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Smart Agricultural Machinery and Mechanization: A Review of Automation, Precision Farming, and Emerging Technologies

Naz M. Ghazi
College of Agriculture, University of Kirkuk, Kirkuk, Iraq

Skala S Othman
College of Agriculture, University of Kirkuk, Kirkuk, Iraq

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Abstract: The emergence of smart agricultural machinery has become one of the key aspects of modern agricultural mechanization driven by the development of automation and precision agriculture technologies along with sensor systems and artificial intelligence. This review provides a thorough synthesis of the technological development of agricultural machineries and how it has been integrated with intelligent systems of operation enabling data-driven, adaptive, and efficient operations of the field. The review examines automation and guidance systems development, precision farming technologies, sensors-based data collection, and artificial intelligence and machine learning use in agricultural machineries. The important issues regarding integration of the system, quality of data, economic viability, and adoption are also discussed. The data highlights the role of smart agricultural machinery as a key aspect of improving the efficiency of operations, resource management, and ensuring sustainability in the contemporary agriculture. Constant studies and responsible use of new technologies must be mandatory in order to achieve the maximum potential of intelligent mechanization of future agricultural systems.

Keywords: Farm automation; Sensor; Artificial intelligence; Machine learning.

Introduction

Mechanization of agriculture has taken a central role in changing the farming systems in terms of increasing the productivity, reducing workforce, and increasing the efficiency of the entire agricultural activities. The initial mechanization was mainly aimed at replacing human and animal labor with mechanical energy thus ensuring that fields activities like tilling, planting, harvesting and transportation could be done promptly. Such inventions formed the basis of modern day farming equipment and played a significant role in the growth of the farmlands and the increase in the yields of the crops on a large scale, on the planet levels (Srivastava et al., 2006).

Over the past decades, the world agriculture has been facing mounting pressures by population growth, food security, climatic variability, scarcity of labor, and the need to make use of natural resources in a sustainable manner. These demands have enhanced the acceleration process of mechanization in conventional machinery with intelligent agricultural machinery systems that combine automation, digital technologies, and real-time data processing. Smart agricultural machinery can be considered a paradigm shift when the machine is not just a mechanical device but an object that can perceive field conditions and process data and be used to adjust to adaptive decisions when carrying out farming activities (Bechar & Vigneault, 2016).

Automation has become the key factor of intelligent agricultural mechanization. The use of technologies, like GPS-based guidance and auto-steering, have significantly increased the accuracy and reduced overlaps and omissions in the field operations, fuel and time efficiencies. This rise in automation allows machinery to vary seeding rates, fertilizer application intensity and spraying intensity with spatial variations in fields, which improves the efficiency of inputs and reduces the environmental impact (Pierce and Nowak, 1999). These machine robots are the technological basis of the precision farming practices.

Precision farming or precision agriculture is a technology that is based on the combination of intelligent machines with positioning devices, sensors and variable-rate technologies, to enable site-specific management of the crop. Precision farming aims to maximize the production and reduce wastage and other negative environmental impacts by using the agricultural inputs as per the real requirements of crops and the soils. Enormous amounts of literature have proven the promise of precision agriculture technologies to promote resource-use efficiency as well as to promote sustainable agricultural production given optimal implementation (Zhang et al., 2002).

The fast development of artificial intelligence and machine learning has also increased the functional ability of smart farming machines. There are growing applications of AI-based algorithms in crop and weed identification, prediction of yield, optimization of machinery routes, operational decision support and more. These systems are able to handle large amounts of data based on sensors, remote-sensing systems and machineries logs and as such enable machines to learn as they go and become better in the long-term. Therefore, the agricultural mechanization is gradually being shifted towards intelligent and autonomous systems (Liakos et al., 2018).

Autonomous machinery and robotics is a significant area of smart mechanization in agriculture. Robotic weeders, harvesting robots and autonomous tractors have left the laboratory phase to the early phases of commercial viability. They have the potential to offer solutions to the labor shortages, increase the precision of operations, and allow constant monitoring of crops, as well as the state of the fields. Nonetheless, there are still obstacles related to system reliability, safety, cost, and regulatory structure, thus limiting usage (Bechar and Vigneault, 2016).

In spite of the technological advancement that has been made in smart agricultural machinery, its adoption has not been evenly spread across the regions and farming systems. The high cost of starting up, lack of access to digital infrastructure, lack of technical know-how, and lack of confidence in the economic benefits are some of the major hurdles to adoption, especially in developing economies. In addition, the long-term environmental and socio-economic effects of high-level mechanization require strict evaluation to make sure that their priorities are in line with the sustainability priorities and rural developmental policies (Lowenberg-DeBoer and Erickson, 2019).

Since the field of smart agricultural mechanization is developing fast and is highly multidisciplinary, it is reasonable to conduct an overview of the current technologies and the new trends. Although several studies have analyzed each of the aspects separately, including automation, precision farming, robotics, or artificial intelligence, a synthesis, which unites these elements in the environment of the whole phenomenon of agricultural mechanization is not very wide. This gap is discussed in this review through the examination of the development, implementation, challenges and future outlook of smart agricultural machinery, with specific reference to automation, precision farming technology, and new intelligent systems.

The aims of this review are to describe the technological development of agricultural mechanization to smart machinery, assess the contribution of automation and artificial intelligence to more effective performance and decision-making of machines, and discuss the issues and gaps in the research that should be filled to facilitate sustainable adoption. This review is important in making a more in-depth comprehension of the manner in which smart agricultural machinery is revamping the contemporary agriculture and future of farming systems.

Methodology of the Review

The current review was developed as a systematic, transparent, and reptible literature review on smart agricultural machinery and mechanisation with specific focus on automation, precision farming, and new technology. To increase the rigor of the reporting, in addition to to make the entire review process fully auditable, the general logic of reporting was consistent with the PRISMA2020 recommendations regarding the systematic reviews, especially transparent documentation of the identification, screening, eligibility, and inclusion criteria (Page et al., 2021).

The protocol was based on the existing evidence-based review principles that are common in applied sciences and technologies research aimed at management. These guidelines focus on clear search methods and clear inclusion criteria, uniform screening, and logical synthesis methodology (Tranfield et al., 2003; Okoli and Schabram, 2010). Despite the fact that the topic area is agricultural engineering, systematic review practices were used in the review design as well and this practice is widely used across the engineering and technology disciplines where formal review protocols are used to reduce bias and increase repeatability (Kitchenham and Charters, 2007).

The search in the literature was carried out via the key academic databases containing peer-reviewed studies in engineering, agricultural technology, and computer science. The search was based mainly on multidisciplinary indexing sites and publisher databases which are generally used in scholarship in the fields of agriculture and engineering. Controlled vocabulary and free-text terms were unified in order to represent the domain of mechanization for example, the smart or digital machinery domain, and enabling technologies. List refers to agricultural mechanisation, farm machinery, smart machinery, automation, precision agriculture, variable-rate technology, guidance systems, sensors, machine vision, robotics, autonomous tractors, artificial intelligence, and machine learning, and other terminology which arise due to digital agriculture and cyber-physical systems. Search strings were modified to the syntaxes of each database. In cases where possible, searches were limited to title, abstract and keywords to limit the search to the most relevant articles. In line with best practice of structured reviews, the search procedure was recorded in a recorded form to facilitate replication, such as the final query strings, the date of search execution, and the number of records retrieved at each source (Okoli and Schabram, 2010; Page et al., 2021).

A priori eligibility criteria were used to narrow the focus of the review to those studies that inform directly smart agricultural machinery and mechanisation, but not digital agriculture overall. Articles were included as long as they confirmed the presence of at least one of the following requirements in the field of agricultural machinery or mechanised field operations: (i) automation or control systems on the machinery; (ii) one or more of the following functions of precision agriculture, such as guidance, mapping, or variable-rate capabilities; (iii) sensor-based and remotely gathered machine data; (iv) robotics and autonomous field vehicles; and (v) the application of artificial-intelligence and machine-learning systems in machine decision-support, machine perception, machine robotics, or machine optimisation. Only articles are contained in the review, which were empirical research articles, engineering development articles with evaluated validity, and quality review articles that helped to put into perspective the trends in technology. Such studies were wept out as only those dealing with purely biological results and no machinery implications, or dealt only with remote sensing and nothing to do with machinery action, or were conceptual and not specific or validated, or non-scholarly articles not peer-reviewed. Such systematic inclusion logic represents the need to have explicit and repeatable decisions concerning eligibility as highlighted in systematic review guidance (Page et al., 2021; Kitchenham and Charters, 2007).

The process of screening was done in two parts. Titles and abstracts were filtered out during the first stage to eliminate the records that were obviously irrelevant and those that were duplicated. During the second phase, full texts were evaluated in accordance with the eligibility criteria to verify relevance and fit in methods. Each of these stages was recorded to promote transparency in the ultimate reporting of those studies that were included and those excluded, according to the PRISMA2020 requirements of traceability between the initial identification and ultimate inclusion (Page et al., 2021). The review used standardised decision rules based on the guidance of systematic review methodology to enhance uniformity in the screening process, and reduce subjective judgments and increase reproducibility (Okoli and Schabram, 2010; Tranfield et al., 2003).

The use of quality appraisal and evidence characterisation has been included as the area of the review comprises a variety of heterogeneous types of studies including controlled field experiments, prototype validations, and algorithmic evaluations. Instead of using one medical-style risk-of-bias instrument, which could be inappropriate to the engineering research, the review assessed the strength of the studies based on metrics that are usually suggested to conduct a structured review in technology research, such as problem definition, methods reproducibility, the suitability of the evaluation design, sufficiency of performance metrics, and limitations disclosure. This method is in line with more general principles that systematic reviews are to exercise quality considerations that are adequate to the research tradition and type of evidence being studied (Kitchenham and Charters, 2007; Tranfield et al., 2003).

A structured template was used to extract data to ensure that all studies captured similar information. The elements that were extracted were the agricultural operation context, the type and level of autonomy of the machinery, sensor modalities, positioning and control architecture, the computational or AI methods used, the training or validation data where applicable, the evaluation metrics and the reported results, which were accuracy, efficiency, input savings, operational reliability and implementation constraints. In cases where there were field trials in the studies, the extraction of site conditions and operational parameters was also taken to assist in interpretation of transferability. A systematic and standalone literature review should use a structured extraction process as it decreases errors and assists in making sure that synthesis is based on consistently retrieved evidence (Okoli and Schabram, 2010; Page et al., 2021).

That method of synthesis was descriptive mapping followed by thematic integration. To start with, the evidence base was systematized and categorized into themes that align with the objectives of the review, such as automation and control, precision farming machinery operations, sensing and data collection, robotics and autonomy, and AI-based analytics and decision support. Second, to determine convergent outcomes, common constraints, and situations that can be used to adopt technologies, the review compared technologies among these themes with each other, finding infrastructure requirements, farm-scale considerations, and cost implications of implementation. This is a type of structured narrative synthesis that is employed in multidisciplinary reviews wherein the evidence is heterogeneous and meta-analysis is inappropriate and it serves the purpose of the review to determine the technology trajectories or research gaps (Tranfield et al., 2003; Okoli and Schabram, 2010).

Lastly, the review documented the overall screening pathway, selection choices, and logic of synthesis to facilitate the creation of a PRISMA-like flow diagram and allow the final paper to provide transparent methodological information according to the existing reporting frameworks (Page et al., 2021).

Agri-Mechanization Evolutionary Process.

Agricultural mechanization as a process is long and complex, and the agrarian systems have adapted to the changing socio-economic realities, technological developments, and production demands. Mechanization was not a one-technological revolution; it was a smooth transformation trend of change that was driven by the need to raise the productivity of labor, enhance timely operation, and expand the area of arable land. A clear understanding of this historical trend is essential to put into perspective the arrival of intelligent agricultural machinery as well as to value the technological paths that have shaped the modern agrarianized agriculture.

The first form of agricultural mechanization was characterized by the use of primitive hand tools and animal-powered implements. In order to sustain prolonged periods of time, the energy resources of humans and animals formed the major sources of agricultural production thus limiting the nature and extent of agricultural activities. Tractors like plows, harrows, and seeders were designed in a way that increased the manual labor, but was limited by biological sources of energy. Though the technologies were salient technologies in their temporal context, the productivity of the technologies was small and dependent on labor supply and animal health at a greater extent (Rijk, 1989).

The Industrial Revolution marked a turning point of changes of agricultural mechanization. The development of metallurgy, manufacturing and mechanical engineering helped in the production of better and more durable farm implements. The steam-driven machines became one of the earliest machine innovations that were introduced in the field of agriculture especially in non-portable work like threshing. Although the use of steam power highlighted the possibilities of mechanical energy to transform agriculture, its use in large-scale context was limited due to its high prohibitive costs, complexity of operation, and safety (Binswanger, 1986).

Fundamentally during the early twentieth century, agricultural mechanization was reconfigured with the introduction of the internal combustion engines. Animal traction was gradually replaced by gasoline and diesel-powered tractors, which provided greater power, reliability, and flexibility of operation. Due to the expansion of tractors, farmers were able to operate their fields faster and more efficiently, which led to numerous dramatic improvements in their labor productivity and farm size. This stage of mechanization also enabled standardization of machines and creation of specialized equipments in planting, cultivating, harvesting and post-harvesting (Kutzbach, 2003).

Mechanization of agriculture took a new step after popularizing the use of tractors which was typified by specialization in functions and integrating systems. Design of machinery started to give more consideration to the optimization of the performance by certain crops and farming systems. An example of this stage is combine harvesters, precision seed drills and mechanized irrigation systems where machines were designed to perform multifaceted tasks with increased precision and reduced manpower. At this time, the mechanization has been one of the core elements in the strategies of agricultural modernization, especially in the industrialized countries (Pingali, 2007).

Electronics and digital technologies are new powerful determinants of agriculture mechanization that appeared in the late twentieth century. More accurate control of the operations of the machines and the precondition of automation occurred due to the incorporation of electronic sensors, microprocessors, and control systems into farm machines. Yield monitors, electronic engine management, and primitive onboard diagnostics were only a shift in the thinking of a strictly mechanical system towards the mechatronic machinery with mechanical, electrical, and electronic components (Auernhammer, 2001).

The introduction of precision agriculture also increased the pace of mechanization further by focusing on the spatial and temporal variation in field conditions. Increasingly, mechanized systems were modeled as reacting to site-specific information as opposed to the homogeneous assumptions of a field. Integration of the global navigation satellite systems, computer mapping and computerized controllers allowed the machinery to implement the inputs at different rates depending on the soil properties, the crop conditions and the management goals. This was a paradigm change in how mechanization can be used to help in efficiency in the use of resources and safeguard the environment (Stafford, 2000).

Over the past few years, the computing, communication, and data analytics have had a massive impact on the development of agricultural mechanization. Sensors technologies, wireless connectivity, and embedded computing have come together and have made possible the creation of smart agricultural equipment that can acquire real-time data and use it to make adaptive control decisions. These machines will have the ability to dynamically adjust operational parameters in accordance with changing field conditions to drive mechanization to greater degrees of intelligence and autonomy (Blackmore et al., 2007).

Beyond structural changes in agriculture, such as the shortage of labor and the rising cost of energy, and the growth of environmental restrictions, have influenced the movement toward smart mechanization. These forces have enhanced the need to have machinery systems that are not only effective but also adaptable, expandable and green. Therefore, modern mechanization approaches are progressively preempting a system-level optimization, agricultural machinery performance and farm management targets as well as sustainability objectives (FAO & UNIDO, 2008).

However, the mechanization process in the global context has had a heterogeneous presence in regions. Mechanization in many developing nations is still limited due to lack of access to capital, fragmented land parcels and lack of support facilities. This has created disproportional adoption trends and chronic dependence on practices that are labor intensive. These regional inequalities can only be understood to come up with pathways of mechanization that must be region specific and inclusive, and not that a universal technological model is applicable everywhere (Pingali, 2007).

Altogether, the history of agricultural mechanization shows that the process of adapting technology is a continuous process that is influenced by economic, social, and environmental factors. Since animal-powered tools to machineries driven by engines, and manually operated systems to smart machines with a computer, mechanization has continued to increase the ability of agriculture to meet the ever-increasing demands. This historical approach provides the necessary understanding of the basis on which modern smart agricultural machines have been built and the necessity to ensure that future mechanization plans are in tandem with sustainability, robustness and technological incorporation.

Intelligent Farming Implementations and Design.

Smart agricultural machinery is a new step in the development of the process of agricultural mechanization, which is characterized by the introduction of sensing, control, computing, and communications technologies into the traditional agricultural mechanical systems. In contrast to the conventional farming equipment that mainly performs specific mechanical functions, intelligent machinery is programmed to observe the surrounding environment, information, and modify its behaviour in accordance with the dynamism in the field. This change is part of a wider adoption of cyber-physical systems in agriculture whereby physical equipment and digital intelligence are an integrated system to aid precision, efficiency, and autonomy (Wolfert et al., 2017).

The idea of smart agricultural machinery is directly interconnected with the idea of smart farming and digital agriculture. In its most basic form, a smart machine is a combination of mechanical subsystems, electronic hardware, embedded software and connection to data. These elements allow the machine to gather data when it uses sensors, process this data with controllers or artificial intelligence and implement optimised actions when it makes use of actuators. The resulting system architecture enables the machines to cease manual or strictly automated control in favor of adaptive and semi-autonomous control (Tzounis et al., 2017).

Architecturally speaking, one can also define smart agricultural machinery as a layered system. The lowest level is the mechanical and power-train parts which provide traction, implement operation and transfer of energy. This is topped by the sensing layer that has position, speed, force and soil properties, crop, and environmental sensors. These sensors give the raw data to be used in the decision-making and situational awareness. Such common sensing systems may be GNSS receivers, inertial measurement unit, optical cameras, multispectral sensors, and load or pressure sensors attached to the machine parts (Noguchi, 2004).

The information received by the sensors is manipulated in control and computation layer of the architecture. This layer usually includes embedded controllers, on-board computers, and software modules that have the data fusion, signal processing and control logic. Control algorithms must control functional capabilities of the machine such as steering, speed regulation, implement-depth adjustment, and application rate optimization. In more advanced systems, other software modules can be added to contain decision rules or learning-based models to add further performance to the system.Embedded computing power has also become progressively accessible which has facilitated more advanced control tactics such as model-based control and machine-learning-supported adaptation (Bac et al., 2014).

Another critical architecture element of smart agricultural machines is communication. Machines need to communicate with each other and external communication with other machines, farm management systems, and cloud-based systems. Today, standardisation of communication protocols is of pivotal importance to the interoperability and successful exchange of data. The ISO 11783 standard, often referred to as ISOBUS, offers an accepted standard of communication between implants and tractors in agricultural machinery, allowing them to communicate with each other plug-and-play and coordinate with each other (ISO, 2019).

The smart agricultural machinery architecture is characterized by the integration of the positioning and navigation subsystems. The GNSS-based guidance systems enable machines to pinpoint their location to a great degree of precision and to trace the predetermined paths when operating in the field. Navigation architecture has been of special concern to applications like autonomous tractors and robotic field vehicles when localisation and motion control of the vehicle are extremely important to ensure safe and efficient movement (Noguchi, 2004).

Architectural designs of smart agricultural machinery are becoming more connected to the outside information systems. The wireless communication technologies allow machines to send operational data to the farm management platforms, get prescription maps, and coordinate activities between fleets of machines. This interconnectedness enables the use of data to make decisions at the farm level and to integrate machinery with larger precision farming and farm management information systems. The architecture is a manifestation of the shift towards networked systems of standalone machines in digital agro-ecosystems (Wolfert et al., 2017).

The interaction between human beings and machines is still an essential point to be taken into account when developing smart agricultural machine architecture. Despite the rise in automation and autonomy, operators should be in a position to monitor the status of a system, interfere when required and know how the machine behaves. The interface of complex machine architectures with human operators is provided by user interfaces, such as in-cab displays and control panels or decision-support dashboards. The approach to smart machinery systems should include effective interface design to guarantee safety, usability, and trustworthiness among the operators (Tzounis et al., 2017).

The smart agricultural machine should also be designed to meet the aspect of robustness and reliability in the harsh operating conditions. Agricultural lands subject any machinery to dust, moisture, vibrations and extreme temperatures, which may impact sensor functionality, electronics, and communication network. Therefore, redundancy, fault detection and fail-safe techniques should be integrated in system architecture to ensure the system remains functional and safe in the face of change. The needs set by agricultural machinery architecture are not present in many other cyber-physical systems (Bac et al., 2014).

On the whole, the ideas and design of smart agricultural machinery represent the integration of mechanical engineering, electronics, computer science and agricultural systems expertise. Combining sensing, computation, control, and communication into one system, smart machinery offers the technical basis of automation, precision farming, and new autonomous systems. This architecture is fundamental in understanding the existing abilities, design constraints, and future research and development in the smart agricultural mechanisation field.

Agricultural Machinery Automation.

Automation has proven to be a hallmark of modern agricultural machinery, a symptom of the larger paradigm shift of mechanization as relying on operator intervention to systems that can perform tasks with considerably reduced human intervention. In agronomic context, automation refers to the implementation of control systems, sensors and actuators that autonomously execute machine tasks in response to preset instructions or real-time feedback regulation systems. The motivation behind the incorporation of automation in farm machinery is the need to increase precision of operations, reduce the need to depend on human forces, ensure safety and increase efficiency at large in agricultural production systems (Reid et al., 2000).

The initial developments of automation in agricultural equipment mainly focused on simpler control mechanisms, including control of engine speed, implement depth and power transfer. Mechanical and hydraulic control systems could only allow automated performance of tasks to a degree and did not allow adaptation to changing conditions in the field. The introduction of electronic control units was an extremely important breakthrough, as it allowed managing machine operations more accurately and reliably. These inventions formed the foundation of further advanced systems of automation by enabling feedback-controlled adjustments instead of the fully manual changes (Stout, 1990).

Automated guidance and steering systems are some of the most popular automation systems embraced in the agricultural industry. These systems combine world navigation satellite systems together with onboard controllers to steer machinery on predetermined paths at a high level of accuracy. The use of automated steering helps in reducing fatigue of the operators, the efficiency of the field coverage and minimisation of overlaps and gaps during the course of activities like planting, spraying and harvesting. Previous research shows that the automation of guidance can significantly improve operational efficiency and use of inputs in comparison with manual steering (Reid et al., 2000).

Automation has also been widely used to introduce control in agricultural machinery. Automated control systems can be used to vary the rate of seeding, fertilizer rates and the intensity of sprays to accommodate spatial variations within fields. These systems are based on sensors and advanced control algorithms to modify machine outputs as they occur and, as such, allow site-specific management practices. Precision farming is built on automated implementation control as one of its main components and it is here that mechanisation leads to environmental stewardship and resource efficiency (Stafford & Ambler, 1994).

Variable-rate technology is the idea that represents a higher level of automation, which integrates sensing, decision-making, and actuation. Variable-rate systems automatically make changes in the application of farm inputs depending upon prescription maps or real-time sensor data. Such technologies have been demonstrated to decrease the cost of input, environment and preserve or even enhance the yield of crops. Automation also guarantees that such systems can be used over large field areas and they will consistently behave in an accurate way which cannot be achieved through simple manual control (Auernhammer, 2001).

Greater levels of automation include supervisory and semi-autonomous systems of control. In these systems, machines perform the work without human intervention as human operators oversee performance and intervene when the system fails. Examples are automated headland turning, adaptive speed control and obstacle detection systems. These functions increase safety and performance without sacrificing a human-in-the-loop structure necessary to complex and uncertain agricultural conditions (Wilson, 2000).

Automation has an important role in the development of fully autonomous farming machines as well. Autonomous systems require complete automation of all machine activities such as perception, navigation, decision-making and actuation. Even though in commercial agriculture full autonomy is not yet achieved, experimental and early commercial systems do show that highly automated operation with controlled conditions is possible. Such advances make it clear that with the ability to reach autonomy, the presence of a strong automation architecture is a condition (Thornton et al., 2017).

Although there are many advantages to the use of automation in farm machinery, there are a few challenges associated with its use. Barriers are the complexity of the system, reliability in extreme field environments, high initial cost of investment, and the training the operator needs. Further, automation leads to increasing reliance on electronic parts and programs, and issues associated with maintenance, interoperability and system failure. These issues require careful system design and ongoing testing of the automation systems in actual operation (Wilson, 2000).

All in all, automation has changed the farming machinery that was used in manual mode to smart machinery that can perform its work accurately and consistently. Automation boosts the performance of mechanised agriculture through the decrease in the number of people working in the field and the increase in the accuracy of operations, making it easier to go to the next stage of precision farming and autonomous machinery. Knowledge of automation purpose and constraints cannot be disregarded to assess the existing mechanisation approaches and shape the future of smart agricultural machinery.

Precision Farming Technologies in Smart Machinery

Precision farming technologies are a pillar of modern smart agricultural machinery as they enable mechanized systems to operate with more accuracy in spatial and temporal variability in the agricultural field. Unlike the traditional farming patterns where fields are considered as homogenous entities, precision farming recognises the differences in the soil properties, crop development and environmental factors. This information is used to optimise field tasks by intelligent machines with accuracy technologies to increase resource-use efficiency and productivity and reduce environmental effects (McBratney et al., 2005).

Precision farming is comprised of smart farming machines combined with positioning technologies. Global Navigation Satellite Systems help machines to determine where they are with a great deal of accuracy and repeatability and become the basis of guidance, mapping, and site-specific management. GNSS-based machines are useful in tracking of paths, traffic cultivation, and seasonal similarity, helping to align the mechanised actions with spatial data layers and enable a congruent application of precision management procedures (Taylor et al., 2007).

Geographic information systems are extremely important in precision farming as they provide a platform where the spatial data recorded by smart machines and field sensors can be stored, analyzed and visualized. GIS tools are regular in producing yield maps, soil maps, and management zones and enable farmers and managers to recognise patterns of variability and develop specific interventions. Combined with the machinery control system, GIS-based prescription maps make it possible to implement variable-rate operations automatically, tying the analysis directly to the action of the mechanised system (Moran et al., 1997).

Precision farming systems installed on smart agricultural machines are based on sensor technologies. On-machine sensors get real time information about crop condition, soil properties, and machine performance. Optical sensors are extensively used in measuring the crop vigor and nutrient status, and the soil sensors provide data on moisture content, electrical conductivity, and compaction. Such sensor-based measurements allow machinery to dynamically react to field conditions to facilitating the map-based as well as sensor-based precision farming strategies (Adamchuk et al., 2004).

Variable-rate technology is one of the oldest and the most influential implementations of precision farming in smart machinery. Variable-rate technology (VRT) systems automatically change the input application rates, e.g. seed, fertilizer, agrochemicals, depending on spatial information or real-time sensor feedback. VRT ensures that there is no over-application and minimized costs of production by making input application consistent with the real needs of the field and minimizes the adverse environmental impacts. Several studies have also shown the agronomic and economic advantages of application of variable-rate in situations based on correct information and sound machinery control mechanisms (Gebbers and Adamchuk, 2010).

The use of yield monitoring systems fitted in harvesting machines has played a significant role in enhancing precision farming. This information will be an important feedback on the effectiveness of the management practices and a basis of further accuracy interventions. The adoption of smart machinery has changed the conventional harvest operations that are only production activities to data-collection processes (Blackmore et al., 2003).

Precision farming technologies also help in better management of machinery and efficiency in operation. Smart machinery is able to generate optimal travel paths, minimize unneeded passes and minimize compaction of the soil by combining spatial data with machine performance measurements. An example of precision technologies used to increase agronomic performance and machine efficiency is controlled traffic farming system that is made possible by accurate guidance and repeatable machine tracks (Tullberg et al., 2007).

Even with the potential, precision farming technologies face a number of challenges associated with the quality of data, integration, and economic feasibility of the system. Precision farming will require proper data collection and proper data interpretation and proper implementation by the machinery systems. Irregularities in sensor operations, data management complications, and the costly equipment may limit uptake, especially by small and medium-sized farms. To overcome these issues, further refining of user friendly systems, standardisation of data formats and improving the integration of machinery, software platform and decision support tool became necessary (McBratney et al., 2005).

On the whole, smart farming technologies integrated in agricultural machinery give a potent system to improve mechanised agriculture. Precision farming allows better management of agricultural systems by connecting spatial data, sensing technologies and automated machine control. These technologies are a very important linking point between the relatively old mechanisation and new intelligent and autonomous machines, which explains why they are at the center of the future of smart agricultural production systems.

Data Acquisition Systems and Sensors.

The technology behind smart agricultural machinery includes sensors and data-acquisition systems which allow such machinery to derive meaning out of the field conditions, keep track of operational performance, and aid in the data-driven decision making. Automation, precision farming, intelligent control, etc. are advanced features that cannot be achieved without quality sensing and systematic data acquisition. Sensors in intelligent mechanization translate physical, chemical and biological variables into digital data that may be manipulated by onboarding controllers or external information systems which is the first stage of the data-information-decision chain.

Agricultural sensors are of two major categories, which are determined by the nature of the variable that is measured by the sensor and how it is to be used by the machinery system. The typical ones are soil sensors, crop and plant sensors, environmental sensors, machine-state sensors and positioning sensors. These categories have specific functions in the realization of mechanized operations; some of the sensors watch the moisture of the soil and the condition of nutrients, others observe the speed, load and fuel consumption of machines. The different types of sensors are combined to give a wide situational awareness and the adaptability of intelligent agricultural machines (Viscarra Rossel et al., 2010).

The best studied sensor applications in smart agriculture refers to the soil-sensing sensors. The soil moisture, electrical conductivity, temperature and compaction sensors provide essential data to be used in irrigation management as well as optimization of the tillage and traffic control. More accurate results may be gained by proximal soil-sensing methods which send information directly to field equipment, thus it is possible to map soil properties with a high degree of spatial resolution. These data make it possible to manage the sites specifically and enhance the efficacy of water, energy, and input (Robinson et al., 2008).

Crop and plant sensors are needed to estimate the conditions of crops and control variable-rate functionalities. Optical and multispectral sensors on machinery or implements measure canopy reflectance and vegetation indices which are related to biomass, nitrogen status, and plant health. The thermal sensors, which indicate the variation in canopy temperature, are used to infer crop water stress. These sensing schemes can be used to real-time assess the crop conditions and dynamic control of the input application in the field (Jones, 2004).

Environmental sensors are the ones which give contextual information which helps in determining crop development and machine operation. Air temperature, humidity, solar radiation, wind speed and rainfall measurements are needed to streamline the spraying processes, irrigation schedules and when to harvests will occur. Environmental sensors can assist in automated decision rules taking into consideration weather-related constraints by being integrated into machine systems, thus improving the safety of the mission, its effectiveness and minimizing the chances of off-target effects (Ruiz-Garcia et al., 2009).

Machine-state sensors are very important when it comes to measuring the performance and health of the agricultural machine operations. Some of the variables that are measured by such sensors are engine speed, torque, fuel consumption, hydraulic pressure, implement position, vibration, and load. Data provided by machine-state sensors can be used to control through automated control, predictive maintenance, and optimization. Intelligent farm implements are able to detect abnormal machine performance, minimize downtimes and improve reliability of operations in the harsh field conditions (Stone et al., 2000).

Smart machinery systems necessitate data-acquisition systems that need positioning and motion sensors. Absolute positioning is through the global navigation satellite system where the inertial measurement unit would give the data on the direction, acceleration, and angular velocity. Positioning and motion sensor data integration allows the accurate localization, navigation and direction control, especially in automated and autonomous work. The proper operation of precision field activities, which are accurate and safe, requires proper gathering of the data of these sensors (Grewal et al., 2013).

Data-acquisition systems comprise the interface between the sensors and the higher-level processing or control modules. These systems perform signal processing, sampling, synchronization and data storage or transmission. The data-acquisition system used in agricultural machines has to run well during vibration, dust, moisture and high-temperature conditions. Firm hardware design and correct sampling methodology are thus critical to the assurance of data integrity and reduction of signal noise in real world operating environment (Campbell and Norman, 1998).

The growing amount of sensor information obtained by intelligent agricultural machines and its variety make the efficient management and communication of these data essential. In-flight preprocessing of data-acquisition systems can include downsampling and feature selection before transmission. Real-time data transfer to farm-management systems or cloud computing platforms through wireless communication technologies can enable machines and operations to integrate data. It is necessary to detect efficient data collection and control methods to convert the raw sensor signals into useful information (Ruiz-Garcia et al., 2009).

The sensor and data-acquisition systems can be subject to diverse limitations even though they can be utilized in the agriculture sector. Precision of measurement could be influenced by sensor calibration, drift, or time degradation. Both field conditions and biological systems are variable creating uncertainty that makes it difficult to interpret the data. In addition, the heterogeneity of sensors implemented on widespread machine platforms necessitates standardization and interoperability that happen to be major problems in smart agricultural mechanization (Viscarra Rossel et al., 2010).

Altogether, sensors and data-acquisition systems are the most basic components of smart agricultural machinery. Such systems provide automation, accuracy in farming and smart control by facilitating ongoing monitoring of the soil, crops, environmental factors and machine operation. The way smart mechanization evolves will also depend on the improvement of sensor technology, data-augmentation devices, and data assimilation methods in the future and define the success of new technologies in agriculture.

Smart Agricultural Machinery with Artificial Intelligence and Machine Learning.

Machine learning (ML) and artificial intelligence (AI) are now considered as the revolutionary technologies in production of smart agricultural machines allowing systems to switch between the rule-based automation to data-driven adaptive intelligence. Application In the field of agricultural mechanization, AI refers to computation procedures that can enable machines to observe their environment, process and analyze complex data, learn, and make decisions with less human input. ML as a subfield of AI focuses on algorithms that improve in performance by being exposed to data instead of being written in explicit code. Collectively, these technologies form an essential facilitator of smart and self-contained farming equipment.

The increased supply of sensor data, increases in computational power, and improvement in learning algorithms have driven the integration of AI into agricultural machines. Modern intelligent equipment produces massive amounts of data on sensors which track the soil conditions, crop conditions, machine condition, and environmental factors. AI offers the analytical tools that are necessary to identify meaningful patterns in these data streams and convert them into actionable decisions in the field operations. This is necessary to deal with the complexity and variability of an agricultural system (Kamilaris and Prenafeta-Boldu, 2018).

The use of ML techniques in smart farming machinery on perception has been widely implemented. Convolutional neural networks of computer-vision systems allow machines to detect crops, weeds, fruits, and obstacles in real time with the help of camera and imaging data. These functions aid automated weeding, discerning harvesting, and heedless evading in autonomous field operations. ML-based techniques show higher resilience to changing lighting conditions, crop development, and conditions at the field compared to the conventional ones in the image-processing (LeCun et al., 2015).

In smart machines, AI is also a key component of decision support and optimisation. Crop yield, input requirements and operational optimisation parameters e.g. speed, path planning and rate of application are predicted using supervised and unsupervised learning algorithms. Machinery control has also been studied using reinforcement learning methods where the systems learn the best actions after interacting with the environment. Such methods facilitate flexibility in behaviour capable of enhancing efficiency and decrease utilization of resources in the long run (Shamshiri et al., 2021).

The AI-based data fusion and decision-making are crucial in navigation and autonomy in agricultural machinery. ML algorithms combine the information of GNSS, inertial sensors, cameras, and lidar to provide robust localisation and navigation on the field in challenging and unstructured environments. AI allows machinery to deal with a sense of uncertainty, anomaly, and react to dynamic challenges, which are typical issues in agriculture. These functions are necessary to the safe use of autonomous tractors and robotic field cars (Duckett et al., 2018).

Predictive maintenance and machinery health monitoring with the use of AI have also been implemented. Through the analysis of trends in machine-state sensor data, ML models are able to identify the early indicators of component failures, predictive useful life and facilitate anticipatory maintenance scheduling. This is an application that ensures reduced downtime, reduced maintenance expenses and enhanced reliability of agricultural machinery systems that have to work in harsh field conditions. One of the important economic advantages of AI implementation in mechanised agriculture is predictive maintenance (Zhang et al., 2019).

Even if it has the potential, AI adoption in agricultural machinery is accompanied by a number of difficulties. The quality and representativeness of training data is very important to the performance of ML models, which may be challenging to collect in heterogeneous agricultural settings. Crop, soil, climatic, and management practices variations constrain the generalisability of models that have been trained on small data sets. Moreover, the hardware onboard hardware may not be able to run the more complex AI algorithms, which might require the use of hybrid architectures that integrate edge computing with cloud-based processing (Kamilaris and Prenafeta-Boldu, 2018).

Interpretability and trustworthiness of AI systems is another factor that needs to be taken into consideration. Most ML models, especially deep-learning systems, are black boxes which complicates the processes by the operators and engineers to comprehend the decision-making. Safety-critical systems like autonomous machinery may not be accepted and regulated without transparency. The field of explainable AI focuses on mitigating this issue by creating models and tools that allow understanding decision-making and still perform well (Samek et al., 2017).

There are also ethical, legal, and socio-economic concerns that the introduction of AI into agricultural machines will bring. Greater autonomy brings issues to do with liability, data ownership, workforce diminishing, and equitable access to technology. To solve these problems, engineers, policymakers, and other stakeholders must work together to make sure that AI leads to sustainable and inclusive agricultural progress instead of increasing the existing inequalities (Ameen, 2025; Hasan et al., 2024; Shamshiri et al., 2021).

Finally, AI and ML are the next stage of technological progress in smart agricultural equipment, as they allow the systems to sense, study and evolve in the sophisticated agricultural settings. AI greatly expands mechanised farming by improving its perception, decision making, autonomy and maintenance. Although not all the technical and socio-economic obstacles have been eliminated, further studies and sustainable implementation of AI have significant potential in enhancing productivity, efficiency, and sustainability in the agricultural systems of the future. In that regard, AI can be viewed as a characteristic of the future of agricultural mechanisation.

Conclusion

The current review confirms that intelligent agricultural machinery is one of the important trends in agricultural mechanization, which is implemented by applying automation and precision farming techniques, sensing systems, and artificial intelligence. A combination of these technologies has brought about a significant improvement in precision and efficiency of agricultural machines working in sophisticated field conditions and at the same time making them more flexible. Despite the existing issues in the form of cost, quality of data, integration of different systems, and adoption, the further technological advancement and research across the disciplines is expected to increase the role of smart machinery in sustainable and productive agricultural systems. In line with this development, smart agricultural mechanization is an important mechanism to the future of modern, data-driven agriculture.

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