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# A generalised and scalable framework for modelling incursions, surveillance and control of plant and environmental pests

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## ABSTRACT

Invasive plant and environmental pests can seriously impact environment, economy, health and amenity. It is challenging to form response policies given the diversity of pest species; complex spatiotemporal interplay between arrival, spread, surveillance, and control; and limited field data when pests are rare/absent. Models can provide useful decision support through the exploration of incursion pathways and comparison of surveillance and control strategies. However, increased use of quantitative models to inform pest management requires adaptable modelling frameworks. The new Australian Priority Pest and Disease modelling framework (APPDIS) allows pest models to be constructed through user configuration choices for a broad range of different pest types. Pest populations may be defined as point incursions, established populations, or estimated mechanistically from environmental criteria. Spread occurs at multiple scales, through either simple mathematical kernels, or more complex spatial pathways, depending on data availability and pest type. Useful experiments can be conducted on general surveillance, specific surveillance, and treatment regimes. Control activities are dynamically resource-constrained and costed for relative comparisons in terms of benefit and cost. A case study on a tramp ant incursion is provided for illustrative purposes.

## 1. Introduction

Plant and environmental pests can inflict serious damage to the economy, environment, human health, and social amenity (Davis, 2009). It typically falls to government to construct and fund robust policies for the early detection of, and response to, harmful invasive pests. However, it can be challenging to form cost effective policies given the inherent uncertainty of, and complex spatiotemporal interplay between, the arrival, spread, detection and control of exotic pests (Schmidt et al., 2010; Keith and Spring, 2013). Further, when a pest is rare or absent there may be limited local experience and field data to inform policies for surveillance and control/eradication. Models can help policy makers explore:

- potential entry points and arrival rates of invasive pests (Douma et al., 2016; Sikes et al., 2018; Faulkner et al., 2020; Camac et al., 2020),
- potential distribution of a pest species in an environment (Sutherst et al., 1999; Phillips et al., 2006; Deutsch et al., 2008; Aurambout et al., 2009; De Meyer et al., 2010; Yang et al., 2013; De Villiers et al., 2015),
- potential spread of a pest (Renton et al., 2011; Rebaudo et al., 2011; Adeva et al., 2012; Rasmussen and Hamilton, 2012; Lustig et al., 2017; Cook at el., 2019; Briscoe et al., 2019),
- surveillance and treatment strategies (Parry et al., 2006; Keith and Spring, 2013; Parnell et al., 2014; Baxter et al., 2017),
- the effect of resource and/or cost constraints on surveillance and treatment (Bogich et al., 2008; Kompas and Che, 2009; Hauser and McCarthy, 2009; Rout et al., 2011; Kompas et al., 2016; Spring et al., 2017).

It is, however, very difficult to encompass all aspects of an invasive pest incursion into a single decision support model. The challenge of modelling population spread and control is magnified by the diversity of plant and environmental pests, modes of dispersal, and availability of data for estimating biophysical and economic relationships in detection and control. A detailed spatially-explicit model of an individual pest may capture life-cycle and ecological specifics, and take into account

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environmental heterogeneity, but can be complex and expensive to construct, and may not readily translate to other pests. Generalised mathematical models are simpler and cheaper to build but may not capture pest-specific ecological nuances and environmental heterogeneity.

These challenges in pest spread modelling have resulted in a lack of general-purpose modelling frameworks, despite the large number of problem-specific models that have been developed. It has been argued that spread simulation models with the capacity to capture complex spatio-temporal processes, such as human-assisted and vector-borne spread, have prohibitive time and resource costs in developing, parameterizing, and testing the models (Robinet et al., 2012). This reflects an assumption that biosecurity management personnel may lack the time and/or expertise to conduct such analyses. Most general-purpose modelling frameworks for informing pest risk analysis have consequently focused on capturing simpler processes governing pest arrival and spread (Rafoss, 2003; Robinet et al., 2012; Kehlenbeck et al., 2012). There remains a need for general-purpose modelling platforms with the capacity to capture complex spatio-temporal processes.

The Australian Priority Pest and Disease modelling framework (APPDIS) is an attempt to incorporate the key aspects of invasive pest arrival, spread, detection and control in a pragmatic ‘middle ground’ modelling approach – incorporating both generalised and pest-specific techniques. An APPDIS user can create a variety of pest-specific models by supplying datasets and parameter values (ie., model creation is largely a configuration activity that does not require specialised mathematical reformulation and/or recoding). When field or environmental data is scarce or unreliable, APPDIS can be configured to spread a pest through simple aggregative mathematical pathways. Alternatively, data permitting, APPDIS can be configured to spread a pest through individual data-driven pathways that consider pest ecological nuances and environmental heterogeneities.

Effective early detection surveillance can pre-emptively lower a country’s potential liability for incursion costs. Modelling approaches need to consider the likely points where a pest can establish and potential spread in relation to surveillance intensity and extent. Scenarios need to consider the likely success of response activities at the initial detection in order to identify the value of surveillance. An APPDIS model allows a pest to be introduced anywhere in the study area at any point in time. Once established, a pest population spreads over time and space according to environmental suitability, via both natural and assisted spread pathways. The simulated initial detection of a pest may arise from general surveillance or early detection surveillance via a permanent trapping grid. APPDIS allows useful experimentation on the cost effectiveness of a trapping grid design (via configurable trap locations, spacings, lure types, costs, and sensitivity/specificity), and the implications of early versus late detection.

Containment and eradication of a pest relies upon adequate delimitation of an incursion. It can be challenging to estimate the distribution of a pest in relation to presence and absence data, particularly for pests with broad host ranges, complex spread pathways, and poor detectability. There are options to either increase surveillance to better understand the extent of the incursion or to increase treatment intensity and extent in order to cover uncertainty. Even for well-studied pests, there can be gaps in the understanding of ecology, surveillance efficacy, and control strategies. The significance of uncertainty is often not appreciated until viewed in the context of a control and containment program. Spatiotemporal models can be useful for testing scenarios with complex relationships that are subject to a great deal of uncertainty. APPDIS allows useful experimentation on the cost effectiveness of delimiting surveillance and post-treatment surveillance (via configurable trap spacings, lure types, costs, and sensitivity/specificity), and treatment (via configurable treatment schedules, efficacy and cost). All control actions simulated by APPDIS have user-defined durations, costs, and resource requirements. This allows investigation into the impact of resource shortfalls on the efficacy and cost of managing an incursion.

A case study on the potential eradication of an established tramp ant population illustrates the steps in configuring an APPDIS pest model and provides some examples of model use. Firstly, the tramp ant population is allowed to spread unchecked and emergent spread rates are compared with field observations. Secondly, surveillance and treatment options are enabled and a sensitivity analysis is conducted on the effect of trap spacing on the cost effectiveness of eradication. It is important to note that the purpose of the case study is to demonstrate configuration and use of the modelling framework, and is not intended to inform policy on potential eradication of the pest in question.

## 2. Methods

### 2.1. The APPDIS modelling framework

APPDIS is a new modelling framework that can be used to instantiate models of the spread and control of plant and environmental pests. It is the Plant Health equivalent of the Australian animal disease modelling framework AADIS (Bradhurst et al., 2015), which can be used to instantiate models of livestock disease such as foot-and-mouth disease, bluetongue, classical swine fever and African swine fever.

APPDIS pest models are stochastic discrete-event simulations similar to geographic automata (Torrens and Benenson, 2005; Laffan et al., 2007). The study area of interest is represented by a grid delineated by lines of latitude and longitude. The modelling unit of interest is a cell within the grid. Each cell has environmental attributes (such as elevation, average weekly temperature, annual rainfall, human population density, vegetation index, land use category and average weekly wind speed), that can be used to estimate the spatiotemporal habitat suitability of the cell for a pest of interest.

The problem of modelling the incursion, spread, detection, and control of a pest in a gridded environment is reduced to seven separate sub-problems:

- which cells are initially populated with the pest?
- how does the within-cell abundance of the pest change over time?
- when/how might the pest population spread between cells?
- how cost effective are surveillance activities at detecting the pest?
- how cost effective are treatment programs at controlling/eradicating the pest?
- how cost effective are post-treatment surveillance activities at detecting residual pest populations?
- how do resource constraints affect surveillance, treatment and post-treatment activities?

#### 2.1.1. Definition of an initial pest population

The grid extent and cell dimensions of an APPDIS model are user configurable and facilitate regional studies (inside a localised grid) up to national-scale studies (inside a much larger grid). The choice of cell size will largely depend on the pest being modelled, the extent of the study area, and the granularity of the relevant environmental data. A large cell size may not capture within-cell spatial heterogeneities in vegetation, land use, elevation, temperature, etc. A small cell size captures spatial temperature heterogeneities (data granularity permitting) but comes with a computational overhead for large grids. It is advisable to restrict the total number of grid cells to under 1,048,576 so that the raster data input comma-separated value (CSV) file (which is indexed row-major order on cell ID), can be opened by a standard desktop spreadsheet program.

APPDIS provides three ways for a user to define the initial pest population in the grid:

- point incursion – one or more cells may be explicitly seeded with a pest propagule. This represents an undetected post-border arrival of an exotic pest, for example, at a port.
- established population – an established pest population can be defined via pre-defined population densities or counts per cell, perhaps informed by field data.
- built-in mechanistic species distribution model – the location of the initial pest population can be automatically estimated by the model based on configurable ranges of environmental criteria such as temperature, vegetation, water sources, elevation, rainfall, land use, etc.

### 2.1.2. *Within-cell abundance of a pest*

Each infested cell agent has an embedded population model that estimates the population density of a pest within a cell over time, for example, via logistic growth (Kingsland, 1982; Kehlenbeck et al., 2012; Law et al., 2003). This represents how a pest population in a naive cell may initially grow exponentially, but then growth will slow as the population approaches the carrying capacity of the cell (Roughgarden, 1975). The carrying capacity of a cell is derived from user-defined habitat suitability data specific to the pest being modelled. This allows pest abundance to vary across the model grid based on environmental variables such as temperature, elevation, land use, rainfall, and vegetation).

A logistic population growth rate is unlikely to be a static value, and actual population values may not be available from empirical studies. APPDIS allows the growth rate to vary with temperature, perhaps informed by laboratory data on pest development and mortality response to temperature. This approach allows colder temperatures to be associated with negative growth rates and trigger seasonal declines of a population. Fig. 1 illustrates how a logistic function can have a constant growth rate R or a variable growth rate R(τ) that depends on temperature τ.

The logistic growth model for a temperature-dependent growth rate is given by Equation (1).

$$d(t) = \frac{K}{1 + \left\{\frac{K}{d(t-1)} - 1\right\} e^{-R(\tau)}} \qquad \text{(Eqn. 1)}$$

where

d(t) = pest population density on day t (normalised with respect to carrying capacity K)
K = carrying capacity of the cell (normalised across all cells)
R(τ) = pest population growth rate for temperature τ

If the population in a cell falls below a configurable threshold it becomes quiescent and declines to extinction over a configurable period. This approximates an Allee effect (Stephens and Sutherland, 1999) whereby small or sparse populations (represented by very low cell population densities), can suffer from reduced population growth that leads to extinction.

Although not yet investigated, it would be possible for a cell agent to have multiple population models, each corresponding to a distinct species. This functionality could be useful for exploring interspecific mutualism with respect to presence and abundance.

### 2.1.3. *Between cell spread of a pest*

As the within-cell population density of a pest increases or decreases over time (per the embedded population model), the rising or falling 'dispersal pressure' within the infested cell affects the probability of between-cell spread. The steady short-range spread of a pest between adjoining cells is modelled by a diffusion pathway. The sporadic longer-range spread of a pest between cells is modelled by one or more jump pathways.

*2.1.3.1. Diffusive spread between adjoining cells.* The progressive spread of a pest from an infested cell into an adjoining candidate cell is modelled with a stochastic diffusion process that considers:

- the infested cell's pest population density
- the infested cell's environmental conditions (e.g., certain wind and/or temperature criteria may be required for diffusion to occur) (optional)
- the environmental suitability of the candidate cell (so that more suitable cells will have a higher probability of pest incursion than less suitable cells) (optional)
- the elevation gradient between the centroids of the source and candidate cell (optional)

Daily decisions as to whether an infested cell diffuses into the

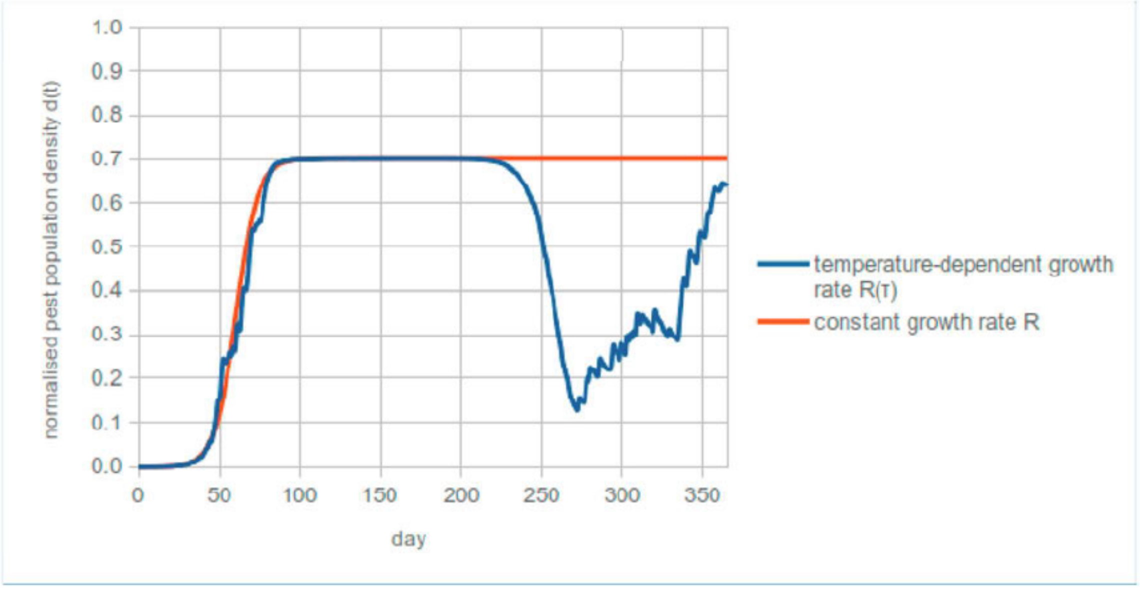


**Fig. 1.** A logistic growth function with a constant growth rate (R = 0.15) compared to one with a temperature-dependent growth rate R(τ). In both cases the normalised carrying capacity K is 0.7.

adjoining candidate cells are made by sampling from binomial distributions of the probability of diffusion (Equation (2)).

$$p_d(t) = 1 - \{1 - P_d\, S\, \delta\, \lambda\, \varepsilon\}^{d(t)} \quad \text{(Eqn. 2)}$$

where

$p_d(t)$ = probability of diffusion occurring on day t
$P_d$ = baseline daily probability of diffusion of a viable number of pests from an infested cell into another cell (configurable per land use category of the infested cell)
S = relative suitability of the candidate cell (normalised across all cells) (optional)
$\delta$ = distance weight for the infested and candidate cells (optional)
$\lambda$ = temperature weight of the infested cell (optional)
$\varepsilon$ = elevation weight for the infested and candidate cells (optional)

The (optional) distance weight $\delta$ is a simple relative measure of distance between the centroids of the source infested cell and the adjoining candidate cells, and dampens the probability of diffusion into the north-west, south-west, north-east and south-east neighbours ($\delta = 0.7$), as opposed to the north, south, west, and east neighbours ($\delta = 1.0$).

The (optional) temperature weight $\lambda$ is derived from the relationship between the average weekly temperature $\tau$ for the infested cell and four configured temperature thresholds for pest activity: min, optimal_lower, optimal_upper and max.

$\lambda = 0$ (for $\tau <$ min)
$\lambda$ = linear increase from 0 to 1 (for min $\leq \tau \leq$ optimal_lower)
$\lambda = 1$ (for optimal_lower $\leq \tau \leq$ optimal_upper)
$\lambda$ = linear decrease 1 to 0 (for optimal_upper $\leq \tau \leq$ max)
$\lambda = 0$ (for $\tau >$ max)

The (optional) elevation weight $\varepsilon$ is derived from the gradient between the centroids of the infested cell and the candidate cell. It allows the user to increase/decrease the probability of diffusion uphill/downhill (per 100 m difference in elevation).

The baseline daily probability of diffusion $P_d$ includes the probability of post-dispersal establishment in the candidate cell. A diffusion event conveys a user-defined propagule from the source infested cell to the destination cell. If the destination cell is naïve then it acquires an equation-based population model (Equation (1)) with the propagule as the initial population. If the destination cell is already infested, then the propagule is added to the population and the population model recalculated. A cell can receive multiple diffusion events over the course of a simulation. APPDIS allows environmental criteria (temperature, habitat suitability, elevation, etc.) to be disabled, in which case diffusion is driven purely by the daily probability $P_d$, which in turn can be estimated by reverse engineering observed spread velocities of the pest.

*2.1.3.2. Jump spread between cells.* Invasive pest populations may spread over multiple scales. Whilst natural dispersal may result in short-range diffusive spread, less predictable mechanisms such as windborne spread and human-mediated dispersal can lead to longer-range jumps (Robinet et al., 2009; Gippet et al., 2019). The sporadic longer-range spread of a pest from an infested cell into non-adjoining cells is modelled with one or more stochastic jump processes that consider:

- the infested cell's pest population density
- the infested cell's environmental conditions (e.g., certain wind and/or temperature criteria may be required for a jump to occur) (optional)
- the environmental suitability of the candidate destination cell (optional)
- the human population density of the infested cell (optional)
- the land use of the infested cell (optional)
- the land use of the candidate destination cell (optional)
- waterways in the infested and candidate destination cells (optional)

Daily decisions as to whether an infested cell disperses into a distant cell are made by sampling from a binomial distribution of the probability of a jump event (Equation (3)).

$$p_j(t) = 1 - \{1 - P_j\, \omega\, \lambda\}^{d(t)} \quad \text{(Eqn. 3)}$$

where

$p_j(t)$ = probability of a jump occurring on day t
$P_j$ = baseline daily probability of a jump occurring
$\omega$ = human population density of the infested cell (normalised across all cells) (optional)
$\lambda$ = temperature weight of the infested cell (optional)

The jump direction may be random, influenced by the land use category of the source and destination cells, or influenced by the weekly prevailing wind direction. The jump distance is determined by sampling from a BetaPERT (Vose, 2008) distance distribution. A catchment area of cells is formed at the site of the jump landing based on either a user-defined Moore neighbourhood range or radial distance. The jump destination cell is then selected from the candidates within the catchment area either randomly or based on suitability criteria.

As per diffusion, the baseline daily probability $P_j$ of a jump occurring includes the probability of post-dispersal establishment in the candidate cell. A jump event conveys a user-defined propagule from the source infested cell to the destination cell. If the destination cell is naïve then it acquires an equation-based population model with the propagule as the initial population. If the destination cell is already infested, then the propagule is added to the population and the population model recalculated. A cell can receive multiple jump events over the course of a simulation. $P_j$ can be estimated either from expert opinion or the frequency that satellite pest colonies are observed arising unexpectedly some distance from a known infested area.

### 2.1.4. General surveillance

General surveillance by members of the public is an important means of early detection of plant and environmental pests (Cacho et al., 2010; Hester and Cacho, 2017; Wilson et al., 2004). All cells that have both a pest population and a human population are scanned daily for detections by a stochastic process that considers:

- the infested cell's pest population density
- the infested cell's human population density
- the sensitivity of the observer

The probability of a general surveillance detection event occurring on any given day is adapted from Sharov et al. (1998) and Bogich et al. (2008), and is given by Equation (4).

$$p_{TP}(t) = 1 - e^{-d(t)\, \omega\, S_e} \quad \text{(Eqn. 4)}$$

where

$p_{TP}(t)$ = probability of a true positive detection occurring on day t
$\omega$ = human population density of the infested cell (normalised across all cells)
$S_e$ = sensitivity of the observer

The observer sensitivity for unmanaged cells is defined separately to that for managed cells. A managed cell is defined as any cell that is undergoing, or has undergone, delimiting surveillance or treatment. The model provides the option of the first general surveillance detection occurring on a fixed day rather than on a stochastically determined day.

This allows useful experimentation on the impact of ‘time to detection’ on incursion severity and cost. Fig. 2 uses Equation (4) (with Se = 0.70), to illustrate how the probability of a general surveillance detection varies with respect to the normalised pest population density and the normalised human population density.

### 2.1.5. *Early detection surveillance*

There is considerable interest in the cost effectiveness of surveillance strategies for invasive species (Field et al., 2004; Gerber et al., 2005; Bogich et al., 2008; Hauser and McCarthy, 2009; Kompas and Che, 2009; Cacho et al., 2010; Epanchin-Niell et al., 2014; Holden et al., 2016). APPDIS allows the user to define a permanent trapping grid of geo-located traps with specified lure types. All cells that have both a pest population and a permanent trap location are scanned daily for active detections. The detection of a pest population is modelled with a stochastic process that considers:

- the infested cell’s pest population density
- the lure type and spacing of traps in the infested cell
- the sensitivity of the surveillance process (traps and personnel)
- the specificity of the surveillance process (traps and personnel)

The probability of a true positive detection occurring on day t is adapted from Sharov et al. (1998) and Bogich et al. (2008), and is given by Equation (5).

$$p_{TP}(t) = 1 - e^{-a(t)\,\varphi\,S_e} \qquad \text{(Eqn. 5)}$$

where

$p_{TP}(t)$ = probability of a true positive detection on day t
$a(t)$ = pest area of the infested cell in hectares on day t
$\varphi$ = trap density (traps per hectare) in the infested cell (= 10,000/(trap spacing in metres)$^2$)
$S_e$ = sensitivity of the surveillance process (traps and personnel)

As the pest area a(t) of an infested cell is not actually known (as cells are atomic), it is proxied by multiplying the normalised population density of the cell d(t) by the cell area in hectares. The model also provides the option of the first early detection occurring on a fixed day rather than on a stochastically determined day. This allows useful experimentation on the impact of ‘time to detection’ on incursion severity and cost. Fig. 3 uses Equation (5) with Se = 0.96 to illustrate how the probability of early detection inside a 10-ha cell varies with the normalised pest population density and trap spacing.

If a surveyed cell does not yield a true positive result, then it is checked for a false positive result. The probability of a false positive detection occurring is given by Equation (6).

$$p_{FP} = 1 - S_p \qquad \text{(Eqn. 6)}$$

where

$p_{FP}$ = probability of a false positive detection
Sp = specificity of the surveillance process (traps and personnel)

If a surveyed cell does not yield a positive result, then a true/false negative result is assigned according to the actual absence/presence of the pest in the cell.

### 2.1.6. *Delimiting surveillance*

After a pest population has been detected in a cell, the surrounding cells undergo delimiting surveillance. Delimiting surveillance comprises a configurable number of periodic surveillance visits. Delimiting surveillance operates in either Moore mode (where the cells in the Moore neighbourhood of the detected cell are surveyed), or Radial mode (where all cells within a configurable distance of the detected cell are surveyed). The detection of a pest population through delimiting surveillance is modelled by a stochastic process that considers:

- the surveyed cell’s pest population density
- trap spacing in the surveyed cell
- the sensitivity of the surveillance process (traps and personnel)
- the specificity of the surveillance process (traps and personnel)

The daily probability of a true positive detection is given by Equation (5). If a cell does not yield a true positive result it is then checked for a false positive detection (Equation (6)). A positive surveillance result triggers a treatment program. If a cell does not yield a positive result, then a true/false negative result is assigned according to the actual absence/presence of the pest in the cell. The pest is deemed absent from a cell once a configurable number of consecutive negative surveillance results has been reached.

### 2.1.7. *Treatment*

All cells that have yielded a positive result (true or false), from general surveillance, early detection surveillance, or delimiting surveillance, undergo a treatment program. A treatment program comprises a configurable number of treatments, conducted at a configurable period. Each treatment reduces the population by a percentage amount (determined stochastically between a configured minimum and maximum reduction). A pest population is deemed extinct if a treatment

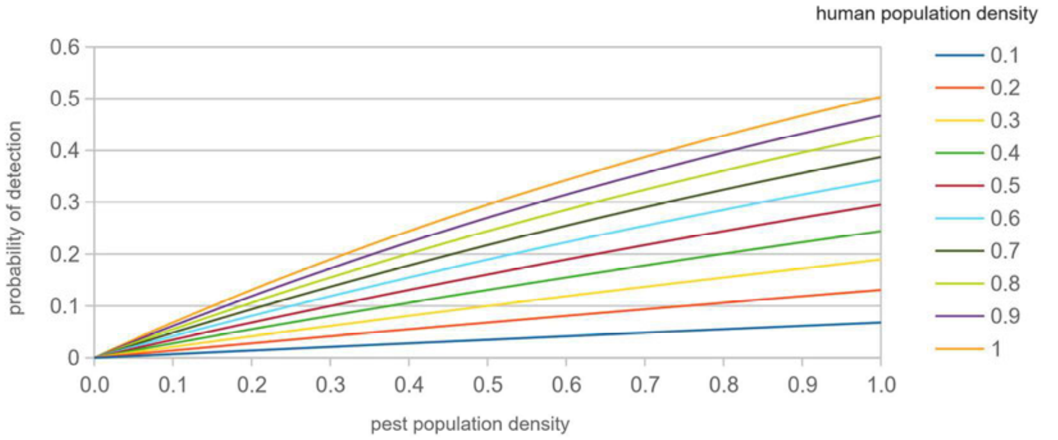


**Fig. 2.** Probability of general surveillance detection with respect to pest population density and human population density.

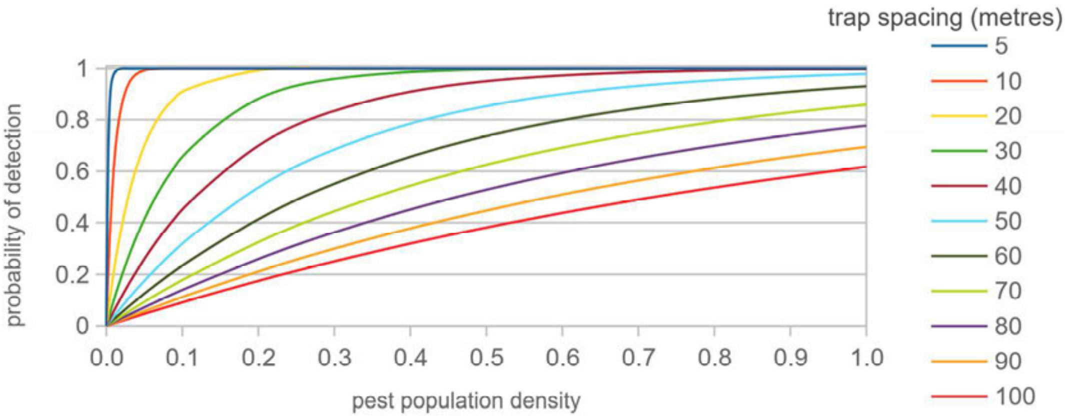


**Fig. 3.** Probability of specific surveillance detection in relation to pest population density and trap spacing.

program reduces it to below the configured minimum population size. A treatment program may operate in Spot mode (where only the detected cell is treated), Moore mode (where all cells in the Moore neighbourhood of the detected cell are treated), or Radial mode (where all cells within a configurable distance of the detected cell are treated).

### 2.1.8. *Post-treatment surveillance*

Post-treatment surveillance commences at a configurable period after the completion of the last scheduled treatment. A post-treatment surveillance program comprises a configurable number of periodic surveillance visits. Post-treatment surveillance is modelled with a stochastic process that considers:

- the surveyed cell's pest population density
- the trap spacing in the surveyed cell
- sensitivity of the surveillance process (traps and personnel)
- specificity of the surveillance process (traps and personnel)

As per delimiting surveillance, the daily probability of a true positive detection is given by Equation (5). If a cell does not yield a true positive result it is then checked for a false positive detection (Equation (6)). A positive post-treatment surveillance result triggers another treatment program. If a cell does not yield a positive result, then a true/false negative result is assigned according to the actual absence/presence of the pest in the cell. A cell is deemed free of the pest after a configurable number of consecutive negative surveillance results.

### 2.1.9. *Resourcing*

The active surveillance and treatment of plant and environmental pests are typically resource-constrained processes (Rout et al., 2011; McCarthy et al., 2012). An APPDIS 'resource' is abstract in the sense that it is a (user-defined) set of personnel/equipment/supplies required to carry out a specific job. The model maintains pools for each resource type (early detection surveillance, delimiting surveillance, treatment, and post-treatment surveillance). The resourcing profile for each pool is configurable as to whether resource levels are fixed or vary over time.

When a field operation is scheduled a resource is requested from the corresponding pool. If a resource is available, then it is 'borrowed' from the pool and the field operation commences. If a resource is not available, then the field operation is queued until such time as the required resource becomes available. Once a field operation has completed, the resource is 'returned' to the pool.

The model reports the daily resource usage for early detection surveillance, delimiting surveillance, treatment, and post-treatment surveillance. Resource pools can be configured to be 'unlimited' in which case resources are always immediately granted upon request. In this mode the resourcing profile of an outbreak is a model output instead of a model input that constrains the efficacy of the control program.

### 2.1.10. *Implementation highlights*

The APPDIS modelling framework utilises an agent-based modelling platform (Bradhurst, 2015) which can operate in four modes: contagious livestock disease, vector-borne livestock disease, plant/environmental pests, and human disease. When modelling the spread and control of contagious disease in livestock, the agents are herds, farms (containers of one or more herds), saleyards and abattoirs. When modelling the spread and control of plant and environmental pests, the agents are cells in a lattice environment. When modelling the spread and control of insect vector-borne livestock disease (such as bluetongue), the agents are herds, farms, saleyards, abattoirs, and cells. When modelling the spread and control of human disease the agents are people. Descriptions of the vector-borne livestock and human disease modes will appear in future papers. The modelling behaviour (livestock disease, plant/environmental pests, or human disease) of an instantiated model is purely determined by the configuration files and database loaded.

An APPDIS agent can have an embedded population model of the within-agent abundance over time. For example, when modelling an exotic fruit fly incursion each infested cell agent has an embedded temperature-dependent logistic growth model that predicts the within-cell population over time. An agent can also have an embedded infection model of the within-agent prevalence of a pathogen in the population. For example, when modelling the spread of a contagious disease in feral pigs each infected cell agent has an embedded SEIRD (Susceptible, Exposed, Infectious, Recovered, Deceased) compartmental disease model (implemented as a system of ordinary differential equations), that predicts the within-cell infected and infectious prevalence of the disease over time. The interplay between a cell agent's population and infection models will be described in a separate paper. The details of the population and infection models are private to the agent, which means that alternate within-cell models can be used without impacting the greater model.

APPDIS models scale well as the agents are threadless and lightweight. APPDIS agents interact in a spatially-explicit disaggregated environment comprised of threaded 'components' that operate concurrently and independently (Bradhurst, 2015). Examples of components relevant to contagious livestock disease include local spread, direct spread, saleyard spread, indirect spread, airborne spread, movement restrictions, surveillance, tracing, vaccination, stamping out and post-outbreak surveillance (Bradhurst et al., 2015). Examples of components relevant to plant/environmental pests include unaided diffusive spread, human-mediated hitchhiking spread, wind-assisted airborne spread, early detection surveillance, general surveillance, delimiting surveillance, treatment, and post-treatment surveillance. All APPDIS components are independent and can be separately enabled/disabled. As the implementation of each component is private, alternate components can be swapped in and out. For example, the implementation of a treatment component can completely change without impacting the rest of the model.

APPDIS has a concurrent software architecture that allows it to take advantage of the cheap parallelism available with multi-core personal computers. This, together with other design efficiencies, such as an in-memory database and grid-based spatial indexing, allow APPDIS to efficiently conduct national-scale simulations (Bradhurst et al., 2016). Further details on the underlying model and software architecture can be found in Bradhurst (2015) and Bradhurst et al. (2016).

The primary APPDIS outputs are CSV files which can be post-processed statistically. APPDIS also provides a graphical user interface for interacting with the model and dynamic visualisation of incursions as they unfold. The ability for APPDIS to convey incursion and management concepts visually may suit it to classroom use. Fig. 4 is a screenshot of APPDIS depicting a hitchhiking escape of a tramp ant population from within the managed area. The population model of any cell can be visualised, for example, Fig. 4 depicts the population of cell 70814 being knocked down over the course of a treatment program and the residual population recovering over time.

### 2.1.11. *Verification and validation*

The APPDIS and AADIS modelling frameworks have a common underlying software baseline (Bradhurst, 2015). APPDIS thus inherits from previous AADIS verification and validation activities, and modelling studies (Bradhurst, 2015; Bradhurst et al., 2015; Bradhurst et al., 2016; Garner et al., 2016; Bradhurst et al., 2019; Firestone et al., 2019; Bradhurst et al., 2021; Firestone et al., 2020).

APPDIS models were instantiated for Anoplolepis gracilipes (yellow crazy ant) and Bactrocera dorsalis (Oriental fruit fly) case studies during development of the framework. A model has also been developed of the spread of disease in feral pigs. The yellow crazy ant model is described in this paper, and the Oriental fruit fly and feral pig models will be described in separate future papers. APPDIS validation will be an ongoing process as each new pest (or pest group) model instantiation will require separate validation.

### 2.1.12. *Hardware and platform specifications, and software availability*

APPDIS is written in Java (Oracle, 2020), and employs open-source products such as SQL Power Architect (SQL Power Group, 2020), PostgreSQL (2020), OpenMap (BBN, 2016) and Log4j (Apache, 2020). APPDIS runs under either Linux™ or Windows™ with a recommended minimum hardware configuration of a quad-core processor, 16 GB RAM and a 1920 × 1080 display resolution. The model is available at no cost for non-commercial use under a licensing agreement with the Australian Department of Agriculture, Water and the Environment.

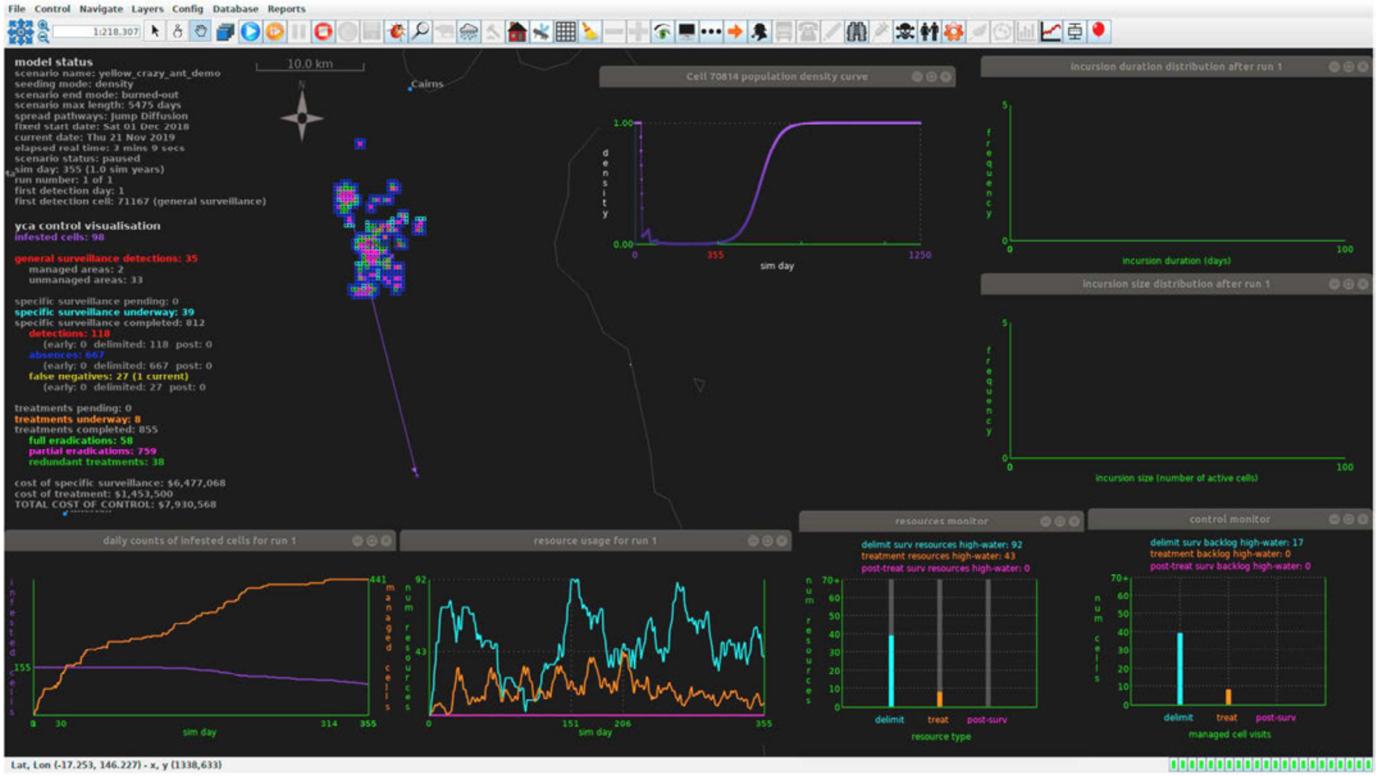
## 2.2. *Case study: Established population of tramp ants*

Tramp ants are a diverse group of invasive ant species that can severely impact native species and habitats, agriculture, forestry, human health and social amenity. If introduced they can rapidly establish and spread through natural and human-mediated dispersal (Abbott, 2005; Hoffman, 2014).

An example of a tramp ant that is a concern to Australia is Anoplolepis gracilipes (yellow crazy ant (YCA)). YCA causes severe ecological damage (Abbott, 2005, 2006), and can affect the horticulture industry by farming sap-sucking scale insects for honeydew. This can lead to larger infestations of pests on host plants (Haines and Haines, 1978b; Lach and Barker, 2013; Helms, 2013), and an increase in the risk of disease being transmitted to plants through insect vectors. Supercolonies are formed through colony budding and the absence of intraspecific aggression (O'Dowd et al., 1999).

### 2.2.1. *Model setup*

*2.2.1.1. Study area.* This study area for this case study was approximately 18,724 km$^2$ (bounded by latitudes −16.450 to −17.941 and longitudes 145.090 to 146.149). A cell size of 10 ha was chosen to reflect the observation that a YCA supercolony spanning an area less than 10 ha tends to be a single contiguous population, whereas a supercolony spanning an area greater than 10 ha tends to be comprised of fragmented



**model status**
scenario name: yellow_crazy_ant_demo
seeding mode: density
scenario end mode: burned-out
scenario max length: 5475 days
spread pathways: Jump Diffusion
fixed start date: Sat 01 Dec 2018
current date: Thu 21 Nov 2019
elapsed real time: 3 mins 9 secs
scenario status: paused
sim day: 355 (1.0 sim years)
run number: 1 of 1
first detection day: 1
first detection cell: 71167 (general surveillance)

**yca control visualisation**
infested cells: 98

general surveillance detections: 35
managed areas: 2
unmanaged areas: 33

specific surveillance pending: 0
specific surveillance underway: 39
specific surveillance completed: 812
detections: 118
(early: 0 delimited: 118 post: 0
absences: 667
(early: 0 delimited: 667 post: 0
false negatives: 27 (1 current)
(early: 0 delimited: 27 post: 0

treatments pending: 0
treatments underway: 8
treatments completed: 855
full eradications: 58
partial eradications: 759
redundant treatments: 38

cost of specific surveillance: $6,477,068
cost of treatment: $1,453,500
TOTAL COST OF CONTROL: $7,930,568

delimit surv resources high-water: 92
treatment resources high-water: 43
post-treat surv resources high-water: 0

delimit surv backlog high-water: 17
treatment backlog high-water: 0
post-treat surv backlog high-water: 0

Lat, Lon (-17.253, 146.227) - x, y (1338,633)

**Fig. 4.** APPDIS spread and control visualisation.

populations (Hoffmann, 2014).

APPDIS raster data layers were defined for:

- land use (sugar cane farms, sugar cane railway corridors, managed land, natural areas)
- watercourses
- elevation
- human population density
- YCA habitat suitability (land = suitable, sea/lakes = unsuitable)

YCA densities have previously been estimated at between 0.2 million and 3.5 million per hectare (Haines and Haines, 1978a), and up to 20 million per hectare (Abbott, 2005). As the habitat suitability data layer for this study was very simple, a conservative grid-wide carrying capacity of 2 million YCA per hectare was chosen. This means that every land cell is deemed equally suitable for YCA with a nominal carrying capacity of 20 million. This simplistic assumption could be improved with a richer habitat suitability layer that incorporates variables such as rugosity and food sources in the determination of cell suitability, which in turn would provide heterogeneity in cell carrying capacity.

The initial YCA population (Fig. 5) spanned 154 cells. Cell population densities were synthesized, graduating from a population of 20 million in cells at the centre of large clusters, down to 2000 in cells at the edge of clusters. This resulted in an overall initial YCA population of approximately 310 million across 1540 ha. The initial YCA population of any subsequently infested cell was an arbitrary propagule, deemed to comprise 24 workers and 1 queen.

*2.2.1.2. Within-cell abundance.* The abundance of the YCA population within an infested cell over time was represented by a deterministic logistic growth function (Equation (1)) with a temperature-independent population growth rate $R(\tau) = 0.025$ based on the assumption that for an ideally suitable 10 ha cell, an uncontrolled YCA population will take approximately 2 years to grow from a single propagule ($n = 25$) to 99% of the cell carrying capacity ($n = 19.8M$). This implies that 50% of the carrying capacity is reached after 454 days. Natural contractions of YCA populations (Abbott, 2006) were not modelled.

*2.2.1.3. Diffusive spread of YCA between adjoining cells.* An APPDIS diffusion spread pathway was instantiated to model the steady spread of YCA over time to adjoining cells. The baseline daily probability of diffusion Pd (required for Equation (2)), depends on the land use category of the infested cell (Table 1). This allows heterogeneity in the diffusive behaviour. For example, diffusion in a cane farm cell (where natural budding is perhaps augmented by short-range movements arising from within-farm activities such as harvesting), is assumed to be more vigorous than diffusion in a national park cell (that is primarily due to natural budding).

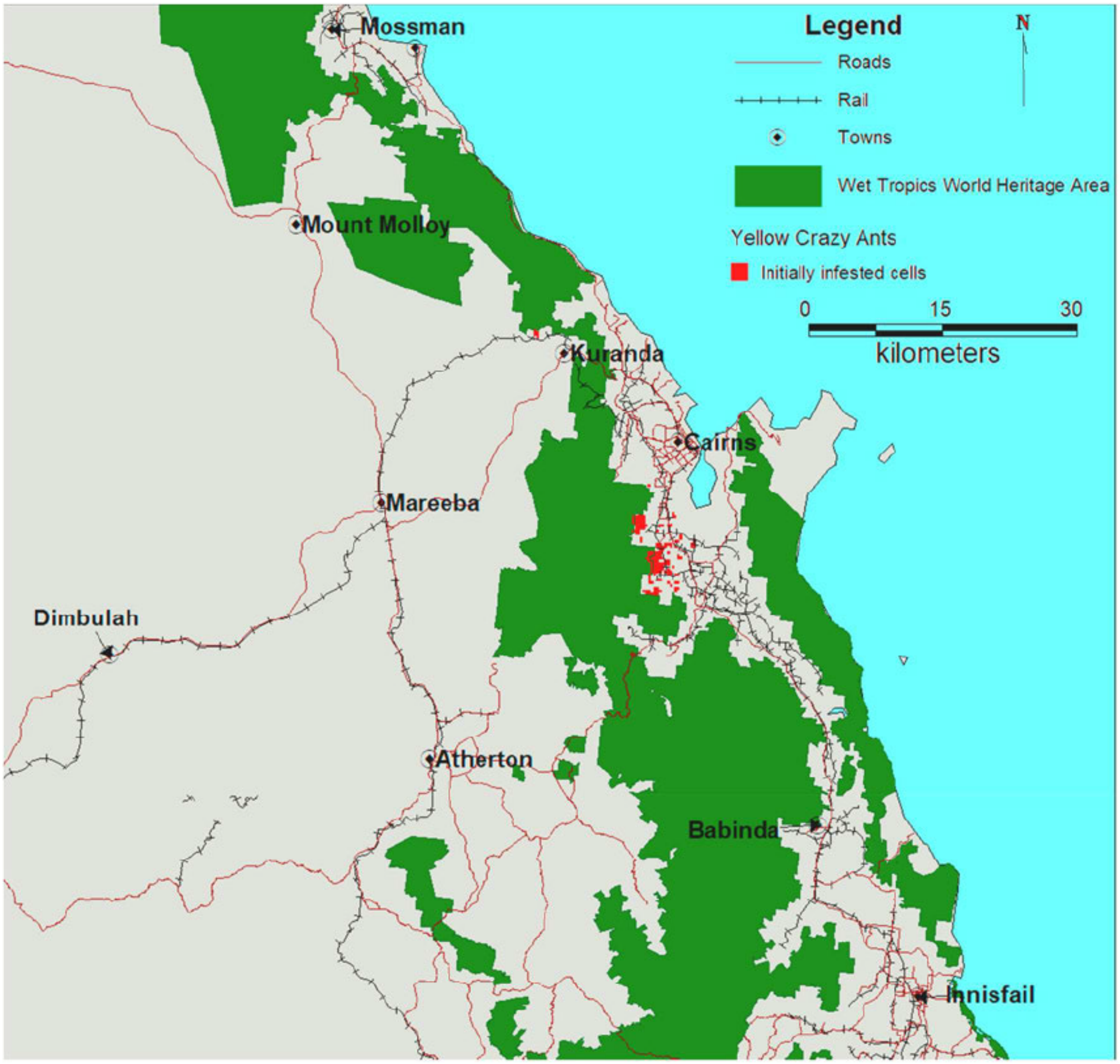


**Fig. 5.** Initial yellow crazy ant population.

**Table 1**
Selected parameterisation of the YCA diffusion pathway.

| Parameter | Value |
|---|---|
| Dependent on land use | true |
| Daily diffusion baseline probability $P_d$ on a cane farm | 0.000445[1] |
| Daily diffusion baseline probability $P_d$ in a railway corridor | 0.000083[2] |
| Daily diffusion baseline probability $P_d$ in managed land | 0.000083[2] |
| Daily diffusion baseline probability $P_d$ in a natural area | 0.000028[3] |

[1] based on the assumption that a cane farm cell with maximal YCA population (i.e., at carrying capacity), has a 15% chance of diffusing into another cell within a year, i.e., Pd = 1 – (1–0.15) (1/365).

[2] Based on the assumption that a cell with maximal YCA population (i.e., at carrying capacity), in a railway corridor or on managed land, has a 3% chance of diffusing into another cell within a year, i.e., Pd = 1 – (1–0.03) (1/365).

[3] Based on the assumption that a cell with maximal YCA population (i.e., at carrying capacity), in a natural area, has a 1% chance of diffusing into another cell within a year, i.e., Pd = 1 – (1–0.01) (1/365).

*2.2.1.4. Spread between non-adjoining cells due to sugar cane farming activities.* An APPDIS jump spread pathway was instantiated to model the sporadic spread of YCA due to medium-range hitchhiking from sugar cane farming activities. Jumps were parameterised to only originate from cells containing sugar cane farms, and only end in cells that had either sugar cane farms or railway corridors. The ability to define the baseline daily probability $P_j$ (Equation (3)) per land use category allows heterogeneity in the jumping frequency (Table 2). For example, jumps between cane farms (brought about by harvesting activities spanning multiple farms), can be defined differently to jumps from cane farms to cane railway corridors (brought about by cane rail transportation).

Seasonal variations in cane farming activities were not modelled, i.e., the pathway represents average cane jumps over the course of a year.

*2.2.1.5. Spread between cells due to human-mediated hitchhiking.* An APPDIS jump spread pathway was instantiated to model the sporadic spread of YCA via human-mediated hitchhiking (unrelated to cane farming activities). Jumps were parameterised to only involve cells with a non-zero human population density (Table 3). Although the model allows a proportion of jumps to end in non-populated cells (simulating for example, movements into natural areas), the feature was not enabled for this case study.

*2.2.1.6. Spread between cells due to rafting.* An APPDIS jump spread pathway was instantiated to model the sporadic spread of YCA due to rafting. Jumps were parameterised to only originate from cells containing watercourses, and only end in lower elevation cells that contain watercourses (Table 4).

*2.2.1.7. General surveillance.* An APPDIS general surveillance component was instantiated per Table 5.

*2.2.1.8. Specific surveillance and treatment.* APPDIS delimiting surveillance, treatment, and post-treatment components were instantiated per Table 6.

**Table 2**
Selected parameterisation of the YCA sugar cane farming jump pathway.

| Parameter | Value |
|---|---|
| Dependent on land use | true |
| Daily jump baseline probability $P_j$ onto a cane farm | 0.000289[1] |
| Daily jump baseline probability $P_j$ into a railway corridor | 0.000289[1] |
| Jump distance (minimum, most likely, maximum) (km) | BetaPERT[2] (0.5, 2, 20) |

[1] based on the assumption that a cell with maximal YCA population (i.e., is at carrying capacity), has a 10% chance of a sugar-cane farming hitchhiking jump into another cell within a year, i.e., $P_j = 1 - (1-0.1)$ ($^{1/365}$)

[2] Vose (2008).

**Table 3**
Selected parameterisation of the YCA human-mediated hitchhiking jump pathway.

| Parameter | Value |
|---|---|
| Dependent on human population density | true |
| Daily jump baseline probability $P_j$ | 0.000289[1] |
| Proportion of jumps allowed into non-populated areas | 0.0 |
| Jump distance (minimum, most likely, maximum) (km) | BetaPERT (0.5, 10, 75) |

[1] based on the assumption that a cell with maximal YCA population (i.e., is at carrying capacity), and maximal human population (i.e., normalised human population density of 1.0), has a 30% chance of a human-mediated hitchhiking jump into another cell within a year, i.e., $P_j = 1 - (1-0.3)$ ($^{1/365}$)

**Table 4**
Selected parameterisation of the YCA sugar cane farming jump pathway.

| Parameter | Value |
|---|---|
| Dependent on land use | false |
| Dependent on human population density | false |
| Dependent on temperature | false |
| Dependent on gradient | true |
| Dependent on watercourses | true |
| Daily jump baseline probability $P_j$ | 0.000141[1] |
| Jump distance (minimum, most likely, maximum) (km) | BetaPERT (0.5, 0.5, 5) |

Seasonal variations in rafting likelihood were not modelled, i.e., the pathway represents average rafting jumps over the course of a year.
1Based on the assumption that a cell with maximal YCA population (i.e., is at carrying capacity), has a 5% chance of rafting jump into another cell within a year, i.e., $P_j = 1 - (1-0.05)$ ($^{1/365}$)

**Table 5**
YCA general surveillance parameterisation.

| Parameter | Value |
|---|---|
| General surveillance mode | Passive |
| Observer sensitivity $S_e$ in managed areas | 0.60 |
| Observer sensitivity $S_e$ in unmanaged areas | 0.25 |

**Table 6**
YCA specific surveillance and treatment parameterisation.

| Parameter | Delimiting surveillance | Treatment | Post-treatment surveillance |
|---|---|---|---|
| Mode | Moore | Spot | Spot |
| Visit duration (per cell) | 21 days | 7 days | 21 days |
| Trap spacing | 10 m | N/A | 10 m |
| Sensitivity $S_e$ | 0.99 | N/A | 0.99 |
| Specificity $S_p$ | 1.00 | N/A | 1.00 |
| Effectiveness | N/A | 0.8 to 0.95 | N/A |
| Visit cost | A$10 per trap | A$1700 per cell | A$10 per trap |
| Interval between visits | 90 days | 28 days | 180 days |
| Minimum number of visits | 8 | 6 | 4 |

*2.2.1.9. Resources.* The APPDIS resources component was set to Unlimited i.e., surveillance and treatment activities were not resource constrained.

### *2.2.2. Scenario 1 - uncontrolled spread*

The established YCA population (Fig. 5) was allowed to spread without surveillance or treatment for 30 years and the emergent rates and extent of spread recorded. The scenario was repeated 50 times.

### *2.2.3. Scenario 2 – sensitivity of delimiting surveillance trap spacing*

The established YCA population (Fig. 5) was allowed to spread in conjunction with surveillance and treatment programs. The delimiting surveillance trap spacing parameter (Table 6) was systematically varied between 2 and 100 m, while the post-treatment surveillance trap spacing was held constant at 10 m. 500 iterations of the scenario were run for each trap spacing. The maximum length of a scenario was limited to 15 years (5475 days).

#### 2.2.4. *Scenario 3 - sensitivity of post-treatment surveillance trap spacing*

The established YCA population (Fig. 5) was allowed to spread in conjunction with surveillance and treatment programs. The post-treatment surveillance trap spacing parameter (Table 6) was systematically varied between 2 and 100 m, while the delimiting surveillance trap spacing was held constant at 10 m. 500 iterations of the scenario were run for each trap spacing. The maximum length of a scenario was limited to 15 years (5475 days).

## 3. Results

### 3.1. *Scenario 1 results - uncontrolled spread*

Table 7 provides a summary of uncontrolled YCA spread over 30 years.

Convergence estimates the percentage standard error E of the sample mean with 95% confidence for a given number of iterations (Equation (7)) (Driels and Shin, 2004).

$$E = \frac{100 z_c S_x}{\overline{x}\sqrt{n}} \tag{Eqn. 7}$$

where

E = percentage standard error of the sample mean
$z_c$ = confidence coefficient (1.96 = 95%)
$S_x$ = sample standard deviation
$\overline{x}$ = sample mean
n = number of runs

Fig. 6 provides a snippet of the yearly spread report for the case study. The model outputs the population density for each active cell at the end of every year, for each simulation run.

The model creates a pest distribution risk map that represents how often a cell was infested across all iterations of a particular scenario. Fig. 7 presents a colour-coding of cells in the study area where the most frequently infested cells are encoded in red and the least frequently infested cells in yellow.

### 3.2. *Scenario 2 results – sensitivity of delimiting surveillance trap spacing*

Table 8 and Figs. 8 and 9 summarise the effect of delimiting surveillance trap spacing on the average cost and effectiveness of control/eradication.

**Table 7**
Simulation results for 50 iterations of 30 years of uncontrolled yellow crazy ant spread.

| Model outcome | Value |
|---|---|
| YCA population increase[1] | 310 million → 124 billion |
| Initial infestation area increase [1] | 154 cells (1540 ha) → 6936 cells (69,360 ha) |
| Final infestation area convergence[2] | 2.90% |
| Number of diffusion events[1] | 105 per year |
| Managed land diffusion rate[1] | 119 m per year |
| Cane farm diffusion rate[1] | 132 m per year |
| Cane railway diffusion rate[1] | 90 m per year |
| Natural area diffusion rate[1] | 68 m per year |
| Cane-related jump rate[1] | 41 jumps per year |
| Human-mediated jump rate[1] | 16 jumps per year |
| Rafting jump rate[1] | 13 jumps per year |

[1] averaged over 50 runs.
[2] percentage standard error of the sample mean (95% confidence).

### 3.3. *Scenario 3 results - sensitivity of post-outbreak surveillance trap spacing*

Table 9 and Figs. 10 and 11 summarise the effect of post-treatment surveillance trap spacing on the average cost and effectiveness of control/eradication.

## 4. Discussion

### 4.1. *Uncontrolled spread*

The average YCA diffusion rate over a 30-year period ranged from 68 m/year in natural areas up to 132 m/year in cane farming areas. This is broadly in line with reported budding distances of 125 m/year on average (range 37–402) (Haines and Haines, 1978a), and up to 182 m per year (Abbott, 2006). Note that cells may have multiple land uses (e.g. cane + managed, railway + managed) and each cell diffuses based on its highest risk land use. This can artificially boost the diffusion rate for the lower risk land use of the cell (e.g. a managed cell with cane fields contributes correctly to the overall cane diffusion rate but over-contributes to the overall managed land diffusion rate).

Dispersion via winged flight of queens (fission) was not explicitly modelled as it is unclear whether this is an important means of dispersal for YCA (Rao et al., 1991; Haines et al., 1994; O'Dowd et al., 1999; Abbott et al., 2014; Hoffmann, 2014). It would have been possible, data permitting, to include a fission jump pathway as the model supports multiple concurrent jump spread pathways.

Longer range sporadic spread of YCA via hitchhiking is more unpredictable and harder to quantify than steady diffusive spread. The probability of spread via human-mediated hitchhiking is influenced by an infested cell's pest population density and human population density, however, the frequency and distance of such jumps is largely driven by expert opinion and inference from unexpected satellite colonies. For example, an unexpected appearance of YCA in Russett Park, Queensland (30 km from the nearest known infestation near Cairns, Queensland), was attributed to hitchhiking via the transportation of landscaping materials.

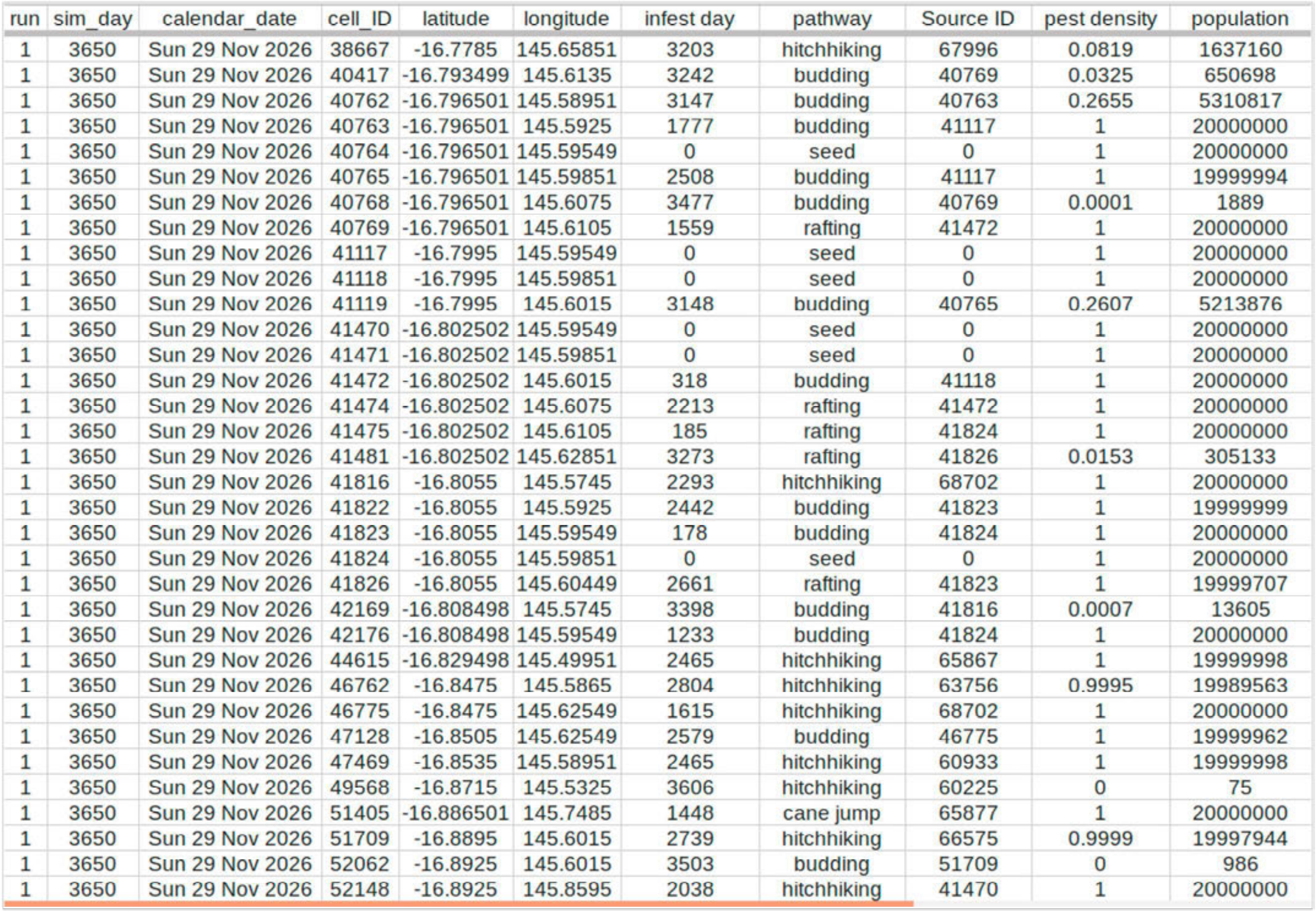
As illustrated in Fig. 7, one of the outputs of APPDIS is a risk map of spread – driven by the number of times a cell is infested over a series of scenario runs. The land uses of the resultant infested cells can be analysed to provide an estimation of the potential long-term impact on agricultural, residential, and environmentally sensitive areas. This case study strongly suggests that 30 years of uncontrolled spread of YCA would lead to significant incursions into the Wet Tropics World Heritage Area.

The simulation produced very good convergence (2.90%) of the mean number of infested cells after 50 iterations. This implies there is 95% confidence of only 2.90% standard error in the distribution of the sample mean.

### 4.2. *Sensitivity of surveillance trap spacing*

The cost of control was largely independent of delimiting surveillance trap spacings greater than 20 m, but rose steeply for trap spacings less than 20 m (Fig. 8). The cost of control was weakly dependent on post-treatment surveillance trap spacings greater than 10 m, and rose steeply for trap spacings less than 10 m (Fig. 10).

The effectiveness of control (measured by population reduction and incursion duration), was far more sensitive to post-treatment surveillance trap spacing than delimiting surveillance trap spacing. Figs. 8 and 9 shows how the YCA population was reduced by 99% within 15 years for all delimiting surveillance trap spacings. In contrast, only post-treatment surveillance trap spacings between 2 and 10 m resulted in a



| run | sim_day | calendar_date | cell_ID | latitude | longitude | infest day | pathway | Source ID | pest density | population |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 3650 | Sun 29 Nov 2026 | 38667 | -16.7785 | 145.65851 | 3203 | hitchhiking | 67996 | 0.0819 | 1637160 |
| 1 | 3650 | Sun 29 Nov 2026 | 40417 | -16.793499 | 145.6135 | 3242 | budding | 40769 | 0.0325 | 650698 |
| 1 | 3650 | Sun 29 Nov 2026 | 40762 | -16.796501 | 145.58951 | 3147 | budding | 40763 | 0.2655 | 5310817 |
| 1 | 3650 | Sun 29 Nov 2026 | 40763 | -16.796501 | 145.5925 | 1777 | budding | 41117 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 40764 | -16.796501 | 145.59549 | 0 | seed | 0 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 40765 | -16.796501 | 145.59851 | 2508 | budding | 41117 | 1 | 19999994 |
| 1 | 3650 | Sun 29 Nov 2026 | 40768 | -16.796501 | 145.6075 | 3477 | budding | 40769 | 0.0001 | 1889 |
| 1 | 3650 | Sun 29 Nov 2026 | 40769 | -16.796501 | 145.6105 | 1559 | rafting | 41472 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41117 | -16.7995 | 145.59549 | 0 | seed | 0 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41118 | -16.7995 | 145.59851 | 0 | seed | 0 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41119 | -16.7995 | 145.6015 | 3148 | budding | 40765 | 0.2607 | 5213876 |
| 1 | 3650 | Sun 29 Nov 2026 | 41470 | -16.802502 | 145.59549 | 0 | seed | 0 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41471 | -16.802502 | 145.59851 | 0 | seed | 0 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41472 | -16.802502 | 145.6015 | 318 | budding | 41118 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41474 | -16.802502 | 145.6075 | 2213 | rafting | 41472 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41475 | -16.802502 | 145.6105 | 185 | rafting | 41824 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41481 | -16.802502 | 145.62851 | 3273 | rafting | 41826 | 0.0153 | 305133 |
| 1 | 3650 | Sun 29 Nov 2026 | 41816 | -16.8055 | 145.5745 | 2293 | hitchhiking | 68702 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41822 | -16.8055 | 145.5925 | 2442 | budding | 41823 | 1 | 19999999 |
| 1 | 3650 | Sun 29 Nov 2026 | 41823 | -16.8055 | 145.59549 | 178 | budding | 41824 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41824 | -16.8055 | 145.59851 | 0 | seed | 0 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 41826 | -16.8055 | 145.60449 | 2661 | rafting | 41823 | 1 | 19999707 |
| 1 | 3650 | Sun 29 Nov 2026 | 42169 | -16.808498 | 145.5745 | 3398 | budding | 41816 | 0.0007 | 13605 |
| 1 | 3650 | Sun 29 Nov 2026 | 42176 | -16.808498 | 145.59549 | 1233 | budding | 41824 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 44615 | -16.829498 | 145.49951 | 2465 | hitchhiking | 65867 | 1 | 19999998 |
| 1 | 3650 | Sun 29 Nov 2026 | 46762 | -16.8475 | 145.5865 | 2804 | hitchhiking | 63756 | 0.9995 | 19989563 |
| 1 | 3650 | Sun 29 Nov 2026 | 46775 | -16.8475 | 145.62549 | 1615 | hitchhiking | 68702 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 47128 | -16.8505 | 145.62549 | 2579 | budding | 46775 | 1 | 19999962 |
| 1 | 3650 | Sun 29 Nov 2026 | 47469 | -16.8535 | 145.58951 | 2465 | hitchhiking | 60933 | 1 | 19999998 |
| 1 | 3650 | Sun 29 Nov 2026 | 49568 | -16.8715 | 145.5325 | 3606 | hitchhiking | 60225 | 0 | 75 |
| 1 | 3650 | Sun 29 Nov 2026 | 51405 | -16.886501 | 145.7485 | 1448 | cane jump | 65877 | 1 | 20000000 |
| 1 | 3650 | Sun 29 Nov 2026 | 51709 | -16.8895 | 145.6015 | 2739 | hitchhiking | 66575 | 0.9999 | 19997944 |
| 1 | 3650 | Sun 29 Nov 2026 | 52062 | -16.8925 | 145.6015 | 3503 | budding | 51709 | 0 | 986 |
| 1 | 3650 | Sun 29 Nov 2026 | 52148 | -16.8925 | 145.8595 | 2038 | hitchhiking | 41470 | 1 | 20000000 |

**Fig. 6.** Yellow crazy ant simulation spread report (snippet only).

99% population reduction within 15 years (Figs. 10 and 11). The effectiveness of control decreased markedly as post-treatment surveillance trap spacing increased, with a trap spacing of 100 m yielding no net population reduction after 15 years. This suggests that the effectiveness of post-treatment surveillance is a vital aspect of pest eradication. Fig. 10 indicates that a post-treatment surveillance trap spacing of 18 m minimised the cost of control at approximately A$23.5M and resulted in an average 95% population reduction. However, to achieve an average 99.99% population reduction, the required 2-m post-treatment surveillance trap spacing would, however, incur a much higher cost of approximately A$163M.

The decrease in control effectiveness with increased post-treatment surveillance trap spacing is also reflected by the average model runtime per iteration. In scenario 2 where the post-delimiting surveillance trap spacing was held steady at 10 m while the delimiting surveillance trap spacing was varied, the average model runtime (per scenario iteration) was reasonably stable (average = 60.50 s, standard deviation = 9.68) (Table 8). In scenario 3 where the delimiting surveillance trap spacing was held steady at 10 m while the post-outbreak surveillance trap spacing was varied, the average model runtime (per scenario iteration) was strongly dependent on trap spacing (ranging from 28.04 to 141.75 s). This is due to the additional treatment and post-treatment surveillance activities (and hence simulation processing) required when the surveillance strategy is less effective (reflected by higher false negative results (Table 9)).

The high sensitivity of control cost-effectiveness to post-treatment surveillance trap spacing is perhaps because post-treatment surveillance is typically conducted in cells with very small pest densities. As shown in Fig. 3, the model's implementation of specific surveillance is highly sensitive to trap spacing at low pest population densities. An incorrect determination of pest absence in a treated cell (after 4 successive false negative results), leads to cell populations that will recover over time. In the absence of an early detection surveillance system, the subsequent detection of a residual population relies on general surveillance. The probability of a general surveillance detection is, however, greatly reduced at low pest and human population densities (Fig. 2).

The simulations produced very good convergence for the mean total cost of control (<1.7%). This implies 95% confidence that there is at most 1.7% standard error in the distribution of the sample mean, and that 500 iterations of the scenarios were sufficient.

### 4.3. Advantages and limitations of the APPDIS modelling approach

Decision support tools that represent the spread of a pest in an environment range from simple aggregative mathematical models to complex pest-specific spatial simulations. Aggregative mathematical models generally do not take host and environmental heterogeneity into account, but are concise, easy to parameterise, scalable, computationally efficient, and may be readily extensible to other pests. They can be very useful for the fast prototyping of incursion dynamics, especially when data is scarce or unreliable. Detailed spatially explicit and pest-specific simulations can capture environmental and host heterogeneities, but are data dependent, can be complicated to construct and parameterise, may not scale well computationally, and may not be readily extensible to other pests.

The APPDIS modelling framework attempts to find a pragmatic

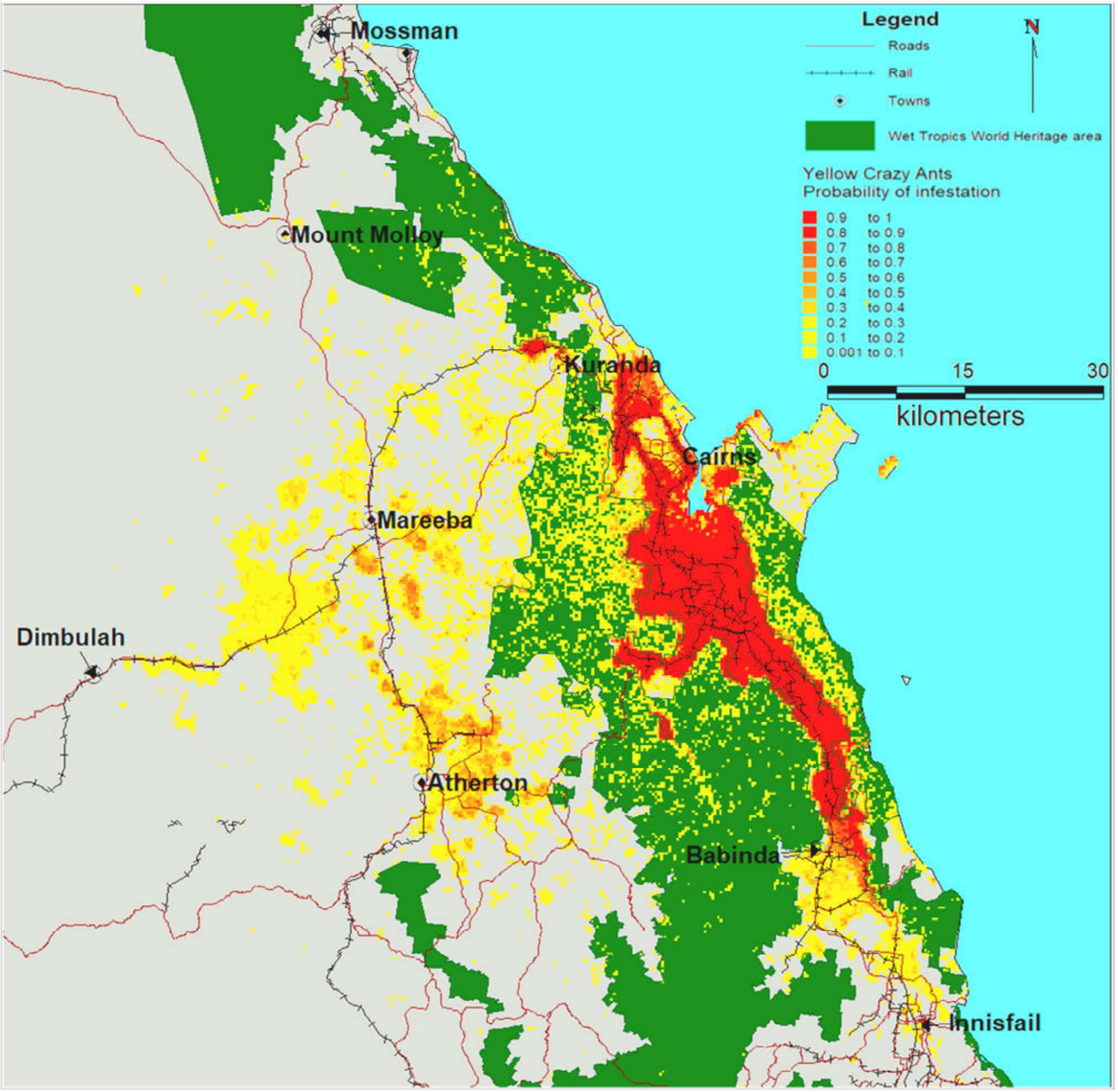


**Fig. 7.** Projected yellow crazy ant distribution after 30 years of uncontrolled spread.

**Table 8**
Average effect of delimiting surveillance trap spacing on control effectiveness and cost.

| Trap spacing (metres) | Outbreak length (days) | Delimiting surveillance cost (A $ million) | Treatment cost (A$ million) | Post-treatment surveillance cost (A $ million) | Total cost of control convergence | Delimiting surveillance false negatives | Reduction in infested cells | Average model runtime per iteration (secs) |
|---|---|---|---|---|---|---|---|---|
| 2 | 4113 | 504.64 | 0.27 | 6.34 | 0.50% | 0.58 | 99.25% | 64.25 |
| 5 | 4182 | 80.54 | 0.26 | 6.35 | 0.27% | 7.59 | 99.50% | 45.98 |
| 8 | 4227 | 31.65 | 0.27 | 6.46 | 0.45% | 17.90 | 99.14% | 44.2 |
| 10 | 4281 | 20.31 | 0.27 | 6.51 | 0.31% | 23.28 | 99.16% | 54.73 |
| 15 | 4255 | 9.05 | 0.27 | 6.68 | 0.26% | 34.59 | 99.20% | 56.23 |
| 20 | 4354 | 5.10 | 0.27 | 6.79 | 0.26% | 45.29 | 99.12% | 51.91 |
| 30 | 4431 | 2.28 | 0.27 | 6.99 | 0.24% | 61.73 | 99.07% | 52.75 |
| 40 | 4469 | 1.28 | 0.27 | 7.09 | 0.23% | 75.37 | 98.99% | 58.46 |
| 50 | 4471 | 0.82 | 0.27 | 7.14 | 0.24% | 86.22 | 99.13% | 72.05 |
| 60 | 4490 | 0.57 | 0.27 | 7.21 | 0.26% | 95.89 | 98.84% | 66.25 |
| 70 | 4455 | 0.41 | 0.27 | 7.21 | 0.24% | 103.26 | 99.13% | 71.67 |
| 80 | 4474 | 0.31 | 0.27 | 7.22 | 0.26% | 110.18 | 98.85% | 70.91 |
| 90 | 4508 | 0.25 | 0.27 | 7.22 | 0.25% | 115.87 | 99.03% | 68.00 |
| 100 | 4434 | 0.19 | 0.27 | 7.22 | 0.24% | 120.49 | 99.16% | 69.59 |

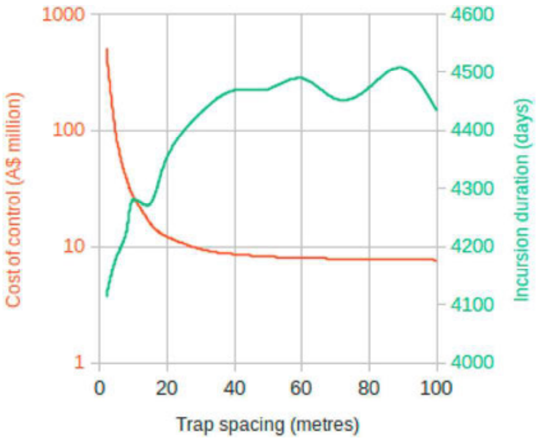


**Fig. 8.** Effect of delimiting surveillance trap spacing on incursion duration and control cost.

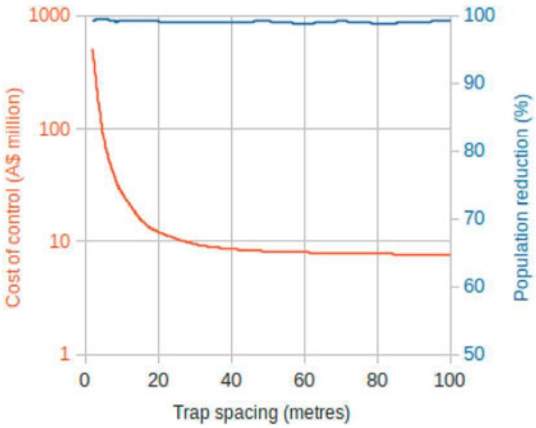


**Fig. 9.** Effect of delimiting surveillance trap spacing on control effectiveness and cost.

middle ground between the biological and ecological fidelity of a complex pest-specific spatial model, and the extensibility of a generalised mathematical model. APPDIS is flexible in that a user can configure either simple or complex spread models. In studies where field data is scarce or unreliable, a simple mathematical spread model is obtained by disabling the environmental data layers and configuring an aggregative diffusion kernel based on predicted spread rates. A complex spread model can be achieved by enabling environmental data layers and configuring individual spread pathways that consider heterogeneities in elevation, temperature, wind speed, vegetation, land use, human population density, etc.

Once a model is spreading a pest in a way that is congruent with available field data and expert opinion, a decision support tool should allow useful experimentation with surveillance and control strategies. A further design tension exists between implementing detailed pest specific detection/control options that may not be readily extensible to

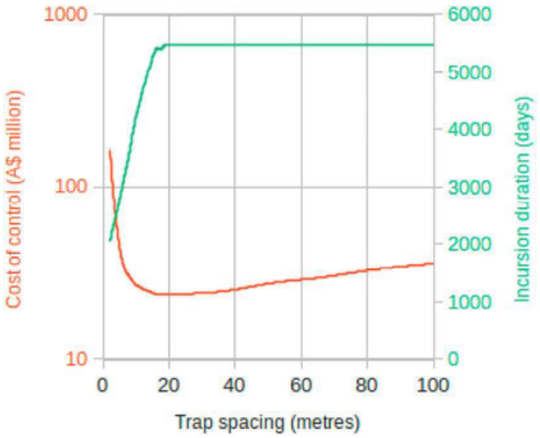


**Fig. 10.** Effect of post-treatment surveillance trap spacing on incursion duration and control cost.

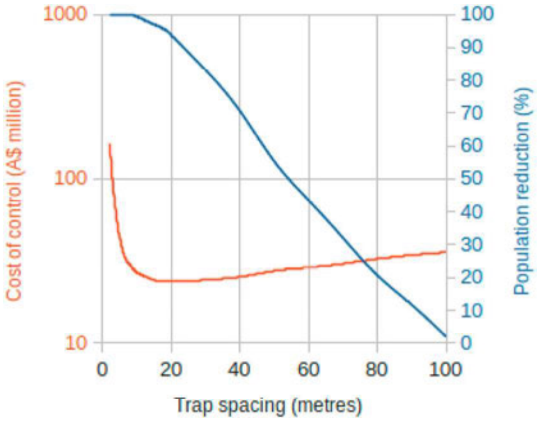


**Fig. 11.** Effect of post-treatment surveillance trap spacing on control effectiveness and cost.

**Table 9**
Average effect of post-treatment surveillance trap spacing on control effectiveness and cost.

| Trap spacing (metres) | Outbreak length (days) | Delimiting surveillance cost (A $ million) | Treatment cost (A$ million) | Post-treatment surveillance cost (A $ million) | Total cost of control convergence | Post-treatment surveillance false negatives | Reduction in infested cells | Average model runtime per iteration (secs) |
|---|---|---|---|---|---|---|---|---|
| 2 | 2049 | 20.07 | 0.26 | 143.39 | 0.10% | 0.05 | 99.99% | 28.04 |
| 5 | 2796 | 20.10 | 0.26 | 23.57 | 0.14% | 10.29 | 99.90% | 34.37 |
| 8 | 3611 | 20.18 | 0.26 | 9.74 | 0.21% | 31.56 | 99.64% | 40.74 |
| 10 | 4233 | 20.27 | 0.27 | 6.51 | 0.25% | 48.59 | 99.31% | 49.00 |
| 15 | 5262 | 20.73 | 0.27 | 3.24 | 0.46% | 97.29 | 96.95% | 60.69 |
| 20 | 5470 | 21.36 | 0.27 | 2.03 | 0.60% | 151.01 | 93.78% | 58.94 |
| 30 | 5475 | 22.87 | 0.28 | 1.09 | 0.73% | 269.86 | 83.12% | 74.41 |
| 40 | 5475 | 24.37 | 0.29 | 0.69 | 0.86% | 378.37 | 70.68% | 94.89 |
| 50 | 5475 | 26.72 | 0.31 | 0.49 | 0.92% | 481.37 | 55.37% | 109.78 |
| 60 | 5475 | 28.30 | 0.32 | 0.36 | 1.07% | 566.74 | 43.54% | 117.59 |
| 70 | 5475 | 29.99 | 0.33 | 0.28 | 1.33% | 650.54 | 32.11% | 123.97 |
| 80 | 5475 | 32.17 | 0.34 | 0.22 | 1.51% | 718.66 | 20.69% | 131.17 |
| 90 | 5475 | 33.92 | 0.36 | 0.19 | 1.66% | 780.78 | 11.66% | 136.57 |
| 100 | 5475 | 35.36 | 0.37 | 0.15 | 1.48% | 836.07 | 1.87% | 141.75 |

other pests and/or jurisdictions, and implementing generalised detection/control options that may not be detailed enough for the pest under study. Again, APPDIS attempts to find a pragmatic middle ground by providing detection/control options that are detailed enough to be useful yet abstract enough to extend to a range of pests. Surveillance and treatment regimes are configurable by the user in generalised terms such as duration, cost, resource requirements, efficacy, sensitivity, and specificity. As the underlying pest spread mechanisms are stochastic, a control policy can be trialed against a distribution of plausible incursions. In this way, despite inherent uncertainty in how an exotic pest population may spread, confidence can be gained as to the likelihood of a particular policy to achieve the desired control/eradication outcome.

Configuring an APPDIS model for a pest (or pest group) requires personnel versed in pest ecology, plant health policy, and the APPDIS modelling platform (including the assembly of supporting data, parameterisation, designing and running incursion scenarios, and statistical interpretation of simulation results). The configuration effort required when employing disaggregated (data-driven) spread pathways is considerably more than that required for aggregative mathematical pathways. An advantage of a disaggregated approach to modelling spread (by simulating each spread pathway separately), is that control measures can be applied to specific spread pathways. For example, consider a pest that spreads through a windborne pathway and a market-driven pathway. With a disaggregated modelling approach, it is easy to test the effect of movement restrictions on the market-driven pathway whilst still allowing the airborne pathway to spread the pest. This is more difficult when all spread pathways are aggregated into a single mathematical spread mechanism.

A disadvantage of grid-based modelling approaches is that point-based agricultural entities such as orchards, nurseries and markets are not represented. It would be possible to extend APPDIS to include point-based entities and directed spread pathways (as is the case with the AADIS framework), however this would require further development of the framework and consultation with domain experts to ensure that entities and networks are captured in an abstract way that extends to as many pest species as possible.

Whilst models can assist with preparedness and planning for incursions and in some cases response, they can suffer silently from poor assumptions, sub-standard data, inadequate validation, and improper use. Flawed models have the potential to mislead rather than inform, particularly when modelling outputs are detailed and appear definitive. APPDIS is primarily a data-driven model and as such, relies heavily on the quality of the underlying data and parameterisation. Each instantiation of APPDIS for a new pest species (or pest species group), will require a separate validation process that fosters user trust in the model assumptions, data, parameterisation, and capabilities. APPDIS models are best suited to relative comparisons between control and resourcing strategies, rather than predicting incursion outcomes in absolute terms.

### *4.4. Conclusions*

APPDIS is a general-purpose plant and environmental pest modelling framework that is extensible (not tied to a specific pest), scalable (operable regionally and nationally), and flexible (offering simple equation-based spread pathways or complex data-driven pathways that capture heterogeneity in the host environment). APPDIS allows relative comparisons of strategies for early detection surveillance, delimiting surveillance, treatment, and post-treatment surveillance, with respect to efficacy, resource usage and cost. The case study has demonstrated the potential for APPDIS to assist with decision support for both plant pests and environmental pests. Importantly, APPDIS is extensible to a range of pests via user configurable parameters (i.e., without the need for specialised mathematical reformulation and/or computer programming).

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## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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# 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).

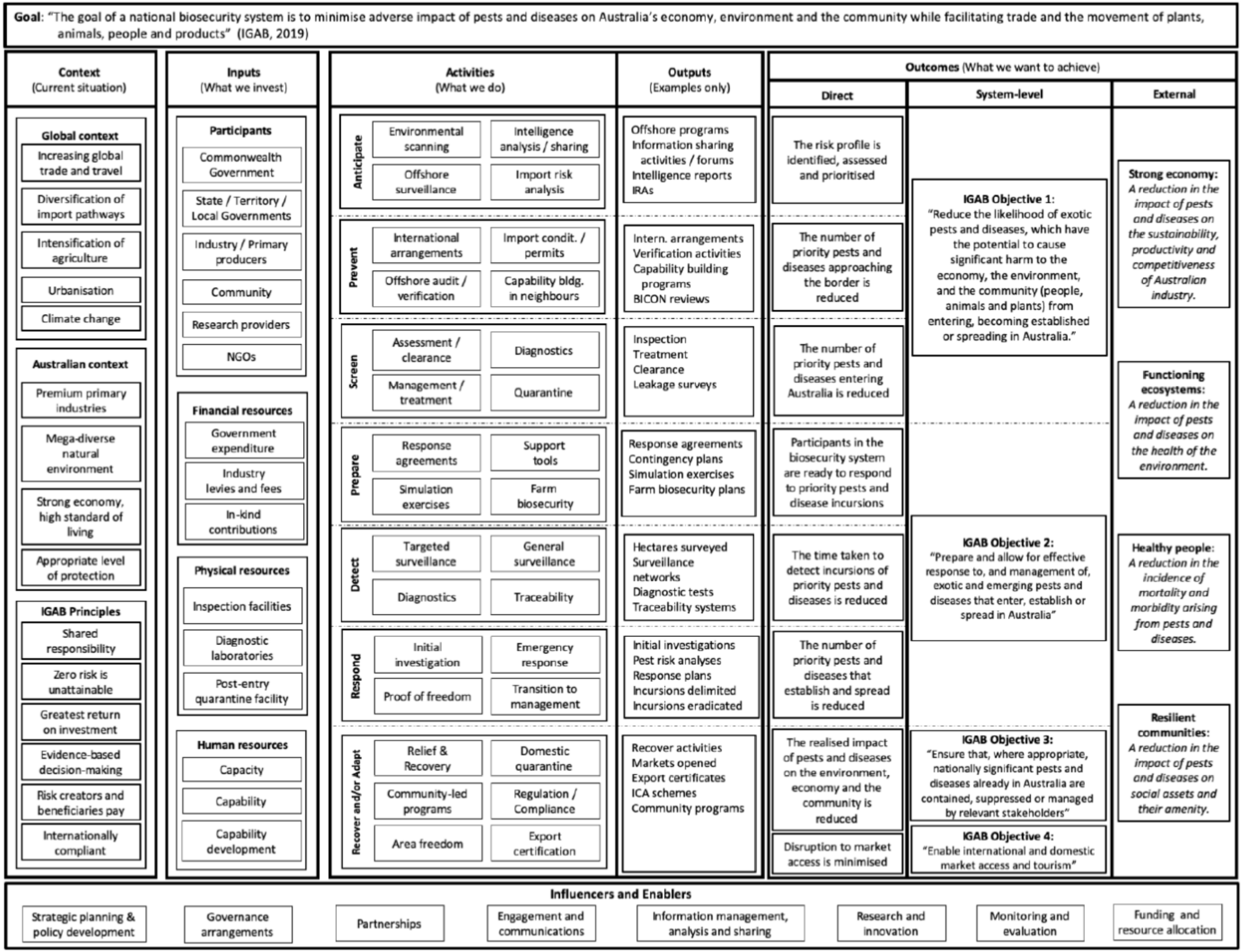

Figure 1: Australia's biosecurity system logic (Dodd *et al.*, 2017; updated in Schneider & Arndt, 2020).

## 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 | Exemplar Species | Establ. Rate (count p.a.) | Spread Rate (km p.a.) | Damage$_{Agric.}$ (% Yield) | … | Damage$_{Infras.}$ (% Yield) |
|---|---|---|---|---|---|---|
| Source: RRRA | ABARES* | RRRA | ABARES* | ABARES | | 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:

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

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.

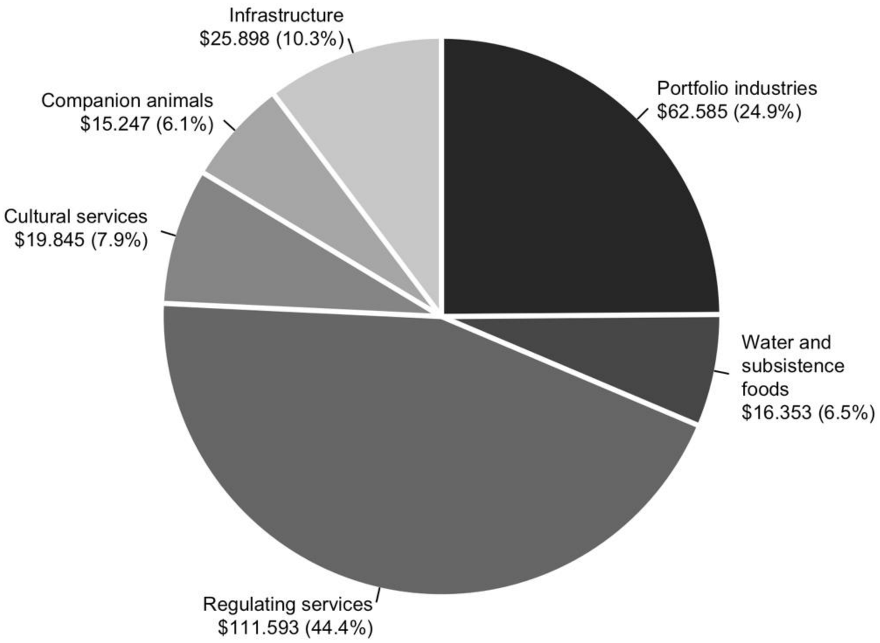

Figure 2: Annual flow (billions A$) of benefits from assets vulnerable to biosecurity hazards.

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).

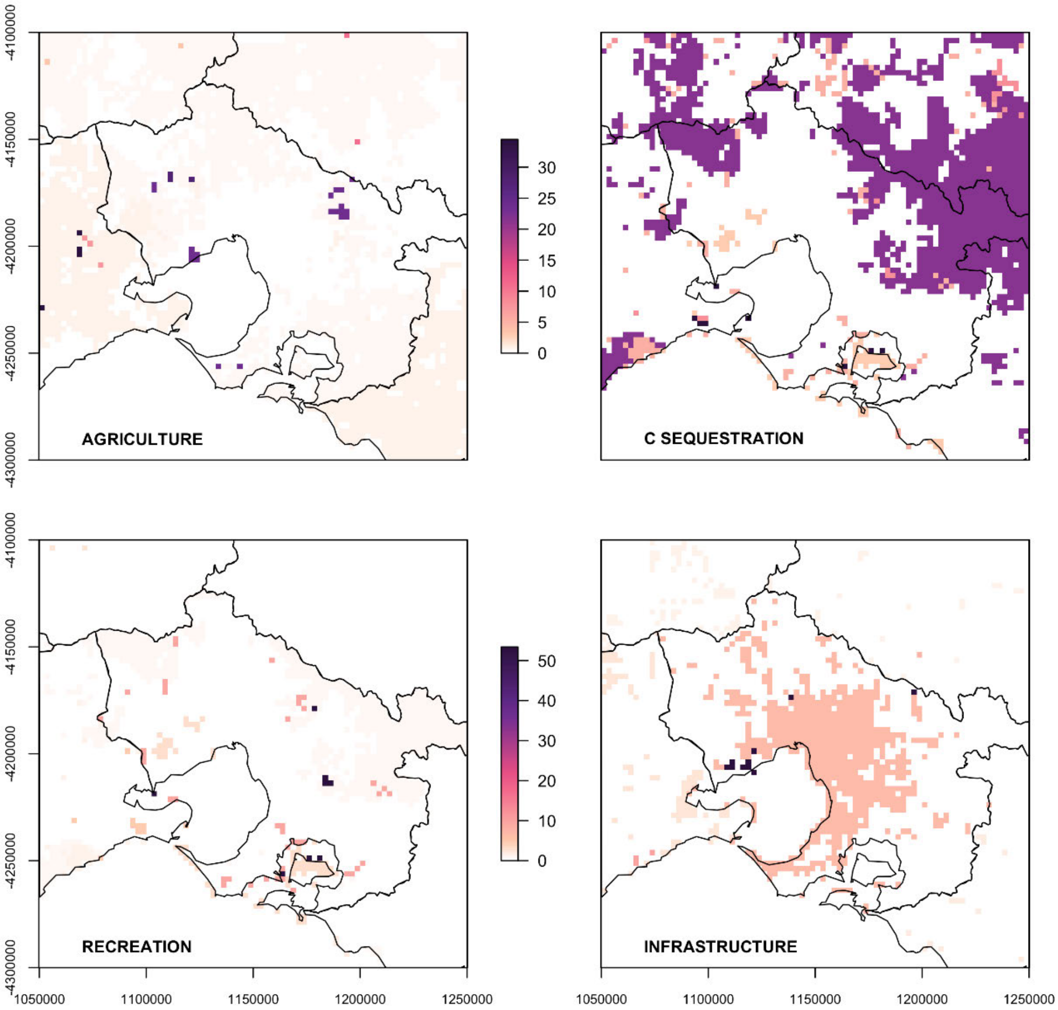

Figure 3: Annual flow of benefits (A$M) per 2500m x 2500m area from assets vulnerable to biosecurity hazards for selected asset types. Extent shown is 100km x 100km area centred on the Port Phillip and Westernport NRM region (Melbourne, Australia).

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.

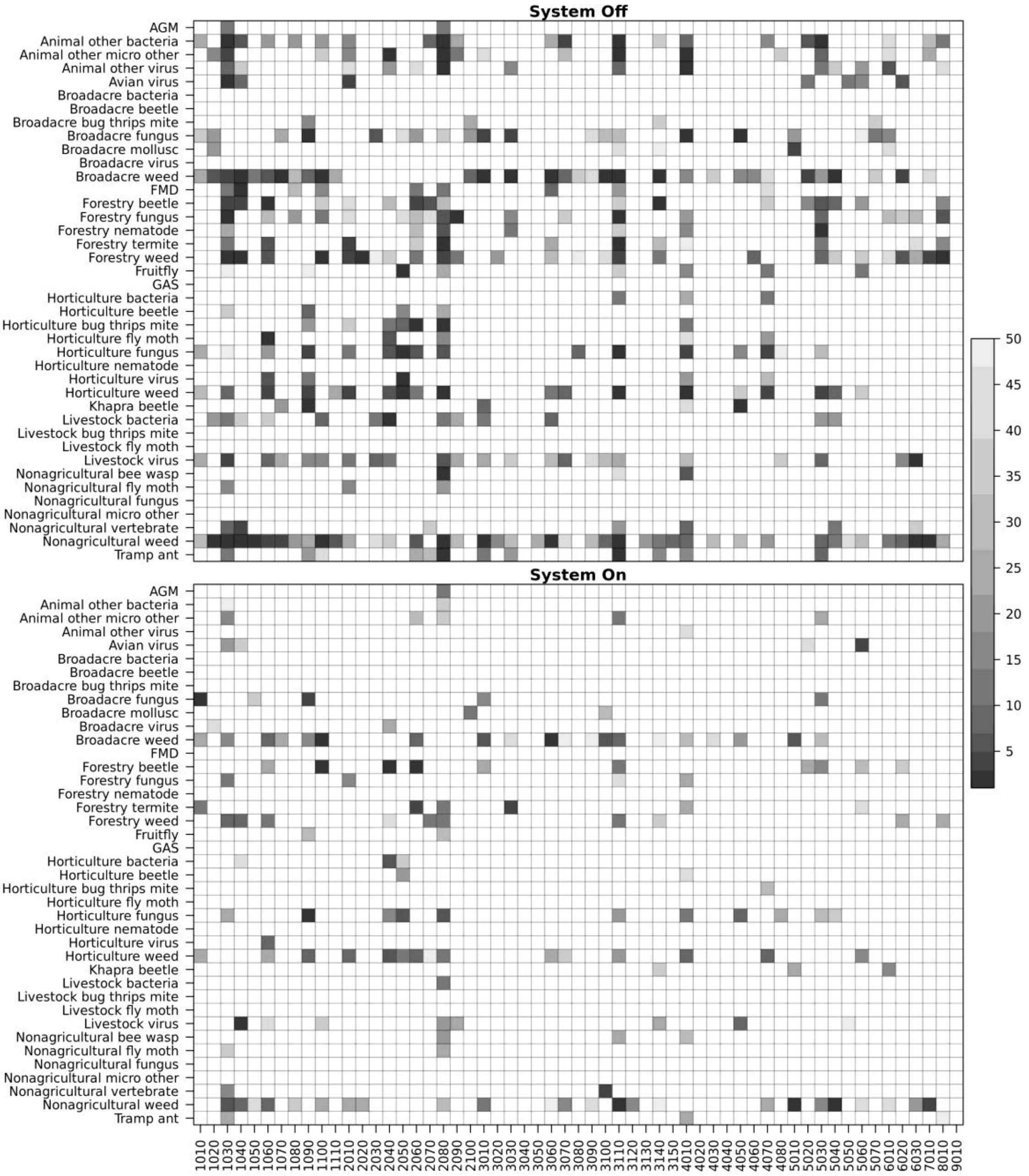

Figure 4: Location of initial establishments over time by functional group and NRM region for a single 50-year simulation of the system 'off' versus the system 'on'. The colour indicates the year of establishment (darker is earlier/longer).

## 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).

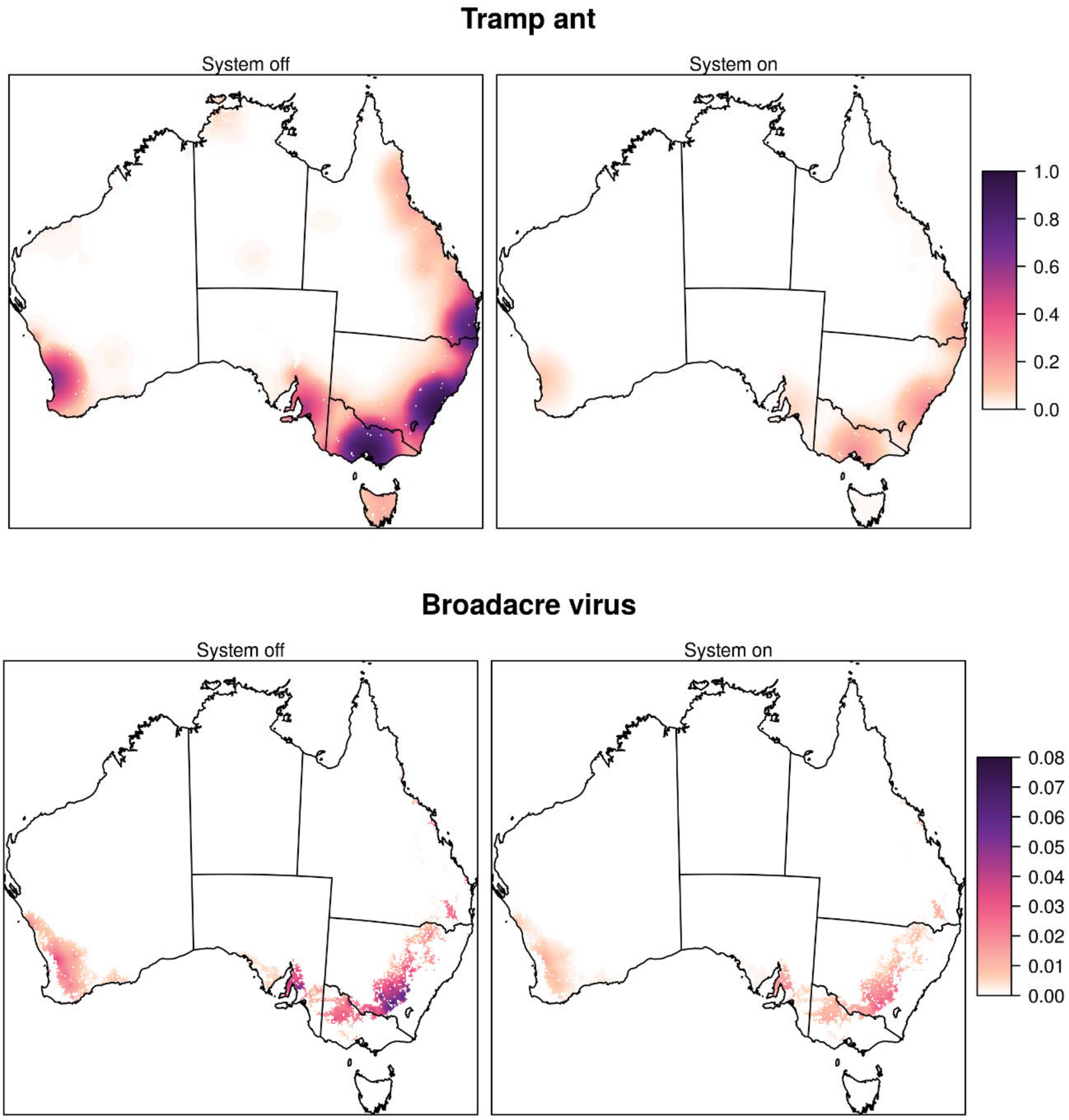

Figure 5: Probability of a pixel being infested/infected with either a tramp ant or a broadacre virus in the year 2040 dependent on the state of the biosecurity system.

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).

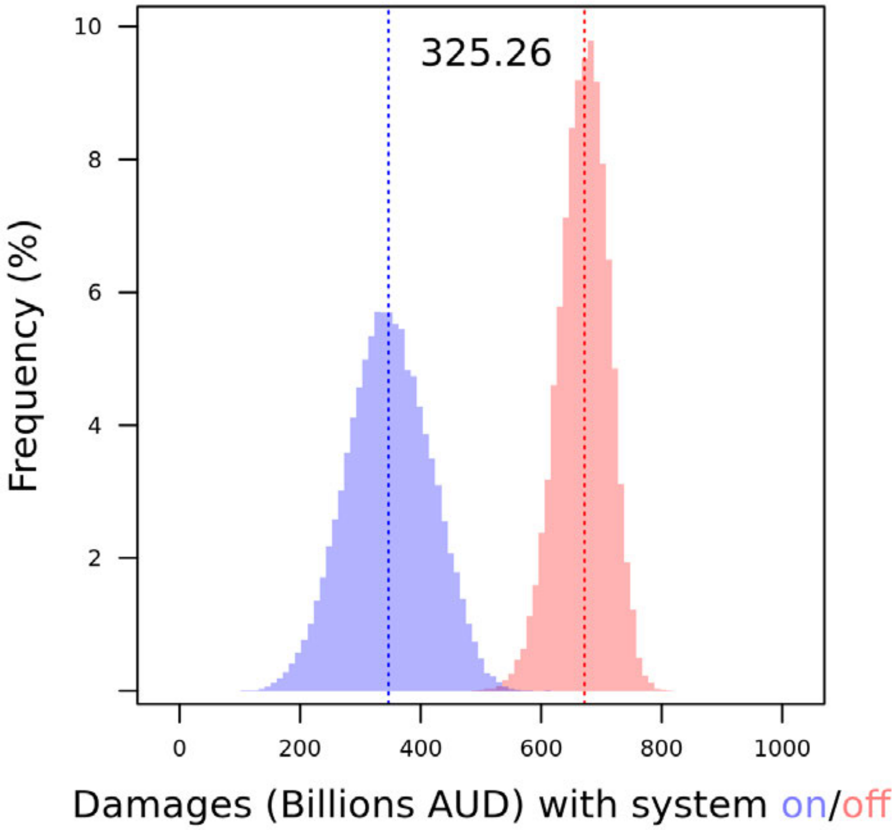

Figure 6: Overall damages over 50 years with the system on/off. Dotted line indicates the median damage estimate and the number indicates the damages avoided (benefit).

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%).

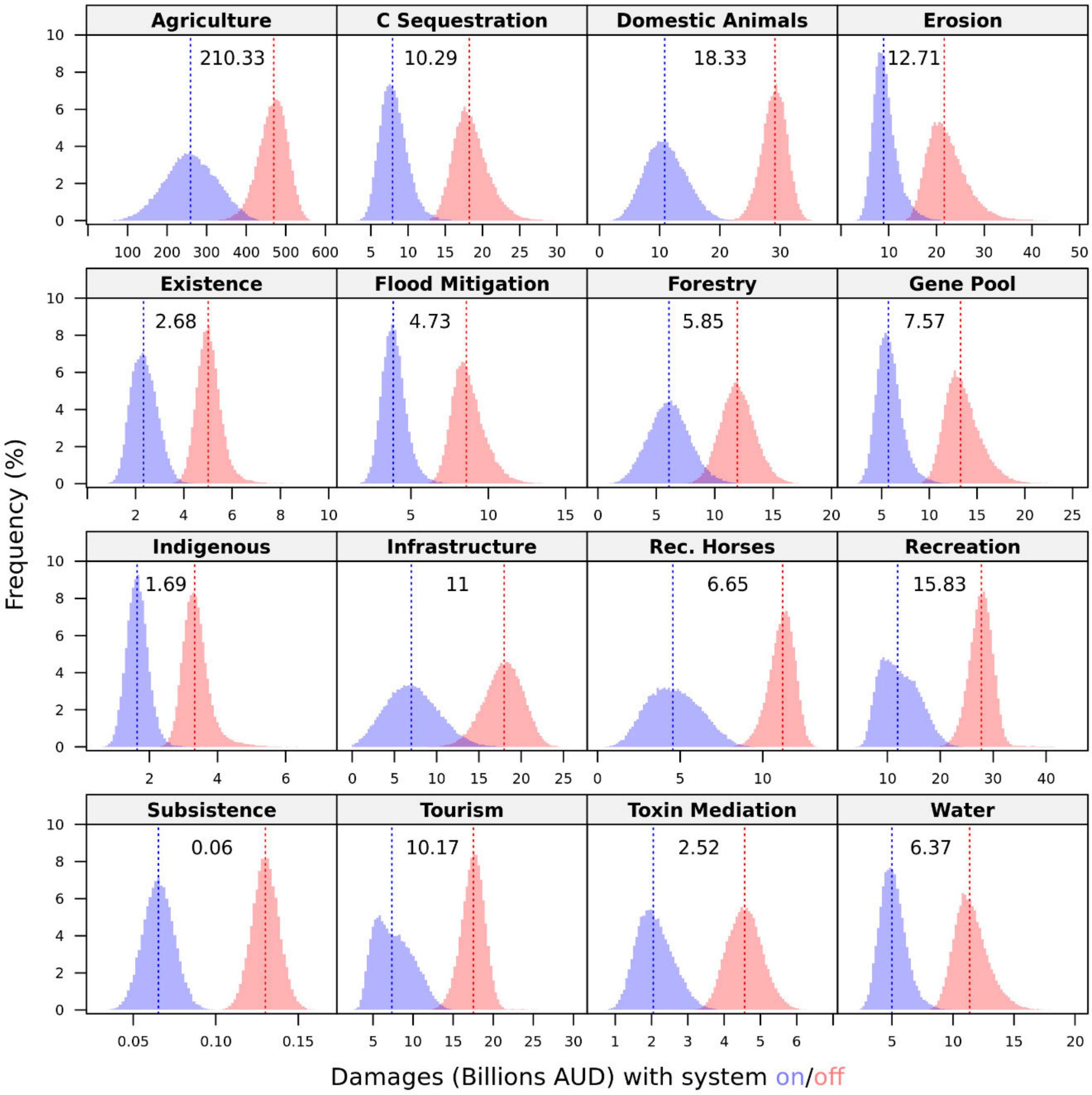

Figure 7: Total damages by asset over 50-years with the system on/off. Dotted lines indicate the medians and the number the damages avoided.

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).

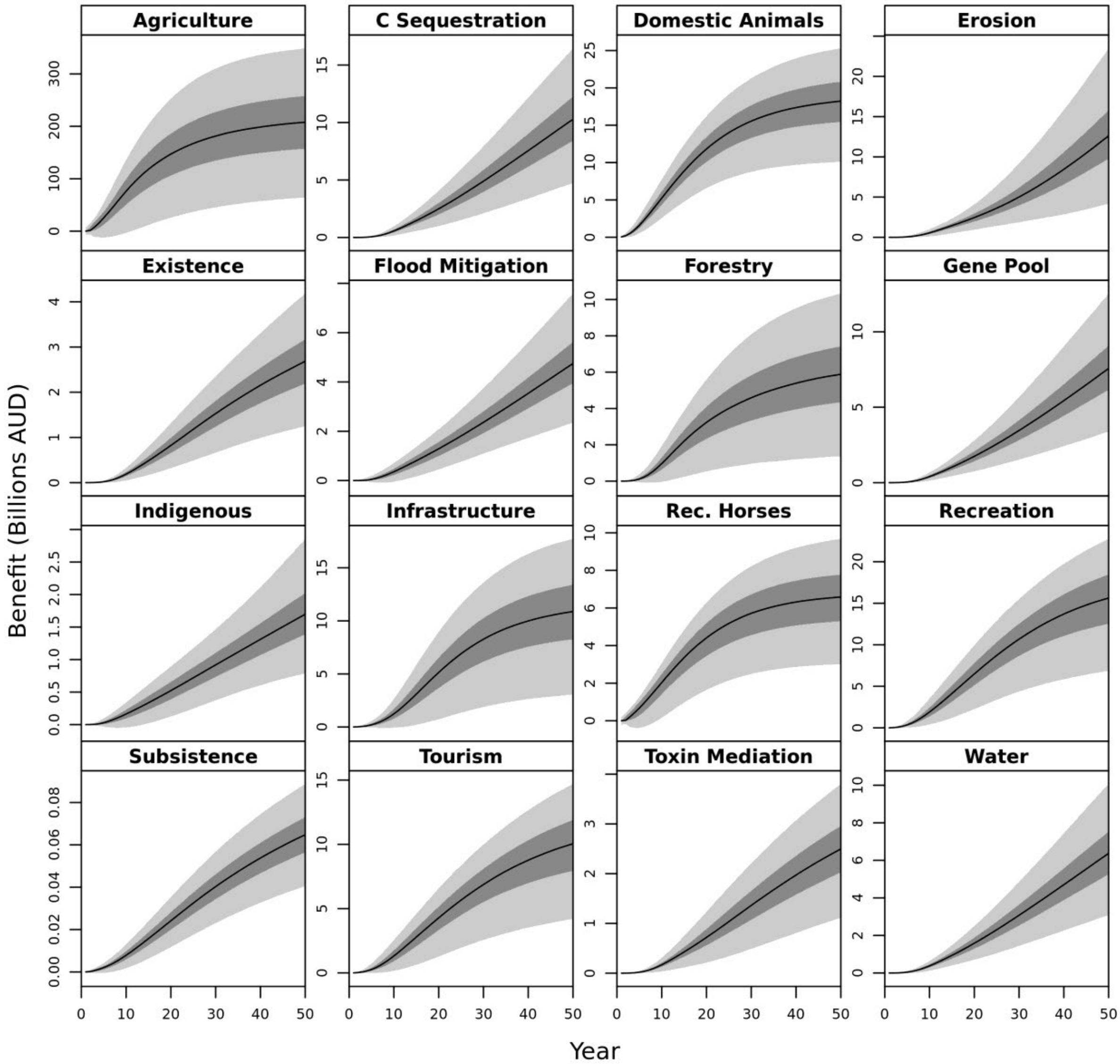

Figure 8: Total benefits of the biosecurity system, by asset, over 50 years. Solid line is the median, dark shading is the 50% interval, light shading is the 95% interval.

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

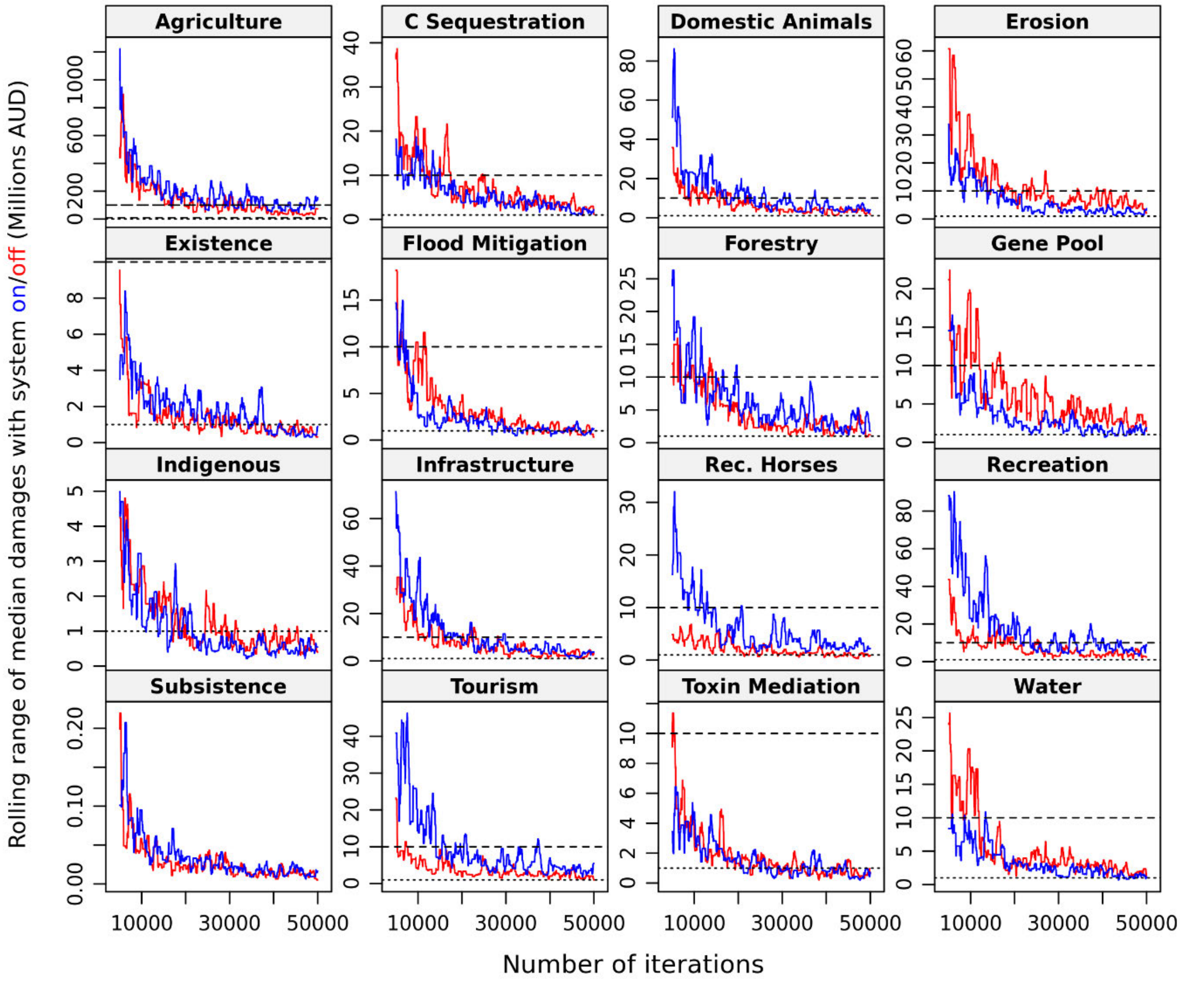

Figure 9: Variation in the median damage estimates over the last 1000 simulations. Red line is system off, blue line is system on. Dotted, en-dash and em-dashed lines indicate 1M, 10M and 100M variation in the median, respectively.

## 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.

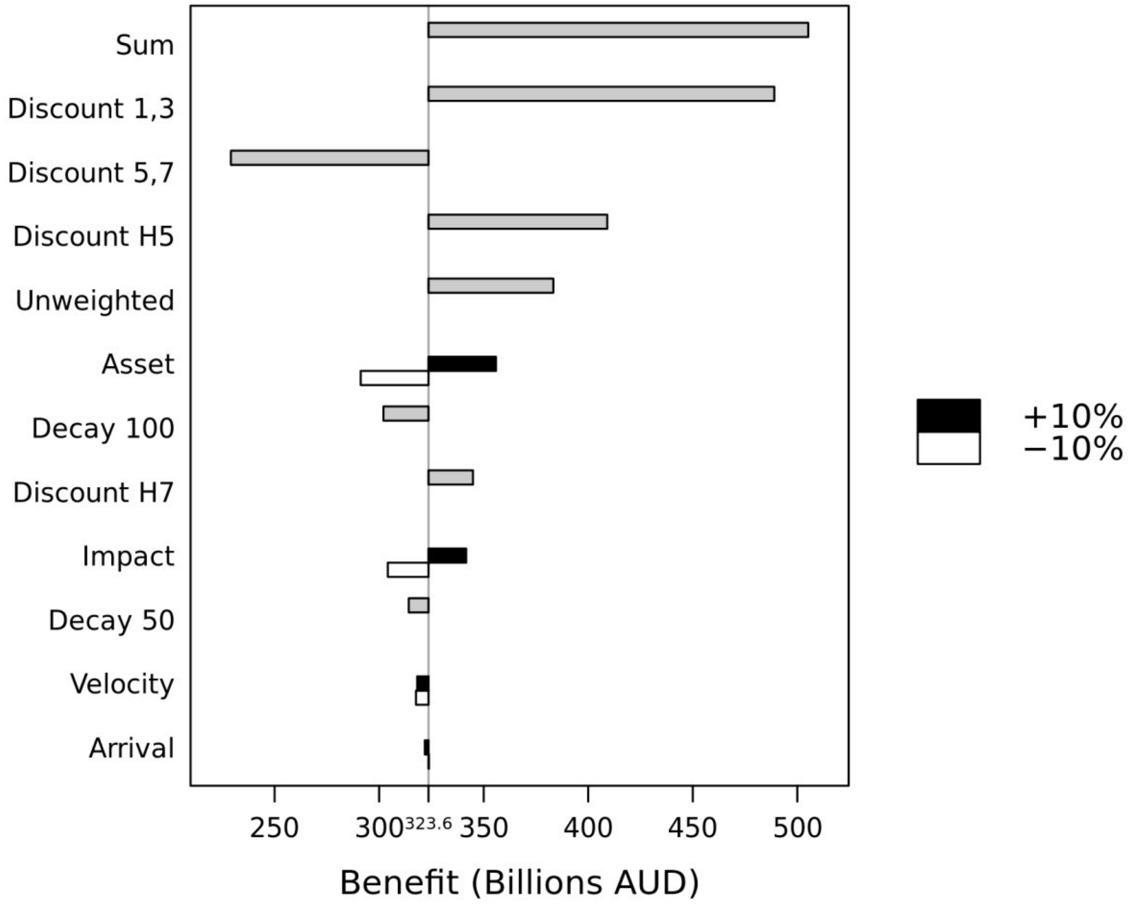

Figure 10: Sensitivity of the median benefit estimate to changes in select input variables. Coloured bars indicate a 10% change in the input, grey bars indicate a discrete change. Length indicates relative sensitivity to the input (i.e., influence increases with length).

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.

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PERSPECTIVES AND PARADIGMS

# The contribution of passive surveillance to invasive species management

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**Abstract** It has been recognised for some time that the community has an important role to play in invasive-species management. Reports from the community about new incursions can lead to significant cost savings when this early detection results in shorter management programs. Unfortunately there is little to guide invasive-species managers on cost-effective ways to elicit and incorporate information from the public in their pest-management programs. Not all community surveillance is equal: some information from the public about the presence of pests and diseases may arise from chance encounters, other data may be reported by stakeholders from a particular industry or by groups of volunteers organised on the basis of citizen science activities. While the resources, activities and effort required to encourage each type of community surveillance are known to differ, very little is known of the relationships that determine effectiveness, and thus the appropriate level of investment that would be required to encourage a particular level of reporting. In this research we focus on passive surveillance—the most fortuitous type of community surveillance—and review the current knowledge base on measuring its cost and effectiveness. We aim to stimulate the research required to improve our understanding of passive surveillance, and we provide guidance on the type of data that should be collected by agencies to enable this research. This information could then provide us with the ability to design optimal surveillance portfolios that integrate the surveillance opportunities provided by the public to best advantage.

**Keywords** Passive surveillance · General surveillance · Citizen science · Community engagement · Biosecurity · Cost-effectiveness

## Introduction

Biological invasions cause significant damage worldwide through their effects on human health, the environment and the economy (Aukema et al. 2011; Pimentel et al. 2005). As a result, considerable amounts of public and private funds are spent across the globe managing invasions (Sinden et al. 2004).

Surveillance is an essential part of invasive species management programs. The surveillance literature is extensive but its focus has been on decision-making in the *active surveillance* context, where targeted searching is conducted by trained personnel (Baxter and Possingham 2011; Bogich and Shea 2008; Cacho et al. 2006; Epanchin-Niell et al. 2014; Yemshanov et al. 2014; Spring and Kompas 2015) with little coverage

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of how to incorporate surveillance undertaken by members of the public into decision-making (Cacho et al. 2010; Cacho and Hester 2011; Cacho et al. 2007; Keith and Spring 2013). This is despite long-standing recognition within biosecurity agencies of the usefulness of reports from members of the community of their encounters with invasive species (Beale et al. 2008; MAFBNZ 2008). This recognition stems from important detections of new incursions, or new foci of existing incursions, as a result of reports by members of the public. For example, in Australia, reports from the public led to the initial discovery of the European wasp (Davis and Wilson 1991) and Khapra beetle (*Trogoderma granarium*) (Beale et al. 2008) in Western Australia, and red imported fire ant (RIFA) (*Solenopsis invicta*) in Queensland (Jennings 2004). In New Zealand members of the public were responsible for initial discovery of RIFA, crazy ant (*Paratrechina longicornis*), carpenter ants (*Camponotus* sp.*)* and fall web worm (*Hyphantria cunea*) (Froud et al. 2008), painted apple moth (*Teia anartoides*) (Harris 1988) and white-spotted tussock moth (*Orgyia thyellina)* (Hosking 2003).

Recognition of the usefulness of community surveillance for detecting new incursions, or new foci of incursions, has resulted in pest and disease management programs routinely including some level of investment in community engagement activities to encourage reporting. Such activities might include pest displays, newspaper or magazine articles, identification cards, posters or even rewards. The reporting mechanism is often through a telephone ‘hotline’ where calls are screened and subsequently directed to the relevant government agency for further action, which might include a site visit to confirm a detection followed by treatment and targeted surveillance by the agency.

Despite the routine nature of investment in community engagement activities in pest and disease management programs, little is known about the effectiveness of these activities. This means the level of community reporting that could be expected for a given level of investment cannot be estimated with information currently available. The most pressing knowledge gaps include: the types of activities that induce the most reporting; the likelihood that particular types of people will report pests; the reliability of these reports; and how characteristics of pests and diseases affect the level of reporting. Pest and disease management programs would greatly benefit from improved knowledge about passive surveillance, both in terms of detection of outlier infestations and early detection of new invasions.

In this paper we propose a typology for community surveillance but focus on the least studied type of community surveillance: *passive* surveillance. We provide a conceptual model for incorporating passive surveillance into incursion management programs, suggest the type of research needed to estimate optimal investment in passive surveillance, and propose a framework for gathering data.

## The surveillance continuum

The use of reports from the community of their encounters with invasive species has been variously termed passive surveillance (Cacho et al. 2010; Froud et al. 2008; MAFBNZ 2008), general surveillance (Hammond 2010) and citizen science (Silvertown 2009), each term indicating a surveillance process that is different to the organised, deliberate searching undertaken by pest management agencies. Passive surveillance, general surveillance and citizen science are often used interchangeably but there are important differences between them that need to be understood when planning types and amounts of investment in surveillance programs.

Describing and defining surveillance undertaken by the general public is not easy because sometimes their detections of invasive species occur completely by chance, while at other times they occur as the result of organised community or industry activities—there are different degrees to which detections can be considered accidental or fortuitous. This is illustrated using a ‘surveillance continuum’ (Fig. 1). At one extreme is the *active*, targeted surveillance carried out by pest-management agencies, involving deliberate, coordinated search for new or managed pests and diseases. At the other extreme is *passive* surveillance where members of the community report chance sightings of pests and diseases at their discretion. Their reports are particularly valuable if they lead to detections of new pests and diseases or information about new outbreaks of known incursions. Intermediate forms of detection include citizen science, where scientists and volunteers collaborate on specific pest and disease surveillance projects (see for example: Devictor et al. 2010; Dickinson et al. 2010; Silvertown 2009) and general

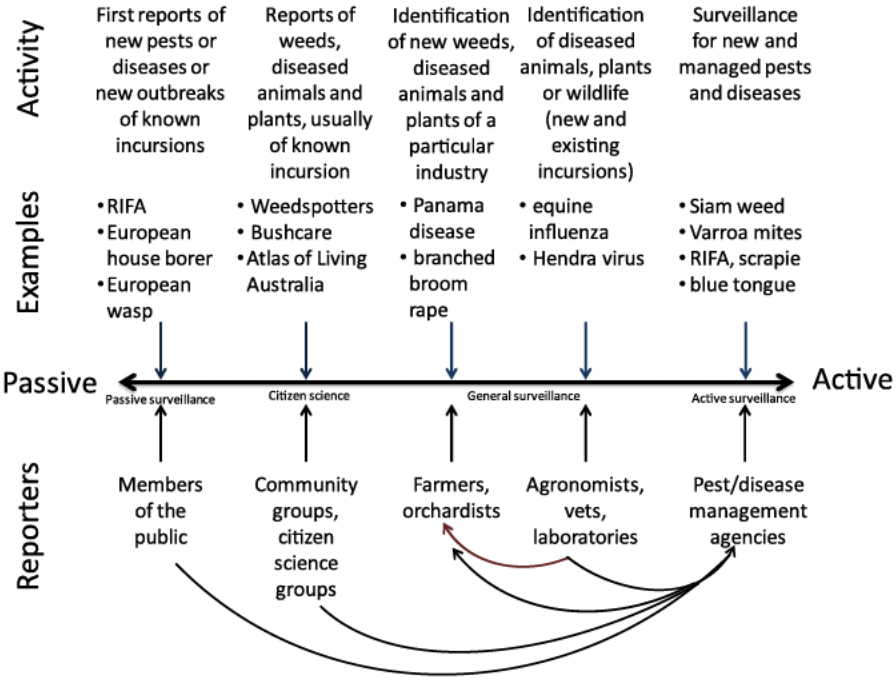

**Fig. 1** Illustration of the surveillance continuum with selected Australian examples

surveillance where stakeholders of agricultural industries detect and report incursions that affect their particular industry (see for example: del Rocio Amezcua et al. 2010; Hammond 2010; Hernández-Jover et al. 2011; Rautureau et al. 2012).

## Passive surveillance

Passive surveillance can be defined as any encounter with a pest by members of the public that is reported to the relevant authority. As discussed earlier, passive surveillance is the most fortuitous and accidental of all types of community surveillance (Fig. 1). It is activated and maintained through public awareness campaigns and their associated community engagement activities.[1] Community engagement activities about invasive species are known to raise awareness of that issue (Marchante et al. 2010; Martin 2007; Reis et al. 2011), result in increased passive surveillance (Brooks and Galway 2008; Witmer et al. 2007), reduce reporting times following detection (Hawley 2007), and increase cost-effectiveness of public engagement events over time (Cacho et al. 2012).

The action of detecting a pest by a member of the public is known as a *passive detection* (Cacho et al. 2010). Understanding the factors that drive the *probability of passive detection*—the likelihood that a pest or disease will be detected and reported—is key to understanding the level of investment required to achieve a given level of passive surveillance. The probability of passive detection depends on (1) the probability that a species is present in the landscape × (2) the probability of a person detecting it × (3) the probability that it is reported (given it is detected). In this paper we describe a framework for data collection that would allow us to understand how to increase (2) and (3), with (1) given. Keith and Spring (2013) used data collected during the RIFA Eradication Program in Queensland to report the only known published estimates of the probability of passive detection: 0.02 and 0.01 per month for urban and rural areas respectively. The difference in the values reflects the lower population density in rural areas. These are considered to be 'background' estimates because they do not distinguish between passive detections made before community engagement and after community engagement, but are nevertheless valuable.

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[1] We acknowledge the importance of community reporting that is not in response to any pest-specific community engagement activity—often these reports are responsible for the first known incursions of a pest. The level of biosecurity awareness that drives those completely passive detections is not explored in this paper.

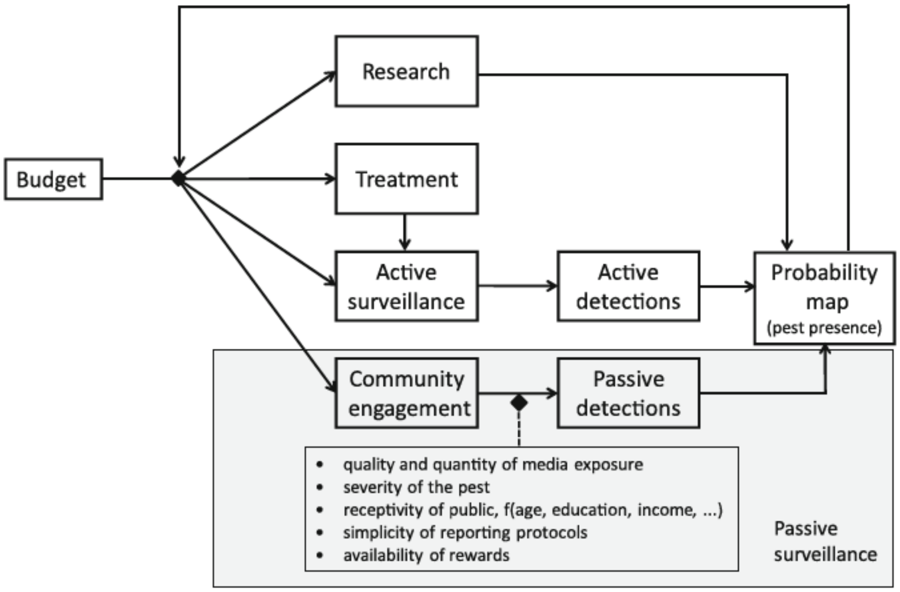

**Fig. 2** Conceptual model of a pest-management protocol featuring passive surveillance and community engagement

## Incorporating passive surveillance into pest and disease management programs

Agencies involved in the management of invasive species must allocate a limited budget across a range of activities. Their decision problem is illustrated in Fig. 2. The budget constrains the options available to design and implement a management strategy, but the goal should be to use the budget as efficiently as possible. The management strategy regulates the allocation of resources based on the best information available, often represented as a probability map. This might be a detailed map containing actual probabilities, or a priority list of sites to be monitored and treated as necessary.

There are usually four key activities that are funded as part of pest-management programs: treatment of known infestations; research to improve future management decisions; active surveillance; and community engagement to encourage the public to keep an eye out for the pest and report infestations—passive surveillance. The optimal allocation of resources between these activities will depend on their relative effectiveness and cost, with the allocation changing as management actions evolve in response to an incursion. The relationship between the effort put into passive surveillance and its outcomes is difficult to measure compared with the other activities in Fig. 2 whose effectiveness can be measured in more direct ways (Baxter and Possingham 2011; Cacho et al. 2006; Leary et al. 2013; Moore et al. 2011; Reed et al. 2015).

Ideally, pest management authorities would know the probability of passive detection and how this value relates to the probability of successfully achieving particular management goals. This is illustrated in Fig. 3. Increases in the probability of passive detection improve the probability of achieving eradication and containment (Panel A). The key is to understand the level of investment in passive surveillance required to induce particular values of the probability of passive detection and how this affects the management program. For example, increasing the probability of passive detection from ***a*** to ***b*** in Panel (A) (0.3–0.7 in this example) results in the probability of successfully eradicating a pest rising from 0 to 0.3, total eradication program costs fall from $4.8 to 3M (Panel B)—the pest is eradicated more quickly. Without information on the level of investment in community engagement activities required to induce the increase in probability of passive detection, we can only conclude that a pest management agency should be willing to spend up to $1.8M on these activities.

## Research needs and data requirements

Unfortunately current knowledge and data collection practices by pest-management agencies do not provide enough evidence to quantify the relationship between

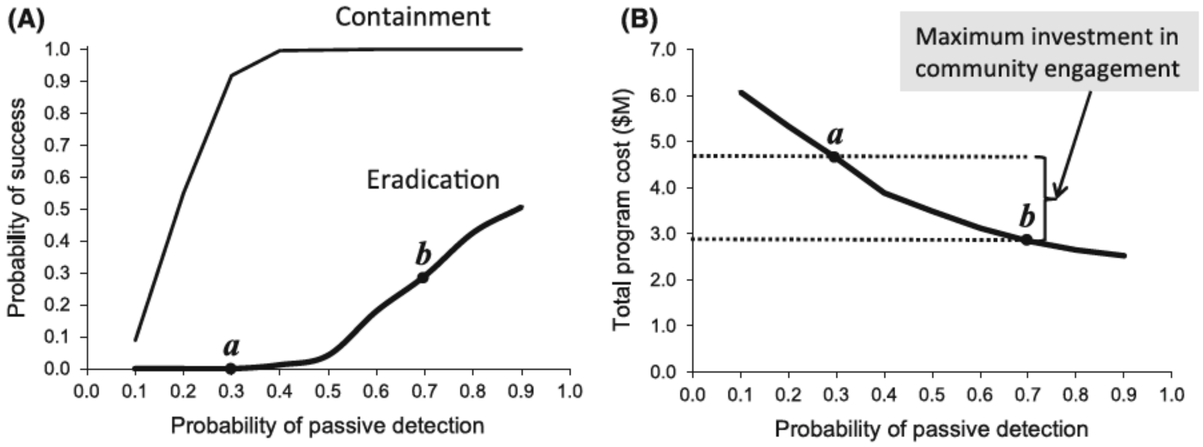

**Fig. 3** An illustration of the effect of passive surveillance (as probability of passive detection) on the probability of successful eradication and containment of a pest (**a**) and on the cost of achieving this success (**b**). Improving the probability of passive detection improves success and reduces total program costs. In this example the maximum investment in community engagement to increase the probability of passive detection from ***a*** to ***b*** in (**a**) would be the vertical difference between ***a*** to ***b*** in (**b**). *Source* redrawn from simulation data reported in Cacho et al. (2012) and Cacho and Hester (2011)

investment in community engagement and the subsequent changes to reporting by the public. There are many dimensions to this problem and understanding the intricacies is crucial to designing efficient community engagement strategies.

Undertaking community engagement activities in invasive species management has similarities with public policy initiatives such as encouraging natural disaster preparedness, providing a hotline to encourage the reporting of neighbourhood crime to police, or persuading people to wear a face mask during an influenza epidemic. Such behaviours generally require some effort on the part of the individual, and while they may or not may not have individual benefits they all have substantial public benefit. There is evidence that the propensity of members of the public to undertake these behaviours is influenced by demographic factors, including age, socio-economic status and ethnicity. Studies demonstrating these relationships have been in areas that include weed management (McCluggage 2004), influenza communication campaigns (Bish and Michie 2010; Eastwood et al. 2009; Gray et al. 2012), law enforcement (Huq et al. 2011), and natural hazard preparedness (Paton et al. 2006).

The literature on community engagement and public attitudes to invasive species (Bremner and Park 2007; DEFRA 2008; Kruger et al. 2012) suggests that the response of the public to awareness activities surrounding invasive species is likely to depend on[2]:

1. Attributes of the community engagement activities, such as message content, media channels, additional media reporting, provision of feedback, ease of reporting, frequency and location of activities;
2. Demographic factors within a community, such as age, gender, knowledge, altruistic or materialistic tendencies and concern for the environment.
3. Attributes of the pest, such as its potential to cause physical harm or financial costs, and its detectability within the local environment;

We now explain how each of these might be measured.

## Attributes of community engagement activities

To understand whether attributes of different activities make them more or less effective in terms of the probability of passive detection, information should be collected on the type of activity undertaken, the timing and location of any reports made, and the number of

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[2] It may also be the case that active surveillance activities in an area—visibility of traps and pest-management officers—could in turn increase the probability of passive detection, although this remains to be tested.

detections resulting from these reports, including the number of false positives. There are several ways to measure effectiveness of a given activity, for example: the total number of detections; the number of detections per time period; or the number of reports (positive and negative) per time period. These values could simply be monitored for each activity over time or formal statistical measures could be designed to determine the relationship between effectiveness and explanatory factors such as pest characteristics, event duration, location and reporter characteristics. To test hypotheses regarding these relationships, data with enough variation in all factors are required so that statistical tests can be applied.

### Demographic factors

People respond in different ways to information campaigns, advertisements, rewards and other activities designed to stimulate passive surveillance. Assuming that reporting procedures are available and are not onerous, people's responses, in combination with the presence of the pest in a particular area, will determine the probability of passive detection.

Community engagement activities will raise community awareness temporarily and have limited spatial influence (Cacho et al. 2012). This means it is important to understand the spatial reach of a particular event and the length of time that the event will remain in the memory of the public. This would allow pest-management agencies to choose the appropriate timing and location of community engagement events. The spatial influence of events is difficult to ascertain as events vary in size, duration and population catchment and hence would vary in their spatial influence. There are also likely to be spatio-temporal correlations between events and passive detections that must be disentangled using statistical techniques.

Cacho et al. (2012) reported frequency distributions of distances between events and subsequent passive detections in the RIFA Eradication Program in Queensland (Fig. 4). For a single year the authors found a 'distance threshold' at approximately 4.2 km, at which the average event starts losing its effect on public awareness (Fig. 4a), but high variability of the data means that statistical tests are not significant. A similar relationship was found when all previous years of events were used, with the distance threshold at just above 1 km (Fig. 4b), suggesting that the effect of events depreciates over time.

### Attributes of the pest and invaded environment

An important aspect of passive surveillance programs is the ability of the reporter to accurately identify the target species being reported. This is likely to be related to the characteristics of the pest and whether it is easily identifiable in the landscape. Of particular concern is the rate of false positives, where the target pest is reported as present when it is in fact absent. The false positive rate is important because, in order to eradicate an invasion, all detections reported by the public must be followed up and the pest treated if present. A rate of false positives that is too high will result in wasted program resources by leading to unnecessary active surveillance (Spring and Cacho 2015) and may negate the benefits of passive detections.

False positives may also occur because the pest is hard to identify or because the community engagement activities have been badly designed or targeted but this remains to be tested. False positives may also decrease over time as knowledge about a pest improves. The widespread use of smartphones in the community has allowed the development of applications that may result in a reduction in false positives. Some applications send photos of a suspected pest or disease to pest-control agencies for identification and verification, while others contain photos of invasive species that should be reported.

Reliability of reports about a pest, either in response to a particular activity or bundle of activities, may be measured from data on the number of reports and the number of false positives over time. Froud et al. (2008) used positive predictive value (PPV)—the proportion of the total number of reports that are confirmed as positive—to measure the reliability of the general public's calls to New Zealand's Exotic disease and pest emergency hotline. Over a 3-year period, although the PPV was only 2%, reports from the public were responsible for 49% of all the new exotic organism detections (355 detections in total). Cacho et al. (2012) used PPV in their analysis of data from the RIFA Eradication Program in Queensland to suggest the program's community engagement activities had become more effective over time—PPV increased from 1.1 to 6.1% during the first 10 years of the

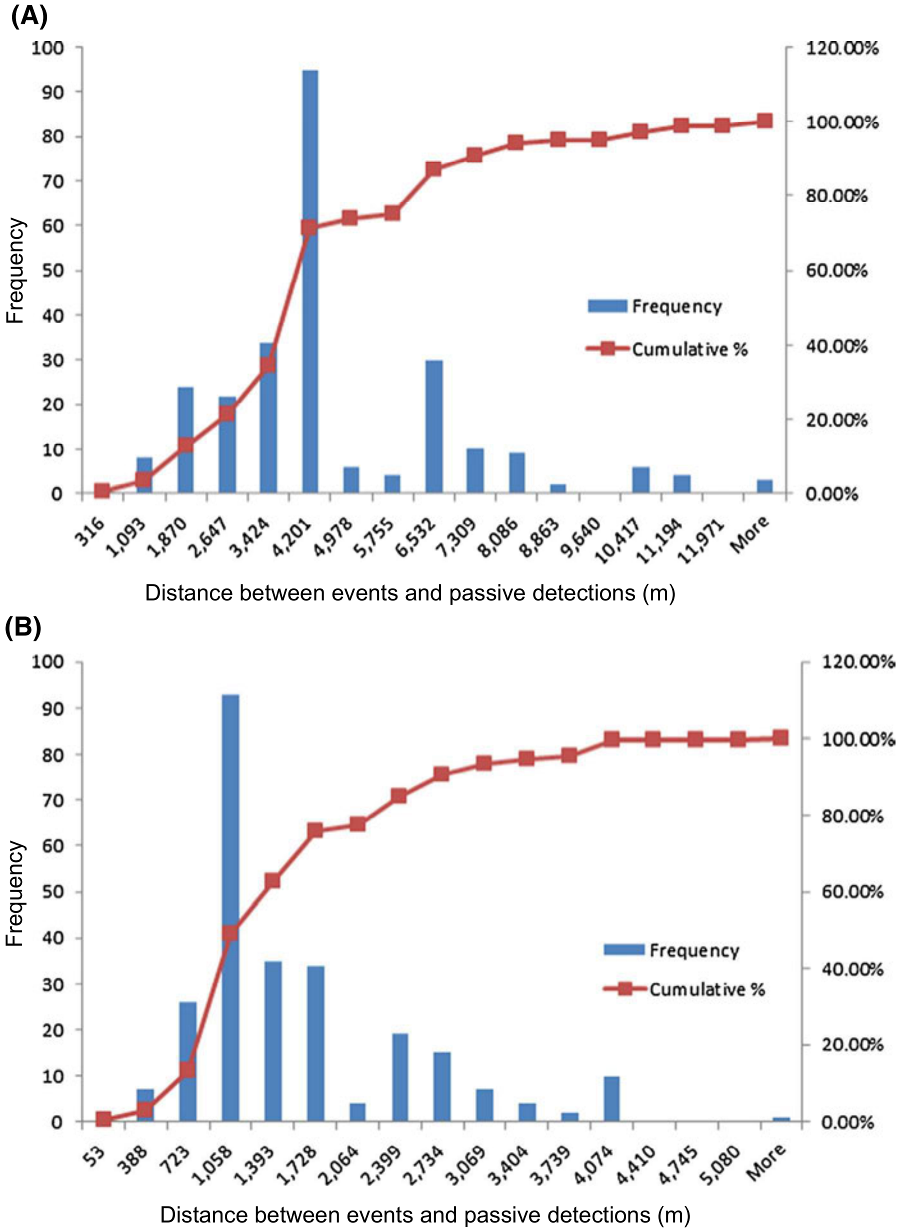


**Fig. 4** (**a**) histogram of distances from each passive detection in 2008 to the nearest event in 2007; there appears to be a distance threshold at ~4.2 km at which the average event loses its effect on public awareness. (**b**) histogram of distance from each passive detection in 2008 and the nearest event for all years prior to 2008; again there is a clear threshold, but this time at just over 1 km. *Source* Cacho et al. (2012)

program. The question is then whether the damage that was avoided through passive detections outweighs the cost of following up on all public reports.

If enough published results were available, a meta-analysis (Dodd et al. 2015; Gurevitch and Hedges 1999) of community engagement activities could be used to test hypothesis regarding pest characteristics that make them amenable to detection and reporting by the public. Anecdotal evidence suggests pest characteristics that make them amenable to reporting include: whether they bite or sting; whether they are easily observable and identifiable in the landscape;

and whether a pest is easily distinguishable from similar species in the landscape.

Unfortunately not enough published data are available for any meaningful meta-analysis to be undertaken currently. Additional data collection from current and past programs will be required. New data collection could also involve expert consultations and detection experiments with volunteers (Hauser et al. 2012; Moore et al. 2011).

## Investment in community engagement

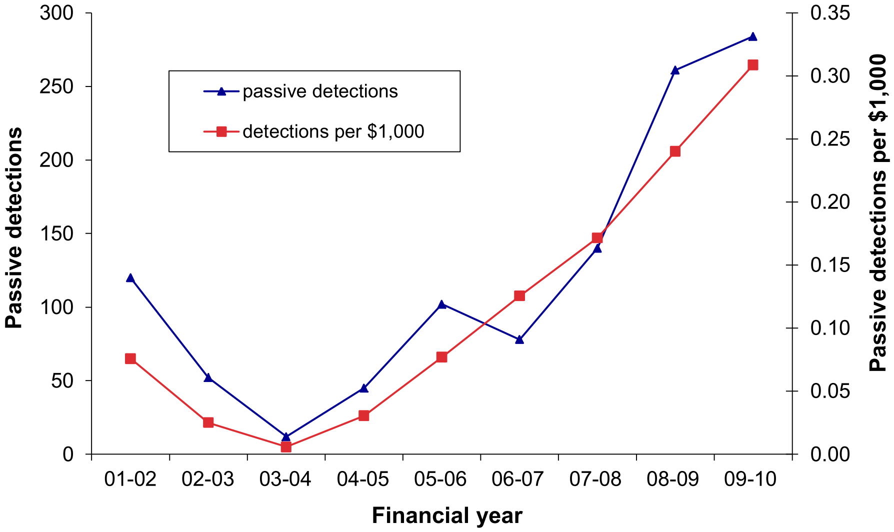
The key reason for collecting and analysing data on community engagement activities is to efficiently allocate limited pest-control budgets to passive surveillance. As discussed earlier, the optimal allocation of resources to community engagement activities, and thus to passive surveillance, depends on their relative cost-effectiveness compared to the other activities that are usually funded as part of pest-management programs (Fig. 2). Measuring the cost-effectiveness of passive surveillance would require analysis of community awareness activities, relating expenditure on the activities to particular outcomes, such as the number of reports or detections by members of the public. Data on the spatial and temporal aspects of the awareness activities and subsequent reports, including characteristics of the individuals making the reports, would also provide useful information to allow better targeting of activities and events. This type of data is seldom recorded or reported by pest-management agencies.

Although this has not been proven empirically, one would expect passive detections to exhibit diminishing returns with respect to exposure to community engagement activities. This may be related to the timing, intensity and location of activities, but may also be related to the diverse range of attitudes in human populations.

(Cacho et al. 2012) calculated the change in the frequency of passive detections per $1000 spent on community engagement for the RIFA Eradication Program in Queensland (Fig. 5). Although a significant increase in detections per dollar is evident between 2003 and 2010, this cannot be used as a measure of cost-effectiveness of community-engagement. The increase in passive detections could have been caused by a combination of factors, including an increase in the number of nests available to be detected, combined with human population growth in the area infested leading to more people being available to detect nests.

In the current context the costs of community engagement depend on the types and scale of activities undertaken, the benefits are improved detections of invasive species, leading to reduced future damages. The only known attempt to estimate the monetary value of community engagement to enhance passive surveillance is that of Cacho et al. (2012), who estimated the savings in active surveillance that were achieved through reports from the public in the RIFA

**Fig. 5** The number of passive detections and passive detections per $1000 per financial year for the RIFA Eradication Program in Queensland. *Source* Cacho et al. (2012)



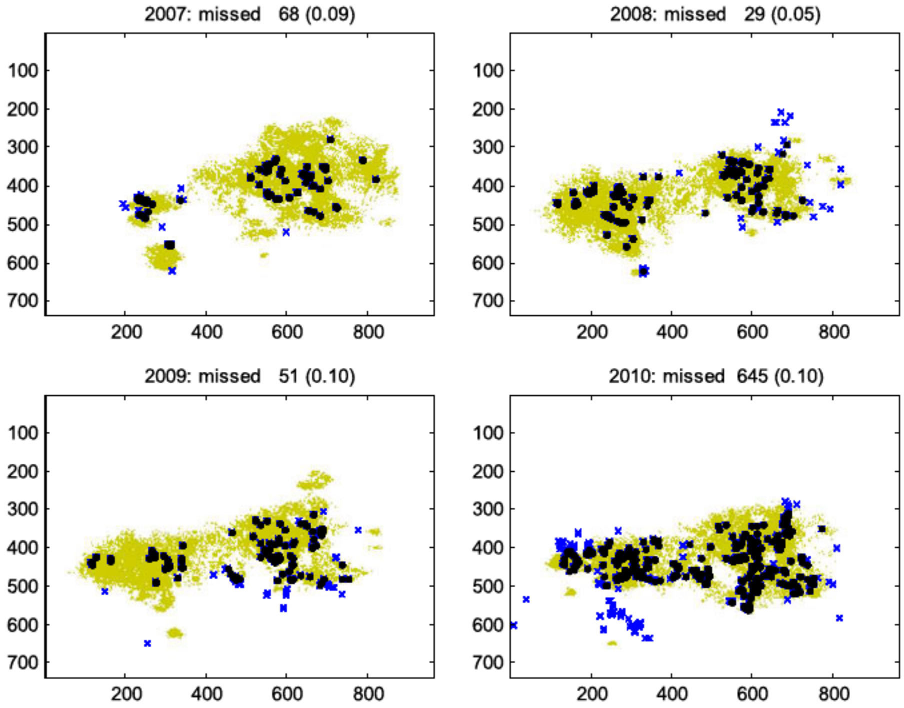


**Fig. 6** Detection maps for fire ants (*Solenopsis invicta*) invasion in Brisbane, Australia for 2007 to 2010. Actual detections are indicated with *x markers*, *green dots* represent the area that would be covered with active surveillance when a large budget (enough to cover 80,000 ha) is available. Search points were allocated based on probability maps generated using the model of Schmidt et al. (2010), which calculates probability of pest presence spatially at annual intervals based on known ant colony locations using a Bayesian approach. *Blue x markers* indicate actual passive detections that would not have been detected if only passive surveillance were available. These missed detections for different budgets were used to construct a counterfactual to calculate the value of community engagement in the RIFA program

Eradication Program in Queensland. They estimated that $1m invested in public engagement activities had resulted in $60m saved in active surveillance costs between 2006 and 2010. To calculate this figure it was necessary to construct a counterfactual—the likely outcome in the absence of community engagement activities—and this involved some modelling. The amount of active search that would have been required to detect all the known ant colonies in the period 2006–2010 if passive surveillance had not been available was estimated from the data. In the counterfactual, all nests had to be detected using active surveillance, with the search area allocated based on a probability map (Fig. 6) generated using a modified version of the model of Schmidt et al. (2010). Combining this information with an active search cost of $400/ha, resulted in an annual return of $52 million in avoided active surveillance costs. Comparing this figure to an average community engagement budget over the same period of $860,000 results in a return on investment of $60 per $1 invested in community engagement.

As can be seen in this example, to generate credible estimates of the benefits and costs of passive surveillance we require a counterfactual, which is unobservable. This means we need to combine empirical evidence with modelling of the managed spread process. The data required to generate solid estimates of the counterfactual is not available for most invasions, hence our emphasis on the need to collect the right data.

## The optimal level of passive surveillance

Economic principles prescribe that resource allocation should be based on marginal quantities (rates of change) rather than absolute quantities. The optimal operating point is where the marginal benefit of an action equals its marginal cost. In many practical situations, however, it is not possible to calculate the cost and benefit functions required to derive marginal values through differentiation. This is one reason benefit-cost analysis (BCA) is popular. In BCA total benefits are compared to total costs (in present-value terms) for different scenarios, and the alternative with the highest benefit-cost ratio is selected (Hester et al. 2013).

In the current context, the optimal level of passive surveillance would be where the marginal cost of increasing passive detection by one unit equals the marginal benefit of doing so. That is the point at which the resources employed to activate and maintain passive surveillance are used most efficiently. The actual optimisation problem is more complex than this because of its dynamic nature—pests available to be detected today depend on previous control actions that have been taken, and the marginal benefit and marginal cost functions may change through time.

To estimate the marginal cost of passive surveillance we need to derive a function relating expenditure on community engagement activities to the probability of passive detection. The derivative of this function could then be used to calculate the marginal cost of increasing passive detection probability. On the benefit side, the ideal approach would be to measure the additional benefit as the avoided damage achieved by increasing passive detection probability plus the reduction in eradication costs from savings in eradication-program duration (Kompas et al. 2016). In practice, measuring this relationship would require experiments where the treatment can be compared to a control. Alternatively, the benefit function could be inferred through modelling (as in Cacho et al. 2012).

## Concluding comments

There is no doubt that the community has an important role to play in the management of invasive species. This could occur through involvement of organised groups of volunteers in citizen science activities, using information supplied by stakeholders of a particular industry, or through individuals who are motivated to report chance sightings of pests as they go about their everyday life. The typology we present is aimed at improving the way we manage biological invasions by understanding how different types of community surveillance operate within a continuum.

We focus on passive surveillance, the extreme in the surveillance continuum for which very little is known. Despite expenditure on community engagement activities becoming a routine aspect of pest-management programs across the globe, only a small amount of published research on aspects of community engagement effectiveness exists. Our aim is to suggest a course of action for research on passive surveillance and to identify data needs. Our ultimate aim is to guide collection of quantitative information that will enhance our understanding of passive surveillance in a meaningful way, as a component in a surveillance continuum. Much of the data required for the analysis is relatively easy to collect.

Research linking the effectiveness of different types of community engagement activities to passive surveillance is needed not only to improve efficiency in the use of public funds, but also to reduce the damage caused by invasions through early detection with assistance of the public. This research must consider spatial and temporal variation in the invasion process as well as its interactions with human populations. Filling the research gaps identified in this paper should enable the development of cost-effective strategies to get the most out of members of the community in managing invasive species.

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