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Robust surveillance of animal diseases: An application to the detection of bluetongue disease

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ABSTRACT

Control of endemic, exotic, and emerging animal diseases critically depends on their early detection and timely management. This paper proposes a novel approach to evaluate alternative surveillance programs based on info-gap theory. A general modeling framework is developed explicitly accounting for severe uncertainty about the incursion, detection, spread, and control of exotic and emergent diseases. The model is illustrated by an evaluation of bluetongue disease surveillance strategies. Key results indicate that, when available, vaccination of the entire population is the most robust strategy. If vaccines are not available then active reporting of suspect clinical signs by farmers is a very robust surveillance policy.

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1. Introduction

Animal disease outbreaks cause significant costs to societies, through loss of productivity and death in livestock industries (Rich and Winter-Nelson, 2007). For example, it has been recently reported that endemic animal diseases may reduce productivity by around 17% in the United Kingdom and by up to 50% in developing countries (Flint and Woolliams, 2008). Along with losses in the husbandry sector, zoonotic animal diseases can have a direct impact on humans, affecting public health. Thus it is imperative to develop sound scientific knowledge to support surveillance and disease management decisions (Singer et al., 2011). Climate change, movement of people and animals, and increasing trade flows may facilitate the spread of exotic diseases and emergence of new diseases (Racloz et al., 2007). These relatively new factors create uncertainty and further challenge agencies managing and controlling animal diseases.

One of the main difficulties in managing exotic and new infectious diseases arises from uncertainty about how, when and where diseases may emerge and how they may spread through an animal population. Specifically, there may be lack of knowledge on how animals are infected; how the disease manifests; and on the transmission of infectious agents. Animal health authorities must take into account all these risk factors when deciding how to invest limited resources on systems firstly, to identify new or exotic infectious disease and secondly, to control them taking into account these risks (Prattley et al., 2007). In recent years risk-based decisions and novel forms of animal disease surveillance have been developed and increasingly used (Paiba et al., 2007; Doréa et al., 2011). However, risk management frameworks critically depend

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on the availability of accurate estimations using probability distributions (Sanson and Thornton, 1997). When such probability distributions are not available or are not credible, traditional methods may not be suitable for evaluating alternative options.

The aim of this study is to evaluate animal disease surveillance strategies under severe uncertainty. We propose an alternative to risk and probability based methods to aid decisions regarding a set of surveillance strategies when data are unavailable or not credible.

Disease surveillance is the systematic collection, analysis and interpretation of data on diseases occurring in a population, enabling the implementation of measures to control their impact (OIE, 2004). A number of studies have evaluated alternative surveillance options (Sanson and Thornton, 1997; Horan and Fenichel, 2007; Prattley et al., 2007; Williams et al., 2009). Hennessy (2007) identified a number of issues when addressing animal health problems: the first is that each disease (or at best class of diseases) is different and requires a different approach. As an example, it is inappropriate to generalize results obtained for foot and mouth disease (FMD) to bovine spongiform encephalopathy. A second issue is that animal production systems, prevention strategies, private and governmental interventions, possible spread to human populations and severity of disease all impact optimal management strategies (Hennessy, 2007). Therefore, decisions on animal disease management are also hindered by disease and institution specific sources of uncertainties.

Surveillance and disease control strategies may be complementary activities. The sooner an agency is aware of a disease on an animal population or on the environment, the quicker it can implement intervention strategies and the lower the expected total costs (Kompas et al., 2006). There are alternative surveillance strategies, depending on the type of disease and efforts of different agencies involved in surveillance and management activities (Prattley et al., 2007). Allocating resources for surveillance activities requires information and knowledge on the biology and ecology of the disease, description of surveillance costs, production losses estimates and the costs of eradication (Kompas et al., 2006). In the case of endemic diseases, there generally is a very good knowledge about their characteristics. For exotic diseases, decision makers can rely on probabilistic distributions of key parameters to assess alternative surveillance options. Even so, since infectious agents may adapt to the new environment, there is a degree of uncertainty about the validity of prior information. Also, timeliness of disease detection and control can be seriously compromised by incorrect strategies and failures in laboratory tests (Doréa et al., 2011). For emerging diseases, critical probability distributions will not be defined. In such cases probabilistic models and expected utility models may not be the most appropriate to evaluate alternative surveillance strategies.

Here we analyze surveillance and intervention strategies for bluetongue disease in England and Wales. This viral disease is exotic in England and Wales and information is publicly available concerning a previous outbreak. The assumptions and surveillance options we make in our study are intended to enable an exploration of theoretical approaches to decision making. We are not concerned with exploring or evaluating policy-making in England and Wales.

Bluetongue is a vector-borne disease of high economic importance caused by the bluetongue virus (BTV) and is capable of infecting a wide range of ruminant species (Hourrigan and Klingsporn, 1975; Mellor and Wittmann, 2002). This is a special case of exotic diseases, although we know about the agent and vaccines are available, the spread patterns are uncertain. BTV is spread by a vector, a biting midge (*Culicoides*), from other infected animals (Wilson and Mellor, 2008; Maclachlan, 2011). Among domestic animals, sheep present a high mortality and morbidity although noticeable clinical signs and death have also been documented in cattle, especially in the case of BTV serotype 8 in Europe (Elbers et al., 2008). We chose this as a theoretical but realistic example for the application of the info-gap approach; it is not intended as a review of the actual bluetongue disease outbreak in England.

While certain serotypes of BTV have been continuously present in certain regions of the Mediterranean Basin since 1998 (Mellor and Wittmann, 2002; Saegerman et al., 2008), this disease was considered exotic in northern Europe (Thiry et al., 2006; Sperlova and Zendulkova, 2011). In the summer/fall 2006 an outbreak of this disease occurred in Belgium, Luxemburg, Netherlands, western Germany and northwestern parts of France affecting approximately 2000 holdings by mid January 2007 and causing considerable production losses and low to moderate mortality rates (Carpenter et al., 2009). In Germany mortality rates varied from approximately 6–13% in cattle and 37–41% in sheep (Conraths et al., 2009). The net costs of this outbreak in the Netherlands alone were estimated to be up to 32.4 million Euros in 2006 and between 164 and 175 million Euros in 2007 (Velthuis et al., 2010). In August 2007, the first BTV infected farm in England was identified near Ipswich and two more farms in Cambridgeshire, three in Kent and one in Sussex were subsequently infected (DEFRA, 2008a). These infections were considered the result of new independent introductions from the continent (Szmaragd et al., 2009). As of July, 5th 2011 DEFRA stated that the UK is officially declared free from bluetongue (DEFRA, 2011).

Since the Mediterranean Basin and the northern European regions have quite distinct ecological conditions, it has been argued that bluetongue outbreak in northern Europe might have been associated with climate change, which may allow for better overwintering of the virus and an expansion in the range of *Culicoides imicola*, the main BTV vector (Purse et al., 2005). However, a study conducted in Italy, found no evidence of a geographic expansion of *C. imicola* between 2000 and 2008 (Conte et al., 2009). Also, researchers claim that the increase in animal movements, along with exceptional warm winters and summers in 2006–2008, might also explain the outbreak of bluetongue in 2008 (Mehlhorn et al., 2008). Moreover, recent studies suggest that the BTV may have been spread by another vector (Hoffmann et al., 2009). Still, since this first outbreak, farmers throughout England have been encouraged to adopt preventive measures, namely through vaccination, though the vaccination uptake rates by farmers presented high variability.

The paper proceeds as follows: first we develop a conceptual framework for decision-making when there is not information about critical parameters of diseases. Then we illustrate the usefulness of this model for the analysis of disease surveillance and management activities in the context of an animal population characterized by multiple subpopulations, contagion mechanisms, disease vectors, and surveillance and control capabilities.

2. Material and methods

Though our framework is particularly suited for evaluation of emerging disease surveillance strategies, it can also be used for exotic diseases when uncertainty persists. We envisage a system to detect the introduction of a pathogen in an animal population, characterized by multiple subpopulations, contagion mechanisms, disease vectors, and surveillance and control capabilities. For example, a disease introduced into a subpopulation can spread among members of the subpopulation directly. Certain diseases can be spread by vectors within and between subpopulations. For endemic and most exotic diseases the clinical signs and consequences are well known; for new diseases this is not necessarily the case. Moreover infectious agents often evolve, changing the dynamics of the disease and its impacts. Damage can be restricted through early detection and use of management tools such as vaccination, when available, and vector control to manage disease outbreaks. Because many uncertainties in the management decision problem cannot be captured by probability distributions, we adopt an info-gap decision theory perspective on uncertainty and robustness (Ben-Haim, 2006).

2.1. Theoretical model

Info-gap decision theory (Ben-Haim, 2006) is primarily prescriptive, providing support to decision makers under uncertainty. Distinct from traditional alternatives, the info-gap approach is not a closed computational methodology but rather a flexible perspective on decision analysis whose assessments assist decision makers in evaluating options, developing strategies, and evolving preferences. An info-gap is a disparity between what is known, referred to as the nominal model, and what needs to be known in order to make a comprehensive decision. The theory is based on a model of uncertainty, a model of the system that generates outcomes, and a performance requirement.

Specific formulation of an info-gap model of uncertainty depends on the type of initial information available which is then invested in determining the structure of a family of nested sets of uncertain events. Nesting imposes the property of "clustering" which is a characteristic as well as a unifying feature of a wide range of info-gap models of uncertainty; *e.g.*, convex, non-convex, continuous, discrete, bounded, unbounded, hybrid, as well as others employing various measures of deviation.

The uncertainty model, system model, and performance requirement are combined in formulating a robustness function which supports the choice of action. From an info-gap perspective, a decision which achieves an acceptable outcome over a large range of uncertain realizations is preferable to a decision which fails to achieve an acceptable outcome even under small error. Info-gap theory takes the position that the best strategy is the one that satisfies the decision maker with an outcome that is both acceptable and makes the decision maker as immune as possible from an unacceptable outcome. In brief, an info-gap robust optimal decision maximizes the reliability of an adequate outcome. In this way a robustness function generates preferences on available decisions.

We envision a vector of surveillance and management policies through time, denoted $\mathbf{x}$, and a vector of uncertain model elements (*e.g.*, parameters, probabilities, structural relationships), named ε. These two vectors are the exogenous variables in a system model, $V(\mathbf{x}, \varepsilon)$, where V is the expected net present value of the surveillance program. An info-gap uncertainty model characterizes the uncertainty about ε as a family of nested sets with $\alpha < \alpha'$ implying that $U(\alpha, \varepsilon_0) \subseteq U(\alpha\prime, \varepsilon_0)$ where ε_0 depicts what is known about uncertain model elements. The info-gap system model is reflected in the evaluation of $V(\mathbf{x}, \varepsilon)$ which is compared to a performance requirement, V^*. Preferences over $\mathbf{x}$ are generated by a robustness function $\hat{\alpha}(x)$, which identifies the best choice achieving an acceptable outcome over the largest range of uncertain realizations. The model predicts the policy or decision ($\mathbf{x}$) that provides as much immunity as possible from an unacceptable outcome. The info-gap optimal robust decision is the solution to:

$$(1)\underset{(x)}{\text{Maximize}} \quad \hat{\alpha}(x) = \max\{\alpha : (\max V(x, \varepsilon)) \leq V^*\}$$

We illustrate this framework with an application to bluetongue disease presented in the next section. The flexibility afforded by an info-gap perspective on choice enables very complicated and uncertain animal disease systems to be modeled and analyzed. Moreover, as also shown in the application, the performance of existing policy can often be leveraged for guidance on setting a performance requirement for the real world. Aside from enabling severely uncertain systems to be analyzed, some of the most basic decision problems shown in the literature (*e.g.*, Render et al., 2012) can also be dealt with using the info-gap paradigm, namely traditional decision criteria such as maximin and maximax are special cases of info-gap in very simple decision contexts.

2.2. Application to the evaluation of bluetongue surveillance

As described in our conceptual info-gap model we need to define a system model that depends on two vectors, one containing alternative surveillance options and the other containing uncertainty elements. Our system model denotes the total surveillance and intervention costs incurred to contain a bluetongue outbreak. Table 1 describes the surveillance options set (the vector $\mathbf{x}$ in our conceptual model) and uncertainty model elements (the ε vector).

The distribution of the net present value for total economic costs comprises both *ex ante* and *ex post* incursion costs. The *ex ante* costs include: expenditures on surveillance and vaccination programs. *Ex post* costs comprise increased surveillance cost and productivity losses

Table 1
Bluetongue surveillance options and info-gap uncertainty model elements.

Surveillance options (x)	Uncertainty model elements (ε)
Do nothing	Probability of incursion
Conduct surveillance in high risk region (HRR)	Probability of transmission between regions
Conduct surveillance low risk region (LRR)	Probability of detection and reporting from the farmers
Conduct surveillance on both HRR and LRR	Extension of HRR
Vaccinate in HRR	
Vaccinate and conduct surveillance in HRR	

associated with the disease. These are associated with infertility, abortions and decreases in growth rates. We also considered costs due to movement restrictions (with unit cost per animal), fallen animals, insecticide treatment and export market losses.

As Table 1 shows there may be severe information limitations in some key variables of our problem. Our uncertainty vector parameters comprise the daily probability of an incursion ($p_{\text{incursion}}$), the degree of animal mixing, which affects disease transmission rates within a region (ρ_{mix}), the probability that the farmer will correctly detect and report the disease (p_{report}) and uncertainty over the extent of the high risk area (θ_{mis}). The last parameter is modeled as a mismatched allocation of vaccines and detection efforts to the non-targeted region. Recall that these parameters are all elements of the uncertainty vector ε.

The corresponding info-gap models are expressed as the sets: $U_{p_{\text{incursion}}}(\alpha,\ p^0_{\text{incursion}})$, $U^j_{\rho_{\text{mix}}}j(\alpha,\ \rho^0_{\text{mix}})$ $U^j_{\theta_{\text{mis}}}(\alpha, \theta^0_{\text{mis}})$, and $U^j_{p_{\text{report}}}(\alpha,\ p^0_{\text{report}})$. The value of α is unknown and unbounded and expresses the idea that possibilities expand as the info-gap grows, imbuing α with its meaning of "horizon of uncertainty" (Ben-Haim, 2006). The larger is the value α, the greater the range of uncertainty over which the objective function will be evaluated. Given that bluetongue is an exotic disease we have estimates from the literature on the values of these parameters. Thus we use superscript "0" to indicate what is known about the parameter values. In Electronic supplementary material (ESM) we detail the epidemic–economic model linked to our info-gap system model.

Following Prattley et al. (2007), we assume that the government agency is risk averse and therefore will adopt a surveillance protocol that assures that the maximum possible total costs of a bluetongue epidemic are below a predefined unacceptable threshold (TC_{max}). The acceptable level for the government is uncertain and as a form of sensitivity analysis we propose two thresholds or aspiration levels according to their degree of exigency: *medium performance* where the agency aims to guarantee that maximum possible costs of an outbreak are below 10% of the value of the cattle population ($\text{TC}_{\text{max\_medium}}$) and *high performance* where they are below 5% of such value ($\text{TC}_{\text{max\_high}}$)[1].

By using several aspiration levels we could evaluate the consistency of the results to the chosen levels. Given that our epidemic model is stochastic, a distribution of outcomes instead of a single value is obtained for each horizon of uncertainty. We selected the expected total costs to be compared with the performance criteria. We define our performance requirement as:

$$E(\text{TC}) = \text{TC}_{\text{max}}. \tag{2}$$

An important feature of the info-gap theory is that uncertainty is user defined and there are many alternative formulations in the literature (Ben-Haim, 2006). In this case we evaluate the horizon of uncertainty α using an exponential function to emphasize the sampling of the parameter space for small values. The evaluation is done in such a way that the value of the parameters as the horizon of uncertainty increases leads to worse scenarios. For example we investigate how increasing the probability of introduction of the disease ($p_{\text{incursion}}$), the degree of mixing between individuals in the same region (ρ_{mix}) and the lack of knowledge of the extent of the high risk area (θ_{mis}) from their original value to a value close to one (right hand side of Eq. (3)) and decreasing the probability of the farmers detecting and reporting the disease (p_{report}) from their original value to a value close to zero (left hand side of Eq. (3)) following:

$$e^{-c\alpha}\varepsilon^0 \leq \varepsilon^0 \leq \min[(d - e^{-c\alpha})\varepsilon^0, 1];\ \alpha \in [0, 1] \tag{3}$$

where c and d are scale constants. For an adequate sampling of the parameter space we set $c = 2$ and $d = 10$. Info-gap theory identifies the best policy as the policy that enables the objective function to achieve a performance requirement over the widest range of values of uncertain elements (Ben-Haim, 2006). The most robust policy will be the one that presents most immunity to unacceptable outcomes. We employ a robustness function $\hat{\alpha}$:

$$\hat{\alpha}(x)\max[\alpha : \max_{\varepsilon^0 \in U_{\varepsilon^0}(\alpha,\varepsilon^0)}\{E(\text{TC}[\chi^j])\} \leq \text{TC}_{\text{max}}] \tag{4}$$

$\hat{\alpha}$ is equal to the maximum value of α, in such a way that the 99.9th percentile of the net present value of total costs fulfills the performance criterion given different surveillance levels and uncertainty in the parameters $p_{\text{incursion}}$, ρ_{mix}, p_{report} and θ_{mis}. χ^j indicates the proportion of farms with sentinel animals that are inspected in region j. The host and vector dynamics between different clinical stages are modeled using epidemic compartmental models that consist of systems of differential equations (see Electronic supplementary material for a detailed description). The epidemic model builds on that of Gubbins et al. (2008) and Szmaragd et al. (2009). We construct a dynamic discrete–time metapopulation[2] epidemic–economic model considering the entry, spread, detection and control of bluetongue. We then employ a susceptible-latent-infectious-recovered-dead model to describe the two main types of hosts (cattle and sheep).

[1] These thresholds were chosen for illustrative purposes only, they do not reflect official policy goals.

[2] A metapopulation model considers groups of populations of the same species separated spatially in fragmented habitats and interacting at a certain level.

Finally we develop a susceptible-exposed-infectious-dead model to model the dynamics of the vector. The epidemic–economic model and the info-gap analysis are implemented in the R language and environment for statistical computing (R Development Team, 2005).

The allocation of resources between detection and vaccination is complex due to severe uncertainty over the probability of bluetongue emergence in each region and the rate of transmission within and between regions. Our model was based on the surveillance strategy of bluetongue recommended by the EU Commission Regulation 1266/2007 (European Commission, 2007). This regulation defines a protection zone with a radius of 100 km and a surveillance zone of 150 km radius from the center of the original outbreak. In our model, and consistent with England and Wales bluetongue control strategy (DEFRA, 2008b), we defined a "high risk region" (HHR) with a radius of 100 km around the observed outbreaks in 2007 (protection zone); and a "low risk region" (LRR) comprising the rest of England and coinciding with the surveillance zone. In each year we only modeled the period from the end of the spring to mid autumn, as in colder months the vector is not active and thus the risk of disease spread is virtually zero (European Commission, 2007).

3. Results

The results of our application are presented in four panels at Fig. 1, each corresponding to an element of the uncertainty set. The proportion of farms on which surveillance was conducted was set at 0.006 because this level of surveillance minimized the expected costs; higher levels of surveillance led to very costly surveillance programs and were not considered. We evaluated a range of vaccination levels from 0% to 100%. Within each scenario, the higher the overall level of vaccination the lowest the expected total costs and the higher the robustness of the policy assessed. Hence the most robust policy in the case of BTV in England was a policy that vaccinated all the cattle in both HRR and LRR.

Because vaccines might not be available against exotic diseases in general or the number of vaccines available might be limited, we also studied the most robust allocation when: (i) there were not vaccines, the surveillance budget was limited and only a certain number of sentinel animals could be deployed (we employed a maximum number of sentinel animals equal to a proportion of 0.006 of the cattle in the HRR); (ii) only a limited number of vaccines were available (we employed a number equal to the vaccines needed to vaccinate all the animals in the HRR); and (iii) resources for surveillance and vaccines were available at the levels specified in (i) and (ii). For the combinations (i)–(iii) we evaluated whether it was most robust to deploy all limited resources in the HRR, deploy all to the LRR or deploy half of the resources to each region.

Panel A shows that vaccination of the HHR is the most robust policy when there is uncertainty over transmission rates through cattle movements. A vaccination policy covering 100% of the population in both regions would be able to avoid higher outbreak costs (was robust at the high performance level), even if perfect mixing among cattle occurred. Interestingly, a policy of surveillance in only the HRR produced a similar robustness and other robust policies such as total vaccination in the HRR were robust at the high performance level (Fig. 1A) even under perfect cattle mixing.

When vaccines are not available, early detection and effective intervention are crucial. In this case, the least robust surveillance strategy would be to deploy detection efforts on the LLR followed by dividing limited detection resources between both regions. This result is also consistent with uncertainty in the location of the HHR and probability of incursion (Fig. 1A, B and D). However, if farmers are capable of reporting the disease (Fig. 1C), surveillance in the HRR is not robust and is an inefficient allocation of resources. Surveillance, in this case, is not a robust strategy and performs worse, than a *laissez faire* policy because surveillance expenses can be avoided as long as farmers capacity of reporting is greater than 0.1.

Under uncertainty over the incursion rate, policies vaccinating only in the LRR or no vaccination at all were not robust even at the medium performance level (Fig. 1B). The most robust policies involved vaccination of the HRR (combined or not with surveillance) and attained a robustness similar to a policy vaccinating all the animals in both regions (Fig. 1B). Therefore under very high incursion rates, the system is more protected if the government can rely on a very effective intervention strategy such as vaccination.

One of the main features of bluetongue surveillance strategies in England and Wales is to raise awareness. When farmers are well informed and vigilant about the potential occurrence of these clinical signs they are more likely to report the diseases. Their active reporting can be a low cost and extremely effective way to detect the early emergence of disease. Panel C reveals that when we are uncertain about farmers reporting, the most robust strategies involve vaccination of HRRs. More importantly these results hold even for low probabilities of accurate reporting by farmers, demonstrating the payoff of involving farmers on the detection of emerging diseases.

Panel D reports results on uncertainty on the actual extension of the HRR. When this is the case there may be an unintended allocation of vaccines and surveillance in regions where the probability of entry is low. The results showed that a policy of surveying and vaccinating in the HRR was robust to severe uncertainty about its actual extension values of '20–50%', however, the robustness of policies based on regions delimitation was much lower than a conservative policy vaccinating all the animals (Fig. 1D). A policy focusing on surveillance in the HRR was more robust than a policy focusing on vaccination of the HRR for high uncertainty about the extension of the HRR. The reason for this is that even if a large proportion of surveillance efforts are misallocated to the LRR, the proportion correctly allocated to the HRR still has an important protective impact. Moreover, a small amount of surveillance in the LRR is beneficial. In contrast, vaccination was less effective when there is uncertainty over the extension of the HRR. This is because allocation of vaccine to the LRR instead of the HRR reduces the ability to control the epidemic in the HRR. As a result, a policy of surveillance of the

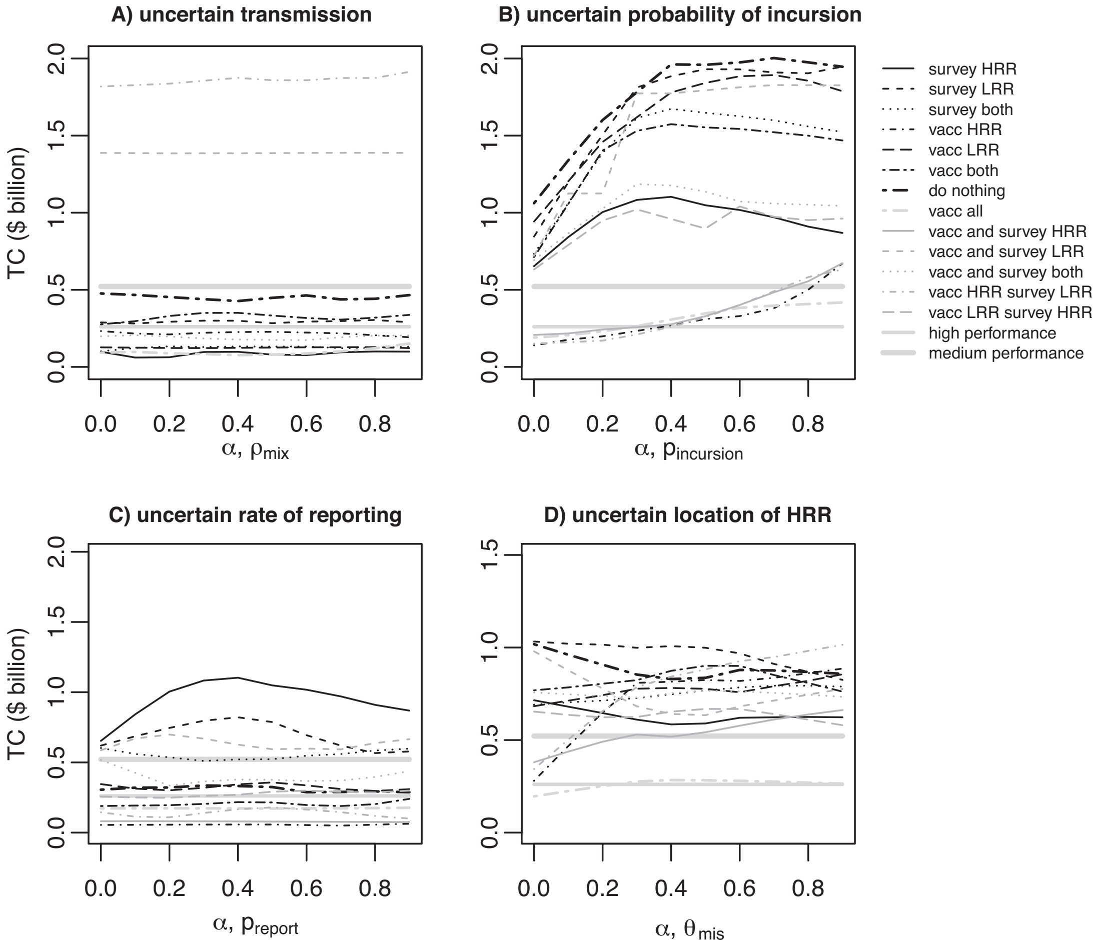

Fig. 1. Evaluation of the robustness of vaccination and surveillance policies for bluetongue. HRR: high risk region; LRR: low risk region. TC: net present value of total costs expressed in US 2009 Dollars; vacc: vaccination. Note: the probability of farmers' reporting was set to zero except for panel C. The horizontal axis represents the uncertainty horizon α. The higher is α the higher is the uncertainty over the true value of the parameters.

HRR appears more robust than a policy of vaccination for high levels of uncertainty (Fig. 1D).

The identification of the boundaries of high and LRRs is facilitated by: (1) knowledge of the pathways of entry of a disease; (2) the spatial distribution of climatic variables affecting the probability of disease incursion and, (3) the structure of the production system that promotes disease spread. Accounting for the spatial heterogeneity of the risk of disease incursion and spread offers an opportunity to identify robustly protective and cost-effective surveillance strategies.

4. Discussion

Our results indicate that, in a landscape divided by a small HRR and a large LRR, the most robustly protective policies, under limited number of vaccines involved prioritization of the vaccination and surveillance of the animals in the HRR. In the case of bluetongue in England, ideally all the animals in both regions should be vaccinated, however, if vaccine uptake by farmers is limited, efforts should be devoted to increase uptake in identified HRRs. The model suggests that vaccination could contribute to limiting the size of an outbreak and reduce the risk of spread to the larger LRR. In addition, consistent with epidemic theory, vaccination policies were able to avert large outbreaks. Under the surveillance and vaccination costs used, vaccination appears as a more robustly cost-effective strategy and extensive surveillance programs (with more than 0.6% sentinel animals) might be prohibitively expensive. However, it must be borne in mind that these results are predicated on our underlying assumptions, which include a considerable horizon of uncertainty regarding the risk of incursion. If that risk was constrained then the vaccination strategy might be identified to be less robust due to its costs. Likewise, when costs for surveillance were importantly over or under-estimated, different conclusions might result. This can be investigated further through sensitivity analysis.

Interestingly our results are consistent with Prattley et al. (2007), though those results are based on portfolio theory. These authors also found that, when there are limited resources to be distributed across competing locations and animal populations, resources should be primarily allocated to high risk areas. However the lower risk areas should not be completely neglected and the appropriate level of resource allocation critically depends on the risk assessment and the level of uncertainty (Prattley et al., 2007).

We chose relatively high performance requirements in the info-gap model. The reality is that investment in bluetongue surveillance competes for limited resources with other surveillance programs and thus a lower value might be imposed. However, public funding of surveillance programs may be complemented with a surveillance strategy promoting active reporting of suspect clinical signs by farmers

The results showed that, if vaccines were not available, greater surveillance of the HRR was robustly protective but intensive surveillance on both regions was not. Conducting surveillance of HRRs are consistent with findings on the invasive alien species surveillance literature. For example Hauser and McCarthy (2009) showed that regions with a high probability of invasive species occurrence should have intensive surveillance. In our case, surveillance of the HRR implies high avoided costs because of prompt detection of incursion and the opportunity for rapid intervention. Surveillance of the HRR was a very robust strategy even under perfect mixing of individuals within regions. This result can be interpreted from a reverse perspective: a surveillance strategy accurately targeted to the high risk areas can achieve the same results as a presumably much more costly preventive policy consisting of the restriction of the spatial movement of animals between farms to reduce disease transmission.

The results regarding the robustness of the surveillance of the HRR does not imply that the LRR should not have any surveillance efforts. In the case of severe lack of knowledge of the extension of the HRR, an unintended proportion of the surveillance efforts were allocated to the LRR. This resulted in a robust policy that also prevented outbreaks in the LRR. This logic did not apply to vaccine allocation between regions when there is high uncertainty over the extension of the HRR. Similarly, failing to vaccinate the HRR, is the least robust strategy. This option hinders the chances of successfully preventing the epidemic from emerging in either of the regions. Our results illustrate the value of knowledge related to accurate identification of high risk areas. Where a seasonal effect is also present, as in the case of BTV, then high risk can be attributed to space and time.

5. Conclusion

This research analyses decisions over surveillance system options for the detection of exotic and emerging diseases, when there are important gaps on the information required to make appropriate decisions. We assume the aim of an agency is to avoid a serious outbreak under severe uncertainty over detection and spread of an animal disease. In such cases, the agency may want to design a system that is robust to a set of uncertainties. Such systems should be designed to prevent total losses to society beyond a given level of performance.

Specifically, we considered the economic and epidemiological conditions that make surveillance strategies robust when there are uncertainties about the probabilities of the disease incursion, mix of animal populations, extension of high-risk regions and probability of farmer's detection and reporting the disease. We illustrated this framework on the surveillance of bluetongue disease in England and Wales, evaluating alternative surveillance and intervention options to contain outbreaks. Although our research is not intended to reflect official policy in England and Wales, our conclusions can inform policy. We find that ideally all the animals should be vaccinated but if vaccine uptake is limited, total vaccination in HRRs should be a priority. Furthermore, and robustness can be dramatically increased with farmer involvement in surveillance.

We believe our approach is an alternative to the recently proposed risk based surveillance systems (Stärk et al., 2006). Moreover, our modeling framework can be particularly useful and relevant for decision makers charged with developing a surveillance system that detects new diseases and or known diseases in new environments.

Here we only considered two types of regions, a low and a high risk area, and we did not fully consider the interactions between vector and animal movements. In the future we aim to look in more detail at the spatial and time dimension of this problem. We think that it may be useful to adopt a network approach where each farm is a node linked with each other and there are flows of animals and vectors. This should provide a more detailed and practical sense on how a robust surveillance system should be designed.

Conflict of interest statement

Neither of us have conflict of interest to declare.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.prevetmed.2012.01.011.

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