

AI-BASED ENVIRONMENTAL RISK MANAGEMENT FOR CLIMATE CHANGE: CURRENT ADVANCES, CHALLENGES, AND FUTURE DIRECTIONS

Muhammad Zeeshan Abdullah¹, Javeria Sameer², Qamar Abbas^{*3}, Almas Sana⁴, Eman Idrees⁵, Rimsha Khalid⁶, Sanaullah⁷, Hassan Dad⁸, Rukhsar Fatima⁹

^{1,7,8,9}Faculty of Soil and Environmental Science, Muhammad Nawaz Shareef University of Agriculture, Multan

²College of earth and environmental science (CEES), University of the Punjab

^{3,4}Institute of Zoology, University of The Punjab, Lahore

⁵Department of Environmental Science, Government College University, Lahore

⁶Faculty of Science and Technology, Government Sadiq College Women University, Bahawalpur

^{*3}qamar.zoologist@gmail.com

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Corresponding Author: *

Qamar Abbas

Abstract

Climate change is the enhancement of the spatial complexity, magnitude and frequency of environmental hazards, thereby enhancing the need for integrated and adaptive environmental risk assessment and management. While physics-based models of climate and hazards continue to be fundamental, they may suffer from limitations in terms of computational complexity, spatial resolution, availability of heterogeneous data, and timely incorporation of new and rapidly evolving environmental and socioeconomic data. The review focuses on the use of AI-aided approaches to climate risk assessment for the environment, such as machine learning, deep learning, and geospatial AI, and hybrid physics-AI models. AI can combine satellite data, GIS layers, IoT sensors, climate data, and socioeconomic data to enhance hazard prediction, specifically for floods, wildfires, droughts, extreme heat and other climate hazards. In addition to hazard forecasting, AI can support the exposure characterization, vulnerability assessment, dynamic risk estimation, risk prioritization, and early warning, preparedness, adaptation, resource allocation, and long-term risk reduction decision support. There are, however, many key challenges to overcome such as data scarcity, data quality, geographic transferability, data retrofitting, model interpretability, uncertainty quantification, model computational demands, governance, equity, and operational readiness. Hybrid physics-AI architectures, prospective validation, uncertainty-aware and explainable models, integrated multi-hazard frameworks, satellite-IoT and edge-computing systems and responsible human oversight are future areas to be prioritized for research. In summary, AI has significant potential to complement existing environmental science and help move away from reactive disaster management to dynamic, evidence and adaptive governance of climate risk.

1. INTRODUCTION

Hazards are becoming more common in a spatially varied, temporally dynamic way, and with varying consequences in social, economic and environmental impacts, all of which are increasingly being expressed as climate change. Rather than just physical events, floods, wildfires, droughts, cyclones and extreme heat are better understood as expressions of combinations of hazard intensity, exposure of human populations, infrastructure, ecological conditions and socioeconomic vulnerability. These interactions are becoming more complex, revealing key weaknesses in traditional environmental risk-management frameworks, most notably when decisions need to be taken quickly and at increasing spatial resolutions. Recent studies and literature suggest a shift in disaster management from a reactive and predominantly prevention-focused perspective to a more proactive and adaptive approach, combining traditional environmental science and risk assessment techniques with the use of artificial intelligence (AI) tools (Hossain, 2026; Tsakiroglou et al., 2026).

The floods in Pakistan in 2022 are a special case highlighting the extent to which climate-induced hazards can be manifested in a multi-dimensional manner affecting society. Around one-third of the country received heavy monsoon rainfall, resulting in over 33 million affected persons, more than 1,700 fatalities reported and almost 8 million internally displaced persons. Over 2 million houses were damaged, large tracts of farmland were impacted and over a million livestock were lost. Economic loss and damages were estimated at US\$30 billion and some have estimated at US\$40 billion while millions of people were pushed into a deeper state of poverty and outbreaks of water borne diseases were reported (Nay et al., 2022; Imran et al., 2026). Escalating environmental disruption patterns have been reported from the wildfire prone state of California and Australia, the cyclone-affected region of Bangladesh as well as cyclone-affected regions of Europe and South Asia with severe heat waves (Niklas et al., 2022). Rather than the hazards of climate change

becoming more intense, the information that needs to be used to face these hazards is becoming more complex. At present, conventional physics-based tools, such as General Circulation Models (GCMs), continue to play a key role in understanding the processes in the atmosphere and oceans and are the foundation of climate projections. However, the limits of spatial resolution, computational requirements and the capacity to rapidly update measurements from new data sources identified by the source literature remain. Conventional climate-model resolutions are typically 10 – 100 km, and may be inadequate for decision-making at the level of the individual community, infrastructure, agricultural land, and/or localized hazards (Elsherif and Taha, 2025; Sillmann et al., 2024; Dritsas and Trigka, 2025). These restrictions are especially significant under high-temporal and high-spatial resolution conditions, such as in the context of quickly changing events, where decision-makers need to rely on information at a finer spatial and temporal resolution (Christofi et al., 2025).

One complementing analytical ability of AI is its ability to discover complex nonlinear relations among large and heterogeneous data sets, where all the relation between the data elements are not explicitly known beforehand. They can be satellite observations, ground-based sensors, historical climate data, geographic information system (GIS) layers and socioeconomic indicators, among others, in environmental applications. These inputs can then be fed into machine learning systems to detect spatial patterns and to forecast environmental conditions, classify risk, and predict future changes that can then be incorporated into environmental management decisions (Yetgin, 2025; Roy et al., 2024; Kemarau et al., 2025). Importantly, the use of AI is not intended to be a substitute for physical climate science. Instead, it has the major potential for complementing physical modeling with fast pattern recognition, data integration, downscaling, vulnerability assessment and dynamic updating of risk information. One of the key concepts in the field of AI-supported environmental risk assessment is that a hazard is

not necessarily a risk. Risk is a function of the physical hazard, the population or property at risk and the susceptibility:

$\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability}$

This is a useful conceptual link between the prediction of environmental conditions and risk management. While hazard based models can provide a sense of where flooding, wildfire, drought or extreme heat may happen, risk management must also include information on who or what is in the hazard area and how vulnerable those within the hazard area may be. The focus of the source manuscript is thus on incorporating environmental data and socioeconomic and spatial data to create a more relevant risk profile for real world decision-making.

The advent of earth observations data has also enhanced this potential. The data from platforms like MODIS, Sentinel, and Landsat can offer multiple observations of land-surface properties, vegetation health, thermal events, and other environmental factors at a region-wide scale, while the data from IoT sensor networks can offer more fine-grained observations and more frequent observations at a smaller scale. These can be merged with reanalysis products and socioeconomic datasets to build multidimensional interpretations of environmental risk (Tran and Hoang, 2025; Ferrario et al., 2026). Supervised methods like Random Forest and Extreme Gradient Boosting (Boost), deep learning models such as Convolutional Long Short-Term Memory (ConvLSTM) networks and Vision Transformers, and unsupervised methods such as K-Means and Isolation Forest were identified in the reviewed source literature. Hybrid model and hybrid model which combine both physical constraints are also gaining popularity where solely empirical relationships cannot capture environmental processes (Huang et al., 2023; Slater et al., 2023; Zahmatkesh and Zech, 2026). But, as AI technologies become more advanced, they do not automatically make AI-powered risk management systems better than others.

The evidence compiled in the source suggests that reported performance gains are highly context-

dependent in terms of the availability of data, context of the environment, prediction horizon, and the quality of the validation. Given the importance of using dense observational networks for training models, it is likely that such models will be less effective if moved to areas with sparse monitoring or significantly different environments. This is important as it is often the regions with the highest climate vulnerability that also have the lowest data infrastructure. (Peng et al., 2024; Lewis et al., 2023; Detthamrong et al., 2026). Therefore, the performance of the algorithms needs to be taken into account in conjunction with data representativeness, transferability, uncertainty, and institutional capacity—rather than numerical accuracy measures only. In addition, there is an increasing separation between prediction and decision support. The key to a technically perfect prediction is not necessarily to be an effective risk-management action. Competing priorities, uncertainty, socioeconomic consequences and institutional responsibilities all play a role in environmental decisions (Valtonen et al., 2024; Sachdeva et al., 2025; Arsenoia et al., 2026). The literature examined then leaves questions regarding the implications of algorithmic outputs for decision-making during interactions with policy makers, emergency managers, technical experts, and impacted communities. This is especially crucial for models that are more complex, in which the internal logic of the model may be hard for non-specialist decision makers to understand.

The role of Explainable AI and human oversight is therefore becoming crucial enablers of responsible environmental AI, and not just nice-to-have features on the technically best-performing model (Anderson, 2026). In this context, this review focuses on the scientific and technological underpinning of AI-driven environmental risk assessment, the state-of-the-art of AI applications in major environmental hazards and the potential for embedding AI in environmental risk management and decision support systems (Alotaibi and Nassif, 2024). Special focus is placed on the incorporation of heterogeneous environmental and socioeconomic data, machine-

learning, deep-learning and hybrid physics-AI approaches and the conditions under which reported improvements in predictive performance can be used for real-world environmental resilience (Gacu et al., 2025). Recurring issues such as data scarcity, model transferability, interpretability, validation, computational issues, equity, and governance also are taken into account. The goal is not only to demonstrate the possibility of AI to enhance prediction but to critically evaluate the circumstances, times and conditions where AI's environmental risk management can offer scientifically defensible and operationally meaningful improvement over traditional methods.

2. Scientific and Technological Foundations of AI-Based Environmental Risk Assessment

Environmental risk assessment based on AI is essentially a problem of integration. The contexts and decisions for responding to climate risks are rarely just about a single variable or a single observation platform, and they involve the simultaneous interpretation of information about the environment, space, time, infrastructure, and social and economic context. The framework outlined in the source then moves beyond prediction of hazard towards a multi-dimensional framework of observations being converted to estimates of hazard, exposure, vulnerability, and consequently, risk (Muccione et al., 2024; Attoh and Amarnath, 2025; Ugliotti et al., 2025). The scientific significance of this distinction is that an algorithm can be right about the physical event and yet have limited information on the actual impacts on vulnerable and exposed populations or assets if the distribution and vulnerability of exposed populations and assets are not included. From a methodological perspective, the different types of AI methods can be classified based on their learning process from the information available. Supervised learning is the type of learning where the outcome of the observations is known to form a relationship with the predictors and the target variables (Kalaycıoğlu et al., 2023; Panigrahi et al., 2023; Schwalbe and Finzel, 2024). Some of the key supervised methods to be

recognized in environmental applications are Random Forest and boost models (source). Some of these techniques are especially promising when environmental variables (such as precipitation, vegetation indices, soil moisture, topography, or remotely sensed thermal variables) are correlated with measurable variables (such as drought intensity, flood occurrence, or temperature anomalies) (Przeździecki et al., 2023; Afroz et al., 2023). The major benefit is that they can model the relationship between several predictors that are not necessarily strictly linear, without having to express the relationship between each predictor explicitly.

Deep-learning techniques offer another ability, namely learning hierarchical representations from complex, temporal or spatial data. The models are relevant to tasks that involve both spatial and temporal variations in the environmental state, such as in the case of ConvLSTM networks, or where the spatial patterns in large image-based datasets are important, such as with Vision Transformers. The source states that these are approaches applied to problems with environmental risk that varies across space, such as flood inundation, wildfire spread, and other environmental risks. Their use is becoming more common as the amount of high-resolution satellite and sensor data becomes available, but they also have a much more complicated representation, so they require more training data, computational resources, and model interpretation (Afroz et al., 2023; Ahmed et al., 2023; Zhang and Wang, 2024). Unsupervised Learning is used for a different problem in analysis. Methods like K-Means clustering and Isolation Forest can detect patterns, groups or anomalies in environmental data without relying on predefined outcome labels. This can be helpful when there are no reliable labels for the outcomes, which is often the case in environmental monitoring. This can help identify abnormal environmental conditions or areas of vulnerability that vary in space and could instead be used to supplement supervised prediction systems, instead of replacing those (Essamlali et al., 2024). One of the hallmarks of the modern environmental AI is the growing

ubiquity of remote sensing and geospatial information. Satellite platforms offer spatially extensive observations that can be repeated over time, and GIS can enable the spatially or geographically positioning of environmental variables onto populations, infrastructure, agricultural areas, and other exposed assets. The source indicates that MODIS, Sentinel and Landsat data are important inputs and localized observations can be provided at much finer temporal scale using IoT networks. Bringing these sources together facilitates the shift of environmental models from individual measurements to spatially explicit models of risk (Montillet et al., 2024).

Analytical value of such integration is in data fusion. For a flood-risk model, for instance, precipitation information, hydrological information, elevation information and land-surface information could characterize the hazard, while population or infrastructure information could characterize exposure. Likewise, the thermal observation along with vegetation characteristics and meteorology can be used for wildfire assessment, while vegetation indices and soil-moisture anomalies can be used for agricultural drought assessment. The source therefore promotes heterogeneous data stream and its use as a basis for integrated risk profile. Another area of improvement is physics-informed and hybrid AI methods (Wassie et al., 2022; Putrama and Martinek 2024). While purely empirical models can be used to build statistical relationships between past data, physical processes are at play in environmental systems that may vary when the conditions are not well represented in the training set. Hybrid methods try to harness the pattern-recognition abilities of AI but hold predictions back with known physical relationships. According to the source, this combination of machine learning, deep learning, and physical principles is an important way to create flexible and scientifically constrained models. These methods are especially relevant for climate-risk assessment, as future environmental conditions may not be just a repeat of the past. Another key

element of the frame is model evaluation (Willard et al., 2022; Valevski et al., 2025). Disclosed in the reviewed source are the metrics that can be used to evaluate different environmental prediction and classification tasks, including R², root mean square error (RMSE), mean absolute error (MAE), F1-score, and intersection over union (IoU).

The measure used for assessing the success of the appropriate metric depends on the scientific question: for regression-based predictions, error-based or explained-variance-based metrics can be used, while spatial classification and image-segmentation problems use classification and spatial-overlap-based metrics (Jindanil et al., 2023). A unique artificial. Importantly, AI models are, wherever possible, compared against existing baselines instead of just their absolute performance. However, if numerical performance is the only measurement, then environmental reliability cannot be guaranteed. Completeness of data, geographic data gaps, lack of monitoring infrastructure, and complexity of models are cited as some of the factors that can compromise seemingly strong AI performance (Podobnikar, 2025). These constraints are particularly relevant when AI-generated content is utilized in the creation of public policies or disaster management decisions. An environmental model should thus be evaluated both in terms of its predictive accuracy and for robustness, transferability, interpretability and suitability for the decision context where it is to be applied. This is a shift in thinking from just an algorithm to an adaptive information system, AI-based environmental risk assessment. It works best when the information it receives is of good quality and is representative of the entire population, its scientific assumptions are sound, its validation process is appropriate, the ways in which uncertainty is communicated are clear, and the institutional design around the conversion of prediction to action is robust. The source's discussion of AI is thus a basis for a framework that uses computational intelligence to augment rather than supplant physical environmental science, expert interpretation, and human decision-making.

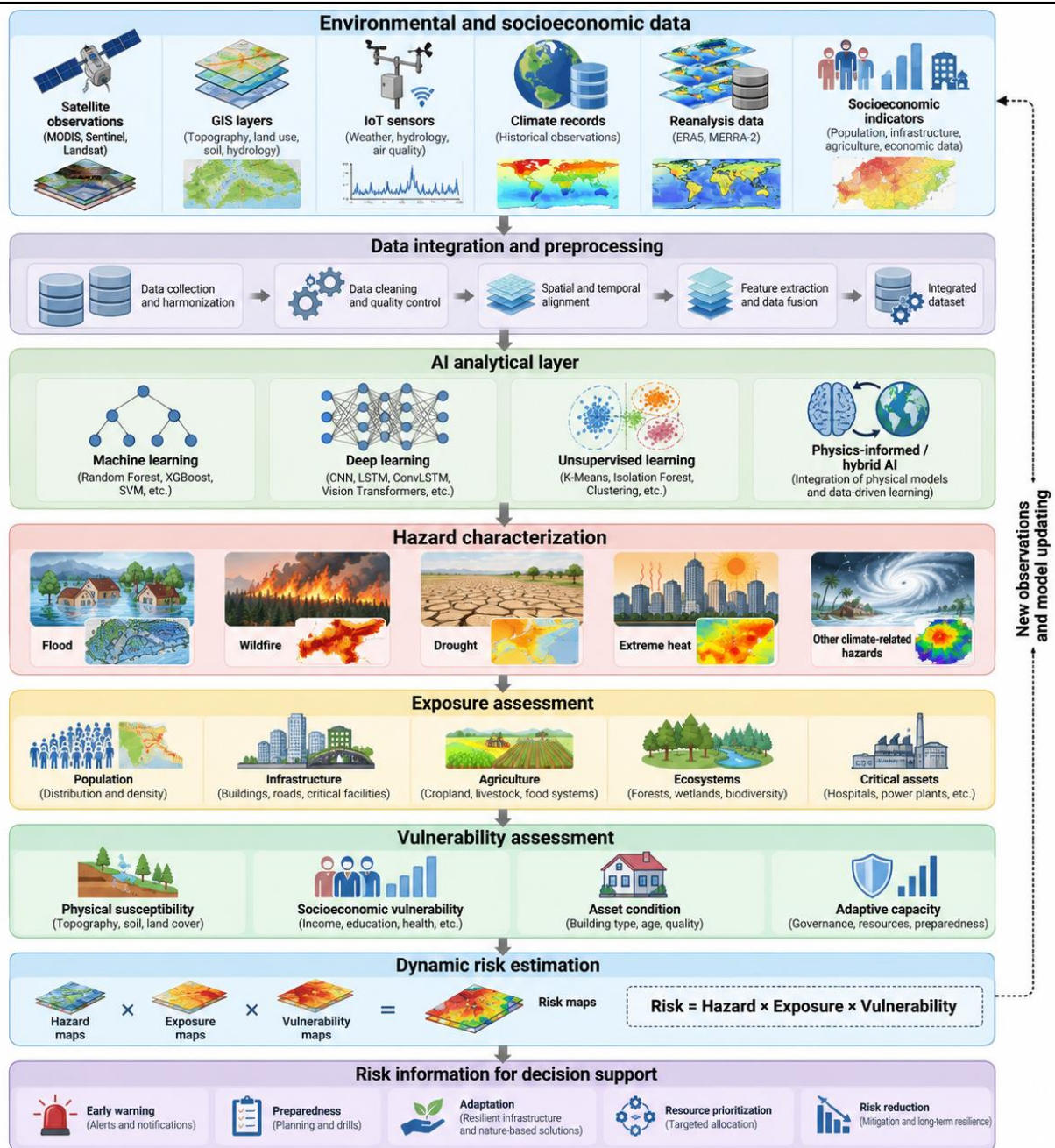


Figure 1. Conceptual architecture of AI-based environmental risk assessment

3. Current Evidence and Applications across Climate-Related Hazards

From a more purely experimental analytical tool, artificial intelligence has moved to a more prominent role in climate-risk assessment, as suggested by the recent literature. In the studies reviewed, the main benefit of AI is the integration of large and heterogeneous data sets, and the

ability to capture both space and time complex relationships that are challenging to represent with traditional methods. The source review covers applications from flood inundation, wildfire propagation, drought in agriculture, and drought in urban areas, and includes techniques such as ensemble approaches, based on trees, deep neural networks, and hybrid physics-AI systems. But the

evidence is not conclusive that any one algorithm is consistently superior in all environmental settings (Yaghoubi et al., 2024). The dependence of model performance on the type, resolution, completeness and representativeness of the available data, and the prediction horizon and features of the environmental system under prediction continues to be strong (Materia et al., 2024). One of the most straightforward applications of AI is in flood risk assessment, where spatial and temporal variability are pronounced and the need for fast assessment of event size and extent is crucial. The literature reviewed here has included applications of Convolutional Long Short-Term Memory (ConvLSTM) models to inundation characterization and flood event timing and spatial evolution using synthetic aperture radar (SAR) observations and elevation information. One of the advantages of SAR is that it can be used to obtain information where optical satellite observations are limited by cloudiness. These datasets, along with the other environmental information, provide the inputs for AI systems to learn relationships between the hydrometeorological conditions and the spatial evolution of inundation. The source specifically mentions the two metrics of RMSE and F1-score as important evaluation metrics for flood applications, as well as the peak-flow arrival time. During a flash flood event, these skills become more relevant. While conventional assessments might involve processing data of rainfall, hydrological, topographic, and observational data in sequence, trained AI systems can handle multiple data layers more or less in parallel after deployment (Zanella et al., 2023). According to the source, AI-driven flood forecasting can yield more granular spatial data and facilitate early warnings and resource planning. It also mentions that some of the methods have helped in lowering the error rate in the timing of floods by about 35-45%. The values reported should be understood as expected enhancements for the specific study, and not as general benchmarks for performance since the degree of improvement varies with the baseline model, the area of study, the input data, and the

time horizon of the forecast and the design of the validation. Wildfire prediction is a different modeling problem, as fire behavior is partially dependent upon interactions between vegetation, fuel availability, temperature, moisture, topography and meteorological parameters, especially wind. The source mentions using MODIS thermal observations along with wind data in a Vision Transformer approach to assessment of wildfire spread. The goal here is not only to determine if a wildfire is occurring, but to describe the development of the burn perimeter and the spread of fire in space. Intersection over Union (IOU) is thus determined as a suitable spatial-performance measure. The reviewed literature outlined above suggests that AI can analyse thermal data and weather conditions to predict fire spread, which could offer more granular data than methods using single observations or flights and manual interpretation of thermal imagery.

Another significant application of agricultural drought is in relation to the effects on agricultural productivity, which are often manifested indirectly as vegetation stress, soil moisture deficits, and so on. Random Forest regression is cited as an important methodology employed in the prediction of droughts with the help of Normalized Difference Vegetation Index (NDVI) and soil-moisture anomalies (SMA), according to the source (Mansoor and Chung, 2024). Agricultural drought is often assessed through the application of environmental indicators over time that describe the accumulation of water stress, whereas, predicting floods or wildfires is often done on an event basis. Regression-based AI can thus generate estimates of drought severity or a drought-induced yield loss probability based on a collection of remotely sensed and environmental variables. The amount of variance in the data that is explained by the model can be evaluated using r^2 , or explained variance. According to the source, the drought models based on Random Forest classifiers in the literature have provided often performance levels greater than 0.85. Again, this is not a general guideline for the expected performance of all drought applications. Instead,

it illustrates that if the right predictors are available and sufficient training data, then tree-based ensemble methods can work well. The basic point is more significant than the number itself: the incorporation of remotely sensed vegetation indicators with hydrological and soil moisture data can significantly improve the prediction of droughts, as opposed to using only one climatic variable.

Spatial Resolution is also important for Urban and Extreme heat Assessment. The actual heat exposure varies significantly across the cities due to the variations in land cover, vegetation, building density, surface characteristics, and anthropogenic effects. The source focuses on the use of Landsat thermal data and albedo data for characterizing surface-temperature anomalies for deep Extreme Gradient Boosting approaches. One of the key assessment metrics is determined as the mean absolute error (MAE). The value of these methods is that they can be used to create a representation of heat exposure from remotely sensed thermal observations that can be disaggregated into a spatial representation that can then be merged with demographic and socioeconomic data. A key methodological trend, common to all the applications, is the reliance on the combination of several data modalities for the best performance of the AI, instead of relying on the complexity of algorithms alone. Satellite observations provide spatial delineation in a broad sense, ground sensors and IoT can deliver localized measurements, climate and reanalysis datasets can give temporal context, GIS layers can give topographic/land-use information and socioeconomic datasets can give exposure and vulnerability information. The source states that the main information sources in modern environmental-risk research with AI are MODIS, Sentinel, Landsat, IoT networks, ERA5 reanalysis data, and socioeconomic indicators (Bayouhdh et al., 2022; Iversen et al., 2026).

This data-integration ability is especially vital to transition from hazard prediction to risk assessment. An actual forecast of a flood at a specific site only gives a partial answer to the effects of the flood. The effects of the same hazard

intensity can be markedly different according to variations in population density, infrastructure condition, and reliance on agriculture, economic assets, and adaptability. The source thus stresses integrating hazard information with socioeconomic and asset-level information. Groups of communities with comparable vulnerability characteristics can be identified using K-Means clustering, and computer-vision and geospatial techniques can be used to assess buildings and infrastructure from either satellite or drone data. (Dodman et al., 2023; Mittal et al., 2023; Hofmeister et al., 2024). The source's asset-level framework is also transitioning towards integrated risk assessment. The ability to describe coastal substations, transport corridors, agricultural areas and urban living areas by hazard type, exposure density, and vulnerability allows for the determination of the location of specific hazard and vulnerability sub-affinities. Specific hazard and vulnerability sub-affinities can be defined by the location of a specific hazard and exposure density, and by the vulnerability of the area, for coastal substations, transport corridors, agricultural land, and urban residential areas. This will allow risk assessment based on the relative risk of the various locations within a hazard zone instead of assuming that all locations are equally at risk. These strategies can be useful in determining resource allocation as disaster management resources are inherently constrained and need to be prioritized. These systems are, however, decision-support systems and should not be relied upon as a substitute for institutional judgment.

Evidence also indicates that the hybrid physics-AI models are increasingly playing a bigger role. Empirical models may be very flexible, but can pick out relationships that are unique to the historical conditions in the data used to train the model. This can become a problem if the environmental states to which the models are exposed are quite different than those of the history. Hybrid methods strive to overcome this shortcoming by adding physical constraints or information related to the physical process to data-driven learning. That's because the source says

such methods can be valuable in data-scarce settings and can serve to keep predictions "physically plausible. The results of hybrid models and AI models are encouraging but ought to be taken with a pinch of salt. It shows high levels of accuracy (over 92%) for some applications of XGBoost in flood classification, and significant improvements in flood-timing prediction for certain approaches. The findings show the capabilities of AI, but not that AI is always superior to traditional models. Comparisons between studies are difficult because of differences in the datasets, geographical settings, target variables, validation and performance metrics. A model that has been successful in a well-instrumented watershed cannot necessarily be expected to be successful in a different climatic or geographic location (Friedrich and Friede, 2024). An issue of transferability is one of the most salient findings of the reviewed evidence. The training distributions of AI systems are necessary for their functioning. If there are plenty of and representative observations, then complex algorithms can be used to identify very informative relationships. However, the same algorithms can learn from incomplete or biased representations of environmental reality, when monitoring networks are sparse. This is a significant issue in areas that are most vulnerable to climate change, where monitoring systems may be the least developed part of the infrastructure, but environmental risks are most dire. Technical performance is mentioned separately from the context in which a model is planning to be used, thus recognizing unequal access to data and infrastructure as an important equity issue. The challenge of the temporal dimension further complicates the situation. Many AI models are based on past observations, assumes that past relationships continue to be informative for prediction. The assumption is challenged by the change in climate because the statistical properties of environmental systems can vary as a function of time. Therefore, a model that has high validation to historical data might not have the same reliability in environments outside of the model training distribution. The analysis of the source is broader

and highlights that the apparent benefit of AI is greatest for applications with abundant data and short- to medium-term forecasts and that it can turn negative—or even negative outright—in some settings, for example, where monitoring is sparse or the longer the prediction horizon. This difference between retrospective model performance and operational reliability is very important. Reported results are often based on historical data and also retrospective validation, which can give useful information about predictive capability, but which may not fully capture the uncertainties that arise when deployed in the real time.

There are a number of challenges that operational systems face, including missing observations, sensor failures, changing land use, unusual weather conditions, communication limitations and decisions made under uncertainty. The source, therefore, calls for further long-term studies, prospective validation and comparison with well-calibrated traditional methods. The other key one is interpretability. These high-performing deep-learning and ensemble models could identify intricate environmental connections, but their results may not be explained in a manner easily understood by policy makers, emergency managers, or impacted communities. This brings the difference between predictive competence and decision legitimacy. A risk score can be statistically correct, but hard to justify if decision makers do not understand why a specific area was deemed to be at high risk. The source also highlights the necessity of Explainable AI and human oversight in the responsible deployment of AI in the environment (Eloranta and Boman, 2022; Radanliev et al., 2024). Overall, the available data thus provide only a qualified judgment on the effectiveness of AI. When high quality observations, suitable algorithms, sufficient computing power and robust validation can be provided, there are significant benefits to be gained from AI. It is particularly useful in the case of Spatio-temporal complex environmental processes, from which observations are gathered continuously and where decisions need to be made quickly and at fine spatial scales. However,

increasingly complex algorithms cannot overcome a lack of observations, under-representation of vulnerable groups, poor validation, or weak institutional capacity. Hence, the literature

provides support for an integrated approach that combines AI with physical modeling, remote sensing, domain knowledge and existing risk management institutions.

Table 1. Representative AI applications across climate-related environmental hazards

Climate-risk domain	Dominant AI architecture	Principal data inputs	Primary prediction/assessment target	Representative evaluation metric	Evidence highlighted in the source	Principal limitation
Flood inundation	ConvLSTM	SAR/radar observations, elevation data	Inundation extent and peak-flow arrival time	RMSE, F1-score	AI can integrate spatial and temporal information to produce detailed flood predictions; selected approaches report reductions in flood-timing error	Performance depends strongly on hydrological observations, geographic transferability, and event-specific validation
Wildfire spread	Vision Transformers	MODIS thermal observations, wind vectors	Burn-perimeter development and fire-spread patterns	IoU	Deep-learning approaches can integrate thermal and meteorological information for spatial wildfire assessment	Fire behavior is highly dynamic and sensitive to meteorological and landscape conditions
Agricultural drought	Random Forest regression	NDVI, soil-moisture anomalies	Drought severity and yield-loss probability	R^2 / explained variance	Tree-based models can effectively integrate vegetation	Accuracy depends on quality and representativeness of environment



					and soil moisture indicators; some source-reviewed applications report performance >0.85	al and agricultural observations
Urban heat	Deep Extreme Gradient Boosting	Landsat thermal observations, albedo data	Surface-temperature anomalies/spikes	MAE	AI can generate spatially detailed estimates of urban thermal conditions	Fine-scale urban heterogeneity and socioeconomic exposure require additional contextual data
Multi-hazard/environmental risk	Hybrid ML/deep learning and physics-AI	Satellite, GIS, sensor, climate, reanalysis, and socioeconomic datasets	Integrated hazard, exposure, vulnerability, and risk	Multiple task-specific metrics	Hybrid and integrated frameworks can combine physical constraints with data-driven pattern recognition	Standardized cross-hazard validation and long-term operational evidence remain limited

The performance statements in this table summarize the applications and metrics reported in the uploaded source; they should not be interpreted as universal performance benchmarks across all geographic or climatic settings.

The evidence as a whole suggests that the most significant scientific contribution of AI-based environmental risk assessment is its ability to link up high volume environmental observations to spatial and temporal specific risk information. Various AI architectures have been adapted to various environmental structures and data types,

as illustrated by flood, wildfire, drought, and heat applications. But the more powerful evidence does not warrant the abandonment of traditional environmental models for AI. Rather, it enables a complementary architecture with machine learning for flexible pattern recognition, physical models for process-driven constraints, remote sensing to offer spatial extent and socioeconomic information for context to help turn hazards into meaningfully expressed risk. The next step in the review is to consider how AI predictions can be translated into operational risk management, asset

prioritization, early warning and climate adaptation decisions, and this comprehensive outlook is vital for this process.

4. Integrated AI Applications for Environmental Risk Management and Decision Support

Predicting hazards and managing environmental risks are two important stages in the application of AI. Making predictions about the location of a flood, wildfire, drought or heat event is only the first step in risk reduction; identifying who, what, where and how vulnerable any activities and assets that may be affected is a crucial step in meaningful action. The literature reviewed is therefore increasingly starting to view AI as an integrative decision support tool that can integrate hazard information along with exposure and vulnerability data to create spatially explicit risk information. In this manner, environmental assessment takes a step away from hazard-only mapping to a more holistic representation of potential impacts. One of the significant advancements is the incorporation of socioeconomic vulnerability into AI-driven risk assessments. Traditional hazard maps are able to identify physically exposed areas but can consider all exposed areas to be the same. However, in reality, vulnerability is different across income groups, housing conditions, and population profiles, access to services, infrastructure quality, health and adaptive capacity. The source provides examples of clustering approaches like K-Means clustering to create communities of similar vulnerability characteristics, and computer vision analysis of buildings and infrastructure based on satellite and drone images. Integration of environmental risk can be interpreted within the context of characteristics of the affected population and built environment, as well as hazard intensity.

This has significance in urban and coastal areas where exposure and vulnerability can be quite variable in a relatively small geographical area. For instance, a coastal area can also be home to residential areas, transport infrastructure, industrial sites, agriculture, and critical infrastructure. If a uniform hazard classification is available, it will be of limited value in determining

the priorities for protection of assets. AI powered geospatial assessment should instead integrate hazard intensity and asset characteristics and socioeconomic data to enable differentiated risk prioritization. Examples of such applications mentioned in the source include coastal vulnerability assessment, building-damage detection, and infrastructure-risk mapping. An asset-level classification is a convenient addition to this. The source provides a multi-criteria risk matrix, where the hazard vector, exposure density, vulnerability score and AI derived risk priority are used to characterize different assets. In the illustrative framework, sea level rise and storm surge-exposed coastal substations get a high vulnerability score and a critical priority and arable farmland exposed to chronic thermal drought gets a lower priority. Transport corridors that are at risk from landslides or heavy rain and urban residential areas at risk of flash flooding are given intermediate priority. While these values are examples of how a framework might be applied and are not general thresholds, the methodology used is illustrative of the steps required to transform AI-generated risk information into a prioritization system for allocating resources.

The value of this approach for practice is that it is an approach adopted in a context of limited resources for climate adaptation and disaster preparedness. It is impractical for governments and emergency-management organizations to protect all assets at the same level. Risk-based prioritization can therefore help identify areas to intervene where a reduction in potential losses is expected to be the largest. In this regard, AI can complement and augment, but not supplant, institutional judgment with a uniform analytical framework for assessing geographically dispersed risks. This is especially true of infrastructure networks where the failure of a high value asset can have repercussions outside of the hazard area. AI-driven systems can also aid dynamic risk mapping. AI frameworks can continuously update with new satellite observations, sensor data, and environment conditions while producing maps dynamically, unlike traditional, periodical maps generated using historical data. Risk indicators are

continuously updated as new information is collected and risk profiles adjust to the evolving environmental circumstances. This can be especially important with rapidly changing hazards where the spatial risk distribution could vary significantly over hours or days. The benefits of dynamic risk estimation is greatest when it is tied to early-warning systems. A prediction is only useful if it makes it to decision makers in time to have an impact on action. Forecasts from Artificial Intelligence could help contribute to alerts through detecting changes in environmental variables ahead of hazardous conditions, and continuously refining risk estimates as new observations are made. For flood management, for instance, precipitation, water level, radar, and topographic data can be updated to create a more up-to-date inundation estimate. These same ideas can be used for wildfire spread and drought development as well as extreme heat. The source tells us that flood forecasting with the help of AI can be used for warning and better resource allocations, and that the movement is from analytical prediction towards operational decision support. This very same approach can be used in climate adaptation planning beyond the context of disaster response. Risk information at a fine enough spatial scale can help to pinpoint areas where adaptation measures could be most needed. Combinations of hazard exposure and vulnerability can be used to prioritize coastal infrastructure, transportation systems, agriculture, and urban residential areas. This helps to move away from a purely regional-based approach to adaptation planning toward a more spatially explicit approach. Hyper-local forecasting, asset-level assessment, and geospatial AI are cited as vital aspects of this new trend by the source.

One area that's significant is the ability to use AI for multi-hazard assessment. Rarely do climate risks happen in isolation. Excessive rainfall can cause a combination of flooding, landslides, loss of infrastructure and agricultural damage, and hot and dry conditions can amplify the wildfire hazard risk. This risk-management approach with individual hazard models can then underestimate the cumulative or cascading effects. Multiple

hazard layers with common exposure and vulnerability information may be used to identify areas that are subject to multiple hazards. The source highlights the multi-hazard assessment as a core goal of AI-based environmental risk systems, but also notes that full implementation of the operational aspects is still being developed. However, the use of AI for decision support also needs to be carefully qualified. The source highlights a conflict in the literature between those who claim that AI outputs are enough to make an automatic or semi-automatic risk classification and those who suggest that algorithmic predictions should be part of a broader deliberative discourse and process that includes technical experts, policy makers, and affected communities. This disagreement highlights a key conceptual difference between the two: environmental risk is not only a physical quantity. Social values and institutional responsibilities are also a part of decisions on acceptable risk, allocation of resources, evacuation, investments in infrastructure, and adaptation priorities. Thus, risk scores created using AI should not be used to make decisions but rather should guide them.

This is another argument for human-in-the-loop environmental AI. Human oversight is especially critical when predictions have significant impacts on communities and/or critical infrastructure. It is important that decision makers recognize both the predicted risk and the uncertainty in that prediction, the key drivers of the prediction and the limitations of the data. The source therefore highlights the need to adhere to explainability and supervision by humans as key measures to prevent improper use of black-box models. There is, in general, a conceptual alignment from AI-assisted prediction to AI-supported adaptive risk governance. The first phase involves using AI to analyze data from the environment to find hazards. In the second, hazard information will be integrated with exposure and vulnerability to establish risk estimates. These estimates are used to inform early warning, preparedness, adaptation and resource prioritization in the third. New observations can then be fed back into the model to make further adjustments in the risk

assessment. This feedback structure is more adaptable to a changing climate than a static risk

classification in that information systems adapt to the changing environment.

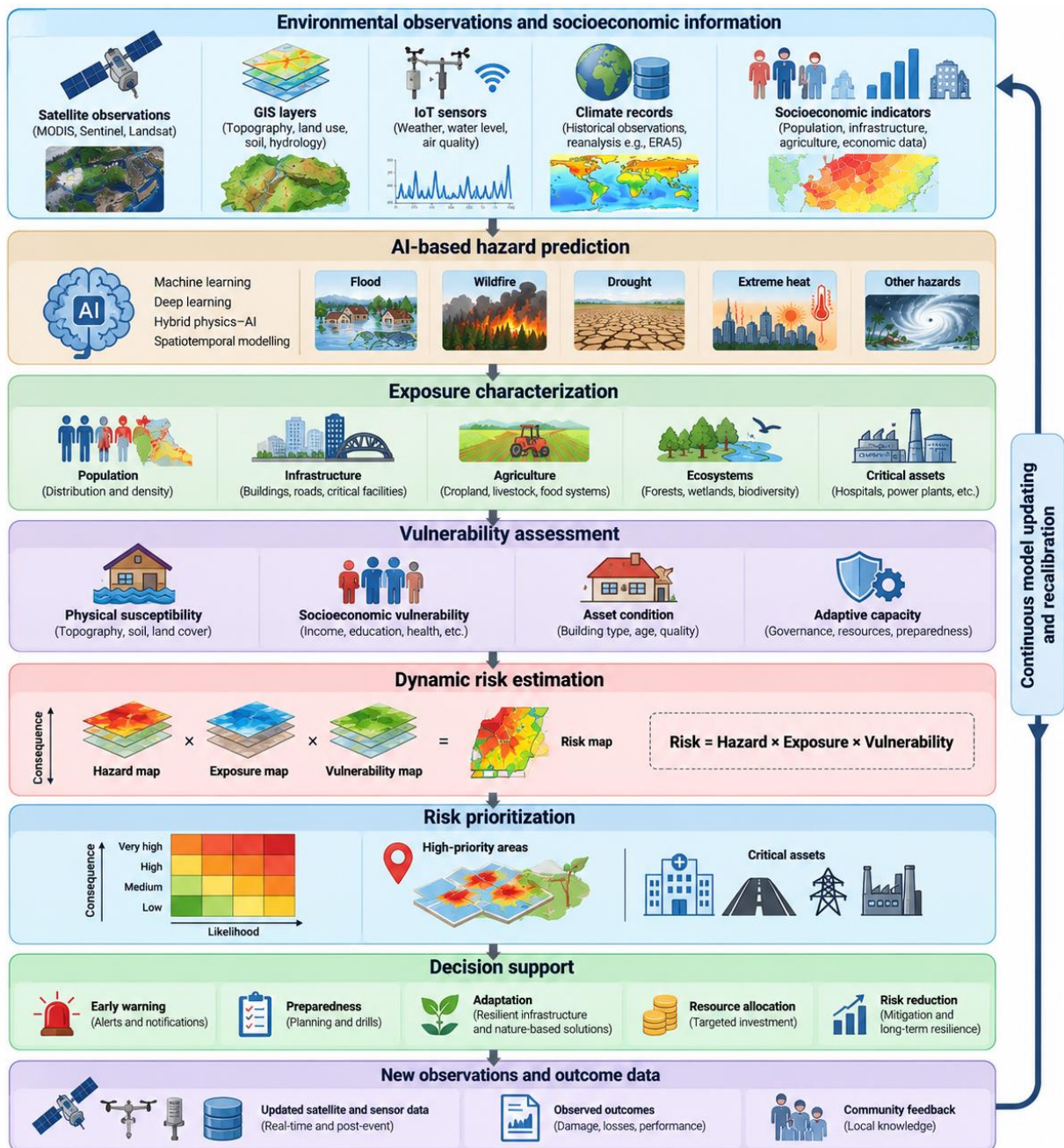


Figure 2. A transition from environmental observation, hazard prediction using AI, and exposure and vulnerability assessment, to dynamic risk estimation and operational decision support. The feedback loop is illustrated, integrated with a framework. A framework with integrated transition from

environmental observation, hazard prediction using AI, to exposure and vulnerability assessment, dynamic risk estimation, and operational decision support. The feedback loop shows that new observations and outcomes are

continuously incorporated to update the model and implement adaptive risk management.

5. Challenges, Research Gaps and Future Directions

While significant methodological advances have been made, existing evidence suggests that AI cannot overcome climate risk management challenges on its own. Rather, evidence of the technical capability versus operational readiness gap is a constant feature of the literature. While the models are becoming more advanced, there are still relatively few standard approaches for model validation, uncertainty quantification, governance, and deployment. According to the source, this imbalance is one of the most outstanding challenges in the field, although technical performance might not always mean reliable decision-making under varying climatic and institutional conditions. Data availability and quality is the first big problem. AI models rely heavily on their training and validation data. Environmental data can be missing, have measurement errors, be at different spatial resolution, or have uneven temporal coverage. These problems are of particular consequence in low-monitoring areas. A model which was developed largely from data from a highly observed environment might then have good apparent performance, but be poorly calibrated for an environment with low observation density. It points to the ensuing equity paradox, in which communities most vulnerable to climate change could be the least included in the datasets on which the climate change models that would serve to protect them are based. There is no easy way to solve this problem by making the algorithms more complex. More complex models can use the high quality data to detect more information, but only from the data observed; the model cannot accurately predict the processes in the environment which are not observed. To this end, future studies should be given more attention to the development of low-cost sensing infrastructure, integrating various sensors with satellites, standardizing environmental data bases, and participatory data collection. The more

representative the data sets, the more reliable will be the environmental AI, and this reliability will likely be more beneficial than ever growing model complexity.

The second challenge is model transferability and generalization. Environmental relationships are place and time specific. Model results for one watershed, urban area or agricultural system or wildfire environment may differ considerably from those of another. The advantage of machine-learning and deep-learning methods seems to be the greatest in data-rich environments and may weaken in areas where densities of monitoring points are lower or when predictions are made further into the future, the source states. This indicates that all reported performance should be taken in the context of the environmental and data conditions in which they were recorded. This problem is even more important in the context of climate non-stationarity. Although the historical data is often used as the basis for model training, the statistics of environmental systems may alter with changing climate. A model that has been well calibrated on past observations may not be well calibrated to predict future observations if the future conditions differ from the training conditions. The source considers this to be a structural deficiency of risk frameworks which have the implicit assumption of a stable baseline. Thus, future AI systems need to include features for identifying distribution shifts, tracking model drift, and adjusting predictions as the environment evolves. Another significant gap is in the methodology for validation. The merits of retrospective validation is that it gives some confidence that a model is able to simulate known environmental conditions and that the model will be able to simulate an unprecedented event, but it is not as useful for developing the confidence in how the model will simulate the unprecedented event. A significant amount of literature is based on historical validation and thus may be vulnerable to overestimating reliability in a non-stationary climate (source). In fact, prospective, multi-year validation and independent testing of AI systems in different geographical regions is

required to ensure the reliability of AI systems after deployment.

In addition, there is a need for more stringent comparison with the conventional models. A high R^2 , RMSE or classification accuracy alone does not imply that an AI model is more useful than a well-calibrated conventional model in practice. Comparisons should consider predictive accuracy, computational requirements, data requirements, interpretability, uncertainty, operational latency, and maintenance requirements and cost. The source highlights direct cost-effectiveness comparisons to proven conventional strategies as a major research need. Other factors that make adoption at the operational level difficult are interpretability and accountability. Complex ensemble and deep-learning models can generate accurate predictions, but at the same time, the reasons for the risk levels assigned to certain locations are not well understood. This is a challenge when a prediction is put forward as a basis for evacuation decisions, infrastructure investments or allocation of public resources. From the literature surveyed in the source, Explainable AI is found to be one of the significant solutions to this issue, but the connection between explainability and predictive performance is still poorly understood. It's not just a technical question of clarity. Institutional and legal defensibility must also be achieved in environmental risk decision-making. Reproach can't be solely laid at the feet of the algorithm if a prediction is wrong with an automated system. The roles of human decision-makers, model developers, data providers and institutions could vary. This makes it imperative to have clear governance frameworks that outline the processes for reviewing, documenting, communicating and acting upon AI predictions. High consequence environmental decisions should therefore not be made without human oversight, but as part of the process (Correa et al., 2025; Ruschemeier and Hondrich 2024; Batool et al., 2025).

Another worry is computational sustainability. AI systems, especially large deep-learning architectures, may need significant processing power to develop the model and train it. AI's

energy and computational demands also pose environmental concerns, according to the source. This poses an important paradox: the technology should be assessed in relation to its resource demand and environmental impact – a technology for climate adaptation needs to be assessed with regard to its resource demand and environmental impacts. The model efficiency, low power inference, edge computing and proportionality of computational effort to the value of the decision are therefore to be taken into account in future work. The same is true for equity. In general, well-resourced institutions appear to have been more effective in building monitoring systems, computational capabilities and embedding AI into operational risk management systems. Despite being more exposed to climate hazards, some areas with lower incomes and climate vulnerability may have substantially less resources. It is therefore maintained that transferability and accessibility are to be considered as fundamental criteria for evaluation and not just marginal ones. AI-based climate resilience shouldn't be yet another domain for technology to be concentrated in well-resourced contexts (Rahwan and Muthukrishna, 2025).

Future research should, therefore, shift towards physics-guided and hybrid AI frameworks that incorporate physics principles and data-driven learning. The methods can help to make the physical consistency better and make it more robust even if historical data are incomplete or future conditions are different from the historical ones. Another source specifies hyper-local prediction, monitoring by satellites, edge computing, and physics-guided machine learning as key areas for the future. Satellite observations combined with low power IoT systems are especially suitable for the near real-time nature of environmental monitoring. In addition to covering a wide spatial extent, satellite platforms have the ability to offer high-frequency measurements at specific locations. The integration of these information sources may be useful to overcome the dilemma of spatial coverage versus temporal resolution. In addition, edge computing could help to further shorten the

communication delays by performing some of the inference at the point where observations are taken. But this has to be tested with empirical data and not assumed to be superior. The source also suggests a longer-term shift to foundation models, self-supervised climate transformers and low power edge deployments. The proposed timeline extends to 2026-2028 for development of the models and laying foundations, 2029-2031 for increased operational deployment, and eventually increasingly autonomous operation from that time onward. The value of this statement must be interpreted as a visionary proposal and not a definite vision for the future of technology. Prospective advancement of data availability, model reliability, computational efficiency,

governance, and institutional acceptance will dictate its feasibility. Of course, the most critical research agenda is not only to build more advanced algorithms but to create systems of environmental AI that are reliable, equitable, interpretable and operationally validated. The next steps in future studies should thus incorporate technical innovation with forward-looking validation, uncertainty quantification, stakeholder involvement, governance and cost-effectiveness analysis. These dimensions will be more likely to be part of the assessment of models to make the assessment more meaningful to the field in terms of climate resilience rather than an add-on after algorithm development.

Table 2. Major challenges, research gaps, and future priorities in AI-based environmental risk management

Challenge	Current gap	Scientific/operational consequence	Priority direction
Data scarcity and quality	Missing, inconsistent, or spatially uneven environmental observations	Poor calibration and reduced reliability in data-scarce regions	Low-cost sensing, satellite-IoT integration, standardized datasets
Geographic transferability	Models may perform differently outside their training region	Limited generalization across climates and landscapes	Cross-region validation and domain adaptation
Climate non-stationarity	Historical relationships may change under future climate conditions	Declining predictive reliability and distribution shift	Continuous recalibration and regime-shift detection
Retrospective validation	Many studies rely on historical rather than prospective testing	Potential overestimation of operational performance	Multi-year prospective validation
Interpretability	Complex models can provide opaque risk estimates	Difficult policy justification and accountability	Explainable and uncertainty-aware AI
Computational demand	Large models can require substantial energy and infrastructure	Increased operational cost and environmental footprint	Efficient models, edge AI, and low-power inference
Equity and accessibility	Climate-vulnerable regions may have weaker data infrastructure	Unequal access to AI-enabled resilience	Capacity building, participatory data, accessible technologies
Governance and accountability	Limited standardized rules for AI-assisted decisions	Unclear responsibility for incorrect decisions	Human oversight and explicit governance frameworks
Multi-hazard integration	Hazards are often modeled separately	Compound and cascading risks may be underestimated	Integrated multi-hazard frameworks

Cost-effectiveness	Limited direct comparison with conventional models	Uncertain practical value of AI investment	Comparative economic and operational evaluation
Physics-AI integration	Purely empirical models may struggle under novel conditions	Reduced physical consistency outside training distributions	Physics-guided and hybrid AI
Operational deployment	Technical demonstrations exceed long-term field implementation	Limited evidence of sustained real-world effectiveness	Longitudinal monitoring and adaptive model governance

Table note: The table synthesizes the challenges and research priorities identified in the uploaded manuscript. It is intended as a conceptual research agenda rather than a ranking of the relative importance of individual challenges.

6. Conclusion

AI is playing a growing role in enhancing climate-risk assessment by combining diverse climate, physical, and social variables and allowing for more agile, climate-driven hazard and vulnerability analysis. It is most useful not as a substitute for traditional environmental science, but as a complementary tool to physical models for high-resolution prediction, dynamic risk estimation and decision support. However, data availability, data non-stationarity, data limited transferability, data interpretability, computational requirements, and data unequal access limit the reliable deployment. To enable future progress, a combination of physics-AI systems, prospective validation, uncertainty-aware and explainable models, robust data infrastructure, and responsible governance are needed. In the end, AI can enable a shift in the paradigm from reactive disaster response to adaptive, evidence-based, and more equitable climate-risk management.

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