Synergising decision making and interventions across human health and environment: concepts for designing a model for infectious diseases

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Abstract

The impact of environmental factors on human health outcomes is well established. It is therefore not surprising that interventions aimed at improving human health are often environmental-based, such as restoring riparian vegetation for flood mitigation, with a view to reducing associated infectious disease transmission. Yet the risks and benefits of these interventions on the environment itself are rarely measured, or weighed up against potential health gains. One of the challenges with such an evaluation is the requirement for cross-sectoral support from decision makers in both the health and environmental sectors. To facilitate this support, cross-sectoral models are required that simultaneously estimate the impact of proposed environmental interventions on both sectors. Despite their obvious value, a systematic search of the peer-reviewed literature did not identify any model that concurrently models the impact of environmental intervention on *both* environmental and human infectious disease related outcomes. In this paper, we conceptually explore potential approaches for designing such a model, using leptospirosis as a case study to highlight the various data sources, spatial scales, temporal scales and required system behaviour that would need to be integrated for a cross-sectoral model of this complexity. By comparing these system requirements against the strengths and limitations of individual modelling techniques, we demonstrate the potential benefits of a hybrid-ensemble approach that uses component models from different frameworks. By combining the strengths of the different techniques to tackle this wicked problem, such a modelling approach supports the prioritisation of environmental interventions that optimise the overall benefit by considering impacts on both human health and the environment.

Keywords

cross-sectoral model; environmental modelling; infectious disease; ecohealth; environmental health

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1. Introduction

There has long been recognition of the impact of environmental factors, including land-use and ecosystem health, on human health outcomes, particularly in relation to infectious diseases (Cunningham et al., 2017; Harrison et al., 2019; Pienkowski et al., 2017). The notion of ecosystem services (World Health Organization, 2005) provides a unifying framework for emphasising the value of environmental interventions (i.e. changes to the environment that are designed to benefit human health and/or the environment) to improvements in human wellbeing (including social, mental and physical health). Well-functioning ecosystems deliver supporting ecosystem services (e.g. photosynthesis, nitrogen cycling) that in turn improve human wellbeing via provisioning ecosystem services (e.g. water, food, fibre), regulatory ecosystem services (e.g. water quality, natural hazard mitigation, disease regulation), and cultural ecosystem services (e.g. spirituality, education, recreation) (World Health Organization, 2005). Environmental interventions could therefore potentially offer benefits for both the environmental and human health sectors.

However, implementing such environmental interventions and evaluating the outcomes brings with it a number of challenges, including fostering collaboration between sectors (e.g. environment and health), particularly in the face of uncertainty regarding the relative benefits for each sector; assessment of potential risks and the overall financial costs across sectors (e.g. the environmental sector paying for interventions that improve human health, but with little benefit for the environment). To overcome some of these challenges, models that simultaneously model outcomes for both sectors are required to assist decision-makers in prioritising interventions that maximise the overall gains across both sectors. Environmental interventions aimed at improving either human health or the environment have sometimes resulted in positive outcomes for one sector, but negative (often unpredicted) outcomes for the other.

For instance, reforestation in New York State, USA, led to growth in the deer population and subsequently an increase in tick-bites and cases of Lyme disease in humans (Barbour & Fish, 1993). In the reverse situation, draining swamps and wetlands has been used as control measures for malaria (i.e. improving human health), but destroys biodiversity hotspots and refugia (Keiser et al., 2005). In other cases, such as deforestation, changes to land use may provide temporary economic benefit, but lead to long-term negative environmental and human health effects (Hahn et al., 2014). There are however scenarios with the potential to benefit both sectors, such as improved wastewater treatment and pathogen reduction from wetland restoration (Bateganya et al., 2015), avoided increases in diarrhoea and acute respiratory infection from preventing deforestation (Pienkowski et al., 2017), and improvements to mental and physical health with the provision of biodiverse urban greenspaces (Lai et al., 2019; Stanhope et al., 2020).

Gaining cross-sectoral support for proposed interventions requires evidence of potential benefits for the outcome of focus (e.g. an infectious disease), and an integrated risk assessment that adequately considers possible positive and adverse effects across sectors before implementing the intervention. Pre-intervention assessments also need to consider the appropriate spatial and temporal scales of influence. Both the natural environment and human health domains represent complex systems, and the decisions related to such systems are often classed as wicked problems. Due to various cognitive, social, and cultural biases decision makers can find it difficult to reason about such complex situations, especially when part of the system is outside of their field of expertise (Sterman, 2002; Gregory, 2012),

To facilitate this cross-sectoral reasoning (Elsawah et al., 2020), modelling techniques are commonly used to help structure and optimise decision-making by capturing the relationships between the system's components. These can involve simple linear relationships, or more complex interactions, such as nonlinearity, time lag, feedback loops, and various types of uncertainties. Modelling the estimated impact of proposed environmental interventions on both the health and environmental sectors requires models that are able to handle this complexity, and will likely involve a combination of process models examining the mechanisms of the systems, as well as pattern models that explore correlations between factors (Scoones et al., 2017).

Throughout our paper, we avoid the use of the term "integrated model", owing to its varied meaning, e.g. models that integrate across different sectors, or that integrate different modelling techniques (Kelly et al., 2013). Instead, for clarity, we refer here to models that include components from both human health and environmental sectors as "cross-sectoral models", and those that combine different modelling techniques as "hybrid models". The term "ensemble model" is used to refer to models composed of independent sub-models, which may or may not be of the same type.

Within the public health discipline there have been calls for a greater focus on systems thinking and modelling, over traditional linear methods (Carey et al., 2015; Rutter et al., 2017). Furthermore, the emergence of the Ecohealth, One Health (Harrison et al., 2019), and Planetary Health (Whitmee et al., 2015) approaches to human health reflect a growing recognition of the link between humans and their environment. In this paper, we build on this body of work by reviewing literature on the use of cross-sectoral models for simultaneously modelling the impact of environmental interventions on the environment and infectious diseases in humans. Using leptospirosis (a zoonotic infectious disease) as a case study of a human health outcome, our paper contributes to the broader literature by outlining the requirements and considerations for a cross-sectoral model to concurrently examine the effect of proposed environmental interventions for both the human health and environment sectors. Finally, we discuss the processes required for framing such a complex multi-sectoral problem, examine characteristics of potential modelling techniques that could be used, and determine the suitability of each technique and combination of techniques for providing solutions to such wicked problems.

2. Literature Review

To identify potential modelling techniques that have previously been used to concurrently modelled the impact of environmental interventions on both human infectious disease and the environment, we conducted a systematic literature search. We focused on infectious diseases because there are often direct links between the environment, the vector/reservoir, and the risk of infection in humans. Details of the systematic search are reported in the Supplementary Material.

No studies were identified that concurrently modelled the impact of environmental interventions on both human infectious disease and the environment. We did however identify studies that evaluated the human infectious disease outcomes of environmental interventions, without consideration for the environmental outcomes. For example, Pienkowski et al. (2017) explored the relationship between deforestation and various health outcomes, and the potential role of protected areas for environmental conservation on human disease risk. Similarly, the link between land use change and disease was considered by Vanwambeke et al. (2007). From the alternative perspective, evaluating the effect of disease interventions on the environment, Rydzanicz et al. (2009) considered the positive environmental effects of different vector control methods. These examples demonstrate the importance of considering cross-sectoral implications of interventions, and highlight the need for the application of more advanced modelling techniques that allow for multiple objectives and outcomes to be evaluated simultaneously.

Cross-sectional modelling is not a new approach for the health nor environmental sectors, with previous studies simultaneously investigating economic outcomes with infectious diseases outcomes in humans (Aragrande & Canali, 2020; Grace et al., 2017), or livestock (Choudhury et al., 2013), and others simultaneously looking at environmental and economic outcomes (Shelton & Dalzell, 2017; Tallis et al., 2008). We argue that equivalent work is required at the nexus between environment and infectious diseases. While the absence of these papers in our search is not conclusive evidence that such work has not been undertaken, it does suggest that these studies are rare, and that guidance on suitable modelling techniques for doing so is potentially required.

3. Leptospirosis

To explore how a cross-sectoral impact modelling technique could be developed to estimate the effect of environmental interventions on both environmental and human health outcomes, we have used leptospirosis in Fiji as a case study. Leptospirosis was chosen because transmission is strongly driven by environmental factors, and the complex interactions between humans, animals, and their environment (Lau & Jagals, 2012), with multiple exposure pathways that vary between socio-ecological niches (Lau et al., 2017; Mayfield et al., 2018b). Furthermore, leptospirosis can result in significant physical, mental, and social impacts on affected persons and populations (Bharti et al., 2003).

Leptospirosis is a zoonotic disease, caused by *Leptospira interrogans* (World Health Organization, 2003), and is transmitted to humans via direct contact with infected mammals (including rodents, livestock, and wildlife), or contact with water and soil contaminated with *Leptospira* from the urine of infected mammals (Bharti et al., 2003). Leptospirosis is one of the most common bacterial zoonosis worldwide, causing more than 1 million severe infections annually, and is particularly common in tropical and subtropical regions, especially in developing countries (Bharti et al., 2003; Costa et al., 2015). Leptospirosis is an emerging infectious disease in many contexts; epidemics are increasing in frequency, severity, and distribution with recent unprecedented outbreaks resulting from the combined driving forces of climate change and extreme weather events (e.g. flooding, cyclones), population growth, urbanisation, poverty, and agricultural intensification (Lau et al., 2010). The Pacific Islands, including Fiji, are particularly prone to leptospirosis outbreaks because of the tropical climate, frequent cyclones and flooding, and close contact with animals, amongst other factors (Lau et al., 2010; Togami et al., 2018).

Models to predict, prevent and manage outbreaks of infectious diseases, like leptospirosis, are needed to ensure that limited resources are used in a cost-effective manner, with consideration of both synergies and possible adverse impacts of interventions across sectors. Multi-sectoral intervention strategies have been recommended for effective control of leptospirosis (Naing et al., 2019), but evidence is lacking for the effectiveness of such interventions on both leptospirosis and environmental outcomes. Only a few studies have specifically assessed the impact of actual interventions such as livestock control (Ryu et al., 2017), or modelled the potential impact of interventions such as rodent control (Holt et al., 2006) or the use of prophylactic antibiotics during the post-flooding period (Schneider et al., 2017). Most studies have only assessed risk factors and drivers of transmission, and used results to develop recommendations for interventions that are likely to work (Dhewantara et al., 2020; Mayfield et al., 2018a; Nwafor-Okoli et al., 2010).

Recommended strategies to reduce human leptospirosis include reducing human exposure through behavioural change and managing environmental drivers of transmission and outbreaks (see Table 1). If such interventions are to be ranked and prioritised, their environmental and human health impacts need to be estimated using various modelling techniques that also consider other factors, such as climate and human behaviour (as indicated in Figure 2). We focus primarily on environmental-based interventions rather than other types of interventions because they are more likely to affect both human health and the environment. Our approach does not dismiss the importance of other preventative measures, such as behavioural or medical interventions. On the contrary, evaluating the environmental-based interventions provides decisions makers an opportunity to optimise strategies by considering environmental approaches together with other options.

Table 1: Examples of potential interventions to prevent leptospirosis

Intervention category	Examples
Rodent control	• Improving sanitation in homes and communities (Lau et al., 2012b; Suwanpakdee et al., 2015) • Education regarding garbage systems (Naing et al., 2019)
Reducing human exposure through behaviour change	• Protective footwear and clothing (Sarkar et al., 2002) • Increasing awareness of disease to reduce exposure (Lau et al., 2012b) • Avoiding contact with rodents and polluted fresh water (Lau et al., 2012b)
Managing environmental drivers of transmission and outbreaks	• Improved management of livestock (e.g. moving piggeries further away and downhill from houses) (Lau et al., 2012b) • Flood mitigation (Kawaguichi et al., 2008; Lau et al., 2012b; Mayfield et al., 2018a) which can be achieved through environmental interventions upstream including re-meandering, adding coarse sediment, reopening side channels, removing dams, decreasing bank slopes, adding floodplains and riparian wetlands (Nilsson et al., 2018), floodplain conservation (Kousky & Walls, 2014), as well as engineering controls (e.g. check dams (Abbasi et al., 2019))

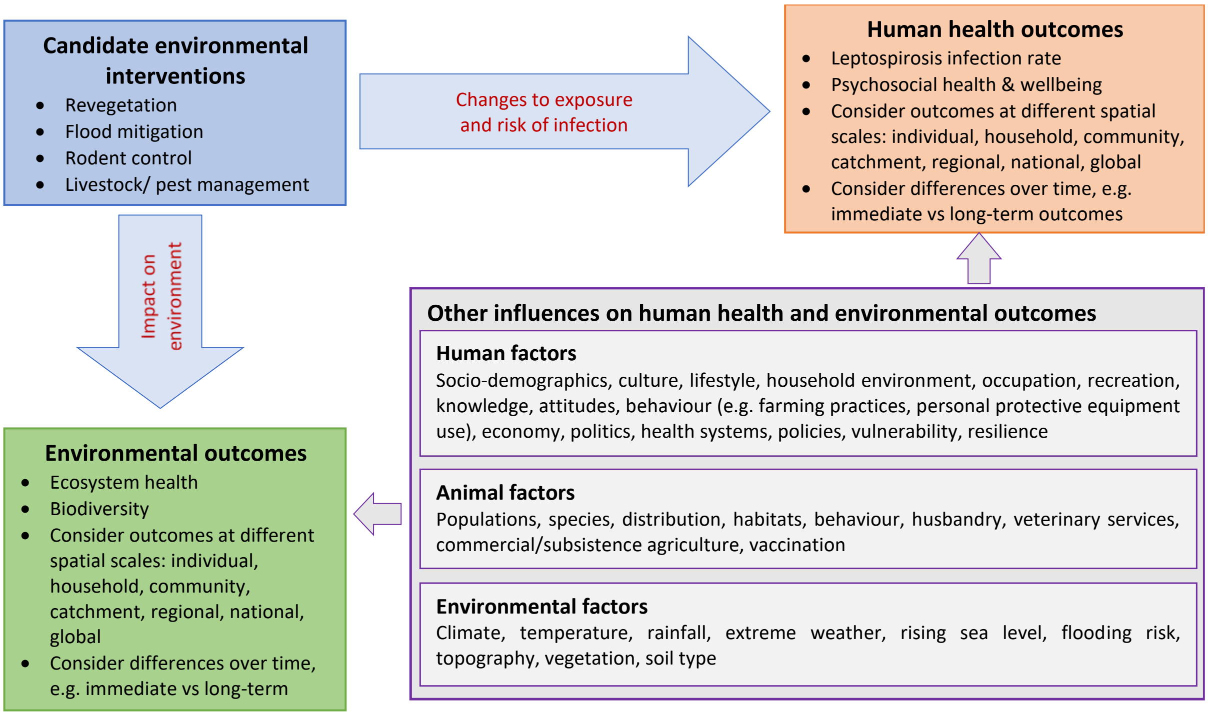

Figure 2: High level conceptual framework of how candidate environmental interventions may lead to both human health and environmental outcomes, with consideration for other (human and environmental) influences.

4. Model design process

To describe the requirements for a cross-sectoral impact model, we apply a holistic approach, starting first with a big picture view of the system to be captured, and then singling out the component of interest (leptospirosis incidence, i.e. rate of new infections). This component is then refined by describing potential drivers and expected model outputs, as well as data availability for our case study. We also consider the system behaviours that the model is expected to demonstrate, such as dynamic interactions and data integration from various sources. The model design process would in principle continue by deciding on model families, functional forms, and specific processes for defining and estimating parameters. Having explored a selection of different modelling techniques available, and their pros and cons, we also consider a hybridisation of modelling techniques.

Before decisions on appropriate modelling techniques can be made, the first step in the design process is to describe the main system components and links using a qualitative conceptual framework (Argent et al., 2016). A qualitative conceptual framework should be developed through reviews of the literature and consultation with experts and stakeholders from all relevant fields (e.g. infectious disease, public health, environmental health, ecosystem services, ecosystem health, agriculture, social services), be biologically plausible, and consider relevant spatial and temporal scales. Our conceptual framework (Figure 2) consists of four main components: i) candidate environmental interventions, ii) potential human health outcomes resulting from these interventions, iii) potential impact of the interventions on the environment, and iv) other factors (human, animal, and environment) that could influence human and environmental outcomes.

5. Model requirements

This section details the requirements of a model for leptospirosis infection risk, and what additional requirements are needed to be able to integrate such a model into a cross-sectoral analysis. We focus on spatial and temporal scales, data sources, and system behaviour, as summarised in Table 2, and described below.

Table 2: Model requirements for evaluating the impact of environmental-based interventions on environmental and health outcomes for leptospirosis in Fiji

Parameter	Value	Description	Source
Spatial scale	Regional or village level	Dependent on the intervention being evaluated	-
Temporal scale	Weeks to months for outbreak prediction Months to years for environmental changes	Dependent on the intervention being evaluated	-
Potential inputs	Socioeconomic data	Including poverty, education, urbanisation, access to clean water, availability of electricity	Government census data
	Occupational, behaviour and lifestyle data	Including farming and other outdoor occupations, recreational activities.	Government census data, household surveys
	Agricultural data	Livestock presence or absence within a village, or agricultural density within a region. Subsistence farming. Veterinary services. Animal vaccination programs.	Government census data
	Land use / land cover data	Forest, agricultural or residential/commercial	Satellite and remote sensing data
	Biodiversity data	Species richness, or abundance/persistence of particular species	Field survey or local expert knowledge
	Pollution data	Primarily water quality	Environmental monitoring data
Potential outputs	Probability of leptospirosis outbreak	What is the probability of an outbreak occurring within a village or region?	Model predictions
	Predicted infection rates	What is the likely impact on infection rates within a village or region?	Model predictions
	Environmental impact	What is the impact on species survival for animals and plants? What is the impact on biodiversity? What is the expected change in water quality?	Model predictions
Model behaviours	Feedback loops	Model is required to represent feedback loops for simulations covering multiple time steps	-
	Interactions and inter-dependencies	Model is required to represent key variable interactions, such as the link between urbanisation and poverty	-
	Model transparency	System is required to provide information on the influence of each variable on predicted outcomes	-
	Model uncertainty	Quantification of input variables and prediction uncertainty. Model structure error addressed through credible justifications rather than explicit quantification	-

5.1 Spatial and Temporal Scales

The appropriate spatial scale is a critical consideration in the development of hybrid, cross-sectoral impact models. In particular, aligning the relevant or available scale (both spatial and temporal) from models originating from different sectors can be challenging (Elsawah et al., 2020). Previous models of the potential benefits of different environmental interventions for leptospirosis have been implemented at scales as fine as sub-village levels in Fiji (Lau et al., 2017) and American Samoa (Lau et al., 2012a; Lau et al., 2012b). There is also evidence to show that the relative importance of drivers for leptospirosis prevalence varies across space (Mayfield et al., 2018a). Environmental variables therefore need to be available at a scale that reflects these variations, with previous work suggesting a 250 m resolution may be appropriate (Mayfield et al., 2018a).

The spatial and temporal scales of influence for the environmental interventions may depend on the location for which the model is developed, including the geography, land-use, and distance to other towns/villages. For instance, if flood mitigation is one of the environmental interventions being investigated, the temporal scale should consider the frequency and timing of flooding in the region. Similarly, moving piggeries downhill from the community may reduce human leptospirosis in that community (Lau et al., 2012b), but may also have a downstream negative environmental impact, due to the increased risk of *Leptospira* entering the waterways and exposing downstream communities. The spatial range of the study should therefore include communities downstream that may come into contact with *Leptospira* within the period that *Leptospira* can survive in the environment (potentially weeks under optimal conditions). If multiple potential interventions are being considered within the model, these may also influence the relevant spatial and temporal scales.

Determining which intervention, or combination of interventions, would optimise overall outcomes for both human health and environment necessitates a model capable of handling data on different spatial and temporal scales. For example, the leptospirosis outcome(s) can be considered at the individual, community, regional, or national levels (Lau et al., 2016). In contrast, the environmental outcomes may need to be assessed at a catchment or ecosystem scale, while sociodemographic data are generally assessed based on census areas and political boundaries. Datasets used as inputs for the leptospirosis component would therefore need to cover a larger geographic area if used to evaluate the flow-on effects on the environment, rather than just on disease outcomes.

5.2 Data sources

Both the environmental and infectious disease literature indicate multiple sources of available information for quantifying model inputs. Sources include satellite data (Mayfield et al., 2017; Wang et al., 2017), questionnaires (Lau et al., 2016; Sturrock et al., 2013), or field surveys on infection prevalence (WoldeKidan et al., 2019), with most studies combining data from multiple sources. For both the environmental and human aspects, when empirical data are not available or cultural context is important, information can also be elicited from experts or local populations (Mayfield et al., 2020a; Scoones et al., 2017). This is equally applicable for determining what factors to include, the relationships between the system components, and quantifying the strengths of the relationship.

Focusing on the illustrative case study area of Fiji, data for modelling leptospirosis are available at four levels: regional (environmental, geography, socioeconomic, and livestock), village (urbanisation, livestock presence, and domestic animal presence), household (household construction, and animal presence), and individual (demographics, occupation, and behaviours) (Lau et al., 2016). Excellent government data are available for Fiji covering agricultural use (both commercial and subsistence farming), and a range of infrastructure information such as urbanisation, and the availability of metered water and electricity. Census data are also available covering many demographic factors such as ethnicity, poverty levels and education. High resolution geographic data (50 m) on the physical environment, such as slope, elevation and distances to roads or waterways are freely available from sources such as the Fiji Ministry of Lands and Mineral Resources, Fiji Ministry of Agriculture, Landcare Research Institute, Fiji National Census, and the World Bank. For simple correlation or exploratory studies, data on past climatic variables, such as rainfall and temperatures, are also freely available for most countries. However, if the model is required to examine future scenarios under expected changes in climatic conditions, connections to other climate data sources may be required.

Much of the data needed to integrate the leptospirosis component more broadly with environmental outcomes are similar to that mentioned above, although the range of potential environmental impacts necessitates a number of additional datasets. While the same satellite data used in the leptospirosis component could provide geo-referenced information on land-use and vegetation cover, including for historical time steps, more detailed environmental data on other indicators, such as biodiversity or ecosystem health (Jenkins et al., 2016; Jenkins et al., 2010) would require ground surveys or local expert knowledge. As such, a mix of quantitative and qualitative data would likely be used when integrating the health component with wider environmental outcomes.

The same is true for natural hazards such as floods, where local knowledge and data on previous floods may be suitable for examining correlations in the status quo, however, more complex hydrological models would be needed to examine the full range of effects on flood risk that result from environmental interventions (Paquette & Lowry, 2012). Ideally, the expected impact of an intervention would be evaluated using empirical evidence. For leptospirosis in Fiji, data linking leptospirosis risk with key drivers such as agriculture and flooding risk are available at the household and village levels (Lau et al., 2016).

5.3 System behaviour

The modelling technique used for the cross-sectoral impact will be expected to adequately capture certain system behaviours. For infectious diseases, interactions between explanatory variables can affect the predicted outcome. For example, the degree to which poverty affects the risk of leptospirosis has been shown to be disproportionally higher in urban areas compared to rural areas (Lau et al., 2017). Feedback loops are also important for any model looking to predict the outcomes over time, rather than as a static snapshot (e.g. capturing the effect of an immune memory from past infections on the risk of new infections). It would be beneficial for the model to also include explicit representation of disease testing and detection characteristics, given the important role of detection errors (for example caused by sampling bias or errors in laboratory tests) in both model calibration and evaluation of interventions.

In addition to structural features of the model, model predictions will also need to capture a number of spatial and temporal dynamics, consistent with a pattern oriented modelling approach (Grimm et al., 2005). Long term prediction of leptospirosis occurrence is unlikely to be precisely accurate, but the time series and spatial distribution should adequately capture peaks associated with seasonal conditions and disease clusters (Stephen & Karesch, 2014). For management purposes, it is important that relationships between disease occurrence and key interventions are adequately captured in terms of impact lag and total number of cases. Short term predictions or forecasts are also expected to be sufficiently accurate to at least support prioritisation of intervention resources, though this accuracy is understood to be conditional on data that adequately capture the situation at the time.

Even with future improvements in modelling and computational power, it is likely that significant uncertainty will remain around model predictions. Optimisation methods are also likely to be used to explore the effect of different interventions and performance under different assumptions. This raises issues around computational efficiency – the model needs to run quickly enough that reasonably large numbers of model runs are possible. It is expected that input and prediction uncertainty will need to be explicitly quantified, but structural error will be more likely to be dealt with through credible justifications rather than a multi-model ensemble approach. A computationally efficient model, however, leaves this open as a possibility.

The construction of the model and its application should aim to identify ranges of parameters and drivers that would need to be explored in order to evaluate robustness of any intervention. Robustness in this context refers to "a measure of the insensitivity of the performance of a given strategy to future conditions" (Maier et al., 2016). The management of uncertainties and unknowns is a challenge for preventing and managing infectious diseases, including epidemics (World Health Organization, 2015). As is the case with most epidemiological studies, uncertainty can result from random or systematic errors (Burns et al., 2014). However, when predictions are being made, uncertainties may also relate to future politics, climate, socio-economic and technological change (Maier et al., 2016). While strategies for managing uncertainty in models have recently been used in some epidemiological studies (Li et al., 2019) their use remains uncommon, especially in public health.

6. Potential modelling techniques

Modellers have a wide array of potential techniques to choose from when deciding how best to design a model. The variation in the underlying approaches for different modelling families, which include empirical data-based, conceptual-based, agent-based and rule-based (Jakeman et al., 2006), means that each approach has its own set of strengths and weakness that make them more or less suited to predicting the outcomes of interventions, and more broadly within a cross-sectoral model. Here we describe the characteristics of four different representative methods: multivariable regression, artificial neural networks (ANNs), BNs, and system dynamics (SD). While the list of described methods is not exhaustive, those presented here have been selected to illustrate the relevant characteristics of the various approaches. Multivariable regression and ANNs (Hastie et al., 2009) are representative of simple and complex data-based methods, respectively (Jakeman et al., 2006). BNs (Fenton & Neil, 2013) are described to show the advantages of conceptual-based models that look to incorporate the structure of the system (Jakeman et al., 2006; Kelly et al., 2013). Finally, SD modelling (Sterman, 2000) is offered as example of a dynamic approach that incorporates both the structure and dynamics of the system (for example, over time) (Jakeman et al., 2006; Kelly et al., 2013).

Multivariable regression, such as generalised linear models (GLMs), is widely used and understood, but has limited ability to model causality or incorporate unknowns and uncertainties (Hastie et al., 2009). This results in poor capacity to disentangle the intricate associations between risk factors, drivers, triggers, and outcomes (Burns et al., 2014; Landuyt et al., 2013). Another disadvantage of multivariable regression models is that they rely on high quality empirical data, and it can be difficult to quickly update them during rapidly evolving epidemics and/or a changing environment (Lau et al., 2017). More complex data-based algorithms, such as ANNs, have benefited in recent years from a surge of research on deep learning approaches (Hinton, 2018). Although ANNs are able to handle interactions between the predictors and non-linear relationships in the data, their lack of transparency makes them less suited than other models for situations where understanding the mechanisms within a system is a key objective (Mayfield et al., 2020b).

In BNs (Fenton & Neil, 2013) the structure of the network can be used to represent the causal relationships between variables. Using Bayes' theorem of conditional probability, BNs determine probabilities from cause to effect using forward propagation, from effect to cause using backward propagation, and characterise both magnitude and direction of associations, whilst explicitly accounting for and representing uncertainty in these relationships. BNs are particularly useful for facilitating scenario analysis as they can capture the probability of events under complex scenarios, conduct predictive as well as diagnostic analyses, and perform sensitivity and trade off analysis to determine the best leverage points within systems for reducing risk (Landuyt et al., 2013). However, BNs also have certain limitations when modelling complex systems: they are not dynamic models and cannot easily incorporate feedback loops, meaning they have limited utility for modelling continuous system behaviour over time. Although dynamic BNs (that incorporate a time component) have been used, they become unwieldy after a few discrete time steps, because the nodes of the BN need to be replicated for each time step. Dynamic BNs are therefore generally considered impractical for modelling complex systems (Uusitalo, 2007). While both BNs (Lau et al., 2017; Mayfield et al., 2018b) and regression (Lau et al., 2016) have been used previously to model the risks of leptospirosis infection, neither option easily allows feedback loops to be included.

SD (Sterman, 2000) modelling is increasingly being applied in the environmental health field (Currie et al., 2018). SD modelling is based on continuous time, where the state of variables (stocks) change in a continuous way rather than displaying abrupt changes. These changes are modelled using difference and differential equations or infinitesimal accumulation processes (integration) over time to represent the interconnections in a system. SD models consist of stocks (that represent accumulations within systems, e.g. number of infections), flows (that represent the movement of material or information, e.g. number of new infections/unit time) and auxiliary variables (that control flows, such as the infection rate over time in % per unit time). The components are linked to form feedback loops: reinforcing feedback loops cause growth or decline within systems, while balancing loops cause goal seeking and stabilising behaviour. Combinations of reinforcing and balancing loops, and shifts in their dominance over time, result in complex system behaviour (e.g. growth, collapse, oscillations, or erratic). SD models have been used to build susceptible-infected-recovered (SIR) models of disease transmission (Bjørnstad et al., 2020).

Many decision-making scenarios will require a geographic map of the output at a spatial scale relevant to the problem at hand. While there are spatially-explicit methods, such as geographically weighted regression (Mayfield et al., 2018a; Mayfield et al., 2018b) that consider the influence and importance of variables over space, any of the above-mentioned methods can be combined with a geographic information system (GIS) to display the model outputs and create risk maps (Dhewantara et al., 2019; Mayfield et al., 2017). At a basic level, BNs capture uncertainty through probability distributions, and uncertainty in SD and regression models can be explored through Monte Carlo analyses.

7. Ensemble and Hybrid modelling

The modelling techniques described in Section 6 illustrate that each has certain characteristics and behaviours that will be either an advantage or disadvantage depending on the problem being addressed (Kelly et al., 2013; Mayfield et al., 2020b). While each modelling option has its own strengths, such as incorporating expert data (BNs) or facilitating feedback loops (SD), none offer the complete set of characteristics to achieve the required balance of complexity, data sources and system transparency described in Section 5. Hybrid modelling (Hamilton et al., 2015; Voinov & Shugart, 2013) will therefore be needed to combine the strengths of each modelling techniques. This reasoning is in line with the 'system of systems' approach (Nielsen et al., 2015) which is gaining momentum as an overarching framework for designing models that are able to represent the inter-connectedness of different systems (such as disease transmission and the natural environment). One suggested approach for combining these complex systems uses a tiered architecture to link component models at different levels of abstraction, such as at the systems and process levels. This approach allows for more detailed process models to be included as components of a larger system level model to support high level decision making (Little et al., 2019).

There are numerous successful examples of hybrid-ensemble models, where the output from one model is used to provide input(s) for another, without either necessarily being implemented using the same modelling approach. Li et al. (2019) combined a spatially explicit, agent-based model with existing climate, species distribution modelling and land-use change models to look at the impact of various climate and socio-economic scenarios on the spread of Lyme disease. Xu et al. (2019) used a spatially-explicit agent-based model to predict the transmission of lymphatic filariasis in American Samoa over time. Holzkämper et al. (2012) developed an integrated decision support tool for catchment management where complex process models were coupled and used to generate probability distributions for various scenarios using Monte Carlo simulations. These distributions were then used to parameterise a user-friendly BN suitable for use by decision makers. BNs have also been combined successfully with state and transition models as a way to incorporate feedback loops (Chee et al., 2016).

The examples above demonstrate how a hybrid modelling approach could be beneficial for predicting the impact of environmental-based interventions on both environmental and leptospirosis outcomes as well as incorporating the varying complexities and data sources that arise in the course of cross-sectoral modelling challenges. For example, no single technique can easily incorporate the expert opinion on predicting ecological impacts of restoring a riparian zone, with the complex feedback loops and relationships required to evaluate the impact of the same intervention on flooding risk. An additional method (or combination of methods) may be required to predict the end effect of flood reduction on leptospirosis risk in the community.

For infectious diseases, transmission can often depend on stochastic random, often exogenous events, such as extreme weather events or natural disasters. In this context BNs could be useful for causal risk assessment, but data needed to parameterise the models are often unavailable for novel or rare scenarios (such as a major flood). One approach to modelling this scenario is to incorporate uncertainty using a Monte Carlo simulation model and use this analysis as the input to a BN (e.g. Borsuk et al., 2012; Holzkämper et al., 2012). The approach can also be applied in other data-poor scenarios where models such as SD models can assist by producing probability distributions to parameterise BNs and reduce rather than amplify uncertainty (e.g. Hafezi et al., 2021). Such model generated distributions help avoid cases where the BN is left in a state of maximum uncertainty (uniform probability distributions). The Monte Carlo simulations with the SD models are carried out by specifying probability distributions for uncertain variables using three parameters: type (e.g. normal, Weibull, triangular), mean, and variance. Parameters could also be determined from empirical data, expert opinion, or some combination of these.

An example of how this might be applied to combine the disease risk model into the wider cross-sectoral model could involve a hydrological flood model used to parameterise a BN (e.g. Goodarzi et al., 2021) linked with a GIS (e.g. Mayfield et al., 2018b; Sahin et al., 2019). In a separate component, a model for predicting the impact of an infrastructure intervention on flooding throughout the catchment area could be developed using SD (e.g. Mai et al., 2020; Rehman et al., 2019). The predictions of this model could then be used to parameterise a BN, incorporating additional local knowledge of specific areas. BNs would also be suitable for incorporating local expert knowledge on the predicted effects of the intervention on local ecology (e.g. Tantipisanuh et al., 2014). For the final component, GLMs are suitable for preliminary investigations on the drivers of leptospirosis, which could inform model designers about which variables are most relevant to include (Lau et al., 2012a). Any of these methods can be linked with a GIS to provide spatially-explicit inputs and mapped outputs (e.g. Mayfield et al., 2017; Sahin et al., 2013). Specific geospatial models, such as geographically weighted regression or Kriging, can be used where data are spatially correlated (Mayfield, 2018a; Viroj et al., 2021).

One final advantage of a hybrid modelling approach is that it easily facilities different levels of user engagement for different components. For example, a hydrological model may be purely data driven and developed by expert modellers using a complex systems approach and then included as a component in an ensemble model (Mussap et al., 2017). For other components, the use of local knowledge might be critical for integrating the social-cultural factors, and therefore require a participatory approach with local residents working together with data modellers (Scoones et al., 2017). In these scenarios a conceptual-based modelling technique such as BNs or SD might be employed. Yet another component might look at the effects of an intervention on biodiversity and require that data be elicited from experts using a structured process (Mata et al., 2016). Other components might look to explore trends in available empirical data, making use of techniques such as ANNs.

8. Conclusion

Despite the increasing recognition of the links between the health of the environment and infectious disease transmission, models that facilitate cross-sectoral decision making by allowing for a collaborative evaluation of environmental interventions are rare. The use of cross-sectoral models in other areas, such for optimising environmental and economic factors, is not uncommon, and indicates a willingness in the modelling community to tackle models spanning multiple domains. However, the complexity of quantitatively representing wicked, cross-sectoral, and multi-dimensional problems means that no individual modelling technique will be ideal for representing every component within the system. The case study presented here provides an illustration of the range of data and system behaviours required by even a simple representation of such a problem. By comparing these system requirements against the strengths and limitations of individual modelling techniques, we demonstrate that no single modelling technique is likely to meet all these requirements. Instead, hybrid-ensemble approaches that use component models from different frameworks are a more likely candidate as they can take advantage of the strengths of each technique. Exploration of novel modelling approaches are needed to develop models that can concurrently benefit human health and the environment, thus promoting cross-sectoral collaboration and optimising the use of limited resources.

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