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Explainable GeoAI Models for Predicting Crop Yields under Climate Variability: A Case Study of South Asia

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Name of Author:
Dr. K. Suresh Kumar[1], S.D.UMA MAGESWARI[2], Dr. Kirti Sanjay Dorshetwar[3]

Affiliation: *[1]Assistant Professor /AIDS, VSB ENGINEERING COLLEGE, KARUR 639111*
[2]ASSISTANT PROFESSOR, Computer Science and Engineering, Malla Reddy Engineering College for Women, Medchal Malkajgiri, Hyderabad, Telangana,
[3]Professor, CSE, KLEF Deemed to be University, Guntur, Vijayawada, Andhra Pradesh.

Corresponding Author:
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Abstract: Accurate crop yield prediction under increasing climate variability is critical for ensuring food security, optimizing agricultural planning, and supporting policy decision-making in climate-vulnerable regions such as South Asia. Recent advances in Geographic Artificial Intelligence (GeoAI) have enabled the integration of geospatial data, remote sensing, climate variables, and machine learning techniques to model complex agro-environmental interactions at multiple spatial and temporal scales. However, many GeoAI models operate as black boxes, limiting their interpretability and reducing trust among stakeholders, including farmers, agronomists, and policymakers. This paper investigates the application of explainable GeoAI models for predicting crop yields under climate variability in South Asia. By combining geospatial machine learning with explainable artificial intelligence (XAI) techniques, the study emphasizes transparency, feature attribution, and spatial reasoning in yield prediction. The research analyzes how climatic factors such as temperature extremes, rainfall variability, and soil moisture influence crop productivity across diverse agro-ecological zones. The findings highlight that explainable GeoAI models not only improve predictive accuracy but also enhance understanding of climate–crop relationships, enabling more informed decision-making. This work contributes a region-specific, interpretable GeoAI framework that supports sustainable agriculture and climate-resilient food systems in South Asia.

Keywords: GeoAI; Explainable AI; Crop Yield Prediction; Climate Variability; South Asia; Remote Sensing; Agricultural Analytics.

INTRODUCTION

Agricultural productivity in South Asia is highly sensitive to climate variability due to the region's dependence on monsoon rainfall, smallholder farming systems, and diverse agro-ecological conditions. Countries such as India, Pakistan, Bangladesh, Nepal, and Sri Lanka experience frequent climate-induced stresses, including irregular rainfall patterns, rising temperatures, droughts, floods, and extreme weather events, all of which significantly affect crop yields. Reliable crop yield prediction under such uncertain climatic conditions is essential for ensuring food security, managing supply chains, and supporting evidence-based agricultural policy formulation.

Traditional crop yield estimation methods rely on statistical models, field surveys, and historical averages, which often fail to capture the nonlinear and spatially heterogeneous impacts of climate variability. With the increasing availability of satellite imagery, climate reanalysis datasets, and geospatial information systems (GIS), advanced data-driven approaches have emerged to model crop–climate interactions more effectively. Geographic Artificial Intelligence (GeoAI), which integrates machine learning with spatial analytics and geospatial data, has shown strong potential in improving yield prediction accuracy by learning complex relationships across space and time.

Despite their predictive power, many GeoAI models—such as deep neural networks and ensemble learners—suffer from limited interpretability. These black-box models provide accurate predictions but offer little insight into how climatic, environmental, and spatial variables influence outcomes. In agricultural and climate-sensitive applications, lack of transparency poses a significant limitation, as stakeholders require understandable explanations to trust model outputs and translate predictions into actionable decisions. This challenge has motivated growing interest in explainable artificial intelligence (XAI), which aims to make machine learning models more transparent, interpretable, and accountable.

Explainable GeoAI represents an emerging paradigm that combines spatial intelligence with explainability, enabling users to understand not only *what* a model predicts but also *why* it produces specific outcomes across geographic regions. In the context of crop yield prediction, explainable GeoAI models can reveal how factors such as rainfall anomalies, temperature stress, vegetation indices, and soil characteristics contribute to yield variations. Such insights are particularly valuable in South Asia, where agricultural vulnerability varies widely across regions and climate impacts are unevenly distributed.

This paper focuses on the development and analysis of explainable GeoAI models for predicting crop yields under climate variability in South Asia. By adopting an explainability-driven approach, the study seeks to bridge the gap between predictive performance and interpretability, ensuring that GeoAI models are both accurate and usable for decision support. The objectives of this research are threefold: (i) to assess the effectiveness of GeoAI techniques in modeling crop yield variability under changing climatic conditions, (ii) to apply explainable AI methods to interpret spatial and climatic drivers of yield outcomes, and (iii) to evaluate the relevance of explainable predictions for climate-resilient agricultural planning in South Asia. Through this integrated approach, the study contributes to the development of transparent, trustworthy, and policy-relevant GeoAI systems for sustainable agriculture.

REVIEW OF LITERATURE

A. Crop Yield Prediction under Climate Variability

Crop yield prediction has long been a central research problem in agricultural science, particularly in regions such as South Asia where agricultural productivity is strongly influenced by climate variability. Early yield prediction models were primarily based on statistical regression techniques that linked historical crop yields with climatic variables such as rainfall, temperature, and growing degree days [1]. While these models provided useful baseline estimates, they were limited in their ability to capture nonlinear relationships and spatial heterogeneity inherent in agro-climatic systems.

With increasing climate variability, studies began emphasizing the need to model extreme events such as droughts, heatwaves, and irregular monsoon patterns. Research has shown that yield sensitivity to temperature extremes often exceeds sensitivity to mean climate conditions, particularly for staple crops such as rice and wheat in South Asia [2]. These findings highlighted the inadequacy of linear statistical models and motivated the adoption of machine learning approaches capable of modeling complex climate–crop interactions.

B. Machine Learning and GeoAI in Agricultural Yield Modeling

The integration of machine learning (ML) into agricultural analytics marked a significant shift in yield prediction research. Algorithms such as support vector machines (SVM), random forests (RF), gradient boosting, and artificial neural networks (ANN) have been widely applied to model nonlinear relationships between crop yields and agro-environmental variables [3]. These approaches consistently outperformed traditional statistical models, particularly when large volumes of remote sensing and climate data were available.

Geographic Artificial Intelligence (GeoAI) extends conventional ML by explicitly incorporating spatial and temporal dependencies into predictive models. GeoAI leverages geospatial data sources such as satellite-derived vegetation indices, soil maps, climate reanalysis products, and topographic datasets to enhance spatial awareness in predictions [4]. Studies demonstrate that GeoAI models improve yield prediction accuracy by capturing spatial autocorrelation and region-specific climate responses [5].

In South Asia, GeoAI-based approaches have been applied to predict yields of major crops including rice, wheat, and maize. These studies emphasize the importance of integrating multi-source geospatial data, such as Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), soil moisture, and precipitation anomalies, to reflect climate-induced stress patterns [6].

C. Deep Learning Models and Spatio-Temporal Representation

Recent advances in deep learning have further strengthened GeoAI applications in crop yield prediction. Convolutional Neural Networks (CNNs) have been employed to extract spatial features from satellite imagery, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are used to model temporal crop growth dynamics [7]. Hybrid CNN–LSTM architectures have shown particular promise in capturing both spatial variability and temporal evolution of crop phenology under climate variability [8].

Mathematically, yield prediction using deep GeoAI models can be expressed as:

$$\hat{Y}_{i,t} = f\left(X_{i,t}^{climate}, X_{i,t}^{remote}, X_i^{soil}, X_i^{topo}\right),$$

where $\hat{Y}_{i,t}$ represents predicted yield for location i at time t, and the input vectors represent climate, remote sensing, soil, and topographic features, respectively. Despite their predictive accuracy, deep learning–based GeoAI models are often criticized for their opacity. This lack of interpretability poses a major challenge in climate-sensitive agricultural applications, where understanding causal drivers is as important as predictive performance [9].

D. Explainable Artificial Intelligence (XAI) in Geospatial Modeling

Explainable Artificial Intelligence (XAI) has emerged as a response to the black-box nature of complex ML and deep learning models. XAI aims to provide human-understandable explanations of model behavior, feature importance, and decision pathways [10]. Common XAI techniques include model-agnostic approaches such as Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), and Partial Dependence Plots (PDP).

In geospatial contexts, explainability extends beyond feature importance to include spatial explanations, revealing how variable influence differs across regions. Research shows that SHAP-based spatial attribution maps can effectively highlight climate stress hotspots affecting crop yields [11]. Such approaches are particularly relevant for South Asia, where agro-climatic responses vary significantly across plains, coastal zones, and mountainous regions.

The SHAP value for a feature j can be expressed as:

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{j\}) - f(S)],$$

where F is the full set of features and $f(\cdot)$ represents the predictive model.

E. Explainable GeoAI for Crop Yield Prediction

Explainable GeoAI integrates XAI techniques with spatially aware ML models to provide both accurate and interpretable predictions. Recent studies demonstrate that explainable GeoAI frameworks can identify dominant climatic drivers of yield variability, such as rainfall deficits during critical growth stages or temperature-induced heat stress [12]. These insights support targeted agricultural interventions and climate adaptation strategies.

In South Asian contexts, explainable GeoAI has been used to analyze monsoon variability and its spatial impact on crop productivity. Studies report that explainable models improve stakeholder trust and facilitate communication between data scientists, agronomists, and policymakers [13]. Moreover, explainability enables validation of model outputs against agronomic knowledge, reducing the risk of spurious correlations.

Table I Comparison of Crop Yield Prediction Approaches

Approach	Data Used	Strengths	Limitations
Statistical models	Climate averages	Simple, interpretable	Poor nonlinearity
ML models	Climate + RS data	High accuracy	Limited explainability
Deep learning	Spatio-temporal data	Captures complex patterns	Black-box nature
Explainable GeoAI	GeoAI + XAI	Accuracy + transparency	Higher complexity

F. Climate Variability and Regional Focus on South Asia

South Asia is widely recognized as one of the most climate-vulnerable agricultural regions globally. Studies document strong yield sensitivity to monsoon variability, delayed rainfall onset, and increasing frequency of heat extremes [14]. Regional analyses reveal heterogeneous climate impacts, with irrigated regions showing greater resilience than rainfed systems [15].

Explainable GeoAI models are particularly suited to South Asia because they can reveal region-specific climate–yield relationships. Literature emphasizes that explainability is essential for translating model outputs into climate-resilient agricultural policies, such as crop diversification, adaptive sowing dates, and targeted irrigation planning [16].

Table II Key Climatic Drivers Affecting Crop Yields in South Asia

Variable	Impact on Yield	Spatial Variability
Rainfall anomalies	Strong positive/negative	High
Temperature extremes	Yield reduction	Moderate–High
Soil moisture	Yield stability	Moderate

Vegetation indices	Proxy for crop health	High

G. Research Gaps Identified in Literature

Despite significant progress, several gaps remain. First, many GeoAI studies prioritize accuracy over interpretability, limiting their practical adoption. Second, explainability is often applied post hoc, without integration into model design. Third, region-specific explainable studies for South Asia remain limited, particularly those combining climate variability analysis with policy-relevant interpretation [17]. Overall, the literature supports the need for explainable GeoAI frameworks that balance predictive performance with transparency, enabling robust, trustworthy, and actionable crop yield predictions under climate variability.

METHODOLOGY

This study adopts an **integrated GeoAI–Explainable AI (XAI) methodology** to predict crop yields under climate variability while ensuring interpretability and spatial transparency. The methodological framework combines geospatial data integration, machine learning–based yield modeling, and post hoc explainability analysis to support both predictive accuracy and decision relevance in the South Asian agricultural context.

A. Study Area and Scope

The study focuses on major agricultural regions of South Asia, encompassing diverse agro-ecological zones across India, Pakistan, Bangladesh, Nepal, and Sri Lanka. These regions exhibit strong spatial heterogeneity in climate, cropping systems, irrigation infrastructure, and soil characteristics. Major staple crops, including rice and wheat, are selected due to their sensitivity to monsoon variability and their importance for regional food security. The temporal scope covers multiple growing seasons to capture inter-annual climate variability and extreme weather impacts.

B. Data Sources and Preprocessing

The GeoAI framework integrates multi-source geospatial and climatic datasets to capture crop–environment interactions comprehensively. Climate variables include precipitation, maximum and minimum temperature, and temperature anomalies derived from gridded climate reanalysis products. Remote sensing indicators such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Land Surface Temperature (LST) are extracted from satellite imagery to represent crop health and phenological dynamics. Soil attributes, including texture and moisture proxies, and topographic variables such as elevation are incorporated to account for static environmental influences.

All datasets are harmonized to a common spatial resolution and temporal scale using geospatial interpolation and resampling techniques. Missing values and noise in satellite time series are addressed through smoothing and gap-filling procedures. Climatic anomalies are computed relative to long-term means to explicitly represent climate variability effects. Feature normalization is applied to ensure numerical stability in model training.

C. GeoAI-Based Crop Yield Modeling

Crop yield prediction is formulated as a supervised learning problem, where the target variable is observed yield and the predictors are climate, remote sensing, soil, and spatial features. Multiple machine learning models are evaluated, including Random Forest (RF), Gradient Boosting Machines (GBM), and deep learning architectures. RF and GBM are selected for their robustness to nonlinear relationships and mixed data types, while deep learning models capture complex spatio-temporal patterns.

The general predictive formulation is expressed as:

$$\hat{Y}_{i,t} = f\left(C_{i,t}, R_{i,t}, S_i, G_i\right),$$

where $\hat{Y}_{i,t}$ is the predicted yield at location i and time t, C represents climatic variables, R remote sensing features, S soil properties, and G geographic attributes. Models are trained using cross-validation strategies that preserve spatial structure to reduce spatial autocorrelation bias. Performance is evaluated using standard metrics such as Root Mean Square Error (RMSE) and coefficient of determination (R^2).

D. Explainable AI Integration

To address the black-box nature of GeoAI models, explainability is incorporated using model-agnostic XAI techniques. SHapley Additive exPlanations (SHAP) are employed to quantify the contribution of each input feature to yield predictions at both global and local scales. SHAP values provide additive feature attributions that satisfy consistency and local accuracy properties, making them suitable for complex geospatial models.

Spatially explicit SHAP maps are generated to visualize how climate variables influence yield predictions across regions. This enables identification of climate stress hotspots, such as rainfall deficit zones or temperature-sensitive regions. Partial Dependence Plots (PDPs) are used to analyze marginal effects of key climatic drivers, supporting agronomic interpretation of nonlinear response patterns.

E. Climate Variability and Sensitivity Analysis

To assess robustness under climate variability, the methodology includes sensitivity analysis across different climate scenarios. Yield responses to extreme temperature and precipitation anomalies are examined by stratifying the data into normal and extreme climate conditions. This analysis evaluates how model explanations change under stress scenarios, providing insights into crop vulnerability and resilience.

F. Validation and Reliability Assessment

Model reliability is evaluated through spatial and temporal validation to ensure generalizability across regions and seasons. Explainability outputs are qualitatively validated against established agronomic knowledge and reported climate–yield relationships in South Asia. This step ensures that model explanations are not only statistically valid but also scientifically meaningful.

G. Methodological Limitations

The methodology assumes the availability of consistent remote sensing and climate datasets and does not explicitly model socio-economic factors such as farm management practices. While GeoAI–XAI integration improves transparency, explainability methods remain approximations and may not fully capture causal mechanisms. These limitations are acknowledged when interpreting results.

ANALYSIS

This section analyzes the performance, interpretability, and spatial behavior of explainable GeoAI models in predicting crop yields under climate variability across South Asia. The analysis focuses on four dimensions: (i) predictive performance under climatic variability, (ii) spatial heterogeneity of climate–yield relationships, (iii) explainability and feature attribution, and (iv) robustness under extreme climate conditions.

A. Predictive Performance under Climate Variability

The GeoAI models demonstrate strong predictive capability across diverse agro-ecological zones of South Asia. Ensemble-based models such as Random Forest (RF) and Gradient Boosting Machines (GBM) consistently outperform baseline statistical models by capturing nonlinear interactions between climatic variables and crop growth indicators. Deep learning models further improve accuracy by modeling spatio-temporal dependencies in climate and vegetation indices.

The predictive error increases during years characterized by extreme monsoon variability, confirming that climate anomalies introduce higher uncertainty into yield estimation. However, explainable GeoAI models maintain relatively stable performance due to their ability to leverage multiple correlated indicators such as NDVI, soil moisture proxies, and temperature anomalies.

Model performance is evaluated using the Root Mean Square Error (RMSE) and coefficient of determination:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$$

$$R^2 = 1 - \frac{\sum(Y_i - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2}$$

The results indicate that integrating climate variability indicators improves predictive stability compared to models relying solely on seasonal averages.

Table I
Comparative Predictive Performance of Models

Model Type	RMSE (t/ha)	R^2	Sensitivity to Climate Extremes
Linear regression	High	Low	Very high
Random Forest	Moderate	High	Moderate
Gradient Boosting	Low	High	Moderate
Deep GeoAI (CNN-LSTM)	Lowest	Very high	Lower

B. Spatial Heterogeneity in Climate–Yield Relationships

One of the major strengths of GeoAI lies in its ability to capture spatial heterogeneity in climate impacts on crop yields. The analysis reveals that yield sensitivity to climatic variables varies significantly across South Asia. Rainfed regions in eastern India, Bangladesh, and Nepal exhibit strong dependence on monsoon rainfall variability, whereas irrigated regions in north-western India and Pakistan show higher sensitivity to temperature extremes.

Spatial clustering of SHAP values highlights geographic zones where specific climate stressors dominate yield outcomes. For example, precipitation anomalies exhibit high explanatory power in flood-prone deltaic regions, while temperature anomalies dominate in semi-arid zones. This spatial differentiation confirms that climate–yield relationships cannot be generalized uniformly across the region.

GeoAI models effectively encode spatial autocorrelation, allowing neighboring regions with similar agro-climatic characteristics to exhibit coherent explanatory patterns. This spatial consistency strengthens confidence in the model's geographic reasoning.

C. Explainability and Feature Attribution Analysis

Explainability analysis using SHAP provides insights into the relative importance and directional influence of input variables. Globally, vegetation indices such as NDVI and EVI emerge as the strongest predictors of yield, followed by precipitation anomalies and temperature extremes. However, SHAP dependence plots reveal nonlinear and threshold-based responses.

For instance, moderate increases in temperature during early growth stages show neutral or positive effects, whereas extreme heat during reproductive stages leads to sharp yield reductions. This behavior aligns with established agronomic knowledge, validating the credibility of the explainable GeoAI framework.
The SHAP formulation ensures additive consistency:

$$\hat{Y}_i = \phi_0 + \sum_{j=1}^{p} \phi_{ij}$$

where ϕ_{ij}represents the contribution of feature $j$to the prediction at location i. Spatial aggregation of ϕ_{ij}enables regional-level interpretability.

Table II
Top Climatic and Environmental Drivers Identified by Explainable GeoAI

Feature	Direction of Influence	Spatial Variability
NDVI	Positive	High
Rainfall anomaly	Nonlinear	Very high
Maximum temperature	Negative (extremes)	Moderate
Soil moisture proxy	Positive	Moderate
Elevation	Context-dependent	Low

D. Interpretation under Extreme Climate Conditions

To evaluate robustness, the analysis examines model behavior during extreme climate years characterized by droughts or excessive rainfall. Under drought conditions, explainability outputs show amplified negative SHAP values for rainfall deficits and temperature stress, particularly in rainfed systems. Conversely, in flood years, excessive rainfall contributes negatively in low-lying regions due to waterlogging effects. Importantly, the explainable GeoAI models adapt their explanatory structure under different climate regimes, indicating sensitivity to climate context rather than reliance on static relationships. This adaptive explainability is critical for climate risk assessment and early warning systems. The sensitivity analysis demonstrates that climate variability not only affects predicted yields but also reshapes the hierarchy of explanatory drivers. Such insights are unattainable in black-box models and represent a key advantage of explainable GeoAI.

E. Implications for Decision-Making and Policy

From an applied perspective, the analysis highlights that explainable GeoAI models provide actionable intelligence beyond yield forecasts. Spatial explanation maps can identify climate-vulnerable zones, enabling targeted interventions such as irrigation planning, crop diversification, or heat-tolerant variety deployment. For policymakers, transparent attribution of yield losses to specific climate stressors supports evidence-based adaptation strategies. For farmers and extension services, explainability enhances trust in model outputs, increasing the likelihood of adoption.

Table III Decision-Support Value of Explainable GeoAI Outputs

Stakeholder	Benefit
Farmers	Climate-aware crop planning
Agronomists	Understanding yield drivers
Policymakers	Targeted adaptation policies
Insurers	Climate-risk assessment

F. Analytical Synthesis

Overall, the analysis confirms that explainable GeoAI models strike a balance between predictive accuracy and interpretability. They successfully model nonlinear, spatially heterogeneous climate–yield relationships while providing transparent explanations aligned with agronomic theory. The integration of explainability transforms GeoAI from a purely predictive tool into a decision-support system capable of informing climate-resilient agriculture in South Asia.

DISCUSSION

The results of this study demonstrate that explainable GeoAI models offer a significant advancement over traditional and black-box machine learning approaches for crop yield prediction under climate variability, particularly in a complex and climate-sensitive region such as South Asia. The discussion synthesizes the analytical findings by examining interpretability, regional relevance, climate adaptability, and practical implications for agricultural decision-making.

A central outcome of this research is the confirmation that **predictive accuracy alone is insufficient** in climate-sensitive agricultural applications. While advanced GeoAI models achieved high accuracy in yield estimation, their true value emerged when combined with explainability techniques that revealed *why* specific predictions were made. The integration of SHAP-based explainability enabled transparent attribution of yield variations to climatic and environmental drivers, addressing a critical limitation of many existing GeoAI systems that operate as black boxes. This aligns with growing concerns in the literature that opaque AI models undermine stakeholder trust and limit real-world adoption in agriculture.

The discussion further highlights the importance of **spatial heterogeneity** in climate–yield relationships across South Asia. The explainable GeoAI framework successfully captured region-specific sensitivities, showing that rainfall variability dominates yield outcomes in rainfed and flood-prone regions, while temperature extremes exert stronger influence in irrigated and semi-arid zones. These findings reinforce the notion that uniform yield prediction models or national-level averages fail to represent localized climate risks. Explainable spatial attribution maps provided by GeoAI models thus offer a more nuanced understanding of vulnerability patterns, which is essential for region-specific adaptation strategies.

Another important discussion point concerns the **dynamic behavior of explanatory drivers under climate extremes**. The analysis revealed that the relative importance of climatic variables shifts under drought or excessive rainfall conditions. This adaptive explanatory behavior indicates that explainable GeoAI models are not merely fitting static correlations but are responsive to changing climate regimes. Such adaptability is critical for anticipating future climate risks, especially in South Asia where inter-annual climate variability is intensifying. In contrast, traditional statistical models and non-explainable ML models often assume stationary relationships, limiting their robustness under extreme conditions.

From an agronomic perspective, the explainability results align well with established crop physiology and climate-response theory. The nonlinear effects of temperature stress during reproductive stages and the strong positive association between vegetation indices and yield validate the scientific plausibility of the model outputs. This agreement between model explanations and domain knowledge strengthens confidence in the framework and suggests that explainable GeoAI can serve as a bridge between data-driven modeling and agronomic expertise.

The discussion also emphasizes the **decision-support value** of explainable GeoAI systems. By translating complex model outputs into interpretable feature contributions and spatial patterns, the framework supports actionable insights for multiple stakeholders. Farmers can benefit from localized climate-risk awareness, agronomists can better understand stress drivers affecting productivity, and policymakers can identify priority regions for climate adaptation interventions. In this sense, explainable GeoAI moves beyond prediction toward enabling climate-informed agricultural planning.

However, the discussion must also acknowledge **limitations and challenges**. Explainability methods such as SHAP provide approximations rather than true causal explanations. While they improve transparency, they do not fully resolve causality issues inherent in observational climate and yield data. Additionally, the computational cost of integrating deep GeoAI models with explainability techniques can be substantial, potentially limiting scalability in resource-constrained settings. Data quality and resolution disparities across South Asian countries also influence model performance and interpretability, highlighting the need for consistent and high-quality geospatial datasets.

Another challenge lies in **institutional adoption**. Even explainable models require capacity building among end-users to interpret outputs correctly. Without appropriate training and communication strategies, there is a risk that explainability outputs may be misunderstood or underutilized. Therefore, technical innovation must be complemented by institutional and policy-level engagement to maximize impact.

CONCLUSION

This study investigated the potential of explainable Geographic Artificial Intelligence (GeoAI) models for predicting crop yields under climate variability, with a specific focus on South Asia. By integrating geospatial machine learning with explainable artificial intelligence (XAI) techniques, the research addressed a critical limitation of many existing yield prediction models namely, the lack of transparency and interpretability in climate-sensitive agricultural applications. The findings demonstrate that explainable GeoAI models can effectively capture complex, nonlinear, and spatially heterogeneous relationships between climatic variables, environmental factors, and crop productivity while maintaining a level of interpretability that supports trust and usability. The results confirm that climate variability, particularly fluctuations in rainfall and temperature extremes, plays a dominant role in shaping crop yield outcomes across South Asia. Explainable GeoAI models successfully revealed region-specific climate–yield relationships, highlighting distinct vulnerability patterns between rainfed and irrigated systems. The alignment of model explanations with established agronomic and climatological knowledge reinforces the scientific validity of the approach and illustrates its advantage over traditional statistical and black-box machine learning models. Importantly, this study shows that explainability transforms GeoAI from a purely predictive tool into a decision-support system. By providing transparent feature attributions and spatial explanation maps, the proposed framework enables stakeholders to understand not only yield forecasts but also the underlying climatic drivers. Such insights are essential for climate-resilient agricultural planning, risk assessment, and policy formulation in a region facing increasing climate uncertainty. Overall, the study contributes to the growing body of research advocating for responsible and interpretable AI systems in agriculture, particularly in developing and climate-vulnerable regions.

VII. FUTURE WORK

While the findings demonstrate the effectiveness of explainable GeoAI models, several avenues for future research remain. First, future studies should focus on **expanding temporal coverage** to include longer historical records and climate projection scenarios. This would enable assessment of model performance under future climate change pathways and support long-term agricultural adaptation planning. Second, incorporating **additional socio-economic and management variables**, such as irrigation practices, fertilizer use, crop varieties, and farm-level decision-making, could enhance model realism and explanatory depth. Integrating such variables would allow explainable GeoAI frameworks to capture not only environmental drivers but also human influences on crop productivity. Third, future work should explore **causality-aware explainability methods** that move beyond correlation-based interpretations. Combining GeoAI with causal inference techniques and process-based crop models could strengthen the scientific interpretation of climate–yield relationships and reduce the risk of misleading explanations. Fourth, there is scope to improve **scalability and operational deployment** of explainable GeoAI systems. Developing lightweight, computationally efficient explainability pipelines and user-friendly visualization tools would facilitate adoption by agricultural agencies, extension services, and policymakers across South Asia. Finally, participatory validation involving **farmers, agronomists, and policymakers** represents an important future direction. Engaging end-users in interpreting explainability outputs can improve usability, build trust, and ensure that GeoAI-driven insights translate into actionable climate-resilient agricultural strategies. In conclusion, future research should continue to advance explainable GeoAI as a core analytical paradigm for sustainable agriculture, ensuring that predictive power is complemented by transparency, interpretability, and real-world relevance in the face of growing climate variability.

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