Where to Invest Project Efforts for Greater Benefit: A Framework for Management Performance Mapping with Examples for Potato Seed Health

C. E. Buddenhagen,^{1,2,3,4} Y. Xing,^{1,2,3} J. L. Andrade-Piedra,⁵ G. A. Forbes,⁵ P. Kromann,^{5,6} I. Navarrete,^{5,7,8} S. Thomas-Sharma,⁹ R. A. Choudhury,^{1,2,3,10} K. F. Andersen Onofre,^{1,2,3,11} E. Schulte-Geldermann,^{12,13} B. A. Etherton,^{1,2,3} A. I. Plex Sulá,^{1,2,3} and K. A. Garrett^{1,2,3,†}

¹ Plant Pathology Department, University of Florida, Gainesville, U.S.A.

² Food Systems Institute, University of Florida, Gainesville, U.S.A.

³ Emerging Pathogens Institute, University of Florida, Gainesville, U.S.A.

⁴ AgResearch, Ltd., Ruakura, Hamilton, New Zealand

⁵ International Potato Center, Lima, Peru

⁶ Field Crops, Wageningen University and Research, Lelystad, The Netherlands

⁷ Centre for Crop Systems Analysis, Wageningen University and Research, Wageningen, The Netherlands

⁸ Knowledge, Technology and Innovation, Wageningen University and Research, Wageningen, The Netherlands

⁹ Department of Plant Pathology and Crop Physiology, Louisiana State University Agricultural Center, Baton Rouge, U.S.A.

¹⁰ School of Earth, Environment, Marine Science, University of Texas, Rio Grande Valley, U.S.A.

¹¹ Department of Plant Pathology, Kansas State University, Manhattan, U.S.A.

¹² International Potato Center, Nairobi, Kenya

¹³ Department of Agriculture, University of Applied Sciences Bingen, Bingen, Germany

Accepted for publication 9 August 2021.

ABSTRACT

Policymakers and donors often need to identify the locations where technologies are most likely to have important effects, to increase the benefits from agricultural development or extension efforts. Higher-quality information may help to target the high-benefit locations, but often actions are needed with limited information. The value of information (VOI) in this context is formalized by evaluating the results of decision making guided by a set of specific information compared with the results of acting without considering that information. We present a framework for management performance mapping that includes evaluating the VOI for decision making about geographic priorities in regional intervention strategies, in case studies of Andean and Kenyan potato seed systems. We illustrate the use of recursive partitioning, XGBoost, and Bayesian network models to characterize the relationships among seed health and yield responses and environmental and management predictors used in studies of seed degeneration. These analyses address the expected performance of an intervention based on geographic predictor variables. In the Andean example, positive selection of seed from

asymptomatic plants was more effective at high altitudes in Ecuador. In the Kenyan example, there was the potential to target locations with higher technology adoption rates and with higher potato cropland connectivity, i.e., a likely more important role in regional epidemics. Targeting training to high management performance areas would often provide more benefits than would random selection of target areas. We illustrate how assessing the VOI can contribute to targeted development programs and support a culture of continuous improvement for interventions.

Keywords: agricultural development, analytical and theoretical plant pathology, disease, disease control and pest management, ecology and epidemiology, Ecuador, geographic information system, intervention ecology, Kenya, machine learning, pest management, potato, seed degeneration, techniques, translational science, value of information, virology, virus, yield gap

†Corresponding author: K. A. Garrett; karengarrett@ufl.edu

C. E. Buddenhagen and Y. Xing contributed equally to this work.

Funding: This research was undertaken as part of, and funded by, the CGIAR Research Program on Roots, Tubers and Bananas (RTB), supported by CGIAR Trust Fund Contributors (<https://www.cgiar.org/funders/>). Support was also given by the CGIAR Research Program on Climate Change and Food Security (CCAFS), Bill and Melinda Gates Foundation grant OPP1080975, U.S. Department of Agriculture National Institute of Food and Agriculture grants 2015-51181-24257 and 2020-51181-32198, U.S. Department of Agriculture Animal and Plant Health Inspection Service grant 11-8453-1483-CA, United States Agency for International Development Feed the Future Haiti Appui à la Recherche et au Développement Agricole project grant AID-OAA-A-15-00039, U.S. National Science Foundation grant EF-0525712 as part of the joint National Science Foundation–National Institutes of Health Ecology of Infectious Disease program, U.S. National Science Foundation grant DEB-0516046, and the University of Florida.

*The e-Xtra logo stands for “electronic extra” and indicates that three supplementary figures are published online.

The author(s) declare no conflict of interest.

Copyright © 2022 The Author(s). This is an open access article distributed under the CC BY 4.0 International license.

A central problem in applied spatial ecology is how to partition management efforts across landscapes. Interventions by governments or development organizations are often designed to increase regional crop yield, for example by improving disease management. International, governmental, and nongovernmental organizations that seek to reduce poverty, enhance food security, and support ecosystem services need strategies to geographically target interventions after identifying priorities using participatory approaches with stakeholders. We propose management performance mapping as a tool for translating experimental results to support the identification of geographic priorities by policy makers and donors. Management performance mapping consists of scaling up models based on an often limited number of observations, to visualize how specific interventions are likely to perform at a regional scale (Altieri and Nicholls 2008; Grassini et al. 2015; van Bussel et al. 2015; van Wart et al. 2013a). It can be thought of as an approach to characterizing resource management domains (Eswaran et al. 2000) specifically for the purpose of determining management performance. Management performance mapping can have several applications, such as providing a summary of recommendations for extension programs or evaluating which type of management is most effective for a set of

locations. In this article, we focus on management performance mapping to inform targeting of interventions to support a management component known to be effective under some circumstances, where the goal is to identify the locations where it will be most effective. This approach may be particularly useful in low-income countries, especially where smallholder farmers have fewer management options, and there is interest in making a valuable new option available through a system intervention. Management performance mapping can be implemented to visualize the impact of proposed interventions, to improve decision making and policymaking, as a component of adaptive management in development (Fig. 1).

Digital or precision agriculture and species distribution models both address components of spatial prioritization and are thus related to management performance mapping. The question of how to optimize information use for decision making is addressed at the within-field scale in precision agriculture (Tittonell and Giller 2013), allowing well-resourced farmers, and potentially smallholder farmers (Cook et al. 2003), to collect and use spatially explicit datasets (in near real time) about crop performance. Inputs such as fertilizer, pesticides, and irrigation are applied to areas of the field where they are most needed to optimize yields.

Species distribution models address the problem of optimal targeting indirectly by providing information about where invasive (or endangered) species, including pathogens, are most likely to be found (Austin 2007; Hijmans and Graham 2006; Sheppard et al. 2014), often grappling with problems in statistical inference (Stolar and Nielsen 2015) that are also relevant to management performance mapping. Species distribution models are generally designed to draw inference beyond the regions where data were collected by estimating species niche parameters based on maps of species occurrence or abundance throughout a species' native and introduced range (Bourdôt and Lamoureaux 2019; Phillips et al. 2018; Sutherst and Maywald 1985; Wang et al. 2017). Management performance mapping for disease management can incorporate both information about which environments are conducive to pathogen and vector reproduction and spread, and which environments are conducive to effective management.

The value of information (VOI) concept is useful for evaluating the benefits of basing strategies on management performance mapping. Assessing the VOI involves quantifying the expected benefit of

reducing uncertainty about decision making (Canessa et al. 2015), as described further below. VOI analyses offer a means of both evaluating information and benefits, and assessing the role of uncertainty when comparing management options (Canessa et al. 2015; Hirshleifer and Riley 1979; Macauley 2006). VOI analyses compare outcomes from decision making with and without particular units of information, taking into account the stakes for making good or bad decisions, such as differences in yield or profit (Fig. 2). In studies of willingness-to-pay, such as farmer willingness-to-pay for technologies, the utility functions for technologies are closely related to the VOI (Asante et al. 2011; Breidert et al. 2006; Hanemann 1991). Of course, decision makers' willingness to act based on information is necessary for information valuation to be meaningful. For example, overly confident decision makers may not be influenced by new information, or they may not reflect on the uncertainty that is inherent in the information available. Many examples in the VOI literature focus on agriculture, such as the uncertainty risk distribution for farm yield (Hirshleifer and Riley 1979), the value of weather forecasting for farmers (Lave 1963), and risk assessment for crop futures (Danthine 1978). A related area of application of VOI concepts is in invasion biology more generally and in conservation biology, where decisions must also be made about where to prioritize efforts (Canessa et al. 2015; Johnson et al. 2017; Wilson 2015). VOI analyses have so far seen little application in plant pathology, crop epidemiology, or seed system development, where they have the potential to improve research prioritization and decision making.

We present case studies of management performance mapping and the application of VOI analysis that focus on smallholder management of "seed degeneration" in agricultural systems. Seed degeneration is the reduction in yield or quality caused by an accumulation of pathogens (often viruses) and pests in planting material over successive cycles of propagation, where vegetatively propagated crops deserve particular attention because of their higher risk of disease transmission (Thomas-Sharma et al. 2016). Establishing improved seed systems is challenging, in part because of the many system components that must be integrated for seed system success (Almekinders et al. 2019; Bentley and Vasques 1998; Gildemacher et al. 2009; Jaffee and Srivastava 1994; McEwan et al. 2021; McGuire and Sperling 2016; McQuaid et al. 2016; Sperling 2008). In informal seed systems, farmers typically use seed saved from the previous growing season or acquire seed locally from other farmers or informal seed producers, often leading to reduced yields. Yield reduction can range from 5 to 50% (Devaux et al. 2010), especially when farmers are unfamiliar with approaches for selecting seed from their fields with reduced pathogen risk. Despite the challenges (Almekinders et al. 2019), seed system improvement has great potential for improving regional agriculture by providing healthier seed of better varieties, and it has been a major focus of agricultural development efforts funded by many agencies (e.g., national plant protection agencies, the Bill and Melinda Gates Foundation, the U.S. Agency for International Development, and the Food and Agriculture Organization) (Almekinders et al. 1994; Jaffee and Srivastava 1994; McGuire and Sperling 2016).

Optimizing yield by reducing disease impacts and by improving seed quality is a primary goal of many seed system interventions. Governments and institutions with a strong focus on science for development, such as CGIAR, work on a suite of factors linked to seed system health (e.g., as described by Andrade-Piedra et al. 2020). Farmer training efforts focus on options for effective disease management and optimal decision making. International development efforts for improved seed systems seek to increase farmer access to disease-free, high-quality seed of disease-resistant varieties; to improve on-farm management practices; to implement "integrated seed health strategies" (Thomas-Sharma et al. 2016); and to implement realistic phytosanitary thresholds (Choudhury et al. 2017). Despite these efforts, many systems remain largely informal with suboptimal seed, sourced on-farm or locally, even after interventions. For example, 98% of potato seed sources in the Andes were reported as informal (Devaux et al. 2010; Louwaars et al. 2013). Interventions

Management performance mapping steps	Andes case study	Kenya case study
1) Formulate questions about the performance of a specific management strategy across a geographic region	1) Where does positive selection of farm-saved potato seed provide the greatest benefit in Ecuador and Colombia?	1) Where does positive selection of farm-saved seed provide the greatest benefit in three regions of Kenya?
2) Assemble data related to the performance of the management strategy	2) Per plant yield, viruses, seed age, altitude, and management (including positive selection)	2) Positive selection adoption rate and yield response to positive selection
3) Identify predictor variables for management performance	3) Altitude, variety, and time since seed replacement - identified using Bayesian networks and classification trees	3) Proportional differences in regional adoption rates
4) Estimate management performance across the geographic study region	4) Extrapolation based on altitude for major potato regions of Ecuador and Colombia	4) (No extrapolation in this case study)
5) Evaluate the value of information for management intervention or policy	5) Comparison of intervention yield benefits with and without acting on information about altitude, variety and time since seed replacement	5) Comparison of intervention yield benefits with and without acting on information about adoption rates
6) Evaluate what additional information may be needed before proceeding in participatory planning sessions		
7) Design intervention based on geographic locations identified		
8) Monitor project outcomes and iteratively adapt strategies based on new data and stakeholder input		

Fig. 1. Steps in the management performance mapping pipeline. Selected development interventions should ideally take place in a culture of continuous improvement, based on ongoing monitoring and evaluation with stakeholders, and incorporating experimentation to facilitate adaptive management. Two case studies show how the steps may be implemented. Management performance mapping operates in this context by scaling up field-, farm-, and plot-derived information to larger-scale landscapes, regions, or countries.

are more likely to succeed if they are affordable and help farmers to be profitable (McGuire and Sperling 2013; Sperling et al. 2013). As an example, positive selection is an on-farm management intervention that can provide large yield benefits, e.g., 28 to 55% increases (mean 32%) (Gildemacher et al. 2011, 2012; Schulte-Geldermann et al. 2012) and is often recommended as part of an integrated seed health strategy (Thomas-Sharma et al. 2016). Using positive selection, farmers select healthy-appearing plants and mark them for later harvesting of seed. Training farmers in the techniques of positive selection can be an effective component of an integrated seed health strategy, and we use positive selection as the example management tactic in our case studies.

A challenge for management performance mapping (as for species distribution modeling, digital agriculture, and most analyses designed to draw inference about larger geographic areas) is to make the most of the available data while avoiding overinterpretation of results. Often data regarding agricultural management performance exist, or can be collected inside of existing intervention projects, but the data are collected at the scale of fields, farms, or individual plant performance measures. Multiple factors influence plant productivity apart from management, generating uncertainty about the pay-off from management choices even where data are relatively abundant. We discuss the use of limited data in the context of our examples below.

Our objectives in this study are to (i) introduce and illustrate the concept of management performance mapping and associated methods, (ii) introduce the use of VOI analysis in this context, and (iii) illustrate the application of management performance mapping for potato seed degeneration management by positive selection of seed in the Andes and in Kenya. We also illustrate how analysis of likely management performance at individual sites can be combined

with other geographic considerations, such as using a location’s cropland connectivity risk index (Xing et al. 2020) as a proxy for its potential role in epidemic spread for the region.

MATERIALS AND METHODS

As an overview, we begin by describing the steps involved in producing management performance maps (Fig. 1), using the example of training farmers in positive selection to identify plants more likely to produce healthy seed. Next, we illustrate management performance mapping for a seed degeneration dataset from a potato seed study in Ecuador and a study of management adoption in Kenya (Gildemacher et al. 2012; Kromann et al. 2017). As a step in preparing the Andean management performance maps, we illustrate the application of recursive partitioning, gradient boosting with XGBoost, and Bayesian networks for assessing the influence of disease, environmental factors, and management on yield. We evaluate the potential VOI for guiding the selection of locations in development interventions for potato seed health in Ecuador and Kenya based on the estimated effects, although we note that in these cases more data would be needed before proceeding to action in the field based on these analyses. We illustrate steps 1 through 5 of the management performance mapping pipeline (Fig. 1), whereas steps 6 through 8 would also be key to achieving outcomes in the field in an adaptive management approach (Shea et al. 2014). To illustrate the potential for combining management performance mapping (evaluated for each geographic pixel independently) with other types of spatial processes, such as the potential roles of locations in epidemic spread, we provide an example of integration with a cropland connectivity analysis (Xing et al. 2020), described below.

Fig. 2. The value of information (VOI) for data used to guide site selection for interventions can be evaluated as illustrated here for a hypothetical case. Suppose there are three types of environment, each equally common, and a measure of how well the management being evaluated performs in each environment: improvements in yield in environments A, B, and C of 4, 1, and 0 units, respectively. If sites are selected at random for intervention, without information about yield in the different environments, the average benefit from management is 1 2/3 units. If sites are selected considering the information about better management performance in environment A, and thus only environment A is targeted, then the average benefit from management is 4 units. If misinformation leads to the incorrect belief that management is more effective in environments B and C and these environments are equally targeted, then the average benefit from management is 1/2 unit. The VOI comparing informed site selection with random site selection is 2 1/3 units. The VOI comparing informed site selection with misinformed site selection is 3 1/2 units.

Step 1: Formulate questions regarding the performance of a specific management strategy across a geographic region.

In these case studies, we evaluate the effects of positive selection of farm-saved seed potato for virus disease management. In general, the identification of management strategies for evaluation will likely be more successful if the process includes participatory input from stakeholders. In the Andean case study, our questions are these: Where would training in positive selection likely produce the greatest benefit for yield in Ecuador and Colombia? And how do the variety grown and the time since seed replacement influence the benefit for yield? In the Kenyan case study, our question is this: Where would training in positive selection likely produce the greatest benefit for yield, choosing among three regions of Kenya?

Step 2: Assemble data related to the performance of the management strategy.

We use two datasets as case studies. The first dataset was obtained from a study on potato production in the Ecuadorian Andes that was designed for estimating parameters related to seed degeneration (Kromann et al. 2017). The study monitored seed degeneration in two potato varieties, at three altitudes, and considered the use of on-farm seed management options. The two varieties were INIAP-Fripapa and Superchola (perceived by farmers to be susceptible and resistant to degeneration, respectively). The field trials were conducted during three cycles of planting at three sites representing three altitudes (<2,700 m above sea level (masl), 3,000 masl and >3,400 masl, where the field site at <2,700 masl was moved during the experiment). Only one field site was present at each altitude per year. Thus, 12 49-m² plots were planted each year, comprising two plots of each of two varieties at each of the three altitudes (sites). In each whole plot, three types of seed management were applied to subplots: positive selection, roguing, and random selection. The response variables included (i) virus incidence (*Potato virus X* (PVX), *Potato virus Y* (PVY), *Potato virus S* (PVS), *Potato leaf roll virus* (PLRV), *Andean potato latent virus* (APLV), and *Andean potato mottle virus* (APMoV)) in plants at emergence, flowering, and in tubers, evaluated using a double-antibody sandwich enzyme-linked immunosorbent assay (DAS-ELISA), (ii) incidence and severity of pest damage and diseases in tubers, and (iii) tuber yield (Kromann et al. 2017).

This study in Ecuador was designed to estimate parameters for seed degeneration modeling (Thomas-Sharma et al. 2017). Relevant model components were related to seed health (virus incidence, time/seasons since certified seed was last obtained), variety, environmental factors (weather), management (seed propagation and selection) and yield data for samples of individual potato plants (Kromann et al. 2017). Given that a single site represented each altitude in this dataset, variability within a scenario could be evaluated only at the level of individual plants, with some treatment combinations missing from the final data (Supplementary Fig. S1). Lack of replication at the field level is a limitation for management performance mapping because an analysis intended for providing recommendations for project implementation would be stronger if multiple farms per altitude provided estimates of farm-to-farm variation in management performance within an altitude range. We focus on yield as the response in the management performance mapping example, with potential predictors being farm altitude (across three altitudes), seasons since certified seed was obtained, and the management performance of positive selection compared with roguing or random seed selection as management strategies. Climate variables (precipitation, humidity, and temperature from the WorldClim database [Fick and Hijmans 2017]) were also evaluated as potential predictors but were not identified as effective predictors of either disease incidence or yield, probably at least in part because only three fields per year were evaluated (data and analysis not shown). Precipitation and minimum temperature data 6 months after planting were retained in the Bayesian network analysis to illustrate associations with altitude, where the minimum temperature might be expected to be associated with reduced vector activity.

The second dataset was composed of published data describing potato seed health management, and positive selection training and adoption rates, in three counties in Kenya (Gildemacher et al. 2012). The study evaluated adoption rates using focus group discussions and individual interviews, sampling six groups at random from each of the three counties, with provisions designed to avoid false positive results (Gildemacher et al. 2012). We used these data to illustrate integrating information about the likelihood that farmers in a region would adopt a technology, another key component of intervention success.

Step 3: Identify predictor variables for management performance.

There are many potential predictor variables for performance indicators, and a wide range of methods can be used to identify important predictors, including classification analysis, regression analysis, generalized linear models, and generalized additive models. We illustrate three types of machine learning algorithms (recursive partitioning, gradient boosting with XGBoost, and Bayesian network analysis) to evaluate potential predictors, focusing on yield as the response for a management performance indicator. These methods were used to identify predictor variables for the effect of positive selection on yield for the Kromann et al. (2017) dataset. We explore the potential roles of factors including virus incidence in yield reduction. In studies designed for immediate application, the emphasis might be on simpler approaches to identifying key predictors for management performance mapping.

Classification and regression trees. Classification and regression trees have been applied in agricultural systems for land and soil classification, climate change impact assessment, risk assessment, and evaluation of toxin levels and disease conduciveness in plants (Caley and Kuhnert 2006; Etter et al. 2006; Langemeier et al. 2017; Novak and LaDue 1999; Paul and Munkvold 2004; Tittonell and Giller 2013). The recursive partitioning method depicts and supports the interpretation of outputs in a decision-tree format useful for system interpretation. The performance of models can usually be improved using boosting ensemble approaches such as gradient boosting with XGBoost (Chen and Guestrin 2016). We used the *rpart* package (Therneau and Atkinson 2019) in R version 4.0.5 (R Core Team 2021) to analyze the Kromann et al. (2017) dataset, along with the *xgboost* package (Chen et al. 2021) and *mlr* package (Bischl et al. 2016; Rhys 2020) to tune hyperparameters and to produce a summary tree, where Supplementary Figure S1 presents the code used and the output (note that a newer package, *mlr3* [Lang et al. 2019], is now available.) Two-thirds of the data were randomly selected as the training dataset, with the remainder being designated as the test dataset. The complexity parameter was set to 0.01 and the maximum depth to 12. A comparison of the test to training dataset was made using a linear model (*lm* function). In XGBoost the learner was a regression method. For the task, the potato yield was set as target variable with altitude, cycles of on-farm propagation, variety, and management as predictor variables. We tuned seven hyperparameters in XGBoost (eta, 0 to 1; gamma, 0 to 10; max_depth, 1 to 20; min_child_weight, 1 to 10; subsample, 0.5 to 1; colsample_bytree, 0.5 to 1; and nrounds, 30) and used 10-fold cross-validation. A random search across hyperparameter values was evaluated in 500 iterations. We assessed model accuracy using the root mean square error. Hyperparameters obtained from XGBoost were used to produce a final decision tree using recursive partitioning, and a summary tree from XGBoost was also evaluated (Supplementary Fig. S2).

Effect of seed selection, cycles of on-farm propagation, and altitude on yield, evaluated with recursive partitioning (Andes). We evaluated yield as the response variable, with predictors being the use of positive selection (as opposed to roguing or random seed selection), the number of cycles of on-farm propagation (either three seasons or less than three seasons), and the effect of altitude (across three altitudes). Because altitude is available as a potential geographic predictor variable for the region, it is a candidate for extrapolating analysis of the performance of positive selection to a wider area in step 4 (Fig. 1).

Effect of potato variety and its interactions on yield, evaluated with recursive partitioning (Andes). In a previous study of a grower cooperative in Tungurahua, Ecuador, the varieties Superchola (one of the most important potato varieties in Ecuador) and INIAP-Fripapa were reported to be sold and grown at a ratio of approximately 2:1 by volume (Buddenhagen et al. 2017). Our analysis of the Kromann et al. (2017) dataset also focuses on these two varieties. We evaluated the effects of variety, altitude, and management by estimating mean per-plant yields across treatment combinations and by using recursive partitioning using the *rpart* package.

Bayesian networks. Bayesian networks have been applied in natural resource management systems for applications including vegetation classification, optimal decision making, disease management, adaptive management of wildlife habitat, and expert elicitation (Aguilera et al. 2011; Geenen and Van Der Gaag 2005; Howes et al. 2010; Kristensen and Rasmussen 2002; Perez-Ariza et al. 2012). A Bayesian network is a directed, acyclic graph in which nodes represent variables and links represent dependencies. The relationships between variables are quantified in conditional probability tables, where the set of all tables together represents the full joint distribution. Important strengths of the Bayesian network method include its ability to infer probabilistic relationships among many variables simultaneously. A potential limitation of this method is that combinations of continuous and categorical data can be problematic for some commonly used Bayesian network algorithms (Aguilera et al. 2011). R packages for Bayesian network analysis include *bnlearn*, *gRain*, and *pcalg* (Nagarajan et al. 2013). We selected Netica (Norsys Software Corp., Vancouver, Canada) for this illustration because it is relatively affordable, the algorithms it uses allow for immediate updating of conditional probabilities based on selected levels for variables, it has a powerful graphical interface, and it has been widely used in ecological and environmental analyses (Aguilera et al. 2011). In Netica, causal chain networks for the Andean potato data (Kromann et al. 2017) were constructed relating yield, management variables, environmental variables, and virus incidence. Netica default settings were implemented in the analysis, with conditional probabilities evaluated using the counting-learning algorithm, initializing the network with all conditional probabilities uniform.

Effect of positive selection on yield, evaluated in Bayesian networks (Andes). The benefit of positive selection was evaluated in a Bayesian network in Netica, focusing on the third cycle of on-farm propagation when there would tend to be the greatest effect of management choices on virus populations. From the conditional probability tables we estimated yields above and below the threshold altitude identified in the analysis, 2,895 masl (7.7 t/ha and 3.2 t/ha, respectively, converted from the individual plant weights). The nodes in the networks were selected to explore the role of viruses in the system, because Netica provides a useful visualization of the interactions among many variables.

Regional differences in adoption of training recommendations (Kenya). In this case study, we evaluated regional differences in farmers' adoption of positive selection after training (Table 1), reported by Gildemacher et al. (2012) for three Kenyan counties: Nakuru at 46%, Nyandarua at 19%, and Narok at 18%.

Step 4: Estimate management performance across the geographic study region. For positive selection of on-farm seed in the Andes, we selected for analysis and extrapolation a major potato-growing region stretching from southern Ecuador to southern

Colombia. Using potato production geographic data layers from a global, spatially disaggregate subnational crop production statistics database, the Spatial Production Allocation Model (SPAM) 2005 v3.2 Global Data (IFPRI and IIASA 2016), we focused on pixels with >200 ha potato production per pixel (where a pixel represented 5-arc minutes, approximately 10,000 ha). In the study area, 51% of potato production is at altitudes above 2,895 m (the altitude threshold identified in the analyses above) based on SPAM estimates (You et al. 2012). The resulting management performance map will indicate that these regions would be priorities for targeting training in positive selection if decisions are based solely on this analysis of the data from Kromann et al. (2017).

For positive selection of on-farm seed in Kenya, rather than extrapolating the estimates of management performance for positive selection, we simply compared the relative performance of the counties (Table 1). The resulting management performance map will indicate prioritization among these counties if decisions for targeting positive selection training are based solely on the data from Gildemacher et al. (2009).

Step 5: Evaluate the value of information for management intervention or policy. We assessed the value of information for decisions about where to invest management interventions, for the estimates from data in Kromann et al. (2017). Greater vector activity is often assumed at lower altitudes, suggesting that positive selection for virus management in seed materials would be more important at lower altitudes. Interestingly, the field observations in Ecuador, although based on a limited number of fields, suggest that the reverse may be true (Supplementary Fig. S1). We evaluated the VOI from management performance mapping to guide selection of intervention locations for the scenario where this counterintuitive observation is indeed representative for the region, while keeping in mind that integration of data from more sites would be important before implementing decisions based on the analysis.

For the purposes of this illustration, we considered cases where decision makers either have or do not have information regarding the estimated geographic differences in management performance (Fig. 2). In the absence of information, they might select any location for management with equal probability. An estimate of the value of information would be the difference in the benefit of investment for locations selected based on the information ("informed location selection") and the benefit for locations selected randomly ("uninformed location selection"). For example, informed site selection might direct site selection to farms above or below the altitude threshold identified in analysis, depending on whether higher or lower altitudes provide greater benefits. In the case where decision makers have a prior belief that is not supported by the data, and it is in fact an incorrect belief, the value of information would be the difference between investment outcomes based on the misconception ("misinformed location selection") and outcomes based on informed investments. For example, there could be a prior belief that a particular pathogen will be more prevalent at lower altitudes, owing to a higher abundance of vectors, resulting in a prior belief that positive selection would be more important at lower altitudes. We evaluated uninformed, misinformed, and informed management choices related to spatially distributed differences in yield, disease, variety, and the rates with which best practices are adopted.

VOI for positive selection targeting in the Andes. Comparison of yield improvements resulting from positive selection training,

TABLE 1. Regional adoption rates after training in positive selection for potato seed in Kenya and the expected benefit (U.S. dollars) of training given the adoption rate (Gildemacher et al. 2011, 2012) (the average benefit is that expected under random allocation of the training effort to the regions without regard to adoption rates)

County	Observed adoption rate	Per-household benefit	Expected benefit of training in year 1
Nakuru	0.46	156	72
Nyandarua	0.19	156	30
Narok	0.18	156	28
			Average benefit 44

with and without the information from Kromann et al. (2017), has as a first step determining how common each trait combination is in the landscape being considered. Subsequently, the probability of randomly including a particular trait combination can be estimated. The proportion of Ecuadorian farmers using certified seed was previously reported as 2% (Devaux et al. 2010), and many farmers lack access to certified seed, although for some organized farming groups the proportion using certified or quality-declared seed can be as high as 46% (Buddenhagen et al. 2017). We take the frequency of farms in this landscape being planted with certified seed (“new seed”) at any given time as being approximately 2% (so that a farm drawn at random has a probability, $P = 0.02$, of being planted with certified seed, although this is an approximation because it is generally the wealthier farmers, government programs, or nongovernmental organizations who acquire certified seed). Farm altitude, based on the geographic analysis described above for higher-density potato regions, is above the altitude threshold identified in recursive partitioning approximately 51% of the time. For simplicity, we treat the proportions of potato variety planted as 33% INIAP-Fripapa and 66% Superchola, based on estimates for the province of Tungurahua from Buddenhagen et al. (2017).

VOI for targeting positive selection in Kenya. The average benefit of positive selection was reported by Gildemacher et al. (2012) as 3.4 tons per ha (~\$350 per ha). This translated to a per-household benefit of \$156 per season for a farm of average size for the region. Meanwhile, the cost of training was \$38 per farmer. In this case, the expected first-year benefit was \$44 per household when training occurred in a randomly selected region (without regard to adoption rate) (Table 1). We compared the outcome for random region selection with the outcome using information on frequencies of adoption.

Integration with another criterion for selecting priority locations: Cropland connectivity (Ecuador and Colombia). The data layer of estimated management performance is one important factor for deciding where to prioritize management efforts. The management performance map developed up to this stage is generated pointwise, in that it treats each location (point) as independent from other locations. However, some locations will have more important roles in epidemics than others, owing to factors such as the location’s position in spatial epidemic networks. Thus, targeting some locations will have more important effects to slow regional epidemics, for seed degeneration pathogens, including viruses, that tend to spread from one field to another. We evaluated the layer of management performance estimates for positive selection integrated with a data layer of the potato “cropland connectivity risk index,” a measure of the likely importance of locations for spatial movement through potato-growing areas (Margosian et al. 2009; Xing et al. 2020), as described below.

The potato cropland connectivity analysis was based on the potato crop harvested area data from SPAM 2005 v3.2 Global Data (IFPRI and IIASA 2016). As noted, the data has pixel resolution 5-arc min, and those cells with harvested areas greater than 200 ha were included in the cropland connectivity risk analysis (Xing et al. 2020). As described in more detail by Xing et al. (2020), the link weights for pairs of cells were evaluated in a sensitivity analysis (uncertainty quantification) for gravity models (scaled so that maximum weights were = 1) incorporating both inverse power-law models $c_i c_j d_{ij}^{-\beta}$ (parameter β as 0.5, 1, and 1.5) and negative exponential models $c_i c_j \exp(-\gamma d_{ij})$ (parameter γ as 0.05, 0.1, 0.2, 0.3, and 1), where c_i is the cropping density in cell i , and d_{ij} is the distance between cells i and j . The sensitivity analysis was conducted to represent a wide range of potential pathogen dispersal parameters. The inverse power law and negative exponential models are commonly useful in describing dispersal gradients for pathogens and vectors. Three network link thresholds (0.001, 0.0001, 0.00001) were applied separately to each adjacency matrix to represent three different scenarios in the network analysis in the sensitivity analysis.

A cropland connectivity risk index (CCRI) was calculated as the scaled weighted sum of betweenness centrality, node strength, the

sum of nearest neighbors’ node degrees, and eigenvector centrality, as in Xing et al. (2020). For each realization in the sensitivity analysis, the mean CCRI was evaluated across the 24 parameter combinations, including the range of inverse power-law and negative exponential parameters intended to represent the potential range of dispersal traits for pathogens important in this system. Finding the mean importance of a location in spread through an epidemic network allowed us to represent importance for epidemic spread on average across a range of potential pathogen dispersal parameters. The mean CCRI was mapped in combination with the map of management performance estimates, to identify locations important both for the CCRI (indicating a potentially important epidemic role) and for management benefits from positive selection.

RESULTS

Step 3 outcome: Identification of predictor variables for management performance. *Positive selection and yield for Andean potato.* In the recursive partitioning analysis, the *rpart* model based on the training dataset provided an adequate fit for the test data ($R^2 = 0.35$, $MSE = 33.65$, $P < 2.2 \times 10^{-16}$). The variables were ranked in importance as altitude > cycles of on-farm propagation > management > variety. A summary of XGBoost results is presented in Supplementary Figure S2. Higher per-plant yields were generally obtained from the variety INIAP-Fripapa (compared with Superchola) in the first two cycles of on-farm propagation, the highest yields being obtained at altitudes above 3,278 masl (Fig. 3). The highest yields for the variety Superchola were observed at altitudes above 2,895 masl. If a farmer can afford to replace seed more frequently, and the farm is above 2,895 masl, the variety INIAP-Fripapa has higher yields when compared with Superchola (market values were comparable in 2016: U.S.\$0.29 and 0.33 per kg, respectively).

Plants in the third cycle of on-farm propagation yielded 33% less per plant compared with the first cycle. The benefits of positive selection allowed yields to approach the average yields for recently purchased certified seed. There were no differences with respect to variety in the third cycle of on-farm propagation, suggesting that positive selection was equally valuable to cultivation of both varieties for seed that had gone through more than two planting cycles.

The Bayesian network analysis indicated that high-yielding plants were found more commonly in plots where first-generation certified seed was used, at higher altitudes, for the variety INIAP-Fripapa, and where there was a lower minimum temperature and higher rainfall 6 months after planting, as well as lower incidence of PVX, APMV, APLV, and PVS (Fig. 4; Supplementary Fig. S3). Positive selection was less likely to be the management implemented if the yield was low. All the viruses, except PVY, and PLRV for low-yield plants, were more likely to be absent (frequency = 0) than present. Each virus was relatively more likely to be absent if a plant was in the high-yield category compared with plants in the low-yield category (Fig. 4). Another cycle of data collection would be useful for understanding the interactions and effects of viruses in this system.

Adoption of positive selection for Kenyan potato. This analysis was based on the probability of adoption of positive selection, where higher adoption rates resulted in a higher payoff for intervention investment. Adoption rates were 46, 19, and 18% in three counties (Table 1) (Gildemacher et al. 2011, 2012). Thus, based on this criterion, selection of the county with a 46% adoption rate would approximately double the benefits obtained from a training intervention focused only where there was 18% or 19% adoption.

Step 4 outcome: Estimation of management performance across the geographic study region, and integration with cropland connectivity estimates. *Applying models to a map of the relevant region and integrating data layers for Andean potato.* The mapped estimates of the management performance of positive selection for Andean potato yield (based on altitude) and the locations where potato cropland connectivity risk was highest

based on the mean CCRI (Fig. 5) (the mean CCRI across results for a range of parameter values for inverse power law and negative exponential models of dispersal gradients) were combined to identify locations both (a) independently likely to have the best management outcomes and (b) likely important for regional management of disease spread (high mean CCRI). Locations that met both criteria were observed near the border of Ecuador and Colombia, and near Ambato and Riobamba in Ecuador (Fig. 5).

Technology adoption rates for three counties in Kenya. The county with the highest adoption rate for positive selection, Nakuru (Table 1), was intermediate in terms of the regional cropland connectivity index (Fig. 6). The cropland connectivity index was high for multiple locations in and near Nyandarua county. Consideration of these two factors could argue for targeting northeastern areas in Nakuru, whereas additional factors for consideration are addressed in the Discussion.

Step 5 outcome: Evaluation of the value of information for management intervention or policy. *VOI for targeted implementation of positive selection (yield as response, Bayesian networks to identify predictors, Andes).* For equivalent farm sizes at altitudes above and below 2,895 masl (representing 49% of the cultivated area), we estimated the benefit of training under uninformed (random) site selection by using the weighted mean of the benefit above and below 2,895 masl (representing 51% of the cultivated area), which is 6.5 tons per ha ($[0.51 \times 7.7] + [0.49 \times 3.2] = 6.5$).

The estimated benefit under informed site selection, selecting locations above 2,895 masl, is 7.7 t/ha: a difference of 1.2 tons per ha compared with random site selection. Under misinformed site selection, if the assumption was that positive selection provides more benefits at low altitude (perhaps based on reasoning regarding greater pathogen load at lower altitudes), the benefit is 3.2 tons per

ha; 4.5 tons per ha less than the optimal allocation, and 3.3 tons per ha less than the uninformed (random) site selection option.

VOI for targeted implementation of positive selection (yield as response, recursive partitioning to identify predictors, Andes). If positive selection training targeted farmers randomly with respect to the observed frequency of the categories, the weighted mean benefit of positive selection would be 8.7 tons per ha (Fig. 3). Preferentially targeting sites at high altitude (but sampling randomly with respect to seed age and variety) provided greater benefits (9 t/ha); otherwise, targeting low-altitude sites provided lower benefits (8.3 t/ha). Targeting farmers who planted farm-saved seed 3 years since purchasing of certified seed provided little benefit: 8.8 tons/ha compared with random targeting of farmers (under the scenario where use of certified seed is rare at 2%). Targeting the 2% who do use certified seed provided a benefit of 3.1 tons/ha, although these more successful farmers may not need interventions. By far the greatest benefit was provided by targeting farmers who grew the variety INIAP-Fripapa (a benefit of 10.9 t/ha) as opposed to Superchola (a benefit of 7.6 t/ha).

Regional differences in adoption of training recommendations in Kenya. In the example of Kenyan potato seed technology adoption, targeted selection of high-adoption-rate areas for training (where the per-farmer benefit was U.S.\$72) would increase the return by U.S.\$28 per farmer trained (Table 1). Realized benefits would vary depending on the farm size.

DISCUSSION

The examples we present show how management performance mapping can be used to target sites for project interventions. We illustrate how identifying locations where positive selection of

Fig. 3. Decision tree from recursive partitioning, with per plant yield (grams) of potato in Ecuador as the response variable, based on the Kromann et al. (2017) dataset. Branches to the left are results when the logical statements at the nodes are true, and branches to the right are results when the logical statements are false. The upper numbers in the boxes are the mean yields for that condition, and the percent values are the proportion of the data for which the condition applies. For “Altitude <2,895,” “yes” indicates potato fields altitude <2,895 masl. For “Cycle >= 2,” “yes” indicates cycles of on-farm propagation equal to 2 or 3, and “no” indicates 1 cycle. For “Management = Random,” “yes” indicates that random seed selection was implemented, and “no” to that option indicates that positive selection was implemented. For “Variety = Superchola,” “no” indicates that the variety was INIAP-Fripapa (darker shading indicates a higher number of “no” answers for that condition compared with other conditions).

Fig. 4. Ecuadorian potato yield (g/plant) and the factors associated with yield from a Bayesian network analysis performed in Netica using the Kromann et al. (2017) dataset. The two network views indicate the conditional probability distribution of a set of 12 potential predictor variables for plants with **A**, low yield and **B**, high yield, with 20 links identified among the variables. Note that directed links (with arrowheads) represent probabilistic dependencies between the nodes that are connected rather than indicating causality. For each variable (node), frequencies are shown as percentages (e.g., in the variety node, given low potato yield, the variety Fripapa is cultivated at 42.8% frequency). Positive selection was less likely to be the management implemented for cases where the potato yield was low (25.9% in network A) compared with cases where yield was high (33.6% in network B). Virus variables indicate incidence. All the viruses except *Potato virus Y*, and *Potato leaf roll virus* for low-yield plants, were more likely to be absent (frequency = 0) than present. Each virus was more likely to be absent if a plant had B, a high yield than if it had a low yield (MAP = months after planting).

on-farm saved seed has the highest performance for increasing yield (Andes) or how the highest adoption rates, and thus per-farmer benefits (Kenya) can provide substantial regional benefits. Although the examples we present here would require additional information to advance to the field with confidence (steps 6 through 8 in Fig. 1), they illustrate how a management performance mapping framework can be implemented. A nongovernmental organization or a government extension agency with limited resources could use management performance mapping to better target development interventions. We compared uninformed and informed allocation of resources for scenarios where the management performance models are correct (i.e., scenarios where the data perfectly represent the region of interest), to assess the value of the information used for targeting interventions. In a simple scenario, using Bayesian network analysis to identify altitude as a management performance predictor, we found that the benefit of positive seed selection was highest (an increase of 4.5 t/ha) at high altitudes, and uninformed allocation of farmer training would provide a net benefit of 1.2 tons per ha less than that obtained by targeted training. If this scenario holds as more data become available, incorrectly assuming that better outcomes for positive selection would be obtained at lower altitudes, perhaps because aphid vector activity was thought to be higher, would have produced 3.3 and 4.5 tons per ha less for random site selection and optimal allocation, respectively (see discussion in Bertschinger et al. 2017).

Adoption rates are key to successful interventions (Parsa et al. 2014). Based on the data regarding the benefits of adoption rates of positive selection of seed in Kenya, we found that unless adoption rates were >24%, the first-year benefit per household would not

exceed the U.S.\$38 per farmer cost of training (although, presumably, the benefits would continue to accrue in subsequent years). Also, random allocation of training effort would yield a benefit of only U.S.\$44 (over the cost of the training) per household. Gildemacher et al. (2012) pointed out that adoption rates were lower in drought years, suggesting that prediction of adoption rates could be difficult if based on regional patterns in a single year. Observed adoption rates may vary in predictable ways based on disease incidence in the current or previous season, in-season weather conditions, language spoken, literacy, cultural differences between trainer and trainee, wealth, or other factors. When these relationships are understood and spatial data are available for key predictor variables for adoption, these variables could form a part of the selection criteria for farmer training initiatives (and the approach to the training could be altered to improve adoption rates).

Our example decision, deciding where to implement training for improved disease management, represents a class of decisions where there is confidence that the activity will provide some degree of benefit. Management performance mapping is applied to guide implementation to locations where there is some evidence that the benefit will be greater than in other locations. For this class of decisions, the risk is often low that limited data are worse than no data at all. In the management performance mapping context, the null hypothesis is often that the benefit of implementation will be the same in all locations. In evaluating where there is evidence to reject this hypothesis, there is not a strong motivation to avoid false positive results or type I errors (rejecting a null hypothesis when the null hypothesis is true), because a false negative or type II error (failing to reject a null hypothesis when the null hypothesis is false) is arguably just as problematic. The main risk of “bad data” would be from data with a strong bias that would lead to misinformed decisions. The cost due to “bad data” may also go up if the logistical costs (e.g., of transport, communications) of targeting locations incorrectly identified are higher than those of targeting locations at random or selecting locations based on convenience. There is the potential for these risks to be managed in real time during project implementation by incorporating distributed or “big” data sourced from farmer phone apps, rapid disease detection methods, or citizen science initiatives (Boykin et al. 2019; Nakato et al. 2016). In our example data from Ecuador, the only estimate of uncertainty within a scenario was based on variability among individual plants, whereas a person making decisions regarding regional priorities

Fig. 5. Ecuador and southern Colombia, with higher potato production regions indicated (harvested area >200 ha). Higher altitudes were identified in an analysis of the Kromann et al. (2017) dataset as having greater yield benefits from positive selection of plants for on-farm seed saving, and an altitude of 2,895 masl was used as a cutoff in this map to separate potentially higher and lower management performance. Pixels >2,895 masl altitude (51% of the pixels) are indicated with a dot. The graticules are 1-degree squares. Higher values of the potato cropland connectivity risk index estimated for Ecuador and southern Colombia are shown by darker colors, indicating likely more important roles in potato disease epidemics. Targeting sites for farmer training in positive selection might be based on the combination of being at higher altitudes for higher positive selection performance, and being in high cropland connectivity locations such that improved management would likely have higher potential to positively influence disease risk of surrounding regions.

Fig. 6. Cropland connectivity in the area of three counties in Kenya, where darker shading indicates a higher mean cropland connectivity risk index. Potato cropland connectivity is a measure of the likely importance of a pixel for epidemic spread for potato-specific pathogens. When the three counties indicated were studied to evaluate adoption rates for positive selection of plants for on-farm seed saving, Nakuru county was reported to have more than twice the adoption rate of the other two counties. Targeting for training in positive selection methods could take into account the higher adoption rate in Nakuru and the higher cropland connectivity in Nyandarua, subject to the considerations addressed in the Discussion.

would strongly prefer to have information about farm-to-farm variability within each scenario. One of the potential applications of VOI analysis is to determine whether collecting more or better data on management performance is justified (Ades et al. 2004), not just for the sake of more statistical power in general but because the information improves farmer decision making under a realistic range of conditions. Weighing the VOI and the cost of information is another consideration for data collection.

Two key factors for adoption of positive selection are market price and the varieties grown in a region, in terms of their rates of seed degeneration. The number of seasons over which positive selection is adopted is also an important factor helping to determine the return on investment in training. The study of adoption rates in Kenya was performed once and may have been limited to the circumstances at the time of sampling. At the time of the training in positive selection, there was a shift in Nyandarua from the variety Tigoni to Shangi, so there might have been more interest in acquiring the new variety than in improving old seed stock (Kaguongo et al. 2008; Okello et al. 2018). Nyandarua also has an apparent role in the spread of potato cyst nematode in the region (Mburu et al. 2018; Mwangi et al. 2015), along with bacterial wilt problems, which may have made positive selection less effective there. Potato farming has a longer history in Nyandarua. In Narok, potatoes are less important and conditions are less favorable, with the main potato variety grown being Dutch Robijn. In Nakuru, with the highest adoption rate, more varieties are grown and potato farming is more recent, and in general the growing conditions are favorable for the crop. These differing factors in the three counties, combined with changes over time, such as the occurrence of droughts, can modify the likelihood of adoption of positive selection. The yield improvements from positive selection in Kenya, averaging 30% (Schulte-Geldermann et al. 2012), make it an attractive technology for development investments. In this system, there is the possibility of farmers actually improving seed quality over time, rather than simply slowing decline, and understanding this potential could also support decisions. Formulating a strategy for targeting positive selection in Kenya would be strengthened by new data on how the differences among these and other counties influence the current likelihood of technology adoption.

Combining data layers for evaluating optimal intervention strategies can provide more insight, along with potential challenges resulting from uncertainty and different spatial resolutions (Sutton and Armsworth 2014). Evaluating the risk of disease caused by cropland connectivity (Xing et al. 2020) or other measures of the risk of disease spread, in combination with independent location characteristics, can position the analysis in the larger context of disease management for the region. Cropland connectivity may change over the course of the year as potato is present or absent. For example, in Kenya, some parts of Nyandarua county, including Njambini and Oljororok, practice year-round potato cultivation because of the availability of groundwater from the Aberdare mountain range during the dry season. Growing three crops a year is very common and likely affects pest and disease cycles. Consistently highly connected locations may be more important targets for achieving impacts on regional epidemic spread, although there is the potential for highly connected locations experiencing high inoculum loads to

respond poorly to some types of management. A broader systems analysis (for example, impact network analysis (Garrett 2021; Garrett et al. 2018), which integrates across management performance, socioeconomic, or innovation networks (Fritsch and Kauffeld-Monz 2010; Leeuwis and Aarts 2011) and biophysical networks, including epidemic networks) can aid in identifying intervention locations that prioritize across multiple goals. For farmer decision making, flexible decision rules and reducing the variability of risk may be priorities (Andrieu et al. 2015; Bert et al. 2006).

Crop and epidemic models may provide valuable data layers for management performance mapping if they incorporate spatially mappable variables. Estimating the effects of management strategies, for example, resistant variety deployment, depends on understanding the yield potential, perhaps based on a combination of weather or climate data and data on regional crop management practices (Araya et al. 2010; Reynolds et al. 2018; van Wart et al. 2013b). Disease modeling may be used to evaluate the likely effects of management, like addressing the problem of seed degeneration (Jones et al. 2010; Thomas-Sharma et al. 2017). Spatial epidemic components such as seed trade networks (Andersen Onofre et al. 2021; Andersen et al. 2019; Buddenhagen et al. 2017; Delaquis et al. 2018; McQuaid et al. 2017) may also be valuable elements of more refined management performance mapping.

Management performance mapping to identify target locations for interventions, and the VOI analysis therein, is potentially useful for many problems experienced in agriculture or intervention ecology. There is a constellation of approaches that address related goals. Yield gap analyses that incorporate maps can address some of the same goals as management performance mapping (Grassini et al. 2015; Lobell et al. 2015, 2009; Schulthess et al. 2013; Silva et al. 2017; van Bussel et al. 2015; van Ittersum et al. 2016). For example, yield gap analysis attempts to identify the most important factors that influence yield, especially factors that are controllable. The focus of management performance mapping for intervention targeting, however, is on providing spatial information about the intervention impact of management options. Management performance maps would ideally incorporate and account for interacting human dimensions (e.g., learning, financial liquidity, capital, institutions) (Arneth et al. 2014) as well.

The benefits from management performance mapping may be enhanced if maps and VOI calculations are updated with new information sources as they become available in an adaptive management scheme (Bennett et al. 2018; Shea et al. 2014). Empirical data can be supplemented with models, expert opinion, and local knowledge (Andersen Onofre et al. 2021; Petsakos et al. 2018; Tulloch et al. 2014) to help users understand changes in factors including pesticide resistance, new varieties, and new management such as irrigation. Projects may expand because of new stakeholder priorities and new situations on the ground. New pests and pathogens may enter a region (Bebber et al. 2014), and they will likely necessitate alterations to current best management practices. A recent example from Ecuador is potato purple top disease, which has become a major production constraint (Caicedo et al. 2015; Castillo Carrillo et al. 2018). The epidemic has developed since the Ecuadorian experiments reported here were performed. Very recently, *Candidatus Liberibacter solanacearum*, associated with zebra chip disease, and its vector, the

TABLE 2. Potential criteria for identifying priority sites for project interventions (for example, training farmers to use positive selection for improved seed health)

Criterion	Rationale
Regions where expected absolute benefit is greatest	Greatest benefit to regional food production
Regions where expected proportional gain is greatest	Greatest benefit to regional farmers
Regions where outcomes before intervention are lowest	Benefit to regions in greatest need
Regions where outcomes before intervention are highest	Benefit to regions currently best adapted for production
Incorporating measures of uncertainty at the farm level	
Regions where the fifth percentile benefit is greatest	Consistent benefit across farmers
Regions where the trimmed mean is greatest	Greatest benefit for typical farmers

tomato potato psyllid *Bactericera cockerelli*, have been reported in Ecuador (Caicedo et al. 2020; Castillo Carrillo et al. 2019). New strategies for best management practices for potato pests and diseases in Ecuador will need to address purple top and the risk of zebra chip, including uncertainty about causal agents.

In considering how to bring about the greatest project benefits, multiple outcomes may be important, and they may include a combination of benefits and environmental costs of management (Laurance et al. 2014), pesticide effects on nontarget species in disease management, or conservation management focusing on both biodiversity hotspots and locations with keystone species (Smith et al. 2007). Our examples addressed management performance mapping with performance defined in terms of the mean performance observed. Other potential criteria for selecting regions for investment might emphasize different priorities (Table 2). Effective altruism concepts can be used to target stakeholders to maximize research benefit (Garrett et al. 2020). Although technology adoption rates may be a key factor, projects may also give consideration to why adoption rates are low. Where adoption rates are low, projects could investigate what resources may be limiting for managers, like smallholder farmers, and whether there is an effective way to compensate for those limitations.

In summary, management performance mapping provides a process to extrapolate from available data to provide evidence-based input about where to invest in disease and crop management or training initiatives. Scenario analyses to support decision making (Wiebe et al. 2018) can build on the framework developed here, integrating management effects on yield with other ethical considerations for prioritizing project locations.

ACKNOWLEDGMENTS

We thank the *Phytopathology* editor and reviewers that improved this manuscript.

LITERATURE CITED

- Ades, A. E., Lu, G., and Claxton, K. 2004. Expected value of sample information calculations in medical decision modeling. *Med. Decis. Making* 24:207-227.
- Aguilera, P. A., Fernández, A., Fernández, R., Rumí, R., and Salmerón, A. 2011. Bayesian networks in environmental modelling. *Environ. Model. Softw.* 26:1376-1388.
- Almekinders, C. J., Walsh, S., Jacobsen, K. S., Andrade-Piedra, J. L., McEwan, M. A., de Haan, S., Kumar, L., and Staver, C. 2019. Why interventions in the seed systems of roots, tubers and bananas crops do not reach their full potential. *Food Secur.* 11:23-42.
- Almekinders, C. J. M., Louwaars, N. P., and de Bruijn, G. H. 1994. Local seed systems and their importance for an improved seed supply in developing countries. *Euphytica* 78:207-216.
- Altieri, M. A., and Nicholls, C. I. 2008. Scaling up agroecological approaches for food sovereignty in Latin America. *Development* 51:472-480.
- Andersen, K. F., Buddenhagen, C. E., Rachkara, P., Gibson, R., Kalule, S., Phillips, D., and Garrett, K. A. 2019. Modeling epidemics in seed systems and landscapes to guide management strategies: The case of sweet potato in Northern Uganda. *Phytopathology* 109:1519-1532.
- Andersen Onofre, K. F., Forbes, G. A., Andrade-Piedra, J. L., Buddenhagen, C. E., Fulton, J., Gatto, M., Khidsheli, Z., Mdivani, R., Xing, Y., and Garrett, K. A. 2021. An integrated seed health strategy and phytosanitary risk assessment: potato in the Republic of Georgia. *Agric. Syst.* 191: 103144.
- Andrade-Piedra, J. L., Almekinders, C. J. M., McEwan, M. A., Kilwinger, F. B. M., Mayanja, S., Mulugo, L., Delaquis, E., Garrett, K. A., Omondi, A. B., Rajendran, S., Kumar, P. L., and Thiele, G. 2020. User guide to the toolbox for working with root, tuber and banana seed systems. CGIAR Research Program on Roots, Tubers and Bananas. RTB, Lima, Peru.
- Andrieu, N., Descheemaeker, K., Sanou, T., and Chia, E. 2015. Effects of technical interventions on flexibility of farming systems in Burkina Faso: Lessons for the design of innovations in West Africa. *Agric. Syst.* 136:125-137.
- Araya, A., Keesstra, S. D., and Stroosnijder, L. 2010. A new agro-climatic classification for crop suitability zoning in northern semi-arid Ethiopia. *Agric. For. Meteorol.* 150:1057-1064.
- Arneth, A., Brown, C., and Rounsevell, M. D. A. 2014. Global models of human decision-making for land-based mitigation and adaptation assessment. *Nat. Clim. Chang.* 4:550-557.
- Asante, B. O., Otoo, E., Wiredu, A. N., Acheampong, P., Osei-Adu, J., and Nsiah-Frimpong, B. 2011. Willingness to adopt the vine multiplication technique in seed yam production in the forest savanna transition agro-ecological zone, Ghana. *J. Dev. Agric. Econ.* 3:710-719.
- Austin, M. 2007. Species distribution models and ecological theory: A critical assessment and some possible new approaches. *Ecol. Modell.* 200:1-19.
- Bebber, D. P., Holmes, T., and Gurr, S. J. 2014. The global spread of crop pests and pathogens. *Glob. Ecol. Biogeogr.* 23:1398-1407.
- Bennett, J. R., Maxwell, S. L., Martin, A. E., Chadès, I., Fahrig, L., and Gilbert, B. 2018. When to monitor and when to act: Value of information theory for multiple management units and limited budgets. *J. Appl. Ecol.* 55:2102-2113.
- Bentley, J. W., and Vasques, D. 1998. The seed potato system in Bolivia: organisational growth and missing links. Agricultural Research and Extension Network, Network Paper No. 85.
- Bert, F. E., Satorre, E. H., Toranzo, F. R., and Podestá, G. P. 2006. Climatic information and decision-making in maize crop production systems of the Argentinean Pampas. *Agric. Syst.* 88:180-204.
- Bertschinger, L., Bühler, L., Dupuis, B., Duffy, B., Gessler, C., Forbes, G. A., et al. 2017. Incomplete infection of secondarily infected potato plants—an environment dependent underestimated mechanism in plant virology. *Front. Plant Sci.* 8:74.
- Bischi, B. M., L., Kothhoff, L., Schiffner, J., Richter, J., Studerus, E., Casalichio, G., and Jones, Z. M. 2016. mlr: Machine learning in R. *J. Mach. Learn. Res.* 17:1-5.
- Bourdôt, G. W., and Lamoureaux, S. L. 2019. *Abutilon theophrasti* - a comparison of two climate niche models. *N. Z. J. Agric. Res.* 64:211-222.
- Boykin, L. M., Sseruwagi, P., Alicai, T., Ateka, E., Mohammed, I. U., Stanton, J. A. L., Kayuki, C., Mark, D., Fute, T., Erasto, J., and Bachwenkizi, H. 2019. Tree lab: Portable genomics for early detection of plant viruses and pests in Sub-Saharan Africa. *Genes (Basel)* 10:632.
- Breider, C., Hahsler, M., and Reutterer, T. 2006. A review of methods for measuring willingness-to-pay. *Innov. Mark.* 2:8-32.
- Buddenhagen, C. E., Hernandez Nopsa, J. F., Andersen, K. F., Andrade-Piedra, J., Forbes, G. A., Kromann, P., Thomas-Sharma, S., Useche, P., and Garrett, K. A. 2017. Epidemic network analysis for mitigation of invasive pathogens in seed systems: Potato in Ecuador. *Phytopathology* 107:1209-1218.
- Caicedo, J., Crizón, M., Pozo, A., Cevallos, A., Simbaña, L., Rivera, L., et al. 2015. First report of “*Candidatus* Phytoplasma aurantifolia” (16SrII) associated with potato purple top in San Gabriel-Carchi, Ecuador. *New Dis. Rep.* 32:20.
- Caicedo, J. D., Simbaña, L. L., Calderón, D. A., Lalangui, K. P., and Rivera-Vargas, L. I. 2020. First report of ‘*Candidatus* Liberibacter solanacearum’ in Ecuador and in South America. *Australas. Plant Dis. Notes* 15:6.
- Caley, P., and Kuhner, P. M. 2006. Application and evaluation of classification trees for screening unwanted plants. *Austral Ecol.* 31:647-655.
- Canessa, S., Guillera-Aroita, G., Lahoz-Monfort, J. J., Southwell, D. M., Armstrong, D. P., Chadès, I., et al. 2015. When do we need more data? A primer on calculating the value of information for applied ecologists. *Methods Ecol. Evol.* 6:1219-1228.
- Castillo Carrillo, C., Fu, Z., and Burckhardt, D. 2019. First record of the tomato potato psyllid *Bactericera cockerelli* from South America. *Bull. Insectol.* 72:85-91.
- Castillo Carrillo, C., Paltrinieri, S., Bustamante, J. B., and Bertaccini, A. 2018. Detection and molecular characterization of a 16SrI-F phytoplasma in potato showing purple top disease in Ecuador. *Australas. Plant Pathol.* 47:311-315.
- Chen, T., and Guestrin, C. 2016. XGBoost: A Scalable Tree Boosting System. Pages 785-794. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.
- Chen, T., He, T., Benesty, M., Khotilovich, V., Tang, Y., Cho, H., Chen, K., Mitchell, R., Cano, I., Zhou, T., Li, M., Xie, J., Lin, M., Geng, Y., and Li, Y. 2021. xgboost: Extreme gradient boosting. R package version 1.4.1.1.
- Choudhury, R. A., Garrett, K. A., Klosterman, S. J., Subbarao, K. V., and McRoberts, N. 2017. A framework for optimizing phytosanitary thresholds in seed systems. *Phytopathology* 107:1219-1228.
- Cook, S., O'Brien, R., Corner, R., and Oberthur, T. 2003. Is precision agriculture irrelevant to developing countries. Pages 115-120 in: Precision Agriculture. J. Stafford and A. Werner, eds. Wageningen Academic Publishers, Wageningen, Netherlands.
- Danthine, J.-P. 1978. Information, futures prices, and stabilizing speculation. *J. Econ. Theory* 17:79-98.
- Delaquis, E., Andersen, K. F., Minato, N., Thuy, C. T. L., Karssenberg, M. E., Sophearith, S., Wyckhuys, K. A. G., Newby, J., Burra, D. D., Srean, P., Phirun, I., Niem, L. D., Nhan, P. T., Garrett, K. A., Almekinders, C. J. M., Struik, P. C., and de Haan, S. 2018. Raising the

- stakes: cassava seed networks at multiple scales in Cambodia and Vietnam. *Front. Sustain. Food Syst.* 2:73.
- Devaux, A., Ordinola, M. E., Higon, A., and Flores, F. A. (eds.) 2010. El sector papa en la región andina: Diagnóstico y elementos para una visión estratégica. International Potato Center, Bolivia, Ecuador y Perú.
- Eswaran, H., Beinroth, F. H., and Virmani, S. M. 2000. Resource management domains: a biophysical unit for assessing and monitoring land quality. *Agric. Ecosyst. Environ.* 81:155-162.
- Etter, A., McAlpine, C., Wilson, K., Phinn, S., and Possingham, H. 2006. Regional patterns of agricultural land use and deforestation in Colombia. *Agric. Ecosyst. Environ.* 114:369-386.
- Fick, S. E., and Hijmans, R. J. 2017. WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. *Int. J. Climatol.* 37:4302-4315.
- Fritsch, M., and Kauffeld-Monz, M. 2010. The impact of network structure on knowledge transfer: an application of social network analysis in the context of regional innovation networks. *Ann. Reg. Sci.* 44:21-38.
- Garrett, K. A. 2021. Impact network analysis and the INA R package: Decision support for regional management interventions. *Methods Ecol. Evol.* 12:1634-1647.
- Garrett, K. A., Alcalá-Briseño, R. I., Andersen, K. F., Brawner, J., Choudhury, R. A., Delaquis, E., Fayette, J., Poudel, R., Purves, D., Rothschild, J., and Small, I. M. 2020. Effective altruism as an ethical lens on research priorities. *Phytopathology* 110:708-722.
- Garrett, K. A., Alcalá-Briseño, R. I., Andersen, K. F., Buddenhagen, C. E., Choudhury, R. A., Fulton, J. C., Hernandez Nopsa, J. F., Poudel, R., and Xing, Y. 2018. Network analysis: A systems framework to address grand challenges in plant pathology. *Annu. Rev. Phytopathol.* 56:559-580.
- Geenen, P. L., and Van Der Gaag, L. C. 2005. Developing a Bayesian network for clinical diagnosis in veterinary medicine: From the individual to the herd. In: *Proceedings of the Third Bayesian Modelling Applications Workshop*. Edinburgh, Citeseer.
- Gildemacher, P. R., Demo, P., Barker, I., Kaguongo, W., Woldegiorgis, G., Wagoire, W. W., et al. 2009. A description of seed potato systems in Kenya, Uganda and Ethiopia. *Am. J. Potato Res.* 86:373-382.
- Gildemacher, P. R., Leeuwis, C., Demo, P., Borus, D., Schulte-Geldermann, E., Mundia, P., et al. 2012. Positive selection in seed potato production in Kenya as a case of successful research-led innovation. *Int. J. Technol. Manag. Sustain. Dev.* 11:67-92.
- Gildemacher, P. R., Schulte-Geldermann, E., Borus, D., Demo, P., Kinyae, P., Mundia, P., et al. 2011. Seed potato quality improvement through positive selection by smallholder farmers in Kenya. *Potato Res.* 54:253-266.
- Grassini, P., van Bussel, L. G. J., Van Wart, J., Wolf, J., Claessens, L., Yang, H., et al. 2015. How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. *Field Crops Res.* 177:49-63.
- Hanemann, W. M. 1991. Willingness to pay and willingness to accept: How much can they differ? *Am. Econ. Rev.* 81:635-647.
- Hijmans, R. J., and Graham, C. H. 2006. The ability of climate envelope models to predict the effect of climate change on species distributions. *Glob. Change Biol.* 12:2272-2281.
- Hirshleifer, J., and Riley, J. G. 1979. The analytics of uncertainty and information-an expository survey. *J. Econ. Lit.* 17:1375-1421.
- Howes, A. L., Maron, M., and McAlpine, C. A. 2010. Bayesian networks and adaptive management of wildlife habitat: Bayesian networks and adaptive management. *Conserv. Biol.* 24:974-983.
- IFPRI and IIASA. 2016. Global Spatially-Disaggregated Crop Production Statistics Data for 2005. Version 3.2. International Food Policy Research Institute (IFPRI) and International Institute for Applied Systems Analysis (IIASA).
- Jaffee, S., and Srivastava, J. 1994. The roles of the private and public sectors in enhancing the performance of seed systems. *World Bank Res. Obs.* 9:97-117.
- Johnson, F. A., Smith, B. J., Bonneau, M., Martin, J., Romagosa, C., Mazzotti, F., et al. 2017. Expert elicitation, uncertainty, and the value of information in controlling invasive species. *Ecol. Econ.* 137:83-90.
- Jones, R. A. C., Salam, M. U., Maling, T. J., Diggle, A. J., and Thackray, D. J. 2010. Principles of predicting plant virus disease epidemics. *Annu. Rev. Phytopathol.* 48:179-203.
- Kaguongo, W., Gildemacher, P., Demo, P., Wagoire, W., Kinyae, P., Andrade, J., et al. 2008. Farmer practices and adoption of improved potato varieties in Kenya and Uganda. International Potato Center, Lima, Peru.
- Kristensen, K., and Rasmussen, I. A. 2002. The use of a Bayesian network in the design of a decision support system for growing malting barley without use of pesticides. *Comput. Electron. Agric.* 33:197-217.
- Kromann, P., Andrade-Piedra, J. L., Navarrete, I., Taipe, A., and Gómez, J. 2017. Dataset for: Potato seed degeneration in Ecuador. *Int. Potato Cent.* V2.
- Lang, M., Binder, M., Richter, J., Schratz, P., Pfisterer, F., Coors, S., Au, Q., Casalichio, G., Kothhoff, L., and Bischl, B. 2019. mlr3: A modern object-oriented machine learning framework in R. *Journal of Open Source Software*. <https://joss.theoj.org/papers/10.21105/joss.01903>
- Langemeier, C. B., Robertson, A. E., Wang, D., Jackson-Ziems, T. A., and Kruger, G. R. 2017. Factors affecting the development and severity of Goss's bacterial wilt and leaf blight of corn, caused by *Clavibacter michiganensis* subsp. *nebraskensis*. *Plant Dis.* 101:54-61.
- Laurance, W. F., Clements, G. R., Sloan, S., O'Connell, C. S., Mueller, N. D., Goosem, M., et al. 2014. A global strategy for road building. *Nature* 513:229-232.
- Lave, L. B. 1963. The value of better weather information to the raisin industry. *Econometrica* 31:151-164.
- Leeuwis, C., and Aarts, N. 2011. Rethinking communication in innovation processes: Creating space for change in complex systems. *J. Agric. Educ. Ext.* 17:21-36.
- Lobell, D. B., Cassman, K. G., and Field, C. B. 2009. Crop yield gaps: their importance, magnitudes, and causes. *Annu. Rev. Environ. Resour.* 34:179-204.
- Lobell, D. B., Thau, D., Seifert, C., Engle, E., and Little, B. 2015. A scalable satellite-based crop yield mapper. *Remote Sens. Environ.* 164:324-333.
- Louwaars, N. P., de Boef, W. S., and Edeme, J. 2013. Integrated seed sector development in Africa: A basis for seed policy and law. *J. Crop Improv.* 27:186-214.
- Macauley, M. K. 2006. The value of information: Measuring the contribution of space-derived earth science data to resource management. *Space Policy* 22:274-282.
- Margosian, M. L., Garrett, K. A., Hutchinson, J. S., and With, K. A. 2009. Connectivity of the American agricultural landscape: Assessing the national risk of crop pest and disease spread. *BioScience* 59:141-151.
- Mburu, H., Cortada, L., Mwangi, G., Gitau, K., Kiriga, A., Kinyua, Z., et al. 2018. First report of potato cyst nematode *Globodera pallida* infecting potato (*Solanum tuberosum*) in Kenya. *Plant Dis.* 102:1671.
- McEwan, M. A., Almekinders, C. J. M., Andrade-Piedra, J. L., Delaquis, E., Garrett, K. A., Kumar, L., Mayanja, S., Omondi, B. A., Rajendran, S., and Thiele, G. 2021. "Breaking through the 40% adoption ceiling: Mind the seed system gaps." A perspective on seed systems research for development in One CGIAR. *Outlook Agric.* 50:5-12.
- McGuire, S., and Sperling, L. 2013. Making seed systems more resilient to stress. *Glob. Environ. Change* 23:644-653.
- McGuire, S., and Sperling, L. 2016. Seed systems smallholder farmers use. *Food Secur.* 8:179-195.
- McQuaid, C. F., Sseruwagi, P., Pariyo, A., and van den Bosch, F. 2016. Cassava brown streak disease and the sustainability of a clean seed system. *Plant Pathol.* 65:299-309.
- McQuaid, C. F., van den Bosch, F., Szyniszewska, A., Alicai, T., Pariyo, A., Chikoti, P. C., et al. 2017. Spatial dynamics and control of a crop pathogen with mixed-mode transmission. *PLOS Comput. Biol.* 13:e1005654.
- Mwangi, J. M., Kariuki, G. M., Wakeke, J. W., and Grudler, F. M. 2015. First report of *Globodera rostochiensis* infesting potatoes in Kenya. *New Dis. Rep.* 31:18.
- Nagarajan, R., Scutari, M., and Lèbre, S. 2013. Bayesian networks in R with applications in systems biology. Springer-Verlag, New York.
- Nakato, G. V., Beed, F., Bouwmeester, H., Ramathani, I., Mpiira, S., Kubiriba, J., et al. 2016. Building agricultural networks of farmers and scientists via mobile phones: Case study of banana disease surveillance in Uganda. *Can. J. Plant Pathol.* 38:307-316.
- Novak, M. P., and LaDue, E. 1999. Application of recursive partitioning to agricultural credit scoring. *J. Agric. Appl. Econ.* 31:109-122.
- Okello, J. J., Lagerkvist, C. J., Kakuhenzire, R., Parker, M., and Schulte-Geldermann, E. 2018. Combining means-end chain analysis and goal-priming to analyze Tanzanian farmers' motivations to invest in quality seed of new potato varieties. *Br. Food J.* 120:1430-1445.
- Parsa, S., Morse, S., Bonifacio, A., Chancellor, T. C. B., Condori, B., Crespo-Perez, V., et al. 2014. Obstacles to integrated pest management adoption in developing countries. *Proc. Natl. Acad. Sci.* 111:3889-3894.
- Paul, P. A., and Munkvold, G. P. 2004. A model-based approach to preplanting risk assessment for gray leaf spot of maize. *Phytopathology* 94:1350-1357.
- Perez-Ariza, C. B., Nicholson, A. E., and Flores, M. J. 2012. Prediction of coffee rust disease using Bayesian networks. Pages 259-266 in: *Proceedings of the Sixth European Workshop on Probabilistic Graphical Models*.
- Petsakos, A., Hareau, G., Kleinwechter, U., Wiebe, K., and Sulser, T. B. 2018. Comparing modeling approaches for assessing priorities in international agricultural research. *Res. Eval.* 27:145-156.
- Phillips, C. B., Kean, J. M., Vink, C. J., and Berry, J. A. 2018. Utility of the CLIMEX 'match climates regional' algorithm for pest risk analysis: an evaluation with non-native ants in New Zealand. *Biol. Invasions* 20:777-791.
- R Core Team. 2021. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>
- Reynolds, M., Kropff, M., Crossa, J., Koo, J., Kruseman, G., Molero Milan, A., et al. 2018. Role of modelling in international crop research: Overview and some case studies. *Agronomy (Basel)* 8:291.
- Rhys, H. I. 2020. Machine Learning with R, the tidyverse, and mlr. Manning Publications, Shelter Island, New York.

- Schulte-Geldermann, E., Gildemacher, P. R., and Struik, P. C. 2012. Improving seed health and seed performance by positive selection in three Kenyan potato varieties. *Am. J. Potato Res.* 89:429-437.
- Schulthess, U., Timsina, J., Herrera, J. M., and McDonald, A. 2013. Mapping field-scale yield gaps for maize: An example from Bangladesh. *Field Crops Res.* 143:151-156.
- Shea, K., Tildesley, M. J., Runge, M. C., Fonnesbeck, C. J., and Ferrari, M. J. 2014. Adaptive management and the value of information: Learning via intervention in epidemiology ed. Andrew P. Dobson. *PLOS Biol.* 12:e1001970.
- Sheppard, C. S., Burns, B. R., and Stanley, M. C. 2014. Predicting plant invasions under climate change: Are species distribution models validated by field trials? *Glob. Change Biol.* 20:2800-2814.
- Silva, J. V., Reidsma, P., Laborte, A. G., and van Ittersum, M. K. 2017. Explaining rice yields and yield gaps in Central Luzon, Philippines: An application of stochastic frontier analysis and crop modelling. *Eur. J. Agron.* 82:223-241.
- Smith, C. S., Howes, A. L., Price, B., and McAlpine, C. A. 2007. Using a Bayesian belief network to predict suitable habitat of an endangered mammal—The Julia Creek dunnart (*Sminthopsis douglasi*). *Biol. Conserv.* 139:333-347.
- Sperling, L. 2008. When Disaster Strikes: A guide to assessing seed system security. International Center for Tropical Agriculture. Cali, Columbia.
- Sperling, L., Ortiz, O., and Thiele, G. 2013. Seed systems. Conceptual frameworks for guiding practical interventions. CGIAR.
- Stolar, J., and Nielsen, S. E. 2015. Accounting for spatially biased sampling effort in presence-only species distribution modelling. *Divers. Distrib.* 21:595-608.
- Sutherst, R. W., and Maywald, G. F. 1985. A computerised system for matching climates in ecology. *Agric. Ecosyst. Environ.* 13:281-299.
- Sutton, N. J., and Armsworth, P. R. 2014. The grain of spatially referenced economic cost and biodiversity benefit data and the effectiveness of a cost targeting strategy: spatial grain in conservation planning. *Conserv. Biol.* 28:1451-1461.
- Therneau, T., and Atkinson, B. 2019. rpart: Recursive Partitioning and Regression Trees. R package version 4.1-15.
- Thomas-Sharma, S., Abdurahman, A., Ali, S., Andrade-Piedra, J., Bao, S., and Charkowski, A., et al. 2016. Seed degeneration in potato: The need for an integrated seed health strategy to mitigate the problem in developing countries. *Plant Pathol.* 65:3-16.
- Thomas-Sharma, S., Andrade-Piedra, J., Carvajal Yepes, M., Hernandez Nopsa, J. F., Jeger, M. J., Jones, R. A. C., et al. 2017. A risk assessment framework for seed degeneration: informing an integrated seed health strategy for vegetatively propagated crops. *Phytopathology* 107:1123-1135.
- Tittonell, P., and Giller, K. E. 2013. When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. *Field Crops Res.* 143:76-90.
- Tulloch, A. I. T., Tulloch, V. J. D., Evans, M. C., and Mills, M. 2014. The value of using feasibility models in systematic conservation planning to predict landholder management uptake: management feasibility models. *Conserv. Biol.* 28:1462-1473.
- van Bussel, L. G. J., Grassini, P., Van Wart, J., Wolf, J., Claessens, L., Yang, H., et al. 2015. From field to atlas: Upscaling of location-specific yield gap estimates. *Field Crops Res.* 177:98-108.
- van Ittersum, M. K., van Bussel, L. G. J., Wolf, J., Grassini, P., van Wart, J., Guilpart, N., et al. 2016. Can sub-Saharan Africa feed itself? *Proc. Natl. Acad. Sci.* 113:14964-14969.
- van Wart, J., Kersebaum, K. C., Peng, S., Milner, M., and Cassman, K. G. 2013a. Estimating crop yield potential at regional to national scales. *Field Crops Res.* 143:34-43.
- van Wart, J., van Bussel, L. G. J., Wolf, J., Licker, R., Grassini, P., Nelson, A., et al. 2013b. Use of agro-climatic zones to upscale simulated crop yield potential. *Field Crops Res.* 143:44-55.
- Wang, C., Hawthorne, D., Qin, Y., Pan, X., Li, Z., and Zhu, S. 2017. Impact of climate and host availability on future distribution of Colorado potato beetle. *Sci. Rep.* 7:4489.
- Wiebe, K., Zurek, M., Lord, S., Brzezina, N., Gabrielyan, G., Libertini, J., et al. 2018. Scenario development and foresight analysis: Exploring options to inform choices. *Annu. Rev. Environ. Resour.* 43:545-570.
- Wilson, E. C. F. 2015. A practical guide to value of information analysis. *Pharmacoeconomics* 33:105-121.
- Xing, Y., Hernandez Nopsa, J. F., Andersen, K. F., Andrade-Piedra, J., Beed, F. D., Blomme, G., Carvajal Yepes, M., Coyne, D. L., Cuellar, W. J., Forbes, G. A., Kreuzer, J. F., Kroschel, J., Kumar, P. L., Legg, J. P., Parker, M., Schulte-Geldermann, E., Sharma, K., and Garrett, K. A. 2020. Global cropland connectivity: A risk factor for invasion and saturation by emerging pathogens and pests. *BioScience* 70:744-758.
- You, L., Crespo, S., Guo, Z., Koo, J., Ojo, W., Sebastian, K., et al. 2012. MapSpaM—Home of the Spatial Production Allocation Model. <https://mapspam.info/>