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Forecasting the population development of within-season insect crop pests in sub-Saharan Africa: the Pest Risk Information Service

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Smallholder farmers are the mainstay of the agricultural economies of sub-Saharan Africa (SSA), where they produce several crops, predominantly centered on maize. Smallholder productivity remains limited resulting from a range of confounding factors, but a primary cause is loss from pests and diseases, particularly insects. To improve productivity, recommendations for the mitigation of crop loss globally include early-warning and management systems for in-season indigenous pests. There are many early-warning systems in temperate regions; however, such systems are poorly established in Africa. This is in part due to the need for a combination of pest modeling, data handling and dissemination infrastructure, capacity, and resource provision. While each of these components is progressing in Africa, the means to successfully deploy such systems remain limited. To bridge this, the development of the Pest Risk Information Service (PRISE) began in 2017 for farmers in SSA. Implemented in Kenya, Ghana, Malawi, and Zambia, PRISE developed temperature-driven phenology models for major maize, bean, and tomato pests. Using downscaled and processed Earth Observation data to drive the models, PRISE partnered with African national agencies to communicate pre- and in-season pest alerts that forecast the time to act against key insect pests. Alerts were designed to be integrated into country-specific Good Agricultural Practice (GAP) recommendations to provide a complementary package to agricultural stakeholders. End line studies with farmers showed that those who received information about the target crops including PRISE pest forecasts, generally reported better outcomes in terms of reduced losses and increased incomes compared with farmers who did not.

Key words: forecasting, insect crop pest, sub-Saharan Africa, modeling, Earth Observation

Smallholder farms (<2 ha) account for 73.8% of the farms in sub-Saharan Africa (SSA) (Lowder et al. 2021). Increasing the productivity of these farmers will be essential if the United Nations' Sustainable Development Goals of reducing poverty and improving livelihoods are to be achieved (Lowder et al. 2021). In general, smallholders in SSA tend to grow staples, particularly maize (*Zea mays* L.), along with other crops for income. In these growing systems, severe crop losses have been frequently reported for most of the major crops. Crop losses in SSA are above the global average, and without adequate control measures, pests (arthropods, pathogens, vertebrates, and weeds) can account for large losses (Oerke 2006). Recent research in maize has demonstrated that 30% of total yield is lost to pests (Savary et al. 2019). These losses from pests are from the seasonal presence of complexes of indigenous pests (Constantine et al. 2021) and also from new invasive or transboundary pests (Early et al. 2016). The impact of these pests is of particular concern in low-income countries as smallholder agriculture is central to their economies and to the livelihoods of the majority of their populations (Wiggins et al. 2010). Insects form a major component of these pest complexes and are frequently the main cause of crop loss in SSA. For example, high economic impact and losses have been reported on maize due to fall armyworm, *Spodoptera frugiperda* (J.E. Smith), (Pratt et al. 2017, Savary et al. 2019, Eschen et al. 2021) and African maize stalkborer, *Busseola fusca* (Fuller) (Savary et al. 2019). On tomatoes the causes of most of these losses are due to the tomato leafminer, *Phthorimaea absoluta* Meyrick (Eschen et al. 2021; Pratt et al. 2017). Insects are also important vectors of seriously damaging plant diseases such as maize lethal necrosis disease (Ohlsen and Wilson 2022). In addition to this, climate change is affecting the distribution and seasonal occurrence of pests which in turn may exacerbate their impact in some regions (Robinet and Roques 2010, IPPC Secretariat 2021).

In recent decades, much progress has been made in SSA and other regions with low-income countries, with the provision of enhanced extension services which provide insect pest identification and "best practice" management advice to smallholders (and governments). Examples of these are the Plantwise Plus program (www.plantwise.org) and PlantVillage (https://plantvillage.psu.edu/). However, the density at which populations of key pests begin to cause significant damage can be relatively low (e.g., 2 larvae per 10 plants for fall armyworm); hence, it may be too late to retain maximum yields by the time a farmer notices the pest (Jaramillo-Barrios et al. 2020).

More generally though, it has long been recognized by pest management practitioners that one of the most effective tools for reducing crop losses from insect pests is the prevention of pest population increases at the start of a crop season (Pretty and Bharucha 2015). Indeed, prevention is a central principle of Integrated Pest Management (IPM) (Barzman et al. 2015). Depending on the insect pest, there are several tools that have been recommended for use during crop establishment to help reduce the risk of pest attack (e.g., sanitation of crop-growing areas, good planting practices and use of resistant crop varieties). However, major insect pests still manage to invade crops, especially in low-income countries thus farmers need to take actions against the stage/s of the insect that cause the damage. A more effective approach, especially where there are threats from multiple insect pests, is that of forecasting new pest distribution and abundance through pest risk mapping. Where pests are already established, or for already detected pests invading a crop, utilizing early-warning systems of population development and growth can be effective. Such methods allow advance alerts to be sent to national agricultural organizations, farmers and others involved in crop production. The advance alerts allow time for preparation of interventions that prevent a pest from reaching its economic injury level. Most forecasting systems are based on meteorological data because factors such as temperature are important drivers of the early stages of insect pest population development (Prasad and Prabhakar 2012). Since most crops across the globe are already threatened by a range of serious resident indigenous insect pests annually, the development of seasonal early-warning systems for within-crop pests has received much attention (Prasad and Prabhakar 2012, Moore and Remais 2014). Such early warnings provide a forecast for farmers at the start of a crop season of the optimum time during the growth of the crop to apply a recommended pest management intervention against the damaging stages (referred to here as the "times to act"). These systems need to be coupled with a pest monitoring component for the early detection of a pest in an area and that are used to activate the early warnings.

To date, early-warning systems have largely been developed in temperate regions where a high proportion of the countries are high income. This is because systems require capacity and resources for the pest modeling component and the outreach to farmers. Additionally, they need access to large data sets to develop models and to drive the systems. Both national and local early-warning systems have been developed depending on the extent of distribution of the pest. In most systems, phenology modeling has been at the core, as the physiological responses of insects are dependent on temperature and heat accumulation between lower and upper development thresholds (Jarošík et al. 2011). The values of the upper and lower thresholds are species specific, nonetheless closely related species tend to have similar values. The most common types for within-season insect pest forecasting are temperature-driven development rate models. In particular, those that assume a linear relationship between these parameters ("degree-day models") are well suited to temperate region insect pests with discrete generations and are simple to implement (Prasad and Prabhakar 2012, Orlandini et al. 2017). There has been much debate about how much the linear relationship may be too simple and several models exist where a nonlinear relation is used (Rebaudo and Rabhi 2018). However, the former models remain popular for practical forecasting (e.g., see Barker et al. 2020). These models provide the development time of an insect (and of the individual immature stages) in terms of constant number of degree-days. Given this, the development time of an insect in the field can be measured by the input of daily temperatures into the model to accumulate degree-days. The models are usually started from a "biofix date," commonly taken as the time of year when development starts such as the warming of soil. The models have been developed and used extensively since the 1970s (Welch et al. 1978). Temperature data have been generally obtained from ground-based meteorological stations as these are well distributed across most countries in temperate regions.

There has also been substantial interest in within-crop season early-warning systems in low-income countries. This interest has intensified over the last decade with the rise in serious insect pest issues. In SSA, several studies have highlighted the wide range of stakeholders who would welcome developments in this technology (Brown et al. 2022). However, in most tropical and subtropical regions, such as SSA, such forecasting systems have been either absent or, where they do exist, tend to be focused on major eruptive transboundary pests and run by international organizations (e.g., the FAO Desert Locust Information Service [DLIS]). Several major constraints have been suggested as reasons for this situation such as lack of the necessary national infrastructure and institutional linkages to develop such systems (Taylor et al. 2023). In addition, there has been the lack of high spatial and temporal resolution temperature data in developing countries to drive pest early-warning systems (Moore and Remais 2014). In SSA, this is particularly serious constraint given the importance of agriculture to national economies and livelihoods. Also, given the mixed crop smallholder farming systems, farmers need to manage a variety of pests on a range of crops during a growing season and they generally have limited time and resources to monitor their crops (Nwilene et al. 2008).

On a global scale, developments in access to Earth Observation (EO) data together with rapid strides in computer technology over the last decade or so are allowing significant developments in pest forecasting. This is because data sets covering large areas can now be rapidly processed to provide early-warning products (Marques da Silva et al. 2015, Taylor et al. 2023). In addition, messaging to farmers has been revolutionized by equal strides in increasing access to mobile phones by farmers in most parts of the world (World Bank 2019) coupled with the integration of communications technology (e.g., short messaging services—SMS) into extension services and the increase in geographical reach by using this technology (Taylor et al. 2023). Most importantly, all of these developments are allowing low-income countries to overcome the previous major technical barriers to the development of pest early-warning systems.

Here we describe the development and trialing of the Pest Risk Information SErvice (PRISE) for SSA which, at its core, was based on these key technological advances. The PRISE was started in 2017 and included 4 countries in SSA: Ghana, Kenya, Malawi, and Zambia. During the development of PRISE, the focus was on a selection of major insect pests of mixed-maize farming systems because this is the predominant smallholder cropping system in these countries (Food and Agriculture Organization. 2023) and prioritized by key government stakeholders. The aim of PRISE was to develop an early-warning system coupled with pest monitoring that operate at a local level across each country.

First, we summarize the insect pests included in PRISE that were used to pilot the system, how these were chosen and the development stages modeled for application of management options. Second, an outline is given of the phenology modeling developed for these insects for forecasting population development and growth from the beginning of the crop season, how these models were used to predict the "times to act," and how some of the models were scientifically validated. Third, the general design of the PRISE system is covered, including the EO data used for forecasting and the PRISE data cube. The data cube is where the models and EO data are integrated with other static data to generate early-warning forecasts with high spatial and temporal resolution suitable for each partner country. Fourth, we discuss how pest monitoring was integrated with the early warning and the form and method of delivery of the forecast messaging to farmers used. Finally, we cover the results of trials of the messaging with farmers in the implementing countries.

The Insect Crop Pests, the Developmental Stages Used for Modeling, and the Development of Phenology Models

The Insect Crop Pests Included in PRISE

In SSA, the crops in smallholder mixed-maize farming consist of maize grown as the main staple, which may also be traded when there is an excess, along with a variety of other crops either grown for subsistence or as cash crops (Matusso et al. 2014). Two other crops commonly grown are common beans (*Phaseolus vulgaris* L.), mostly for subsistence (Katungi et al. 2009), and tomatoes (*Solanum lycopersicum* L.) as cash crops for local and export markets (Maertens et al. 2012). In general, maize and beans are planted at the beginning of the rainy seasons; however, there may be further plantings of beans later in the season. While there is some planting of tomatoes during the rains, this crop is more commonly planted toward the end of the rains to avoid attacks by fungi.

In consultation with representative national agricultural organizations in each country through national stakeholder workshops, several widespread and seriously damaging indigenous insect pests from each crop were identified for possible inclusion in the phenology modeling. Because of limitations on resources and time for validation of models, 7 species from the initial lists were finally chosen for inclusion (Table 1). This list includes most of the major insect crop pests that currently occur in SSA. The inclusion of fall armyworm was added shortly after the final list was agreed, as this notorious species invaded most countries in SSA from 2017 onwards (Day et al. 2017). Some of the insects in Table 1 are polyphagous; however, the initial focus was to develop phenology models on one major crop host and then explore how the model might be used for other crop hosts (see Discussion).

In general, all these insect pests tend to be locally resident in crop-growing areas where they overseason in wild host or volunteer crops or enter a diapause to bridge periods when no hosts are available; their relative survival rates being dependent on the environmental conditions in any 1 yr. If their survival rates are good, then invasion of a crop is usually at the start of the crop season, with most egg-laying taking place when a crop has reached the preferred growth stage for the insect.

There is much information available about the best management practices to use against the insect pests listed in Table 1, including the developmental stages that should be targeted once a pest has invaded a crop. This is discussed later—see Pest monitoring, PRISE messaging, and dissemination to farmers. However, although country-specific information varies (according to resources and products available), the developmental stages to be targeted and the type of intervention are common to all countries. These are listed for each insect pest in Table 1 (see https//:plantwiseplusknowledgebank.org). The larval stage is a common stage to be targeted for all the insect pests in Table 1, but in some cases (e.g., the tomato leafminer), the adult stage is also listed, especially, those invading the crop at the start of the season. For PRISE, the focus was placed on the development of phenology models for the development and growth of the larval stages.

The Development of Insect Phenology Models

The aim was to develop the simplest type of phenology model that would still provide a means to produce accurate forecasts of the optimum time for farmers to make an appropriate management intervention based on the time from crop planting. Such models are also more easily applied across a range of varying geographies. These forecasts were only made for the insect attacks on the first crop

Table 1. Crops and pests included in PRISE (2017–2022)

Crop	Species common name[a]	Scientific name	Life stage recommended to be targeted and general type of control[c]
Maize	Spotted stem borer	*Chilo partellus* (Swinhoe, 1885)	Larvae—plant-based products; insecticides
	African maize stalk borer	*Busseola fusca* (Fuller, 1901)	Larvae—plant-based products; insecticides
	Fall armyworm[b]	*Spodoptera frugiperda* (J. E. Smith, 1797)	Larvae—insecticides
Beans (common)	Bean fly (=bean stem maggot)	*Ophiomyia phaseoli* (Tryon, 1895) *O. spencerella* (Greathead, 1971)	Larvae—plant-based products; insecticides
Beans (common)	Pea leafminer[b]	*Liriomyza huidobrensis* (Blanchard, 1926)	Adults—traps and chemicals Larvae—plant-based products; insecticides
Tomato	Tomato leafminer	*Phthorimaea absoluta* Meyrick, 1917	Adults—pheromone traps Larvae—Plant-based products; insecticides; biopesticides
	Tobacco whitefly[b]	*Bemisia tabaci* (Gennadius, 1889)	Adults—traps and chemicals Larvae—plant-based products; insecticides
	Cotton bollworm[b]	*Helicoverpa armigera* (Hübner, 1809)	Larvae—chemicals; biological control agents

[a] The most frequently used common name is given.

[b] Insect pests that are polyphagous but the major crop used in PRISE is listed here (see text).

[c] The principal stage to be targeted once a pest has successfully invaded a crop. Only the general type of intervention is mentioned as specific products are country specific. Plant-based products are mostly neem based.

plantings, and in the early stages of crop growth, as the main purpose was to prevent the rapid population buildup that usually happens at the start of crop seasons.

The common types of simple temperature-driven development rate models, “degree-day models,” can be used to predict when an insect population reaches the start or end of a stage/instar, or the appropriate maximum number in a stage/instar, but only for temperate region insect pests with discrete generations and with development stages that remain distinct (Orlandini et al. 2017). In tropical and subtropical regions, insect species tend to breed continuously with overlapping stages and generations, and thus, such models can only be generally used for the first occurrence of the insect in a crop (Krishnaiah et al. 1997). Phenology models do exist that factor in continuous breeding, but these include other demographic parameters besides development (Tonnang et al. 2017). These models can be used to predict the development of the immature stages of an insect with continuous breeding but only by simulation (Tonnang et al. 2017). Such a process would rapidly become overcomplex for an early-warning system that needs to include multiple pests in any one crop season. Thus, for PRISE, a different approach to modeling was adopted.

Two types of phenology models were developed in PRISE, and these were all for the larval stage of the insect pests. For some species, where there are several larval instars and a long development duration, the models were focused on the early instars of the larval stage. The first (model type A) was a model used for all the insect pests and was the main model used in PRISE for the prediction of the likely optimum time to make a management intervention against the larval stage/larval instars. It was based on an extension of the simple temperature–development rate relation degree-day model, but applied where there is continuous breeding of a pest insect. For this, the model was used to calculate the time and duration (in degree-days) of appearance of each of a series of cohorts of the larval stage/instar that result from the first periods of successive daily egg laying early in the season. These times were then used to estimate the common period when the larval stage/instar was present from all the cohorts. This period was used as the window for the application of a management intervention. The second model (model type B) was more detailed and only developed for 3 of the more serious pests that attack crops also grown for cash: fall armyworm, the tomato leafminer, and the bean fly. This was to allow the use of an economic or action threshold as an optimum time to act. For this model, the population development and growth of the larval stage/instar of each species from crop planting were related to cumulative degree-days, specific to each species. This was to enable the prediction of when economic or action thresholds had been reached. For this, the concept of action thresholds was used (Overton et al. 2021). These are only known for a few of the more serious pests but tend to be used where little is known about the economic thresholds for insect crop pests in SSA. Like economic thresholds, action thresholds are used to predict the optimum time to apply an intervention, that is, when crop losses from a pest are likely to be equal to or exceed the cost of an intervention. Action thresholds are based on the best available information and, where possible, expressed as an approximate pest density per plant or unit area. Information is available in the literature for fall armyworm and the tomato leafminer, but not for the bean fly. For the last species, estimates were made from the field studies (for model build—see below) of the time from planting to when the larval stages of the fly started maximum population growth. This point was used (converted to a density) as an approximate action threshold and used to estimate the corresponding value of the cumulative degree-days. The latter was then used as the “time to act.”

The methods used for each model type in more detail were as follows:

Model type A.

For this model, the simple temperature-driven rate model was used but applied to a series of cohorts that result from continuous breeding. Here, this refers to egg laying by female insect pests continuously over a period of days when the right stage of a crop appears after planting. The basic construction of the simple degree-day model is given by several authors, for example, Damos and Savopoulou-Soultani (2012), and this model has been used by various authors to calculate in degree-days, using the species-specific lower and upper development thresholds, the average development time (start to finish) of individual immature stages and the total development time of many insect pests including all pests in Table 1. The published parameters from the model was used for each species (Table 1) to calculate the time of appearance and duration of the larval stage/instars resulting from adults laying eggs on a number of successive days from crop planting. The literature used for each species is listed in Supplementary Table S1. Each day represented a cohort of eggs, and the model was used separately for each cohort. Data on the length of each main egg-laying period (in days) for each of the pests were also taken from the literature. The timing of crop planting and the length of each egg-laying period vary between insect species, but for model construction, data for the first, and sometimes the second, periods for each insect were used. The timing of appearance and duration of the set of cohorts were then used to estimate the common period, resulting from the overlap of each developing cohort in the set, when the larval stage or larval instars to be targeted (depending on the insect pest) in all the cohorts would be present in the crop at the same time. There would only be a certain degree of overlap of the larval stage/instars to be targeted in the set of cohorts as the development of each cohort from the start of egg laying would be delayed by 1 day. This period or window of time (in degree-days) from the beginning of each egg-laying period represented the time when the likely maximum number of the larval stage/instars would be present in the crop (referred to as maximum larval incidence [MLI]). This window of time was then used as the prediction of when maximum mortality of the larval stage/instars early in the crop season could be achieved by applying a management intervention. The windows were converted back to approximate calendar days to facilitate messaging.

Model type B.

A published model for fall armyworm describes the method for model B development in detail including the estimation of when the action threshold had been reached (see Lowry et al. 2022). This method is summarized here. Papers on the modeling of the tomato leafminer and bean fly are in preparation. The model was also based on the temperature–development rate relationship. However, in this case, and for each of the 3 species, the cumulative proportion of the total final larval stage/instar population to be targeted with an intervention was modeled in relation to a predictor variable, the cumulative degree-days from crop planting. The total period used for modeling was taken as the approximate time for one complete generation to be completed. The cumulative degree-days were calculated using the specific lower and upper thresholds for development for each of the species (see Supplementary Table S1). This approach has been used for a few other insect pests (Kumral et al. 2008, Knutson and Muegge 2010). The main model used in PRISE was the 2-parameter logistic model, as this has been shown to be useful for several insect population emergence and development data (e.g., see Broatch et al. 2006). For example, the fall armyworm model accurately fitted the field population data collected in Zambia (Lowry et al. 2022). Various statistics were used to measure the fit of the model because of the general complexity of using existing measures for evaluating the fit of nonlinear models (see Lowry et al. 2022 for discussion). Using this model, the cumulative proportional emergence of the larval stage/instar was used for fall armyworm and tomato leafminer to estimate the time, in degree-days, when the action threshold (taken from the literature) for these species had been reached (also referred to as the MLI for convenience). So, this model produced a single prediction time of the optimum time to apply an intervention. As with the output of model A, this time was converted to an approximate time in calendar days.

As population data were needed for estimation of the cumulative proportion of the total final larval stage/instar population for model type B, field studies were conducted by national agricultural centers and CABI regional centers in some of the implementing countries in SSA to collect population growth data over several crop seasons. This was done in Zambia for fall armyworm and Kenya for the tomato leafminer (Table 2). Population data for the bean fly were taken from the literature, but additional data were collected in Kenya (Table 2). Field plots of each crop were established either in national agricultural research centers (Fig. 1) or private/smallholder farms. For the cumulative degree-day calculations, European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) 2-m air temperature (t2m) data were used. The air temperature at 2 m was chosen as this provided a good approximation to average temperatures at crop level. These data sets were used to calculate and accumulate degree-days from hourly temperatures. Only temperatures that fell between the lower and upper development thresholds were used for each insect phenology model.

Parameterization and regional use of the models.

Only one version of each model types A and B was developed for the 4 countries, so each model only had one set of parameters. Model type A parameters (lower and upper development thresholds and

Table 2. The location, field season, and approximate altitude of the field sites used to collect population data for the development of model type B for 3 insect pests. Note that the data used for the bean fly model was taken from the literature (see text)

Species	Country	Administrative regions	Field sites[a]	Crop season population collected	Altitude (masl)
Fall armyworm	Zambia	Central Province Lusaka Province	Chisamba ZARI Research Center, Chilanga Chongwe	Main crop season, 2018/2019 and 2019/2020	1,100–1,500
Tomato leafminer	Kenya	Machakos County	KALRO Katumani Research Station Mbilini Mikuyu	Short rains, 2019/2020	1,600
Bean fly	Kenya	Nairobi City County	National Agricultural Laboratories University of Nairobi Kabete campus field station	Long rains, 1985	1,700

[a] Field sites were at private farms (mostly smallholder) except where mentioned.

Fig. 1. The establishment of a field plot of common beans at KALRO, Katumani, Machakos County, Kenya, October 2018. Photograph courtesy of S.T. Murphy.

degree-day development times of immature stages) were taken from the literature. For model type B, the cumulative degree-days were again, estimated using species-specific lower and upper development thresholds from the literature and the data for population growth of the larval stage/instar, for parameterization of the logistic model, was collected in various countries, depending on the insect species (Table 2). Thus, the same model of types A and B for each insect was used in all the participating countries to make predictions of the time to act. This was on the basis that physiological time, expressed as degree-days, is fairly constant for a species. There is some variation in the lower and upper development thresholds in the published literature for some species, but this is mostly down to how these were measured experimentally. For PRISE, we used data from published studies that used natural diets for the insects for the estimation of these thresholds.

The start date to run the models.

This date for the model types A and B, known as the "biofix date," was assumed to be the time of crop planting, marked by the beginning of the rainy seasons. This was because maize and common beans are planted as seeds, which is a known date (Hassan 1996), whereas the time of the first emergence of the crop depends on the rate of germination, which is dependent on multiple local environmental factors. Tomatoes are planted as seedlings, so in this case, the date of transplanting was used as the biofix date. Where necessary, an offset component was added into both types of models to factor in either the time for a crop to germinate and/or reach the growth stage preferred by the larval stage/instar of each insect species, to start the models. An example of this is discussed for fall armyworm, model type B, in Lowry et al. (2022).

A comparison of the single prediction of the optimum time to apply an intervention from the type B models for the 3 species was made with the windows of time from the type A models. For fall armyworm and tomato leafminer, the prediction time from model B fell within the window of time predicted by model type A; for the bean fly, the prediction time from model B fell at the end of the window of time predicted by model type A.

The Validation of the Models

It is important to assess the practical value of phenology models with farmers, and this was done for all the type A and B models; this is discussed later. However, it is also important to scientifically validate phenology models once they are formulated, and this needs to be replicated at several independent field sites (Welch et al. 1981, Nowatzki et al. 2002). This was done by the research organization collaborators in PRISE, not with farmers. Work on this has been underway for the type B models as these models predict the population growth of the larval stage/instars developing in a crop over the time of the first generation; this can be compared with independent data sets on population growth collected in other areas. In the case of fall armyworm, this method has been discussed by Lowry et al. (2022). For this species, additional data sets on population growth of the larvae were collected in 2 major maize-growing counties in Kenya (Table 3). In each county, 3 maize fields were selected for the study, and then data from these were combined for each county. For both counties, the 2-parameter logistic model for fall armyworm gave an accurate prediction (measured using the Pearson correlation coefficients where values were all greater than 0.96) of the observed values of larval population growth. On average, the predictions differed from the observed by approximately 2.45 days (see Lowry et al. 2022 for further details). Similar work has also been completed for the tomato leafminer (Lowry et al., in prep) and bean fly (Finch et al, in prep).

The scientific validation of the type A insect models was complicated as ideally, this required a replicated comparison of the prediction of the time to act window from each species model with observed data on early larval stage/instar incidence from field studies. This was not possible in the life of the PRISE project. However, a qualitative analysis was also made for the type A models for fall armyworm, tomato leafminer and bean fly by comparing the time (in degree-days) predicted by the models of the first appearance of the larval stage (from crop planting) with the same event obtained from the field data collected for validating the type B models. For the 3 species, a close correspondence was found with a variance of 2–5 days shown for each species. Nonetheless, further analysis of the scientific validation of type A models is ongoing, so within the time of the field seasons available to PRISE, more emphasis was placed on the value of the predictions of the type A model to farmers.

Producing Forecasts: The PRISE System Design, Data Sources, and the Agrometeorological Data Cube

The PRISE System Design

The PRISE system produces 2 types of advisories for farmers on the optimum time to apply an intervention to protect their crops from a particular insect pest. The first sent out is based on historic average temperatures. Then another is sent out, based on near-real-time temperature conditions in the beginning period of the current month, which is used to adjust the first set of advisories should the temperatures deviate from the average. The optimum times to intervention (time to act) are derived from the insect model predictions.

To achieve this, at the beginning of each calendar year, 12 monthly optimum times to intervention estimates are generated based on average temperature conditions since 2009 (current historic estimates are based on data between 2009 and 2022). This allows the PRISE system to provide farmers each month with an estimate of the time (in days), from their crop planting time, before acting against pests, based on average weather conditions for a particular locality. These are sent out at the beginning of each month. Following this, on the 13th of the month, a separate forecast is produced for the current month, based on temperature data from the first 10 days of the month, and this is used to adjust the initial forecast if necessary. For this, it is assumed that temperature conditions are autocorrelated (especially in the tropics), and thus the temperature conditions present in the first 10 days are likely to represent temperature conditions in the immediate future. Based on this assumption, degree-day accumulations per calendar day (known as the "degree-day delta") are calculated for the current month, from which time to act estimates can be generated. Therefore, this estimate takes the current month's temperature into account, which may be cooler or hotter than the long-term average. The forecasts are produced for each of the grids that cover the main cropping areas of each country. The size of the grids is determined by the available resolution of the EO data sets used, and this is covered below.

The way the PRISE system acquires, generates, and stores this data is shown in the left-hand pane of Fig. 2. The main components of this system are described below.

Table 3. The location, field season, and approximate altitude of the field sites in Kenya used to collect population data for the validation of the Fall Armyworm model type B.

County	Altitude (masl)	Timing
Machakos	1,500–1,600	Short rain season, 2019
Kiambu	2,000–2,100	Short rain season, 2020

Data Sources

The calculation of MLI (= time to act) estimates, derived from the phenology models, is done using 2 different 2-m air temperature data sets. The first, the ERA5 reanalysis t2m data set (Hersbach et al. 2020) is used to generate MLI/time to act estimates based on past temperature conditions (2009–2022). This data set has a spatial resolution of 0.25°, global spatial coverage, hourly time steps, and is available from 1950 to present. It was chosen due to its spatial coverage of all the PRISE implementing countries, subdaily temporal resolution (allowing degree-day calculation), temporal coverage (allowing multiyear temperature conditions to be represented in long-term averages), and the fact that it is an established temperature data set used for scientific work over Africa (Gleixner et al. 2020, Hersbach et al. 2020, Guigma et al. 2021a, b) . In parallel to this, operational archive ECMWF t2m data from the High-Resolution Atmospheric forecast model (ECMWF 2022) are used to generate the "near-real time" advisories each month. The forecast t2m data have a spatial resolution of 0.1°, global spatial coverage, hourly time steps and is updated twice daily. The key reason for this choice of data set was the fact that these data are available within 48 h. This allows us to access and use data from the first 10 days of the month by the 13th of the month. The ECMWF High-Resolution Atmospheric forecast model data are governed by the Creative Commons Attribution 4.0 International (CC-BY-4.0). Both temperature data sets are spatially regridded to 0.05° × 0.05° latitude/longitude grids using the nearest neighbor resampling method before further use in the PRISE system.

Spatial averages of the time to act estimates were calculated over administrative districts in PRISE countries. Further to this, a crop mask was used to exclude land types unsuitable for crop growth across these administrative units such as bare ground or bodies of water. This mask was generated from the 2019 land cover classification gridded data set, which has a 300-m spatial resolution (Copernicus Climate Change Service 2019) and was spatially regridded to 0.05° using a majority filter. Spatial averages were generated by clipping the gridded data to each administrative feature and then taking the spatial mean of the clipped subset of data.

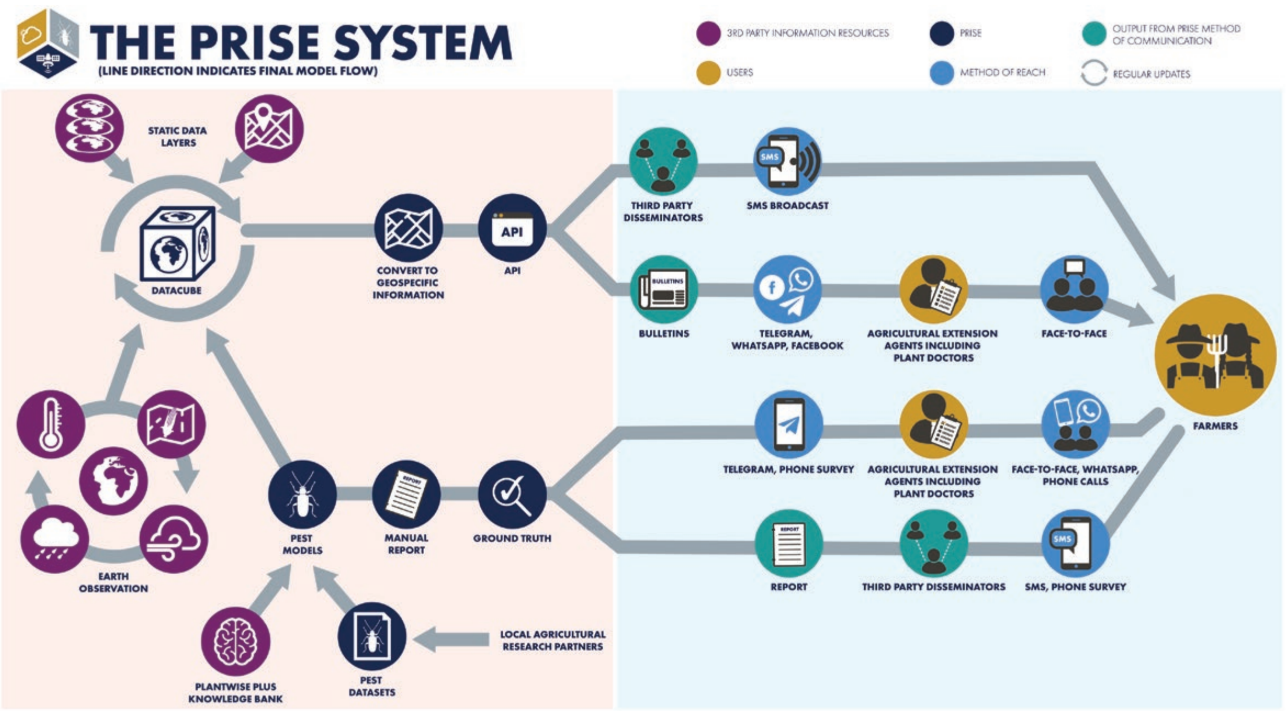

Fig. 2. Schematic representation of the PRISE system. (Left) The models and data sources used and how these flow into the data cube. (Right) The output flows such as third party dissemination channels and crowdsourced data feedback routes.

The Agrometeorological Data Cube

At the heart of PRISE is a "data cube": an efficient system for assembling, storing, and analyzing multiple large spatiotemporal data sets. The data cube is composed of:

- Data files (stored as cloud-optimized geo-tiffs), covering the entire continent of Africa with hourly data since 2001,
- A database, to manage the individual data files,
- A codebase to automate downloading data from external sources,
- A codebase to run the models/algorithms to generate the PRISE products, and
- An application programming interface (API) to allow users to access the results via a www, Python, or Representational State Transfer (REST) interface.

Code for the cube is written in the Python programming language. The PRISE products generated from the downloaded temperature data are the degree-day delta and the optimum time to apply an intervention (time to act) for each of the insect pests. These products were generated as gridded spatiotemporal data sets of numerical values. The gridded data sets cover 4 rectangular geographic regions that are centered over, and include the entirety of, Kenya, Malawi, Ghana, and Zambia. An example is shown for the optimum time to apply an intervention (usually a chemical, but the advice being country specific) against the larval stage of the tomato leafminer (Fig. 3). The PRISE data cube can be interrogated by external users via an API. The API can convert the gridded numerical data into spatially averaged numerical values associated with individual administrative districts. An example is again given for the tomato leafminer (see Fig. 4).

Pest Monitoring, PRISE Messaging, and Dissemination to Farmers

Given the practical complexities of setting up pest monitoring systems for the first detection of a pest for a range of pests across all administrative units across each country, a different approach was taken in PRISE. As most of the insect pests were widely distributed in each country, monthly alerts for a time to act (plus management options—see below) for a particular pest were sent to all administrative units where a crop attacked by the pest is usually grown. In each crop season, farmers were then advised to use the alerts as a prompt to scout their crops and act if they saw evidence of pest presence.

The PRISE forecasts of the time to act (the "when") are designed to be integrated into country-specific Good Agricultural Practice (GAP) recommendations (the "what") to provide a complementary package to agricultural stakeholders and smallholder farmers. GAP advice was taken from the suite of PlantwisePlus content (https://plantwiseplusknowledgebank.org); this includes a range of farmer and agricultural advisor-orientated crop management advisory information, compiled and updated by international and national experts, and are tailored to individual countries that are dynamic to environmental variances and user resources. For all the major crops included in PRISE, GAP recommendations include advice about preliminary general preventative measures to reduce the risk of attack by pests and diseases. The advice covers aspects such as removal of previous infested plant material, good planting practices and other more specific measures, depending on the major pests that regularly occur in an area. However, despite these, the main insect pests still manage to invade crops so the time to act messages were sent out jointly with the preliminary GAP advice. The type of content from PlantwisePlus used to inform PRISE GAP recommendations were the Pest Management Decision Guides (PMDGs) which provide an IPM approach to diagnostics and management options. PlantwisePlus also supports a network of "Plant Clinics," where farmers can meet in person and seek help with crop problems from "Plant Doctors." These are agricultural extension agents with enhanced training and knowledge of pest and disease management as provided by the PlantwisePlus, and formally Plantwise, program. Wider messaging can be scheduled into dissemination activities in advance, notably for translating into local languages and local reviews, with the time to act forecasts being available at fixed periods each month using the

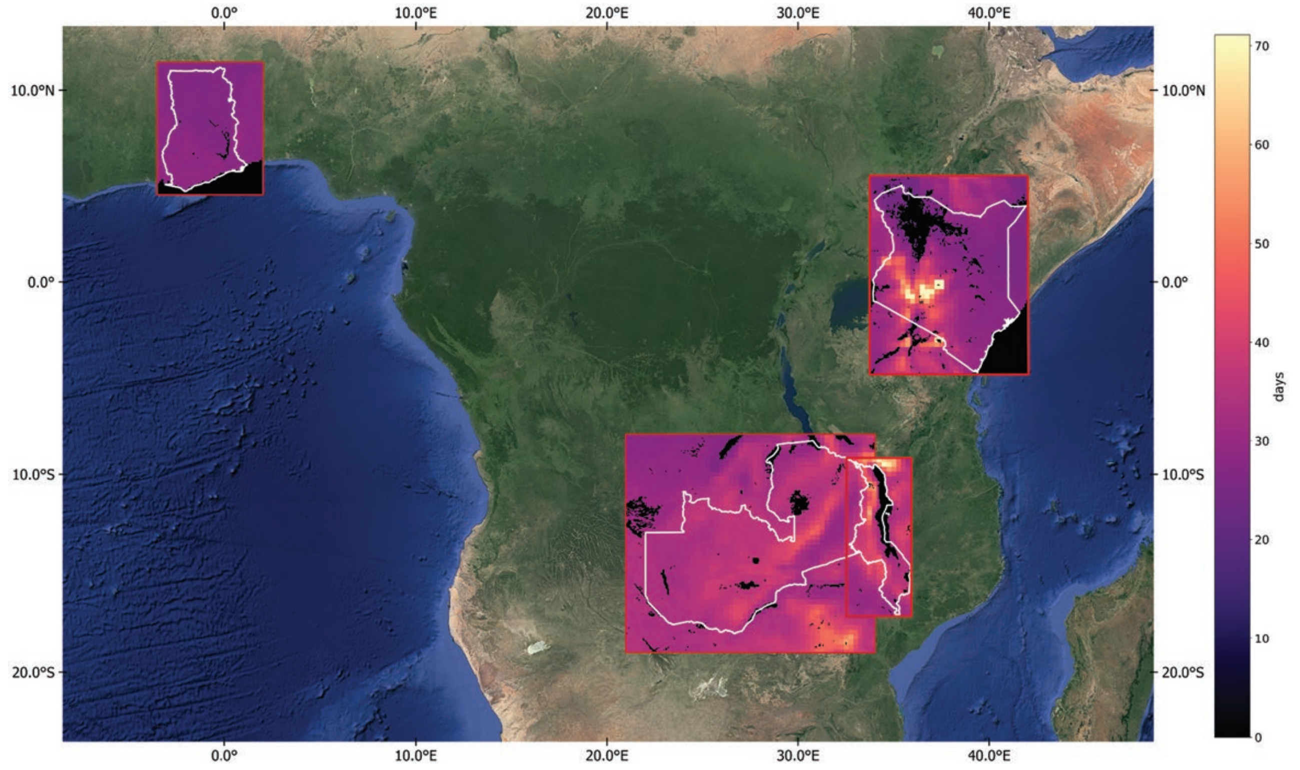

Fig. 3. Example MLI values generated by the PRISE system. MLI midpoint values for *Phthorimaea absoluta* in August 2022. Data generated for 4 geographic regions covering Ghana, Kenya, Malawi, and Zambia (each country is outlined in the figure). The gradient in the scale represents the number of days between planting and recommended time to act. Areas where crops cannot be grown (open water and bare ground) are masked by being set to zero (zero values are excluded when spatial averages are later calculated). Background: Map data ©2021 Google.

standard output format: "If you planted in [month] the best time to take direct action against [pest – if seen/reported locally] will be [x to y] days from planting." where x and y refer to a range of days around a specific date to provide farmers with a realistic period to prepare resources and act on their land. An example of the type of set of messages sent out for fall armyworm is shown in Box 1.

The PRISE system envisaged that the messaging element to the time to act forecast "package" would be reviewed, updated, and distributed in-country to smallholder farmers by third parties, such as national extension services, private sector communications, or appropriate projects. The benefit of this package was that it is flexible and can be easily integrated into existing communication campaigns.

For the messaging, during the project timeline, several dissemination activities were carried out across the 4 countries to trial the use of the time to act forecasts using different channels and formats (see Table 4). Thus, messages were sent to farmers either via an extension service or directly by SMS. It is important to acknowledge that there are numerous existing specialist organizations across SSA who are fully equipped and experienced to share information across rural farming community networks. By collaborating with such organizations, it was possible to build on existing infrastructure to disseminate the forecasts using the leading methods. Each of the dissemination activities is discussed further below.

By converting the forecast data into maps coupled with the PlantwisePlus GAP information, bulletins (PDF documents) were developed twice per month, combining the PRISE action alert with the relevant diagnostic and management advice from the corresponding PMDGs. They were then disseminated to national agricultural extension agents, including—and principally focusing on—the PlantwisePlus network of Plant Doctors. The bulletins have been reviewed by in-country stakeholders throughout the project life cycle, resulting in a useful decision-support tool that extension workers continue to rely on when meeting with smallholder farmers.

One of the primary channels for mass messaging across developing countries is SMS and the most preferred in some regions (Sharma et al. 2021). Although there is often contradictory evidence on the outcomes of such practices (Bolarin et al. 2022), it was a process that was trialed with Precision Development (PxD) and iCow in Kenya, Esoko in Ghana, and the Zambian Integrated Agriculture Information Management System (ZIAMIS) in Zambia.

In the case of the collaboration with PxD in Kenya, PRISE built on the successful Ministry of Agriculture Information service (MoA-INFO) SMS system, which was established in 2018 to give GAP advice on fall armyworm in Kenya. Time to act from the PRISE system SMS text alerts were added to the usual GAP messages based on the crop-based subscription a user had signed up to for a particular season. At the end of crop seasons, telephone surveys with farmers were conducted with the aim to understand the effectiveness of the messaging (Table 5), but later, similar telephone surveys with farmers were conducted during mid-crop seasons to gather information about planting times, when fall armyworm and other pests were first seen and when action was taken (see below and Table 5). Thus, initially, and based on a 2019 telephone survey of 1,213 farmers, the PRISE SMS was "fully understood" by 87% of recipients and 85% said that they would opt-in to receive messages in again. This was a result of the reduced amount of fall armyworm they experienced by using the time to act messages (Mbugua et al. 2021). In 2021, the service was expanded to include the other 2 crops and one major insect pest of each: common bean—bean fly and tomato—tomato leafminer. A telephone survey carried out at the end of the

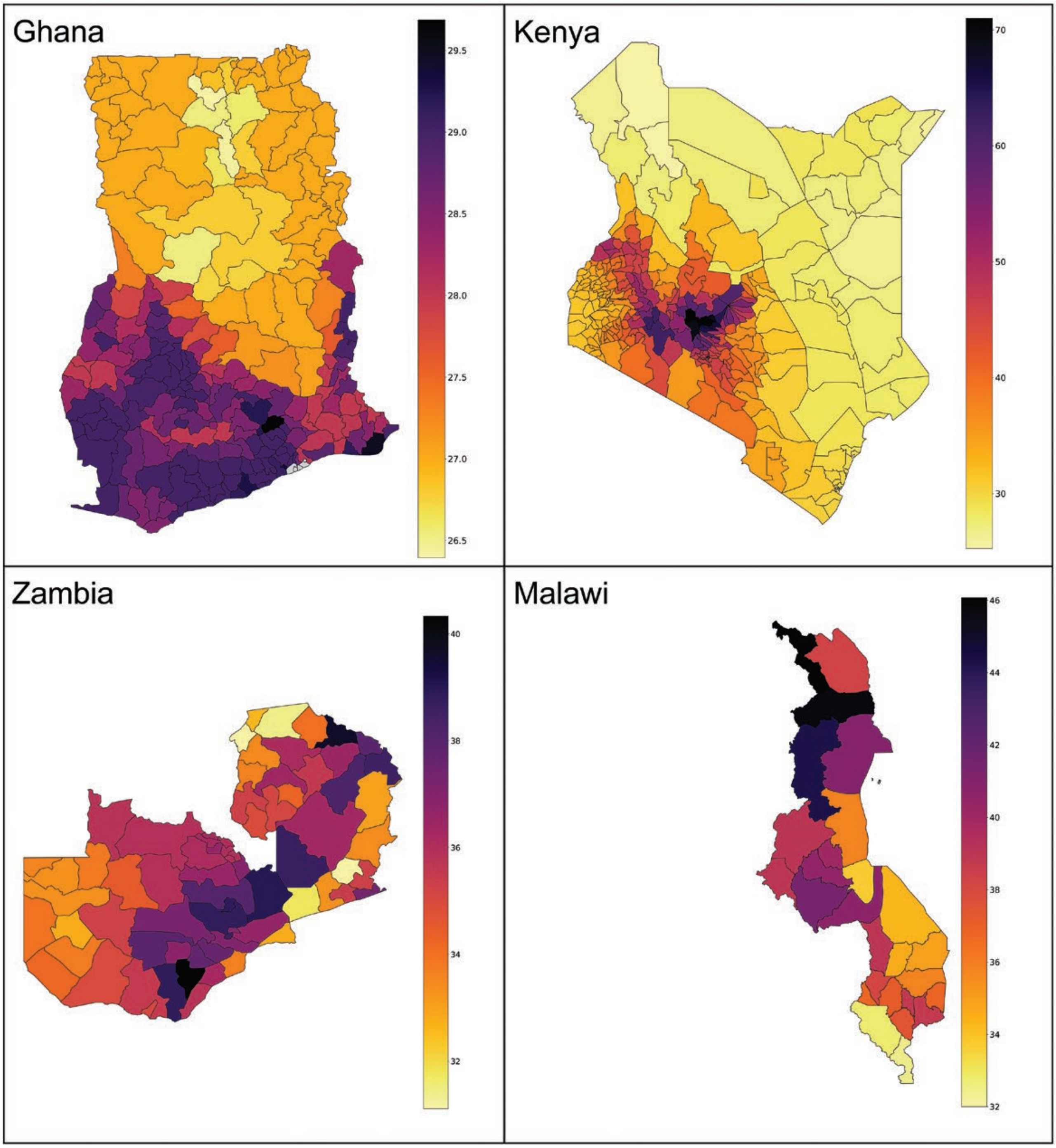

Fig. 4. Example MLI values generated for *Phthorimaea absoluta* in August 2022 spatially averaged over administrative districts in the 4 PRISE countries. These are examples of how the data are displayed when it is sent to partners as bulletin maps. Color represents the number of days between planting and recommended time to act, and the scale varies between different countries due to differences in temperature ranges.

2020–2021 short rain season of 449 farmers indicated a high proportion (maize—87%, bean—91%, and tomato—85%) of farmers considered the time to act messages to be “right” based on what they experienced in the field.

One of the primary limitations of SMS text messaging is literacy rates amongst rural communities in SSA, and as such, the use of audio-based approaches is a popular mode for sharing information (Silvestri et al. 2021). The PRISE team collaborated with Farm Radio Trust (FRT) in Malawi to send the forecasts to farming communities using local Zodiak radio stations. A weekly slot on the radio was used to share the latest forecast data and the best crop management practices to carry out based on the GAP information. One of the notable elements of the campaign and specifically due to FRT’s expertise, was the inclusion of farmer telephone calls into the radio show to discuss local challenges and recommendations. The use of audio messaging was a component of the seasonal campaigns carried out in Ghana in partnership with Esoko, a digital-orientated farmer advisory and data collection service provider working in 10 African countries from 2020 to 2022. They had experienced issues with literacy in the past and have since championed the use of supplementary audio messaging translated into local languages.

In addition to disseminating information, PRISE used crowdsourcing techniques to collect data from users to develop the service. Methods included semi-automated chatbot messaging with Plant Doctors to gather information on regional pest emergence, 2-way SMS to ask farmers about their location, planting date and pest observations, and additional telephone surveys. For the last, midseason telephone surveys collected timely information about farmers' experiences around monitoring and tackling pests (Table 4). End-of-season surveys were used to evaluate whether information had been communicated and understood effectively and to gather feedback on how the system could be improved; for example, by providing additional information to farmers in particular localities on observations from pest monitoring such as the early activity of a particular pest. With 2-way SMS, users were asked to report observations from the field and in the case of fall armyworm send information on crop stage and infestation levels. In the 2021–2022 Kenya short rain season, 47% of users replied to at least one SMS question after receiving PRISE forecasts. Summaries of incoming pest reports were fed back to farmers through SMS updates, e.g., "[Pest] has been reported in your area, be prepared…" and in the form of maps in bulletins to provide users regular updates on reported pest levels throughout the early stages of the season and complement the forecast messaging.

Box 1. Example of messages sent to farmers for Fall armyworm.

"We use weather information to predict how FAW will develop in your area. We will send you updates on when spraying pesticides should be most effective."

"If you spray pesticides, it is most effective when Fall Armyworm are young. Based on your weather conditions, we can predict how FAW will spread."

"If you planted in <MONTH> the best time to spray with pesticides will be <XX> to <XX> days after planting. Until then you can use other methods."

"Did you know you can use other methods to manage Fall Armyworm before spraying with pesticides? Reply A for more from MoA-INFO."

Table 4. Dissemination channels for PRISE "time to act" pest forecasts (for "Plant Doctors," see text)

Country	Dissemination channels
Kenya	Bulletins (plant doctors) SMS (text)
Ghana	Bulletins (plant doctors) SMS (text and voice) Community information centers (announcement via loudspeakers)
Malawi	Bulletins (plant doctors) SMS (text) Radio
Zambia	Bulletins (plant doctors) SMS (text)

Trialing the PRISE Forecast Outputs With Smallholders: Impact and Feedback

For the trialing of the PRISE alerts with farmers, predictions of model type A for all the insect pests were used in all countries and across all crops, apart from the farmers covered by PxD in Kenya; for these, the predictions of model type B were used to assess how well these performed (see later).

Farmer surveys were completed in each pilot country during 2021 to assess evidence of impact on farmers who received PRISE pest alerts (i.e., model type A) for the project duration compared with those who did not. Surveys were conducted in 10, 5, 5, and 16 counties/districts in Ghana, Kenya, Malawi, and Zambia, respectively, interviewing a total of 3,603 households. Key indicators measured included impact on crop losses due to the insect pests, farmer reported yields and income. The studies compared treatment groups, who were smallholder farmers who received PRISE forecasts (covering several pest species) coupled with GAP messaging, with control groups, who were smallholder farmers who did not receive this information but were similar in other respects, such as agro-ecological zone, farming systems, and socioeconomic conditions (Table 6).

The main tools used were farm-level surveys using structured questionnaires administered in-person. Questions were designed to provide various insights including into crop losses due to pests, yields, and incomes associated with the crops targeted in that country, i.e., one or more including maize, beans, and tomatoes. In each country, the local study teams used regression analysis, including propensity score matching (PSM) (Heinrich et al. 2010), local area treatment effect (LATE) (Nguezet et al. 2011), or endogenous switching regression (ESR) models (Läpple et al. 2013) to address potential endogeneity or selection bias, and to account for other potential confounding factors or sources of errors. PSM was used to analyze the impact of the PRISE intervention in the Malawi, Kenya, and Zambia end-of-pilot studies on farming income, preharvest crop losses, and

Table 5. The timing and the focus of the questions asked in the telephone surveys

Country	Timing	Survey focus
Kenya	Short rain season (2019/2020) End of season survey	Maize planting timing and practices, fall armyworm infestation levels and responses, advisory message feedback and understanding
Kenya	Short rain season (2020/2021) Two rounds of midseason surveys End of season survey	Pest management practices for maize, bean and tomato (monitoring, prevention, pesticides), pest incidence, feedback on "time to act" messages
Kenya	Long rain season (2021) Two rounds of midseason surveys	Pest management practices for maize, bean and tomato (monitoring, prevention, pesticides), pest incidence, feedback on "time to act" messages
Kenya	Short rain season (2021/2022) Two rounds of midseason surveys	Bean and tomato planting and practices. Presence and management of fungal pests

food insecurity for the treatment group compared to the control group. Multiple matching algorithms (nearest neighbor matching; stratified matching; Kernel-based matching) were used to test the robustness of the analysis.

LATE was used in the Malawi analysis only to account for some respondents in the survey who were in areas where plant doctors did not operate and were initially regarded as part of the control group. However, they received the PRISE alerts via nationwide radio coverage. This group made up 19% of the “control group.” To address this issue, the LATE estimate was calculated (Imbens and Angrist 1994). The LATE estimates the impact of the project on those who were offered and enrolled in the program (compliers). ESR, using instrumental variables, was used in Ghana to take account of unobserved heterogeneity (Tambo et al. 2023).

Results varied across countries and crops, as was expected, but an overall positive impact was noted for some but not all farmers who had received the PRISE forecasts, either with or without other GAP information, especially in relation to a reduction in crop losses (see Supplementary Table S2). The differences were more pronounced for male-headed households as compared to those headed by women, with significant reductions in crop losses seen for men for all crops and all countries apart from bean and tomato crops in Malawi. However, for women, the only significant reductions in crop losses were observed in Kenya for all crops and in Zambia for maize. No significant changes in levels of crop losses were seen for any crops in female-headed households in Malawi.

When income levels were compared between treatment and control households, fewer significant changes were seen (see Supplementary Table S2). In Zambia, both male- and female-headed households saw increases in maize income, while men experienced an increase in bean income and women an increase in tomato income. In Malawi, men also increased their maize and tomato incomes and in Kenya their bean income. No female-headed households in either Kenya or Malawi saw significant income increases for any crop. In Ghana, while all households increased their maize yield, only jointly headed households increased their income from their maize crop (see Supplementary Table S3); note, the study in Ghana did not include bean or tomato crop (Tambo et al. 2023).

Table 6. Results from study comparing smallholder farmers who received PRISE forecasts coupled with GAP messaging (treatment group) and smallholder farmers who did not receive this information but were similar in other respects, such as agro-ecological zone, farming systems, and socioeconomic conditions (control group). Table shows number of respondents per survey

Country	Treatment group (% women)	Control group (% women)
Kenya end of pilot	481 (25)	466 (33)
Ghana end of pilot	377 (16)	511 (15)
Malawi end of pilot	492 (60)	327 (59)
Zambia end of pilot	520 (33)	429 (32)

Further to these findings, additional farmer-level surveys were conducted in Kenya through PxD where alerts were based on model type B predictions. For this, a survey was conducted after the long rains in 2021 and carried out via phone with 2000 farmers, who had signed up to MoA-INFO, which was a 2-way messaging service. The survey focused on maize and beans only, as tomato cropping is not commonly carried out in the long rains. Some of the farmers also received PRISE messaging, and these farmers were the treatment group, while farmers who just received MoA-INFO messaging were the control group (Table 7). The long rain results, while not analyzed through any econometric approach, showed interesting results for yield and income for maize and bean farmers. For maize, both yield and income increased for those farmers that had received the PRISE and MoA-INFO messaging, while for bean farmers, their income increased, but not their yield. This appears to be due to lower input costs (bean seed, manure/fertilizer, other pest management costs).

Taken as a whole, the various trials with farmers did not allow a quantitative comparison of the effectiveness of the 2 types of models. The predictions of both models, overall provided benefits to most of the groups of the farmers. However, given the predictions of the time to act of type B model fell within the window range of those of type A model for fall armyworm and tomato leafminer, and at the end of the window for bean fly, the similarity of the findings was expected.

Discussion

In SSA, agriculture is seen by governments and aid-agencies as key to addressing issues of poverty and to driving the overall growth and future development of those countries (Garrity et al. 2012). Much investment has been made over recent decades at national and local levels to help countries and farmers access lucrative export markets through crop improvements or the investment in cash crops. An example of the latter is through the promotion of growing export cash crops by smallholders to improve incomes at the family and community levels (English et al. 2006). However, the annual burden of insect pests, both indigenous and the ever-rising tide of new invasive species, places a major constraint on the development of most crops (Gitonga et al. 2009). Often, outside the growing season, indigenous insect pest species remain hidden in crop residues, volunteer crops, and wild hosts, only invading crop systems when environmental conditions (particularly weather and especially temperature and precipitation) favor local dispersal and reproduction. There may also still be some transboundary movement of some species in Africa as well, for example fall armyworm, but the extent of this is not known. Unsurprisingly, in some areas, farmers place pests—especially insects—as *the* major constraint to crop production (Constantine et al. 2021). As a result, the provision of easily accessible best practice management information for pests to national agricultural organizations and farmers has been seen as essential. Frequently, the advice in much of this information relies heavily on farmers having skills in pest identification, life cycles, and monitoring pest densities; and for the last, it is difficult for farmers to monitor their crops effectively as

Table 7. Results of a phone survey conducted after the long rains in 2021 via phone with 2000 maize and bean farmers who received MoA-INFO text alerts (control) and MoA-INFO Text Alerts + PRISE alerts (treatment)

Crop and insect pest	Avg per farmer	Treatment (received PRISE alerts + MoA INFO Alerts)	Control (MoA-INFO Alerts only)
Maize, Fall Armyworm	Harvest kg/ha	2,089	1,988
	Income Ksh/ha	18,020	15,733
Bean, bean fly	Harvest kg/ha	425	475
	Income Ksh/ha	10,486	10,203

many insect pests are hard to detect during the early stages of their development and the pests develop quickly. In addition, time for monitoring is limited as smallholder farmers, especially women who frequently do most of the work, are already heavily burdened by agriculture and household workloads (Martey et al. 2022a, 2022b).

Given this overall situation, it is critical that best practice management advice is coupled with a pest monitoring and early-warning system (Brown et al. 2022). When the arrival or activity of a pest has been confirmed in an area, the early-warning system should operate from the start of a crop season and advise about developing the pest problems together with a forecast on the optimum time to apply the management interventions. In this article, the PRISE early-warning system coupled with how advice about pest monitoring has provided a means to do this for major insect crop pests of maize, bean, and tomato in Ghana, Kenya, Malawi, and Zambia. It demonstrates how previous major technical barriers that countries faced were overcome through the utilization of the advances in EO data, and computer and messaging technology mentioned earlier.

In PRISE, the monitoring of developing pest problems in any locality within an administrative unit for farmers is provided by local extension services or neighboring farmers who have spotted a pest; identification of pests is also now aided in many localities by the presence of plant clinics. However, local monitoring may be improved using the 2-way SMS, where users are asked to report observations from the field, as early trials have improved the rate and extent of the reporting. In parallel, a forecast for the optimum time to apply an intervention (plus advice on the best practice) for a particular crop/insect pest is relayed to extension service providers or by SMS messaging direct to farmers in all administrative areas where the crops are grown at the start of a crop season. Farmers are then able to use the information received to plan for the date advised for them to act should a pest be confirmed in their locality.

The forecasts in PRISE are based on the phenology model predictions. There is a vast literature on analytical pest phenology models (Orlandini et al. 2017), and these models vary in complexity in terms of the form of the function in the models that relate the rate of development to temperature (Prasad and Prabhakar 2012, Orlandini et al. 2017). The 2 model forms presented here, based on the simple degree-day model and that factor in continuous breeding and overlapping stages, proved from the field validation studies on 2 insect pests, fall armyworm and tomato leafminer, to be accurate for forecasting: model type A gave a robust prediction of immature development rate, and model type B of immature stage population growth. Both predictions were from the first crop planting at the start of a crop season. Currently, the data used to drive the pest models is hourly reanalysis/forecasts of air temperature 2 m above the land surface. However, PRISE partner Assimila Ltd has been undertaking additional research to refine temperature measurements such that they more accurately reflect the temperature at crop canopy level. It is envisaged that these refinements will be included in PRISE in the future.

The PRISE models take time, effort, and resources to create and validate. During the pilot phase, project staff were actively involved in interrogating the data cube and generating the forecasts needed, and in some cases also developed the best practice pest management messages into which the PRISE forecasts were integrated. Capacity building to facilitate national partners' ability to take on responsibility for interrogating the data cube and developing their own forecasts for crops, pests, and geographies of interest was a component to the pilot phase. More emphasis on this in future is required to sufficiently ensure smooth transition. Through targeted capacity development and the deployment of hybrid training approaches (virtual and in person), national agencies can continue to make use of the PRISE model data collection protocols, data handling and management best practices, and model creation and validation processes to proliferate on the number of validated pest models for themselves and other countries to use. These can then be integrated into a range of dissemination networks, running on the PRISE datacube on an ongoing basis. This approach complements a need for capacity development with a standardized approach to pest modeling and changing geographic research priorities.

Over recent years, there has been a rapid increase in the number and variety of mobile-phone-mediated services targeted at smallholder farmers in SSA, known as m-agri services, including those based on SMS, Unstructured Supplementary Service Data (USSD), mobile applications (apps), and helplines. The range of m-agri services includes those that connect buyers to sellers, provide information about crop farming and livestock, and market prices. Another technical improvement that is anticipated is the use of the GPS facility on smartphones, which would enable GAP and time to act messages to be targeted more effectively; currently, farmers report their location when they subscribe to a messaging service. The use of GPS could also enable feedback from farmers and others on the presence or absence of pests of interest to be incorporated into the data cube to enhance the precision of future forecasts. This will be more feasible as smartphone ownership and mobile data network accessibility levels increase in SSA.

The end line studies conducted have shown that smallholder farmers who received information about the target crops (maize, beans, and tomato), including PRISE pest forecasts, generally reported better outcomes in terms of reduced losses and increased incomes compared to farmers who did not receive specific time to act messaging together with other GAP advice. This was for all the insect pests included in PRISE (Table 1), thus indicating that the forecasts from the models of the species where direct validation studies are still ongoing are useful. There are indications that the specific time to act messaging provides further benefits to farmers beyond standard GAP information, and this will be explored further. However, it is worth noting that the gains seen were more prevalent for male farmers rather than women farmers. Further work will be needed with dissemination partners to target women farmers to sign up for extension messaging services to ensure they receive the time to act messages directly. In addition, to enable women farmers to benefit from the messaging, it will be necessary to work with partners to address the social norms that constrain women's access to land, credit, farming inputs, etc. so that they are able to respond to the time to act messaging in full.

The PRISE data cube holds a wealth of data collated, stored, and processed that has great potential beyond its current use case of pest forecasting, and as such, the PRISE system has scope for expansion and development beyond its current performance. First, the existing portfolio of validated PRISE models can be calibrated for broader geographic application in other African countries, and beyond. An approach to calibrating these models in new agro-ecological zones is currently under development. It remains the case that appropriate dissemination partners in new countries are to be sought; in addition to leveraging partnerships, CABI already has with national agricultural and extension agencies such as the PlantwisePlus Plant Doctor network.

In the pilot phase, the PRISE project focused on 3 crops and 8 priority pests with the PRISE alerts being targeted at smallholder farmers. A second stage of PRISE's further development includes expanding the PRISE system to explore the appropriateness of the existing insect models for other common crops in those cases where a species is polyphagous. In addition, the system will be expanded to cover a wider range of insect and other arthropod crop pests and fungal plant diseases. Making full use of the existing data, supplemented by further data, can support additional agro-climatic risk advisories in an increasingly unpredictable world. These modeled data (i.e., modeled weather forecasts, water availability, drought, flooding, risk of extreme temperatures) can be reproduced in a range of bespoke and accessible formats, and developing means to address multiple climate-driven hazards in new models would provide a holistic early-warning advisory resource for location-specific actionable advice for a broader range of agricultural stakeholders beyond smallholder farmers. The intention is then to develop a fee-paying service targeted at commercial farmers, agro-input suppliers, and the agricultural finance sector, among others, with a view to generating revenue that enables PRISE to migrate toward a sustainable business model.

Supplementary Material

Supplementary material is available at *Journal of Integrated Pest Management* online.

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