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Tsinghua University

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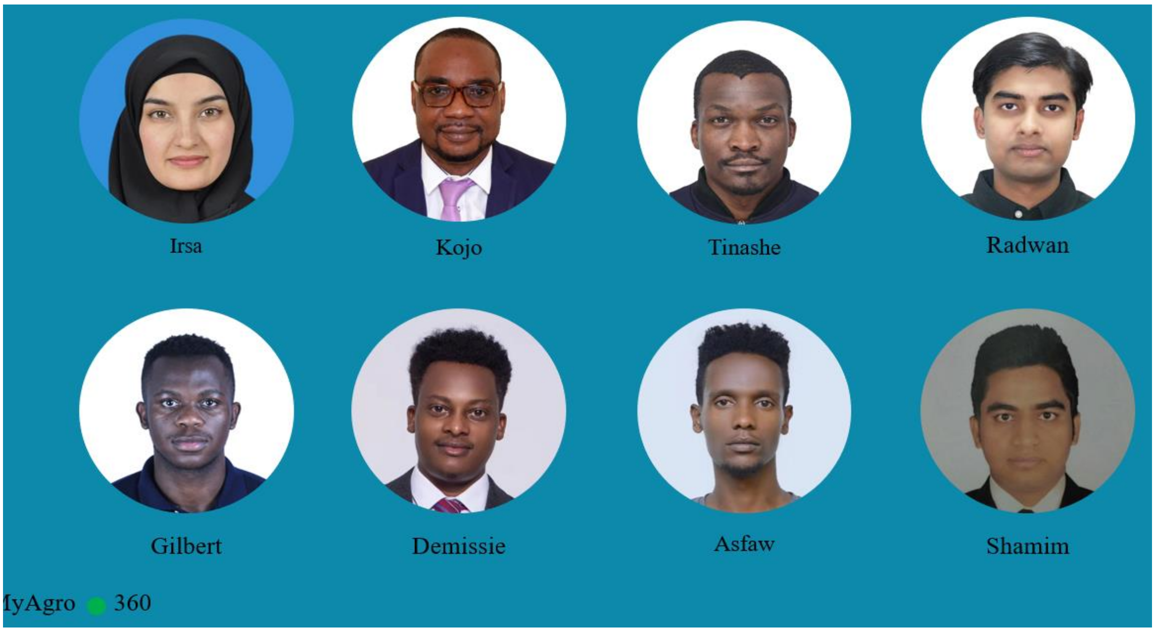
Team members on this project



Team members' bio and their contributions on the project

Name	Role	Degree	Research Interest	Affiliation	Contribution
Irsa Ejaz	Leader	PhD	Hyperspectral Imaging	China Agricultural University, Beijing	Key figures, compilation, formatting the whole report
Kojo Ahiakpa	Co-Lead	PhD	Crop Genomics/Business Innovations	Huazhong Agricultural University, Wuhan Co-Founder and Team Lead, Africa Farmnet Limited, Accra, Ghana	Financial plan figures, designed outline
Tinashe Mangudhla	Member	PhD	Management Science and Engineering	University of Science and Technology of China	Solutions, risk assessment
Md Radwanul Karim	Member	Masters	Mechanical and Vehicle Engineering	Beijing Institute of Technology, Beijing	Solutions
Bryan Gilbert Murengami	Member	Masters	Electromechanical Product Design & Development	Fuzhou Agricultural and Forestry University	Improvised all the figures
Shanko Demissie Daniel	Member	Masters	Recommendation System	Central South University	Introduction; cost and management
Hizkel Asfaw Worku	Member	Masters	Remote Monitoring	Wachemo University	Introduction; key technologies
Shamim Hossan	Member	Undergraduate	Food Science and Engineering	Jiangnan University, Wuxi, Jiangsu	Introduction; Stress factors

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List of Abbreviations

AI: Artificial Intelligence

BYDV: Barley yellow dwarf virus

CAADP: Comprehensive African Agriculture Development Programme

CeO_2: Cerium dioxide

CMV: Cucumber mosaic virus

CNN: Convolutional Neural Networks

GIS: Geographic Information System

GPS: Global Positioning Systems

HSI: Hyspectral Imaging

JA: Jasmonic Acid (JA)

LSTM: Long Short-Term Memory networks

ML: Machine Learning

NaCl: Sodium Chloride

P: Phosphorus

PESTEL: Political, Economic, Social, Technology, Legal, Environment

PSII: Photosystem II

RNN: Recurrent Neural Networks

SWOT: Strengths, Weaknesses, Opportunities, Threats

UAV: Unmanned Aerial Vehicle

UV: Ultra-violet

Zn: Zinc

Abstract

Plant stresses, such as drought, heat, cold, salinity, and pest infestation, can significantly impact crop yields and threaten food security. Artificial intelligence (AI) can help farmers to cope with these stresses in several ways. Rapid technological advancements have made it necessary for farmers to acquire new skills and to keep up with modern technologies to remain competitive. This can lead to additional stress as they try to adapt to rapidly changing technology while also running a profitable business. The long-term impacts of stress in agriculture are significant. In order to detect abiotic stressors on plants, several machine learning models (MLs) have been developed with the assistance of unmanned aerial vehicles (UAVs) equipped with hyperspectral, multispectral, and infrared imagers. In addition, a robust artificial intelligence and geographical information system (AI/GIS) mobile and web-based solution; "MyAgro360" was recently developed by Africa Farmnet Limited to identify diseases and pests that affect crops and provides recommendations for management control to farmers that use it. The AI/GIS-powered scouting and scanning features in MyAgro360 can accurately detect fall armyworms and other biotic stresses at multiple stages and can provide early control measures for users. Machine learning algorithms can be used to analyse large datasets of plant genetic information to identify genes that are associated with stress tolerance. This information can be used to develop crop varieties that are more resilient to stress. Overall, AI can help farmers to monitor, detect, and respond to plant stresses more effectively, ultimately improving crop yields and ensuring food security.

1. Introduction

Recent studies have shown that remote and proximal sensors can assess crop physiological and biochemical changes after stress damage (Wei et al., 2017, Murphy et al., 2020, Wu et al., 2021). These methods use spectral indices and chlorophyll fluorescence variables to identify and assess frost damage (Perry et al., 2017, Fitzgerald et al., 2019, Nuttall et al., 2019). Cold and drought stress directly alter energy flow from PSII reaction centres to quinone, affecting PSII performance (Kalaji et al., 2016, Rapacz, 2007). Chlorophyll fluorescence imaging has been shown to estimate thylakoid membrane damage soon after freezing in common wheat (Rapacz and Woniczka, 2009) (Figure 3). Hyperspectral imaging showed preliminary nitrogen balance of wheat seedlings under frost stress (Wu et al., 2012). Zhang et al. (2017) used NIR spectroscopy to evaluate wheat gluten enzymatic activity in real time. Bunaciu et al. (2012) used FTIR spectroscopy to create the PLSR models to measure medicinal plant antioxidant enzymatic activity. Vergara-Diaz et al. (2020) examined leaf and ear metabolites using full-range spectra. Again, eco-physiological study benefits from hyperspectral regression models. Although while separate frost and drought stress sensing have been explored, it is unclear how combined stress and its detection differ from sensing individual stresses; and in combination with AI/GIS working models (Murphy et al., 2020, Choudhury et al., 2022).

MyAgro360 is an integrated AI/GIS-powered mobile and web solution that provides users with a comprehensive digital farm management and traceability, e-extension, and last mile stakeholder management. MyAgro360 also enable users to map their farms in real-time, scout and scan suspected stresses including pests and diseases for accurate identification and management, plan, record, digitise and track farm activities, learn from an audio-visual library, access location-based weather forecast and extension workers, access agro-inputs from nearby agro-shops, trade on our Asime ecommerce platform, and engage lastmile stakeholders. MyAgro360 is an enhanced redesign of our earlier innovation, Igeza which won a second runner up Frontier Innovation award in the USAID FAWTech Challenge in 2018, Cape Town, South Africa.

Our business is built on a subscription and commission-based models, where farmers pay a small fee to access our platform or earn a percentage of the value of transactions facilitated on our platform. Our value proposition lies in our ability to provide smallholder farmers with access to previously inaccessible markets and technology options, while also helping them to improve their productivity and profitability. By leveraging AI and GIS technology, we are able to provide real-time weather information, reduce transaction costs, and facilitate transactions between farmers and buyers. Our platform also provides farmers with access to a range of quality inputs and advisory services, helping them to adopt modern and sustainable farming practices. Through our platform, we are creating a more inclusive and efficient and smart agricultural ecosystem, helping to improve the livelihoods of smallholder farmers and build a more resilient food system in Africa.

1.1. The Problem

Agriculture is the backbone of most developing economies and a lever for global food security. Nonetheless, existing food production is in jeopardy as a result of climate change, as extreme weather events culminate in temperatures that are suitable for insect pests (biotic), which in turn causes plant membrane breakdown and reduces agricultural output. Pests and diseases are obstacles to crop production, and farmers have to spend a significant amount of money to purchase pesticides and engage in other forms of disease control. Hence, to minimise yield losses and hazards to global food security, these stresses need to be alleviated at the farmer level prior to the manifestation of observable symptoms. Plant stresses, such as drought, heat, cold, salinity, and pest infestation, can significantly impact crop yields and threaten food security. Artificial intelligence (AI) can help farmers to cope with these stresses in several ways (Figure 8).

Machine learning algorithms can be used to analyse large datasets of plant genetic information to identify genes that are associated with stress tolerance. This information can be used to develop crop varieties that are more resilient to stress. Overall, AI can help farmers to monitor, detect, and respond to plant stresses more effectively, ultimately improving crop yields and ensuring food security. In order to detect abiotic stressors on plants, several machine learning models (MLs) have been developed with the assistance of unmanned aerial vehicles (UAVs) equipped with hyperspectral, multispectral, and infrared imagers.

1.2. Objectives of the Study

A robust artificial intelligence and geographical information system (AI/GIS) mobile and web-based solution; "**MyAgro360**" was recently developed by Africa Farmnet Limited to identify diseases and pests that affect crops and provides recommendations for management control to farmers that use it. However, this solution needs to be tested in a variety of environments, including those with varying levels of stress, intensities, and on different kinds of pests and diseases, so that it could be used on range of crops. We merged this solution with ML models developed by Irsa's lab to detect both frost and drought (abiotic stressors) and fall armyworm (biotic stressor) on wheat and maize production in China and Ghana (Figure 8).

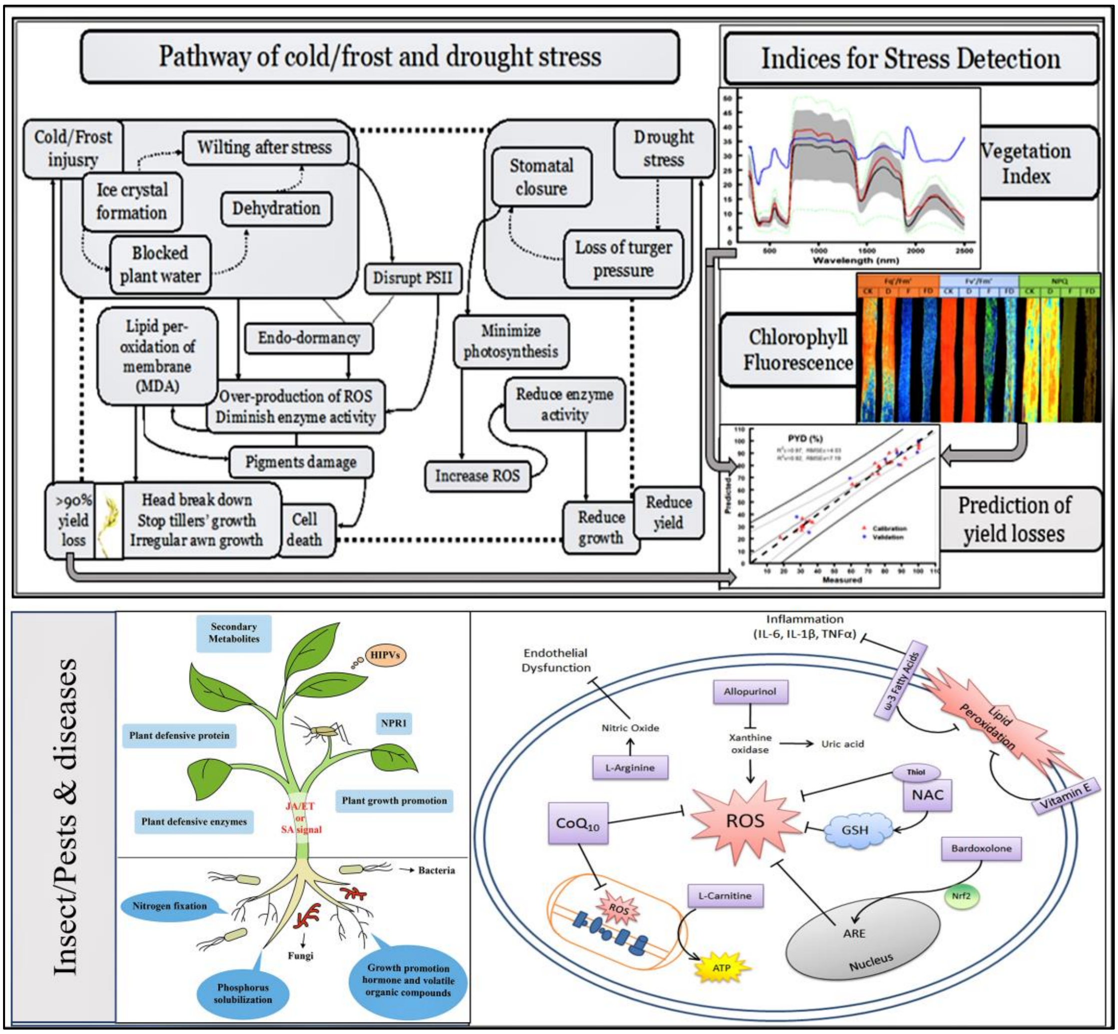

Figure 1: A schema of stress mechanisms and impact on crop yield and productivity. **Source:** Authors' work.

2. Literature Review

2.1. Abiotic Stresses

Stress in physical terms is defined as mechanical force per unit area applied to an object. In response to the applied stress, an object undergoes a change in the dimension, which is also known as strain. As plants are sessile, it is tough to measure the exact force exerted by stresses and therefore in biological terms it is difficult to define stress. A biological condition, which may be stress for one plant may be optimum for another plant. The most practical definition of a biological stress is an adverse force or a condition, which inhibits the normal functioning and well-being of a biological system such as plants (Jones et al., 1989). Various abiotic as well as biotic stress signals for plants are given below by Mahajan et al., 2005.

2.1.1. Cold Stress

Each plant has its unique set of temperature requirements, which are optimum for its proper growth and development. A set of temperature conditions, which are optimum for one plant may be stressful for another plant. Many plants, especially those, which are native to warm habitat, exhibit symptoms of injury when exposed to low non-freezing temperatures (Lynch 1990). These plants including maize (*Zea mays*), soybean (*Glycine max*), cotton (*Gossypium hirsutum*), tomato (*Lycopersicon esculentum*) and banana (*Musa* sp.) are in particular sensitive to temperatures below 10–15°C and exhibit signs of injury (Guy 1990; Hopkins 1999).

The symptoms of stress induced injury in these plants appear from 48 to 72 h, however, this duration varies from plant to plant and also depend upon the sensitivity of a plant to cold stress. Various phenotypic symptoms in response to chilling stress include reduced leaf expansion, wilting, chlorosis (yellowing of leaves) and may lead to necrosis (death of tissue). Chilling also severely hampers the reproductive development of plants for example exposure of rice plants to chilling temperature at the time of anthesis (floral opening) leads to sterility in flowers (Jiang et al., 2002). The success of many crops' rests on their ability to with stand the freezing temperature of late spring or early autumn frost. Therefore, tolerance to freezing temperatures is in particular important for the sustainability of agricultural crops.

As understanding the basics of a disease is essential for its cure, in the same way understanding of how freezing induces its injurious effects on plants is essential for the development of frost tolerant crops. The real cause of freeze-induced injury to plants is the ice formation rather than low temperatures. It is noteworthy to mention here that dehydrated tissues such as seeds and fungal spores can survive at very low temperatures without any symptoms of injury. Even cryopreservation is a common method for storage of seeds and other biological materials, which is based on the fact that water essentially solidifies without the formation of ice crystals.

2.1.2. Salinity Stress

Salinity is a major environmental stress and is a substantial constraint to crop production. Increased salinization of arable land is expected to have devastating global effects, resulting in 30% land loss within next 25 years and up to 50% by the middle of 21st century (Wang et al., 2003). High salinity causes both hyperionic and hyperosmotic stress and can lead to plant demise. Sea water contains approximately 3% of NaCl and in terms of molarity of different ions, Na+ is about 460 mM, Mg^{2+} is 50 mM and Cl around 540 mM along with smaller quantities of other ions. Salinity in a given land area depends upon various factors like amount of evaporation (leading to increase in salt concentration), or the amount of precipitation (leading to decrease in salt concentration).

Weathering of rocks also affects salt concentration. Inland deserts are marked by high salinity as the rate of evaporation far exceeds the rate of precipitation. Agricultural lands that have been heavily irrigated are highly saline. As drier areas in particular need intense irrigation, there is extensive water loss through a combination of both evaporation as well as transpiration. This process is known as evapotranspiration and as a result, the salt delivered along with the irrigation water gets concentrated, year-by-year in the soil. This leads to huge losses in terms of arable land and productivity as most of the economically important crop species are very sensitive to soil salinity.

Maladies caused by salt stress on plant cells arise from the following;

- Disruption of ionic equilibrium: Influx of Na^+ dissipates the membrane potential and facilitates the uptake of Cl^- down the chemical gradient.

- Na+ is toxic to cell metabolism and has deleterious effect on the functioning of some of the enzymes (Niu et al., 1995).
- High concentrations of Na+ causes osmotic imbalance, membrane disorganization, reduction in growth, inhibition of cell division and expansion.
- High Na+ levels also lead to reduction in photosynthesis and production of reactive oxygen species (Yeo 1998).

2.1.3. Nutrient Stress

Abiotic stress and soil nutrient limitation are environmental conditions that reduce plant growth, productivity, and quality. In natural and agricultural ecosystems, one of the most common soil-related abiotic stress is low phosphorus (P) availability, which limits crop productivity in more than 70% of globally available arable land. To overcome the low availability of inorganic P in the soil, the application of large amounts of fertilizers is the main strategy to maintain crop yields. Although the molecular mechanisms of the low-P stress response have been studied in detail, the epigenetic regulatory mechanisms remain unknown. Chu et al. 2020 evaluated changes in DNA methylation, gene expression, and siRNA abundance in response to low-P stress in two soybean genotypes with different P efficiencies. DNA methylation levels were higher under low-P stress in both genotypes, and transcriptional alterations in some genes were found to be associated with changes in methylation.

A low availability of P is also a limiting factor for potatoes. P can become toxic when accumulated at high concentrations (500 µM). In the study by Chea et al., (2020), plant morphology, mineral allocation, and metabolites were assessed under P deficiency and toxicity; the study also evaluated the ability of rhizobacteria to enhance plant biomass and P uptake. A reduction in plant height and biomass under P deficiency was observed, along with altered mineral concentration and allocation. The stress induced by P deficiency and toxicity was evident by the accumulation of proline.

Hornyák et al., 2020 studied nutritional stress in vitro and in planta, analyzing several embryological (e.g., developed ovules, embryo sacs, and pollen viability) and yield parameters. Flowers grown in vitro with severely reduced nutrient content showed dramatic degeneration of embryo sacs. In planta, reducing flower competition was found to be the most promising treatment to improve yield by increasing the frequency of developed embryo sacs and the average number of mature seeds. These effects could result from increased production of SA and jasmonic acid (JA) that promote more effective pollinator attraction. High bicarbonate concentrations in calcareous soils with high pH affect crop performance (e.g., Fe deficiency). The ability to mobilize poorly soluble Fe is key to tolerance.

2.1.4. Heavy Metal Stress

Exposure to heavy metals impairs morphological, physiological, biochemical, and molecular processes in plants. Pb and Cd in the environment severely affects plant growth and yield. In contrast, plants acquire Zn from soil for their vital functions. Shafiq et al., (2020) reported that Zn facilitates the accumulation and transport of Pb and Cd in the aerial parts of maize plants. In addition, the interaction of Zn, Pb, and Cd interferes with the uptake and translocation of other divalent metals. This study highlights how DNA methylation and histone acetylation affect metal stress tolerance through Zn transporters and alerts against the overuse of Zn fertilizers in metal-contaminated soils. Cerium dioxide (CeO_2) nanoparticles are pollutants of emerging concern as they are rarely immobilized in the environment. In the study of Skiba et al., 2020, CeO_2 nanoparticles (CNPs) were proved to affect metals uptake. In particular, a decrease in Cu, Zn, Mn, Fe, and Mg is found in the roots while a reversed process was observed for Ca.

2.1.5. Ozone, UV, & Light Stresses

Ultraviolet (UV) radiation, especially UV-B, has long been considered a stressor for plants, causing DNA, protein, and membrane damage. One of the strategies adopted by plants to counteract UV stress is the synthesis of antioxidant molecules (e.g., phenolic and flavonoid compounds) as well as UV-B screening molecules. In the study by Yoon et al., (2021) investigated the spatial interception of UV-B radiation of kale (Brassica oleracea L. var. Acephala) grown under supplemental UV-B LED using ray-tracing simulation using a high-resolution portable 3D scanner and leaf optical properties. UV-B-induced phenolic compounds and flavonoids accumulated largely, and UV-B was more intercepted in younger leaves. The effect of the UV-B intercept on the flavonoid content was substantially higher than leaf age.

Overall, the study paves the way to explore the physical and physiological basis of the intraindividual distribution of phenolic compounds. The study of Wójtowicz et al., (2021) focused on a mutation, namely, ch1, that affects chlorophyllide an oxygenase

(CAO), the enzyme responsible for chlorophyll b synthesis. They understood the strategy for compensation mechanism of the photosynthetic apparatus during low chlorophyll b content by characterizing and comparing the performance and spectral properties of the photosynthetic apparatus related to the lipid and protein composition in four selected Arabidopsis ch1 mutants and two Arabidopsis ecotypes. The exposure of mutants with lower chlorophyll b content to short-term and long-term low-light stress enabled a shift in the structure of both PSI and PSII via spectral analysis and thylakoid composition studies. Both ecotypes, Col-1 and Ler-0, reacted to high-light conditions in a way resembling the response of ch1 mutants to normal conditions. The authors suggested how the conversion of chlorophyll a to b might be regulated depending on the light stress conditions.

2.1.6. Drought Stress

One of the negative effects of climate change is soil water deficit, which results in drought stress. Many studies applied a molecular approach to identify involved mechanisms underlying drought tolerance. Water stress may arise as a result of two conditions, either due to excess of water or water deficit.

Flooding is an example of excess of water, which primarily results in reduced oxygen supply to the roots. Reduced O_2 results in the malfunctioning of critical root functions including limited nutrient uptake and respiration. The more common water stress encountered is the water deficit stress known as the drought stress. Removal of water from the membrane disrupts the normal bilayer structure and results in the membrane becoming exceptionally porous when desiccated. Stress within the lipid bilayer may also result in displacement of membrane proteins and this contributes to loss of membrane integrity, selectivity, disruption of cellular compartmentalization and a loss of activity of enzymes, which are primarily membrane based.

In addition to membrane damage, cytosolic and organelle protein may exhibit reduced activity or may even undergo complete denaturation when dehydrated. The high concentration of cellular electrolytes due to the dehydration of protoplasm may also cause disruption of cellular metabolism. The components of drought and salt stress cross talk with each other as both these stresses ultimately result in dehydration of the cell and osmotic imbalance. Virtually every aspect of plants physiology as well cellular metabolism is affected by salt and drought stress. Drought and salt signaling encompasses three important parameters (Liu et al., 1943).

- Reinstating osmotic as well as ionic equilibrium of the cell to maintain cellular homeostasis under the condition of stress.
- Control as well as repair of stress damage by detoxification signaling.
- Signaling to coordinate cell division to meet the requirements of the plant under stress.

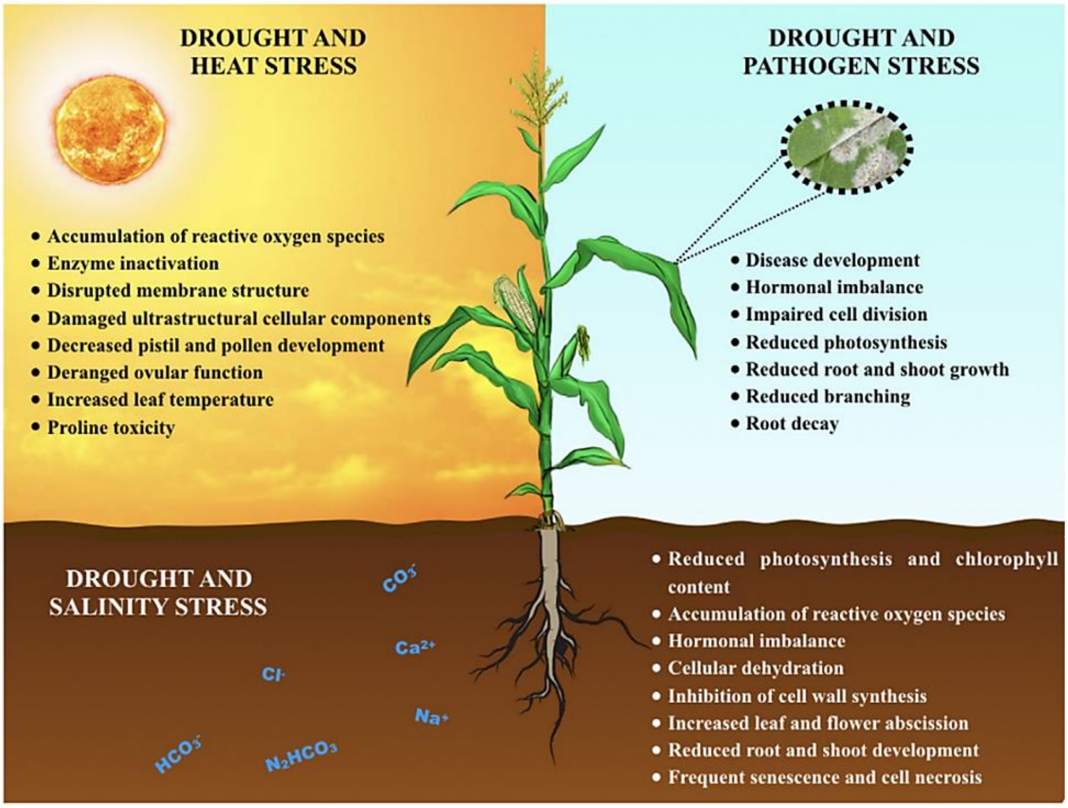

Figure 1: Combined effects of different stress conditions on plants (Ahluwalia et al., 2021).

2.1.7. Combined Drought and Pathogens

Plant's response to the co-occurrence of drought and pathogen stress has been widely studied. These responses depend on plant type, developmental stage, severity, duration of each stress and the effect of both stresses at the cellular level (Mittler 2006). Effects of drought and pathogen infection may result as a consequence of each other and can either be additive or antagonistic (Carter and Chen 2009; Ramegowda and Senthil-Kumar 2013) (Figure 1). Their combinatorial effects on roots are extensive. Reduced length of roots, root rot disease development, reduced fresh weight of roots, number of root hair and magnitude of branching, hormonal imbalance, impaired cell division and root decay are some of the effects of drought and pathogen stress seen on plants (Sharma and Pande 2013; Zhan et al., 2015) (Figure 1).

Water potential of plants is usually an indicator of soil moisture levels and its maintenance is very important for proper functioning of the plant vascular system (Figure 1). During drought stress, the plant's primary response is the closure of stomata to prevent water loss due to transpiration. However, in cases of pathogen infection, this response is interrupted (Pandey et al., 2015; Choudhary et al., 2016). Under mild drought conditions, the basal defense of a plant is activated which defends it against pathogenic infection. Although, under severe drought conditions the pathogenic infection can be aggravated due to release of cellular nutrients into the apoplast (Gupta et al., 2020; Ramegowda et al., 2014).

Susceptibility of plants to drought and pathogen infection may be due to their incapability to modify tolerance mechanisms and intensification of the damage caused by any of the stresses. Lastochkina et al. (2020) reported that exposure of wheat to drought stress and fungal pathogen, Fusarium culmorum, the causal agent of common root rot and seedling blight, resulted in higher malondialdehyde content, increased leaf yellowing, decreased root and shoot growth, and decline of biomass accumulation in comparison to individual stress (Figure 1). In other cases, drought-stressed plants showed resistance to certain pathogens that required consistently moist or humid environmental conditions. Under drought stress conditions, N. *benthamiana* plants showed fewer disease symptoms upon infection with the fungal pathogen, Sclerotinia sclerotium (causal agent of white mould) as opposed to pathogen infected well-watered plants (Ramegowda and Senthil-Kumar 2013).

2.2. Biotic Stresses

2.2.1. Fall armyworm

Fall armyworm, Spodoptera *frugiperda* (*Lepidoptera: Noctuidae*), is a polyphagous pest that originated from the American continents. It feeds on approximately 353 plant species belonging to 76 plant families and prefers to feed on economically important crops such as maize, sorghum, rice, millet, and sugarcane (Day et al., 2017; Montezano et al., 2018). S. *frugiperda* has the ability to damage various crops rapidly and hence deteriorates the nutritional value of the infested crops. This pest has spread into all of north-eastern India and damaged the maize crop (Firake et al., 2019). Before 2016, S. *frugiperda* was only found in South and North America. The occurrence of this pest was reported in Africa in 2016 and spread in Europe in 2018.

In Asia, it was first reported in India in 2018 and damaged the maize crop (Firake et al., 2019). A year after the first invasion into Asia, S. frugiperda was found in Indonesia and West Africa. In Pakistan, S. *frugiperda* was initially found on maize crop in the Sindh province in the southern part of Pakistan in 2019, and has now spread to different regions of the country and affects maize, millet, and sorghum (Gilal et al., 2020). The damage amount of S. *frugiperda* feeding on maize crop is substantial; losses of 73% in Latin America and 21–53% in Africa have been reported (Day et al., 2017).

S. *frugiperda* larvae feed on the stem, leaves, and reproductive parts of their host plants. Two strains of S. *frugiperda* have been reported worldwide: corn strain and rice strain. The corn strain mostly prefers maize and sorghum, while the rice strain mostly prefers pastures including rice. The change in the population of any insect pest depends on the nutrition and properties of their host plants, which influence their population growth (Huang et al., 2018). Life history traits of insects, including growth, reproduction, survival, etc., are affected by the different nutrition of different host plants that insects feed on during their larval stages. Demographic studies play an important role in population dynamics and pest status in the field. Although the most preferable crop of S. *frugiperda* is maize other crops can be suitable hosts in the absence of maize crops. Given the further dispersion of S. frugiperda in Pakistan, there is a dire need to reveal the biological performance of this pest on other economically important crops such as wheat, sorghum, and rice (Idrees et al., 2022).

2.2.2. Plant Viruses

The impression from the ninth report of the International Committee for the Taxonomy of Viruses is that there are not very many viruses of plants. The report list just under 1000 different species (King et al., 2012). However, the vast majority of these are from crop plants, and recent studies of plant virus biodiversity using metagenomic approaches are revealing the abundance and novelty of plant viruses. Viruses are abundant in wild plants, from the tropics to Antarctica (Hopkins et al., 2014) with infection incidence as high as 60% based on current and older technologies, and most are turning out to be novel. Other than through seed dispersal most plants do not move across significant distances; hence their horizontally-transmitted viruses must be moved by others. Most often the vectors for plant viruses are insects, although below ground transmission also occurs through nematodes, chytrids or plasmodiophorids.

The relationships among plants, insects and viruses are ancient, and it is not surprising that they are intimate and complex. Insect's vectors are in turn colonized by other entities, and endosymbiotic bacteria produce compounds that are involved in plant virus transmission as well (Morin et al., 1999).

Insect transmission of plant viruses is usually categorized in four ways (Table 1), depending on how long the insect needs to feed to acquire the virus, how long it remains viruliferous, how long it must feed to transmit the virus, and whether or not the virus circulates through the insect gut and/or propagates in the insects, comprehensively reviewed by Bragard et al., (2013). These transmission modes affect the evolution of plant–virus–insect relationships.

Table 1: Major modes and characteristics of insect transmission.

Type of transmission	Acquisition time	Retention time	Transmission time	Insects
Non-persistent	Minutes	Minutes to hours	Minutes	Aphids, thrips (via pollen)
Semi-persistent	Minutes to hours	Minutes to hours	Minutes to hours	Aphids, beetles, leafhoppers, mites, thrips, whiteflies
Circulative	Hours to days	Hours to days to life	Hours to days	Aphids, leafhoppers, treehoppers, whiteflies
Circulative-propagative	Hours to days	Days to life to generations	Days to life	Aphids, leafhoppers, mites, thrips, planthoppers

2.2.3. Transmission by Aphids

Aphids are also small plant-feeding insects that are probably the best-studied of all the plant virus vectors. Some viruses such as Cucumber mosaic virus (CMV) are generalists in terms of transmission, and can be vectored by hundreds of different aphid species in a non-persistent manner, whereas other viruses such as Barley yellow dwarf virus (BYDV) have a very specialized interaction with aphids and specific virus strains are transmitted by individual aphid species in a circulative manner (McElhany et al., 2012).

When given a choice, aphids are attracted to CMV-infected plants, but once they begin to feed the plants are induced to produce anti-feeding compounds. This moves the insects rapidly away from the plant to new hosts, a strategy that enhances the transmission of CMV, which only requires very brief feeding periods both for acquisition and transmission (Carmo-Sousa et al., 2014). This work led to the hypothesis that viruses can induce volatiles that attract insect vectors, but the persistently-transmitted viruses induce pro-feeding behavior as well, while the no persistently-transmitted viruses induce anti-feeding behavior to rapidly move vectors off once the virus is acquired (Mauck et al., 2012).

2.3. Cost of stress on agricultural productivity

Rapid technological advancements have made it necessary for farmers to acquire new skills and to keep up with modern technologies to remain competitive. This can lead to additional stress as they try to adapt to rapidly changing technology while also running a profitable business. The long-term impacts of stress in agriculture are significant.

In addition, ongoing financial and personal stress can negatively impact family relationships and social well-being, leading to further mental health and societal issues. Addressing stress in agriculture requires a comprehensive approach that focuses on supporting the unique needs of farmers and farm workers. This includes providing access to financial resources, promoting mental and emotional health services, improving work and safety conditions, and encouraging positive cultural attitudes towards farmers and agriculture.

2.3.1. Applications of Artificial Intelligence (AI)

There are numerous applications of artificial intelligence (AI) in agriculture that are being explored and developed. Here are some examples:

Precision farming: AI can be used to analyze data from sensors, drones, and satellites to develop a detailed understanding of soil composition, weather patterns, and plant growth stages. This information can be used to optimize crop management and maximize yields while minimizing resource waste.

Crop monitoring and disease detection: AI algorithms can identify crop diseases and pests using images captured by drones or smartphones with high accuracy.

This helps farmers take targeted actions to prevent and manage the spread of the disease, reducing crop losses.

Climate modeling and prediction: Big data analytics and machine learning models can be used to predict changes in weather patterns and their impact on crop production. This allows farmers to make informed decisions about planting, irrigation, and harvesting schedules.

Robotics and automation: Autonomous robots are being developed that can perform tasks such as planting, weeding, and harvesting crops. These robots use computer vision and machine learning algorithms to navigate through fields and perform tasks with precision.

Decision support systems: AI can help farmers make more informed decisions about crop management by analyzing data from various sources, such as the weather forecast, crop health sensors, and market prices.

Supply chain management: AI can optimize supply chain logistics by predicting demand, shipping routes, and delivery schedules. This can improve efficiency while reducing costs and waste.

Predictive maintenance: AI algorithms can be used to identify equipment failures before they occur, enabling proactive maintenance and minimizing downtime.

Overall, the application of AI in agriculture has the potential to revolutionize the industry's approaches to crop management, yield optimization, and sustainability.

2.3.2. Machine Learning (ML) in Agriculture

Machine learning is a developing field with numerous agricultural applications. Farmers and agricultural experts are investigating how machine learning technologies might boost crop yields, cut water consumption, and detect pests and diseases (Figure 2). Machine learning could help farmers use resources more efficiently and produce food more sustainably in the future. Machine learning in agriculture allows farmers to use lavish amounts of data about climate change, crop and soil conditions, and other environmental variables to make informed decisions about plant and animal treatment. Due to shifting climatic conditions and market trends, the farming sector faces several risks and uncertainties, resulting in large production losses and wasted resources. While decades of experience and increasingly precise meteorological data have assisted farmers in making reasonable forecasts, there is still far.

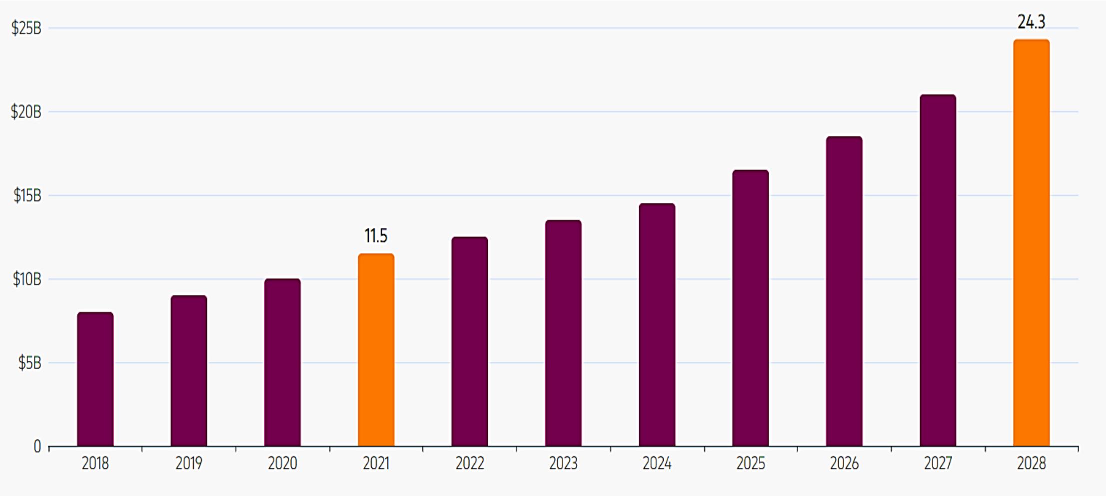

Figure 2: Smart agriculture market (stats for ML) by value, 2018-2028 (*Data source: BlueWeave Consulting*).

2.4. Key Technologies in Agriculture

Agriculture is one of the most significant industries in the world, as it is critical to feeding the world's rising population. In recent years, technology has played a key role in increasing agricultural efficiency and productivity. Precision agriculture, remote sensing and geospatial analysis, and the usage of drones are some of the main agricultural technologies.

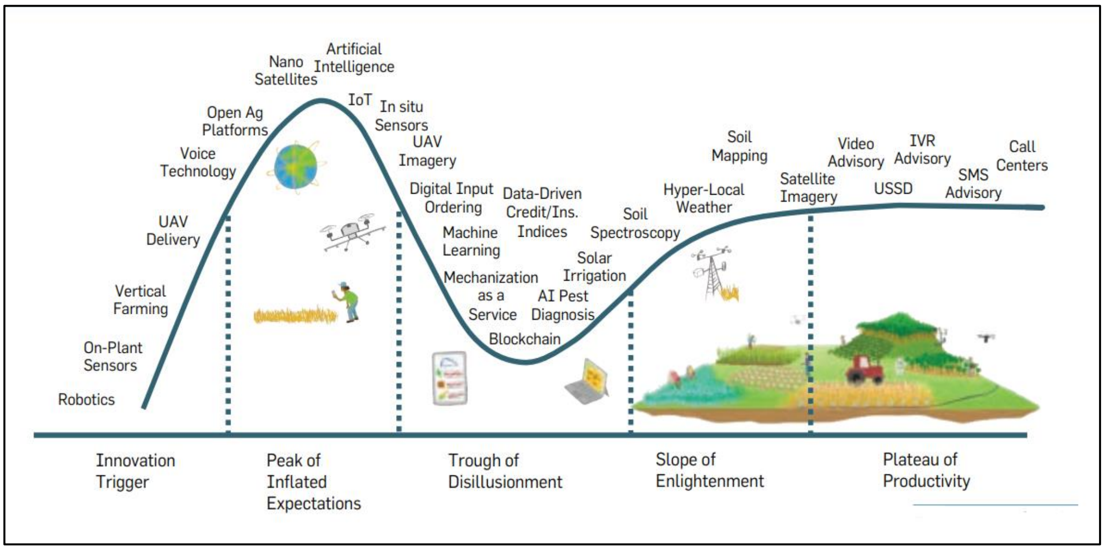

Figure 3: Applications of AI in agriculture and their role in plateau of productivity.

2.4.1. Precision Agriculture

Precision agriculture is the use of technology to enhance crop production while reducing the impact on the environment. This technology enables farmers to monitor and adjust inputs such as water, fertilizer, and pesticides, resulting in higher yields and reduced costs (Table 2). Precision agriculture also allows farmers to use data and analytics to make informed decisions about planting, harvesting, and resource management (Cox 2002).

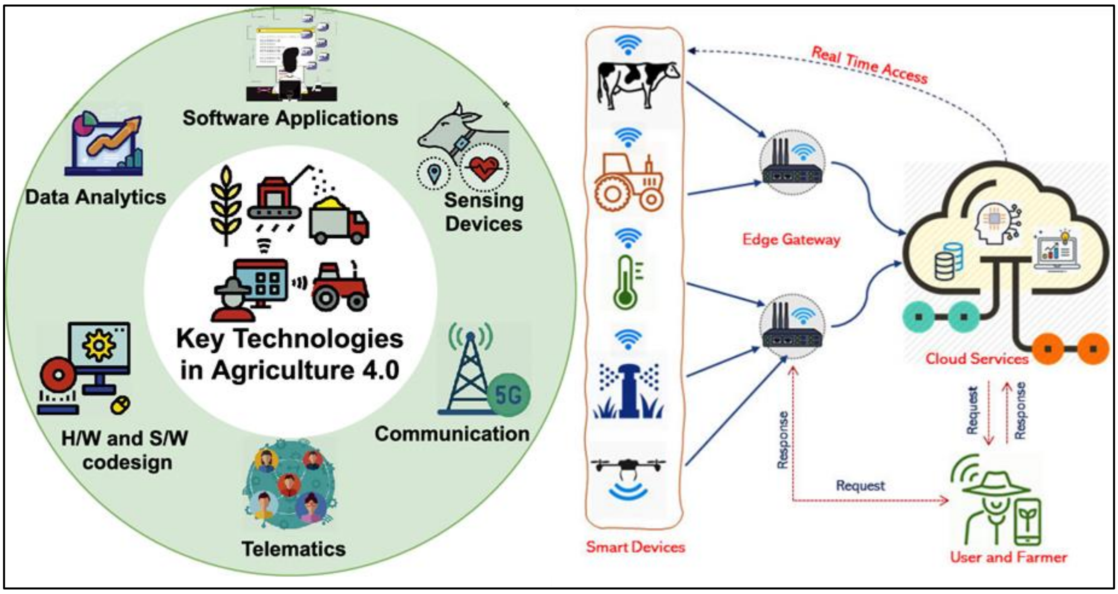

Figure 4: Key technologies in Agriculture and their gateway to cloud computing

2.4.2. Remote Sensing and Geospatial Analysis

Remote sensing and geospatial analysis are tools that offer farmers with extensive information on their crops, soil, and landscape. Remote sensing is the use of aerial and satellite imagery to monitor crop health, identify stress points, and detect changes in vegetation over time. Geospatial analysis, on the other hand, employs geographic data to generate maps and models that may be used to plan, manage, and evaluate agricultural systems (Sishodia et al., 2020).

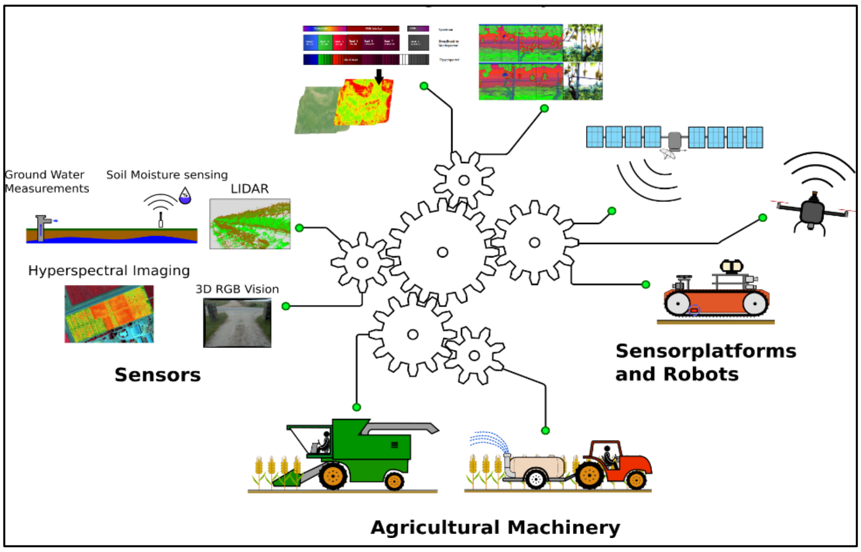

Figure 5: Use in agriculture machinery, sensors and robots in agriculture to enhance productivity.

2.4.3. Drones

Drones are increasingly being used in agriculture for a variety of purposes such as crop monitoring, mapping, and sensing. Drones can be equipped with a variety of sensors that provide farmers with data on plant growth, soil moisture, and temperature. This technology can be used to increase yield, reduce costs, and inhibit environmental impact (Dutta and Goswami 2020) (Figure 6).

2.5. Innovative Solutions in Smart Agriculture in Developing Countries

Smart agriculture is the application of technology to farming in order to increase crop production, reduce losses, and increase efficiency in the agricultural industry. Developing countries are using smart agriculture to address food security issues, promote economic growth, and improve farmer livelihoods (Figure 6).

2.5.1. Innovation in Smart Agriculture

Precision agriculture is one of the innovative solutions in smart agriculture, which involves integrating technology such as Global Positioning Systems (GPS), drones, and sensors to increase crop yields, reduce waste, and save expenses.

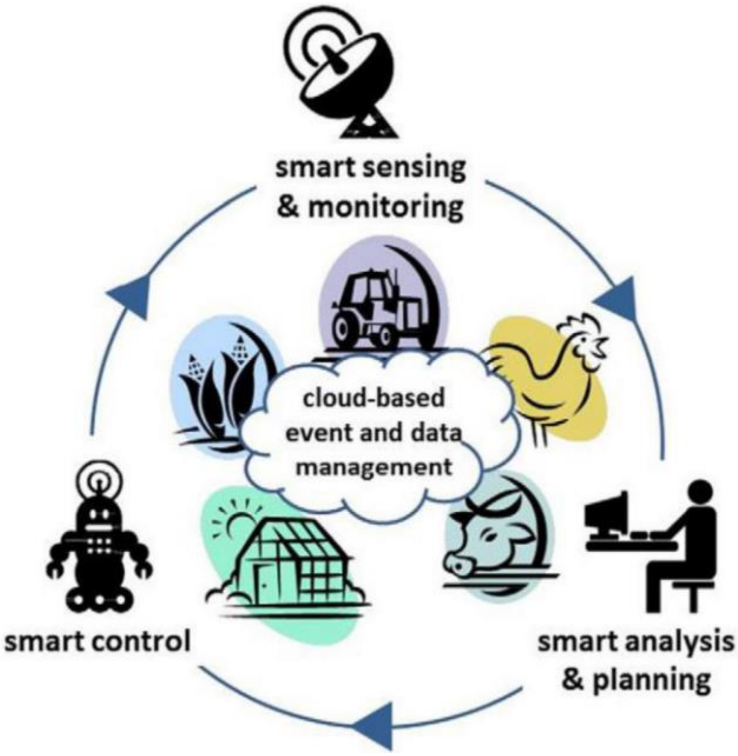

Figure 6: Cloud-based event and data management using smart sensing, control, analysis, and planning.

Precision agriculture has been adopted in developing nations such as India, where farmers spray crops and collect data on soil moisture, plant health, and nutrient levels using drones. This practice has enhanced crop yield, reduced the use of pesticides, and improved profitability for smallholder farmers. Another advancement in smart agriculture is the use of artificial intelligence (AI) to improve agricultural decision-making (Figure 7). AI technology can evaluate huge amounts of data to provide farmers with accurate predictions and insights on the weather, soil conditions, and crop health. PEAT, a German-based digital start-up, has developed an AI-based application called Plantix that can identify nutrient deficits in soil as well as plant pests and diseases, giving farmers ideas on how to apply fertilizer to increase harvest quality. This app has improved the productivity and income of smallholder farmers by enabling them to make informed decisions (Figure 7).

Smart irrigation is another innovative solution in smart agriculture that addresses water scarcity in developing countries. Traditional irrigation methods are not efficient and may lead to overuse of water resources. Smart irrigation systems use sensors, weather data, and AI technology to optimize water use by providing precise amounts of water at the right time. In Jordan, a smart irrigation system has been developed to ensure efficient water use in the cultivation of high-value crops such as strawberries (Massadeh et al., 2014). This system has reduced water waste and increased crop yield by up to 20% (Figure 7).

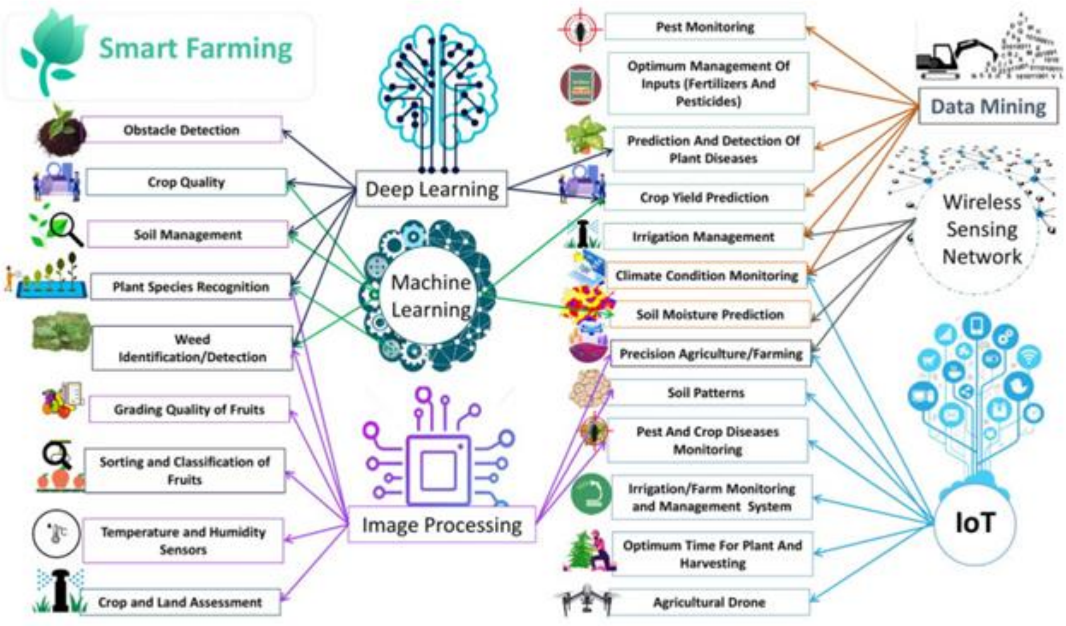

Figure 7: Smart farming via image processing, deep learning, and machine learning

3. Smart Agriculture

Smart agriculture is revolutionizing farming by incorporating advanced technologies and artificial intelligence (AI) to optimize agricultural practices, enhance productivity, and minimize environmental impact. This innovative approach leverages data-driven techniques and cutting-edge tools to address challenges in the agricultural sector, ultimately ensuring greater efficiency and sustainability.

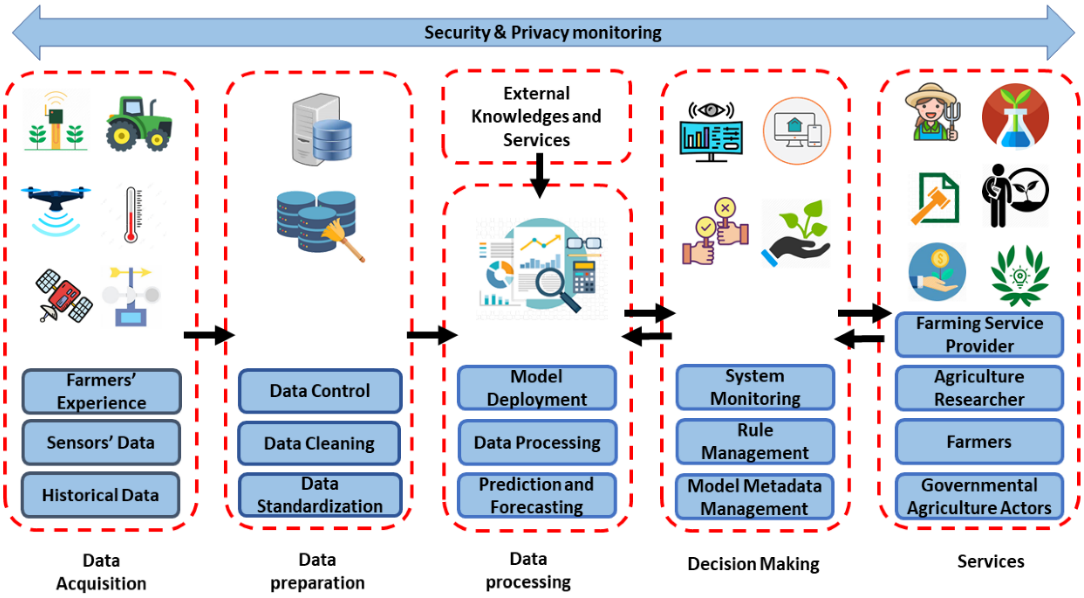

Figure 8: Security and privacy monitoring in agriculture from data acquisition to preparation and processing and decision making to final services in agriculture sector.

Integrating AI in smart agriculture has opened up new possibilities for farmers and agricultural stakeholders. Utilizing machine learning algorithms and advanced analytics, AI can process vast amounts of data from various sources, such as satellite imagery, drones, and ground-based sensors. This data is then used to make informed decisions regarding crop health, pest and disease management, irrigation, and soil management, among other aspects of farming (Figure 9).

Furthermore, AI-powered predictive models help forecast crop yields, enabling better decision-making regarding planting, harvesting, and marketing strategies. Automation and robotics also play a crucial role in smart agriculture, with AI-driven machines performing tasks such as planting, harvesting, and spraying with greater precision and efficiency.

Therefore, the fusion of smart agriculture and AI has the potential to transform the agricultural sector, making it more resilient, sustainable, and capable of meeting the ever-growing global food demands.

Table 2: Use of Machine Learning Techniques in Agriculture

Crop Management	Water Management	Soil Management	Livestock Management
Yield prediction Disease detection Weed detection Crop recognition Grading by quality Selective breeding	Irrigation monitoring Leak detection Weather monitoring Weather prediction Water usage prediction	Pesticides and fertilizers Fertility prediction Soil sensitivity Moisture prediction Organic carbon Insect detection	Animal monitoring Precision livestock Production quality Living conditions Grazing control

3.2. Application of Deep Learning in Smart Agriculture

3.2.1. Stress Detection

Deep learning techniques, such as Convolutional Neural Networks (CNNs) and object detection algorithms (e.g., YOLO, Faster R-CNN), can be employed to detect and recognize stress in agricultural fields (Redmon et al., 2016). That is, by analyzing images captured by drones or ground-based cameras, these algorithms can identify objects, such as rocks, equipment, and other obstacles, allowing for more efficient and safe navigation of autonomous agricultural machinery.

3.2.2. Crop Quality

Deep learning models, such as CNNs, can be utilized to analyze images of crops and assess their quality based on visual attributes like colour, size, shape, and presence of defects (Ghosal, Singh, Sarkar 2018). These models can be trained on large datasets containing labelled images of crops with varying quality, allowing for accurate and efficient crop quality assessment.

3.2.3. Soil Management

Deep learning techniques can be used to analyze remote sensing data, such as multispectral and hyperspectral images, to assess soil properties and conditions. These models can help identify patterns and trends in soil health, nutrient levels, and moisture content, enabling more targeted and efficient soil management practices.

3.2.4. Weed Identification and Detection

Deep learning models, particularly CNNs, can be employed for weed identification and detection in agricultural fields. In analyzing high-resolution images captured by drones or other remote sensing technologies, these models can accurately identify and locate weeds, guiding targeted herbicide applications and reducing chemical usage, as revealed by (Dyrmann, Karstoft, & Midtiby, 2016).

3.2.5. Prediction and Detection of Plant Diseases

Deep learning techniques can be used to analyze images of plant leaves and other tissues to detect and classify plant diseases. By training CNNs or other deep learning models on large datasets containing images of healthy and diseased plants, these models can provide early and accurate detection of plant diseases, enabling timely intervention and treatment. In identifying plant diseases, various approaches have been employed for detection. For instance, this method was used (Ramcharan et al., 2018) to predict that Cassava's susceptibility to viral infections poses a risk to food security in sub-Saharan Africa.

3.2.6. Crop Yield Prediction

Deep learning models, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, can be used to predict crop yields based on historical data, weather conditions, and other relevant factors. By incorporating real-time data from sensors, satellite imagery, and other sources, these models can provide accurate and timely yield forecasts, helping farmers make informed decisions about harvesting, storage, and marketing. Thus, You (2017) utilized a deep Gaussian process for predicting crop yield based on remote sensing data in developing countries.

3.3. Application of Machine learning in Smart Agriculture

3.3.1. Machine Learning for Precision Agriculture

Machine learning can be employed in various aspects of smart farming to analyze large datasets and provide insights that can help farmers optimize their operations. By integrating machine learning algorithms into farm management systems, farmers can make data-driven decisions, improve resource allocation, and increase overall productivity. Several studies highlight the importance of machine learning (Zhang, Wang & Wang, 2002, Liakos, Busato, Moshou, Pearson, & Bochtis, 2018).

3.3.2. Crop Quality and Soil Management

Smart farming solutions can incorporate advanced sensor technologies, such as soil sensors and remote sensing data, to monitor soil health and crop quality. These sensors can provide real-time information about soil nutrients, pH levels, and moisture content, enabling farmers to make informed decisions about fertilization, irrigation, and other management practices. Machine learning algorithms can also analyze this data to identify patterns and trends that can be used to optimize soil management strategies, ultimately improving crop quality and yields.

3.3.3. Weed Detection and Control

Using computer vision and machine learning techniques, smart farming solutions can automatically detect and identify weeds in the field (Dyrmann, Karstoft, & Midtiby, 2016). Drones and other remote sensing technologies can be used to capture high-resolution images of the fields, which can then be processed by machine learning algorithms to identify weeds and their locations. This information can be used to guide the targeted and precise application of herbicides, reducing the overall use of chemicals and minimizing their impact on the environment.

3.3.4. Crop Yield Prediction

Smart farming solutions can leverage machine learning algorithms to predict crop yields based on historical data, current weather conditions, and other relevant factors. These predictions can help farmers plan their harvesting schedules, storage requirements, and marketing strategies, ultimately improving their profitability. By incorporating real-time data from sensors, satellite imagery, and other sources, these machine-learning models can be continuously updated and refined to provide more accurate yield forecasts.

3.3.5. Soil Moisture Prediction

Machine learning can be used to develop predictive models for soil moisture levels. By analyzing data from soil sensors, weather stations, and remote sensing technologies, these models can provide farmers with insights into the future moisture conditions of their fields. This information can help farmers optimize their irrigation schedules, conserve water resources, and maintain optimal soil moisture levels for crop growth. Additionally, such predictive models can also help farmers prepare for and mitigate the impacts of drought and other extreme weather events.

3.4. Application of Image Processing in Smart Agriculture

3.4.1. Plant Species Recognition

Image processing techniques can be used to recognize and classify plant species based on their unique morphological features, such as leaf shape, colour, and texture. Convolutional Neural Networks (CNNs) and other deep learning approaches can be employed to analyze images of plants and identify their species with high accuracy (Wäldchen & Mäder, 2018). To improve recognition performance, large datasets containing labelled images of various plant species can be used to train these models.

3.4.2. Weed Identification/Detection

Computer vision and image processing techniques can be utilized to detect and identify weeds in agricultural fields. Thus, in capturing high-resolution images of the fields using drones or other remote sensing technologies, these techniques can analyze the images to identify weeds and their locations. Machine learning algorithms, such as CNNs, can be trained on labelled datasets containing images of different weed species and used to classify them in real-time (Dyrmann, Karstoft, & Midtiby, 2016). This information can guide targeted and precise herbicide applications, reducing chemical use and environmental impact.

3.4.3. Grading of the Quality of Fruits

Image processing can be used to assess the quality of fruits based on their external appearance, such as colour, size, shape, and presence of defects. Algorithms can be developed to analyze images of fruits captured using cameras or other imaging devices and to classify them into different quality grades. Machine learning techniques, such as deep learning, can improve the grading process's accuracy and efficiency, allowing for a more consistent and objective fruit quality assessment.

3.4.4. Sorting and Classification of Fruits

Image processing and computer vision technologies can be used to automate the sorting and classification of fruits based on their size, colour, shape, and other visual attributes (Brosnan, & Sun, 2002). By capturing images of fruits as they move along a conveyor belt or other processing equipment, these technologies can analyze the images and sort the fruits into different categories. This can help streamline the packing process and ensure that fruits of similar quality are grouped together, ultimately improving the efficiency of the supply chain and reducing waste.

3.4.5. Integration of Temperature and Humidity Sensors

Temperature and humidity sensors can be integrated into smart farming solutions to monitor and control the microclimate conditions in the agricultural environment. Image processing techniques can be used to analyze thermal and humidity data captured by these sensors, allowing farmers to make informed decisions about irrigation, ventilation, and other climate control measures. By combining this sensor data with other sources of information, such as weather forecasts and crop growth models, farmers can optimize their management practices and improve the overall productivity and sustainability of their operations.

4. Our Solution

MyAgro360 addresses the lack of access to accurate and real-time agricultural data, which lead to inefficient farming practices and reduced productivity. By leveraging AI and GIS technologies, MyAgro360 help users to map their farms, collects and records farm activities, provides location-based weather information, traceability and transparency in value chain, and thus, providing farmers with insights and recommendations to optimise their operations and improve yields.

MyAgro360 solves the lack of precision pest and disease identification, lessening waste of resources and negative environmental impacts through the use of pesticides. By using AI and GIS-powered precision tools, MyAgro360 help farmers to precisely identify pests and diseases with recommended control, reducing waste and minimising the impact on the environment (Figure 10).

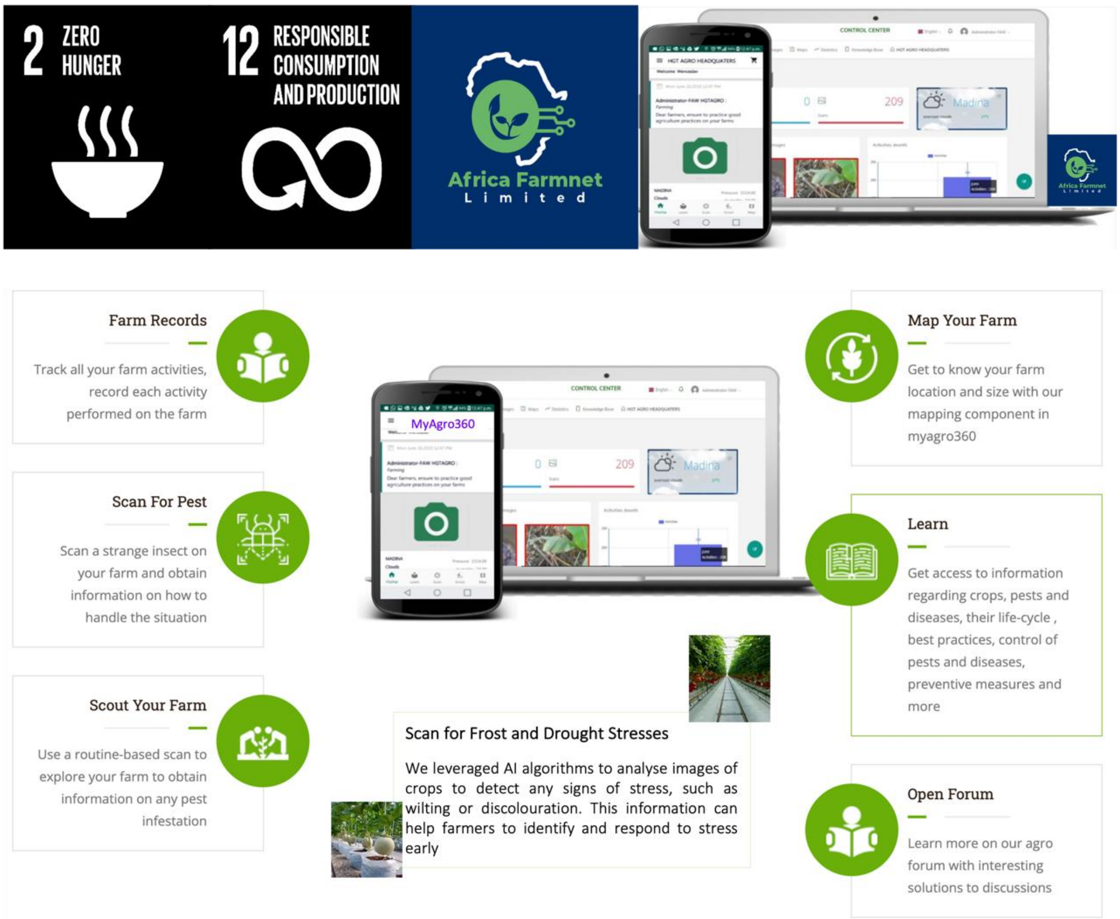

Figure 9: Mobile and web dashboards of MyAgro360, our AI/GIS-powered solution.

MyAgro360 also addresses the challenges faced by smallholder farmers in developing countries, such as limited access to markets, access to inputs and access to expert advisory. By providing farmers with access to MyAgro360 digital platforms that leverage AI and GIS technologies, MyAgro360 connects farmers with markets options, and provides them with real-time information and advisory to help improve their farming practices and profitability. Our solution directly addresses goals 2 and 12 of the sustainable development goals (Figure 10).

4.1. Stress Detection and Management

MyAgro360, an AI-driven application was used to identify abiotic stressors (frost and drought), pests and diseases on wheat in China and maize in Ghana grown under ambient conditions. This information can help farmers to take appropriate action, such as applying targeted pesticides or implementing integrated pest management strategies (Figure 11).

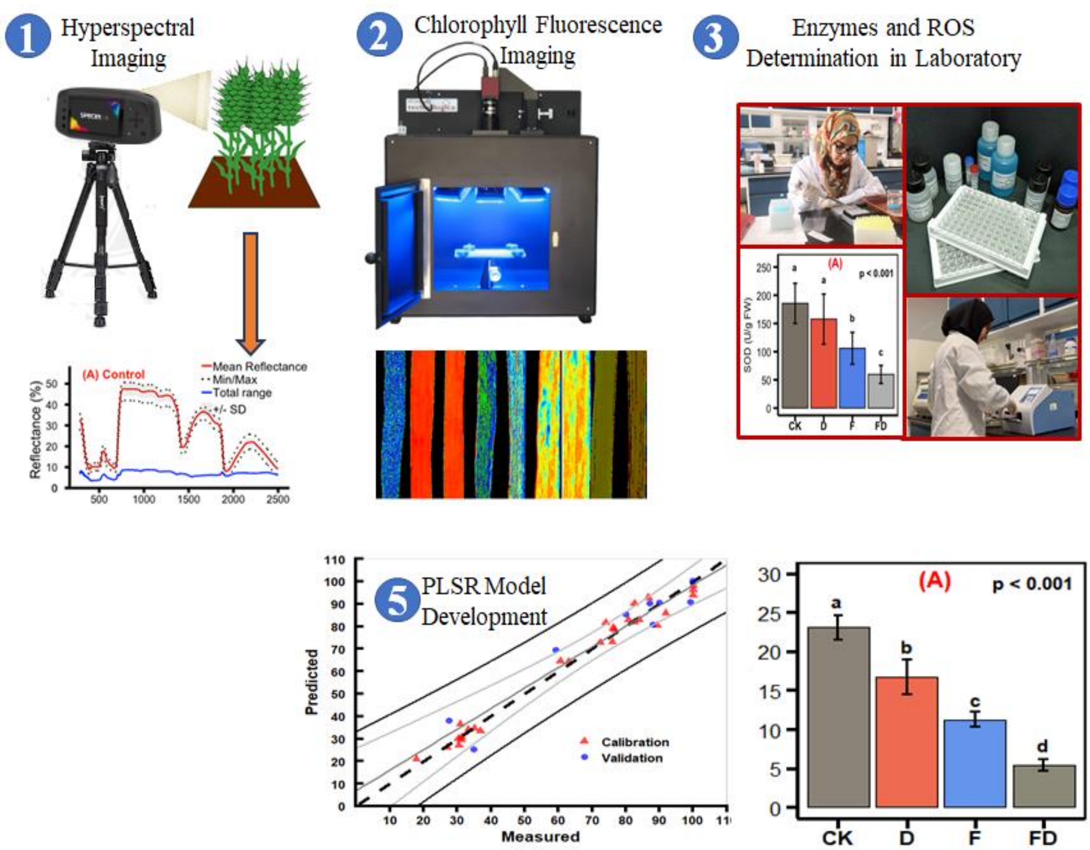

Figure 10: Initial outputs from MyAgro360, our AI/GIS-powered solution. Hyperspectral imaging based on output from AI-scanned images, chlorophyll fluorescence imaging, enzymes and reactive oxygen species model outputs.

5. Analytical Approaches

5.1. Market Analysis

The agritech industry is experiencing significant growth in Africa, with a focus on using technology to improve agricultural productivity, increase food security, and support sustainable farming practices. According to a report by the African Development Bank, the agritech market in Africa is projected to reach $5.9 billion by 2022, driven by increasing demand for food, rising incomes, and technological innovations.

Several factors are contributing to the growth of the agritech industry in Africa, including the increasing adoption of mobile phones, the availability of affordable smartphones, and the growth of digital payment systems. This has led to the development of innovative solutions, such as mobile-based agricultural advisory services, e-commerce platforms for agricultural inputs, and digital payment systems for farmers (Figure 12). In addition to these developments, the African Union's Comprehensive African Agriculture Development Programme (CAADP) has set a target of 6% annual growth in the agricultural sector by 2025. This is expected to drive the adoption of agritech solutions to increase productivity and efficiency in the sector.

Figure 11: Market, competitor and customer analyses for MyAgro360 in Africa.

The target market for our agritech startup in Africa consists of farmers, agribusinesses, and other stakeholders in the agricultural value chain. The size of the target market varies by country, but in general, the agricultural sector is a significant contributor to the economies of most African countries. The demographics of the target market vary depending on the specific solution being offered. For example, mobile-based agricultural advisory services are more popular among younger farmers who are more comfortable using mobile phones. In contrast, e-commerce platforms for agricultural inputs are more attractive to older farmers who are more familiar with traditional distribution channels. The purchasing power of target customers in Africa also varies widely depending on the country and the specific market segment. While some farmers may have limited resources, others may be more affluent and have greater purchasing power.

5.2. Risk Analysis

5.2.1. Internal Risks: SWOT Analysis

Strengths

- Innovative AI/GIS-powered solution for real-time farm management and traceability.
- Comprehensive platform addressing multiple agricultural pain points.
- Award-winning technology and previous successful implementation.
- Access to previously inaccessible markets and technology options for smallholder farmers.
- Real-time weather information and advisory services for farmers.

Weaknesses

- Limited testing in various environments and stress levels.
- Dependence on technology and internet access for farmers.
- Subscription and commission-based models may not be affordable for all smallholder farmers.
- Need for continuous updates and improvements to stay ahead of the competition.

Opportunities

- Expanding agritech market in Africa with potential for significant growth.
- Leveraging AI advancements for improved accuracy and efficiency.
- Collaboration with government and non-government organizations to promote sustainable farming practices.
- Expansion to other crops and countries.

Threats

- Increasing competition from other agritech startups in Africa.
- Unpredictable changes in the agricultural landscape due to climate change.
- Potential regulatory hurdles and compliance requirements.
- Dependence on external funding for research and development.

5.2.2. External Risks: PESTEL Analysis

Political

- Government support for the agricultural sector and agritech initiatives.
- International organizations are promoting sustainable farming practices.
- Regional political stability and cooperation.

Economic

- Growing agritech market in Africa with potential for high returns.
- Increasing demand for food and higher incomes in Africa.
- Varying purchasing power among target customers.

Social

- Increasing adoption of technology among farmers in Africa.
- Changing demographics with younger farmers adopting mobile technology.
- Need for sustainable farming practices to ensure food security.

Technological

- Rapid advancements in AI, GIS, and remote sensing technologies.
- Increasing availability of affordable smartphones and mobile internet access.
- Development of digital payment systems and mobile-based agricultural services.

Environmental

- Climate change impacts on agriculture, including extreme weather events and increased pest pressures.
- Need for sustainable farming practices to minimize environmental impact.
- Increasing awareness of the environmental consequences of pesticide use.

Legal

- Compliance with regional and national regulations for agritech solutions.
- Intellectual property protection for proprietary technologies.
- Data privacy and security regulations for user data.

6. Competition

The agritech industry in Africa is still in its early stages, and there are relatively few large, established players. However, there are several emerging startups that are making significant inroads in the market (Figure 13). Some of the major competitors in the African agritech industry include:

Farmerline: Farmerline is a Ghanaian agritech company that develops solutions to increase access to farm inputs and simplify transactions throughout the agricultural value chain.

Farmcrowdy: A Nigerian startup that connects smallholder farmers with investors, who provide funding for farming activities in exchange for a share of the profits.

Apollo Agriculture: A Kenyan startup that provides smallholder farmers with access to agricultural inputs, credit, and advice through a mobile-based platform.

Zenvus: A Nigerian startup that provides precision agriculture solutions, such as soil testing and crop yield forecasting, using sensors and data analytics.

Agrocenta: A Ghana-based startup that provides a mobile-based platform for farmers to share knowledge and information with each other.

Our primary competitive advantages are our deep understanding of the African agricultural ecosystem, gained through years of working directly with farmers, agribusinesses, policymakers, key stakeholders, and buyers. This has allowed us to tailor our platform to the specific needs of smallholder farmers in Africa, providing them with access to markets, and inputs that were previously unavailable to them (Figure 13).

MyAgro360 uses advanced technology, such as AI and GIS, to provide real-time data and insights to farmers, agribusinesses, and buyers. This has enabled us to provide more personalised and efficient services, reducing transaction costs and improving the accuracy of our recommendations.

Product Feature	MyAgro360	Farmerline	Agrocenta	Apollo Agriculture
Design	+		+	
Performance	+	+		+
Price	+			+
Quality	+	+		+
Additional Functions	+	+		
Customisation	+	+	+	
Product Service Life	+		+	
Overall Assessment	7	4	3	3

Figure 12: Competitor product analyses of leading agritech startups in Africa

7. Financial Plan

The financial estimates for our startup are contingent on a variety of things, including the nature of our pricing mechanism and the magnitude of the agritech industry. Yet, MyAgro360 has the potential to earn significant market share through the sale of licensing rights, usage rights, and subscriptions.

7.1. Revenue Projections

Our subscription-based pricing model costs $1000 per year, and the estimated target customers in the target market is 5,000 farmers, agribusinesses, and aggregators per each country (Table 3). The following is a breakdown of the anticipated revenue for the first four years of business.

Table 3: Revenue projections for the first four years.

Year	Adoption rate	Users	Cost ($)	Revenue
2023	10	350	3000	1050000
2024	25	2000	3000	6000000
2025	50	3500	3000	10500000
2026	75	5000	3000	15000000

7.2. Cost Projections

The costs associated with the development, deployment, and maintenance of MyAgro360 will depend on the complexity of the solution, the number of developers and engineers involved, and the hosting and server costs (Table 4). Assuming a conservative estimate of $200,000 in development costs and an ongoing annual cost of $50,000 for hosting, maintenance, and updates, the cost projections for the first four years would be as follows:

Table 4: Cost projections for the first four years.

Year	Maintenance	Updates + Marketing	Total
2023	300,000	50,000	350,000
2024	50,000	50,000	100,000
2025	50,000	50,000	100,000
2026	70,000	50,000	120,000

7.3. Projected Cashflow

On the basis of the forecasts for both revenues and expenditures, the following would be the net income for the first three years (Table 5).

Table 5: Cash flow projections for the first four years.

Year	Cash Flow
2023	700,000
2024	5,900,000
2025	1,0400,000
2026	14,880,000

7.4. Breakeven Analysis

The break-even point is the point at which MyAgro360 will be able to cover all of its expenses. If we use the estimates from above, the point at which we would be profitable would be when we acquire around 1,000 users per year. In order for MyAgro360 to generate a profit in its first year of operation, the company will need to achieve an adoption rate of at least 10%.

8. Conclusion

In order to prevent yield losses, techniques for quickly detecting and predicting abiotic and biotic stressors are crucial. In this study, we looked at how well hyperspectral (HSI) and chlorophyll fluorescence imaging (CFI) combined with artificial intelligence (AI) and geographical information system (GIS) work in simulating natural settings to assess wheat responses to frost (4°C) and drought (40% soil moisture content) stress at the booting stage and accurately identify fall armyworm and maize streak disease in maize. Flag leaf water content, photosynthetic rate, and enzyme activity were examined in addition to their typical HSI full range reflectance (280-2500 nm) and CFI values. Partial least square regression (PLSR) models were developed to investigate the utility of HSI for monitoring cellular damage in terms of enzymatic activity, and spectral indices were computed to characterise the responses to both isolated and combined stressors. Most of the work done on PLSR models for enzymes focused on the reflection at 360, 700, 1400, 1900, and 2460 nm. The highest R2c (0.99), R2v (0.94), and R2d (0.93), as well as the largest ratio of prediction to deviation, were found in superoxide dismutase, peroxidase, and ascorbate peroxidase, respectively (4.04, 3.06, and 3.85).

Cold stress, both alone and in conjunction with dryness, and reduced CFI. Through measuring enzymatic activity and reactive oxygen species (ROS), PLSR models confirmed that the most important variables were the ratio vegetation stress index (RVSI), the green difference vegetation index (GDVI), the difference vegetation index (DVI), and the normalised difference water index (NDWI). There was a high association between spectral index and enzyme activities in predicting crop failures. This means that HSI and CFI methods were able to detect coupled frost and drought conditions for fast quantification. The AI/GIS-powered scouting and scanning features in MyAgro360 accurately detected fall armyworms at the pupal stage and accurately provided early control measures for users.

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