ARPHA Preprints

PREPRINT

Author-formatted, not peer-reviewed document posted on 13/06/2025

DOI: https://doi.org/10.3897/arphapreprints.e161943

Simple network models integrate global change, social dynamics and management interventions in biosecurity scenario analysis

Christopher E. Buddenhagen, Christopher McGrannachan, Graeme Bourdôt, Shona Lamoureaux, Karen, A. Garrett, Geoff Kaine, Norman Mason

ARPHA Preprints Author-formatted, not peer-reviewed document posted on 13/06/2025. DOI: https://doi.org/10.3897/arphapreprints.e161943

Simple network models integrate global change, social dynamics and management interventions in biosecurity scenario analysis

Christopher E. Buddenhagen[1], Christopher McGrannachan[2], Graeme Bourdôt[3], Shona Lamoureaux[3], Karen A. Garrett[4], Geoff Kaine [5], Norman W.H. Mason[5]

[1] AgResearch Limited, Lincoln Research Centre, Lincoln, New Zealand

[2] Manaaki Whenua–Landcare Research, Auckland, New Zealand

[3] AgResearch Limited, Ruakura Research Centre, Hamilton, New Zealand

[4] Plant Pathology Department and Global Food Systems Institute, University of Florida, Gainesville, U.S.A.

[5] Manaaki Whenua–Landcare Research, Hamilton, New Zealand

Corresponding author: Norman Mason MasonN@landcareresearch.co.nz

Abstract

Global change and public participation are both areas of considerable uncertainty in estimating the success of biosecurity response strategies but are poorly integrated in most available models. We introduce *INApest()*, a novel network simulation method which integrates social and global change factors, as well as pest biology and multiple management variables in scenario analyses of biosecurity responses. *INApest()* separates the management response into four key parameters: probability of detection; management adoption; eradication of local populations; spread reduction (e.g. through movement restrictions or hygiene measures). It also permits simulation of biosecurity responses which evolve organically as new incidences of the pest are detected and information about the pest and management technologies spread through the network. We demonstrate selected functionality of *INApest()* using *Nassella neesiana* (Chilean Needle Grass; CNG), a slow-spreading pasture weed that impacts animal health, as a case-study. Realistic historical CNG spread rates are reproduced under a no management scenario using dispersal kernels derived from known natural and human mediated spread mechanisms. Scenario analyses comparing over 15,000 parameter combinations reveal that communication of invasive threat to farms neighbouring known infestations significantly reduces the management efficacy (farm-scale eradication probability and spread reduction) required for successful containment. We use targeted simulation experiments to show how *INApest()* permits assessment of cross-border consequences of local management decisions, and the effect of communication between landowners on management success.

INApest() has the potential to be used at multiple scales and to explore a wide range of management, global change and social scenarios.

Keywords: invasive species; pasture; dispersal; simulation; pest control; border protection; risk assessment; agriculture; spread modelling; climate; land use; habitat; detection; eradication

Introduction

Global change, encompassing shifts in climate, land use and global trade (Hulme 2009, Chapman et al. 2017, Marchioro and Krechemer 2021, Capinha et al. 2023), coupled with socio-economic factors such as public participation and information spread within social networks (Reeve et al. 2000, Kaine and Wright 2022), play pivotal roles in shaping the spread of pests (used here to refer to all invasive alien species) and influence the success or failure of biosecurity management responses (Yletyinen et al. 2021). While studies often tackle these elements in isolation when addressing invasive species management, there is a scarcity of simulation tools that comprehensively integrate across factors such as the biology of the invader, climate change, management efficacy, outreach endeavours, and societal involvement (Hulme et al. 2023). The recent Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) invasive species assessment identified the ability to integrate global change factors as a gap in pest response planning and incorporation of social factors as a gap in pest response implementation (Sankaran et al. 2023). The IPBES review also emphasised that objective scenario analysis is seldom employed in pest response planning and implementation, suggesting that we lack accessible, fit-for-purpose scenario analysis tools (Sankaran et al. 2023). Further, a recent horizon scan within the “One Biosecurity” framework noted the need for simulation models which capture the full complexity of invasion processes, management interventions and social factors in pest response planning (Hulme et al. 2023). In this study we build on existing network-based modelling approaches (Jeger et al. 2007, Pautasso et al. 2010a, Garrett et al. 2018, Cope et al. 2019, Frost et al. 2019, Garrett 2021, Adiga et al. 2022, Runghen et al. 2023) to integrate social and global change factors in a multidimensional pest response framework, with the aim of providing scenario analysis tools which are more likely to be adopted in response planning and implementation.

Pest scenario analysis: responding to a wicked problem

Prioritising management effort among pests or between sites at risk of invasion is among the greatest strategic challenges facing biosecurity systems globally (Panetta 2009, Simberloff 2009, Renteria et al. 2017, Simberloff et al. 2018). Potentially harmful introduced species often establish at multiple sites before detection, by which time eradication may be considered infeasible (Panetta 2004, Panetta and Lawes 2005). Consequently, for incipient invaders or “sleeper pests” the benefits

of control efforts may primarily be via prevention of spread rather than reducing the impacts they have on the already invaded sites (Bourdôt et al. 2015, Buddenhagen and Tye 2015). Biosecurity planners require robust methods for deciding when and how to intervene, and for demonstrating the value of control efforts to potential funders (e.g. stakeholders, central or local governance bodies) and affected communities.

Scenario analysis is a valuable yet underutilized tool for evaluating management strategies by integrating multiple factors (Wiebe et al. 2018, Sankaran et al. 2023). Regulators and land managers often approach these scenarios as informal thought experiments, rather than using formal models with defined assumptions and objective success criteria (Simberloff 2009, Buddenhagen and Tye 2015, Panetta 2015). Developing flexible, purpose-built frameworks for pest scenario analysis remains a challenge.

Capturing the complexity of pest responses: the multidimensional nature of invasion processes and management responses

Developing fit-for-purpose pest scenario frameworks is challenging due to the need to integrate processes in three key areas: invasive spread (biology), the social dynamics that influence threat awareness and management decisions (social and cultural), and management effectiveness (management) (Simberloff et al. 2018, Garrett 2021, Sankaran et al. 2023). These three areas are expected to interact to produce different outcomes related to the rate, extent and impact of the invader.

Invasive spread is influenced by interacting elements which are often imperfectly known or hard to predict, including; distributions of initial infestations, connectivity of suitable habitat patches, natural and human-aided dispersal pathways and global change factors, particularly those that affect habitat suitability (Gallien et al. 2010, Panetta et al. 2011, Ferrari et al. 2014, Lustig et al. 2017). Effectiveness of pest management responses is influenced by the ability to detect or correctly identify new infestations, eradicate known infestations and prevent spread through movement restrictions and hygiene measures (Panetta and Lawes 2007, Simberloff 2009, Panetta et al. 2011, Howell 2012, Buddenhagen and Tye 2015). Social attitudes to pests (based on perceived impacts to economic or other values) and connectivity within social networks may affect the likelihood that information is shared within social networks, as well as the receptiveness of agents to information either from within the network or external sources (e.g., Buddenhagen et al. 2017, Garrett 2021, Yletyinen et al. 2021)

Interactions between factors influencing invasive spread, management and information sharing create abundant potential for pest management responses to exhibit complex systems behaviour, where *a priori* prediction of outcomes from initial conditions is challenging because similar starting conditions may yield vastly different outcomes (Ferrari et al. 2014, Garrett et al. 2018, Seebens et al. 2019). Simulation-based scenario analyses are well suited to capturing potential complex system behaviour, relative to statistical or deterministic modelling techniques (Jeger et al. 2007, Garrett et al. 2018, Green 2023, Yang et al. 2023).

Many pest prioritisation and planning frameworks incorporate global change factors, especially species distribution models, including those that incorporate climate change (Leung et al. 2012, Phillips et al. 2018, Roigé and Phillips 2021), with some approaches also incorporating natural and human-mediated dispersal processes, and basic management variables such as detection and eradication probabilities (Jamieson et al. 2022). However, frameworks incorporating global change factors often don't consider social factors such as management adoption probability or the spread of information about pests through social networks (Buddenhagen et al. 2017, Garrett 2021). Socioecological network models define nodes (e.g., geographical locations or agents) and the links between them, representing associations like invasion pathways or links in socioeconomic networks (Sayles et al. 2019, Yletyinen et al. 2021). Network models can integrate biological factors such as dispersal ecology and habitat suitability and social aspects like knowledge dissemination and management adoption to permit joint simulation of pest spread between locations and information transfer between human actors (Behr et al. 2017, Buddenhagen et al. 2017, Andersen et al. 2019, Garrett 2021). This makes socioecological network models particularly well-suited to evaluating invasive species management strategies. However, to our knowledge these models do not explicitly incorporate global change factors such as climate or land use change.

Integrating global change and social factors in multidimensional management scenarios

The primary goal of this study was to develop simulation methods which use simple matrix operations to integrate across multiple global change and social factors in a multidimensional pest response framework. To this end we extend an existing socioecological network modelling framework - Impact Network Analysis (INA) (Garrett 2021) - which simultaneously simulates the spread of pests and information about pest management technologies within socioecological networks. Using the spread of the pest plant *Nassella neesiana* (Trin. & Rupr.) Barkworth (Chilean needle grass) between pastoral farms within New Zealand as our study system, we present simulation experiments demonstrating the potential of our framework to explore the following questions:

1) What is the relative effect of multiple management variables, the rate of information spread, climate change and interactions between them on pest spread and the likelihood of pest management success?
2) How does the decision to manage a pest in one region impact pest response outcomes in neighbouring regions? How will these benefits be affected by climate change?
3) What is the potential benefit of communication about a pest within social networks for improving management response outcomes under current and future climates?

Methods

INApest: – a new socioecological network modelling framework

We present a new simulation function (Figure 1) named *INApest()*, which was originally built as a wrapper around the *INAscene()* function of the impact network analysis R package of Garrett (2021). The latest version of *INApest()* uses generic R commands to replace the operations performed by *INAscene()*. We named our function *INApest()* because our focus is on the biosecurity application of Impact Network Analysis to the management of harmful bioentities such as pests, weeds and pathogens (for simplicity we use the term pest to cover all these categories henceforth). Code for the *INApest()* core function is available from a GitHub repository (Mason, 2023). A full list of required and optional parameters is provided in the Supplemental Material.

INAscene() models the spread of both bioentities (e.g., invasive species or biological control agents) and information (about management practices to reduce or enhance bioentity survival) within socioecological networks (Garrett 2021, Etherton et al. 2025). It also permits inclusion of management adoption probability and eradication probability to model management effectiveness. This functionality potentially provides a great deal of power for assessing competing management strategies for invasive species management in socioecological systems.

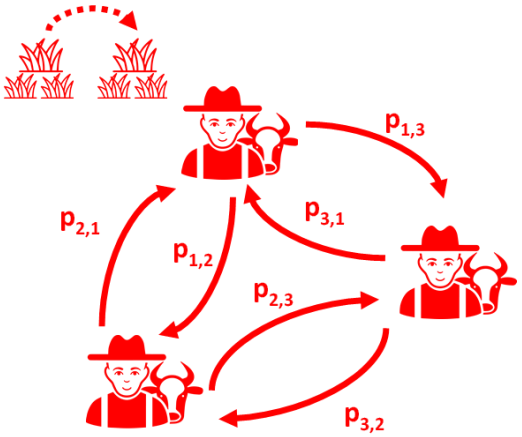
INApest() inherits the ability of *INAscene()* to simultaneously simulate the spread of a pest and the spread of information about the pest through socioecological networks. Pest spread is determined by the biophysical adjacency matrix, which is an asymmetric matrix of dispersal probabilities, with the values in rows indicating the probability of dispersal from the target node to all other nodes and the columns indicating the probability of dispersal to the target node from all other nodes. The spread of information is determined by the socioeconomic adjacency matrix, which can also be asymmetric.

INApest() treats bioentity spread differently from *INAscene()* by allowing explicit definition of separate short distance (e.g., self-mediated) and long distance (e.g. human-mediated) dispersal

processes (Wichmann et al. 2009, Pautasso and Jeger 2014, James et al. 2015, Kelly et al. 2020). It also permits explicit moderation of colonisation probability by environmental factors such as climate and land use or land cover. This is achieved through multiplying the columns of the biophysical adjacency matrix (which contain the probability of dispersal to each node from all other nodes) by a vector of establishment probabilities. Establishment probabilities may be updated at each timestep, thus allowing changes in habitat suitability through time to be incorporated in simulating pest spread.

ARPHA Preprints *Author-formatted, not peer-reviewed document posted on 13/06/2025.* DOI: https://doi.org/10.3897/arphapreprints.e161943

Invasive spread and management



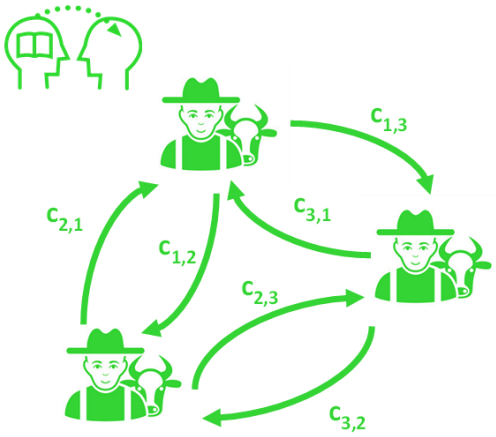
Establishment

est_{1t} est_{2t} est_{3t}

X

BioPhysical Adjaceny Matrix				Invaded?		Survived?		Spread reduction
-	$p_{1,2}$	$p_{1,3}$		I_{1t}		$B[s_{1t}(1-M_{1t}e_{1t})]$		$(1-M_{1t}sr_{1t})$
$p_{2,1}$	-	$P_{2,3}$	X	I_{2t}	X	$B[s_{2t}(1-M_{2t}e_{2t})]$	X	$(1-M_{2t}sr_{2t})$
$p_{3,1}$	$p_{3,2}$	-		I_{3t}		$B[s_{3t}(1-M_{3t}e_{3t})]$		$(1-M_{3t}sr_{3t})$

Information spread



SocioEconomic Adjaceny Matrix				Detected?
1	$c_{1,2}$	$c_{1,3}$		D_{1t}
$c_{2,1}$	1	$c_{2,3}$	X	D_{2t}
$c_{3,1}$	$c_{3,2}$	1		D_{3t}

Invasive spread and management parameters

est_{1t} establishment probability in site 1 and time t

$p_{1,2}$ dispersal probability from site 1 to site 2

I_{1t} Invasion status in site 1 at timestep t

$B[]$ random binomial process (n=1)

s_{1t} survival probability

M_{1t} managing status

e_{1t} eradication probability

sr_{1t} spread reduction

Information spread parameters

$c_{1,2}$ communication probability

D_{1t} Detection status

Figure 1: Schematic diagram indicating key features of *INApest()* that differ from *INAscene()*. Through a simple set of matrix operations habitat suitability, dispersal probability between sites, multiple management parameters and social network structure are integrated to permit simultaneous simulation of both pest and information spread.

Another key departure of *INApest()* from the *INAscene()* function is that the spread of information through the network is dependent on the spread (and detection) of the pest. This is achieved through multiplying the rows of the socioeconomic adjacency matrix by a binary vector tracking the presence of detected extant infestations. This reflects the reality that agents (e.g., farmers) may only become receptive to information about a pest they know is present, or nearby (e.g., neighbouring farm) and imminently threatening (Hester and Cacho 2017, Kaine and Wright 2022, Etherton et al. 2023). In simple terms *INAscene()* simulates the spread of information about pest management technologies while *INApest()* simulates spread of information about the threat of invasion. Provision of the socioeconomic adjacency matrix is not required to run *INApest().* In such cases there is assumed to be no spread of information between nodes.

INApest() permits a more nuanced approach to modelling invasive species management by explicitly separating the management response into detection, management adoption, spread reduction and eradication components. Detection probability is the probability of detecting the pest in each timestep. Management only occurs after detection of the pest, or receipt of information from nodes with extant detected infestations. Zero management scenarios can be implemented simply by setting detection probability to zero in all nodes. Management adoption is the probability that management is implemented on a given farm in a given timestep. Eradication probability is applied as a reduction to the annual survival rate of local populations when management is applied. Spread reduction is applied as a reduction in the dispersal probability from nodes when management is applied. Once a node obtains information it always potentially applies management, even once the pest has been eradicated from that node.

A key additional feature of *INApest()* is the ability to weight initial infestations by risk of invasion from external sources (e.g. proximity to an international port or airport) and to incorporate ongoing invasion from external sources in simulating pest spread. Similarly, it is possible to select nodes which have information at the start of simulations (e.g. sentinel sites) and incorporate communication of information from external sources (e.g. biosecurity officers, consultants, media and social media) in simulating the spread of information through the network. Details of outputs from *INApest()* are provided in Supplementary Material.

Study system: Chilean needle grass invasion in NZ pastoral farms

We used *INApest()* to model the spread and management of the regionally restricted weed *Nassella neesiana* (Trin. et Rupr.) Barkworth (Chilean needle grass; CNG) which is established in limited areas in the Hawkes Bay, Marlborough, and Canterbury regions of New Zealand (Connor et al. 1993). Under current climates in New Zealand, 15 million ha is climatically suitable, though much less than 1% is currently invaded, and more area is expected to become suitable with climate change (Kriticos et al. 2004, Bourdôt et al. 2012, 2015). Establishment of CNG on dairy farms is largely prevented by intensive pasture management (high nutrient inputs and short return grazing intervals), wetter soils and competition from dense swards of ryegrass and clover (Bourdôt et al. 2015), so that it is justifiable to focus on modelling spread within the sheep and beef sector, rather than across all pastoral lands. Additional information on the impacts, status, reproduction and spread of CNG in New Zealand is provided in the Supplementary Material.

In New Zealand, invasive species management is often devolved to local government authorities once eradication is declared infeasible. Consequently, invasive species management and investment decisions are often taken at the local government (region) level. One consequence of this localised approach is that pest management planning often does not consider the benefits of control measures for reducing or preventing spread across administrative boundaries. This is the case for CNG where the cost of containing extensive infestations in the Hawke's Bay Region threatens political support for control measures within this region. Abandonment of control measures may increase the risk of spread to neighbouring regions where CNG is not present. This is especially concerning for the Manawatū-Whanganui Region, where sheep and beef farming is a major contributor to the regional economy.

Simulation experiments

We chose a small set of simulation experiments to illustrate some of the questions that *INApest()* might address within the context of regional-scale CNG management responses:

1. **Validation:** Considering historic infestation data, do our dispersal kernels produce realistic spread rates under a zero-management scenario?

2. **Varying multiple management parameters under changing climates**: Which management parameters, and interactions between management parameters have the greatest influence on time integrated metrics of CNG invasion and management response success under changing climates?

3. **Cross border consequences of management decisions**: How do management decisions in a CNG source region (Hawke's Bay) affect management outcomes in a neighbouring region (Manawatū-Whanganui)?

4. **Effect of improved communication:** How much would warning farms that neighbour known CNG infestations about the threat of invasion improve management outcomes in the Manawatū-Whanganui region?

Setting up the scenarios

At-risk locations (nodes) were defined as sheep and non-dairy (beef) cattle farms listed in the land-use database Agribase (Sanson 2000) with suitable climates for the establishment of CNG. Climatic suitability was estimated through the eco climatic niche model CLIMEX (Sutherst 1985) presented by Bourdôt et al. (2012) for present day (2020) climate, and a future climate scenario –based on the moderate A1B scenario (IPCC 2000) for 2090. The eradication probability parameter was set at 0.048 and was derived from data on declines in seedbank density under glyphosate herbicide control of CNG infestation (Bourdôt and Hurrell 1992). Distances (in metres) between farms were recorded as the minimum Euclidean distance between farm boundaries. Separate dispersal probabilities were estimated for short-distance (self-mediated) and long-distance (human-mediated) dispersal processes. Additional information on obtaining scenario parameters is provided in the Supplementary Material.

Varying multiple management parameters under changing climates: Marlborough region

INApest() offers the potential to explore many (thousands, or even tens of thousands) management scenarios, which can be useful when realistic management options are poorly known, or in assessing the management settings required to achieve desired management outcomes. To explore this potential, we simulated CNG spread in the Marlborough region under current and future climates while varying multiple management parameters. In all scenarios the management probability parameter was set to 0.9, reflecting the high motivation of farmers to manage CNG infestations (Kaine and Wright 2022).

The other parameters varied and levels used were:

- communication probability (0, 0.025, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.5, 0.75) between neighbouring farms (<150 m apart), otherwise 0.
- detection probability (0.025, 0.05, 0.075, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4, 0.5, 0.75)
- eradication probability (0, 0.025, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.5, 0.75)
- spread reduction (0.05, 0.1, 0.3, 0.5, 0.9, 0.99, 0.999)

These analyses used the information spread option provided by *INApest()* by permitting information transfer from farms with known (i.e. detected) extant CNG infestations to neighbouring farms within a critical distance of 150 m, which reflects the upper limit of natural annual spread for CNG (Bourdôt 2010). The probability of farms within the critical distance of known infestations receiving information (i.e. potentially implementing management) was defined by the 'communication probability' parameter. This represents the probability that farms at risk of invasion receive and absorb information about CNG monitoring and management from biosecurity officers or the likelihood that owners of at-risk farms will permit biosecurity officers to monitor for CNG on their farms.

Invasive spread under each parameter combination and climate scenario was summarised as infested farm-years (expressed as a percentage of the maximum potential value). A value of 100 (maximum possible value) indicates that every farm was infested in every year of every realisation. We also recorded management success as a binary variable using the restriction of infested farm-years to <1% of the potential maximum value as our success criterion. This illustrates the potential for scenario analyses to reveal management strategies likely to achieve success against an objective success criterion.

To explore the relative effect of each management parameter and climate scenarios and interactions between them on invasive spread and management success we fitted extreme gradient boosted regression trees of invasive spread and management success against management parameters and climate change scenario (Chen and Guestrin 2016). Visualisation of outcomes for selected combinations of detection and communication probability under each climate scenario was also used to assess combinations of eradication and spread reduction values required to achieve management success.

Cross-border consequences of management decisions

This simulation experiment explored the impact of CNG management decisions in the Hawke's Bay region (which contains a widespread CNG infestation) on management outcomes in the currently non-infested Manawatū–Whanganui region under current and future (2090) climates. Two management scenarios were applied in the Hawke's Bay (detection probability of 0 or 0.2). Eradication probability was set at 0.049, spread reduction at 0.999 (reflecting the combined effect of seed production prevention and stringent hygiene measures), management probability at 0.9 and communication probability (to farms <150m from known extant infestations) at 0.25. Hawke's Bay simulation results were used to calculate invasion probabilities between individual Hawke's Bay and Manawatū–Whanganui farms. These were summarised to produce a matrix (farms x years) of annual cross-region invasion probabilities for Manawatū–Whanganui farms. These cross-region invasion

matrices were supplied as the "InvasionRisk" parameter to the *INApest()* function call to simulate invasions in the Manawatū–Whanganui region. Invasions were initiated through a random binomial process using values in the first column of the cross-region invasion matrix, and cross-region invasion probabilities were updated at each time step to reflect temporal changes in invasion risk from the Hawke's Bay region. In the Manawatū–Whanganui simulations detection probability values from 0 to 0.7 were analysed. All other management parameters were identical to those used in the Hawke's Bay simulations. For each combination of detection probability and climate scenarios, 100 separate simulation runs were performed. Infested farm years were calculated for each simulation at each level of detection probability and timeseries of invasions examined for a selected level of detection probability (0.05).

Effect of improved communication

This simulation experiment compared CNG invasive spread in the Manawatū–Whanganui region under scenarios with and without communication between farms about the threat of CNG invasion. In the scenarios including communication, information spread was permitted to farms within 150 m of known infestations and the annual communication probability parameter was set at 0.25. Cross-region invasion probabilities from Hawke's Bay to Manawatū-Whanganui farms (the InvasionRisk parameter in *INApest()* function calls) were derived from simulation in Hawke's Bay scenarios with detection probability = 0.2. All other management parameters were kept identical to those used in the previous simulation experiment. For each combination of detection probability and climate scenario, 100 separate simulation runs were performed. Infested farm years were estimated for each level of detection probability and timeseries of invasions examined for a selected level of detection probability (0.05).

Results

Validation against historic invasion

The CNG implementation of *INApest()* was validated against historic spread data from an initial infestation in the Blind River area of Marlborough, Northeastern South Island, New Zealand. The initial infestation used in simulations was taken from infestation map of Bourdôt and Hurrell (Bourdôt and Hurrell 1989). Two other historic data points were obtained from Bell (2006) who provided estimates of the number of pastoral properties infested in 2000 and 2005 (black-filled circles in **Figure 2**). Historic data points derived from Bell (2006) were well within the 95% confidence limits (across 100 separate runs) of the *INApest()* simulation results, and similar to the median values (with a difference of three infested farms for the first point and five for the second point, Figure 2). According to the model, under current climatic conditions and zero management CNG would invade, on average, over 150 farms after 80 years (roughly 2065) in the Marlborough

region, with the upper bound of the 95% confidence interval being over 200 infested farms. The increase in infested farms was linear, indicating the invasion did not approach an asymptote within the simulation period.

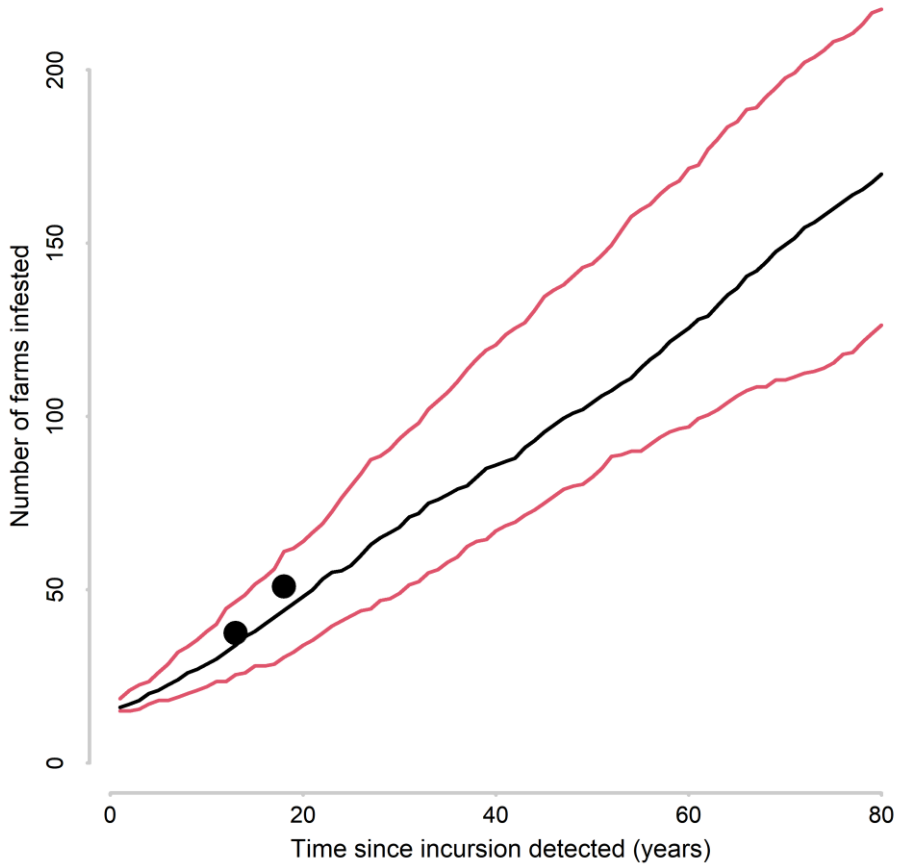


Figure 2: Median (black line) and 95% confidence limits (red lines) of number of nodes (i.e. sheep and beef farms) in the Marlborough region of New Zealand invaded by Chilean needle grass in *INApest()* simulations under current climatic conditions, with no management (i.e., detection prob. = 0) and with initially infested farms derived from Bourdôt and Hurrell (1989). Black filled circles are data points derived from Bell (2006).

Varying management parameters under changing climates: Marlborough region

Detection probability and eradication probability had by far the strongest influence both on invasion rates (infested farm years, expressed as a percentage of maximum potential value) and management success (probability of limiting invasion to <1% of maximum potential infested farm years) in XGBoost models (Table 1). Spread reduction and communication had a moderate influence with climate scenario being the least influential predictor. This indicates that, considering a very broad range of potential management parameters, efforts aimed at increasing detection probability and eradication are likely to provide the largest benefits in reducing CNG infestation rates in Marlborough.

The largest interaction effect for infestation rates was between eradication probability and spread reduction (Figure 3a). Increases in spread reduction greatly reduced invasion rates when eradication probability was less than 0.2, while eradication had a strong effect on invasion rates at all levels of spread reduction. There was a sizeable interaction between climate scenario and detection probability, with invasion rates being around 50% higher under the future (2090) climate scenario at the lowest levels of detection, while at higher levels of detection the effect of climate was minimal (Figure 3b).

The largest interaction effect for management success was between eradication and detection, with scenarios where both eradication and detection probability were greater than 0.25 giving the highest probability of success (Fig. 3c). There was also a sizeable interaction between detection probability and communication probability, with increases in communication greatly enhancing success probability when detection was less than 0.2 (Figure 3d).

Table 1: Relative influence of management variables and climate scenarios on CNG infested farm years and probability of management success (infested farm years <1% of the maximum potential value) in cross-validated XGBoost regression trees. Gain is the reduction in unexplained variance each time a predictor is used to make a new branch; Frequency is the proportion of times a predictor is used to make a new branch and Coverage is the proportion of observations involved in branches using the predictor. Values are means and 95% confidence intervals across 10 separate fold models, where different portions of the dataset are withheld for validation.

Infested farm years

Predictor	Gain	95% CI	Frequency	95% CI	Coverage	95% CI
Eradication	0.40	0.08	0.38	0.03	0.39	0.09
Detection	0.38	0.08	0.37	0.04	0.41	0.10
Spread reduction	0.11	0.04	0.09	0.04	0.10	0.05
Communication	0.09	0.04	0.13	0.04	0.08	0.02
Climate	0.03	0.02	0.03	0.03	0.02	0.00

Success probability

Predictor	Gain	95% CI	Frequency	95% CI	Coverage	95% CI
Eradication	0.46	0.00	0.28	0.00	0.32	0.00
Detection	0.35	0.00	0.28	0.00	0.27	0.00
Communication	0.09	0.00	0.23	0.00	0.19	0.00
Spread reduction	0.09	0.00	0.17	0.00	0.16	0.00
Climate	0.01	0.00	0.05	0.00	0.06	0.00

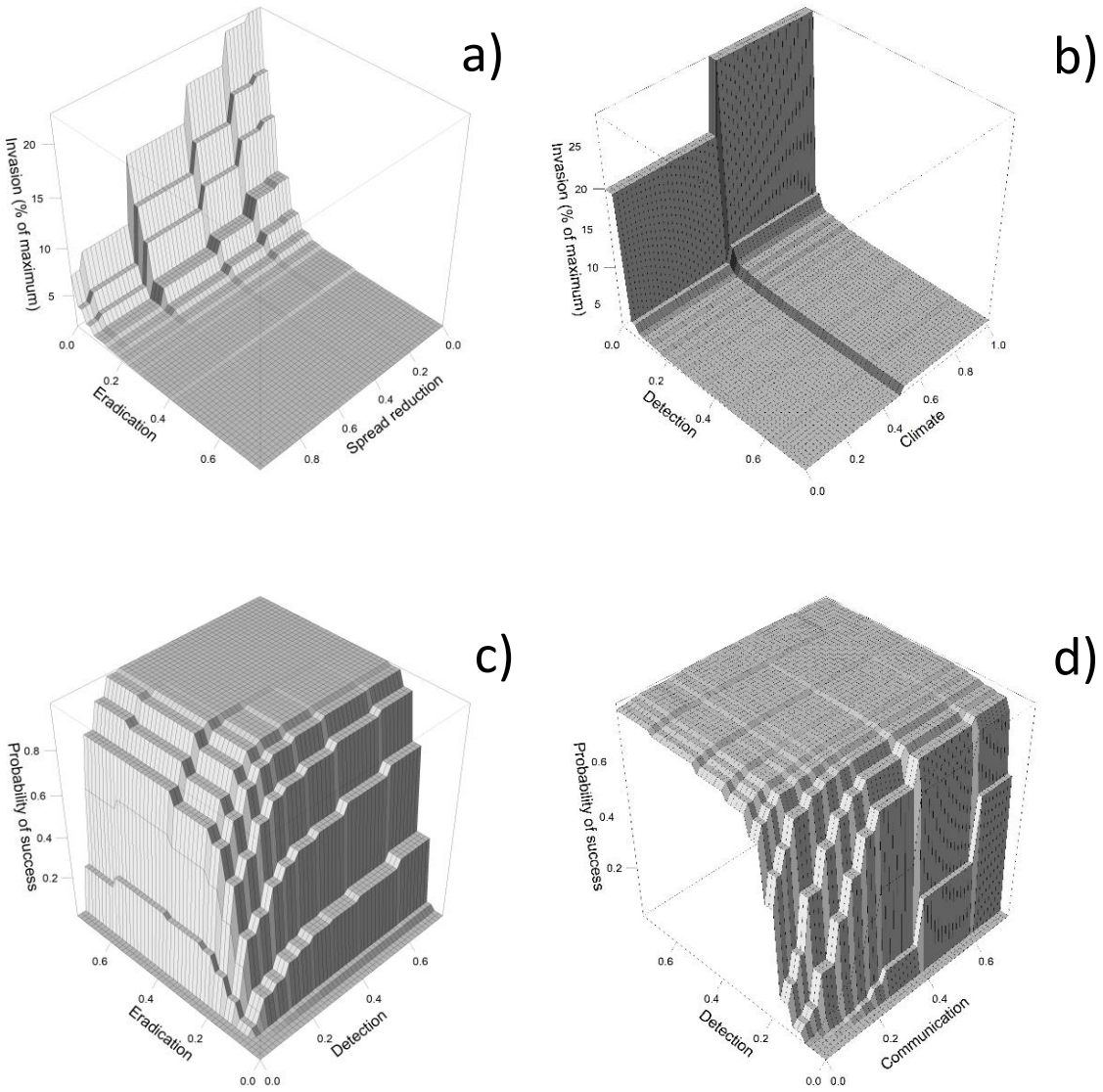


Figure 3: Perspective plot of interactions between predictor variables within the XGBoost models fitting variation in CNG invasion rates (a,b) and management success (c,d) to management parameters and climate. (a) Increases in spread reduction greatly reduced invasion rates when eradication probability was less than 0.2, while eradication has a strong effect on invasion rates at all levels of spread reductions. (b) invasion rates were about 10% higher under the 2090 climate scenario at the lowest levels of detection probability. (c) scenarios where both eradication and detection probability were greater than 0.25 gave the highest probability of success. (d) At the lowest levels of detection invasion rates were 50% higher under the future climate scenario.

Figure 4 presents contour plots of CNG invasion rates (infested farm years, expressed as a percentage of maximum potential value) with respect to eradication probability and spread

reduction for selected combinations of detection and communication probability under current and future climates. Irrespective of climate, no combination of eradication and spread reduction reduces invasion below the 1% containment threshold with zero communication and low detection probability (i.e., there are no aquamarine areas on contour plots, Fig 4a,e). Despite this, the invasion rate is much higher under future climate for this combination of detection and communication (i.e. more red, orange and yellow areas). Under both climate scenarios increasing communication at the lower level of detection greatly decreases invasion rates but does not aid in restricting invasions below the 1% containment threshold (compare Fig 4a,c and Fig 4e,g respectively). At high levels of detection under both climate scenarios (Fig 4b,d,f,h) the contour demarcating the <1% success criterion indicates that the eradication probability required to achieve success declines linearly with increasing spread reduction. This shows that the effectiveness of eradication methods required for success may be reduced if more stringent movement restrictions and hygiene measures are implemented. Finally, the addition of communication at high detection rates causes a ~25% reduction in the eradication rate required to achieve success under current climates across all levels of spread reduction and a ~30-50% reduction under future climates (compare Fig 4b,d and Fig 4f,h respectively).

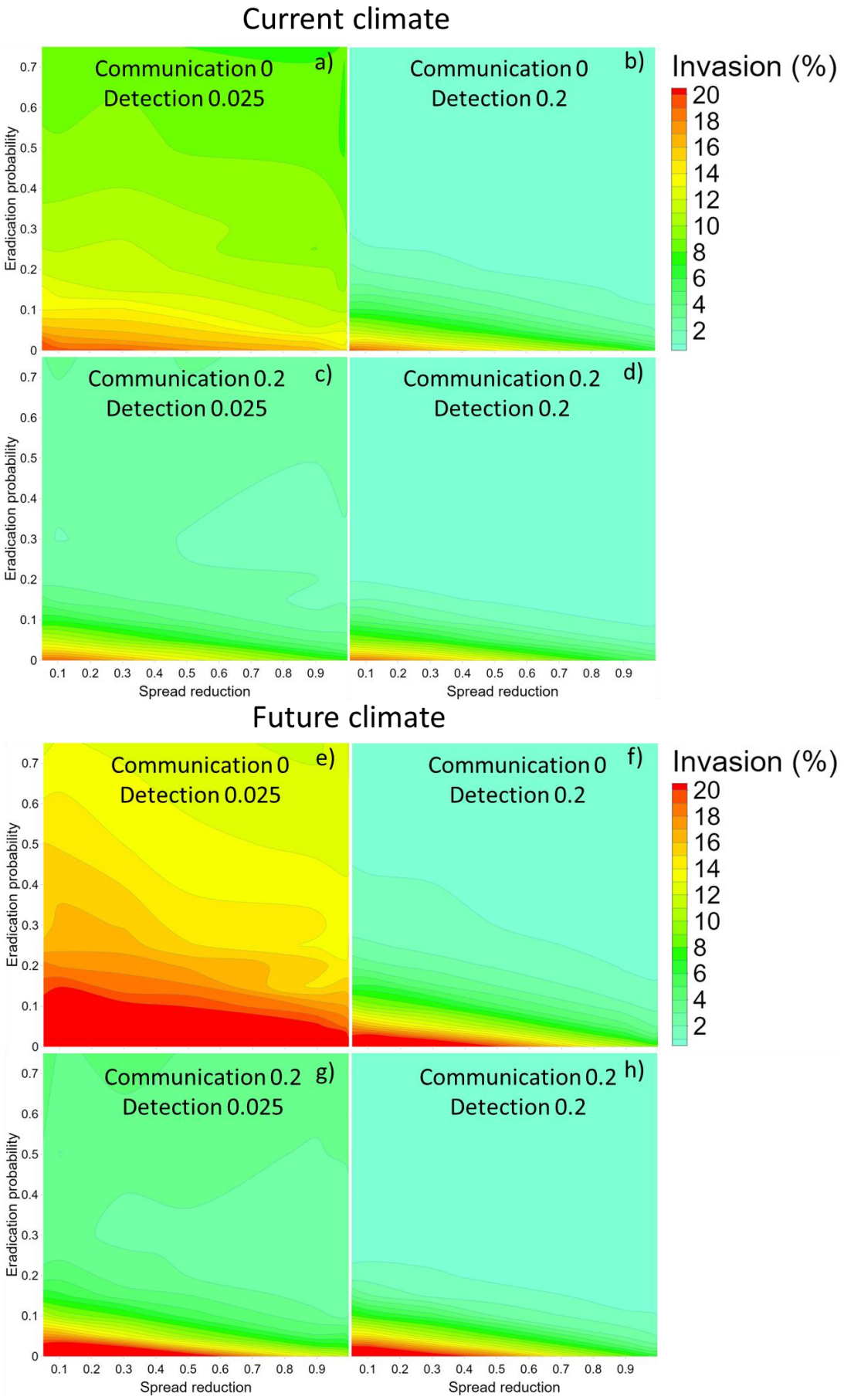

Current climate
Communication 0
Detection 0.025
a)
Communication 0
Detection 0.2
b)
Communication 0.2
Detection 0.025
c)
Communication 0.2
Detection 0.2
d)
Invasion (%)
20
18
16
14
12
10
8
6
4
2
Eradication probability
Spread reduction
Future climate
Communication 0
Detection 0.025
e)
Communication 0
Detection 0.2
f)
Communication 0.2
Detection 0.025
g)
Communication 0.2
Detection 0.2
h)

Figure 4: Contour plots of mean (across simulations) CNG infested farm years (expressed as a percentage of the maximum possible – all farms infested in every year of each simulation) from Chilean needle grass *INApest()* simulations in the Marlborough region under *current* (a-d) and *future* (e-h) climatic conditions. Areas covered by the lightest aquamarine shade indicate management success following the criterion that infested farm years are less than 1% of potential maximum. Each panel shows results for each combination of eradication probability and spread reduction given different levels of annual farm-level detection probability ("Detection") and annual communication probability to farms neighbouring known infestations ("Communication"). Spread reduction measures could relate to possible movement restrictions or hygiene strategies that reduce the likelihood of a farm exporting propagules. Given the seed bank longevity an eradication probability of 0.05 is considered realistic.

Cross-border consequences of management decisions

Implementing control of CNG populations in the source region (Hawkes Bay) greatly reduced the mean number of invasion events in the neighbouring non-infested region (Manawatū-Whanganui) under both climate scenarios (Fig 5a,b). Under the zero-management scenario in the source region, the number of invasion events increased with time to just under 15 per year under current climate and 40 per year under future climate. At the end of the simulation period (80 years) almost all farms in the non-infested region had a less than 1 in 100, 000 annual chance of invasion from the source region under current climate and with management of populations in the source region (Fig 5c). Meanwhile, under future climates most farms in the eastern portion of the non-infested region (i.e. closest to the source region) had at least a 1 in 10, 000 annual chance of invasion (Fig. 5d). With zero management of source populations and under current climate almost the entire non-infested region had at least a 1 in 1000 annual chance of invasion (Fig. 5e). Similarly, under zero management at the source, and under the future climate scenario many farms in the eastern portion of the non-infested region have at least a 1 in 100 annual chance of invasion (Fig. 5f).

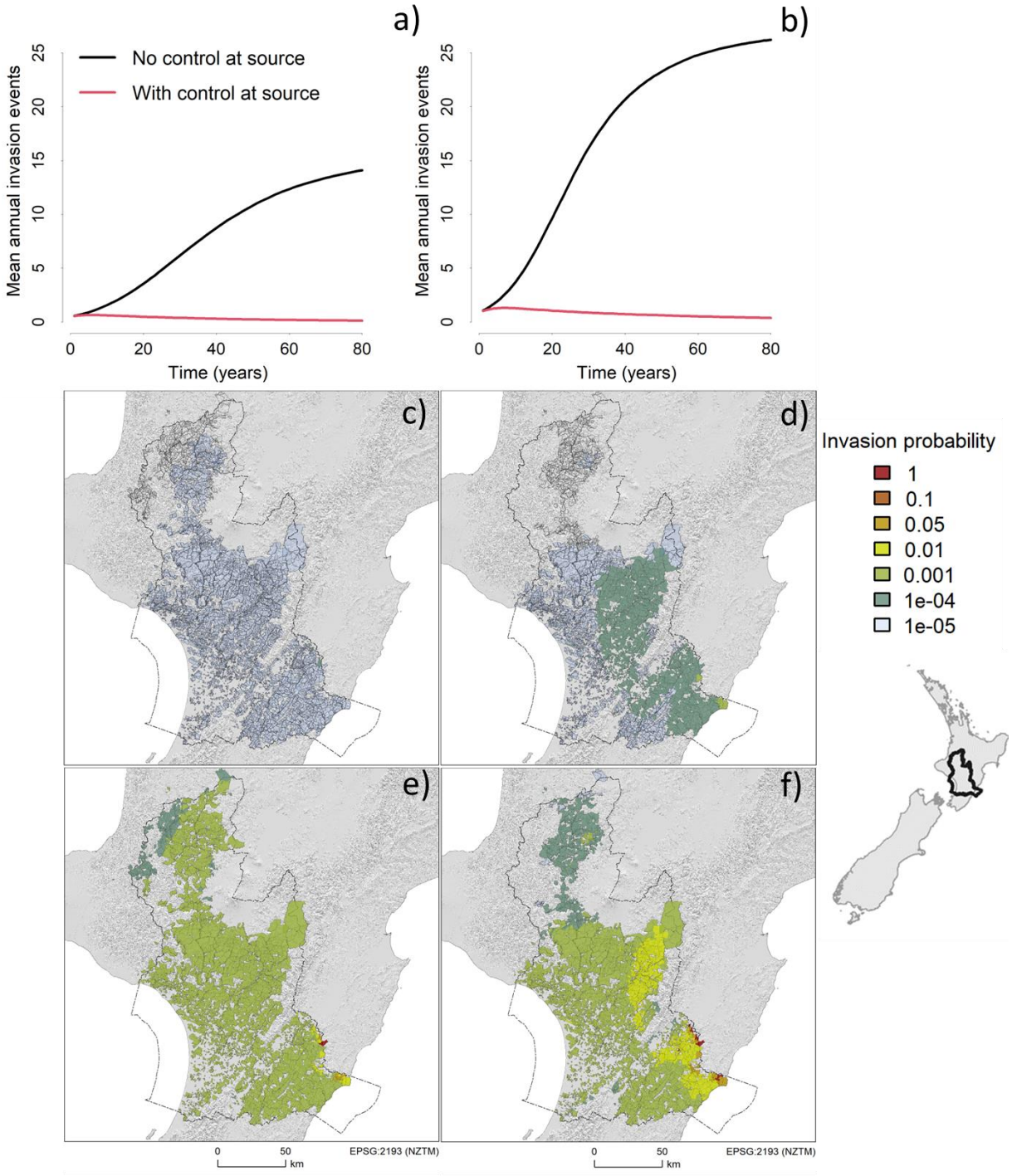


Figure 5: Timeseries of mean annual invasion events from source populations of CNG in the Hawke's Bay region to the Manawatū-Whanganui region of New Zealand under current (a) and future (b) climate and maps of individual farm annual invasion probability at the end of the simulation period (c-f). Red and black lines in a and b indicate, respectively, results from scenarios where management either is ("With control at source", detection probability = 0.2) or is not ("No control at source", detection probability = 0) applied to infested farms in the source region. Invasion heat maps at the end of the simulation period under current climate for the "With control at source" and "No control

at source" scenarios are presented in c and e respectively. Corresponding maps for future climate are presented in d and f.

Absence of management in the source region greatly reduced management efficacy (i.e. caused higher infestation rates) in the non-infested region at all levels of detection probability, and this effect is exacerbated under future climatic conditions (Fig. 6); here results are expressed in terms of farm-years infested – a time integrative measure of impact. Absence of management causes an excess of between 12,000 and 25,000 infested farm years under current climate (for non-zero detection probabilities) and an excess of 25,000 to 30,000 under future climate. This demonstrates that even under intensive management regimes (high detection probability) in the currently non-infested region, lack of management in the source region leads to higher rates of infestation in the neighbouring (currently non-infested) region.

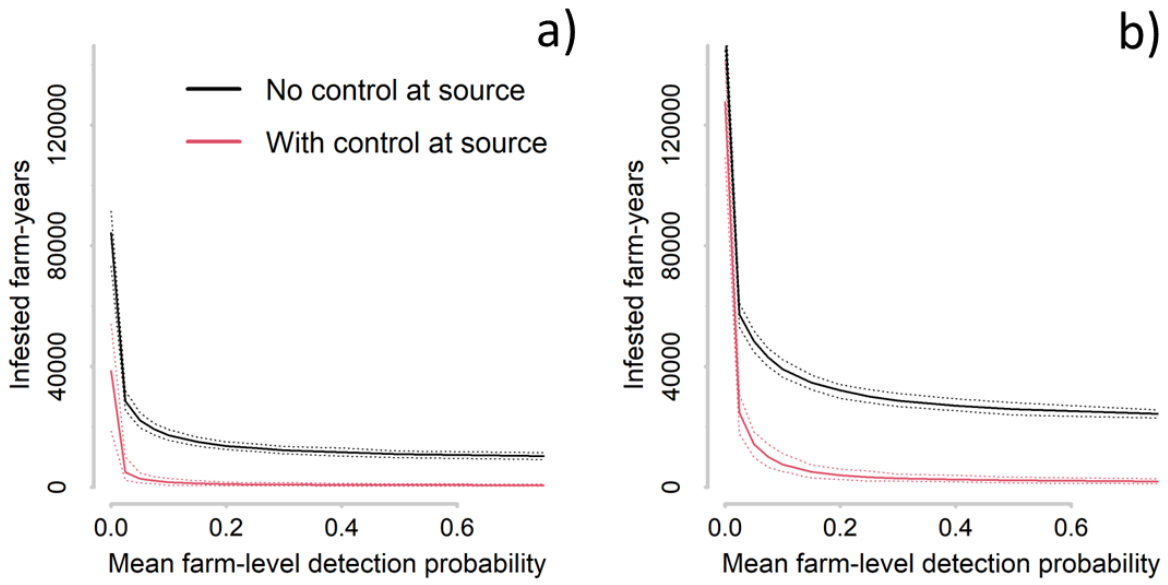


Figure 6: Infested farm years (the mean sum of infested farms across all years of individual simulation runs), under current (a) and future climatic conditions (b) in CNG *INApest()* simulations with differing farm-level mean annual detection probabilities for the Manawatū–Whanganui region of New Zealand under current and future climate. Initial invasions were derived through random selection weighted by invasion probability from infested farms (as of 2021) in the Hawke's Bay region and simulations incorporated ongoing invasion derived from *INApest()* simulations in the Hawke's Bay region where management either is ("With control at source", detection probability = 0.2, red lines) or is not ("No control at source", detection probability = 0, black lines) applied to infested farms in the source region. Solid lines indicate median values, and dashed lines indicate 95% confidence bounds (across individual simulation runs).

Results for a single level of detection probability (0.05) in Manawatū-Whanganui reveal how the impacts of management decisions in Hawke's Bay develop over time (Figure 7a,b) with respect to the number of farms infested. Under both climate scenarios, the absence of management in Hawke's Bay leads to the number of infested farms reaching a persistently high plateau relative to scenarios where CNG control is implemented in Hawke's Bay. By the end of the simulation period (80 years), absence of management in the Hawke's Bay produced an excess of around 500 farms infested annually under current climate and around 700 under future climate. Maps of individual farm-level invasion probability (i.e. proportion of simulations in which a farm is infested at a given timestep) in Manawatū-Whanganui at the end of the simulation period under current climate (Figure 7c,e) reveal a region-wide increase in invasion rates in the absence of CNG management in the Hawke's Bay region, relative to adoption of control in Hawke's Bay. There was evidence of very high (>0.7, i.e. infested in >70% of simulations) infestation probability in farms bordering Hawke's Bay (on the south-eastern edge, Fig 7e) and throughout most of Manawatū-Whanganui region farm-level invasion probability increased to between 0.1 and 0.3 (i.e. farms were infested in 10-30% of simulations). The spatial pattern of results was very similar under future climate (Fig 7d,f), the main difference being that invasion probability was between 0.3 and 0.5 for most farms in the absence of management in Hawke's Bay. The maps also indicate reduced invasion probability under future climate in the extreme north of Manawatū-Whanganui (compare Fig 7c,d and 7e,f respectively), indicating that future climates may be less favourable to CNG invasion in this area.

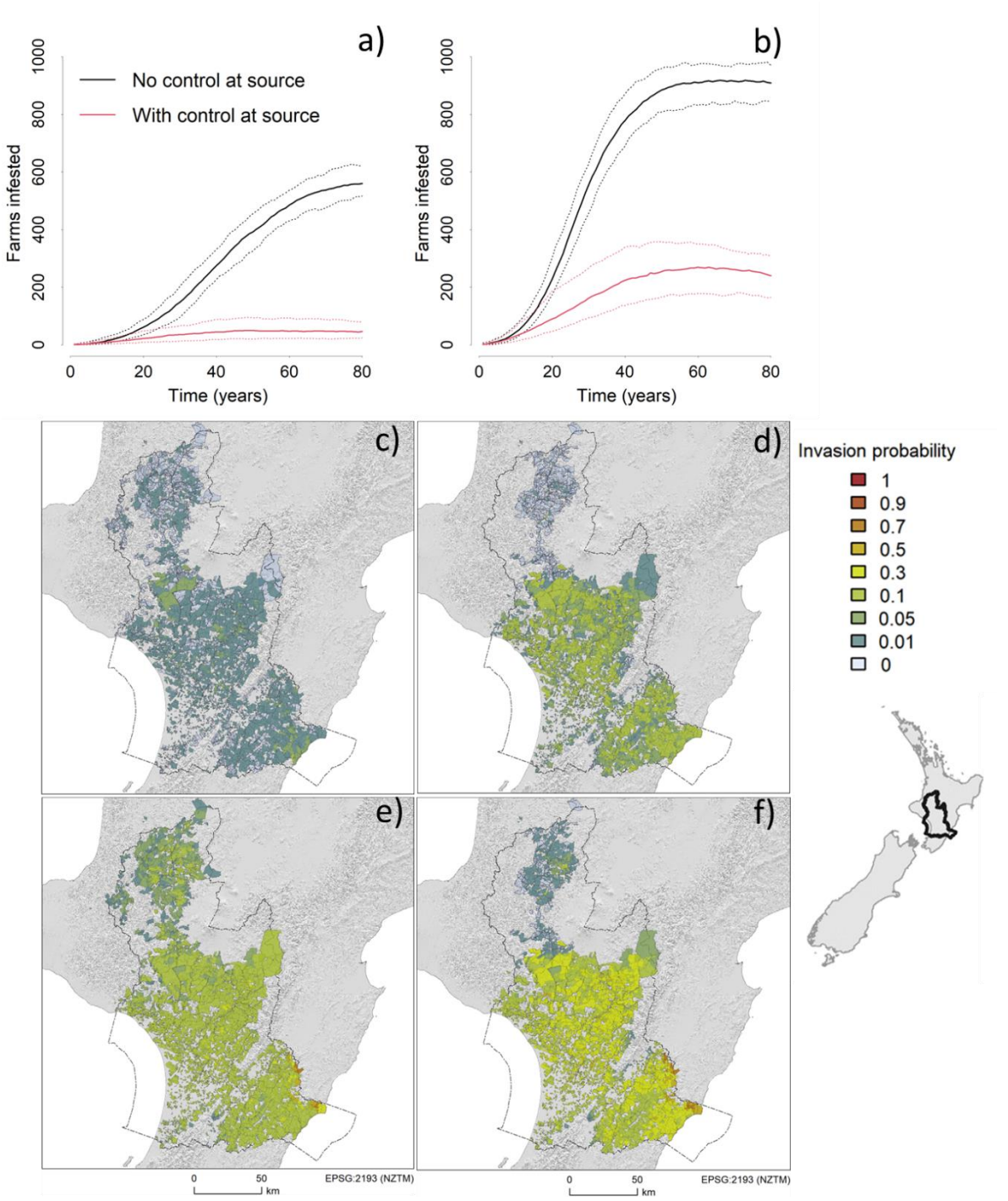


Figure 7: Timeseries of infested farms under a moderate management scenario (annual farm-level detection probability = 0.05) in the Manawatū-Whanganui region incorporating invasion risk from source populations in the Hawke's Bay region under current (a) and future (b) climate and maps of individual farm invasion probability (proportion of simulations in which a farm is infested) at the end of the simulation period (c-f). Red and black lines in a and b indicate, respectively, results from scenarios where management either is ("With control at source", detection probability = 0.2) or is not ("No control at source", detection probability = 0) applied to infested farms in the source region

(Hawke's Bay). Solid lines indicate median values and dashed lines indicate 95% confidence bounds (across individual simulation runs). Invasion heat maps at the end of the simulation period under current climate for the "With control at source" and "No control at source" scenarios are presented in c and e respectively. Corresponding maps for future climate are presented in d and f.

Effect of improved communication

Figure 8 illustrates how climate change, communication and detection probability interact. Results from simulations in the Manawatū–Whanganui region for hypothetical invasions from the Hawke's Bay show that at low-to-moderate levels of detection probability the addition of communication between neighbouring farms reduces CNG infestation rates (Figure 8a,b). This effect is much more apparent under future climatic conditions (compare Figure 8a and 8b). Results for a single level of detection probability (0.05) emphasise the increased benefit of between-farm communication under future climatic conditions (compare Fig 8c and 8d). Adding between-farm communication results in 250 fewer farms infested annually by the end of the simulation period under current climate, and 1, 500 fewer farms infested under future climate. Maps of individual farm invasion probability at the end of the simulation period reveal that when communication between neighbouring farms occurs under current climatic conditions most farms are very unlikely to be infested (invasion probability < 0.05, Figure 8e). By contrast, in the absence of between-farm communication and under future climatic conditions, most farms are very likely to be infested by CNG (invasion probability > 0.7, see the dark orange- and red-shaded areas in the Figure 8h). These results indicate that enhancing communication between farms will be increasingly important in limiting the spread and impacts of future CNG incursions in the Manawatū–Whanganui region under future climates.

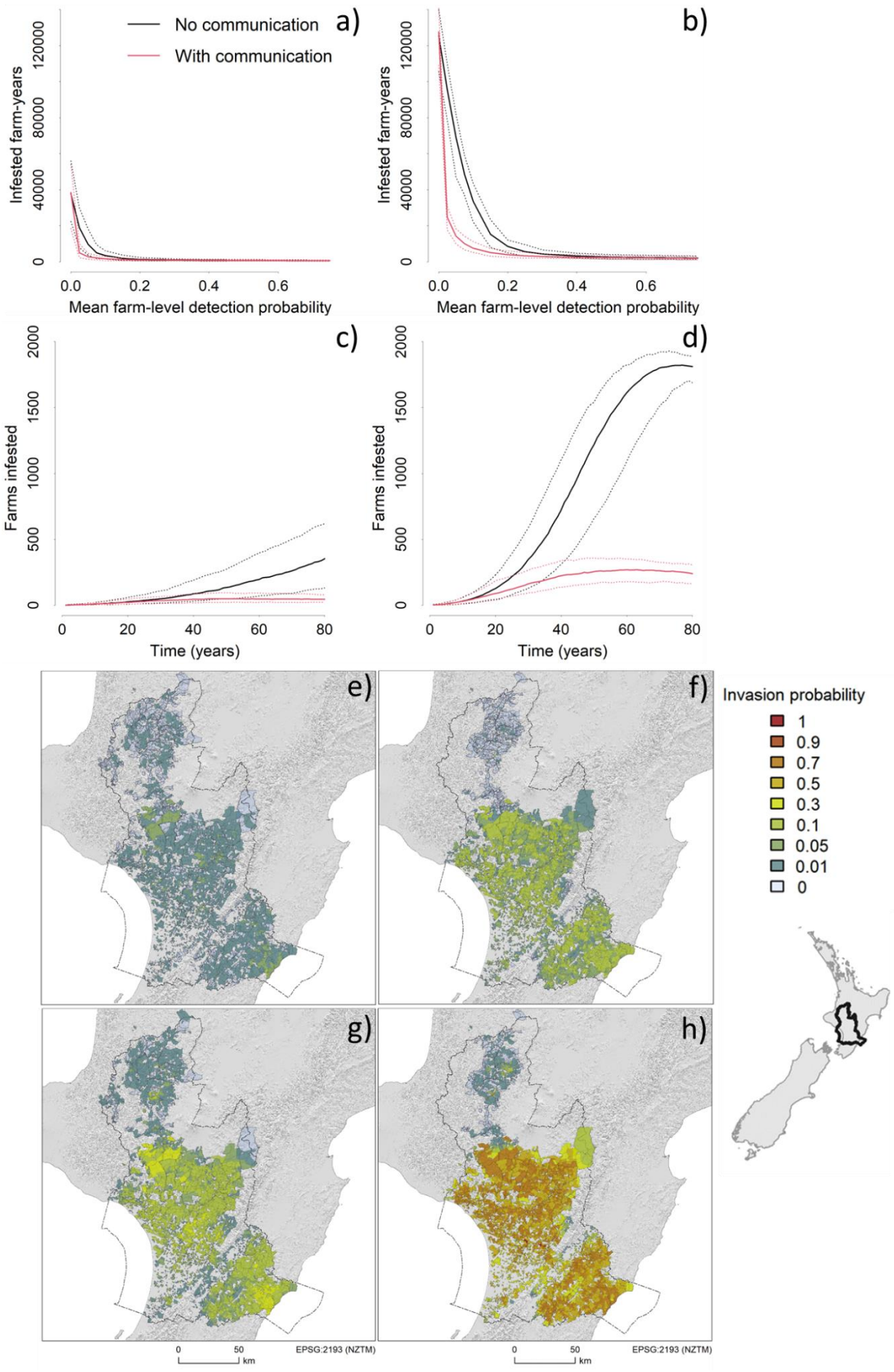

a)
No communication
With communication
Infested farm-years
0
40000
80000
120000
0.0
0.2
0.4
0.6
Mean farm-level detection probability
b)
Infested farm-years
0
40000
80000
120000
0.0
0.2
0.4
0.6
Mean farm-level detection probability
c)
Farms infested
0
500
1000
1500
2000
0
20
40
60
80
Time (years)
d)
Farms infested
0
500
1000
1500
2000
0
20
40
60
80
Time (years)
e)
f)
g)
h)
Invasion probability
1
0.9
0.7
0.5
0.3
0.1
0.05
0.01
0
0
50
km
EPSG:2193 (NZTM)
0
50
km
EPSG:2193 (NZTM)

Figure 8: Infested farm years (the mean sum of infested farms across all years across individual simulation runs) for multiple mean farm-level detection probabilities under current (a) and future (b) climates for the Manawatū-Whanganui region. Red and black lines indicate, respectively, results from scenarios where farms near known infestations either are or are not warned by of potential invasion ('With communication', or ' No communication'). Time series of infested farms for a single level of detection probability level (0.05) under current (c) and future (d) climates for either communication scenario and maps of Chilean needle grass invasion probability (across separate simulation runs) of individual farms after 80 years where farms near known infestations either are (e,f) or are not (g,h) warned of potential invasion and under current (e,g) and future (f,h) climatic conditions.

Discussion

In this study we present a method for pest management scenario analysis using simple matrix operations to integrate global change and social factors into models of pest spread and management. This method successfully reproduces historic invasion patterns and enables the exploration of numerous parameter combinations. These simulations demonstrate the potential for this method to reveal which variables most strongly reduce pest spread and enhance management success. Additionally, they help identify the effect of interactions between variables and the parameter combinations that maximize the success of management responses.

Our simulations also demonstrate the potential for our novel method to permit the design of targeted experiments to address specific issues, such as the impact of local management decisions on invasions across political boundaries and how improved communication within social networks might enhance pest management outcomes. While the experiments in this study cover only a small subset of possible questions, they demonstrate the potential of these simple, but flexible, simulation tools.

In the following sections, we discuss the broader implications of our results for using simulation-based scenario analyses in pest management planning and prioritization. We also highlight key functionalities of our proposed tools that were not explored in the current experiments.

Matrix-driven simulation models for multidimensional pest scenario exploration

We analysed over 15,000 scenarios of CNG invasion in the Marlborough region, examining the effects of management effectiveness (detection, eradication, and spread reduction), social factors (management adoption and information dissemination), climate change, and their interactions on invasive spread and management success. While previous studies (Jeger et al. 2007, Pautasso et al.

2010b, Buddenhagen et al. 2017, Andersen et al. 2019, Garrett 2021) have shown the potential of simulation-based scenario methods for exploring pest management, our study is the first to integrate global change, social factors, and multiple management parameters into pest management outcomes using simple matrix-driven simulation models. Our new method, combined with flexible statistical tools like gradient boosted regression trees, offers unprecedented predictive power for understanding how interactions between various factors can influence pest management outcomes. A key strength of this approach is its ability to identify the specific combinations of management parameters that are most likely to lead to success. By revealing how the likelihood of success varies across the full range of factors that biosecurity planners must consider, this method can help overcome the barriers to using objective scenario analyses in pest response prioritization and planning.

Cross-border consequences of management actions

Improving coordination between jurisdictions has been highlighted as a key strategy to mitigate the spread and impacts of pests (Pluess et al. 2012, IPBES 2023), particularly in the wake of climate change and pest range shifts (Walther et al. 2009). This includes more cohesive regional, national and international policy and regulations and developing risk assessments that include the effect of policy, the public and relevant industries on pest spread (IPBES 2023, Maher et al. 2024). However, cross-border considerations and coordination are often lacking in weed risk assessments (Beaury et al. 2021, Maher et al. 2024) resulting in disjointed efforts in monitoring and controlling problematic weeds and identifying their impacts on neighbouring regions (Bourdôt and Buddenhagen 2023). For CNG invasions, *INApest()* simulations revealed a hundredfold increase in the annual chance of a farm in the non-infested Manawatu-Whanganui region being invaded by CNG when no management is enacted in the infested Hawke's Bay, under both current and future climate scenarios. This highlights the potential for *INApest()* to reveal the impacts of poor coordination in pest management across jurisdictions.

INApest() has potential applications for strengthening cross-border weed management. At a regional or national scale, *INApest()* can be incorporated into planning of border and early post-border responses for changing trade patterns, such as increases in the number of imported and exported products and resources, and changes in import source countries and regions. This is particularly relevant for managing and monitoring pests and their dispersal pathways, as escape from horticulture and agriculture are among the most important pathways contributing to pest introductions (Buddenhagen et al. 2021, McGrannachan et al. 2021). At a local level, the network simulation model can be incorporated with decision-support tools to advise farmers of the

management implications and solutions for pest infestations, and the risk these infestations impose on their own and neighbouring properties (Bagavathiannan et al. 2020). This could be particularly beneficial for farm properties that border other regional jurisdictions with different weed regulations, to help raise awareness and foster cross-border management action with neighbouring farm owners. Increasing frequency and intensity of major disturbance events such as flooding predicted with climate change (Ministry for the Environment 2018, Bodeker et al. 2022) has the capacity to increase the risk of cross-border weed infestations. *INApest()* could be useful in predicting the risk of cross-border weed spread from such disturbance events under different management scenarios, as has been shown with flooding events during Cyclone Gabrielle in Hawkes Bay (Buddenhagen et al. 2024).

Benefits of improved communication

Model simulations using *INApest()* have demonstrated the potential importance of information dissemination between neighbouring properties in reducing pest spread, particularly under the threat of future climate change. In *INApest()* communication of the threat of invasion increases pre-emptive management adoption by landowners neighbouring known infestations. Pre-emptive management is critical to the success of pest management responses by increasing early detection and eradication of new infestations and reducing spread from existing infestations, hence reducing medium-to-long term control costs (Epanchin-Niell and Hastings 2010, Diagne et al. 2021), and impacts on production of affected industries (Saunders et al. 2017). Our simulation results, along with existing literature emphasise the importance of including processes that affect pre-emptive management in methods for simulating pest management responses.

Enhanced communication between landowners can benefit pest management outcomes via other processes, such as increased preparedness and capacity of neighbouring landowners to deal with new and spreading infestations, including through increased cooperation and coordination of control efforts, or through the sharing of control costs (Gass et al. 2009). Enhanced communication between landowners may also promote the socialisation of best management practices (Wilson et al. 2009), although communication may also influence some landowners to adopt less expensive and less effective practices in hopes of reducing overall costs (Etherton et al. 2023). Lastly, sustained communication between landowners builds trust and cohesion within communities, leading to better cooperation, coordination and outcomes when responding to current (Schelhas et al. 2021) and possibly future pest threats.

Unexplored potential of matrix-based simulation methods

The generalised simulation processes and flexibility in input parameter definition provided by simulation methods such as *INApest()* offer a much broader range of scenario analyses than can be demonstrated in a single study. Unexplored functionality includes the ability to: incorporate spatiotemporal variation in habitat suitability, management parameters and pest invasive biology; include different node types (e.g. livestock sale yards and pastoral farms in the context of CNG spread by livestock transport) in socioecological networks; examine the effect of social network structure on the spread of information about pest threats; compare strategies for increasing awareness about pest threats and management though information sources external to social networks (e.g., media, social media and extension officers; Garrett et al. 2018, Garrett 2021).

This flexibility makes *INApest()* well-suited to sit within highly integrative biosecurity planning systems such as the "One Biosecurity" framework (Hulme et al. 2023). *INApest()* is able to incorporate information provided by rapid pest spread model parameterisation frameworks (e.g., IBRAM; Jamieson et al. 2022) and complex natural dispersal processes such as directional spread (e.g. upstream to downstream or with prevailing wind; Planchuelo et al. 2016)) or through biotic dispersal vectors (e.g. fruit-eating birds). It can also incorporate detailed information on human, livestock or other transport movements (Mason et al. 2021) and transport networks (Seebens et al. 2019, Rocabert et al. 2024) which influence human-aided pest dispersal.

Impact assessment has been highlighted as an important, often neglected aspect of pest simulation frameworks (Hulme et al. 2023). The outputs provided by *INApest()*, by tracking invasion and management status of individual farms in individual years permit estimation of impacts including management costs, decreases in agricultural production, biodiversity and social or cultural ecosystem values.

While *INApest()* does not explicitly include local population dynamics (rate of increase, carrying capacity and propagule production) in modelling spread or impacts, these can be included in calculating dispersal probabilities contained within adjacent matrices. A separate function - *INApestMeta()*[1] - is available which demonstrates that it is possible to implement a metapopulation model tracking local populations and propagule production within a simulation framework that retains all the functionality provided by *INApest(),* which has been parameterised for the invertebrate pest *Tetranychus evansi* (tomato red spider mite) in New Zealand. The ability to model local populations and propagule production may be particularly important where pest reproduction

[1] https://github.com/manaakiwhenua/SleeperPests/blob/main/INApest%20INapestMeta%20core%20function%20code/INApestMeta.r

rates vary considerably (e.g. terrestrial arthropods, Hulme 2017)and where impacts and dispersal are strongly influenced by local population density. Collectively, *INApest()* and *INApestMeta()* provide flexibility to adapt scenario analyses to the level of information available on pest invasive ecology.

Conclusion

Integrating global change and social factors in realistically complex management frameworks may overcome barriers to use of scenario analyses in pest response prioritisation and planning. Our approach to invasive species scenario analysis provides users with a means to understand the levers that managers can pull and how they might interact to influence the success of pest management responses.

References

Adiga A, Palmer N, Baek YY, Mortveit H, Ravi SS (2022) Network models and simulation analytics for multi-scale dynamics of biological invasions. Frontiers in Big Data 5: 796897. https://doi.org/10.3389/fdata.2022.796897

Andersen KF, Buddenhagen CE, Rachkara P, Gibson R, Kalule S, Phillips D, Garrett KA (2019) Modeling epidemics in seed systems and landscapes to guide management strategies: the case of sweet potato in northern Uganda. Phytopathology® 109: 1519–1532. https://doi.org/10.1094/PHYTO-03-18-0072-R

Bagavathiannan MV, Beckie HJ, Chantre GR, Gonzalez-Andujar JL, Leon RG, Neve P, Poggio SL, Schutte BJ, Somerville GJ, Werle R, Acker RV (2020) Simulation models on the ecology and management of arable weeds: Structure, quantitative insights, and applications. Agronomy 10: 1611. https://doi.org/10.3390/agronomy10101611

Beaury EM, Fusco EJ, Allen JM, Bradley BA (2021) Plant regulatory lists in the United States are reactive and inconsistent. Journal of Applied Ecology 58: 1957–1966. https://doi.org/10.1111/1365-2664.13934

Behr DM, Ozgul A, Cozzi G (2017) Combining human acceptance and habitat suitability in a unified socio-ecological suitability model: a case study of the wolf in Switzerland. Durant S (Ed.). Journal of Applied Ecology 54: 1919–1929. https://doi.org/10.1111/1365-2664.12880

Bell M (2006) Spread of Chilean needle grass (*Nassella neesiana*) in Marlborough New Zealand. New Zealand Plant Protection 59: 266–270. https://doi.org/10.30843/nzpp.2006.59.4417

Bodeker G, Tait A, Morgenstern O, Noone D, Revell L, McDonald A, Cullen N, Renwick J, Katurji M (2022) Aotearoa New Zealand climate change projections guidance: interpreting the latest IPCC WG1 report findings. MInistry for the Environment, Wellington, New Zealand, 51pp.

Bourdôt G (2010) Chilean needle grass (*Nassella neesiana*) – a review of the scientific and technical literature. AgResearch Ltd., Lincoln, New Zealand. Report to the Chilean Needle Grass Action Group, 18pp.

Bourdôt G, Basse B, Kriticos D, Dodd M (2015) Cost-benefit analysis blueprint for regional weed management: *Nassella neesiana* (Chilean needle grass) as a case study. New Zealand Journal of Agricultural Research 58: 325–338. https://doi.org/10.1080/00288233.2015.1037460

Bourdôt GW, Hurrell GA (1989) Cover of *Stipa neesiana* Trin. & Rupr. (Chilean needle grass) on agricultural and pastoral land near Lake Grassmere, Marlborough. New Zealand Journal of Botany 27: 415–420. https://doi.org/10.1080/0028825X.1989.10414122

Bourdôt GW, Hurrell GA (1992) Aspects of the ecology of *Stipa neesiana* Trin. & Rupr. seeds. New Zealand Journal of Agricultural Research 35: 101–108. https://doi.org/10.1080/00288233.1992.10417707

Bourdôt GW, Buddenhagen CE (2023) The cost of doing nothing about a sleeper weed–Nassella neesiana in New Zealand. Chu L (Ed.). PLOS ONE 18: e0295574. https://doi.org/10.1371/journal.pone.0295574

Bourdôt GW, Lamoureaux SL, Kriticos DJ, Watt MS, Brown M (2010) Current and potential distributions of *Nassella neesiana* (Chilean needle grass) in Australia and New Zealand. In: Australasian Weeds Conference. Council of Australasian Weed Societies, Christchurch Convention Centre, Christchurch, New Zealand, 424–427.

Bourdôt GW, Lamoureaux SL, Watt MS, Manning LK, Kriticos DJ (2012) The potential global distribution of the invasive weed *Nassella neesiana* under current and future climates. Biological Invasions 14: 1545–1556. https://doi.org/10.1007/s10530-010-9905-6

Buddenhagen CE, Tye A (2015) Lessons from successful plant eradications in Galapagos: commitment is crucial. Biological Invasions 17: 2893–2912. https://doi.org/10.1007/s10530-015-0919-y

Buddenhagen CE, Bourdot G, Mason N (2024) Chilean needle grass: Impacts of Cyclone Gabrielle on Chilean needle grass dispersal and distribution. AgResearch, 15pp. Available from: https://doi.org/10.57935/AGR.26018665.v1 (December 18, 2024).

Buddenhagen CE, Rubenstein JM, Hampton JG, Rolston MP (2021) The phytosanitary risks posed by seeds for sowing trade networks. Uludag A (Ed.). PLOS ONE 16: e0259912. https://doi.org/10.1371/journal.pone.0259912

Buddenhagen CE, Hernandez Nopsa JF, Andersen KF, Andrade-Piedra J, Forbes GA, Kromann P, Thomas-Sharma S, Useche P, Garrett KA (2017) Epidemic network analysis for mitigation of invasive pathogens in seed systems: Potato in Ecuador. Phytopathology® 107: 1209–1218. https://doi.org/10.1094/PHYTO-03-17-0108-FI

Capinha C, Essl F, Porto M, Seebens H (2023) The worldwide networks of spread of recorded alien species. Proceedings of the National Academy of Sciences 120: e2201911120. https://doi.org/10.1073/pnas.2201911120

Chapman D, Purse BV, Roy HE, Bullock JM (2017) Global trade networks determine the distribution of invasive non-native species. Global Ecology and Biogeography 26: 907–917. https://doi.org/10.1111/geb.12599

Chen T, Guestrin C (2016) XGBoost: A scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. San Francisco, California, USA, 785–794.

Connor HE, Edgar E, Bourdôt GW (1993) Ecology and distribution of naturalised species of *Stipa* in New Zealand. New Zealand Journal of Agricultural Research 36: 301–307. https://doi.org/10.1080/00288233.1993.10417727

Cope RC, Ross JV, Wittmann TA, Watts MJ, Cassey P (2019) Predicting the risk of biological invasions using environmental similarity and transport network connectedness. Risk Analysis 39: 35–53. https://doi.org/10.1111/risa.12870

Diagne C, Leroy B, Vaissière A-C, Gozlan RE, Roiz D, Jarić I, Salles J-M, Bradshaw CJA, Courchamp F (2021) High and rising economic costs of biological invasions worldwide. Nature 592: 571–576. https://doi.org/10.1038/s41586-021-03405-6

Epanchin-Niell RS, Hastings A (2010) Controlling established invaders: integrating economics and spread dynamics to determine optimal management. Ecology Letters 13: 528–541. https://doi.org/10.1111/j.1461-0248.2010.01440.x

Etherton BA, Plex Sulá AI, Mouafo-Tchinda RA, Kakuhenzire R, Kassaye HA, Asfaw F, Kosmakos VS, McCoy RW, Xing Y, Yao J, Sharma K, Garrett KA (2025) Translating Ethiopian potato seed networks: Identifying strategic intervention points for managing bacterial wilt and other diseases. Agricultural Systems 222: 104167. https://doi.org/10.1016/j.agsy.2024.104167

Etherton BA, Choudhury RA, Alcalá-Briseño RI, Xing Y, Plex Sulá AI, Carrillo D, Wasielewski J, Stelinski LL, Grogan KA, Ballen F, Blare T, Crane J, Garrett KA (2023) Are avocados toast? A framework to analyze decision-making for emerging epidemics, applied to laurel wilt. Agricultural Systems 206: 103615. https://doi.org/10.1016/j.agsy.2023.103615

Ferrari JR, Preisser EL, Fitzpatrick MC (2014) Modeling the spread of invasive species using dynamic network models. Biological Invasions 16: 949–960. https://doi.org/10.1007/s10530-013-0552-6

Friedman JH, Popescu BE (2008) Predictive learning via rule ensembles. The Annals of Applied Statistics 2. https://doi.org/10.1214/07-AOAS148

Frost CM, Allen WJ, Courchamp F, Jeschke JM, Saul W-C, Wardle DA (2019) Using network theory to understand and predict biological invasions. Trends in Ecology & Evolution: S016953471930134X. https://doi.org/10.1016/j.tree.2019.04.012

Gallien L, Münkemüller T, Albert CH, Boulangeat I, Thuiller W (2010) Predicting potential distributions of invasive species: where to go from here? Diversity and Distributions 16: 331–342. https://doi.org/10.1111/j.1472-4642.2010.00652.x

Gardener MR, Whalley RDB, Sindel BM (2003a) Ecology of *Nassella neesiana*, Chilean needle grass, in pastures on the Northern Tablelands of New South Wales. I. Seed production and dispersal. Australian Journal of Agricultural Research 54: 613. https://doi.org/10.1071/AR01075

Gardener MR, Whalley RDB, Sindel BM (2003b) Ecology of *Nassella neesiana*, Chilean needle grass, in pastures on the Northern Tablelands of New South Wales. II. Seedbank dynamics, seed germination, and seedling recruitment. Australian Journal of Agricultural Research 54: 621. https://doi.org/10.1071/AR01076

Garrett KA (2021) Impact network analysis and the INA R package: Decision support for regional management interventions. Methods in Ecology and Evolution 12: 1634–1647. https://doi.org/10.1111/2041-210X.13655

Garrett KA, Alcalá-Briseño RI, Andersen KF, Buddenhagen CE, Choudhury RA, Fulton JC, Hernandez Nopsa JF, Poudel R, Xing Y (2018) Network analysis: A systems framework to address grand challenges in plant pathology. Annual Review of Phytopathology 56: 559–580. https://doi.org/10.1146/annurev-phyto-080516-035326

Green DG (2023) Emergence in complex networks of simple agents. Journal of Economic Interaction and Coordination 18: 419–462. https://doi.org/10.1007/s11403-023-00385-w

Greenwell B M (2017) pdp: an R package for constructing partial dependence plots. The R Journal 9: 421. https://doi.org/10.32614/RJ-2017-016

Hester SM, Cacho OJ (2017) The contribution of passive surveillance to invasive species management. Biological Invasions 19: 737–748. https://doi.org/10.1007/s10530-016-1362-4

Howell CJ (2012) Progress toward environmental weed eradication in New Zealand. Invasive Plant Science and Management 5: 249–258. https://doi.org/10.1614/IPSM-D-11-00001.1

Hulme PE (2009) Trade, transport and trouble: managing invasive species pathways in an era of globalization. Journal of Applied Ecology 46: 10–18. https://doi.org/10.1111/j.1365-2664.2008.01600.x

Hulme PE (2017) Climate change and biological invasions: evidence, expectations, and response options. Biological Reviews 92: 1297–1313. https://doi.org/10.1111/brv.12282

Hulme PE, Beggs JR, Binny RN, Bray JP, Cogger N, Dhami MK, Finlay-Smits SC, French NP, Grant A, Hewitt CL, Jones EE, Lester PJ, Lockhart PJ (2023) Emerging advances in biosecurity to underpin human, animal, plant, and ecosystem health. iScience 26: 107462. https://doi.org/10.1016/j.isci.2023.107462

IPBES (2023) Summary for policymakers of the thematic assessment report on invasive alien species and their control of the intergovernmental science-policy platform on biodiversity and ecosystem services. In: Roy HE, Pauchard A, Stoett P, Renard Truong T, Bacher S, Galil BS, Hulme PE, Ikeda T, Sankaran KV, McGeoch MA, Meyerson LA, Nuñez MA, Ordonez A, Rahlao SJ, Schwindt E, Seebens H, Sheppard AW, Vandvik V (Eds), IPBES Secretariat, Bonn, Germany, 41. https://doi.org/10.5281/zenodo.7430692

IPCC (Ed.) (2000) Emissions scenarios: summary for policymakers; a special report of IPCC Working Group III. Intergovernmental Panel on Climate Change, 20 pp.

James TK, Dowsett CA, Trolove MR (2015) Identification and enumeration of weed seeds in chopped maize being transported for silage. New Zealand Plant Protection 68: 118–123. https://doi.org/10.30843/nzpp.2015.68.5879

Jamieson LE, Woodberry O, Mascaro S, Meurisse N, Jaksons R, Brown SDJ, Ormsby M (2022) An integrated biosecurity risk assessment model (IBRAM) for evaluating the risk of import pathways for the establishment of invasive species. Risk Analysis 42: 1325–1345. https://doi.org/10.1111/risa.13861

Jeger MJ, Pautasso M, Holdenrieder O, Shaw MW (2007) Modelling disease spread and control in networks: implications for plant sciences. New Phytologist 174: 279–297. https://doi.org/10.1111/j.1469-8137.2007.02028.x

Kaine G, Wright V (2022) Attitudes, involvement and public support for pest control methods. Conservation 2: 566–586. https://doi.org/10.3390/conservation2040038

Kelly JE, Quinn JC, Nielsen SG, Weston P, Broster JC, Weston LA (2020) Causative factors influencing epizoochorous dispersal of weed seeds by sheep and associated carcass contamination in southern Australia. Weed Research 60: 221–231. https://doi.org/10.1111/wre.12415

Kriticos D, Lamoureaux S, Bourdôt G, Pettit W (2004) Nassella tussock: current and potential distribution in New Zealand. New Zealand Plant Protection 57: 81–88.

Leung B, Roura-Pascual N, Bacher S, Heikkilä J, Brotons L, Burgman MA, Dehnen-Schmutz K, Essl F, Hulme PE, Richardson DM, Sol D, Vilà M (2012) TEASIng apart alien species risk assessments: A framework for best practices. Ecology Letters 15: 1475–1493. https://doi.org/10.1111/ele.12003

Lustig A, Worner SP, Pitt JPW, Doscher C, Stouffer DB, Senay SD (2017) A modeling framework for the establishment and spread of invasive species in heterogeneous environments. Ecology and Evolution 7: 8338–8348. https://doi.org/10.1002/ece3.2915

Maher J, Virtue J, Stringham OC, Cassey P (2024) Discrepancies in Australian jurisdiction-based regulation of invasive plants. Invasive Plant Science and Management 17: 267–280. https://doi.org/10.1017/inp.2024.26

Marchioro CA, Krechemer FS (2021) Prevention is better than cure: Integrating habitat suitability and invasion threat to assess global biological invasion risk by insect pests under climate change. Pest Management Science 77: 4510–4520. https://doi.org/10.1002/ps.6486

Mason, NWH (2023) INApest and INApestmeta core function code. Available from: https://github.com/manaakiwhenua/SleeperPests/tree/main/INApest%20INApestMeta%20core%20function%20code.

Mason W, Cuttance E, Madin B, Sadler R, Cowled B, Stevenson M, Firestone S, Pfeiffer C (2021) Analyses of New Zealand stock movement data. Biosecurity New Zealand, 79pp. Available from: https://www.mpi.govt.nz/dmsdocument/49114-Analysis-of-New-Zealand-Stock-Movement-Data.

Mayer M (2024) hstats: Interaction statistics. CRAN. Manual, 45pp. Available from: https://CRAN.R-project.org/package=hstats.

McGrannachan CM, Pagad S, McGeoch MA (2021) A multiregional assessment of transnational pathways of introduction. NeoBiota 64: 43–67. https://doi.org/10.3897/neobiota.64.60642

Ministry for the Environment (2018) Climate change projections for New Zealand: Atmosphere projections based on simulations from the IPCC fifth assessment. Wellington, New Zealand, 131pp. Available from: https://environment.govt.nz/assets/Publications/Files/Climate-change-projections-2nd-edition-final.pdf.

Panetta FD (2004) Seed banks: the bane of the weed eradicator. In: Sindel B, Johnson S (Eds), Proceedings of the 14th Australian Weeds Conference. Weed Society of New South Wales, Wagga Wagga, New South Wales, Australia, 523–526.

Panetta FD (2009) Weed eradication-An economic perspective. Invasive Plant Science and Management 2: 360–368. https://doi.org/10.1614/IPSM-09-003.1

Panetta FD (2015) Weed eradication feasibility: lessons of the 21st century. Novak S (Ed.). Weed Research 55: 226–238. https://doi.org/10.1111/wre.12136

Panetta FD, Lawes R (2005) Evaluation of weed eradication programs: the delimitation of extent: Evaluation of weed eradication programs. Diversity and Distributions 11: 435–442. https://doi.org/10.1111/j.1366-9516.2005.00179.x

Panetta FD, Lawes R (2007) Evaluation of the Australian branched broomrape (*Orobanche ramosa*) eradication program. Weed Science 55: 644–651. https://doi.org/10.1614/WS-07-058.1

Panetta FD, Cacho O, Hester S, Sims-Chilton N, Brooks S (2011) Estimating and influencing the duration of weed eradication programmes. Journal of Applied Ecology 48: 980–988. Available from: http://dx.doi.org/10.1111/j.1365-2664.2011.02000.x.

Pautasso M, Jeger MJ (2014) Network epidemiology and plant trade networks. AoB PLANTS 6. https://doi.org/10.1093/aobpla/plu007

Pautasso M, Xu X, Jeger MJ, Harwood TD, Moslonka-Lefebvre M, Pellis L (2010a) Disease spread in small-size directed trade networks: the role of hierarchical categories. Journal of applied ecology 47: 1300–1309.

Pautasso M, Dehnen-Schmutz K, Holdenrieder O, Pietravalle S, Salama N, Jeger MJ, Lange E, Hehl-Lange S (2010b) Plant health and global change - some implications for landscape management. Biological Reviews: no-no. https://doi.org/10.1111/j.1469-185X.2010.00123.x

Phillips CB, Kean JM, Vink CJ, Berry JA (2018) Utility of the CLIMEX 'match climates regional' algorithm for pest risk analysis: an evaluation with non-native ants in New Zealand. Biological Invasions 20: 777–791. https://doi.org/10.1007/s10530-017-1574-2

Planchuelo G, Catalán P, Delgado JA (2016) Gone with the wind and the stream: Dispersal in the invasive species *Ailanthus altissima*. Acta Oecologica 73: 31–37. https://doi.org/10.1016/j.actao.2016.02.006

Pluess T, Jarošík V, Pyšek P, Cannon R, Pergl J, Breukers A, Bacher S (2012) Which factors affect the success or failure of eradication campaigns against alien species? Adler FR (Ed.). PLoS ONE 7: e48157. https://doi.org/10.1371/journal.pone.0048157

Reeve IJ, Kaine G, Lees JW, Barclay E (2000) Producer perceptions of pasture decline and grazing management. Australian Journal of Experimental Agriculture 40: 331. https://doi.org/10.1071/EA98018

Renteria JL, Rouget M, Visser V (2017) Rapid prioritization of alien plants for eradication based on climatic suitability and eradication feasibility. Austral Ecology 42: 995–1005. https://doi.org/10.1111/aec.12528

Rocabert C, Fenet S, Kaufmann B, Gippet JMW (2024) Accounting for the topology of road networks to better explain human-mediated dispersal in terrestrial landscapes. Ecography 2024: e07068. https://doi.org/10.1111/ecog.07068

Roigé M, Phillips CB (2021) Validation and uncertainty analysis of the match climates regional algorithm (CLIMEX) for Pest risk analysis. Ecological Informatics 61: 101196. https://doi.org/10.1016/j.ecoinf.2020.101196

Runghen R, Llopis-Belenguer C, McNeill MR, Dalla Riva GV, Stouffer DB (2023) Using network analysis to study and manage human-mediated dispersal of exotic species. Biological Invasions. https://doi.org/10.1007/s10530-023-03122-3

Sankaran K, Schwindt E, Sheppard AW, Foxcroft LC, Vanderhoeven S, Egawa C, Peacock L, Castillo ML, Zenni RD, Müllerová J, González Martínez AI, Bukombe JK, Wanzala W, Mangwa DC (2023) IPBES Invasive Alien Species Assessment: Chapter 5. Management; challenges, opportunities and lessons learned. Zenodo https://doi.org/10.5281/ZENODO.7430733

Sanson RL (2000) Agribase – Introduction and history. In: Proceedings of the New Zealand Veterinary Association Epidemiology and Animal Health Management Branch Seminar, Wallaceville, Upper Hutt, New Zealand, 23-24 November 2000. Massey University, Wallaceville, Upper Hutt, New Zealand, 61–64.

Saunders JT, Greer G, Bourdôt G, Saunders C, James T, Rolando C, Monge J, Watt MS (2017) The economic costs of weeds on productive land in New Zealand. International Journal of Agricultural Sustainability 15: 380–392. https://doi.org/10.1080/14735903.2017.1334179

Sayles JS, Mancilla Garcia M, Hamilton M, Alexander SM, Baggio JA, Fischer AP, Ingold K, Meredith GR, Pittman J (2019) Social-ecological network analysis for sustainability sciences: a systematic review and innovative research agenda for the future. Environmental Research Letters 14: 093003. https://doi.org/10.1088/1748-9326/ab2619

Schelhas J, Alexander J, Brunson M, Cabe T, Crall A, Dockry MJ, Emery MR, Frankel SJ, Hapner N, Hickman CR, others (2021) Social and cultural dynamics of non-native invasive species. Invasive species in forests and rangelands of the United States: A comprehensive science synthesis for the United States Forest sector: 267–291.

Seebens H, Briski E, Ghabooli S, Shiganova T, MacIsaac HJ, Blasius B (2019) Non-native species spread in a complex network: the interaction of global transport and local population dynamics determines invasion success. Proceedings of the Royal Society B: Biological Sciences 286: 20190036. https://doi.org/10.1098/rspb.2019.0036

Simberloff D (2009) Eradication—preventing invasions at the outset. Weed Science 51: 247–253. Available from: https://www.jstor.org/stable/4046727.

Simberloff D, Keitt B, Will D, Holmes N, Pickett E, Genovesi P (2018) Yes We Can! Exciting Progress and Prospects for Controlling Invasives on Islands and Beyond. Western North American Naturalist 78: 942. https://doi.org/10.3398/064.078.0431

Snell K, Grech C, Jamie D (2007) National best practice management manual Chilean needle grass. Victorian Government, Melbourne 82.

Sutherst R (1985) A computerised system for matching climates in ecology. Agriculture, Ecosystems & Environment 13: 281–299. https://doi.org/10.1016/0167-8809(85)90016-7

Taylor S, Conolly J, Gruber A (2016) Chilean needle grass (*Nassella neesiana*) control – the ACT experience. In: Twentieth Australasian Weeds Conference. Perth, 223–227.

Walther G-R, Roques A, Hulme PE, Sykes MT, Pyšek P, Kühn I, Zobel M, Bacher S, Botta-Dukát Z, Bugmann H (2009) Alien species in a warmer world: risks and opportunities. Trends in Ecology & Evolution 24: 686–693. https://doi.org/10.1016/j.tree.2009.06.008

Wichmann MC, Alexander MJ, Soons MB, Galsworthy S, Dunne L, Gould R, Fairfax C, Niggemann M, Hails RS, Bullock JM (2009) Human-mediated dispersal of seeds over long distances. Proceedings of the Royal Society B: Biological Sciences 276: 523–532. https://doi.org/10.1098/rspb.2008.1131

Wiebe K, Zurek M, Lord S, Brzezina N, Gabrielyan G, Libertini J, Loch A, Thapa-Parajuli R, Vervoort J, Westhoek H (2018) Scenario development and foresight analysis: exploring options to inform choices. Annual Review of Environment and Resources 43: 545–570. https://doi.org/10.1146/annurev-environ-102017-030109

Wilson RS, Hooker N, Tucker M, LeJeune J, Doohan D (2009) Targeting the farmer decision making process: A pathway to increased adoption of integrated weed management. Crop Protection 28: 756–764. https://doi.org/10.1016/j.cropro.2009.05.013

Yang K, Li J, Liu M, Lei T, Xu X, Wu H, Cao J, Qi G (2023) Complex systems and network science: a survey. Journal of Systems Engineering and Electronics 34: 543–573. https://doi.org/10.23919/JSEE.2023.000080

Yletyinen J, Perry GLW, Burge OR, Mason NWH, Stahlmann-Brown P (2021) Invasion landscapes as social-ecological systems: Role of social factors in invasive plant species control. People and Nature 3: 795–810. https://doi.org/10.1002/pan3.10217

Supplement

Status of Chilean needle grass invasion in NZ

The primary impacts of Chilean needle grass are on the sheep and beef farming sector, since the awned seeds readily attach to wool or fur, causing animal welfare problems by painfully penetrating hides (and eyes in sheep), and impacting wool, meat and hide quality *(Gardener et al. 2003a, 2003b)*. The economic losses from the invasion are estimated to be 25% of annual production based on the need to exclude stock from infested paddocks while plants are seeding from December to March (a large portion of the Southern Hemisphere growing season) *(Bourdôt et al. 2015)*.

For CNG epizoochorus and endozoochorus dispersal may occur, but most seeds fall within 2.8 meters of the plant (no wind dispersal), and estimated rates spread range from 7 to 140 m/year (Connor et al. 1993). Local and long-distance dispersal between farms is known to occur through transport of stock, in hay, on clothing and by dirty machinery (Snell et al. 2007). Its awned panicle-borne seeds can persist for 7-10 years underground (Bourdôt and Hurrell 1992), or for months in sheep wool (Gardener et al. 2003a, 2003b). The cleistogamous seeds with vestigial awns may persist hidden in the base of live tussocks for months as well (Taylor et al. 2016). Consequently, eradication requires persistent application of control over at least 10 years to kill plants germinating from the seed bank and to prevent seeding.

In New Zealand, invasive species management is often devolved to local government authorities once eradication is declared infeasible. Consequently, invasive species management and investment decisions are often taken at the local government (region) level. Due to potential impacts to agriculture and difficulty of

eradication CNG is currently included in Regional Pest Management Plans in 13 of 16 regions in NZ, either to facilitate its control (where present) or, if not present, to detect it early and prevent its establishment. One consequence of this localised approach is that pest management planning often does not consider the benefits of control measures for reducing or preventing spread across administrative boundaries. This is the case for Chilean Needle Grass where the cost of containing extensive infestations in the Hawke's Bay Region threatens political support for control measures within this region. Abandonment of control measures may increase the risk of spread to neighbouring regions where Chilean needle grass is not present. This is especially concerning for the Manawatū-Whanganui Region, where sheep and beef farming is a major contributor to the regional economy.

INApest() input, simulation process and outputs

INApest() was originally a wrapper built around the *INAscene()* function of the impact network analysis R package of Garrett (2021). Functionality formerly provided by *INAscene()* is now performed using generic R commands. We chose the name INApest for our new function to emphasise our focus on the application of Impact Network Analysis to the management of invasive or otherwise undesirable bioentities. A key departure of the *INApest()* simulation process from the *INAscene()* function is that the spread of information through the network is dependent on the spread (and detection) of the bioentity. This reflects the reality that agents (e.g. farmers) may only seek or accept information on invasive species management when there is a realistic possibility of their area of responsibility (e.g. farm) being invaded. In simple terms, *INApest()* simulates the spread of information about the near-term risk of invasion, whereas *INAscene()* simulates the spread of information about pest management technologies. *INApest()* also treats bioentity spread differently by allowing explicit definition of separate short distance (e.g. self-mediated) and long distance (e.g. human-mediated) dispersal processes and also permits explicit moderation of invasion by environmental factors such as climate.

The *INApest()* function includes several input preparation steps followed by a timestep loop. Finally, a series of summary outputs are saved to disk. Below we detail the inputs (both required and optional), data preparation steps, simulation processes and outputs.

Required Inputs

The inputs required for running *INApest()* are:

- **SDDprob**: A matrix of short-distance (self-mediated) dispersal probabilities between each pair of nodes (e.g. farms). This can be asymmetrical (i.e. can have source and sink nodes). Rows contain probabilities of spread from the row node to other nodes. Columns contain probabilities of the column node being invaded from other nodes.

- Management parameters. Each can be given as a single value, a vector (nodes) or a matrix (nodes x timesteps)

  - **DetectionProb**: Node-level detection probability in each timestep
  - **ManageProb**: Node-level management adoption probability in each timestep subsequent to detection
  - **EradicationProb**: Node-level eradication probability of local populations under management in each timestep
  - **SpreadReduction**: Node-level spread reduction when management adopted

- Data on initial infestation or invasion risk, with the following options:
  - **InitialInvasion**: A vector of initially infested nodes
  - **InvasionRisk**: A vector (nodes) or matrix (nodes x timesteps) of invasion risk probabilities.
  - **InitBioP**: The proportion of nodes infested at the beginning of simulations.

- Additional parameters:
  - **Nperm**: the number of permutations (independent realisations using same starting parameters)
  - **Nsteps**: the number of timesteps for each permutation
  - **ModelName**: Used in filenames to store outputs to disk. This helps with convenience in post-processing

Optional inputs

INApest() can take a variety of optional inputs to expand on the basic functionality:

- **EnvEstabProb**: Environmentally-determined establishment probability for each node. If not provided all values are set to 1 for no environmental limitation on establishment. Can be supplied as a single number, vector (nodes) or matrix (nodes x timesteps).

- **Survival**: Environmentally-determined survival probability for each node. If not provided, all values are set to 1 for no environmental limitation on survival. Can be supplied as a single number, vector (nodes) or matrix (nodes x timesteps).

- **LDDprob**: A matrix of long-distance (human-mediated) dispersal probabilities between each pair of nodes (e.g. farms). This can be asymmetrical (i.e. can have source and sink nodes). Rows contain probabilities of spread from the row node to other nodes. Columns contain probabilities of the column node being invaded from other nodes.

- **SEAM:** socioeconomic adjacency matrix containing information transfer probabilities between nodes. This can be asymmetrical (i.e. can have source and sink nodes). Rows contain probabilities of information transfer from the row node to other nodes. Columns contain probabilities of the column node receiving information from other nodes. If not provided all information transfer probabilities are set to zero.

- Standard deviations for each of the management variables. These may be given as a single number or vector (nodes). If standard deviation is not provided an arbitrary value of 10% of the mean value is applied

- Data on initial information, with the following options:
  - **InitialInfo**: A vector of nodes with information at start of simulations
  - **ExternalInfoProb**: Vector of probabilities of communication from external sources
  - **InitInfoP:** Proportion of nodes with information at start of simulations

- **OngoingExternalInvasion**: Logical value determining whether or not to include ongoing invasion from external sources. Default value is FALSE.
- **OngoingExternalInfo**: Logical value determining whether or not to include ongoing communication from external sources. Default value is FALSE.
- **OutputDir**: Directory for storing results.
- **DoPlots**: Logical value determining whether or not to print line graphs of simulation results. Default value is TRUE.

Data preparation

If long-distance dispersal probabilities are provided, short-distance and long-distance probabilities are combined by treating each process as separate trials in estimating dispersal probability:

```
DispProb = 1-(1-SDDprob)(1-LDDprob)
```

Establishment probability (**EnvEstabProb**) moderates invasion through multiplication of each column of the dispersal probability matrix by the establishment probability of the corresponding node. In this way establishment affects the probability of nodes being invaded but not the probability of nodes being sources of invasion. This results in the biophysical adjacency matrix (BPAM):

```
BPAM = sweep(DispProb,2,EnvEstabProb,`*`)
```

If EnvEstabProb is provided as a matrix (nodes x timesteps), BPAM is updated within each timestep.

Initiating simulations

If a vector of initially infested nodes is not provided, initial infestations are generated through random sampling for each permutation. In the simplest case, where only the initial proportion of infested nodes (**IntiBioP**) is provided, infested nodes are selected through unweighted randomisation:

```
Infested = sample(1:nrow(SDDprob),size = ceiling(nrow(SDDprob)*InitBioP))
```

If invasion risk probabilities (**InvasionRisk**) are provided as a vector AND the initial proportion of infested nodes (**IntiBioP**) is provided, initially infested nodes are selected through weighted randomisation:

```
Infested = sample(1:nrow(SDDprob),size = ceiling(nrow(SDDprob)*InitBioP),prob = InvasionRisk)
```

If initial infestation proportion is not provided, a random binomial process is used to define initial infestation status:

```
Infested = rbinom(1:nrow(SDDprob),size = 1,prob = InvasionRisk)

Infested = which(Infested == 1)
```

If InvasionRisk is supplied as a matrix, the first column of values is used to select initial infestations via a weighted random binomial process

```
Infested = rbinom(1:nrow(SDDprob),size = 1,prob = InvasionRisk[,1])

Infested = which(Infested == 1)
```

A binary vector coding initial infestation status (**InitBio**) is then initiated, with initially infested nodes assigned a value of 1.

```
InitBio = rep(0,times = nrow(SDDprob))

InitBio[Infested] = 1
```

If a binary vector of initial infestation status (**InitialInvasions**) is provided in the function call, this is used as the **InitBio** vector in all simulations.

If a vector of initial information status is not provided, nodes with information at the start of simulations are selected through random sampling for each permutation. In the simplest case, where only the initial proportion of nodes with information (**IntiInfoP**) is provided, nodes are selected through unweighted randomisation:

```
Info = sample(1:nrow(SDDprob),size = ceiling(nrow(SDDprob)*InitInfoP))
```

If probabilities of receiving information from external sources (**ExternalInfoProb**) are provided as a vector AND the initial proportion of nodes with information (**IntiInfoP**) is provided, initially infested nodes are selected through weighted randomisation:

```
Info = sample(1:nrow(SDDprob),size = ceiling(nrow(SDDprob)*InitInfoP),prob = ExternalInfoProb)
```

If initial information proportion is not provided, a random binomial process is used to define initial information status:

```
Info = rbinom(1:nrow(SDDprob),size = 1,prob = ExternalInfoProb)

Info = which(Info == 1)
```

If ExternalInfoProb is supplied as a matrix, the first column of values is used to select initial information nodes via a random binomial process

```
Info = rbinom(1:nrow(SDDprob),size = 1,prob = ExternalInfoProb[,1])

Info = which(Info == 1)
```

A binary vector coding initial information status (**InitInfo**) is then initiated, with initial information nodes assigned a value of 1.

```
InitBio = rep(0,times = nrow(SDDprob))

InitBio[Infested] = 1
```

If a binary vector of initial information status (**InitialInfo**) is provided in the function call, this is used as the **InitInfo** vector in all simulations.

If no information on initial information status or probability of receiving information from external sources is provided, a binary initial information vector (**Initinfo**), which depends on the presence of the bioentity and annual detection probability is generated through a random binomial process:

```
InitInfo = rbinom(1:nrow(SDDprob),size = 1,prob = InitBio*NodeDetectionProb)
```

Vectors tracking the invasion (**Invaded**) and information status (**HaveInfo**) of each node are initiated using, respectively, values in the **InitBio** and **InitInfo** vectors.

Values for each of the management variables at each node (**NodeDetectionProb**, **NodeEradicationProb**, **NodeSpreadReduction**, **NodeManageProb**) are applied to each node through a random normal process. Where management variables are provided as a matrix (nodes x timesteps), management variables are updated within each timestep.

Temporary matrices for storing results of invasion and information spread at each timestep are declared ahead of the timestep loop (declaring these at each timestep reduces processing speed when there is a large number of nodes):

```
RandBPAM <- BPAM

RandSEAM <- SEAM
```

Simulation process within each timestep

Within each timestep a binary management vector is generated through a random binomial process depending on the possession of information and node management adoption probability:

```
Managing = rbinom(1:nrow(SDDprob),size = 1,prob = NodeManageProb*HaveInfo)
```

and a vector tracking known extant infestations is generated depending on the presence of the pest at each node and the possession of information by agents:

```
Detected = Invaded*HaveInfo
```

Populations dying out naturally (based on survival probability) and/or from management are removed:

Invaded <- Invaded*rbinom(n=nrow(SDDprob),size = 1,prob = NodeSurvival*(1-NodeEradicationProb*Managing))

Spread probabilities are moderated by spread reduction through multiplication of rows of the biophysical adjacency matrix by the spread reduction vector in managing nodes:

RandBPAM[] <- rbinom(n=nrow(SDDprob)^2, size=1, prob = BPAM*Invaded*(1-Managing*NodeSpreadReduction))

In this way spread reduction captures both the reduction in self-mediated dispersal arising through management of local populations and hygiene measures or movement restrictions designed to prevent human-mediated dispersal.

If a socioeconomic adjacency matrix is provided, information transfer only occurs from nodes where extant infestations have been detected:

RandSEAM[] <- rbinom(n=nrow(SDDprob)^2, size=1, prob = SEAM*Detected)

Invasion status (**Invaded**) and information (**HaveInfo**) vectors are updated in accordance with pest and information spread results:

NewInvasion = ifelse(colSums(RandBPAM)>0,1,0)

Invaded[Invaded == 0] = NewInvasion[Invaded == 0]

InfoTransferred = ifelse(colSums(RandSEAM)>0,1,0)

HaveInfo[HaveInfo == 0] = InfoTransferred[HaveInfo == 0]

If the **OngoingExternalInvasion** parameter is set to TRUE, the invasion status vector is updated with any new invasions from external sources.

ExternalInvasion = rbinom(1:nrow(SDDprob),size = 1,prob = InvasionRisk)

Invaded[Invaded == 0] = ExternalInvasion[Invaded==0]

Where **InvasionRisk** is provided as a matrix (nodes x timesteps), external invasion risk is updated in each timestep.

Similarly, if the **OngoingExternalInfo** parameter is set to TRUE, the information status vector is updated with any new communications from external sources.

ExternalInfo= rbinom(1:nrow(SDDprob),size = 1,prob = ExternalInfoProb)

HaveInfo[HaveInfo == 0] = ExternalInfo[HaveInfo ==0]

Where **ExternalInfoProb** is provided as a matrix (nodes x timesteps), external invasion risk is updated in each timestep.

The information vector is then updated for any newly detected infestations:

```
NewHaveInfo =  rbinom(1:nrow(SDDprob),size = 1,prob = Invaded*NodeDetectionProb)

HaveInfo[HaveInfo==0] = NewHaveInfo[HaveInfo==0]
```

Finally, the management adoption and detection vector (including new detections) and updated invasion and information vectors are stored for post-simulation output generation.

Output generation

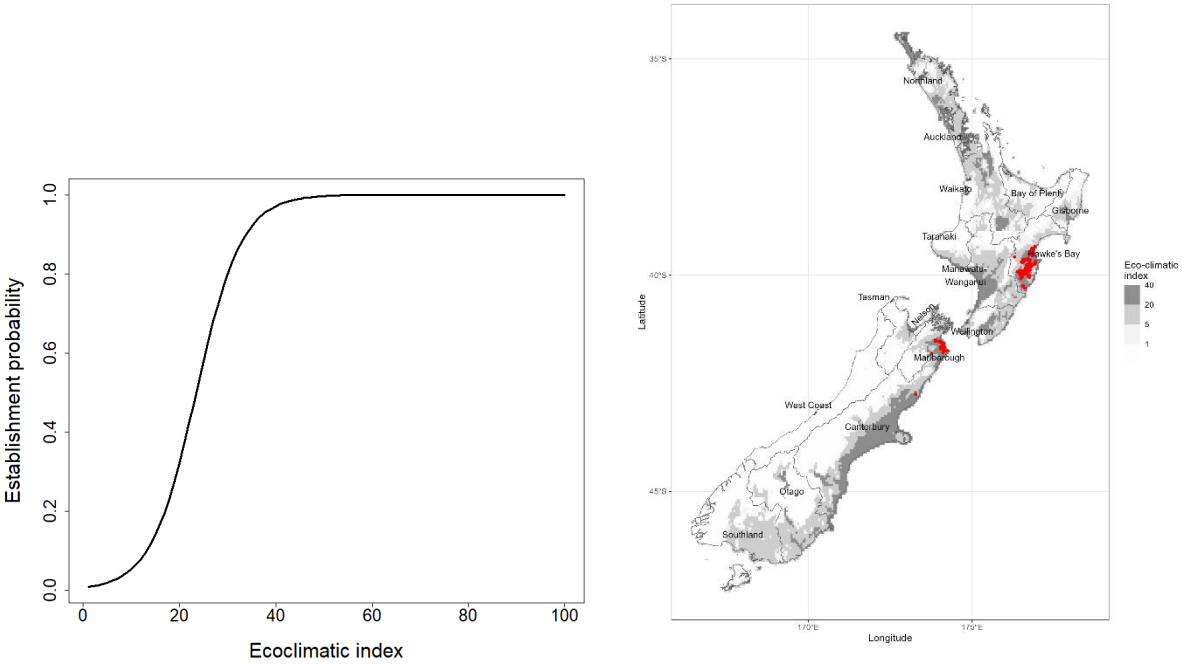
Results for invasion, management adoption and detection are saved to disk as 3-dimensional arrays (nodes x timesteps x permutations) in .rds files to facilitate post-hoc processing (e.g. for impact estimation). A 2-dimensional array (nodes x timesteps) of invasion probability (across permutations) for each node in each timestep is also stored in a .rds file. By default, line graphs plotting timeseries for individual permutations of:

- the number of infested nodes
- the number of detected extant infestations
- the number of nodes implementing management
- the proportion of extant infestations detected

are saved in separate image files. Line graphs plotting timeseries of the median and 95% confidence bounds across permutations are also plotted. The user can choose not to plot line graphs by setting input parameter **DoPlots** to FALSE in the *INApest()* function call.

Estimating climatic suitability and dispersal, establishment and eradication probabilities

Mean ecoclimatic index (EI) values for each farm were obtained by intersecting farm polygons with climate predictions. Farms with a mean EI value ≥6 were considered climatically suitable (Bourdôt et al. 2010). EI values were converted to establishment probabilities using a logit function with intercept -5 and coefficient 0.21287. This curve provides a relatively rapid rate of increase in establishment probability at low EI values and is forced to pass through the point EI = 30, establishment probability = 0.8 (Supplemental Figure 1).



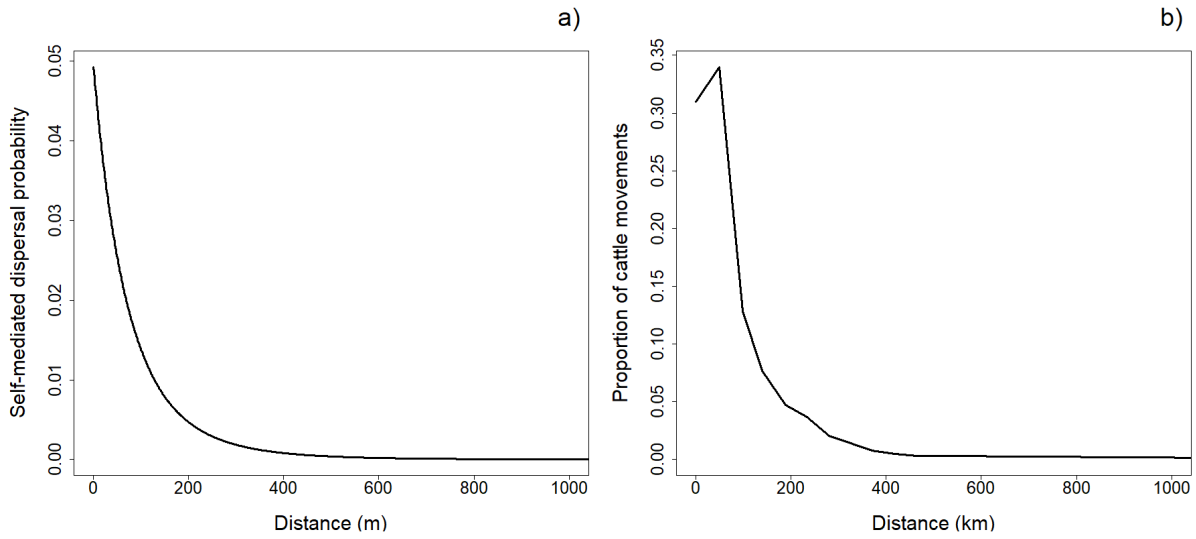
Supplemental Figure 1: Chilean needle grass establishment probability against ecoclimatic index values sourced from CLIMEX, map of climate suitability is shown with known occurrences in NZ.

The eradication probability parameter used data from Bourdôt (2010) describing declines in seedbank density under management of CNG infestation with glyphosate herbicide, which predict a 95% chance of seedbank density declining to less than 1 seed per hectare after 14 years of management. This equates to an annualised patch-scale eradication probability of 0.193. An annual probability of discovering all infested patches on each farm of 0.25 was assumed, yielding a final farm-scale annual eradication probability of 0.048. This was used as the "EradicationProbability" parameter in *INApest()* function calls.

Both self- (ecological – anemochorous and ectozoochorous) and human-mediated (socioeconomic – transport of contaminated animals, hay and machinery) dispersal were estimated as a function of shortest Euclidean distance between at-risk farms within each region. Self-mediated dispersal probability (Supplemental Supplemental Figure a) was modelled using a 'Pareto' distribution using the *ppareto*() function within R package "*actuar*" (Dutang et al., 2008, 2022; Bullock et al. 2017; García and Borda-de-Água 2017). Parameters supplied to the function were: shape parameter = 7; scale parameter = 500. Resulting probabilities were multiplied by a threshold (i.e. zero-distance) probability of 0.05, representing a 1-in-20 year risk of invasion between adjacent farms. Distances between farms were calculated as the minimum Euclidean distance between farm boundaries, so that distance = 0 for farms with a shared boundary. Self-mediated dispersal probabilities between at-risk farms within the same region were stored in a symmetrical matrix. These were used as the **SDDprob** input in *INApest()* function calls. Self-mediated dispersal probabilities were also calculated between each farm within a region and all other at-risk farms in New Zealand. These were

stored in separate matrices covering all possible pairs of regions. These data contributed to the generation of the **InvasionRisk** parameter in *INApest()* function calls.

Human-mediated dispersal probability was scaled by distance-dependent cattle movement probabilities (Supplemental Supplemental Figure b) derived from the National Animal Identification Tag (NAIT) database (Mason et al., 2021b). These probabilities were weighted so that probability of dispersal from each at-risk farm to all other at-risk farms in New Zealand summed to 1. Each farm was assigned a constant annual long-distance dispersal rate (i.e., mean dispersal events per-year) of 0.05. The mean number of long-distance dispersal events between each pair of farms was estimated as the product of the long-distance dispersal rate and the weighted long-distance dispersal probability. Mean annual long-distance dispersal event values were then converted to dispersal probabilities using the Poisson distribution to estimate the annual probability of at least one dispersal event occurring. Human-mediated dispersal probabilities between at-risk farms within the same region were stored in a symmetrical matrix. These were used as the **LDDprob** input in *INApest()* function calls. Human-mediated dispersal probabilities were also calculated between each at-risk farm within a region and all other at-risk farms in New Zealand. These were stored in separate matrices covering all possible pairs of regions. These data contributed to the generation of the **InvasionRisk** parameter in *INApest()* function calls.



Supplemental Figure 2: Self-mediated dispersal probability of Chilean needle grass (a) and proportion of cattle total movements (b) against Euclidean distance between nodes (note the different y axis limits).

Validation against historic invasion

In this scenario we compared *INApest()* simulation results under a zero-management scenario (detection probability = 0) with historic data on CNG spread in the Marlborough region. Initially infested farms, as of 1988, were derived from the infestations mapped by Bourdôt and Hurrell (1989). These were used as the InitialInvasion parameter in INApest() function calls. The number of

infested farms in the year 2000 and 2005 were derived from Bell (2006). These were compared with results from *INApest()* to assess whether the CNG implementation provided realistic spread rate estimates. Dispersal kernels used for this scenario are described above.

XGBoost implementation

Cross-validated XGBoost models, fitting 10 fold models (where a separate portion of the data is withheld for evaluation in each fold model) were fitted using the *xgb.cv()* function of the xgboost R packgage (Chen and Guestrin 2016). The influence of each predictor variable within XGBoost models is quantified using the complementary metrics - “gain”, the reduction in unexplained variance each time a predictor is used to make a new branch; “frequency”, the proportion of times a predictor is used to make a new branch and “coverage”, the proportion of observations involved in branches using the predictor; within the function *xgb.importance()* of the xgboost R package. Partial dependence plots of each predictor’s effect on the response independent of all other predictors were produced using the *partial_dep()* function of the pdp R package (Greenwell 2017). Two-way interactions between predictors were estimated using the *h2_pairwise()* function of the hstats R package (Mayer 2024) which implements the method proposed by Friedman and Popescu (2008). Predictor importance, partial dependence plots and interactions were estimated separately for each fold model. This permits estimation of model output sensitivity to allocation of data to training and validation subsets, which is an indicator of model generality.