Key Result Summary: Valuing Australia's Biosecurity System

CEBRA Project 170713

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Executive Summary

Australia operates one of the most comprehensive biosecurity systems in the world. However, due to the system's size and complexity, it is unclear exactly how much monetary *'value'* it generates and where that value is generated within the system. Without a clear understanding of the net benefits obtained from the existing investment in biosecurity activities it is difficult to determine the extent to which the system is achieving its desired objectives (i.e., its *'health'*) and also whether there is scope to increase either the value or health of the system by altering the allocation of resources.

Past attempts to value the biosecurity system have been based on ad-hoc and/or qualitative statements of overall benefits or limited to specific major pests or diseases, such as an estimate of the consequences of a foot and mouth disease outbreak in Australia. Consequently, where benefit estimates do exist, they have typically been calculated using incompatible measures of value; inconsistent or incomplete monetisation of impacts; contradictory assumptions or counterfactuals; and/or over different temporal or spatial scales. To the best of our knowledge, no one has ever successfully completed an economic evaluation of an entire biosecurity system.

Given the scale of the task of estimating value at the system level, a staged approach was required.

- Phase One (Dodd *et al.*, 2017) delivered a comprehensive review of the biosecurity economics literature, a detailed description of Australia's biosecurity system, four small case studies highlighting critical issues (knowledge gaps) identified by the project team, and an overarching framework for accurately estimating the value of Australia's biosecurity system.
- Phase Two (Stoeckl *et al.*, 2018) delivered a comprehensive review of the non-market valuation literature relevant to biosecurity, developed a detailed framework for extending DAWE's existing consequence measures to include non-market values, including a method for properly aggregating measures of value up to the system scale, and prepared two detailed case studies demonstrating proof of concept for a whole-of-system approach.
- Phase Three (outlined here) implemented our novel whole-of-system approach to valuation. We first compiled estimates of the annual flow of benefits (both market and non-market) arising from sixteen different assets vulnerable to biosecurity hazards, and thus protected by the Australian biosecurity system – including the distribution of those assets across space. We then developed a bespoke, spatially explicit, bio-economic simulation model capable of simultaneously modelling the arrival, spread and impact of 40 functional groups of species on those sixteen assets, over time. Finally, we completed 50,000 iterations of the model with the biosecurity system 'on' for 50 years, and another 50,000 with the system 'off', to estimate the future damages that may be avoided due to the operation of Australia's biosecurity system (i.e., its benefits), and subtracted from those the government's forecast expenditure (i.e., its costs), in order to determine its Net Present Value (A$).

The total flow of benefits arising from assets vulnerable to biosecurity hazards was calculated to be A$251.52 billion per annum, or A$5.696 trillion over 50 years (discounted at 3-5%). In the absence of a biosecurity system we forecast that approximately A$671.94 billion in damages attributable to newly introduced pests and diseases would be incurred by these assets over the next 50 years. Instead, we estimate that these damages would decline by approximately A$325.26 billion (the benefit) to A$346.67 billion in response to the system's operation (at a cost of A$10.45 billion).

Thus, we estimate the Net Present Value of Australia's Biosecurity System to be A$314 billion (95% interval: 156.47b - 466.86b) at an average return on investment of 30:1 (95% interval: 15-45:1).

As the first estimates of their kind it is difficult to properly contextualise our results other than to say that they appear plausible given the existing evidence. We further recognise the many necessary assumptions and limitations in our analysis and, as such, view our estimates as the beginning of a discussion about system valuation rather than its end. Nevertheless, it is clear from our analysis that the continued operation of Australia's biosecurity system over the next fifty years will yield large positive benefits for Australians.

1 Introduction

1.1 Biosecurity in Australia

Australia has a comparative advantage relative to many developed countries due to its diverse geography, extensive natural resources and the absence of most of the world's major pests and diseases. This allows producers to achieve higher yields with lower production costs, and to receive higher prices for goods in premium international markets. Australia also has a mega-diverse natural environment that provides significant *'ecosystem services'* including clean air and water, pollination and amenity (Daily, 1997; Millennium Ecosystem Assessment, 2005; Pejchar & Mooney, 2009). This biophysical environment helps to facilitate Australia's strong economy and high standard of living.

Whilst Australia's island geography has long acted as a natural barrier to the movement of pests and diseases (Kloot, 1984; McLoughlin, 2001), globalisation is increasing the rates of movement of both people and goods into Australia from areas where these pests and diseases are more widespread (Ricciardi, 2007; Hulme, 2009). As a consequence, the frequency of pest and disease incursions into Australia continues to increase for most taxonomic groups (Dodd *et al.*, 2015; Seebens *et al.*, 2017). The stated goal of Australia's biosecurity system is to reduce the likelihood of these pest and disease incursions and their adverse consequences on human, animal and plant health, the environment and the economy (Nairn *et al.*, 1996; Beale *et al.*, 2008; COAG, 2012). But what is a biosecurity 'system'?

Remarkably, the concept of a biosecurity system is only vaguely defined in the literature – academic and government. Government agencies typically describe biosecurity as a continuum of measures categorised based on *where* they operate: offshore [pre-border], border and onshore [post-border] (COAG, 2012; Craik *et al.*, 2017). Conversely, the academic literature tends to describe biosecurity as a continuum of measures categorised based on *when* the action is occurring relative the generalised invasion curve: prevention, eradication, containment and asset-based protection (Rout *et al.*, 2011; Robertson *et al.*, 2020). Though, neither approach clearly articulates *what* specific actions make up these measures nor *how* they are organised into a system of controls designed to minimise impacts.

To that end, during year one of our project, we developed a logic model (Figure 1) that describes how Australia's biosecurity system converts inputs (via activities) into outcomes (Dodd *et al.*, 2017). Our view is that a biosecurity system encompasses all of the activities undertaken to minimise the impacts of introduced pests and diseases on the community, the economy and the environment – regardless of whether they are undertaken by government, industry or the community. Drawing on the approach taken by New Zealand for their Biosecurity 2025 direction statement (MPI, 2016), our model blends the two normative frameworks (above), and supplements them with the supporting (e.g., risk analysis and surveillance) and enabling (e.g., legislation and engagement) activities that collectively ensure on-ground management is delivered efficiently and effectively.

For the purposes of this analysis, however, we limit our scope to the activities delivered by the Biosecurity and Compliance Group of the Australian Government Department of Agriculture, Water, and the Environment (DAWE). Thus, our analysis considers the costs and benefits of the biosecurity activities undertaken by the Australian government outside Australia, at the Australian border, and immediately within it (where the activity is paid for by DAWE). The additional costs and benefits arising from activities delivered by the States and Territories within the border were not modelled.

Our original detailed description of Australia's Biosecurity System, including supporting text, can be found in Dodd *et al.* (2017) and an updated version found in Schneider and Arndt (2020).

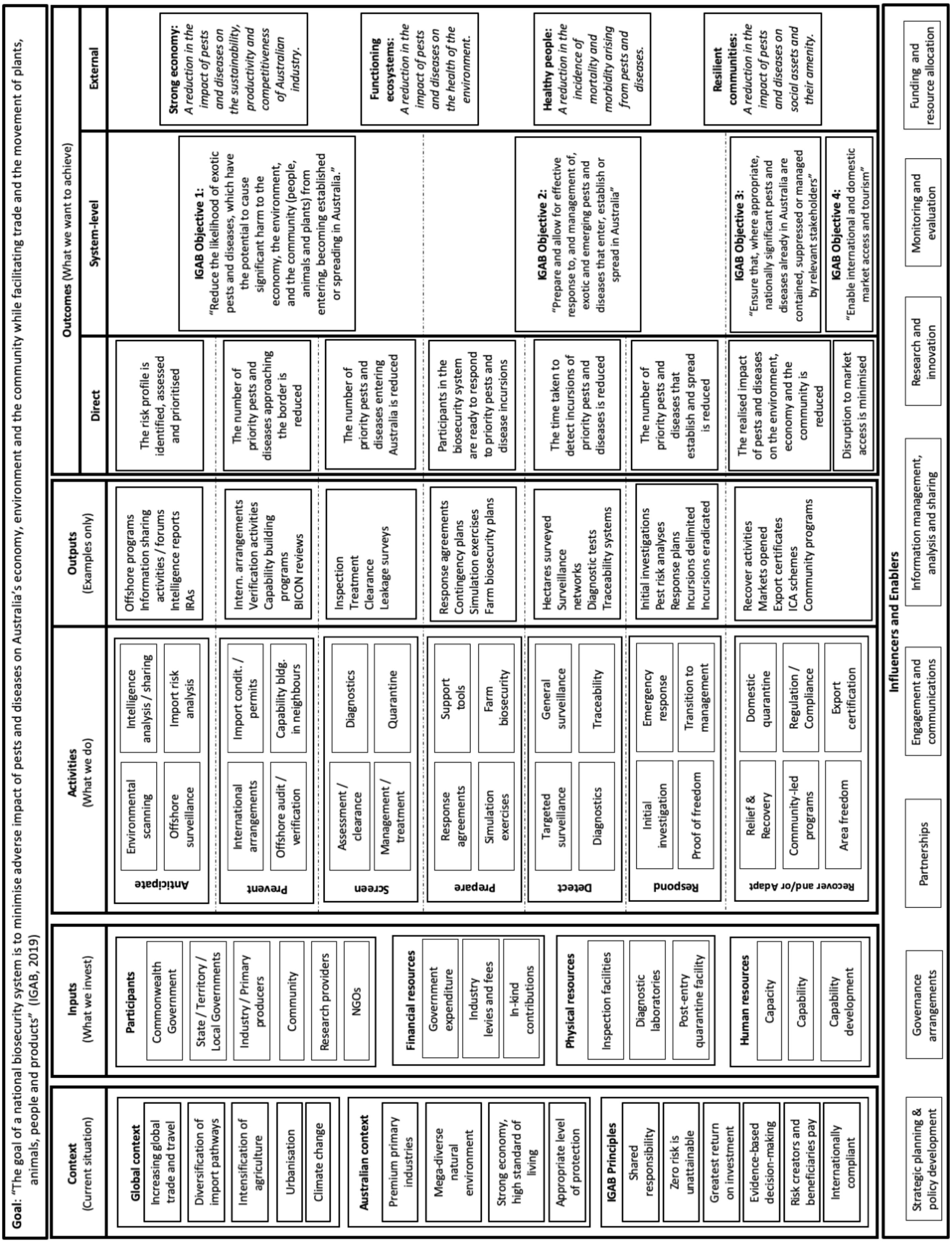

Figure 1: Australia's biosecurity system logic (Dodd *et al.*, 2017; updated in Schneider & Arndt, 2020).

1.2 Estimating the value of biosecurity systems

A wide range of methods have been used in the scientific literature to infer the economic benefits arising from biosecurity activities. Based on the >300 economic analyses identified in our literature review, several general observations can be made. Typically, these analyses fall into three broad categories: consequence analysis, cost-benefit analysis and optimisation. However, only the latter two, cost-benefit analysis and optimisation, provide measures of 'value', and the overwhelming majority of these studies focus on either a single species or a single intervention. None of the studies reviewed analysed a realistic biosecurity system which protects a diverse range of assets, from numerous potential hazards using multiple interventions (although see Hafi *et al.*, 2015).

Estimating the value of a system is much more complicated than simply adding together the values of its parts. To illustrate why this is the case, we will work through a selection of issues arising from a simple example based on a well understood hazard – foot and mouth disease (FMD). In 2013, the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) estimated that the economic impact [consequence] of a large FMD outbreak in Australia would be $52b (Buetre *et al.*, 2013). However, this doesn't imply that the value generated by preventing an FMD outbreak is $52b, only what the consequences would be should an outbreak occur.

Instead, the value of a system is usually determined by the reduction in both the likelihood of an outbreak occurring and the consequences of an outbreak when one does occur (i.e., the change in 'expected value'), minus the costs of implementing the system. This is illustrated in Table 1.

Table 1: A stylised approach for estimating the expected (annual) net present value of a system aimed at preventing, detecting and eradicating foot and mouth disease.

No Biosecurity System (the 'counterfactual')		
Annual likelihood:	0.05	(1:20 year return frequency)*
Consequence:	-$100,000,000,000*	
Expected Value (loss):	-$5,000,000,000	
Biosecurity System (the 'status quo')		
Annual likelihood:	0.01	(1:100 years)*
Consequence:	-$52,000,000,000	
Expected Value (loss):	-$520,000,000	
Expected Benefit (avoided loss):	$4,480,000,000	
Biosecurity System Cost:	$100,000,000*	
Expected Net Present Value:	**$4,380,000,000**	

* Indicates hypothetical estimates included for the purposes of illustration.

What becomes clear, when presenting the information in this way, is the importance of correctly describing what would happen in the absence of the biosecurity system as the reference point (the 'counterfactual') from which we estimate the system's net present value. Since the counterfactual cannot be observed, it must be estimated, and no such analysis has been undertaken for Australia. We also don't know the relative likelihoods of the two outbreak scenarios (small and large) modelled by Buetre *et al.* (2013). Calculating an expected value requires an understanding of the distribution of possible outcomes and their relative likelihoods in order to identify the most likely scenario, however, what Buetre *et al.* (2013) report are essentially realistic best and worst-case scenarios.

Each of these estimates are also based on an assumption of *ceteris paribus;* all things remaining as they are. That is, when the consequences of an FMD outbreak are estimated, it is assumed that no other pest or disease outbreaks will occur. Whilst this may be a reasonable assumption in the status quo scenario, in the absence of a biosecurity system (the counterfactual) outbreaks of several pests or diseases will almost certainly co-occur. As such, the interaction between the outbreaks must be considered in order to prevent the double counting of damages. In this scenario we are therefore interested in the additional, rather than absolute, consequence of each additional pest or disease.

Once we start to aggregate the consequences of multiple outbreaks it also becomes critical that the consequences are estimated using consistent measures and assumptions so that we don't end up comparing apples with oranges. For example, the consequences estimated by Buetre *et al.* (2013) are measured in terms of impacts on producers (ignoring consumers) whereas the consequences of many pests and diseases, particularly those affecting the environment, are often measured in terms of impacts on consumers (ignoring producers) (e.g. Beville *et al.*, 2012; Akter *et al.*, 2015). If the aim is to aggregate the consequences of these two outbreaks into a single estimate of monetary 'value' then impacts on both producers and consumers (e.g. surplus measures) must be estimated for each pest or disease (Sinden & Griffith, 2007; Soliman *et al.*, 2010; Heikkilä, 2011; Epanchin-Niell, 2017).

It is important to emphasise at this point that this example is not intended to suggest that the analysis of Buetre *et al.* (2013) is not informative. Rather, it seeks to highlight the significantly higher information requirements for undertaking a cost-benefit analysis relative to a consequence analysis and the substantial complexity that arises when trying to aggregate the costs and benefits of multiple species, assets and interventions (see also Liu *et al.*, 2014; Hafi *et al.*, 2015). If we are to make a defensible estimate of the value of Australia's biosecurity system, we will first need to develop novel ways to cut through this complexity without divorcing ourselves from reality.

Issue 1: Uncertainty and complexity

One of the inescapable realities of biosecurity is extreme uncertainty. However, it is important to note that not all of this uncertainty is due to a lack of knowledge (also referred to as 'incertitude'); in fact, much of our uncertainty is due to randomness (also referred to as 'variability') (see Regan *et al.*, 2002; Burgman, 2005). For example, it could be said that our uncertainty about which species will arrive, when and where arises predominately from the randomness of the introduction processes more so than a lack of knowledge about pathways (especially within border inspection agencies, such as the Department of Agriculture, Water and the Environment (DAWE)). Whilst randomness can't be reduced in the same way that knowledge gaps can be closed, advances in high performance computing now allow us to model this randomness 'stochastically' in an epidemiologically authentic way (Bradhurst *et al.*, 2015; Bradhurst *et al.*, 2016).

The challenge, then, is how to sensibly model all of the potential biosecurity hazards (i.e., pests and diseases) mitigated by a biosecurity system. Seebens *et al.* (2017) recently found that no fewer than 16,926 species have established 'alien' populations outside their native range, globally. Modelling the impacts of all these species is clearly intractable, however, at least two options exist for simplifying the problem. The first is to recognise that the biosecurity system is designed to mitigate only the impact of priority (syn. 'high-risk') pests and diseases, whilst simultaneously facilitating the trade of 'very-low but not zero' risk commodities in line with an Appropriate Level of Protection (ALOP; Beale *et al.*, 2008; Craik *et al.*, 2017). One could then argue, based on the findings of Williamson and Fitter (1996) and Diez *et al.* (2009), that only a small subset (c. 10%) of the total pool of species are likely to cause nationally significant impacts in Australia and, thus, warrant modelling.

Of course, this raises the subsequent question of: which species to model? This is where our second option for simplification arises. Rather than modelling individual species, several recent studies (e.g., Aukema *et al.*, 2011; Epanchin-Niell *et al.*, 2014) have classified species into 'functional groups' according to their mode of action. This type of classification is common in practice where one will frequently hear the terms 'fruit flies', 'tramp ants', 'broadleaf weeds', etc. The key reason for why this approach is so common in practice is because the impacts of species within a group and their management controls are highly similar. Thus, one could also argue that it doesn't matter exactly which of the species within a group is modelled, provided it is representative of the larger functional group (and that the groups are representative of the full suite of hazards). Following such an approach may allow us to estimate system-level values from as few as 50 pests and diseases.

Issue 2: Individual versus aggregate damages

In the traditional risk management model (as presented in Table 1) the value of a risk control (e.g., border inspection for tramp ants) is modelled by subtracting the cost of the intervention from its expected benefits (i.e., a risk-adjusted net present value; rNPV) (Boardman *et al.*, 2011). Thus, it is common to see the one-off (often yearly) intervention costs subtracted from the expected benefits (in our case avoided damages) accrued over an extended time period (e.g., 20 years). However, we don't believe that this is appropriate for biosecurity at the system level - for two reasons. Firstly, biosecurity hazards persist in the environment (unless they are eradicated) so the [additional] damages that arise from any subsequent incursion of the same species are diminished due to its pre-existence. Therefore, the realised risk reduction of an intervention will frequently be less valuable than what is predicted by the net difference between the expected values of the managed and unmanaged likelihoods and consequences - as was presented earlier in the introduction (Table 1).

Further, by relaxing our assumptions about *ceteris paribus* (i.e., allowing multiple species to arrive) we can no longer assume that the consequences of each hazard are independent. Even if we choose to simplify the problem by classifying pests and diseases into functional groups we still end up with circumstances where multiple groups (e.g., sap suckers, borers and defoliators) impact upon the same asset (e.g., forestry). As we have discussed with stakeholders several times throughout this project, though, you can't kill the same cow (or tree) twice. Taken together, these two issues mean that the calculation of aggregate damages (as a precursor to estimating the risk reduction) must allow for the interaction of outbreaks. This isn't a trivial undertaking. Relative to the existing biosecurity risk literature, which comprises mostly single hazard x single asset studies, correctly addressing this kind of question requires a framework several orders of magnitude more complex (e.g., a 10 hazard x 5 asset model, allowing interactions, is 10 x 10 x 5 = 500 times more complex).

Issue 3: Ongoing versus one-off benefits and costs

Complexity also arises in the modelling of species interactions through the need to consider both space and time explicitly. In their simplest form, biosecurity benefit-cost analyses model impacts using logistic growth functions and per unit area control costs and/or damages (Soliman *et al.*, 2015; Epanchin-Niell, 2017). Exactly where a species is, and when, isn't important in this framework as it rests on the assumption that space is homogenous. However, in a multi-hazard x multi-asset model knowing which pests and diseases are present, where, and when is essential for correctly estimating the aggregate impact of those species (i.e., to avoid double counting). Besides requiring us to move to a spatially explicit modelling framework, our need to consider many species simultaneously also mandates the internalisation of the likelihood component of the risk assessment (because we need to know the likelihood that subsequent outbreaks will occur when estimating consequences), rendering traditional 'one-off' [exogenous] likelihood times consequence methods obsolete.

This change also influences how we incorporate the costs of operating the biosecurity system. If the consequences of a species are influenced by the arrival of a second species (as we have argued above) then the consequences of the first depend on the arrival (and spread) rate of the second. In the traditional model, the expected value (likelihood × consequence) is equal to the average per annum damage from a hazard (in the long run). Therefore, one can easily find examples where the cost of a risk reduction measure is expressed as a one-off, yearly, amount. The problem with this, as we have illustrated above, is that the arrival (and spread) rate of a subsequent species is dependent on the amount of investment in risk reduction. That is, consequence estimates are conditional on continued expenditure. As such, when estimating the value of an intervention targeting multiple species, one must calculate costs and benefits over the same time horizon.

Our proposal is to flip the existing hazard focussed approach on its head and instead focus on assets. Rather than estimating the long run impact of a set of hazards by summing their individual impacts, we propose that system level impacts would be best derived by first estimating the flow of benefits arising from assets protected by the system and then estimating the decline in the value of those assets that would occur should species arrive, spread and impact at their forecast rates. Whilst such an approach is a significant departure from the traditional risk analysis methods, we believe that this approach is the only one that adequately addresses the theoretical considerations that we outlined above. It also puts assets (e.g., agriculture, environment, etc.) at the heart of our analysis – which is important – because the sole purpose of the system is to protect these assets. It is worth reiterating that we are not aware of any existing biosecurity models capable of such an analysis.

1.3 Aims and organisation of this report

This report summarises the key results arising from the Centre of Excellence for Biosecurity Risk Analysis (CEBRA) project 170713 – Value of Australia's biosecurity system. The primary focus of this report is to outline the methodology of our final bioeconomic analysis and to present its key findings in a readily digestible format. Consequently, all of the details relating to our preliminary analyses (i.e., our system definition, literature reviews, methodological development and rationale, proofs-of-concept, data gathering, etc.) are omitted here for clarity. For further details we direct the reader to Dodd *et al.* (2017), Stoeckl *et al.* (2018) and Stoeckl *et al.* (2020).

2 Methods

We first compiled estimates of the annual flow of benefits (both market and non-market) arising from sixteen different assets vulnerable to biosecurity hazards, and thus, protected by the Australian biosecurity system – specifically, the distribution of those assets across space. We then developed a bespoke, spatially explicit, bio-economic simulation model capable of simultaneously modelling the arrival, spread and impact of 40 functional groups of species on those sixteen assets, over time. Finally, we completed 50,000 iterations of the model with the biosecurity system 'on' for 50 years, and another 50,000 with the system 'off', to estimate the future damages that may be avoided due to the operation of Australia's biosecurity system (i.e., its benefits), and subtracted from those the government's forecast expenditure (i.e., its costs), in order to determine its Net Present Value.

2.1 Data Collection

Asset values and locations

Our estimates of the spatial distribution of asset values builds on the work outlined in Stoeckl *et al.* (2020). To briefly re-cap, benefit transfer techniques were used to estimate the annual flow of benefits arising from sixteen sub-classes of assets for each of Australia's 56 Natural Resource Management (NRM) regions. A breakdown of the asset classes, which extend on the well-known Common International Classification of Ecosystem Services (CICES) framework (Haines-Young & Potschin, 2012), is included in Table 2.

Table 2: Asset classes used in the analysis.

Relevant Capital	Asset Type	Asset Class	Sub-class
Natural	Provisioning	Portfolio Industries	Agriculture
			Forestry
		Indigenous Subsistence	Subsistence
		Water for Consumption	Water
	Regulating	Erosion Control	Erosion Control
		Flood Control	Flood Control
		Genepool / Nursery	Genepool
		Carbon Sequestration	Carbon Sequestration
		Mediation of Soil / Air	Toxin Mediation
	Cultural	Residents – Use	Recreation / Aesthetics
		Residents – Non-Use	Existence / Bequest
		Non-Residents - Use	Tourism
		Indigenous – Non-Use	Indigenous
	Companion Animals	Pets (Cats, Dogs, etc)	Domestic Animals
		Horses (non-racing)	Recreational Horses
Physical	Infrastructure	Dwellings / Utilities	Infrastructure

For those assets traded in markets (such as agricultural commodities, forestry products and infrastructure) the annual flow of benefits, per region, was sourced directly from Australian Bureau of Statistics datasets (ABS, 2017c, d, 2018a). For those assets not traded in markets (such as erosion control, toxin mediation, tourism, etc.), the annual flows of benefits were estimated using benefit transfer functions fitted to data from pre-existing studies of ecosystem service values housed within The Economics of Ecosystems and Biodiversity (TEEB) database (Van der Ploeg & De Groot, 2010). Expenditure on companion animals was sourced from Animal Medicines Australia (2016) for pets and Gordon (2001), O'Sullivan (2012) and Macleay (2018) for horses. For a fuller description of our asset valuation see Stoeckl *et al.* (2020).

To allocate these values across space we first constructed a series of 2500m x 2500m raster grids for each of the factors known to influence asset value (Table 3). Each spatial dataset was projected, rasterised, aggregated and resampled (as required) to ensure a common resolution and extent. The data were projected using the Australian Albers (equal area conic) coordinate system (EPSG:3577). Categorical datasets were aggregated by mode and resampled using nearest neighbour methods. Continuous datasets were aggregated by sum and resampled using bilinear interpolation. A summary of the datasets used, including any transformations applied, is included in Table 3.

Table 3: Summary information of the spatial data used in the analysis.

Dataset	Units	Format	Aggregation	Resampling	Source
NRM Region	Categorical (name)	Polygon	Mode	Nearest Neighbour	(DoEE, 2017)
Land Use	Categorical (ALUM L2)	50m Raster	Mode	N/A	(ABARES, 2017)
Vegetation Type	Categorical (MVG)	100m Raster	Mode	Nearest Neighbour	(DoEE, 2018)
Total Population	Continuous (count)	Polygon (ASGS[1] MB)	Sum	Bilinear Interpolation	(ABS, 2017b)
Indigenous Population	Continuous (count)	Polygon (ASGS[1] SA2)	Sum	Bilinear Interpolation	(ABS, 2017a)
International tourists	Categorical (name)	Polygon (ASGS[1] TR)	Mode	Nearest Neighbour	(various[2])

[1] ASGS is the Australian Statistical Geography Standard (ABS, 2018b).
[2] Tourist visitation was sourced from each jurisdictions tourist bureau. See Stoeckl *et al.* (2020) for details.

Depending on how the original benefit transfer had been undertaken we then utilised several generic methods for distributing the total value across space within an NRM region.

Asset values based on per-hectare estimates

For asset values, such as carbon sequestration, that had been calculated based on the number of hectares of specific vegetation types, such as forests, within an NRM region we could simply assign the original per-hectare value to a pixel based on its size and vegetation type.

Assets: Flood mitigation, water purification, gene pool / nursery, erosion control, toxin mediation, carbon sequestration, existence / bequest and indigenous cultural values (8).

Asset values determined based on per-person estimates

For asset values, such as domestic pets, that had been calculated based on the number of people normally residing in an NRM region we could assign a value to a pixel based on its population.

Assets: Indigenous subsistence and domestic pets (2).

Asset values determined based on per-person and per-hectare estimates

For asset values, such as domestic recreation, that had been calculated based on the number of people normally residing in an NRM region – but where the benefits are received away from the person's normal place of residence – we converted the per-person estimate to a per-hectare one based on the area available for the activity (i.e., recreating) before proceeding as above.

Assets: Domestic recreation, international tourism and recreational horses (3).

Asset values based on ABS estimates

For asset values, such as agriculture, that were obtained from the Australian Bureau of Statistics we first determined the number of hectares of specific land uses (e.g., horticulture) within an NRM region and then used those to convert the NRM scale estimates of the relevant commodity values to per-hectare estimates before proceeding as above.

Assets: Agriculture, forestry and infrastructure (3).

Pixels lacking both an NRM region AND a land use OR a vegetation type (predominately ocean) were excluded/masked from the analysis in order to avoid unnecessary calculation, leaving 1.3M pixels.

Species arrival, spread and impacts

The demographic parameters required to properly characterise the hazards (i.e., pests and diseases) were obtained from three separate sources. An example species is included in Table 4.

Table 4: Summary of demographic input parameters used in the analysis and their respective sources. The 'broadacre mollusc' functional group is displayed as an example.

Functional Group Source: RRRA	Exemplar Species ABARES*	Establ. Rate (count p.a.) RRRA	Spread Rate (km p.a.) ABARES*	$\text{Damage}_{\text{Agric.}}$ (% Yield) ABARES	…	$\text{Damage}_{\text{Infras.}}$ (% Yield) ABARES*
Broadacre Mollusc	Golden Apple Snail	0.05	0.7	-0.20	…	-0.00

* These datasets required additional post-processing by the project team as described below.

Functional groups, exemplar species and their respective establishment rates.

Our choice of functional groups [of species] mirrors those used in DAWE's Risk-Return Resource Allocation (RRRA) model (see details in Craik *et al.*, 2017). RRRA is probabilistic model that uses Bayes nets (Korb & Nicholson, 2003), parameterised using internal DAWE data and expert judgement, to estimate the change in likelihood of about 60 pest and disease groups entering and establishing in Australia as a function of investment level. Therefore, rather than replicate existing work, we used these estimates as the basis for our functional groups, exemplar species and their respective establishment rates. The rates used in this analysis (counts per annum) for the status-quo 'system on' scenario were extracted from RRRA on 17 September 2019 with all controls set to 'ON'. Aquatic pests and zoonoses were excluded from the dataset due to limitations in our ability to model them correctly, leaving 40 functional groups for modelling / analysis (Appendix 6.1).

Spread rates and portfolio industry impacts

In its current configuration, RRRA also includes monetary consequence measures for the impacts of each functional group on portfolio industries (agriculture, fisheries and forestry). These measures have been adapted from estimates provided by ABARES (Hafi & Addai, 2014; Hafi *et al.*, 2014) plus a handful of other pre-existing studies (e.g., Buetre *et al.*, 2013). In their original format the ABARES estimates could not simply be re-purposed for our analysis (for the reasons we outlined earlier), however, the raw data contained within these reports could. Thus, we obtained the majority of the relevant spread rates (years to % host occupancy) and portfolio industry impact estimates (% yield or price reduction) from these studies. To convert the elicited spread rates (years to % host occupancy) to a geometric measure (km per annum) we sourced the relevant host areas from the most recent production statistics (ABARES, 2018; ABS, 2018a; HIA, 2019) from which we were then able to derive the intrinsic growth rate, carrying capacity and asymptotic velocity (see Hui & Richardson, 2017). Where gaps existed in the original ABARES datasets, parameters were sourced from the literature.

Non-market impacts

ABARES has similarly elicited estimates of the non-market (i.e., environmental, social, etc.) impacts of each of the functional groups utilised within RRRA (Chesson *et al.*, 2014; Parsons & Arrowsmith, 2014). These estimates were provided in the form of a five-point Likert score (0-4) representing the extent and intensity of impact across a series of environmental attributes (e.g., amenity, regulating, water, atmosphere, etc.). To convert these into % yield reductions we first re-aligned the ABARES categories with our modified CICES categories to ensure that they were separable (i.e., they don't overlap). We then collated from the peer reviewed literature a dataset of observed or elicited (e.g., choice modelled) estimates of the percentage damage to specific non-market assets attributable to biosecurity hazards. For each asset type (e.g., regulating, cultural; Table 2) we then used a logistic function (midpoint=2, steepness=2) to align the properties of the two distributions. That is, the median Likert score was transformed to the median % damage estimate from the literature (by asset type). A more detailed description of our re-scaling method can be found in Stoeckl *et al.* (2020).

System cost and effectiveness

The cost (expenditure) of the system is equal to the total expenditure by the Australian Department of Agriculture, Water and the Environment (DAWE; which includes appropriations and cost-recovery, thus, at least some of the direct cost to industry is also captured). An estimate of the expenditure by DAWE on biosecurity activities was included in the recent Craik review of Australia's biosecurity arrangements (Craik *et al.*, 2017), and we use that as the nominated cost base for our analysis.

As we described in the introduction, the value of any intervention (from a single control through to an entire system of controls) is determined by contrasting what is expected to occur with and without the intervention and subtracting from that the intervention's cost (Boardman *et al.*, 2011). In our case, that contrast is the net difference (i.e., the avoided damage) between the damages that would occur if the system was completely turned off (the 'counterfactual') and the damages that we expect will occur despite the current system (the 'status quo'). We modelled these two scenarios, and thus, the system's effectiveness through the use of two sets of establishment frequencies on the basis that pre-border and border biosecurity activities mostly reduce the likelihood of establishment, whilst post-border activities mostly reduce their consequences. Therefore, in addition to those for the status-quo 'system on' scenario (described above), the establishment rates (counts per annum) for the counterfactual 'system off' scenario were also extracted from RRRA on 17 September 2019 with all controls set to 'OFF'. The full set of establishment rates is included in Appendix 6.1.

2.2 Model Construction

Arrival

The arrival of each functional group (when) was modelled as a Poisson process, where the number of arrivals in any given time step was modelled by taking a random draw from a Poisson distribution with lambda set to the relevant RRRA establishment frequency (count p.a.). As an establishment rate we were then able to assume that the pest or disease established in a pixel that contains susceptible host. Thus, the establishment of each arrival (where) was modelled by sampling with replacement from the set of pixels known to contain susceptible host. The probability of arrival in an individual pixel was weighted by the human population density in the Moore neighbourhood (focal pixel plus the eight adjoining pixels) based on Dodd *et al.* (2016) and Ward *et al.* (2019).

Spread

Following their arrival, each species was dispersed to all susceptible host pixels whose centroid could be reached by the species within one year at asymptotic velocity. Thus, if a species with a velocity of 5km p.a. was present in a pixel at time t, it was spread to all hosts within 5km at time t+1.

However, because ABARES' spread rates were derived from estimates of years to % host occupancy, jump dispersal must also occur or the implied intrinsic growth rates won't be realised (because the host arrangement is neither homogenous nor contiguous). To model the jump diffusion process, we first split the landscape up into patches. A patch was defined as the collection of pixels separated by a distance less than the dispersal (diffusion) distance of the exemplar. Because jump dispersal is, by definition, human mediated we then split these patches by NRM region to ensure that within and between patch movement reflects the density of human activity (Brander *et al.*, 2012; De Groot *et al.*, 2012; Firestone *et al.*, 2012; Hudgins *et al.*, 2017). A jump dispersal event was triggered by a species reaching the edge (including internal edges) of a patch. The number of jumps given a jump event was modelled as a Poisson process where lambda was set to the count required to achieve the elicited intrinsic growth rate (validated using 1000 simulations of each exemplar). The jump targets were sampled with replacement from the set of patches of susceptible host. The probability of jumping to an individual patch was weighted by the negative exponential ($t_{1/2}$=20km) distance to each target patch (from the source pixel) multiplied by the human population of the target patch.

The exception to this diffusion / jump dispersal framework was our approach to modelling FMD. Because the overwhelming majority of the impact attributable to FMD is trade related and would, therefore, apply to all of Australia we used an infinite dispersal distance for the functional group in the model, triggering an impact in all of the susceptible host pixels immediately upon an arrival.

Impact

At each time step, the aggregate impact of the species present in each pixel was estimated by calculating the product of their respective yield reductions multiplied by the value of the asset in each pixel, summed over all pixels. That is:

$$(1) \qquad \mathrm{Damage}_{\mathrm{p,a,t}} = \left(1 - \prod_{s}\left(1 - yield\,reduction_{s,a} \times \mathbb{1}_{\mathrm{s,p,t}}\right)\right) \times \mathrm{asset\ value}_{\mathrm{p,a}}$$

where, *a* is an asset, and **1** indicates the presence of species *s*, in pixel *p*, at time *t*. For example, if two species are present in a pixel and both reduce the yield of a particular asset by 20%, their combined impact is 36% (1-((1-0.2)*(1-0.2)))=0.36. If the value of the asset in that pixel is $1000, the damage is then $360. Our rationale for this choice of functional form is discussed in Appendix 6.3.

2.3 Value Estimation

Simulation settings

50,000 iterations of each system state (on / off) were modelled over a 50-year time horizon in order to properly contrast the two scenarios. A summary of the model settings is included in Table 5.

Table 5: Summary of key simulation parameter settings.

Parameter	Setting
Assets at risk	16 (see Table 2)
Spatial resolution	Australia, 2500m x 2500m (1.3M pixels)
Biosecurity Hazards	40 (see Appendix 6.1)
Temporal resolution	50 years, 1-year intervals
Iterations	50,000 of each state (100,000 total)
Discount rates	5% (financial) and 3% (environmental)

Damages and avoided damages (benefits)

Damages were first estimated, by asset, at the pixel scale (following equation 1, above). Pixel scale damages were then summed, by asset, for each time step. Yearly damages, by asset, were then discounted according to their asset type (financial / environmental; Table 5). Total damages, by asset, for each iteration were calculated by summing the discounted yearly damage. Overall damages (all assets combined) were then simply the sum of total damages (by asset).

The median benefit was estimated by calculating both the difference between the median overall damage estimates for the two system states ('system on' / 'system off') and by calculating the pairwise difference between the equivalent iteration of the alternate states (i.e., the overall damages of the n^{th} iteration of 'system off' minus the overall damages of the n^{th} iteration of 'system on'). The latter allowed us to estimate the variability in the benefit estimate.

Net present value (benefits minus costs)

Finally, we estimated the Net Present Value (NPV) of the biosecurity system by subtracting the [financial] costs of the system's operation from the median benefit calculated above. Costs were assumed to remain constant over time, subject to a net discount rate of 5% per annum (Table 5). Convergence was assessed by a rolling variance and the standard error of the mean (Appendix 6.2).

Unless otherwise specified, all data processing and analyses were undertaken in the R software environment for statistical computing and graphics v3.6.2 (R Core Team, 2019) with the following packages installed: data.table (Dowle & Srinivasan, 2019), dplyr (Wickham *et al.*, 2019), flock (Popivanov, 2016), fst (Klik, 2019), gdalUtilities (O'Brien, 2019), lattice (Sarkar, 2008), latticeExtra (Sarkar & Andrews, 2016), magrittr (Bache & Wickham, 2014), raster (Hijmans, 2019), rasterVis (Perpiñán & Hijmans, 2019), Rcpp (Eddelbuettel & François, 2011), readr (Wickham *et al.*, 2018), reticulate (Ushey *et al.*, 2019), rnaturalearth (South, 2017), sessioninfo (Csárdi *et al.*, 2018), sf (Pebesma, 2018), sp (Bivand *et al.*, 2013), stars (Pebesma, 2019), tibble (Müller & Wickham, 2019), and tidyr (Wickham & Henry, 2019). Python 3.6.9 (Van Rossum & Drake, 2009) was specifically used to rasterise the ABS mesh blocks with the following packages installed: geopandas (Jordahl *et al.*, 2019), rasterio (Gillies & others, 2013), shapely (Gillies & others, 2007), and numpy (Oliphant, 2006).

3 Results

The total flow of benefits arising from assets vulnerable to biosecurity hazards was calculated to be A$251.52 billion per annum, or A$5.696 trillion over 50 years (discounted at 3-5%). In the absence of a biosecurity system we forecast that approximately A$671.94 billion in damages attributable to newly introduced pests and diseases would be incurred by these assets over the next 50 years. However, we estimate that these damages would decline by approximately A$325.26 billion (the benefit) to A$346.67 billion in response to the system's operation (at a cost of $10.45 billion).

Thus, we estimate the Net Present Value of Australia's Biosecurity System to be A$314 billion (95% interval: 156.47b - 466.86b) at an average return on investment of 30:1 (95% interval: 15-45:1).

3.1 Assets

Total flow of benefits from assets vulnerable to biosecurity hazards

As outlined in Stoeckl *et al.* (2020) the total value of the flow of benefits from assets vulnerable to biosecurity hazards was estimated to be A$251.52 billion per annum (Figure 2). Taken over a 50-year period (the horizon of this analysis), and discounted at between 3-5% (Table 5), these assets are expected to provide more than A$5.696 trillion of benefits (NPV) to Australians.

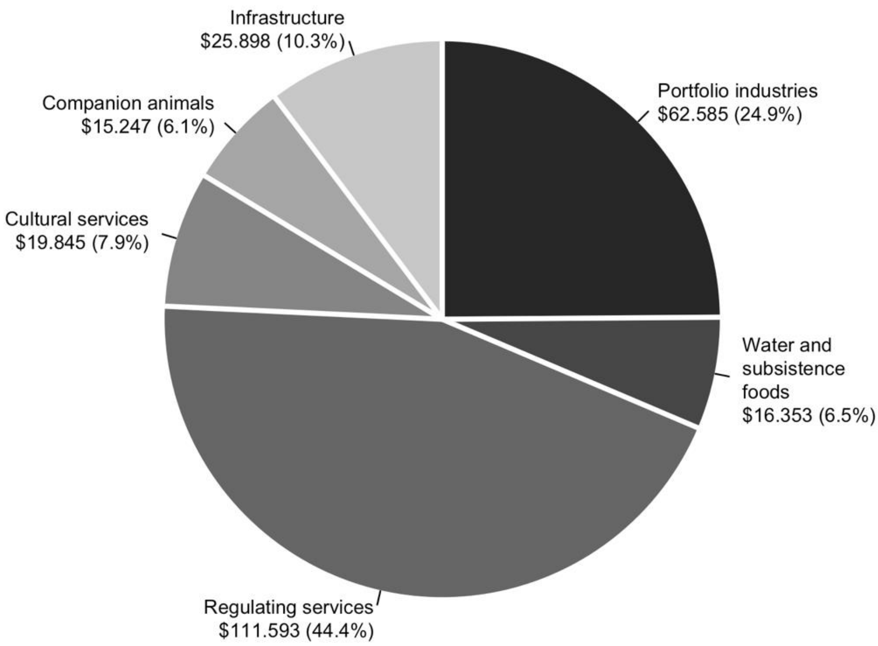

Figure 2: Annual flow (billions A$) of benefits from assets vulnerable to biosecurity hazards.

Regulating services (e.g., erosion prevention, carbon sequestration, etc.) were found to be the highest value asset (A$111.59b p.a.), followed by portfolio industries (i.e., agriculture and forestry; A$62.59b p.a.) and infrastructure (A$25.90b p.a.), respectively. Assets generally not traded in the market – largely goods and services related to the environment – contributed almost 59% to the total asset values, whilst so called 'market' values (e.g., agriculture) contributed the remaining 41%.

Location of assets vulnerable to biosecurity hazards

The distribution of asset values across space (both within and between NRM regions) was found to be highly heterogenous. In addition to the distinct variation between NRMs outlined in Stoeckl *et al.* (2020), we also observed considerable variation within NRM regions. Using the Port Phillip and Westernport NRM region as an example (Figure 3), distinct context-specific patterns can be seen in the spatial arrangement of asset values. In the case of agriculture, horticultural regions are easily identified by their relatively high per unit area values (compared with broadacre industries), whilst more subtle differences in the value of broadacre industries, particularly livestock grazing, can also be observed at regional boundaries - reflecting the regional differences in profitability (Figure 3).

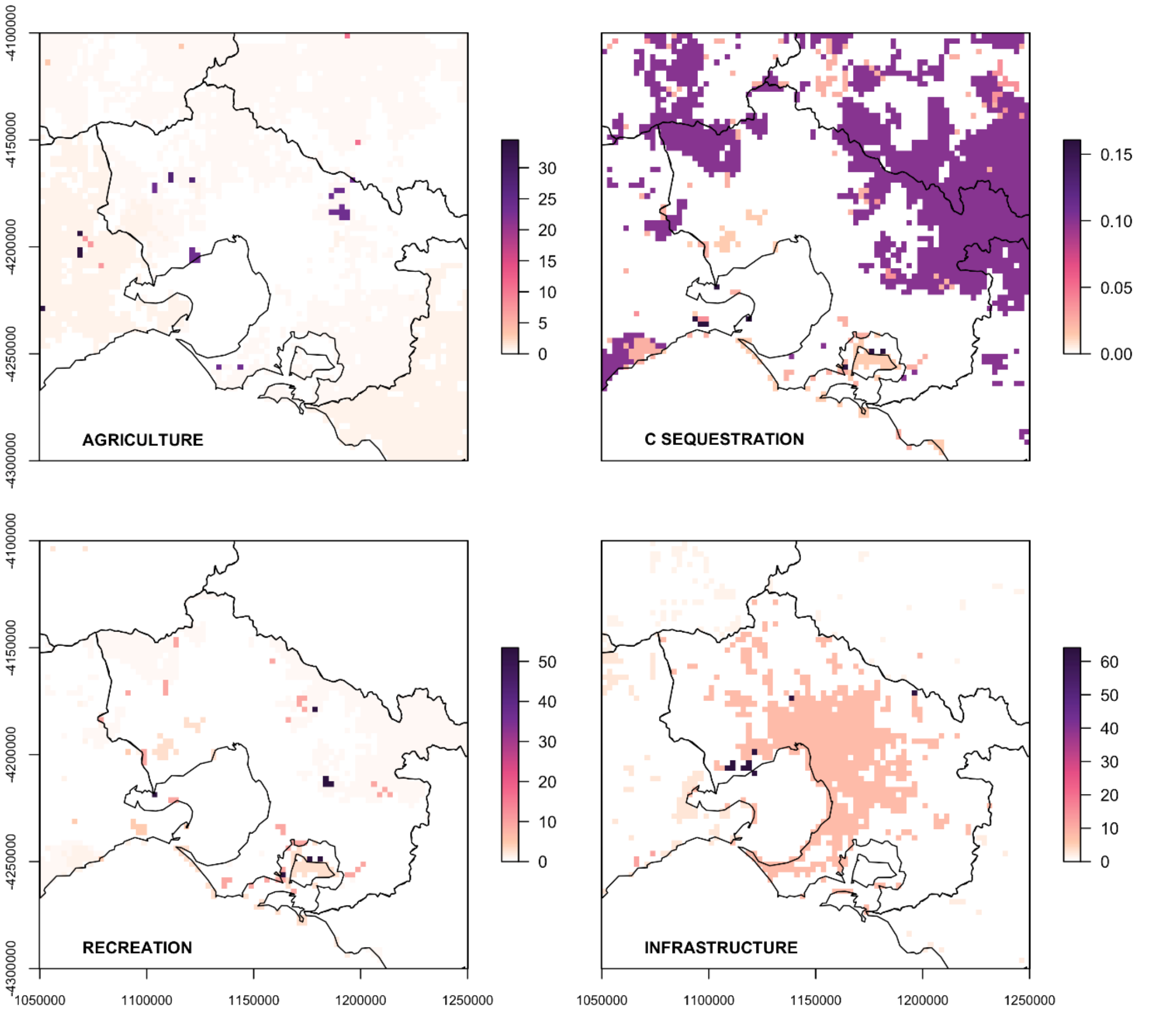

Figure 3: Annual flow of benefits (A$M) per 2500m x 2500m area from assets vulnerable to biosecurity hazards for selected asset types. Extent shown is 100km x 100km area centred on the Port Phillip and Westernport NRM region (Melbourne, Australia).

A completely contrasting pattern can be observed in the arrangement of carbon sequestration. Here, values are driven solely by vegetation type with the highest values in mangrove, wetland, forest and woodland areas with little variation across regional boundaries. Similarly contrasting patterns can be found in each of the 16 asset classes and 56 NRM regions (data not shown), suggesting that the realised impact of the modelled pests and diseases is likely highly dependent on when and where an species establishes in the first instance. Significant biogeographic barriers also separate assets in Western Australia and Tasmania from the rest of Australia, isolating impacts.

3.2 Hazards

Arrival over space and time

In the absence of its biosecurity system we expect that an average of 27.52 species would establish each year in Australia (1376.36 over 50 years; RRRA Unit, 2019). With the system turned 'on' the expected number of establishments declines by 81% to 5.20 per year (260.17 over 50 years; Appendix 6.1). Due to our use of naïve risk maps (see Section 2.2), the majority of the incursions occur along the populous east coast (from Cairns to Adelaide) plus a small area adjacent to Perth in the south west. A paired comparison of what might occur under the two system states is shown in Figure 4 – note the cases of multiple hazards affecting the same industry in a single region.

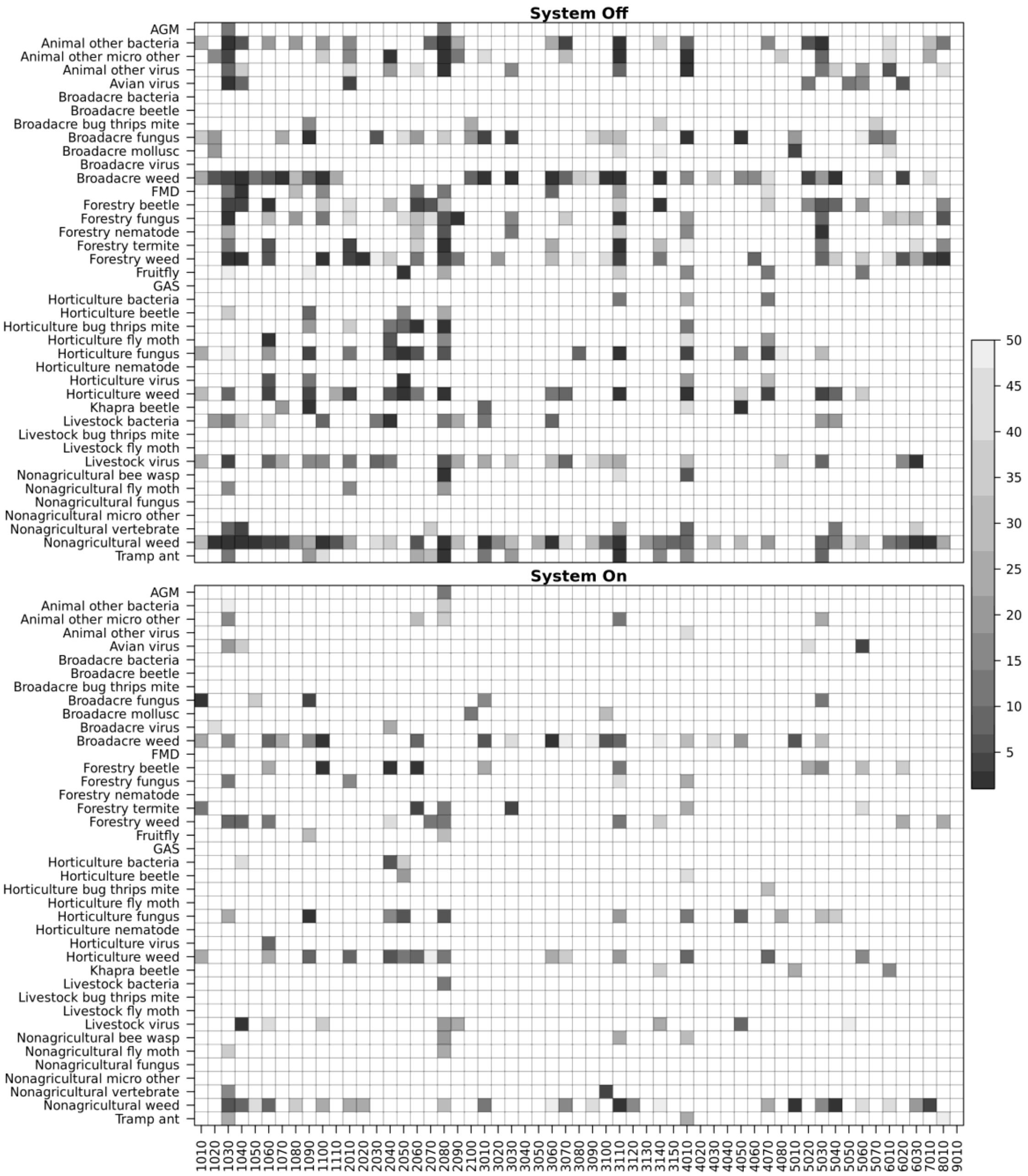

Figure 4: Location of initial establishments over time by functional group and NRM region for a single 50-year simulation of the system 'off' versus the system 'on'. The colour indicates the year of establishment (darker is earlier/longer).

Spread over space and time

The net effect of reducing the number of incursions that occur is a reduction in the probability that any given area will be affected by a particular pest or disease in the future (and, thus, incur impacts). For example, our modelling suggests that without a biosecurity system in place the probability of a tramp ant establishment in each of Brisbane, Sydney and Melbourne in the next 20 years is almost 100%, but that current biosecurity controls reduce that likelihood to around 20% (Figure 5).

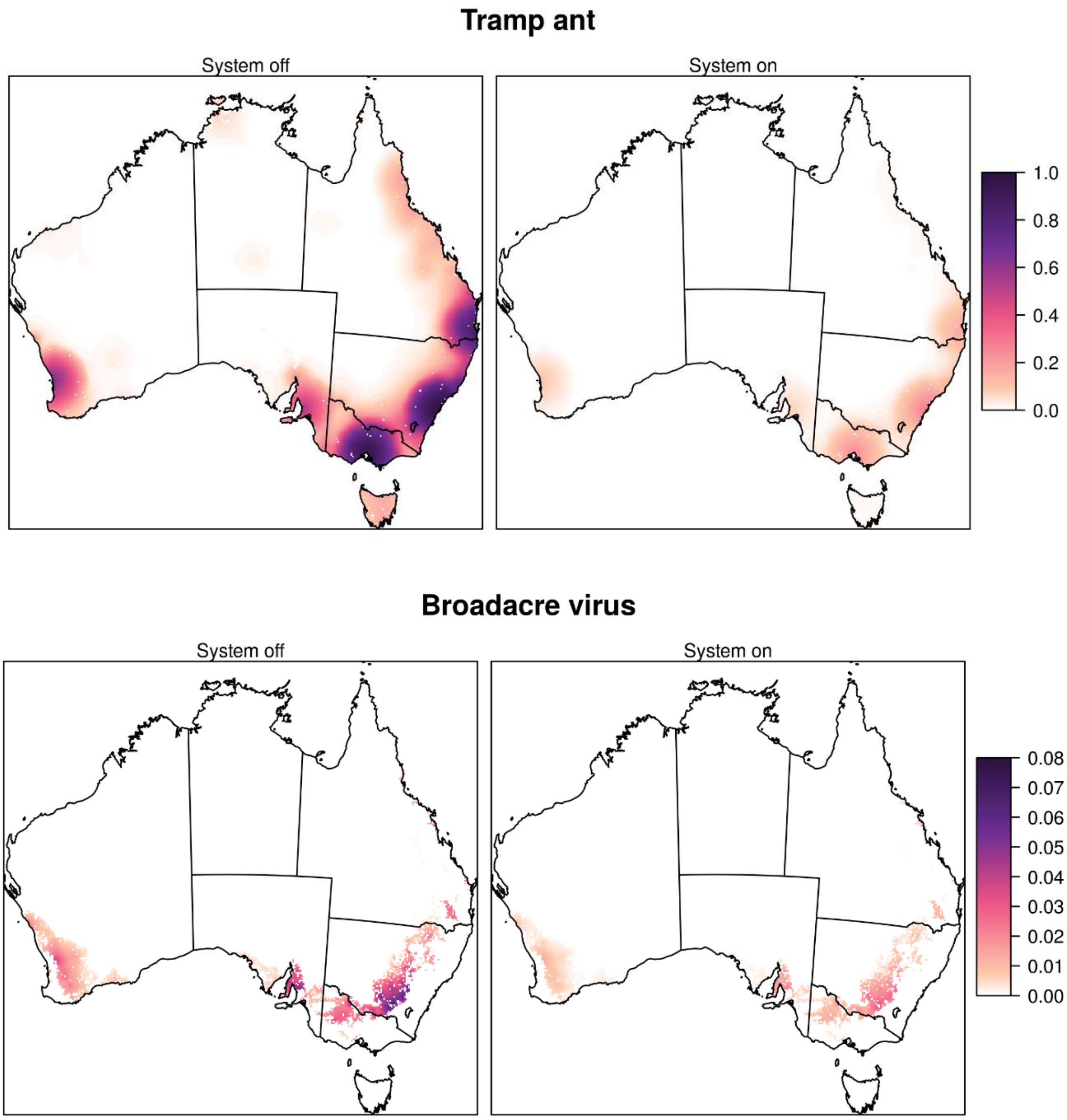

Figure 5: Probability of a pixel being infested/infected with either a tramp ant or a broadacre virus in the year 2040 dependent on the state of the biosecurity system.

It is important to note that these maps represent the absolute probability of occupancy in a 20-year period, not the relative probability of establishment given an arrival – as is usually shown in species [potential] distribution models and so called 'risk maps' (see Camac *et al.*, 2019). Hence, when considering the broadacre virus example, it is possible to infer that the probability of a virus being prevalent across the entire West Australian wheatbelt in 20 years is approximately halved due to the operation of the system (Figure 5).

3.3 Damages (Avoided) - Benefits

Total damages avoided

Should the biosecurity system cease to operate we forecast that A$671.94 billion in damages attributable to newly introduced pests or diseases disease would be incurred in Australia over the next 50 years (range: A$487.84b – A$813.04b). Instead, we estimate that A$325.26 billion in damages will be avoided due to the ongoing operation of the system (which reduces damages to A$346.67 billion (range: $107.79b – $616.16b); Figure 6). The 95% intervals for the avoided damages (benefit) were A$166.92b - A$477.32b (Table 6).

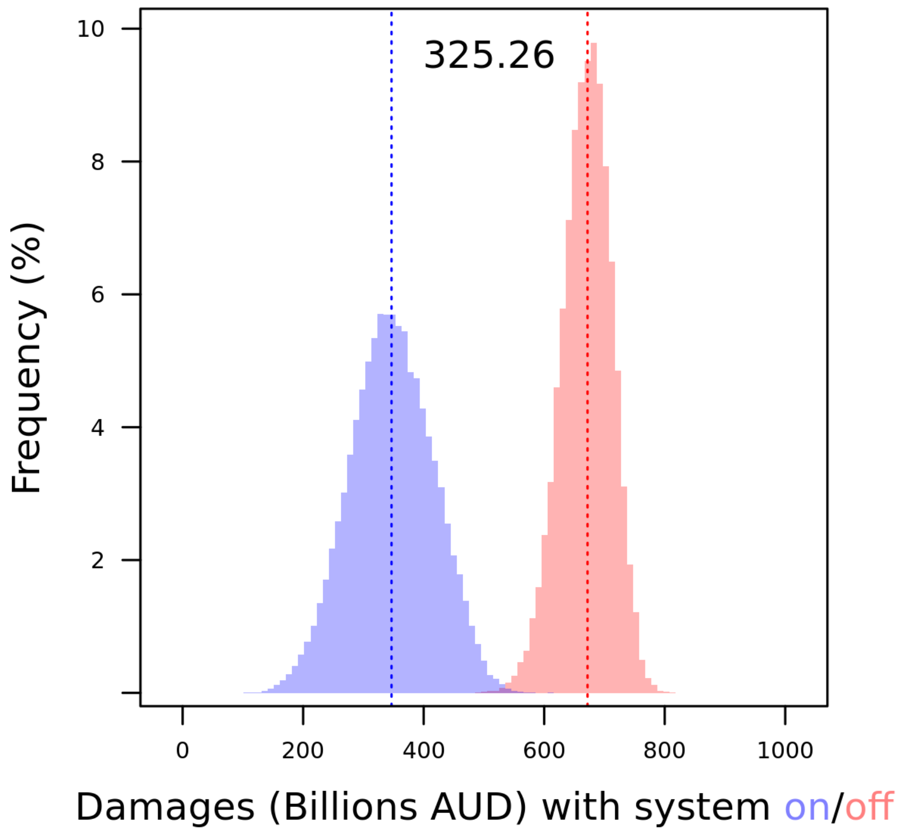

Figure 6: Overall damages over 50 years with the system on/off. Dotted line indicates the median damage estimate and the number indicates the damages avoided (benefit).

Examination of the cumulative distributions (not shown) indicates that the biosecurity system clearly demonstrates first-order stochastic dominance over the no-biosecurity counterfactual. A rank-sum test estimates that the probability that the system's benefits are greater than zero is 99.999%.

The stability (convergence) of these estimates was assessed by calculating the effect on the median by increasing the number of iterations. This was done by calculating a cumulative median for iterations 1 through 50,000, and then calculating the range of that median (i.e., the maximum – the minimum) for a rolling 1000 simulation window (Figure 9; Appendix 6.2). Except for Agriculture (which continues to vary by up to A$100M), all the asset types had a range of less than A$10M at 50 years, with several less than A$1M. Thus, we expect that our estimates have converged to within 0.03% of the true median.

Benefits by asset type

Agriculture was the largest beneficiary of the system's operation (A$210.33b), followed by domestic animals (A$18.33b), recreation (A$15.83b) and erosion control (A$12.71b; Figure 7). In contrast to the balance of overall asset values, those assets traded in markets (e.g., agriculture, infrastructure, etc.) avoided the larger proportion of damages (A$252.16b; 77%), with 'non-market' (e.g., regulating, cultural services, etc.) comprising the balance of the impacts (A$73.10b; 23%).

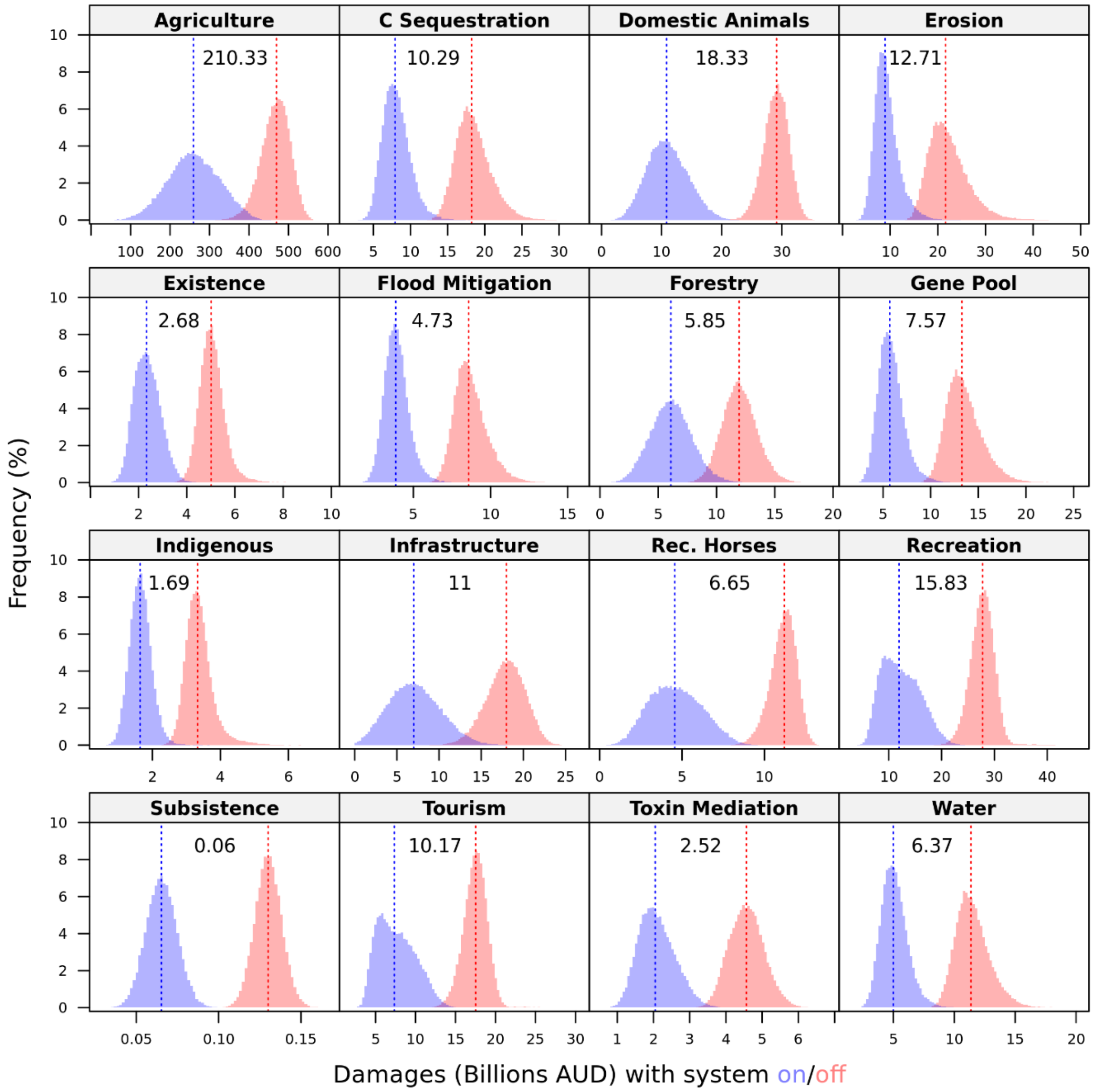

Figure 7: Total damages by asset over 50-years with the system on/off. Dotted lines indicate the medians and the number the damages avoided.

The relative balance of these impacts is driven by several factors (some of which are structural), though, the most critical is the stark difference in the spread rates and yield reductions between the various functional groups. For example, many of the hazards affecting extensive agriculture (e.g., wheat stem rust, bluetongue) have spread rates in excess of 50 km p.a., whereas many of the exemplars chosen to represent hazards affecting the environment have rates less than 10 km p.a. with smaller effects on asset yield. We will return to this issue later in the discussion.

Benefits over time

The timing of the benefits also varies considerably between asset classes (Figure 8). Where an asset is affected by an animal disease (e.g., agriculture, domestic animals and horses), damages quickly accrue in the counterfactual before tapering off once the disease fully occupies its potential host range and discounting reduces the benefits. Conversely, for environmental assets affected largely by invasive plants and vertebrate pests (e.g., water, carbon sequestration and erosion control) damages continue to increase across the 50-year study period, albeit from a lower base (Figure 8).

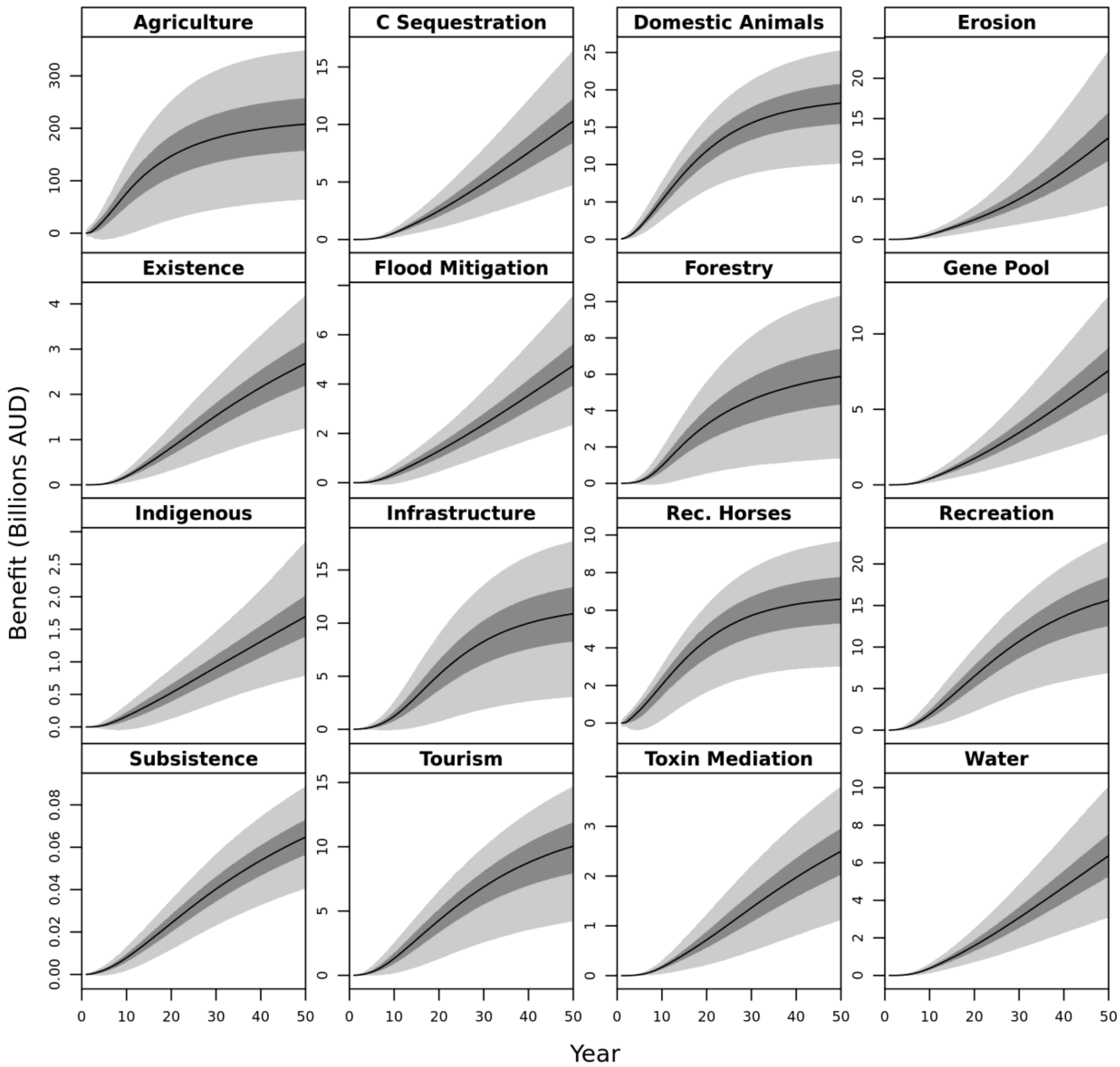

Figure 8: Total benefits of the biosecurity system, by asset, over 50 years. Solid line is the median, dark shading is the 50% interval, light shading is the 95% interval.

These differences in timing also reflect the spatial arrangement of the various assets, particularly, the proximity of those assets to the pathways of introduction (Figure 3 and 4). As was highlighted in Stoeckl *et al.* (2020), agriculture, infrastructure and recreation/tourism are all heavily clustered in the populous coastal NRM regions making them highly vulnerable to human mediated introductions in the short-term (Figure 8) relative to regulating services assets which dominate Australia's interior.

3.4 Costs

Government expenditure

Expenditure on biosecurity activities by the Australian Department of Agriculture, Water and the Environment in 2016-17 was reported in Craik *et al.* (2017) to be $A572.67m. Taking this level to be approximately fixed in real terms (noting the discussion in Craik *et al.*, 2017), this corresponds to an estimated expenditure of approximately A$10.45b over the 50 year horizon of our analysis.

As highlighted in the introduction, this omits the costs (and benefits) associated with post-border controls delivered by State and Territory government biosecurity agencies within Australia.

3.5 Net Present Value of Australia's Biosecurity System

Given our median estimate of A$325.26 billion in avoided damages (benefit) and a forecast expenditure (cost) of A$10.45 billion, we estimate the Net Present Value of Australia's Biosecurity System over 50 years to be A$314 billion (95% interval: 156.47b - 466.86b) at an average return on investment of 30:1 (95% interval: 15-45:1). Our estimates of value over time are in Table 6.

Table 6: Net Present Value (A$billions) of Australia's biosecurity system over time. The 95% interval is shown in brackets.

Time (Years)	Avoided Damages (A$billion)	Costs (A$billion)	Net Present Value (A$billion)	Average ROI (NPV/Cost)
10	95.19 (9.39 – 153.87)	4.42	90.77 (4.97 – 149.45)	20:1 (1 - 33:1)
20	195.32 (66.92 – 304.71)	7.13	188.19 (59.79 – 297.58)	26:1 (8 - 41:1)
30	257.58 (111.45 – 391.30)	8.80	248.78 (102.65 – 382.50)	28:1 (11 - 43:1)
40	297.41 (143.25 – 442.44)	9.82	287.59 (133.43 – 432.62)	29:1 (13 - 44:1)
50	325.26 (166.92 – 477.31)	10.45	314.81 (156.47 – 466.86)	30:1 (15 - 45:1)

4 Discussion

To the best of our knowledge, these results represent the first ever estimate of the value of an entire biosecurity system (or even a substantial part of a system). As the first estimates of their kind it is difficult to properly contextualise our results other than to say that they appear plausible given the existing evidence. We further recognise the many necessary assumptions and limitations in our analysis and, as such, view our estimates as the beginning of a discussion about system valuation rather than its end. Nevertheless, it is clear that the continued operation of Australia's biosecurity system over the next fifty years will yield large positive benefits for Australians.

4.1 Comparative value

Over the last twenty years, as the negative effects of global species exchange have become clearer, an increasing amount of effort has gone into quantifying the monetary impacts of pests and disease. The most well-known of these analyses is the work of Pimentel *et al.* (2000) and its various updates (e.g., Pimentel *et al.*, 2005), though, several more credible analyses have recently emerged with an increasing emphasis on the impacts of invertebrates (e.g. Bradshaw *et al.*, 2016; Paini *et al.*, 2016). Within Australia, the two most well-known empirical estimates of impact are A$4b p.a. for invasive plants (Sinden *et al.*, 2004) and A$420m p.a. for vertebrate pests (Bomford & Hart, 2002). However, whilst these analyses are useful for conveying the magnitude of the impacts caused by introduced pests (and diseases), the majority of the available estimates (summarised in Olson, 2006; Heikkilä, 2011; Marbuah *et al.*, 2014) relate to damage that has occurred despite the presence (or absence in some cases) of biosecurity controls rather than the damages that were avoided.

Nevertheless, we can use these figures to calibrate our estimate of damages under the 'status quo'. In year two of the project (Stoeckl *et al.*, 2018), we compiled a dataset of the % reductions in GDP attributed to species grouped by the traditional biosecurity sectors (e.g., animal diseases, plant pests, pest plants, etc.). If we take the median estimate for each of these groups (assuming that they are separable) and add them together we expect approximately a 1% decline in GDP, despite the system being 'on'. Utilising a different method, in their global analysis, Paini *et al.* (2016) also estimated that Australia should expect a decline of approximately 1% of GDP due to invasive species given the current global trade environment. One percent may sound small but, given Australia's current GDP of A$1.887 trillion (ABS, 2020), a 1% reduction over 50 years (discounted at 5%) is approximately A$344.51b. This level of impact is almost identical to our median estimate (A$346.67 billion) of the damages that we expect to occur despite the system (Figure 7; Table 6) giving us confidence that our 'system on' estimate is reasonably well calibrated, notwithstanding the vast differences in approach.

Much has also been made of the 'invasion curve' in Australian biosecurity since its popularisation by Biosecurity Victoria in 2009 (Biosecurity Victoria, 2009, 2010). In particular, the benefit cost ratios (BCR) included in the diagram have been extensively used to justify an increased emphasis on prevention and early intervention / eradication (see discussion in Kompas *et al.*, 2019). Remarkably, the origins of this chart are not well understood, and the references from which the BCRs were drawn are even more opaque. For the record, the chart originated in Chippendale (1991) and was revised by Hobbs and Humphries (1995) before being styled by Biosecurity Victoria in 2009 for their biosecurity strategy and subordinate policy frameworks (Biosecurity Victoria, 2009, 2010). It was at this time that the ratios were added, however, the origins of these numbers remain unclear. The recollection of those involved in 2009 is that they were most likely drawn from AEC Group (2006).

Although the efficiency of prevention over control is well established (Leung *et al.*, 2002; Olson & Roy, 2002; Leung *et al.*, 2005; Finnoff *et al.*, 2007), there is [of course] no set BCR for an outcome. Therefore, whilst our estimate of the average ROI (30:1; Table 6) is correctly positioned within the range of BCRs shown on 'the curve', it is a somewhat meaningless comparison. This is because the BCRs on the diagram, regardless of their origin, relate to single interventions targeting single species. At the system level, a risk control that 'prevents' two species might have double the benefit, but the addition of a second control might conversely double the cost; either way, the returns from any outcome (e.g., prevention) are clearly not fixed. Further, the prevention vs control literature (from which these ratios are frequently drawn) is dominated by optimisation analyses; that is, studies that determine the optimal level of investment in prevention vs control (e.g., Moore *et al.*, 2010; Rout *et al.*, 2011). Though, in practice, most jurisdictions employ the use of an ALOP. This requires them to reduce risk to a specified level well beyond what may be theoretically optimal in order to minimise the likelihood of damages, but at a diminishing marginal return (Dodd *et al.*, 2017). We speculate that this is why the average system level returns might be lower than some may expect based on analyses of single species returns (Keller *et al.*, 2007; though, see Leung *et al.*, 2014; Arthur *et al.*, 2015). Nevertheless, the fact that our results are again in the expected range is reassuring.

Our decision to focus on cumulative damage to assets rather than the expected consequences of the various hazards will have also moderated our estimate of the damages that might occur in the counterfactual and, thus, our estimate of the system's value. At the beginning of this project almost no guidance existed as to how one should go about properly constructing a 'no biosecurity' counterfactual, and even now (three years on) we are still not aware of any other attempts to construct one (though, see Essl *et al.*, 2019). But what we have learned is, that the theoretical issues raised in the introduction do matter, and that if we had failed to develop a method to address them then we would have grossly overstated potential damages (by >80%; Appendix 6.3). Looking closely at the data (Figure 4 & Figure 5), it is clear that outbreaks of higher spread species routinely interact in the 'system off' state, creating significant potential for double counting and/or aggregation errors. As we expected, we can also see saturation (complete infection/infestation of the entire host range) occurring within several of the functional groups (due to their high arrival rates in the counterfactual; Appendix 6.1), validating our earlier arguments that the use of traditional likelihood x consequence methods would overstate the risk in this context. The trade-off to this is, of course, an increase in the data required to estimate these potential impacts and a significant increase in the computational complexity. Despite this, it appears that the new Alien Scenarios project (Essl *et al.*, 2019) is proceeding in a similar direction, suggesting that our novel approach is sound.

Several other [model] structural decisions likely also influence (downward) our final value estimate. Perhaps the most notable is the absence any of post-border intervention by the states/territories. This doesn't affect the system 'off' counterfactual, but it will undoubtedly increase the damages that occur with the system 'on', and hence, reduces the overall value estimate (both benefits and costs). More subtly, several of the functional groups, particularly the non-agricultural (syn. environmental) and animal-other (syn. domestic animal) groups, should probably be split as the diversity within these groups was difficult to model accurately through a single exemplar. This has also likely led to an underestimation of some environmental damages, in our opinion. Similarly, as we discussed in Stoeckl *et al.* (2020), our estimates of damage to indigenous cultural values are also likely a gross underestimate given that they are predicated on the application of western methods, however well intentioned. Taking all of this into consideration – the calibration of the status quo estimate; the ROI in the right range; the properly constructed counterfactual; and the various omissions – we consider our results to be highly plausible in the context of the existing evidence base.

4.2 Limitations

Irrespective of our belief that our estimates are well calibrated it is critical that we acknowledge the many necessary limitations and assumptions upon which they are based. Mostly, these limitations arise due to significant knowledge gaps and data deficiencies forcing us to make assumptions or rely on expert judgement in lieu of empirical data. For example, as we discussed in Stoeckl *et al.* (2018), there is a paucity of Australian studies that examine the impact of pests or diseases on assets other than agriculture, therefore, benefit transfer techniques must be relied on to obtain such data. Our approach to this has been clear – where sufficient data existed, we used that data to inform our inputs, but where it didn't, we omitted that element from our analysis. As such, our analysis does not consider impacts on social or human capital. Nor does it consider aquatic or zoonotic species. Whenever we transferred values, we used medians rather than means, therefore, minimising the influence of outliers. Similarly, wherever ambiguity existed about the assignment of a value to a group we always defaulted to the lower estimate. Whilst, in aggregate, these decisions will lower our overall estimate of value we believe that such an approach provides the most defendable result.

It is also important that we are explicit about the macro-scale nature of our modelling framework. That is, we manage the complexity associated with modelling the impacts of 40 groups of species on 16 classes of assets by generalising and abstracting over large spatial and temporal scales. An example of this is our use of naïve risk maps (Section 2.2). Risk maps, better termed establishment likelihood maps, seek to describe the relative likelihood of an species establishing at a location based on factors such as host presence, climate suitability, and propagule pressure given proximity to pathways (Venette *et al.*, 2010; Camac *et al.*, 2019). As such, they are specific to each individual species, however, because we modelled species groups, we needed a more generic solution. Therefore, rather than take the bottom up (individual species) approach, we instead worked top down developing a naïve risk surface based on the existing studies of all species (Dodd *et al.*, 2016; Ward *et al.*, 2019). These sorts of generic / naïve approaches do invariably mean that some accuracy is lost at the individual species level, but we know from recent studies of generic dispersal kernels (Hudgins *et al.*, 2017) that such methods perform surprisingly well in aggregate. It is for these reasons that we also don't ever intend to report damages at anything lower than the NRM scale, even though it is possible to do so. Thus, it is important to reiterate that our model is not designed to answer micro-scale questions.

Rather, our desire has been to create a generic framework for system-level valuation within which detail can be progressively added and data refined. In its current format our model is highly generic, however, considerable potential for extension and refinement exists. Obvious extensions include: the addition of post-border interventions, revision of the exemplar species, and the development of more nuanced establishment and dispersal modes for different pest and disease types. Longer-term refinements might also include: dynamic elements such as increasing arrival rates, land-use changes, or climate change; the calculation of broader (second round) economic impacts; and ultimately stochastic optimisation. Though, as our sensitivity analysis indicates, the greatest improvements in accuracy are likely to come from a more detailed understanding of several processes for which we currently have very little evidence, such as: non-market asset values; spatially explicit estimates of establishment risk; and the cumulative effects of multiple pests on different types of assets (Appendix 6.3). Keeping this in mind, we have worked hard when developing the model to ensure that it can be easily updated, and re-run as new knowledge and data become available. For these reasons we see the completion of this framework as the beginning of a discussion about system valuation rather than its end.

4.3 Conclusions

Over the last three years we have sought to develop a transparent, repeatable and robust estimate of the value generated by Australia's biosecurity system – something that, to the best of our knowledge, has never been successfully achieved. In that time, we have delivered:

Year 1 (Dodd et al., 2017)

- a comprehensive review of the biosecurity economics literature;
- a detailed description of Australia's biosecurity system;
- four small case studies highlighting critical issues identified by the project team; and
- a framework for accurately estimating the value of Australia's biosecurity system.

Year 2 (Stoeckl et al., 2018)

- a comprehensive review of the non-market valuation literature relevant to biosecurity;
- a method for extending DAWE's consequence measures to include non-market values;
- a method for properly aggregating measures of value up to the system scale; and
- two detailed case studies demonstrating proof of concept for a whole-of-system approach.

Year 3 (outlined here)

- estimates of the annual flow of benefits arising from 16 assets across 56 NRM regions;
- estimates of the distribution of those assets (both market and non-market) across space;
- estimates of the % damage to non-market assets attributable to 40 species groups; and
- a bespoke, spatiotemporal asset damage simulation model.

Through the implementation of our model, we have generated what we consider to be the most defensible estimate of the value of Australia's biosecurity system possible, given the available data. Not surprisingly, that estimate indicates that continued investment in biosecurity will yield hundreds of billions of dollars of benefits for Australians, our economy, and our environment. Though, more practically, we have developed a transparent and repeatable framework for modelling the value of biosecurity interventions at the system scale, strengthening our scientific capability. Given the current extent of global connectedness, this has never been more important.

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6 Appendices

6.1 Functional groups of pests and diseases

#	Functional group	Exemplar	Establ. Off[1]	Establ. On[1]
1	AGM	Asian gypsy moth	0.064875	0.02538
2	Animal other bacteria	Contagious equine metritis	1.82087	0.110891
3	Animal other micro other	Equine babesiosis	1.82087	0.110891
4	Animal other virus	Equine influenza V	0.997636	0.104064
5	Avian virus	Highly pathogenic avian influenza	0.706801	0.057457
6	Broadacre bacteria	Angular leaf spot	0.001005	1.71E-04
7	Broadacre beetle	Large grain borer	0.001154	6.98E-05
8	Broadacre bug thrips mite	Russian wheat aphid	0.105546	7.07E-04
9	Broadacre fungus	Wheat stem rust	0.407039	0.148583
10	Broadacre mollusc	Golden apple snail	0.186469	0.067908
11	Broadacre virus	Cotton leaf curl virus	0.026626	0.011386
12	Broadacre weed	Red witchweed	2.890491	0.835709
13	FMD	Foot and mouth disease	0.291542	0.037885
14	Forestry beetle	Asian long-horned beetle	0.942236	0.175363
15	Forestry fungus	Pine pitch canker	1.624083	0.161894
16	Forestry nematode	Pine wilt nematode	0.088554	0.015222
17	Forestry termite	Termites	0.785426	0.153526
18	Forestry weed	False indigo-bush	1.850884	0.353497
19	Fruit fly	Papaya fruit fly	0.243165	0.054189
20	GAS	Giant African snail	0.008382	0.002192
21	Horticulture bacteria	Citrus canker	0.064326	0.013816
22	Horticulture beetle	Colorado potato beetle	0.087465	0.029697
23	Horticulture bug thrips mite	Thrips	0.361281	0.065253
24	Horticulture fly moth	False codling moth	0.133884	0.003539
25	Horticulture fungus	Citrus powdery mildew	0.855012	0.264786
26	Horticulture nematode	Potato cyst nematode	0.00851	7.06E-04
27	Horticulture virus	Tomato black ring nepovirus	0.089152	0.024963
28	Horticulture weed	Generic *Cyperus*	3.190966	0.873629
29	Khapra beetle	Khapra beetle	0.298485	0.066239
30	Livestock bacteria	Haemorrhagic septicaemia	0.58023	0.037485
31	Livestock bug thrips mite	Varroa mite	0.008176	0.002652
32	Livestock fly moth	Screw worm fly	0.007332	0.001442
33	Livestock virus	Bluetounge	1.05971	0.075572
34	Non-agricultural bee wasp	Generic *Hymenoptera*	0.191834	0.035317
35	Non-agricultural fly moth	Generic *Diptera*	0.152683	0.034531
36	Non-agricultural fungus	Dutch elm disease	2.89E-10	1.09E-10
37	Non-agricultural micro other	Dutch elm disease	3.86E-04	2.76E-05
38	Non-agricultural vertebrate	Black spined toad	0.178296	0.033167
39	Non-agricultural weed	Mexican feather grass	4.872387	1.162085
40	Tramp ant	Red imported fire ants	0.523536	0.051603

[1] These establishment frequencies were produced using the Risk Return Resource Allocation (RRRA) model designed by the Department of Agriculture, Water and Environment (RRRA Unit, 2019). The model was run on 17/09/2019 using data from the 2018/19 financial year. The model was first run with all government biosecurity controls set to their 'current' settings (the 'system on' scenario), and run a second time to model the scenario where all biosecurity controls are disabled (the 'system off' scenario). RRRA modelling requires a number of simplifications and assumptions. It uses departmental and inter-agency data sources, some of which are not designed for analytical purposes and therefore have limited accuracy. Substantial uncertainty is inherent in some model parameters and not currently quantified. Ongoing model improvements and data updates will influence results (see Appendix 6.3).

6.2 Convergence of estimates

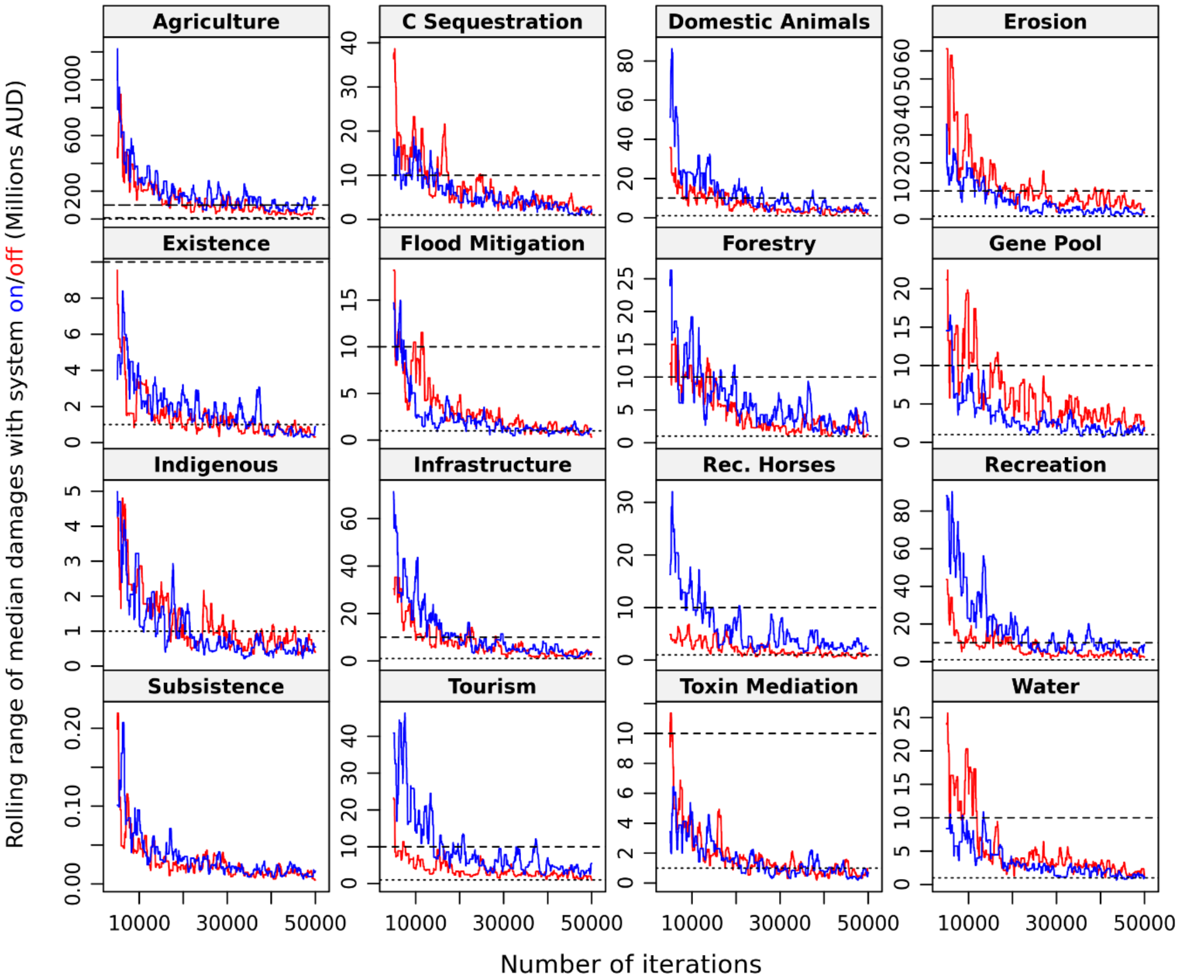

Figure 9: Variation in the median damage estimates over the last 1000 simulations. Red line is system off, blue line is system on. Dotted, en-dash and em-dashed lines indicate 1M, 10M and 100M variation in the median, respectively.

6.3 Sensitivity Analysis

Methods

To determine the relative sensitivity of our final benefit estimate to uncertainty in the input values we varied each of the key parameters (or sets of parameters) either by +/- 10% of their baseline value (continuous inputs) or off/on (discrete inputs). For each of the parameters we then completed 20,000 simulations of the model (whilst holding all others constant) and re-calculated the benefit.

Discrete changes included: adding yield losses together rather than calculating their product ('Sum'); varying the discount rates by +/- 2% absolutely rather than relatively ('Discount 1,3' & '5,7'); using hyperbolic rather than exponential discounting ('Discount H5' & 'H7'); distributing the probability of establishment uniformly across space rather than heterogeneously ('Unweighted'); and increasing the distance decay to 50 and 100 km ('Decay 50' & '100'), respectively.

Results

A tornado chart summarising our results is shown in Figure 10. For reference, a +/- 10% change in asset values resulted in +/- 10% change in benefits. Thus, the benefit estimate was [most] sensitive to how yield losses were aggregated, discount rates, and how establishment risk was distributed.

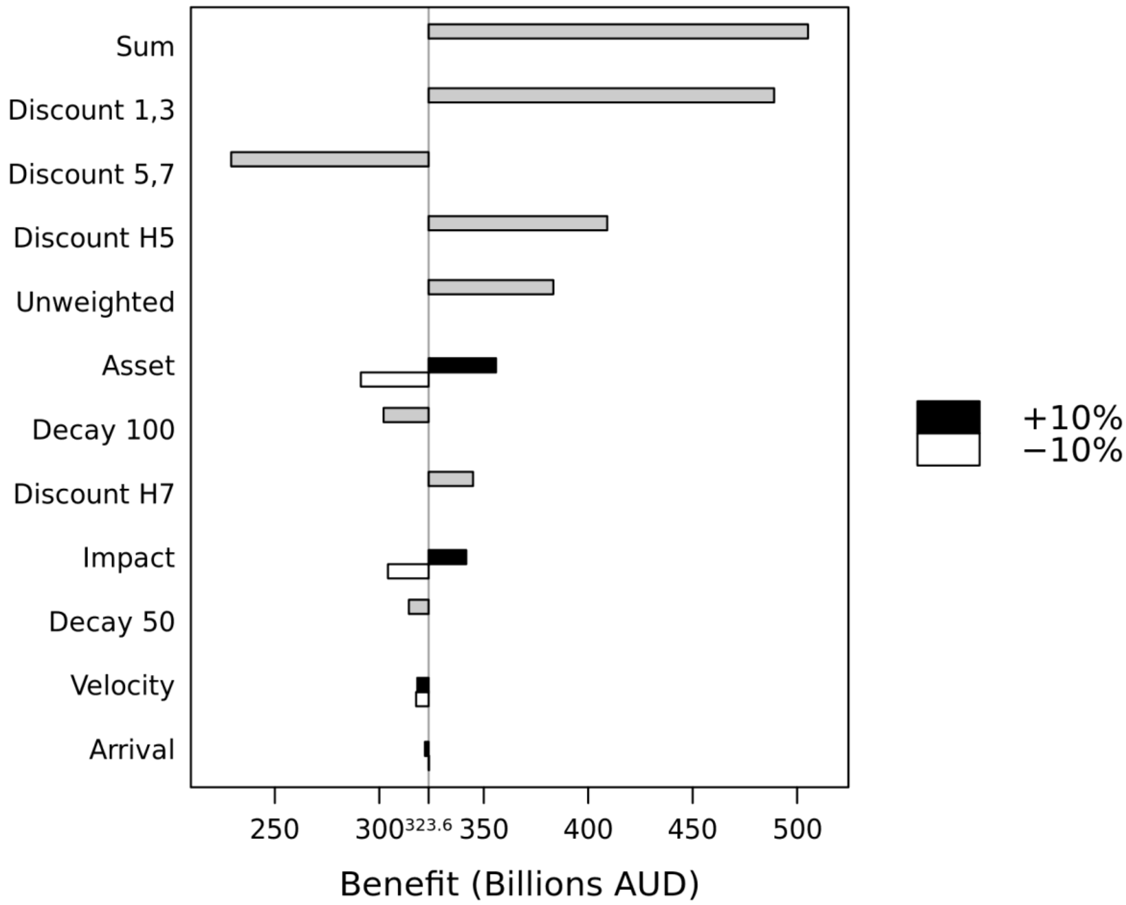

Figure 10: Sensitivity of the median benefit estimate to changes in select input variables. Coloured bars indicate a 10% change in the input, grey bars indicate a discrete change. Length indicates relative sensitivity to the input (i.e., influence increases with length).

Conversely, the benefit estimate was relatively insensitive to arrival and spread (velocity) rates, yield losses (impact) and the degree of distance decay - at least in comparison to the other parameters. For example, a 10% change in arrival rates resulted in a <1% change in the benefit (Figure 10) where discrete choices to sum yield losses across species and distribute establishment risk homogenously across space would result in a >80% change (increase) in the benefit estimate (data not shown).

Discussion

The results of our sensitivity analysis confirm our hypothesis that the theoretical considerations raised in the introduction are indeed significant issues that require careful attention. In particular, our choice of functional form – that yield will decline proportionately, rather than additively – had a significant influence on the benefit estimate (Figure 10), by preventing losses exceeding the value of the asset (due to double counting). Our rationale for this choice is that yield losses are frequently expressed in relative terms and, as such, their absolute impact is known to be variable dependent on an assets value. Thus, it's only a small stretch to argue that if the stock of the asset has declined due to damage caused by an existing incursion (or any other reason), that it will continue to decline proportionately to the revised asset value for each subsequent harm until there is nothing left to damage. Though, we're not aware of any examples of where this assumption has been tested or, more generally, where the effects of multiple species on an asset have been objectively measured.

Likewise, our choice of discount rate had a significant effect on the final benefit estimate. Discount rates are well understood to be contentious (Weitzman, 1998, 2001), and it is important to clarify that the rates that we have chosen here are lower than those recommended by both the Australian Productivity Commission (Harrison, 2010) and the Office of Best Practice Regulation (OBPR, 2007). However, both of these recommendations were made based on the market rates of return in the period leading up to the Global Financial Crisis. Since then, marginal rates of return to capital have significantly declined and are likely to remain depressed for some time given the state of the global economy. Nevertheless, we have conducted sensitivity analyses at the suggested rates, and these are included for reference. We have also explored the effect of using hyperbolic discounting which better accounts for issues related to inter-generational equity (Weitzman, 1998, 2001).

It is also important that we briefly discuss the extent to which our results are dependent on the establishment rates sourced from RRRA given the potential uncertainty surrounding their accuracy (see the explanatory notes included in Appendix 6.1). In short, our analysis indicates that the final value of the system is relatively insensitive to the set of parameters that are potentially the most problematic (i.e., the establishment rates) and, as such, we are satisfied that our findings are robust to any uncertainty in their accuracy. Looking closely at the results (e.g., Figure 6), we can see that the damages that occur in the 'system off' state have a lower variance. This is because damages are limited by the value of the assets. Thus, if the establishment rates exceed the threshold required to completely erode the assets, then small changes in these rates will have little effect on damages. In fact, the avoided damages will decline (as we see for velocity in Figure 10) because damages will increase more quickly in the 'system on' state than in the 'system off' state decreasing overall value.

Taken together, our results highlight the need to think clearly about theoretical issues when constructing a counterfactual, because many of the assumptions underpinning the methods used to estimate the risk of biosecurity hazards in the status quo do not hold in that context. Unfortunately, few examples of properly constructed counterfactuals exist in the biosecurity/biodiversity literature (Ferraro & Pattanayak, 2006; Bull et al., 2014), and none consider multi-pest x multi-asset damages as we have here. This is clearly a priority area for further research.