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Queensland Fruit Fly Invasion of New Zealand: Predicting Area Suitability Under Future Climate Change Scenarios

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Cover design by Penny Thomson
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On the cover is the Australian tachinid fly (*Trigonospila brevifacies*), a parasitoid of other insects, specifically larvae of a number of Lepidoptera. It was introduced into New Zealand as a biological control agent for pest leaf roller moths, is also known to affect non-target and non-pest species, and to compete with native parasitoids.

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Queensland fruit fly invasion of New Zealand: Predicting area suitability under future climate change scenarios

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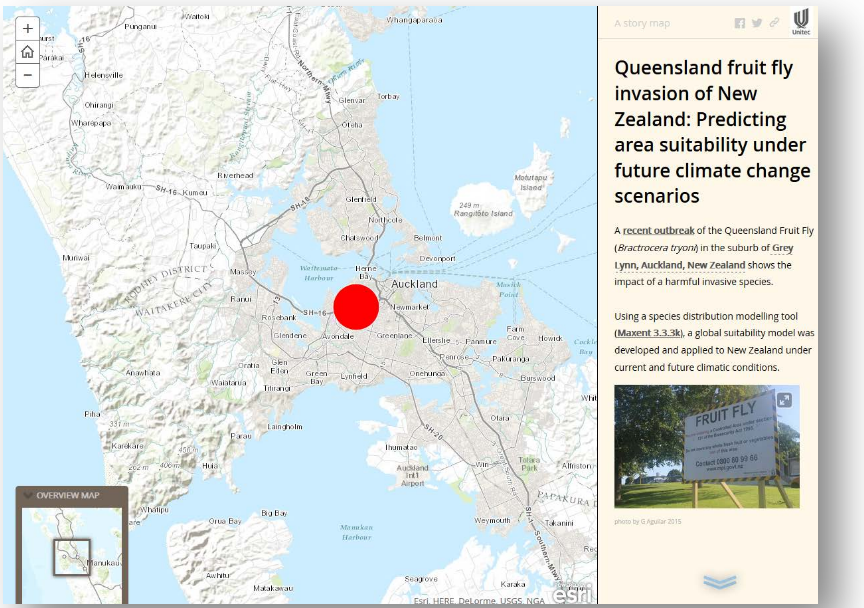
Abstract

*The Queensland fruit fly (*Bactrocera tryoni*) is a significant horticultural pest in Australia, and has also established in other parts of the Pacific. There is a significant risk to New Zealand of invasion by this species, and several recent incursions have occurred. The potential effects of climate change on the distribution and impacts of invasive species are well known. This paper uses species distribution modelling using Maxent to predict the suitability of New Zealand to the Queensland fruit fly based on known occurrences worldwide and Bioclim climatic layers. Under current climatic conditions the majority of the country was generally in the lower range, with some areas in the medium range. Suitability prediction maps under future climate change conditions in 2050 and 2070, at lower emission (RCP 2.6) and higher emission (RCP 8.5) scenarios generally show an increase in suitability in both the North and South Islands. Calculations of the shift of suitable areas show a general movement of the centroid towards the south-east, with the higher emission scenario showing a greater magnitude of movement.*

Click here to visit the Queensland fruit fly suitability prediction map



Keywords: Invasive species, climate change, species distribution modelling, Maxent, RCP 2.6, RCP 8.5.

Introduction

The Queensland fruit fly *Bactrocera tryoni* (Froggatt) (Diptera: Tephritidae) is consistently described as the most damaging pest to Australia's horticulture industries (Mo et al., 2012; Bateman, 1991; Dominiak, 2011) with an annual economic cost averaging around $25.7 million from 2003 to 2008 (Oliver 2007). The impacts of the pest on Australia's horticulture industries are well documented, with outbreaks reported in commercial fruit farms since the late 1890s (Dominiak & Ekman 2013).

The Queensland fruit fly is endemic to the eastern states of Australia but has a well-documented history of spreading to other areas through the transport of fruit or with human assistance (Dominiak & Coombes, 2009; Dominiak et al; 2000). It is now established in some south Pacific island nations (Drew et al; 1978) with detections also reported in New Zealand, the most recent occurring in February of 2015, requiring an immediate response and the setting up of a quarantine zone within Auckland City (Ministry of Primary Industries, 2015). The source of the Queensland fruit fly is most likely to be Australia, New Caledonia, French Polynesia or other islands where it has established and subsequently been transported by passengers to Auckland or other ports of entry through fruit and other host goods. (Ministry of Primary Industries, 2015). The estimated impact of a Queensland fruit fly incursion to the kiwifruit industry of New Zealand alone is estimated to range from a low of $2 million to $430 million per year (KVH, 2014). The lower figure is based on operational costs associated with incursion by a single fly . The greater cost is associated with the worst case scenario where a breeding population results in indirect impacts to horticulture involving the closing of markets and costs of quarantine measures (KVH, 2014). Such recognised economic cost, plus the impact on native ecosystems, requires the production of models that inform a risk assessment process. These are needed for the development of strategies and effective management plans. The model must include environmental drivers that directly impact the distribution of the fruit fly. Climate change is recognised as one of the most important factors (Hellmann et al., 2008).

The potential effects of climate change on the predicted range and distribution for invasive species are well-recognised, with the majority of research efforts focusing on predicting the spatial characteristics of species distribution for management and conservation purposes (Broennimann et al., 2007; Elith et al., 2010; Gallien et al., 2010; Gramvölgyi & Hufnagel, 2013; Taylor et al., 2013). Modelling the suitability of an area for an invasive species, particularly at large spatial scales, most often uses climate as the major environmental variable. This is based on the assumption that environmental conditions of known species can help identify suitable areas, or determine the potential of other areas, for the organism to successfully occupy and establish itself (Peterson & Vieglais, 2001; Daehler et al., 2004), including distributions affected by climate change (Beaumont et al., 2005).

The approach used in this paper involved species distribution modelling (SDM) which produces maps depicting the potential distribution of a species. SDM algorithms and software use species occurrence data and environmental conditions existing at their geographical locations (Araújo & Guisan 2006; Guisan et al., 2013). Published scientific articles illustrate that SDM use has significantly increased over the last 20 years, particularly for species suitability at novel locations and different time periods, including past and future (Robinson et al., 2011; Guisan et al., 2013). Examples include: the identification of priority areas for species invasion, establishment and spread (Soberon et al., 2001; Roura-Pascual et al., 2009, Poulus et al., 2012); habitat suitability for threatened and/or endangered species (Puschendorf et al., 2009, Wilson et al., 2011); and predicting distribution of native or endemic species (Evangelista et al., 2008). Other studies have modelled the suitability of relatively unexplored or little studied areas as well as under future and past conditions using global circulation models and climate scenarios (Nabout et al., 2010, Khanum et al., 2013). More importantly, SDMs are used to inform and support decisions on invasive species management in different parts of the world. Australian authorities have used SDMs as part of invasive species detection, prevention and impact mitigation programmes, including risk assessment for approving the import of new plant species (Pheloung et al., 1999) and the classification of weeds of national significance (NTA 2007; 2009).

In this work, we use Maxent (v3.3.3k) (Philipps et al., 2006) as the modelling tool to determine and describe the suitability of New Zealand to the Queensland fruit fly under current and future climate scenarios. Maxent has also been tested widely and used for the modelling of a large number of terrestrial and marine species at different geographic and time scales (Fourcade et al., 2014; Elith & Graham 2009; Reiss et al., 2011). The tool is reported to provide better or more robust performance compared to other approaches (Elith et al., 2006). Maxent was used to model invasive species (Domíguez-Vega et al., 2012; Elith et al., 2006; De Queiroz et al., 2013), endangered or threatened species (Shochat et al., 2010), crops (Blanchard et al., 2015) and even species in ancient periods (Connolly et al., 2012).

Methodology

Species distribution modelling requires species occurrences and environmental layers to produce a prediction of habitat suitability over an area of study. We used occurrence data from the Global Biodiversity Information Facility (GBIF: http://www.gbif.org), reports of invaded and established populations and well-known outbreaks (Clarke et al., 2011). The entire set of available geographic locations of occurrences was used, based on the finding that the entire range of distributions is more useful in predicting the spread of invasive species compared to just using the occurrences from its native range (Beaumont et al., 2009).

Environmental layers for current conditions consisted of the Bioclim dataset downloaded from the Worldclim database for current conditions (Hijmans et al., 2005). The Bioclim dataset represents values derived from 1950-2000 and consists of 19 climatic variables, 11 of which are temperature based and 8 precipitation related. Representing annual trends, seasonality and limiting environmental variables or extreme conditions, the Bioclim dataset has been found to be more informative than measures such as monthly temperature and precipitation averages. It has found acceptance and common use, particularly for species distribution modelling (Guisan & Thuiller, 2005; Wasowicz et al., 2014; Wakie et al., 2014).

To represent the future conditions consisting of lower and higher emission scenarios, we used available downscaled datasets described in the IPCC 5th report (CMIP5) based on Relative Concentration Pathways (RCP) (IPCC, 2013; Carrero et al., 2014). Two scenarios of the CCSM4 model (Gent et al., 2011), RCP 2.6 and RCP 8.5, representing the lowest and highest emission scenarios, were downloaded for the years 2050 and 2070 from the Worldclim database. RCP 2.6 represents a mean global warming increase of 1.0°C with a likely range of 0.4°C to 1.6°C from 2046 to 2065 and an increase of 1.0°C with a likely range of 0.3°C to 1.7°C from 2081 to 2100. Over the same time periods, the higher emission RCP 8.5 projects an increase of 2.0°C with a likely range of 1.4°C to 2.6°C for the earlier period and an increase of 3.7°C with a likely range of 2.6°C to 4.8°C for the later years (IPCC, 2013). Using the dichotomy of a lower and upper emission scenario directly feeds into available options in the environmental risk assessment framework required for mitigation and adaptation strategies (Jones, 2001).

To minimise multicollinearity within the variable set, highly correlated Bioclim variables were identified using the SDMToolbox in ArcMap (Dorman et al., 2013; Brown, 2014) to check if the cross-correlation is within acceptable values (Pearson correlation coefficient values less than -0.8 or greater than 0.8). The initial run with the modelling software Maxent identified variables with low percent contribution and these were further excluded from the final model run. When the final Maxent model was run, the top five Bioclim variables in terms of percent contribution to the model were used (Table 1).

Variable	Description	Percent contribution
bio18nz	Precipitation of the warmest quarter	35.7
bio1nz	Annual mean temperature	25.9
bio7nz	Temperature annual range	21.6
bio19nz	Precipitation of the coldest quarter	9.6
bio14nz	Precipitation of the driest month	7.2

Table 1.
Variables that were not correlated (Pearson coefficient <= 0.8).

Maxent (ver 3.3.3k), the modelling tool used, is based on a machine learning algorithm called maximum entropy. Maxent attempts to find the probability distribution that is the most spread out or close to uniform, based on constraints dictated by the information available. This information is based on two sources: the observed occurrence records; and environmental conditions of the area of concern (Evangelista et al., 2008; Phillips & Dudick, 2008). Maxent is also classified as a correlative model that uses presence and background points to assess the available environment for model calibration and testing (Elith et al., 2011). While other modelling tools require presence and absence data, Maxent only requires presence data, making it more convenient for the large majority of species where only occurrence data is available, a characteristic of most datasets sourced from museums or online databases (Guisan et al., 2013).

To develop the model, Maxent was run with global environmental data at 2.5 arc minutes resolution. The model was projected to the entire New Zealand land mass for current and future scenarios with higher resolution 30 arc-second (0.00833 degrees or approximately 1 kilometre) rasters. This is similar to the work of Berry et al., (2002) where a European model was projected onto Britain and Ireland for modelling the distribution of 54 species. Developing the local model from a larger extent has the advantage of the calibration data containing the range of environmental variables of the smaller area, making unnecessary the need to extrapolate values outside the range of the calibration (Pearson, 2007).

To compare differences in the predicted presence or predicted absence between current and future conditions, each output map was reclassified to binary maps with the threshold set at the 10th percentile of the calculated probability values. Values less than the threshold are set to 0, representing absences and values greater than the threshold are set to 1 to represent presence. To compare between different years and between scenarios, each pair of rasters was added with the second raster multiplied by 2 to provide 4 different possible values (0,1,2,3). For example, if a raster for RCP2.6 for year 2050 is added to the current period, the resulting raster with a value of 0 represents absence in both years, 1 represents a range contraction (present only in current years), 2 represents a range expansion (absent in current and present in future year) and 3 represents presence in both years. Similar to the output of the tool SDMToolbox developed by Brown (2014), this calculation provides an overall area measurement of the presence or absence in the scenarios compared and more importantly, shows the total area where the probability of occurrence corresponding to species range has increased or expanded and decreased or contracted.

Using the SDMToolbox (Brown, 2014) allowed the creation of centroid shift lines that describe the overall shift and direction of the change of the expected range representing presence of the species between two time periods. For each climate scenario, two centroid shifts were created, one between current conditions and 2050 and another representing the shift between 2050 and 2070. The direction and magnitude of the shift represents overall change for the entire area modelled and should be used with caution when local or subregion change is considered. However, for national or regional strategy formulation, the directionality information may prove valuable in setting risk mitigation strategies related to impacts of climate change on a national scale (Huntley et al., 2008; VanDerWal et al., 2013).

The final Maxent model was run with 2500 iterations, with cross validation and 10 replicate runs, to generate more robust results consisting of the average of the output rasters. To evaluate model performance, the AUC (Area Under the Curve of the ROC (Receiving Operator Characteristics)) is calculated and used as a measure of performance (Swets, 1988). The AUC provides an indication of the model's capability to distinguish between presence and absence (or pseudo-absence which is automatically created by Maxent). AUC values range from 0.5 to 1 where AUC values greater than 0.9 are deemed to reflect high or good performance, while AUC values nearing 0.5 are no better than random (Peterson et al., 2011). The percentage contribution of each variable to the resulting probability maps is also produced, providing information on the importance of each to the model output.

Results

Results of the global model showed the greatest suitability for the Queensland fruit fly in its native and invaded range, including the east coast of Australia and some south Pacific islands. However, the model also shows areas in Taiwan, Vietnam, southern central China, South America, east of Madagascar and the south-east of the United States and adjacent Caribbean islands to have a similar high suitability (Figure 1). Mean probability for the raster output was 0.028 with a standard deviation of 0.092 with a maximum probability of 0.948.

When projected into New Zealand current conditions and using the range of intensity values consistent with the global model, the majority of the country's potential suitability is in the lower range of values with some areas in the medium range. The southern east coast of the North Island is found to have a medium range of suitability for the fruit fly (Figure 2A). This has implications for the wine and other horticulture industries, such as pip fruit (Clothier et al. 2013) in those areas. Some similarities to Australia can be found, including the most suitable areas being found on the eastern coast, with the central and western areas much less suitable or even unsuitable. The degree of suitability of the North Island is within the medium to low suitability range, except for the central mid areas and higher elevations which show the least suitability.

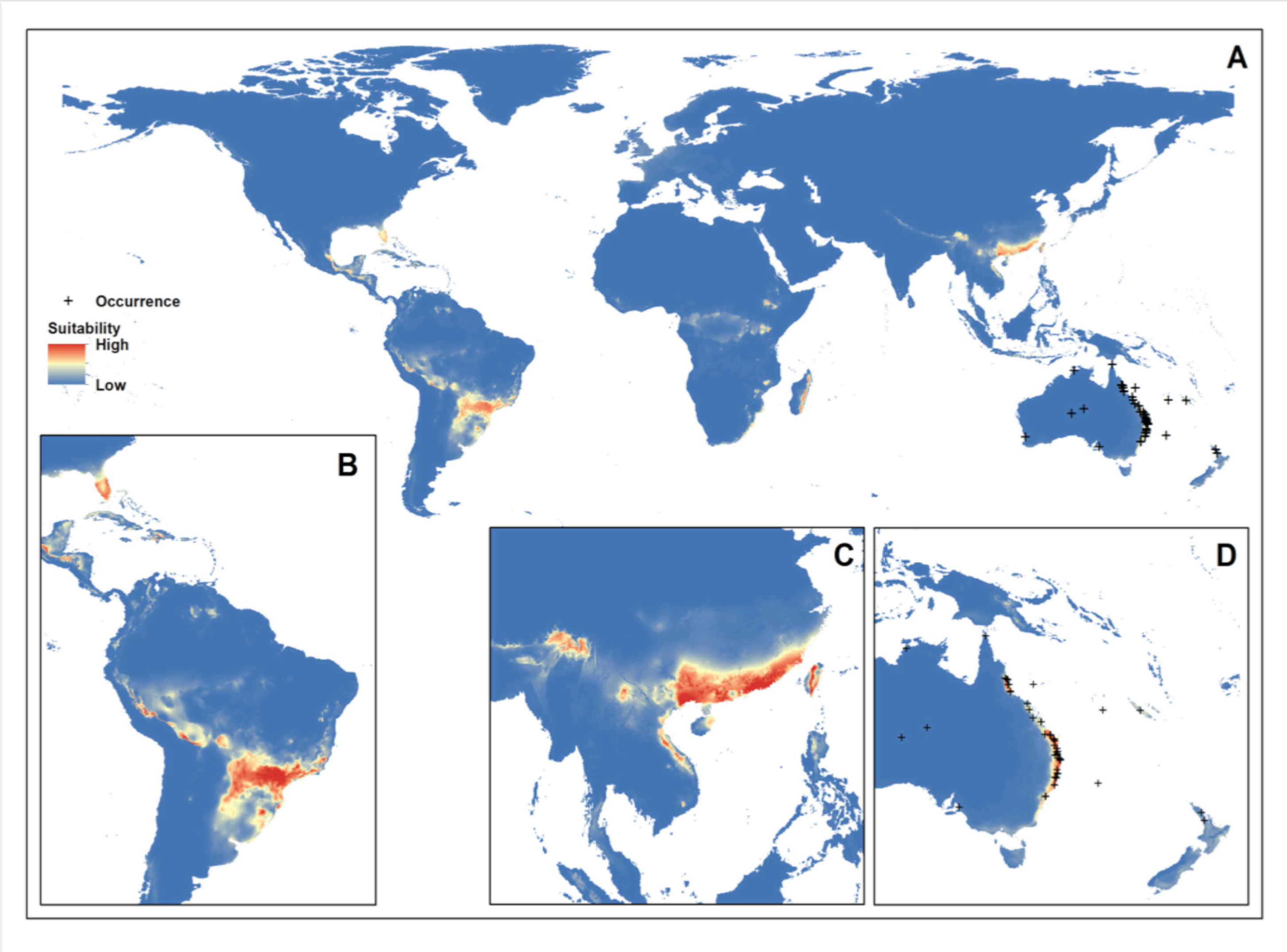


Figure 1.
Global suitability map for the Queensland fruit fly (A) with suitable areas in South America, Mexico and Florida (B), China, Taiwan and Vietnam (C) and in its native range in Australia (D).

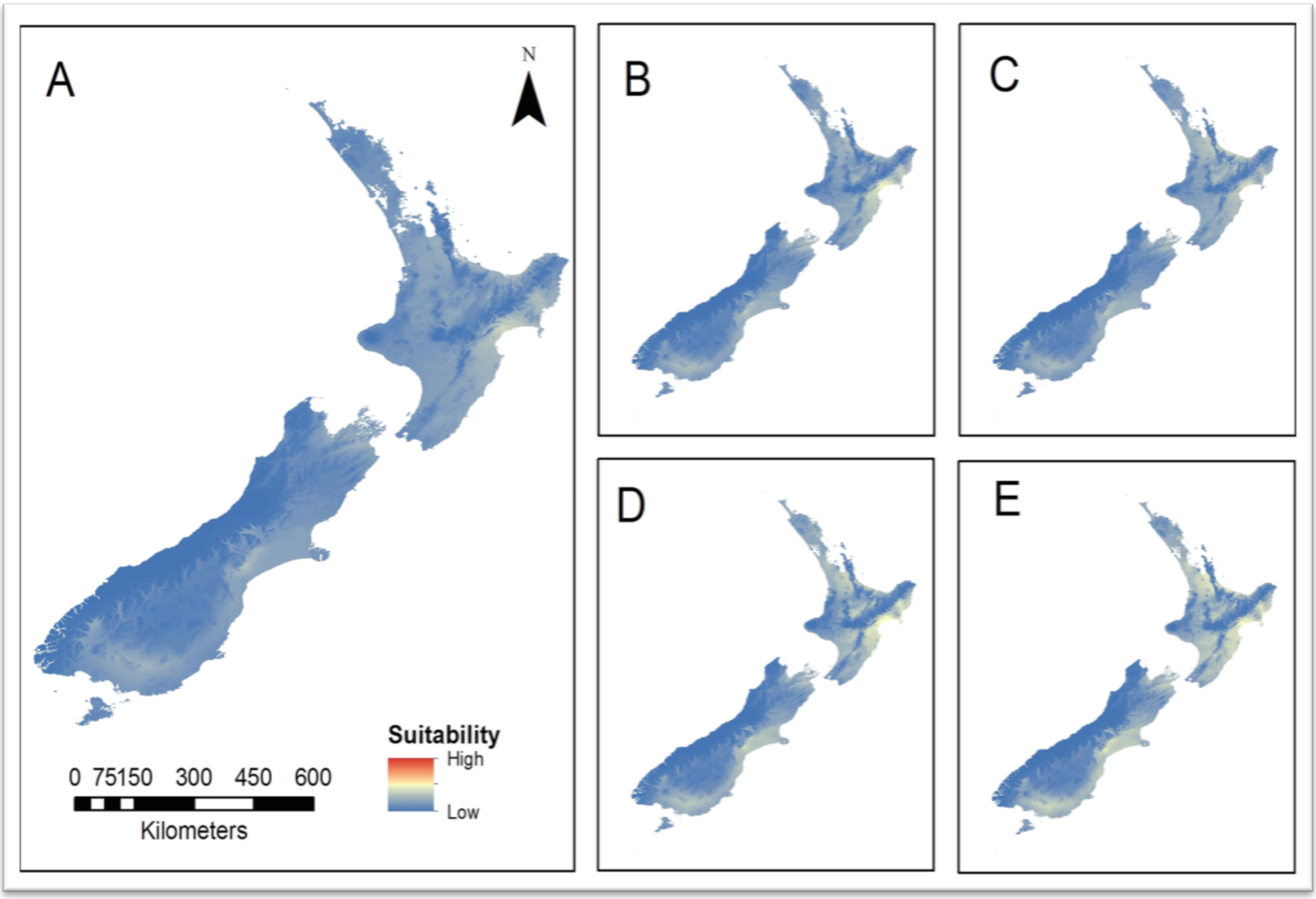


Figure 2.
Suitability prediction maps for the Queensland fruit fly under Current Conditions [A], future climate change scenarios: RCP 2.6 for years 2050 [B], 2070 [C]; RCP 8.5 for years 2050 [D] and 2070 [E].

Future climate scenario prediction results show different scenarios depending on the emission rate and the year projected. For the lower emission RCP 2.6 for the year 2050, there is an increase in suitability in both the North and South Islands, which changes in 2070 with the northern part of the South Island showing more suitable areas (Figure 2B and 2C) and the highest suitable areas of the southern central North Island increasing in suitability. For the higher emission scenario RCP 8.5, in year 2050 the mid north and east of the North Island shows higher suitability, with continued increase in suitability in 2070. The higher elevation areas such as Taranaki, the mountain ranges from the East Cape to Cook Strait that form a barrier between the eastern and western sides of the North Island and the high mountainous areas of the South Island show much less suitability compared to the other areas.

The lower emission scenario generally shows lesser suitability compared to the higher emission scenario. While there is not much difference in terms of consistent areas of comparatively higher suitability, differences between intensity values are obvious, with the latter year (2070) generally showing a higher probability of predicted presence.

	Year	Average Maximum Probability
	Current	0.441
RCP 2.6	2050	0.541
	2070	0.532
RCP 8.5	2050	0.580
	2070	0.662

Table 2.
Maximum probability values for suitability returned by Maxent per scenario/year.

The highest probability value of the species occupying an individual raster or pixel is found in the RCP 8.5 year 2070 scenario, while the lowest predicted value is found in the current period (Table 2). The higher emission scenario, RCP 8.5, consistently shows higher maximum values for species occurrence probability, compared to the current period and both future years of the lower emission RCP 2.6.

The average of the thresholded rasters produced by Maxent, using the 10th percentile criteria per scenario, shows increasing areas of presence for the Queensland fruit fly under current conditions (Figure 3A), compared to both low and high emission scenarios (Figures 3B-3E). In terms of magnitude, the higher emission RCP 8.5 scenario shows greater presence areas for both the North and South Islands. Consistent absence is shown in the mountain ranges of the North Island, most prominently in an area which stretches from the East Cape to the Cook Strait. A band from the Taranaki region across to East Cape also shows a consistent absence. For the South Island, from very minimal presence in current conditions, future climate warming increases the presence areas in the Canterbury plains and the top of the South Island for the lower emission scenario. The higher emission scenario shows a much wider spread along the east coast. For the RCP 8.5 scenario in 2070, presence is predicted in the southernmost region of the South Island.

In current conditions, rasters representing presence accounted for 5.90% of the total, increasing to 19.59% and 20.35% for RCP 2.6 for the years 2050 and 2070. The higher emission scenario, RCP8.5, shows a greater increase, with 28.93% and 38.98% for 2050 and 2070 respectively. Consistent with warming conditions, the increased predicted presence is directly proportional to the level of emissions used in the projection. For the low emission scenario, the change between years 2050 and 2070 is not as distinct when compared to the higher emission scenario RCP 8.5.

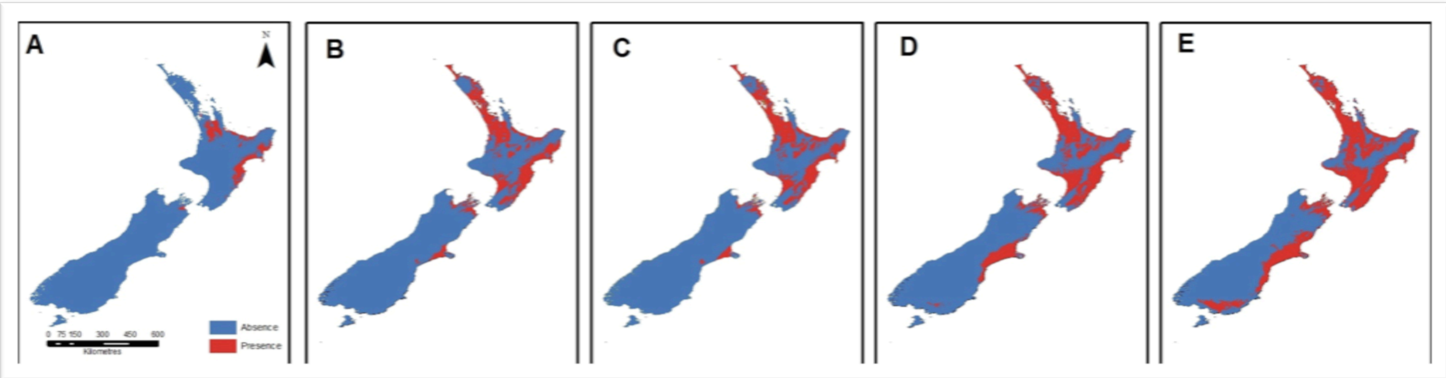


Figure 3.
Thresholded binary maps depicting presence and absence in current conditions [A], RCP2.6 2050 [B] and 2070 [C], RCP 8.5 2050 [D] and 2070 [E].

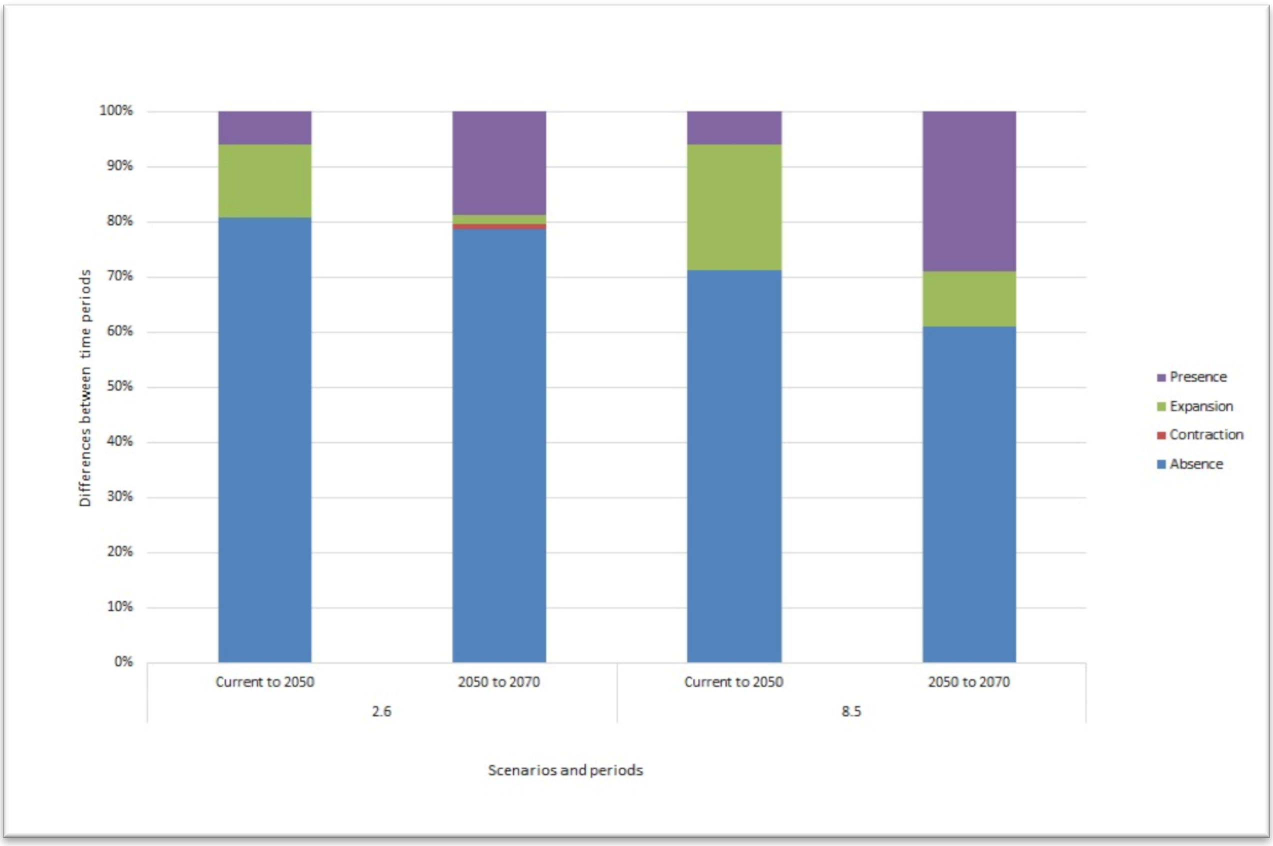


Figure 4.
Breakdown in area composition of species range between projected New Zealand current and future climate change scenarios.

Results of calculating the range based on thresholded values show that for the lower emission scenario RCP 2.6, the range expansion or increase in the area favourable for the fruit fly between 2050 and 2070 is evident without any contraction in the range (Figure 4). The only contraction in range is a small difference from 2050 to 2070 for RCP 2.6. A smaller increase of the range expansion between 2050 and 2070, compared to current conditions and 2050, is also shown.

The higher emission scenario RCP 8.5 on the other hand, shows a higher increase in presence areas compared to RCP 2.6 between the current period and 2050 as well as from 2050 to 2070. Both emission scenarios show a decrease in areas from which the species is predicted to be absent (from 93.5% in current conditions to 82% for RCP 2.6 and 71% for RCP 8.5 for the year 2070).

When centroids of the different range areas were calculated, the location of the centroid in the North Island shifted quite similarly (towards the south-west) between current conditions in both the lower and higher emission scenarios in the year 2050. However, the lower emission scenario centroid shifted very slightly to the north from 2050 to 2070, while the higher emission centroid continued its shift towards the south-west with a more southerly direction than the preceding period (Figure 5). In terms of magnitude of the shift, the RCP 8.5 scenario shows a greater shift for both period pairs compared to the lower emission scenario. Figure 5 also shows the predicted range contraction or expansion as well as presence and absence areas for both scenarios between years 2050 and 2070.

Model evaluation results showed the AUC with a mean of 0.960 with a standard deviation of 0.042,

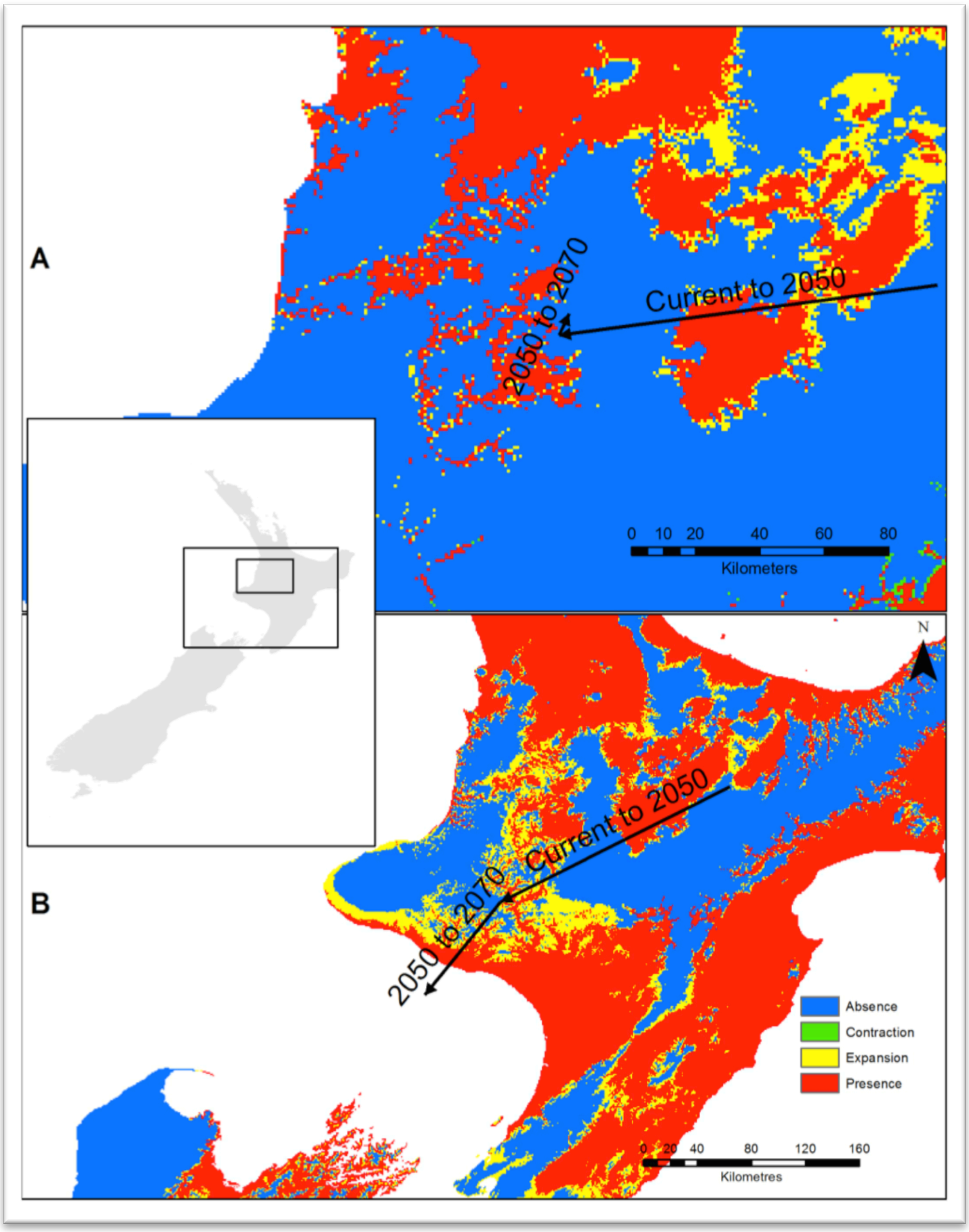


Figure 5.
Centroid shift between current conditions and RCP 2.6 overlaid on top of the range change between current period and 2070 [A] and RCP 8.5 overlaid on top of range change between current period and 2070 [B].

indicating an acceptable performance of the model (greater than 0.90).

Discussion

This study presents a demonstration of species distribution modelling using Maxent to predict the suitability of New Zealand to an invasive species in current and future climate change scenarios. The worldwide model generated from known occurrences (including outbreak locations) and Bioclim climatic layers, as environmental layers of the correlative model, not only predicts the suitability of countries around the world but also indicates sources of possible invasion, based on countries with predicted high suitability.

Available transportation systems and infrastructure facilitating the movement of fruit and other products between these areas provide a major cause for concern for the invasion and subsequent establishment of viable populations in invaded areas. The current border pest management system is being continuously challenged by the sheer volume of people travelling, with 3.3 million visitors from Australia and New Caledonia resulting in 5,000 instances of fruit intercepted in 2013 alone (KVH, 2014).

As potential sources of invasion, information on highly suitable countries needs to be included in the required risk analysis as potential sources of invasion (Hulme 2009; Perrings et al., 2005; Andersen et al., 2004). Related information that can further refine the risk assessment in terms of invasion sources would be the volume of trade in items with which the species can be transported (mainly fruit), data on passengers with food items, trade partnership agreements, and biosecurity infrastructure at points of origin. With Auckland currently the area receiving the highest amount of imported volume and greatest number of inbound passengers, the recent outbreak of the Queensland fruit fly in one of its suburbs, as well as previous outbreaks in nearby areas, may provide clues on this pathway aspect of invasion.

The maps of potential distribution of the Queensland fruit fly in New Zealand, in current and future climate scenarios, consistently identified the majority of the country's terrestrial area as having a low predicted suitability in current conditions. However, a warming climate, represented by both low and high emission scenarios, generally increases the predicted presence areas, a finding that is of concern as a substantial part of the country, including the majority of the North Island and the east coast of the South Island, becomes eventually suitable for the species. Although overall invasion and establishment is influenced by microclimate variability, local species interactions and dispersal mechanisms (Sinclair et al., 2010), the maps of range expansion serve as a preliminary set of information underpinning both likelihood and consequence factors of a national scale risk assessment process. For local councils and government agencies in the areas of varying risk, the risk assessment results may contribute to the prioritisation of resources and formulation of strategies. Input from the horticulture industry on any predicted responses to climate change would also be useful. It is suggested that there would be a reduction in production of apples, kiwifruit and grapes in some areas, as the local climate becomes less favourable to growing those species, and expansion into new regions (Clothier et al. 2013).

The results of range calculation, where there is a range contraction in the RCP 2.6 scenario, is consistent with its inherent characteristics, i.e. an increase in emissions until the mid-century is expected to be followed by a decrease consistent with the lag of the effect of worldwide mitigation efforts to reduce emissions globally (Carraro et al., 2014). This trend is further supported in Table 2 where there is an increase from the current maximum probability to year 2050 but a decrease from 2050 to 2070 for RCP 2.6. The higher emission scenario consistently shows results with a greater range of suitability values and a greater increase of the geographical range compared to the lower emission scenario between the years 2050 and 2070.

The shift in the centroid is consistent with most climate change studies showing a poleward drift of range centroids for most species in climate change conditions (Berry et al., 2010; Gramvölgyi & Hufnagel 2013; Tingley et al., 2014). For the Queensland fruit fly, this result is consistent with its ecophysiology as discussed by Clarke et al. (2011). A further refinement in this aspect is the addition of environmental variables such as elevation, land cover or vegetation, soil moisture and other physiologically important conditions that may improve the prediction (Clarke et al., 2011). Socio-economic variables such as population density, transportation networks and the surveillance system in place may also prove to be valuable additions to the model.

In light of recent outbreaks of the Queensland fruit fly in Auckland, the generation of predictive maps is considered a preliminary effort providing options to inform the risk assessment process required to address present and future outbreaks. While further refinement and investigations are required to assess, validate and enhance model outputs, the process in developing the predictive outputs can be applied to different invasive species in a wide range of spatial and times scales.

Conclusions

Predictive models depicting the spread and distribution in New Zealand of the invasive and damaging Queensland fruit fly produced suitability maps for current and future climate conditions. Results show that current climatic conditions are in the lower probability range of suitability. However, a warming climate results in an increase in suitability that corresponds proportionally with the emission scenario: the higher the emission scenario, the greater is the area suitable for the species. Calculations of the shift of suitable areas show a general movement of the centroid towards the south-east, with the higher emission scenario depicting a greater magnitude of movement. The suitability maps produced may be considered a preliminary step in providing options for risk assessment processes required in dealing with the current and future outbreak or invasion potential of the Queensland fruit fly.

Click here to visit the Queensland fruit fly suitability prediction map

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References

Andersen MC, Adams H, Hope B, Powell M 2004. Risk assessment for invasive species. Risk analysis 24(4): 787-793.

Araújo MB, Guisan A 2006. Five (or so) challenges for species distribution modelling. Journal of Biogeography 33(10): 1677-1688. doi:10.1111/j.1365-2699.2006.01584.x

Bateman MA 1991. The impact of fruit flies on Australian horticulture. *Horticultural Policy Council Report No. 3*. ISBN 0642161100.

Beaumont LJ, Hughes L, Poulsen M 2005. Predicting species distributions: use of climatic parameters in BIOCLIM and its impact on predictions of species' current and future distributions. Ecological Modelling 186: 250-269.

Berry PM, Dawson TP, Harrison PA, Pearson RG 2002. Modelling potential impacts of climate change on the bioclimatic envelope of species in Britain and Ireland. Global Ecology and Biogeography 11: 453-462.

Blanchard R, O'Farrell PJ, Richardson D M 2015. Anticipating potential biodiversity conflicts for future biofuel crops in South Africa: incorporating spatial filters with species distribution models. GCB Bioenergy 7(2): 273-287.

Broennimann O, Treier UA, Müller-Schärer H, Thuiller W, Peterson AT, Guisan A 2007. Evidence of climatic niche shift during biological invasion. Ecology Letters 10(8): 701-9. doi:10.1111/j.1461-0248.2007.01060.x

Brown J L 2014. SDMtoolbox: a python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. Methods in Ecology and Evolution 5(7): 694-700.

Carraro C, Lanza A, Tavoni M 2014. All You Need to Know About the IPCC 5th Assessment Report. Mitigation of Climate Change. Review of Environment, Energy and Economics-Re3.

Clarke AR, Powell KS, Weldon CW, Taylor PW 2011. The ecology of *Bactrocera tryoni* (*Diptera: Tephritidae*): What do we know to assist pest management? Annals of Applied Biology 158: 26-54. doi:10.1111/j.1744-7348.2010.00448.x

Clothier B, Hall A, Green S 2012. Chapter 6: Horticulture. Adapting the horticultural and vegetable industries to climate change. In Clark A & Nottage R 2012. Impacts of Climate Change on Land-based Sectors and Adaptation Options. A Technical Report for the Ministry of Primary Industries. Pg 237-292.

Connolly J, Manning K, Colledge S, Dobney K, Shennan S 2012. Species distribution modelling of ancient cattle from early Neolithic sites in SW Asia and Europe. The Holocene 22(9):997e1010.

Daehler CC, Denslow JS, Ansari S, Kuo HC 2004. A risk-assessment system for screening out invasive pest plants from Hawaii and other Pacific islands. Conservation Biology 18: 1-9.

De Queiroz D L, Majer J, Burckhardt D, Zanetti R, Fernandez J I R, de Queiroz E C, ... dos Anjos N 2013. Predicting the geographical distribution of *Glycaspis brimblecombei* (*Hemiptera: Psylloidea*) in Brazil. Australian Journal of Entomology 52(1): 20-30. doi:10.1111/aen.12001

Domíguez-Vega H, Monroy-Vilchis O, Balderas-Valdivia C J, Gienger C M, Ariano-Sánchez D 2012. Predicting the potential distribution of the beaded lizard and identification of priority areas for conservation. Journal for Nature Conservation 20(4): 247-253. doi:10.1016/j.jnc.2012.04.003

Dominiak BC 2011. Review of grapes *Vitis sp*. as an occasional host for Queensland fruit fly *Bactrocera tryoni* (Froggatt) (Diptera: Tephritidae). Crop Protection 30(8): 958-961 doi:10.1016/j.cropro.2011.02.028

Dominiak BC, Campbell M, Cameron G, Nicol H 2000. Review of vehicle inspection historical data as a tool to monitor the entry of hosts of Queensland fruit fly *Bactrocera tryoni* (Froggatt) (Diptera: Tephritidae) into a fruit fly free area. Australian Journal of Experimental Agriculture 40: 763-771.

Dominiak BC, Coombes N 2009. Fruit carrying characteristics of travellers into a quarantine zone in New South Wales in 1999/2000. Plant Protection Quarterly 24: 14-19.

Dominiak BC, Ekman JH 2013. The rise and demise of control options for fruit fly in Australia. Crop Protection 51: 57-67.

Dormann CF, Elith J, Bacher S, Buchmann C, Carl G, Carre G, Marquez JRG, Gruber B, Lafourcade B, Leitao PJ, Munkemuller T, McClean C, Osborne PE, Reineking B, Schroder B, Skidmore AK, Zurell D, Lautenbach S 2013.

Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36(1): 27-46.

Drew RAI, Hooper GHS, Bateman MA 1978. Economic Fruit Flies of the South Pacific Region. Brisbane, Australia: Queensland Department of Primary Industries.

Elith J, Graham C, Anderson R, Dudik M, Ferrier S, Guisan A, Hijmans R, Huettmann F, Leathwick J, Lehmann A, Li J, Lohmann L, Loiselle B, Manion G, Moritz C, Nakamura M, Nakazawa Y, Overton J, Peterson A, Phillips S, Richardson K, Scachetti Pereira R, Schapire R, Soberon J, Williams S, Wisz M, Zimmermann, N 2006. Novel methods improve prediction of species' distribution from occurrence data. Ecography 29: 129-151.

Elith J, Graham C 2009. Do they? How do they? Why do they differ? On finding reasons for differing performances of species distribution model. Ecography 32: 66-77.

Elith J, Phillips S, Hastie T, Dudik M, Chee Y, Yates CJ 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions 17: 43-57.

Elith J, Kearney M, Phillips S 2010. The art of modelling range-shifting species. Methods in Ecology and Evolution 1(4): 330–342. doi:10.1111/j.2041-210X.2010.00036.x

Evangelista P, Kumar S, Stohlgren T, Jarnevich C, Crall A, Norman J, Barnett D 2008. Modelling invasion for a habitat generalist and specialist species. Diversity and Distributions 14: 808-817.

Fourcade Y, Engler J O, Rödder D, Secondi J 2014. Mapping Species Distributions with MAXENT Using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. PLOS ONE, 9(5): e97122. doi:10.1371/journal.pone.0097122

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(3): 331-342. doi:10.1111/j.1472-4642.2010.00652.x

Gent PR, Danabasoglu G, Donner LJ, Holland MM, Hunke EC, Jayne SR, Lawrence DM, Neale RB, Rasch PJ, Vertenstein M, Worley PH, Yang ZY, Zhang M 2011. The community climate system model version 4. Journal of Climate 24: 4973-4991. doi:10.1175/2011JCLI4083.1

Gramvölgyi A, Hufnagel L 2013. Impacts of climate change on vegetation distribution no. 1 climate change induced vegetation shifts in the palearctic region. Applied Ecology and Environmental Research 11(1): 79-122.

Guisan A, Thuiller W 2005. Predicting species distribution: offering more than simple habitat models. Ecology Letters 8(9): 993-1009.

Guisan A, Tingley R, Baumgartner JB, Naujokaitis-Lewis I, Sutcliffe PR, Tulloch AIT, Regan TJ, Brotons L, McDonald-Madden E, Mantyka-Pringle C, Martin TG, Rhodes JR, Maggini R, Setterfield SA, Elith J, Schwartz MW, Wintle BA, Broennimann O, Austin M, Ferrier S, Kearney MR, Possingham HP, Buckley YM 2013. Predicting species distributions for conservation decisions. Ecology Letters 16: 1424-1435. doi:10.1111/ele.12189

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25(15): 1965-1978. doi:10.1002/joc.1276

Hulme PE 2009. Trade, transport and trouble: managing invasive species pathways in an era of globalization. Journal of Applied Ecology 46(1): 10-18.

Huntley B, Collingham YC, Willis SG, Green RE 2008. Potential impacts of climatic change on European breeding birds. PLOS ONE 3(1): e1439.

IPCC 2013. Summary for Policymakers. In: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker, T.F., D. Qin, G.K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jones RN 2001. An environmental risk assessment/management framework for climate change impact assessments. Natural Hazards 23(2-3): 197-230.

Khanum R, Mumtaz AS, Kumar S 2013. Predicting impacts of climate change on medicinal asclepiads of Pakistan using Maxent modeling. Acta Oecologica 49: 23-31. doi:10.1016/j.actao.2013.02.007

KVH (Kiwifruit Vine Health) 2014. Financial impact of a fruit fly incursion to New Zealand's kiwifruit industry March 2014. Retrieved from http://www.kvh.org.nz/vdb/document/98983

Mo J, Dominiak BC, Stevens MM, Reynolds OL 2014. Pest behaviour insights from quarantine surveillance of male Queensland fruit fly, *Bactrocera tryoni* (Froggatt) (Diptera: Tephritidae). Crop Protection 62: 55-63. doi:10.1016/j.cropro.2014.04.005

Ministry of Primary Industries (MPI) 2015. Queensland Fruit Fly (QFF) - Pathway Report. Retrieved from http://www.biosecurity.govt.nz/files/pests/queensland-fruit-fly/qff-pathway-report.pdf

Nabout JC, Soares TN, Diniz-Filho JA, De Marco Júnior P, Telles MPC, Naves RV, Chaves LJ 2010. Combining multiple models to predict the geographical distribution of the Baru tree (*Dipteryx alata* Vogel) in the Brazilian Cerrado. Brazilian

Journal of Biology - Revista Brasleira de Biologia 70(4): 911-9. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/21180894

NTA 2007. Northern Territory weed risk management user guide. Natural Resources Division, Department of Natural Resources, Environment, The Arts and Sport, Northern Territory of Australia, Palmerston, NT, Australia.

NTA 2009. Northern Territory weed risk assessment report: *Andropogon gayanus* (gamba grass). Natural Resources Division, Department of Natural Resources, Environment, The Arts and Sport, Northern Territory of Australia, Palmerston, NT, Australia.

Oliver J 2007. Summary of national fruit fly-related activities stocktake released. Plant Protection News. February 2007.

Pearson RG 2007. Species' Distribution Modeling for Conservation Educators and Practitioners. Synthesis. American Museum of Natural History.

Perrings C, Dehnen-Schmutz K, Touza J, Williamson M 2005. How to manage biological invasions under globalization. Trends in Ecology & Evolution 20(5): 212-215.

Peterson A, Soberon J, Pearson R, Anderson R, Martinez-Meyer E, Nakamura M, Araújo M 2011. Ecological niche and geographic distribution. Princeton and Oxford: Princeton University Press. 314 p.

Peterson AT, Vieglais DA 2001. Predicting species invasions using ecological niche modelling: new approaches from bioinformatics attack a pressing problem. BioScience 51: 363-371.

Pheloung PC, Williams PA, Halloy SR 1999. A weed risk assessment model for use as a biosecurity tool evaluating plant introductions. Journal of Environmental Management 57(4): 239-251.

Phillips S, Dudik M 2008. Modeling of species distribution with Maxent: New extensions and a comprehensive evaluation. Ecography *31*: 161-175.

Phillips S, Anderson R P, Schapire R E 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling, 190(3-4): 231-259.

Poulos H, Chernoff B, Fuller P, Butman D 2012. Ensemble forecasting of potential habitat for three invasive fishes. Aquatic Invasions 7(1): 59-72. doi:10.3391/ai.2012.7.1.007

Puschendorf R, Carnaval AC, VanDerWal J, Zumbado-Ulate H, Chaves G, Bolaños F, Alford, RA 2009. Distribution models for the amphibian chytrid *Batrachochytrium dendrobatidis* in Costa Rica: proposing climatic refuges as a conservation tool. Diversity and Distributions 15(3): 401-408. doi:10.1111/j.1472-4642.2008.00548.x

Reiss H, Cunze S, Konig K, Neumann H, Kroncke I 2011. Species distribution modelling of marine benthos: A North Sea case study. Marine Ecology Process Series 442: 71-86.

Robinson LM, Elith J, Hobday AJ, Pearson RG, Kendall BE, Possingham HP, Richardson AJ 2011. Pushing the limits in marine species distribution modelling: Lessons from the land present challenges and opportunities. Global Ecology and Biogeography 20: 789-802. doi:10.1111/j.1466-8238.2010.00636.

Roura-Pascual N, Brotons L, Peterson AT, Thuiller W 2009. Consensual predictions of potential distributional areas for invasive species: A case study of Argentine ants in the Iberian Peninsula. Biological Invasions 11(4): 1017-1031. doi:10.1007/s10530-008-9313-3

Shochat E, Lerman SB, Anderies JM, Warren PS, Faeth SH, Nilon CH 2010. Invasion, competition, and biodiversity loss in urban ecosystems. BioScience 60(3): 199-208.

Sinclair S, White M, Newell GR 2010. How useful are species distribution models for managing biodiversity under future climates? Ecology and Society 15(1): 8.

Soberon J, Golubov J, Sarukhan J 2001. The importance of *Opuntia* in Mexico and routes of invasion and impact of *Cactoblastis cactorum* (Lepidoptera : Pyralidae). Florida Entomologist 84: 486-492.

Swets JA 1988. Measuring the accuracy of diagnostic systems. Science 240(4857): 1285-1293.

Taylor S, Kumar L 2013. Potential distribution of an invasive species under climate change scenarios using CLIMEX and soil drainage: A case study of *Lantana camara* L. in Queensland, Australia. Journal of Environmental Management 114: 414-422. doi:10.1016/j.jenvman.2012.10.039

Tingley R, Vallinoto M, Sequeira F, Kearney MR 2014. Realized niche shift during a global biological invasion. Proceedings of the National Academy of Sciences of the United States of America 20: 1-6. doi:10.1073/pnas.1405766111

VanDerWal J, Murphy HT, Kutt AS, Perkins GC, Bateman BL, Perry JJ, Reside AE 2013. Focus on poleward shifts in species' distribution underestimates the fingerprint of climate change. Nature Climate Change 3(3): 239-243.

Wakie TT, Evangelista PH, Jarnevich CS, Laituri M 2014. Mapping current and potential distribution of non-native *prosopis juliflora* in the afar region of Ethiopia. PLOS ONE 9(11): e112854. doi:10.1371/journal.pone.0112854

Wasowicz P, Pasierbinski A, Przedpelska-Wasowicz EM, Kristinsson H 2014. Distribution patterns in the native vascular flora of Iceland. PLOS ONE 9(7): e102916. doi:10.1371/journal.pone.0102916

Wasowicz P, Przedpelska-Wasowicz EM, Kristinsson H 2013. Alien vascular plants in Iceland: Diversity, spatial patterns, temporal trends, and the impact of climate change. Flora - Morphology, Distribution, Functional Ecology of Plants, 208: 648-673. doi:10.1016/j.flora.2013.09.009

Wilson JRU, Richardson DM, Rouget M, Proches S, Amis MA, Henderson L, Thuiller W 2007. Residence time and potential range: crucial considerations in modelling plant invasions. Diversity and Distributions 13: 11-22.

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