Developing models for the spread and management of National Priority Plant Pests

Technical Report for CEBRA project 170606

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Executive Summary

Invasive plant pests and diseases pose a significant threat to Australia in terms of agricultural production losses, loss of market access, environmental damage, and loss of amenity. Australian governments invest in the mitigation of these risks through improved border management, early detection surveillance, and effective contingency plans for containment and eradication. Effective deployment of resources for early detection surveillance will pre-emptively lower Australia's potential liability for incursion costs.

The significant resources consumed during emergency response to major pests can be reduced by a more informed understanding of the relationship between pests, the incursion environment and surveillance information. Modelling can guide policy makers on the appropriate course of action for response management, including technical feasibility and the cost benefit of eradication or containment. It is, however, extremely challenging to develop a generic decision support tool for plant pests and diseases given their tremendous diversity (spanning insects, bacteria, viruses, fungi, molluscs, and nematodes). Species-specific models may offer high biological and ecological fidelity and allow pest-specific policy questions to be posed, but may not be readily extended to other pests. Generalised models may cover a broad range of pests but be unable to adequately represent biological and ecological subtleties, and support policy specific to individual pests.

The mandate of CEBRA project 170606 'Developing models for the spread and management of National Priority Plant Pests', was to develop a flexible modelling framework that would allow decision support tools to be constructed cost efficently for a wide range of plant pests and pathogens. The chosen approach was to redevelop the Commonwealth's Australian Animal DISease Model (AADIS), to simulate the spread and control of plant pests, on both a regional and national scale. The new model is called APPDIS - the Australian Plant Pest and DISease model.

APPDIS can represent a pest population as a point incursion or an established population at specified locations. The pest population waxes and wanes over time based on configurable criteria such as temperature, rainfall, elevation,

vegetation, land use, and wind. Spread is modelled through steady diffusion into adjoining areas (for example, through natural dispersal), and/or sporadic longer-range jumps (for example, via human-mediated hitchhiking). Detection of a plant pest may occur through general surveillance, early detection surveillance (based on an established trapping grid), or delimiting surveillance. A multi-part treatment program progressively reduces a pest population and is followed by post-treatment surveillance that will either conclude that the pest has been eradicated, or trigger further treatment. All control and eradication activities are dynamically constrained by the available resources, and costed for the purposes of relative comparisons of control strategies.

The APPDIS modelling platform is a flexible decision support framework to assist policy makers evaluate strategies for the detection and control/eradication of economic and environmental pests, with respect to efficacy and cost. As per the AADIS model, incursions, detection, surveillance, treatment, and proof of freedom are all graphically visualised as they occur. The model may thus also be useful for communicating incursion dynamics and policy concepts in a classroom setting.

Two case studies are provided to illustrate the flexibility of the model: a regional-scale study of the control/eradication of an established tramp ant population, and a national-scale study of the detection and eradication of an exotic fruit fly, after a point incursion.

Acknowledgements

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Glossary of acronyms

Name	Description
AADIS	Australian Animal DISease model
APPDIS	Australian Plant Pest and DISease model
ABARES	Australian Bureau of Agricultural and Resource Economics and Sciences
ABM	Agent-based model
CA	Cellular automaton
CEBRA	Centre of Excellence for Biosecurity Risk Analysis
CSV	Comma-Separated Values
DDL	Data definition language
EBM	Equation-based model
FMD	Foot-and-mouth disease
FSM	Finite-state machine
GA	Geographic automaton
GIS	Geographic information system
ha	hectare
JVM	Java Virtual Machine
NPPP	National Priority Plant Pest
NDVI	Normalized Difference Vegetation Index
PDF	Probability density function
SQL	Structured Query Language
YCA	Yellow Crazy Ant

1 Introduction

1.1 Project overview

In 2016, Australian governments identified and endorsed 42 groups of plant pests as National Priority Plant Pests (NPPP), in order to focus attention on major threats posed to agriculture, environment and amenity. Biosecurity activities to manage the risk associated with NPPP include improved border management, early detection surveillance, and effective contingency plans for containment and eradication.

The considerable resources consumed by early detection surveillance and emergency response, can be reduced by a more informed understanding of the relationship between pest ecology, the incursion environment, surveillance information, and control methods. These spatiotemporal relationships can, however, be complex and difficult to understand without the aid of computer-based models.

The mandate of CEBRA project 170606 ‘Developing models for the spread and management of National Priority Plant Pests’, was to develop a flexible modelling framework that would allow cost efficient decision support tools to be constructed for a wide range of plant pests and pathogens. The chosen approach was to redevelop the Commonwealth’s Australian Animal DISease Model (AADIS) (Bradhurst et al., 2015; 2016), to simulate the spread and control of plant pests, on both a regional and national scale. The AADIS model, was originally created to assist with the development of emergency animal disease policy. It allows relative comparisons to be made (in terms of efficacy and cost), between candidate strategies for the

detection of, control of, and proof of freedom from, animal disease. This report describes the redevelopment of the AADIS model as APPDIS (the Australian Plant Pest and Disease model), a decision support tool to help guide policy on early detection surveillance and response management strategies for plant pests.

Effective early detection surveillance can pre-emptively lower Australia's potential liability for incursion costs. Modelling approaches need to consider the likely points where a pest can establish and the early stages of 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. The APPDIS model allows a plant pest incursion to be simulated anywhere in Australia 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 plant pest may arise from early detection surveillance (based on a national trapping grid), or general surveillance. 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 plant pest relies upon adequate delimitation of an incursion. It can be challenging to estimate the extent 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 efficacy and cost). All control actions simulated by APPDIS have user-defined durations, costs, and resource requirements. This allows useful investigation into the impact of resource shortfalls on the efficacy and cost of managing an incursion.

Case studies on an established invasive ant and an exotic fruit fly incursion are provided to illustrate the detailed modelling process needed to develop a reasonable plant pest model. The invasive ant case study is a regional-scale simulation of an established plant pest population and looks at the feasibility and cost of eradication. The exotic fruit fly case study is a national-scale simulation of pest point introductions at various locations around Australia, and looks at the likely time to detection, and feasiblity and cost of control. The case studies demonstrate a range of population growth, spread, surveillance, and treatment options available in APPDIS. It is important to note that the purpose of this project is the development of a modelling framework for future use by plant health specialists in the study of specific plant pests. As such, the case studies are for illustrative and explorative purposes rather than making a definitive statement on the pests in question.

There will of course be challenges in the adoption of the APPDIS model as a plant health decision support tool. The model will need

to be separately configured and validated for each plant pest under study. This will require 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).

This project aligns with the strategic objectives of the Department of Agriculture and Water Resources to safeguard Australia's animal and plant health status in order to maintain overseas markets and protect the economy and environment from the impact of exotic pests and diseases, through the implementation of emergency response arrangements (Department of Agriculture and Water Resources, 2019a; 2019b).

1.2 Report overview

Section 1 introduces the project.

Section 2 provides context for the project with a brief review of plant pest modelling.

Section 3 presents the APPDIS conceptual model. This includes how a study area is defined, how the abundance of a pest population is represented, how the pest population spreads via jump-diffusion processes, and how populations are detected, treated and deemed absent.

Section 4 outlines the software implementation of the conceptual model.

Sections 5 and 6 describe a regional-scale case study on the spread, and control of an established tramp ant population near Cairns.

Section 7 describes a national-scale case study on the spread and control of an exotic fruit fly after a point introduction at the port of Cairns.

Section 8 provides an overall discussion on the project findings including model limitations, applicability of the model to other plant pests, and possible future work.

1.3 Project workshops

A project launch workshop was held on the 29th August 2017 at the Department of Agriculture in Canberra. The workshop was attended by plant health specialists from the Department of Agriculture (Biosecurity Plant and the Office of the Chief Plant Protection Officer), the Australian Bureau of Agricultural and Resource Economics (ABARES), and the NSW Department of Primary Industries. Advice and consensus was sought from the participants on the project charter and plans. The workshop report is provided as Appendix B.

A second project workshop was held on the 21st June 2019 at the Department of Agriculture in Canberra. The workshop was attended by plant health specialists from the Department of Agriculture (representing agricultural and environmental biosecurity), ABARES, and the Biosecurity Analytics Centre.. The APPDIS model prototype was demonstrated via the two case studies and feedback sought from the participants on the usefulness of the model as a decision support tool for NPPP. The workshop report is provided as Appendix C.

2 Modelling approaches for plant pests

Emergency response planning for exotic pests can be challenging when there is limited understanding of their ecology, and/or the pest is absent or rare.

Theoretical models allow policy makers to explore a variety of incursion scenarios and the effectiveness of different surveillance and treatment strategies. Models can be broadly classified as ecological (simulating species distribution and/or spread), control (simulating surveillance and treatment mechanisms), or a combination of both.

In this section we describe how a useful NPPP model should include a means of specifying the initial pest population; a means of representing population dynamics over time and space; and a means of applying policy-based surveillance, control and eradication measures to the population, in order to assess efficacy, resource requirements and cost.

2.1 Species distribution models

Species distribution models (SDMs) have been widely used for modelling the static distribution of native and exotic plant pests across a large geographic space. Correlative SDMs, such as MaxEnt (Phillips, Anderson & Schapire, 2006), relate spatially explicit environmental data to pest occurrence records (Aurambout et al., 2009; De Meyer et al., 2010). While MaxEnt is limited in its use of climate variables (important in determining species distributions (Yang et al., 2013; Deutsch et al., 2008)), the model estimates the relative contribution of each environmental variable to an

occurrence record. Although SDMs may be limited by coarse input data, outputs can help explain large changes in potential habitats of pests (Sultana et al., 2017). These models are restricted to using presence-only data to tune model parameters, which is a considerable limitation given that critical exotic pests are rarely detected.

Mechanistic SDMs such as CLIMEX are similar to correlative SDMs, but use a physiological setting to fit the environmental niche of the pest to occurrence records (De Villiers et al., 2015; Sutherst, Murdiyarso & Widayati, 1999). These models are more biologically rational, but they are harder to parameterise. While the climate data backing CLIMEX is more refined than MaxEnt, the lack of other environmental parameters in CLIMEX is a considerable limitation (Kriticos et al., 2003). Mechanistic SDMs can also require microclimate datasets which are difficult to obtain for a broad range of pests.

SDMs are a useful starting point for understanding the extent of the area that is at risk and, to a lesser extent, the areas that may have relatively high or low establishment and growth potentials if the pest were introduced there. However, incursions are dynamic processes and to effectively prepare for them, there is a need to explore where the pest may arrive and how it will spread.

2.2 Population dynamics models

Population dynamics models can represent the incursion characteristics that need to be managed over time. DYMEX (Parry, Aurambout & Kriticos, 2011) is one example that uses the life cycle of a pest to drive population dynamics (Sutherst, Maywald & Russell, 2000). Another is the Generic Pest Forecast System (GPFS) (Hong et

al., 2015) which represents multiple processes in population dynamics such as growth rate as a function of temperature, and mortality independently driven by cold stress, heat stress, and soil moisture. Population dynamics models like GPFS and DYMEX are generally not spatially enabled due to higher demand for computational resources. GPFS has been used in a large-scale spatially explicit model (Magarey et al., 2015), but DYMEX has only been used at small spatial scales (Whish et al., 2015). Large-scale spatial models are needed to understand population behaviour across heterogeneous landscapes (such as national-level simulations) (Lopes, Spataro & Arditi, 2010).

Underlying these sophisticated modelling systems are some basic mathematical models to represent population growth and spread. The logistic growth function (Kingsland, 1982) can be implemented cell-wise in a spatial model (Kehlenbeck et al., 2012; Law, Murrell & Dieckmann, 2003). The logistic function requires three parameters: an initial population, a carrying capacity (which can vary spatially with environments (Roughgarden, 1975)), and a growth rate (typically varying with temperature). While the logistic function is simple and has been criticised for not explicitly representing biological processes and assuming homogenous growth rates between individuals (Kingsland, 1982), it is still frequently used.

A number of spatial models have been developed to project population growth over large geographical areas such as stage structured and impulsive differential equation models. Stage structured models can simulate population dynamics for discrete life-stages, where dispersal and reproduction vary with environmental/host variables (Crespo-Perez et al., 2011). Impulsive population models better represent population dynamics (Xiao, Cheng & Qin, 2006), but require considerable expertise to use them.

2.3 Control models

Control models consider the interaction of surveillance and potential eradication and response strategies in response to detecting an incursion.

Surveillance models need to relate the resources that are applied to finding an invading pest to the probability of detecting the pest given the state of the population at that surveillance point. Sensitivity of detection is an elementary driver of surveillance value and yet can difficult to calculate. Lure concentration and distance from trap have been used together to model trapping efficiency (Branco et al., 2006). The effect of trap distance and lure concentration on capture rates can be determined theoretically, but spatial environmental variation can have an impact on capture rates (Manoukis, Hall & Geib, 2014; Renton et al., 2017).

Most treatment models are built for managing established pests and often rely on some threshold to initialise a management strategy. Treatment models for eradication and containment however need to account for the probability of sub-detectable populations in carrying an incursion forward. Models that combine surveillance and treatment typically have been used to estimate total control program cost (Bogich, Liebhold & Shea, 2008; Gerber, Beger, McCarthy & Possingham, 2005; Field et al., 2004; Hauser & McCarthy, 2009; Holden, Nyrop & Ellner, 2016). Costs could relate to early detection traps (set up, maintenance, or sample collection), delimiting surveillance traps (set up, maintenance, or sample collection), or the treatment process (treatment substance preparation, application of treatment, and post treatment surveillance). While the ultimate benefit is eradication of the pest, the quantified benefit is the minimisation of costs. Combined control models have been used extensively to determine the optimal

trapping density (Epanchin-Niell et al., 2014; Bogich, Liebhold & Shea, 2008). However, these specialised models rarely consider the complete incursion scenario, instead exploring an isolated management scenario.

Models for incursion management, like all models, will be simplifications of real systems. For example, models that characterise spread as an increasing uniform circle with radius, r, that grows with time (Epanchin-Niell et al., 2014; Bogich, Liebhold & Shea, 2008), will be unrealistic in heterogeneous environments. Similarly, pest populations might be represented to grow logistically with constant growth rate (Epanchin-Niell et al., 2014), when in reality, growth rate may be influenced by environmental variables such as temperature. Other models may disregard population dynamics entirely, instead enhancing the incursion model by determining the probability of pest arrival coupled with a probability of detection at each time step (Hauser & McCarthy, 2009; Holden, Nyrop & Ellner, 2016). Models should preferably be kept as simple as possible to answer the questions that they are built to address. However, for incursion management, it is often difficult to understand the relationships between components until they can be seen interacting with each other in a rich spatiotemporal environment.

2.4 Useful features for an NPPP model

Invasive exotic pests such as those on the list of National Priority Plant Pests often lack robust data on incursion likelihood, population dynamics and spread pathways, surveillance strategies, and effectiveness of treatments. Models that simulate specific components of the incursion-eradication process may need to simplify, or make assumptions on, the non-modelled components.

For example, a surveillance optimisation model for a specific pest might simplify the underlying spread mechanism by assuming a constant growth rate (Branco et al., 2006). Customisable models that simulate many aspects of an incursion can allow simplications and assumptions to be assessed. This is especially useful when minimal information is available on the pest under study.

Invasive pest populations may spread over multiple scales. For example, natural dispersal may result in short-range diffusive spread while wind vectors and/or human-mediated dispersal may result in longer-range sporadic jumps (Renton et al., 2017). Most invasive pest spread models will require at least two spread scales (Figure 1). The spread pathways in a model should be highly configurable as the frequency, direction, and distance of pest movements will be species-specific.

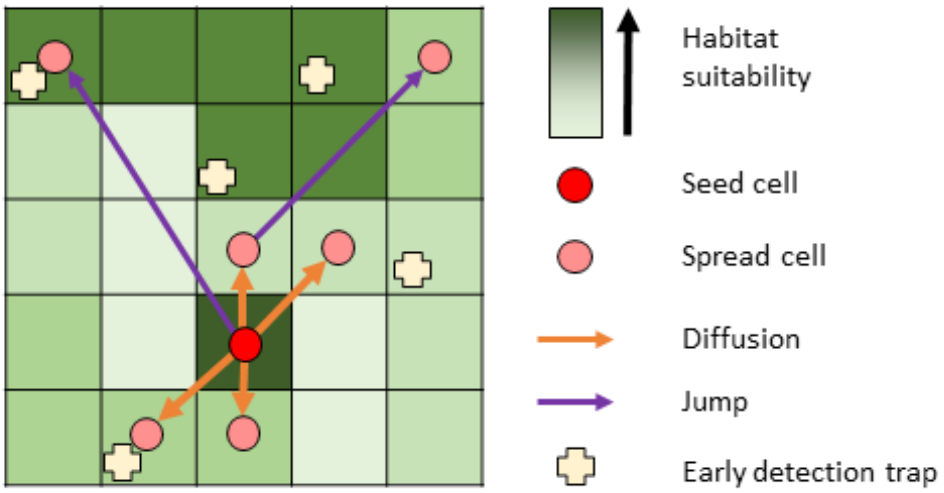

Figure 1. Spread pathways from a seed cell in a spatial and fully dynamic model.

Early detection trapping grids or surveillance strategies already exist for some high priority pests and so an NPPP model should be able to incorporate baseline activities prior to a detection. Selectively relocating traps and running simulations should be

facilitated by the model structure, allowing the user to trial several trap network patterns. In addition to specific surveillance carried out by trap networks, general surveillance detections by members of the public should also be incorporated into the model framework as it has been shown to be an important aspect of early detection (Cacho et al., 2010; Hester & Cacho, 2017; Wilson et al., 2004).

Once an emergency pest has been detected, additional surveillance is implemented to delimit the population. Surveillance strategies are determined by the pest in question and the detection scenario. As such, an NPPP model's surveillance component should be flexible and not tied to specific pests or policies.

Treatment strategies within the modelling platform need to be customisable for different chemical or cultural treatments and associated with resources to implement the strategy. Both the effectiveness of the treatment and the structure of the implementation need to be manipulated within the model to explore the plausible outcomes. Treatment strategies and responses are highly dependent on the uncertainty surrounding the incursion scenario and industry / government politics which can lead to a quite complex decision-making process.

In summary, National Priority Plant Pests are an ecologically diverse group comprising insects, bacteria, viruses, fungi, molluscs, and nematodes, and in some cases are vector-borne. The pests all have potential to inflict serious economic and/or environmental harm to Australia. There are limited opportunities for early detection and control/eradication policies to be informed from first-hand experience. There is a need for a generalised plant pest decision support tool that is flexible (not tied to a specific pest), scalable (operable regionally and nationally), accounts for heterogeneity in the host environment, and allows relative comparisons of strategies

for early detection surveillance, delimiting surveillance, treatment, and post-treatment surveillance, with respect to efficacy, resource usage and cost. Importantly, a generalised plant pest model should be extensible to a range of pests via user configurable parameters, i.e., not requiring specialised mathematical reformulation and/or computer programming.

3 Conceptual model

In this section we describe the key components of the APPDIS model from a conceptual point of view, i.e., focusing on high level design decisions rather than implementation specifics.

The APPDIS plant pest model is stochastic discrete-event simulation based on a geographic automata (Torrens and Benenson, 2005; Laffan et al., 2007). The study area of interest is represented by a grid delineated by equidistant lines of latitude and longitude. The modelling unit of interest is a cell within the grid. Each cell has environmental attributes (e.g., elevation, average weekly temperature, annual rainfall, human population density, vegetation index, land use category, average weekly wind speed, etc.), that determine the suitability of the cell for a plant pest of interest. The initial presence of a plant pest may be explicitly set on a cell-by-cell basis, or estimated by the model according to configurable environmental criteria. The abundance of a plant pest in a cell depends on the time that the population has been present and on the environmental suitability of the cell.

The problem of modelling the abundance and spread of a plant pest in a gridded environment is reduced to two separate sub-problems: within-cell abundance and between-cell spread. The within-cell

abundance of a pest is modelled with an equation-based approach and the between-cell spread of a pest is modelled with a stochastic agent-based approach. In this sense, APPDIS can be thought of as a hybrid agent-based model where each (cell) agent may have an embedded mathematical sub-model representing a pest population.

3.1 Within-cell abundance and spread

3.1.1 Logistic growth model

The population density of a pest within a cell over time is estimated with a logistic growth function, representing how the population initially grows exponentially, and then the growth rate decreases as the population approaches the carrying capacity of the cell. The carrying capacity of a cell is the theoretical maximum number of individuals that the cell can sustain. Cell carrying capacities can vary across the model grid, driven by environmental variables (such as temperature, elevation, land use and vegetation), that influence pest numbers.

The logistic growth model is given by Equation 1.

$$d(t) = \frac{K}{1 + \left\{\frac{K}{D_0} - 1\right\} e^{-Rt}} \qquad \text{(Eqn. 1)}$$

where

$d(t)$ = pest population density on day t

D_0 = initial pest population density (on day t=0)

K = normalised carrying capacity of the cell

R = pest population growth rate parameter on day t

The normalised carrying capacity K of a cell is derived from user-defined cell suitability data specific to the pest being modelled.

3.1.2 Logistic growth rate

The slope of a logistic growth curve is determined by the growth rate parameter R. If the initial population density and a subsequent population density at a fixed point in time are known, a constant population growth rate R can be estimated using Equation 2.

$$R = \frac{\ln\left(\frac{D_0}{D_x}\right) + \ln\left(K - D_x\right) - \ln\left(K - D_0\right)}{-x} \qquad \text{(Eqn. 2)}$$

where

R = population growth rate

D_0 = normalised population density on day 0

D_x = normalised population density on day x

K = normalised carrying capacity of the cell

Figure 2 illustrates how the slope of the logistic growth increases with the growth rate.

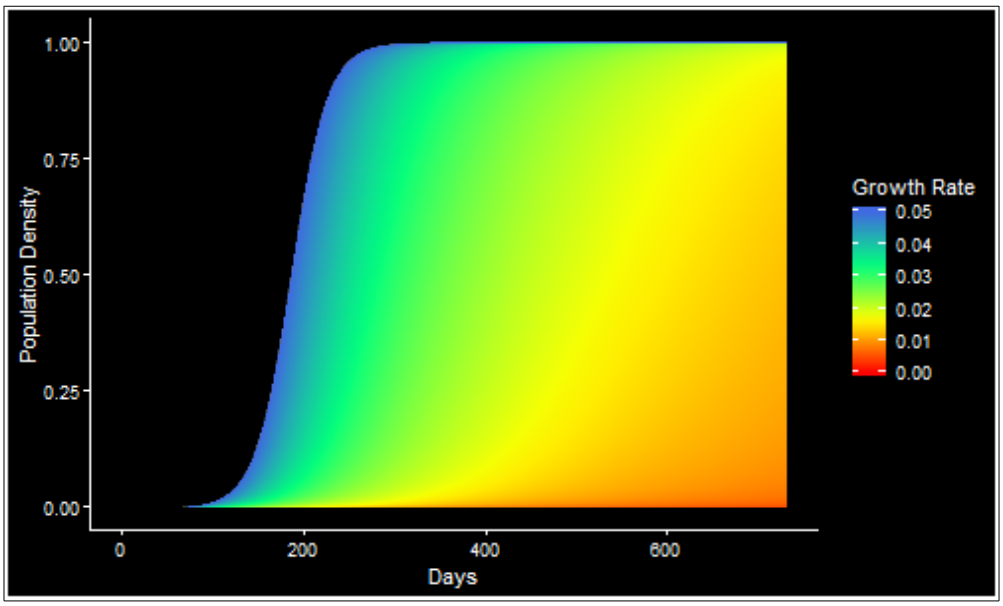

Figure 2. Logistic growth curves across a range of growth rates R.

Case study 1 (Sections 5 and 6) provides an example of APPDIS utilising a constant logistic growth rate.

The population growth rate R, however, is unlikely to be a static value, and actual population values may not be available from empirical studies. Alternatively, R can be estimated from published laboratory data on pest development and mortality in response to temperature. Case study 2 (Section 7) provides an example of APPDIS utilising temperature dependent logistic growth, and the derivation of growth rate parameters. This approach allows colder temperatures to be associated with negative growth rates and thus trigger seasonal declines of a population.

3.2 Between-cell spread

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

3.2.1 Diffusive spread between adjoining cells

The progressive spread of a plant pest from an infested cell into an adjoining naive cell is modelled with a stochastic diffusion process based on the following factors:

- the source cell's pest population density
- the source cell's environmental conditions (e.g., wind and/or temperature criteria) (optional)
- the environmental suitability of the destination cell

- the elevation gradient between the source and destination cells (optional)

The probability of a diffusion event occurring on any given day is given by Equation 3.

$$p_d(t) = 1 - \left(1 - P_d S_d w_d w_t w_e\right)^{d(t)} \qquad \text{(Eqn. 3)}$$

where

$p_d(t)$ = probability of diffusion occurring on day t

P_d = baseline daily probability of diffusion occurring (configurable per land use category)

S_d = normalised suitability of the destination cell

w_d = distance weight between the source and destination cells

w_t = temperature weight of the source cell (optional)

w_e = elevation weight of the source cell (optional)

d(t) = normalised population density of source cell on day t

The distance weight w_d is derived from the distance between the centroids of the source infested cell and the candidate adjoining cell. It simply represents the decreased probability of diffusion into the north-west, south-west, north-east and south-east neighbours (w_d = 0.7071), as opposed to the north, south, west and east neighbours (w_d = 1.0). (Note that the diffusion pathway can optionally be configured to include non-adjoining cells, in which case the distance weight is calculated from a spatial kernel based on the centroids of the source and destination cells, with either linear or exponential decay.)

The (optional) temperature weight w_t is derived from the relationship between the average weekly temperature t for the cell

and four configured temperature thresholds for pest activity: min, optimal_lower, optimal_upper and max.

$w_t = 0$ (for $t < min$)

w_t = linear increase from 0 to 1 (for $min \leq t \leq optimal\_lower$)

$w_t = 1$ (for $optimal\_lower \leq t \leq optimal\_upper$)

w_t = linear decrease 1 to 0 (for $optimal\_upper \leq t \leq max$)

$w_t = 0$ (for $t > max$)

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

3.2.2 Jumps between cells

The sporadic longer-range spread of a plant pest from an infested cell into naive cells is modelled with a stochastic jump process based on the following factors:

- the source cell's pest population density
- the source cell's environmental conditions (e.g., wind, temperature) (optional)
- the environmental suitability of the destination cell
- the human population density of the source cell (optional)
- the land use of the source cell (optional)
- the land use of the destination cell (optional)
- waterways in the source and destination cells (optional)

The probability of a jump event occurring on any given day is given by Equation 4.

$$p_j(t) = 1 - \left(1 - P_j H_s S_d w_t\right)^{d(t)} \qquad \text{(Eqn. 4)}$$

where

$p_j(t)$ = probability of a jump occurring on day t

P_j = baseline daily probability of a jump occurring

H_s = normalised human population density of source cell (optional)

S_d = normalised suitability of the destination cell

w_t = temperature weight of the source cell (optional)

d(t) = normalised population density of source cell on day t

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.

3.2.3 Network-based spread between cells

The spread of plant pests arising from directed movements within production system-specific networks is an important potential pathway for the spread of plant pests and diseases. For example, a plant wholesaler might routinely and exclusively transport products within an established nework of plant retailers. This type of directed spatiotemporal spread can be handled by the underlying AADIS architecture. For example, the animal disease model simulates consignments from various farm types to saleyards, mixing of animals at the saleyard, and onward batching to farms, abattoirs or export. This style of spread is very industry specific and was not part of the initial model development which focussed more on generalised spread pathways. Network-driven spread could be developed as part of a follow-on modelling project on a plant pest for which there is sufficient network-based movement data.

3.3 Control and Eradication

3.3.1 General Surveillance

All cells that have both a pest population and a human population are scanned daily for detections by the general public. The detection of a pest population is modelled with a stochastic process based on the following factors:

- 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, Liebhold and Roberts (1998) and Bogich, Liebhold and Shea (2008), and is given by Equation 5.

$$\boxed{p_d(t) = 1 - e^{-d(t)\ \mathrm{Hs\ Se}}} \qquad \text{(Eqn. 5)}$$

where

$p_d(t)$ = probability of detection occurring on day t

d(t) = normalised pest population density of infested cell on day t

H_s = normalised human population density of the infested cell

S_e = sensitivity of the observer

The observer sensitivity for unmanaged cells is defined separately to that for managed cells. A managed cell is any cell that is undergoing, or has undergone, delimiting surveillance or treatment.

Figure 3 uses Equation 5 (with S_e = 0.70), to illustrate how the probability of detection varies with respect to the normalised pest population density and the normalised human population density.

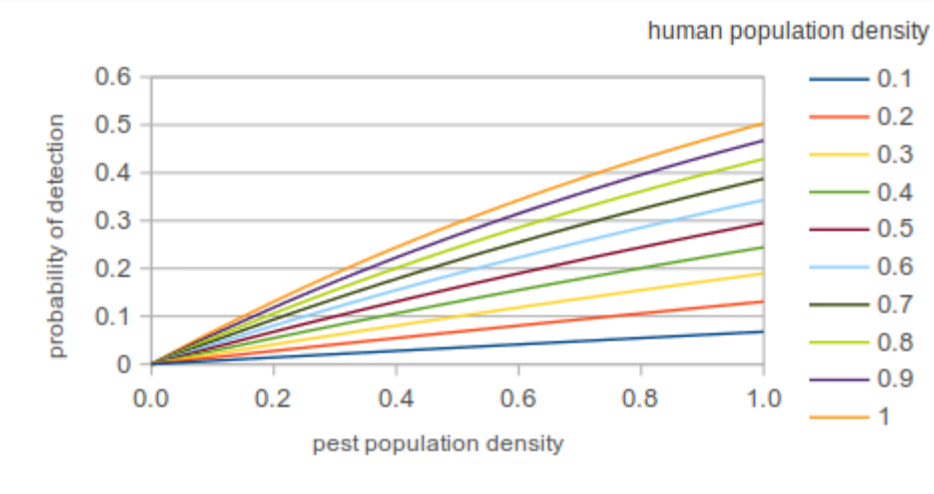

Figure 3. Probability of general surveillance detection with respect to pest population density and human population density

3.3.2 Early detection Surveillance

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 based on the following factors:

- 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, Liebhold and Roberts (1998) and Bogich, Liebhold and Shea (2008), and is given by Equation 6.

$$p_{TP}(t) = 1 - e^{-d(t)\,\mathrm{A}\,Td\,\mathrm{Se}} \qquad \text{(Eqn. 6)}$$

where

$p_{TP}(t)$ = probability of a true positive detection on day t

d(t) = normalised population density of source cell on day t

A = cell area (hectares)

T_d = trap density (traps per hectare) in the infested cell = 10000 / (trap spacing in metres)^2

S_e = sensitivity of the surveillance process (traps and personnel)

Figure 4 uses Equation 6 (with A = 10 ha and S_e = 0.96), to illustrate how the probability of detection inside a cell varies with trap spacing.

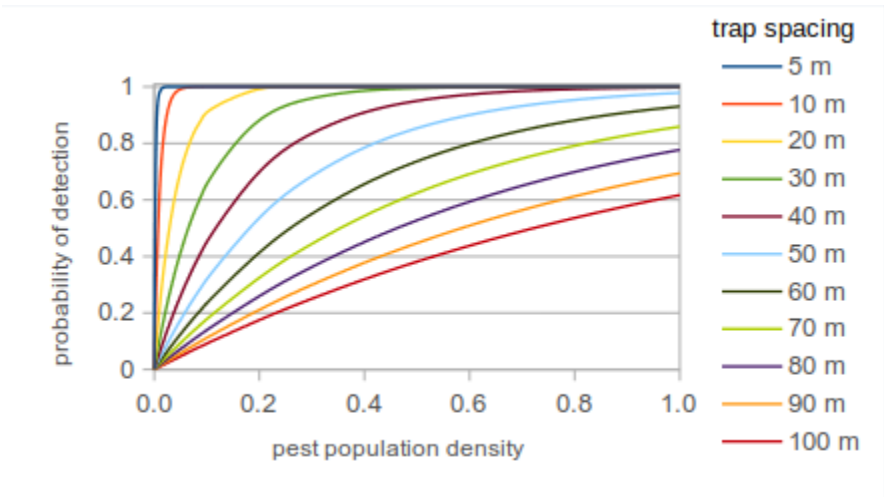

Figure 4. Probability of specific surveillance detection with respect to pest population density and trap spacing (in metres)

Figure 5 uses Equation 6 (with A = 10 ha and S_e = 0.96), to more clearly illustrate how the probability of detecting small pest populations is very sensitive to the trap spacing inside the cell.

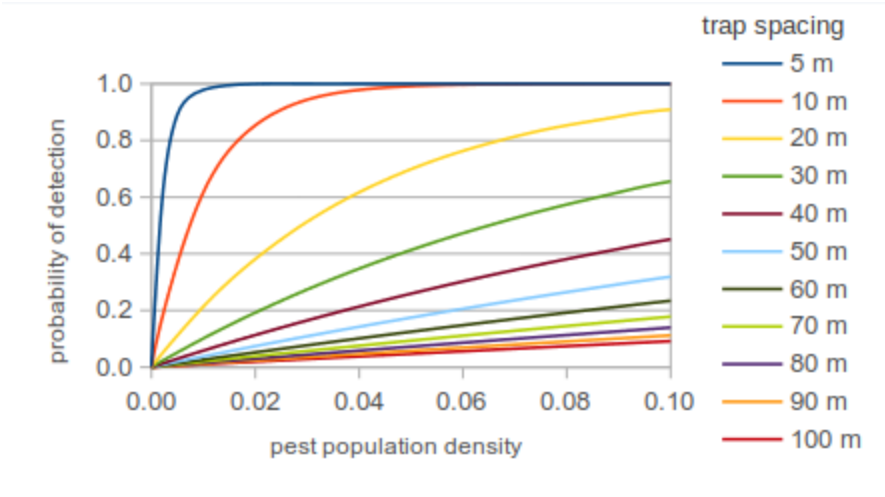

Figure 5. Probability of specific surveillance detection of small pest populations with respect to trap spacing (in metres)

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 7.

$$\boxed{p_{FP} = 1 - Sp} \qquad \text{(Eqn. 7)}$$

where

p_{FP} = probability of a false positive detection

S_p = specificity of the surveillance process (traps + 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. Note that for most plant

pest applications, specificity will be set to 1 so that all positives, after undergoing the full suite of testing, will be considered true.

3.3.3 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 surveillance visits conducted at a configurable period. 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 as a stochastic process based on the following factors:

- 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 probability of a true positive detection occurring on day t is given by Equation 6.

If a cell does not yield a true positive result it is then checked for a false positive result. The probability of a false positive detection occurring is given by Equation 7.

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.

3.3.4 Treatment

All cells that have yielded a (true or false) positive result 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 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).

3.3.5 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 surveillance visits, conducted at a configurable period. Post-treatment surveillance is modelled with a stochastic process based on the following factors:

- 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)

The probability of a true positive detection occurring on day t is adapted from Sharov, Liebhold and Roberts (1998) and Bogich, Liebhold and Shea (2008), and is given by Equation 6.

If a cell does not yield a true positive result it is then checked for a false positive result. The probability of a false positive detection occurring is given by Equation 7.

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.

A cell is deemed free of the pest after a configurable number of consecutive negative surveillance results.

3.3.6 Resourcing

Early detection surveillance, delimiting surveillance, treatment and post-treatment surveillance are all dynamically constrained by available resources. A ‘resource’ is an arbitrary set of personnel/equipment/supplies required to carry out a specific job. If there are insufficient resources to carry out a job, then the job is queued until sufficient resources are available. The model maintains resource pools for each resource type (early detection surveillance, delimiting surveillance, treatment and post-treatment surveillance). The capacity of each pool increases linearly from an initial minimum level up to a maximum level as shown in Figure 6.

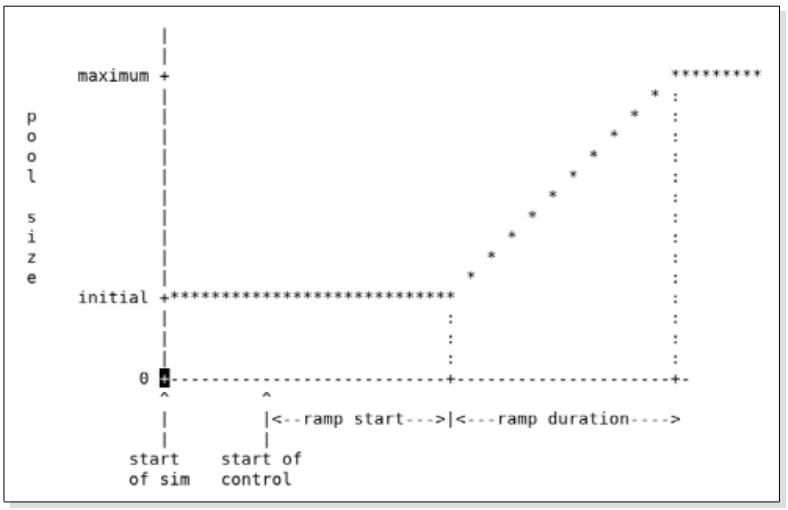

Figure 6. Dynamic allocation of resources

The model reports the daily resource usage for early detection surveillance, delimiting surveillance, treatment and post-treatment surveillance. If resourcing is set to ‘unlimited’ then the resourcing levels become a model output (as opposed to a model input that dynamically constrains the response).

4 Software model

The Australian Animal Disease model (AADIS) (Bradhurst et al., 2015), is an epidemiological model developed under funding from the Australian Government Department of Agriculture. AADIS is a spatially-explicit simulation model that combines equation-based and agent-based modelling techniques to represent the spread and control of emergency disease in livestock. Note that an ‘agent’ in a modelling context does not refer to an ‘infectious agent’, it is simply an abstraction of the modelling unit of interest, and will vary with the modelling domain. For example, when modelling the spread of a virus in domestic livestock the agent might be a herd of animals, whereas when modelling the spread of virus in a human population the agent might be an individual person. The abundance of a pathogen within an AADIS agent is modelled mathematically, while the spread of the pathogen between agents is represented with an agent-based stochastic model. AADIS is written in Java (Oracle, 2015), and employs open-source products such as SQL Power Architect (SQL Power Group, 2015), PostgreSQL (PostgreSQL, 2015), OpenMap (BBN, 2015), and Log4J (Apache, 2012).

The following sections describe plant pest specific modifications to the AADIS modelling framework required to create the APPDIS modelling framework. UML diagrams (Fowler & Scott, 2000), are used to convey the key class relationships.

4.1 Database subsystem

APPDIS uses the PostgreSQL relational database to store datasets that may be large and/or have cross dependencies. Each table in the database has a corresponding comma-separated values (CSV) input

file. A user updates the database by editing the CSV file corresponding to the table of interest and then rebuilding the entire database (to ensure relational integrity between tables). A user may only add/delete/modify rows of an existing table. The creation of a new database table or the addition of new columns to an existing table is a software development activity.

The Weather Grid Data database table was updated with the following new (per grid cell) attributes:

- suitability – user defined measure of the suitability of the grid cell to support a pest population
- population density – initial (normalised) pest population density of the grid cell
- human population – human population count per grid cell
- land use A – user defined measure of land use within the cell
- land use B – user defined measure of land use within the cell
- land use C – user defined measure of land use within the cell
- land use D – user defined measure of land use within the cell
- land use E – user defined measure of land use within the cell
- watercourses – absence/presence of watercourses in the cell

4.2 Configuration subsystem

4.2.1 Disease configuration

The Disease Configuration class was updated with the following new parameters:

4.2.1.1 Within-cell pest population

- enabled – determines whether the plant pest is enabled.
- name – the name of the plant pest being modelled.
- min suitability – the minimum suitability value required for a grid cell to support a plant pest population.
- suitability transform – optional linear or log transformation of the cell suitability scores before use.
- population model – the means by which the within-cell growth of a plant pest population is modelled. Currently the only valid value is 'logistic'. Note that the carrying capacity of the cell is determined by the normalised suitability.
- temperature dependent - determines whether the population model depends on temperature.
- logistic growth rate – only applies when the population model is not temperature dependent.
- temperature dependent logistic growth rates – the set of growth rates corresponding to each temperature in the configured 'active' range for the plant pest. Only applies when the population model is temperature dependent.
- min temperature - the minimum mean weekly temperature (degrees Celsius) required for a grid cell to support a plant pest population.
- optimal temperature_lower - the lower bound of the ideal temperature (degrees Celsius) for the plant pest population.
- optimal temperature_upper - the upper bound of the ideal temperature (degrees Celsius) for the plant pest population.

- max temperature - the maximum mean weekly temperature (degrees Celsius) allowable for a grid cell to support a plant pest population.
- rainfall dependent - determines whether the presence of the plant pest depends on rainfall.
- min rainfall - the minimum annual average rainfall (mm) required for a grid cell to support a plant pest population.
- max rainfall - the maximum annual average rainfall (mm) allowable for a grid cell to support a plant pest population.
- elevation dependent - determines whether the presence of the plant pest depends on elevation.
- min elevation - the minimum elevation (metres above sea level) required for a grid cell to support a plant pest population.
- max elevation - the maximum elevation (metres above sea level) allowable for a grid cell to support a plant pest population.
- max population – the maximum number of pests that a 100% suitable cell can carry.
- point introduction population – the initial number of pests in a naive cell after a user-defined point introduction (e.g., via arrival in a shipping container)
- extinction population – the number of pests in a cell that is deemed insufficient to sustain a viable population.
- quiescence enabled - determines whether a plant pest population enters a quiescent state when the temperature falls below the configured minimum temperature.

- quiescence max days – the maximum number of days outside the allowable temperature range that a plant pest population in a grid cell can survive quiescently.

4.2.1.2 Steady spread of a plant pest population into adjoining cells

- diffusion enabled – determines whether the plant pest diffusion (spatial kernel) pathway is enabled.
- diffusion name – the name of the plant pest diffusion process being modelled, e.g., budding.
- diffusion baseline probability – baseline probability that the plant pest population in a given grid cell will diffuse out of the cell on any given day.
- diffusion radius – maximum extent (km) of the spatial kernel from the centroid of the source grid cell.
- diffusion decay mode – linear or exponential.
- diffusion decay exponent - only applicable to exponential decay mode.
- diffusion temperature dependent - determines whether the diffusion of the plant pest depends on temperature.
- diffusion min temperature - the minimum mean weekly temperature (degrees Celsius) at which diffusion of the plant pest can occur. Only applies when plant pest diffusion is temperature dependent.
- diffusion elevation dependent - determines whether the diffusion of the plant pest depends on elevation.

- diffusion elevation increase effect – the dampening effect (0.0 to 1.0) that an increase in elevation (from source cell to target cell) has on the probability of diffusion. Only applies when plant pest diffusion is elevation dependent.
- diffusion elevation decrease effect - the amplifying effect (0.0 to 1.0) that a decrease in elevation (from source cell to target cell) has on the probability of diffusion. Only applies when plant pest diffusion is elevation dependent.
- diffusion wind dependent - determines whether the diffusion of the plant pest depends on wind.
- diffusion max wind speed – the maximum average weekly wind speed (km/hour) at which diffusion can occur. Only applies when plant pest diffusion is wind dependent.
- diffusion initial cell population - the plant pest population size in a naive cell immediately after a diffusion event has occurred.

4.2.1.3 Sporadic spread of a plant pest population into other cells

- jump enabled – determines whether the plant pest jump pathway is enabled
- jump name – the name of the plant pest jumping process being modelled, e.g., hitchhiking.
- jump_land_use_dependent_baseline_probabilities – baseline probabilities (per land use category) that a plant pest population will jump out of a cell on any given day.
- jump baseline probability – baseline probability that a plant pest population will jump out of a cell on any given day (only

applicable if the land use dependent baseline probabilities are not defined)

- jump mode – windborne (where the jump bearing is influenced by wind direction), random (where the jump bearing is randomly chosen), or directed (where destination cells must meet land use eligibility criteria)
- human population dependent - determines whether plant pest jumps are influenced by human population
- human_population_source_mandatory – determines whether jumps may only occur from cells that have human population density > 0
- human_population_destination_mandatory – determines whether jumps may only land in cells that have human population density > 0
- human_population_destination_leakage (percentage) - allows some jumps to stochastically to land in cells that have human population density = 0. Only applies when human_population_destination_mandatory is set to true. This reflects, for example, a hitchhiking jump into a wilderness area.
- jump_land_use_source_dependencies – determines the eligible land use categories for jump sources
- jump_land_use_destination_dependencies – determines the eligible land use categories for jump destinations
- jump temperature dependent - determines whether plant pest jumps depend on temperature.

- jump min temperature - the minimum mean weekly temperature (degrees Celsius) at which a plant pest jump can occur. Only applies when plant pest jumps are temperature dependent.
- jump min distance – 1st parameter for the betaPERT (Vose, 2008) distribution governing jump distance (km).
- jump most likely distance – 2nd parameter for the betaPERT distribution governing jump distance (km).
- jump max distance – 3rd parameter for the betaPERT distribution governing jump distance (km).
- jump initial cell population - the plant pest population size in a naive cell immediately after a jump event has occurred.

4.2.2 Scenario configuration

The Scenario Configuration class was updated with the following new parameters:

4.2.2.1 Scenario definition

- scenario end mode – determines how a scenario ends:
  (a) fixed – the scenario ends on a user-specified fixed day.
  (b) burned-out – the scenario ends when there are no active or quiescent cells.
  (c) spread-distance – the scenario ends when spread has reached a specified distance (km). Only applicable to point incursions.
  (d) sentinel – the scenario ends when spread reaches the first user-specified sentinel cell.

- seed mode – determines how the initial plant pest population is established:
  (a) manual - the initial plant pest population is defined via specfic grid cell IDs in the scenario configuration file.
  (b) endemic - the initial plant pest population is derived by the model according to environmental criteria specified in the disease configuration file.
  (c) density – the initial plant pest population is defined by user-supplied (per-cell) population density values specified in the Weather Grid Data database table.

- num manual seeds - the number of grid cells to be manually seeded with a plant pest population. Only applies to 'manual' seed mode.

- seed cell IDs - the identifiers of the grid cells to be manually seeded with a plant pest population. Only applies to 'manual' seed mode.

4.2.2.2 Reporting

- plant pest spread report enabled – enabling/disabling of the per-run plant pest spread summary report

- plant pest control report enabled – enabling/disabling of the per-run plant pest control and eradication summary report

- plant pest distribution report enabled – enabling/disabling of the plant pest distribution report (across all runs)

- plant pest weekly dump enabled - enabling/disabling of a weekly detailed report on all cells with either an active or quiescent plant pest population.

- plant pest monthly dump enabled - enabling/disabling of a monthly detailed report on all cells with either an active or quiescent plant pest population.
- plant pest yearly dump enabled - enabling/disabling of a yearly detailed report on all cells with either an active or quiescent plant pest population.
- plant pest daily map snapshot enabled - enabling/disabling of a daily snapshot of the map (depicting the cells with either an active or quiescent plant pest population at that point in time).
- plant pest weekly map snapshot enabled - enabling/disabling of a weekly snapshot of the map (depicting the cells with either an active or quiescent plant pest population at that point in time).
- plant pest monthly map snapshot enabled - enabling/disabling of a monthly snapshot of the map (depicting the cells with either an active or quiescent plant pest population at that point in time).
- plant pest yearly map snapshot enabled - enabling/disabling of a yearly snapshot of the map (depicting the cells with either an active or quiescent plant pest population at that point in time).
- plant pest five-yearly map snapshot enabled - enabling/disabling of a five-yearly snapshot of the map (depicting the cells with either an active or quiescent plant pest population at that point in time).
- plant pest ten-yearly map snapshot enabled - enabling/disabling of a ten-yearly snapshot of the map

(depicting the cells with either an active or quiescent plant pest population at that point in time).

- plant pest dump day of month – the day of the month (1..31) on which to take a dump/map snapshot.

4.2.2.3 General surveillance

- general surveillance enabled – enabling/disabling of passive detections from members of the general public
- general surveillance sensitivity – sensitivity of an observer in an unmanaged area
- general surveillance managed area sensitivity – sensitivity of an observer in an managed area
- general surveillance mode (passive or fixed) – allows the first general surveillance detection to be either stochatic or occur on a fxed day.
- general surveillance first detection day – the fixed day of the first detection. Only relevant when the general surveillance mode is passive.
- general surveillance first detection cell – the fixed cell where the first detection occurs. Only relevant when the general surveillance mode is passive.

4.2.2.4 Early detection surveillance

- early detection surveillance enabled - enabling/disabling of active detections via the national trapping grid
- early detection surveillance trap lure type – the trap lure type specific to the plant pest being modelled. Sample values are: methyl eugenol, cuelure, capilure, other.

- early detection surveillance period – the period (in days) at which a trap is inspected and a result obtained.
- early detection surveillance trap service cost – the cost (in A$) for a visit to inspect/service a trap.
- early detection surveillance resources – the number of resources required to inspect/service a trap.
- early detection surveillance sensitivity – the sensitivity of the surveillance process (traps and personnel)
- early detection surveillance specificity – the specificity of the surveillance process (traps and personnel)
- early detection surveillance min_resources – the minimum number of resources available to conduct early detection surveillance.
- early detection surveillance max_resources – the maximum number of resources available to conduct early detection surveillance.
- early detection surveillance resources ramp start – the number of days after a detection that the number of available resources start increasing (from the minimum to the maximum)
- early detection surveillance resources ramp length – the number of days required to move from the minimum number of resources to the maximum number of resources.

4.2.2.5 Delimiting surveillance

- delimiting surveillance enabled - enabling/disabling of delimiting surveillance

- delimiting surveillance mode – 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).
- delimiting surveillance duration – the period (in days) it takes to conduct surveillance in a cell
- delimiting surveillance period – the period (in days) between surveillance visits
- delimiting surveillance min visits – the minimum number of visits required before a determination that the pest is 'absent' may be made.
- delimiting surveillance trap service cost – the cost (in A$) for a visit to inspect/service a trap
- delimiting surveillance resources – the number of resources required to conduct surveillance in a cell
- delimiting surveillance sensitivity – the sensitivity of the surveillance process (traps and personnel)
- delimiting surveillance specificity – the specificity of the surveillance process (traps and personnel)
- delimiting surveillance trap spacing – the spacing (in metres) between traps
- delimiting surveillance min_resources – the minimum number of resources available to conduct surveillance in a cell
- delimiting surveillance max_resources – the maximum number of resources available to conduct surveillance in a cell

- delimiting surveillance resources ramp start – the number of days after a detection that the number of available resources start increasing (from the minimum to the maximum)
- delimiting surveillance resources ramp length – the number of days required to move from the minimum number of resources to the maximum number of resources.

4.2.2.6 Treatment

- treatment enabled - enabling/disabling of treatment programs
- treatment mode – either Spot mode (where only detected cells are treated), 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).
- treatment duration – the period (in days) it takes to conduct surveillance in a cell
- treatment period – the period (in days) between surveillance visits
- treatment min visits – the minimum number of visits required before a determination that the pest is 'absent' may be made.
- treatment visit cost – the cost (in A$) to treat a cell
- treatment resources – the number of resources required to treat a cell
- treatment min effectiveness – the minimum reduction in population (%) from a single treatment
- treatment max effectiveness – the maximum reduction in population (%) from a single treatment

- treatment trap spacing – the spacing (in metres) between traps
- treatment min_resources – the minimum number of resources available to treat a cell
- treatment max_resources – the maximum number of resources available to treat a cell
- treatment resources ramp start – the number of days after a detection that the number of available resources start increasing (from the minimum to the maximum)
- treatment resources ramp length – the number of days required to move from the minimum number of resources to the maximum number of resources.

4.2.2.7 Post-treatment surveillance

- post-treatment surveillance enabled - enabling/disabling of post-treatment surveillance
- post-treatment surveillance duration – the period (in days) it takes to conduct surveillance in a cell
- post-treatment surveillance period – the period (in days) between surveillance visits
- post-treatment surveillance min visits – the minimum number of visits required before a determination that the pest is 'absent' may be made.
- post-treatment surveillance visit cost – the cost (in A$) to inspect/service a trap.
- post-treatment surveillance resources – the number of resources required to conduct surveillance in a cell

- post-treatment surveillance sensitivity – the sensitivity of the surveillance process
- post-treatment surveillance specificity – the specificity of the surveillance process
- post-treatment surveillance trap spacing – the spacing (in metres) between traps
- post-treatment surveillance min_resources – the minimum number of resources available to conduct surveillance in a cell
- post-treatment surveillance max_resources – the maximum number of resources available to conduct surveillance in a cell
- post-treatment surveillance resources ramp start – the number of days after a detection that the number of available resources start increasing (from the minimum to the maximum)
- post-treatment surveillance resources ramp length – the number of days required to move from the minimum number of resources to the maximum number of resources.

4.3 Population subsystem

4.3.1 Population and Logistic classes

Grid cells are agents in the APPDIS agent-based model (ABM) (akin to herds, farms, and saleyards in the AADIS model) (Figure 7). A grid cell is capable of hosting a plant pest population with growth characteristics determined by the Logistics class. A population could be represented by any growth model, however, only temperature-dependent and temperature-independent logistic growth models are currently implemented.

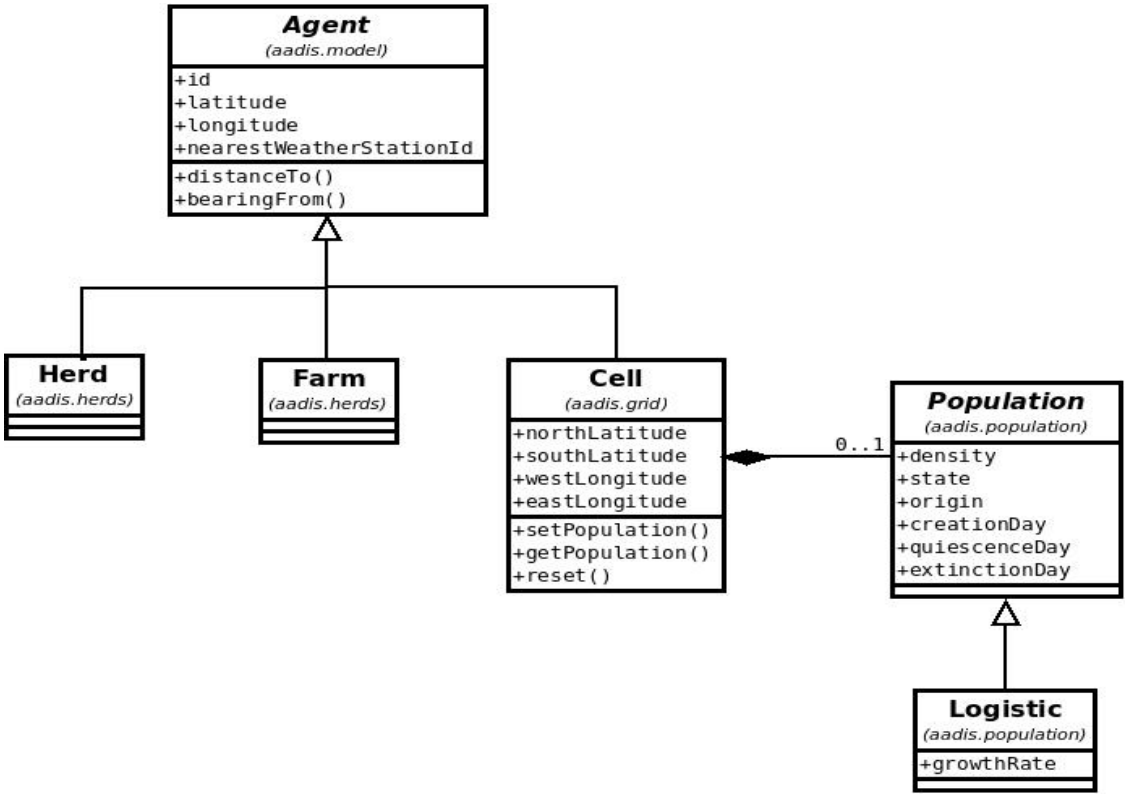

Figure **7.** Cell, Population and Logistic classes

4.4 Grid subsystem

4.4.1 Grid Manager class

The Grid Manager class (Figure 8) maintains the cache of Cell agents. The ABM Scheduler synchronously updates the agent caches at the conclusion of each simulation day's asynchronous processing. The Grid Manager maintains dynamic lists of cells that correspond to the active and quiescent plant pest populations.

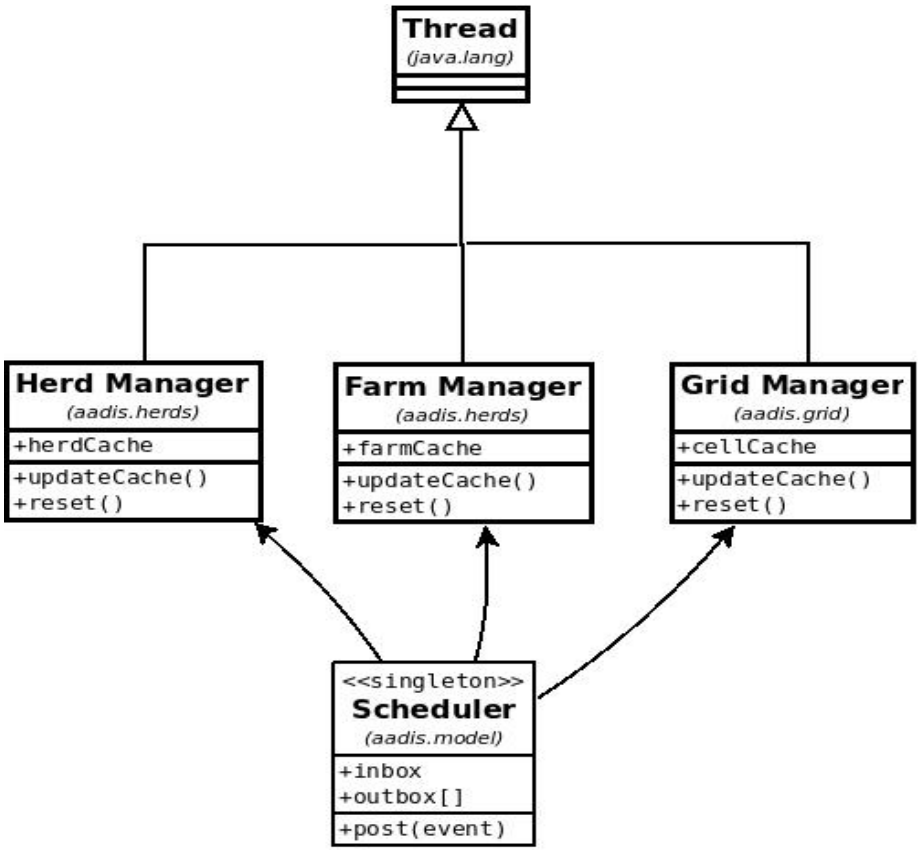

Figure 8. Grid Manager

4.5 Plant Pest subsystem

A new Plant Pest abstract class was created that extends the APPDIS ABM Environment class in a similar fashion to the Spread, Control and Vector abstract classes. Three Plant Pest concrete classes were

created: Plant Pest Presence, Plant Pest Diffusion and Plant Pest Jump (Figure 9). As with all APPDIS ABM components the Plant Pest Presence, Diffusion, Jump, General Surveillance, Active Surveillance classes operate concurrently and independently (Bradhurst et al., 2015; 2016).

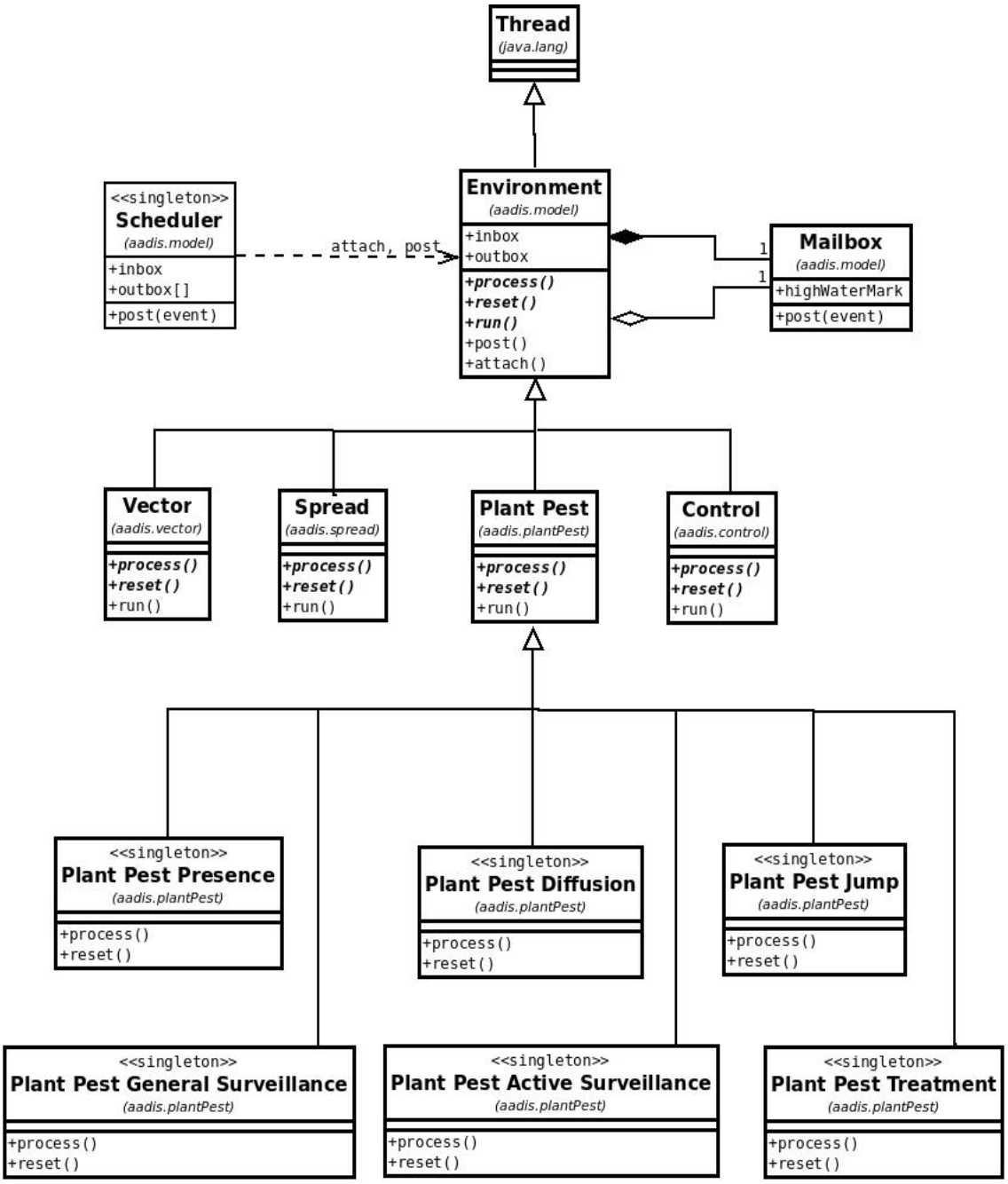

Figure **9.** Plant Pest subsystem

4.5.1 Plant Pest Presence class

The Plant Pest Presence class is responsible for

- Establishing the initial plant pest population based on the configured seeding mode (manual, endemic or density). In manual mode the seed cells are specified via cell IDs set in the scenario configuration file. In endemic mode the seeds cells are determined by the model based on the configured suitability, rainfall, temperature and elevation criteria. In density mode the seed cells are all cells in the Weather Grid Data database table with a population density > 0. A plant pest population is introduced into each seed cell by creating and attaching a Logistic (Population) object to the Cell agent. The Population object predicts the population density of the plant pest in the cell over time.
- Determining whether an active plant pest population becomes quiescent (based on the weekly mean temperature falling below the configured minimum).
- Determining whether a quiescent plant pest population becomes active again (based on the weekly mean temperature rising above the configured minimum within the maximum number of days that a population can remain quiescent).
- Determining whether a quiescent plant pest population becomes extinct (based on the weekly mean temperature remaining below the configured minimum beyond the maximum number of days that a population can remain quiescent).

4.5.2 Plant Pest Diffusion class

The Plant Pest Diffusion class stochastically determines whether the plant pest population in a cell spreads into surrounding grid cells. For each active source cell, a set of candidate destination cells is derived based on the configured spatial kernel radius. The probability that diffusion will occur on any given day is influenced by the plant pest population density of the source cell, the suitability and average weekly temperature of the candidate cell, and the distance and elevation difference between the cells. If a candidate cell is deemed to have been diffused into it is seeded with a new plant pest population by creating and attaching a Logistic (Population) object to the Cell agent.

4.5.3 Plant Pest Jump class

The Plant Pest Jump class stochastically determines whether the plant pest population in a cell jumps into grid cells that lie beyond the diffusion radius. An active cell is only eligible as a jump source if it meets the configured criteria for temperature, land use, rainfall and elevation. The jump distance is determined by sampling the configured betaPERT distribution. The jump bearing is dictated by the configured jump mode - windborne (governed by wind direction) or random. The probability that a jump will occur on any given day is influenced by the plant pest population density of the source cell and the suitability of the candidate cell. If a candidate cell is jumped into it is seeded with a new plant pest population by creating and attaching a Logistic (Population) object to the Cell agent.

4.5.4 Plant Pest General Surveillance class

The Plant Pest General Surveillance class performs daily scans of all infested cells that also have a human population. The probability of

a detection increases with pest density and human population density (per Section 3.4.1). Only true positive detections are generated.

4.5.5 Plant Pest Active Surveillance class

The Plant Pest Active Surveillance class conducts early detection surveillance, delimiting surveillance and post-treatment surveillance (per Sections 3.4.2, 3.4.3 and 3.4.5). True/false positives and true/false negatives are generated according to the configured sensitivities and specificities (per Section 4.3.2).

4.5.6 Plant Pest Treatment class

The Plant Pest Treatment class performs conducts treatment programs on detected cells per Section 3.4.4). Each treatment in a program reduces the pest population by a stochastic proportion (per Section 4.3.2).

4.5.7 Plant Pest Resources class

The Plant Pest Resources class maintains a pool of user-defined resources for early detection surveillance, delimiting surveillance, treatment and post-treatment surveillance (per Section 3.4.6). The Plant Pest General Surveillance, Plant Pest Active Surveillance and Plant Pest Treatment classes request resources from the pools. If a resource cannot be provided for a job then the client classes queue the job until such time as the resource request can be met.

4.6 Visualisation & Graphical User interface

- A Plant Pest Presence layer was created to dynamically visualise the plant pest population as either graduated colours

depicting densities (Figure 21), or directed arrows depicting the jump/diffusion spread network (Figure 22).

- A Plant Pest Distribution layer was created to dynamically visualise the aggregated plant pest population (over all scenario iterations) as a graduated risk map (Figure 23).
- A Plant Pest Control Layer was created to dynamically visualise general surveillance, early detection surveillance, delimiting surveillance, treatment, and post-treatment surveillance (Figure 10).
- The Visualisation Toggle was updated to allow access to the new plant pest layers.
- The Visualisation Key was updated to dynamically report statistics on infested cells and managed cells (Figure 10).
- The Cell Popup (Figure 10) was updated to display plant pest attributes. Plant pest Population Density curves (Figure 10) can be displayed via the Cell Popup.
- A Trap Dialog (Figure 11) was created to display the national trapping grid. Each trap can be queried and the details viewed via the new Trap Popup.
- The Grid Dialog (Figure 12) was updated with display controls for the pest suitability and land use layers.
- An Infestation Curve popup (Figure 10) was created to dynamically display daily counts of infested cells vs daily counts of managed cells.
- A Resources Monitor (Figure 10) was created to dynamically display resource pool capacity.

- A Resources Profiler was created to dynamically display resource usage. When resource usage is unlimited the Resources Profiler depicts the resourcing required during the incursion. An example is provided in Figure 16 where the maximum number of delimiting surveillance resources (cyan) required at any given time was 75, maximum treatment resources was 45 and maximum post-treatment resources was 40. When resource usage is limited, the Resources Profiler depicts the periods of overload. An example is provided in Figure 17 where the maximum number of delimiting surveillance resources was limited by the pool size of 40.
- A Control Monitor (Figure 10) was created to dynamically display current control actions and backlogs (due to insufficient resources).
- A General Surveillance Dialog (Figure 13) was created for dynamically adjusting general surveillance parameters (Section 4.3.2).
- A Specific Surveillance Dialog (Figure 14) was created for dynamically adjusting early detection surveillance, delimiting surveillance, and post-treatment surveillance parameters (Section 4.3.2).
- A Treatment Dialog (Figure 15) was created for dynamically adjusting treatment program parameters (Section 4.3.2).
- The Scenario Dialog was updated to allow individual enabling/ disabling of the diffusion, jump, early detection surveillance, delimiting surveillance, treatment, post-treatment surveillance and resources components.

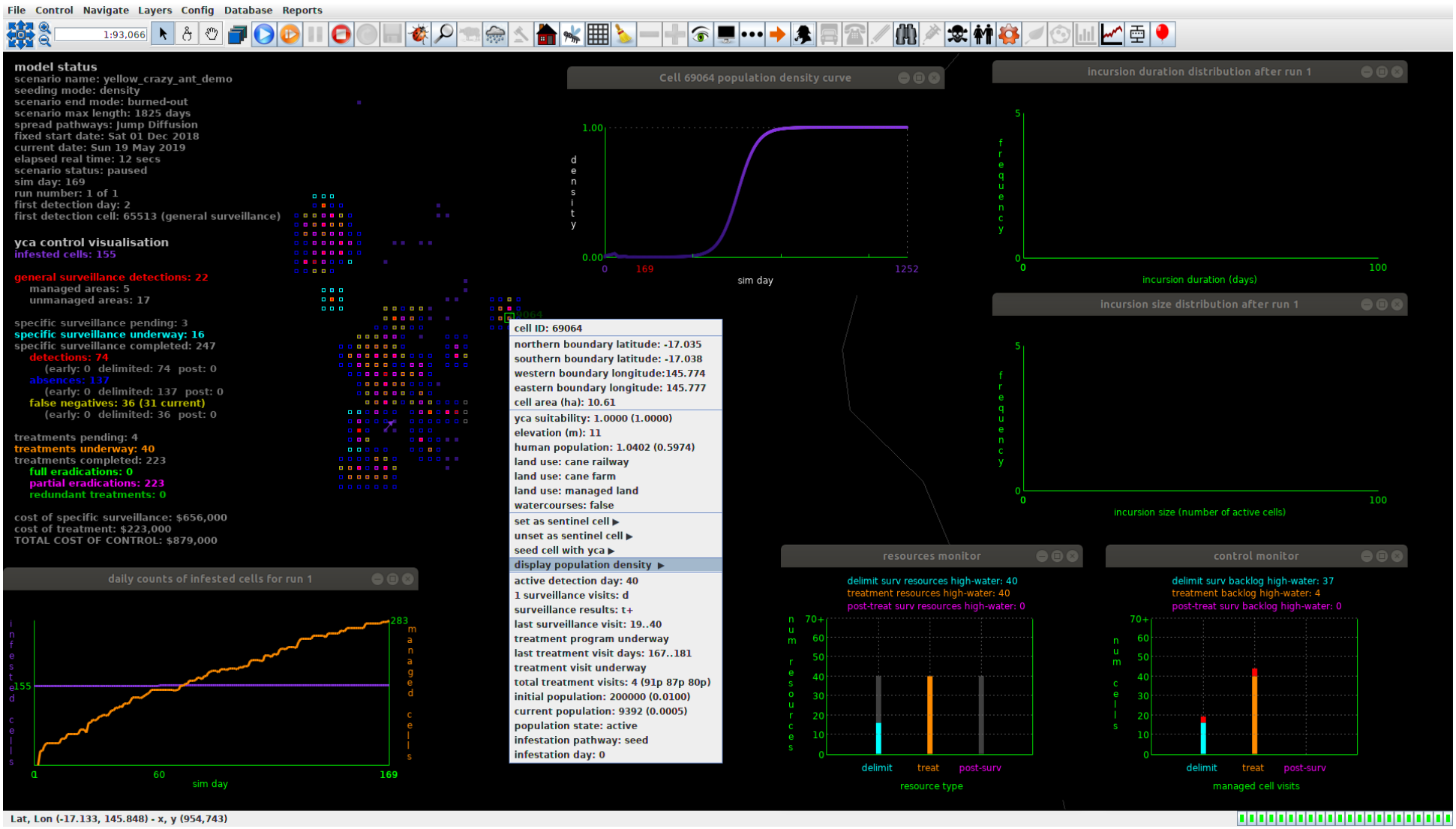

Figure 10. Plant Pest Control Visualisation

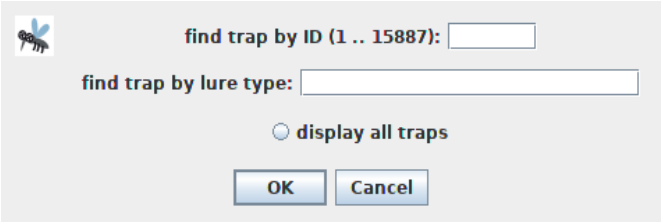

Figure 11. Trap Dialog (early detection surveillance trapping grid)

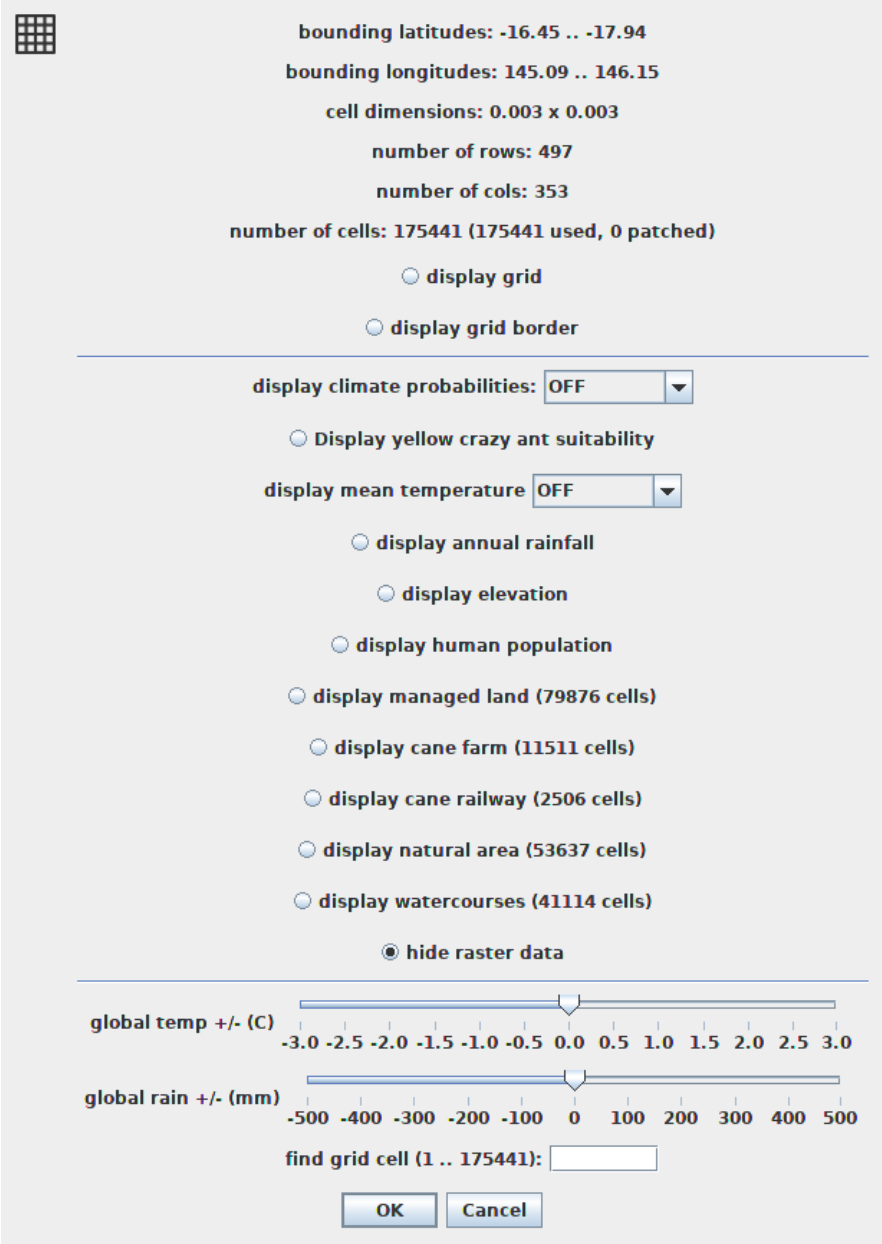

Figure 12. Grid Dialog

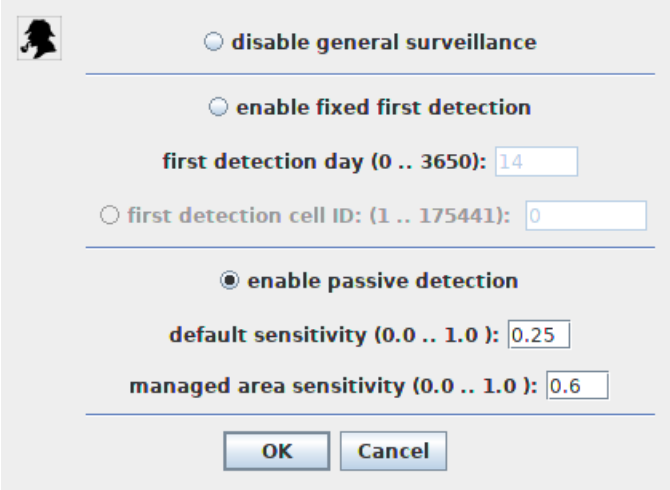

Figure 13. General Surveillance Dialog

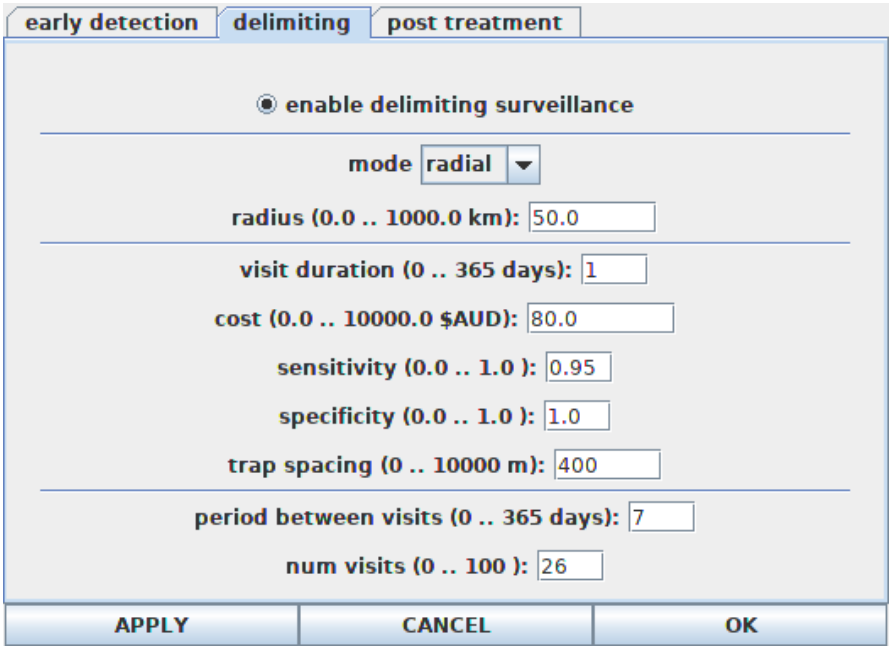

Figure 14. Specific Surveillance Dialog

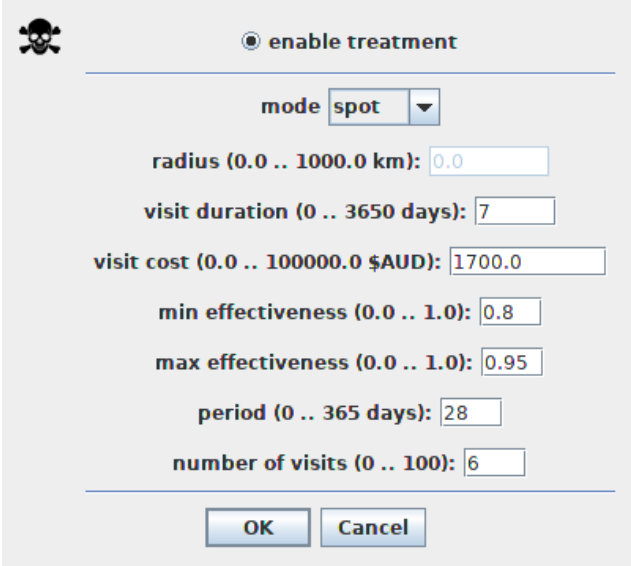

Figure 15. Treatment Dialog

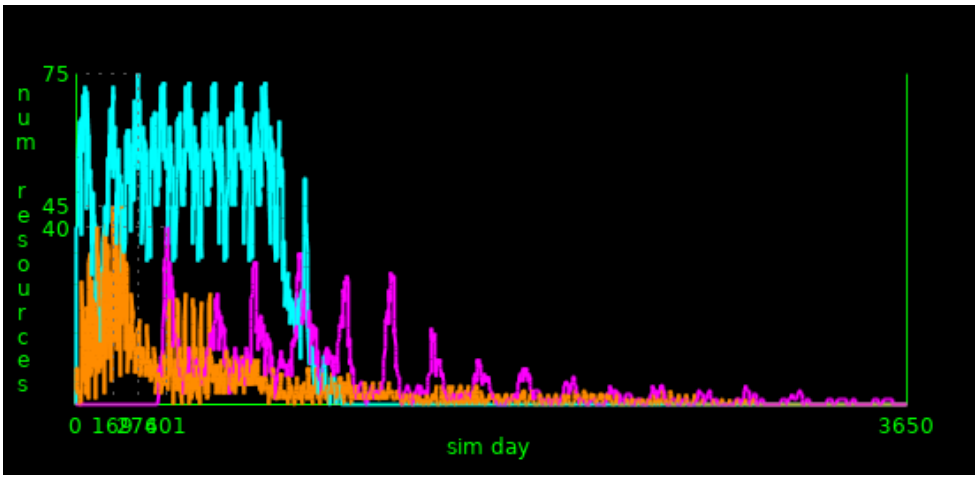

Figure 16. Resources Profiler with unlimited resources

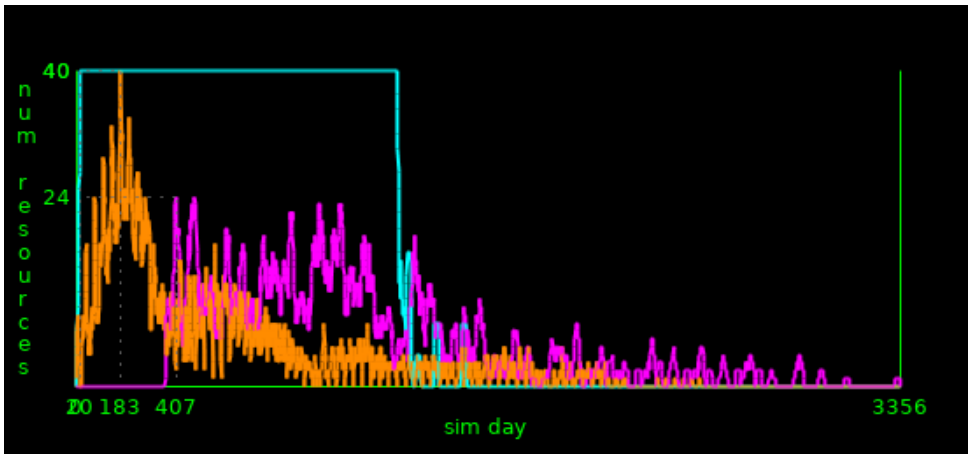

Figure 17. Resources Profiler with limited resources

4.7 Reports

A Plant Pest Spread Report class was created that reports (on a per-run basis):

- number of cells with an endemic plant pest population
- number of cells with an active plant pest population
- number of cells with a quiescent plant pest population
- number of cells with no plant pest population
- number of cells where a plant pest population arose via the diffusion mechanism
- number of cells where a plant pest population arose via the jump mechanism

A Plant Pest Control Report class was created that reports (on a per-run basis):

- day and means of first detection
- number of general surveillance detections
- number of early detection surveillance true/false positives/negatives
- number of delimiting surveillance true/false positives/negatives
- number of treated cells
- number of successful/unsuccessful treatments
- number of post-treatment surveillance true/false positives/negatives
- costs – early detection surveillance, delimiting surveillance, treatment, post-treatment surveillance, total

A Plant Pest Dump class was created that reports on a weekly, monthly or yearly basis:

- the plant pest population state of each grid cell (free, active or quiescent)
- the population density of each grid cell that has a plant pest population

A Plant Pest Map Dump class was created that takes a graphical snapshot of the map on daily, weekly, monthly, yearly, 5-yearly or 10-yearly basis.

4.8 Documentation

The configuration guide was updated with descriptions of all new user configurable parameters.

5 Case study 1a: Tramp ant uncontrolled spread

5.1 Introduction

Tramp ants are a diverse group of aggressive, invasive ant species that can severely impact native species and habitats, agriculture and forestry, and human health and social amenity (Department of Agriculture, 2018). If introduced they can rapidly establish and spread through natural and human-mediated dispersal (Abbott, 2005; Hoffman, 2014). Several Tramp ant species, including *Wasmannia auropunctata* (electric ant), and *Solenopsis invicta* (red imported fire ant), which are both present in Australia, are on the National Priority Pest List.

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 & Haines, 1978b, Lach & Barker, 2013; Helms, 2013), and an increase in the risk of disease being transmitted to plants through insect vectors. (Department of Agriculture, 2018). Supercolonies are formed through colony budding and the absence of intraspecific aggression (O'Dowd et al., 1999).

The purpose of the case study is to demonstrate use of the new APPDIS plant pest modelling functionality in the context of tramp ants. Yellow crazy ant was chosen for the case study due to the availability of expert opinion and data on infestations near Cairns. It is anticipated that YCA model construction will be readily transferable to other tramp ant species (for example, red imported fire ant), with only minor parameter changes (Section 8). Note that the purpose of the case study is to illustrate model usage and not draw conclusions on yellow crazy ant control and/or eradication.

5.2 Method

The grid for this case study was a regional-scale bounding box with latitudes -16.450 to -17.941 and longitudes 145.090 to 146.149, and 0.003 x 0.003 decimal degree cells (approximately 10 ha each). The initial YCA population (Figure 18) was defined through density seeding mode, i.e., the locations and densities of the initial population (spanning 154 cells or approximately 1540 hectares), were defined in the Weather Grid Data database table.

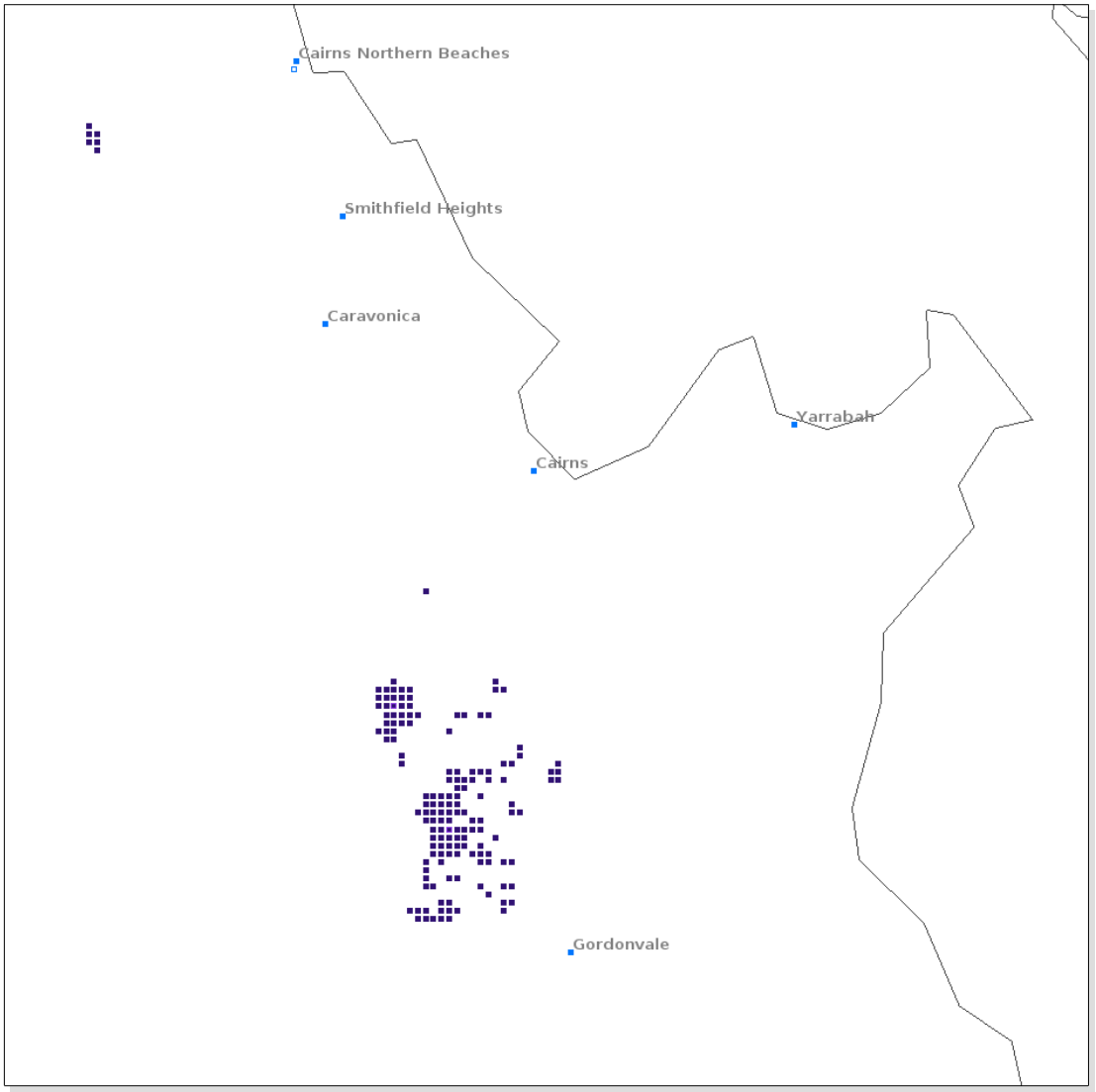

Figure 18. Initial yellow crazy ant cell populations

Modelling in terms of 10 hectare cells reflected the observation that a YCA supercolony spanning an area less than 10 hectares tends to be a single

contiguous population, whereas a supercolony spanning an area greater than 10 ha tends to be comprised of fragmented populations (Hoffmann, 2014).

YCA densities have previously been estimated at between 0.2 million and 3.5 million per hectare (Haines & Haines, 1978a), and up to 20 million per hectare (Abbott, 2005). As the habitat suitability data layer for this study was very simple (land=suitable, sea/lakes=unsuitable), 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 in future versions of the model by incorporating 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 population sizes of the 154 seed cells 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 spread across approximately 1540 hectares. A YCA propagule is arbitrarily defined as comprising 1 queen and 24 workers.

The within-cell abundance of a YCA population over time was modelled with a temperature independent logistic growth function (Section 2).

The spread of YCA between cells was modelled through four concurrent stochastic spread pathways:

1) the steady diffusive spread of YCA over time to adjoining cells. This is mainly attributed to natural budding, however, in some cells the process is accelerated, for example, in cells that contain cane farms the spread is augmented by short-range (intra-cell) hitchhiking jumps from localised cane farming activities.

2) the sporadic spread of YCA over time to non-adjoining cells due to medium-range hitchhiking related to cane farming activities (Section 4). Spread between cane farms was defined separately than spread from cane farms to cane railway corridors.

3) the sporadic spread of YCA over time to other_cells due to human-mediated hitchhiking unrelated to cane farming.

4) the sporadic spread of YCA over time to other cells due to rafting.

As the APPDIS model is stochastic, any given simulation scenario must be run multiple times to allow distributions of outcomes (YCA spread patterns and rates) to emerge. The summary outputs of a single example run is provided in Section 5.3.

5.2.1 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 (Section 3), with a temperature independent population growth rate. The population growth rate, R, was estimated at 0.025 using Equation 2 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) (Figure 19). This implies that 50% of the carrying capacity is reached after 454 days.

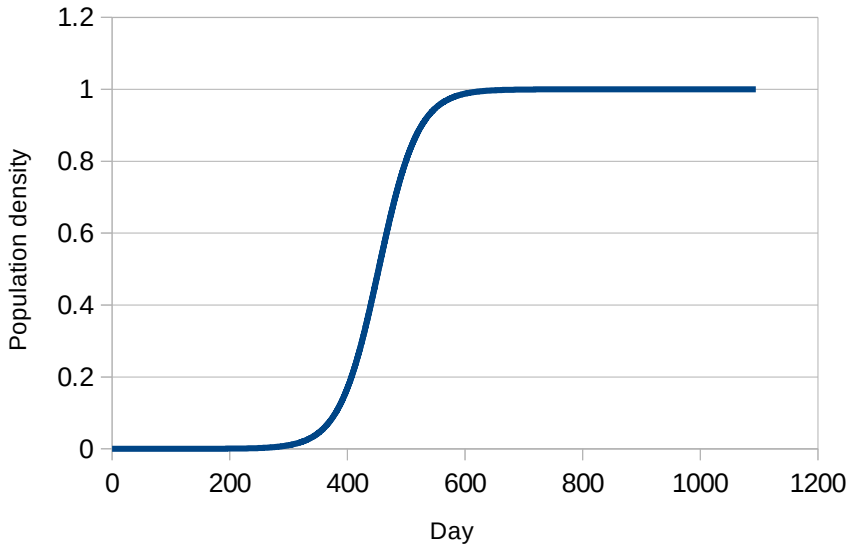

Figure 19. Yellow crazy ant within-cell population density curve

Natural contractions of YCA populations (Abbott, 2006) were not modelled.

5.2.2 Diffusive spread of YCA between adjoining cells

The diffusive spread of YCA from an infested cell into an adjoining naive cell was modelled with Equation 3 (Section 3).

The baseline daily probability of diffusion P_d was derived with Equation 8.

$$P_d = 1 - (1 - p)^{1/d} \qquad \text{(Eqn. 8)}$$

where

P_d = daily probability of an event occurring

p = overall probability of an event occurring at least once in a specified period of interest d

d = the period of interest (days)

The overall probability of diffusion p depends on the land use category of the infested cells. This allows heterogeneity in the diffusion behaviour. For example, diffusion on a cane farm (where natural budding is perhaps augmented by short-range movements arising from within-farm activities such as harvesting), can be defined differently to diffusion in a national park (that is primarily due to natural budding). The baseline daily probabilities of diffusion out of a 10 hectare cell are derived using Equation 8 with the assumptions in Table 1.

Table 1. Daily probabilities of YCA diffusive spread

Land use category of source cell	**Period**	**Overall probability p**	**Daily baseline probability P_d**
Cane farm	3 years	40%	0.000466
Cane railway corridor	3 years	8%	0.000076
Managed/used land	3 years	8%	0.000076
Natural area	3 years	3%	0.000028

The initial YCA population of a newly infested cell is deemed to be a propagule (comprising 24 workers and 1 queen).

5.2.3 Spread between non-contiguous cells due to sugar cane farming activities

The spread of YCA from an infested cell into a non-adjoining naive cell via sugar cane farming activities was modelled with Equation 4 (Section 3).

The baseline daily probability P_j was defined per Equation 10 and depended on the land use category of the *destination* cell. This allowed heterogeneity in the jumping behaviour. For example, jumps between cane farms (brought about, for example, by harvesting activities spanning multiple farms), could be defined differently to jumps from cane farms to cane railway corridors (brought about by cane rail transportation). The baseline daily probabilities of diffusion out of a 10 hectare cell were derived using Equation 8 with the assumptions in Table 2.

Table 2. Daily probabilities of YCA jumps related to cane farming

Land use category of source cell	Land use category of destination cell	Period	Overall probability	Daily probability P_j
Cane farm	Cane farm	1 year	10%	0.000289
Cane farm	Cane railway corridor	1 year	10%	0.000289

Cane farming related hitchhiking jumps are independent of the human population density in the source and destination cells.

The distance of jumps due to cane farming activities are sampled from a BetaPERT distribution (minimum 0.5 km, most likely 2 km, maximum 20 km).

The initial YCA population of a newly infested cell is deemed to be a propagule (comprising 24 workers and 1 queen).

Seasonal variations in cane farming activities were not modelled, i.e., the pathway represents average cane jumps over time.

5.2.4 Spread between cells due to human-mediated hitchhiking

The spread of YCA from an infested cell into another naive cell via human-mediated hitchhiking (unrelated to cane farming activities), was modelled with Equation 4 (Section 3).

The baseline daily probability P_j was defined per Equation 8 and arose from the assumption that if a cell has a maximal YCA population (i.e., is at carrying capacity), and has a maximal human population (i.e., normalised human population density of 1.0), there is (arbitrarily) a 30% chance of a human-mediated hitchhiking jump into a another cell within a year:

$$Pj = 1 - (1 - 0.3)^{(1/365)}$$

$$Pj = 0.000977$$

Human-mediated hitchhiking jumps may occur between cells with land use classifications as follows:

- from managed/used land to other managed/used land
- from managed/used land to cane railway corridors
- from managed/used to land to natural areas
- from cane railway corridors to managed/used land
- from cane railway corridors to other cane railway corridors
- from cane railway corridors to natural areas
- from natural areas to other natural areas
- from natural areas to managed/used land
- from natural areas to cane railway corridors

A source cell must have a human population density greater than zero for a hitchhiking jump to occur. A destination cell generally must have a human population density greater than zero for a hitchhiking jump to occur, however, the model allows for random infrequent hitchhiking events to occasionally occur from a populated area into a non-populated area (e.g., wilderness).

The human population density of the source cell influences the probability of a jump occurring.

Human-mediated jump distances are sampled from a BetaPERT distribution (minimum 0.5 km, most likely 10 km, maximum 75 km).

The initial YCA population of a newly infested cell is deemed to be a propagule (comprising 24 workers and 1 queen).

5.2.5 Spread between cells due to rafting

The spread of YCA from an infested cell into a naive cell via rafting was modelled with Equation 4 (Section 3).

The baseline daily probability P_j was defined per Equation 8 and arose from the assumption that if a 10 hectare cell with waterways has a maximal YCA population (i.e., is at carrying capacity), there is a 5% chance of a rafting jump into another cell within a year:

$$Pj = 1 - (1 - 0.05)^{(1/365)}$$

$$Pj = 0.000141$$

Rafting jumps are independent of the land use category and human population density of the source and destination cells.

The distance of a rafting jump is sampled from a BetaPERT distribution (minimum 0.5 km, most likely 0.5 km, maximum 5 km).

The initial YCA population of a newly infested cell is deemed to be a propagule (comprising 24 workers and 1 queen).

Seasonal variations in rafting likelihood were not modelled, i.e., the pathway represents average rafting jumps over time.

5.2.6 Spread pathway summary

Table 3 provides a summary of the various spread pathways where

cane = cells that contain one or more cane farms

railway = cells that contain a cane railway corridor

managed = cells that contain managed/used land

natural = cells that contain natural areas

water = cells that contain one or more watercourses

Table 3. Summary of YCA spread pathways

Spread pathway	Source cell type	Destination cell type	Baseline probability	Dependent on human population density	Distance	Initial population in a newly infested cell
Diffusion	cane railway managed natural	any any any any	0.000466 0.000076 0.000076 0.000028	no	Adjoining cells only	25
Cane farm jumps	cane cane	cane railway	0.000289 0.000289	no	BetaPERT (0.5, 2, 20) km	25
Hitchhiking (human-mediated) jumps	railway, managed, natural	railway, managed, natural	0.000977 (dampened by the source cell human population density)	yes	BetaPERT (0.5, 10, 75) km	25
Rafting jumps	water	water	0.000141	no	BetaPERT (0.5, 0.5, 5) km	25

Table 4 uses Equation 4 to illustrate the daily probabilities of a jump for minimal and maximal YCA and human population densities. It illustrates how the probabilities of cane-related and rafting jumps jump are independent of the human population density of the source cell.

Table 4. Examples of daily probabilities of YCA jumps

Cell YCA population	Cell normalised YCA population density	Cell human population	Cell normalised human population density	Daily probability of cane jump	Daily probability of hitchhiking jump	Daily probability of rafting jump
min (25)	1.25×10^{-6}	min (1)	0.002	3.61×10^{-10}	2.30×10^{-12}	1.76×10^{-10}
min (25)	1.25×10^{-6}	max (531)	1.0	3.61×10^{-10}	1.22×10^{-9}	1.76×10^{-10}
max (20M)	1.0	min (1)	0.002	2.89×10^{-4}	1.84×10^{-6}	1.41×10^{-4}
max (20M)	1.0	max (531)	1.0	2.89×10^{-4}	9.77×10^{-4}	1.41×10^{-4}

5.3 Scenario

The initial YCA population (Figure 18) was allowed to spread without intervention for 30 years. The scenario was repeated 50 times.

5.4 Results

Table 5 provides a summary of uncontrolled YCA spread over 30 years. A sample resultant YCA population and infestation network (i.e one of the 50 iterations) are provided in Figures 21 and 22. Figure 23 illustrates how a stochastic model such as APPDIS produces distributions of outcome variables.

Table 5. Simulation results for 50 iterations of 30 years of uncontrolled yellow crazy ant spread

Model outcome	**Value**
Scenario length	30 years
Initial YCA population size	310 million

Final population size[1]	124 billion
Initial infestation area[1]	154 cells (approx. 1540 ha)
Final infestation area[1]	6936 cells (approx. 69,360 ha)
Final infestation area convergence[2]	2.90%
Num diffusions[1]	3164
Managed land diffusion rate[1]	119 metres/year
Cane farm diffusion rate[1]	132 metres/year
Cane railway diffusion rate[1]	90 metres/year
Natural area diffusion rate[1]	68 metres/year
Cane-related jump rate[1]	41 jumps/year
Human-mediated jump rate[1]	16 jumps/year
Rafting jump rate[1]	13 jumps/year
Simulation run time[1]	5.3 hours

[1]averaged over 50 runs

[2]percentage standard error of the sample mean (95% confidence)

Convergence estimates the percentage standard error *E* of the sample mean with 95% confidence for a given number of iterations (Equation 9) (Driels and Shin, 2004).

$$E = \frac{100\, z_c S_x}{\bar{x}\sqrt{n}} \qquad \text{(Eqn. 9)}$$

where

E = percentage standard error of the sample mean

z_c = confidence coefficient (1.96 = 95%)

S_x = sample standard deviation

x = sample mean

n = number of runs

Figure 20 provides a snippet of the 'yearly dump' output for Case Study 1a. The model outputs the population density for each active cell at the end of every year, for each simulation run.

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

Figure **20.** Yellow crazy ant simulation report (snippet only)

Figure 21 provides an example of a yellow crazy ant population after 30 years of uncontrolled spread (iteration 40 of 50). The varying population densities of each cell are encoded with shades of purple – the lighter the shade the higher the population density.

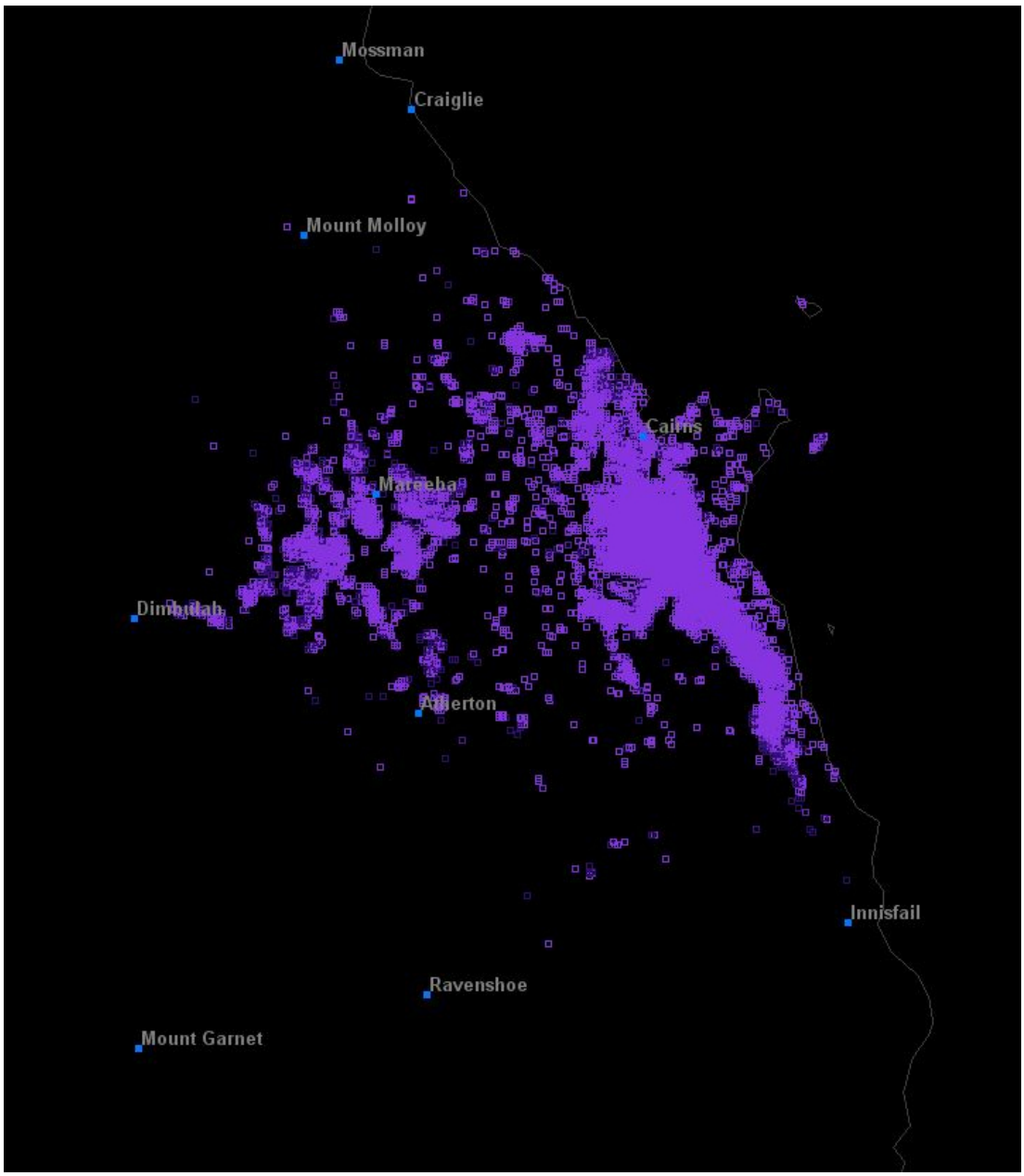

Figure 21. Sample yellow crazy ant population density map

Figure 22 provides an example of a yellow crazy ant infestation network after 30 years of uncontrolled spread (iteration 40 of 50). Diffusions are represented by short orange arrows, cane-related jumps by yellow arrows, human-mediated hitchhiking jumps by red arrows and rafting jumps by cyan arrows.

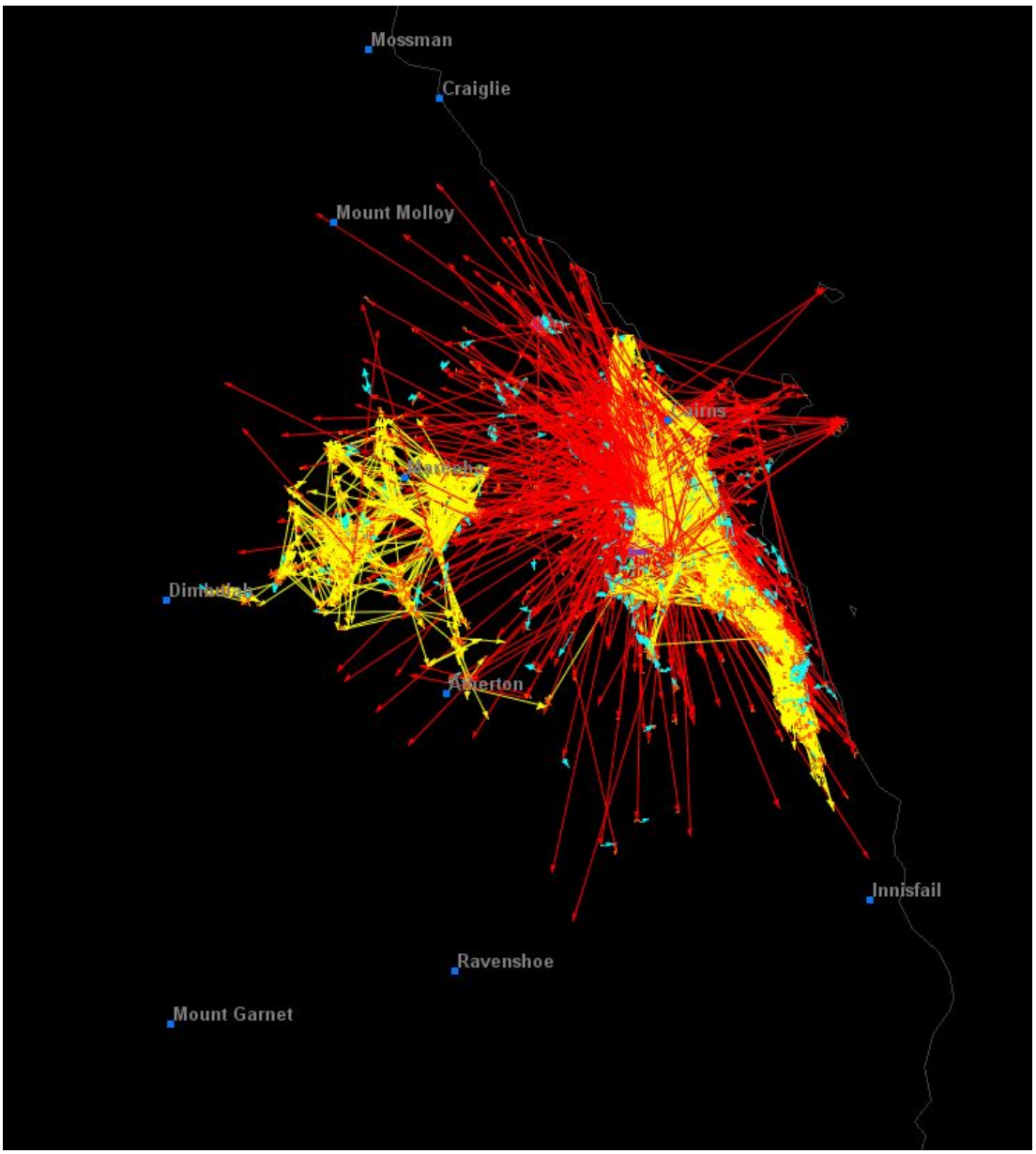

Figure 22. Sample yellow crazy ant spread pathway network map

Figure 23 illustrates the distribution probabilities of YCA after 30 years of uncontrolled spread. The 50 scenario iterations are aggregated into a single distribution map whereby cells that most frequently hosted a YCA population are encoded in red and cells that least frequently hosted a YCA population are encoded in blue. The encoding between distribution probability and colour is provided on the left hand side of the model output.

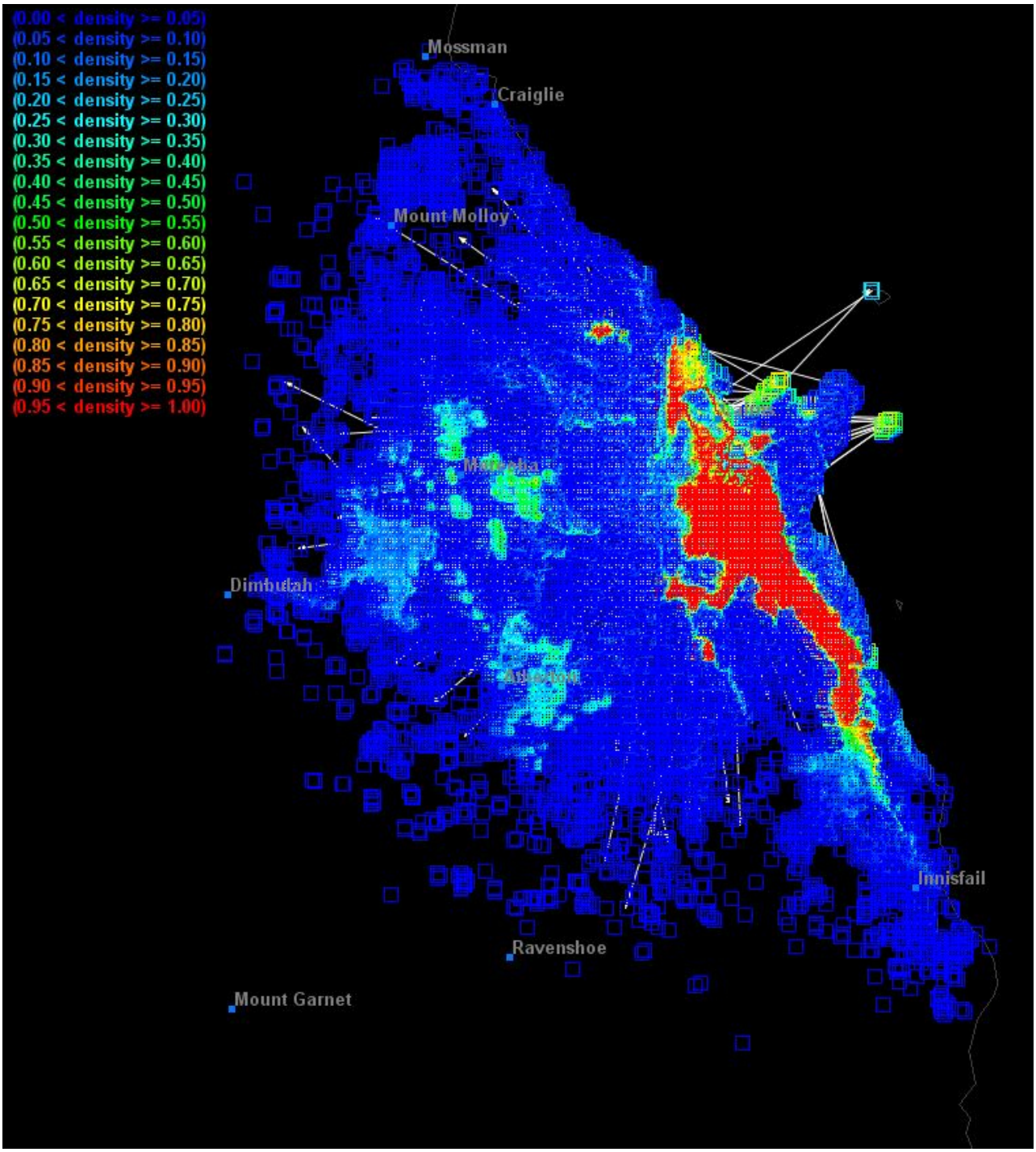

Figure **23.** Sample yellow crazy ant distribution risk map

5.5 Discussion

This case study explicitly took land use heterogeneity into account when simulating the diffusive spread of YCA between cells. This allowed, for example, spread to be more vigorous in cells that have cane farming activities than cells in natural areas where unaided dispersal is the main driver.

The average YCA diffusion rates over a 30 year period (ranging from 68 metres/ year in natural areas up to 132 metres/year in cane farming areas), was broadly in line with published budding distances of up to 182 metres per year (Abbott, 2006), and 37 to 402 (average 125) metres per year (Haines & Haines, 1978a). [Note that cells may have multiple land uses (e.g. cane + managed, railway + managed). Each cell diffuses based on its highest risk land use and this can artificially boost the diffusion rate for the lower risk land use of the cell (e.g. a managed cell with cane 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 should be noted that, data permitting, it would be easy 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, a 30 km movement of YCA from near Cairns to a residential dwelling in Russett Park (on the edge of the Wet Tropics World Heritage Area), was attributed to the transportation of landscaping materials

As illustrated in Figure 23, one of the outputs of AAPDIS 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 (Figure 24).

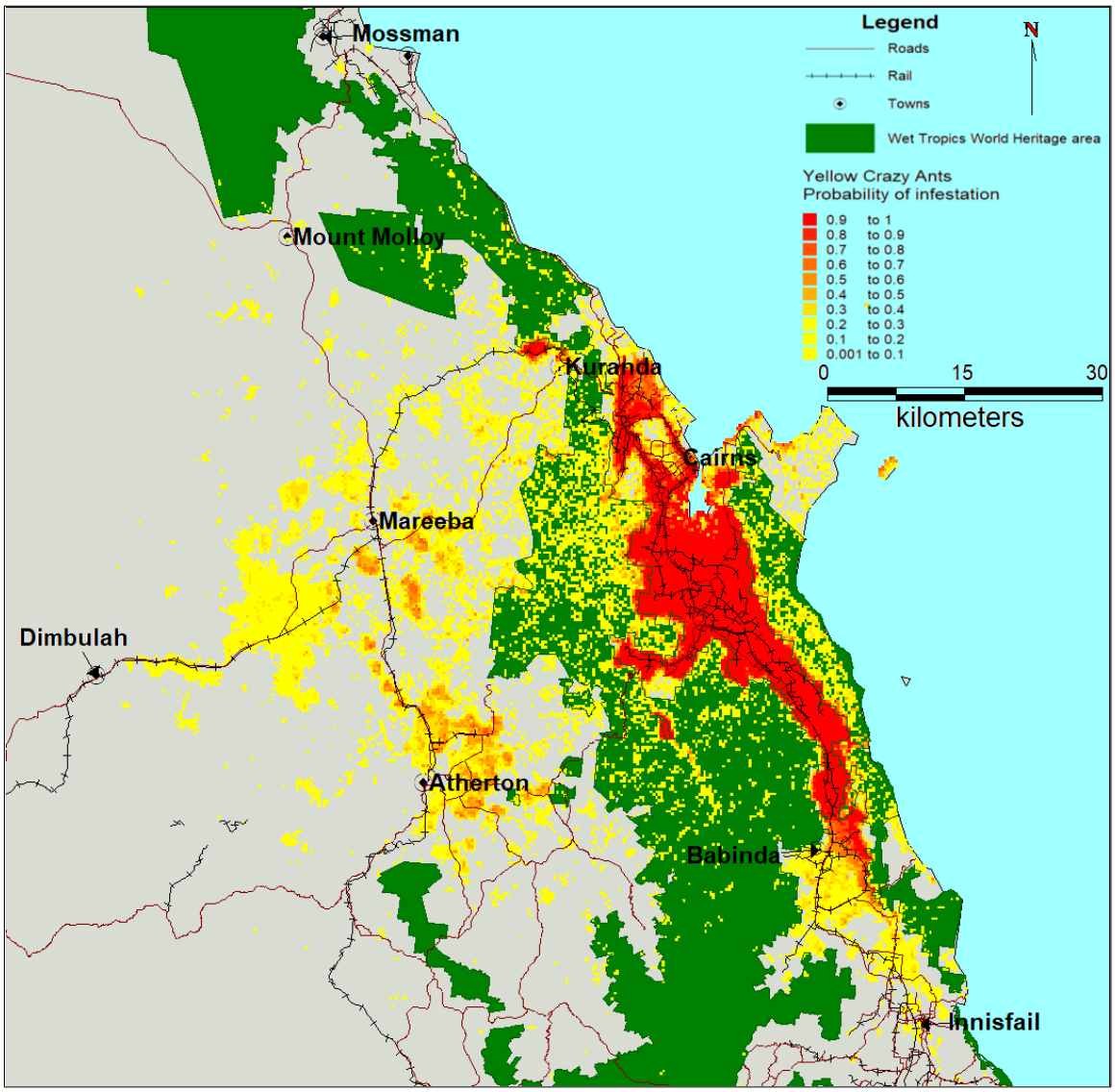

Figure **24.** Risk map of YCA spread in the World Heritage Area after 30 years of uncontrolled spread

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 mean. This is perhaps related to the very simple suitability data layer (1=land; 0=ocean/lake). A more expressive suitability data layer (as employed in Case Study 2) would likely produce more variability in the infestation network.

6 Case study 1b: Tramp ant control and eradication

6.1 Introduction

This case study looks at the effect of trap spacing (for both delimiting and post-treatment surveillance), on the cost and efficacy of eradicating an established population of yellow crazy ants.

6.2 Method

The initial YCA population and spread pathway parameterisation from Case Study 1a (Sections 5.1 and 5.2) were re-used, and general surveillance, delimiting surveillance, treatment, and post-treatment surveillance pathways added.

6.2.1 Model parameterisation

The model parameterisation for the control and eradication pathways is provided in Tables 6 to 10. Refer to Sections 4.3.2 for explanations of the parameters. Note that parameter values are for illustrative purposes only and will vary according to the specific control/eradication strategies that a model user wishes to compare.

Table 6. YCA general surveillance parameterisation

Parameter	**Value**
Observer sensitivity in managed areas	0.60
Observer sensitivity in unmanaged areas	0.25
General surveillance mode	Passive

Table 7. YCA delimiting surveillance parameterisation

Parameter	**Value**
Mode	Moore
Visit duration (per cell)	21 days
Trap spacing	10 metres
Trap sensitivity	0.99
Trap specificity	1.00
Visit cost (per trap)	A$10
Interval between visits	90 days
Minimum number of visits	8
Resourcing	Unlimited

Table 8. YCA treatment parameterisation

Parameter	**Value**
Treatment mode	spot
Visit duration (per cell)	7 days
Minimum effectiveness	0.8
Maximum effectiveness	0.95
Treatment cost (per cell)	A$1700
Interval between visits	28 days
Minimum number of visits	6
Resourcing	Unlimited

Table 9. YCA post-treatment surveillance parameterisation

Parameter	**Value**
Visit duration (per cell)	21 days
Trap spacing	10 metres

Sensitivity	0.99
Specificity	1.00
Visit cost (per trap)	A$10
Interval between visits	180 days
Minimum number of visits (before result)	4
Resourcing	Unlimited

6.2.2 Scenarios

(a) Investigating the effect of delimiting surveillance trap spacing on control cost and effectiveness

The trap spacing parameter for delimiting surveillance (Table 7) was systematically varied between 2 and 100 metres. The trap spacing parameter for post-treatment surveillance (Table 9) was held constant at 10 metres. 500 iterations of the scenario were run for each trap spacing. The maximum length of a scenario was limited to 15 years (5475 days).

(b) Investigating the effect of post-treatment surveillance trap spacing on control cost and effectiveness

The trap spacing parameter for post-treatment surveillance (Table 9) was systematically varied between 2 and 100 metres. The trap spacing parameter for post-treatment surveillance (Table 7) was held constant at 10 metres. 500 iterations of the scenario were run for each trap spacing. The maximum length of a scenario was limited to 15 years (5475 days).

6.3 Results

An example of the APPDIS dynamic visualisation of the control and eradication of an established YCA population is provided in Figure 10 (Section 4). Table 10 and Figures 24 to 26 summarise the effect of delimiting surveillance trap spacing on the average cost and effectiveness of control/eradication.

Table 10. Effect of delimiting surveillance trap spacing on control effectiveness and cost

Trap spacing (m)	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 runtime per iteration (secs)
2	4113	504.64	0.27	6.34	0.50%	0.58	99.25%	64
5	4182	80.54	0.26	6.35	0.27%	7.59	99.50%	46
8	4227	31.65	0.27	6.46	0.45%	17.90	99.14%	44
10	4281	20.31	0.27	6.51	0.31%	23.28	99.16%	55
15	4255	9.05	0.27	6.68	0.26%	34.59	99.20%	56
20	4354	5.10	0.27	6.79	0.26%	45.29	99.12%	52
30	4431	2.28	0.27	6.99	0.24%	61.73	99.07%	53
40	4469	1.28	0.27	7.09	0.23%	75.37	98.99%	59
50	4471	0.82	0.27	7.14	0.24%	86.22	99.13%	72
60	4490	0.57	0.27	7.21	0.26%	95.89	98.84%	66
70	4455	0.41	0.27	7.21	0.24%	103.26	99.13%	72
80	4474	0.31	0.27	7.22	0.26%	110.18	98.85%	71
90	4508	0.25	0.27	7.22	0.25%	115.87	99.03%	68
100	4434	0.19	0.27	7.22	0.24%	120.49	99.16%	70

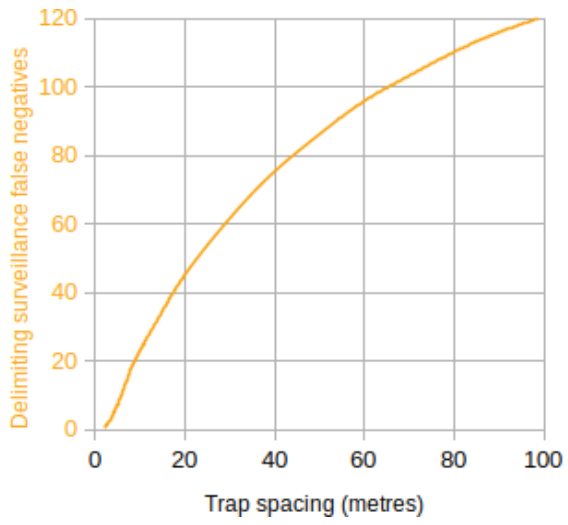

Figure 25. Effect of trap spacing on delimiting surveillance false negative results

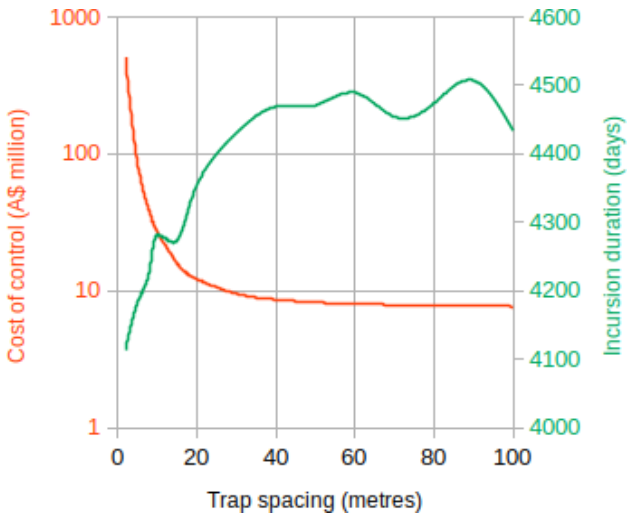

Figure 26. Effect of delimiting surveillance trap spacing on incursion duration and control cost

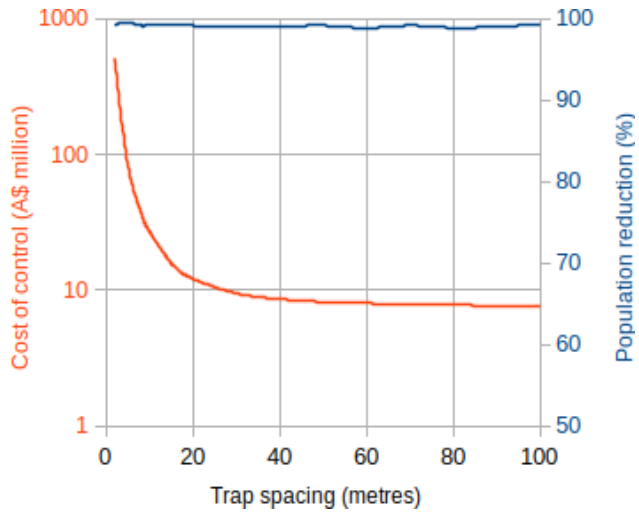

Figure 27. Effect of delimiting surveillance trap spacing on control effectiveness and cost

Table 11 and Figures 28 to 30 summarise the effect of post-treatment surveillance trap spacing on the average cost and effectiveness of control/eradication.

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

Trap spacing (m)	Outbreak length (days)	Delimiting surv. cost (A$ million)	Treatment cost (A$ million)	Post-treatment surveillance cost (A$ million)	Total cost of control convergence	Post-treatment surv. false negatives	Reduction in infested cells	Average runtime per iteration (secs)
2	2049	20.07	0.26	143.39	0.10%	0.05	99.99%	28
5	2796	20.10	0.26	23.57	0.14%	10.29	99.90%	34
8	3611	20.18	0.26	9.74	0.21%	31.56	99.64%	41
10	4233	20.27	0.27	6.51	0.25%	48.59	99.31%	49
15	5262	20.73	0.27	3.24	0.46%	97.29	96.95%	61
20	5470	21.36	0.27	2.03	0.60%	151.01	93.78%	59
30	5475	22.87	0.28	1.09	0.73%	269.86	83.12%	74
40	5475	24.37	0.29	0.69	0.86%	378.37	70.68%	95
50	5475	26.72	0.31	0.49	0.92%	481.37	55.37%	110
60	5475	28.30	0.32	0.36	1.07%	566.74	43.54%	118
70	5475	29.99	0.33	0.28	1.33%	650.54	32.11%	124
80	5475	32.17	0.34	0.22	1.51%	718.66	20.69%	131
90	5475	33.92	0.36	0.19	1.66%	780.78	11.66%	137
100	5475	35.36	0.37	0.15	1.48%	836.07	1.87%	142

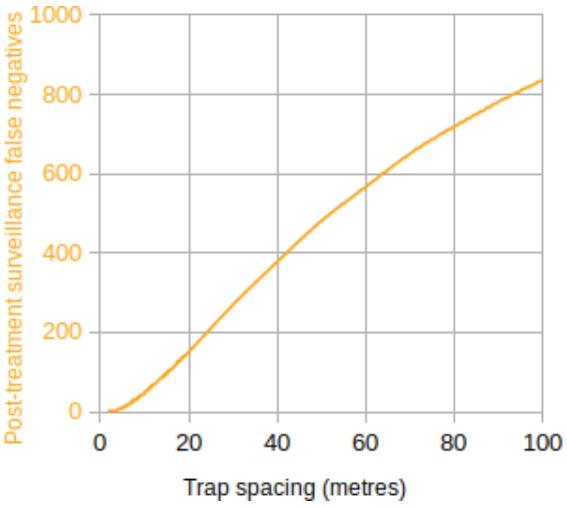

Figure 28. Effect of trap spacing on post-treatment surveillance false negative results

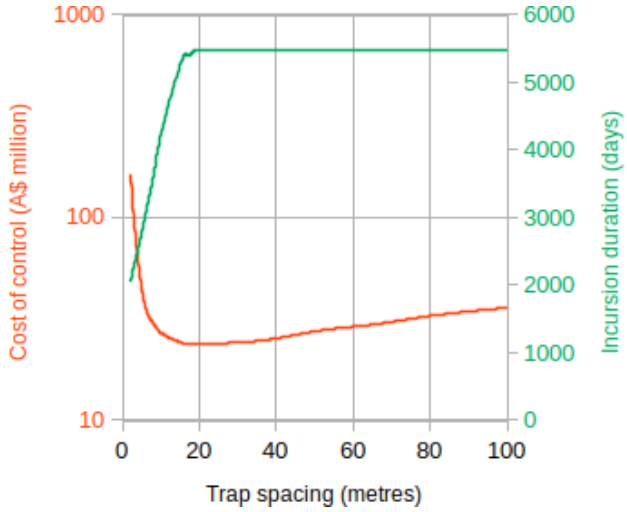

Figure 29. Effect of post-treatment surveillance trap spacing on incursion duration and control cost

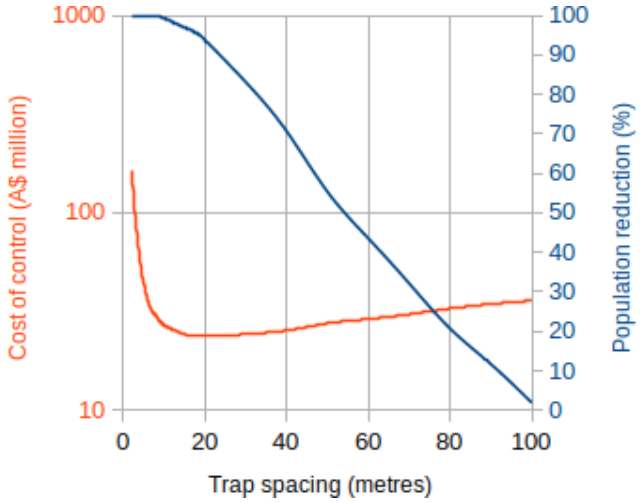

Figure 30. Effect of post-treatment surveillance trap spacing on control effectiveness and cost

6.4 Discussion

Figures 25 and 28 illustrate how false negative surveillance results increased with trap spacing (for both delimiting and post-treatment surveillance).

The overall cost of control rose steeply when delimiting surveillance trap spacings were less than 20 metres (Figure 26) and when post-treatment surveillance trap spacings were less than 10 metres (Figure 29).

The effectiveness of control tended to be far more sensitive to post-treatment surveillance trap spacing than delimiting surveillance trap spacing. Figure 27 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 metres resulted in a 99% population reduction within 15 years. Further, the effectiveness of control decreased steadily as post-treatment surveillance trap spacing increased (Figure 30), with a trap spacing of 100 metres yielding no net population reduction after 15 years. This suggests that the effectiveness of post-treatment surveillance is an important aspect of pest eradication. Figure 25 indicates that a trap spacing of 18 metres minimised the cost of control at approximately A$23.5M and resulted in an average 95% population reduction. In order to achieve an average 99.99% population, the required 2-metre post-treatment surveillance trap spacing would incur a cost of approximately A$163M.

The high sensitivity of control effectiveness to post-treatment surveillance trap spacing is perhaps because post-treatment surveillance is typically conducted in cells with very small pest densities. As discussed in Section 3.4.2 (Figures 4 and 5), 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 population densities (Figure 3, Section 3.4.1).

For the uncontrolled spread scenario, the model on average, took 5.9 hours to complete a single scenario iteration of 30 years of uncontrolled YCA spread. This reflects the high computational load associated with large numbers of infested cell agents (on average, there were 6936 infested cells after 30 years). In contrast, for the control and eradiction scenario, the model on average, took 73 seconds to complete a single scenario iteration.

The simulations produced very good convergence for the mean total cost of control (< 1.6%). This implies 95% confidence that there is at most 1.6% standard error in the distribution of the mean, and that 500 iterations of the scenarios were sufficient.

7 Case study 2: Exotic fruit flies

7.1 Introduction

Oriental fruit fly (*Bactrocera dorsalis*) is extremely damaging to horticultural industries due to its wide host range, ability to attack unripe fruit, and dominance over competing fruit fly species (CABI, 2015). In addition to ecological damage, Oriental fruit fly invasions cause significant market access problems. In Australia, an incursion of Oriental fruit fly occurred in Cairns in 1995 (Bellas, 1996) and was successfully eradicated through a program that concluded in 1999. The losses associated with market access restrictions are estimated to have been $100 million ($140 million 2012 AUD at 2.5%) (Cantrell et al., 2002). Full market access was granted when the Pest Quarantine Area was rescinded in August 1998. The first detection in 1995 was a general surveillance detection by a farmer and it is likely that the incursion had been present for many generations before reaching that location (Meats et al., 2008). This late detection is often attributed to the decision in 1992 to remove an early detection trapping grid.

In this case study we model a similar incursion in Cairns, this time with an early detection trapping grid in operation. We also explore similar scenarios in Brisbane, Hobart, Melbourne, Sydney, and Perth, other examples of cities that have high volumes of arriving travellers and/or imported goods, and may be exposed to exotic pest incursions.

7.2 Method

The grid for this case study was a national-scale bounding box with latitudes -9.16 to -43.855 and longitudes 112.70 to 153.795, and 0.045 x 0.045 decimal degree cells (approximately 2500 ha). Initial Oriental fruit fly populations were seeded as a point introduction to a grid cell in each city. Mean weekly temperature data are assigned to each cell in the grid.

7.2.1 Within-cell growth

Within-cell population abundance was modelled with a temperature-dependent logistic growth function (Section 3.2). Estimation of the parameters for carrying capacity and growth rates are provided below.

7.2.1.1 Carrying capacity

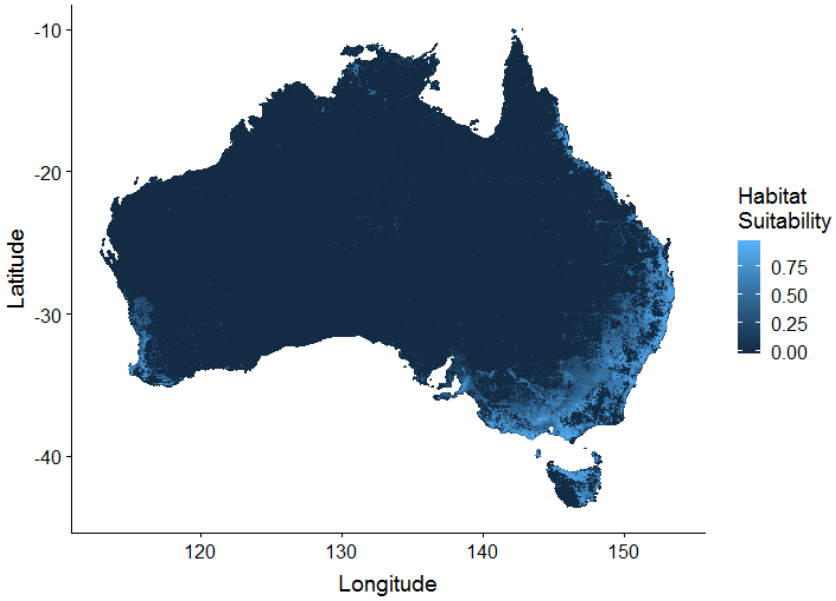

Figure 31. Oriental fruit fly cell suitability data layer

The cell suitability data layer for Oriental fruit fly (Figure 31), was derived from Normalised Difference Vegetation Index (NDVI) data and land use type. This layer represents cell-specific carrying capacity, also referred to as habitat suitability, varying between 0 and 1. Details of the data layer are described in Camac et al., 2019.

The carrying capacity of a cell was determined by the cell's suitability score and the maximum carrying capacity of an ideally suitable cell (set to 1.25 million). For example, a cell with a suitability score of 0.2 can accommodate at most 0.2 x 1.25 million flies = 250,000 flies.

7.2.1.2 Temperature dependent growth rates

The lifecycle time of *Bactrocera dorsalis* can range from a month up to several months in cooler areas. Density dependent mortality increases if oviposition

occurs in fruit already containing eggs. Some species of tephritid fruit flies are deterred from oviposition by the rotting fruit odours produced by larvae feeding on the flesh of the fruit (Fitt, 1984; Muryati et al., 2017). During the egg and larval stage, protection from the climate is provided by the fruit. The larvae remain inside the fruit until completion of the third instar, where larvae emerge to pupate in the soil beneath the host plant. Although the organisms are no longer protected by the fruit, the soil offers some thermal insulation. Pupae are sensitive to high levels of moisture in the soil, however this is not currently included as a data layer in the APPDIS model.

The unconstrained temperature dependent growth rate (i.e., ignoring the effects of carrying capacity), at temperature, T, is given by Equation 10:

$$R_T = \frac{\log\left(\frac{D_0}{D_t}\right)}{-t_T} \qquad \text{(Eqn. 10)}$$

where

R_T = growth rate at temperature T

D_0 = the initial population size

D_t = the final abundance of adult females

t_T = time to complete a full life cycle

To produce temperature dependent growth rate parameters, we consider a single adult female (i.e. D0 = 1), believed to lay approximately over 1000 eggs in her lifetime (Yousheng, Farong & Huanping, 1996; Ye & Liu, 2007). We assume a 1:1 female to male sex ratio in wild populations (shown to be 0.99:1 by Luo et al., 2009), so half of these adults will make up the final abundance of adult females (Dt). Of the eggs, a proportion will progress to the larval and pupal stages before emerging as adults. Survivorship of a cohort will be affected by ambient temperature and other mortality due to predators, parasitoids and accidents. Given the difficulty in experimentally estimating other mortality factors, there is little evidence to draw on in the literature. However it is apparent that even under optimal conditions with unrestricted growth, three generations would result in $(1000/2)^3$ = 125 million flies, which is

not consistent with observations of fruit fly populations. As temperature effects on survival have been well studied and are expected to have a major impact on both the establishment potential and growth rates, the shape of the growth rate function with respect to temperature has first been estimated from empirical studies and then later rescaled to take into account other mortality factors.

The method by which Dt was estimated is outlined in Figure 32. Survivorship curves associated with each life stage show the proportion of fruit fly entering the subsequent life stage over a range of temperatures.

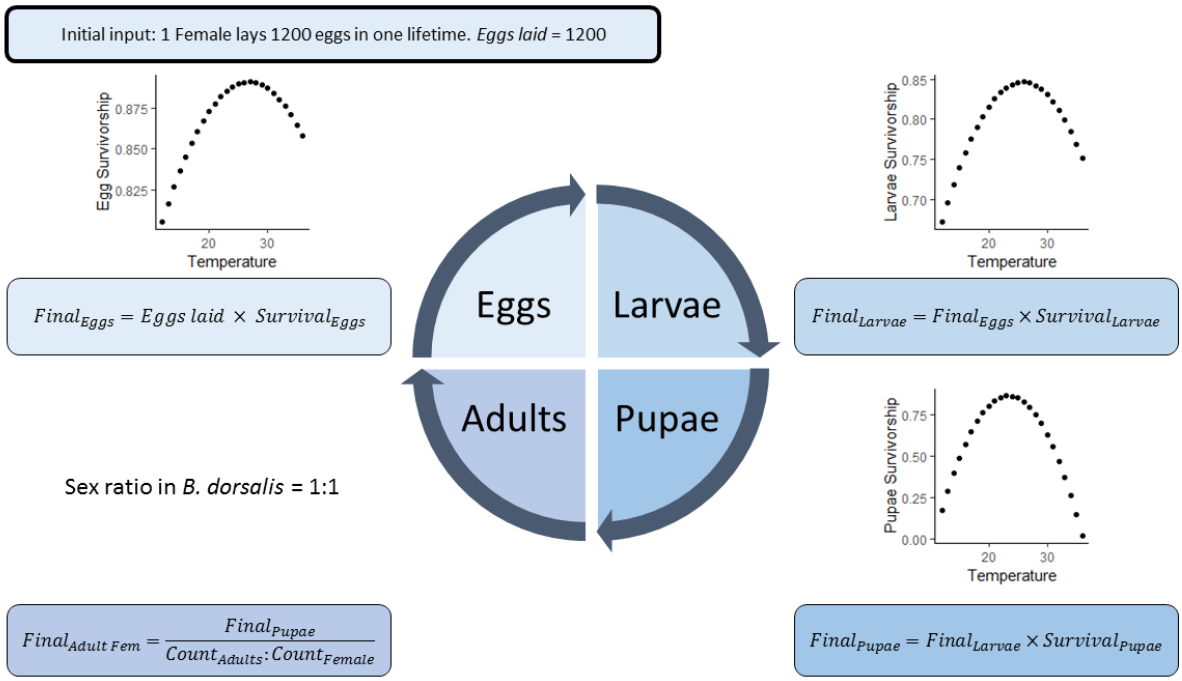

Figure 32. Method to estimate D_t for *Bactrocera dorsalis* by calculating survivorship in each life stage.

Tables 12 to 14 present data from five studies where the development time and survivorship of fruit fly populations were measured in response to temperature manipulations (Danjuma et al., 2014; Rwomushana et al., 2008; Luo et al., 2009; Vargas et al., 2000; Jiajiao et al., 2000). The various species described in these papers are now considered synonyms of *Bactrocera dorsalis*. Each of these studies set out to determine the effects of temperature on population dynamics, covering the optimal growth range. We have ignored similar papers

seeking to find total mortality thresholds for extermination as they typically cover a very small temperature range at each end of the thermal performance curve, and mortality will occur over very short periods (Hsu et al., 2018; Kaliyan et al., 2007). Moreover, we have ignored papers with total temperature exposure over sub-daily extents and papers that analyse only one temperature.

Table 12. Data for egg survivorship and development time across a range of temperatures

Species	Temperature (ºC)	Development time (days)	Survival Rate (%)	Reference
Bactrocera papayae	15	5.05	81.87	Danjuma et al., 2014
Bactrocera invadens	15	5.71	90.67	Rwomushana et al., 2008
Bactrocera dorsalis	17	3.61	85.2	Luo et al., 2009
Bactrocera dorsalis	18.5	3.2	74	Vargas et al., 2000
Bactrocera dorsalis	18.96	2.96	N/A	Jiajiao et al., 2000
Bactrocera papayae	20	2.7	87.2	Danjuma et al., 2014
Bactrocera invadens	20	2.88	94.8	Rwomushana et al., 2008
Bactrocera dorsalis	21	2.52	89	Luo et al., 2009
Bactrocera dorsalis	23.18	1.96	N/A	Jiajiao et al., 2000
Bactrocera dorsalis	23.5	2	83	Vargas et al., 2000
Bactrocera dorsalis	24	2	85	Vargas et al., 2000
Bactrocera dorsalis	24.14	1.54	N/A	Jiajiao et al., 2000
Bactrocera papayae	25	1.53	85.6	Danjuma et al., 2014
Bactrocera dorsalis	25	1.55	92.4	Luo et al., 2009
Bactrocera invadens	25	1.69	93.47	Rwomushana et al., 2008
Bactrocera papayae	27	1.22	88.4	Danjuma et al., 2014
Bactrocera dorsalis	28.08	1.17	N/A	Jiajiao et al., 2000
Bactrocera dorsalis	29	1.25	89.8	Luo et al., 2009
Bactrocera papayae	30	1.11	90.93	Danjuma et al., 2014
Bactrocera invadens	30	1.41	93.6	Rwomushana et al., 2008
Bactrocera dorsalis	31.02	1.04	N/A	Jiajiao et al., 2000
Bactrocera dorsalis	33.56	NA	0	Jiajiao et al., 2000
Bactrocera papayae	35	1.03	81.8	Danjuma et al., 2014
Bactrocera invadens	35	1.24	87.47	Rwomushana et al., 2008

Table 13. Data for larval survivorship and development time across a range of temperatures

Species	Temperature (ºC)	Development time (days)	Survival Rate (%)	Reference
Bactrocera papayae	15	27.84	73.21	Danjuma et al., 2014
Bactrocera invadens	15	35.95	83.54	Rwomushana et al., 2008
Bactrocera dorsalis	17	23.73	71.2	Luo et al., 2009
Bactrocera dorsalis	18.5	11.1	72	Vargas et al., 2000
Bactrocera dorsalis	18.96	11.19	N/A	Jiajiao et al., 2000
Bactrocera papayae	20	12.16	80.79	Danjuma et al., 2014
Bactrocera invadens	20	14.99	90.29	Rwomushana et al., 2008
Bactrocera dorsalis	21	15.02	74	Luo et al., 2009
Bactrocera dorsalis	23.18	9.49	N/A	Jiajiao et al., 2000

Bactrocera dorsalis	23.5	7.3	78	Vargas et al., 2000
Bactrocera dorsalis	24	7.7	83	Vargas et al., 2000
Bactrocera dorsalis	24.14	7.99	N/A	Jiajiao et al., 2000
Bactrocera papayae	25	7.13	85.08	Danjuma et al., 2014
Bactrocera dorsalis	25	12.36	85	Luo et al., 2009
Bactrocera invadens	25	9.48	98.61	Rwomushana et al., 2008
Bactrocera papayae	27	6.56	83.88	Danjuma et al., 2014
Bactrocera dorsalis	28.08	6.83	N/A	Jiajiao et al., 2000
Bactrocera dorsalis	29	9.31	78.4	Luo et al., 2009
Bactrocera papayae	30	6.51	80.09	Danjuma et al., 2014
Bactrocera invadens	30	7.85	93.31	Rwomushana et al., 2008
Bactrocera dorsalis	31.02	6.04	N/A	Jiajiao et al., 2000
Bactrocera dorsalis	33.56	NA	0	Jiajiao et al., 2000
Bactrocera papayae	35	5.28	66.27	Danjuma et al., 2014
Bactrocera invadens	35	6.64	84.52	Rwomushana et al., 2008

Table 14. Data for pupal survivorship and development time across a range of temperatures

Species	Temperature (ºC)	Development time (days)	Survival Rate (%)	Reference
Bactrocera papayae	15	29.14	66.8	Danjuma et al., 2014
Bactrocera invadens	15	34.08	72.16	Rwomushana et al., 2008
Bactrocera dorsalis	17	25.12	24.4	Luo et al., 2009
Bactrocera dorsalis	18.5	24.9	68	Vargas et al., 2000
Bactrocera dorsalis	18.96	19.83	N/A	Jiajiao et al., 2000
Bactrocera papayae	20	13.19	74.35	Danjuma et al., 2014
Bactrocera invadens	20	13.59	92.91	Rwomushana et al., 2008
Bactrocera dorsalis	21	16.95	81.4	Luo et al., 2009
Bactrocera dorsalis	23.18	12.9	N/A	Jiajiao et al., 2000
Bactrocera dorsalis	23.5	12.2	59	Vargas et al., 2000
Bactrocera dorsalis	24	12.4	66	Vargas et al., 2000
Bactrocera dorsalis	24.14	11.45	NA	Jiajiao et al., 2000
Bactrocera papayae	25	9.73	80.22	Danjuma et al., 2014
Bactrocera dorsalis	25	11.91	88.8	Luo et al., 2009
Bactrocera invadens	25	10.02	95.51	Rwomushana et al., 2008
Bactrocera papayae	27	8.4	81.52	Danjuma et al., 2014
Bactrocera dorsalis	28.08	8.7	N/A	Jiajiao et al., 2000
Bactrocera dorsalis	29	9.58	83.8	Luo et al., 2009
Bactrocera papayae	30	7.16	80.01	Danjuma et al., 2014
Bactrocera invadens	30	8.5	95.4	Rwomushana et al., 2008
Bactrocera dorsalis	31.02	8.35	N/A	Jiajiao et al., 2000
Bactrocera dorsalis	33.56	NA	0	Jiajiao et al., 2000
Bactrocera papayae	35	NA	0	Danjuma et al., 2014
Bactrocera invadens	35	NA	0	Rwomushana et al., 2008

While there have been several instances of controlled temperature data being used to develop species distribution models (de Villiers et al., 2015; Stephens

et al., 2007) and population dynamics models (Hong et al., 2015; Yousheng, Farong & Huanping, 1996; Yonow et al., 2004), they face significant limitations. Relative humidity ranging from 40% to 75% has been used across these studies. Populations in each study originated in different locations globally, covering Kenya, Hawaii, Australia, Thailand, and China. Local adaptation of the species to source habitats may contribute to variation in the results.

Vargas et al., (2000) conducted the only experiment with diurnally varied temperature comprising a high (day) and low (night). Therefore, for this study, we have averaged the high and low temperature to match the data to the other studies, despite the approach of Vargas et al., (2000) being optimal. Constant temperature experiments are known to lead to underestimations of development thresholds (Rwomushana et al., 2008).

The data used to produce the daily survivorship curves in Figure 32 was collected in laboratory based experiments, where populations were exposed to a constant temperature. Populations were independently exposed to a range of temperatures until the eggs had passed through all life stages and emerged as adults, or survivorship was 0. This survivorship data was fitted to a second order polynomial (Equation 11).

$$\boxed{S_T = \beta_2 T^2 + \beta_1 T^1 + \beta_0} \qquad \text{(Eqn. 11)}$$

where

S_T = survivorship at a given temperature

T^n = temperature to the power n

β_n = parameter associated with temperature to the power n

Table 15. Parameters for the second order polynomial model used to predict survivorship in each life stage

Parameter	Eggs	Larvae	Pupae
β_2	-0.0003913	-0.0009182	-0.00534
β_1	0.0209900	0.0474099	0.24976
β_0	0.6096139	0.2345832	-2.05723

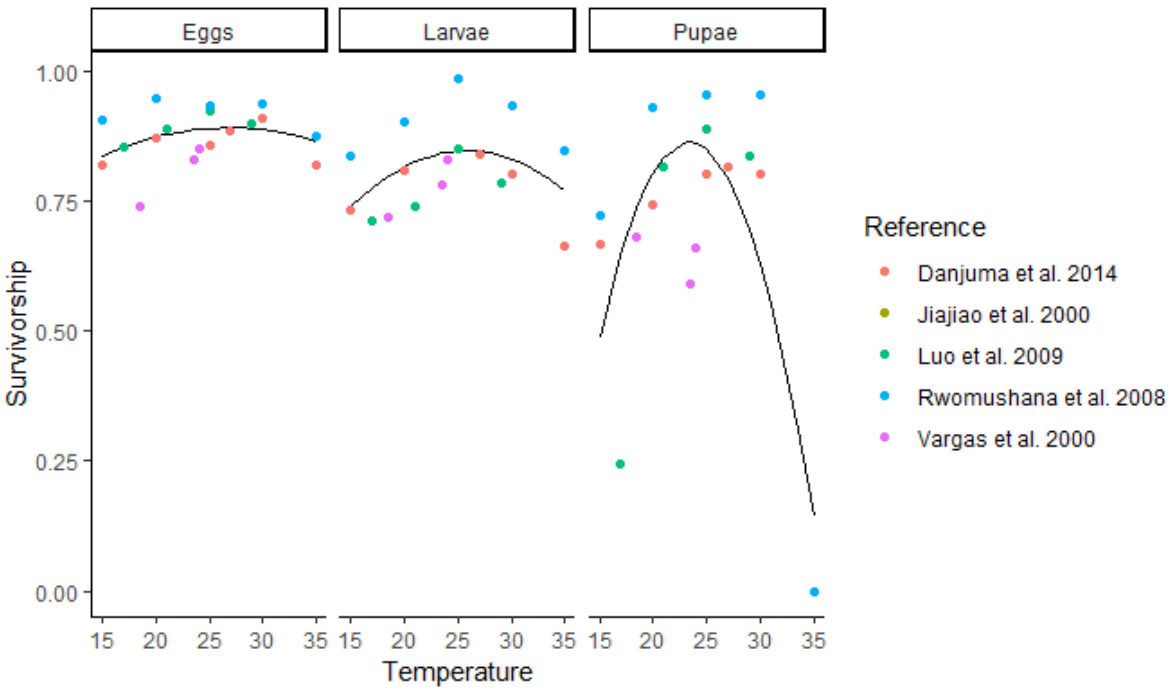

Figure 33. Survivorship curves show variation across a temperature range in each life stage. Data is shown in points, coloured by data source. Lines represent the polynomial model fitted to the data.

The time taken for the experimental populations to pass through each life stage was recorded for each constant temperature. A polynomial model of the form described in Equation 11 was fitted to the development time data to predict the effect of temperature on development time in each life stage. While the form of the equation predicts increasing development time once a high optimum mean daily temperature of 29˚C is exceeded, this rarely occurs in the Australian dataset and effects are expected to be negligible. Through a simple

polynomial addition, a quadratic model for total development time with parameters is presented in Table 16.

Table 16. Parameters for the second order polynomial model used to predict time taken to complete each life stage

Parameter	Eggs	Larvae	Pupae	Total time
α_2	0.01587	0.1034	0.1185	0.23777
α_1	-0.97830	-6.1459	-6.8485	-13.9727
α_0	16.10941	96.8000	107.3041	220.2135

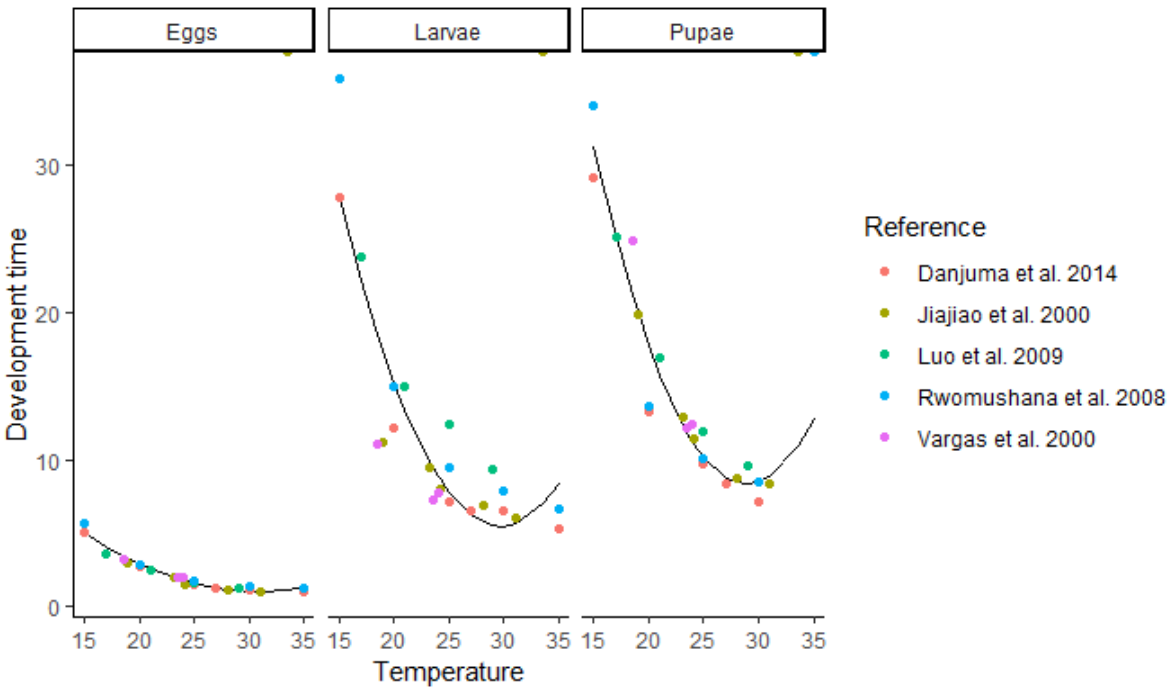

Figure 34. Time taken to pass through each life stage shown to vary across a temperature range. Data is shown in points, coloured by data source. Lines represent the polynomial model fitted to the data.

Temperature specific times were summed to get the total time to complete a full life cycle. Total development times provide the denominator in Equation 10, t_T. Values for the growth rate parameter at selected temperatures are displayed in Figure 35 as black points.

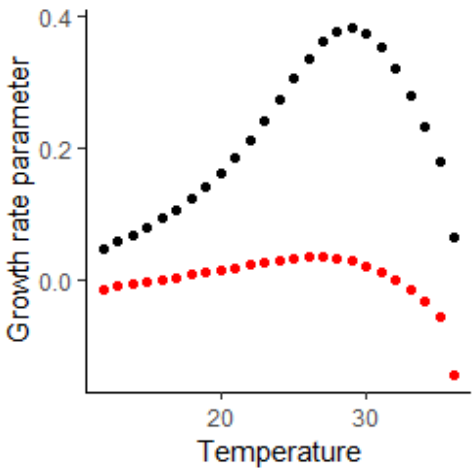

Figure 35. Variation in growth rate parameter (R_T) across a range of temperatures. Original data displayed as black points. Rescaled values to account for less optimal conditions in nature are displayed as red points.

The red points in Figure 35 show a set of growth rate parameters that have been re-scaled from the original. Values are adjusted based on an estimate of a baseline growth rate (e.g., number of females produced per female), if the effects of mean temperature are ignored. There is a lack of information in the literature as to the impact of these factors, so we have taken the quite arbitrary approach of testing values that create population growth that seems characteristic of what has been observed in previous incursions. When calculating growth rate parameters, we assumed that the maximum growth rate for a given adult female is 3. These adjusted values are displayed in Figure 35 as red points. Sensitivity testing of the model to this value and discussion of the outcomes with experts is essential before the model can be used for making pest management decisions.

7.2.1.3 Testing the logistic growth model

The logistic growth model was prototyped in the R programming language (RStudio Team, 2015) to trial growth rate parameters for subsequent use in the APPDIS model. Figure 36 provides a comparison of population densities generated by the prototyped logistic growth model and the eventual APPDIS implementation, for the same capacity values and temperature data.

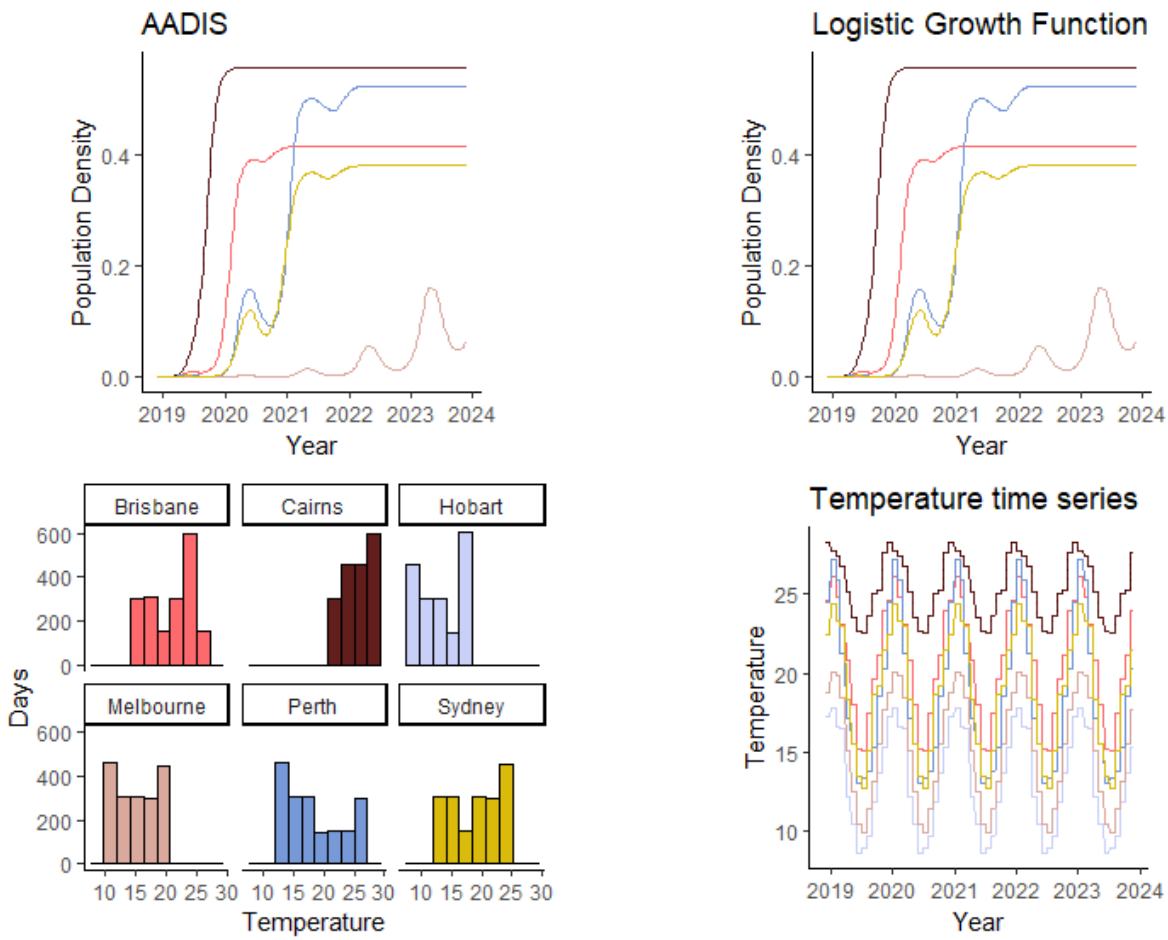

Figure 36. Testing the logistic growth model against the output in APPDIS using temperature data for different cities

Hobart is not seen in the time series plots of population density due to early local extinction through cold temperature stress.

7.2.1.4 Limitations of the temperature-dependent logistic growth model

A key limitation with a data-driven model such as APPDIS is when there is shortage of localised field data for the pest of interest. Data may exist from other countries and different environments, however, caution is needed in applying these data to predict behaviour of the pests in a novel and/or naive Australian environment. For example, literature describing fruit fly growth rates are primarily based on laboratory experiments, which can be difficult to translate to natural conditions. Growth rate experiments may expose fruit fly eggs to a constant temperature and record the times to develop into adults, or alternate between two temperatures to replicate day and night. While the cumulative effects of temperature stress over various time scales can be

monitored under constant exposure, the natural variability in temperature is not represented. In natural environments, temperature variability can have considerable effects on the abundance of an ectotherm. An environment which regularly exposes ectotherm populations to temperatures outside of their thermal tolerance range, even for short periods, will typically be uninhabitable regardless of whether these extremes are interspersed with habitable temperatures.

APPDIS currently employs mean weekly temperature data which implies that all simulation days in a week have the same temperature value. In reality, of course, temperatures may fluctuate over a wide range during a day, and over a week. Sporadic temperature extremes within a week may have a significant impact on mortality and population growth, however, this is not captured by a mean weekly temperature approach. Temperature data such as the Bureau of Meteorology Atmospheric high-resolution Regional Reanalysis for Australia (BARRA) and the Bureau of Meteorology Australian Gridded Climate Data (AGCD) are available at hourly and daily timescales, respectively. These data could potentially be used to increase temporal resolution of the temperature data layer and therefore the sensitivity of the within-cell population dynamics model to intra-week extremes. There is, however, a computational cost associated with increased temporal resolution. It may also be useful to augment the average temperature data with minimums and maximums.

A large cell size does not capture spatial temperature heterogeneities within the cell, for example, due to elevation changes. A small cell size captures spatial temperature heterogeneties (data granularity permitting), but comes with a computational overhead for large grids.

Temperature is not the only factor affecting population growth. Predation, parasitism and disease may significantly influence mortality but may be difficult to estimate. The egg lay observed in laboratories may far exceed that achieved in the wild due to increased mortality, and competition for mates and hosts. Temperature-based functions can be useful to estimate the ranges over which population growth is possible, but translating these into predictive

models of growth rates is challenging due to imperfect knowledge of wild populations and other factors influencing population dynamics.

As described in Sections 3.3 and 3.4, the between-cell spread pathways and surveillance components are dependent on the within-cell pest population density (i.e., dispersal pressure). This means that the model as a whole is sensitive to the assumptions and limitations of the within-cell growth model.

7.2.2 Between-cell spread

Selected model parameters for between-cell spread (Section 3.3) are provided in Table 17.

Table 17. Selected model parameters for Oriental fruit fly

Parameter	**Value**
Max cell population	1,250,000
Temperature dependent	True
Minimum active temperature	12°C[1]
Optimal temperature lower	27°C[1]
Optimal temperature upper	33°C[1]
Maximum active temperature	36°C[1]
Minimum diffusion temperature	18°C[1]
Minimum jump temperature	18°C[1]
Rainfall dependent	False
Elevation dependent	False
Quiescence enabled	False
Seeding mode	Manual
Diffusion baseline probability	0.28[2]
Diffusion spatial kernel radius	10 km
Jump baseline probability	0.3[3]
Human population dependent	True

Jump mode	Random
Jump distance	BetaPERT(10, 50, 500) km[4]

[1]Temperature parameters were derived from Rwomushana et al., 2008; Ye and Liu, 2005; Zhang et al., 2008; CABI, 2015; and Kean, 2015.

[2]The baseline daily probability of diffusion was based on the assumption that a fully infested cell has a 99.995% chance of diffusing into an adjoining cell within one month:

$P_d = 1 – (1 – 0.99995)^{(1/30)}$, such that the daily probability of dispersal is,

$P_d = 0.280$.

Recall from Equation 3 (Section 3.3.1) the daily probability of a cell with population density d(t) diffusing into an adjoining cell is:

$$p_d(t) = 1 – (1 – P_d\ S_d\ w_d)^{d(t)}$$

where:

$p_d(t)$ = probability of diffusion occurring on day t

P_d = baseline daily probability of diffusion occurring

S_d = normalised suitability of the destination cell

w_d = distance weight between the source and destination cells

d_t = population density of the source cell on day t

[3]The baseline daily jump probability arises from the assumption that a population in a fully infested cell has a 1% chance of a jump into a non-adjoining cell within a year:

$Pj = 1 – (1 – 0.01)^{(1/365)}$

$Pj = 0.00003$

Using Equation 4 (Section 3.3.2) the daily probability of a jump from a cell with population density d(t) into a non-adjoining cell is:

$$p_j(t) = 1 – (1 – P_j\ S_d)^{d(t)}$$

[4]The jump spread pathway represents human-mediated dispersal.

7.2.3 Early detection surveillance

Early detection surveillance was based on the national grid of traps with methyl eugenol lures (Figure 37; Section 3.4.2). Traps were visited once every 14 days, with each visit costing A$40 (adjusted from Royer pers. comm. 2012). Cost variations due to trap location (e.g., proximity to the office the inspector leaves from, or proximity to other traps), were not taken into account. The daily sensitivity of the early detection surveillance process (traps and personnel), was set to 0.95 per day and the specificity set to 1.00.

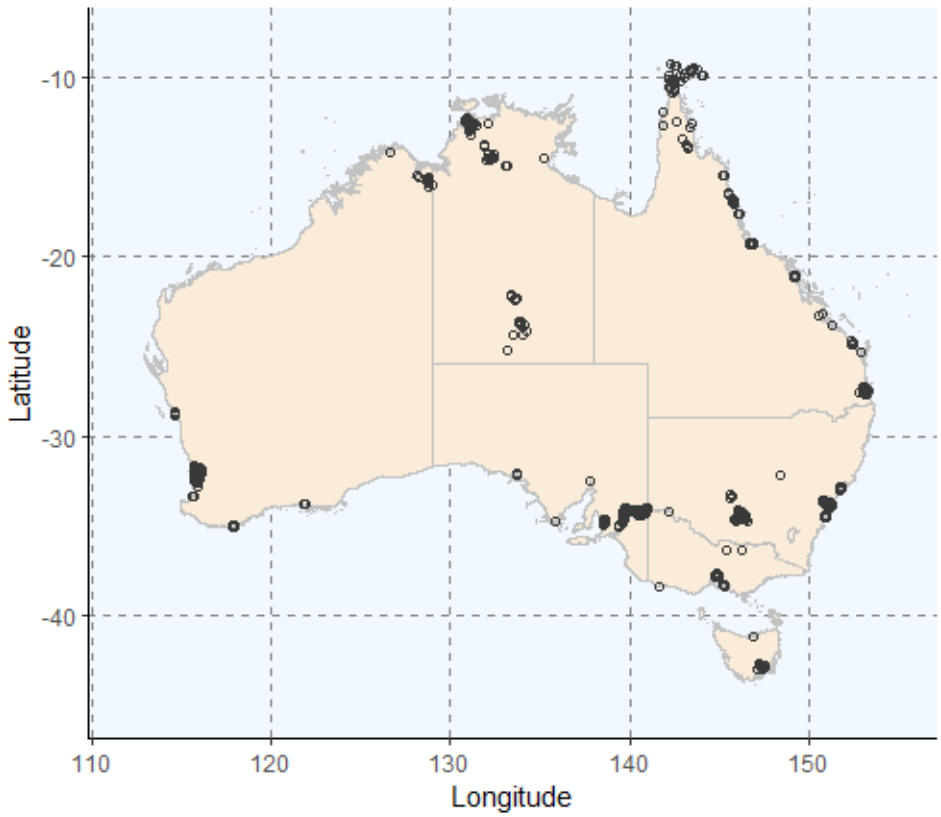

Figure 37. Early detection trap grid for Oriental fruit fly (methyl eugenol lures).

7.2.4 General surveillance

General surveillance (Section 3.4.1) was configured to operate in passive mode with a daily observer sensitivity of 0.25 in unmanaged areas and 0.75 in managed areas.

7.2.5 Delimiting surveillance

Delimiting surveillance (Section 3.4.3) was carried out in all cells within 50 km of each detected cell, at a trap spacing of 400 metres. Surveillance visits were conducted weekly for a minimum of 26 weeks, with each trap service costing $30. The daily sensitivity of the delimiting surveillance process (traps and personnel), was set to 0.95 per day, and the specificity set to 1.00.

7.2.6 Treatment

Treatment was conducted in all cells within a 10 km radius of each declared infested cell. A treatment program comprised 6 treatments, each taking 7 days at a cost of $1000, repeated every 14 days. Each treatment reduced a cell's population stochastically by between 80% and 95%.

7.2.7 Post-treatment surveillance

Post-treatment surveillance was carried out in all treated cells, at a trap spacing of 400 metres. Surveillance visits were conducted weekly for a minimum of 26 weeks, with each trap service costing $30. The daily sensitivity of the post-treatment surveillance process (traps and personnel), was set to 0.95 per day, and the specificity set to 1.00.

7.2.8 Scenarios

7.2.8.1 Unconstrained spread

An incursion of 100 Oriental fruit flies was introduced in December into the cities of Brisbane, Cairns, Hobart, Melbourne, Perth and Sydney. The population was allowed to spread without intervention for a maximum period of 5 years. The scenario was repeated 100 times for each point introduction site.

7.2.8.2 Detection and control

An incursion of 100 Oriental fruit flies was introduced in December into the cities of Brisbane, Cairns, Hobart, Melbourne, Perth and Sydney. The population was allowed to spread in parallel with the operation of the early detection surveillance, general surveillance, treatment, and post-treatment surveillance

processes. The maximum length of a scenario was 5 years. The scenario was repeated 1000 times for each point introduction site.

7.3 Results

7.3.1 Unconstrained spread

Table 18 summarises the results of five years (maximum) unconstrained spread of Oriental fruit fly after separate point introductions in December of 100 flies in the cities of Brisbane, Cairns, Hobart, Melbourne, Perth and Sydney.

Table 18. Simulation results for five years of unconstrained Oriental fruit fly incursion (no treatment).

Model outcome variable	Brisbane	Cairns	Hobart	Melbourne	Perth	Sydney
Seed cell suitability	0.3965	0.5323	0.5129	0.4195	0.5000	0.3638
Cumulative infested cells[1]	3485.2	1824.4	1.0	18.6	362.0	365.4
Final population (million)[1]	230.7	720.1	0	0.1	10.3	5.5
Diffusion rate (km per year)[1]	5.0	7.2	0	0.1	3.7	3.4
Maximum spread (km)[1]	558.7	882.6	0	209.2	334.4	398.0
Time to first detection (days)[1]	331.3	213.6	N/A	1031.8	431.4	462.4
Scenario iteration runtime (seconds)[1]	128.1	251.4	5.3	40.8	56.2	51.5
Convergence[2]	1.48%	0.34%	0%	4.17%	2.11%	2.80%

[1]averaged over 100 runs

[2]convergence (per Table 5) of the cumulative number of infested cells

Figure 38 shows an example of an Oriental fruit fly population after five years of unconstrained spread from a point introduction in December at Cairns airport (iteration 100 of 100). The varying population densities of each cell are encoded with shades of purple – the lighter the shade the higher the population density.

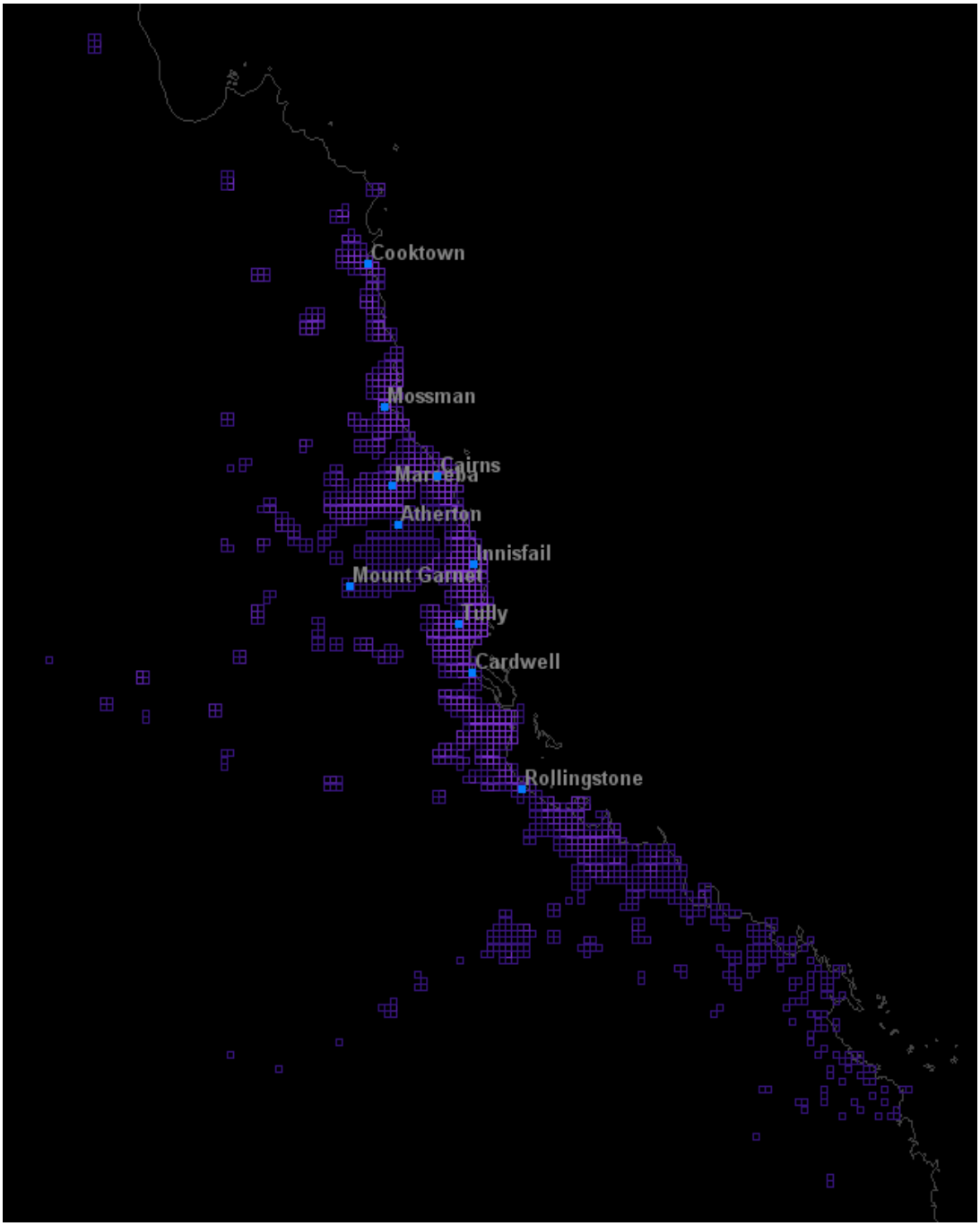

Figure 38. Example of an Oriental fruit fly population density map after 5 years of unconstrained spread from a point introduction in Cairns

Figure 39 provides an example of an Oriental fruit fly population spread pathway network after five years of unconstrained spread from a point introduction in December at Cairns airport (iteration 100 of 100). Natural dispersal (diffusions) are depicted as short orange arrows and human-mediated hitchhiking (jumps) are depicted as long red arrows. Over the five-year simulation there were 323 diffusions and 1107 jumps.

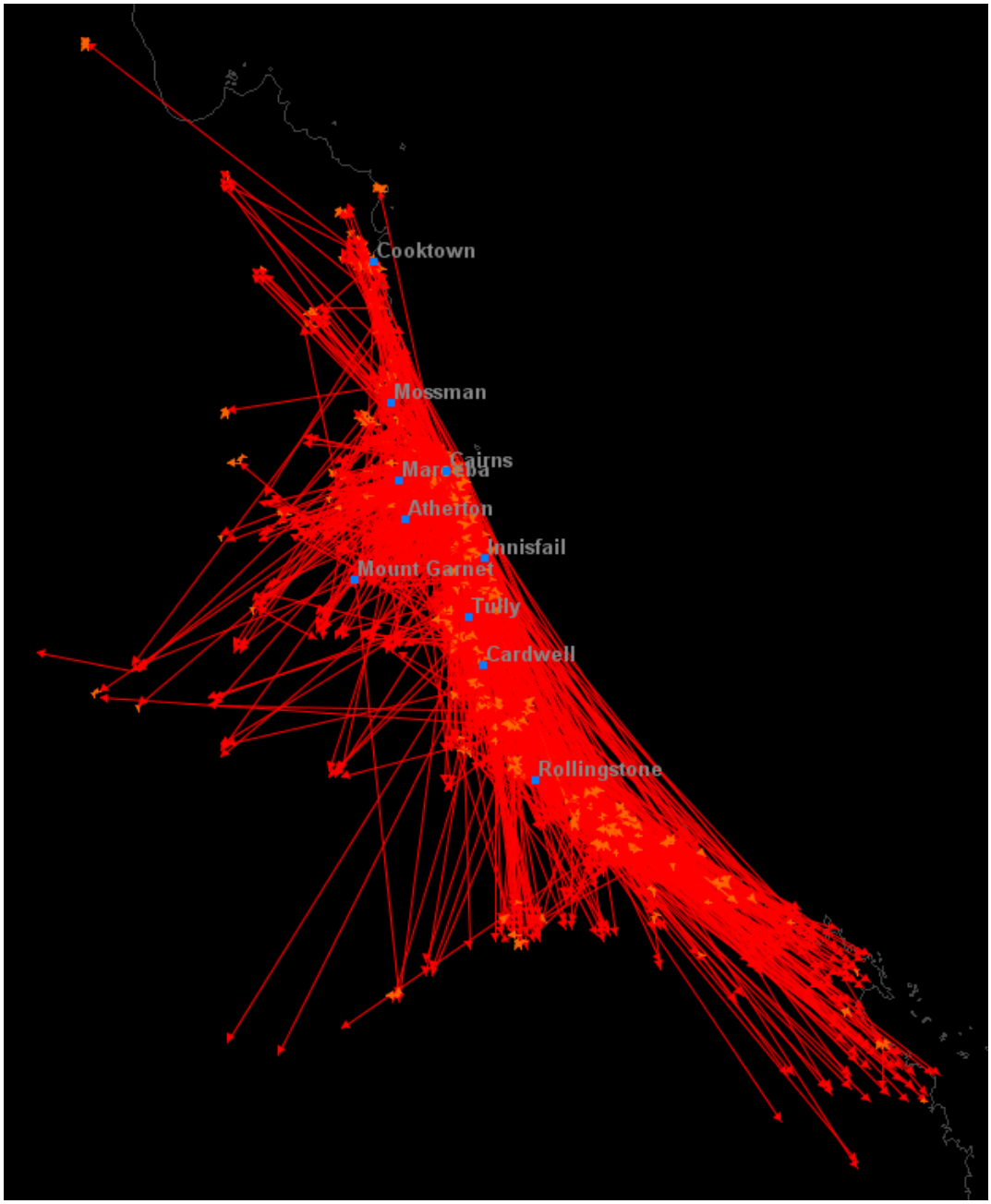

Figure 39. Example of an Oriental fruit fly spread pathway network map after 5 years of unconstrained spread from a point introduction in Cairns

Figure 40 illustrates the distribution probabilities of Oriental fruit fly presence after five years of unconstrained spread from a point introduction in Cairns in December. The results of all 100 iterations are presented as a frequency map whereby cells that were always invaded by Oriental fruit flies are encoded in red and cells that least frequently hosted a population are encoded in blue.

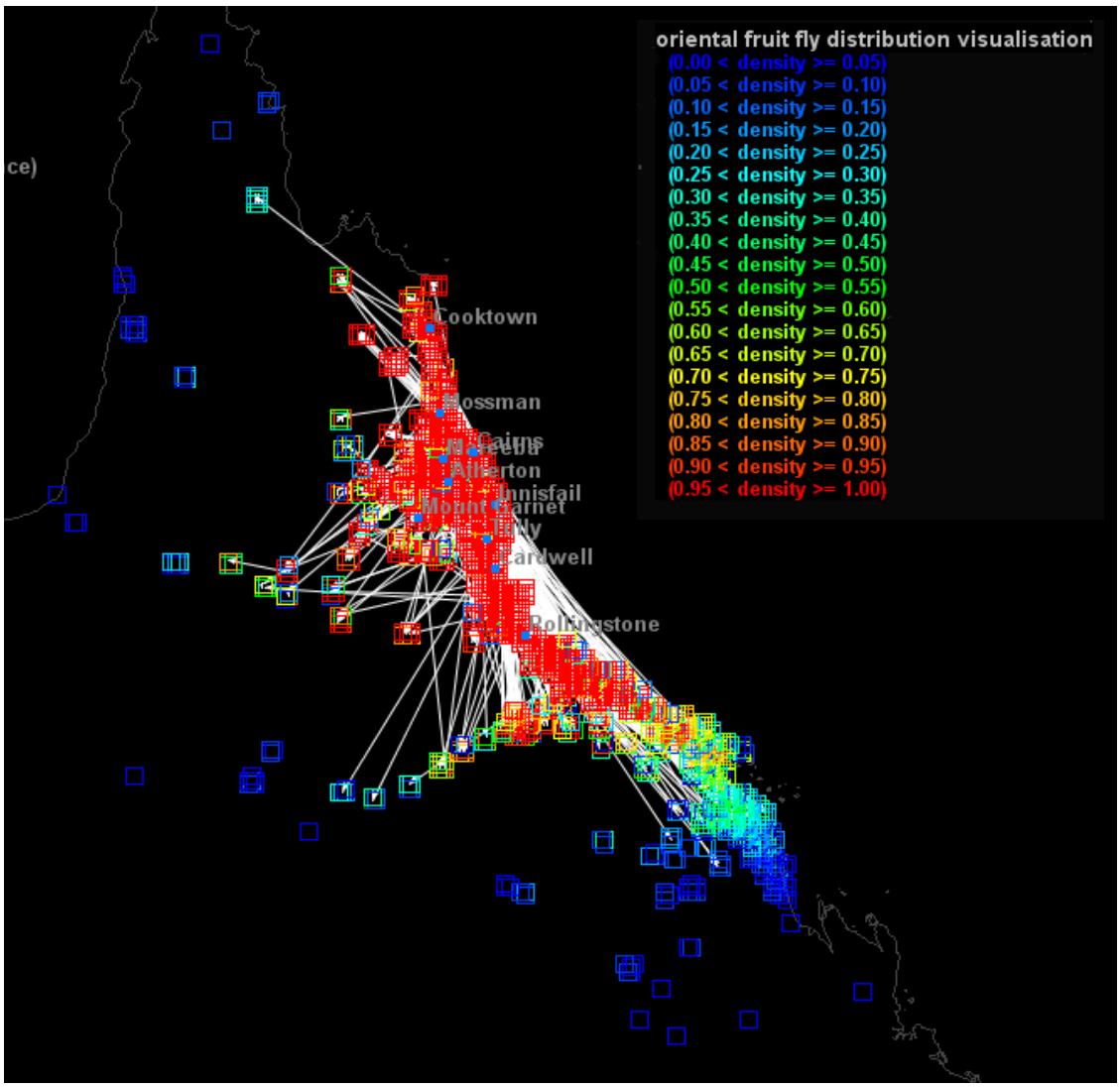

Figure 40. Oriental fruit fly distribution map from 100 five-year simulations of unconstrained spread after a point introduction in Cairns

7.3.2 Detection and Control

Table 19 summarises the results of the control response to incursions of Oriental fruit fly after separate point introduction of 100 flies in December in the cities of Brisbane, Cairns, Hobart, Melbourne, Perth and Sydney. All values are averaged over 1000 simulations. The maximum length of a simulation was capped at 5 years.

Table **19**. Simulation results for detection and control of Oriental fruit fly incursions

Model outcome variable	Brisbane	Cairns	Hobart	Melbourne	Perth	Sydney
Seed cell suitability	0.3965	0.5323	0.5129	0.4195	0.5000	0.3638
Cumulative infested cells[1]	7.1	8.3	1.0	3.4	6.1	5.2
Natural (undetected) extinctions (% of runs)	0%	0%	99.4%	0%	0%	0%
Maximum spread (km)[1]	69.3	44.8	0.6	58.2	37.8	72.0
Time to first detection (days)[2]	340.5	213.5	165.8	960.6	426.5	444.1
Delimiting surveillance cost (A$ million)[2]	49.16	27.56	33.46	36.49	29.25	25.80
Number of treatments[2]	293.9	221.0	186.0	186.8	195.1	214.6
Treatment cost (A$ thousand)[2]	49.00	36.64	31.00	31.14	32.54	35.79
Post-treatment surveillance cost (A$ million)[2]	5.14	4.21	2.76	2.95	3.34	3.57
Eradication within 5 years (% of runs)	94.6%	98.5%	100.0%	97.8%	98.4%	97.4%
Total incursion cost (A$ million)[2 3]	54.35	31.80	36.25	39.47	32.62	29.40
Incursion duration (years)[1]	2.6	2.0	0.8	3.6	2.4	2.5
Scenario iteration runtime (secs)[1]	41.4	28.7	10.7	56.5	34.7	33.1
Convergence[4]	7.15%	8.02%	0.55%	4.79%	4.27%	4.98%

[1]averaged over 1000 runs [2]averaged over the number of runs where detection and treatment occurred (i.e the population did not die out naturally)

[3]not including the constant background cost of early detection surveillance

[4]convergence (per Table 5) of the cumulative number of infested cells

Figure 41 shows a snapshot of a simulated response to an incursion of oriental fruit fly in Cairns (day 1144 of iteration 18). The control visualisation depicts general and specific surveillance outcomes, treatments, and eradication success. Active surveillance cells are shown in cyan, delimited free cells are shown in blue, and eradicated cells are shown in green.

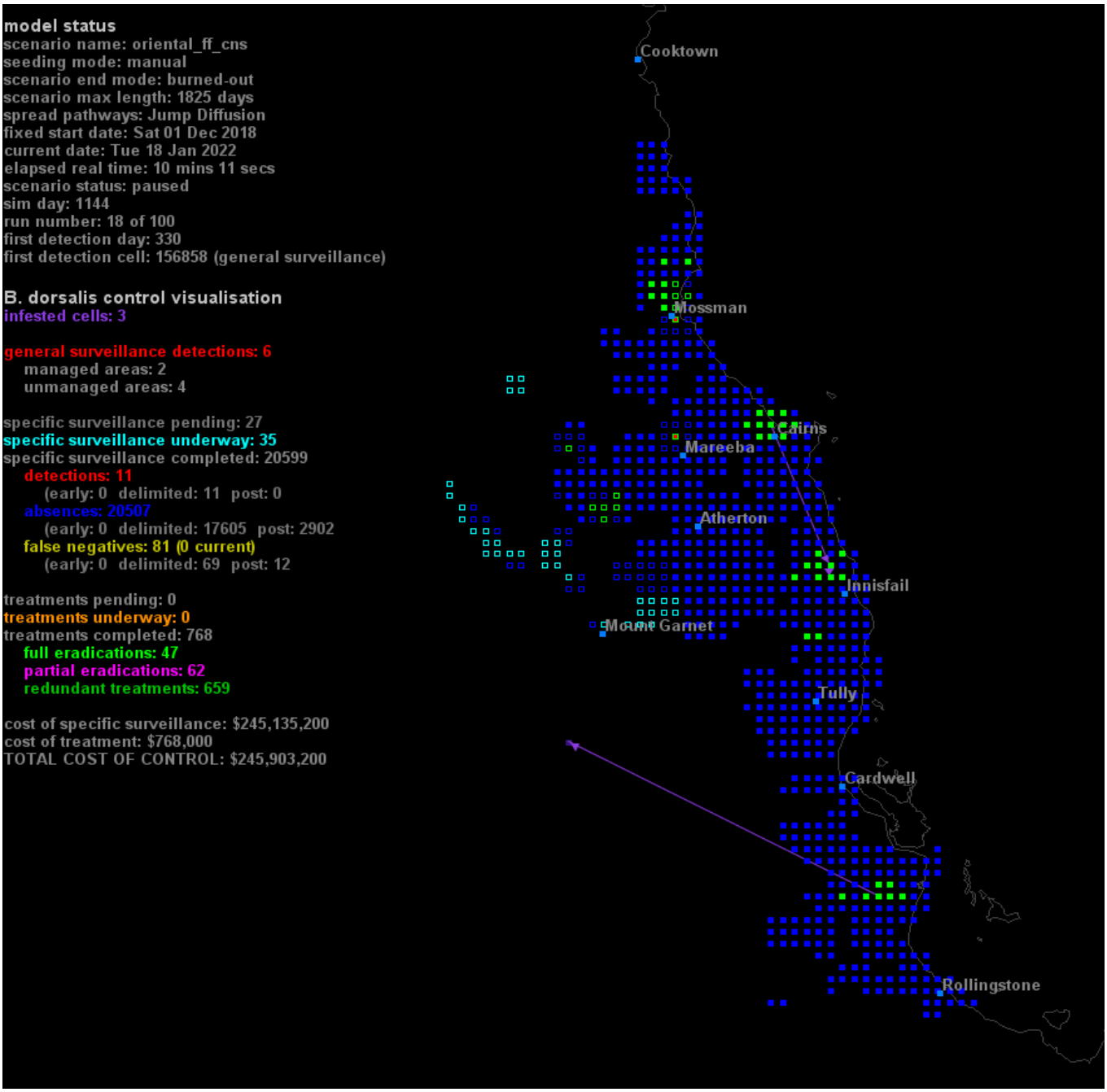

Figure 41. Example of a simulated response to an Oriental fruit fly incursion in Cairns

7.4 Discussion

The extent of an incursion is influenced by the temperature driven growth of populations, and the availability and connectivity of environmentally suitable cells within range of the pest. Figure 42 depicts the distributions of maximum incursion distance (including response actions), from the seed cell. Populations always established and spread in Brisbane and Cairns, with spread distance consistently greater than 200 km and 500 km, respectively. Populations sometimes spread well in Perth, with some scenarios spreading similar distances to those in sub-tropical Brisbane. Similar cell suitability scores between Perth and Brisbane was thought to drive this result despite the cooler climate of Perth. Populations struggled to spread in Sydney with almost 70% of scenarios staying within a 10 cell radius of the initial incursion. Populations typically failed to establish in Melbourne and Hobart despite the high suitability of the seed cells and surrounding cells. This was due to the sustained colder climate naturally suppressing and eradicating the populations.

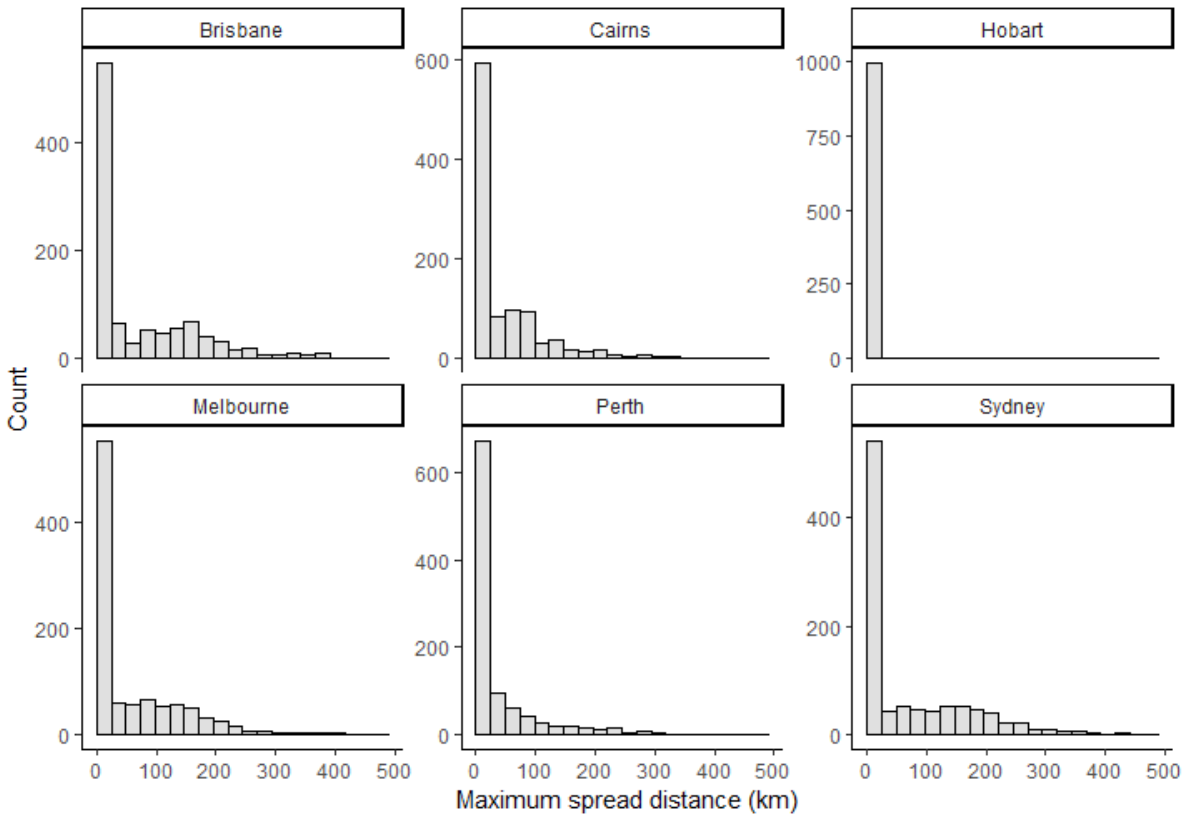

Figure 42. Oriental fruit fly spread distances from initial seed cell. Histograms show variation in outcomes for 1000 five year simulations for six Australian cities. Control strategies were active in these simulations.

The length of an incursion (as measured from the first day of the seeded simulation, until the completion of cell management and declaration of pest freedom), varied between cities and is displayed in Figure 43. There was a fixed minimum incursion duration for Brisbane, Cairns, Perth and Sydney. This reflects the period, upon first detection of a pest, to conduct the minimum required delimiting surveillance, treatment and post-treatment surveillance regimes before an area can be declared free of the pest. The fixed minimum duration was not observed for Hobart and Melbourne as often the colder climate lead to population extinction before a detection event could occur.

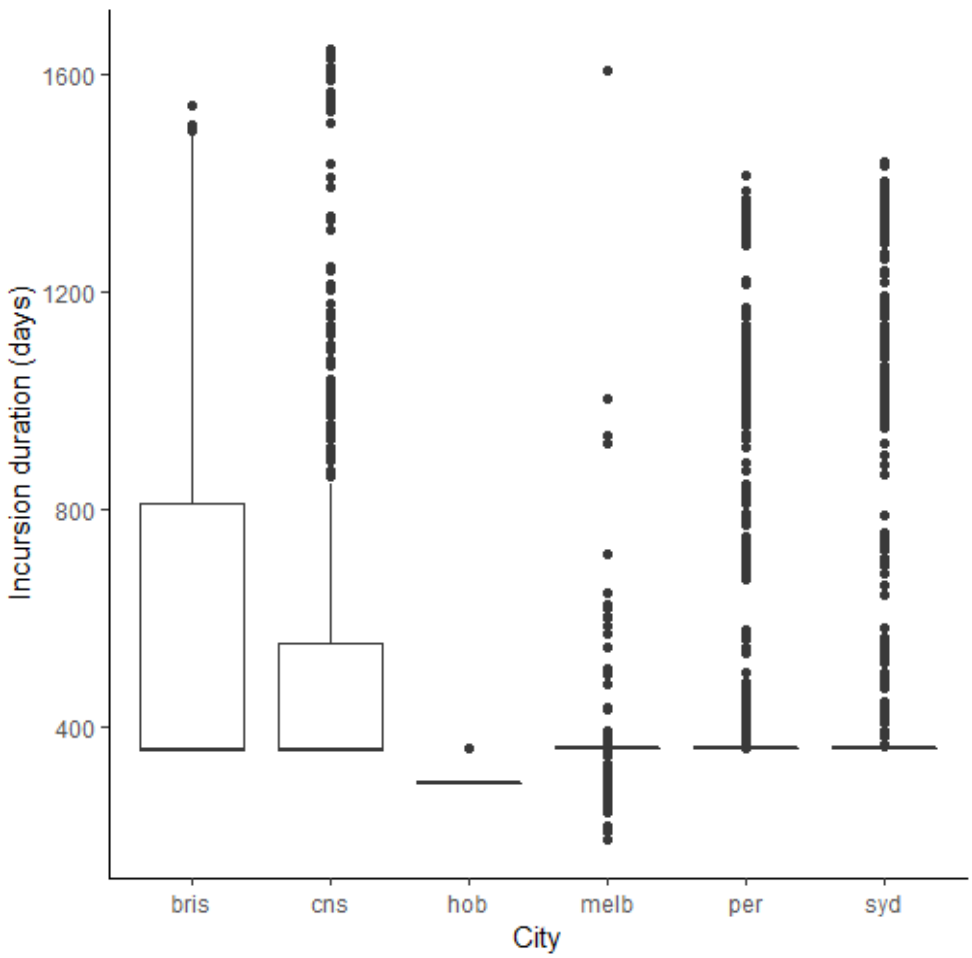

Figure 43. Oriental fruit fly incursion durations for each of the cities in this case study. This is calculated as days before first detection subtracted from total simulated time

Despite typically small incursion extents in Melbourne (Figure 42), the duration of an incursion in Melbourne is typically larger than the other cities. Characteristics of the trapping grid near the Melbourne seed cell, combined with the very slow growth in Melbourne, means that occasionally a pest will

persist without much spread for a significant amount of time. Conversely, incursions in Cairns are shorter than those in Brisbane due to the improved early detection grid positioning, despite the former being better suited to Oriental fruit fly. This emphasizes the importance of grid design and is something that could be explored in future simulations using a variety of grid networks and an analysis of initial incursion pathways.

In Figure 44 the zero mean cost for incursions in Hobart indicates that Oriental fruit fly generally failed to establish due to unsuitable climate and was very rarely detected. This figure also illustrates the dangers associated with late detection of an Oriental fruit fly incursion in favourable climates such as Brisbane and Cairns. In Sydney, the total control cost remains similar for a range of incursion durations.

The cost of delimiting surveillance is notably high in these simulation outputs, and it is suggested that this parameter is subject to review and a sensitivity analysis. This may help to determine an improved total cost estimate. Specifically, running simulations with varying radius for the radial delimiting surveillance method would give a good estimate of the change in cost compared to the change in incursion time and extent. This would allow an analysis of optimal delimiting strategy.

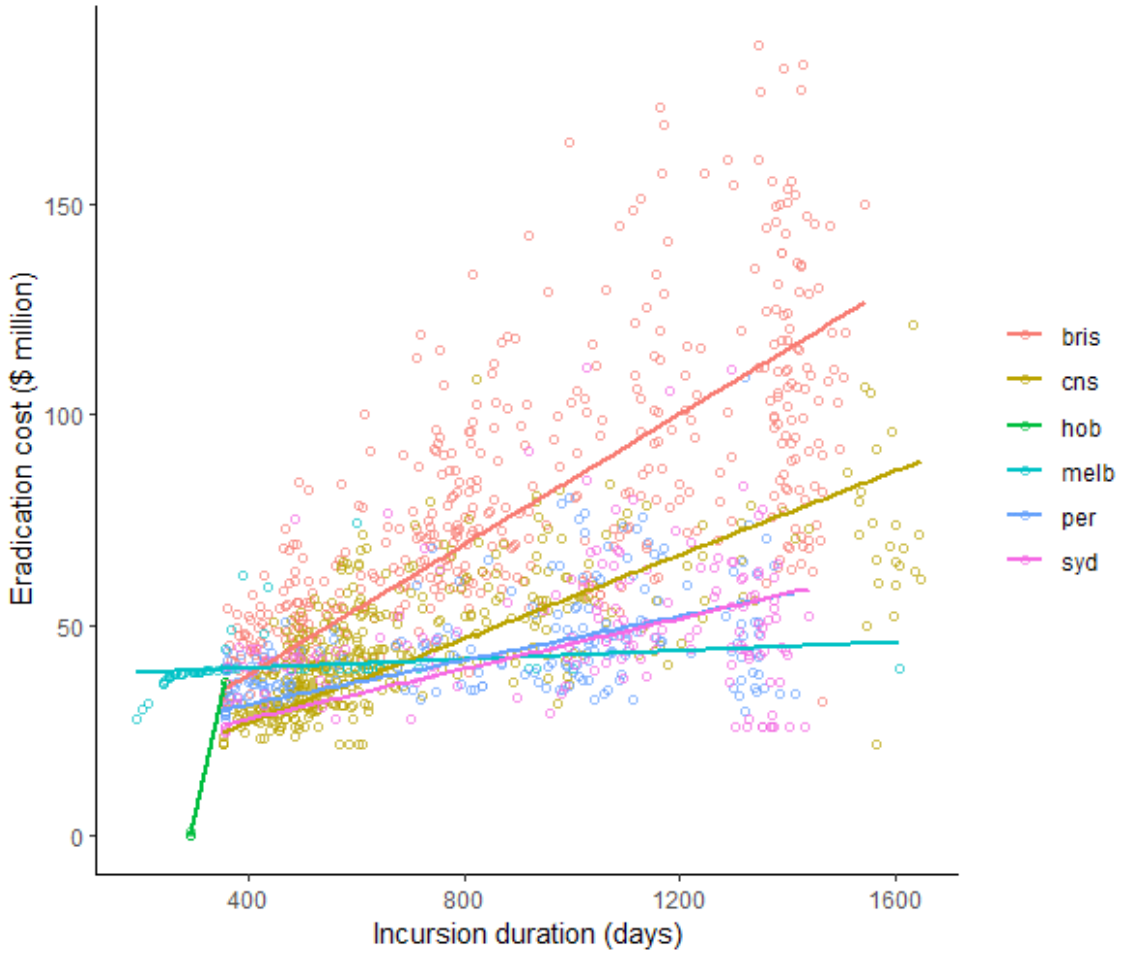

Figure 44. Cost of surveillance and treatment for a given incursion. Each point represents one simulation beginning on 1st December, where 1000 simulations for each city follow their respective linear trend.

8 Discussion

8.1 Conclusions

National Priority Plant Pests represent a serious threat to Australia, both environmentally and economically. NPPPs require efficient detection mechanisms and effective response strategies. However, often due to the lack of opportunities to trial control strategies on exotic species in the field, it can be difficult to understand the complex spatiotemporal interplay between spread, surveillance and control. Models can be useful decision support tools for exploring potential spread pathways, and comparing response strategies in terms of relative benefit and cost.

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

The APPDIS modelling framework attempts to find a pragmatic middle ground between the biological and ecological fidelity of a complex pest-specific spatial model, and the extensibility of a generalised model. APPDIS is flexible in that a user can configure either simple or complex spread models. A simple mathematical spread model is obtained by disabling the environmental data layers and configuring a single 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

take heterogeneities in elevation, temperature, wind speed, vegetation, land use, and human population, into account.

Once a model is spreading a pest in a way that is congruent with field data (if available), and expert opinion, a decision support tool should allow useful experimentation with early detection and control strategies. A further design tension exists in that a model may provide quite detailed pest specific detection/control options that may not be readily extensible to other pests, or provide 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 easily extensible 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 spread mechanism is stochastic, a control policy is trialled 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.

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, a pest may spread through both 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.

The goal of this project was to produce a general purpose decision support framework for future use by plant health specialists. The case studies were selected to illustrate APPDIS operating in two quite different ways (Table 20).

Table 20. Case study key differences

	Tramp ant case study	**Exotic fruit fly case study**
Modelling scale	Regional	National
Study area grid (km^2)	18,758 km^2	17,391,864 km^2
Cell size (approx.)	10 ha	2500 ha
Number of cells	175,441	703,923
Cell suitability layer	Binary (land or water)	Biotic (Camac et al., 2019)
Incursion type	Established population	Point introduction
Initially populated cells	1540 cells	1 cell
Initial population size	310,000,000	100
Within-cell growth rate	Temperature independent	Temperature dependent
Diffusive spread	Yes	Yes
Human-mediated jumps	Yes	Yes
Agriculture-specific jumps	Yes	No
Rafting jumps	Yes	No
General surveillance	Yes	Yes
Early detection surveillance	No	National trapping grid
Delimiting surveillance Mode	Moore	Radial
Treatment Mode	Spot	Radial
Post-treatment surveillance	Yes	Yes
Resourcing	Unlimited	Constrained

The primary APPDIS inputs are configuration files (Section 4.3) and database files (Section 4.2), and the primary outputs are CSV report files (Section 4.3.2.2), 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 (Figure 10). The ability for APPDIS to

convey incursion concepts visually perhaps suits it to classroom use (as has been the case with the AADIS model).

In summary, the project has produced a general purpose pest modelling framework that is flexible (not tied to a specific pest), scalable (operable regionally and nationally), accounts for heterogeneity in the host environment, and 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 studies have demonstrated the potential for APPDIS to assist with decision support for both plant pests and environmental pests. Importantly, APPDIS is extensible to other pests via user configurable parameters, i.e., specialised mathematical reformulation and/or computer programming is not required.

8.2 Limitations

As the APPDIS model is data-driven it must be carefully and separately parameterised for each plant pest under study. This should be done collaboratively with experts familiar with the pest and candidate detection and control strategies.

The case studies, whilst attempted to be parameterised realistically, are purely to illustrate the newly developed modelling framework. As such, if the model is to be used to address specific ecological/policy questions on YCA or Oriental fruit fly then the spread and control parameters should be reviewed and refined by experts working in those particular pest spaces.

Due to lack of data on National Priority Plant Pests in an Australian context, it is recommended that the model not be used to guide a response to a specific incursion in real time. It is best suited as a ‘peace time’ decision support tool to assist preparedness and planning across a range of assumptions.

8.3 Future work

It may not be feasible to develop detailed spread and control models for all NPPPs. An alternative is to develop generic models for functional groups of

pests. Groupings could, for example, be based on similarities of species, thermal tolerance, spread modalities, and control strategies.

Case study 1b (Section 6) provided a rudimentary sensitivity analyses on trap spacing for both delimiting surveillance and post-treatment surveillance. Other key parameters (e.g., surveillance mode, sensitivity, specificity, radius; treatment mode, radius; delimiting surveillance treatment radius), require similar analyses.

APPDIS allows the first detection of an incursion to be made stochastically or to be fixed on a set day. This feature could be used to investigate the consequences of early/late detection with respect to effectiveness and cost of control.

APPDIS allows response actions to be constrained by finite resource pools or unlimited (Sections 3.4.6 and 4.6.7, Figures 16 and 17). Case study 1b illustrated unconstrained control and case study 2 illustrated constrained control. Further work could be conducted on the impact of resource shortages on the effectiveness and cost of control.

The model requires ongoing validation for each plant pest under study. A suggested approach is to parameterise APPDIS for a prevalent and well-studied organism that shares functional traits with a National Priority Plant Pest. For example, a Queensland fruit fly model may assist with the validation of the Oriental fruit fly model. It is noteworthy that the Queensland fruit fly has expanded to southern parts of Australia, previously thought to be climatically hostile to a fruit fly.

There is great potential for plant pest entry risk maps (Camac et. al., 2019), to inform the selection of seed cells when modelling pest incursions. This will allow pest detection and eradication simulation experiments to be intelligently targetted at high-risk entry points.

8.4 Application to other plant pests

The new components developed for APPDIS for plant pests have emerged from the tramp ant and exotic fruit fly case studies. This section considers the

modelling components that may be required for other National Priority Plant Pests so that APPDIS can address strategic incursion management questions.

General surveillance can be a significant component of response programs where public awareness campaigns can be responsible for a significant number of new reports. Pests that are large, colourful or likely to cause noticeable damage to high value plants are good candidates for enhanced general surveillance programs, as are nuisance pests such as ants and bees that directly affect people. Refinement of the general surveillance module to vary reporting rates in response to awareness campaigns could be used to explore the relative contribution of general surveillance options on delimiting a pest.

Movement restrictions on pests of produce are one of the major mechanisms for managing pest incursions. Movement restrictions are not currently implemented in APPDIS, although it should be relatively simple to incorporate a mechanism that reduces the probability of jump dispersal beyond a configurable radius.

For each of the NPPPs, there are known areas of uncertainty that will prevent the construction of models that could be predictive enough to employ with any great confidence. In general, while the growth rates and mortality of pests and diseases in laboratory conditions are often known, their behaviour in natural areas and in diverse microclimates within the modelling units is not. Surveillance efficacy is often poorly understood and, with the exception of complete removal of host plants, the effectiveness of control methods for eradication in novel environments are also not known with confidence.

Of the biological components, spread parameters are usually the most poorly understood at a resolution that is required for accurate invasion modelling. While recapture and trapping techniques can give some indication of dispersal behaviour under limited conditions, the success of eradication is likely to be sensitive to the dispersal kernels. For those pests that are carried by people, either through trade or hitchhiking, there is still significant research required to better understand the association between pests and the distance over which viable propagules are carried.

For some pests, such as the brown marmorated stink bug and gypsy moth, there are quite complex temperature requirements that lead to critical behaviours in the life cycle. It is not sensible for these complex functions to be included specifically within APPDIS, however, it may be possible to model the functions offline, and then plug the population growth values back into APPDIS in the manner that was done for the fruit fly model. However, in the same way that the fruit fly model was challenging to interpret around weekly mean temperatures, it is likely to be difficult to model the biological subtleties with this coarse information.

It requires some experience to interpret the impact of local spread and biological growth on the increase in populations within a cell. For a pest that is a poor disperser across distances much smaller that a cell, it is likely that there will be come considerable lag time before a pest infests enough sites within the cell to start increasing at an exponential rate. Note that if the implemented temperature dependent/independent logistic growth model is unsuitable for some pests then it would be possible to provide alternative within-cell population growth models, however, this would require software modification.

For some pests, the ability of the landscape to support the pest may change dramatically over time. Some examples include floral sources for pest bees and the availability of hosts plants and alternative hosts around cropping cycles.

The adage of models only being as good as what goes in, needs to be considered seriously before embarking on a new pest modelling exercise. Foremost, there needs to be a clear strategic learning outcome identified before starting. This outcome will determine the spatial and temporal scales for attacking the problem. Once a suitable modelling scale is identified, literature need to be consulted to determine whether there is enough information to construct a credible model of growth and spread within this resolution. Related to this is the collection of spatial data that will define the extent of the invading population and the favourability of the environment that will support pest populations within the cells. The collation of this information is not a trivial task. If the aim of the investigation is around eradication and containment,

then the modeller needs to assess the quality of information about the efficacy of both surveillance and response.

In finalising this project, we have made an assessment of the prospects for APPDIS to assist in understanding the surveillance and management of incursion of the top 20 NPPPs (Table 21). These assessments touch on some of the data required, the modelling scales that will be useful and whether there is any real need to model the incursion in order to understand components of the incursion process. It can be seen that many of the NPPPs are not suited for modelling of this sort, while for some others, modelling will be useful to understand components of surveillance and control. In some cases the model results will be challenged by a lack of understanding of the biological parameters. However, there are some groups of pests where modelling is likely to help identify critical information gaps and to highlight strategies that are needed to successfully respond to pests with particular attributes.

Table 21. Options for modelling under the current APPDIS configurations and further requirements

	Pest group	Common name	Growth	Extents	Spread	Surveillance	Control	Prospects
1	*Xylella fastidiosa* and confirmed and unconfirmed vectors	Xylella and vectors	Vector / disease complex difficult to model.	Probably treat as unrestricted, due to weed hosts but some uncertainty. Local to district scales most relevant.	Vector spread by diffusion, potential jump diffusion of vectors and disease on propagating material	Visual surveillance will be low efficacy and multiple level surveillance for the pest and the disease would be required.	Destruction of hosts and management of vectors possible	Model could examine the challenges faced by responses with low surveillance efficacy.
2	*Trogoderma granarium*	Khapra beetle	Growth rates will be available	Extents are primarily abstract and will be limited to the stored product distribution chain.	No natural spread, jump dispersal from importer stores only	Surveillance on premises basis	Control on premises basis	No need for spatial modelling on APPDIS platform, simple models would suffice
3	Exotic, economic fruit fly (both lure	Fruit fly	Case study demonstrated, further growth					Demonstrated model for considering strategies.

	Pest group	Common name	Growth	Extents	Spread	Surveillance	Control	Prospects
	and non-lure responsive)		parameters could be examined for other species.					
4	*Tilletia indica*	Karnal bunt	Temperature dependant growth rates for Karnal bunt should be available. Influence of wetness and humidity are likely to be significant.	Cereal growing areas are accessible	Natural spread within districts may be able to be modelled. Jump dispersal on machinery is possible	Surveillance will generally need to be based on samples from farm or district level aggregations in the grains distribution network.	Chemical and destruction methods implemented but movement restrictions on the bulk handling network difficult to model	Could model some natural spread characteristics in relation to farm level sampling. Control within distribution network not enabled.
5	*Candidatus* Liberibacter asiaticus (and other strains)	Huanglongbing and vectors	Vector / disease complex difficult to model.	Limit to residential and citrus horticultural land uses	Vector spread by diffusion, potential jump diffusion of vectors and disease on propagating material	Multiple level surveillance for the pest and the disease would be required.	Destruction of hosts and management of vectors possible	Model could examine the challenges faced by responses with low surveillance efficacy.

	Pest group	Common name	Growth	Extents	Spread	Surveillance	Control	Prospects
	complex							
6	*Lymantria* spp.	Gypsy moths	Detailed growth models are available but are dependent on complex responses to temperature.	Unrestricted although the capacity for spread in natural environments uncertain	Some natural spread parameters available from ABARES reports. Human spread may not be significant.	Trapping methods able to be implemented as for fruit flies.	Control through chemical sprays implemented.	Spread of gypsy moth through residential areas from key hazard areas could be modelled but APPDIS platform may not add any significant value to simple models.
7	*Solenopsis* . and other exotic tramp ant species	Exotic invasive ants	Case study demonstrated	Unrestricted	Current spread based on crazy ant could be extended to examine other species.	Multiple surveillance methods including general surveillance, trapping and inspections.	Control methods are documented for several species and could be validated against programs.	Demonstrated model for considering strategies could be parameterised for other species. Models could provide insight into the compliance rates, surveillance and treatment efficacy needed for successful eradication.
8	Internal and	Bee mites	Varroa mite growth rates	Difficult to ascertain the	Some spread information	Surveillance can be through multiple methods but hive	Control methods would include standstills of hive	Modelling in port areas could be useful. There is an

	Pest group	Common name	Growth	Extents	Spread	Surveillance	Control	Prospects
	external mites of bees (*Apis* spp.)		are available.	feral bee population. Some records available on commercial hive locations but access is restricted.	available from New Zealand but mechanisms are not well understood. Movement from hives, swarms and drifting bees.	inspections and swarms will be the most useful. Surveillance of swarms in port areas could be flagged as higher likelihood	movements, treatment of hives and possibly destruction of hives.	existing CSIRO model that has explored some of the parameters. Previous models have suggested that eradication is unlikely.
9	*Lissachatina fulica*	Giant African snail	Data should be available	Unrestricted	Spread through diffusion and jumps on goods and machinery	Visual surveillance and general surveillance will be important	Proportional reduction treatments can be implemented.	Model is unlikely to provide any significant insights into management
10	*Halyomorpha halys*	Brown marmorated stink bug	Complex daylength and hibernation required	Extent is unrestricted although establishment potential could be set higher in areas which are both exposed to pathways and	Spread through diffusion and jumps on goods and machinery	Surveillance by trapping is probably poor. Visual inspections will target fruiting trees in spring and summer and aggregation areas in autumn. APPDIS would need some amendments to manage this.	Control methods are limited but local sprays around infested areas may be used.	Model would likely need significant modification to address eradication strategies. Some critical biological information may be poorly understood.

	Pest group	Common name	Growth	Extents	Spread	Surveillance	Control	Prospects
				close to food plants				
11	*Bactericera cockerelli* / *Candidatus* Liberibacter solanacearum	Tomato-potato psyllid and Clso	Vector / disease complex difficult to model.	Probably treat as unrestricted, due to weed hosts but some uncertainty	Vector spread by diffusion, potential jump diffusion of vectors	Surveillance can be implemented using traps. Efficacy poorly understood	Destruction of hosts and management of vectors possible. Management of movements through produce restrictions likely.	Model could examine the challenges faced by responses with low surveillance efficacy.
12	*Puccinia graminis* f. sp. *tritici* (exotic strains)	Ug99	Temperature dependant growth rates for cereal rusts should be available. Influence of wetness and humidity are likely to be	Cereal growing areas are accessible	Natural spread is likely to occur quickly within districts may be able to be modelled across districts.	Surveillance programs are in place for endemic diseases.	Control is most likely to be through resistance management.	Could model some natural spread characteristics across districts but unlikely to be useful for improving resistance management strategies.

	Pest group	Common name	Growth	Extents	Spread	Surveillance	Control	Prospects
			significant.					
13	*Diuraphis noxia* (sexual type)	Russian wheat aphid	Information likely to be available.	Cereal growing areas are accessible		Likely to be very low general surveillance efficacy.	Unlikely to be modelled.	Unlikely to be considered further although an interesting case study to parameterise to see if the detection scenario can be reproduced.
14	*Xanthomonas citri* subsp. *citri*	Citrus canker	Growth models available although some uncertainty about spread at a local level that could affect growth implemented within a cell	Limit to residential and citrus horticultural land uses	Vector spread by diffusion, potential jump diffusion of disease on propagating material	Visual surveillance and general surveillance	Destruction of hosts and chemical	Model could examine the challenges faced by responses with slow spread
15	*Puccinia*	Guava rust/	Models	Unrestricted	Rapid wind-borne	Visual surveillance and some	limited	Some existing models have

	Pest group	Common name	Growth	Extents	Spread	Surveillance	Control	Prospects
	psidii sensu lato (exotic strains)	Eucalyptus rust	available Ag Vic	although probably variable	spread, possibly leading to spread across Bass Strait.	general surveillance in natural areas that are poorly covered.		dealt with spread of eucalyptus rusts but there are limited options to manage incursions.
16	Air-borne Phytophthora spp.	Airborne phytophthora	May be poorly understood	Unrestricted although probably variable	Wind and soil spread, local dynamics likely to be important to model outputs.	Visual surveillance and general surveillance likely once significant impacts showing.	limited	Limited options to manage incursions.
17	Exotic bee (*Apis* spp.)	Exotic bees	Growth rates of colonies are probably not well known although some information from *A. cerana*	Fairly unrestricted although at management scales, the distribution of floral sources over time could be useful. APPDIS does not currently support	Some spread information available from New Zealand but mechanisms are not well understood. Movement from hives, swarms and drifting bees.	Surveillance can be through multiple methods but hive inspections and swarms will be the most useful. Surveillance of swarms in port areas could be flagged as higher likelihood	Control methods would operate on nests or swarms.	Modelling in port areas could be useful although may not be very informative unless high resolution floral maps are created.

	Pest group	Common name	Growth	Extents	Spread	Surveillance	Control	Prospects
				variable carrying capacity				
18	*Fusarium oxysporum* f. sp. *cubense* Tropical race 4	Panama disease (Tropical race 4)				Surveillance by visual surveillance poor. Farm level general surveillance likely driven by motivation to report	Control methods about on-farm management	
19	*Globodera* spp.	Potato cyst nematodes				Surveillance very poor	Limited, mostly movement restrictions	No useful modelling scale within APPDIS
20	*Liriomyza* spp.	Liriomyza flies	Some information through cesar	May be some restrictions on some species.	Multiple spread mechanisms, could	Surveillance as a combination of trapping and visual inspections. Some complexity in detection.	Limited control options	May be able to investigate surveillance efficacy but no suitable control mechanisms.

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Appendix A: Workshop 1 report

CEBRA Project 170606
Developing models for the spread and management of National Priority Plant Pests

Workshop report

Tuesday 29 August 2017
Department of Agriculture and Water Resources
18 Marcus Clarke St, Canberra

Purpose

This workshop was held to canvass expert opinion on the plans for CEBRA project 170606 'Developing models for the spread and management of National Priority Plant Pests'. The workshop brought together plant pest science and policy specialists at both a national and state level to discuss the potential for enhancing the Australian Animal Disease Model (AADIS) to enable simulation modelling of national priority plant pests (NPPPs) in Australia.

Agenda

The workshop agenda is provided in Appendix A.

Participants

The workshop participants are listed in Appendix B.

Session 1: Project context and goals

Mark Stanaway welcomed the participants and outlined the goals for the workshop:

- introduce the AADIS model and how it has been used by Animal Health
- determine potential uses for the AADIS model in a Plant Health context
- discuss the types of plant pests that might be appropriate to model
- determine the data, skills and pest information needed as model inputs

Each workshop participant provided a one-minute overview of their background and how it may benefit the project.

Session 2: Overview and demonstration of the AADIS model

Richard Bradhurst provided attendees with an overview and demonstration of the AADIS model. AADIS is referred to as a hybrid model as it combines mathematical and agent-based modelling techniques. An equation-based model (EBM) is embedded inside each (herd) agent of an agent-based model (ABM). The EBM (for example, a SEIR compartmental model), captures the spread of disease within a herd while the ABM captures the spread of disease between herds. This tactic reduces the number of agents required for a national scale

model from over 1,000,000 animal agents to less than 250,000 herd agents. This in turn allows the model to be computationally efficient such that national-scale simulations of the spread and control of animal disease can be conducted on a laptop.

Of particular interest were the AADIS modifications recently completed under CEBRA project 1608B ('Decision-support tools for vector-spread animal disease'). This project introduced a new type of AADIS agent: the grid cell. A cell agent's EBM (in this case a temperature dependent logistic growth model), models the population density of an (insect) vector population over time within the grid cell. The ABM models the spread of the vector population between grid cells with a stochastic jump-diffusion process that takes into account multiple layers of raster data (cattle density, temperature, rainfall, elevation and wind). The initial vector population can be (a) computed by the model based on configured criteria for environmental parameters such as temperature, rainfall, elevation, etc), (b) defined by point introductions (e.g., at a port), or (c) derived from externally generated abundance/risk maps.

Session 3: The applicability of AADIS to plant pests

Mark Stanaway lead a discussion on possible uses of the AADIS model in a plant pest context. He noted that AADIS operates in two 'modes': farm (per the foot-and-mouth disease demonstration) and raster (per the Culicoides vector demonstration). There is intuitive cross-over between the modelling of insect vectors in raster mode and the modelling of plant pests. The usefulness of farm mode for plant pests will depend on how the model is used and the specific pests.

Possible uses of AADIS include:

- Preparedness and planning. The model can be used to simulate 'what-if' scenarios of spread and management strategies. This may assist decision makers in the prioritisation of plant pests, policy formulation, and the allocation of finite budgets between surveillance and control.
- Early detection surveillance planning. The model could be used to investigate the potential spread of plant pests in specific high-risk areas or 'hot spots'. This could inform the establishment of trapping and/or surveillance programs aimed at early detection of an incursion and thus more cost-effective management.
- Early response management. The model could help predict outbreak extents for the purpose of informing delimiting surveillance activities. At the time of detection the model might assist with estimates of the location and time of incursion.
- Late response management. The model could help estimate the probability of area freedom for both domestic and international trade purposes.

Potential users of AADIS include the Plant Health Policy Branch, the Chief Plant Protection Office, and the states/territories. The following pest information will be needed in order to modify, configure and run AADIS:

- spread

- growth
- establishment
- pathways
- surveillance efficacy
- controls

The availability and robustness of this data will influence the complexity of the model (aggregated pathways such as jump-diffusion vs disaggregated pathways such as airborne plumes and nursery trade movements), and the choice of case studies. Sometimes simple models are more appropriate than complex models, for example, when data is scarce or unreliable. In some cases it is not sensible to model at all, for example, if there are simply too many unknowns with a pest's ecology, distribution and/or epidemiology.

Tony Arthur mentioned that he previously developed a spread model (written in R) of Siam weed. Mark said that although the focus of the project is national priority plant pests the Siam model may still be a useful resource for the project.

Session 4: Project plans

Mark Stanaway described how the first year of the project focuses on incursion and spread (both natural and human assisted), while the second year focuses on detection and control. The broad schedule for the project is provided in Appendix C.

Sessions 5 and 6: Case studies and the requisite data

Mark Stanaway tabled the top 30 national priority plant pests:

NPPPs 1 to 10	NPPPs 11 to 20	NPPPs 21 to 30
Xylella / Sharpshooter	Tomato potato psyllid	Fire blight
Khapra beetle	UG 99 wheat stem rust	Hessian fly
Fruit Flies	Russian wheat aphid	Texas root rot
Karnal bunt	Citrus canker	Wheat stem sawfly
Huanglongbing / psyllid vectors	Eucalyptus rust	Golden apple snail
Gypsy moths	Airborne Phytophthora	Barley stripe rust
Tramp ants	Exotic bees	Cereal cyst nematode
Bee parasites	Panama disease (TR4)	Plum pox virus
Giant African snail	Potato cyst nematodes	Exotic drywood termites
Brown marmorated stink bug	Liriomyza leaf miners	Exotic subterranean termites

The following criteria were used by the group to assess the suitability of the NPPPs as case studies:

- Good knowledge of spread parameters

  → Data on wind, water, transport, directed spread

  → Ecology / Epidemiology

- Good knowledge of establishment points

  → Host material / habitats

  → Ecology / Epidemiology

- Good knowledge of surveillance sensitivity

  → Trapping efficacy, visual inspection, latent periods

  → Relationship with modelling scales

- Good knowledge of control technology

  → Effectiveness of baits, destruction, sprays

The group assessed the pests that would satisfy most of the above criteria and suggested the following would make useful case studies for the project.

- exotic fruit flies (Mediterranean fruit fly, *Ceratitis capitata* and oriental fruit fly, *Bactrocera dorsalis*)
- vectored disease (huanglongbing, '*Candidatus*' Liberibacter asiaticus /Asian citrus psyllid, *Diaphorina citri*)
- exotic invasive ants (Raspberry ants, *Nylanderia fulva*, browsing ants, *Lepisiota frauenfeldi*, red imported fire ant, *Solenopsis invicta* and electric ant, *Wasmannia auropunctata*.

Session 7: The Animal Health experience with AADIS

Rachel Iglesias described how AADIS arose from a PhD scholarship funded by the Department of Agriculture and Water Resources and replaced the regional-scale AusSpread model. AADIS is primarily a decision-support tool that informs preparedness and planning for emergency animal disease. It has been used in FMD modelling studies on the value of vaccination, the impact of resource limitations, and early decision indicators.

AADIS has recently been extended to model the distribution and spread of insects (primarily in their role as vectors). Test cases have included *Culicoides brevitarsis*, *Culex gelidus* and *Haematobia irritans exigua*.

AADIS is currently deployed on departmental personal computers, that whilst DAWR assets, are not part of the departmental network. The main reason for this is the difficulty in white-listing a constantly evolving custom software product (there have been 41 versions of AADIS released in 5 years).

Session 8: Project outcomes

Richard Bradhurst described the difference between the classic 'waterfall' approach to software development and the modern 'agile' approach. With an agile approach there are iterative incremental software releases that help to flush out issues earlier in the development life cycle. This in turn lowers project risk as flaws in the project direction and specification are detected earlier. This project will follow an agile approach with regular minor software releases in addition to the scheduled major releases (refer to Appendix C).

Verification is the process of determining whether a software implementation agrees with the specification, i.e. are we building the product right? It is largely internal to the software development process and consists of activities such as unit tests, module tests and integration tests.

Validation is the process of determining whether the specification meets the customer's needs, i.e., are we building the right product? Is it fit for purpose? Examples of validation include relative (cross-model) comparison and retrospectively modelling past (known) outbreaks.

Sensitivity analysis is the process of gauging model response to systematic variation of parameters. This helps prioritise the importance of specific data/parameters.

Given the difficulties of white-listing AADIS for use on the departmental network the project will proceed based on stand-alone laptops with potential client-server solutions investigated as a parallel activity.

Session 9: Wrap-up and next steps

Mark Stanaway and Richard Bradhurst summarised the next steps for the project during the 2017/2018 financial year:

- A literature review of previous modelling studies on the first case study (fruit fly).
- Extension of the AADIS software architecture to include plant pests.
- Collection and translation (to the AADIS database schema) of fruit fly data required by the model.
- Production of a prototype model of fruit fly incursion and spread.
- Ongoing refinement and improvement of the model through iterative software releases for assessment by Plant Health personnel.
- Interim software release in February 2018.
- Final software release and project report (detailing the validation and sensitivity analysis activities) submitted in June 2018.

The first case study will be used to flush out general issues with modelling plant pests in AADIS. The second and third case studies will only be started once significant progress has been made on the first case study.

Participants were thanked for their attendance and the meeting was closed at 16:30.

Appendix A - Agenda

Developing models for the spread and management of National Priority Plant Pests (CEBRA Project 170606)

Tuesday 29 August 2017 9am – 4.15pm
Emergency Management Room (M.2.02)
Department of Agriculture and Water Resources
18 Marcus Clarke St, Canberra

Time	Activity	Lead
9:00	Welcome and housekeeping	Mark Stanaway
9:05	Project context and goals	Susie Collins
9:15	Introductions – each participant to provide a one minute overview of their experience and how it may be helpful for the project	Mark Stanaway
9:30	AADIS overview and demonstration	Richard Bradhurst
10:15	The applicability of AADIS to plant pests	Mark Stanaway & Richard Bradhurst
10:30	Break	
10:45	Group discussion on project plans • desired outcomes • case studies • engagement with stakeholders	Mark Stanaway & Richard Bradhurst
11:30	Group discussion on possible case studies for the project, e.g., fruit fly, fire ant, citrus greening	Mark Stanaway
12:30	Lunch	
1:30	Group discussion on case study data 1 requirements and availability 2 resources (GIS skills, availability, etc)	Mark Stanaway & Richard Bradhurst
2:30	The Animal Health experience with AADIS	Rachel Iglesias
3:00	Break	
3.15	Group discussion on project outcomes 1) AADIS modifications 2) deliverables 3) adoption	Richard Bradhurst & Mark Stanaway
4:00	Wrap-up and the next steps for the project	Mark Stanaway
4:15	Close	

Appendix B - Participants and affiliation

Participants	Affiliation
Tony Arthur	ABARES, DAWR
Richard Bradhurst	CEBRA, UoM
Robyn Cleland	ACPPO, DAWR
Susie Collins	Biosecurity Plant, DAWR
Cheryl Grgurinovic	Biosecurity Plant, DAWR
Craig Hull	Biosecurity Plant, DAWR
Rachel Iglesias	Biosecurity Animal, DAWR
John de Majnik	Biosecurity Plant, DAWR
Louise Rossiter	NSW Department of Primary Industries
Mark Stanaway	Biosecurity Plant, DAWR
Apologies	
Kylie Calhoun	Biosecurity Plant, DAWR
Iain East	Biosecurity Animal, DAWR
Graeme Garner	Biosecurity Animal, DAWR
Daryl Hardie	Department of Agriculture and Food, Western Australia
Sarah Hilton	Biosecurity Plant, DAWR
Greg Hood	Biosecurity Plant, DAWR
Tom Kompas	CEBRA, UoM
Kim Ritman	ACPPO, DAWR
James Walker	Biosecurity Plant, DAWR
Project team	
Marion Healy	Biosecurity Plant, DAWR (project sponsor)
Susie Collins	Biosecurity Plant, DAWR (project leader)
Mark Stanaway	Biosecurity Plant, DAWR (project leader)
Sally Troy	Biosecurity Plant, DAWR (project leader)
Tom Kompas	CEBRA UoM (project leader)
Richard Bradhurst	CEBRA UoM

Key

ABARES: Australian Bureau of Agricultural and Resource Economics and Sciences

ACPPO: (Office of the) Australian Chief Plant Protection Officer

CEBRA: Centre of Excellence for Biosecurity Risk Analysis

DAWR: Department of Agriculture and Water Resources

UoM: University of Melbourne

Appendix C – Project Schedule

Phase/Milestone	Due
Year 1: Modelling the incursion and spread of NPPP:	
NPPP incursion and spread workshop: • Review of existing AADIS spread mechanisms for applicability to NPPP. • Identification of NPPP functional groups to test the suitability and availability of data and parameterisation for the AADIS spread mechanisms. • Formulation of NPPP incursion and spread case studies.	August 2017
Workshop report provided to DAWR	September 2017
Data and parameterisation needed for NPPP incursion and spread case studies provided by DAWR	October 2017
Interim software delivery	February 2018
Draft report provided to DAWR project leaders for comment	May 2018
Year 1 final report and final software delivery	June 2018
Year 2: Modelling the detection and control of NPPP:	
NPPP detection and control workshop: • Review of existing AADIS control mechanisms for extensibility to NPPP. Identification of NPPP-specific control measures to be implemented. • Identification of data and parameterisation required for the AADIS NPPP control mechanisms. • Formulation of NPPP detection and control case studies.	July 2018
Workshop report provided to DAWR	August 2018
Data and parameterisation needed for NPPP control case studies provided by DAWR	September 2018
Interim software delivery	February 2019
Draft report provided to DAWR project leaders for comment	May 2019
Year 2 final report and software delivery	June 2019

Appendix B: Workshop 2 report

CEBRA Project 170606
Developing models for the spread and management of National Priority Plant Pests

Workshop report

Friday 21 June 2019
Department of Agriculture and Water Resources
18 Marcus Clarke St, Canberra

Purpose

This workshop was held to canvass expert opinion on the prototype of the plant pest spread model developed under CEBRA project 170606 'Developing models for the spread and management of National Priority Plant Pests'. The purpose of the workshop was to demonstrate and describe the prototype, and seek feedback from plant pest science and policy specialists.

Outcomes

Workshop participants agreed that the AADIS model provides a useful tool for investigating response strategies to manage plant pest incursions. However, uncertainty about the ecology of pests and the efficacy of surveillance and response methods does not favour use of the model for tactical decision making during responses.

The growth and spread components of the crazy ant and Oriental fruit fly model were considered reasonable, although difficult to validate. Further work is required to check the surveillance and response parameters and costings.

The current prototype contains the range of components that would allow it to be applied to functional groups of National Priority Plant Pests in a general sense. Extensions to the modelling system were discussed that would allow greater flexibility and rigour in modelling plant pest spread. The value of these extensions needs to be considered in terms of specific modelling applications.

Agenda

The workshop agenda is provided in Appendix A.

Participants

The workshop participants are listed in Appendix B.

Session 1: Project context and workshop goals

Mark Stanaway opened the workshop and welcomed the participants. Each workshop participant introduced themselves. Mark provided a brief overview of the project and outlined the goals for the workshop:

- to obtain feedback on the ecology and control aspects of the ant and fruit fly models

- to obtain feedback on the richness of the AADIS modelling platform for applying to National Priority Plant Pests
- to identify useful ways in which the model can be used by biosecurity agencies.

Session 2: AADIS overview and demonstration of prototype

Richard Bradhurst provided attendees with a brief overview of the AADIS model including its origins as a model of emergency animal disease (EAD). The AADIS model has been updated to provide a suite of modelling components that can be applied to modelling plant pest incursions and their detection and control. AADIS is referred to as a hybrid model as it combines mathematical and agent-based modelling techniques. Each epidemiological unit (or agent), has an embedded equation-based model (EBM) that represents the spread of a pathogen/pest inside the agent. When modelling a plant pest, the agent is a cell in a grid and the EBM is a logistic growth equation. The spread of a pathogen/pest between agents is implemented by an agent-based model (ABM). The ABM provides a variety of stochastic spread pathways and control/eradication policies.

The model prototype was used to demonstrate the two case studies for the project: an established population of tramp ants and a point incursion of an exotic fruit fly.

Case Study 1 (established population of yellow crazy ants):

- regional study area of approximately 18,000 km^2 near Cairns, Queensland
- 10 hectare cells.
- initial population of approximately 300 million ants across 154 cells.
- within-cell abundance is modelled with a temperature independent logistic growth function.
- between-cell spread may occur via budding diffusion, sugar cane related jumps, human-mediated hitchhiking jumps and rafting jumps.
- detections may occur passively through general surveillance or actively via delimiting surveillance
- treatment program carried out in all detected cells
- post-treatment surveillance program leads to either further treatment or declaration of freedom
- control/eradication response is dynamically constrained by available resources and costed

Case Study 2 (point incursion of oriental fruit fly at the Port of Cairns):

- national study area of approximately 17,000,000 km2
- 25km^2 hectare cells.
- initial population of 25 flies
- within-cell abundance is modelled with a temperature dependent logistic growth function.
- between-cell spread may occur via natural dispersal diffusion and human-mediated hitchhiking jumps
- detections may occur through general surveillance, early detection surveillance (based on the national network of methyl eugenol traps) or delimiting surveillance
- treatment program carried out in all detected cells

- post-treatment surveillance program leads to either further treatment or declaration of freedom
- control/eradication response is dynamically constrained by available resources and costed

Session 3: Modelling within-cell abundance – habitat and climate suitability, the logistic growth model

James Milner provided an overview of how intra-cell population dynamics are represented in the AADIS framework:

- fruit fly physiology – a general overview of fruit fly physiology covering life stages, growth and mortality
- logistic growth – modelled with a logistic function constrained by an initial population density, a carrying capacity, and a growth parameter
- parameterisation – the following parameters are adjustable within the logistic growth model
    - initial cell population – written into the model as a fixed value
    - carrying capacity – determined for each cell by a habitat suitability raster layer where suitability is a function of land-use type and a vegetation index (NDVI)
    - growth rate – modelled by combing functions that determine the response of development and mortality to temperature, where functions are constructed based on data in the scientific literature

James explained how the logistic growth model is implemented in the AADIS framework and how this determines within-cell population dynamics, and how it can be customised to a specific pest using three parameters: initial cell population, carrying capacity, and growth rate. Two parameterisation examples were illustrated for Queensland fruit fly and Oriental fruit fly, with the differences displayed as time series for different cities around Australia.

Session 4: Modelling between-cell spread

Richard Bradhurst provided further details (equations and configuration options), on the pathways through which pests spread between cells:

- natural dispersal – modelled with a stochastic diffusive spatial kernel that depends on the source cell pest density, destination cell suitability, and distance
- agriculture-related jumps – modelled with a stochastic jump process that depends on the source cell pest density and land use, and the destination cell suitability and land use
- human-mediated hitchhiking jumps - modelled with a stochastic jump process that depends on the source cell pest density and human population density, and destination cell suitability and human population density
- rafting jumps – modelled with a stochastic jump process that depends on the source cell pest density and waterways, the destination cell suitability and waterways, and the gradient between the cells.

Richard described how the spread pathways are independent, concurrent and configurable. For example, rafting could be replaced by nuptial flights by simply modifying the jump pathway name and configuration data.

Session 4: Modelling detection and control

Richard Bradhurst provided further details (equations and configuration options), on the surveillance and control/eradication components of the ABM:

- general surveillance – modelled by a stochastic process that depends on a cell's pest population density, human population density, and the sensitivity of the observer. Observers in managed areas such as cropping systems have a higher sensitivity than those in unmanaged areas.
- early detection surveillance – modelled with a stochastic process based on the national trapping grid. Detection depends on trap density, trap lure type, source cell pest density, and trap sensitivity.
- delimiting surveillance - modelled with a stochastic process that depends on trap density, source cell pest density, and trap sensitivity. Surveillance is conducted around detected cells based on either the immediate neighbour cells or inside a radius. A positive result triggers a treatment program. A cell is deemed free after a configurable number of consecutive negative results.
- treatment – a treatment program is comprised of a configurable number of periodic treatments. Each treatment reduces the cell's pest population by a configurable proportion. Extinction occurs if the population has been reduced to below the configured minimum viable population by the end of the treatment program
- post-treatment surveillance - modelled with a stochastic process that depends on trap density, source cell pest density, and trap sensitivity. A positive result triggers a re-treatment program. A cell is deemed free after a configurable number of consecutive negative results.

Richard described how the control components are independent, concurrent and configurable. The active surveillance and treatment components are dynamically constrained by available resources. If insufficient resources are available then control actions are queued. The model reports the efficacy of surveillance (true/false positives/negatives), efficacy of treatment (successful/unsuccessful eradication), and the overall cost of surveillance and treatment.

Session 5: Group discussion

Mark Stanaway led a group discussion on the model and the project. Comments from the group included:

- The model could be extended to represent directed network-based spread pathways such as transport and logistics networks that depend on farm type and season but these would also need resources to manage the risk data.
- Modelling mortality rates explicitly rather than the current aggregated logistic population growth rate would be more realistic and transparent.
- Surveillance visits do not take into account variability in the time needed to service trap sites. This could be addressed by taking into account the distance from a trap to the nearest control centre, or establishing trap groupings for teams.

- The current model only allows a single treatment mode at each cell and could be extended to include multiple modes such as spot and radial treatments running at the same time.
- Treatment choices may depend on cell characteristics such as whether the pest is in an urban or rural area.
- Most useful applications for plant pests will be at a regional rather than national scale. The model may be a useful tool for investigating spread rates and management options in specific areas.
- The resourcing and cost data in the prototype is for test purposes only. This should be improved before running the case study simulations for the final report.
- The prototype will need to undergo at least a rudimentary validation process prior to running the case study scenarios for the final report.
- The final report should explain how the model might be extended to other plant pests and identify the data required. Given the large number and variety of national priority plant pests, it would be useful to identify functional groups of pests to describe the information required for modelling.
- The final project report should manage reader expectations by carefully describing potential modelling applications, caveats, and expertise and resources required for use.

Session 6: Wrap-up and close

Participants were thanked for their attendance and the meeting was closed at 15:45.

Appendix A - Agenda

Developing models for the spread and management of National Priority Plant Pests (CEBRA Project 170606)

Friday 21 June 2019 9am – 3.45pm
Meeting room: M2.02
Department of Agriculture and Water Resources
18 Marcus Clarke St, Canberra

Time	Activity	Lead
9:00	Welcome, housekeeping & introductions	Mark Stanaway
9:15	Project context and progress Workshop goals	Mark Stanaway
9:30	AADIS overview/recap Case study 1 demonstration – tramp ants Case study 2 demonstration – exotic fruit flies	Richard Bradhurst
10:30	Break	
11:00	Modelling within-cell abundance – habitat and climate suitability, the logistic growth model	James Milner
11:30	Modelling between-cell spread – natural dispersal, movement in produce, human-mediated hitchhiking, rafting	Richard Bradhurst
12:30	Lunch	
1:30	Modelling detection and control – general, early detection and delimiting surveillance, treatment, post-treatment surveillance, absence, resourcing, costs	Richard Bradhurst
2:30	Group discussion on the model thus far • pros and cons • data requirements and availability • parameterisation requirements • calibration and validation	Mark Stanaway Richard Bradhurst James Milner
3:00	Break	
3.15	Group discussion on project outcomes • potential uses for the model • training requirements • adoption hurdles • future work	Mark Stanaway
3:45	Wrap-up and close	Mark Stanaway

Appendix B - Participants and affiliation

Participants	Affiliation
Tony Arthur	ABARES
Richard Bradhurst	CEBRA, UoM
Matthew Calverley	Biosecurity Plant, Plant Health Policy
Susie Collins	Biosecurity Plant, Plant Health Policy
Sophie Peterson	Biosecurity Plant, Plant Health Policy
Greg Hood	Biosecurity Policy and Implementation, Biosecurity Integrated Information Systems & Analytic Program
Craig Hull	Biosecurity Plant Science & Risk Assessment, Tropical Fruits
James Milner	Biosecurity Plant, Plant Health Policy
Haydon Morgan	Biosecurity Plant, Plant Health Policy
Natalie O'Donnell	Environmental Biosecurity Office
Amit Singh	Biosecurity Plant, Plant Health Policy
Mark Stanaway	Biosecurity Plant, Plant Health Policy
Apologies	
Nathaniel Bloomfield	ABARES, DA
Jennifer Brooks	Biosecurity Plant, Plant Health Policy
Cheryl Grgurinovic	Biosecurity Plant, Plant Health Policy
John de Majnik	Biosecurity Plant, Plant Health Policy
Sarah Hilton	Biosecurity Plant, Plant Health Policy
Tom Kompas	CEBRA, UoM
Heleen Kruger	Environmental Biosecurity Office
Kim Ritman	ACPPO
Liesl Taylor	Biosecurity Plant, Plant Health Policy
Project team	
Marion Healy	Biosecurity Plant (project sponsor)
Susie Collins	Biosecurity Plant (project leader)
Mark Stanaway	Biosecurity Plant (project leader)
Tom Kompas	CEBRA, UoM (project leader)
James Milner	Biosecurity Plant
Richard Bradhurst	CEBRA, UoM

Key

ABARES: Australian Bureau of Agricultural and Resource Economics and Sciences

ACPPO: (Office of the) Australian Chief Plant Protection Officer

CEBRA: Centre of Excellence for Biosecurity Risk Analysis

UoM: University of Melbourne