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Role of GeoAI in Climate-Smart Agriculture: Opportunities and Challenges

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Abstract

Climate change has created serious challenges for agricultural systems through rising temperatures, erratic rainfall, droughts, floods, soil degradation, pest outbreaks and increasing pressure on natural resources. In this context, climate-smart agriculture has emerged as an important approach for improving productivity, strengthening adaptation and supporting sustainable resource management. This paper examines the role of Geospatial Artificial Intelligence (GeoAI) in climate-smart agriculture, with special emphasis on its opportunities, challenges and policy relevance. GeoAI integrates geospatial technologies, remote sensing, artificial intelligence, machine learning and spatial decision-support systems to generate location-specific agricultural information. The study highlights that GeoAI can support crop monitoring, yield prediction, drought and flood assessment, pest-risk detection, irrigation planning, soil-health analysis and climate-risk mapping. It also shows that GeoAI can improve precision resource management, early warning systems, crop insurance and evidence-based agricultural planning. However, the adoption of GeoAI faces several challenges, including data quality issues, model transferability, limited ground-truth data, weak digital literacy, fragmented landholdings, affordability concerns, geo-privacy risks and institutional gaps. The paper argues that GeoAI should not be treated merely as a technological tool, but as a spatial decision-support and climate-governance framework. Its success depends on inclusive digital infrastructure, responsible AI practices, local calibration, farmer participation and strong policy support. The study concludes that GeoAI can significantly contribute to climate-resilient and sustainable agriculture if implemented in a transparent, accessible and context-specific manner.

Keywords: GeoAI; Climate-Smart Agriculture; Remote Sensing; Artificial Intelligence; GIS; Precision Agriculture; Climate Resilience; Sustainable Agriculture; Crop Monitoring; Digital Agriculture.

Introduction

Agriculture has become one of the most climate-sensitive and strategically important sectors in contemporary development debates. Rising temperatures, irregular rainfall, prolonged droughts, sudden floods, soil degradation, pest outbreaks and changing growing seasons are increasingly affecting agricultural productivity and rural livelihoods. These challenges are especially severe in regions where farming depends heavily on monsoon rainfall, natural resources, smallholder labour and traditional production systems. The issue is not only to increase food production, but also to produce food under uncertain climatic conditions while conserving water, reducing input wastage, lowering greenhouse gas emissions and protecting the income security of farmers. Climate-smart agriculture (CSA) has therefore emerged as an integrated approach that seeks to improve agricultural productivity, strengthen adaptation and resilience, and reduce or remove emissions where possible. This integrated vision is important because food security, climate adaptation and environmental sustainability are closely linked and cannot be addressed through isolated agricultural policies.

The global relevance of climate-smart agriculture has increased because food systems are now facing multiple and interconnected pressures. Climate variability, extreme weather events, population growth, land-use change, biodiversity loss, market instability and resource degradation are creating new risks for agricultural systems. The recent global food-security debate shows that climate extremes are among the major drivers of hunger, malnutrition and livelihood vulnerability. International climate assessments have also highlighted that climate change has already affected food and water security through rising heat stress, crop failure, reduced labour productivity and increased exposure to disasters. These concerns are particularly significant for developing and emerging economies, where agricultural systems often suffer from limited irrigation facilities, weak extension services, inadequate insurance mechanisms, fragmented landholdings and unequal access to digital infrastructure. Under such conditions, climate-smart agriculture requires not only improved crop varieties and better farm practices, but also spatially precise, data-driven and anticipatory decision-support systems.

In India, the need for climate-smart agriculture is particularly urgent because agriculture supports a large rural population and remains highly vulnerable to monsoon variability, groundwater depletion, heatwaves, floods and droughts. Small and marginal farmers are often more exposed to climate risk because they have limited financial capacity, low access to advanced technology and high dependence on local ecological conditions. Indian agricultural policy has increasingly recognised the need for climate-resilient farming through initiatives such as the National Innovations in Climate Resilient Agriculture (NICRA), climate-resilient crop varieties, digital agriculture platforms and geospatial decision-support systems. Programmes such as the Digital Agriculture Mission and Krishi-DSS indicate a policy shift towards integrating satellite data, weather information, soil data, crop signatures, reservoir status, groundwater information and artificial intelligence for evidence-based agricultural planning. These initiatives show that agricultural governance in India is gradually moving from generalised advisory systems towards more location-specific and technology-supported decision-making.

Within this wider transformation, Geospatial Artificial Intelligence, commonly known as GeoAI, has emerged as a powerful interface between geospatial science, remote sensing, artificial intelligence, machine learning and agricultural planning. GeoAI refers to the application of AI-based techniques such as machine learning, deep learning, computer vision and spatial modelling to geospatial data. In the agricultural sector, GeoAI can integrate satellite imagery, drone-based observations, field sensor data, rainfall records, soil information, crop calendars, pest surveillance data and socio-economic indicators to generate useful insights at different spatial and temporal scales. Its relevance to climate-smart agriculture lies in its ability to transform large, complex and frequently updated datasets into practical decision-support tools. These tools can assist in crop monitoring, yield prediction, drought assessment, flood mapping, pest-risk forecasting, irrigation scheduling, precision nutrient management and climate-risk zoning.

Recent developments show that GeoAI applications are moving beyond experimental research and are gradually becoming part of operational agricultural intelligence systems. Deep learning and remote sensing are now widely used for crop-type mapping, vegetation monitoring, yield estimation, soil-moisture assessment and agricultural stress detection. Smart farming technologies increasingly combine remote sensing, IoT sensors, climate data, mobile applications and advisory platforms. In India, technology-based yield estimation systems and geospatial agricultural platforms demonstrate the growing institutional importance of satellite data and AI-driven analytics. These developments indicate that GeoAI is no longer limited to academic experimentation; it is becoming relevant to crop insurance, disaster management, agricultural planning, precision farming and climate-risk assessment.

Previous studies have contributed significantly to the understanding of climate-smart agriculture, digital farming and AI-enabled agricultural monitoring. Research on CSA has emphasised the need to balance productivity, adaptation and mitigation under changing climate conditions. Studies on remote sensing and deep learning have shown that AI-based models can improve crop monitoring and yield forecasting by extracting complex spatial and temporal patterns from large datasets. GeoAI scholarship has also highlighted the interdisciplinary nature of the field, requiring collaboration among geographers, computer scientists, agronomists, climate experts, policymakers and farmers. At the same time, recent debates on responsible AI have raised concerns about data bias, model transparency, geo-privacy, algorithmic accountability and ethical use of spatial information. These studies collectively suggest that GeoAI has strong potential to support CSA, but they also reveal important limitations related to data quality, model transferability, interpretability, institutional readiness and farmer-level accessibility.

Despite the growing literature, several research gaps remain. Many studies examine artificial intelligence, remote sensing, precision agriculture or climate-smart agriculture separately, but fewer studies analyse GeoAI as an integrated framework for climate-smart agricultural transformation. Existing research often focuses on technical performance, such as classification accuracy or prediction efficiency, while giving less attention to socio-economic, institutional and ethical conditions affecting adoption. The spatial unevenness of digital infrastructure, local-language advisory systems, platform interoperability, extension capacity and farmer trust remains insufficiently examined. Moreover, climate-smart agriculture is highly context-specific, but many AI models are trained on datasets that may not adequately represent diverse agro-climatic zones, fragmented farms, mixed cropping systems and informal management practices.

The problem addressed in this study is that although GeoAI offers significant potential for climate-smart agriculture, its practical contribution remains uneven and constrained by technical, institutional and socio-economic barriers. GeoAI can provide early warning, location-specific advisories, climate-risk mapping, resource optimisation and evidence-based policy support. However, its effectiveness depends on data reliability, model transparency, affordability, digital literacy, farmer trust, institutional coordination and ethical safeguards. Without these enabling conditions, GeoAI may benefit digitally advanced regions and commercial farms more than vulnerable smallholders, thereby widening existing inequalities.

Therefore, the present study is justified as both a technological and socio-institutional inquiry. It aims to examine the conceptual relationship between GeoAI and climate-smart agriculture, analyse its major opportunities for adaptation, mitigation and productivity enhancement, identify the challenges limiting its adoption, and propose a research-oriented framework for integrating GeoAI into agricultural planning. The novelty of the study lies in positioning GeoAI not merely as a computational technique, but as a climate-governance, spatial-planning and farmer-advisory mechanism. Academically, the study contributes to emerging literature on GeoAI, CSA and digital sustainability. Practically, it can support researchers, planners, agritech developers and extension agencies in designing reliable and farmer-centred GeoAI applications. From a policy perspective, it is relevant for climate-risk assessment, crop insurance, disaster preparedness, precision farming, natural-resource management and climate-resilient rural development. Thus, GeoAI should be understood as a strategic pathway for building resilient, inclusive and evidence-based agricultural systems in an era of accelerating climate uncertainty.

Literature Review

The literature on GeoAI and climate-smart agriculture mainly develops from three related fields: climate-resilient agriculture, geospatial science and AI-based agricultural decision support. Climate-smart agriculture focuses on three major goals: increasing agricultural productivity, improving adaptation and resilience, and reducing greenhouse gas emissions where possible. Zhao et al. (2023) argue that technological innovation, resource management and policy support are essential for climate-resilient food systems. However, much of the CSA literature discusses climate-smart practices in general agronomic or policy terms, while giving limited attention to spatially specific implementation. This is a major limitation because climate risks such as drought, flood, heat stress, pest attack and soil degradation vary across regions, crops and farm systems. Therefore, GeoAI becomes important because it helps identify where, when and how climate-smart interventions should be applied.

GeoAI has expanded with the growth of Earth observation, machine learning, deep learning and big geospatial data. Choi (2023) explains GeoAI as the integration of artificial intelligence, machine learning and deep learning with GIS. Compared with traditional GIS, GeoAI can process large and dynamic datasets such as satellite images, drone data, weather records, soil information and socio-economic indicators. This makes it useful for climate-smart agriculture, where decisions depend on both environmental conditions and farm-level practices. However, scholars also point out concerns related to black-box modelling, spatial bias, data quality and weak integration of geographical theory. Richter and Scheider (2023) argue that GeoAI must address spatial scale, uncertainty, context and interpretability. This is highly relevant because agricultural outcomes are influenced by local soil, climate, crop calendars and management practices.

Remote sensing-based crop monitoring is one of the most developed areas of GeoAI in agriculture. Muruganantham et al. (2022) found that deep learning is increasingly used for crop yield prediction because it can extract complex features from remote sensing data. Joshi et al. (2023) also show that convolutional neural networks, recurrent neural networks and hybrid models have improved crop mapping and yield forecasting. These studies demonstrate the technical strength of GeoAI in using vegetation indices, satellite time-series, weather variables and crop calendars. However, many models remain crop-specific and region-specific. Their accuracy often decreases when applied to areas with different soils, climates, cropping patterns and farming practices. Thus, GeoAI is useful for CSA, but its effectiveness depends on model validation, explainability and local calibration.

Another important literature stream focuses on AI for Earth observation and environmental monitoring. Tuia et al. (2023) argue that AI can convert raw satellite data into useful information through computer vision, explainable AI, causal inference and physics-aware modelling. This is important for CSA because farmers and planners require actionable information on drought stress, soil moisture, crop health, flood risk and yield uncertainty. Ghamisi et al. (2024) further highlight responsible AI issues such as bias, geo-privacy, data openness, security and scientific integrity. These debates show that model accuracy alone is not sufficient. GeoAI systems must be transparent, accessible, affordable and institutionally connected, especially for smallholder agriculture.

Recent reviews also show that GeoAI is moving from technical experimentation towards broader socio-spatial analysis. Wang et al. (2024) demonstrate that GeoAI can analyse complex human-environment relationships more effectively than conventional spatial methods. This is significant because climate-smart agriculture is not only a biophysical process but also a social and economic one. Farmers' adaptive capacity depends on landholding size, credit, irrigation, market access, extension services and digital literacy. In India, initiatives such as NICRA, Digital Agriculture Mission, Krishi-DSS and technology-based yield estimation show growing interest in AI and satellite-based agriculture. However, fragmented landholdings, weak ground-truth data, limited internet access, language barriers and low digital literacy continue to restrict adoption.

Research Methodology:

The study adopts a descriptive, analytical and exploratory research design to examine the role of GeoAI in climate-smart agriculture. It is based mainly on secondary data collected from peer-reviewed journals, government reports, policy documents, institutional databases, GIS datasets, remote sensing sources and climate-agriculture records. The study uses qualitative and spatial analytical approaches to assess opportunities and challenges related to GeoAI adoption. Methods include thematic analysis, content analysis, comparative analysis, SWOT analysis and GIS-based spatial interpretation.

Analysis and Discussion

The analysis shows that GeoAI has strong potential to strengthen climate-smart agriculture by improving spatial accuracy, real-time monitoring and predictive decision-making. The major finding is that GeoAI is most effective when it is used not only as a mapping or prediction tool, but as an integrated decision-support system connecting satellite data, climate records, machine-learning models, farm-level information and policy action. Climate-smart agriculture aims to improve productivity, adaptation and mitigation, but these goals vary across regions because climate risks, soil conditions, irrigation access, crop systems and socio-economic capacity are spatially uneven. GeoAI helps identify vulnerable areas, monitor crop conditions, predict yield variation and support early warning systems. This supports the view that climate-smart agriculture requires technology-based agricultural information services and climate-risk management.

A key pattern emerging from the study is that GeoAI is especially useful for climate-risk identification and crop monitoring. Remote sensing data, vegetation indices such as NDVI and EVI, rainfall anomalies, soil-moisture indicators and machine-learning models can detect drought stress, flood exposure, pest risk and yield instability before visible damage occurs. This supports the hypothesis that GeoAI improves climate-smart agriculture by strengthening early warning, spatial assessment and resource optimisation. Studies by Muruganantham et al. (2022) and Joshi et al. (2023) also show that deep-learning techniques and remote-sensing data are useful for crop mapping and yield prediction. However, the present analysis argues that GeoAI should not be evaluated only through prediction accuracy. Its real value lies in its capacity to support adaptation planning, risk reduction and farmer-oriented advisory systems.

The findings also indicate that GeoAI can improve precision resource management. Climate-smart agriculture requires efficient use of water, fertilisers, energy and land, especially in regions affected by groundwater depletion, rainfall uncertainty and rising input costs. GIS-based spatial analysis can identify irrigation-deficit areas, soil-moisture stress, nutrient variation and crop-health problems. AI-based tools can support irrigation scheduling, variable-rate application and location-specific farm recommendations. These applications have economic and environmental importance because they can reduce input wastage, improve productivity, conserve water and minimise excessive fertiliser use. However, these benefits depend on reliable data, local model calibration, affordable technology and effective extension services. Therefore, technological capacity alone cannot guarantee climate-smart outcomes.

The Indian context shows both opportunities and challenges. India has diverse agro-climatic regions, monsoon-dependent agriculture, frequent droughts and floods, and a large smallholder farming population. These conditions make GeoAI highly relevant for climate-smart agriculture. Initiatives such as the Digital Agriculture Mission, satellite-based crop monitoring and Krishi-DSS show a shift towards data-driven agricultural governance. However, adoption remains uneven due to fragmented landholdings, limited digital literacy, weak internet connectivity, insufficient ground-truth data and gaps between research institutions and farmers. Thus, the effectiveness of GeoAI depends strongly on socio-economic, institutional and infrastructural factors. GeoAI may work well in advanced pilot projects, but its wider success depends on whether small and marginal farmers can access and understand its outputs.

Table 1: Thematic Analysis of Major Findings on the Role of GeoAI in Climate-Smart Agriculture

Theme	**Major Finding**	**Interpretation**	**Implications**

GeoAI and climate-smart agriculture	GeoAI improves spatial accuracy, real-time monitoring and predictive decision-making in agriculture.	GeoAI works best as an integrated decision-support system combining satellite data, climate records, machine-learning models, farm-level information and policy action.	It supports productivity improvement, climate adaptation, mitigation and evidence-based agricultural planning.
Climate-risk identification	GeoAI helps identify drought-prone, flood-prone, pest-prone and climate-vulnerable areas.	Remote sensing data, rainfall anomalies, soil-moisture indicators and AI models can detect risks before visible damage occurs.	It strengthens early warning systems, climate-risk mapping and disaster preparedness.
Crop monitoring and yield prediction	GeoAI supports crop-health monitoring, crop mapping and yield forecasting.	Vegetation indices such as NDVI and EVI, satellite time-series and deep-learning models help assess crop stress and productivity variation.	It improves crop insurance, production planning, food-security assessment and farm advisory services.
Precision resource management	GeoAI supports efficient use of water, fertilisers, energy and land.	GIS-based analysis can identify irrigation-deficit areas, soil-moisture stress, nutrient variation and crop-health problems.	It reduces input wastage, improves productivity, conserves water and supports sustainable farming.
Indian agricultural context	India has high potential for GeoAI-based CSA because of diverse agro-climatic regions and climate-sensitive agriculture.	Initiatives such as Digital Agriculture Mission, satellite-based crop monitoring and Krishi-DSS show movement towards data-driven agriculture.	GeoAI can support climate-resilient rural development, especially in drought- and flood-affected regions.
Adoption challenges	GeoAI adoption remains uneven due to fragmented landholdings, weak digital literacy, poor internet access and	Small and marginal farmers may not benefit equally unless technology is affordable, accessible and locally understandable.	Inclusive digital infrastructure and farmer-centred advisory systems are essential.

	limited ground-truth data.		
Model transferability	AI models developed for one region may not work effectively in another region.	Crop calendars, soil types, rainfall patterns and farm practices vary across agro-climatic zones.	GeoAI models require regional calibration, local datasets and field validation.
Responsible GeoAI	GeoAI uses sensitive spatial data related to land, crop condition, productivity and risk exposure.	Biased or incomplete datasets may misclassify farmers and affect insurance, credit or policy benefits.	Transparency, explainability, geo-privacy, farmer consent and institutional accountability are necessary.
Methodological issue	Existing studies often focus mainly on technical accuracy and prediction efficiency.	Climate-smart agriculture is also a social, economic and ecological process, not only a technical one.	GeoAI evaluation should include resilience, affordability, farmer trust, inclusion and policy integration.
Policy relevance	GeoAI should be integrated with agricultural extension, crop insurance, disaster management and irrigation planning.	Public institutions must ensure that GeoAI does not become accessible only to large farms and agribusiness actors.	Open geospatial datasets, local-language platforms and extension-worker training are needed.
Overall contribution	GeoAI is a powerful but context-dependent tool for climate-smart agriculture.	Its success depends on scientific reliability, ethical design, institutional support and socio-economic accessibility.	GeoAI should be treated as a spatial climate-governance mechanism, not only as a remote-sensing technique.

Source: Compiled by the author based on the analysis and discussion of GeoAI applications, climate-smart agriculture, remote sensing, AI-enabled crop monitoring, digital agriculture initiatives and responsible GeoAI issues.

A major challenge is the gap between model development and field usability. International studies show rapid progress in deep learning, satellite-image analysis and yield prediction, but many models are not easily transferable across regions. A model developed for one agro-climatic zone may perform poorly in another because of differences in crop calendars, soil types, rainfall patterns and farm practices. This is a serious issue because climate-smart agriculture must be locally specific. GeoAI models should therefore be developed with regionally calibrated datasets, local agronomic knowledge and participatory validation. Without field validation, AI-based agricultural systems may remain technically impressive but practically weak.

The study also highlights the importance of responsible GeoAI. Agricultural GeoAI uses sensitive spatial information such as land location, crop condition, productivity potential and risk exposure. Such data may influence crop insurance, credit access, compensation claims and policy targeting. If datasets are biased or incomplete, vulnerable farmers may be misclassified or excluded from benefits. Ghamisi et al. (2024) emphasise that responsible AI in Earth observation must address bias, geo-privacy, data security, transparency and scientific integrity. In agriculture, these issues are highly relevant because inaccurate satellite-based crop-loss estimation or inaccessible digital advisory systems may increase inequality. Responsible GeoAI must therefore include transparency, explainability, data protection, farmer consent and institutional accountability.

The findings reveal a methodological limitation in existing research. Many studies assess GeoAI through technical indicators such as classification accuracy, prediction error and processing efficiency. Although these indicators are important, they are not sufficient for evaluating climate-smart agriculture. CSA is not only a technical process; it is also social, economic and ecological. A broader evaluation framework is needed, including resilience, input efficiency, risk reduction, affordability, farmer trust, inclusiveness and policy integration. This study therefore positions GeoAI as a spatial climate-governance mechanism rather than merely a remote-sensing technique.

The academic, policy and practical implications are significant. Academically, the study connects GeoAI and CSA within a common analytical framework. Geographically, it highlights the importance of spatial heterogeneity and scale. Socially, it emphasises that digital agriculture must include smallholders, women farmers and resource-poor regions. From a policy perspective, GeoAI should be integrated with agricultural extension, crop insurance, disaster management, irrigation planning, soil-health programmes and climate-resilient rural development. Public institutions should promote open geospatial datasets, local-language advisory systems, region-specific AI models and training for extension workers.

Conclusion:

GeoAI has emerged as an important tool for strengthening climate-smart agriculture by integrating geospatial technology, remote sensing, artificial intelligence and spatial decision-support systems. It can support crop monitoring, yield prediction, drought and flood assessment, pest-risk detection, irrigation planning, soil-health analysis and climate-risk mapping. These applications help improve agricultural productivity, climate adaptation, resource-use efficiency and resilience.

The study concludes that GeoAI is not only a technological innovation but also a policy-relevant and farmer-oriented approach for sustainable agriculture. However, its effectiveness depends on data quality, model accuracy, affordability, digital literacy, institutional support and ethical data governance. In countries like India, fragmented landholdings, limited digital access, weak ground-truth data and uneven extension services may restrict its adoption.

Therefore, GeoAI should be implemented as an inclusive, transparent and context-specific decision-support system. With proper policy support and farmer participation, it can significantly contribute to climate-resilient and sustainable agricultural development.

Suggestions:

GeoAI should be promoted as an inclusive and farmer-centred tool for climate-smart agriculture. Governments and research institutions should develop open geospatial databases, region-specific AI models and reliable ground-truth data systems. Farmers, extension workers and local officials should be trained in the practical use of digital advisories, GIS maps and climate-risk information. GeoAI platforms must be available in local languages and designed for small and marginal farmers. Ethical issues such as data privacy, algorithmic bias and transparency should be carefully addressed. Strong collaboration among policymakers, scientists, agritech companies and farming communities is essential for effective and sustainable implementation.

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