


Chapter 9

Innovative Digital Technologies to Monitor and Control Pest and Disease Threats in Root, Tuber, and Banana (RT&B) Cropping Systems: Progress and Prospects



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Abstract This chapter provides the first comprehensive review of digital tools and technologies available for the identification, monitoring, and control of pests and diseases, with an emphasis on root, tuber, and banana (RT&B) crops. These tools include systems based on identification keys, human and artificial intelligence-based identification based on smart applications, web interfaces, short messages

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services (SMS), or combinations thereof. We also present ideas on the use of image recognition from smartphones or unmanned aerial vehicles (UAVs) for pest and disease monitoring and data processing for modeling, predictions, and forecasting regarding climate change. These topics will be presented in the context of their current development and future potential but also the challenges, limitations, and innovative approaches taken to reach end users, particularly smallholder farmers, and achieve impacts at scale. Finally, the scope and limitation of private sector involvement demonstrates the need of publicly funded initiatives to maximize sharing of data and resources to ensure sustainability of unbiased advice to farmers through information and communication technology (ICT) systems.

9.1 Introduction

Globalization and climate change are exacerbating condition under which we lose 20–40% of global crop production to pests and diseases annually, especially in food-deficit regions with fast-growing populations. Weak existing pest and disease surveillance systems in developing countries have resulted in slow responses to large-scale outbreaks and epidemics in Africa and Asia, e.g.:

- Various cassava (*Manihot esculenta* Crantz) virus diseases.
- Desert locust (*Schistocerca gregaria* Forskål).
- Fall armyworm (*Spodoptera frugiperda* J.E. Smith) in maize (*Zea mays* L.) and many other crops.
- *Fusarium* wilt (*Fusarium oxysporum* f. sp. *cubense* (E.F. Sm.) W.C. Snyder & H.N. Hansen) in banana (*Musa* sp.)
- Maize lethal necrosis disease (MLND; coinfection with maize chlorotic mottle virus (MCMV) and one of several viruses from the Potyviridae group).
- Wheat (*Triticum aestivum* L.) rust (*Puccinia triticina* Erikss).

All of these have had devastating impacts on food security. Pests and diseases continue to devastate agricultural production and are expected to intensify with ever-increasing movement of people and planting material, disruption of natural habitats by encroachment through human activities, and climate change. As we write, the COVID-19 pandemic reminds us that the keys to controlling these threats are early detection, rapid and reliable diagnosis, and efficient tracking of spread – all of which can be enhanced with evolving digital technologies.

9.2 Digital Disease Identification Tools

Crop diseases are responsible for significant economic losses in agriculture worldwide. Monitoring of crop health and early detection of new diseases are essential to reduce disease spread and facilitate effective field management practices. Crop

disease detection, generally carried out through scouting or field inspections, is often supplemented by diagnostic tools based on serological methods and polymerase chain reaction (PCR) tests. Field inspection for early disease detection is assessed as prevalence (present or not) at the field, farm, village, and/or landscape levels. This process is large scale, challenging, and time-consuming (Johansen et al. 2014). These limitations on direct field inspection methods have led scientists to investigate advanced and novel techniques that could rapidly and economically obtain crop health information (Heim et al. 2019; Steward et al. 2019). Several novel and noninvasive methods have been developed in the last decade, which are sensitive, reliable, standardized, high throughput, rapid, and cost-effective (Golhani et al. 2018). Frontline remote sensing (RS) methods coupled with machine learning (ML) is one of the emerging approaches to provide reliable and precise technical support for real-time and large-scale crop disease detection and monitoring. Remote sensing permits the noninvasive measurement of crops' biophysical and biochemical parameters and thus allows for nondestructive monitoring of crop health status (Ramcharan et al. 2017; Lu et al. 2015). Various imaging sensors – visible, thermal, multispectral, and hyperspectral – have been studied for crop disease detection (Mishra et al. 2020). The applications of these techniques have been gradually developed from novel sensor development, high-throughput image acquisition, processing, and computing, leading to image segmentation and disease classification with algorithm development. In the following sections, examples of these techniques will be described with a focus on root, tuber, and banana (RT&B) crops.

9.2.1 Smartphone Image-Based Disease Detection and Classification

Deep learning is an innovative method for image processing and object detection providing high accuracy in the classification of various crop diseases (Kamilaris and Prenafeta-Boldú 2018). Smartphone-based AI-powered apps could alert farmers and expedite disease diagnosis, potentially preventing or limiting pest and disease outbreaks. Even though many developing countries' farmers do not have access to these advanced tools, increased Internet infiltration, smartphone penetration, and offline models offer new outfits for infield crop disease detection.

Cassava provides food for more than 500 million African people every single day. Several diseases affect cassava, causing larger yield losses. Farmers (and even extension workers) struggle to correctly identify the various diseases. To that end, scientists at Penn State University have created an innovative solution that uses AI through Google's open-source TensorFlow technology. In collaboration with the International Institute of Tropical Agriculture (IITA), and working through the CGIAR Research Program on Roots, Tubers and Bananas (RTB) and the CGIAR Platform for Big Data in Agriculture, the team developed PlantVillage Nuru, an application built by annotating over 200,000 images of diseased cassava plants to

train a machine to recognize various diseases and make predictions about a farmer's crop's health in less than one second (Fig. 9.1). It can identify symptoms of the cassava mosaic disease (CMD; caused by different species of plant pathogenic viruses), cassava brown streak virus disease (CBSD), and the feeding damage of mites (e.g., the green mite, *Mononychellus tanajoa* (Bondar)). With PlantVillage Nuru, an extension worker or farmer can point their phone over a specific cassava leaf, and a box will pop around any areas with symptoms with the diagnosis. In some cases, it will guide the farmer to scan several leaves from different parts of the plant to arrive to a more reliable result (Mrisho et al. 2020; Ramcharan et al. 2017; Ramcharan et al. 2019). Once a disease is diagnosed, farmers can simply push a button to request advice on how to respond.

Collaborations with other research centers and organizations have helped extend the power of PlantVillage Nuru to other crops:

- International Potato Center (CIP) for potato: (*Solanum tuberosum* L.) diseases (late blight, *Phytophthora infestans* (Mont.) de Bary; early blight, *Alternaria solani* Sorauer) and various viral diseases.
- United Nations Food and Agricultural Organization (FAO) and the International Maize and Wheat Improvement Center (CIMMYT) for maize: fall armyworm infestations.

The app is available for android mobile phones through the Play Store and for Apple phones through its App Store. The same AI technology is also being used extensively in support of the FAO's surveillance of desert locust using the PlantVillage-developed app eLocust3m and FAMEWS (Fall Armyworm Monitoring and Early Warning System).

For many years, banana disease surveillance and mapping has relied on in-person field surveys by knowledgeable scientists and trained field staff. This approach is restricted by high cost, limited human capacity, and inability to access more remote locations. In addition, the lack of capacity for farmers and some local extension workers to identify and/or differentiate between the different biotic diseases and constraints often hampers timely intervention efforts. Scientists from the Alliance of



Fig. 9.1 Using PlantVillage Nuru to identify plant diseases with a cellphone

Bioversity International and CIAT developed an AI-powered smartphone app called Tumaini (“hope” in the Swahili language) that is capable of identifying and differentiating symptoms of six banana diseases:

- *Xanthomonas* wilt of banana (BXW) caused by the bacterium *Xanthomonas vasicola* pv. *musacearum*.
- Banana bunchy top disease (BBTD) caused by the banana bunchy top virus (BBTV).
- The soilborne fungal disease *Fusarium* wilt caused by *Fusarium oxysporum* f. sp. *cubense* (E.F. Sm.)
- Banana blood disease caused by the blood disease bacterium (*Pseudomonas celebensis*) of banana.
- Black leaf streak disease (BLSD) or black sigatoka caused by the fungus *Pseudocercospora fijiensis*, formerly known as *Mycosphaerella fijiensis*
- Banana weevil (*Cosmopolites sordidus* Germar).

The Tumaini AI app was developed using a dataset of over 18,000 field images collected by banana experts. The app is freely available on Google Play Store.

The integration of these AI-powered apps in a multilevel sensing system for disease surveillance (e.g., comprising satellites, UAVs, AI apps, and ground truthing; covered below) is necessary to monitor crop health at different scales. Data collected through the smartphone app and obtained from drone and satellite image analysis is expected to be fed into the PestDisPlace (Sect. 9.2.5) surveillance and mapping platform, to create an early warning system, and advise research, extensions and advisory services, and National Plant Protection Organizations (NPPOs) of ongoing banana disease spread, linked risks, and priority zones for surveillance. See, for example, the PlantVillage warning maps for locust¹ or dedicated ArcGIS boards where the data from smartphone-derived observations is integrated with NASA soil moisture data and NOAA HYSPLIT wind models and soil maps from ISRIC.²

9.2.2 *Aerial (UAV or Satellite) Image-Based Disease Detection and Classification Tools*

Rapid technology development in unmanned aerial vehicles (UAVs) and the availability of low-cost UAVs carrying sensors provide the opening to capture high spatial and spectral resolution data, especially for disease detection across fields and landscapes. The ability to capture the crop phenotypic differences in this complex multidimensional system is necessary to better understand host-pathogen interactions (Steward et al. 2019). The combination of aerial image information and

¹https://plantvillage.psu.edu/panel/analytics/locust_surveys

²<https://arcg.is/0aHGHi>

AI-based approaches can provide an accurate, high-throughput method for crop disease detection under real-world conditions (Boulent et al. 2019; Selvaraj et al. 2020). Working Benin and the Democratic Republic of the Congo, Selvaraj et al. (2020) demonstrated that banana fields and production zones can be mapped through both drone and satellite image analysis. In addition, these authors developed algorithms to detect BXW- and BBTD-infected plants or mats on drone images. These outputs will contribute to health status mapping in banana production zones (Kamilaris and Prenafeta-Boldú 2018; Selvaraj et al. 2019; Ramcharan et al. 2017; Selvaraj et al. 2020).

In potato research, detection of diseases through remote sensing has been advanced for late blight (Gold et al. 2020; Ray et al. 2011; Duarte-Carvajalino et al. 2018) and viruses (Chávez et al. 2009; Chávez et al. 2010; Griffel et al. 2018; Polder et al. 2019). Whereas there are clear challenges to implementing such technologies routinely at a landscape or regional level, obvious direct application could be available through automated screening for resistance in breeding trials and rapid screening for diseases in seed multiplication plots. Indeed, CIP is currently validating the use of airborne multispectral and high-resolution RGB (red, green, and blue) multi-temporal imagery acquired by UAV to monitor late blight infection in breeding plots, potentially reducing disease scoring time from several days to hours.

To our knowledge, current disease detection systems focus on single sensor-based solutions and often lack the integration of multiple information sources. Moreover, using UAV to monitor larger landscapes is often challenging; thus, at larger geographic scales, satellite-based machine learning (ML) models could help classify overall crop health. Such general crop health information could then be further assessed using UAVs and AI-powered smartphone-based sensors to detect the specific reason(s) of an observed poor plant health status. Therefore, it is essential to combine high-resolution imagery data with advanced ML algorithms to acquire ground truths through mobile apps. UAVs and high-resolution satellites can capture a large number of high-quality spectral-temporal aerial images, becoming the ultimate technology for classifying crop yield for purposes of monitoring plant health and determining economic value (Burke and Lobell 2017; Ji et al. 2018). The real-time tracking of crop disease spread and impact at the regional, national, and global scales can be realized if large-scale data integration analysis is achieved. With the development of multisource remote sensing data, the fusion of multisource data may be a future development trend.

9.2.3 Tools for Modeling, Including Backcasting and Forecasting of Pest and Disease Incidence to Deliver Decision Support Intelligence to Smallholder Farmers

The application of models can be a powerful tool to understand pest and disease epidemiology. Simulations and forecasts with these models can provide advice to farmers and other actors in the agricultural sector to manage crop protection.

Different agroclimatic modeling approaches have been developed that range from simple analytical to complex simulation models and use actual and/or predicted climate data such as temperature, precipitation, humidity, and, in the case of atmospheric transport models, wind currents (Orlandini et al. 2020). Their applications can be roughly divided into two categories: risk assessment and forecasting.

Risk assessment tools, typically including maps and longer time scales (seasonal/annual), can be used to predict the potential distribution and damage of non-indigenous or indigenous pests due to climate change. They can also support farmers and decision-makers in pre-season planning for pest and disease management and/or advise on timing and location for monitoring and surveillance. Forecasting tools, on the other hand, generate predictions within the growing season to provide farmers with information for daily or weekly decision-making.

Under RTB, the Insect Life Cycle Modeling (ILCYM) software was further developed as a generic open-source software platform that enables the development of phenology models and linked to geographic information systems (GIS) to generate risk maps at different geographic scales (Tonnang et al. 2013). The ILCYM software facilitates the selection and compilation of temperature functions for development, survival, and reproduction of different life stages of insects of interest, including parameters for variability in these processes. This information is used to generate life table parameters for a given range of constant and fluctuating temperatures as input data. The software can then simulate pest population development with their specific age-stage structure that allows temporal and spatial simulations of population parameters according to real or interpolated temperature data. ILCYM has been applied to understand pest potential spread and impacts under current and future climates for a wide range of crops including potato and cassava (Kroschel et al. 2013; Sporleder et al. 2008; Mwalusepo et al. 2015; Aregbesola et al. 2020; Khadioli et al. 2014; Rao and Prasad 2020; Mujica et al. 2017; Azrag et al. 2017; Soh et al. 2018; Fand et al. 2014; Fand et al. 2015; Rebaudo et al. 2016). It was also used to compile a Pest Distribution and Risk Atlas for Africa³ for several crops to support the preparedness of policymakers and farmers to implement timely adaptation strategies (Kroschel et al. 2016). Models have also been developed with ILCYM for biocontrol agents (such as parasitoids) of invasive pests to provide advice on the probable success of establishment in pest-invaded regions and control efficiency under varying climatic conditions (Kroschel et al. 2016). Researchers have also used these models to study the effect of different biocontrol application intervals and rates (e.g., for *Phthorimaea operculella* granulovirus) for controlling the potato tuber moth, *Phthorimaea operculella* (Zeller) (Sporleder and Kroschel 2008). Recently, the approach was expanded to include risk assessment and guide surveillance for insect-transmitted viruses as demonstrated for the potato yellow vein virus (PYVV) (Gamarra et al. 2020a; Gamarra et al. 2020b).

The use of risk maps to guide surveillance can be further refined by combining establishment risks as modeled (e.g., by ILCYM) with geographic cropland patterns

³<http://cipotato.org/riskatlasforafrica/>

which represent an important factor contributing to risk of pest entry. The cropland connectivity risk patterns were modeled for RT&B crops globally by Xing et al. (2020), and the approach of combining these maps with establishment, activity, and generation risk indices modeled by ILCYM is currently being tested to monitor the possible spread of the North American potato psyllid (*Bactericera cockerelli* (Sulc)) into Colombia and Peru, which moved through Ecuador in recent years, causing significant crop losses and environmental impacts (Douthwaite 2020). Local in-country spreading pathways can be further analyzed by studying seed networks, as was done for potato in Ecuador (Buddenhagen et al. 2017). Although ILCYM is currently geared for risk assessment through generating complete life cycle models, these models can be also used to simulate in-season population development based on prevailing weather data – thus appropriate for forecasting as well (Kroschel et al. 2013). Initial steps to implement and validate such forecasts have been initiated in the central Andes by CIP and its partners for a number of important potato pests in the region.

Models for plant diseases have been developed primarily for airborne diseases. Among RT&B crops, late blight of potato has received much attention with at least 16 different models⁴ developed to predict onset and progress of the disease. These models have been implemented with relative success in Europe and North America, providing farmers with alerts and recommendations about when to start and how frequently to use control measures based on prevailing weather conditions and cultivars planted.

The LATEBLIGHT model, originally developed to simulate late blight epidemics in the Andes (Andrade-Piedra et al. 2005b; Andrade-Piedra et al. 2005c), was later shown to perform quite well over a range of tropical environments (Andrade-Piedra et al. 2005a; Blandón-Díaz et al. 2011). More recently, BLIGHTSIM, a mechanistic model that accounts for diurnal oscillating temperatures, was developed to predict changes in severity that might be expected due to climate change (Narouei-Khandan et al. 2020).

Temperature, humidity, and rainfall (and leaf wetness) are the main drivers of these models, and they work well when reliable weather data are available in the relevant geographies. Unfortunately, this is rarely the case in most low-income countries. Although this limitation may be alleviated soon by using downscaled weather information modeled from satellite-acquired remote sensing data, simple models based on farmers' weather observations may provide a low-tech solution that still can provide meaningful advice for control. With that in mind, a simple handheld tool for late blight management was developed consisting of three concentric circles: the two outer circles can be moved to select options for answers to two questions and the inner third circle provides the recommendation (Fig. 9.2) (Pérez et al. 2020). The answers to each question provide a number. The individual numbers should be added, and if the sum is above a certain threshold, the advice is to apply control measures. The three different circles are used depending on the

⁴<http://ipm.ucanr.edu/DISEASE/DATABASE/potatolateblight.html>



Fig. 9.2 Handheld decision support tool discs help determine pest and disease control measures for (a) susceptible, (b) moderately resistant, and (c) resistant potato varieties (Pérez et al. 2020)

susceptibility and resistance of the potato cultivars planted, which are classified as low, medium, and high. Cultivars will have to be categorized for each country and geographic region depending on what varieties are grown. During validation experiments, handheld tool for late blight management gave relatively good disease control in all cases, but was more effective among highly susceptible cultivars compared to traditional local spraying regimes in Ecuador and Peru. The application of the tool resulted in equal or lower numbers of fungicide sprayings per season and reduced the environmental impact (Pérez et al. 2020).

9.2.4 Nucleic Acid (NA) Sequence-Based Digital Surveillance Systems for Pathogens and Pests

There is high potential for the use of genetic data of pests and pathogens to strengthen current conventional approaches for surveillance. High-throughput sequencing (HTS) technologies applied to field diagnostics are increasing the amounts of nucleic acid sequences that become available as data. The availability of genetic data will turn out to be most relevant for early warning detection of the introduction and potential spread of different strains of pests and pathogens. These technologies were adapted early for plant virus research and discovery with sweetpotato and a few other crops (Kreuze et al. 2009; Adams et al. 2009).

Since its inception, many new viruses and variants in RT&B crops have been discovered and characterized, contributing to the rapid identification of novel diseases or pathogen variants and subsequent to the design of specific diagnostic assays (De Souza et al. 2013; Wang et al. 2013; Abad et al. 2013; Fuentes et al. 2012; Cuellar et al. 2011a; Cuellar et al. 2011b; Souza Richards et al. 2014; Kreuze et al. 2013; Kreuze et al. 2009; Monger et al. 2010; Carvajal-Yepes et al. 2014; Hanafi et al. 2020; Kreuze et al. 2020; Kutnjak et al. 2014; Leiva et al. 2020). HTS technologies have also been used to evaluate, e.g., the diversity and evolution of CBSD

in East Africa (Alicai et al. 2016), a countrywide mapping of potato viruses in Peru⁵ (Fuentes et al. 2020; Fuentes et al. 2019a; Silvestre et al. 2020; Fuentes et al. 2019b), regional characterization of cassava viruses in Southeast Asia (Siriwan et al. 2020), and a continent-wide mapping of sweetpotato viruses in Africa⁶. This work has enabled the identification of new viruses, but also indicated prevalence of known but understudied viruses. For example, the analysis of the African sweetpotato virome revealed that begomoviruses are the third most common viruses of sweetpotato in Africa, meriting further study, which showed they could cause significant yield impacts despite being almost symptomless, thus requiring clear attention in clean seed production as well as setting breeding targets (Wanjala et al. 2020). Conversely, badnaviruses were found to be almost ubiquitous in sweetpotato but lacked any detectable effect on sweetpotato, and thus were ruled out as a matter of concern for production (Kreuz et al. 2020).

The recent Ebola virus and SARS-CoV-2 epidemics have revealed the potential of HTS technologies to track the evolution of virus epidemics in near real time and have provided the scientific community with novel tools and platforms that can be applied to any other pathogen. One can foresee that massive sequence information will continue accumulating and be made available through different public databases. One excellent example is the International Nucleotide Sequence Database Collaboration, which comprises the DNA DataBank of Japan (DDBJ), the European Nucleotide Archive (ENA), and GenBank (Arita et al. 2021). These three organizations curate and exchange DNA sequence data daily and, at present, host more than 70 million sequences corresponding to bacteria, fungi, and viruses. Even so, affected countries still hesitate to share data because these are public domain databases, through which data can be accessed and used anonymously, which can create policy and/or intellectual property issues. However, there is hope as evidenced by the GISAID-Initiative,⁷ developed for near-real-time reporting of viruses related to the bird flu virus (H5N1) and SARS-CoV-2.

The availability of large amounts of DNA sequences requires robust bioinformatic pipelines that can analyze the data in real time (preferably open source). With that in mind, the Nextstrain system was developed (Hadfield et al. 2018), which is currently heavily used to track the evolution of SARS-CoV-2, but can be applied to any virus of interest. So far, only a few examples of the use of such tools in surveillance of crop pathogens have been published (Siriwan et al. 2020; van de Vossenberg et al. 2020; Leiva et al. 2020). As more novel, portable, and affordable next generation sequencing (NGS) technologies take over classic time-consuming diagnostic tools based on biological isolation, PCR-based approaches, and phenotypic evaluation of disease response in specific host genotypes (Boonham et al. 2013), their use and applications will expand to the surveillance of other major crop pests and pathogens. Recent efforts to integrate such information with field data (incidence of

⁵<http://potpathodiv.org/index.html>

⁶<http://bioinfo.bti.cornell.edu/virome/>

⁷www.gisaid.org

symptoms and pests) are currently implemented in the platform PestDisPlace (Cuellar et al. 2018).

9.2.5 *Data Management and Open Data*

Efforts have been made to aggregate data and monitor the spread of crop disease by integrating data into one platform that combines different surveillance methods, such as field inspections, PCR test results, published literature, and ML diagnosis using mobile applications. One such effort is PestDisPlace⁸ (Cuellar et al. 2018), an online database, surveillance, and visualization platform, used to standardize the collection, analysis, and sharing of surveillance data acquired by multiple research teams. The platform uses these disparate data sources to create user-friendly geolocated visualizations of longitudinal pest and disease data from different spatial locations. The data visualization has enabled scientists working in the field to use PestDisPlace to understand trends and use the platform as an easy-to-understand communication tool for engaging with decision-makers and scientists in disease-affected countries. PestDisPlace is currently crowdsourcing disease monitoring data from CGIAR researchers and their partners, including national plant protection institutions mandated with crop protection.

PlantVillage has a similar database that visualizes pest and disease reports collected by its AI-powered apps (Nuru, FAMEWS, eLocust3m).

The tools described in the previous sections all generate huge amounts of data that can be used further as input for more extensive analysis and other kinds of modeling. Good data management and open access are crucial components of knowledge discovery and innovation (Wilkinson et al. 2016). However, in academia and research, only peer-reviewed publications have traditionally been considered outputs of science. But that tendency is changing a bit now as data are earning recognition as a legitimate research product that can be validated, preserved, cited, and credited (Kratz and Strasser 2015a; Kratz and Strasser 2015b; Data Citation Synthesis Group: Joint Declaration of Data Citation Principles. 2014).

Even though agriculture trails most sectors in terms of digitalization (Manyika et al. 2015), more and more data are being produced by research organizations, academia, governments, and farmers through mobile phones and social media. The management, dissemination, and reuse of data can contribute to building resilience to food system shocks. The CGIAR Big Data Platform has shown that organizing and disseminating open data on agriculture, applying analytics on this data, and working with agricultural stakeholders, such as farmer organizations, can help building resilience to pest and disease outbreaks, climate impacts, and land degradation (Jimenez and Ramirez-Villegas 2018).

⁸<https://pestdisplace.org/>

9.3 Decision Support Systems (DSS)

The fourth global evolution of agriculture will be causally linked to the emergence and use of technologies including smartphones and smart applications, Internet of Things (IoTs), artificial intelligence, cloud computing, remote sensing, and others (Zhai et al. 2020). These technologies are progressively evolving, increasingly used under various agricultural production contexts, and generating unprecedented volume of data. However, stakeholders and farmers often find it challenging to access, process, and digest these data into practical knowledge that can guide decision-making (Taechatanasat and Armstrong 2014).

In many smallholder farming systems where RT&B crops are cultivated, extension and advisory services are often overwhelmed or nonfunctional (Fabregas et al. 2019). Thus, to manage and mitigate threats of pests and diseases, farmers require reliable information to guide timely action. Digital DSS platforms that support and complement existing extension systems hold promise for sustainable RT&B crop production. These digital DSS vary in their overall function, content, and sophistication, but they can meet user needs in ways that transcend the capabilities of traditional extension systems and advisory services.

It should be noted that DSS tools are not exclusively Internet dependent and often built with the intent of democratizing information access across age, education, gender, and socioeconomic classes. Experience with smallholder RT&B farming systems suggests that male and female farmers face similar constraints in accessing DSS tools that are smartphone based due to limited or lacking Internet access and capability to use such devices. Yet, recent evidence suggests that disparity exists in access to (and ownership of) basic phones relative to gender and age class among farmers (Adewopo et al. 2021). Equitable capacity building of target tool users can accelerate adoption as these various tools are deployed across diverse geographies.

9.3.1 Short Messaging Service Systems

Short messaging service (SMS) systems have been adapted for rapid delivery of agricultural advisory services, including specific recommendations on best practices to tackle biotic threats on farm, information on specific precautions to mitigate incidence, or timely alerts for risks of pest outbreaks or disease infection and spread. SMS systems have proven to be an effective entry point to empower smallholder farmers because they are easy to deploy on basic cellphones and do not cost additional investment to receive information. Depending on use contexts and goals, farmers can informally exchange messages with each other, or respond to messages promptly to engage the sender, within a DSS setup. Several SMS-based DSS have been successfully tested and deployed to support data collection and information exchange on RT&B pests and diseases. In coastal Tanzania, the Commonwealth

Agricultural Bureau International (CABI) and other extension and advisory partners have facilitated SMS messaging among farmers to share information about cassava whiteflies (*Bemisia* spp.), a major pest in the region, and how to identify and remove infected cassava plants⁹. Project-based pilots of SMS for decision support, social enterprises, and private businesses – like Esoko¹⁰ and EcoFarmer¹¹ – are advancing the frontiers of SMS application for other purposes, such as exchange of information on prices and market information on potato in Zimbabwe (Ifeoma and Mthitwa 2015). While there are limited examples of SMS-based DSS that are exclusively focused on RT&B pest or disease surveillance, vendors or service providers have the flexibility to configure their systems to meet emerging demands for basic surveillance information at village or farm level. Therefore, RT&B-focused SMS systems can be enriched with periodic information on pest and disease threats, enhanced as a bidirectional information exchange tool, or integrated with more robust systems to offer the recipients direct access to further information or resources.

Despite its potential advantages, SMS deployment for surveillance and control of RT&B pests and diseases can be constrained by some factors. Although SMS is a low-cost pathway to reach a vast number of farmers and enables quick dissemination of information, user response to the message can be passive because the SMS nudge does not suffice as an incentive for immediate action. Similarly, the literacy levels of recipient can limit the interpretation of the message; therefore, smallholder RT&B farmers who have little or no formal education are often at a disadvantage. Furthermore, it is easy for recipients to ignore SMS-based DSS (e.g., incident alerts, control measures, preventive practices) when the risk or threat is not considered imminent.

Recently, the Bill & Melinda Gates Foundation has invested funds in PlantVillage to test the hypothesis that data on important diseases can be collected from SMS. This experiment will take advantage of a collaboration between PlantVillage, iShamba (which sends messages to farmers), and the TV show *Shamba Shape Up*, a popular show watched by over nine million farmers in Kenya. Using USSD (Unstructured Supplementary Service Data), the project will ask farmers what they grow and what pests they observe among their crops.

9.3.2 Interactive Voice Response (IVR) Advisory

Interactive voice response (IVR) technology allows users to interact with a pre-programmed host computer system through a telephone keypad or by speech recognition. Generally, the IVR-based DSS for farmers has a major advantage over

⁹<https://cabi-uptake.netlify.app/>

¹⁰www.esoko.com

¹¹www.ecofarmer.co.zw

SMS-based systems because it does not require basic literacy for effective use – only the ability to listen, select numbers on phone, or verbally respond to voice prompts. However, developing and operationalizing IVR systems is more complex because it requires voice coding and algorithms that route user selection through the system and return relevant content. In addition to the complexity of the back-end system, higher costs of connectivity are associated with IVR-based DSS because users often need to dial into the system to initiate information exchange, which often accrue mobile connection fees by the service provider.

Despite the promising aspects of IVR systems and their compatibility with the contexts of smallholder farmers, it is rare to find real-world application of IVR for reporting or monitoring of RT&B pests and diseases. One of the earliest assessments of IVR to support agricultural decision-making (Patel et al. 2010) reported a significant improvement in information sharing among smallholder farmers in rural India. It is noteworthy that prior to the testing of IVR within agricultural systems, this technology has been successfully used to curate timely information on chronic health problems (Piette 2000), and this success could be adapted for agriculture contexts, especially for pest and disease surveillance. Recently, digital agriculture enthusiasts have begun exploring entry points to introduce DSS directly to farmers or to support adoption and integration into extension and advisory services.¹² As these initial efforts mature, it is likely that vendors and service providers will have compelling information to design IVR systems as versatile DSS that offer broad information services and products to the target end users.

9.3.3 *Smart Applications (Smart Apps)*

The growing use of smart devices (primarily tablets and phones) in smallholder farming systems is creating unprecedented opportunity to engage farmers with robust and content-rich DSS for RT&B pest and disease monitoring and control. Smart devices have unique functions that allow users to access and exchange digital contents in various formats, either separately or complementarily to achieve desired user engagement and experience. In addition to the multi-format functions, smart devices are generally built with capacity to record actual locations (geocoordinates) of user inputs and observations, thereby facilitating rapid acquisition of georeferenced datasets, a critical input for spatially explicit near-real-time assessment of status and risks of pests and diseases at local, regional, or national scales.

¹²For instance, in 2020, a project funded by Bill & Melinda Gates Foundation to develop an IVR system for plant pest and disease surveillance in Ghana, where farmers are engaged to ensure timely reporting and control (<https://www.ausvet.com.au/ivr-for-plant-health/>). Similarly, in 2017, the CGIAR supported Viamo and Voto Mobile to develop an IVR system that connects farmers to market intelligence among farmers in Nepal (<https://bigdata.cgiar.org/inspire/inspire-challenge-2017/using-ivr-to-connect-farmers-to-market/>)

In most smallholder farming systems, the use of smart devices remains relatively low, but the high interest in smart digital tools constitutes a viable entry point for innovation among stakeholders, including farmers (McC Campbell et al. 2018). Therefore, various smart apps are emerging for the diagnosis, surveillance, and control of pests and diseases in RT&B crops. These include:

- The Plantix app,¹³ developed by PEAT GmbH (Germany), which supports rapid diagnosis for detection of pests, diseases, and nutritional deficiencies in banana, cassava, potato, sweetpotato (*Ipomoea batatas* (L.) Lam.), and other crops.
- The BXW app¹⁴ (Fig. 9.3), developed by a consortium of partners (led by IITA), supports monitoring of banana *Xanthomonas* wilt (BXW) disease with combined functionality of awareness messaging, diagnosis, control, and agronomic recommendations.
- The Crop Disease Surveillance (CDS) app, developed by IITA, is designed for cost-effective surveillance for cassava virus diseases in Nigeria; it facilitates rapid diagnosis through digital image-based analysis, communication among the quarantine officials, notification of pest risk, and facilitation of emergency response. This app was later expanded for use against banana bunchy top virus (BBTV) surveillance in Nigeria.

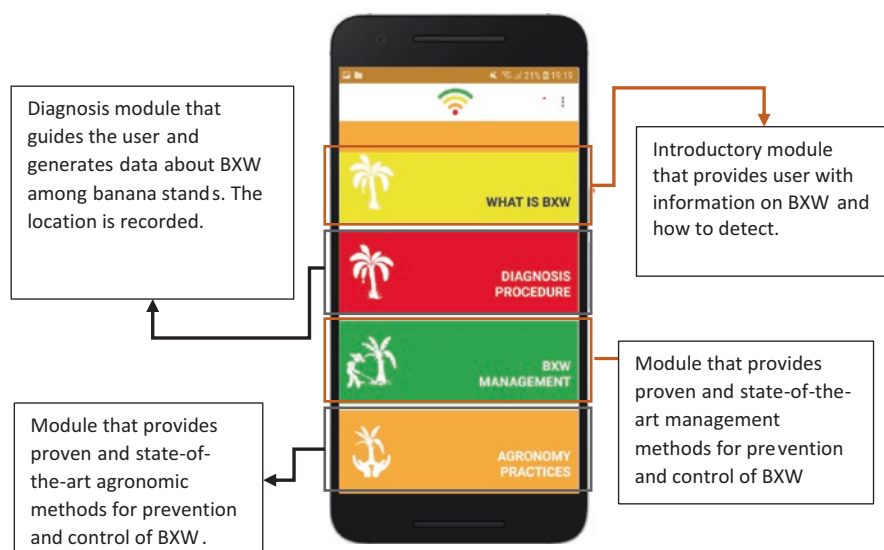


Fig. 9.3 The homepage interface of the smartphone-based BXW app, an example of a smart decision support system (DSS) for the surveillance and control of banana *Xanthomonas* wilt (BXW) disease

¹³ www.plantix.net

¹⁴ www.ict4bxw.com

- The PlantVillage Nuru app (Fig. 9.1) was collaboratively developed by several researchers from Penn State University, FAO, IITA, CIP, and CIMMYT for the diagnosis of plant diseases, including cassava and potato (Ramcharan et al. 2017; Ramcharan et al. 2019; Mrisho et al. 2020).
- Others (including Tumaini and PestDisPlace apps) that are highlighted in the next section.

Most of these smart apps have been tested in the field, are available through the Android Play Store, and are being evaluated or tweaked to optimize user experience.

The sustainability of smart applications depends somewhat on various technical and contextual factors. For example, scaling up the use of apps across geographies depends on the proliferation of smart devices among smallholder farmers or last-mile extension delivery agents. Similarly, although some of the apps work in offline mode, the availability of Internet coverage is critical for initial downloads, data exchange with back-end servers, and synchronization of the app and content updates. The commitment of vendors and/or institutional hosts is indispensable to progressively iterate over the core and ancillary functionalities of these smart apps in response to user demands.

Several systems are already having impact in improving production of RT&B crops at the community level:

- PlantVillage Nuru has been available for free download since June 2018, and since that time, more than 15,000 reports have been generated in 32 cassava-growing countries of the tropics, using the cassava pest and disease identification component. An important feature of this work has been the promotion of the role of “lead farmers” who are equipped with the basic smartphones required to download and use the app and work with their communities to help farmers to learn about the symptoms and damages caused by the main pests and diseases of cassava, as well as guiding them in the application of appropriate control practices. Users in Tanzania and Nigeria are also invited to check on the availability of certified planting material through using the SeedTracker app¹⁵, which is a system for the registration and certification of farmers producing high-quality planting material. The widespread use of the PlantVillage Nuru app has made an important contribution to improving the health of cassava production systems in western Kenya, and farmers have given testimony to the value that these changes are making to their livelihoods^{16,17}. PlantVillage Nuru is also being expanded for application to other RT&B crops, notably potato and sweetpotato, and this development will extend the benefits being realized by producers to other parts of the world.
- The Tumaini AI-powered app, which detects various diseases and a pest of banana, is free available for download on Google Play Store since June 2019;

¹⁵ www.seedtracker.org

¹⁶ <https://bigdata.cgiar.org/blog-post/success-story-from-cassava-farmers-in-busia-county-kenya/>

¹⁷ <https://plantvillage.psu.edu/blogposts>

since that time, the app has been downloaded over 2000 times, mostly by users in Asia. For example, in India, the Tumaini app was discussed and demonstrated on two famous radio and TV channels of Tamil Nadu where banana cultivation is omnipresent. In addition, the Tumaini app utility and functions are being promoted at farmer's exhibitions in Tamil Nadu, while in collaboration with Indian state agricultural universities, farmers and growers are being trained in the app use through agricultural college students in the framework of village stay programs.

- The BXW app is being co-validated in the field with a network of 65 village-level extension agents (known as farmer promoters) who have successfully reached over 4200 farmers (Fig. 9.4), and independently completed over 2500 diagnosis within banana farms, across 8 districts in Rwanda. Based on the data flow, robust georeferenced data on BXW incidence is being generated, through farm-level usage of the app, to assess spread and potential factors that impact the dynamics of the disease. Further, the agronomic information and BXW control methods were disseminated through an IVR-based system, under the auspices of Viamo¹⁸, to circumvent the constraints associated with low smartphone usage among smallholder farmers. The information on banana was accessed by over 10,000 unique callers (mainly farmers) over a period of 8 weeks, with 87% of randomly surveyed users reporting their knowledge of agronomic and control practices improved after accessing the digital platform.



Fig. 9.4 Enthusiastic Rwandan banana farmers who are interacting with beta version of ICT4BXW app during field testing. (Photo credits: IITA)

¹⁸<https://viamo.io>

Despite what is described in the examples above, assumptions about the impact of the innovations have to be tested over time and relevant M&E frameworks can help to build up evidence while identifying the limitations of assessing direct impact (e.g., lagged effect and indirect impacts).

9.4 Future Perspectives

9.4.1 *Development of Integrated and Interoperable Systems and Major Challenges to Overcome*

Many different databases and apps have been developed to track and identify diseases globally, but are generally used only for a single crop or disease or promoted by a single research center, thus limiting the use of the data to a specific community of practice. Once developed, these communities become vested in their systems and unlikely to change to another platform, because their home platforms have been tailored to their needs. However, if the data captured by these different platforms could be shared more broadly, it would benefit all involved and could be reused to support many specific use cases, including the tracking of epidemics, modeling, providing farmers with advice, and supporting seed systems.

Within RTB collaborating organizations and the broader CGIAR collaborating partners, several such databases and apps have been developed. To enable the sharing of data between these platforms, the concept of an AgDx alliance was proposed between platforms of the CGIAR and other publicly funded, nonprofit organizations dedicated to research for development and education in agriculture with the aim to improve plant health globally through ICT tools. As an alliance of individual platforms, tools and databases are aimed at supporting agricultural health in different aspects AgDx commits to address former shortcomings through the development of application program interfaces (APIs) to facilitate data sharing between platforms and/or by providing links between complementary ICT tools where appropriate.

The AgDx alliance is taking steps to create data interoperability among platforms, starting with data harmonization. Through a collaborative and community-based process, AgDx standardized a core set of data elements that form the first data interoperability step. This standardization process ensures that data elements will have the same semantic meaning by agreeing on definitions and scale and enable effective exchange of data.¹⁹

¹⁹The AgDx community created a cross-reference of all common data fields and the standardization process divided the data fields into two groups: one for pests and one for disease data. Examples of basic shared data fields include the affected crop, the location, severity, incidence, and scale data. Disease data fields include the disease name, pathogen type, and pathogen name. In comparison, pest name, pest origin, and pest type are pest-specific examples. The dataset includes

An application program interface (API) will facilitate data exchange and interoperability between various data systems and platforms of the AgDx alliance. An API is a set of protocols and definitions that work as an intermediary that allows computing units to communicate, exchange, or retrieve information or perform a function. Specifically, the AgDxAPI will be a Web Service API. Web services allow computing systems to communicate with each other over a network. The AgDx database or platform exposing a web service will define resources in the form of computer files such as images and audio files or outputs of a computing function as standard computer formats such as JSON (Ecma International 2017) and XML (W3C 2009). Using the REST API architecture style, a de facto standard for creating Web Service APIs (Fielding et al. 2017), AgDxAPI will allow implementing systems to communicate which services and resources are available and how to request these resources. Using APIs has been proven successful in creating interoperability across agricultural research, such as in the plant breeding community (Selby et al. 2019).

All participating databases and platforms will implement the AgDxAPI specification into their systems. Each database will customize the API so that service calls will retrieve data in the agreed format and scale. Harmonizing the core exchange dataset with existing ontologies such as the Crop Ontology (Shrestha et al. 2010) and the in-development Plant Crop Stress Ontology²⁰ will be the next step to enhance data standardization. To this end, AgDx is engaging with the Ontology Community of Practice of the CGIAR Big Data Platform (Arnaud et al. 2020). This community has experience in creating and integrating ontologies with platforms and APIs in agricultural research. Another next step for the AgDxAPI specification will be to include an expanded list of data elements for specific domains. For example, AgDxAPI imaging could be an extension to allow for more detailed retrieval of images stored in different databases. This feature is critical for machine learning.

9.4.2 Approaches to Scaling (Opportunities, Packaging, Strategies, Public and Private Partnerships, Expected End Users, and Impacts)

Digital tools for pest and disease identification and surveillance have become a busy “space” in recent years, with rapid developments in several component technology areas, such as high-throughput sequencing, remote sensing, artificial intelligence, and the development of web platforms and phone apps. These changes are being built on rapidly expanding communications architecture that is making it increasingly easy to share digital technologies and associated information with rural

both the common names and scientific names for crops, pathogens, pests, and linkages to other related computer systems such as the GenBank (Sayers et al. 2021).

²⁰<https://github.com/Planteome/plant-stress-ontology>

farmers. According to the GSM Association²¹, some of the most rapid gains are being made in sub-Saharan Africa, where mobile Internet users are expected to increase from 272 million (26%) in 2019 to 475 million (39%) by 2025, and smart-phone connections are expected to increase from 44% to 65% over the same period. Meanwhile, the interoperability of tools will likely be a major factor for effectively scaling applications among smallholder RT&B farmers. This has been an important feature of the work of the CGIAR's RTB research program, where significant efforts have been undertaken to foster links and information exchange among a range of digital surveillance tools.

Efforts are underway to incorporate this approach into plans for the new OneCGIAR, which would aim to bring together the majority of the digital surveillance tools being used throughout the CGIAR at present. Promoting the use of this anticipated platform of applications at farm level will require a diverse set of innovative partnerships with the public and private sectors. Recent experience with the rollout of test and trace digital tools for SARS-CoV-2 has demonstrated that specific solutions may need to be tailored for different countries and geographies and that applications will achieve greatest impact where there are strong partnerships between private technology providers and public institutions. Ultimately, the likelihood of any individual farmer using a specific digital tool will depend on the perceived benefit that the tool delivers. This highlights the importance of ensuring that disease surveillance tools are packaged with business development tools for the same crop. Many commercial digital platforms have been set up in recent years to provide a range of e-extension services, including a growing number established by phone providers as well as others set up by dedicated electronic agro-support services, such as Esoko in Africa and ImpactTerra in Southeast Asia. Building coalitions with these types of providers and national extension systems appears to be the best opportunity for scaling digital surveillance solutions and meeting the needs of farmers down to the last mile.

9.4.3 911 For Planet Earth

In 1937, England established the world's first emergency number: 999. By calling this number, any person could access the emergency services. All countries now have such numbers, allowing persons to make phone calls for help without coins or credits.

African farmers, and smallholder farmers around the world, need extension advisory support to cope and adapt to climate change. There are a lot of advices available such as planting drought-tolerant crops, promoting soil moisture conservation, engaging in water harvesting, tree planting, and other activities that are known to increase resiliency to climate shocks. As more pest data becomes available, we can

²¹<https://www.gsma.com/mobileeconomy/sub-saharan-africa/>

integrate them with weather forecasts and satellite observations as demonstrated by the response to desert locust crisis of 2020/2021 (discussed above, <https://arcgis.com/arcgis/0aHGHi>). Available advices from various public sources (including scientific inputs from CGIAR, NASA, FAO, NOAA) are considered as public good, and they are often synthesized by organizations like the United Nations, who readily draw from the global community of scientists (CGIAR, universities, federal agencies). But because of very high data costs in places like Africa, smallholder farmers, or the communities to which they belong, cannot afford to access this “free advice.”

Millions of smallholder farmers are unable to access digital information as public goods because they cannot afford airtime for basic or smartphone usage. Considering extant global-scale emergency and crises, it will be relevant to deploy an emergency response system, similar to 911. Such a system can be developed to function in a way that it provides science-based advice and coping strategies to farmers through free and accessible platforms. Such platforms offer contents in various forms and formats, including well-illustrated videos on proven farming practices, advice on climate-resilient crops, and strategies to combat pests.

9.5 Conclusions and Ways Forward

Digital tools and systems for monitoring and controlling pest and disease threats in smallholder farming systems are crucial for ensuring food and nutrition security around the world and into the future. However, achieving and sustaining this goal requires cohesive engagement between digital tool developers, researchers, extension and advisory services, and farmers to define specific problems and opportunities and develop suitable digital solutions. Despite the array of digital DSS tools and platforms that have been developed and deployed for other use cases within and beyond agriculture, their adaption or use is still in its infancy with RT&B cropping systems. This suggests wide opportunity to innovate for impacts in RT&B farming systems, leveraging existing knowledge and experiences, and rapidly integrating tools and methods for efficient mitigation of pest and disease risks at scale.

Smartphone penetration and usage is expected to increase globally, especially in developing countries, while Internet coverage will improve, reaching even the most remote regions through new satellite systems (GSMA Intelligence, 2020). Consumer smartphone capabilities, including image capture and integration with other sensors, are also expected to evolve, thus creating new opportunities for innovative applications to advance plant health, including major RT&B crops. Machine learning algorithms are likely to improve simultaneously with new generation satellite-derived remote sensing data on various agrometeorological variables (including precipitation, soil moisture, temperature), which can be accessed and used for decision support in near real time. Combining these assets with improved analytical methods for image processing, downscaling data, and crowdsourcing of information, the prospects are good for accurate forecasting and prediction of pest and disease risks at global and local scales to support timely decision-making and action.

Despite the gains in coverage and use of ICT tools across developing countries described in this chapter, there is a considerable gender gap, especially in regard to Internet use. This gender gap is significantly larger in most developing countries and even more so in rural settings. To date, we lack studies analyzing the digital gender divide in the agricultural sector or how ICT tools may influence gender disparities in agricultural settings. Such studies are urgently needed in this era when digital agriculture is rising; we must take care not to inadvertently fuel more gender inequality.

The vision of a dynamic and robust pest and disease surveillance system that allows for reflexive learning and inclusive iteration of tools can be achieved with proper consideration of user needs, contextual realities, and aspirational thinking for technology development and deployment. For instance, efficient information exchange from different data sources is indispensable for scalable analytics on pest and disease dynamics in RT&B cropping systems, and this aspect requires common data definition standards – an effort which has been initiated by CGIAR researchers through the AgDx alliance initiative. An initial version of AgDxAPI has been developed based on a similar approach implemented by crop breeders (named BrAPI; Selby et al. 2019). The AgDxAPI is currently in its pilot stage, leveraging PestDisPlace and PlantVillage tools under field conditions. As an agricultural research for development organization, the OneCGIAR may have an important role to play as a trusted broker for harnessing and disseminating data streams across diverse sources and institutions.

In conclusion, the impact of monitoring and controlling RT&B pests and diseases can be quite nuanced, especially when accounting for direct net impacts on yield. However, the cost of inaction would be perilous. Assessing returns on investment in DSS for RTBs should include various ancillary benefits, including gender-sensitive equitable access to information, youth empowerment for last-mile service delivery, and ease of resource demand on national extension advisory systems.

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