

AI, IoT and Remote Sensing in Precision Agriculture

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1. Introduction

The global population is projected to reach nearly 10 billion by the end of the 21st century, posing unprecedented challenges for agricultural systems to ensure food security while maintaining sustainability [1]. Achieving a proportional increase in agricultural production to feed this growing population is one of humanity's most pressing challenges. This goal must be pursued against a backdrop of climate change, resource depletion, and increasingly frequent extreme weather events, all of which threaten the stability of global food systems [2]. To address these challenges, the integration of advanced technologies such as automation, sensors, yield monitors, the Internet of Things (IoT), drones, and robotics is essential. These tools, combined with Geographic Information Systems (GISs), artificial intelligence (AI), highly structured mathematical models, and big data analytics, form the foundation of a global “Digital Twin” for agriculture [3,4]. This conceptual framework enables the creation of virtual replicas of agricultural systems, facilitating site-specific conservation and management practices that enhance productivity, income, and global sustainability [5,6]. Spatial analysis of agricultural data plays a pivotal role in this context, allowing for precise decision making and resource optimization [7]. By leveraging these technologies, we can develop resilient agricultural systems capable of meeting future demands while minimizing environmental impacts.

Satellite and aerial imagery, along with ground-based sensors and yield monitors, provide critical insights into production variability at both macro- and micro-scales. These technologies enable the processing, representation, and modeling of vast amounts of agricultural data, facilitating precision agriculture practices [8,9]. Spatiotemporal models, in particular, offer significant advantages over traditional spatially explicit models by capturing the dynamic interplay between space and time, which is essential for understanding complex agricultural systems [10]. Hierarchical models further enhance this capability by addressing complex interactions through the specification of parameters that vary across multiple levels, often via the introduction of random effects [11]. This approach allows for more accurate predictions and tailored management strategies, ultimately improving crop yields and resource efficiency. By integrating these advanced modeling techniques with high-resolution data, we can better address the challenges of agricultural variability and sustainability in the face of global change.

The spread of transboundary plant pests and diseases, caused by fungi, bacteria, or viruses, has intensified significantly in recent years, leading to substantial agricultural losses and posing a serious threat to global food security [12,13]. These pathogens primarily spread through human activities, wind dispersal, or vector-borne mechanisms, making their control and prediction particularly challenging [14]. The spatial patterns of these outbreaks are influenced by a complex interplay of environmental, climatic, and socioeconomic factors. For instance, changes in climate—such as increased temperatures and altered



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precipitation patterns—create favorable conditions for the proliferation and spread of pests and diseases [15,16]. Additionally, shifts in land use, agricultural practices, and human habits further complicate our understanding of these processes, making it difficult to predict and mitigate their impacts [17]. Recent studies have highlighted the importance of hotspot mapping and regional analyses to identify areas at higher risk of pest introductions, taking into account environmental, anthropogenic, and spatial factors [18]. These approaches provide valuable insights into the drivers of pest spread and help prioritize surveillance and control efforts.

Addressing these challenges requires a multidisciplinary approach that integrates ecological, epidemiological, and socioeconomic data to develop effective monitoring and management strategies. Individual-based spatial epidemiological models, for example, offer a powerful tool for simulating the spread of plant diseases and evaluating the effectiveness of control measures [19]. Furthermore, optimized surveillance sampling strategies enable more efficient delimitation of outbreaks and resource allocation [20–22]. Bayesian statistical models have also proven useful in predicting disease risk [23]. By combining these advanced modeling techniques with real-time data and predictive analytics, we can improve our ability to anticipate and respond to emerging plant health threats, ultimately safeguarding agricultural productivity and global food security.

2. An Overview of Published Articles

This Special Issue brings together six cutting-edge research articles that explore innovative approaches to address critical challenges in precision agriculture, leveraging advanced technologies, such as the Internet of Things (IoT), machine learning (ML), and deep learning (DL). These studies collectively highlight the transformative potential of data-driven methodologies in enhancing agricultural productivity, sustainability, and decision making, offering solutions to some of the most pressing issues in modern farming.

The articles cover a wide range of agricultural challenges, from crop yield prediction and phenology forecasting to aquaculture management and automated quality assessment. By employing advanced modeling techniques, remote sensing, and hybrid optimization methods, the research demonstrates how digital tools can revolutionize agricultural practices. These contributions emphasize the importance of interdisciplinary collaboration and technological innovation in building resilient and efficient systems capable of adapting to a rapidly changing world.

Together, these studies showcase the diverse applications of IoT, ML, and DL in tackling agricultural challenges. By integrating cutting-edge technologies with domain-specific expertise, this Special Issue advances the development of more efficient, sustainable, and resilient agricultural systems, paving the way for future innovations in the field.

While the contributions gathered in this Special Issue represent significant advancements in the field of precision agriculture, they also underscore the need for further discussion and research to fully grasp the complexities inherent in modeling agricultural systems. The integration of technologies such as IoT, machine learning, and deep learning has opened new avenues for innovation, ensuring their accessibility and addressing the multifaceted interactions between environmental, climatic, and socioeconomic factors. Nonetheless, challenges still remain in scaling these solutions. It is my hope that this Special Issue will serve as a catalyst for stimulating new research initiatives, fostering interdisciplinary collaboration, and promoting actionable strategies to address the pressing challenges of modern agriculture. By building on these foundations, we can move closer to developing sustainable, efficient, and resilient agricultural systems that meet the needs of a growing global population.

3. Conclusions

In conclusion, this Special Issue highlights the critical role of advanced technologies and data-driven approaches in addressing the multifaceted challenges of modern agriculture. As the global population approaches 10 billion, the need for sustainable, efficient, and resilient agricultural systems has never been more urgent. The integration of tools such as IoT, AI, remote sensing, and spatiotemporal modeling offers transformative potential for enhancing productivity, optimizing resource use, and mitigating the impacts of climate change and pest outbreaks. The six articles featured in this Special Issue demonstrate innovative applications of these technologies, from crop yield prediction and phenology forecasting to disease surveillance and aquaculture management. However, the complexities of agricultural systems demand continued interdisciplinary collaboration and research to overcome barriers such as scalability, accessibility, and the dynamic interplay of environmental and socioeconomic factors. By building on the foundations laid out in this Special Issue, the scientific community can drive forward the development of sustainable solutions that ensure food security and environmental stewardship for future generations.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
DL	Deep learning
GISs	Geographic information systems
IoT	Internet of Things
ML	Machine learning

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