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Enhancing system resilience to climate change through artificial intelligence: a systematic literature review

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The growing urgency of climate change necessitates innovative strategies to enhance system resilience across many sectors. Artificial Intelligence (AI) emerges as a transformative tool in this regard, yet existing research remains fragmented across sectors and regions. We conducted a systematic literature review of 385 peer-reviewed articles published between 2000 and early 2025, following the PRISMA protocol. The analysis classifies AI applications across nine key sectors and evaluates their relevance to adaptation, mitigation, or both. AI methodologies and regional distribution were also assessed. The findings show a dominant focus on adaptation (64.4%), with only 16% of studies addressing mitigation, and 19.4% engaging both. Classical Machine Learning techniques are the most used (51.4%), followed by deep learning models (22.3%). Regional disparities are evident: Asia and global-scale studies account for two-thirds of the literature, while Africa and South America are underrepresented. Sectorally, agriculture and urban infrastructure receive the most attention. Despite the promise of AI, major challenges persist in data access, model transparency, and equitable deployment, particularly in vulnerable regions. This review distinguishes itself by offering a comprehensive, cross-sectoral synthesis and emphasizing system-level resilience. It highlights the need for regionally tailored AI solutions, interdisciplinary collaboration, and ethical frameworks to ensure AI contributes meaningfully to global climate resilience efforts.

KEYWORDS

artificial intelligence (AI), system resilience, climate change, green transition, sustainable development, climate adaptation, machine learning

1 Introduction

The escalating impacts of climate change pose profound challenges to global economic, social, and environmental stability. Extreme weather events, rising sea levels, shifts in biodiversity, and increasing resource scarcity threaten critical systems across various sectors, necessitating robust adaptation and mitigation strategies. In response to these multifaceted risks, Artificial Intelligence (AI) has emerged as a powerful tool for enhancing resilience across diverse domains, from agriculture and energy to disaster management and healthcare. AI's ability to process vast amounts of data, generate predictive models, optimize resource allocation, and support decision-making has positioned it as a powerful enabler of systemic adaptation and climate-informed decision-making. However, despite its growing adoption, a systematic understanding of how AI contributes to resilience remains limited.

While individual and community-level resilience (micro-level) is undeniably important—for instance, household adaptive behaviors or psychological resilience—our review concentrates on system-level (macro-level) resilience. This is because our interest lies in how large-scale systems and sectors (energy grids, agricultural systems, cities, etc.) can withstand climate shocks, an area where AI interventions often have broader policy and infrastructural implications. We acknowledge that micro-level resilience contributes to systemic resilience; however, including both scales broadens the scope beyond a manageable range. Thus, we choose to maintain a macro focus, and we discuss this as a limitation of our study.

Resilience has been extensively explored in economic, environmental, health, and social sciences, with definitions often centered on the ability of systems to absorb shocks, adapt to changing conditions, and recover from disturbances. In the context of climate change, resilience refers to the capacity of communities, industries, and ecosystems to withstand and respond effectively to climate-induced stressors. While AI holds promise in enhancing these adaptive capacities, there is still a lack of comprehensive research that systematically examines its role across different sectors and geographical regions. Previous studies have explored specific applications of AI, such as climate modeling, disaster risk reduction, and sustainable resource management. However, a fragmented understanding persists regarding the extent to which AI facilitates resilience-building efforts and the key methodological approaches used in AI-driven climate solutions.

AI's technical capabilities (such as predictive modeling, optimization algorithms, and pattern recognition) directly contribute to resilience in different ways across sectors. For instance, in agriculture, AI-based predictive models can enable farmers to anticipate droughts or pest outbreaks, thus safeguarding crop yields (building agricultural resilience). In urban planning, optimization algorithms can design smarter infrastructure networks that continue to function during extreme events (enhancing urban resilience). In disaster management, pattern recognition from satellite imagery can expedite damage assessment and response. By mapping these capabilities to resilience outcomes (anticipation, robustness, rapid recovery), we frame how AI serves as a resilience-building tool.

This systematic literature review addresses these gaps by analyzing existing research on AI applications that bolster resilience against climate-related challenges. The study identifies, categorizes, and evaluates AI-driven approaches across multiple sectors, assessing their contributions to climate adaptation and mitigation. Specifically, the paper examines the distribution of AI applications across key resilience-related sectors, including agriculture, water management, energy, disaster preparedness, urban planning, and health, such as:

- Classify AI methodologies used in resilience-building efforts, differentiating between machine learning techniques, deep learning models, remote sensing technologies, and hybrid approaches and highlight case studies.
- Analyze the adaptation-mitigation focus of AI applications, distinguishing studies that emphasize climate adaptation, mitigation, or both.
- Explore regional disparities by assessing the geographical distribution of research on AI and resilience, highlighting underrepresented regions and potential research gaps.

More explicitly this review is providing an answer to the following research questions:

- In which sectors are AI applications for climate resilience most prevalent, and where are they lacking?
- What types of AI methodologies are being applied, and how does their usage distribute between adaptation and mitigation contexts?
- How is the existing research geographically distributed, and do we see gaps in regions most vulnerable to climate change?
- What common challenges and opportunities emerge from the literature regarding AI's contribution to resilience?

Our review of 385 academic papers reveals significant trends in AI-driven resilience research. A majority (64.4%) of studies focus on adaptation, addressing challenges such as climate forecasting, risk assessment, and infrastructure resilience. Only 16% emphasize mitigation, while 19.4% integrate both approaches, underscoring the need for stronger AI contributions to emissions reduction strategies.

In terms of AI methodologies, Classical Machine Learning/General ML dominate the field, appearing in 51.4% of studies, followed by Deep Learning (22.3%), and Traditional Machine Learning & Ensemble Models (8.3%) and Natural Language Processing & Text Mining (2.3%). More specialized approaches, including Hybrid Multi-Method AI (6.5%), Statistical & Econometric Models (2.9%), Remote Sensing & GeoAI (2.0%), and Reinforcement Learning & Graph-Based Methods (1.0%), remain underutilized in resilience-related research. The remaining 3.3% are Domain-Specific/Other Specialized Methods.

The regional analysis highlights disparities in research focus. The largest proportion of studies adopt a global perspective (34.3%), followed by Asia (31.9%) and Europe (11.7%), while Africa (7.5%), North America (10.4%), Oceania (2.3%), and South America (1.8%) are comparatively underrepresented. These findings suggest an uneven distribution of AI research, with potential gaps in regions most vulnerable to climate change impacts.

The remainder of this paper is organized as follows: Section 2 defines the notion of resilience used in this paper in the face of Climate Change. Section 3 outlines the methodology used in our systematic literature review. Section 4 presents the key findings, including sectoral classification, AI typologies, and regional disparities, while Section 5 highlights key limitations, research gaps, and future directions. Finally, Section 6 concludes the study by summarizing key takeaways.

2 Resilience in the face of climate change adaptation and mitigation

Resilience is a foundational concept in climate change adaptation and mitigation, widely applied across multiple disciplines, including economics, environmental sciences, and social policy. While definitions of resilience vary, they converge on the idea that it reflects the capacity of systems—whether ecological, economic, or infrastructural—to absorb shocks, adapt to changing conditions, and recover without losing their core functionality (Nisioti et al., 2023; Nyangon, 2024). Given the accelerating pace of climate-related disruptions, resilience has become a strategic priority for policymakers, businesses, and international organizations seeking to minimize vulnerabilities and enhance adaptive capacity.

In the economic literature, resilience is often framed in terms of the ability of economies to withstand climate shocks—such as extreme weather events, natural disasters, and supply chain disruptions—without experiencing long-term losses in productivity and welfare (Hallegatte, 2014). Economic resilience is closely linked to structural factors, including the diversification of industries, robustness of financial systems, and effectiveness of policy interventions (Briguglio et al., 2014).

From an ecological standpoint, resilience refers to the ability of ecosystems to maintain their structure and function despite environmental stressors, such as deforestation, biodiversity loss, and climate variability (Walker et al., 2004). Ecosystem resilience is influenced by factors such as species diversity, resource availability, and ecosystem connectivity, which determine the system's ability to recover from disturbances and sustain ecological services.

At the meso-level, resilience is also widely discussed in the context of infrastructure and urban planning, where it pertains to the ability of cities and critical infrastructure to withstand and recover from climate-related hazards, such as flooding, heatwaves, and sea-level rise (Meerow et al., 2016).

This paper adopts a macroeconomic and systemic perspective on resilience, focusing on how AI applications contribute to enhancing the resilience of large-scale systems—including economies, industries, and critical infrastructure—rather than examining individual or micro-level resilience, as is often explored in health sciences or behavioral studies. Unlike psychological resilience, which pertains to individuals' capacity to cope with stress (Bonanno, 2004), our analysis centers on how AI-driven innovations strengthen economic, environmental, and infrastructural resilience at a broader scale.

3 Methodology

The review is conceived as a Systematic Literature Review (SLR) to synthesize insights on how artificial intelligence contributes to enhancing system resilience to climate change. This approach is grounded in the SLR methodology as delineated by Tranfield et al. (2003). Such a methodology is selected for its ability to ensure transparency, reproducibility, and robust evidence aggregation while minimizing bias. The process is meticulously guided by the PRISMA framework (Moher et al., 2009), which provides a structured protocol for documenting every phase of the review—from the formulation of the search strategy to the synthesis of findings. In addition, the CADIMA online tool is instrumental in managing the review workflow by facilitating automated data extraction and screening, thereby ensuring the consistent application of criteria across all stages (Kohl et al., 2018).

TABLE 1 Search string.

Search string	
Search string: ("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks" OR LLM OR "Large Language Model") AND (Resilience OR "System Robustness" OR "System Adaptability" OR "Vulnerability Reduction" OR "Robust Systems") AND ("Climate Change" OR "Global Warming" OR "Climate Variability" OR "Climate Crisis" OR "Climate Adaptation" OR "Climate Mitigation" OR "Climate Resilience")	
Database	**Results**
https://app.dimensions.ai	680
https://www.scopus.com	485
https://www.webofscience.com	447

Source: Authors.

3.1 Data sources and search strategy

To construct a comprehensive review of literature, three primary databases are chosen: Scopus, Web of Science, and Dimensions.ai. The first two are selected due to their rigorous indexing criteria and broad coverage of relevant disciplines. Dimensions.ai is chosen as a complement because it is known for its extensive reach and innovation in indexing; it aggregates publications (including those with Crossref DOIs) across many fields and can sometimes index newer or interdisciplinary works not yet included in Web of Science or Scopus. Google Scholar is not employed, as it includes a substantial amount of non–peer-reviewed literature (e.g., reports, theses), which can introduce noise; this review remains confined to peer-reviewed studies.

The search strategy is carefully developed by combining key terms from three thematic domains: (a) AI technical terms, (b) resilience-related terms, and (c) climate-related terms. The search is restricted to peer-reviewed articles published in English (due to resource and interpretation constraints), with the literature confined to studies from January 1, 2000 to February 4, 2025, thereby capturing two and a half decades of AI applications in climate resilience. This calibrated approach ensures a balance between breadth and precision, capturing studies directly relevant to the application of artificial intelligence in enhancing system resilience in the context of climate change. See Table 1 for the search string.

3.2 Study selection process

The initial database search yields 1,612 records, which are subsequently refined to 926 unique entries after the removal of duplicates. These records undergo a preliminary screening of titles and abstracts to ascertain their relevance to the intersection of artificial intelligence and climate resilience. This stage results in the exclusion of 272 records that do not meet the thematic requirements. Following this, 654 full-text articles are rigorously evaluated for eligibility, ensuring that each study meets the overall focus of the review.

3.3 Inclusion and exclusion criteria

A detailed set of inclusion and exclusion criteria is applied to the full-text articles to ensure relevance and quality (Table 2). Eligible studies are required to focus on systems, sectors, or domains—such as energy, water, agriculture, transportation, or biodiversity protection—and on stakeholders including policymakers, practitioners, and communities affected by climate change. In addition, the studies need to present an explicit discussion of artificial intelligence applications, including machine learning, neural networks, and predictive analytics, as a means of enhancing system resilience. Finally, only primary studies reporting measurable outcomes—such as improved adaptability, reduced vulnerability, enhanced recovery capacity, or optimized sustainability metrics—are included. This rigorous set of criteria ensures that only the most pertinent and high-quality research is retained for analysis. 11 studies were excluded due to a “lack of measurable outcomes” (target criteria) representing 4.3% of all excluded papers at the full-text level.

To ensure consistency in applying the inclusion and exclusion criteria, the two authors conduct a double screening on a sample subset of records to develop a common understanding of the inclusion criteria.

3.4 Reporting and flow diagram

The entire review process is succinctly represented in a PRISMA flow diagram, which outlines the methodological progression from the initial identification of 1,612 records to the final inclusion of 385 studies. This diagram visually encapsulates the key stages of the review—from the initial identification phase and duplicate removal to the rigorous screening based on titles and abstracts, followed by the comprehensive full-text eligibility assessment (see Figure 1).

TABLE 2 Inclusion and exclusion criteria.

Key element	Criteria
Population	Studies must focus on systems, sectors, or domains impacted by climate change (e.g., energy, water, agriculture, transportation, biodiversity protection) or on stakeholders involved in implementing AI solutions for resilience (e.g., policymakers, practitioners, communities).
Index test	Selected studies must explicitly discuss the application of AI technologies to enhance system resilience in the context of climate change mitigation, adaptation, or the green transition. This includes AI methods such as machine learning, neural networks, or predictive analytics.
Target	Papers must report measurable outcomes related to system resilience, such as improved adaptability, reduced vulnerability, enhanced recovery capacity, or optimized sustainability metrics (e.g., increased renewable energy integration or improved resource management).

Source: Authors.

4 Results

This systematic review synthesizes 385 studies on the role of AI in enhancing resilience against climate-related challenges. Our analysis reveals a dominant focus on adaptation strategies, with 64.4% of the studies addressing climate adaptation, 19.4% integrating both adaptation and mitigation, and only 16% centering exclusively on mitigation efforts.[1] This distribution underscores the prevailing emphasis on AI-driven solutions for climate resilience, highlighting a relative gap in research targeting mitigation strategies.

The publication trend of AI applications in climate resilience demonstrates a rapid and exponential growth in recent years (Figure 2). Between 2012 and 2018, research output was minimal, with only a handful of studies published. A significant acceleration is observed from 2020 onward, particularly in the past 2 years. In 2023, 70 papers (18.18%) were published, but the most striking surge occurred in 2024, which accounts for 199 papers—over half (51.69%) of the total sample. This substantial rise underscores a growing academic and policy interest in leveraging AI for climate resilience.

Even though our literature review only extends to February 4, 2025, 41 identified papers (10.65%) published in 2025 (an increase of 71% compared to the 24 papers published in the same period in 2023, and an increase of 14% compared to the 36 papers published in the same period in 2024), suggesting that this research area is poised for even greater expansion throughout the year. This upward trajectory highlights the increasing recognition of AI’s potential in addressing climate-related challenges and suggests that AI-driven climate resilience will remain a key research frontier in the coming years.

The regional distribution of AI applications in climate resilience research reveals significant disparities (Figure 3). Asia (31.9% of papers) and global-scale studies (34.3%) receive the most attention, whereas South America (1.8%) and Oceania (2.3%) remain critically understudied. Africa accounts for 7.5% of studies, underscoring the pressing need for greater AI-driven climate resilience research in vulnerable regions. Europe (11.7%) and North America (10.4%) have moderate representation; however, some key sectors—particularly climate and agriculture—remain underexplored in these region. One striking fact is that although only 7.5% of studies focus on Africa, the continent is among the most vulnerable to climate change impacts (according to IPCC report of 2024 among other sources),with severe projected impacts on agriculture, water security, and health. This mismatch between research attention and climate risk is concerning. It

1 This dominance of adaptation-focused studies is statistically significant (two-sample test of proportions of the three categories of adaptation, mitigation and both, $p < 0.0001$), underscoring a real skew in research attention.

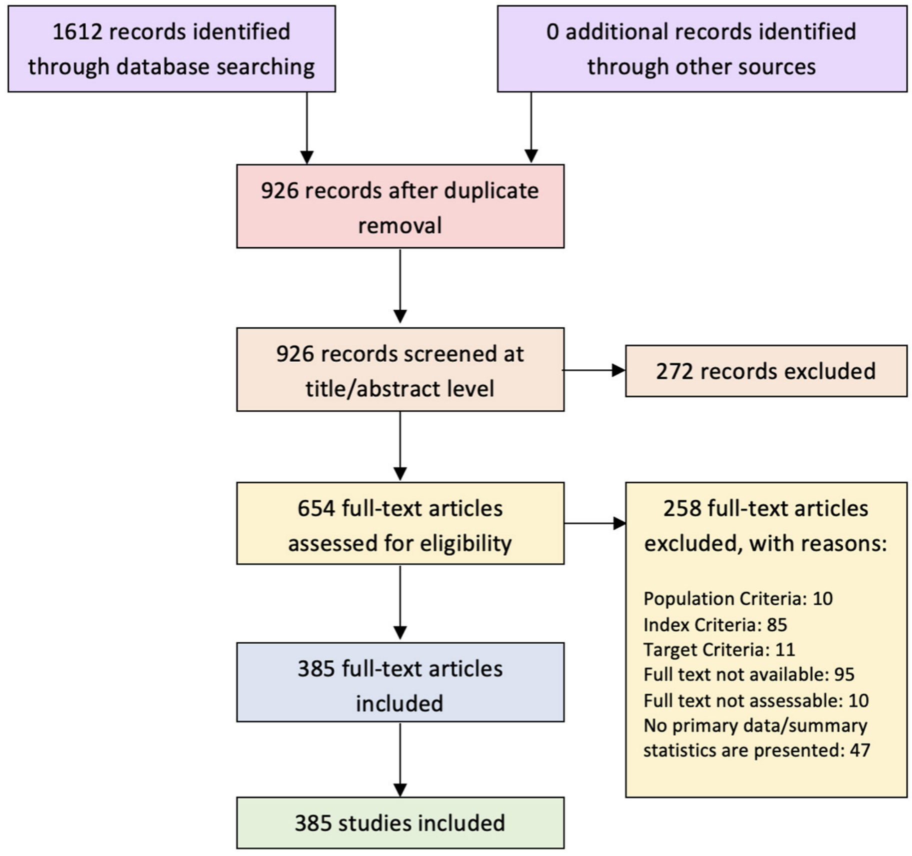

FIGURE 1
PRISMA flow diagram of the systematic literature review.

suggests that the regions that could benefit the most from AI-driven resilience solutions are currently the least studied. For policy, this underrepresentation means current AI tools may not be tailored to African contexts, and there is a pressing need to invest in research and capacity building in these regions.

The sectoral breakdown of reviewed studies by region highlights most researched areas in each region. "Agriculture, Forestry, and Food" emerges as the dominant focus in South America and Africa, whereas it receives comparatively less attention in North America and Oceania. As anticipated, Oceania shows the highest proportion of studies related to "Coastal and Marine" and "Climate and Weather Monitoring," reflecting the region's vulnerability to climate-related challenges. Overall, the distribution of AI applications across sectors mirrors regional priorities and contextual needs (Figure 4).

To further dissect the role of AI in climate resilience, studies are classified based on the type of AI tools employed. As illustrated in Table 3, We acknowledge that the categories listed in Table 3 group both AI techniques (e.g., Deep Learning, NLP) and application contexts (e.g., GeoAI). While not strictly taxonomic, this pragmatic categorization reflects how these terms appear in the reviewed literature. For clarity: NLP is treated as a methodological class of models specialized in human language processing, while GeoAI is understood here as the application of AI tools to geospatial data—i.e., a domain of application rather than a technical approach.

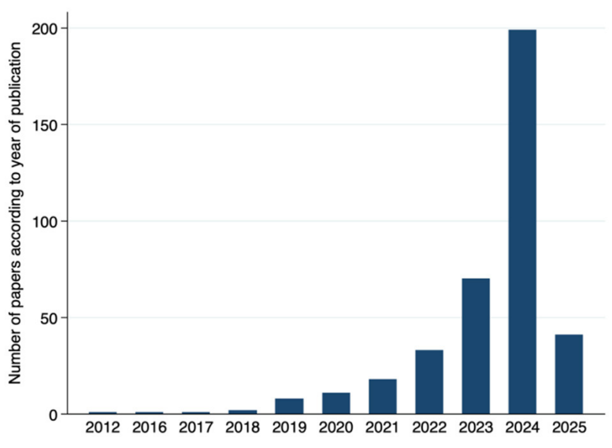

FIGURE 2
Number of published papers according to the year of publication until 04/02/2025.

This hybrid categorization was retained to preserve fidelity to how studies self-described their methodology.

Classical Machine Learning/General ML approaches constitute the most frequently utilized methods, representing 51.43% of

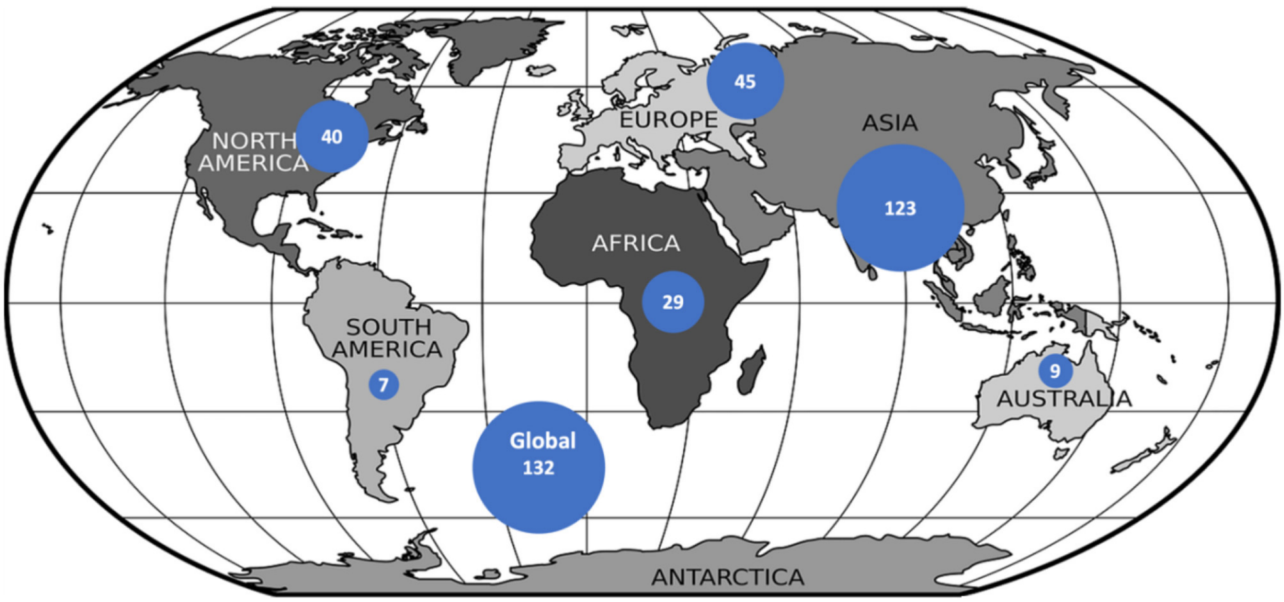

FIGURE 3
Number of publications by geographic focus.

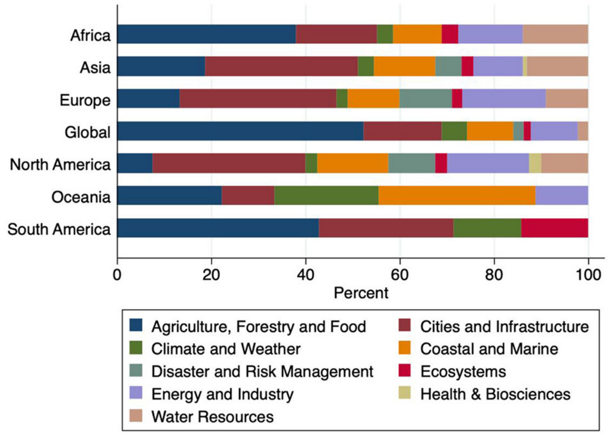

FIGURE 4
Sectoral breakdown of reviewed studies by geographical regions.

TABLE 3 Frequency of AI types used in the reviewed studies.

Type of AI applied	Frequency	Percent
Deep learning/neural network models	86	22.34
Domain-specific/other specialized methods	12	3.12
Classical machine learning/general ML	198	51.43
Hybrid/multi-method approaches	25	6.49
Natural language processing & text mining	9	2.34
Reinforcement learning & graph-based methods	4	1.04
Remote sensing & GeoAI	8	2.08
Statistical & econometric models	11	2.86
Traditional machine learning & ensemble methods	32	8.31
Total	385	100

Source: Authors.

the reviewed studies. Deep learning techniques, including neural network models, account for 22.34%, reflecting their increasing adoption for complex predictive modeling and pattern recognition tasks. Traditional machine learning and ensemble models comprise 8.31%, while hybrid and multi-method approaches contribute 6.49% of the reviewed applications. Despite the widespread integration of machine learning techniques, domain-specific and specialized AI models remain underrepresented, accounting for just 3.12% of studies. Similarly, reinforcement learning and graph-based approaches constitute a mere 1.04% of applications, indicating limited exploration of these advanced methodologies in climate resilience. Remote sensing and GeoAI applications, crucial for environmental monitoring and disaster prediction, appear in only 2.08% of studies, suggesting an opportunity for further research in leveraging satellite and geospatial data for climate adaptation. Statistical and econometric models, which traditionally inform policy and economic resilience planning, comprise 2.86% of the reviewed literature.

For the sake of clarity and interpretability, we provide below a brief explanation of each category, as derived from the content and methods described in the reviewed studies:

Deep Learning/Neural Network Models (22.34%): This category includes studies that applied neural network-based models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Deep Belief Networks (DBNs). These methods are typically used for processing unstructured data, including imagery, time series, and sequential data, particularly in domains like climate forecasting, satellite image analysis, and disaster prediction.

Domain-Specific/Other Specialized Methods (3.12%): This group captures AI techniques that are highly customized or proprietary to a specific application domain. Examples include agent-based models used in environmental simulation, biologically inspired models, or systems embedded with domain knowledge (e.g., crop-specific AI in agriculture). These methods are often tailored for particular use cases and are not easily generalizable across sectors.

Classical Machine Learning/General ML (51.43%): The most frequent category, it includes standard non-deep-learning techniques such as decision trees, support vector machines (SVMs), k-nearest neighbors (KNN), logistic regression, and Naive Bayes classifiers. These models are often used for classification, regression, or clustering and are considered foundational within AI applications. In many reviewed studies, the specific method was not deeply described—hence the general "ML" label.

Hybrid/Multi-Method Approaches (6.49%): This category encompasses studies that combine two or more AI methods—such as integrating neural networks with optimization algorithms (e.g., genetic algorithms or fuzzy logic), or blending machine learning with physical modeling. These hybrid approaches aim to overcome limitations of single models by enhancing performance, robustness, or interpretability.

Natural Language Processing & Text Mining (2.34%): This group includes studies using NLP for extracting insights from unstructured textual data—such as policy documents, social media, or news feeds. Techniques include named entity recognition, sentiment analysis, topic modeling (e.g., LDA), and transformer-based models like BERT. These are often used to understand public perceptions of climate risk or analyze institutional responses.

Reinforcement Learning & Graph-Based Methods (1.04%): These advanced AI techniques involve dynamic decision-making (reinforcement learning) or structured data representation (graph-based learning). While less common in the reviewed literature, some studies apply reinforcement learning for adaptive system control (e.g., in energy grids), and graph neural networks for modeling interdependent systems or climate networks.

Remote Sensing & GeoAI (2.08%): This refers to AI applications that process geospatial data, satellite imagery, or LiDAR datasets. Techniques in this group include GeoAI, image classification, spatial clustering, and object detection used in environmental monitoring, urban heat mapping, deforestation tracking, and flood extent estimation.

Statistical & Econometric Models (2.86%): Though not strictly AI, these models were often used in conjunction with AI tools or as benchmarks. They include regression-based models, ARIMA time-series forecasting, panel data analysis, and other econometric techniques commonly used in climate economics, policy assessment, or risk quantification.

Traditional Machine Learning & Ensemble Methods (8.31%): This subset of classical ML focuses on ensemble-based techniques, such as Random Forests, Gradient Boosting Machines (e.g., XGBoost), and bagging. These models combine multiple learners to enhance predictive accuracy and reduce variance. They were commonly used in climate-related classification tasks (e.g., land cover, hazard zones) and outperformed simpler single-model approaches in many cases.

These findings indicate a strong reliance on Classical Machine Learning/General ML and deep learning for climate resilience research while highlighting underutilized areas such as reinforcement learning, remote sensing applications, and hybrid modeling techniques. The next sections delve into sector-specific trends, exploring how AI applications are distributed across the 9 key identified sectors, namely, Agriculture, Forestry and Food; Cities and Infrastructure; Climate and Weather Monitoring; Coastal and Marine; Disaster and Risk Management; Ecosystems; Energy and Industry; Health; and Water Resources (see Table 4). Given the vast number of studies identified in some sectors, it is not feasible to cite all of them. Consequently, a subset of the most representative works is selectively referenced to illustrate the key elements of each sector.

4.1 Agriculture, forestry and food sector

The agriculture sector, a cornerstone of global food security, is facing unprecedented challenges due to the combined pressures of climate change and resource limitations (Rojas, 2021). Its vulnerability to climate variations poses a significant threat

TABLE 4 Sectors in which AI technology enhances the resilience toward climate change.

Sector of the papers	Frequency	Percent	Description
Agriculture, forestry and food	117	30.39%	AI for precision agriculture, crop yield prediction, land use planning, and food security.
Cities and infrastructure	98	25.45%	AI applied to smart urban planning, infrastructure resilience, and sustainable city systems.
Climate and Weather monitoring	17	4.42%	AI used in climate modeling, meteorology, and early warning systems.
Coastal and marine	46	11.95%	AI applied to coastal zone management, ocean monitoring, and marine biodiversity.
Disaster and risk management	19	4.94%	AI for hazard prediction, emergency response, risk mapping, and crisis management.
Ecosystems	9	2.34%	AI for ecosystem monitoring, biodiversity conservation, and habitat protection.
Energy and industry	46	11.95%	AI to optimize renewable energy systems, emissions reduction, and industrial efficiency.
Health	2	0.52%	AI to assess and respond to climate-related health risks such as heat stress, and support health system resilience.
Water resources	31	8.05%	AI for water quality monitoring, drought prediction, and watershed management.
Total	385	100%	

to its stability and productivity. Altered climatic conditions, including shifts in temperature, humidity, and rainfall patterns are profoundly affecting agricultural practices (Sejian et al., 2022). Simultaneously, extreme weather events, such as droughts, floods, and heatwaves, are increasingly jeopardizing crop yields and the overall agricultural output; the brunt of drought-related damages, accounting for a staggering 83% of global losses between 2006 and 2016 (Rojas, 2021). The situation is further compounded by rising CO_2 levels and the proliferation of invasive pests, leading to altered cropping patterns and reduced crop diversity (Rojas, 2021). Hence climate change poses a serious challenge to the resilience of the agricultural sector.

Forests, recognized as essential for climate change mitigation due to their capacity for carbon sequestration, are also at risk (Kacic et al., 2023; Meng et al., 2023). The sustainability of forest ecosystems is increasingly compromised by climate change, particularly rising global temperatures and unsustainable human activities (Rammer et al., 2021). To combat these challenges, Climate-Smart Agriculture (CSA) offers an integrated approach to address climate change while ensuring sustainable agricultural production, food security, and the wellbeing of rural communities (Usigbe et al., 2024). Remote Sensing (RS) technologies play a crucial role in monitoring and managing agricultural systems in the face of climate change, providing essential data for informed decision-making (Al-Jabri et al., 2025).

4.1.1 AI applications in agriculture, forestry and food sector

AI is significantly impacting the agriculture, forestry, and food sectors through applications such as predictive analytics, remote sensing, and decision support systems, offering capabilities in learning, reasoning, and self-correction that are essential for processing vast amounts of data and extracting actionable insights. Predictive analytics leverages AI algorithms to analyze historical data, including weather patterns, soil conditions, and crop performance, to forecast future agricultural outcomes (Guntuka, 2024). These models enable informed decisions, optimize resource allocation, and mitigate risks associated with climate change (Causevic et al., 2024). Machine learning (ML) is used to predict crop yields, pest outbreaks, and market trends, facilitating proactive measures to minimize losses and maximize productivity (Yadav et al., 2024). For instance, AI-powered systems can accurately forecast crop yields by integrating meteorological data, pesticide records, and historical crop yield data, as demonstrated by the use of gradient boosting models (Feng et al., 2022).

The Next Generation Agricultural Stress Index System (ASIS) supports drought management through machine learning, benefiting parametric crop insurance and early warning systems (Feng et al., 2022). Remote sensing technologies, such as satellite imagery and aerial surveys, enhance large-scale assessments of forests and agricultural lands (Xu et al., 2021) and agricultural drought modeling (Dadrass Javan et al., 2025). AI analyzes these images to monitor forest cover changes, biomass estimation, and illegal logging detection, while in agriculture, it assesses crop health, soil moisture, and disease outbreaks (Agho et al., 2024). AI-driven forest monitoring improves biodiversity insights (Causevic et al., 2024), and its integration with remote sensing strengthens agricultural resilience and prescriptive decision-making (Feng et al., 2022). AI-powered decision support systems provide farmers with real-time insights by integrating data from sensors, weather forecasts, and markets (Tupalo, 2024). These systems optimize irrigation, fertilization, and pest control, reducing environmental impact while increasing efficiency (Ali et al., 2025). AI also aids in identifying crop diseases and nutrient deficiencies through image recognition and sensor analysis (Usigbe et al., 2024). ML models further refine drought response predictions by evaluating interactions between continuous and categorical variables (Liang et al., 2024).

Beyond cultivation, AI improves post-harvest logistics and supply chain management, optimizing solar dryers, cold storage, and equipment maintenance (Usigbe et al., 2024; Kumar D. et al., 2024). AI and blockchain enhance transparency, fair pricing, and efficiency in food distribution (Mu et al., 2024). Additionally, text mining tools detect chemical hazards and seafood risks by analyzing scientific and media sources (Mu et al., 2024).

AI also advances crop resilience by identifying stress response genes linked to heat, drought, and salt stress, supporting the development of stress-resistant crop varieties (You et al., 2025).

These AI applications contribute to resilience by enabling early detection of crop stress and pest outbreaks, improving the timing and precision of interventions. This proactive capacity reduces vulnerability to climatic variability and promotes adaptive management. Optimizing water use through AI-driven irrigation models also enhances robustness against drought and water scarcity.

4.1.2 Mechanisms for enhancing resilience

AI application is enhancing the resilience of agriculture, forestry, food safety via a number of methods. Precision farming improves pest control, harvesting, and resource use (Guntuka, 2024), while predictive analytics aids in forecasting crop yields, climate conditions, and market trends (Rebez et al., 2024). Climate-smart agriculture (CSA) benefits from AI-driven climate monitoring and adaptive strategies (Zidan and Febriyanti, 2024).

AI optimizes supply chains through early pest detection, logistics forecasting, and risk analytics, mitigating climate-related threats (Usigbe et al., 2024; Ahvo et al., 2023). In forestry, AI enhances Earth observation, IoT-enabled monitoring, and remote sensing, improving conservation and illegal logging detection (Wang G. G. et al., 2024). AI-powered food safety systems identify contamination risks in supply chains (Mu et al., 2024).

It also supports renewable energy integration by optimizing energy use in agriculture (Kumar D. et al., 2024). Machine learning models help manage drought risks and support crop resilience by identifying stress response genes (Liang et al., 2024; Na and Na, 2024; You et al., 2025). In livestock, AI monitors animal health and behavior, reducing heat stress impacts (Sejian et al., 2022). AI enhances resilience in agriculture and food systems through predictive analytics for crop yield, early pest detection, and real-time climate-smart decision-making. These tools enable proactive adaptation, reduce crop losses, and optimize irrigation and supply chains, increasing robustness against droughts, pests, and supply shocks.

4.2 Cities and infrastructure

The 21st century is often called the "century of the city" because more than half of the global population resides in urban areas (Amen, 2024), making these hubs critical for determining our resilience. However, cities face escalating threats from floods, hurricanes, wildfires, and other extreme weather events intensified by climate change (Wang J. et al., 2024). Climate change exacerbates urban flooding, leading to overwhelmed drainage systems and extensive infrastructure damage (Lu et al., 2023). Coastal cities encounter additional threats from rising sea levels and storm surges. The "7.20" extreme rainfall event in Zhengzhou, China, highlights the urgent need for improved emergency and stormwater management strategies (Lu et al., 2023). Additionally, the increase in impermeable surfaces due to urbanization reduces vegetation's capacity to absorb excess water, further heightening flood risks (Li et al., 2024). The Urban Heat Island (UHI) effect intensifies heatwaves, leading to increased energy consumption, elevated air pollution, and health risks (Wen et al., 2024). For example, between 2014 and 2023, ∼48,000 heat-related deaths occur in Germany (Goh et al., 2024). Furthermore, flooding and extreme weather events disrupt transportation networks, affect the movement of people and goods, and result in significant economic consequences (Cassottana et al., 2022).

In sum, cities face escalating threats from climate-induced hazards. This topic receives substantial attention in the literature, with over one-fourth of the identified papers (specifically, 98 studies) focusing on the applications of AI in cities and infrastructure.

4.2.1 AI application for cities and infrastructure

AI emerges as a powerful tool for addressing these complex issues, offering capabilities to analyze vast datasets, predict future events, optimize resource allocation, and enhance decision-making (Yang et al., 2022a). AI plays a critical role in climate resilience and urban planning by enhancing predictive capabilities, disaster management, and resource optimization (Chew et al., 2025). Machine learning algorithms forecast extreme weather events such as floods, heatwaves, and hurricanes, enabling proactive measures to mitigate risks (Kumar G. D. et al., 2024; Al-Raeei, 2024; Habib et al., 2024). AI-powered early warning systems help communities prepare for disasters, while predictive models assess flood risks, building damage, and traffic flow to improve emergency response planning (Lu et al., 2023; Cassottana et al., 2022; Klepac et al., 2022).

Geospatial AI (GeoAI) integrates spatial data with AI methods to improve flood hazard mapping, urban planning, and disaster management (Kumaş and Aslan, 2025; Rezvani et al., 2024). The combination of AI with Geographic Information Systems (GIS) and Building Information Modeling (BIM) enhances risk assessment, leading to more resilient infrastructure and sustainable urban environments (Kopiika et al., 2025).

AI-driven decision support systems (DSS) optimize energy consumption, traffic management, and waste reduction, helping cities reduce greenhouse gas emissions and improve air quality (Al-Raeei, 2024; Cassottana et al., 2022). AI-powered smart technologies improve heating, ventilation, and transportation systems, reducing congestion and emissions. Additionally, AI enhances waste management by identifying recycling opportunities and streamlining logistics, fostering a circular economy (Al-Raeei, 2024).

4.2.2 Mechanisms for enhancing resilience

AI plays a crucial role in identifying and mitigating climate-related risks within urban environments (Al-Raeei, 2024). Predictive modeling allows AI to forecast extreme weather events with greater accuracy, providing communities valuable time to prepare (Al-Raeei, 2024; Habib et al., 2024). During extreme rainfall events, AI proves particularly effective in managing flood risks by analyzing urban water flows and optimizing drainage systems, as well as predicting potential water contamination or infrastructure damage that could disrupt essential services (Habib et al., 2024). Smart cities harness digital technologies such as IoT sensors, big data, and AI to improve quality of life and the efficiency of public services (da Silva et al., 2024). These interconnected systems not only monitor environmental variables but also enable rapid interventions during emergencies such as floods or heatwaves (da Silva et al., 2024).

AI further enhances community resilience against climate change and pandemic-related challenges. AI-driven platforms facilitate real-time data sharing among urban planners and health authorities, improving resource management and response coordination during crises (Al-Raeei, 2024).

In urban settings, AI strengthens resilience by enabling smart infrastructure management, predictive maintenance of critical systems, and optimized traffic and energy flows. AI-driven modeling also supports climate risk assessment and urban planning, reducing vulnerability to extreme weather and heat stress.

Moreover, the literature highlights several empirical studies and case studies; a selection of these is detailed in Table 5.

4.3 Climate and weather monitoring

This category covers studies focusing on climate prediction models, weather early warning systems, and related monitoring tools. As the volume and complexity of climate data continue to grow, there is an increasing need for advanced data infrastructures and analytical methods, including artificial intelligence (Rahman et al., 2024). AI offers considerable potential to enhance the accuracy, speed, and responsiveness of early warning systems, which are essential for both climate adaptation and risk reduction (Neset et al., 2024; Jones et al., 2023). Reflecting this growing interest and importance, 17 papers are classified under the "Climate and Weather Monitoring" category in our review. Among these papers, a small fraction include a mitigation component, likely because they inform long-term climate mitigation strategies (e.g., improving climate models for policy or clean energy production).

TABLE 5 Selected cases of AI applications for enhancing urban resilience.

Area of AI application	Description	Source
AI-driven urban park design	AI optimizes urban park design to improve thermal comfort and air quality through enhanced shading and vegetation placement.	Chen et al., 2025
AI for flood risk assessment	AI assesses flood risks using geospatial technology and deep-learning, integrating local knowledge to enhance adaptive capacity.	Haripriya et al., 2024
AI in roadway infrastructure	AI analyzes vulnerabilities in roadway infrastructure with Climate Impact Vulnerability Scores (CIVS) and multi-criteria decision analysis.	Chang and Hossain, 2024
Smart sustainable systems enhanced by AI	AI enhances flood damage assessments using multi-criteria decision-making computations, improving accuracy and response strategies.	Habib et al., 2024

Source: Authors.

However, this category primarily focuses on prediction and monitoring rather than direct mitigation implementation.

4.3.1 AI application in climate and weather monitoring

AI-driven predictive analytics enhances climate modeling by improving the accuracy of precipitation and temperature forecasts. Machine learning techniques, such as random forest algorithms and seasonal bias correction, refine climate projections, providing more reliable tools for policymakers and planners (Tang et al., 2024). AI-powered climate models integrate historical climate data to simulate interactions between the atmosphere, oceans, land, and biosphere, supporting decision-making in agriculture and other climate-sensitive sectors (Gatla, 2019). AI also aids in predicting extreme weather phenomena, strengthening risk management and adaptation strategies (Gatla, 2019).

AI strengthens climate adaptation and resilience through early warning systems, leveraging live data from weather sensors, satellite imagery, and social media to detect and predict climate hazards (Neset et al., 2024). These systems support communities in taking preventive measures, while also optimizing renewable energy systems and driving proactive adaptation initiatives.

In remote sensing, AI processes satellite imagery and drone feeds to enhance impact-based weather warnings, particularly for urban flooding risk assessment (Neset et al., 2024). AI-powered tools integrate visual sensing inputs and social media feeds to assess and adjust warning levels in real time (Neset et al., 2024). AI's role in Climate Data Management Systems (CDMS) further strengthens climate monitoring and predictive capabilities by automating real-time data processing and risk assessment (Rahman et al., 2024).

In conservation, AI identifies climate-resilient coral reefs by integrating environmental and ecological data through neural network models, predicting coral health indices and guiding conservation efforts (Mayfield et al., 2022). AI also enhances decision support systems by mapping vulnerabilities to extreme weather, supporting local adaptation efforts, and improving long-term climate monitoring (Neset et al., 2024).

4.3.2 Mechanisms for enhancing resilience

AI interventions enhance system resilience by improving adaptability, managing risks, and supporting strategic decision-making across diverse sectors, thereby contributing to a more sustainable and resilient future (Rahman et al., 2024). Machine learning refines climate models, enabling more accurate precipitation and temperature forecasts that support decision-making across sectors (Tang et al., 2024; Gatla, 2019).

AI strengthens risk management by powering early warning systems that analyze real-time data from sensors, satellite imagery, and social media, allowing communities to prepare for climate hazards (Neset et al., 2024). It also enhances Climate Data Management Systems (CDMS) by automating data analysis and improving responses to climate variability and extreme events (Rahman et al., 2024).

In conservation, AI identifies climate-resilient coral reefs by using neural networks to predict coral health indices based on environmental data, informing conservation strategies (Mayfield et al., 2022). By analyzing satellite imagery, drone feeds, and traffic camera data, AI detects flood risks and processes social media and sensor inputs to help authorities assess and respond to emergencies (Neset et al., 2024).

AI improves climate and weather resilience by enhancing forecasting accuracy and timeliness. Through machine learning, large-scale environmental data are transformed into actionable insights, enabling early warning systems, scenario simulations, and preparedness measures that help communities and sectors anticipate and adapt to climatic shifts.

4.4 Coastal and marine

The coastal and marine sector represents a confluence of dynamic ecosystems and substantial socio-economic interests, rendering it exceptionally vulnerable to the escalating impacts of climate change (Ayinde et al., 2024). Coral reef ecosystems, often referred to as the "rainforests of the sea," serve as biodiversity hotspots that provide essential habitats for numerous marine species. Mangrove forests, another critical component of the coastal and marine sector, offer a range of ecosystem services, including coastal protection, carbon sequestration, and habitat provision (Maina et al., 2021). Coastal wetlands, including saltmarshes and peat swamp forests, also face significant risks due to climate change (Wen and Hughes, 2022). Sea-level rise poses a direct threat to these wetlands, leading to habitat loss and altered ecosystem functions. Changes in disturbance dynamics, such as increased flooding and erosion, further exacerbate these vulnerabilities. Understanding the complex interplay of factors affecting coastal wetland resilience is crucial for assessing our resilience in the face of climate change. This category covers ocean-related climate resilience issues—such as sea-level rise, coastal erosion, and marine ecosystem degradation—with 46 papers identified under this topic (representing 11% of the reviewed literature).

4.4.1 AI application in coastal and marine

AI enhances coastal and marine resilience through predictive analytics, remote sensing, decision support systems, and ecosystem monitoring.

Predictive analytics

AI models forecast sea-level changes, storm surges, and precipitation patterns, supporting proactive adaptation (Cheye et al., 2024; Ian et al., 2023). Advanced neural networks, such as BALSSA and D-BALSSA, improve storm surge prediction accuracy, enabling timely disaster warnings (Ayinde et al., 2024; Ian et al., 2023).

Remote sensing

AI processes satellite and drone data to monitor coastal ecosystems, mangrove coverage, and coral reef health (Yang et al., 2022b; Maina et al., 2021; Mayamanikandan et al., 2024). AI-powered classification models quantify changes in coastal vegetation, contributing to conservation strategies (Mayamanikandan et al., 2024).

Decision support systems

AI-driven platforms integrate biodiversity data, climate projections, and anthropogenic pressures to inform coastal management decisions and evaluate conservation trade-offs (Gesami and Nunoo, 2024; Rathoure and Ram, 2024).

Ecosystem monitoring and species identification

AI analyzes sensor, drone, and satellite data to assess ocean conditions, marine biodiversity, and pollution levels, helping identify environmental threats and patterns (Gesami and Nunoo, 2024). Convolutional neural networks rapidly identify and count microfossils, aiding plankton diversity analysis and resilience assessments (Godbillot et al., 2024).

Coastal flood risk models

GeoAI models, including random forests and artificial neural networks, predict coastal flood risks by evaluating factors such as extreme sea levels, elevation, and mangrove proximity, thereby supporting targeted mitigation strategies (Atmaja et al., 2024).

4.4.2 Mechanisms for enhancing resilience

AI enhances the resilience of coastal and marine systems by improving predictive capabilities, enabling proactive management, and supporting adaptive strategies.

Improved adaptability

AI-driven insights help identify vulnerable areas, prioritize interventions, and assess climate resilience measures (Cheye et al., 2024). Adaptive management, informed by real-time feedback and data-driven models, optimizes conservation site selection and intervention strategies (Gesami and Nunoo, 2024; Maina et al., 2021).

Coastal flood risk management

GeoAI approaches integrate mangrove proximity and natural defenses into flood prediction models, emphasizing nature-based solutions for coastal protection (Atmaja et al., 2024). Studies highlight mangroves' role in reducing coastal flood occurrences, underscoring the need for conservation and restoration (Atmaja et al., 2024).

Early warning systems

AI processes large datasets to forecast sea-level rise and precipitation patterns, enhancing early warning systems for timely evacuations (Cheye et al., 2024). The BALSSA model significantly improves storm surge predictions, facilitating disaster mitigation (Ian et al., 2023).

In coastal and marine environments, AI supports resilience by predicting sea-level rise impacts, mapping vulnerable zones, and modeling coastal erosion and marine biodiversity shifts. These applications enable early interventions, better marine resource management, and adaptation strategies for coastal infrastructure.

Additionally, the literature highlights several empirical studies and case studies, which are detailed in Table 6.

4.5 Disaster and risk management

The increasing frequency and intensity of climatological and hydrological hazards, particularly floods, necessitate advanced disaster and risk management strategies (Abdel-Mooty et al., 2022). Climate change drives more extreme weather events, intensifying impacts on urban areas and vulnerable populations (Haggag et al., 2021; Abdel-Mooty et al., 2022). The anticipated rise in extreme rainfall events, sea levels, and flood risks underscores the need for proactive disaster management strategies (Abdel-Mooty et al., 2022). AI-driven models support long-term adaptation planning and help policymakers develop resilient communities. AI rapidly reshapes the landscape of disaster and risk management by enhancing predictive capabilities, optimizing response strategies, and improving resource allocation. AI technologies—particularly machine learning (ML) and deep learning (DL)—are now integral to various facets of disaster management, from early-stage risk assessment to post-disaster recovery.

This category refers to applications focused on preparedness, emergency response, and risk assessment for climate-related disasters, with 19 papers identified in this field.[2]

4.5.1 AI application in disaster and risk management

AI enhances disaster forecasting by analyzing vast datasets to predict the probability and impact of events (Abdel-Mooty et al., 2022; Mosavi et al., 2020). Machine learning (ML) models integrate historical disaster records with climate indices, improving flood prediction accuracy (Tasnuva et al., 2024). Techniques such as

2 This category should be distinguished from Climate and Weather Monitoring since the latter is about observing and predicting climate/weather phenomena, while Disaster and Risk Management is about managing the risks and responses to those phenomena.

TABLE 6 Examples of AI use for strengthening coastal and marine resilience.

Area of AI application	Description	Source
Coral reef resilience	Machine learning assesses sea surface temperature anomalies and bleaching recovery potential, guiding conservation efforts.	Novi and Bracco, 2022
Mangrove conservation	AI identifies mangrove vulnerability drivers, supporting targeted restoration policies.	Amaral et al., 2023
Coastal flood prediction	GeoAI models enhance flood risk assessments by integrating factors such as extreme sea levels and mangrove cover.	Atmaja et al., 2024
Storm surge prediction	The BALSSA model improves storm surge forecasts, leveraging machine learning and real-time data for better preparedness.	Ian et al., 2023

Source: Authors.

Random Forest (RF) models, Support Vector Machines (SVM), and ensemble models refine flood hazard mapping and support strategic planning (Cilli et al., 2022; Composto et al., 2025). In wildfire prediction, AI assesses fire risk based on climate and vegetation indices, while explainable AI (XAI) enhances model interpretability for effective resource allocation (Cilli et al., 2022). AI also contributes to avalanche risk assessment by using intelligent learning models to improve forecasting accuracy (Mosavi et al., 2020).

Remote sensing and geospatial analysis

AI processes satellite imagery and remote sensing data to map disaster impacts and monitor environmental changes (Composto et al., 2025; Singh and Hoskere, 2023). ML algorithms analyze Sentinel-1 and Sentinel-2 imagery to enhance flood extent mapping, leveraging the Normalized Difference Water Index (NDWI) and Google Earth Engine (GEE) for near-real-time assessments (Composto et al., 2025). AI also supports wildfire and landslide vulnerability mapping by integrating topographic and vegetation data (Fernández-Guisuraga et al., 2024; Kerle et al., 2019).

Decision support systems (DSS)

AI-driven DSS integrate predictive models, risk assessments, and real-time data streams to support decision-making in disaster response (Cilli et al., 2022; Hahn et al., 2024). Early Warning Systems (EWS) analyze sensor data, weather patterns, and social media activity to detect hazards and guide evacuation protocols (Hahn et al., 2024). AI also optimizes resource allocation during disaster response by forecasting demand and directing aid where needed (Singh and Hoskere, 2023). Advanced AI techniques, such as deep reinforcement learning, enable autonomous systems to adapt to dynamic disaster conditions (Hahn et al., 2024).

Post-disaster damage assessment

AI accelerates damage assessment using deep learning and Convolutional Neural Networks (CNNs) trained on pre- and post-disaster imagery (Singh and Hoskere, 2023). AI-driven Ultra-High-Resolution Aerial (UHRA) imagery analysis refines damage prediction models, overcoming traditional satellite image limitations. AI-powered drones assess casualties and structural damage, enabling comprehensive disaster impact evaluation (Singh and Hoskere, 2023).

Community resilience and social vulnerability assessment

AI evaluates community resilience and social vulnerability by analyzing socio-economic variables and social media data (Abdel-Mooty et al., 2022; Moghadas et al., 2023). Disaster Risk Indices (DRI) leverage ML models to identify high-risk communities, while text mining and topic modeling extract key insights from disaster-related discussions (Prakash et al., 2024).

Autonomous recovery robots

AI-powered recovery robots enhance disaster response operations by executing search and rescue, firefighting, and infrastructure repairs (Sun L. et al., 2024). These robots integrate advanced AI algorithms to navigate hazardous environments and prioritize lifesaving efforts based on ethical decision-making principles (Sun L. et al., 2024).

4.5.2 Mechanisms for enhancing resilience

AI plays a critical role in enhancing disaster resilience by mitigating climate risks, improving adaptability, and strengthening overall disaster management strategies. Its ability to analyze large datasets, forecast disaster impacts, and optimize resource allocation supports effective resilience-building efforts (Hossin et al., 2025).

AI enhances predictive accuracy, enabling proactive measures for disaster mitigation. AI models analyze climate variables to forecast extreme weather events such as floods, hurricanes, and wildfires, guiding early warnings and preparedness actions (Composto et al., 2025; Singh and Hoskere, 2023). In wildfire-prone areas, AI integrates temperature, humidity, and vegetation cover data to assess fire risks and inform preventive resource deployment (Cilli et al., 2022).

AI fosters real-time insights and flexible disaster response by integrating data from sensors, social media, and weather forecasts (Hahn et al., 2024; Costa et al., 2024). AI-driven monitoring enables decision-makers to dynamically adjust strategies, ensuring more effective disaster response efforts (Nakhaei et al., 2023).

AI strengthens disaster management across all phases—prevention, preparedness, response, and recovery (Nakhaei et al., 2023; Sun L. et al., 2024). AI-driven decision support systems optimize resource allocation, enhance early warning systems, and facilitate rapid damage assessment, enabling communities to recover more efficiently (Hossin et al., 2025). Additionally, AI supports long-term resilience by guiding sustainable land use planning and infrastructure development, reducing future climate

TABLE 7 Selected cases of AI applications in disaster and risk management.

Area of AI application	Description	Sources
Wildfire risk management	AI analyzes wildfire occurrences in Mediterranean landscapes, identifying climate as the primary driver. Integrated with decision support systems, it aids forest managers in fire prevention and management.	Cilli et al., 2022
Post-disaster damage assessment	AI-driven Ultra-High-Resolution Aerial (UHRA) imagery and transformer models achieve 88% accuracy in multi-class damage predictions, enhancing post-disaster assessments.	Singh and Hoskere, 2023
Disaster response coordination	AI processes social media data to identify emerging needs and coordinate disaster responses. Text mining and topic modeling provide insights into disaster impacts and response effectiveness.	Moghadas et al., 2023
Pluvial flood risk prediction	A machine learning model implements spatio-temporal constraints to improve pluvial flood risk prediction, identifying vulnerable areas under different climate change scenarios.	Allegri et al., 2024
Disaster risk indices (DRI)	Machine learning-based disaster risk indices (DRI) provide localized insights into coastal vulnerabilities, enabling policymakers to develop targeted interventions and enhance community preparedness.	Prakash et al., 2024
Critical infrastructure systems (CIS) resilience	AI-driven strategies enhance post-shock emergency responses of Critical Infrastructure Systems (CIS), using deep learning for swift damage assessment and adaptive emergency responses.	Sun L. et al., 2024

Source: Authors.

vulnerabilities (Sun L. et al., 2024). Table 7 presents selected cases of AI application in this area.

AI contributes to disaster resilience through rapid risk assessments, real-time hazard prediction, and optimized emergency response logistics. By identifying patterns and predicting impacts, AI empowers authorities and communities to act faster, mitigate damages, and recover more effectively after extreme events.

4.6 Ecosystems

Ecosystems are complex networks of living organisms and their physical environments, yet they face increasing threats from climate change and human activities (Levy and Shahar, 2024). Changes in surface roughness, albedo, and seasonal cycles create intricate climate feedback loops, increasing the risk of abrupt ecosystem state shifts with ecological, economic, and societal consequences (Levy and Shahar, 2024).

Dryland ecosystems, such as those in Central Asia, are highly vulnerable to overgrazing, land use changes, and desertification, requiring systematic assessment using remote sensing and GIS-based frameworks like Vigor-Organization-Resilience-Service (VORS) (Bi et al., 2024).

Climate change forces shifts in animal behaviors, phenology, and distribution, affecting species survival (Levy and Shahar, 2024). Rising temperatures facilitate the spread of invasive alien plants (IAPs), reducing native vegetation resilience and increasing biodiversity loss (Mtengwana et al., 2021). Projected temperature increases of 3–6°C, coupled with declining precipitation, further threaten indigenous species and intensify competition for resources (Mtengwana et al., 2021).

Changing precipitation patterns and the proliferation of drought-tolerant invasive species (e.g., Acacia saligna, A. longifolia, A. cyclops) reduce streamflow and invade riparian zones, threatening fynbos shrublands and protected areas (Mtengwana et al., 2021).

Addressing ecosystem challenges necessitates comprehensive assessment frameworks, predictive modeling, and integrated conservation strategies. Our review identifies nine papers focused on ecosystem resilience, proposing AI and machine learning (ML) tools to analyze ecosystem dynamics, forecast climate-driven changes, and enhance conservation efforts to ensure the protection and sustainability of these vital systems. While ecosystem-based approaches offer dual adaptation–mitigation benefits, we find that AI applications in this sector are primarily described in the context of adaptation. None of the reviewed studies in this category explicitly target mitigation, which is why Figure 5 shows 0% mitigation for Ecosystems. This highlights a gap in the literature: AI is not yet widely applied to ecosystem-based mitigation, presenting an opportunity for future research.

4.6.1 AI application in ecosystems

AI-driven predictive analytics improve ecosystem forecasting by modeling species distribution, invasive species spread, and soil erosion susceptibility. Techniques like Random Forest (RF), Maximum Entropy (MaxEnt), and Boosted Regression Trees (BRT) predict species distribution under changing climatic conditions, aiding conservation planning (Mtengwana et al., 2021). AI models also assess soil erosion risks using the Revised Universal Soil Loss Equation (RUSLE), Artificial Neural Networks (ANN), and Support Vector Machines (SVM), informing climate-resilient land management strategies (Senanayake and Pradhan, 2022).

Remote sensing technologies combined with AI offer real-time insights into ecosystem health, land cover changes, and biodiversity patterns. AI enhances the analysis of high-resolution satellite imagery, sensor networks, and camera trap data, translating raw environmental data into actionable ecological insights (Levy and Shahar, 2024). Convolutional Neural Networks (CNNs) automate land use classification, improving ecosystem monitoring, while the Vigor-Organization-Resilience-Service (VORS) framework integrates remote sensing and deep learning to assess desertification risks and ecosystem responses (Bi et al., 2024).

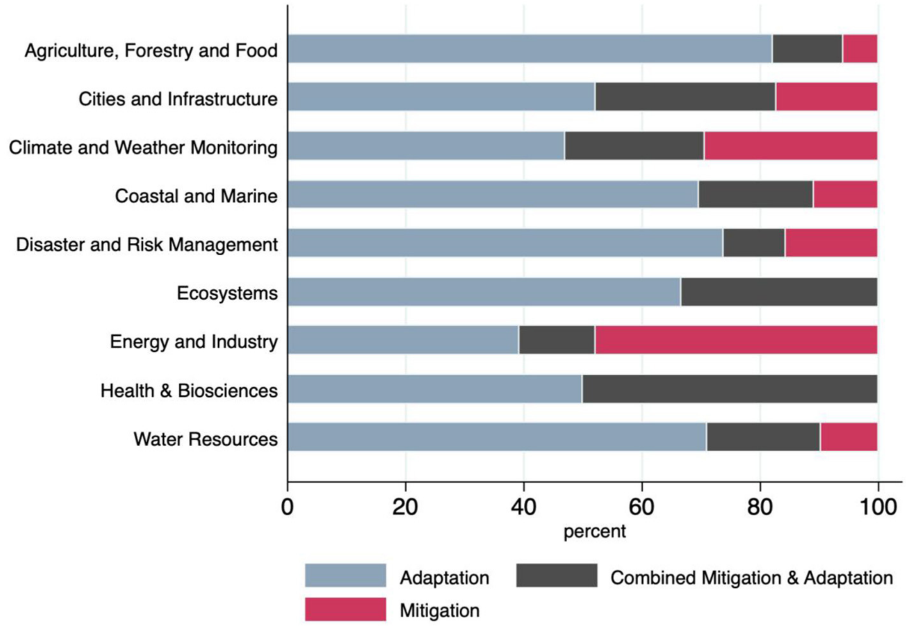

FIGURE 5
Share of mitigation and adaptation actions by sector (%).

Decision support systems (DSS) powered by AI integrate predictive analytics and remote sensing data to guide conservation strategies. These systems optimize resource allocation, identify priority areas for conservation, and evaluate management interventions (Levy and Shahar, 2024). AI refines microclimate modeling, improving bias correction and downscaling techniques, enhancing habitat suitability assessments under different climate scenarios (Levy and Shahar, 2024). AI also helps control invasive alien plants (IAPs) by identifying high-risk areas and informing targeted management efforts (Mtengwana et al., 2021).

4.6.2 Mechanisms for enhancing resilience

AI strengthens ecosystem resilience by addressing climate risks, improving adaptability, and bolstering overall ecosystem health.

AI predictive models forecast climate change impacts, enabling proactive measures to mitigate damage (Yu R. et al., 2019). AI analyzes climate datasets to predict future risks—such as increased soil erosion vulnerability—and informs targeted climate resilience strategies (Bi et al., 2024). It also models the distribution of invasive species, assisting in effective management (Mtengwana et al., 2021). Early warning systems monitor environmental indicators to detect ecological stress, such as declining grassland resilience, allowing timely intervention (Wu et al., 2023). Risk assessment frameworks, like the VORS system, integrate diverse datasets to evaluate vulnerability in arid pastoral ecosystems (Bi et al., 2024).

AI enhances adaptability by supporting ecosystem responses to environmental changes. AI-driven species distribution models (SDMs) predict shifts in species ranges under climate change, informing conservation planning (Dutra Silva et al., 2019). AI refines microclimate modeling, improving bias correction and habitat suitability assessments, and enables targeted conservation strategies (Levy and Shahar, 2024). It also supports adaptive management by continuously evaluating conservation effectiveness and adjusting strategies using real-time sensor and camera trap data (Levy and Shahar, 2024).

AI strengthens resilience by enabling comprehensive ecosystem health assessments. Remote sensing and deep learning analyze spatiotemporal patterns to identify areas needing intervention (Bi et al., 2024). AI assists in biodiversity conservation by determining priority protection areas and informing strategies for mitigating climate impacts (Levy and Shahar, 2024). It also supports the control of invasive species and guides ecosystem restoration by identifying optimal recovery strategies (Mtengwana et al., 2021). In coastal environments, AI tracks kelp forest trends, guiding resilience-building measures (Nicholson et al., 2024).

AI aids ecosystem resilience by monitoring biodiversity, modeling habitat changes, and detecting deforestation or ecosystem degradation in real-time. These tools facilitate timely conservation actions, improve ecosystem service management, and support adaptive strategies under environmental stress.

4.7 Energy and industry

The energy and industrial sectors are fundamental to economic development but are also among the most vulnerable to climate change. These sectors face significant challenges in maintaining operational stability while transitioning toward low-carbon and climate-resilient systems.

Climate change directly affects energy generation, transmission, and distribution, increasing the risk of system failures and energy shortages. Extreme weather events—such as hurricanes, heatwaves, and winter storms—cause physical damage to power infrastructure, disrupting supply chains and grid operations (Nyangon, 2024). Events such as Hurricane Maria in 2017 and Winter Storm Uri in 2021 demonstrate the fragility of energy infrastructure, with transmission and distribution networks particularly vulnerable to high winds, flooding, and prolonged extreme temperatures (Nyame et al., 2024). Hydropower generation declines due to shifting precipitation patterns and reduced river runoff, while solar and wind energy outputs become more variable under changing climate conditions (Nyangon, 2024). Additionally, thermoelectric plants reliant on cooling water—such as fossil fuel, biomass, and nuclear facilities—face increasing risks of efficiency losses and operational shutdowns due to water scarcity and rising temperatures (Nyangon, 2024).

Given these vulnerabilities, strengthening resilience in the energy and industrial sectors is essential. This need is widely recognized in the literature. This systematic review identifies 46 papers focused on these sectors, accounting for 12% of all reviewed studies.

4.7.1 AI application in energy and industry

Artificial Intelligence (AI) is transforming the energy and industrial sectors by improving efficiency, sustainability, and resilience in response to climate change and growing resource demands (Babiarz et al., 2024). Through predictive analytics, remote sensing, decision support systems, and optimization algorithms, AI enables smarter energy management, enhances industrial operations, and reduces environmental impacts (Mohammadi Lanbaran et al., 2024).

AI-driven predictive analytics play a crucial role in forecasting energy demand, preventing equipment failures, and optimizing resource distribution (Mugalakhod and Nirmanik, 2022). Machine learning models analyze historical and real-time data from smart meters, weather stations, and IoT devices to anticipate energy consumption patterns, allowing for real-time grid adjustments and efficient integration of renewable energy sources (Zhang et al., 2025). AI also enhances predictive maintenance by identifying anomalies in sensor data to prevent costly equipment failures, particularly in offshore wind farms where maintenance operations are logistically challenging (Yu Q. et al., 2024). Additionally, AI-powered weather forecasting improves renewable energy management by predicting fluctuations in solar and wind power generation, ensuring better grid stability and resource allocation (Inderwildi et al., 2020).

In remote sensing, AI enhances monitoring capabilities by processing satellite imagery and sensor data to assess infrastructure conditions, environmental changes, and disaster impacts (Ghasemkhani et al., 2024). AI algorithms analyze images to detect damage to power lines and substations, enabling rapid assessment and prioritization of repairs, thereby strengthening system resilience (Nyame et al., 2024). AI-driven remote sensing also supports environmental monitoring by tracking deforestation, pollution levels, and illegal land use changes, while facilitating disaster response through rapid damage assessment and targeted resource allocation in affected areas (Inderwildi et al., 2020).

Decision support systems (DSS) powered by AI integrate data from multiple sources to provide actionable insights for strategic planning, risk management, and operational efficiency. In smart grids, AI optimizes energy flow, reduces waste, and enhances reliability through real-time management of electricity distribution. AI-driven energy management systems in buildings and industries analyze renewable energy supply and consumer behavior to optimize appliance operations and reduce energy costs. AI also strengthens industrial risk management by identifying potential hazards and improving safety measures in manufacturing and resource extraction operations.

AI revolutionizes renewable energy by enhancing efficiency, detecting energy patterns, optimizing supply, and supporting autonomous energy management (Adul et al., 2025). AI-powered smart homes use real-time energy optimization to reduce consumption and store surplus energy for later use, contributing to more sustainable energy systems (Mugalakhod and Nirmanik, 2022). Digital twin technology, which enables 3D modeling, real-time monitoring, and visualization, improves grid management, facilitates predictive maintenance, and enhances industrial process efficiency (Zhou and Liu, 2024). In the industrial sector, AI optimizes resource utilization, reduces waste, and advances sustainable business models by incorporating environmental impact assessments into decision-making (Alahmadi, 2025).

4.7.2 Mechanisms for enhancing resilience

AI-driven climate modeling and early warning systems improve risk management by analyzing vast datasets to forecast extreme weather events and energy demand fluctuations (Nyangon, 2024; Sarosh et al., 2024). Machine learning enhances predictive analytics by integrating real-time sensor data with historical climate patterns to identify vulnerabilities and optimize response strategies (Nyame et al., 2024). AI-powered risk assessments combine climate, operational, and financial data to inform mitigation strategies and improve energy system reliability (Carannante et al., 2024).

AI optimizes energy systems through smart grids, microgrids, and dynamic line rating (DLR) (Yang W. et al., 2024). Smart grids enhance energy distribution by adjusting power flow in real time, reducing waste, and improving stability (Zhang et al., 2025). Microgrids increase resilience by maintaining an independent energy supply during disruptions, while DLR systems optimize transmission efficiency by adapting to environmental conditions (Nyame et al., 2024). AI also facilitates demand-side management (DSM) through dynamic pricing and energy consumption forecasting, improving grid flexibility and efficiency (Mohammadi Lanbaran et al., 2024). Additionally, some AI applications enhance model interpretability, which is crucial for building trust and ensuring that AI-driven decisions are transparent, accountable, and more equitable (Awijen et al., 2024; Akter et al., 2024).

Predictive maintenance powered by AI reduces infrastructure failures and operational downtime (Yu Q. et al., 2024). Machine learning detects anomalies in energy systems, enabling proactive maintenance and preventing costly outages (Ghasemkhani et al., 2024). AI-driven management of distributed energy resources

(DERs), such as solar and wind power, enhances energy security and grid flexibility (Bulut et al., 2025). Grid-Enhancing Technologies (GETs) leverage AI for real-time monitoring and adaptive solutions to improve resilience (Mohammadi Lanbaran et al., 2024; Nyame et al., 2024).

Case studies illustrate AI's effectiveness. In Texas, AI-enabled DERs played an important role in managing extreme conditions during the 2021 energy crisis (Nyangon, 2024). In Tokyo, microgrids maintain power supply during the 2011 earthquake (Nyame et al., 2024). In China, AI minimizes disruptions during Super Typhoon Lekima by dynamically adapting power transmission systems (Nyame et al., 2024). In California, deep learning algorithms optimize electricity demand responses during extreme heat events (Nyame et al., 2024).

AI enhances energy and industrial resilience by managing demand-supply imbalances in smart grids, optimizing renewable energy integration, and ensuring operational continuity through predictive maintenance. These capabilities reduce system fragility and adapt operations to climate variability and disruptions.

4.8 Health

The health outcomes associated with climate change, particularly extreme heat, are diverse and far-reaching. They include not only direct heat-related illnesses such as heatstroke and dehydration but also the exacerbation of chronic conditions like cardiovascular and respiratory diseases, kidney dysfunction, and mental health disorders (Jack et al., 2024). The elderly, due to their reduced physiological capacity to regulate body temperature, are particularly vulnerable to these effects (Boudreault et al., 2024). Similarly, individuals with pre-existing cardiovascular or respiratory conditions face heightened risks, as their bodies are less able to cope with the physiological stress induced by high temperatures. There is a substantial body of literature examining the various pathways through which climate change adversely affects human health, primarily by exacerbating existing health conditions. Rocque et al. (2021), for instance, conducted a systematic review of this growing field, and the World Health Organization (WHO) has also placed strong emphasis on the health impacts of climate change.[3] Despite this recognized importance, our review identified only two studies that specifically address the resilience of health systems to climate-related risks, revealing a significant gap in the literature and underscoring the need for further research in this area.

4.8.1 AI application in health

At the macro level, AI-driven predictive analytics forecast heat-related illnesses by integrating meteorological, regional, and demographic data. Multi-region models improve accuracy in identifying high-risk areas, enabling proactive health interventions. Deep learning models—particularly ensemble tree-based and neural network algorithms—outperform traditional statistical approaches in predicting morbidity and mortality trends (Boudreault et al., 2024).

Decision support systems (DSS) powered by AI improve resource allocation and emergency preparedness by identifying vulnerable populations and optimizing medical response strategies. AI-driven DSS direct healthcare resources where they are needed most and support personalized interventions for individuals at high risk of climate-related health issues (Boudreault et al., 2024). Additionally, remote sensing technologies combined with AI provide high-resolution heat hazard mapping by analyzing satellite imagery, land surface temperature (LST), and vegetation indices. These insights inform urban planning strategies, such as increasing green spaces, improving cooling infrastructure, and implementing zoning policies that mitigate the urban heat island (UHI) effect (Jack et al., 2024).

Early warning systems (EWS) leverage AI to integrate real-time data from weather forecasts, health surveillance systems, and socioeconomic indicators, delivering timely alerts for extreme heat events. These systems facilitate targeted public health interventions—such as cooling centers and early response plans—thereby improving community resilience (Jack et al., 2024).

4.8.2 Mechanisms for enhancing resilience

AI enhances climate risk management by predicting both short- and long-term health impacts of extreme heat, allowing for proactive planning and resource allocation (Boudreault et al., 2024). By integrating weather forecasts and climate projections, AI models forecast heat-related health risks, enabling timely preventive measures such as activating emergency response plans, issuing public health advisories, and mobilizing resources to protect vulnerable populations. In the long term, AI supports climate adaptation by assessing the projected burden of heat-related illnesses, helping policymakers design more effective mitigation strategies (Boudreault et al., 2024).

AI improves adaptability by identifying population-specific vulnerabilities and tailoring interventions accordingly (Boudreault et al., 2024). By analyzing the differential impacts of heat on various demographic groups, AI facilitates targeted public health messaging and interventions. For instance, if AI models detect that short-term heat exposure significantly affects a specific population, authorities can implement tailored outreach programs emphasizing hydration and early medical intervention.

In the health sector, AI supports resilience by forecasting disease outbreaks, improving healthcare logistics, and enabling personalized interventions. These systems strengthen preparedness, ensure continuity of care during climate-induced stresses, and reduce health vulnerabilities in at-risk populations.

Table 8 presents selected case studies and empirical evidence supporting these findings.

4.9 Water resources

Water resources are fundamental to human societies and ecosystem resilience, yet climate change poses severe and escalating

3 https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health

TABLE 8 Examples of artificial intelligence applications in health.

Location	AI application	Source
Quebec, Canada	Machine learning models predict heat-related health outcomes across multiple regions, with deep learning models achieving high accuracy.	Boudreault et al., 2024
Abidjan and Johannesburg	AI-powered early warning system using clinical, socioeconomic, and remote sensing data to analyze heat-health impacts.	Jack et al., 2024
Ahmedabad Heat Action Plan	AI-supported early warning system enhances coordination and community outreach to mitigate heat-related mortality and morbidity.	Jack et al., 2024

Source: Authors.

TABLE 9 AI tools for enhancing water resource resilience.

Mechanism	Description	Source
Enhanced predictive modeling	AI-driven models forecast rainfall, streamflow, and groundwater recharge to support proactive planning and resource allocation.	Banerjee et al., 2024; Bizimana et al., 2024; Kartal, 2024
Data-driven decision support systems	AI integrates diverse data sources into decision-making tools for water management, improving climate adaptation and disaster risk reduction.	Henriksen et al., 2022
Optimized water allocation strategies	AI-driven deep learning methods allocate water efficiently among sectors, minimizing economic losses and promoting sustainability.	Zhang et al., 2022
AI-enhanced early warning systems	AI analyzes real-time data to improve flood and drought early warnings, enabling timely response and risk mitigation.	Bizimana et al., 2024; Ghaith et al., 2022; Koutsovili et al., 2023
Infrastructure resilience & predictive maintenance	AI assesses risks to water infrastructure, optimizing predictive maintenance and flood management strategies.	Barman et al., 2024; Liu and Zhao, 2024

Source: Authors.

risks to their availability, quality, and infrastructure. In this review, 31 papers address water resources, representing 15.8% of the reviewed literature—highlighting the extensive body of work in this area.

Climate change threatens water security by intensifying extreme hydrological events, exacerbating scarcity, degrading water quality, and straining infrastructure (Granata and Di Nunno, 2025; Kartal, 2024; Zhang et al., 2022). Rising temperatures and shifting precipitation patterns increase the frequency of floods and droughts, disrupting water availability and infrastructure reliability. Snowmelt-dependent regions experience increasingly erratic runoff, heightening the risk of winter floods and summer shortages (Granata and Di Nunno, 2025).

Water scarcity worsens, particularly in arid regions, due to increased evaporation and reduced groundwater recharge, intensifying competition among agricultural, industrial, and domestic users (Henriksen et al., 2022). Sea-level rise further threatens coastal freshwater supplies by increasing saltwater intrusion into aquifers (Nikoo et al., 2024).

Water quality also deteriorates. Higher temperatures promote algal blooms in lakes and reservoirs, while intense rainfall increases runoff of pollutants—such as sediments and pesticides—contaminating freshwater sources (Henriksen et al., 2022). Many water treatment facilities, designed for past climate conditions, now struggle to manage these evolving challenges (Xiong et al., 2024).

Infrastructure resilience is at risk, as dams, reservoirs, and treatment plants become increasingly inadequate to handle shifting water volumes. Climate-induced fluctuations in groundwater levels disrupt agricultural and urban water supply systems, underscoring the need for integrated water resource management (Henriksen et al., 2022). The most vulnerable populations, particularly in the Global South, face the greatest risks as water sustainability becomes increasingly uncertain (Lawal et al., 2023). Urgent adaptation strategies and resilient infrastructure are critical to addressing these challenges.

4.9.1 AI application in water resources

AI offers a suite of powerful tools that transform the management and protection of water resources (Bizimana et al., 2024; Sarwar et al., 2025). One key area of application is predictive analytics, where machine learning models forecast rainfall patterns, streamflow, and groundwater levels. These models integrate diverse data sources—including weather forecasts, historical hydrological data, and remote sensing observations—to deliver accurate and timely predictions. For instance, Long Short-Term Memory (LSTM) networks are used for both short-term and long-term flood forecasting by processing time series of temperature and rainfall data (Dtissibe et al., 2024). AI also predicts future water demand by analyzing factors such as population growth, economic activity, and climate conditions, thereby guiding efficient and sustainable water allocation (Johnson et al., 2024). In addition, machine learning models forecast water quality parameters—such as nutrient levels, sediment concentrations, and pollutants—based on land use, climate, and industrial activity, enabling proactive water quality management and pollution prevention (Mallya et al., 2023).

In remote sensing, AI algorithms analyze satellite imagery to identify and monitor water bodies—including lakes, rivers, and wetlands—thereby tracking changes in water availability and assessing climate impacts on aquatic ecosystems (Mallya et al., 2023). AI models also perform land use and land cover mapping from satellite data, which is crucial for hydrological modeling and water resource management. For example, the Cellular Automata Markov model projects future land use changes, which are then integrated into hydrological models to evaluate their impact on water resources (Barman et al., 2024). Furthermore, AI-driven algorithms map flood extents from satellite imagery, providing near-real-time information essential for disaster response and recovery (Sarwar et al., 2025).

Decision support systems powered by AI further enhance water management by integrating diverse data sources and models to inform strategies for Integrated Water Resources Management (Henriksen et al., 2022). These systems help decision-makers evaluate trade-offs between various water uses and determine the most sustainable and equitable allocation strategies. Real-time monitoring and control of water infrastructure—such as dams, canals, and treatment plants—are also enabled by AI, optimizing operations to reduce water losses and improve quality (Johnson et al., 2024).

An emerging application in this realm is the use of digital twins, which combine real-time sensor data with hydrological models to enhance risk knowledge and support decision-making (Henriksen et al., 2022). These digital twins predict and monitor physical conditions on a daily basis, including wetness and drought indices, and are integral to early warning systems for extreme events (Ghaith et al., 2022). In wastewater treatment, AI optimizes processes to enhance pollutant removal and reduce energy consumption; machine learning algorithms, for example, optimize incineration processes at treatment plants to achieve significant energy savings (Xu et al., 2024).

4.9.2 Mechanisms for enhancing resilience

AI interventions significantly enhance climate risk management, adaptability, and resilience in the water resources sector through several concrete mechanisms. Enhanced predictive modeling enables proactive planning by forecasting rainfall patterns, streamflow, and groundwater recharge under various climate change scenarios (Banerjee et al., 2024). These AI-driven models support timely resource allocation and are recommended for climate adaptation efforts in places like Kigali, Rwanda (Banerjee et al., 2024; Bizimana et al., 2024; Kartal, 2024). Data-driven decision support systems further empower water management strategies by integrating diverse data sources (Heo et al., 2024). For example, the HIP digital twin in Denmark leverages real-time data and hydrological models to support climate adaptation, water management, and disaster risk reduction, providing critical insights into water-related risks (Henriksen et al., 2022).

Optimized water allocation strategies driven by AI ensure efficient distribution of water among various sectors. In China, deep learning methods allocate flood drainage rights in the Yellow River Watershed, protecting public health, minimizing economic losses, and promoting sustainable development (Zhang et al., 2022). AI also strengthens early warning systems for floods and droughts by analyzing real-time data to provide timely alerts that enable rapid response and damage mitigation. A flood prediction methodology that integrates synchronization analysis with deep learning exemplifies how early warnings effectively identify vulnerable areas (Bizimana et al., 2024; Ghaith et al., 2022; Koutsovili et al., 2023).

Furthermore, AI contributes to water infrastructure resilience through predictive maintenance. For instance, a hybrid SWAT-ANN model assesses the impacts of climate change on sediment yield in an Eastern Himalayan sub-watershed, informing proactive flood and erosion management strategies that strengthen infrastructure resilience (Barman et al., 2024; Liu and Zhao, 2024).

AI improves water resource resilience through precision forecasting of floods and droughts, real-time management of water distribution, and anomaly detection in water systems. These applications support adaptive water governance and reduce exposure to hydrological extremes (Table 9).

5 Limits, gaps and future directions

While AI presents transformative opportunities for enhancing climate resilience across multiple sectors, several limitations, research gaps, and challenges must be addressed to ensure its effective and equitable deployment. Key concerns include scalability, data availability, interpretability, ethical considerations, and the need for interdisciplinary collaboration.

This review is limited to English-language studies, which may bias the findings geographically. Research published in other languages—potentially covering regions like Latin America or East Asia in more detail—is not captured, meaning our regional analysis may underestimate activity in those areas. Future reviews benefit from multilingual searches or international collaborations to incorporate non-English literature.

Although this review focuses specifically on system resilience, we acknowledge that the concept of climate risk is closely linked and often complementary. Future research could explore this adjacent dimension more directly—for instance, by examining how AI applications contribute both to the reduction of climate risks and to the enhancement of resilience across sectors.

A notable limitation of this review is its exclusive focus on macro-level (systemic) resilience. While individual and community-level (micro-level) resilience—such as household adaptive behaviors or psychological resilience—is undeniably important and contributes meaningfully to overall system resilience, this level remains outside our defined scope. Our aim is to investigate how large-scale systems and sectors (e.g., energy grids, agricultural systems, urban infrastructures) withstand and adapt to climate shocks, which aligns more directly with the types of AI interventions that influence policy, infrastructure, and governance. Including both micro- and macro-level studies would significantly broaden the review's scope beyond a manageable range. Nonetheless, we recognize this as a limitation and encourage future research to explore how AI supports micro-level resilience. Such work may yield valuable insights into how AI technologies enhance individual and community adaptation and, in turn, strengthen systemic resilience.

While our review identifies numerous studies that report positive outcomes of AI applications—such as improved crop yields, better resource allocation, or enhanced forecasting accuracy—it is equally important to acknowledge studies that highlight barriers, trade-offs, or mixed results. For instance, in the agriculture sector, AI-powered decision support systems may demonstrate high performance in data-rich, technologically advanced regions, but their scalability in low-income or resource-constrained settings is limited by factors such as digital infrastructure gaps, cost barriers, and limited technical capacity. Some studies explicitly note that AI tools are often designed without considering the needs or constraints of smallholder farmers, leading to limited adoption. Similarly, climate information systems that rely on mobile apps or online platforms may perform well where digital literacy is high but fail to reach marginalized communities with limited connectivity. These contrasting findings underscore that AI's effectiveness is highly context-dependent and that equity, scalability, and local capacity are essential considerations in designing and deploying AI for climate resilience. By engaging with these conflicting perspectives, we aim to present a more balanced and critical synthesis of the literature.

5.1 Overall limitations

5.1.1 Scalability and accessibility

A critical limitation of AI adoption, particularly in sectors such as agriculture and water management, is the cost and accessibility of advanced AI solutions (Choudhary et al., 2024). Many small-scale farmers and water-stressed communities lack the resources to implement high-tech solutions, necessitating affordable, open-source AI platforms and low-cost sensor technologies—such as geo-sensing—to broaden accessibility. Future research supports the development of open-access AI tools and incentivizes public-private partnerships that enable resource-constrained users to access affordable, context-specific technologies. Initiatives that standardize and disseminate low-cost, scalable solutions across regions play a pivotal role in reducing this accessibility gap.

5.1.2 Data availability, quality, and integration

AI's effectiveness relies heavily on high-quality, diverse datasets, yet many regions—especially in the Global South—face data scarcity and inconsistencies (Henriksen et al., 2022; Lawal et al., 2023). A key challenge noted is data scarcity in climate-vulnerable regions or for rare extreme events. To address this, future research can employ techniques such as transfer learning—leveraging models trained on data-rich regions and fine-tuning them on data-poor contexts—and synthetic data generation (e.g., using simulation or GANs to create plausible data for training). These approaches can help overcome data limitations. For instance, Maity et al. (2024) demonstrate the use of transfer learning in a climate context, indicating its promise in improving model performance where local data are limited.

In climate modeling, AI-based simulations demand extensive computational resources, making them less feasible for resource-constrained institutions (Gatla, 2019). AI-driven climate projections must integrate historical extreme weather events with localized adaptation strategies (Neset et al., 2024). Similarly, in marine science, integrating satellite imagery, *in-situ* sensor data, and citizen science contributions could provide a more holistic understanding of oceanic and coastal systems (Yang et al., 2022b).

To address these challenges, we recommend expanding open climate data repositories, improving cross-border data-sharing frameworks, and employing techniques such as transfer learning and synthetic data generation to maximize the value of limited datasets. Enhanced interoperability standards across data sources also foster more integrated and reliable AI models.

5.1.3 Model interpretability and trust

One of the most pressing gaps across sectors is AI model interpretability and transparency (Gatla, 2019; Awijen et al., 2024). Many AI models—particularly deep learning algorithms—function as "black boxes," making it difficult for policymakers and practitioners to understand or trust their predictions (Boudreault et al., 2024). In disaster risk assessment, limited model transparency reduces adoption among decision-makers and emergency responders (Abdel-Mooty et al., 2022). Explainable AI (XAI) methods—such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME)—require further development to enhance interpretability and trust (Singha et al., 2024).

Recent advances introduce techniques to improve transparency, including activation visualization (e.g., saliency maps, Grad-CAM), feature importance analysis, and sensitivity analysis. These methods provide insights into which input features most influence a model's predictions, helping stakeholders trust AI-based recommendations. Future studies should prioritize embedding AI into practical applications, particularly in high-stakes decision contexts such as infrastructure planning and emergency response. Integrating human-in-the-loop approaches also supports more transparent and collaborative decision-making.

5.1.4 Ethical considerations and equity

AI's deployment raises critical ethical concerns, including algorithmic bias, data privacy, and social inequality (Galaz et al., 2021; Mmbando, 2025). AI models are not neutral—they often reflect the assumptions and limitations of the data and developers behind them. As a result, these systems can reinforce or even amplify existing societal disparities. For example, in disaster management, AI-driven tools such as flood prediction models or evacuation planning systems may rely on datasets that overlook informal settlements or lack data on marginalized populations. Consequently, vulnerable communities risk being excluded from early warning systems or emergency services, despite being among the most at risk (Tasnuva et al., 2024). This not only reduces the effectiveness of AI interventions but also exacerbates inequalities in disaster outcomes.

To address these issues, there is a growing call for equity-centered AI research and governance frameworks that promote inclusive design, participatory data collection, and transparent decision-making. For instance, Cheye et al. (2024) emphasize the importance of involving local communities in developing

AI tools for climate resilience to ensure that solutions are both context-sensitive and socially just. We recommend that future research embed interdisciplinary teams—including ethicists and social scientists—into the AI development process. Furthermore, equity impact assessments and bias audits should become standard practice in climate-related AI applications. Targeted funding and research support for underrepresented regions, such as Africa and South America, help address systemic disparities in research output and technology access.

To mitigate algorithmic bias and promote equity, we propose integrating established AI governance frameworks such as the Organisation for Economic Co-operation and Development (OECD) (2019)—which emphasize fairness, transparency, accountability, and robustness—and the IEEE Ethically Aligned Design framework (Chatila et al., 2018). These provide actionable guidance for responsible AI development in climate resilience applications. Researchers and practitioners should conduct bias audits to evaluate whether AI models systematically underperform for marginalized groups, use datasets that reflect demographic and regional diversity, and incorporate participatory design practices to engage local communities in AI tool development. Galaz et al. (2021) underscore the importance of governance mechanisms that prevent “data colonialism”—the imposition of models developed in the Global North onto data-sparse regions in the Global South.

5.1.5 Algorithmic bias and data colonialism risks in underrepresented regions

A significant ethical concern that emerges from our review is the risk of algorithmic bias and data colonialism, particularly in underrepresented and resource-constrained regions. Most studies originate from high-income contexts (e.g., Europe, North America, and East Asia), often using datasets, assumptions, and models tailored to those settings. When such AI tools are applied in the Global South without adequate adaptation or local involvement, they may misrepresent realities, deliver inaccurate predictions, or overlook key socio-environmental dynamics. This can lead to ineffective or even harmful decision-making. For example, an AI model trained on European agricultural data may underperform when applied to Sub-Saharan climates, yet still be promoted due to lack of alternatives. Moreover, these communities are often excluded from the design, training, and governance of these technologies, further reinforcing asymmetries of power and knowledge production. To mitigate these risks, future AI development for climate resilience must prioritize equity-centered design, local data sovereignty, and participatory methods. Frameworks such as the OECD AI Principles and the IEEE Ethically Aligned Design can help operationalize these goals. Additionally, investment in regional AI infrastructure, capacity building, and context-sensitive datasets is critical to avoid repeating historical patterns of marginalization in a new digital form.

5.2 Sector-specific gaps and research directions

Each sector faces distinct challenges that require targeted AI advancements.

5.2.1 Agriculture, forestry and food

Current AI models lack regional customization, which limits their ability to account for soil conditions, market dynamics, and climate variability (Choudhary et al., 2024). Future research focuses on developing localized datasets, incorporating participatory AI design, and integrating AI tools with genomic resources to enhance crop climate resilience (Taloba and Rayan, 2025).

5.2.2 Cities and infrastructure

Key challenges include inadequate real-time flood forecasting (Chitwatkulsiri and Miyamoto, 2023), limited AI-driven infrastructure monitoring (Chew et al., 2025), and the scarcity of high-quality data for predictive maintenance (Habib et al., 2024). Future work should integrate AI with geospatial analysis for improved risk assessment, strengthen real-time monitoring systems, and develop physics-informed AI models to support infrastructure sustainability (Yang et al., 2022a).

5.2.3 Climate and weather monitoring

AI-enhanced climate models must improve forecast precision and scalability while addressing data gaps in extreme weather events (Rahman et al., 2024). Future research explores hybrid models that combine AI with physics-based approaches to improve long-term climate projections (Ayinde et al., 2024).

5.2.4 Marine and coastal systems

Current AI models lack generalizability across different geographic regions (Yang et al., 2022b). Future research focuses on integrating AI with Earth system models to better predict coastal flooding, erosion, and sea-level rise (Sun H. et al., 2024).

5.2.5 Disaster and risk management

This sector faces critical gaps in predictive accuracy, real-time data integration, and decision-making frameworks. Current flood forecasting models struggle with limited sensor coverage, reducing predictive reliability (Hahn et al., 2024). AI-driven emergency response systems operate without standardized frameworks, which hinders large-scale deployment (Sun L. et al., 2024). Moreover, existing risk assessments often overlook long-term resilience, focusing primarily on immediate hazard response (Abdel-Mooty et al., 2022). Future research should improve AI interpretability, enhance multi-hazard risk modeling, and integrate socio-technical resilience strategies.

5.2.6 Energy and industry

The sector encounters major challenges in grid resilience, energy efficiency, and decarbonization. Climate-induced variability, outdated grid infrastructure, and financial risks for investors hinder the integration of renewable energy (Yang H. et al., 2024). While AI-driven energy management and predictive analytics improve system efficiency, gaps remain in cross-regional energy trade and regulatory frameworks for long-term sustainability (Babiarz et al., 2024). Future research should enhance real-time adaptive grid management, improve energy storage solutions, and leverage AI for dynamic industrial efficiency and emissions reduction (Mugalakhod and Nirmanik, 2022).

5.2.7 Water resources

AI models must become more scalable and transferable across different watersheds and hydrological contexts (Mallya et al., 2023). Current research focuses on developing AI-driven digital twins for real-time water monitoring and integrating socio-economic factors into water allocation models to enhance equity and efficiency (Henriksen et al., 2022).

5.2.8 Health

Many AI-based health surveillance systems do not differentiate between all-cause and climate-specific mortality trends, which limits their ability to pinpoint heat-related illnesses, respiratory diseases, or vector-borne outbreaks (Boudreault et al., 2024). Future research should refine AI models to deliver cause-specific health risk predictions and incorporate multiple interacting climate stressors for improved public health planning (Jack et al., 2024).

Beyond these sector-specific observations, it is also important to highlight a broader methodological gap that cuts across domains—namely, the underutilization of certain advanced AI techniques such as reinforcement learning. Despite its theoretical relevance to dynamic climate adaptation, Reinforcement Learning (RL) was found in only 1.04% of the studies reviewed. This is surprising given RL's strengths in sequential decision-making under uncertainty—an essential requirement in adaptive systems such as energy grid management, real-time irrigation control, or floodgate operation. Several reasons may explain this underutilization. First, RL often requires extensive training environments or simulation-based data, which may not be readily available or realistic for many climate-related applications. Second, the integration of RL into physical or policy systems is complex due to high stakes, safety concerns, and limited interpretability. Lastly, RL remains a relatively new technique in environmental and climate sciences, where uptake often lags behind more established machine learning methods. Nonetheless, the potential of RL remains strong. We encourage future research to explore its use in autonomous adaptation systems, real-time climate response, and multi-agent coordination, especially in sectors like water, energy, and infrastructure where dynamic control is key.

5.3 AI, resilience, and the sustainable development goals

The role of AI in enhancing climate resilience intersects closely with the broader global development agenda, particularly the United Nations Sustainable Development Goals (SDGs). Our findings align most directly with SDG 13 (Climate Action), as many AI applications examined support adaptation planning, disaster risk reduction, and emissions monitoring (United Nations, 2015; Vinuesa et al., 2020). However, the implications extend further. SDG 2 (Zero Hunger) is addressed through AI-enhanced agricultural systems that improve crop forecasting, reduce input waste, and promote food security (Sachs et al., 2019). SDG 9 (Industry, Innovation and Infrastructure) is advanced by AI-supported infrastructure monitoring, predictive maintenance, and smart grid technologies (Vinuesa et al., 2020). SDG 11 (Sustainable Cities and Communities) is promoted through AI-driven urban resilience strategies such as flood prediction, traffic optimization, and energy efficiency improvements. At the same time, we caution that AI must be deployed equitably to avoid reinforcing existing disparities—thus connecting to SDG 10 (Reduced Inequalities) and the overarching SDG principle of "leaving no one behind" (Galaz et al., 2021). By embedding ethical, participatory, and context-aware approaches in AI development, researchers and practitioners can ensure that AI contributes meaningfully to a more resilient and sustainable future.

5.4 A framework for equitable AI deployment in low-resource regions

To make these recommendations actionable, we propose several concrete steps. First, interdisciplinary collaboration should be operationalized through the creation of funded research consortia that bring together AI scientists, climate experts, local governments, and civil society. Programs like Horizon Europe, the Green Climate Fund, or regional development banks can earmark specific calls for such joint efforts. Second, national governments and development partners should co-develop open-access, regionally tailored data platforms—co-managed by national meteorological services and academic institutions—to enhance local AI capacity. Third, technical training programs on explainable AI and ethical data governance should be embedded into climate adaptation strategies, targeting local practitioners, not just researchers. Lastly, we recommend embedding participatory AI design practices into public procurement criteria, ensuring that solutions funded or adopted by public actors are inclusive and socially grounded.

To support just and context-aware AI deployment in climate resilience, we propose a framework inspired by recent work from Jain et al. (2024a,b). Their studies demonstrate that equitable AI implementation requires not only technical innovation but deep engagement with local realities, especially in climate-vulnerable and resource-constrained regions.

Jain et al. (2024a) highlight how embedding AI and machine learning in South Asia's water-energy-food systems succeeds only when local capacity is developed and interdisciplinary collaboration is fostered. Similarly, Jain et al. (2024b) emphasize that inclusive design—drawing on indigenous and local knowledge—and strong policy alignment are essential to ensure AI solutions are ethically grounded and responsive to local needs. These studies underline the risks of data colonialism, where externally developed models may be applied without adaptation, reinforcing inequality and eroding trust.

Our proposed framework calls for the integration of local expertise, participatory design, data sovereignty, and governance mechanisms that align AI deployment with development goals such as the SDGs. Doing so can help ensure AI serves as a tool for

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resilience, not exclusion, and supports climate adaptation efforts that are effective, inclusive, and sustainable.

One concrete path toward regionally tailored AI models is through participatory design frameworks, which engage local stakeholders—such as community groups, NGOs, and government agencies—throughout the AI development cycle. This process ensures that both the problems addressed and the resulting solutions are grounded in local priorities, values, and infrastructural realities. Participatory design not only improves the relevance and cultural acceptability of AI tools, but also supports better data integration by leveraging indigenous knowledge systems and community-sourced datasets. In regions with limited computational infrastructure, tailoring might also involve simplifying models or deploying them through mobile-friendly or offline platforms. Srivastava and Maity (2023) provide a compelling example of such approaches in action, demonstrating how locally co-developed models yielded more sustainable and trusted applications in low-resource settings. Future research should document participatory methodologies explicitly, helping establish best practices for inclusive and context-sensitive AI deployment.

6 Conclusion

This systematic literature review highlights the critical role of Artificial Intelligence (AI) in enhancing resilience against climate-related challenges across various sectors. The analysis of 385 peer-reviewed studies reveals a predominant focus on adaptation strategies (64.4%), with relatively less emphasis on mitigation (16%) and integrated adaptation–mitigation approaches (19.4%). These findings suggest that AI applications are primarily leveraged to support climate adaptation efforts rather than directly reducing emissions.

The review further categorizes AI applications by sector, identifying Agriculture, Forestry, and Food (30.39%) and Cities and Infrastructure (25.45%) as the most extensively studied areas. In contrast, sectors such as Health (0.52%) and Ecosystems (2.34%) remain significantly underrepresented. In terms of AI methodologies, Classical Machine Learning/General ML dominate (51.43%), followed by Deep Learning techniques (22.34%). However, emerging approaches—such as Reinforcement Learning (1.04%) and Remote Sensing & GeoAI (2.08%)—remain underexplored, presenting opportunities for future research.

The rapid and exponential growth in AI applications for climate resilience is evident in publication trends. Research output remains limited before 2018, followed by a sharp acceleration from 2020 onward. In 2024 alone, over half (51.69%) of the reviewed studies appear, reflecting a surge in academic and policy interest in AI-driven climate solutions. Notably, despite the review covering only until early 2025, 10.65% of the studies already originate from this year, indicating sustained momentum and an expanding research agenda in this critical field.

From a regional perspective, AI applications in climate resilience exhibit uneven distribution, with Asia (31.9%) and Global studies (34.3%) receiving the most attention, while regions such as South America (1.8%) and Oceania (2.3%) remain critically understudied. Africa accounts for 7.5% of studies, highlighting the need for increased AI-driven climate resilience research in vulnerable regions. Europe (11.7%) and North America (10.4%) have moderate representation but remain underexplored in certain sectors, particularly in the contexts of climate and weather monitoring and agriculture. Addressing these disparities is crucial to ensuring that AI-driven climate adaptation strategies are contextually relevant and equitably distributed.

Despite AI's growing importance in resilience-building, several limitations persist, including challenges related to data availability and quality, scalability, model interpretability, and ethical considerations. Addressing these issues requires interdisciplinary collaboration, improved access to high-quality datasets, and the development of explainable AI models to enhance trust and adoption. Additionally, sector-specific research gaps—such as AI-driven health resilience and integrated AI frameworks for water management—demand attention to ensure that AI solutions remain inclusive, equitable, and effective across diverse contexts.

Future research should expand AI applications beyond well-studied areas, integrate AI with emerging technologies such as digital twins, and ensure that AI-driven climate resilience strategies remain accessible to vulnerable communities. By addressing these gaps, AI plays a pivotal role in fostering sustainable, adaptive, and resilient systems capable of mitigating the growing threats of climate change

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

YF: Conceptualization, Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing, Methodology, Resources. RA: Conceptualization, Supervision, Validation, Writing – original draft, Writing – review & editing. OM: Formal analysis, Investigation, Methodology, Resources, Software, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that this research is conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

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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.2025.1585331/full#supplementary-material

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