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Intelligent Machines and Plant Disease Forecasting Systems: Digital Solution for Managing Crop-Stressors Toward Food Security in Africa

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Abstract

Agriculture in sub-Saharan Africa is facing increasing threats from climate change, pest and disease outbreaks, water stress, and diminishing labor availability. Traditional methods of managing these issues, such as manual pest control and field surveillance, are no longer viable for large-scale farming operations. The integration of intelligent technologies, including artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), and drones, offers innovative solutions. These technologies, alongside plant disease forecasting platforms like PLANTPlus, WISDOM, FAST, and EPIDEM, can accurately predict pest and disease risks based on environmental and edaphic data. By enabling timely and precise interventions, such systems enhance crop productivity, reduce reliance on agrochemicals, and contribute to a more sustainable and food secure future for Africa. This review explores the potential of these digital tools in mitigating agricultural losses and stresses the importance of their adoption in the region.

Introduction

African agriculture is seriously constrained by many stress variables including high pest and disease pressures, weeds as well as water stress to mention a few. In the horn of Africa for example, locust swarms covering 925 square miles have been detected over arable lands in Kenya. Also, destruction of 800 square miles of croplands and 350,000 MT of cereal grains have been attributed to these voracious insect pest in Ethiopia. These countries lost an estimated 8.56 billion USD from attacks of locusts alone (Cullinan, 2020). In 2022, about 80% of crop yield reductions which occurred in Nigeria and elsewhere in the West African region were induced by diseases amongst other biotic influences (Leadership, 2023). These losses were estimated at over 200 billion USD, and no doubt contributed hugely to malnutrition in many parts of the region (The Guardian, 2023). Yield losses ranging from 40-91% have been reported due to effects of weeds including Striga infestation on cereals, legumes, oil seeds, and root and tuber crops grown in the region (Imoloame et al., 2021). Crop yield losses estimated at approximately 4.5 to 10 billion USD in Nigeria alone, and about 95 to 200 billion USD in the African region in general have been attributed to weeds and other biotic pressures respectively (Sibuga, 2009; David et al., 2022; Agritech, 2023; Kyari, 2025). All these thus warrant concerted control towards mitigating food insecurity in the continent (TNH, 2004).

Classical pest and disease detection, and assessment techniques involving manual crop inspection, scouting for pest populations, and visual disease assessments in the field, and their subsequent identification are laborious, time consuming, and requires huge numbers of personnel to execute, especially in large farmsteads (Patil & Kumar, 2021; Enyiukwu et al., 2023). Besides, these operations are also constrained by steep field topography (Kryzanowski & Kutcher, 2010; Cardillo et al., 2018). Conventional techniques alongside long term panic spraying of crops with agro-pesticides do not constitute sustainable solutions to mitigate biotic pressures or other stress factors in modern crop production. On the other hand, implementation of technology-assisted pests, disease and stress detection on crops and their control using intelligent machines, and plant pest and disease forecasting systems (otherwise called digital warning systems) would in no small measure contribute to cushioning global food insecurity (Chakrabarti & Mittal, 2023).

Early detection of pests or diseases and their control is one of the important aspects of plant pest and disease forecasting (PPDF) systems used in modern precision agriculture. Weather-based forecasting systems is considered an important part of agricultural decision support system in any region (Sangeetha et al., 2025). Such system utilizes weather data (temperature, rainfall, and relative humidity), leaf wetness or other variables that support pest or microbial growth to predict possible occurrence and/or intensity of a pest or disease outbreak. Effective forecasting of pest and disease pressures on the basis of climatic data can help farmers on a continuing basis in the design of disease, pest or stress management and execution of timely interventions in farming concerns (Tilva et al., 2013; Nwauzoma, 2016; Zahra et al., 2023).

Plant pest and disease forecasting (PPDF) is defined as a digital system which tries to predict the incidence, intensity and degree of damage of crops from pest or disease attacks in a given area at a particular time or season (Nath et al., 2020). PPDF systems uses environmental and edaphic conditions to predict a disease and notifies the growers whether or not application of control measures will sufficiently justify control interventions, and add to overall gains in the farm economy (Prasad, 2012).

PPDF systems therefore seeks to accurately predict when the three factors of host, pathogen (pest) and environment, which participate in disease development or pest onslaught, will sufficiently interact in such a manner that disease or pest attacks can occur (Nath et al., 2020), and cause economic losses to the farm economy. In most cases, though the host status can be reasonably known and presence of the pathogen/pest determined through previous cropping history or survey in the area, the environmental conditions remain a major determinant of the presence of a pest or pathogen per season per year (Sangeetha et al., 2025). It also affects the pest's or pathogen's ability to cause outbreaks. For example, for fungal grey spot of corn to occur, leaves of the susceptible cereal must remain wet for a long time; hence, pest and disease forecasting attempts to estimate when the ambient environment will favour pest emergence or disease development.

Nwauzoma (2016) and Zahra et al. (2023) in like manner, emphasized that geographic information system (GIS), GPS, geo-statistics when incorporated with digital remote sensing resources and platforms have enabled accurate analysis of big data, and mapping of pest population, and ultimately fine tuning prediction of several plant pests or diseases such as late blight disease of *Solanum* species in the Del Fuerte Valley (Nelson et al., 1999; Andamon, 2024). Nelson et al. (1999) reported also that these digital technologies have been effectively utilized to forecast occurrence of cotton leaf curl disease in Pakistan and cotton leaf crumple in Arizona, USA.

Pest and Disease Forecast Systems: Why Implement One?

In the field, PPDF systems basically helps farmers or growers to make effective decisions regarding plant pest or disease, and possible methods to adopt for their control. Often, the system usually ask the growers a series of questions about the susceptibility of the host crop, and makes recommendation for or against pesticide interventions, taking the current and expected weather conditions into account. Hazzard (2012) and Nath et al. (2020) reported that compared to classical calendar schedules, Tomcast, a PPDF system for example, reduced the frequency of pesticide application by 50% in tomato without compromising its fruit yield or fruit quality than the conventional every 7-10 day protectant spray approach. Crop growers often faced the dilemma of, whether to spray or wait due to variability of incidence and severity of plant pests and diseases. PPDF systems help producers to make timely decisions concerning disease management, to avoid early inoculations or to slow down the rate of an epidemic, and represents a boon to growers by encouraging only wise and as-needed use of pesticides (Esker et al., 2013). The system therefore supports producers' decision making processes, with respect to costs-benefits of pesticide use, suitability of particular planting materials, specific crop or variety in a particular area and promoting sustainability, amongst others (Rithesh et al., 2023).

The level of damage on the hosts' tissues and attendant reductions in yield of the crop is another factor that would motivate a producer towards deciding whether or not to apply pesticides. If the intervention is minor, keeping disease levels below damage thresholds will provide economic benefits which outperforms conventional approaches. In the final analysis, PPDF systems can be used to select for appropriate pest or disease management method, such as foliar pesticides application (Esker et al., 2013; Rithesh et al., 2023).

Several workers are of the view that the major reasons for plant pest or disease forecasting is that it provides a means for determining whether a pest or disease will occur, where and when it will occur, and when a given management practice should be applied (Murmu et al., 2020; Petrovic et al., 2023; Sangeetha et al., 2025). It also helps to stimulate our intellect to identifying the remaining gaps in our knowledge of environmental factors, and their impacts on the progress of the pest or disease (Anonymous, 2012).

Intelligent machines: A necessity for sustainable Agriculture – Why adopt them

Traditional agriculture in the modern world is constrained by a plethora of factors including increasing pest and disease pressures, effects of climate change such as droughts, flooding and landslides, outdated farming techniques and obsolete technologies, overdependence on synthetic pesticides, poor seed quality, and urbanization of choice farmlands, dwindling availability of farm-hands, and rapid population growth amongst other variables (Vota, 2024; Ambali et al., 2024). The problem of increasing food production to meet the needs of exploding human population projected to hit 9.2 billion across the nations by 2050 (Pawlak & Kolodziejczak, 2020) without compromising the environment and sustainability also stares conventional agriculture in the face (Mizik, 2022). Against this backdrop, traditional farming practices is reported to have so far failed below gross expectations in meeting the food needs of the people especially in Africa where nearly 800 million Africans (60% of the populace) lack unrestricted access to safe nutritious foods since 2021 (Ambali et al., 2024, Zhang et al., 2024).

Traditional farming methods is a labour intensive concern involving many tasking and tedious operations from land preparation, seeding, crop health management, sorting, storage and marketing. It also involves inundation of crops with broad-spectrum pesticides using classical spray equipment, which often exposes the farm-hands to inhalation and/or other forms of absorption of toxic chemicals. Many of these conventional operations have often been reported to lead to soil and environmental degradations (Kaur et al., 2024). In addition to PPDF, intelligent digital technologies especially robotics, such as autonomous tractors and drones, would in the overall make agriculture a sustainable concern by contributing significantly to the tenets of precision agriculture namely productivity, profitability and predictability (Shinde, 2023; Wakchaure et al., 2023).

Globally agriculture is facing dwindling availability of especially young farmhands leading to rising labour costs (MDF, 2025). Intelligent farm machines could accomplish farm chores such as milking, plowing, seeding, harvesting, sorting and grading operations timely, faster, accurately and efficiently without human interventions (Robinson, 2018). By so doing, they could contribute to assuaging the shortage of farm hands and eliminating wastages in farming concerns associated with manual labor. Robots could also autonomously analyze soil nutrient status, dampness as well as crop health conditions, and determine extent to fertigate or to apply specific pesticides by precision. Agritecture (2024) noted that autonomous mobile robots equipped with vision sensors, cameras, GPS, and magnetic tapes are able to gather environmental information that could adequately permit planting and harvesting. Those equipped with necessary vision sensors are noted to recognize and remove weeds on their own, thus creating or maintaining the right growth environment for the crop to thrive (Pereira, 2023; Hokuyo, 2024). MDF (2025) reported that smart farming and mechatronics integrating IoT, AI, and other autonomous systems contributed 413 billion Euros to EU economy on annual basis.

Generally, Alka et al. (2024) reported that adoption and utilization of digital farm machines in precision agriculture is significantly greater in developed countries when compared with developing nations of the third worlds. Adoption of intelligent digital systems in smart European agriculture for operations such as seeding, soil moisture monitoring, fertilizer application, milking and harvesting ranged between 33% in Poland to 70% in Czech Republic (Petrovic et al., 2024). A study finds this to be essential because farmers in developed economies, to a very large extent, use hi-tech farming equipment in large monoculture farmsteads, alongside with modern irrigation facilities (Castle et al., 2016), which are compatible, and integrate easily with other digital devices or systems.

A recent survey documented up to 92.96% willingness on the part of African, Nigerian farmers in particular, to adopt and upscale to using PPDF and other intelligent machines in handling farming operations and crop health (Ezeaku et al., 2024). On the other hand, other African farmers and less developed communities are mainly smallholder traditional and subsistence entrepreneurs. It is reported that 40% of these rural farmers are hesitant on adopting smart farming due to concerns about reliability, and returns on investment (MDF, 2025). Other constraints are prohibitive costs of these modern equipment, lack of sensitization and access to low interest loans, lack of skilled technicians to operate and maintain these hi-tech equipment. Also, inability of governments to incentivize and/or subsidize these modern inputs amongst other socio-economic and cultural factors such as land tenure, and small multi-cropped farmsteads have been adduced as limiting speedy transition to precision agriculture in the region (Odifa, 2024; Ezeaku et al., 2024; Mordor Intelligence, 2025). Overall, only 15-20% of mid-level farms in the continent have actually embraced and adopted smart agriculture (Gabriel & Gandorfer, 2023).

This review examines the place of intelligent machines and significance of plant pest, disease or stress forecasting systems as digital solution for effective management of biotic and abiotic stressors of agricultural crops towards food security in Africa.

Data Collection

Data used in this review, except otherwise stated, were generated from papers published on the subject matter from 2004-2025 obtained from searching online databases including google, google scholar, and Researchgate. The keywords (or combination of keywords) used for the searches include Intelligent robots, agricultural robots, robotics in agriculture, precision agriculture, information technology in agriculture, AI in agriculture, ML in agriculture, plant disease forecasting systems, plant pest forecasting systems, digital warning systems in agriculture, conditions for plant pest/disease development. Materials with strong relationship to the subject matter written in English were included in the review (Table 1) while others written in languages other than English were excluded (Enyiukwu et al., 2020).

Table 1: Keywords or combination of keywords used in the different search engines to obtain data.

Keywords/combination of keywords	Google	Google scholar	ResearchGate	Mean
Intelligent robots	35	10	10	66
Agricultural robots	21	12	8	41
Robotic in agriculture	40	16	21	77
Precision agriculture	18	19	20	47
ITC in agriculture	29	10	13	52
Artificial intelligence	44	19	12	75
Machine learning	23	16	18	51
Plant disease forecasting	16	7	10	33
Plant pest forecasting	13	10	10	33
Digital warning systems	5	3	7	15

Features of a Good Plant Pest and Disease Forecast System

The principle behind a good PPDF system is to determine whether there is a risk that a disease or pest attack is likely to occur, or that the intensity of the attack is likely to increase. Therefore, a PPDF system should satisfy the following criteria if it were to be successfully adopted by agricultural stakeholders:

Simplicity: The system should be simple in design, and functionality so as to be easy for use by stakeholders in farming concerns. The level to which a PPDF system is accepted by producers is related to how simple and easy it is for stakeholders in the agricultural industry to use (Prasad, 2012; Thomidas et al., 2024; ESNRR, 2023).

Reliability: The system must use remote sensing and other digital technologies to monitor and obtain data on real time environmental variables, analyze and use same to reliably predict likelihood of particular pest or disease outbreak and/or severity of its attack, and then offer appropriate management recommendations (Prasad, 2012; Bayer, 2021; Thomidas et al., 2024; Dasari et al., 2024).

Cost effective and adoptable: This is one of the most important features to consider about PPDF systems. PPDF systems, as a matter of fact, involve huge expense of resources on the farm economy, therefore, they must be reliable and overtly cost effective. It should only be installed for use on high value crops, and for highly devastating irregular pest or disease rather than one that occurs every year, and can potentially cause serious damage (loss) to the yield and quality of agricultural products (Prasad, 2012; ESNRR, 2023). Growers and other stakeholders in the agro-allied concerns consider very highly the simplicity, reliability and cost profiles of PPDF above other features in order to adopt and install a forecast system (Prasad, 2012; ESNRR, 2023; Thomidas et al., 2024).

Communication: A PPDF system must have a simple and reliable means of communication of the outcomes of the system to farmers such as SMS alerts. Such simple channel is very necessary for successful implementation of the pest or disease forecasts since the system is meant to serve a wide variety of growers with diverse backgrounds (Prasad, 2012; Bayer, 2021).

Economic control measures: A PPDF is meant for timely preventive control rather than curative interventions. It must have appropriate management technology of the pest or disease in place for use by growers to effectively checkmate attacks on high value crop (possibly a cash crop). Hence, the system should reliably aid the growers to make informed decision about selecting less susceptible crop or cultivars, or to rotate crops to reduce disease or pest pressures based on its recommendations. It is only in this way would it be able to offset the economic impacts and cost implications of development, and incorporation of the system in the farm plan (Bayer, 2021; Dasari et al., 2024).

Environmental concerns and sustainability: The PPDF system would also aid growers to avoid unnecessary or blanket sprays of synthetic pesticides which besides being costly on the farm overhead, could degrade the environment killing non- target species and disrupting the food web (Prasad, 2012; ESNRR, 2023).

PPDF systems would fulfill the above principles relative to the initial pest population or pathogen density against prevailing environmental conditions between cropping seasons (Nath et al., 2020). It must estimate the amount of initial inocula as in Stewart's disease in corns. Alternatively, it would estimate abundance of primary and secondary sources of inocula as in the case of apple scab or assess whether climatic conditions are favorable for development of secondary inoculum of pests or pathogens (Prasad, 2012; Esker et al., 2013).

Environmental Parameters Affecting Plant Disease Development and Forecasting

Epidemics is triggered by specific weather patterns favouring the pest or pathogen on a susceptible host. Disease development or pest attack basically requires interaction of factors of host, pathogen/pest and a conducive environment, the environment being, in most cases, the limiting variable. Some environmental factors affecting plant disease development or pest attacks include:

a. Rainfall and high relative humidity effects

Microbial leaf spots diseases such as tan spot, stagnospora or septoria blotch are favored by damp leaf conditions. Long periods of leaf wetness, portends increased risk for such disease development or exacerbation to its severity, if already present (Byamukama, 2022). In rainy years, rainfall for 2 consecutive days followed by warm humid conditions increased the risk and permit development of blight disease on susceptible potato varieties. Humidity (>85%) and leaf wetness in cool weather predispose onions, peas, lettuce and spinach to powdery mildews (AUSVEG, 2023).

b. Temperature effects

Blisters and swellings caused by *Albugo candida* on the heads of Brassicas could result in 100% yield reduction of the crop. The disease is favored by mild temperatures (<24^{o}C) lasting about 4 consecutive hours (AUSVEG, 2023). In India, temperature of <27^{o}C persisting for 15 h consecutively in a week has been reported to spur blight development on susceptible potato crop varieties (Prasad, 2012).

Interplay of climate variables on disease development: An example

White mold (*Sclerotinia sclerotiorium*) of bean is a devastating disease in New York and other bean growing areas in the USA (Shah et al., 2019). The fungus overwinters in bean debris. Moisture is very important for the fungus to develop, grow, and penetrate and colonize target host tissues such as mature flowers. A thin film of moisture is required for the infection to spread from diseased flowers to other aerial organs of the plant. However, development of lesions and spread of the disease on organs ceases unless the water film persists. Equally important is wind speed which affects the rate at which soil and plant surfaces dry. Hence, this disease is common in high plant population farms or those surrounded by dense vegetation, which conditions will limit proper air circulation in the crop field (McCreary et al., 2016; Cornel University, 2023).

A long chilling (<15^{o}C) period is required before the fungal spores germinate, become infective and cause white mold. However, high temperature is noted to inhibit or greatly delay spores infectivity (McCreary et al., 2016; Cornel University, 2023). On the other hand, development of lesions and spread of the disease on bean plants, takes place on low to moderate temperatures (McCreary et al., 2016).

Weather Variables and Plant Disease Prediction

PPDF systems use weather variables such as rainfall, relative humidity, temperature, and wind speed to predict likelihood of disease or pest attacks. Predicting epidemics in agriculture emphasize early identification of weather patterns or variables in a season that correlate with a particular disease or pest outcome at some later point (Shah et al., 2019). Accurate forecast system for white mold disease of bean, for example, is based on daily measurement of environmental variables (rainfall, relative humidity and temperature) which warranted use of remote sensing data.

Some prediction models noted that for white mold to occur on beans that the soil moisture content must remain damp or wet for 10 days. The wetness period in soils triggers production of infective fungal spores, and development of white mold on bean plants in weeks before peak flowering. Other factors that affects the disease development include high relative humidity, low wind speed and dense vegetation cover (McCreary et al., 2016; Shah et al., 2019). Therefore, the lack of regional forecast tool for white mold disease is one of the fundamental factors that had contributed and fueled the perception amongst growers that growing snap beans in New York is riskier than raising other crops (Shah et al., 2019).

Similarly, the duration of leaf wetness and temperature downscaled to the nearest farm location were reported to be used to monitor and predict downy mildew and anthracnose of grapes caused by *Elsinoe ampelina* in both artificially and naturally infected vineyard fields in the Americas (Seem, 2004; Carisse et al., 2020).

Mathematical Models for Prediction of Plant Diseases

A PPDF model is a mathematical representation of the relationship between factors of environment, host plant and pathogen/pest that culminates in development of an infection or pest attack. The output is usually presented as an equation, a table or graphics denoting levels of probable disease risk expressed in numbers, predicted disease occurrence, host damage, inoculum density or potential (Broome et al., 2023) (Table 2). The underlying principle behind some of these mathematical PPDF models is the critical pest or disease threshold (CDT). This means that for the pest or disease to cause economic loss, it must affect 20% of the host plant population or induce 5% host plant tissue damage. Such models typically use degree and duration of leaf wetness, relative humidity and temperature values obtained from regional weather stations (Table 2), crop variety and growth stage as well as information on prevailing inoculum density/pest population at a given temperature from neighborhood surveys (Magaray et al., 2005; Newlands, 2018; Bloome et al., 2023).

For example, for powdery mildew caused by (*Leveilla taurica*) to occur in tomato, the disease model presented in Table 2 assumes that under favorable environmental conditions as highlighted above, there must in addition be large number of potent inoculum of the pathogen in the field, and that the host tomato cultivar must be susceptible to the pathogen, and that fungicide(s) could provide effective control of the disease for at least a 10-day period. This model has aided growers of tomato crop in California, USA to make informed control decision of the disease and increase tomato yield in the area (Bloome et al., 2023).

The growers of corn in Iowa USA have been availed a reliable predictive model for tar spot of corn and mycotoxins in a National Predictive Modeling Tool Iinitiative (NPMTI). This model accurately predicts likelihood of attack of tar spot and mycotoxin contamination of corn using temperature, dew point, humidity, and rainfall to forecast favorable matrix of environmental conditions that would culminate in appearance of the disease in corn growing areas (Kick & Robertson, 2024). The application which is available on smart phones has also been reported to correctly predict occurrence of gray leaf spot, northern leaf blight, southern rust, Curvularia leaf spot and vomitoxin contamination of corns (Kick & Robertson, 2024). The models, however, are limited in some degree due to they are more time consuming since data is manually generated and non-automatic compared to AI-assisted models.

Table 2: Model for predicting incidence of *Leveilla taurica* in tomato.

Condition of Host	Damage Expected on host	Recommended Fungicide Intervention	6-day Post-treatment Assessment
All nonconductive days	None	Do not apply fungicide	Re-assess after 6 days
All conducive days	Serious tissues damage	Spray the host crop	
All moderate days	Fair tissue damage	Do not apply fungicide	Re-assess host after3 days
All moderate and nonconductive days, no 2 non-conducive days are consecutive	Nil to fair damage on host tissues	Do not apply fungicide	Re-assess host after3 days
At least one series of at least 2 consecutive nonconductive days conducive days	Nil to fair damage on host tissues	Do not apply fungicide	Re-assess host after 6 days after last nonconductive period
At least 3 consecutive days, no 2 non-consecutive days are consecutive	Fair to serious damage on host tissues	Spray the host crop	16 days post-spray (spray day = day 1).
Less than 3 conducive days, no 2 non-conducive days are consecutive	Fair damage on host tissues	Do not apply fungicide	Re-assess the host plant 1 day afterwards

Source: Bloome et al. (2023).

Computer-Based Plant Pest and Disease Forecasting Systems

PPDF is considered as one of the most important tools in modern agriculture (Adhikary & Rai, 2021). Accuracy of prediction of an epidemic risk, coupled with ability of the system to deliver timely control measure in addition to financial implication of the system on the farm economy influence the choice of PPDFs to be adopted by growers and stakeholders (Ghent et al., 2013; Nath et al., 2020). The earliest designed simple, accurate and effective digital forecasting system for Stewart's corn wilt relied solely on variations in environmental temperature in January to February, since it was known that low seasonal temperatures kill the disease vector so that the disease do not occur, and moderate to high temperatures on the other hand, favorably support the vector and thereby could encourage disease occurrence (Pataky, 2004; Bayer, 2021).

Table 3: Some PPDF programs used for forecasting occurrence of diseases on some crops in modern agriculture.

S/N	PLANT PDF PROGRAMME	DISEASE/PATHOGEN	PLANT/CROP
1.	FAST	*Alternaria solani*	Tomato, potato
2.	EPIDEM	*Alternaria solani*; Early blight	Tomato
3.	TOMCAST	Anthracnose, *Septoria* spp., *Alternaria* sp.	
4.	WISDOM	Late blight	Potato, tomato
5.	MELCAST	Anthracnose, gummy stem blight, *Alternaria* sp.	Water and musk melon
6.	MARYBLIGHT	Fire blight	Apples
7.	EPIVEN	Scab disease	Apples
8.	EPICORN	Southern corn leaf blight	Corns
9.	BLITECAST	Late blight	Potato
10.	JHULCAST	Late blight	Potato
11.	SIMCAST	*Phytophtora infestans*	Potato
12.	EPIMAY	Southern maize leaf blight	Maize

Sources: Nath et al. (2020), Adhikary & Rai (2021)

a. Regional PPDF systems / models

Several central computer-aided forecast systems have been developed in the USA, Germany, South Africa, Netherlands and other parts of Europe. According to Kumar et al. (2016), web-based PPDF systems have been used to forecast occurrence and severity of tan spot, Septoria leaf blotch, leaf rust, Fusarium head blight and scab of wheat. These have also aided in the prediction of attacks of mustard aphids (*Lipaphis erysini*) and diseases using LAMP technology. Some PPDF systems include EPIPRE (Epidemiology, prediction and prevention) a multiple pest/disease forecasting system developed in Netherlands, PLANTplus, FAST for predicting Alternaria solani induced blight in tomato, TOMCAST for blight in potato, asparagus, carrot, celery and pistachio and BLITECAST, EPIVEM, EPICORN for scab and southern leaf blight, respectively amongst many others (Table 3). These PPDF systems are interactive web-based digital platforms that interface with any device with internet connectivity using environmental data obtained over a region by central regional weather stations such as the Enviro-Weather station of the Michigan State University. All that the growers need to do is to choose location nearest to their crop farms to connect to the system (Kumar et al., 2016). BLITECAST, for instance, uses average relative humidity (RH) values of 95% and temperature to predict blight on potato/tomato while TOMCAST and FAST use average leaf wetness, RH, and temperature to forecast occurrence and intensity of blight on tomato, potato and recently asparagus, carrot and celery (Bayer, 2021). Information to and from growers on the respective pest and disease occurrence, density and potential damage intensity on the target crop are then transmitted to the growers usually via smartphones and computers.

PLANTplus is a digital PPDF system developed in the Netherlands which uses automatic data of weather variables for the detection and control of late blight (*Phythophtora infestans*) and early blight (*Alternaria solani*) of potato. In addition, the model incorporates data on the life cycle of the pathogen and growth stage of unprotected part of the host crop. Thereafter, it recommends when and what type of fungicides to apply on affected crops at the lowest effective dosage for both plant and ecological health. PLANTplus platform enables data transfer such as crop variety and growth stage, weather data and fungicide treatment options between producers and other authorized agricultural stakeholders through appropriate digital channels such as Windows software and SMS alerts. PLANTplus is divided into 3 sub-models:

1. Unprotected part of the crop: Tracks growth of new leaves and degradation of previously applied chemicals;

2. Infection events of the disease: Tracks formation of spores on each infected leaf, dispersal of spores into the air and germination of spores/penetration into unprotected leaves.

3. Combination of 1 and 2 above to form treatment recommendation.

The model effectively interprets the data based on parameters I and 2 above, and provides a recommendation on whether or not the application of fungicides is likely or necessary. However, the choice of fungicide to use is ultimately at the producer's discretion.

The system, based on considered input data, could make the following recommendation for chemical types depending on how long ago the host has been potentially infected: no treatment, treatment with contact fungicide to be considered/necessary at this point, treatment with trans-lamina fungicide to be considered/necessary, or that treatment with systemic fungicide to be considered/necessary at this stage.

An infection in less than 24 hours will involve treatment with a contact fungicide while older infections (greater than 48 hours) will be treated either with a systemic fungicide; based on the weather condition (rainfall and wind speed) expected to prevail in the following week. Such recommendations helps producers to make plant health management plans ahead of time.

Bayer (2021) noted that PPDF systems could save growers 3 rounds of fungicides sprays per year. Similarly, PLANTplus has assisted potato growers in South Africa in the control of early and late blight diseases of potato timely, and reduce number of fungicide sprays as against popular calendar schedules. It also allowed for large scale continuous crop and field monitoring throughout the growing season, and contributed positively to estimated and actual crop yields, and has contributed immensely to improved returns on farm investments (van der Waals et al., 2003; Enyiukwu et al., 2023).

Soybean rust disease (SBR) represented a potentially huge threat to soybean production in the 2005 cropping season in USA. The US Department of Agriculture (USDA) developed a warning system for the SBR fungus surveillance, prediction and management. The SBR platform is a web-based country level forecast system that delivers useful information used by stakeholders to mitigate the damaging effects of the disease through timely preventive management (Roberts et al., 2006). These workers reported that the system aided in the prediction and management of SBR resulting in increased farmers' income by 11-299 USD per plot at the end of the 2005 season.

In India, the National Oceanic and Atmospheric Administration used high resolution digital remote sensing and satellite based systems to effectively predict yield of 8 different crops on a region-wide basis at 84.87% accuracy (Ferencz et al., 2004). These systems are simple, reliable, affordable and powerful tools which could be used by smallholder growers in developing countries to monitor crop health and estimate yield (Ferencz et al., 2004; Ali et al, 2022). Though they are grossly cheaper, their reliance on downscaled weather data from regional weather stations makes them less likely accurate compared with on-site digital PPDF platforms (Bayer, 2021).

b. On-site PPDF systems/models

On-site or site-specific PPDF systems as the name implies capture and provide soil and other environmental data on specific locations of the farm enterprise. Their data are usually more precise and accurate compared with those downscaled from regional central weather stations (Singh et al., 2012; Bayer, 2021).

Spattering raindrops during violent storms are known to spread *Septoria* infections. This spread the spores of the pathogen from near ground to upper leaf canopy and neighbouring crops, forming a critical factor in tailoring good disease forecast for *Septoria*. Prediction of likelihood of *Septoria* and its management outbreak have been based largely on classical features of climatic conditions and calendar fungicide schedules (Kuna-Bronioswski et al., 2015). These workers, however, used electric field to measure the number of spattering and range of dispersal of spore-ladden soil particles and used the information so obtained to determine the occurrence and severity of *Septoria* infection.

Association between weather variables and incidence of blast disease of rice in addition to various other fungal diseases of the crop has been reported. The blast disease of rice develops and spreads rapidly under cool ambient temperatures and frequent heavy rains during the heading season of the crop, resulting to serious economic losses in the farm economy. Also, heavy rainfall at rice booting stage has been implicated for development of false smut (*Villossiclava virens*) in rice crop whereas cool wet weather, and rain storms favor the development of bacterial blight (*Pseudomonas syringae* pv *glycinea*) on susceptible soybean hosts (Malvick, 2018; Wang et al., 2019). Some workers in Asia in recent years used Softmax activation function (AF) program based on artificial neutral network on weather variables to predict occurrence of rice blast by 92.15% accuracy (Patil & Kumar, 2021).

Internet of things (IoT) can be used to collect environmental information for forecasting plant diseases and pest populations, especially on-farm, whereas remote sensing could be used to monitor, predict and map these parameters on a regional scale. Wang et al. (2018) used support vector machine and wavelet transformation to forecast the likelihood of occurrence of 3 kinds of cucumber diseases with mean accuracy of over 86%. In South Africa, Fruit-look is a digital PPDF system used to monitor, and successfully irrigate grape farms, while Chameleon has been adopted and successfully employed in irrigation systems of smallholder farm enterprises of Tanzania, Mozambique and Zimbabwe. These PPDF systems were reported to reduce irrigation frequency by 50% as against conventional approaches (Ncube et al., 2018).

Similarly, GIS is reported to provide valuable digital warning tools in modern plant pathology towards speedy and precise forecasting of plant pest and pathogen populations and distributions. It provides real time information on the frequency of these parameters based on host crop resistance, short term weather conditions and turn the data into a geographic information map (Andamon, 2024). In the Great Lake Region of Central Africa, bananas constitute a huge percentage of the diet of its inhabitants. This cherished crop was reported to be threatened by Banana Xanthomonas Wilt (BXW). Some workers reliably utilized GIS to collect data on the distribution of BXW in the region, which aided performing spatial analysis (patterns), and thus, permitted understanding of the geographical distribution (extent) and mapping of areas already affected or projected to be affected by the disease (Boumeester et al., 2010). These workers linked the data obtained to BXW severity in the target areas to dependency on bananas and overall food security of inhabitants in the region. Forecast on the imminent risk or otherwise of BXW was shared to stakeholders via the internet. Generally, based on the crop resistance and weather data, GIS holds strong potentials to turn real-time information on crop distribution, and frequency of many plant diseases or disease severity into a discreet disease map (Andamon, 2023).

High costs to purchase, maintain on-site digital PPDF hardware, and to calibrate sensitive sensors in addition to generating big data as in GIS-connected systems which require expertise to handle are some of the constraints militating their wide-scale adoption and use (Bayer, 2021).

Climate Change and Its Impacts on Agriculture

Following the observation of El Nino effects over the Sahara in the 1980's, there have been reports of global warming and climate change which adversely affects agricultural productivity (Sadiku & Sadiku, 2011). Nwafor (2008) projected that crop yield may fall up to 50% due to unprecedented changing climate patterns especially in sub-Saharan Africa with rain-fed farming systems. Seasonal changes in precipitation and temperature patterns will change growing seasons, affect schedules of crop planting and harvesting, water availability, disease and pest populations, and weeds dynamics, among others. All these will contribute strongly to food insecurity in the landscape (Sangeetha et al., 2025).

Warmer climates with higher CO2 levels will lead to shift in geographic distribution and increase in virulence of pests/pathogens and pests resistance to antimicrobials, and cause higher disease and pest infestations levels, reduced crop yield , thereby increasing the risk of pesticides use on aquifer quality and biodiversity (Hatfield et al., 2008; Lahlali et al., 2024; Abdullahi et al., 2025). In Tanzania, increases in pests and disease dynamics in crop production with the accompanying reductions in yields attendant from climate change, have led farmers to abandoning certain crops especially maize, to planting resistant species of other cereals, and growing pigeon pea instead of cowpeas (Sadiku & Sadiku, 2011; Maffie, 2021). It has been reported that climate change affect pest/pathogen evolution. Some workers noted that virulence mechanisms such as toxins and harmful proteins, reproduction, survival, emergence and spread of new biotic strains is seriously affected by rising temperatures and humidity levels (Velasquez et al., 2018; Singh et al., 2023).

Rising CO2 concentration in the atmosphere and subsequent elevated higher temperatures amongst other variables of climate change phenomenon are expected to impact agriculture through prolonged droughts, thunderbolts, submersion of crop fields, landslides and lodging of crops by strong winds, increase in certain pest and disease incidences and severities (Nwafor, 2008). Elevated GHGs hinder photosynthesis increasing vulnerability of host plants to biotic invasion (Kumar & Mukhopadhyay, 2024). In the face of climate patterns changing to the extremes, these would potentially impact farm production negatively., Traditional approaches to farm management would not sustain food security for the estimated 9.2 billion humans in the earth by 2025. This makes it imperative to tilt agriculture towards innovative digital and precision systems to enhance crop and soil health monitoring, pest assessment and control for improved yield and sustainability (Defani et al., 2024).

For instance, high soil moisture and prolonged leaf wetness in warm weather favor some foliar diseases and soil-borne pathogens such as *Phytophthora* spp. *Pythium* spp., *Phoma* sp., *Rhizoctonia solani*, and *Sclerotium rolfsii* and make plant parasitic nematodes to proliferate. Singh et al. (2023) and Abdullahi et al. (2025) noted that such condition exacerbated the severity of potato blight (*P. infestans*) and stem canker of oilseed rape caused by *Phoma* sp. Also, increased ambient temperatures was reported to favor germination of *Puccinia substriata* var. *indica* causal agent of devastating rust of pearl millet (*Pennisetum glaucum*) around the world, and *Cerospora beticola* incitant of leaf spot of sugar beet (de Carvalho et al., 2006; Rangel et al., 2020) Elevated temperatures occasioned by climate change have been implicated in altering bacteria behavior causing them to secrete resistant polysaccharides in their cell walls leading to more antimicrobial resistant (AMR) species (Das et al., 2016; Kumar & Mukhopadhyay, 2024).

The response of pests and plant diseases to climatic variables such as temperature, precipitation and humidity is well documented, and formed the fundamental predicate used in many PPDF models. Garrett et al. (2021) were of the opinion that these biotic pressures exacerbate under prolonged or extreme changes in these weather variables, meaning that climate change would potentially increase pests and disease attacks. PPDF can help mitigate climate change by accurately predicting likelihood of pest/disease incidence, spread or severities based on possible interaction of plant, pathogen and the ecosystem (Kumar & Mukhopadhyay, 2024). These digital models would represent proactive interventions for efficient production resource management on the one hand, reduced pest pressure and improved yields on the other (Defani et al., 2024).

In Nigeria delays in on-set of rains and long harmattan periods are akin to climate change phenomenon. As an adaptive measure in the short term, smallholder farmers in the semi-arid Sahel ecology are substituting millet to growing sorghum considered more drought tolerant, and planting cassava and early maturing cowpeas in fadamas. However, in the long term, Paul et al. (2020) and Songol et al. (2021) reported that intelligent robots and UAVs equipped with ML, AI, and sensitive sensor remains a digital intervention that can aid in mitigating devastating climate change effect with its attendant biotic and abiotic stressors on intensive large scale farming concerns. Intelligent autonomous robotics coupled to digital algorithms, AI and several kinds of sensors such as light, temperature, relative humidity, soil moisture and nutrient or weather sensors can monitor and diligently asses crop health.

Decreasing amounts in cultivable lands in Morocco, and falls in numbers of available young farm hands to work in farms and plantations in South Africa and many other parts of Africa is rising. For instance, labor shortages dropped from 21% in 2021 to 19% in 2022 in South Africa. These coupled with soil degradation, water scarcity, aggravating climate change effects are making farmers turn to intelligent autonomous machines for chores such as fertilizer application, seeding, irrigation and harvesting etc. to sustainably address these challenges and increase crop yields and produce quality (Mordor Intelligence, 2025).

These intelligent machines can autonomously and effortlessly defile unfavorable climatic conditions to fertigate crops, zap off insect pests and stubborn weeds, apply pesticides when necessary, mow, prune, thin and pick ripe fruits in farmsteads based on sharp computer vision. In the overall, they save time, costs, labor and make agriculture a sustainable and precision concern, thus guaranteeing food security (Zhang & Qiao, 2024).

Machine-assisted farm resources optimization is reported at about 30% in many parts of Europe, and they could increase produce quality and gross farm yield by not less than 20% (MDF, 2025). Mechatronics market size as it were in Africa today stands at USD 80.45 million this year due to their many positive dividends on the farm economy and ecological or human health (Mordor Intelligence, 2025).

In the West African sub-region, smart farming is gradually being embraced and adopted. For instance in Ghana, AI, big data and blockchain are being used to manage soil health, and mitigate unethical practices to inform transparency, traceability and enhancement in cocoa foods. Also, in Benin Republic, Burkina Faso and Cote d'Ivoire, AI is employed in predicting soil properties and acidity, sensing weather patterns and riverine pysico-chemical properties, agrochemical levels in banana, peas, cassava, rice, corn, cotton seed and sugarcane production whereas Nigeria utilizes AI, IoT sensors and blockchain to track livestocks, address soil health issues, manage irrigation and effectively monitor water quality (Degila et al., 2023). However, adoption of these digital technologies are still generally low in smallholder farms (<20%) due largely to low digital literacy and capital outlay (Gabriel & Gandorfer, 2023; Choruma et al.,2024).

Plant Pest and Disease Forecasting and Food Security in Nigeria

Effective method to ameliorate the impact of pest and diseases on Nigerian agriculture will require reliable scientific data through weather forecasting and long term projections of pest and diseases dynamics, patterns and severities (Sadiku & Sadiku, 2011). Brussel (2009) noted that adaptive measures to forestall and prevent downturns in agricultural production occasioned by ravaging pest and diseases attendant from climate change will range from Hi-tech solutions to adjustments in farm management and structure. So far some of the adjustments in structure and farm management strategies have been outlined above in some African countries including the Sahel ecologies of Nigeria. One of the important steps to reduce the vulnerability of agriculture to climate hazards is to develop advanced early warning systems to predict events (Ajibade & Shokemi, 2003). In the face of climate change, good forecasting system are becoming increasingly important. Disease outbreaks may not occur in historically known locations, so it is important to accurately predict when or where they may occur (ESNRR, 2023). Such warning systems will aid growers well in advance in making decisions on site of planting, planting date, seed stock and fungicides use (Reatjes et al. 2003).

Black pod disease (BPD) of cocoa is prevalent in West Africa where incidence rate of 40-90% of the disease has been recorded, causing high per season cocoa yield losses with a propensity for total crop yield loss if not adequately and timely managed. The disease is characterized by leaf blight, stem cancer, pod rot and death of the crop. Primary infection of the disease in the region occur in June or August to October which coincides with torrential rains (Etaware, 2019). Development of a warning system against BPD is seen as a vital necessity in Western Nigeria where cocoa production is high. ETAPOD is an alert system which could forecast occurrence and intensity of BPD in Western region of Nigeria as well as other areas with strong potential to suffer significant economic losses if the disease occurs (Etaware et al., 2020). The system has recorded 95-100% accuracy for prediction of BPD in two states of western Nigeria, and its accuracy was dependent on a large part, on the accuracy of weather data inputted into the system. In the overall, the system would contribute to reduced misuse of fungicides and fungicide poisoning through toxic chemical residues in treated cocoa beans. It will also increase availability of cocoa BPD-disease free seeds and improved farmers' income in the long run (Etaware, 2019; Etaware et al., 2020).

Precision agriculture operations require incorporating digital technologies including AI, ML, IoT, climatic sensors, drones and satellite systems (GIS, GPS) to offset shortages in food supply. Ignitia is a PPDF platform that delivers timely weather forecast to rural farmers. The platform uses GPS to predict localized weather forecast at 84% accuracy to rural farmers via SMS, which helps producers to make decision on farm-chain operations thereby reducing moldiness and mycotoxin contamination of cereal grains, nuts and legumes. Ignitia is reported to increase farmers' income due to reduced associated risks and losses by 80% (Ogunfuwa, 2017).

Water is one of the essential variables in agriculture especially in crop production. Water insufficiency has been identified as one of the fundamental challenges facing farmers in some agricultural zones of Nigeria. Real time data on water status in agricultural soils is important in aiding growers to plan schedules on proper irrigation using smart digital systems. Some studies indicated that Internet of Things (IoT) could assist producers to smartly monitor and observe water status of agricultural soils and, automatically activate smart watering systems to deliver required amount of water to support growing crops. Tevatronic is one such automatic wireless system that could digitally sense low soil water levels real time and, automatically initiate irrigation and fertilization cycles on-farm. (Ogunfuwa, 2017). Application of digital alert systems in crop production seeks to predict possible onset (early stage pre-symptomatic stage) or change in intensity of certain diseases or pests as crop matures (Fenu & Malloci, 2021). BlueRiver technonology is another digital system that uses computer vision and AI algorithm to observe crop fields against weed populations, detect and quantify weed population density and then activate their smart removal from field (Ogunfuwa, 2017).

AirSmart is an AI-driven solution platform that collects and analyze data from UAVs, satellites, soil sensors and IoT to optimize water, fertilizer and pesticides usage and offers data driven farm management recommendations to growers. A similar platform, Kitovus, is another AI-driven platform which remotely senses soil and crop health and offers agronomic recommendations for yield optimizations to farmers connected to the platform (Vota, 2024). According to Vota (2023), another digital platform Apollo Agriculture, uses ML to analyze satellite imagery and big data captured from soil and the weather to provide smallholder farmers with automated agronomic, farm input and financing data. Up to 71.07 to 99.62% accuracy has been documented in ML assisted monitoring and prediction of weeds, insect pests and diseases attacks in farmsteads in several parts of the world (Meena et al., 2023).

The Federal Ministry of Agriculture in Nigeria, noted that UAVs and AI have been employed to assess forest health within her borderlines with intent to detect undue logging and deforestation, and maintain sustainable forestry management. In similar manner, Peru agricultural authorities had employed IoT with capacity to analyze certain weather variables including CO^2, CO, NO^2, CH^4 and other greenhouse gases to monitor rainforests and also track illegal logging of the forest resources (Umeh & Haruna, 2018). On the one hand, in order to optimize grazing practices, IoT and AI-powered sensors have been used to track location of cattle and their nomadic herders as well as the cattle health while on the other hand the technology have been deployed in monitoring and assessing water quality in wetlands and fish ponds in some parts of Nigeria so as to align with global best practices in fish farming (FMAFS, 2023). It has also been used as digital solutions to track and discover bees with colony collapse disorder in rainforest zones of Peru (Umeh & Haruna, 2018).

Impact of Intelligent Machines in Agriculture

Contemporary agriculture faces the serious challenge of increased weeds and pest pressures, falling soil fertility levels and diminishing supply of farmhands. These constraints greatly affect sustainable production of food, fiber and, biofuels which constitute the basic goals of agriculture. Weeds constitute the most important biotic pressure to agricultural production in both developing and developed countries resulting in loss of 2.7 million tons of grains annually, this may get worse due to impact of climate change reported to supercharge growth of certain weeds. This, amongst many other factors, necessitated the engagement of automation and robotics in farm operations, and processes, so as to ensure increased farm output, production efficiency, and waste reduction. Robots and other intelligent machines remedy existing or imminent farm-labor shortages through task-specific sensing. In some advance farming concerns, certain cobolts are replacing low-skill workers in labor-intensive activities such as manual weeding, pruning, and fruit or vegetable harvesting (Viugiokas, 2019; Chanhan, 2020; Cope, 2023; Liu, 2023). In some other places, AI-moderated weed killing drones (Fig 1a) with capacity to sense, identify and kill weeds in mega-corn and wheat farmsteads without drenching the entire crop or field with chemicals are being utilized for weed control. Such Unmanned Aerial Vehicles (UAVs) has been reported to achieve 96% accuracy on weed targets, and reduce the use of eco-toxic herbicides by 90% (Liu, 2023).

Figure 1a. Drones spraying a cropland against pests of cereals in India. Source: Panwar (2023).

Computer-based sensors and actuators including machine vision, laser-based sensors, GPS etc. are being incorporated into Intelligent mobile robots fitted with computerized ability to sense, see or observe agricultural activities are being engaged in precision agriculture especially in mega-farming concerns. This has shifted operator activities in agricultural tasks to such digital machines (Emmi, 2014). Intelligent tractors (driver-less) are increasingly replacing conventional agricultural tractors for seeding or planting operations, while armed robots have been developed and are increasingly employed in various forms of fruit picking activities in industrialized and resource-rich farms of first world countries (Cope, 2023). Also, these intelligent machines are programmed to provide insect grafting, efficient and effective plant specific-pesticides sprays, and plant-specific fertigation, which significantly reduce wastages or overuse in water and phyto-sanitary farm-inputs; thereby reducing environmental degradation (Wang et al., 2022; Robotnik, 2022; Petrovic et al., 2023). Surveillance cameras and their AI borne on unmanned aerial vehicles (UAVs) (otherwise called drones) keep open eyes on farmsteads – tracking crop growth, crop health, identifying nutrient or water deficient parchments, weeds, disease and pest infested areas with high resolution, remarkable precision and accuracy on real time basis (Fig 1b). Furthermore, drought monitoring, fertilizer usage, crop biomass or yield estimation or water stress assessments are captured using UAVs (Rejeb et al., 2022). Use of UAVs have been noted by some workers to optimize resource use, grossly increasing efficiency of use of factors of agricultural production such as fertilizers, water, herbicide, and farm productivity, and also optimizing sugarcane densities by 26%, 26%, 30%, 90% and 100% respectively (Youstory, 2023; Petrovic et al., 2023).

Figure 1b. Drones spraying a cropland against pests/diseases of cereals in Nigeria. Source: FMAFS (2023).

Locust swarms remain one of the major insect pest challenges to sub-African agriculture, causing massive damage to vegetation and cultivated agricultural fields (TNH, 2004). It is reported that over 100 million people are affected by attacks by locust swarms despite classical monitoring and management (Klein et al., 2021). These crop devastating insects lay eggs in moist soils, and therefore vegetation and soil moisture variables hugely encourage locust growth and reproduction. Remote sensing is one of the powerful sources of fast and effective data collection concerning locust management. Insect pest researchers employ a range of digital tools including RS, GPS, GIS and other intelligent digital tools to monitor soil moisture and vegetation wetness, and hence reliably predict where locusts might reproduce, and swarm next before they can harm agricultural crops. Such researchers use UAVs assisted by other digital programs such as GIS to develop, analyze and map locust-prone locations; emphasize their stages, and issue warnings on their migration tendencies. The powerful and high resolution cameras borne on these UAVs clearly capture crop damage intensities, which information are often extrapolated to non-affected areas (Mark, 2020). Cellphones and other handheld devices could provide reasonable ground level data about locust infestation. In China, farmers and local authorities use a web-based decision support system that provides real time spatial site-specific information to effectively and accurately track and control locusts (Yao et al., 2017). A mobile GPS-enabled application (e-Locust 3g) provides reports on locusts and their stages of development. This cellphone application also allows geo-referenced chat data to be transmitted to connected users (Mark, 2020).

In India, Laser weeding robotics equipped with high resolution cameras and AI-powered software system and 150W CO^2 laser jet accurately identifies weeds with capacity to blast off 200,000 weeds per hour. This robot has been used in organic farms on over 40 different crop plants (Pereira, 2023). FarmBots is a small robot and multitask digital farm assistant that can hoe, weed, seed, make furrows and transport produce within the farm with the aid of some mechanical attachments. So far over 300 ha of land has been cultivated using FarmBots in India. Stout Cultivator another small robot uses tractor drawn mechanical blades and high-power AI assisted computer plant recognition system to identify and differentiate crops and weeds, and then kill off the weeds with 99.99% accuracy (Pereira, 2023).

Owusu (2024) was of the opinion that many countries in Africa including Nigeria, Ghana, Morocco, Ethiopia, and Kenya are embracing digital precision agriculture (smart farming) by use of robotics for pest and disease surveillance, crop health monitoring and autonomous weeding and harvesting. Over 50% of farm produce are lost postharvest due to bruises and microbial contamination. In order to reduce such food wastages that occur postharvest, autonomous sensor-bearing robotics with sharp computer vision that accurately assess fruit ripeness and execute precision harvesting to mitigate bruising and microbial contamination of produce have been developed. One such smart system is the see and spray robot developed by the BlueRiver technology which uses computer vision to monitor and precisely spray weeds in farms (Petrovic et al., 2023). In Kenya and Nigeria, Farmdroid and BlueRiver robots efficiently harvest 20 tons of tomato fruits with minimal damage daily respectively. In South Africa and Morocco Trimble robots have been trained to harvest up to 10 tons of strawberry with precision on daily basis. Also , in Nigeria, Agropro robotics capable of harvesting 10 ha of maize farms on a daily basis has been used in the arid zones of the country to harvest maize cobs (Ambali et al., 2024). In Nigeria, AgTech Startups developed innovative mobile applications such as Farmhowdy, OgaFarmer, HelloTractor, Releaf, Agricorp, and ThriveAgric for smallholder farmers on various farming operations.

Blockchain Technologies (BCTs) are digital ledger systems whose data are difficult to alter amongst users connected on the platform. They are reported to provide decentralized, transparent and unchangeable solutions to meet difficulties faced by growers such as lack of trust from consumers, difficulty in tracking food origins and inefficiencies in managing supply chains (Panwar et al., 2023). Blockchains provide detailed information about food origins, ensuring consumers know exactly where their food comes from, because each step of a food journey is recorded in this digital ledger making for easy tracking from farms to grocers (Funk, 2023; Panwar et al., 2023; Kelvin et al., 2025). The ledger also retains data on temperature, RH, and rainfall and soil health from sensors connected to the system. At harvest growers use this data to understand which parameter impacted their crop the most and correcting same in future endeavors. Blockchain technology is used to monitor and imbibe sustainable and global best farming practices. It records data on synthetic pesticides and fertilizers use, energy and water use which are available to both consumers and concerned watchdogs. In so doing, it helps to document crop varieties and their genetic information used by respective farmers, optimize resource use., Hence, carbon footprints and toxic emissions from agricultural concerns are easily tracked on such unchangeable digital platform (Funk, 2023). Blockchain technologies, therefore, have the obvious merits in agriculture especially when linked with IoT, RS, and UAVs through encouraging smart farming such as smart irrigation amongst many others with focus to produce food transparently, ensure tracing and tracking food items back and forth, improve quality control and food safety, and ultimately ensuring environmental sustainability (Xiong et al., 2020; Funk, 2023).

IBM Food Trust used BCT to track about 4 million kilograms of olive oil from production through supply chains around the world (Funk, 2023). Some workers are of the opinion that coupling BCT to AI or IoT facilitates advance predictive analysis. Such synergy allows for collecting, verifying, and analysis of big data to obtain information about crop yield, weather variables, and market trends which growers could incorporate to plant, plan and optimize agricultural practices (Funk, 2023). One of the major challenges facing farming concerns is inefficiency in managing supply chains (Panwar et al., 2023). Recently in Nigeria, IoT or AI-powered blockchains have been used to effectively connect farmers directly with buyers matching supply with user demands and ensuring efficient distribution of produce to the right markets in real time (Ijitade & Ekpe, 2024).

Challenges of adopting PPDF systems and intelligent machines in Africa

Precision agriculture is not without constraints. According to Funk (2023), Ambali et al. (2024) and Hokuyo (2024), some of the challenges constraining the adoption of intelligent robotics and PPDF systems are:

Capital intensiveness: PPDF and robotics are modern and expensive equipment. Installing and using them in farming concerns involves huge initial cost outlay. These appear to be best suited for large holder intensive farms with huge financial assets and liquidity (MDF, 2025).

Data processing cost: These modern digital standalone precision farm equipment generate complex remotely sensed 'big data' which requires advance software and expertise to interpret outcomes from analysis from such data. Thermal imaging UAVs generate detailed soil water maps, however, it takes grounded expertise to be able to carefully understand and interpret them in detail relative to irrigation application for efficient water management and food security (Ajam & Yavuz, 2024; Oyedepo & Oyedepo, 2024).

Power supply systems: Robotics and PPDF systems require and utilize substantial and steady supply of electrical energy. Providing continuous supply of energy is warranted so as not to disrupt smooth functioning of the systems. Where necessary technology is available, renewable sources of power such as winds and solar should be tapped to maintain uninterrupted supply of electricity.

Poor or limited connectivity: Strong linkage to internet, Wi-Fi, Bluetooth or infrared technology connections and in some cases conventional SMS services are strongly imperative to connect the systems one to another, and to communicate outcomes and recommendation to and from growers. Lack of steady and reliable digital connectivity impairs adoption and use of these technologies (Choruma et al., 2024, Oyedepo & Oyedepo, 2024).

Lack of credit facilities: Lack of access to long term soft loans and incentives to farmers such as subsidy on digital equipment including small robots, BCT and PPDF systems, and tax burdens on high value cash crops impacts smallholder farming economies (Oyedepo & Oyedepo, 2024).

Urbanization: Choice areas previously used for agriculture have been converted to building attractive cities as such forcing able youths to migrate to these improved places of abode leaving agriculture in want of expertise and energetic young farmhands.

Lack of human and capital infrastructure such as high speed satellite systems, powerful ground based sensors to control UAVs, and trained skilled technical workers (Oyedepo & Oyedepo, 2024), to man and service digital systems remains a strong impediment. Lack of interest on the part of policy makers, and government at all tiers to fund research, development and investment in intelligent robotics, mechatronics and PPDF systems have been adjudged recalcitrant impediments to adoption of broad scale precision agriculture in Africa. This runs contrary to what obtains in the EU where the Union designated and mapped out 387 billion Euros to encourage investment in smart farming technologies (MDF, 2025).

Governmental and cultural policies on agriculture: Governmental policies and cultural standards such as the land tenure system of land ownership where lands are inherited and shared amongst siblings in a community from one generation to another that does not or poorly support migration to intensive large-holder precision agriculture, and general lack of sensitization campaigns to this end affect adoption of modern technologies that make agriculture sustainable (Onomu & Aliber, 2024; Oyedepo & Oyedepo, 2024). Also, unlike the EU which for instance allocated 95 billion Euros in funding innovations in smart farming and mechatronics (MDF, 2025). In Africa, however, lack of research grants to the academia to pursue research in digital systems, establishment of hi-tech demonstration farms on one hand, and incentives or subsidies from the governments to support and ameliorate costs of hi-tech digital products impede adoption and migration to precision agriculture.

Conclusion

In conclusion, intelligent digital machines and PPDF systems are vital to sustainable African agriculture, occupying a prime place in the face of changing climatic patterns, resistant weeds, disease and pest dynamics, and dwindling access to safe and secure food. Adoption and utilization of on-farm, satellite-based systems and unmanned aerial vehicle must be vigorously encouraged by all levels of governments and NGOs to detect, assess and mitigate rising pests, disease and abiotic influences on crop production knowing that these farming constraints are supercharged by climate change, so that quest towards food security in Africa would be realized.

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