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Modelling plant health for policy

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Abstract

Plant health is relatively poorly funded compared to animal and human health issues. However, we contend it is at least as complex and likely more so given the number of pests and hosts and that outbreaks occur in poorly monitored open systems. Modelling is often suggested as a method to better consider the threats to plant health to aid resource and time poor decision makers in their prioritisation of responses. However, like other areas of science, the modelling community has not always provided accessible and relevant solutions. We describe some potential solutions to developing plant health models in conjunction with decision makers based upon a recent example and illustrate how an increased emphasis on plant health is slowly expanding the potential role of modelling in decision making. We place the research in the Credibility, Relevance and Legitimacy (CRELE) framework and discuss the implications for future developments in co-construction of policy-linked models.

1. Introduction

Pests and diseases have adversely affected humanity throughout the recorded history, either directly through infection and infestation of our bodies, or indirectly by attacking animals and plants. Pandemics, like the one caused by SARS-CoV-2 [1] and by Spanish influenza virus [2] or animal disease outbreaks like 2001 Foot-and-mouth (FMD) epidemic in the UK [3] understandably have received large attention. However, plant epidemics like the 1846 Irish potato famine [4], the 1943 Bengal Famine [5] or the Ash dieback epidemic [6], clearly demonstrate the interconnectedness between the health of humans, animals, plants and ecosystems. Policy makers increasingly look to mathematical models to predict the invasion and spread, to evaluate the economic, environmental and societal impact and to carry out the cost-benefit analysis of possible control strategies [7].

The growing impacts of the of invasive plant pest and diseases introductions is well documented [8]. There is a general view that that interventions to prevent or slow the spread of plant pests and diseases have, for a variety of reasons, been too little and too late [9]. An evaluation of the plant health regime in the European Union (EU) concluded that "*In emergency situations, the limited support and lengthy decision-making process results in measures being taken too slowly, too late*." [10].

Plant health dynamics take place in a complex system of interacting environmental, social and economic factors characterised by significant uncertainty across a large number of key system variables [11, 12]. Analysis of plant health risks needs to account for such complexities to inform decision and policy makers where success is invisible (environmental, social and economic losses that do not occur). Invisible success can only be considered by the application of tools that are able to create an ex-ante baseline – that state of the system where the pest/disease is not present or where it is present but having lower impact due to mitigating responses [9].

Rapidly expanding and changing trade pathways (e.g. numbers of products and volumes, move to internet based trading) and changing trends (e.g. demand for large trees and novel foods) provide opportunities for new pests and disease to enter and establish [e.g. 13-16]. It has been estimated that 26,000 plant species have been introduced into the UK compared to a native flora of 1,600 [17]. This provides a conveyor belt pathway for non-native pests and disease. The damages that these can lead to are potentially significant: Hill et al [6] estimated the damage caused by Ash dieback to the UK at £15bn, greater than the estimates of damage due to FMD.

Despite this, plant heath generally receives less funding than animal health [9] but the "conveyor belt" and the scale of the damages are increasing pressure upon public sector capacity and budgets for plant health management. Increasingly there has been a move to prepare for likely incursions in order to reduce the risks and consequences of pest/disease outbreaks occurring in the future [18]. Such analyses need to consider key elements of the invasion and potential responses such as surveillance performance, prevalence when found, subsequent rates of spread and the performance of eradication and control options. These analyses are often undertaken with limited or poor data which partly relate to the relatively small budgets available for plant health. The result is that there is normally significant variability and uncertainty within the computationally complex analyses presenting a challenge when integrating these models into the policy making process [7]. Dupre et al [19] highlight the lack of involvement in the construction and use models that can form a major part of such analyses. These difficulties are exacerbated when acknowledging that decision makers are time pressured and seldom have the luxury of long-term research [7]. Often, they are tasked with producing a response within hours, days or weeks. Such rapid action is necessary given the small window of opportunity for eradication. As Hewitt et al [20] illustrate, decision makers preferred and adopted a simple touchscreen application and not a more complicated, research focussed spatial model. Further, Smetschka and Gaube [21] show that participatory modelling allows the integration of the most relevant issues and for the co-development of scenarios and strategies with stakeholders.

Scientific evidence can inform environmental decision making by considering ranges of options and clarify the implications of choices. The science-policy interface literature acknowledges the issues in bringing research into policy making [22]. Scientists bemoan the lack of impact their research in policy and conversely policy makers lament the lack of context and real-world insight [23, 24]. A common factor in the literature is the degree to which scientific information is usable by policy which in itself is dependent on the perspective and capacity of those involved. Usability is a factor of, for example, accessibility and transmission of evidence, type of knowledge, evidence standards (including uncertainty), as well as the degree to which it can lead to a response or action [24, 25] at an appropriate spatial or temporal scale [26]. Barriers to the uptake of scientific evidence include organisation culture, values and ethics, resources, and entrenched commitments. Facilitators of useable knowledge include the co-production of knowledge [27, 28] and social learning [29].

Dun and Laing [30] like Cook et al [7] suggest that a key gap in this landscape is the lack of consideration of the demand for information in addressing the needs of policy and decision makers and how research and policy interact accounting for what policy makers themselves value most in research. Dunn and Laing [30] consider the prominent contention that the key attributes for effective knowledge to action are *credibility* (adequate, authoritative, trustworthy), *relevance* (particularly in terms of spatial and temporal scales), and *legitimacy* (an unbiased and respectful process). These attributes (often abbreviated to CRELE) are challenged by Dunn and Laing [30] given a limited empirical verification. By conducting 72 structured interviews with policy makers in the urban water sector, they found CRELE to be a poor predictor of the concerns of policy makers over usability of research and that *applicability*, *comprehensiveness*, *timing* and *accessibility* (ACTA) better summarise the concerns of policy makers. This in effect increases the importance of relevance in the CRELE view. Whilst credibility and legitimacy are of great importance to the scientist's world view, they are less important outside the research environment. *Accessibility* refers to knowledge that is created with the end user in mind, that avoids jargon and is communicated effectively. *Comprehensiveness* recognises the broader interdisciplinary environment of the decision maker and the need to contextualise ideas within a broad range of real-world considerations including the economic and financial consequences. *Timing* acknowledges the cycles that policy and business decision makers work within whereby windows of opportunity for action need to be incorporated. Finally, *applicability* links the research to solutions to the problems faced that guide implementation (not just concepts) that are tailored to the specific issue and variables.

This view was prevalent in a recent project undertaken for UK plant health policy [31]. Amongst the objectives for the work were that it should be:

- flexible and transparent, be clear and simple to follow, and be readily updatable with existing assessments as new evidence becomes available.
- responsive to time constraints facing decision-making

Whilst close engagement was not explicit in the brief, the above objectives chime closely with elements of both the CRELE and ACTA frameworks, possibly more so for the latter. In the following sections we describe some of the challenges of providing modelling for policy within the plant health system, the policy challenges, the role of modelling and finish with potential challenges and solutions.

2. Nature of the system

Although in many ways plant epidemiology is dealing with similar issues to veterinary or medical sciences, there are substantial differences that in many respects make it more challenging to predict and control. For an outbreak of plant epidemic to be initiated and for the pest or pathogen to spread, a number of conditions need to be fulfilled. Van der Plank [32] and Zadoks & Schein [33] summarised these conditions in the form of a disease triangle, with corners comprised of Host, Pest and Environment [34]; this concept can be applied across all fields of epidemiology and used to compare the different approaches. Firstly, in medical epidemiology, there is only one primary host: the human being, whereas veterinary epidemiology deals with a limited number of hosts, both domestic and wild animals. However, only a few animal species are classed as important from a societal standpoint. For plants, the situation is very different, as there is a large number of plant genera providing ecological or agricultural services. The domesticated and wild hosts for the same plant pest are often found in proximity to each other with high levels of cross-over. Although zoonotic disease, e.g. Ebola [35] and wild/domesticated crossover, e.g. bTB in badgers and livestock [36], are important in human and animal diseases, there are many more plant examples of that type [37, e.g. wheat stem rust [38]. Secondly, the multiple plant and tree hosts are affected by a large number of pests and pathogens, many of which have a broad range of hosts, e.g., *Xylella* spp.is currently believed to have over 563 hosts, a number that has increased in the last few years as more is learnt about the pest [39, 40]; the UK Plant Health Risk Register [41] currently lists well over 1,000 threats, many of which are insects or fungal pathogens. Plant pests and diseases are also more difficult to detect because of the lack of obvious symptoms and long latent periods, and due to the sheer number and acreage of hosts (or large mixed species area with randomly located hosts) that would need to be monitored. Finally, plant pests often have complex life cycles driven by environmental conditions (e.g., temperature, rainfall) which make it necessary to consider factors that otherwise are less relevant in human or animal diseases.

Although some plant epidemics and pest outbreaks are indeed devastating and hence draw the public and the politician attention (e.g. Ash dieback in the UK [6]), the general appreciation of them is low. This is also partly because there are usually ways to substitute the market or non-market services of plants or, for trees, the impact is over a long time period making the impact less noticeable [6]. Thus, the outbreaks might draw less publicity and less effort is often invested in surveillance or controlling movements, unlike strict controls that exist on movement of livestock or companion animals. Imports are also less regulated, as it has been relatively easy to source seeds and other plant material online [42, 43]. The lack of monitoring combined with a number and area of hosts means that lower quality data are available, although this is potentially changing with the advent of remote sensing [44 – 46].

Once the outbreak occurs, there are often fewer control options available [47], with destruction or clear-felling often the only option. The loss of chemical control due to regulatory control and increasing resistance [48] partly parallels the rise of Anti-Microbial Resistance (AMR) in medical and veterinary medicine [49], but the scale of the problem is potentially larger. In many cases there are no options but to adapt to the pest or pathogen once it becomes established, even though there are substantial losses associated with this strategy. In the short term, this strategy can be associated with “do nothing” option. However, many plant pests become fully established once they arrive, leading to long term consequences which need to be accounted for, but are highly uncertain, such as ash dieback leading to a potential collapse in the whole ecosystem supported by the host [50].

The decision how, or indeed whether, to control is often to some extent driven by economic considerations. The livestock losses are relatively easily quantifiable, although the impact of the UK FMD outbreak on animal and farmer welfare and well-being has long been underestimated [3]. The impacts of plant, and even more forest, pests and diseases are often irreversible [51], as once a keystone species is lost, the whole ecosystem can collapse [50]. Although market impacts are important in the agricultural setting and in timber production, plant pests often affect non-market ecosystem values [52, 53 and 12 for a comprehensive review of the valuation literature on values associated with woodlands]. The estimation of these is notoriously difficult but the inclusion in case of the Ash dieback epidemic in the UK shows the scale is at least comparable with the FMD outbreak [6].

3. Policy challenges

There is a strong economic argument (which includes estimates for non-market impacts) for the public support of plant health policies, and this is now generally accepted at national level decision making. However, it is not always easy to define success in terms of prevention or control of diseases, as the consequences of “doing nothing” are not always apparent. This is particularly difficult for plant and even more for forest pests, where such consequences might only become apparent years or even decades after the initial incursion. The invisible (and often slow) nature of success potentially leads to two effects: firstly, the under allocation of resources to plant health; and secondly, the misallocation of resources within plant health. The extent of these effects has not been quantified But Ward [9] provided a view on the cost-effectiveness of the typical responses from those who manage plant pest and disease to a new outbreak based upon decades of managing public plant health inspection resources in the UK. Figure 1 shows a series of lagged steps that delay response to plant pests that lead to less cost effectiveness solutions. Stakeholder response is reactive to events with awareness of the problem and willingness to respond lagging entry, spread and symptoms. The cost effectiveness illustrates the value of prevention and early detection as well as implying (where it dips below the x-axis) that there is a point at which response options (eradication and control should cease and that stakeholders should learn to live with the pest. The cost effectiveness estimation is dependent upon knowledge of the multiple host-pest system variables and uncertainties described above i.e. how to allocate scarce resources when faced with multiple threats of differing probabilities of invasion and levels of impact.

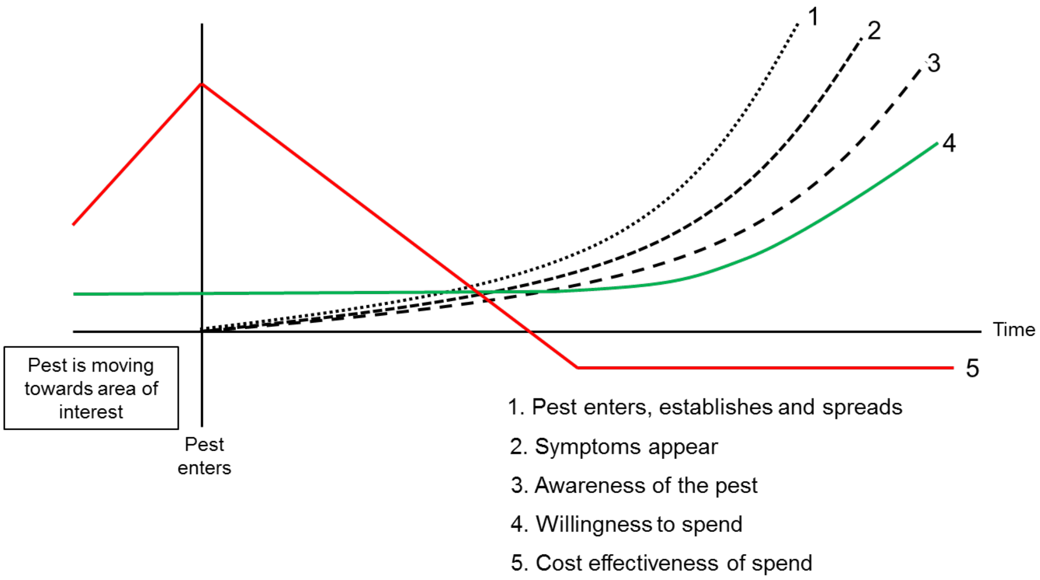

Figure 1. Pest progression, willingness to respond, and cost effectiveness

Cook et al [7] highlight the often short timeframes available to decision makers (*ACTA – timing*), particularly during outbreaks. It is not uncommon for almost all decision support people to be time-pressured and they therefore require methods to estimate the benefits and costs of response options that can be delivered rapidly. Initial decisions need to account for potential economic, environmental and social impacts (*ACTA – comprehensiveness*) with the decision likely to be implemented under conditions of significant uncertainty. This speed reflects the limited window of opportunity for successful eradication. It also highlights the need for authorities to prepare for likely future pests by considering the major threats and conducting ex-ante analyses i.e. with respect to Figure 1, acting in time prior to the y-axis.

Biosecurity decision makers at a national level will likely have access to a number of in-house and external experts across a wide range of disciplines that are necessary to provide the wide range of inputs required for modelling plant health related scenarios. With respect to modelling, this poses the question as to the degree to which the policy leads are au fait with the modelling methods and the inherent shortcomings given the data available and the full range of uncertainties and gaps (*ACTA – applicability and accessibility*). Cook et al [7] suggest that "*Public officials and community stakeholders charged with the responsibility of making these decisions are often naive about what science can and cannot say about complex systems. In these situations, policymakers tend to rely on a limited number of "heuristic principles"* [54] *to help them simplify the process of judgment*". Such heuristics might, for example, give greater weight to particular locations or to economic impacts over environmental. To this end it is important that such officials are aware of inherent limitations implicit in modelling approaches in order to account for the uncertainties within the decision-making process. This includes an awareness of how the decision might change as new information becomes available and, potentially, a willingness to change the decision in this light.

Jones [11] identifies a number of critical factors for determining policy response options. These factors themselves involve a set of complex economic, social and environmental interactions [55]:

- The prevalence of a pest when found is a function itself of the performance and scale/scope of the detection system [56]. Relating this to the Ward diagram (Figure 1) limited or poorly applied detection effort or asymptomatic characteristics make it more likely that initial detection could be at a point where any action aimed at controlling the pest is not cost effective and the response should be to adapt to its presence.
- The rate of spread of the pest/disease is a function of its own lifecycle and movement capabilities as well as the degree to which human activities contribute.
- The impact of the pest on the host can vary from yield/quality reduction, to mortality effects or morbidity effects that lead to mortality through other means. Knowledge of the precise impacts of the pest/disease on ecosystem services is almost always imperfect. As is the value of the host itself including the range of services it provides. There are significant uncertainties in our understanding of how pest impacts lead to changes in ecosystem services and consequently on human welfare.
- The efficacy of the policy response is also uncertain particularly with gaps in information from the above factors. For example, movement restrictions may slow the spread of pest associated with the plant trade, but it is very difficult to know whether there will be full and or effective compliance or if some actors may simply elect to flout the rules.
- The decision makers also engage with a wide range of stakeholders whose objectives may be in conflict (*CRELE – credibility and legitimacy*). Stakeholders include: agriculture, horticulture (food and ornamental crops), forestry, landscaping, and management of parks & gardens (including local authorities); resulting in a complex and heterogeneous set of private and public stakeholders. As pests move through the landscape, different stakeholders with different knowledge and incentives come into contact both with the pest and each other leading to an array of potential responses that have implications for policy responses.

Thus, public decision makers have a particularly complex and difficult task when dealing with plant health issues.

4. The application of modelling to policy

Mathematical modelling has a long history in addressing challenges presented by pest and disease outbreaks [34], from predicting the temporal and spatial extend, through estimation of losses to evaluation of control measures [7]. Increasingly, the modelling is linked with economics and behavioural sciences [57], and actively used in policy making [7]. However, too often such multidisciplinary research suffers from being conducted in separate silos, rather than through a close interdisciplinary collaboration of the research team and inclusion of stakeholders at each stage of the development; effort is needed to actively break such barriers.

To illustrate the use of modelling within a plant health policy setting, here we describe a decision support tool developed in Jones *et al.*[31] and (Kleczkowski *et al.*[58] to illustrate the challenges and potential solutions to address them; similar tools have been described in [7]. The aim of these two projects was to provide a generalised (*ACTA – applicability*), transparent (*ACTA – accessibility*), and quantified tool to estimate risks and impacts of plant and tree pests and diseases and to estimate the role of climate change in the potential economic losses. The tool allows comparing the cost-effectiveness of different response options. The framework was also designed to enable decisions on whether or not to eradicate, contain or learn to live with a problem.

Although not explicitly using the CRELE or ACTA frameworks, the brief addressed these attributes by requiring that the decision support system to:

- Be a quantified framework that allows for economic, social, environmental, political, technical and legal considerations (*CRELE - credibility, ACTA - comprehensiveness*);
- Include critical factors such as rate of spread, size of known distribution of threat; social, environmental and economic 'value at risk'; sectoral / community considerations; wider environmental threat posed by the threat; public acceptability of control and management options; regulatory and legal context (*CRELE - Legitimacy, ACTA - applicability*);
- Apply to a range of threats from the UK Plant Health Risk Register (*CRELE - Relevance, ACTA - timing*);
- Be flexible and based on transparent assumptions, and be clear and simple to follow, applicable to other threats and provide support to readily update existing assessments

as new evidence becomes available (*CRELE - Credibility, Legitimacy, ACTA - accessibility*).

- Be responsive to the very different time constraints facing decision-making within the scenarios of eradication, containment and management (*CRELE - Relevance, ACTA - timing*).

We responded by constructing a framework which consists of three elements: (i) the epidemiological model, (ii) the valuation and impact model, and (iii) the uncertainty evaluation. Following intensive consultation with the stakeholders and a number of workshops at which we presented different versions, the framework was implemented in R [59] using Shiny package [60]. The close interaction with stakeholders and policy makers was designed to ensure accessibility (addressing *Accessibility* in the ACTA framework) by involving them in co-production of the system.

There exists the whole range of modelling approaches that can be used, depending on the availability of data. For the decision support system to be accessible to a wide range of stakeholders it needed to be user-friendly and simple while remaining as accurate and powerful as possible (thus satisfying both *Comprehensiveness* and *Applicability* in the ACTA framework while addressing *Credibility* and *Relevance* in CRELE). In particular, the model structure needs to be adapted to the policy objectives and to the existing data; this will often limit the choice of the model structure.

There exists a range of different models that could be used to predict the future of an outbreak; for a current review see [34]. At one end of the scale there are simple Risk Assessment models like those discussed in (Heikkilä J. , 2011) and (Leung, et al., 2012), which essentially follow a semi-quantitative methodology by using an algorithm that combines scores given by assessors to produce the overall risk and impact. Such approaches, whilst intuitively appealing (e.g. UK Plant Health Risk Register), are essentially static and do not account for nonlinearities inherent in epidemiological processes, like the invasion threshold described in terms of the reproductive number (Kleczkowski et al, 2019b). At the other end, are the Agent Based Models (ABMs) which attempt to represent individual dynamics of all relevant entities (either individual plants or trees, or more likely, fields or forest patches). ABMs, while very successful in predicting the course of a particular outbreak, have a limited generality as they are closely tied up to a particular host distribution and pest properties. They also have high data demand, which is not often possible, particularly in the plant health context. The choice of the model needs also to be driven by the balance between *Comprehensiveness* and *Applicability* on one hand and *Accessibility* and *Timing* on another. The first two of these factors originate in a recognition that the real-life applications are complex and require multidisciplinary approach. This often leads to inclusion of too many processes which cannot be readily and comprehensively parameterised within the time frame of the project. At the same time, the model needs to capture the essential features of the process.

For pest and disease support [61] and [62] recommend that the main components of the model are (a) entry, (b) establishment, (c) spread and (d) impact (economic, social and environmental), with the considerations in terms of the probability of each step [7]. The model consisted of six elements [58]: (i) the epidemiology module describing spread, (ii) the pest arrival (entry) module, (iii) the control module, (iv) the economic module addressing the impact, (v) the weather and climate module, and (vi) the reporting module.

The model is described in detail in [31] and [58]. Similar to Cook et al. [7], we found that a metapopulation approach is often an appropriate selection in a situation when data are limited. In this approach, the region is subdivided into discrete units but the host and pest distributions within each region are irrelevant. The area of infestation in our model follows a Susceptible-Infected/Infested-Removed/Dead model [58] in each region, with cross-infestation representing either focal expansion or establishment of new foci [7]. Conversely, reduction in cross-infestation between regions can be interpreted as a prevention strategy; given the constraints of the project we assumed that the pest is already present in one part of the region. This assumption has been relaxed in subsequent developments of the model [58].

The modelling approach was a compromise between the need to capture key elements of the spread and the lack of detailed data and information. For example, spread within the subpopulation was assumed to be homogenous and the model did not include any spatial heterogeneity on the economic side. The population age structure was assumed to be constant. Although the key advantage of the model was the explicit inclusion of uncertainty in the parameters for spread and values at risk, there was no inclusion of the demographic stochasticity. Finally, the model did not explicitly include cryptic and latent classes.

The model was parameterised using a combination of literature search, expert elicitation (including expert workshops) and rigorous parameter estimation. The exact arrival point and timing of the pest is usually unknown and can span years if not decades, particularly for tree pests. Areas and locations of host are often well established, although the role of trees outside woodlands or volunteer plants in facilitating spread is not clear. The rates of pest or pathogen spread can often be obtained from other studies or by fitting the model to existing data. Both approaches are not without problems. Papers reporting values are mostly for different locations and climatic conditions and some are for different sub-species; this is particularly difficult for rare or novel pests. The values are often model-dependent and, as different studies use different models, the results might not be transferable. Data are difficult to obtain and are often biased by observational effort. The estimation of the spread is therefore characterised by large uncertainties, structural (e.g. different models), systematic (e.g. under-reporting or different hosts) and random.

We found that the impact of pests or pathogens on values is even less established. The efficacy of control beyond clear-felling is highly unknown for many forest pests and for agricultural pests there is an added complication of loss of chemical control and rise of resistance. Although there are general estimates of the market and non-market values [64], values of losses due to infestation or infection are much less well established (see [6]). So, whilst there are methods available to estimate non-market impacts, they are currently not sufficient to be able to apply to broad policy questions beyond the rather old Willis *et al*. [64] estimates (which are the main input to the estimates used in Defra's Tree Health Resilience Strategy, [63]). The non-market valuation estimates available do not fully account for the potential range of possible lost values. Some impacts will be currently unquantifiable (e.g. shared values, health and well-being) but might be dominating the discourse.

One of the key elements of any decision support systems for plant or tree health is the need to account of multiple sources of uncertainty. Analysts can be encouraged to perform sensitivity analysis in order to assess how future uncertainties can affect the choice between the control policy options and deciding whether any is preferable to "do nothing". Another key factor in ensuring the successful construction and uptake of the model is the iterative and adaptive nature of the design development. For example, we found the model to be better suited not to be used directly to make the decision but instead to be used to provide information to decision makers in evaluation of scenarios. This type of use requires the joint construction of a narrative by direct and indirect users with assistance of modellers. This underscores the importance of the *Relevance* in the CRELE framework in the process of balancing the *Credibility* and *Legitimacy* (essential to the scientific aspect of the modelling) with *Relevance* as captured by the ACTA framework (a key to usability of research).

Given the balance of assumptions and scope of such decision support tools, we feel that they could be used (i) to answer broad questions concerning the future threats of different pests and pathogens in relative terms, (ii) to explore initial feasibility options for the scale of control necessary for a specific well-documented pest/pathogen, (iii) to provide rapid, early stage assessment of the likely impact of certain pests and pathogens, and (iv) to engage with stakeholders to illustrate the effects of control strategies and climate change.

This approach should be treated as part of a larger framework, combined with risk analysis approaches that broadly to identify key pests and diseases. In turn, the middle-range generic models – as discussed here – can provide rapid early stage evaluation or to answer broad questions about the long-term behaviour. Subsequently, for detailed management advice for a specific pest or pathogen, a bespoke epidemiological model should be developed and carefully parameterised.

5. Solutions and challenges

In 2012 Ash dieback was detected for the first time in the UK. This devastating disease of ash had a significant impact on the future direction of plant health in the UK with a Tree Health and Plant Biosecurity Expert Taskforce. Amongst its recommendations in the final report (Defra, 2013) were a group relating to plant pest and pathogen modelling:

- Capacity to model the spread of different pests and pathogens to predict their rate of spread, the effectiveness of different control measures, and to identify key epidemiological parameters and hence prioritise research needs;
- Models should be developed in advance for specific known threats while generic models should be available as the basis for studying novel threats (*ACTA – timing*);
- Models should be open to examination and testing by the research community and be as transparent as possible to all stakeholders (*ACTA – accessibility*);
- Models should be refined and updated based on field verification data obtained whilst dealing with new or established pests and pathogens; and
- Ecological and epidemiological models should be constructed so that, according to the problem, they can be easily linked to diverse models of economic and social drivers and responses (*ACTA – applicability*)

There has been movement to varying degrees across all these recommendations. ADB meant that plant health, and tree health in particular, moved up the policy agenda in the UK to the extent it is now directly incorporated in the stated priorities of the responsible Government department. This increased awareness and focus on plant health can be seen, for example, in the range of UKRI calls, the development of preparedness plans for high priority pests (e.g. *Xylella fastidiosa* and Emerald Ash Borer). These have increased the number of academics familiar with different aspects of the subject matter. Further, Defra has constructed a plant health modelling framework which now has three or four academic based consortia that will respond to rapid calls for research into different policy issues. However, the expansion of modellers familiar with this space has not increased significantly. These calls and frameworks, in combination with the development of pest specific preparedness boards and the model described in section 4, allows for the development of models in advance of threats being realised.

Of particular note from our experience when modelling plant health outbreak scenarios with Government officials responsible for developing response options was the degree to which discussion around the model assisted in understanding of the importance of evidence gaps and how these gaps translated into wide ranges in outcomes and therefore possible policy success. This would appear to support the Dunn & Laing [30] perspective that relevant scientific research and modelling (it needs to be applicable, comprehensive, timely and accessible) is crucial for it to have traction/impact in policy development.

The model in section 4 also illustrates movement towards transparency with the model code being shared. Data remains a problem. The relatively limited funding for plant health reduces the data that can be collected and the data that does exist is often difficult to extract or obtain. To our knowledge, the model described in section 4 remains a somewhat rare example of a model linked to economic and social impacts. Attempts to link drivers of outbreaks remains an under researched area.

Conclusions

Models can only have an impact if decision makers account for their outputs in maintaining or changing a position. Decision makers are time poor and cannot be expected to be able to assimilate all the potential interactions within a complex system. Thus, model developers need to recognise trade-offs between addressing complexity inherent in the policy question and producing tools that will inform decision makers. Co-design principles can begin to overcome some of the barriers to the wider use of models in decision making. However, it is not just about using the models. It is also about creating shared understanding of a wider set of factors: providing insights to decision makers on the effects of uncertainty in key parameters on model outcomes (and how that might effect changes in decisions) as well as the range of factors that are missing from the models e.g. political risks including social acceptability of the decision. Elements of both the CRELE and ACTA frameworks were apparent in the case study presented.

The recent outbreak of COVID-19 further illustrates the importance of the role of modelling in policy making and the stakeholders and indeed general public trust in such models [66, 67]. It is too early yet to evaluate the direct impact of the pandemic on plant health but COVID measures could lead to reduced trade and travel [68] thereby lower the risk of plant pests and diseases through trade. On the other hand, it could lead to reduced government budgets for inspections and surveillance and so increase the risk.

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