Assessing Ant Pathways to Better Inform Site Selection for Ant Surveillance

CEBRA Project No. 170615, Surveillance Allocation

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Executive Summary

The National Invasive Ant Surveillance (NIAS) programme was initiated in 2003, following the detection of red imported fire ants in Auckland, 2001. At present, NIAS sets and inspects approximately 45000 traps per season, spread amongst the sea ports, air ports and (to a lesser extent) the thousands of transitional facilities around the country that devan cargo. An MPI approved provider in Entomology screens all the ant species in the traps around the country. All exotic ant species are validated by MPI's Plant Health and Environment laboratory (PHEL). All specimens are kept and stored up to one year and and exotic species are used as reference samples by PHEL. All diagnostic data are stored in the National Invasive Ant Surveillance Database.

Resources do not allow for annual targeted surveillance at each of the transitional facilities. The NIAS uses ongoing risk analyses to determine at which sites to perform surveillance, with consideration of the type of freight, volume, port of origin, and history of contamination when allocating resources. There is limited evidence underpinning the current selection of sites for surveillance. The overall objective of this project was to improve the understanding of the patterns of invasive ant incursions into New Zealand in order to focus surveillance effort on sites with the highest risk.

Pathway-level arrival modelling, combined with mathematical optimisation, is able to provide a clear, well justified scientific rationale for allocating resources for surveillance. This project applied such techniques to data provided by the Ministry for Primary Industries to generate a priority list for surveillance within regions, along with an optimal trap number allocation strategy. Whilst there were some discrepancies between the number of traps allocated in this report and the allocation as given by National Invasive Ant Surveillance programme, these were minimal and should be easily remedied if desired.

The major finding of this project is to provide confirmation that the National Invasive Ant Surveillance program largely maintains an optimal allocation of resources for detecting invasive ant arrivals into New Zealand.

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1. Introduction

Globalisation and trade can inadvertently lead to the transport of invasive species around the world, well beyond their natural ranges. Ants are one particular insect group which has spread rapidly into new regions and countries by hitchhiking on passengers, goods and containers, and there are potentially severe environmental and economic implications of these species becoming established in new regions. One of the most well-known examples is the introduction of yellow crazy ants (*Anoplolepis gracilipes*) onto Christmas Island, Australia. Here they have formed high density super-colonies and have caused a catastrophic trophic cascade through the rainforest ecosystem, starting with the extirpation of the endemic red land crab (O'Dowd et al., 2003).

In NZ alone there are 29 exotic ant species that have already become established, far more than the 11 native species (Ward et al., 2006; Ward and Edney-Browne, 2015). Ants are one of the common insect groups intercepted at NZ's borders. In the 50 years from 1955–2005 there were 4,355 interceptions of 115 different species. Border control and surveillance post-border are the main ways in which exotic ants are detected in NZ, but the effectiveness of detecting ants at the border varies with different trade pathways, ranging from 48% for maritime cargo, to 78% for passengers (Ward et al., 2006). The low detection rate in maritime cargo is unsurprising given more than 550,000 sea containers arrive in NZ annually and less than 30% are inspected. Nearly a quarter of inspections detect ant contamination (Ward et al., 2006). Detections on maritime cargo are generally on containers and used vehicles, predominantly from Asia, in contrast detections from air cargo and passengers are on fresh produce, predominantly arriving from the Pacific (Ward et al., 2006).

Following the detection of red imported fire ant (*Solenopsis invicta*), ranked in the top 100 of the world's worst invasive pests, in Auckland in 2001 the National Invasive Ant Surveillance (NIAS) programme was initiated and deployed in 2003. The objective of NIAS is to detect exotic ants incursions early to prevent establishment (Gunawardana et al., 2013). The post-border NIAS programme detects 10–12 exotic ants in NZ each year from surveys at international ports and transitional facilities (Figure 1.1). It is extremely difficult to determine the origin of an invasive ant or trace the incursion pathway because most ants are discovered at a food source not associated with any specific container. Selecting among the thousands of transitional facilities spread around the country for invasive ant surveillance is currently done on anecdotal evidence and/or speculation of high risk sites. If it is possible to determine the origin of ant incursions and the sites with the greatest risk, it would be possible to target surveillance based on site risk profiles.

Transitional facilities are currently selected for surveillance based on the perceived risk from attributes of both the containers and sites including: first port of origin, volume of containers, commodity types, and whether there has been a previous detection. Prior to this report, there was no evidence to suggest that these variables are important predictors of ant incursions. For detection of ants it is also important to consider species traits, including cryptic behaviour, nesting habits, and body size, as these can all influence detection rates (Ward et al., 2006).

The spread and establishment of invasive ants is less likely to be influenced by interspecific competition from NZ's 11 native ant species, than by climatic conditions. Furthermore, they are likely to be concentrated around cities with large international ports: Auckland, Tauranga and Napier (Ward, 2007). Between 2003–2013 Napier Port received less than 0.001% of full containers and about 10% of empty containers arriving in NZ, but had the greatest diversity of tramp ant species intercepted at the border ($n = 8$) and, relative to the number of containers received, had very high number of detections ($n = 19$). Auckland had the greatest absolute number of ant detections ($n = 33$) but received almost 50% of full containers and 20% of empty containers. The discrepancy is attributed to more favourable climatic conditions in Napier (Gunawardana et al., 2013). The 28 exotic species already established in NZ are found in the warmer climates of the north island and northern regions of the south island (Ward, 2007). Abiotic and climate variables, including rainfall, temperature and soil type, considerably influence ant distributions and the success of ant incursions (Ward, 2007; Gunawardana et al., 2013).

The overall objective of this project is to improve our understanding of the patterns of invasive ant incursions into NZ in order to focus surveillance effort on sites with the highest risk. This study will use data for all ant species that have been intercepted in NZ or at the border. The study will focus on the risk of incursion and will not determine the establishment potential of ant species.

Developing risk profiles for sites will enable sites to be selected for targeted surveillance based on scientifically defensible rationale. Specifically, the project aims to:

- Develop a better understanding of the arrival patterns of invasive ants into NZ;
- Provide improved and scientifically justifiable site selection for invasive ant surveillance;
- Create risk profiles of sites, in particular transitional facilities, where ants are more likely to arrive;

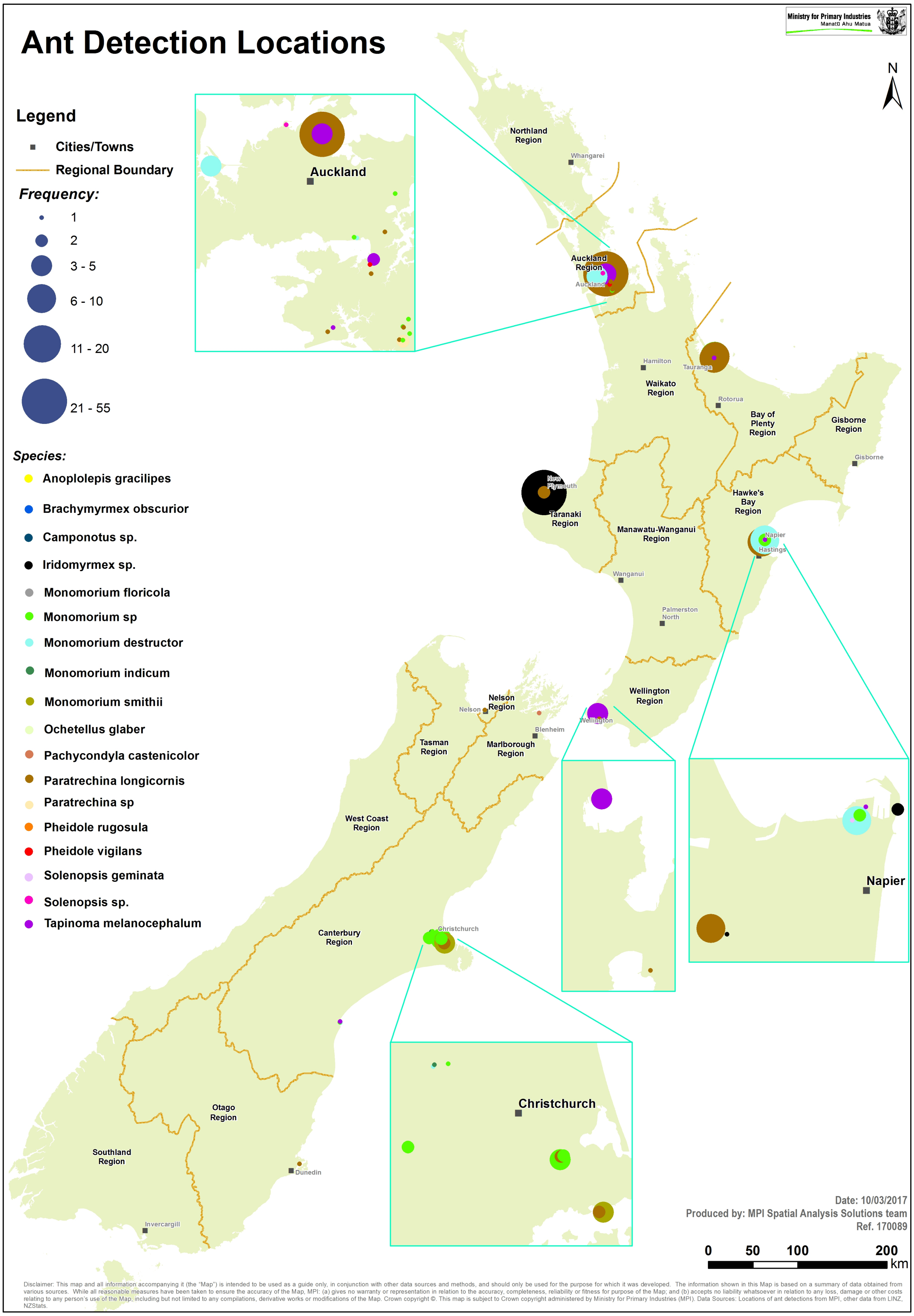

Figure 1.1.: Spatial representation of all the ant interceptions in New Zealand through the National Invasive Ant Surveillance programme 2003–2017.

- Identify key risk variables affecting invasive ant arrivals that can help to inform site selection for the NIAS programme; and
- Provide a basic understanding of the pathway using a systems approach.

1.1. The National Invasive Ant Surveillance Programme

The annual National Invasive Ant Surveillance programme (NIAS) was established by the Ministry of Agriculture and Forestry (now Ministry for Primary Industries, MPI) in 2003 following a response to a red imported fire ant (RIFA, Solenopsis invicta) incursion at the Auckland International Airport in 2001. The incursion was subsequently eradicated.

NIAS was primarily developed as an early warning system designed to detect newly established nests of invasive ant species at high risk sites around New Zealand. High risk sites are locations associated with the arrival of international trade such as sea and airports and transitional facilities that devan containers.

How the NIAS Programme Targets Newly Arrived Ant Species

High-risk sites for ant entry are determined by ongoing pathway and site risk analyses undertaken annually by MPI. High risk sites include seaports, airports, sea container storage sites and Approved Transitional Facilities (ATF) that receive international freight for devanning. Risk analysis includes consideration of freight type, volume, port of origin and history of contamination at each site.

Once reviewed, sites are then scheduled to be surveyed from mid-summer to early autumn each surveillance season. Sites visited from year to year vary. For example major ports (sea and air), high risk sites and container storage yards are visited each year, however smaller ATF sites may only be visited every 2 or 3 years or even as a single one-off visit in a season.

The NIAS programme targets these risk sites by exploiting the biology and behaviour of newly arrived ant species over the summer period when ants are likely to arrive and remain active. Ants that have hitchhiked on an item of cargo are unlikely to remain on that item for long, particularly if they have been disturbed by cargo movements and unloading. There are specific immediate biological needs that they will require on arrival. Ants therefore will set up a nest in as short a time as possible and immediately start to locate food and moisture. This means that newly established nests are likely to be close to where the imported item of cargo was first landed or stored.

Newly landed ants are also limited by the available habitat for nest construction. Most ports, container yards and devanning sites feature large tracts of flat concrete or asphalt pads that are constantly disturbed by vehicle traffic etc., and so are not suitable as nest sites. Ants will therefore seek undisturbed 'ant habitat' around the margins of concrete or asphalt pads where there are cracks or gaps in the surface where some vegetation (weeds) and detritus have accumulated (e.g., around light poles, fence-lines, gutters, drains, buildings etc.).

While these sites may be better than open concrete, they are often still reasonably inhospitable to ants, and frequently have limited food and moisture available. This means that newly formed nests may not be productive and will be in constant need for resources and therefore, continuously send out foragers to find new sources of food. For this reason ant surveillance is undertaken close to ant habitat where foraging ants are likely to be detected. The NIAS programme targets ant habitat by systematically placing baited pottles[1] with food at selected facilities and ports. By offering a high-energy food source (carbohydrate and protein) in an environment that is typically depauperate of food for ants, the programme maximises the chances of foraging exotic ants finding, recruiting, and then being captured in baited pottles with food.

Pottle Trap Deployments

The identified risk sites are surveyed by ground teams. Systematic grids of small plastic pottles, alternately baited with either carbohydrate (sugar solution) or protein (peanut butter, oil and sausage meat) are placed every 10 x 10 m using GPS. Each pottle is bar-coded and tracked. Ants locate to these pottles with their natural foraging behaviour and will recruit additional worker ants to feed upon the bait. This results in an abundance of ants being present inside the pottle upon collection. Pottles are left out at a site for approximately two hours at environmental conditions conducive for ant foraging. In conjunction with the pottle deployment, visual surveillance is also undertaken. Aproximately 99% of all exotic ant detections have been found in the baited traps. Some exotic ant species are hard to visually distinguish between endemic or introduced species already present in New Zealand without the aid of a microscope. Pottles are taken to the laboratory to identify any exotic ants captured inside the pottles. The pottle is tracked back to the site of detection where eradication procedures are undertaken if exotic ants are present inside the pottle.

History of Detections

Since NIAS has been operating there has been on average 12 to 15 exotic ant detections per annum around the country. Most of the detections are found in the North Island such as Auckland, Napier and Tauranga. This probably reflects the surveillance effort

[1] A pottle is a baited trap with food attractant to attract foraging ants for detection.

in these regions because they receive a larger proportion of international trade which increases the propagule pressure of ants arriving into New Zealand. Northern New Zealand is also conducive for ant establishment due to average warmer temperatures. During NIAS the survey is started a month later in the South Island to coincide with the warmest month of the Summer season which is conducive to ant foraging.

Current Prioritisation of Sites

'Tramp' ant species are versatile and can hitch-hike on almost every commodity so all commodities need to be considered in the risk analysis for the NIAS survey. Ants are good at monopolising their environment and utilising micro-climates particularly close to concrete structures that retain heat. Thus all sites around NZ need to be considered for surveillance. During the NIAS programme, ant nests have been detected in the South of the South Island in areas that we would least expect them to be.

There are a large number of devanning sites around the country and the resources allocated to the NIAS programme does not permit all these sites to be surveyed annually. There needs to be a rationale based around good quality data to help inform the NIAS programme on where to look for ant incursions and to prioritise these sites given that the programme has limited resources to survey all sites.

1.2. This Report

This report details the modelling of ant arrivals into New Zealand and subsequent site prioritisation for invasive ant surveillance, performed as Phase II of CEBRA Project 170615. An outline of the mathematical details underpinning the prioritisation of a trapping network are provided in Chapter 2, with detailed exposition in Appendix C. Data available for use in modelling are described in Chapter 3. Exploratory analysis of the data and model outlines are provided in Chapter 4. Results of the application of the models and optimisation to ant arrivals into New Zealand are discussed in Chapter 5, where we distinguish between allocations that may not account for arrival rate uncertainty, and those that do. In Chapter 6 we discuss the implications of this work, and a number of possible extensions.

2. Trapping Network and Optimal Allocation

The trapping network distribution within each site for NIAS is highly complex. As discussed in Section 1.1, traps (pottles) are placed in highly structured, contiguous areas, such as along margins of concrete or asphalt pads. Craddock and Mattson (2017) provides details of trap placements for the 2017 NIAS deployment.

Trap placement such as that described above for NIAS is very likey to result in spatially dependent trapping probabilities, due to the complex topography and environment of each site. To analyse such a network requires an understanding of how such geographical constraints impact upon trapping sensitivity, as well as complex simulation to assess how the uneven distribution of traps in each site impacts detectability (Camac et al., 2018).

In this report, we will make the simplifying assumption that each area consists of uniform areas of the trapping grid. That is, the trapping network in a site consists of a uniformly spaced grid of traps.

Suppose that we have J sites over which we want to optimise trap allocation, and that over the course of a season (or year), we expect to see Y_j arriving ants into site j, $j = 1, \ldots, J$. Suppose that in site j, we place n_j traps that work together to give a probability P_j of detecting an ant if present. We then expect to miss (not detect) $M_j = Y_j \cdot (1 - P_j)$ ants over the course of a season.

A suitable target for optimisation is to minimise the number of ants that are missed by the trapping network each season (Hauser and McCarthy, 2009), however other options are also available (Cannon, 2009). Over all sites, the expected number of ants that are missed is

$$\begin{aligned} M &= \sum_{j=1}^{J} M_j \\ &= \sum_{j=1}^{J} Y_j \cdot (1 - P_j). \end{aligned} \tag{2.1}$$

The allocation of traps to sites is further constrained by the total number of traps available[1] and an appetite for risk minimisation whereby a minimum number of traps is to be laid at each site *irrespective of the expected number of arrivals*. Thus, our objective is to minimise M (Equation 2.1), subject to the total number of traps laid being less than a fixed amount, $\sum_j n_j \leq N$, and the number of traps at each site being greater than a fixed amount, $n_j \geq c_j$.

Site prioritisation is determined (not surprisingly) by the expected number of ants caught; that is, we allocate traps in priority to $Y_j \cdot P_j$. The actual number of traps allocated to each site can be found in a closed form (Hauser and McCarthy, 2009; McCarthy et al., 2010), the details of which are derived in Appendix C. An R package, `surveillanceAllocation`, has been developed to perform the calculations. Instructions on how to install and use the `surveillanceAllocation` for allocating traps to sites is provided in Appendix D.

2.1. Establishment Risk

A risk of ant establishment index could be included in the objective function for optimal allocation (Equation 2.1). Using climate matching and/or local environment suitability, a localised risk score could be included. For example, suppose that the risk of ant establishment at a site j is R_j; then the target of optimisation becomes:

$$M = \sum_{j=1}^{J} R_j \cdot Y_j \cdot (1 - P_j)$$

We do not pursue adjustment for ant establishment risk further in this report, but refer the reader to Camac et al., 2018 for details on a framework to include such a risk score into the allocation[2].

> **Recommendation** *Risk of ant establishment should be investigated as an option to include in the objective function for optimal allocation.*

A reviewer recommended CLIMEX climate matching, and cited "Utility of the CLIMEX 'match climates regional' algorithm for pest risk analysis: an evaluation with non-native ants in New Zealand" (n.d.). We had considered climate matching but decided it was out of scope at the time as we were wanting to understand the arrival patterns and pathways better. A cautionary approach needs to be taken if using climate matching to determine establishment potential of ants. In Author LP's experience, ant

[1]Within a fixed budget, the number of traps is a function of costs per trap to set and then inspect the trap. This cost is taken as fixed (across sites) for this report.

[2]We note that the number and location of nests detected is currently being collected, however the data is not sufficiently long term at present.

behaviour is key to establishment as they tend to use micro-climates for nest development in concrete structures or objects that retain heat and have a North-west facing aspect. Author LP has found nests of sub-tropical species at the most southern sites in New Zealand during surveillance.

2.2. Information and Data Requirements

The optimal allocation requires two key pieces of information to proceed: estimates of the number of arriving ants, Y_j, and estimates of the site trapping probabilities, P_j. Estimating the number of arriving ants is the focus of Chapter 3, where we detail models to enable forecasts of Y_j.

Trapping probabilities for a site depend upon the probability that a single trap captures an ant if it is present in the traps area of attraction (Chapter C). Hartley and Lester (2005) estimate individual trap detection probabilities for a range of ant species detected during the 2004/2005 seasons of NIAS. Their estimates ranged from 0.005 (*T. albipes*) to 0.231 (*I. anceps*). For this project, we will use a range of trapping probabilities, including the estimate of 0.005, to demonstrate the effect that the various probability settings have on the allocation of trap numbers.

3. Available Data

We now turn to a discussion (and exploration) of the types of data available for estimating the number of ants arriving at each site. As discussed in Section 2.2, this number is required in order to allocate trap numbers optimally to each site.

3.1. Description of the Pathways of Exotic Ants

The network diagram (Figure 3.1) provides some of the main links in the incursion process for ants. The blue squares represent the main network nodes, the green and pink diamonds provide secondary or tertiary nodes in the network. Ideally data on all the major nodes would be contained within the four main datasets to provide information on risk for incursions and what attributes could be used to determine high risk sites for surveillance. A description of the nodes is below.

Transport type: the border interceptions data (Section 3.2.1) provides information on where the interceptions were made (e.g. sea and air cargo);

Country of origin: is recorded in the border interceptions data (Section 3.2.1) and transitional facility detections data (Section 3.2.2);

Surveillance locations: all datasets provide some information on the location of the incursion but the resolution differs from the city to complete address;

Detection methods: each of the datasets provides different detection methods. E.g. the NIAS (Section 1.1) is from a standardised surveillance program with baited traps, and the post-border detections are ad hoc reports from passive surveillance;

Biotic factors: the species of ants detected are not included in all datasets. This resolution is provided in the border interceptions data (Section 3.2.1) and post-border targeted surveillance data (i.e. NIAS). If required, information such as life history and environmental requirements can be established for these species from appropriate literature;

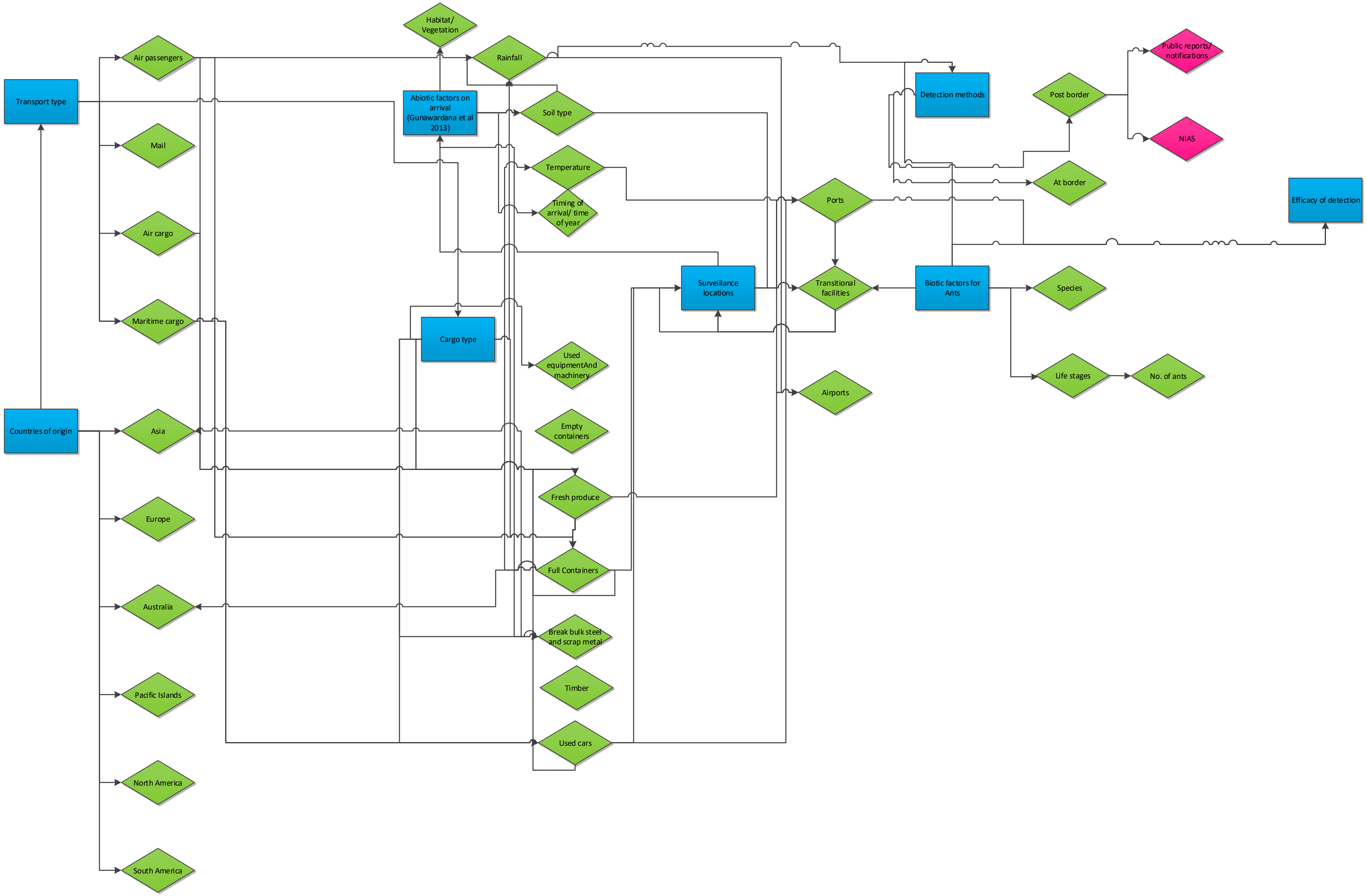

Figure 3.1.: Network diagram of the ant pathway into New Zealand, and relationship with post-border surveillance. Blue nodes are main categories; green nodes are sub-categories, and the pink nodes are surveillance data sources.

Abiotic factors: the environmental conditions around the ports and transitional facilities can be established from climate and soil data, potentially using Land Environments of New Zealand (LENZ) data (*Land Environments of New Zealand (LENZ)* n.d.);

Efficacy of detection: at present, the efficacy of detection of each type is unknown, and would have to be attained via expert elicitation, or by making some assumptions;

Cargo type: the border interceptions data (Section 3.2.1) contains details on what type of cargo the ants were found on.

3.2. Data Overview

To date the project has identified and collated all of the available data sources on invasive ant surveillance and incursion reports in NZ. There are four main datasets (Table 3.1), which we will detail below, including any issues found to date.

Table 3.1.: Overview of the datasets available for modelling.

Data name	Date range	Number of entries
Ant detections at the border	2002–2016	2502 individual detections
Ants found on containers	2006–2016	6541 entries, 2104 individual containers
Ant detections from post border passive surveillance	2002–2016	572 individual detections
NIAS Surveillance data	2007–2017	501573 entries; 223 invasive ants detected

3.2.1. Border Interceptions

This dataset contains interceptions from cargo (sea and air) commodities, passengers and in/on containers at the border. The dataset covers the period July 2001 to October 2016, and has approximately 2500 entries. Fields in this dataset include: site name/address, location, intercept area, country of origin origin (the first port that the vessel left or was loaded from — does not take into account other ports visited), host commodity, genus, species, sex, life stage, number found, and life state.

The site name field records a descriptive name for where the interception was made, for example Auckland Port. The diversity in description here is considerable, and will require manual editing to be useful. The location field records the macro-level location the interception was made, for example, Auckland. We consider that for this project, location is likely to be sufficient, as volumes (if available) for passengers and containers are likely to only exist at that macro level.

To prepare for modelling, we need to consider at what level aggregation will be appropriate. The site name is too 'dirty' for geolocating the data. For example, site name includes such descriptors as *Auckland Port*, *MPI Auckland BC*, *MPI Auckland Wharf* and *MAFBNZ Auckland Wharf*.

Recommendation *Border interception data should include a definitive GPS location of the detection as well as a descriptive site name.*

Recommendation *Site names should be normalised so that site name changes can be tracked. For example,* MPI Auckland Wharf *and* MAFBNZ Auckland Wharf *appear to refer to the same site.*

The macro-level location field name appears to be the most appropriate higher-level location descriptor present in the border interceptions dataset. However, it is still unclear as to which geographical level this field relates to[1]. By manually interrogating the descriptions, it appears that the location field presently refers to one of the sixteen Regions of New Zealand, as defined for local government purposes. With this in mind, some minor editing was still required, Table B.1 shows how location was recoded into Regions of New Zealand.

Table 3.2 shows the top five locations of border interceptions over the data period. Auckland carries the largest number of interceptions by a large margin. Table 3.3 shows the top three areas in which interceptions are made at the border; most are made in sea cargo. Country of origin is also instructive as to where propagule pressure may be arising; Table 3.4 shows that the Pacific Islands are a large source of interceptions.

Table 3.2.: Top five location of border interceptions, 2001–2016.

Location	Number	Percentage (%)
AUCKLAND	1713	68.5
MID CANTERBURY	322	12.9
BAY OF PLENTY	190	7.6
WELLINGTON	118	4.7
HAWKES BAY	56	2.2

[1] Note that if the recommendation regarding GPS locations is accepted, then a higher-level geographical aggregation field is unnecessary, as it can be directly coded using the GPS coordinate and standard GIS software.

Table 3.3.: Top three intercept areas of border interceptions, 2001–2016.

Intercept Area	Number	Percentage (%)
SEACARGO	1385	55.4
AIRCARGO	647	25.9
PASSENGER	362	14.5

Table 3.4.: Top five originating countries for border interceptions, 2001–2016.

Country of origin	Number	Percentage (%)
FIJI	694	27.7
AUSTRALIA	287	11.5
TONGA	195	7.8
SAMOA	181	7.2
PAPUANEW	170	6.8

The host commodity description provides details on where the ants were found, for example on a container, in a consignment of coconuts, or on passenger personal effects. Similar to the site name field, there is a large array of commodity descriptions. These will require classification into the network diagram nodes (Figure 3.1) e.g. 'Fresh produce' if we are to use them.

The detections detailed in Tables 3.2– 3.4 are for all ant species. Also included in the border interceptions data are the genus and species names of the ants found. We will use this information to classify an interception as either an invasive or non-invasive ant.

Ant taxonomy has changed within the period of data available. Invasive ant species names are listed in Table 3.5, and can be edited in the datasets during analysis to ensure consistency in species names.

3.2.2. Transitional Facility Detections

This dataset contains ant detections on containers found in transitional facilities; that is, these are post-border detections. The dataset covers the period December 2005 to November 2017 and has approximately 6500 rows. Many of these rows relate to the same individual container; the database provides details on all decisions related to the container, for example, inspection and treatment. Each of the containers is however, associated with an ant detection, of which there are approximately 2100 individual

Table 3.5.: Invasive ant species that are most likely to be targeted via the National Invasive Ant Surveillance programme.

Genus	Species	Common name
Wasmannia	*auropunctata*	Little fire ant
Solenopsis	*geminata*	Tropical fire ant
Solenopsis	*invicta*	Red Imported fire ant
Paratrechina	*longicornis*	Brown crazy ant
Anoplolepis	*gracilipes*	Yellow crazy ant
Nylanderia	*fulva*	Tawny crazy ant
Lepisiota	*fraunfeldi*	Browsing ant
Lepisiota	spp	
Camponotus	spp	Carpenter ant species
Tapinoma	*melanocephalum*	Ghost ant
Trichomyrmex	*destructor*	Singapore ant
Tetramorium	spp	
Nylanderia	*vaga*	
Nylanderia	*bourbonica*	
Nylanderia	spp	
Technomyrmex	*albipes*	
Iridomyrmex	*anceps*	
Iridomyrmex	spp	
Pheidole	*fervens*	
Pheidole	spp	

containers. For this dataset, we only consider **unique** container numbers as detections.

This dataset includes the loading port and country, the port of arrival, and the location of the transitional facility. Many of the transitional facilities are also geocoded, with approximately 85% having GPS coordinates recorded. Following this, we used the address fields to match addresses in the dataset with an online matching service (Google Maps Platform). Address matching was largely successful, with a limited number of addresses matched to the city level only. As a result, any further analysis should use city/region as the smallest geographical unit[2].

> **Recommendation** *Ant detections in transitional facilities should include a definitive GPS location of the detection as well as a descriptive site name.*

Whilst GIS software could be used to recode GPS coordinates to any aggregated region, we have hard-coded these as an initial step. As the border interceptions data is

[2]For example by using the GPS coordinates of the city General Post Office or similar.

coded to arrival region (as opposed to arrival port), we have aggregated the transitional facility detections to the respective region of arrival. Table B.2 shows the recoding to Regions of New Zealand.

As the port of arrival is known, we could make the assumption that these detections are border interceptions for the purpose of informing ant arrival rate analyses (Chapter 4). Note that we do not make the same assumption using the NIAS data—detections as part of NIAS cannot be ascribed necessarily to any particular pathway, meaning that it would be impossible to include in the arrival modelling.

> **Assumption** *Port of arrival records about containers with detections in transitional facilities are accurate. These detections can be added to the border detections for modelling the arrival rate (Chapter 4).*

Unfortunately the dataset does not include details on origin, genus and species of the ants, so we cannot tell if the ants are endemic or invasive nor can we effectively infer the source of their arrival as containers do not generally arrive direct to a country from its source. A better approach would be to inspect a subset of containers for any contamination arriving at ports and trace their movements from various countries to infer invasiveness — as all container movements are tracked in Port Authorities databases. This was out of scope for this project as access can be both costly and difficult.

> **Recommendation** *MPI should inspect a subset of containers for any contamination arriving at Ports and trace their movements from various countries to infer invasiveness.*

Specimen species were not identified due to operational processes rather than by lack of entomological resources. MPI has the needed expertise to identify all ants morphologically to species level.

> **Recommendation** *Ant detections in transitional facilities should be identified to species level to determine status as endemic or invasive.*

3.2.3. Post-border Detections via Passive Surveillance

This dataset contains ant detections that are recorded through passive surveillance. These detections are made from notifications to the Ministry for Primary Industry's pest and disease hotline, and cover May 2002 through to October 2016, with approximately 570 detections.

Fields recorded in the dataset include: the location, which records the city of the detection, and the genus, species and sex. Country of origin is also recorded in some cases, however this is deduced from interviewing the person who reported the detection. Not only is this prone to error, a large number of records are missing this information.

Table 3.6 shows the top five locations that had detections made via passive surveillance over the time period of the data. These locations roughly correspond with the locations of border interceptions (Table 3.2).

Table 3.6.: Top five locations for passive surveillance detections, 2002–2016.

Location	Number	Percentage (%)
AUCKLAND	210	36.7
BAY OF PLENTY	83	14.5
MID CANTERBURY	74	12.9
WELLINGTON	54	9.4
WHANGANUI	22	3.8

3.3. Container and Passenger Volumes

Two datasets containing volumes of container arrivals and incoming passenger arrivals were provided. Container arrivals were coded to multiple locations, so to be consistent, were recoded as in Section 3.2.2, see Table B.2 for details. Figure 3.2 shows the number of containers arriving into New Zealand Regions for the period 2004/2005–2017/2018. Data were provided for 2000-2003, but inconsistencies were found, so this data removed. Anecdotally, ant arrivals are associated with empty containers, so we expect that container volumes will be important in predicting ant arrivals. The volume-arrivals relationship will be explored further in Chapter 4.

Passenger volumes were available by New Zealand airport and country of origin for the period 2013/2014–2016/2017, and are shown in Figure 3.3. Whilst detections of ants on passengers and passenger effects make up approximately 15% of all detections (Table 3.3), the short time span available of volume data means that sufficient modelling using passenger volumes as a covariate is unlikely to be possible.

Recommendation *A longer time-series of air passenger volumes per port should be gathered.*

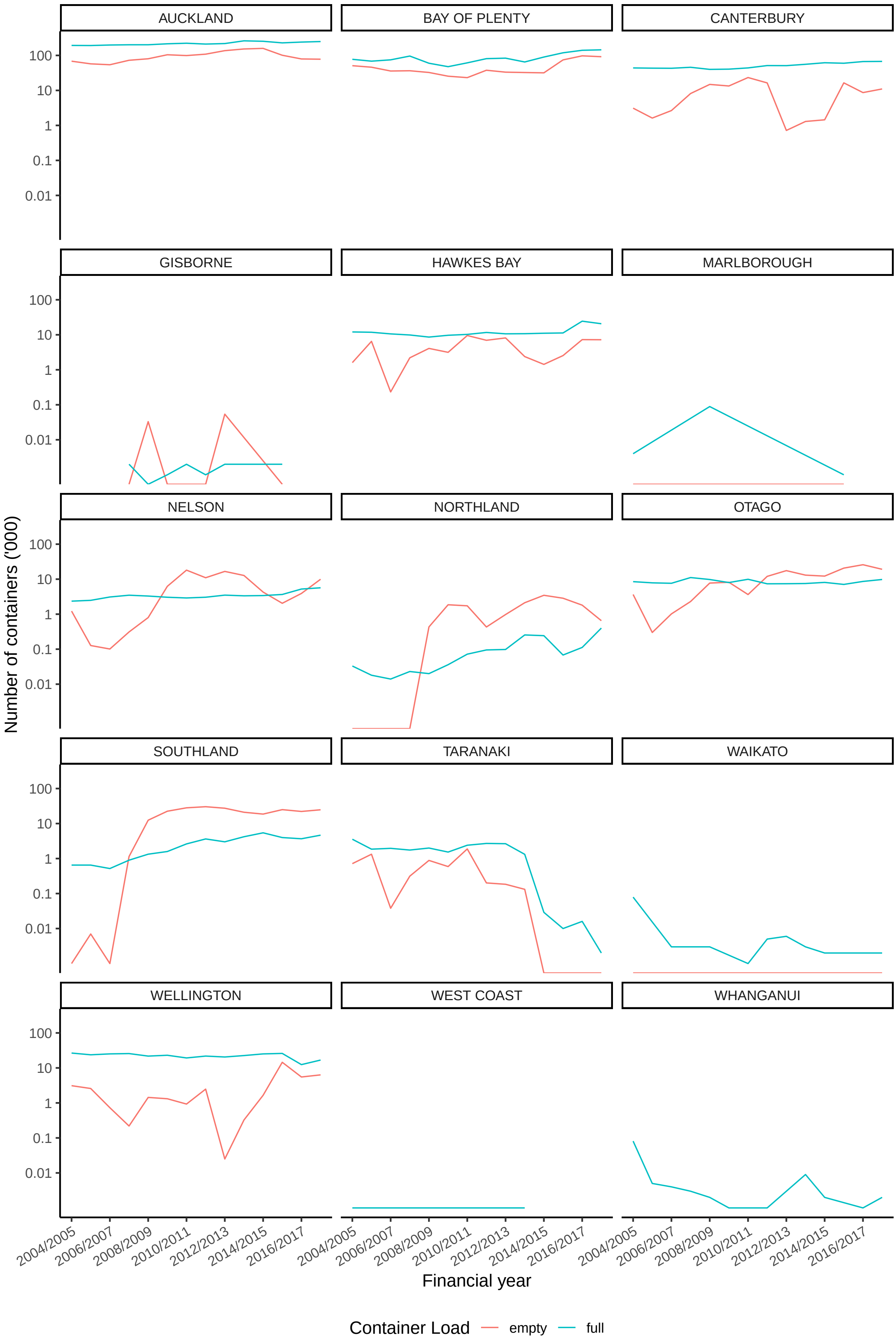

Figure 3.2.: Volume of containers arriving into New Zealand regions. The data are shown as the number of thousands of full and empty containers.

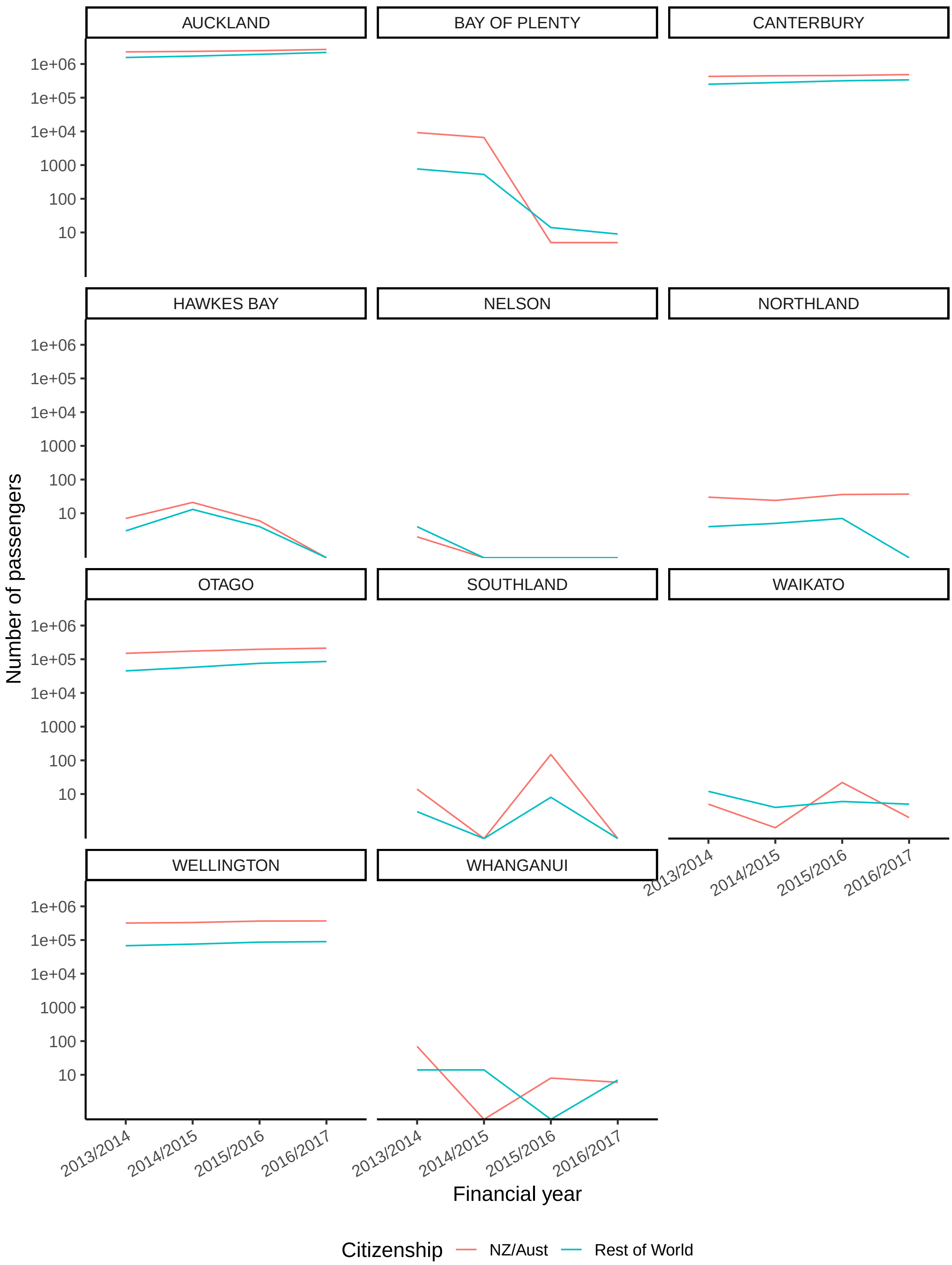

Figure 3.3.: Number of passengers arriving into New Zealand Regions. The data are shown as the number of New Zealand and Australian Citizens and Rest of World.

4. Arrival rates

4.1. Exploratory Analysis

Figure 4.1 shows monthly ant detections at the border. In this figure, detections from all ports and pathways (sea and air cargo, passengers and passenger effects, mail and other) are aggregated. The figure shows that there is slight uptick in detections during the warmer months (December to April), but this not a large seasonal effect. This limited seasonality leads us to aggregate the detections by year for modelling; for this report, we aggregate by financial year (July–June): any minor uptick in detections will be captured in this choice of aggregation duration.

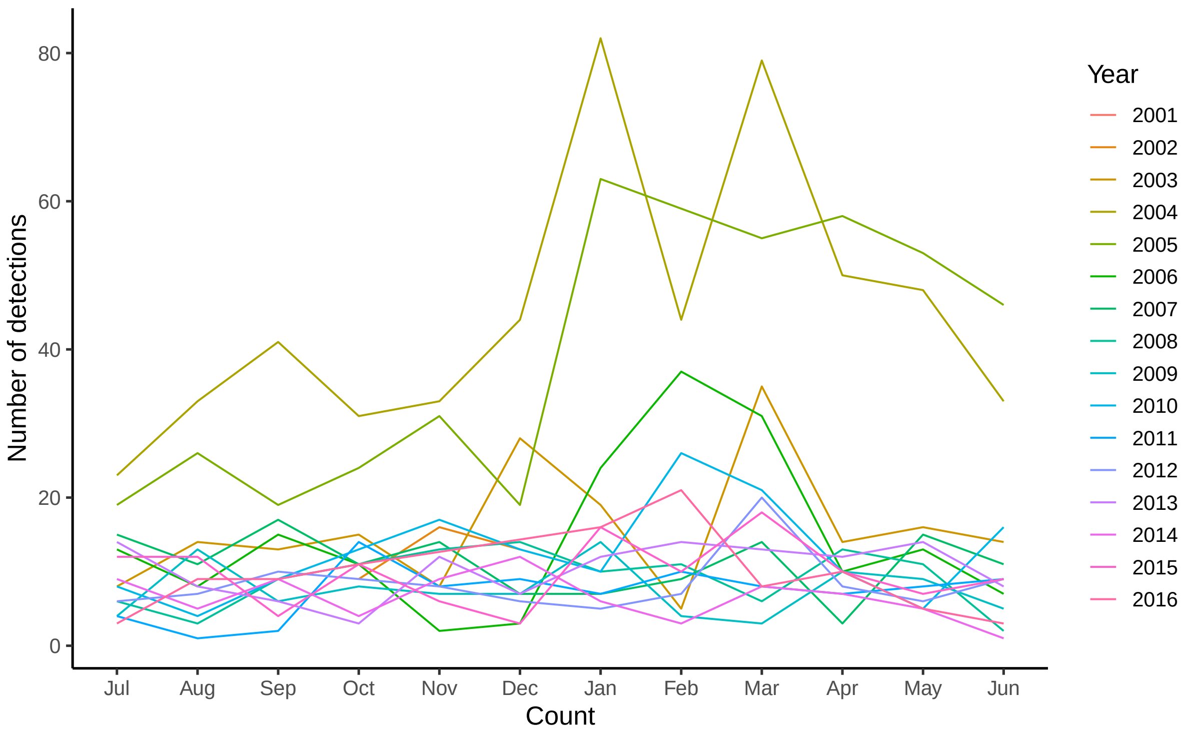

Figure 4.1.: Monthly ant detections at the border. Data are aggregated over all New Zealand ports, and include sea and air cargo, as well as passenger and passenger effects, mail and other detections. 2004 (82 in Jan) and 2005 (63 in Jan) stand out.

Figure 4.2 shows how the number of detections from containers arriving from various world regions has changed over time. This figure suggests little change over time in the detection pattern, aside from arrivals from Melanesia, which appear to be decreasing, and Polynesia, where detections started increasing around 2006/2007, then started decreasing around 2011/2012. From a modelling perspective, Figure 4.2 suggests that the detection rate per year should depend on the world region of origin. Polynesia (khaki, highest in 2016/2017) and Melanesia (light blue, second highest in 2016/2017) stand out, with South-eastern Asia (dark blue, third highest in 2016/2017) and Australia and New Zealand (red, fourth in 2016/2017) also distinguished from the other countries. It is also possible that terms allowing the relationship between time and region of origin be included in modelling, however there is likely to be limited data to model this relationship fully.

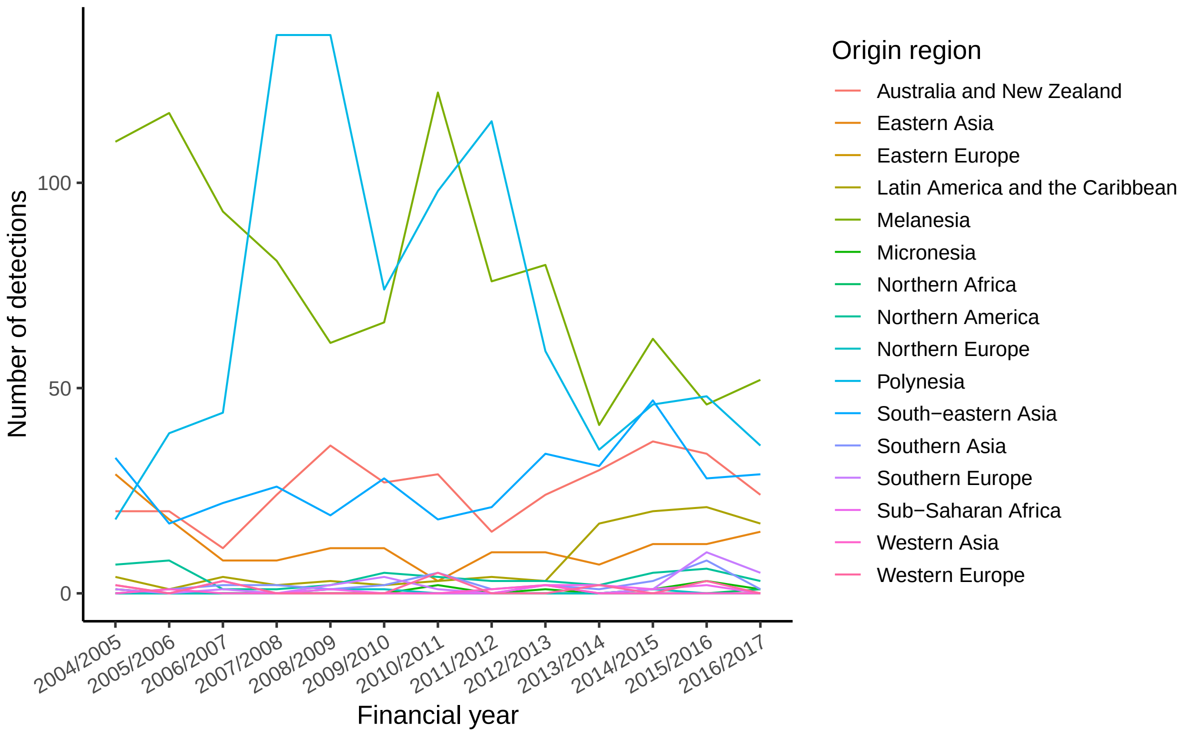

Figure 4.2.: Yearly ant detections by region of origin.

Figure 4.3 shows the number of detections over time by the New Zealand region of arrival. This figure suggests that detections into the Auckland region (highest in all years) increased starting around 2006/2007, and then began decreasing around 2010/2011. The opposite relationship is seen in the Bay of Plenty region (second highest), where detections started decreasing around 2005/2006, then began increasing around 2013/2014. It is clear that the region of arrival should be an important factor in modelling. Figure 4.4 further breaks down the region of arrival relationship by pathway of arrival[1]. Auckland is the highest across air and sea cargo.

Figure 4.5 shows the number of detections over time by both the region of origin

[1]'Other' pathways include the mail pathway and undetermined pathways. We model this pathway for the allocation exercise, but acknowledge that this pathway is likely to be difficult to plan surveys for.

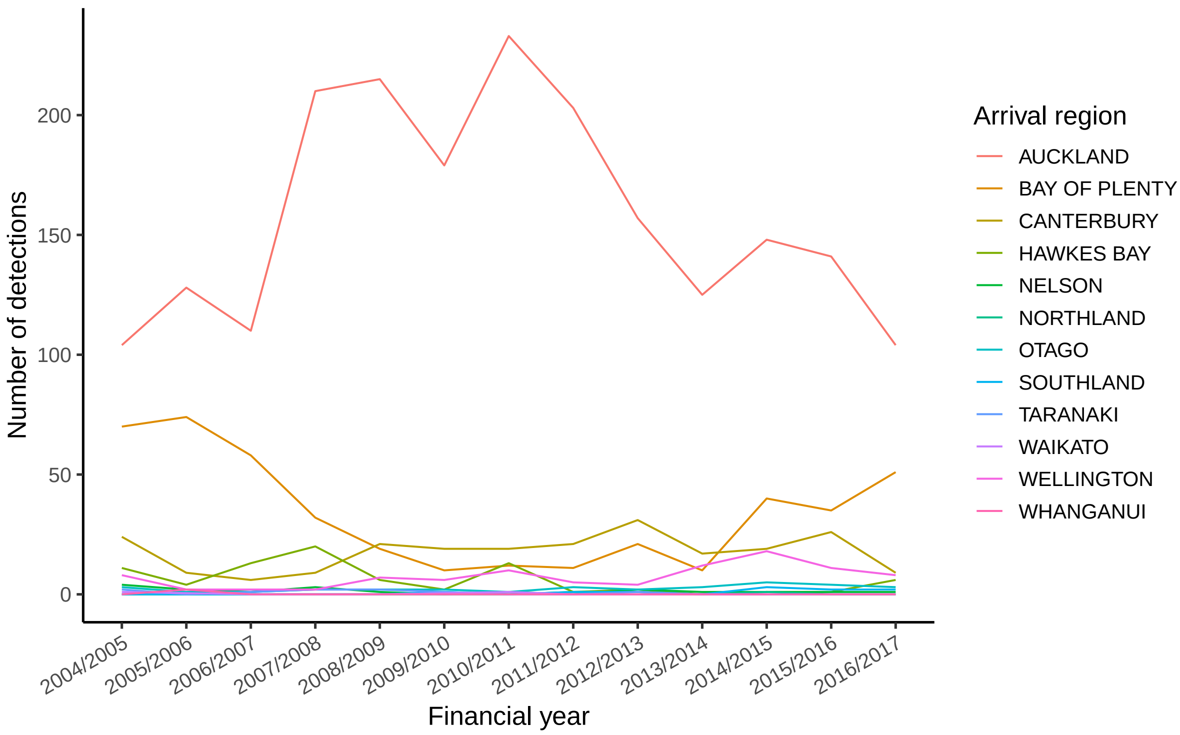

Figure 4.3.: Yearly ant detections by region of arrival.

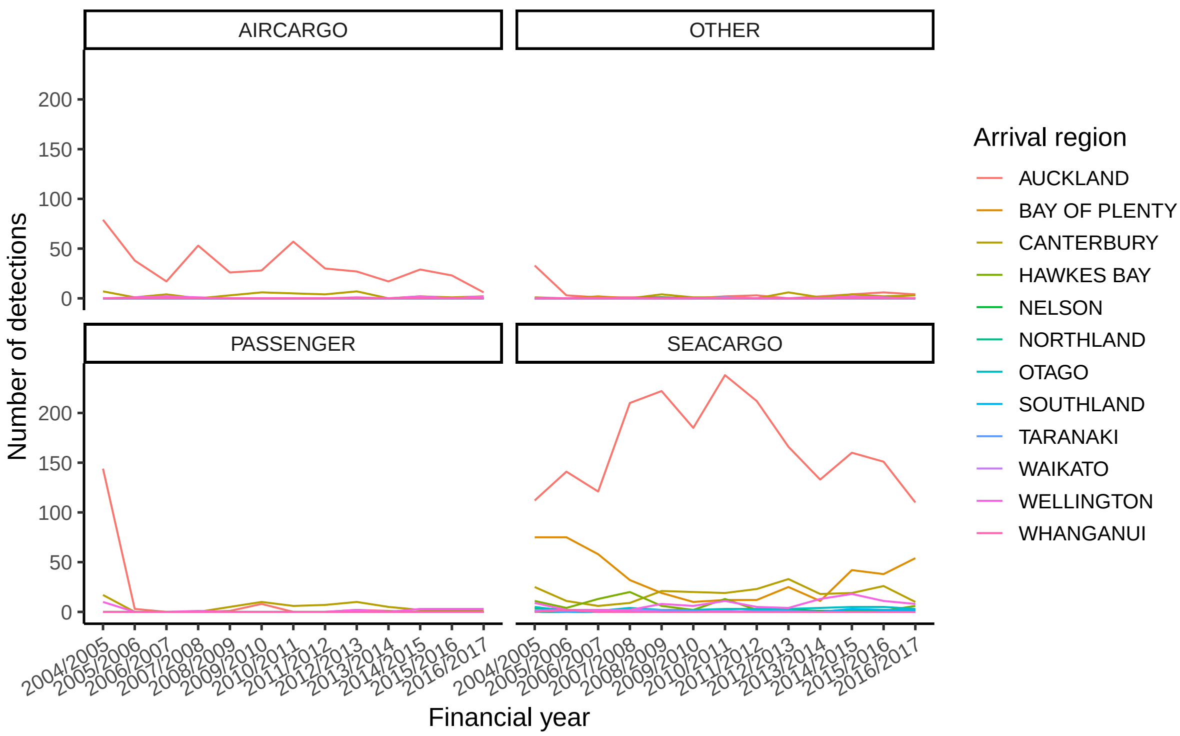

Figure 4.4.: Yearly ant detections by region of arrival and pathway.

and region of arrival. This suggests for example, that ants arriving into Auckland from Polynesia started increasing around 2008/2009, and then started decreasing around 2010/2011; this is in contrast to ants arriving into the Bay of Plenty from Polynesia, with detections sharply declining from around 2005/2006. This figure suggests that the relationship over time is likely to be complex and different for each world region and arrival region combination. It is also clear that there will be limited data to support any relationships in regions such as Southland and Waikato, and that either aggregating or removing these regions entirely may be necessary.

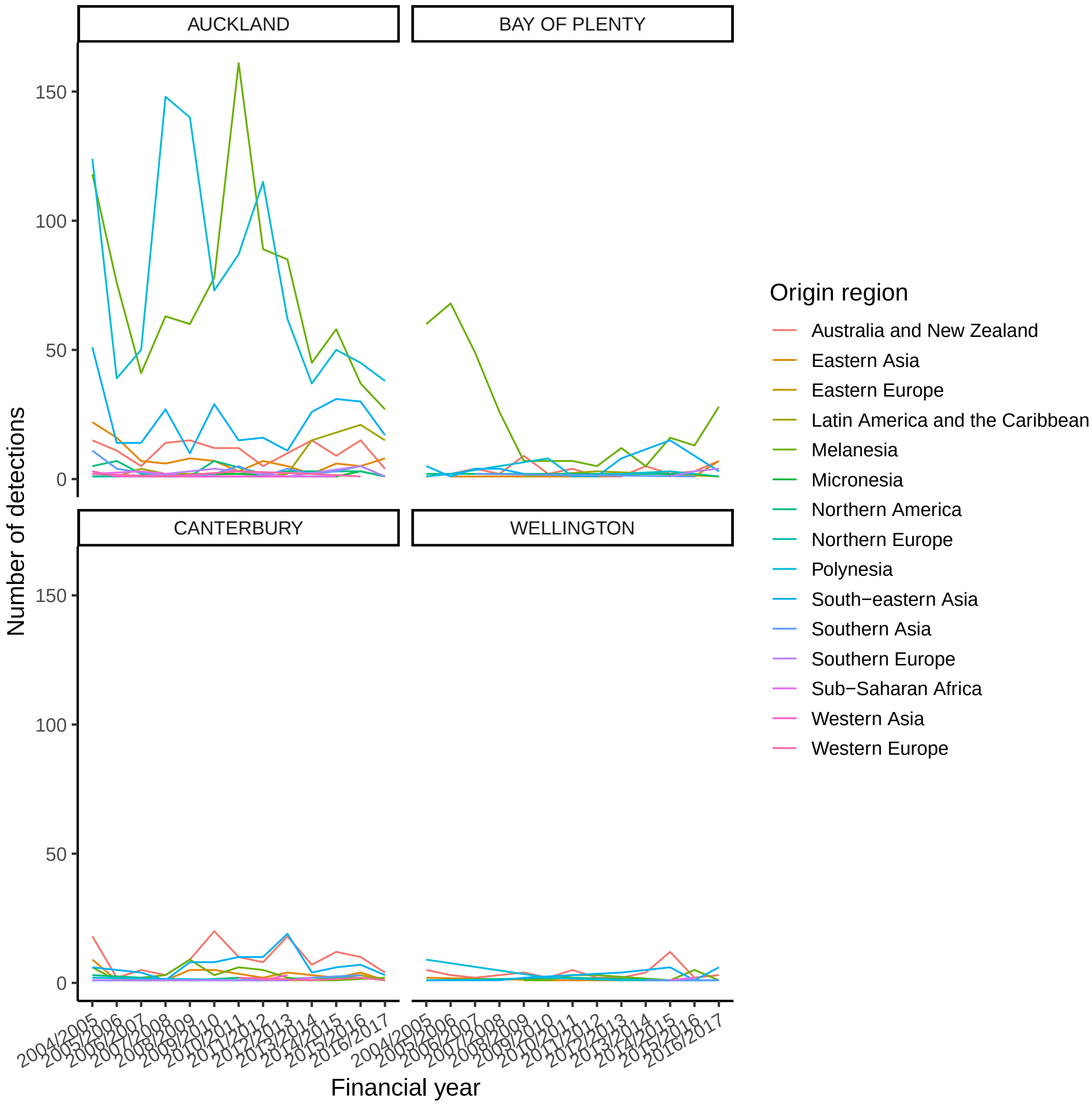

Figure 4.5.: Yearly ant detections by region of origin and region of arrival.

Figure 4.6 shows the relationship between the number of detections and the number of containers arriving at each region of arrival, split by full or empty container status. This shows that the number of detections is likely to be positively associated with the number of containers. It is possible that there is a different effect for full containers arriving at Auckland, but we acknowledge the limited data to estimate such a relationship.

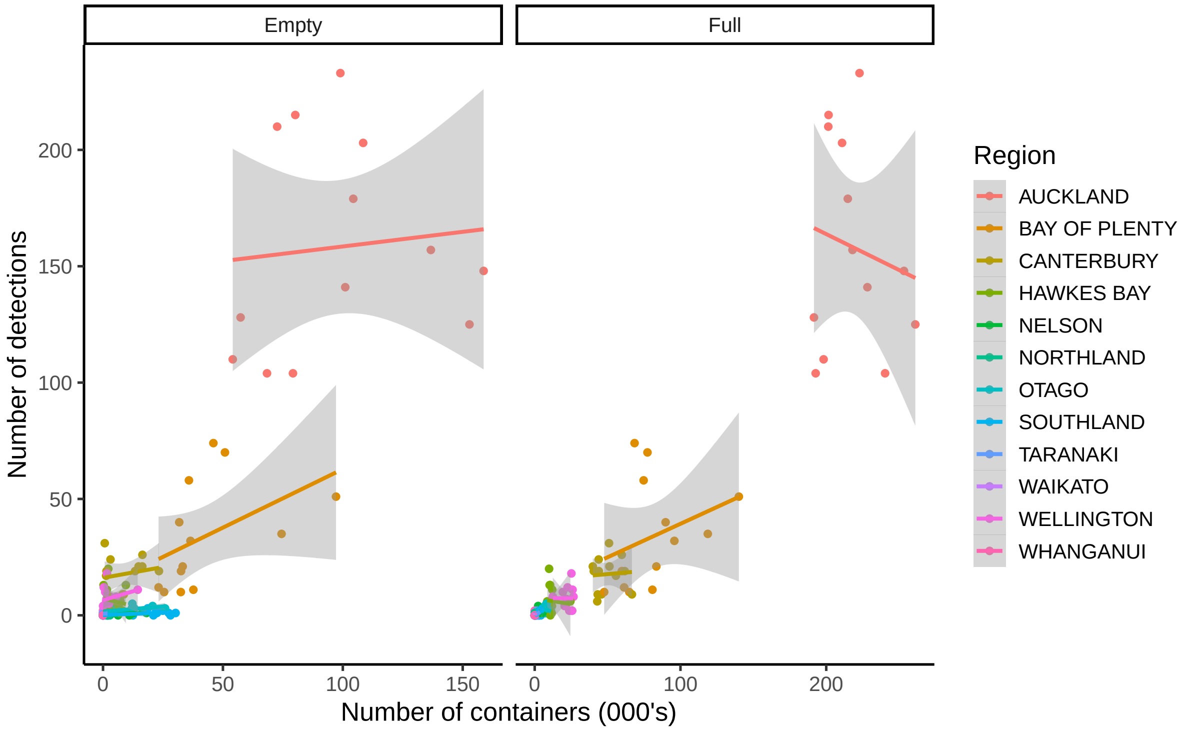

Figure 4.6.: Number of detections by number of containers per year on the seacargo pathway, within each region of arrival. The figure also shows the estimated linear relationship between volume and arrivals within each region per year.

4.2. Modelling Overview

Equation (2.1) requires two inputs, the probability of detecting an ant if present, P_j (which in turn depends upon the individual trap detection probability p_j, Appendix C), and the number of ants arriving into site j, Y_j. It is unlikely that individual trap detection probabilities, p_j, will change drastically (if at all) between seasons, so we assume that we do not need to model this input.

> **Assumption** *Individual trap detection probabilities are fixed, and given. Furthermore, individual trap detection probabilities do not change between seasons.*

The number of ants arriving into site j, Y_j, is assumed to change season-to-season, given the evidence presented in Chapter 3. A model is thus required to **forecast** the number of ants arriving into each port, so that the allocation of traps can be prepared ahead of the trapping season. All evidence in Chapter 3 suggests that the arrival rates will differ (at a minimum) for the various introduction pathways (Figure 4.4) and regions of New Zealand (Figures 4.3 and 4.4). It is likely that the number of ants arriving on the seacargo pathway is related to the volume of shipping containers on that pathway, but that there is unlikely to be any specific differences in this relationship for specific regions, or whether containers are full or empty.

Identifying all ants upon interception at the border is prohibitively expensive. Therefore the data do not reliably indicate whether a specimen is endemic or invasive.

Assumption *Modelling all ant arrivals (both endemic and invasive) is necessary, given we do not necessarily know whether an ant is endemic or not within transitional facilities.*

In modern ecological modelling, it is very often assumed that imperfect detection is present. For example, this may be due to human factors (different observers), movement and arrival patterns of animals, or even limits to detection of survey instruments. If the effect of imperfect detection is unknown, it can be costly and difficult to estimate, for example requiring multiple overlapping field surveys at each site. In this report, we assume that the trap sensitivity is constant between sites. This is because all traps within the programme are deployed with the same methodology and timing. Each ant species may respond differently to the trap for food preference type due to seasonal demand. However all ant species are catered for as both protein and carbohydrate food source are deployed in traps.

This assumption means that relative associations between the number of ants arriving into each site are maintained, resulting in an allocation maintaining the same relative association between sites. In Chapter 5, we perform the optimal allocation for a range of trapping probabilities to demonstrate the impact that this uncertainty has on the allocation of traps to sites.

Assumption *Trap sensitivity is constant across all sites. This assumption means that we can ignore imperfect detection of traps.*

Recommendation *Modelling of the air passenger pathway should take air passenger volume into consideration (following the gathering of a longer time-series of volumes).*

4.2.1. Final Model Descriptions

Appendix E provides the mathematical details of the models fit to the ant arrivals data, the comparisons between the models, and how the final model form was chosen. Separate models were fit to each of the four pathways (seacargo, aircargo, passengers and passenger effects, and other modes of entry). Table 4.1 provides a descriptive overview of the predictors used for each of the pathways to forecast future ant arrival numbers.

Table 4.1.: Predictors used for final ant arrival forecasting models.

Pathway	Predictors
Seacargo	Region of arrival, total container volume
Aircargo	Region of arrival, year/season of arrival
Passengers	Region of arrival, year/season of arrival (region-specific)
Other	Region of arrival, year/season of arrival

Figures 4.7– 4.10 show the median forecast (along with 80% and 95% prediction intervals for the forecast) for ants arriving into New Zealand regions for the year 2017/2018[2]. These figures demonstrate that the small number of arrivals into each region leads to considerable variation in the forecasted number of arrivals. The seacargo forecasts for the larger regions are not entirely satisfactory. It appears that the container volume predictor does not account for enough variation, and that there is still residual variation, which would perhaps be accounted for by a smooth year term. Unfortunately, it was not possible to model this region-specific smooth term easily, and we recommend that investigating the use of a smooth term in this model be performed.

Recommendation *Modelling of the seacargo pathways should investigate using 'smooth' functions of year for forecasting.*

[2]The model for aircargo had the predicttion intervals as (0,0), hence they don't show in the figure.

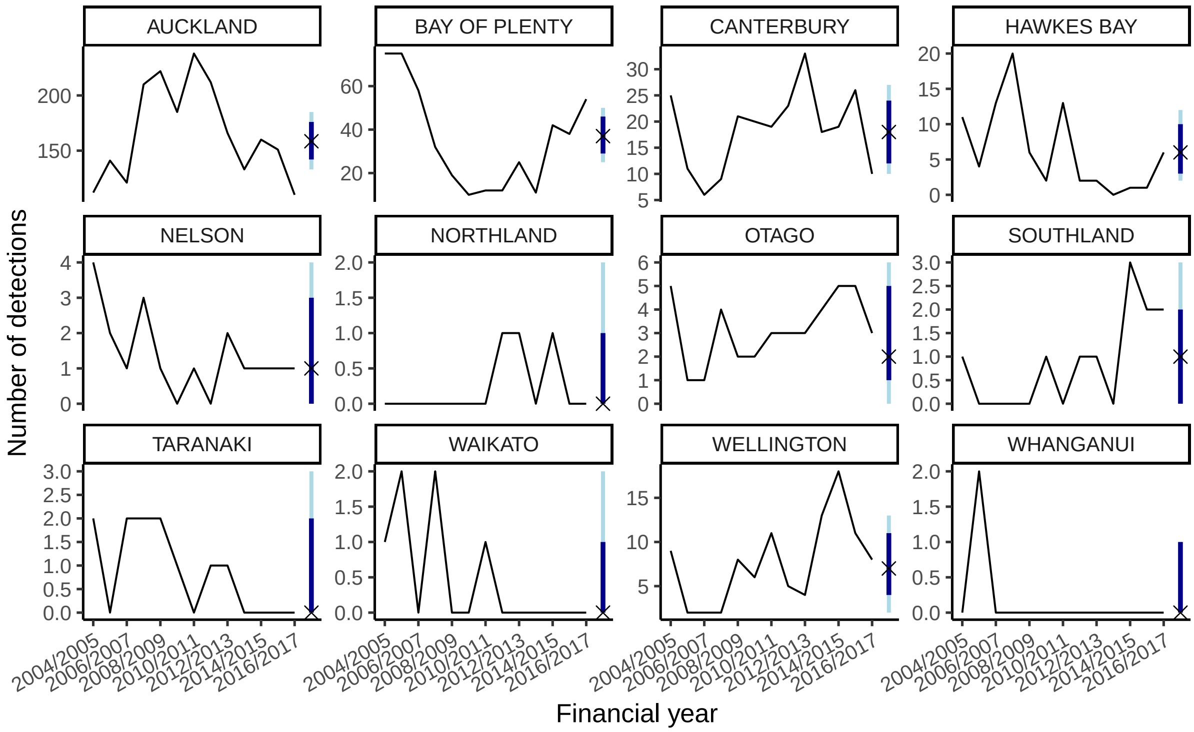

Figure 4.7.: Forecasted number of ant arrivals via the seacargo pathway for 2017/2018 (black cross). The dark blue and light blue lines show 80% and 95% prediction intervals respectively.

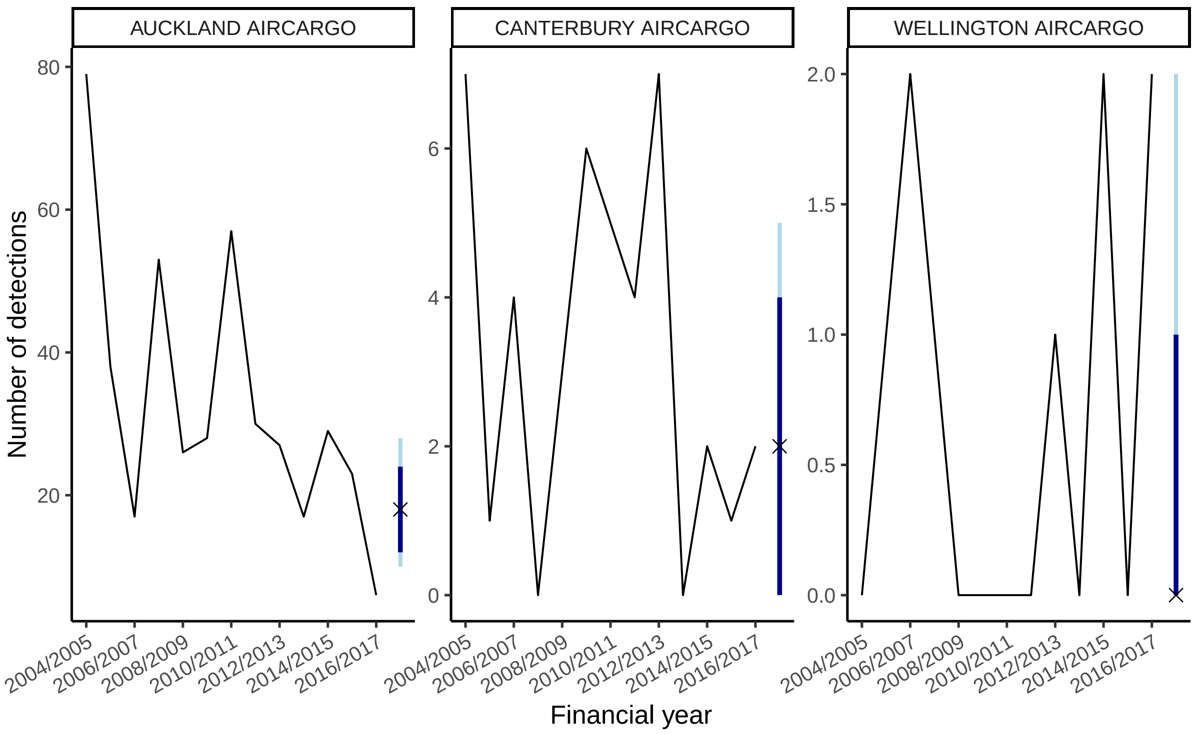

Figure 4.8.: Forecasted number of ant arrivals via the aircargo pathway for 2017/2018 (black cross). The dark blue and light blue lines show 80% and 95% prediction intervals respectively.

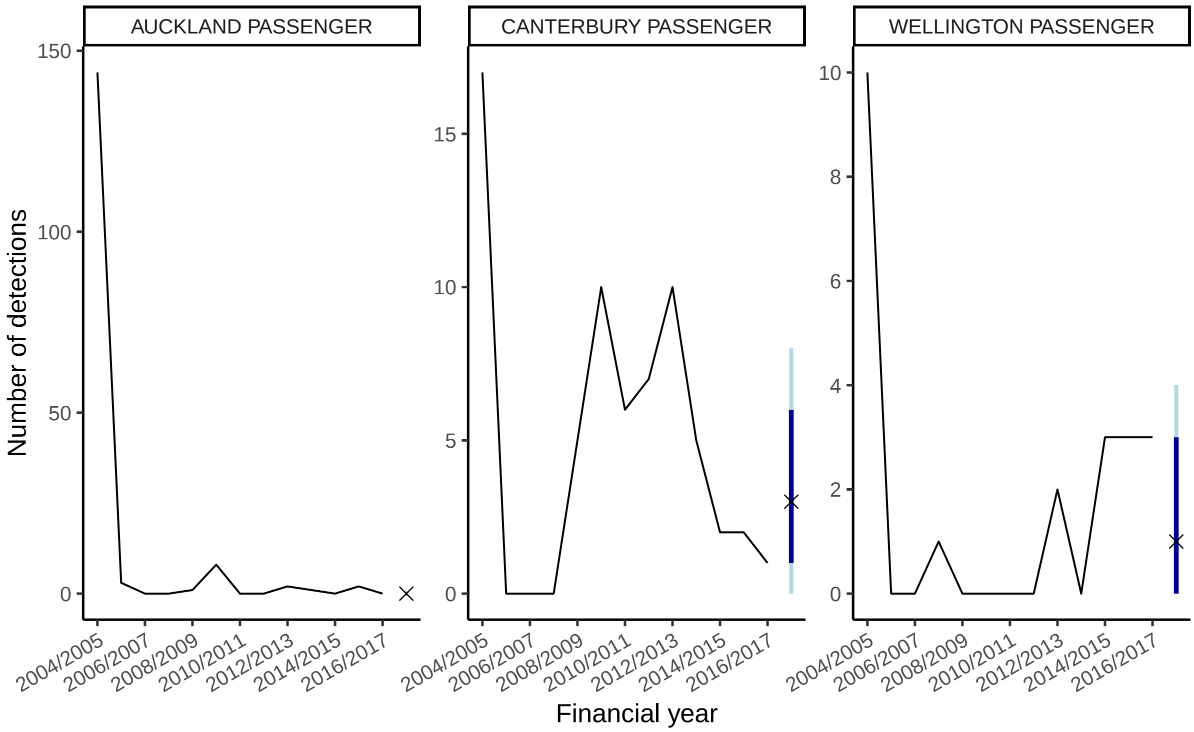

Figure 4.9.: Forecasted number of ant arrivals via the passenger pathway for 2017/2018 (black cross). The dark blue and light blue lines show 80% and 95% prediction intervals respectively.

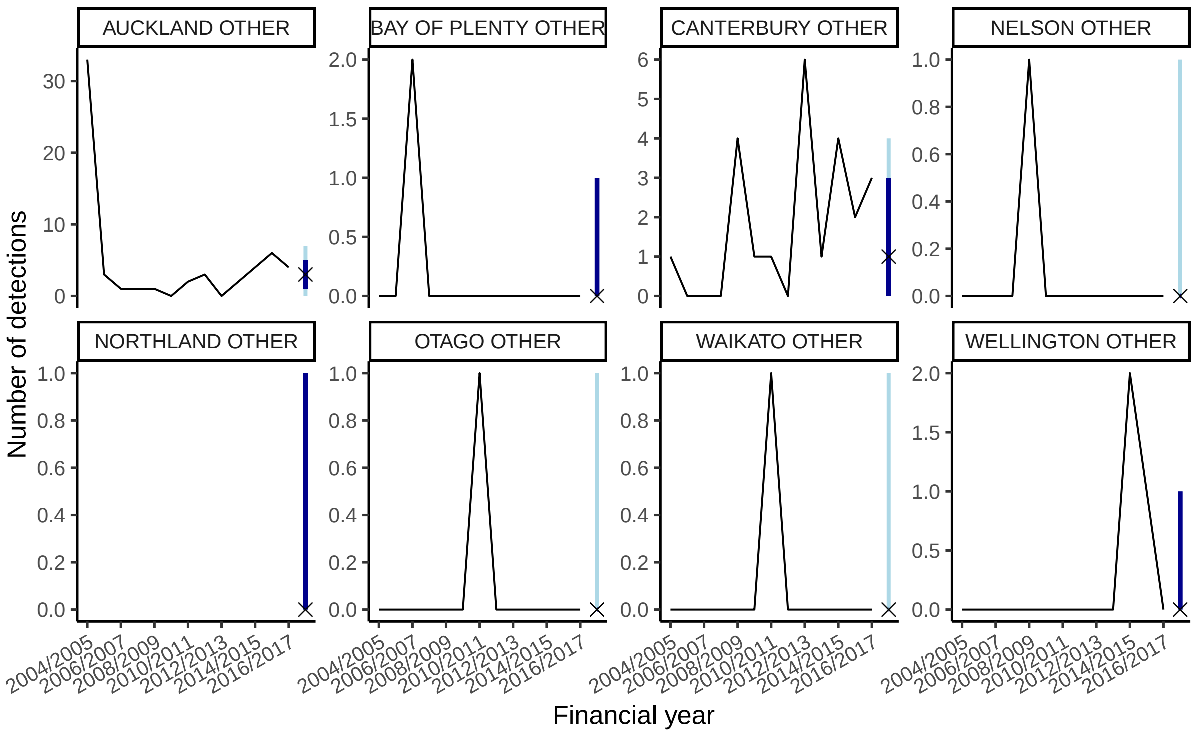

Figure 4.10.: Forecasted number of ant arrivals via the other pathway for 2017/2018 (black cross). The dark blue and light blue lines show 80% and 95% prediction intervals respectively.

5. Optimal Allocation

We used statistical modelling to forecast the number of ants arriving into each port (Section 4.2). The method we have used in this report is Bayesian regression, which means that for each region, we forecast the *distribution* of the number of ants. Uncertainty from the modelling is a key feature of the approach proposed in the report which allows the trade-off of a restricted allocation budget to be understood.

In this chapter, we show the results of the allocation of a fixed number of traps across all pathways that were modelled in Chapter 4. We demonstrate the allocation using the approximate number of traps allocated by NIAS in 2017/2018, which was 45000, and individual trap detection probabilities to demonstrate a variety of effectiveness of traps. As discussed in Section 2.2, we include the trap detection probability 0.005 from Hartley and Lester (2005), along with trap detection probabilities $1e^{-5}, 1e^{-4}, 0.001, 0.01$. These trap detection probabilities vary from very ineffective traps, through to reasonably effective traps. Finally, we also make the restriction that each region/pathway combination must have at least 500 traps allocated as a risk minimisation effort.

Modelling the arrival rates as per this report and then performing the allocation is not useful in a purely decision making context, as the output for each region of New Zealand is a distribution of trap numbers (and site priority), i.e., there is one allocation for each possible outcome from the model. We recommend that as an input into deciding the allocation, that a summarised version of the modelling output be used to allocate trap numbers.

Recommendation *A summarised version of the ant arrival forecasts should be used to allocate trap numbers to regions as in input to a final allocation.*

5.1. Optimal Allocation Results

Table 5.1 shows the optimal allocation based on the median forecast number of ants arriving into each region[1] by each pathway combination, for a range of trap detection probabilities; also shown is the forecasted number of arrivals into each region and pathway combination. The general pattern from Table 5.1 shows that priority is given

[1] As per the previous recommendation, this is the summarised forecast that is used in the allocation.

mostly to sea ports (the SEACARGO pathway), as has occurred historically with NIAS. Comparing Craddock and Mattson (Table 6, 2017, reproduced as Table 5.2 in this report) with the results from this project (Table 5.1, assuming $p = 0.005$) shows that allocations are largely similar, however there are some differences. As an example, the Port of New Plymouth (Taranaki Region) was allocated 4000 traps by NIAS, but only 500 (TARANAKI SEACARGO in Table 5.1) using the framework of this report.

Table 5.1.: Allocations of number of traps to regions and pathways, for multiple individual trap detection probabilities. **Arrivals** shows the forecasted number of arrivals (both invasive and non-invasive ants) into each region and pathway combination. The total number of traps allocated is 45000.

Region	Arrivals	p = 1e-5	p = 1e-4	p = 1e-3	p = 0.005	p = 0.01
AUCKLAND AIRCARGO	18	500	1252	4120	3053	2919
AUCKLAND OTHER	3	500	500	2328	2694	2740
AUCKLAND PASSENGER	0	500	500	500	500	500
AUCKLAND SEACARGO	159	32500	23038	6299	3488	3137
BAY OF PLENTY OTHER	0	500	500	500	500	500
BAY OF PLENTY SEACARGO	37	500	8458	4841	3197	2991
CANTERBURY AIRCARGO	2	500	500	1923	2613	2699
CANTERBURY OTHER	1	500	500	1230	2475	2630
CANTERBURY PASSENGER	3	500	500	2328	2694	2740
CANTERBURY SEACARGO	18	500	1252	4120	3053	2919
HAWKES BAY SEACARGO	6	500	500	3022	2833	2809
NELSON OTHER	0	500	500	500	500	500
NELSON SEACARGO	1	500	500	1230	2475	2630
NORTHLAND OTHER	0	500	500	500	500	500
NORTHLAND SEACARGO	0	500	500	500	500	500
OTAGO OTHER	0	500	500	500	500	500
OTAGO SEACARGO	2	500	500	1923	2613	2699
SOUTHLAND SEACARGO	1	500	500	1230	2475	2630
TARANAKI SEACARGO	0	500	500	500	500	500
WAIKATO OTHER	0	500	500	500	500	500
WAIKATO SEACARGO	0	500	500	500	500	500
WELLINGTON AIRCARGO	0	500	500	500	500	500
WELLINGTON OTHER	0	500	500	500	500	500
WELLINGTON PASSENGER	1	500	500	1230	2475	2630
WELLINGTON SEACARGO	7	500	500	3176	2864	2825
WHANGANUI SEACARGO	0	500	500	500	500	500

Table 5.1 further demonstrates the effect of changing the individual trap detection probability. As individual trap detection probabilities decrease, many more trap numbers are allocated to the regions/pathways that are forecast to have large numbers of

Table 5.2.: Total number of traps deployed by NIAS in 2017. This is a reproduction of Table 6, Craddock and Mattson (2017).

Location	Traps deployed
Auckland	4133
Auckland (Ports)	4791
Auckland International Airport	3298
Christchurch	1434
Christchurch International Airport	2213
Christchurch Port (Lyttelton)	973
Dunedin	527
Napier	1366
Napier (Port)	3578
Nelson (Port)	2140
New Plymouth (Port)	4041
Northport	218
Otago (Port)	1213
Queenstown Airport	500
Tauranga	163
Tauranga (Port)	6233
Taurange (Mt Maunganui)	1769
Timaru (Port)	1851
Wellington	512
Wellington (Port)	2706
Wellington International Airport	649
Whangarei	310

ants arriving. It is not until individual trap detection probabilities reach $1e^{-3}$ that trap allocations are more widely spread. It is also apparent that if individual trap detection probabilities increase beyond $1e^{-3}$, the effect is to even out the trap allocation.

Table 5.3 shows the forecasted number of ants arriving, along with the forecasted number of ants not detected[2] under each individual trap detection probability. It is clear that the dominance of Auckland Port in terms of ant arrivals has a significant effect on the number of ants that go undetected. If individual trap detection probabilities are low, then the vast majority of traps get allocated to Auckland Port, with the result that most ants in all other locations and pathways are undetected. Table 5.3 can be used to manage a risk appetite. For example, if we are willing to accept that up to 7 ants may go undetected, then we can either raise the number of traps allocated (above 45000 as per this example), or make certain that we use traps that have a detection probability greater than $1e^{-3}$.

[2] The `surveillanceAllocation` software outputs the forecasted number of ants going undetected.

As per the previous recommendation, using the summarised data should be a primary input into decision making. As discussed at the beginning of this chapter, the output of our modelling approach is a full distribution of the forecasted number of ants arriving into each region and pathway combination. The optimal allocation can be performed using a random draw from each of these distributions, and repeated a large number of times this gives us a distribution of the number of traps allocated to each region, and subsequently, the priority of each.

Figures A.1a–A.1g and A.2a–A.2g show the distribution of ranks and number of traps respectively, as allocated to each region and pathway combination. It is clear from Figure A.1a that Auckland Port is always the first priority, followed by the Bay of Plenty ports. Canterbury ports and Auckland airport are neck and neck for the third and fourth priorities.

Figures A.2a–A.2g show that the variability in the allocation is quite large. For example, Auckland Port could have between 3000 and 5000 traps allocated, depending on the forecasted number of ants arriving. This suggests that some care be taken in making decisions based on the optimal allocations derived in this report. These allocations should be seen as an input into allocation decisions, rather than a hard and fast rule. As discussed earlier, using the summarised forecasts is a good idea.

Recommendation *Optimal allocation should be used as an input into a decisions about trap allocations, rather than being used as a hard and fast rule.*

Table 5.3.: Number of forecasted ant arrivals and the number of ants not detected for each individual trap detection probability.

Trap Probability	Total Arrivals	Total Undetected
p = 1e-5	259	215
p = 1e-4	259	94
p = 1e-3	259	7
p = 0.005	259	0
p = 0.01	259	0

6. Discussion

The objectives of this project were to provide a basic understanding of the pathways used by exotic ants (Section 3.1); to better understand the patterns of exotic ant arrivals into New Zealand and the key components/variables to inform arrival risk (Chapter 4); to profile risk sites, and in particular transitional facilities (Section 5.1); and to provide a scientific/evidence-based rationale of site selection for the NIAS program (Chapter 5). This report documents the project team's achievements against these objectives.

During the course of the project, it became apparent that the data were of insufficient quality to fully realise the specific application to invasive ants. Ants detected at the border for the most part had sufficient descriptions to enable detailing if they were invasive or not, however the transitional facilities data did not have such detail (Section 3.2.2).

The exotic ants pathway was described via a network diagram (Figure 3.1). This diagram provided a low-level description of the arrival pathways and provided a basis for understanding the patterns of arrivals and possible modelling of the arrival rates. Data were of sufficiently quality to enable transportation modes (sea cargo, air cargo etc) and countries of origin to be interrogated, along with the region of arrival. No data were provided on the efficacy of detection, so we assumed that this was constant (yet unknown) for all pathways. The type of cargo (goods classifications) and whether containers were a full or half load were also provided and investigated in the modelling.

Initial analyses showed that the Auckland region and sea cargo were the two largest pathways for ant arrivals, a result that was entirely expected. Exploratory figures (Chapter 4) showed that there was limited seasonality in the rate of arrivals, so we took the decision to aggregate the number of arrivals by year. Whilst the were changes in year to year arrival rates (Figure 4.1), there was no discernible pattern for an overall increasing or decreasing rate.

There were some interesting patterns within the country of origin data, with decreases in ants arriving from Melanesia and Polynesia in recent years for example, these patterns were not able to be modelled. With the large number of possible pathway, country of origin and arrival region combinations, there was an insufficient amount of data to enable estimation of such specific rates. As discussed in Section 4.2.1 and detailed in Appendix E, models were successfully built including as predictors: the region of arrival, year/season of arrival, and volume of containers (sea) arriving.

Prior to beginning the modelling efforts it was (anecdotally) thought that the volume of *empty* sea containers would be a significant predictor in predicting arrivals risk. Figure 4.6 however, provided some indication that this may not be the case, with similar patterns for both full and empty containers and the number of ants arriving into each region. This was confirmed during modelling, and thus the total volume of containers were used.

For the other pathways, no suitable predictors were provided for the full time period of modelling. The number of passengers entering New Zealand airports (classified by Australian or New Zealand travellers vs rest of the world) were provided for the four latest years, but no information was available for the number of air containers arriving. Given the volume of containers was a key predictor for the number of ants arriving into each region, it could be assumed that this is likely to hold for both air cargo and air passengers. Thus, it is recommended that both these datasets be collected, and in the case of air passengers, extended, and then the modelling performed again.

Related to the discussion above regarding the large number of combinations possible within the country of origin and arrival regions, the large spread of detections within transitional facilities meant that an analysis detailed to the level of profiling such facilities was not possible. However, given that the detections in tranisitional facilities were made mostly on containers that could be traced back to the region of arrival, these data were used in estimating the arrival rates. For the purposes of allocating trap numbers to transitional facilities, it is suggested that the total allocation of traps to a region be further allocated to between sites. Primarily this will be the airports and seaports (if they exist in that region), but risky transitional facilities could also have traps allocated, with these sites prioritised in the same way that the NIAS prioritises them currently.

Recommendation *Trap numbers be allocated to risky transitional facilities following allocation of traps to regions. Risky transitional facilities should be decided as they are currently in the NIAS.*

The NIAS program largely prioritises sea ports, and the north island of New Zealand. Whilst reasonable, there is no documented evidence of the factors that impact the allocation of traps to each site, rather reference to 'risk factors' is discussed as the reasoning behind the allocations. Chapter 2 and Appendix C lay out the mathematical details that provide a scientific justification for the trap allocations within NIAS. Chapter 5 applies these formulations to the data provided for this project, with the results showing that by and large, the NIAS is allocating trap numbers appropriately. Whilst it is envisaged that wholesale changes will not be made as a result of this project, the major finding is that there is a reasonable, scientifically sound justification for trap allocation, and the current NIAS is close to the optimal allocation.

We have provided several recommendations at the beginning of this report. These recommendations will enable further study of the ant arrival pathways into New Zealand, and primarily provide the opportunity to model not only all ants, but invasive ants in particular. More comprehensive data on key predictors in some pathways will provide greater precision in the forecasting of ant arrivals, however in the absence of such data, allocations of traps within the NIAS should continue, comfortable in the knowledge that they are close to optimal.

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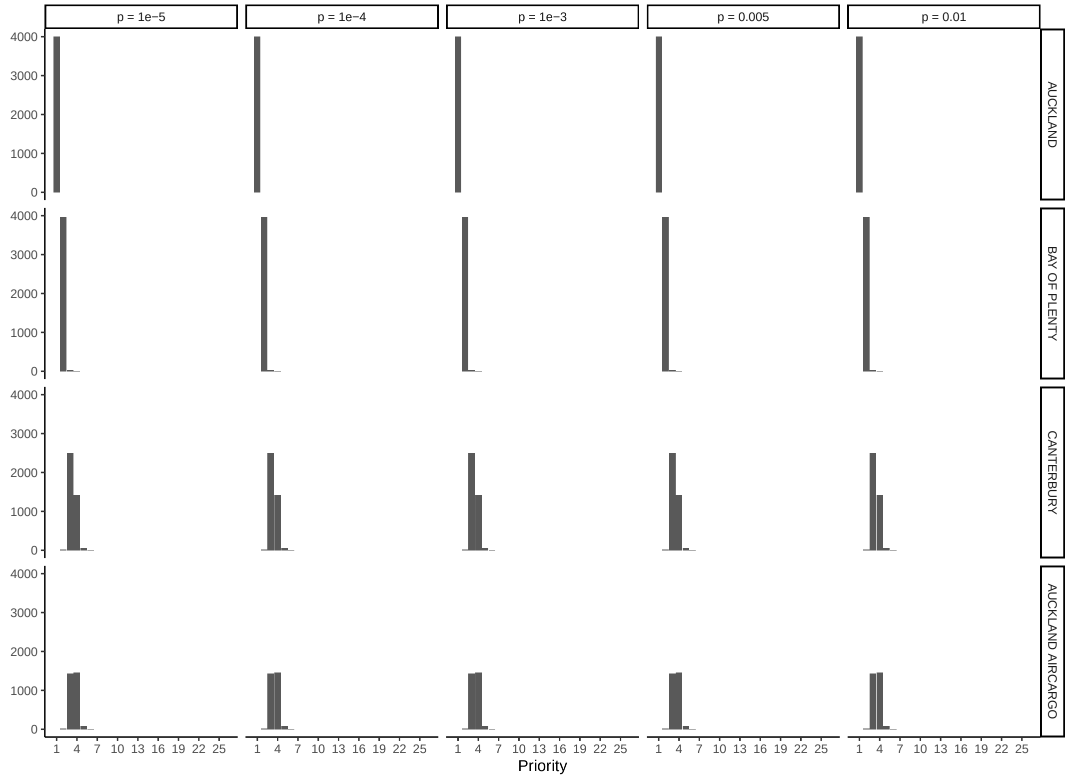
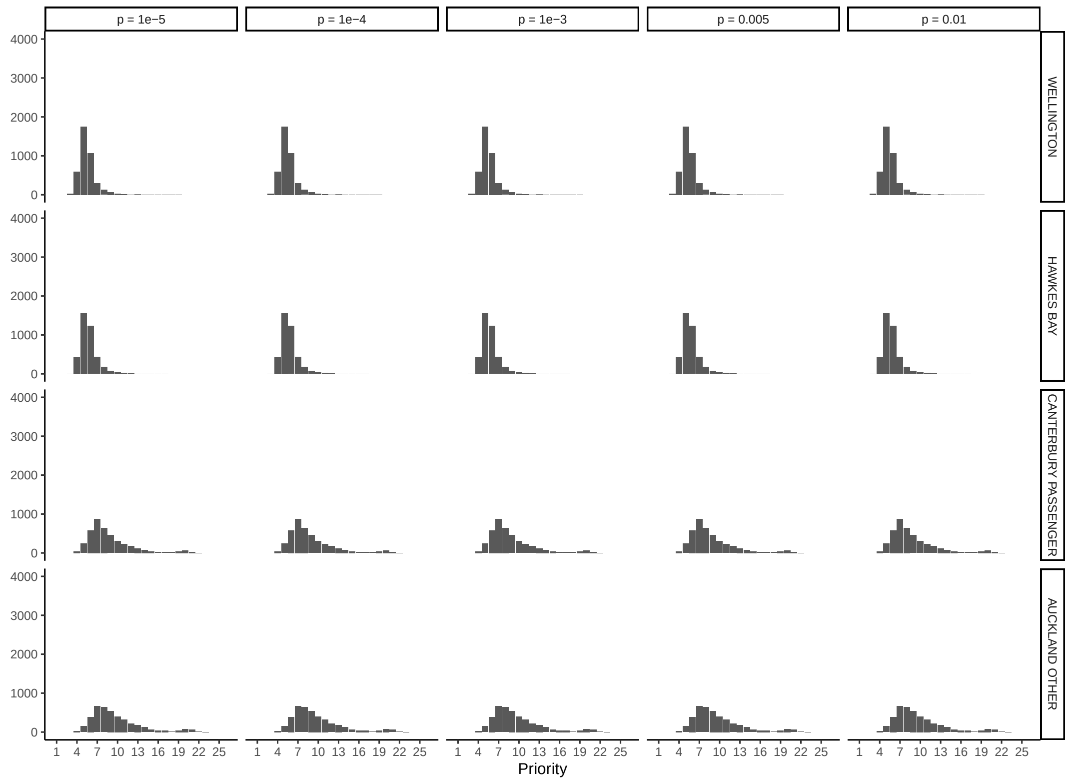
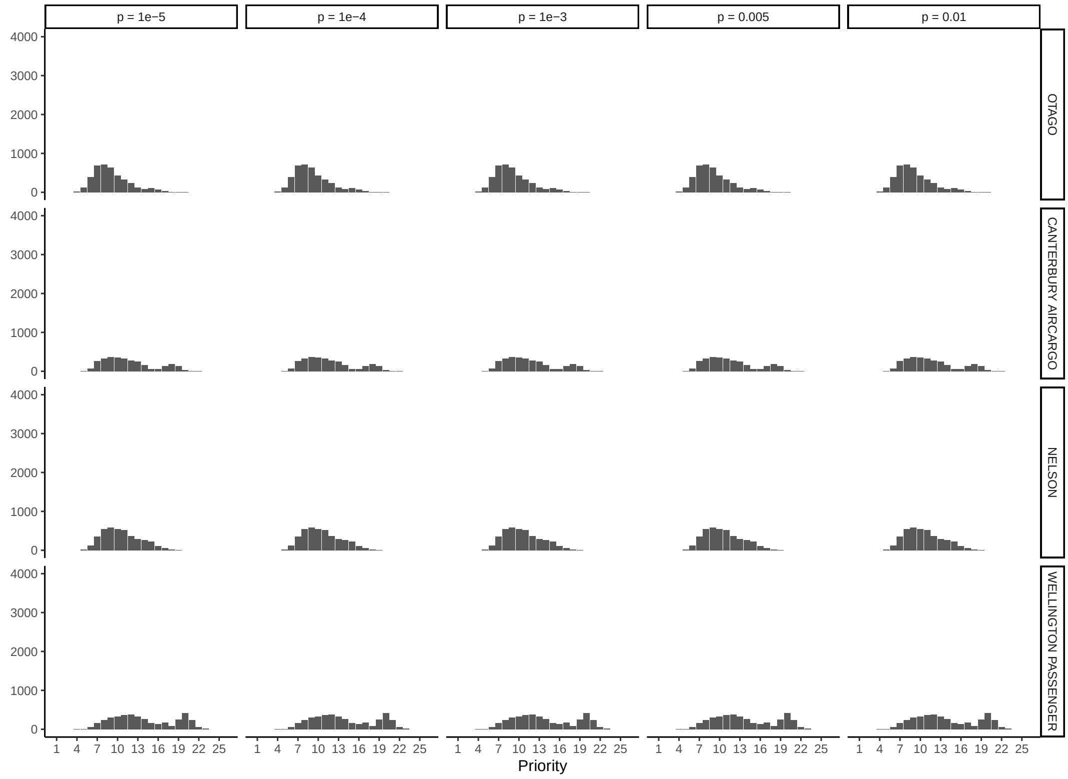
A. Allocation Histograms



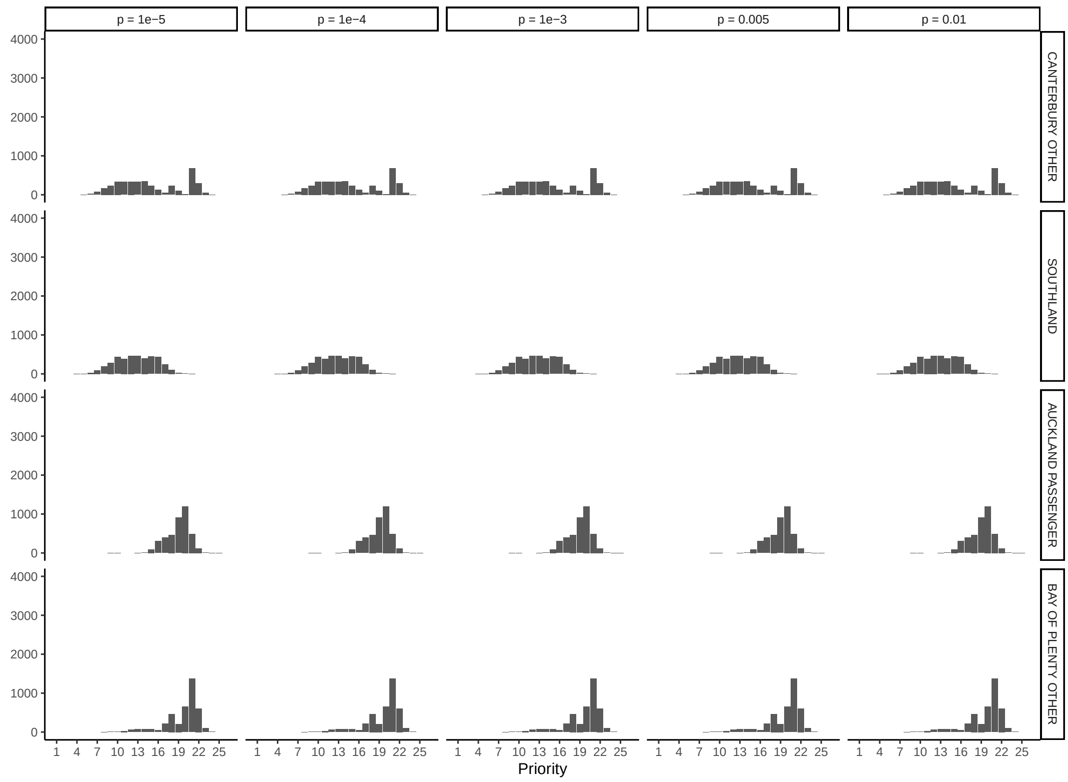
(a) Priority histograms from the full optimal allocation simulation, top four region pathway combinations. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



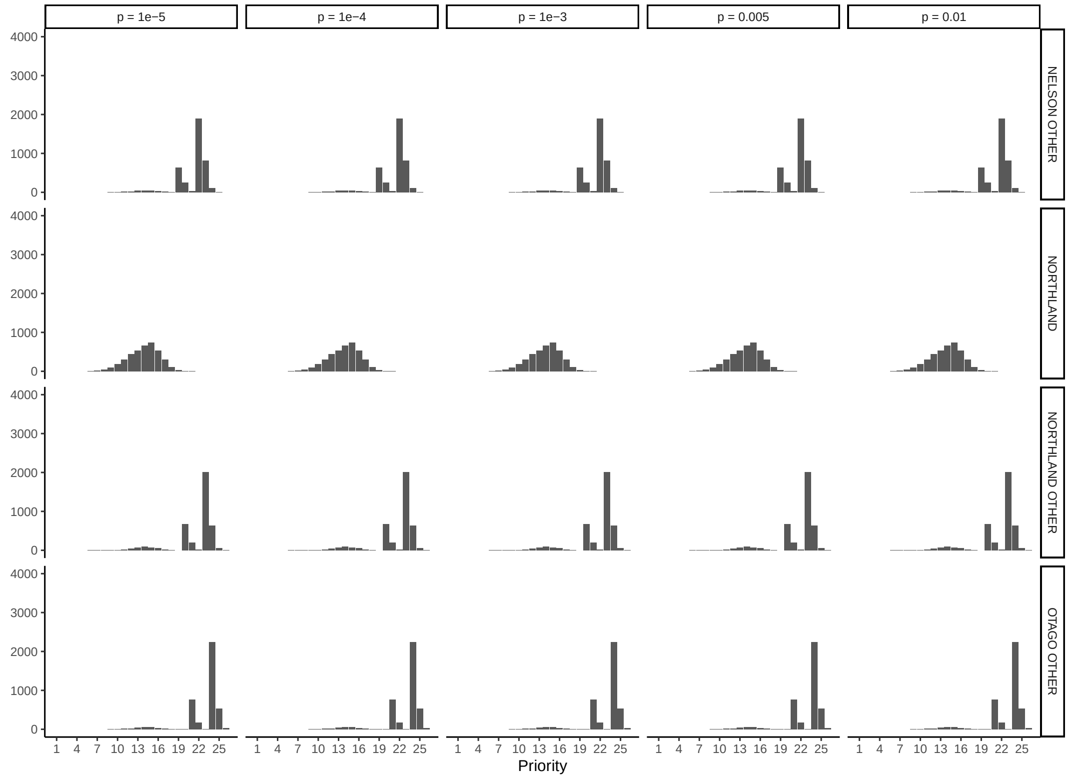
(b) Priority histograms from the full optimal allocation simulation, region-pathway combinations 5–8. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



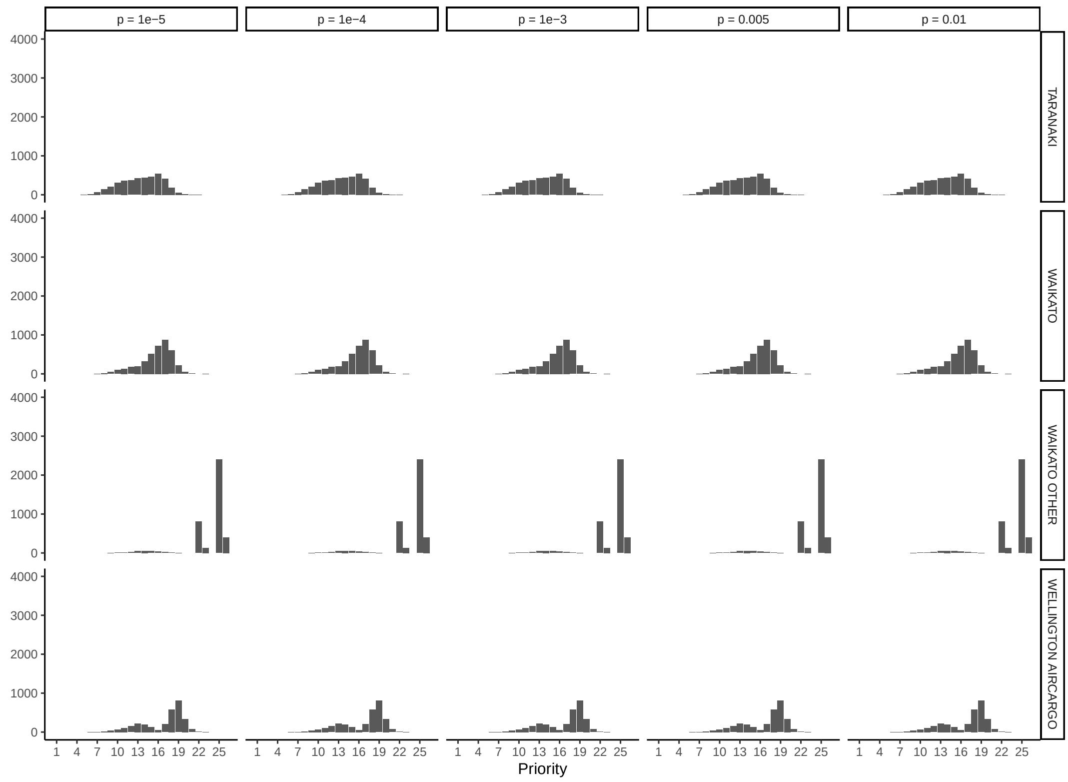
(c) Priority histograms from the full optimal allocation simulation, region-pathway combinations 9–12. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



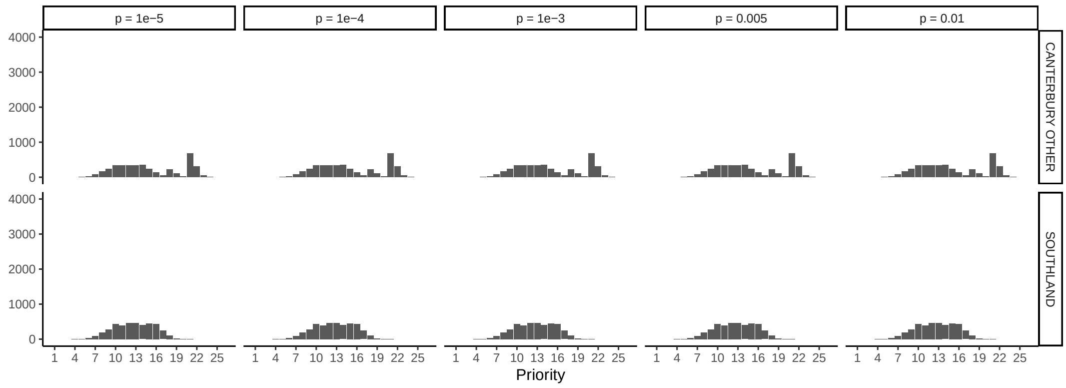
(d) Priority histograms from the full optimal allocation simulation, region-pathway combinations 13–16. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



(e) Priority histograms from the full optimal allocation simulation, region-pathway combinations 17–20. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.

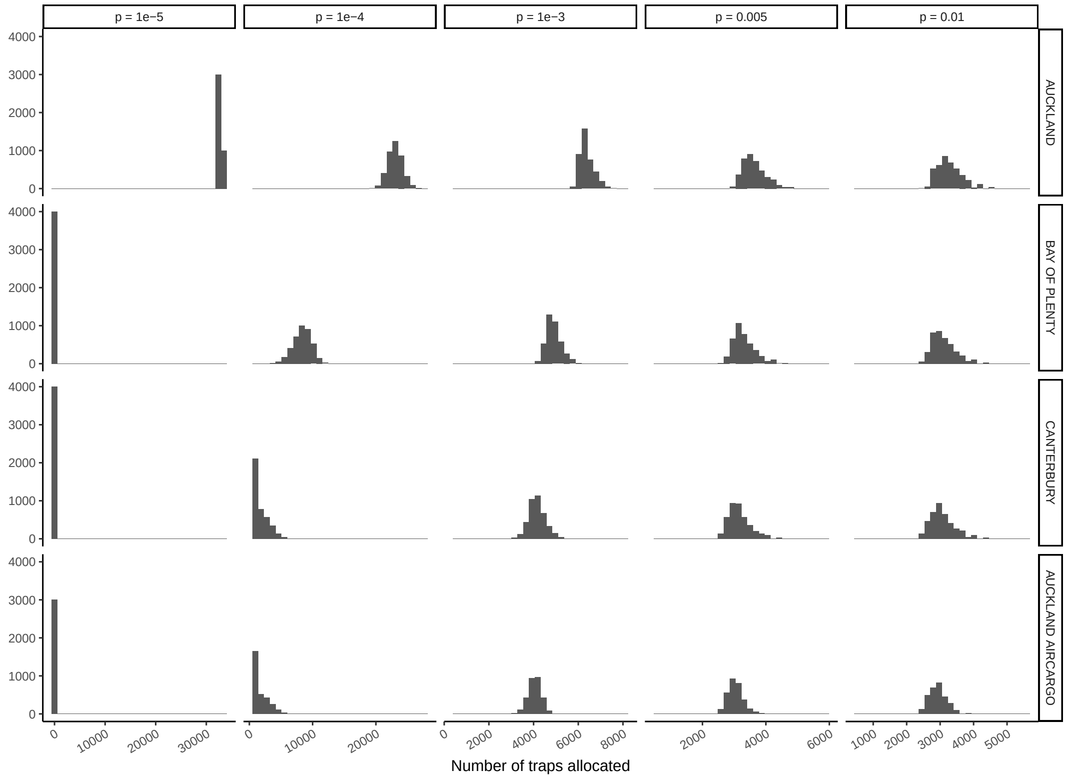


(f) Priority histograms from the full optimal allocation simulation, region-pathway combinations 21–24. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.

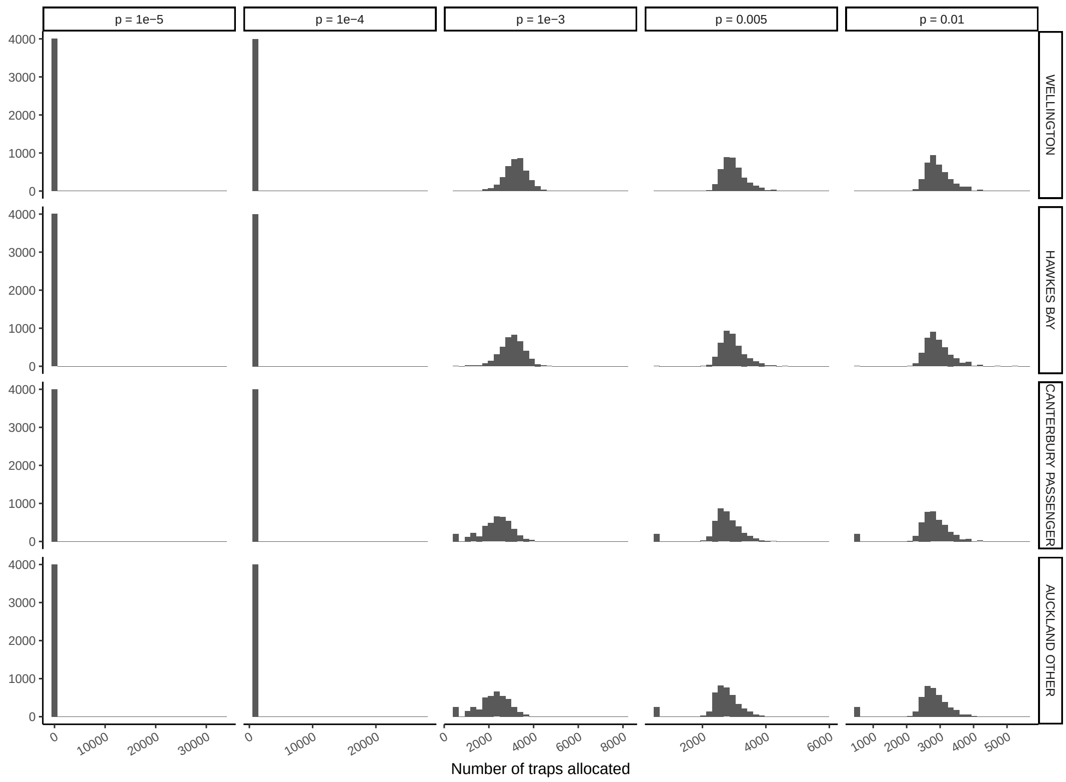


(g) Priority histograms from the full optimal allocation simulation, region-pathway combinations 25–26. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.

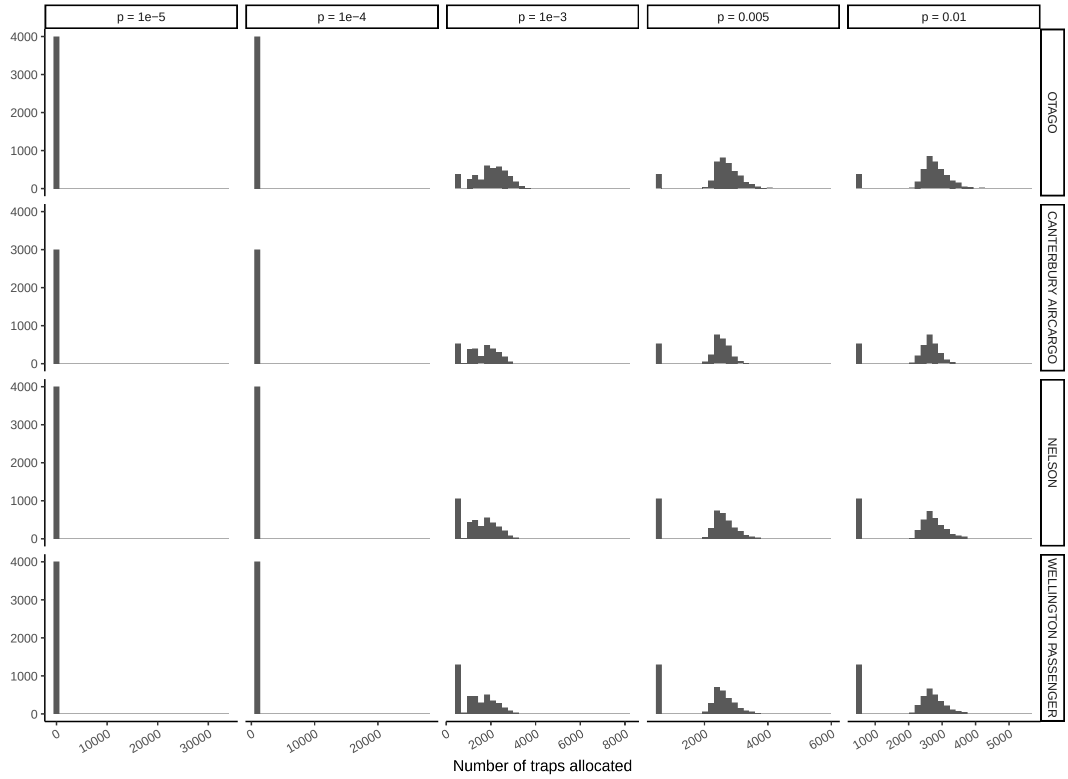
Figure A.1.: Priority histograms from the full optimal allocation simulation. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



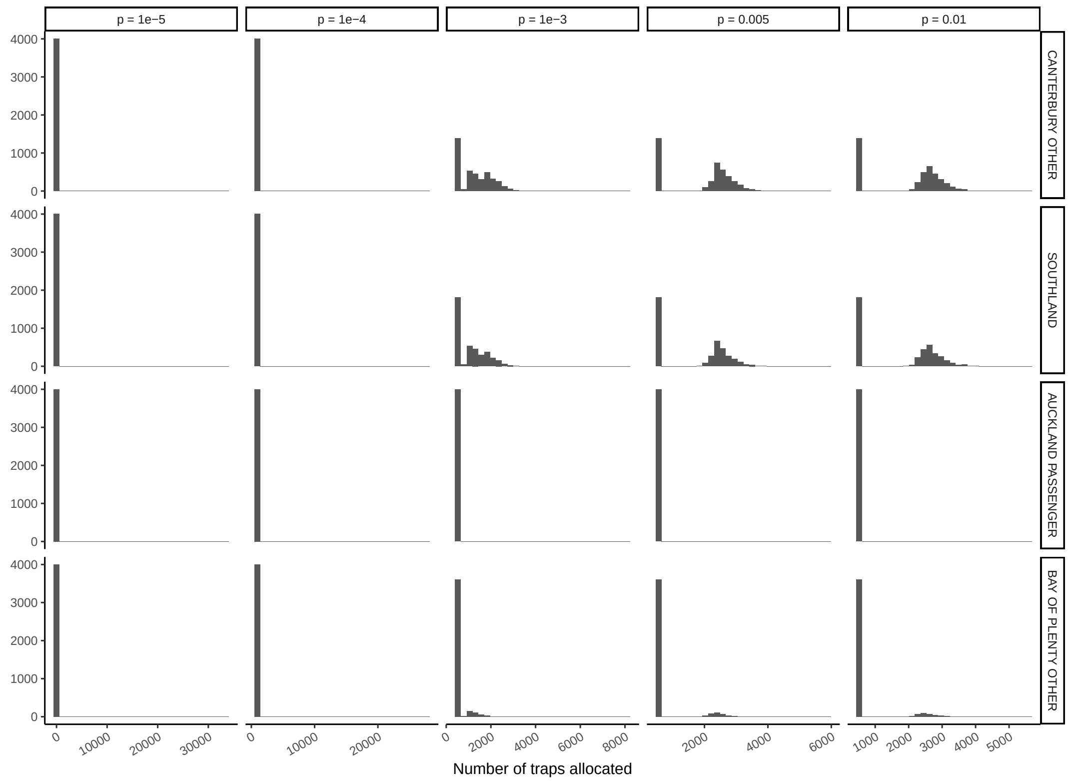
(a) Allocation histograms from the full optimal allocation simulation for the top four region-pathway combinations. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



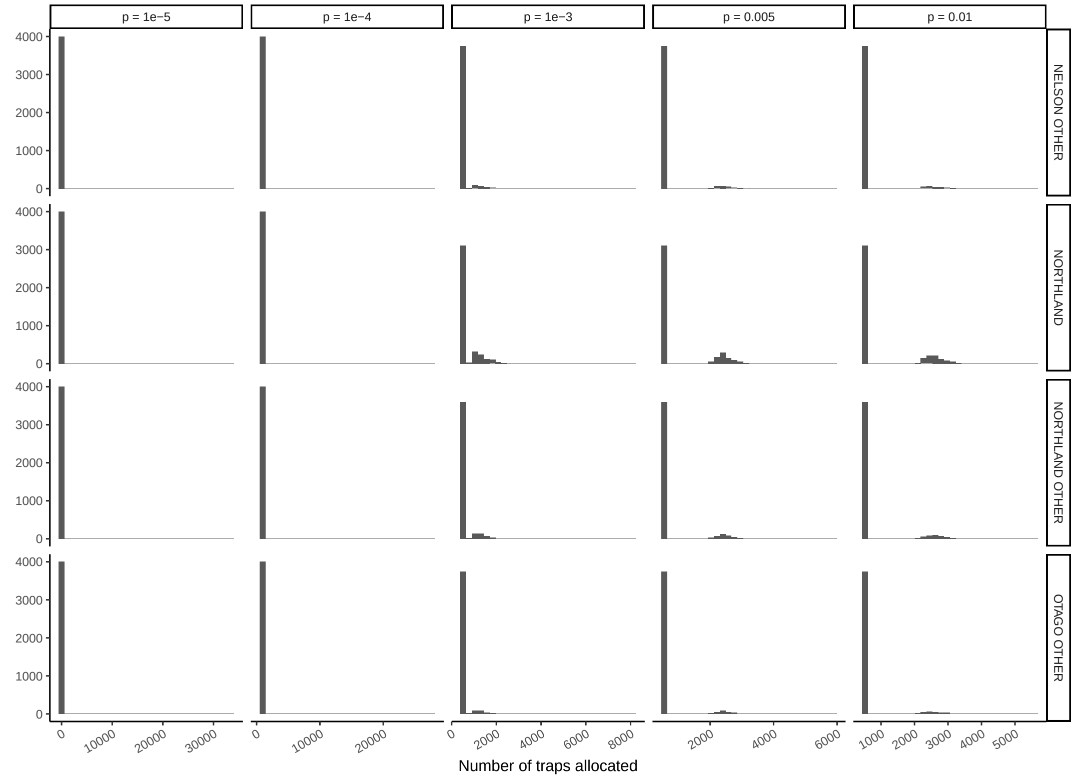
(b) Allocation histograms from the full optimal allocation simulation for region-pathway combinations 5–8. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



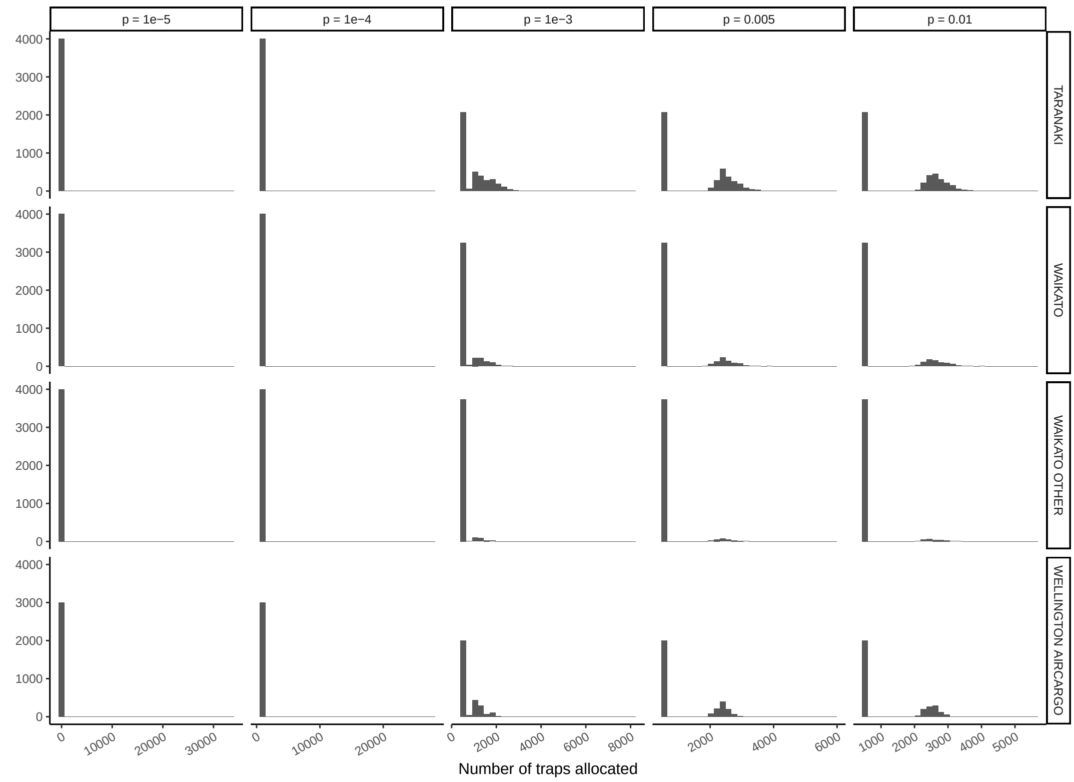
(c) Allocation histograms from the full optimal allocation simulation for region-pathway combinations 9–12. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



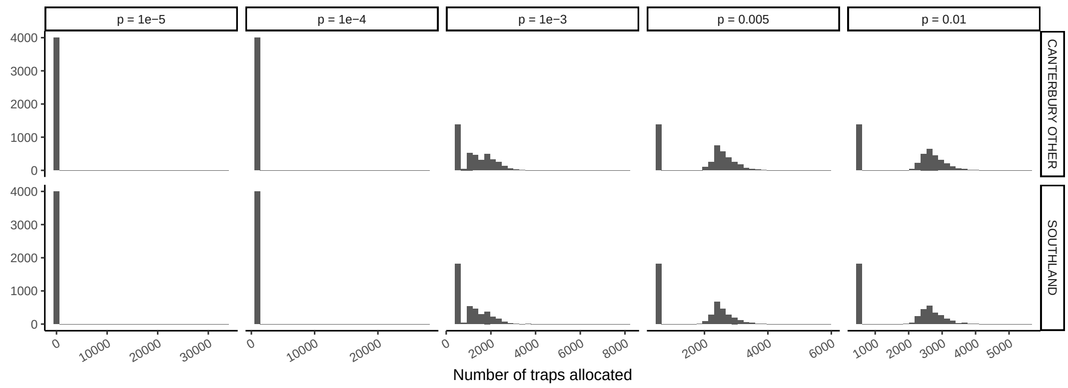
(d) Allocation histograms from the full optimal allocation simulation for region-pathway combinations 13–16. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



(e) Allocation histograms from the full optimal allocation simulation for region-pathway combinations 17–20. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



(f) Allocation histograms from the full optimal allocation simulation for region-pathway combinations 21–24. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.



(g) Allocation histograms from the full optimal allocation simulation for region-pathway combinations 25–26. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.

Figure A.2.: Allocation histograms from the full optimal allocation simulation. Region and pathway combinations are ordered by the median number allocated using individual probability $p = 0.005$.

B. Location Lookup Tables

Due to inconsistencies in the way locations are recorded between the various datasets (e.g. Section 3.2.1), all locations were matched to New Zealand Regions. Table B.1 shows how location was recoded into Regions of New Zealand. Table B.2 is similar, showing the recoding of the transitional facility and volume data in New Zealand Regions.

Table B.1.: Location name cleaning for the border interceptions data. The original name is shown in the left column, with the coded region in the right column. Locations *No Data* and *OS* were treated as missing data.

Original Name	Region
Dunedin	Otago
South Canterbury, SC, Mid Canterbury	Canterbury
SL	Southland
WO	Waikato
No Data, OS	

Table B.2.: Location name cleaning for the transitional facilities data. The arrival port is shown in the left column, with the coded region in the right column.

Arrival Port	Region
Auckland	Auckland
Christchurch	Canterbury
Dunedin	Otago
Hamilton	Waikato
Invercargill	Southland
Lyttelton	Canterbury
Mount Maunganui	Bay of Plenty
Napier	Hawkes Bay
Nelson	Nelson
New Plymouth	Taranaki
Opua	Northland
Port Chalmers	Otago
Queenstown	Otago
Regional- Akaroa	Canterbury
Regional- Ardmore	Auckland
Regional- Ashburton	Canterbury
Regional- Bluff	Southland
Regional- Chatham Island	Chatham Islands
Regional- Hastings	Hawkes Bay
Regional- Kaitaia	Northland
Regional- Levin	Whanganui
Regional- Lower Hutt	Wellington
Regional- Marsden Point	Northland
Regional- Mount Wellington	Auckland
Regional- Oamaru	Otago
Regional- Onehunga	Auckland
Regional- Otago Harbour	Otago
Regional- Picton	Marlborough
Regional- Spring Creek	Marlborough
Regional- Taharoa	Waikato
Regional- Taupo	Waikato
Regional- Waharoa	Waikato
Regional- Wanganui	Whanganui
Regional- Waverley Harbour	Whanganui
Regional- Westport	West Coast
Tauranga	Bay of Plenty
Timaru	Canterbury
Wellington	Wellington
Whangarei	Northland

C. Optimal Allocation Derivation

In this appendix, we present a derivation of the optimal allocation of traps to sites. As per Chapter 2, assume that the number of ants arriving into site j, is a random variable Y_j, $j = 1, \ldots, J$. Suppose that we have traps that have a probability p_j of detecting an ant in its radius of attraction, if the ant is present. Furthermore, we assume that the traps form an independent network, such that if n_j traps are set at site j, the probability that the entire network of traps in site j detects an ant is $P_j = 1 - (1 - p_j)^{n_j}$ (from the Binomial probability distribution). Conversely, the probability that the ant is not detected by any of the traps is $1 - P_j$.

From Equation (2.1), we wish to minimise the number of ants that are not detected, $M = \sum_j Y_j \cdot (1 - P_j)$, subject to the total number of traps available, N, and with the further restriction that in each site, we may wish to have a minimum number of traps set, $n_j \geq c_j$.

Hauser and McCarthy (2009) derive a closed form solution for this problem when there is no minimum number of traps, i.e. $c_j = 0$. Here we will lay out the solution and the algorithm to calculate the optimal allocation as an extension to Hauser and McCarthy (2009) when $c_j \geq 0$.

To begin, we first make the approximation that $e^{-p_j n_j} \approx (1 - p_j)^{n_j}$. This is a standard approximation when $p_j < 1$ and $p_j n_j >> 1$ and can be shown via a Taylor series expansion.

The problem statement becomes:

$$\text{Minimise } M = \sum_{j=1}^{J} Y_j e^{-p_j n_j}$$

$$\text{s.t. } n_j \geq c_j \text{ and} \tag{C.1}$$

$$N = \sum_{j=1}^{J} n_j \tag{C.2}$$

We can solve this optimisation problem using Lagrangian multipliers and introducing the Karush-Kuhn-Tucker conditions: for $\mu_j, j = 1, \ldots, J$ and λ multipliers, we require:

$$-\frac{\partial M}{\partial n_j} = -\mu_j - \lambda \tag{C.3}$$

$$\mu_j \geq 0 \tag{C.4}$$

$$-\mu_j(c_j - n_j) = 0 \tag{C.5}$$

Now suppose that there exists a set K, such that for $j \in K$, $\mu_j = 0$ and $n_j > c_j$. Further assume that the complementary set K' exists, such that for $j \in K'$, $\mu_j > 0$ and $n_j = c_j$. Let $|K|$ be the cardinality of the set K. Then

$$\begin{aligned} Y_j p_j e^{-p_j n_j} &= -\lambda \text{ (from C.3)} \\ \Rightarrow n_j &= -\log\left(\frac{-\lambda}{Y_j p_j}\right)/p_j \end{aligned} \tag{C.6}$$

From C.2 we have

$$\begin{aligned} N &= \sum_{j\in K} n_j + \sum_{j\in K'} c_j \\ N - \sum_{j\in K'} c_j &= -\log\left(\frac{-\lambda}{Y_j p_j}\right)/p_j \\ \Rightarrow N' &= -\log(-\lambda)\cdot\frac{|K|}{\bar{p}} + |K|\cdot\bar{n} \end{aligned} \tag{C.7}$$

$$\begin{aligned} \text{where } N' &= N - \sum_{j\in K'} c_j \\ \bar{p} &= |K|/\sum_{j\in K} p_j^{-1} \text{ and} \\ \bar{n} &= \frac{1}{|K|}\sum_{j\in K}\frac{\log(Y_j p_j)}{p_j} \end{aligned}$$

Rearranging C.7 gives $-\lambda = \exp\left[\bar{p}(\bar{n} - N'/|K|)\right]$, and substituting into C.6 gives

$$n_j = \frac{\log(Y_j p_j)}{p_j} + \frac{\bar{p}}{p_j}\cdot\left(\frac{N'}{|K|} - \bar{n}\right). \tag{C.8}$$

For the alternative set K', we have $n_j = c_j$, thus from C.3 we have

$$\begin{aligned} Y_j p_j e^{-p_j c_j} &= -\mu_j + \exp\left[\bar{p}(\bar{n} - N'/|K|)\right] \\ \Rightarrow \mu_j &= \exp\left[\bar{p}(\bar{n} - N'/|K|)\right] - Y_j p_j e^{-p_j c_j}. \end{aligned} \tag{C.9}$$

Now, for $j \in K$, we require $n_j > c_j$, i.e.

$$\log(Y_j p_j) + \bar{p} \cdot \left(\frac{N'}{|K|} - \bar{n} \right) > c_j p_j$$
$$\Rightarrow Y_j p_j > \exp\left\{ c_j p_j - \bar{p} \cdot \left(\frac{N'}{|K|} - \bar{n} \right) \right\} \tag{C.10}$$

and for $j \in K'$, we require $\mu_j > 0$, which we get from rearranging C.9. Putting these two requirements together, and setting $K = 1, \ldots, k^*$ and $K' = k^* + 1, \ldots, J$, we must have

$$Y_{k^*} p_{k^*} > \exp\left\{ c_{k^*} p_{k^*} - \bar{p} \cdot \left(\frac{N'}{|K|} - \bar{n} \right) \right\} > Y_{k^*+1} p_{k^*+1}$$

This means that we can prioritise sites in order of $Y_j p_j$. To find the optimal allocation, that is the k^* where for $j \leq k^*$ we set n_j as in C.8, we have the following algorithm:

1. Calculate $Y_j p_j$ and put in descending order.

2. For each $k = 1, \ldots, J$, calculate:

$$\bar{p}_k = \frac{k}{\sum_{j=1}^{J} p_j^{-1}}$$
$$\bar{n}_k = \frac{1}{k} \sum_{j=1}^{J} \frac{\log(Y_j p_j)}{p_j}$$
$$t_k = \exp\left\{ c_k p_k - \bar{p}_k \cdot \left(\frac{N'}{|K|} - \bar{n}_k \right) \right\}$$

3. Calculate the 'cost' of choosing only the first k sites, M_k. For $k = 1, \ldots, j-1$, if $Y_k p_k > t_k > Y_{k+1} p_{k+1}$, set

$$M_k = t_k \cdot \frac{k}{\bar{p}_k} + \sum_{i=k+1}^{J} Y_j$$

otherwise, there's no feasible solution, so set M_k to NA. For $k = J$, if $Y_J p_J > t_J$, set $M_J = t_J \cdot \frac{J}{\bar{p}_J}$, else M_j is set to NA.

4. Choose the optimal k^* as that k which minimises M_k. Calculate $\bar{p}_{k^*}$ and $\bar{n}_{k^*}$ as previously, and then for $j = 1, \ldots, k^*$, set the optimal allocation as

$$n_j^* = \frac{\log(Y_j p_j)}{p_j} + \frac{\bar{p}_{k^*}}{p_j} \left(\frac{N'}{k^*} - \bar{n}_{k^*} \right)$$

for $j = k^* + 1, \ldots, J$, set $n_j^* = c_j$.

D. surveillanceAllocation

The surveillanceAllocation R package is available for installation via CEBRA's Bitbucket server: surveillanceAllocation. The easiest way to install surveillanceAllocation is to use the R package devtools, which allows installation of R packages from version control repositories. Code chunk D.1 demonstrates how to install surveillanceAllocation.

R Chunk D.1.

```
## Install devtools first, if not installed
## install.packages("devtools")
devtools::install_bitbucket("cebra/surveillanceAllocation")
```

surveillanceAllocation requires a csv/spreadsheet of trapping sites, organised by row. There are two required columns: 1) a column containing the expected number of arrivals (or the index of establishment, Section 2.1) and 2) a column containing the individual trap detection probabilities (which can be site-specific if required). An optional third column containing minimum trap numbers can also be provided. Figure D.1 shows an example dataset.

	A	B	C	D
1	Site	Arrivals	Probability	MinTraps
2	1	83	0.0056454	7
3	2	58	0.0030356	1
4	3	7	0.0369198	8
5	4	61	0.0034105	1
6	5	85	0.0017149	8
7	6	18	0.007742	5
8	7	61	0.0016041	3
9	8	56	0.0014756	9
10	9	54	0.0818638	3
11	10	7	0.0326754	7

Figure D.1.: Example dataset for entry into the surveillanceAllocation R package.

After reading the data into the R session, there is a single command that will perform the allocation, optimal_allocation. Required input is the data, character strings for the names of the arrival, cost and (if required) minimum trap columns, and the total number of traps available for allocation. Code Chunk D.2 demonstrates reading in the data and running the optimal allocation for the example data in Figure D.1, with a total allowance of 500 traps. In this example, seven sites are given an allocation above their minimum trap requirements, with sites 6, 7 and 8 allocated their minimum trap requirements (lowest priority).

R Chunk D.2.

```
## Attach the library
library(surveillanceAllocation)
## Read in the data (assumes it is in the current working directory)
data <- read.csv("arrivals_spreadsheet.csv", header = TRUE)
## Run the allocation
allocate <- surveillanceAllocation::optimal_allocation(
  df = data,
  cost_var = "Arrivals",
  prob_var = "Probability",
  N = 500,
  include_min = TRUE,
  min_var = "MinTraps"
)
## Show the result
dplyr::select(allocate, Site, `Arrivals` = cost, `Min Traps` = mins,
  `Optimal Allocation` = opt_n, `Allocated Sites` = opt_k_all)
```

```
##    Site Arrivals Min Traps Optimal Allocation Allocated Sites
## 1     9       54         3           42.00463              NA
## 2     1       83         7          211.55274              NA
## 3     3        7         8           16.23181              NA
## 4    10        7         7           14.60269              NA
## 5     4       61         1          112.10967              NA
## 6     2       58         1           70.97774              NA
## 7     5       85         8           15.52073               7
## 8     6       18         5            5.00000              NA
## 9     7       61         3            3.00000              NA
## 10    8       56         9            9.00000              NA
```

E. Arrival Rate Models

During exploratory data analysis and preliminary modelling, we found that allowing for group-level effects at the country of origin by region of arrival level produced estimates with unsatisfactory levels of variability. Thus, we focus here on models that aggregate to the New Zealand Region of arrival level. For the model formulations within each pathway (Appendices E.2–sec:other-models), we let Y_{jt} by the number of detections made at region j, financial year t, and assume this has a Poisson distribution with rate λ_{jt}: $Y_{jt} \sim \text{Poisson}(\lambda_{jt})$. All models were fit using RStan version 2.18.2 (Stan Development Team, 2019) and R version 3.5.3 (R Core Team, 2019).

E.1. Model Choice

For each pathway, we used cross-validation to choose the best performing model. Our prediction target is a forecast of the number of ants arriving into each region, thus our cross-validation strategy is to build the model using T years of data, and predict to the $T + 1$ year data. We do this sequentially until all data is used in the training data, and average the error from the forecasts. The model with the minimum average forecast error is chosen as the best model.

E.2. Models for Seacargo Arrivals

Let $V_{jt} = F_{jt} + E_{jt}$ be the total volume of containers arriving at region j during year t, where F_{jt} and E_{jt} are the volume of full and empty containers respectively. Further, let g denote the region of origin, and similar covariates can be formed. F_{jtg} for example, is the volume of full containers arriving at region i in financial year t from region of origin g. The models tested for the number of ant arrivals in seacargo are as follows:

1. The rate of detections depends only upon the *total* volume of containers arriving at each region.

$$\log \lambda_{jt} = \alpha_j + \beta V_{jt} \tag{M1}$$

2. The rate of detections depends upon the total volume of full and empty containers *separately*, arriving at each region.

$$\log \lambda_{jt} = \alpha_j + \beta F_{jt} + \gamma E_{jt} \tag{M2}$$

3. The rate of detections depends upon the volume of containers *from each region of origin* arriving into each NZ region.

$$\log \lambda_{jt} = \alpha_j + \sum_{g=1}^{G} \beta_g V_{jtg} \tag{M3}$$

4. The rate of detections depends upon the volume of full and empty containers *separately* from each region of origin arriving into each NZ region.

$$\log \lambda_{jt} = \alpha_j + \sum_{g=1}^{G} (\beta_g F_{jtg} + \gamma_g E_{jtg}) \tag{M4}$$

5. The rate of detections depends upon the total volume of containers arriving at each region, with *separate effects* for each region.

$$\log \lambda_{jt} = \alpha_j + (\beta + \beta_j) V_{jt} \tag{M5}$$

6. The rate of detections depends upon the total volume of full and empty containers separately, arriving at each region, with *separate effects* for each region.

$$\log \lambda_{jt} = \alpha_j + (\beta + \beta_j) F_{jt} + (\gamma + \gamma_j) E_{jt} \tag{M6}$$

Table E.1 shows the average forecast errors for each model in the seacargo pathway. Model M1 has the minimum forecast error, and is used for optimal allocation in Chapter 5.

Table E.1.: Average forecast error for models in the seacargo pathway.

Model	AFE
M1	30
M2	37
M5	38
M3	50
M6	66
M4	NA

E.3. Models for Aircargo Arrivals

The number of incoming air containers per year was not available for this project, and with no other possible covariates, the range of models tested included the arrival region and year of entry:

1. The rate of detections depends only upon the region of arrival.

$$\log \lambda_{jt} = \alpha_j \tag{M1}$$

2. The rate of detections depends upon the region of arrival and year of arrival.

$$\log \lambda_{jt} = \alpha_j + \beta A_{jt} \tag{M2}$$

3. The rate of detections depends upon the region of arrival and year of arrival with *separate year effects* for each region.

$$\log \lambda_{jt} = \alpha_j + \beta_j A_{jt} \tag{M3}$$

Table E.2 shows the average forecast errors for each model in the aircargo pathway. Model M2, has the minimum forecast error, and is used for optimal allocation in Chapter 5.

Table E.2.: Minimum average forecast error for models in the aircargo pathway.

Model	AFE
M2	6.6
M3	6.9
M1	11.3

E.4. Models for Passengers

Preliminary investigations showed that the number of years of available passenger volume data were not sufficient for forecasting ant arrivals on the passenger and passenger effects pathway. The range of models tested included the arrival region and year of entry:

1. The rate of detections depends only upon the region of arrival.

$$\log \lambda_{jt} = \alpha_j \tag{M1}$$

2. The rate of detections depends upon the region of arrival and year of arrival.

$$\log \lambda_{jt} = \alpha_j + \beta A_{jt} \tag{M2}$$

3. The rate of detections depends upon the region of arrival and year of arrival with *separate year effects* for each region.

$$\log \lambda_{jt} = \alpha_j + \beta_j A_{jt} \tag{M3}$$

Table E.3 shows the average forecast errors for each model in the passenger and passenger effects pathway. Model M3, has the minimum forecast error, and is used for optimal allocation in Chapter 5.

Table E.3.: Minimum average forecast error for models in the passenger and passenger effects pathway.

Model	AFE
M3	2.9
M2	3.4
M1	10.3

E.5. Models for Other Modes of Entry

Other modes of entry include mail and post entry quarantine sites. The range of models tested included the arrival region and year of entry:

1. The rate of detections depends only upon the region of arrival.

$$\log \lambda_{jt} = \alpha_j \tag{M1}$$

2. The rate of detections depends upon the region of arrival and year of arrival.

$$\log \lambda_{jt} = \alpha_j + \beta A_{jt} \tag{M2}$$

3. The rate of detections depends upon the region of arrival and year of arrival with *separate year effects* for each region.

$$\log \lambda_{jt} = \alpha_j + \beta_j A_{jt} \tag{M3}$$

Table E.4 shows the average forecast errors for each model in the 'other' pathway. Model M2, has the minimum forecast error, and is used for optimal allocation in Chapter 5.

Table E.4.: Minimum average forecast error for models in the other modes of entry pathway.

Model	AFE
M2	1.5
M1	1.7
M3	1.7