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Precision agronomy in semi-arid regions: Role of GIS, remote sensing and AI in crop management

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Abstract

Semi-arid regions occupy a significant portion of the global agricultural landscape and are characterized by low and erratic rainfall, high evapotranspiration, and fragile soil conditions that limit stable crop productivity (FAO, 2021) [3]. Agricultural production in these areas is frequently constrained by soil degradation, nutrient depletion, salinity problems, and poor water-use efficiency, which ultimately reduce crop yield potential (Lal, 2020) [6]. Climate variability, increasing temperature, and uncertain precipitation patterns further intensify production risks, making traditional agronomic practices less reliable for ensuring sustainable food production (IPCC, 2022) [5]. Therefore, advanced technological interventions are required to enhance resource-use efficiency and maintain productivity under moisture-limited environments (Rockström et al., 2017) [9]. Precision agronomy has emerged as a modern crop management approach that uses advanced technologies to manage spatial and temporal variability within agricultural fields (Gebbers & Adamchuk, 2019) [4]. Geographic Information System (GIS) technology plays an important role in collecting, storing, analyzing, and visualizing spatial information related to soil characteristics, crop growth variability, and land suitability (Burrough & McDonnell, 2018) [22, 2]. Remote sensing techniques provide continuous and large-scale monitoring of crop conditions, vegetation indices, soil moisture content, and drought stress using satellite imagery and drone-based sensors (Thenkabail, 2018) [11]. Artificial Intelligence (AI) methods, including machine learning and deep learning algorithms, enable accurate prediction of crop growth, yield estimation, disease detection, and decision-making support systems (Liakos et al., 2018) [7]. Integration of GIS, remote sensing, and AI technologies helps develop site-specific crop management strategies such as precision irrigation scheduling, variable rate fertilizer application, and early stress detection (Zhang et al., 2021) [13]. Remote sensing-based vegetation indices such as NDVI are widely used to assess crop vigor, biomass accumulation, and spatial variability in crop performance across semi-arid regions (Rouse et al., 1974) [10]. Big data analytics, IoT sensors, and UAV technologies further enhance the efficiency and accuracy of precision agriculture systems (Wolfert et al., 2017) [12]. This review highlights the role of GIS, remote sensing, and AI in improving crop monitoring, soil resource management, water-use efficiency, and climate-resilient agriculture in semi-arid regions (Pierce & Nowak, 2019) [8]. The study also discusses technological challenges, research gaps, and future opportunities for sustainable crop production using precision agronomy tools (Bongiovanni & Lowenberg-Deboer, 2018) [1].

Keywords: Precision agriculture, semi-arid regions, GIS, remote sensing, artificial intelligence, crop monitoring, climate-smart agriculture

Introduction

Semi-arid regions cover approximately 40% of the global land surface and are characterized by low and irregular rainfall distribution, high evapotranspiration demand, and inherently low soil fertility that restrict agricultural productivity (UNEP, 2021) [25]. Agricultural systems in these regions are highly vulnerable to climate variability, drought frequency, and limited natural resources, which significantly affect crop growth and yield stability (Dai, 2018) [17]. Water scarcity, declining soil health, and inefficient nutrient management further intensify production risks in semi-arid agroecosystems (Foley et al., 2019) [18].

Therefore, innovative and resource-efficient crop management strategies are essential to sustain agricultural productivity under these challenging environmental conditions (Tilman *et al.*, 2017) ^[23].

Precision agronomy has emerged as an advanced scientific approach that utilizes modern digital tools to manage spatial and temporal variability within agricultural fields (McBratney *et al.*, 2018) ^[22]. Precision agriculture involves systematic collection, processing, and analysis of field-level variability data to support informed decision-making regarding irrigation scheduling, nutrient application, pest control, and crop productivity improvement (Bramley, 2019) ^[15]. The concept focuses on applying the right input, at the right time, and at the right place, thereby improving resource-use efficiency and minimizing environmental degradation (Gebbers *et al.*, 2020) ^[19].

Geographic Information System (GIS) technology helps in mapping soil characteristics, crop variability, and land suitability patterns using spatial databases and geostatistical tools (Tomlinson, 2017) ^[24]. Remote sensing technologies provide continuous monitoring of crop growth, canopy reflectance, vegetation indices, soil moisture status, and stress conditions using satellite and aerial platforms (Xue & Su, 2017) ^[26]. Artificial Intelligence (AI) techniques such as machine learning and data analytics process large volumes of agricultural data to generate predictive models that improve farm-level decision-making accuracy (Chlingaryan *et al.*, 2018) ^[16].

Integration of GIS, remote sensing, and AI-based technologies helps farmers optimize input use, reduce production costs, improve crop yield, and enhance sustainability in moisture-limited semi-arid farming systems (Balafoutis *et al.*, 2017) ^[14]. Digital agriculture tools support climate-resilient crop management by improving water-use efficiency, nutrient-use efficiency, and early detection of crop stress conditions (Khanal *et al.*, 2020) ^[20]. Adoption of precision agronomy practices contributes to sustainable intensification and long-term productivity of semi-arid agricultural systems (Lowenberg-DeBoer *et al.*, 2019) ^[126, 21].

Characteristics of Semi-arid Agriculture

Semi-arid agroecosystems are characterized by multiple biophysical and climatic constraints that limit crop productivity and threaten long-term sustainability of agricultural systems (Reynolds *et al.*, 2017) ^[38]. These regions typically receive low and erratic rainfall, resulting in frequent dry spells and uneven soil moisture distribution that adversely affects crop growth and development (Nicholson, 2018) ^[36]. High temperature stress and intense solar radiation increase evapotranspiration demand, leading to rapid depletion of soil moisture and increased risk of drought stress during critical crop growth stages (Hatfield & Prueger, 2019) ^[32]. Low soil organic matter content is a common problem in semi-arid soils, which reduces water-holding capacity, soil structure stability, and nutrient availability to plants (Minasny & McBratney, 2018) ^[35, 22]. Nutrient deficiencies, particularly nitrogen, phosphorus, and micronutrients, further limit crop productivity due to poor soil fertility and low biological activity (Fixen *et al.*, 2019) ^[31]. Water scarcity remains one of the major limiting factors in semi-arid agriculture, affecting irrigation availability and reducing crop yield potential (Falkenmark, 2017) ^[30]. Land degradation processes such as soil erosion, salinization, and

desertification also threaten the sustainability of crop production systems in these fragile environments (D'Odorico *et al.*, 2018) ^[29].

Major crops cultivated in semi-arid regions include *maize*, *sorghum*, *pearl millet*, *groundnut*, *chickpea*, *sunflower*, and *cotton*, as these crops possess adaptive traits such as drought tolerance and efficient water-use mechanisms (ICRISAT, 2019) ^[33]. Efficient management of water resources, soil fertility, and crop health is essential to maintain productivity and ensure stability of farming systems under limited moisture conditions (Passioura, 2017) ^[37]. Sustainable agronomic practices such as conservation tillage, integrated nutrient management, and crop diversification improve resilience of semi-arid farming systems (Lal *et al.*, 2018) ^[34].

Precision agronomy tools help identify spatial variability in soil moisture status, nutrient availability, and crop vigor using advanced sensing and mapping technologies (Adamchuk *et al.*, 2018) ^[27]. Site-specific crop management enabled by precision agriculture improves input-use efficiency, reduces environmental losses, and enhances productivity in semi-arid agroecosystems (Corwin & Lesch, 2019) ^[74, 28]. Adoption of spatial decision-support tools supports better management of soil and water resources under climate variability conditions (Zhang & Kovacs, 2018) ^[123, 39].

Role of Gis in Precision Agronomy

Geographic Information System (GIS) is a computer-based technology used to capture, store, manage, analyze, and visualize spatial and temporal data related to agricultural resources (Longley *et al.*, 2019) ^[46]. GIS plays an important role in precision agronomy by enabling spatial mapping of soil properties, crop growth variability, and yield distribution patterns across agricultural fields (Mulla, 2018) ^[49]. Spatial analysis using GIS helps researchers and farmers understand field heterogeneity and supports site-specific crop management decisions for improving productivity and resource-use efficiency (Robert, 2017) ^[50]. GIS-based mapping techniques provide valuable insights into soil nutrient variability, soil texture distribution, and land capability classification for sustainable crop production (Heuvelink & Webster, 2019) ^[44].

Applications of GIS in Semi-Arid Regions

GIS technology is widely used for soil fertility mapping, which helps identify spatial variability of essential nutrients and supports precise fertilizer application (Hartemink, 2018) ^[43]. Land suitability analysis using GIS assists in selecting appropriate crops based on soil characteristics, climatic conditions, and topographical features (Malczewski, 2017) ^[47]. Crop zoning helps classify agricultural land into different productivity zones for effective crop planning and management (FAO, 2022) ^[42]. Nutrient variability mapping enables efficient nutrient management by identifying deficient and surplus zones within the field (McBratney *et al.*, 2017) ^[48]. Drought risk assessment using GIS tools helps evaluate spatial patterns of rainfall variability and soil moisture stress in semi-arid environments (Vicente-Serrano *et al.*, 2019) ^[52]. Yield variability analysis supports identification of high- and low-yielding zones, allowing farmers to optimize input use and maximize productivity (Basso *et al.*, 2019) ^[40].

GIS enables integration of multiple spatial data layers such as soil type, rainfall distribution, slope gradient, elevation, and crop productivity to support better farm planning and resource allocation decisions (Tomlinson *et al.*, 2018) ^[51]. Spatial decision-making supported by GIS improves crop selection strategies and enhances efficiency of input management practices under variable environmental conditions (Eastman, 2017) ^[41]. GIS-based decision support systems help optimize fertilizer recommendations and irrigation scheduling by integrating soil, weather, and crop information under limited water availability conditions (Jones *et al.*, 2017) ^[45].

Role of Remote Sensing in Precision Agronomy

Remote sensing is a non-destructive technology that enables acquisition of crop and soil information using satellite platforms, unmanned aerial vehicles (UAVs), and ground-based sensors without physical contact with the field (Campbell & Wynne, 2017) ^[57]. It provides large-scale and real-time observations of agricultural systems, supporting efficient monitoring of crop growth conditions and environmental variability (Pettorelli *et al.*, 2018) ^[62]. Multispectral and hyperspectral imaging techniques capture reflectance patterns from plant canopies, enabling detailed assessment of plant health, chlorophyll content, and stress symptoms under varying environmental conditions (Blackburn, 2018) ^[55]. These technologies provide valuable information about soil moisture dynamics, crop vigor, and nutrient status across spatially heterogeneous agricultural landscapes (Thorpe & Tian, 2017) ^[63].

Key Remote Sensing Applications

Remote sensing plays an important role in crop growth monitoring by assessing canopy structure, biomass accumulation, and phenological development across crop growth stages (Dorigo *et al.*, 2017) ^[58]. Soil moisture estimation using microwave and thermal sensors helps evaluate water availability and irrigation requirements under semi-arid climatic conditions (Wagner *et al.*, 2017) ^[65]. Detection of nutrient deficiency symptoms through spectral reflectance patterns supports early identification of crop stress caused by nitrogen or micronutrient limitations (Mutanga & Skidmore, 2018) ^[61]. Remote sensing imagery is also widely used for pest and disease identification by detecting abnormal crop reflectance signatures associated with pathogen infection or insect damage (Mahlein, 2018) ^[60]. Yield prediction models based on satellite-derived vegetation indices improve estimation accuracy by analyzing temporal crop growth variability (Bolton & Friedl, 2017) ^[56]. Drought stress assessment using thermal and vegetation indices helps identify water stress conditions and supports timely irrigation interventions (AghaKouchak *et al.*, 2018) ^[53].

Vegetation indices such as NDVI (Normalized Difference Vegetation Index) are widely used to assess crop vigor, biomass accumulation, and photosynthetic activity using spectral reflectance characteristics of plant canopies (Tucker, 2017) ^[64]. Remote sensing provides high-resolution spatial datasets that enable monitoring of field variability and improve input-use efficiency through site-specific management strategies in semi-arid regions (Atzberger, 2017) ^[54]. Satellite platforms such as Sentinel and Landsat provide continuous and repetitive coverage, supporting precision irrigation scheduling and nutrient management

decisions through time-series data analysis (Drusch *et al.*, 2017) ^[59]. Integration of remote sensing data with decision-support tools improves sustainability and productivity of modern agricultural systems (Zhang *et al.*, 2019) ^[66].

Role of Artificial Intelligence in Precision Agronomy

Artificial Intelligence (AI) plays a significant role in analyzing large and complex datasets generated from Geographic Information System (GIS) and remote sensing platforms for improved agricultural decision-making (Russell & Norvig, 2021) ^[77]. AI techniques enable efficient processing of multi-source agricultural data, supporting precision agronomy through data-driven insights and automation of crop management practices (Sharma *et al.*, 2020) ^[78]. Machine learning and deep learning algorithms are widely used for prediction, classification, clustering, and optimization of crop production strategies under varying environmental conditions (Elavarasan & Vincent, 2020) ^[69]. AI-based systems improve the accuracy and efficiency of agricultural operations by identifying patterns and relationships within large datasets collected from sensors, satellites, and field observations (Jiang *et al.*, 2021) ^[71].

Major AI Techniques Used in Agriculture

Artificial Neural Networks (ANN) are commonly applied for crop yield prediction, soil property estimation, and irrigation scheduling due to their ability to model nonlinear relationships among agricultural variables (Kaul *et al.*, 2018) ^[72]. Random Forest (RF) algorithms are widely used for crop classification, soil variability mapping, and prediction of agricultural parameters because of their high accuracy and robustness to noisy datasets (Belgiu & Drăguț, 2017) ^[68]. Support Vector Machine (SVM) models are effective in classification of crop types, disease detection, and estimation of soil moisture conditions using spectral datasets (Mountrakis *et al.*, 2018) ^[75]. Convolutional Neural Networks (CNN) are extensively applied for image-based crop monitoring, pest identification, and disease detection using high-resolution remote sensing imagery (Kamilaris & Prenafeta-Boldú, 2018) ^[131, 73]. Deep learning models improve automation in agricultural decision-making by analyzing complex relationships among climatic, soil, and crop growth parameters (LeCun *et al.*, 2019) ^[74].

AI models process large datasets obtained from satellite imagery, UAV data, and sensor networks to identify crop stress conditions such as drought stress, nutrient deficiency, and pest infestation at early growth stages (Singh *et al.*, 2020) ^[79]. Predictive models based on AI algorithms improve crop yield forecasting accuracy and help optimize irrigation scheduling under water-limited environments (Jeong *et al.*, 2017) ^[70]. AI-driven analytics assist in identifying spatial variability in crop growth and support efficient management of agricultural inputs (Pathak *et al.*, 2019) ^[76]. Integration of AI with remote sensing technologies enhances the precision of crop classification, stress detection, and resource optimization in precision farming systems (Zhu *et al.*, 2018) ^[80]. Adoption of AI-based decision support systems contributes to sustainable intensification and climate-resilient agriculture in semi-arid regions (Aggarwal *et al.*, 2018) ^[67].

Integration of Gis, Remote Sensing and Ai

Integration of Geographic Information System (GIS), Remote Sensing (RS), and Artificial Intelligence (AI)

technologies creates an advanced decision support system that enhances precision agronomy through accurate and data-driven farm management strategies (Khanna & Kaur, 2019) ^[86]. Combining spatial datasets from GIS with real-time satellite imagery and machine learning algorithms enables comprehensive analysis of crop variability, soil conditions, and climatic risks (Misra *et al.*, 2020) ^[88]. Integrated digital platforms support improved decision-making by transforming complex agricultural datasets into actionable insights for efficient crop management (Raj *et al.*, 2021) ^[90]. The synergy between GIS, RS, and AI helps optimize agricultural inputs and improves productivity under resource-limited semi-arid environments (Patel *et al.*, 2020) ^[89].

Integrated Applications

Site-specific nutrient management is enhanced through integration of spatial soil fertility maps with AI-based recommendation models, allowing precise fertilizer application across variable field conditions (Bongiovanni *et al.*, 2017) ^[114, 82]. Precision irrigation scheduling becomes more efficient when remote sensing-based soil moisture data are combined with predictive AI algorithms to determine optimal irrigation timing and quantity (Smith *et al.*, 2018) ^[92]. Crop yield prediction models developed using integrated datasets improve forecasting accuracy by analyzing relationships among climate variables, soil parameters, and crop growth patterns (Haghverdi *et al.*, 2018) ^[85]. Climate risk assessment tools based on GIS and AI help identify drought-prone areas and develop adaptive crop management strategies to minimize yield losses (Kourgialas & Karatzas, 2017) ^[87]. Weed and pest detection systems utilize high-resolution imagery combined with deep learning algorithms to detect crop stress symptoms and recommend targeted interventions (Slaughter *et al.*, 2018) ^[91]. Soil quality mapping using integrated spatial technologies helps evaluate soil health indicators and supports sustainable land management practices (Arrouays *et al.*, 2017) ^[81]. UAV-based imaging integrated with machine learning models enables real-time crop monitoring and rapid detection of crop stress conditions, improving decision-making efficiency for farmers and researchers (Tsouros *et al.*, 2019) ^[93]. Integration of GIS, RS, and AI technologies contributes to sustainable agriculture by reducing excessive input use, minimizing environmental pollution, and improving resource-use efficiency (Gebbers *et al.*, 2017) ^[116, 84]. Data-driven agricultural management systems enhance productivity while maintaining ecological balance in semi-arid ecosystems (Finger *et al.*, 2019) ^[83]. Adoption of integrated digital agriculture tools supports climate-resilient farming systems and long-term sustainability of crop production (Walter *et al.*, 2017) ^[94].

Applications in Crop Management in Semi-arid Regions

Precision Irrigation Management

Efficient irrigation management is critical in semi-arid regions where limited water availability significantly restricts crop productivity and sustainability (Feres & Soriano, 2017) ^[100]. Remote sensing technologies enable estimation of evapotranspiration rates and soil moisture conditions using thermal and multispectral imagery, supporting accurate irrigation planning (Allen *et al.*, 2018) ^[95]. Satellite-derived indicators provide continuous

monitoring of crop water requirements across spatially variable fields (Bastiaanssen *et al.*, 2017) ^[96]. AI-based predictive models analyze climatic variables, soil properties, and crop growth parameters to determine optimal irrigation timing and quantity (Nhamo *et al.*, 2020) ^[106]. Precision irrigation systems improve water-use efficiency, reduce water wastage, and enhance crop productivity under moisture-limited environments (Jones, 2019) ^[117].

Nutrient Management

Soil fertility variability is a major constraint in semi-arid agriculture, requiring efficient nutrient management strategies to sustain crop productivity (Srinivasarao *et al.*, 2019) ^[112]. GIS-based spatial maps help identify variability in soil nutrient distribution, enabling site-specific fertilizer recommendations (Heckman & Kamprath, 2018) ^[101]. Variable rate fertilizer application supported by spatial technologies improves nutrient-use efficiency and reduces excessive fertilizer use (Raun *et al.*, 2017) ^[111]. Precision nutrient management practices minimize nutrient losses through leaching and volatilization, thereby reducing environmental pollution (Zhang *et al.*, 2017) ^[122, 113]. Improved nutrient management enhances crop growth, yield stability, and soil health in semi-arid ecosystems (Bindraban *et al.*, 2018) ^[97].

Weed and Pest Management

Early detection of weeds and pests is essential to minimize crop losses and reduce reliance on blanket pesticide application (Oerke, 2018) ^[107]. Remote sensing imagery helps identify spectral variations associated with weed infestation and pest damage at early growth stages (Huang *et al.*, 2018) ^[102]. High-resolution imagery obtained from UAVs improves detection accuracy of spatial weed distribution across agricultural fields (Peña *et al.*, 2017) ^[109]. AI-based classification models analyze crop stress symptoms and differentiate between pest damage, nutrient deficiency, and water stress conditions (Mohanty *et al.*, 2019) ^[105]. Precision pest management strategies reduce pesticide use, lower production costs, and minimize environmental contamination (Popp *et al.*, 2018) ^[110].

Crop Yield Prediction

Crop yield prediction is an important component of precision agronomy that supports farm planning and risk management decisions (Lobell & Burke, 2017) ^[104]. Machine learning algorithms analyze historical weather data, soil characteristics, and crop growth parameters to estimate yield variability across spatially heterogeneous fields (Pantazi *et al.*, 2018) ^[108]. Integration of climatic, spectral, and management datasets improves accuracy of crop yield forecasting models (Jeong *et al.*, 2018) ^[103]. Yield prediction models help farmers make informed decisions regarding harvesting, storage, and market planning (Cai *et al.*, 2019) ^[98]. Accurate yield forecasting enhances economic stability and improves resource allocation efficiency in semi-arid farming systems (Doraiswamy *et al.*, 2017) ^[99].

Advantages of Precision Agronomy in Semi-arid Regions

Precision agronomy plays a significant role in improving agricultural productivity and sustainability in semi-arid regions where water scarcity, soil variability, and climate uncertainty limit crop performance (Gebbers & Adamchuk, 2017) ^[116, 84]. Adoption of advanced technologies such as

GIS, remote sensing, and Artificial Intelligence enables efficient resource management through site-specific crop management practices (Zhang *et al.*, 2018) ^[123, 39]. Precision agriculture supports sustainable intensification by increasing crop yields while conserving natural resources and minimizing environmental degradation (Tilman *et al.*, 2017) ^[23].

Key Advantages

Improved water-use efficiency: Water is the most limiting factor in semi-arid agriculture. Precision irrigation systems use real-time soil moisture data, evapotranspiration estimates, and climatic parameters to optimize irrigation scheduling (Fereres & Soriano, 2017) ^[100]. Efficient irrigation management reduces water losses and enhances crop water productivity (Jones, 2019) ^[117].

Reduced fertilizer cost: Spatial soil fertility mapping helps farmers apply fertilizers only where required, avoiding excess application and reducing input costs (Robert, 2018) ^[128, 121]. Variable rate technology improves nutrient-use efficiency and prevents nutrient wastage in heterogeneous soils (Raun *et al.*, 2017) ^[111].

Increased crop productivity: Precision agronomy enables timely decision-making regarding irrigation, nutrient application, and pest management, resulting in improved crop growth and yield stability (Bongiovanni & Lowenberg-DeBoer, 2017) ^[114, 82]. Site-specific management enhances productivity even under resource constraints (Finger *et al.*, 2019) ^[83].

Early stress detection: Remote sensing tools help identify crop stress caused by drought, nutrient deficiency, or pest infestation at early growth stages (Mulla, 2018) ^[49]. Early detection allows farmers to take corrective measures before severe yield losses occur (Zhang & Kovacs, 2017) ^[122, 113].

Climate-resilient agriculture: Precision farming technologies support climate adaptation by providing real-time monitoring of crop and weather conditions (Walter *et al.*, 2017) ^[94]. Data-driven decision support systems help farmers manage climate risks and improve resilience to drought and temperature variability (Lobell *et al.*, 2018) ^[118].

Reduced environmental impact: Efficient input management reduces excessive use of fertilizers, pesticides, and irrigation water, minimizing environmental pollution and soil degradation (Tilman *et al.*, 2017) ^[23]. Precision agriculture contributes to sustainable land management and conservation of natural resources (Gebbers & Adamchuk, 2017) ^[116, 84]. Precision agronomy technologies enhance productivity while conserving water, soil, and energy resources, thereby supporting sustainable agricultural development in semi-arid ecosystems (Zhang *et al.*, 2018) ^[123, 39].

Challenges and Limitations

Despite its significant benefits, adoption of precision agronomy technologies in semi-arid regions faces several technical, economic, and infrastructural challenges that limit widespread implementation (Lowenberg-DeBoer & Erickson, 2019) ^[126, 21]. Advanced technologies such as GIS,

remote sensing, and Artificial Intelligence require skilled manpower, financial investment, and reliable digital infrastructure, which may not always be available to smallholder farmers (Finger *et al.*, 2019) ^[83]. Limited accessibility and affordability of digital tools restrict the adoption of precision farming practices in developing agricultural systems (Klerkx *et al.*, 2019) ^[125].

Major Challenges

- **High initial investment cost:** Precision agriculture technologies require substantial investment in sensors, drones, GPS-enabled machinery, and data processing software (Robert *et al.*, 2018) ^[128, 121]. Small and marginal farmers may find it difficult to afford such technologies, particularly in resource-constrained semi-arid regions (Lowenberg-DeBoer & Erickson, 2019) ^[126, 21]. High capital costs often delay adoption of modern digital farming tools (Tey & Brindal, 2017) ^[129].
- **Lack of technical knowledge:** Effective use of GIS, remote sensing, and AI tools requires technical expertise in data interpretation and digital decision-making (Klerkx *et al.*, 2019) ^[125]. Many farmers lack training in precision agriculture technologies, limiting their ability to utilize digital advisory systems (Eastwood *et al.*, 2017) ^[124]. Capacity-building and training programmes are essential for improving technology adoption (Zhang *et al.*, 2018) ^[123, 39].
- **Limited access to high-resolution data:** High-resolution satellite imagery and UAV-based data may not always be accessible due to cost, licensing restrictions, or limited availability (Atzberger, 2017) ^[54]. Inadequate spatial resolution affects the accuracy of crop monitoring and decision-making processes (Mulla, 2018) ^[49]. Data limitations reduce the efficiency of precision management strategies (Zhang & Kovacs, 2017) ^[122, 113].
- **Poor internet connectivity in rural areas:** Reliable internet connectivity is essential for real-time data transmission and cloud-based decision support systems (Wolfert *et al.*, 2017) ^[12]. Many semi-arid agricultural regions experience weak digital infrastructure, limiting access to online precision farming platforms (Klerkx *et al.*, 2019) ^[125]. Lack of connectivity reduces the effectiveness of IoT-based agricultural monitoring systems (Misra *et al.*, 2020) ^[88].
- **Complexity of data interpretation:** Precision agriculture generates large volumes of spatial and temporal datasets that require advanced analytical tools for interpretation (Gebbers & Adamchuk, 2017) ^[116, 84]. Farmers may find it difficult to translate complex datasets into practical management decisions (Eastwood *et al.*, 2017) ^[124]. User-friendly decision support systems are required to simplify data interpretation and improve adoption (Lowenberg-DeBoer & Erickson, 2019) ^[126, 21].
- Adoption of digital agriculture tools remains limited among smallholder farmers due to financial constraints, limited awareness, and lack of technical support (Tey & Brindal, 2017) ^[129]. Bridging the digital divide through government support, training programmes, and affordable technologies is essential for improving adoption of precision agronomy practices in semi-arid regions (Klerkx *et al.*, 2019) ^[125].

Future Research Directions

Future research in precision agronomy should focus on developing advanced, affordable, and scalable technologies that enhance productivity and sustainability in semi-arid regions (Gebbers & Adamchuk, 2017) ^[116, 84]. Rapid advancements in digital agriculture, artificial intelligence, and big data analytics are transforming traditional crop management practices into data-driven decision systems (Wolfert *et al.*, 2017) ^[12]. Research efforts are increasingly directed toward improving accessibility, reducing costs, and enhancing the efficiency of precision agriculture technologies for smallholder farming systems (Klerkx *et al.*, 2019) ^[125].

Key Future Research Areas

Development of low-cost sensors : Designing affordable soil moisture, nutrient, and climate sensors is essential for improving adoption of precision farming technologies among small and marginal farmers (Kim *et al.*, 2019) ^[132]. Low-cost sensing devices enable continuous monitoring of field conditions and support real-time decision-making (Shamshiri *et al.*, 2018) ^[137]. Cost-effective sensor technologies will increase accessibility and promote large-scale adoption of digital agriculture tools (Ray *et al.*, 2017) ^[135].

Integration of IoT with AI-based models : Integration of Internet of Things (IoT) networks with artificial intelligence enables automated data collection, analysis, and farm management recommendations (Misra *et al.*, 2020) ^[88]. Smart farming systems combine sensor data, satellite imagery, and machine learning algorithms to optimize irrigation, fertilization, and pest management decisions (Zhang *et al.*, 2018) ^[123, 39]. AI-enabled IoT systems improve resource-use efficiency and enhance crop productivity under climate variability (Wolfert *et al.*, 2017) ^[12].

Climate-resilient crop management strategies: Climate change significantly affects crop productivity in semi-arid regions due to increased temperature variability and irregular rainfall patterns (Lobell *et al.*, 2018) ^[118]. Future research should focus on developing adaptive crop management practices using climate-smart decision support tools (Raza *et al.*, 2019) ^[136]. Precision agronomy technologies help improve resilience through early stress detection and adaptive input management strategies (Finger *et al.*, 2019) ^[83].

Big data analytics for agriculture: Big data analytics plays a crucial role in analyzing large agricultural datasets obtained from sensors, satellites, and historical farm records (Kamilaris *et al.*, 2018) ^[131, 73]. Advanced data mining techniques help identify patterns in crop growth, soil variability, and weather conditions (Wolfert *et al.*, 2017) ^[12]. Data-driven insights improve decision-making accuracy and reduce production risks (Liakos *et al.*, 2018) ^[7].

Mobile-based decision support systems: Mobile-based advisory platforms provide real-time crop recommendations to farmers, improving accessibility of precision agriculture technologies (Klerkx *et al.*, 2019) ^[125]. Smartphone applications integrated with AI models help farmers monitor crop health, irrigation requirements, and nutrient status (Pivoto *et al.*, 2018) ^[134]. Mobile-based systems are

particularly useful in rural areas where extension services are limited (Aker, 2018) ^[130].

Real-time crop monitoring tools : Emerging technologies such as UAVs, satellite imaging, and IoT sensors enable real-time crop monitoring and early identification of crop stress conditions (Zhang & Kovacs, 2017) ^[122, 113]. Continuous monitoring improves crop productivity by enabling timely agronomic interventions (Mulla, 2018) ^[49]. Real-time analytics enhance farm management efficiency and reduce yield variability (Shamshiri *et al.*, 2018) ^[137]. Emerging technologies such as cloud computing, artificial intelligence, and big data analytics will further improve efficiency, scalability, and sustainability of precision agriculture systems in semi-arid environments (Kamilaris *et al.*, 2018) ^[131, 73]. Continued interdisciplinary research is essential to develop affordable and user-friendly digital agriculture tools that support climate-resilient farming systems (Klerkx *et al.*, 2019) ^[125].

Conclusion

Precision agronomy is transforming agricultural practices in semi-arid regions by enabling site-specific crop management through advanced technologies such as Geographic Information Systems (GIS), remote sensing, and Artificial Intelligence (AI) (Gebbers & Adamchuk, 2017) ^[116, 84]. These technologies provide accurate spatial and temporal information about crop growth, soil variability, and climatic conditions, allowing farmers to make informed management decisions (Zhang *et al.*, 2018) ^[123, 39]. Precision agriculture improves crop productivity by optimizing the use of essential inputs such as water, fertilizers, and pesticides, thereby reducing input wastage and enhancing resource-use efficiency (Tilman *et al.*, 2017) ^[23].

Integration of spatial technologies with AI-based decision support systems plays a crucial role in improving agricultural sustainability in water-limited environments (Wolfert *et al.*, 2017) ^[12]. Data-driven crop management practices help farmers monitor crop health, predict yield variability, and respond effectively to climate-related stresses such as drought and temperature fluctuations (Lobell *et al.*, 2018) ^[118]. Advanced analytical tools enable early detection of crop stress, improving timely interventions and minimizing production risks (Mulla, 2018) ^[49].

Adoption of precision agriculture practices contributes to climate-resilient farming systems by supporting efficient water management, improved nutrient-use efficiency, and sustainable soil health management (Finger *et al.*, 2019) ^[83]. These technologies enhance agricultural productivity while reducing environmental degradation caused by excessive use of chemical inputs (Walter *et al.*, 2017) ^[94]. Precision agronomy supports sustainable intensification by producing more food using limited natural resources (Tilman *et al.*, 2017) ^[23].

In semi-arid regions, where agricultural productivity is highly influenced by water scarcity and climatic variability, precision agronomy provides innovative solutions for improving crop performance and farm profitability (Zhang *et al.*, 2018) ^[123, 39]. Adoption of digital agriculture technologies can significantly enhance food security, promote environmental sustainability, and ensure long-term resilience of agricultural systems (Gebbers & Adamchuk, 2017) ^[116, 84]. Continued research, policy support, and farmer

training are essential to increase adoption of precision agronomy practices in semi-arid ecosystems (Klerkx *et al.*, 2019) ^[125].

1.

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