

Research Insight Open Access

Comprehensive Precision Agriculture Technology to Achieve Maximum Cotton **Yield**

Shanjun Zhu, Mengting Luo 🔀

Institute of Life Science, Jiyang College of Zhejiang A&F University, Zhuji, 311800, China

Corresponding email: mengting.luo@jicat.org

Cotton Genomics and Genetics, 2025, Vol.16, No.2 doi: 10.5376/cgg.2025.16.0006

Received: 03 Jan., 2025 Accepted: 18 Feb., 2025 Published: 01 Mar., 2025

Copyright © 2025 Zhu and Luo, This is an open access article published under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Preferred citation for this article:

Zhu S.J., and Luo M.T., 2025, Comprehensive precision agriculture technology to achieve maximum cotton yield, Cotton Genomics and Genetics, 16(2): 48-56 (doi: 10.5376/cgg.2025.16.0006)

Abstract Cotton is an important cash crop and textile raw material globally, playing a vital role in the economies of many producing countries, but its yield growth has stagnated under conventional farming methods. This study comprehensively reviews the application of precision agriculture technologies in cotton production, focusing on key innovations such as remote sensing, GPS-guided machinery, variable rate technology (VRT), the internet of things (IoT), and data analytics platforms. It explores how these tools can help improve yields, resource efficiency, and environmental sustainability. The integration of big data, machine learning, and decision support systems (DSS) further enhances field decision-making, forecasting, and risk management. A case study in Xinjiang, China illustrates the real-world benefits and challenges of implementing precision agriculture in major cotton-producing regions. While these technologies have shown clear advantages in increasing productivity and reducing input costs, barriers such as high investment, technical skills gaps, and data management issues remain. Future advances in artificial intelligence, robotics, and supportive policy frameworks will play a key role in scaling up smart farming practices, ensuring sustainable and profitable cotton cultivation in the face of global agricultural challenges.

Keywords Precision agriculture; Cotton yield; Remote sensing; IoT; Decision support systems

1 Introduction

Cotton is a vital crop with significant economic importance, particularly in regions where it serves as a primary agricultural product. The global cotton industry supports millions of jobs and contributes substantially to the economies of many countries. Cotton production is not only crucial for the textile industry but also plays a role in the agricultural sector's overall economic health (Lambert et al., 2015; Jumanov et al., 2022).

Precision agriculture has emerged as a transformative approach in cotton farming, aiming to enhance productivity and sustainability. This method leverages advanced technologies such as remote sensing, yield monitors, and soil testing to optimize resource use and improve crop yields (Neely et al., 2016). The integration of internet of things (IoT) devices and machine learning further enhances the ability to monitor and manage crops effectively, reducing environmental impact and increasing economic returns (Sharma et al., 2021; Nyéki and Neményi, 2022; Durai et al., 2024). The need for precision agriculture in cotton farming is driven by the challenges of resource limitations, climate variability, and the necessity to increase efficiency and profitability (Watson et al., 2016; Baio et al., 2017).

This study aims to comprehensively analyze precision agriculture technologies and their applications in cotton cultivation and explore the economic benefits, technological advancements, and practical applications of these technologies in achieving maximum cotton yields. The scope of the study includes reviewing the current practices, challenges, and future prospects of precision agriculture with a focus on improving cotton production efficiency and sustainability.

2 Core Components of Precision Agriculture in Cotton

2.1 Remote sensing and satellite imaging

Remote sensing and satellite imaging are pivotal in precision agriculture, particularly for cotton production. These technologies enable the monitoring and assessment of agricultural lands, providing critical data on crop biomass,



http://cropscipublisher.com/index.php/cgg

phenology, and yield at various scales. For instance, the use of Landsat 8 and other satellite technologies allows for the prediction and mapping of cotton lint yield by analyzing crop indices such as NDVI and other vegetation indices (Haghverdi et al., 2018; Sishodia et al., 2020). Remote sensing facilitates the application of variable rate technologies (VRT) by providing high-resolution images that inform precise input applications, such as fertilizers and water, thereby optimizing resource use and enhancing yield (Filintas et al., 2022).

2.2 GPS-guided machinery and variable rate technology (VRT)

GPS-guided machinery and VRT are integral to precision agriculture, offering precise control over agricultural inputs. These technologies enable site-specific crop management by applying inputs like seeds, fertilizers, and water according to field variability. The integration of GPS with automatic controllers and sensors allows for the precise application of inputs, which is crucial for optimizing cotton yield and reducing environmental impact (Ali et al., 2024). Studies have shown that precision agriculture techniques, including VRT, can lead to significant increases in crop yield and reductions in water and fertilizer usage, highlighting their effectiveness in sustainable farming practices.

2.3 Internet of things (IoT) and sensor networks

The internet of things (IoT) and sensor networks are transforming precision agriculture by providing real-time data on environmental conditions, crop health, and soil quality. IoT devices equipped with optical sensors can monitor critical indicators such as temperature, humidity, and chlorophyll content, which are essential for maintaining optimal growing conditions for cotton (Saha et al., 2023; Durai et al., 2024). These sensors transmit data wirelessly to central servers for analysis, enabling predictive analytics and informed decision-making regarding irrigation, pest management, and fertilizer application (Figure 1) (Alahmad et al., 2023). The use of IoT and wireless sensor networks enhances the efficiency of precision agriculture by reducing labor costs and increasing productivity (Shafi et al., 2019; Sanjeevi et al., 2020).

Technologies (B) Remote LIDAR Artificial Neural sensing Vision Learning Network Intelligence Applications SHHHH Nutrients Disease Drops Counting Woods Pests Harvesting Spraying Estimates

Figure 1 Sensing technologies and their applications in agriculture (Adopted from Alahmad et al., 2023)

3 Data Analytics and Decision Support Systems (DSS)

3.1 Big data integration from multiple sources

In precision agriculture, the integration of big data from various sources is crucial for optimizing crop yield and resource management. The use of unmanned aerial systems (UAS) and IoT sensors allows for the collection of real-time data on crop growth, soil conditions, and environmental factors. This data is then integrated into decision



http://cropscipublisher.com/index.php/cgg

support systems to enhance agricultural practices. For instance, a study highlights the use of UAS to capture RGB data for developing a Digital Twin framework, which forecasts cotton crop features such as canopy cover and height, thereby aiding in yield prediction and biomass estimation (Pal et al., 2019). Additionally, the integration of diverse data sources, including historical weather data and soil nutrient analysis, enables personalized recommendations for farmers, enhancing decision-making and risk management (Singh et al., 2024).

3.2 Machine learning and predictive modeling

Machine learning (ML) plays a pivotal role in precision agriculture by analyzing complex datasets to predict crop yields and optimize farming practices. Various ML models, such as random forests, XGboost, and artificial neural networks, have been employed to predict cotton yield and determine the impact of management and environmental variables (Dhaliwal et al., 2022). These models facilitate informed decision-making by predicting suitable crops, detecting diseases, and optimizing irrigation (Mohyuddin et al., 2024). Moreover, ML techniques, including support vector regression and ensemble methods, have been used to enhance prediction accuracy and decision-making capabilities, contributing to sustainable farming practices (Bachu et al., 2024).

3.3 DSS tools for cotton farmers

Decision support systems (DSS) are essential tools for cotton farmers, providing insights into irrigation scheduling, crop management, and yield optimization. For example, an irrigation DSS based on forecasted rainfall and water stress indices has been shown to significantly increase cotton yield and water productivity in arid climates (Chen et al., 2020). Furthermore, IoT-based DSS frameworks integrate multiple soil and environmental parameters to predict soil moisture content and optimize irrigation control schemes, ensuring efficient water use and maintaining uniform moisture levels across fields (Keswani et al., 2020). These tools empower farmers to make data-driven decisions, ultimately enhancing crop yield and resource efficiency.

4 Impact of Precision Agriculture on Cotton Yield and Sustainability

4.1 Yield enhancement through site-specific management

Precision agriculture significantly enhances cotton yield through site-specific management techniques. By utilizing technologies such as GPS, IoT sensors, and variable rate technology (VRT), farmers can apply inputs precisely where needed, optimizing crop yield. For instance, precision nitrogen management in Bt cotton has shown to improve seed cotton yield by aligning nitrogen application with crop demand, thereby enhancing nitrogen use efficiency (Gupta et al., 2022). Additionally, precision agriculture practices have demonstrated a 20% increase in crop yield by addressing inter- and intravariability in cropping systems.

4.2 Efficient use of resources and input cost reduction

Precision agriculture contributes to the efficient use of resources and reduction of input costs by minimizing waste and optimizing input application. For example, precision nitrogen management not only improves yield but also reduces nitrous oxide emissions, showcasing a dual benefit of resource efficiency and environmental protection. Moreover, precision agriculture has been shown to reduce water and fertilizer usage by 40%, leading to significant cost savings. The use of site-specific management strategies also results in economic benefits through cost savings and increased profits, as evidenced by studies on various crops (Bahmutsky et al., 2024).

4.3 Environmental and ecological benefits

The environmental and ecological benefits of precision agriculture are substantial. By reducing the overuse of fertilizers and pesticides, precision agriculture minimizes environmental impacts such as greenhouse gas emissions and pesticide runoff. Precision farming techniques, such as site-specific sensing and management, allow for targeted input use, reducing agrichemical residuals and promoting environmental sustainability (Finger et al., 2019). Additionally, precision agriculture practices have been shown to decrease greenhouse gas emissions by 14% in sugarcane production, highlighting their potential for broader ecological benefits (Sanches et al., 2023).

5 Challenges and Limitations in Adoption

5.1 Economic and infrastructure barriers

The adoption of precision agriculture technologies (PATs) is often hindered by significant economic and infrastructure barriers. High initial costs and the need for substantial investments in technology infrastructure are



http://cropscipublisher.com/index.php/cgg

major deterrents for many farmers, particularly those managing smaller operations (John et al., 2023). The economic cost barrier is further exacerbated by the size and income differences among farmers, which influence their ability to invest in new technologies (Barnes et al., 2019). Additionally, the lack of adequate infrastructure, such as reliable internet connectivity and access to advanced machinery, poses a significant challenge, especially in rural and underdeveloped regions (Lowenberg-DeBoer and Erickson, 2019).

5.2 Technical knowledge and training gaps

A critical challenge in the adoption of precision agriculture is the gap in technical knowledge and training among farmers. Many farmers lack the necessary skills and understanding to effectively implement and manage these technologies (Pathak et al., 2019). This knowledge gap is particularly pronounced among small-scale farmers, where digital literacy and technological interoperability are significant hurdles. The complexity of precision agriculture technologies requires comprehensive training programs to equip farmers with the skills needed to utilize these tools effectively (Lambert et al., 2015). Without adequate training and support, the potential benefits of precision agriculture remain largely untapped.

5.3 Data management and privacy concerns

Data management and privacy concerns are increasingly becoming significant barriers to the adoption of precision agriculture technologies. The vast amounts of data generated by these technologies require robust data management systems, which many farmers find challenging to implement (Ofori and El-Gayar, 2020). Moreover, concerns about data privacy and security are prevalent, as farmers are wary of how their data might be used or shared without their consent. These concerns are compounded by the lack of clear regulatory frameworks to protect farmers' data, leading to hesitancy in adopting technologies that rely heavily on data collection and analysis (Lambert et al., 2015).

6 Case Study: Precision Agriculture Implementation in a Cotton-Producing Region 6.1 Background and cultivation system of Xinjiang, China

Xinjiang, located in northwestern China, is a major cotton-producing region, known for its arid climate and challenging agricultural conditions, including limited water and heat resources, as well as prevalent soil salinity issues. Over the past three decades, Xinjiang has seen significant advancements in cotton cultivation techniques, leading to a consistent increase in cotton yields. The region has developed three generations of cultivation technology systems, focusing on efficient utilization of light, heat, water, and fertilizers (Feng et al., 2024). These advancements have transformed Xinjiang into one of the world's largest cotton producers, despite its environmental challenges.

6.2 Applied precision technologies and interventions

In Xinjiang, precision agriculture technologies have been implemented to optimize resource use and improve cotton yields. Drip irrigation has been a key intervention, significantly increasing boll weight, yield, and water productivity compared to traditional furrow irrigation methods (Kuang et al., 2024). Additionally, a decision-making system based on reinforcement learning has been developed to provide precise irrigation strategies, maximizing cotton yield while reducing water consumption. Remote sensing and crop models have also been utilized to estimate cotton yield accurately, integrating satellite and environmental data to enhance yield predictions (Figure 2) (Lang et al., 2023). Furthermore, management zones have been delineated using machine learning and remote sensing to address soil salinization and optimize resource allocation.

6.3 Outcomes, benefits, and lessons learned

The implementation of precision agriculture technologies in Xinjiang has led to several positive outcomes. Drip irrigation and optimized fertigation strategies have improved cotton yield and fiber quality, while also enhancing water and nitrogen use efficiency (Hou et al., 2024). The use of reinforcement learning for irrigation decision-making has further increased yields and reduced water usage, aligning with sustainable water management goals (Chen et al., 2023). The delineation of management zones has allowed for more targeted resource application, addressing soil salinity issues and improving overall farm management (Wang et al., 2023). These interventions have collectively contributed to the region's ability to achieve high cotton yields despite

http://cropscipublisher.com/index.php/cgg

environmental constraints. The lessons learned from Xinjiang's experience highlight the importance of integrating advanced technologies and tailored management practices to overcome regional agricultural challenges and enhance productivity.

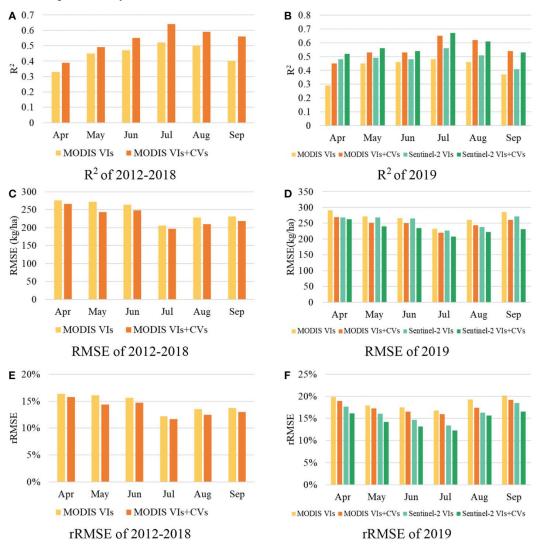


Figure 2 Testing performance [R2 (A, B), RMSE (C, D) and rRMSE (E, F)] of cotton yield prediction only with remote sensing variables and combined with climate variables using the LSTM model for the whole growing season during 2012-2018 and 2019, respectively (Adopted from Lang et al., 2023)

7 Future Directions and Recommendations

7.1 Integration of AI, robotics, and automation

The integration of AI, robotics, and automation in precision agriculture is pivotal for maximizing cotton yield. AI technologies, such as machine learning and computer vision, are transforming traditional farming by enabling real-time data analysis and decision-making, which enhances efficiency and sustainability (Hoque and Padhiary, 2024; Padhiary et al., 2024). Robotics, including autonomous tractors and drones, facilitate precise operations like planting, monitoring, and harvesting, reducing labor costs and increasing operational efficiency (Agrawal and Arafat, 2024). Future advancements should focus on developing energy-efficient AI models and improving sensor technologies to overcome current limitations such as high operational costs and technical complexity.

7.2 Policies and support for technology adoption

To fully realize the potential of precision agriculture technologies, supportive policies and infrastructure are essential. Governments and private sectors must collaborate to provide training, infrastructure, and region-specific solutions for farmers (Yousafzai et al., 2024). Policy support can address challenges such as high implementation



http://cropscipublisher.com/index.php/cgg

costs and data privacy concerns, fostering an environment conducive to technological adoption (Akintuyi, 2024). Additionally, initiatives to bridge the digital divide in rural areas and ensure affordable access to technology for small-scale farmers are crucial (Daraojimba et al., 2024).

7.3 Research needs and innovation opportunities

Ongoing research is needed to explore new frontiers in precision agriculture, such as the integration of blockchain, big data analytics, and cloud computing to enhance transparency and decision-making. Innovation opportunities lie in developing robust AI solutions that are accessible and scalable, particularly for smallholder farmers (Naresh et al., 2024). Further research should also focus on ethical considerations and the environmental impact of AI technologies, ensuring sustainable practices that align with global food security goals (Debnath and Basu, 2023). By addressing these research needs, precision agriculture can continue to evolve, offering innovative solutions for sustainable crop production and maximum yield.

8 Concluding Remarks

Precision agriculture technologies have significantly contributed to enhancing cotton yield by optimizing resource use and improving management practices. The integration of GPS, IoT sensors, and variable rate technology (VRT) has led to a 20% increase in crop yield and a 40% reduction in water and fertilizer usage, demonstrating the effectiveness of these technologies in promoting sustainable farming practices. UAV-based systems have enabled real-time monitoring of crop responses to environmental and management factors, allowing for more informed agronomic decisions. AI-driven systems have further enhanced yield prediction accuracy by 15% and reduced water and fertilizer use by up to 30% and 20%, respectively, without compromising yields. These advancements underscore the potential of precision agriculture to maximize cotton yield while minimizing environmental impact.

The successful implementation of precision agriculture technologies in cotton farming requires context-specific strategies that consider local environmental conditions, soil variability, and socio-economic factors. For instance, site-specific variable-rate (SSVR) technologies allow for targeted nematicide applications, reducing costs and sustaining yield levels. Adoption patterns among cotton farmers indicate that larger operations with access to diverse information sources are more likely to adopt technology bundles, highlighting the need for tailored strategies that address the unique challenges faced by smaller farms. Additionally, the integration of remote sensing and soil analyses has proven effective in optimizing irrigation and fertilization practices, further emphasizing the importance of adapting technologies to specific agricultural contexts.

The future of smart cotton farming lies in the continued development and adoption of precision agriculture technologies that are scalable and adaptable to diverse farming landscapes. Overcoming barriers such as high initial costs, technical expertise requirements, and data privacy concerns will be crucial for broader adoption. Collaborative efforts from policymakers, agricultural organizations, and technology providers are essential to develop accessible and cost-effective solutions that empower farmers with actionable insights for improved farm management. As these technologies evolve, they hold the promise of transforming cotton farming into a more sustainable, efficient, and profitable endeavor, ultimately contributing to global food security and environmental sustainability.

Acknowledgments

We are grateful to Mr. Xu for critically reading the manuscript and providing valuable feedback that improved the clarity of the text.

Conflict of Interest Disclosure

The authors affirm that this research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

References

Agrawal J., and Arafat M., 2024, Transforming farming: a review of AI-powered UAV technologies in precision agriculture, Drones, 8(11): 664. https://doi.org/10.3390/drones8110664



http://cropscipublisher.com/index.php/cgg

Akintuyi O., 2024, Adaptive AI in precision agriculture: a review: investigating the use of self-learning algorithms in optimizing farm operations based on real-time data, Research Journal of Multidisciplinary Studies, 7(02): 016-030.

https://doi.org/10.53022/oarjms.2024.7.2.0023

Alahmad T., Neményi M., and Nyéki A., 2023, Applying IoT sensors and big data to improve precision crop production: a review, Agronomy, 13(10): 2603. https://doi.org/10.3390/agronomy13102603

Ali A., Hassan M., and Kaul H., 2024, Broad scope of site-specific crop management and specific role of remote sensing technologies within it—A review, Journal of Agronomy and Crop Science, 210(4): e12732.

https://doi.org/10.1111/jac.12732

Bachu L., Kandibanda A., Grandhi N., Athina D., and Ande P., 2024, Machine learning for enhanced crop management and optimization of yield in precision agriculture, In: 2024 8th international conference on I-SMAC (IoT in social, mobile, analytics and cloud) (I-SMAC), IEEE, pp.1289-1293.

https://doi.org/10.1109/I-SMAC61858.2024.10714733

Bahmutsky S., Grassauer F., Arulnathan V., and Pelletier N., 2024, A review of life cycle impacts and costs of precision agriculture for cultivation of field crops, Sustainable Production and Consumption, 52: 347-362.

https://doi.org/10.1016/j.spc.2024.11.010

Baio F., Da Silva S., Da Silva Camolese H., and Neves D., 2017, Financial analysis of the investment in precision agriculture techniques on cotton crop, Engenharia Agricola, 37(04): 838-847.

https://doi.org/10.1590/1809-4430-ENG.AGRIC.V37N4P838-847/2017

Barnes A., Soto I., Eory V., Beck B., Balafoutis A., Sánchez B., Vangeyte J., Fountas S., Wal T., and Gómez-Barbero M., 2019, Exploring the adoption of precision agricultural technologies: a cross regional study of EU farmers, Land Use Policy, 80: 163-174.

https://doi.org/10.1016/J.LANDUSEPOL.2018.10.004

Chen X., Qi Z., Gui D., Sima M., Zeng F., Li L., Li X., and Gu Z., 2020, Evaluation of a new irrigation decision support system in improving cotton yield and water productivity in an arid climate, Agricultural Water Management, 234: 106139.

https://doi.org/10.1016/j.agwat.2020.106139

Chen Y., Yu Z., Han Z., Sun W., and He L., 2023, A decision-making system for cotton irrigation based on reinforcement learning strategy, Agronomy, 14(1):

https://doi.org/10.3390/agronomy14010011

Daraojimba D., Adewusi A., Asuzu O., Olorunsogo T., Iwuanyanwu C., and Adaga E., 2024, AI in precision agriculture: a review of technologies for sustainable farming practices, World Journal of Advanced Research and Reviews, 21(1): 2276-2285.

https://doi.org/10.30574/wjarr.2024.21.1.0314

https://doi.org/10.1016/j.compag.2022.107107

Debnath B., and Basu S., 2023, AI-powered precision agriculture: reshaping farming for efficiency, sustainability, and global impact, International Journal on Agricultural Sciences, 14(2): 63-66.

https://doi.org/10.53390/ijas.2023.14203

Dhaliwal J., Panday D., Saha D., Lee J., Jagadamma S., Schaeffer S., and Mengistu A., 2022, Predicting and interpreting cotton yield and its determinants under long-term conservation management practices using machine learning, Computers and Electronics in Agriculture, 199: 107107.

Durai R., Vijayakumar R., Lakshmisridevi S., Bhanu S., and Arunkumar U., 2024, IoT Based optical sensor network for precision agriculture, In: 2024 international conference on optimization computing and wireless communication (ICOCWC), IEEE, pp.1-7.

https://doi.org/10.1109/ICOCWC60930.2024.10470879

Feng L., Wan S., Zhang Y., and Dong H., 2024, Xinjiang cotton: achieving super-high yield through efficient utilization of light, heat, water, and fertilizer by three generations of cultivation technology systems, Field Crops Research, 312: 109401.

https://doi.org/10.1016/j.fcr.2024.109401

Filintas A., Nteskou A., Kourgialas N., Gougoulias N., and Hatzichristou E., 2022, A comparison between variable deficit irrigation and farmers' irrigation practices under three fertilization levels in cotton yield (*Gossypium hirsutum L.*) using precision agriculture, remote sensing, soil analyses, and crop growth modeling, Water, 14(17): 2654.

https://doi.org/10.3390/w14172654

Finger R., Swinton S., Benni N., and Walter A., 2019, Precision farming at the nexus of agricultural production and the environment, Annual Review of Resource Economics, 11(1): 313-335.

https://doi.org/10.1146/ANNUREV-RESOURCE-100518-093929

Gupta R., Shankar A., Ma B., Bhatt R., Al-Huqail A., Siddiqui M., and Kumar R., 2022, Precision nitrogen management in Bt cotton (*Gossypium hirsutum*) improves seed cotton yield and nitrogen use efficiency, and reduces nitrous oxide emissions, Sustainability, 14(4): 2007. https://doi.org/10.3390/su14042007

Haghverdi A., Washington-Allen R., and Leib B., 2018, Prediction of cotton lint yield from phenology of crop indices using artificial neural networks, Computers and Electronics in Agriculture, 152: 186-197.

https://doi.org/10.1016/J.COMPAG.2018.07.021

Hoque A., and Padhiary M., 2024, Automation and AI in precision agriculture: innovations for enhanced crop management and sustainability, Asian Journal of Research in Computer Science, 17(10): 95-109.

https://doi.org/10.9734/ajrcos/2024/v17i10512



http://cropscipublisher.com/index.php/cgg

Hou X., Fan J., Zhang F., Hu W., and Xiang Y., 2024, Optimization of water and nitrogen management to improve seed cotton yield, water productivity and economic benefit of mulched drip-irrigated cotton in southern Xinjiang, China, Field Crops Research, 308: 109301.

John D., Hussin N., Shahibi M., Ahmad M., Hashim H., and Ametefe D., 2023, A systematic review on the factors governing precision agriculture adoption among small-scale farmers, Outlook on Agriculture, 52(4): 469-485.

https://doi.org/10.1177/00307270231205640

https://doi.org/10.1016/j.fcr.2024.109301

Jumanov D., Kuziboyev J., and Izzatullayev L., 2022, Agricultural technology and cotton yield, In: IOP conference series: earth and environmental science, IOP Publishing, 1112(1): 012025.

https://doi.org/10.1088/1755-1315/1112/1/012025

Keswani B., Mohapatra A., Keswani P., Khanna A., Gupta D., and Rodrigues J., 2020, Improving weather dependent zone specific irrigation control scheme in IoT and big data enabled self driven precision agriculture mechanism, Enterprise Information Systems, 14(9-10): 1494-1515.

https://doi.org/10.1080/17517575.2020.1713406

Kuang N., Hao C., Liu D., Maimaitiming M., Xiaokaitijiang K., Zhou Y., and Li Y., 2024, Modeling of cotton yield responses to different irrigation strategies in Southern Xinjiang Region, China, Agricultural Water Management, 303: 109018.

https://doi.org/10.1016/j.agwat.2024.109018

Lambert D., Paudel K., and Larson J., 2015, Bundled adoption of precision agriculture technologies by cotton producers, Journal of Agricultural and Resource Economics, 40(2): 325-345.

Lang P., Zhang L., Huang C., Chen J., Kang X., Zhang Z., and Tong Q., 2023, Integrating environmental and satellite data to estimate county-level cotton yield in Xinjiang Province, Frontiers in Plant Science, 13: 1048479.

https://doi.org/10.3389/fpls.2022.1048479

 $Lowenberg-DeBoer\ J.,\ and\ Erickson\ B.,\ 2019,\ Setting\ the\ record\ straight\ on\ precision\ agriculture\ adoption,\ Agronomy\ Journal,\ 111(4):\ 1552-1569.$

https://doi.org/10.2134/AGRONJ2018.12.0779

Mohyuddin G., Khan M., Haseeb A., Mahpara S., Waseem M., and Saleh A., 2024, Evaluation of machine learning approaches for precision farming in smart agriculture system: a comprehensive review, IEEE Access, 12: 60155-60184.

https://doi.org/10.1109/ACCESS.2024.3390581

Naresh R., Singh N., Sachan P., Mohanty L., Sahoo S., Pandey S., and Singh B., 2024, Enhancing sustainable crop production through innovations in precision agriculture technologies, Journal of Scientific Research and Reports, 30(3): 89-113.

https://doi.org/10.9734/jsrr/2024/v30i31861

Neely H., Morgan C., Stanislav S., Rouze G., Shi Y., Thomasson J., Valasek J., and Olsenholler J., 2016, Strategies for soil-based precision agriculture in cotton, In: Autonomous air and ground sensing systems for agricultural optimization and phenotyping, SPIE, 9866: 104-110.

https://doi.org/10.1117/12.2228732

Nyéki A., and Neményi M., 2022, Crop yield prediction in precision agriculture, Agronomy, 12(10): 2460.

https://doi.org/10.3390/agronomy12102460

Ofori M., and El-Gayar O., 2020, Drivers and challenges of precision agriculture: a social media perspective, Precision Agriculture, 22(3): 1019-1044. https://doi.org/10.1007/s11119-020-09760-0

Padhiary M., Saha D., Kumar R., Sethi L., and Kumar A., 2024, Enhancing precision agriculture: a comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation, Smart Agricultural Technology, 8: 100483.

 $\underline{https://doi.org/10.1016/j.atech.2024.100483}$

Pal P., Landivar-Bowles J., Landivar-Scott J., Duffield N., Nowka K., Jung J., Chang A., Lee K., Zhao L., Pathak H., Brown P., and Best T., 2019, A systematic literature review of the factors affecting the precision agriculture adoption process, Precision Agriculture, 20(6): 1292-1316. https://doi.org/10.1007/s11119-019-09653-x

Saha P., Kumar P., Kathuria S., Gehlot A., Pachouri V., and Duggal A., 2023, Precision agriculture using internet of things and wireless sensor networks, 2023 international conference on disruptive technologies (ICDT), IEEE, pp.519-522.

 $\underline{https://doi.org/10.1109/ICDT57929.2023.10150678}$

Sanches G., Bordonal R., Magalhães P., Otto R., Chagas M., Cardoso T., and Luciano A., 2023, Towards greater sustainability of sugarcane production by precision agriculture to meet ethanol demands in south-central Brazil based on a life cycle assessment, Biosystems Engineering, 229: 57-68. https://doi.org/10.1016/j.biosystemseng.2023.03.013

Sanjeevi P., Prasanna S., Sivakumar B., Gunasekaran G., Alagiri I., and Anand R., 2020, Precision agriculture and farming using internet of things based on wireless sensor network, Transactions on Emerging Telecommunications Technologies, 31(12): e3978.

https://doi.org/10.1002/ett.3978

Shafi U., Mumtaz R., García-Nieto J., Hassan S., Zaidi S., and Iqbal N., 2019, Precision agriculture techniques and practices: from considerations to applications, Sensors, 19(17): 3796.

 $\underline{https://doi.org/10.3390/s19173796}$

Sharma A., Jain A., Gupta P., and Chowdary V., 2021, Machine learning applications for precision agriculture: a comprehensive review, IEEE Access, 9: 4843-4873.

https://doi.org/10.1109/ACCESS.2020.3048415



http://cropscipublisher.com/index.php/cgg

Singh S., Sethi S., Sharma R., Vaibhavi D., and Tiwari A., 2024, Precision agriculture monitoring system, In: 2024 15th international conference on computing communication and networking technologies (ICCCNT), IEEE, pp. 1-6.

https://doi.org/10.1109/ICCCNT61001.2024.10724188

Sishodia R., Ray R., and Singh S., 2020, Applications of remote sensing in precision agriculture: a review, Remote Sensing, 12(19): 3136. https://doi.org/10.3390/rs12193136

Thompson N., Bir C., Widmar D., and Mintert J., 2018, Farmer perceptions of precision agriculture technology benefits, Journal of Agricultural and Applied Economics, 51(1): 142-163.

https://doi.org/10.1017/aae.2018.27

Wang N., Xu D., Xue J., Zhang X., Hong Y., Peng J., Li H., Mouazen A., He Y., and Shi Z., 2023, Delineation and optimization of cotton farmland management zone based on time series of soil-crop properties at landscape scale in south Xinjiang, China, Soil and Tillage Research, 231: 105744. https://doi.org/10.1016/j.still.2023.105744

Watson S., Segarra E., Yu M., Li H., Lascano R., Bronson K., and Booker J., 2016, Technological efficiency gains in irrigated cotton production, Texas Journal of Agriculture and Natural Resources, 17: 72-86.

Yousafzai I., Akram M., Zia F., and Adanan K., 2024, The impact of AI technologies on precision agriculture, International Journal of Artificial Intelligence, 11(2): 88-98.

 $\underline{https://doi.org/10.36079/lamintang.ijai-01102.776}$



Disclaimer/Publisher's Note

The statements, opinions, and data contained in all publications are solely those of the individual authors and contributors and do not represent the views of the publishing house and/or its editors. The publisher and/or its editors disclaim all responsibility for any harm or damage to persons or property that may result from the application of ideas, methods, instructions, or products discussed in the content. Publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.