Bayesian networks to compare pest control interventions on commodities along agricultural production chains

ABSTRACT

The production of an agricultural commodity involves a sequence of processes: planting/growing, harvesting, sorting/grading, post-harvest treatment, packing, and exporting. A Bayesian network has been developed to represent the level of potential infestation of an agricultural commodity by a specified pest along an agricultural production chain. It reflects the dependency of this infestation on the predicted level of pest challenge, the anticipated susceptibility of the commodity to the pest, the level of impact from pest control measures as designed, and any variation from that due to uncertainty in measure efficacy. The objective of this Bayesian network is to facilitate agreement between national governments of the exporters and importers on a set of phytosanitary measures to meet specific phytosanitary measure requirements to achieve target levels of protection against regulated pests. The model can be used to compare the performance of different combinations of measures under different scenarios of pest challenge, making use of available measure performance data. A case study is presented using a model developed for a fruit fly pest on dragon fruit in Vietnam; the model parameters and results are illustrative and do not imply a particular level fruit fly infestation of these exports; rather they provide the most likely, alternative or worst case scenarios of the impact of measures. As a means to facilitate agreement for trade, the model provides a framework to support communication between exporters and importers about any differences in perceptions of the risk reduction achieved by pest control measures deployed during the commodity production chain.

KEY WORDS: Pest Risk Analysis; Systems Approach; modelling.

1. INTRODUCTION

Pest Risk Analysis, which can be abbreviated to the initials PRA,[1] is 'The process of evaluating biological or other scientific and economic evidence to determine whether an organism is a pest, whether it should be regulated, and the strength of any phytosanitary measures to be taken against it'.[2,3] PRA has four phases: Initiation (including identification of the hazard), Risk Assessment (evaluating probability, consequences, and uncertainty), Risk Management (choices between measures, their efficacy, feasibility, impacts), and Risk Communication.

One of the important roles of a national plant protection organization (NPPO), the governmental authority implementing plant health policy, is to facilitate the reduction of risk posed by pests associated with imported commodities, in order to achieve an appropriate level of protection for their country's plant resources.[4] In the Risk Management phase of a PRA, phytosanitary measures are presented and evaluated in relation to the objective of management in proportion to the identified risk. During this phase, evidence is collected and expert judgement may be given about the best measure, or combination of measures, to apply to trade or other pathways to achieve an appropriate level of protection. Historically, single phytosanitary measures, such as post-harvest fumigants, were widely accepted owing to their demonstrated high efficacy. A single measure may not provide the necessary assurance of protection, however, or may be unacceptable for environmental, food quality, or cost reasons. In such instances, a combination of measures, each of which is only partially effective in reaching the appropriate level of protection, may be employed as described in the International Standard for Phytosanitary Measures (ISPM) No. 14.[5] This is referred to in plant health as a Systems Approach. One of the challenges of employing such an approach has been the lack of an agreed method for determining the risk reduction achievable by a combination of measures.[6] Determination of the efficacy of measures for equivalence agreements [4] has also been a barrier to market access.[7,8]

Bayesian networks can provide a means to estimate and compare the efficacy of measures, or combinations of measures. Bayesian networks are well established as a sound statistical framework to integrate information from diverse sources such as empirical data, expert opinion, and model output, and have been used in a wide variety disciplines, including conservation,[9] forensic science,[10] health,[11] environmental and resource management,[12] and biosecurity.[13]

Bayesian networks allow uncertainty in model variables to be expressed.[14] The ISPM No. 11[15] explains the importance of considering and documenting uncertainty in a PRA; both pest challenge and the efficacy of measures can be predicted with varying accuracy and it is essential to take these uncertainties into account, so providing the user with a powerful tool for reasoning under uncertainty.[14] Bayesian networks are acyclic directed hierarchies of dependency between variables which describe how the probabilities of the events being modelled interact; these hierarchies are readily presented graphically so it is easy to see the assumptions that are being made about the variables and dependencies between them.[14] This can provide a common framework for a group's understanding of the issue concerned and so assist in the building of consensus for action. Tools based on Bayesian networks have been developed in the context of PRA for Risk Assessment;[16,17] here we extend their use to Risk Management.

The work described here was carried out as part of the project called 'Beyond Compliance'[18] funded by the Standards and Trade Development Facility (STDF). The project aims to enhance competency and confidence for NPPOs in the South East Asian sub-region to apply Systems Approaches to reduce the risk of introducing regulated pests through trade. The project developed and tested a suite of three decision-support tools for pest risk management by using case studies involving four countries within the South East Asian region: Vietnam, Thailand, Malaysia, and the Philippines. The three decision-support tools – production chains, elicitation templates, and Bayesian networks – were designed to help structure, parameterize, and analyse the pest risk management problem, respectively. The production chain is a detailed flowchart which shows the steps in the production of the commodity and the points where actions of any kind affecting production can be taken. The elicitation template, implemented using a spreadsheet, provides a framework within which pest management experts can collate and define the effects of potential control interventions that may be used at different points on the production chain. The Bayesian network is a model of the probability of pest infestation on the production chain parameterized using the information recorded using the elicitation template.

This paper describes the Bayesian network in detail by specific reference to one of the project case studies: the potential infestation by fruit fly (*Bactrocera* spp.) of dragon fruit (*Hylocereus undatus*) grown in Vietnam for export to the Republic of Korea. Although the model development and output were specific to fruit fly in dragon fruit in Vietnam, this case study demonstrates a methodology that can be widely applied to other such systems. The general goals of the project were to offer greater inclusion of stakeholders in development of pest risk management plans, increase confidence of the NPPO staff in trade negotiations, and facilitate new opportunities for trade.

2. METHOD

The Bayesian network is a model of the probability of pest infestation along the production chain of an agricultural commodity, parameterized with the information collected and collated using an elicitation template. The Bayesian network is a description of the stages and activities of the production chain and of the concurrent pest threat from the pest species concerned. The factors affecting changes in the probability of pest infestation are distinguished and modelled in sequence. Software developed for Bayesian network construction (GeNIe2)[19] provided a convenient, widely-accessible platform that also offered graphical representation and analysis tools. In this application, the Bayesian network is essentially a single chain in which the nodes represent the predicted level of pest infestation of the commodity at a sequence of points in time. It starts with an initial probability distribution of potential infestation which was based on stated assumptions regarding the prevalent pest population size and the susceptibility of the commodity in production. Nodes located in side-branches of the chain allow the effects of phytosanitary measures to be incorporated; these interventions may reduce the existing infestation of the commodity or prevent new pest challenge, or both. Other nodes in the side-branches allow the possibility for new pest challenge to occur at points along the chain, such as during post-harvest handling. The phytosanitary measures are grouped according to the stages along the production chain where they can be implemented.

All potential control interventions relevant to the case study were included in the model and different combinations can be examined by selecting or de-selecting measures as required; a measure is de-selected by setting its efficacy to ‘Negligible’. In this way the Bayesian networks can be used to assess the risk-reduction capability of a combination of control measures across the full spectrum of potential pest challenge, as expressed in the probability distributions contained in the pest infestation nodes.

An important feature of Bayesian networks is that evidence may be added at any stage to express some level of greater knowledge. This enables specific situations to be examined, for example, where the level of pest challenge is known with greater accuracy. With this in mind, 'control points' are indicated in the model at which evidence may be available. Three such stages were identified in the case study: pest surveillance in the field, fruit-sorting after harvest, and export quarantine inspection. For example, if from field surveillance in a specific case, it was inferred that pest infestation of the commodity was likely to be 'Low' at the end of the growing season, then the model is updated with this estimate and the range of predicted outcomes is then relevant in the context of the evidence provided.

The graphical depiction of the Bayesian network developed for the threat of fruit fly on dragon fruit in Vietnam shows the model structure (Figure 1). The rectangles in which probability distributions are displayed are described as nodes and the arrows which link them as arcs. The model variables constitute the nodes in the Bayesian network and there is a probability table associated with each node, which describes either (a) its marginal probability distribution, when it has no parent nodes, or (b) its conditional probability distribution, when it has one or more parent nodes.(20) The nodes which do not have parents (i.e., have arcs leaving but not entering) contain a probability distribution specified by the user using the elicitation template; for example, the initial fruit fly challenge was believed to have a 90% chance of being 'Low' and a 10% chance of being 'High'. The nodes which have arcs entering them contain a conditional probability table (CPT); these are explained below. All variables are described as a series of ordinal categories with an associated probability distribution of the categories. Pest infestation is described as ‘Negligible’ if it is below the level of detection[1], ‘High’ if it is above the level that would be easily detected and ‘Low’ if it is between these limits. Uncertainty in fruit fly challenge can then be expressed, for example, as a 90% chance that it will cause a ‘Low’ infestation and a 10% chance that it will cause a ‘High’ infestation (Figure 1).

Each control measure is described by a sub-model which contains three nodes (Figure 2); on the main model page (Figure 1) sub-models are shown as rounded rectangles. For each measure sub-model the user specified a probability distribution of their beliefs about maximum measure efficacy, ‘High’, ‘Low’, or ‘Negligible’, that would be achievable under ideal conditions. To allow situations which are not ideal to be represented, an estimate is included of how likely it is that the full potential efficacy of a measure would be achieved under the actual field conditions. The default used was a high standard of implementation. A ‘Low’ implementation standard was defined as a reduction in maximum efficacy of 50%. A low implementation standard may result from changes in conditions, e.g., rain soon after pesticide application, or sub-standard management practice, e.g., incorrectly calibrated equipment, poor application technique, or labour/time constraints. The likely efficacy of the measure as actually implemented, taking into account implementation standard, is determined using the CPT shown in Table 1a. ‘High’, ‘Low’, and ‘Negligible’ measure efficacy were defined as described below in terms of the estimated change that each was expected to cause to the level of infestation.

Using the elicitation template, the maximum efficacy of a measure was elicited on a five-point scale (very low to very high). The Bayesian network represents the variable with fewer

[1] Detection using typical methods of pest surveillance or monitoring which meet NPPO guidelines or detection which occurs through other routine procedures such as fruit sorting

states (Negligible, Low, and High). 'Negligible' corresponds to no effect (or measure not used) so the five-point scale was reduced to two points (Low, High) by dividing the scale in half and describing the probability associated with the lower half as 'Low' and the upper half as 'High'. Table 2 shows the efficacies of the measures, so described. The elicitation of values on a five-point scale allows the possibility for any future versions of the Bayesian network to take advantage of this finer resolution in expert perception.

As far as was consistent with a realistic representation of the problem, the CPTs in the network defined relationships between variables deterministically. In the CPT (Table 1a), for example, if maximum efficacy of measure is 'Negligible', then the efficacy as implemented must also be 'Negligible'; no distribution of probability is necessary. Where more than one possible category of outcome could occur, a probability distribution was defined by project partners. While this introduced complexity, it represented realistic expectations and the associated assumptions are transparent (Table 1). It is an important feature of the approach that, throughout, assumptions can be questioned by any stakeholder and the impact of alternative perceptions tested using the model.

In the case of Table 1a, if the maximum possible efficacy of measure is 'High' and the implementation standard is also 'High', then the efficacy as implemented is also considered to be 'High'. On the other hand if the implementation standard is 'Low' then there is only a 50% chance that efficacy as implemented will be 'High' and a 50% chance that it will be 'Low'.

The assumptions shown in Table 1a are identical for all the measure sub-models so differences between measures are specified in the nodes defining maximum efficacy and implementation standard. A structured process was used to elicit these values for each measure.

Using one of the other tools from the wider project, the spreadsheet-based elicitation template, the users entered their expectations, which were instantaneously displayed as histograms of the probability distributions so that the values for all measures could be viewed simultaneously thus providing valuable feedback to the user. This facilitated review and amendment as well as consistency of values between measures.

A sequence of four stages of the production chain were identified: last season, this season, harvesting, and packing. The model has a modular structure which, with minor variations, is repeated at each of these stages. The infestation is first updated with any new pest challenge since the previous stage; this incorporates the effects of any measures used which may reduce this pest challenge. Thereafter the direct effect of any control measures on the infestation of the fruit is taken into account. These two steps are then repeated for the next stage but the details differ because of the different numbers of potential measures which are available either to prevent new pest challenge or to reduce existing infestation of the fruit. The points at which different measures act can be seen in Figure 1.

More than one measure may be implemented at each stage. In such cases it is necessary to determine a combined efficacy. Logically, this must be at least as high as the efficacy of the most effective measure but where a number of measures have the same efficacy, the additional possibility was introduced that several low-efficacy measures in combination have some probability of being equivalent to a high-efficacy measure. The assumptions for the combination of two measures are specified in the CPT, Table 1b. If one measure delivers 'High' efficacy, then clearly the addition of other measures will not reduce this. At the other extreme, if a measure has 'Negligible' efficacy (if it was not implemented, or if implementation was very poor), then the combined efficacy equals that of the other measure. If both measures have

‘Low’ efficacy then there is some chance (12%) that the combined efficacy will be ‘High’ (Table 1b). A straightforward extension of this logic is applied when combining more than two measures. In the case study, the equivalent chance of a ‘High’ efficacy outcome when three ‘Low’ efficacy measures were combined was 24%.

Having calculated the combined efficacy of the measures acting at a particular stage, their effect on pest infestation was determined according to the CPT, Table 1c. If the effect of a measure is ‘Negligible’ then it has no effect on pest infestation. If the effect of a measure is ‘Low’, then there is a 67% chance that a ‘High’ infestation is reduced to a ‘Low’ infestation but a 33% chance that it will remain ‘High’. Similarly, there is a 67% chance that a ‘Low’ infestation is reduced to ‘Negligible’ but a 33% chance that it will remain ‘Low’. If the effect of a measure is ‘High’ the impact on pest infestation is much greater; a ‘High’ infestation is assumed to have no likelihood of remaining ‘High’ but has a 0.1% chance of being reduced to ‘Low’ and a 99.9% chance of being reduced to ‘Negligible’. A ‘Low’ infestation has a very small chance (0.0001%) of remaining ‘Low’ but a high (99.9999%) chance of being reduced to ‘Negligible’. This CPT, which provides definitions of measure efficacy in terms of reduction in pest infestation, is necessarily the most complex in the model.

At points along the production chain, measures may be implemented which reduce pest infestation but pest infestation may also increase owing to new pest exposure. The final CPT (Table 1d) defines the level of pest infestation resulting from additional pest challenge at points along the production chain. If either the existing level of infestation or the infestation due to new pest challenge is ‘High’ then the result is also ‘High’. If either is ‘Negligible’ the result is determined solely by the other. The only situation requiring a non-deterministic outcome is where both the existing level of infestation or the infestation due to new pest challenge are

‘Low’; in this case there is a 12% chance that the result would be a ‘High’ infestation (and hence an 88% chance that it would be ‘Low’).

The values in all the CPTs shown in Table 1 were based on the experience of the project team which included members specifically experienced in dragon fruit pest management. The expectations of the pest managers was particularly critical concerning their interpretation of the meaning of ‘High’ and ‘Low’ with respect to the efficacy of a measure and what these terms would imply for the level of fruit fly control in dragon fruit. The team of people involved in model-building allowed judgements from industry, NPPOs, scientists, and other stakeholders to be taken into account. Information to quantify the Bayesian network was obtained through a systematic elicitation process using the elicitation template to provide instant feedback in workshop discussion so allowing amendment and consensus-building. Similarly, network structure was developed interactively by constructing network diagrams in a workshop setting and through repeated circulation of draft network structures.

3. RESULTS

To illustrate the use of the Bayesian network, the situation was considered where current practice employed a highly effective measure, the use of vapour heat treatment (VHT) at the packing house, to achieve an appropriate level of protection. The model was used to investigate combinations of measures that might be used to replace VHT and achieve similar levels of protection. The illustration (Table 3) shows a comparison of six scenarios each with a different combination of measures:

- Scenario 1 – No measures
- Scenario 2 – Measure 10.4 VHT only

- Scenario 3 – Measure 10.4 VHT plus Measure 11.1 Boxes and Measure 12.1 Sealed vehicles
- Scenario 4 – As Scenario 3 but replacing Measure 10.4 VHT with Measures 3.1 & 6.2 Sanitation and Measure 6.3 Sorting
- Scenario 5 – As Scenario 4 but adding Measure 5.2 Fruit bagging
- Scenario 6 – As Scenario 5 but also adding Measures 6.1 & 10.1 Boxes/covers

A typical pattern of pest challenge is illustrated with a greater chance of new pest infestation in the field than at the post-harvest stages of the production chain. The small chance of additional pest challenge in the later stages of the production chain should however be taken into account in selecting fruit fly management measures. The pattern of pest challenge is described Table 3 along with the results obtained using scenarios which employ different combinations of measures.

As a reference point, Scenario 1, where no measures are used, resulted in a 70% chance of a 'Low' infestation and a 30% chance of a 'High' infestation at the point of export. Measure 10.4 VHT is known to be very highly effective against fruit fly and if Measure 10.4 VHT is then employed on its own this resulted in a 99% chance of a 'Negligible' infestation and a 1% chance of a 'Low' infestation at the point of export (Scenario 2). The efficacy of VHT is known to be much higher than this (Table 2) but if measures to prevent subsequent infestation are omitted then detectable infestation at export may result. In Scenario 3, the addition of measures to protect the fruit from re-infestation following VHT (Measures 11.1 and 12.1) resulted in an appropriate level of protection.

If Measure 10.4 VHT is not employed, it will clearly be necessary to replace it with a measure or combination of measures which deliver similar high levels of protection. In Scenarios 4, 5, and 6, having removed Measure 10.4 VHT, progressively more measures are added until an equivalent level of protection is obtained. In Scenario 4, two measures concerned with sanitation (Measures 3.1 and 6.2) are added, together with removal of infested fruit during sorting (Measure 6.3). This resulted in a 92% chance of a 'Negligible' infestation, a 7% chance of a 'Low' infestation, and a 1% chance of a 'High' infestation (Table 3). Though an insufficient level of protection for export, this reduction would still make a significant contribution to the management of the pest. Fruit bagging is expected to be fairly effective to prevent both fruit fly already present in the particular field and also fruit fly originating from the wider environment. Modelling the addition of Measure 5.2 Fruit bagging achieved a significant improvement but there is still a 2% chance of 'Low' infestation (Scenario 5). Finally, in Scenario 6, the further addition of measures to prevent fruit fly challenge during and after harvest (Measures 6.1 and 10.1) provided a combination which achieved comparable levels of protection to VHT.

There are two types of variable: those associated with pest challenge and those associated with the measures. Model analysis tools within the GeNIe software[19] were used to assess the sensitivity of pest infestation at export to pest challenge at different times and to the measures used in the scenario. The results are summarized in Table 4; the sensitivity to each variable is not fixed but depends on its own value as well as that of other variables in the model associated with a particular scenario.

In Scenario 1 with no control measures, the result was very sensitive to pest challenge at all points throughout the chain. The result was not sensitive to any measures as none were used in this scenario. In Scenario 2, which incorporated the highly effective VHT treatment, any infestation occurring up to that point was controlled by VHT and as a result the outcome was sensitive only to pest challenge occurring after the VHT treatment. In Scenario 3, management of any late challenge was introduced by Measures 11.1 and 12.1. This scenario was characterized by much higher sensitivity to the VHT treatment than to any other variables.

When other measures were modelled to replace VHT, the reduction of final infestation was more sensitive to events at different points in the chain. Of the three measures introduced in Scenario 4 (3.1, 6.2, and 6.3), Measure 6.2 was thought to have the most effect (Table 2) and this was reflected by the sensitivity of the result to this measure. It is interesting to note that the final outcome was then also sensitive to fruit fly challenge immediately following Measure 6.2, between harvesting and packing. In Scenario 5 another measure, fruit bagging (5.2), was added, which was also thought to be quite effective (Table 2). With the inclusion two quite effective measures (6.2 and 5.2), both acting at points relatively early in the chain, sensitivity to pest challenge remained important between harvesting and packing. The result was no longer very sensitive to pest challenge in the field because fruit bagging managed this. It is interesting that the outcome shows only moderate sensitivity to fruit bagging in this scenario even though this measure is effective. The reason is that, under this scenario, the final outcome hinges more on pest challenge events subsequent to this measure.

The final point of potential pest challenge in the chain occurs between packing and export but in Scenario 3 onwards, Measures 11.1 and 12.1 were incorporated to manage this. Finally, in Scenario 6, two more measures (6.1 and 10.1) were added to reduce the fruit fly challenge at harvesting and between harvesting and packing, respectively. As a consequence, the outcome became more sensitive to Measure 5.2, fruit bagging. In this scenario, a set of measures (6.1, 10.1 11.1, and 12.1) were implemented to reduce fruit fly challenge at all points subsequent to fruit bagging. Scenario 6 is therefore characterized by high sensitivity to fruit bagging as this was then the key measure preventing the important fruit fly challenge in the field. This scenario illustrates the value of maintaining the benefits of an effective measure which acts early in the production chain through the use of subsequent measures to prevent re-infestation. It is worth noting that high sensitivity remains to potential re-infestation between harvesting and packing; if this scenario were implemented, this implies particular value in ensuring measures to manage pest challenge at this point are operating well.

Quarantine inspection is included in the model as a measure but is not employed in this case study. It can be regarded as a control measure because affected lots or units which are found are removed and prevented from being included in the shipment. It is also regarded as highly effective (Table 2). In practice, it is undesirable for the shipment to fail the inspection and the objective in this illustration was to find a set of measures that achieves adequate protection without the extra security provided by the inspection.

The six scenarios described here are illustrative of the use of the tool to explore potential measure combinations but other combinations are feasible and will depend on the constraints prevailing in particular circumstances. The intention of the results illustrated is to show how the model might be used to compare sets of control measures which might constitute alternatives to current practice and offer equivalent risk reduction.

One of the most important practical results so far has been the direct value for plant health practice which has emerged from the model-building process itself: a clarification of the variables and their interactions which need to be taken into account in pest risk management decision-making. The full range of tools developed in the project: the production chain, the elicitation template, and the Bayesian network, have not yet been used in trade discussions related to phytosanitary issues. However, the NPPO in the Philippines has been able to use the production chain, and associated descriptions of measure efficacy provided by the elicitation template, in resolving non-compliance disputes on bananas and pineapples with China early in 2014. The tools demonstrated an understanding of the set of measures being applied by the exporting industry and allowed the Philippine and Chinese authorities to focus on marginal improvements that would meet the importing phytosanitary requirements more effectively.

4. DISCUSSION

A model of the level of pest infestation at points along a commodity production chain has been developed and used to illustrate comparisons between alternative combinations of control measures with the objective of informing the selection of measures to offer an equivalent level of protection to existing procedures. The use of a Bayesian network for this exercise allows the varying effect and uncertainty of factors affecting pest infestation to be incorporated and reflected in the uncertainty of model outcomes. Sensitivity analysis of the model can highlight both those measures and those periods of pest challenge which have most impact on the final outcome. In implementing a system of measures it is useful to know which components are most critical and where any failures are likely to cause the largest risk. Model parameterization was by expert judgement so the results should be seen in this context; they show what these judgements imply for the likely efficacy of combinations of measures. Particularly where evidence is lacking, these judgements may err, making the contribution of such a model particularly important in providing a clear statement of beliefs which can be challenged.

The three tools developed in the project – the production chain, the elicitation template, and the Bayesian network – together promote a systematic consideration of the issues to help build deeper understanding and clarity and therefore confidence for a person conducting negotiations. By making Systems Approaches to Pest Risk Management more visible for exporters and importers in this way, it has been evident that much value is obtained directly from structuring the problem in the form of a descriptive network, the production chain. It is then a natural extension of the descriptive network to integrate the probabilistic performance estimates of the measures as a Bayesian network.

It is expected to be important for exporters to make use of the production chain and the elicitation template as well as the Bayesian network to prepare importer NPPOs for negotiations which involve the use arguments based on output of the Bayesian network itself. For this it may not be imperative that the outputs of any of the tools be shared with the importing NPPO directly. However, in the case of some disagreement on a particular point, the great advantage from the clarity and transparency of the tools when applied is to support communication about concerns and to encourage precision in exactly where the two parties disagree. The values used in the models are clearly displayed in the elicitation template and can easily be adjusted in the Bayesian network to demonstrate the impact of the other party's assumptions or conclusions, so preventing negotiations being delayed by concerns which turn out to have little impact on the overall risk management. The tools are therefore intended to provide an effective communication aid between NPPOs. The exporting NPPO could demonstrate both official and commercial practice measures, after consulting with its domestic stakeholders (e.g., industry, shippers, etc.); the importing NPPO could justify a decision to its own stakeholders.

A criticism which is often made of Bayesian networks concerns the large number and the difficulty of estimating a large number of probabilities which, here, define the probability distributions of the risk factors as well as the conditional probabilities used to integrate the risk factors. Recent work to improve European decision-support schemes in PRA – 'Prima phacie'[(21,22)] and 'PRATIQUE'[(23,24)] – used networks analogous to Bayesian networks but with parameterization of the risk factors made possible by offering users choices from restricted sets of probability distributions which had direct correspondence to an existing risk-rating system with which PRA practitioners were already familiar. In these projects, parameterization of the CPTs was made easier by integrating nodes two at a time and by restricting the CPTs to a small set of alternative configurations, so offering alternative ways in which the risks expressed in the parent two nodes could be integrated.[(16,25)] Here also, by restricting the CPTs to two dimensions and by using deterministic CPTs as far as is reasonable, the underlying assumptions of the model can be described by a small set of tables or matrices; only four of these used are in the model (Table 1). As with the earlier applications in Pest Risk Assessment, the deliberate use of limited parameter sets facilitates consistency, ease of interpretation, and review.[(26)]

Central to Bayesian approaches is the inclusion of evidence and here there are two particular examples related to the sensitivity of the model to the addition of evidence. Each model component (node) is represented by a probability distribution and the inclusion of evidence means that a distribution may be replaced by a known value or by a distribution with lower variance. This reduces uncertainty and may alter the final probability distribution of model outcome. For example, an importing NPPO may wish to have further proof of the efficacy of a control measure and the model could then support decisions regarding requirements for verification measures. Addition of a proposed verification measure at a particular point in the production chain could be modelled by the inclusion of hypothetical evidence about the value of a node and its potential value examined through model queries. It may be revealed that potential evidence associated with the effect of a particular measure has little influence on the final outcome of the model. This might imply that particular control measures are redundant or at least that verification at that point would not be useful.

A second example relates to the concepts of hazard analysis and critical control points (HACCP) in food safety methodology. This involves monitoring the uptake of control procedures and/or their effects, and taking any necessary responsive corrective action. This paradigm has a broad parallel in the work described here in that there are points along a chain of events where evidence can be obtained about pest challenge which may then inform further control actions. The Bayesian network can be used to model control points first by incorporating evidence (or hypothetical evidence) of pest infestation at one or more control points in the production chain, then by adding or removing measures conditionally upon the evidence. By running model queries this way, a more HACCP-like responsive approach to the use of measures could be investigated.

For a limited number of cases it is possible to construct more quantitative models of the pests associated with a pathway of entry.[(17)] In most cases, however, parameter estimation in PRA relies heavily on judgement. A more descriptive, categorical description of pest infestation, as used here, is therefore a widely compatible reflection of expert understanding. The model has a general structure that can be adapted to a wide range of pests associated with the production chains of agricultural commodities. It is described here in the context of a particular case study involving a potential fruit fly infestation of the dragon fruit production chain in Vietnam.

The complex probability calculations resulting from running queries against the model, and updating the probability distributions of the variables, are encoded in Bayesian network modelling software and do not require the operator to be conversant with the methods and algorithms used. The meaning and effects of model parameters are however very accessible to scrutiny at a conceptual level and this enabled non-modellers to interact effectively with the Bayesian network models. In the Vietnam case study, for example, the plant protection officers and dragon fruit farmers did so equally well. If the system of measures and pest infestation levels were described using only mathematical equations they would be less generally accessible.[18] The fact that Bayesian network models can provide a simple and clear visual representation of potentially complex systems, involving many variables and inter-relationships, makes them particularly appealing as a modelling framework in a biosecurity context when stakeholders with diverse backgrounds need to be engaged.

Acknowledgments

The project team would like to acknowledge the STDF for funding and for guidance and support in the project. The active participation of the International Plant Protection Convention and the regional plant protection organization (the Asia and Pacific Plant Protection Commission) was greatly appreciated. The authors would like to thank other members of the project team from Vietnam, particularly Mr. Luong Ngoc Quang, for valuable inputs to the work. Although this paper focuses on a case study from Vietnam, from the perspective of the wider project, particular thanks are also due to project collaborators: W. N. Wan Ismail, H. Tahir, A. Y. Othman, and L. Jumaiyah of the Crop Protection and Plant Quarantine Division, Department of Agriculture, Kuala Lumpur, Malaysia; A. Sivapragasam, K. Y. Lum, and M. J. Sue of CABI, Serdang, Selangor, Malaysia; T. Pradyabumrung of the National Bureau of

Agricultural Commodity and Food Standards, Ministry of Agriculture and Cooperatives, Bangkok, Thailand; C. Salyapongse of the Office of Agricultural Regulation, Department of Agriculture, Bangkok, Thailand; and L. Q. Marasigan, M. B. Palacpac, L. Dulce, G. G. F. Panganiban, T. L. Soriano, and E. Carandang of the Plant Quarantine Service, Manila, the Philippines. We are grateful to Rebecca Murphy for editing the manuscript.

REFERENCES

1. [FAO] Food and Agriculture Organization of the United Nations. 2011. ISPM No. 5: Glossary of phytosanitary terms. Rome, Italy: International Plant Protection Convention, FAO. 23 pp.
2. [FAO] Food and Agriculture Organization of the United Nations. 2006. ISPM No. 1: Phytosanitary principles for the protection of plants and the application of phytosanitary measures in international trade. Rome, Italy: International Plant Protection Convention, FAO. 10 pp.
3. [FAO] Food and Agriculture Organization of the United Nations. 2007. ISPM No 2: Framework for pest risk analysis. Rome, Italy: International Plant Protection Convention, FAO. 12 pp.
4. [FAO] Food and Agriculture Organization of the United Nations. 2005. ISPM No 24: Guidelines for the determination and recognition of equivalence of phytosanitary measures. Rome, Italy: International Plant Protection Convention, FAO. 11 pp.
5. [FAO] Food and Agriculture Organization of the United Nations. 2002. ISPM No. 14: The use of integrated measures in a systems approach for pest risk management. Rome, Italy: International Plant Protection Convention, FAO. 12 pp.

6. Quinlan M, Ikin R. 2009. A review of the application of systems approach to risk management in plant health. EU Framework 7 Research Project, PRATIQUE (Enhancements of Pest Risk Analysis Techniques). Deliverable 4.2. 58 pp.
7. [IPPC] International Plant Protection Organization. 2013. Market access. A guide to phytosanitary issues for national plant protection organizations. Rome, Italy: FAO. 40 pp.
8. Quinlan M. 2013. A review of the application of equivalence between pest risk management measures. Report to the International Plant Protection Convention. Rome, Italy: IPPC Secretariat. 70 pp.
9. Johnson S, Marker L, Mengersen K, Gordon CH, Melzheimer J, Schmidt-Küntzel A, Nghikembua M, Fabiano E, Henghali J, Wachter B. 2013. Modeling the viability of the free-ranging cheetah population in Namibia: an object-oriented Bayesian network approach. *Ecosphere* 4(7):art90.
10. Taroni F, Aitken C, Garbolino P, Biedermann A. 2006. Bayesian networks and probabilistic inference in forensic science. Chichester, UK: John Wiley & Sons Ltd.
11. Waterhouse M, Morton A, Mengersen K, Cook D, Playford G. 2011. Role of overcrowding in meticillin-resistant *Staphylococcus aureus* transmission: Bayesian network analysis for a single public hospital. *J Hosp Infect* 78:92–96.
12. Barton DN, Kuikka S, Varis O, Uusitalo L, Henriksen HJ, Borsuk M, de la Hera A, Farmani R, Johnson S, Linnell JDC. 2012. Bayesian networks in environmental and resource management. *Integr Environ Assess Manag* 8:418–429.
13. Schemann K, Lewis FI, Firestone SM, Ward MP, Toribidio J, Taylor MR, Dhand NK. 2013. Untangling the complex inter-relationships between horse managers' perceptions of effectiveness of biosecurity practices using Bayesian graphical modelling. *Prev Vet Med* 110:37–44.

14. Pearl J (1988) Probabilistic reasoning in intelligent systems. San Francisco (CA), USA: Morgan Kaufmann Publishers, Inc.

15. [FAO] Food and Agriculture Organization of the United Nations. 2013. ISPM No. 11: Pest risk analysis for quarantine pests. Rome, Italy: International Plant Protection Convention, FAO. 36 pp.

16. Holt J, Leach AW, Knight JD, Griessinger D, MacLeod A, van der Gaag DJ, Schrader G, Mumford JD. 2012. Tools for visualising and integrating pest risk assessment ratings and uncertainties. *EPPO Bull* 42:35–41.

17. Holt J, Leach AW, Schrader G, Petter F, MacLeod A, van der Gaag DJ, Baker RHA, Mumford JD. 2013. Eliciting and combining decision criteria using a limited palette of utility functions and uncertainty distributions: illustrated by application to pest risk analysis. *Risk Anal* 34:4–16.

18. Mengersen K, Quinlan MM, Whittle PJL, Knight JD, Mumford JD, Wan Ismail WN, Tahir H, Holt J, Leach AW, Johnson S, Sivapragasam A, Lum KY, Sue MJ, Othman Y, Jumaiyah L, Tu DM, Anh NT, Pradyabumrung Y, Salyapongse C, Marasigan LQ, Palacpac MB, Dulce L, Panganiban GGF, Soriano TL, Carandang E, Hermawan. 2012. Beyond Compliance: project on integrated systems approach for pest risk management in South East Asia. *EPPO Bull* 42:109–116.

19. University of Pittsburgh. 2010. GeNIe2. Pittsburgh (PA), USA: Decision Systems Laboratory, University of Pittsburgh. [accessed on 2014 December 14]. Available from: https://dslpitt.org/genie/

20. Jensen FV, Nielsen TD. 2007. Bayesian networks and decision graphs. New York (NY), USA: Springer Science + Business Media LLC.

21. MacLeod A, Anderson H, van der Gaag DJ, Holt J, Karadjova O, Kehlenbeck H, Labonne G, Pruvost O, Reynaud P, Schrader G, Smith J, Steffek R, Viaene N, Vloutoglou

I. 2010. Prima phacie: a new European Food Safety Authority funded research project taking a comparative approach to pest risk assessment and methods to evaluate pest risk management options. *EPPO Bull* 40:435–439.

22. MacLeod A, Anderson H, Follak S, van der Gaag DJ, Potting R, Pruvost O, Smith J, Steffek R, Vloutoglou I, Holt J, Karadjova O, Kehlenbeck H, Labonne G, Reynaud P, Viane N, Anthoine G, Holeva M, Hostachy B, Ilieva Z, Karssen G, Krumov V, Limon P, Meffert J, Niere B, Petrova E, Peyre J, Pfeilstetter E, Roelofs W, Rothlisberger F, Sauvion N, Schenck N, Schrader G, Schroeder T, Steinmöller S, Tjou-Tam-Sin L, Ventsislavov V, Verhoeven K, Wesemael W. 2012. Pest risk assessment for the European Community plant health: a comparative approach with case studies [Internet]. [cited 2013 November 13]. Available from: www.efsa.europa.eu/en/supporting/doc/319e.pdf
23. Baker RHA, Battisti A, Bremmer J, Kenis M, Mumford J, Petter F, Schrader G, Bacher S, DeBarro P, Hulme PE, Karadjova O, Lansink AO, Pruvost O, Pysek P, Roques A, Baranchikov Y, Sun JH. 2009. PRATIQUE: a research project to enhance pest risk analysis techniques in the European Union. *EPPO Bull* 39:87–93.
24. Baker RHA. 2012. An introduction to the PRATIQUE research project. *EPPO Bull* 42:1–2.
25. Holt J, van der Gaag DJ, Leach AW, MacLeod A, Baker RHA, Mumford JD. 2014. A quantitative interpretation of the Entry Section of the EPPO Decision Support Scheme for Pest Risk Analysis. *EPPO Bull* 44:1–8.
26. Schrader G, MacLeod A, Petter, F, Baker RHA, Brunel S, Holt J, Leach AW, Mumford JD. 2012. Consistency in pest risk analysis – how can it be achieved and what are the benefits? *EPPO Bull* 42:3–12.

List of Figures

Figure 1. Bayesian network of pest infestation on a production chain: model structure developed for fruit fly on dragon fruit in Vietnam. Letters in brackets refer to Table 1 and indicate the conditional probability table used in each node. In all nodes the categories ‘Negligible’, ‘Low’, and ‘High’ are ordered so that the risk on infestation increases from top to bottom; a negligible pest challenge and a high measure efficacy both imply least risk. Probabilities shown correspond to Scenario 6.

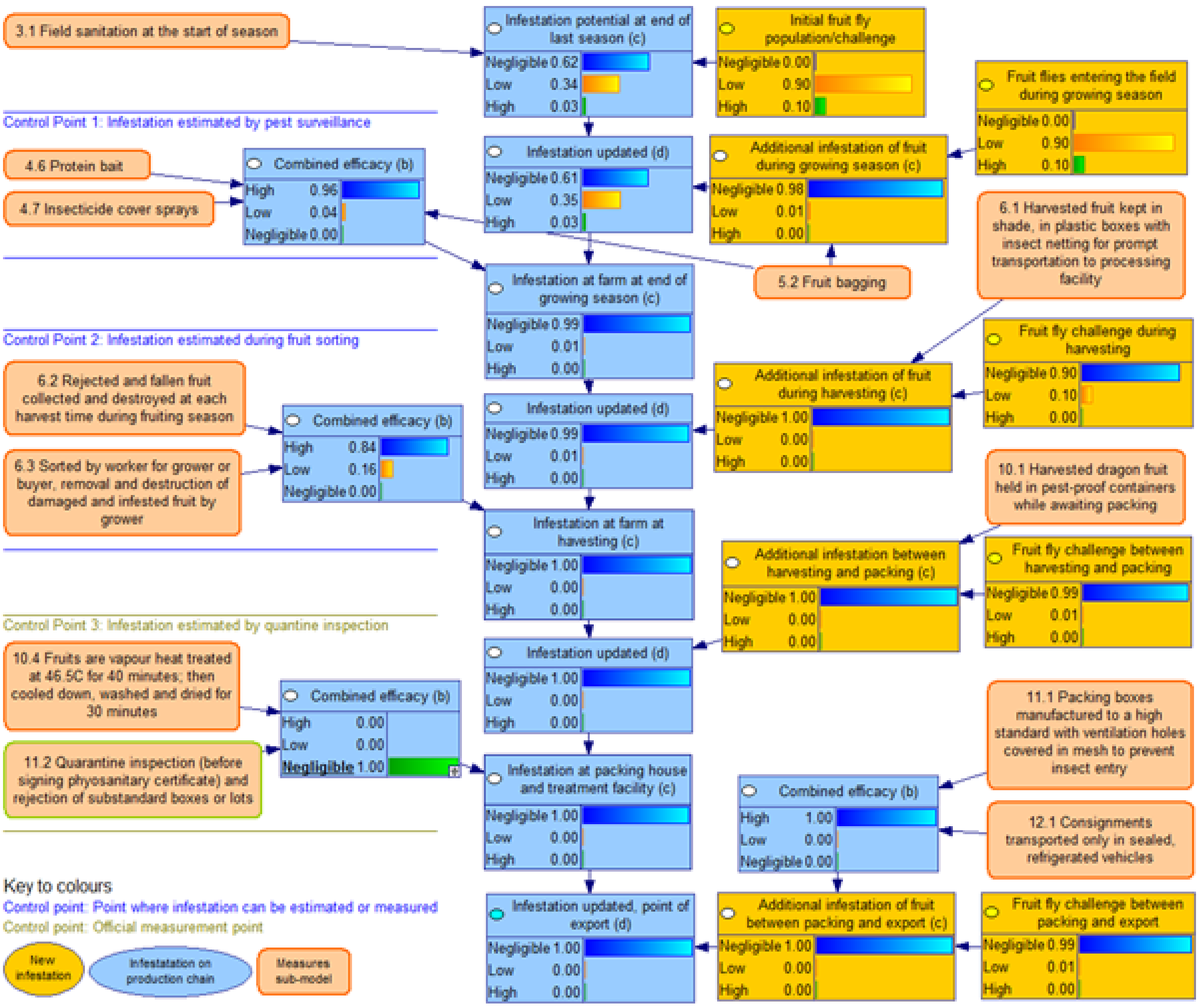

Figure 2. Measure 3.1 sub-model structure. All measure sub-models have the same structure.