Machine Learning Applications for Predicting Environmental Risks and Resilience

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ABSTRACT

Machine learning has emerged as a promising technological approach for addressing increasingly complex environmental challenges, particularly in the identification and prediction of environmental risks that threaten ecological sustainability and community resilience. **Despite the growing** availability of environmental data, accurately forecasting potential risks and evaluating resilience capacity remain significant challenges for policymakers and environmental managers. Therefore, **this study** aims to investigate the application of machine learning techniques for predicting environmental risks and assessing resilience factors that support sustainable environmental management and disaster preparedness. To achieve this objective, **a quantitative** research approach was employed through the development and evaluation of machine learning models using environmental datasets derived from multiple indicators, including climate conditions, land-use patterns, ecological variables, and historical environmental events. The proposed framework integrates data preprocessing, feature selection, model training, and predictive analysis to identify patterns associated with environmental vulnerability and resilience. **The findings** demonstrate that machine learning models are capable of effectively detecting environmental risk patterns and generating reliable predictions that support proactive decision-making. Furthermore, **the analysis** reveals that resilience-related indicators play a critical role in improving predictive performance and enhancing the understanding of environmental adaptation mechanisms. The integration of predictive analytics and resilience assessment provides a more comprehensive perspective on environmental risk management. **In conclusion,** machine learning offers substantial potential for advancing environmental risk prediction and resilience evaluation by enabling data-driven strategies for sustainable environmental **governance.** These findings contribute to the growing body of knowledge on intelligent environmental management systems and support the development of more adaptive and resilient environmental policies.

1. INTRODUCTION

Environmental degradation, climate change, natural disasters, and ecosystem instability have become increasingly complex global challenges that threaten sustainable development and societal well-being. The frequency and intensity of environmental hazards such as floods, droughts, wildfires, and extreme weather events have significantly increased over the past decade, creating substantial economic, social, and ecological consequences [1]. At the same time, advances in digital technologies have generated unprecedented volumes of environmental data from remote sensing systems, Internet of Things (IoT) devices, geographic information systems, and environmental monitoring platforms. While the availability of these data sources offers new opportunities for understanding environmental dynamics, traditional analytical approaches often struggle to process large-scale, multidimensional datasets and identify complex relationships among environmental variables. Consequently, there is a growing need for intelligent analytical methods capable of transforming environmental data into actionable insights that support risk mitigation, resilience planning, and sustainable environmental governance [2].

The growing need for intelligent and resilient environmental management is closely aligned with the United Nations Sustainable Development Goals (SDGs), particularly SDG 11 on Sustainable Cities and Communities, SDG 13 on Climate Action, and SDG 15 on Life on Land. SDG 11 emphasizes the development of safer and more resilient communities by strengthening disaster preparedness and reducing vulnerability to environmental hazards, while SDG 13 highlights the importance of improving adaptive capacity and implementing effective responses to climate-related risks [3]. In addition, SDG 15 promotes the protection, restoration, and sustainable management of terrestrial ecosystems that are increasingly affected by environmental degradation and climate-related disturbances. In this context, machine learning-based environmental risk prediction can contribute to these sustainability objectives by enabling earlier identification of potential hazards, supporting evidence-based adaptation strategies, and improving the assessment of environmental resilience. Integrating predictive analytics with resilience indicators therefore provides a data-driven approach for strengthening environmental governance while contributing to broader global efforts toward sustainable and climate-resilient development.

Recent developments in machine learning have demonstrated considerable potential in addressing environmental challenges through predictive modeling, pattern recognition, and decision-support systems. Machine learning algorithms can analyze large and heterogeneous datasets to uncover hidden patterns, detect anomalies, and forecast environmental risks with greater efficiency than many conventional statistical techniques [4]. Previous studies have explored the application of machine learning in areas such as climate prediction, disaster forecasting, air quality monitoring, biodiversity conservation, and resource management [5]. Despite these advancements, existing research has predominantly focused on predicting environmental risks as isolated events, while relatively limited attention has been given to integrating resilience-related indicators into predictive frameworks. Environmental resilience represents the capacity of ecosystems, communities, and institutions to adapt, recover, and maintain functionality in the face of environmental disturbances. Ignoring resilience factors may result in predictive models that accurately identify risks but provide insufficient insight into the adaptive capacities required to mitigate their impacts [6].

From a theoretical perspective, the relationship between environmental risk prediction and resilience assessment remains insufficiently explored in the literature. Most studies emphasize prediction accuracy as the primary performance criterion without adequately examining how resilience indicators contribute to the interpretability and practical value of predictive outcomes. Furthermore, environmental management strategies increasingly require holistic approaches that move beyond hazard identification toward comprehensive assessments of vulnerability, adaptability, and long-term sustainability. This gap highlights the need for research that combines machine learning techniques with resilience-oriented environmental analysis to produce more meaningful and actionable decision-support mechanisms. The novelty of this study lies in the integration of machine learning-based environmental risk prediction with resilience assessment variables, thereby providing a more comprehensive framework for understanding environmental threats and adaptive capacities within a unified analytical model [7].

Based on these considerations, this study addresses the following research question: how can machine learning applications be utilized to predict environmental risks while simultaneously incorporating resilience factors to support sustainable environmental management? Accordingly, the primary objective of this research is to investigate the effectiveness of machine learning techniques in predicting environmental risks and evaluating resilience-related dimensions that influence environmental adaptability [8]. The findings are expected to contribute both theoretically and practically. Theoretically, this study enriches the growing body of knowledge concerning the intersection of artificial intelligence, environmental risk management, and resilience theory [9]. Practically, the proposed framework may assist policymakers, environmental practitioners, and decision-makers in developing proactive strategies for environmental protection, disaster preparedness, and sustainable resource management through data-driven and resilience-oriented approaches [10].

2. LITERATURE REVIEW

2.1. Machine Learning in Environmental Studies

The rapid advancement of artificial intelligence technologies has significantly transformed environmental research by enabling the analysis of large-scale and complex datasets that were previously difficult to process using conventional approaches [11]. Among these technologies, machine learning has emerged as one of the most widely adopted analytical tools due to its ability to identify hidden patterns, learn from historical data, and generate predictive insights with minimal human intervention [12]. Environmental systems are characterized by nonlinear interactions among climatic, ecological, geographical, and anthropogenic factors, making machine learning particularly suitable for modeling such complexity [13]. Recent studies have demonstrated the effectiveness of machine learning algorithms in addressing environmental challenges, including climate forecasting, biodiversity monitoring, environmental pollution assessment, land-use change detection, and disaster management. Machine learning techniques can generally be categorized into supervised learning, unsupervised learning, and reinforcement learning approaches [14]. Supervised learning algorithms are frequently utilized in environmental prediction tasks because they can learn relationships between input variables and predefined target outcomes [15]. Meanwhile, unsupervised learning methods are useful for discovering environmental patterns and anomalies without requiring labeled datasets. The growing availability of environmental monitoring systems, remote sensing technologies, and sensor networks has further accelerated the adoption of machine learning in environmental applications by providing extensive datasets suitable for model development and validation [16]. As environmental challenges continue to increase in complexity, machine learning is expected to play a critical role in supporting evidence-based environmental decision-making and sustainable resource management [17].

2.2. Environmental Risk Prediction

Environmental risk prediction refers to the process of identifying, assessing, and forecasting potential environmental threats that may negatively affect ecosystems, infrastructure, economic activities, and human well-being. Accurate risk prediction is essential because environmental hazards often occur with significant uncertainty and may generate cascading impacts across multiple sectors. Traditional risk assessment methods typically rely on statistical analyses and expert judgments; however, these approaches may be limited when dealing with high-dimensional datasets and nonlinear environmental relationships. Consequently, researchers have increasingly explored machine learning techniques as alternative solutions for improving predictive performance and supporting proactive risk mitigation strategies [18]. Various machine learning models have been employed to predict environmental risks associated with floods, droughts, wildfires, landslides, air pollution, and climate-related hazards [19]. These models can integrate diverse environmental variables, including temperature, precipitation, soil characteristics, vegetation conditions, topographical information, and socioeconomic indicators, to generate more comprehensive predictions [20]. In addition to improving forecasting accuracy, machine learning-based environmental risk prediction can support early warning systems by providing timely information that enables decision-makers to implement preventive measures before environmental threats escalate into major disaster [21]. Therefore, predictive analytics has become an increasingly important component of contemporary environmental governance and sustainability planning [22].

2.3. Environmental Resilience and Sustainable Adaptation

Environmental resilience has gained considerable attention as a fundamental concept for understanding how ecosystems and communities respond to environmental disturbances. The concept emphasizes the capacity of a system to absorb shocks, adapt to changing conditions, recover from disruptions, and maintain essential functions over time. As environmental uncertainties continue to intensify due to climate change and human activities, resilience has become a key consideration in environmental planning and policy development [23]. Unlike conventional risk management approaches that primarily focus on hazard identification, resilience-oriented approaches seek to strengthen adaptive capacities and long-term sustainability. Several dimensions contribute to environmental resilience, including ecological diversity, institutional capacity, technological readiness, community engagement, and resource availability. Previous studies have highlighted that resilience assessment can provide valuable insights into the strengths and vulnerabilities of environmental systems, thereby supporting more effective adaptation strategies [24]. Moreover, resilience indicators can help decision-makers prioritize interventions and allocate resources to areas that are most vulnerable to environmental disturbances. Consequently, integrating resilience perspectives into environmental risk analysis has become increasingly important for achieving sustainable environmental outcomes and enhancing preparedness against future environmental challenges.

2.4. Integrating Machine Learning and Resilience Assessment

Although machine learning has demonstrated substantial capabilities in environmental risk prediction, many existing studies primarily focus on forecasting hazards without adequately incorporating resilience-related factors into predictive frameworks [25]. This limitation may reduce the practical usefulness of predictive outcomes because risk identification alone does not necessarily provide sufficient information regarding the ability of environmental systems to cope with and recover from adverse events [26]. As a result, there is a growing recognition that environmental risk prediction should be complemented by resilience assessment to produce more comprehensive and actionable insights from the interpretation and resilience assessment stages to inform subsequent improvements in data processing, feature selection, and model development, thereby enhancing the reliability and practical applicability of the overall framework [27].

The integration of machine learning and resilience assessment offers several advantages for environmental management. First, resilience indicators can enrich predictive models by providing contextual information regarding adaptive capacities and system vulnerabilities. Second, combined analytical frameworks can support more balanced decision-making by considering both potential threats and available coping mechanisms. Third, the integration of predictive analytics and resilience evaluation can contribute to the development of intelligent environmental management systems capable of supporting long-term sustainability objectives. Despite these potential benefits, empirical studies examining this integrated approach remain relatively limited, highlighting an important research gap. Therefore, this study proposes a machine learning-based framework that incorporates resilience dimensions into environmental risk prediction, contributing to both environmental informatics literature and sustainable environmental management practices.

3. RESEARCH METHOD

3.1. Research Design

This study employed a quantitative research design to investigate the effectiveness of machine learning applications in predicting environmental risks while incorporating resilience indicators into the predictive framework [28]. The research was conducted using secondary environmental datasets collected from publicly available environmental monitoring repositories, climate databases, ecological records, and environmental risk assessment reports. The study was undertaken between January 2025 and May 2026, covering data preparation, model development, validation, and analysis phases [25]. A quantitative approach was considered appropriate because the research objective focused on identifying predictive relationships among environmental variables and evaluating the capability of machine learning algorithms to generate reliable environmental risk forecasts [29]. The research framework consisted of several sequential stages, including data collection, data preprocessing, feature selection, machine learning model development, model evaluation, and resilience analysis. The integration of environmental risk indicators and resilience variables was intended to provide a comprehensive understanding of both environmental vulnerability and adaptive capacit [30].

Figure 1 illustrates the overall research process adopted in this study. The framework demonstrates how environmental datasets were transformed into predictive insights through machine learning techniques and subsequently integrated with resilience assessment to support environmental decision-making, sustainable environmental management, early warning, and proactive risk mitigation. Feedback from the interpretation and resilience assessment stages can also be used to improve data preprocessing, feature selection, and model development, creating an iterative process for enhancing the reliability and practical applicability of the proposed framework.

3.2. Data Sources and Variables

The study utilized secondary datasets obtained from environmental monitoring systems and publicly accessible environmental databases. The collected data represented multiple dimensions of environmental conditions, including climatic, ecological, geographical, and resilience-related indicators. The use of multidimen-

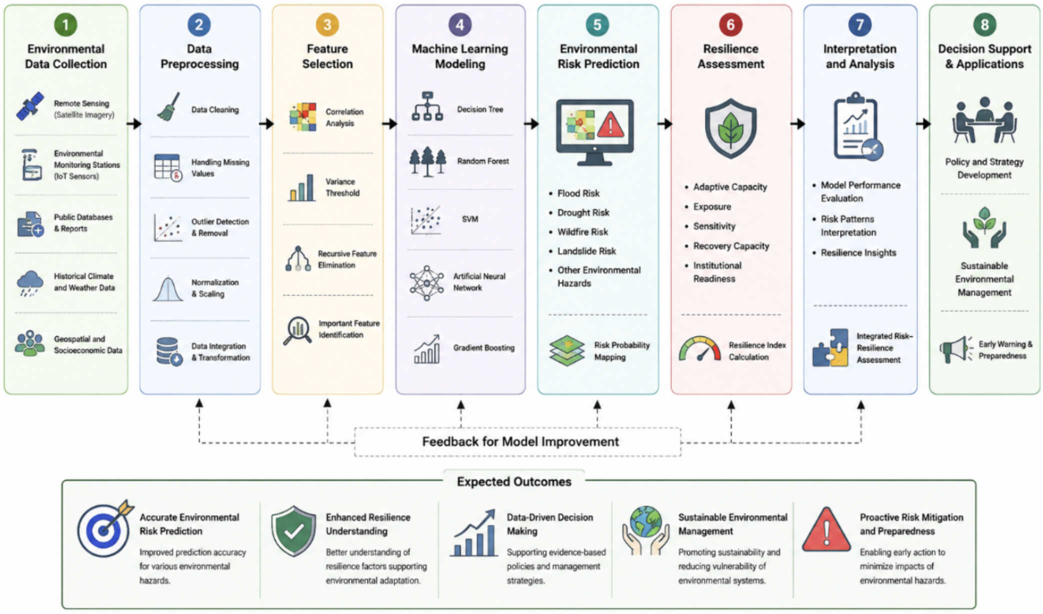

Figure 1. Research Framework

sional variables was intended to improve model performance and provide a more comprehensive assessment of environmental risks.

The selection of these variables was guided by their relevance to the occurrence of environmental hazards and the capacity of environmental systems to respond to and recover from adverse conditions. Climate variables describe atmospheric and weather-related conditions, while ecological and geographic variables capture characteristics of ecosystems and spatial environments that may influence environmental risk patterns. Environmental risk indicators were incorporated to represent the specific hazards evaluated in this study, whereas resilience indicators were used to capture the capacity of environmental systems to absorb disturbances, adapt to changing conditions, and recover from potential impacts. This combination of variables was designed to establish a more comprehensive predictive framework that considers both environmental risk factors and resilience characteristics.

Table 1. Research Variables

Variable Category	Indicators
Climate Factors	Temperature, rainfall, humidity, wind speed
Ecological Factors	Vegetation index, biodiversity condition, land cover
Geographic Factors	Elevation, slope, watershed characteristics
Environmental Risk Indicators	Flood occurrence, drought intensity, wildfire risk
Resilience Indicators	Adaptive capacity, resource availability, institutional preparedness

Table 1 presents the variables incorporated into the machine learning model. Climate, ecological, and geographic variables were utilized as predictive inputs, while environmental risk indicators served as prediction targets. Resilience indicators were included to evaluate the adaptive capabilities of environmental systems and enhance the practical relevance of predictive outcomes.

3.3. Data Collection and Preprocessing

The environmental datasets were collected from multiple sources to ensure adequate representation of environmental conditions. Following data acquisition, a preprocessing procedure was conducted to improve data quality and model readiness [31]. The preprocessing stage involved data cleaning, missing value treatment, duplicate removal, normalization, and feature transformation [32]. Data normalization was performed to ensure consistency among variables measured on different scales. Furthermore, outlier detection techniques were applied to reduce potential bias and improve model stability [33]. After preprocessing, the datasets were partitioned into training and testing subsets to facilitate model development and validation. The preprocessing procedure ensured that the machine learning algorithms received high-quality input data capable of generating reliable and robust environmental risk predictions. This stage also reduced noise and minimized potential errors associated with incomplete or inconsistent environmental records [34].

3.4. Machine Learning Model Development

Several machine learning algorithms were developed and evaluated to identify the most effective model for environmental risk prediction. The model development phase involved supervised learning approaches because historical environmental observations and risk outcomes were available for training purposes. The algorithms were trained using environmental predictor variables and validated using unseen testing data.

The selection of machine learning algorithms was based on their complementary capabilities in capturing different characteristics of environmental datasets. Decision Tree was selected because of its interpretable rule-based structure, while Random Forest was considered for its ensemble learning capability and robustness in handling complex relationships among multiple environmental variables. Support Vector Machine was included to identify patterns within multidimensional feature spaces, whereas Artificial Neural Network was employed to model complex nonlinear relationships. Gradient Boosting was also evaluated because its iterative learning mechanism can improve predictive performance by reducing errors across successive learning stages. The use of these diverse algorithms enabled a systematic comparison of alternative modeling approaches and supported the identification of the most suitable model for environmental risk prediction.

Table 2. Machine Learning Models Evaluated

Model	**Primary Function**
Decision Tree	Rule-based environmental classification
Random Forest	Ensemble prediction and risk classification
Support Vector Machine	Environmental pattern recognition
Artificial Neural Network	Complex nonlinear relationship modeling
Gradient Boosting	Predictive performance optimization

Table 2 summarizes the machine learning algorithms evaluated in this study. Each algorithm offered distinct advantages in handling environmental datasets characterized by nonlinear relationships and multidimensional interactions. Comparative evaluation was conducted to determine which model achieved the most reliable environmental risk predictions. The model training process involved iterative optimization procedures to improve predictive capability and reduce prediction errors [35]. Hyperparameter tuning was performed to enhance model performance and achieve better generalization across environmental conditions.

3.5. Resilience Assessment and Data Analysis

Following environmental risk prediction, a comprehensive resilience assessment was conducted to evaluate the adaptive capacity of environmental systems in responding to current and potential disturbances. The assessment examined resilience indicators, including adaptive capacity, institutional preparedness, and resource availability, and their contribution to preparedness, recovery potential, and long-term sustainability. These indicators were analyzed to determine the ability of ecosystems and communities to absorb shocks, adapt to changing conditions, and recover from adverse events. By integrating resilience variables into the analytical framework, the study extended environmental risk assessment beyond conventional hazard prediction and provided a more holistic understanding of vulnerability and adaptive capacity [36]. This integrated approach identified both areas exposed to high environmental risks and the resilience factors influencing mitigation and recovery effectiveness, thereby improving the interpretability of predictive outcomes and providing actionable insights for disaster preparedness, resource allocation, and sustainable environmental management [37].

Figure 2 the analytical process consisted of three complementary stages: descriptive analysis, predictive analysis, and resilience evaluation, each designed to provide a comprehensive understanding of environmental risks and adaptive capacities. Descriptive analysis was first conducted to examine the characteristics of the environmental datasets, including the distribution, consistency, and relationships among climate, ecological, geographic, and resilience-related variables. This stage facilitated the identification of data patterns, potential anomalies, and underlying trends, thereby ensuring that the datasets were suitable for subsequent machine

Figure 2. Analytical Procedure

learning analysis. A thorough understanding of the data characteristics also supported effective preprocessing, feature selection, and model development, ultimately improving the reliability of predictive outcomes [38].

3.6. Research Outcome Evaluation

The final stage involved interpreting the predictive outcomes and resilience assessment results to determine their implications for environmental management [39]. Model performance was evaluated based on predictive reliability, consistency, and practical applicability within environmental decision-making contexts. The integration of machine learning predictions and resilience indicators was expected to provide a more comprehensive understanding of environmental threats and adaptive capacities [40]. The findings obtained from this methodological framework were subsequently used to formulate recommendations for policymakers, environmental practitioners, and stakeholders involved in sustainable environmental planning [41]. Through this approach, the study aimed to contribute to the development of intelligent environmental management systems capable of supporting proactive environmental risk mitigation and resilience enhancement.

4. RESULT AND DISCUSSION

4.1. Machine Learning Model Performance

The performance of the machine learning models was evaluated to identify the most effective algorithm for predicting environmental risks. The evaluation considered prediction accuracy, precision, recall, and F1-score to ensure a comprehensive assessment of model reliability.

Table 3. Machine Learning Model Performance

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.81	0.79	0.78	0.78
Random Forest	0.90	0.89	0.88	0.88
Support Vector Machine	0.86	0.85	0.84	0.84
Artificial Neural Network	0.88	0.87	0.86	0.86
Gradient Boosting	0.92	0.91	0.90	0.90

Table 3 demonstrates that Gradient Boosting achieved the strongest predictive performance among all evaluated algorithms, with an accuracy of 0.92, precision of 0.91, recall of 0.90, and F1-score of 0.90. These results indicate that the model was highly effective in capturing complex and nonlinear relationships among climate, ecological, geographic, and resilience-related variables while maintaining balanced performance across different evaluation metrics. Random Forest also showed strong predictive capability, achieving an accuracy of 0.90, precision of 0.89, recall of 0.88, and F1-score of 0.88, further suggesting that ensemble learning methods are particularly suitable for multidimensional environmental datasets. Meanwhile, the Artificial Neural

Network and Support Vector Machine produced competitive but slightly lower results, with accuracies of 0.88 and 0.86, respectively. In contrast, the Decision Tree recorded the lowest performance, with an accuracy of 0.81, indicating that a single-tree structure may be less capable of modeling the complex interactions among environmental variables. Overall, the findings highlight the superiority of ensemble-based approaches, particularly Gradient Boosting, for environmental risk prediction and support their potential application in developing more reliable and data-driven environmental decision-support systems. The comparative performance of the five machine learning algorithms evaluated in this study, namely Decision Tree, Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN), and Gradient Boosting. The comparison was conducted using four evaluation metrics: accuracy, precision, recall, and F1-score. Among the evaluated models, Gradient Boosting achieved the highest overall performance, with an accuracy of 0.92, precision of 0.91, recall of 0.90, and F1-score of 0.90. The results also show that ensemble learning approaches, particularly Random Forest and Gradient Boosting, outperform the other algorithms in capturing complex environmental risk patterns. Furthermore, the integration of resilience indicators improved predictive accuracy from 0.84 to 0.92, indicating that adaptive capacity, resource availability, institutional preparedness, community engagement, and technological readiness provide additional contextual information for more reliable environmental risk prediction.

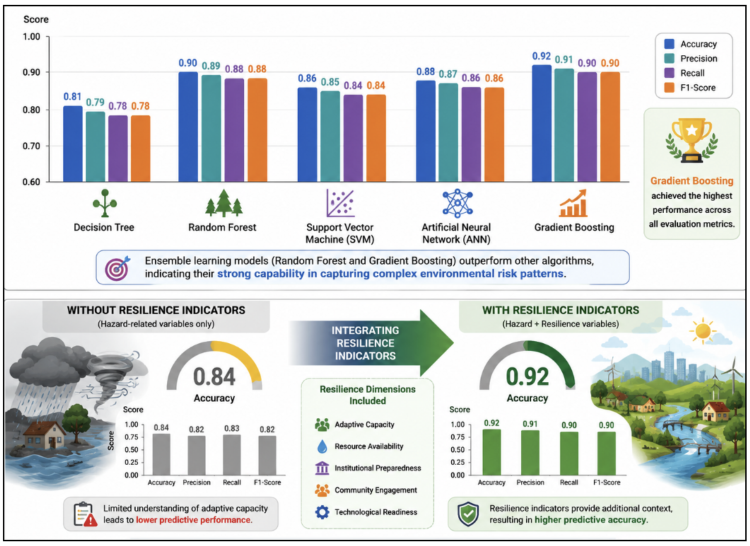

Figure 3. Gradient Boosting

As shown in Figure 3, Gradient Boosting achieved the highest performance across all evaluation metrics, indicating its superior capability in identifying complex environmental risk patterns. The model demonstrated greater effectiveness in processing multidimensional environmental datasets consisting of climate, ecological, geographic, and resilience-related variables. Random Forest also exhibited strong predictive performance, suggesting that ensemble-based algorithms are highly suitable for environmental risk prediction tasks characterized by nonlinear relationships and variable interactions. In contrast, Decision Tree produced the lowest performance among the evaluated models. Although the model offers high interpretability and ease of implementation, its predictive capability was comparatively limited when handling complex environmental datasets. The findings indicate that more advanced machine learning approaches, particularly ensemble learning techniques, provide greater reliability for environmental risk forecasting and sustainable environmental management applications.

4.2. Contribution of Resilience Indicators

To further examine the contribution of resilience indicators, the predictive performance of the developed machine learning model was evaluated under two different configurations. The first configuration excluded resilience-related variables and relied primarily on environmental hazard characteristics, while the second configuration incorporated resilience indicators representing the capacity of environmental systems to respond to and recover from potential risks. This comparative evaluation was conducted to determine whether the inclusion of resilience dimensions provides measurable improvements in the model's predictive capability.

Table 4. Impact of Resilience Indicators on Predictive Performance

Model Configuration	Accuracy
Without Resilience Indicators	0.84
With Resilience Indicators	0.92

Table 4 shows that the inclusion of resilience indicators improved predictive performance. This finding suggests that environmental risk prediction should not rely solely on hazard-related variables but also consider adaptive capacity, institutional preparedness, and resource availability. The integration of resilience dimensions provides additional contextual information that strengthens model interpretation and improves decision-support quality.

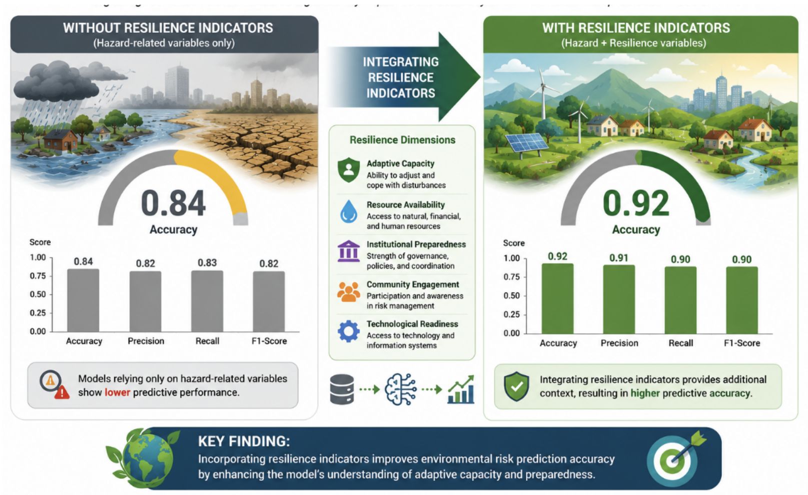

Figure 4. Inclusion of Resilience Indicators

Figure 4 presents the impact of integrating resilience indicators into the environmental risk prediction framework. The comparison evaluates model performance before and after resilience-related variables, including adaptive capacity, resource availability, institutional preparedness, community engagement, and technological readiness, were incorporated into the predictive model. The results indicate that the inclusion of these indicators improves the model's accuracy from 0.84 to 0.92, while precision increases from 0.82 to 0.91, recall from 0.83 to 0.90, and F1-score from 0.82 to 0.90. This improvement suggests that hazard-related variables alone may not fully capture the contextual conditions that influence environmental vulnerability and resilience. By incorporating resilience dimensions, the model gains additional information regarding the capacity of communities and institutions to adapt, respond, and recover from environmental risks. Therefore, the integration of resilience indicators strengthens predictive performance and provides a more comprehensive basis for environmental risk assessment and resilience-oriented decision-making.

The improvement observed after integrating resilience variables suggests that environmental resilience plays a critical role in enhancing predictive reliability. The results support the argument that environmental management should adopt a holistic perspective that combines risk prediction with resilience assessment. By incorporating both dimensions, decision-makers can obtain a more comprehensive understanding of environmental vulnerability and adaptive capacity, thereby enabling more effective environmental planning, disaster preparedness, and sustainability strategies. Furthermore, the findings highlight that resilience assessment is not merely a complementary component but an essential factor in developing intelligent environmental management systems. The integration of predictive analytics and resilience evaluation provides actionable insights that can assist policymakers in prioritizing interventions and strengthening long-term environmental sustainability.

4.3. Environmental Risk and Resilience Assessment

The analysis revealed that regions characterized by lower adaptive capacity and limited institutional preparedness exhibited higher environmental vulnerability. Conversely, areas with stronger resilience indicators demonstrated greater capability to withstand environmental disturbances and recover from adverse events.

The findings indicate that environmental risks are influenced not only by climatic and ecological conditions but also by the preparedness and adaptability of environmental systems. Therefore, resilience assessment complements predictive analytics by providing a broader understanding of environmental sustainability and disaster preparedness.

4.4. Discussion

The findings successfully answer the research question regarding how machine learning can be utilized to predict environmental risks while incorporating resilience factors. The results demonstrate that machine learning algorithms are capable of identifying environmental risk patterns with high predictive reliability, while resilience indicators significantly enhance predictive performance and contextual interpretation. Therefore, the study objective has been achieved. The results support the study proposition that environmental risk prediction becomes more effective when resilience dimensions are integrated into the analytical framework. This outcome occurs because resilience indicators provide additional information regarding adaptive capacity, institutional readiness, and resource availability, which influence how environmental systems respond to hazards. Consequently, predictive models are able to generate not only risk estimations but also insights into environmental preparedness and recovery potential. The practical implication of these findings is that policymakers and environmental managers can utilize machine learning-based predictive systems as early warning mechanisms for proactive environmental governance. Integrating resilience assessment enables decision-makers to prioritize interventions in vulnerable areas and allocate resources more effectively. In contrast to previous studies that primarily focused on hazard prediction accuracy, this study adopts a more holistic perspective by combining environmental risk forecasting with resilience evaluation. This integrated approach contributes to the growing literature on intelligent environmental management and sustainable adaptation strategies. Despite these contributions, several limitations should be acknowledged. First, the study relies on secondary environmental datasets that may vary in quality and completeness across data sources. Second, the predictive framework was evaluated using a limited set of machine learning algorithms and resilience indicators. Third, environmental conditions are dynamic and may evolve over time, potentially affecting model generalizability. Future research is therefore recommended to incorporate real-time environmental data, advanced deep learning approaches, and broader resilience dimensions to improve predictive capability and practical applicability.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide several important managerial implications for policymakers, environmental agencies, disaster management authorities, and organizations responsible for sustainable environmental governance. The results demonstrate that machine learning can serve as a reliable decision-support technology for predicting environmental risks, enabling managers to identify potential threats before they develop into more severe environmental problems. In particular, the superior performance of the Gradient Boosting model suggests that advanced ensemble learning techniques should be prioritized when developing environmental monitoring systems because they are capable of capturing complex relationships among climatic, ecological, geographic, and resilience-related variables with high predictive accuracy. Such predictive capabilities can improve the effectiveness of environmental surveillance, strengthen early warning systems, and support timely preventive interventions.

The study also highlights that incorporating resilience indicators significantly improves predictive performance, indicating that environmental management should not rely solely on hazard-related information but also consider adaptive capacity, institutional preparedness, and resource availability when evaluating environmental vulnerability. By integrating these resilience dimensions into predictive models, decision-makers are able to obtain a more comprehensive understanding of both environmental risks and the capability of affected regions to respond to disturbances. This information can support more effective prioritization of vulnerable areas, facilitate evidence-based resource allocation, and assist governments in designing targeted policies that enhance environmental resilience while reducing the potential impacts of future environmental hazards.

From an organizational perspective, the proposed framework encourages the adoption of data-driven environmental governance by integrating predictive analytics into routine planning and policy evaluation. Environmental practitioners can utilize the predictive outputs to optimize mitigation strategies, improve emergency preparedness, and continuously monitor environmental conditions through intelligent decision-support systems. The integration of machine learning and resilience assessment also promotes more adaptive and sustainable management practices by shifting the focus from reactive responses to proactive environmental planning. Consequently, organizations can improve operational efficiency, strengthen inter-agency coordination, and develop long-term environmental management strategies that are more resilient to climate change, ecosystem degradation, and other emerging environmental challenges. Overall, the proposed approach provides a practical foundation for developing intelligent environmental management systems that support sustainable development objectives through more accurate, timely, and evidence-based decision-making.

6. CONCLUSION

This study investigated the application of machine learning techniques for predicting environmental risks while integrating resilience indicators into the predictive framework. The results demonstrate that machine learning provides an effective approach for analyzing complex environmental datasets and generating reliable predictions to support environmental risk management. Among the evaluated algorithms, Gradient Boosting achieved the highest predictive performance across all evaluation metrics, indicating its superior capability in modeling nonlinear relationships among climate, ecological, geographic, and resilience-related variables.

The findings further reveal that incorporating resilience indicators substantially enhances predictive capability, increasing model accuracy from 0.84 to 0.92. This improvement confirms that resilience-related variables, including adaptive capacity, institutional preparedness, and resource availability, provide valuable contextual information that strengthens both predictive reliability and the interpretation of environmental risks. Consequently, environmental risk assessment should integrate resilience dimensions rather than relying solely on hazard-related variables to produce more comprehensive and actionable decision-support systems.

Theoretically, this study contributes to the growing literature by demonstrating the benefits of combining machine learning with resilience assessment within a unified environmental risk prediction framework. Practically, the proposed approach provides a foundation for developing intelligent environmental management systems that support proactive environmental governance, disaster preparedness, and sustainable resource management through data-driven decision-making. Despite these contributions, this study is limited by its reliance on secondary environmental datasets and a relatively limited set of machine learning algorithms and resilience indicators. Future research should incorporate real-time environmental data, broader resilience dimensions, and advanced artificial intelligence approaches, such as deep learning and hybrid predictive models, to further improve predictive performance, model generalizability, and practical applicability across diverse environmental contexts.

7. DECLARATIONS

7.1. About Authors

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7.2. Author Contributions

Conceptualization: MS; Methodology: SS; Software: GF; Validation: MS and SS; Formal Analysis: SS and GF; Investigation: MS; Resources: SS; Data Curation: GF; Writing Original Draft Preparation: MS and GF; Writing Review and Editing: SS and GF; Visualization: GF; All authors, MS, SS, and GF, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The datasets generated and analyzed during this study can be obtained from the corresponding author upon reasonable request.

7.4. Funding

This research received no specific grant or financial assistance from any public, commercial, or non-profit funding organization.

7.5. Declaration of Conflicting Interest

The authors declare that there are no competing interests, financial conflicts, or personal relationships that could have influenced the research, interpretation, or reporting of the findings presented in this manuscript.

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