Leveraged Cognitive Data Analytics and Artificial Intelligence to Enhance Sustainable Agricultural Practices: A Systematic Review

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***Abstract*—This systematic review examines the transformative role of Cognitive Data Analytics (CDA) and Artificial Intelligence (AI) in advancing sustainable agricultural practices, with a primary objective to evaluate their applications in Precision Agriculture (PA), Internet of Things (IoT), smart irrigation, and Geographic Information Systems (GIS) from 2020 to 2025. Key findings highlight AI predictive modeling, IoT real-time monitoring, and GIS spatial analysis improving crop yields, water conservation, and environmental management. Challenges such as high costs, technical expertise gaps, and regional disparities hinder adoption. The review underscores the need for supportive policies and farmer training to enhance food security and sustainability by 2030.**

Keywords—Cognitive data analytics; sustainable agriculture; harnessing AI for agriculture; precision agriculture; environmental sustainability; food security

I. Introduction

Agricultural practice pertains to the methodologies and techniques utilized in farming to augment productivity and sustainability, encompassing both crop management and livestock stewardship. The term embodies the integration of contemporary technologies to enhance efficiency in both outdoor and indoor environments, such as agricultural fields and greenhouses [1]. The adoption of Internet of Things (IoT) technologies, for instance, facilitates real-time data collection through interconnected devices, enabling precision farming practices that optimize resource use and enhance crop management [48]. This integration of advanced technologies, including IoT, sets the stage for transformative approaches like Cognitive Data Analytics (CDA) and Artificial Intelligence (AI), which further revolutionize sustainable agriculture by improving decision-making and resource efficiency.

A. Artificial Intelligence in Sustainable Agriculture

Integrating AI into sustainable agriculture is revolutionizing farming practices. The utilization of AI in sustainable agriculture assists farmers in enhancing aspects such as productivity, resource management, and pest control by collecting data and employing it to optimize agricultural processes [2]. This technology facilitates precise applications of inputs, mitigates waste, and minimizes environmental impact. Moreover, it automates repetitive tasks, thereby improving productivity and efficiency while advocating for responsible farming practices [47]. Furthermore, AI aids farmers in reducing waste, minimizing environmental impact, and simultaneously increasing productivity while addressing challenges such as elevated costs and the necessity for technical expertise, ultimately contributing to food security and environmental sustainability [2].

1) Cognitive data analytics. CDA is an advanced approach that integrates cognitive processes into data analysis, enabling users to derive insights from complex datasets, particularly in the context of big data. This approach is crucial as it automates and enhances traditional data analysis methods, allowing for the processing of both structured and unstructured data [3]. CDA systems interact with users, learning from these interactions to improve the analysis process. This interaction is facilitated through technologies like natural language processing and machine learning, which help in hypothesis generation and decision making [4].

2) Precision agriculture. Precision Agriculture (PA) is a farming management strategy and system that uses technology and data to enhance agricultural productivity and sustainability. By focusing on the variability of soil and crop conditions and the precise placement of seeds, fertilizers, and pesticides, PA enables farmers to make informed decisions regarding resource allocation, ultimately leading to increased yields, reduced costs, and environmental impact [5].

3) Internet of things and smart irrigation. IoT in agriculture involves many connected devices with sensors that collect and exchange data, enabling precision farming such as seed placement, resource optimization like water management, disease detection in agricultural crops, and improved decision making by providing historical and real time data for analysis. This helps farmers to make data driven decisions that enhance productivity, improve crop yield, and reduce waste. Furthermore, the information on soil conditions, weather, and crop health obtained by IoT also improves the quality and quantity of crops while decreasing production costs, which in turn enhances farmers' profitability [49].

Smart irrigation also uses the principles of the IoT, utilizing a connected system of automation, such as sensors, to optimize crop management. Real-time data on soil moisture, weather, and crop needs is gathered, which helps farmers make informed

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decisions about watering schedules and amounts. Such information promotes efficient and sustainable water usage [50].

4) Geographic information systems. Geographic Information Systems (GIS) in agriculture involve the use of technologies such as sensors and AI to visualize and analyze agricultural data, including soil quality, climate conditions, and land features. Such analysis enables farmers to make data-driven decisions regarding land use and crop management [51]. Furthermore, it also aids in resource management, such as water consumption and soil nutrient management, enhancing production efficiency, supporting regulatory compliance, and helping to resolve land use conflicts, ultimately benefiting agricultural operations [52].

B. Purpose and Scope of Study

This systematic review aims to investigate the applications of CDA and AI in sustainable agriculture, focusing on their contributions to precision agriculture, intelligent agricultural management systems, and GIS and IoT-based solutions. The study aims to comprehensively analyze how these technologies enhance agricultural productivity, resource efficiency, and environmental sustainability. This review will examine the following aspects:

- The study discusses the current and projected advancements in sustainable agriculture by 2030.
- The utilization of CDA and AI in precision agriculture and innovative farming ecosystems.
- The major applications of CDA and AI in GIS, IoT, and intelligent agricultural management systems.
- The key challenges and opportunities for adopting these technologies in agriculture.

By systematically reviewing relevant studies published between 2020 and 2025, this research aims to deepen the understanding of the transformative potential of CDA and AI in agriculture, providing insights for farmers, researchers, policymakers, and stakeholders to promote sustainable agricultural practices.

C. Significance and Future Implications

The use of AI in sustainable farming involves using intelligent data analysis to improve precision farming, better resource management with IoT and smart irrigation, and making better decisions with geographic information systems. These integrations contribute to an increase in productivity, resource management efficiency, crop yield, and sustainability in farming practices [53].

The remainder of this study is structured as follows: the methodology section outlines the systematic review design, search strategy, and quality assessment using PRISMA and the Critical Appraisal Framework (CAF). The results section presents findings across CDA, PA, IoT, and GIS. The discussion synthesizes cross domain insights and regional variations. The limitations section addresses study constraints and research opportunities. Finally, the conclusion summarizes the potential of CDA and AI for sustainable agriculture.

II. Methodology

A. Systematic Review Design and Thematic Focus

This study presents a systematic review that synthesizes existing literature on the applications of Cognitive Data Analytics (CDA) and Artificial Intelligence (AI) in sustainable agriculture.

B. Research Questions

The study is guided by the following research questions:

- What are the current and projected advancements in sustainable agriculture by 2030?
- How are CDA and AI utilized in precision agriculture?
- What are the major applications of CDA and AI in intelligent agricultural management systems, GIS and IoT-based solutions?
- What are the main challenges and opportunities for adopting CDA and AI in agriculture?

C. Framework

Four categories structure this systematic review: CDA, PA, GIS, and the Internet of Things and Smart Irrigation (IoT). These domains represent the primary areas where CDA and AI are currently making significant contributions to sustainable agriculture. Separating them allows for an analysis of the studies based on the research questions. This format enables a focused exploration of the unique challenges and opportunities within each technological area. The review aims to provide a comprehensive and comparative understanding of how AI decision making, predictive analytics, geospatial tools, and smart technologies are shaping the future of sustainable agriculture.

D. Search Strategy

Researchers conducted a comprehensive literature search across academic databases, IEEE, Scopus, MU, and Google Scholar, to identify studies on innovative agricultural practices and technological integration from 2020 to 2025. The search employed keyword combinations targeting sustainable agriculture, smart farming, agricultural technology, Analytics CDA, AI, PA, IoT, smart irrigation, and GIS. The following are examples of search queries that were used:

- "Cognitive Data Analytics" AND ("Sustainable Agriculture" OR "Smart Farming" OR "Agricultural Technology")
- ("Sustainable Agriculture" OR "Smart Farming" OR "Agricultural Technology") AND ("Cognitive Data Analytics" OR "AI in Agriculture" OR "Machine Learning in Farming")
- "Precision Agriculture" AND "AI Applications"
- ("IoT in Agriculture" OR "Smart Irrigation" OR "Drones in Agriculture") AND "Farming Integration"
- "Geographic Information Systems in Farming" OR "GIS and Remote Sensing for Agriculture"

The five year timeframe was selected to capture recent advancements in CDA and AI, reflecting rapid technological evolution in sustainable agriculture. Excluding studies from before 2020 to maintain relevance to current trends, but may limit historical depth.

E. Data Extraction

A standardized data extraction form will be used to collect information, including:

- Author(s), publication year and journal or conference.
- Study objectives, methods and sample size.
- Key findings related to technology perception, innovation requirements and machine learning.
- Outcomes and limitations.

F. Screening Process

Researchers conducted the selection and screening of research articles through a structured process to ensure their relevance and quality:

- Title Screening - All retrieved studies were first screened by title to exclude studies that did not relate to the main topics of AI, CDA, GIS, and sustainable or precision agriculture of this study.
- Abstract Screening - Studies are then reviewed by analyzing the abstracts to assess if the studies have relevance to the research questions.

Subsequently, the criteria for inclusion and exclusion are presented to ascertain the appropriateness of this review.

G. Inclusion and Exclusion Criteria

The inclusion criteria are composed of four fundamental elements:

- Peer-reviewed journal articles, conference papers or technical reports.
- Published between 2020 and 2025.
- Focus on AI, CDA, GIS, IoT, drones, or precision agriculture.
- Studies that present empirical data, case studies or real-world applications.

Two fundamental elements make up the exclusion criteria:

- Opinion articles or general discussions without empirical evidence.
- Studies that focus only on traditional agricultural methods without technological integration.

H. Quality Assessment

To ensure the review was thorough and relevant, we checked the quality of each chosen study using the PRISMA guidelines. Systematic reviews assessing compliance with PRISMA guidelines have an average compliance rate of 73% [6]. Statistics underscore the importance of PRISMA and enable better data filtering and quality assessment for this systematic review [7].

To ensure the reliability and validity of the selected studies, this review employs the Critical Appraisal Framework (CAF). This framework adheres to a structured narrative approach to evaluate methodological rigor and relevance without assigning numerical scores. Each study shall be subjected to critical review based on the following factors:

- Is the study contextually relevant to sustainable agriculture and AI applications?
- Are the research design and methods clearly described?
- Are data sources credible and well documented?
- Does the study provide a clear, logical analysis of findings?
- Does the study acknowledge its limitations?
- Up-to-date with existing literature in sustainable agriculture and AI?

Each study will undergo qualitative synthesis instead of a numerical ranking, ensuring an evaluation that is both transparent and contextually relevant. Studies that do not meet essential criteria (e.g., lack of methodological clarity or unreliable data) will be excluded from the final review. By utilizing CAF, this systematic review upholds methodological rigor, transparency, and depth while steering clear of oversimplified scoring systems.

III. RESULTS

A. Inclusion and Exclusion of Works Using PRISMA

This systematic review examined a total of 376 research studies identified across academic databases: IEEE, Scopus, MU, and Google Scholar. These studies were distributed across four categories: Cognitive Data Analytics (CDA), Precision Agriculture (PA), Internet of Things (IoT), and Geographic Information Systems (GIS). The screening process and the application of the inclusion and exclusion criteria led to the selection of 262 studies for potential inclusion, while 114 studies were excluded. The main reason for exclusion was that the publication year fell outside the review's scope of 2020 to 2025, as specified in the exclusion criteria, while 12 studies were also excluded due to duplication across databases. The inclusion and exclusion of works using the PRISMA methodology are illustrated in Fig. 1.

PRISMA Flow Diagram illustrating the screening process for study inclusion, with 376 initial records retrieved from Google Scholar (154 studies), IEEE (90 studies), Scopus (60 studies), and MU (56 studies). After title and abstract screening, 262 studies were included, with 114 excluded (102 outside the 2020 to 2025 scope and 12 duplicates).

B. Quality Assessment with Critical Appraisal Framework

To guarantee the inclusion of high-quality and relevant studies, each selected article was assessed utilizing the Critical Appraisal Framework (CAF). This framework is specifically developed to conduct a qualitative evaluation of methodological rigor and thematic relevance by addressing six guiding questions:

- (Q1) Is the study contextually relevant to sustainable agriculture and AI applications?
- (Q2) Are the research design and methods clearly described?
- (Q3) Are data sources credible and well-documented?
- (Q4) Does the study provide a clear, logical analysis of findings?
- (Q5) Does the study acknowledge its limitations?
- (Q6) Is the study up-to-date with existing literature in sustainable agriculture and AI?

Each criterion was assessed with a "Yes" or "No", and the total number of "Yes" responses per study was recorded. The results of this assessment are presented in Table I. Additionally, each study was categorized under one of the four categories explored in this review: Precision Agriculture (PA), Geographic Information Systems (GIS), Cognitive Data Analytics (CDA), or Internet of Things and Smart Irrigation (IoT).

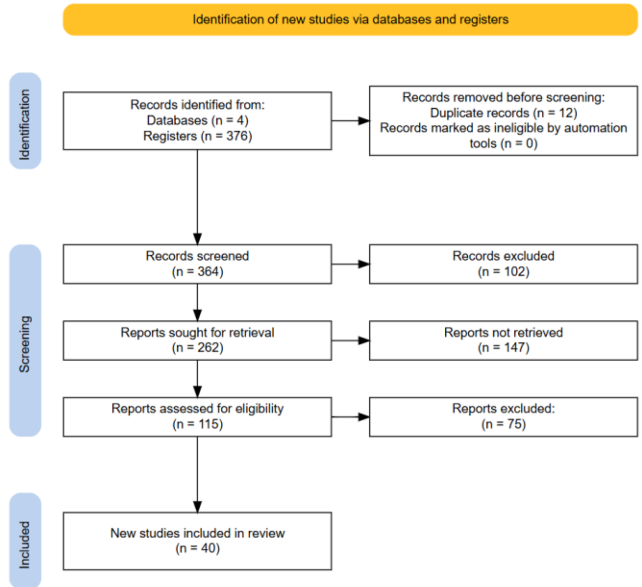

Fig. 1. Inclusion and exclusion of works using PRISMA.

TABLE I. FRAMEWORK FOR CRITICAL EVALUATION OF SELECTED RESEARCH STUDIES

Study ID	Topic	Q1	Q2	Q3	Q4	Q5	Q6	Total of Yes
[1]	PA	Yes	Yes	Yes	Yes	No	Yes	5
[8]	GIS	No	Yes	Yes	Yes	No	No	3
[9]	PA	Yes	Yes	Yes	Yes	Yes	Yes	6
[10]	CDA	Yes	Yes	Yes	Yes	Yes	Yes	6
[11]	CDA	Yes	No	Yes	No	Yes	Yes	4
[12]	PA	Yes	Yes	Yes	Yes	No	Yes	5
[13]	CDA	No	Yes	Yes	Yes	No	No	3
[14]	GIS	No	Yes	Yes	Yes	Yes	No	4
[15]	PA	Yes	Yes	Yes	Yes	No	Yes	5
[16]	GIS	Yes	Yes	Yes	Yes	Yes	Yes	6
[17]	GIS	No	Yes	Yes	Yes	Yes	No	4
[18]	GIS	Yes	Yes	Yes	Yes	Yes	Yes	6
[19]	CDA	No	No	Yes	No	No	No	1
[20]	IOT	Yes	Yes	No	No	No	Yes	3
[21]	IOT	Yes	Yes	No	Yes	Yes	Yes	5
[22]	CDA	Yes	No	Yes	Yes	Yes	Yes	5
[23]	GIS	Yes	No	No	Yes	No	Yes	3
[24]	CDA	Yes	Yes	Yes	Yes	No	Yes	5
[25]	IOT	Yes	Yes	Yes	No	Yes	Yes	5
[26]	IOT	Yes	Yes	Yes	Yes	Yes	Yes	6
[27]	PA	Yes	Yes	Yes	Yes	Yes	Yes	6
[28]	IOT	Yes	Yes	Yes	Yes	Yes	Yes	6
[29]	IOT	Yes	No	Yes	No	No	Yes	3
[30]	PA	No	Yes	Yes	Yes	Yes	Yes	5
[31]	CDA	Yes	Yes	Yes	Yes	No	Yes	5
[32]	IOT	Yes	No	Yes	Yes	Yes	Yes	5
[33]	GIS	Yes	Yes	Yes	Yes	No	Yes	5
[34]	IOT	Yes	Yes	Yes	No	Yes	Yes	5

[35]	IOT	Yes	Yes	Yes	Yes	Yes	Yes	6
[36]	GIS	Yes	No	Yes	No	No	Yes	3
[37]	PA	No	No	Yes	No	No	No	1
[38]	CDA	Yes	Yes	Yes	Yes	Yes	Yes	6
[39]	PA	Yes	Yes	Yes	Yes	Yes	Yes	6
[40]	IOT	Yes	No	Yes	No	No	Yes	3
[41]	PA	Yes	Yes	Yes	Yes	Yes	Yes	6
[42]	PA	Yes	Yes	Yes	Yes	No	Yes	5
[43]	CDA	Yes	Yes	Yes	Yes	Yes	Yes	6
[44]	GIS	No	Yes	Yes	Yes	No	No	3
[45]	GIS	No	Yes	No	Yes	No	No	2
[46]	CDA	Yes	Yes	Yes	Yes	Yes	Yes	6
Total: 40	CDA = 10, GIS = 10, IOT = 10, PA = 10	Yes = 31 No = 9	Yes = 31 No = 9	Yes = 36 No = 4	Yes = 31 No = 9	Yes = 22 No = 18	Yes = 32 No = 8	

Footnote: Q1 = Is the study contextually relevant to sustainable agriculture and AI applications?; Q2 = Are the research design and methods clearly described?; Q3 = Are data sources credible and well documented?; Q4 = Does the study provide a clear, logical analysis of findings?; Q5 = Does the study acknowledge its limitations?; Q6 = Is the study up to date with existing literature in sustainable agriculture and AI?

The CAF's assessment indicated that many chosen studies, when evaluated using PRISMA, were very well done, with many of them meeting all six set criteria. The studies that achieved high scores consistently demonstrated clarity in their design, reliability of data, and relevance to the research objectives. Conversely, a limited number of studies received low scores due to ambiguous methodologies, an outdated context, or a lack of relevance to core topics. Studies that garnered fewer than four "yes" responses were deemed to possess low appraisal quality and were consequently excluded from the final results. This process ensured that only the most relevant and methodologically sound studies contributed to the outcomes of this systematic review.

C. Results and Findings

This section presents the results of the systematic review organized according to four categories: CDA, PA, GIS, and IoT. These categories are selected to illustrate how CDA and AI contribute to the transformation of sustainable agriculture. Each category is reviewed in accordance with the research questions.

1) Artificial intelligence and cognitive data analytics. Agriculture is a field, where technological change in traditional farming practices has been evolving through the impact of AI and CDA. Research studies explore the potential of this technological change to improve efficiency and sustainability in agricultural systems. This section demonstrates how AI and CDA are being integrated into agriculture, highlighting recent advancements, applications, and challenges. Only studies that scored at least four points in the critical appraisal process, as shown in Fig. 2, were included in the final analysis to ensure that the findings are of highest quality.

Recent advancements in AI and CDA are transforming agricultural practices by enabling data driven systems that enhance productivity and resource efficiency. Studies project that by 2030, these technologies will significantly improve farming through robotic platforms, automated crop monitoring, and predictive modeling for optimized irrigation and fertilization [10, 31]. For example, Explainable AI (XAI) has been applied to coffee quality assessment to identify key quality defects or determinants, which offer transparency that would not be possible with traditional subjective evaluations [46]. Additionally, hybrid learning models using Convolutional Neural Networks (CNN) have achieved 91% accuracy in predicting orange quality by combining visual and structured data, lessening the need for manual inspections [24]. Additionally, AI precision techniques in Oman, optimize crop management, pest control, and irrigation to improve yield and water conservation [31]. These innovations address labor shortages, enhance decision making, and promote sustainable practices across diverse agricultural contexts [10, 13].

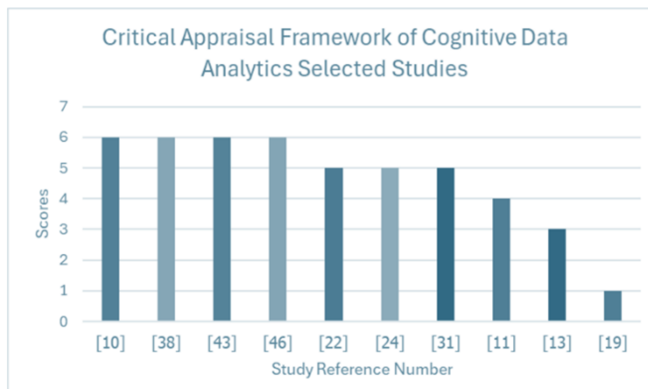

Fig. 2. Critical appraisal framework for selected cognitive data analytics related studies.

AI and CDA are pivotal in developing intelligent agricultural management systems that create innovative farming ecosystems. These systems encompass autonomous tractors, IoT based drones for pest control, soil nutrient mapping tools, and climate responsive irrigation platforms [10, 11, 24]. For example, drones equipped with deep neural networks allow for accurate detection of plant diseases and targeted pesticide application to improve pest control efficiency [11]. However, challenges like high initial development costs, fragmented data, diverse soil types, and limited technical expertise in regions like India with small landholdings hinder consistent adoption, necessitating technical support and infrastructure for maintenance for these systems [38, 43]. To help with this, more

AI techniques like fuzzy logic, artificial neural networks, genetic algorithms, and sensor technology are employed to enhance the efficient cultivation, monitoring, and harvesting of agricultural systems [13].

Adopting AI and CDA in agriculture faces challenges that require strategic interventions to realize their full potential. Key points of adoption include individual characteristics, environmental and structural factors, technology accessibility, and demographic considerations [43]. Building trust with agricultural farmers through informed policy and education is essential to increasing adoption rates [43]. For example, the transparency provided by XAI fosters stakeholder confidence in AI quality assessments and potentially standardized processes like coffee production [46]. However, despite these challenges, when supported by continued research, investment, and customized regional solutions, AI and CDA offer significant benefits that contribute to increased productivity, environmental sustainability, and food security [31, 43].

2) Precision agriculture. Precision agriculture significantly benefits from CDA and AI, utilizing real time sensor data and machine learning to enable targeted application of water, pesticides, and nutrients, thereby optimizing yields while conserving resources [38]. Furthermore, only studies that scored at least four points in the critical appraisal process were included in the final analysis, as shown in Fig. 3.

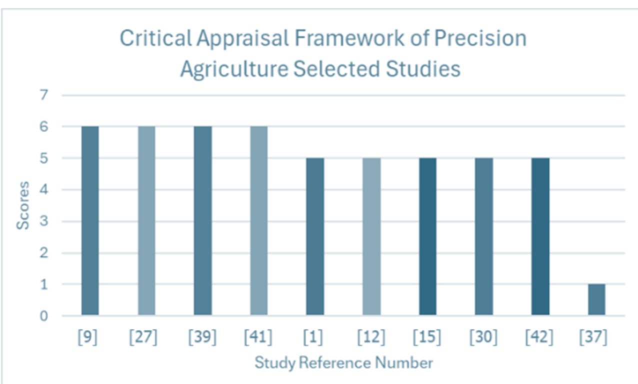

Fig. 3. Critical appraisal framework for selected precision agriculture related studies.

Recent advancements in precision agriculture underscore its potential to revolutionize agricultural practices by 2030, aligning with global sustainability goals [1]. AI driven technologies enable precise field monitoring, obstacle detection, and yield forecasting, including reinforcement learning based mapping by unmanned ground vehicles [12] and predictive modeling for legume crop yields under climate change scenarios [15]. These systems enhance decision making by providing farmers with geo referenced data on soil conditions, water stress, and crop health [12, 15]. Additionally, deploying LPWAN technologies in regions like Karnataka, facilitates power energy optimization, enabling real time data transmission for precision irrigation and resource management [1].

Innovative biosensing applications, such as electrochemical impedance spectroscopy (EIS) for detecting ozone stress in plants [27], advance precision agriculture. These sensors monitor environmental pollutants by analyzing plant hydrodynamic responses [27]. The system offers a noninvasive method for real time environmental monitoring with 92% confidence in detecting excess ozone when pooling data from multiple plants [27]. Thermal canopy segmentation provides precise temperature extraction from plant canopies, enhancing stress detection and irrigation efficiency with a mean average precision of 99.2% and an Intersection over Union score of 92.28% [42].

Despite these advancements, challenges persist, including high implementation costs, technological disparities between farmers and experts, and the complexity of managing large datasets [30]. Inconsistent adoption across regions, coupled with variable environmental conditions, further complicates scalability [30, 43]. Nevertheless, the benefits of precision agriculture enhanced productivity, reduced resource waste, and improved environmental sustainability as a cornerstone for achieving food security and climate resilience [15, 30]. Realizing its full potential requires supportive policies, farmer training, and stakeholder collaboration to bridge technological gaps and foster trust [43].

3) Internet of things and smart irrigation. Integrating the IoT into innovative irrigation systems revolutionizes precision agriculture by enabling real time monitoring and efficient resource management. This section examines the role of the IoT in transforming irrigation practices, highlighting recent advancements, applications, and challenges. Once again, studies with at least four points in the critical appraisal process were included in the final analysis, as shown in Fig. 4.

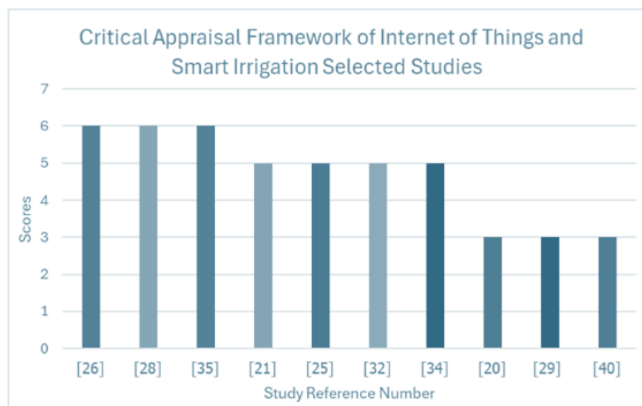

Fig. 4. Critical appraisal framework for selected internet of things and smart irrigation related studies.

IoT based innovative irrigation systems are projected to significantly enhance water use efficiency and crop productivity by 2030, supporting global sustainability objectives such as Sustainable Development Goal [1]. These systems leverage IoT sensors and wireless communication modules to monitor soil moisture, temperature, and humidity in real time [25, 34]. Furthermore, the IoT based irrigation system and soil moisture sensors allow farmers to set customized moisture thresholds, automatically activating irrigation to prevent overwatering or underwatering [25]. Similarly, some systems use a fuzzy inference system and energy saving sensor networks to choose the best cluster heads and send data, which aids in making better automated irrigation decisions based on environmental conditions [28].

Advanced predictive irrigation systems integrate Internet of Things (IoT) technology with machine learning (ML) and data analytics to accurately forecast irrigation needs, thus accomplishing substantial water savings when compared to traditional methodologies [32, 35]. These systems employ adaptive scheduling algorithms and digital farming solutions, such as mobile and web frameworks, which facilitate remote monitoring and control, alleviating farmers' workload and enhancing their decision-making processes [35]. Ethical design considerations, encompassing privacy and security measures through comprehensive use case analysis, further establish user trust in IoT-based irrigation systems [21]. Performance evaluations indicate consistent soil conditions and enhanced water efficiency, with several systems documenting improved crop yields under diverse environmental conditions [32, 34].

Despite these advancements, challenges remain, including high initial setup costs, technical complexities, and the need for reliable data accuracy [32, 35]. Limited technical expertise among farmers and inconsistent connectivity in rural areas hinder widespread adoption [21, 25]. However, the benefits of IoT-based smart irrigation, optimized water use, increased productivity, and alignment with sustainable farming practices position it as a critical tool for addressing climate change and food security [34, 35]. To maximize its potential, supportive policies, farmer training, and infrastructure development are essential to overcome barriers and promote scalable implementation [21, 32].

4) Geographic information systems: Geographic Information Systems (GIS) have emerged as a pivotal technology in precision agriculture, facilitating spatial data analysis and visualization to enhance farming practices and environmental management. This section examines the integration of GIS into agricultural systems, with a focus on recent advancements, applications, and challenges. Studies that included a minimum of four points in the critical appraisal process were incorporated into the final analysis, as illustrated in Fig. 5.

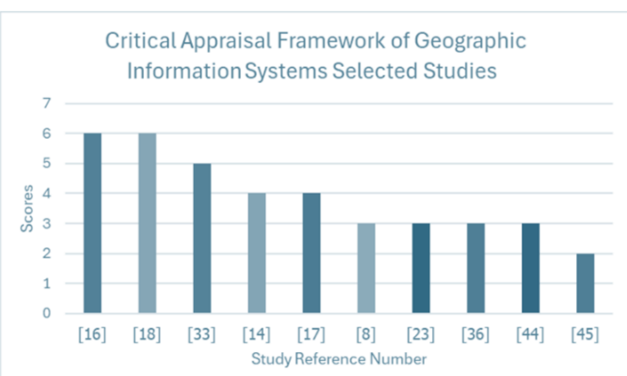

Fig. 5. Critical appraisal framework for selected geographic information systems related studies.

As demonstrated by three studies, the integration of AI and GIS technologies significantly enhances agricultural productivity, environmental management, and sustainable urban planning. In Kenya, an AI based chatbot combined with GIS provided potato farmers with location specific advice and access to quality seeds, achieving an 88.05% effectiveness rate and an 80% likelihood of future use [16]. In coastal Bangladesh, GIS coupled with machine learning mapped soil salinity across 977.94 km² with 92.1% accuracy to support integrated coastal zone management [18]. Similarly, in Chennai, using a GIS technique called the Normalized Difference Vegetation Index (NDVI) to aid sustainable urban planning showcased 82% of the study area as vegetation with 91% accuracy [14]. These findings highlight the transformative potential of AI and GIS systems in addressing food security, environmental challenges, and urbanization.

Innovative educational approaches further amplify GIS adoption. A multidisciplinary course that combines GIS with data visualization and edge devices equips students to analyze real-world agricultural data, fostering interdisciplinary skills for precision agriculture [33]. These applications enhance resource management, improve crop yields, and address environmental challenges such as soil salinity and land cover changes [14, 18]. However, the lack of comprehensive cooperative education frameworks hinders skill development for GIS implementation [17]. Nonetheless, GIS still offers many benefits, including improved food security, enhanced environmental monitoring, and informed policymaking [16, 18]. Investments in farmer training, data infrastructure, and supportive policies are needed for technological advances and to ensure scalable adoption [14, 33].

5) Cross-domain insight. Integrating CDA, PA, IoT, and GIS creates synergistic opportunities for sustainable agriculture. XAI in CDA, as applied to coffee quality assessment [46], enhances farmer trust in IoT-based smart irrigation systems [25] by providing transparent decision-making, addressing skepticism in automated irrigation. Similarly, GIS spatial analysis in Bangladesh mapped soil salinity with 92.1% accuracy [18], guiding PA's sensor placement for ozone stress detection [27]. This linkage optimizes resource use, reducing waste and improving yields across diverse regions.

Combining IoT's real-time data [34] with CDA's predictive models [24] enables dynamic irrigation and pest control, achieving 91% accuracy in orange quality prediction. GIS-based advice for Kenyan potato farmers [16] complements PA's field monitoring [12], tailoring practices to local conditions. These cross-domain integrations foster intelligent farming ecosystems, enhancing productivity and sustainability. By linking transparent AI [46], sensor data [27], real-time monitoring [34], and spatial analysis [16], these technologies address trust barriers and scalability challenges, supporting global food security by 2030.

IV. DISCUSSION

The systematic review elucidates the transformative potential of Artificial Intelligence (AI) in advancing sustainable agriculture across four key domains: Cognitive Data Analytics (CDA), Precision Agriculture (PA), Internet of Things (IoT), and Geographic Information Systems (GIS). The integration of

AI technologies demonstrates how these innovations enhance decision making clarity and farm efficiency. For instance, IoT based smart irrigation systems utilize real time soil moisture data and predictive analytics to significantly improve water use efficiency, thereby supporting objectives such as the Sustainable Development Goals. Furthermore, GIS, when integrated with AI, facilitates accurate analysis aimed at addressing significant environmental and food security challenges. Collectively, these advancements underscore the capability of CDA and AI to develop intelligent farming systems that enhance yields while minimizing resource waste.

Regional variations significantly influence CDA and AI adoption in agriculture. In high-resource settings like Oman, AI-driven precision techniques supported by robust infrastructure optimize crop management and water conservation [31]. Conversely, low-resource regions like rural India face connectivity and cost barriers, limiting IoT and GIS scalability [38]. Policy interventions, such as subsidies for IoT sensors or cooperative training programs, can bridge these gaps, promote equitable technology uptake and enhance sustainability across diverse agricultural contexts.

Nevertheless, the adoption of these technologies encounters significant challenges that require substantial effort, such as high initial costs, fragmented data systems, and limited technical expertise, which hinder consistent implementation. For instance, drones integrated with deep neural networks demonstrate potential for enhancing pest control; however, their advancement is constrained by infrastructural and maintenance issues. This systematic review underscores the necessity for tailored regional solutions to address diverse agricultural conditions, emphasizing that research and investment are critical for the utilization and enhancement of such technologies. Additionally, precision agriculture benefits from real-time sensor data and machine learning; however, its success is contingent upon accessible training for farmers and robust data systems. Geographic Information Systems (GIS) applications are also essential for collaborative education, equipping farmers with the necessary skills for effective technology utilization. By addressing these challenges through policy support and farmer engagement, Controlled Digital Agriculture (CDA) and Artificial Intelligence (AI) can significantly contribute to sustainable farming practices, thereby improving productivity, fostering environmental sustainability, and enhancing global food security by 2030.

V. Limitations and Future Directions

The focus on studies published between 2020 and 2025 limits this systematic review. While its emphasis keeps the research current, it may overlook earlier studies that could provide essential or deeper background on CDA and AI in agriculture. This systematic review excludes opinion-based studies, which can omit valuable perspectives from farmers or experts. This study utilizes research from academic databases like IEEE, Scopus, and Google Scholar, which can often miss other studies, especially those in different languages, as the search was conducted exclusively in English.

The variety of farming conditions presents another limitation, as differing soil types, climates, and technological access across regions complicate the implementation of a systematic review. For example, IoT based irrigation systems perform well in controlled settings, but their effectiveness in rural areas with poor connectivity remains uncertain. This systematic review emphasizes high quality studies that may have overlooked innovative yet less rigorous research that could provide valuable insights.

Future research should prioritize underexplored regions and employ specific methodologies to address adoption challenges. Mixed methods field studies can assess farmer perceptions of IoT in low connectivity areas, while cost-benefit analyses evaluate the economic viability of AI-driven systems. Interdisciplinary collaborations with agronomists can refine crop models, and sociologists can explore cultural barriers to technology trust. Partnerships with policymakers are essential to design region-specific AI deployment strategies, ensuring equitable access and scalability.

VI. Conclusion

This systematic review confirms the crucial roles of artificial intelligence and cognitive data analytics in transforming sustainable agriculture, offering solutions that enhance productivity, conserve resources, and bolster environmental resilience. Innovations such as AI predictive models, IoT-based smart irrigation, and GIS-driven spatial analysis demonstrate significant advancements in precision farming, water management, and environmental monitoring. These developments support global sustainability goals by positioning agriculture as a vital solution to food security and climate change challenges by 2030.

Despite challenges such as elevated expenses, technical complexities, and regional disparities impeding the widespread adoption of this technology, this review emphasizes the necessity for supportive policies, comprehensive farmer training, and infrastructural development to address these obstacles and foster global utilization. Stakeholders can fully leverage and trust these technologies by establishing trust through transparent AI systems and committing themselves to cooperative education. The intelligent integration of CDA, AI, IoT, and GIS presents an opportunity to engage in sustainable farming practices, thereby ensuring enhanced productivity, environmental sustainability, and global food security in the face of climate change and rising population numbers.

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REFERENCES

[1] Faryadi, S., & Velni, J. M. (2020). A reinforcement learning-based approach for modeling and coverage of an unknown field using a team of autonomous ground vehicles. *International Journal of Intelligent Systems*, *36*(2), 1069–1084. https://doi.org/10.1002/int.22331

[2] Khadka, R. B., & Kumar, P. (2024). Enhancing Sustainability in Agriculture through Artificial Intelligence. *International Scientific Journal of Engineering and Management*, *03*(12), 1–7. https://doi.org/10.55041/isjem02192

[3] Shyr, J., Chu, J., & Woods, M. (2018). Cognitive data analysis for big data. In *Springer handbooks of computational statistics* (pp. 23–47). https://doi.org/10.1007/978-3-319-18284-1_2

[4] Asakiewicz, C. (2016). Cognitive Analytics for making better Evidence-Based Decisions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2965767

[5] Beg, A., & Chauhan, N. S. (2024). Microcontroller Implementation in Precision Planting: A review. *Asian Journal of Advances in Agricultural Research*, *24*(2), 21–33. https://doi.org/10.9734/ajaar/2024/v24i2489

[6] B. Gundogan, N. Dowlut, S. Rajmohan, R. Mimi, C. Borrelli, M. C. Millip, C. Iosifidis, Z. Yagazie, U. Ginimol, M. Mathew, J. Alexander, R. Fowler and A. Agha, "Assessing the compliance of systematic review research works published in leading dermatology journals with the PRISMA statement guidelines: A systematic review," 2020, doi: 10.1016/J.JDIN.2020.07.007.

[7] S. Hullumani & R. Raghumahanti, "PRISMA Guidelines and Search Strategy," 2024, doi: 10.6084/m9.figshare.25013264.

[8] Alipbeki, O., Alipbekova, C., Sterenharz, A., Toleubekova, Z., Aliyev, M., Mineyev, N., & Amangaliyev, K. (2020). A Spatiotemporal Assessment of Land Use and Land Cover Changes in Peri-Urban Areas: A Case Study of Arshaly District, Kazakhstan. *Sustainability, 12(4),* 1556. https://doi.org/10.3390/su12041556

[9] PraveenaSri, P., & Prasuna, V. N. P. (2024). AI Applications of Clean Energy Innovations. *IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), 1–6*. https://doi.org/10.1109/CONECCT62155.2024.10677112

[10] Bhasme, M., Ulhe, P., & Gokhe, S. (2024). AI in Agriculture: The Future of Robotic Farming and Automation. *2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI), 1–7*. https://doi.org/10.1109/IDICAIEI61867.2024.10842885

[11] Refaai, M. Reda. A., Dattu, V. S., Gireesh, N., Dixit, E., Sandeep, Ch., & Christopher, D. (2022). Application of IoT-Based Drones in Precision Agriculture for Pest Control. *Advances in Materials Science and Engineering, 1–12*. https://doi.org/10.1155/2022/1160258

[12] Na, M. H., & Na, I. S. (2024). AI-Powered Predictive Modelling of Legume Crop Yields in a Changing Climate. *Legume Research. 47(8),* 1390-1395. https://doi.org/10.18805/LRF-790

[13] Wu, L., Lin, X., Chen, Z., Huang, J., Liu, H., & Yang, Y. (2021). An Efficient Binary Convolutional Neural Network With Numerous Skip Connections for Fog Computing. *IEEE Internet of Things Journal, 8(14),* 11357–11367. https://doi.org/10.1109/JIOT.2021.3052105

[14] Narayani, A. R., Nagalakshmi, R., & Pakrasi, D. (2023). Application of geoinformatics to classify the landcover from satellite imagery using NDVI – A case of peri-urban regions of Southern Chennai. *IOP Conference Series: Earth and Environmental Science, 1210(1)*, 012034. https://doi.org/10.1088/1755-1315/1210/1/012034

[15] Upadhyay, R., & Kamble, M. (2024). Artificial Intelligence in Precision Agriculture: A Comprehensive Review. *7th International Conference on Contemporary Computing and Informatics (IC3I),* 918–923. https://doi.org/10.1109/IC3I61595.2024.10829061

[16] Korir, M. K., Mwangi, W., & Kimwele, M. W. (2023). Artificial Intelligence-Based Chatbot Model Providing Expert Advice to Potato Farmers in Kenya. *IEEE AFRICON,* 1–6. https://doi.org/10.1109/AFRICON55910.2023.10293557

[17] Pathak, S., & Laikram, S. (2022). Cooperative education during Covid-19 pandemic: Enhancing legal rights and professional development of interns in Thailand. *International Journal of Disaster Resilience in the Built Environment, 13(2),* 133–149. https://doi.org/10.1108/IJDRBE-08-2021-0098

[18] Sarkar, S. K., Rudra, R. R., Sohan, A. R., Das, P. C., Ekram, K. M. M., Talukdar, S., Rahman, A., Alam, E., Islam, M. K., & Islam, A. R. Md. T. (2023). Coupling of machine learning and remote sensing for soil salinity mapping in coastal area of Bangladesh. *Scientific Reports, 13(1)*, 17056. https://doi.org/10.1038/s41598-023-44132-4

[19] Kim, T. Y., Ku, H., & Lee, S.-Y. (2020). Crop Enhancement of Cucumber Plants under Heat Stress by Shungite Carbon. *International Journal of Molecular Sciences*, *21(14)*, 4858. https://doi.org/10.3390/ijms21144858

[20] Bobade, G., Dhule, C., Khadilkar, R., Agrawal, R., & Morris, N. C. (2023). Design of Smart Irrigation System Based on MLA. *IEEE World Conference on Applied Intelligence and Computing (AIC),* 174–179. https://doi.org/10.1109/AIC57670.2023.10263833

[21] Gvk, S., Bhumireddy, M. R., Rao, M., Bapat, J., & Das, D. (2024). Ethical Design of Edge-based Smart Irrigation System by use Case Analysis. *IEEE 13th International Conference on Communication Systems and Network Technologies (CSNT),* 491–498. https://doi.org/10.1109/CSNT60213.2024.10545792

[22] Liu, J., Zhou, Y., Li, Y., Li, Y., Hong, S., Li, Q., Liu, X., Lu, M., & Wang, X. (2023). Exploring the Integration of Digital Twin and Generative AI in Agriculture. *15th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC),* 223–228. https://doi.org/10.1109/IHMSC58761.2023.00059

[23] Reddy, K. P., Roshni Thanka, M., Edwin, E. B., Ebenezer, V., S, S. K., & Joy, P. (2024). Farm_era: Precision Farming with GIS, AI Pest Management, Smart Irrigation, Data Analytics and Optimized Crop Planning. *International Conference on Inventive Computation Technologies (ICICT),* 1134–1140. https://doi.org/10.1109/ICICT60155.2024.10544687

[24] Prasad, C., Kumar, S., & Damodar Rathod, S. (2024). Hybrid Ensemble Model for Accurate Orange Quality Prediction Using CNN, Random Forest and Gradient with Multispectral Data Integration. *International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA),* 1–4. https://doi.org/10.1109/ICAIQSA64000.2024.10882172

[25] Rao, S., Kumar, P., Kumari, N., Choudhary, A., Shukla, A. K., & Bhateja, A. (2023). Implementation of IoT-Based Smart Irrigation System for Agricultural Transformation. *IEEE World Conference on Applied Intelligence and Computing (AIC),* 1001–1007. https://doi.org/10.1109/AIC57670.2023.10263854

[26] Passias, A., Tsakalos, K.-A., Rigogiannis, N., Voglitsis, D., Papanikolaou, N., Michalopoulou, M., Broufas, G., & Sirakoulis, G. Ch. (2024). Insect Pest Trap Development and DL-Based Pest Detection: A Comprehensive Review. *IEEE Transactions on AgriFood Electronics, 2(2),* 323–334. https://doi.org/10.1109/TAFE.2024.3436470

[27] Kernbach, S. (2024). In-situ biological ozone detection by measuring electrochemical impedances of plant tissues (No. arXiv:2411.16321). arXiv. https://doi.org/10.48550/arXiv.2411.16321

[28] Kumar, K. A., & Jayaraman, K. (2020). Irrigation control system - data gathering in WSN using IOT. *International Journal of Communication Systems, 33(16),* e4563. https://doi.org/10.1002/dac.4563

[29] El Mokh, F., Nagaz, K., & Masmoudi, M. M. (2024). Long-term potato response to different irrigation scheduling methods using saline water in an arid environment. *Frontiers in Agronomy, 6,* 1426034. https://doi.org/10.3389/fagro.2024.1426034

[30] Maleki, R., Shams, S. M., Chellehbari, Y. M., Rezvantalab, S., Jahromi, A. M., Asadnia, M., Abbassi, R., Aminabhavi, T., & Razmjou, A. (2022). Materials discovery of ion-selective membranes using artificial intelligence. *Communications Chemistry, 5(1),* 132. https://doi.org/10.1038/s42004-022-00744-x

[31] M G, D., Jopate, R., & Albalushi, R. A. R. A. (2024). Optimizing Sustainable Agriculture in Oman Through AI-Driven Precision Techniques. *2nd International Conference on Computing and Data Analytics (ICCDA),* 1–4. https://doi.org/10.1109/ICCDA64887.2024.10867335

[32] Ed-Daoudi, R., Alaoui, A., Ettaki, B., & Zerouaoui, J. (2024). Optimizing Sustainable Cultivation Through Smart Irrigation. *Journal of Information Sciences*, *22*(2). https://doi.org/10.34874/IMIST.PRSM/jis-v22i2.45154.

[33] Byrd, V. L., Saraswat, D., & Ahmad, A. (2023). Pilot Course in Data Visualization with a Multidisciplinary Approach: Technology+Agricultural Engineering. *IEEE Frontiers in Education Conference (FIE)*, 1–9. https://doi.org/10.1109/FIE58773.2023.10343451

[34] Rif'an, M., & Irianto, K. D. (2024). Precision Agriculture System with IoT: An Approach to Increase Production and Efficiency. *International Journal Software Engineering and Computer Science (IJSECS), 4(3),* 1305–1316. https://doi.org/10.35870/ijsecs.v4i3.3259

[35] Abioye, E. A., Hensel, O., Esau, T. J., Elijah, O., Abidin, M. S. Z., Ayobami, A. S., Yerima, O., & Nasirahmadi, A. (2022). Precision Irrigation Management Using Machine Learning and Digital Farming Solutions. *AgriEngineering, 4(1),* 70–103. https://doi.org/10.3390/agriengineering4010006

[36] Shofiyati, R. (2022). The Role of Remote Sensing Technology (Latest Geospatial) for Agriculture in Indonesia: 2nd International Conference on Smart and Innovative Agriculture (ICoSIA 2021), Yogyakarta, Indonesia. https://doi.org/10.2991/absr.k.220305.037

[37] Ma, Z., & Zhao, J. (2023). QoS Aware Resource Management in Mobile Edge Computing for Emerging Artificial Intelligence (AI) Applications. *19th International Conference on Mobility, Sensing and Networking (MSN),* 238–245. https://doi.org/10.1109/MSN60784.2023.00045

[38] Mohan, S. S., Venkat, R., Rahaman, S., Vinayak, M., & Babu, B. H. (2023). Role of AI in Agriculture: Applications, Limitations and Challenges: A Review. *Agricultural Reviews*, *44*(2), 231–237. https://doi.org/10.18805/ag.R-2215

[39] Das, S. S., Behera, D. D., Nayak, B. B., Patjoshi, P. K., & Dash, S. (2024). Role of AI in Improving Climate Change and Achieving Sustainable Development: Cases from Odisha. *Grenze International Journal of Engineering & Technology (GIJET)*, *10*(2,Part 3), 2142–2149.

[40] Gayathri, M., Shunmugam, D. A., & Ishwariya, A. (2021). Smart irrigation system using IoT. *International Journal of Innovative Research in Multidisciplinary Perspectives, 9(3),* 27. https://doi.org/10.37082/IJIRMPS.2021.v09i03.027

[41] Rathinavel, L., Singh, S., Rai, P. K., Chandra, N., Jothinathan, D., Gaffar, I., Pandey, A. K., Choure, K., Waoo, A. A., Joo, J. C., & Pandey, A. (2024). *Sustainable Microalgal Biomass for Efficient and Scalable Green Energy Solutions: Fueling Tomorrow. Fuels, 5(4),* 868–894. https://doi.org/10.3390/fuels5040049

[42] P, H., Mk, C., Rh, L., C, R., G, S. K., & K, S. (2025). Thermal canopy segmentation in tomato plants: A novel approach with integration of YOLOv8-C and FastSAM. *Smart Agricultural Technology*, *10*. https://doi.org/10.1016/j.atech.2025.100806

[43] Sood, A., Bhardwaj, A. K., & Sharma, R. K. (2024). Towards sustainable agriculture: Key determinants of adopting artificial intelligence in agriculture. *Journal of Decision Systems, 33(4),* 833–877. https://doi.org/10.1080/12460125.2022.2154419

[44] Dao, K. M., Yabar, H., & Mizunoya, T. (2020). Unlocking the Energy Recovery Potential from Sustainable Management of Bio-Resources Based on GIS Analysis: Case Study in Hanoi, Vietnam. *Resources, 9(11),* 133. https://doi.org/10.3390/resources9110133

[45] Khater, E.-S. G., Ali, S. A., Afify, M. T., Bayomy, M. A., & Abbas, R. S. (2022). Using of geographic information systems (GIS) to determine the suitable site for collecting agricultural residues. Scientific Reports, 12(1), 14567. https://doi.org/10.1038/s41598-022-18850-0

[46] Sermmany, K., Wanjantuk, P., & Leelapatra, W. (2024). Utilizing Explainable Artificial Intelligence (XAI) to Identify Determinants of Coffee Quality. 2024 21st International Joint Conference on Computer Science and Software Engineering (JCSSE), 696–703. https://doi.org/10.1109/JCSSE61278.2024.10613641

[47] Sharma, B., Singhvi, R., Chauhan, P., & Naik, N. (2024). A study to know the role of AI and sustainability in agriculture. *INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT*, *08*(01), 1–13. https://doi.org/10.55041/ijsrem28318

[48] More, A. (2024). IoT in Agriculture. *Acta Scientific Agriculture,* 39–42. https://doi.org/10.31080/asag.2024.08.1370

[49] S, K. (2018). IoT in Agriculture : Smart Farming. International Journal of Scientific Research in Computer Science Engineering and Information Technology, 181–184. https://doi.org/10.32628/cseit183856

[50] Devendiran, R., Rao, P. S., Turukmane, D. A. V., Prasad, B., Sathiyaraj, A., & Pulipati, S. (2023). *Smart Irrigation: Revolutionizing Water Management in Agriculture for Sustainable Practices and Improved Crop Yield*. 651–656. https://doi.org/10.1109/icrtac59277.2023.10480750

[51] Butora, A., Soloniewicz, B., Schwartz, C., Aziz, C., Su, S., & Mahmoud, M. (2022). *The Practical use of GIS in Agriculture*. 1525–1529. https://doi.org/10.1109/csci58124.2022.00270

[52] Sangirova, U., Yunusov, I., Ahmedov, U. K., Namozov, J. A., Dustmurodov, G. G., & Khakimov, R. (2020). *Features of GIS application in agriculture and logistics*. *918*(1), 012140. https://doi.org/10.1088/1757-899X/918/1/012140

[53] Mim, M. I., Sultana, F., & Hasan, M. R. (2025). AI-Powered Autonomous Farming: The Future of Sustainable Agriculture. *European Journal of Theoretical and Applied Sciences*, *3*(1), 11–31. https://doi.org/10.59324/ejtas.2025.3(1).02