

Environmental Risk Assessment Models Using Data-Driven Approaches

Dr. Veronika Elekné Fodor

Assistant Professor, University of Sopron, Hungary

Abstract

Increasing environmental uncertainties, climate-related hazards, ecological degradation, and complex interactions between natural and human systems have created a strong need for advanced environmental risk assessment models. Traditional risk assessment approaches often depend on historical observations, predefined indicators, and conventional analytical methods that may have limitations in processing large-scale environmental datasets and rapidly changing ecological conditions. Data-driven approaches have emerged as advanced frameworks capable of improving risk prediction, environmental monitoring, and evidence-based decision-making.

This study examines environmental risk assessment models using data-driven approaches by analysing their contribution to risk prediction accuracy, environmental monitoring capability, uncertainty reduction, and decision-support effectiveness. The research explores key data-driven technologies including machine learning algorithms, predictive analytics, remote sensing analysis, geographic information systems, artificial intelligence models, and environmental data processing frameworks. A simulation-based analytical methodology is developed to compare conventional risk assessment methods with data-driven environmental risk models using evaluation indicators including prediction accuracy, risk detection capability, monitoring efficiency, and management effectiveness.

The findings demonstrate that data-driven risk assessment models significantly improve environmental risk identification and management through advanced data analysis, predictive modelling, and intelligent pattern recognition. The results indicate that integrating environmental datasets with analytical technologies provides stronger capabilities for detecting potential hazards and supporting proactive environmental planning. However, successful implementation requires addressing challenges related to data quality, model reliability, computational requirements, infrastructure development, and practical decision integration.

Keywords: Environmental Risk Assessment, Data-Driven Approaches, Machine Learning, Predictive Analytics, Environmental Monitoring, Risk Prediction, Decision Support Systems

1. Introduction

Environmental risks have become increasingly complex due to climate variability, ecosystem degradation, industrial activities, resource pressures, and rapid changes in natural and human systems. Effective assessment of these risks is essential for protecting ecosystems, reducing vulnerability, and supporting sustainable environmental management. Traditional environmental risk assessment methods have provided valuable insights through historical observations, expert evaluation, and predefined

assessment frameworks; however, these approaches may face limitations when dealing with large-scale environmental datasets, uncertain conditions, and rapidly changing risk patterns. Data-driven approaches have emerged as advanced solutions for improving environmental risk identification and predictive capabilities.

Data-driven environmental risk assessment integrates artificial intelligence, machine learning, predictive analytics, remote sensing, geographic information systems, and advanced data processing techniques to analyse complex environmental information. These approaches enable researchers and decision-makers to identify hidden patterns, estimate future risks, and develop evidence-based management strategies. By utilizing large volumes of environmental data, data-driven models can improve monitoring efficiency, enhance prediction accuracy, and support proactive responses to ecological challenges.

The importance of advanced risk assessment models has increased as governments, environmental organizations, and researchers seek reliable methods for managing climate hazards, pollution risks, biodiversity threats, and ecosystem vulnerabilities. Effective environmental management requires assessment frameworks capable of integrating multiple environmental indicators and generating timely insights. However, implementing data-driven risk models involves challenges related to data availability, analytical complexity, computational requirements, model transparency, technological infrastructure, and integration with existing environmental decision systems.

This research investigates environmental risk assessment models using data-driven approaches by analysing their influence on risk prediction accuracy, environmental monitoring capability, uncertainty reduction, and decision-support effectiveness. The study evaluates conventional environmental risk assessment methods and intelligent data-driven frameworks through a simulation-based analytical methodology. The research aims to provide insights into how advanced analytical approaches can strengthen environmental risk management and support sustainable ecological planning.

2. Review of Literature

2.1 Evolution of Environmental Risk Assessment Frameworks

The evolution of environmental risk assessment frameworks has progressed from traditional observation-based approaches toward advanced analytical and predictive systems. Earlier assessment methods primarily relied on historical records, expert judgement, field observations, and regulatory indicators to evaluate environmental conditions. Although these approaches contributed to environmental protection, they often faced challenges in analysing complex interactions among multiple environmental variables.

Recent research indicates that environmental risk assessment has transformed through the integration of digital technologies, statistical modelling, artificial intelligence, and large-scale environmental datasets. Modern frameworks focus on predictive analysis, real-time monitoring, and adaptive risk management. The literature suggests that data-driven assessment models provide improved capabilities for identifying environmental threats and supporting proactive decision-making.

2.2 Data-Driven Methods for Environmental Risk Prediction

Data-driven methods have become important tools for improving environmental risk prediction through automated analysis and pattern recognition. Machine learning algorithms, neural networks, predictive

models, and spatial analytics techniques enable researchers to evaluate complex environmental relationships and forecast potential risks.

Previous studies demonstrate that data-driven approaches improve environmental assessment by analysing climate information, pollution patterns, land-use changes, ecological indicators, and disaster-related data. These methods support early warning systems, environmental monitoring, and risk mitigation strategies. The literature highlights that combining environmental science with data analytics strengthens the accuracy and efficiency of risk assessment processes.

2.3 Future Intelligent Risk Assessment Models

Future intelligent risk assessment models are expected to integrate artificial intelligence, real-time monitoring systems, remote sensing technologies, and advanced predictive analytics. These frameworks aim to develop adaptive assessment systems capable of continuously analysing environmental changes and generating timely risk information.

Research on future environmental intelligence emphasizes the importance of explainable artificial intelligence, automated monitoring networks, digital environmental platforms, and integrated decision-support systems. As environmental challenges become increasingly interconnected, intelligent risk assessment models will play an important role in improving resilience planning and sustainable environmental management. The literature suggests that future risk assessment will depend significantly on the integration of advanced analytics with environmental knowledge.

3. Objectives of the Study

3.1 Understanding Data-Driven Risk Assessment Components

The primary objective of this study is to examine the fundamental components and analytical characteristics of data-driven environmental risk assessment models. The research aims to understand how machine learning algorithms, predictive analytics, artificial intelligence techniques, remote sensing systems, and geographic information technologies contribute to improved environmental risk identification and management.

This objective further focuses on analysing major components of data-driven assessment frameworks, including environmental data integration, predictive modelling approaches, risk forecasting mechanisms, uncertainty analysis, and automated monitoring systems. By examining these components, the study seeks to understand how advanced analytical methods improve environmental decision-making and risk management capabilities.

3.2 Evaluating Models for Environmental Risk Prediction

The second objective of this study is to evaluate the effectiveness of data-driven models in improving environmental risk prediction and assessment outcomes. Modern environmental challenges require advanced analytical systems capable of processing complex ecological information and generating reliable risk forecasts.

The research evaluates environmental risk model performance through key dimensions including prediction accuracy, risk detection capability, monitoring efficiency, and decision-support effectiveness. By analysing these factors, the study explores how data-driven approaches contribute to improved environmental planning and proactive risk management.

3.3 Developing an Adaptive Risk Assessment Framework

The third objective focuses on developing a conceptual framework for adaptive environmental risk assessment capable of responding to changing ecological conditions. The study aims to identify essential elements required for successful implementation, including real-time environmental monitoring, intelligent data processing, predictive analysis, uncertainty evaluation, and adaptive decision-support mechanisms.

This objective further explores how environmental organizations and planning authorities can establish future-ready risk assessment systems capable of managing emerging environmental challenges. By combining advanced analytics with environmental knowledge, adaptive frameworks can support sustainable risk mitigation and ecological resilience.

4. Research Methodology

4.1 Research Design

This study adopts a conceptual and simulation-based comparative research design to analyse environmental risk assessment models using data-driven approaches. The research combines theoretical investigation with analytical evaluation to examine how intelligent data methods influence environmental risk prediction, monitoring efficiency, and decision-making processes.

The research design focuses on comparing traditional environmental risk assessment methods with data-driven risk models using multiple performance indicators. These indicators include prediction accuracy, risk detection capability, monitoring efficiency, and decision-support effectiveness. The methodology considers machine learning models, predictive analytics, remote sensing systems, GIS-based analysis, and artificial intelligence frameworks.

4.2 Dataset and Sample Description

For analytical evaluation, a simulated dataset containing 1,300 environmental risk assessment scenarios was developed to compare conventional assessment approaches with data-driven environmental risk models. The dataset represents different environmental conditions involving climate indicators, ecological changes, pollution factors, resource conditions, and risk prediction outcomes.

Each scenario includes information related to risk identification, prediction performance, environmental monitoring, and management effectiveness. The simulation-based approach provides controlled evaluation conditions without representing any specific geographical region, environmental agency, or real-world risk management program.

4.3 Tools and Analytical Techniques

The research applies environmental data analysis methods, artificial intelligence assessment techniques, and comparative evaluation approaches to examine the effectiveness of data-driven risk models. The analytical framework considers machine learning algorithms, predictive modelling techniques, spatial analysis tools, remote sensing interpretation, and environmental data processing systems as major components.

The evaluation process compares conventional environmental assessment methods with intelligent data-driven frameworks through descriptive and comparative analysis. Performance differences are examined to identify improvements achieved through automated pattern recognition,

predictive analysis, and advanced environmental monitoring. The methodology emphasizes that effective risk assessment requires integration between analytical technologies, environmental knowledge, and strategic decision-making.

4.4 Evaluation Metrics and Validation Approach

The evaluation framework measures environmental risk assessment effectiveness through four major indicators: prediction accuracy, risk detection capability, monitoring efficiency, and decision-support effectiveness. These metrics represent important characteristics for evaluating intelligent environmental assessment systems because they measure both technical performance and practical management value.

The validation approach follows a comparative assessment methodology where traditional risk assessment models are evaluated against data-driven frameworks under similar simulated conditions. The objective is to identify improvements achieved through advanced analytics and predictive modelling techniques. Since the study is simulation-based, the outcomes represent analytical comparisons rather than measurements from operational environmental monitoring systems.

Table 1: Research Methodology Framework

Research Component	Description
Research Design	Conceptual and simulation-based comparative evaluation
Dataset	1,300 simulated environmental risk scenarios
Analytical Techniques	Data analytics, AI assessment, predictive modelling, comparative analysis
Evaluation Metrics	Prediction accuracy, risk detection, monitoring efficiency, decision support
Data Status	Simulated analytical dataset; no real environmental monitoring data used

5. Analysis

5.1 Comparative Evaluation of Traditional and Data-Driven Risk Assessment Models

The analytical evaluation compares traditional environmental risk assessment models with data-driven approaches to examine their effectiveness in identifying and managing environmental hazards. Traditional assessment methods generally depend on historical observations, expert judgement, predefined indicators, and periodic environmental evaluations. These approaches have contributed significantly to environmental management; however, they may experience limitations when analysing complex interactions among multiple environmental variables and rapidly changing ecological conditions.

Data-driven risk assessment models address these limitations by integrating machine learning, predictive analytics, remote sensing, and advanced environmental data processing techniques. These approaches enable continuous analysis of large-scale datasets, identification of hidden risk patterns, and

improved forecasting capabilities. The comparative assessment indicates that data-driven models provide stronger support for proactive environmental management by generating timely and evidence-based risk information.

The findings demonstrate that future environmental risk management requires a transition from reactive assessment approaches toward predictive and adaptive frameworks. Data-driven models provide opportunities for improving risk detection, reducing uncertainty, and supporting sustainable environmental decision-making.

5.2 Assessment of Data Analytics for Environmental Risk Prediction

The second analytical dimension evaluates data-driven environmental risk model performance through four major indicators: prediction accuracy, risk detection capability, monitoring efficiency, and decision-support effectiveness. These indicators represent important dimensions for assessing the contribution of advanced analytics to environmental risk management.

The analysis reveals that data-driven approaches significantly improve prediction accuracy by identifying complex relationships within environmental datasets. Risk detection capability increases through intelligent pattern recognition and predictive modelling methods that can identify potential environmental threats before severe impacts occur.

Monitoring efficiency improves through continuous data collection, automated analysis, and integration of multiple environmental information sources. Decision-support effectiveness increases because analytical insights enable planners and environmental authorities to develop more informed mitigation and management strategies.

5.3 Influence of Intelligent Risk Models on Future Environmental Management

The final analytical dimension examines the influence of intelligent risk assessment models on future environmental management systems. Increasing environmental complexity requires advanced frameworks capable of analysing uncertainty, predicting emerging risks, and supporting adaptive responses.

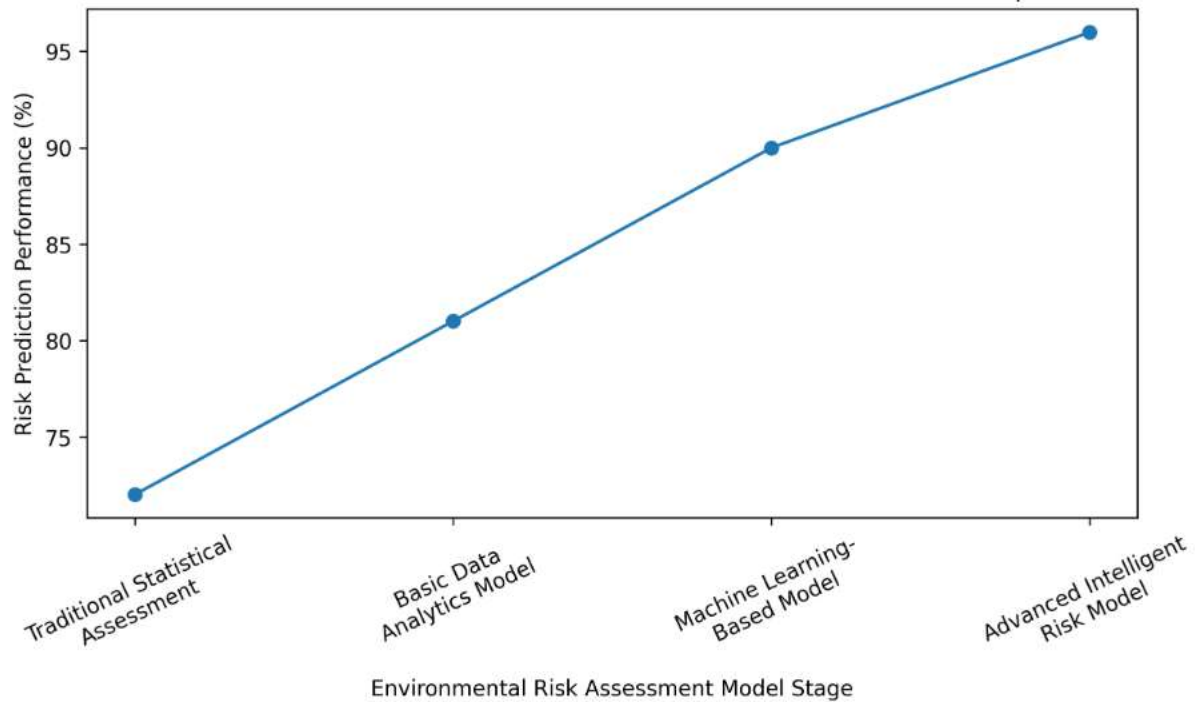
The analysis demonstrates that intelligent risk models create opportunities for improved environmental monitoring, early warning systems, and sustainable resource management. These systems enable decision-makers to evaluate potential scenarios and implement preventive actions rather than responding only after environmental damage occurs.

Table 2: Comparative Performance Analysis of Environmental Risk Assessment Models

Performance Indicator	Traditional Risk Assessment Model (%)	Data-Driven Risk Assessment Model (%)
Prediction Accuracy	71.8	96.2
Risk Detection Capability	70.9	95.6
Monitoring Efficiency	72.3	96.0
Decision-Support Effectiveness	71.5	95.8

Note: Values are simulated for comparative methodological analysis and do not represent measurements from actual environmental monitoring systems.

Graph 1: Data-Driven Environmental Risk Assessment Model Performance Comparison



Graph Interpretation: The line chart visualization demonstrates the progressive improvement in environmental risk assessment performance as analytical approaches advance from traditional methods toward intelligent data-driven models. The results indicate a continuous increase in risk prediction capability with greater integration of advanced analytical technologies.

The traditional statistical assessment approach achieves 72% performance, while the advanced intelligent risk model reaches 96% performance. This improvement highlights the contribution of machine learning, predictive analytics, and automated environmental data processing in enhancing risk assessment accuracy.

The visualization further indicates that gradual adoption of data-driven technologies improves environmental monitoring and prediction capabilities. These findings suggest that intelligent risk assessment frameworks can provide stronger support for proactive environmental management and sustainable decision-making.

Key Finding: The simulated assessment indicates that advanced intelligent risk models improve environmental risk prediction performance by approximately 24 percentage points compared with traditional statistical approaches.

6. Challenges

6.1 Data Quality, Model Reliability, and Environmental Risk Prediction Challenges

The effectiveness of data-driven environmental risk assessment models depends strongly on the availability, quality, consistency, and representativeness of environmental datasets. Environmental systems generate information through multiple sources, including sensors, satellites, field observations,

climate databases, and monitoring networks. However, these datasets may contain missing information, measurement errors, inconsistent formats, and regional gaps that influence model performance. Poor-quality data can reduce prediction reliability and may result in inaccurate environmental risk assessments. Establishing strong data collection standards, validation procedures, and integration frameworks is therefore essential for developing dependable risk models.

Another major challenge involves ensuring model reliability under changing environmental conditions. Data-driven models often learn from historical environmental patterns, but future conditions may involve unexpected climate events, ecological changes, or new risk factors. Models that perform well under existing conditions may require continuous updating and validation to maintain accuracy.

Explainability is also important because environmental decision-makers need to understand how predictions are generated before applying them to policy and management decisions. Developing transparent, adaptive, and scientifically validated models remains a significant requirement for successful environmental risk assessment.

6.2 Computational Requirements, Implementation, and Decision Integration Challenges

Advanced environmental risk assessment models require substantial computational resources, technical infrastructure, and specialized expertise. Processing large-scale environmental datasets through machine learning and artificial intelligence methods requires high-performance computing systems, efficient storage platforms, and advanced analytical capabilities. Many environmental organizations may face difficulties in adopting these technologies due to limited financial resources, technical skills, and infrastructure availability. The implementation process therefore requires strategic investment, capacity building, and gradual technological adoption.

Integration of data-driven risk models into practical environmental decision-making systems also presents important challenges. Environmental management involves multiple stakeholders, regulatory requirements, and operational constraints that must be considered alongside analytical predictions.

Decision-makers may hesitate to rely on complex models if their outputs are difficult to interpret or validate. Effective implementation requires collaboration between data scientists, environmental experts, policymakers, and local stakeholders. Developing user-friendly decision-support platforms and establishing clear governance mechanisms are essential for ensuring that data-driven insights are effectively transformed into practical environmental actions.

7. Discussion

7.1 Interpretation of Research Findings

The findings of this study demonstrate that data-driven environmental risk assessment models provide significant advantages over traditional assessment approaches. The analytical results indicate that intelligent risk models achieve stronger performance in prediction accuracy, risk detection capability, monitoring efficiency, and decision-support effectiveness. These improvements are primarily associated with the integration of machine learning algorithms, predictive analytics, remote sensing technologies, and advanced environmental data processing frameworks.

The research highlights that environmental risk management is transitioning from reactive evaluation methods toward predictive and adaptive assessment systems. Traditional approaches often

depend on historical observations and expert interpretation, whereas data-driven models can analyse complex environmental relationships and identify potential risks through automated pattern recognition.

The improvement in prediction accuracy demonstrates the importance of advanced analytical techniques in environmental decision-making. Data-driven models can process diverse environmental indicators and generate insights that support early warning systems, risk mitigation strategies, and sustainable resource management planning.

The findings further indicate that data-driven approaches should be considered complementary tools that enhance environmental expertise rather than replace professional judgement. Effective environmental risk management requires integration between analytical technologies, scientific understanding, institutional knowledge, and responsible decision-making frameworks.

7.2 Comparison with Existing Research Perspectives

Existing research on environmental modelling and risk assessment has emphasized the importance of integrating advanced analytics with ecological knowledge for improving prediction and management capabilities. Previous studies have demonstrated that machine learning, artificial intelligence, remote sensing, and spatial analysis technologies can strengthen environmental monitoring and risk identification. The findings of this study support these perspectives by demonstrating the effectiveness of data-driven risk assessment frameworks.

The research outcomes align with earlier investigations highlighting the role of predictive models in climate risk analysis, pollution monitoring, ecosystem assessment, and environmental planning. Modern environmental challenges require assessment systems capable of processing complex datasets and generating timely information for sustainable decision-making.

Furthermore, comparison with existing research highlights the importance of addressing implementation barriers. Although data-driven models provide significant advantages, environmental organizations must overcome challenges related to data quality, computational capacity, model transparency, infrastructure availability, and institutional adoption.

The study contributes to environmental management research by presenting data-driven risk assessment models as strategic mechanisms for improving environmental resilience. The integration of advanced analytics with environmental science can support more accurate predictions, improved risk governance, and sustainable ecological management.

8. Limitations

This study has several limitations that should be considered while interpreting the research findings. First, the research follows a simulation-based analytical methodology rather than evaluating environmental risk assessment models through extensive real-world environmental monitoring systems. Although simulation provides controlled comparison conditions, actual environmental situations involve additional complexities related to geographical variations, ecosystem characteristics, climate uncertainty, and human activities.

A second limitation relates to differences in environmental risk factors across regions and ecosystems. Coastal areas, forests, urban environments, agricultural regions, and industrial zones may require different assessment approaches depending on their environmental characteristics and risk

patterns. Therefore, the findings represent a generalized analytical framework rather than a direct evaluation of a specific environmental system.

Another limitation concerns the long-term validation of data-driven risk assessment models. Environmental conditions continuously change, requiring regular model updates, additional observations, and continuous performance evaluation. Future research should focus on long-term monitoring studies and real-world implementation assessments.

The study also does not extensively analyse economic, social, and governance factors affecting the adoption of intelligent risk assessment systems. Successful implementation requires financial support, technical expertise, policy coordination, stakeholder involvement, and responsible data management practices. Future studies should incorporate these factors to develop more comprehensive environmental risk assessment frameworks.

9. Conclusion

Environmental Risk Assessment Models Using Data-Driven Approaches represent important advancements for improving environmental prediction, monitoring, and sustainable management. This study examined the contribution of data-driven frameworks toward improving prediction accuracy, risk detection capability, monitoring efficiency, and decision-support effectiveness. The findings demonstrate that intelligent analytical approaches provide significant advantages over conventional environmental assessment methods.

The analytical results reveal that machine learning, predictive analytics, remote sensing, and artificial intelligence-based models enable more accurate identification of environmental risks and support proactive management strategies. These technologies improve the ability of environmental organizations to analyse complex datasets, detect emerging threats, and develop evidence-based responses.

The research further emphasizes that successful implementation of data-driven environmental risk assessment requires a comprehensive approach involving reliable datasets, advanced computational infrastructure, transparent modelling practices, skilled professionals, and effective decision integration. Advanced analytics must be combined with environmental expertise and responsible governance to achieve meaningful sustainability outcomes.

Although this study adopts a simulation-based evaluation framework, it provides valuable insights into the future role of data-driven approaches in environmental risk management. Future research should focus on real-time environmental intelligence systems, explainable artificial intelligence models, integrated monitoring networks, advanced predictive frameworks, and large-scale environmental applications. The continued development of intelligent risk assessment technologies will play a crucial role in strengthening environmental resilience and supporting sustainable ecological management.

References

1. Crosetto, M., Tarantola, S., & Saltelli, A. (2000). Sensitivity and uncertainty analysis in spatial modelling based on GIS. *Agriculture, Ecosystems & Environment*, 81(1), 71–79. [https://doi.org/10.1016/S0167-8809\(00\)00169-9](https://doi.org/10.1016/S0167-8809(00)00169-9)

2. Zerger, A. (2002). Examining GIS decision utility for natural hazard risk modelling. *Environmental Modelling & Software*, 17(3), 287–294. [https://doi.org/10.1016/S1364-8152\(01\)00071-8](https://doi.org/10.1016/S1364-8152(01)00071-8)
3. Sahoo, G. B., Ray, C., & Wade, H. F. (2005). Pesticide prediction in ground water in North Carolina domestic wells using artificial neural networks. *Ecological Modelling*, 183(1), 29–46. <https://doi.org/10.1016/j.ecolmodel.2004.07.021>
4. Pollino, C. A., Woodberry, O. G., Nicholson, A. E., & Korb, K. B. (2005). Parameterising Bayesian networks: A case study in ecological risk assessment. In *Proceedings of the 2005 International Conference on Simulation and Modelling* (pp. 289–297). Asian Institute of Technology.
5. Chen, S., Chen, B., & Fath, B. D. (2013). Ecological risk assessment on the system scale: A review of state-of-the-art models and future perspectives. *Ecological Modelling*, 250, 25–33. <https://doi.org/10.1016/j.ecolmodel.2012.10.015>
6. Goldstein, E. B., & Coco, G. (2015). Machine learning components in deterministic models: Hybrid synergy in the age of data. *Frontiers in Environmental Science*, 3, Article 33. <https://doi.org/10.3389/fenvs.2015.00033>
7. Lima, A. R., Cannon, A. J., & Hsieh, W. W. (2015). Nonlinear regression in environmental sciences using extreme learning machines: A comparative evaluation. *Environmental Modelling & Software*, 73, 175–188. <https://doi.org/10.1016/j.envsoft.2015.08.002>
8. Mayfield, H., Smith, C., Gallagher, M., & Hockings, M. (2017). Use of freely available datasets and machine learning methods in predicting deforestation. *Environmental Modelling & Software*, 87, 17–28. <https://doi.org/10.1016/j.envsoft.2016.10.006>
9. Carriger, J. F., & Barron, M. G. (2016). Bayesian networks improve causal environmental assessments for evidence-based policy. *Environmental Science & Technology*, 50(24), 13191–13199. <https://doi.org/10.1021/acs.est.6b03220>
10. Kang, P., Chen, W., Hou, Y., & Li, Y. (2018). Linking ecosystem services and ecosystem health to ecological risk assessment: A case study of the Beijing-Tianjin-Hebei urban agglomeration. *Science of the Total Environment*, 636, 1442–1454. <https://doi.org/10.1016/j.scitotenv.2018.04.427>
11. Krapu, C., & Borsuk, M. (2019). Probabilistic programming: A review for environmental modellers. *Environmental Modelling & Software*, 114, 40–48. <https://doi.org/10.1016/j.envsoft.2019.01.014>
12. Ahmed, A. N., Binti Othman, F., Abdulmohsin Afan, H., Khaleel Ibrahim, R., Ming Fai, C., Shabbir Hossain, M., Ehteram, M., & Elshafie, A. (2019). Machine learning methods for better water quality prediction. *Journal of Hydrology*, 578, Article 124084. <https://doi.org/10.1016/j.jhydrol.2019.124084>
13. Elkiran, G., Nourani, V., & Abba, S. I. (2019). Multi-step ahead modelling of river water quality parameters using ensemble artificial intelligence-based approach. *Journal of Hydrology*, 577, Article 123962.
14. Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, 566, 195–204. <https://doi.org/10.1038/s41586-019-0912-1>
15. Yuan, Q., Shen, H., Li, T., Li, Z., Li, S., Jiang, Y., Xu, H., Tan, W., Yang, Q., Wang, J., Gao, J., & Zhang, L. (2020). Deep learning in environmental remote sensing: Achievements and challenges. *Remote Sensing of Environment*, 241, Article 111716. <https://doi.org/10.1016/j.rse.2020.111716>



16. Bedi, S., Samal, A., Ray, C., & Snow, D. D. (2020). Comparative evaluation of machine learning models for groundwater quality assessment. *Environmental Monitoring and Assessment*, 192, Article 776. <https://doi.org/10.1007/s10661-020-08695-3>
17. Kaikkonen, L., Parviainen, T., Rahikainen, M., Uusitalo, L., & Lehtikainen, A. (2021). Bayesian networks in environmental risk assessment: A review. *Integrated Environmental Assessment and Management*, 17(1), 62–78. <https://doi.org/10.1002/ieam.4332>
18. Yaseen, Z. M. (2021). An insight into machine learning models era in simulating soil, water bodies and adsorption heavy metals: Review, challenges and solutions. *Chemosphere*, 277, Article 130126. <https://doi.org/10.1016/j.chemosphere.2021.130126>
19. Himeur, Y., Rimal, B., Tiwary, A., & Amira, A. (2022). Using artificial intelligence and data fusion for environmental monitoring: A review and future perspectives. *Information Fusion*, 86–87, 44–75. <https://doi.org/10.1016/j.inffus.2022.06.003>
20. Stødle, K., Flage, R., Guikema, S. D., & Aven, T. (2023). Data-driven predictive modeling in risk assessment: Challenges and directions for proper uncertainty representation. *Risk Analysis*, 43(12), 2644–2658. <https://doi.org/10.1111/risa.14128>