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PRECISION AGRICULTURE IN MANGO ORCHARD: A REVIEW

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ABSTRACT

Precision agriculture is revolutionizing the management of mango orchards by integrating advanced technologies to optimize yield, enhance resource efficiency, and minimize environmental impact. This approach leverages various components such as Global Positioning Systems (GPS), Geographic Information Systems (GIS), remote sensing, and Internet of Things (IoT) devices for precise monitoring and management. Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, play a significant role in capturing high-resolution imagery for mapping orchard health, pest infestations, and water stress. AI-driven analytics and Decision Support Systems (DRIS) provide actionable insights by analyzing data from diverse sources. Remote sensing technologies, including satellite and drone imagery, facilitate the early detection of diseases and nutrient deficiencies. IoT sensors monitor soil moisture, temperature, and other critical parameters, ensuring optimal irrigation and reducing water wastage. This abstract outlines the potential of these advanced technologies to transform traditional mango cultivation into a data-driven, efficient, and environmentally responsible practice.

Key words: Precision agriculture, Remote sensing, Internet of things, Artificial Intelligence, Unmanned aerial vehicle, VRT, Sensors.

Introduction

The limited ability of traditional agricultural systems to sustainably satisfy the needs of contemporary agriculture has led to their criticism after being used for millennia. In an era of climate uncertainty, conventional systems frequently lack the efficiency and scalability needed to feed a fast-expanding population, even though they may have cultural importance and occasionally show sustainability. Therefore, it has become more and more clear that we need to move toward more sophisticated and technologically driven techniques (Mgendi, 2024). In advanced countries, precision farming is being performed. However, it is still in its early stages in the India. The world's second-largest fruit grower is India. Therefore, using a few components of precision farming in fruit crop production is one of the greatest ways to improve land, create jobs, improve farmers' economic status and increase nutritional security. Modern agricultural techniques have undergone a radical paradigm change with precision farming, sometimes referred to as precision agriculture (PA). Precision farming, which often involves careful planning from production to postharvest and processing, uses information, technology and management to improve horticulture's productivity, sustainability and efficiency (Roberson, 1999).

Nowadays, mangos (*Mangifera indica* L.) are grown in over a thousand nations. It is among the most significant fruit crops grown in tropical and subtropical areas. According to (Rajith Singh and Saxena, 2005), mangoes are unmatched by other fruits in terms of area, production, nutritional content, and attractiveness. About half of the world's mango output comes from India, which has the greatest area (Sauco, 2013). Over 40% of all fruit land in India is used for mango cultivation. It is crucial to enhance output using the resources at availability due to the massive population growth and rising demand. According to (Kumar, 2017), inadequate orchard management, dense canopies with broader spacing, poor sunlight interception, and inadequate ventilation are the primary causes of India's low mango output. These factors also encourage a higher occurrence of pests and diseases. Since agriculture uses the most water globally, precision agriculture relies heavily on effective water application (Jiang *et al.*, 2011). Saving water in agriculture could be feasible without having a major effect on yield (Greaves and Wang, 2017). Perea *et al.* (2017) state that high-value fruits, where quality assurance is a key factor in determining profitability, benefit greatly from precision irrigation.

Components of Precision Farming

In precision farming, variability across time and location is managed and understood. Based on survey data, this system matches inputs to field conditions using site-specific inputs, including computer systems, GPS systems, GIS systems, RS systems, VRA systems, yield mapping technologies, soil and crop sensing technologies, DRIS and SSNM for precision horticulture and waste management in relation to precision horticulture in a particular site.

Computer system

Computers have aided in the definition of precision farming as a management approach that makes decisions using information technology (Best *et al.*, 2005). Acquiring, managing, analyzing, and producing a significant amount of geographical and temporal data are all necessary for precision farming. As computer software for precision farming has improved throughout time, so too has the expertise required to manage farm variability and make informed judgments (Ampatzidis *et al.*, 2009).

Geographic information system

The Geographic Information System (GIS), which is made up of an organized set of computer hardware, software, geographic data and human resources, is a crucial tool for effectively gathering, storing, updating, manipulating, analyzing, and displaying all forms of geographically referenced information (Miller *et al.*, 1999). The leap from mapping to spatial thinking is made possible by the modeling and data management components of GIS research. Miller and Paice (Miller *et al.*, 1998) claim that because GIS includes base maps of topography, soil type, nutrient level, soil moisture, pH, fertility, and weed and insect severity, it may be utilized to apply prescribed rates of fertilizers or pesticides. Additionally, it may link with other decision support tools and incorporate various kinds of data.

Global positioning system

The Global Positioning System (GPS) was developed by the US Department of Defense (DOD). The positioning system operates with the help of many satellite constellations. Advances in positioning systems have made precision agriculture a reality. The main technical milestone is represented by these advancements. GPS provides an accurate locating method for variable rate technologies used in the field (Srivastava *et al.*, 2009). It enables agricultural equipment to be positioned within inches of one another, regulates how inputs are administered by machines, recommends fertilizer and insecticides according to the properties of the soil. Every GPS work must distribute and store position data from a single system situated at a central vehicle, such a tractor (Mondal, 2004). Spilker claims that the main advantage of a central system is that position data is calculated according to the application and delivered directly to the site of use (Spilker, 1996).

Remote sensing

Crop electromagnetic emittance and reflectance data obtained remotely by satellite or aircraft can provide important information about a number of topics, including plant growth, soil health, and weed infestation. This type of information, which is also economically priced, may be very helpful for site-specific crop management programs (Schachtl *et al.*, 2005). This technology can help precision agriculture since it makes it relatively easy to provide field parameters. In precision agriculture, remote sensing tools like LiDAR sensors and multispectral cameras support data-driven decision making. Multispectral cameras are able to identify minute changes in crop reflectance that might be signs of disease outbreaks, stress, or nutrient shortages. Farmers benefit greatly from this early detection capabilities as it enables them to see problems early in the growing season and take appropriate action, improving crop health and production (Ma *et al.*, 2021; Rosas *et al.*, 2022).

Furthermore, LiDAR sensors make it easier to create accurate elevation models of fields, providing important information about the properties of the terrain. Farmers may use this data for a number of things, including designing drainage systems, assessing the topography to determine the best water flow, and comprehending topographical changes that could affect crop health (Rivera *et al*., 2023).

Drones (Unmanned aerial vehicles)

Drones, sometimes referred to as unmanned aerial vehicles, have revolutionized precision agriculture data collecting. UAVs can collect high-resolution data and images across vast agricultural regions when outfitted with advanced sensors and cameras. Drone-captured aerial imagery offers a bird's-eye perspective of fields, which is crucial for monitoring crop health and producing intricate field maps. This picture helps pinpoint problem areas, such as insect infestations, water stress or pests in mango orchards, allowing farmers to take preventative action.

Sensors and Internet of things (IoT)

The Internet of Things (IoT) in agriculture is built on sensors, which are essential parts of contemporary precision agriculture (Mekonnen *et al*., 2020; Karunathilake *et al*., 2023). These gadgets are placed thoughtfully throughout fields to continually gather real-time data on a range of environmental variables. The network of these sensors that are connected to one another and to central data processing systems is known as the Internet of Things. This network gives farmers instant access to vital data on crop health, temperature, humidity, and soil moisture so they can make well-informed decisions.

Artificial intelligence (AI) and machine learning

In order to handle and analyze large datasets, derive significant patterns and insights, and provide predictions or recommendations based on incoming data, artificial intelligence (AI) and machine learning have become extremely potent technologies (Lay, 2023). One of the best examples of the amazing potential that machine learning and artificial intelligence (AI) have for precision agriculture is crop disease prediction (Shin *et al*., 2023; Adli *et al*., 2023). Machine learning models are capable of reliably forecasting disease outbreaks by utilizing historical data on crop maladies and taking into account a variety of environmental parameters, including weather, soil moisture levels, and insect populations.

Another crucial use of machine learning and artificial intelligence (AI) in precision agriculture is yield prediction (Punithavathi, 2023). To predict crop yields with remarkable precision, these sophisticated algorithms make use of a multitude of variables, such as past yield records, weather predictions, soil properties, and crop growth stages (Neményi, 2022). AI-driven yield prediction models make use of this extensive dataset to give farmers insightful information that is crucial for resource allocation, harvest planning and well-informed marketing choices.

In reality, AI and machine learning are essential to precision agriculture, transforming farming methods and opening the door to lucrative and sustainable operations. Farmers may improve crop yields and profitability by utilizing these tools to make timely choices and allocate resources as efficiently as possible. In order to improve Artificial Intelligence (AI)-assisted Landsat-8 image analysis for mango orchard detection and mapping, machine learning approaches are essential. Advanced algorithms like Rf, KNN, NB, Svm and Cart are used in these methods to precisely analyze the intricate spectral fingerprints that are exclusive to mango orchards from satellite data.

Support Vector Machines (SVM): The utilization of Support Vector Machines (SVM) in the identification of mango trees using satellite data has become a noteworthy development in the field of agricultural management (Vaghela, 2012). Among the several properties found in satellite photography, the supervised learning algorithm SVM is successful in identifying mango plants. The SVM model learns to correctly categorize pixels by being trained with labeled data that represents the characteristics of mango trees as well as other components like soil or vegetation.

Random Forest (RF): Using Random Forest models to identify mango trees from satellite data has become a useful tool in agricultural management (Chabalala *et al.*, 2022). An ensemble learning method called Random Forest excels at deciphering complicated datasets like satellite photos. Random Forest is able to distinguish mango trees from other objects in the image by using several decision trees that have been trained on different criteria. Random Forest improves its accuracy and resilience through the ensemble learning process, which aggregates predictions from several models. The fundamental ideas of Random Forest include building and combining decision trees to provide predictions, even though it lacks a single equation like some other algorithms.

Classification and Regression plants (CART): Because of its interpretability and versatility, the CART model is frequently used to identify mango plants using satellite data. CART is very skilled at managing the intricacies involved in satellite imagery processing since it operates by recursively segmenting the feature space. In order to build a decision tree for mango tree detection, CART uses a variety of spectral and spatial parameters that are taken from satellite data. The nodes in this tree stand for feature thresholds and the branches show the binary choices made in response to these thresholds (Anderson *et al.*, 2019).

Naive Bayes (NB) : Because of its simplicity and efficiency, the Naive Bayes model is a widely used technique for identifying mango trees from satellite data (Zhang *et al*., 2024). This model, which is based on the Bayes theorem, determines the likelihood that an event will occur while taking into account past knowledge of potentially relevant situations. The Naive Bayes model functions in the context of mango tree detection by assuming that characteristics obtained from satellite data are conditionally independent given the class label, i.e., whether mango trees are present or not.

Yield estimation using machine learning techniques : Before the era of machine learning, fruit identification was accomplished by just taking pictures of orchards and utilizing several segmentation techniques, including as K-means, watershed, contour detection, and decision trees, to identify the fruit's size, shape, color, and texture. Since it eliminates the work required by human intellect, machine learning (ML), a branch of artificial intelligence, is widely employed by researchers. It creates a trained model for (given) input characteristics derived from source objects using a collection of algorithms (Kamilaris *et al*., 2017; Liakos *et al.*, 2018). (Qureshi *et al*., 2017) used photos of mango tree canopies to suggest a technique for the accurate identification of fruits. They used two methods: The first method used a collection of filters on the input image to distinguish between pixels that were fruit and those that weren't. In contrast to a circular form, the second examined the borders of mango fruits as an ellipse. When the results were contrasted with those of other machine learning methods, such as Support Vector Machines (SVM) and K-nearest neighbors (kNN), the suggested approach showed an F_1 score of 0.68.

Advances in Unmanned Aerial Vehicle platforms for mango orchards

Unmanned aerial vehicles (UAVs) or drones are aircraft that fly in a predetermined direction at a certain speed under remote control. UAV availability has grown significantly in recent years, and there are now a wide variety of models, ranging from fixed-wing to multi rotor. Furthermore, the use of UAVs with vertical takeoff and landing (VTOL) systems in orchard management has gained attention due to recent advancements in the field (Mesas-Carrascosa *et al*., 2018; Torres-Sanchez, Lopez-Granados *et al*., 2018). VTOL UAVs are simple to operate and are not limited by site conditions or inclement weather. In certain case studies, customized UAVs have also surfaced to fulfill specific needs in addition to the UAVs already stated (Stefas *et al*., 2019). In orchard management, these UAVs are thought of as distant sensing and imaging tools. However, UAVs are also active. For example, UAVs used for spraying provide a fresh approach to the security of traditional manual pesticide application (Gao *et al*., 2019).

Identifying fruit trees with diseases

Visual observations in the field combined with laboratory analysis are the traditional methods for identifying diseases of fruit trees. These approaches have limitations in terms of time-cost efficiency and trustworthy evaluation (Khan *et al*., 2018; Pan *et al*., 2014; Srivastava and Sadistap, 2017). Exploring the complicated sensitivity of an indicator for a specific disease diagnosis problem has shown potential with machine learning. According to O'Neill *et al*. (2016), UAV-based fruit-crop disease monitoring has been used for a few different disease kinds, but it is still crucial to look into its suitability for monitoring serious illnesses like Panama disease in bananas. Furthermore, disease identification based on aerial photos from UAVs is inexpensive in terms of both time and equipment and may offer orchard scouting across a wider region.

Pesticides treatment for mango orchards

The improper and unregulated use of pesticides damages ecosystems and pollutes protected regions, affecting biological processes. Furthermore, hand spraying exposes employees to dangerous chemicals in a high-risk environment. UAV-based solutions are suggested as being safer, more accurate, and more cost-effective than manual spraying or manned agricultural aircraft in the precision agriculture literature on pesticide spraying systems in orchards (Martinez-Guanter *et al*., 2019; Zhang *et al*., 2017). However, without a sensible spraying plan and accurate and thorough information support such as the identification of tree crown sections that are considered target spraying areas, aerial spraying may not be effective in practice.

SSNM and DRIS for horticultural precision farming

The diagnosis and recommendation integrated system (DRIS) are a comprehensive method to crop mineral nutrition that influences the integrated set of standards that reflect the calibration of plant tissues, soil composition, environmental factors, and farming techniques as functions of crop output (Beaufils, 1973). The capacity to diagnose crops at any stage of growth and to prioritize the nutrients that are limiting output in order of significance are the two main benefits of the DRIS technique. To complete the diagnostic and prediction application of the leaf analysis, an integrated diagnosis and suggestion system has been created. By optimizing these variables, conditions are created that increase the likelihood of achieving greater production and quality. DRIS uses a survey approach, in which a large number of locations are chosen at random from all around the region. Samples of soil and leaves are collected for examination at each location, and information about the fertilizer and manures that were applied is noted. The majority of soils come from basaltic parent material, and they frequently lack certain nutrients, such as N, P, Fe, Mn and Zn59.

For this reason, the traditional approach to nutrition management, which mostly involves applying macronutrients in orchards, has not been very effective in increasing productivity (Srivastava and Singh, 2004). A practical solution to overcome nutritional limitations and to maximize the productive potential of particular orchard locations is soil test-based site-specific nutrient management (SSNM). Fields are separated into management zones, sometimes known as grids, under site-specific management, and each zone is measured and controlled independently. Producers must have access to the knowledge and technology needed to carry out a thorough management plan in order to perform site-specific management.

Expert system software for Mango nutritional disorders

Verma *et al.* (2018) created expert system software on nutritional disorders and deficiencies in mangos to diagnose the five main nutrient diseases—potassium, boron, copper, zinc and magnesium. Following diagnosis, the program suggests appropriate management choices for the detected condition or deficit. It facilitates wise decision-making and effectively empowers orchardists in the sharing of knowledge (Parthiban *et al.*, 2020).

Advance techniques of Precision farming

Nutrient Management Strategies in mango orchard

Variable Rate Technology (VRT) : The application of VRT in horticulture demonstrates how precision farming may significantly increase the effectiveness of farm management strategies and resource utilization efficiency. Variable rate applicators employ GPS technology to pinpoint their exact location inside the field. It takes accuracy to apply the appropriate quantity of inputs at the appropriate locations. Real-time data from sensors that monitor variables including crop health, fertilizer levels, and soil moisture is used by certain advanced systems. An onboard computer reads these maps and sensor data and then determines the required application rates for every zone. The control system then automatically modifies the spreader or sprayer settings to apply the appropriate amount of fertilizer, lime, pesticides, or other inputs in line with the prescription map (Bongiovanni, 2004). Even while the total amount of fertilizer and lime consumed may not decrease, more efficient use of these inputs may yield higher returns on investment from an economic perspective. With VRT, application rates may be progressively changed, which is crucial for finding a balance between achieving the desired outcomes and avoiding unnecessary overlaps. Continuous developments in machine learning, data analytics, and sensor technologies might further enhance VRT systems (Sishodia *et al.,* 2020).

Water Management Strategies in Mango orchard

Wireless Sensor Networks (WSN) : Wireless sensor networks, or WSNs, offer practical solutions for enhancing field water management, particularly in the area of real-time soil moisture level monitoring. By positioning sensor nodes around a field, farmers may obtain vital information on soil moisture remotely, enabling more precise and efficient watering methods. Wireless sensor networks (WSN) are playing an increasingly significant role in precision agriculture, particularly in the area of real-time data collection and processing for irrigation system improvement. By combining these networks with state-of-the-art irrigation systems, farmers may greatly increase crop health and water efficiency. Wireless sensor networks enhance irrigation systems. This sensor makes it possible to monitor soil moisture in real time. Data from sensor nodes is wirelessly sent to a central system for analysis and remote access. 3G, 4G, or even ADSL networks are commonly used for this.

Farmers may now monitor farming conditions without physically being present because to this (Kumar *et al.*, 2022). Even the watering can be set to run automatically as needed. The combination of automated irrigation systems and real-time soil moisture data allows for precise control over water delivery. Systems like the automated center-pivot may target areas that need the most watering while avoiding over irrigation by modifying the water output of individual spray nozzles based on the moisture data received.

Variable Rate Irrigation (VRI) System: The initial phase in the VRI systems process is a thorough assessment of the soil, topography, and crop health differences in the field. This data may be gathered using a variety of methods, including remote sensing devices, aerial photography and soil moisture sensors. Most VRI devices are controlled and automated by sophisticated software that decodes information from weather stations, sensors, and plant-based indicators through the use of algorithms. The quantity of water needed in different crops' zones is decided by this program in real time. By allocating water based on the specific needs of each agricultural region, VRI significantly reduces water waste. Studies like those by Yule *et al.* (2008), Hedley and Yule (2009) have demonstrated that water reductions of 10% to 25% are achievable. Through the prevention of both under and over irrigation, precise water management fosters the best possible plant development circumstances, which can raise crop quality and yield. The potential for crop gains and the decrease in water use more than balance the significant cost benefits of VRI technology. A significant barrier for small-scale farmers in particular may be the difficulty of installing and maintaining VRI equipment. For the initial setup, a substantial sum of money needs to be invested on technology and training. Strong data analytics skills are required to handle the enormous volumes of data produced by VRI system.

Identification of horticultural crop diseases in precision farming

Spectroscopy: Spectroscopy has emerged as a crucial method for horticultural crop disease diagnosis because it can investigate the interactions between electromagnetic radiation and plant tissues. This method detects subtle changes linked to illness by measuring the absorption, reflection, or transmission of light over a variety of wavelengths in plant samples (Sankaran *et al.*, 2010). By comparing the spectral fingerprints of healthy and sick plants, spectroscopy may be used to detect disease signs before they become noticeable to the naked eye (Couture *et al*., 2018). To detect illnesses, horticulturists employ a variety of spectroscopic methods, including visible-near-infrared (VNIR), mid-infrared (MIR) and hyperspectral imaging. For instance, VNIR spectroscopy is helpful for assessing metabolic alterations connected to the development of illness, whereas MIR spectroscopy is commonly used to investigate structural and compositional changes in plant tissues. Atherton *et al.* (2015) used fluorescence imaging spectroscopy in combination with computer vision and machine learning techniques to categorize healthy and sick leaves in horticulture crops. They segmented fluorescence pictures using normalized graph techniques, and then they extracted texture features from the segmented images using co-occurrence matrices. These collected characteristics served as the inputs for a support vector machine classifier. In Florida, Pydipati *et al.* (2006) employed machine vision control technology and artificial intelligence to identify citrus illnesses early. This method made it simpler to identify diseases and provide fungicides exactly where they were required.

Application of pesticides in precision farming

Technology based on Canopy Sensors: The development of ultrasonic canopy sensor-based pesticide applicators has greatly increased precision agriculture, particularly for orchard crops such as mango, apple, etc. where careless pesticide application might have negative environmental effects (Skolik *et al*., 2018). At IIT Kharagpur, an ultrasonic canopy sensor-based pesticide applicator was developed. Only after detecting the presence automated device saves a substantial quantity of insecticide/pesticide (about 45–50%) by ensuring that spraying occurs only where it is needed (Tiwari, 2019). Similarly, a sprayer that uses ultrasonic of the target plant's canopy does it begin to spray insecticide. When mounted on a tractor, this sensor, such as the Pro wave 400EP14D, was developed elsewhere. When paired with the appropriate electronics and a personal computer, these sensors enable the real-time identification of canopy structures. An RGB camera is used by Hocevar *et al.* (2014) to identify canopies in their machine vision-based automated orchard sprayer prototype. The system evaluates the captured images in real time to modify the pesticide spray flow to fit the curve of the apple tree canopy. This technique allows for the adjustment of the spray through controlled electric valves, as well as the variation of chemical volume and liquid flow rate. Additionally, a Crop Identification System (CIS) based on ultrasonic sensors was developed in order to identify the characteristics of the target canopy and enable optimal spray deposition on the leaves by modifying the application rate in accordance with the size and density of the canopy (Llorens *et al*., 2011).

Automated Yield Monitoring System

Automated yield monitoring, which provides farmers with real-time data on yield variability on their farms, is a crucial component of precision agriculture. By measuring this variability, farmers may make informed decisions to reduce costs, increase output and improve system efficiency (Khan, 2019). Such a system typically includes of color cameras, a laptop computer mounted atop a Specialized Farm Motorized Vehicle (SFMV), proprietary software, and a real-time kinematics-global positioning system (RTK-GPS) for mapping fruit production in real time. Farmers can map and accurately monitor the production of their harvested fruits and vegetables with this setup (Farooque, 2013).

Automated Harvesting System

Handpicking and other labor-intensive methods are commonly used while harvesting fruits and other horticultural crops. These methods are cost-effective and large-scale scalability are constrained, though. Numerous mechanical harvesting methods have been studied since the 1960s in an effort to address this issue. To help in fruit detachment, these methods include limb shaking, air blasting, canopy shaking, trunk shaking, and the use of chemical agents. These methods may increase output, but they usually struggle to maintain fruit uniformity in terms of size and quality. Color cameras in the vision control system provide the control with data on the location and separation of fruits. By using vision technology, these machines can choose sizes and preserve fruit quality, increasing total harvesting efficiency. Despite their potential advantages, automated harvesting systems are currently in the research and development stage and have not yet reached commercialization due to problems including low efficiency, limited intelligence, and high initial investment costs (Kleine, 2015). In order to develop more efficient harvesting robots that meet the needs of horticultural crops, researchers are attempting to get over these challenges. With further advancement, automated harvesting technologies have the potential to revolutionize harvesting practices in the agricultural sector by reducing labor costs and increasing productivity (Pereira *et al.,* 2017).

Summary

Precision agriculture integrates advanced technologies to optimize mango orchard management, enhancing productivity, resource efficiency and sustainability. Key components include GPS (Global Positioning System) and GIS (Geographic Information Systems) for precise mapping and monitoring of orchards. These systems allow targeted interventions by identifying spatial variability in soil, crop health and environmental conditions. Remote sensing and drones (Unmanned Aerial Vehicles - UAVs) are critical for capturing real-time data on canopy health, pest infestations and stress levels. High-resolution imagery from these tools provides insights into growth patterns and areas requiring attention. Similarly, IoT (Internet of Things) devices, such as soil moisture sensors and weather stations, collect continuous data, enabling real-time decision-making. Technologies like DRIS (Diagnosis and Recommendation Integrated System) assess nutrient imbalances, ensuring precise fertilizer application. Artificial Intelligence (AI) and machine learning enhance data analysis, predicting pest outbreaks and optimizing irrigation and pesticide application schedules. Automated machinery further supports uniform operations, reducing labor and resource usage. Advanced techniques in precision farming, such as variable rate application (VRA) of fertilizers and pesticides, ensure tailored inputs, minimizing waste and environmental impact. UAVs facilitate precise pesticide spraying and monitoring hard-to-reach areas, while AI-driven analytics forecast yield trends, guiding harvesting strategies. Overall, the integration of these technologies in mango orchards improves yield quality, reduces costs, and promotes sustainable agricultural practices.

Conclusion

In India, precision farming has the potential to usher in the next green revolution by generating both rural riches and food security. Despite being in its infancy in India, there are several chances for adoption. The majority of Indian farms are rainfed and depend on engineers, scientists and agriculturists in addition to government intervention to advance the usage of precision farming due to scarcer inputs including labor, water, fertilizer and weather patterns. Indian horticulture would benefit from precision agriculture if it were to increase yields and economic returns per field while minimizing environmental harm. Precision agriculture has a lot of promise for the future. Future developments will spur additional innovation and make agricultural systems even more effective and productive, especially in the areas of artificial intelligence, blockchain for data security, and precision robots. Adopting this cutting-edge technology, improving training and education initiatives, fortifying legal frameworks, and encouraging environmental stewardship will all be crucial factors in the field's advancement. We can create a more resilient, sustainable, and lucrative agricultural industry that satisfies the demands of a growing world population while protecting our planet's resources for coming generations by utilizing precision agriculture.

References

Adli, H.K. *et al*. (2023). Recent advancements and challenges of aiot application in smart agriculture: a review. *Sensors*, **23**, 7. https://doi. org/10.3390/s23073752.

Ampatzidis, Y.G., Vougioukas S.G. and Bochtis D.D. (2009). A yield mapping system for hand-harvested fruits based on RFID and GPS location technologies: Field testing. *Prec Agric*., **10(1)**, 63-72.

Anderson, N., Underwood J., Rahman M., Robson A. and Walsh K. (2019). Estimation of fruit load in mango orchards: tree sampling considerations and use of machine vision and satellite imagery. *Precision Agriculture*, **20**, 823–839. https://doi.org/10.1007/s11119-018-9614-1

Atherton, D., Watson D.G., Zhang M., Qin Z. and Liu X. (2015). Hyperspectral spectroscopy for detection of early blight (*Alternaria solani*) disease in potato (*Solanum tuberosum*) plants at two different growth stages. In : *2015 ASABE Annual International Meeting* (p. 1). American Society of Agricultural and Biological Engineers.

Beaufils, E.R. (1973). Diagnosis and recommendation integrated system (DRIS). *Soil Sci. Bull.* No. 1, University of Natal, S. Africa.

Best, S., Leon L. and Claret M. (2005). Use of precision viticulture tools to optimize the harvest of high quality grapes. **2005**, 249-258.

Bongiovanni, R. and Lowenberg-DeBoer J. (2004). Precision agriculture and sustainability. *Precision Agriculture*, **5**, 359-387.

Chabalala, Y., Adam E. and Ali K.A. (2022). Machine learning classification of fused Sentinel-1 and Sentinel-2 image data towards mapping fruit plantations in highly heterogenous landscapes. *Remote Sensing*, **14 (11)**, 2621. https://doi.org/10.3390/rs14112621

Couture, J.J., Singh A., Charkowski A.O., Groves R.L., Gray S.M., Bethke P.C. and Townsend P.A. (2018). Integrating spectroscopy with potato disease management. *Plant Disease*, **102(11)**, 2233-2240.

De Kleine, M.E. and Karkee M. (2015). A semiautomated harvesting prototype for shaking fruit tree limbs. *Transactions of the ASABE*, **58(6)**, 1461-1470.

Farooque, A.A., Chang Y.K., Zaman Q.U., Groulx D., Schumann A.W. and Esau T.J. (2013). Performance evaluation of multiple ground based sensors mounted on a commercial wild blueberry harvester to sense plant height, fruit yield and topographic features in real-time. *Comput. Electron. Agric.*, **91**, 135-144.

Galan Sauco, V. (2013). World wide Mango production and Market: Current, Situation and Future Prospects. *Acta Horticulture*, **992**, 37-48.

George, Mgendi (2024). Unlocking the potential of precision agriculture for sustainable farming. *Discover Agriculture*, **2**, 87 | https://doi.org/10.1007/s44279-024-00078-3

Greaves, G.E. and Wang Y.-M. (2017). Effect of regulated deficit irrigation scheduling on water use of corn in southern Taiwan tropical environment. *Agricult. Water Manage.*, **188**, 115-125

Hedley, C.B. and Yule I.J. (2009). A method for spatial prediction of daily soil water status for precise irrigation scheduling. *Agricult. Water Manage.*, 96(12):1737- 1745.

Hoèevar, M., Širok B., Godeša T. and Stopar M. (2014). Flowering estimation in apple orchards by image analysis. *Precision Agriculture*, **15**, 466-478.

Jiang, Q., Fu Q. and Wang Z. (2011). Delineating site-specific irrigation management zones. *Irrigation and Drainage* **60 (4)**, 464-472.

Kamilaris, A., Kartakoullis A. and Prenafeta-Boldu F.X. (2017). A review on the practice of big data analysis in agriculture. *Comput. Electron. Agric.*, **143**, 23–37. doi: 10.1016/j.compag.2017.09.037

Karunathilake, E.M.B.M., Le A.T., Heo S., Chung Y.S. and Mansoor S. (2023). The path to smart farming: innovations and opportunities in precision agriculture. *Agric. N*, **13**, 8. https://doi.org/10.3390/agriculture13081593.

Khan, S. and Hussain M.M. (2019). IoT enabled plant sensing systems for small and large scale automated horticultural monitoring. In : *2019 IEEE 5th World Forum on Internet of Things* (WF-IoT). IEEE.303-308.

Koirala, Anand (2020). Precision agriculture: Exploration of machine learning approaches for assessing mango crop quantity. CQUniversity. *Thesis*. https://doi.org/10.25946/13411625

Kumar, M.R., Ahir P.B., Mrinmoy D. and Utkarsh K. (2022). Cloud IoT Applications in Agricultural Engineering. In : *Cloud IoT Systems for Smart Agricultural Engineering*. Chapman and Hall/CRC;1-16.

Kumar, A., Malik S., Chaudhary P. and Kumar N. (2017). Studies on the growth and flowering of different mango (*Mangifera indica* L.) cultivars under Western Uttar Pradesh conditions. *J. Pharmacog. Phytochem*., 439-442.

Lay, L. *et al*. (2023). Evaluation of soybean wildfre prediction via hyperspectral imaging. *Plants*, **12**, 4. https://doi.org/10.3390/PLANTS1204 0901

Liakos, K.G., Busato P., Moshou D., Pearson S. and Bochtis D. (2018). Machine learning in agriculture: a review. *Sensors*, **18**, 2674.

Llorens, J., Gil E., Llop J. and Escolà A. (2011). Ultrasonic and LIDAR sensors for electronic canopy characterization in vineyards: Advances to improve pesticide application methods. *Sensors*, **11(2)**, 2177-2194.

Ma, M., Liu J., Liu M., Zeng J. and Li Y. (2021). Tree species classifcation based on sentinel-2 imagery and random forest classifer in the eastern regions of the qilian mountains. *Forests*, **12**, 12. https://doi.org/10.3390/F12121736.

Mekonnen, Y., Namuduri S., Burton L., Sarwat A. and Bhansali S. (2020). Review—machine learning techniques in wireless sensor network based precision agriculture. *J Electrochem Soc.*, **167**(3), 037522. https://doi.org/10.1149/2.0222003jes.

Miller, P.C. and Paice M.E. (1998). Patch spraying approaches to optimise the use of herbicides applied to arable crops. *J Royal Agric Soc Eng*., **159**, 70-81.

Miller, R.O., Pettygrove S. and Denison R.F. (1999). Site Specific Relationships between Flag Leaf Nitrogen, SPAD Meter Values and Grain Protein in Irrigated Wheat. *Crop Sci Soc America*, **1999**, 113-122.

Mondal, P., Tewari V.K. and Rao P.N. (2004). Scope of precision agriculture in India. In: *Proc of International conference on emerging technologies in agricultural and food engineering, Kharagpur, India*, **101(6)**, 28.

Neményi, M. *et al*. (2022). Challenges of sustainable agricultural development with special regard to Internet of Things: Survey. *Prog Agric Eng Sci.*, **18(1)**, 95–114. https://doi.org/10.1556/446.2022.00053.

Parthiban, S., Santhi V.P., Snehapriya M.S., Indumathi K. and Masilamani P. (2020). Recent Advances in Enhancing the Productivity of Mango (*Mangifera indica* L.) through Hi-tech Practices. *Int. J. Curr. Microbiol. App. Sci.*, **9(08)**, 1850-1864. doi: https://doi.org/10.20546/ijcmas.2020.908.212

Perea, R.G.I., Daccache A., Dý´az A.R.G., Poyato E.C. and Knox J.W. (2017) Modelling impacts of precision irrigation on crop yield and in-field water management. *Precision Agriculture*.

Pereira, C.S., Morais R. and Reis M.J. (2017). Recent advances in image processing techniques for automated harvesting purposes: A review. In : *2017 intelligent systems conference (IntelliSys)*. IEEE. 566- 575

Punithavathi, R. *et al*. (2023). Computer vision and deep learning-enabled weed detection model for precision agriculture. *Comput Syst Sci Eng*., **44(3)**, 2759–2574. https://doi.org/10.32604/CSSE.2023.027647.

Pydipati, R., Burks T.F. and Lee W.S. (2006). Identification of citrus disease using color texture features and discriminant analysis. *Comput. Electron. Agric.*, **52(1-2)**, 49-59.

Qureshi, W.S., Payne A., Walsh K.B., Linker R., Cohen O. and Dailey M.N. (2017). Machine vision for counting fruit on mango tree canopies. *Precis. Agric*., **18**, 224–244. doi: 10.1007/s11119-016-9458-5

Rivera, G., Porras R., Florencia R. and Sánchez-Solís J.P. (2023). LiDAR applications in precision agriculture for cultivating crops: A review of recent advances. *Comput Electron Agric*., **207**, 107737

Roberson, G.T. (1999). 644 Precision Agriculture Technology for Horticultural Crop Production. *Hort Science*, **34(3)**, 558E-558.

Rosas, J.T.F., de Carvalho Pinto F.A., Queiroz D.M., Melo Villar F.M., Magalhaes Valente D.S. and Nogueira Martins R. (2022). Cofee ripeness monitoring using a UAV-mounted low-cost multispectral camera. *Precis Agric*., **23(1)**, 300–318.

Sankaran, S., Mishra A., Ehsani R. and Davis C. (2010). A review of advanced techniques for detecting plant diseases. *Comput. Electron. Agric*., **72(1)**, 1-13.

Schachtl, J., Huber G. and Maidl F.X. (2005). Laser-induced chlorophyll fluorescence measurements for detecting the nitrogen status of wheat (*Triticum aestivum* L.) canopies. *Precision Agric*., **6**, 143-156.

Shin, J., Mahmud M.S., Rehman T.U., Ravichandran P., Heung B. and Chang Y.K. (2023). Trends and prospect of machine vision technology for stresses and diseases detection in precision agriculture. *AgriEngineering*, **5(1)**, 20–39. https://doi.org/10.3390/agriengineering50100 03.

Sishodia, R.P., Ray R.L. and Singh S.K. (2020). Applications of remote sensing in precision agriculture: A review. *Remote Sensing*, **12(19)**, 3136.

Skolik, P., McAinsh M.R. and Martin F.L. (2018). Biospectroscopy for plant and crop science. In : *Comprehensive analytical chemistry*. *Elsevier,* **80**, 15-49.

Spilker, J.J. (1996). Overview of GPS operation and design. *Global Positioning System: Theory and applications*, **1**, 29-55.

Srivastava, A.K., Singh S. and Diware V.S. (2009). Site-specific nutrient management in 'Mosambi'sweet orange. *Better Crops-India*, **3(1)**, 10-11.

Srivastava, A.K. and Singh S. (2004). SiteSpecific nutrient management in 'Mosambi' Sweet Orange. *Comm. Soil Sci. & Pl. Anal*., **35(17/18)**: 2537-2550 (2004 and 2006).

Tiwari, P.S., Sahni R.K., Kumar S.P., Kumar V. and Chandel N.S. (2019). Precision agriculture applications in horticulture. *Pantnagar J. Res*., **17(1)**, 1-10.

Vaghela, H.P. *et al*. (2022). Comparison of Support Vector Machine and k-Nearest Neighbor Classifiers for Tree Species Identification. *Indian J. Radio & Space Physics* (*IJRSP*), **50(4)**, 204–210.

Verma, Tarun Adak and Kailash Kumar (2018). An Expert System for Identification of Nutrients Deficiency/ Disorder and Their Management Advisories in Mango (*Mangifera indica* L.). *J. Agricult. Physics,* **18 (1)**, 74 - 81.

Yule, I.J., Hedley C.B. and Bradbury S. (2008). Variablerate irrigation. In 12th Annual Symposium on Precision Agriculture Research & Application in Australasia, Sydney. 24-26.

Zhang, Y., Wang M., Mango J., Xin L., Meng C. and Li X. (2024). Individual tree detection and counting based on highresolution imagery and the canopy height model data. *Geo-spatial Information Science*, p. 1–17. https://doi.org/10.1080/10095020.2024.2336604