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Epidemiology of Lumpy Skin Disease in Cattle: Prevalence, Risk Factors, and Implications for Control in Karachi, Pakistan

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Abstract

The effects of climate change on agriculture are very profound, including food security and the financial stability of developing countries. Thus, Artificial Intelligence (AI), Internet of Things (IoT), and Digital Twins (DTs) are significant in changing agriculture to a data-enabling, real-time system to develop crop management, high productivity, and climate mitigation. Such technologies are useful in predicting the time of droughts and scheduling the irrigation timetable based on climatic changes, and also in deciding on the appropriate crop rotation within a particular area. AI and IoT may be combined to create DTs to facilitate climate-resilient precision farming. This technology embraces agricultural workplaces, livestock surveillance, crop harvesting, crop protection, and predictive maintenance systems. It also changes how agriculture is practised by examining huge amounts of information to predict the impact of climate change. Precision agriculture is an AI-driven technology that uses micro-localised applications, which are informed by synthetic sensory data, drones, and satellite data. Whereas Smart agriculture combines AI, Big Data Analytics, IoT, and DT to collect, unite, and interpret information from many sources. With AI-powered models, future weather conditions, insects, and disease outbreaks are predictable, allowing for early intervention and increased crop production. Such insights culminate in better allocation of resources, optimisation of agricultural activities, and high farm productivity amidst climate change. As a consequence, the DT technology can be a game-changer in the field of agriculture in the future. In this study, DT in conjunction with IoT sensors and AI models has been explained conceptually and potentially as useful in precision agriculture to adjust to the rise in climate change by anticipating droughts, optimising irrigation, and enhancing crop control through real-time data analysis.

Keywords: AI, IoT, Digital Twins, smart farming, climate resilience.

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1. Introduction

The foundation of human life is agriculture, which furnishes the necessary needs of the people like food, textile and other things (AK Sivaraman et al. 2026). But the issue of climate change has greatly affected the agricultural output with dire consequences on world food availability and economic security, especially in the third world and developing states. Conventional agricultural practices are not always adequate to handle the challenges and ambiguities brought about by climate change, and that is where modern technological solutions in the agricultural sector are greatly desired. Modern agricultural issues have necessitated the use of technology-based solutions (MA Rahu et al. 2022). The newest technologies, such as AI and the IoT, which are usually combined in the DT technology, can revolutionise agricultural work. With the use of DT technology, it is possible to build virtual copies of physical objects, procedures, or schemes that exist in a vibrant environment in real-time. These DTs are built based on real-time information about the IoT devices and highly qualified AI analytics that can yield positive outcomes of optimising crop production, enhancing efficiency, and mitigating the risks associated with climatic conditions (M Awais et al. 2025).

DTs are particularly handy when it comes to multi-scale challenges related to the problem of climate change. By simulating the real-life farm settings in a virtual environment with the use of both technical scenarios and environmental variables, farmers are able to test various methods of managing their farms. To illustrate, using historical weather information together with current environmental information, DTs are able to predict any droughts, optimise the irrigation schedule, and prescribe the crop rotation based on the climatic conditions (A Abadi et al. 2025). To create efficient DT systems, climate-resilient agriculture is more and more dependent on the combination of AI and IoT. IoT devices help to analyse this data and identify trends, predict outcomes, and give recommendations with the help of AI. Using DT systems, farmers are able to test and apply simulated solutions in a virtual environment where risks do not exist, and precision, sustainability, and adaptability in agricultural management are improved. Moreover, DTs provide the chance to optimise the supply chain, monitor livestock, and perform predictive maintenance of agricultural equipment (S Kumar et al. 2026). Digital Twins can be discussed as a groundbreaking solution in the current agriculture sector, offering real-time monitoring and historical data on the processes occurring in the field to enhance the climate-resistance of the agricultural space with the help of the latest technology and expertise in the field. The study gives a detailed account of DTs, their concept, technology, and how they are used in solving climate-related problems. This enables the researchers to emphasise how crucial DTs are to sustainable and climate-resilient agriculture (R Gund et al. 2025).

2 The Concept of DTs

DTs are digital versions of real-world systems that are capable of simulating, monitoring, and improving their real-world equivalents. They create a dynamic representation of the real thing using ambient data, IoT sensors, and machine learning algorithms. Farmers and agricultural administrators can create comprehensive virtual descriptions of fields, crops, irrigation systems, and entire farming operations using DT (A Goel et al. 2026). DTs are better models that can predict outcomes and simulate various scenarios to help farmers make better choices about resource usage, productivity, and climate change. The models are three-dimensional ideas that include data collection, data analytics, and real-time feedback (Hussain Muzamil et al. 2025). By linking the actual and virtual worlds, improving decision-making abilities, boosting output, and advocating for ecologically friendly agricultural practices and affairs, agribusiness DTs improve work performance in agricultural operations management. They give farmers a versatile and adaptable way to deal with the unforeseen changes caused by climate change, which results in unpredictable weather patterns and unfavourable environmental conditions (R. Zhang et al. 2025). This study's conceptual framework is given as:

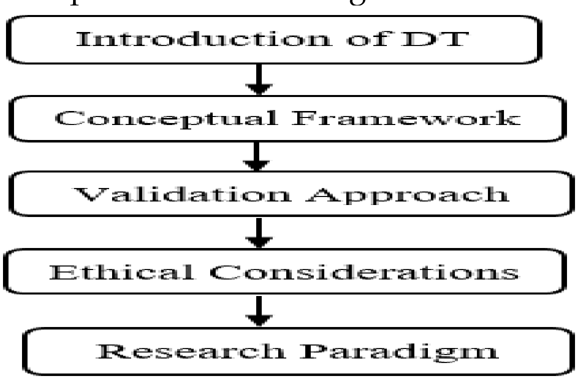

Figure 1: Conceptual framework

3 AI's Place in Climate Resilience

AI is transforming the farming sector by helping to predict, suppress, and adjust to climate change. Machine learning, deep learning, predictive analytics, and other AI-based tools help forecast climatic events using any dataset to allow efficient resource use and efficient agricultural processes. Due to predictive modelling, agricultural decision-support AI systems have been developed using weather patterns, soil conditions, and the yield production of crops. AI is also increasingly becoming a critical part of precision agriculture, lowering the cost of inputs with micro-localised applications, artificial sensory data, drones, and satellite data. The contribution of AI to climate resilience is substantial, as it can be used to develop adaptive strategies that can ensure the agricultural systems become more resilient to natural disasters (Karim, Sarang et al. 2025).

4 IoT Contribution to Climate Resilience

The Internet of Things (IoT) is a network of sensors and devices used in agricultural operations to gather, distribute, and analyse environmental data. To provide farmers with up-to-date information and enable them to make well-informed decisions. It is possible to program the IoT-based system to react to extreme weather events, including droughts, floods, and overheating. Sensors such as soil moisture are useful in enabling farmers to optimize irrigation systems to maximize on the minimization of wastage and water scarcity, whereas temperature and humidity sensors detect the microclimate to enable farmers to manage crops accurately. This information is input into an analytic, action-suggestion digital platform that allows the farmers to comprehend their operations and react to the dynamics of the changing climate better. Precision agriculture is another area where IoT devices are useful because it enables making decisions with more specificity and enhance the efficiency of waste management and resource usage. An IoT application is essential in improving early warning technologies on the impact of climate change on agriculture, and supportive to alteration and alleviating climate change impacts (Sayed Mazhar Ali et al. 2025).

5 Digital Twin Integration for Climate Resilience

DTs maximise modelling, real-time data collection, and predictive analytics to improve agriculture's climate resilience. To produce dynamic data-driven models of land, crops, irrigation systems, and farming equipment, they connect agricultural systems with digital data. These digital copies also feature IoT sensor data feeds and accurate weather forecasts, which provide the best climate-farm interaction discretion for modelling and farming systems (M Savoia et al. 2026). Boosting output, reducing climate risks, and promoting ecological sustainability through modelling helps agriculture. DTs can be used by farmers to enhance climate adaptation by creating simulations of how farm systems will react under various conditions (Douvi D et al. 2026). In order to reduce the impact of climate change on yield losses, resource inefficiency, and environmental degradation, the simulated trials can be used to enhance crop management, irrigation, and pest control. To improve agriculture's climate resilience, DTs make the most of modelling, real-time data collection, and predictive analytics. This leads to the creation of dynamically data-dependent land, crop, irrigation system, and farming equipment bids through these digitally connected agriculture systems. Consequently, it enhances agricultural production but alleviates the risks that are associated with climate change and ensures that environmentally friendly practices are implemented. To predict agricultural performance, a DT can include crop modelling, soil moisture, and weather forecasts. When paired with auxiliary technologies like the Internet of Things (IoT), artificial intelligence (AI), geographic information systems (GIS), cloud computing, and blockchain, digital twins become a part of the digital agri-digital ecosystem. Environmental conditions can be monitored, irrigation can be optimised, disease outbreaks can be predicted, resources can be made more efficient, and supply chain transparency can be increased. Among the elements that enable scalable and energy-efficient operations are sensor networks, data analytics systems, simulation models, and modular IoT systems (Rathva, R. et al. 2026).

6 Smart Farming through Integrated Data and Decision-Making

A DT architecture in smart agriculture comprises interconnected layers in which IoT sensors are used to gather real-time information about the soil moisture, temperature, humidity, crop health, and environmental conditions. This data is delivered to the cloud or edge computing platforms, where it can be stored and processed by use of communication systems like LoRa, WiFi, or cellular. Information is processed by data analytics, AI, and machine learning models to generate and constantly update an online representation of the real farm, which is a virtual farm system. Monitoring, simulation, and predictive analysis are then facilitated by the DT platform, and visualisation dashboards give knowledge to farmers or managers so that they can make informed decisions and manage their resources efficiently. (Sihare, M., et al. 2026).

Data-driven agriculture, also known as smart agriculture, is the use of IoT, AI, Big Data analytics, and DTs (Fig. 2) to gather, aggregate, and process data from multiple sources so that farmers may use that knowledge to make wise decisions.

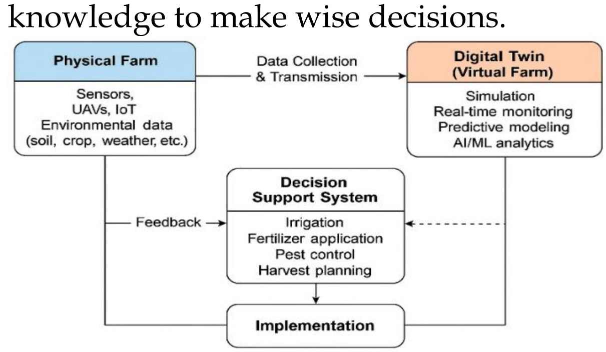

Figure 2: (a) Digital Twin Architecture in smart farming (Awais, M. et al. 2025).

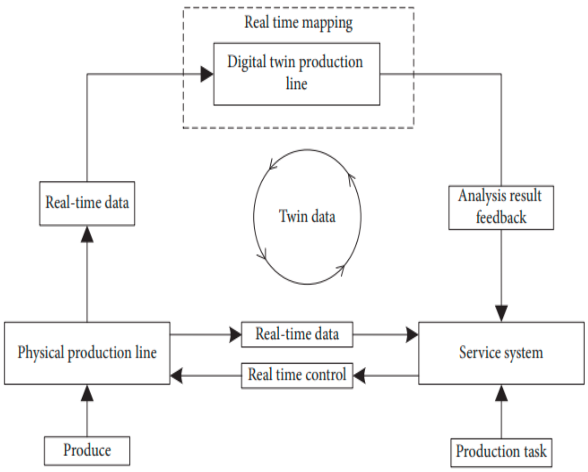

Figure 2: (b) Schematic diagram of Digital Twin architecture (Li, J. et al. 2022)

7 Applications of DT

The constant rise in population of the planet, weather issues, and climate change put a strain on the farming reserves. Thus, a key component was the use of more creative ideas to enhance the agricultural industry and raise crop quality. The potential for automation and innovative technology to integrate and utilise a wide range of data attracted attention and elevated the smart agriculture approach to the top of farmers' agendas in recent times. One of the promising approaches with enormous potential to advance the agriculture industry is the DTs method. According to (MA Rahu et al. 2024), it is a virtual representation tool used to model and mimic actual agricultural systems, which typically change over time. In order to improve the use of DTs in agricultural operations, the DT model integrates a variety of data and information sources, such as sensor data, satellite data, and AI technologies. To bridge the gap between theory and practical application of digital twins in a variety of fields, including crop monitoring and management, livestock productivity and health, soil ecology and fertility, precision irrigation, and water management, one can achieve a significant milestone by contrasting the real and hypothetical worlds (Nassar, N. et al, 2026).

The agricultural method is experiencing a great shift due to the incorporation of digital technologies, where people are striving to solve global problems like global warming, overpopulation, and scarcity of resources. DT, which enables real-time virtual modelling of property, processes, and machinery, is one of these developments that has gained relevance as a novel concept in the agricultural area. These applications increase sustainability and productivity (MA Rahu et al. 2026), resource use, and enhance the resilience of agricultural systems. Nevertheless, various obstacles such as the heterogeneity of data, the lack of adequate infrastructure, the great cost of implementation, and social-economic imbalances are impeding the widespread use of DTs. This research study also discusses blockchain-enhanced data ecosystems, Industry 5.0 interfaces, federated DT networks, and quantum-assisted simulations. By encouraging intelligent, sustainable, and inclusive food agriculture practices, DTs, the cornerstone of Agriculture 5.0, have the potential to completely transform the global food system (Arti, Garima et al. 2026).

8. Challenges and Limitations

Agriculture can benefit greatly from DT technology, a type of digital transformation, especially in terms of increasing efficiency. However, a variety of operational, social, and technical obstacles stand in the way of DT's widespread adoption. Technical obstacles are related to data interoperability, infrastructure limitations, model correctness, and real-time calibration. By incorporating cutting-edge technologies like edge computing and AI into DT systems, the aforementioned problems can be fixed, and the agriculture management process can be improved. High implementation costs, inadequate digital skills, and farmers' resistance to using contemporary technology are socioeconomic concerns. In order to overcome these challenges, it needs to be well coordinated in the form of public-private partnerships, which will finance the construction of infrastructure, share spending, and pass the digital knowledge through community training. Furthermore, an ultimate agriculture operation of DT needs close support and cross-sector collaborations. Partnership among the growers, technology professionals, and decision-makers is beneficial to the establishment of a robust and safe farming environment (Quy, L.K., 2026).

Nevertheless, there are still challenges, such as the scalability and multi-layer environment, data integration, incompatibility between systems, high initial costs, and inefficiencies in the operation. Resolving such problems involves joint research, gradual implementation programs (i.e., pilot projects), and standard data protocol development (Hosseinzadeh, M. et al. 2026). Although DT technology has great potential for climate-resilient agriculture, there are various challenges that confine its broad usage and applicability. These are both technical, economic, and socio-political challenges (R. Zhang et al. 2025).

8.1 Data Availability and Quality

The quality and quantity of available data collected on a physical farm are crucial to the success of a DT. However, Full sensor coverage (Rahu Mushtaque Ahmed et al. 2024) is inefficient with large farms or distributed agriculture, since the sensor coverage is insufficient to produce full digital models. Problems with sensor calibration may provide errors that are transmitted via AI prediction models. The heterogeneity of data sources of various sensors or external sources (satellite images, drones) is complex to preprocess. Poor or lacking historical data. Poor quality: It is challenging to train predictive AI models using poor quality historic data, thus restricting the usefulness of simulations with poor quality historic data to predict crop growth or climate events. In most developing areas, the unavailability of comprehensive environmental data limits the development of accurate DTs.

8.2 High Implementation Costs

Implementation of a full-scale DT system is capital-intensive for several reasons:

IoT infrastructure: It requires thousands of connectivity solutions, sensor devices, and gateways (Rahu Mushtaque et al. 2023).

Cloud or edge computing: HPCs are demanded to handle and store big data in real time.

Software development: AI models, simulation software, and integration frameworks can usually demand expert knowledge. Maintenance and upgrading of sensors, drones, and platforms require regular calibration, firmware updates, and maintenance. These costs may be prohibitive to smallholder farmers or cooperative farming communities, and so it is only large commercial farms or government-sponsored pilot projects that may adopt these costs.

8.3 Technical Complexity

DTs combine IoT, AI, and cloud computing into an ecosystem, which introduces the major technical complexity:

Difficulty in integrating the system:

A heterogeneous system of sensors, drones, satellite data, and AI models will be connected only with the help of state-of-the-art interoperability frameworks.

Complexity:

Crop growth, soil processes, and effects of climate are non-linear and stochastic, and thus require more complex simulation models. The capability to process sensor data with great frequency and update the digital twin in real time: The capabilities will necessitate powerful computing pipes.

User expertise:

The user might require training on how to interpret the outputs of the DT and then apply the data-driven recommendation. Due to the absence of expert intervention, there exists a threat that the decisions made on the basis of the digital twin can be suboptimal or misleading.

8.4 Data Privacy and Security

Agricultural DTs can gather sensitive data such as:

Boundaries and location of farm, financial information, and crop production, IBM practices in cultivating the property.

Risks include:

Data breaches. Data may be accessed unlawfully by other parties, which may impact economically and competitively to the farm or company.

Cyberattacks:

A breach of the IoT networks or cloud systems may interfere with operations. Policy gaps: In most countries, there are no policy frameworks and laws regulating the ownership, use, and sharing of agricultural data, and this can create problems of mistrust and abuse of this information. The need to make sure that there is end-to-end encryption, that the data is securely stored, and that there are clear data governance structures further complicates and makes it more expensive.

8.5 Infrastructure Limitations in Developing Countries

The adoption of DT in the low-resource environment has structural barriers:

Poor internet access: Rural communities can be poorly connected to broadband or mobile networks to transmit sensor data in real-time.

Power supply problems: IoT sensors and devices are often dependent on a consistent power supply, be it electricity or solar, which may not be available everywhere or at all.

The gap in access to technology: Small farmers might not have access to smartphones, computers, or AI platforms that can be used to connect with the digital twin.

Professional human resources: DT deployment is hindered by the absence of local knowledge in the areas of IoT implementation, AI modelling, or cloud computing.

As a result, DT in such settings tends to be restricted to pilot projects or highly subsidised programs, and expansion to some level of national coverage is a significant challenge. Summary: Although digital twins can ensure precise agriculture, resilient climate, and sustainable use of resources, they will be limited by: Lack of data and quality, setup and operation high costs, Complexity of technicality and computation, the issue of security and privacy, and Poor infrastructure in developing countries.

To deal with these challenges, this requires the support of the policy, training sessions, affordable technology solutions, and strong data governance frameworks.

9. Case Studies and Real-World Implementations

9.1 Smart Farms Using Digital Twins

1. Bowery Farming – Indoor Vertical Farms (USA)

The world is referring to one of the greatest examples in Bowery Farming, a massive vertical farm operator, which has a complex digital twin framework known as the Bowery Operating System to control the environmental factors, crop development, lighting schedules, nutrients provision, and harvesting on-the-fly. Bowery can continuously optimise the health and growth of its plants by combining the sensor data streams of thousands of sensors in their digital twin. Because of this, the result has seen crops that grow exponentially faster than the traditional practices, and less water is used by as much as ten times, and no use of pesticides in their regulated ecosystems (Kumar, S. et al. 2026).

2. Smart Greenhouse Systems

Digital twins have been used in commercial greenhouse settings to model and regulate microclimate situations like CO_2, humidity, moisture, and temperature. They operate on real-time data gathered by IoT sensors and models based on AI to predict plant stress and pest outbreaks, and the most appropriate time to irrigate. The virtual representation of greenhouse sections will enable farmers and greenhouse operators to visualise it to predict the results of applying the interventions before using the real world to reduce the chance of risk and squander resources.

3. Farm-scale Water Resource Digital Twin (NZ Case)

In New Zealand, a watershed-scale digital twin system was built by collaborating with farmers in a watershed through the use of soil moisture sensors, weather stations, river flow monitors, and groundwater information to model water use on 23,000 hectares of farmland. Such a system makes irrigation efficient at the farm and regional levels, enhancing the total performance of water and contributing to drought management programs (Fenemor, A. et al. 2010).

9.2 Agricultural Digital Twin Projects Worldwide

1. Digital Twin Orchards

The tree-level digital twins have been created by researchers using a mixture of 3D LiDAR or drone imagery with sensor data. The virtual twin of each tree enables the growers to track the growth trend, impacts, and disease symptoms of individual trees. The digital twin model aids in making pruning decisions efficiently and early forecasting the possible outbreaks, which enhances the prediction of crop quality and yield across orchard systems.

2. IoT-Enabled Farmland Monitoring Frameworks

The proposed projects, such as the one developed by Mustafa Angin, combine Lorawan wireless Internet of Things sensor networks with UAV images and deep learning algorithms to monitor the plants, identify weeds and diseases, and make real-time decisions. The hybrid system shows how the digital twin frameworks can be flexible enough to include various data sources and AI analytics within a single platform.

3. Automated Irrigation Digital Twins in Europe

DTs have been applied in Southern Portugal in the field and have been utilised in commercial vineyards by adjusting irrigation schedules automatically based on the sensor data of the environment and environment estimates. These systems consider the water stress and soil moisture, making it possible to manage water accurately and prevent over- or under-irrigation.

9.3 Success Stories in Precision Agriculture

1. Precision Resource Optimisation

In various digital twin applications in orchards, vineyards, and open fields, real-time data from soil sensors and weather stations, as well as data from imaging drones, have led to predictive irrigation schedules that have led to increased efficiency in water use and less waste of fertilisers. Such systems also enable simulation of what-if scenario which enables farmers to test strategies they intend to use in crops before implementation, which reduces losses in trial and error by far.

2. Enhanced Crop Monitoring and Decision Support

Digital twin systems that are AI and machine learning models (MA Rahu et al. 2024) have demonstrated great success in detecting crop pests and diseases at an early stage. In certain prototype applications, such predictive models enable the farmer to act before the large-scale outbreaks and promote the health and stability of crops overall.

3. Sustainability and Environmental Impact

Summary of Impact in these examples, and application, there are obvious, quantifiable advantages:

Increased productivity and uniformity of yields: The real-time simulation and prediction models can be used to make more informed decisions.

Increased climate resilience: DTs contribute to predicting the stress reactions to drought or other extreme weather conditions and create adaptive agricultural strategies.

Scalability and flexibility: implementations come in small greenhouse units to watershed-wide implementation. Pilot researches have shown that DTs may be used to cut down water consumption by 15-30, chemical application by 10-20 and livestock illness by 24-48. They also enhance the 8-15 per cent prediction of yield. (Aggarwal, M. et al. 2026).

10 Comparative analysis of DT with existing Smart Farming Technologies

Annexure (A)

11. Future Research Directions

Although it is already proven that DT can play a significant part in improving agricultural performance and climate resilience, some research directions can also enhance its application, scalability, and effectiveness. These guidelines emphasise the aspects of technological innovation, access, and governance. Future research in DTs for smart agriculture should focus on integrating Deep Learning models for more accurate prediction, detection, and climate impact analysis using large-scale multimodal farm data. Reinforcement learning can be explored for autonomous decision-making in irrigation, fertilisation, and pest control by learning optimal actions from continuous environmental feedback. Hybrid models combining physics-based crop models with AI techniques can improve the reliability and interpretability of DT simulations. Further work is also needed on real-time DT demonstrations and field-scale deployments to validate practical performance. Additionally, forward analysis using DT can support long-term scenario forecasting for climate change adaptation, resource optimisation, and sustainable farm management strategies. Future research can explore: Convolutional Neural Networks (CNNs) for high-resolution crop image analysis and pathology.

Generative AI: In the case of scenario modelling, farmers should be able to model the results of vegetable crops given various environments or management techniques.

Combining these intelligent AI models, the DT may become not just a basic monitoring tool, but a dynamic decision support system, adaptable and able to work with the extremely changing climatic and environmental conditions.

Edge Computing for Real-Time Farm Analytics:

Less dependence on constant high-speed internet, and therefore, DTs are more viable in remote or low-connection areas.

Energy-efficient computing through

reducing large-scale cloud transfers.

Research opportunities: Creating lightweight AI models which can be executed by edge devices with low computational capabilities.

Balancing between real-time analytics and complex simulations: Hybrid edge-cloud architectures.

Edge device security measures to avoid tampering or breach of data. Edge-enabled DTs would be able to convert both small and large farms into incredibly responsive and self-adaptive agricultural systems.

Digital Twin Platforms for Smallholder Farmers:

The majority of currently implemented DTs are capital-intensive and optimised for large commercial farms, which limits their applicability to smallholder farmers, particularly in developing nations. Future studies must be on cost-effective, scalable DT platforms:

Mobile-interfaces:

The Smartphone applications can provide visually appealing interfaces and useful guidance.

Community DT platforms:

Predictive analytics and resource optimisation for communities: Cooperative DT services are offered to smallholder farmers to make the benefits of predictive analytics and resource utilisation available to them. Creating these platforms would create democratic access to precision agriculture technologies that would enable millions of smallholders to increase yield, decrease waste, and also adapt to climate change.

Integration of climate-prudent agriculture: Bringing together DT research and national and international policies on climate action to achieve the most environmental benefits.

Ethical AI governance:

To make sure that the decisions made by AI-based DT do not disadvantage small farmers unintentionally or cause unfair distributions of the resources. Future studies in this field ought to consider policy strategies that can counterbalance innovation, sustainability, and inclusiveness, such that the adoption of DT may be beneficial to every stakeholder in the agricultural sector.

High-level Artificial Intelligence deployment with predictive functions. Stored and processed decision-making closer to the edge. Low-cost inclusion platforms for smallholder farmers. Good policy and governance structures to enable equitable, safe, and sustainable implementation. Through these channels, DT will be developed into a transformative solution to the sustainability of agriculture and climate resilience globally, beyond being a high-tech innovation. Future studies of DTs, in the smart agriculture field, ought to aim at establishing standardised DT architectures to guarantee interoperability and scalability across agricultural systems and platforms. It is necessary to combine DT models with GIS and remote sensing systems, such as satellite and drone cameras, in order to enhance the spatial tracking and the analysis of crop conditions. The economic feasibility and technology adoption studies should also be carried out by the researchers to check the cost-benefit factors and the obstacles to the farmers. Pilot deployments of DT systems are necessary to test the actual performance and reliability of these systems. Also, there is a need to develop strong data security, privacy, and governance systems to safeguard the sharing of data, ownership, and reliable deployment of digital twins in agriculture.

13. Conclusion

Real-time data about crops, soils, and Equipment may be provided by the DTs, which would help farmers make better decisions and lower the danger of climate change. Nevertheless, there are several challenges, including the high costs, inability to integrate the data, concerns about security, and a deficiency in expertise, which have to be overcome. The agri-sector, policy, and technological stakeholders must work together to eliminate these challenges. The potential of DTs in the future is enormous, as novel technologies such as connected climate prediction, autonomous systems, and machine learning models expand the possibilities of this group. Prediction and autonomous interventions based on AI, as well as the capability to model and simulate different climatic conditions, have great potential in farm productivity and resilience in a changing environment. By bridging the digital and physical divide, DTs can improve agriculture's resilience, sustainability, and efficiency and prepare the industry to face the challenges of a world that is changing quickly due to population growth.

At the lower levels, such as the farm, IoT sensor networks to constantly feed farm digital twins to monitor and provide decision support should be embraced. Pilot projects and training programs should be encouraged, where farmers should be able to apply the DT-based suggestions practically. At the policy levels Governments ought to promote the use of DT by financing smart agriculture infrastructure, rural connectivity, and cheap IoT devices. Facilitate open DT systems and AI farm models through partnerships between the public and the private sectors. Fund demonstration farms and research initiatives on a large scale to prove the technologies of DT and inform sustainable agriculture and climate-resistant farming policies. However, with the present innovation, it is possible to envision a future in which technology and nature coexist to create a more sustainable and environmentally friendly food system.

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Annexure (A)

Aspect	Traditional Smart Farming Technologies	Digital Twin–Based Smart Farming
Core Concept	Uses IoT devices, sensors, drones, GPS, and data analytics to monitor and manage farm activities.	Creates a virtual replica of the physical farm system that continuously synchronises with real-time data.
Data Processing	Data is collected from sensors and analysed for decision support, often separately for specific tasks.	Integrates real-time multi-source data (IoT sensors, UAVs, weather data, soil data) into a unified virtual model.
System Integration	Often, task-specific or fragmented systems are used for irrigation monitoring, crop health monitoring, or drone imaging.	Provides system-level integration, simulating the entire farm ecosystem, including crops, soil, climate, and machinery.
Decision-Making	Supports data-driven recommendations, but decisions are usually reactive.	Enables predictive and prescriptive decision-making through simulations and scenario analysis.
Simulation Capability	Limited or static models; mainly used for monitoring and reporting.	Offers dynamic simulations of crop growth, irrigation strategies, and environmental conditions before applying them in reality.
Automation Level	Automation in specific processes (e.g., smart irrigation, automated tractors).	Enables closed-loop automation, where decisions generated in the digital model can automatically control farm systems.
Real-Time Feedback	Provides real-time monitoring but limited continuous synchronisation.	Maintains bi-directional data exchange between the physical farm and digital model, allowing continuous updates and optimisation.
Resource Optimization	Improves efficiency in irrigation, fertilisation, and pesticide use.	Enhances optimisation through predictive modelling; studies indicate digital twins can reduce water usage by up to 25% and fertiliser waste by 10–15%. (*MDPI*)
Visualization	Dashboards showing sensor readings or field images.	Provides interactive 3D or data-driven virtual farm environments for better analysis and monitoring.
Scalability & Future Integration	Limited integration across the farm lifecycle and supply chain.	Can integrate AI, machine learning, robotics, AR/VR, and supply chain systems for complete agricultural ecosystem modelling.