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LEVERAGING DATA, MODELS & FARMING INNOVATION TO PREVENT, PREPARE FOR & MANAGE PEST INCURSIONS: DELIVERING A PEST RISK SERVICE FOR LOW-INCOME COUNTRIES

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ABSTRACT

Globally, pests (invertebrates, vertebrates, pathogens, weeds) can cause estimated annual losses of between 20-40%, but higher losses are disproportionately experienced by many low-income countries as agriculture is the mainstay of the majority of the people and of national economies. Pests pose a major barrier to these countries to meet the aims of the UN Sustainable Development Goals, particularly SDG2 "End hunger, achieve food security and improved nutrition and promote sustainable agriculture". However, solutions, in the form of pest risk alert systems coupled with major advances in technology are now providing opportunities to overcome this barrier in low-income countries. In this paper we review these systems and the advances in data availability, management and modelling and communication technology and illustrate how these can provide new and novel

solutions for the development of agricultural pest and disease early warning and risk mapping systems and contribute to improved food systems in low-income countries. In conclusion, we identify key areas for the UNFSS that will help guide governments to engage with these developments.

1. INTRODUCTION

Globally, pests (invertebrates, vertebrates, pathogens, weeds) remain a major barrier to crop production with annual losses estimated at between 20- 40% (FAO, 2019). The impact of pests is particularly acute in many low-income countries as agriculture is the mainstay of the majority of the people and also of the national economies (Perrings, 2007; Pratt et al., 2018; Wiggins et al., 2010). Additionally, climate change is predicted to increase the likelihood, frequency, and impact of pests in the future, resulting in increased crop losses thus causing damage to the economy of low-income countries. For instance, Deutsch et al (2018) predicted that global yield losses of major grains will increase by 10-25% per degree of global mean surface warming. The vulnerabilities of these countries are further exacerbated because of the small size of farms which often witness outbreak of transboundary and /or new invasive pests (Early et al., 2016) and multiple indigenous pests (Constantine et al., 2021).

A number of factors such as weak phytosanitary systems and inadequate human, financial and infrastructure capacity are exacerbating the problem caused by these pests. There are weak linkages between research and national systems, resulting in gaps in effectively translating research into policy for their management. Significant progress has been made in the last decade in providing means for access to important knowledge about the identification of important pest groups such as arthropods, plant pathogens and weeds and their controls, both at a national and smallholder farmer levels (e.g. the global Plantwise programme (www.plantwise.org) and PlantVillage (https://plantvillage.psu.edu/)) but information about pests is generally not accessed by users until a pest has reached a damaging stage; for example, in the case of farmers, this is when pest symptoms become most apparent. Thus, crop yield losses remain high (Pratt et al., 2017). Additionally, existing knowledge on how to manage pest and disease incursions has also become more difficult to apply given the changing backdrop of weather patterns and the effect this has on the phenology of pest and disease outbreaks (Castex et al., 2019; Chidawanyika et al. 2019) or the range expansion of invasive alien species (Kalnicky et al., 2019). In all, pests pose a major barrier to these countries to meet the aims of the UN Sustainable Development Goals, particularly SDG2 “End hunger, achieve food security and improved nutrition and promote sustainable agriculture” but all the SDGs depend to some extent on the delivery of improved food systems. However, solutions, in the form of pest risk alert systems, do exist that address this barrier and major advances in technology are now providing opportunities to apply these in low-income countries.

It is well established in Integrated Pest Management (IPM) that ‘prevention is far more effective than cure’ (Barzman et al., 2015; Pretty and Bharucha, 2015) and this critical tenet of IPM is key to reducing losses from pests and improving crop yields.

Although preventative measures emphasize aspects such as the use of healthy seed or maintaining healthy soil etc, the colonization by multiple indigenous pests or even the invasion of new pests in smallholder farms within a cropping season is inevitable in most regions. Hence, the provision of timely pest risk prediction information through risk mapping or early warning systems is of paramount importance. Active communication of real time information enables intelligent mobilization of resources by national governments, other actors in the food value chains and/or early action by farmers to prevent pest populations from reaching economically damaging levels.

The development of national pest risk assessment and early warning systems can be complex though. It requires the combining of expertise of different actors, well beyond those in pest modelling and pest management alone (Magarey and Sutton, 2007; FAO 2007). Many advances have been made in pest modelling and several types of model are now available for pest risk mapping and early warning (Orlandini et al., 2017; Tonnang, et al., 2017). However, equally important is the availability and access to suitable input data sources (e.g., pest data, weather data) to build or drive such systems, a deep understanding of farmer decision making, and efficient communication means to deliver risk information to end users; for the last, in the case of farmers, this involves large numbers of people spread over vast areas. As a result, pest risk systems have mostly been developed in high income countries and only applied in low-income countries for a handful of significant pests (e.g., transboundary pests in Africa, see Box 1) and for import and export market access, but this situation is now changing. Recent innovations and advances in data availability (e.g., earth observation (EO) data, meteorological data), data architectures, data management workflows, computing power and communications technology has allowed for increasingly sophisticated risk assessment and decision support systems to be developed and extended to end users. In particular, there has been a developing interest in the use of weather and environmental data derived from EO sources as such data are available for large areas (Marques da Silva et al., 2015). EO data have already proved to be useful in broad scale alert systems such as Global Forest Watch (GFW), the Famine Early Warning Systems Network (FEWS NET) and the Group on Earth Observations Global Agricultural Monitoring Initiative (GEOGLAM).

These advances in data availability and data management may now be combined with advances made in the field of extension and have the opportunity to make significant improvements in the field of pest prediction and subsequent extension of messages. Increasing access to mobile phone technology (World Bank, 2019) along with the emergence of ICT-based advisory extension services has allowed the extension sector to disseminate advice through multiple complementary communication channels such as Short Message Services (SMS) and Unstructured Supplementary Service Data (USSD) on broader scales than previously possible (Thakur et al., 2016, Tambo et al., 2019).

Here we discuss how these advances, in terms of data availability, management and modelling and communication technology have provided new and novel solutions for the development of agricultural pest and disease early warning and risk mapping systems in low-income countries. In particular, we explore how this provides opportunities to improve food systems and identify key areas for the UNFSS that will help guide governments engage with these developments.

2. Technology Developments and Their Application to Pest Risk

Several pest risk prediction systems are now in place or in development for low-income countries which forewarn of within season pest and disease incursions. These systems provide alerts about near-future potential geographic hotpots of transboundary pests or build-up of local pests which can be used at any scale (national, regional and local) for warning of potential pest outbreaks.

Developments of these systems with a wide outreach have been possible with the onset of increasingly accessible high-quality data with high spatial resolution derived from EO and meteorological sources used to drive the models, and the collation and generation of field and laboratory data to build, train and test the models.

Access to datasets and data Management

Through numerous projects an immense number of datasets on occurrence, abundance, and prevalence of pests, have been collected across many countries. However, these data remain scattered, are not widely accessed, and used, and no mechanisms exist for bringing these datasets together enabling sharing for multiple uses. Data are heterogeneous owing to the diversity of their sources, differences in objectives for collection, and multiple storage and retrieval formats however, recently, with the advancement in data collection and collation instruments like crowdsourcing, EO and geospatial tools, and cross-cutting analytics like artificial intelligence (AI) and internet of things (IoT), the development of cloud-based platforms (e.g. 'data hubs') and mobile apps for real-time pest detection and risk profiling is highly possible. This enables the integration of historical and ongoing collections of pests and associated natural enemy data from disparate sources as its centerpiece and may act as repositories which may be utilized to build and validate pest risk prediction systems.

With the availability of such diverse data sources several initiatives have been underway to combine and utilize these data for the development of pest risk or other applications. For example, *icipe* through the data management, modelling, and geo-information (DMMG) unit is establishing a state-of-art data management workflow (DMWf) and advancing the use of 'big data' and cloud-based cross-cutting processing technologies that allow harmonized storage and analysis of petabytes of various data types. This includes observational, experimental, simulation and derived datasets. The observational data are commonly collected through open-ended survey, observation and the use of equipment and devices to monitor and record information. Experimental data are obtained through functional involvement by the data collector that create and gauge the change to establish causal relationships. Simulation data are obtained through mimicking known processes and applying computer-based methods to reproduce, while derived data are the result of the application of formulae to transform the information. The DMWf provides a collaborative framework with cooperation between data scientists and information communication technology (ICT) experts.

With relatively more complex datasets, the opportunity for more sophisticated data handling methods has emerged. AI allows the exploration and utilization of large datasets and predictors, the expansion of assessments beyond binary outcomes, and takes into account the costs of different types of forecasting errors to generate improved and accurate knowledge for decision making with feedback and accountability in the context of IPM. Approaches such as machine learning (ML) and deep learning (DL) enable the characterization, discrimination, classification, prediction, forecast and utilization of existing knowledge in pest management for appropriate interventions.

Improved access to Earth Observation and meteorological data

EO data are complex and require specialised human and technical capacity to process and manipulate the source data into compatible formats for analysis which can often be lacking in developing countries and organisations. Space agencies are leaders in the use of EO data and are increasingly driving initiatives to make data more widely accessible and standardised to require less processing (O'Connor et al., 2020). One such initiative is the Group on Earth Observations (GEO), an intergovernmental partnership developed to promote accessibility and the subsequent use of EO. Key goals of GEO are to promote the use of open access and sustainable data sharing to support research, improved decision making and therefore benefit agricultural stakeholders.

Increased collaboration between EO and biological pest risk modelling experts and cutting-edge actors in extension of information have allowed these data sources to be utilised at a broad spatial scale to benefit those in receipt of early warning information. Data derived from EO sources can provide a consistent stream of measurements at regular time intervals with global coverage. These data can include various vegetation indices which may be related to plant biomass or vigor (i.e. Normalized Difference Vegetation Index: NDVI), or used within reanalysis datasets to give a broad range of atmospheric, land and oceanic climate variables (i.e. ERA5 ECMWF dataset https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5). The quality, accuracy and availability of these data are increasing with each new space program (ESA,2020).

Well established vegetation proxies, such as the NDVI have been used effectively by the FAO since 2010 to measure the amount of 'green area' to monitor potential locust habitat recession and growth (see box 1). These data have helped direct local teams on the ground to survey localities at higher risk of locust population build up and thus help direct monitoring and control resource (Renier et al. 2015). Recently, data from the European Space Agency (ESA) have been used to classify different tree species and crop types (Persson et al., 2018, Van Tricht et al., 2018) and now such data are being used to monitor agricultural weed problems such as Striga or 'witchweed' in Kenya (Mudereri et al., 2020) and *Parthenium hysterophorus* or 'famine weed' in Africa and Asia. These weeds can be successfully mapped using EO technology (Kganyago et al., 2017, CABI, 2021) and species-level mapping solutions can offer great benefits to policy makers, who with knowledge of a weed's distribution at a national scale can implement suitable management programs.

High quality data feeds of meteorological observations are essential as broadscale modelling approaches such as those used in pest risk prediction systems rely on an accurate estimation of localised conditions like temperature, humidity and rainfall (Magarey, 2005). Mechanistic or deductive models use detailed knowledge of the pest/disease biology to predict the response of the organism to a specific climatic driver (Venette, 2010, Donatelli et al 2017), therefore access to accurate, high spatial and temporal resolution datasets is essential for the correct estimation of insect and disease outbreaks. In the recent past, weather data feeds for early warning systems have used observations from meteorological stations either set up as regional networks or farmer owned stations (Gleason 2008, Magarey et al 2001, Cressman, 2016). However, networks require funds for their upkeep and coverage can be geographically unrepresentative of the needs of a study or altogether limited (Colston et al. 2018). Climate data products derived from EO sources and reanalysis datasets have the potential to overcome these issues by providing complete coverage at good spatial and temporal resolutions and can offer a wider range of variables which may be applicable to modelling needs (Colston et al 2018). Improved access to sophisticated weather models such as the Unified Model (a numerical weather prediction model) available from the UK Met office have also contributed to the development of disease early warning systems. Recent advances in the availability and access to these data have advanced the capabilities of models to deliver near real time information. This increasing amount and accessibility of data from varied sources offers great opportunities to inform agricultural stakeholders to make better decisions when it comes to plant health challenges, and thus moving towards reducing crop losses as outlined in SDG 2. Recent projects such as PRISE (Pest Risk Information Service) project funded by the UK Space Agency (UKSA), and a near real time early warning system to predict future potential hotspots of two wheat diseases in Ethiopia (Allen-Sader et al 2019) have utilised access to these improved data sources for the purpose of pest and disease early warning systems. Both systems have extended messages to relevant stakeholders (governments, farmers, extension workers) in order to inform better management decisions with the ultimate aim to reduce crop losses.

Validation of EO data and models

Pest and disease risk prediction models driven using EO data inputs require field data for testing and validating species incidence and development. Historically, data collection in pest early warning systems has been limited by ground surveys which may fail as a result of political unrest, border disputes, and inaccessible terrain or can be limited by funds to generate these data, however although detailed controlled studies remain vital for testing EO and pest models, there are now opportunities to collect supporting data from a much larger source. Increase in access to digital communication technology (GSMA, 2020) enables data to be collected directly from farmers and to enrich early warning systems. This citizen science approach is adapting to new technologies that smartphones provide (GPS, digital cameras, internet connectivity). Many efforts are also ongoing to build AI based tools (applications and sensors) for pest and disease detection and identification through image processing (www.plantvillage.psu.edu ; https://www.inaturalist.org/home) which may be used for in field diagnostics of pests and diseases or to assess local pest/disease pressure. The collation of accurate, or in terms of iNaturalist "research grade" datasets (Ueda, 2021) relating to pest presence may contribute to the build, calibration and validation of early warning models. There is a growing societal acceptance of mass participation projects and advances in statistical approaches allow these data to be analysed in a less-structured way (Pocock et al., 2017). In order to be sustainable, these systems need to consider the incentives and motivations for users to contribute data. This surveillance method contributes vital observations in support of national and international programs, detecting pest incidence outside of formal research studies, extension services, border control checks and the work of plant protection organisations (Brown et al., 2020).

Rolling-out a cost-effective surveillance and early warning system to manage the acute desert locust crisis.

The desert locust, *Schistocerca gregaria* (Orthoptera:Acrididae) is an eruptive, transboundary pest which affects Africa and parts of Asia. Under certain conditions, the locust forms large swarms which affect large geographies and severely impact food production. Given the relationship between local environmental conditions, abundance of vegetation and locust biology, it is possible to use state of the art approaches to collect data on locust presence, monitor movement, model the potential spatial extent of the locusts and assess crop damage to produce a dynamic and reactive response to locust outbreaks. In addition, schemes such as the FAO Desert Locust Information Service (DLIS) are able to forewarn of potential conditions which may lead to the formation of swarms, thus preventing future swarms. Below are the ways in which technology and data should be utilized in frontline countries in response to the *S. gregaria* outbreak 2019-2021.

Activity	Example
Monitoring presence of populations	• Innovative digital tools like smart phone Apps (e.g., e-locust3M), as means of crowdsourcing, for real-time desert locust data collections, tracking and monitoring the spread of the pest. • High-resolution remote sensing systems mounted on unmanned aerial vehicles (UAV), i.e., drones, for timely desert locust surveillance and monitoring in remote and/ or inaccessible areas.
Monitoring of habitats/potential habitats	• Use of newly launched earth observation (EO) tools (e.g., satellite-based vegetation coverage, wind speed/ direction and soil moisture) of relatively better spatial and temporal resolutions to monitor desert locust habitats.
Monitoring of movement	• Ground-based radar systems to track and monitor desert locust breeding sites and hoppers migrations.
Collation of data	• Harmonize and standardize the existing national and centralized open-source desert locust data systems/ platforms to receive and store 'big data' transmitted from crowdsourcing tools and drones.
Early warning	• Develop desert locust early warning and early action platforms using combinations of above-mentioned tools, machine learning (ML) and artificial intelligence (AI) algorithms.
Future situations/scenarios	• Assess vegetation and crop damage due to desert locust using long-term EO data, ML and AI algorithms. • Use of historical long-term (e.g., 30 years) satellite-based climate data and AI algorithms to assess the impacts of climate change on desert locust occurrence and forecast future desert locust outbreaks weeks and months in advance to enhance targeted and effective interventions

3. POTENTIAL FOR IMPROVING PLANT HEALTH SYSTEMS AND LIVELIHOODS- THE REQUIREMENT FOR EFFECTIVE EXTENSION

The key aim of pest risk prediction systems should be to communicate risks and mitigation strategies to those who need the information most, with the aim to reduce potential losses, and allow time for sustainable interventions to be made. Such extension messaging should consider the technological capabilities of the end user. Rapid large-scale investment in telecommunication and the subsequent reduced cost of mobile phones and internet connectivity has resulted in the widespread accessibility of mobile phones across Africa and Asia including its most rural areas (World Bank, 2019) with an estimated 34% of the surveyed population owning a smartphone in Kenya, and 53% owning an older device without internet connectivity (Krell et al 2020).

As a result of the increase in mobile phone ownership, ICT-based advisory extension services have evolved to use communication channels such as SMS and USDD. With the direct to farmer and local language adoption capabilities of SMS, it is considered the most impactful single communication method in terms of improving farmer knowledge and practice changes in Sub Saharan Africa (Silvestri et al 2020). A recent example is an initiative set up in 2018 through collaboration between Kenya’s Ministry of Agriculture, Livestock, Fisheries and Cooperatives (MoALFC) and Precision Agriculture and Development (PAD) to disseminate advisory messages relating to Fall Armyworm (*Spodoptera frugiperda*) (Bakirdjian, 2020). The initiative has grown to provide actionable advice for ten crops, and has demonstrated broadscale uptake by reaching over half a million farmers, and in an additional pilot study on Fall armyworm, in collaboration with PRISE, 59% of 6000 farmers who received timely SMS pest alert warnings self-reported changing their management practices with positive outcomes (Mbugua et al., 2021). Similar programmes across Africa and India showed a 4% average yield gain has been associated with digital agriculture programs, demonstrating a positive impact on livelihoods (Fabregas et al., 2019). This can be achieved at significantly lower costs compared with traditional agricultural advisory services. Estimates show the cost per farmer reached by SMS services to be between 28 and 122 times cheaper per year compared to funding in person farmer field days (Low and Thiele., 2020; Quizon et al., 2001; Ricker-Gilbert et al., 2008). An integrated approach including in person farmer visits, farmer field days and digital advisory services can offer more sustainable and effective extension.

4. CONCLUSIONS AND FUTURE ACTIONS

The bringing together state of the art advances in data availability, resolution, management and architecture along with new extension approaches that can deliver rapid and timely information, stands to make real changes to how pest risk can be communicated to end users in a timely way. The resulting synergy in these individual improvements can be combined to result in real gains in terms of yield on the ground and make headway towards the sustainable development goals such as SDG2. To keep momentum of the synergy of these approaches, there are several aspects which could be considered in the near future.

The collation and curation of data from disparate sources is key to being able to drive the build and validation of pest risk models and to exploit opportunities from the 'big data' and machine learning approaches. Data should be published openly (when possible) following FAIR principles, so that data are findable, accessible, interoperable and reusable. Openly accessible data can be shared through common interactive web platforms such as the Global Biodiversity Information Facility (GBIF) or institutional repositories such as those hosted by CABI, FAO or IITA. This will bridge the data gap in national, regional and local surveillance and improve data systems, linkage and sharing of pest data. Overall, the modelling platforms themselves can serve as means of communication and networking. It is important to ensure that these early warning and monitoring systems are truly sustainable (self-managing and self-funding) in the long-term, and public-private partnerships will be key in ensuring this. Moreover, projects should ensure that the data and related materials, both digital and non-digital, should be accompanied by proper metadata and documentation in a way that facilitates the verification, replication and, if possible, reuse and remix of the data.

The exploitation and interpretation of 'big data' can be used to develop geospatial cloud-based tools and mobile apps that can be operationally utilized for 'real-time' insect and weed surveillance, monitoring and forecasting. To do this, a complete, accurate and reliable DMWf is required with advanced skills in common data models (CDM), data warehouse and repository, modelling methods and analytics including ML, AI, design thinking, system thinking, system dynamics and computer vision algorithms. This information can be used to better learn, adapt and transform risk into knowledge to change practice. For instance, applying AI on a CDM extract, could uncover hidden patterns, unknown correlations, trends, preferences, and other information that can help stakeholders making better and more informed decisions for the target insect pests and weeds. AI may be utilised for the optimisation of spatial positioning of pest traps which auto-disseminate sustainable interventions such as biopesticides (Guimapi et al. 2019).

Global environmental monitoring platforms provide portals for policy and national and regional decision makers to view datasets and reports, however there is now an opportunity to bring early warning to a farmer level. Advances in digital technology have demonstrated great opportunities to disseminate data to local scales and communicate this information to aid decisions made in the field. To achieve greater impact, these large datasets must be turned into timely information which can support agricultural decision making at a local scale, to avoid preventable losses. To be effective, pest early warning system outputs must reach the farmer in the form of actionable advice. In order to effectively manage pest and diseases, farmers need timely warnings on taking preventative actions, advice of when to prepare and stock plant protection products, and alerts on the optimum times to monitor their crops for particular problems and in order to act. The combination of this improved extension with the availability of high quality, high temporal and spatial resolution datasets which can drive models within pest risk prediction systems is opening up opportunities to extend the outputs of models to broader geographical audiences and reach those who need the information most. There is also an opportunity to combine early warning model outputs with models relating to management practices. Research projects investigating the estimated time to kill of traditionally slower acting biopesticides, combined with information of pest phenology can lead to the optimization of the timing of application of more sustainable interventions such as entomopathogenic fungi (CABI, 2021).

For smallholder farmers and rural communities, the uptake of new digital solutions can often be limited by access to smartphones and other mobile tools, technological literacy, and willingness to change farming practices, many of which can be linked to gender and wealth (World Bank, 2019). As such, the diversity of target users' needs to be incorporated into the development and rollout of new services, with users taking on different roles which may not require high-level digital literacy. Numerous studies have agreed with the statement that digital extension will not replace face-to-face and more traditional advisory practices and therefore, new services need to take a more user-centred approach to support smallholder decision making (Steinke et al., 2020).

Looking to the future, for the successful uptake of the pest risk prediction systems there needs to be a sufficient level of multidisciplinary involvement across the plant health sector, from governments and policymakers to extension services and smallholder farmers (Winarto, 2018). The adoption of novel technologies into existing plant health services needs to be taken up at a national level, with the ability to be disaggregated across regional and local platforms. National-level uptake or endorsement of early warning pest services could potentially benefit existing pest monitoring and plant health systems, notably in low-income countries by supporting the sharing of knowledge across boundaries and improving decision making, resulting in improved food security and farmer incomes (Rivera and Alex, 2004. Chapman and Tripp, 2003).

For the long-term sustainability of early warning systems, the technological infrastructure and capabilities that are available in western countries need to be made accessible to low-income countries. Capacity building for key actors, organisations and services in the plant health system is an integral part of promoting the uptake and success of such innovations which incorporate EO data and the use of models. Sufficient training and support are required to promote the adoption of novel systems into national, regional and local early warning dissemination services.

If digital-based technologies of any theme are to create sustainable lasting impacts on farmers and crop health systems, policymakers need to shift to a more inclusive digital understanding and acceptance (Steinke et al., 2020). Governments, private sector, development partners and donors can promote successful digital services through increased investment rather than short-term projects, with more focus on capacity building and user-centred design processes. For example, governments may seek to partner with private-sector and development partners in the provision of digital services, especially when incentives align, including commercial terms, data privacy and ownership rights (Lutz et al., 2021). Innovation at any level will always require investment, but with an extensive portfolio of existing technologies and services in the agricultural advisory sector, it is apparent that novel applications must be applied under collaborative, cross-cutting processes.

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