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RESEARCH ARTICLE

A simple Bayesian network to interpret the accuracy of armyworm outbreak forecasts

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Abstract

Forecasting of outbreaks of armyworm (larvae of the moth *Spodoptera exempta*) employs information from rain gauges and moth traps. Rainfall is an independent variable, but moth catch is affected by rainfall, and outbreak risk is affected by both moth catch and rainfall. A simple Bayesian network was used to describe these relationships and so derive conditional probabilities. The data were from a new initiative, community-based forecasting of armyworm in Tanzania, in which outbreak risk for a village is determined locally from a single moth trap and rain gauge located within the village. It was found that, following a positive forecast, an armyworm outbreak was approximately twice as likely to occur as would be expected by chance. If the forecast was negative because of insufficient moths, outbreaks were half as likely as would be expected by chance. If the forecast was negative because of insufficient rain, however, the outbreak probability remained similar to chance: an aspect of the forecast that requires improvement. Overall, a high forecasting accuracy can be achieved by village communities using simple rules to predict armyworm outbreaks.

Introduction

Armyworm larvae cause devastating but highly localised damage to cereal crops and grassland (Scott, 1991), and poor monitoring and forecasting constrain efficient control operations in many parts of east Africa (Iles & Dewhurst, 2002). The adult moths arrive in large numbers at new locations being borne by prevailing winds and concentrated by convergent wind flows associated with rainstorms (Rose *et al.*, 1987, 1995). Thus, eggs are laid at high densities, and larvae emerge to destroy crops where previously no armyworm was present. The protection of crops from armyworm requires that intensive scouting is carried out in areas of high outbreak risk, and the role of forecasting is to provide information about this risk.

Historically, forecasting procedures in Tanzania involve an institutional hierarchy of operations: farmers and local extension officers, district agricultural officers, central government, regional organisations (Odiyo, 1990; Day & Knight, 1995). Forecasting is carried out at more centralised levels based on information obtained from lower levels, and the forecast is passed back from central to lower levels for action. The system relies therefore on participation at all levels and on rapid information flow. Centralised forecasting can be technically complex, integrating moth catch and meteorological information on a country-wide basis and comparing the current situation with historical records (Day *et al.*, 1996). Though the general principles of armyworm forecasting are well established (Rose *et al.*, 2000), the production of a centralised forecast has remained a matter of experience and judgement by the national or regional forecaster concerned.

As first conceived, during a project workshop, community-based forecasting alleviates the problems associated with complex information flow and instead, the forecast is both generated and acted on at the local level, the village community (Knight, 2001). In community-based forecasting, a participating village makes an armyworm outbreak forecast for that village based only on the information obtained from a single *Spodoptera exempta* pheromone trap and a single rain gauge, both sited within the village. In order to implement community-based forecasting, it was necessary both to accommodate the limited, local nature of the information and to provide clear instructions during the training of village forecasters. To this end, the forecasting decision was reduced to a simple set of rules (Day, 2004; Holt, 2004), which were reproduced in the training materials (Day *et al.*, 2002).

With the results obtained from the first community-based armyworm forecasting pilot studies, this study examines the accuracy of the new forecasting method. The first pilot studies were carried out in Kilosa in 2002 (Njuki *et al.*, 2002). Since then the Kilosa initiative has continued and further pilots have been carried out in new locations in Tanzania, Kenya and Ethiopia (Holt, 2005). This study is concerned only with an assessment of the accuracy of the forecasting in its ability to correctly predict armyworm outbreaks. The approaches used in training and evaluation, the response of the farmers and the lessons for uptake and implementation will be described in detail elsewhere; the initiative has been very successful so far (Day, 2003; Mushobozi, 2004).

Materials and methods

The forecast relies on a simple set of conditions, which if met, constitute a positive forecast that an armyworm outbreak will occur. The three conditions are the presence of vegetation, the occurrence of a minimum amount of rainfall and the capture of a minimum number of moths. The forecast is made weekly, and the thresholds for rainfall and moths, respectively, are that more than 5 mm falls on at least one day in the week and a total of 30 moths are captured during the course of the week. All three conditions must hold for the forecast to be positive. The thresholds have the following rationale. The ecology of armyworm is intimately linked to rainstorms, the moths requiring a small amount of rainfall for successful oviposition and the larvae rely on young lush vegetation on which to feed; Holt and Day (1993) and Holt *et al.* (2000) described these interactions in a model of armyworm population dynamics. A rainfall threshold of 5 mm indicates more than a light shower, sufficient for reproduction to take place and to begin to stimulate vegetation growth. The moth threshold recommended in the Armyworm Handbook is >30 moths caught in one night (Rose *et al.*, 2000). Based on the experience of the National Armyworm Forecaster for Tanzania (W. Mushobozi) and following some analysis of historical records from the Tanzania National forecasts (Holt, 2004), we used a modified, less conservative threshold of 30 moths over the course of 1 week.

Three sets of data were selected from those years and villages where forecasting took place throughout the appropriate period of the armyworm season and where there was sufficient variability on the occurrence of outbreaks. Those seasons in which no outbreaks occurred were omitted. The data examined were Kilosa district, 02/03 season (total of 70 forecasts from four villages), Kilosa district 03/04 season (total of 88 forecasts from five villages) and Moshi/Hai districts 03/04 season (total of 68 forecasts from four villages). In each village, rainfall and moth catches were recorded and armyworm outbreaks were also reported as observed.

We examine the occurrence of reported outbreaks in relation to conditions required for a positive forecast. The forecast is made on a particular day of the week, but an outbreak can be reported at any time. It is therefore necessary to define a period within which an outbreak can be regarded as associated with a particular forecast and to this end a 2-week window was used. Except for the very start of the forecasting period in Kilosa 03/04, vegetation was present throughout, and so it was necessary only to consider two of the three conditions in this analysis, that is, rainfall and moths.

The forecasting decision can be usefully described using a simple Bayesian network. There are three variables or nodes: rainfall (R), moths (M) and armyworm outbreak (A), all having two states, the rainfall and moths thresholds are met or they are not; an outbreak is reported or it is not. Rainfall is independent of the other variables, but the occurrence of moths is affected by rainfall and the occurrence of outbreaks is affected by both rainfall and moths. This leads to the directed network (Fig. 1) in which the probability that the moth threshold is exceeded is conditional upon rainfall and the probability that an outbreak occurs is conditional upon both moths and rainfall. The joint distribution can therefore be factored as

$$\mathrm{P}(A, M, R) = \mathrm{P}(A|M, R) \cdot \mathrm{P}(M|R) \cdot \mathrm{P}(R) \qquad (1)$$

Each variable has two states, so the full network has $2^3 = 8$, which are mutually exclusive and exhaustive (Fig. 2). The prior probability of rain is therefore calculated by summing the probabilities of all the states with rain across all the states of the other variables, that is, 1–4 inclusive (Fig 2).

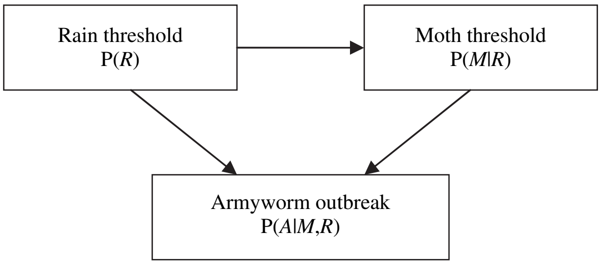

Figure 1 A Bayesian network illustrating local armyworm outbreak forecasting using information from a single moth trap and rain gauge (see text for details).

$$\mathrm{P}(R) = \sum_{A', M'} \mathrm{P}(A', M', R) \quad (2)$$

The prior probabilities of moths and armyworm outbreaks are calculated in a similar way. The combined probability of moths and rain

$$\mathrm{P}(M, R) = \sum_{A'} \mathrm{P}(A', M, R) \quad (3)$$

can be factored and rearranged to give the conditional probability of moths given rain

$$\mathrm{P}(M|R) = \mathrm{P}(M, R)/\mathrm{P}(R) \quad (4)$$

Similar calculations give the conditional probabilities of armyworm outbreaks given rain, and armyworm outbreaks given moths. Rearrangement of Eqn 1 gives the conditional probability of armyworm outbreaks given both moths and rain

$$\mathrm{P}(A|M, R) = \mathrm{P}(A, M, R)/[\mathrm{P}(M|R) \cdot \mathrm{P}(R)] \quad (5)$$

Results

The frequencies of occurrence of each of the eight possible combinations of events (states) are shown for the three data sets in Table 1. The joint probabilities P(*A*,*M*,*R*) were obtained by counting the number of cases of each and then dividing by the total number of cases (Table 1). From these, all other probabilities were calculated as detailed above. The joint probability distributions from the three data sets were similar suggesting some generality in the results (χ^2 = 13.42, 14 d.f., *P* not significant).

The three prior probabilities P(*R*), P(*M*) and P(*A*) had a reasonable balance between an event occurring and not occurring, such that potential existed for all 2^3 combinations to occur. Combining the three data sets, the rain threshold was exceeded in about 58% of cases; the moth threshold, 40% of cases and outbreaks occurred, 37% of cases (Fig. 3).

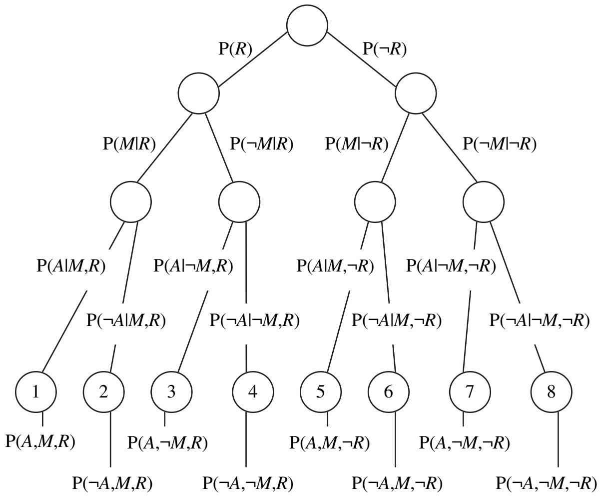

Figure 2 The full network showing all possible states (¬ is used to denote 'not', see text for details).

Of primary interest was the extent to which the prior probability of an outbreak was altered by information about rainfall or moth catch. With information about whether the rainfall threshold was exceeded (but no moth catch information), the conditional probability of an outbreak P(*A*|*R*) averaged about 0.45, a relatively small increase on the prior probability of 0.37, but one which was consistent for the three data sets (Fig. 3). Combining all three data sets, there was a significant association between rain and outbreaks (χ^2 = 7.64, 1 d.f., $P < 0.01$). With prior information about whether the moth threshold was exceeded (but no rain information), the conditional probability of an outbreak P(*A*|*M*) averaged about 0.73, nearly double the prior probability (association between outbreaks and moths, χ^2 = 84.03, 1 d.f., $P < 0.001$). With both rain and moth information, the conditional probability P(*A*|*M*,*R*) was slightly but consistently higher at about 0.80.

Table 1 Joint distributions of cases and the probabilities of each in the three data sets. Armyworm outbreak reported A, moth threshold exceeded M, rainfall threshold exceeded R, ¬ denotes 'not'

	Kilosa 0203		Kilosa 0304		Moshi/Hai 0304	
States	Cases	*P*	Cases	*P*	Cases	*P*
A,*M*,*R*	17	0.24	23	0.26	14	0.21
¬*A*,*M*,*R*	4	0.06	2	0.02	8	0.12
A,¬*M*,*R*	2	0.03	1	0.01	1	0.01
¬*A*,¬*M*,*R*	15	0.21	29	0.33	15	0.22
A,*M*,¬*R*	4	0.06	5	0.06	3	0.04
¬*A*,*M*,¬*R*	6	0.09	3	0.03	2	0.03
A,¬*M*,¬*R*	4	0.06	5	0.06	4	0.06
¬*A*,¬*M*,¬*R*	18	0.26	20	0.23	21	0.31
Total	70		88		68	

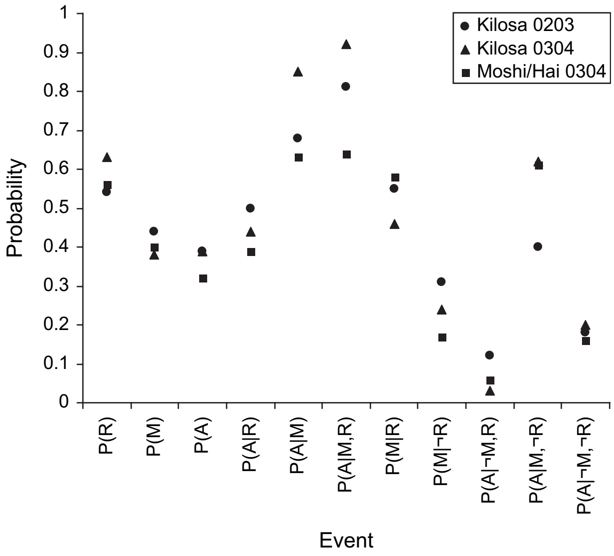

Figure 3 Prior probabilities of the rain and moth thresholds being exceeded and of an armyworm outbreak occurring, compared with the conditional probabilities of an armyworm outbreak, given various combinations of rainfall and moth catch. Prior probabilities of rain, moths and armyworm outbreaks, P(*R*), P(*M*) and P(*A*), respectively; conditional probabilities of moths given rain and no rain, P(*M*|*R*) and P(*M*|¬*R*), respectively; conditional probabilities of armyworm outbreaks given rain, moths, both rain and moths, rain without moths, moths without rain and neither moths nor rain P(*A*|*R*), P(*A*|*M*), P(*A*|*M*,*R*), P(*A*|¬*M*,*R*), P(*A*|*M*,¬*R*) and P(*A*|¬*M*,¬*R*), respectively.

Though the direct effect of rainfall on outbreak probability was not very large, moth catches were clearly associated with rainfall. The probability of the moth catch exceeding the threshold rose to an average of 0.52, given the rain threshold was exceeded and fell to 0.24, when it was not exceeded (association between moths and rain, $\chi^2 = 84.03$, 1 d.f., $P < 0.001$) (Fig. 3). Rainfall was therefore important in influencing moth catches even if there was relatively little direct effect on the probability of an outbreak.

An outbreak forecast was regarded as positive if both the moth and the rain thresholds were exceeded. The positive forecast was correct if an outbreak subsequently occurred. The probability of a correct positive forecast was therefore $P(A|M,R) = 0.80$ and the probability of an incorrect positive forecast, $P(\neg A|M,R) = 0.20$. Negative forecasts are more complicated as they are issued under three different circumstances: rain above threshold but moths below threshold, moths above threshold but rain below threshold, both below threshold. Important differences existed between the probabilities associated with each, and the last three columns of Fig. 3 show the probabilities of incorrect negative forecasts, that is when outbreaks occurred but the threshold conditions were not met. The probabilities of correct negative forecasts are 1 minus these values and when the moth catch was below threshold, the conditional probabilities of correct negative forecasts therefore averaged 0.93 and 0.81, when the rain threshold was and was not exceeded, respectively (Table 2). A low moth catch was therefore a reliable basis for a negative forecast. The conditional probability of a correct negative forecast when the moth but not the rain threshold was exceeded was 0.50, so an *incorrect* forecast was equally probable in such situations. If the moth catch exceeded the threshold, therefore, lack of rain was not a good basis to issue a negative forecast.

Discussion

No systematic attempt has previously been made to quantify the accuracy of armyworm forecasts, though Odiyo (1990) reported some verification. Prior to the community-based forecasting initiative, the geographic scale involved was comparatively large. In Tanzania, forecasts are made for each district using a sparse network of traps, perhaps one or two in each district. Holt (2004) examined the Tanzania national armyworm trap catch and rainfall reports for the 1994/95 armyworm season, a season with reasonably complete trap records. There were several instances of armyworm outbreaks taking place in one part of a district, which were undetected by a trap located in another part of the district. Equally, there were instances of high trap catches and rainfall when no outbreak was reported. Frequently, however, traps in neighbouring districts showed similar temporal patterns of moth catch, and so the district trap network was a general indicator of regional armyworm population build up.

Table 2 Conditional probabilities (combining the three data sets) of correct and incorrect, positive and negative forecasts. Negative forecasts occur under three different circumstances, and the probabilities of each is shown separately

	Threshold Exceeded*		Outbreak	Conditional
Forecast	Moths	Rain	Outcome	Probability
+ve	y	y	Correct	0.80
+ve	y	y	Incorrect	0.20
−ve	n	y	Correct	0.93
−ve	n	y	Incorrect	0.07
−ve	y	n	Correct	0.50
−ve	y	n	Incorrect	0.50
−ve	n	n	Correct	0.81
−ve	n	n	Incorrect	0.19

*y, yes; n, no.

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The community traps operate on geographic scales closer to the ecology of armyworm, village as opposed to district, and the chances of unreported outbreaks are also less. This provides an opportunity for a more meaningful evaluation than has so far been possible. The data from the pilot studies comprised a total of 226 forecasts made over two seasons in nine villages, sufficient samples to begin to assess the accuracy of the forecast. Though the forecasting rules have an established biological basis, they were essentially formulated heuristically. This article presents the first results from the analysis of community-based forecasting of armyworm, and it is useful to evaluate both the structure of the rules and the values of the thresholds. Caution is required, however, in suggesting implementation of changes to the rules as this would have major retraining implications for participating villages.

The forecasting rules as conceived have proved to be a reasonably good predictor of armyworm outbreaks. The probability of an outbreak following a positive forecast was approximately twice that expected by chance. Some modification to the forecasting rules may need to be considered in the definition of the conditions required for a negative forecast. If the moth catch was below threshold, then the negative forecast was reasonably accurate with the probability of an outbreak dropping to less than half that expected by chance. A problem arose, however, for cases where the moth catch was above threshold, but the rain threshold was below threshold: here, the probability of an outbreak was actually slightly larger than that expected by chance. Whether or not, the requisite amount of rain fell in a particular week and at the specific location of the rain gauge appeared not to be such an important constraint to the subsequent occurrence of outbreaks. This may be because rain may have fallen at other locations in the village or in previous weeks and as a result, conditions suitable for moth oviposition and larval development may exist even if the rain threshold was not exceeded. Indeed, given that vegetation was present (the necessary third condition for a positive forecast) probably means that food was available for the larvae. The presence of vegetation is clearly dependent on adequate amounts of rainfall, and as such, it provides a measure of rainfall that changes less quickly than rainfall itself. If there is no green vegetation in the form of crops or grasses, then there is no risk of armyworm attack; this condition can be regarded as defining the season for which armyworm forecasting is necessary.

The importance of rainfall in armyworm movement and ecology is well studied (Tucker & Pedgley, 1983; Rose *et al.*, 1987, 1995). Some participating farmers also reported a perception that armyworms were associated with rains (Njuki *et al.*, 2004), but the conditional probability of outbreaks, given rain exceeding the threshold, indicated only a small effect. It is perhaps instead, the indirect effect of rain upon moth occurrence that makes it appear that a better correlation with rain exists than is really the case. With information about moth catch only, the probability of a subsequent outbreak was nearly as high as when rainfall information was also included.

The pilot studies have so far been carried out in villages at high risk of armyworm attack. Indeed, the prior probability of outbreaks was between 0.3 and 0.4; a relatively high chance of armyworm attack somewhere in the village in any one week, high enough perhaps to warrant routine monitoring of fields even if no forecast was available. Farmers reported visiting fields more often in response to positive forecasts (Njuki *et al.*, 2004), so the forecast information has changed farmer actions in a way that may improve armyworm control and reduce yield losses. It is, however, not easy to separate the effect of the information contained in the forecast from the general raising of awareness of armyworm.

As further data become available, it will become possible to make a more detailed critical appraisal of the forecasting rules, for example, the values of the thresholds. So far a threshold of 30 moths has been used throughout, ignoring the so-called 'trap factor', that the number of moths caught is known to depend on the position of the trap (Odiyo, 1979). Thus, in principle, each trap could be individually calibrated with its own threshold; whether the extra complication introduced by such a refinement is warranted must await sufficient data to calibrate each village trap. This study takes the important step of establishing that even with simple, general rules the forecast is currently operating with relatively high accuracy.

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