Border biosecurity interceptions for air passengers – assessing intervention methods and analytic tools

Nicholas. P Moran[*,1] (0000-0002-7331-0400),

Anca M. Hanea[1] (0000-0003-3870-5949),

Andrew P. Robinson[1] (0000-0002-0509-6043)

[1]Centre of Excellence for Biosecurity Risk Analysis (CEBRA), School of BioSciences, The University of Melbourne, Parkville, Victoria 3010, Australia

*Corresponding author: Nicholas P. Moran (nicholas.moran@unimelb.edu.au)

Short running title: Air passenger biosecurity interventions

Abstract

At-border interventions are a critical step along the biosecurity continuum, to measure and control the risks associated with the cross-border movement of people and goods. Air passengers are a high-volume pathway for a range of biosecurity risk materials, against which various interventions may be used (e.g., manual searches, detector dogs, x-rays, etc.). Using a large interception database for air passengers entering the southern Australian state of Tasmania, this study applies common statistical modelling tools to assess the efficacy of interventions (namely, dog detectors, and bag searches), and to identify pathway risk factors (e.g., flight origin/route). Tasmania is an island state, and its environment and industries have benefited from a low level of invasive pests due to their geographic isolation. Therefore, relatively strict at-border interventions are used to prevent the entry of new pests, including some serious invasive pests already present on mainland Australia (e.g., Queensland and Mediterranean fruit fly, *Bactrocera tryoni*, *Ceratitis capitata*). This analysis considered the effects of interventions on both voluntary declarations by passengers and also detections of undeclared risk material on passengers. The analysis also focused on biosecurity risk items generally (e.g., fruits and vegetables, meat products, cut flowers), and items that are specifically considered to be fruit-fly hosts. The results highlight the strong positive effects of detector dogs on the rate of interceptions, particularly of items detected on passengers. Conducting bag searches also appears to increase interceptions, both by increasing the rate of items being detected and by encouraging voluntary declarations. Sensitivity analyses then test the robustness of results to modelling implementation methods and distributional assumptions. This study demonstrates how statistical modelling can provide robust insights into biosecurity interventions and risk factors along pathways, and further highlights the value of high-quality interception data resources for informing and improving biosecurity systems.

Keywords: border biosecurity, detector dogs, sniffer dogs, pathway risk analysis, passenger screening, invasive species, fruit fly, *Bactrocera tryoni*, *Ceratitis capitata*.

1 Introduction

Biosecurity border interventions seek to balance the need for the cross-border movement of goods and people against their biosecurity risks. Although intervention policies inherit from a common framework of international agreements (Outhwaite, 2010), there are substantial differences in the policies and implementation of biosecurity interventions across jurisdictions. These differences produce variation in the risk of pest introductions across states, countries and regions (Whattam et al., 2014; Epanchin-Niell et al., 2021). Australia's biosecurity system tends to have a higher appropriate level of protection and to implement comparatively stricter interventions than many other jurisdictions (Whattam et al., 2014; Black & Bartlett, 2020). This is partially due to the opportunity presented by Australia's historical isolation, which has made its primary industries relatively pest-free on a global scale. However, contemporary activities such as tourism and trade are reducing this isolation and increasing the risk of pest introductions. Recent studies estimate an aggregated cost of invasive species to Australia to be AU$389.59 billion since the 1960s (Bradshaw et al., 2021), and a net present value of AU$314 billion for the national biosecurity system in terms of the assets that it protects (A. Dodd et al., 2020; Stoeckl et al., 2023). This highlights the critical importance of ensuring that border interventions act as effective barriers against biosecurity threats.

This is particularly true for the Australian island state of Tasmania (Fig. 1). Due primarily to their geographic and evolutionary isolation, island ecosystems possess a disproportionate level of the earth's endemic species and support a large percentage of its biodiversity (Kier et al., 2009; Weigelt & Kreft, 2013). Tasmania has specifically been identified as a major centre of endemism for Australian flora, for example, more than half of the 30 native Eucalyptus species in Tasmania are endemic (Crisp et al., 2001; Potts et al., 2016). This isolation is an asset to agricultural producers who benefit from a relatively low-pest environment, but this also creates a biosecurity challenge because islands can be particularly vulnerable to the impacts of invasive pests and diseases (Keitt et al., 2011; Fraser, 2016; Brettell et al., 2021). For example, a 2018 incursion of Queensland fruit fly ('Qfly', *Bactrocera tryoni*) in northern Tasmania cost millions in direct eradication costs in addition to further indirect costs (e.g., via temporary market access losses; Blake, 2019). Furthermore, globalisation is expected to increase movement across borders in both goods and people and to continue to bridge the geographic barriers that once kept Australia and Tasmania isolated (A. J. Dodd et al., 2015; Seebens et al., 2017, 2021).

Air passengers are an important high-volume pathway for pest introductions, with around 20 passengers arriving annually in Australia in 2023-24 (BITRE, 2024). Pests may be introduced via luggage (e.g., via infested fruit) or by being attached to passenger clothing or belongings (e.g., soil on shoes or sports equipment; McNeill et al., 2011; Pace et al., 2022; Robinson & McNeill, 2022). Air passenger pathways may be particularly important for pest insects, including Mediterranean fruit fly ('Medfly', *Ceratitis capitata*; Liebhold et al., 2006; McCullough et al., 2006). Passengers are also a pathway for animal diseases, for example, measures targeting African swine fever detected a yearly average of 33,684 pork products from 2% of screened passengers entering Australia from 2021/22 – 2023/24; (DAFF, 2024). Interventions on these pathways must therefore be able to mitigate a high volume and a diverse range of biosecurity threats.

A range of risk mitigation tools can be employed at multiple points on the air passenger pathway, from pre-departure, in-transit and on-arrival screening/inspection phases of the biosecurity continuum (Whattam et al., 2014; Sequeira & Griffin, 2014). Common at-border interventions for air passengers in Australia include manual examination, dog detector teams, and x-rays (Inspector-General of Biosecurity, 2022).

Detector dogs may be particularly valuable in air passenger screening, being able to screen large volumes of passengers and luggage efficiently, and able to be trained to target general biosecurity materials as well as specific pests and diseases (Whattam et al., 2014; Moser et al., 2020). Nonetheless, there are limited studies assessing their efficacy relative to other intervention methods.

Furthermore, biosecurity interventions are often targeted towards specific flights to maximise the utility of limited resources, e.g., flight-based-traveller profiles used to target international arrivals into Australia (Inspector-General of Biosecurity, 2019). Therefore, further empirical evidence about the relative efficacy of different interventions may help target intervention resources towards the highest-risk arrivals.

The analysis of biosecurity interception/surveillance data is prone to some common issues in statistical modelling, including zero-inflation (i.e., where data includes a large proportion of zeros, for example where detections of targeted items are rare), overdispersion (e.g., where variance is much higher than predicted), and censoring (e.g., if data is only recorded where contamination is detected; Kachigunda, 2020; Turner et al., 2020; Trouvé & Robinson, 2021; Kachigunda et al., 2022). Failing to account for overdispersion or zero-inflation in data can lead to biased or inaccurate parameter or error estimates (Harrison, 2014; Feng, 2021; Campbell, 2021). Although some studies suggest that the outputs of mixed-effects models can be robust to violations of distributional assumptions (e.g., Schielzeth et al., 2020; Knief & Forstmeier, 2021), exploring the potential effects of model design and implementation may be important considerations when using interception data to inform biosecurity decision-making.

Focusing on domestic interstate flight arrivals into Tasmania, the goal of this study is to assess the efficacy of passenger interventions and pathway risk factors on biosecurity interceptions. This focuses on both general biosecurity risk material ('BRM') interceptions, and interceptions of BRM material specifically relevant to Qfly and Medfly (collectively referred to as fruit fly, 'FF'). Preventing FF incursions has been a focus of Tasmania's border biosecurity system, particularly following the 2018 incursion. This study uses recent air pathway intervention data for Tasmania. These data are rich resources for our remit, as they include records for all commercial arrivals, as well as relevant data on the types/amount of BRM intercepted. This provides a valuable opportunity to apply statistical modelling approaches and assess their sensitivity to implementation methods. The specific aims of this analysis were:

1. To determine the relative effects of different interventions (namely, dog detector teams and luggage searches) on the rates of BRM and FF host interceptions, including voluntary declarations by passengers and involuntary detections of items by biosecurity officers. We did not make any specific directional predictions about the effects of searches and detector dogs on interceptions.
2. To identify pathway-risk heterogeneity based on the origin and specific routes of flights. We expected substantial variation in interception rates related to flight origin and route, which may be used to identify high-risk arrivals.
3. To test whether our results are sensitive to overdispersion and zero-inflation by imple-

menting Bayesian mixed models with zero-inflated Poisson and negative binomial distributions. We expected the outputs of models and the estimated effects of intervention methods to be robust to different implementation approaches.

2 Methods

Data context and overview

Tasmania is an island state (see Fig. 1), with a cool temperate climate, unique natural ecosystems characterised by high endemism (Potts et al., 2016; Crisp et al., 2001), and a large primary industry sector with and income from agriculture, forestry and fishing industries worth around AU$3.5 billion in 2022–23, or ∼9% of the Gross State Product (ABS, 2023). Local industries, communities, and natural ecosystems benefit from the state's relative isolation and low levels of pests, including species that are present elsewhere in Australia, such as Qfly, Medfly, tomato potato psyllid (*Bactericera cockerelli*), and grape phylloxera (*Daktulsphaira vitifoliae*; Cook & Fraser, 2015; Florec et al., 2013; Moir et al., 2022; Skinner, 2018).

The main entry pathway for passengers is by air, with a significant but smaller volume of

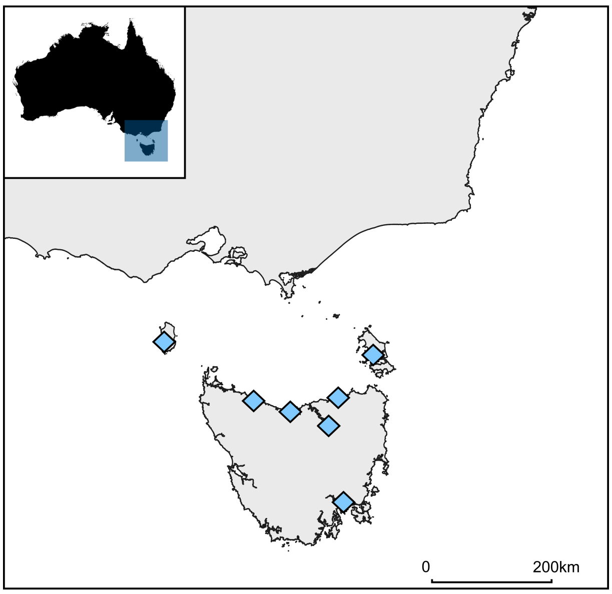

Figure 1: Location of Tasmania in relation to mainland Australia (inset), including the locations of the seven arrival ports for air passengers, namely (clockwise from top left) King Island, Burnie (Wynard), Devonport, Launceston, Bridport, Flinders Island, and Hobart. (Note, airports have been anonymised for the remainder of the analysis and labelled Airport_A, Airport_B. etc.)

maritime arrivals (e.g., ferries, cruise vessels, private vessels, etc.). Interceptions from air passengers are recorded in the Biosecurity Activity Database System (referred to as 'BAS data'), from which data from 1/Jan/2019 – 1/Sept/2023 was available. There are BAS interception records for 59,917 domestic interstate flight arrivals, carrying over 6.5 M passengers ($\sim$1.4 M/year on average), from which 66,675 BRM interceptions were made.

BRM items are generally defined to include fresh produce (i.e., fruits and vegetables), animal products including seafood, live animals, plant material (e.g., nursery stock, seeds), and soil attached to sports equipment or clothing. Biosecurity interventions for Tasmania have a particular focus on preventing incursions of FF into Tasmania, and a large subset of BRM interceptions (43,803, or approximately 2/3) are of items considered to be FF hosts. For this analysis, FF hosts include 130 taxa listed as Medfly and/or Qfly hosts in the Plant Biosecurity Manual Tasmania 2023 (Biosecurity Tasmania, 2023). For details of BRM and FF host item definitions and of intercepted BRM items, see Supplementary Materials A.

Data processing

Data for 59,917 arrivals was found to be within the scope of analysis, which excludes flights from international origins or within the state, and flights with no data (i.e., cancelled, diverted, missed, or cleared remotely; $\sim$14% of all records). A further subset of 27 records was excluded because of apparent data entry issues, and 25 arrivals into one airport were excluded as no commercial flights arrive at this location, and interceptions for the remaining private arrivals were extremely low, causing computational issues with model implementation. As only a small fraction of actual arrivals are excluded, and missed arrivals do not appear to be targeted/biased towards specific arrivals, we are confident that these exclusions do not reduce the operational relevance of the analyses.

Six count variables were used as response variables, namely:

1. the total number of BRM interceptions per flight (*N_Total*);
2. the number of BRM declarations by passengers (*N_Declarations*);
3. the number of undeclared BRM interceptions (*N_Detections*);

4. the total number of FF host interceptions per flight (*N_Total_FF*);
5. the number of FF host declarations by passengers (*N_Declarations_FF*); and,
6. the number of undeclared FF host interceptions (*N_Detections_FF*).

Total BRM and FF host interceptions are the sum of their corresponding declared and undeclared detection counts. Both BRM and FF variables were used to explore how interventions perform against both general biosecurity threats as well as high-priority/high-risk biosecurity materials. Both detections and declarations were included to explore how interventions influence both voluntary and involuntary compliance behaviour in passengers (e.g., whether detector dogs primarily increase interception through direct detections, or whether they also encourage voluntary declarations).

The number of interceptions was calculated as the sum of each distinct type of BRM/FF host material, separated by the passenger (e.g., if 2 passengers are intercepted each carrying 3 types of BRM, *N_Total* = 6). The rationale is that each commodity type may represent a distinct biosecurity threat, as may the same kind of commodity being carried by two separate passengers.

Statistical analysis A: Intervention and pathway risk effects

Generalized linear mixed effects ('glm') models with a Poisson distribution were implemented via package 'lme4' (v1.1-33, Bates et al., 2015), in the R statistical environment (v4.2.3, R Core Team, 2013). This was chosen for the primary analysis, as lme4 is an accessible package that can implement models using common distributions, relative to more complex Bayesian implementation methods that may be required for more advanced model types. Therefore, this approach may be more relevant for use by non-academic users such as biosecurity managers.

Four fixed effects were included, namely: arrival airport (*Location*), intervention regime (*Regime*), number of bag searches (*BagSearchCount*), and number of passengers per flight (*PassengerCount*). *Regime* includes five combinations of dog detector teams ('DDTs') and biosecurity inspectors ('BIs'), i.e. one BI, two BIs, one DDT, one DDT with one BI, and two DDTs. Both DDTs and BIs have been deployed across all airports. Airports were included as fixed effects, as they may differ both in their interception efficacy and in the underlying rates of contamination on flights arriving at each location. Count predictor variables (i.e., passenger and bag search counts) were square-root transformed and Z-scaled to reduce skewness, to improve both model performance and the interpretability of effect estimates (per Schielzeth, 2010).

Models included two random effects, to assess the level of variance associated with the flight's state of origin (*FlightOrigin*) and specific flight route (*FlightNumber*; nested within origin). Flights without a number recorded were categorised as 'Itinerant/Other', with a large majority considered to be private non-commercial arrivals, but also likely to include a small percentage of commercial flights for which their numbers were not entered into the database. For further details of model structure see Supplementary Materials B.

Unless otherwise stated, all values in square brackets below represent 95% confidence intervals (or credibility intervals for Bayesian models below; '95CI') for the estimated effects. The statistical significance of any fixed effects is inferred from whether their 95CIs include zero. Random effects are assessed based on how much variance is explained in models, and whether 95CIs for any specific random intercept predictions include zero. Where appropriate, parameter/effect estimates below have been converted to percentage changes in the expected number of interceptions for ease of interpretability. Marginal means were extracted from models using the package 'emmeans' (v1.8.7, Lenth, 2023), to estimate expected interception rates under different intervention regimes.

Statistical analysis B: Model sensitivity

Sensitivity to overdispersion and zero-inflation was tested by re-fitting a subset of models in a Bayesian framework via the package 'brms' (v2.19.0, Bürkner, 2017). From the six response variables used in the main analysis, two were selected for sensitivity analyses. These were the total BRM interceptions (*N_Total*, i.e., the most inclusive aggregation of interception data), and the number of FF host declarations (*N_Declarations_FF*, i.e., the most sparse response variable).

Four alternative distributions were tested for each response variable, namely Poisson (as in the main analysis but implemented in a Bayesian framework), zero-inflated Poisson, negative binomial, and zero-inflated negative binomial. These were chosen as common alternatives to account for cases with excess zeros and overdispersion in ecology and other fields where count data is common (Campbell, 2021; Lindén & Mäntyniemi, 2011; Pittman et al., 2022). Models used the same fixed and random effects specifications as in the glm models, with default non-informative priors to reflect our lack of prior knowledge for parameter estimates (chains = 3, iterations = 3000, warmup = 1000). The outputs for the fixed effects of intervention regimes and bag searches and the random intercepts associated with flight origins were estimated and qualitatively compared between models.

Measures of model fit were also estimated for all models, i.e., Akaike/Watanabe–Akaike information criterion 'AIC'/'WAIC' as a measure of the quality of model fit for the dataset, and marginal and conditional R^2 values as measures of the proportion of variance explained by fixed effects and both fixed and random effects respectively (via package 'performance', v0.10.3, Lüdecke et al., 2021; Nakagawa & Schielzeth, 2013). Overdispersion and zero-inflation tests were also conducted (also via 'performance').

3 Results

Intervention and pathway risk effects

Models identified significant effects of biosecurity interventions upon interceptions of both BRM and FF host items. Full results, code, models and outputs are available via Open Science Framework (doi: [access via review-only link]), and detailed model outputs are available in the Supplementary Materials B. Estimated BRM and FF host interception rates were significantly higher when detector dogs were present. For example, the estimated total BRM interceptions (*N_Total*) per flight with one DDT was 0.88 [0.80, 0.96], compared to 0.50 [0.46, 0.55] for one BI. This effect appeared to primarily be driven by increases in the number of detections, with DDTs having strong positive effects on BRM and FF host item detections (Fig. 2).

The number of bag searches conducted (performed both by DDTs and BIs) had a positive effect on the estimated total, declared, and detected BRM counts. Unsurprisingly, the square-root number of bag searches per arrival was associated with a per-unit increase in total BRM interceptions of 24.0% [23.3%, 24.6%]. A similar effect was found for BRM declarations (i.e., 23.8% [22.8%, 24.9%]) and detections (i.e., 24.1% [23.3%, 24.9%]). Similar effects were observed for FF host interceptions in total (23.8% [23.0%, 24.6%], declarations (23.2% [22.1%, 24.4%]), and detections (24.3% [23.2%, 25.4%]). In both cases, the effect was similar for detections and declarations, suggesting that conducting more bag searches increases the rate of BRM being detected and encourages more declarations. As expected, increased passenger counts were also associated with increased interception rates across all response variables. Finally, there were also some differences between arrival airports in their estimated interception rates (see Supplementary Materials B).

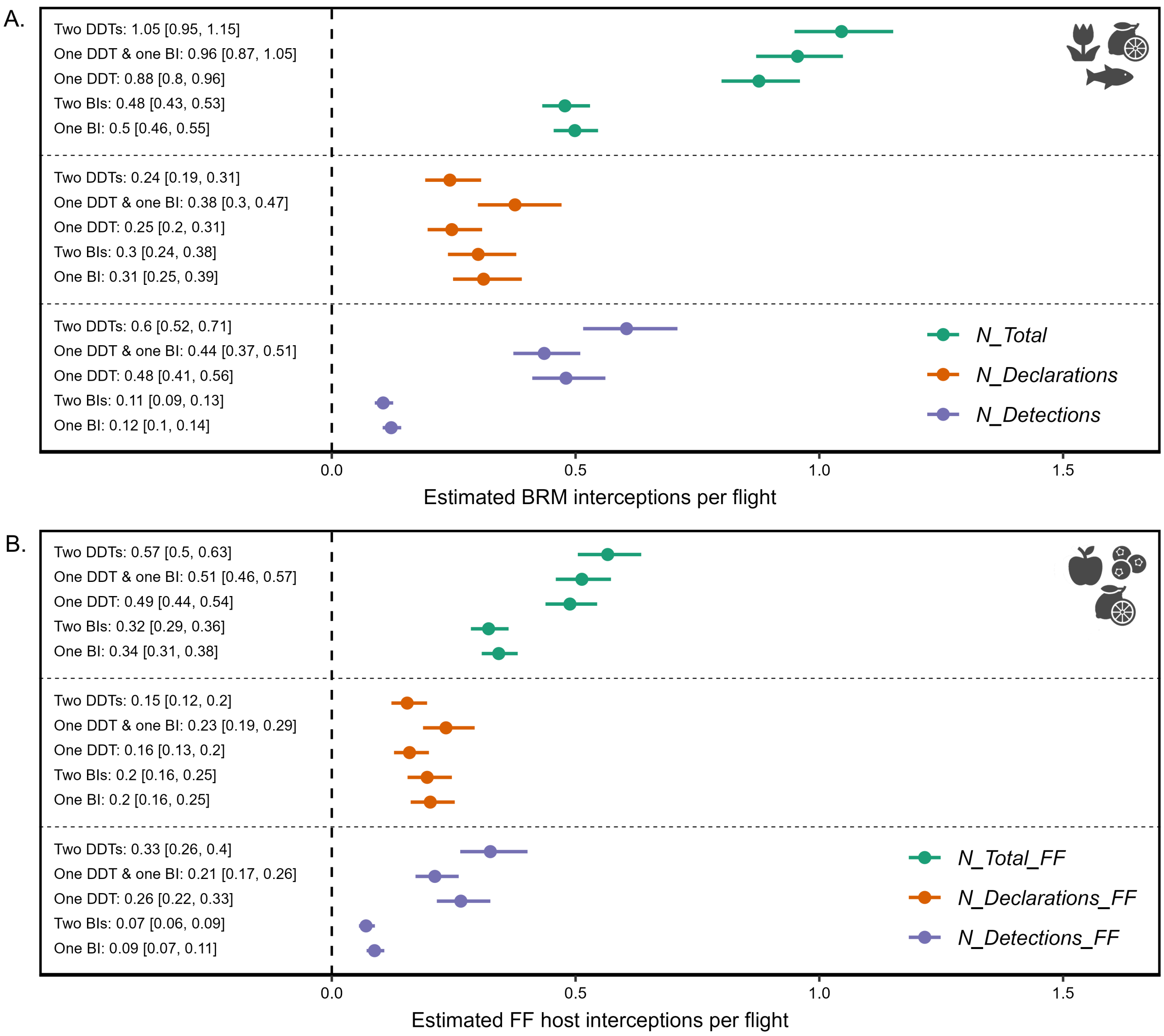

Figure 2: Estimated interception rates for air passenger interception regimes, for (A) BRM interceptions and (B) FF host items. Note, that estimated rates are the predicted number of interceptions per flight, and are independent of other factors included in the models (i.e., are estimated based on a flight with a mean number of passengers, and a mean number of bag searches, and averaged across arrival airports). Total, declared and detected rates come from distinct models, so estimates are not expected to be additive.

Random factors flight number and flight origin both explained some variance in interception rates (e.g., for *N_Total*, $V_{FlightOrigin} = 0.004$, $V_{FlightNumber} = 0.042$), although the random effects only explained a small proportion of variation relative to fixed effects (i.e., for *N_Total*, $R^2_{marginal} = 0.543$; $R^2_{conditional} = 0.570$, proportional $V_{FlightOrigin} = 0.002$, and proportional $V_{FlightNumber} = 0.025$). It should also be noted that the overdispersion may lead to overestimates of R^2 values (e.g., Harrison, 2014), so these values should be interpreted cautiously. Nonetheless, random intercept predictions for flight origin show how pathway factors may be used to identify and target interceptions towards higher risk arrivals (Fig. 3). Similar pathway heterogeneity can also be identified for flight number (see Supplementary Figs. B.1– B.2).

Model sensitivity

Tests showed that models used in the main analysis for *N_Total* and *N_Declarations_FF* both had probable zero-inflation (ratio of predicted to observed zeros: 0.85 and 0.92, respectively), and overdispersion was present in both cases (*N_Total*: dispersion ratio = 1.634, $\chi^2 = 97786.221$, $P < 0.001$; *N_Declarations_FF*: dispersion ratio = 1.709, $\chi^2 = 102303.640$, $P < 0.001$). No-

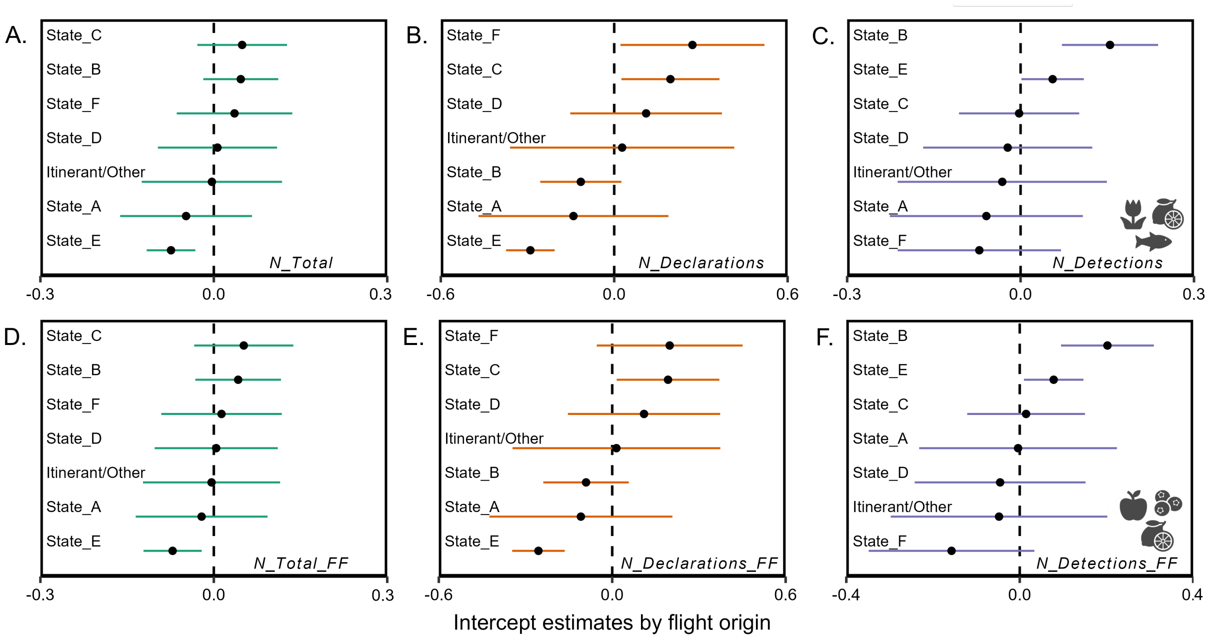

Figure 3: Predicted random intercepts by flight origin for (A-C) BRM interceptions, declarations, and detections; and (B) FF host interceptions, declarations, and detections. Error bars represent 95CIs, and intervals that do not include zero are considered to have significantly higher or lower levels of BRM interceptions than an average flight. Intercept estimates are in the modelled unit, i.e., the log of the proportional difference between the group and the overall expected BRM/FF host count.

tably, overdispersion can be a common consequence of zero-inflation, in which case a zero-inflated Poisson approach may be sufficient to account for both issues (see Yang et al., 2009). Measures of model fit also showed that all models accounting for zero-inflation had lower WAIC scores than those that did not, whereas negative binomial models had lower scores compared to Poisson models (see Supplementary Table B.1).

Nonetheless, sensitivity analysis showed that the outputs were relatively robust to implementation methods, with the patterns identified qualitatively similar between implementation types, but with some variation in the magnitude and uncertainty of effects. Estimated interception rates under differing regimes showed similar patterns when using a Bayesian implementation, although with slightly greater uncertainty (e.g., the estimated rate with one BI was 0.50 [0.44, 0.57] compared to 0.50 [0.46, 0.55] in the main model; see Fig. 4). Incorporating zero-inflation into Poisson models led to higher rate estimates (see also Supplementary Fig. B.3). Whereas, negative binomial models produced lower estimates of BRM interceptions, while also

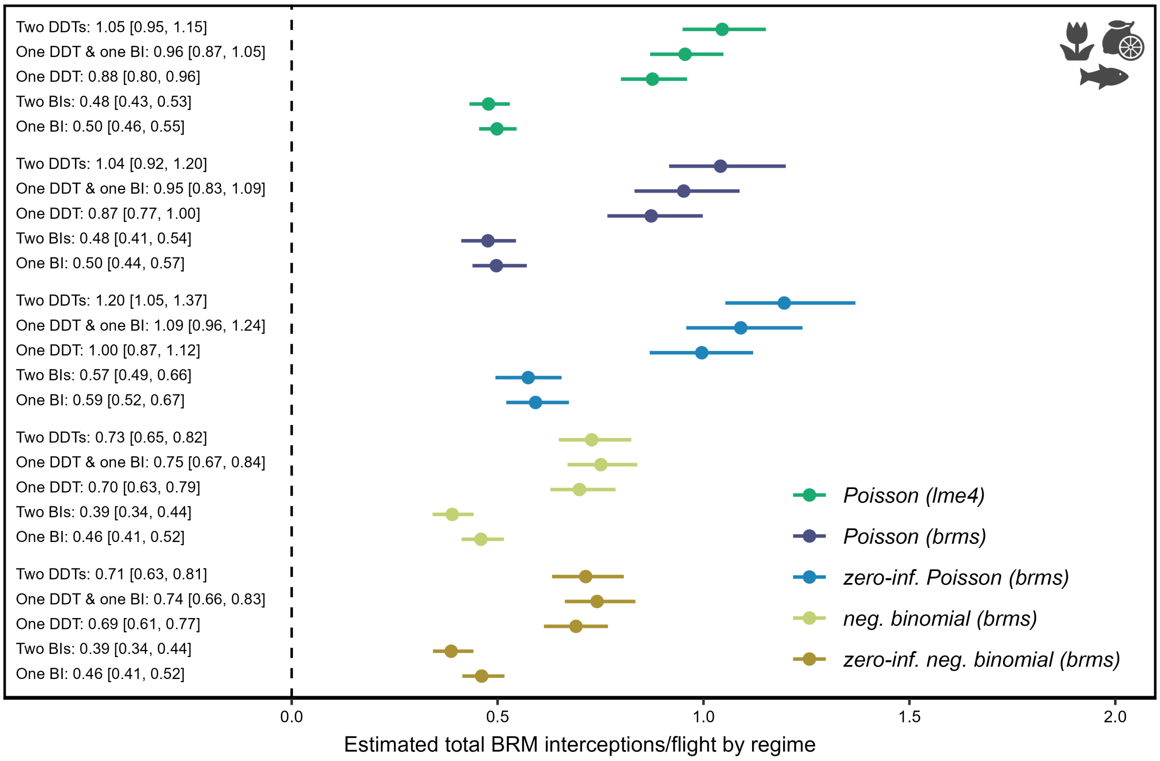

Figure 4: Estimated BRM interception rates for air passenger intervention regimes using different model implementations. Estimates are for five different model implementations, based on the modelled distribution and on a frequentist (lme4) vs Bayesian (brms) framework (see further details under Supplementary Table B.1).

showing similar differences between regimes.

Random intercept predictions also appeared to show qualitatively similar patterns for FF host detections (Fig. 5) and BRM interceptions (Supplementary Fig. B.4). Bayesian approaches produced greater uncertainty in the mean intercept estimates/predictions when directly comparing the Poisson implementation in lme4 and brms (Fig. 4,. 5), although the means were relatively consistent.

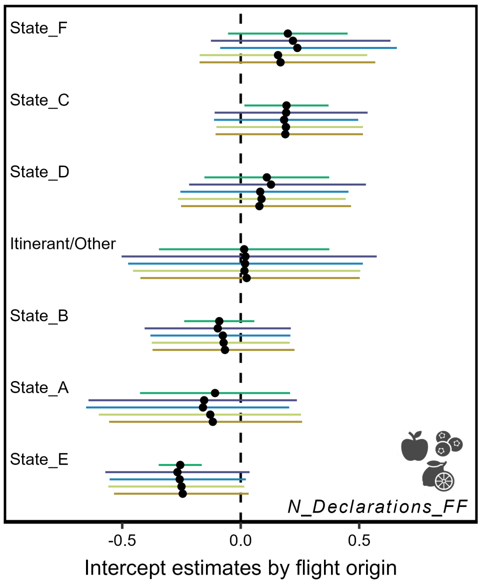

Figure 5: Predicted random intercepts for FF host item detections, by flight origin. Estimates are included from five different model implementations, which from the top include the following; (green) Poisson-lme4; (purple) Poisson-brms; (blue) zero-inflated Poisson-brms; (gold) negative binomial-brms; and, (orange) zero-inflated negative binomial-brms. Intercept estimates are in the modelled unit, i.e., the log of the proportional difference between the group and the overall expected FF host count.

4 Discussion

Biosecurity interceptions were strongly influenced by the methods used, for example, the number of bag searches conducted increased both detections and declarations from passengers. This suggests that increased effort in active at-border surveillance by officers will increase the efficacy of interventions by promoting both voluntary compliance by passengers and detections of undeclared risk items that may otherwise have been missed. Similarly, dog detector teams are increasingly deployed for border interventions along high-volume phytosanitary risk pathways, both in Australia and many other countries (Whattam et al., 2014; Inspector-General of

Biosecurity, 2022). Few studies have quantitatively assessed the efficacy of detector dogs, although a recent study from Williams & Sharp (2023) showed how the presence of a dog versus an officer alone can alter passenger behaviour including eye contact, gestures or interactions with the officer/dog. Our study provides further insights into the effects dogs may have on passenger behaviour and the rate of interceptions at airports. The increase also appears to be largely driven by detections of undeclared items instead of voluntary declarations, suggesting that dogs may be particularly useful for capturing a component of the biosecurity risk material that may otherwise not be found through more passive, voluntary compliance-based methods (e.g., public awareness and education campaigns, biosecurity signage and announcements).

The ability to analyse pathway risk heterogeneity is limited by the type of data collected on pathway risk factors. Despite the relatively limited set of pathway factors included in models and the relatively small proportion of total variance explained by these factors, models were able to identify specific flight origins and routes as potentially high- and low-risk arrivals. This shows how interception data may be useful for supporting risk-based approaches to interventions (e.g., Australia's flight-based-traveller profiles; Inspector-General of Biosecurity, 2019) by identifying higher and lower risk arrivals to allocate limited resources to these arrivals (Trouvé et al., 2024). These analyses can provide important quantitative evidence supporting targeted resource allocations at the border, particularly when combined with further contextual information such as pre-border pest prevalence data or estimates of potential post-border impacts. While Tasmania currently targets 100% of air arrivals, risk-based approaches could include decisions about where and when to allocate their most effective methods (e.g., DDTs), or to potentially identify a subset of low-risk arrivals that can be met with less resource-demanding methods (e.g., passive interventions, signage, amnesty bins).

While this data is valuable in identifying how interventions or pathway risk influence the actual interception rates, many unknowns remain that limit our ability to fully quantify the risk of incursions along this pathway. For example, the risk of FF establishing through this pathway would require us to estimate the actual volume of BRM on flights and the proportion of those items infested with FF (i.e., contamination/infestation rates), the proportion of risk material missed (i.e., leakage), or the viability of any FF individuals or larvae that may infest any of the risk material. These parameters may be estimated using complementary methods, such as endpoint surveys that target a subset of passengers as manual or X-ray searches to estimate BRM contamination rates (Mannix et al., 2024). Samples of intercepted BRM may also be further tested to measure their pest contamination/infestation rates. In many cases, particularly in biosecurity, empirical data is lacking. Structured expert judgement may then be used to elicit unknown parameters from relevant experts (e.g., biosecurity managers, entomologists, academics, etc.), using advanced methods to directly elicit uncertainty in parameter estimates and incorporate this uncertainty into the decision-making process (Hemming et al., 2018; Bau et al., 2024). Therefore, although this study highlights the value of interception data for informing biosecurity practices, additional knowledge is required to more completely assess and quantify risk across a biosecurity continuum.

This study used a simple and common approach for count data (i.e., regression modelling based on a Poisson distribution), performed with modelling tools that are accessible, and relatively easy to implement. Sensitivity analysis suggested that the outputs of this approach were qualitatively similar to approaches using more advanced tools (i.e., Bayesian modelling methods), or distributions (e.g., that account for zero-inflation). Although there were some notable differences in outputs, for example, interception rates estimated from negative binomial models tended to be lower, suggesting that failing to account for over-dispersion may lead to slight overestimates of predicted rates. Also, Bayesian methods tended to lead to higher uncertainty estimates around fixed- and random-effect parameters, so may represent a more conservative approach to modelling pathway risk factors. Therefore, while our conclusions were generally robust to implementation methods, sensitivity analysis may also be a valuable step for providing additional information for decision-makers about the robustness of any conclusions drawn from modelling. In this case, however, the operational interpretation of the simpler models was borne out by the more complex models.

Finally, effective at-border interventions are a key step in the biosecurity continuum. As at-border interventions become more sophisticated and widely implemented, large interception data sets will inevitably become more available to researchers and biosecurity decision-makers. This study highlights how this data can be a valuable resource for informing management decisions for Tasmania and can provide empirical evidence to support the implementation of risk-based approaches or the use of specific methods such as detector dogs, which can improve resource allocations and lead to more effective interventions at borders.

Data availability statement

For privacy and operational purposes, all identifying information has been anonymised from datasets, including airport names, flight numbers, etc. Fully anonymised datasets, analysis code, models and outputs are all available at the Open Science Framework (doi: [access via review-only link, https://osf.io/78tv9/?view_only=f2128031528348599c165b644d2c776f]).

Supplementary information

Additional supporting materials include the following:

A – Composition of BRM and FF host interceptions

B – Supplementary model outputs

Acknowledgments

We acknowledge Biosecurity Tasmania and its staff for supporting this project and specifically thank Rae Burrows, Andrew Bishop, Ryan Wilkinson, Meg Flanagan, Renee Tiggs, Guy Westmore, Emma Hutchinson, Cameron Healey, Jason Paul, Alex Matthews, Liam Harrex, Jesse Siebler, Christian Knapp, Andrew Carter, Deepa Adhikari, Elise Baniowski, Marlene Quinn, and Chris Jones. Finally, we thank Dr. David Rolls for his important contribution to the development of this project.

Declarations

Funding

The project received funding from Biosecurity Tasmania, Department of Natural Resources and Environment Tasmania.

Competing interests

The authors declare that they have no conflict of interest.

Authors' contributions (CRediT taxonomy)

NPM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Resources, Validation, Visualization, Writing – original draft.

AMH: Conceptualization, Methodology, Supervision, Writing – review & editing.

APR: Conceptualization, Methodology, Funding acquisition, Supervision, Writing – review & editing.

References

ABS. (2023). *Australian National Accounts: State Accounts, 2022-23 financial year: Table 7. Expenditure, Income and Industry Components of Gross State Product, Tasmania, Chain volume measures and current prices* (Tech. Rep.). Canberra, Australia: Australian Bureau of Statistics. Retrieved 2024-11-14, from https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-state-accounts/latest-release

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015, October). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*, 1–48. Retrieved from https://doi.org/10.18637/jss.v067.i01 doi: 10.18637/jss.v067.i01

Bau, S., Hanea, A., Robinson, A. P., & Burgman, M. (2024). Elicit: Using Structured Elicitation in Biosecurity. In *Biosecurity: A Systems Perspective.* CRC Press. (Num Pages: 20)

Biosecurity Tasmania. (2023). *Plant Biosecurity Manual Tasmania 2023 Edition.* Department of Natural Resources and Environment Tasmania. Retrieved 2023-05-16, from https://nre.tas.gov.au/biosecurity-tasmania/plant-biosecurity/plant-biosecurity-manual

BITRE. (2024). *Airport traffic data* (Tech. Rep.). Canberra, Australia: Bureau of Infrastructure and Transport Research Economics, The Department of Infrastructure, Transport, Regional Development, Communications and the Arts. Retrieved 2024-11-13, from https://www.bitre.gov.au/publications/ongoing/airport_traffic_data

Black, R., & Bartlett, D. M. F. (2020). Biosecurity frameworks for cross-border movement of invasive alien species. *Environmental Science & Policy*, *105*, 113–119. doi: 10.1016/j.envsci.2019.12.011

Blake, M. (2019, November). *Report of the Independent Review of the Queensland Fruit Fly incursion in Tasmania* (Tech. Rep.). Department of Natural Resources and Environment Tasmania. Retrieved 2023-05-12, from https://nre.tas.gov.au/about-the-department/independent-review-of-the-queensland-fruit-fly-response

Bradshaw, C. J. A., Hoskins, A. J., Haubrock, P. J., Cuthbert, R. N., Diagne, C., Leroy, B., ... Courchamp, F. (2021, July). Detailed assessment of the reported economic costs of invasive species in Australia. *NeoBiota*, *67*, 511–550. doi: 10.3897/neobiota.67.58834

Brettell, L. E., Martin, S. J., Riegler, M., & Cook, J. M. (2021). Vulnerability of island insect pollinator communities to pathogens. *Journal of Invertebrate Pathology*, *186*, 107670. doi: 10.1016/j.jip.2021.107670

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of statistical software*, *80*(1), 1–28. doi: 10.18637/jss.v080.i01

Campbell, H. (2021). The consequences of checking for zero-inflation and overdispersion in the analysis of count data. *Methods in Ecology and Evolution*, *12*(4), 665–680. doi: 10.1111/2041-210X.13559

Cook, D. C., & Fraser, R. W. (2015). Eradication versus control of Mediterranean fruit fly in Western Australia. *Agricultural and Forest Entomology*, *17*(2), 173–180. doi: 10.1111/afe.12093

Crisp, M. D., Laffan, S., Linder, H. P., & Monro, A. (2001). Endemism in the Australian flora. *Journal of Biogeography*, *28*(2), 183–198. doi: 10.1046/j.1365-2699.2001.00524.x

DAFF. (2024). *Annual report 2023-24* (Tech. Rep.). Canberra, Australia: Department of Agriculture, Fisheries and Forestry. Retrieved 2024-11-13, from https://www.agriculture.gov.au/about/reporting/annual-report

DNRET. (2023). *Traveller's Guide to Tasmanian Biosecurity - What You Can and Can't Bring into Tasmania.* Retrieved 2023-11-14, from https://nre.tas.gov.au/biosecurity-tasmania/biosecurity/travellers-guide-to-tasmanian-biosecurity-what-you-can-and-cant-bring-into-tasmania

Dodd, A., Stoeckl, N., Baumgartner, J., & Kompas, T. (2020). *Key Result Summary: Valuing Australia's Biosecurity System* (Tech. Rep.). Centre of Excellence for Biosecurity Risk Analysis, University of Melbourne. Retrieved 2023-04-21, from https://cebra.unimelb.edu.au/__data/assets/pdf_file/0020/3535013/CEBRA_Value_Docs_KeyResultSummary_v0.6_Endorsed.pdf

Dodd, A. J., Burgman, M. A., McCarthy, M. A., & Ainsworth, N. (2015). The changing patterns of plant naturalization in Australia. *Diversity and Distributions*, *21*(9), 1038–1050. doi: 10.1111/ddi.12351

Epanchin-Niell, R., McAusland, C., Liebhold, A., Mwebaze, P., & Springborn, M. R. (2021). Biological Invasions and International Trade: Managing a Moving Target. *Review of Environmental Economics and Policy*, *15*(1), 180–190. doi: 10.1086/713025

Feng, C. X. (2021, June). A comparison of zero-inflated and hurdle models for modeling zero-inflated count data. *Journal of Statistical Distributions and Applications*, *8*(1), 8. doi: 10.1186/s40488-021-00121-4

Florec, V., Sadler, R. J., White, B., & Dominiak, B. C. (2013). Choosing the battles: The economics of area wide pest management for Queensland fruit fly. *Food Policy*, *38*, 203–213. doi: 10.1016/j.foodpol.2012.11.007

Fraser, G. (2016). Biosecurity and food security—effective mechanisms for public-private partnerships. *Food Security*, *8*(1), 83–87. doi: 10.1007/s12571-015-0535-9

Harrison, X. A. (2014). Using observation-level random effects to model overdispersion in count data in ecology and evolution. *PeerJ*, *2*, e616. doi: 10.7717/peerj.616

Hemming, V., Burgman, M. A., Hanea, A. M., McBride, M. F., & Wintle, B. C. (2018). A practical guide to structured expert elicitation using the IDEA protocol. *Methods in Ecology and Evolution*, *9*(1), 169–180. doi: 10.1111/2041-210X.12857

Inspector-General of Biosecurity. (2019). *Pest and disease interceptions and incursions in Australia* (Tech. Rep.). Canberra, Australia: Department of Agriculture and Water Resources. Retrieved 2023-06-02, from https://www.igb.gov.au/current-and-completed-reviews

Inspector-General of Biosecurity. (2022). *Efficacy and adequacy of department's X-ray scanning and detector dog screening techniques to prevent entry of biosecurity risk material into Australia* (Tech. Rep.). Canberra, Australia: Department of Agriculture and Water Resources. Retrieved 2023-09-12, from https://www.igb.gov.au/current-and-completed-reviews

Kachigunda, B. (2020). *Remote islands are vulnerable to non-indigenous species: Utilization of data analytics to investigate potential modes of introduction and pest interceptions* (PhD Thesis, Murdoch University). Retrieved 2024-11-14, from https://researchportal.murdoch.edu.au/esploro/outputs/doctoral/Remote-islands-are-vulnerable-to-non-indigenous/991005542668407891

Kachigunda, B., Mengersen, K., Perera, D. I., Coupland, G. T., Van der Merwe, J., & McKirdy, S. (2022). Use of mixed-type data clustering algorithm for characterizing temporal and spatial distribution of biosecurity border detections of terrestrial non-indigenous species. *PLoS ONE*, *17*(8-Aug). doi: 10.1371/journal.pone.0272413

Keitt, B., Campbell, K., Saunders, A., Clout, M., Wang, Y., Heinz, R., … Tershy, B. (2011). The global islands invasive vertebrate eradication database: a tool to improve and facilitate restoration of island ecosystems. In *Island Invasives: Eradication and Management: Proceedings of the International Conference on Island Invasives* (pp. 74–77). International Union for Conservation of Nature (IUCN) Gland, Switzerland.

Kier, G., Kreft, H., Lee, T. M., Jetz, W., Ibisch, P. L., Nowicki, C., … Barthlott, W. (2009). A global assessment of endemism and species richness across island and mainland regions. *Proceedings of the National Academy of Sciences*, *106*(23), 9322–9327. doi: 10.1073/pnas.0810306106

Knief, U., & Forstmeier, W. (2021, December). Violating the normality assumption may be the lesser of two evils. *Behavior Research Methods*, *53*(6), 2576–2590. doi: 10.3758/s13428-021-01587-5

Lenth, R. V. (2023). *emmeans: Estimated Marginal Means, aka Least-Squares Means.* Retrieved from https://CRAN.R-project.org/package=emmeans (R package version 1.8.7)

Liebhold, A. M., Work, T. T., McCullough, D. G., & Cavey, J. F. (2006). Airline Baggage as a Pathway for Alien Insect Species Invading the United States. *American Entomologist*, *52*(1), 48–54. doi: 10.1093/ae/52.1.48

Lindén, A., & Mäntyniemi, S. (2011). Using the negative binomial distribution to model overdispersion in ecological count data. *Ecology*, *92*(7), 1414–1421. doi: 10.1890/10-1831.1

Lüdecke, D., Ben-Shachar, M. S., Patil, I., Waggoner, P., & Makowski, D. (2021). performance: An R package for assessment, comparison and testing of statistical models. *Journal of Open Source Software*, *6*(60). doi: 10.21105/joss.03139

Mannix, E., Baumgartner, J. B., Bau, S., Bland, L. M., Robinson, A. P., & Page, N. (2024). Profiling and Automation. In *Biosecurity* (pp. 211–230). CRC Press.

McCullough, D. G., Work, T. T., Cavey, J. F., Liebhold, A. M., & Marshall, D. (2006). Interceptions of Nonindigenous Plant Pests at US Ports of Entry and Border Crossings Over a 17-year Period. *Biological Invasions*, *8*(4), 611–630. doi: 10.1007/s10530-005-1798-4

McNeill, M., Phillips, C., Young, S., Shah, F., Aalders, L., Bell, N., ... Littlejohn, R. (2011). Transportation of nonindigenous species via soil on international aircraft passengers' footwear. *Biological Invasions*, *13*(12), 2799–2815. doi: 10.1007/s10530-011-9964-3

Moir, M. L., Croeser, L., Telfer, D., Fenner, C., & McCauley, R. (2022). Value-adding in biosecurity surveillance and monitoring: Testing colour and non-target semiochemical lures on Psylloidea and Pentatomoidea. *Journal of Applied Entomology*, *146*(10), 1333–1342. doi: 10.1111/jen.13074

Moser, A. Y., Brown, W. Y., Bizo, L. A., Andrew, N. R., & Taylor, M. K. (2020). Biosecurity Dogs Detect Live Insects after Training with Odor-Proxy Training Aids: Scent Extract and Dead Specimens. *Chemical Senses*, *45*(3), 179–186. doi: 10.1093/chemse/bjaa001

Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution*, *4*(2), 133–142. doi: 10.1111/j.2041-210x.2012.00261.x

Outhwaite, O. (2010). The International Legal Framework for Biosecurity and the Challenges Ahead. *Review of European Community & International Environmental Law*, *19*(2), 207–226. doi: 10.1111/j.1467-9388.2010.00678.x

Pace, R., Ascolese, R., Miele, F., Russo, E., Griffo, R. V., Bernardo, U., & Nugnes, F. (2022). The Bugs in the Bags: The Risk Associated with the Introduction of Small Quantities of Fruit and Plants by Airline Passengers. *Insects*, *13*(7), 617. doi: 10.3390/insects13070617

Pittman, B., Buta, E., Garrison, K., & Gueorguieva, R. (2022). Models for Zero-Inflated and Overdispersed Correlated Count Data: An Application to Cigarette Use. *Nicotine & Tobacco Research*, *25*(5), 996–1003. doi: 10.1093/ntr/ntac253

Potts, B. M., Sandhu, K. S., Wardlaw, T., Freeman, J., Li, H., Tilyard, P., & Park, R. F. (2016). Evolutionary history shapes the susceptibility of an island tree flora to an exotic pathogen. *Forest Ecology and Management*, *368*, 183–193. doi: 10.1016/j.foreco.2016.02.027

R Core Team. (2013). *R: A language and environment for statistical computing.* Retrieved from https://www.r-project.org/ (Publisher: Vienna, Austria)

Robinson, A. P., & McNeill, M. R. (2022). Biosecurity and post-arrival pathways in New Zealand: relating alien organism detections to tourism indicators. *NeoBiota*, *71*, 51–69. doi: 10.3897/neobiota.71.64618

Schielzeth, H. (2010). Simple means to improve the interpretability of regression coefficients. *Methods in Ecology and Evolution*, *1*(2), 103–113. doi: 10.1111/j.2041-210X.2010.00012.x

Schielzeth, H., Dingemanse, N. J., Nakagawa, S., Westneat, D. F., Allegue, H., Teplitsky, C., … Araya-Ajoy, Y. G. (2020). Robustness of linear mixed-effects models to violations of distributional assumptions. *Methods in Ecology and Evolution*, *11*(9), 1141–1152. doi: 10.1111/2041-210X.13434

Seebens, H., Bacher, S., Blackburn, T. M., Capinha, C., Dawson, W., Dullinger, S., … Essl, F. (2021). Projecting the continental accumulation of alien species through to 2050. *Global Change Biology*, *27*(5), 970–982. doi: 10.1111/gcb.15333

Seebens, H., Blackburn, T. M., Dyer, E. E., Genovesi, P., Hulme, P. E., Jeschke, J. M., … Essl, F. (2017). No saturation in the accumulation of alien species worldwide. *Nature Communications*, *8*(1), 14435. doi: 10.1038/ncomms14435

Sequeira, R., & Griffin, R. (2014). The biosecurity continuum and trade: Pre-border operations. In G. Gordh & S. McKirdy (Eds.), *The Handbook of Plant Biosecurity: Principles and Practices for the Identification, Containment and Control of Organisms that Threaten Agriculture and the Environment Globally* (pp. 119–148). Dordrecht: Springer Netherlands.

Skinner, W. (2018). Presence Through Absence: Phylloxera and the Viticultural Imagination in McLaren Vale, South Australia. *Asia Pacific Journal of Anthropology*, *19*(3), 245–263. doi: 10.1080/14442213.2018.1461916

Stoeckl, N., Dodd, A., & Kompas, T. (2023). The monetary value of 16 services protected by the Australian National Biosecurity System: Spatially explicit estimates and vulnerability to incursions. *Ecosystem Services*, *60*, 101509. doi: 10.1016/j.ecoser.2023.101509

Trouvé, R., Bland, L. M., Robinson, A. P., Ducey, M. J., & Hester, S. M. (2024). Screen: Designing Sampling Schemes for Border Inspection. In *Biosecurity* (pp. 69–82). CRC Press.

Trouvé, R., & Robinson, A. P. (2021). Estimating Consignment-Level Infestation Rates from the Proportion of Consignment that Failed Border Inspection: Possibilities and Limitations in the Presence of Overdispersed Data. *Risk Analysis*, *41*(6), 992–1003. doi: 10.1111/risa.13592

Turner, R. M., Plank, M. J., Brockerhoff, E. G., Pawson, S., Liebhold, A., & James, A. (2020). Considering unseen arrivals in predictions of establishment risk based on border biosecurity interceptions. *Ecological Applications*, *30*(8), e02194. doi: 10.1002/eap.2194

Weigelt, P., & Kreft, H. (2013). Quantifying island isolation–insights from global patterns of insular plant species richness. *Ecography*, *36*(4), 417–429. doi: 10.1111/j.1600-0587.2012.07669.x

Whattam, M., Clover, G., Firko, M., & Kalaris, T. (2014). The biosecurity continuum and trade: Border operations. In G. Gordh & S. McKirdy (Eds.), *The Handbook of Plant Biosecurity: Principles and Practices for the Identification, Containment and Control of Organisms that Threaten Agriculture and the Environment Globally* (pp. 149–188). Dordrecht: Springer Netherlands. (doi: 10.1007/978-94-007-7365-3_6)

Williams, E. E. M., & Sharp, R. A. (2023). Some effects of detection dogs on passenger behavior at border control ports. *Journal of Applied Behavior Analysis*, *56*(2), 377–387. doi: 10.1002/jaba.985

Yang, Z., Hardin, J. W., & Addy, C. L. (2009, September). Testing overdispersion in the zero-inflated Poisson model. *Journal of Statistical Planning and Inference*, *139*(9), 3340–3353. doi: 10.1016/j.jspi.2009.03.016