedness and response action. The analysis was performed for the users in the agriculture, water resources,

TABLE 3 | Summary of data requirement, data collection methods, and sample.

Data requirement	Methods/tools	Sample
Cross-sectional primary data on current use of weather and climate information in decision-making	Field visits Farmers' interviews Focus group discussions	Food crop farmers (397) All Farmers Association of Nigeria (1) Fadama Water User Association (1)
	Consultation meetings Key expert interviews	Water resources managers (2) Disaster risk managers (2)
Cross-sectional primary data on the most useful weather information, and weather information needs with respect to forecast kinds, types, and timescales	Field visits Focus group discussions Focus group discussions	Food crop farmers (397) Family heads and female groups (4) All Farmers Association of Nigeria (1) Fadama Water User Association (1)
	Expert interviews	Agricultural extension officers (2) Water resources managers (2) Disaster risk managers (2) Meteorology expert (1)
Survey data on delivery method that users considered most satisfied communication channel for future interest in weather forecast services	Field visits Farmers interviews Focus group discussions	Food crop farmers (397) All Farmers Association of Nigeria (1) Fadama Water User Association (2)
	Expert interviews	Agricultural extension officers (2) Water resources managers (2) Disaster risk managers (2) Meteorology expert (1)
Total		Food crop farmers (397) Experts (8)

and disaster risk reduction sectors. The optimization of weighted aggregated function methodology was applied in this study, which enables to reach the highest accuracy of estimation (Zavadskas et al., 2012).

The weighted sum model (WSM) is one of the best known and often applied multi-criteria decision-making methods in recent times for evaluating a number of alternatives in terms of a number of decision criteria. A given MCDM problem is defined on *m* alternatives and *n* decision criteria (Alinezhad and Khalili, 2019). $w_j$denotes the relative significance of the criterion and x_{ij} is the performance value of alternative *i* when it is evaluated in terms of criterion *j*. Then the total relative importance of alternative *i*, denoted as $Q_i^{(1)}$, ($\overline{x_{ij}}$– normalized value of *j*-th criterion of *i*-th alternative) (Bagočius et al., 2013; Alinezhad and Khalili, 2019):

$$Q_i^{(1)} = \sum_{j=i}^{n} \overline{x_{ij}} w_j \tag{7}$$

where linear normalization of initial criteria values is applied, that is:

$$\overline{x_{ij}} = \frac{x_{ij}}{\max_i x_{ij}}, \tag{8}$$

if $\max_i x_{ij}$value is preferable or

$$\overline{x_{ij}} = \frac{\min_i x_{ij}}{x_{ij}}, \tag{9}$$

If $\min_i x_{ij}$ value is preferable.

According to the weighted product model (WPM), the total relative importance of alternative *i*, denoted as$Q_i^{(2)}$, is expressed as stated (Bridgman, 1922; Miller and Starr, 1969; Triantaphyllou and Mann, 1989):

$$Q_i^{(2)} = \coprod_{j=1}^{n} \left(\overline{x_{ij}}\right)^{w_j} \tag{10}$$

There was an attempt to apply a joint criterion for determining a total importance of alternative, giving equal contribution of WSM and WPM for total evaluation (Saparauskas et al., 2011):

$$Q_i = 0.5Q_i^{(1)} + 0.5Q_i^{(2)} \tag{11}$$

Based on previous research (Saparauskas et al., 2011; Zavadskas et al., 2012) and supposing the increase of ranking accuracy and, respectively, the effectiveness of decision-making, the Weighted Aggregated Sum Product Assessment (WASPAS) method for ranking of alternatives is proposed in the current study. Following Eqs. (7), (10), and (12), the expression can be written as follows:

$$Q_i = \lambda \sum_{j=1}^{n} \overline{x_{ij}} w_j + (1-\lambda) \prod_{j=1}^{n} \left(\overline{x_{ij}}\right)^{w_j},\ \lambda\text{=0,..., 1.} \tag{12}$$

Accuracy of Estimation Based on Initial Criteria Values

It is proposed to measure the accuracy of WASPAS based on initial criteria accuracy and when $\lambda = 0, \ldots, 1$. When $\lambda = 0$, WASPAS is transformed to WPM; and when $\lambda = 1$, WASPAS is transformed to WSM. Assuming that errors of determining the initial criteria values are stochastic, the variance σ^2 or standard deviation σ is a measure of dispersion in the distribution.

Optimization of Weighted Aggregated Assessment

The variances of estimates of alternatives (Simanaviciene and Ustinovicius, 2012) in WASPAS depend on variances of WSM and WPA as well as coefficient λ. Accordingly, the aim of the current part of the study is to calculate optimal values of λ, that is, to find minimum dispersion $\sigma^2(Q_i)$ and to assure maximal accuracy of estimation. Optimal values of λ can be found when searching extreme of function. The optimal values of λ can be found when searching extreme function:

$$\lambda = \frac{\sigma^2\left(Q_i^{(2)}\right)}{\sigma^2\left(Q_i^{(1)}\right) + \sigma^2\left(Q_i^{(2)}\right)} \tag{13}$$

The optimal values of λ should be calculated for every alternative before applying WASPAS. Optimal λ may vary depending on ratio of $\sigma^2\left(Q_i^{(1)}\right)/\sigma^2\left(Q_i^{(2)}\right)$ in every particular case. The variances $\sigma^2\left(Q_i^{(1)}\right)$ and $\sigma^2\left(Q_i^{(2)}\right)$ should be computed:

$$\sigma^2\left(Q_i^{(1)}\right) = \sum_{j=1}^{n} w_j^2 \sigma^2\left(\overline{x_{ij}}\right), \tag{14}$$

$$\sigma^2\left(Q_i^{(2)}\right) = \sum_{j=1}^{n}\left(\frac{\prod_{j=1}^{n}\left(\overline{x_{ij}}\right)^{w_j} w_j}{\left(\overline{x_{ij}}\right)^{w_j}\left(\overline{x_{ij}}\right)^{(1-w_j)}}\right)^2 \sigma^2\left(\overline{x_{ij}}\right) \tag{15}$$

Estimates of variances of normalized initial criteria values are computed as stated:

$$\sigma^2\left(\overline{x_{ij}}\right) = \left(0.05\overline{x_{ij}}\right)^2 \tag{16}$$

Ranking of WCI Alternatives

A multiple criteria decision-making problem is aimed at determining the most accurate relative importance of alternatives and ranking alternative decisions. Here, our MCDM problem is defined on 13 weather and climate information (WCI) alternatives in agriculture and water resources, but there are 11 alternatives in the disaster risk reduction and delivery channels. There are 6 decision criteria in all the alternatives. Relative significances of criteria were determined by means of entropy (Saparauskas et al., 2011).

Model Specification: Heckman Probit Selection Model

Heckman probit selection model was used to analyze key drivers of individual decisions to use WCI in drought hazard preparedness as a climate-smart strategy. Models with two-step regressions are used to correct for the selection bias generated during a decision-making process, which requires more than one step, hence justifying the application of Heckman's sample selectivity probit model (Heckman, 1976; Maddison, 2006). Two probits were estimated, namely the Access model and the Decision model, for the study. Heckman probit selection model was used to analyze major drivers of farmers' use of WCI in taking drought hazard preparedness decisions. The model specification started with the first step of analyzing determinants of farmers' access to WCI (selection model) and the second step is the use of WCI for decisions on early responses for drought preparedness, conditional on the first stage of farmers' access (outcome model). In this study, respondents are expected to have access to WCI as a strategy for drought hazard preparedness, and then decide whether to use the WCI or not in their planning decisions conditional on the first stage. Granted, WCI would primarily be of interest to farmers who have access to climate services and as the second decision stage is a sub-sample of the first stage; however, it is likely that the second stage subsample is non-random and different from those who have access to WCI but failed to uptake due to certain reasons. This leads to a sample selectivity problem since only those who have access to WCI as potential strategy will take preparedness actions by using it, whereas it requires inferring about the access made by the agricultural population as whole.

The probit model for sample selection assumes that there exists an underlying relationship. The latent equation given by:

$$y_j^* = x_j\beta + u_{1j} \tag{17}$$

Such that the binary outcome is only observed given by the probit model as

$$y_j^{probit} = \left(y_j^* > 0\right) \tag{18}$$

The dependent variable is observed only if the observation j is observed if the selection equation:

$$y_j^{select} = \left(z_j\delta + u_{2j} > 0\right) \tag{19}$$

$$u_1 \sim N(0, 1)$$

$$u_2 \sim N(0, 1)$$

$$corr(u_1, u_2) = \rho$$

where,

x is a k-vector of regressors and z is an m-vector of repressors;

u_1 and u_2 are error terms jointly normally distributed, independently of x and z with zero expectations. When $\rho \neq 0$, standard probit techniques applied to Equation (17) give biased results. Hence, the Heckman probit provides consistent, asymptotically efficient estimates for all parameters in such models (StataCorp, 2003). Marginal analysis was performed to determine the effect of using weather information for drought hazard preparedness plan. Marginal effect of a unit change in an independent variable on the probability $P(Z = 1|X = x)$ was obtained given that all other variables are held constant, and mathematically expressed as

$$\frac{\delta P\left(Z_i = 1|x_i\right)}{\delta x_i} = \frac{\delta E\left(Z_i = 1|x_i\right)}{\delta x_i} = \varphi\left({x_i}'^{\beta}\right) \tag{20}$$

The algebraic representation of the Heckman's two-equation latent dependent variable models are given as

$$u_i^* = \left(w_i^{'}\phi\right) + \mu_i \tag{21}$$

(selection model)............

$$v_i^* = \left(y_i^{'}\beta\right) + \varepsilon_i \tag{22}$$

(outcome model)............
Consequently, the linear specification of Heckman's probit selection model is given as

$$u_i^* = \phi_0 + \phi_1 w_1 + \phi_2 w_2 + \phi_3 w_3 + ... + \phi_n w_n + \mu \tag{23}$$

....
where

u_i^* = access by an i^{th} farmer to WCI as a drought hazard preparedness strategy

w_i = vector of exogenous explanatory variables of probability of access to WCI as a drought hazard

preparedness strategy by the i^{th} farmer

ϕ = vector of parameter estimates of the regressors hypothesized to influence the probability that a farmer has access to WCI

In Heckman's probit outcome model, the dependable was a binary variable, whether a farmer has uptake WCI or not. Therefore, the linear specification of Heckman's outcome model is given as

$$v_i^* = \beta_0 + \beta_1 y_1 + \beta_2 y_2 + \beta_3 y_3 + ... + \beta_n y_n + \varepsilon \ldots \ldots \ldots . (24)$$

where

v_i^* = use of WCI for drought preparedness actions by the i^{th} farmer

$y_i^{'}$ = vector of exogenous explanatory variables of probability of using to WCI as a drought hazard

preparedness strategy by the i^{th}farmer

β = vector of parameter estimates of the regressors hypothesized to influence the probability that a farmer has used WCI as a strategy for drought hazard preparedness.

RESULTS AND DISCUSSION

Socio-Demographic Characteristics of the Respondents

The descriptive statistics shows that 83.07% are male respondents while 16.93% are females. This explains the dominance of male farmers in farming than females. This was attributed perhaps to certain sociocultural factors that limit female appearances in public discussions compared with the men, thus resulting in inequality differences in decision-making capacity. These differences may highlight why more male farmers participate in public interactions than females and not necessarily in the farming sector. It was mentioned in the FGDs that male household heads were traditionally authorized to speak in public, which put women away from public interactions.

FAO (2018) asserted that women had opportunities to organize themselves into various farmers groups to enable their participation in agricultural development issues in Nigeria, yet there are persistent gender inequalities and feelings of marginalization compared with men due to cultural and societal values, and religious restrictions. Women rarely participate in public agricultural development project discussions, which reduce their contributions toward achieving broader socio-economic development goals. An average farmer is 45 years old; the oldest is 87 years while the youngest is 17 years. It implies that most respondents are within economically active age when their ability to take risky decisions especially the use of weather and climate information (WCI) is the basis for drought preparedness plan. An average farmer is aged 45 years; most of the respondents are within their economically active age during which they can still take decisions on innovative weather risk management strategies as basis for adaptation actions. Over 70% have acquired formal education where on average an individual has spent about 9 years in completing junior secondary education. An average respondent has completed junior secondary education (mean = 8.91years), which is likely to positively influence their decisions on WCI as basis for early action against drought hazard in the study area.

Experience plays a key role in risk management decisions. Farmers' experience distribution indicates that an average respondent has spent about 24 years in agriculture. The farmer with the longest farming experience has spent 76 years while the youngest has 2 years of farming experience. The expected knowledge of impacts of drought hazard in the agro-ecology should facilitate the use of WCI in taking climate-smart decisions. Average household size was 11 members. The largest family consists of 28 persons. The majority value social capital at the grassroots, which is expected to influence the use of WCI services through family interactions compared with small families who are constrained by joint household decision-making processes. Farm size cultivated ranges between 0.5 and 50 ha. The distribution on **Table 1** shows that there are 75% medium holder farmers; 16% are smallholders while 9% are commercial farmers with farm size above 10 ha. On average, a farm size of 5.4 ha is reported, thus the result supports previous studies that medium-scale farmers dominate the savannah middle belt of Nigeria. In view of this, medium-scale farmers could be considered as a reliable pathway for the uptake of WCI in protecting their investments against erratic rainfall, false start rain, late onset, and dry spells common to the drying ecological area.

Further observations reveal that 65.8% of the respondents are associated with a farmers' group while 34.2% do not belong. Farmers' group membership should strongly contribute to information-sharing opportunities that allow for early action, using WCI in fostering climate-smart decisions. Only about 25% have accessed formal loans from financial institutions during the farming season. Lack of access to formal financial resources is discouraging to farmers pursuing use of WCI. This situation might prevent decisions that could lead to early action for drought preparedness. Access to credit might enhance farmers' capacity in protecting their investments through climate-smart decisions by uptake WCI to ensure good harvests that is capable of paying back their loans. Weather advisory information could assist in guaranteeing loan repayments if they are used to improve decisions and minimize losses. A total of 55.3% of the respondents have access to agricultural extension services while 44.7% do not. The result indicates a close distribution somewhat on the condition that if extension services are functioning effectively, then it is likely that farmers will have access to weather information. It is evident that about 45% might likely have been cut off from access to weather information if relying on agricultural extension services. Hassan and Fullen (2019) expressed that training agricultural extension services that farmers were already aware of and trusted through participatory communication processes will assist in transforming WCI into advisories, and offer a potential opportunity for scaling up among end users. Amwata et al. (2018) and Mpandeli and Maponya (2013) found that the integration of climate information services into household decision-making through agricultural extension services enhance climate resilient agriculture through informed agricultural adaptation decisions.

With regards to early warnings from WCI, 68% have no access to WCI compared with those who confirmed their access, the 32% of the respondents as shown in **Table 4**. A sizable number of the population were cut off from accessing improved climate information services with indication that in the case of a likely drought hazard, delayed decisions might be consequential to agri-investment management operations. Attention is needed on the remaining 68% who said they had no access to WCI. If not urgently addressed, the situation could aggravate their vulnerability to drought hazard by putting their livelihoods and assets under serious threat of unpredictable rainfall, early cessations, and dry spell conditions as mentioned during focus group discussions (FGDs) with men and women farmers' groups. The income poverty line explains that both the poor and lower-income earners remain the largest portion of farming population in the middle savannah belt. Average income was N690,936 per annum. In terms of percentile distributions, N216,000.00 is obtained as the 25th percentile annum income while N480,000.00 represents the 75th percentile annual income. The maximum income was N8 million per annum while N8,000.00 was the minimum income in the study area. It is likely that poor household income may be preventing farming households from the uptake of climate information services due to prevailing poor economic conditions.

Observed Weather and Climate Changes With Impact on Rural Livelihoods

As observed in **Figure 2**, the distribution of the most impactful rainfall changes in the past 5 years as experienced by the sampled farmers. Erratic rainfall is the most perceived impactful rainfall changes on agricultural production and livelihood activities by 75.4% of sampled respondents, and delayed rainfall is the next impactful to farmers by 72.2% while late onset is considered the third most impactful rainfall changes to the respondents in the past 5 years expressed in the distribution. Furthermore, early cessation, dry spell experience, and short length of growing season are other rainfall change elements that are critical to food security in the savannah belt of Nigeria.

Drivers of Using WCI in Drought Hazard Preparedness

Heckman selection probit model was used to explore determinants of weather and climate information (WCI) uptake for drought hazard preparedness actions given that they have sufficient access to the warning information so as to avoid sample selection bias. The first stage of the model is if a respondent has access to WCI (selection model) while the second stage considers whether a respondent has used WCI or not in taking drought hazard preparedness actions conditional on the first stage (outcome model). The model was tested for its appropriateness by comparing the dependence of the error terms in the outcome and selection equations. The results gave evidence of a sample selection problem since rho was significantly different from zero (Wald test for independent equations = 50.88, $p =$ 0.000), thus appropriate to apply the Heckman probit model. The maximum likelihood (ML) function of the Heckman model was significant (Wald $\chi^2 = -0.614$, $p = 0.000$), hence the model had a strong explanatory power. **Table 5** presents results from the ML estimation together with the marginal effects, which explained the expected change in the probability of uptake and/or no uptake of WCI in drought hazard preparedness action given a unit change in an independent variable from the mean value, *ceteris paribus*.

The Heckman probit outcome model results presented in 5 highlighted that farmers' decisions to take drought hazard preparedness actions are driven by a number of factors indicated by the coefficients of the sample model. Gender of the respondents, farmers' experience, annual farm income, and persistency of erratic rainfall significantly increase the likelihood of farmers to take drought hazard preparedness decisions as early action for protection against loss of agricultural investments. Farmers' group membership and distance to weather station negatively affect their decisions in taking drought hazard preparedness actions. Institutional factors especially access to bank credits, market linkage, access to advisory services from WCI, and access to local interpretation of agricultural impacts are positively correlated with the uptake of WCI for drought hazard preparedness decisions, but they are not significant at farm level.

Results from the selection model explained that level of education, extension training services and ownership of a simple mobile handset exhibited positive significant effects, which will increase the likelihood of respondents' access to WCI. However, only radio battery expenses showed a negative significant effect, which decreases the likelihood of access to WCI in the study area.

The marginal impact analysis presented in **Table 6** revealed the marked differences in the respondents' ability to take drought preparedness actions based on the WCI received. Male farmers have more probability of using WCI in drought preparedness and

TABLE 4 | Socio-demographic characteristics of respondents.

Farmers' characteristics	Obs (%)	Mean	SD	SEM	Min.	Max.
Sex						
Male	83.07	0.83	0.37	0.021	0	1
Female	16.93					
Age (years)	100	45.66	14.09	0.797	16	87
Level of education (years)	100	8.91	6.09	0.341	1	16
Farmers' experience (years)	100	23.98	13.44	0.760	2	76
Household size (number)	100	11.02	7.76	0.439	1	28
Farm size (ha) <2.00	16	5.41	7.28	0.412	0.5	50
2.00–10.00	75					
>10.00	9					
Farmers' group membership						
Yes	65.8	0.66	0.475	0.027	0	1
No	34.2					
Bank loan						
Access	24.9	0.25	0.433	0.024	0	1
No access	75.1					
Agricultural extension services						
Access	55.3	0.55	0.498	0.028	0	1
No access	44.7					
Distance to weather station	100	1.16	5.102	0.288	3	48
Access to climate information						
Yes	31.9	0.32	0.467	0.026	0	1
No	68.1					
Drought information						
Used	35.5	0.35	0.479	0.027	0	1
Never used	64.5					
Farmers' income (N) (annual)	31.4	690,936	1,043,907	59,005	8,000	8,000,000
<N216,000 (annual minimum wage)	20.8					
N240,000–N480,000	47.8					
> N480,000–N720,000						

Source: Field survey (2019). $1 equivalent to N320 during this study.

response given that a unit change from being a female to male respondent increases the probability of using WCI in drought preparedness by 23.3%. On average, the marginal effect of an additional unit increase in the experience shows that there is 11.73% increase in probability that respondents would use WCI in drought preparedness, *ceteris paribus*. Good and bad previous experiences and increasing vulnerability to weather variations will influence continuous practice.

The positive marginal effect of farm income suggests that by an infinitesimal increase in income, there is more likelihood that respondents would use WCI in preparation for drought on average, *ceteris paribus*. It is an indication that respondents would have the capacity to sustain the cost of adjustment. The positive marginal effect of erratic rainfall as observed shows that as persistent frequency of erratic rainfall increases by a unit, the probability that respondents will use WCI in drought preparedness increases by 21.7% on average, *ceteris paribus*.

The negative marginal effect of group membership shows that as group cohesion and social interaction increase by a unit, the probability that respondents would use WCI in drought preparedness will decline by 16.0% on average, *ceteris paribus*. The provision of safety nets and local interest-free credit arrangement might be the reason for this outcome. However, the purpose of its establishment could be re-modified to enable respondents benefit from early warnings from WCI, thereby ensuring protection from a potential drought hazard. Likewise, on average, the negative marginal effect of an increasing unit distance of meteorological station will result in 0.9% decrease in the probability that respondents would use WCI warnings in preparedness against a potential drought hazard, *ceteris paribus*, in the savannah belt of Edo State, Nigeria.

Users and Non-users of WCI in the key Economic Sectors

A low usage of WCI was observed among the respondents across the three economic sectors. In agriculture, 33.0% of the respondents reported use of WCI in taking some

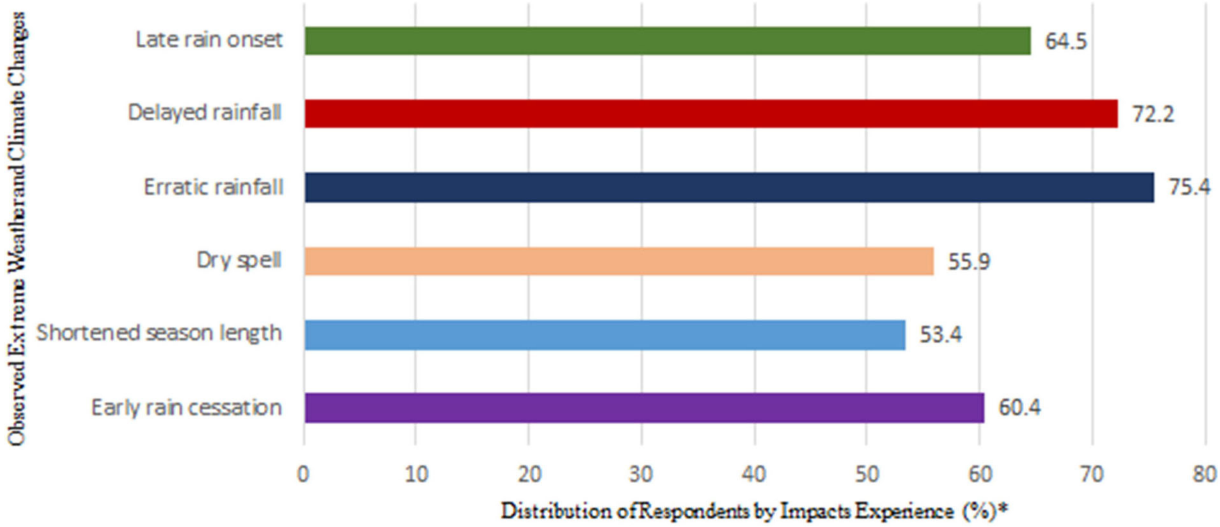

FIGURE 2 | Distribution of most impactful weather and climate changes in the past 5 years.

agricultural decisions while 67.0% did not use WCI in their agricultural operational decisions. In the water resources sector, 43.0% of the respondents have used WCI to enhance water use decisions planning, and a considerable 57% of the respondents do not use WCI during the 2019 farming season. Further distribution reveals that in the disaster risk reduction sector, 26% of the respondents used WCI to plan ahead of likely drought shock while 74% of the respondents did not consider WCI in any decision-making. The likely economic consequences might be poor management of resources, poor timing of activities, and overall decline in productivity due to loss and damage. **Figure 3** presents the distribution of users and non-users of WCI across different key economic sectors.

Fadama farmers are the major WCI users for water resources. During focus group discussions, those smallholder farmers who are Fadama (irrigation) farmers explained that their pre-season farm plans were based on advance timely weather information to save them from needless costs of materials and irrigation. Accurate forecast information on expected rainfall amount, onset, and cessation of rainy season were identified to assist in their agricultural water use plan, minimize operational cost, and enhance their pre-season preparedness in optimizing their capital investments. For disaster risk reduction, 26% of the respondents are using WCI for decision planning but still represent the least percentage of users of WCI across the user groups while 74% of the respondents were non-users of WCI in the disaster risk reduction sector.

The non-users of WCI attributed their reasons to delay in access to WCI, unreliable early warnings, absence of advisories services by forecasters, low trust in weather forecasts due to non-specificity with reference to their geo-locations, and dissatisfaction with television as major means of WCI communication without feedback opportunity. Expert interviews conducted further reveals that the poor financial capacity and negligence in terms of budgetary provisions for the Agricultural Extension Services Department in disseminating WCI with agro-weather advisory services have been the major drawback to efficient coverage of WCI and farmers' access at local scale in facilitating investment decision-making, hence it is an important policy priority that should be addressed so as to enhance the use of WCI in Nigeria.

Usefulness of WCI for Drought Hazard Preparedness Decisions

A number of WCI products send services have been produced by the Nigerian Meteorological Agency (NiMet) for stakeholders to solve the selection problem of managing their exposures to weather and climate hazards in the dry savannah agroecological zones of Nigeria. Many of these WCI are capable of handling multiple quantitative and qualitative criteria. Multi-criteria (MCA) decision-making problem is aimed at determining the most accurate relative importance of alternatives and ranking alternative decisions. Extensive multi-criteria decision-making (MCDM) approaches have been applied for selecting the best alternative, which users have been found to be the most appropriate for them in making adjustment decisions and plans, such as the analytic hierarchy process, analytic network process, case-based reasoning, data envelopment analysis, fuzzy set theory, genetic algorithm, mathematical programming, and their hybrids.

This study shows that the model developed by applying two different MCDM methods is suitable to solve such complicated location problems. The set of weighted criteria used for

TABLE 5 | Heckman results of access to WCI and its usage in drought hazard preparedness.

Variables	Drought hazard preparedness (Outcome model)		Access to WCI (Selection model)	
	Coefficient	SE	Coefficient	SE
Sex (male = 1)	0.233**	0.115	−0.238	0.414
Age (years)	−0.002	0.004	−0.010	0.015
Education (years)	−0.012	0.017	0.192***	0.029
Farmer's experience (years)	0.011***	0.004	0.004	0.017
Household size (number)	0.002	0.006		
Farm size (ha)	0.003	0.004		
Group membership (yes = 1)	−0.160**	0.081	0.137	0.322
Bank credit (yes = 1)	0.179*	0.112	−0.029	0.319
Informal loans (yes = 1)	−0.024	0.081	−0.938	0.307
Agric. extension service	−0.031	0.098	0.331***	0.377
Market linkage (yes = 1)	0.004	0.095	−0.021	0.020
Farm income (*N*)	7.46e−08**	3.88e−08	2.39e−07	2.33e−07
Erratic rainfall (yes = 1)	0.217**	0.093	0.256	0.360
Number of dry spells			0.022	0.031
Weather station distance (km)	−0.009**	0.004		
Weather advisory services (yes = 1)	0.082	0.187	−0.323	0.598
Weather local interpretation (yes = 1)	0.160	0.182	0.581	0.535
Repeated operational cost (*N*)			−1.63e-07	8.85e-07
Listening to weather report (number)	−0.001	0.001	0.001	0.001
Radio-battery expenses (*N*)	−3.42e-07	1.52e-06	−6.66e-06*	5.06e-06
Owns radio (yes = 1)			−0.012	0.373
Owns simple handset (yes = 1)	−0.034	0.088	0.568*	0.353
Owns smartphone (yes = 1)	−0.060	0.086	0.240	0.428
Constant	0.466	0.350	−0.964	0.806
Total observations	173			
Censored obs	53		Uncensored obs	120
Rho	−0.614		Wald χ^2 (20)	50.88
Prob > χ^2	0.000			
Sigma	0.375			

***Statistically significant at 0.01.
**Statistical significant at 0.05.
*Statistical significant at 0.1.
Source: Field survey (2019).

alternative WCI assessment and preferred delivery channels are presented in **Table 7**.

Initial normalized decision-making matrix and relative significances of criteria (criteria weights) (Saparauskas et al., 2011) are presented for agriculture in **Table 8**, water resources in **Table 9**, and disaster risk reduction in **Table 10**. The estimated results of applying Weighted Aggregates Sum Product Assessment (WASPAS) (Lashgari et al., 2011; Haque, 2016) when $\lambda = 0.5$ are presented for agriculture, water resources, and disaster risk reduction accordingly. The ranking order of alternatives and their relative importance is shown in **Figures 3–5**. As can be observed from the graph, even ranking order of alternatives can vary depending on λ values. Accuracy of calculations is measured according to the applied WASPAS algorithm when $\lambda = 0.5$ (Simanaviciene and Ustinovicius, 2012).

The results of the multi-criteria decision-making problem (MCDM) using the WASPAS framework is presented for agriculture sector in **Table 11**, water resources sector in **Table 12**, and disaster risk reduction sector in **Table 13**.

Users' Needs for WCI Across key Economic Sectors

The list of criteria to be considered during the WCI assessment process has resulted in a significant finding based on proper stakeholders' direct engagement during the preparation of the inception report. These are outcomes from various interactions and discussions that limit the risk of institutional or personal bias. Given that the stakeholder comprises representatives from various WCI user groups, the identified criteria encompass a range of preferences from different categories of people.

TABLE 6 | Marginal impact of using WCI in drought hazard preparedness.

Variable	δy/δx[†]	SE	Z-value	P > |*z*|
Sex (male = 1)	0.233**	0.115	2.02	0.043
Age (years)	−0.002	0.004	−0.53	0.579
Education (years)	−0.012	0.017	−0.73	0.463
Farmer's experience (years)	0.117**	0.004	2.39	0.017
Household size (number)	0.002	0.006	0.45	0.655
Farm size (ha)	0.003	0.004	0.83	0.408
Farmer's group membership (yes = 1)	−0.160**	0.081	−1.98	0.048
Bank credit (yes = 1)	0.179*	0.112	1.59	0.111
Informal loans (yes = 1)	−0.024	0.081	−0.30	0.764
Agricultural extension services (yes = 1)	−0.031	0.098	−0.32	0.750
Market linkage (yes = 1)	0.004	0.095	0.04	0.964
Farm income (yes = 1)	7.46e-08**	0.000	1.92	0.055
Erratic rainfall (yes = 1)	0.217**	0.093	2.32	0.020
Weather station distance (km)	−0.009**	0.004	−2.14	0.033
Weather advisory services (yes = 1)	0.082	0.187	0.44	0.661
Weather local interpretation (yes = 1)	0.160	0.182	0.88	0.378
Listening to weather reports (Number)	−0.001	0.000	−0.54	0.589
Radio-battery expenses (*N*)	−3.42e-07	0.000	−0.23	0.822
Simple mobile handset (yes = 1)	−0.034	0.088	−0.39	0.694
Smartphone (yes = 1)	−0.061	0.086	−0.70	0.481

[†]*y = Linear prediction (predict) = 0.8680.*
[**]*Statistically significant at 0.05.*
[*]*Statistically significant at 0.1.*
Source: Field data (2019).

This final outcome of the analysis present the ranking of the WCI alternatives. For agriculture in **Figure 4**, the ranking shows rainfall amount (0.95), rainfall onset and cessation dates (0.84), and rainfall distributions (0.81) to be the most useful WCI needed by end users for them to uptake WCI products and services especially in preparing for drought risk with appropriate response arrangements. However, in the context of water resources in **Figure 5**, rainfall intensity (0.91), rainfall cessation date (0.89), rainfall distributions (0.87), and length of dry season (0.79) are most preferred in the water resources management sector for facilitating drought risk preparedness and response action. For disaster risk reduction in **Figure 6**, heat intensity (0.96), rainstorms (0.91), and drought alerts (0.78) are ranked to be the most useful WCI needed for decision-making to strengthen the adaptive capacity of users in anticipation of likely future drought hazard.

These WCI considered as the most important will assist users in reducing vulnerability to drought hazard with its associated impact on their livelihood activities in these key economic sectors. Effective drought management systems through provisions of water dams, irrigation canals, and water pump facilities require high budget implications and technical capacity, which are less available in the study area. It is clearly understood that the provision of rainfall amount, rainfall intensity, heat intensity, and rainstorms have proved to be relatively the most useful WCI that meet users' needs in the savannah belt of Nigeria. These WCI products and services will assist users in managing drought hazard by facilitating their decisions in taking appropriate preparedness actions to prevent loss and damages of agricultural livelihood investments in view of the relative importance of the criteria along with the existing users' preferences and the characteristics of WCI products and services.

This is an emerging insight for the Nigerian Meteorological Agency (NiMet) to intensify its effort toward delivering weather and climate services that are user oriented and decision driven in the savannah belt of Nigeria.

Usefulness of WCI Timescale to Users

The most preferred WCI timescales by users are described in **Figure 7**, thus expected to make future improvements in the value of weather forecasting and its utilization in Nigeria.

One common factor was that users need forecasts on short-to-medium timescales to facilitate resource planning for efficient utilization and management. In the disaster risk management sector, 82% of the respondents mostly preferred S2S forecast information to other timescales followed by 68% who wanted extended range forecasts and medium range forecasts. The results support the need for risk preparedness to ensure safety of the respondents through early warnings of high-impact events usually within 2 weeks to a season (White et al., 2017; Moron et al., 2018). The S2S timescales enable users with sufficient time within 2 weeks to 2 months to make adequate plans such as evacuation arrangements, and planning food and water provisions ahead of a drought crisis as well as relief materials to minimize income shrinking that might result from crop losses.

The water resources sector recorded 96% of the sampled actors who mostly wanted S2S forecasts, and 70% preferred extended range forecasts and nowcasting forecasts. These three timescales were the most relevant to domestic water users, irrigation farmers within water user associations, and water resources planners. They provide ample opportunity for adaptation response plans, which include rainwater harvesting, reservoir tanks, and smart water use technologies for irrigation ahead of likely dry spells and water stress in the savannah area. In the agricultural sector, 92% were interested in S2S forecasts, extended range forecast by 69% of the respondents, and next by 72% who wanted nowcasting hourly forecasts. Basically, the S2S timescales allow window time periods during which sufficient risk management decisions with respect to crop choices and livestock varieties, purchase of agricultural inputs, irrigation water arrangements, and efficient allocation and utilization of resources are made ahead of a farming season.

Preferred Delivery Method of Forecast Communications

The analysis of the delivery methods of receiving WCI reveals different preferences in the study area. Results from the ranking show mobile telephone, radio, agricultural extension officers, farmers' groups, and contact farmers/specialist as the most preferred delivery methods of receiving WCI by end users for them to uptake WCI products and services especially in preparing for drought risk with appropriate response

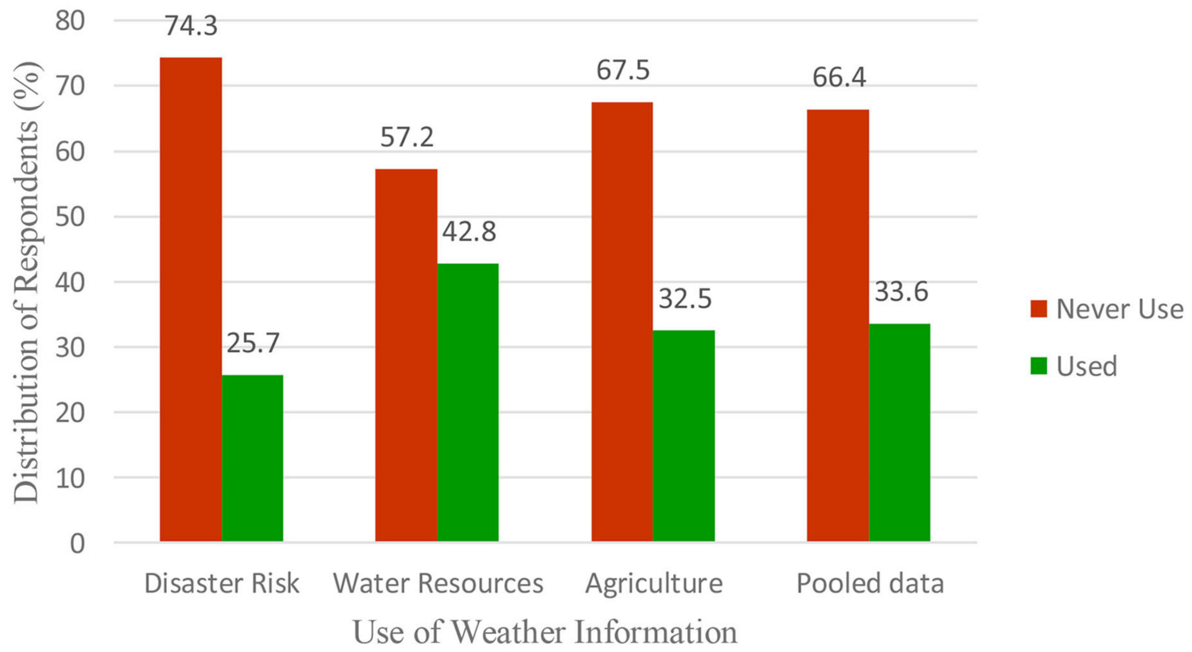

FIGURE 3 | Distribution of users and non-users of WCI for drought hazard preparedness.

TABLE 7 | Weighted criteria weighted for alternative assessment.

Criterion	Importance	Units	Weights in key sectors (%)		
			Agriculture	Water resources	Disaster risk reduction
Weather and climate information					
Timeliness	Modera5te	"1–4"	20.0%	15.0%	15.0%
Presentation format	Low	"1–4"	10.0%	10.0%	10.0%
Location specific	Moderate	"1–4"	15.0%	20.0%	15.0%
Local content	Moderate	"1–4"	15.0%	10.0%	10.0%
Accuracy	Very high	"1–4"	15.0%	20.0%	25.0%
Decision advisories	Very high	"1–4"	25.0%	25.0%	25.0%
Delivery channels			***Weights***		
Timeliness	Low	"1–4"	10.0%		
Accessibility	Very high	"1–4"	20.0%		
Feedback	Very high	"1–4"	20.0%		
Wider coverage	Moderate	"1–4"	15.0%		
Mobility	Very high	"1–4"	20.0%		
Expensiveness	Moderate	"1–4"	15.0%		

Scale of "1–4" implies very important = 4; somewhat important = 3; important = 2; not important = 1.
Source: Authors' compilation.

arrangements. Within the context of agriculture, water resources, and disaster risk reduction, the five delivery channels are ranked to be the most useful, efficient, and convenient mode of WCI dissemination required by users for decision-making and to strengthen their adaptive capacity by preparing for anticipated future drought.

These WCI products and services will assist users in managing drought hazard by facilitating their decisions in taking appropriate preparedness actions to prevent loss and damages of agricultural livelihood investments in view of the relative importance of the criteria along with the existing users' preferences and the characteristics of WCI products and services.

The results of the multi-criteria decision-making problem (MCDM) using the WASPAS framework are presented to determine the most preferred WCI delivery channels. The estimates of normalized decision matrix[a] are shown in **Table 14**

TABLE 8 | Estimates of normalized decision matrix[a] and relative significances of criteria (criteria weights) (Agriculture).

Weights	15%	10%	15%	10%	25%	25%
Criteria	**Timeliness**	**Format**	**Location specificity**	**Local content**	**Accuracy**	**Advisory warnings**
Weather and climate information						
Rainfall onset date	0.8	1	0.7	2.0	0.7	1.0
Rain cessation date	0.8	1	0.7	2.0	0.7	1.0
Growing season length	0.5	1	0.3	2.0	1.0	1.0
Rainfall amounts	1.0	1	1.0	2.0	0.7	1.0
Rainfall distributions	0.8	1	0.7	2.0	1.0	0.8
Dry spell distribution	0.5	1	0.7	2.0	0.7	0.8
Soil moisture	0.5	1	0.3	1.0	0.7	0.5
Temperature reports	0.5	1	0.7	1.0	0.7	0.5
Heat intensity	0.3	1	0.7	1.0	0.7	0.5
Evaporation	0.5	1	0.7	1.0	0.7	0.5
Drought alerts	0.5	1	0.7	2.0	0.7	0.5
Cloud	0.5	1	0.7	1.0	0.7	0.8
Wind speed	0.3	1	0.3	1.00	0.7	0.3

[a] The normalization of the decision matrices and all computations were performed with the aid of the Excel-based software tool used to program the WASPAS as a decision support tool. Source: Authors' estimation.

TABLE 9 | Estimates of normalized decision matrix[a] in water resources and relative significances of criteria (criteria weights) (Water Resources).

Weights	15%	10%	15%	10%	25%	25%
Criteria	**Timeliness**	**Format**	**Location specificity**	**Local content**	**Accuracy**	**Advisory warnings**
Weather and climate information						
Rain cessation date	0.8	1.0	1.0	1.0	0.7	1.0
Rainfall amounts	0.5	1.0	1.0	1.0	0.7	0.8
Rainfall distributions	1.0	1.0	1.0	0.5	0.7	1.0
Rainfall intensity	0.8	1.0	0.8	1.0	1.0	1.0
Water levels	0.5	0.8	0.5	0.5	1.0	0.8
Groundwater	0.8	0.5	0.5	0.5	0.7	0.3
Run-off analysis	0.8	0.8	0.5	0.5	0.3	0.5
Evapotranspiration	0.5	0.5	0.3	0.5	0.3	0.3
Temperature reports	0.5	0.3	0.3	0.5	1.0	0.3
Streamflow	1.0	0.5	0.5	0.5	0.3	0.8
Soil moisture	1.0	0.8	0.8	0.5	0.7	0.8
Drought alerts	1.0	0.5	0.5	1.0	0.7	0.8
Dry season length	1.0	0.8	0.8	1.0	0.7	0.8

[a] The normalization of the decision matrices and all computations were performed with the aid of the Excel-based software tool used to program the WASPAS as a decision support tool. Source: Authors' estimation.

while the ranking of the alternative methods of WCI delivery channels are presented in **Table 15**.

It is noteworthy that these delivery channels as the most preferred method of delivering weather information have much been linked to their opportunities that will allow for provision of advisory services that come with agro-meteorologists or agricultural extension specialists that will guide them on the next course of action in reducing their cost of adaptation. These delivery channels allow for feedbacks to correct likely errors made. Mobile phone is a communication method that is portable, fast, and has wider technology-driven pieces of information. Its efficiency has been well promoted and supported in the important sectors of disaster risk management, water resources, and agriculture on rural scale in Africa, including Nigeria. WCI through farmers' group or association is another tool of communication channel. Focus group discussions show that most of the respondents prefer to receive WCI through their associations because of social cohesion and stakeholdership

TABLE 10 | Estimates of normalized decision matrix[a] and relative significances of criteria (criteria weights) (Disaster risk reduction).

Weights	**15%**	**10%**	**15%**	**10%**	**25%**	**25%**
Criteria	**Timeliness**	**Format**	**Location specificity**	**Local content**	**Accuracy**	**Advisory warnings**
Weather and climate information						
Rainfall amounts	0.3	0.5	0.5	0.8	0.5	0.3
Water levels	1.0	0.8	0.5	1.0	0.5	0.8
Dry spell distribution	1.0	1.0	1.0	0.3	0.5	0.5
Drought alerts	1.0	0.8	1.0	0.5	0.5	1.0
Temperature reports	0.5	0.5	0.5	0.3	0.5	0.8
Temperature distribution	0.5	0.8	0.3	0.3	0.3	0.3
Heat intensity	1.0	1.0	0.8	1.0	1.0	1.0
Wind velocity	0.8	1.0	0.8	0.3	0.8	0.5
Rainstorms	1.0	1.0	1.0	0.8	0.8	1.0
Thunderstorms	1.0	0.5	0.8	0.3	0.8	0.5
Lightning alerts	0.8	0.5	0.3	0.5	0.5	0.5

[a] *The normalization of the decision matrices and all computations were performed with the aid of the Excel-based software tool used to program the WASPAS as a Decision Support Tool.*
Source: Authors' estimation.

TABLE 11 | Optimality criteria by applying weight aggregation of WASPAS method.

	$\sigma^2\left(Q_i^{(1)}\right) = \sum_{j=1}^{n} w_j^2 \sigma^2\left(\overline{x_{ij}}\right),$	$\sigma^2\left(Q_i^{(2)}\right) = \sum_{j=1}^{n}\left(\frac{\Pi_{j-1}^{n}\left(\overline{x_{ij}}\right)^{w_i} w_j}{\left(\overline{x_{ij}}\right)^{w_i}\left(\left(\overline{x_{ij}}\right)^{(1-w_i)}\right)}\right)^2, \sigma^2\overline{\left(x_{ij}\right)}$	$\lambda = \frac{\sigma^2\left(Q_i^{(2)}\right)}{\sigma^2\left(Q_i^{(1)}\right)+\sigma^2\left(Q_i^{(2)}\right)}$	**Ranking alternatives by optimal λ**
Rainfall onset date	0.85	0.84	0.84	2
Rain cessation date	0.85	0.84	0.84	2
Growing season length	0.75	0.69	0.72	5
Rainfall amounts	0.95	0.94	0.95	1
Rainfall distributions	0.81	0.80	0.81	4
Dry spell distribution	0.71	0.70	0.70	6
Soil moisture	0.58	0.55	0.56	11
Temperature reports	0.63	0.60	0.61	9
Heat intensity	0.58	0.53	0.55	12
Evaporation	0.63	0.60	0.61	9
Drought alerts	0.65	0.63	0.64	8
Cloud	0.69	0.67	0.68	7
Wind speed	0.46	0.04	0.25	13

Source: Authors' estimation.

that exist within the same community range. They enjoyed mutual trust and could jointly take investment risk decision. Poorly ranked delivery methods are television, newspapers, private non-governmental organizations, meteorological website, meteorological officers, and NiMet's website mainly due to their poor access.

DISCUSSION

Determinants of Using WCI in Drought Preparedness Decisions

The outcome model shows that the positive coefficient of gender significantly increases the likelihood of farmers' decision to use WCI in drought hazard preparedness decisions. The implication of this result is that male farmers are more likely to use WCI in taking drought hazard preparedness decisions than female farmers. This result supports the argument that male-headed households are often considered to be more favored in receiving information about new technologies, thus they take risky decisions more than female-headed households. This might be associated with certain sociocultural factors such as religious or cultural factors that restrict women taking household decisions. Men are responsible for decision-making processes in the savannah belt.

The longer farmers had stayed in farming as a primary mean of livelihood, the more likely that they would use WCI in drought hazard preparedness decisions. This result is well connected to the fact that farmers have acquired experiences over time

TABLE 12 | Optimality criteria by applying weight aggregation of WASPAS method.

	$\sigma^2\left(Q_i^{(1)}\right) = \sum_{j=1}^{n} w_j^2 \sigma^2\left(\overline{x_{ij}}\right),$	$\sigma^2\left(Q_i^{(1)}\right) = \sum_{j=1}^{n} w_j^2 \sigma^2\left(\overline{x_{ij}}\right),$	$\lambda = \frac{\sigma^2\left(Q_i^{(2)}\right)}{\sigma^2\left(Q_i^{(1)}\right)+\sigma^2\left(Q_i^{(2)}\right)}$	**Ranking alternatives by optimal λ**
Rain cessation date	0.90	0.88	0.89	2
Rainfall amounts	0.80	0.77	0.78	5
Rainfall distributions	0.88	0.86	0.87	3
Rainfall intensity	0.91	0.90	0.91	1
Water levels	0.69	0.66	0.67	8
Groundwater	0.51	0.47	0.49	11
Run-off analysis	0.53	0.51	0.52	10
Evapotranspiration	0.35	0.34	0.35	13
Temperature reports	0.46	0.39	0.43	12
Streamflow	0.60	0.57	0.59	9
Soil moisture	0.75	0.73	0.74	6
Drought alerts	0.72	0.70	0.71	7
Dry season length	0.80	0.79	0.79	4

Source: Authors' estimation.

TABLE 13 | Optimality criteria by applying weight aggregation of WASPAS method.

	$\sigma^2\left(Q_i^{(1)}\right) = \sum_{j=1}^{n} w_j^2 \sigma^2\left(\overline{x_{ij}}\right),$	$\sigma^2\left(Q_i^{(2)}\right) = \sum_{j=1}^{n}\left(\frac{\Pi_{j=1}^{n}\left(\overline{x_{ij}}\right)^{w_i} w_j}{\left(\overline{x_{ij}}\right)^{w_i}\left(\left(\overline{x_{ij}}\right)^{(1-w_i)}\right)}\right)^2, \sigma^2\overline{\left(x_{ij}\right)}$	$\lambda = \frac{\sigma^2\left(Q_i^{(2)}\right)}{\sigma^2\left(Q_i^{(1)}\right)+\sigma^2\left(Q_i^{(2)}\right)}$	**Ranking alternatives by optimal λ**
Rainfall amounts	0.43	0.39	0.41	2
Water levels	0.71	0.69	0.70	5
Dry spell distribution	0.68	0.62	0.65	3
Drought alerts	0.80	0.76	0.78	1
Temperature reports	0.54	0.52	0.53	8
Temperature distribution	0.34	0.31	0.32	11
Heat intensity	0.96	0.96	0.96	10
Wind velocity	0.66	0.62	0.64	13
Rainstorms	0.91	0.90	0.91	12
Thunderstorms	0.65	0.61	0.63	9
Lightning alerts	0.50	0.48	0.49	6

Source: Authors' estimation.

with understanding of the changing ecological characteristics of their areas, and the incidence of losses of their agricultural investments from the shock of severe dry spells whenever they are ill-prepared. They have also practiced different indigenous coping strategies over the years, thus they are aware of the strategies that work for them or those that had failed. The current speed of aridity arising from early cessation and dry spells has modified known variability patterns such that farmers have been confronted with economic losses they are not equipped to handle, despite their farming experience. This implies the need for anticipatory and planned adaptation as drought hazard preparedness to prevent losses at a local scale. Farmers' income increases the likelihood they will use WCI climate-smart decisions by an infinitesimal change. This is likely attributed to scale of their marginal productivity since majority of the farmers are predominantly medium-scale farmers. Hence, farmers with higher income are more likely to give trial to drought hazard preparedness as a safety net for climate protection to prevent or reduce potential future losses.

Increasing erratic rainfall pattern observed by respondents was found to increase farmers' likelihood to use WCI in drought hazard preparedness in the savannah zone. Increasing magnitude of unpredictability, that is, climate variability, is increasing farmers' propensity to respond early to climate-smart options toward protection and enhancing their adaptive capacity. The inverse coefficient of farmers' group membership implies that the more farmers become members to group associations, the less likely they will use WCI in their drought hazard preparedness

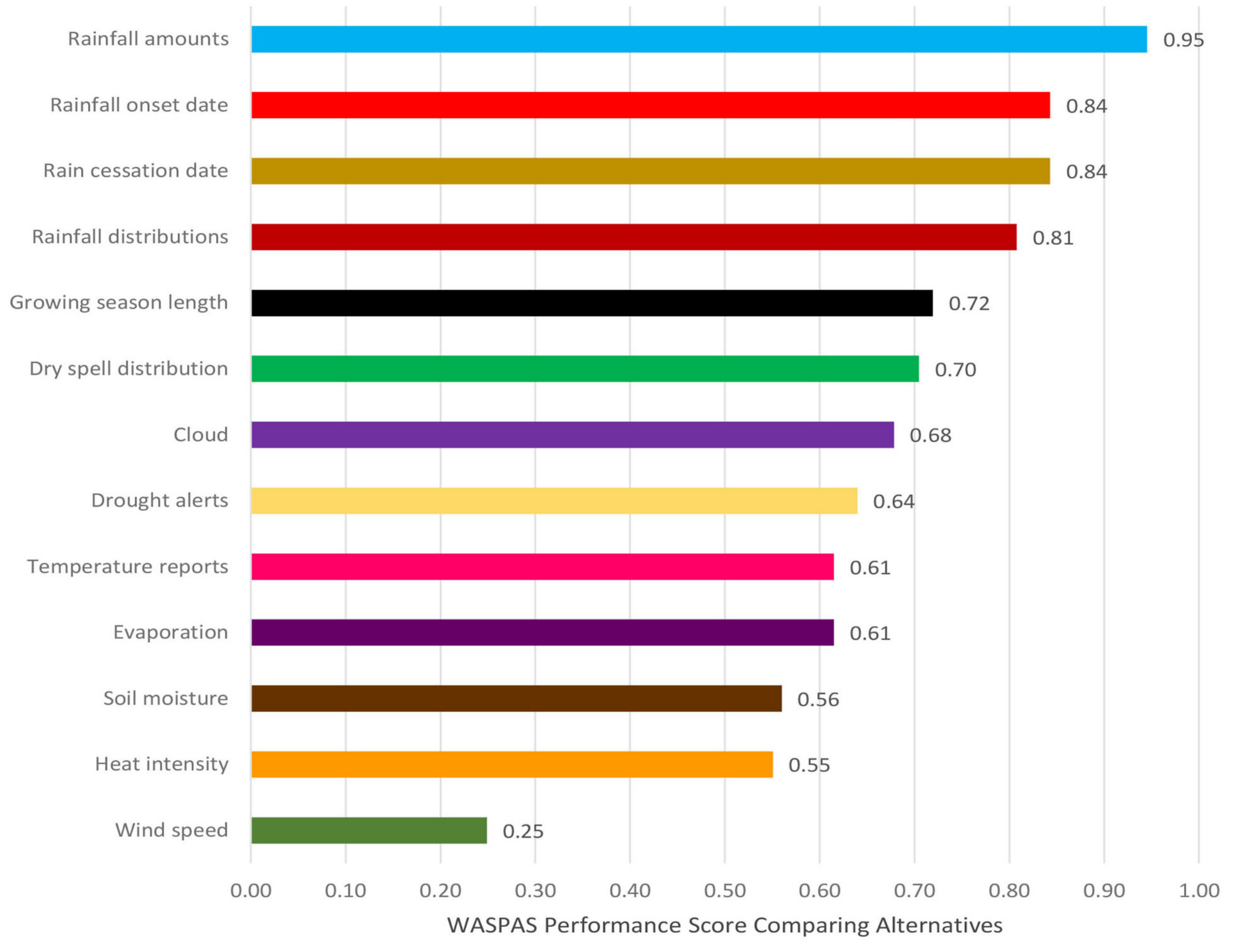

FIGURE 4 | Ranking relative importance of WCI alternatives in agriculture.

plans. Local farmers are known for their loyalty and long attachment to their associations by trusting the decision-making pattern existing within their networks. They are more likely to implement a group/joint safety net in case of adverse weather conditions such as a slow event as that of drought. This explains the reason why it would significantly reduce the probability of using WCI in drought hazard preparedness planning in the study area.

The negative coefficient of distance to weather station also explains that proximity to meteorological station will boost farmers' confidence in WCI provided in their localities. The farther a farming community is away from the nearest weather station, the less likely they will use WCI in taking climate-smart actions. Farmers prefer to trust warning information provided by climate information service providers from a meteorological station sited close to their communities. They are more interested in warning information from WCI that are specific to their farm geographies and match with their location or climatological conditions, rather than general WCI over a large region being communicated. In locations where weather stations are sited, average distance of meteorological stations to rural communities is too far as observed by end users. The problem of unfit and inappropriate WCI within communities thereby explains reasons for the distance of meteorological stations to significantly reduce the probability of using WCI in preparing ahead of potential drought hazard in the study area.

For the selection model, only education of farmers, access to extension training services, and ownership of simple mobile handset device showed positive significant effects on access to WCI. Education is an important factor that determines access to early warnings from WCI. Farmers' education has a positive significant effect on farmers' access to WCI, thus as respondents become more educated, it is more likely that they will have more access to weather information. Their ability to understand weather predictions and quickly adjust their management decisions is more enhanced to meet local climate changes based on their better knowledge of present and future weather conditions. Extension training services show a positive significant effect on respondents' access to

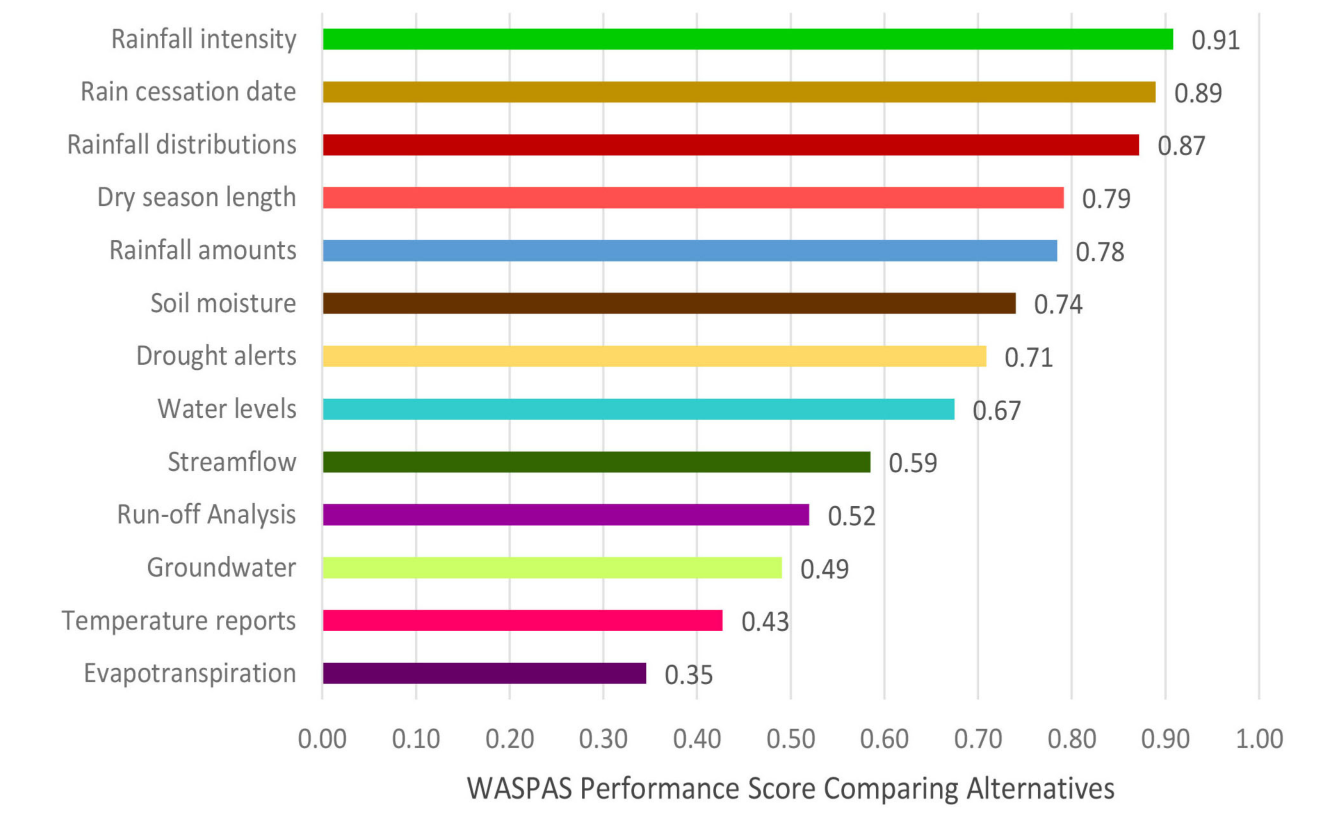

FIGURE 5 | Ranking relative importance of WCI alternatives in water resources.

WCI early warnings. The more respondents have contact with extension training officers, the more likelihood that they will have access to WCI early warnings. Periodic extension education and training services serve as opportunities to share up-to-date information on fluctuations in weather parameters and appropriate advisory services on weather-related managements. Functional extension service system has great potential in facilitating early action decisions on disaster risk preparedness and management.

Ownership of simple mobile handset device also has a significant positive effect on access of the respondents to WCI. Increasing ownership of simple mobile telephones will increase the likelihood of access of the respondents to early warnings from WCI. When forecasts are made such as rainfall forecasts, and advisory agricultural calendars and drought alerts are communicated *via* text messages, it increases spatial coverage within a relatively short time. Such text message information can be revisited several times during a hazard preparedness decision process. This is an important driver of access to early warnings from WCI for climate-smart decisions.

Users' Preferences for WCI in Drought Preparedness and Response

Given that the disaggregated results reveal that majority of the end users of WCI are from the water resources sector especially Fadama farmers who are mainly irrigation farmers, and next are users in agriculture, irrigation planning against dry spells and likely long droughts are taken seriously to avert loss and damage of agricultural investments. These results supported previous studies on reasons for low use of WCI in Africa. Kumar et al. (2020) have expressed the need for more accurate, time-specific, trusted, and actionable climate information. This is expected to facilitate high potential, improve use, and need for climatic information services if tailored for farmers' needs for improving agricultural decision-making (Niang, 2011). Nkiaka (2019) observed that low awareness, understanding, and accessibility of WCI, low relevance and users' capacity to take decision, distrust in forecasts, and institutional barriers such as fragmented institutional framework with overlapping roles are major barriers to uptake of weather and climate information in sub-Saharan Africa (Schaer and Hanonou, 2017). Singh et al. (2018) further explained that despite an increasing number of climate model simulations, there is largely poor usage of WCI because the information produced and disseminated is often irrelevant and not reliable to inform decision-making at local scale, particularly for farmers and government agencies as secondary users or planning purposes in managing climate risks. Anders and Stein (2016) observed that consistency, reliability, and relevance of the WCI to farmers' needs were fundamental in integration of climate information into household decision-making.

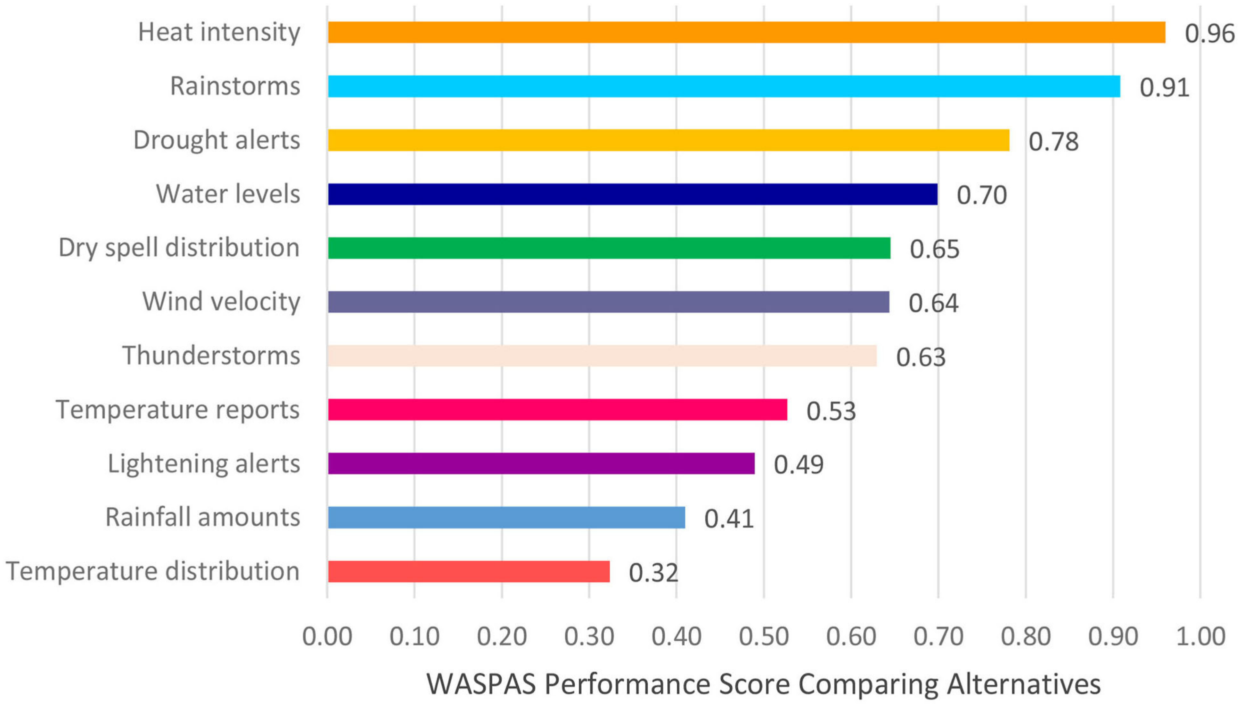

FIGURE 6 | Ranking relative importance of WCI alternatives in disaster risk reduction.

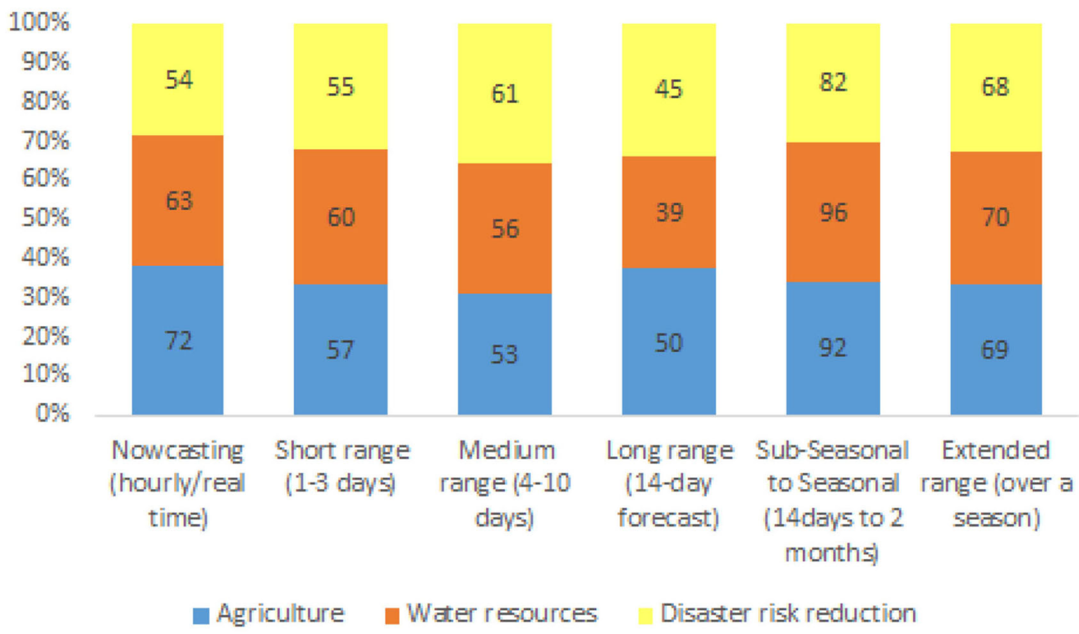

FIGURE 7 | Distribution of preferred WCI timescales by users.

TABLE 14 | Estimates of normalized decision matrix[a] and relative significances of criteria (criteria weights) (Delivery channels).

Weights	**10%**	**20%**	**20%**	**15%**	**20%**	**15%**
Criteria	**Timeliness**	**Accessibility**	**Feedback**	**Coverage**	**Mobility**	**Expensiveness**
Weather and climate information						
Contact farmers/specialist	0.8	0.8	1.0	0.8	1.0	1.3
Farmers' groups	1.0	0.8	1.0	1.0	1.0	1.3
Agric. extension officer	1.0	1.0	1.0	0.8	1.0	1.3
Radio	1.0	1.0	1.0	1.0	1.0	2.0
Television	0.5	1.0	0.3	0.8	0.5	1.0
Mobile telephone	1.0	0.5	1.0	1.0	1.0	2.0
Newspaper	0.3	0.5	0.5	0.8	0.3	1.3
Meteorological Agency_website	0.3	0.5	0.5	0.8	0.5	1.0
Meteorological Agency_officers	0.3	0.5	0.3	0.5	0.3	1.0
University/research institutes	0.5	0.5	0.5	0.5	0.8	1.0
Private organizations	0.5	0.5	0.5	0.8	0.5	1.3

[a] *The normalization of the decision matrices and all computations were performed with the aid of the Excel-based software tool used to program the WASPAS as a decision support tool.*
Source: Authors' estimation.

TABLE 15 | Optimality criteria by applying weight aggregation of WASPAS (Delivery channels).

	$\sigma^2\left(Q_i^{(1)}\right) = \sum_{j=1}^{n} w_j^2 \sigma^2\left(\overline{x_{ij}}\right),$	$\sigma^2\left(Q_i^{(2)}\right) = \sum_{j=1}^{n}\left(\frac{\Pi_{j-1}^{n}\left(\overline{x_{ij}}\right)^{w_i} w_j}{\left(\overline{x_{ij}}\right)^{w_i}\left(\left(\overline{x_{ij}}\right)^{(1-w_i)}\right)}\right)^2, \sigma^2\overline{\left(x_{ij}\right)}$	$\lambda = \frac{\sigma^2\left(Q_i^{(2)}\right)}{\sigma^2\left(Q_i^{(1)}\right)+\sigma^2\left(Q_i^{(2)}\right)}$	**Ranking alternatives by optimal λ**
Contact farmers/specialist	0.94	1.08	1.01	1
Farmers' groups	1.00	1.16	1.08	1
Agric. extension officer	1.01	1.00	1.01	1
Radio	1.15	1.11	1.13	1
Television	0.66	0.59	0.63	8
Mobile telephone	1.05	0.97	1.01	1
Newspaper	0.59	0.50	0.54	10
Meteorological Agency_website	0.59	0.55	0.57	9
Meteorological Agency_officers	0.45	0.39	0.42	11
University/research institutes	0.63	0.60	0.61	7
Private organizations	0.66	0.62	0.64	6

Source: Authors' estimation.

Ziervogel et al. (2010) show similar results of low use of weather forecast information due to delay in access to short-term decision-making forecast services and doubting its reliability. Lemos et al. (2012) identified disconnection between weather service providers and users as one key constraint limiting the use of climate information in Africa. Farmers also expressed their worries about the inability of the agricultural extension agents in disseminating timely weather and climate information on a wide coverage due to lack of funding for such special role. Ouedraogo et al. (2018) concluded that huge operational cost involved right from forecast production to dissemination and training of users for effective use of weather and climate information as major institutional barriers to the wide coverage and use of climate forecast information.

Appropriateness of WCI

The appropriateness of WCI needed by the primary users across the major climate-sensitive sectors reveals that the specific WCI needs are rainfall onset and cessation, and drought alerts to decide types of adaptation measures in preparing for likely dry spells and loss of standing crops. This is very important to food crop farmers in taking various agri-investment expenditures during pre-cropping season and crop management decisions afterwards especially when to start land preparation, seed planting, type of weeding, and pest control selections, and agricultural water use management for crop management operational activities during the dry season.

Rainfall onset and cessation forecasts provide an opportunity for sustainable water and irrigation system planning, which encourage women's participation in all-year-round agricultural income livelihoods that are the largest percentage of food producers and domestic water users by keeping safe domestic water in the savannah area. The results also underscore the need for enhancing water resources for irrigation development. WCI on rainfall onset and cessation are helpful to develop appropriate measures that will enhance irrigation of crops that are suitable for cultivation and increase the length of growing season in the study area. These results are critical policy pointers that meteorological service providers should engage user community in these climate-sensitive sectors to identify their actual needs and form an alliance through which WCI can be co-produced for specific locations and fit into different agroecological zones. Meteorological agencies should endeavor to use agro-meteorological information for packaging WCI capable of taking timely management decisions such as drought-resistant crops and livestock, and develop a drought contingency plan with a range of scales from days to entire cropping season in the water and agricultural sectors.

The results obtained agree with those of Carr et al. (2017) that rural users of WCI are less concerned with the sophistication associated with scientific weather monitoring or numerical prediction capacity of forecasters but interested in receiving useable weather information that are location specific and provided with robust advisory services that will assist them in taking informed decisions on their agricultural investments. It implies that it is difficult for rural users to articulate their needs around numerous WCI products and services produced by meteorological agencies, even if unavailable (FAO, 2019d). They are faced with numerous socio-economic barriers to understand diverse weather services being produced by the forecasters. What is important is the extent of using WCI, which depends on usability of the WCI and low complexity in decision-making, not the varying amount of information made available to users (Anders and Stein, 2016). Service providers should therefore leave out evaluations of weather dynamics but focus on the simplicity of communicating weather reports. This approach would enhance the use of different WCI alternatives of information to allow for quick decision-making. In emphasizing the characteristics of useful types of weather and climate information, forecast should be relevant or useful for decision-making on a spatial scale. The information needs to contain predictions, threat assessments, warnings and alerts, and guidance for appropriate preparedness decisions (Amadi and Chigbu, 2014).

Results obtained are also in line with Tall et al. (2012) who noted that seasonal forecast information issued early allows disaster risk managers to make advance preparation for anticipated hazards, hence science-based early warning informed decisions usually trigger action in anticipation of forecast events, thereby moving decision-makers to action and overcome traditional barriers to the use of climate information. The sub-Saharan Africa has been identified as one of the most susceptible regions to variability in the length of growing season and very low access to basic resources such as irrigation water. Smallholder farmers require different types of climate information at different periods during the farming season. Similar studies have established that WCI is critical in building adaptive capacity of farmers in addressing climate risks. Lugen et al. (2018) observed that smallholder farmers need information on the expected rainfall amount and its distribution as well as the length of the growing season provided through short range information such as sub-seasonal and seasonal forecasts to make important decisions on the range of actions, from crop types to plant for the season. The number of rainy days and dry spells are also crucial in making decisions on when to plant, disease management, and harvesting times (Coulibaly et al., 2015). The onset and cessation of rainy season is of utmost significance to agriculture in many West African countries because the sector is largely rain fed (Sobowale et al., 2016).

Rainfall onset and cessation dates have implication for food security and water resource management. Onset date information is highly valuable for local agricultural production especially for rainfed crop farmers. The knowledge about length of cropping seasons are valuable for planning, organization, and implementation of agricultural activities—timely preparations in mobilizing labor, seeds, and other inputs. It will be helpful for farmers to improve their decisions about selection of crop types and varieties. Informed farmers can also reduce the operational costs associated with re-planting process, therefore optimizing their investments. Likewise, changes in onset and cessation dates affect livelihood activities of men and women differently based on gender differences and capacity to absorb stress and shocks. Women usually engage in subsistent agriculture during cropping season but are helpless during prolonged dry seasons while men do diversify into non-farm alternative livelihoods. They oftentimes bear the major burden of water shortages for household utilization and irrigation agriculture due to rainfall changes, as previously concluded by Mbajiorgu et al. (2017).

Tembo-Nhlema et al. (2019) explained that participatory planning between weather service providers and users at early stages of forecast development can generate information that is credible, legitimate, and salient by potential users. User engagement is an effective approach that could bridge the divide between producers and users. Weather scientists are not always the best at understanding user needs or communicating, which justifies co-production partnership with user stakeholders (Porter and Dessai, 2017). Rather than expecting much of dissemination responsibilities from climate information producers, there may be a role for user engagement, boundary agents, or knowledge brokers who can bridge the divide (Cvitanovic et al., 2015; Guido et al., 2016). Co-producing weather forecast information has the benefits of ensuring scientific credibility, legitimacy, and salience to users (Buontempo et al., 2014).

These empirical findings are in line with FAO (2019a), which ascertained that the two most important elements influencing crop growth and development are temperature and water availability. They are both needed in facilitating decisions related to crop management practices and optimizing the production or minimizing the risk of the farming systems in response. Various studies have further highlighted that the information produced does not necessarily meet user needs, in terms of timeframe, spatial scale, and applicability (Vincent et al., 2016, 2017; Singh and Singh, 2017) while also reiterating the fact that improved weather information alone is not adequate but needs to be useful and usable to decision-makers (Dilling and Lemos, 2011; Lemos et al., 2012; Jones et al., 2015).

Amadi and Chigbu (2014) further underscore the need for accurate and timely climate information and demonstrate that the management of current climate-related risks and long-term adaptation requires customization of climate information so that it would be relevant to end users, helping to prevent climate extremes from becoming disasters and threats to livelihoods. Forecast-based information issued early in the year allows disaster risk managers to make advance preparation for anticipated hazards, pre-position disaster relief items in strategic locations across communities and families, update flood contingency plans, and alert vulnerable communities and decision-makers in reducing number of lives, property, and livelihoods to be lost (Tall et al., 2012; Merz et al., 2020). The National Research Council (1999) stated that increase in forecast skill is not a panacea, given that improved forecasts remain far from perfect but often ill-suited for direct use in decision-making. The usefulness of forecasts is dependent on both accuracy and their relationship to recipients' informational needs and coping strategies.

One major hindrance found in this study to opportunities of WCI users is the poor access to some important and highly consequential WCI, however which to the meteorological agencies they look negligible, for instance, early warnings and advisory information temperature, water levels, evaporation, and windstorms. Hence, most often, meteorological agencies do not make robust early warnings about them available to the user community. Antwi-Agyei et al. (2021) observed that among those that have accessed some kind of WCI, it was noticed that still the majority were just receiving WCI relating to rainfall with a fewer number of those who had received information on other vital WCI products and services, especially temperature and windstorms.

Timescale of WCI in Facilitating Preparedness

A number of recent empirical studies carried out on the potential of subseasonal-to-seasonal (S2S) forecasts in the planning of activities in climate-sensitive sectors at a regional or national scale include adaptation plans that may be necessary in solving climate variability and climate change problems such as droughts and floods as extreme weather shocks (Olaniyan et al., 2018). Haigh et al. (2015) explained that historical climate information and long-term climate outlooks are less useful in agricultural risk management compared with current weather, short-term forecasts, or monthly climate projections, even if they may be more useful to certain types of decision-making. FAO (2019b) had also identified that during the pre-season, farmers need weather information to determine the most suitable crop(s) for a particular region based on crop water requirements before a season starts and at the end of the season. Seasonal climate outlooks for specific agro-climate zones are needed to facilitate adaptation conditions due to inherent uncertainty. Vitart et al. (2017) observed that the fundamental problem of limiting usability of forecasts has been a concern for development actors. The medium range time-scales appear too short for any meaningful mitigating action to be taken, and there exists a gap between the medium- and long-range time-scale forecasts. It is unfortunate because many vital management decisions with regards to agriculture and food security, water management, and disaster risk reduction, health, etc. are made within this gap. As demands for reliable weather and climate forecasts are increasing, forecasts from S2S models are regarded as a new frontier for atmospheric predictability research to improve users' decision-making processes in many key weather and climate-dependent socio-economic sectors.

Bacci et al. (2020) found that users of agro-meteorological forecasts were highly interested in receiving 2 weeks to a season forecast information for local decision-making processes in crop management especially for extreme weather phenomena with a strong impact on crops and livestock. Weather forecast of very intense phenomena and dry spells during the next 2 weeks to about 3 months are specifically appreciated. It is therefore more beneficial and relevant to tailor weather and climate information to specific end users' needs. Ouedraogo et al. (2018) have also observed that the most useful and needed weather and climate information in the agriculture sector include cumulative rainfall and dry spells every 10 days (decadal frequency) prior to the beginning of the season, seasonal forecast once in a year, and the onset and cessation dates once in a year. Throughout the season, 10-day agro-meteorological advices on better adaptation of farmers' practices, and 3-day weather forecasts for rainfall and temperature focus on extreme events such as drought forecast (FAO, 2019c).

In numerous studies conducted by White et al. (2017), it is observed that users are used to short- to medium-term weather forecasts in taking decisions compared with long-term scales. The S2S weather and climate forecasts have potentials to support decision-makers in protecting life and property, production resources, and wellbeing. S2S timescales could provide window opportunity of decision-making in drought disaster management using short-to-long-range predictions (Goddard et al., 2014). Seasonal forecasts provide monitoring information and early contingency planning such as food relief purchases and training; subseasonal forecasts provide the early warnings and alerts for preparedness while short-range weather forecasts facilitate resettlements and distribution of aid (Vitart, 2014). This strengthens capacity of disaster risk reduction managers in adjusting and adapting accordingly to commence preparedness activities as well as supporting important shift to short-term actions when drought shock strikes. It offers an opportunity for disaster risk reduction managers to track the progress of the slowly supporting transition from seasonal outlooks to weather forecasts to inform both drought risk planning and systematic response (Tadesse et al., 2016). Many of the disaster preparedness actions that can be taken based on risk of extreme events require time to activate, some of which include purchasing disaster response supplies such as food, water, and drug during drought that can take several weeks (Boston Consulting Group, 2015).

White et al. (2017) found that S2S weather and climate forecasting has the capacity to fill the gap between short-range weather services and long-range seasonal outlooks for water resources management. Extended range of lead time enables preparedness and plans decisions to be made in a range of sectors including continuous monitoring of forecasts, updating community warnings, initiating preparedness activities, revising water allocations, and activating water conservation practices. WSWC CDWR (2016) reaffirmed that S2S forecasts on the probability of evaporation, runoff, or likelihood of atmospheric river events are useful for drought control in water resources management. Prior to the beginning of the seasons, Fadama farmers in the established water user associations and water managers can make farm irrigation infrastructure planning, water allocations during drought, and hydropower scheduling decisions on water supply in reservoirs to sustain all-year-round agricultural productions in the savannah area. In the agricultural sector, S2S forecast timescale on rainfall departures also have applications in managing drought in the food security sector by making transportation plans for large quantities of food during food crisis when it happens (White et al., 2017). It gives reliable longer-range forecasts, which allow users to take risk reduction actions against extreme events such as droughts.

NASEM (2016) found that S2S forecast information on weather elements are capable of fostering adaptation capacity against drought shock by enhancing strategic agribusiness planning decisions, specifically the purchase of seeds, scheduling irrigation, susceptibility to diseases, and making adjustment decisions on stocking rates in livestock, and application of nutrients, pesticides, and herbicides by users in agriculture. Vitart (2014) further reiterated that while a seasonal forecast of rainfall totals might inform strategic decisions regarding crop-planting choices, a few weeks in advance, S2S forecasts of extremes such as rainfall extremes, rainfall onset and cessations, heat, and decay have the capacity that would be particularly useful to add valuable information for irrigation scheduling, and pesticide and fertilizer application. It could be used as dynamic updates to an existing cropping calendar, such as for the estimation of crop yields. Clements et al. (2013) highlighted that the S2S timeframe is highly relevant in agriculture, noting that S2S forecasts and outlooks in agriculture support crop management operational decisions on input use, especially pesticides and fertilizers, the timing of irrigation, spraying and harvesting, product marketing, and commodity pricing.

Efficient Delivery Channels of WCI

It was previously observed that most of the WCI communication methods were poorly accessible to most farmers because they are costly, weak in coverage, and lack feedbacks in the interiors of rural villages. A limited number of respondents have television or access to newspapers in the interior of the rural villages. The low level of education and civilization have also constrained farmers in decoding information received through WhatsApp services and websites, while absence of agricultural extension workers was observed as a key barrier. These findings agreed with other studies that effectiveness of WCI depends strongly on the disseminating systems, distribution channels, recipients' modes of understanding and perception about the information sources, and format of presentation. Forecast interpretations are likely to be strongly affected by individuals' pre-existing mental models such that when forecasts turn out to be wrong, they have strong negative influences on the future use of forecast information (National Research Council, 1999). Future improvements in the use of WCI have to focus on combining the use of contact experts/specialists, mobile phones, farmers' groups/associations, and redefined agricultural extension officers as major pathways to forecast information communication. This presents further evidence that weather service providers should consult and engage users when developing WCI product and services to ensure relevance and usability.

Wilkinson et al. (2018) ascertained that forecast-based mechanisms should be provided and used at scales suitable for humanitarian and disaster risk management decision-making through the use of different sources of local and national delivery mechanisms. Kumar et al. (2020) concluded that informal contacts, especially peer farmers, and information technology platforms such as smart mobile phones were among the major sources of receiving climatic information at local scale by local farmers. This could play an increasingly vital role in tailoring information exchange and communication with local farmers in helping them make climate-sensitive decisions. Mobile phones and social networks have also been widely used as the most sustained dissemination methods given that the choice of plain text messages simplified the process of communication from the central to the local level (Bacci et al., 2020). Ouedraogo et al. (2018) expressed that the most innovative stressors of WCI such as short message service (SMS), community radios by local language, and mobile applications effectively engage producers, technicians, and policy-makers for feedback interactions. Agro-meteorological information has successfully been used by rural radios as the main information media/channel to access WCI in rural areas (Oyekale, 2015a). Farmers' leaders also have a cultural mandate to share WCI they regularly receive with members of their respective communities (Ouedraogo et al., 2018). Mittal and Mamta Mehar (2016) also supported these results that farmers would normally use multiple information sources that may be complementary or substitutes to each other, which implies that a single source of information does not satisfy all WCI needs of all categories of users.

PERSPECTIVES AND OUTCOMES

This paper has some interesting perspectives provided for the WCI users, service providers, and private support institutions. The major determinants of the use of WCI by rural households are male gender, farmers' experience, income, and persistent incidence of erratic rainfall in the study area. Male farmers have more propensity to use WCI more than female famers in taking drought preparedness and response. Likewise, farmers' experience would increase their likelihood to use WCI. This is reasonable because good and bad previous experiences and increasing vulnerability to weather variations will influence continuous usage. As farmers' income gets better, they are more inclined to use WCI in decision-making because they have economic capacity to sustain the cost of adjustment.

Persistent frequency of erratic rainfall increases the use of WCI as drought preparedness increases. However, as group membership improves and the unit distance of meteorological station is farther away from communities, their interest on the usage of that WCI decreases. They rely on the local information received, safety nets, and local interest-free credit arrangement of their association. However, the purpose of establishing group membership should be re-modified to enable communities to benefit from early warnings from the WCI, thereby ensuring preparedness and protection from potential drought hazard.

There is still a relatively low uptake of WCI among rural communities who dominate the largest percentage of the population. Users of WCI accounted for only 33.0% of the respondents who reported use of WCI in taking agricultural decisions; 43.0% of the respondents have used WCI to enhance water use decision planning in the water resources while 26% of the respondents used WCI to plan ahead of likely drought shock, as disaster risk reduction. Multi-criteria (MCA) decision-making analysis provides an accurate ranking of alternative WCI to determine the usefulness of the many WCI products and services through the Meteorological Office, thereby identifying what users considered as useful WCI for decision-making across key economic sectors.

Rainfall amount, rainfall onset and cessation dates, and rainfall distributions are the most useful WCI needed by end users for them to uptake WCI products and services especially in preparing for drought risk with appropriate response arrangements in the central savannah belt of Nigeria. Regarding water resources, rainfall intensity, rainfall cessation date, rainfall distributions, and length of dry season are the most useful WCI for water resource management while the ranking shows that heat intensity, rainstorms, and drought alerts are ranked to be the most useful for users in disaster risk reduction and in fostering resilience toward anticipated future drought hazard. The drying conditions of the study are explained reasons for the interest in rainfall amounts and the distributions are needed to plan for drought preparedness actions, water supply issues for domestic purposes and agricultural water supplies, and raising emergency alerts. They are most important to decide when to start land preparation and seed planting in the agriculture sector, and water supply planning and drought alerts by water planners in the water resources. These WCI are considered as the most important that will assist users in reducing their vulnerability to drought hazard with its associated impact on their livelihood activities in those key economic sectors.

The most useful WCI timescales across different stakeholders are identified as short range (1–3 days) to medium (4–10 days) timescales to facilitate resource planning for efficient utilization and management. In all the sectors, subseasonal-to-seasonal (S2S) information is the most highly rated. This study supports the need for early warnings of high-impact events usually within 2 weeks to a season. S2S timescales allow sufficient time (2 weeks to 2 months) to enable users to make adequate risk preparedness and adaptation plans that will minimize economic damage and losses. The users' most preferred delivery methods of receiving WCI are mobile telephone, radio, agricultural extension officers, farmers' groups, and contact farmers/specialist for efficiency and convenient criteria in enhancing users' decision capacity to uptake WCI products and services.

The emerging outcome of this paper is that there is a need for a policy drive that will make WCI forecasting systems include impact-based forecast estimates and response advisory across a wide range of natural hazards. There is a high demand for short-range forecasts, especially the sub-seasonal to seasonal forecasts for operational activities in water resource management and the intra-seasonal forecasts in agriculture. NiMet, the Meteorological Agency mandated by the Federal Government for the provision of weather and climate services, should liaise with the primary and secondary users in co-developing close-range WCI. The Agency should link with user groups in various farming communities especially to incorporate male farmers' groups with considerable years of farming experience of the agro-ecology to enable them to bring their local experiences into co-production of WCI. This initiative will produce WCI that are on-demand and location specific. Second, the Agency should shift its focus to the production of rainfall amount, rainfall onset and cessation dates, and rainfall distributions for agriculture users; rainfall intensity, rainfall cessation date, rainfall distributions, and length of dry season for water resources users; and heat intensity, rainstorms, and drought alerts for the disaster risk reduction. These are WCI that actually meet user needs in Central-Southern Nigeria, and their availability will fast track rapid uptake in their various decision-making processes in the region. Packaging subseasonal to seasonal (S2S) and medium-range (4–10 days) WCI timescale should be given utmost attention by the Meteorological service providers to make their products and services receive wide coverage of various users.

This study also recommends that the National Meteorological Office should have a collaborative engagement with contact farmers, specialists, and agricultural extension workers as supportive pathway to disseminate WCI. Such arrangement will facilitate rapid uptake of WCI in operational decision-making among rural communities due to the strong socio-cultural relationships and exchange that exist among rural people. NiMet should have a Memorandum of Understanding (MoU) with telecommunication operators to take advantage of their massive mobile telecommunication installations in reaching more rural households with WCI on their mobile phones. Such initiatives will enable the possibility of producing location-specific WCI locations, strengthening local delivery arrangements of WCI products and services, and re-designing feedback mechanisms between users and service providers to improve on their services at local scale. A seamless collaborative effort in bringing scientific outputs and users' needs together will increase the utility of weather forecast information through systematic efforts. NiMet should improve on its engagement with the stakeholders, principally the agricultural extension and planning office, water management authorities, and disaster risk and emergency response personnel as partner institutions. These policy actions in designing robust collaborative framework for useable information based on user needs will improve the use of WCI in managing decision points against probable extreme events and mainstream preparedness into an existing decision-making apparatus of rural communities in Central-Southern Nigeria.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

DA and JM developed the concept idea and designed the methodology. DA collected the field data and wrote the article. DA performed the data analysis while EA provided insights on meteorological aspect of the analysis. JM, AT, and PA-A reviewed and edited the article. All authors contributed to the article and approved the submitted version.

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Extreme Events and Production Shocks for Key Crops in Southern Africa Under Climate Change

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Many studies have estimated the effect of climate change on crop productivity, often reflecting uncertainty about future climates by using more than one emissions pathway or multiple climate models, usually fewer than 30, and generally much fewer, with focus on the mean changes. Here we examine four emissions scenarios with 720,000 future climates per scenario over a 50-year period. We focus on the effect of low-frequency, high-impact weather events on crop yields in 10 countries of Southern Africa, aggregating from nearly 9,000 25-kilometer-square locations. In the highest emissions scenario, median maize yield is projected to fall by 9.2% for the region while the 5th percentile is projected to fall by 15.6% between the 2020s and 2060s. Furthermore, the frequency of a low frequency, 1-in-20-year low-yield event for rainfed maize is likely to occur every 3.5 years by the 2060s under the high emissions scenario. We also examine the impact of climate change on three other crops of considerable importance to the region: drybeans, groundnuts, and soybeans. Projected yield decline for each of these crops is less than for maize, but the impact varies from country to country and within each country. In many cases, the median losses are modest, but the losses in the bad weather years are generally much higher than under current climate, pointing to more frequent bouts with food insecurity for the region, unless investments are made to compensate for those production shocks.

Keywords: climate change, yield shocks, climate uncertainty, yield emulator, crop models, Southern Africa, food production, food security

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INTRODUCTION

A number of authors have investigated the likelihood of experiencing increased climate variability under climate change (Pendergrass et al., 2017; Bathiany et al., 2018; van der Wiel and Bintanja, 2021). Fewer have investigated the implications of uncertainty regarding emissions pathways coupled with uncertainty concerning the effects on future climate possibilities while accounting for inter-annual variation. Here, we investigate the implications of both climate uncertainty and variability for crop production in Southern Africa. Our motivation is to better understand low-yield events because of their effects on food insecurity.

Most of world's poor and food-insecure people live in rural areas and are smallholder farmers, fishermen, and agricultural laborers (FAO et al., 2018). Their diets consist almost entirely of food produced locally. Weather shocks, therefore, can be extremely disruptive for the nutrition and health of these households, limiting food availability and increasing local market prices, sometimes causing permanent health consequences, especially for young children.

The Sustainable Development Goals (SDGs; see United Nations, 2015) seek to address these issues through various channels. SDG1, ending poverty, targets building resilience of farmers to climate shocks and improving social protection. SDG2, ending hunger and food insecurity, includes a component for doubling the productivity and income of small-scale food producers. Until 2014, household food insecurity had been steadily declining. Since then, the number of food insecure people has risen each year and is projected to continue to rise through the decade, suggesting that the SDGs cannot be achieved by their target date of 2030 (FAO et al., 2020).

Climate change increases the difficulty of meeting the goals by reducing the average yields for most crops and most countries. This phenomenon has been well studied. However, no one has conducted a rigorous analysis on the effect of future climate change on yields in the years with adverse weather shocks. Those years are most vital for the SDGs, because they include the greatest food shortfalls for rural families, thus highlighting the need for effective social protection programs. If the event is sufficiently enduring, severe, and widespread, a regional crisis may ensue as multiple nations struggle to compensate for shortfalls through trade and through substitution of alternative foods (Gaupp et al., 2020).

Understanding the effect of future adverse weather shocks on production would enable governments to develop the capacity needed to address the crisis after it happens or invest beforehand in mitigating measures to reduce the degree of crisis. With sufficient information, even farmers themselves could take steps to mitigate the impact by choosing certain crops, cultivars, and production technologies.

This analysis focuses on 10 countries of Southern Africa, a region in which 44% of the population is food insecure (Thome et al., 2018), in large part due to the frequency of droughts and pests. Thome et al. (2018) estimate that the percent of food insecure will decline over the next 10 years in the region, while the FAO et al. project that the absolute number of food insecure will double in the same period of time (FAO et al., 2020). The difference in direction between the two statistics—one in percent, one in numbers—is partly due to the growing population over that time, but also due to differences in definitions of which countries are part of Southern Africa.

We do detailed analysis on maize, drybeans, groundnuts, and soybeans, key crops for the region, ranking 1, 3, 4, and 6 by total harvested area (**Table 1**). This article focuses most on maize, largely because it is the region's leading source of calories and protein (followed by wheat in both cases), but we include sections on the other three, as well.

Maize production accounts for more than 2.6 times the calories and 2.2 times the amount of protein than wheat and represents roughly 32% of both total calories and proteins consumed in the region (FAO, 2020). Perhaps more importantly, maize represents 41.1% of the harvested area of the region (FAO, 2020), implying that the diets of smallholders may have a much higher proportion of maize than are indicated in the aggregate numbers that include urban areas.

TABLE 1 | Top 10 crops by harvested area in Southern Africa.

Rank	Crop	Hectares (2012–2015)	Percent of total
	All crops	*25,699,084*	
1	Maize	9,923,745	38.6%
2	Cassava	2,272,911	8.8%
3	Beans, dry	1,594,988	6.2%
4	Groundnuts	1,507,403	5.9%
5	Sorghum	925,219	3.6%
6	Soybeans	850,835	3.3%
7	Millet	798,656	3.1%
8	Seed cotton	728,783	2.8%
9	Sunflower seed	654,058	2.5%
10	Wheat	589,690	2.3%

Source: FAOSTAT (FAO, 2020).

We address the implications of climate change for the frequency and severity of major production shortfalls over the next four decades. As far as we can tell, this is the first focused analysis on low-yield events conducted for any region in the world that used a spatially- and temporally-consistent dataset that was large enough to investigate the behavior of the tails of yield distributions. Burke et al. (2015) tell us that out of approximately 100 studies they reviewed, the median number of climate models used to investigate the effect of climate on agricultural productivity was 2. In this study, we use 720,000 per emissions scenario—almost 3 million total.

Most studies that explore these issues tend to focus on yield variation associated with climate and weather and almost never consider the impact of climate on the changes in the tail of the distribution. Ostberg et al. (2018) use spatially- and temporally consistent data for 4 emissions scenarios (RCPs), 5 GCMs (i.e., climate models), and 5 crop models to build a very sparse emulator. They investigate yield variation but are limited by the number of weather simulations (it appears they only used one weather pathway over a multi-year period). Liu et al. (2021) investigated yield variability of wheat in China due to climate change, but their analysis is limited by the number of climate models (5) and weather simulations (25) used, and the number of sites (8). Chen et al. (2018) analyze the long-term impacts of climate change under 2 emissions scenarios in China, using 4 GCMs and up to 20 weather simulations each. Stuch et al. (2020) compute yields and variability of maize, sorghum, and millet for Sub-Saharan Africa for one emissions scenario and 6 GCMs, but it is not clear that they used a spatially-consistent weather input, which would render any national aggregation incorrect—though their primary objective is at the pixel level. Earlier works focusing on yield variation include Torriani et al. (2007) which examined maize and wheat yield in Switzerland and Thornton et al. (2009), which analyzed maize and drybeans in East Africa.

To investigate these extreme climate-driven low-yield events, we deploy a large suite of potential future smoothed climates (moving averages of precipitation and temperature)—7,200 for each of 4 emissions scenarios. These climate ensembles, labeled hybrid frequency distributions (HFDs), are developed specifically to estimate the distribution of potential climate outcomes to 2060 (Schlosser et al., 2012, 2020, 2021). Further, we overlay these climates with 100 spatially- and temporally-consistent deviations from the mean from historical climate data at each pixel—almost 9,000 pixels of quarter-degree (25-km) resolution—to give 720,000 potential paths for future climates per emissions scenario. Overlaying these 100 sets of data adds in the inter-annual variation that was missing from the smoothed climates. This set of 720,000 weather paths from 2020 to 2069 is taken as the best available estimate of the full distribution of possible growing conditions that farmers may experience over the next four decades. Details of the process used are in a companion article (Thomas et al., 2022).

The large number of climates that account for inter-annual variation allow us to consider extreme events, emphasizing confluences of climate and weather together that are particularly unfavorable to yields. The large number of pixels also allows us to consider impact on yields at various scales. However, computational burdens present considerable barriers. To render the problem tractable, three steps are taken. We deploy an intelligent sampling framework that preserves the moments of key climate outcomes critical to yields out to order three, thereby reducing the number of climate pathways to 455 per emissions scenario. Furthermore, because yields are calculated at pixel level annually to 2069 for multiple crops, soils, and levels of input use, 455 climate pathways remain computationally prohibitive for detailed crops models. To expedite computation of yields, a statistical crop emulator for each of the four focus crops is developed and deployed.

While the process used to compute pixel-based yields was computationally intensive, it is similar to the process used by the international teams that participate in the Agricultural Model Intercomparison and Improvement Project (AgMIP) Gridded Global Crop Model Intercomparison (GGCMI). See for example Müller and Robertson (2014) and Rosenzweig et al. (2014), and more recent work of Ostberg et al. (2018), Franke et al. (2020), Jägermeyr et al. (2021), and Zabel et al. (2021). In some of the research of GGCMI, they use crop model results directly with climates that have both inter-annual variation and uncertainty across multiple models. In others, they use emulator output. The innovation presented in this articles comes in using the methodology with such a large number of climates which allow for more confidence in examining the tail of the distribution which describes the low-yield events that are the main focus of this study.

MATERIALS AND METHODS

IGSM-HFD Climate Data

The climate ensemble that forms the basis for this analysis provides an opportunity to evaluate not only the distribution of future climates under a given emissions scenario, it enables us to evaluate an arguably complete distribution of abiotic consequences of climate change on crop yields. It is from the MIT Integrated Global System Model (MIT-IGSM, Reilly et al., 2018) which simplifies climates by considering only elevation (vertical) and latitudes so that the computing time is reduced to allow for a wider range of possible patterns of change. In order to expand longitudinally, eighteen GCMs from CMIP5 are used.

There are four emissions scenarios used in the ensemble:

- Reference (REF): There are no explicit emissions mitigation policies anywhere in the world, though it allows for energy policies that lead to some renewable energy and fuel efficiency that are motivated by other reasons besides mitigation.
- Paris Forever (PF): Assumes that countries meet the mitigation targets in their Nationally Determined Contributions (NDCs) and those targets are met throughout the century.
- 2C: Reflects an effort to limit climate change to no higher than a 2°C global average at 2100 through globally coordinated, smoothly rising carbon price. This scenario reflects the uncertainty of the climate response in the MIT Earth System Model (MESM, Sokolov et al., 2018) and leads to an overall probability of achieving the target of 66%.
- 1p5C: Similar to 2C, but targeting a 1.5°C global average at 2100.

The MIT-IGSM produces 400 smoothed climates per emissions scenario, so combining these with the 18 GCMs gives 7,200 hybrid-frequency distributions (which we will generally refer to as "climate models") per scenario. These provide monthly data from 2020 to 2069 for precipitation and mean daily temperature. The ensemble is described in more detail in in Schlosser et al. (2020, 2021).

Princeton Global Forcings Weather Data

To generate realistic future weathers that are consistent in both space and time, we add historical inter-annual climate variation on top of the smoothed monthly climate change information in the 7,200 climate models. Details are provided in Thomas et al. (2022). The weather data is from the Princeton Global Forcings (PGF) dataset, version 3 (based on Sheffield et al., 2006). This dataset provides daily weather data for a number of weather variables, including the ones relevant to this analysis: precipitation and daily minimum and maximum temperatures. The data spans the period from the beginning of 1948 to the end of 2016. It is at a quarter degree resolution, which in most places reflects rectangles with 25–30 km on each edge. For most of our work we are interested in monthly data, so we aggregate the data, summing the precipitation and computing monthly values for mean daily maximum and mean daily minimum temperatures.

We also use the PGF data to create the baseline climate to add the HFDs to by taking monthly averages from monthly precipitation, daily maximum temperature, and daily minimum temperature at each pixel for the period 1981 to 2000.

Gaussian Quadrature

It is both computer-intensive and time-consuming to perform complex operations on 720,000 weathers. For the purposes of this study, notably modeling crop yields, it was more practical to operate with a subset. The least complicated option would have been to use random sampling to extract the subset. Instead, we decided to follow the methodology of Arndt et al. (2015) and use a Gaussian quadrature (GQ) reduction that allowed us to exactly reproduce the first, second, and third moments of all 720,000 weathers for key regions, time periods, and variables.

Using that procedure, we were able to reduce the number of weathers to 455 per emissions scenario while still maintaining representation across the diverse range of possibilities. For the purpose of considering extreme events, a salient advantage of the GQ approach is its tendency to seek out less common (or more extreme) weathers, giving relatively less weight, and choosing relatively few more common weathers and giving those weathers relatively more weight. More detail on generating future climates from the smoothed climates of the MIT-IGSM and the variation provided by the PGF historical data and on the GQ procedure can be found in a companion article (Thomas et al., 2022).

DSSAT Crop Modeling

The Decision Support System for Agrotechnology Transfer (DSSAT) is crop simulation software suite that consists of multiple crop-specific mathematical models (Jones et al., 2003). The models "grow" the crop in daily time increments using daily weather data. In this paper, the weather data is provided by a process that combines the daily weather from the PGF dataset together with the MIT-IGSM, using a subset of climates selected using the Gaussian quadrature sampling. Our DSSAT analysis used soils from Koo and Dimes (2010) which consists of 27 types, of which 18 are found in the study area.

Providing daily weather to DSSAT is usually straightforward. DSSAT has a weather simulator sub-package that generates consistent daily data based on monthly climate statistics provided by the user. However, the daily weather data generated by the weather simulator are not spatially-consistent: the weather in one pixel (location) is not correlated with the weather in a neighboring pixel. Therefore, in order to generate yields that are representative at a higher unit of aggregation, such as the national level, an alternative process needs to be done.

Given that the PGF dataset has daily historical weather data, we are able to generate daily future weather data that exactly reflects the monthly future data that we simulated. However, the storage requirement for daily simulated rainfall and temperature for each pixel in the 10-country study area for the 50 years of the study for 455 climates for each of the 4 emissions scenarios is extremely large. Furthermore, the computational time to generate daily simulated data along with the computational time for the crop model to simulate crop yields based on that daily data make it prohibitive in our case. In order to take advantage of the modeling abilities of DSSAT but not be constrained by the computational challenges of running so many simulations, we decided to build a crop yield emulator.

Building a Crop Yield Emulator

A crop yield emulator is meant to quickly take climate inputs and possibly a few additional variables and generate a corresponding yield for each crop. The emulators are built by regressing yields on monthly climate parameters and other relevant variables (Blanc and Sultan, 2015; Ostberg et al., 2018; Franke et al., 2020), and the parameters estimated in the regression are used to predict yields both in and out of sample.

To generate yield values to use in building the emulators, we sample 1 out of 16 pixels in our study area, using a regular grid with pixels separated by 1 degree. Furthermore, we limit our sampling to simulated climates from the 2020 to 2035 period from the 1p5C emissions scenario (lowest emissions scenario) and for 2054 to 2069 from the REF scenario (highest emissions scenario). This is done to make sure we have weathers reflecting both ends of the spectrum of possibilities, from low temperatures to high temperatures, exploring the feasible bounds for the region both in the present and in the future. For these pixels and particular climates, we produce simulated daily weather corresponding to the 455 climates per emissions scenario selected by the GQ procedure. The daily weather data is passed to DSSAT, which produces the yield at each pixel for a cultivar that is appropriate for the region for each crop in this study. In some of the simulations, we apply two different levels of nitrogen fertilizer so that we would be able to calculate a yield response for fertilizer use.

If actual yield data were available for various locations in the region—and assuming this data could be linked to the corresponding monthly climate data for the growing months—those yields could be used instead of yields from DSSAT. Several authors have used county-level annual yields (Schlenker and Roberts, 2009; Lobell et al., 2011; Dell et al., 2014; Miao et al., 2015; Thomas, 2015) in regressions for their studies of the effect of climate change on crop productivity. However, in addition to that kind of data not being available for our study area, these authors were unable to include variables that would allow estimation of yield response to chemical fertilizer or to atmospheric CO_2 fertilization—the latter being limited by CO_2 levels being highly correlated to each year (with the year being used to estimate the rate of technological change in agriculture). DSSAT is able to supply yield responses to both.

In order to control for unmeasured influences on yield at each location, authors using historical aggregated yield statistics typically use first differencing or fixed effects rather than a simple cross-sectional approach. However, in our analysis, because we have modeled data, we can control for all location-specific variables in the statistical analysis. That is, when running DSSAT, we fix farm-management practices to be identical at all locations. The only things that differ are the climate and the soils. DSSAT produces the same yield for any two locations in the world if both locations have the same soil and daily climate. Therefore, it is appropriate to forego fixed effects models and instead run cross-sectional regressions for each of the 18 soils in our study area, which we do.

A crop model such as DSSAT can be trained to mimic conditions in a farmer's field with careful observation of management practices, a good knowledge of the soils and cultivar, and an accurate measure of soil starting conditions such as water and nutrient content. When using DSSAT over such a large, heterogeneous area, local conditions cannot be reproduced due to lack of information, so the best generalizations possible are made. However, when using DSSAT—or the corresponding emulator—for this kind of analysis, researchers doing this kind of work trust that by keeping farm management practices constant, they can reasonably predict yield changes due to climate change, which is the goal of the analysis.

One of the advantages of running a separate regression for each soil type rather than including soil parameters in one big regression—unless interaction terms between soils and precipitation is included—is that it allows much more varied response of yield to precipitation based on the soil. Crops grown in soils that retain moisture well would presumably need less precipitation than crops grown in soils that are poor in water retention. The secondary purpose of emulators is to be able to simplify the relationship between climate and yield so that it can be understood more intuitively than the complex processes programmed into crop modeling software.

In the model used to build the emulator for each crop, let m index the month in relationship to the planting date (e.g., the first 30 days after planting is considered month 1); T represent the mean daily maximum temperature for the month; and P represent the total precipitation in the month. In numerous studies of climate impact on agriculture, authors focus almost entirely on some measure of temperature and some measure of precipitation. We opted for using monthly values because they are readily available from climate models. We chose mean daily maximum temperature for the month because we found it to be slightly more intuitive and since it is usually the high temperatures that reduce potential yields. In previous work, we attempted to include an additional temperature measure—mean daily minimum temperature—but because it is highly correlated with the mean daily maximum temperature, it did not lead to very much improvement in the fit of the model.

It would be possible to run regression variables at shorter time intervals than a month, but the advantage of doing that is limited, because only inter-annual variation could be rescaled, since the smoothed MIT-IGSM data came as monthly data. Shorter time intervals also present challenges interpreting the results. Weekly data, for example, would require 4 times as many parameters. It would also be possible to use longer time intervals, such as 2-month, 3-month, or entire growing season values. This would blur some of the impacts of climate on yields since plants change in their reaction to climate depending upon their phase of growth.

We estimate the response function as piecewise-linear in both T and P. A piecewise linear function imposes very little structure onto the yield response except for continuity. This flexible functional form seems to be very important for some crops at high values of precipitation and high and low values of temperature, because lower order polynomials (linear, quadratic, and cubic) can force regressions that generally have few observations at climate extremes to permit very large residuals for such values, as well as predict yields poorly at extreme values.

To define variables to be used for piecewise linear estimation, let z represent either T or P. Divide z into n groups such that $z_{min} < z_1 < z_2 < \ldots < z_{n-1} < z_{max}$. Define n-1 new variables z_{zk}, where $k = 1, 2, \ldots, n-1$, which are equal to 0 if $z < z_k$ and $z - z_k$ otherwise. For example, if $T = 23°C$, T_{20} would be 3 while T_{25} would be 0. In the emulator developed in this study, we examine values of temperature and precipitation in the region during the cropping months, and choose to divide monthly precipitation into groups divided at 25, 50, 100, 175, 250, and 350 mm. For mean daily maximum temperature for each month, we divide

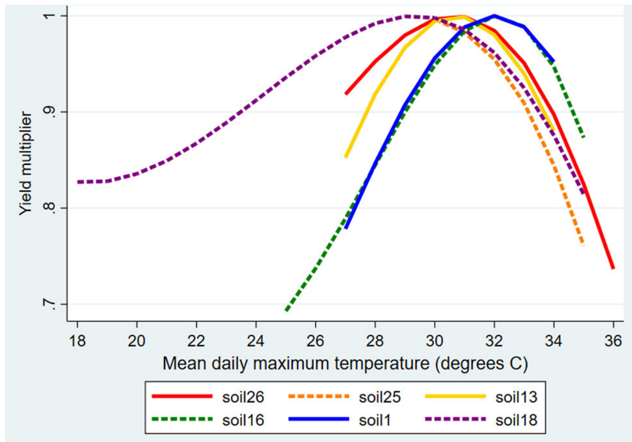

FIGURE 1 | Relative yield benefits for high-yield rainfed maize on the six most common soil types in response to the mean daily maximum temperature of the second month, °C. Using a cubic specification for rainfall and mean daily maximum temperature, with log yield as the dependent variable. Each soil is mapped over the range from the 5th to 95th percentile for temperatures used in building the emulator.

them at 20, 25, 28, 30, 32, 34, and 37 degrees Celsius. For each soil type, water (rainfed or irrigated), and crop we estimate yield, y, at pixel, i, in year, t, as

$$y_{it} = \sum_{m=1}^{4}\left[\beta_0 T_{itm} + \sum_{j=1}^{7}\left(\beta_j T_{itm}^{T_j}\right) + \gamma_0 P_{itm} + \sum_{r=1}^{6}\left(\gamma_r P_{itm}^{P_r}\right)\right] + \alpha_0 + \varepsilon_{it}$$

After estimating maize with a piecewise regression, we noted that the piecewise linear estimates gave results that were essentially cubic, so we opted to estimate maize with a cubic polynomial, which is slightly more intuitive than piecewise linear for our many people interested in this research presented here. The maize equation, estimated for 3 different crop varieties each with two types of crop water (rainfed and irrigated), and with corresponding assumptions about the amount of nitrogen fertilizer, f, to use with each variety, is given by

$$\log(y_{it}) = \sum_{m=1}^{4}\left(\beta_0 + \beta_1 T_{itm} + \beta_2 T_{itm}^2 + \beta_3 T_{itm}^3 + \gamma_0 + \gamma_1 P_{itm} + \gamma_2 P_{itm}^2 + \gamma_3 P_{itm}^3\right) + \alpha_0 + \alpha_1 f_{it} + \varepsilon_{it}$$

With 18 different soils, 4 different months each, 4 crops, 2 crop water regimes, and in the case of maize, 3 varieties, it is difficult to graphically present all of the estimated values. The parameter estimates are available in the supplement. Instead, we present some figures for illustrative purposes, showing the type of yield response curves produced by the emulator. **Figure 1** shows the yield response to temperature during the second month of the growing season on the six major soil types (out of 18 in our study area). We chose the second month because the weather during that month is critical for the production of maize,

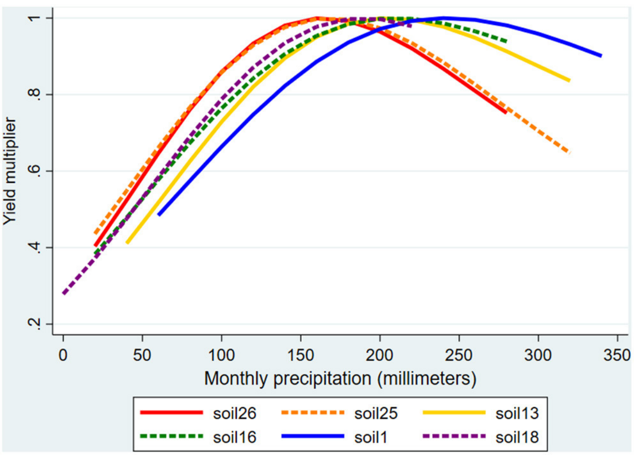

FIGURE 2 | Relative yield benefits for high-yield rainfed maize on the six most common soil types in response to rainfall in the second month, millimeters. Using a cubic specification for rainfall and mean daily maximum temperature, with log yield as the dependent variable. Each soil is mapped over the range from the 5th to 95th percentile for temperatures used in building the emulator.

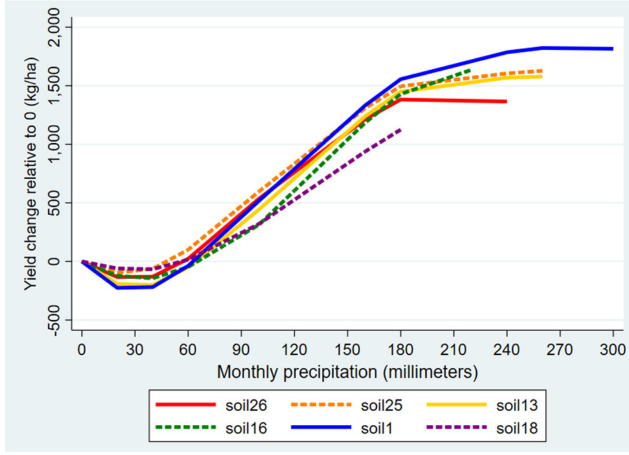

FIGURE 3 | Relative yield benefits for rainfed groundnuts on the six most common soil types in response to rainfall in the second month, millimeters. Used a piecewise linear specification with seven segments for rainfall and the same for mean daily maximum temperature, with yield as the dependent variable. Each soil is mapped over the range from the 5th to 95th percentile for temperatures used in building the emulator. Yields are relative to the yield for no rainfall.

because it is associated with the silking when the plant focuses on reproductive growth, and the yield responsiveness to climate is largest. The range of the curves shown in the figure are limited to the 5th to 95th percentiles of the values found for each soil type. What we see in **Figure 1** is that while the optimal temperature for the second month differs between soil types, it peaks somewhere between 29 and 32°C, with temperatures above and below the peak limiting the yields. We see for the most abundant soil where maize is grown, soil 26 (the numbers are codes used for a set of soil characteristics developed by Koo and Dimes) that the yield peaks at 30.7°C, which is in the range for what a number of analyses have found for optimal growing temperature.

We also see that for most soils, a less than ideal but still plausible temperature can lead to up to a 20% reduction in yield. Note that this is a reduction for temperature during a single month. If other months also have less than ideal temperatures, then the effect is multiplicative for the log specification and additive when yield is the dependent variable. Because crops have an optimal temperature at which maximum yields are obtained, it is difficult to have intuition about the effect of climate change on yields due to heterogeneity across locations and months of the growing season. Too cold and an increase in temperature increases yields;[1] too hot and an increase in temperature decreases yields. Near the peak, an increase in temperature might not change the yield. Countries with diverse climates will experience a wide range of yield effects from climate change and might experience all three types of effects.

Figure 2 shows yield responses to rainfall in the second month of the growing season for the six major soil types in the study area. Soils have different water holding capacities, so it is not surprising that optimal rainfall ranges from around 160 to 240 mm for this month. We see from the graphs that even 1-month droughts can have a profound effect on maize yield. For the soils in **Figure 2**, precipitation at around 20 mm in the month leads to around a 50–60% reduction in maize yield. This shows the value of supplemental irrigation in places where rainfall is unreliable. We also see from the graphs that too much rain can lead to a reduction in yield, though the affect varies across soil types.

Though not reported here, we experimented with other explanatory variables such as interaction terms between temperature and precipitation and using cumulative seasonal rainfall in addition to monthly rainfall. While the R-squared improved slightly it took away from being able to have intuition in how the yield responds to different climate values, so we decided not to include them.

Figure 3 shows the yield responses to rainfall in the second month of the growing season for rainfed groundnuts on the six most common soils for the region. Unlike the maize response to rainfall in cubic specification, we do not note any sizable reduction in yield for high levels of rainfall for any of the soil types here.

RESULTS

Evaluating the Impact of Climate Change on Maize Yields

Future yields are predicted for the 455 Gaussian quadrature climates for each of the emissions scenarios and for all 50-years of the time period under study, using the regression parameters discussed in the previous section. The predictions are computed at each quarter-degree pixel and for each year from 2020 to 2069. In order to aggregate the yields to the country level, SPAM 2010 (You et al., 2014) is used to provide estimations of the number of

[1]Parts of Southern Africa can experience cold weather, since it extends below 34 degrees South and also has several peaks above 3,400 meters elevation.

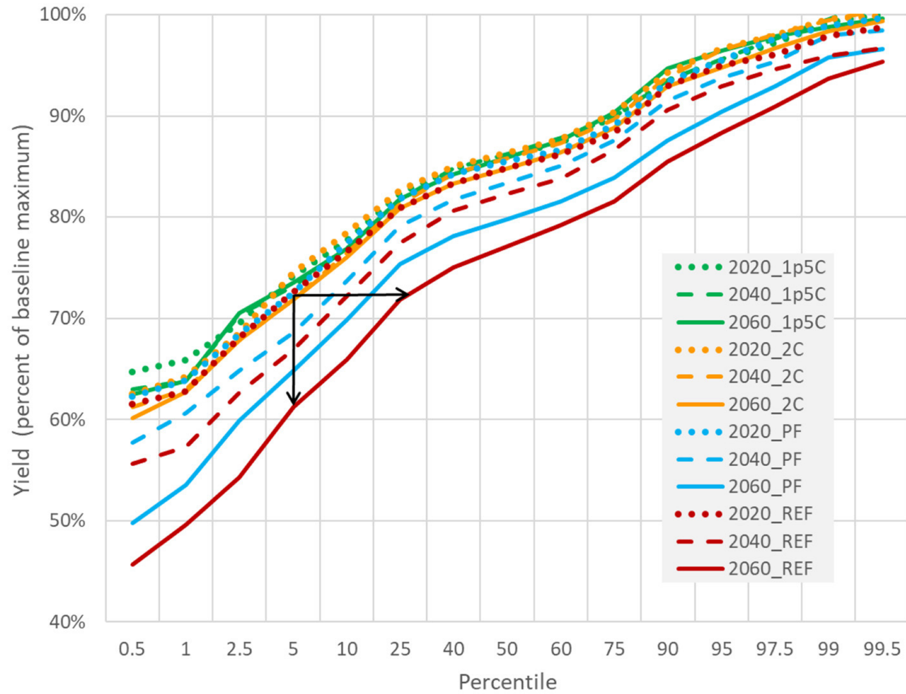

FIGURE 4 | Modified distribution function of climate change on rainfed maize yields for the 10-country study area across decades and across emissions scenarios. Source: Authors.

hectares of each crop that are grown in each pixel. This allows us to compute total national production and total cultivated area, which by dividing production by area gives the appropriate measure of mean national yield for every year.

Figure 4 illustrates the distribution of maize yields for 3 different decades under the 4 different emissions scenarios, based on a representative selection of climates and weathers under those scenarios. 1.5C has the lowest greenhouse gas (GHG) emissions and represents the level that will keep average temperature change at 1.5°C; followed by 2C (keeping temperatures at 2°C); PF, based on keeping the Paris Agreement levels forever; and REF, which is unconstrained by international treaties (Schlosser et al., 2020, 2021). We note that the yield distributions change very little by the 2060s for the 1.5C and 2C scenarios—an important finding in itself, because it suggests that the region would be unaffected in the aggregate—though it would be at national and subnational levels—if global emissions can be capped at levels suggested by the IPCC and others. Yields decline noticeably in the PF scenario and even more so in the REF scenario, pointing to the fact that higher emissions have greater negative consequences for agricultural productivity for the region.

In **Figure 4** we also note that the consequences for higher emissions on maize yields are greater for the low-yield years than for the high-yield years. The importance of such a finding is that while yield loss in a typical year is something to be concerned about, yield loss in a bad-weather, low-yield year can lead to much greater consequences for food insecurity and hunger, not only for small-holder farmers relying on home production but by driving prices for staple foods higher, burdening both rural non-farm and urban households. If governments and donors fail to account for the much stronger climate impact on production in years with adverse weather, they could potentially under-invest in climate adaptation and resilience. Since almost all previous studies focus on the average impact, this is likely to have been the case thus far.

The depth of the impact can be measured in several ways, but the arrows in **Figure 4** suggest two of them. First, we can look at the change in yields in the tail of the distribution. At the 5th percentile, for example, we see that the yield in the 2060s REF scenario is 13 percentage points lower than the baseline in the 2020s. That is, if typical (median) yield at the regional level is 2,000 kilograms per hectare, the baseline 5th percentile is about 73% of that, or around 1,450 kilograms per hectare. But in the 2060s PF scenario, it is another 11% points lower (226 kg/hect)—so the yield in a 1-in-20-year event would no longer be 1,450 kg/hect but 1,224 kg/hect. While the median in the 2060s REF is 91% of the baseline median, the 5th percentile in the 2060s REF is 84% of the baseline 5th percentile. This way of considering the costs of climate change during low-yield years is given by the vertical arrow in **Figure 4**, which shows change in yield for the 5th percentile from the 2020s to the 2060s.

A second way to consider the impact of the magnitude of changes in yields in the tail of the distribution is in the frequency of low-yield events. An event in the 5th percentile will occur on average every 20 years. That is, yields that low or lower occur 5% of the time, which means 5 out of 100 years, or equivalently, 1 out

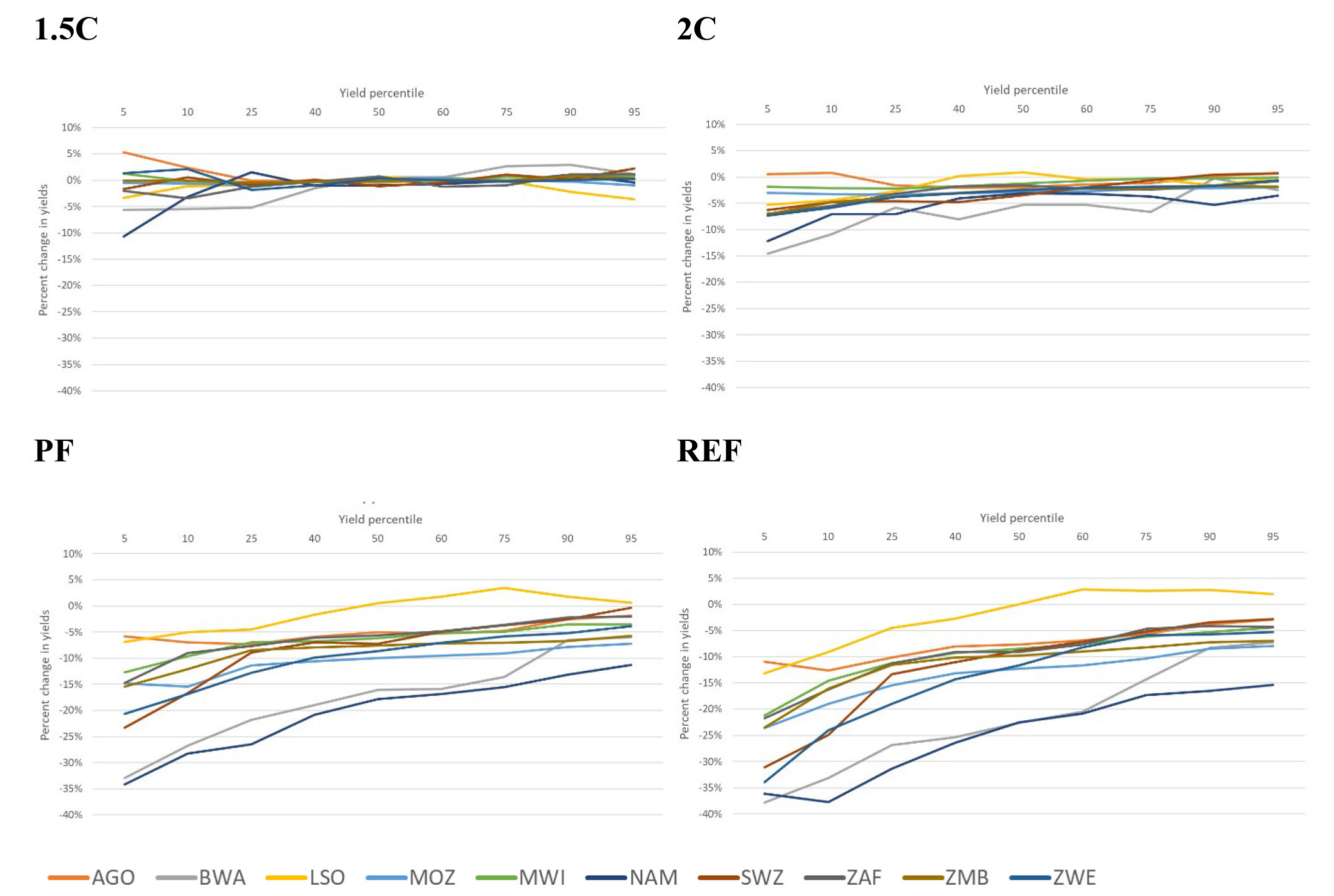

FIGURE 5 | Impact of climate change on change in rainfed maize yields by country and percentile, 2020s to 2060s. Source: Authors.

of 20 years. We can ask how frequently today's low-yield, 20-year event will occur in the future under climate change. Under the REF scenario in the 2060s, we can see that a 20-year event in the baseline will occur every 3.5 years in the 2060s, as illustrated by the horizontal line in **Figure 4**.

Thus far, we have considered the aggregated impact on yields for the region. However, effects on individual localities must be considered as the climate varies across the region, and climate change will affect the region differently across locations. Since our analysis is done at a pixel level (quarter-degree or roughly 25 km), we can aggregate the results to any level we choose. In **Figure 5**, we compare the change in yield distributions in each of the 10 countries. Focusing on the high-emissions REF scenario, we find that for almost all of the countries, low-yield years will experience greater relative yield losses than typical years—just as we saw for the regional aggregate.

This rule does not hold for Angola for the REF scenario, as the left tail of the distribution does not drop off rapidly, but in fact rises higher in the 1st percentile (not pictured). Meanwhile, the left tail is higher at the 5th percentile than at the median in the other emissions scenarios. This shows that we cannot assume what will happen with the relative impact of climate change for low-yield vs. median-yield years. We also see in the REF scenario that Botswana, Namibia, Eswatini and Zimbabwe exhibit more of a negative response during low-yield years than what the regional aggregate showed.

With diminished emissions we note much smaller impact on yields across all percentiles of the distribution—an important and not well-accounted benefit of reducing emissions. Nonetheless, even in the lowest emissions scenario, 1.5C, we see that there is often a much larger yield effect during years experiencing low-yield events compared to normal years.

Table 2 displays median yield changes by country and for the region. In the highest emissions scenario, median yields will decline by 9.2% by the 2060s due to climate change, but only 3.1% by the 2040s. The decline is smaller in the PF scenario, and virtually no change in the two lowest emissions scenarios. The table shows that not all countries will be impacted evenly, as the REF scenario projects that by the 2060s, Botswana and Namibia will have the highest losses for the region, followed by Mozambique and Zimbabwe.

Since we have noted a heterogeneous effect across the region at the national level, we would expect that there would also be a heterogeneous impact of climate change within countries. **Figure 6** presents the percentage point difference between the 50th and 5th percentiles, representing the relative

TABLE 2 | Change in median yield for rainfed maize under climate change for 4 emissions scenarios from 2020s in 2040s and 2060s.

	1.5C		2C		PF		REF	
	Change 2020s–2040s	Change 2020s–2060s	Change 2020s–2040s	Change 2020s–2060s	Change 2020s–2040s	Change 2020s–2060s	Change 2020s–2040s	Change 2020s–2060s
Region	0.2%	–0.2%	–0.6%	–0.6%	–2.5%	–6.7%	–3.1%	–9.2%
Angola	1.0%	–0.4%	–1.2%	–1.9%	–1.8%	–5.0%	–2.2%	–7.7%
Botswana	1.4%	0.6%	0.0%	–5.3%	–3.8%	–16.1%	–7.7%	–22.6%
Eswatini	–0.2%	–1.1%	–0.8%	–3.5%	–3.1%	–7.2%	–1.7%	–8.8%
Lesotho	1.1%	0.7%	1.7%	0.9%	2.6%	0.5%	3.4%	0.0%
Malawi	–0.5%	–0.3%	–0.6%	–1.2%	–2.3%	–6.2%	–3.2%	–8.5%
Mozambique	–0.2%	0.2%	–1.3%	–2.8%	–4.2%	–10.0%	–4.9%	–12.3%
Namibia	1.2%	–1.0%	–0.7%	–3.0%	–8.2%	–17.8%	–8.1%	–22.5%
South Africa	1.5%	0.7%	0.5%	–1.6%	–0.9%	–5.6%	–1.3%	–9.1%
Zambia	–0.3%	–0.2%	–1.2%	–2.4%	–2.6%	–7.6%	–3.0%	–9.8%
Zimbabwe	–0.6%	0.3%	–0.8%	–2.5%	–3.4%	–8.7%	–2.7%	–11.6%

impact of climate change on low-yield years compared to typical years.

In the high-emissions REF scenario, much of the northern part of the region, which tends to have higher rainfall than the southern portion exhibits only a small difference between yield change at the 50th percentile and yield change at the 5th percentile. Some sites had fewer losses at the 5th percentile. However, other regions within countries have much higher losses in the bad-weather, low-yield years, such as those along the northeast coast of South Africa.

Some areas—including large portions of Angola, South Africa, and Zimbabwe—exhibit greater yield losses (smaller yield gains) at the medians than at the 5th percentile in the lower emissions scenarios. The same areas exhibit smaller yield losses in the higher emissions scenario.

Schlenker and Roberts (2009), using historical yield data at the national level estimate regression models linking yields to temperature and precipitation. Using 16 older AR4 GCMs and a single emissions scenario, they project the impact on maize yields on several African countries, including 4 in our study area. They predict very large yield losses, particularly for Zambia (around 38%) and South Africa (around 30%), and lower for Malawi and Mozambique (around 18% for each). They also project uncertainty based on variation across climate models and uncertainty in their parameter estimates. This differs from what we did here, because our sources of uncertainty include inter-annual variation in climate and uncertainty over the future emissions.

As mentioned, after analyzing the changes in yields in the tail of the distribution, we consider the frequency of low-yield events. **Table 3** shows how often the yield of a 20-year event in the 2020s will occur in the 2040s and in the 2060s. At the regional level under the REF emissions scenario, the 20-year event occurs roughly twice as often by the 2040s but nearly six times as often by the 2060s. Many of the countries only indicate a modest shift by the 2040s, but by the 2060s, the frequency largely increases in each country except Lesotho, which experiences a relatively small doubling in frequency compared to the 2020s.

The PF and REF scenarios both exhibit an increase in frequency of extreme events from the 2020s to the 2040s and again from the 2040s to the 2060s. For both the 1.5C and 2C scenarios, the frequency of low-yield events generally stops increasing after the 2040s, and the level in the 2040s is much less than in either the PF or REF scenarios. In Angola, the frequency of low-yield events in the 2060s in is less than the frequency in the 2020s. The negative effects of climate change appear to stop and even reverse in the 1.5C scenario, at least in some countries.

Figure 7 shows the spatial heterogeneity that informs the national level data in **Table 3**. Not surprisingly, however, it is similar in appearance to **Figure 6**. The bright red regions in the REF scenario are projected to have four times the number of low-yield events in the 2060s. These maps could potentially help planners identify areas to target for interventions to reduce risk for farmers. Every country includes a number of regions in which low-yield events actually decline by the 2060s in the 1p5C scenario.

Evaluating the Impact of Climate Change on Drybean Yields

Importance for the Countries of the Region

Drybeans represent an important source of plant protein for the region, with almost all of the production staying within each country for food as well as seed supply (FAO et al., 2020). For four of the ten countries in the region, drybeans represent the third most important crop in terms of area cultivated, as they do for the region as a whole. According to FAOSTAT (FAO, 2020) however, they do not appear to be very important for production in Namibia, Botswana, and Zambia (the latter two do not seem to produce any), and are of only modest importance in South Africa, Zimbabwe, and Eswatini. Angola is the largest producer in the region, with almost half the cultivated area and 40% of the production. The highest yields are produced by Namibia (which has <0.01% of the region's total area for drybean cultivation) and South Africa.

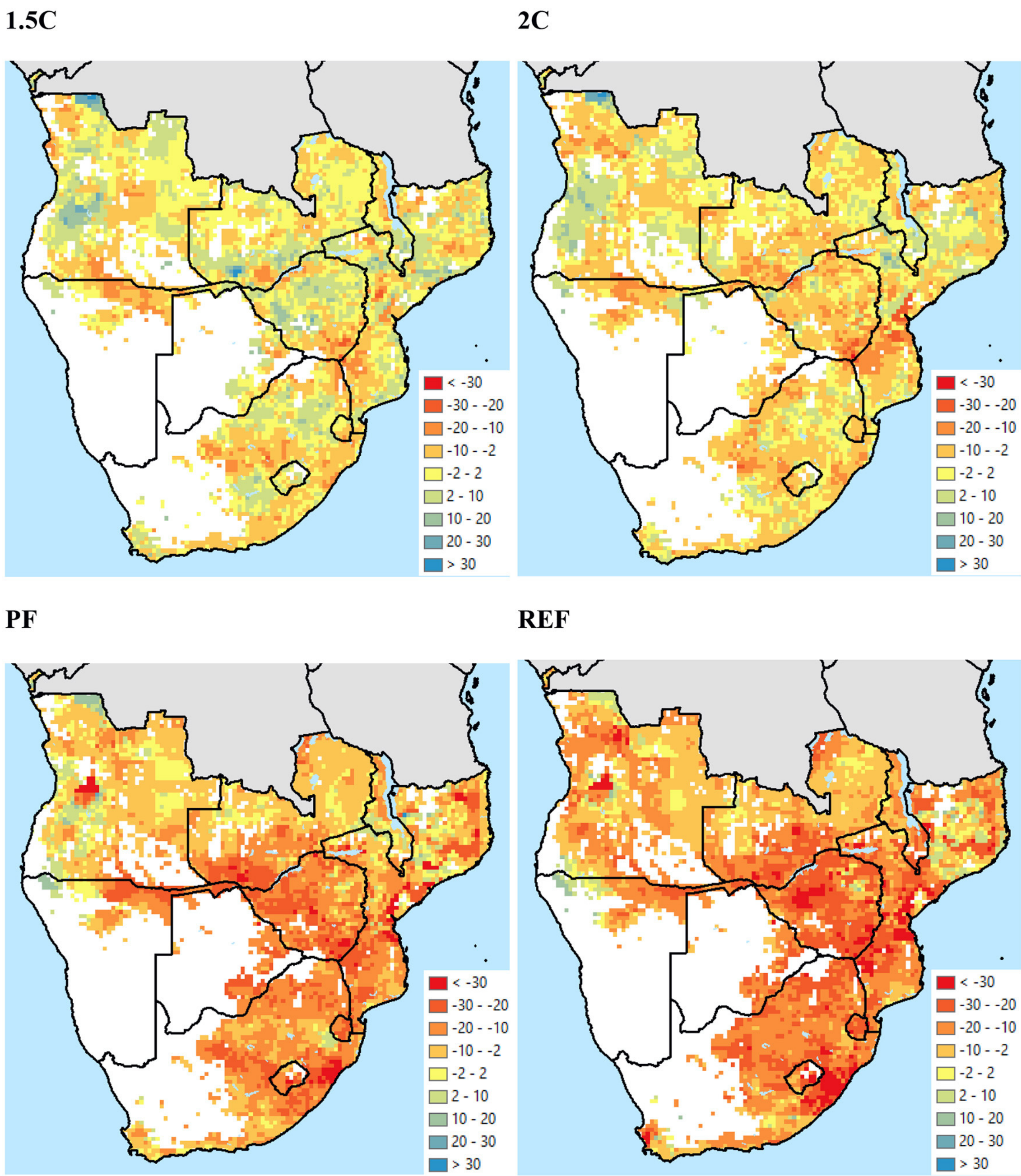

FIGURE 6 | Percentage point difference between change in yield of rainfed maize from baseline for the 50th percentile and change for the 5th percentile, REF scenario, 2020s to 2060s. Source: Authors. The map shows only areas that grow rainfed maize.

Yield Changes

In generating yields for the emulator using DSSAT, we used four varieties of drybean that were appropriate for the region, and selected the highest yielding variety among the four at each pixel, year, and climate. The projected impact of climate change on rainfed drybean production is shown in **Table 4**, which focuses in on only two of the four emissions scenarios, 2C and PF. Under the low emissions scenario (2C), most countries for which drybean production is important experience very little yield reduction even through the 2060s. However, under the higher emissions scenario, Angola is projected to have a nearly 7% yield reduction by the 2060s, followed by Mozambique and Malawi, with losses under 6%. Lesotho's drybean production, on the other hand, will not be affected much at all by climate change. The largest losses will be seen in Namibia and Zimbabwe, for which drybean production is not of great importance.

TABLE 3 | Frequency of 20-year low-yield events for rainfed maize from 2020s in 2040s and 2060s, REF scenario.

Area	1.5C 2040s	1.5C 2060s	2C 2040s	2C 2060s	PF 2040s	PF 2060s	REF 2040s	REF 2060s
Region	15.3	16.3	13.3	13.1	11.7	6.5	9.6	3.5
Angola	20.7	33.7	20.1	21.0	13.9	12.3	12.7	7.1
Botswana	18.1	14.9	14.3	10.8	10.8	6.3	10.8	5.0
Eswatini	17.8	17.1	15.5	12.1	11.6	7.1	13.8	6.3
Lesotho	20.9	14.3	16.0	14.8	23.1	12.7	12.8	10.2
Malawi	16.8	21.8	10.6	17.1	15.3	8.0	11.2	4.7
Mozambique	16.5	18.7	16.5	16.1	12.9	7.1	9.9	4.2
Namibia	14.1	14.1	14.5	12.9	10.9	5.5	14.6	5.6
South Africa	16.7	16.6	11.9	12.3	10.3	8.2	10.2	6.7
Zambia	19.5	19.8	12.3	9.1	10.6	5.1	7.1	3.3
Zimbabwe	19.4	21.4	15.2	14.0	12.3	8.1	8.8	5.2

The frequency of 1-in-100 year low-yield events, however, will have a greater effect on Eswatini, for which they will occur 5 times as often, and Lesotho, for which they will occur 4 times as often. Even Angola will see a much great frequency, with those extreme events occurring 2.5 times as often.

Evaluating the Impact of Climate Change on Groundnut Yields

Importance for the Countries of the Region

Groundnuts are the fourth most important crop for the region as measured by area cultivated. It is the second most important crop for both Malawi and Zambia, however, representing 9.0 and 9.6% of cultivated area. It is also of high importance to Angola, Mozambique, and Zimbabwe, ranking fourth or fifth among all crops for each country, and 6.7% of cultivated area or above.

Yield Changes

Table 5 shows the impact of climate change on groundnuts. We generated yields in DSSAT for two groundnut varieties that were appropriate for the region, and selected the highest yielding variety of the two at each pixel, year, and climate. Of the crops for which groundnuts are of high importance, Zimbabwe shows the greatest potential climate impact. At the lower emissions scenario, even by the 2060s, yield reductions should only be around 3%, but at the higher emissions level, losses should be over 6% by the 2040s and over 10% by the 2060s. South Africa, which has only 1% of area in groundnuts, could experience 20% yield reduction by the 2060s compared to production in the 2020s.

On the positive side, Malawi, which is the region's leading producer and second highest with groundnut area cultivated, should have yield only slightly affected by climate change, with reductions even by the 2060s under the high emissions scenario at <2%.

However, in terms of extreme low-yield events, Mozambique, which has the region's highest amount of area in groundnut cultivation should see events occur almost 5 times more frequently, and Angola, Zimbabwe, and South Africa should see them occur 3 times more frequently.

Evaluating the Impact of Climate Change on Soybean Yields

Importance for the Countries of the Region

Soybeans are the sixth most important crop for the region, but this is driven in large part by South Africa, for which soybeans are the second most important crop in terms of cultivated area. South Africa produces almost 70% of the region's soybeans and has just under 64% of the region's soybean area. Soybeans also appear to be of moderate importance to Zambia and to a lesser extent to Malawi and Zimbabwe. According to FAOSTAT (FAO, 2020), five of the region's ten countries do not grow any soybeans.

Yield Changes

Table 6 tells us that the region's largest soybean producer, South Africa, will experience virtually no yield impact from climate change. Because the computation is done at the pixel level and the pixels are weighted by the modeled cultivated area inside them, it is difficult to know precisely why the high emissions scenario shows less yield reduction in the 2060s than in the 2040s, and less than the low emissions scenario in the 2060s. But it may simply be that soybeans are cultivated in areas in which the current temperature is slightly sub-optimal, and additional warming take it past optimal, but not very far past.

Zimbabwe is projected to experience the largest losses for soybeans from climate change at almost 11% in the 2060s under the higher emissions scenario, though it only represents around 2% of total cultivated area for the country. Nonetheless, we see that under the lower emissions scenario, yield reductions will be much less.

For all of the countries in the study area—including South Africa—by the 2060s under the higher emissions scenario, the frequency of extreme low-yield events will at least double and perhaps triple in frequency. Strangely, this is true in South Africa across all decades and emissions scenarios, reflecting that the worst effect of climate change on soybean yields will be experienced by the 2040s. However, for some of the other countries, lower emissions reduce the frequency of extreme low-yield events.

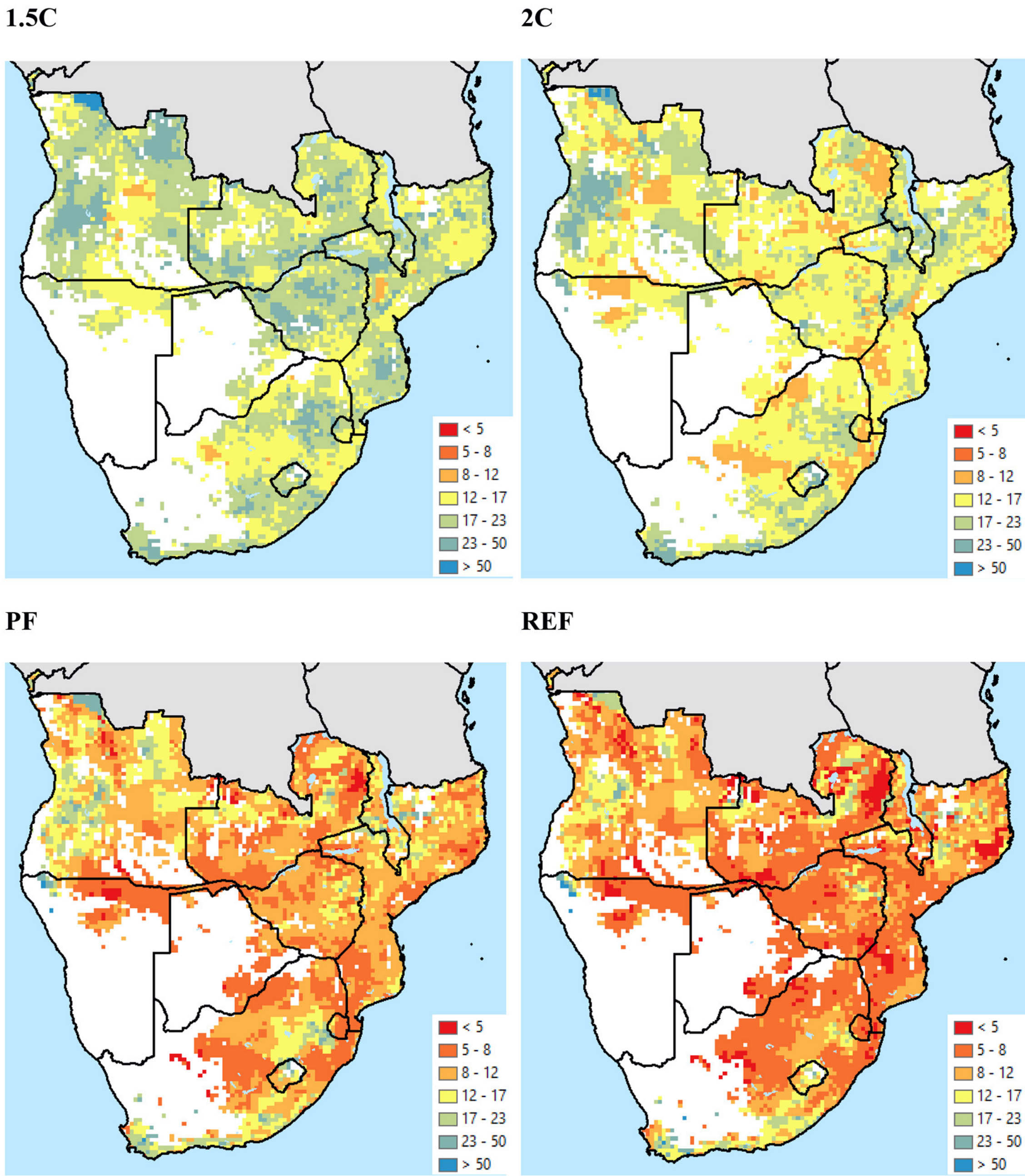

FIGURE 7 | New frequency of 20-year low-yield events for rainfed maize in 2060s under REF relative to 2020s REF. Source: Authors.

DISCUSSION

We have carefully analyzed the impact of climate change on yields of four key crops for Southern Africa. Our analysis considered not just the median impacts but the effects on extreme events—years with very low yields due to adverse weather. The analysis was done at a very fine spatial resolution with the results aggregated to each of the ten countries in the region. We saw not only how climate change will impact agriculture in typical years, but how in bad years the impact on agriculture in most cases will be greater.

We focused most on maize, which is an invaluable commodity for the region as the leading source of both calories and protein for consumers in the 10 countries of Southern Africa while occupying 41% of the region's cultivated area. Maize provides the main source of nutrition for some of the most food insecure people of the region. Investigating how a changing climate will affect maize production in low-yield years has

TABLE 4 | Changes in median yields and frequency of catastrophic yields for rainfed drybeans under climate change.

	Change in median yield relative to 2020s "2C"				Frequency of 1 in 100 year event relative to 2020s "2C"			
	2C		PF		2C		PF	
ISO	2040s	2060s	2040s	2060s	2040s	2060s	2040s	2060s
AGO	−0.8%	−0.3%	−4.5%	−6.9%	94	92	36	41
LSO	0.3%	−0.3%	−0.2%	−0.2%	52	56	31	24
MOZ	−0.6%	−1.3%	−3.2%	−5.8%	189	361	209	134
MWI	−0.6%	−0.6%	−2.4%	−5.5%	109	159	96	101
NAM	−3.4%	−7.3%	−14.5%	−24.4%	60	57	50	29
SWZ	−1.5%	−3.4%	−4.1%	−5.4%	45	45	30	19
ZAF	0.3%	−0.7%	−0.2%	−2.6%	61	84	55	59
ZWE	−0.6%	−2.8%	−3.1%	−8.7%	158	118	63	50

Botswana and Zambia do not have any drybean area reported in FAOSTAT (FAO, 2020) between 2012 and 2015. The frequency shows how often (in years) the 100-year event is projected to occur. Baseline was taken from the lower emissions scenario ("2C") for the 2020s. Values were computed for 9-year intervals using the Gaussian quadrature samples.

TABLE 5 | Changes in median yields and frequency of catastrophic yields for rainfed groundnuts under climate change.

	Change in median yield relative to 2020s "2C"				Frequency of 1 in 100 year event relative to 2020s "2C"			
	2C		PF		2C		PF	
ISO	2040s	2060s	2040s	2060s	2040s	2060s	2040s	2060s
AGO	0.1%	−0.7%	−2.4%	−5.6%	96	70	77	31
BWA	3.0%	−4.5%	−5.3%	−15.8%	97	93	50	32
MOZ	−1.1%	−1.2%	−4.8%	−7.4%	71	63	56	22
MWI	0.1%	−0.2%	−0.3%	−1.9%	120	105	106	57
NAM	−0.7%	−8.1%	−12.9%	−27.7%	53	41	32	20
SWZ	−1.2%	−3.1%	−4.9%	−8.1%	60	54	39	22
ZAF	−1.1%	−7.3%	−11.5%	−20.0%	54	53	36	31
ZMB	0.5%	−0.4%	−0.6%	−3.3%	140	99	90	42
ZWE	−0.9%	−3.0%	−6.1%	−10.5%	84	74	51	32

Lesotho does not have any groundnut area reported in FAOSTAT (FAO, 2020) between 2012 and 2015. The frequency shows how often (in years) the 100-year event is projected to occur. Baseline was taken from the lower emissions scenario ("2C") for the 2020s. Values were computed for 9-year intervals using the Gaussian quadrature samples.

TABLE 6 | Changes in median yields and frequency of catastrophic yields for rainfed soybeans under climate change.

	Change in median yield relative to 2020s "2C"				Frequency of 1 in 100 year event relative to 2020s "2C"			
	2C		PF		2C		PF	
ISO	2040s	2060s	2040s	2060s	2040s	2060s	2040s	2060s
AGO	0.7%	0.0%	−1.9%	−4.4%	115	116	60	42
MWI	0.1%	0.8%	0.4%	−1.6%	113	101	105	49
ZAF	0.2%	−1.5%	−0.7%	−0.1%	43	54	44	36
ZMB	−0.9%	−1.2%	−1.6%	−1.8%	102	79	66	43
ZWE	−1.2%	−1.8%	−5.3%	−10.7%	83	76	47	32

Botswana, Lesotho, Mozambique, Namibia, and Eswatini do not have any soybean area reported in FAOSTAT (FAO, 2020) between 2012 and 2015. The frequency shows how often (in years) the 100-year event is projected to occur. Baseline was taken from the lower emissions scenario ("2C") for the 2020s. Values were computed for 9-year intervals using the Gaussian quadrature samples.

revealed that if emission levels are high, the low-yield, 1-in-20-year events for the region produce 16% lower yields in the 2060s than in the 2020s, while at the median year, the yields will be 9% lower. Furthermore, the frequency at which the 1-in-20-year low-yield event occurs will decrease to 1-in-3.5-year events.

Averaging across a large area tends to hide losses that can be locally high. Examining the impact of climate change on the cropping sector for countries of the region, Botswana could be the country hit the hardest among the 10 in the study area, because of the importance of maize to farmers and because of the severity of the impact of climate change on maize yield.

On the other hand, Lesotho appears to benefit from climate change at the median of the projections, though very little. However, the change in frequency of extreme low-yield events could adversely impact even countries like Lesotho, with the frequency of low-yield events increasing to 3 or 4 times the rate that they are currently occurring.

This study on the impact of climate change, uncertainty, and inter-annual variability on agricultural production is also essentially one dealing with issues of food insecurity under climate change. Except for soybeans, the crops examined in this study are ones that are produced and consumed by subsistence farmers, so that increasing the frequency of low-yield events is also a threat to food security which in many countries is a much bigger problem in rural areas than urban.

This kind of analysis is immensely useful for both the public and private sector in evaluating the benefits of longer-term investments designed to support agriculture and nutrition. The long-term costs of low yields can be significant, between loss of life; child malnutrition, which can lead to reduction in lifetime earning potential; and loss of capital and livestock (if households sell items to compensate for food shortages). As costs of losses in low-yield years are higher than costs in median years, it is likely that governments and businesses have under-estimated the full cost of climate change and have therefore under-invested in things such as irrigation, insurance (crop and weather), agricultural research and extension, and capacity for delivering social protection, all of which—if sufficiently invested in—could reduce the losses during bad-weather years.

This analysis could assist in optimally targeting interventions sub-nationally, since our findings show that the effect of climate change is spatially heterogeneous, with some parts of countries facing much larger losses than others. Focusing on the areas that will be hit the hardest could potentially give more return to investment in impact mitigation strategies. Interventions could include introducing new crops—such as millet in place of sorghum or maize—in areas that are likely to be most affected by climate change hardest hit.

Finally, while we have used the large climate ensemble to examine low-yield agricultural events, the data and methodology could be applied to a wider range of climate impacts including the effects on livestock, human labor, hydrology, energy, and infrastructure.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

TT was the lead writer of this paper and generated weathers for DSSAT, built the emulators, and generated the final yield output used. RR produced the DSSAT results and advised on the emulator, as well as helped in editing. KS provided overall guidance and particularly supported irrigation inputs for crop production. CA served as principal investigator of the project and wrote the basic Gaussian quadrature program, assisted on its application to this project, and helped in editing. All authors contributed to the article and approved the submitted version.

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Using a Large Climate Ensemble to Assess the Frequency and Intensity of Future Extreme Climate Events in Southern Africa

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This paper uses 7,200 smoothed climate change projections for each of the four emissions scenarios, together with inter-annual variation provided by detrended historical climate data to investigate changes in growing season (wettest 3 months) weather patterns from the 2020s to the 2060s for ten countries of Southern Africa. The analysis is done in 8,888 quarter-degree pixels by month. Temperature unequivocally rises in the region, but it rises relatively less along the coasts, particularly on the eastern side of the region. Precipitation has trended downward for much of the region since 1975, but relatively little change in precipitation is projected between the 2020s and the 2060s. Under the higher emissions "Paris Forever" scenario, we found that by the 2060s, the 1-in-20-year low-rainfall events will occur twice as frequently in most of the region, though it will occur less frequently in northwestern Angola. The 1-in-20-year high-rainfall events will occur 3 to 4 times as often in northeastern South Africa and twice as often in most of Angola.

Keywords: climate change, climate uncertainty, Southern Africa, risk, climate extreme events

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INTRODUCTION

For determining the full effect of climate change—particularly as it is applied to agriculture, but also to human life and all sectors of the economy—we must understand sources of uncertainty and sources of variability. First, there is uncertainty in regard to the future flow of greenhouse gas (GHG) emissions, and therefore in regard to future amounts of CO_2 in the upper atmosphere at points in the future. Second, even if we had full knowledge regarding the amount of CO_2, there is still uncertainty as to how the mean climate would be affected (Kunreuther et al., 2014; Chen et al., 2021; IPCC, 2021; Lee et al., 2021). Finally, even if we had certainty about CO_2 levels and mean climate, there would always be inter-annual and intra-annual variation.

In what follows, we consider four different emissions scenarios in ten countries of Southern Africa: Angola, Botswana, Eswatini, Lesotho, Malawi, Mozambique, Namibia, South Africa, Zambia, and Zimbabwe. For each of the emission scenarios, we consider 7,200 smoothed climate change projections with monthly values spanning 2019 to 2069. We also augment each of the smoothed climate projections with 100 different 51-year sequences randomly drawn by year with replacement from a 69-year detrended historical dataset. This gives us a total of 720,000 variation-augmented climate projections for each emissions scenario.

This article is an extension of earlier work on the impact of climate change in the region (Fant et al., 2015; Schlosser and Strzepek, 2015; Arndt et al., 2019) that used a large ensemble of climate models (based on the older AR4/CMIP3 rather than the AR5/CMIP5 used here) but which did not adequately address climate variability, without which, investigating changes in climate extremes is not possible. The novelty of this approach is in using a large ensemble of climate futures [100 times the size used in the previous work of Schlosser and Strzepek (2015)] so that the tails of the distribution are more fully modeled, more completely taking into account uncertainty and variability.

Collins et al. (2013) explore the range of climate model predictions from CMIP5 across various emissions scenarios and climate models at the global level, and IPCC (2013) shows maps focusing on Southern Africa. Seneviratne et al. (2012) provides a very thorough discussion on both observed and modeled weather extremes (though with a greater focus on observed), though at the global level. Seneviratne et al. (2021) updates the earlier work in the just-released IPCC assessment report.

Assessing the magnitude of climate change and the added effects of climate uncertainty and inter-annual variability enables research to better investigate the impact of climate shocks on sectors of the economy dependent on weather, such as agriculture, infrastructure, energy, and construction. In a related paper, we use the future variation-augmented climate projections to assess the impact on agricultural production in the region (Thomas et al., 2022).

Southern Africa is an important region to study the effects of climate because of the importance of agriculture to the region for its contribution to GDP, for employment, and for food insecurity, which is a problem for the region (Thome et al., 2018; FAO et al., 2020).

MATERIALS AND METHODS

MIT-IGSM Future Climate Data

In this paper, we use results from a large ensemble of projected changes in monthly precipitation and near-surface air temperature for ten nations of Southern Africa (Schlosser et al., 2020, 2021). The ensemble is developed by integrating pattern-change responses derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5) climate models with the Massachusetts Institute of Technology Integrated Global Systems Model (MIT-IGSM), an earth-system model coupled to a global economic model that evaluates uncertainty in socio-economic growth, anthropogenic emissions, and global environmental response.

The methodology used to combine the two relies on pattern-kernels of regional change from climate models (Schlosser et al., 2012) and the application of these patterns of change to downscale the zonal output of the MIT Integrated Global System Model (Reilly et al., 2018). IGSM operates in the dimensions of latitude and elevation (depth) only, so that they might consider a wider-range of potential climates that can develop out of assumptions surrounding emissions, demographics, and the economy. Approaches that consider the longitude with elevation and latitude take much longer to run and require much greater computing power.

In order to expand these results longitudinally, the authors use a Taylor series expansion that allows them to construct a full grid of climate-change pattern kernels, using CMIP5 climate models. There are many CMIP5 models available for use, but many centers producing these models produce more than one. The authors chose to use only one model per center to avoid biasing the ensemble's representativeness.

The MIT-IGSM produces 400 unique results for each emissions scenario. Each of these are spread out longitudinally using 18 GCMs from CMIP5 [these are detailed in Schlosser et al. (2021)], giving the ensemble 7,200 members of a hybrid frequency distribution (HFD) per emissions scenario. The version of the data used in the analysis in this paper is one in which each member is smoothed by averaging over a multi-year period, preserving the trend, or signal but removing the variation.

The MIT-IGSM evaluated four scenarios of future climate and socio-economic development to span a range of possible actions to reduce greenhouse gas emissions through the twenty-first century (Schlosser et al., 2021). These emissions scenarios are:

- Reference (REF): No explicit climate mitigation policies anywhere in the world. It can be seen as a baseline.
- Paris Forever (PF): Assumes that countries meet the mitigation targets in their Nationally Determined Contributions (NDCs) and those targets are met throughout the century.
- 2C: Reflects an effort to limit climate change to no higher than a 2°C global average by the year 2100 through globally coordinated, smoothly rising carbon price. This scenario reflects the uncertainty of the climate response in the MIT Earth System Model (MESM, Sokolov et al., 2018) and leads to an overall probability of having 66% of the runs using this emissions scenario keeping the global average at or below 2°C.
- 1p5C: Similar to the 2C, but aims to limit warming to no higher than 1.5°C. The probability of achieving this target in this emissions scenario is 50%.

To simplify the exposition in this paper, we often elect to focus on the more plausible models (our subjective interpretation): the 2C and PF.

Princeton Global Forcings Historical Weather Data

While we expect quite a range of uncertainty reflected across the possible smoothed climate change projections, we also know that year-to-year variation is quite important for agriculture and many other human endeavors. To simulate inter-annual variation in a manner that is spatially and temporally consistent, we decided to base the values on historical weather provided the Princeton Global Forcings (PGF) dataset, version 3 [based on (Sheffield et al., 2006)]. This dataset provides daily weather data for a number of weather variables, including the ones relevant to this analysis: precipitation and daily minimum and maximum temperatures. The data spans the period from the beginning of 1948 to the end of 2016. It is at a quarter degree resolution, which in most places reflects rectangles with 25–30 kilometers on each edge. For most of our work we are interested in monthly data, so we aggregate the data, summing the precipitation and computing monthly values for mean daily maximum and mean daily minimum temperatures. Because the HFD data represents deviations from the climate of 1981–2000, we also used PGF to provide this baseline climate information.

Combining Smoothed Climate Change Projections and Historical Weather Variability

Belcher et al. (2005) proposed a technique for generating feasible future weathers that account for climate change which they called "morphing." They used it for thermal simulation of buildings, but the idea can be applied to other problems, such as assessment of future agricultural production or water availability. In their version, they added the smoothed climate "delta" (with "delta" signifying a change in a variable)—that quantifies how a smoothed (or averaged) climate variable shifts between the baseline climate and the future climate—to the historical weather value to produce what they call the "design" weather and what we will call here the "variation-augmented climate change projection." Their method has the advantage of preserving spatial relations and temporal relations (intra-annual and inter-annual). However, as used in their original idea, it gives only one sequence of future weather at each pixel.

Augmenting smoothed climates has the advantage over the original GCMs in two ways. First, the models are downscaled to a much finer spatial resolution that is required for studies on the effect of climate on agriculture, since agricultural production (and modeling) relies on location-specific weather and land characteristics, with the original GCMs at ∼250-kilometer resolution and the down-scaled resolution being ∼30-kilometer resolution. Second, the original GCMs would need to be run repeatedly to give enough samples to adequately account for the tails due to both uncertainty and inter-annual variation, and those are not available and take tremendous computing power to produce.

We maintain the spirit of what Belcher et al. (2005) did, but adapt it to recognize that climate change has already affected at least some of the historical sequence, which is contrary to their implicit initial assumptions. To compensate for the climate signal that is already in the historical data, we use regressions to remove the trend and keep the variation around the trend as the value that we are interested in using to produce variation using our Monte Carlo simulation procedure. The inter-annual variation and the climate delta then both get added to the baseline climate value.

Specifically, for each variable in the historical weather dataset, we took the monthly series of 69 yearly values at each pixel and regressed them on a constant, a value for year, and a value equal to 0 for years <1975 and the year minus 1975 for values greater. This gave us a piecewise linear regression over time that assumed that the effect of climate change altered the trend in 1975. It gives us one trend prior to 1975 and one trend after 1975, but the trend lines meet at the year 1975, and therefore are dependent on each other. The year 1975 was chosen because in annual global temperature graphs, there is a clear shift in rate of temperature change that took place somewhere in the 1970s. Many studies de-trend with a straight line for the entire time period, which strikes us as wrong because it fails to acknowledge any shift in the climate since the 1940s. On the other hand, over-correcting by using some kind of non-parametric method such as loess or localized polynomial would remove inter-decadal variation, which we wanted to keep in due to the nature of the smoothing for the MIT-IGSM. There is no perfect solution, but the method used in this paper seemed better than the others considered. We estimated these regressions for each variable-pixel-month and retained the residual from each year. These are the "variation deltas" – the inter-annual variation measures – which form the basis for future random draws of weather in the Monte Carlo procedure.

Mathematically, let $v_{i,yr,m}$ be the value of a monthly weather statistic from the PGF database for pixel i, year yr, and month m, where v is monthly precipitation or mean daily maximum or minimum temperature for the month. The variable $yr75$ is defined as 0 if $yr \leqq 1975$ and $yr - 1975$ if $yr > 1975$. We estimate the following regression:

$$v_{i,yr,m} = b_{0,i,m} + b_{1,i,m} yr + b_{2,i,m} yr75 + \epsilon_{i,yr,m} \tag{1}$$

where $b_{0,i,m}$ is the intercept term, $b_{1,i,m}$ is the parameter associated with yr, $b_{2,i,m}$ is the parameter associated with yr75, and $e_{i,yr,m}$ is the residual of the regression, which is the variation delta that we will use to in the Monte Carlo simulation.

We also adapt the morphing method further, by generating multiple sequences of feasible future sequences of climate variations. Our idea is to keep 12-month sequences for the entire study area together as a single unit, drawing randomly with replacement from the 68 or 69 12-month sequences. Our goal is to come close to attaining ideal simulated data: one which maintains spatial relations, intra-annual relations, and minimizes the degree of inter-annual correlation that is lost by artificially breaking the data into 12 consecutive month segments.

We recognize that there is correlation in precipitation in consecutive months. It is an important characteristic of the growing season that the rainfall through the season be consistent. Since the growing season in many locations spans the time from one calendar year into the next, we decided that we did not want to use the calendar year as our unit of observation to draw for random weathers in the future. Instead, we created what we call "meteorological years" that begin during the dry season. Most specifically, they begin in the middle month of the driest 3-consecutive-month period (by pixel). This allowed us to take data from 69 calendar years and convert it into 68 meteorological years that were less serially correlated than the calendar year values.

We created baseline climate variables at each pixel to which the climate changes from the HFDs could be added. We did this by summing the daily precipitation for each pixel-year-month combination and by taking the mean of the daily minimum and maximum temperatures for each pixel-year-month. After doing this, using only data from 1981 to 2000, we took averages of these pixel-year-month combinations by pixel-month.

We added the smoothed climate change deltas by year to these baseline variables. For precipitation we added the precipitation change. For both the mean daily maximum temperature and mean daily minimum temperature we added the mean daily temperature change—which was the only temperature variable provided in the HFDs. We took the 2- by 2.5-degree smoothed climate change rectangles and assumed that the shift was identical for all of the 80 quarter-degree pixels within the historical weather dataset located within the larger rectangle. The result was quarter-degree resolution smoothed climate projections.

On top of these smoothed values, we added the variation deltas to give us variation-augmented climate projections. For each emissions scenario, we have 7,200 smoothed climate change projections, and overlaid 100 variation delta datasets on each to give us a total of 720,000 variation-augmented climate projections spanning 51 years for each month and close to 9,000 pixels.

RESULTS

Characteristics of the Smoothed Climate Change Projections

Figure 1 shows the magnitude of the median across 7,200 models for changes in annual precipitation between 2020 and 2050 under the PF scenario. The changes are relatively small in magnitude, with the highest decline reaching to around 30 millimeters per year. The areas with the largest decreased precipitation are located in the mid-latitude band encompassing part of Zimbabwe and central Mozambique, along with northern Botswana and Namibia, and southern Zambia and Angola. There are other areas of loss in western South Africa and southern Botswana and Namibia. There are also areas with small increases reaching to around 30 millimeters. Areas of increased precipitation are located in southeastern South Africa and northwest Angola, along with small portions of northern Mozambique and northern Zambia.

Figure 2 shows the median value of the projected change in the mean daily maximum temperature for 2050 under the PF scenario relative to the baseline period. Coastal areas on both coasts, though especially on the eastern side of the continent, show lower temperature increases than the interior. Coastal region medians are generally below 1.75°C, while the interior is above 1.75°C, with a large portion above 2°C. As we will see in a later section, the highest temperature increase is located in the area that already has the highest temperature. See Schlosser et al. (2021) for a more complete treatment of the climate data.

Historically Observed Climate Patterns

The study area spans arid and semi-arid land in the southwest quadrant of the region up through sub-humid land in the northern and eastern parts of the region. **Figure 3** shows the precipitation of the wettest 3 consecutive months. There are many similarities between rainfall in the wet 3 months and annually (not shown), but one difference is that the higher annual rainfall of much of the eastern part of the region—eastern South Africa, southern Mozambique and Lesotho—is not fully reflected in high rainfall in the wet 3 months. This is because the southeastern part of the region has reasonably high rainfall even in their driest months, reflecting a precipitation pattern with little intra-annual variation.

Many crops are adversely impacted by high temperatures during the growing season. **Figure 4** shows the mean daily maximum temperature of the warmest month of the wettest 3 months. If the wettest 3 months reflect the growing season—as it does in most locations—this temperature measure is a good indicator of how stressed crops will become. Schlenker and Roberts (2009) and Lobell et al. (2011a,b) found that temperatures above around 29 or 30 degrees C reduce yields of rainfed maize. Similar results have been found for other grains (Lobell et al., 2011b) and for soybeans (Schlenker and Roberts, 2009; Lobell et al., 2011b). **Figure 4** shows that even before the effects of climate change are accounted for, much of the study area is past the optimal temperature for maize cultivation.

Figure 5 shows that there is significant variation across the region for which months are the wettest 3 months, though most of the area has the wet season spanning the summer months: from November-December-January to February-March-April. In the extreme southwest, there is a relatively small area that with peak rainfall in the winter: mostly May-June-July.

Figure 6 shows the change in annual precipitation between 1975 and 2015 at each pixel computed by the regressions that generated the "variation deltas." Most of the study area has gotten drier over that period—though the trends are only statistically significant at the 10% level in a small portion of the area. Parts of Mozambique, in particular, have lost more than 150 millimeters over that 40-year period. Parts of Zambia, Zimbabwe, Botswana, South Africa, and Angola have seen drops of over 100 millimeters. At the same time, extreme northwest Angola has seen an increase of 150 millimeters during that period. While not perfectly matching at every pixel, the trends noted by the regression from historical data are similar to the median changes from the 7,200 climate models for the period between 1990 and 2020 (not pictured). That is, the median of the climate models (PF scenario, in particular) shows a relatively steep decline through 2020, and levels off after 2020.

Variation-Augmented Climates

From the pool of 68 independent meteorological years that were computed using the PGF historical weather dataset, we took 5,100 random draws with replacement and used those draws to give 100 51-year collections of climate variation deltas that we could use to add to the smoothed climate change data to give variation augmented climate change data. The distribution of the precipitation draws for the wettest 3 months aggregated to the country level is found in **Figure 7**. We see that Botswana, Namibia, Zimbabwe, Eswatini and to a lesser extent, South Africa, have longer right tails than left. Malawi and Zambia have longer left tails. Mozambique, Lesotho, and Angola are mostly even.

Figure 8 shows the distribution of temperature deltas derived from the detrended PGF data converted to meteorological years and drawn for 100 51-year intervals. These were aggregated from pixel to national level. Eswatini and Namibia appear to have

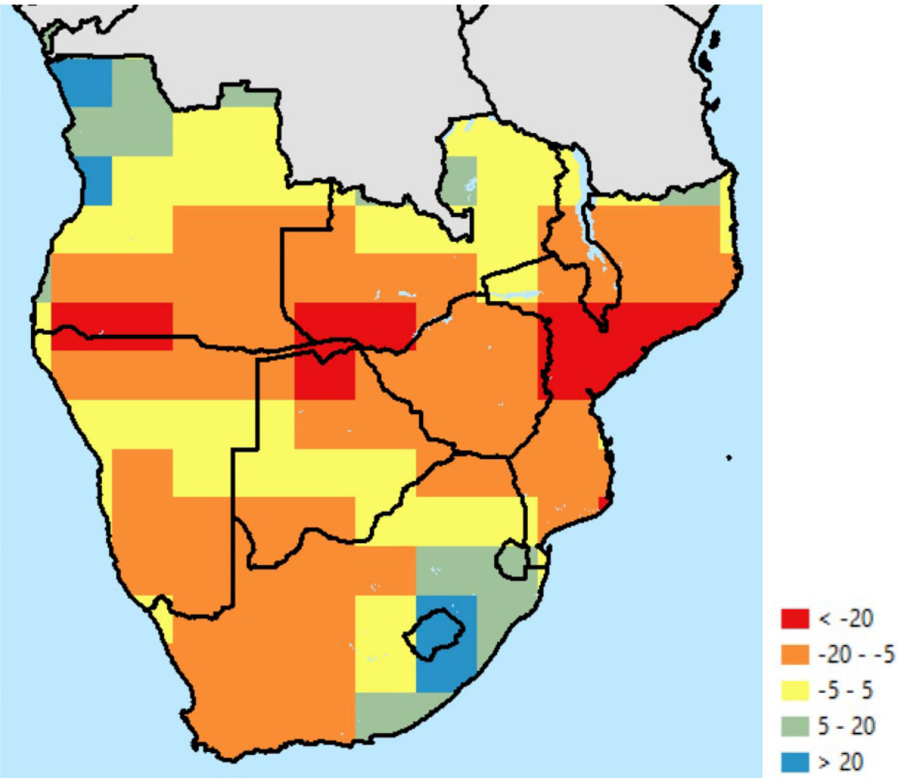

FIGURE 1 | Median projected change in annual precipitation across the ensemble of 7,200 smoothed climate change projections from 2020 to 2050 under the PF scenario, millimeters. Source: Authors calculations, based on Schlosser et al. (2021).

longer left tails (greater uncertainty toward cooler temperatures) when measured from the median value. The other countries appear to be mostly balanced.

Using the 100 51-year collections of variation deltas, we add them to the 7,200 smoothed climate change projections for each scenario, to get 720,000 variation-augmented climate change projections per emissions scenario as our complete set of possibilities. With such large numbers, it enables us to examine the full statistical distributions of future climate. In particular, given increasing uncertainty in climate over time, skewness in most climate uncertainties and in some of the variability from historical weather, it is not very obvious what the combined distributions will look like. Studying them, as well as using them to inform crop models and hydrological models in companion papers, will allow us to better understand the fuller cost of climate change, including valuation of shocks, which in turn will help us more accurately value investments to mitigate the costs of climate change, including investments in agricultural research, crop insurance, infrastructure, irrigation, storage, and social protection.

In the left graph of **Figure 9**, we see the rainfall distribution for the wettest 3 months averaged across Zambia using 9 years of annual data for each plot on the graph[1]. The first thing to note is the large difference between the spread of the smoothed climate—which is the uncertainty across about the mean climate given an emissions scenario—compared to that of the variation-augmented climate—which combines both the uncertainty and the inter-annual variation. It shows that the inter-annual rainfall variation is larger than the uncertainty (as can be seen by the difference between the right and left tails of the smoothed climate from the right and left tails of the variation-augmented climate), though by 2060s under PF the contribution of each component is more even since the uncertainty over the magnitude of the mean changes to climate is fairly large by then.

The smoothed climate box and whiskers plots can be important for planning and investing purposes because it gives some idea of the likelihood surrounding a particular future. Often too little is understood about the degree of uncertainty, which can result in poor investments and planning for an outcome that might not actually happen. In some cases, policymakers have been told by researchers with limited access to models that there will be less precipitation in the future, and as a result, investments might have been made reflecting that belief. Once the uncertainty is properly accounted for, information about the distribution of climate futures could lead to a more nuanced and ultimately more helpful investment plan and policy response.

The distributions for the two emissions scenarios are very similar in the 2020s, but by the 2060s the uncertainty and variation is slightly larger for PF than for 2C, with the PF notably

[1]The 2020s span 2021-2029, the 2040s span 2040-2048, and the 2060s span 2060-2068.

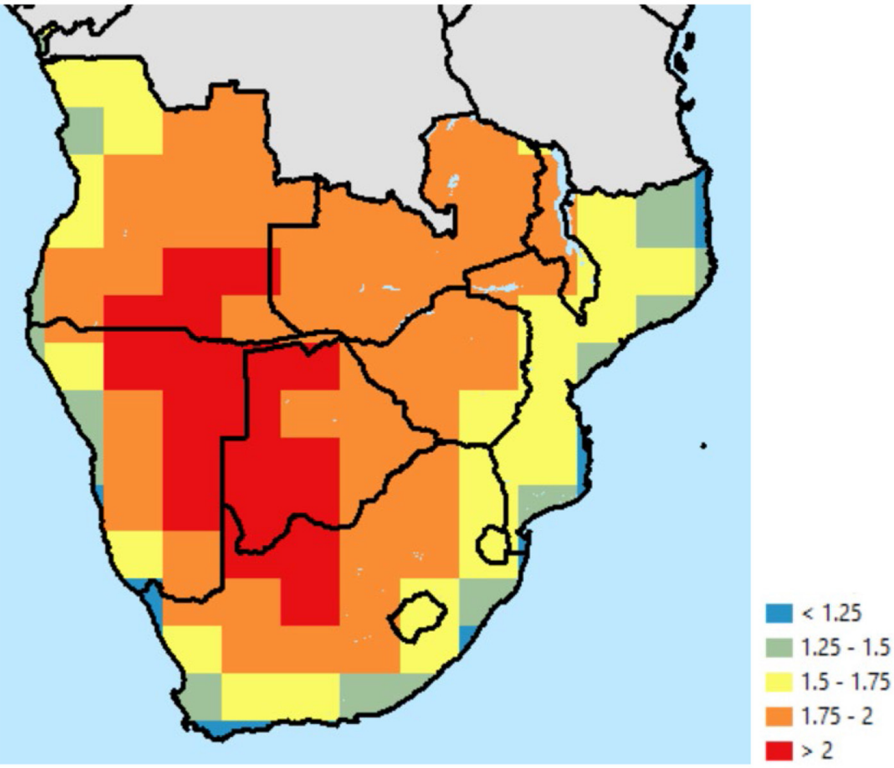

FIGURE 2 | Median projected change in daily maximum temperature across the ensemble of 7,200 smoothed climate change projections from the baseline period (1981–2000) to 2050 under the PF scenario relative to the baseline period, ^{0}C. Source: Schlosser et al. (2021).

having a longer left tail. Additionally, it appears that the left tails of the variation-augmented climate distributions are slightly longer than the right tails, which implies that drought extreme events are projected to be stronger (in terms of distance from the median) than flood extreme events.

The right graph of **Figure 9** shows the distribution of the mean daily maximum temperature for the warmest month of the wet 3 months for Zambia. We note several differences from what we noted with precipitation. First, uncertainty concerning the mean of the temperature measure has a relatively stronger influence when compared to the corresponding inter-annual variability than for what we observed with precipitation. Second, we see that unlike precipitation, for which the medians changed very little, with temperature the medians are rising, and they rise much more with PF than with 2C. The right tail grows faster over time than the median does, and the left tail does not change much over time at all. This is potentially bad news for agriculture, since for most crops, productivity drops off rapidly at higher temperatures.

More specifically, looking at the 2060s and comparing the two variation-augmented plots in **Figure 9**, the medians for the high emissions scenario is roughly 1°C higher than for the low emissions, but the extreme part of the tails have a 3°C difference. This is just one indicator of how much more severe climate extreme events could become in the future. It can help us see the importance of reducing GHG emissions globally even now, because it foreshadows the potential cost of unconstrained emissions.

In balance, however, it could be that even with high emissions, the future climate mean could be realized as one of the more optimistic models, in which case the crisis could be only minor. In the 2C emissions scenario, the median in the 2060s is 1.5°C above that of the 2020s. Such a rise would be harmful to agriculture, but clearly not as harmful as one of the hotter climate models tells us it could be.

We also graphed the precipitation distributions for other countries (see **Supplementary Material**) and noted the skewness of each. We found that Angola, Botswana, Namibia, and Eswatini had long tails to the right. That is, the model extremes were higher on the high rainfall end than on the low rainfall end. At the same time, Mozambique, Malawi, Zambia, Lesotho, South Africa, and Zimbabwe had much longer tails to the left, favoring bigger dry extremes.

Table 1 summarizes the median changes in climate and the range of combined uncertainty and inter-annual variation of precipitation during the wettest 3 months by pixel and aggregated to the national level. **Table 1** confirms that changes in the median across decades and across emissions scenarios is very small in every single nation in the study area.

The second thing we notice in **Table 1** is that the range of uncertainty rises across decades given any emissions scenario. Third, we see that the increase in uncertainty over time is much

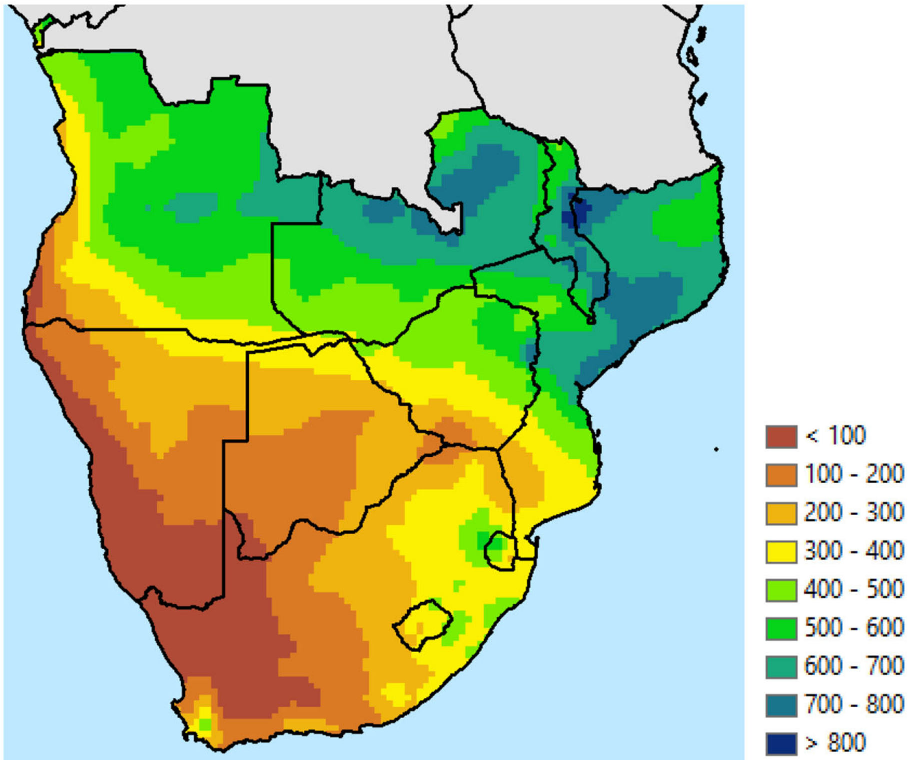

FIGURE 3 | Rainfall in wettest 3 months, millimeters, 1981–2000. Source: Authors' calculations based on Princeton Global Forcings, version 3 [2018, based on Sheffield et al. (2006)].

greater for the higher emissions scenario, with the range twice as large in South Africa for the "PF" compared to the "2C" in the 2060s, though only 25 percent larger in the case of Angola. We also see that the range of uncertainty can be quite large relative to the median. In the case of the "PF" scenario for Zimbabwe in the 2060s, the range from the 5th to the 95th percentile is 54 percent of the median rainfall.

Table 2 shows the distribution across countries for the variation-augmented climate change for the mean daily maximum temperature for the warmest month of the wettest 3 months for each pixel. Unlike the case for precipitation in which the median did not change much across decades and across emissions scenarios, we note that across all countries, temperatures are projected to rise. However, for the lower emissions "2C" scenario, the changes are small. Most countries are projected to experience only a 0.2°C increase over the next 20 years, followed by a 0.1°C increase in the following 20 years.

However, with the higher emissions "PF" scenario, temperatures are projected to rise between 0.5° and 0.7°C in the next 20 years, depending upon the country. And between the 2020s and the 2060s, temperatures are projected to rise 1.1° to 1.5°C. Under both scenarios, the increases are in addition to the increases already experienced since the 1970s.

As noted for ranges in climate uncertainty and inter-annual variability for precipitation, the ranges for temperature also increase through time and are larger for the higher emissions scenarios. As for the skewness in the uncertainty about temperature change, all 10 countries have longer right tails than left. Referring to the values used to construct **Table 2**, the median to 95th percentile range for Zambia and Zimbabwe is at least 90 percent larger than the 5th to median range. And for Botswana and Malawi it is around 70 percent larger. For the other 6 countries, the difference ranges from 20 percent to 45 percent.

Graphs for the distributions in **Tables 1**, **2** are found in **Supplementary Figures 1**, **2**. These figures not only show the skewness of the data for every year between 2020 and 2069, but they also show that for some countries, the distribution often has more than one peak, similar to what is seen in bivariate normal distributions. **Supplementary Figure 3** contains precipitation graphs and **Supplementary Figure 4** contains temperature graphs similar to those in **Figure 9** for the other 9 countries of the Southern Africa study area.

Even though we noted in **Figure 9** that there were only little changes in the left-tail of the precipitation projections in the future for Zambia, we look further at the tails in **Table 3**, focusing on the frequency of relatively rare 1-in-100-year events. **Table 3** has data for not only Zambia but for all 10 countries in the study area. It has data on both the dry year and wet year events, using the 2020s and the low emissions scenario as the baseline level, and seeing what the new frequency is for baseline occurrence.

The problem with reading box and whiskers plots like those in **Figure 8** is that because of the size of the dots in the plot,

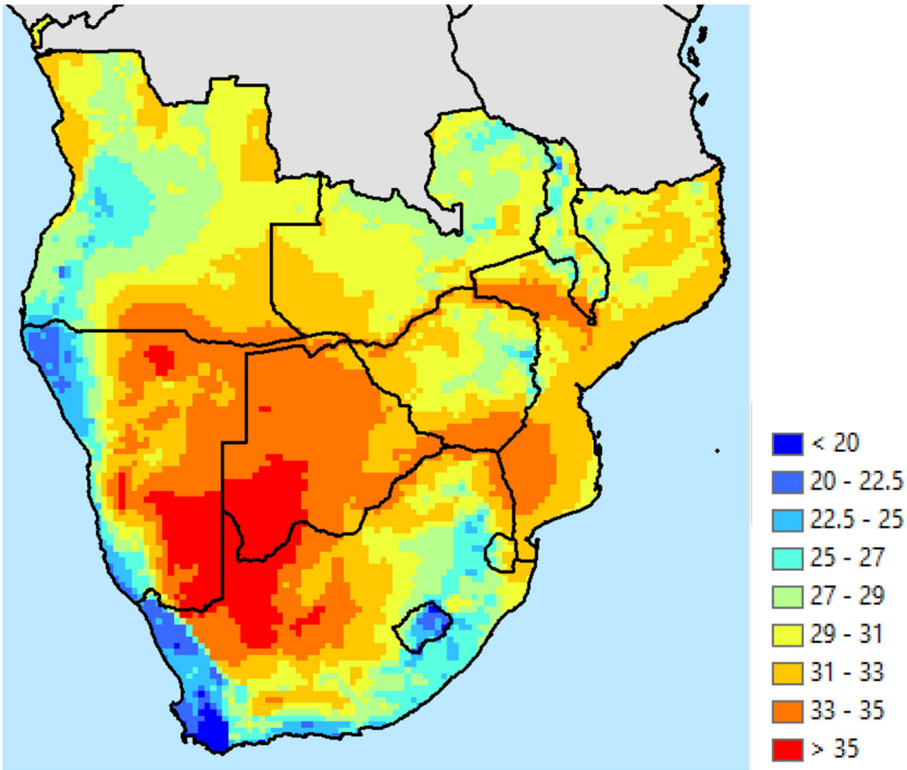

FIGURE 4 | Mean daily maximum temperature for the warmest month in the wettest 3 months, ^{0}C, 1981–2000. Source: Authors' calculations based on Princeton Global Forcings, version 3 [2018, based on Sheffield et al. (2006)].

it is difficult to see how thick the tails are. However, when we look at **Table 3** and using the 1-in-100-year low rainfall event during the wet season for the 2020s as a baseline to measure against, we see that although the tail appeared to be moving leftward over time, it actually was moving rightward for Zambia. 1-in-100-year dry events will become rarer there, occurring once every 242 years by the 2060s under 2C and once every 177 years by the 2060s under PF. Zambia is not unique in having such events become rarer: Angola and Malawi also have the dry year extremes become rarer under 2C in both the 2040s and 2060s, though not true by the 2060s under the PF scenario.

More common are the increases in the occurrence of rare dry years, as seen especially under the PF scenario in the 2060s. Lesotho, Botswana, Eswatini, and Mozambique all will expect the 1-in-100-year dry events to occur 4 times more frequently by then. Namibia, Zimbabwe, and South Africa will see them occurring 2.5 times as frequently.

Figure 10 shows the pixel-level changes in frequency of 20-year events by the 2060s under the REF scenario. Northwestern Angola will see dry events less frequently in the 2060s under climate change with the REF scenario, while southern Angola will see them occur roughly twice as often as the baseline 1981–2000 climate. Much of Zambia will have modest increases in dry years, while much of the rest of the study area will see dry years occur about twice as often. The parts of coastal Namibia that appear to have an increased frequency of 4 times is in a very dry area, and the increase reflects a quantitatively small decline.

Table 3 also has information on the occurrence of 1-in-100-year wet events in the wet season. By the 2060s, Botswana will be much less likely to experience a rare extremely wet year, only seeing it occur once every 351 years. On the other hand, by the 2060s under the PF scenario, Angola will experience them 4 times more frequently, Lesotho more than 3 times as often, and Malawi roughly 2.5 times as often.

Figure 11 shows the frequency of high-rainfall, 20-year events by the 2060s under the REF emissions scenario. Frequency triples and quadruples in northeastern South Africa, and doubles in much of the eastern coast of South Africa, southern Mozambique and Zimbabwe, northern Zambia, and eastern Botswana, and north and central Angola. Namibia's large increase along the coast is in a low rainfall area and the increase is quantitatively small.

Table 4 shows the results of the same kind of analysis except for mean daily maximum temperature of the warmest month of the wettest 3 consecutive months—and in absolute change in temperature in °C rather than in percent change. The largest increases occur for the high emissions scenario by the 2060s, with values averaging around a 0.8°C increase over the 2020s and a 0.5°C increase relative to the 2040s.

However, what is of greatest concern is the frequency of extreme high temperature events. Events that happen every 1-in-100 years will become commonplace by the 2060s, if the PF

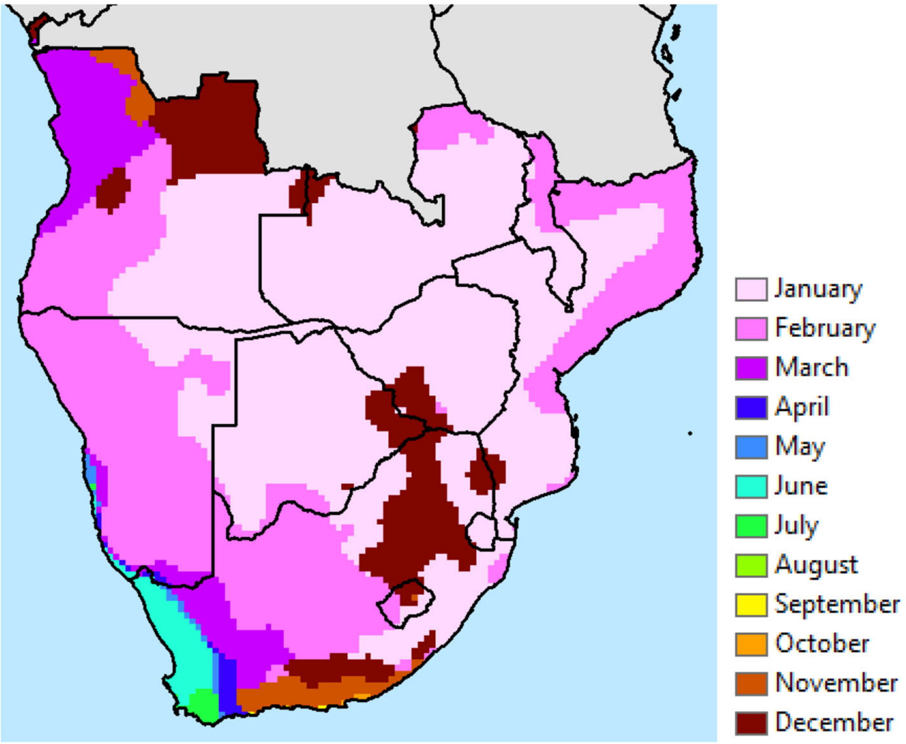

FIGURE 5 | Middle month of wettest 3 months, 1981–2000. Source: Authors' calculations based on Princeton Global Forcings, version 3 [2018, based on Sheffield et al. (2006)].

scenario proves to be correct. For Angola, this kind of event will occur every year, though for Eswatini it will only occur on average every fifth year.

On the other hand, if emissions rates can be lowered, by the 2060s, 1-in-100-year events will occur only once every 13 years (in the case of Angola) or even less frequently—1-in-33 years in the case of Eswatini. Even by the 2040s under the higher emissions scenario, the frequency of extreme heat events will become common, ranging from every 3 years for Angola to every 13 years for several countries (Lesotho, Eswatini, and Zimbabwe).

Making such events much more common will create challenges for farmers in a number of ways. We mentioned two of them: lower yields due to heat-stress and lower livestock productivity due to heat stress. It also will lower productivity of labor, because people also suffer from heat stress, and will have negative health consequences, particularly for seniors and those who are malnourished or sick. It may also lower the efficiency of farm machinery, since engines and moving parts are subject to stress under higher temperatures.

DISCUSSION

In this paper we described the development of smoothed climate ensembles (Schlosser et al., 2021) and their subsequent enhancement with inter-annual variation derived from historical weather in such a way that we were able to consider the full-range of effects of climate change on ten countries of Southern Africa. By augmenting the ensemble of smoothed climate change projections with inter-annual variation derived from historical observations in the manner used here, we were able to assess how the frequency and magnitude of precipitation and temperature extremes might change over time, starting with projections at a fine resolution that were then aggregated to the national and regional levels.

The fine-scale analysis together with the focus on low-frequency weather events allows for more detailed sub-national planning that together with linking to other models could allow for developing targeted investments that could be of great benefit to farmers and local planners dealing with infrastructure and energy.

Because the MIT-IGSM dataset used in this study spanned all of continental Africa and the PGF historical weather dataset provides global gridded weather data (as do a number of other datasets), the methods in this study can readily be applied to all other countries in Africa. Furthermore, while there are many advantages of using 7,200 climate models for Africa (such as providing a more complete distribution of climate futures), it would be possible to use fewer models for applications on other continents, taking advantage of the suites of downscaled models provided by CCAFS (Navarro-Racines et al., 2020) or WorldClim (Fick and Hijmans, 2017), for two examples.

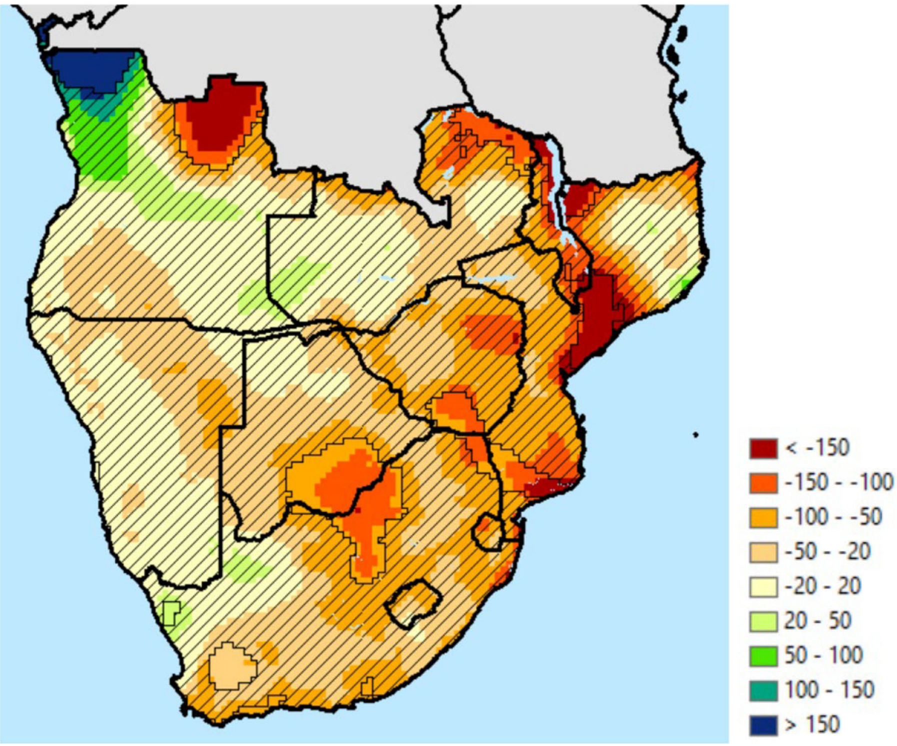

FIGURE 6 | Fourty year trend in change to annual precipitation, 1975–2015, millimeters. Source: Authors, using Princeton Global Forcings daily precipitation. Hash marks show areas with <10% joint statistical significance on the sum of the parameters associated with yr and yr 75 from Equation (1).

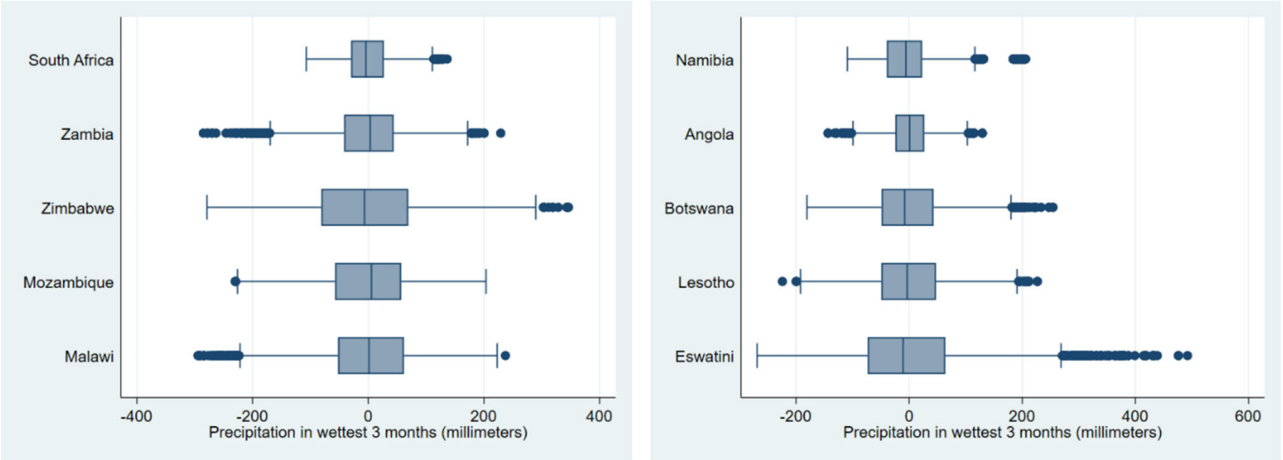

FIGURE 7 | Variation in historical precipitation of the wettest 3 months by country based on detrended monthly data, 1948–2016. Source: Authors' calculations based on Princeton Global Forcings, version 3 [2018, based on Sheffield et al. (2006)]. For box and whisker plots, the box is bounded by the 25th and 75th percentiles, with the mid-line inside the box showing the median. The length from the 25th to the 75th percentile is called the inter-quartile range (IQR). The endpoint of the whiskers is the point that just lies within a distance of 1.5 times the IQR from the ends of the boxes. Any point beyond the whiskers is plotted individually.

This paper focused on the weather during the 3 wettest consecutive months for each pixel because we were primarily concerned with how climate change will impact the agricultural sector. We discovered that median precipitation is not projected to change much. However, largely because of an increase in uncertainty under climate change, the frequency of both extreme high precipitation and extreme low precipitation events will increase.

The largest changes will occur with temperature, which will rise at the median, but will rise by

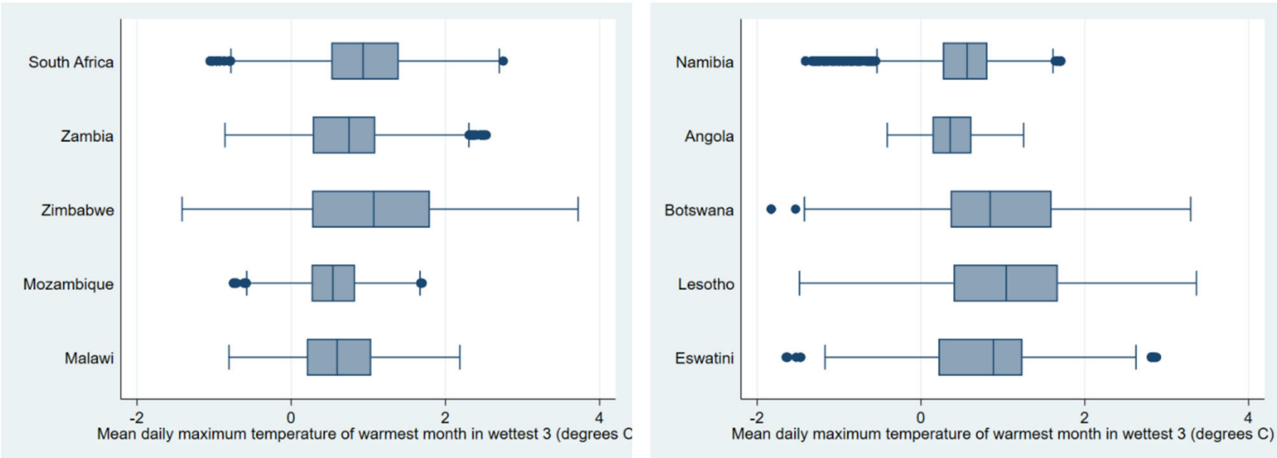

FIGURE 8 | Variation in historical mean daily maximum temperature for the warmest month of the wettest 3 months by country from detrended monthly data, 1948–2016. Source: Authors' calculations based on Princeton Global Forcings, version 3 [2018, based on Sheffield et al. (2006)]. For box and whisker plots, the box is bounded by the 25th and 75th percentiles, with the mid-line inside the box showing the median. The length from the 25th to the 75th percentile is called the inter-quartile range (IQR). The endpoint of the whiskers is the point that just lies within a distance of 1.5 times the IQR from the ends of the boxes. Any point beyond the whiskers is plotted individually.

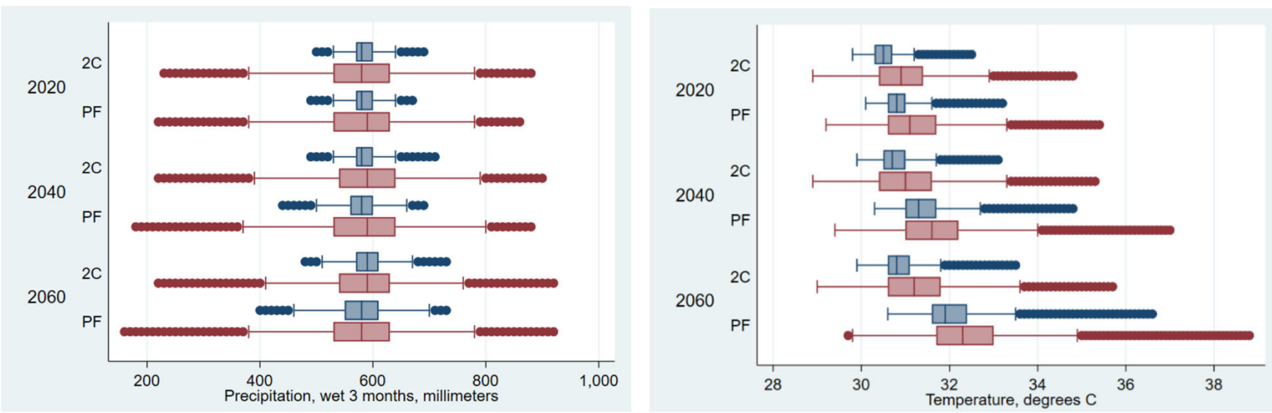

FIGURE 9 | Uncertainty and variation in future precipitation and temperature for Zambia. Source: Authors' calculations. Values are for total precipitation during the wettest 3 months and the mean daily maximum temperature for the warmest month during the wettest 3 months of the year for each pixel, for the given decade, aggregated to the country level. For box and whisker plots, the box is bounded by the 25th and 75th percentiles, with the mid-line inside the box showing the median. The length from the 25th to the 75th percentile is called the inter-quartile range (IQR). The endpoint of the whiskers is the point that just lies within a distance of 1.5 times the IQR from the ends of the boxes. Any point beyond the whiskers is plotted individually. Blue is for the smoothed climate projections. Red is for the variation-enhanced climate projections.

even more in the high temperature tails of the distributions. Furthermore, we discovered large differences between the lower emissions scenario and the higher emissions scenario.

While many will find the results regarding frequency of extreme weather events of interest in their own right, the authors were interested in accounting for climate uncertainty and inter-annual variability for related analyses of irrigation, hydropower, and agriculture for the region. Findings for South Africa are in Arndt et al. (2021) and for the agricultural impact on the Southern Africa region, results can be found in a companion article in this special issue (Thomas et al., 2022).

Regarding agricultural adaptation to climate change, it is likely that spontaneous adaptation will occur at the farm and household level, even without government assistance. For example, farmers may be able to

- Move locations of their farms within the country to areas with lower mean temperatures.
- Change crops or crop varieties to ones that are more heat resistant.

TABLE 1 | Median precipitation and variation for the wettest 3 months across climate models and multiple years in selected decades, in millimeters.

	Medians						Range, 5th-95th percentiles					
	2C			PF			2C			PF		
Country	2020s	2040s	2060s	2020s	2040s	2060s	2020s	2040s	2060s	2020s	2040s	2060s
Angola	450	451	452	451	450	449	60	72	81	53	75	101
Botswana	193	193	194	192	190	188	67	81	90	75	110	150
Eswatini	413	415	416	418	423	429	117	142	158	134	199	276
Lesotho	333	334	335	335	336	338	70	85	95	105	159	220
Malawi	627	628	630	627	627	627	134	163	182	114	172	235
Mozambique	557	560	563	556	558	561	126	154	172	132	198	263
Namibia	128	128	128	126	123	120	47	56	62	50	72	95
South Africa	213	213	214	213	214	215	26	32	36	36	53	72
Zambia	582	583	585	582	580	580	100	121	135	88	134	182
Zimbabwe	376	377	378	376	372	367	93	112	125	103	150	199

Source: Authors' calculations.
Variability includes inter-annual variation based on historical weather as well as uncertainty surrounding the future of greenhouse gas emissions and the resulting change in mean climate over time.

TABLE 2 | Median value for mean daily maximum temperature and variation during the wettest 3 months across climate models and multiple years in selected decades, in ^{0}C.

	Medians						Range, 5–95th percentiles					
	2C			PF			2C			PF		
Country	2020s	2040s	2060s	2020s	2040s	2060s	2020s	2040s	2060s	2020s	2040s	2060s
Angola	30.4	30.6	30.7	30.6	31.1	31.7	0.9	1.0	1.2	0.9	1.2	1.7
Botswana	35.1	35.3	35.4	35.3	36.0	36.8	1.3	1.5	1.7	1.4	2.0	2.6
Eswatini	30.0	30.2	30.3	30.2	30.8	31.3	0.9	1.1	1.2	1.0	1.4	1.9
Lesotho	24.4	24.6	24.7	24.6	25.1	25.7	0.9	1.1	1.2	1.0	1.4	1.9
Malawi	30.0	30.2	30.3	30.2	30.8	31.4	0.8	1.0	1.1	1.0	1.4	1.9
Mozambique	32.0	32.1	32.3	32.2	32.7	33.3	0.8	1.0	1.2	0.9	1.3	1.8
Namibia	32.1	32.3	32.4	32.3	32.9	33.5	0.9	1.1	1.2	1.0	1.4	1.9
South Africa	30.0	30.2	30.3	30.3	30.8	31.4	0.8	1.0	1.1	0.9	1.2	1.6
Zambia	30.5	30.7	30.8	30.8	31.3	31.9	1.1	1.3	1.5	1.2	1.8	2.4
Zimbabwe	31.7	31.9	32.1	31.9	32.6	33.3	1.3	1.6	1.8	1.4	2.1	2.9

Source: Authors' calculations.
Variability includes inter-annual variation based on historical weather as well as uncertainty surrounding the future of greenhouse gas emissions and the resulting change in mean climate over time.

- Shift their planting months slightly to months with cooler temperatures and not too-diminished levels of rainfall.
- Build shelters or plant trees to provide shade for their livestock. And with sufficient power availability and in conditions where it makes economic sense, fans and air-conditioning can be used.
- Shift outdoor work to cooler hours of the day or possibly even in the night or early morning.

Nevertheless, policy makers can do things to assist farmers in their efforts to adapt. These include

- Investment in developing cultivars and livestock that are heat resistant.
- Investment in irrigation (there is some evidence that irrigation cools temperatures in the cropping zone and that irrigated crops produce higher yields than rainfed crops because most years the rainfall is suboptimal for maximal yields).
- Consider whether there are cooler parts of the country that could be developed without adverse environmental impacts, and assist with legislation and infrastructure to facilitate voluntary movement of farmers to those areas.
- Commit to mitigation of GHG emissions and work in bilateral and global forums to encourage all nations to contribute.

TABLE 3 | Change in frequency of very high and very low precipitation years for the wet 3 months of the year.

	Percent change in median precipitation relative to 2020s for "2C"				Frequency of low rain event that was 1-in-100 in 2020s for "2C"				Frequency of high rain event that was 1-in-100 in 2020s for "2C"			
	2C		PF		2C		PF		2C		PF	
ISO	2040s	2060s	2040s	2060s	2040s	2060s	2040s	2060s	2040s	2060s	2040s	2060s
AGO	1.3%	1.1%	1.6%	0.9%	171	127	181	82	46	38	37	24
BWA	1.3%	0.0%	0.1%	−1.9%	76	61	44	25	94	351	101	351
LSO	2.1%	1.4%	2.2%	2.1%	104	74	41	23	52	73	38	29
MOZ	0.2%	1.1%	−0.5%	0.1%	72	67	45	27	73	61	74	56
MWI	0.8%	1.6%	0.5%	0.7%	105	130	101	69	57	42	84	42
NAM	1.6%	−1.3%	−0.8%	−5.2%	81	77	52	36	83	147	105	205
SWZ	−0.8%	0.0%	−0.3%	2.0%	72	66	38	26	115	92	118	80
ZAF	1.5%	1.2%	1.6%	2.1%	95	76	63	42	54	80	56	73
ZMB	1.4%	0.7%	1.1%	−0.3%	165	242	154	177	80	62	95	65
ZWE	3.0%	2.0%	1.4%	−0.5%	90	84	52	35	75	97	68	66

Source: Authors' calculations.
Values account for inter-annual variation based on historical weather as well as uncertainty surrounding the future of greenhouse gas emissions and the resulting change in mean climate over time.

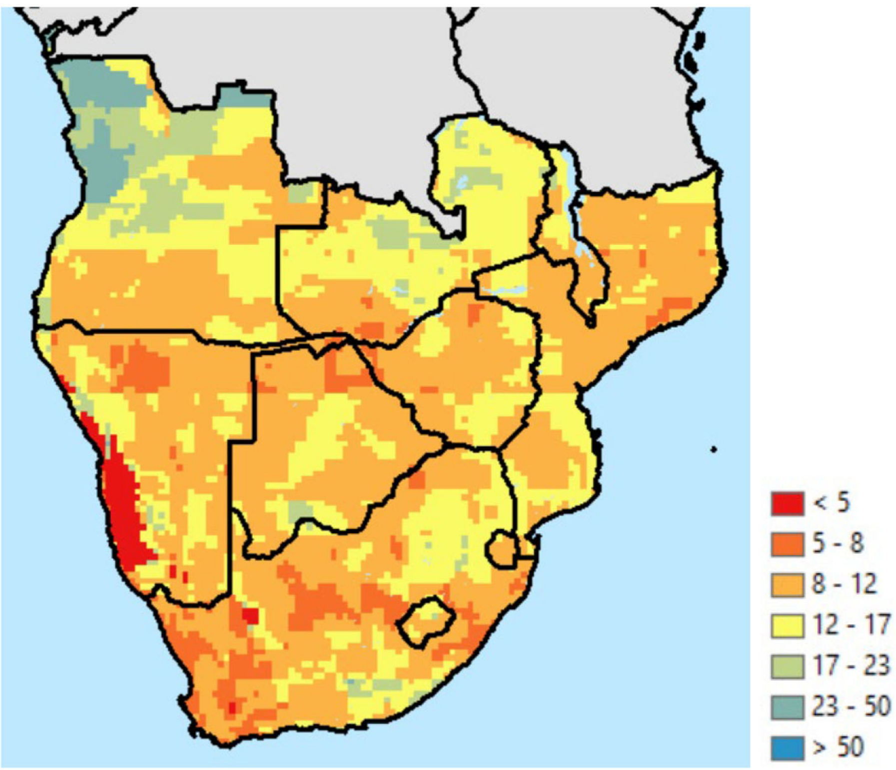

FIGURE 10 | Frequency of 20-year low-rainfall events under climate change, REF scenario, 2060s (baseline 2020s 2C). Source: Authors.

For future studies, alternative methods might be used to produce inter-annual variability measures that allow for a larger subset of variation deltas to choose from or which better preserve inter-annual correlation. Unrelated to the manner in which the variation deltas are drawn, it would also be of interest to investigate the impact of increases in the variability of precipitation, given that several authors have argued for the likelihood of experiencing increased weather variability under climate change (Pendergrass et al., 2017; Bathiany et al., 2018; van der Wiel and Bintanja, 2021).

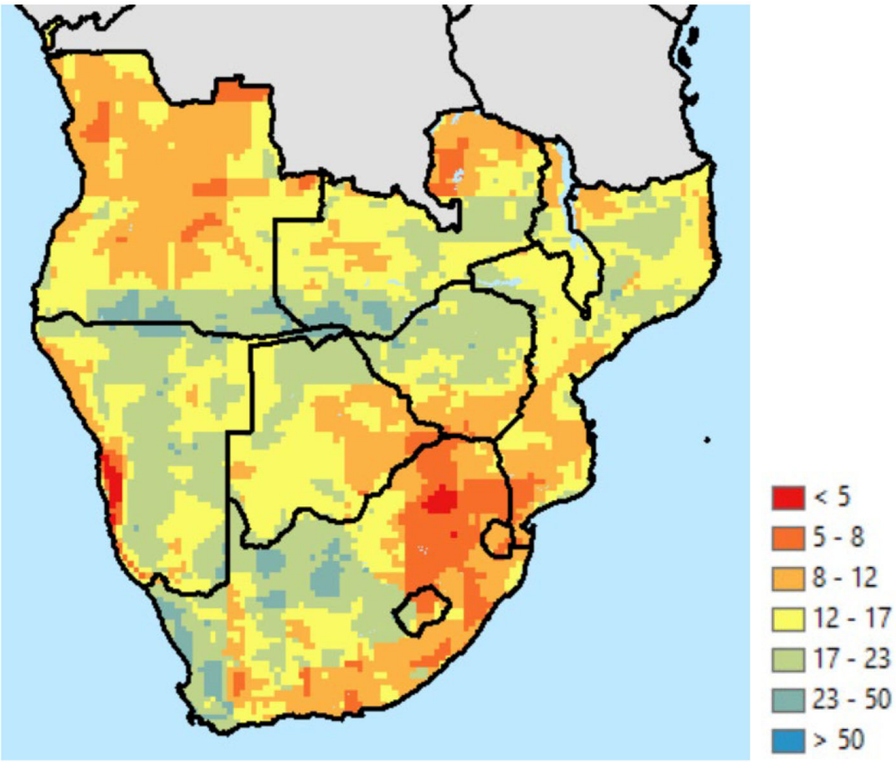

FIGURE 11 | Frequency of 20-year high-rainfall events under climate change, REF scenario, 2060s (baseline 2020s 2C). Source: Authors.

TABLE 4 | Change in frequency of very high temperature years for the wet 3 months of the year.

	Percent change in median temperature relative to 2020s for "2C" in ^{0}C				Frequency of high temperature event that was 1-in-100 in 2020s for "2C"			
	2C		PF		2C		PF	
ISO	2040s	2060s	2040s	2060s	2040s	2060s	2040s	2060s
AGO	0.1	0.3	0.2	0.7	26	13	3	1
BWA	0.2	0.4	0.3	0.9	44	24	10	4
LSO	0.2	0.4	0.2	0.7	54	30	13	4
MOZ	0.1	0.3	0.2	0.7	36	21	5	2
MWI	0.1	0.3	0.3	0.7	38	22	6	2
NAM	0.2	0.3	0.3	0.8	33	20	5	2
SWZ	0.2	0.3	0.2	0.7	45	33	13	5
ZAF	0.2	0.3	0.2	0.8	28	17	5	2
ZMB	0.1	0.3	0.2	0.7	44	24	8	3
ZWE	0.1	0.3	0.3	0.7	56	28	13	4

Source: Authors' calculations.
Values account for inter-annual variation based on historical weather as well as uncertainty surrounding the future of greenhouse gas emissions and the resulting change in mean climate over time.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

TT was the lead writer of this paper and developed the method of augmenting the smoothed climate change projections with inter-annual variation. CS generated the future climate data. KS provided overall guidance and additional checks, particularly for precipitation and PET. CA served as principal investigator of the project and consulted on methodology and use of his Gaussian quadrature routine. RR consulted on daily weather construction. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fclim.2022.787721/full#supplementary-material

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How Climate Extremes Influence Conceptual Rainfall-Runoff Model Performance and Uncertainty

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Rainfall-runoff models are frequently used for assessing climate risks by predicting changes in streamflow and other hydrological processes due to anticipated anthropogenic climate change, climate variability, and land management. Historical observations are commonly used to calibrate empirically the performance of conceptual hydrological mechanisms. As a result, calibration procedures are limited when extrapolated to novel climate conditions under future scenarios. In this paper, rainfall-runoff model performance and the simulated catchment hydrological processes were explored using the JAMS/J2000 model for the Berg River catchment in South Africa to evaluate the model in the tails of the current distribution of climatic conditions. An evolutionary multi-objective search algorithm was used to develop sets of parameters which best simulate "wet" and "dry" periods, providing the upper and lower bounds for a temporal uncertainty analysis approach to identify variables which are affected by these climate extremes. Variables most affected included soil-water storage and timing of interflow and groundwater flow, emerging as the overall dampening of the simulated hydrograph. Previous modeling showed that the JAMS/J2000 model provided a "good" simulation for periods where the yearly long-term mean precipitation shortfall was <28%. Above this threshold, and where autumn precipitation was reduced by 50%, this paper shows that the use of a set of "dry" parameters is recommended to improve model performance. These "dry" parameters better account for the change in streamflow timing of concentration and reduced peak flows, which occur in drier winter years, improving the Nash-Sutcliffe Efficiency (NSE) from 0.26 to 0.60 for the validation period 2015–2018, although the availability of climate data was still a potential factor. As the model performance was "good" (NSE > 0.7) during "wet" periods using parameters from a long-term calibration, "wet" parameters were not recommended for the Berg River catchment, but could play a large role in tropical climates. The results of this study are likely transferrable to other conceptual rainfall/runoff models, but may differ for various climates. As greater climate variability drives hydrological changes around the world, future empirically-based hydrological projections need to evaluate assumptions regarding storage and the simulated hydrological processes, to enhanced climate risk management.

Keywords: climate extremes, drought, rainfall-runoff modeling, temporal model uncertainty, climate change

INTRODUCTION

The frequency, duration and intensity of droughts around the world are increasing, resulting in the widespread loss of natural vegetation and wildlife, economic instability and increases in anthropogenic water use (IPCC, 2021). While in some situations, specific regions have benefitted in terms of more favorable climates for crop growth and enhanced carbon dioxide fertilization (Bond and Midgley, 2012), meteorological shortfalls and the intensification of dry periods will impact many vulnerable regions which do not have the economic ability to adapt (Collier et al., 2008; Allison et al., 2009). The expectation is that precipitation variability, exaggerated by increasing temperatures and resulting evapotranspiration, will plague many parts of Africa for the unforeseen future (Engelbrecht and Monteiro, 2021). The Western Cape (WC) of South Africa has been subject to an increased meteorological drought frequency (1–3 years: Watson et al., 2022) and recently experienced an intense drought between 2015 and 2018, where reservoir levels collectively dropped to a low of 17% (DWS, 2018). Research has mainly focused on the mechanisms affecting local precipitation (Wilks, 2011), characterizing the meteorological (Archer et al., 2019) and agricultural drought (Watson et al., 2022). While recent climate change projections have been developed for Africa (Haensler, 2010; Haensler et al., 2011; Archer et al., 2018; Weber, 2018; Lim Kam Sian et al., 2021; Majdi et al., 2022), their bearing on local hydrological condition and function affect the development of appropriate adaptation strategies and the rate at which Africa acts to reduce the effects of global warming (Kusangaya et al., 2014). Furthermore, uncertainty still remains whether hydrological models can reproduce hydrological flows considering future non-stationary climatic conditions, which has been an issue for rainfall-runoff model applications around the world (Deb and Kiem, 2020; Fowler et al., 2020).

SWAT (Arnold et al., 1998), a common conceptual rainfall-runoff model, has been used as a predictive tool to assess the impact of different climate change projections on the future water resource availability in different African settings (Akoko et al., 2021; Chomba et al., 2021; Maviza and Ahmed, 2021; Osman et al., 2021). Using historical conditions, hydrological process simulations for rainfall-runoff models have been calibrated with historical streamflow measurements and other hydroclimatic observations. Accounting for additional spatial variables has improved rainfall-runoff model performance and the overall inclusion of different hydrological processes (Vaze et al., 2011; Khakbaz et al., 2012). Furthermore, the advancement of rainfall-runoff modeling into fully automated calibration procedures such as the use of the Non-dominated Sorting Genetic Algorithm (NSGA-II: Deb et al., 2002) and parameter uncertainty analysis such as the Monte Carlo Analysis (MCA: Hornberger and Spear, 1981), criteria-based performance assessments (Krause and Boyle, 2005), Generalized Likelihood Uncertainty Estimation (GLUE: Beven and Binley, 1992), and Dynamic Identifiability Analysis (DYNIA: Wagener et al., 2002) has improved hydrological model applications around the world. Although physical inputs (e.g., climate, topography, soil, hydrogeology, and land use) form spatial inputs in most distributed rainfall-runoff models (e.g., SWAT: Arnold et al., 1998; J2000: Krause, 2001, PRMS/MMS: Leavesley et al., 1996), conceptual and empirical parameters which are often calibrated based on streamflow measurements, are impacted by non-stationary climate conditions (Deb and Kiem, 2020) and complex hydrological processes are often inferred from only river flow measurements (Jakeman and Hornberger, 1993). As a result, recent concerns have been raised about the ability of "bucket" type rainfall-runoff models in reproducing hydrological conditions under future projections and in particular how these methods assume long-term stationary storage conditions (Fowler et al., 2020).

In this study, the performance of the JAMS/J2000 rainfall-runoff model was assessed during periods of climate extremes between 1984 and 2018 for the Berg River catchment in South Africa (**Figure 1**). The different climate extremes were distinguished using the Soil Moisture Deficit Index (SMDI: Narasimhan and Srinivasan, 2005; Watson et al., 2022) into periods of "wet" and "dry". Yearly average values of 1$>$ SMDI <-1 were used to differentiate between "wet" and "dry" years. The NSGA-II (Deb et al., 2002), an evolutionary multi-objective search algorithm was used to develop sets of parameters which "best" simulate "wet" and "dry" periods for the JAMS/J2000 model of the Berg River. To identify parameters which may vary in both space and time, as a function of a change in hydroclimatic and other biophysical processes, DYNIA (Wagener et al., 2002) was used. Further to the temporal uncertainty of different parameters across "wet" and "dry" periods, we aim to demonstrate the extent of climatic disturbance with which a single parameter set can simulate catchment hydrological processes within a certain degree of efficiency. As unstable climate conditions begin to affect conceptual assumptions regarding soil water and aquifer storage, as well as water use behavioral changes within the system, understanding temporal parameter variability is required to develop more dynamic rainfall-runoff models which are required for climate change-based assessments.

ENVIRONMENTAL SETTING

The Berg River is a meso-scale catchment with an extent of 7,700 km^2, which is located on the West coast, South Africa (**Figure 2**). The catchment supports a large agricultural sector (Claassen, 2015), used in inter-basin water supply (Muller, 2002), as well as hosting an ecologically significant estuary (Sinclair et al., 1984). The catchment falls within the Cape Fold Belt, a thrust belt which resulted in the formation of a sequence of sedimentary rock layers known as the Cape Supergroup (Johnson et al., 2006). The catchment drains the Hottentots-Holland and Haweqwa Mountains, which receive the bulk of precipitation with a maximum of 3,198 mm/annum and are hosted by the Cambrian Table Mountain Group sandstones (TMG) in the Southern tip of the catchment. The TMG is widely known as a highly productive secondary fractured rock aquifer with estimated recharge values of between 13 and 27% of Mean Annual Precipitation (MAP) (Weaver and Talma, 2005;

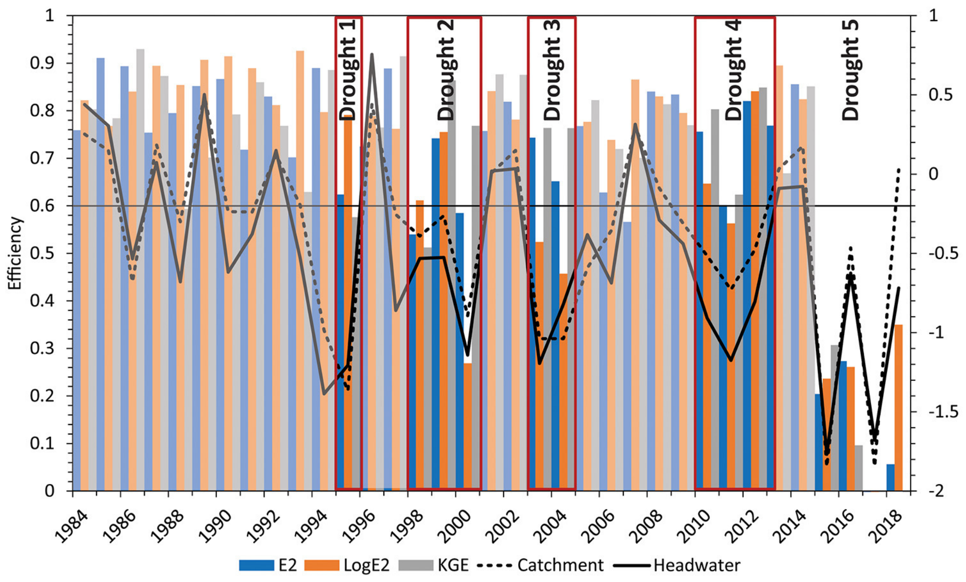

FIGURE 1 | The long-term (1984–2018) efficiency of the JAMS/J2000 model for the Berg River catchment (after Watson et al., 2022), represented as the yearly Nash–Sutcliffe [NSE; Nash, 1970] efficiency in standard form (E2) and logarithmic form (logE2) as well as with the Kling- Gupta efficiency (KGE). The simulated Soil Moisture Deficit Index (SMDI) for the Berg River catchment (black dashed line) and headwater (black line), indicating a reduce performance during "dry" periods when the simulated SMDI was < −0.5.

Wu, 2005; Miller et al., 2017). Precipitation reduces to 700–800 mm/annum near the town of Paarl, where an alluvial aquifer is often thick (15–20 m) and underlain by the Malmesbury Group shales (MG). Groundwater recharge rates for the alluvial aquifer are between 0.2 and 3.4% (Conrad et al., 2004), but as much as 6% of MAP (Vetger, 1995) while less is known about recharge rates for the MG.

Precipitation reduced to 300–400 mm/annum toward Velddrif at the catchment outlet (Lynch, 2004), where the river flows into the Atlantic ocean. Major reservoirs are present in the catchment headwaters (Berg River, Wemmershoek and Voëlvlei dams: 130 (Million) Mm^3, 58, and 164 Mm^3, respectively), as well as downstream of these reservoirs on the main river channel (Misverstand dam: 8 Mm^3). Other significant reservoirs (Theewaterskloof dam: 480 Mm^3, Steenbras dam: 33 Mm^3, Clanwilliam dam: 121 Mm^3) in the Breede and Olifants/doorn Water Management Areas (WMAs), comprise the bulk surface water supply sources in the area.

Precipitation in the Berg River and much of the Mediterranean winter precipitation parts of the WC, is generally received in the months June, July August (JJA) with 50%, followed by March, April, May (MAM) with 23% of the total yearly amount (Watson et al., 2022). September, October, November (SON) and December, January, February (DJF) make up the remaining 19 and 8% of the yearly precipitation amounts. As a result, streamflow is mainly generated JJA, with 61% of the total flow, followed by the SON, MAM, and DJA months with 26, 9, and 4%, respectively (Watson et al., 2022). The temporal variability of MAP within the region, over the last 34 years (1984–2018), shows a higher degree of variability for valley regions (51% of valley MAP) compared with headwater areas (34% of headwater MAP) (Watson et al., 2022). Meteorological droughts have been mostly associated with shortfalls in MAM precipitation (Archer et al., 2019; Watson et al., 2022) (years 2000, 2015, and 2017) but for the drought years: 1994, 2004, and 2011 <50% was received in DJF (**Table 1**). In 1997 and 2003 meteorological drought was mainly caused by shortfalls in SON and JJA, respectively. Hydrological dry periods in the catchment have been characterized by shortfalls in the SON months with 51% less streamflow, followed by MAM, JJA, and DJF with 38, 32, and 5% less. The years 2003, 2015, and 2017 had between 60 and 87% less streamflow, although the Berg River dam construction in 2004 has contributed to more recent reduced streamflow. Agricultural drought, simulated using the Soil Moisture Deficit Index (SMDI) and the JAMS/J2000 rainfall/runoff model (with the same setup as this paper) occurred for the years 1995, 1998–2000, 2003–2004, 2010–2012, and 2015–2017 (Watson et al., 2022) (**Figure 3**). To assist in understanding the environmental setting and the methodological approach, commonly used abbreviations and acronyms are summarized in **Table 2**.

MATERIALS AND METHODS

The Berg River was modeled using the JAMS/J2000 distributed rainfall-runoff model (Krause, 2001, 2002; Krause and Kralisch, 2005) which was used to simulate the catchment hydrological processes (**Figure 1**). These include the model's ability to conceptually simulate processes which result in the generation of surface runoff, interflow (sub-surface runoff) and baseflow, as well as flow dynamics at a hillslope/small scale (**Figure 4**). The model was run on a daily timestep for the periods 1983–2018 with a 1-year initialization period (1983). The spatial modeling units

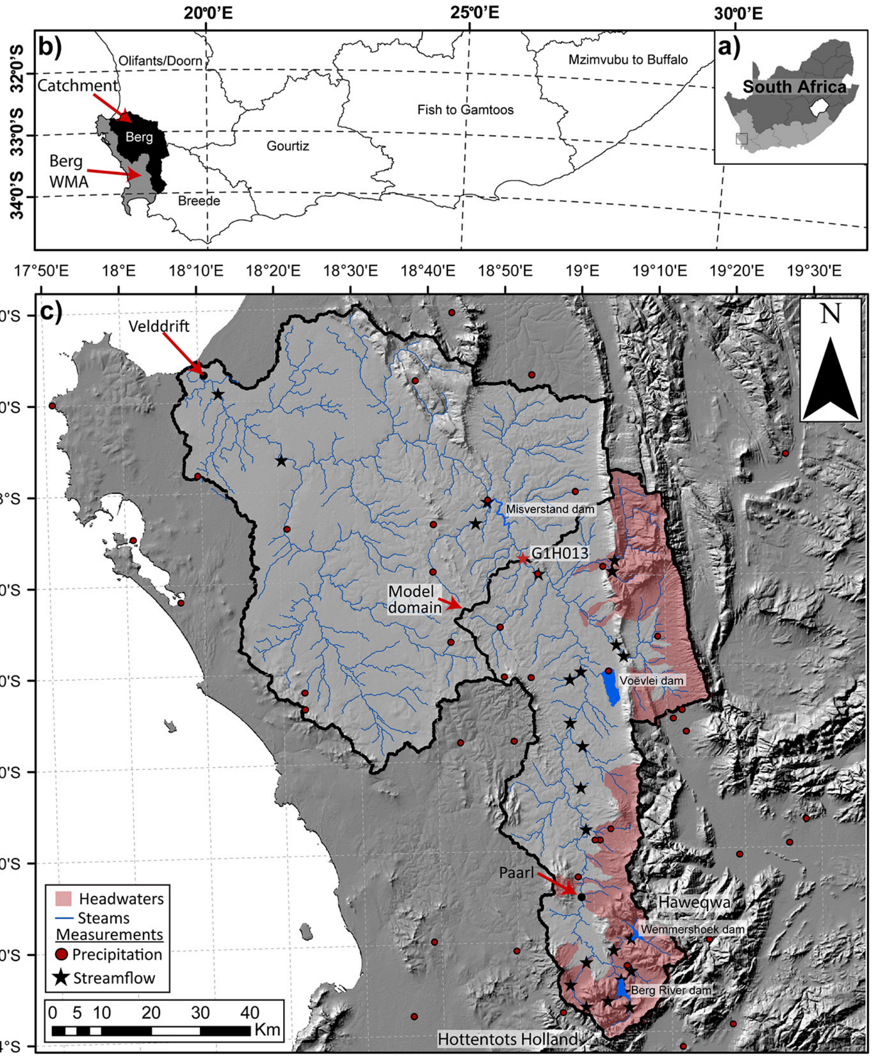

FIGURE 2 | **(a)** Location of the Western Cape (WC) within South Africa, **(b)** Berg River Water Management Area (WMA) surrounded by other WMA's within the WC (Breede, Olifants/doorn), **(c)** Berg River catchment showing locations of precipitation stations (red points), streamflow monitoring (black star), G1H013 gauge (red-star), the modeling domain and locations of major towns, reservoirs (Berg River, Wemmershoek, Voëlvlei and Misverstand dams), the major town of Paarl in context with the mountain ranges of the Hawequa and Hottentots Holland and headwater areas (>300 M A.S.L: red polygon).

were determined by following a Hydrological Response Unit (HRU) delineation procedure after Flügel (1995), together with a river reach delineation after Pfennig et al. (2009). Together with a minimum sub-basin size (7.2 km^2), HRU size (0.4 km^2) and a map overlay procedure the web-based GRASS-HRU delineation tool (Schwartze, 2008) was used to create the model HRUs and reach segments. The climate forcings were determined through a model regionalization approach, using local input data. Below a description is provided of the model input data, the model calibration/validation, the streamflow time of concentration and the sensitivity analysis. The methodological approach focused on the modifications made between the long-term, "dry" and "wet" period calibrations, as well as the analysis using DYNIA for temporal model uncertainty. For further details regarding the HRU delineation, the regionalization procedure of the climate data and model based calculations refer to Watson et al. (2020) and Krause (2001). Furthermore, only a summary of the model input data was presented, as a detailed breakdown of the model input data is available in Watson et al. (2020, 2021a, 2022).

Model Inputs

The input data for the JAMS/J2000 model include spatial and temporal data. The climate forcings (including all climate variables) and streamflow measurements form the temporal data for the model, while a Digital Elevation Model (DEM) and maps of hydrogeology, soil and land use form the spatial data used in the HRU delineation. The climate forcings were collected from the World Meteorological Organization (WMO) as Global Surface Summary of the Day (GSOD) data (NOA, 2016), the Agricultural Research Council (ARC), the South African Weather

TABLE 1 | The difference in precipitation of a three-month split of the long-term average for the years (– value shows increase, + values decrease) 1994, 1997, 2000, 2003–2004, 2011, 2015, and 2017 for the catchment.

Dry years	Total shortfall (%)	MAM (% avg)	JJA (% avg)	SON (% avg)	DJF (% avg)
1994	12	31	−2	7	**57**
1997	18	29	0	**41**	46
2000	27	**53**	30	−5	13
2003	25	29	**35**	7	−13
2004	23	45	19	−4	**52**
2011	21	−2	28	18	**50**
2015	34	**70**	13	55	2
2017	32	**70**	21	0	64

Years 1994 and 1997 (red highlights major shortfalls) resulted in a low simulated Soil Moisture deficit Index (SMDI) for the following years 1995 and 1998, while low SMDI in the years 2000, 2003–2004, 2011, 2015, and 2017 was simulated within the respective year.

Services (SAWS) and the Department of Water Affairs and Sanitation (DWS). The gap filled SRTM 90 m (Shuttle Radar Topography Mission), was the DEM which was used. A 1:250,000 geological map (Visser and Theron, 1973; Theron, 1990; CGS: Gresse, 1997), the Harmonized World Soil Database (HWSD) (Version 1.2) (Batjes et al., 2012) and the 2013–2014 South African National Land-Cover dataset (GeoTerraImage, 2015) formed the maps of hydrogeology, soil and land use which were used. Additionally, regional literature and pedotransfer functions (Schaap, 2002) were used to parameterize the spatial data for the model.

Climate Forcings and Streamflow Data

Daily totals of precipitation, solar radiation, as well as daily average windspeed, relative humidity and air temperature were collected for the periods 1983-11-01 to 2018-12-31 (±35 years). Additionally, daily minimum and maximum air temperature

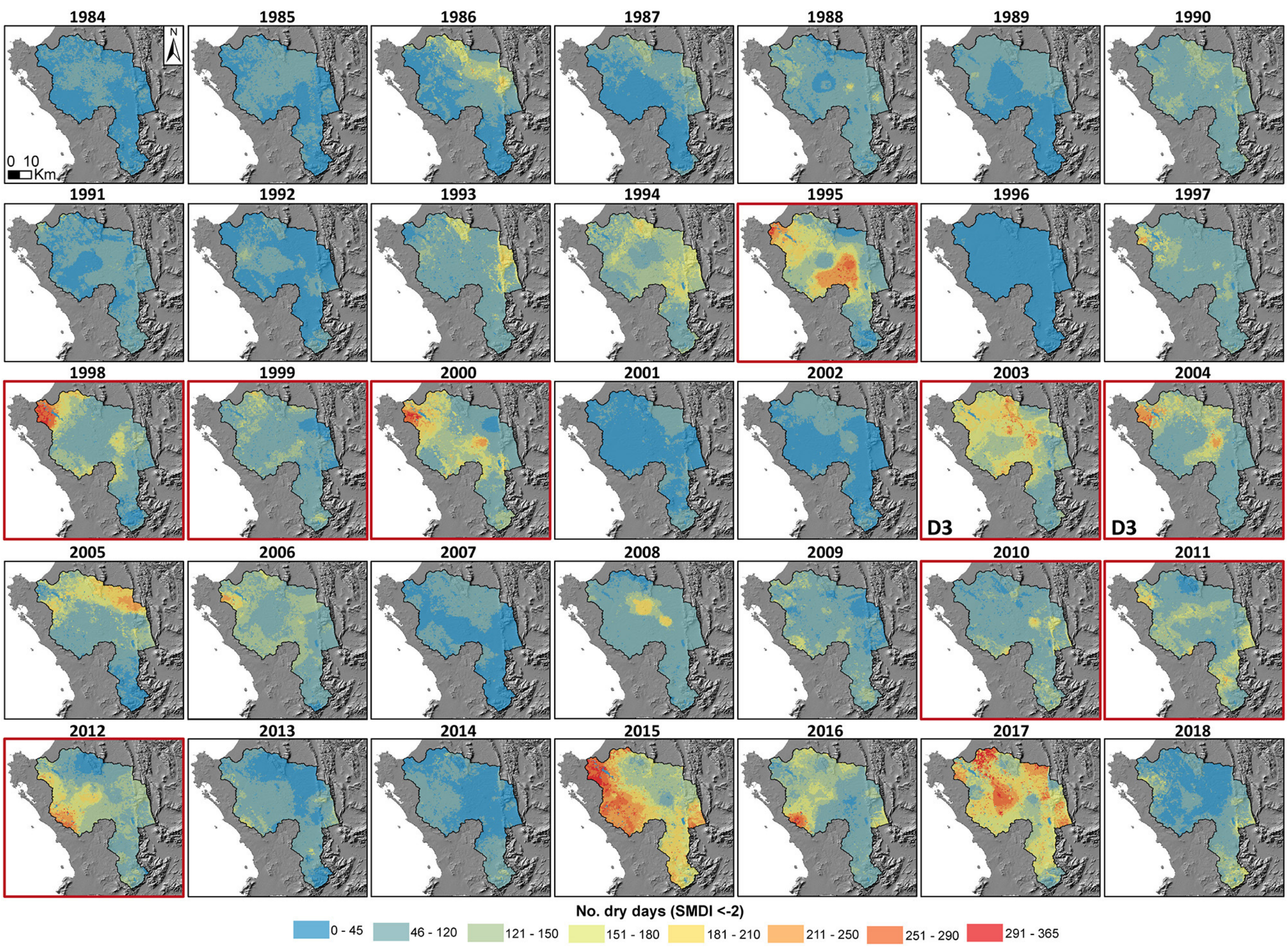

FIGURE 3 | The number of dry days where the simulated Soil Moisture Deficit Index (SMDI) was between −2 and−4 for the periods 1984–2018 for the Berg River catchment. Severely dry years included: 1995, 2000, and 2003/2004, where >250 dry days were simulated for parts of the catchment. The droughts of 1995, 2000, and 2012 were influenced by prior dry years (>120 dry days). Unlike these droughts, 2003/2004 and 2015/2017 were preceded by wet years. While similarities between the onset of the 2003/2004 drought, the 2015/2017 drought was significantly drier and possibly influenced by anthropogenic water use (after Watson et al., 2022). Source: https://www.elsevier.com/about/policies/copyright.

TABLE 2 | A list of the commonly used acronyms and abbreviations used for this study.

Acronyms and abbreviations	
MAP	Mean Annual Precipitation
MAM	March, April, May
JJA	June, July, August
SON	September, October, November
DJF	December, January, February
NSGA-II	Non-dominated Sorting Genetic Algorithm
MCA	Monte-Carlo-Analysis
DYNIA	Dynamic Identifiability Analysis
NSE	Nash-Sutcliffe Efficiency standard squared form (E2)
LogNSE	logarithmic Nash-Sutcliffe Efficiency (logE2)
pBias	Relative volume error
KGE	Kling-Gupta Efficiency
HRU	Hydrological Response Unit
SMDI	Soil Moisture deficit index
IDW	Inverse Distance Weighting
MPS	Middle Pore Storage
LPS	Large Pore Storage
RD1	Surface runoff
RD2	Interflow (sub-surface runoff)
RG1	Fast groundwater flow (upper aquifer)
RG2	Slow groundwater flow (lower aqufier)

were required for the calculation of potential evapotranspiration rate using calculations by Allen et al. (1998). The total number of stations were 49 for precipitation, 16 for air temperature, 11 for relative humidity, 14 for windspeed and six for solar radiation. Of these stations, not all records covered the 35-year simulation, which was important for the selection of the regionalization approach. Although Kriging and other geostatistical approaches result in a lower measurement bias (Borga and Vizzaccaro, 1997), Inverse Distance Weighting (IDW) was used as it performs well for dense station networks (Dirks et al., 1998), as well as being more robust in terms of missing records (Ly et al., 2013; Watson et al., 2020). To understand the relative HRU to precipitation station distance which impacts model temporal uncertainty, a separate modeling approach which computes the regionalization statistics for each HRU, as well as a spatial aggregate for the entire model run was used (Watson et al., 2020).

Daily average streamflow was available from 27 gauging locations across the catchment. Although, of these gauges, 19 had poor record quality and were impacted by upstream reservoirs. While a multi-gauged calibration could be used to constrain differences in sub-basin hydrological processes for the Berg River, the bulk signal from the most downstream gauge was used in this study. Records from the most downstream, relatively natural G1H013 (Drieheuwels) 1983-11-01 to 2018-12-31 were used as the bulk of the catchment river flow (**Figure 2**). Additional reservoir outflow from the Berg River dam (G1H077 gauge) and Wemmershoek dam (G1H080 gauge) for the periods 2006-06-01 to 2018-10-01 were included in the model. To account for reservoir operations, the outflow from each reservoir was included by substituting the observed data with the simulated streamflow for reservoir reach segments for time periods where reservoir release data was available. For further detail and a description on the simulation of reservoir outflow using the JAMS/J2000 refer to Watson et al. (2022).

Spatial Parameters

Local hydrogeological literature (Conrad et al., 2004; SRK, 2009), bulk aquifer properties (Domenico and Schwartz, 1990; Tankard et al., 2012) and previous JAMS/J2000 models for the region (Bugan, 2014; Treumer, 2016; Watson et al., 2018, 2019, 2020, 2021a,b, 2022) were used to determine: (1) maximum storage capacity, (2) storage coefficient, (3) maximum aquifer thickness, and (4) recession coefficient of the upper and lower aquifer. The upper (primary) aquifer is a conceptual representation of quaternary sediments, weathered material and fractured rock aquifers and is indicative of fast groundwater within the JAMS/J2000 model. The lower (secondary) aquifer represents the regional groundwater contribution of shales and the basement aquifer, as slow groundwater in JAMS/J2000.

The Rosetta lite pedotransfer function (Schaap, 2002) within the HYDRUS model (Šimunek et al., 2006), together with the HWSD textural characteristics [% Sand, Silt and Clay (SSC)] were used to determine the input soil parameters for the JAMS/J2000 model. The model makes use of two soil pore storages namely; Middle Pore Storage (MPS: 0.2–50 μm) and Large Pore Storage (LPS: $>50\,\mu$m). The soil textural characteristics were used to generate soil hydraulic properties (theta vs. depth), using a constant upper and lower head boundary, for 0, 60, and 15,000 mbar pressure ranges. The available water holding capacity (AWC) of the soil, represented as MPS, was determined by subtracting the soil water holding at 15,000 and 60 mbar. LPS was determined by the subtraction of the water holding capacities at 0 and 60 mbar. The effective water holding capacity of these soil water storages were determined by multiplying the derived water holding capacities by the effective soil depth from HWSD. Two calibration parameters, AC adaption (LPS) and FC adaption (MPS) were additionally used to scale the air capacity and AWC of the soil according to the simulated streamflow.

The land use parameters: (1) albedo (%), (2) monthly surface resistances assuming sufficient water supply, (3) Leaf Area Index (LAI) for vegetational growth periods, (4) effective vegetation heights for growth periods, (5) root depth, and (6) sealed grade value (impervious areas) are required by the JAMS/J2000 model. Local and international literature (Johnson, 1983; Van, 1984; Crain, 1998; Amer and Hatfield, 2004; Munitz et al., 2017) were used to determine the land use parameters for the respective map land use classes. Additionally, vegetation interception (a_rain) and linear reduction of potential evapotranspiration (soilLinRed) calibration factors were used to scale evapotranspiration and interception according to the simulated streamflow.

Model Calibration and Validation

In general, conceptual rainfall-runoff models can be written after Wagener et al. (2002) as:

$$\left(\hat{y}t\middle|\theta\right) = g\left(t|I,\theta\right) \qquad (1)$$

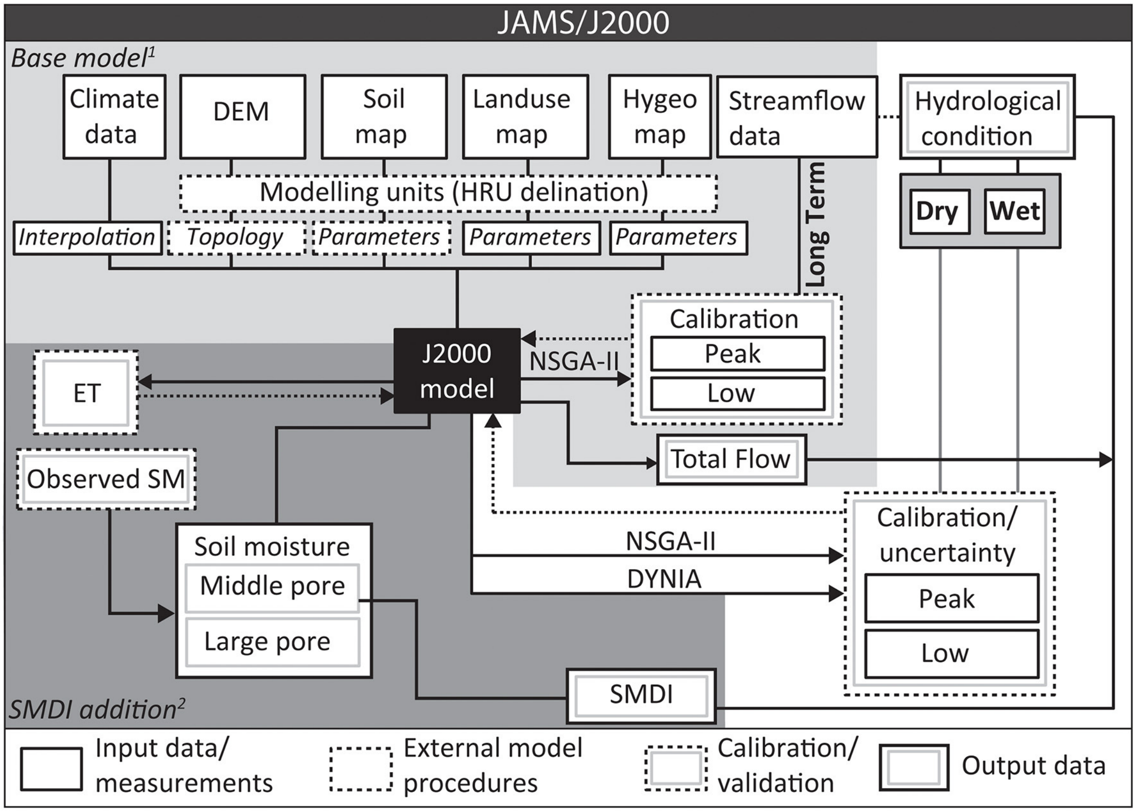

FIGURE 4 | A schematic of the process-oriented JAMS/J2000 distributed rainfall-runoff model (after Krause, 2002), the input data, Hydrological Response Unit Delineation (HRU) and variables required for the base model (after Watson et al., 2020), the addition of the Soil Moisture Deficit Index (SMDI) component (after Watson et al., 2022) used for the assessment of "wet" and "dry" years. The use of the NSGA-II (Non-dominated Sorting Genetic Algorithm: Deb et al., 2002) to refine parameters for "wet" and "dry" years which form the upper and lower bounds (θ_{dry}; θ_{wet}) used in the Dynamic Identifiability Analysis (DYNIA: Wagener et al., 2002).

where I is a matrix system input, t is the timestep, θ is a parameter vector or parameter set, $g(.)$ is a collection of usually non-linear functions and $\hat{y}$ is the simulated system output at timestep t using parameter set θ. The objective of the automated calibration procedure, the Non-dominated Sorting Genetic Algorithm NSGA-II (Deb et al., 2002), was to estimate θ that best represents the conditions of the natural system using pre-defined parameter vector thresholds ($\theta_{\max}|\theta_{\min}$). The evaluation of θ is performed as:

$$\varepsilon\ (t|\theta) = y\,(t) - \hat{y}\,(t|\theta) \tag{2}$$

where $y\,(t)$ is the observed system output. The residual, which represents the objective function (OF) and used to assess model performance efficiency, made use of different criteria to assess aspects of the simulated hydrograph (Legates and McCabe, 1999; Moriasi et al., 2007; Kundzewicz et al., 2018). The selected efficiency criteria used by the NSGA-II included the Nash-Sutcliffe Efficiency (NSE; Nash, 1970) in standard squared form (E2), logarithmic form (logE2), with the relative volume error (pBias) and the Kling-Gupta-Efficiency (KGE; Gupta et al., 2009) used as *post-hoc* performance evaluation outside the optimization process. The calibration procedure was applied three times, 10,000 model runs each, optimizing the objective function for the different periods: 1984–1995 as a long-term series, 1995, 1998, 2000, 2003–2004, and 2011 as dry periods only and 1984–1997, 1999, 2001–2002, and 2005–2010 as wet periods only (after Watson et al., 2022). These calibrations resulted in the determination of $\theta_{long-term}$; θ_{dry} and θ_{wet} which best represent the natural system during the selected periods. A subsequent validation using $\theta_{long-term}$ was performed for the periods 1996–2004, 2009–2014, and 2015–2018 using θ_{dry}. The validation included assessing the model's performance prior and post the Berg River reservoir construction and where release data was not measured (from either of the reservoirs: 1996–2004) and where reservoir release data was available (2009–2014). The validation of θ_{dry}.parameter set was evaluated in terms of the most recent drought (2015–2018). Given that there were limited high altitude available precipitation stations, the modeling approach was not tailored to simulating flood extremes, as future more frequent droughts are the most concern for the WC. As a result, the evaluation of θ_{wet} was done using the entire "wet" timeseries (calibration only) to contrast the parameters for $\theta_{long-term}$ and θ_{dry}.

Streamflow Time of Concentration

The rate at which simulated streamflow reaches the catchment outlet using the different parameter sets ($\theta_{long-term}$, θ_{dry}, and θ_{wet}) was determined through a theoretical model procedure. This involved modifying the input precipitation data, selecting a long model initialization period with no precipitation events and removing the reservoir outflow components from the model. A timeseries which includes one large precipitation event (100 mm/day on 01-01-1985, zero values for the other timesteps) for a single station/interpolation position was used as the input precipitation data. To ensure that the peak flow rate could be easily detected, a long model initialization was used (2 years-01-01-1983) to allow the storages to stabilize. The streamflow time of concentration was then calculated as the difference between the time of the one event and the flow rate peak at the catchment outlet.

Sensitivity Analysis

The Monte-Carlo-Analysis (MCA), together with the Dynamic Identifiability Analysis (DYNIA: Wagener et al., 2002) was used to understand the relative importance/uncertainty of the different parameters in the simulated hydrological processes of the Berg River using the J2000/JAMS model. The approach utilized 5000 model runs with the Nash-Sutcliffe Efficiency (NSE; Nash, 1970) in standard squared form (E2) and logarithmic form (logE2) as evaluation criteria. In order to understand the relative sensitivities of the parameters θ and ones influenced by climatic disturbances, θ_{dry} values were compared with θ_{wet} from the NSGA-II calibration. To reduce the overall number of parameters and to include parameters with the most notable solution direction differences, parameters identified as the most sensitive in a previous study were selected for the MCA and DYNIA (Watson et al., 2021b). These parameters likewise were presumed to have the largest impact (most sensitive) on the simulated streamflow time of concentration. Using a met-model approach the MCA parameters were increased/decreased between θ_{dry} and θ_{wet}. Furthermore, the effects of these increases/decreases on the simulated streamflow were determined. The results from the MCA were analyzed using DYNIA for the periods 1984–2014 with a moving window of 300 days and a fixed box count of 10 with an interval of 100.

RESULTS

To understand the factors which impact model performance during periods of drought, these results included the simulated and observed streamflow during dry periods (1995, 1998, 2000, 2003–2004, and 2011) using parameter sets $\theta_{long-term}$ and θ_{dry}. Additionally, parameters set $\theta_{long-term}$ and θ_{wet} were used as a comparison for wet (1984–1997, 1999, 2001–2002, and 2005–2010) periods. The different parameter sets were used to understand conceptual rainfall-runoff relationship changes which occur during these periods and how the model parameter adjustments were required to capture this behavior. The analysis of these different parameter sets included the breakdown of the water balance, with particular reference to the storage changes. The temporal uncertainty analysis (DYNIA), together with the SMDI simulation of the catchment (after Watson et al., 2022) were used to identify parameters affected by "dry" and "wet" periods. Surface runoff as RD1, interflow as RD2, fast groundwater flow as RG1 and slow groundwater flow as RG2 represent the conceptual simulated flow components by the model. Likewise, they are visualized using the hydrographs but also spatially as a sub-catchment flow contribution in the results. For further region-specific drought characterization refer to Section ENVIRONMENTAL SETTING (Watson et al., 2020, 2022).

Simulated and Observed Streamflow

While the JAMS/J2000 model was run on a daily timestep and performance evaluated using daily data, the resultant plots and tables aggregate streamflow as daily averages each month, and as an average three-month yearly split (DJF, MAM, JJA, SON) to depict the model's ability to simulate the seasonal dynamics of the catchment. In general, and using the long-term parameters, the model was able to achieve a E2 of 0.59, LogE2 of 0.50 and bias of 0.15 for the dry periods compared with the long term (1984–1995) calibration with an E2 of 0.81, LogE2 of 0.87 and bias of −0.07 (**Table 3**, **Figure 5**). The long-term parameters generally underestimated streamflow during DJF months by 38% with an average simulated streamflow of 1.7 m^3s^{-1} for January months compared with the observed of 3.0 m^3s^{-1} (**Figure 5**). MAM and SON months were better simulated with an average difference of 10%, most noticeably with an average simulated streamflow of 7.3 m^3s^{-1} compared with the observed of 7.3 m^3s^{-1} for the October months. Unlike the model under simulations for DJF, MAM and SON months, the model tended to over simulate streamflow in JJA by as much as 29%, highlighted by an average simulated streamflow of 31.1 m^3s^{-1} compared with the observed of 21.8 m^3s^{-1}. The 1996–2004 model validation using the long-term parameters achieved a E2 of 0.77, LogE2 of 0.70 and bias of −0.01 compared with a E2 of 0.80, LogE2 of 0.82 and bias of 0.02 for the periods 2009–2014 (Watson et al., 2022).

Using the dry parameters, the model calibration was able to achieve a E2 of 0.77, LogE2 of 0.76 and bias of 0.03 for the dry periods (**Figure 5B**). The dry parameters generally overestimated streamflow by 5% for DJF and JJA months, while streamflow for MAM months were overestimated by as much as 13%. The best simulated streamflow was for February months with 3.0 m^3s^{-1} compared with an observed of 3.0 m^3s^{-1}. The worst months include May with a simulated streamflow of 11.0 m^3s^{-1} compared with 8.4 m^3s^{-1} which was observed. Unlike the model overestimations for DJF, JJA, and MAM months, SON was underestimated by around 9% with most noticeable deviations for September months with a simulated streamflow of 11.7 m^3s^{-1} compared with 14.5 m^3s^{-1} observed. For the validation period the "dry" parameters achieved an E2 of 0.60, while LogE2 was 0.28.

For the wet periods, the model calibration achieved a E2 of 0.74, LogE2 of 0.82 and bias of 0.01 using the wet parameters (**Figure 5B**). In comparison, the long-term parameters resulted in a E2, LogE2 and bias of 0.70, 0.78, and −0.04, respectively, for the wet periods. In general, the wet parameters underestimated streamflow in DJF and SON by as much as 27%, highlighted by

TABLE 3 | The selected parameters (from the NSGA-II) used for the JAMS/J2000 model to capture the hydrological behavior of the Berg River catchment, showing the Nash-Sutcliffe Efficiency (NSE; Nash, 1970) in standard form (E2), logarithmic form (logE2) results for the calibration (long-term 1984–1995, dry 1995, 1998, 2000, 2003–2004, and 2011, and wet 1983–1997, 1999, 2001–2002, and 2005–2010) and validation periods (1: long-term 1996–2004, 1: dry 2015–2018) (2: long-term 2009–2014).

Name of parameter	Type	Description of parameter	Calibration range	Parameter sets		
				Long term	Dry	Wet
AC_Adaptation	**Soil-water**	**Multiplies the volume of the large pore storage of soil**	**0.8–1.5**	**1.3**	**1.5**	**0.9**
FC_Adaptation	Soil-water	Multiplies the volume of the middle pore storage of soil	0.8–1.5	1.5	1.5	1.5
soilLinRed	ET	Actual ET parameter, governing the reduction of potential ET according to the soil moisture	0–10	0.9	0.1	0.1
soilDiffMPSLPS	Soil-water	MPS/LPS diffusion coefficient	0–10	8.4	0.0	4.0
soilDistMPSLPS	Soil-water	MPS/LPS distribution coefficient for inflow	0–10	5.7	0.2	0.1
soilMaxInf Summer	**Soil-water**	**The maximum infiltration capacity of soil in the summer period**	**0–200**	**197.0**	**199.7**	**140.1**
soilMaxinfWinter	Soil-water	The maximum infiltration capacity of soil in the winter period	0–200	119.0	198.7	195.9
soilConcRD1	Soil-water	Surface runoff delay parameter	0.5–5	1.5	1.3	1.1
soilConcRD2	**Soil-water**	**Interflow delay parameter**	**0.5–5**	**4.8**	**5.0**	**1.6**
soilOutLPS	Soil-water	Outflow parameter of the large pore storage	0–10	6.9	0.2	0.0
soilMaxPerc	Soil-water	Conductivity adaption parameter for leaching water to the groundwater storage	0–20	13.6	20.0	19.9
soilLatVert	Soil-water	Distribution coefficient for LPS outflow to lateral and vertical flow path	0.1–10	9.8	9.8	9.8
gwRG1RG2dist	Groundwater	Distribution parameter for the slow and fast groundwater runoff	0–1	0.6	0.7	0.9
gwRG1Fact	**Groundwater**	**Fast groundwater (slow interflow) delay**	**0–10**	**9.0**	**2.5**	**10.0**
gwRG2Fact	**Groundwater**	**Base flow delay**	**0–10**	**0.0**	**9.0**	**0.0**
flowrouteTA	**Flow routing**	**Stream routing parameter (overall dampening of the hydrograph)**	**0–20**	**10.5**	**7.9**	**5.4**
Efficiencies	**Calibration**	E2	**0–1**	0.81	0.77	0.78
		LogE2	**0–1**	0.87	0.76	0.87
	Validation1	E2	**0–1**	0.77	0.60	n/a
		LogE2	**0–1**	0.70	0.28	n/a
	Validation2	E2	**0–1**	0.63	n/a	
		LogE2	**0–1**	0.56	n/a	

Bold parameters form part of the temporal model uncertainty analysis (DYNIA).

an average simulated streamflow of 6.0 m^3s^{-1} compared with an observed of 8.2 m^3s^{-1} for November months. MAM and JJA streamflow tended to be over simulated by as much as 18% and in particular for June where daily average simulated streamflow was 55.7 m^3s^{-1} compared with 44.7 m^3s^{-1} observed.

Simulated Flow Components

While the hydrographs were used to compare the long-term, dry and wet parameters for the entire modeling duration (1984–2014), the spatial plots and contribution statistics (**Table 4**) compare the dry and wet parameters with long term parameters under both dry (**Figure 6**) and wet (**Figure 7**) periods.

The hydrograph of the long-term parameter model was dominated by RG2 with 40% of the total flow, followed by RD1, RG1, and RD2 with 27, 17, and 16%, respectively (**Figure 5C**). August generated the largest amount of RG2 with 375 mm/year followed by 323 mm/year of surface runoff in July. The hydrograph of the wet parameter model was likewise dominated by RG2 but with 42% of the total flow, followed by RD2, RD1, and RG1 with 24, 22, and 12%, respectively. July generated the largest amount of RG2 with 454 mm/year followed by 414 mm/year for RG2 in August. The hydrograph of the dry parameter model was likewise dominated by groundwater, but in the form of RG1 with 43% of the total flow, followed by RD2, RD1, and RG2 with 28, 24, and 5%, respectively. July generated the largest amount of flow, but in the form of RD1 with 245 mm/year followed by 235 mm/year for the same month from RD2.

During the dry period, RD1 using both the long-term and dry parameters was dominated by contributions from the catchment headwaters (southern tip and east boundary) with only a 3% contribution difference between the two parameter sets and a flow of 170–320 mm/yr (**Figure 6**). While there was a 10% contribution difference in RD2 between the long-term and dry parameters, similar spatial contributions were simulated for the dry period. Using the long-term parameters groundwater flow was split between RG1 and RG2 as 21 and 39%, respectively for

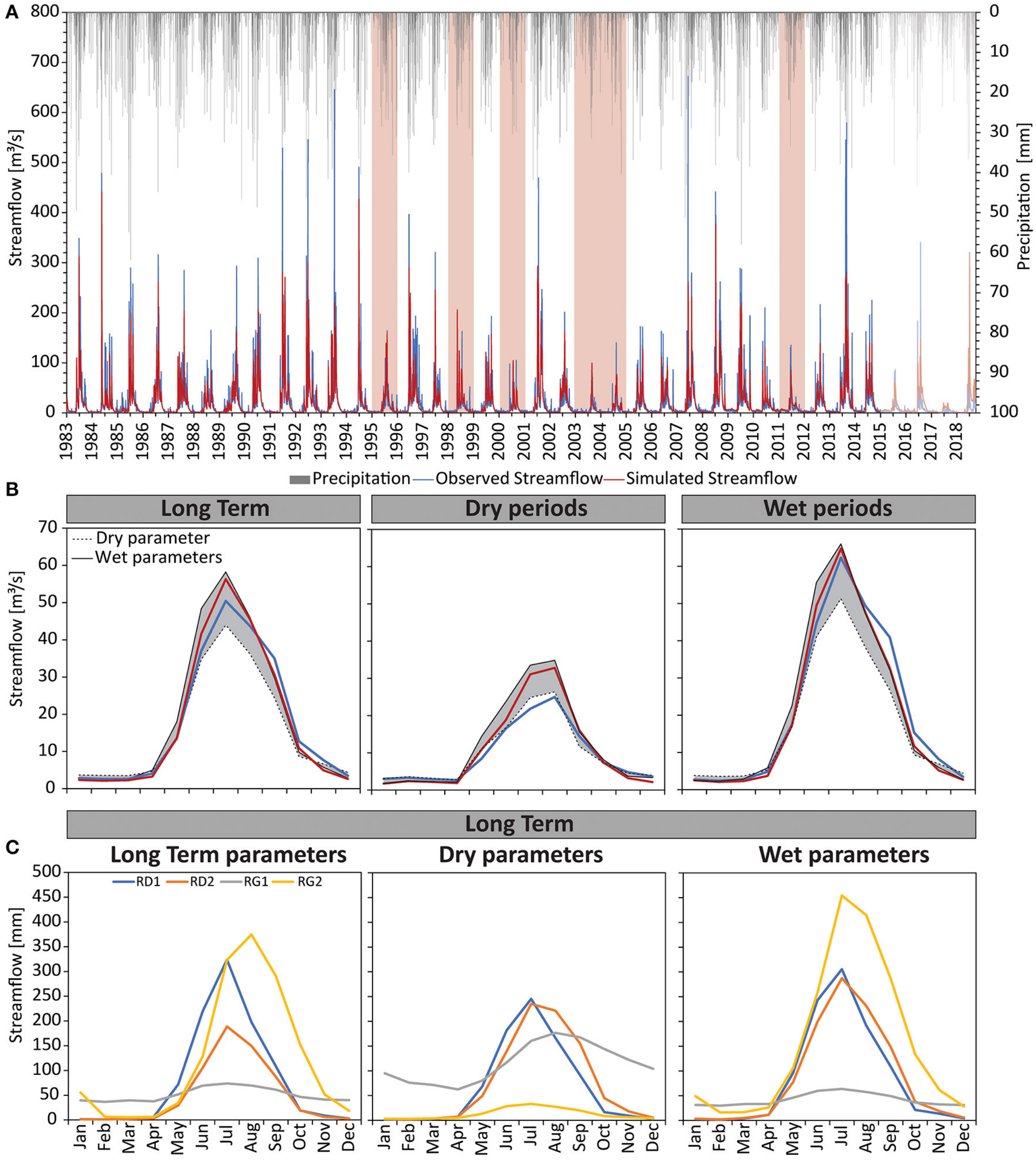

FIGURE 5 | (A) The long-term (1984–2018) time series of the simulated (red line) and observed streamflow (blue line) with precipitation (gray bar) and the identified dry periods (1995, 1998, 2000, 2003–2004, and 2011) (pink bar). **(B)** The simulated monthly hydrograph for the long term timeseries, dry and wet periods using $\theta_{long-term}$, θ_{dry} and θ_{wet} where the dry (dashed line) and wet (black line) parameters form the upper and lower simulation limits (grayed area). **(C)** The difference between the simulated hydrological flow components using $\theta_{long-term}$, θ_{dry} and θ_{wet} where RD1 was surface runoff (blue line), RD2 was interflow (orange line), RG1 was fast groundwater flow (gray line) and RG2 was slow groundwater flow (yellow line). $\theta_{long-term}$ and θ_{wet} had a similar flow component breakdown with a dominance of surface runoff and slow groundwater flow, unlike θ_{dry} where the flow components were more equally split between surface runoff and interflow with fast groundwater the next most dominant.

the dry period. RG2 using the long-term parameters simulated major contributions from valley areas in the south and east boundary of the catchment. Unlike the groundwater contribution using the long-term parameters for the dry period, when using the dry parameters RG1 contributed 51% compared with only 2% from RG2. Furthermore, the catchment valley contributed limited RG2 and the bulk from RG1 of 20–100 mm/yr for most of the valley sub-catchments.

During the wet period, RD1 was simulated as a maximum of 530 mm/yr in the catchment headwater area (**Figure 7**) with

TABLE 4 | A summary of the total flow contribution and the percentage of simulated surface runoff (RD1), interflow (RD2), fast groundwater (RG1) and slow groundwater (RG2) using the parameters $\theta_{long-term}$, θ_{wet} and θ_{dry} for wet periods (1983–1997, 1999, 2001–2002, and 2005–2010) and dry periods (1995, 1998, 2000, 2003–2004, and 2011).

Parameters	RD1 (mm/yr)	RD2 (mm/yr)	RG1 (mm/yr)	RG2 (mm/yr)	Total (mm/yr)
Wet periods					
Long term	21,523	12,255	12,409	34,707	80,894
Contribution (%)	27	15	15	43	N/A
Wet	22,022	21,738	8,702	43,632	96,094
Contribution (%)	23	23	9	45	N/A
Dry periods					
Long term	10,686	5,758	8,769	15,996	41,209
Contribution (%)	26	14	21	39	N/A
Dry	9,164	9,319	20,149	757	39,389
Contribution (%)	23	24	51	2	N/A

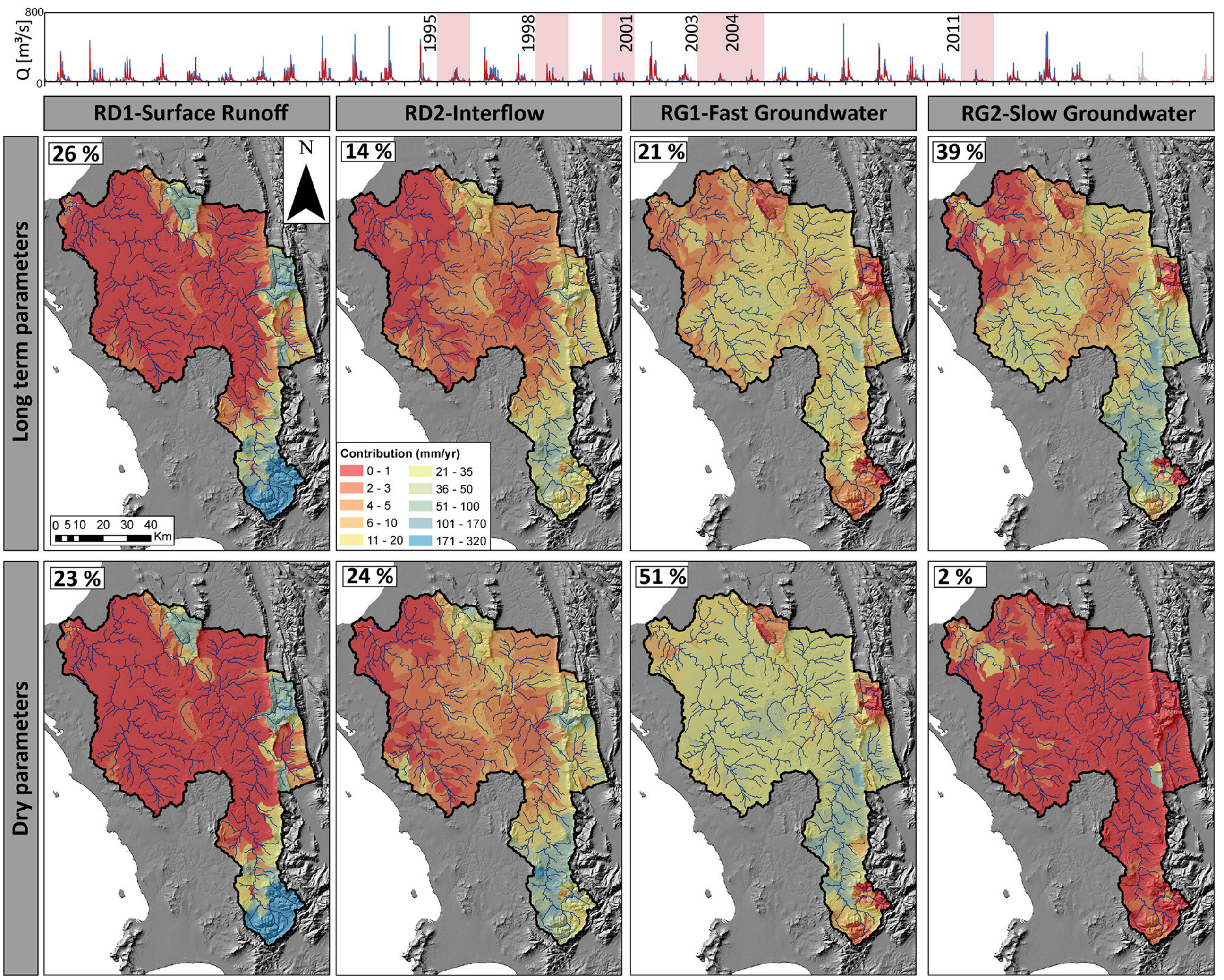

FIGURE 6 | The long-term (1984–2018) time series of the simulated (red line) and observed streamflow (blue line) with the yearly contribution of surface runoff (RD1), interflow (RD2), fast groundwater (RG1) and slow groundwater (RG2) for the identified dry periods (1995, 1998, 2000, 2003–2004, and 2011) using the parameters $\theta_{long-term}$ and θ_{dry} with the average percentage contribution for each of the flow components. Spatially $\theta_{long-term}$ and θ_{dry} were similar, with a dominance of flow in the catchment headwater areas (south), but differed by the total contribution for interflow (10%), slow (30%) and fast groundwater (37%).

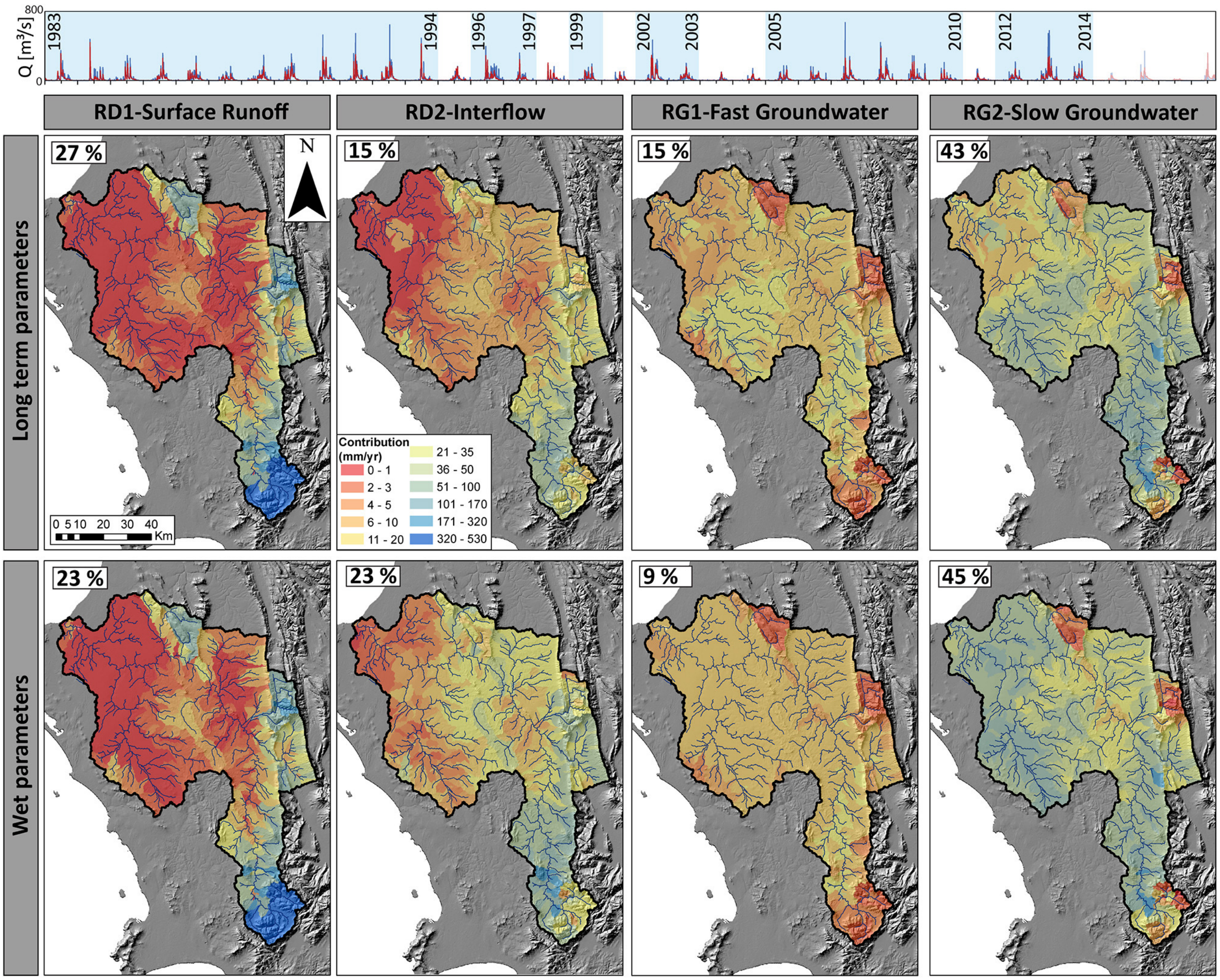

FIGURE 7 | The long-term (1984–2018) time series of the simulated (red line) and observed streamflow (blue line) with the yearly contribution of surface runoff (RD1), interflow (RD2), fast groundwater (RG1) and slow groundwater (RG2) for the identified wet periods (1983–1997, 1999, 2001–2002, and 2005–2010) using the parameters $\theta_{long-term}$ and θ_{wet} with the average percentage contribution for each of the flow components. Spatially $\theta_{long-term}$ and θ_{wet} are similar, but differ by the contribution of interflow (8%) and fast groundwater (6%).

a parameter set contribution difference of 4%. The parameter sets produced similar representations of RG1 and RG2, differing by 6 and 2%, respectively. Spatially valley areas contributed the most RG2 with between 35 and 100 mm/yr for both the long-term and wet parameter sets. RD2 was the major difference in the simulated flow components between the long-term and wet parameter sets with an 8% difference and between 2 and 20 mm/yr flow nearest the outlet compared with 0–5 mm/yr flow for the long-term parameters.

Simulated Water Balances and Time of Concentration

Overall, simulated streamflow as a percentage of the total water balance (including storage changes) was simulated as 15, 13, and 16%, respectively for the long-term, dry and wet parameter sets for the periods 1984–2014 (**Figure 8**). Simulated storage, which was determined as the difference between precipitation, evapotranspiration and streamflow, was between −177 (loss) and 79 (gain) mm/yr for the wet parameter set, compared with −43 to 23 mm/yr and −37 to 20 mm/yr for the long-term and dry parameter set, respectively. For the dry years 1995 and 1998, both long-term and dry parameter sets simulated a storage gain, with an average of 13 and 11 mm/yr respectfully. The dry years 2000, 2003–2004, and 2011 were simulated as a storage loss, with an average of −4 and −2 mm/yr using the long-term and dry parameter sets. Wet years, such as 1996, 2001, and 2002 were simulated with an storage loss of 117 mm/yr using the wet parameters compared with 2 mm/yr for the long-term parameters. The resultant effect of the dry, wet and long-term parameters was a streamflow time of concentration (TC) of 4, 2, and 5 days, respectively.

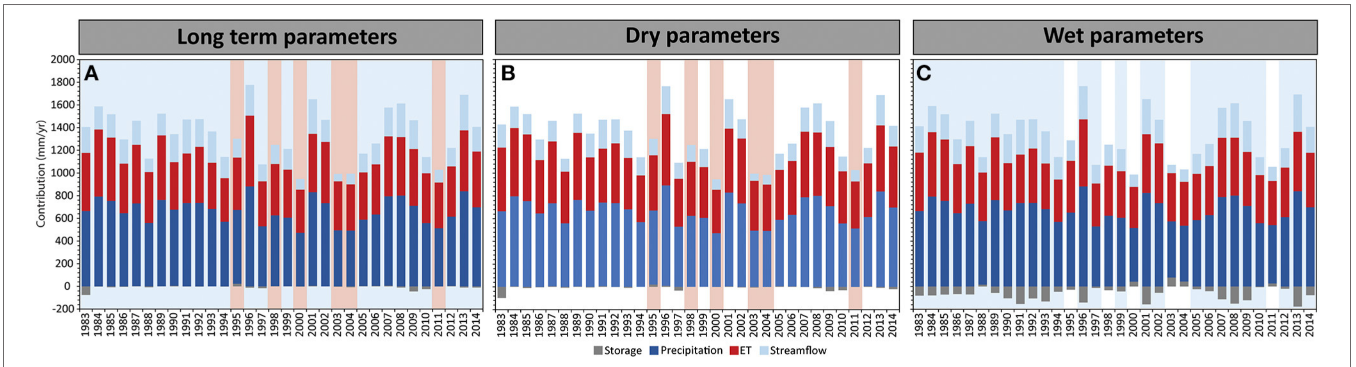

FIGURE 8 | The simulated water balance (mm/yr) for the periods 1984–2014 (including 1 year of initialization 1983 to show storage stabilization), which includes yearly precipitation (P: blue bar), evapotranspiration (ET: red bar), streamflow (Q: light blue bar) and storage (ΔS: gray bar) using the **(A)** $\theta_{long-term}$, **(B)** θ_{dry}, and **(C)** θ_{wet} parameter sets. **(B)** $\theta_{long-term}$ and θ_{wet} differ with simulated storage (55 mm/yr), but was similar in terms of ET (12 mm/yr). $\theta_{long-term}$ and θ_{dry} were similar in terms of simulated storage (1 mm/yr) but differ in terms of simulated ET (27 mm/yr).

Temporal Model Uncertainty

The deviation between the upper and lower bounds for the simulation period (1984–2014) and changes in the "best" parameter value (dark gray pixels) illustrate parameters which impact the temporal uncertainty of the model (**Figure 9**). The impact of the baseflow delay parameter (gwRG2Fact) and the maximum infiltration capacity of the soil (soilMaxInfSummer) was limited, as the "best" value for gwRG2Fact was constant at <0.02 and 155 for the soilMaxInfSummer parameter (but had limited sensitivity). During the periods 1995–2005, the surface runoff delay parameter (soilConcRD2) was stable and "best" around the maximum value of 4.8. For the same period, scaling of air capacity (AC_Adaptation) had likewise limited temporal uncertainty with a "best" value of 1.45, but uncertainty increased during the transition between wet and dry periods (**Figure 10**). The fast groundwater delay parameter (gwRG1Fact) during the periods 1995–2005 was temporally uncertain during the transition between dry and wet periods, but mostly tended toward a "best" value of 3. The streamflow routing parameter which dampens the overall hydrograph (flowrouteTA) for the periods 1995–2005 tended around the "best" value of 7.8, but was more optimal at 5.5 during the wet periods between 2001 and 2003 (**Figure 9**). For the periods 1984–1994 and 2005–2010, which were mainly wet, AC_Adaptation, gwRG1Fact and SoilConcRD2 the optimal values varied between the upper and lower bounds. The drought of 2011 resulted in temporal uncertainty in AC_Adaptation, gwRG1Fact, SoilConcRD2 and wet periods of 2012–2014 resulted in the "best" value of flowrouteTA tending to 5.5 compared with prior values of 7.8.

DISCUSSION

The application of conceptual rainfall-runoff models calibrated under relatively common normal, i.e., well understood, climatic conditions can significantly affect the interpretation of hydrological responses both observed under climate extreme conditions, and their projection using future climate scenarios. Such application risks the advancement of mal-adaptive responses to climate change, and inappropriate allocation of scarce resources. Given the risk that climate change poses to the Western Cape and much of semi-arid Southern Africa, the aim of this paper was to assess model related performance and uncertainty under extreme climate conditions, referred to as "wet" and "dry" periods and the applicability of conceptual rainfall-runoff models for future climate change-based assessments in Africa. Natural vegetation cover changes in the Berg River were estimated to have increased by more than 14% from 1986/7 to 2007 (Stuckenberg et al., 2012), which impacts streamflow and temporal model uncertainty, but were not considered. Furthermore, irrigation which was estimated as 5% of the total catchment area (van Niekerk et al., 2018) did not form part of the modeling approach, due to limitations in the current water use estimates for different vegetation types in the catchment.

A shift by the agricultural sector and the increase in domestic groundwater use has been suggested to aggravate the drought conditions in the Western Cape of South Africa and the meteorological and agricultural droughts progression to more severe long-term forms (hydrological and groundwater drought) (Watson et al., 2022). This was supported by local aquifer level measurements, satellite-based groundwater thickness reductions (Gravity Recovery and Climate Experiment: GRACE) and hydrological change drawn from rainfall-runoff models. While, the presumed increase in groundwater use was supported by a multitude of factors, current rainfall-runoff models assume stable storage conditions and the signal to noise ratio (Xue et al., 2013) during dry periods affects model performance and uncertainty. This approach uses the JAMS/J2000 model as a metric of other conceptual rainfall-runoff models, but large differences in the representation of hydrological processes have even been reported between different conceptual rainfall-runoff models where the signal to noise ratio is low (Arnaud et al., 2011; Hattermann et al., 2017; Eeckman et al., 2019). Furthermore, it is likely that more physically based models, such as SWAT (Arnold et al., 1998) and TOKAPI (Ciarapica and Todini, 2002) could respond differently to climatic extremes based on model structures,

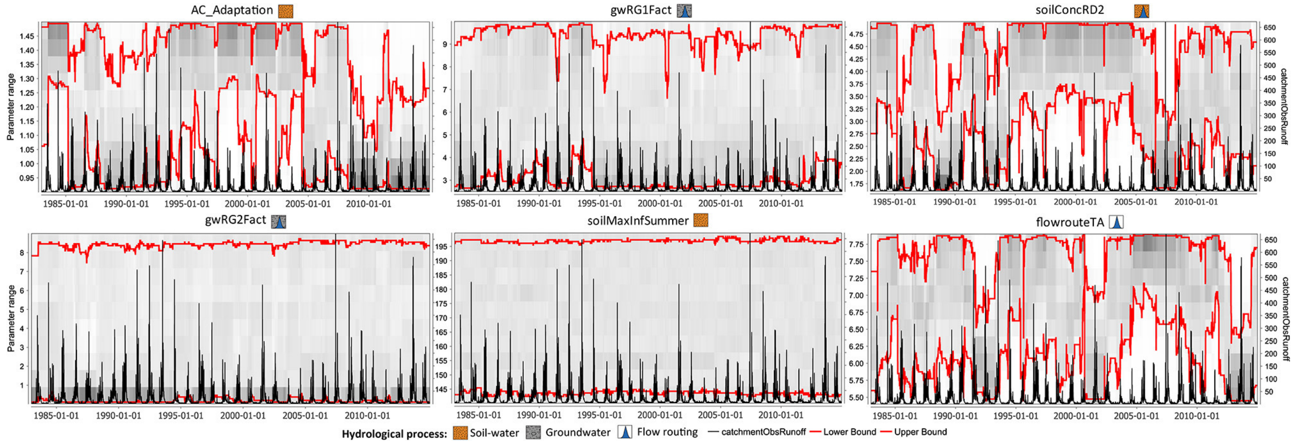

FIGURE 9 | The Dynamic Identifiability Analysis (DYNIA: Wagener et al., 2002) using the Nash–Sutcliffe (NSE; Nash, 1970) efficiency in standard form (E2) for the selected parameters showing the upper and lower parameter bounds of the Monte Carlo Analysis (MCA: red line). The soil-water parameters include scaling of air capacity (AC_Adaption), the Surface runoff delay parameter (SoilConcRD1) and the Maximum infiltration rate during summer parameter (soilMaxInfSummer). Groundwater parameters include Fast groundwater delay (gwRG1Fact), Slow groundwater delay (gwRG2Fact). The routing parameters include the Surface runoff delay parameter (SoilConcRD1), Fast groundwater delay (gwRG1Fact), Slow groundwater delay (gwRG2Fact) and the stream routing parameter (FlowrouteTA). Parameters which have temporal uncertainty show a variability in the upper and lower parameter bounds and where the “best” parameter sets (gray blocks) varies across the simulated time series. These parameters include the AC_Adaption, gwRG1Fact, SoilConcRD1 and FlowrouteTA.

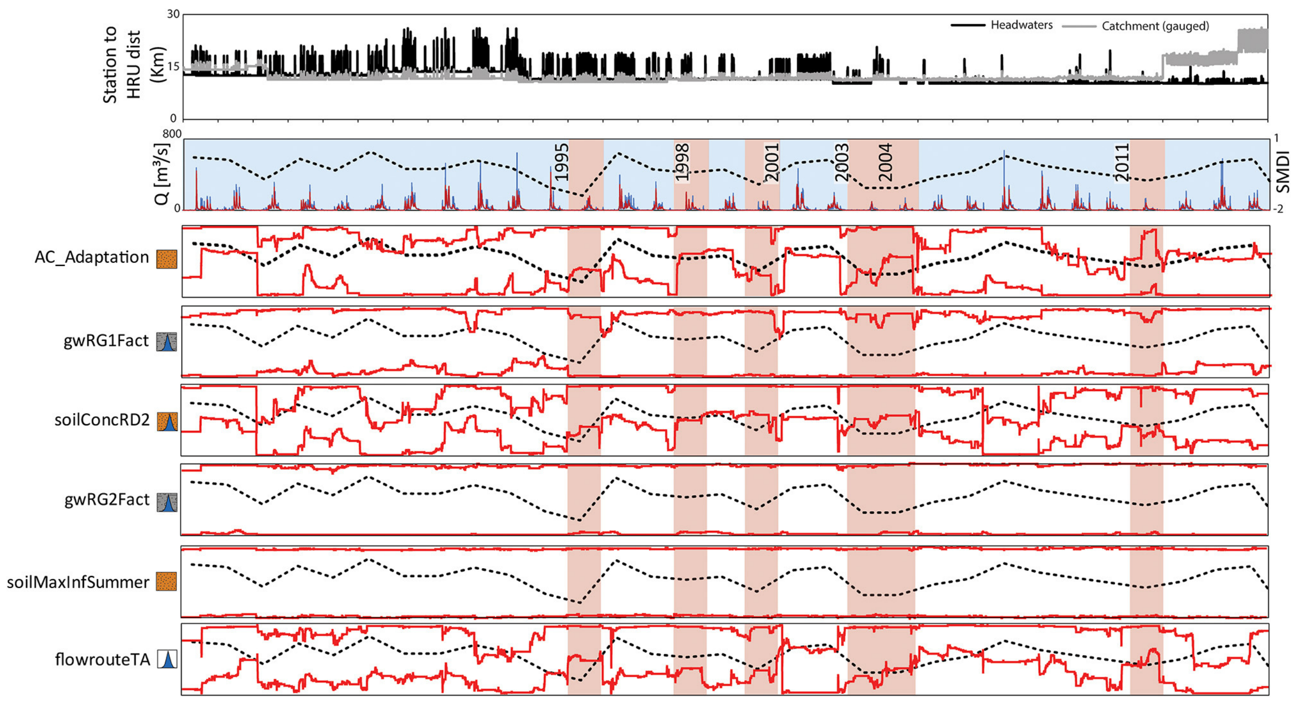

FIGURE 10 | The precipitation to HRU distance in the catchment headwater (black line) and for the gauged portion (gray line), simulated (red line) and observed streamflow (blue line), the simulated Soil Moisture Deficit Index (black dashed line) (after Watson et al., 2022). The upper and lower bounds of the Dynamic Identifiability Analysis (DYNIA) using the Nash–Sutcliffe (NSE; Nash, 1970) efficiency in standard form (E2) for the selected parameters showing temporal parameter uncertainty, considering the station to HRU distance, simulated SMDI and the streamflow for different “dry” and “wet” periods. The alignment of these three datasets show three periods of similar model uncertainty from 1984–1994, 1995–2005, and 2006–2014.

but also when considering additional measures of hydrological processes (soil moisture, evapotranspiration, deep percolation) to validate process simulations.

Impact of Climate Extremes on Model Uncertainty

In a related study for the Berg River, Watson et al. (2022) illustrated that the performance of the JAMS/J2000 model varied for different "dry" and "wet" years and where a "good" simulation (NSE > 0.6: Waters, 2014), using a single long term parameter set, was possible for a yearly meteorological shortfall of 28%, which also corresponded to a 53% reduction in MAM precipitation. After this threshold was exceeded, model related performance dropped to an NSE of 0.59 in 2000, and more significantly to 0.26 (Watson et al., 2022) for the years 2015–2017 (although groundwater abstractions were not considered by the model), where the meteorological shortfall was 32–34% (70% reduction in MAM precipitation). As dry periods lower the signal to noise ratio and the water balance becomes tighter, different parameter combinations become better suited and changes in simulated flow components can often be required. Furthermore, seasonal shift such as the reduction of precipitation for MAM, which reduces soil-moisture prior to winter (JJA), impacts streamflow dynamics and peak flow. Most noticeable were changes to the time of concentration, where TC reduced by 1 day between the different dry and long-term parameters. Furthermore, there were changes to the overall contribution of fast and slow groundwater, but these flow components are more conceptual than driven by physical data. The overall outcome on the simulated hydrology using the long-term, "dry" and "wet" parameters is not unexpected given that this study utilizes a single downstream calibration. River flows in the Berg River catchment are particularly dependant on headwater contributions, and while these areas were highlighted as the most affected in Watson et al. (2022), the headwater gauging records show the largest amount of change and a concern for regional water security.

The temporal uncertainty analysis DYNIA showed parameter sensitivity changes during different "dry" and "wet" periods (**Figures 8**, **9**). In particular, the scaling of air capacity (AC_adaptation), a highly sensitive parameter which can affect the simulation of different flow components and TC, showed uncertainty after 2004 and remains stationary past the drought of 2011 where SMDI was between −0.5 and 0.5. Some of this uncertainty, can be attributed to the construction of the Berg River dam in 2004 which also affected the temporal uncertainty of the simulated interflow rate (soilConcRD2) and not represented by SMDI. The use of the reservoir component, which substitutes simulated streamflow with reservoir outflow, could further affect model parameter sensitivity after 2006. While there was still a large amount of noise using DYNIA for the periods 1984–1994, where SMDI was between 0.3 and −0.5, the shift between "dry" to "wet" conditions or vice versa, resulted in the largest amount of parameter uncertainty for the analysis period. From our study we conclude that links between temporal model uncertainty and meteorological/agricultural drought indices can improve the understanding of model capabilities in the light of future non-stationary climate conditions, although data availability and its variability influences model applications in Southern Africa. Furthermore, reliable forecasting systems at seasonal and sub-seasonal scale require the integration of hydrological modeling tools with other hydro-climatic indicators and tracers to consider the associated system change during climatic instabilities.

Development of Dynamic Parameter Rainfall-Runoff Models

The number of parameters with which a model simulates hydrological behavior is an important consideration during model development. Too few parameters result in poor seasonal and sub-seasonal simulations, while too many parameters result in model overfitting (e.g., Whittaker et al., 2010). The use of a set of "dry" parameters improved the model's performance for the dry analysis period (E2 of 0.59–0.76 and LogE2 of 0.50–0.78), as well as the 2015–2018 validation period with an improvement of E2 from 0.26 to 0.60. The availability and variability of climate data impacted the predictions made after 2014 (**Figure 10**), where the precipitation station to HRU distance increase by 5 km (15–20 km). Anthropogenic groundwater extraction may have affected the residual between simulated and observed low flows, although logE2 improved from 0.17 to 0.28 for the periods 2015–2018 when switching from the long-term to the dry period parameters. While the use of "wet" parameters also improved model performance for the wet periods (E2 0.70–0.74 and LogE2 of 0.78–0.82), these improvements are less significant for semi-arid WC. The resultant effect is that for future predictions in Mediterranean WC, a "dry" set of parameters are recommended for periods where meteorological shortfalls exceed 28% per year and where MAM precipitation is reduced by more than 50%. As a result, a dynamic parameter model, which may use drought indices, such as the Standardized Precipitation Index (SPI) or Standardized Precipitation Evapotranspiration Index (SPEI), as triggers has the potential to better account for climate extremes. While a "wet" parameter set is not recommended in the context of semi-arid Southern Africa, it might be more applicable for tropical regions and where a shift in monsoons are expected. Although this study focuses on the use of different parameter sets for climatic extremes, it should be noted that additional effort can still be placed in selecting a single more robust parameter set. For example, the long-term and "wet" parameters have a higher groundwater contribution than the "dry" parameters and additional metrics which validate flow component proportioning could be used to refine solutions generated by the NSGA-II. Likewise, multi-site/gauged calibrations have the potential to reduce the impacts of climatic extremes on model performance. These added modeling requirements highlight the need for dynamic and flexible modeling systems, which will be required in simulating future climatic extremes and this was demonstrated by these results.

Implications for Water Management

Climate change will impact water availability and in turn likely cause changes in land use and increases in anthropogenic water use. These changes have already occurred within the

2015–2018 drought for the WC and understanding the impacts to the water cycle components and the feedback loops of different hydrological processes is important and ongoing. As groundwater becomes a resource with which municipalities and water management agencies use to reduce the risk of climate change, understanding the cause-and-effect relationship between groundwater recharge and changes in precipitation seasonality is important for the management of this resource in a sustainable manner.

Projections of future hydrological conditions, built off processed based distributed modeling, are needed by a variety of stakeholders, who oversee the management of water resources, particularly in the context of catchment water management agencies and municipalities. As the results from hydrological modeling systems become increasingly more important for water management under climate change, there is a growing need for cross sectoral management including dam management, agricultural and mining activities as well as domestic and industry water consumption for water yield planning. For assessing the impact of increasing climate extremes as anticipated in Mediterranean South Africa, this requires modeling approaches which are well-understood and verified in terms of their performance, uncertainty, limitations and potential. Additionally, the importance of continuing scientific monitoring and the development of new approaches/tools are required to reduce hydrological projection uncertainty under climatic change. In particular for the WC, understanding the increased groundwater consumption and the quantification of these amounts are required if future model predictions are to be useable.

CONCLUSION

The ability to simulate catchment hydrological behavior is dependent on data availability and variability, as well as the model calibration and validation approach. Predictions of hydro-meteorological extremes, such as droughts, are often not well simulated when observed infrequently within the calibration period, but crucial for the assessment of climate and hydrological risk and their current and future management. As the occurrence and duration of these extremes are likely to increase in the future in Mediterranean South Africa, model performance, uncertainty and representation need to be assessed during different climatic extremes. In our study, we have shown that a temporal uncertainty analysis provides the means to assess model parameters which are impacted by different "wet" and "dry" periods. For JAMS/J2000 model of the Berg River catchment, soil-water storage, timing of interflow, and groundwater flow, as well as the overall dampening of the simulated hydrograph were the parameters most affected by climatic extremes. Furthermore, the predicted time of streamflow concentration shifted when using different "dry" and "wet" period parameters, affecting the simulated peak flow. Although long-term model simulations are required for climate change predictions, a switch between "dry" and long-term simulations are recommended for future model applications in the region. Furthermore, long-term historical calibrations are unlikely to have the capabilities to simulate future hydrological flows and further model developments are still required for parameters affected by climate variabilities.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

Conceptualization and writing—reviewing and editing: AW, PR, JH, and GM. Methodology and software: AW and SK. Data curation and writing—original draft preparation: AW and JH. Visualization and investigation: AW. Project administration: JH and GM. Software and validation: SK and AW. All authors contributed to the article and approved the submitted version.

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From research to practice: Adapting agriculture to climate today for tomorrow in Ethiopia

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Eighty percent of the world's agriculture is rainfed, making it highly vulnerable to climate fluctuations and stresses, such as those brought about by climate variability and change. Sub-Saharan Africa and Ethiopia in particular have experienced a significant increase in climate variability over the past decade, which has led to more frequent weather extremes such as floods and droughts. Because 85% of Ethiopia depends upon agriculture for its livelihoods, such rainfall shortages or excesses can impede food production, access to financial and natural assets, and the ability to recover in subsequent crop seasons. This means that climate variability in agriculture not only affects the availability of the food Ethiopians consume, but also the income of its smallholder farmers. Variability in rainfall and temperature can also have adverse effects on livestock and the pastoralists whose livelihoods depend upon it. Thus, all development planning and practice in the agriculture and related sectors need to take climate variability and long-term climate change into account. Climate services can contribute to the alleviation of a range of climate-sensitive development challenges, including agricultural production and food security. The Adapting Agriculture to Climate Today for Tomorrow (ACToday) approach of the International Research Institute for Climate and Society (IRI), Columbia University, USA, aims to develop climate service solutions through enhancement of the availability and effectiveness of climate information in national policy, planning, management, and other decision-making processes in countries that are particularly dependent on agriculture and vulnerable to the effects of climate variability and change. It targets improved food security, nutrition, environmental sustainability and economic outcomes in these countries by promoting the use of climate information and services to manage current climate risks, while laying the foundation for adaptation to future climatic conditions. In this Perspective, we share experiences from the implementation of the ACToday project and approach in Ethiopia, outlining its accomplishments and challenges. In doing so, we characterize best practices and pitfalls to avoid to ensure climate knowledge and information truly meet the needs of climate-informed decision making and climate-smart policy and planning. We also outline pragmatic guidance to ensure activities designed to evolve climate research into services are done so appropriately, responsibly, and sustainably to bridge the gap between those who produce climate information and those who ultimately use it.

KEYWORDS

climate services, food security, SDG2: zero hunger, agriculture, Ethiopia, resilience, climate information, climate variability

Introduction

Changes in climate have resulted in widespread, pervasive impacts to ecosystems and people, including increases in the intensity of weather extremes such as droughts and floods (IPCC, 2021). Such shifting temperature and precipitation patterns have affected the productivity of many climate-sensitive sectors, especially agriculture, resulting in reduced food availability and increased food prices, ultimately jeopardizing food security, nutrition, and livelihoods of millions of people across the globe (IPCC, 2022). The implications of this challenge are especially pronounced in places like Ethiopia where over 85% of the population representing more than 70 million people (USAID, 2021) are reliant upon rain-fed agriculture sector for their livelihoods. It is here that climate extremes such as drought have caused widespread failure of seasonal crops, inadequate forage and massive deaths of livestock in pastoralist communities, and hunger affecting millions of people and resulting emergency food aid averaging $1.1. billion per year (Mera, 2018). And it is here that even in the absence of extremes, changing seasonality—such as rainy season onset, cessation, and duration of the rainy season (Wakjira et al., 2021)—necessitates the use of climate information to inform agricultural planning.

The availability of climate information, however, has not automatically resulted in its effective use in decision-making processes to support adaptation in Ethiopia or elsewhere generally. For this to happen, the information has needed to be made accessible and appropriately tailored to match what users need in terms of skill, scale, and lead time, and produced in formats that can be well-integrated within knowledge systems (Machingura et al., 2018; Singh et al., 2018). Indeed, successful examples of the use of climate information in decision-making in wider Africa have predominantly used daily, weekly, and seasonal climate information—in other words, information over short time horizons—with very little evidence of long-term climate projections being integrated into local decision-making, particularly for farmers, pastoralists and sub-national governments (Stone and Meinke, 2006; Jones et al., 2015; Singh et al., 2018).

Such is the case and the challenges confronting Ethiopia in the use of climate information in decision-making. Despite the priority placed on addressing issues of adaptation and resilience-building in strategic planning and a wide range of freely available and already existing climate information products, significant barriers still remain that inhibit theoretically useful information from actually being usable and ultimately used in adaptive decision-making. These barriers stem from a failure to recognize and account for the reality that the way theoretically useful information is transformed into sector-relevant and decision-relevant knowledge (translated), communicated to users (transferred), and the degree to which the user has the capacity to actually understand and act on the information (use), all of which affect whether and the degree to which the information enables climate adaptation. In other words, even the best-available climate information, when divorced from decision-making processes and poorly integrated within systems, institutions, and products that enable its use or fail to acknowledge the role of decision-makers in their design and refinement, can ultimately be doomed to be ineffective at supporting adaptation.

In this Perspective, we share experiences from the recently concluded Adapting Agriculture to Climate Today, for Tomorrow (ACToday) project in Ethiopia and its namesake approach, which acknowledges the ongoing and common disconnect between the availability of often high-quality climate information and its access and use on the ground. We do so with the purpose of outlining pragmatic guidance and examples of concrete strategies and decision support systems that can be employed to increase the relevance of climate information in decision-making at multiple levels in practice.

Approach

The Adapting Agriculture to Climate Today, for Tomorrow (ACToday) Columbia World Project (2017–2022) (Fiondella, 2021), which has been implemented in six agriculture-dependent countries (Figure 1) across the world (Ethiopia, Senegal, Vietnam, Bangladesh, Colombia, and Guatemala) embodies a holistic approach for improving the availability, access, and use of high-quality climate information that goes beyond its mere generation to recognize a broader ecosystem of actors and actions as necessary for enabling its effective application and design as services. In its mission to create

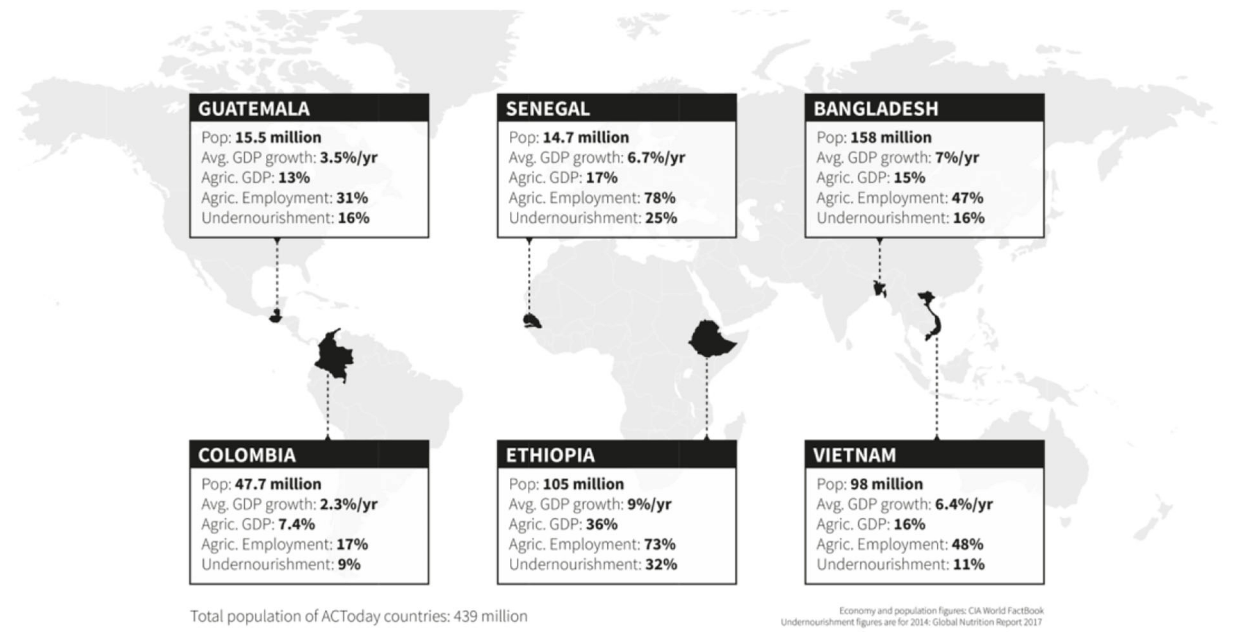

FIGURE 1
ACToday approach countries of implementation. The ACToday approach was intentionally mplemented in six agriculture-dependent countries with varying institutional arrangements, histories, cultures, and enabling environments across the world, in order to gain insights and lessons on how climate services might be best implemented in different contexts.

climate service solutions that help end hunger, achieve food security, improve nutrition, and promote sustainable agriculture (United Nations Sustainable Development Goal 2), it has adopted a framework that emphasizes four mutually reinforcing and interconnected "pillars" of climate services—generation, translation, transfer, and use—as foundational for supporting and enabling adaptive action (Figure 2).

Moreover, in its pursuit of advancing climate services that are useful, usable, and used, it recognizes that climate scenarios that project conditions 50 or 100 years in the future, while valuable for understanding longer-term climate change, are misaligned with the needs of decision-makers today, which are deeply impacted by shorter-term climate variability. Whether it is a farmer needing to make key agricultural decisions for a season or within a season based on temperature or rainfall patterns, a humanitarian aid worker who needs to anticipate and respond to climate extremes such as a drought or flood, or even a policymaker who must plan and arrange for agricultural inputs and investments annually, there is a need for climate information on shorter time and spatial scales that can pragmatically inform and be integrated within specific decisions and decision-making processes for adaptation (Stone and Meinke, 2006; Jones et al., 2015; Machingura et al., 2018; Singh et al., 2018). The ACToday approach rests on the premise that co-developing adaptive solutions that are relevant to the decision horizons and needs of today and accompanied by specific actions that are systematically integrated along the four pillars will also enable the kind of resilience building and systems architecture that enables adaptation tomorrow, in the long-run. And it was intentionally implemented in six agriculture-dependent countries with varying institutional arrangements, histories, cultures, and enabling environments across the world, in order to gain insights and lessons on how climate services might be best implemented in different contexts.

In Ethiopia, for example, the government has a clearly defined strategy for the implementation of the Sustainable Development Goals (SDGs), which have been integrated into its national Growth and Transformation Plan (GTP). All executive organs of the federal government, the regional states and city administrations implement SDGs as an integral part of the GTP. Moreover, the country has made significant investments in climate services information systems (Lennard et al., 2018) through the Ethiopian Meteorological Institute (EMI) and instituted a number of national and sectoral strategies, policies, programs, and plans including the Climate Resilient Green Economy (CRGE) strategy, the National Adaptation Plan (NAP), the second Five-Year Growth and Transformation Plan (GTP-II), the Agricultural Sector Policy and Investment Framework (PIF), and two phases of the Agricultural Growth Program (AGP). As such, the implementation of the ACToday approach in Ethiopia entailed supporting and strengthening the existing system and efforts by identifying key gaps in the provision of decision-relevant climate services and working with both national and international institutions along the entire

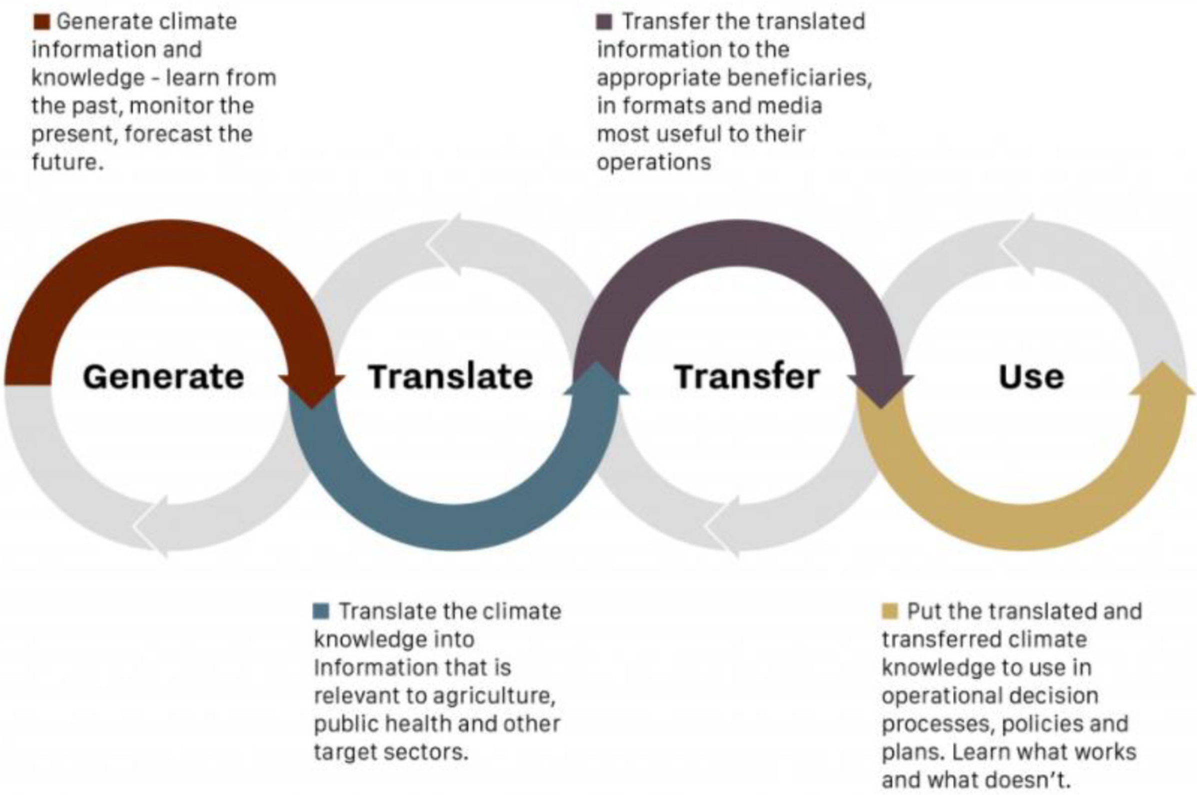

FIGURE 2
The four pillars of climate services. The four pillars of climate services include the generation, translation, transfer, and use of climate information. Source: Fiondella (2021).

spectrum of climate services and its functional pillars (Figure 3). This included the Ethiopian Meteorological Institute (the main institution for the "generation" and some "translation" of climate information), the Ethiopian Institute of Agricultural Research (the main gatekeeper of use of climate information and technology for the country responsible for its "translation and transfer"), and the Ministry of Agriculture (with its significant roles in both "transfer" and also "use" of climate information through its advisory and extension systems).

The goal of this Perspective, however, is not to unpack or compare the implementation of climate services amongst different ACToday project countries, which has been done elsewhere to some extent for Africa (Hansen et al., 2022). Rather, it is to give concrete examples of the implementation of a holistic approach to the development of climate services in the context of Ethiopia, accompanied by good practices arising from experience and research, that might inform the development of climate services in other contexts where strong political will and high-quality climate information have not materialized into climate-informed decision-making.

In what follows, therefore, we share experiences from the implementation of the ACToday approach in Ethiopia along each of the four climate services pillars, outlining accomplishments, challenges, and guidance shaped by both research and practice to ensure climate knowledge and information are transformed into services that meet the needs of climate-informed decision making and climate-smart policy and planning. In this context, the partnerships, initiatives, and tool development pursued were a direct reflection of an intentional strategy to address and connect the full spectrum of climate services along these pillars (Figure 3).

Decision-relevant climate services in action

Generation: Building the backbone of climate services

The generation of high-quality climate data underpins the quality of both the information and the services which are derived from it. As such, actions to improve the availability of reliable, timely, and trustworthy climate data are a critical first step in the development of effective climate services.

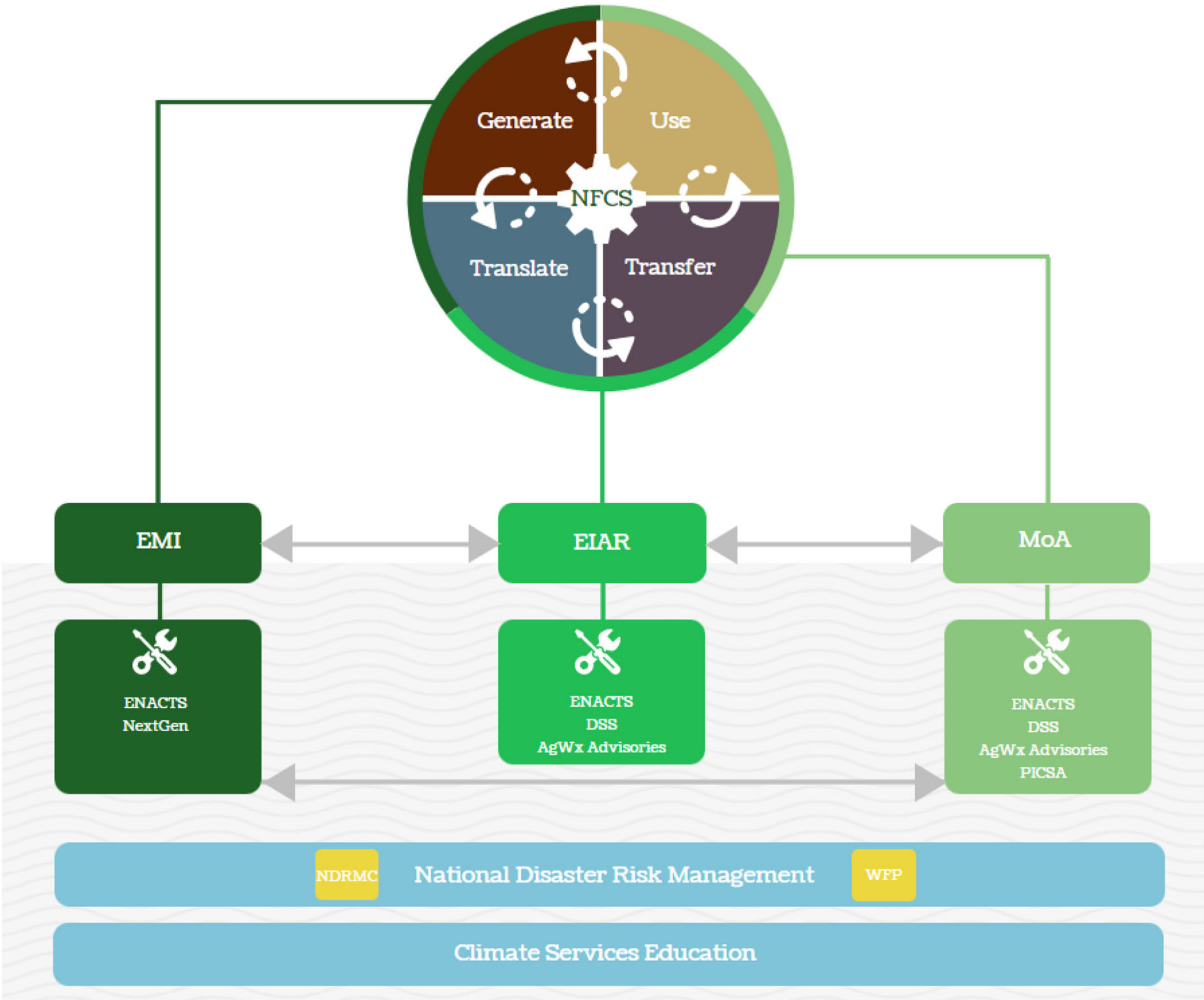

FIGURE 3
ACToday core national partners in Ethiopia—The Ethiopian Meteorological Institute (EMI), Ethiopian Institute of Agricultural Research (EIAR), and Ministry of Agriculture (MoA)—and their relationship to the four pillars of climate services. The National Framework for Climate Services (NFCS) drives coordination of institutions and actions across each of these pillars, as depicted in the center of the wheel, while actions to support national disaster risk management and foundational capacity building and education on climate risk management are considered cross-cutting and support all pillars and institutions.

In Ethiopia, as in many parts of Africa, the Ethiopian Meteorological Institute (EMI), which is mandated with collecting and providing weather and climate information, has confronted challenges around the collection of climate data arising from geographically sparse and poorly maintained surface and upper air stations alongside underinvestment in satellite data reception and processing systems (Dinku et al., 2018a; Lennard et al., 2018). The result of these challenges is a shortfall of meteorological information generally but with particular implications for agricultural and food security planning, monitoring, and early warning, though meteorological data observations have continued to be collected over the years.

To address this sub-optimal information environment, the ACToday project and approach in Ethiopia, as in the other five countries where it was implemented, leveraged the IRI's Enhancing National Climate Services (ENACTS) initiative to advance the availability of high-quality climate data. This was done by introducing a methodology to blend rainfall and temperature observations collected by national weather services with freely available global products derived from satellite data and climate model reanalysis products (Nsengiyumva et al., 2021). Through this merging method of on-the-ground station data with satellite rainfall estimates and climate model reanalysis products, ENACTS enabled Ethiopia to fill temporal and spatial gaps in the observational record extending back to 1981, helping the country to better characterize its past and current climate as well as predict its future one (Research Outreach, 2020; Dinku et al., 2022a). Moreover, the ACToday approach's incorporation of ENACTS advanced the use of an open-source R-based software with an easy-to use graphical user interface called the Climate Data Tool (CDT) in Ethiopia and 23 other primarily African countries, which ensures quality-control of rainfall and temperature observations, alongside the performance of an array of analyses and visualization capabilities that are important for other pillars of climate services (Dinku et al., 2022b). It did this by carrying out targeted capacity building trainings not just with the EMI, but with agricultural research institutions such as the Ethiopian Institute of Agricultural Research (EIAR), which is the main gatekeeper for the introduction of new technology, including climate services, in the country, as well as universities like Arba Minch University, which carry out research to understand linkages between climate and multiple sectors such as that of agriculture. In this same way, the web-based Automatic Weather Station Data Tool (ADT), has helped to address challenges in accessing and processing Automatic Weather Station (AWS) data collected by different systems and networks such as Vaisala, Edkon, Campbell, and KOICA, which are on different servers and in different formats, by enabling data quality control, processing, and visualization (Faniriantsoa and Dinku, 2022).

Because of both ENACTS and its component tools, such as CDT and ADT, Ethiopia has been able to evolve its historical, monitoring, and forecast capabilities using the best-available, quality-controlled data. And, most recently, because of these foundational improvements to underlying data, the country has also advanced its seasonal forecasting capabilities through the implementation of the Next Generation (NextGen) forecasting system. The NextGen forecasting system, which is based on more than 25 years of research and now implemented in 6 countries and two regional climate centers, has helped forecasters such as those at EMI to select the best climate models for any area of interest through a process-based evaluation. Moreover, it automates the generation and verification of tailored predictions at multiple timescales (weeks to months) and at multiple levels—regional (East Africa), national, or even sub-national (Columbia University, 2020; Acharya et al., 2021; Ehsan et al., 2021). While there are many advantages of the NextGen forecasting system in terms of improving the tailoring, communication, and ultimately usability of information, which will be discussed later in the paper, its enormous contribution in transitioning the country from subjective consensus forecasting to operational objective climate information that forms the backbone of any successful climate service cannot be overstated.

These free, open-source innovations (CDT, ADT, and NextGen), all of which have been co-produced and arisen out of the ENACTS initiative and accompanying datasets, might therefore be considered for adaptation and use by countries and organizations seeking to improve the quality of the climate data that underlies climate information and services such as forecasts. Moreover, regional climate centers such as the IGAD Climate Prediction and Applications Center (ICPAC) in East Africa and the Regional Center for Training and Application in Agrometeorology and Operational Hydrology (AGRHYMET) in West Africa might be considered resources for expanding the use of and capacitating new users on these tools to improve the generation of high-quality climate information beyond the Ethiopian context, since these centers have been intentionally capacitated on these innovations.

Translation: Transforming data into actionable information

While high-quality climate data underpins high-quality climate information, it is not sufficient to ensure that such information is actually useful or even usable as a climate service. Even the best-available data can be rendered useless if it is not appropriately tailored to the needs of various decision-makers as information, if it is poorly accessible or communicated, or if users are not capacitated to understand or even access it. There is a difference between information that is theoretically useful, usable, and actually used (Grossi and Dinku, 2022), and climate services aim to bring into harmony all of these qualities to inform decision-making and support adaptation.

Cognizant of this reality, the ACToday approach in Ethiopia and elsewhere has centered on advancing decision-relevant climate information through the translation of climate data into information products driven by user needs. In practice, this has meant advocating for and supporting increased interactions between the EMI (the national meteorological service) and various current and potential users of its information products, in line with the recommendations of the literature for decision-relevant, fit-for-purpose services (Vincent et al., 2017, 2018; Christel et al., 2018; Hansen et al., 2019a,b; Ncoyini et al., 2022). Through these interactions, a process called co-production has enabled the co-development of decision support systems, tools, visualizations, and even financial instruments that have allowed shapeless data to take form as useful knowledge products and services. Instead of a one-way "push" of information to users, such co-production has involved a two-way, iterative and collaborative process of knowledge construction between those who generate climate information at the EMI and those who use it. This process has manifested itself as various coproduction workshops with the EMI and actors from across various sectors and national institutions involved in supporting food security and nutrition in Ethiopia, such as the Ministry of Agriculture (MoA), the National Disaster Risk Management Commission (NDRMC), Ministry of Health, EIAR, and the Ministry of Water, Irrigation and Electricity (EIAR), as well as international nonprofits such as the World Food Programme (WFP), the Food and Agriculture Organization (FAO), and the Global Alliance for Improved Nutrition (GAIN).

While we cannot outline each decision support system or tool co-developed through the ACToday project or its concomitant approach here, three illustrative examples demonstrate the impact and importance of translating climate data and information into products that are useful for the agricultural sector: the Enhancing National Climate Services (ENACTS) maprooms, the NextGen Agricultural Drought Monitoring and Warning System (NADMWS), and the SIMAGRI decision support tool. In doing so, each of these products add to the expansive body of evidence demonstrating the insufficiency of merely generating high-quality climate information divorced from accompanying efforts to ensure easy access, clear communication, appropriate delivery, and capacity building (Sarewitz and Pielke, 2007; Goddard et al., 2010; Dilling and Lemos, 2011; Lemos et al., 2012; McNie, 2013; Jones et al., 2015; Vincent et al., 2017; Nkiaka et al., 2019; Photiadou et al., 2021), and the importance of coproduction processes in ensuring services are both driven by and truly meet user needs (Christel et al., 2018; Vincent et al., 2018; Hansen et al., 2019a; Ncoyini et al., 2022).

High-resolution visualizations and analyses: The ENACTS maprooms

In Ethiopia, like many African countries, a major obstacle for making climate information available and supporting its analysis is limited human capital, a lack of financial resources, and poor technical capacity (Dinku et al., 2018b). Earlier in this paper, we described how the Enhancing National Climate Services (ENACTS) initiative is improving the availability and generation of high-quality climate data through its merging method of station and satellite data, as well as through derived tools like CDT and ADT. It has also, however, contributed greatly to the translation and transformation of this data into a rich suite of downloadable interactive visualizations and analytics tools known as "maprooms" that are feely and openly accessible on the web (Ethiopian Meteorological Institute, 2022a). Through these dynamic visualizations, users can access information that has been translated, or transformed, into products that inform specific decisions and which have been co-produced with people from different sectors such as agriculture (Ethiopian Meteorological Institute, 2022b), water (Ethiopian Meteorological Institute, 2022c), and even health (Ethiopian Meteorological Institute, 2022d).

Within the ACToday project, which primarily targeted the agriculture sector, Climate and Agriculture maprooms (Ethiopian Meteorological Institute, 2022b) allowed for easy organization of a collection of interactive historical maps and location-specific analyses. This, in turn, enabled actors in the agriculture sector to more easily visualize things like frequency of rainy days, wet and dry spells, and the onset and duration of the rainy season (Grossi and Dinku, 2022), while downscaled seasonal rainfall forecasts at high resolution also provided locally-relevant information to facilitate agricultural planning (Hansen et al., 2019a). These freely available interactive "maproom" visuals and graphs of climate data have played large role in making EMI's climate information more accessible and usable by translating past, present, or future climate conditions into expected impacts and management advisories for different decision-makers. With index insurance, for example, a key risk management tool for farmers, ENACTS data and maprooms have enabled insurance experts to visualize rainfall patterns over wide areas, in turn creating conditions to scale up insurance in Ethiopia by giving these local experts the tools they need to tailor products to specific areas of coverage (Enenkel et al., 2019; International Research Institute for Climate and Society, 2021).

Contextualized and tailored information: The NextGen agricultural drought monitoring and warning system

Another knowledge product made possible by ENACTS data but rendered impactful from the translation of this underlying data into a decision-relevant format is the NextGen Agricultural Drought Monitoring and Warning System (NADMWS). In Ethiopia, drought is a persistent and devastating challenge to the lives and livelihoods of millions of people, with increasing frequency and magnitude at both long and short time scales (Kassaye et al., 2021). While the challenge is not new, part of the problem for mitigating their persistent and devastating effects has arisen from an unmet need for timely and accurate climate information about the onset and development of country-wide drought conditions (AICCRA, 2022). This part of the challenge can and was addressed through the generation of high-quality, spatially and temporally complete climate data through ENACTS and derived NextGen forecasts, which were combined with agricultural datasets and information. However, another significant part of the problem has emerged from the reality that even when available, the information is not easily accessible or in a decision-relevant format for those working in the humanitarian space to act upon (AICCRA, 2022). The development of NADMWS tackled these component challenges in parallel by addressing the issues related to data and information provision in tandem with those related to their translation and communication. Using satellite-based remote sensing technology, combined with detailed land-use maps, seasonal forecasts, national crop statistics, crop phenology and other country-specific data, any user can now freely monitor agricultural areas or "hotspots" with a high likelihood of water stress at the national, regional, zonal and woreda (district) levels (Ethiopian Institute of Agricultural Research, 2022). But perhaps most critically for decision-makers, the system simulates and automates the analysis that an expert in remote sensing would undertake and simplifies the interpretation and use of the data for users who are not remote sensing experts. The development of this tool is an example of a situation where use of climate information in decision-making, particularly by those in the disaster risk reduction and management (DRR/M) sector, was constrained not only by a lack of high-quality information but poor communication of that information. Tackling the former without addressing the latter through an easily accessible and automated NADMWS interface would have resulted in an incomplete solution to a complex problem rooted not just in information asymmetry but communication inefficiencies and poor analytical capacity.

Similarly, the Livelihoods, Early Assessment and Protection (LEAP) early warning-early response tool (World Food Programme Ethiopia Country Office, 2013) in use by the Government of Ethiopia and other humanitarian actors is another example of a tool built on a foundation of high-quality ENACTS data but made actually impactful from its design to translate this ground and satellite data across the nation into early warning and early response information that allows the critical programs such as the Government of Ethiopia's Productive Safety Net Programme (PSNP), which serves millions of chronically food-insecure rural households, to be scaled up immediately in case of a climate disaster.

User-friendly interfaces and sectoral relevance: The SIMAGRI decision support tool

SIMAGRI, another example of a user-friendly decision support tool developed to translate climate information into agricultural and economic terms that can support strategic and tactical decisions in crop production, was first successfully developed by the IRI and its partners in the context of South America (Han et al., 2019). With the support and collaboration with key actors and programs such as EIAR, EMI, IRI, and CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), it was adapted and co-developed for the African context for the first time in Ethiopia, as both a desktop and web tool (SIMAGRI-Ethiopia, 2022) through the ACToday project. The tool helps users such as agricultural experts and extension officers to translate both historical climate and downscaled forecast information (Han and Ines, 2017) into agricultural and economic terms for decision-making, by enabling the exploration of different "what-if" scenarios with various inputs (including weather, soil conditions, fertilizers, and planting dates) to estimate yield and determine optimal management practices. This tool can be taken as an example of and emulated as a resource that helps bring together traditionally disparate agricultural, climate, and price information into one place to transform it into something relevant for decision-making and planning.

Transfer: Communicating information in useful formats

Communication refers to the transfer of the translated information to the appropriate users or beneficiaries in formats and media most useful for their operation (Fiondella, 2021). In the same way that having limited and poor quality climate data (generation) or poorly tailored and contextualized information (translation) can stymie the ultimate uptake and usefulness of climate information within decision-making, so too can inappropriate and poorly designed communication methods, means, and channels limit the effectiveness climate services.

In the context of Ethiopia, working with and through partners with long-standing relationships with various user communities, as well as directly interfacing with user communities through co-production workshops with EMI has been invaluable in understanding not only the kinds of information needed but how it might be best communicated and systematized to scale and sustain its use. This is in line with literature demonstrating the importance and effectiveness of climate information producers and users interacting to create truly decision-relevant products, and good practices of users playing an active role in informing and even leading the development of products intended to serve them (Christel et al., 2018; Vincent et al., 2018; Hansen et al., 2019a; Ncoyini et al., 2022).

In the three aforementioned examples of knowledge products and tools (ENACTS, NADMWS, and SIMAGRI), for example, having the translated and sector-relevant climate information freely available online and formatted even for mobile phones has been important means of communicating and making available these products. For example, with SIMAGRI, transitioning the tool online and formatting the web page for mobile phones was an important communication choice, as the initial desktop version required users to install the software package on their computer. This was problematic because computer access is limited in Ethiopia, with less than a percent (0.22%) of people having access to desktop or laptop computers (Adam, 2012). This access is even more limited in rural areas. Similarly, how the information is presented is also very important. For instance, in the NextGen forecast maproom (Ethiopian Meteorological Institute, 2022e), the choice to display the forecast in a flexible format (Figure 4) was an important communication choice, as users can now choose their own probabilistic thresholds of interest to determine if rainfall will exceed certain amount or percentile of the average, precipitation of a region, rather than having them predefined (Grieser, 2014; Hansen et al., 2021). This format has been transformative for those in the agriculture sector, who need

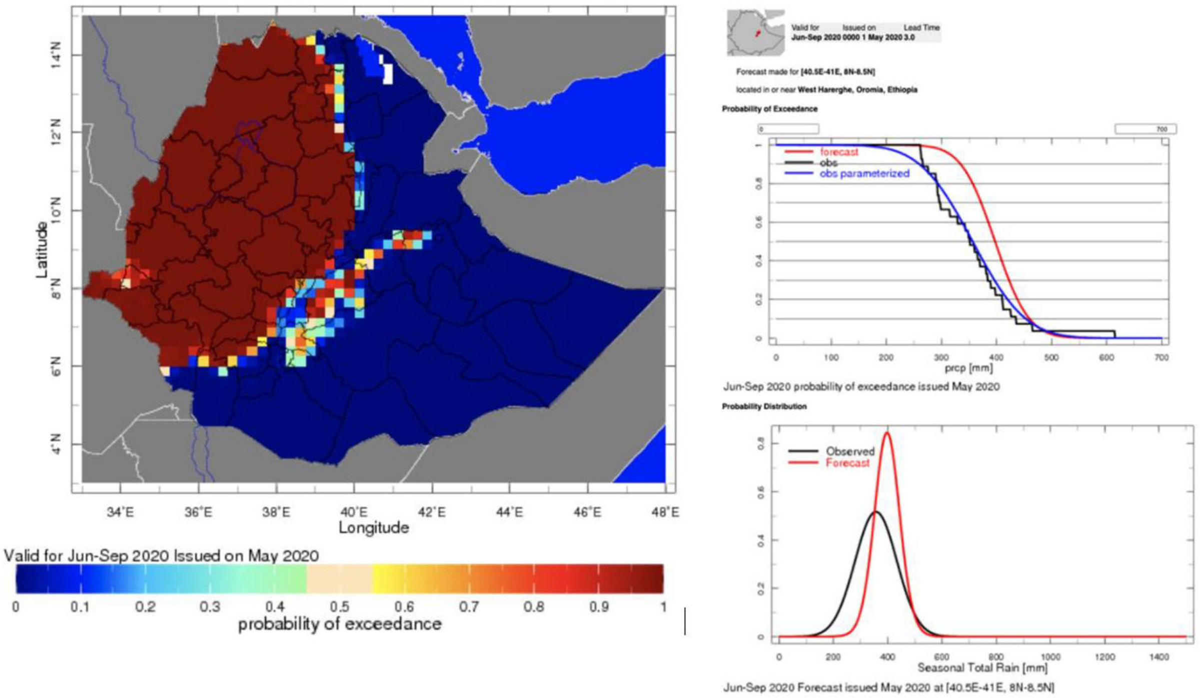

FIGURE 4
The NextGen flexible seasonal forecast format for Ethiopia. Both the map and graphs above, screenshots from the EMI's NextGen maproom (Ethiopian Meteorological Institute, 2022e), show in different formats the probability of seasonal rainfall exceeding 600 mm for the Kiremt (June–September) 2020 rainy season for any point in the country, as forecasted in May 2020. With the choice to communicate the seasonal forecast in this flexible format, any user can define any threshold (600 mm in this example) of interest to examine probability of exceedance of rainfall, rather than having those values predetermined in terciles, making the forecast more sector-relevant for agricultural decision-making.

such information to choose crop and cultivar choice, amongst other things.

Those seeking to develop climate information services in similar or other contexts, therefore, should consider not only the availability of information, but think critically about questions relating to communication (most appropriate mediums of communication for the population, frequency of communication, interactivity and inclusivity of the communication method) in their design.

Use: Integrating with systems, policy, processes, and plans

Beyond format and presentation, however, linking and integrating translated products within wider systems, both digital and human, has been critical for promoting their use. With SIMAGRI, for example, the system is not a standalone system, but rather is being integrated with Ethiopia's Digital AgroClimate Advisory Platform (EDACaP) to enable its use and be harmonized with a wider package of climate services for humanitarians, extension, and other actors interfacing with farmers. Similarly, with ENACTS maprooms, the generation and translation of climate data into sector- and decision-relevant knowledge products is insufficient if decoupled from the foundational capacity building on how to use these tools that has taken place iteratively both with national and sub-national EMI staff, but also others users including the extension system. Capacity building workshops with various sectoral users, from UN agencies to NGOs, university students, disaster risk management, agricultural extension, and even meteorological service staff themselves have been crucial for promoting uptake. This is also critical for ensuring regular, iterative feedback to improve, evolve, and co-develop new tools to meet specific user needs. This is how the sector-specific parts of the ENACTS maproom been developed over time.

Beyond this, the development of new climate risk management curricula and short training courses (Figure 5) targeting each of the aforementioned groups, including instruction on how to access maprooms and other EMI climate information products, has been key for ensuring these capacity building efforts will be sustained and continue to evolve beyond the life of the project (Braun et al., 2022). These efforts have targeted Ethiopia's Agricultural Vocational Education and Training (ATVET) program and colleges. They have also targeted farmers with the Participatory Integrated Climate Services for Agriculture (PICSA) approach

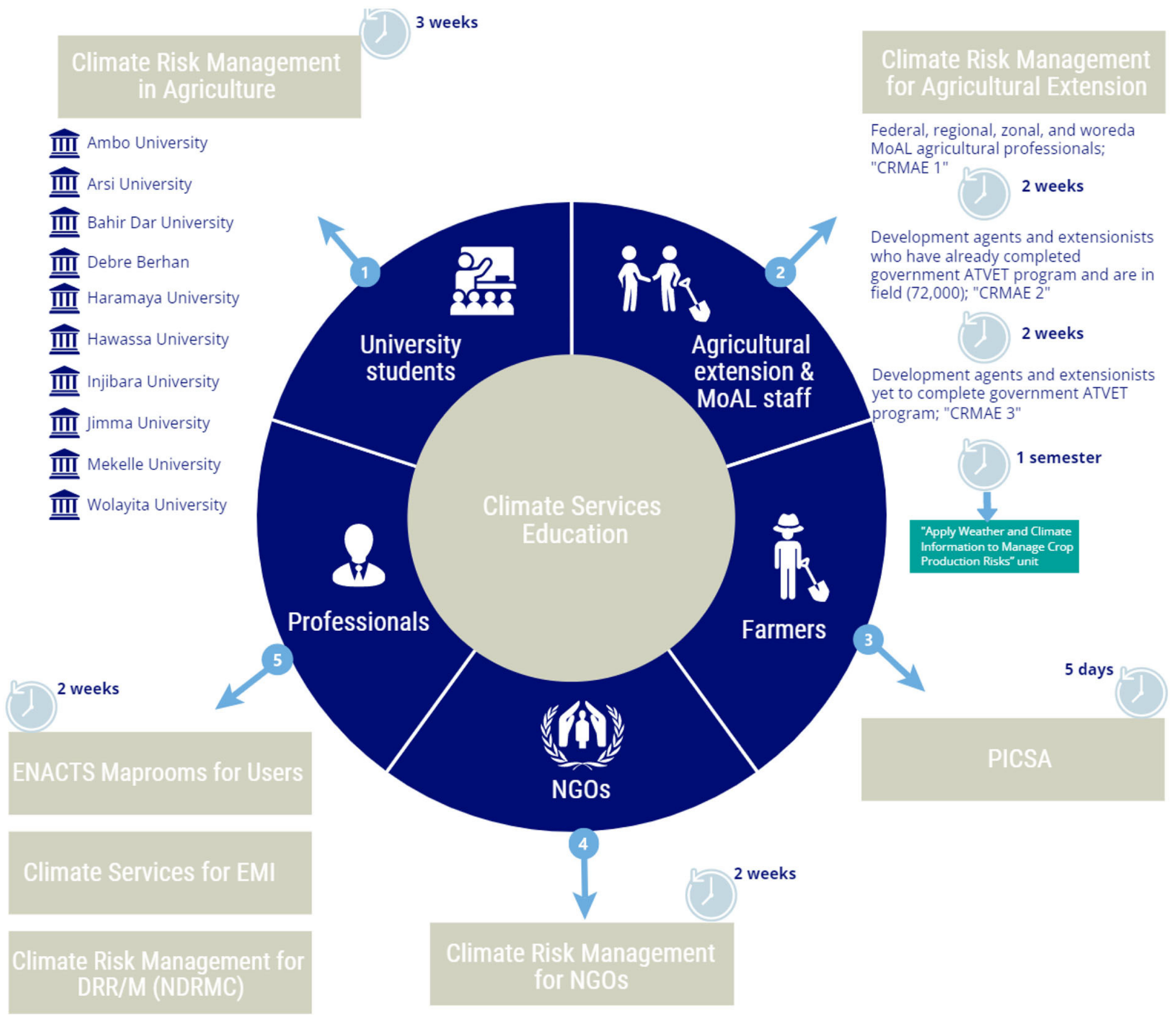

FIGURE 5
Groups targeted with foundational capacity building and curricula on climate risk management in Ethiopia. Each brown box represents a different curriculum or training package developed through the ACToday approach on climate risk management, while clocks represent the recommended implementation time for each curriculum.

(Dorward et al., 2015) for climate-informed decision and agricultural planning at the farmer level. For PICSA, high-quality climate products and automated analyses have been integrated within the approach's field implementation through the development of a PICSA Maproom interface (National Meteorological Agency, 2022) that allows users to easily display and download a batch of products required for the training of farmers, such as the season onset and cessation, seasonal rain forecasts (NextGen), and a variety of other information products. Such location-specific climate information is important for informing a variety of choices and planning decisions at the farm level in Ethiopia's various agro-ecological zones, from planting date to cultivar selection, timing of fertilizer application, and other practices affected by the crop calendar.

In this same vein, the launch of Ethiopia's National Framework for Climate Services (NFCS), an institutional mechanism to coordinate, facilitate and strengthen collaboration among national institutions to improve the co-production, tailoring, delivery and use of science-based climate predictions and services, has been paramount in institutionalizing and sustaining the actions necessitated by the four pillars just described.

Discussion and future directions

Even when researchers or meteorological agencies strive to produce the best-available information that users need, significant barriers may still remain that inhibit that "useful" information from actually being both "usable" and "used" (McNie, 2013; Vincent et al., 2018; Grossi and Dinku, 2022). The way theoretically useful information is developed (generated) and then transformed into decision-relevant knowledge (translated), communicated to users (transferred), the degree to which the user has the capacity to actually understand and act on the information, and the enabling environment and how well this information is integrated within national systems, processes, policies, and plans (use) all affect whether and the degree to which information actually enables climate adaptation.

In Ethiopia, even where there is a strong national meteorological service producing high-quality historical, monitoring, and forecast data, actions to ensure this information is freely accessible, broadly disseminated in various formats, tailored to user needs, and coupled with foundational capacity building have been essential in transitioning climate data to climate information and ultimately climate services that meet the needs of decision-makers at multiple levels. Those seeking to implement climate services in similar contexts where a strong meteorological service has not resulted in similarly strong climate-informed decision-making on the ground, therefore, should take special heed of and learn from the lessons already outlined in this paper, as well as those summarized below:

- **When working to advance climate services within a particular country or context, ensure the partnership strategy reflects each component of a holistic climate services framework.** In other words, partners should include the full spectrum of actors, ministries, or organizations working to generate, translate, transfer, and promote use of climate services. Working myopically with actors or institutions who only work on one or some of these aspects without bringing them together with others along the spectrum of the climate services pillars will likely result in climate services that may be useful or usable, but not ultimately used in practice.
- **While different institutions may have different roles along the climate services framework, one should strive to create spaces for sustained and iterative interactions between and amongst them. Policy can be an efficient way of doing this.** In promoting interactions between producers and users of climate information, for example, the NFCS as a policy framework has been and can be an important mechanism for systematizing, institutionalizing, formalizing, or even initiating interactions between climate information generators and various sectoral communities that may have only occurred on an *ad hoc* basis (or not at all) in the past. In this same way, it can align expectations on the mandates and roles of different institutions in advancing climate services within a country, and create a positive enabling environment for inclusivity in these efforts.
- **When undertaking the co-production process, it is not always necessary to start from scratch, and the process to identify and co-develop new products can be informed and benefit from capacity building on existing products.** With EMI and its users, for example, especially those who have been historically underserved with climate services such as those in the pastoral or nutrition sectors, users may suffer from the "you don't know what you don't know" paradox, whereby they may have difficulty articulating their needs if they are unaware of what is feasible or even already existing in the technological realm. Demonstrating existing products within the country or even elsewhere can serve as an important reference and jumping-off-point for discussion on co-developing and adapting new tools for various users. For instance, training and demonstration on EMI's Agriculture Maproom to agricultural experts and having participants work with its different components led to their realization that a new Maproom tool to determine crop suitability using rainfall and temperature thresholds was needed and would be useful in their work.
- **Climate services should be well-integrated within knowledge systems and leverage educational infrastructure—both formal and informal– where possible.** As described earlier, the ACToday approach in Ethiopia advanced the co-development of both climate risk management curricula and short training courses targeting agricultural experts and extension staff, university students and researchers, NGOs, disaster risk management staff, and EMI itself to promote the use of climate information (the use pillar). Rather than one-off trainings at these various institutions, the approach was mindful to design for and embed the co-produced curricula within existing educational ecosystems and architecture, such as university structures and the ATVET program (formal) and short in-service trainings (informal), to ensure outcomes and capacity building could be sustained and scaled in the long-term. Moreover, the training and curricular efforts were designed not in isolation but to strengthen relationships and connections between capacity building target groups. Those trained in climate risk management at the university level doing studies in climate-sensitive topics such as agriculture or natural resource management, for example, may go on to work within the extension system as subject matter specialists guiding the development agents who work most closely with farmers at the local level or even the National Disaster Risk Management Commission (NDRMC), the main government agency dealing with all food security and disaster warning activities in Ethiopia. Capacity building strategies should therefore consider how informal and formal educational architecture can be leveraged to sustain the development of knowledge and skills to use climate services in the long-run, but also bear in mind how these informal and formal systems might

reinforce, build upon, or otherwise interact with each other to maximize learning and impact.

- **Look before you leap when engaging with user communities.** In seeking to co-identify useful climate information and services, bear in mind that there may be pre-existing programming, experiences, and relationships that can be leveraged. In Ethiopia, there is a long history of engagement with the EMI and various users from the NDRMC, MoA, and elsewhere. Additionally, longstanding research programs such as CCAFS have heavily shaped and gained experiences and valuable lessons from implementation of climate services both in Ethiopia and the wider continent. Consultation with such stakeholders regarding past efforts to co-identify and co-prioritize climate services needs with users can prevent redundant efforts and wasting of resources that can be used elsewhere along the pillars of producing effective climate services.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

AG wrote the first draft of the manuscript. TD provided review as the leader of the ACToday project in Ethiopia. Both authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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