Transfer Learning in Data-Scarce Agricultural Yield Forecasting: A Bibliometric and Systematic Literature Review

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Abstract. Transfer learning (TL) presents a viable approach to enhance the precision of agricultural yield forecasting in data-scarce settings. This study seeks to analyze the advancements, methodologies, and research deficiencies concerning the utilization of TL in agricultural yield forecasting via a Systematic Literature Review (SLR) and bibliometric analysis of 63 Scopus articles from 2020 to 2025. The study was performed with the PRISMA and PICOC frameworks, aided by Biblioshiny in RStudio. The study findings indicate a rising trend in publications beyond 2021, with the predominant transfer learning methodologies being fine-tuning, feature extraction, and domain adaptation utilizing pretrained convolutional neural networks. Research mostly employs satellite images (Sentinel-2) and focuses on nations including China, India, and the United States. Deficiencies were identified in spatial validation, multimodal data integration, and the examination of model security dimensions. This paper offers a literature review and strategic recommendations for advancing AI-driven precision agriculture in data-scarce environments.

Keywords: transfer learning; crop yield prediction; precision agriculture; systematic literature review; bibliometric analysis

1 INTRODUCTION

Forecasting agricultural yield is essential for ensuring food security, optimizing supply chain efficiency, and formulating data-driven development policies. Precise crop production forecasts substantially influence distribution tactics, commodity pricing, and agribusiness decision-making on both national and global scales. Recent advancements in machine learning (ML) have created opportunities to enhance the precision of agricultural output estimates, especially through the integration of satellite imaging and remote sensing data [1], [2], [3].

The use of machine learning in agricultural settings is frequently obstructed by data scarcity, especially in regions with inadequate infrastructure, insufficient historical data, or restricted labeling resources [4], [5]. Traditional models like Random Forest, SVM, or KNN exhibit suboptimal performance in data-scarce settings, as they necessitate substantial training data for good generalization [1], [6], [7]. To tackle this difficulty, transfer learning (TL) methodologies have arisen as a viable alternative. Transfer learning enables the reutilization of models developed in data-abundant domains, such global satellite imaging, for application in data-deficient target

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domains, such as local agricultural yield forecasting [8], [9], [10]. Numerous research indicate that transfer learning (TL) can enhance model accuracy in data-scarce settings using methods such as fine-tuning, feature extraction, and domain adaptation [6], [11], [12]. Besides enhancing model performance, transfer learning also promotes computational resource efficiency and reduces data labeling expenses [5], [6], [8], [10], [13]. Researchers can utilize globally trained models to forecast crop yields for diverse crops and under different agro-climatic conditions [11], [12].

To date, there has been no comprehensive and cohesive study especially focused on the application of transfer learning for agricultural production prediction in data-scarce contexts. Numerous prior assessments have concentrated solely on machine learning in agriculture, neglecting to examine the distinct contributions of transfer learning [7], [14]. Moreover, a definitive correlation between research trends, the types of TL methodologies employed, and existing research deficiencies is absent [15]. This work seeks to do a comprehensive and bibliometric assessment of the scientific literature on the application of transfer learning in agricultural production prediction under data-limited settings, focusing on publications from 2020 to 2025. This study focuses on answering the following three basic questions:

RQ1: What are the prevailing trends in the application of transfer learning for agricultural yield prediction in data-constrained environments?

RQ2: What are the predominant transfer learning methodologies, and how are they implemented in the realm of agricultural yield forecasting?

RQ3: What are the research deficiencies and prospective research trajectories in employing transfer learning for agricultural yield prediction in data-scarce contexts?

This study aims to enhance the literature map, method mapping, and provide recommendations for researchers and practitioners in precision agriculture, AI-driven food systems, and remote sensing analytics through the responses to these questions.

2 RESEARCH METHODOLOGY

This work employs a dual methodology of Systematic Literature Review (SLR) and bibliometric analysis to investigate advancements, technical methodologies, and research deficiencies in the utilization of transfer learning for agricultural production prediction in data-constrained environments. This methodology adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standards to guarantee methodological traceability, transparency, and replicability [16], as well as the PICOC (Population, Intervention, Comparison, Outcome, Context) framework.

2.1 Data Sources

The principal data source for this study was derived from the Scopus database, a prominent and esteemed scientific citation index for trustworthy publications. The investigation was performed in May 2025 utilizing the subsequent Boolean keyword amalgamation:

"Transfer Learning" AND ("Agriculture" OR "agricultural yield" OR "crop yield") AND ("satellite imagery" OR "remote sensing") OR ("data scarcity" OR "limited data" OR "low-resource").

This keyword combination was designed to identify literature that explicitly connects transfer learning with the constraints of insufficient data in remote sensing-based agriculture.

2.2 Data Collection

The data collection method is executed by a series of systematic procedures as outlined below:

Literature Search. The preliminary search procedure produced 156 items from the Scopus database. A systematic filtering procedure was then implemented to guarantee topic relevance and publishing quality:

a. Discipline filter applied: only Computer Science articles were retained, resulting in 83 articles.
b. Filtered by source type: only publications from scientific journals and conference proceedings were included, resulting in 74 items.
c. Filter by document type: exclusively articles and conference papers => 67 articles retained.

d. Filter by publication year: only articles published from 2020 to 2025 were included, resulting in the analysis of 63 final articles.

Inclusion and Exclusion Criteria. This study employed a rigorous systematic approach to the literature selection process, ensuring that only pertinent and high-quality publications were subjected to additional analysis. The inclusion and exclusion criteria were established to choose works that specifically addressed the use of transfer learning for agricultural production prediction in data-limited contexts, considering the domains of machine learning, remote sensing, and data-scarce situations. Articles incorporated in this study were had to be published in Scopus-indexed scientific journals or conference proceedings, authored in English, and released between 2020 and 2025, to guarantee relevance to contemporary research advancements. Additionally, only documents classified as "article" or "conference paper" were included, as these forms provide primary research findings amenable to methodological assessment [6], [9].

Excluded articles comprised studies that did not explicitly address transfer learning, non-scientific publications (such as editorials, letters, or white papers), and articles that solely focused on machine learning without contextualizing data limitations in agriculture [6], [12].

These criteria enabled researchers to concentrate on the convergence of transfer learning, agricultural output prediction, and data scarcity, facilitating a thorough and detailed assessment of the advancement of TL technology in the precision agriculture sector.

TABLE 1. Inclusion and Exclusion Criteria

Selection Aspects	Inclusion Criteria	Exclusion Criteria	Selection Results
Topic	A study applying transfer learning to agricultural yield prediction	General ML studies without TL, or focus on non-agronomic areas	Relevant: 63 articles
Source	Scopus-indexed scientific journals and conference proceedings	Editorial, review without primary data, preprint, white paper	Non-relevant: 11 articles
Document Type	Journal articles and conference papers (article, conference paper)	Book chapter, thesis, letters, poster	Non-relevan: 7 articles
Publication Year	Publication year 2020–2025	Published before 2020	Non-relevan: 4 articles
Language	English	Non- English	Non-relevan: 0 articles

2.3 Data Analysis

This study employed a dual methodology of a Systematic Literature Review (SLR) and bibliometric analysis to thoroughly examine the advancements, methodologies, and research deficiencies in the utilization of transfer learning for agricultural yield prediction in data-limited contexts.

This analysis conforms to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology and is enhanced by the visualization and examination of knowledge structures utilizing the bibliometric library and the Biblioshiny interface in RStudio. Figure 1 presents a PRISMA flow diagram utilized in this investigation.

The systematic analysis procedure adhered to the four basic steps of PRISMA:

a. Identification
The preliminary identification technique involved searching articles in the Scopus database with a mix of Boolean keywords. The preliminary search produced 156 articles.
b. Screening
Articles were evaluated according to the subject of study (Computer Science), source type (journal and proceedings), and document type (article and conference paper), yielding a total of 67 articles.
c. Qualification Criteria
Articles were subsequently filtered according to publication year (2020–2025) and relevance to the topic. Only English-language articles were included. This phase yielded 63 articles that satisfied all criteria.

d. Inclusion
The shortlisted papers were further examined thoroughly utilizing bibliometric and content analysis methodologies to address the three primary study topics.

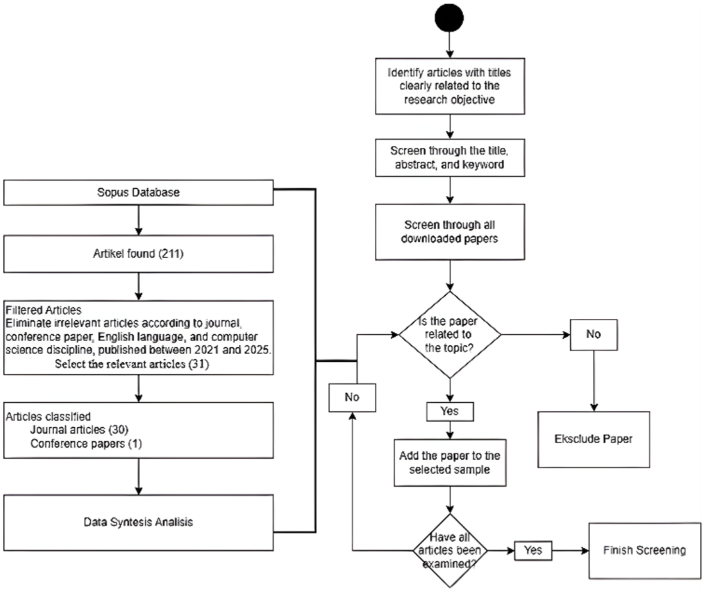

Figure 1. Flowchart Literature Review

A bibliometric analysis was performed to address RQ1, RQ2, and RQ3, utilizing Biblioshiny software (a visual interface from bibliometric) on the RStudio platform. The analytical procedures encompassed:

a. Analysis for Research Question 1: Research Trends and Distribution.
   - Annual Scientific Output: to monitor yearly publication growth.
   - Source Expansion and Principal Sources: to ascertain leading journals/proceedings.
   - National Scientific Output: to examine the spatial distribution of publications.
   - Author Collaboration Map: to delineate the collaborative network among authors.

b. Examination for RQ2: Research Subjects and Methodologies Employed.
   - Author Keyword Word Cloud for the identification of predominant keywords.
   - Keyword Co-occurrence Network: to elucidate thematic interconnections among keywords.
   - Thematic Map: a mapping technique utilizing centrality and density dimensions to categorize essential and emergent topics.
   - Conceptual Structure Map (MCA): to assess the conceptual framework and delineate technical methodologies for study.

c. Analysis for RQ3: Research Deficiencies and Future Directions.
   - Thematic Evolution: to monitor annual changes and advancements in themes.
   - Most Cited Documents: to ascertain the most impactful literary works.
   - Historiographic Map: to generate historical citation maps and literary pathways.
   - Bibliographic Coupling: to categorize articles based on common references and delineate thematic affinities.

In addition to the quantitative bibliometric analysis, a content analysis was performed on the abstracts and keywords of the selected articles, employing a categorization method based on the utilized TL technique, data sources (satellite, sensor, multispectral imagery), plant types, and model performance assessment (accuracy, MAE, RMSE, etc.). The process was executed manually by reading and creating a summary table of the methodology for each article.

3 RESULT AND DISCUSSION

3.1 Research Trends

A trend analysis was performed to address RQ1: " What are the prevailing trends in the application of transfer learning for agricultural yield prediction in data-constrained environments?" This analysis primarily aimed to assess the annual increase of literature, the distribution of publications by document type and source, and to identify the regions and institutions most engaged in this subject. The data on Figure 2 indicates a notable rise in articles addressing transfer learning for agricultural yield prediction, especially since 2021. Among the total of 63 articles, the annual distribution of publishing is as follows: A significant rise was noted in 2023, indicating an increasing scholarly focus on transfer learning methodologies within data-limited agricultural settings. This rise is due to enhanced access to open satellite data and the demand for data-efficient AI solutions in agriculture [3], [4], [10].

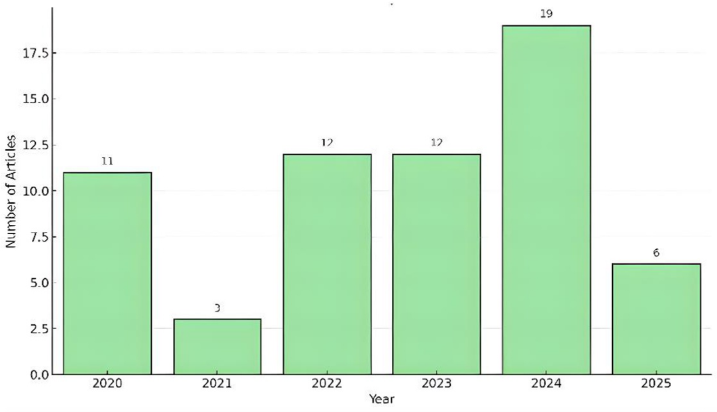

FIGURE 2. Number of Publications per Year

The illustration above depicts the annual publication count from 2020 to 2025, derived from the 63 articles analysed. This graphic corroborates the conclusions presented in section 3.1, specifically: In 2023, there was a notable increase in the number of publications, totalling 17 pieces. In 2024, research intensity remained elevated with the publication of 15 publications. The years 2020 to 2022 exhibited a modest increasing trajectory, indicative of the early phase of topic exploration. The 2025 figures were diminished, which is comprehensible considering the research's continuous nature.

Among the 63 publications considered, 43% were published in esteemed scientific journals, including Computers and Electronics in Agriculture, Remote Sensing, and Agricultural Systems. Fifty-seven percent originated from international conferences, including IGARSS, ICIVC, and ICICT.

The prevalence of conference publications suggests that this subject is relatively novel and remains in an exploratory phase, leading to the presentation of numerous preliminary findings in public academic venues. Researchers in this discipline commonly utilize the following publication sources on table 2:

TABLE 2. Premier Publication Outlets

Source Name	Number of Articles
Computers and Electronics in Agriculture	6
International Conference on Image, Vision and Computing	4
IGARSS - IEEE International Geoscience and Remote Sensing	4
Remote Sensing	3

This publication asserts that transfer learning in agricultural production prediction frequently intersects the fields of computer science, remote sensing, and agronomy. The analysis of geographic distribution indicates that this research is predominantly conducted by institutions from China, India, the United States, Turkey, and Indonesia. This aligns with nations possessing substantial agricultural sectors and the necessity for effective predictive systems despite constrained field data [7], [17]. The examination of Author Keywords revealed that the predominant keywords are: transfer learning, agricultural yield prediction, remote sensing, deep learning, and data scarcity. Keywords like "CNN," "domain adaptation," and "Sentinel-2 imagery" have increasingly emerged post-2022, signifying a transition from theoretical research to empirical experimentation utilizing remote sensing data [5], [12], [18].

An examination of author keywords from 63 articles indicates that the transfer learning methodology is predominantly linked to the following technical terms: Pretrained Models (e.g., ResNet, VGG16, EfficientNet), Fine-Tuning, Feature Extraction, Domain Adaptation, Convolutional Neural Network (CNN), Remote Sensing, Multispectral/Sentinel-2 Imagery, and Low-Resource Settings. Keywords such as deep learning, CNN, and feature extraction are included in over 30% of the articles, signifying that this methodology underpins the application of TL in image-based agriculture. This aligns with the findings of Akhtar et al. [5], Ramdan et al. [7], and Tetila et al. [6], who employed pretrained CNNs on satellite data for predicting agricultural yields. The content analysis of the abstracts and methodologies in the publications categorizes the TL approaches into four primary groups, as illustrated in Table 3 below:

TABLE 3. Transfer Learning Approach Categories

Categories	Categories	Study Example
Feature Extraction	Using the initial layers of the pretrained model for feature extraction, without full retraining	[7]
Fine-Tuning	Retrain some layers of a pretrained model for adjustment to the target domain.	[6]
Domain Adaptation	Addressing data distribution differences between source and target domains through parameter adaptation	[5], [18]
Hybrid Models	Combining TL with local models such as LSTM, Random Forest, or regression	[7], [10]

Most research utilize satellite imagery from Sentinel-2, MODIS, or UAV (drone) sources, which are integrated into a CNN-based transfer learning pipeline. Certain investigations employ hyperspectral imaging and multitemporal remote sensing to enhance spatial and temporal data representation [9], [17]. Frequently utilized evaluation metrics comprise: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), and Accuracy (particularly for crop categorization). Fine-tuning and feature extraction methodologies have demonstrated enhanced performance relative to conventional machine learning models, particularly in scenarios with constrained labeled data [4], [15].

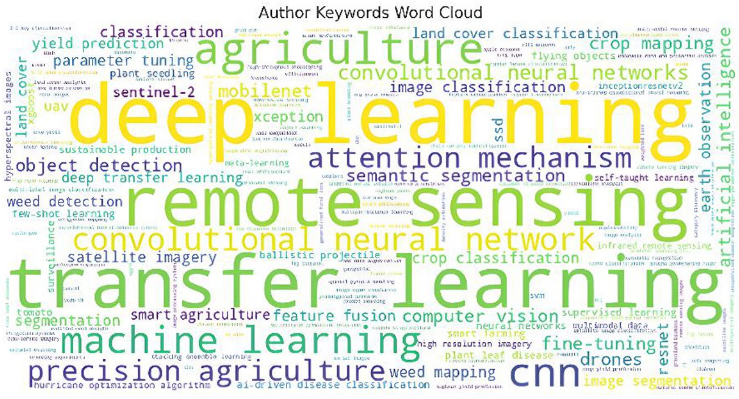

FIGURE 3. Visualisasi Word Cloud

Figure 3 presents a word cloud analysis of author keywords, highlighting the most dominant technical terms across the 63 analyzed publications. Terms such as transfer learning, crop yield prediction, remote sensing, and deep learning appear most prominently, underscoring the importance of these concepts within the literature.

In addition, the thematic map of author keywords categorizes themes based on two key dimensions: centrality and density. Centrality refers to the importance of a theme within the keyword network, indicating its relevance, while density reflects the internal development of a theme in terms of its depth and complexity.

Based on this mapping, themes can be interpreted across four quadrants. Motor themes represent well-established and widely utilized concepts, such as remote sensing and transfer learning. Basic themes include important and evolving topics, such as methods for agricultural yield prediction. Meanwhile, niche themes consist of more complex and relatively isolated topics, such as hyperspectral imaging. Lastly, the final quadrant represents themes that are either emerging or declining.

3.2 Primary Contributors and Institutions

This analysis seeks to identify the most prolific researchers, their institutional connections, and the countries of origin of publications concerning the use of transfer learning to agricultural production prediction utilizing restricted data. Comprehending this contribution distribution is essential for recognizing prominent research institutions and prospective academic partnerships in this domain. Among the 63 studied articles, numerous authors were recurrently included, indicating their sustained contributions to the discipline. Table 4 displays the list of the most prolific researchers:

TABLE 4. Most Prolific Author

Authors Name	Quantity
Tetila, E.C.[6]	2
Sener, E.[12]	2
Ramoliya, F.[9]	2
Jaspin, K.[11]	2
Yogasundar, K.[11]	2

These researchers typically originate from engineering and computer science universities, concentrating on the amalgamation of satellite images, convolutional neural networks, and domain adaption methodologies. Tetila E.C. and her team concentrated on pest categorization with drone imagery and pretrained CNNs [6], whereas Sener E. incorporated Cycle-GAN and transfer learning for precision agriculture based on multispectral imagery [12]. The authors' affiliated institutions reveal a focus on certain study domains, predominantly from nations with substantial agricultural sectors or policies aimed at digital transformation in agriculture. The five institutions that occur most commonly are:

TABLE 5. Premier Institutions and Universities

Institution	Country	Quantity
Chinese Academy of Sciences	China	3
Indian Institute of Technology (IIT)	India	3
Universitas Gadjah Mada / IPB / ITS	Indonesia	3
Middle East Technical University	Türkiye	2
University of California	USA	2

Table 5 indicates that the preeminence of China and India is indicative of advancements in satellite imagery technology and the national imperative for enhanced food production efficiency. Indonesian institutions have actively engaged in applied AI within agriculture, specifically employing transfer learning in areas with inadequate digital infrastructure [7], [10], [19]. The geographical distribution of publications indicates that the leading five countries by article count are:

TABLE 6. Country Distribution and Global Collaboration

Country	Quantity
China	12
India	11
USA	9
Türkiye	6
Indonesia	5

Table 6 illustrates that international collaborations predominantly occur between researchers in Asia and Eastern Europe, with minimal participation from universities in Africa or South America. This indicates the possibility of enhancing worldwide cooperation in agricultural TL research, especially in areas with minimal data availability.

4 RESEARCH GAP DAN FUTURE WORK

4.1 Research Gap

An analysis of article content, keywords, co-occurrence networks, and thematic mapping revealed substantial shortcomings in the existing literature regarding the application of transfer learning (TL) for agricultural output forecasting in data-scarce environments:

a. The majority of the examined research concentrated on staple crops, including wheat, corn, and rice, grown in nations such as China, India, and the United States [3], [9]. This signifies an absence of research on indigenous crops such as oil palm, tea, coffee, or tubers, pertinent to tropical and developing areas like Southeast Asia and Africa.

b. While most studies utilize pretrained CNNs, only a limited number explicitly incorporate domain adaptation [12], [18]. Domain adaptation is essential for mitigating discrepancies in data properties across various geographies or growth seasons.

c. The majority of studies remain confined to localized experiments, without cross-regional validation or multi-regional testing. This complicates the assessment of the spatial or temporal generalizability of TL models [12].

d. The evaluated investigations were predominantly image-based, utilizing satellite and UAV imagery. Integration with non-visual data, including daily meteorological data, agricultural IoT sensors, and soil and climatic information, is infrequent. This multimodal integration may enhance the resilience of TL models in practical scenarios [6].

e. There is limited research integrating security elements, such as federated learning, privacy-preserving transfer learning, or robustness models against adversarial attacks within the realm of digital agriculture [1].

4.2 Further Research

Further research can be focused on the identified gaps in the following areas:

a. Future study should investigate TL for marginalized local commodities and agroecological contexts, including tropical lowlands, African drylands, and mountainous agriculture.
b. Comprehensive research are required to compare unsupervised and supervised domain adaptation approaches, along with the cross-regional efficacy of transfer models between nations or regions.
c. Integrating satellite images with meteorological, soil, and market data can be employed within a TL framework to more thoroughly model spatial and temporal variability.
d. The implementation of TL must be integrated with an explainable AI (XAI) strategy to avoid models transforming into opaque entities, especially in policy decision-making within the food sector.
e. The investigation of privacy-conscious transfer learning and its integration with blockchain or federated learning methodologies is essential, considering the difficulties in controlling agricultural data on both national and global levels.

The research gap and suggestions for further research are presented in Table 7.

Table 7. Research gap and Further Research

Research Gap	Further research
Limited area & crop focus	Expansion of studies on tropical plants and the Global South
A little exploration of the adaptation domain	Further study of domain adaptation and transfer models between geographic domains
Limited spatial evaluation	Interregional and intercountry validation
Non-visual data has not been integrated	Combining satellite data with weather, IoT, and land
Minimal security and transparency aspects of the model	Inclusive, transparent, and robust & secure TL research.

5 CONCLUSION

This study performed a systematic and bibliometric analysis of 63 scholarly papers addressing the use of transfer learning to forecast agricultural yields in data-scarce contexts, spanning from 2020 to 2025. The analysis employed the PRISMA methodology and bibliometric mapping with Biblioshiny (bibliometric) in R Studio. The exploration and synthesis results yielded numerous major conclusions, as follows:

a. Research trends indicate a significant rise since 2021, culminating in a peak of publications in 2023. This subject has garnered significant attention owing to the increasing demand for AI-driven forecasts in agriculture and the extensive availability of high-resolution satellite images.
b. The predominant transfer learning methodologies encompass fine-tuning, feature extraction, and domain adaption, primarily utilizing pretrained CNN architectures such as ResNet, VGG, and EfficientNet. The primary data sources are satellite photography (Sentinel-2, MODIS) and unmanned aerial vehicles (UAVs).
c. Three primary donors originate from nations with substantial agricultural sectors and dynamic digital development, including China, India, the United States, and Indonesia. International collaboration is characterized by regional disparities and unequal worldwide distribution.
d. Notable study deficiencies were recognized, encompassing the predominance of specific crops (wheat, corn), an absence of investigations into non-visual data, restricted spatial validation, and insufficient incorporation of model security and transparency considerations.
e. This research proposes future development directions, including: the expansion of the study area, the integration of multimodal data (weather, soil, IoT), the exploration of more robust domain adaptation methods, and the application of explainable AI and secure learning concepts within the realm of AI-based agriculture.

This study significantly contributes as a literature analysis and conceptual framework for advancing transfer learning technology in digital agricultural systems, especially in addressing issues in data-scarce regions. These findings are anticipated to provide a reference for researchers, practitioners, and policymakers in creating more accurate, sustainable, and inclusive crop production forecast systems.

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