PAN POLSKA AKADEMIA NAUK

JOURNAL OF WATER AND LAND DEVELOPMENT

e-ISSN 2083-4535

ITP-PIB

Polish Academy of Sciences (PAN) Institute of Technology and Life Sciences – National Research Institute (ITP – PIB)

JOURNAL OF WATER AND LAND DEVELOPMENT
DOI: 10.24425/jwld.2025.153522
2025, No. 64 (I–III): 181–193

Using artificial intelligence for sustainable crop production – a comprehensive review with a focus on potato production

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RECEIVED 24.09.2024 ACCEPTED 10.01.2025 AVAILABLE ONLINE 04.03.2025

Abstract: The article discusses the critical role of artificial intelligence (AI) in modern agriculture, with a particular focus on potato production. AI technologies are becoming essential tools enhancing both efficiency and sustainability in farming practices. By utilizing big data analysis, precision monitoring, and automation, AI can significantly improve agricultural outcomes. For instance, AI algorithms can optimise the use of natural resources and chemical inputs, leading to improved yield forecasting and more effective management of diseases and pests that affect crops. Additionally, AI can play a key role in agriculture with is its capability to monitor soil conditions and assess soil fertility. This enables farmers to optimise fertilisation techniques, leading to improved crop health but also better water management through precise irrigation practices. These advancements are especially crucial in addressing the rising food demand posed by global population growth, while simultaneously managing limited environmental resources. Despite the numerous benefits offered by AI, its implementation in agriculture faces challenges. High technology costs and the need for extensive education and training for farmers can hinder widespread AI adoption. Therefore, future research should aim at developing affordable AI solutions and comprehensive training programmes to maximise the technology's potential in fostering enhanced sustainable food production globally.

Keywords: artificial intelligence, crop management, data analysis, potato cultivation, sustainable production

INTRODUCTION

In recent years, the agricultural sector has witnessed significant changes driven by technological advancements. Among these, artificial intelligence (AI) has been playing a crucial role in the industry's transformation, making production more efficient and sustainable. As the global population continues to rise, the demand for food increases, necessitating innovative approaches to farming practices. Technologies based on AI encompass robotics, data analytics, remote sensing, and natural language processing, all of which support farmers in making informed decisions and enhancing productivity (Veeragandham and Santhi, 2020). These technologies provide actionable solutions to optimise agricultural processes, leading to improved crop quality and minimised losses. As agricultural production becomes increasingly complex, farmers are increasingly adopting AI tools to monitor and analyse data related to their crops. These advanced systems enable the efficient collection of information regarding environmental conditions, soil quality, and plant health. For instance, the utilisation of remote sensing technology allows farmers to monitor land using drones and satellite imagery, facilitating early detection of plant health issues (Meshram *et al.*, 2021). This proactive approach contributes to timely interventions and effective management of fertilisers and pesticides.

Moreover, integrating AI into farm management equips farmers with tools necessary to optimise supply chains. By analysing demand and supply data, they can better anticipate market requirements, reducing food waste and improving sales planning (Tripathi *et al.*, 2023). The introduction of AI-driven systems, including automated irrigation management tools, significantly enhances the efficiency of water resource usage, a critical factor in addressing global climate challenges. AI also enables automation in agricultural practices such as harvesting and planting, leading to increased productivity and reduced dependence on manual labour (Araújo *et al.*, 2023). These innovations are particularly vital for promoting sustainable food production methods amid a growing global population.

Despite the promising benefits AI in the agricultural sector, fully harnessing its potential requires adequate investments in technological infrastructure and the development of digital skills among agricultural workers. These investments are essential to ensure that AI improves sustainability, increases yields, and enhances farming efficiency while simultaneously minimising environmental impact.

POTATO PRODUCTION MANAGEMENT: GLOBAL AND LOCAL PERSPECTIVES

Potato (*Solanum tuberosum* L.) is the world's fourth most important crop, after corn, wheat, and rice. According to the Food and Agriculture Organization of the United Nations (FAO), global potato production was about 370 Tg in 2022, with China, India and Russia being the largest producers. China remains in the top position, accounting for more than 90 Tg, or nearly 25% of total global production. India ranks second with approximately 50 Tg (FAO, 2024). In Europe, Poland plays a significant role as one of the main potato producers, alongside Germany and France. According to Poland's Central Statistical Office (Pol.: Główny Urząd Statystyczny), national potato production reached about 8.5 Tg in 2023. This reflects some stability in production compared to the past few years, albeit with slight fluctuations due to climate change and the variety of cultivation methods used. Despite this stability, the cultivated area in Poland has been steadily decreasing, prompting farmers to enhance productivity and efficiency on existing farmland. Against the backdrop of global trends, Poland continues to adopt modern technologies and sustainable farming practices to meet growing market demands (GUS, 2024).

POTATO PRODUCTION MANAGEMENT: KEY ASPECTS AND CHALLENGES

To meet both local and export needs, efficient and sustainable management of potato farms is becoming crucial. Managing a potato farm involves several key stages of production, each with unique challenges and requirements. The process begins with selecting the right varieties to match local climate and soil conditions. Different varieties differ in their disease resistance, water requirements, and length of the growing season, all of which directly impact yield potential. Soil preparation is another critical step, ensuring high fertility and proper drainage. Fertile soil, supported by proper fertilisation techniques, is essential to maximise crop productivity, while water management plays a key role, especially in the context of climate change. According to publicly available data from United States Agency for International Development (USAID), effective irrigation practices are essential to take into account potato's high water demand during tuber formation to secure high quality yields. Disease and pest control pose some of the most serious challenges for potato producers. Pests such as the potato beetle and diseases like potato blight can severely reduce yields, necessitating regular monitoring and the implementation of integrated crop protection programmes. The volatility of health challenges and regulations restricting pesticide use force farmers to seek new, sustainable solutions. Other key issues include efficient harvesting and storage. Proper timing minimises losses, while optimal storage ensures proper quality of stored tubers. Moreover, conditions, such as high humidity and low temperature, are essential to reduce spoilage and extend storage life. Sustainable potato management requires integrating market and economic aspects. Price volatility and market accessibility introduce additional challenges, requiring farms to maintain high operational efficiency and quickly adapt to dynamic market conditions. In summary, successful potato production depends on sustainable approach that integrates traditional practices with modern technology and innovation (Ahmad and Sharma, 2023). As technologies such as drones, data analytics, and machine learning (ML) evolve, farms can optimise their operations more efficiently, increasing yields while minimising environmental impact. This progress enables farmers to meet growing market demands, contributing to food security (Guo *et al*., 2019; Hoy and Wrenn, 2020; Kadigi *et al*., 2020; Pavlović *et al*., 2020; Thidar *et al*., 2020; Fujiyoshi *et al*., 2021; Sarangi *et al*., 2021; Ahmad and Sharma, 2023).

APPLICATION OF ARTIFICIAL INTELLIGENCE IN POTATO PRODUCTION

THE ROLE OF ARTIFICIAL INTELLIGENCE IN THE TRANSFORMATION OF POTATO PRODUCTION

Artificial intelligence is gaining recognition as a key driver of transformation in the agricultural sector, including potato production. AI encompasses a range of technologies, including machine learning, data analytics, robotics, and predictive systems, all of which enhance efficiency, precision, and sustainability of agricultural production. Its significance lies in its ability to process and analyse vast amounts of data from sensors, satellites, and drones. This allows farmers to gain precise information about weather patterns, soil conditions, and plant health. In potato cultivation, this analysis capability allows for optimal management of resources and prediction of risks such as pest infestations and disease outbreaks. Advancements in AI offer development opportunities in potato production, including more precise farming, reducing the use of water, fertilisers, and pesticides, which are key factors for improving productivity and sustainability. Additionally, automating cultivation processes with robotics increases productivity and reduces reliance on manual labour. AI also holds a great potential for enhancing efficiency of supply chain and logistics. Predictive systems can forecast yields and manage inventory, helping farmers to plan sales and distribution more effectively. In the long term, AI can increase global food availability by optimising production processes and minimising losses. Currently, AI in potato production is evolving rapidly, with the potential to further integrate more advanced technologies, allowing for more accurate and faster response to food production challenges (Niedbała and Piekutowska, 2018; Gómez *et al*., 2019; Paudel *et al*., 2021; Piekutowska *et al*., 2021; Patnaik and Padhy, 2022; Kurek *et al*., 2023; Aslan *et al*., 2024). This manuscript presents the most important areas where AI supports agricultural production, with a particular focus on potato cultivation.

Table 1 lists various applications of AI in potato production, along with their descriptions, benefits, examples of technologies used, and related scientific work. The analysis of these aspects provides a better understanding of how AI contributes to sustainable development of the agricultural sector.

Table 1. Examples of the application of artificial intelligence in potato cultivation

AI application	Description	Benefits	Examples of technologies	Sample works
Plant health monitoring	use of sensors and imaging to assess plant condition	early detection of diseases and pests	drones, multispectral cameras	Qaswar, Bustan and Mouazen (2024), Wand and Su (2024)
Irrigation optimisation	algorithms for analysing soil moisture data and weather forecasts	reduced water loss, improved yields	IoT systems, predictive models	Jimenez-Lopez, Ruge-Ruge, Jimenez-Lopez (2021), Vianny *et al.* (2022)
Yield prediction	analysis of historical data and weather conditions to forecast yields	better planning and harvest management	machine learning algorithms	Piekutowska *et al.* (2021), Niedbała and Piekutowska, 2018)
Harvest automation	robotic systems for harvesting crops under optimal conditions	increased efficiency and reduced labour costs	agricultural robots	Abdelhamid *et al.* (2024)
Pest management optimisation	AI for risk analysis and optimising pesticide use	reduced chemical usage and improved soil health	multi-criteria algorithms	Talukder *et. al.* (2023), Kariyanna and Sowjanya (2024)

Source: own elaboration.

MONITORING AND ANALYSIS OF THE SOIL ENVIRONMENT

The application of AI and ML in agriculture is a crucial step towards sustainable farmland management, including potato farms, where soil quality plays a key role in crop quality and yield. Modern technology enables precise soil monitoring through the use of sensors and advanced analytical techniques. Recent research indicates that sensor networks can collect data on moisture, pH, and nutrient levels, which, when analysed using ML algorithms, allow for accurate predictions of soil fertility changes and the development of effective fertilisation strategies. Dubois, Teytaud, and Verel (2021) presented how sensor networks integrated with ML can significantly improve soil management through real-time monitoring and prediction of soil properties. AI-based soil abundance assessment can determine soil diversity at the micro- and macro-levels. A paper by Maia, Lurbe, and Hornbuckle (2022) showed that ML models can accurately predict the variability of soil properties in different parts of a field, enabling more precise application of soil additives and minimising fertiliser use. This approach not only optimises resource use but also reduces the environmental impact of chemicals. Neural networks and regression algorithms are also used to determine soil grain size, a key factor affecting soil structure and water retention capacity. By providing accurate information on grain size, these AI-driven methods help farmers better understand soil water retention and mechanical properties, enabling them to adjust tillage operations to crop specific needs. As Wang and Su (2024) point out, integrating AI with soil testing plays a key role in sustainable agriculture by lowering carbon footprints and increasing production efficiency.

The prediction and analysis of soil texture using artificial intelligence are becoming essential for improving ecosystem health, agricultural productivity, and sustainable land management. Traditional methods of soil texture analysis, such as sieving and sedimentation, tend to be time-consuming, costly, and require complex data processing, often leading to subjective and erroneous conclusions. AI-driven tools, including machine learning and deep learning (DL), offer a faster alternative and more accurate alternative by analysing compositional, spectral, and geographic data. AI not only reduces the time and costs of conventional analysis but also enables scalability through cloud computing and mobile applications. This allows farmers and land managers to adjust cultivation practices. A key challenge remains ensuring data quality, interpretability, and systems integration, which requires collaboration among scientists, engineers, and decision makers (Awais *et al.*, 2023; Liu *et al.*, 2023). Artificial intelligence plays a key role in modern approaches to soil water resource (SWC) monitoring. Traditional measurement methods, such as frequency domain reflectance (FDR) and time domain reflectance (TDR), can be susceptible to climate variability. The innovative 2020 Active Heated Optical Fibre (AHOF) method allows for more precise measurements through short heat pulses in the soil. However, despite its effectiveness, AHOF requires error correction, which is accomplished through artificial neural networks (ANNs) (Liu *et al.*, 2023). Additional climate layers are incorporated into ANN models to enhance the accuracy of results in irrigation forecasting and agricultural management. In precision agriculture, neural networks support the analysis of sensor data on pH, moisture, and soil mechanical structure, aiding informed decision-making. Models such as the multilayer perceptron show lower mean square errors (*MSE*) and root mean square errors (*RMSE*) compared to other ANN models (Roshan, Kazemitabar and Kheradmandian, 2022).

Work continues to create global-scale remote databases for SWC. Adaptive neuro fuzzy inference system (ANFIS) models outperform traditional statistical models in precision and efficiency, offering implicit insights into SWC variables (Hosseini *et al.*, 2021). Understanding soil texture and water content is crucial for proper crop management, and AI-powered tools offer advanced solutions for optimising soil and water resource management. The introduction of AI technology in soil monitoring not only improves precision but also ensures rapid and efficient management of agricultural resources. With innovative sensors like the arrayed fibre Bragg grating (AH-FBG), AI enables customised approaches to different soil conditions, improving the efficiency and sustainability of agricultural operations under changing climatic conditions (Awais *et al*., 2023; Liu *et al*., 2023). Artificial intelligence models and digital soil mapping (DSM) have become the standard for predicting soil properties. When combined with advanced ML algorithms, such as random forests (RFs), extreme gradient boosting (XGBoost), and deep neural networks (DNN), these technologies significantly improve the accuracy of soil texture and moisture prediction. While conventional mapping methods often lack accuracy, the use of DSM with quantile regression forest (QRSs) has achieved high precision in assessing soil fertility. However, limitations remain for some soil nutrients, including nitrogen and potassium. Alternative technologies, such as self-organising maps and ANFIS models, offer advanced opportunities for error correction and improved efficiency. Data quality remains a key element, making careful data collection and processing essential.

Feature engineering and integration of domain knowledge enhance accuracy of soil nutrient estimations. It is worth noting that the choice of ML techniques should also take into account interpretability and statistical properties of the data to ensure reliable predictions. Finally, integrating agricultural knowledge strengthens confidence in modelling results, indicating the need for further innovation and research into AI-driven sustainable soil management (Hounkpatin *et al*., 2022; Folorunso *et al*., 2023).

Soil nutrient variability can reduce crop yields, making accurate soil fertility classification and effective fertiliser application essential for increasing crop productivity. Currently, soil fertility levels are assessed by laboratory tests of soil samples, and fertilisers are applied according to calculations based on soil nutrient availability.

The use of artificial intelligence in cropland soil analysis, particularly in estimating soil organic carbon (SOC), is crucial in understanding soil function. A study by Emadi *et al.* (2020) used advanced ML algorithms, such as support vector machines (SVMs), ANNs, regression trees, RFs, extreme gradient boosting, and DNN, to predict SOC. The models were trained using 1879 soil samples and 105 auxiliary variables, with a genetic algorithm used to select effective features. The DNN model proved to be the most effective, showing the lowest prediction error and high accuracy, confirming its usefulness in processing large data sets. The results show that precipitation is the main factor influencing SOC variability, with soils covered with lush vegetation exhibiting the highest SOC content. The use of DNN's flexible structure allows for more detailed extraction of information from ancillary data, making it a promising tool for forecasting SOC maps at the provincial level with minimal uncertainty.

Understanding soil structure variability within a field is crucial for modern agriculture, which seeks to minimise input use by precisely adjusting fertiliser and water rates to meet crop needs (Kempenaar *et al*., 2017). A reliable method for studying soil variability is measuring soil electrical conductivity (*EC*), which indicates the soil's ability to conduct electricity. The *EC* serves as a key indicator of soil compactness and sorptive capacity, both of which affect fertility. By measuring *EC,* farmers map soil variability, estimate yield potential, and accurately determine sampling and fertiliser application sites. Adjusting fertiliser application rates to match varying soil conditions helps prevent nutrient deficiencies and excesses, thus protecting the environment and reducing costs. Site-specific fertiliser application rates minimise the risk of environmental pollution and reduce production costs (Nawar *et al*., 2017; Kiełbasa, 2020; Mazur, Gozdowski and Wójcik-Gront, 2022). This knowledge is actively used by potato farmers. A study by Cambouris *et al.* (2006) evaluated the effectiveness of soil electrical conductivity in determining homogeneous management zones (MZs), which are crucial for site-specific crop management (SSCM). The study revealed that two MZs provided optimal conditions, showing significant differences in water regime and soil properties, such as sandy sediment thickness, water table depth, and chemical composition. The analysis also showed significant differences in potato yields between the MZs, mainly due to differences in water availability. The results suggest that *EC* can be an effective tool for determining MZ in fields where soil properties affect moisture availability.

AI-driven technologies are increasingly used for determining soil fertility zones (Schillaci *et al*., 2021; Denora *et al*., 2022). These technologies enable precise mapping of varying soil fertility within a single field. This allows farmers to tailor inputs such as fertiliser and irrigation to local needs, leading to cost optimisation and increased production efficiency. Machine learning algorithms can also forecast long-term soil changes, offering valuable insights for developing management strategies well in advance (Awais *et al*., 2023). In conclusion, modern AI-driven soil quality assessment on potato farms presents a promising step towards more precise, efficient, and sustainable agriculture. The use of AI and ML in soil evaluation and analysis is transforming traditional management methods into intuitive, data-driven systems, helping to increase yields while protecting the environment. AI-based technologies can identify nutrient deficiencies and soil defects by analysing data from various sources, including soil sensors, soil testing drones, and smartphone cameras. This allows farmers to assess the amount of organic matter that should be added to the soil to improve its structure and properties. Additionally, artificial intelligence and its supporting technologies facilitate efficient processing of both structured and unstructured data (Javaid *et al*., 2023).

FERTILISATION

Modern agriculture advocates precision in fertilisation, ensuring that nutrients are applied in optimal amounts to meet crop needs while minimising excess (Shanmugavel *et al*., 2023). In potato production, variable rate fertilisation is commonly used, enabling farmers to use fertiliser in precisely defined quantities, tailored to the specific field conditions. This approach ensures that each part of the field receives the necessary resources needed for optimal plant growth, significantly reducing waste and lowering operating costs. The technology leads to higher yields and better use of available resources, making agriculture more efficient and sustainable (Kempenaar *et al*., 2017). Artificial intelligence plays a crucial role in optimising mineral fertilisation rates for potatoes. In a study by Tkatek *et al.* (2023), an accurate model was developed to determine optimal levels of nitrogen, phosphorus, and potassium for high quality and yield. The analysis included 900 field experiments available on Kaggle, comparing predictive models such as k-nearest neighbour (KNN), SVM, naive Bayes classifier (NB), decision tree (DT), RFs and XGBoost. The models were evaluated using mean and median squared errors (*MAE* and *MSE*), and coefficients of determination (R^2). The results showed that the XGBoost model had the highest R^2, and *MSE* and *MAE* values outperforming other models. Finally, a hardware implementation of the system was proposed to assist farmers in effective fertiliser management in field practices.

Using ML algorithms and real-time data from soil and plant sensors, variable rate application (VRA) systems tailor fertiliser application rates to the specific needs of different zones of the field. This approach optimises nutrient use, increases yields, and reduces environmental impact by reducing over-fertilisation and surface runoff. Integrating remote sensing technologies, such as normalised difference vegetation index (*NDVI*), improves these applications with real-time assessment of plant health and soil quality. A study by Qaswar, Bustan and Mouazen (2024) on potato crops showed that variable rate nitrogen (VR-N), applied using near-infrared spectroscopy and satellite data, improves fertiliser management. The results show that VR-N reduced nitrogen use by 50% in high fertility zones, while increasing it by 25–50% in low fertility zones, leading to an 8.1% increase in potato yields. The technology tested provided a relative gross income of €374.83 per ha compared to uniform fertiliser application, highlighting both economic and environmental benefits. Agronomists and farmers can apply these findings to increase potato yields and reduce environmental impacts through precise nitrogen management (Qaswar, Bustan and Mouazen, 2024).

Another study by Coulibali, Cambouris, and Parent (2020) evaluated the use of ML techniques as an alternative to traditional statistical models for making fertiliser selection recommendations in potato production at a local scale. A large amount of field trial data was analysed, considering variety traits, soil properties, weather indices, and fertiliser rates of N, P and K as predictor variables. Five models: Mitscherlich, KNN, RFs, NNs and Gaussian processes (GP) were compared for optimal N, P and K rates determined by marketable yield and tuber size and density. The ML models outperformed the Mitscherlich trivariate model, achieving R^2 of 0.49 to 0.59 for marketable yield, which was better than the 0.37 obtained by the Mitscherlich model. These coefficients for large tubers ranged from 0.55 to 0.64, and for medium tubers from 0.60 to 0.69. The NN and GP models performed particularly well in predicting optimal fertiliser rates for commercial potato yields. The GP model stood out in risk assessment due to its probabilistic approach, which proved beneficial for fertiliser recommendations in the Quebec region. Additionally, the integration of historical weather data strengthened the models' effectiveness, despite the lack of precise forecast data.

The article by Sujatha and Jadhair (2023) presents state-of-the-art approaches to soil fertility classification using machine and deep learning, following PRISMA guidelines. The study aims to explore methods used by researchers to effectively predict and classify soil fertility and discusses fertiliser recommendation systems. It demonstrates that ML-based techniques can provide highly accurate soil fertility assessments. The article emphasises the importance of maintaining adequate soil nutrient levels and addressing nutrient deficiencies. The authors identify research gaps and outline challenges in soil fertility classification and fertiliser recommendations, suggesting new research directions to develop more affordable solutions. A model has also been developed that has the potential to help farmers enhance soil fertility while reducing fertiliser costs.

IRRIGATION OPTIMISATION

Artificial intelligence offers innovative solutions for optimising crop irrigation, including potato farming. Precision irrigation based on artificial intelligence aims to deliver the right amount of water to plants at the right time and place (Kumar *et al.*, 2023). By integrating weather forecast data, soil moisture sensors, and plant requirements, AI algorithms create tailored irrigation schedules (Abioye *et al.*, 2022). This method prevents overwatering, minimises water loss through evaporation and runoff, and ensures that water goes where it is needed most. A review article by Talaviya *et al.* (2020) discussed irrigation automation using various AI technologies, pointing out their effectiveness. Al-Zubaidi *et al.* (2019) evaluated an IoT-based Integrated Water Management (IEWM) system, which achieved higher accuracy (98.7%) compared to traditional systems (87%). The IEWM system, which is an expert AI system integrated with IoT sensors, responds faster and more efficiently than traditional solutions. In addition, Chaithra *et al.* (2021) proved the impact of water stress on crop yields, highlighting that based on sensor data, drip irrigation at 25% depletion of available soil moisture produced the highest yields. This approach helps maintain adequate moisture levels, promoting better nutrient uptake and improving yield factors. Crop irrigation system optimisation uses a variety of Internet of Things (IoT) components that monitor parameters such as soil moisture, temperature, weather conditions, and other environmental variables. The collected data is stored in the cloud, where ML algorithms process it for analysis and forecasting. In a paper by Vianny *et al.* (2022), a hybrid irrigation system model was proposed using KNN, gradient boosting-based trees (GBT), long-term memorisation, and Spearman rank. The KNN algorithm was used to gather the closest sensor information, while GBT and long short-term memory (LSTM) were used to predict actual values and analyse time series. Admittedly, the study was conducted on a banana crop in 2020 and 2021, and the results indicated 31.4% water savings for a single banana plant, resulting in a significant reduction in fresh water and energy consumption. It is worth noting that similar analyses are also performed for potato crops, but the results remain at the pilot study stage. Research by Jimenez-Lopez, Ruge-Ruge and Jimenez-Lopez (2021) demonstrated innovative water management in potato cultivation by using deep learning algorithms to predict irrigation recommendations. Three models were analysed, including a one-dimensional convolutional neural network (1-DCNN), a LSTM and a hybrid convolutional LSTM. Climatic variables, such as temperature, precipitation, soil water content, and evapotranspiration, were collected daily for three years at two weather stations in the Usochicamocha irrigation area. The models were trained and validated using Python, with results showing that the CNN-LSTM model achieved the highest precision with *MSE* values of less than 0.067 and *RMSE* of less than 0.258. The model also achieved an R^2 of 0.96. Ultimately, the results prove that deep learning techniques are an effective tool to support farmers in making irrigation optimisation decisions, ultimately leading to significant improvements in water management for potato crops.

With the increasing demand for water, assessing the water footprint of potato crops has become crucial for sustainable agricultural water management. The goal of the research conducted by Abdel-Hameed *et al.* (2024) was to develop and compare four ML models: support vector regression (SVR), RF, extreme gradient gain (XGB) and ANNs, to predict the blue water footprint (BWF) of potatoes in three governorates in the Nile Delta, Egypt. Meteorological variables, such as maximum and minimum temperature, relative humidity, rainfall, and water vapour deficiency, were used to determine the impact on BWF from 1990 to 2016. The analysis showed that the XGB model, especially in the Sc5 scenario that included water vapour deficiency and rainfall data, produced the best forecasting results.

The results described above suggest that the developed models can significantly support decision-making in water management and the development of agricultural water use efficiency policies. Further research should focus on improving these models so that they can be applied to different climatic and environmental conditions. In this regard, the use of ML techniques in water footprint assessment is a promising approach for achieving sustainable agricultural development.

MONITORING PLANT GROWTH AND DEVELOPMENT DURING THE GROWING SEASON

Monitoring potato growth and development is key to achieving optimal yields and increasing agricultural efficiency. While traditional methods, such as manual inspections or laboratory analysis, have been widely used, they gradually give way to modern technologies, including artificial intelligence, which enables more precise and efficient monitoring. Algorithms are used to analyse data from various sources, including satellite imagery, drones, soil sensors, and video cameras, to provide a comprehensive assessment of plant growth. Vegetation indices, such as *NDVI*, are used to assess the health of crops by analysing their photosynthetic activity. AI-based growth models, such as neural networks (NNs) and machine learning (ML), can predict potential risks from diseases and pests, as well as growth disorders resulting from environmental stress. Growth analysis involves measuring plant height, biomass distribution, and number of leaves, enabling the optimisation of agronomic treatments such as irrigation, fertilisation, and crop protection. The data supports farmers in making more informed decisions, leading to increased yields while reducing production costs. Monitoring potato growth and development through remote sensing is based on the assessment of aboveground biomass (AGB), which provides information on growth, physiological conditions, and light use efficiency. The AGB is a key indicator for determining the nitrogen fertilisation index (*NNI*) and nitrogen status of the crop. Remote sensing makes it possible to measure AGB in a non-invasive way by analysing light reflection at specific wavelengths. This correlates with crop cover and biomass production parameters. Unmanned aerial vehicles (UAVs) are often used for seasonal monitoring of potato AGB, offering high spatial and temporal resolution. Hyperspectral UAV sensors are particularly effective in recording variability in plant cover structure. Plant height and cover texture are also key parameters in AGB modelling, and the use of light detection and ranging (LIDAR) technology enables precise estimation of canopy structure. The assessment of nitrogen and chlorophyll content in potato leaves is conducted using NIR and red-resolution reflectance, which supports fertilisation management. High-resolution satellite and ground data enable calibration and improvement of biomass models, whereas metrics such as chlorophyll IndexRedEdge (CIred-edge) and (chlorophyll absorption reflectance index)/(soil adjusted vegetation index) (*TCARI*/*OSAVI*) help assess leaf nitrogen status. By integrating these approaches and use of techniques, farmers can optimise production and resource efficiency in potato crops (Peng *et al.*, 2021; Tenreiro *et al.*, 2021; Mukiibi *et al.*, 2024).

Monitoring the leaf area index (*LAI*) is an important parameter in assessing potato growth and development, as it directly relates to photosynthesis, biomass accumulation, and evapotranspiration. Remote sensing can be used to estimate *LAI* by utilising data from UAVs equipped with hyperspectral sensors and multispectral satellites. While no single platform can simultaneously provide high spectral, spatial and temporal resolution, research on combining different optical sensors on different platforms is yielding promising results. Ground-based sensors such as multispectral cameras and CropViev device are often used to calibrate UAV and satellite data. Models, such as PROSAIL, allow simulation of vegetation cover reflectance as a function of *LAI*. Empirical relationships between vegetation indices and *LAI* show varying levels of accuracy, typically in the R^2 range of 0.52 to 0.95. Indices based on red and near-infrared bands, such as *NDVI*, are often used but can be less sensitive at high *LAI* values. Alternative indices that minimise the impact of soil reflectance are more suitable for accurate *LAI* assessment, making these techniques an indispensable tool for agronomic management (Mukiibi *et al.*, 2024).

The most popular vegetation index used in assessing potato growth and development is the *NDVI*. It is widely used since it allows assessment of plant health based on photosynthetic activity, as reflected in spectrometric changes in visible and near-infrared reflectance. The highest correlation of *NDVI* values with potato yield occurs during the tuber stage of the BBCH scale[1], at the BBCH 41–49 stage, when plants reach maximum vegetative growth and full crown coverage. During the season, *NDVI* threshold values can range from 0.3, indicating early development, up to 0.9, indicating high photosynthesis and healthy plant cover. High *NDVI* values during the tuber formation stage (BBCH 41–49) are strongly correlated with potential tuber yield. At this stage, the maximum photosynthetic output is transported to developing tubers (Vreugdenhil *et al.*, 2007).

In addition to *NDVI*, other vegetation indices effectively support the assessment of potato growth and development. Soil-adjusted vegetation index (*SAVI*) and modified soil adjusted vegetation index (*MSAVI*) minimise the impact of soil, which is particularly useful at early growth stages. The green normalised difference vegetation index (*GNDVI*), with its green reflectance analysis, provides information on chlorophyll content, which is crucial for assessing plant health. The enhanced vegetation index (*EVI*), with its greater resistance to weathering, provides more accurate measurements in a variety of environments. These indices, often used in combination with the *NDVI*, provide a comprehensive picture of plant health to support decisions on fertilisation, irrigation and crop protection strategies (Huete,

[1] The BBCH-scale is used to identify the phenological plant development stages. The BBCH-scales series has been developed for a range of crop species, where similar growth stages of each plant are given the same code. The BBCH is the abbreviation reflecting the names of original stakeholders: "Biologische Bundesanstalt, Bundessortenamt und CHemische Industrie".

1988; Chen, 1996; Politi, Cutler and Rowan, 2012; Delegido *et al.*, 2013; Xue and Su, 2017; Liu *et al.*, 2022).

Parameters related to plant growth and development, such as *LAI*, chlorophyll content, vegetative indices like *NDVI* and other spectral indices, are key to assessing potato health and growth rate. These indicators enable accurate predictions of tuber yield, which is important for optimising agricultural practices and increasing crop productivity. Despite the growing understanding of their importance, there is a shortage of scientific publications exploring the application of advanced ML techniques for estimating these parameters, in particular photosynthetic productivity in potatoes. The use of such algorithms can improve the accuracy of yield forecasting and increase the efficiency of resource management in agriculture. Further research is needed to fully realise the ML potential in promoting sustainable potato farming. It is worth mentioning that some scientific studies have explored the use of ML in forecasting vegetation indices. Most of the parameters presented and discussed in this section are used in the development of predictive models, as discussed below (Luo *et al.*, 2019; Luo *et al.*, 2020; Mukiibi *et al.*, 2024).

CLASSIFICATION AND PREDICTION OF TUBER YIELD

Predictive and classification models are becoming increasingly important in potato cultivation, helping to optimise productivity and sustainability. These models enable more accurate forecasting by analysing historical weather, soil, and agronomic data. They also help identify potential risks, such as diseases and pests, enabling faster preventive responses. The models support farmers in making informed decisions about irrigation, fertilisation, and crop protection, leading to increased production efficiency. Intelligent systems can classify various plant traits, such as tuber size and quality, helping to select suitable planting materials. Introducing models into daily farming practices can also reduce costs through precise resource management. As a result, farmers can more effectively adapt to changing climatic and market conditions.

The application of advanced analytical technologies in potato cultivation represents a key direction in the development of modern agriculture (Niedbała and Piekutowska, 2018; Hara, Piekutowska and Niedbała, 2021; Cravero *et al.*, 2022; Barrios-Ulloa *et al.*, 2023). AI-driven potato tuber yield forecasting has become an essential tool in modern agriculture. Pre-harvest forecasts are particularly valuable for efficient logistics planning and resource management, helping to minimise financial losses. Algorithms such as NNs and RFs analyse weather conditions and soil quality data. The most accurate models achieve prediction errors of just 5–10%, which is considered very good (Piekutowska *et al.*, 2021; Kurek *et al.*, 2023).

Recent innovations in machine learning (ML) and deep learning (DL) have revolutionised potato yield forecasting, offering more accurate and detailed predictions. These algorithms use data collected by satellites, drones, and weather and soil sensors to identify anomalies and relationships in the data, increasing the precision of prediction models. A key strength of ML and DL is their ability to continuously learn and adjust forecasts based on new data, enabling allowing for rapid adaptation to changing agricultural conditions. Moreover, these models facilitate yield forecasting at the field and individual plant levels, which is essential for precise and targeted intervention. With access to detailed data, farmers can optimise watering, apply precision fertilisation and pest control, and improve productivity and efficiency in the long run. The integration of ML and DL in agriculture not only supports individual farmers but also affects the entire supply chain, stabilising the market and minimising the risk of food insecurity. However, implementing these technologies comes with challenges, such as the need for high quality and large amounts of data, and the interpretability of forecast results (Cao *et al.*, 2021; Bali and Singla, 2022; El-Kenawy *et al.*, 2024).

The study by Piekutowska *et al.* (2021) developed linear and nonlinear models to predict tuber yields of three early potato varieties: 'Arielle', 'Riviera' and 'Viviana'. The models were developed using 2010-2017 data from official experiments in northern and northwestern Poland. A linear model was created using multiple linear regression (MLR), while a non-linear model was based on ANNs, both designed to predict yields up to June 20. These models used agronomic, phytophenological, and meteorological data, with their performance verified on independent datasets. Validation included six measures of error, such as global relative approximation error (*RAE*), root mean square error (*RMS*), mean absolute error and mean percent absolute error (*MAPE*). Most of the models had *MAPEs* below 15%, and the NY1 neural model outperformed the RY1 regression model in terms of quality and accuracy of predictions.

Gomez *et al.* (2019) developed a potato yield forecasting model using satellite remote sensing. They used data from Sentinel 2 satellites collected by the European Space Agency over three growing seasons, using different ML models. The analysis tested nine algorithms with different processing scenarios, based on spectral data from red, red-edge and infrared light bands. The regression quantile lasso (11.67% *RMSE*, R^2 = 0.88 and 9.18% *MAE*) and leap backwards (10.94% *RMSE*, R^2 = 0.89 and 8.95% *MAE*) models performed best after removal of variables with correlations above 0.5. In contrast, the SVM radial algorithm (11.7% *RMSE*, R^2 = 0.93 and 8.64% *MAE*) performed better without feature selection, and the random forest model effectively predicted yields in Castilla y León (11.16% *RMSE*, R^2 = 0.89 and 8.71% *MAE*).

A study by Kurek *et al.* (2023) explored the application of ML methods to forecast yields of potatoes for French fries in Poland. They used extensive agronomic, climatic, soil, and satellite data from 36 commercial potato fields collected over five growing seasons (2018–2022). The data was used to develop three models: non-satellite, satellite, and hybrid. The non-satellite model, based on 85 traits, excluded vegetation indicators, while the satellite model included these indicators among 128 traits. The hybrid model, combining all available features, included 165 features, making it the most comprehensive approach. The results showed that the hybrid model, particularly enhanced by detecting outliers using SVMs, achieved the lowest mean absolute percentage error (*MAPE*) of 5.85%, highlighting the effectiveness of integrating different data sources. In comparison, non-satellite and satellite models showed higher *MAPE* values, indicating their lower accuracy. Advanced data processing techniques, such as principal component analysis (PCA) and outlier detection methods (LOF and One-Class SVM), were crucial to optimising feature selection and improving forecast accuracy.

A recent study on the use of artificial intelligence for potato tuber yield assessment examined the effectiveness of various predictive models in potato yield forecasting, focusing on ML algorithms, such as gradient boosting and XGBoost, and deep learning models, including graph-based NNs (GNNs) and LSTMs. The models were evaluated using performance measures such as *MSE*, *RMSE,* and *MAE* to assess their accuracy. Gradient boosting achieved *MSE* of 0.03438 and R^2 of 0.49168, while XGBoost showed a slightly higher *MSE* of 0.03583 and R^2 of 0.35106. As regards deep learning models, GNNs achieved *MSE* of 0.02363 and R^2 of 0.51719, showing the best overall performance. Strong potential was demonstrated by LSTMs and GRUs, with mean squared errors (MSEs) of 0.03177 and 0.03150, respectively. The ability of GNNs and LSTMs to capture complex spatio-temporal patterns contributes to their high accuracy. The study underscores the importance of advanced predictive models in making informed decisions and supporting sustainable agricultural practices in potato cultivation (El-Kenawy *et al.*, 2024).

Yield forecasting is a crucial aspect of modern agriculture, enabling informed crop management decisions and ensuring the stability of food production. Each year, new methods emerge that significantly improve the accuracy of yield forecasts. In particular, AI methods such as NNs, RFs and SVMs revolutionise the performance of prediction models. Deep learning algorithms, such as LSTM and graph-based NNs, are also widely used. Although other methods, such as linear regression, are also used, they mainly serve as benchmarks for evaluating the effectiveness of advanced AI techniques. With advanced data processing techniques, these models are increasingly accurate, reaching minimum mean absolute percentage error (*MAPE*) of 5–6%. The results indicate that integrated AI approaches produce lower forecast errors, confirming their effectiveness. The development of these technologies is steadily improving prediction accuracy, opening up new opportunities in agricultural production management.

Classification models play a key role in potato cultivation, enabling precise analysis of various aspects related to potato growth and variety identification. Research by Liu *et al.* (2020) used spectroscopic technology to classify potato growth stages. The experiments took place in China and covered various growth stages, such as tillering (S1), tuber formation (S2), tuberisation (S3), and ripening (S4). The SVM-based model achieved excellent results, showing 100% accuracy on the training set and 97.37% on the test set.

A study by Khorramifar *et al.* (2021) used an electronic nose and chemometric methods, such as PCA, linear discriminant analysis algorithm (LDA), and ANN, to identify different potato varieties. These studies also highlighted the importance of classification, achieving accuracies of 100% for the LDA method and 96% for the ANN method, using nine sensors in laboratory settings. As technology develops, classification of potato varieties is becoming more complex yet more efficient. The analysis and classification of different growth stages and varieties of potato is of great importance in the context of crop management. In light of the increasing demand for food due to growing populations, the ability to accurately monitor and classify is invaluable in ensuring agricultural sustainability. Classification not only allows for better management of resources but also for early identification of potential disease and pest threats. Classification models, such as CWT-SPA-SVM for spectroscopic analysis or chemometric methods for variety identification, can significantly improve production efficiency. With modern technology, farmers are able to make more informed agronomic decisions, which supports sustainable development. In the face of changing climatic conditions and market demands, advanced classification models not only support farmers but are also crucial to the stability of the entire food supply chain. As a result, scientific approaches to classification are becoming the foundation of modern agriculture.

STORAGE

Artificial intelligence is transforming potato harvest and storage management, introducing new opportunities to optimise and increase the efficiency of the entire process. By analysing large data sets, such as soil conditions, weather, moisture levels, and previous yield data, ML models can predict the optimal harvest time to maximise yield and quality. Machine learning models, including regression, decision trees, and NNs, are ideal for predicting potato storage performance. Regression models identify relationships between variables and outcomes, decision trees offer intuitive visualisations of decision paths, and NNs, especially deep learning models, can handle complex patterns in large data sets, providing high-precision predictions (Cao *et al.*, 2021; Akhter and Sofi, 2022).

In the context of storage, algorithms can monitor and analyse storage conditions, such as temperature and humidity, which helps keep potatoes in the best possible condition for longer periods. Machine learning can also predict potential issues, such as disease or rot, before they become serious threats, enabling early intervention (Jakubowski and Królczyk, 2020).

A study by Khorramifar *et al.* (2023) explored the use of an electronic nose (e-nose) combined with ML techniques to predict potato shelf life. The study assessed changes in the quality of potatoes during storage by analysing sugar and carbohydrate content. It used various ML models, such as PCA, support vector machines, and ANNs. The results showed that quadratic discriminant analysis (QDA) and multivariate discriminant analysis (MDA) achieved more than 90% accuracy in classifying the quality of potatoes in storage facilities. This approach enabled effective monitoring of quality and reliable prediction of potato shelf life.

Another interesting study by Coulibali, Cambouris, and Parent (2020) showed how ML can optimise potato storage conditions. The researchers developed predictive models using KNN algorithms, RFs, and NNs to determine the optimal levels of nitrogen, phosphorus, and potassium for high tuber quality and yield. The models took into account weather, soil, and land management data. The ML-based models outperformed traditional methods, offering more accurate predictions for medium-sized tubers and specific density. This enabled more precise fertiliser applications, better storage conditions and reduced losses.

Potato storage control goes beyond disease assessment; it also involves managing germination (Di *et al.*, 2024). The quality of potato tubers depends on maintaining several parameters at appropriate levels during storage. One of these parameters is germination activity, which begins in the meristematic regions of the tubers (eyes). Uncontrolled sprouting activity is a significant issue, leading to a shortened shelf life and increased sugar content, adversely impacting the commercial value of both seed tubers and processed potato products, such as fried goods. A study by Rady *et al.* (2020) compared the capabilities of three different optical systems: (1) visible/near-infrared (Vis/NIR) interactive spectroscopy, (2) Vis/NIR hyperspectral imaging, (3) NIR transmittance, as well as ML methods in detecting potato germination activity based on the number of embryonic leaves (LC). The study was conducted on Frito Lay 1879 and Russet Norkotah varieties stored at different temperatures. The developed classification models analysed both varieties together and classified tubers as showing high or low germination activity. Measurements were made on both whole tubers and sectioned samples to evaluate the impact on identifying germination activity. Sequential forward selection was used to select wavelengths, while classification was performed using the KNN method, least squares discriminant analysis and independent modelling analogy. The highest classification accuracy values were obtained for the hyperspectral imaging system, reaching 87.5% and 90% for the sectioned and whole samples, respectively. The study of various optical techniques and ML methods is a first step towards developing a portable optical device for early detection of germination activity, which can significantly enhance potato storage management.

Implementing ML systems in agriculture requires high-quality data and knowledge of ML and data science techniques. Future efforts should focus on improving the accuracy of models, integrating IoT sensors, and creating user-friendly interfaces for farmers (Osipov, Filimonov and Suvorov, 2021). In addition, these technologies can help manage logistics by optimising transportation and delivery volumes, ultimately reducing costs and minimising losses. Integrating ML into potato harvest and storage management allows for more informed decision-making, leading to a more sustainable and efficient agricultural production process (Kutyauripo, Rushambwa, and Chiwazi, 2023).

CHALLENGES AND FUTURE DIRECTIONS OF DEVELOPMENT

Artificial intelligence offers opportunities for major transformation in agriculture, particularly in crop production, increasing productivity, sustainability, and resource management. Potato cultivation, a staple food crop worldwide, could benefit greatly from AI innovations. However, the widespread adoption of artificial intelligence in this field comes with several challenges, including economic, educational, and technological barriers.

The most important of these challenges is the significant financial investment required to implement AI technology in potato cultivation. Precision farming tools, such as AI-based drones and smart sensors used to monitor crop health and optimise inputs, can be too expensive for small and medium-sized farmers. The high initial costs associated with these technologies may discourage their use, especially in developing regions where financial resources are limited. Removing these barriers through subsidies, financial incentives, and shared funding models is crucial for the broader integration of AI.

Successful implementation of AI technologies in agriculture requires a workforce skilled in both agricultural practices and data science. Currently, there is a significant education gap, as many farmers lack the technical knowledge to effectively use AI tools. To bridge the gap, it is necessary to develop training programmes and educational initiatives to equip farmers with skills necessary to fully utilise the potential of artificial intelligence. This requires cooperation between academic institutions, government agencies, and technology companies to develop and implement accessible educational programmes.

Moreover, the availability of artificial intelligence technology is unevenly distributed across regions, contributing to disparities in agricultural productivity. While advanced technologies, such as ML algorithms for crop prediction and automated irrigation systems, are mainly concentrated in developed countries, regions with limited access remain at a disadvantage. Efforts to democratise artificial intelligence technologies and make them more accessible to all potato producers, regardless of geographic location, are essential to ensure equitable benefits.

Future research should focus on developing affordable AI solutions tailored to the needs of potato farmers, especially those operating on a smaller scale. Innovative low-cost sensors, open source AI platforms, and scalable technologies can help reduce financial barriers and make AI tools more accessible to a variety of agricultural operations. Joint efforts involving governments, non-governmental organisations (NGOs), and the private sector can facilitate the development and dissemination of these cost-effective solutions. In parallel with the development of AI, the educational resources available to farmers should also be expanded. Improved educational programmes, such as online training modules, workshops, and field demonstrations, should be developed to teach farmers how to effectively integrate artificial intelligence into their daily operations. By fostering a culture of continuous learning and adaptation, these programmes will enable farmers to realise the full potential of AI technology. Promoting global cooperation in accessing AI technologies can help bridge the gap between high-tech and developing regions. Initiatives focused on technology transfer, knowledge sharing, and international research partnerships can facilitate widespread adoption of AI in potato farming around the world. By sharing best practices and innovations, the global agricultural community can increase resilience and productivity of potato crops around the world. While integrating artificial intelligence into the potato crop comes with challenges related to cost, education and technology availability, these can be addressed through strategic initiatives and collaboration.

As artificial intelligence continues to revolutionise crop production, its thoughtful application to potato cultivation can lead to sustainable agricultural practices that meet global food demand. Future research and policy efforts should prioritise making artificial intelligence tools available and affordable, ensuring that all farmers benefit from these advanced technologies (Cambouris *et al*., 2014; Sewell *et al*., 2017; Taneja *et al*., 2023; El-Kenawy *et al*., 2024; Elshaikh, Elsheikh and Mabrouki, 2024).

TECHNOLOGICAL AND FINANCIAL BARRIERS FOR SMALL PRODUCERS INIMPLEMENTING AI TECHNOLOGY IN POTATO CULTIVATION

The implementation of AI technology in potato cultivation by small-scale producers faces a number of technological and financial barriers that can hinder the adoption of the innovation. First, the complexity of the technology poses a major challenge, as many small farms lack sufficient knowledge of advanced systems such as ML or data analytics. This complexity can be overwhelming for farmers, discouraging them from using new solutions. In addition, the lack of adequate infrastructure, such as high-speed internet or sensors, is a barrier that limits the ability to collect and analyse data needed to use AI effectively.

Integrating new technologies with existing farm management systems can also be a challenge. Small farms may find it difficult to implement innovations that are not compatible with their existing practices. Introducing new technologies involves steep learning curve, and as such can also be time-consuming. Farmers may need significant educational support to successfully adopt new tools. From a financial perspective, high implementation cost is a major obstacle. The upfront expenses associated with purchasing hardware, software, and implementing AI technologies can be prohibitive for small producers. Additionally, small farms often have difficulty obtaining financing to invest into innovative technologies. Traditional financial institutions may be reluctant to lend to projects perceived as high risk, further limiting access to capital. Limited budget adjustments on small farms mean that producers may be reluctant to experiment with new technologies. Many of these farms focus on short-term profits, which can lead them to view AI investments as unprofitable. While the implementation of AI technologies typically yields long-term benefits, it requires a change in thinking and approach to investment. To overcome these obstacles, it will be crucial to provide access to education, financial support, and the creation of partnership programmes to integrate innovative solutions into everyday farming practices. Collaboration between governments, NGOs, and the private sector is of paramount importance to enable small producers to benefit from the potential of AI in their operations. The development of these technologies and their effective implementation can bring significant benefits to small-scale potato producers, as well as contribute to the overall sustainability of agriculture (Wakchaure, Patle, and Mahindrakar, 2023; Zavodna, Überwimmer and Frankus, 2024).

CONCLUSIONS

The integration of artificial intelligence in crop production, particularly in potato cultivation, represents transformative potential in both economic and ecological spheres. Several key points were highlighted during this discussion, underscoring the significant impact AI technologies can have on improving agricultural practices. The primary conclusion is the ability of AI to optimise yield prediction through advanced data analysis, enabling farmers to make better-informed decisions. Machine learning models can analyse huge data sets – from historical yield records to real-time weather patterns – providing predictive insights that improve planning and resource allocation. This optimisation contributes directly to increased productivity, reduced waste, and ultimately improved profitability for farmers. Moreover, AI technologies, such as precision farming tools, play a key role in resource management. By enabling the precise application of water, fertiliser, and pesticides, these tools not only improve the quality of crops and yields but also reduce the environmental impact of agriculture. Artificial intelligence-based irrigation and nutrient management systems are an example of how technology can align agricultural practices with sustainable ecological principles, minimising excessive use and runoff of agrochemicals. From an economic standpoint, the application of AI to potato cultivation can contribute to significant cost reductions. Automating labour-intensive tasks, such as planting, monitoring, and harvesting, with AI-based robotics can reduce labour costs and mitigate labour shortages. In addition, decision support systems that provide insights into market trends and crop inventories which can help growers optimise sales strategies and improve market competitiveness.

From an environmental perspective, artificial intelligence contributes to more sustainable farming practices. Precise monitoring of crop and soil health reduces reliance on chemicals, supports biodiversity, and improves soil health. Additionally, increased productivity supports the conservation of natural resources such as water, which is increasingly important in the context of climate change and global water scarcity.

In summary, the application of artificial intelligence in potato cultivation offers myriad benefits, from increasing economic efficiency to supporting environmentally sustainable practices. As these technologies continue to evolve, they hold the promise of not only transforming traditional cultivation methods but also contributing to global sustainability efforts in agriculture. The future of AI in agriculture looks promising, with the potential to usher in a new era of intelligent, resilient, and environmentally friendly agricultural systems.

CONFLICT OF INTERESTS

The author declares no conflict of interests.

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