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A Hybrid AI-IoT Enabled Green Environmental Management System (GEMS) for Predictive, Sustainable, and Climate-Smart Agriculture: A Eco-Friendly Technology for Future Perspectives

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Abstract
Green technology (GT) is a broad term and a field of new innovative ways to make environmental friendly changes in daily life. It is created and used in a way that conserves natural resources and the environment. The use of green technology is supposed to reduce the amount of waste and pollution that are created during production and consumption. Digital agriculture encompasses a wide range of technologies, most of which have multiple applications along the agricultural. Organic farming can provide quality food without adversely affecting the soil's health and the environment, however, a concern is whether large-scale organic farming will produce enough food for India's large population value chain. Production systems and the policies and institutions that underpin global food security are increasingly inadequate. Sustainable agriculture should aim at branch resources management in order to meet human needs, both present and future, by maintaining and improving at the same time the quality of the environment and by protecting natural resources.
The aim of this study is to highlights the sustainable development of green environment ecosystem and how modern digitalization may contribute on agriculture and crop cultivation.
As awareness of our impact on the environment increases, environmentally friendly technology will likely expand as well. Green technologies could assist in decreasing the carbon intensity, promoting energy and resource efficiency, and avoiding serious environmental degradation. This would result in improving environmental quality, human welfare and social equity, while reducing the risk of resource scarcities, and move toward Sustainable Development Goals (SDGs). The environmental protection, resource conservation and addressing other socio-economic aspects for sustainable development are essential. The green initiatives adopted for resource conservation, and environmental protection shall help sustain higher economic growth rate necessary to fulfill basic needs with some acceptable quality of life in the future. Digital technology changes economic activity by lowering the costs of replicating, transporting, tracking, verifying, and searching for data.

Keywords: Digitalization, SDGs, cultivation, Green technology

1. Introduction
Green technology (GT) is a broad term and a field of new innovative ways to make environmental friendly changes in daily life. It is created and used in a way that conserves natural resources and the environment. It is meant as an alternative source of technology that reduces fossil fuels and demonstrates less damage to the human, animal, and plant health, as well as damage to the world [1]. The use of green technology is supposed to reduce the amount of waste and pollution that are created during production and consumption. It is also referred to as environmental technology and clean technology. Although it is difficult to precisely define the areas that are covered by green technology, it can safely be said that "GT is the development and application of products, equipment and systems used to conserve the natural environment and resources, which minimizes and reduces the negative impact of human activities [2]. Eco-friendly technology is also known as clean tech, green tech and environmental tech, eco-friendly technology can help preserve the environment through energy efficiency and reduction of harmful waste. Green tech innovators use the latest environmental science and green chemistry to reduce the harmful impact of human activity

on the earth [3]. Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs. Sustainable development is the organizing principle for meeting human development goals while simultaneously sustaining the ability of natural systems to provide the natural resources and ecosystem services on which the economy and society depends [4]. Agriculture has changed dramatically, especially since the end of Second World War Food and fiber productivity soared due to new technologies, mechanization, increased chemical use, specialization and government policies that favoured maximizing production. Digital agriculture refers to tools that digitally collect, store, analyze, and share electronic data and information along the agricultural value chain [5]. Organic farming can provide quality food without adversely affecting the soil's health and the environment; however, a concern is whether large-scale organic farming will produce enough food for India's large population. Organic farming unites all agricultural systems that maintain ecologically, socially and economically advisable agricultural production. Organic farming has potential to overcome drawbacks of conventional farming [6].

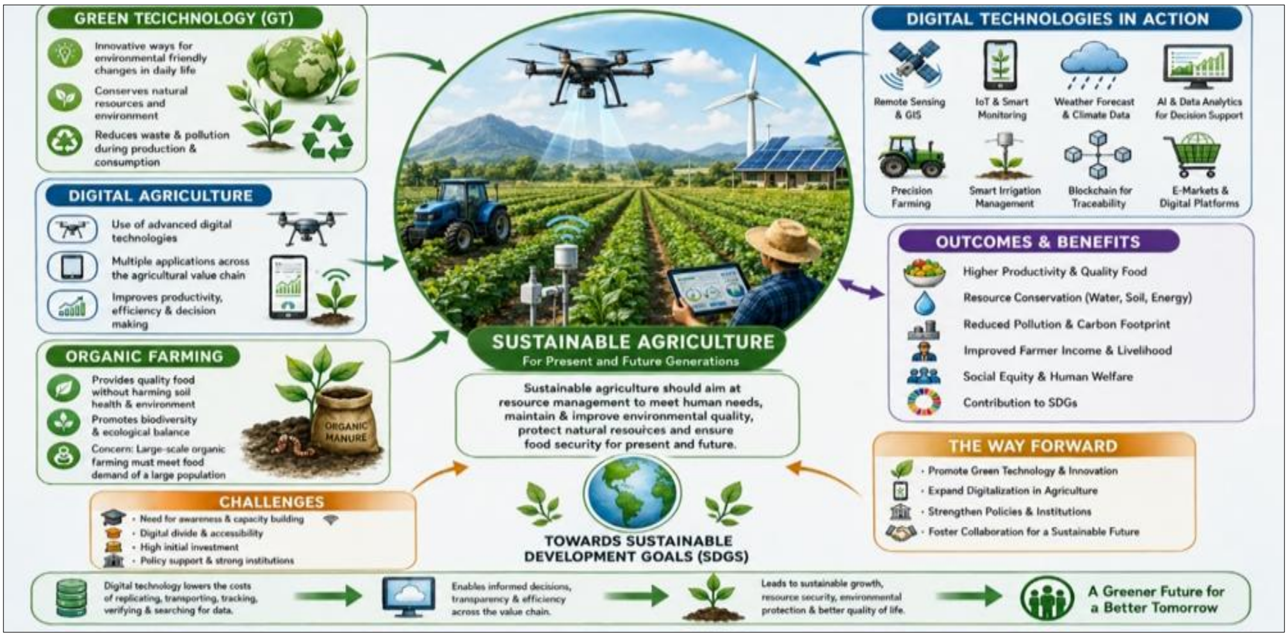

Fig: Graphical abstract image of Synergistic Integration of Green Technology and Digitalization for Sustainable Crop Production Systems.

Digitalization in the agri-food system clearly has the potential to play an increasingly important role in achieving global food security and improving livelihoods especially in rural areas. The Digital Council could help unleash the potential that digitalization has, to transform the people's lives and enable them to escape the poverty they have faced for generations [7]. Modern agricultural technologies, aim at maximization of productivity/unit area/unit time and promote the cultivation of high-yielding varieties, hybrids or genetically modified plants with intensive use of fossil-fuel-based energy, synthetic chemical fertilizers, pesticides and irrigation water, which are leading to degradation of natural resource base, emergence of soil-nutrient disorders, soil and environmental degradation, loss of bio-diversity, development of new biotypes of pathogens and pests, chemical contamination of soil and water bodies and finally to human and animal health hazards [8]. This necessitates to have an alternative agriculture method which can help to develop a friendly eco-system while sustaining and increasing the crop productivity. Organic farming is recognized as the best known alternative to the conventional agriculture and area under such farming is increasing in India and abroad over the years. Organic agriculture is gaining momentum as an alternative method to the modern system [9]. However, there are a number of constraints impeding Indian farmers, from adopting of Farmers' apprehension lies in non-availability of sufficient amount of organic supplements [10].

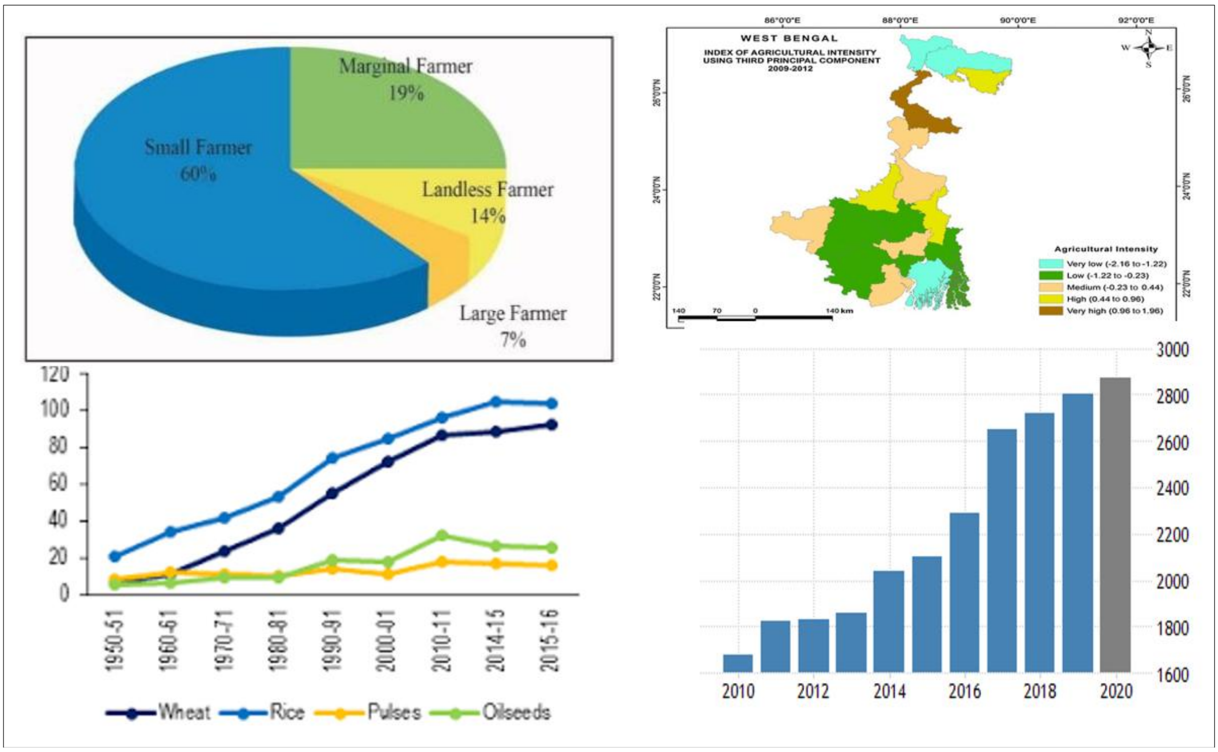

Fig 1: Demographical and epidemiological statistical scenario of Growth rate of agricultural productivity and Regional model for agricultural in West Bengal [8,10].

2. Concept of Green Environmental Management Systems (GEMS): Green Environmental Management Systems (GEMS) represent an integrated and systematic framework designed to guide organizations, particularly within the agricultural sector, toward environmentally responsible and economically viable practices [11]. Unlike traditional environmental management approaches that focus primarily on regulatory compliance, GEMS adopts a proactive and holistic strategy that embeds sustainability into every stage of production, resource utilization, and policy implementation [12]. The novelty of GEMS lies in its ability to bridge ecological preservation with technological advancement, enabling agriculture to evolve into a resilient and climate-smart system [13].

At its core, GEMS integrates environmental policies, operational practices, and innovative technologies to minimize ecological degradation while maximizing productivity [14]. It emphasizes a lifecycle-based approach, where environmental impacts are assessed and managed from input acquisition to final agricultural output [15]. This systems-based thinking ensures that sustainability is not treated as an isolated goal but as a continuous and adaptive process aligned with long-term development objectives.

2.1 Principles of GEMS: The foundational principles of GEMS are centered on sustainability, efficiency, and accountability. Resource efficiency and conservation form the backbone of the system, encouraging optimal use of water, soil, and energy resources through precision techniques and conservation strategies [16]. Pollution prevention and waste reduction are addressed by minimizing chemical inputs, promoting biodegradable alternatives, and implementing circular economy models such as recycling agricultural residues [17].

Another key principle is the adoption of renewable energy sources, including solar-powered irrigation systems and bioenergy derived from agricultural waste, which significantly reduces dependency on fossil fuels [18]. Sustainable production and consumption ensure that agricultural outputs meet current demands without compromising future resource availability. Additionally, environmental compliance and governance reinforce adherence to regulatory standards while promoting transparency, monitoring, and ethical responsibility in agricultural operations [19].

2.2 Components of GEMS: The operational structure of GEMS is built upon several interconnected components that facilitate its implementation [20]. Environmental policy formulation serves as the initial step, where clear sustainability goals and commitments are defined at institutional or farm levels. This is followed by strategic planning and implementation, which involve the integration of eco-friendly technologies, digital monitoring tools, and sustainable farming practices [21].

Monitoring and evaluation mechanisms play a critical role in assessing environmental performance through indicators such as soil health, water usage efficiency, and carbon emissions [22]. Advanced tools like remote sensing and data analytics can enhance this component by providing real-time insights. Continuous improvement processes ensure that GEMS remains adaptive, incorporating feedback, technological innovations, and evolving environmental standards to refine practices over time [23].

2.3 Role of GEMS in Agriculture: In the agricultural context, GEMS acts as a transformative approach that aligns productivity with ecological sustainability. It promotes integrated pest management (IPM), which reduces reliance on chemical pesticides by combining biological control, crop rotation, and resistant crop varieties. Organic farming practices are also encouraged, enhancing soil fertility and biodiversity while eliminating harmful chemical inputs [24].

Water conservation techniques, such as drip irrigation and rainwater harvesting, are integral to GEMS, particularly in regions facing water scarcity. Soil health management is another critical aspect, involving the use of organic amendments, crop diversification, and minimal tillage practices to maintain soil structure and nutrient balance [25].

The novel contribution of GEMS lies in its potential integration with digital agriculture technologies. By incorporating sensors, artificial intelligence, and data-driven decision-making, GEMS can optimize resource use, predict environmental risks, and enhance overall farm efficiency. This convergence creates a sustainable agricultural model that not only reduces environmental impact but also improves economic outcomes for farmers [26].

In summary, GEMS provides a comprehensive and forward-looking framework for sustainable agriculture. Its emphasis on integration, innovation, and continuous improvement positions it as a key driver in achieving environmental resilience and long-term agricultural sustainability [27].

3. Green Technology in Agriculture: Green technology (GT) in agriculture represents a transformative shift toward environmentally sustainable and resource-efficient farming systems [28]. It encompasses the development, adaptation, and implementation of innovative tools and practices that minimize ecological footprints while maintaining or enhancing agricultural productivity [29]. In the context of Green Environmental Management Systems (GEMS), green technology plays a pivotal role by aligning agricultural practices with ecological sustainability, climate resilience, and long-term food security goals [30]. The integration of green technology is not merely an environmental necessity but also a strategic approach to address the growing challenges of soil degradation, water scarcity, biodiversity loss, and greenhouse gas emissions [31].

A key aspect of green technology in agriculture is the diversification of eco-friendly innovations that can be applied across the farming value chain. Renewable energy systems, such as solar-powered irrigation pumps and wind energy for farm operations, significantly reduce dependence on fossil fuels and lower carbon emissions [32]. These systems are particularly relevant in rural and remote areas where grid electricity access is limited. Biodegradable materials, including organic mulches and bio-based packaging, offer sustainable alternatives to synthetic plastics, thereby reducing soil and environmental contamination [33]. Precision irrigation systems, such as drip and sprinkler irrigation integrated with sensor-based monitoring, ensure optimal water use efficiency by delivering water directly to plant roots based on real-time soil moisture data [34]. Additionally, eco-friendly fertilizers and pesticides, including biofertilizers and biopesticides derived from natural sources, contribute to soil health restoration and reduce the harmful impacts of chemical residues on ecosystems and human health [35].

The benefits of green technology in agriculture extend beyond environmental conservation and directly influence productivity, economic viability, and social well-being [36]. One of the most significant advantages is the reduction in pollution and waste generation [37]. By minimizing chemical inputs and promoting renewable energy use, green technologies help mitigate air, water, and soil pollution [38]. Resource conservation is another critical benefit, as these technologies enable efficient utilization of water, energy, and nutrients, thereby reducing input costs and enhancing sustainability [39]. Improved soil quality is achieved through the use of organic amendments and reduced chemical interference, which enhances microbial activity and nutrient cycling [40]. Furthermore, the promotion of biodiversity through eco-friendly practices supports ecosystem stability, pollination, and natural pest control mechanisms, which are essential for resilient agricultural systems [41].

From a research perspective, green technology in agriculture presents significant opportunities for innovation and interdisciplinary collaboration [42]. Emerging studies are focusing on the integration of green technologies with digital agriculture tools such as artificial intelligence, Internet of Things (IoT), and remote sensing [43]. This convergence enables the development of smart and sustainable farming systems capable of real-time monitoring, predictive analytics, and adaptive management [44]. For instance, AI-driven models can optimize the application of biofertilizers based on crop requirements and environmental conditions, while IoT-enabled sensors can enhance the efficiency of renewable energy systems in agriculture [45]. Such advancements not only improve productivity but also contribute to climate-smart agriculture by reducing emissions and enhancing resilience to climate variability [46].

Despite its numerous advantages, the adoption of green technology in agriculture faces several challenges that need to be addressed through targeted research and policy interventions [47]. High initial investment costs remain a major barrier, particularly for small and marginal farmers who constitute a significant portion of the agricultural workforce in developing countries like India [48]. Although green technologies offer long-term economic benefits, the lack of financial support and access to credit limits their widespread adoption [49]. Additionally, there is a considerable gap in awareness and technical knowledge among farmers regarding the benefits and implementation of these technologies. This highlights the need for capacity-building programs, extension services, and farmer education initiatives to promote adoption [50].

Another critical challenge is the limited accessibility of advanced technologies in rural and remote areas. Infrastructure constraints, such as inadequate electricity supply, poor internet connectivity, and lack of technical support, hinder the effective implementation of green technologies [51]. Addressing these issues requires coordinated efforts from governments, research institutions, and private stakeholders to develop affordable, scalable, and region-specific solutions. Furthermore, there is a need for robust policy frameworks that incenti*vize* the adoption of green technologies through subsidies, tax benefits, and research funding [52].

In conclusion, green technology in agriculture is a cornerstone of sustainable development within the GEMS framework [53]. Its ability to reduce environmental impacts while enhancing productivity and resource efficiency makes it a critical component of future agricultural systems [54]. However, to fully realize its potential, it is essential to overcome existing challenges through innovation, policy support, and capacity building. Continued research and technological integration will play a vital role in advancing green agriculture and ensuring food security in an environmentally sustainable manner [55].

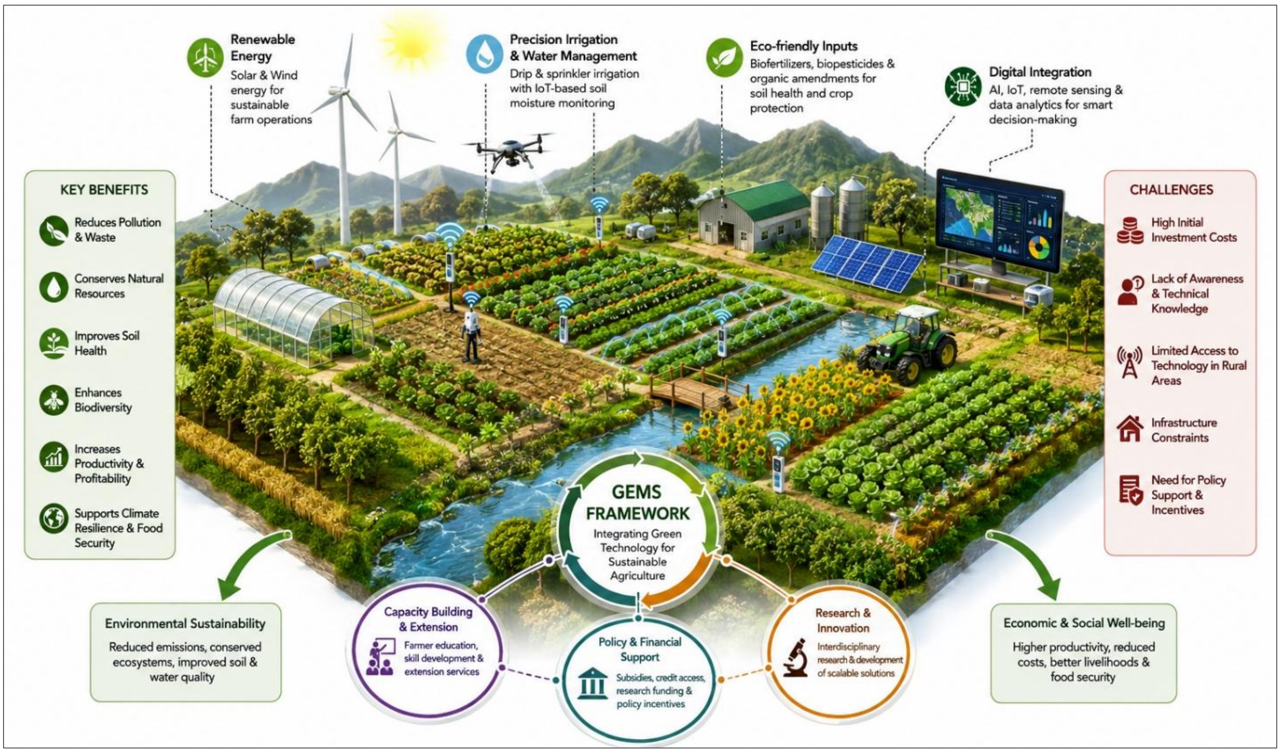

Fig 2: This 3D schematic illustrates the integration of green technologies such as renewable energy, precision irrigation, eco-friendly inputs, and digital agriculture within the GEMS framework. It highlights the interconnection between environmental sustainability, economic viability, and social well-being, along with key benefits and adoption challenges [49,50].

4. Digitalization in Agriculture

Digitalization in agriculture represents a transformative shift from conventional farming practices to data-driven, technology-enabled systems that enhance productivity, sustainability, and environmental management [56]. In the context of Green Environmental Management Systems (GEMS), digital agriculture acts as a critical enabler by integrating ecological principles with advanced technological tools [57]. This integration allows for precise resource utilization, reduced environmental impact, and improved decision-making processes, thereby supporting sustainable agricultural development [58].

4.1 Key Technologies

The foundation of digital agriculture lies in the adoption of advanced technologies that facilitate real-time monitoring, predictive analysis, and automation [59]. The Internet of Things (IoT) plays a pivotal role by connecting sensors, devices, and machinery across agricultural fields. IoT-enabled sensors can monitor soil moisture, temperature, humidity, and nutrient levels, allowing farmers to make informed decisions regarding irrigation and fertilization. This reduces excessive input use and minimizes environmental degradation [60].

Artificial Intelligence (AI) and Machine Learning (ML) further enhance agricultural efficiency by analyzing large datasets to identify patterns and predict outcomes [61]. AI-based models can forecast crop yields, detect diseases at early stages, and recommend optimal farming practices. This predictive capability is particularly significant in mitigating risks associated with climate variability and pest outbreaks [62].

Geographic Information Systems (GIS) and remote sensing technologies provide spatial and temporal data that support precision agriculture. Satellite imagery and drone-based monitoring enable detailed assessment of crop health, land use patterns, and environmental conditions. These technologies allow farmers to apply inputs selectively, reducing waste and improving productivity [63].

Big data analytics integrates information from multiple sources, including weather data, soil conditions, and market trends, to provide actionable insights. By leveraging big data, farmers and policymakers can optimize supply chains, improve market access, and enhance overall agricultural efficiency [64].

4.2 Applications: Digital technologies have diverse applications in agriculture, significantly transforming traditional practices. Precision farming is one of the most important applications, where inputs such as water, fertilizers, and pesticides are applied in precise quantities based on real-time data [67]. This not only improves crop yield but also conserves resources and reduces environmental pollution [68].

Crop monitoring systems utilize drones, sensors, and AI algorithms to track plant health and growth patterns. Early detection of diseases and nutrient deficiencies allows for timely interventions, preventing crop losses and reducing the need for chemical treatments [69].

Weather forecasting is another critical application, particularly in regions like India where agriculture is highly dependent on climatic conditions [70]. Advanced predictive models provide accurate weather forecasts, enabling farmers to plan sowing, irrigation, and harvesting activities effectively [71].

Supply chain optimization is facilitated through digital platforms that enhance transparency and efficiency [72]. Blockchain technology, combined with big data analytics, ensures traceability of agricultural products, reduces post-harvest losses, and improves market linkages. This contributes to better pricing and increased income for farmers [73].

4.3 Impact on Sustainability: The integration of digital technologies in agriculture has profound implications for sustainability, aligning closely with the objectives of GEMS [74]. One of the most significant impacts is the reduction of resource wastage [75]. By using data-driven approaches, farmers can optimize the use of water, fertilizers, and pesticides, thereby minimizing environmental pollution and conserving natural resources [76].

Digital agriculture also contributes to reducing greenhouse gas emissions. Efficient input management and precision farming techniques lower the carbon footprint of agricultural activities [80]. Additionally, the adoption of renewable energy-powered technologies, such as solar-powered irrigation systems, further enhances environmental sustainability [81].

Another important aspect is the improvement of soil health and biodiversity. Reduced chemical usage and targeted interventions help maintain soil fertility and protect beneficial organisms. This supports long-term agricultural productivity and ecological balance [82].

From a research perspective, digital agriculture opens new avenues for innovation and interdisciplinary collaboration. The integration of AI, IoT, and environmental science enables the development of advanced models for sustainable farming [83]. These models can simulate various scenarios, predict environmental impacts, and guide policy decisions [84].

The socio-economic benefits of digitalization are equally significant. Increased productivity and efficiency lead to higher farmer incomes and improved food security [85]. Digital platforms also facilitate knowledge dissemination and capacity building, empowering farmers with the skills needed to adopt sustainable practices.However, challenges such as the digital divide, high implementation costs, and lack of technical expertise must be addressed to ensure equitable adoption. Bridging these gaps requires coordinated efforts from governments, research institutions, and private sectors [86].

The study of digitalization in agriculture within the GEMS framework is highly significant as it provides a holistic approach to sustainable development [87]. It highlights the potential of integrating environmental management with technological innovation to address global challenges such as climate change, resource scarcity, and food insecurity [88]. By focusing on eco-friendly technologies and data-driven solutions, this research contributes to the advancement of sustainable agricultural practices and supports the achievement of Sustainable Development Goals (SDGs) [89].

In conclusion, digital agriculture is not merely a technological advancement but a paradigm shift toward sustainable and resilient farming systems. Its integration with green environmental management systems offers a promising pathway for achieving long-term environmental sustainability, economic growth, and social equity [90].

5. Integration of GEMS and Digital Agriculture: The integration of Green Environmental Management Systems (GEMS) with modern digital agriculture represents a transformative paradigm in sustainable farming. This convergence creates a dynamic, data-driven, and environmentally responsible agricultural framework that aligns ecological conservation with technological advancement. While GEMS provides a structured approach to environmental protection through resource optimization and pollution control, digital agriculture enhances operational efficiency through real-time monitoring, predictive analytics, and automation. Together, they form a holistic system capable of addressing the dual challenges of food security and environmental sustainability [91].

5.1 Synergistic Benefits: One of the most significant advantages of integrating GEMS with digital agriculture is enhanced resource efficiency. Traditional agricultural practices often lead to excessive use of water, fertilizers, and pesticides, resulting in environmental degradation. However, digital tools such as IoT-based soil sensors and satellite imaging enable precise application of inputs based on real-time field conditions [92]. When guided by GEMS principles, this precision ensures minimal resource wastage while maintaining ecological balance. For instance, smart irrigation systems can regulate water usage according to soil moisture levels, thereby conserving water resources and preventing groundwater depletion [93].

Another critical benefit is the reduction of environmental impact**.** GEMS emphasizes pollution control and sustainable resource management, while digital agriculture provides the tools necessary to implement these goals effectively. Technologies such as remote sensing and AI-driven crop health monitoring allow early detection of pest infestations and diseases, reducing the need for excessive chemical interventions. This not only lowers greenhouse gas emissions but also minimizes soil and water contamination, contributing to long-term environmental health [94].

The integration also significantly improves decision-making capabilities**.** Data-driven agriculture enables farmers and policymakers to make informed decisions based on accurate and timely information. Big data analytics and machine learning algorithms can analyze weather patterns, soil conditions, and crop performance to provide actionable insights. When integrated within a GEMS framework, these decisions are aligned with sustainability goals, ensuring that economic productivity does not compromise environmental integrity. This synergy is particularly valuable in climate-sensitive regions where adaptive strategies are essential for resilience [95].

Furthermore, the combination of GEMS and digital technologies leads to increased productivity and economic viability**.** Precision farming techniques optimize crop yields by ensuring that each plant receives the appropriate amount of nutrients and care. Automation reduces labor costs and enhances operational efficiency. Importantly, sustainable practices supported by GEMS improve soil fertility and ecosystem health over time, ensuring consistent productivity in the long term. This integrated approach thus supports both immediate agricultural output and future sustainability [96].

6. Organic Farming and Sustainability

Organic farming has emerged as a cornerstone of sustainable agriculture, aligning closely with the principles of Green Environmental Management Systems (GEMS). Within the broader context of eco-friendly technological advancement and digital transformation, organic farming represents a biologically harmonious approach that minimizes environmental degradation while ensuring long-term agricultural productivity. However, in the modern era, the integration of digital technologies into organic farming practices introduces a novel dimension—enhancing efficiency, scalability, and scientific precision [97].

From a sustainability perspective, organic farming contributes significantly to soil health, which is a fundamental component of agricultural resilience. Unlike conventional systems that rely heavily on synthetic fertilizers, organic farming promotes the use of compost, green manure, and crop rotation. These practices improve soil structure, increase microbial activity, and enhance nutrient cycling. This biological enrichment not only boosts fertility but also strengthens the soil's capacity to retain water, making it more resilient to drought and climate variability. Within the GEMS framework, such practices align with resource conservation and ecological balance, ensuring minimal disruption to natural ecosystems [98].

Another significant advantage of organic farming is the reduction of chemical inputs, which directly impacts environmental and human health. The absence of synthetic pesticides and herbicides reduces soil and water contamination, thereby preserving biodiversity in agricultural landscapes [99]. Beneficial organisms such as pollinators, earthworms, and soil microbes thrive in organic systems, contributing to natural pest control and ecological stability. This biodiversity-driven resilience is particularly relevant in the context of climate change, where adaptive and regenerative agricultural systems are essential [100].

Despite these advantages, organic farming faces several critical limitations that challenge its large-scale adoption, particularly in countries like India with high population pressure [101]. One of the primary concerns is lower yield compared to conventional farming systems, especially during the transition phase from chemical-based to organic practices [102]. This yield gap raises questions about food security and the ability of organic systems to meet national demand. Additionally, organic farming is labor-intensive, requiring manual weed control, diversified cropping, and continuous monitoring of soil and plant health. These factors increase production costs and may limit adoption among smallholder farmers who lack sufficient labor or financial resources [103].

Scalability remains another major challenge. While organic farming is highly effective at a local or small-scale level, its expansion to large agricultural systems requires robust supply chains, certification processes, and market support. Without adequate institutional backing and policy incentives, the widespread implementation of organic farming may face economic and logistical barriers. This is where the integration of digitalization becomes crucial, offering innovative solutions to overcome these limitations [103].

The role of digital technologies in organic farming represents a transformative shift toward precision sustainability. Tools such as Internet of Things (IoT) sensors, satellite imaging, and artificial intelligence (AI)-based analytics enable real-time monitoring of soil moisture, nutrient levels, crop health, and pest activity. These technologies allow farmers to make data-driven decisions, optimizing resource use while maintaining organic integrity. For instance, predictive analytics can forecast pest outbreaks, enabling timely biological interventions rather than reactive chemical treatments [104].

Furthermore, digital platforms facilitate knowledge dissemination and farmer connectivity. Mobile applications and cloud-based systems provide access to best practices, weather forecasts, and market information, empowering farmers with actionable insights. This reduces dependency on traditional trial-and-error methods and enhances the scientific basis of organic farming. In the context of GEMS, such digital integration supports continuous monitoring, evaluation, and improvement—key components of environmental management systems [105].

Blockchain technology also holds promise in strengthening organic farming systems by ensuring transparency and traceability in the supply chain. Consumers can verify the authenticity of organic products, thereby increasing trust and market value. This not only benefits farmers economically but also promotes ethical and sustainable consumption patterns [106].

From a research perspective, the integration of organic farming with digital agriculture opens new avenues for interdisciplinary innovation. Studies focusing on soil microbiome analysis, climate-resilient crop varieties, and AI-driven decision support systems can significantly enhance the productivity and sustainability of organic systems. Moreover, combining traditional ecological knowledge with modern digital tools creates a hybrid model that is both culturally relevant and technologically advanced [107].

7. Policy and Institutional Framework

The successful implementation of Green Environmental Management Systems (GEMS) integrated with modern digital agriculture requires a robust, adaptive, and forward-looking policy and institutional framework. Such a framework must not only address environmental sustainability but also ensure technological inclusivity, economic viability, and long-term resilience of agricultural systems. In the context of developing economies, particularly India, this integration holds immense research significance as it bridges the gap between traditional agricultural practices and advanced technological innovations.

A comprehensive policy framework should begin with the establishment of clear sustainability goals aligned with environmental protection, resource conservation, and climate resilience. Governments must formulate policies that encourage the adoption of green technologies such as renewable energy-based irrigation systems, eco-friendly fertilizers, and precision farming tools. These policies should be supported by financial incentives, including subsidies, tax benefits, and low-interest loans, to reduce the economic burden on farmers and agribusinesses. Importantly, policy design must incorporate region-specific agricultural needs, considering variations in climate, soil conditions, and socio-economic factors [108].

Institutionally, the role of governmental bodies, research institutions, and private sector stakeholders is critical. Agricultural ministries and environmental agencies must collaborate to create integrated governance models that ensure coordinated implementation of GEMS. Research institutions and universities should focus on interdisciplinary studies that combine environmental science, data analytics, and agricultural engineering to develop innovative solutions. Public-private partnerships (PPPs) can accelerate the deployment of digital tools such as artificial intelligence-based crop monitoring systems, IoT-enabled sensors, and satellite-driven advisory services [109].

A key aspect of this framework is digital infrastructure development. Reliable internet connectivity, cloud-based platforms, and data-sharing mechanisms are essential for the effective functioning of digital agriculture systems. Governments must invest in rural digital infrastructure to bridge the digital divide, ensuring that small and marginal farmers can access advanced technologies. Furthermore, the establishment of centralized agricultural data repositories can facilitate real-time decision-making, improve transparency, and enhance predictive capabilities for crop yield and climate risks [110].

Capacity building and skill development are equally important components of the institutional framework. Farmers must be trained to use digital tools and adopt sustainable practices effectively. Extension services should be modernized to include digital platforms, mobile applications, and remote advisory systems. Training programs should not only focus on technical skills but also emphasize environmental awareness, enabling farmers to understand the long-term benefits of sustainable practices.

Regulatory mechanisms must also be strengthened to ensure compliance with environmental standards. Policies should mandate the monitoring of soil health, water usage, and carbon emissions in agricultural activities. The integration of digital technologies can facilitate real-time monitoring and reporting, improving accountability and enforcement. Additionally, certification systems for organic and sustainable farming practices should be streamlined to encourage wider adoption and ensure market credibility.

From a research perspective, there is a growing need to evaluate the effectiveness of policy interventions and institutional arrangements in promoting sustainable agriculture. Longitudinal studies and pilot projects can provide valuable insights into the socio-economic and environmental impacts of GEMS and digital agriculture integration. Evidence-based policymaking should be prioritized, using data analytics and field-level observations to refine strategies and address emerging challenges.

Another critical dimension is the alignment of national policies with global sustainability agendas. The policy framework should support commitments to climate change mitigation, biodiversity conservation, and sustainable development. This includes promoting climate-smart agriculture practices, enhancing carbon sequestration through soil management, and reducing greenhouse gas emissions from farming activities. International collaboration and knowledge exchange can further strengthen policy effectiveness by incorporating global best practices.

8. Socio-Economic Impacts

The integration of Green Environmental Management Systems (GEMS) with modern digital agriculture represents a transformative shift in the agricultural sector, not only from an environmental standpoint but also in terms of socio-economic development. This transition is particularly significant in developing countries like India, where agriculture remains a primary source of livelihood for a large population. The socio-economic impacts of this integration extend across income generation, employment patterns, food security, and social equity, while also presenting notable challenges that require strategic intervention.

8.1 Benefits

One of the most critical socio-economic benefits of adopting GEMS and digital agriculture is the potential for increased farmer income. By utilizing digital tools such as precision farming technologies, real-time monitoring systems, and predictive analytics, farmers can optimize input usage—including water, fertilizers, and pesticides—thereby reducing production costs while improving crop yield and quality. GEMS further enhances this by promoting resource-efficient practices and minimizing environmental degradation, ensuring long-term productivity of agricultural land. The combined effect results in higher profitability and financial stability for farmers.

Another significant advantage is job creation across multiple sectors. The transition toward digital agriculture necessitates a workforce skilled in operating advanced technologies such as drones, sensors, and data analytics platforms. This creates new employment opportunities in agri-tech services, data management, equipment maintenance, and environmental monitoring. Additionally, GEMS encourages the development of green jobs related to renewable energy, waste management, and sustainable resource utilization. These emerging job roles contribute to rural economic development and reduce migration pressure on urban areas.

Improved food security is another major outcome. Digital agriculture enhances the efficiency of food production systems by enabling accurate forecasting, disease detection, and climate adaptation strategies. GEMS ensures that these productivity gains are achieved sustainably, preserving soil health, water resources, and biodiversity. Together, they support a stable and resilient food supply chain capable of meeting the demands of a growing population. This is particularly crucial in regions vulnerable to climate change and resource scarcity.

Moreover, the integration of GEMS and digitalization promotes social inclusivity by providing access to information and services that were previously unavailable to small and marginal farmers. Mobile-based advisory systems, digital marketplaces, and financial inclusion platforms empower farmers with knowledge and market access, reducing dependency on intermediaries and improving their bargaining power.

8.2 Challenges

Despite these benefits, several socio-economic challenges hinder the widespread adoption of GEMS and digital agriculture. One of the primary issues is the digital divide, which refers to the gap between those who have access to digital technologies and those who do not. In rural areas, limited internet connectivity, lack of digital literacy, and inadequate infrastructure prevent many farmers from benefiting from advanced agricultural technologies. This disparity can exacerbate existing inequalities, leaving smallholder farmers at a disadvantage compared to larger, technologically equipped farms.

High implementation costs also pose a significant barrier. The initial investment required for adopting digital tools such as sensors, drones, and data platforms can be prohibitively expensive for small and marginal farmers. Similarly, implementing GEMS involves costs related to infrastructure development, training, and compliance with environmental standards. Without adequate financial support, subsidies, or access to credit, many farmers may be unable or unwilling to adopt these innovations.

Another critical challenge is the need for skill development. The successful implementation of digital agriculture and GEMS requires a workforce equipped with technical knowledge and environmental awareness. However, the current agricultural labor force often lacks the necessary training and education to effectively utilize these technologies. This creates a gap between technological availability and practical usability. Addressing this issue requires targeted capacity-building programs, extension services, and educational initiatives to enhance farmers' skills and adaptability.
From a research perspective, these challenges highlight the need for interdisciplinary approaches that combine technological innovation with socio-economic policy frameworks. Future research should focus on developing cost-effective and scalable solutions tailored to local conditions, particularly for smallholder farmers. Additionally, studies should explore the role of public-private partnerships, government interventions, and community-based models in facilitating the adoption of GEMS and digital agriculture.

9. Conclusion & Future Perspectives

The sustainable development of agriculture requires a comprehensive approach that integrates environmental conservation with technological innovation. Green Environmental Management Systems (GEMS) provide a structured framework for managing environmental impacts, while digital agriculture offers tools for enhancing efficiency and productivity. The combination of these approaches can significantly contribute to achieving sustainability goals by reducing environmental degradation, improving resource efficiency, and ensuring food security. Although challenges such as high costs and limited accessibility remain, strategic policies, technological advancements, and increased awareness can facilitate the widespread adoption of sustainable practices. Ultimately, the integration of green technologies and digitalization represents a promising pathway toward a sustainable and resilient agricultural future. The significance of usage of technology in the agricultural sector has been recognized with the main purpose of meeting the food requirements of the individuals. India has bio-fertilizers and local market for organic produce [16]. Agriculture is the main occupation of the people of West Bengal in India. It has an important place in the economy of the district. Demographical and epidemiological statistical scenario of Growth rate of agricultural productivity and Regional model for agricultural in West Bengal made progress in agriculture, but productivity of the major agricultural and horticultural crops is low in comparison to other countries [17]. There are still deficits in the usage of technology. Yields per hectare of food grains, fruits and vegetables within the country are far the below global averages. Even India's most productive states are behind the global average. Similarly, the productivity of pulses and oilseeds can be increased, through giving consideration to the seeds, soil health, pest management, crop life-saving irrigation methods and post-harvest technology. As awareness of our impact on the environment increases, environmentally friendly technology will likely expand as well [18]. Green technologies could assist in decreasing the carbon intensity, promoting energy and resource efficiency, and avoiding serious environmental degradation. This would result in improving environmental quality, human welfare and social equity, while reducing the risk of resource scarcities, and move toward Sustainable Development Goals (SDGs). The environmental protection, resource conservation and addressing other socio-economic aspects for sustainable development are essential [19]. The environmental protection, resource conservation and addressing other socio-economic aspects for sustainable development are essential. The green initiatives adopted for resource conservation, and environmental protection shall help sustain higher economic growth rate necessary to fulfill basic needs with some acceptable quality of life in the future. The green initiatives adopted for resource conservation, and environmental protection shall help sustain higher economic growth rate necessary to fulfill basic needs with some acceptable quality of life in the future. Digital technology changes economic activity by lowering the costs of replicating, transporting, tracking, verifying, and searching for data [20].

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