



# Machine Learning Applications in Climate Risk Prediction and Adaptation

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## Abstract

Climate-related hazards increasingly affect communities, infrastructure, ecosystems, agriculture, water resources, and economic activity, creating a growing need for anticipatory approaches to climate-risk management. Conventional statistical and process-based models remain essential for understanding climatic systems, yet the expanding availability of remote-sensing observations, meteorological records, geospatial information, socioeconomic indicators, and high-frequency environmental data has created opportunities for complementary machine-learning applications. This study examines the role of machine learning in climate-risk prediction and adaptation planning through a simulation-based comparative framework. Four climate-related hazards—floods, droughts, heatwaves, and wildfires—are evaluated using synthetic environmental and vulnerability indicators representing precipitation, temperature anomalies, soil moisture, vegetation dryness, terrain characteristics, population exposure, and infrastructure sensitivity. The analytical framework compares a conventional statistical baseline with machine-learning-enhanced prediction and examines how risk scores can support adaptation prioritization.

Simulation results indicate that machine-learning models can improve the identification of nonlinear and multidimensional relationships relevant to climate-risk forecasting. Average prediction accuracy increased from 71.0% under the conventional baseline to 87.0% under the machine-learning-enhanced scenario. The strongest simulated accuracy was observed for heatwave prediction at 90%, followed by flood risk at 88%, wildfire risk at 86%, and drought risk at 84%. These results are illustrative rather than empirical field findings. The study further argues that prediction accuracy alone is insufficient for effective adaptation. Climate-risk analytics must integrate hazard probability with exposure, vulnerability, uncertainty, interpretability, local knowledge, and feasible adaptation responses. Machine learning is therefore most valuable when embedded within transparent climate-risk governance systems and combined with physical climate knowledge, geospatial analysis, human expertise, and continuous model validation.

**Keywords:** Machine learning; climate risk; climate adaptation; climate hazards; predictive analytics; flood prediction; drought prediction; heatwave risk; wildfire risk; environmental intelligence

## 1. Introduction

Climate-related hazards create interconnected risks for human settlements, public infrastructure, food systems, water resources, ecosystems, health, and economic activity. Flooding can damage transport and utility networks, prolonged drought can reduce agricultural and water-system reliability, heatwaves can

increase mortality and energy demand, and wildfires can affect ecosystems, settlements, air quality, and emergency-response capacity. Climate-risk management therefore requires more than retrospective assessment. Decision-makers increasingly need analytical systems capable of identifying emerging risk, estimating where impacts are likely to concentrate, and providing sufficient lead time to implement adaptation measures.

Climate risk is inherently multidimensional. A hazardous climatic event does not create equal consequences in every location because impacts depend on the interaction among hazard intensity, exposure, vulnerability, adaptive capacity, and local socioeconomic conditions. A severe rainfall event occurring over an uninhabited landscape may generate comparatively limited societal loss, whereas a lower-intensity event affecting a densely populated and poorly drained settlement may produce substantial disruption. Climate-risk prediction must consequently move beyond weather forecasting alone and incorporate information describing the systems and populations exposed to climatic hazards.

Machine learning provides a complementary analytical capability for this purpose because climate-risk datasets are often large, heterogeneous, spatially distributed, temporally dependent, and nonlinear. Remote-sensing imagery, precipitation records, temperature observations, soil-moisture estimates, vegetation indices, topographic information, infrastructure inventories, land-use data, and socioeconomic indicators can collectively create high-dimensional analytical environments. Research in Earth-system science has emphasized the potential of deep learning to extract complex spatiotemporal structures from large geoscientific datasets while also stressing the value of hybrid approaches that integrate data-driven methods with physical understanding.

Applications have already emerged across multiple hazard domains. Flood-prediction research has documented the use of artificial neural networks, support-vector machines, decision trees, adaptive neuro-fuzzy methods, and hybrid approaches for rainfall-runoff and flood forecasting. Wildfire research similarly includes machine-learning applications in fire detection, susceptibility assessment, fire-weather analysis, behavior prediction, mapping, and management. Climate-risk assessment literature further demonstrates substantial use of decision trees, random forests, artificial neural networks, remote sensing, ensemble techniques, and hybrid models, particularly for floods and landslides.

Despite this potential, machine-learning prediction should not be equated automatically with climate adaptation. A model can identify areas of elevated hazard while providing little guidance concerning which interventions are feasible, equitable, affordable, or institutionally appropriate. Adaptation requires translating analytical risk information into decisions about infrastructure reinforcement, land-use planning, ecosystem management, water conservation, heat-health interventions, emergency preparedness, agricultural adjustment, and other context-specific measures. The present study therefore examines machine learning not only as a predictive technology but as a decision-support component connecting climate-risk identification with adaptation prioritization.

## **2. Review of Literature**

### **2.1 Machine Learning in Climate and Earth-System Analytics**

The increasing volume of Earth-observation and environmental data has expanded opportunities for data-driven climate analysis. Traditional statistical approaches remain valuable because they often provide transparent relationships and interpretable parameters, but they may encounter limitations when relationships among predictors are strongly nonlinear or contain complex spatial and temporal interactions.



Reichstein and colleagues emphasized that deep-learning approaches can exploit spatial and temporal context within Earth-system datasets and argued for closer integration between physical process understanding and data-driven learning. Their analysis is important for climate-risk applications because purely statistical pattern recognition can produce apparently strong predictive performance without representing physically credible relationships. Hybrid approaches can help constrain learning with environmental knowledge and improve scientific interpretability.

Zennaro and colleagues examined machine-learning applications in climate-change risk assessment and identified substantial growth in the use of these methods. Their review found that decision trees, random forests, and artificial neural networks were among the recurrent techniques, while remote-sensing information played a major role in representing spatial and temporal characteristics of exposure and vulnerability. The review also identified weaker coverage of future climate scenarios, cascading hazards, and compound risks, indicating that high model performance under historical conditions does not automatically establish reliable performance under changing climatic regimes.

Machine learning therefore provides significant pattern-recognition capability but should be evaluated within the nonstationary context of climate change. Relationships learned from historical observations can evolve as temperature distributions, precipitation regimes, land use, infrastructure, population patterns, and ecosystem conditions change.

## **2.2 Hazard Prediction Across Floods, Droughts, Heatwaves, and Wildfires**

Flood prediction represents one of the most developed applications of machine learning within hydro-climatic risk management. Mosavi, Ozturk, and Chau reviewed numerous machine-learning approaches for flood forecasting and demonstrated the broad use of artificial neural networks, support-vector machines, decision-tree-based methods, hybrid techniques, and other computational models. Machine learning is particularly useful where complex rainfall-runoff relationships and large environmental datasets make conventional model formulation difficult.

Wildfire science presents similarly complex prediction problems because ignition, fuel characteristics, vegetation condition, weather, terrain, human activity, and climate interact across different spatial and temporal scales. Jain and colleagues identified hundreds of machine-learning applications across wildfire research, including fire detection and mapping, risk assessment, occurrence prediction, fire behavior, fire effects, and management. Their review also stresses that domain expertise remains essential because high computational capability does not ensure physically realistic fire modeling.

Machine-learning methods have also been increasingly applied to landslide susceptibility and other climate-sensitive hazards. Comparative reviews indicate movement from expert-based susceptibility approaches toward statistical and machine-learning methods capable of integrating terrain, rainfall, geological, vegetation, and land-use variables. Similar principles apply to drought and heatwave prediction, where models can combine historical climate indicators, soil and vegetation conditions, remote-sensing observations, and socioeconomic exposure to identify patterns associated with elevated risk.

## **2.3 From Risk Prediction to Climate Adaptation**

Climate-risk prediction creates practical value only when analytical information supports decisions that reduce vulnerability or exposure. Adaptation may involve physical infrastructure, ecological

interventions, technological systems, behavioral change, institutional reform, financial instruments, emergency preparedness, or changes in spatial planning.

Adaptation feasibility varies considerably across locations. Singh and colleagues emphasize that adaptation options must be assessed through multiple dimensions rather than technical effectiveness alone. Institutional, economic, technological, social, geophysical, and other constraints can determine whether an apparently beneficial intervention is realistically implementable.

Climate resilience of critical infrastructure provides an important example. Kumar and colleagues developed a framework linking climate extremes, infrastructure risk, machine-learning applications, and resilience planning. Their work demonstrates how predictive analytics can contribute to broader resilience strategies involving the capacity to anticipate, absorb, adapt, and recover from extreme events.

The literature therefore suggests that the greatest contribution of machine learning lies not in replacing established climate science but in augmenting climate-risk intelligence. Machine learning can help process high-dimensional data, identify spatial risk patterns, improve early warning, and prioritize areas requiring intervention, while adaptation planning remains dependent on human judgment, physical knowledge, institutional capacity, and social context.

### **3. Objectives of the Study**

#### **3.1 Climate-Risk Prediction Objective**

The first objective is to examine the potential of machine-learning methods to improve prediction across multiple categories of climate-related hazards. Floods, droughts, heatwaves, and wildfires are considered because they represent different climatic and environmental processes and require distinct combinations of predictor variables.

The study specifically evaluates whether a machine-learning-enhanced analytical framework can identify complex nonlinear risk relationships more effectively than a simplified conventional statistical baseline under simulated conditions.

#### **3.2 Integrated Risk-Assessment Objective**

The second objective is to move beyond hazard probability by incorporating exposure and vulnerability into the analytical framework. An accurate prediction of extreme weather has limited adaptation value if it does not identify which populations, infrastructure, ecological systems, or economic activities are most vulnerable.

The study therefore conceptualizes climate risk as a combined function of hazard likelihood, exposure, and vulnerability rather than treating climatic probability as the complete risk measure.

#### **3.3 Adaptation Decision-Support Objective**

The third objective is to investigate how machine-learning-generated risk scores can support adaptation prioritization. Prediction outputs are considered alongside possible interventions such as flood-resilient drainage, drought preparedness, heat-health response, vegetation management, early warning, and infrastructure protection.

#### **The principal research question is:**

How can machine-learning applications improve climate-risk prediction while supporting transparent, context-sensitive, and actionable climate adaptation planning?

## 4. Research Methodology

### 4.1 Research Design

The study adopts a simulation-based comparative research design. This approach was selected because authenticated meteorological, geospatial, socioeconomic, and adaptation-outcome datasets from a defined study region were not provided. The results therefore illustrate analytical relationships rather than representing observations from an actual climate-risk monitoring program.

A synthetic dataset of 1,600 climate-risk scenarios was conceptually constructed, with 400 scenarios allocated to each of four hazard categories: flood, drought, heatwave, and wildfire. Each scenario represented a unique combination of environmental conditions, exposure characteristics, and vulnerability indicators.

The analytical workflow compared a conventional statistical-risk baseline with a machine-learning-enhanced approach. The purpose was not to establish that machine learning universally outperforms physical or statistical modeling but to examine situations in which nonlinear and interacting predictor relationships may provide an advantage.

### 4.2 Predictor Variables and Analytical Procedure

The simulated feature structure included precipitation intensity, antecedent rainfall, temperature anomaly, soil moisture, vegetation dryness, topographic characteristics, land-cover conditions, population exposure, infrastructure sensitivity, and adaptive-capacity indicators.

The exact predictors varied according to hazard type. Flood analysis placed greater emphasis on precipitation, terrain, soil saturation, and drainage characteristics. Drought analysis emphasized precipitation deficit, temperature, soil moisture, and vegetation condition. Heatwave prediction incorporated temperature anomalies, duration, urban characteristics, and population exposure. Wildfire prediction incorporated temperature, vegetation dryness, wind-related conditions, terrain, and fuel characteristics.

**Climate risk was represented conceptually as:**

$$CR_i = H_i \times E_i \times V_i$$

**where:**

$CR_i$  = climate-risk score for scenario  $i$ ,

$H_i$  = modeled hazard probability or intensity,

$E_i$  = exposure index, and

$V_i$  = vulnerability index.

For analytical purposes, the simulated data were divided conceptually into training, validation, and testing components using a 70:15:15 allocation. Candidate machine-learning models included random forest, gradient boosting, and artificial neural network configurations. A simplified statistical classifier represented the conventional baseline.

**Table 1: Simulation-Based Climate-Risk Analytical Framework**

| Methodological Element | Specification          | Analytical Purpose                |
|------------------------|------------------------|-----------------------------------|
| Research design        | Comparative simulation | Evaluate predictive approaches    |
| Simulated scenarios    | 1,600                  | Provide balanced analytical cases |

|                          |                                                                |                                                                            |
|--------------------------|----------------------------------------------------------------|----------------------------------------------------------------------------|
| Hazard categories        | Flood, drought, heatwave, wildfire                             | Evaluate multiple climate risks                                            |
| Scenarios per hazard     | 400                                                            | Maintain comparative balance                                               |
| Environmental predictors | Precipitation, temperature, soil moisture, vegetation, terrain | Represent hazard conditions                                                |
| Risk-context predictors  | Exposure, infrastructure sensitivity, adaptive capacity        | Extend analysis beyond hazard alone                                        |
| Conventional baseline    | Simplified statistical classification                          | Establish comparison                                                       |
| ML approaches            | Random forest, gradient boosting, neural network               | Capture nonlinear relationships                                            |
| Data allocation          | 70% training, 15% validation, 15% testing                      | Support model evaluation                                                   |
| Evidence status          | Synthetic and illustrative                                     | Prevent simulated findings from being treated as observed climate outcomes |

#### 4.3 Evaluation and Adaptation Prioritization

Prediction accuracy was used as the primary comparative indicator because the study aims to demonstrate differences in hazard classification performance. In a real climate-risk study, additional metrics would be necessary, including precision, recall, F1-score, area under the receiver operating characteristic curve, calibration error, false-negative rate, spatial validation, and uncertainty intervals.

False negatives deserve particular attention in high-impact climate-risk applications. A model that incorrectly classifies a severe flood or heatwave condition as low risk may create larger societal consequences than a moderate increase in false alarms. Performance evaluation should therefore reflect decision consequences rather than maximizing average accuracy alone.

Adaptation prioritization was conceptually based on the combined climate-risk score. High-risk scenarios with high exposure and vulnerability received greater intervention priority than scenarios characterized by high hazard but low societal exposure.

Four broad adaptation categories were mapped to the hazard analysis: structural protection, ecosystem-based adaptation, preparedness and early warning, and demand or behavior management.

### 5. Analysis

#### 5.1 Comparative Prediction Performance

The simulated analysis indicates that machine-learning-enhanced prediction generated higher classification accuracy across all four hazard categories than the simplified conventional baseline.

**Table 2: Simulated Climate-Risk Prediction Performance**

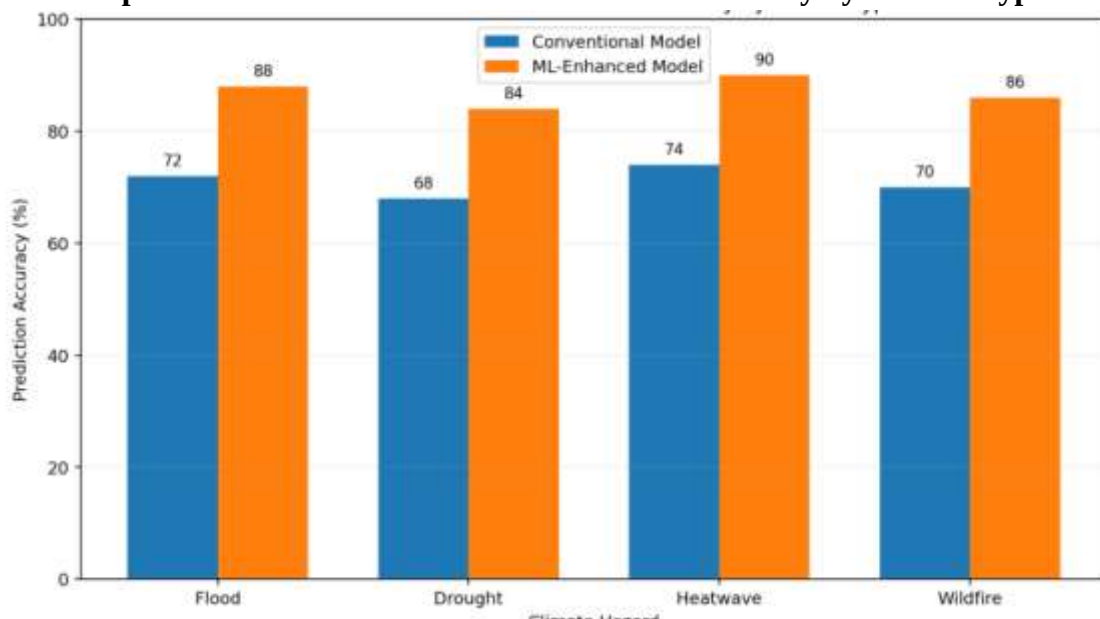
| Climate Hazard | Conventional Model Accuracy (%) | ML-Enhanced Accuracy (%) | Improvement (Percentage Points) | Illustrative Adaptation Application       |
|----------------|---------------------------------|--------------------------|---------------------------------|-------------------------------------------|
| Flood          | 72                              | 88                       | +16                             | Drainage, flood warning, zoning           |
| Drought        | 68                              | 84                       | +16                             | Water allocation, irrigation planning     |
| Heatwave       | 74                              | 90                       | +16                             | Heat-health alerts, cooling interventions |
| Wildfire       | 70                              | 86                       | +16                             | Fuel management, evacuation preparedness  |
| Average        | 71                              | 87                       | +16                             | Integrated climate-risk planning          |

The conventional approach generated an average prediction accuracy of 71%, whereas the machine-learning-enhanced framework achieved an average of 87%. The absolute difference was therefore 16 percentage points.

The modeled performance increase should not be generalized directly to operational climate systems. Its purpose is to demonstrate how a model capable of representing nonlinear and interactive relationships might outperform a simplified linear or statistical baseline under conditions favorable to machine learning.

## 5.2 Hazard-Specific Prediction Accuracy

**Graph 1: Simulated Climate-Risk Prediction Accuracy by Hazard Type**



Heatwave prediction generated the highest machine-learning accuracy at 90%, compared with 74% under the conventional baseline. Flood prediction increased from 72% to 88%, while wildfire prediction increased from 70% to 86%. Drought prediction showed the lowest absolute machine-learning accuracy among the four hazards but still increased from 68% to 84%.

**The relative increase in average prediction accuracy was:**

$$\frac{87-71}{71} \times 100 \approx 22.5\%$$

This percentage describes the simulated comparison and is not an estimate of the improvement that organizations or governments should expect from actual machine-learning deployment.

The apparent advantage of machine learning reflects its simulated ability to model interactions among predictors. For example, flood risk may depend simultaneously on rainfall intensity, antecedent soil moisture, terrain slope, drainage capacity, and urban surface characteristics. The effects of these variables may not be additive or linear.

### 5.3 Translation of Prediction into Adaptation Decisions

Improved prediction becomes meaningful only when it changes decision quality. An adaptation-oriented climate-risk system should therefore connect predictive outputs with intervention thresholds.

A high flood-risk score, for example, may trigger enhanced drainage inspection, reservoir-management adjustments, emergency communication, temporary infrastructure protection, or evacuation readiness. A high drought-risk score may trigger water-demand controls, agricultural advisories, irrigation scheduling, or allocation of emergency water reserves.

Heatwave prediction may support public-health alerts, cooling-center activation, modified working schedules, targeted outreach to vulnerable populations, or urban cooling interventions. Wildfire-risk predictions can assist fuel-management planning, surveillance allocation, temporary access restrictions, and emergency-response positioning.

Machine learning can therefore increase adaptation value through **prioritization**. Rather than distributing adaptation resources evenly, decision-makers can identify locations where hazard probability overlaps with high exposure and vulnerability.

**A useful adaptation-priority formulation can be expressed as:**

$$AP_i = CR_i \times F_i$$

**where:**

$AP_i$  = adaptation-priority score,

$CR_i$  = estimated climate-risk score, and

$F_i$  = feasibility or urgency weighting.

This additional factor is important because the highest modeled risk may not always correspond with the intervention that can be implemented most effectively or immediately.

## 6. Challenges

### 6.1 Data Quality, Nonstationarity, and Generalization

Machine-learning models depend on the quality, representativeness, and continuity of their training data. Climate-risk datasets may contain missing observations, inconsistent spatial resolution, sensor errors, changes in monitoring systems, biased reporting, and uneven coverage between highly monitored and data-poor regions.

A further challenge arises from climate nonstationarity. Machine-learning models commonly learn relationships from historical observations, yet climate change can alter the statistical distribution of temperature, precipitation, drought duration, wildfire conditions, and extreme events. A model that performs strongly on historical data may therefore lose accuracy when future conditions move outside the range represented during training.

Zennaro and colleagues identified limited application of machine learning to future climate scenarios compared with current-condition risk assessment and also highlighted gaps relating to cascading and compound climate risks.

Model development should consequently incorporate temporal validation, out-of-region testing, scenario stress testing, uncertainty assessment, and periodic recalibration.

## **6.2 Explainability and Physical Consistency**

Complex machine-learning models can produce highly accurate predictions while providing limited explanation of the mechanisms underlying those predictions. This becomes problematic when models support decisions affecting public safety, infrastructure expenditure, land-use restrictions, or allocation of scarce adaptation resources.

Climate-risk systems therefore benefit from interpretable analytical tools such as feature-importance analysis, partial-dependence relationships, local explanation methods, uncertainty estimates, and sensitivity testing.

Interpretability should also include physical plausibility. Reichstein and colleagues emphasize the potential value of integrating deep learning with Earth-system process understanding rather than relying exclusively on unconstrained data-driven relationships.

A flood model should not receive institutional trust merely because its validation accuracy is high. Analysts must also examine whether influential predictor relationships are hydrologically plausible and stable across relevant climatic conditions.

## **6.3 Equity, Data Gaps, and Adaptation Governance**

Climate-risk prediction may inadvertently reinforce existing inequalities when data availability differs among communities. Wealthier urban areas may possess dense sensor networks, detailed infrastructure databases, and high-resolution population information, whereas rural or disadvantaged regions may have limited monitoring coverage.

A model trained primarily on data-rich regions may consequently perform less reliably in communities that are already more vulnerable to climatic impacts.

Adaptation decisions introduce an additional governance challenge. Analytical systems may identify a location as high risk, but decisions concerning relocation, infrastructure investment, water allocation, agricultural support, or emergency intervention involve social values and distributional consequences that cannot be determined solely by algorithms.

Machine learning should therefore inform rather than replace participatory adaptation governance. Local communities, climate scientists, engineers, planners, emergency managers, public-health professionals, and policymakers should remain involved in interpreting model outputs and evaluating feasible interventions.

## 7. Discussion

### 7.1 Interpretation of Predictive Performance

The simulated results indicate that machine learning can strengthen climate-risk prediction when risk depends on complex combinations of environmental, spatial, and vulnerability variables. The modeled improvement was consistent across flood, drought, heatwave, and wildfire scenarios, suggesting that data-driven approaches can provide a flexible analytical structure across different hazard domains.

This interpretation is consistent with the wider climate-risk literature. Flood-prediction research has documented substantial application of machine-learning approaches for complex hydrological forecasting. Wildfire research similarly demonstrates the value of random forests, artificial neural networks, support-vector machines, decision trees, and related techniques across multiple components of wildfire science and management.

However, performance comparisons between machine learning and conventional models require careful design. Machine-learning models should not be compared with deliberately weak baseline methods simply to demonstrate superiority. Operational studies should compare models against credible statistical, physical, and hybrid alternatives using identical testing data and appropriate temporal or spatial holdouts.

The principal question should therefore not be whether machine learning is universally superior but under which conditions it adds predictive and decision-making value.

### 7.2 Role of Hybrid Climate Intelligence

Climate-risk management is particularly suitable for hybrid modeling because both physical processes and empirical patterns contain valuable information.

Physical climate and hydrological models incorporate scientific knowledge concerning atmospheric circulation, energy balance, rainfall-runoff processes, soil behavior, vegetation dynamics, and other mechanisms. Machine-learning models can complement these approaches through residual correction, downscaling, emulation, pattern identification, data fusion, and rapid prediction.

Reichstein and colleagues argue that combining process knowledge and deep learning represents an important direction for data-driven Earth-system science. Such integration may improve generalization because physical constraints can reduce the likelihood that a model learns relationships that are statistically convenient but environmentally implausible.

Hybrid climate intelligence may also improve trust among decision-makers. A prediction supported by both process-based evidence and interpretable machine-learning patterns is often easier to evaluate than an opaque output generated independently of established climate science.

### 7.3 From Prediction Accuracy to Adaptation Effectiveness

The most important implication of the analysis is that predictive accuracy should not be treated as the final measure of climate-risk analytics.

An extremely accurate flood model has limited social value if warnings do not reach vulnerable populations. A drought model cannot improve water security if institutions lack mechanisms for reallocating water or supporting affected farmers. A heatwave model will not reduce mortality if public-health agencies cannot translate warnings into cooling, outreach, or occupational-protection measures.

**Adaptation therefore involves a chain of actions:**

Data → Prediction → Risk Interpretation → Prioritization → Intervention → Monitoring → Learning

Failure at any stage can weaken the value of the analytical system.

Research on adaptation feasibility supports this broader perspective because adaptation options are constrained by institutional, economic, technological, social, and environmental conditions.

Machine learning should therefore be evaluated through decision-oriented measures in addition to predictive statistics. Relevant indicators may include warning lead time, avoided exposure, reduction in false-negative high-risk events, improved allocation of adaptation resources, reduction in recovery time, and increased resilience of critical services.

## 8. Conclusion

Machine learning offers substantial opportunities to enhance climate-risk prediction by integrating large and heterogeneous environmental, geospatial, infrastructural, and socioeconomic datasets. Its capability to represent nonlinear relationships makes it particularly relevant for complex climate-related hazards whose impacts emerge from interactions among meteorological conditions, landscape characteristics, exposure, and vulnerability.

The simulation-based analysis presented in this study demonstrated higher modeled prediction accuracy for machine-learning-enhanced approaches across floods, droughts, heatwaves, and wildfires. Average simulated accuracy increased from 71% under the conventional baseline to 87% under the machine-learning framework. Heatwave prediction achieved the highest modeled accuracy at 90%, followed by flood risk at 88%, wildfire risk at 86%, and drought risk at 84%. These values are explicitly illustrative and should not be interpreted as empirical performance from an operational climate service.

The study further demonstrates that climate-risk prediction should not be reduced to hazard classification. Adaptation requires understanding who and what is exposed, why particular systems are vulnerable, which interventions are feasible, and how uncertainty should influence decisions. Machine learning becomes strategically useful when predictions are translated into targeted adaptation measures such as early-warning systems, resilient infrastructure, water-resource planning, heat-health programs, ecosystem management, and emergency preparedness.

The most defensible pathway is therefore not a replacement of climate science by machine learning but the development of hybrid climate intelligence. Physical models, machine learning, remote sensing, local knowledge, vulnerability assessment, and expert judgment can jointly provide stronger support for climate-risk governance than any single method operating independently. When embedded within transparent and participatory adaptation systems, machine learning can help transform expanding climate data resources into earlier warnings, more focused interventions, and better-informed decisions for climate-resilient development.

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