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Future crop risk estimation due to drought, extreme temperature, hail, lightning, and tornado at the census tract level in Louisiana

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Louisiana is one of the most hazard-prone states in the U.S., and many of its people are engaged directly or indirectly in agricultural activities that are impacted by an array of weather hazards. However, most hazard impact research on agriculture to date, for Louisiana and elsewhere, has focused on floods and hurricanes. This research develops a method of future crop loss risk assessment due to droughts, extreme low and high temperatures, hail, lightning, and tornadoes, using Louisiana as a case study. This approach improves future crop risk assessment by incorporating historical crop loss, historical and modeled future hazard intensity, cropland extent, population, consumer demand, cropping intensity, and technological development as predictors of future risk. The majority of crop activities occurred and will continue to occur in south-central and northeastern Louisiana along the river basins. Despite the fact that cropland is decreasing across most of the state, weather impacts to cropland are anticipated to increase substantially by 2050. Drought is by far the costliest among the six hazards, accounting for \$56.1 million of \$59.2 million (~95%) in 2050-projected crop loss, followed by extreme cold (\$1.4 million), extreme heat (\$1.0 million), tornadoes (\$0.4 million), hail (\$0.2 million), and lightning (\$0.05 million), respectively. These findings will assist decision-makers to minimize risk and enhance agricultural resilience to future weather hazards, thereby strengthening this economically-important industry in Louisiana and enhancing food security.

KEYWORDS

weather impacts, natural hazards, crop loss, resilience, Louisiana, risk assessment

Introduction

Increases in population and development bring a sharp increase in the risk (i.e., the product of the probability of a hazardous event and the consequences of that event) associated with weather hazards (Bushra et al., 2021). This risk is exacerbated by policy that incentivizes development without considering the additional complications in mitigating risk to the increasing hazard exposure. The encouragement of additional development only further increases vulnerability and reduces resilience to the hazard in a positive feedback mechanism. Ultimately, environmental, social, and economic sustainability become impractical unless compensating action is taken.

While loss and risk occur in a wide range of ways, much weather hazard research focuses on property damage (e.g., Mostafiz et al., 2020a; 2021a; 2021b; 2021c; 2021d; 2022a) and casualties (e.g., Jonkman 2005). Although such research is beneficial, the risk posed to agriculture is often ignored. Moreover, the risk to agriculture posed by less-catastrophic weather hazards such as those due to lightning (e.g., Zhang et al., 2011), hail (e.g., Changnon 1972), mid-latitude wave cyclones (e.g., Mukherjee et al., 2018), and other weather hazards is also important and understudied, even as underutilized data sources, including comprehensive historical loss databases and sophisticated model output to estimate the changing hazard intensities, exist to improve such future risk assessments (Mostafiz 2022c). Assessing weather hazard risk to agriculture precisely and accurately, especially in spatially heterogeneous areas, is also often problematic due to a coarse scale of analysis. Another complication is that future population and/or land cover changes confound projection of the future risk to agriculture.

The purpose of this research is to address these gaps by developing a geospatially-based risk assessment method for census-tract-level future crop loss due to drought, extreme cold and hot temperatures, hail, lightning, and tornadoes, using Louisiana, one of the most weather-vulnerable U.S. states, as a case study.

Background

Geospatial approaches to understanding the changing weather hazard risk have proliferated in recent years. For example, Kebede and Nicholls (2012) showed that flood exposure increases are a function of the spatial distribution of socio-economic variables (i.e., economic development, urbanization, and population growth). In an analysis of socio-economic factors contributing to natural hazard exposure at the U.S. county-scale, Preston (2013) found that despite disaster risk management successes, the U.S. continues to face dire consequences of increasing economic losses due to extreme weather events. The first Intergovernmental Panel on Climate Change (IPCC) report (Cutter et al., 2012) confirmed these assertions by reporting that societal exposure (and therefore risk as defined here) is a product of development processes on hazardous landscapes and also is an anticipated key driving force contributing to future vulnerability to extreme weather events (Pielke Sr et al., 2007; Hinkel et al., 2010). There remains a paucity of risk assessment work at a scale more local than county-level, especially while also considering changing hazard intensities (Gnan et al., 2022a, 2022b; Mostafiz et al., 2022b, Mostafiz et al., 2022 R. B.; Rahim et al., 2022).

Several recent studies have focused on risk assessment and/or exposure/loss due to drought (e.g., Bushra et al., 2019). Wilhite (2000) noted that drought and agricultural losses in general stand out among weather hazards in terms of risk and exposure, and both are increasing sharply, and lamented the long-problematic lack of reliable, accurate, and accessible historic loss data. More recently, drought monitoring and crop loss prediction has improved with the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor in the National Oceanic and Atmospheric Administration (NOAA) Suomi National Polar-Orbiting Partnership (S-NPP) satellite, which was launched in 2011 (Kogan et al., 2015). Numerous studies suggest that crop growing cycle exposure to drought and other hazards, including extreme temperatures and hail, is increasing with time (Potopova et al., 2016) and is likely to continue increasing, resulting in decreasing crop yields (Guo et al., 2017; Leng and Hall 2019), though benefits of CO_2 fertilization and adaptations may be underestimated. Analyses at shorter time scales improve efforts to identify drought impacts on crop yields (Peña-Gallardo et al., 2019). Many of these themes are echoed in the fourth (U.S.) National Climate Assessment (NCA4) from the U.S. Global Change Research Program (USGCRP; Gowda et al., 2018).

Similarly, several recent studies have focused on projecting future risk due to extreme temperatures. Forzieri et al. (2017) concluded that European weather-related risk in 2100 due to cold, heat waves, and other hazards has increased 50-fold over the 1981–2010 period due to the increase in population exposed amid global warming. Zhang and Hu (2018) studied risk assessment of extreme cold temperature events in China using a copula distribution model based on intensity and duration of the hazard. In a crop-focused extreme temperature risk assessment, Annan and Schlenker (2015) found that in the U.S., insured soybeans and corn have 43 and 67 percent more sensitivity, respectively, to extreme heat than uninsured crops, and extreme heat is well-understood to decrease crop yields in Georgia and the Carolinas (Eck et al., 2020). Some (e.g., Lesk et al., 2016) have explained that extreme cold is less impactful than extreme heat, because cold temperatures usually occur outside of the normal growing season. In addition, if the warming temperatures occur uniformly across the seasonal cycle, extreme low temperatures will become less frequent.

However, others (e.g., Gu et al., 2008) have suggested that the opposite net effect may occur—that rising temperatures may cause increased vulnerability to cold by inducing premature budding and growth before a subsequent unseasonable cold outbreak.

Overall future crop loss due to hail has not been considered comprehensively, yet improved understanding of such losses is economically important, as crop loss due to hail averages approximately 1 percent of the U.S. national annual crop output (Changnon 1972). Leigh and Kuhnel (2001) modeled loss and risk assessment associated with hail for the Sydney, Australia, region, for insurance purposes. Zhou et al. (2016) assessed the hail damage to potatoes in Washington using aerial multispectral imagery at different growth stages and seasons. Wang et al. (2016) found that hail risk increased (1950–2009) in China at different growing stages of cotton in their county-level GIS-based spatiotemporal study. Púčik et al. (2019) noted that crop loss probability increases when the hail size exceeds 2–3 cm, for central Europe.

Lightning impacts are generally considered to be decreasing vis-à-vis death rate (Mills 2020), but this trend is presumably driven by increased awareness facilitated by technological development, with the risk of injuries and crop and property loss still present. While much research has been invested in identifying lightning risk and its impact on property loss (e.g., Villamil et al., 2015; Mostafiz et al., 2020b; Brooks et al., 2020; He et al., 2020), little research focuses on the lightning-induced risk to crop loss. Kocur-Bera (2018) identified the most sensitive places in Poland to damage from lightning, in addition to drought, cold temperatures, hail, and other hazards, but the short (2010–2014) period of record limits conclusions.

Changnon et al. (2001) suggested that from 1950 to 1997, normalized tornado crop losses in the U.S. displayed no temporal trend. Subsequent work on tornado-driven risk assessments has been conducted for losses to nuclear plants (Reinhold & Ellingwood 1982) and property (Mostafiz et al., 2020b; Refan et al., 2020), and generalized tornado-induced losses have been conducted at the community (Masoomi & van de Lindt 2018), and local scales. While not tornadic in nature, the 2020 Iowa derecho (Hosseini et al., 2020) poignantly demonstrates the tremendous crop damage that can result from severe weather in general. However, a need remains for comprehensive analysis of future tornado risk focused on crop loss.

Regardless of whether the hazard examined is drought, extreme temperatures, hail, lightning, or tornadoes, increasing evidence (e.g., Rahman & Rahman 2015) suggests that a comprehensive management plan in at-risk areas, guided by both traditional and scientific considerations, is vital for assessing risk, enhancing resilience, and progressing toward sustainability. Climate change complicates efforts to improve management strategies and makes the future risk due to these hazards even more uncertain. In projecting the probable economic risk for extreme weather events at various return periods under IPCC scenarios, Franzke and Czupryna (2020) found that the risks can be increased by 3-to-5.4-fold for the U.S. by 2060. Such future risk assessments must incorporate methods for projecting population growth accurately (Wu et al., 2018).

TABLE 1 Total cropland in Louisiana (Source: U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) 2020).

Year	Total cropland (Acres)
1997	5,567,627
2002	5,071,537
2007	4,691,344
2012	4,275,637
2017	4,345,843

Some attempts have been made to quantify resilience that would be useful for agriculture, such as Lam et al. (2016, 2018), who introduced the resilience inference measurement (RIM) approach. While methods such as the RIM model are useful for quantifying resilience, a similarly appropriate means of assessing the risk remains elusive. This is problematic because risk must be evaluated accurately and precisely at the planning stage for development.

In this study, it is hypothesized that, despite a temporally decreasing land cover in crops in Louisiana (Table 1), crop loss from these hazards will increase by 2050 (Gowda et al., 2018) as additional crop yield (Table 2) and production (Table 3) escalate the risk, primarily driven by the increasing population, consumer demand, and exposure to the hazards due to climate change. Enhanced data and methodological techniques are employed to improve the estimation of crop loss risk to these hazards and thereby enhance the likelihood of improved planning for mitigation, adaptation, and resilience.

Drought, extreme cold, extreme heat, hail, lightning, and tornadoes are selected for analysis here because, with some notable exceptions (e.g., Smith and Katz 2013; Smith and Matthews, 2015) they are understudied, significant, crop-damage-producers statewide, and are important for Louisiana's State Hazard Mitigation Plan (SHMP). Moreover, with the exception of drought, crop losses due to these hazards can be assessed relatively easily using existing data sources, in contrast to more catastrophic hazards (e.g., floods and hurricanes) in which crop damage occurs from multiple sources (i.e., wind, lightning, tornadoes, etc.) simultaneously but is not partitioned by hazard.

Study area

The U.S. state of Louisiana is highly vulnerable to extreme weather events both in terms of physical exposure as well as in terms of economic and human impacts, given the concentration

TABLE 2 Yields of the top five Louisiana crops by value (source: USDA NASS 2020).

Year	Soybeans (bushels/acre)	Corn (bushels/acre)	Rice (pounds/acre)	Cotton (pounds/acre)	Hay (tons/acre)
1949	15	20	1,825	329	1.29
1959	23.5	31	2,850	476	1.45
1969	20.5	37	3,500	551	1.82
1979	28	54	3,910	712	2.21
1989	22	95	4,430	672	2.6
1999	27	121	5,000	709	2.4
2009	39	132	6,300	745	2.8
2019	48	165	6,380	1,035	2.5

TABLE 3 As in Table 2, but for total production (source: USDA NASS 2020).

Year	Soybeans (1,000 bushels)	Corn (1,000 bushels)	Rice (1,000 cwt)	Cotton (1,000 bales)	Hay (1,000 tons)
1949	345	14,540	10,822	651	395
1959	4,536	12,183	12,910	491	554
1969	32,964	4,477	21,385	482	647
1979	93,800	2,214	20,643	690	849
1989	38,500	13,490	21,488	868	781
1999	26,730	39,930	30,825	901	912
2009	36,660	80,520	29,217	349	1,064
2019	41,280	89,925	26,408	582	975

of people and assets in high-risk areas, especially along the Gulf of Mexico (Mostafiz et al., 2021a). Catastrophic loss events causing more than $1 billion in damage are frequent. Since 1980 alone, Louisiana has been impacted by 25 severe storms, 19 tropical cyclones, 12 droughts, 9 floods, 7 winter storms, and 1 freeze—each causing over $1 billion (2020 Consumer Price Index (CPI) adjustment) in economic damage (NOAA National Centers for Environmental Information (NCEI, formerly known as the National Climatic Data Center (NCDC), 2020). The Southern Plains/Southwest drought and heat wave of spring-summer 2011 cost $14.2 billion (2020 CPI adjusted) and caused 95 deaths in Arizona, Kansas, Louisiana, New Mexico, Oklahoma, and Texas (NOAA NCEI 2020). This drought spanned 107 consecutive weeks and is arguably the longest to hit Louisiana, from 04/20/2010 to 05/01/2012, with approximately 65 percent of Louisiana land cover suffering from exceptional drought (D4) in late June 2011 (United States Drought Portal, 2020). The southeastern U.S. winter storm of January 2000 caused four deaths and $1.1 billion in damage over numerous states, including Louisiana. Severe weather, including high winds, hail, and tornadoes, caused $1.4 billion in damage across several southern states including Louisiana in April 2020 (NOAA NCEI 2020). With agriculture contributing over $3.1 billion, or 2.9 percent of the state's gross domestic product (University of Arkansas Division of Agriculture 2021), the vulnerability of Louisiana agriculture to weather hazards is substantial, including to the leading crops featured in Tables 2 and 3.

Data

Crop loss data (1960–2019) at the parish level by hazard type originates from the Spatial Hazards Events and Losses Database for the United States (SHELDUS®; Center for Emergency Management and Homeland Security (CEMHS) 2020), which collects its data from the NCEI Storm Events reports. According to NOAA NCEI (2018, p. 14), "crop damage information may be obtained from reliable sources, such as the U.S. Department of Agriculture (USDA), the county (i.e., parish in Louisiana) agricultural extension agent, the state department of agriculture, crop insurance agencies, or any other reliable authority. Crop damage amounts may be obtained from the USDA or other similar agencies." It should be noted that for

TABLE 4 Indicator of hazard severity, data source, and years analyzed, by hazard in Louisiana.

Hazard	Indicator of hazard severity	Data source	Years analyzed
Drought	Weekly drought intensity	U.S. Drought Monitor	2000–2017
Extreme Cold	Annual frequency of days with temperatures <32°F	National Centers for Environmental Information (NCEI)	1992–2017
Extreme Heat	Annual frequency of days with temperatures >95°F	NCEI	1992–2017
Hail	Hail days per year	National Severe Storms Laboratory (NSSL), University of Oklahoma	1982–2011
Lightning	Lightning density per year	NCEI	1986–2012
Tornado	Tornado days per year	Storm Prediction Center (SPC)	1950–2016

Louisiana, drought-induced crop damage was only reported and available to SHELDUS beginning in 1996.

Because the intended purpose of vegetation determines whether its loss is considered as crop damage or property damage (NOAA 2018), this analysis excludes timber, as forested land cover is assumed to be unharvested and/or property rather than crop. By contrast, pasture is considered as cropland because its intended purpose is assumed to be consumed, although loss of the animals that consume the pasture are not considered as crop loss here, but would instead be considered as property loss. Moreover, because SHELDUS does not itemize losses by crop, a "bulk" analysis of all crops is undertaken here. Annual crop loss in SHELDUS are adjusted to 2019$. The indicators of historical hazard severity and their data sources are shown in Table 4.

Because risk is a product of the probability and consequence of the hazard occurrence, and the latter is a function of the cropland value, the hazard intensity data must be accompanied by data on historical and future cropland extent, demand, and population (which impacts demand). For this reason, Louisiana historical land cover data for 2001, 2003, 2006, 2008, 2011, 2013, and 2016 were downloaded from the National Land Cover Database (NLCD) archived by U.S. Geological Survey (USGS, 2016). Rasters containing the only two categories for crops in the NLCD classification system (pasture/hay (category 81) and cultivated crops (category 82)) comprise the cropland cover data, from the NCLD database. Louisiana crop market values available every 5 years from 2002 to 2017 from U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS, 2020) and crop export values available annually (2002–2017) from USDA Economic Research Service (2017) were used as indicator of crop demand. Historical and 2050-projected population data for the world and U.S. were acquired from the U.S. Census Bureau (2020) to assess population growth for projecting that demand to 2050. Louisiana census-tract shapefiles were downloaded from the U.S. Census Bureau (2016). The census tract is the best geographic scale to represent the crop land cover and crop loss because census blocks and block groups are too localized (e.g., <0.01 mi2), while parishes and the state level are too coarse to provide an effective representation for cropland to represent individual crops.

Methods

Because the methodology involves many steps, a flowchart (Figure 1) is used to provide guidance on each step, described in detail in the subsections below.

Historical hazard intensity

For each week, shapefiles of drought intensity from the United States Drought Monitor, (2017), coded according to the first two columns in Table 5, were rasterized using the value in the second column of Table 5, with a pixel size of 0.0005 × 0.0005 decimal degrees. The drought value for each raster cell was averaged across all weeks (2000–2017), providing the mean weekly historical drought intensity by cell.

In the extreme cold and high temperature analysis, for 139 stations within and adjacent to Louisiana (1/1/1992 to 10/14/2017), any daily data that were missing, erroneous (e.g., minimum temperature exceeds maximum temperature on that day), or spurious (following Global Historical Climate Network-Daily (NOAA, 2017a)) criteria, were discarded. Furthermore, any station with discarded temperature data exceeding 10 percent of days were removed, as were stations with less than 5 years of data. These criteria narrowed the analysis to 102 stations. The mean annual frequency of days having temperatures below 32°F, and in a separate analysis, above 95°F, were mapped using "ordinary kriging" with a spherical semivariogram, cell size of 0.0005 × 0.0005 degrees, and variable search radius of 12 points.

Methods for analyzing intensity of the other three hazards were relatively straightforward. A map of mean annual (1982–2011) frequency of days with hail of 0.75 + inches in diameter within 25 miles (NOAA National Severe Storms Laboratory 2014) was digitized. Then, a triangulated irregular network (TIN), with these hail-day contour lines generated as hard edge, was developed. This TIN was then rasterized using

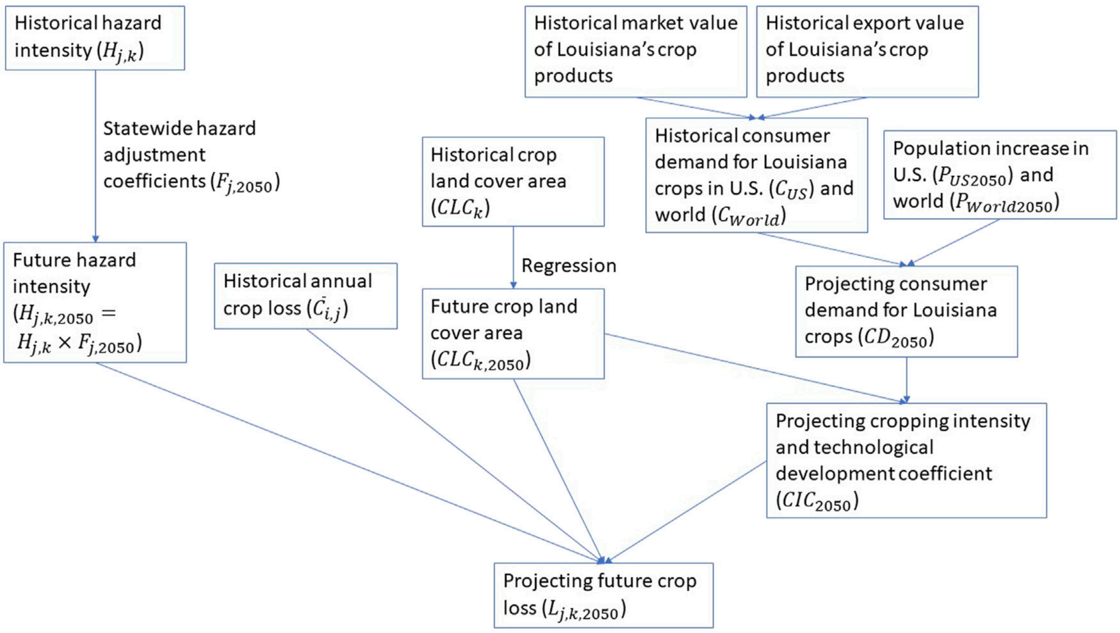

FIGURE 1
Methodological framework.

TABLE 5 Pixel values in drought intensity calculation.

Category	Value for drought intensity analysis
D0 (Abnormally Dry)	0
D1 (Moderate Drought)	1
D2 (Severe Drought)	2
D3 (Extreme Drought)	3
D4 (Exceptional Drought)	4
Normal or Wet Conditions	No value

linear interpolation at a cell size of 0.005 × 0.005 degrees. Mean annual lightning strike data (1986–2012) were acquired in netCDF format from NOAA, (2017b). These data were rasterized to 4 km × 4 km cells and converted using lightning density in flashes mi-2 yr-1. Tornado touchdown point data (1950–2016) were acquired from the U.S. Storm Prediction Center (SPC; 2017). These data were then processed to calculate the mean annual frequency of days having a touchdown within 40 km, at a 100 m × 100 m cell size, using a spatial probability density heat map derived from kernel density estimation (Epanechnikov 1969) in QGIS®. Further details regarding the methodology employed in assessing historical hazard intensity for extreme cold, hail, lightning, and tornado are described in Mostafiz et al. (2020b).

For each hazard j, where j is 1 through 6, the mean historical hazard intensity by census tract k, where k is 1 through 1148 ($H_{j,k}$), was calculated. $H_{j,k}$ is one of the key factors used for calculating projected crop loss by 2050.

Future hazard intensity

A distinctive feature of our method is the use of statewide adjustment coefficients to represent hazard intensity in future year x; this produced $H_{j,x}$ of all six hazards taken individually. Because hazard frequencies and/or magnitudes may change in the future, statewide adjustment coefficients for hazard j in future year x ($F_{j,x}$) were computed considering NCA4-projected (USGCRP 2017) changes to the hazard. Future hazard intensity was then projected in each census tract k ($H_{j,k,x}$) by modifying historical hazard intensities $H_{j,k}$ using the statewide adjustment coefficients $F_{j,x}$ (Eq. 1).

$$H_{j,k,x} = H_{j,k} \times F_{j,x} \quad (1)$$

It was then necessary to determine the values of $F_{j,x}$. For drought, although Louisiana precipitation is expected to change little by 2100 (Easterling et al., 2017, their Figure 7.5), enhanced evapotranspiration caused by increased temperatures may result in drying soils by 2100 over much of the continental U.S., including Louisiana, at least under the higher radiative forcing and emissions scenario (Wehner et al., 2017; their Figure 8.1).

TABLE 6 Examples regression-based projection of crop land cover area (km^2) by 2050 by census tract ($CLC_{k,2050}$).

Census tract	2001	2004	2006	2008	2011	2013	2016	Intercept	Slope	2050
22001960300	124.1	123.9	123.3	123.3	122.9	122.9	122.7	318.8	(0.10)	119.3
22003950400	129.3	126.9	124.6	121.5	119.9	120.4	120.4	1,415.9	(0.64)	96.5
22005030102	6.1	6.1	5.8	5.8	5.8	5.8	5.7	62.7	(0.03)	4.7

Projecting Consumer Demand for Louisiana Crops.

These changes will impact soil moisture availability in Louisiana. Specifically, in Louisiana, winter, spring, and summer soil moisture decreases, made with a "medium" degree of confidence, are projected to be large relative to natural variability (Wehner et al., 2017). For these reasons, an increase in drought hazard of 25 percent was assumed for the state by 2050, or $F_{drought,2050} = 1.25$.

Similarly, $F_{j,x}$ for extreme heat was considered to increase by 20 percent ($F_{extreme\ heat,2050} = 1.20$), based on data in NCA4 by Vose et al. (2017; their Figure 6.9), although their figure used 90°F as the threshold rather than the 95°F used in the historical analysis here. As described in Mostafiz et al. (2020b), changes to the extreme cold temperature hazard were assumed to parallel the projected changes to the annual mean frequency of sub-0°C days. Vose et al. (2017; their Figure 6.9) also estimated such changes. Thus, $F_{j,x}$ for extreme cold temperature was assumed to decrease by 20 percent by 2050 ($F_{extreme\ cold,2050} = 0.80$).

An analogous method of representing the severe storm (hail, lightning, and tornado) hazards as that presented in Mostafiz et al. (2020b) was employed here. Specifically, the method of assigning $F_{j,x}$ was determined by weighing the results of current modeling-based literature. One line of theoretical consideration suggests that the frequency and/or intensity of severe thunderstorms in Louisiana capable of producing hail and lightning may decrease. This is because the expected increasing temperatures through at least 2050 would shift the cold/warm air mass interface and associated polar front jet stream poleward, leaving Louisiana less frequently near the peak area for tornadic development (i.e., along vigorous cold fronts trailing from mid-latitude wave cyclones). The increasing temperatures would also decrease the frequency/intensity of hail events because the percentage of time and vertical extent that subfreezing temperatures exist in the cumulonimbus clouds that produce hail would decrease with increasing temperatures. The seasonality of the magnitudes of projected warming is likely to be less important for this analysis than it might be for most other locations, because severe thunderstorms and tornadoes show less seasonality in Louisiana than in most other places.

However, other factors suggest increasing frequency/intensity of future hail- and lightning-producing thunderstorms and tornadoes. Thunderstorm and tornadic activity is most likely when energetic, near-surface air underlies much colder air, so the continued surface warming would destabilize the atmosphere, tending toward a net enhancement of severe storm activity. Brooks (2013) concluded that the vertical temperature gradient, or instability, as represented by a severe weather index known as convective available potential energy (CAPE, measured in J kg^{-1}), is expected to increase. However, Brooks (2013) also noted the compensating effect of expected weakening of the vertical wind shear that spawns tornadoes. Gensini et al. (2014) suggested that atmospheric instability (as represented by frequency of days with abundant CAPE) is likely to weaken over nearly all of Louisiana, for the 2041–2065 period vs. 1981–1995. Collectively, this research guides our assignment of $F_{j,x}$ of a 10 percent decrease for hail, and a 10 percent increase for lightning and tornadoes by 2050 compared to the present ($F_{hail,2050} = 0.90$; $F_{lightning,2050} = 1.10$; $F_{tornado,2050} = 1.10$). Of course, different hazard intensities would be derived for similar analyses for projections of years other than 2050.

For each hazard, a sensitivity analysis is run, to produce loss estimates for 2050 assuming an over- or under-estimation by 10 percentage points. For example, the 25 percent increase in the drought hazard would mean that the sensitivity analysis is run assuming values of 1.15, 1.25, and 1.35 for $F_{j,x}$.

Quantifying historical annual crop loss and projecting crop land cover change

SHELDUS-based historical, inflation-adjusted (to represent 2019$) crop loss by parish ($i$) was aggregated to annual total by hazard (j) and used to represent the economic impacts of past events. For each i and j, mean annual crop loss, $\bar{C}_{i,j}$ was computed as the mean historical annual crop loss (2019$) for the 60-year period from 1960 to 2019 (excepting drought, for which, as explained earlier, crop loss was available for Louisiana only since 1996), as depicted in Eq. 2.

$$\bar{C}_{i,j} = \frac{\left[C_{i,j,1960} + C_{i,j,1961} + C_{i,\ j,1962} + \ldots + C_{i,j,2018} + C_{i,j,2019}\right]}{60} \tag{2}$$

The crop land cover area (CLC) from NLCD (including pasture and hay) of each census tract (k) was calculated for the available years (2001, 2004, 2006, 2008, 2011, 2013, and 2016; CLC_k). The CLC_k for 2050 was then projected by fitting a

TABLE 7 Total market value of crop products in Louisiana (USDA NASS 2020).

Year	Market value of crop ($ million)
2017	2,061
2012	2,784
2007	1,605
2002	1,066
Mean	1,879

TABLE 8 Total export value of crop products in Louisiana (USDA Economic Research Service 2017).

Year	Export value of crop products ($ million)
2017	1259
2016	1133
2015	1350
2014	1604
2013	1614
2012	1653
2011	1439
2010	1253
2009	982
2008	1069
2007	985
2006	711
2005	664
2004	703
2003	688
2002	495
Mean	1100

regression line through the historical land cover area. Each CLC_k for 2050 was verified to fall between zero and the census tract area. The data and regression parameters for three example census tracts (k) are shown in Table 6.

Projecting consumer demand for louisiana crops

A method of estimating future consumer demand of those crops based on trends historical and current consumption (i.e., domestic vs. international) and future population projections was necessary. Specifically, the percentage of domestic vs. international consumption was calculated from the mean historical market value (Table 7) and export value (Table 8) of Louisiana's crop-based products. Tables 7,8 suggest that 58.5 percent of Louisiana crops is exported (i.e., consumed. Internationally, C_{World} or 0.585), and therefore, 41.5 percent is consumed domestically ($C_{U.S.}$ or 0.415). U.S. Census Bureau (2020) estimates that U.S. population will increase by 16.9 percent by 2050 (P_{US2050}) and world population is estimated to increase by 26.4 percent ($P_{world2050}$). Assuming no changes in consumer demands, competition, innovation, and consumption patterns, the consumer demand increase coefficient of Louisiana crops for 2050 (CD_{2050}) was computed as a weighted average, or as

$$CD_{2050} = 1 + (C_{World} \times P_{World2050} + C_{US} \times P_{US2050}) = 1.225 \tag{3}$$

Thus, assuming that the production will meet this demand, an additional 22.5 percent of crop value (2019$) will be exposed to hazards by 2050.

Projecting cropping intensity and technological development coefficient

It was assumed that technological development will increase agricultural efficiency, as for global trends (Foley et al., 2011), to meet the increasing CD_{2050} for Louisiana's crops, despite the NLCD-regression-projected 9.5 percent decrease in Louisiana's areal cropland from 2016 to 2050. Thus, the projected crop land cover coefficient in 2050 (CL_{2050}) is the quotient of 100 divided by (100—9.5), or 1.105. The future cropping intensity and technological development coefficient for 2050 (CIC_{2050}) was estimated simply as

$$CIC_{2050} = CD_{2050}\, x\, CL_{2050} = 1.225\, x\, 1.105 = 1.354 \tag{4}$$

This approach assumes that consumer demand increase and crop land cover decrease contribute equally toward the intensity/technological development coefficient.

Projecting future crop loss

Because overall crop loss is impacted by both the presence and intensity of the hazard acting on the crop land cover in a given census tract, a method of representing each is important. For each hazard (analyzed separately), the parish-level, hazard-and-cropland-adjusted loss ratio $LR_{i,j,2016}$ was calculated by dividing the mean annual historical parish-level crop loss ($\bar{C}_{i,j}$, from SHELDUS) by the product of historical hazard intensity ($H_{j,k}$) and baseline 2016 crop land cover area ($CLC_{k,2016}$) for each census tract within that parish (n), or

$$LR_{i,j,2016} = \frac{\bar{C}_{i,j}}{\sum_{k=1}^{n}\left(H_{j,k} \times CLC_{k,2016}\right)} \tag{5}$$

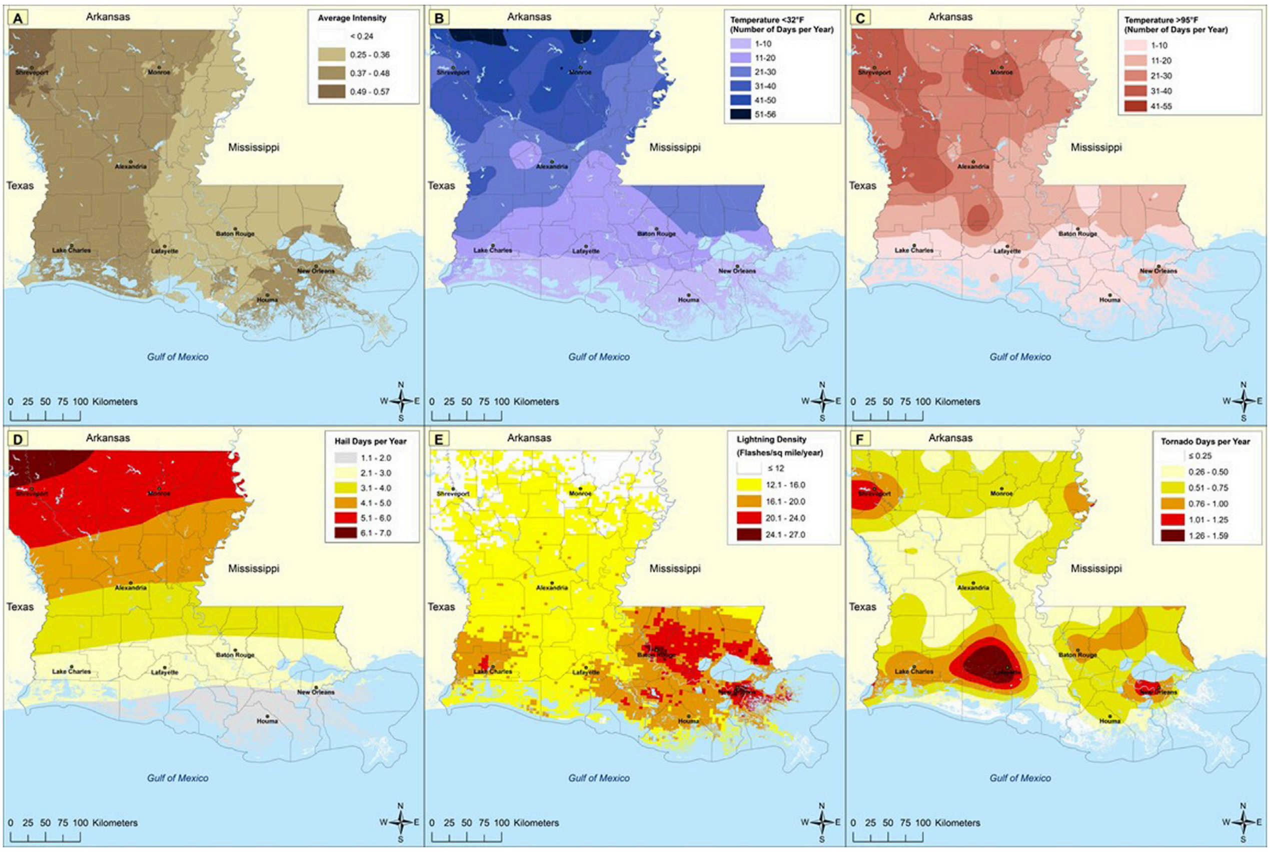

FIGURE 2
Historical mean hazard intensity (H_j) in Louisiana: **(A)** drought (2000–2017), **(B)** extreme cold temperature (1992–2017; Mostafiz et al., 2020b), **(C)** extreme heat (1992–2017), **(D)** hail (1982–2011; Mostafiz et al., 2020b), **(E)** lightning (1986–2012; Mostafiz et al., 2020b), and **(F)** tornado (1950–2016; Mostafiz et al., 2020b).

This method assigns the total historical parish loss based on the sum of the product of these factors.

To estimate census-tract-level crop loss by hazard in 2050 ($L_{j,k,2050}$), $LR_{i,j,2016}$ from Eq. 5 is applied to the future mean annual hazard intensity ($H_{j,\,k,2050}$; from Eq. 2), future cropping intensity and technological development coefficient (CIC_{2050}; from Eq. 4), and crop land cover area ($CLC_{j,2050}$; as calculated by the example in Table 6) within the census tract, or

$$L_{j,k,2050} = LR_{i,k,2016} \times H_{j,\,k,2050} \times CIC_{2050} \times CLC_{j,2050} \qquad (6)$$

Results and discussion

Historical and future hazard intensity

Historical hazard intensity (H_j) for each hazard is mapped in Figures 2A–F. The northwestern part of Louisiana is the most vulnerable section of the state to drought, extreme heat, and hail (Figures 2A,C,D, respectively). Not surprisingly, extreme cold temperatures are most common throughout northern Louisiana (Figure 2B). Lightning density is concentrated inurban areas, particularly in the southeast (Figure 2E). Tornado intensity peaks prominently in south-central Louisiana, with a secondary area of maximum intensity in northwestern Louisiana (Figure 2F).

Projected changes to the hazard intensities ($H_{j,\ 2050}$) by 2050 are shown in Figures 3A–F. Decreases in the extreme cold temperature and hail frequencies are apparent by comparing Figures 2B to 3B and 2D to 3D, respectively. The lightning-intensity hazard is projected to increase for southeastern Louisiana (compare Figures 2E to 3E).

Historical and future projected change in crop land cover

The majority of crop cultivation occurs in south-central and northeastern Louisiana and along the major river basins (Figure 4A). Figure 4B shows the change in crop land cover at the census tract level from 2016 to 2050 in Louisiana. Crop

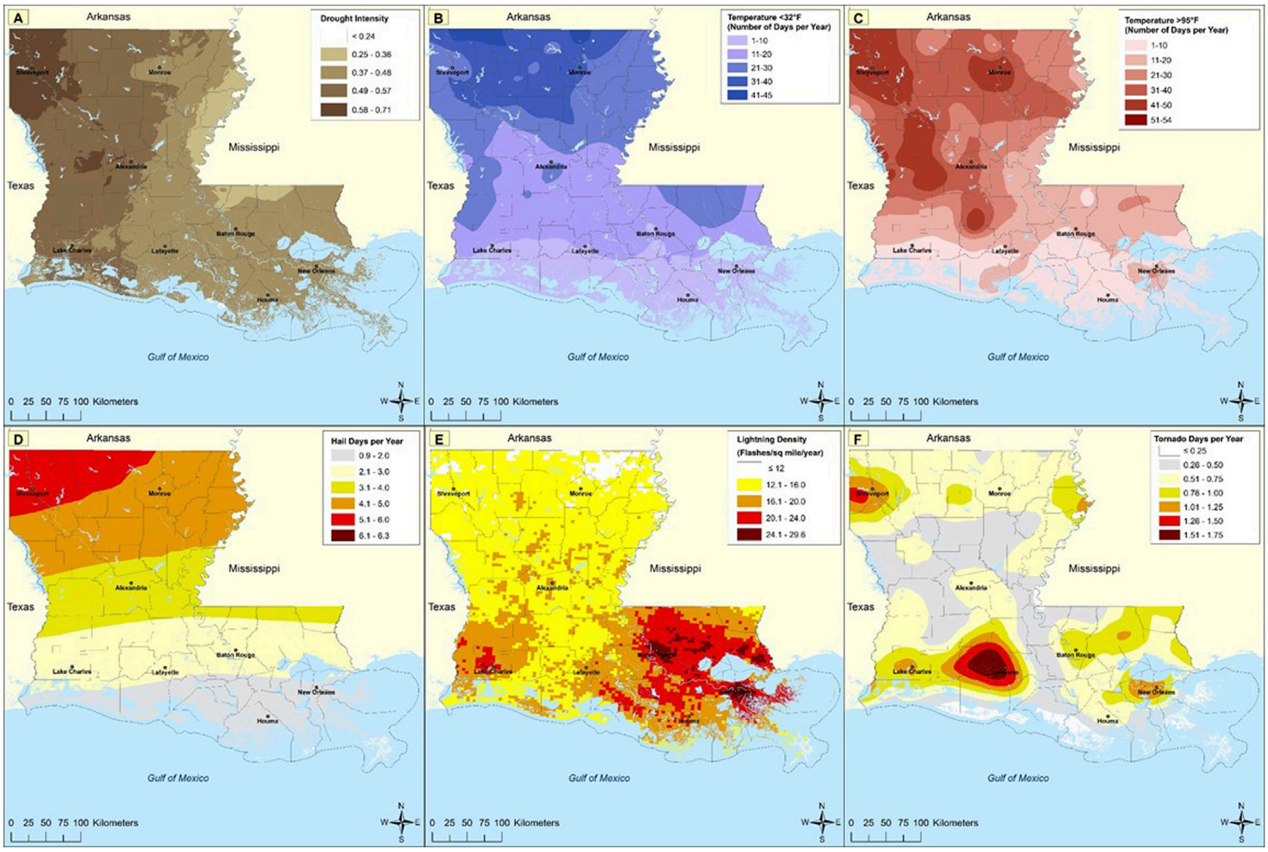

FIGURE 3
As in Figure 2, but for projected future hazard intensity in Louisiana by 2050.

land cover is decreasing in the vast majority of the state, but especially in coastal, north-central, northwestern, and southeastern Louisiana (Figure 4B). Increases in crop land cover are sporadic but are mostly in the northeastern part of the state. By 2050, 320 census tracts are projected to have no crop land cover, compared to 207 census tracts in 2016. CLC is projected to increase in only 24 census tracts and decrease in 722 census tracts, with no change projected in 402 census tracts. Urban infringement and abandonment of coastal lands are major reasons for the anticipated decreases.

Historical and future projected annual crop loss

Historical annual crop losses due to each of the six hazards in Louisiana are shown in Supplementary Appendix S1A. On a statewide basis, drought caused 93.1 percent of historical average annual crop losses from the hazards analyzed here (Table 9). This result is largely consistent with that from Fahad et al. (2017). The relatively smaller positive impact of climate change via extreme cold rather than via extreme heat tends to support the Lesk et al. (2016) position over that of Gu et al. (2008). Caddo (northwestern Louisiana) had the greatest historical annual crop loss due to drought among the parishes ($6,397,949 or 16.3 percent of Louisiana's total; Supplementary Appendix S1A). Likewise, Terrebonne and Lafourche (south-central Louisiana) and St. James (southeastern Louisiana) experienced the largest historical annual crop loss from extreme cold ($43,647 or 2.6 percent of the statewide total; Supplementary Appendix S1A) and hot temperatures ($14,020 or 1.9 percent of Louisiana's total; Supplementary Appendix S1A), respectively. One caveat of this result is that since crop types are not distinguished, it is likely that losses due to high-value crops, such as the citrus orchards in Plaquemines Parish, are underestimated in this analysis. Franklin Parish (northeastern Louisiana) and Cameron Parish (southwestern Louisiana) had the greatest historical annual crop loss due to hail ($31,070 or 19.9 percent of the statewide total; Supplementary Appendix S1A) and lightning ($439 or 11.7 percent of Louisiana's total; Supplementary Appendix S1A), respectively. Finally, St. Landry Parish in south-central Louisiana sustained the highest historical annual crop loss due to tornado ($77,107 or 24.3 percent of the total; Supplementary Appendix S1A). No historical crop losses

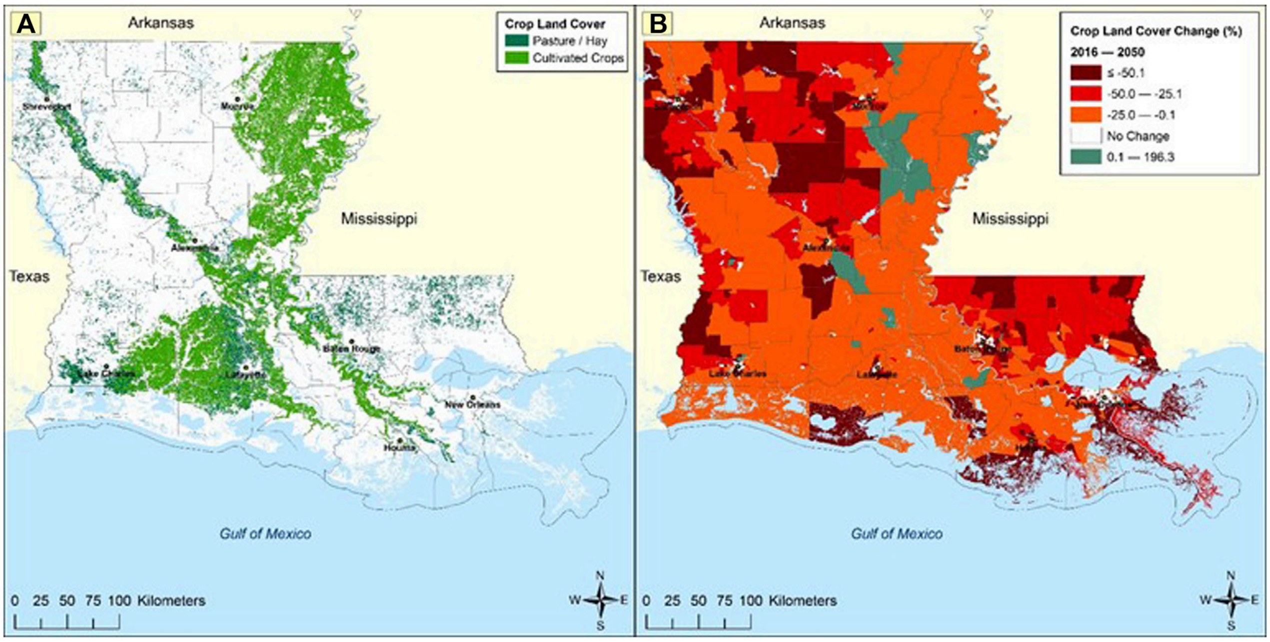

FIGURE 4
Crop land cover in 2016 **(A)** and change in crop land cover at the census tract level from 2016 to projection for 2050 **(B)**, in Louisiana.

TABLE 9 Comparison of Louisiana statewide crop loss, by hazard: Historical vs. 2050-projected.

Hazard	Average annual crop loss 1960–2019 (2019$)	Projected annual crop loss in 2050 (2019$)	Projected change (%)
Drought	$39,196,210	$56,141,812	43.23%
Extreme Cold	$1,711,019	$1,445,347	−15.53%
Extreme Heat	$734,551	$962,216	30.99%
Hail	$155,956	$184,450	18.27%
Lightning	$3,750	$4,587	22.32%
Tornado	$316,764	$444,435	40.30%
Total	$42,118,250	$59,182,847	40.52%

due to tornado were reported for Beauregard, Caldwell, Cameron, De Soto, Jackson, La Salle, and Red River parishes.

By 2050, total annual crop loss ($L_{j,2050}$), and therefore risk, is expected to increase by about 40.5 percent (2019$), with drought comprising 94.9 percent of the total (Table 9). Crop losses due to extreme heat, hail, lightning, and tornado are projected to increase substantially but remain relatively minor shares of total losses. Of these, hail is an interesting case, because $L_{j,2050}$ increases despite a decreasing future hazard intensity ($F_{j,\ 2050}$) and increasing CD_{2050}. Extreme cold temperature will decrease in $L_{j,2050}$ due to global warming despite the increased CD_{2050}.

Figures 5A–F shows the widely varying ranges for $L_{j,2050}$ by hazard, as was noted previously in Table 9. The absence of crop loss (i.e., risk) in a given area likely infers the absence of crop cultivation (e.g., urban census tracts) and/or historical crop loss for that hazard rather than absence of severe weather threat.

The risk due to drought by 2050 (Figure 5A) is projected to be greatest where the combination of hazard exposure (i.e., northwestern location), cropland (i.e., south-central and northeastern Louisiana), and a history of crop losses occur (i.e., Caddo, Vermilion, Avoyelles, St. Landry, Assumption, Calcasieu, and Jefferson Davis parishes). As was the case for historical data, Caddo is projected to remain the parish with the

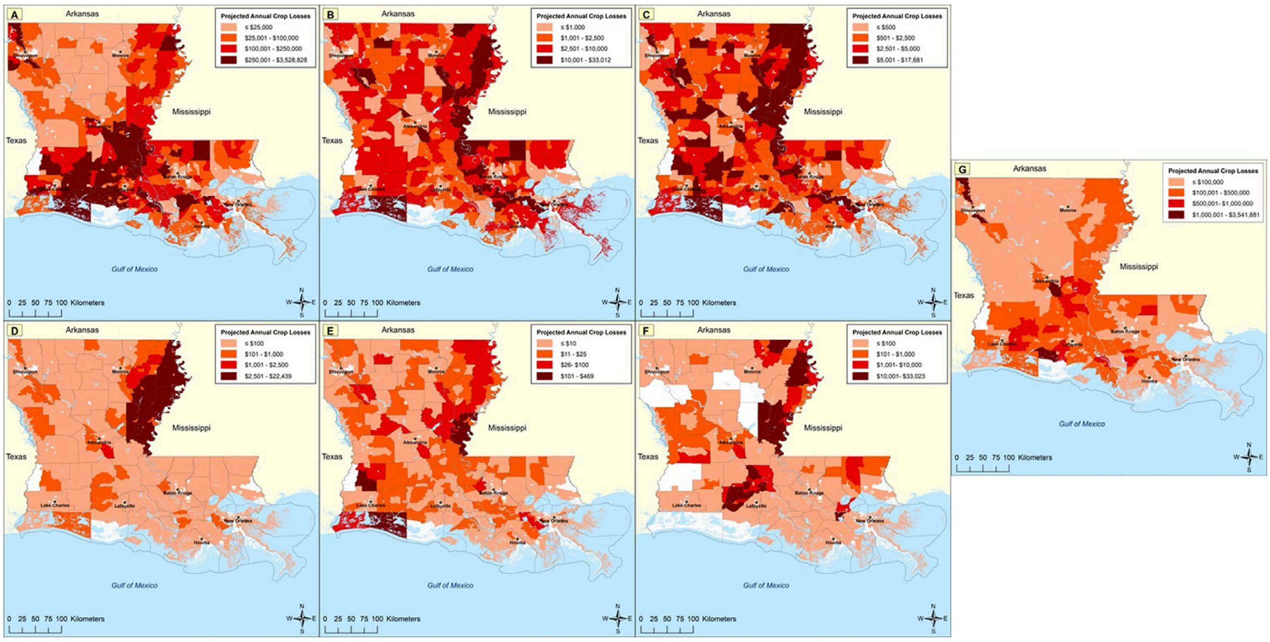

FIGURE 5
Projected annual crop loss (2019$) by Louisiana census tract, 2050: Drought **(A)**, extreme cold temperature **(B)**, extreme heat **(C)**, hail **(D)**, lightning **(E)**, tornado **(F)**, and total **(G)**.

greatest annual crop loss among the parishes ($8,386,852 or 14.9 percent of Louisiana's total; Supplementary Appendix S1B) by 2050.

Projected risk from extreme cold temperature annual crop loss in 2050 (Figure 5B) varies substantially by parish but the risk is relatively evenly distributed throughout Louisiana. Assumption Parish (south-central Louisiana) may have the highest annual crop loss ($45,734 or 3.2 percent of the statewide total) due to extreme cold temperatures in 2050 (Supplementary Appendix S1B). The greatest annual extreme cold temperature loss is projected to be in census tract 22121020300 in West Baton Rouge Parish of central Louisiana ($33,011). Extreme heat risk is also projected to be evenly distributed but is more concentrated in the northeastern part of Louisiana (Figure 5C). St. James Parish is projected to have the highest annual crop loss ($21,273) among the parishes (2.2 percent of the state's total; Supplementary Appendix S1B). Annual crop loss peaks at $ 17,681 in census tract 22021000100 within Caldwell Parish.

Interestingly, cold temperatures pose more of a risk than hot temperatures in Louisiana, despite the projected increased temperatures. It should be noted that extreme heat and the much larger drought risk go hand-in-hand, so some of the extreme heat risk is likely to be accounted for by the drought analysis. Also, because cold and heat waves typically engulf large areas, the SHELDUS data resolve many of the historical crop losses due to extreme cold and heat at a coarse regional scale, causing the historical annual crop loss values due to extreme heat (and separately, due to extreme cold) to be assigned equally across many parishes (Supplementary Appendix S1A). The method employed here allows projected loss to vary across parishes by distributing the loss based on current and projected changes to land cover by census tract and spatial variability in hazard intensity (Supplementary Appendix S1B).

The crop risk to the hail hazard in 2050 is projected to peak in northeastern Louisiana, including Catahoula, Concordia, East Carroll, Franklin, Madison, and Tensas parishes (Figure 5D). Franklin Parish is projected to have the greatest annual crop loss among the parishes ($38,442 or 20.8 percent of Louisiana's total; Supplementary Appendix S1B). The census tract with the highest projected annual crop loss due to hail ($22,439 in census tract 22065960200) is in Madison Parish.

Lightning risk is projected to peak in sparsely-populated southwestern and northeastern Louisiana (Figure 5E) where hazard, CLC, and historical crop loss overlap. This spatial peak in risk occurs despite a higher hazard intensity elsewhere (see again Figure 3E), as the higher hazard intensity is occurring in largely non-agricultural areas. Cameron Parish is projected to have the greatest annual crop loss ($561) among the parishes (12.2 percent of Louisiana's total; Supplementary Appendix S1B). Annual crop loss peaks at $468 in Cameron Parish (census tract

TABLE 10 Sensitivity analysis of annual crop loss (i.e., risk) estimates statewide in Louisiana for each hazard by 2050, for 10 percent overestimation or underestimation of the hazard intensity change (2019$).

Hazard	Overestimate $F_{j,x}$ by 10 percent	Modeled $F_{j,x}$ (Eq. 6)	Underestimate $F_{j,x}$ by 10 percent	Difference from Eq. 6
Drought	$60,633,159 (+35%)	$56,141,812 (+25%)	$51,650,468 (+15%)	±8.0%
Extreme Cold	$1,264,683 (−30%)	$1,445,347 (−20%)	$1,626,021 (−10%)	±12.5%
Extreme Heat	$1,042,399 (+30%)	$962,216 (+20%)	$882,030 (+10%)	±8.3%
Hail	$163,953 (−20%)	$184,450 (−10%)	$204,941 (0%)	±11.1%
Lightning	$5,006 (+20%)	$4,587 (+10%)	$4,172 (0%)	±9.1%
Tornado	$484,836 (+20%)	$444,435 (+10%)	$404,030 (0%)	±9.1%
Total	$63,594,036	$59,182,847	$54,771,662	±7.5%

22023970100), likely because it is one of the few tracts in Cameron with intense cultivation.

Tornado risk is anticipated to remain much higher than that of hail and lightning. Acadia Parish in southwestern Louisiana is projected to have the highest annual crop loss ($112,376 or 25.3 percent of the state total) due to tornado in 2050 (Supplementary Appendix S1B). At the census tract scale, peak losses are projected to be in the large, northeastern Louisiana census tracts in Catahoula, Concordia, Morehouse, southern East Carroll, and western Madison parishes (Figure 5F). The greatest annual tornado loss is in census tract 22095071100 in St. John the Baptist Parish ($33,022).

Sensitivity analysis

A brief sensitivity analysis to demonstrate the impact of different model assumptions regarding future conditions for each hazard, taken one at a time, is presented in Table 10. The final column in Table 10 shows the estimated change in annual crop loss if an underestimate or overestimate in modeled values of ten percentage points occurs. Interestingly, due to compensating effects of hazard intensities that are projected to increase (i.e., drought, extreme heat, lightning, and tornado) vs. those expected to decrease (i.e., extreme cold and hail), an "across-the-board" underestimation or overestimation for all six hazards leads to bulk total property losses that change by only ±7.5 percent (i.e., bottom row of Table 10).

Study limitations

Because of the lack of model-output data with high confidence at the sub-state scale, the geographical distribution of the hazards is assumed to be constant over space throughout Louisiana. Similarly, projected temporal changes in hazard intensity by 2050 are assumed to be consistent statewide. In reality, changing frequencies and intensities of synoptic weather patterns that produce extreme weather conditions will not be consistent across space, even at the sub-state scale.

The reliability of the crop loss as projected for the year 2050 depends on the accuracy of input data (i.e., historical hazard intensity, historic crop loss, and crop market and export values) and model estimations (i.e., future hazard conditions, future crop land cover changes, population projection, changing consumer demand, cropping intensity, and technological development). The consideration of annual values can introduce inaccuracies and uncertainties, as climate changes are assumed to occur differently by season, yet the climate model uncertainties still lag behind uncertainties of other models, such as hydrological, at the seasonal scale (Joseph et al., 2018). Human cultural and economic changes, including wealth/GDP, product preferences, adaptations (e.g., changing competition from other producers), and policy are not incorporated in the study.

This study's source for historic crop losses (SHELDUS) has limitations. First, despite including loss estimates across all hazard types and magnitudes, gaps and biases in these estimates exist in SHELDUS. For example, because SHELDUS assumed the lower bound of the logarithmic range (e.g., $5,000 to $50,000) that NOAA's NCEI (NCDC at the time) had been using to report loss estimates prior to 1996, losses tended to be underestimated for the earlier decades. Furthermore, indirect losses, including employment hours, health problems during evacuation, and complications caused by other storm-induced stressors, are not included (Gall et al., 2009). A known issue with loss databases and their application to projections of losses is how compound events are categorized. Zscheischler et al. (2018) acknowledged that loss underestimates could occur due to the accounting of compound events as only one hazard type. In the case of the present analysis, given that SHELDUS losses are divided equally, some errors are naturally introduced and unavoidable as the U.S. National Weather Service, the data source for SHELDUS, reports losses as compound event totals only and forgoes estimation by hazard type. A final limitation regarding the crop loss data is that because SHELDUS did not itemize crop loss by crop, the data availability necessitated a "bulk" analysis of all crops, which in fact masks the influences of different climatic extremes on the individual crops.

Data management decisions by the responsible agencies can also introduce uncertainties when used for purposes in this research. For example, although the U.S. National Weather Service strives to collect county-scale loss data, losses from some events are reported only at the multi-county scale. In such cases, SHELDUS partitions losses equally among the affected counties, regardless of differences in population, population density, or development. Because the scale of such events is so broad, the most glaring example of this type of generalization of losses is for extreme heat; nearly all parishes were assigned the same historical crop loss value (Supplementary Appendix S1A). Despite the limitations, SHELDUS data have been used successfully in similar research (e.g., Li et al., 2015; Rohli et al., 2016; Hahn et al., 2017; Paul and Sharif 2018; Mostafiz et al., 2020b) and remains the best available source for U.S. hazard-induced crop loss data.

Summary and conclusion

This study offers an approach for improving risk estimates for six important weather hazards using the example of Louisiana, one of the most weather-vulnerable U.S. states. The method avoids, where possible, aggregating data to a county-level risk. The finer-resolution spatial analysis is valuable because uneven population distribution and/or hazard exposure often makes the scale of natural hazard-induced damage, and therefore the risk, spatially heterogeneous and/or localized. This work also circumvents another perennial complication in risk assessment by incorporating estimates of future changes in both the local hazard intensity and crop land cover; one or both of these factors are often ignored in projecting risk. While our approach certainly cannot avoid making gross assumptions, the use of localized, weighted, model-based projections of crop land cover, consumer demand, and future hazard intensities to estimate census-tract-level risk of crop loss due to several severe weather hazards in Louisiana, United States, by 2050, enhances our current understanding of current and future severe weather impacts.

The major findings of this research are:

1) While the majority of cropland occurs and will continue to occur in south-central and northeastern Louisiana along the river basins, crop activity is decreasing in southeastern and northwestern Louisiana and is increasing in parts of the northeast.
2) By 2050, crop risk, measured as likelihood of economic loss, statewide is likely to continue to be dominated by drought, which is projected to account for \$56 million of the \$59 million (~95%) in crop loss by 2050.
3) Extreme cold is likely to continue to produce more damage than extreme heat (although the latter often occurs in tandem with drought), despite the projected warming climate.
4) Tornadoes, hail, and lightning will remain the fourth, fifth, and sixth riskiest hazards examined, respectively.
5) The northeastern part of the state can be expected to remain impacted relatively more heavily than other parts of the state by extreme heat, hail, lightning, and tornadoes.

The findings in this study will help decision-makers to make crops more resilient to future hazards, thereby strengthening the economically-important agriculture industry in Louisiana and enhancing food security.

Work based on a similar methodology is needed to evaluate future risk from other hazards in other locations. Moreover, more sophisticated projections of cropland, consumer demand, cropping intensity, technological development, and demography will improve model projections of future losses, enhancing decision-making for allocating resources to mitigate and adapt to these natural hazards.

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

RM developed the detailed methodology, collected and analyzed the data, and developed the initial text. RR developed the atmospheric projections and edited early and late drafts of the text. CF conceptualized the hazard quantification and census tract methodologies and revised the text. MG provided the SHELDUS data and revised the text. NB provided oversight on analysis, particularly regarding the crop land cover projections, and revised the text.

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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.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.919782/full#supplementary-material

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