



## Enhancing Crop Yield Prediction in Agriculture Using Advanced Data Science Techniques

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### ABSTRACT

Agriculture is undergoing a digital transformation with the integration of data science techniques to optimize crop yield prediction. This paper uses advanced data science methodologies to revolutionize agricultural practices, including machine learning, predictive analytics, and remote sensing. We delve into the challenges of traditional agricultural methods, the potential benefits of incorporating data science, and real-world applications of data-driven approaches in crop yield prediction. Furthermore, we discuss the integration of IoT sensors, satellite imagery, and weather data to develop accurate predictive models, enabling farmers to make informed decisions and enhance productivity. Through case studies and empirical analysis, we highlight the efficacy of data science in agriculture and its transformative impact on food security, sustainability, and economic growth.

**Key words:** agriculture, data science, crop yield prediction, machine learning, predictive analytics, remote sensing, IoT sensors, satellite imagery, weather data, sustainability.

### INTRODUCTION

The integration of data science in agriculture represents a fundamental shift in farming practices. Traditionally reliant on empirical knowledge and manual labor, agriculture now leverages advanced technologies and data analysis techniques to optimize processes and enhance productivity. Crop yield prediction holds immense importance in modern agriculture. It enables farmers, policymakers, and stakeholders to make informed decisions, allocate resources effectively, and ensure food security. Accurate predictions help farmers plan planting schedules, manage inventory, mitigate risks, and optimize marketing strategies.

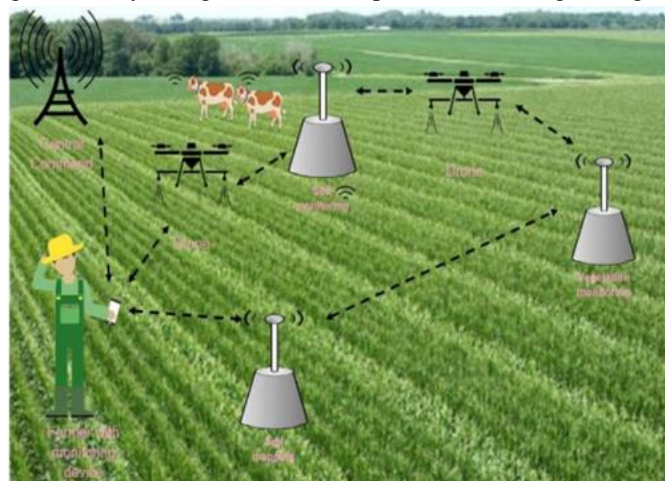


Figure 1: Precision Agriculture [1]

The objectives of this paper are multi-faceted. Firstly, it aims to provide an overview of the integration of data science in agriculture, encompassing various methodologies and techniques employed in the field. Secondly, it seeks to underscore the significance of crop yield prediction in modern agriculture and its implications for stakeholders. Additionally, the paper discusses challenges and limitations associated with crop yield prediction and the adoption of data science in agriculture. Furthermore, the paper intends to present case studies, real-world examples, and best practices for implementing data-driven approaches in agriculture. It aims to offer recommendations and insights for practitioners, researchers, and policymakers considering the adoption of data science in agriculture. Lastly, it outlines future directions and emerging trends in agricultural data science, highlighting its potential impact on agriculture and food security.

Integrating data science in agriculture represents a fundamental shift in farming practices. Traditionally reliant on empirical knowledge and manual labor, agriculture now leverages advanced technologies and data analysis techniques to optimize processes and enhance productivity.

### TRADITIONAL AGRICULTURAL METHODS AND CHALLENGES

Several inherent limitations constrain traditional farming techniques. These methods rely heavily on manual labor and empirical knowledge, often lacking the integration of modern technology. Such reliance on outdated practices poses challenges in contemporary agriculture.

Traditional farming heavily depends on natural weather patterns, leaving crops vulnerable to adverse conditions like droughts, floods, and extreme temperatures. Soil degradation is another concern, as continuous cultivation without proper soil management leads to erosion and loss of fertility. Pest and disease management often involves excessive chemical pesticides and fertilizers, posing risks to human health and the environment. Additionally, traditional farming practices demand substantial resources like land, water, and labor, which may not always be readily available [1-2].

Predicting crop yields accurately is a complex task. Limited data availability, particularly in traditional agricultural systems, challenges gathering comprehensive data on weather, soil, and crop performance. The intricate interactions among various factors influencing crop growth, such as weather conditions, soil properties, and management practices, make modeling yield predictions challenging. Spatial and temporal variability further complicates the matter, as different regions experience unique conditions that must be accounted for in predictive models. Finally, uncertainty and risk are inherent in crop yield prediction due to the stochastic nature of agricultural systems and external factors beyond farmers' control.

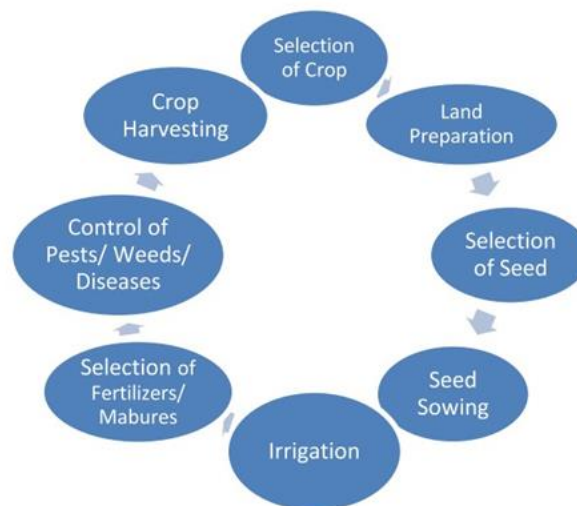


Figure 2: Traditional Agriculture Cycle [1]

To overcome the limitation and challenges associated with traditional farming methods and remote sensing, to collect and analyze vast amounts of data [3-6]. By integrating diverse data sources and employing machine learning algorithms, data-driven models can provide more accurate predictions of crop yields. Moreover, data-driven approaches enable precision agriculture techniques, where farmers can optimize resource use and management practices tailored to specific field conditions. Decision support systems based on data-driven

insights empower farmers to make informed decisions, enhancing agriculture productivity, sustainability, and profitability.

### DATA SCIENCE TECHNIQUES IN AGRICULTURE

Data science encompasses various methodologies to extract insights and knowledge from data. These methodologies include statistical analysis, machine learning, data mining, and predictive analytics. In agriculture, data science methodologies are applied to various aspects of farming, including crop yield prediction, soil health monitoring, pest management, and resource optimization.

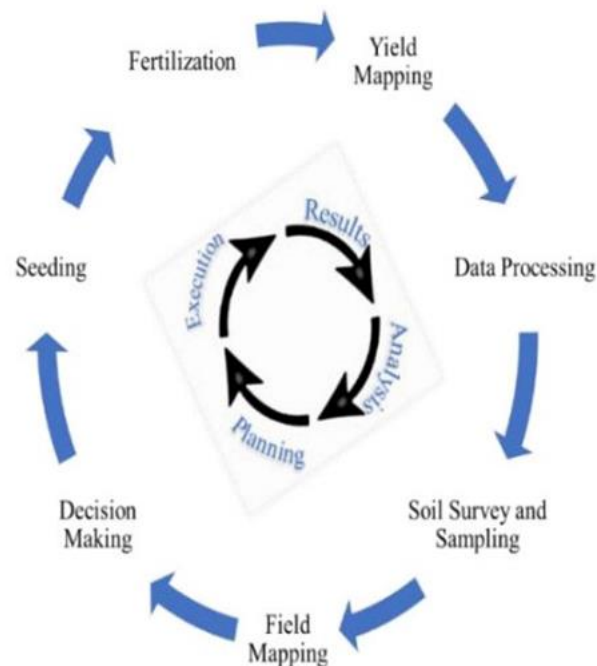


Figure 3: Precision agriculture cycle [1]

Machine learning techniques play a crucial role in predicting crop yields accurately. These techniques leverage historical data on weather patterns, soil properties, crop characteristics, and management practices to develop predictive models. Supervised learning algorithms, such as regression and classification, are commonly used for yield prediction [7-8]. These models learn from past observations to predict future crop yields based on input variables. Ensemble methods like random forests and gradient boosting improve prediction accuracy by combining multiple models. Machine learning models can account for complex interactions among various factors influencing crop growth, leading to more accurate and reliable yield predictions.

Predictive analytics uses historical and real-time data to forecast future events and trends. Predictive analytics optimize various farming practices in agriculture, including irrigation management, pest control, and fertilizer application. By analyzing data on weather conditions, soil moisture levels, pest populations, and crop growth stages, predictive analytics models can generate actionable insights for farmers. These insights help farmers decide when to irrigate, apply pesticides, or fertilize crops, maximizing yield while minimizing resource use and environmental impact [9-12]. Predictive analytics also enables proactive risk management by alerting farmers to potential threats, such as pest outbreaks or adverse weather events, allowing them to take preventive measures in advance.

Remote sensing technologies, such as satellite imagery and aerial drones, are valuable tools for monitoring and analyzing crops. These technologies provide high-resolution images of agricultural fields, allowing farmers to assess crop health, detect pest infestations, and identify stress or nutrient deficiency areas. Remote sensing data can be integrated with machine learning algorithms to develop predictive models for crop yield estimation and early detection of crop diseases. By regularly monitoring crop conditions from a distance, farmers can identify potential problems early and take timely corrective actions to prevent yield losses. Remote sensing also enables

precision agriculture techniques, where farmers can apply inputs like water and fertilizers more efficiently based on real-time crop data, leading to improved productivity and sustainability.

In summary, data science techniques play a crucial role in modern agriculture by enabling accurate crop yield prediction, optimizing agricultural practices, and facilitating remote monitoring and analysis of crops. Farmers can make data-driven decisions to enhance productivity, profitability, and sustainability in farming operations by leveraging advanced methodologies such as machine learning and predictive analytics.

### **INTEGRATION OF DATA SOURCES**

The importance of diverse data sources cannot be overstated in agricultural analytics. Agriculture is a complex system influenced by many factors, including weather patterns, soil characteristics, crop genetics, pest dynamics, and management practices. Integrating data from various sources is essential to understanding agricultural systems and making informed decisions comprehensively. Diverse data sources provide valuable insights into different aspects of farming operations. For example, weather data helps farmers understand how climatic conditions affect crop growth and development. Soil data provides information on soil fertility, moisture levels, and nutrient content, enabling farmers to make informed decisions about fertilization and irrigation. Crop data, including genetic information and growth stages, helps farmers monitor crop health and make timely interventions to prevent yield losses [13-17].

By integrating data from diverse sources, agricultural analytics can provide a holistic view of farming operations, allowing farmers to optimize resource use, improve productivity, and mitigate risks. Moreover, diverse data sources enable the development of more accurate predictive models and decision support systems, leading to more informed and effective agricultural management practices.

Integrating IoT (Internet of Things) sensors is revolutionizing agriculture by enabling real-time data collection and monitoring of agricultural systems. IoT sensors are deployed in fields to collect data on various parameters such as soil moisture, temperature, humidity, and crop health. These sensors transmit data wirelessly to a central database or cloud platform, which can be analyzed in real-time. Real-time data from IoT sensors provides farmers with actionable insights into crop conditions and environmental factors. For example, soil moisture sensors help farmers optimize irrigation schedules by providing information on soil moisture levels, preventing over-irrigation and water wastage. Temperature and humidity sensors allow farmers to monitor microclimatic conditions in their fields, helping them identify potential risks such as frost or heat stress. By integrating IoT sensors with data analytics tools, farmers can make real-time data-driven decisions, improving productivity, efficiency, and sustainability in agriculture. Moreover, IoT sensors enable precision agriculture techniques, where farmers can apply inputs such as water and fertilizers more precisely, reducing costs and environmental impact [9].

Satellite imagery is a powerful tool for crop monitoring and analysis in agriculture. Satellites with remote sensing technologies capture high-resolution images of agricultural fields, providing valuable information on crop health, growth, and spatial variability. Satellite imagery allows farmers to monitor large agricultural areas efficiently and cost-effectively. Farmers can detect crop stress, pest infestations, and nutrient deficiencies by analyzing satellite images early, allowing for timely interventions to mitigate yield losses. Satellite imagery also enables farmers to monitor crop growth stages, assess field variability, and optimize management practices such as planting density and irrigation scheduling. Additionally, satellite imagery can be integrated with machine learning algorithms to develop predictive models for crop yield estimation and forecasting. By analyzing historical satellite data alongside other relevant data sources, such as weather and soil data, farmers can generate accurate predictions of future crop yields, helping them make informed decisions about resource allocation and market planning.

Weather data plays a crucial role in predictive modeling for agriculture. Weather conditions significantly impact crop growth, development, and yield potential. By incorporating weather data into predictive models, farmers can anticipate how weather patterns affect crop performance and take proactive measures to mitigate risks and optimize management practices. Weather data provides information on temperature, precipitation, humidity, wind speed, and solar radiation, influencing crop growth and development. Predictive models use historical weather data to identify patterns and trends and forecast future weather conditions. Predictive models can generate accurate predictions of crop yields, pest outbreaks, and disease epidemics by analyzing weather data alongside other relevant factors, such as soil moisture and crop genetics. Moreover, weather data is essential for

risk management in agriculture. Farmers can prepare for adverse weather events such as storms, droughts, and frosts by monitoring weather forecasts and alerts, minimizing potential damage to crops and infrastructure. Weather data also helps farmers optimize irrigation scheduling, pest control strategies, and harvesting operations, improving productivity and profitability [12].

Integrating diverse data sources, including IoT sensors, satellite imagery, and weather data, is essential for agricultural analytics. These data sources provide valuable insights into crop conditions, environmental factors, and management practices, enabling farmers to make informed decisions and optimize agriculture productivity, efficiency, and sustainability.

### **BENEFITS AND IMPACTS OF DATA SCIENCE IN AGRICULTURE**

Data science profoundly enhances crop yield and productivity in agriculture. By leveraging advanced analytics and machine learning algorithms, farmers can gain valuable insights into factors affecting crop growth, such as weather conditions, soil health, pest dynamics, and management practices. These insights enable farmers to optimize agronomic decisions, including planting schedules, irrigation management, fertilization, and pest control strategies. Farmers can maximize crop yield and productivity by making data-driven decisions, leading to increased profitability and food production.

Furthermore, data science enables precision agriculture techniques, where farmers can tailor management practices to specific field conditions. For example, by using IoT sensors and satellite imagery to monitor crop health and environmental conditions in real time, farmers can apply inputs such as water and fertilizers more precisely, reducing waste and optimizing resource use. Precision agriculture improves yield and productivity and minimizes environmental impact by reducing chemical runoff and greenhouse gas emissions [2].

Data science improves resource utilization and efficiency in agriculture by optimizing resource allocation and management practices. Farmers can identify opportunities to optimize resource use, such as water, fertilizers, and energy, by analyzing historical and real-time data on weather patterns, soil properties, and crop performance. For example, farmers can implement precise irrigation scheduling using predictive models to forecast water requirements based on weather forecasts and soil moisture levels, minimizing water wastage and maximizing crop yield. Moreover, data science enables farmers to identify and address inefficiencies in agricultural operations, such as machinery utilization, labor management, and supply chain logistics. Farmers can identify bottlenecks and inefficiencies in production processes by analyzing farm operations and performance metrics, improving overall productivity and profitability.

Data science is crucial to food security and sustainability in agriculture. By optimizing crop yield and productivity, data-driven approaches help ensure an adequate food supply to meet the growing global demand. Moreover, by improving resource utilization and efficiency, data science reduces agriculture's environmental footprint, including water usage, chemical inputs, and greenhouse gas emissions. Furthermore, data science enables farmers to implement sustainable farming practices, such as conservation tillage, cover cropping, and integrated pest management. Farmers can make informed decisions to protect natural resources and enhance ecosystem resilience by analyzing data on soil health, biodiversity, and ecosystem services. Sustainable farming practices promote long-term food security and contribute to environmental conservation and biodiversity preservation [5].

Data science presents significant economic implications and opportunities for agricultural growth. By improving crop yield and productivity, data-driven approaches increase farm profitability and income generation for farmers. Moreover, by optimizing resource utilization and efficiency, data science helps reduce production costs and improve profit margins. Furthermore, data science drives innovation and technological advancement in agriculture, leading to the development of new products, services, and business models. For example, integrating IoT sensors, drones, and artificial intelligence technologies in agriculture opens up new opportunities for precision farming, autonomous machinery, and farm management systems. These technological innovations create new economic opportunities for farmers and stimulate growth and investment in the agricultural sector [3].

In summary, data science has transformative benefits and impacts on agriculture, including enhancing crop yield and productivity, improving resource utilization and efficiency, contributing to food security and sustainability, and driving economic growth and innovation. By harnessing the power of data-driven approaches, agriculture

can address the challenges of feeding a growing global population while promoting environmental sustainability and economic prosperity.

### **CHALLENGES AND LIMITATIONS**

Data privacy and security concerns are paramount in agricultural data science. With the increasing digitization of farming operations and the collection of vast amounts of data, there is a growing concern about protecting sensitive information, such as farm management practices, crop yields, and financial data. Farmers and agricultural stakeholders must navigate the complexities of data privacy regulations and ensure data is collected, stored, and shared securely to prevent unauthorized access or misuse.

Technical data integration and analysis challenges pose significant hurdles in agricultural data science. Agricultural data comes from diverse sources, including IoT sensors, satellite imagery, weather stations, and farm management systems, each with its own data formats, structures, and quality standards. Integrating and harmonizing disparate data sets require sophisticated data integration techniques and robust data management systems. Moreover, analyzing large volumes of data and extracting meaningful insights require advanced analytical tools and computational resources, which may be limited in rural and developing regions [8].

Adoption barriers and challenges farmers face hinder the widespread adoption of data-driven approaches in agriculture. Farmers, especially smallholders and traditional growers, may lack access to the necessary technology, infrastructure, and technical expertise to implement data science solutions effectively. Moreover, there may be resistance to change and skepticism towards new technologies among farmers accustomed to traditional farming methods. Overcoming these adoption barriers requires targeted capacity-building efforts, farmer education programs, and incentives to promote adopting data-driven practices.

Ethical considerations in agricultural data science raise important questions about the responsible use of data and technology in farming. Data ownership, consent, transparency, and fairness must be carefully addressed to ensure that agricultural data science benefits all stakeholders, including farmers, consumers, and the environment. For example, there may be concerns about the exploitation of farmer data by agribusiness companies or the unintended consequences of algorithmic decision-making on farm livelihoods and rural communities. Ethical frameworks and guidelines are needed to govern agricultural data collection, use, and sharing, ensuring that data science benefits society while upholding ethical standards and values.

In summary, addressing the challenges and limitations of agricultural data science requires a multi-faceted approach that addresses data privacy and security concerns, technical challenges in data integration and analysis, adoption barriers faced by farmers, and ethical considerations in data-driven decision-making. By addressing these challenges, agricultural data science can realize its full potential in transforming farming practices, improving productivity and sustainability, and ensuring equitable access to agricultural resources and benefits.

### **BEST PRACTICES AND RECOMMENDATIONS**

Implementing data science techniques in agriculture necessitates the establishment of clear guidelines and protocols. These guidelines should include defining objectives, assessing data availability and quality, ensuring data privacy and security, investing in data infrastructure, training and capacity building, and monitoring and evaluation.

Overcoming challenges and barriers is crucial for successfully adopting and integrating data-driven approaches in agriculture. Strategies to address these challenges include addressing data privacy and security concerns, bridging the digital divide, promoting adoption and awareness, providing incentives and support, and fostering collaboration and knowledge sharing [15].

Policymakers, researchers, and agricultural practitioners play a critical role in driving the adoption and implementation of data-driven approaches in agriculture. Recommendations for these stakeholders include developing policy frameworks, investing in research and development, supporting innovation and entrepreneurship, fostering public-private partnerships, and promoting data sharing and open access.

In conclusion, implementing data science techniques in agriculture requires careful planning, collaboration, and investment from policymakers, researchers, and agricultural practitioners. By following best practices and recommendations, stakeholders can harness the power of data-driven approaches to address challenges, optimize farming practices, and promote sustainability and resilience in agriculture.

### **FUTURE DIRECTIONS AND EMERGING TRENDS**

Advancements in data science can potentially revolutionize agriculture in various ways. Precision Agriculture Evolution: Continued advancements in machine learning and AI algorithms will enable more precise and accurate predictions, leading to enhanced precision agriculture techniques. This includes finer-tuned management decisions at the farm level, such as optimized planting schedules, targeted irrigation, and personalized pest management strategies. Predictive analytics in agriculture will become more sophisticated, leveraging big data analytics and predictive modeling to anticipate crop yields, pest outbreaks, and disease prevalence with higher accuracy. This will empower farmers to make proactive decisions, mitigate risks, and optimize resource allocation. Data science will play a crucial role in developing climate-smart farming solutions to address the challenges of climate change. This includes the development of resilient crop varieties, adaptive agricultural practices, and climate risk assessment tools to help farmers adapt to changing environmental conditions and mitigate climate-related risks. Integration of blockchain technology will enhance transparency, traceability, and trust in agricultural supply chains. Blockchain-enabled systems can provide immutable records of agricultural transactions, ensuring food safety, quality assurance, and fair market practices. This will benefit consumers, producers, and other stakeholders by fostering transparency and accountability in the food supply chain.

Emerging technologies and innovations in agricultural data analytics are poised to reshape farming practices. Remote sensing technologies, such as hyperspectral imaging and LiDAR (Light Detection and Ranging), will provide finer-resolution data on crop health, soil properties, and environmental conditions. This will enable more detailed and accurate monitoring of agricultural systems, leading to improved decision-making and resource management. The proliferation of IoT devices in agriculture will enable real-time monitoring and control of farm operations. IoT sensors embedded in soil, plants, and machinery will provide continuous data streams on key parameters such as soil moisture, temperature, crop growth, and equipment performance. This real-time data will facilitate precision agriculture practices and automation of farming tasks, resulting in increased efficiency and productivity. AI-driven Artificial intelligence and robotics will drive automation in agriculture, leading to the development of autonomous farming systems. AI-powered robots and drones equipped with advanced sensors and machine learning algorithms will perform tasks such as planting, weeding, spraying, and harvesting with greater precision and efficiency. This will reduce labor requirements, improve operational efficiency, and minimize environmental impact [16-21].

Future research and development efforts in agricultural data science will address key challenges and explore new frontiers. Data Interoperability and Integration: Research is needed to develop standardized data formats, protocols, and interoperability frameworks to facilitate seamless agricultural data integration and exchange across heterogeneous systems and platforms. This will enable more comprehensive and holistic analyses of agricultural systems, leading to better-informed decision-making and resource management. Research efforts will focus on developing advanced analytics techniques, such as spatiotemporal modeling, multi-scale simulation, and optimization algorithms, to support sustainable agriculture practices. This includes optimizing resource use, minimizing environmental impact, and enhancing resilience to climate change. Research is needed to investigate the socio-economic implications of data-driven agriculture, including its impact on farm economics, rural livelihoods, and food security. This includes assessing the distributional effects of adopting data-driven technologies, identifying barriers to adoption, and designing policies and interventions to promote equitable access and benefits.

In conclusion, the future of data science in agriculture holds immense potential for driving innovation, sustainability, and resilience in farming practices. Advancements in data science techniques, emerging technologies, and ongoing research efforts will continue to shape the future of agriculture, addressing key challenges and unlocking new opportunities for growth and development.

### **CONCLUSION**

Throughout the paper, we explored the evolution of data science in agriculture, recognizing its transformative potential in modernizing farming practices. We discussed traditional agricultural methods and their limitations, emphasizing the need for data-driven approaches to address challenges such as crop yield prediction. The paper also outlined various data science techniques employed in agriculture, including machine learning, predictive analytics, remote sensing, and IoT sensors. We explored the benefits and impacts of data science in agriculture,

including enhanced crop yield, resource utilization, food security, and economic growth. Furthermore, we addressed challenges such as data privacy, technical barriers, adoption hurdles, and ethical considerations in agricultural data science.

The transformative impact of data science on agriculture cannot be overstated. By harnessing the power of data analytics, farmers can make informed decisions, optimize resource allocation, and improve productivity. Predictive modeling and analytics enable farmers to anticipate crop yields, identify pest outbreaks, and mitigate risks, leading to more efficient and sustainable farming practices. Remote sensing technologies provide valuable insights into crop health and environmental conditions, enabling precision agriculture and proactive management strategies. IoT sensors facilitate real-time monitoring and control of farm operations, enhancing efficiency and automation. Overall, data science empowers farmers to overcome challenges, adapt to changing environmental conditions, and drive innovation in agriculture.

Looking ahead, the future of data-driven agriculture holds immense promise for addressing global challenges such as food security, climate change, and sustainable development. Advancements in data science techniques, emerging technologies, and ongoing research efforts will continue to drive innovation and transformation in farming practices. Data-driven agriculture offers solutions to optimize resource use, minimize environmental impact, and enhance resilience to climate variability. Moreover, data-driven approaches can promote inclusivity and equity in agriculture by providing smallholder farmers access to valuable information and resources. As we move forward, collaboration between stakeholders, investment in research and development, and policy support will be essential to realize the full potential of data-driven agriculture and its significance in addressing global challenges.

In conclusion, data science has emerged as a powerful tool in modern agriculture, offering transformative solutions to enhance productivity, sustainability, and resilience. By leveraging data-driven approaches, we can overcome challenges, unlock new opportunities, and build a more sustainable and equitable future for agriculture.

#### REFERENCES

- [1]. A. Sharma, A. Jain, P. Gupta and V. Chowdary, "Machine Learning Applications for Precision Agriculture: A Comprehensive Review," in *IEEE Access*, vol. 9, pp. 4843-4873, 2021[Online]. Available: <https://ieeexplore.ieee.org/abstract/document/9311735>
- [2]. Mavridou E, Vrochidou E, Papakostas GA, Pachidis T, Kaburlasos VG. "Machine Vision Systems in Precision Agriculture for Crop Farming," *Journal of Imaging*. 2019; 5(12):89. [Online]. Available: <https://www.mdpi.com/2313-433X/5/12/89>
- [3]. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. "Machine Learning in Agriculture: A Review." *Sensors*. 2018; 18(8):2674. [Online]. Available: <https://www.mdpi.com/1424-8220/18/8/2674>
- [4]. S. Dimitriadis and C. Goumopoulos, "Applying Machine Learning to Extract New Knowledge in Precision Agriculture Applications," 2008 Panhellenic Conference on Informatics, Samos, Greece, 2008, pp. 100-104, [Online]. Available: <https://ieeexplore.ieee.org/abstract/document/4621545>
- [5]. J. V. Stafford, "Implementing precision agriculture in the 21<sup>st</sup> century," *J. Agricult. Eng. Res.*, vol. 76, no. 3, pp. 267–275, Jul. 2000.
- [6]. J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future Gener. Comput. Syst.*, vol. 29, no. 7, pp. 1645–1660, Sep. 2013.
- [7]. F. Nex and F. Remondino, "UAV for 3D mapping applications: A review," *Appl. Geomatics*, vol. 6, no. 1, pp. 1–15, Mar. 2014.
- [8]. V. I. Adamchuk, J. W. Hummel, M. T. Morgan, and S. K. Upadhyaya, "On-the-go soil sensors for precision agriculture," *Comput. Electron. Agricult.*, vol. 44, no. 1, pp. 71–91, 2004.
- [9]. H. Jawad, R. Nordin, S. Gharghan, A. Jawad, and M. Ismail, "Energy efficient wireless sensor networks for precision agriculture: A review," *Sensors*, vol. 17, no. 8, p. 1781, Aug. 2017.
- [10]. R. Sharma, S. S. Kamble, A. Gunasekaran, V. Kumar, and A. Kumar, "A systematic literature review on machine learning applications for sustainable agriculture supply chain performance," *Comput. Oper. Res.*, vol. 119, Jul. 2020, Art. no. 104926.



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- [11]. K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," *Sensors*, vol. 18, no. 8, p. 2674, 2018.
- [12]. A. L. Samuel, "Some studies in machine learning using the game of checkers," *IBM J. Res. Develop.*, vol. 3, no. 3, pp. 210–229, Jul. 1959.
- [13]. A. M. Turing, "Computing machinery and intelligence," in *Parsing the Turing Test*. Dordrecht, The Netherlands: Springer, 2009, pp. 23–65.
- [14]. C. F. Gaitán, "Machine learning applications for agricultural impacts under extreme events," in *Climate Extremes and Their Implications for Impact and Risk Assessment*. Amsterdam, The Netherlands: Elsevier, 2020, pp. 119–138.
- [15]. S. J. Parikh and B. R. James, "Soil: The foundation of agriculture," *Nature Educ. Knowl.*, vol. 3, no. 10, p. 2, 2012, Art. no. 15. [Online]. Available: <https://www.nature.com/scitable/knowledge/library/soil-the-foundation-of-agriculture-84224268/>
- [16]. F. R. Troeh and L. M. Thompson, *Soils and Soil Fertility*. Oxford, U.K.: Oxford Univ. Press, 1993.
- [17]. E. Acar, M. S. Ozerdem, and B. B. Ustundag, "Machine learning based regression model for prediction of soil surface humidity over moderately vegetated fields," in *Proc. 8th Int. Conf. Agro-Geoinformat. (AgroGeoinformat.)*, Istanbul, Turkey, Jul. 2019, pp. 1–4.
- [18]. E. Tarihi. (2016). Polarimetric Decompositions Tutorial. Accessed: Feb. 13, 2017. [Online]. Available: [https://earth.esa.int/documents/653194/656796/Polarimetric\\_Decompositions.pdf](https://earth.esa.int/documents/653194/656796/Polarimetric_Decompositions.pdf)
- [19]. X. Wang, W. Hu, K. Li, L. Song, and L. Song, "Modeling of soft sensor based on DBN-ELM and its application in measurement of nutrient solution composition for soilless culture," in *Proc. IEEE Int. Conf. Saf. Produce Informatization (IICSPI)*, Chongqing, China, Dec. 2018, pp. 93–97.
- [20]. S. Park, J. Im, S. Park, and J. Rhee, "AMSR2 soil moisture downscaling using multisensor products through machine learning approach," in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, Milan, Italy, Jul. 2015, pp. 1984–1987.
- [21]. R. Reda, T. Saffaj, B. Ilham, O. Saidi, K. Issam, L. Brahim, and E. M. El Hadrami, "A comparative study between a new method and other machine learning algorithms for soil organic carbon and total nitrogen prediction using near infrared spectroscopy," *Chemometric Intell. Lab. Syst.*, vol. 195, Dec. 2019, Art. no. 103873.