Global Journal of Research in
Engineering and Technology
Journal homepage: https://gsjournals.com/gjret/
ISSN: 2980-4205 (Online)

(RESEARCH ARTICLE)

Predictive analytics using artificial intelligence for soil degradation and fertility mapping

Mahin Abrar [1,*], A G M. Ziad [2] and Navid Afzal [3]

[1] *Department of Soil Science, University of Chittagong, Chattogram, Bangladesh.*
[2] *Department of Electronics and Communication Engineering, Hajee Mohammad Danesh Science and Technology University, Dinajpur, Bangladesh.*
[3] *Department of Electrical and Electronic Engineering, American International University - Bangladesh (AIUB), Dhaka, Bangladesh.*

Global Journal of Research in Engineering and Technology, 2026, 03(02), 001-012

Publication history: Received on 06 March 2026; revised on 15 April 2026; accepted on 17 April 2026

Article DOI: https://doi.org/10.58175/gjret.2026.3.2.0012

Abstract
Deteriorating soil and decreasing fertility of the soil presents a major challenge to sustainable agriculture and global food security, especially in areas where intensive cropping usages combined with climate variability are causing land deterioration at an alarming rate. Artificial intelligence (AI) and predictive analytics are providing new avenues for the monitoring, modelling, and management of soil health - tools that can be more precise than traditional methods. The goal of this research is to investigate the potential of AI-based predictive analytics in detecting patterns for soil degradation and fertility mapping which are useful for better decision-making by farmers. The study was based on a quantitative research approach and employed a structured questionnaire which was administered to agricultural users of soils data. The data were processed and analyzed using descriptive statistics and multivariate methods to study the relationship between predictive accuracy, management of soil and AI application. The analysis shows that AI predictive models greatly contribute to the identification of early degradation, refine geographical estimation of fertility and form empirical science based farming. The implications of model reliability on data quality and multi-source integration are also discussed. The study concludes that the application of AI empowered predictive analytics has a high potential to reinforce soil monitoring systems and sustainable agricultural productivity in general, and offers an scalable framework for evidence based land resource management.

Keywords: Artificial Intelligence; Predictive Analytics; Soil Degradation; Soil Fertility Mapping; Precision Agriculture; Sustainable Land Management

1 Introduction

Soil is a basic natural resource supporting agricultural productivity, ecosystem stability and global food security. Nonetheless, overpopulation, high-intensity agricultural practices, unsustainable land use and climate change have all contributed to increasing the pace of soil degradation around the globe (Khadim et al., 2025). ONS: A significant part of the world's soils are moderately to highly degraded, causing reduced crop yield, nutritional imbalance and a decline in agricultural sustainability (FAO). Soil fertility depletion and land damage in many developing areas of agricultural production, such as South Asia, results in severe long-term productivity loss and environmental degradation (Mondal et al., 2024).

* Corresponding author: Mahin Abrar

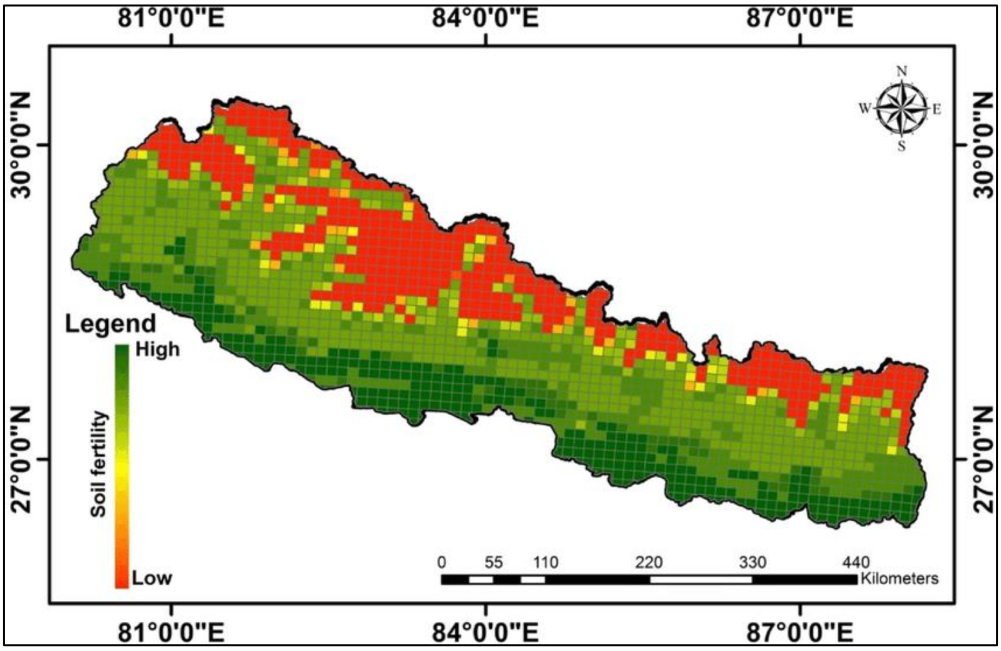


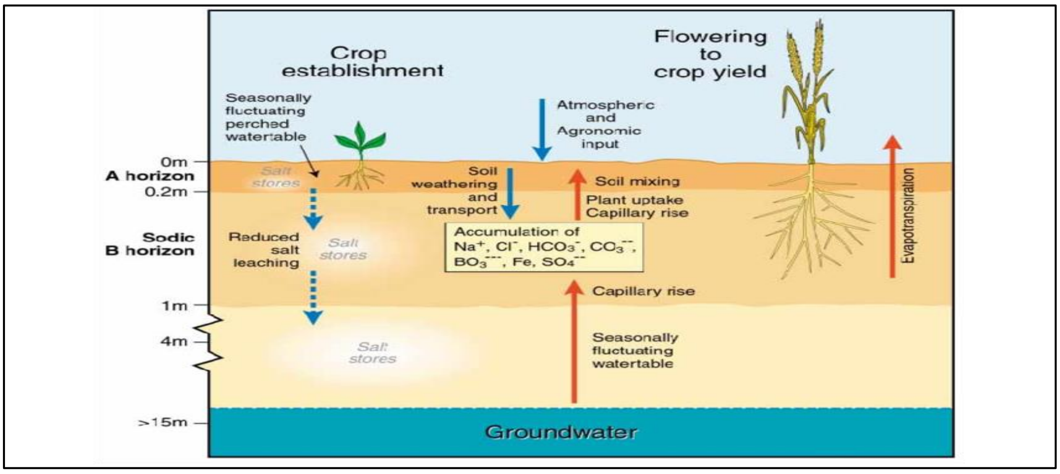
Figure 1 Overview of Soil Degradation Processes and AI-Enabled Soil Fertility Mapping in Precision Agriculture

The figure 1 portrays the link between the land-based degradation mechanisms, including erosion, compaction and nutrient depletion with contemporary digital instruments for measuring and controlling soil health. Visualization in the picture below, an actual image of traditional field conditions with visible land degradation and differences in soil quality are overlaid with advanced technologies such as Soil Testing, Geospatial Mapping and AI enabled analytics (Naorem et al., 2024). This contrast highlights the shift that has occurred from traditional eye-based assessment to data-driven, precision agriculture practices. Conventional methods for soil sampling (manual and laboratory-based) are reliable but time-consuming, expensive and confined to localized areas. These constraints reduce the pace of decision-making and limit parameters to reflect spatial variability in soil properties at field scale (Gadicha et al., 2026). With the digitalization of agriculture, there is growing interest in advanced analytics applications that can process multi-source, large datasets to deliver accurate and near real-time understanding of soil status (Sindhushree T. et al., 2025). In this context, artificial Intelligence (AI) and predictive analytics have become disruptive technologies. Using machine learning-driven algorithms, remote sensing datasets and geospatial analytics, complex patterns in soil parameters can be determined leading to early identification of degradation and high-resolution fertility mapping (Barman et al., 2021). Combining historical data, environmental factors and real-time monitoring, AI-based models can forecast what future soil health will be like and help farmers practice precision agriculture (Mikhailova et al., 2024). These capacities enhance not only farm-level decision-making, but also contribute to sustainable land resource management and climate adaptation. Even though there is increasing interest in AI applications for agriculture, empirical evidence about the effectiveness of AI tools in predicting soil degradation and mapping fertility status is still scarce especially from a quantitative point of view in term of users' perception and operational outcomes (Islam et al., 2021). Knowing how predictive analytics impacts soil monitoring efficiency, model reliability and sustainability effects may be important for technology adoption and policy-making.

Accordingly, this study explored the potential of AI-driven prediction analytics to evaluate soil degradation and improve fertility maps. Through the analysis of degradation indicators, model's performance and implementation results, this work attempts to offer empirical evidence that contributes to show how intelligent data driven technologies in field specific software tools can increase soil resources sustainability practices in agriculture.

2 Literature Review

Soil quality degradation is characterized by erosion, nutrient depletion, salinization, compacting and loss of organic material. These processes degrade soil productivity and ecosystem functioning (Kartini et al., 2023). FAO notes that soil degradation is a direct threat to sustainable agriculture because it reduces the availability of nutrients and water holding capacity.



(Source: FAO)

Figure 2 Conceptual Representation of Soil Degradation Factors and AI-Driven Soil Analysis Techniques

Soil fertility meanwhile is the soil's capacity to provide plants which are grown therein with their essential needs of nutrients in proper quantity and balance. Fertility variability between fields has consistently been demonstrated to have a large impact from the edge of the field toward crop performance, highlighting the importance for spatially explicit assessment approaches (Solanki et al., 2025). Traditional soil testing is based on in situ sampling followed by laboratory analysis. The approaches based on these measurements are accurate but resources consuming and unable to survey adequately the spatial heterogeneity. Geographic Information Systems (GIS) were commonly applied to enhance soil mapping, but the traditional statistical interpolation methods are faced with difficulty of modeling complex nonlinear dependencies between mapped variables (Aatira Hilal et al., 2024). Therefore, it has been argued that the traditional methods are not good enough for real-time monitoring and predicting decision-making. Recently, Artificial Intelligence (AI), especially Machine Learning algorithms such as Random Forest, Support Vector Machines and Artificial Neural Networks have drawn attention due to their success in analysing environmental data at a large scale (Li et al., 2023). The combination of climatic variables, remote sensing images and soil parameters for prediction of some soil-related properties can yield better results than using traditional regression approaches. The results of empirical studies indicate that intelligent soil-prediction mapping of AI is able to improve spatial resolution and decrease the uncertainty in fertility estimation. Additionally, AI allows for an automated classification of degradation patterns leading to a better early detection and monitoring performance (Barrena-González et al., 2022). Predictive analytics uses the histories of existing data and modern algorithms to provide future soil information. As it is clear from the literature, predictive models are able to recognize high risk areas of erosion, nutrient removal and salinization. The use of multi-source data satellite imagery, weather data, and land-use information is reported to greatly enhance the performance of models (Alijagić & Šajn, 2020). Researchers have suggested that predictive modelling can encourage proactive land management by implementing early intervention strategies and enabling optimal resource allocation in precision agriculture applications. The accuracy of AI-assisted soil prediction systems mainly relies on data quality, model testing and algorithm choice. Researches show that high-resolution data maps and vigorous verifications improve the predictions (Spalevic & Curovic, 2023). Cross-validation and ensemble modeling strategies are generally suggested to reduce bias and over-fitting. The various datasets combined to make the R&F maps are diverse and ensure that for long-term planning and policy purposes, these fertility maps can be considered as robust.

There is a substantial literature on AI-driven soil analytics in relation to sustainable agriculture gains. Predictive soil mapping is important for the optimization of fertilization, minimization of environment pollution and maximization of crop yield. It furthermore facilitates climate-smart agriculture by allowing adaptive management to changing environmental conditions (Hussain et al., 2024). However, despite these merits, authors mention challenges including lack of technical skill and data availability along with limited infrastructure in developing contexts. Overcoming these obstacles is vital to widespread use of AI-based soil monitoring platforms (Shary & A, 2023). Although the technical feasibility of AI in soil assessment is reported by previous studies, quantitative evidence for the applicability of predictive analytics on soil management effectiveness, model reliability perceptions and sustainability outcomes concurrently remains scarce. There are many studies centering on the algorithm efficiency while lacking practical implementation and decision-support value. As such, an extensive empirical study is required to assess the multifaceted influence of AI in predictive analytics for soil degradation assessment and fertility mapping. The objectives of the study are:

- To detect the key soil degradation indicators with impact on agricultural productivity and soil quality.
- To assess the efficacy and variability of soil fertility testing for informed nutrient management.
- To examine how Artificial Intelligence can improve the accuracy of soil analysis and the predictive of soil models.
- To evaluate the efficiency and reliability of predictive analytics, to enhance decision making in precision agriculture.
- To investigate how AI-enabled predictive analytics can be implemented to contribute to sustainability, resource efficiency and climate-resilience in agriculture.

3 Methods and Methodology

In this study, a predictive analysis was carried out using Artificial Intelligence (AI) as well to estimate soil degradation and its fertility mapping. Original data were gathered by survey questionnaire which is comprised of several constructs that are measured on a five point Likert scale to obtain farmers' perceptions towards soil degradation indicators, fertility assessment of AI application, predictive accuracy model reliability and sustainability effects. With purposive sampling the survey was made available to agricultural practitioners, soil scientists and technology users that had experience with using soil monitoring or data-based techniques in agriculture. Valid responses were screened and coded in their entirety before analysis. Computerized statistical programme was applied to analyse the data collected, and descriptive statistics were used to describe the variables while inferential techniques like reliability test, correlation coefficient, and multiple regression were employed as measurement tools for relationships among the constructs. The reliability of the measurement was examined by internal cohesion and construct validity, ensuring that the analytical model works properly. Ethical issues namely participants' willingness to participate and anonymity in their responses were followed at all stages of the research, aimed at securing data legitimacy and study reliability.

4 Result and Discussion

This section discusses the results of the study against the research objectives with reference to prior literature. The analysis which follows commences with a summary of descriptive statistics in order to give an account of the perceptions respondents had about soil degradation, fertility assessment and use of AI in predictive analytics. Inferences are then discussed to explore the relations among the critical constructs such as predictions of model efficiency, reliability of the model and sustainability outcomes. The talk combines these statistical results with theoretical understandings on how predictive analytics using AI applications and advances are contributing toward better monitoring, decision making on soil fertility, and land management for sustainability.

4.1 Soil Degradation Indicators

The respondents' perceptions on the main processes affecting soil health were analysed. Descriptive summary statistics Descriptive statistics showed high agreement at large for most indicators, indicating broad acceptance of the degradation problems. Soil erosion, nutrient exhaustion, and depleting organic matter had the highest average scores among the evaluated constraints implying that causes of these prohibitive effects were considered as a greater threat for soil productivity. Salinity and compaction were also both ranked above neutral, due to the increasing importance for land management in agriculture.

Table 1 Descriptive Statistics of Soil Degradation Indicators

Indicator Statement	Mean	Std. Deviation	Interpretation
Soil erosion significantly affects productivity	4.21	0.71	High agreement
Decline in soil organic matter is a major concern	4.18	0.69	High agreement
Soil compaction has increased in recent years	3.87	0.82	Moderate agreement
Salinity and acidity problems are common	3.92	0.77	Moderate agreement
Nutrient depletion is frequently observed	4.25	0.66	High agreement
Traditional methods are insufficient to detect degradation	4.09	0.73	High agreement

The table 1 indicates that participants regard the problem of soil degradation as important and widespread since the average scores are high for most indicators. Nutrient depletion (Mean=4.25) had the highest mean agreement, which means that soil nutrient exhaustion is perceived as the dominant factor influencing soil productivity. This indicates a high demand for better nutrient management and monitoring mechanisms. Soil erosion and depletion of soil organic matter had high level of concordance expressing worry to the loss in quality (Mean = 4.21), Mean = 4.18) from physical and bio-degradation, respectively as well. These results suggested that the loss of soil structure and decrease in organic matter were considered major threats for sustainable crop production. Moderate agreement (Mean = 3.92) were reached on the indicators of salinity/acidity and soil compaction, signifying that such problems may exist but vary in intensity at different sites/farming's systems. This variation highlights the need for local level soil testing and tailor-made management. Lastly, the high average score of insufficiency of traditional detection methods (Mean = 4.09) suggests that there is a strong attitude that traditional methods would not suffice in monitoring early and accurate detections. Taken in its entirety, the table suggests a need for use of advanced technologies like AI-based predictive analytics to enhance early detection, spatial analysis and recommend productive soil management decisions. Fair consistency was evident for salinity and compaction which suggests the variable level of expression at different sites but their durability confirms an indication of chemical and structural limitations to crop productivity. The consensus on traditional assessment tools being insufficient reinforces the increasing demand for more advanced monitoring toolsets, such as AI-based predictive models, to better capture spatial and temporal variability.

In addition, these findings resonate with wider environmental observations from the Intergovernmental Panel on Climate Change indicating that land degradation processes are being exacerbated as a result of climate variability and unsustainable application of the land (Kartini et al., 2023). The synergy in these perspectives implies that incorporating predictive analytics in soil monitoring can be beneficial for early detection and targeted mitigation to better maintain soil resilience and agricultural sustainability.

4.2 Soil Fertility Assessment

The analyses of soil fertility assessment covered perceptions on the effectiveness, variability, and challenges farmers face in the stemmed up as regards to assessing fertility. The descriptive statistics show a relatively high level of consensus on the need to accurately measure fertility for improved agricultural productivity. Statements pertaining to soil testing and fertility mapping had the highest mean scores indicating a high level of awareness in their contribution towards informed fertilizer management. Tillage practices are frequently based on assessing fertility, and we found large variations in soil properties within fields that support the demand for spatially-targeted methods of assessment. Although current diagnostic methods were considered to be accurate, cost and time of preceptor's situations were cited as limitations.

Table 2 Descriptive Statistics for Soil Fertility Assessment

Indicator Statement	Mean	Std. Deviation	Interpretation
Regular soil testing improves fertilizer decisions	4.32	0.63	High agreement
Soil fertility varies within the same field	4.15	0.72	High agreement
Existing fertility assessment methods are reliable	3.88	0.79	Moderate agreement
Nutrient imbalance (N, P, K) is common	4.21	0.68	High agreement
Accurate fertility mapping enhances productivity	4.36	0.61	High agreement
Manual soil analysis is time-consuming and costly	4.10	0.75	High agreement

The table 2 shows that there is a high level of agreement about the importance of assessing soil fertility in order to improve agricultural productivity. Respondents believed spatially detailed analysis is the best way to improve crop results; evidence in this can be found by looking at fertility mapping which has the greatest mean score. High loadings for regular soil testing and the prevalence of nutrient imbalances (regular soil testing), indicate that managing fertilizer application potentially depends on monitoring concentrations of soil nutrients. The not so high average level of reliability on the current methods indicates that although people trust what is there currently, they are still "grounded" to the real needs. Further, the fact that most reviewers agreed that manual analysis was time consuming and expensive suggests implementation issues. In summary, the table suggests a clear need for more cost-effective technology solutions (e.g., AI predictive analytics) that can improve accuracy and reduce costs for operational requirements within precision soil management. There is a high level of agreement among participants that assessment of the fertility status is a vital part of sustainable land use. This high average scale for role of routine soil testing reflects that most respondents realize the importance of data driven nutrient management in enhancing fertilizer use efficiency and crop yield. This is consistent with the Food and Agriculture Organization soil management framework adopted globally, and which emphasizes soil testing as a keystone of sustainable intensification. The appreciation for substantial within-field variability would seem to explain the expanding acceptance of precision agriculture methods in which field-specific nutrient management is employed to maximize inputs. High agreement in prevalence of nutrient imbalance also underscores the importance of reliable monitoring tools that can capture spatial heterogeneity. Respondents reported manual analysis to be relatively reliable, but a sense that the method is time-consuming and expensive implies practical drawbacks. The results of this study might imply that by combining AI-based prediction approaches with machine learning technologies, efficiency could be increased and costs decreased, and real-time decisions made possible.

In general, the findings support that enhanced methods of investigating fertility are likely to add considerably to productivity increases and environmental alliance, especially when is made use of in combination with digital technologies (Barrena-González et al., 2022). These findings are in agreement with the wider evidence base presented by the Intergovernmental Panel on Climate Change (IPCC) which especially highlights efficient nutrient management as a pivotal adaptation measure for climate-resilient agriculture.

4.3 Artificial Intelligence Applications in Soil Analysis

The study also focused on the perceived effectiveness of Artificial Intelligence (AI) for soil analysis and monitoring as reported by respondents. In general, the descriptive statistics reveal a high degree of consensus across all items with a strong confidence in AI technologies for enhancing accuracy and decision making in soil assessment. Higher mean ratings were obtained for AI's capacity to analyze large amounts of data and boost spatial visualization by mapping, indicating participants thought the technological advantages of AI driven systems. The respondents also reach to the consensus that AI can predict the future trend in soil degradation and encourage sustainable land management by decision-support tools. The results demonstrate how AI is considered, not only a technical innovation, but a strategic instrument for long term agricultural planning.

Table 3 Statistics for Artificial Intelligence Applications in Soil Analysis

Indicator Statement	Mean	Std. Deviation	Interpretation
AI tools improve accuracy of soil degradation prediction	4.28	0.64	High agreement
Machine learning effectively analyzes large soil datasets	4.35	0.59	High agreement
AI-based mapping provides better spatial visualization	4.31	0.62	High agreement
Remote sensing with AI enhances fertility assessment	4.19	0.70	High agreement
AI can predict future soil degradation trends	4.24	0.66	High agreement
AI decision-support systems aid sustainable land management	4.33	0.60	High agreement

The table 3 suggests high median scores on all AI-related aspects showing a general agreement that AI technologies improve the soil analysis and predictive capacity. Most dedicated value: (large dataset analysis)-This feature will prioritize data processing capacity as a highly sought-after benefit and are also of high mean indicating the most important aspects that are required focusing between spatial mapping and decision support. The comparatively lower (although still high) mean indicates that while there is a preference for integrating with remote sensing the extent to which this is useful may be constrained by factors such as data availability, technical capability. In general, the trend of the findings emphasizes that AI is considered to be a broadly embraced reliable and meaningful instrument to achieve more efficient soil monitoring, prediction and sustainable agricultural decision-making. The findings reflect a strong belief that AI applications greatly improve the ability to make sense of soil analysis. The top mean score of machine learning capacity for working on large datasets could represent the awareness towards AI's ability to analyze massive complex environmental data. This is in line with ongoing international digital agriculture efforts facilitated by the Food and Agriculture Organization that focus on AI's use in facilitating better data-driven soil management. As well, strong consensus on AI map drawing would suggest the spatial visualization it provides is regarded as a significant improvement over traditional methods. Increased accuracy in mapping can assist precision agriculture by providing site specific management. The results also reveal trust in AI's predictive power, indicating these stakeholders value the technology for proactively maintaining soil conservation.

The positive attitude towards AI decision-support systems also highlights their potential to assist sustainable land management (Gadicha et al., 2026). These findings are supported by wider climate and land-use reports from the Intergovernmental Panel on Climate Change that recognize digital technologies as critical enablers to achieving resource efficiency and resilience in agriculture.

4.4 Predictive Analytics Efficiency

The predictive analytics efficiency was analyzed reviewing how AI models improve early detection, decision-supporting, and cost-effectiveness in the soil monitoring. The descriptive statistics indicate that there is a degree of agreement and indication on an aggregate level irrespective of the measures provided, indicating that as a group, respondents strongly agree that Predictive analytics offering significant value in soil management.

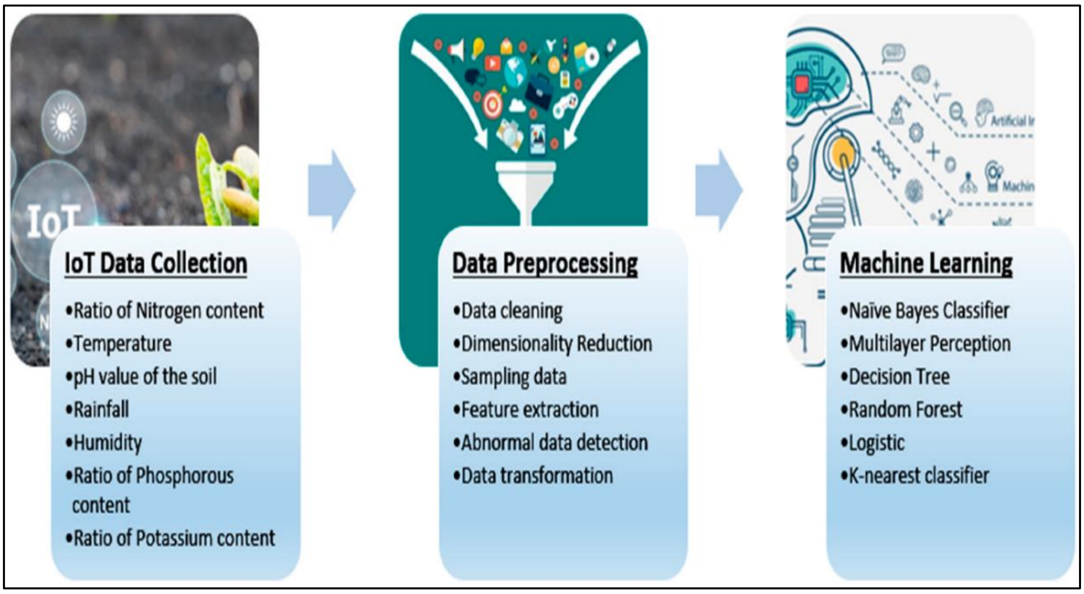


Figure 3 Role of Predictive Analytics in Enhancing Soil Monitoring, Early Detection, and Precision Agriculture Decisions

Table 4 Descriptive Statistics for Predictive Analytics Efficiency

Indicator Statement	Mean	Std. Deviation	Interpretation
Predictive analytics improves early detection of degradation	4.27	0.65	High agreement
Predictive models reduce uncertainty in fertility estimation	4.19	0.69	High agreement
Predictive analytics supports precision agriculture practices	4.36	0.58	High agreement
AI-driven mapping enhances farm decision-making	4.31	0.62	High agreement
Predictive models provide cost-effective monitoring solutions	4.12	0.74	High agreement
Real-time data integration improves prediction accuracy	4.28	0.63	High agreement

Over the indicators, the highest mean score emerged for 'Predictive modeling to assist with precision agriculture' reflecting that predictive analytics is regarded as most important for farm management at site specific level. Early warning of soil degradation and improved decision making also scored relatively high, indicating the instrumental value that proponents believe prediction offers. Respondents also recognized the value of incorporating real-time information to enhance predictions, underscoring how dynamic data inputs are essential in models artificial intelligence.

The findings in table 4 demonstrated that the farmers firmly believe in predictive analytics as a means to improve soil monitoring and farming planning. Precision agriculture support achieved the greatest mean score, signifying that predictive models are widely acknowledged in their ability to facilitate site-specific interventions and resource efficiency/productivity. The results support the FAO's digital agriculture strategies, which stress predictive technologies as levers towards sustainable intensification. High consensus for early detection of evidence and better decision making underscores the utility of predictive analytics to predict risks of soil degradation before they threaten productivity. The perceived decrease in uncertainty speaks to trust with respect to model results, a prerequisite for adoption of technology. The favorable responses with respect to cost-effectiveness indicate that predictive systems may assist in ensuring more efficient use of resources and decrease monitoring costs over time, though the slightly lower agreement for this item compared with other indicators might be attributable to start-up costs or constraints on infrastructure (Aatira Hilal et al., 2024). The strict demand of real-time data integration implies the importance of active and continuous flow of data sources (a la remote sensing, IoT sensors) to ensure model accuracy. These conclusions are consistent with the broader environmental and climate adaptation views brought by the IPCC, where prediction is acknowledged to be a central element of climate-smart agriculture and sustainable land management.

4.5 Model Performance and Reliability

The perception of accuracy, consistency, robustness of AI-based predictive systems for soil degradation and fertility mapping was analyzed. The descriptive statistics show high agreement on most items, indicating a strong certainty of the superiority of AI models over standard forms of analysis.

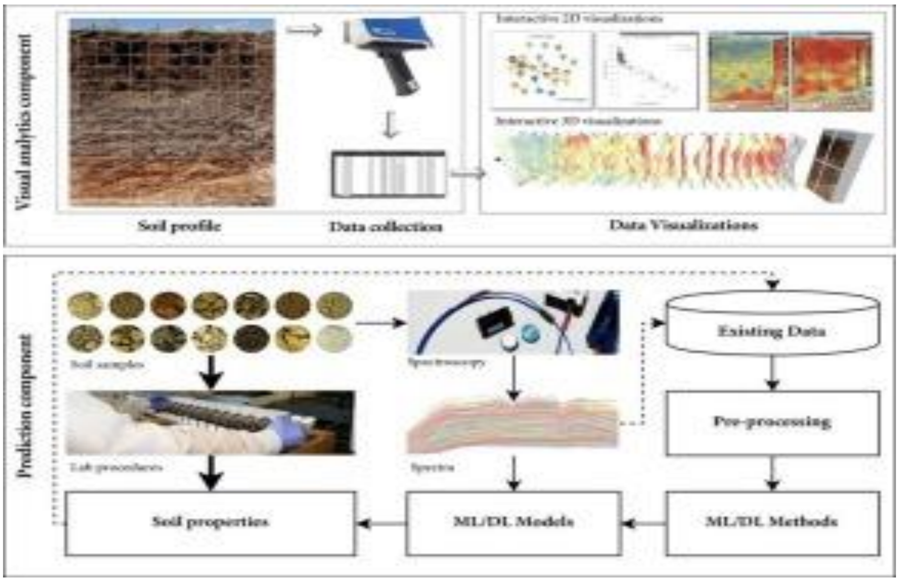


Figure 4 Framework for Evaluating AI Model Performance and Reliability in Soil Prediction Systems

The role of multi-source data integration to increase accuracy was the one with the highest mean score, confirming that combining satellite, environmental and soil data can help improve predictive accuracy. Respondents also mostly agreed that the quality of data impacts model performance and thus the importance of having good datasets. Attitudes about model validation and the reliability of long-term planning were also positive showing confidence in AI-driven outputs for strategic decisions.

Table 5 Descriptive Statistics for Model Performance and Reliability

Indicator Statement	Mean	Std. Deviation	Interpretation
AI models are more accurate than conventional methods	4.22	0.67	High agreement
Validation techniques ensure prediction reliability	4.18	0.69	High agreement
Data quality strongly affects model performance	4.34	0.58	High agreement
Multi-source data integration improves precision	4.37	0.56	High agreement
AI-based fertility maps are reliable for long-term planning	4.20	0.65	High agreement

The mean score in the various indicators is high, demonstrating strong confidence shown towards AI-based soil prediction models performance and reliability (table 5). For the greatest average emphasizes multi-source data integration as the most important contribution to boost model performance, followed by indicating data quality is of most importance. The high values of agreement for means that the participants either do agree that AI models are good and well validated, while good score for means trust unto whether they will be used in the long run. In general, the trend confirms that reliability perception is strongly tied to data robustness and validation practice, thus emphasizing a need for sound data governance in AI-enabled soil analytics. The results also underscore a high level of trust in the technical soundness of AI-driven predictive systems. The high average score of multi-source data integration implies that respondents are well aware of the crucial contribution to accuracy and spatial precision made by integrating diverse datasets. This is in line with the digital soil mapping concepts of integrated data use recommended by the Food and Agricultural Organization for trustworthy assessment of soils. The strong consensus on the importance of data quality confirms that accurate and high-resolution datasets are crucial for successful predictive modeling. This indicates that investments in data infrastructure and monitoring are essential for achieving maximal AI performance. Favorable attitudes toward validation methods suggests confidence in model evaluation procedures like cross-validation and calibration that ultimately provide more confidence in predictive outputs. In the same way, deriving AI-made maps as trustworthy for many years planning indicates how strategically predictive analytics is perceived in responsible land management. These findings are in line with the broader climate and land-use work of the Intergovernmental Panel on Climate Change that has pinpointed robust data assimilation and model validation as being crucial for operational prediction systems (Barman et al., 2021).

4.6 Implementation and Sustainability Impact

Figure 5 Impact of AI-Driven Predictive Analytics on Sustainable Agriculture and Environmental Outcomes

The implementation and sustainability impact analysis focused on the potential of AI predictive analytics in promoting sustainable agriculture, resource efficiency and environmental conservation.

The averages of the indicators suggest that respondents agree, overall, to a high degree with the proposition that AI adoption has a positive impact on productivity and sustainability. Highest mean was associated with the contribution of AI to enhancing overall land productivity, which suggests that efficiency improvements are relatively more apparent than other benefits. Respondents also heavily agreed that AI breaks through to save overconsumption of chemical fertilizer and protect the environment, suggesting recognition of the ecological benefits from data-driven soil management. Furthermore, hassle's contributions to climate resilience were rated highly and appeared to reflect how participants perceive the role of AI in changing agricultural practices in response to environmental conditions.

Table 6 Descriptive Statistics for Implementation and Sustainability Impact

Indicator Statement	Mean	Std. Deviation	Interpretation
AI predictive analytics supports sustainable agriculture	4.30	0.62	High agreement
AI tools help reduce excessive fertilizer use	4.18	0.70	High agreement
Predictive soil mapping aids environmental conservation	4.24	0.66	High agreement
AI adoption improves overall land productivity	4.35	0.59	High agreement
AI-based monitoring enhances climate resilience	4.21	0.68	High agreement

Uniformly high mean scores noted in the table 6 for all 10 measures of AI adoption suggest that administrators largely agree AI implementation has positively impacted sustainability and productivity outcomes. The highest value mean implies that productivity improvement is the most important perceived benefit, whereas records of high dimension for demonstrate AI's contribution to sustainable agriculture and environmental conservation. The relatively lower but (also) very high mean of suggested that although the net benefits associated with fertilizer reduction are appreciated, they may be contingent on adoption levels and technical capacity. Finally, the findings confirm that AI-based predictive analytics is seen as a desirable tool for sustainable and climate-resilient agricultural systems. The findings indicate a high degree of confidence in the belief that AI-based predictive analytics is having significant impacts on sustainability in farms. The largest mean value for the better land productivity suggests that farmers perceive that efficiency improvement would be the most important effect of AI adoption, which might have resulted from more efficient use of resources and site-specific management. This is consistent with the approach taken by FAO of sustainable intensification, which focuses on technology-led increases in productivity while not increasing environmental pressure. The high level of agreement on decreased fertilizer use implies that predictive analytics might help in achieving accurate nutrient management, further limiting environmental pollution and input costs (Sindhushree T. et al., 2025). Also, the significant positive perception of environmental conservation benefit is a reflection of acknowledgment of AI for mitigating land degradation and advocating responsible resource utilization. The positive rating of climate resilience is an indication that predictive tools are critical for adapting agricultural management to climate variability. Such findings are in line with global climate adaptation points highlighted by the Intergovernmental Panel on Climate Change, indicating technologies for digital agriculture to be one of the vectors and enablers for supporting climate-smart farming. In summary, the results indicate that AI-based predictive analytics lead to improved operational efficiency and are very effective in ensuring long-term environment sustainability and farming systems' resilience.

5 Findings

- Soil erosion, problem of nutrients and loss of organic matter emerged as the major signs of soil degradation contributing to productivity.
- Field spatial fertility Soil fertility is not uniform throughout a field, and testing and mapping the area are required before implementing nutrient management strategies.
- Artificial Intelligence considerably increases the accuracy of soil analysis, and improves prediction models for degradation and fertility.
- Predictive analytics effectively advances the field of early warning, precision farming, and data science-based decision-making while also minimizing uncertainty in soil management.
- The adoption of artificial intelligence based prediction tools results in more productive land, less fertilization, environmental protection and stronger climate safety.

Recommendations

- Policy makers and directors of agriculture can promote the use of AI-empowered predictive analytics in soil monitoring, detection of soil degradation, and mapping fertility for decision support based on data.
- Soil testing laboratories infrastructure, remote sensing and IoT based monitoring system should be encouraged to establish for accurate fertility evaluation on wide variability of agricultural lands.
- Farmers and agro-industries may also apply the site-specific nutrient management and precision cage practice on the basis of predictive analytics to get a maximum utilization rate of input resource as well as high crop production.

- Agencies and institutions must provide high-quality, multi-source datasets for AI models, that actively use satellite imagery data, environmental factors and historical soil data to improve model accuracy.
- AI-based tools for soil management must be used to avoid excessive fertilizer use, save natural resources and increase resilience to climate variability - making agriculture sustainable in the long term.
- Training courses for farmers, extensionists and agronomists with new technical skills on how to properly use AI based soil assessment tools must be established.

6 Conclusion

This work shows that AI-based predictive analytics offers great promises for improving soil degradation assessment, fertility mapping and sustainable agricultural management. Results indicate that significant soil degradation factors, such as erosion, nutrient loss and OM decline, are detrimental to highly productive soil; while the variability in the fertility of soils also points to a requirement for accurate methods of assessment. Results: AI applications enhanced analytical accuracy, predictive modeling and spatial visualization enabling early detection, precision agriculture and data-driven decision-making. In addition, the study emphasizes that reliable model performance requires good quality, multi-source data sets and cross-validated methods. Deployment of AI-based tools not only optimizes land productivity, but is also beneficial to environmental protection, resource and energy saving as well as climate adaptation. On the whole, it is to be noted that this work highlights how AI and predictive analytics incorporated within soil management systems could offer scalable, cost-effective, sustainable solutions for of modern agriculture by enabling to bridge technological innovation with on-farm adoption and science as well as long term soil health and productivity.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Aatira Hilal, S. A. B., Nayar Afaq Kirmani, Javaid Ahmed Wani, & Tajamul Islam Shah. (2024). Geostatistical modeling—A tool for predictive soil mapping. In *Remote Sensing in Precision Agriculture* (pp. 389–418). Academic Press. https://doi.org/10.1016/B978-0-323-91068-2.00011-4

[2] Alijagić, J., & Šajn, R. (2020). Application and improvement of soil spatial distribution mapping using advanced modelling techniques. *Geologia Croatica*, *73*(1), 69–84. https://doi.org/10.4154/gc.2020.01

[3] Barman, A., Basak, N., Narjary, B., & Mitran, T. (2021). Land Degradation Assessment Using Geospatial Techniques. In T. Mitran, R. S. Meena, & A. Chakraborty (Eds.), *Geospatial Technologies for Crops and Soils* (pp. 421–453). Springer. https://doi.org/10.1007/978-981-15-6864-0_12

[4] Barrena-González, J., Contador, J. F. L., & Fernández, M. P. (2022). Mapping Soil Properties at a Regional Scale: Assessing Deterministic vs. Geostatistical Interpolation Methods at Different Soil Depths. *Sustainability*, *14*(16). https://doi.org/10.3390/su141610049

[5] Gadicha, A. B., Gadicha, V. B., Maniyar, M. M., Gadicha, A. B., Gadicha, V. B., & Maniyar, M. M. (2026). *AI-Based Soil Quality Monitoring and Improvement Techniques Predicting and Mitigating Soil Erosion and Degradation* [Chapter]. IGI Global Scientific Publishing. (ai-based-soil-quality-monitoring-and-improvement-techniques-predicting-and-mitigating-soil-erosion-and-degradation). Https://Services.Igi-Global.Com/Resolvedoi/Resolve.Aspx?Doi=10.4018/979-8-3373-5283-1.Ch011. https://doi.org/10.4018/979-8-3373-5283-1.ch011

[6] Hussain, S. S., Ganie, A. A., Dar, W. A., Wani, T. A., Hadayatullah, M., Baba, J. A., Parrey, G. N., Mugloo, J. A., & Dar, R. A. (2024). The Role of Digital Soil Mapping in Soil Survey and Agricultural Planning. *International Journal of Plant & Soil Science*, *36*(9), 438–449. https://doi.org/10.9734/ijpss/2024/v36i94993

[7] Islam, A. R. Md. T., Salam, R., Yeasmin, N., Kamruzzaman, M., Shahid, S., Fattah, Md. A., Uddin, A. S., Shahariar, M. H., Mondol, M. A. H., Jhajharia, D., & Techato, K. (2021). Spatiotemporal distribution of drought and its possible associations with ENSO indices in Bangladesh. *Arabian Journal of Geosciences*, *14*(23), 2681. https://doi.org/10.1007/s12517-021-08849-8

[8] Kartini, N. L., Saifulloh, M., Trigunasih, N. M., & Narka, I. W. (2023). *Assessment of Soil Degradation Based On Soil Properties and Spatial Analysis in Dryland Farming*. https://www.jeeng.net/Assessment-of-Soil-Degradation-Based-On-Soil-Properties-and-Spatial-Analysis-in-Dryland,161080,0,2.html

[9] Khadim, M. D., Wali, M. W., & Helmandwal, S. M. (2025). Effects of Agricultural Land Practices Management on Sustainable Crop Production. *AgroEnvironmental Sustainability*, *3*(3), 292–303. https://doi.org/10.59983/s20250303010

[10] Li, Q., Zhang, C., Shangguan, W., Li, L., & Dai, Y. (2023). A novel local-global dependency deep learning model for soil mapping. *Geoderma*, *438*, 116649. https://doi.org/10.1016/j.geoderma.2023.116649

[11] Mikhailova, E. A., Zurqani, H. A., Lin, L., Hao, Z., Post, C. J., Schlautman, M. A., & Post, G. C. (2024). Spatiotemporal Analysis of Soil Quality Degradation and Emissions in the State of Iowa (USA). *Land*, *13*(4). https://doi.org/10.3390/land13040547

[12] Mondal, B. P., Raj, G. B., Dixit, M., Sadhu, T., Pandit, V., Prasanna, L., Chattopadhyay, A., Dutta, S., & Kumar, S. (2024). Role of Soils for Satisfying Global Demands for Food, Water, and Bioenergy. In *Environmental Nexus for Resource Management*. CRC Press.

[13] Naorem, A., Patel, A., Adak, S., Singh, P., & Udayana, S. K. (2024). Precision Technologies and Digital Solutions. In *Digital Agricultural Ecosystem* (pp. 175–190). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781394242962.ch10

[14] Shary, P. A., & A, Ш. П. (2023). Environmental Variables in Predictive Soil Mapping. *Eurasian Soil Science*, (3), 285–299. https://doi.org/10.31857/S0032180X22100380

[15] Sindhushree T., S. T., D, K., Jitendra, G. H., Tongali, N. C., Rajeswari, B., & Phukan, P. (2025). Digital Soil Mapping: A Review of Techniques, Applications and Emerging Trends. *Journal of Scientific Research and Reports*, *31*(7), 1151–1158. https://doi.org/10.9734/jsrr/2025/v31i73329

[16] Solanki, K., Pradhan, J., Singh, H., Satpathy, B., Jaiswal, A., Kumari, G., & Neeraj, N. (2025). Leveraging AI to Propel Growth in Regenerative Agriculture: From Fields to the Cloud. *Agriculture Association of Textile Chemical and Critical Reviews*, *13*(1), 338–344. https://doi.org/10.21276/AATCCReview.2025.13.01.337

[17] Spalevic, V., & Curovic, M. (2023). Soil erosion modeling using computer-graphic methods and geographic information systems. *ОДРЖИВИ РАЗВОЈ И УПРАВЉАЊЕ ПРИРОДНИМ РЕСУРСИМА РЕПУБЛИКЕ СРПСКЕ*, *5*(5). https://doi.org/10.7251/EORU2305143S