Sensors and Materials, Vol. 37, No. 11 (2025) 5013–5030
MYU Tokyo

S & M 4229

Transforming Rural Environmental Governance Using Machine Learning Based on Sensor Data for Sustainable Practices

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(Received March 31, 2025; accepted November 4, 2025)

Keywords: machine learning, rural governance, environmental sustainability, technological infrastructure, stakeholder engagement

The influence of machine learning (ML) technologies on governance effectiveness and environmental management in rural areas was explored in this study. The role of ML and sensor data in enhancing rural environmental governance was investigated, focusing on its impact on decision-making processes and sustainable outcomes. ML is a data-driven method dependent on continuous, real-time input from distributed environmental sensors. Sensor data, collected through wireless sensor networks and remote sensing platforms, are foundational for the high-resolution, multi-modal data (e.g., air quality, water flow, and soil composition) necessary for ML models to conduct predictive modeling and anomaly detection, thereby transforming traditional governance into a proactive system. To understand how ML with sensor data contributes to the development of environmental governance in rural areas, a questionnaire survey was conducted with 101 participants, and the data were analyzed using the Statistical Package for the Social Sciences. ML was used to process the data and identify environmental factors. A positive perception of ML's effectiveness in governance was observed. However, correlations between ML effectiveness and other variables were not significant. The resuslts of analysis of variance showed no significant relationship among technological infrastructure, stakeholder engagement, and perceived effectiveness. While ML based on sensor data holds promise for improving rural governance, its integration must be accompanied by robust infrastructure for tangible environmental benefits. Such results enable an understanding of the potential of ML in rural governance and highlight the need for strategic implementation strategies.

1. Introduction

Environmental governance in rural areas is facing challenges such as climate change, resource depletion, and the intricacies of socio-ecological interactions, which require solutions

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https://doi.org/10.18494/SAM5682

ISSN 0914-4935

for effective management. Machine learning (ML) is a revolutionary means of processing massive environmental data, detecting patterns in it, and creating predictive models to guide governance decisions.(1) Using ML in rural environmental management transforms traditional methods into proactive, data-based ones effectively. ML has been proven to enable augmented pollution monitoring systems to maximize the utilization of natural resources, environmental compliance, and the accurate forecasting of ecological changes. Therefore, ML applications address the shortcomings of traditional governance methods, particularly in underprivileged rural areas where environmental surveillance is hindered by geographical dispersion, inadequate infrastructure, and a lack of technical expertise within regional administrations.(2)

Effective rural environmental governance is closely related to advancements in digital infrastructure, particularly sensing technologies. Conventional environmental monitoring relies on infrequent, labor-intensive sampling, which fails to capture the dynamic, nonlinear environmental processes prevalent in rural ecosystems.(3) Therefore, the effectiveness of ML in environmental governance depends on the quality and density of the input data stream. Thus, it is necessary to study how ML, when powered by multi-source sensor data, provides superior capabilities for pollution source identification, the predictive modeling of natural resource degradation, and optimized resource allocation for environmental protection.(4)

ML is used to process environmental data efficiently to mitigate the service and information divide, and improve bureaucratic processes that previously hindered sustainable development programs in rural areas.(2) A platform with ML and sensor data enables the survey, identification, and execution of necessary policies in rural communities. In particular, modular data representation methods (MDRMs) (Fig. 1) have allowed data semantics in digital platforms to present, analyze, and interact in the governance process through requirements-based intelligent processing.(2) The technological revolution allows rural government systems to evolve their administrative functions and incorporate managerial methodology for environmental protection, economic development, and social welfare goals, which are the three pillars of sustainable development. The geographic, demographic, and fundamental services required for rural areas are also developed using MDRMs.

When using ML, rural environmental governance suffers from limited data, severe intricacy, and implementation barriers. The rural environment is characterized by the scarcity of environmental data collection systems, which limits the effectiveness of environmental

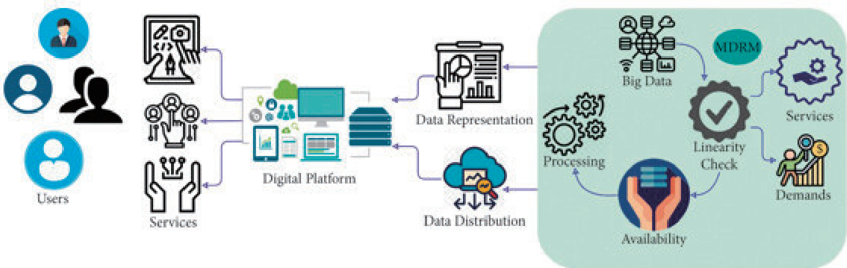

Fig. 1. (Color online) Structure of MDRM.

governance.(5) The limitation of sparse, heterogeneous datasets is also addressed by ML algorithms through transfer learning and data augmentation.

Rural environmental systems depend largely on agricultural practices, natural resource utilization, land use patterns, biodiversity conservation, and human activities. Therefore, ML is necessary for environmental managers to analyze the data with such complexity by detecting nonlinear patterns. ML-based governance also applies to resource constraints in rural areas by optimizing intervention strategies based on cost-effectiveness. Policies can be effectively executed even with a limited budget by employing edge computing to solve complicated issues.(6) Figure 2 shows an example of a smart city structure with AI and ML applications, which can also be applied to rural governance.

In this study, we examined the disconnect between the theory and application of ML and sensor data in the environmental governance of rural areas and the challenges posed by limitations in infrastructure and institutional systems. Despite the promising implementations, the outcomes and impacts of ML environmental governance on rural areas have been insufficiently studied.(7) Therefore, it is necessary to understand the interrelationship between technologies and governance to avoid undesired outcomes when adopting advanced technologies for the sustainable development of rural areas. This study was conducted to suggest a balanced method of using ML and sensor data in rural environmental governance, considering the capabilities and limitations of ML. The results can be used to integrate technological advancement into rural governance by formulating policies. ML is a promising technology to enhance rural environmental governance. However, ML needs to be employed with appropriate algorithms and sufficient environmental data.

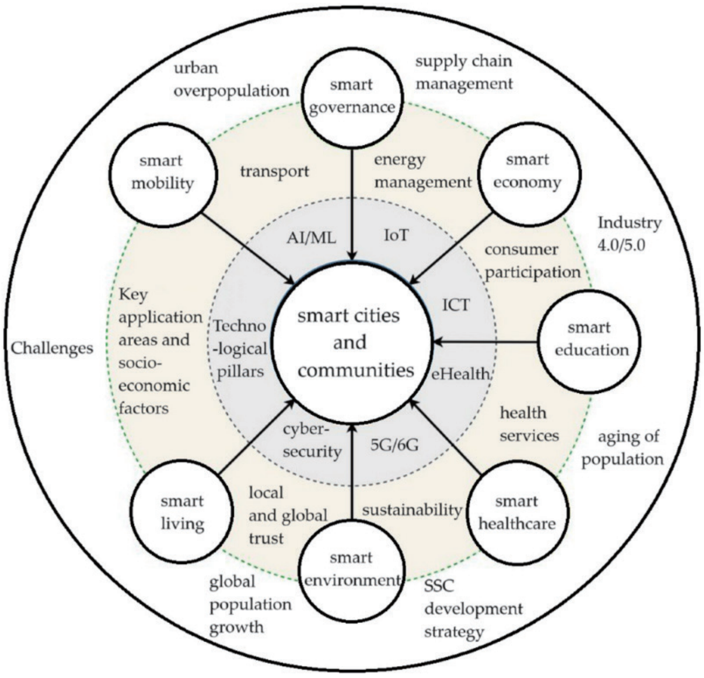

Fig. 2. (Color online) Smart city structure integrated with AI.

2. Background Knowledge

2.1 Sensor technology and ML

The application of ML in environmental governance is predicated on sensor data collected continuously and noninvasively across a heterogeneous rural landscape. Two technological components are essential: environmental sensor deployment and data acquisition. For rural environmental monitoring, various sensors need to be integrated into the IoT infrastructure.

For air quality monitoring, metal oxide semiconductor or electrochemical sensors are used to monitor pollutants, including $PM_{2.5}$, CO_2, and NO_x from agricultural waste burning or local industry.(8) For water quality monitoring, probes to measure pH, dissolved oxygen, turbidity, and chemical oxygen demand are used.(9) Low-power wireless sensor networks (WSNs) equipped with sensors for soil moisture, temperature, electrical conductivity, and nutrient levels are essential for sustainable agriculture and land management.(8) Satellite and unmanned aerial vehicles are employed with multispectral sensors to obtain large-scale, indirect data, such as the normalized difference vegetation index, which is critical for land-use change detection and tracking ecological health, serving as a massive data source for ML classification and regression models.(10,11)

The performance and lifespan of environmental sensors are crucial under harsh rural conditions, which necessitate advanced functional materials to enhance sensitivity and selectivity. Materials, including graphene, carbon nanotubes, and conductive polymers, are widely used in sensor components to significantly improve sensitivity and selectivity at low concentrations. New fabrication techniques, such as 3D printing and the use of flexible, biodegradable substrates, have been introduced to lower the manufacturing and installation cost and increase the robustness of distributed WSNs, enabling their wide-scale deployment across rural areas where frequent maintenance is impractical.(12,13) ML technologies, therefore, inherently depend on the application of these advanced sensing concepts and materials to acquire the necessary environmental data for effective governance.(14)

2.2 ML and sensor data on environmental governance

The evaluation of rural environmental governance requires complex dimensions. In traditional governance evaluation, a limited number of assessments were available owing to a lack of real-time data.(15) In comparison, ML enables multi-dimensional analyses using numerous environmental data. Complex or hidden relationships of the variables can be captured. Using ML, sophisticated models can be constructed to examine changes in the management of natural resources, agricultural practices, land use patterns, biodiversity conservation, and human activities.(16) ML also fosters new governance evaluation approaches in rural areas with accuracy, reliability, and usefulness. Random forest algorithms and regression trees are widely used to evaluate the effectiveness of environmental governance owing to their capability of processing heterogeneous data. These methods enable researchers and policymakers to perform exploratory analysis to determine diverse factors affecting the interactions of individual policy actions and governance instruments (Fig. 3).[17] ML's ability to make sophisticated inferences is useful in evaluating governance components without jurisdictions and complex interrelations and identifying the influences of technology on the components.

Using ML for environmental monitoring in rural areas presents infrastructural and logistical issues. Although digital systems improve environmental management as they enable the real-time monitoring and analysis of collected data, continuous and periodic assessments of the system are required to enhance their performance and improve environmental policy execution (Fig. 4).[18] ML models based on historical environmental data can identify abnormalities, predict adverse impacts on the environment, and recognize risks for proactive action.[19] Such outcomes are useful in rural governance where the early recognition of environmental problems is essential to avoid expensive remedial actions. ML's ability to analyze huge data is described in https://doi.org/10.3389/fenvs.2024.1336088.

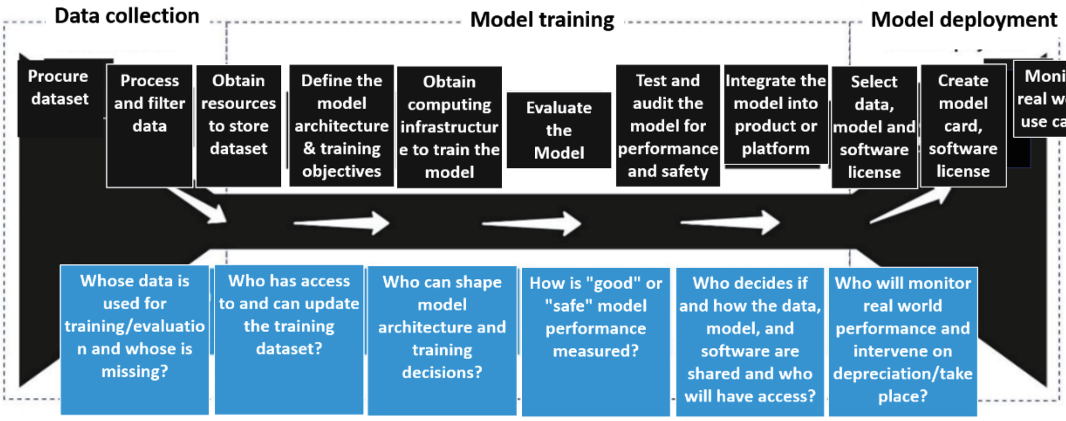

Fig. 3. (Color online) ML usage in data collection, model training, and model deployment.

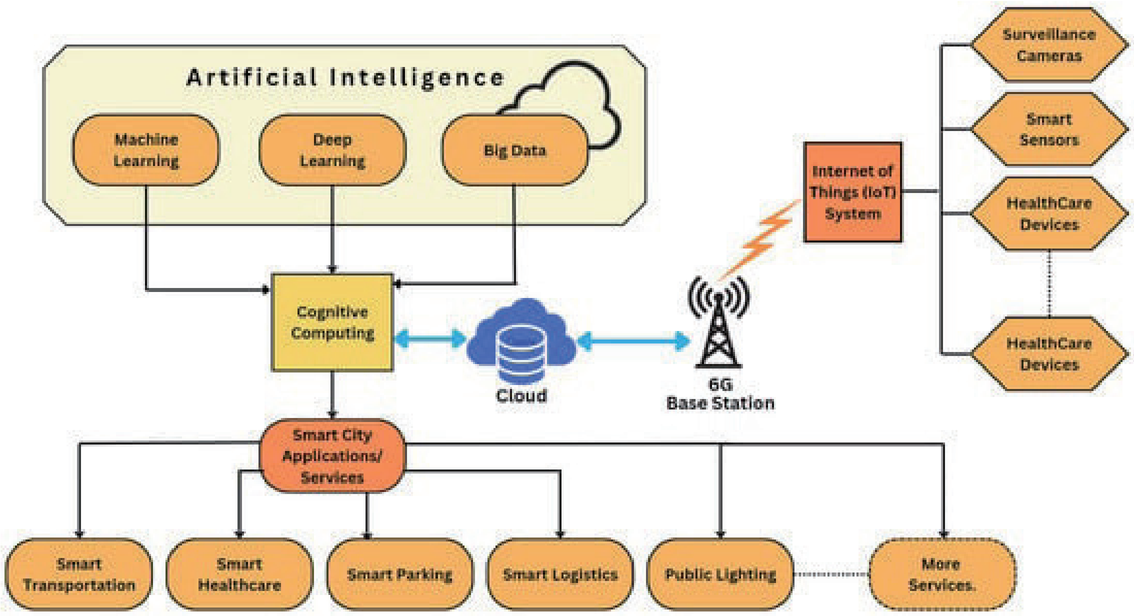

Fig. 4. (Color online) AI used for environmental policy formulation and execution.

Various ML algorithms, including random forest, decision tree, and support vector machine (SVM), are used for classification and regression. They have strengths and weaknesses, and selecting the appropriate model depends on the dataset's nature and usage purposes. To understand their functionalities and applicability, the characteristics and performance of the ML algorithms are compared in Table 1.

The random forest algorithm is an ensemble technique that utilizes predictions from various decision trees to enhance accuracy while minimizing the difference in outcomes of the training and validation sets. Each tree is built using a random data selection. For regression, the final output is calculated using the average of the individual trees' outputs, while classification is performed using the majority vote method. Because of its randomness, the likelihood of overfitting the model is lowered compared with that of a single decision tree. For rural environmental governance, the random forest is most appropriate in accurately forecasting land use changes and pollution since it efficiently deals with interrelations. Random forests are also useful for complex rural ecosystems with multiple factors, including soil types, climate, and agricultural activities, which have nonlinear relationships. The ability to find essential features and manage unknown information makes the random forest method outstanding in processing datasets with a significant number of missing data (Fig. 5).

Owing to their simplicity and ease of understanding, decision trees are often used. They divide the dataset recursively on the basis of the identified features that separate trees. Gini impurity or information gains are used as the feature. Because decision trees are simple to visualize, they are preferred in situations where the models need to be interpreted. In this study, decision trees were used to determine the impact of policy instruments, funding, and community

Table 1
Comparison of ML algorithms.

Algorithm	Type	Purpose
Random forest	Supervised (classification/regression)	Ensemble learning method using multiple decision trees
Decision tree	Supervised (classification/regression)	Build tree-like model based on feature splits
SVM	Supervised (classification/regression)	Maximize margin between classes

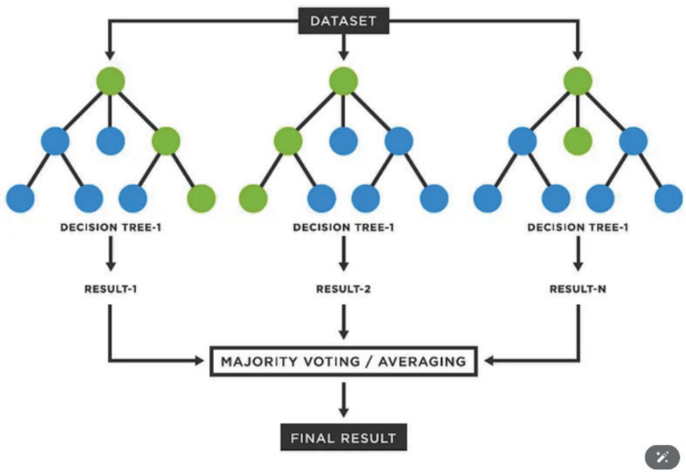

Fig. 5. (Color online) Structure of random forests.

action on sustainable development. Nonetheless, there are challenges associated with decision trees. When using deep trees, overfitting often occurs. Pruning prevents overfitting, but noisy or variable data also undermine the capability of overfitting prevention.

SVM is mainly used in classification problems to find a boundary that separates different regions while maximizing the margin between them. The SVM algorithm performs well when the boundary is separated and nonlinear owing to kernel tricks, which transform features into higher dimensions. SVM is effective in high-dimensional spaces and solves problems with complex and nonlinear relationships between features. In rural environmental governance, SVM is useful in the classification of regions based on environmental status and the detection of regions vulnerable to soil erosion or deforestation. Although powerful, SVM requires high computation costs, especially with large feature sets and effective adjustments with appropriate regularization terms and kernel functions.

3. Technological Factors in Environmental Governance

Advanced technologies such as ML considerably impact the rural area's governance processes and sustainability. The fundamental prerequisite for applying ML in this domain is the acquisition of massive, continuous, and high-resolution environmental data, a process driven by modern sensing technology.(20) The core of effective rural governance is therefore built upon the integration of the sensing concept and advanced materials into the ML framework.

The effectiveness of ML is dependent on the continuous data collection to transition governance from infrequent, labor-intensive sampling to real-time, dynamic monitoring.(3) ML algorithms rely on real-time data from WSNs and IoT devices. Policy-makers tailor the policies to continuous environmental changes. This is crucial in rural areas where environmental degradation is a big threat, as it impacts the local ecosystem and communities.

Beyond in situ sensors, ML is applied to remote sensing data to track large-scale changes in land use and ecological health.(3) ML models are used to analyze these large datasets and identify complex patterns to predict environmental changes. Such predictions enable policymakers to make evidence-based decisions instead of intuitive ones.(19) Such capabilities lead to effective resource allocation, intervention prioritization, and governance effectiveness, which are necessary to ensure environmental policies on rural resource utilization.

Technologies enable the integration of rural areas despite geographical dispersion and low connectivity.(21) Integrating AI into rural governance enhances the efficiency of governance through informed decision-making and improved coordination (Fig. 6). This also encourages stakeholders' participation through the exchange of information and collaboration to improve accountability and transparency in environmental governance. Technologies foster communication between organizations, which is often fragmented owing to hierarchical structures.

To develop a smart governance system, enhance economic growth and social welfare, and achieve sustainable development, environmental management is required. By effectively introducing smart governance in rural areas, the quality of life in rural areas can be enhanced, and effective waste management and robust pollution control are enabled. Incorporating

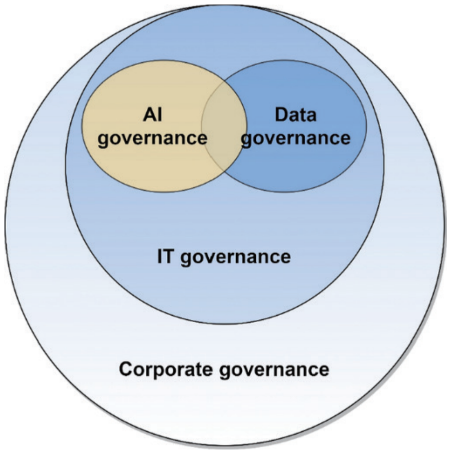

Fig. 6. (Color online) Smart governance in governance structure.

technologies is also important in data-driven decision-making in the governance process.(22) It also increases stakeholder engagement and enables improved management strategies. In addition, digital technologies are used to integrate various knowledge systems into the rural governance process (Fig. 7).

By leveraging technological advancements, rural governance can be more sophisticated than before, and environmental, social, and economic conditions in rural areas can be enhanced. Constructing the rural digital economy significantly decreases the carbon footprint.(23) Decreased carbon emissions are related to higher productivity in agriculture, which is observed in precision farming and resource allocation. Digital governance contributes to enhanced waste management and encourages public engagement in environmental governance.(24) As a result, sustainable economic growth is achieved, economic productivity is increased, and environmental degradation is reduced for sustainable development in rural areas.

By incorporating new technologies, rural areas can experience sustainable development. Rural governments must learn from smart city development. Context-sensitive technological adoption mitigates socio-economic imbalance, data scarcity, infrastructural inadequacy, and other problems in rural areas.(25) For instance, ML is used to develop resource-saving practices by forecasting environmental threats and determining conservation values, thus enabling effective conservation strategies. Digital technologies also encourage citizens to participate in environmental management for an effective decision-making process, which is important in effective rural governance.

Digital technologies in agriculture have enhanced the adaptive management and mitigation of environmental risks in rural areas, thereby contributing to sustainable development. By processing historical meteorological data and developing predictive models, effective proactive and reactive measures are identified to protect rural communities and the environment. In ecosystems highly stressed by drought, flooding, or heat waves, preventive measures need to be identified to minimize economic and environmental damage.(26) The Internet is useful in searching for and adopting smart agricultural technologies that promote sustainable development and decrease the vulnerability of rural areas to climate change. By adopting advanced

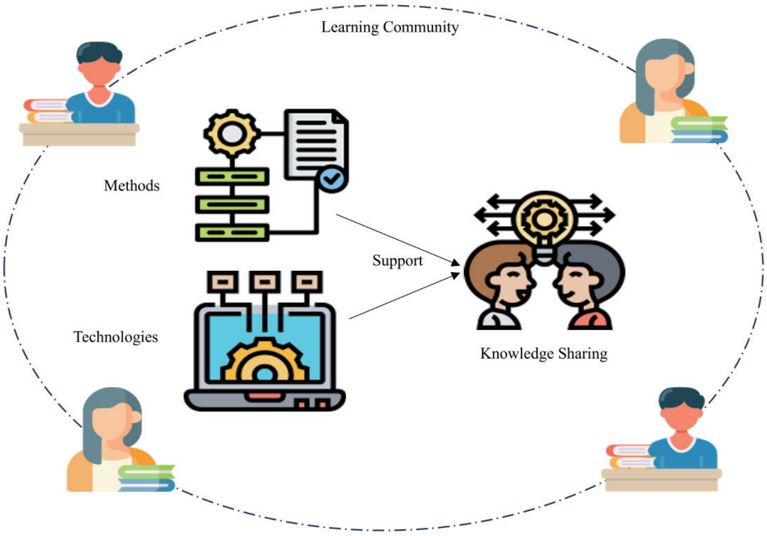

Fig. 7. (Color online) Integration of knowledge systems in governance process.

technologies, the robustness and sustainability of environmental protection and social justice can be enhanced in rural areas.

4. Materials and Methods

We examined the transformative potential of ML in rural environmental governance. A structured questionnaire survey was conducted to analyze the complex relationship between technological innovations and governance mechanisms across different administrative tiers. The relationship between ML implementations and governance effectiveness was analyzed using correlation and regression analyses to explore cause-and-effect patterns and obtain predictive information. On the basis of the results, we discussed how technology integration influences rural governance with resource constraints and geographical dispersion. Cross-sectional and longitudinal factors affecting immediate impacts and evolutionary changes in governance structures were also determined.(27)

4.1 Data collection

The questionnaire was created using a multi-instrument approach to ask about ML implementation in rural environmental governance in terms of technology and governance (Table 2). The questionnaire included questions on institutional structures and governance frameworks, stakeholder perception and attitudes toward technology adoption, and the implementation and effectiveness of ML. Closed-response and open-ended questions were included in the questionnaire on a five-point Likert scale.

The survey was carried out using an online social media platform, WeChat, to increase the response rate of the respondents dwelling in remote areas in Hunan Province, South Central

Table 2
Questionnaire items created in this study.

Section	Number of items	Description
1. Perceived effectiveness of machine learning in governance	5	Respondents' views on how machine learning improves the efficiency, transparency, and decision-making within rural environmental governance
2. Technological infrastructure availability	5	Presence and adequacy of critical technological resources such as internet connectivity, computing power, data storage, expertise, and funding
3. Stakeholder engagement and participation	5	Involvement, information accessibility, participation opportunities, and communication effectiveness among stakeholders within ML-enabled governance
4. Environmental sustainability outcomes	5	Perceptions of tangible environmental improvements linked to machine learning, including pollution reduction, biodiversity, and resource use
5. Challenges and barriers	5	Obstacles to machine learning adoption and effectiveness such as a lack of expertise, funding issues, data quality, stakeholder resistance, and data access

China. Study areas were selected to reflect geographical diversity, involvement in environmental governance, different geographical and ecological zones, and varying levels of technological adoption. Selected rural areas showed significant variations in the number of agricultural households. From 3158 households in the study area, 101 participants were selected using a stratified multistage sampling method considering diverse policies related to rural governance. The participants included village leaders, agricultural cooperative representatives, local environmental officials, technology implementation partners, and community members who were involved in rural governance and presented diverse levels of authority, expertise, and community involvement (Table 3). The response rate to the questionnaire survey was 95%.

4.2 Data analysis

Outliers and missing values were removed in data preprocessing to ensure data quality for analysis. Multiple and logistic regression analyses were performed to evaluate the impact of ML on governance effectiveness and moderation. Variances and metrics were calculated to estimate prediction accuracy and model stability. In their simplest form, these estimates explain to what degree the models are solving problems in available data from different rural areas. The results were interpreted to estimate the impact of regional differences, technological infrastructure, and environmental situations on the introduction of advanced technologies such as ML.

5. Results

The descriptive statistics of the survey results presented the respondents' perceptions of using ML, the availability of technological infrastructure, the inclination towards the participation of stakeholders, and environmental sustainability in rural environmental governance. The mean scores for perceived effectiveness in governance, technological availability, stakeholder engagement, and environmental sustainability were 4.80, 5.00, 5.00, and 4.80, respectively

Table 3
Participant demographics in questionnaire survey.

Gender	Age					
	18–30 (years old)	31–40	41–50	51–60	Over 61	Total
Male	8	12	10	8	5	43
Female	10	15	18	9	6	58
Total	18	27	28	17	11	101

(Table 4). The results indicated the relevance of using ML to improve the governance process and environmental outcomes of rural areas.

There was no correlation between perceived effectiveness in governance, technological availability, stakeholder engagement, and environmental sustainability. However, a high level of stakeholder engagement was related to environmental sustainability outcomes, and ML's effectiveness did not affect technological availability and stakeholder engagement for environmental sustainability (Table 5).

The results of analysis of variance (ANOVA) showed the impact of technological availability and stakeholder engagement on the perceived effectiveness of ML in governance (Table 6). The observed difference between the groups of respondents was not statistically significant. The lack of significance suggested that the variables of the model did not significantly explain the variance in the perceived effectiveness of ML in governance.

The R of the regression model was 0.143, indicating a weak correlation between the dependent variables. The model explained only 2% of the total variance in the perceived effectiveness of ML in governance, with an R^2 of 0.020 (Table 7). The adjusted R^2 was negative (−0.010), indicating overfitting. The standard error of the estimate was 0.36277. The model did not explain how respondents perceived ML's effectiveness in governance, suggesting that more predictors were required to explore the relationship between variables.

The binary classification model showed an overall accuracy of 80%. The precision, recall, and F1-scores for each class (0 and 1) were calculated. For class 0, the model showed a precision of 0.82, a recall of 0.85, and an F1-score of 0.83, indicating that the model identified class 0 with fewer false positives. For class 1, the model's precision, recall, and F1-score were 0.77, 0.73, and 0.75, respectively, indicating the need for model improvement to identify class 1 more accurately (Table 8). The unweighted mean for all classes showed a balanced performance, whereas the weighted average indicated an overall accuracy of 0.80. The model classified areas that necessitated technology introduction.

6. Discussion

6.1 Perceived effectiveness of ML in governance

The mean score for the perceived effectiveness of ML in governance was 4.1782, which showed a positive perception of the respondents. Rural environmental governance can be enhanced through accurate and efficient decision-making based on vast amounts of data.[28] The lack of significant correlation with technological availability, stakeholder engagement, and

Table 4
Descriptive statistics of survey results.

Item	N	Minimum score	Maximum score	Mean	Standard deviation (SD)
Perceived effectiveness of ML in governance	101	3.00	4.80	4.1782	0.36100
Technological availability	101	2.40	5.00	4.1149	0.42459
Stakeholder engagement	101	2.80	5.00	4.0277	0.42805
Environmental sustainability	101	2.20	4.80	3.9228	0.49797
Valid N (listwise)	101				

Table 5
Correlation between scores of variables in questionnaire survey.

Item		Perceived effectiveness of ML in governance	Technological availability	Stakeholder engagement	Environmental sustainability
Perceived effectiveness of ML in governance	Pearson correlation	1	0.061	−0.066	−0.118
	2-tailed significance		0.546	0.512	0.238
	N	101	101	101	101
Technological availability	Pearson correlation	0.061	1	0.002	0.003
	2-tailed significance	0.546		0.983	0.979
	N	101	101	101	101
Stakeholder engagement	Pearson correlation	−0.066	0.002	1	0.123
	2-tailed significance	0.512	0.983		0.221
	N	101	101	101	101
Environmental sustainability	Pearson correlation	−0.118	0.003	0.123	1
	2-tailed significance	0.238	0.979	0.221	
	N	101	101	101	101

Table 6
ANOVA results of survey.

Model parameter		Sum of squares	Degree of freedom	Mean square	F	Significance
	Regression	0.267	3	0.089	0.676	0.569[b]
1	Residual	12.765	97	0.132		
	Total	13.032	100			

a. Dependent variable: perceived effectiveness of ML in governance
b. Predictors: (constant), technological availability, stakeholder engagement, and environmental sustainability

Table 7
Regression model summary.

Model	R	R^2	Adjusted R^2	Standard error of estimate
1	0.143[a]	0.020	−0.010	0.36277

a. Predictors: (constant), technological availability, stakeholder engagement, and environmental sustainability

Table 8
Results of binary classification.

Class	Precision	Recall	F1-score	Support
0	0.82	0.85	0.83	105
1	0.77	0.73	0.75	74
Accuracy			0.8	179
Macro average	0.79	0.79	0.79	179
Weighted average	0.80	0.8	0.8	179

environmental sustainability indicated that the effectiveness of ML in governance was perceived but not translated into environmental impacts. Further study is necessary to elucidate the effects of ML on governance by conducting case studies. The perception of the effectiveness of ML in governance also indicated the need for stakeholders to have adequate technological literacy and capacity. To integrate advanced technology such as ML, infrastructure and skilled manpower must be ensured.[29] Therefore, training and capacity-building programs must be provided to effectively harness the benefits of ML in the governance system.

6.2 Technological availability

Technological availability scored 4.1149, showing that respondents were moderately satisfied with the availability of the technological infrastructure. However, the absence of a robust correlation between technological availability and the perceived effectiveness of ML suggested that infrastructure alone cannot enhance governance outcomes. Technology does not guarantee its effective use; instead, appropriate policies and practices are required to introduce advanced technologies in governance processes.[30] Sophisticated strategies for technology adoption are essential for organizations. The moderate rating for technological availability also revealed persistent problems in rural areas, including limited connectivity and computing resources. Many rural areas face challenges in adopting technology owing to insufficient infrastructure, which undermines the effectiveness of implementing advanced technologies.[31] Infrastructure barriers also need to be addressed so that advanced technologies can be adopted in rural environmental governance, which is constrained by resource availability.

6.3 Stakeholder engagement

Stakeholder engagement scored 4.0277, suggesting that respondents were relatively engaged in technology introduction and usage. Stakeholder participation and environmental sustainability were negatively correlated, which indicated that increased participation resulted in positive environmental outcomes. For inclusive governance and sustainable development, stakeholder engagement is essential to construct a governance system with integrative approaches and societal actors.[2] Active stakeholder engagement enables inclusive governance processes. Digital technologies increase the participation of stakeholders by providing new, low-cost means of sharing and interacting.[29] While stakeholder engagement is necessary, there must be an effective framework to transform the engagement into action. The framework must reflect the difficulties associated with achieving sustainability goals through active engagement and the necessity for holistic methods that encourage technological, social, and environmental engagement.

6.4 Environmental sustainability

The mean score for environmental sustainability was 3.9228, indicating a comparatively lower level of satisfaction than other assessed variables. Although respondents perceived ML as effective in governance, their perception did not show a statistically significant association with their recognition of environmental sustainability. Nonetheless, integrating ML into environmental governance remains essential. ML offers potential to enhance environmental sustainability by supporting predictive analytics and evidence-based policymaking aimed at fostering positive environmental outcomes. Environmental sustainability is intrinsically linked to rural sustainable development, which faces challenges such as limited institutional and financial capacity, geographic dispersion, and complex socio-ecological dynamics. Consequently, technological innovation is imperative to strengthen environmental stewardship and improve governance frameworks, particularly by addressing the technological and socio-environmental dimensions unique to rural contexts.

6.5 Comparison with traditional governance

A significant difference is observed between governance systems with advanced technologies and those relying on traditional methods (Table 9). Traditional governance employs a manual analysis of data. Decisions are made in response to existing problems, rather than predicting issues and developing proactive solutions. Unlike traditional governance, automated processes such as predictive analytics and proactive decision-making are used in governance with advanced technologies. The latter enables timely and effective responses to diverse environmental issues. For more stakeholders to participate in the governance process, transparency and inclusivity must be guaranteed. Governance with advanced technologies is based on adaptability to solve environmental problems, which is vital in the complex and dynamic rural ecosystem. Advanced technologies result in effective and efficient environmental governance. The advantages and disadvantages of various ML models must be considered to apply them also to rural environmental governance (Table 10).

7. Challenges and Recommendations

ML algorithms can be used for monitoring and managing the environment in rural areas. To use them effectively, technological infrastructure, which includes reliable internet access and adequate computing facilities, is required. Data quality also affects the prediction accuracy of ML algorithms.[32] The algorithms depend on high-quality, multi-faceted datasets for learning and predicting environmental parameters. The scarcity of human resources also affects the proliferation of ML algorithms.[33] In using big data for ML algorithms, ethical and privacy issues must be considered, and the transparency and the fairness of governance must also be ensured.[34] Well-defined goals for using ML algorithms are mandated for making appropriate policies to protect the environment. Stakeholders' reluctance to adopt technology must be addressed to enhance their participation in governance processes.

To effectively incorporate ML into rural environmental governance, significant investment in technological infrastructure is required. Rural governments must enhance IT facilities for reliable internet access and adequate computing equipment. Governance effectiveness is needed through administrative cost savings for effective environmental management. The quality of

Table 9
Comparison of traditional governance and governance with advanced technologies.

Item	Traditional governance	Governance with technologies
Data analysis	Manual, periodic, limited scope	Automated, real-time, comprehensive
Decision-making	Reactive, based on historical data	Proactive, data-driven, predictive
Stakeholder engagement	Limited participation, hierarchical	Inclusive, participatory, digital platforms
Environmental monitoring	Manual, localized, infrequent	Automated, widespread, continuous
Adaptability	Slow response to changes	Rapid adaptation to environmental shifts

Table 10
Comparison of ML models.

Classification Model	Advantage	Disadvantage
Logistic regression	Probabilistic approach and information about the statistical significance of features	Logistic regression assumptions must be met and nonlinear relationships exist.
KNN	Simple to understand, fast and efficient for small datasets	The number of neighbors, k, must be chosen, and large datasets are computationally costly.
SVM	Performant, not biased by outliers, not sensitive to overfitting	Nonlinear problems are not solved, and the large number of features is not appropriate.
Kernel SVM	High performance on nonlinear problems, not biased by outliers, not sensitive to overfitting	The large number of features is not appropriate, and the process is complex, computationally intensive.
Naïve Bayes	Efficient, not biased by outliers, works on nonlinear problems, probabilistic approach	Features need to have the same statistical relevance and be independent.
Decision tree	Interpretability, no need for feature scaling, works on both linear/nonlinear problems	Poor results are obtained on small datasets, and overfitting easily occurs.
Random forest	Powerful and accurate, good performance on many problems, including nonlinear ones	Interpretability is limited, overfitting occurs, and the number of trees must be set.
Gradient boosting	High accuracy, different types of features , robust to outliers	Overfitting occurs, and high computation cost and sensitivity to hyperparameters are observed.
XGBoost	Great performance, regularization to prevent overfitting and handle missing values	Tuning is complex, and computation is intensive and less interpretable.

data must also be enhanced by ensuring the efficiency of data collection, integration, and data management. Remote sensing can be used to efficiently collect data. Training programs are also required to educate stakeholders to acquire analytical skills using ML algorithms to provide important information for informed decision-making.

8. Conclusion

We explored the application of advanced technologies, including ML and sensor technology, to enhance decision-making in rural environmental governance, stakeholder engagement, and sustainability. The stakeholders showed a positive perception of using ML and sensor data for governance, albeit the impacts on environmental sustainability remain complex and contextually bound. Technological infrastructure, stakeholder engagement, and environmental sustainability can be enhanced with ML applications. However, appropriate infrastructure and data quality must be ensured to use ML applications as a viable opportunity to develop flexible, participatory, and responsive rural governance systems for environmental issues.

While ML based on sensor data holds promise for improving rural governance, its integration must be accompanied by robust technological infrastructure and effective stakeholder engagement. The study's findings confirm that the primary utility of ML technologies in this context lies in their capacity to handle big data generated by IoT and remote sensing systems. The low-cost, high-resolution data provided by new sensor materials and WSN architectures are the essential ingredient or material that fuels the predictive and analytical power of ML algorithms. By reviewing the theoretical aspects and the difficulties of implementing ML in rural environmental governance, the results of this study provide a basis for policymakers and practitioners to use ML for sustainable rural development. The relationship between technology perception, stakeholder engagement, and environmental sustainability can be used to guide the use of ML in infrastructure improvements, capacity building, ethical consideration, and participatory processes in rural environmental governance. The role of technological innovation and its impact on environmental governance in rural areas for sustainable and environmental development must be further researched. The rural governance system needs to be more robust and sustainable by integrating advanced technologies, including ML, to realize the sustainable development of rural areas. Future research must, therefore, explicitly link the development of new, high-performance sensing materials to the advancement of ML models, as the governance outcomes are ultimately limited by the quality of the data collected at the environmental front-line.

Acknowledgments

This research was supported by 2025 Jilin Provincial Higher Education Scientific Research Project: Study on the Long-term Mechanism of Agricultural-related Universities in Jilin Province Serving the Comprehensive Rural Revitalization (Project Number: JGJX25C187).

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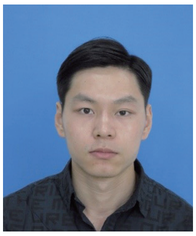

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