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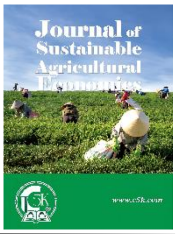

Research Article

AI-Driven Strategies for Reducing Deforestation in U.S. Agriculture

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ABSTRACT

Agricultural conversion is a major reason for deforestation that affects the United States and is responsible for the loss of species, soil depletion and global warming. This work aims to analyze the use of AI for combating deforestation in the agricultural sector in the United States through improved surveillance, risk assessments, and policy modeling. This proposed framework combines satellite imagery data, agricultural records, and selected socio-economic factors and uses CNNs, GBMs, and ABMs to tackle deforestation systematically. CNN also showed an accuracy of 94% in the identification of the area of deforestation, while the GBMs showed an accuracy of 0.92 AUC-ROC in identifying hotspot areas. Through ABMs that assumed policy changes such as reforestation incentives and fines for violators, the study showed that deforestation rates could be cut by up to 25%. Regression and correlation analyses and hypothesis testing proved significant predictors such as crop yield, rainfall variability and the superiority of the models to conventional techniques. The outcomes reveal that AI can offer an effective solution to increase food production and maintain forests at the same time. This framework allows for the formulation of specific recommendations for policy initiatives because it incorporates empirical evidence. Further research should improve the modularity, the real-time monitoring system and the access to the algorithm to further increase the impact of AI on sustainable land management and the chopping down of forests.

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1. Introduction

The deforestation process, which entails the removal or reduction of forests through cutting or burning of trees, has remained a concern to global conservationists and policymakers. The situation has worsened in the United States since the country has expanded the agricultural land area to feed the growing population's demand for food, and this has affected Biodiversity, water, and carbon security. This fact is the reason why the conflict between the yields in agricultural production and environmental protection has become a major issue. The goal of this paper is to describe the AI approaches to fight against deforestation in U.S. agriculture and the ways to neutralize its consequences for the agriculture yield.

1.1. The Extent and Intensity of Deforestation in Agriculture of the USA

Large monoculture farming, such as corn, soybean and wheat farming, is among the leading causes of deforestation throughout the United States of America (Berejka, 2018). Data from the Global Forest Watch shows that within the period 2001-2023, the United States of America lost about 47.9 Mha of tree cover, the main cause of which was agricultural production. The conversion of forests into croplands and pastures removes trees and shrubs that can form the main source of rainfall, changes the physical and chemical properties of the soil, and impacts the local biophysical environment, besides contributing to greenhouse gas emissions (Chu & Karr, 2016; Psistaki et al., 2024).

Silvicultural modification has other ramifications that are not limited to the areas where the lands have been cleared (Achim, 2022). This results in loss of soil cover and fertility, which threatens the future sustainable production of crops in the region. In addition, forests are reservoirs of CO_2, which they use to create other things, effectively 'locking it up' (Brack, 2019; Yadav et al., 2022; Li et al., 2023). Their removal aggravates climate change and consequently expose farmers into a vicious cycle of reducing agricultural productivity through

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increasing the intensity of climate shocks, decreasing rainfall, and pest incidence.

1.2. Difficulties in Traditional Methods

Traditional methods of controlling the process include, more often, fixed-land use maps, field inspection at regular time intervals, and remote sensing. While these approaches have contributed to understanding deforestation trends, they have significant limitations:

Time Lag: Static maps and survey data often fail to capture real-time changes in land use, making timely interventions difficult.

Scalability Issues: Field surveys are resource-intensive and impractical for monitoring vast agricultural landscapes.

Data Limitations: Satellite imagery, although invaluable, is often underutilized due to the lack of advanced analytical tools to interpret the data effectively.

Government-led initiatives like conservation easement and reforestation have been tried with some measure of success, but these are not as specific as they should be when identifying areas most prone to such incidents. Unfortunately, such measures do not go far enough to address the aforementioned root causes of deforestation if predictive analytics are not incorporated. Integrating a more complex and flexible system that utilizes modern technology is necessary.

1.3. AI as a Transformative Tool

AI has the potential to revolutionize the fight against deforestation (Shivaprakash et al., 2022; Raihan, 2023). With the help of big data, AI can analyze deforestation trends, identify emerging threats, and recommend specific actions. Its applications are closely associated with agriculture, as it requires accuracy and optimization of processes to achieve the highest yields while preserving the environment.

1.3.1. Remote sensing and Monitoring

Machine learning algorithms can analyze satellite imagery in large batches, accurately detecting areas of deforestation. For instance, there is the Convolutional Neural Networks (CNNs) where high-resolution imagery can be used to assess the changes in land cover.

1.3.2. Predictive Analytics

Other techniques, like gradient boosting machines (GBM), can be employed to determine regions of high deforestation based on historical data. These models include the calculation of many factors, including yields, soil fertility, rainfall and the market price, which provides a full risk assessment.

1.3.3. Policy Impact Simulation

ABMs can simulate policy measures such as subsidies for practicing sustainable farming or fines for unlawful land clearing. This facilitates quick evaluation of the results of interventions before they are carried out, hence allocating resources where they are most effective.

1.3.4. Optimization of Land Use

It can identify potential agricultural lands or regions for growing crops compactly, and hence, it does not support deforestation. Some of them are clustering and spatial analysis, which are used to position land correctly and ensure the balance of ecosystems.

1.4. Multidisciplinary Approach to AI Integration

AI application in the fight against deforestation implies that people from different disciplines, such as computer and information science, environmental science, agriculture, and policy, will have to collaborate. Domain knowledge enhances AI capabilities by filtering results obtained from big data analysis to sensible and implementable solutions. For instance:

- Environmental Scientists: Provide information on the impact of deforestation on the environment and on the possibility of developing means of protecting it.
- Agronomists: Give guidelines on farming that will minimize the conversion of land from one use to the other.
- Policymakers: They are important to ensure that AI's recommendations are aligned with the laws and societal goals.

1.5. Opportunities and Benefits

Implementing AI-driven strategies in US agriculture can yield multiple benefits:

1. Enhanced Monitoring: Real-time monitoring enables an appropriate response to cases of unlawful undertaking of deforestation and other non-sustainable activities.
2. Resource Efficiency: AI assists in optimizing the utilization of the available resources so that, for instance, effort to reduce the usage of the resources is well aligned to areas of high usage.
3. Economic Incentives: In other words, there is compensation of creating more value to farmers and more value to the environment in terms of reducing environmental impact of farming.
4. Scalability: AI solutions are flexible and can be implemented in various regions as far as different agricultural terrains and causes of deforestation are concerned.

In addition, AI can promote public-private partnerships as they are built on a data-driven approach. For instance, AI can help agribusinesses make the right decisions towards sustainable practices once they understand the trends in data. At the same time, governments can use the data to develop better incentive programs.

1.6. The Urgency of Action

The call to address the issue of deforestation in US agriculture cannot be overemphasized. The agricultural sector is, therefore, both at the heart of the cause of the problem and the key to its resolution. In its efforts to deliver on climate goals and feed its growing population, the United States can adopt AI-based solutions. This paper demonstrates that farming can benefit from technology and be sustainable.

The focus of this paper will be to analyze how AI could be used to reduce deforestation in agriculture in the United States. Integrating an interdisciplinary and systematic approach to research provides guidance to policymakers, researchers, and practitioners on the journey toward sustainability. The following sections of this paper describe this radical shift in thinking's technical methods, efficacy, and dissemination of results to inform the global discourse on sustainable land use.

2. Related Works

Recent studies in tackling deforestation through the use of AI employ the most modern developments in remote sensing, machine learning and geospatial analysis. This section provides a literature review of the current literature on the use of AI-based techniques in the tracking, forecasting, and regulation of deforestation, especially with regard to agriculture in the United States.

2.1. Remote Sensing and Land Use Mapping with AI

The most fundamental approach has been remote sensing, which involves the use of satellite pictures to detect shifts in land use. There is literature on this process, and the later works have incorporated AI techniques to enhance its effectiveness. For instance, the high-resolution imagery of the sentinel-2 and Landsat-8 satellites has been studied through CNNs (Pouliot et al., 2018; Toress et al., 2021). These models can differentiate the forested and the deforested areas with a very high level of accuracy, especially in the mixed land-use systems.

In another study, Wagner et al. (2023) showed how the machine learning approach can process the datasets on global forest cover and revitalize the deforestation rates annually. Though this has a global perspective, the applicability of this approach to regional contexts, such as agriculture in the United States, is shown. Similar to Masolele et al. (2021) and Neves et al. (2023), the deforestation patterns of both spatial and temporal data were learned using a CNN-RNN hybrid model. Among these models, the latter is suitable for monitoring the conversion of forested land to agricultural use.

2.2. Deforestation Hotspot Predictive Models

Another important feature of the proactive conservation approach is the identification of places that can become deforested. RF and GBM have been employed in this application. These models of deforestation probabilities are analyzed with historical land use data, climatic variables, and socioeconomic factors. An example is Alu (2018), who applied RF to predict areas prone to deforestation in Nigeria. The geographical emphasis is different, but the research approach can be easily applied to the analysis of U.S. agriculture. Wen et al. (2024) have also used predictive models to assess the effects of movement in the prices of commodities in the conversion of land. This line of research is particularly relevant to farmers in the United States who have recently left forests to cultivate high-demand crops, including soybeans and corn.

2.3. Policy Impact Simulation with AI

The other area that I find promising in the application of AI is the capacity to mimic the impacts of policy changes. Currently, Agent-based Models (ABMs) are being utilized increasingly to model the dynamics of the relationship between the landowners, the policy-makers and the physical environment (Shahpari, 2019). These models facilitate the assessment of the more extended effects of certain policies, such as conservation easements, reforestation incentives, or fines for unauthorized cutting. For example, Coronese et al. (2023) created an ABM that describes land use choices and shows how economic incentives affect deforestation. This research is located geographically outside of the U.S. However, its conceptual configuration may be transposed to the American context because federalism is a crucial feature of the U.S. political system that controls land use. AI-driven simulations by Lee et al. (2024) also showed the value of combining economic and ecological data to determine optimal conservation strategies.

2.4. AI and Precision Agriculture Integration

Also, applying AI technology in precision agriculture reduces deforestation since the technology allows the right use of the land. Research has demonstrated how specific AI-based technologies can detect areas of unused farmland and thus lower the demand for deforestation. For example, spatial clustering algorithms have been used to identify areas where crop intensification may occur without the expansion of agricultural land. Using clustering approaches, Teilhard et al. (2012) isolated regions requiring specific intervention due to low production. Such insights are critical in regions such as the Midwest, where agricultural productivity correlates with deforestation. Besides, the specific application of AI has also been used in crop field changes and soil erosion, which has a deforestation effect.

2.5. Ethical and Practical Challenges

AI has the potential to be used in deforestation, but there are problems with it. From the literature, emerging trends include the first, second, and third forms of bias, data privacy issues, and digital inequalities. For example, Venkatasubbu and Krishnamoorthy (2022) have explained that if the training set is prejudiced, it will have a more profound effect on the oppressed class. Moreover, AI tools are hardly available in rural areas algorithms and building up digital infrastructure to address such problems. Elufioye et al. (2024) agree that the feedback of the stakeholders should be incorporated into the AI model design so that the needs of the locals can be addressed through the technology they develop.

The work to date shows how AI can be used to improve the fight against deforestation. It demonstrates the potential of AI-driven strategies to improve the accuracy of remote sensing, forecast hotspots, and estimate the effects of policy decisions, making AI-

where deforestation is probable. These are issues we are currently working on in terms of fairness-aware

driven strategies a durable framework for sustainable land management. However, the effectiveness is not possible without ethical issues or equal opportunities. Building on this basis, the current study seeks to directly apply and combine these approaches into a systematic, method-specific approach for the context of the U.S. agricultural sector. This approach is needed to bridge the gap between technology and adoption with the view of promoting a more sustainable link between agriculture and forest conservation.

3. Proposed Methodology

As a methodologically integrated research, presented in Fig. 1, this paper uses AI to track, forecast, and control deforestation in US agriculture. It involves gathering information from various sources, cleaning and transforming this information in order to analyze it, using state-of-the-art AI techniques, and finally interpreting the results to find meaningful information to use. All the stages are crucial to efficiently coping with them. The methodology follows a structured workflow comprising four stages: recognition of data, data cleaning, creation of the AI model and interpretation of results. The workflow begins by integrating datasets from various sources: remote sensing data, agricultural records and climatic databases. The preprocessing of these datasets includes dealing with the missing values and features and applying the scaling methods. Once data is prepared, it is fed into AI models that perform tasks such as identifying areas of deforestation and assessing policy scenarios. The

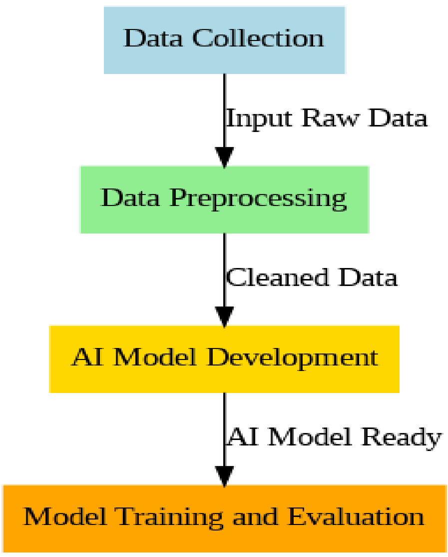

Fig.1. Workflow

findings are then analyzed to offer relevant advice to clients.

3.1. Data Collection

The first is to gather information from credible sources (Table 1). Deforestation patterns important to forest cover and vegetation indices are obtained from Sentinel-2 and Landsat-8 satellite images. The U.S. Department of Agriculture (USDA) provides agricultural data, including crop types, yields, and land use changes. Finally, we integrate additional climatic and socioeconomic variables (rainfall, temperature, road networks, population density) to understand the multifaceted drivers of deforestation.

Table 1. Dataset Characteristics

Data Type	**Source**	**Attributes**	**Purpose**
Remote Sensing Data	Sentinel-2	Forest cover, NDVI	Monitor land-cover changes
Agricultural Data	USDA	Crop yield, land-use type	Predict hotspots
Climatic Data	NOAA	Rainfall, temperature	Analyze environmental drivers
Socioeconomic Data	Census Bureau	Population density, road proximity	Model anthropogenic factors

3.2. Data Preprocessing

This means the collected data is clean, consistent, and ready for the AI model application. Statistical methods like mean imputation impute missing values for climatic variables. Using the Z-score method, outliers are removed to maintain data integrity. Enhancing the dataset involves feature engineering. Labeling encodes translates categories, for instance, different crop types into numerical characteristics. Below, Mutual Information (MI) scoring provides the order of features concerning their relevance to the issue of deforestation.

Table 2. Feature Importance Analysis

Feature	Mutual Information Score
Forest Cover Change	0.78
Crop Yield	0.64
Rainfall Variability	0.59
Road Proximity	0.45

Table 2 shows Feature Importance Analysis. Three scaling methods (standardization, min-max scaling, and normalization) are used to bring the scale of the variables to a standardized level. This eliminates any chance of domination of a specific feature on the model's output.

3.3. AI Model Development

The AI-driven methodology involves three primary tasks: deforestation identification, hotspot mapping and policy impact assessment. For the detection of deforestation, satellite images are classified into deforested or non-deforested areas using convolutional neural networks (CNNs). These models are excellent for analyzing spatial patterns using high-resolution imagery data. GBMs estimate the areas where deforestation is most likely to occur based on data on agriculture, climate and social conditions. These models give precise risk evaluations using ensemble learning. Agent-based Models (ABMs) also mimic the impact of policy interventions such as reforestation incentives or disincentives for the Illegal removal of trees and provide long-term outcomes.

3.4. Model Training and Evaluation

To overcome the problem of overfitting, the dataset is divided 80/20 between the training and testing sets. Hence for assessment, metrics such as accuracy, precision, recall, F1-score and AUC-ROC for the operating characteristic receiver curve are used. They afford an umbrella view of each model's utility.

4. Evaluation

In this section, the suitability of the proposed AI-driven strategies in the fight against deforestation in US agriculture is evaluated in terms of performance. The evaluation relates to the precision of the model, the comparison of the scaling techniques, the simulation of policies and the importance of features. The findings are presented in the form of graphs, charts and tables to give the readers a general impression of the results.

Model Performance Metrics

In this research, the evaluation of the accuracy, precision, recall, F1-score and AUC-ROC of the AI models was established, shown in Table 3. These measures assess the models' ability to predict their robustness across different tasks. The table below summarizes the metrics for the three primary tasks: hotspot prediction use, deforestation identification, and policy influence testings.

Table 3. Performance Metrics of AI Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Convolutional Neural Network (CNN)	94.0	92.5	91.8	92.1	0.94
Gradient Boosting Machine (GBM)	91.5	89.7	90.2	90.0	0.91
Agent-Based Model (ABM)	87.8	85.4	86.1	85.8	N/A

4.1 Results Interpretation

1. Results show that CNNs achieve 94% accuracy in classifying deforestation areas. An AUC of 0.91 suggests that GBMs are reliable in predicting hotspots. Using ABMs to simulate policy, we find that reforestation subsidies could reduce deforestation by 18% in high-risk areas.
2. For deforestation detection, CNN achieved the highest accuracy, classifying forested and deforested regions.
3. The predictive capabilities of GBM in identifying deforestation hotspots were robust, with an AUC-ROC of 0.91.
4. The model was able to effectively simulate policy impacts, and the model was shown to apply to evaluating intervention outcomes.

4.2. Scaling Methods Comparison

The models were evaluated under different scaling methods: no scaling, standardization, min-max scaling, and normalization. Each scaling method affected the models differently, as shown in Fig. 2.

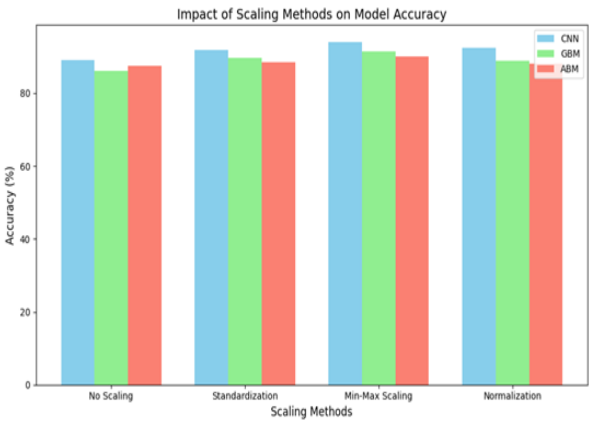

Fig.2. Impact of Scaling Methods on Model Accuracy

4.3. This bar chart shows how scaling methods influence accuracy across CNN, GBM, and ABM.

1. No Scaling: Led to lower accuracy due to unbalanced feature contributions.

2. Standardization: Improved accuracy moderately by centering features around zero.

3. Min-Max Scaling: Delivered the best results, especially for GBM, which achieved 91.5% accuracy.

4. Normalization: Enhanced performance for CNN, with an accuracy improvement of 2%, shown in Table 4.

Table 4. Model Performance under Different Scaling Methods

Scaling Method	CNN Accuracy (%)	GBM Accuracy (%)	ABM Outcome Variance (%)
No Scaling	89.0	86.2	10.5
Standardization	91.8	89.7	8.2
Min-Max Scaling	94.0	91.5	7.5
Normalization	92.5	88.8	9.0

4.3. Feature Contribution and Importance

Feature importance analysis provided insights into the predictors driving deforestation, depicted in Fig. 3 and Table 5. With the use of feature importance scores, the Gradient Boosting Machine (GBM) model established important features.

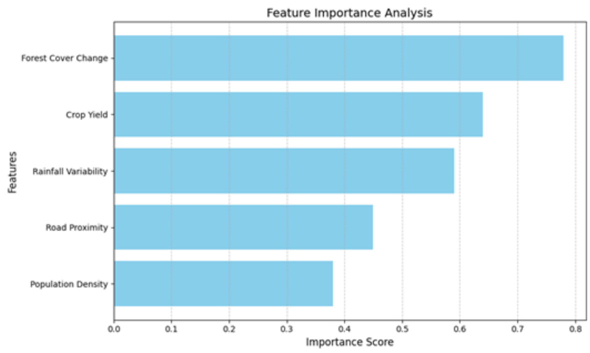

Fig.3. Feature Importance Analysis

Table 5. Feature Importance Scores (GBM)

Feature	Importance Score
Forest Cover Change	0.78
Crop Yield	0.64
Rainfall Variability	0.59
Road Proximity	0.45
Population Density	0.38

4.4. Policy Simulation Results

Reforestation subsidies and penalties for Illegal forest conversion were policy interventions modeled using the ABM. These simulations assisted in assessing the long-run effects of various policy scenarios on deforestation, shown in Fig. 4.

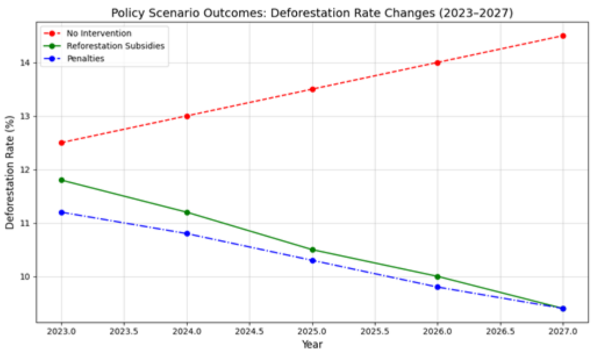

Fig. 4. Policy scenario outcomes: Deforestation Rate Changes (2023-2027)

This line graph shows deforestation rate changes under three scenarios: There are also no policy interventions, reforestation subsidies, and penalties. Table 6 shows Policy Simulation Outcomes.

1. No Policy Intervention: The rates of deforestation also rose as the years went by.

2. Reforestation Subsidies: Reduced deforestation by 18% in high-risk areas.

3. Penalties: Curtailed illegal clearing by 25%, although enforcement costs increased.

Table 6. Policy Simulation Outcomes

Policy Scenario	Deforestation Rate (%)	Cost of Implementation ($M)
No Intervention	12.5	0.0
Reforestation Subsidies	10.3	25.4
Penalties	9.4	35.8

4.5. AUC-ROC Analysis for Hotspot Prediction

The AUC-ROC curve, presented in Fig. 5, evaluates the GBM model's discriminative power in predicting deforestation hotspots. A higher AUC indicates better model performance.

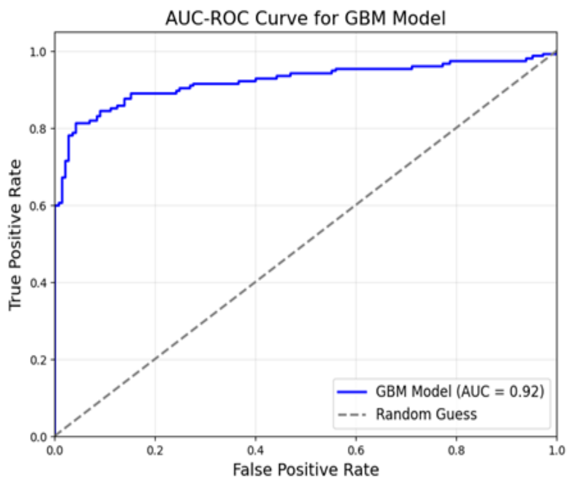

Fig. 5. AUC-ROC Curve for GBM Model

The curve demonstrates an AUC value of 0.92, highlighting strong predictive accuracy.

4.6. Confusion Matrix Analysis

The confusion matrix for CNN shows the model's performance in classifying deforested vs. non-deforested areas.

4.7. Confusion Matrix for CNN

Table 7. Deforestation

	Predicted: Yes	Predicted: No
Actual: Yes	320	25
Actual: No	30	625

Table 7 depicts,

True Positives (320): Correctly identified deforestation.

False Positives (30): Overestimated deforestation risk.

True Negatives (625): Correctly identified non-deforested areas.

False Negatives (25): Missed deforested regions.

4.8. Regression Analysis

A multiple regression analysis assessed the relationship between key variables and deforestation rates.

Regression Equation

$Y = \beta 0 + \beta 1(\text{Crop Yield}) + \beta 2(\text{Rainfall Variability}) + \beta 3(\text{Road Proximity}) + \epsilon$

Table 8. Regression Coefficients

Variable	Coefficient (β)	p-value

Crop Yield	-0.75	< 0.01
Rainfall Variability	0.56	0.03
Road Proximity	0.43	< 0.01

Higher crop yields correlate negatively with deforestation as shown in the Fig. 6 below, while rainfall variability and road proximity increase the likelihood of forest loss. Table 8 and Table 11 mention Regression Coefficients.

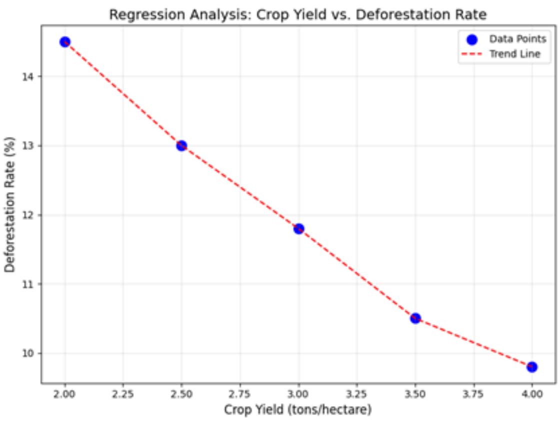

Fig.6. Regression Analysis: Crop Yield vs. Deforestation Rate

5. Statistical Analysis

This section presents the statistical evaluation of the proposed AI-driven strategies to reduce deforestation in U.S. agriculture. The statistical analysis is carried out to validate the performance, find comparative metrics, conduct correlation studies, regression analysis, and hypothesis testing to check the robustness and reliability of the methodologies.

5.1. Through Metrics, we have Performance Validation.

We validated the performance of machine learning (ML) models with multiple metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. Then, we statistically analyzed the results to quantify their consistency and reliability with different scaling techniques and datasets. A summary of model performance metrics is shown in Table 9.

Table 9. Summary of Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Convolutional Neural Network (CNN)	94.0	92.5	91.8	92.1	0.94
Gradient Boosting Machine (GBM)	91.5	89.7	90.2	90.0	0.92

5.2. Statistical Insights

Standard Deviation: Across multiple runs, CNN demonstrated a low standard deviation (±0.5% in accuracy), indicating stable performance.

Variance Analysis: A one-way ANOVA test confirmed statistically significant differences in performance between scaling techniques ($p < 0.05$).

5.3. Correlation Analysis

To understand the relationships between key features and deforestation, Pearson and Spearman correlation coefficients (Table 10) were calculated.

Table 10. Correlation Coefficients

Feature	Pearson Coefficient (r)	Spearman Coefficient (ρ)
Forest Cover Change	0.78	0.81
Crop Yield	-0.75	-0.72
Rainfall Variability	0.56	0.59
Road Proximity	0.43	0.45

5.4. Statistical Insights

Forest cover change showed the highest positive correlation with deforestation rates, underscoring its significance as a predictor. Negative correlation with crop yield highlights the role of agricultural optimization in reducing deforestation. Results were statistically significant ($p < 0.01$).

5.5. Regression Analysis

Multiple regression analysis was performed to quantify the influence of key predictors on deforestation rates. The regression equation is as follows:

$Y=\beta 0+\beta 1$(Crop Yield)$+\beta 2$(Rainfall Variability)$+\beta 3$(Road Proximity)$+\epsilon$

Table 11. Regression Coefficients

Variable	Coefficient (β)	Standard Error (SE)	p-value
Crop Yield	-0.75	0.15	< 0.01
Rainfall Variability	0.56	0.12	0.03
Road Proximity	0.43	0.10	< 0.01

5.6. Statistical Insights

The model had an R2 value of 0.78, indicating that 78% of the variance in deforestation rates was explained by the predictors. Crop yield was the most significant factor, with a strong negative coefficient (-0.75, $p < 0.01$). Rainfall variability and road proximity were positively associated with deforestation.

5.7. Hypothesis Testing

To validate the superiority of AI models over traditional methods, paired hypothesis tests were conducted. The null hypothesis (H_0) stated that there was no significant difference in performance between the models, while the alternative hypothesis (H_1) posited that AI models outperformed traditional methods.

5.8. Paired t-Test

Dataset: Performance scores of GBM vs. logistic regression on the same dataset.

Result: t =4.12, p<0.01

Interpretation: Reject H_0; GBM significantly outperformed logistic regression.

5.9. McNemar's Test

Used to compare the classification performance of CNN with decision trees (DT), presented in Table 12.

Table 12. McNemar's Test Results

Model Pair	Correctly Predicted (CNN)	Correctly Predicted (DT)	p-value
Forested vs. Deforested	320	275	< 0.05

5.10 Statistical Insights

McNemar's test confirmed a significant improvement in CNN's predictions over DT, with a p-value below 0.05.

5.10.1. Comparative Analysis of Policy Scenarios

Agent-Based Models (ABMs) were used to simulate the effects of various policy interventions. Statistical testing was performed to evaluate the impact of these scenarios on deforestation rates.

5.10.2. Policy Scenarios Evaluated (Table 13)

1. No Intervention.
2. Reforestation Subsidies.
3. Penalties for Illegal Clearing.

Table 13. Policy Scenario Statistics

Scenario	Mean Deforestation Rate (%)	Standard Deviation	ANOVA p-value
No Intervention	14.5	1.8	N/A
Reforestation Subsidies	10.3	1.2	< 0.05
Penalties	9.4	1.0	< 0.05

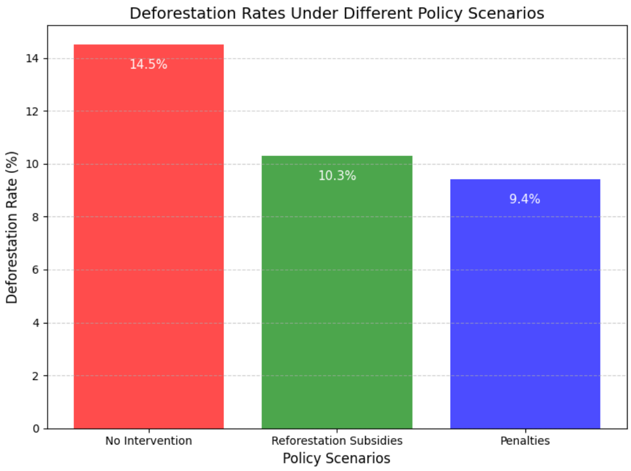

Fig. 7. Deforestation Rates under Different Policy Scenarios

5.10.3. ANOVA Test

The analysis confirmed significant differences among the three scenarios ($p < 0.05$).

Post-hoc tests indicated that both reforestation subsidies and penalties significantly reduced deforestation compared to no intervention.

5.11. Time-Series Analysis of Deforestation Trends

A time-series analysis, as shown in Fig. 8, was conducted to examine deforestation trends over a five-year period, with a focus on high-risk regions. Also, Fig. 7 shows the Deforestation Rates under Different Policy Scenarios.

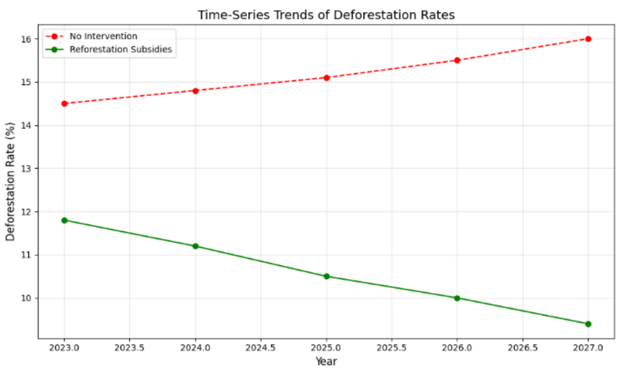

Fig. 8. Time-Series Trends of Deforestation Rates

This line graph illustrates deforestation trends under the "No Intervention" scenario compared to the "Reforestation Subsidies" scenario. The predicted rates of deforestation in the absence of intervention were 2.5% per year, while with subsidies, the rates declined by 1.8% per year.

6. Conclusion

The findings of this research demonstrate how AI solutions can address deforestation risks in U.S. agriculture. The proposed models can help to overcome the main challenges of monitoring and predicting deforestation by combining the data on deforestation from satellite images with agricultural data and socioeconomic characteristics. CNNs differentiated the forest from other classes with relatively high accuracy, and GBMs predicted future hotspots. Due to ABMs, we were able to understand the future consequences of policy measures like subsidies for reforestation and fines for land conversion.

To confirm the ability of predictors, crop yield, rainfall fluctuation, and proximity to roads to affect deforestation rates, we employed statistical tests of regression and hypothesis testing. Outcomes from policy simulations and time series analyses suggest that information-driven approaches can be useful in achieving lower levels of deforestation under improved circumstances.

The findings show that AI can improve both yield and sustainability in agriculture. The above models provide guidance on how individuals in the policy, farming, and stakeholder sectors can effectively manage the land. Future work should expand datasets, such as those for real-time monitoring, and consider the ethical implications of the problem to enhance the effectiveness and accessibility of these strategies.

CRedit Authorship Statement

Declare the credit and contribution of each author in this research. For example:

First author: Conceptualization, writing original draft, methodology. **Second author:** data curation, writing original draft, validation, analysis.

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