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SMART AGRICULTURAL TECHNOLOGIES AND SUSTAINABILITY OF AGRICULTURAL PROJECTS IN KWALE COUNTY, KENYA

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ABSTRACT

The purpose of this study was to examine the influence of smart agricultural technologies on sustainability of agricultural projects in Kwale County, Kenya. Specifically, the study sought to examine the influence of smart crop monitoring technology and remote sensing technology on sustainability of agricultural projects in Kwale County, Kenya. The theoretical framework was guided by the resource-based theory, dynamic capability theory and dynamic managerial capability theory and firm growth theory. The study employed the correlational, cross-sectional survey research design to test non-causal relationships between the study variables. The proportionate stratified random sampling technique was utilized to select a sample size of 174 employees from a target population of 305 employees of the 2 selected agro processing firms in Kwale County, Kenya. A pilot study was conducted to ascertain the validity and reliability of the constructed survey questionnaire. A structured self-administered survey questionnaire was used as the means of collecting primary data. The collected data was processed and entered into the statistical package for social sciences (SPSS) version 26 to create a data sheet used for analysis. Data analysis involved the use of descriptive statistics and inferential statistics. The correlation results indicated that smart crop monitoring technology and remote sensing technology had positive and significant relationship with the sustainability of agricultural projects in Kwale County, Kenya. The regression results indicated that smart crop monitoring technology and remote sensing technology had positive and significant influence on the sustainability of agricultural projects in Kwale County, Kenya. The study recommends that the managers and practitioners within the diverse industries should implement smart agricultural technologies to foster the sustainability of agricultural projects in Kwale County, Kenya. The policymakers within the diverse industries should initiate policy review to encourage managers and practitioners to implement agricultural farming technologies to foster the sustainability of agricultural projects in Kwale County, Kenya. The study recommends intriguing areas for further research. Future research should examine the influence of smart agricultural technologies on project sustainability with government regulation as a moderator in other sectors or contexts.

Key Words:

Remote Sensing Technology, Smart Crop Monitoring Technology, Smart Farming Technologies, Sustainability of Projects, Kenya

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INTRODUCTION

The global food system is grappling with severe, interconnected challenges driven by population growth, climate change, and resource depletion, which threaten food security and nutrition worldwide. The global food system is significantly impacted by the interconnected challenges (Matsuura, 2024), especially with the projected world population of 9.7 billion by 2050 (Gerland, 2023; Nikitović, Magdalenić, & Arsenović, 2024). Climate change, combined with increased population growth, poses a threat to global food security (Saleem *et al.*, 2025). Global food security remains a pressing challenge as population growth, resource scarcity, and climate change place increasing pressure on agricultural systems (Tkemaladze, 2025). The challenges, in turn, threaten global food security and sustainability (Kumar *et al.*, 2022). This demands that agriculture transform itself to feed a growing global population while simultaneously reducing the adverse environmental effects (FAO, 2021; Richard, Qi, & Fitt, 2022). However, agricultural productivity is subject to significant seasonal rainfall variations induced by climate change (Mutengwa, Mnkeni, & Kondwakwenda, 2023). Climate change poses significant risks to the global agricultural sector (Theodory, 2025).

Sub-Saharan Africa is the region most vulnerable to the effects of climate change, owing to its low adaptability and its reliance on agriculture. The effect of climate change is deeply felt in sub-Saharan Africa (Der Tambile *et al.*, 2024). The Sub-Saharan African region is an agrarian economy, with its economic development dependent on a significant transformation of agri-food systems (Maru, Haileslassie, & Zeleke, 2023). The Sub-Saharan Africa owns more than 60% of the world's arable land with over 85% of farmers operating as smallholders (Kombat, Sarfatti, & Fatunbi, 2021). However, most sub-Saharan African countries are unable to embrace food self-sufficiency even though the agricultural revolution is within their reach (Pfunzo, Bahta, & Jordaan, 2024). Unfortunately, food insecurity continues to rise even in less dry areas (Simane, Kapwata, Naidoo, Cissé, Wright, & Berhane, 2025). Farmers in the region are still struggling to raise productivity through conventional farm practices despite the technological revolution in the agricultural sector (Hedden, Hughes, Rothman, Markle, & Maweni, 2021; Were, 2021). It has been noted that almost half of the world's extreme poor live in sub-Saharan Africa (Teferi, Assefa, Tilahun, Wassie, Minh, & Béné, 2024). Kenya's food security is increasingly at risk due to the complex effects of climate change, population growth, and dependence on rain-fed agriculture which makes the continent particularly vulnerable to climate disruptions (Karume, Mondo, & Kiyala, 2024).

Despite years of persistent efforts to increase the production and quality of the world's food resources, food insecurity still exists, particularly in African countries (Wudil, Usman, Rosak-Szyrocka, Pilař, & Boye, 2022). The challenge necessitates innovative solutions that can optimize agricultural practices while minimizing environmental impact (Hendrawati, Narputro, Wicaksana, & Suryana, 2025). Sustainable agriculture aims to increase agricultural productivity, while minimizing negative environmental impacts (Mkala & Kising'u, 2025). It is an important line of research, as it allows increasing agricultural productivity while reducing the consumption of natural resources (Raj & Prahadeeswaran, 2025). However, the agricultural sector faces unprecedented challenges due to population growth, climate change, and resource scarcity (Bashiru, Ouedraogo, Ouedraogo, & Läderach, 2024).

Smart agriculture has emerged as a pivotal approach in modern farming, integrating advanced technologies to enhance productivity and sustainability (Hendrawati *et al.*, 2025). To meet future food demands, crop production must increase by 60–100% by 2050 (Puyu, Ponichtera, Havriliuk, Sheiko, & Kozyrsky, 2025). However, many nations still employ the old manner of farming; farmers are unwilling to use sophisticated technology when farming due to either a lack of expertise, high costs, or because they are uninformed of the advantages of these technologies (Raj & Prahadeeswaran, 2025). The integration of innovative technologies is imperative for the evolution of sustainable and efficient agricultural systems (Devarajan, 2025). Therefore, proactive and inclusive policy interventions are essential to ensure the successful adoption and scalability of smart farming technologies.

Smart farming, also known as precision agriculture or precision farming, has emerged as a transformative approach to modern agriculture, addressing the pressing global challenges of food security, environmental sustainability and resource efficiency (Aarif Ko, Alam, & Hotak, 2025). Smart farming is revolutionizing agriculture by transforming it into a data-driven and intelligent operation (Mkala & Kising'u, 2025). Smart farming is a development that has emphasized information and communication technology used in machinery, equipment, and sensors in network-based hi-tech farm supervision cycles (Dhanaraju, Chenniappan, Ramalingam, Pazhanivelan, & Kaliaperumal, 2022). The smart farming technologies integrate elements such as automation, data analytics, connectivity, and artificial intelligence to enable data-driven decision-making and improve various aspects of farming operations (Koutridi & Christopoulou, 2023; Mhlanga & Dzingirai, 2024). Improving agricultural data systems is crucial for navigating this period of transformation, requiring both technological innovation and institutional changes (Shebanin, Kormyshkina, & Drobitko, 2025). However, challenges such as high implementation costs and data security concerns persist (Puyu *et al.*, 2025).

The use of smart agricultural technologies makes it possible to increase the efficiency of agricultural production, reduce resource consumption and minimize negative impacts on the environment (Aliyeva, Huseynova, & Agabekova, 2025). Smart farming technologies integrate Internet of Things (IoT), artificial intelligence, and data analytics to optimize agricultural practices, improve resource efficiency, and enhance crop yields (Bashiru *et al.*, 2024). Smart farming technologies, including drones, sensors, and robotics, enable precise crop management and resource optimization (Raj & Prahadeeswaran, 2025). Using intelligent agricultural technologies has given farmers more control over raising livestock and cultivating crops, increasing their predictability and efficiency (Devarajan, 2025). The appropriate use of a wide variety of sensors has made the entire operation both more efficient and profitable, due to its accurate monitoring competencies. Sensors are constantly monitoring crops with greater accuracy, detecting any undesirable conditions during the early stages of the crop's lifecycle (Dhanaraju *et al.*, 2022).

The investment in smart agricultural technologies is key to the transformation of the agro-industrial complex, increasing its efficiency and sustainability (Aliyeva *et al.*, 2025). Smart farming has the potential to facilitate the sustainable development of smart cities. However, integrating smart farming into smart city systems presents significant challenges, particularly with respect to the security of their interconnected components (Patwal, Wazid, Das, Singh, Pal, & Park, 2025). Smart farming technologies and big data applications offer opportunities for improved farm decision-making and management (Raj & Prahadeeswaran, 2025). The smart farming technologies are emerging as crucial solutions to address global food security challenges amid population growth, climate change, and resource scarcity (Puyu *et al.*, 2025). However, their adoption and effectiveness depend on factors such as farmers' digital literacy, data sovereignty concerns, and institutional arrangements for data governance (Shebanin *et al.*, 2025).

Despite the vast potential of smart farming technologies, several key constraints continue to hinder their widespread adoption, especially among smallholder farmers in developing countries (Puyu *et al.*, 2025). Smart farming integration into urban ecosystems remains at an initial stage due to a number of economic, technological, and institutional barriers (Shebanin *et al.*, 2025). The main problem is the insufficient development of economic models that justify the feasibility of implementing such technologies in urban environments and their impact on the socio-economic development of local communities (Malik *et al.*, 2023). The concerns around data privacy, system interoperability, and the reliability of predictions in diverse agro-climatic conditions hinder the scalability of smart farming technologies in real-world farming environments (Bashiru *et al.*, 2024). There is a widespread lack of digital literacy and technical skills within the farming community (Devarajan, 2025). The high initial investment cost associated with purchasing, deploying, and maintaining advanced technologies like AI-enabled machinery, sensor networks, UAVs, and IoT devices (Mkala & Kising'u, 2025).

Statement of the Problem

Despite years of persistent efforts to increase the production and quality of the world's food resources, food insecurity still exists, particularly in African countries (Wudil *et al.*, 2022). Unfortunately, food insecurity continues to rise even in less dry areas (Simane *et al.*, 2025). Most sub-Saharan African countries are unable to embrace food self-sufficiency even though the agricultural revolution is within their reach (Pfunzo *et al.*, 2024). The effect of climate change is deeply felt in sub-Saharan Africa (Der Tambile *et al.*, 2024). Farmers in the region are still struggling to raise productivity through conventional farm practices despite the technological revolution in the agricultural sector (Hedden *et al.*, 2021; Were, 2021). It has been noted that almost half of the world's extreme poor live in sub-Saharan Africa (Teferi *et al.*, 2024). Kenya's food security is increasingly at risk due to the complex effects of climate change, population growth, and dependence on rain-fed agriculture which makes the continent particularly vulnerable to climate disruptions (Karume *et al.*, 2024).

Despite the vast potential of smart farming technologies, several key constraints continue to hinder their widespread adoption, especially among smallholder farmers in developing countries (Puyu *et al.*, 2025). The agricultural sector faces growing pressure to meet the increasing demand for food while mitigating environmental damage and being fair to farmers and rural populations (Wudil *et al.*, 2022). However, many nations still employ the old manner of farming; farmers are unwilling to use sophisticated technology when farming due to either a lack of expertise, high costs, or because they are uninformed of the advantages of these technologies (Raj & Prahadeeswaran, 2025). In spite of the increased focus on improving environmental and social sustainability, there is lack appropriate tools to jointly evaluate performance in the environmental and social dimensions. The smart farming technologies are emerging as crucial solutions to address global food security challenges amid population growth, climate change, and resource scarcity (Puyu *et al.*, 2025). However, the influence of smart agricultural technologies on sustainability of agricultural projects has scarcely been studied and need to be better understood to ensure that using smart farming technologies will contribute to the desired development (Martinsson, 2025; Mkala & Kising'u, 2025). Therefore, the general business problem lies in understanding the influence of smart agricultural technologies on sustainability of agricultural projects in Kwale County, Kenya.

Research Objectives

The general objective of this research was to examine the influence of smart agricultural technologies on sustainability of agricultural projects in Kwale County, Kenya. The specific objectives were;

- To determine the influence of smart crop monitoring technology on sustainability of agricultural projects in Kwale County, Kenya.
- To assess the influence of remote sensing technology on sustainability of agricultural projects in Kwale County, Kenya.

In this research, two null hypotheses were tested.

- $H_0 1$: Smart crop monitoring technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya.
- $H_0 2$: Remote sensing technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya.

LITERATURE REVIEW

Theoretical Framework

The theoretical framework was guided by the resource-based theory, dynamic capability theory and dynamic managerial capability theory and firm growth theory.

Resource-Based Theory

The resource-based theory (RBT) of the firm (Barney, 1991; Wernerfelt, 1984) provides a framework for understanding how a firm's unique resources and capabilities can be a source of sustained competitive advantage (Alkaraan *et al.*, 2024). The RBT of the firm (Penrose, 1959; Wernerfelt, 1995) suggests that a firm's distinctive resources, which are valuable, rare, inimitable, and non-substitutable (VRIN) can encompass tangible assets, intangible assets, human capital, organizational capabilities, and other strategic assets that are unique to a firm (Barney, Ketchen Jr, & Wright, 2021). The RBT of the firm (Barney, 1991; Peteraf & Barney, 2003) emphasizes that a firm's VRIN resources can enable the firm to achieve superior sustainability and outperform competitors (Utami & Alamanos, 2022). Therefore, the RBT of the firm provides a relevant theoretical framework to explain influence of smart farming technologies on sustainability of agricultural projects in Kwale County, Kenya.

The RBT of the firm is an influential approach in strategic management. The RBT explores heterogeneity in sustainability across firms through the lens of VRIN resource advantages, and the organization for exploiting their potential (Bosman, 2024). The RBT provides an essential framework to explain and predict the fundamentals of a company's sustainability and competitive advantage (Barney *et al.*, 2021; Chaudhuri, Subramanian, & Dora, 2022; Datche *et al.*, 2023). Therefore, the RBT of the firm provides a relevant theoretical framework to explain influence of smart crop monitoring technology and remote sensing technology on sustainability of agricultural projects in Kwale County, Kenya.

Dynamic Capability Theory

The dynamic capability (DC) theory (Barney, 1991; Barney, 2001; Peteraf, 1993; Teece, Pisano, & Shuen, 1997a) is a strategic management framework that focuses on a firm's ability to adapt, innovate, and reconfigure its resources and capabilities in response to changing external environments and evolving market conditions (Bosman, 2024). The DC theory (Barney, 2018; Peteraf & Barney, 2003; Teece, Pisano, & Shuen, 1997b) posits that a firm's sustainable competitive advantage is derived not only from possessing valuable and rare resources but also from its dynamic capabilities, enabling it to integrate, build, and reconfigure resources to meet the demands of a dynamic market (Alkaraan *et al.*, 2024). Therefore, the DC theory provides a relevant theoretical framework to explain influence of smart farming technologies on sustainability of agricultural projects in Kwale County, Kenya.

The DC theory specifically focuses on how organizations can develop and use their capabilities in a highly dynamic and uncertain environment (Buzzao & Rizzi, 2023; Chen, Michel, & Lin, 2021). The DC theory is suitable for measuring business sustainability in a dynamic environment, as it focuses on a company's ability to change and adapt to the changing environment (Baía & Ferreira, 2024; Teece, 2023). The DC theory concerns the development of strategies for senior managers of successful companies to adapt to radical discontinuous change, while maintaining minimum capability standards to ensure competitive survival (Yoshikuni, Galvão, & Albertin, 2022). Therefore, the DC theory provides a relevant theoretical framework to explain influence of smart crop monitoring technology and remote sensing technology on sustainability of agricultural projects in Kwale County, Kenya.

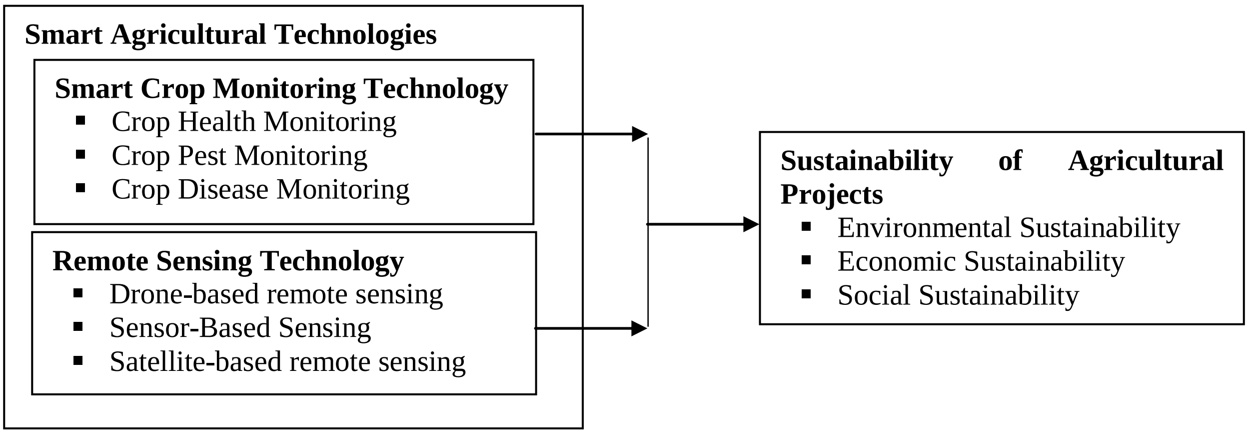
Firm Growth Theory

The theory of the growth of the firm (Lee, 2010; Penrose, 2009) is widely recognized in strategic management (Han & Tong, 2024). The firm growth theory assumes that multifunctional resources enable firms to restructure resources in novel ways to create growth (Ye *et al.*, 2023). The theory of the growth of the firm (Helfat & Eisenhardt, 2004; Penrose, 2009) is one the most commonly used basic theories to explain firm growth and project sustainability (Buckley & de la Torre, 2024; Ye *et al.*, 2023). Therefore, the theory of the growth of the firm provides a relevant theoretical framework to explain to explain the influence of smart agricultural technologies on sustainability of agricultural projects in Kwale County, Kenya.

The theory of the growth of the firm proposes that the relationship between multifunctional resources and firm growth is more closely aligned with firm growth theory (Najafabadi, Sajadi, & Davari, 2022). The theory of the growth of the firm posits that the firm resources can be utilized, redeployed or recombined in different ways to create value (Han & Tong, 2024). The theory of the growth of the firm postulates that entrepreneurs have to choose between different alternatives of how to allocate resources to achieve growth under uncertainty (von Nitzsch *et al.*, 2024). The theory of the growth of the firm suggests that entrepreneurial judgment plays an important role in firm growth (Najafabadi & Sajadi, 2023). Therefore, the theory of the growth of the firm provides a relevant theoretical framework to explain to explain the influence of smart crop monitoring technology and remote sensing technology on sustainability of agricultural projects in Kwale County, Kenya.

Conceptual Framework

The conceptual framework demonstrates that the sustainability of agricultural projects is conceptualized as the dependent variable. However, smart crop monitoring technology and remote sensing technology are conceptualized as the independent variables. Figure 1 presents the conceptual framework.



Independent Variables **Dependent Variable**

Figure 1: Conceptual Framework

Review of Literature on Variables

This section presents a review of the literature relevant to variables of the research.

Smart Crop Monitoring Technology

Smart Crop monitoring in agriculture comprises the systematic observation and assessment of crops throughout their growth cycle to improve productivity and make informed decisions (Victor *et al.*, 2024). It uses a combination of remote sensing (drones, satellites) and ground-based IoT sensors to collect data for real-time analysis, leading to more efficient and productive farming (Wang *et al.*, 2025). Tracking and monitoring crops from germination to harvest is a key aspect of smart agriculture, crucial for optimizing both the quantitative and qualitative productivity of crops (Wang *et al.*, 2025). Precision crop monitoring begins at the germination stage, as seed germination assessment is essential for determining seed quality and predicting the crop's initial yield (Rawat, Awasthi, Mishra, & Faizan, 2025). Innovative methods for monitoring and diagnosing plant diseases are crucial to mitigate these losses (Vidya Madhuri *et al.*, 2025). Although automated weed monitoring systems have advanced significantly, important scientific gaps remain (Taha *et al.*, 2025).

Crop monitoring and scouting is the systematic observation of crops throughout their growth cycle. It involves a close inspection of plants for signs of stress, pests, diseases (Wang *et al.*, 2025). Crop monitoring practice proves invaluable for early issue identification and prompt action. By employing insect traps, such as sticky traps and pheromones, growers can promptly detect the presence of pests and respond accordingly (Li, Wang, & Ding, 2025). The key applications include monitoring crop health, detecting stress from pests or water issues, optimizing irrigation and fertilization, and improving yield predictions through data analytics and machine learning (Selvam & Al-Humairi, 2023). Drones equipped with cameras and sensors can fly over fields, capturing high-resolution images and data on crop health (Wang *et al.*, 2025). This information enables early identification of illnesses, shortages in nutrients, and invasions by pests, facilitating timely interventions to protect crops (Aarif Ko *et al.*, 2025).

As global agriculture shifts to intelligence and precision, crop attribute detection has become foundational for intelligent systems (harvesters, UAVs, sorters). It enables real-time monitoring of key indicators (maturity, moisture, disease) to optimize operations, reducing crop losses by 10%-15% via precise cutting height adjustment—and boosts resource-use efficiency (Li *et al.*, 2025). The transient nature of weather variations makes it difficult to collect accurate and real-time data. To overcome this challenge, researchers have developed smart real-time weather monitoring systems integrated with mobile applications (Selvam & Al-Humairi, 2023). The IoT weather stations can provide localized and real-time weather data specific to the farm's location (Wang *et al.*, 2025). Farmers can use this information to plan their agricultural activities, safeguard against extreme weather events, and reduce climate-related risks (Aarif Ko *et al.*, 2025).

Crop attribute monitoring technology impacts all stakeholders by enabling data-driven decisions across the entire agricultural value chain, from farmers to consumers and the environment. The crop attribute monitoring technology impacts all stakeholders, from smallholder farmers to large-scale agribusinesses (Li *et al.*, 2025). IoT can be used to track the movement of agricultural products from the farm to the consumer (Wang *et al.*, 2025). Sensors attached to storage containers and transportation vehicles monitor factors like temperature and humidity, ensuring product quality and reducing postharvest losses (Aarif Ko *et al.*, 2025). By using satellite, drone, or aircraft-based sensors, farmers and agricultural managers can monitor and manage crops, soil, and environmental conditions more effectively (Dunchev & Aleksov, 2025).

Remote Sensing Technology

The rapid advancement of smart sensor technologies has transformed the landscape of precision agriculture, ushering in a new era of data-driven and sustainable farming practices. The adoption of smart sensor technologies in modern agriculture holds paramount importance in revolutionizing the way we produce food and addressing the numerous challenges faced by the agricultural sector today (Goswami & Singh, 2025). The remote sensing technologies offer cost-effective, scalable and transferable solutions, advancing forest restoration monitoring towards more accurate, efficient and real-time data analysis and interpretation (de Almeida *et al*, 2025). The cutting-edge technologies such as drone-based sensors, hyperspectral imaging, and sensor fusion are explored, highlighting their potential to revolutionize data acquisition and decision-making in agriculture (Scudder & Sampson, 2025). By harnessing the power of the internet of things (IoT) and artificial intelligence, the smart sensor technologies have revolutionized how farmers collect, analyze, and utilize data to optimize crop yield, conserve resources, and enhance overall agricultural efficiency (Aarif Ko *et al.*, 2025). Smart sensors facilitate precision farming by offering detailed insights into spatial variations in soil and crop conditions (Almohaimeed, Abro, & Khan, 2025; Das *et al.*, 2024; Goswami & Singh, 2025). Smart sensors deliver critical data on various agronomic parameters, allowing farmers to oversee and control their crops and fields with an unmatched level of accuracy and effectiveness (Rattanaamporn, Perera, Nguyen, Ngo, & Chahl, 2025).

Remote sensing involves collecting information about objects or areas without physical contact, using airborne or satellite platforms (Dunchev & Aleksov, 2025). The advanced sensors, equipped with cutting-edge capabilities and integrated with modern technologies, offer a wide range of benefits that contribute to more sustainable, efficient, and resilient agricultural practices (Aarif Ko *et al.*, 2025). By relying on precise and timely data, farmers can optimize their resource use, minimize waste, and boost overall productivity (Hussain *et al.*, 2025). The smart sensors deliver high-resolution, real-time data on key parameters like soil moisture, nutrient levels, crop health, and environmental conditions (Hussain *et al.*, 2025). The integration of smart sensors with precision farming practices ushers in a new era of efficient and intelligent agriculture, shaping the future of food production for a growing global population (Das *et al.*, 2024; Goswami & Singh, 2025). By incorporating smart sensors to monitor and analyzed specific aspects of crops, soil, and environmental conditions, precision agriculture empowers farmers to tailor inputs and interventions precisely to the needs of individual plants or areas of the field (Almohaimeed *et al.*, 2025; Rattanaamporn *et al.*, 2025).

Drones, also known as unmanned aerial vehicles (UAVs) are equipped with a range of sensors that can capture various types of data (Hussain *et al.*, 2025). The drone-based sensors have proven to be versatile and indispensable tools for remote sensing and aerial data acquisition across various industries (Rattanaamporn *et al.*, 2025). Drones, equipped with sophisticated sensors, have opened up new possibilities for data collection and analysis from above, offering unique advantages over traditional ground-based methods (Goswami & Singh, 2025). The drone-based sensors have become an integral part of remote sensing and aerial data acquisition, revolutionizing various industries, including agriculture, environmental monitoring, construction, and disaster management (Aarif Ko *et al.*, 2025). Notwithstanding the significant strides made in smart sensor technology, challenges such as sensor calibration, data privacy, interoperability and adoption barriers remain pertinent (Aarif Ko *et al.*, 2025).

Smart sensors consistently gather real-time data regarding critical agricultural factors such as soil moisture, temperature, nutrient concentrations, crop well-being, weather situations, and additional metrics (Rattanaamporn *et al.*, 2025). By promoting precision resource management, smart sensors contribute to environmental sustainability (Hussain *et al.*, 2025). Precision farming through smart sensor technologies leads to increased productivity and profitability (Almohaimeed *et al.*, 2025). Sensor reliability and accuracy are critical considerations in precision agriculture as they directly impact the effectiveness of data-driven decision-making (Scudder & Sampson, 2025). However, various challenges and limitations are associated with ensuring the reliability and accuracy of sensors in agricultural applications. Environmental conditions in agricultural settings can be challenging, characterized by extreme temperatures, humidity, dust, and other factors (Das *et al.*, 2024). The environmental conditions may impact sensor performance and contribute to degradation or malfunctions over time (de Almeida *et al*, 2025). Therefore, remote sensing plays a significant role in modern agriculture by providing valuable data and insights that improve productivity, efficiency and sustainability (Dunchev & Aleksov, 2025).

Sustainability of Agricultural Projects

The sustainability of agricultural projects refers to the ability to meet society’s food, fiber, and fuel needs in the present without compromising the ability of future generations to meet their own needs. It involves using practices like crop rotation, water management, and agroforestry to conserve resources, reduce emissions, and improve soil health (Mathur, Waswani, Singh, & Ranjan, 2022). The sustainability of agricultural projects depends on balancing economic viability, environmental protection, and social equity to ensure current needs are met without compromising future generations (Wijerathna-Yapa & Pathirana, 2022). Sustainable projects also focus on ensuring farmers can earn a fair income, creating resilient local economies, and increasing access to healthy food for communities (Hussain & Velasco-Muñoz, 2021; Mutambara, 2025). Therefore, the sustainability of agricultural projects is a holistic approach that integrates three interconnected pillars: environmental health, economic profitability, and social equity (Hiywotu, 2025).

The sustainability of agricultural projects involves using practices that meet present needs without compromising future generations, focusing on environmental health, economic viability and social equity. The economic sustainability of agricultural projects depends on their ability to be profitable, while reducing long-term costs, ensuring stable income, and building resilience to market and climate volatility (Wijerathna-Yapa & Pathirana, 2022). It is achieved through practices that reduce reliance on expensive chemical inputs, improve resource efficiency, and diversify crops to guard against price swings (Hiywotu, 2025). The sustainable methods can also strengthen local economies by creating stable jobs and ensuring food security for communities (Mutambara, 2025). Smart farming facilitates the economic sustainability of agricultural projects by increasing productivity, optimizing resource use to reduce costs, and enhancing market opportunities and resilience to risks (Konfo *et al.*, 2025).

The environmental sustainability of agricultural projects focuses on methods that maintain ecological health, soil quality, biodiversity, and natural resources, while adapting to climate change and minimizing pollution. Practices like organic farming, agroforestry, no-till farming, and water conservation are key to achieving this, as they reduce greenhouse gas emissions, prevent soil erosion, protect water sources, and enhance biodiversity compared to conventional methods (Hiywotu, 2025). Environmental sustainability is a major priority in sustainable agricultural practices (Coulibaly & Diakite, 2021). Smart farming facilitates the environmental sustainability of agricultural projects smart farming significantly facilitates the environmental sustainability of agricultural projects by optimizing resource use, minimizing pollution and waste, building climate resilience, and preserving natural resources like soil and water (Gryshova *et al.*, 2024).

The social sustainability of agricultural projects focuses on fair labor practices, community well-being, and equitable access to resources and healthy food (Izah, Ogwu, & Salimon, 2025). It involves ensuring safe working conditions, fair wages, and respect for workers' rights, while also supporting the needs of rural communities, promoting food security, and striving for social justice, such as racial equity (Hiywotu, 2025). The approach is a key component of the broader concept of sustainable agriculture, which integrates social, economic, and environmental factors (Wijerathna-Yapa & Pathirana, 2022). Smart farming facilitates the social sustainability of agricultural projects by improving farmers' quality of life, increasing food security, creating new job opportunities, and attracting younger generations to the agricultural sector (Batra *et al.*, 2025).

Empirical Review

Smart Crop Monitoring Technology and Sustainability of Agricultural Projects

Mkala and Kising'u (2025) examined the influence of crop monitoring technology on sustainability of agricultural projects in Kwale County, Kenya. The findings indicated that crop monitoring technology had a positive and significant relationship with sustainability of agricultural projects. The results showed that crop monitoring technology had a positive and significant influence on sustainability of agricultural projects.

Tuyisingize, Habimana, and Hategekimana (2025) examined the influence of remote monitoring technology adoption on livestock farm modernization and project performance. The research focused on the Grow with Agriculture, Livestock and Environment Project (Grow ALE) by Yalla Yalla Group in Rwanda (2021-2024). The results showed that remote monitoring technology adoption had a positive and significant relationship with the farm modernization and project performance. The results indicated that remote monitoring technology adoption had a positive and significant influence on the farm modernization and project performance.

Puyu *et al.* (2025) examined the influence of smart monitoring technologies on economic efficiency and sustainability of the agro-industrial holding in urbanised regions. The findings indicated that the adoption of smart monitoring technologies contributed to a significant increase in crop yields and a reduction in resource costs. The results showed that smart monitoring technologies had positive and significant influence on economic efficiency and sustainability of the agro-industrial holding. The findings indicated that smart farming technologies had positive and significant influence on economic efficiency and sustainability of the agro-industrial holding.

Aliyeva *et al.* (2025) examined the role of investment in the development of smart agricultural monitoring technologies in megacities, with a focus on the implementation of these technologies in Azerbaijan. The results showed that indicated that the main investments were directed towards process automation, precision farming, soil and livestock monitoring, and the use of artificial intelligence and big data to predict crop yields. The results showed that smart monitoring technologies had positive and significant influence on crop yields. The results showed that the introduction of smart agro technologies increases production efficiency through precision farming, the use of drones and satellite technologies, digital platforms, innovations in supply chains, and agro-parks optimise resources, which improve monitoring and reduce costs, increasing the competitiveness of the agricultural sector.

Hossain, Ferdousmou *et al.* (2025) examined the influence of AI-powered solutions on sustainable growth and profit. The findings indicated that smart monitoring solutions had positive and significant influence on agricultural efficiency, profitability and sustainability. The results showed up to a 50 percent boost in agricultural efficiency, profitability and sustainability with AI powered tools.

Remote Sensing Technology and Sustainability of Agricultural Projects

Mkala and Kising'u (2025) examined the influence of remote sensing technology on sustainability of agricultural projects in Kwale County, Kenya. The findings indicated that remote sensing technology had a positive and significant relationship with sustainability of agricultural projects. The results showed that remote sensing technology had a positive and significant influence on sustainability of agricultural projects.

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Martinsson (2025) examined the influence of remote sensing technology on the environmental and social efficiency of European agriculture. The results showed that remote sensing technology had a positive and significant relationship with the sustainability of commercial organizations. The results indicated that remote sensing technology had a positive and significant influence on the sustainability of commercial organizations.

METHODOLOGY

Research Philosophy

The research was guided by the positivist research philosophy which regards the world as made up of observable and measurable facts and assumes that there is an objective reality out there. The positivist research philosophy regards the world as made up of observable and measurable facts and assumes that there is an objective reality out there (Ma & Xie, 2023).

Research Design

The research employed the correlational, cross-sectional survey research design to test non-causal relationships among variables without controlling any of the variables. The design was appropriate for collecting data once from many individuals at a single point in time to test statistical relationships between two or more variables without the researcher controlling or manipulating any of them (Haslam, McGarty, Cruwys, & Steffens, 2024; Leavy, 2022).

Target Population

The target population consisted of the 305 employees of the 2 selected agro processing firms in Kwale County, Kenya. The target population was as per the Kenya Association of Manufacturers (KAM, 2024)'s database as at 31st December, 2024. Table 1 presents the target population.

Table 1: Target Population

Strata	Target Population	Percentage
Kwale International Sugar	190	62.3%
Kenya Bixa	115	39.7%
Total	**305**	**100.0%**

Sampling Frame

A sampling frame is the complete and correct list of population constituency of a given population (Thomassen, le Cessie, van Houwelingen, & Steyerberg, 2024). The sampling frame consisted of the list of the 2 selected agro processing firms in Kwale County, Kenya. The sampling frame was as per the Kenya Association of Manufacturers (KAM, 2024)'s database as at 31st December, 2024.

Sample Size

The Yamane (1967)'s formula was used to determine the sample size and verify that the sample size is sufficiently large (Hiebl, 2023).

$$n = \frac{N}{1+Ne^2)}$$

Where:

n = Sample Size

N = Target Population

e = Sampling Level of Precision

With a target population of 305 employees of the 2 selected agro processing firms in Kwale County, Kenya, the minimum recommended sample size was calculated as:

$$n = \frac{N}{1+N(e)^2} = \frac{305}{1+305\ (0.05)^2} = 174$$

Therefore, the minimum recommended sample size consisted of 174 employees of the 2 selected agro processing firms in Kwale County, Kenya. Extant literature posits that a sample size larger than 30 and less than 500 is deemed appropriate for most research (Bell & Warren, 2023; Saunders, Lewis, & Thornhill, 2023). Table 2 presents the sample size.

Table 2: Sample Size

Strata	Target Population	Sample Size
Kwale International Sugar	190	108
Kenya Bixa	115	66
Total	**305**	**174**

Sampling Techniques

The proportionate stratified random sampling technique was utilized to select a sample size of 174 employees from a target population of 305 employees of the 2 selected agro processing firms in Kwale County, Kenya. The choice of the proportionate stratified random sampling technique was justified by the heterogeneous target population. The proportionate stratified random sampling is a probability sampling technique in which each stratum is given equal chance to be selected randomly in to the sample (Bell, Bryman, & Harley, 2022; Hiebl, 2023).

Data Collection Methods

Primary data was collected using a self-administered structured survey questionnaire. The data collection method was appropriate. The choice of the self-administered structured survey questionnaire was justified by its ability to collect a large amount of information in a reasonably quick span of time (Bell, Warren, & Schmidt, 2022; Dubey & Kothari, 2022; Leavy, 2022).

Data Collection Procedures

A cross-sectional survey-based approach was employed for the collection of primary data. The choice of the cross-sectional survey-based approach was justified by its ability to permit the fast collection of primary data from many different individuals at a single point in time. The cross-sectional survey-based approach facilitates the collection of data from many different individuals at a single point in time (Bujang, Omar, Foo, & Hon, 2024). With the help of 3 research assistants, the researcher utilized the drop and pick method to hand deliver the survey questionnaire. The survey questionnaire was hand delivered to the random sample of 174 employees in Kwale County, Kenya. A continuous follow up on responses was made by the researcher and research assistants.

Pilot Study

A pilot study was conducted to test the validity and reliability of the constructed survey questionnaire. The pilot study was performed with pilot trial sample size of 18 employees of the 2 selected agro processing firms in Kwale County, Kenya. The pilot trial sample size consisted of 10% of the study's sample size. A common rule of thumb for pilot study is that a pilot study should be conducted with a minimum size of at least 10%-20% of the full-scale survey sample size or at least 30-50 respondents (Leong, Hew, Ooi, Tan, & Koohang, 2024). However, the participants in the pilot study were not be part of the main survey.

Data Processing and Analysis

The collected data was checked for accuracy, completeness and consistency. The data was coded, edited, and entered into the Statistical Package for Social Sciences (SPSS) version 26 to create a data sheet that was used for analysis. The descriptive statistics and inferential statistics were used for data analysis. The descriptive statistics were used to compute, summarize the data in respect to each of the study variables and describe the sample's characteristics. The Pearson's product moment correlation analysis was performed to confirm or deny the relationship between the study variables. The Pearson's product moment correlation analysis is performed to determine the nature and the strength of the linear relationship between the variables (Haslam *et al.*, 2024). A multiple linear analysis was performed with sustainability of agricultural projects as the dependent variable and smart crop monitoring technology and remote sensing technology as the predictor variables. The standard multiple linear regression analysis provides a means of objectively assessing the magnitude and direction of each predictor's relationship to its outcome variable).

Model Specification

The multiple linear regressions model was specified as:

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$ ……………………………………….… Model 1

Where:
Y = Sustainability of agricultural projects
β_0 = Constant Term
$\beta_1 - \beta_2$ = Regression coefficients to be estimated
X_1 = Smart Crop Monitoring Technology
X_2 = Remote Sensing Technology
ε = Stochastic Error Term

Hypotheses Testing

In this research, two null hypotheses were tested. The H_01 and H_02 were tested at 5% level of significance (α = 0.05; t = 1.960) to statistically help draw acceptable and realistic inferences. Therefore, the decision rule was to reject the H_0i if the $P \leq 0.05$, and otherwise fail to reject the H_0i if the $P > 0.05$. Table 3 presents the hypotheses testing procedure.

Table 3: Hypotheses Testing

Hypotheses		Model	Hypotheses Testing	Decision Rule
H_01:	Smart crop monitoring technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya.	$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \varepsilon$ Model 1	Standard Multiple regression analysis	H_01: $\beta_1 = 0$ H_11: $\beta_1 \neq 0$ If the $P \leq 0.05$, reject the H_01. If the $P > 0.05$, fail to reject the H_01.
H_02:	Remote sensing technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya.			H_02: $\beta_2 = 0$ H_12: $\beta_2 \neq 0$ If the $P \leq 0.05$, reject the H_02. If the $P > 0.05$, fail to reject the H_02.

FINDINGS

Response Rate

Out of the 174 survey questionnaires distributed for the main study, only 148 valid responses were obtained. Therefore, there was a valid response rate of 85.1%, which was adequate for data processing and analysis. Existent literature posits that survey response rates of 70% or higher are needed if findings are to be considered generalizable (Ericson *et al.*, 2023). Table 4 presents the response rate results.

Table 4: Response Rate

Strata	Frequency	Percentage
Response	148	85.1%
Non-Response	26	15.9%
Total	**174**	**100.0%**

Correlation Results

The Pearson's product moment correlation analysis was performed to confirm or deny the relationships between the study variables. The correlation results indicated that smart crop monitoring technology had a moderately strong positive and significant relationship with the sustainability ($r = .627$, $p \leq 0.05$) of agro processing firms in Kwale County, Kenya. The results showed that remote sensing technology had a strong positive and significant relationship with the sustainability ($r = 0.744$; $p \leq 0.05$) of agro processing firms in Kwale County, Kenya. Table 5 presents the correlation results.

Table 5: Correlation Results

Variable		X_1	X_2	Y
Smart Crop Monitoring Technology (X_1)	Pearson Correlation	1		
	Sig. (2-tailed)			
	n	148		
Remote Sensing Technology (X_2)	Pearson Correlation	.368**	1	
	Sig. (2-tailed)	.000		
	n	148	148	
Sustainability of Agricultural Projects (Y)	Pearson Correlation	.627**	.744**	1
	Sig. (2-tailed)	.000	.000	
	n	148	148	148

**. Correlation is significant at the 0.01 level (2-tailed).

Multiple Regression Results

A standard multiple linear analysis was performed with the sustainability of agricultural projects in Kwale County, Kenya as the dependent variable and smart crop monitoring technology and remote sensing technology as the predictor variables.

Model Summary

From the model summary in table, it is clear that the value of coefficient of correlation (R) was 0.836, suggesting that there was a strong positive correlation between the smart farming technologies and the sustainability of agricultural projects in Kwale County, Kenya. The value of coefficient of determination (R^2) was 0.699, suggesting that the overall model as a whole (the model involving constant, smart crop monitoring technology and remote sensing technology) was able to significantly predict and explain approximately 69.9% of the variance in the sustainability of agricultural projects in Kwale County, Kenya. The value of the adjusted R^2 was 0.694, suggesting that the overall model as a whole (the model involving constant, smart crop monitoring technology and remote sensing technology) significantly predicted and explained 69.4% of the variance in the sustainability of agricultural projects in Kwale County, Kenya.

The value of the std. error of the estimate was 0.199, suggesting that there could be other factors not included in the model in the current study that could predict and explain the remaining 30.6% of the variance in the sustainability of agricultural projects in Kwale County, Kenya. Therefore, there is in need for future research to discover the other smart farming technologies not included in the model in the current study that also predict the remaining variance in the sustainability of agricultural projects in Kwale County, Kenya. The value of the Durbin-Watson test was 2.039, falling within the optimum range of 1.5 to 2.5, suggesting that there was no severe autocorrelation detected in the in the residual values in the datasets. Generally, Durbin-Watson statistics falling within the optimum range of 1.5 to 2.5 indicates that there is no severe autocorrelation detected in the in the residual values in the datasets (Bolin, 2022; Hair & Alamer, 2022; Hair & Sarstedt, 2021). Table 6 presents the model summary results.

Table 6: Model Summary[b] Results

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.836[a]	.699	.694	.218	2.039

a. Predictors: (Constant), Remote Sensing Technology (X_2), Smart Crop Monitoring Technology (X_1)

b. Dependent Variable: Sustainability of Agricultural Projects (Y)

Analysis of Variance

From the ANOVA table, the overall model as a whole (the model involving constant, smart crop monitoring technology and remote sensing technology), achieved a high degree of fit, as reflected by $R^2 = 0.699$, adj. $R^2 = 0.694$, $F(2, 145) = 168.048$, $p \leq 0.05$. The null hypothesis was that the linear combination of predictor variables (smart crop monitoring technology and remote sensing technology) was not able to significantly predict the sustainability of agricultural projects in Kwale County, Kenya. However, the alternative hypothesis was that the linear combination of predictor variables (smart crop monitoring technology and remote sensing technology) was able to significantly predict the sustainability of agricultural projects in Kwale County, Kenya. The standard multiple linear regression results showed that the linear combination of predictor variables (smart crop monitoring technology and remote sensing technology) significantly predicted the sustainability of agricultural projects in Kwale County, Kenya. The null hypothesis was rejected in favor of the alternative hypothesis. Therefore, the decision was that the linear combination of predictor variables (smart crop monitoring technology and remote sensing technology) significantly predict the sustainability of agricultural projects in Kwale County, Kenya. Table 7 presents the ANOVA results.

Table 7: ANOVA[a] Results

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15.970	2	7.985	168.048	.000[b]
	Residual	6.890	145	.048		
	Total	22.860	147			

a. Dependent Variable: Sustainability of Agricultural Projects (Y)

b. Predictors: (Constant), Remote Sensing Technology (X_2), Smart Crop Monitoring Technology (X_1)

Multiple Regression Coefficients

From the coefficients table, when the unstandardized regression coefficients (B) were substituted to the multiple regression model specified for the study, the final predictive equation was:

$Y = 1.649 + 0.253X_1 + 0.333X_2$

The final predictive equation suggested that holding all factors in to account constant (smart crop monitoring technology and remote sensing technology), constant at zero, the sustainability of agricultural projects would be 1.649 in Kwale County, Kenya. The final predictive equation suggested that with all other factors held constant, a unit increase in smart crop monitoring technology would lead to 0.253 unit increase in the sustainability of agricultural projects in Kwale County, Kenya. Moreover, the final predictive equation suggested that with all other factors held constant, a unit increase in remote sensing technology would lead to 0.333 unit increase in the sustainability of agricultural projects in Kwale County, Kenya. Based on the magnitude of the unstandardized regression coefficients (B) of the independent variables, remote sensing technology was the best predictor of the variance in the sustainability of agricultural projects in Kwale County, Kenya.

The multiple regression results indicated that smart crop monitoring technology had a positive and significant influence on the sustainability of agricultural projects in Kwale County, Kenya ($\beta_1 = 0.409$; $t = 8.343$; $p \leq 0.05$) in Kwale County, Kenya. The regression results indicated that remote sensing technology had a positive and significant influence on the sustainability of agricultural projects in Kwale County, Kenya ($\beta_2 = 0.594$; $t = 12.111$; $p \leq 0.05$) in Kwale County, Kenya. Table 8 presents the multiple regressions coefficients results.

Table 8: Multiple Regression Coefficients[a] Results

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	1.649	.124		13.331	.000		
	Smart Crop Monitoring Technology (X_1)	.253	.030	.409	8.343	.000	.837	1.195
	Remote Sensing Technology (X_2)	.333	.027	.594	12.111	.000	.898	1.114

a. Dependent Variable: Sustainability of Agricultural Projects (Y)

Hypotheses Test Results

In this research, two null hypotheses were tested. The H_01 and H_02 were tested at 5% level of significance, $\alpha = 0.05$, $t = 1.960$, and 95% confidence level to statistically help draw acceptable and realistic inferences. Therefore, the decision rule was to reject the H_0i if the $P \leq 0.05$, and otherwise fail to reject the H_0i if the $P > 0.05$.

Hypothesis One Test Results

The H_01 predicted that smart crop monitoring technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya. The decision rule was to reject the H_01 if the $\beta_2 \neq 0$, $t \geq 1.960$, $P \leq 0.05$, and otherwise fail to reject the H_01 if the $\beta_1 = 0$, $t < 1.960$, $P > 0.05$. The regression results indicated that smart crop monitoring technology had a positive and significant influence on the sustainability of agricultural projects in Kwale County, Kenya ($\beta_1 = 0.594$; $t = 12.111$; $p \leq 0.05$) in Kwale County, Kenya. Therefore, the decision was to reject the H_01, and then conclude that smart crop monitoring technology has a significant influence on sustainability of agricultural projects in Kwale County, Kenya. Table 9 presents the hypotheses test results.

Hypothesis Two Test Results

The H_02 predicted that remote sensing technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya. The decision rule was to reject the H_02 if the $\beta_2 \neq 0$, $t \geq 1.960$, $P \leq 0.05$, and otherwise fail to reject the H_01 if the $\beta_2 = 0$, $t < 1.960$, $P > 0.05$. The regression results indicated that remote sensing technology had a positive and significant influence on the sustainability of agricultural projects in Kwale County, Kenya ($\beta_2 = 0.409$; $t = 8.343$; $p \leq 0.05$) in Kwale County, Kenya. Therefore, the decision was to reject the H_02, and then conclude that remote sensing technology has a significant influence on the sustainability of agricultural projects in Kwale County, Kenya.

Table 9: Hypotheses Test Results

Hypothesis	β	t	Sig.	Decision
H_01: Smart crop monitoring technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya.	.409	8.343	.000	Reject the H_01
H_02: Remote sensing technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya.	.594	12.111	.000	Reject the H_02

Discussions

The purpose of this quantitative correlational research was to examine the influence of smart agricultural technologies on the sustainability of agricultural projects in Kwale County, Kenya. Specifically, the research sought to examine the influence of smart crop monitoring technology and remote sensing technology on the sustainability of agricultural projects in Kwale County, Kenya. The Pearson's product moment correlation analysis was performed to confirm or deny the relationship between the study variables. The correlation results indicated that smart agricultural technologies had positive and significant relationship with sustainability of agricultural projects in Kwale County, Kenya. A standard multiple linear analysis was performed with sustainability of agricultural projects as the dependent variable and smart crop monitoring technology and remote sensing technology as the predictor variables. The regression results showed that smart agricultural technologies had positive and significant influence on the sustainability of agricultural projects in Kwale County, Kenya. The findings were consistent with the results of past studies (Aliyeva *et al.*, 2025; Mkala & Kising'u, 2025; Puyu *et al.*, 2025; Tuyisingize *et al.*, 2025).

The first specific objective was to assess the influence of crop monitoring technology on sustainability of agricultural projects in Kwale County, Kenya. The H_01 predicted that smart crop monitoring technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya. The correlation results indicated that smart crop monitoring technology had a strong positive and significant relationship with sustainability of agricultural projects in Kwale County, Kenya. The regression results showed that smart crop monitoring technology had a positive and significant influence on sustainability of agricultural projects in Kwale County, Kenya. Therefore, the decision was to reject the H_01, and then conclude that smart crop monitoring technology has a significant influence on sustainability of agricultural projects in Kwale County, Kenya. The results were consistent with the results of prior studies (Aliyeva *et al.*, 2025; Hossain, Ferdousmou *et al.*, 2025; Mkala & Kising'u, 2025; Puyu *et al.*, 2025; Tuyisingize *et al.*, 2025).

The second specific objective was to determine the influence of remote sensing technology on the sustainability of agricultural projects in Kwale County, Kenya. The H_02 predicted that remote sensing technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya. The correlation results indicated that remote sensing technology had a strong positive and significant relationship with the sustainability of agricultural projects in Kwale County, Kenya. The regression results showed that remote sensing technology had a positive and significant influence on sustainability of agricultural projects in Kwale County, Kenya. Therefore, the decision was to reject the H_02, and then conclude that remote sensing technology has a significant influence on sustainability of agricultural projects in Kwale County, Kenya. The results were in harmony with the results of past studies (Aliyeva *et al.*, 2025; Mkala & Kising'u, 2025; Puyu *et al.*, 2025).

CONCLUSIONS AND RECOMMENDATIONS

The purpose of this quantitative correlational research was to examine the influence of smart agricultural technologies on sustainability of agricultural projects in Kwale County, Kenya. The Pearson's product moment correlation analysis was performed to confirm or deny the relationship between the study variables. The correlation results indicated that smart agricultural technologies had positive and significant relationship with sustainability of agricultural projects in Kwale County, Kenya. A standard multiple linear analysis was performed with sustainability of agricultural projects as the dependent variable and smart crop monitoring technology and remote sensing technology as the predictor variables. The regression results showed that smart agricultural technologies had positive and significant influence on the sustainability of agricultural projects in Kwale County, Kenya.

The first specific objective was to assess the influence of crop monitoring technology on sustainability of agricultural projects in Kwale County, Kenya. The $H_0$1 predicted that smart crop monitoring technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya. The correlation results indicated that smart crop monitoring technology had a strong positive and significant relationship with sustainability of agricultural projects in Kwale County, Kenya. The regression results showed that smart crop monitoring technology had a positive and significant influence on sustainability of agricultural projects in Kwale County, Kenya. Therefore, the decision was to reject the $H_0$1, and then conclude that smart crop monitoring technology has a significant influence on sustainability of agricultural projects in Kwale County, Kenya.

The second specific objective was to determine the influence of remote sensing technology on the sustainability of agricultural projects in Kwale County, Kenya. The $H_0$2 predicted that remote sensing technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya. The correlation results indicated that remote sensing technology had a strong positive and significant relationship with the sustainability of agricultural projects in Kwale County, Kenya. The regression results showed that remote sensing technology had a positive and significant influence on sustainability of agricultural projects in Kwale County, Kenya. Therefore, the decision was to reject the $H_0$2, and then conclude that remote sensing technology has a significant influence on sustainability of agricultural projects in Kwale County, Kenya.

The purpose of this quantitative correlational research was to examine the influence of smart agricultural technologies on sustainability of agricultural projects in Kwale County, Kenya. The Pearson's product moment correlation analysis was performed to confirm or deny the relationship between the study variables. The correlation results indicated that smart agricultural technologies had positive and significant relationship with sustainability of agricultural projects in Kwale County, Kenya. A standard multiple linear analysis was performed with sustainability of agricultural projects as the dependent variable and smart crop monitoring technology and remote sensing technology as the predictor variables. The regression results showed that smart agricultural technologies had positive and significant influence on the sustainability of agricultural projects in Kwale County, Kenya. Therefore, the conclusion was that smart farming technologies significantly influence the sustainability of agricultural projects in Kwale County, Kenya.

The first specific objective was to assess the influence of crop monitoring technology on sustainability of agricultural projects in Kwale County, Kenya. The $H_0$1 predicted that smart crop monitoring technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya. The correlation results indicated that smart crop monitoring technology had a strong positive and significant relationship with sustainability of agricultural projects in Kwale County, Kenya. The regression results showed that smart crop monitoring technology had a positive and significant influence on sustainability of agricultural projects in Kwale County, Kenya. The $H_0$1 was rejected, providing the empirical support for $H_1$1. Therefore, the second conclusion was that smart crop monitoring technology has a significant influence on sustainability of agricultural projects in Kwale County, Kenya.

The second specific objective was to determine the influence of remote sensing technology on the sustainability of agricultural projects in Kwale County, Kenya. The $H_0 2$ predicted that remote sensing technology has no significant influence on sustainability of agricultural projects in Kwale County, Kenya. The correlation results indicated that remote sensing technology had a strong positive and significant relationship with the sustainability of agricultural projects in Kwale County, Kenya. The regression results showed that remote sensing technology had a positive and significant influence on sustainability of agricultural projects in Kwale County, Kenya. The $H_0 2$ was rejected, providing the empirical support for $H_1 2$. Therefore, the first conclusion was that remote sensing technology has a significant influence on sustainability of agricultural projects in Kwale County, Kenya.

The research recommends that the managers and practitioners should consider a holistic reassessment and implementation of the smart agricultural technologies to foster the sustainability of agricultural projects in Kwale County, Kenya. First, the managers and practitioners should consider a holistic reassessment and implementation of crop monitoring technology to foster the sustainability of agricultural projects in Kwale County, Kenya. Second, the managers and practitioners should consider a holistic reassessment and implementation of remote sensing technology to foster the sustainability of agricultural projects in Kwale County, Kenya.

The research recommends that the policy makers should initiate policy review to motivate the managers and practitioners to consider a holistic reassessment and implementation of the smart agricultural technologies to foster the sustainability of agricultural projects in Kwale County, Kenya. First, the policy makers should initiate policy review to motivate the managers and practitioners to consider a holistic reassessment and implementation of crop monitoring technology to foster the sustainability of agricultural projects in Kwale County, Kenya. Second, the policy makers should initiate policy review to motivate the managers and practitioners to consider a holistic reassessment and implementation of remote sensing technology to foster the sustainability of agricultural projects in Kwale County, Kenya.

Limitations and Future Research

The research suggests interesting areas for further research. First, future research should examine the influence of other smart farming technologies on the sustainability of agricultural projects in Kwale County, Kenya in other regions or contexts. Second, future research should examine the influence of smart farming technologies on project sustainability in other industries, sectors or contexts. Third, future research should examine the moderating influence of government regulation on the relationship between smart farming technologies and project sustainability in other sectors, regions or contexts.

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