

The effects of climate variability and the color of weather time series on agricultural diseases and pests, and on decisions for their management

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ABSTRACT

If climate change scenarios include higher variance in weather variables, this can have important effects on pest and disease risk beyond changes in mean weather conditions. We developed a theoretical model of yield loss to diseases and pests as a function of weather, and used this model to evaluate the effects of variance in conduciveness to loss and the effects of the color of time series of weather conduciveness to loss. There were two qualitatively different results for changes in system variance. If median conditions are conducive to loss, increasing system variance decreases mean yield loss. On the other hand, if median conditions are intermediate or poor for disease or pest development, such that conditions are conducive to yield loss no more than half the time, increasing system variance increases mean yield loss. Time series for weather conduciveness that are darker pink (have higher levels of temporal autocorrelation) produce intermediate levels of yield loss less commonly. A linked model of decision-making based on either past or current information about yield loss also shows changes in the performance of decision rules as a function of system variance. Understanding patterns of variance can improve scenario analysis for climate change and help make adaptation strategies such as decision support systems and insurance programs more effective.

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1. Introduction

Understanding and managing the effects of agricultural pests and diseases are major challenges. As a world-wide average, the potential crop yield loss to animal pests and pathogens has been estimated at 18% and 16%, respectively (Oerke, 2006). In livestock, total losses to trypanosomosis alone are estimated at US\$1.3–5 billion (McDermott and Coleman, 2001). Thus, effective management of pests and pathogens is key for making efficient use of natural resources, maintaining income and assets for farmers by reducing losses, and keeping food prices affordable enough to maintain food security. The best form of management is often use of disease and pest resistant varieties or breeds, where development of a new crop variety typically requires a decade and development of new livestock breeds is much slower; benefits of research

may take 40 years to be realized (Alston et al., 2009; Pardey et al., 2006). Where inadequate or no sources of resistance have been found in established crop germplasm, other forms of crop protection are needed to keep pests under control. The development and implementation of new integrated pest management (IPM) strategies are time consuming and the resulting time lag in response to pest and disease problems is one motivation for understanding how climate change will influence pest and disease risk. Several biological features of pests and diseases increase the challenges of predicting the effects of climate change, including the potential for more frequent weather extremes to have particularly strong effects (Coakley, 1979; Rosenzweig et al., 2001).

1.1. Changes in variability and the color of weather time series

Climatic variability and climate extremes have direct effects on crop yield (Challinor et al., 2007; Orlandini et al., 2008; Porter and Semenov, 2005; Trnka et al., 2011; Wheeler et al., 2000). They also have an effect on diseases and pests beyond the effect of changes in mean weather variables (Chaves et al., 2012; Coakley,

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1979; Kriss et al., 2012; Rohr and Raffel, 2010; Scherm and van Bruggen, 1994; Scherm and Yang, 1995). More common occurrence of climate extremes, or potentially new extremes, can also cause a range of problems (Rosenzweig et al., 2001). If extremes become more common, new models may be necessary, if the observed trend of climate change is completely different from climatological averages. ‘Non-analog climates’ are climatic conditions that do not presently exist (Fitzpatrick and Hargrove, 2009). In this context, forecasting future distributions of diseases and pests from current known species climate relationships is highly problematic. This is because the observed distribution of diseases and pests alone provides no clear information about how the species might respond under completely novel environmental conditions (Fitzpatrick and Hargrove, 2009). Thus, model outputs based on extrapolations may lead to substantial errors in managing disease and pest invasions and climate change impacts.

Because of the spatial and temporal correlation imposed by pests and diseases, the effects of climate extremes can extend well beyond the season in which they occur; for example, the inoculum load remaining at the end of a season often strongly affects the inoculum load at the beginning of the next season. For pests or pathogens whose range expansion is limited by conditions for initial establishment, extreme conditions can make new leaps possible. Long distance transport is an important factor in the introduction of new pests and pathogens, and in the annual migrations that many pests or pathogens such as rust fungi make each year to reinvade areas where they cannot overwinter (Li et al., 2010). Extreme storm events that spread pathogens more rapidly will have long-lasting effects. Extremely favorable conditions may also ‘unleash’ new pests/diseases that normally only have minor effects, in addition to making typical pests/diseases more problematic. From managers’ perspectives, there is a qualitative difference in adjusting to greater pressure of a known pest or disease compared to preparing to manage a new pest/disease.

El Niño events, which are similar but likely even more extreme than expected mean temperature changes under climate change, have had a great impact on the abundance and severity of pests and disease in South America. For example, during the 1997 El Niño phenomenon in Peru, mean temperature on the Peruvian coast increased by about 5 °C above the annual average. While infestation of potato by the leafminer fly (*Liriomyza huidobrensis*) decreased, the abundance and infestation severity of all other pests (e.g., the bud midge, *Prodiplosis longifila*; potato tuber moth, *Phthorimaea operculella*; white fly, *Bemisia tabaci*) increased in all agricultural and horticultural crops. The farmers’ only adaptive strategy to cope was applying high doses of pesticide every 2–3 days (Cisneros and Mujica, 1999). It can be expected that climate change consequences and farmers’ future needs for adaptation in other parts of the tropics will be quite similar to such effects observed during El Niño (Kroschel et al., 2010).

Pathogen responses to environment often provide good examples of the importance of climatic extremes and weather, rather than climate per se. Anthrax and Foot and Mouth Disease (FMD) both have a near-worldwide distribution, but episodes of climate variation may prompt sudden emergence or spread. The causative bacteria of Anthrax, *Bacillus anthracis*, form spores that may remain infective for 10–20 years (Baylis and Githeko, 2006). Heavy rainfall stirs up the spores, and a preceding drought event often triggers disease outbreaks (Parker et al., 2002). FMD in dry regions of Africa spreads almost entirely by direct contact (Sutmoller et al., 2003), but can travel several kilometers given cool and humid conditions; wind-borne spread is an essential component in epidemiologic models where such conditions exist (Garner et al., 2006; Rubel and Fuchs, 2005; Sørensen et al., 2000). The economically important viral disease Peste des Petits Ruminants (PPR) appears to be most

prevalent immediately prior to seasonal peaks of rainfall (Wosu et al., 1992) which may reflect optimal conditions for viral survival (Baylis and Githeko, 2006).

The color of an environmental time series refers to how strongly correlated a variable is in time, and whether the correlation is positive or negative. White noise has no correlation in time, such that an environmental variable would have no correlation from one time to another. Blue noise has a negative correlation from one time to the next and so will tend to have high frequency oscillations. Increasing positive correlations between time points yield pink, red, and brown noise, with a tendency to have lower frequency oscillations (examples in Fig. 1). Some degree of positive correlation is often realistic for many variables such as temperature, depending on the resolution and extent considered (Rohani et al., 2004; Vasseur and Yodzis, 2004). Positive correlation will also tend to be more common for epidemic and other population processes, even in a constant environment, especially in the absence of complicating factors such as induced resistance. The color of an environmental time series and associated population time series may logically be related (García-Carreras and Reuman, 2011; Ruokolainen et al., 2009; Wilmers et al., 2007). García-Carreras and Reuman (2011) concluded that climate variables have become relatively bluer over the past century (on an annual basis), such that higher frequency oscillations may also be observed for populations affected by weather.

1.2. Early warning systems/decision support systems

The potential for within-season decision-making by farmers has been a driver for the development of many models of pest and disease risk. Early warning systems (EWS) or decision support systems (DSS) are used to advise farmers when the risk is high or low for a particular pest or disease vector at a specific period of the year. Weather variables are an important part of most EWS and DSS (Table 1). When information about risk is available to farmers (particularly when made available through participatory means, combining analytical and experiential learning (Marx et al., 2007)), they can decide on appropriate actions to be taken, such as making an insecticide application or not, deciding what type of chemical to use, and determining when to spray. Hence, EWS data are used as a tool to judge the relative risk that farmers may experience in the near future and when that risk is likely to occur. Early detection tools in this context can be subdivided in distinct groups depending on the information used for developing the EWS. Within-season forecasting models can also be rescaled for application at greater spatial extents, such as in climate change scenario analysis (Sparks et al., 2011).

The expected increase in climate variability in many regions can increase the need for early warning systems to support agricultural decision makers (Dury et al., 2011; Giorgi et al., 2004; Haylock and Goodess, 2004; Meinke and Stone, 2005; Rosenzweig et al., 2001; Rowell, 2005; Seneviratne et al., 2006). Larger differences among consecutive years, as well as among different weeks of the same year, can make decision-making more difficult and can reduce the value of previous experience. The use of models can support warning systems, especially when they are based on mechanistic approaches describing the physiological relationships between pest/disease and host. Models tend to be of the greatest utility when conditions are neither consistently conducive nor consistently non-conductive to pests and disease. As a result, decision makers who do not have access to robust and reliable model output are likely to experience more difficulty under higher variability. Higher variability in environmental conditions may also make it less likely that farmers adopt resistant varieties if consistent benefits cannot

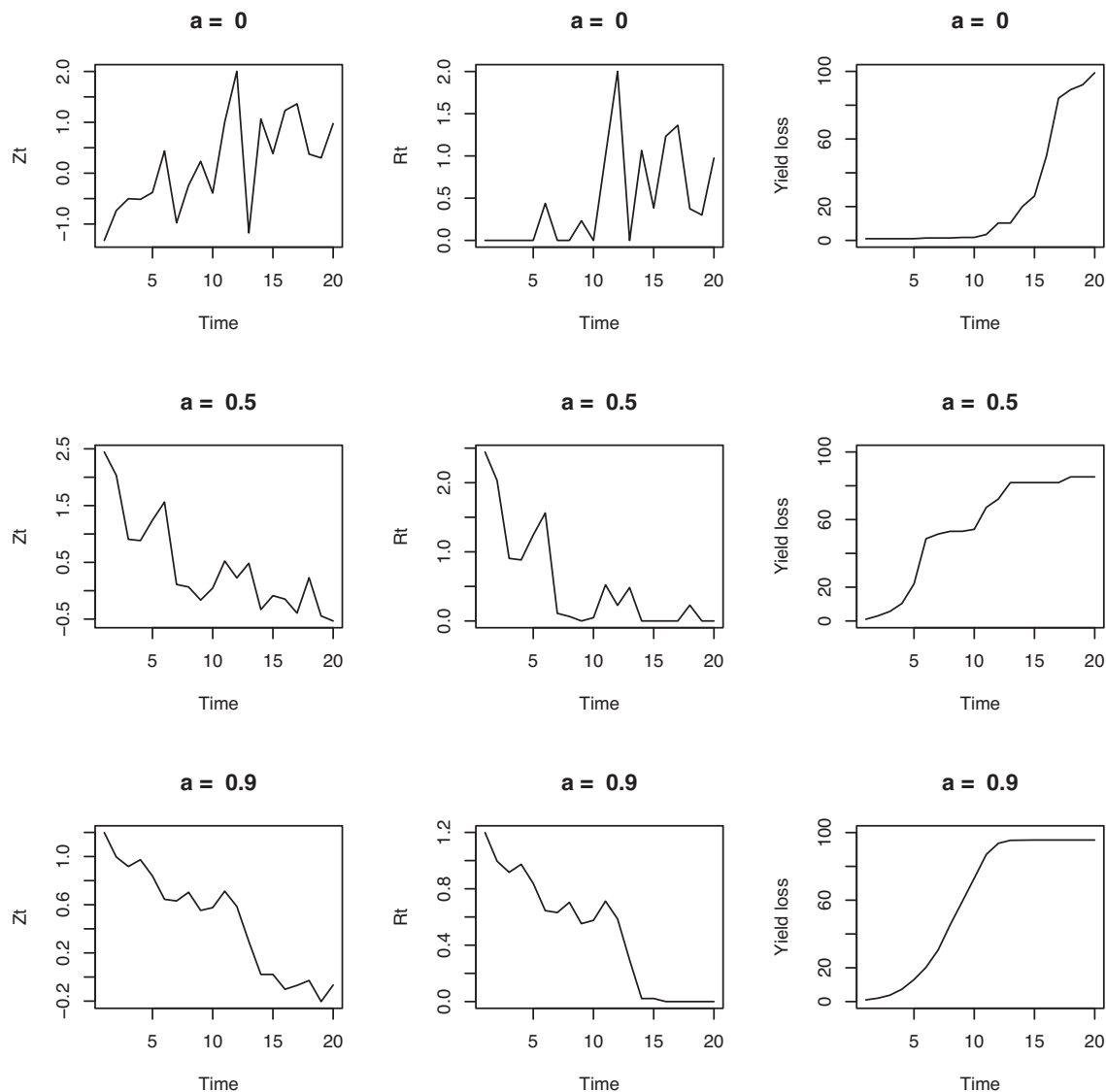


Fig. 1. Examples of the time series generated by the yield loss model. When $a=0$, the Z_t series is white noise. When $a=0.5$ or $a=0.9$, the Z_t series is lighter pink and darker pink noise. As a increases, the greater level of temporal autocorrelation produces a smoother series Z_t . In the no-yield-recovery model, the R_t series of 'weather conduciveness to yield loss from pests or diseases' (from Eq. (1)) has 0 as a minimum value. The resulting cumulative yield loss series (from Eq. (2)) also tend to be smoother for higher a . The examples shown here are for $m=0$ and $\sigma^2=1$ in the no-yield-recovery model.

be readily observed (Garrett et al., 2011) as for drought tolerance (Lybbert and Bell, 2010).

1.3. Decision-making for pest and disease management

When models of productivity, and productivity losses to diseases or pests, are applied in future scenario analyses, another important source of uncertainty is how well people will manage diseases and pests. Higher pest and disease risk imposes greater demands on all people involved in agricultural production, from plant breeders, entomologists and plant pathologists to extension agents and farmers. The demands will be higher on farmers in systems where support from research and extension is not readily available. The question remains whether effective management will be widely implemented, and whether management can be formulated so that it does not substantially reduce profitability or reduce other ecosystem services. Behavioral models of decision-making at the farm level for the context of fragile environments are not yet well developed (Hertel and Rosch, 2010). Moreover, the spatial and temporal correlation resulting from potential pest

and disease spread means that decisions made by some parties will influence pest and disease problems experienced by other parties.

The study of risk assessment, perceptions, communication, and management, developed in response to challenges presented by increasingly technologically-oriented societies (Covello, 1983; Kates and Kasperson, 1983; Slovic, 1987), has provided insight into how people make decisions under risk and uncertainty. Risk perception rather than actual risk is relevant to decision-making (Gent et al., 2011; McRoberts et al., 2011; Slovic and Weber, 2002). Farmers base their crop and livestock decisions on local knowledge systems, resulting from years of observations, experiences, and experiments (Bharara and Seeland, 1994; Gilles and Valdivia, 2009; Marx et al., 2007). In Argentina, farmers faced with uncertainty and risk in a La Niña event were able to handle at most one adaptation decision (Hansen et al., 2004). The degree of dread, fearfulness or gut feeling of angst, in response to hazards such as pests and diseases is an important factor. Andean farmers in three regions of the Andes experiencing climate variability and change had different responses to their sense of dread to hazards, even within communities. This was a function of the resources they had

Table 1

General effects of weather/climate on livestock and crop productivity (in the absence of pests and disease), disease impacts, and arthropod pest impacts.

	Livestock	Crop	Pathogen	Arthropod
Weather variables				
Temperature	Will affect water requirements and health due to heat stress	Affects assimilation rate and phenological phases	Important for determining the rate of infection or development processes	Broadly important for development, survival and reproduction
Precipitation	Indirect through importance for growth of pastures	Important for growth	Proxy for surface wetness and responsible for spore spread in the environment	Affects population dynamics and is key for development of mosquitoes, midges
Photoperiod	Indirect through importance for growth of pastures	Important for vegetative and generative crop development	Affects development of some pathogens	Affects insect development
Solar radiation		Affects plant growth and phenotype	Affects survival of pathogens, particularly wind-dispersed spores	Influences survivorship and egg reproduction and herbivory in plant insect interactions
Surface wetness	Will affect foot health from non-communicable diseases		Key for many foliar diseases (high resolution often used)	
Relative humidity	Will affect water requirements	Important for evapotranspiration	Proxy for surface wetness	Important for survival and activity of ticks and insects especially parasitoids
Soil moisture		Broadly important	Key for many soil-borne plant diseases	Important for insects pupating in soil; may affect tick response to air humidity
Speed of response to weather shifts and extremes	Managers' change to better adapted breeds may be very slow	Change to resistant varieties or species be slow	Rapidly take advantage of conducive extremes	Rapidly take advantage of conducive extremes
Resolution for decision support models				
Spatial	Typically farm-scale, with potential for scaling up	From field to regional and global scale	From field to regional and global scale	From field to regional and global scale
Temporal	Medium- to long-term	Daily or monthly	Hourly or daily	Daily or weekly
Autocorrelation				
Spatial	Low	Low	Potentially high	Potentially high
Temporal	Higher for long-lived animals	Higher for perennials	Potentially high	Potentially high
Model longevity/portability/generalizability (without need for changes in parameters)				
Spatial	Medium	Medium	Low (affected by the hourly temporal resolution)	Lower
Temporal	Longer	Longer	Potentially extremely short	Shorter
Typical farmer knowledge level	High	High	Lower	Moderate

or could access and of the geographical location (Valdivia et al., 2010). It is possible to quantify and predict risk perception in terms of the amount of dread a risk produces, and the amount of knowledge about risks (Hinman et al., 1993; Marks, 2001; Slovic, 1987) and how culture shapes risk perceptions (Gobel, 2002; Johnson and Covello, 1987). People assess risks using rules based systems and association/experiential based systems (Marx et al., 2007; Slovic and Weber, 2002). When the results of these are in conflict, people tend to rely on the associational since past experiences are often more memorable and dominant (Slovic et al., 2002). This is specially the case when the dread of an event is high.

Marx et al. (2007) discuss how decision makers use different types of information. There is a tendency to weight recent experience, such as the last five years. If rare events have not occurred recently, they are given less weight, while people may overreact to recent rare events. This response may be adaptive if the system is changing in a directed manner. People tend to respond to vivid events rather than to statistical information. The 'availability heuristic' makes people tend to assume that the future will be similar to what they have experienced so far.

1.4. Objectives

Scherm and van Bruggen (1994) have previously shown how increasing amplitude in a weather variable such as temperature, compared to a constant temperature, can result in a substantially

different pathogen growth response. Models of human diseases have also evaluated the effect of weather variability (Chaves et al., 2008; Dobson, 2009; Pascual et al., 2008a,b). Here we design a generic model of disease/pest responses to weather variability to address related fundamental questions about the role of variability and extremes in disease/pest management scenarios. It is not designed to be a realistic model for any given system, but we have tried to incorporate many of the most important features of a range of systems, both animal and plant (Borer et al., 2012; Wilkinson et al., 2011), to produce general results. We use the model to provide insights into the following questions and generate hypotheses about these relationships.

- How are losses to diseases/pests affected by changing variability in weather conduciveness, and by changing the color of noise associated with weather conduciveness?
- How does a decision-maker's choice of current versus past information affect losses and profit in these different types of environments?

These weather scenarios can inform the construction of ensemble models, where predictions from several models are pooled, by providing different types of variation, and illustrating the effects of variation on disease/pest impacts.

2. A model of the effects of climate variation

2.1. Effects of climate variation on yield loss to diseases and pests

2.1.1. How are losses to diseases/pests affected by changing variability in weather conduciveness, and by changing the color of noise associated with weather conduciveness?

Weather conduciveness to diseases/pests is a function of a number of weather variables (Table 1). This models starts at the point where the set of relevant weather variables has already been converted to a single measure of conduciveness. In this weather model, the time series model for 'general weather conduciveness to a disease/pest' R_t corresponds to

$$R_t = m_t + Z_t, \quad (1)$$

where m_t captures the trend associated with weather conduciveness. A constant mean weather conduciveness is captured by setting m_t to a constant. Alternately, linear or polynomial trends can be used to reflect expected weather conduciveness as a function of time t . If m_t takes a higher positive value, conducive conditions such that $R_t > 0$ become more common; if m_t is a lower negative number, conducive conditions become rarer. Z_t is the stationary residual that can be modeled as an autoregressive or moving average process to capture the correlation between weather conduciveness at different times. For example, a first order autoregressive model for Z_t corresponds to $Z_t = aZ_{t-1} + (1-a)W_t$, where $|a| < 1$ and W_t is normally distributed mean zero white noise with variance σ^2 . Z_t is a colored noise series when a is nonzero and white noise when a is zero (Fig. 1).

The time series for weather conduciveness is converted to a time series of cumulative yield loss (Y_t) due to the disease/pest, using a logistic growth model. The logistic model incorporates an increase in growth rate over time, until the yield loss begins to approach the maximum possible.

$$Y_0 = 1$$

$$Y_t = \begin{cases} 0 & \text{if } Y_{t-1} < 0 \\ Y_{t-1} + R_t Y_{t-1} \left(1 - \frac{Y_{t-1}}{100}\right) & \text{if } 0 \leq Y_{t-1} \leq 100 \\ 100 & \text{if } Y_{t-1} > 100 \end{cases} \quad (2)$$

where 1 is the starting yield loss condition, 100 is the maximum loss, and the weather conduciveness variable functions as a rate parameter. In the context of livestock, this model would be relevant where 'cumulative yield loss' indicates the proportion of a herd that is infected with a disease burden above a certain threshold. The burden could be due, for example, either to pathogens, such as trypanosomes, or to internal parasites, such as helminths. Just as the weather conduciveness variable subsumes a number of processes, so too does the cumulative yield loss variable: the many processes that lead to pathogen/pest reproduction and the effects of that reproduction on host productivity. Note that the cumulative yield loss can become smaller over time if conditions do not support pest/pathogen development, which would be realistic for scenarios where hosts can recover and compensate for earlier losses. For systems where recovery from yield loss is not realistic, we also include a *no-yield-recovery* model variation where values of $R_t < 0$ are set to 0 (Fig. 1).

It is clear from Eq. (2) that the yield loss is also a stochastic process as it depends on the weather conduciveness at each time instant. By analyzing the statistical behavior of the Y_t process, we can obtain insights into how the mean and the variance of weather conduciveness impact the expected yield loss and its variance. Because of the recursive relationship in (2), analytical derivation of the distribution of Y_t becomes intractable as t increases. However, the mean and variance of Y_t can be derived analytically for small values of t with the algebraic complexity of this derivation

growing with t . From these derivations (along with an inspection of Eq. (2)), we observe an expected behavior – i.e., increasing the mean and variability of the weather conduciveness increases the mean and variability of the yield loss process. However, the exact relationship between the means and the variances is not trivial. In fact, it is easy to show that the mean of the yield loss process at time t ($t > 1$) actually depends both on the mean and the variance of the weather conduciveness process! Furthermore, thanks to the recursive relationship in Eq. (2), we observe that the variance of the yield loss process keeps growing with time t . That is, the variability of the weather conduciveness creates larger variability in the model predicted yield loss for higher values of t . Since analytical derivations of the distribution as well as means and variance get prohibitively complex with increasing t , we used Monte Carlo simulations to characterize the mean and variance of Y_t .

We evaluated the effects of varying σ^2 , the variance of the W_t , across values from near 0 to 9 crossed with the effects of varying m , the mean of R_t , from -2 to 2 for 10 time steps in 1000 simulations at each combination of values using the R programming environment (R Development Core Team, 2011). R script generating the analyses in the figures in this paper is available at <http://hdl.handle.net/2097/13786>. We also crossed the different values for σ^2 and m with a range of values for the coefficient a to compare the effects of a white noise ($a = 0$), light pink ($a = 0.5$), and a darker pink ($a = 0.9$) series. The values of W_t were generated using the normal random number generator `rnorm` in R. The first term of the series was assigned a normal random variable with mean m and variance σ^2 , and the first 100 values of Z_t were discarded before the R_t were generated. The length of the potentially conducive season, in terms of the number of generations, may change because the actual number of days increases or because the generation time changes as a function of changing climate. We interpret the length of the season and the potential yield loss broadly, not necessarily in terms of yield in a single field/herd, but for a location as a whole, where for example there might be multiple overlapping generations of annual crop hosts in different nearby fields.

2.2. Effects of climate variation on farmer decision-making

2.2.1. How does a decision-maker's choice of current versus past information affect losses and profit in these different types of environments?

In the above analyses, yield losses are presented without explicit consideration of management to reduce effects. Here we incorporate the effects of decision-making by managers in a model that compares the results for different types of information managers might choose to use. Suppose a manager must decide whether or not to impose a type of management (such as crop tillage, biocontrol application, or pesticide application) in the middle of a season, in the context of a 10-generation model. The management has a cost to the manager equivalent to 20% of the yield. Its benefit is to reduce R_t to 0 for three time steps.

In this model, the manager can draw on two types of information. First, the final yield loss from three previous years is one form; the decision rule associated with those three years is 'if final yield loss exceeded 20% in two or more of the three previous years, then management should be applied this year.' (For simplicity, we assume that the management treatment was not applied mid-season during those three years. Thus, interpreting high yield loss is complicated by lack of information about whether use of management would have been a good choice to reduce yield loss, or whether conduciveness was so high that management would have been wasted.) Second, the current midseason ($t = 5$ out of 10) yield loss (Y_5) is observed; the decision rule associated with the current yield loss is 'if current yield loss is greater than or equal to 5% but less than 80%, then management should be applied this year.' Note

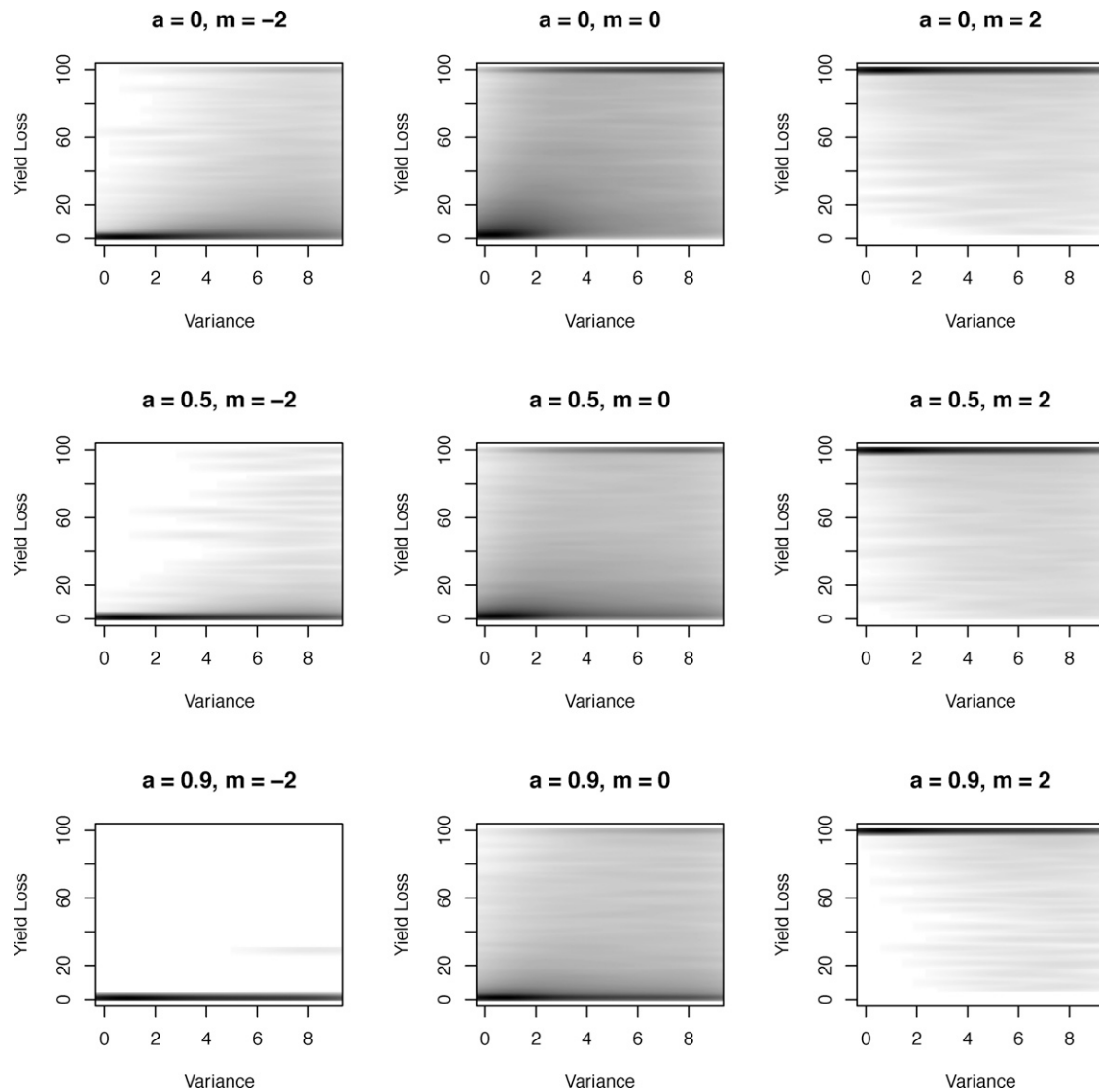


Fig. 2. Percentage yield loss (smoothed) for different values of a and m for the ‘no-yield-recovery’ model for 10 time steps (generations). When $a=0$, there is no temporal correlation, and temporal correlation increases with increasing a . When m is low, weather conduciveness to disease development is low.

that these management rules are not optimized for the available information, and the optimal rules could change with the underlying model parameter values. But we use these rules to examine the effects of different levels of weather variation on the relative success of these rules.

The success of a management decision was evaluated by comparing (a) the end of season yield loss (Y_{10}) without the management, to (b) the end of season yield loss with the management, and whether the benefit of management was greater than the cost of management. If the management decision resulted in a great enough reduction in yield loss, then it was a correct decision from the standpoint of optimizing profit (though not necessarily from a broader ecosystem services standpoint (Cheatham et al., 2009)). We emphasize that the decision rules are the same for all scenarios, and thus have not been optimized for each scenario, but serve to illustrate general properties of the scenarios.

We compared the success of the current versus past information for management decision models in 1000 simulated sets of four seasons per parameter combination, where the final season was evaluated both with and without the management treatment. We evaluated this for parameter combinations described above.

3. Model results

3.1. The effects of variance and the color of time series on yield loss to diseases and pests

The variance of the W_t and the color of the Z_t , determined by a , both influence yield loss (Fig. 2, generated using the R function `smoothScatter`). When the mean rate of yield loss, m_t , is -2 or 0 , higher variance results in higher yield loss. Figure 2 presents the ‘no-yield-recovery’ model, where the mean -2 and the mean 0 case are somewhat more similar, because values of the rate $R_t < 0$ are replaced by 0 so that the cumulative yield loss is monotonic increasing. When the mean rate is 2 , increasing variance in W_t decreases yield loss.

When a is 0 , Z_t is a white noise process. As a becomes larger, Z_t becomes a light pink and then darker pink series. For darker pink series, the ‘less typical’ yield loss results may become less common compared to the white noise series when the mean m_t is high (Fig. 2). For $m_t = 2$ after 10 time steps the yield loss tends to be near 100% for a white noise series, and for darker pink series the yield loss is rarely near zero when the variance is low. For lower values of the mean m_t , moving from white noise to pink noise results in

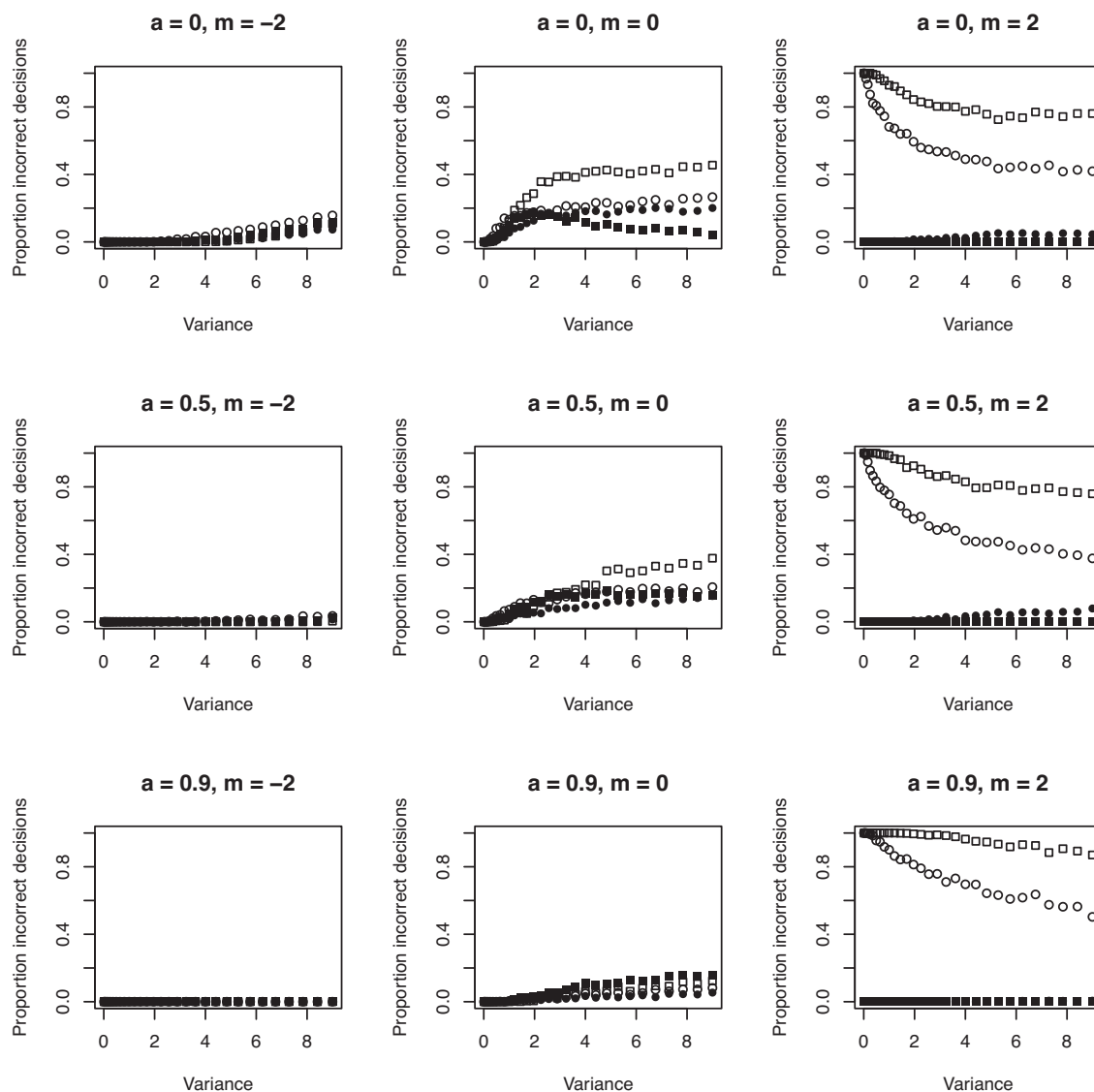


Fig. 3. Proportion incorrect decisions based on two different decision rules about use of mid-season management. When $a = 0$, there is no temporal correlation, and temporal correlation increases with increasing a . When m is low, mean weather conduciveness to disease development is low. Circles indicate performance of decision-making based on current information through the fifth of ten generations; squares indicate performance of decision-making based on past information from three previous years. Filled symbols indicate false negative decisions, such that management was not applied when it would have increased profit. Open symbols indicate false positive decisions, such that management was applied when it decreased profit.

zero yield loss becoming more common, even for higher variance (Fig. 2).

3.2. The effects of variance and the color of time series on farmer decision-making

For the lower mean conduciveness, such that disease or pest conducive conditions are relatively rare, increasing the system variance increases the rate of incorrect decisions after ten time steps (Fig. 3). False negative decisions, such that management is not applied when it would have been profitable, become more common with increasing variance, but then can decline again for white noise. False positive decisions, such that management is applied and results in a reduction in profit, become more common with increasing variance, though the rate of increase declines with higher variance. For system mean $m_t = 0$, the likelihood of false positive reactions becomes higher for the rules based on the past. For system mean $m_t = 2$, conditions are typically conducive enough that for low variance the rules are not optimized and typically result in

false positive responses that are not enough to reduce yield loss adequately. As variance increases, the performance of both types of decision rules improves as scenarios where they can provide benefits become more common. One important advantage of the decision rule based on current conditions is that it includes scouting to determine whether yield loss is already so high by the middle of the season that use of management is a lost cause. Darker pink noise decreases the effect of variance for the lower mean conduciveness cases. For the higher mean conduciveness case, darker pink noise reduces the effect of variance on the rate of false positive decisions for the rule based on current or past information.

4. Discussion

4.1. General results and variations on the model

Climate variability may have important effects on yield losses, independent of changes in mean conditions. This simple model shows how changing variance in weather conduciveness to yield

Table 2

The effects of changes in the probability distribution of weather conduciveness to pests, disease, and impacts.

Change in trait of weather conduciveness to pests and disease	Impact for pests and diseases	Impact for decision makers
Mean	Increasing mean weather conduciveness leads to higher mean potential yield losses	Increasing mean weather conduciveness may make a crop or breed uneconomic to produce
Variance	Increasing variance in weather conduciveness leads to higher mean potential yield losses if mean is low, and leads to lower mean potential yield losses if mean is high	Increasing variance in weather conduciveness increases the importance of good models (good decision rules) for decision makers
Color of noise	Darker pink, red, or brown noise results in longer strings of conducive or non-conductive conditions	Management decision-making can be more successful when conditions are more consistent

loss due to disease or pests (a function of multiple weather variables (Table 1)) can change the *mean* yield loss. If conditions are highly conducive to diseases/pests, increasing variance leads to a decrease in mean yield loss. For the highly conducive conditions, increasing variance also leads to more successful use of decision rules, in that decision rules can prove useful under higher variance while they rarely do under the consistently highly conducive conditions. Increasing variance for scenarios of low conduciveness to disease/pests leads to increases in the mean yield loss and poorer performance of decision rules. Additional forms of variation could also be explored, such as weather conduciveness with a distribution other than normal, where other distributions could have varying higher statistical moments such as skewness (a measure of asymmetry) and kurtosis (a measure of distribution ‘flatness’, or heaviness of distribution tails) (Chaves et al., 2012) (Table 2).

The decision scenario presented in the paper is meant to serve as an example of how one may use a generic model and extract useful information from it. The model in its current form is used to capture a natural phenomenon such as weather conduciveness and its direct impact on yield loss. Based on the model for the physical system, one can design an information, command and control system that serves as the decision maker. If we want to capture the effect of the decision process on the physical system, it is possible to update either R_t or Y_t with an additional “control” term U_t . The control term can be designed to capture the impact of complex decision processes. Z_t models a part of weather conduciveness that is not captured by the trend component. In practice, the exact model for Z_t will be dependent on the epidemic of interest. Our goal in this model was to present a generic framework and while simulations are presented for an autoregressive model with one time lag (AR(1)) for Z_t , the model could readily be modified to evaluate more general autoregressive and/or moving average models (ARMA(p,q)) or even non-stationary time series models for Z_t .

The general framework presented here can be modified to operate on multiple spatial and temporal scales. For example, the time index in the weather conduciveness time series R_t could indicate days, months, seasons or even years, where an oscillating component could represent seasonality in conduciveness and the changing probability of successful overwintering or oversummering. We did not explore the effects of neighboring locations on yield loss at a particular location. This could be evaluated using more mechanistic network models of pathogen or pest movement through space (Moslonka-Lefebvre et al., 2011), and potentially network models for the movement of opinion that modifies decision-making (Garrett, 2012). Alternatively, a relatively simpler two- or three-dimensional autoregressive model for yield loss might be used, where one dimension could be time. An important trait of pests and pathogens is the spatial correlation that they produce through their spread. Spatial autocorrelation can also influence patterns of yield loss, another influence to make loss similar across space and to buffer changes in loss over time (Margosian et al., 2009). In cases where there is increased variation in climate variables and associated increased variation in pathogen or

pest populations, local extinction may also become more common (García-Carreras and Reuman, 2011; Ruokolainen et al., 2009; Wilmers et al., 2007), so that future disease loss at any given location will depend on the spatial structure of conditions suitable to reintroduce pathogens or pests. Similarly, decision-making may also be correlated in space, as farmers compare results for purposes of decision-making, or where a single farmer has responsibility for a number of different fields. Drawing on the results of multiple processes can result in more informed decisions, but conformist social learning can cause group losses in variable environments (Whitehead and Richerson, 2009).

EWS and DSS are needed when a system is variable: if a pathogen or pest is always a problem, or never a problem, there is no need for predictions. The number of cases with yield loss between the bounds 0 and 100 (in the absence of management) increases as the variance increases in the yield loss model (Fig. 2). Good EWS and DSS will be particularly important if the variance in weather conduciveness increases as part of climate change. While it is desirable to minimize both false positives and negatives, in practice one comes at the cost of the other. So, typically, decision rules are designed such that one of the two metrics is minimized while constraining the other to be less than some reasonable acceptable level. This is the basis of Neyman Pearson decision rules where false negatives are minimized subject to a constraint on false positives (Poor, 1994). For example, in the case of EWS, one may decide on the relative level of importance for the two metrics. Based on that, the decision rule thresholds can be adjusted to meet the expected EWS performance. Under the illustrative decision rules evaluated here, false negative decisions are less frequent than false positive decisions, and the false positive decisions show a strong response to system variance. It would also be possible to incorporate other aspects of decision-making making in this modeling framework, such as optimization for a particular level of variance or response to dread, to evaluate the effects of changing variance on performance.

4.2. Addressing pest and disease problems under changing climate variability

Scenarios where weather variance increases will often make good DSS and EWS more important. It would be very useful to have forecasts across a season and beyond, but there are limits to the quality of such long range forecasts. Useful links may be made between epidemic disease emergence (such as Rift Valley Fever) and specific climate events (such as heavy rainfall). Advance forecasts of ENSO events have been used to provide early warning of epidemics. EWS, once established, can be used to (1) direct sentinel surveillance programs, (2) make efficient use of pesticide stores, and (3) target vaccination programs (e.g. Ephemeral Fever in cattle). Farmers with more commercial opportunities may be in a position to invest and use forecasts (Hansen et al., 2004) while others (Patt et al., 2005) find that information that includes alternative strategies also allows vulnerable farmers to adjust. Many management techniques depend on reducing the local level of inoculum,

while temporal and spatial correlation in both weather conduciveness and pathogen population size will cause local inoculum levels to be strongly influenced by regional levels. These management techniques, such as the use of variety mixtures, may be less useful during El Niño years compared to La Niña years, for example, if regional inoculum loads become saturated (Garrett et al., 2009). Management strategies, themselves, may need to be altered to adjust to new scenarios. Global agricultural research is needed to support such adaptation of pest and pathogen management to climate change (Chakraborty and Newton, 2011; Juroszek and von Tiedemann, 2011; Luck et al., 2011; Pautasso et al., 2010; Savary et al., 2011; Shaw and Osborne, 2011).

Understanding the behavioral characteristics of farmers is crucial if appropriate management practices are to be developed to manage pests and diseases (Mumford and Norton, 1984). Mumford and Norton call for obtaining information early on about farmers' perceptions, the constraints they face and their objectives, especially for the development of pest control research and extension. An interdisciplinary research program on adaptation to change in the Altiplano (Valdivia et al., 2010) hypothesized that if results of traditional and expert forecasts were in conflict, farmers would use the traditional assessment model (Slovic et al., 2002). In this assessment, dread of pests and disease was high, as were concerns with the changing climate in the northern region. While local perceptions of the climate trends were similar to observed trends in the last fifty years (Seth et al., 2010), there were also key differences. Perceptions of decreases in rainfall were actually related to faster evapotranspiration due to increased temperatures as well as shifts in the timing of rainfall, and not reduction in total rainfall. Farmers in fragile environments where there is spatial and temporal variability, such as mountainous regions, may have little confidence in forecast information generated outside of their community or neighborhood (Gilles and Valdivia, 2009).

Insurance introduces another realm of decision-making, for those considering purchase and for those public or private groups considering how to offer insurance (Hazell and Hess, 2010). Traditional crop insurance programs have been functioning in developed countries for decades, and the potential has been studied in developing countries. Recently pilot programs have been tested to determine when and how these may be feasible (Norton et al., 2011; Osgood and Warren, 2007; Smith and Watts, 2009). Several studies point to institutional constraints in the implementation of programs in developing countries (Hazell, 1992), and the search for alternative approaches to make insurance viable (Skees et al., 1999). The key is to prevent farmers' loss of assets due to drought or other weather-related risks in Africa, Asia, and the Andes, if ENSO events occur, for example. If farmers do not lose their assets they will be able to invest and recover from the shock, and with insurance incorporate more costly and higher yielding technologies. Traditional index insurance insures against drought, for example (Osgood and Warren, 2007), though new programs are also exploring index insurance for disease and pests (e.g., Norton et al., 2011; Richards et al., 2006). Approaches are being pilot tested in Malawi where the microlending projects actually support the ability to lend during shock events so farmers don't lose their assets. This is an ongoing area of research that could develop alternatives that would reduce dread. A limiting factor for weather-based index insurance is the need for very good estimates of the relationship between weather variables and loss, where consideration of autocorrelation may be necessary in some cases. A model such as the one presented here may be useful for exploring payout scenarios in weather-based insurance schemes for loss to disease and pests.

The utility of EWS also depends upon two basic facilities: (1) the infrastructure required to disseminate the warning and (2) the capability to take appropriate preventive action. In the case of livestock disease, veterinary support and other extension services may

be required, and some degree of planning in advance of a disease outbreak warning is necessary in order to identify the most economically expedient response, which is likely to vary between localities. Prior assessments must balance the cost of vaccination and/or treatment against the value of livestock both in an economic and intrinsic sense so that immediate decisions can be made.

4.3. Biological adaptation

Models designed to predict the future distribution and/or prevalence of pests and pathogens do so primarily by simulating current physiological and phenological behavior in relation to climate, then applying these simulation models to new climate scenarios. This approach has a significant limitation (beyond that of extrapolating empirical relationships past unidentified thresholds, after which the relationship changes), which is that it assumes that the phenotype of the target organism remains constant. In reality, responses to environmental change are likely to take the form not only of demographic and distribution changes that track the altered distribution of optimal conditions, but also of adaptation to new conditions. Such phenotypic responses have been reported in various taxa (e.g. (van Heerwaarden and Hoffmann, 2007; Yom-Tov et al., 2006)), but it is often unclear whether observed changes are due to phenotypic plasticity or microevolution (i.e. adaptation). Phenotypic plasticity is the term given to the phenomenon of different phenotypes (physical, physiological or behavioral) expressed by different individuals that share the same genotype, whereas microevolution denotes adaptive shifts in the distribution of genotypes within populations (Visser, 2008). Apparently adaptive microevolution has been observed in *Drosophila* spp. (Etges and Levitan, 2008; Umina et al., 2005), and phenotypic plasticity is well-documented in tsetse flies (*Glossina* spp.), which are vectors of trypanosomiasis (Terblanche et al., 2006). Rates of microevolution and degrees of plasticity, respectively, will dictate the ability of these two mechanisms to allow species to respond to climate change, and some mismatches between phenotype and environment have already been observed (Memmott et al., 2007). For soilborne disease, adaptation of soil microbes to new climate scenarios has the potential to modify risk both directly and by changing environmental traits such as soil organic matter (Sierra et al., 2010). Variability and autocorrelation in weather conduciveness to disease and pest reproduction modifies the form of selection pressure. More realistic simulation models should, where possible, take into account known degrees of phenotypic plasticity and rates of microevolution when producing forecasts for future climatic scenarios.

4.4. General conclusions

This model illustrates how mean yield losses can change even when mean conduciveness to loss does not. The roles of variance and the color of weather time series, and probably other statistical features such as skewness and kurtosis (Chaves et al., 2012), also need to be considered for formulating strategies in response to climate change (Table 2), by farmers and other decision makers. While farmers and agricultural scientists are the decision makers most commonly considered in the context of pest and disease risk modeling, there are a number of other stakeholders who need to anticipate pest and disease impacts. Understanding likely effects of climate change on agricultural productivity can benefit corporations in terms of their decisions about where to invest. In the public sector, universities and other institutions need to prioritize their investments in agricultural research, teaching and extension. Scenario analysis can also identify potential problems that will lead to larger scale issues, such as human migration and unregulated movement of animals and plant materials. Development agencies

and institutions also need to make decisions about prioritization of development investments to support adaptation strategies. Scales matter when addressing the human dimensions of adaptation in the context of socio-ecological systems (Ostrom, 2007, 2009). Small holder farmer adaptation takes place in a larger context, not only of climate and ecology, but social systems (Valdivia et al., 2010). Decisions made at the local scale (field, farm household) are shaped by the institutions (markets, policies, research and extension, private and public) at larger scales of governance (Valdivia et al., 2010).

We modeled two simple types of observations farmers might use for decision-making. Farmers do access and incorporate a broader range of new knowledge in their decisions (Bebbington, 1991; Valdivia et al., 2010). Use of information often depends on the degree of trust between the decision maker and the risk messenger (Krimsky and Plough, 1988; Slovic, 1993). Two-way participatory communications can enhance trust (Wilkins, 2001) and contextualize the message (Marx et al., 2007). Two-way processes such as participatory research support the inclusion of new knowledge to enable action that is adaptive (Hayward et al., 2004; Howden et al., 2007; Valdivia et al., 2010). These processes are especially critical when the level of uncertainty about future events will increase, and when markets do not function well (information is limited, inputs are not available at all or on a timely basis, or are too expensive, and institutions are unreliable) and rural households lack safety nets. Processes that support understanding of the nature of variability in weather and pest risk, and that strengthen rural community capacities for this purpose, are critical to building resilience at the local and at the macro levels.

Variability in future climate scenarios offers challenges for policy makers. A more parsimonious approach than attempting to draw a single conclusion about future scenarios will be to present the full range of envisaged outcomes and allow policy to be drafted in the form of a response to a set of possible scenarios instead of a single prediction (Stirling, 2010). A practical strategy would then be a general preparedness for all likely eventualities, or at least a hedged compromise in which most potential outcomes could be managed and none would be disastrous. This general ethos is best served by stochastic models wherein parameter values are not fixed, but chosen from an appropriate probability distribution. And rather than treating each time point as an independent draw, taking into account autocorrelation may be important in understanding risk and how to adapt decision-making.

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