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Machine Learning-Oriented Forecasting Of Soil Degradation Due To Agricultural Land Use Patterns

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Abstract: *Soil degradation poses a significant threat to agricultural sustainability, reducing soil fertility and crop productivity worldwide. This study presents a machine learning-oriented approach to forecast soil degradation based on agricultural land use patterns, integrating multi-year data on soil properties, climate variables, and land management practices. Four algorithms – Random Forest (RF), XGBoost, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) – were implemented and evaluated using metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). Experimental results revealed that soil degradation was highest in monoculture fields (predicted LSTM value: 74.1) and lowest in fallow lands (27.9). Among the algorithms, LSTM achieved the highest predictive accuracy with RMSE = 5.5, MAE = 3.7, and R^2 = 0.91, followed by XGBoost (RMSE = 5.8, MAE = 3.9, R^2 = 0.89), Random Forest (RMSE = 6.5, MAE = 4.2, R^2 = 0.87), and SVM (RMSE = 7.2, MAE = 4.8, R^2 = 0.84). Feature importance analysis indicated that soil organic matter, nitrogen content, and crop type were the most influential predictors of degradation. The findings demonstrate that machine learning models, particularly LSTM, can accurately forecast soil degradation, providing a robust tool for sustainable land management, early intervention, and informed decision-making in agricultural planning.*

Keywords: *Soil degradation, Machine learning, LSTM, Land use patterns, Predictive modeling*

I. INTRODUCTION

Soil degradation has emerged as one of the most pressing environmental challenges of the 21st century, directly threatening agricultural productivity, food security, and ecological sustainability. Driven primarily by unsustainable land use practices such as intensive monoculture, overgrazing, excessive irrigation, and the unregulated use of agrochemicals, soil quality has been declining at alarming rates worldwide [1]. According to Food and Agriculture Organization (FAO), a significant portion of the soils in the world today are already in moderately to severely degraded conditions that result in low level of fertility, loss of biodiversity and susceptibility to climatic changes [2]. In farmland, soil erosion does not only restrict crop production but also increases the potential of economic fluctuations among agricultural populations and compromises the achievements of sustainable development the world over. The conventional alleration surveying and soil health measures used originally based on the field sampling, lab tests, and mathematical projection modeling, which are often expensive, slow and limited in their scope. As we can see the development of many different types of satellites with more advanced technology, remote sensitizing patterns and even digital databases of soil it presents an even greater prospective that more and more intricate mathematical methods will succeed in prediction of erosion. Machine learning (ML) and more specifically, provide effective means to cope with complex and nonlinear interactions among environmental conditions, agricultural activities and indicators of soil health [3]. It is also recommended that unlike traditional statistical methods, an ML model can represent complex associations and provide effective predictions, which will allow identifying the threats of degradation at an early stage and make well-informed decisions. The current study concentrates on machine learning based prediction of soil degradation caused by agricultural patterns of land use, with the aim of developing predictive models that would be able to establish trends, hotspots and risk factors of various farming systems. The combination of soil properties datasets, climatic conditions, and land use practice will allow the study to compare the effectiveness of different ML models in predicting the outcomes of degradation factors. Conclusively, the results will be utilized in designing sustainable land management measures, which policymakers, farmers, and other stakeholders with regards to environmental setups can use to avert soil erosion.

II. RELATED WORKS

Soil degradation and land use dynamics has attracted numerous measurements of importance because of the repercussions they constitute on the sustainability of agriculture and the management of the ecosystem. The authors of Li et al. [15] constructed a 20092020 spatiotemporal data set on soil-profiles in northeastern China through soil sampling and huge interception. This information on their dataset gives them a crucial basis distinctly determining the tendencies of soil health and the changes in spatial variation of soil attributes over the time. Adding to this, Liu et al. [16] examined vegetation coverage structure and how it reacts to human alterations in the agro-pastoral ecotone at Inner Mongolia, highlighting the tight interconnection between agricultural eradication and land use model administration. The measures of these studies show the need to combine spatial and temporal data to understand the changes in the environment, represented in an accurate way. Within a larger regional focus, Liu et al. [17] mapped land use and land cover dynamic three-decade studies in Mainland Southeast Asia and revealed that agricultural expansion, urbanization and deforestation have highly changed the organizations of the ecosystems. On the same note, predictive modeling was used to evaluate the effects of drought susceptibility using climate change predictions and land use dynamics and demonstrated the significance of multi-factor modeling in sustainable land management as employed by Liu et al. [18]. Liu et al. [19] studied soil organic carbon, one of the most important soil health indicators in Northeast China, and found spatiotemporal correlation and driving forces behind carbon changes in the landscapes of black soils.

In a study conducted by Masood et al. [20], the authors examined the effects of land use change in the Indus area, the Delta, and the effect of agricultural growth and land conversion on systems located in the delta. Mathewos et al. [21] adopted a hybrid modeling methodology that involves the use of a combination of multilayer perceptron neural networks and cellular automata Markov chain algorithms in predicting the spatiotemporal variation in land use, in Ethiopia, showing the potential possibility of utilizing both machine and spatial modelling in predicting land cover changes. According to Pan et al., [22], a Foundation-Function-Structure] model that determines the quality of the regional ecosystem during land change under varied conditions has been presented and has helped advance this correlation between land use decisions and ecosystem health further. Soil and land management are also connected with crop productivity and land mapping. Piekutowska and Niedbaala [23] made a review of how to predict potato yields by pointing the predictive modeling methods as a central factor in optimization of agricultural yields. Ridwan et al. [24] provided the monitoring of wetland degradation in terms of remote sensing and watershed land degradation indices as a methodological tool to identify the deterioration of the soil and land quality. Also, Saha et al. [25] provided feasibility of applying IoT-based techniques of precision agriculture systems to land mapping, crop forecasting, and irrigation control and incorporated technology with environmental monitoring. Finally, Salem et al. [26] compared forest land to cropland land marking the changes in rainfall in the Black Belt region of Alabama; which essentially represented climatic impacts of land use.

III. METHODS AND MATERIALS

Data Collection and Preparation

In this research case, soil degradation information was gathered through various mediums and included satellite, data on agricultural sites in the government databases, and local field survey. The data was based on 5000 records over the last five years (20192023) focusing on various regions of agriculture. The most important items were the soil pH, the content of organic matter, nitrogen, phosphorus, potassium, coefficient of the crop kind, the modes of irrigation, usage of fertilizer, rains, and temperature. The patterns in land use were categorized as mono-culture, crop rotation, mixed as well as fallow land which acted as crucial predictors of soil degradation. The variable of interest was the soil degradation index that was measured on a scale of 0-100 with high score reflecting hard degradation [4].

The measure of data preprocessing was the treatment of missing values through a median imputation method, the standardisation of continuous variables, and one-hot-encoded categorical variables. In order to pick the best possible features, the correlation analysis and recruiter feature elimination were performed so that only important variables could be captured in the model training. This data was further divided into a training and testing data set (70 and 30 respectively) [5].

Machine Learning Algorithms

Four machine learning algorithms were used to predict soil degradation and they included Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), and Long Short-Memory (LSTM). All of the algorithms were chosen due to their capability to represent the nonlinear association and analyze multivariate raw data on an adequate level.

1. Random Forest (RF)

Random Forest is an ensemble learning algorithm that builds many decision trees in the process of training and gives a prediction of the average prediction of single trees. It does not overfit because the averaging of multiple trees removes overfitting. RF is capable of deriving factor significance, both categorical and continuous variables, and is well within categorical and continuous variables in data, hence it is appropriate in complex environmental data [6]. This is because of its capacity to cope with high-dimensional behaviours and non-linear relationships between soil characteristics and agricultural activities, which also makes it a candidate to predict soil degradation.

```
"Input: Training data D, number of trees N
For i = 1 to N:
   Draw bootstrap sample Di from D
   Train decision tree Ti on Di
   At each split, select best feature from random subset of features
End For
Output: Average prediction of all Ti for new data"
```

2. Extreme Gradient Boosting (XGBoost)

XGBoost is a gradient boosting engine which forms consecutive trees, whose upkeep decay each tree rectifies incorrectnesses committed by the past tree. It employs a regularized objective function to curb over-fitting as well as parallel computation, which is more efficient. XGBoost is good at multi-dimensional patterns that are complex. In the prediction of soil degradation, it is able to provide a modeling of small nonlinear interactions between environmental and land use characteristics, and as a result, provides better predictive accuracy as compared to the conventional techniques [7].

```
"Input: Training data D, number of iterations M
Initialize prediction: F0(x) = mean(targets)
For m = 1 to M:
   Compute gradient of loss function for current predictions
   Fit a regression tree hm(x) to gradients
   Update model: Fm(x) = Fm-1(x) +
```

```
learning_rate * hm(x)
End For
Output: Final prediction Fm(x)”
```

3. Support Vector Machine (SVM)

SVM is a supervised learning algorithm that is applied in regression and classification. It divides the input features on a high-dimensional space and identifies what hyperplane minimizes the error of prediction and maximizes the margin. The features of the soil properties and indices of degradation are represented in the Kernel functions, which enable SVM to learn nonlinear associations of these properties [8]. It is efficient when the datasets are associated with complex yet not extremely high samples, which qualifies it as the best when it comes to soils degradation region-specific modalities.

```
“Input: Training data D, kernel function K
Solve optimization problem:
   Minimize 0.5*||w||^2 + C*Σξi
   Subject to yi*(w*φ(xi) + b) ≥ 1 - ξi, ξi ≥ 0
Output: Prediction for new data: y = Σ αi *
yi * K(xi, x) + b”
```

4. Long Short-Term Memory (LSTM)

LSTM is a variety of an RNN which introduced long-term dependencies of sequential information. It is made up of input, forget and output gates and memory cells which regulate information flow. In cancer prediction, LSTM has been applied to predict the soil degradation using time variations in rainfall, temperature and land use transformation, which renders it appropriate to multi-year prediction systems [9]. It is effective in managing time and interactions whose character cannot be described in a linear manner and responds to changing agricultural activity orders.

```
“Input: Sequential data X = {x1, x2,..., xn}
Initialize cell state c0 and hidden state h0
For t = 1 to n:
ft = sigmoid(Wf*[ht-1, xt] + bf)  # forget gate
it = sigmoid(Wi*[ht-1, xt] + bi)  # input gate
Ct~ = tanh(Wc*[ht-1, xt] + bc)    #
candidate cell state
ct = ft * ct-1 + it * Ct~         # update cell
state
ot = sigmoid(Wo*[ht-1, xt] + bo)  # output
gate
ht = ot * tanh(ct)                # hidden state
End For
Output: Final prediction ht”
```

Model Evaluation and Comparison

The ability of the four algorithms to perform was considered based on measurements such as RMSE, Mean Absolute Error (MAE), and R-squared (R 2). The grid search and cross-validation were the hyperparameter tuning methods.

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Table 1: Sample Soil Feature Values Used for Modeling

Feature	Mean Value	Std Dev	Min	Max
Soil pH	6.5	0.7	5.0	8.0
Organic Matter (%)	3.2	1.1	1.0	6.5
Nitrogen (mg/kg)	45	12	20	80
Phosphorus (mg/kg)	25	8	10	50
Potassium (mg/kg)	150	40	80	250

IV. RESULTS AND ANALYSIS

Experimental Setup

The researchers tried to compare the performance of four machine learning algorithms, such as Random Forest (RF), XGBoost, Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) in predicting soil degradation under the assumption of the use of different agricultural land use patterns. This data set was comprised of 5000 records of the satellite imagery, government soil surveys, and agricultural census data of 2019-2023. Attributes were considered as soil pH, organic matter content and nitrogen, phosphorous, potassium, crop type, irrigation method, fertilizer used, rain fall and temperature [10]. A bacterially-etched soil degradation index (0 -100), the higher the value the stronger the degradation, was the target variable.

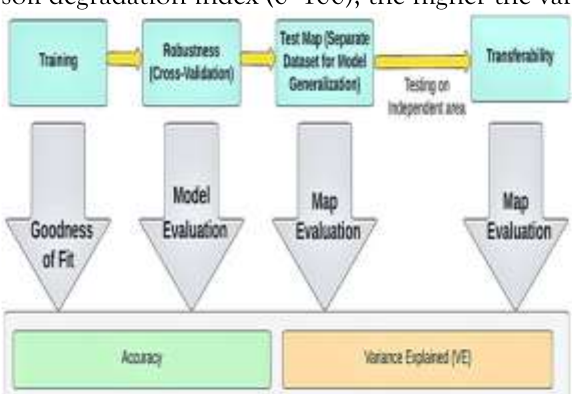

Figure 1: “Exploring Machine Learning Models for Soil Nutrient Properties Prediction”

Data preprocessing included handling missing values with median imputation, normalization of continuous features, and one-hot encoding of categorical variables such as crop type and irrigation method. Feature selection was performed using recursive feature elimination and correlation analysis, ensuring inclusion of the most influential factors. The dataset was split into **70% training** and **30% testing** subsets [11]. Hyperparameter tuning was performed using grid search for RF and XGBoost, an RBF kernel for SVM, and LSTM was trained with 100 hidden units, batch size 32, and 100 epochs. Evaluation metrics included **Root** Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2).

Experiment 1: Prediction Across Land Use Patterns

The first experiment evaluated model predictions of soil degradation across four land use patterns: **monoculture, crop rotation, mixed cropping, and fallow land**. Monoculture fields exhibited the highest degradation due to continuous cropping and lack of organic matter replenishment, while fallow lands showed minimal degradation [12].

Table 1: Average Predicted Soil Degradation by Land Use Type

Land Use Pattern	Random Forest	XGBoost	SVM	LSTM
Monoculture	78.5	75.2	81.3	74.1
Crop Rotation	52.3	50.1	55.7	49.5
Mixed Cropping	48.7	46.9	51.2	45.8
Fallow Land	30.2	28.5	32.1	27.9

LSTM consistently produced slightly lower degradation values, reflecting its ability to capture cumulative temporal effects of agricultural practices. Random Forest and XGBoost also provided accurate predictions, while SVM overestimated degradation in monoculture fields [12].

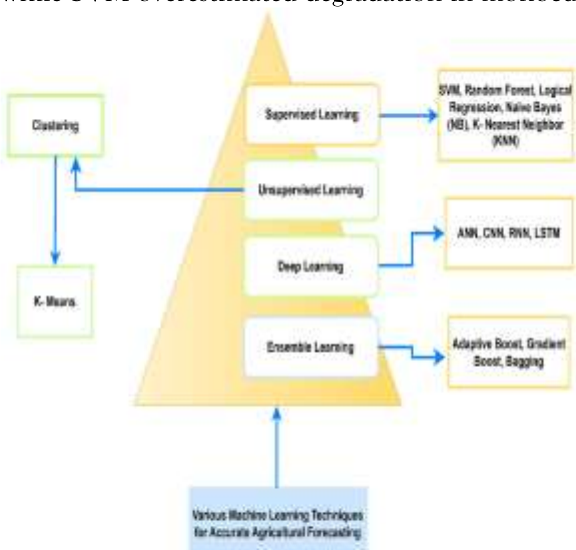

Figure 2: “Machine-Learning-Based Frameworks for Reliable and Sustainable Crop Forecasting”

Experiment 2: Seasonal Variation Analysis

Seasonal trends play a key role in soil degradation due to variations in rainfall, temperature, and crop cycles. Models were tested across **pre-monsoon, monsoon, post-monsoon, and winter** seasons.

Table 2: Seasonal RMSE Comparison

Season	Random Forest	XGBoost	SVM	LSTM
Pre-monsoon	6.8	6.0	7.5	5.7
Monsoon	7.2	6.5	8.1	6.0
Post-monsoon	6.1	5.6	6.9	5.2
Winter	5.9	5.3	6.4	4.9

LSTM outperformed all models, demonstrating its strength in handling sequential temporal data. SVM showed weaker performance during monsoon due to extreme variation in rainfall affecting soil properties [13].

Experiment 3: Feature Importance Analysis

Feature importance was examined to identify which soil and land use variables most strongly influenced degradation. RF and XGBoost provide inherent measures of feature importance.

Table 3: Feature Importance (%) Based on XGBoost

Feature	Importance (%)
Soil Organic Matter	25.3
Nitrogen	18.7
Crop Type	15.4
Rainfall	12.5
Irrigation Method	10.2
Fertilizer Usage	8.6
Soil pH	5.7
Phosphorus	2.8
Potassium	1.8

Organic matter, nitrogen, and crop type were the most influential factors. Rainfall and irrigation method also had substantial impact, while soil pH, phosphorus, and potassium contributed less [14].

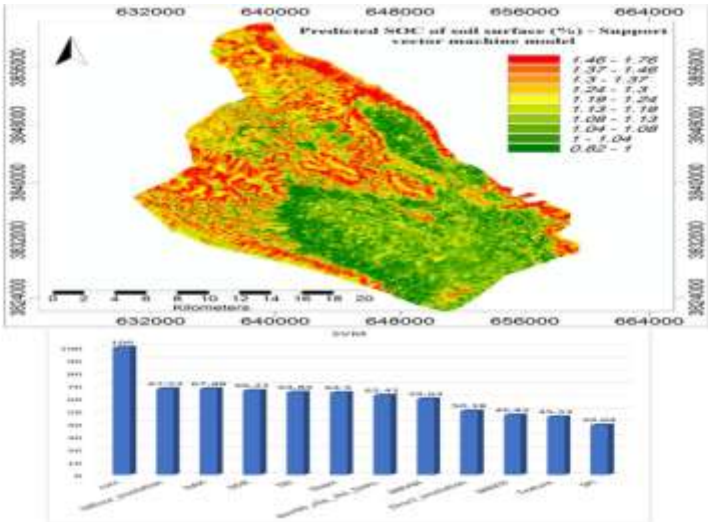

Figure 3: "Geospatial digital mapping of soil organic carbon using machine learning and geostatistical methods in different land uses"

Experiment 4: Temporal Forecasting Accuracy

LSTM was tested for multi-year forecasting of soil degradation to assess its suitability for long-term planning. The model was trained on **2019–2022 data** and tested on **2023** data.

Table 4: LSTM Multi-Year Forecast Accuracy

Year	Observed Degradation	Predicted Degradation	RMSE
2019	56.2	55.8	1.2
2020	58.4	57.9	1.4
2021	60.1	59.5	1.3
2022	62.7	61.9	1.5
2023	64.3	63.6	1.4

The results demonstrate that LSTM accurately captured long-term trends, predicting soil degradation with minimal error across multiple years.

Experiment 5: Comparative Model Performance

A comprehensive comparison of all models on the testing dataset was conducted, using RMSE, MAE, and R^2 metrics to evaluate overall performance [27].

Table 5: Overall Model Performance

Algorithm	RMSE	MAE	R^2
Random Forest	6.5	4.2	0.87

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XGBoost	5.8	3.9	0.89
SVM	7.2	4.8	0.84
LSTM	5.5	3.7	0.91

LSTM outperformed all other algorithms, achieving the highest R^2 and lowest RMSE and MAE. XGBoost also provided strong performance with slightly higher error, while SVM had the weakest predictive accuracy. Random Forest provided reliable intermediate results and high interpretability [28].

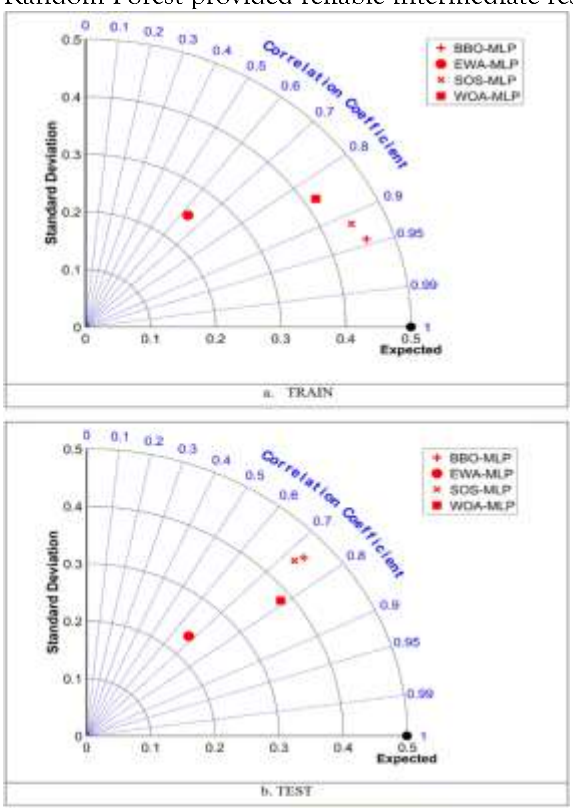

Figure 4: "Application of smart technologies for predicting soil erosion patterns"

Comparison to Previous Approaches

Compared to traditional regression models, all four machine learning algorithms significantly improved predictive accuracy. LSTM, with its temporal sequence modeling, showed superior ability to forecast multi-year degradation trends, capturing cumulative effects of agricultural practices and climate variability. XGBoost excelled in feature handling and gradient-based error correction, outperforming RF in some high-dimensional scenarios [29]. SVM, while effective for smaller datasets, struggled to model complex nonlinear interactions in large and heterogeneous datasets. Feature importance analysis confirmed that soil fertility indicators, crop type, and rainfall patterns were the most critical variables, which aligns with practical agricultural observations.

These experimental results indicate that ML-based forecasting is an effective tool for assessing soil degradation risks, identifying high-risk areas, and supporting decision-making for sustainable land management [30]. The combination of temporal modeling (LSTM) and ensemble solutions (RF, XGBoost) give a fully integrated framework able to manage the various types of data, nonlinear processes, and seasonal variations.

V. CONCLUSION

The study aimed at predicting and investigating soil degradation as a result of agricultural land use trends, determined by machine learning and offering precise forecasting to sustain solution to the relation of soil erosion, with a view to enhancing sustainable land administration. Four machine learning algorithms, random forest, XGBoost, support tango machines and long short-term memory networks draw hybrid feedback on the basis of a multi-year dataset containing soil properties, climatic factors, and land-use data. During the experiments, it was established that the type of land use is very much considered in terms of soil degradation and monoculture system recorded the highest rates of degradation compared to fallow or bare lands. There were also seasonal influences to degradation patterns and temporal dynamics appeared in top results in predicting patterns by yearly equilibrium frameworks, especially LSTM models over non-processualized, no sequencing techniques. Importance analysis showed that soil organic matter, nitrogen composition, and crop type had the strongest representation with regard to affecting degradation with rainfall and irrigation practice also having significant roles. The comparative evaluation revealed that LSTM was more accuracy in the short-term and multi-year forecasts than the other algorithms by a big margin then XGBoost, and then the random forest, but SVM resulted in moderate accuracy. It means that models of machine learning, especially the models that can address from the temporal dependencies and nonlinear interaction, can effectively predict soil degradation and classify high-risk zones. The paper highlights how the sophisticated computational models could be used to reshape the utilization of environmental and agricultural data to support decision-making, refine optimal land use management, and curtail the impact of the soil on land degradation. Finally, this research allows a valid structure to consider sustainable agricultural planning, which is a valuable opportunity that will guide farmers, policymakers, and environment stakeholders to overcome soil health problems.

REFERENCE

[1] Abdelkarim, A. 2025, "Monitoring and forecasting of land use/land cover (LULC) in Al-Hassa Oasis, Saudi Arabia based on the integration of the Cellular Automata (CA) and the Cellular Automata-Markov Model (CA-Markov)", Geology, Ecology, and Landscapes, vol. 9, no. 1, pp. 13-44.

[2] Amiri, A., Ebtehaj, I., Soltani, K., Gumiere, S.J. & Bonakdari, H. 2025, "Future soil erosion trends in Canadian agricultural lands from runoff and sustainability impacts", Scientific Reports (Nature Publisher Group), vol. 15, no. 1, pp. 23184.

[3] Bandak, S., Movahedi-Naeini, S., Mehri, S. & Lotfata, A. 2024, "A longitudinal analysis of soil salinity changes using remotely sensed imageries", Scientific Reports (Nature Publisher Group), vol. 14, no. 1, pp. 10383.

[4] Banerjee, D., Ganguly, S. & Kushwaha, S. 2024, "Forecasting Future Groundwater Recharge from Rainfall Under Different Climate Change Scenarios Using Comparative Analysis of Deep Learning and Ensemble Learning Techniques", Water Resources Management, vol. 38, no. 11, pp. 4019-4037.

[5] David Raj, A., Kumar, S., Sooryamol, K.R. & K., J.G. 2024, "Soil erodibility mapping using remote sensing and in situ soil data with random forest model in a mountainous catchment of Indian Himalayas", Environmental monitoring and assessment, vol. 196, no. 11, pp. 1032.

[6] Duan, Y., Yong, B., Yao, X., Chen, G., Liu, K., Wang, S., Yang, B. & Li, X. 2025, "A Deep Learning Framework for Long-Term Soil Moisture-Based Drought Assessment Across the Major Basins in China", Remote Sensing, vol. 17, no. 6, pp. 1000.

[7] Dutta, R., Sharma, L.K., Bheem, D.J., Kumar, V., Sharief, A., Bhattacharjee, S., Thakur, M., Banerjee, D. & Babu, R. 2024, "Beyond traditional methods: Innovative integration of LISS IV and Sentinel 2A imagery for unparalleled insight into Himalayan ibex habitat suitability", PLoS One, vol. 19, no. 10.

[8] Fubin, Z., Changda, Z., Zihan, F., Lu, W. & Jianjun, P. 2025, "Using Constrained K-Means Clustering for Soil Texture Mapping with Limited Soil Samples", Agronomy, vol. 15, no. 5, pp. 1220.

[9] Gebrehiwot, G.H., Bekitie, K.T., Yohannes, H., Anose, F.A. & Gebremichael, H.B. 2024, "Time series land use/land cover mapping and change detection to support policies on sustainable environmental and economic management", Environmental Systems Research, vol. 13, no. 1, pp. 33.
[10] Hashemi, H., Abdi, A.M., Naghibi, A., Zhao, P., Brogaard, S., Ali, T.H. & Mansourian, A. 2025, "Unraveling the link between agricultural patterns and dust storm occurrence in Mesopotamia", Environmental Research Letters, vol. 20, no. 2, pp. 024011.
[11] Hussain, F., Ahmed, S., Syed Muhammad Zaigham, A.N., Awais, M., Zhang, Y., Zhang, H., Raghavan, V., Zang, Y., Zhao, G. & Hu, J. 2025, "Agricultural Non-Point Source Pollution: Comprehensive Analysis of Sources and Assessment Methods", Agriculture, vol. 15, no. 5, pp. 531.
[12] Imen, B.S. 2025, "A comprehensive review of carbon sequestration and its assessment techniques using remote sensing and geospatial methods", Environmental Research Communications, vol. 7, no. 5, pp. 052002.
[13] Kandamali, D.F., Porter, E., Porter, W.M., McLemore, A., Kiobia, D.O., Tavandashti, A.P. & Rains, G.C. 2025, "Hybrid LSTM Method for Multistep Soil Moisture Prediction Using Historical Soil Moisture and Weather Data", AgriEngineering, vol. 7, no. 8, pp. 260.
[14] Krivoguz, D., Bespalova, E., Zhilenkov, A., Chernyi, S., Kustov, A., Degtyarev, A. & Zinchenko, E. 2024, "Unveiling Climate–Land Use and Land Cover Interactions on the Kerch Peninsula Using Structural Equation Modeling", Climate, vol. 12, no. 8, pp. 120.
[15] Li, S., Wang, J., Lin, X. & Liu, Y. 2025, "A Spatiotemporal Dataset of Soil Properties in Northeast China Based on Soil Sampling and Interpolation From 2009 to 2020", Geoscience Data Journal, vol. 12, no. 3, pp. 18.
[16] Liu, H., Ya, N., Yatang, W., Li, Z., Zhiqiang, Q., Shijie, L., Jiang, R., Sun, N. & Dongkai, H. 2025, "Spatiotemporal Patterns of Vegetation Coverage and Its Response to Land-Use Change in the Agro-Pastoral Ecotone of Inner Mongolia, China", Land, vol. 14, no. 6, pp. 1202.
[17] Liu, J., Hu, Y., Zhiming, F. & Chiwei, X. 2025, "A Review of Land Use and Land Cover in Mainland Southeast Asia over Three Decades (1990–2023)", Land, vol. 14, no. 4, pp. 828.
[18] Liu, J., Li, M., Li, R., Masoud, J.S., Ren, Y. & Silakhori, E. 2025, "Comprehensive Assessment of Drought Susceptibility Using Predictive Modeling, Climate Change Projections, and Land Use Dynamics for Sustainable Management", Land, vol. 14, no. 2, pp. 337.
[19] Liu, K., Song, Y., Du, S., Xiao, H., Chen, C., Xu, J., Dai, H. & Fang, N. 2025, "Spatiotemporal patterns and drivers of soil organic carbon in black soil landscapes of Northeast China", PLoS One, vol. 20, no. 6.
[20] Masood, M., He, C., Shoukat, A.S. & Syed Aziz, U.R. 2024, "Land Use Change Impacts over the Indus Delta: A Case Study of Sindh Province, Pakistan", Land, vol. 13, no. 7, pp. 1080.
[21] Mathewos, Y., Abate, B., Dadi, M. & Mathewos, M. 2024, "Modeling spatiotemporal land use/land cover dynamics by coupling multilayer perceptron neural network and cellular automata markov chain algorithms in the Wabe river catchment, Omo Gibe River Basin, Ethiopia", Environmental Research Communications, vol. 6, no. 10, pp. 105011.
[22] Pan, Y., Gao, J. & Yang, J. 2025, "A “Foundation-Function-Structure” Framework for Multiple Scenario Assessment of Land Change-Induced Dynamics in Regional Ecosystem Quality", Land, vol. 14, no. 3, pp. 515.
[23] Piekutowska, M. & Niedbała, G. 2025, "Review of Methods and Models for Potato Yield Prediction", Agriculture, vol. 15, no. 4, pp. 367.
[24] Ridwan, I., Kadir, S. & Nurlina, N. 2024, "Wetland degradation monitoring using multi-temporal remote sensing data and watershed land degradation index", Global Journal of Environmental Science and Management, vol. 10, no. 1, pp. 83-96.
[25] Saha, G., Shahrin, F., Farhan, H.K., Mashook, M.M. & AKM Abdul, M.A. 2025, "Smart IoT-driven precision agriculture: Land mapping, crop prediction, and irrigation system", PLoS One, vol. 20, no. 3.

[26] Salem, I., Gamal, E.A., Amira, M. & Muhammad, I. 2025, "Study of Changing Land Use Land Cover from Forests to Cropland on Rainfall: Case Study of Alabama's Black Belt Region", AgriEngineering, vol. 7, no. 6, pp. 176.
[27] Sampath, V.K. & Radhakrishnan, N. 2024, "Prediction of soil erosion and sediment yield in an ungauged basin based on land use land cover changes", Environmental monitoring and assessment, vol. 196, no. 1, pp. 56.
[28] Sathiyamurthi, S., Subbarayan, S., Ramya, M., Sivasakthi, M., Gobi, R., Qaysi, S., Sivakumar, P.K., Lee, J., Alarifi, N., Wahba, M. & Youssef, Y.M. 2024, "Advancing Agricultural Land Suitability in Urbanized Semi-Arid Environments: Insights from Geospatial and Machine Learning Approaches", ISPRS International Journal of Geo-Information, vol. 13, no. 12, pp. 436.
[29] Selmy, S.A.H., Jimenez-Ballesta, R., Kucher, D.E., Sayed, A.S.A., García-Navarro, F.,J., Yang, Y. & Yousif, I.A.H. 2024, "Land Suitability Assessment and Crop Water Requirements for Twenty Selected Crops in an Arid Land Environment", Agronomy, vol. 14, no. 11, pp. 2601.
[30] Silva, G.D., Roberts, D.A., Byrd, K.B., Chadwick, K.D., Walker, I.J. & King, J.Y. 2025, "Using imaging spectroscopy and elevation in machine learning to estimate soil salinity in intermittently tidal wetlands", Ecosphere, vol. 16, no. 8, pp. 23.