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**The impacts of climate change on the summerfruit industry
with respect to insect pest incursions**

-

A thesis
submitted in partial fulfilment
of the requirements for the Degree of
Master of Applied Science

at
Lincoln University
by
Karel Richard Lindsay

-

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Abstract of a thesis submitted in partial fulfilment of the
requirements for the Degree of Master of Applied Science.

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Karel Richard Lindsay

It is now well established that climate change is causing a rise in surface air temperatures due to anthropogenic greenhouse gas emissions. Evidence suggests that warmer surface air temperatures are likely to have an impact on species distributions and climatic suitability, potentially resulting in an increase of tropical or sub-tropical insect pest establishments in areas with temperate climates such as New Zealand. The increased risk of these exotic insect pests establishments is likely to affect both native ecosystems and agricultural industries. The New Zealand summerfruit industry is the fourth largest horticultural industry in New Zealand with a valuable export market worth NZ\$30 million per annum. New Zealand currently maintains a valuable fruit fly free status that is maintained by strict biosecurity procedures such as the treatment and inspection of imported fruit and a nationwide trapping grid. However climate change could improve the climatic suitability for particular fruit fly species in New Zealand and increase the risk of permanent establishment..

In the absence of more detailed biological data for target species, any assessment of establishment potential of species under changing conditions often means the use of a species distribution model (SDM) to project climatic suitability in the target area. This research aimed to predict and compare the climatic suitability of major summerfruit producing regions in New Zealand under current climatic conditions and future climate change conditions of *Bactrocera dorsalis*, *B. tryoni*, *B. zonata*, *Ceratitis capitata* and *C. rosa*. A common ecoclimatic assessment model known as CLIMEX and a correlative modelling system comprising multiple SDM models were used to estimate climatic suitability for each species. Climatic suitability predictions for New Zealand were generated for 2040 and 2090 emission scenarios that represented best case, intermediate and worse case scenarios per time frame.

The results using CLIMEX indicated an increase in climatic suitability around the summerfruit producing Hawkes Bay and Marlborough regions for all fruit fly species under all climate change scenarios. High future emission scenarios resulted in a higher increase in climatic suitability. The results with the multiple model system indicated an increase in climatic suitability for *C. rosa* under all climate change scenarios and around all major summerfruit producing regions, an increase in climatic suitability for *B. zonata* only under 2090 climate change scenarios around the summerfruit producing regions, Marlborough and Central Otago and an increase in climatic suitability for *B. dorsalis* around the summerfruit producing region Central Otago. A decrease in climatic suitability for *C. capitata* was observed in all areas under all climate change scenarios and no change from low risk was observed for *B. tryoni*. These results indicate that warmer temperatures may increase or decrease the risk exotic summerfruit insect pest incursions and establishments.

In the event of an incursion or outbreak, knowledge of climatic suitability for exotic fruit fly species that present a serious threat to our horticulture industry will increase the effectiveness of an incursion response by concentrating eradication and spread prevention protocols around locations that are more vulnerable, rather than expend resources and valuable time on locations with a low climatic suitability. Additionally, the industries at risk can use this information to be pro-active and plan for emerging threats.

Keywords: climate change, species distribution models, fruit flies, CLIMEX, summerfruit, biosecurity, distribution range shift,

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Chapter 1

General Introduction

1.1 Global climate change and the IPCC

Climate change and global warming are terms used to describe the current change in global climatic systems due to warming of surface air temperatures. Evidence now indicates that climate change is not naturally occurring but rather the result of accumulative anthropogenic greenhouse gas emissions and deforestation. Measurements taken from ice cores indicate an increase of greenhouse gases by 70% between 1970 and 2004 since pre industrial(IPCC 2007). An increase in greenhouse emissions amplifies the ‘greenhouse effect’ which is the result of the greenhouse gases in the lower atmosphere absorbing thermal radiation off the Earth’s surface. Evidence for climate change occurring can be observed from both climatic measurements and physical changes to the environment. For example, global sea level rose at an average rate of 1.8mm per year from 1961 to 2003 and at an average rate of 3.1mm per year from 1993 to 2003. Of the observed increase in sea level, 58% is from thermal expansion, 28% from melting glaciers and the rest from melting polar ice sheets.

Evidence for surface air temperature increases can be found by observing temperature anomalies from a reference value. Brohan *et al.* (2006) published a report on deviating temperature anomalies from a time series dataset ranging from 1850 to 2005. The reference value in this study was the temperature average during the time period 1960 – 1990. Since then the Climate Research Unit (CRU) and UK Met Office Hadley Centre have updated the temperature anomalies. (Figure 1.1) (Jones 2010). The values in the time period 1961 – 1990 do not average to zero due to the lack of complete temperature recordings in some parts of the world.

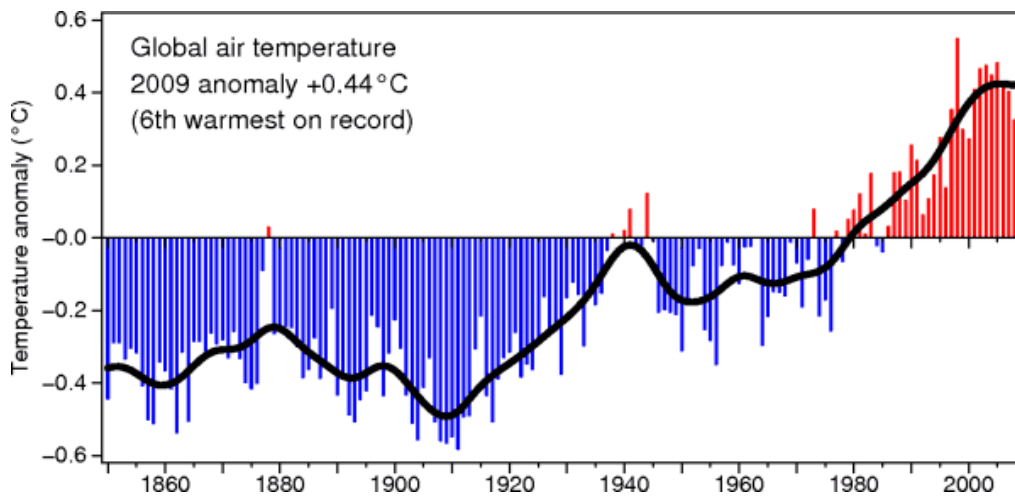


Figure 1.1: Temperature anomalies from 1850 to 2009 (Jones 2010)

Using the same time series dataset, the rate of surface air temperature increase is also observed to be intensifying over time (Jones 2010) (Table 1.1).

Table 1.1: Average global surface air temperature increases per decade through various timescales

Timescale	Temperature Anomaly
1875 – 2005	0.054 +/- 0.016 °C
1901 – 2005	0.084 +/- 0.021 °C
1979 – 2005	0.268 +/- 0.069 °C

The Intergovernmental Panel on Climate Change (IPCC) was established by the United Nations Environmental program (UNEP) and World Meteorological Organisation (WMO) in 1988. Researchers connected to the IPCC review and assess the most recent scientific, technical and social-economical data produced worldwide related to global climate change and produce assessments, special reports and technical reports. These reports provide governments of the world with a clear scientific view on the state of climate change and the potential social and economic consequences.

The predicted temperature range increases are calculated from a range of different scenarios that span best and worst case scenarios referring to potential greenhouse gas emission rates, technological changes and social-economic factors in the future (Figure 1.2) (Nakicenovic and Swart 2000). The A1 scenario describes a future world of “very rapid economic growth, global population that peaks in mid-century, followed by a decline and the rapid introduction of new and more efficient technologies” (Nakicenovic and Swart 2000). The scenario family divides into three different groups that characterise alternative developments of technology:

A1F1 (fossil fuel intensive), A1B (balanced) and A1T (non fossil fuel dependent). The B1 scenario describes the same population projector as A1 scenario but with a more service and information economy, it also describes a reduction in material intensity and introduction of resource efficient technology. The A2 scenario describes a world of national self reliance and preservation of local identities with technology change that is fragmented and slower than other storylines. The last scenario, the B2 scenario, describes a similar heterogeneous world like the A2 scenario with local solutions to economic, social and environmental issues. The B2 scenario also describes more diverse and less rapid changes in technology than the A1 and B1 scenarios.

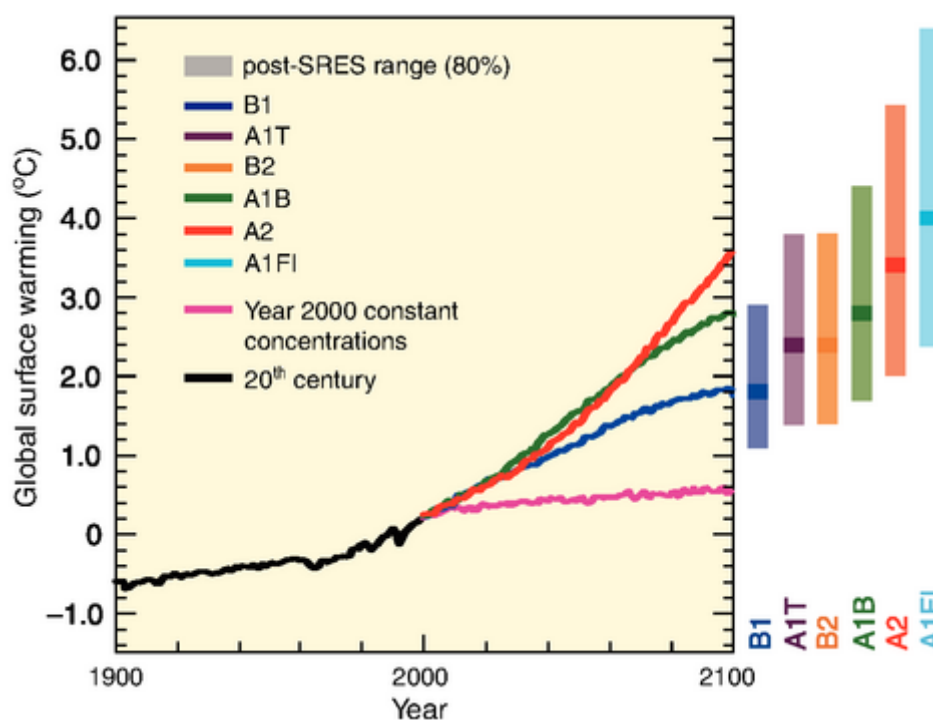


Figure 1.2: IPCC carbon emission scenarios (Nakicenovic and Swart 2000)

The fourth assessment is the most recent working assessment published by the IPCC in 2007. This assessment states an average increase of global surface air temperatures of 0.2 °C per decade during the 21st century across the emission scenarios. If carbon emissions remained at concentrations measured in 2000, there would still be an increase in surface air temperatures by 0.1 °C per decade (Meehl *et al.* 2007). Predicted increases in global surface air temperatures expected around 2090 – 2099 range from 1.1 °C to 6.4 °C across all emissions scenarios relative to 1980 – 1999 (Meehl *et al.* 2007).

1.1.1 New Zealand climate change predictions

A report created by National Institute for Water and Atmosphere (NIWA) and published by the Ministry for the Environment in 2008 (Mullen *et al.* 2008) gives predicted changes in surface air temperatures for 2040 and 2090 relative to 1990 for New Zealand. Global climate change predictions and carbon emission scenarios created by the IPCC were statistically downscaled to portray New Zealand predictions (Mullen *et al.* 2008). This method uses historical observations of New Zealand temperatures and compares it with climate fluctuations to create regression equations. The historical observations are then replaced by model projections to create the predictions (Mullen *et al.* 2008). The analysis only downscaled the A1B emission scenario while the rest of the emission scenarios were scaled differences from the A1B scenario.

The increases in mean annual surface air temperatures predicted for 2040 and 2090 varies across each individual emissions scenario (Table 1.2). Across all models and emission scenarios, climate change predictions in New Zealand range from 0.2 – 2 °C by 2040 and 0.7 – 5.1 °C by 2090.

Table 1.2: Average New Zealand climate change predictions across each carbon emissions scenario
2040 Climate Change Predictions

B1 Scenario	A1T/B2 Scenario	A1B Scenario	A2 Scenario	A1F1 Scenario
0.6	0.8	0.9	1.1	1.3

2090 Climate Change Predictions

B1 Scenario	A1T/B2 Scenario	A1B Scenario	A2 Scenario	A1F1 Scenario
1.3	1.7	2	2.5	2.9

Climate change predictions for New Zealand indicate less warming than what is predicted to occur on a global scale. (Mullen *et al.* 2008). The potential changes in the climate will not be equal across New Zealand with North Island temperatures expected to increase more than South Island temperatures. Warmer temperatures correlated with climate change are also likely to influence rainfall patterns and climatic extremes (Table 1.3). Changes to extreme

weather events may even have more impacts than changes to annual temperatures. Changes to temperatures, rainfall patterns and climatic extremes could depend on how key climatic processes such as the sub-tropical high pressure belt, mid latitude westerly wind circulation and the El Nino Southern Oscillation (ENSO) system respond to the warmer temperatures. There has been an observed increase in ENSO events since the 1970s but there is continual debate on whether this is linked to climate change (Mullen *et al.* 2008).

Table 1.3: Potential climate change in New Zealand

Climate Variable	Direction and Magnitude of Change
Extreme Temperatures	Decrease in extreme cold days during winter and increase in extreme warm days during summer
Rainfall	Increase in rainfall throughout the South Island and decreases in rainfall throughout the North Island
Extreme Rainfall	Heavier and more frequent extreme rainfall events
Snow Cover	Decreased amount and duration of snow cover
Winds	Increases in westerly winds and increases in extreme wind events

1.2 New Zealand summerfruit industry

The term summerfruit includes stone fruit crops such as cherries (*Prunus avium*), plums (*P. domestica*), apricots (*P. armeniaca*), peaches (*P. persica*) and nectarines (*P. persica*). The summerfruit industry in New Zealand is the fourth largest fruit producing crop industry after kiwifruit, pipfruit and avocados and comprises 2300 hectares divided among 350 growers (Summerfruit NZ 2007). Summerfruit production generated NZ\$41 million in the domestic market in the time period 2004 – 2009 and in 2009 alone the export market for summerfruit was valued at \$NZ31 million (Aitken and Hewett 2009). The top summerfruit producing regions in New Zealand are represented in Figure 1.3. Central Otago produces 50% of summerfruit, followed by Hawkes Bay with 30% and Marlborough with 10% (Summerfruit NZ 2007). The summerfruit industry supplies both the export and local markets with proportions varying per crop (Table 1.4).



Figure 1.3: The top summerfruit producing regions in New Zealand. HB = Hawkes Bay, MB = Marlborough, CO= Central Otago

Table 1.4: Total production (tonnes) of each summerfruit crop and proportions sold in export and local markets, 2008-2009 (Summerfruit NZ, 2007)

	Export and NZ Market total (tonnes)	% Export	% NZ Market
Apricots	3,500	29.6	70.4
Cherries	2,630	58.4	41.6
Nectarines	3,300	0.9	99.1
Peaches	3,050	0.8	99.2
Plums	1,970	1.4	98.7

1.2.1 New Zealand and summerfruit regional climate

New Zealand has a complex climate that varies from a warm sub-tropical climate in the north of the North Island to a temperate climate in the South Island. Mountain chains extending down the South Island and parts of the North Island, create a barrier for westerly winds and form two distinctly different climatic regions (NIWA 2010). Locations west of the mountain ranges experience high amounts of rainfall and less variation in temperatures compared to the drier and more variable temperature conditions east of the mountain chains (NIWA 2010).

Mean annual temperatures range from 10 °C in the South Island to 16 °C in the North Island. Temperatures also drop 0.7 °C for every 100 meters of altitude increase.

Summerfruit orchards in Central Otago experience very warm summers with temperatures reaching 20 °C to 26 °C during the afternoon, occasionally rising above 30 °C (NIWA 2010). Winters are very cold with severe, frequent frosts and occasional snowfall. Maximum temperatures in winter during the day range from 3 °C to 11°C. Mean rainfall is low with Alexandra only receiving 300mm annually, resulting in occasional drought conditions. Annual hours of sunshine average around 2050 hours (NIWA 2010). Summerfruit orchards in Marlborough are sheltered by high country in the west and south which accounts for this region having the highest annual sunshine hours (2300 hours) in New Zealand (NIWA 2010). The summers are warm and dry with afternoon temperatures reaching 20°C and 26°C, occasionally rising above 30 °C. Winters are mild with the occasional frost. Temperatures in winter reach between 10 °C and 15 °C during the day. Marlborough also receives little rainfall with Blenheim receiving on average 600mm of rain per year (NIWA 2010). High country to the west also creates a sheltered climate for summerfruit orchards in Hawkes Bay with annual hours of sunshine reaching 2200 hours. Summers are warm, dry and settled with temperatures reaching 20°C to 28°C, occasionally rising above 30°C (NIWA 2010). Extreme temperatures up to 39°C have also been recorded. Winters are mild with temperatures reaching 10°C to 16°C. Heavy rainfall can occur from the east or southeast. Hawkes Bay receives the most rain out of all the summerfruit production areas with 800mm of rain per year (NIWA 2010).

1.2.2 Summerfruit climatic preferences

Summerfruit crop trees are flowering perennials with very specific and sequential climate requirements compared to annual crops and perennial crops such as timber trees and pasture (Summerfruit NZ 2009). Summerfruit production requires hot dry summers and cold winters to fulfil physiological requirements to complete annual processes. During the onset of cooler temperatures in autumn and winter, summerfruit trees will enter dormancy to prevent new bud growth being destroyed by frosts and to break dormancy, accumulated winter chill is required to initiate flowering (Leudeling *et al.* 2009). The threshold temperature for winter chill to accumulate is below 7 °C and degree growing days above 7 °C are required during spring and summer for flowering and fruit ripening (Summerfruit NZ 2009). Summerfruit

trees also tolerate minimal temperature fluctuations during flowering to prevent damage to the flowers (Summerfruit NZ 2009).

1.2.3 Impacts of climate change on summerfruit crops

Climate change may bring positive effects to the industry with increases in mean annual temperatures. Fewer frosts during late autumn and early spring will reduce crop loss and damage to flowers. Warmer temperatures in the spring and summer will also improve fruit quality and size. Less rainfall in some parts of the country will help reduce fungal disease outbreaks and more rainfall in other parts of the country could promote good autumn growth and improved fruit size the following year (Summerfruit NZ 2009).

Changes to annual temperatures may also have negative consequences for the summerfruit industry. A long autumn and an early spring could contribute to a lack of winter chill. Not enough winter chill can lead to temporally spaced flowering, poor or sporadic leafing, varying fruit crop sizes and different stages of fruit maturity at harvest (Hennessey and Greene 1995; Leudeling *et al.* 2009). For example, long term temperature records in Oman indicated a decrease in winter chill hours by 22.7 hours per year between 1983 and 2007 and was linked to the total failure of peach and apricot crops at intermediate altitudes during the 2005/06 season (Leudeling *et al.* 2007).

A study by Leudeling *et al.* (2007) also demonstrated that under future climate change scenarios, there will not be enough winter chill during the cooler months for stone fruit (>700 hours of chilling conditions) to allow the crops to persist in some current summerfruit production locations in the USA.

Warmer temperatures could also alter summerfruit bud development and blooming phenology. Szalay *et al.* (2006) conducted a study on apricot bud development and blooming timing over a 10 year period to compare differences between milder and cooler years. The study demonstrated a difference of 2 months in blooming and 49 day difference in bud development between the coolest year and warmest year. The study by Szalay *et al.* (2006) demonstrates the vulnerability of summerfruit crops such as apricots to changes in phenological events under small temperature changes (Szalay *et al.* 2006). Earlier blooming may be an advantage in advancing the crop but it may also expose the summerfruit trees to frost damage and result in damaged flowers and decreased crop yield (Szalay *et al.* 2006; Summerfruit NZ 2009)

1.3 Impacts of climate change on insect pests

Insects being exothermic organisms rely heavily on the climate for their physiological processes and any changes in the climate can have impacts on many aspects of insect biology and spatial distribution. Climate change could have positive or negative impacts on an insect species, depending on their current environment and climatic tolerances. Insect species likely to benefit will be those currently living below their optimum temperature range at mid range latitudes and altitudes (Deutsch *et al.* 2008). Insect species likely to suffer negative consequences are those from lower latitudes as they will have narrow thermal tolerances due to temperature ranges remaining constant throughout the year (Deutsch *et al.* 2008). Thermal tolerances could be breached and result in extinctions (Deutsch *et al.* 2008). Impacts between and within populations in response to climate change may also differ as organisms occupying the edge of the species range are likely to respond more quickly than organisms of the same species living in optimal conditions in the middle of their range (Sutherst *et al.* 2007a).

1.3.1 Phenological and biological synchronisation alterations

Root *et al.* (2003) documented a change in spring phenology already occurring across a range of flora and fauna as a result of warmer temperatures. The study involved a meta-analysis across 143 studies and found an average change in spring phenology by 5.1 days per decade. Insect pests are documented to be experiencing changes in spring phenology events such as emergence from diapause (Bale *et al.* 2002) and earlier flight activity (Forister and Shapiro 2003). Changes in spring time phenological events could also lead to changes in biological synchronisations. For example, over the last two decades the winter moth (*Operophtera brumata*) egg hatch date has advanced over the bud burst date of its host plant pedunculate oak (*Quercus robur*) (van Asch *et al.* 2007). The biological synchrony between natural enemies and pest host could also be disrupted (Both *et al.* 2009; Thomson *et al.* 2010). The example given by Thomson *et al.* (2010) was of a potential divergence in synchrony between the light brown apple moth (*Epiphyas postvittana*) and Hymenopteran parasitoids under warmer conditions. Such a divergence in synchrony will allow some insect pests to benefit from reduced exposure to natural enemies and therefore result in reduced overall biological control effectiveness. Additionally, biological control programmes that have taken years to establish will be put in jeopardy by the sudden need to use broad spectrum insecticides to combat new threats.

1.3.2 Distribution range shifts

Climate is a strong influencing factor on where a species can persist throughout the year (Birch 1953). Therefore climate change is likely to cause alterations to distributions of some species, particularly exothermic organisms like insect species. The high latitude and altitude climatic boundary is likely shift for most species, but in some species the low latitude and altitude climatic boundary will also shift due to thermal tolerances being breached (Parmesan 1999). Parmesan *et al.* (1999) states that changes in distributions will not only be caused by movement but by the rates of extinctions and colonisations at the northern and southern regions of its distributions.

Currently, sub-tropical insect species may venture outside their regular distribution range and establish populations during warmer summer months but will perish from the cold stress imposed during the winter months. Warmer winters are known to decrease insect mortality (Bale *et al.* 2002; Battisti *et al.* 2005; Kiritani 2007; Bale and Hayward 2009) and maybe the cause of distribution range shifts.

For example, warmer winters have been associated with an increase in distributions of the green stink bug (*Nezara viridula*) in Japan. Tougou *et al.* (2009) compared distribution and climatic records in the early 1960s to a distribution survey done in 2006. A northwards shift in distribution at a rate of 19km per decade was correlated with average winter temperatures increasing by 1.03-1.91 °C and the number of cold days below 5 °C decreasing (Tougou *et al.* 2009). Battitisi *et al.* (2005) correlated a decrease in winter mortality for the pine processionary moth (*Thaumetopoea pityocampa*) with a boundary shift of 87km northwards and 110-230 metres altitude shift over the time period 1974 – 2004. (Parmesan and Yohe 2003) conducted a meta-analysis across publications including 1700 species and found an average range shift per species towards higher latitudes of 6.1 km per decade.

1.3.3 Increased establishment success for invasive pests

Distribution range shifts may also coincide with an increase in establishment success for invasive exotic insect pests. The process of permanent establishment begins with arrival of propagules to a new location via human mediated pathways or through natural migration, followed by colonisation and establishment of viable population and then natural spread (Lockwood *et al.* 2005). For some migratory pests, climate change could increase propagule pressure via an increase in extreme weather events such as wind frequency and intensity

(Sutherst 2000; Ward and Masters 2007). Warmer temperatures may also increase propagule pressure by increasing flight activity. For example, Battisti *et al* (2006) found warmer temperatures increased the flight activity of newly emerging female adult winter pine processionary moths (*Thaumetopoea pityocampa*) which lead to a rapid altitude expansion during a hot summer in southern Europe in 2003. Pathways for invasive pests may also change as a result of different air and sea links in international trade caused by alterations to the sourcing and processing of fresh produce and climate change policies (eg. carbon tax or emissions offset payment) (Parry *et al.* 2007; Roques 2010).

Once the invasive pests arrive in the country, establishment success could be influenced by longer periods of climatic suitability caused by increases in annual temperatures (Sutherst 2000; Cook *et al.* 2002). Establishment success could also be hugely influenced by potential increases in fitness for insect pests. For example, warmer temperatures can increase developmental rates and voltinism of insects (Yamamura and Kiritani 1998; Bale *et al.* 2002; Dukes 2008; Musolin *et al.* 2009). Interestingly, many publications document the negative impacts climate change will have for organisms and overall biodiversity (McCarty 2001; Thomas *et al.* 2004; Winterbourn *et al.* 2008) but in contrast, research investigating insect pest response to climate change generally indicates an increase in fitness and invasion success (Sutherst *et al.* 2007a; Lastuvka 2009). Insect pests display traits such as adaptability to changing environments, ability to survive in extreme environments and ability to rapidly occupy suitable habitats that will put them at an advantage over other species if climate change occurs (Lastuvka 2009).

1.4 Species distribution models and invasion risk

Part of any pest risk analysis by biosecurity organisations is to identify potential locations at risk from exotic pest establishments. Species distribution models in these instances can be used in identifying which locations have suitable habitats for specific exotic species (Elith *et al.* 2006; Elith and Leathwick 2009; Chejara *et al.* 2010). These programs are based on the ecological theory that the geographical distribution of a species is largely influenced by the climate (Hutchinson 1957). Species distribution models infer climatic preferences of a pest species based on their current distributions or physiological response to climate to determine which environmental factors influence a species presence or absence. Ideally, any tools used to simulate population distributions should take into account all processes that affect species distributions (eg. natural enemies, host plant availability). However, these other factors do not have readily available global data that can be incorporated.

There are two distinct approaches to modelling species distributions, the mechanistic and a correlative approach. The mechanistic method assesses the bio-physiological aspects of a species to generate the ideal environmental conditions likely to allow a species to persist (Kearney and Porter 2009). The correlative approach correlates environmental variables at known species localities to define a climatic envelope that is associated with a species presence (Kearney and Porter 2009). The environmental variables are in a Geographic Information System (GIS) raster layer format which has been partitioned into a grid of pixels. Environmental suitability at a particular location is determined by the species climate envelope and environmental variables of that location.

Along with simulating potential distributions based on current conditions, the onset of climate change and potential impacts it may have on insect pest distributions is influencing research into potential distributions under climatic change predictions to estimate future pest invasion risks. For example, Vanhanen *et al* (2007) investigated climate change and potential range shifts for the nun moth (*Lymantria monacha*) and gypsy moth (*Lymantria dispar*) using CLIMEX modelling. Three different climate change scenarios of 1.4°C, 3.6°C and 5.8°C were used to predict a northern range distribution shift northwards by 500-700km and the southern range to expand northwards by 100-900km (Vanhanen *et al.* 2007). Stephens *et al* (2007) investigated the current distributions and potential distributions under climate change for the oriental fruit fly (*Bactrocera dorsalis*) using CLIMEX. The model predicted *B. dorsalis* distributions to expand from tropical and sub-tropical locations to more temperate climates closer to the poles as cold stress boundaries decrease. Northern areas of New Zealand under climate change conditions were considered vulnerable to *B. dorsalis* establishing that includes some of New Zealand's prime horticultural locations. Gutierrez *et al.* (2009) used a physiologically-based demographic model with potential increase of daily average temperatures by 1°C, 2 °C and 3 °C to predict a potential expansion of the olive fruit (*Bactrocera oleae*) northwards from its current distribution in the Mediterranean.

1.5 Tropical summerfruit insect Pests – Tephritidae fruit flies

The literature previously mentioned in this thesis suggests that climate change is likely to allow insect pests of tropical or sub-tropical origin to survive and establish populations in cooler temperate climates. From the New Zealand summerfruit industries perspective, severe tropical insect pests include Tephritidae fruit fly species from the *Bactrocera* and *Ceratitis* genera. These species are highly invasive and are known to cause damage to summerfruit crops. For this research, five fruit fly species were selected based on these characteristics and

include: Oriental fruit fly (*Bactrocera dorsalis*); Queensland fruit fly (*B. tryoni*); peach fruit fly (*B. zonata*); Mediterranean fruit fly (*Ceratitis capitata*) and Natal fruit fly (*C. rosa*).

1.5.1 Biology

These five species naturally habituate in warm and humid climates in low latitude areas. They are multi-voltine with no obvious diapause (Bateman 1972). In a typical developmental lifecycle for a fruit fly species, adult fruit flies insert their eggs beneath the skin of their fruit hosts. The larvae feed inside the host and undergo three instars before undergoing pupation in the soil. After a few days or weeks a sexually mature adult will emerge and mate to start a new cycle (Christenson and Foote 1960). The time period between each lifecycle stage varies between each species of fruit fly. For the species being investigated in this study, the time frame between the eggs being laid and hatching is within 1 -4 days for all five species (Christenson and Foote 1960). When subjected to simulated climates, the larval time period for *B. dorsalis* and *B. tryoni* is between 9 – 31 days, and 6 – 11 days for *C. capitata* and *C. rosa*. Under optimum conditions, the adults for all five species will emerge from pupation after 1 - 2 weeks (Christenson and Foote 1960). Pupation can be much longer under cooler conditions.

1.5.2 Climatic influences

A review by Bateman (1972) on the ecology of fruit flies details environmental moisture as a climatic influence for fruit flies. For example, environmental moisture as measured by summer precipitation was significantly correlated with peak numbers achieved for *B. tryoni* on the southern fringe of its distribution in eastern Australia (Drew and Hooper 1983). Low soil moisture for *B. tryoni* was attributed to a decrease in fecundity in females and an increase in mortality of newly emerging adults as they struggled up through dry soil and into air with low relative humidity (Bateman 1972). The life cycle stages most vulnerable to desiccation are mature larvae just prior to pupation and newly emerged adults from pupation.

Temperature has a major influence on development rates and is therefore a strong climatic influence on abundances and distributions. Summer temperatures will increase developmental rates and result in higher abundances while cooler temperatures in winter will result in lower abundances. Seasonal abundances have also been correlated with a higher number of *C. capitata* interceptions in the USA during the summer months (Liebhold 2006). Each life cycle stage requires a minimal temperature threshold to be reached for development to occur

and has a maximum temperature threshold in which development decreases (see Chapter 2 for details on each of the five species investigated). Thermal accumulation of degree growing days above the minimal developmental threshold is also required to complete a generation.

1.5.3 Quarantine significance

All of the selected fruit fly species are considered serious pests by numerous plant protection and government quarantine organisations. The Ministry of Agriculture and Forestry (MAF) in New Zealand has classified these species as regulated quarantine pests and has placed them on the Schedule of Notifiable Organisms 2006 (MAF 2006). Import Health Standards created by MAF highlight specific procedures designed to prevent fruit fly transportation in fresh produce that are host plants (MAF 2008). Across the Tasman in Australia, the Department of Agricultural and Forestry (DAFF) indicates dangers of exotic fruit flies establishing in Australia. Import Risk Analyses (IRA) produced by DAFF also give specific procedures to prevent exotic fruit flies from arriving into the Australia via commercial trade (DAFF 2010). Over in Europe, all these species except for *C. capitata* are classified by the European Plant Protection Organisation (EPPO) under the Quarantine Pest A1 list. *C. capitata* is on the A2 list due to its current establishment in several countries within the EPPO region (EPPO 1997). In New Zealand, there is an extensive trap monitoring program with about 7385 traps deployed at 3518 locations around main centres, ports, international airports and in areas with high horticultural significance as a preventative measure past the border control (Stephenson *et al.* 2003, Suckling *et al.* 2009). The traps are concentrated in areas of high incursion risk such as Auckland with fewer traps in the South Island due to low climatic suitability (Suckling *et al.* 2009). The traps are placed in the canopy of a potential host fruit tree at each location (Hartley 2009). There are three types of lure used. Cuelure, Trimedlure or Methyl Eugenol and each lure is designed to attract a different species of fruit fly. A dichlorvos insecticide strip is also placed at the bottom of each trap to ensure the fruit flies are killed in the trap and remain in the trap until the next inspection (Hartley 2009). The main target species of this trapping grid includes *C. capitata*, *B. tryoni*, *B. dorsalis* and the melon fly (*B. cucurbitae*) (Suckling *et al.* 2009).

A publication by Worner and Gevrey (2006) modelled insect pest assemblages to determine the risk of invasion using a self organising map for insect pests present and absent in New Zealand. A risk index was calculated and ranked for 845 insect pests found globally. *C. capitata* was ranked the 5th highest absent insect pest species and indicates a high threat of invasion into New Zealand under current climate conditions. Other Tephritidae insect pests

that attack summerfruit were not among the top 100 of absent species in New Zealand, yet climate change could influence the risk index of these species in the future.

1.5.4 Damage

Adult fruit flies oviposit their eggs under the skin of fleshy fruit and larvae develop inside the fruit. The fruit infested by the larvae become either unmarketable or decompose due to larvae creating access points for microorganisms to infect the fruit (Koyama 1989). Without control, fruit flies are capable of destroying entire fruit crops and causing severe economic damage.

Trade restrictions as a result of fruit fly establishments also pose a huge threat to horticultural industries (Koyama 1989; SriRamaratnam 1996). A brief incursion in New Zealand of the of the Mediterranean fruit fly in 1996 resulted in various countries including China, Australia and Japan to imposing trade exclusion zones of various radii around the initial fruit fly find, ranging from just under 10 kilometres to the entire north island (SriRamaratnam 1996).

1.6 Aims and hypothesis

The fruit fly species investigated in this research originate from warm tropical or sub tropical climates. Under current climate conditions, these species are highly unlikely to establish successful populations due to New Zealand's temperate climate with cool winters. However, climate change predictions for New Zealand indicate an increase in annual temperatures that could lead to an increase in climatic suitability for these fruit fly species. Therefore, it is important to use tools such as species distribution models to predict the potential establishment success of severe tropical insect pests for agricultural industries such as the New Zealand summerfruit industry. Another aspect investigated in this research is to compare the potential distributions of each target species using CLIMEX and a correlative approach using a multiple model system.

The aims of this research project are:

- Determine the climatic suitability of five exotic fruit fly pest species known to target summerfruit crops under current climatic conditions and New Zealand climate change predictions.
- Compare predicted distributions produced from CLIMEX and the multiple model approach.

The hypothesis for this project is

- The increase in temperature as predicted by global climate change scenarios will increase the threat of some dangerous exotic Tephritidae insect pests establishing viable populations in New Zealand such that they pose a threat to the New Zealand summerfruit industry.

Chapter 2

Potential Impacts of Climate Change using CLIMEX®

2.1 Introduction

The CLIMEX program is an eco-climatic assessment model developed by CSIRO in Australia. It was first described by Sutherst and Maywald, (1985) in a study investigating climatic suitability of several tick species that affect cattle in Australia. The CLIMEX program has since been enhanced with different versions and further insights into its application (Sutherst *et al.* 1996; Sutherst 2000; Sutherst *et al.* 2007). The CLIMEX program is popular to use due because it is easy to learn and easy interpretation of results by non-speciality scientists and policy makers. It has been used to predict species distributions in over 200 publications.

CLIMEX was developed to enable researchers to predict the geographical distribution of plant or animal species by incorporating climatic response parameters derived or inferred from eco-physiological experiments as well as the existing distribution of a species (Sutherst *et al.* 2007). It determines the species-climatic relationship by assessing which locations have a favourable climate in terms of population growth and it identifies the stressors that may limit the species distribution (Sutherst *et al.* 2007). CLIMEX is also based on an eco-physiological growth model where a population experiences both a favourable and unfavourable season for population growth.

A single figure called the Ecoclimatic index (EI) indicates climatic suitability for any given location. The EI value is calculated from an Annual Growth Index (GIA) and Annual Stress Index (SI)

$$\text{Ecoclimatic Index (EI)} = \text{GI}_A \times \text{SI}$$

In terms of estimating the annual growth index (GI_A) for an insect species, one of the contributing factors is the weekly Temperature Index (TI_w) which describes the response of the species to the daily temperature cycle. The four parameters that define the range of temperatures suitable for population growth are:

DV0 = Lower temperature threshold

DV1 = Lower optimum temperature

DV2 = Upper optimum temperature

DV3 = Upper temperature threshold

Temperatures within the DV1 – DV2 range will maximise the temperature index and any temperature that falls outside the DV0 and DV3 values will cause the temperature index to be zero (Figure 2.1).

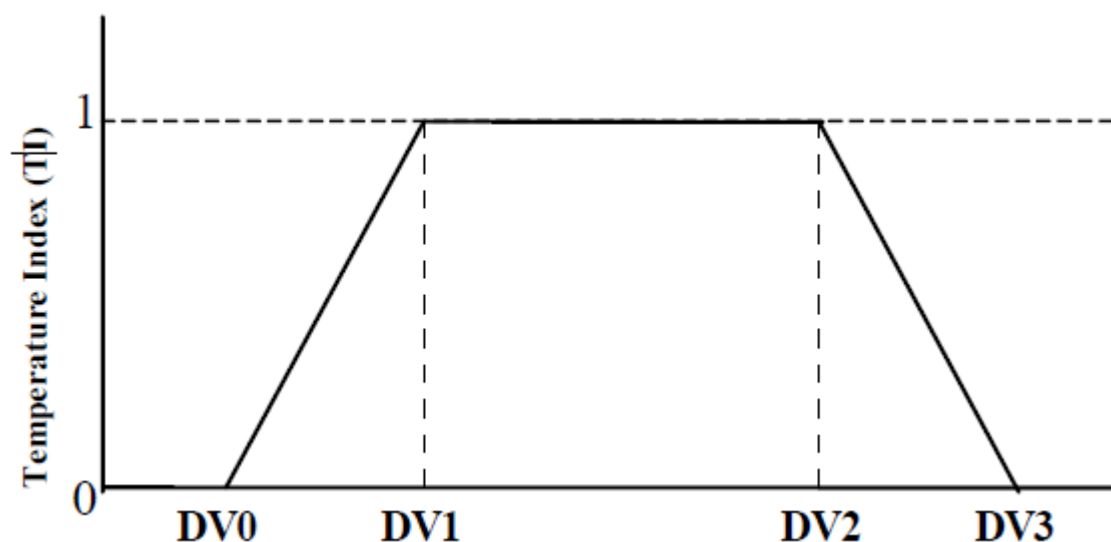


Figure 2.1: Temperature index in relation to defined temperature parameters (Sutherst *et al.* 2007).

Monthly average maximum and minimum temperatures are also incorporated with CLIMEX parameters to calculate the TI_w value. The soil moisture index (MI) is the other contributing factor to the annual growth index and follows the same parameter format as the temperature index. The approximate soil moisture levels in any given place is calculated using from the total precipitation from the previous week with the evapo-transpiration rate (default is 0.8) and soil moisture holding capacity (default is at 100% levels). The weekly growth index is calculated by multiplying the weekly temperature index and weekly soil moisture index.

$$TGI_w = TI_w \times MI_w$$

The climate dataset built into the CLIMEX software is made up of weekly averages so an annual growth index is calculated from the weekly growth index using the formula:

$$GI_A = 100 \sum_{i=1}^{52} GI_{w_i} / 52$$

Thermal accumulation during the growing season (PDD) is the number of days above DV0 required to complete an entire generation, this parameter can also determine the number of generations a species can complete in one year. If this threshold is not reached at any location then the species cannot thrive there (Sutherst *et al.* 2007).

Stress indices are set to limit the species ability to survive adverse conditions during the unfavourable part of the season. If temperatures, for example, fall outside DV1 and DV2 then cold stress or heat stress will begin to accumulate (Sutherst *et al.* 2007). The same thing occurs if moisture levels fall outside SM1 and SM2 as wet and dry stress will begin to accumulate. Each stress index is associated with an accumulation rate and is assumed to increase exponentially (Sutherst *et al.* 2007). The most influential stress for modelling insect invasions into temperate climates is the Cold Stress Temperature Threshold (TTCS) and Cold Stress Accumulation Rate (DTHS). The annual stress index per stressor (for example, cold stress) is calculated using the following formula:

$$\text{Cold Stress} = \text{Cold Stress Rate (THCS)} \times ((\text{Threshold (TTCS)} - \text{average weekly minimal temperature } ^\circ\text{C} \times \text{week number}))$$

An annual stress index can be further calculated by incorporating all the stress indices:

$$SI = (1 - \text{Cold stress}/100)(1 - \text{Dry Stress}/100)(1 - \text{Heat Stress}/100)(1 - \text{Wet Stress}/100)$$

If the accumulated stress index reaches 1, the species will not be able to persist at that particular location (Sutherst *et al.* 2007). CLIMEX contains a 0.5 degree of arc climatic dataset provided by the Climate Research Unit (New *et al.* 1999). The dataset is generated from climate data from the period 1961 – 1990. In this study, the CLIMEX model was used to predict the potential distribution of selected fruit fly species based on climatic suitability of current climatic conditions and climate change predictions specific to New Zealand. These modelled distributions can be used to estimate the risk establishment and the subsequent

threat to the New Zealand summerfruit industry. There are already studies that assess various Tephritidae species potential distributions using CLIMEX including the oriental fruit fly (*Bactrocera dorsalis*) (Stephens *et al.* 2007); Queensland fruit fly (*B. tryoni*) (Yonow and Sutherst 1998) and Mediterranean fruit fly (*Ceratitidis capitata*) (Vera *et al.* 2002), but no studies have used CLIMEX to model the distributions of the Natal fruit fly (*C. rosa*) or peach fruit fly (*B. zonata*).

2.1.1 Research objectives

The aim of this research is to model the potential distributions of five Tephritidae species in New Zealand in response to climate change, using a CLIMEX, to determine the potential threat for the summerfruit industry. Objectives include:

- Collect eco-physiological data and distribution data to calibrate CLIMEX parameters for *C. rosa* and *B. zonata*
- Use CLIMEX to create predicted distributions under current climatic conditions and future climate change predictions specific to New Zealand for all target Tephritidae fruit fly species.
- Identify any major summerfruit producing regions with suitable habitats for target Tephritidae species under current climatic conditions and future climate change predictions specific to New Zealand.

2.2 Methods

2.2.1 Climate change scenarios

Climate change predictions for New Zealand indicate less warming than what is predicted to occur on a global scale (Mullen *et al.* 2008). Therefore, it is important to source climate change predictions that are specific to New Zealand. NIWA created a report for the Ministry for the Environment detailing climate change predictions for New Zealand (Mullen *et al.* 2008). Future surface air temperature predictions were calculated for regional provinces in New Zealand with average and range limits for temperature change predictions per emission scenario (Mullen *et al.* 2008). To estimate the impact of climate change on potential summerfruit insect pests, average surface air temperature increases for 2040 and 2090 were incorporated into CLIMEX. Data from the B1 scenario, A1B scenario and the A1F1 scenario

were selected as being representative of a best case, intermediate and worst case scenario for 2040 and 2090 climate change conditions (Table 2.1).

Table 2.1: Predicted surface air temperature increases indicated by climate change scenarios representing a best case, intermediate and worst case scenario for New Zealand.

	2040	2090
B1 Emissions Scenario	0.6°C	1.3°C
A1B Emissions Scenario	0.9°C	2°C
A1F1 Emissions Scenario	1.3°C	2.9°C

2.2.2 Climatic suitability based on the CLIMEX ecoclimatic Index

The inferred climatic suitability based on the Ecoclimatic Index generated in CLIMEX unfortunately can differ between studies that use this mode to predict species distributions (Table 2.2). The EI value can range from 0 to 100 and some publications use the full EI range. Most studies however suggest values up to 30 as suboptimal 30 and above as optimal conditions for a species to persist. There are also differences in interpretation of which EI values are considered marginal or suitable (Table 2.2)

Table 2.2: Inferred climatic suitability from ecoclimatic index values amongst different publications.

EI Values	Inferred Climatic Suitability	References
0 1 – 10 10 – 20 >20	(Unsuitable) (Marginal) (Suitable) (Optimal)	(Chejara <i>et al.</i> 2010) (Kean 2009) (Kriticos <i>et al.</i> 2006) (Stephens <i>et al.</i> 2007)
0 1 – 5 6 – 25 >25	(Unsuitable) (Marginal) (Suitable) (Optimal)	(Kriticos and Leriche 2010) (Potter <i>et al.</i> 2008) (Potter <i>et al.</i> 2009) (Watt <i>et al.</i> 2009)
0 – 10 11 – 20 21 – 30 31>	(Unsuitable) (Low Suitable) (Moderate Suitability) (High Suitability)	(Barney and DiTomaso 2010)
0 1 – 25 26 – 50 50 – 75 76 – 100	(Unsuitable) (Marginal) (Suitable) (Highly Suitable) (Very Highly Suitable)	(Lawson <i>et al.</i> 2010)

The subjectivity of interpreting EI values for inferred climatic suitability makes it difficult to set your own standards. In this study, I followed a scale previously used in studies by a researcher known to have the most experience in CLIMEX (Kriticos *et al.* 2006) . For this research, the inferred climatic suitability from the Ecoclimatic Index was placed into four categories that followed a common set up: Unsuitable (EI = 0), Marginal (EI = 1 – 10), Suitable (EI = 11 – 20) and Optimal (EI = >20).

2.2.3 CLIMEX Parameters for the five fruit fly species

CLIMEX is a model that requires physiological data from laboratory studies. If appropriate studies are not available, climatic requirements can also be inferred from known current distributions. Initial values for growth indices such as temperature (DV0 – DV3) were derived from physiological experiments that determine developmental rates and developmental thresholds in response to varying temperatures. Soil moisture indices (SM0 – SM3) were set to represent host plant tolerances and were manually calibrated to fit the current distributions of the target species. Some values for stress indices (eg. cold stress and heat stress) were inferred from appropriate research (see below) while other stress indices (eg. dry stress, wet stress, stress accumulation rates) were manually adjusted/calibrated to fit known current distributions.

In this study, CLIMEX parameters were calibrated for *B. zonata* and *C. rosa*. Parameters for *B. dorsalis*, *B. tryoni* and *C. capitata* were sourced from publications.

2.2.3.1 CLIMEX parameters for *B. zonata*

The wet tropical savannah template was used as a baseline for fitting CLIMEX parameters for the peach fruit fly (*B. zonata*). Several studies have reported different upper and lower temperature thresholds and optimum temperature ranges for development and survival (

Table 2.3). Possibly due to differences in populations and experimental design used between studies. The baseline temperature threshold (DV0) was set to 11.7 °C based on evidence from studies by Mohamed (2000) and Duyck *et al.* (2004). The optimum temperature range (DV1 – DV2) was set to 25 and 30 °C based on studies recording optimum growth and low mortality rates between these temperatures (Qureshi *et al.* 1993; Duyck *et al.* 2004). No publications state the maximum temperature for development but it can be inferred from mortality rates at specific temperatures. The upper temperature threshold (DV3) was

therefore set to 33 due to high mortality rates observed at 35 °C (Qureshi *et al.* 1993; Duyck *et al.* 2004). The degree days per generation (PDD) was set to 301 as calculated by Mohamed (2000).

Table 2.3: Temperature parameters for *B. zonata*

	Temperature	References
Baseline temperature	10.78 °C	(Mohamed 2000)
Threshold	12.6 °C	(Duyck <i>et al.</i> 2004)
Optimum temperature range	25 – 30 °C	(Duyck <i>et al.</i> 2004) (Qureshi <i>et al.</i> 1993)
Maximum Temperature Tolerance	33 °C	(Duyck <i>et al.</i> 2004) (Qureshi <i>et al.</i> 1993)

The soil moisture parameters (SM0 – SM3) determine the soil moisture requirements and thresholds. The requirements can be mediated through the soil moisture requirements of their host plants. The permanent wilting point for many crops is about 10% soil moisture levels (Stephens *et al.*, 2007) so the threshold soil moisture level (SM0) was set to 0.1. The optimum soil moisture levels (SM1 and SM2) were set to 0.25 and 1 to represent optimal soil moisture conditions, these figures have also been implemented in previous studies using CLIMEX on fruit flies (Stephens *et al.* 2007; Vera *et al.* 2002). Pupation takes place in the soil and total immersion in water for longer than a day causes mortality (Duyck *et al.* 2006). Therefore, the most suitable SM3 value would be 1 to represent 100% soil saturation but unfortunately the predicted distribution with this figure does not give a good representation of *B. zonata* potential distribution. A SM3 value of 1.5 was used instead to produce a more fitting global distribution.

The heat stress threshold parameter (TTHS) was set to 35 °C based on evidence of heat stress occurring at that temperature (Qureshi *et al.* 1993). The heat stress accumulation rate (THHS) was not altered from the wet tropical template used as it fitted the current distribution well. The cold stress temperature threshold (TTCS) was set at 8 °C which is just below the baseline threshold temperature of 11 °C (Mohamed 2000) and the cold stress accumulation rate (THCS) was adjusted to fit the current distribution.

B. zonata is tolerant of wet and dry conditions as demonstrated by its ability to survive complete immersion in water for long periods of time as well as the other extreme, low rates of humidity (Duyck *et al.* 2006). *B. zonata* tolerance to wet and dry conditions can also be inferred from its distribution ranging across wet tropical conditions in South East Asia and

arid conditions in Egypt and Saudi Arabia (EPPO 1997). The dry stress threshold (SMDS) and stress accumulation rate (HDS) were altered from the wet tropical template to allow *B. zonata* to persist in these arid countries. The wet stress threshold (SMWS) and wet stress accumulation rate (HWS) were not altered from the wet tropical CLIMEX template due to the suitable fit with current distributions.

2.2.3.2 CLIMEX parameters for *C. rosa*

The wet tropical savannah template was used as a baseline for fitting CLIMEX parameters for the Natal fruit fly (*C. rosa*). Several studies have reported different upper and lower temperature thresholds and optimum temperature ranges for development and survival, possibly due to differences in populations and experimental designs (Table 2.4). The baseline temperature threshold in CLIMEX (DV0) was set to 8.2 °C based on the average of the lower temperature thresholds derived from studies by Duyck *et al.* (2002) and Grout and Stolz, (2007) (Table 2.4). The optimum temperature range parameters (DV1 and DV2) were set to 22 and 29 °C by combining the results from Duyck *et al.* 2002, Duyck *et al.*, 2006 and Grout and Stolz (2007) (Table 2.4). The upper temperature threshold (DV3) was set to 33 °C based on calculations by Grout and Stolz, 2007. The growing degree-day threshold per generation (GDD) was estimated at 405 by Duyck *et al* (2002) and this value was incorporated into CLIMEX.

Table 2.4: Temperature parameters for *C. rosa*.

	Temperature	Reference
Lower temperature Threshold	7.97 °C 8.5 °C	(Duyck and Quilici 2002) (Grout and Stoltz 2007)
Optimum temperature range	28.6 °C 22 – 23°C 20 – 30°C	(Duyck and Quilici 2002) (Duyck <i>et al.</i> 2006) (Grout and Stoltz 2007)
Maximum Temperature Tolerance	33°C	(Grout and Stoltz 2007)

The soil moisture parameters (SM0 – SM3) were set in same fashion as for *B. zonata*. The cold stress temperature threshold (TTCS) was set close to the baseline developmental threshold as 6 and the cold stress accumulation rate (DHCS) was set to -0.001 to allow persistence in the cooler parts of its current range in South Africa. The heat stress threshold temperature was set to 33 °C based on evidence from Duyck *et al* (2002) who recorded 100% mortality of *C. rosa* at 35 °C. The heat stress accumulation rate (TTHS) was not altered from the value from the wet tropical savannah template as that value fitted the current distribution

well. The default dry stress parameters (SMDS and HDS) in the wet savannah template indicated vulnerability to desiccation and were found to be suitable for *C. rosa* based on experimental evidence of vulnerability to desiccation (Duyck *et al.* 2006). The default dry stress parameters were matched well with *C. rosa* current distribution. The wet stress threshold (SMWS) was set to 1.5 to correspond with the SM3 value and the wet stress accumulation rate (HWS) was set to 0.05 to match the current distribution of *C. rosa*.

Table 2.5: CLIMEX parameters.

Parameter		<i>B. dorsalis</i>	<i>B. tryoni</i>	<i>B. zonata</i>	<i>C. capitata</i>	<i>C. rosa</i>
Lower temperature threshold	DV0	13	12	11	12	8.24
Lower optimum temperature	DV1	23	25	25	22	22
Upper optimum temperature	DV2	25	33	30	30	29
Upper temperature threshold	DV3	36	36	33	35	33
Lower soil moisture threshold	SM0	0.1	0.1	0.01	0.1	0.1
Lower optimum soil moisture	SM1	0.25	0.5	0.1	0.3	0.25
Upper optimum soil moisture	SM2	1	1.75	1.5	1	0.1
Upper soil moisture threshold	SM3	2.5	2	2.5	1.5	1.5
Cold stress temperature threshold	TTCS	2.5	2	8	10	6
Cold stress accumulation rate	DHCS	-0.002	-0.00025	-0.002	-0.0015	-0.01
Heat stress temperature threshold	TTHS	36	36	35	39	35
Heat stress accumulation rate	THHS	0.005	0.005	0.0002	0.01	0.0002
Dry stress soil moisture threshold	SMDS	0.1	0.1	0.01	0.2	0.1
Dry stress accumulation rate	HDS	-0.024	-0.005	-0.001	-0.02	-0.001
Wet stress soil moisture threshold	SMWS	1.75	2	2.5	1.6	1.5
Wet stress accumulation rate	HWS	0.007	0.002	0.002	0.0015	0.005
Degree days per generation	PDD	470	380	475	622	405
Source		Stephens <i>et al</i> 2007	Yonnow & Sutherst (1998)	In this study	Vera <i>et al</i> (2002)	In this study

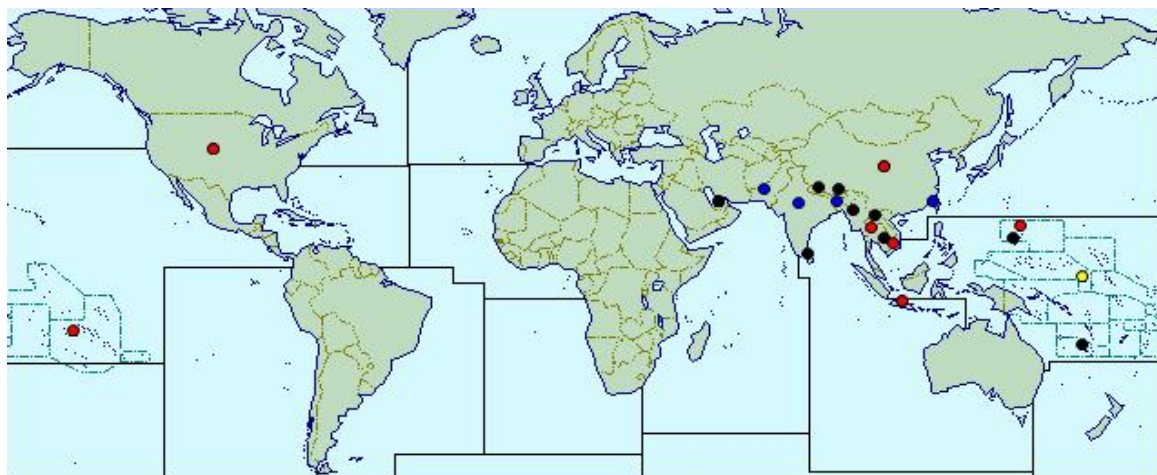
2.3 Results

2.3.1 *Bactrocera dorsalis*

2.3.1.1 Model fit to current distribution range

B. dorsalis is currently wide spread in India and many other countries in South East Asia. This species has also invaded and established permanent populations in Hawaii and Guam. The current distribution map (Figure 2.2) was used to help fit the climatic parameters to produce the predicted distribution (Figure 2.2). The CLIMEX prediction by Stephens *et al.* (2007) almost matches the current distribution except it does not fully include all of India and Pakistan as being climatically suitable despite the recorded wide spread presence at these locations (CPC 2010).

a)



b)

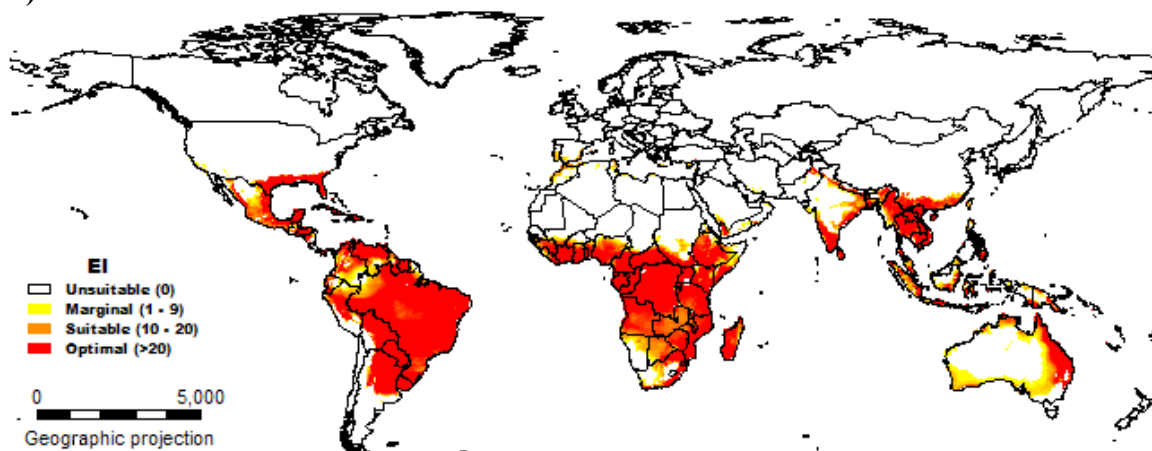


Figure 2.2: Current global distribution of *B. dorsalis* (a) (CPC, 2010) and the predicted CLIMEX distribution (b) based on set parameters.

2.3.1.2 Predicted distributions

The main summerfruit producing regions are indicated by Napier (Hawkes Bay region), Blenheim (Marlborough) and Alexandra (Central Otago). Under current climatic conditions, best case and intermediate 2040 climate change predictions (Figure 2.3), EI values indicate suitable habitat sites north of the North Island but no suitable habitat sites around major summerfruit producing regions. However, worst case 2040 climate change prediction indicate a wider expansion of potential establishment sites across the North Island and includes the summerfruit producing region Hawkes Bay.

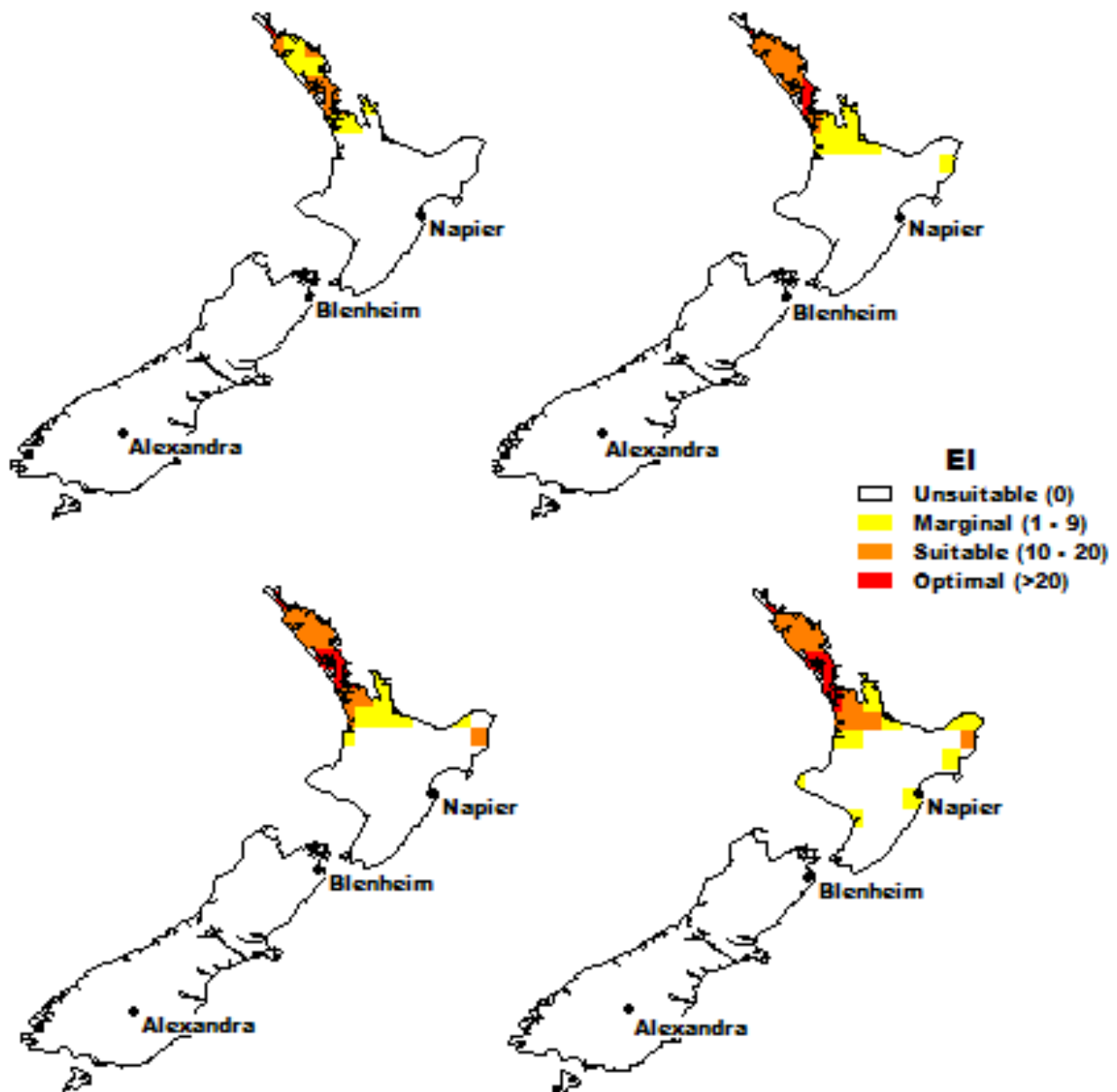


Figure 2.3: Potential distribution of *B. dorsalis* in New Zealand current climate (1961-1990 average), best case 2040 climate change predictions, average 2040 climate change predictions and worst case 2040 climate change scenarios for New Zealand. EI = Eco-climatic Index.

Under best case 2090 climate change predictions (Figure 2.4), EI values indicate many suitable habitat sites around the North Island including the summerfruit producing region Hawkes Bay. Intermediate 2090 climate change predictions and worst case 2090 climate change predictions indicate more suitable habitat sites across the North Island and South Island, including the summerfruit producing regions Hawkes Bay and Marlborough.

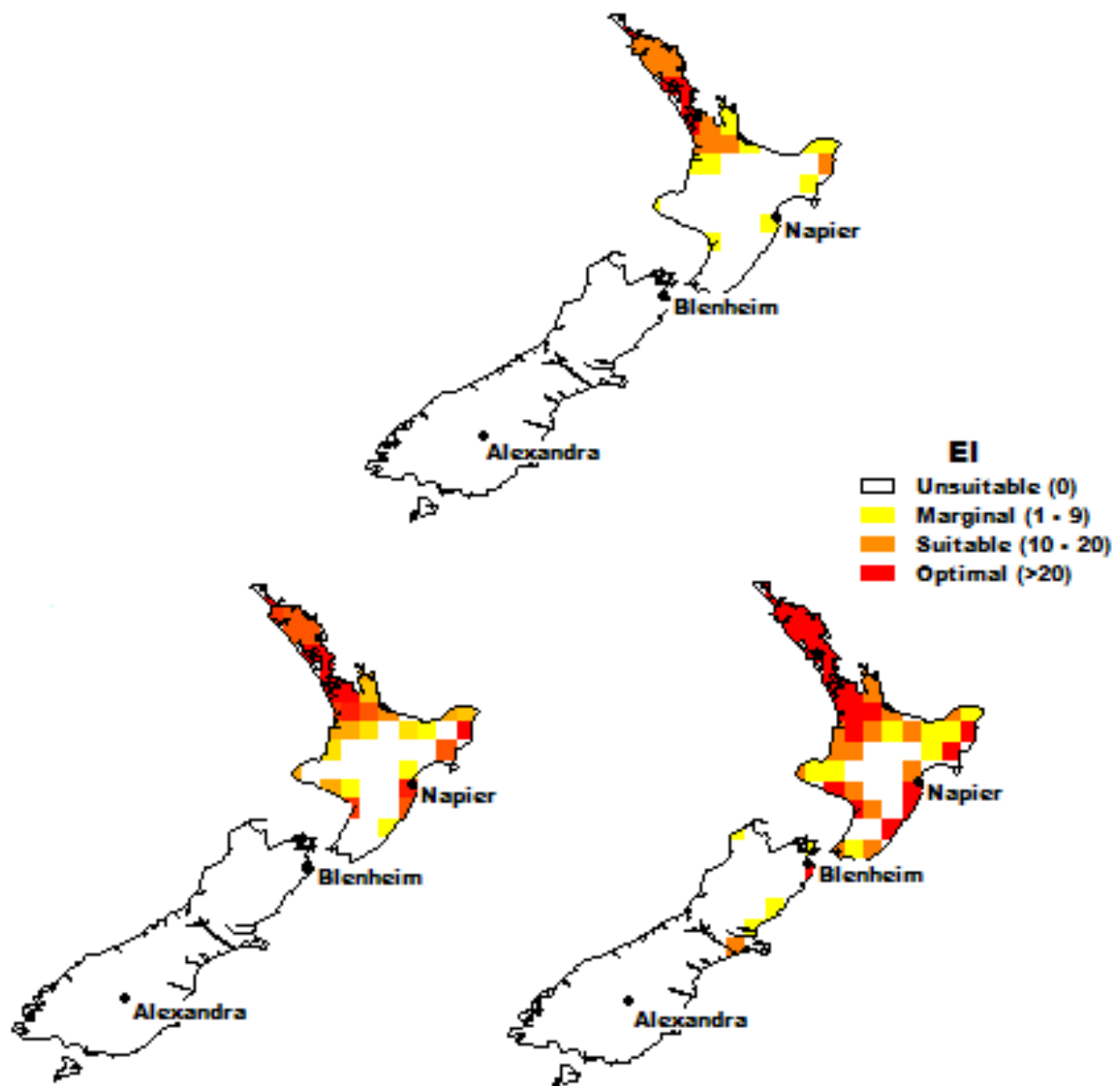


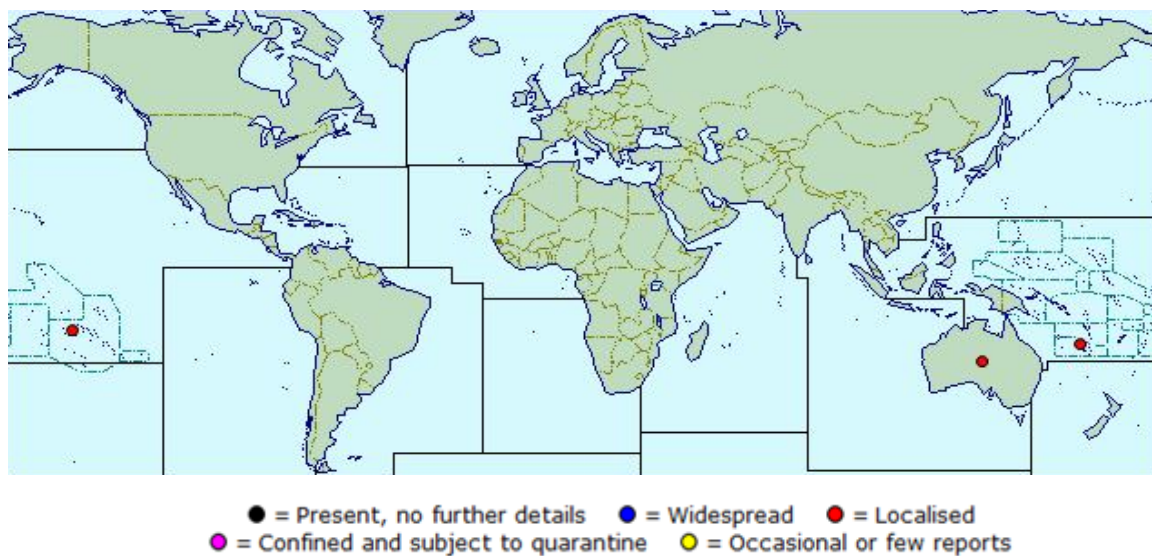
Figure 2.4: Potential distribution of *B. dorsalis* in New Zealand best case 2090 climate change predictions, intermediate 2090 climate change predictions and worst case 2090 climate change scenarios for New Zealand. EI = Eco-climatic Index.

2.3.2 *Bactrocera tryoni*

2.3.2.1 Model fit to current distribution range

The current distribution map (Figure 2.5) was used to help fit the climatic parameters to produce the predicted distribution (Figure 2.5). The current distribution of *B. tryoni* is limited to the eastern half of the states of Queensland, New South Wales, Northern Territory and extreme east of Victoria in Australia. Outbreaks occur in South Australia but fail to establish, possibly linked to the cooler winters (CPC, 2010). There is a restricted distribution in New Caledonia and French Polynesia. The CLIMEX prediction generally fits the current distribution of *B. tryoni*, owing to its small global distribution.

a)



b)

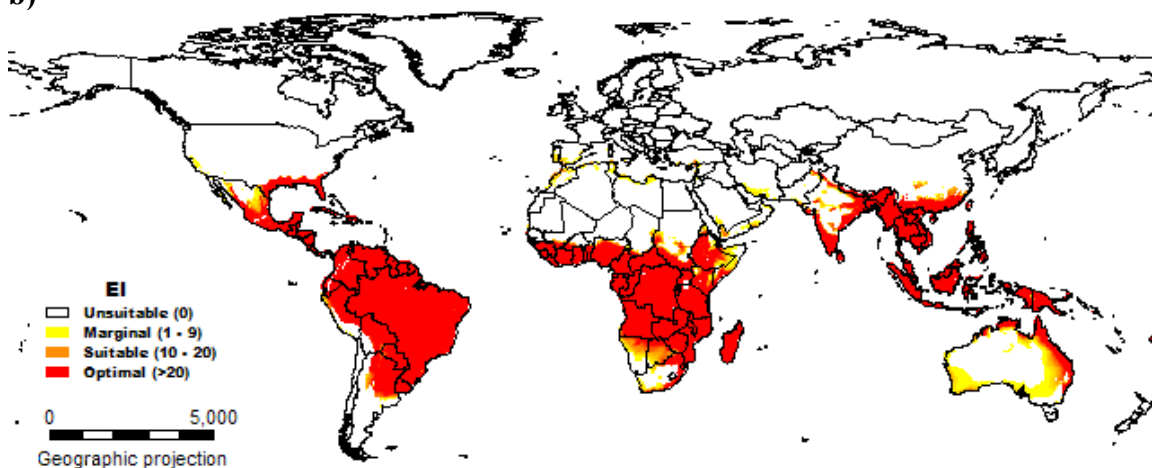


Figure 2.5: Current global distribution of *B. tryoni* (a) (CPC, 2010) and the predicted CLIMEX distribution (b) based on set parameters.

2.3.2.2 Predicted distributions

Under current climate conditions, best case and intermediate 2040 climate change conditions (Figure 2.6), EI values indicate many suitable habitat sites around the North Island but not including any summerfruit producing regions. However, worst case 2040 climate change predictions indicate a small expansion of potential establishment sites across the North Island, including the major summerfruit producing region Hawkes Bay.

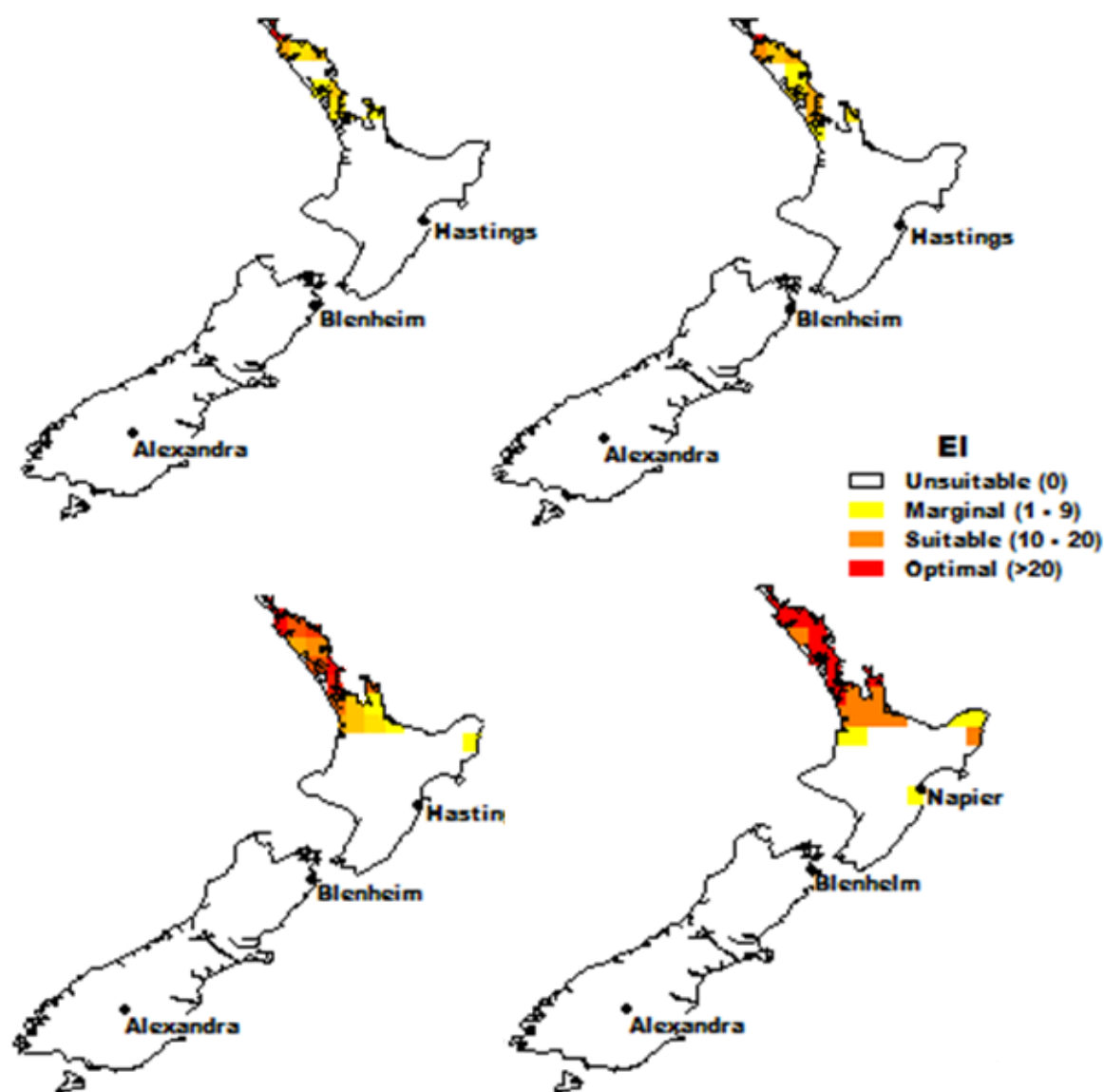


Figure 2.6: Potential distribution of *B. tryoni* in New Zealand current climate (1961-1990 average), best case 2040 climate change predictions, intermediate 2040 climate change predictions and worst case 2040 climate change scenarios for New Zealand. EI = Eco-climatic Index.

Under best case 2090 climate change predictions, EI values indicate suitable habitat sites around parts of the North Island including the summerfruit producing region, Hawkes Bay. Intermediate 2090 climate change predictions and worst case 2090 climate change predictions indicate a wider expansion of suitable habitat sites in the North Island and South Island, including summerfruit producing regions Hawkes Bay and Marlborough.

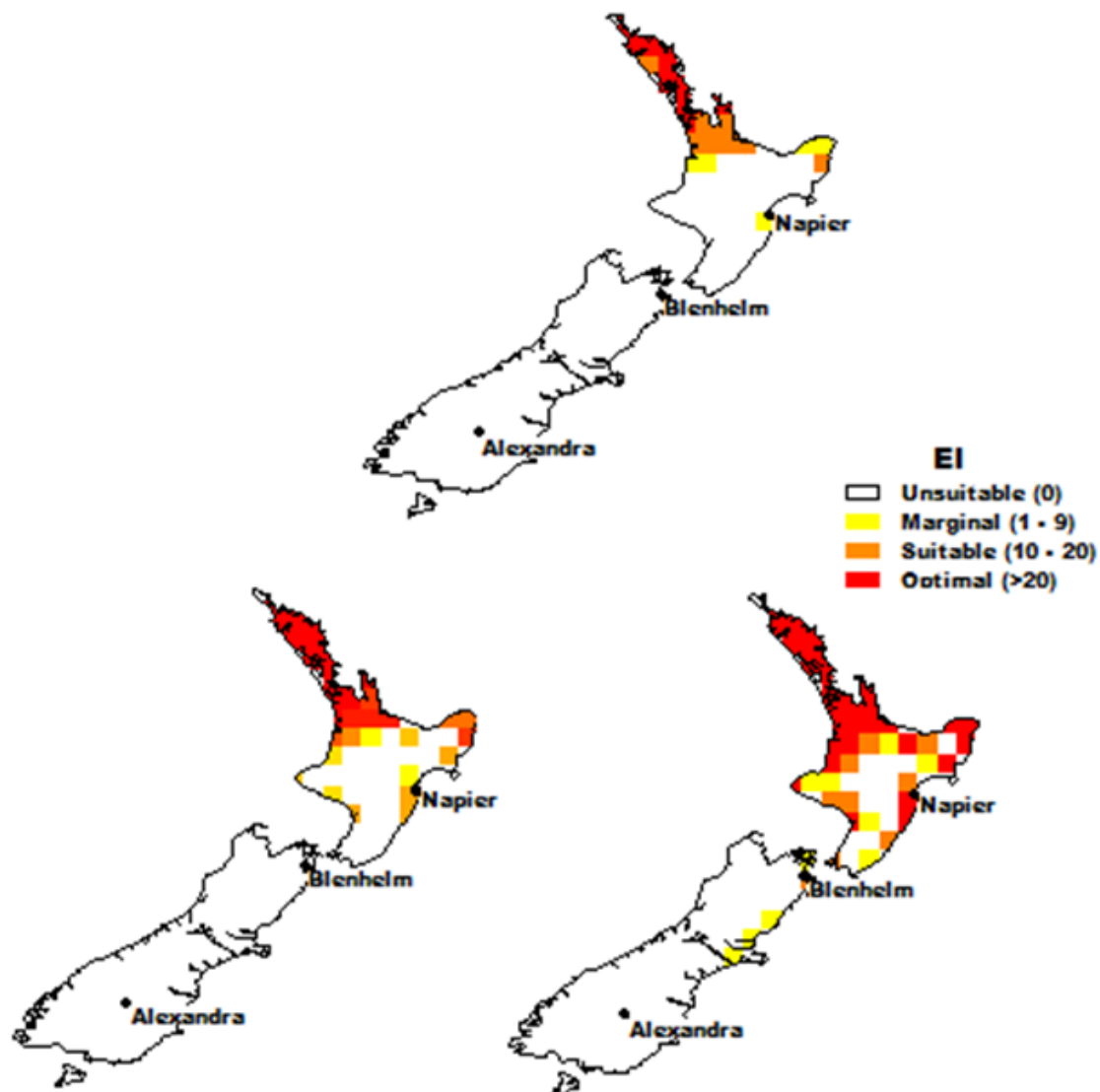


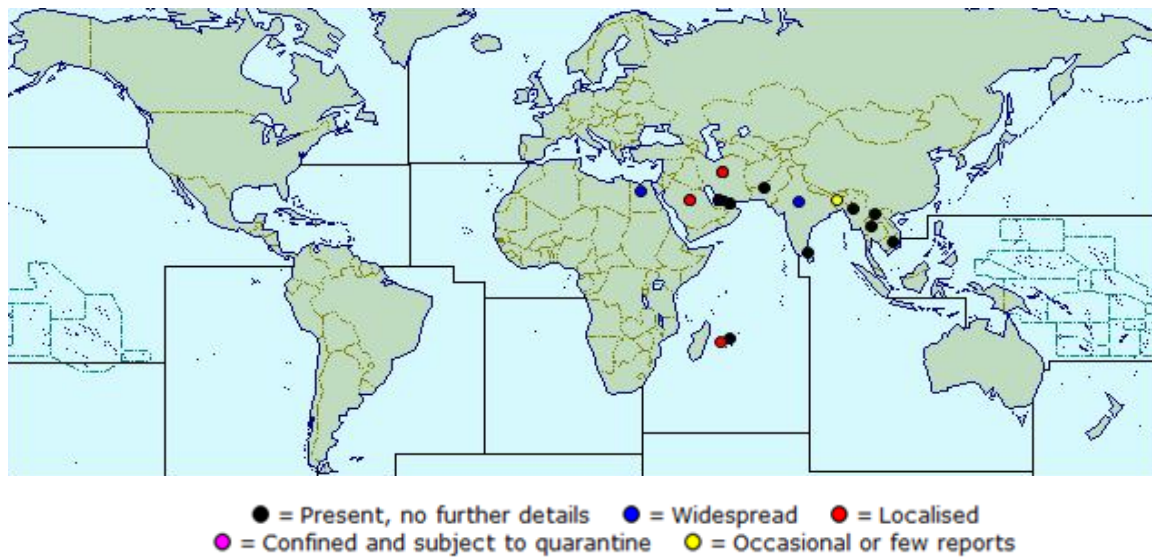
Figure 2.7: Potential distribution of *B. tryoni* under best case 2090 climate change predictions, intermediate 2090 climate change predictions and worst case 2090 climate change scenarios for New Zealand. EI = Eco-climatic Index.

2.3.3 *Bactrocera zonata*

2.3.3.1 *Model fit to current distribution range*

The current distribution of *B. zonata* is widespread throughout India, Egypt and numerous countries in South East Asia. Restricted populations are recorded in arid countries such as Saudi Arabia and Iran. Adventive populations have also been recorded in Mauritius and USA. The invasion of *B. zonata* into different climates such as Egypt and islands in the Indian Ocean indicate an ability to adapt to new climatic conditions. The current distribution map (Figure 2.8) was used to help fit the climatic parameters to produce the predicted distribution (Figure 2.8). While setting the parameters for the CLIMEX simulation, it was not possible to allow widespread persistence of *B. zonata* in Egypt without dropping the soil moisture indices well below what most host plants can tolerate. The Food and Agricultural Organization (FAO) of the United Nations indicate that arable crops are only grown close to the Nile river and around the Nile delta where irrigation is accessible and along the northern coast facing the Mediterranean Sea (FAO 2005). Therefore, the set soil moisture levels allow persistence along the northern coast and Nile delta but not in the middle of Egypt.

a)



b)

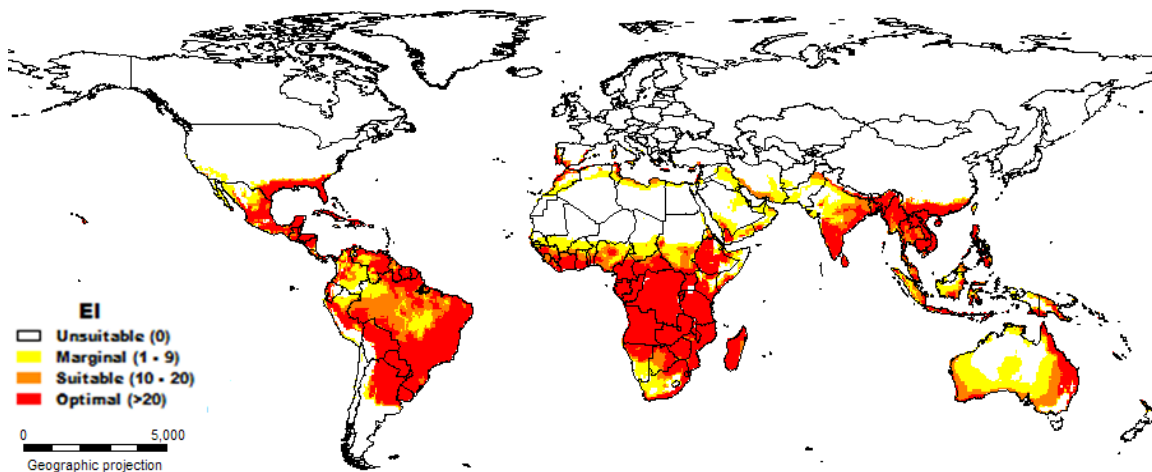


Figure 2.8: Current global distribution of *B. zonata* (a) (CPC, 2010) and the predicted CLIMEX distribution (b) based on set parameters.

2.3.3.2 Predicted distributions

Under current climate conditions, EI values indicate few suitable habitat sites in the North Island but include the summerfruit producing region, Hawkes Bay. Under best case intermediate and worst case 2040 climate change predictions there is an expansion of potential establishment sites across the North Island and into the summerfruit producing region in Hawkes Bay and Marlborough.

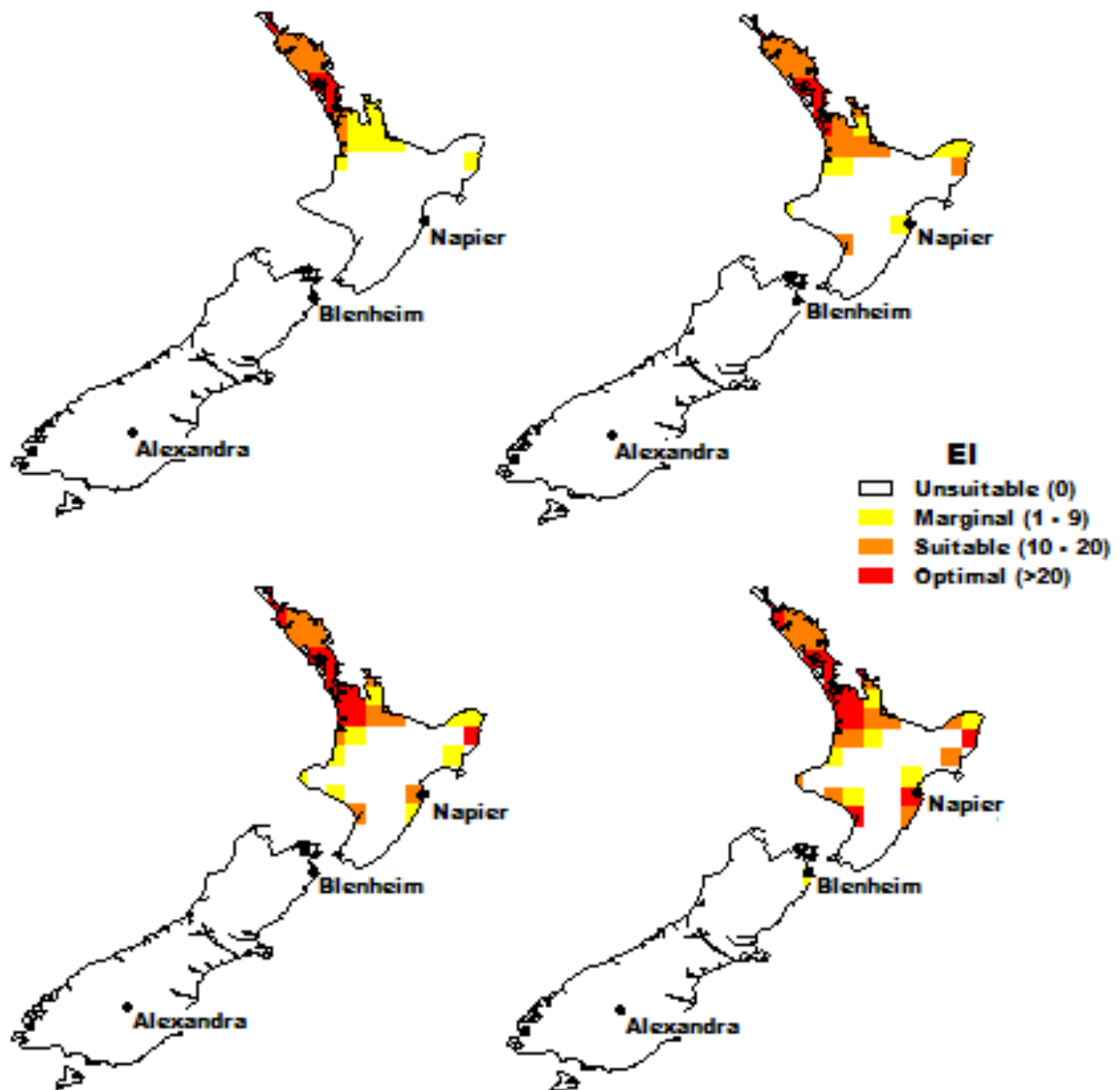


Figure 2.9: Potential distribution of *B. zonata* in New Zealand current climate (1961-1990 average), best case 2040 climate change predictions, intermediate 2040 climate change predictions and worst case 2040 climate change scenarios for New Zealand. EI = Eco-climatic Index.

Under best case 2090 climate change predictions, EI values indicate potential establishment sites around the North Island and South Island including the summerfruit producing regions, Hawkes Bay and Marlborough. Under intermediate and worst case 2090 climate change predictions (Figure 2.10), there is an expansion of suitable habitat sites in the North Island and South Island but does not include the summerfruit producing region Central Otago.

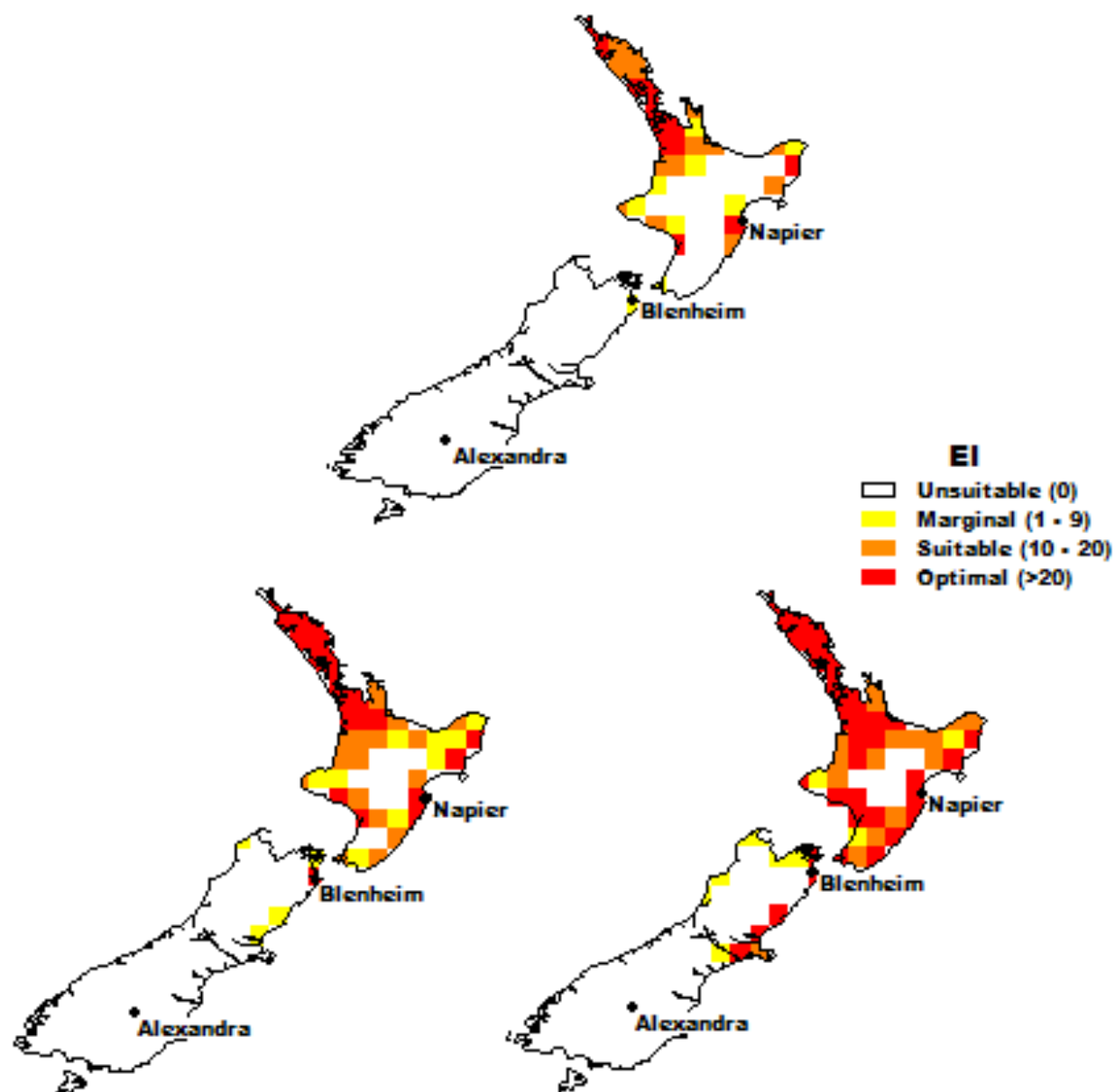


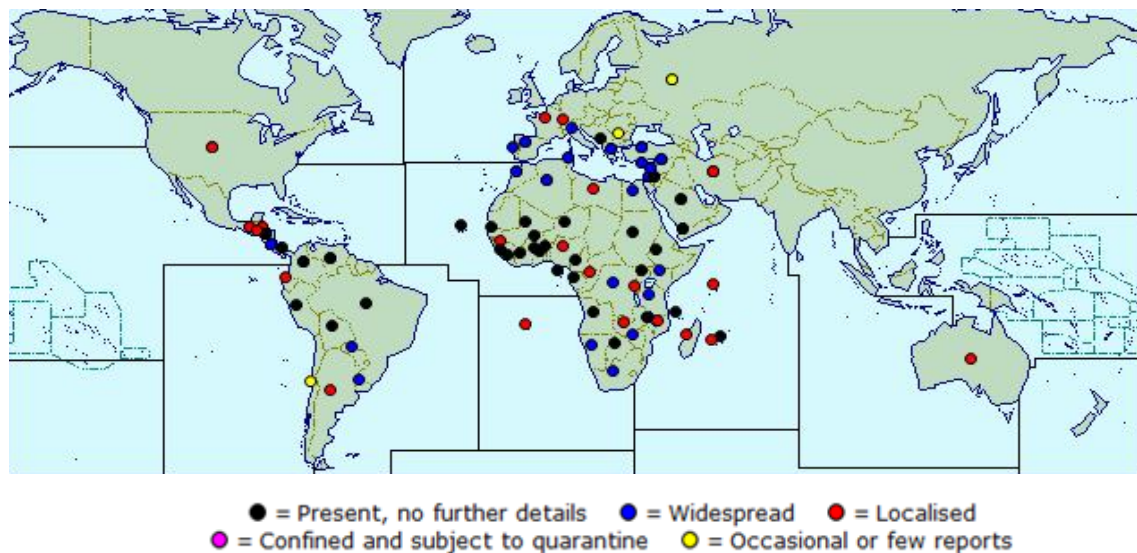
Figure 2.10: Potential distribution of *B. zonata* in New Zealand under best case 2090 climate change predictions, intermediate 2090 climate change predictions and worse case 2090 climate change predictions for New Zealand. EI = Eco-climatic Index.

2.3.4 *Ceratitis capitata*

2.3.4.1 Model fit to current distribution range

The current distribution map (Figure 2.11) was used to help fit the climatic parameters to produce the predicted distribution (Figure 2.11). *C. capitata* is widespread in Africa and is endemic to many sub-Saharan countries. It has spread into Europe, Egypt, Middle East, Australia, Americas and is linked to international trade transportation. An outbreak occurred in New Zealand in 1996. The CLIMEX prediction of *C. capitata* generally fits well with the current distribution except for a few countries that record its absence and are deemed climatically suitable in South America and Africa.

a)



b)

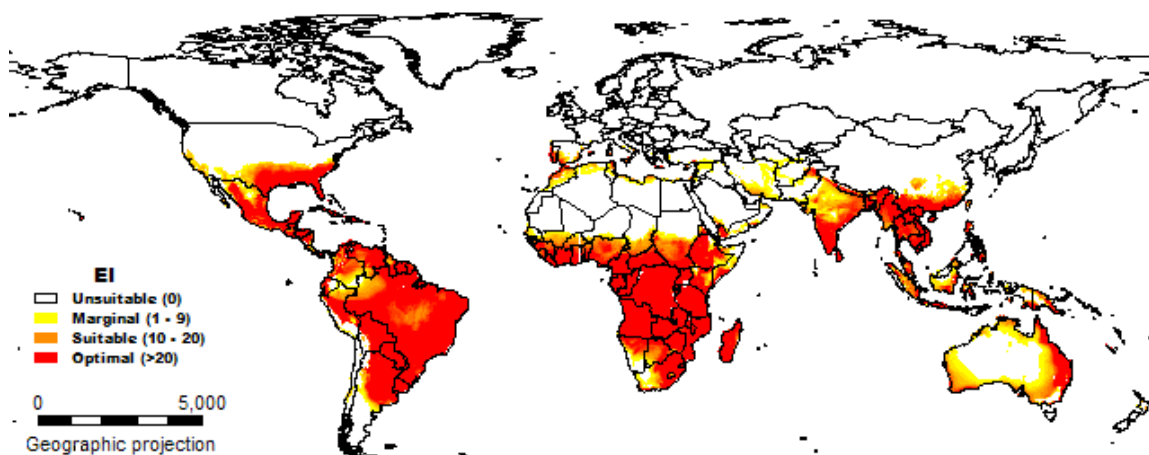


Figure 2.11: Current global distribution of *C. capitata* (a) (CPC, 2010) and the predicted CLIMEX distribution (b) based on set parameters.

2.3.4.2 Predicted distributions

Under current climate scenarios and best case 2040 climate change predictions, EI values indicate suitable habitat sites throughout the North Island, including the summerfruit producing region Hawkes Bay. Additionally, intermediate 2040 climate change predictions and worst case 2040 climate change predictions indicate an expansion of potential establishment sites across the North Island and down the east coast of the South Island, including the summerfruit producing region Marlborough.

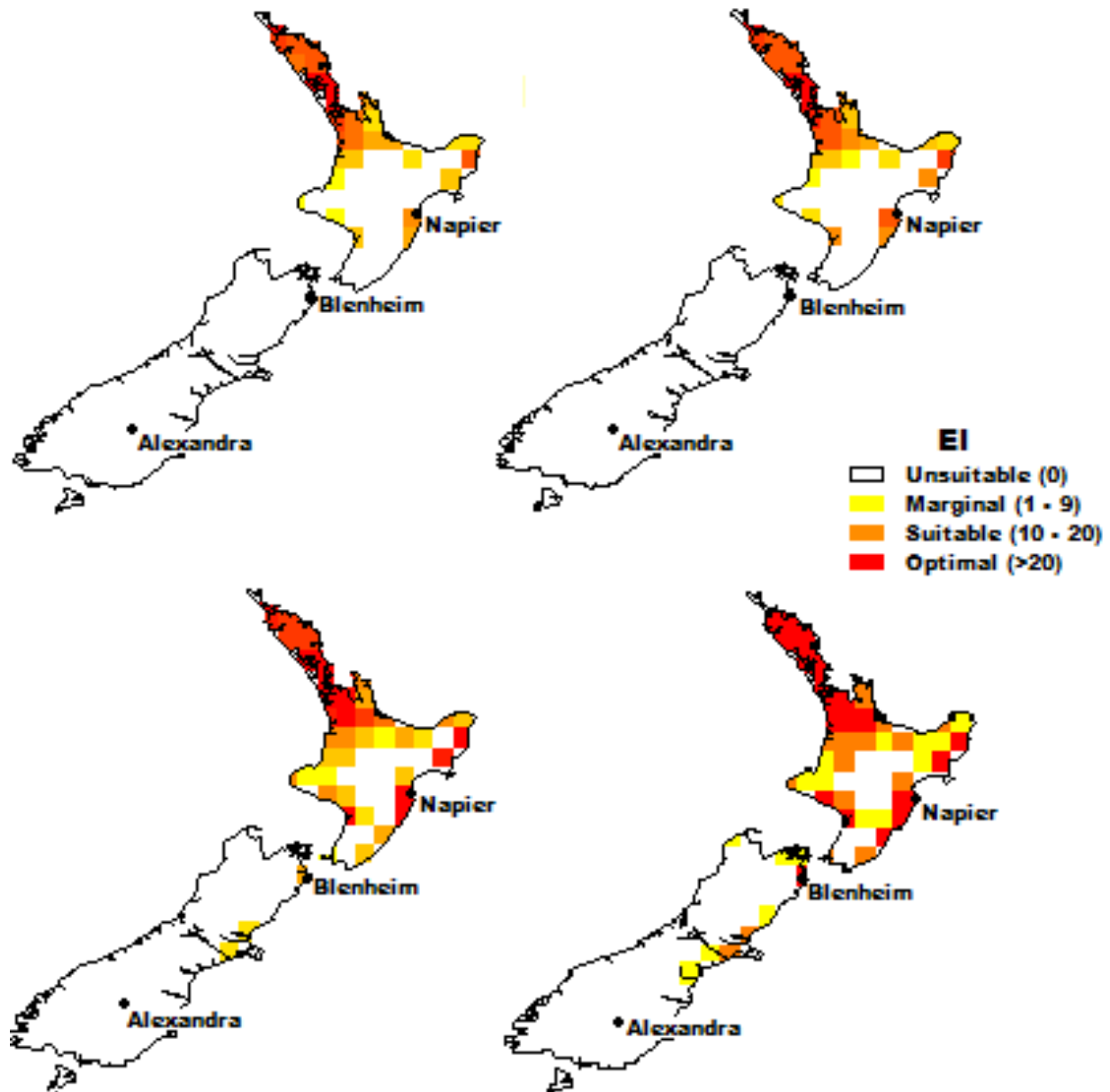


Figure 2.12: Potential distribution of *C. capitata* in New Zealand current climate (1961-1990 average), best case 2040 climate change predictions, intermediate 2040 climate change predictions and worst case 2040 climate change scenarios for New Zealand. EI = Eco-climatic Index.

Under best case and intermediate 2090 climate change conditions, EI values indicate suitable habitat sites an increase in climatic suitability in the North Island and east coast of the South Island, including the summerfruit producing region Hawkes Bay and Marlborough. Worst case 2090 climate change predictions indicate a further expansion of potential establishment sites in the South Island to include the summerfruit producing region Central Otago.

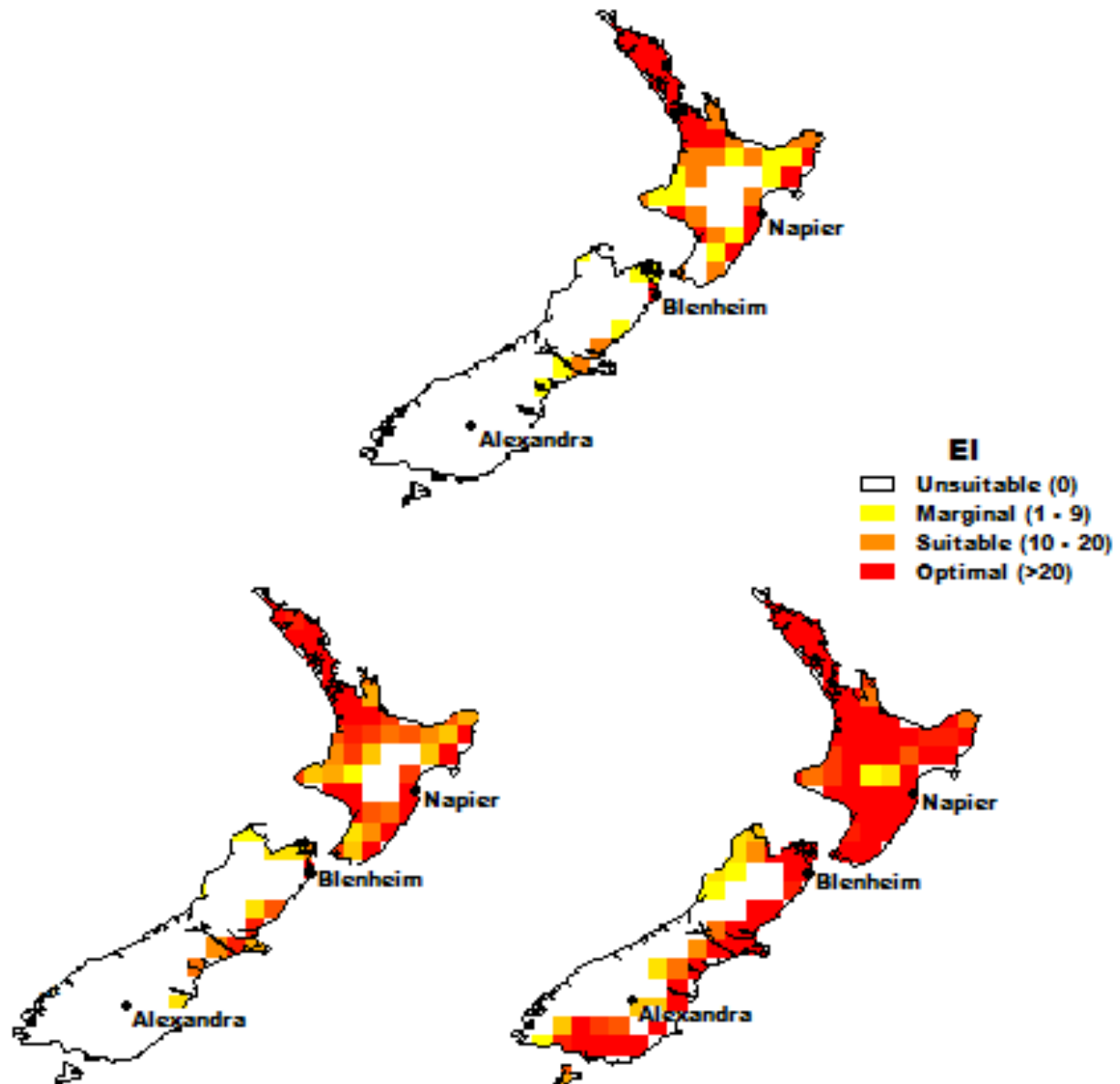


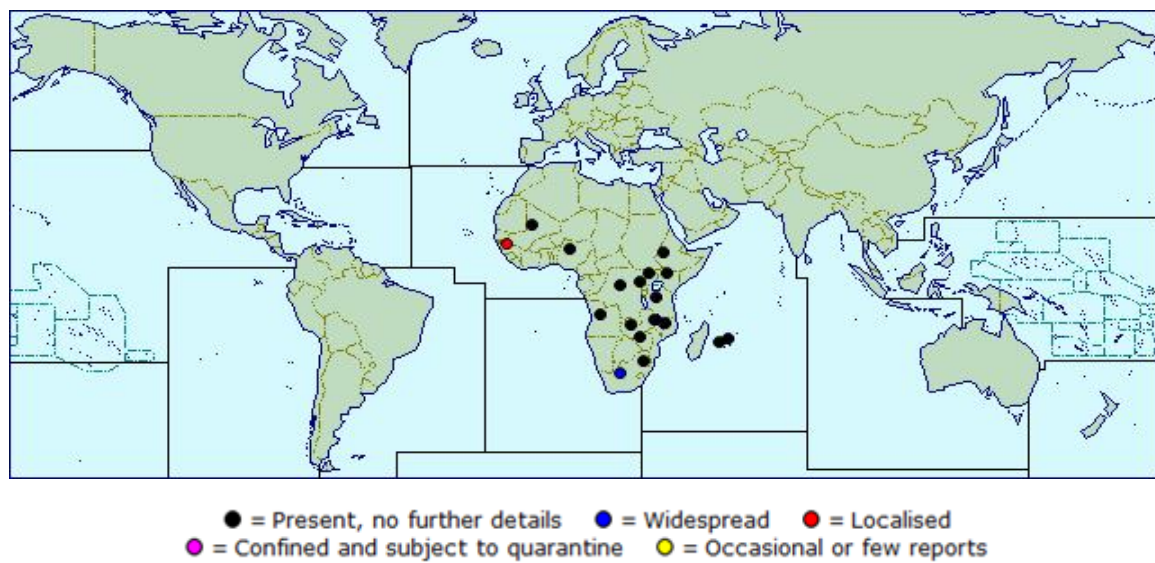
Figure 2.13: Potential distribution of *C. capitata* under best case 2090 climate change predictions, intermediate 2090 climate change predictions and worst case 2090 climate change scenarios for New Zealand. EI = Eco-climatic Index.

2.3.5 *Ceratitis rosa*

2.3.5.1 Model fit to current distribution range

The current distribution of *C. rosa* includes warm and wet climates in Central and Southern Africa and with populations also west Africa in Malawi and Guinea (CPC 2010). The current distribution map (CPC, 2010) (Figure 2.14) was used to fit and calibrate CLIMEX parameters to produce the predicted distribution (Figure 2.14). The CLIMEX model indicates optimum conditions throughout most of native range for *C. rosa*.

a)



b)

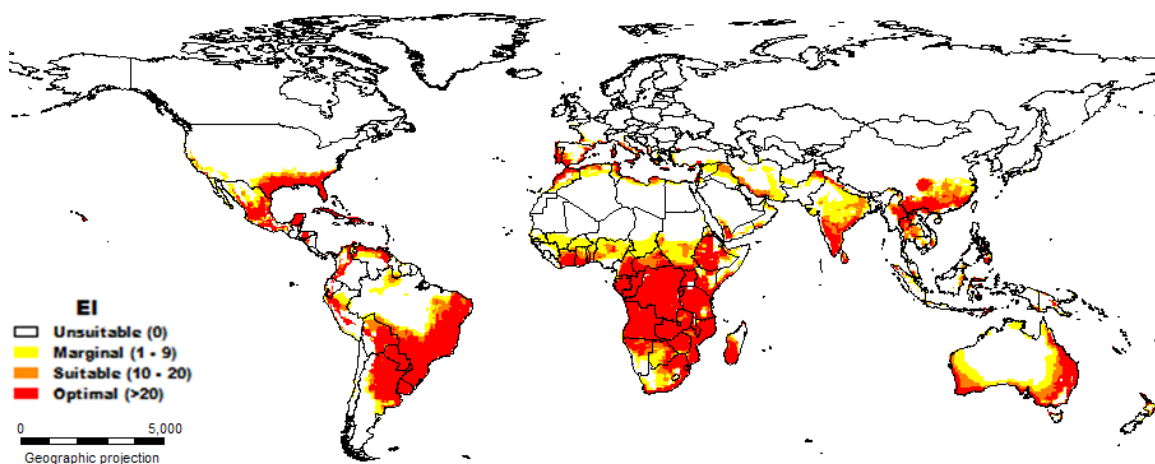


Figure 2.14: Current global distribution of *C. rosa* (a) (CPC 2010) and the predicted CLIMEX distribution (b).

2.3.5.2 Predicted distributions

Under current climate conditions (Figure 2.15), EI values indicate suitable habitat sites around most of the North Island and parts of the east coast in the South Island, including major summerfruit production regions such as Hawkes Bay and Marlborough. Best case, intermediate and worst case 2040 climate change predictions indicate an expansion of suitable habitat sites in the North Island and South Island but do not include the summerfruit producing region Central Otago.

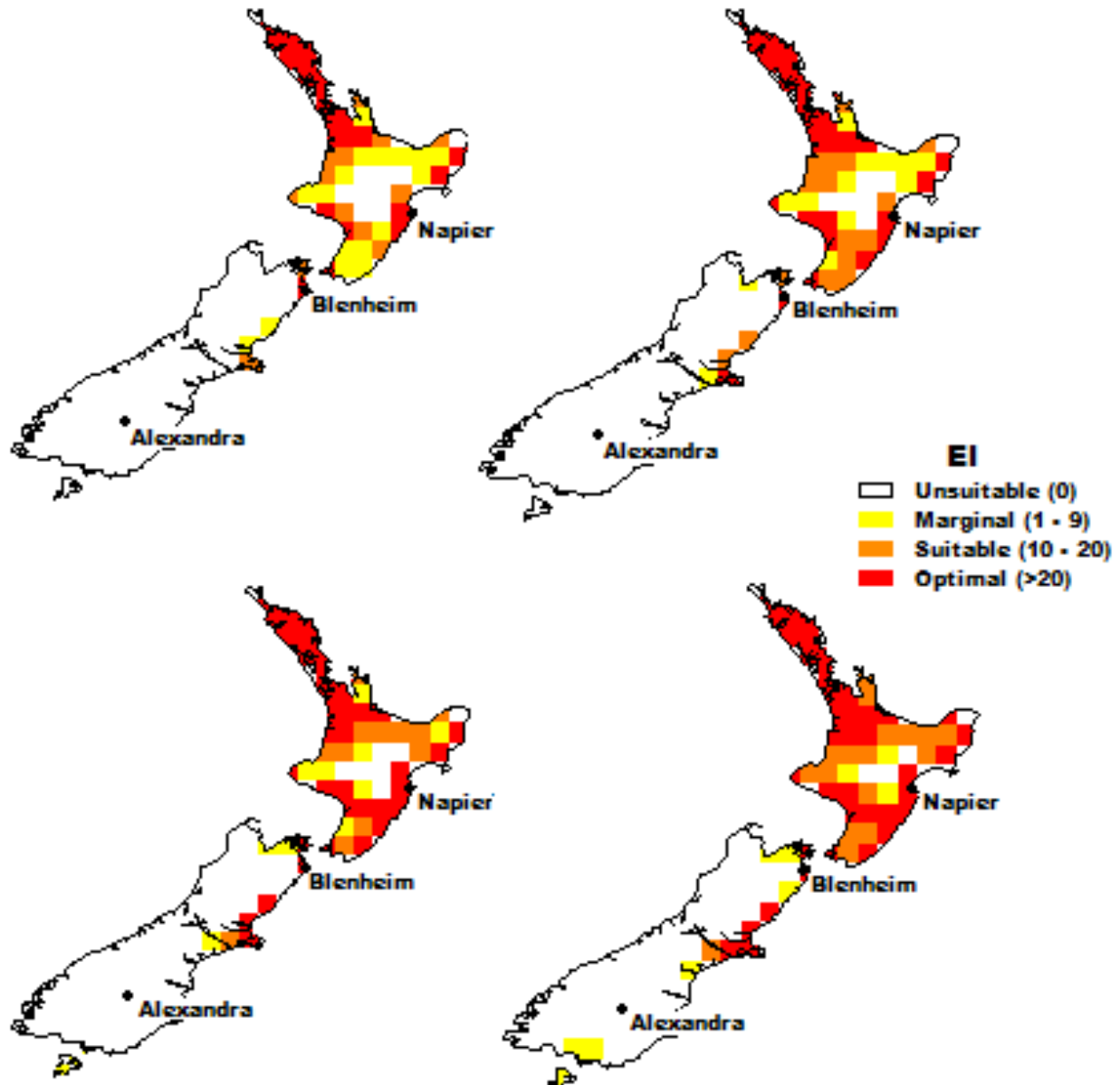


Figure 2.15: Potential distribution of *C. rosa* in New Zealand current climate (1961-1990 average), best case 2040 climate change predictions, intermediate 2040 climate change predictions and worst case 2040 climate change scenarios for New Zealand. EI = Eco-climatic Index.

Under best case, intermediate and worst case 2090 climate change predictions (Figure 2.16), suitable EI values indicate an increase in climatic suitability on both the North and South Island including the summerfruit producing region Hawkes Bay and Marlborough but does not include the summerfruit producing region Central Otago.

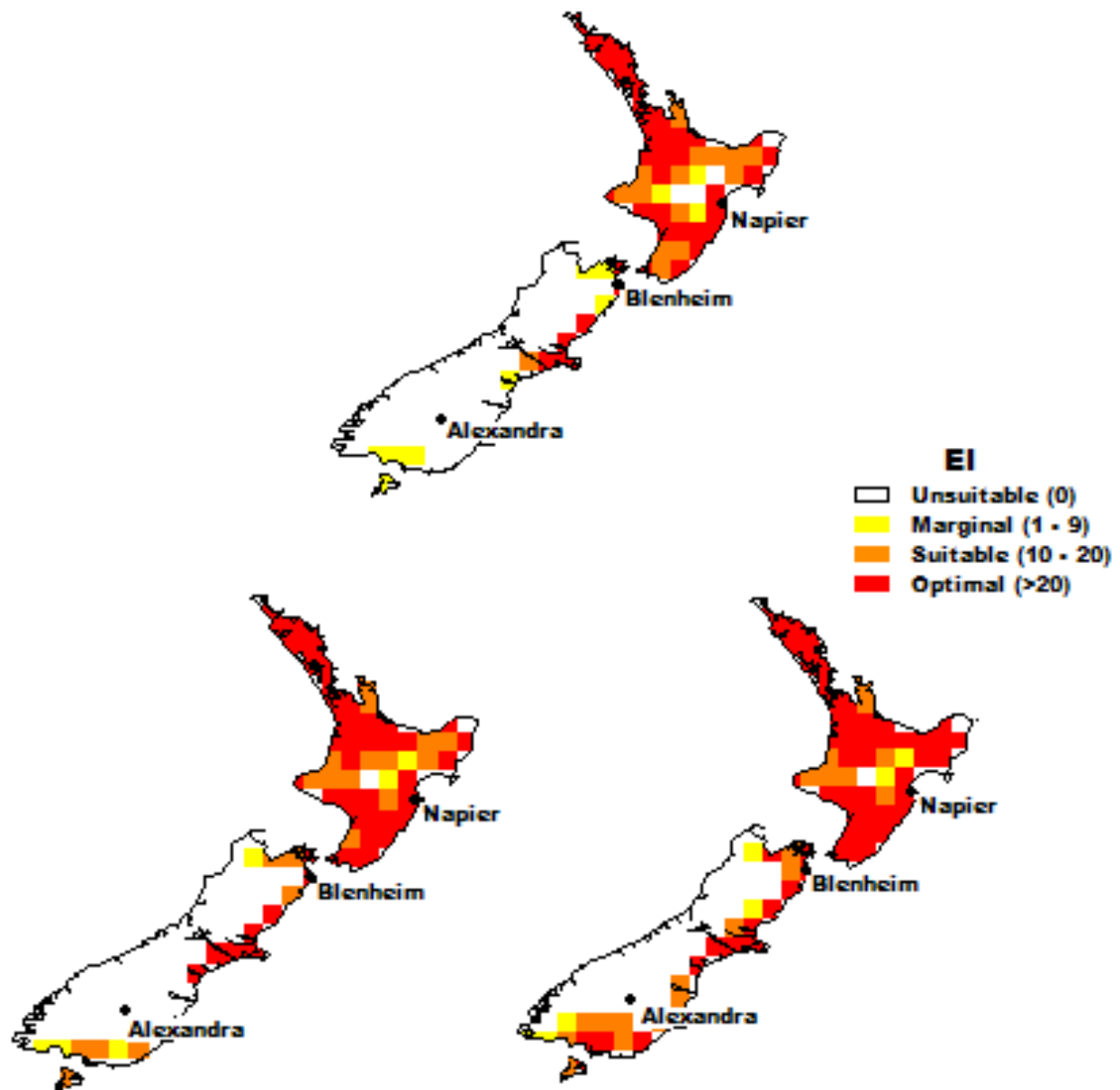


Figure 2.16: Potential distribution of *C. rosa* in New Zealand under best case 2090 climate change predictions, intermediate 2090 climate change scenarios and worst case 2090 climate change predictions for New Zealand. EI = Eco-climatic Index.

2.4 Discussion

The results presented here indicate the directions and magnitude of change to the potential distribution range of some serious fruit fly insect pests in response to climate change. The results identify summerfruit producing regions that could be vulnerable to these fruit fly pests establishing permanent populations if the pests get through border quarantine measures. The first objective for this chapter was to model the potential distribution of the target fruit flies under current climatic conditions. Generally the North Island was more climatically suitable for all target species which correlates with the warmer climate exhibited in the North Island. Currently, the summerfruit producing region Hawkes Bay has a suitable climate for *C. capitata* and *C. rosa* and Marlborough has a suitable climate for *C. rosa* (Table 2.6). Accumulated cold stress was the limiting climatic factor for all species in southern areas of the South Island including the summerfruit producing region Central Otago. Summer temperatures in the South Island are within the optimal temperature range for these fruit fly species but winter temperatures are likely to drop well below the cold stress thresholds set for a long period of time. The accumulative cold stress would prevent populations from establishing all year round.

The summerfruit producing regions, Hawkes Bay and Marlborough are more at risk from all fruit fly pests investigated under New Zealand climate change predictions. Central Otago will only be vulnerable to *C. capitata* under worst case 2090 climate change predictions. However, the magnitude of these changes varies between species and emissions scenarios that represent best case, intermediate and worst case predictions (Table 2.6). There is also difference in climatic suitability for the target species between 2040 and 2090 climate change predictions. The increased annual mean temperatures due to climate change correlates with a decreasing amount of cold stress for these fruit fly species, resulting in an increase in climatic suitability and invasion risk.

A general pattern could be observed between the climatic suitability and each climate change prediction. Under current conditions, suitable EI values surrounded the North of the North Island and throughout each climate change scenario in 2040 and 2090, the range of locations with suitable EI values would extend further south in the North Island to include the east and west coast, further extensions would include the centre of the North Island and east coast of the South Island.

Table 2.6: New Zealand summerfruit producing regions vulnerable to exotic fruit fly establishments under various climate change scenarios. HB = Hawkes Bay, M = Marlborough and CO = Central Otago.

Climate change scenario	<i>B. dorsalis</i>	<i>B. tryoni</i>	<i>B. zonata</i>	<i>C. capitata</i>	<i>C. rosa</i>
Current				HB	HB, M
Best case 2040			HB	HB	HB, M
Intermediate case 2040			HB, M	HB, M	HB, M
Worst case 2040	HB	HB	HB, M	HB, M	HB, M
Best case 2090	HB	HB	HB, M	HB, M	HB, M
Intermediate case 2090	HB	HB	HB, M	HB, M	HB, M
Worst case 2090	HB, M	HB, M	HB, B	HB, M, CO	HB, M

The method of using CLIMEX has the advantage of being readily usable and easily interpreted. This is important when communicating the research to non-scientists such as policy makers or land-use managers. Another advantage CLIMEX has over other statistically correlative methods is that it explicitly integrates physiological processes that influence distributions such as development, predictions are therefore said to be more biologically meaningful (Zalucki and Klinken 2006).

However, CLIMEX has a subjective fitting procedure that enables researchers to manipulate the results such that insidious bias can influence the process. Some CLIMEX parameters can be derived from physiological experiments that test developmental rates and mortality against various climatic gradients such as temperature and humidity. However, many parameters, particularly some stress parameters and accumulation rates cannot readily be sourced from research studies and depend entirely on the user to make the right judgment based on current distributions of the species. While Worner (1988) suggests parameters are not overly sensitive so small changes in the parameter values and do not grossly change the overall results, it still remains to test multiple parameter error. Additionally, because CLIMEX comprises indices that accumulate over time, the effect of cumulative parameter error needs to be investigated. Subjectivity surrounds the inferred climatic suitability from the Eco-climatic Index. Various studies use slightly different values to define optimal or marginal conditions. The contrasting values can lead to ‘fuzziness’ over what the Eco-climatic Index truly indicates with respect to the climatic suitability for a species. Also, these differences create difficulties supporting one’s conclusions when results are compared with other studies. The Eco-climatic Index is measured on a scale that ranges from 0 to 100 and yet, any value

above 20 or 30 is considered optimal conditions for a species, making this index questionable.

Another constraint using the CLIMEX system was the climatic database used. The dataset that comes with CLIMEX version three is based on climatic data retrieved from 1960 – 1990. Climatic data over the last 20 years differs from the climatic data taken from 1960 – 1990. Looking back at the temperature anomalies produced by a time series dataset over the time period 1850 to 2009 (Figure 1.1), there is a rapid increase in warmer years from 1980 and onwards. The non-updated climatic dataset in CLIMEX will not give fully accurate predictions for potential distributions under current climatic conditions. Future versions of CLIMEX will need an updated climatic dataset that includes climate recordings during the 21st century.

In summary, the species distribution models created with CLIMEX predict that New Zealand climate change predictions for 2040 and 2090 are likely to increase the climatic suitability in New Zealand for all fruit fly species investigated. Increases in annual temperatures eases accumulative cold stress to allow these tropical insect pests to potentially survive and establish throughout more locations in New Zealand including summerfruit producing regions. The impacts of climate change will have on fruit fly potential distributions will depend on which emissions scenario is played out in the future.

Chapter 3

Potential Impacts of Climate Change using a Multiple Model System

3.1 Introduction

The correlative approach uses environmental variables at recorded geo-referenced presence and absence localities to define climatic envelopes associated with a species presence and absence. Global species occurrences are sourced from researchers locating the species in the field and recording its geo-referenced location. These occurrence points can be found in museums, herbaria collections, online databases (Elith *et al.* 2006; Venette *et al.* 2010) and studies that research spatial distributions of species. Researchers such as Chefaoui and Lobo, (2008) have suggested that more reliable predictions are produced from presence/absence models than presence only models due to models being able to train on environmental factors that determine an absence. However the accuracy of presence/absence models depends on the reliability of the absence points. Recorded true absences are preferable. However these are often not recorded during surveys, even if they are, it is difficult to confirm that the species is absent simply due to a potentially inadequate search. Also, environmental conditions may be suitable but the species may not have had a chance to occupy that location (Elith and Leathwick 2009). A quick solution to overcome these problems is to calculate a set of pseudo-absences to balance the presence points. Some studies use randomly selected absence points (Stockwell 1999; Stockwell and Townsend Peterson 2002) but there is a potentially large pool of absence points when creating simulations on a global scale. Random selection could also result in pseudo-absence points containing suitable environmental conditions for a species (Engler *et al.* 2004). An alternative approach using a two step process is implemented in this research project.

It is important to test model performance with the same set of input data. Many studies usually use one or two performance criteria, for example, the area under the receiver operator curve (AUC) and the kappa index (Segurado and Araújo 2004; Allouche *et al.* 2006; Elith *et al.* 2006; Williams *et al.* 2009; Lobo and Tognelli 2010).

Numerous correlative models are used to find patterns in environmental data associated with the presence and absence of a species. Each model, depending on the input data, is likely to differ in the discrimination of new data into classifications with some models producing more reliable predictions than others. Therefore, it is important to select a model that will give the most reliable and accurate predictions. The multiple model system is a unique system that uses a range of 10 different performance criteria that tests sensitivity and performance for a range of correlative models to find the best performing model for creating predicted distributions.

3.1.1 Research objectives

The aims of this chapter are the same as Chapter Two. That aim was to model the potential distributions of five Tephritidae fruit fly species in New Zealand in response to climate change to determine potential threats to the summerfruit industry. In this chapter a multiple model system is implemented that evaluates the performance of nine correlative species distribution models to find the best performing model. Objectives for each target fruit fly species include:

- Collate species geo-referenced occurrence points from global databases and research publications
- Calculate suitable pseudo-absence points to balance the number of presence points
- Determine the best sub-set of environmental variables that are most effective for discriminating data
- Determine the most suitable correlative modelling method for creating predicted distributions using the same data and extensive validation.
- Create predicted distributions under current climatic conditions and future climate change predictions specific to New Zealand
- Identify any major summerfruit producing regions at risk under current and future climate change predictions specific to New Zealand

3.2 Methods

The statistical computing program used in this research was 'R' (Team 2008) which is an open source software environment for statistical programming and graphics. The multiple model system was created by the Bio-Protection Centre at Lincoln University. The methods used for testing model performance, selecting suitable environmental variable subsets and calculating pseudo-absence points were sourced from a study by Worner *et al.* 2010. Their research used the method to estimate climatic suitability for 21 species of exotic freshwater invertebrate pests in New Zealand.

3.2.1 Distribution data

The geo-referenced occurrence data for each of the five fruit fly species investigated was sourced from the Global Biodiversity Information Facility (GBIF) (www.gbif.org) an online database and through other various research publications that state geo-referenced recordings of the fruit fly species. The data was checked carefully such that overlapping occurrence points were treated as replicates and removed from the analysis. Also, any geo-referenced points that fell within the same gridded block on the world climate surface used were treated as the same occurrence point.

3.2.2 Environmental data

The environmental data required to observe patterns in species distributions were obtained from WorldClim (www.worldclim.org). The data is compiled from monthly averages measured at various weather stations from a large number of global, national and regional sources (Hijmans *et al.* 2005). The data covers records mostly for the 1950 – 2000 period but varies between locations and weather stations (Hijmans *et al.* 2005). The interpolated climate surfaces for global land areas are at a resolution of 30 arc seconds (approximately 1km spatial resolution) to capture small scale gradients and variations in the climate (Hijmans *et al.* 2005). Nineteen bioclimatic variables are available from WorldClim and have been well used in many studies that model species distributions (Hijmans and Graham 2006; Broennimann *et al.* 2007; Peterson and Nakazawa 2008; Worner *et al.* 2010). Important bioclimatic variables include mean annual temperature, isothermality, temperature seasonality, mean annual precipitation and maximum and minimum temperatures for the warmest and coldest months. The environmental data from WorldClim was converted with ArcGIS from Initial shape files (ESRI) into geospatial co-ordinates in the form of text files to be compatible for use in 'R'. Each occurrence point for each species was then aligned with the closest Worldclim

coordinates using a Euclidean distance measure to characterise the climate from derived bioclimatic variables.

3.2.3 Pseudo-absence data collation

The multiple model approach uses a two-step process to calculate pseudo-absences using support vector machines (SVM) and k-means clustering. The first step is to calculate the global climatic suitability from presence data of the target species by running 100 SVM repetitions using the bioclimatic variables from WorldClim. Running an ensemble of models lowers the prediction error by aggregating results, rather than selecting a single best fit model. Five bioclimatic variables from a total of 19 were excluded during this process to decrease the number of data points and potential for model error. The mean diurnal range variable ((mean of monthly (max temp - min temp))) was excluded due to the likelihood that extreme warm and cold environments would have a similar diurnal range. The mean temperature of the warmest and coldest quarter variables were excluded due to there being other relevant temperature variables such as the maximum temperature of the warmest month and minimal temperature of the coldest month. The precipitations of the wettest and driest quarter were also excluded due to there being other precipitation variables. Worner *et al.* (2010) selected the support vector machine method for this stage due to its capability of handling large sets of data and short computational time for prediction. Potential absence points were defined as locations of very low climatic suitability (posterior probability of less than 0.1 on a scale of 0 – 1). Because this process still results in many thousands of potential absence points, K-means clustering was then employed to group the low climatic suitability locations into k-clusters, based on them sharing similar environmental variables. The numbers of clusters were chosen to be the same as the number of presence points. The geographic location closest to the centroid at each k-cluster was therefore deemed as an absence point.

3.2.4 Variable selection

A subset of bioclimatic variables was selected to minimize collinearity between variables and reduce computational time while achieving similar results. This process involved analysing all variables using a random forest classification algorithm and then a stepwise regression analysis. The random forests algorithm uses an aggregation of many decision trees generated by a random selection of bioclimatic variables to find the best combination of variables to be used to predict new data. When you average over a large set of trees it results in low bias and

low variance. Worner *et al.* (2010) used this algorithm because it has good predictive performance, even when predictive variables are just noise it will not overfit.

3.2.5 Models

The models used are binary classifiers that predict a response variable (presence or absence) from environmental predictors such as temperature and rainfall etc. at a geographic location. These particular models are used when very little information is available on the environmental requirements of species. A brief summary of how each model functions follows:

The quadratic discriminant analysis (QDA) method is one of the oldest statistical classification methods (Fisher 1936). It assumes only two classes of points and that the data is normally distributed with a mean and co-variance. Linear discriminant analysis (LDA) is another classification method that is perhaps the oldest method used to discriminate between classes (Fisher 1936). The method finds a linear combination of variables that best discriminates two or more classes. The measurements are also assumed to be normally distributed but an identical co-variance is assumed between the classes. These two methods both find combinations of variables that are as statistically distinct as possible to create the classes of interest (Zeman and Lynen 2006). For every location, the Mahalanobis distance is used to define the distance of the multivariate vector (x) from the class mean as previously determined by environmental variables at species occurrence points (Worner *et al.* 2010). If the distance between the multivariate vector and a class is small then it is likely the vector belongs to that class.

The logistic regression model (LOG) is a generalisation of linear regression and is used to make predictions for binary variables but also multiclass variables. The probability of a presence or absence (p) for a sample (x) given the class (c) is described by the function.

$$p(c | x) = \frac{e^{\beta_0 + \sum_{i=1}^p \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^p \beta_i x_i}}$$

The logarithm of the odds of the response variable is linear in the co-efficient of predictors. The odds ratio is the probability of the event occurring over the probability of it not occurring (Worner *et al.* 2010).

$$\ln\left(\frac{p(c|x)}{1-p(c|x)}\right) = \beta_0 + \sum_{i=1}^p \beta_i x_i$$

The naive bayes classifier (NB) is naive because it assumes the presence or absence of a particular variable of a class is independent of the presence of absence or any other variable (Worner *et al.* 2010). Attributes are therefore conditionally independent from one another, given the class. A deterministic prediction can be obtained by choosing the most likely class. Decision trees such as the classification and regression trees (CART) and the variant, the conditional tree (CTREE) represent a series of rules that lead to discrimination of a class or value (Usio 2007; Roura-Pascual *et al.* 2011). The root node contains all the samples. Each leaf represents a classification and the branches represent the conjunction of features that lead to particular classifications (Figure 3.1). At each node there is a fraction of the samples and a rule that divides the samples into a two groups. One of the groups will be left behind at a leaf and the other will carry on to a different node with a new rule. Therefore at each leaf there is a group of samples of one type. For every new sample, one looks at which leaf the sample ends up at.

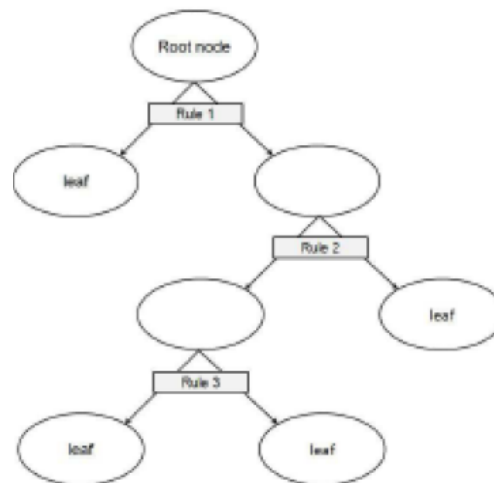


Figure 3.1: Decision tree

The K-nearest neighbour model (KNN) assumes that observations that are close in the multi-dimensional space of predictor variables will be close to each other in the space of the response variable (Worner *et al.* 2010). The class for a new observation or sample is decided between its k-nearest neighbours among the training set of observations (recorded occurrences).

Support vector machines (SVM) input non-linear variables to a high dimensional feature space in an attempt to create a hyperplane in the space between the two classes that is within a maximal margin (Figure 3.2) (Cortes and Vapnik 1995). If no hyperplane exists, the soft margin method can choose a hyperplane with the smallest number of samples on the wrong side (Cortes and Vapnik 1995). A penalty error is used in this case to define the distance to the hyperplane by the Lagrange multiplier. Another method to overcome the lack of a direct hyperplane is to use a functional relationship known as a kernel to map data onto a new hyperspace so that complicated patterns are more simply represented (Drake *et al.* 2006)

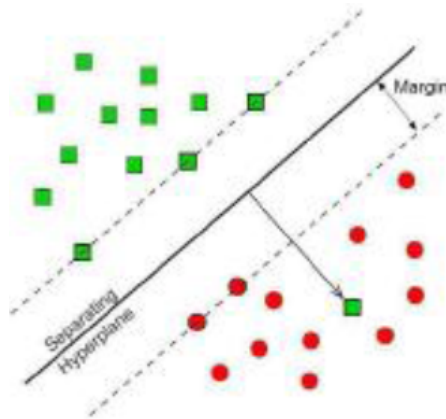


Figure 3.2: Support vector machine hyperplane

The artificial neural network model (NNET) is a classifier that functions like the biological neural system. It is a mesh of neurons organised in several layers. These layers are connected to each other with the outputs of each layer feeding the input to another layer (Figure 3.3). Each layer filters the information by amplifying it or reducing it using an activation function (Worner *et al.* 2010). In this study, the activation function used was a logistic function. The model uses the neuron layers to do repeated sensitivity analysis on variations of the predictor variables, looking for optimal solutions (Williams *et al.* 2009)

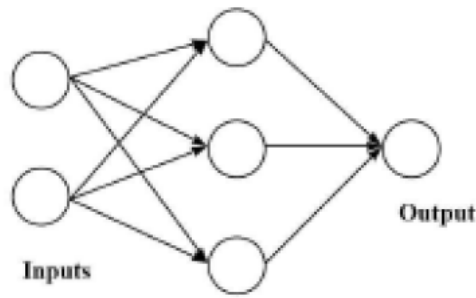


Figure 3.3: Feed-forwarding neural network with one layer

3.2.6 Model selection procedure

Models that generate predictions using presence/absence data are usually evaluated by constructing a confusion matrix that records true positive, true negative, false positive and false negative cases predicted by the model when validated on independent data. Ten different performance measures used in other species distribution modeling studies were used in this study. We use multiple performance measures because all of them have their own advantages and disadvantages and perform differently depending on data characteristics. A brief description of each follows: The accuracy performance measure describes the proportion of correctly predicted sites (ratio of the true positive and true negative cases). If cases are not balanced then precision can be used to describe the true positive ratio against the false positive rate and recall can be used to describe the true positive ratio against the false negative rate. An average of precision and recall comprises the F-score performance measure. Predictions close to 0.5 are uncertain as they are the furthest figure away from either classification of presence or absence so a model uncertainty performance measure was introduced to describe the proportion of cases in which this occurs.

The Receiver Operating Characteristic (ROC) curve (Fielding and Bell, 1997) is a plot of the true positive rate against the false positive rate (Figure 3.4). This curve can show the tradeoffs between the true positive rate and false positive rate. If for example two ROC curves from different models don't intersect then one model performs better than the other. However if curves do intersect then one model is better performing at different ratios of beneficial true positives to false positive costs. The area under curve (AUC) is a performance criteria for model selection using the ROC curve and describes the probability that the model will predict a true positive over a false positive (Benito *et al.* 2009).

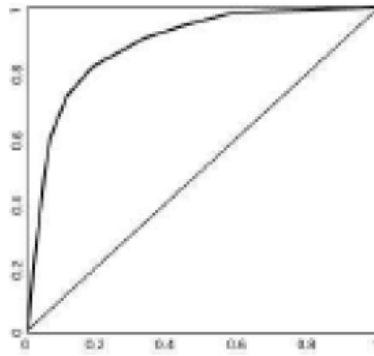


Figure 3.4: Receiver Operating Characteristics curve.

The kappa index compares the overall accuracy of the species distribution model with the accuracy expected to happen by chance. Landis and Koch (1977) proposed a scale for the kappa index (Table 3.1). A kappa index of 1 equals perfect agreement and any value below zero indicates a performance that could have occurred randomly (Allouche *et al.* 2006).

Table 3.1: Kappa Index Scale.

Agreement	Kappa
Excellent	≥ 0.8
Good	0.61 – 0.8
Medium	0.41 – 0.6
Not good	0.21 – 0.4
Bad	0 – 0.2
Very bad	≤ 0

Both bootstrapping and cross validation methods were used to create set-aside validation data for model evaluation. Bootstrapping is a technique of re-sampling the data set with replacement and cross validation is a technique that divides the data up into partitions. Both validation procedures involved re-sampling the data multiple times with a portion of data set aside (about 20-30%). The remaining 70-80% of the data is fitted to the model while the set aside data is used for validation. For each replicate, the set aside data is independent of the data used to fit the model and was removed altogether during the model fitting process. In this study, 200 bootstrap samples were used and 10-fold cross validation with 20 repetitions (5 fold cross validation with 40 repetitions for species with a small number of occurrence points). The bootstrapping 0.632 error and cross validation error were also used as performance measures to estimate the error resulting from using these validation methods.

The nine different models were given a rank for each performance criteria with a rank of 9 indicating the worst performing model and 1 the best. The ranks were summed and the model with the lowest overall rank was deemed the best performing model.

3.2.7 Climate change scenarios

To estimate the impact of climate change on potential summerfruit insect pests, average surface air temperature increases for 2040 and 2090 were incorporated into the multiple model system. Data from the B1 scenario, A1B scenario and the A1F1 scenario were selected as being representative of a best case, intermediate and worst case scenario for 2040 and 2090 climate change conditions (Table 3.2).

Table 3.2: Predicted surface air temperature increases indicated by climate change scenarios representing a best case, intermediate and worst case scenario for New Zealand.

	2040	2090
B1 Emissions Scenario	0.6°C	1.3°C
A1B Emissions Scenario	0.9°C	2°C
A1F1 Emissions Scenario	1.3°C	2.9°C

A number of different environmental variables were used with the multiple model approach but only the mean annual temperature variable was manipulated to represent each scenario. The report by Mullen *et al.* 2008 does detail predicted changes to precipitation levels as a result of climate change. However these were not incorporated into this study because precipitation patterns will not change in the same direction for all areas of New Zealand like annual mean temperatures. The South Island is expected to experience an increase in precipitation while the North Island may experience a decrease in precipitation. The species distribution models require a single figure of altered precipitation levels to create climate change predictions for New Zealand. Fortunately, the annual mean temperature variable was also selected as a significant environmental variable during the variable selection process for each species. Changes in annual mean temperatures were incorporated by adding an average change in temperature for a specific scenario with its standard deviation to every grid cell on the climate surface extracted from WorldClim.

3.3 Results

3.3.1 *Bactrocera dorsalis*

The geo-referenced occurrence points for *B. dorsalis* were sourced from GBIF (www.gbif.org) and from various publications (Liu and Ye 2005; Shi *et al.* 2005; Vargas *et al.* 2007; Satarkar *et al.* 2009; Chou *et al.* 2010). A total of 33 occurrence points for model fitting were used once replicates had been removed (Figure 3.5). The pseudo-absence points were generated from support vector machine repetitions and 33 clusters using k-means clustering (See Appendix A).

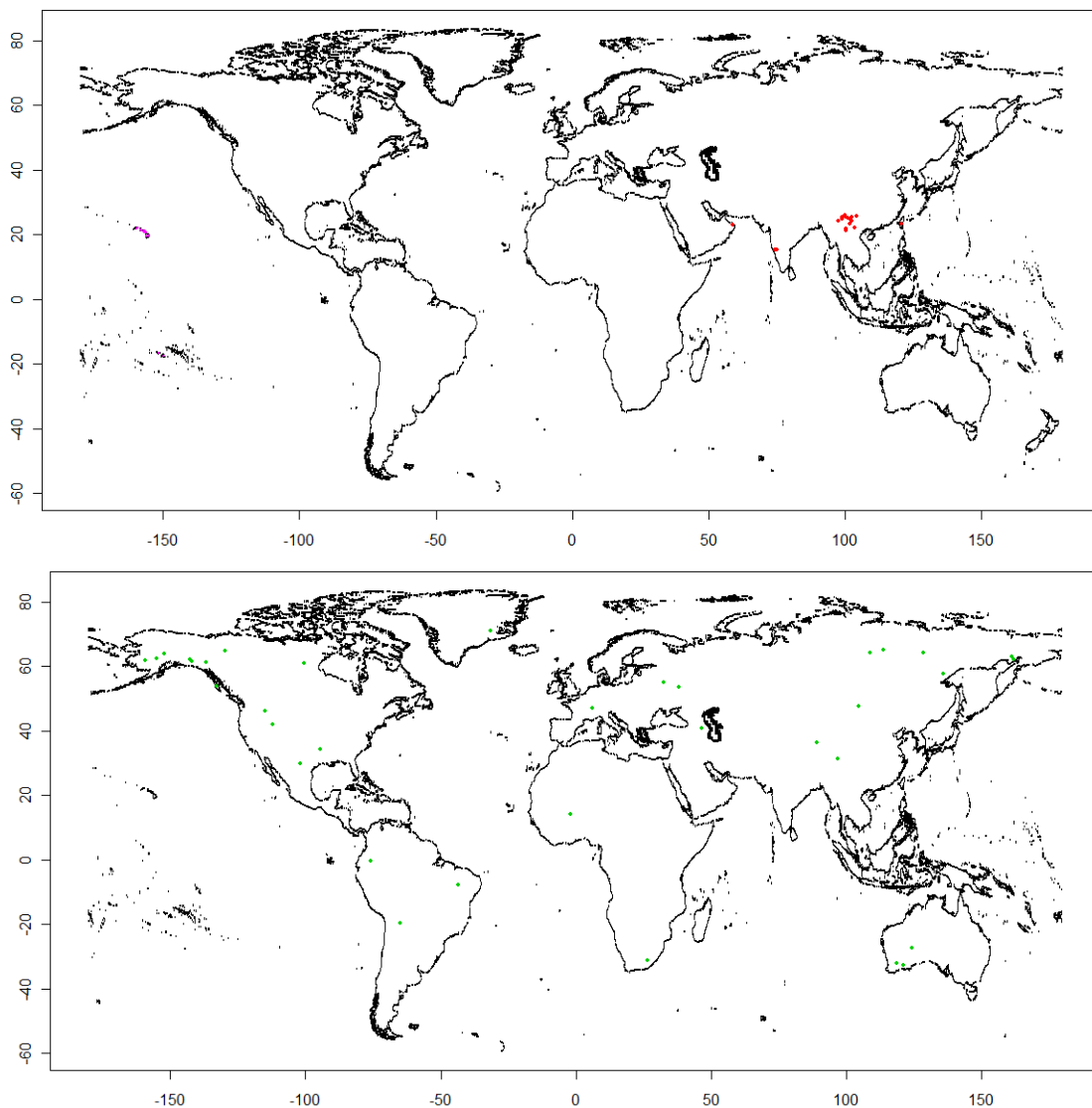


Figure 3.5: Global georeferenced occurrence points for *B. dorsalis* (top) and pseudo-absence points generated (bottom).

3.3.1.1 Important environmental variables

The bioclimatic variables from the WorldClim database selected using the random forest and step-wise linear regression analyses were: Annual Mean Temperature, Isothermality, Max Temperature of Warmest Month and Mean Temperature of Wettest Quarter.

3.3.1.2 Model performance

The variability of performance based on two (ROC curves and boxplots of the kappa index) of the 10 criteria are shown in Figure 3.6. Figure 3.6 shows high variation in the performance of each model and also variability in mean performance over cross-validation replicates between the models, indicating less reliable predictions. However, the average performance of the models remained very high over most performance criteria. The scores and rankings for each model with respect to the 10 performance criteria are shown in Table 3.3. The model with lowest overall rank (best model) was the quadratic discriminant analysis and was selected to create predicted distributions of *B. dorsalis*.

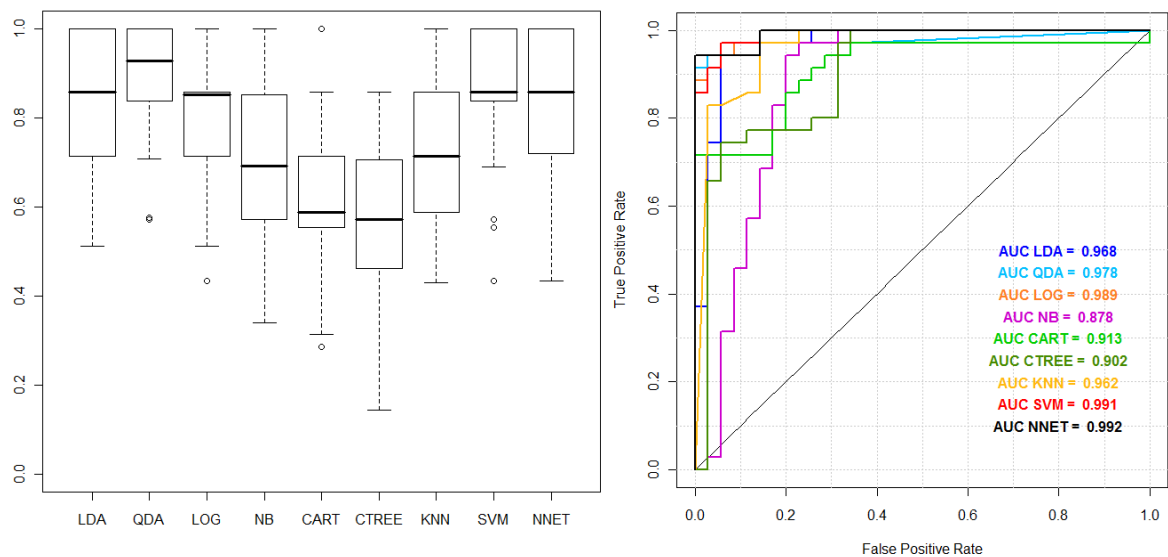


Figure 3.6: Kappa and ROC plots for the eight models compared with cross-validation validation methods. Acronyms for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks.

Table 3.3: Performance criteria and their ranks for the cross validation resampling method.
Abbreviations for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks. Abbreviated performance criteria are, "TSS" for true skill statistic and "auc ROC" for area under curve of receiver operator characteristics.

	Accuracy	rank1	Precision	rank2	Recall	rank3	F.score	rank4	Kappa	rank5	Specificity	rank6	TSS	rank7	Uncertainty
A	0.930357	3	0.90696	5	0.963859	1	0.929932	3	0.853844	3	0.90445	5	0.868312	3	0.057143
A	0.946429	1	0.97827	1	0.914296	7	0.941907	1	0.887935	1	0.98329	1	0.897588	1	0.028571
S	0.919643	5	0.90721	4	0.933899	5	0.91451	5	0.830647	5	0.90955	4	0.843451	5	0.057143
	0.853571	7	0.80671	8	0.9363	4	0.856432	7	0.701006	7	0.78779	8	0.724085	7	0.028571
T	0.810714	8	0.79264	9	0.876786	8	0.81295	8	0.618886	8	0.7738	9	0.650583	8	0.2
EE	0.789286	9	0.81547	7	0.795526	9	0.776123	9	0.575051	9	0.80216	7	0.597688	9	0.3
V	0.869643	6	0.83003	6	0.942857	2	0.872517	6	0.735145	6	0.81903	6	0.761883	6	0.071429
A	0.926786	4	0.9307	2	0.922272	6	0.921728	4	0.846286	4	0.93989	2	0.862161	4	0.042857
T	0.933929	2	0.9299	3	0.937619	3	0.93017	2	0.861054	2	0.9351	3	0.872716	2	0.085714

3.3.1.3 Predicted distributions

The current distribution of *B. dorsalis* ranges throughout locations with warm and wet climates in India, Pakistan and South East Asia. Presence of *B. dorsalis* is also recorded in more arid areas such as Oman (CPC 2010). A global prediction of the climate suitability for *B. dorsalis* is shown using the quadratic discriminant analysis model (QDA) (Figure 3.7). The legend shown is a posterior probability with warmer colours representing higher climatic suitability. Any value above 0.5 indicates suitable climatic conditions

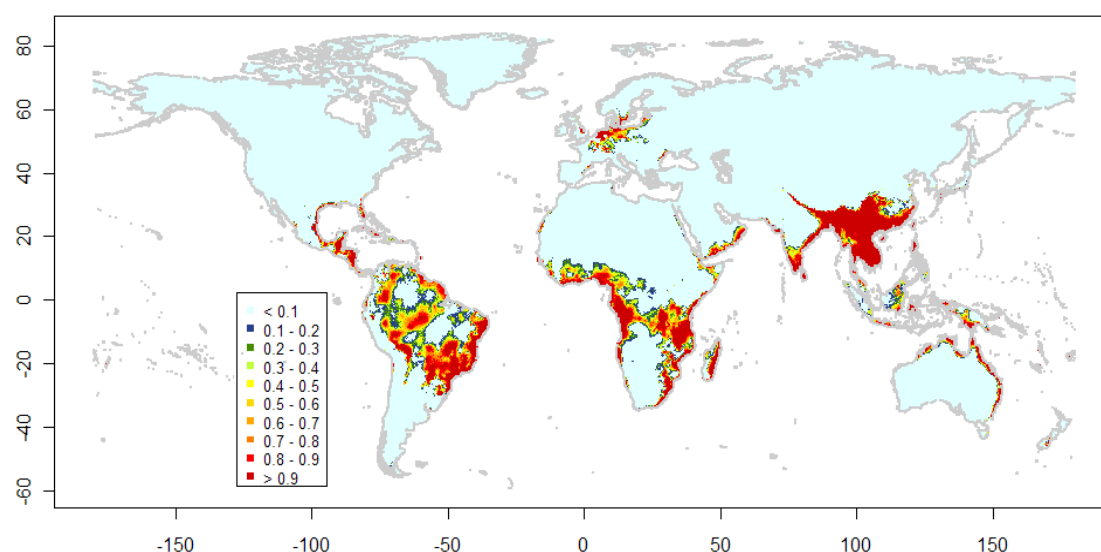


Figure 3.7: Global environmental suitability of *B. dorsalis* using the quadratic discriminant analysis (qda). The legend represents environmental suitability with warmer colours representing higher environmental suitability.

The predicted New Zealand distribution of *B. dorsalis* based on climatic suitability under current climatic conditions and best, worst and intermediate 2040 and 2090 climate change scenarios were generated. Current climate conditions generated suitable habitat sites around areas of the South Island in New Zealand, including the summerfruit producing region Central Otago. 2040 climate change predictions generated few new suitable habitat sites in New Zealand (Figure 3.8).

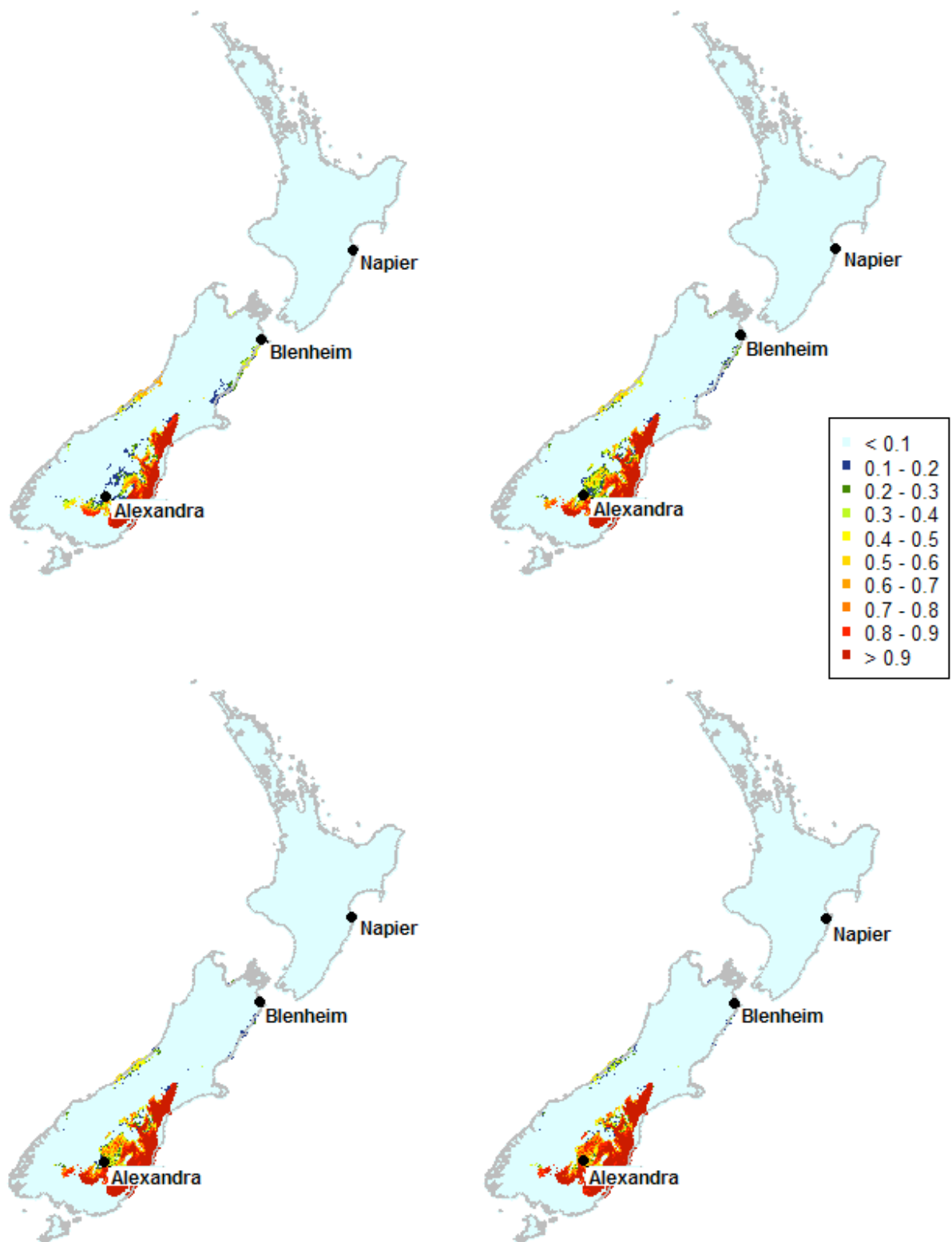


Figure 3.8: Potential distribution of *B. dorsalis* under worst case 2040 climate change scenarios for New Zealand.

Each 2090 climate change scenario again indicates little change to climatic suitability across New Zealand compared with current climate conditions and 2040 climate change predictions (Figure 3.9).

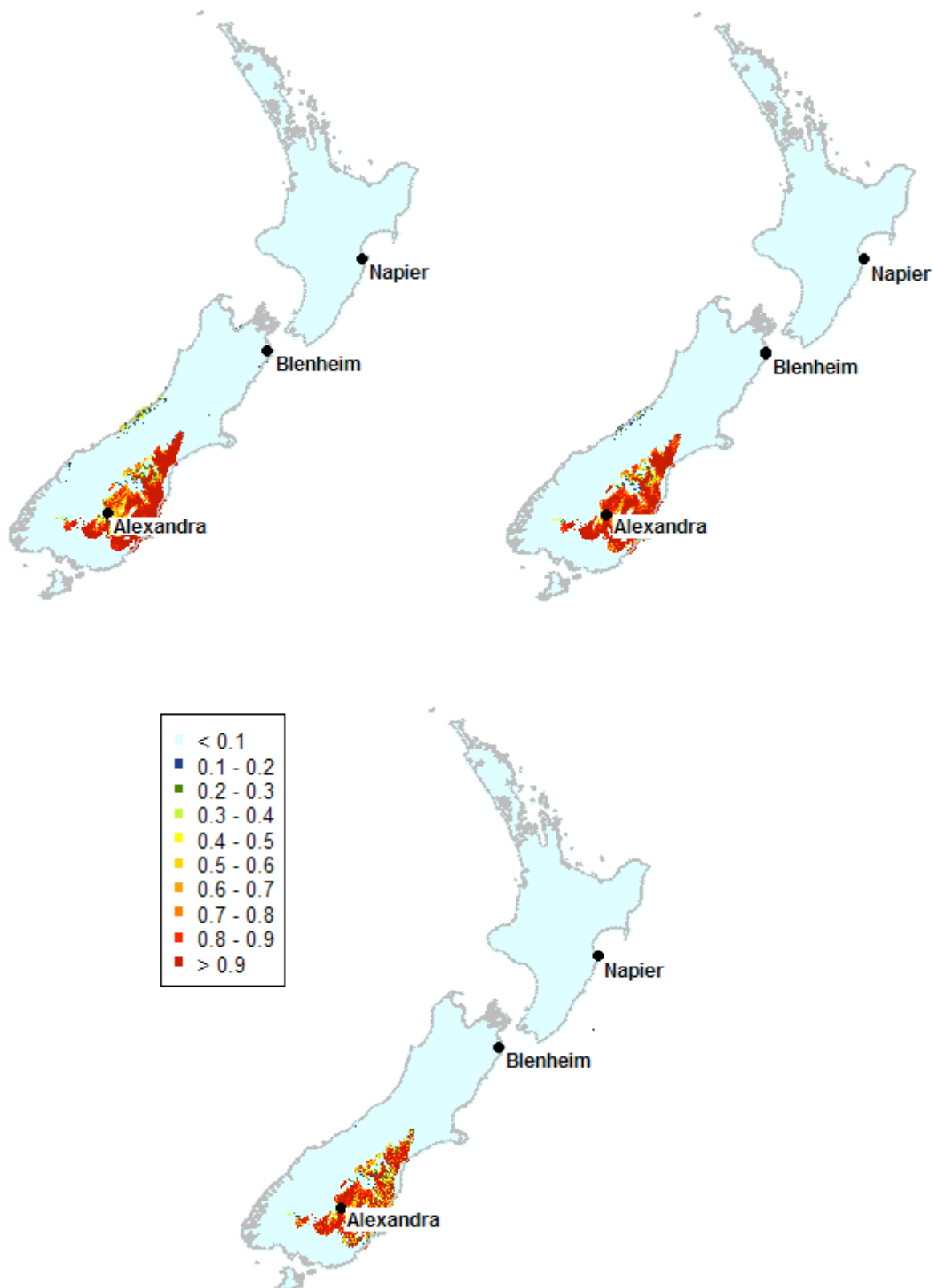


Figure 3.9: Potential distribution of *B. dorsalis* in New Zealand under best case 2090 climate change predictions, intermediate 2090 climate change predictions and worst case 2090 climate change scenarios for New Zealand.

3.3.2 *Bactrocera tryoni*

The georeferenced occurrence points used for *B. tryoni* were sourced from GBIF (www.gbif.org) and Vargas *et al* (2007). A total of 62 occurrence points were used for model fitting once replicates had been removed (Figure 3.10). The pseudo-absence points were generated from support vector machine repetitions and 62 clusters using k-means clustering and support vector machine repetitions (See Appendix A).

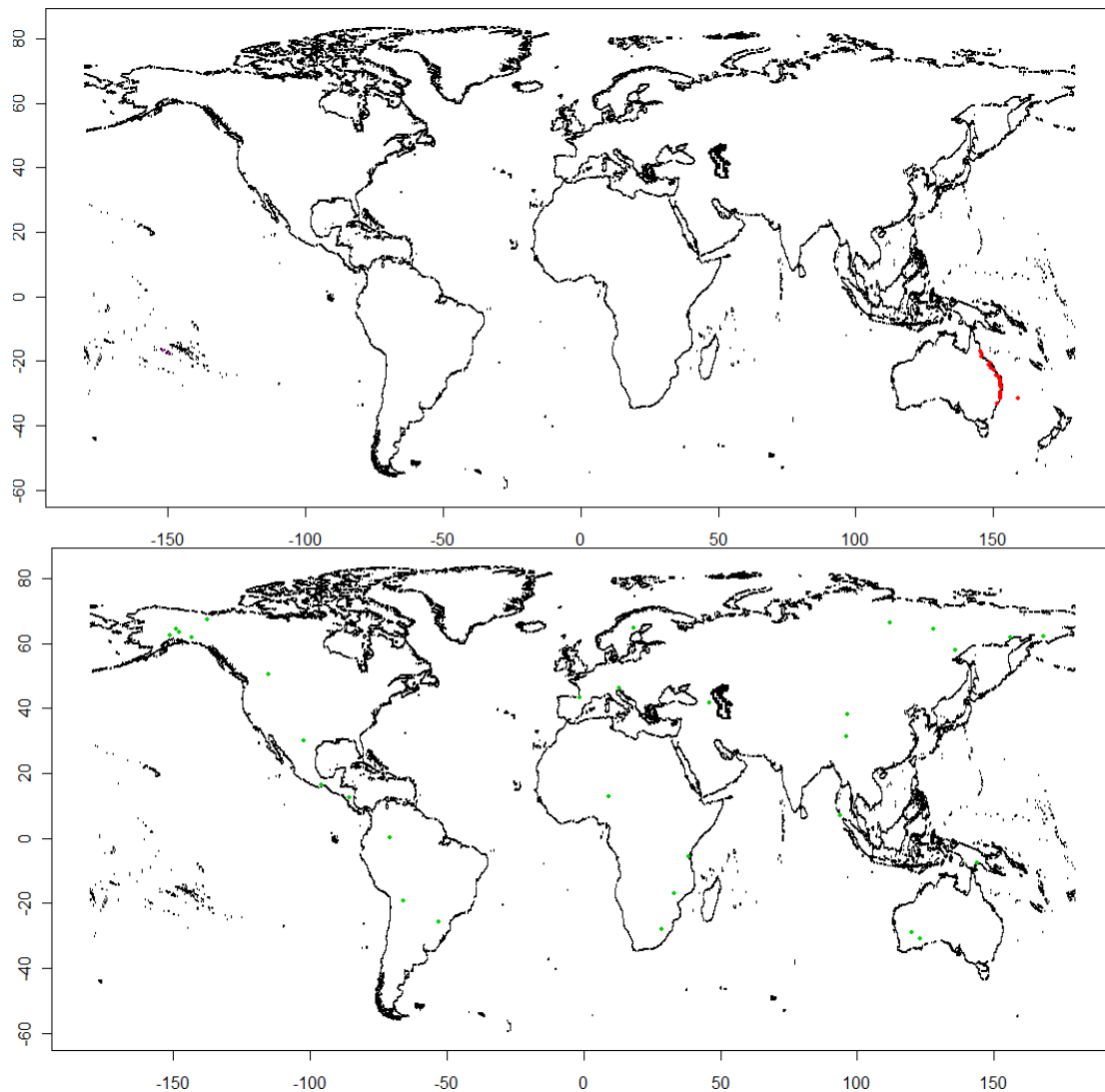


Figure 3.10: Global georeferenced occurrence points for *B. tryoni* (top) and pseduo-absence points generated (bottom).

3.3.2.1 Important environmental variables

The bioclimatic variables from WorldClim selected from the random forest and step-wise linear regression analysis were: Annual Mean Temperature, Isothermality, Temperature Annual Range, Mean Temperature of Wettest Quarter, Annual Precipitation and Precipitation of Warmest Quarter.

3.3.2.2 Model performance

The variability of performance based on two (ROC curves and boxplots of the kappa index) of the 10 criteria are shown in Figure 3.11. Figure 3.11 shows high variation in the performance of some classifiers such as KNN, CART, CTREE and NB, indicating less reliable predictions. However, very low variation with regards to the kappa index score and AUC was also observed for the LDA classifier. The average performance of the models remained very high over most performance criteria. The scores and rankings for each model with respect to the 10 performance criteria are shown in Table 3.4.

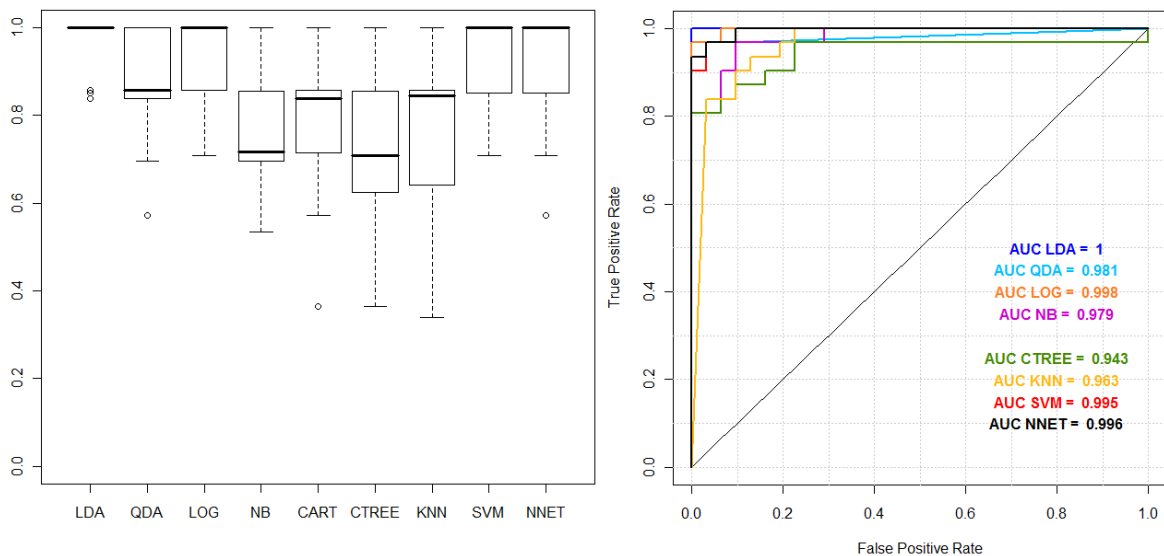


Figure 3.11: Kappa and ROC plots for the eight models compared with cross-validation validation methods. Acronyms for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks.

Table 3.4: Performance criteria and their ranks for the cross validation resampling method.
Abbreviations for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks. Abbreviated performance criteria are, "TSS" for true skill statistic and "auc ROC" for area under curve of receiver operator characteristics.

	Accuracy	rank1	Precision	rank2	Recall	rank3	F.score	rank4	Kappa	rank5	Specificity	rank6	TSS	rank7	Uncertainty
A	0.989286	1	0.97715	2	1	1	0.987564	1	0.977119	1	0.98032	2	0.980317	1	0
A	0.951786	5	0.98493	1	0.920099	7	0.946998	5	0.897491	5	0.98698	1	0.907083	5	0.0322581
S	0.971429	2	0.96886	3	0.972609	3	0.968433	2	0.939447	2	0.97385	3	0.946457	2	0.0322581
	0.8875	7	0.84034	8	0.949663	6	0.883631	8	0.76509	8	0.83841	8	0.788073	7	0.0967742
T	0.908929	6	0.95315	6	0.854038	8	0.894445	6	0.807197	6	0.96497	5	0.819007	6	0.0645161
EE	0.871429	9	0.92102	7	0.82498	9	0.851778	9	0.732472	9	0.92385	7	0.748826	9	0.2096774
V	0.885714	8	0.81938	9	0.981637	2	0.885572	7	0.765599	7	0.80077	9	0.782406	8	0.1290323
A	0.9625	4	0.95448	5	0.969038	4.5	0.958805	4	0.920788	4	0.96039	6	0.929424	4	0.016129
T	0.966071	3	0.96341	4	0.969038	4.5	0.96365	3	0.929393	3	0.96762	4	0.936657	3	0.016129

The models with lowest overall ranks were the linear discriminant analysis, logistic regression and neural networks. However, these models did not produce suitable predicted global distributions. These models indicate high climatic suitability around cool temperate and high latitude regions of the Northern Hemisphere. The fourth lowest ranking model, a support vector machines, was instead used to produce predicted distributions. This particular model showed very high performance on many performance measures for this species and has been shown to give the best performance for many other species (Worner *et al.* 2010).

3.3.2.3 Predicted distributions

The current distribution of *B. tryoni* is limited to the eastern areas of the states of Queensland, New South Wales, Northern Territory and extreme east of Victoria in Australia (CPC, 2010). Restricted distributions also occur in New Caledonia and French Polynesia. A global prediction of climate suitability for *B. tryoni* was created using the support vector machine model (SVM) (Figure 3.12).

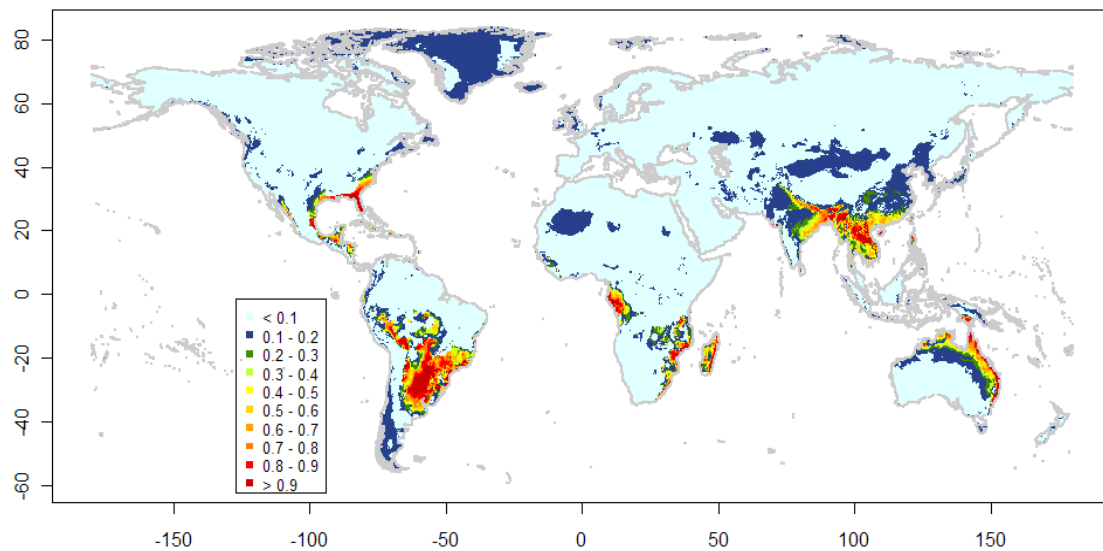


Figure 3.12: Global environmental suitability of *B. tryoni* using the support vector machine model The legend represents environmental suitability with warmer colours representing higher environmental suitability.

The predicted New Zealand distribution of *B. tryoni* based on climatic suitability under current climatic conditions and best, worst and intermediate case 2040 and 2090 climate change scenarios were generated but indicated no suitable habitat sites.

3.3.3 *Bactrocera zonata*

The georeferenced occurrence points for *B. zonata* were sourced from GBIF (www.gbif.org) and from Starkar *et al.* (2009) and Stonehouse *et al.* (2002). A total of 36 occurrence points were used for model fitting once replicates had been removed (Figure 3.13). The pseudo-absence points were generated from support vector machine repetitions and 36 clusters using k-means clustering (See Appendix A).

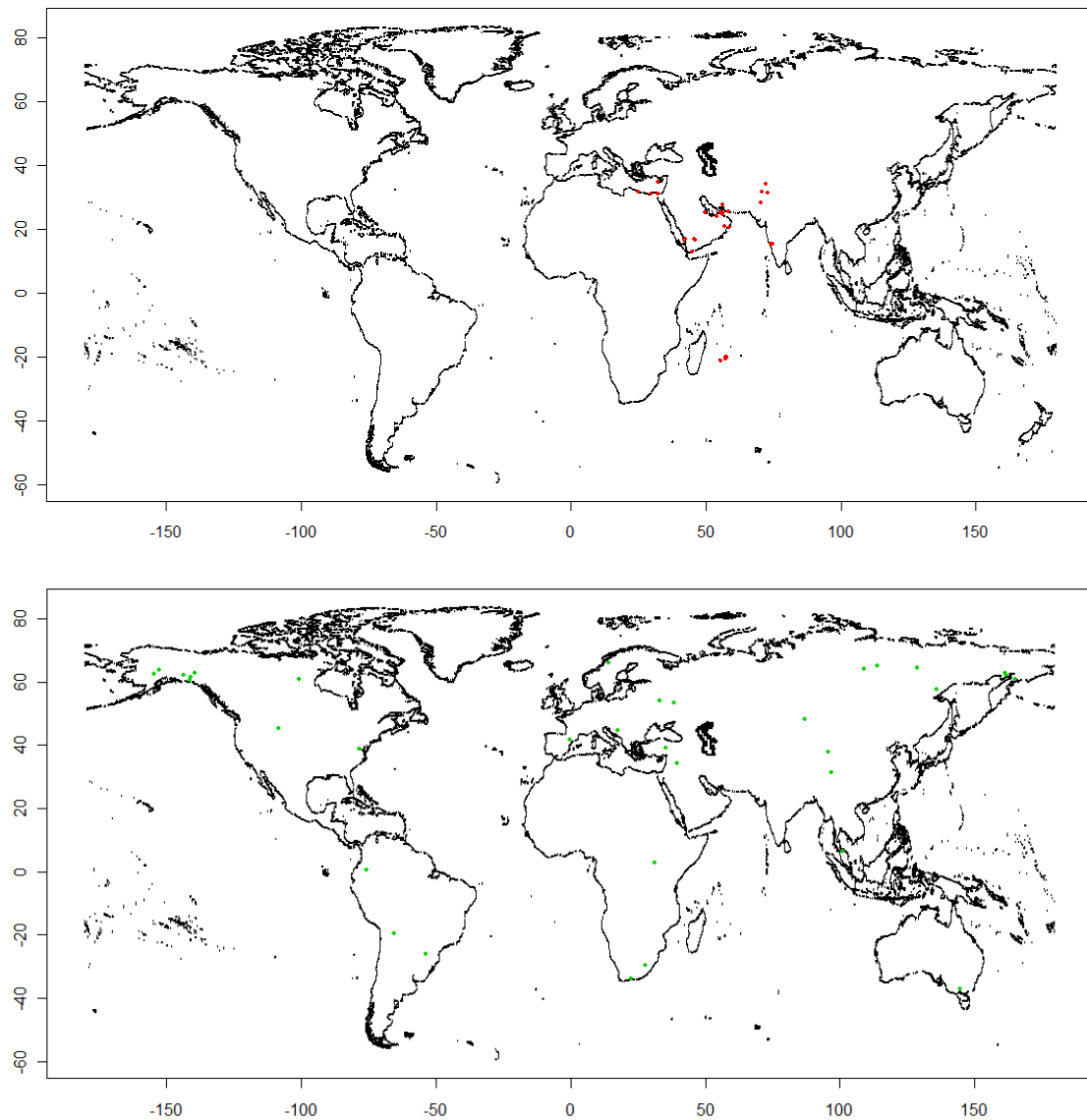


Figure 3.13: Global georeferenced occurrence points for *B. zonata* (top) and global pseudo-absence points generated (bottom).

3.3.3.1 Important environmental variables

The bioclimatic variables from WorldClim selected from the random forest and step-wise linear regression analysis were: Annual Mean Temperature, Max Temperature of Warmest Month, Minimal Temperature of Coldest Month, Mean Temperature of Driest Quarter and Precipitation of Driest Month.

3.3.3.2 Model performance

The variability of performance based on two (ROC curves and boxplots of the kappa index) of the 10 criteria are shown Figure 3.14. Figure 3.14 shows high variation in the performance of each model and also variability in mean performance over cross validation replicates between the models, indicating less reliable predictions. However, the average performance of the models remained very high over most performance criteria. The scores and rankings for each model with respect to the 10 performance criteria are shown in Table 3.5. The models with lowest overall rank were both the quadratic discriminant analysis (QDA) and linear discriminant analysis (LDA). The global prediction using the QDA did not predict high climatic suitability around high latitude regions like the LDA prediction so was used to create predicted distributions of *B. zonata*.

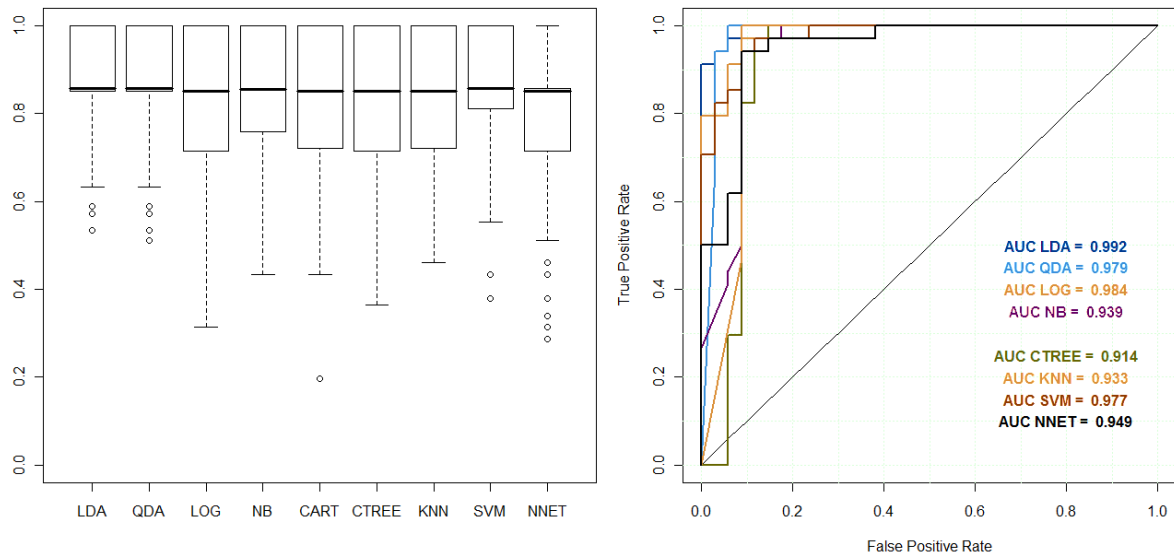


Figure 3.14: Kappa and ROC plots for the eight models compared with cross-validation validation methods. Acronyms for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural network.

Table 3.5: Performance criteria and their ranks for the cross validation resampling method.
Abbreviations for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks. Abbreviated performance criteria are, "TSS" for true skill statistic and "auc ROC" for area under curve of receiver operator characteristics

	Accuracy	rank1	Precision	rank2	Recall	rank3	F.score	rank4	Kappa	rank5	Specificity	rank6	TSS	rank7	Uncertainty
A	0.9475	1	0.93415	2	0.961668	6	0.942754	2	0.888285	1	0.93764	1	0.899305	1	0.0441176
A	0.946786	2	0.93472	1	0.963458	5	0.944124	1	0.887818	2	0.9354	2	0.898859	2	0.0294118
S	0.916429	8	0.91234	4	0.927045	9	0.911852	8	0.824454	8	0.9074	4	0.83445	8	0.1029412
	0.927857	4	0.89183	5	0.971773	3	0.925914	5	0.845928	5	0.88321	5	0.854981	5	0.0147059
T	0.923929	6	0.88778	7	0.968709	4	0.921751	6	0.839752	6	0.88079	7	0.849494	6	0.0147059
EE	0.917857	7	0.8668	9	0.987698	2	0.917249	7	0.82703	7	0.84762	9	0.835319	7	0.0147059
V	0.9275	5	0.8717	8	0.997341	1	0.926228	4	0.846516	4	0.85864	8	0.855982	4	0.0294118
A	0.931071	3	0.91781	3	0.945267	7	0.926842	3	0.852923	3	0.91903	3	0.864301	3	0.0147059
T	0.907857	9	0.88833	6	0.935392	8	0.904279	9	0.804946	9	0.8822	6	0.817594	9	0.0441176

3.3.3.3 Predicted distributions

The current distribution of *B. zonata* ranges throughout locations with warm and wet climates in South East Asia and to warm and dry climates in Middle Eastern countries and Northern Africa (CPC 2010). A global prediction of climate suitability for *B. zonata* was created using the quadratic discriminant analysis (QDA) (Figure 3.15).

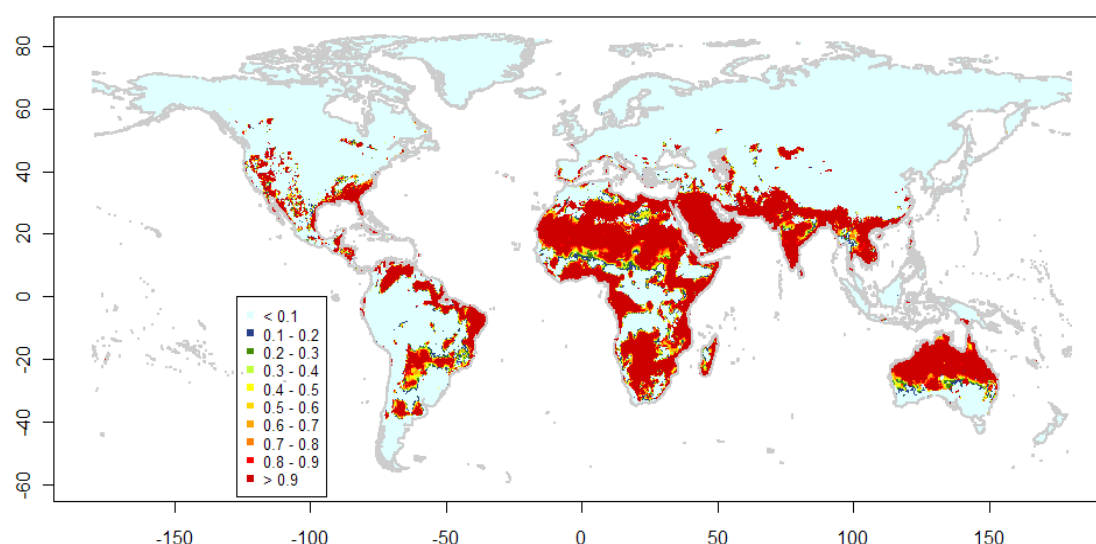


Figure 3.15: Global environmental suitability of *B. zonata* using the quadratic discriminant analysis (qda). The legend represents environmental suitability with warmer colours representing higher environmental suitability.

The predicted New Zealand distribution of *B. zonata* based on climatic suitability under current climatic conditions and best, intermediate and worst case 2040 and 2090 climate change scenarios were generated. Current climate conditions for *B. zonata* indicate no suitable habitats in New Zealand. The best case, intermediate and worst case 2040 climate change scenarios indicate an increasing climatic suitability in some parts of New Zealand, including the summerfruit producing regions Marlborough and Hawkes Bay (Figure 3.16).

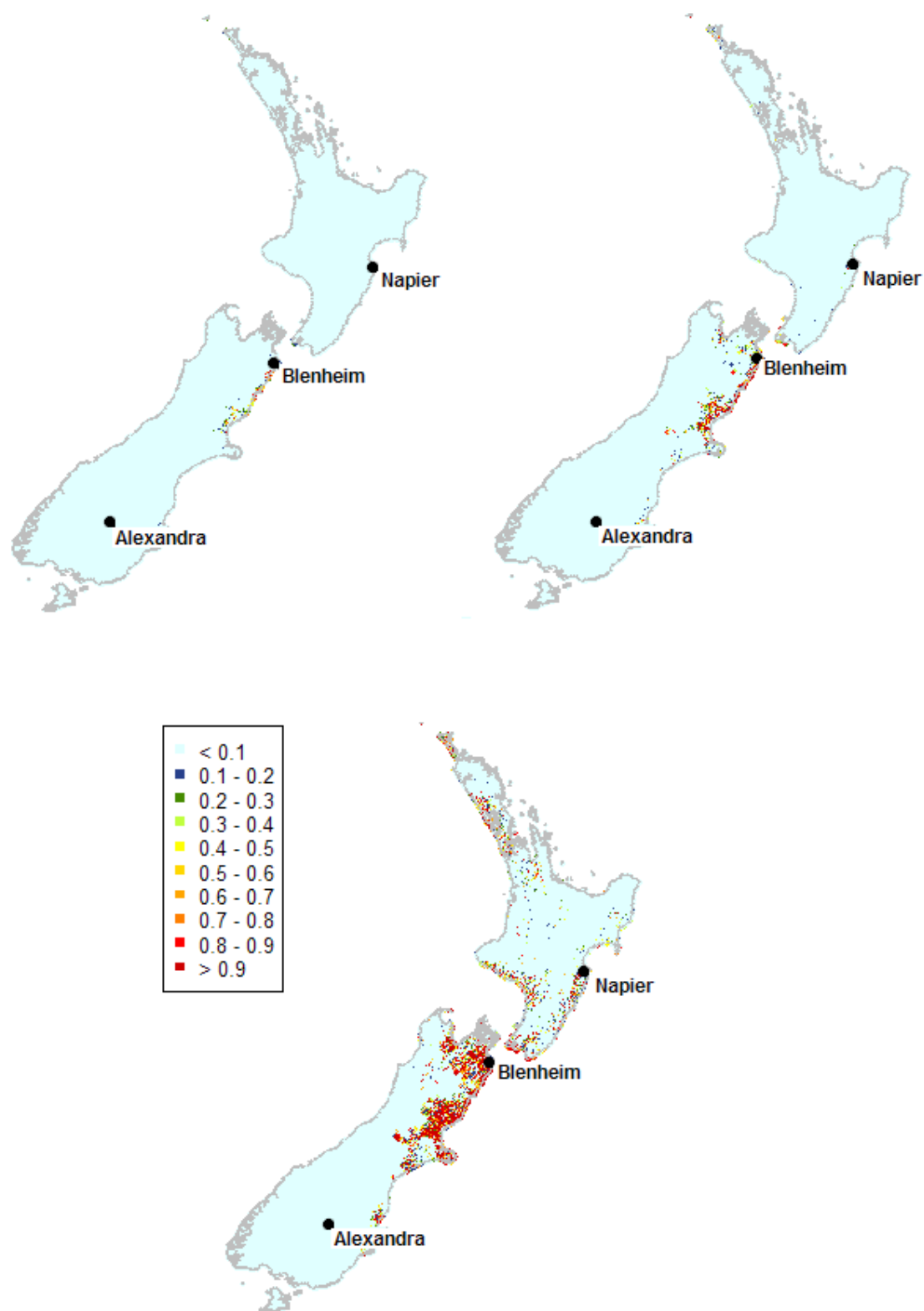


Figure 3.16: Potential distribution of *B. zonata* under New Zealand current climate (1950-2000 average), best case 2040 climate change predictions, intermediate 2040 climate change predictions and worst case 2040 climate change scenarios for New Zealand.

Each 2090 climate change scenario indicates a further increase in climatic suitability for *C. rosa* in New Zealand compared to current climate conditions and 2040 climate change predictions. The increase in climatic suitability includes the summerfruit producing regions Hawkes Bay and Marlborough (Figure 3.17).

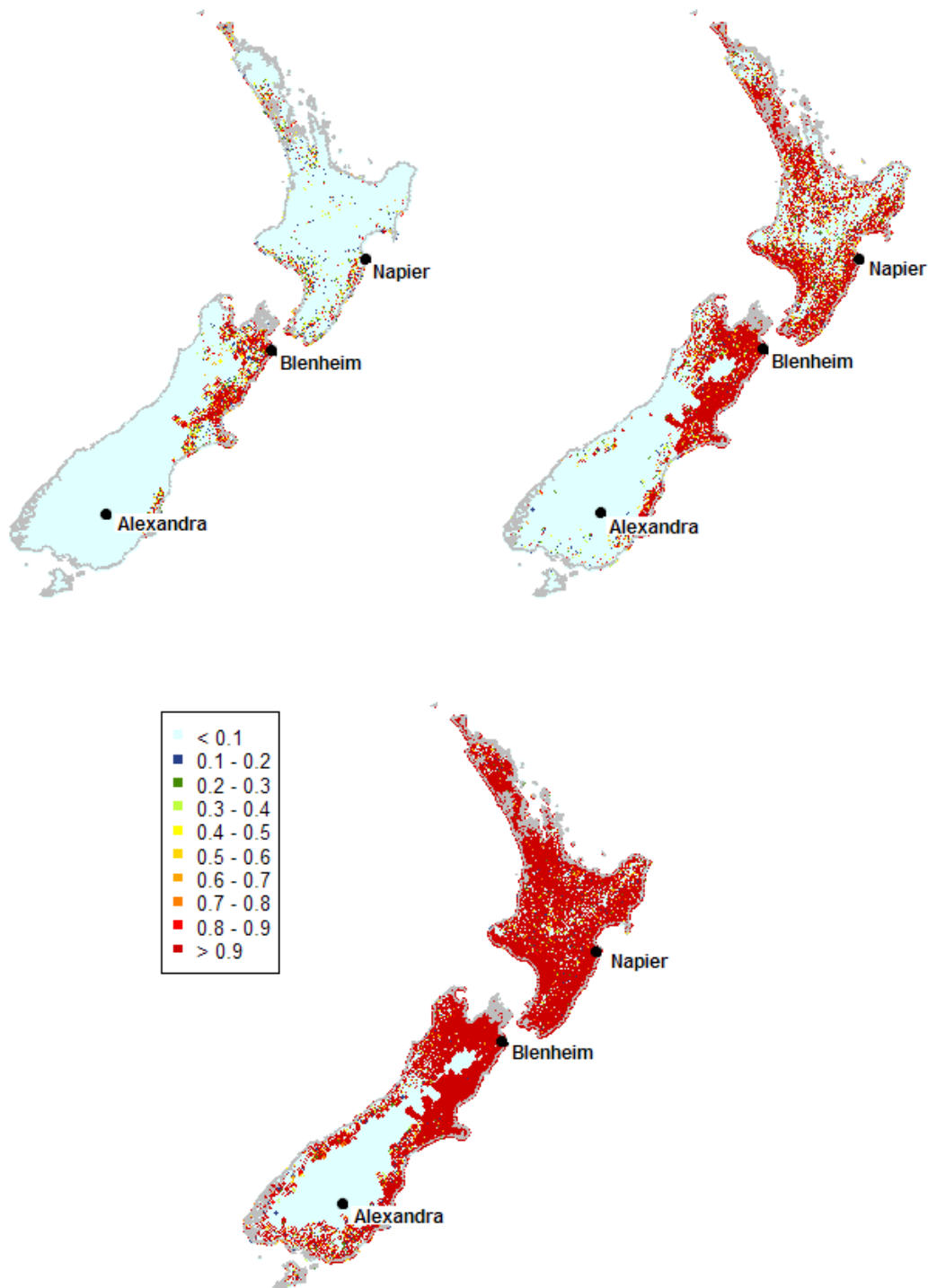


Figure 3.17: Potential distribution of *B. zonata* in New Zealand under best case 2090 climate change predictions, intermediate 2090 climate change predictions and worst case 2090 climate change scenarios for New Zealand.

3.3.4 *Ceratitis capitata*

The georeferenced occurrence points for *C. capitata* were sourced from GBIF (www.gbif.org) and from a publication by Baliraine *et al.* (2004). A total of 138 occurrence points were used for model fitting once replicates had been removed (**Error! Reference source not found.**). The pseudo-absence points were generated from support vector machine repetitions and 138 clusters using k-means clustering (See Appendix A).

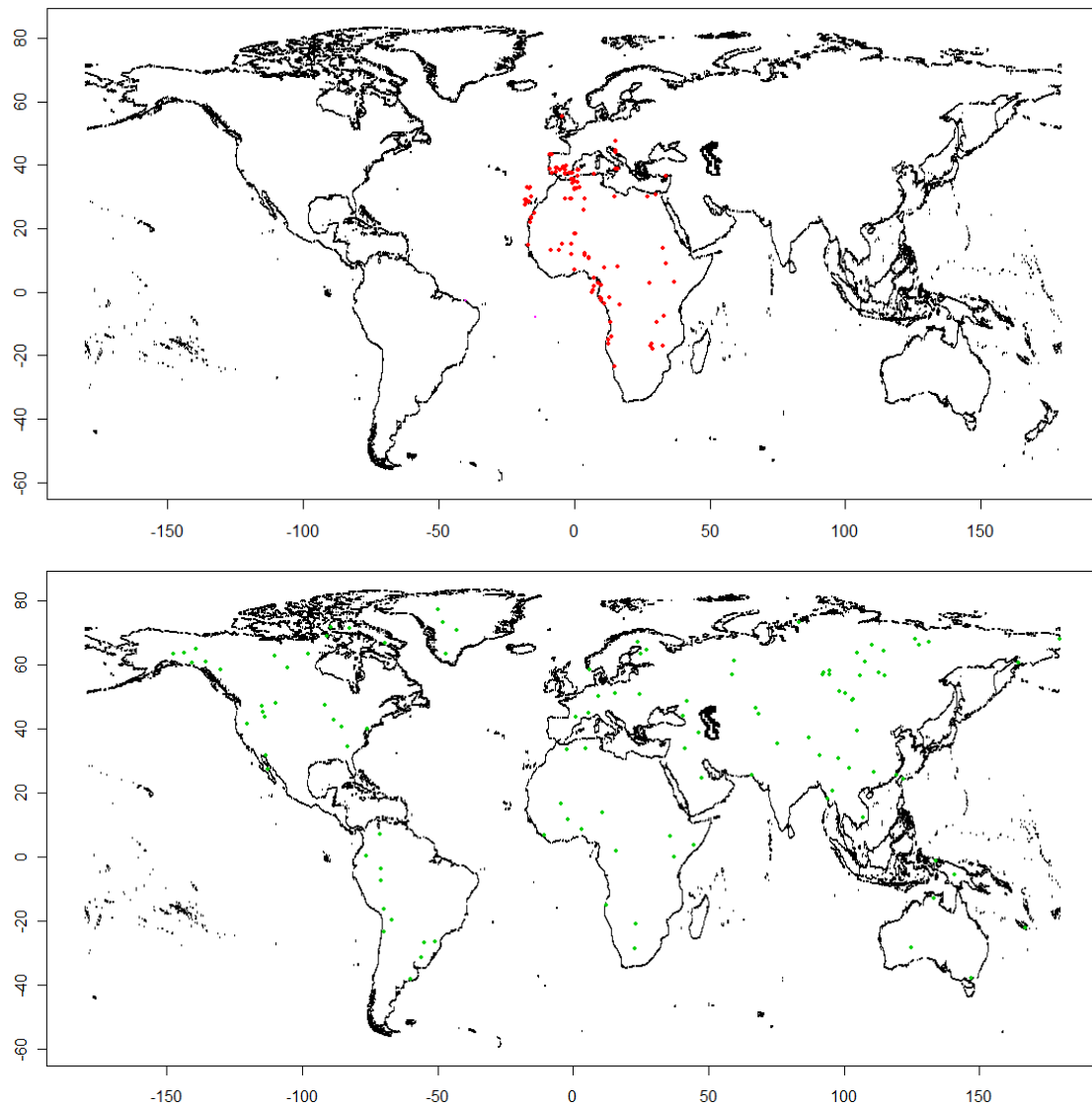


Figure 3.18: Global georeferenced occurrence points for *C. capitata* (top) and pseudo-absence points generated (bottom).

3.3.4.1 Important environmental variables

The bioclimatic variables from WorldClim selected from the random forest and step-wise linear regression analysis were: Annual Mean Temperature, Temperature Seasonality, Min Temperature of Coldest Month, Temperature Annual Range, Mean Temperature of Driest Month and Precipitation of Driest Month.

3.3.4.2 Model performance

The variability of performances based on two of the 10 criteria are shown with ROC curves in Figure 3.19 and a boxplots of the kappa index in Figure 3.20. Figure 3.19 and Figure 3.20 indicate greater variability between modelling methods using the cross validation method than the bootstrapping method. However there was low overall variation in the performance of each model and between models. The average performance of each model remained very high over most other performance criteria. The scores and rankings for each model with respect to the 10 performance criteria are shown in Table 3.6. The model with the lowest rank using the bootstrapping validation method was the neural network (NNET) model and the lowest rank using the cross validation method was the logistic regression (LOG) model. The logistic model was deemed the ‘best model’ due to being the model with the lowest overall rank between the two validation methods.

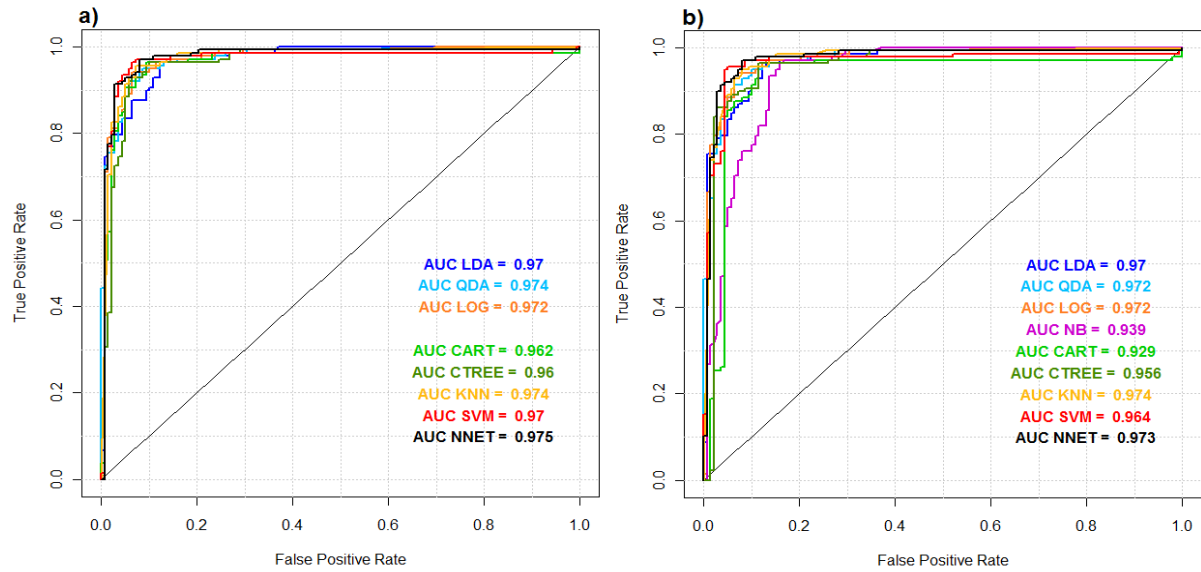


Figure 3.19: ROC plots for the eight models compared with (a) bootstrapping and (b) cross-validation validation methods. Acronyms for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks.

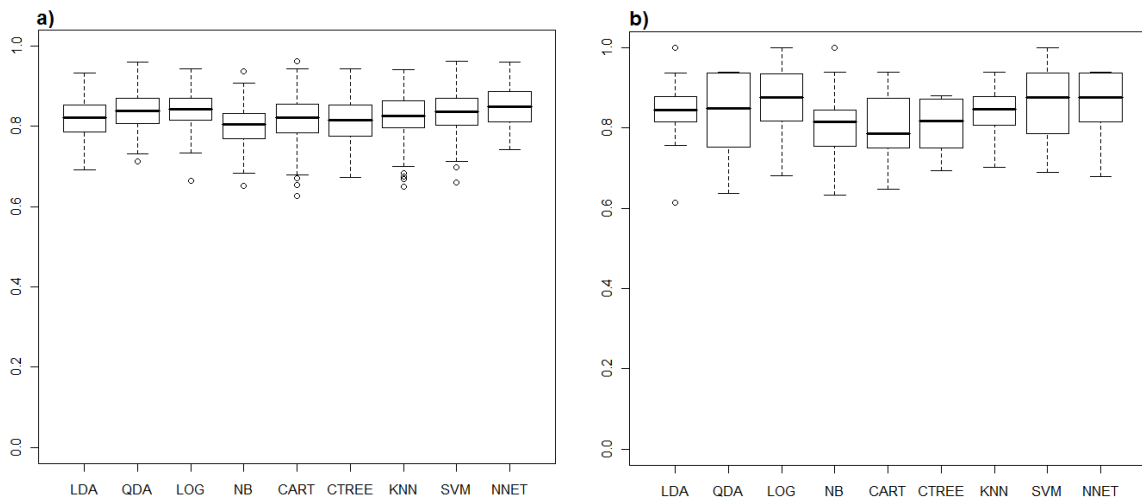


Figure 3.20: Kappa Index plots for the eight models compared with (a) bootstrapping and (b) cross-validation validation methods. Acronyms for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks.

Table 3.6: Performance and their ranks for the re-sampling methods a) bootstrapping and b) cross validation. Abbreviations for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks. Abbreviated performance criteria are, "TSS" for true skill statistic and "auc ROC" for area under curve of receiver operator characteristics.

	Accuracy	rank1	Precision	rank2	Recall	rank3	F.score	rank4	Kappa	rank5	Specificity	rank6	TSS	rank7	Uncertainty
A	0.909442	6	0.87669	8	0.954471	2	0.912946	6	0.818008	6	0.86535	8	0.819821	6	0.0362319
A	0.919912	3	0.92128	1	0.91942	8	0.919395	3	0.838974	3	0.92103	1	0.840445	3	0.0543478
G	0.921257	2	0.91625	2	0.928083	6	0.921245	2	0.841714	2	0.91525	2	0.843333	2	0.0434783
	0.900833	9	0.85851	9	0.960149	1	0.905795	9	0.800685	9	0.84209	9	0.802239	9	0.0181159
T	0.908376	7	0.89768	6	0.925563	7	0.909302	7	0.815896	7	0.89215	7	0.817717	7	0.0942029
EE	0.908057	8	0.91127	4	0.906874	9	0.906945	8	0.815211	8	0.91	4	0.81687	8	0.0978261
V	0.91277	5	0.89646	7	0.934468	5	0.913837	5	0.824771	5	0.89235	6	0.82682	5	0.1050725
A	0.917404	4	0.89951	5	0.941172	3	0.918736	4	0.834098	4	0.89495	5	0.836124	4	0.1086957
T	0.925004	1	0.91301	3	0.941161	4	0.925769	1	0.849324	1	0.91017	3	0.85133	1	0.0833333

a) Boot-strapping

	Accuracy	rank1	Precision	rank2	Recall	rank3	F.score	rank4	Kappa	rank5	Specificity	rank6	TSS	rank7	Uncertainty
A	0.922727	4.5	0.88807	7	0.96881	2	0.924098	4	0.842	4	0.88223	8	0.851039	4	0.0072464
A	0.918182	6	0.91661	2	0.919886	8	0.915702	6	0.832595	6	0.92185	2	0.841736	6	0.0108696
G	0.934848	1	0.91555	3	0.959803	4	0.93531	1	0.866523	1	0.91378	3	0.87358	1	0.0072464
	0.90303	8	0.85567	9	0.969315	1	0.90604	7	0.803419	7	0.84577	9	0.815086	8	0.0036232
T	0.90303	8	0.88764	8	0.927977	7	0.902003	8	0.802946	9	0.88616	7	0.814141	9	0.0507246
EE	0.90303	8	0.92205	1	0.88373	9	0.898764	9	0.803292	8	0.93282	1	0.816549	7	0.0724638
V	0.922727	4.5	0.89881	6	0.952001	6	0.922248	5	0.8419	5	0.89712	6	0.849117	5	0.0253623
A	0.933333	2.5	0.9076	5	0.961034	3	0.931858	2	0.864283	2	0.9105	5	0.87153	2	0.0434783
T	0.933333	2.5	0.9129	4	0.953801	5	0.931665	3	0.86258	3	0.91332	4	0.867117	3	0.0652174

b) Cross-validation

3.3.4.3 Predicted distributions

C. capitata is endemic to many Sub-Saharan countries and is widespread throughout Africa. *C. capitata* is currently known to be highly invasive and has established permanent populations in Europe, Egypt, Middle East, Australia and Americas (CPC 2010). The global prediction of climate suitability for *C. capitata* was created using the logistic regression model (LOG) (Figure 3.21). The legend shown is a posterior probability with warmer colours representing higher climatic suitability. Any value above 0.5 indicates suitable climatic conditions.

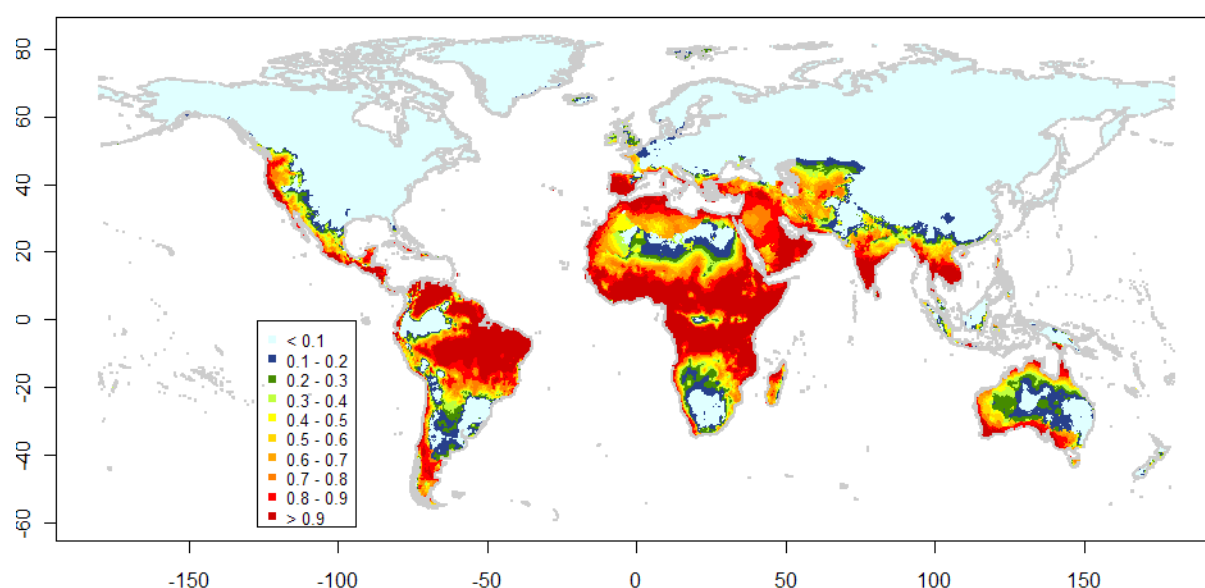


Figure 3.21: Global environmental suitability of *C. capitata* using the logistic regression model. The legend represents environmental suitability with warmer colours representing higher environmental suitability.

The predicted New Zealand distribution of *C. capitata* based on climatic suitability under current climatic conditions and best, intermediate and worst case 2040 and 2090 climate change scenarios were generated. Current climate conditions indicate suitable habitat sites around the far north and southern half of the North Island and east coast of the South Island. Suitable habitat sites include the summerfruit producing regions Hawkes Bay and Blenheim. Best case, intermediate and worst case 2040 climate change predictions indicate decreasing climatic suitability for *C. capitata* (Figure 3.22). The summerfruit producing region Hawkes Bay will not be vulnerable to *C. capitata* according to the predictions produced by this model.

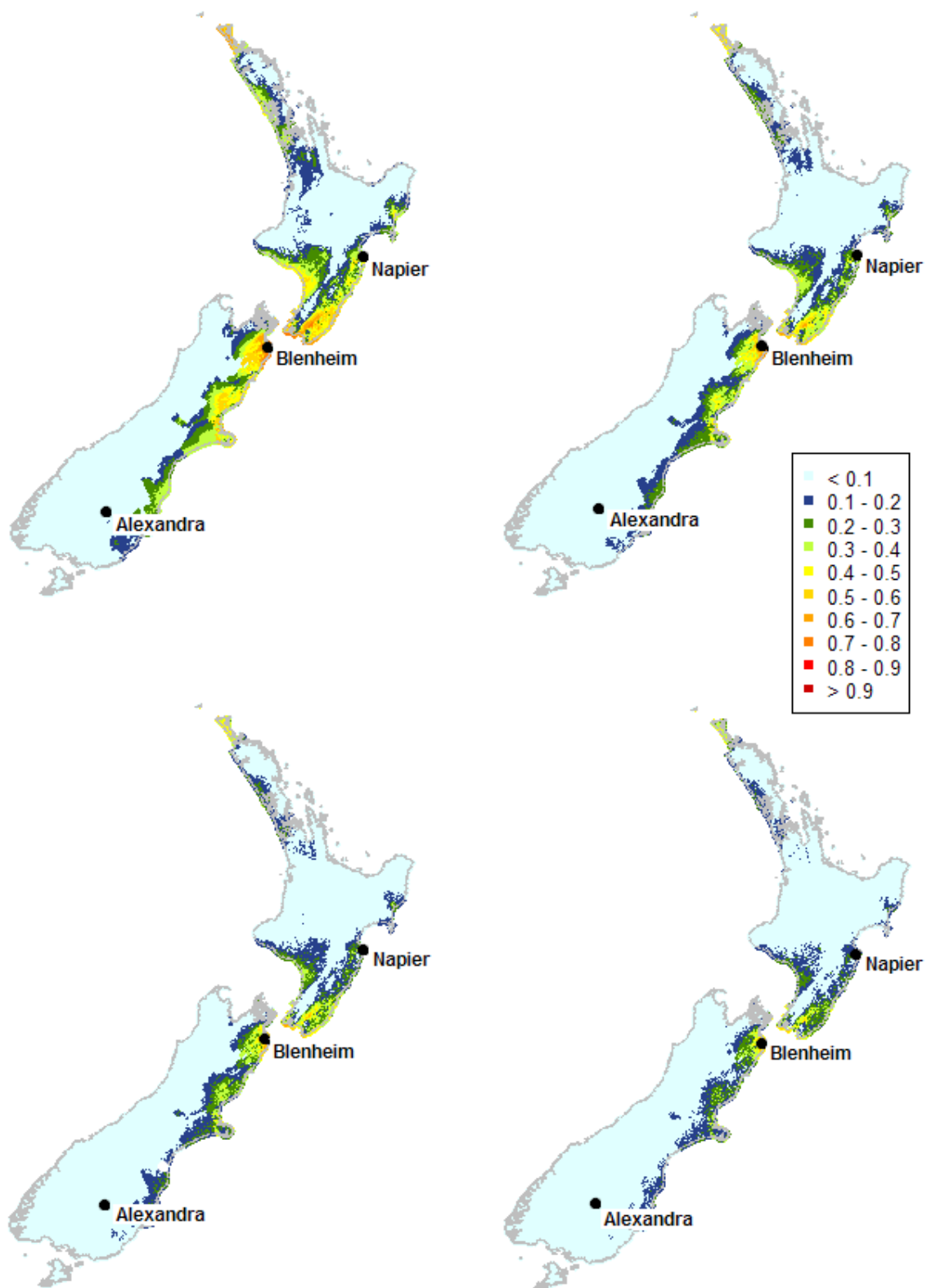


Figure 3.22: Potential distribution of *C. capitata* using the LOG model under New Zealand current climate (1950-2000 average) (top left), best case 2040 climate change predictions (top right), intermediate 2040 climate change predictions (bottom left) and worst case 2040 climate change scenarios for New Zealand (bottom right).

All 2090 climate change scenarios indicate a decrease in climatic suitability for *C. capitata* (Figure 3.23). The summerfruit producing region Blenheim is the only location in New Zealand with a suitable climate under best case and intermediate 2090 climate change predictions. No summerfruit producing regions in New Zealand will be vulnerable to *C. capitata* under worst case 2090 climate change predictions.

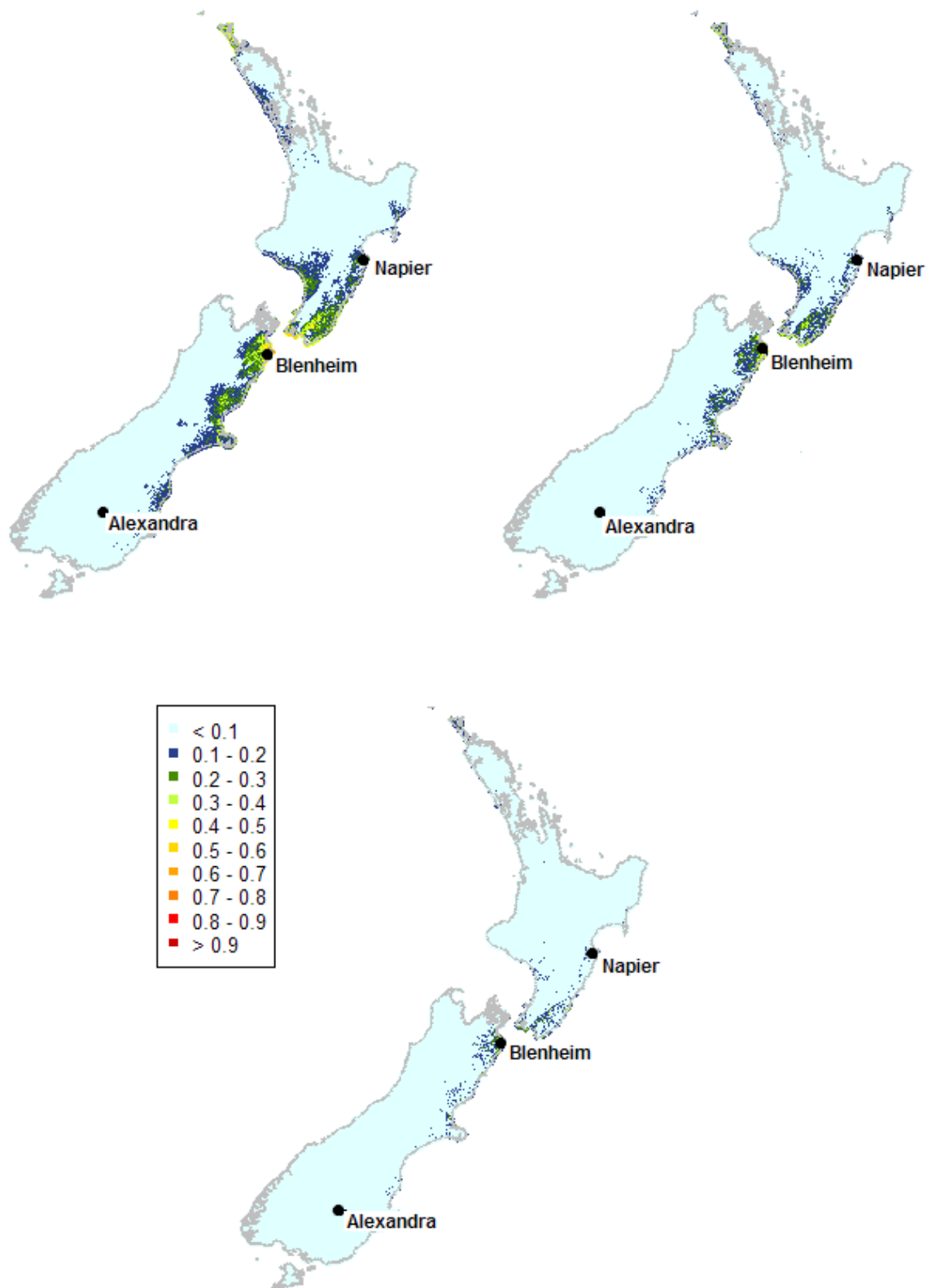


Figure 3.23: Potential distribution of *C. capitata* using the LOG model under best case 2090 climate change predictions (top left), intermediate 2090 climate change predictions (top right) and worst case 2090 climate change scenarios for New Zealand (bottom).

3.3.5 *Ceratitis rosa*

The geo-referenced occurrence points for *C. rosa* were sourced from GBIF (www.gbif.org) and from a publication by Baliaraine *et al.* (2004). A total of 170 occurrences points were used for model fitting once replicates had been removed (Figure 3.24). The pseudo-absence points were generated from support vector machine repetitions and 170 clusters using k-means clustering (See Appendix A).

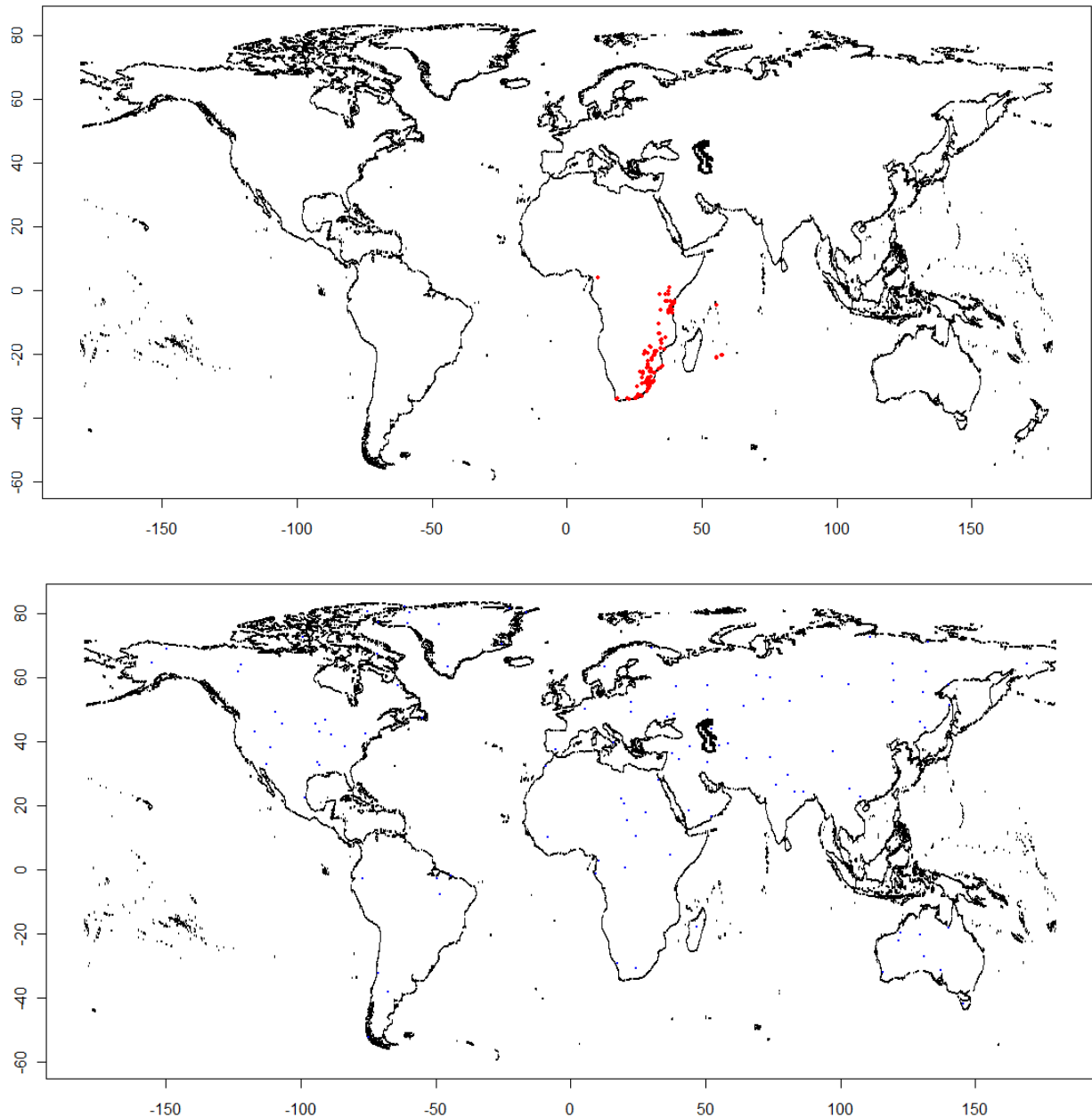


Figure 3.24: Global georeferenced occurrence points for *C. rosa* (top) and pseduo-absence points generated (bottom).

3.3.5.1 Important environmental variables

The bioclimatic variables from WorldClim selected from the random forest and step-wise linear regression analysis were: Annual Mean Temperature, Isothermality, Temperature Seasonality and Annual Precipitation.

3.3.5.2 Model performance

The variability of performance based on two of the 10 criteria is shown the ROC curves in Figure 3.25 and a boxplots of the kappa index shown in Figure 3.26. Figure 3.25 and Figure 3.26 show higher variability between modelling methods when using the cross validation method than the bootstrapping method. The average performance of each model remained very high over most other performance criteria. The scores and rankings for each model with respect to the 10 performance criteria are shown in Table 3.7. The model with lowest rank for both the bootstrapping and cross validation methods was the quadratic discriminant analysis and was selected to create predicted distributions of *C. rosa*.

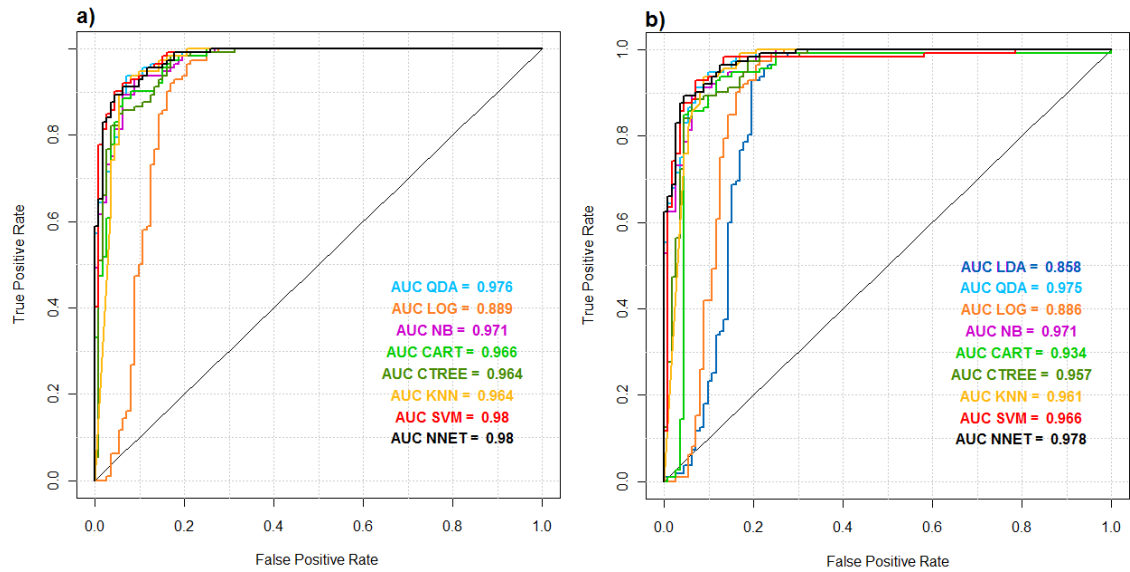


Figure 3.25: ROC plots for the eight models compared with (a) bootstrapping and (b) cross-validation validation methods. Acronyms for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks.

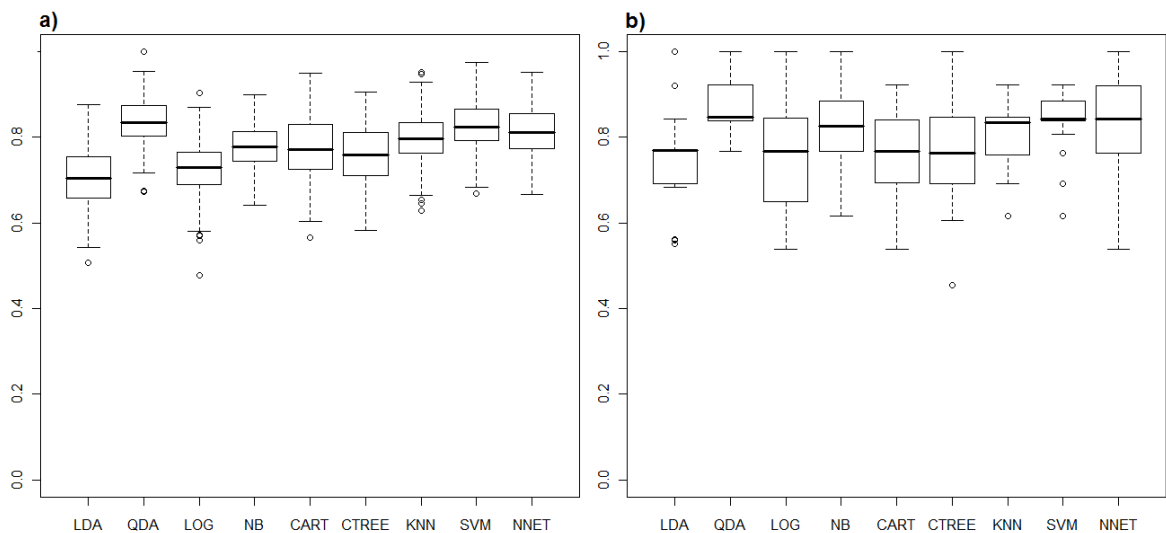


Figure 3.26: Kappa Index plots for the eight models compared with (a) bootstrapping and (b) cross-validation validation methods. Acronyms for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks.

Table 3.7: Performance criteria and their ranks for the re-sampling methods a) bootstrapping and b) cross validation. Abbreviations for the selected models are, "lda" for linear discriminant analysis, "qda" for quadratic discriminant analysis, "log" for logistic regression, "nb" for naive Bayes, "cart" for classification and regression tree, "ctree" for conditional tree, "knn" for k nearest neighbours, "svm" for support vector machine, and "nnet" for neural networks. Abbreviated performance criteria are, "TSS" for true skill statistic and "auc ROC" for area under curve of receiver operator characteristics.

	Accuracy	rank1	Precision	rank2	Recall	rank3	F.score	rank4	Kappa	rank5	Specificity	rank6	TSS	rank7	Uncertainty
A	0.852408	9	0.7758	9	0.990389	1	0.86897	9	0.704804	9	0.71732	9	0.707714	9	0.0535714
A	0.918363	1	0.89624	1	0.946672	4	0.919626	1	0.835964	1	0.89098	1	0.83765	1	0.0669643
g	0.862717	8	0.81625	8	0.935838	6	0.870595	8	0.724673	8	0.79172	8	0.727559	8	0.0669643
	0.889607	5	0.83989	7	0.963017	2	0.896013	5	0.778474	5	0.81764	7	0.780654	5	0.0446429
T	0.887719	6	0.87318	4	0.911826	9	0.889199	6	0.775105	6	0.86681	4	0.778635	6	0.1696429
EE	0.880264	7	0.85902	5	0.912737	8	0.882276	7	0.759535	7	0.84855	5	0.761289	7	0.1696429
V	0.897984	4	0.85303	6	0.96183	3	0.903055	4	0.795374	4	0.83591	6	0.797737	4	0.09375
A	0.913299	2	0.8902	2	0.942954	5	0.91478	2	0.825811	2	0.88462	2	0.827577	2	0.0580357
T	0.907109	3	0.88575	3	0.935704	7	0.908663	3	0.813553	3	0.88001	3	0.815719	3	0.1026786

a) Boot-strapping

	Accuracy	rank1	Precision	rank2	Recall	rank3	F.score	rank4	Kappa	rank5	Specificity	rank6	TSS	rank7	Uncertainty
A	0.871154	9	0.78599	9	1	1	0.876459	9	0.743683	9	0.75916	9	0.759163	9	0.0089286
A	0.938462	1	0.91138	1	0.964384	2	0.936097	1	0.873954	1	0.9145	1	0.878886	1	0.0178571
g	0.878846	8	0.83482	8	0.933331	6	0.878468	8	0.75465	8	0.83149	8	0.764819	8	0.0401786
	0.905769	4	0.85995	5	0.96198	3	0.905256	4	0.808496	4	0.85247	6	0.814451	4	0.0267857
T	0.886538	6.5	0.87114	4	0.898013	9	0.882284	7	0.769071	6	0.87328	4	0.771296	7	0.1116071
EE	0.886538	6.5	0.83881	7	0.937238	5	0.882396	6	0.767997	7	0.83499	7	0.772224	6	0.0446429
V	0.903846	5	0.85833	6	0.958109	4	0.903614	5	0.80452	5	0.85562	5	0.813728	5	0.03125
A	0.921154	2	0.90856	2	0.929562	7	0.915624	2	0.838231	2	0.91241	2	0.841973	2	0.0223214
T	0.913462	3	0.89521	3	0.924287	8	0.90806	3	0.821521	3	0.89861	3	0.822901	3	0.0446429

b) Cross-validation

3.3.5.3 Predicted distributions

The current distribution of *C. rosa* ranges throughout locations with warm and wet climates in Central and Southern Africa and also far west of Africa in Malawi and Guinea (CPC 2010). A global prediction of climate suitability for *C. rosa* was created using the quadratic discriminant analysis (QDA) (Figure 3.27). The legend shown is a posterior probability with warmer colours representing higher climatic suitability. Any value above 0.5 indicates suitable climatic conditions.

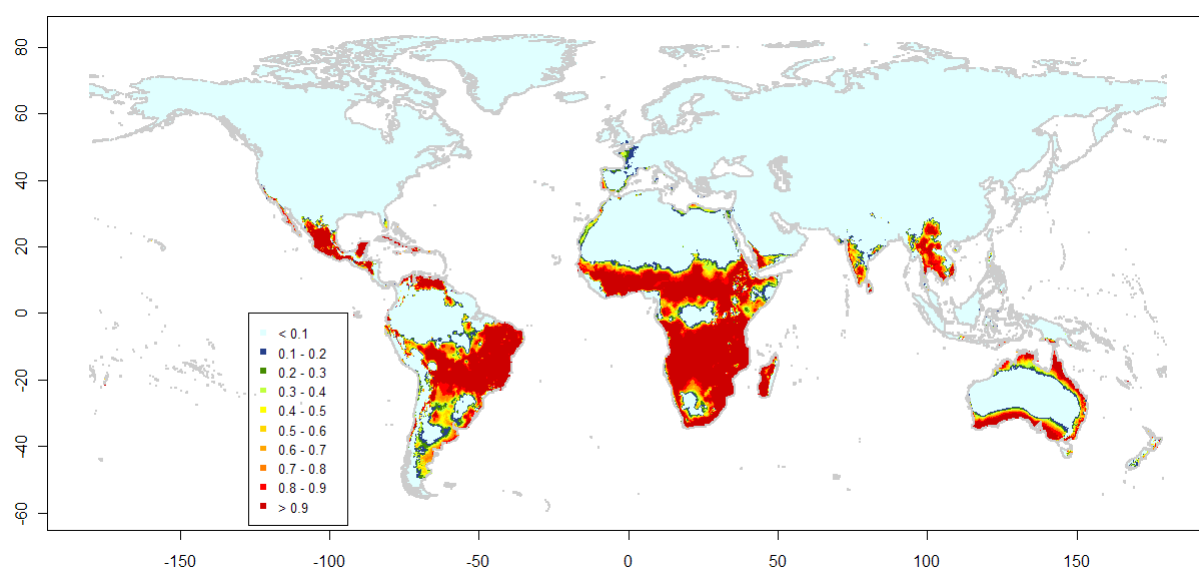


Figure 3.27: Global environmental suitability of *C. rosa* using the quadratic discriminant analysis (QDA). The legend represents environmental suitability with warmer colours representing higher environmental suitability.

The predicted New Zealand distribution of *C. rosa* based on climatic suitability under current climatic conditions and best, intermediate and worst case 2040 and 2090 climate change scenarios were generated. Current climate conditions for *C. rosa* indicate suitable habitats throughout many locations in both the North Island and South Island including all major summerfruit producing region. The 2040 climate change scenarios indicate a further increase in climatic suitability across all summerfruit producing regions (Figure 3.28).

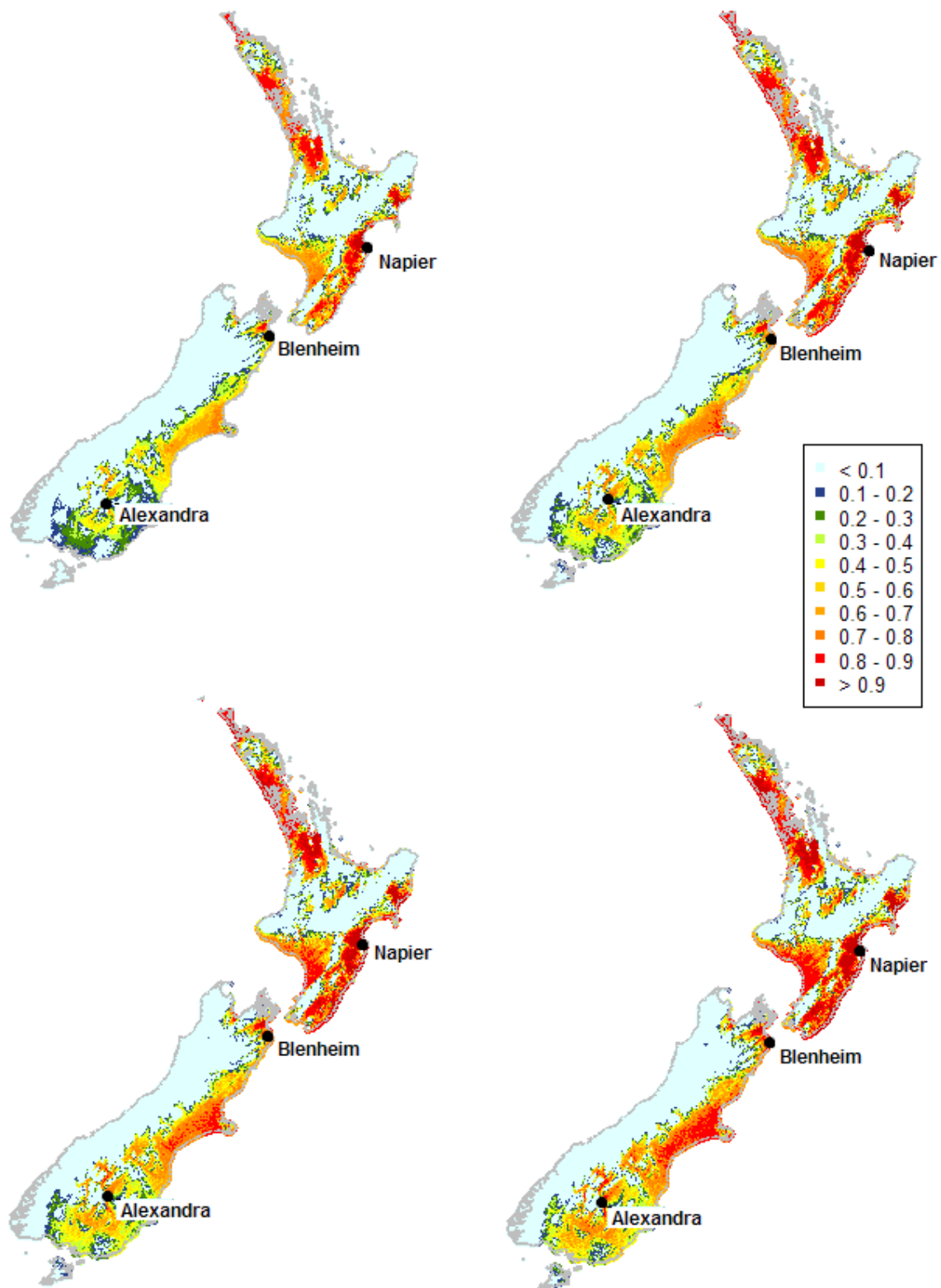


Figure 3.28: Potential distribution of *C. rosa* under New Zealand current climate (1950-2000 average) (top left), best case 2040 climate change predictions (top right), intermediate 2040 climate change predictions (bottom left) and worst case 2040 climate change scenarios (bottom right) for New Zealand.

Each 2090 climate change scenario indicates a further increase in climatic suitability for *C. rosa* throughout New Zealand and summerfruit producing regions (Figure 3.29).

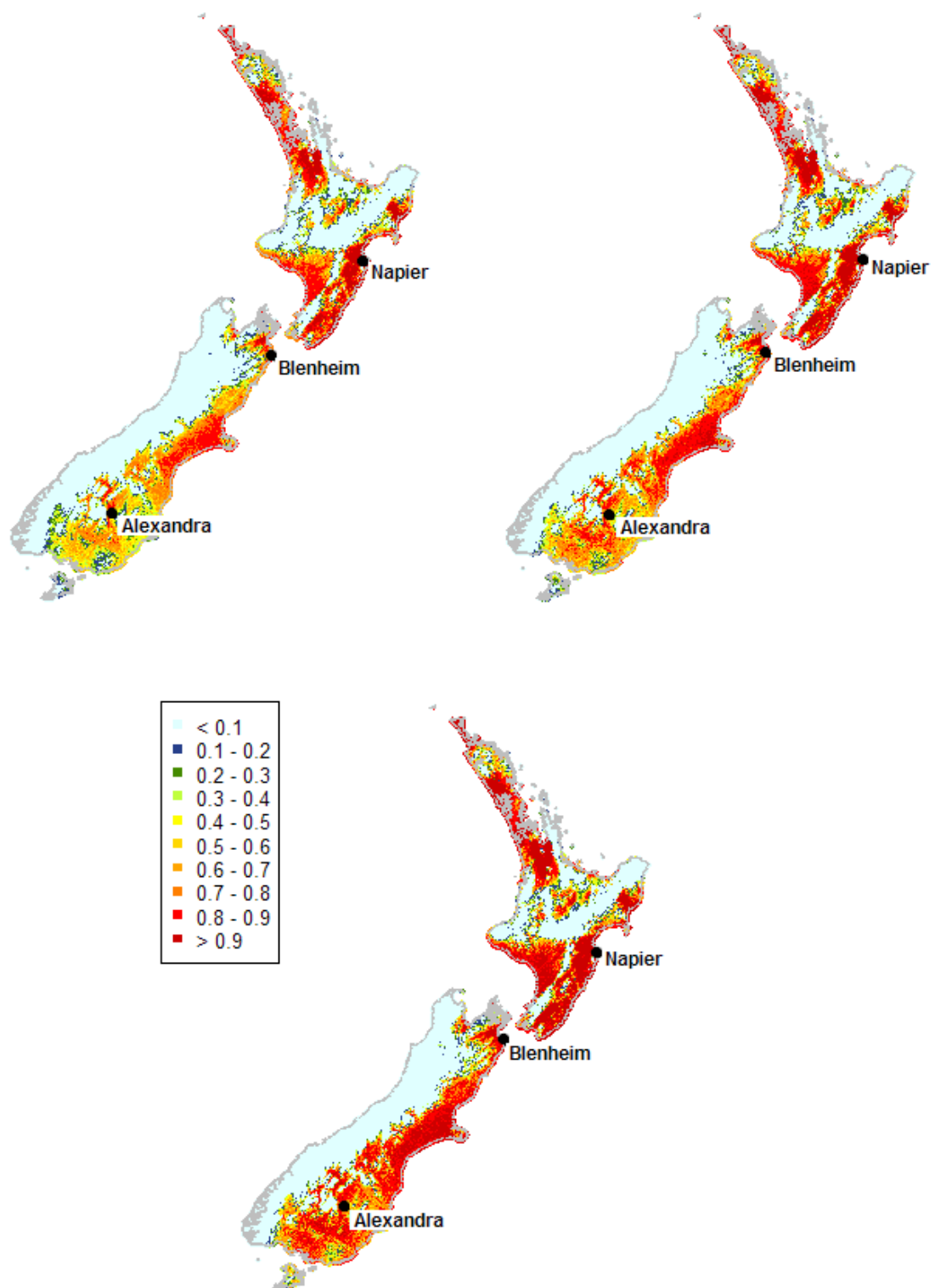


Figure 3.29: Potential distribution of *C. rosa* in New Zealand under best case 2090 climate change predictions (top left), intermediate 2090 climate change predictions (top right) and worst case 2040 climate change scenarios for New Zealand (bottom).

3.4 Discussion

The results presented here again are indicative of the directions and magnitude of change to the potential distribution ranges of some serious fruit fly insect pests in response to climate change. Summerfruit producing regions that potentially have a suitable climate for the establishment of fruit fly pest permanent populations are identified. The first objective was to determine the potential distribution of the target fruit fly species under current climatic conditions. In general, no single location was climatically suitable for all fruit fly species. Model predictions indicated major summerfruit producing regions Hawkes Bay and Marlborough as currently suitable for *C. capitata* and *C. rosa* establishment as well as Central Otago for *B. dorsalis* and *C. rosa*. No locations were indicated as being currently suitable for *B. tryoni* (Table 3.8). When climate change conditions were incorporated, The results generated by the multiple model system indicated an increase in habitat suitability for *B. zonata* under 2090 climate change scenarios around Hawkes Bay and Marlborough and an increase in climatic suitability for *C. rosa* under all climate change scenarios around Hawkes Bay and Marlborough and Central Otago. An increase in climatic suitability for *B. dorsalis* under all climate change scenarios was observed for Central Otago (Table 3.8).

Table 3.8: New Zealand summerfruit producing regions vulnerable to exotic fruit fly establishment under various climate change scenarios. HB = Hawkes Bay, M= Marlborough, CO = Central Otago.

Climate change scenario	<i>B. dorsalis</i>	<i>B. tryoni</i>	<i>B. zonata</i>	<i>C. capitata</i>	<i>C. rosa</i>
current	CO			HB, M	HB, M, CO
best case 2040	CO			M	HB, M, CO
intermediate case 2040	CO		M	M	HB, M, CO
worst case 2040	CO		M	M	HB, M, CO
best case 2090	CO		M	M	HB, M, CO
intermediate case 2090	CO		HB, M		HB, M, CO
worst case 2090	CO		HB, M		HB, M, CO

Worner *et al.* (2010) states that the method used for calculating pseudo-absences from presence points is an improvement over previous methods but that it still needs verification. The main advantage of this method is the very low chance of environmental variables at a selected pseudo-absence being similar to environmental variables found at a recorded occurrence/presence location. If the environmental variables at presence and pseudo-absence locations are similar then the models will not effectively discriminate the data into two

difference classes. However, the pseudo-absence points were not evenly spaced across the globe as intended for *B. dorsalis*, *B. tryoni* and *B. zonata* and led to an accumulation of absence points around localised areas. This result is possibly due to the small sample size of occurrence points for each of these species. A small number of occurrence points means that a smaller number of clusters will be created globally and will increase the chances of the centroids being in close proximity. Clearly, this area requires further research.

The method for analysing model sensitivity and prediction error is also an improvement over other methods. In many studies, only 2 or 3 performance measures are used to analyse model performance. This study incorporated a range of 10 different performance measures to measure how each model performs using the same input data. Additionally, the most accurate and best performing model can be sourced from the model performance test to create predicted distributions. Incorrect model selection may give incorrect estimates of an invasive species potential range and lead to inaccurate assessments of pest risks. Consequently inaccurate results may lead to the wrong mitigation decisions being made when implementing strategies after an incursion or establishment of an invasive species population (Venette *et al*, 2010).

The reason for the performance criteria and the model selection process was because each model is likely to give a different prediction with slightly different conditions that may result in a change in climate suitability for each species. This research indicated that all models performed equally well against the performance criteria. The best ranked model performed similar to the worst ranked model. While this is a good result, it means that it is difficult to select what would be the most suitable model to generate predictions. The similarity in model performance may be due to the performance criteria being similar in the way they assess model performance. Future research could focus on creating new model performance criteria that assesses the models in a different way to what has been used here.

There were nine performance criteria used to critique the performance of each model. The results of some of these performance criteria could be more important than others, such as the area under the Receiver Operative Characteristic curve and the kappa index. Clearly evaluation of performance criteria with accurate or even simulated data is required.

There was an instance where the best performing model was definitely not the most suitable model to use when assessing the model predictions for *B. tryoni*. The ranking system determined the linear discrimination model as the highest performing model, followed by

quadratic discriminant analysis and artificial neural networks. Given that *B. tryoni* is currently distributed in a tropical climate, these three models all produced global predicted distributions with high climatic suitability around high latitude locations in the northern hemisphere. Such errors in the potential global distributions may indicate the lack of ability for linear based models to extrapolate to a global scale using occurrence points that originate from a relatively restricted distribution. Despite that they often performed well with respect to the performance criteria used. Many models used here gave results that were not significantly different from each other, reflecting the interaction of the model architecture with the data which at this stage is very difficult to tease out. The support vector machine has a reputation for being an excellent classifier (Drake *et al.* 2006) and has given sensible results to other studies (Worner *et al.* 2010). This model was the fourth lowest ranking model but with excellent performance and gave a more accurate portrayal of the potential global distribution for *B. tryoni*. While several models can perform exceptionally well one should always check the biological significance and reliability of model output.

The potential distributions produced are heavily influenced by which environmental variables are selected as indeed the absences data used. At times, the environmental variables selected may result in an inaccurate predicted distribution. For example, one of the bioclimatic variables selected for *B. dorsalis* was maximum temperature of the warmest month. High climatic suitability was therefore indicated around areas in the South Island that are known to get the hottest during the summer (NIWA, 2010). However, these locations also experience the coldest minimal temperatures during the winter. If the minimum temperature of coldest month bioclimatic variable was selected as well or instead of maximum temperature it may have resulted in a very different potential distribution. *B. dorsalis* lacks tolerance for cool winters (EPPO, 2010) and therefore this example illustrates that good biological knowledge is important when using these models or interpreting their results.

A potential constraint for any correlative modelling (as indeed for CLIMEX) is a lack of occurrence points and this was observed for *B. dorsalis*, *B. tryoni* and *B. zonata* with 34, 62 and 36 presence locations available, respectively. This was evident in the highly variable box plots of the kappa index within and between models. Problems arise with a small sample size as they may not give a full representation of the environmental predictors that correlate with the presence of a species. A small sample size can also have an impact on model sensitivity and reliability of predictions. A small sample size may allow outliers to have more influence on predictions whereas a large sample size can buffer the effect of outliers. Previous research

by Wieg et al. (2008) also found a decrease in model accuracy and an increase in variability across species and between models when comparing the mean AUC score for a sample size of 10 occurrence points to 30 and 100 occurrence points.

The models used in this study cannot replace more detailed models when much is known about species ecology. There is controversy around the use of correlative models (Zurell *et al.* 2009; Venette *et al.* 2010). Many new approaches are proposed but are soon shown not to live up to expectations (see Rodda & Jarnevich 2011). Any model developed to predict distributions should be checked to determine if the global predicted distribution appears realistic in relation to the current distribution of the species before proceeding to produce other localised predictions. The predictions in this chapter emphasise the importance of being able to obtain a large sample of occurrence points to increase the reliability of pseudo-absence points generated and predictions of potential distributions. Increasing the number of occurrence points can be achieved by collaborating with species experts. Worner *et al.* (2010) successfully obtained presence data for many of the 21 species investigated in their research by contacting specialist researchers. Collaboration with experts was attempted during this research but no additional occurrence points were obtained.

In summary, the multiple model system is a new approach that selects the best performing model from a range of models for each fruit fly species using 10 performance measures with extensive validation. In response to predicted climate change scenarios, the models predicted an increase in suitable habitat sites in New Zealand summerfruit producing regions for *B. dorsalis*, *B. zonata* and *C. rosa*, no change in climatic suitability for *B. tryoni* and a decrease in climatic suitability for *C. capitata*.

Chapter 4

General Discussion

The aim of this research was to predict New Zealand distributions of five exotic fruit fly species that could pose a threat to the summerfruit industry under current and future climate change conditions. A well known modelling program used for modelling species distributions, CLIMEX and a correlative approach using a comparative multiple model system were used to create the predicted distributions. The question whether climate change is likely to increase the climatic suitability of the fruit fly species was investigated.

4.1 Key results

The results generated by CLIMEX indicated an increase in climatic suitability for all five fruit fly species around the summerfruit producing regions Hawkes Bay and Marlborough under all climate change scenarios. The results generated by the multiple model system also indicated an increase in climatic suitability for *B. dorsalis* around Central Otago under 2090 climate change scenarios, an increase in habitat suitability for *B. zonata* under 2090 climate change scenarios around Hawkes Bay and Marlborough and an increase in climatic suitability for *C. rosa* around Hawkes Bay and Marlborough under all climate change scenarios. These results are supported by studies that report changes to insect distributions as a result of warmer temperatures over the last 20-40 years (Parmesan 1999; Parmesan and Yohe 2003; Battisti *et al.* 2005; Tougou *et al.* 2009). Other studies also predict a potential increase in climatic suitability using species distribution models for the oriental fruit fly (*B. dorsalis*) (Stephens *et al.* 2007), olive fruit fly (*B. oleae*) (Gutierrez *et al.* 2009), nun moth (*Lymantria monacha*) and gypsy moth (*L. dispar*) (Vanhanen *et al.* 2007). Species that are predicted to experience an increase in climatic suitability are more likely to establish permanent populations. *C. capitata* is currently known to be highly invasive and has already established populations in Europe, Egypt, Middle East, Australia and Americas. Interestingly, a decrease in climatic suitability was observed for *C. capitata* under climate change conditions using the multiple model system. This result indicates a potential decrease in risk of *C. capitata* being able to establish populations in the future, potentially a favourable result for the New Zealand summerfruit industry. Studies have also documented climate change to potentially cause a decrease in climatic suitability for many other species and result in extinctions due to thermal tolerances being breached (Thomas *et al.* 2004; Parmesan 2006;

Deutsch *et al.* 2008). Changes to the potential distributions observed under climate change conditions are directly correlated with the annual mean temperature bioclimatic variable which was the only variable manipulated to meet predicted climate change conditions for New Zealand.

There is the possibility that the models and environmental variables selected to produce the potential distributions did not produce the most likely prediction map of climate suitability for each species. The species distribution model predictions are based on the output from only the 'best' performing model out of a range of nine models. If a different model out of the nine models was used to create the prediction maps there is a possibility that one or more would predict an increase or decrease in habitat suitability instead. For example, the LOG model was used to predict a decreasing climatic suitability for *C. capitata* under climate change scenarios. However the NNET and SVM models also performed and may have indicated an increase in climatic suitability instead.

Bioclimatic variable selection is very likely to have an impact on distributions predicted under current climatic conditions. The models often predicted suitable climates in areas of New Zealand with the highest maximum temperatures but that had the coldest winters and therefore unlikely to be suitable for species originating from tropical or sub-tropical regions. The reason for this occurring may be due to the bioclimatic variables such as the mean temperature of the coldest quarter and minimum temperature of the coldest month being selected. However, bioclimatic variable selection was not an attributing factor determining climatic suitability under climate change conditions as only the annual mean temperature variable was altered for each species. The results of this study do not fully evaluate the potential impacts of climate change due to potential changes in annual precipitation levels as they were also not incorporated. The climate change predictions set by NIWA in 2008 do detail potential changes to annual precipitation levels. However, these changes were not used in this study because it was beyond the scope of this research. Changes in frequency and intensity of extreme weather events were also not investigated. These could come in the form of an increase in tropical cyclones and changes to the frequency and intensity of warm temperature spells, frosts, floods and droughts (IPCC 2007). All these extreme weather events are likely to have an impact on the climatic suitability for invasive species. For example, an increase in warm temperature spells could create more niche opportunities for exotic species to become grounded with viable populations that can withstand cooler

temperatures after the warm spell. Potential changes in extreme weather events are difficult to measure and predict (IPPC 2007) and is why they have not been incorporated in this study or many other studies that involve climate change impacts.

4.2 Implications

A study published by Summerfruit NZ (2009) indicates the direct effects climate change could have on summerfruit trees, such as not reaching the required winter chill levels needed for flowering, and the potential for an uneven transition from winter to spring. The results of this thesis contributes additional knowledge on how climate change could alter the climatic suitability in New Zealand for exotic fruit flies that are known to cause severe damage to horticultural crops.

No matter how stringent the measures put in place by biosecurity agencies to protect and safeguard New Zealand from exotic pest incursions, there is still the likelihood that a few propagate populations of fruit flies can slip through these controls. In the event of an incursion or outbreak of a serious summerfruit pest such as those investigated here, knowledge of areas with suitable climates and the presence of the host plant could increase the effectiveness of the response by concentrating eradication protocols around vulnerable locations under a particular scenario, thus avoiding wasting resources and valuable time on locations with a low climatic suitability.

The results of this research can also be used and interpreted by other major horticultural industries in New Zealand. The fruit fly species investigated are highly polyphagous. The Crop Pest Compendium (2010) records 3 out of 5 fruit fly species investigated as being serious pests of other major horticultural crops grown in New Zealand including apples (*Malus domesitca*), avocados (*Persia americana*) and grapes (*Vitus Vinifera*). Each of these industries are valued respectively at NZ\$ 396, NZ\$184.5 and NZ\$38.4 million per annum (Aitken and Hewett 2009).

The summerfruit industry and biosecurity officials in New Zealand could prepare for the potential increase in climatic suitability of fruit fly species by increasing vigilance within current strategies used to detect and prevent fruit fly incursions such as the inspection of imported commercial fresh fruit, prevention of fresh fruit smuggling by international arrival passengers and the national fruit fly trapping grid. Currently, the national fruit fly grid only targets the three species that were investigated in this research (*B. dorsalis*, *B. tryoni* and *C.*

capitata). The results of this research indicates that New Zealand summerfruit producing regions could be vulnerable to more fruit fly species than the fruit fly trapping grid is designed to detect. MAF Biosecurity should take action by introducing a wider variety of bait lures that will attract other fruit fly species such *B. zonata* and *C. rosa*. Also, the national trapping grid is currently concentrated in the North Island but the results of this research indicates that a potentially wider range of South Island locations will be suitable for fruit fly establishment under climate change conditions. Therefore, the national trapping grid should be expanded around New Zealand, particularly the South Island, to cope with the potential increase in fruit fly establishment risk.

The potential increase in surface air temperatures and changes to precipitation patterns are likely to cause stress on crops that may result in an increased susceptibility to insect pest damage (Masters and Norgrove 2010, Summerfruit NZ 2008). The implications of an increase in establishment risk for exotic pests may further increase the vulnerability of summerfruit crops to insect pest damage.

Climate change could also cause the current primary summerfruit producing regions to become less climatically suitable due to a potential decrease in winter chill hours required to break dormancy. This could result in an asynchrony between the distributions of summerfruit insect pests currently established in New Zealand and of exotic summerfruit insect pests not established in New Zealand.

4.3 Modelling method evaluation

There were notable disparities between the predicted distributions generated using CLIMEX and the multiple model system. CLIMEX predictions indicated New Zealand to have a more suitable habitat under current and future climatic conditions for all species except *C. rosa* when compared with predictions generated with the multiple model system. One of the main differences is that CLIMEX directly incorporates environmental stressors that accumulate over time. Therefore, all CLIMEX simulations indicated low climatic suitability around areas in New Zealand that experience the coldest winters such as Central Otago. In contrast, 2090 climate change predictions produced by the multiple model system for *B. dorsalis* and all predictions produced for *C. rosa* indicated high climatic suitability around areas in New Zealand with the coolest winters. The multiple model system does use bioclimatic variables that include temperature extremes but does not allow these extremes to accumulate over time

to decrease climatic suitability. Clearly, each modelling method has their own advantages and disadvantages when it comes to creating predicted distributions.

4.3.1 Multiple model system

The multiple model system has the advantage of thoroughly testing model sensitivity and error using the 10 different performance criteria. Many previous studies that use correlative species distribution models only use one or two performance criteria to test the performance of the models. The models will perform differently depending on which performance criteria is used, so it is therefore important to use a larger range of criteria. Using the performance criteria, a best performing model can be selected to create predicted distributions. The extensive model evaluation reduces the risk of ‘over-fitting’ and increases the reliability of the results produced (Worner *et al.* 2010).

When using presence/absence correlative models it is very important to obtain a set of absence points that are reliable. Recorded absences are the most reliable however these are rarely recorded and difficult to obtain. The generation of reliable pseudo-absence points is therefore crucial to ensure the accuracy of the predictions. A potential flaw in pseudo-absence generation is accidentally using pseudo-absence points that contain by chance, environmental conditions that are suitable for a particular species. If there are many of these points then the model classifiers will not be able to effectively discriminate the environmental data and result in an unreliable prediction map. The method used in this research for pseudo-absence generation attempts to minimise this risk by first using an ensemble of one class support vector machine repetitions to determine global climatic suitability. K-means clustering was then used to group the non-suitable areas into clusters. The closest point on the climate surface to the centroid of each cluster was deemed an absence point. Worner *et al.* (2010) states that this method used for calculating pseudo-absences is an improvement over previous methods but that it still needs refinement and further verification.

Despite these good points, one of the disadvantages of using correlative models such as the multiple model system is the requirement of recorded geo-referenced occurrence points which are often difficult to obtain for some species. As with all methods, problems arise with a small sample size that may not give a full representation of the environmental predictors that correlate with the presence of a species. A small sample size may also allow outliers to have more influence on predictions whereas a large sample size can buffer the effects of

outliers. A solution to obtaining more occurrence points is to collaborate with species experts who often have access to more data.

Methods using correlative modelling are being continuously upgraded. Future research could focus on using methods that can prevent over-fitting, improve variable selection, reduce collinearity and improve pseudo-absence selection.

4.3.2 CLIMEX

The CLIMEX program creates predicted distributions based on species physiological response to climate. CLIMEX and other mechanistic models are therefore more biologically supporting to a point as these models incorporate the impacts climate will have on development and the stressors that result in mortality etc (Venette *et al.* 2010; Zalucki. and Klinken, 2006). However, issues as discussed in Chapter 2 surround the subjectivity when setting the climatic parameters as it allows the user to have a lot of influence on the results. The inferred climatic suitability from Ecoclimatic Index figures also varies between publications, which increases the difficulty comparing one's results with other studies that use CLIMEX. The Ecoclimatic index ranges from 0 – 100 but the majority of publications only use the index from 0 – 20 or 25 as means of describing the climatic suitability. Any figure above 20 or 25 is just deemed optimal climatic conditions for a species. This indicates some shortcomings of the index if researchers do not use the full range. CLIMEX parameters that accumulate over time such as stress indices can also accumulate error. This latter consideration indicates how difficult it is to verify or validate the results of a model like CLIMEX. Future versions of CLIMEX could incorporate a feature that allows the user to carry out a sensitivity analysis on the model output.

More detailed modelling with CLIMEX and similar mechanistic approaches could be achieved in the future with continued research into the biological relationship between species and climate, particularly for species environmental limits and tolerances to adverse conditions such as cold or heat stress. Detailed distributions of species will also assist in the calibration of parameters used in CLIMEX.

All species distribution models currently available are unable to incorporate other biological impacts on species distributions such as interactions with natural enemies, niche competitors, flora and fauna compositions and anthropogenic interactions. Also, species distribution models do not incorporate the effects of high resolution variations in the landscape and microclimates. In species distribution modelling, an issue arises with current distribution data

being used to create the potential distributions that are extrapolated outside the current distribution of the species. The occurrence points used in the correlative modelling were sourced from locations that included all other biotic interactions that influence a species distribution. CLIMEX also uses current distribution data to validate and calibrate the environmental parameters. In effect, both types of species distributions models will tend to over-estimate the potential distributions of species.

Despite this, there are ranges of approaches that can be used to increase our understanding of how climate or habitat affects a target population. A recent study by Roura-Pascual *et al.* (2011) used regression trees to examine the interplay between climatic suitability, biotic resistance by native taxa and human modification of habitats for the Argentine ant (*Linepithema humile*) global distribution. The results of this study demonstrated that *L. humile* could persist in locations with low climatic suitability if there is high level of anthropogenic habitat modification. Interactions with closely related species were also shown to have an influence if the climatic suitability was high and the level of anthropogenic habitat modification was low (Roura-Pascual *et al.* 2011).

4.4 Future directions

Future research should investigate how summerfruit insect pests currently established in New Zealand will react to climate change. Some of these pests could also expand their current distribution range. For example, the oriental fruit moth (*Grapholita molesta*) is noted as restricted to summerfruit orchards only as far south as Hawkes Bay (McLaren *et al.* 1999). Climate change is likely to increase the climatic suitability and allow *G. molesta* to establish in the South Island. On the other hand, however, a potential decrease in climatic suitability, as observed for *C. capitata* in this thesis, may also occur for summerfruit insect pests currently established in New Zealand.

As mentioned in Chapter 1, another aspect worth investigating is the potential for climate change to disrupt the distribution and phenological synchrony between summerfruit insect pests currently established in New Zealand and their natural enemies. Any asynchrony is likely to decrease the effectiveness of biological control mechanisms and disrupt Integrated Pest Management (IPM) programs that have taken years to establish. However to predict asynchrony would involve quite different sorts of models and modelling compared to what we have used here.

Future research could investigate if summerfruit trees in New Zealand are likely to experience a decrease in winter chill hours. Summerfruit trees require accumulated winter chill hours to break winter dormancy. Not enough chilling will result in a decrease in flowering and crop yield or even total crop failure. For example summerfruit orchards in Oman experienced a gradual decrease in winter chill hours by 22.7 hours per year between 1983 and 2007 and was linked to the total failure of peach and apricot crops at intermediate altitudes during the 2005/06 season (Leudeling *et al.* 2007). This is a potentially serious threat to the summerfruit industry in New Zealand as current summerfruit producing regions may not be able to produce summerfruit in the future.

The results of this thesis indicate that different modelling methods generate different predicted distributions. A critical modelling task involves combining an ensemble of different prediction maps calculated using the best methods onto the same map to improve confidence in the reliability of species predicted distributions. Worner *et al.* (2010) did something similar by combining the predicted distributions of multiple species onto the same map to indicate where surveillance could be focused to detect high risk species.

The assessment of climate change by the IPCC indicates the average change in global surface air temperatures per decade will be 0.2°C (IPCC 2007). Future research could investigate climatic suitability of invasive exotic species on a per decade basis rather than under predictions specifically given for 2040 and 2090. This method would allow researchers to determine when the climate in New Zealand is likely to become suitable for these species.

Climate change research is ongoing with new measurements and evidence being continuously obtained. New evidence could alter the predicted increases in average surface air temperatures and other aspects of climate change. Therefore species distributions could be refined as new information emerges to produce more accurate predictions of growing locations vulnerable to exotic insect pest establishment. The IPCC is going to publish the next working assessment with updated climate change predictions in 2013 (IPCC 2007).

4.5 Conclusions

With regard to the objectives outlined in Introduction (Chapter 1), this research suggests the following conclusions:

- CLIMEX predictions indicate that all fruit fly species investigated will experience an increase in climatic suitability around the summerfruit producing regions, Hawkes Bay and Marlborough as cold stress is reduced.
- Predictions made with the multiple model system also indicate an increase in climatic suitability for *B. dorsalis*, *B. zonata* and *C. rosa* but also a decrease in climatic suitability for *C. capitata* and no change from low risk for *B. tryoni*.
- The impacts of climate change on climatic suitability are dependent on the rate of increase in surface air temperatures.
- The CLIMEX model is biologically supported but is vulnerable to subjectivity and a lack of verification and validation.
- The method for pseudo-absence generation using the multiple model system decreases the chances that a pseudo-absence point will contain favourable environmental variables for a species but still needs refinement.
- Methods of variable selection and extracting rules from the data need further development.
- A low number of occurrence points can affect model reliability and pseudo-absence generation when using correlative species distribution models.
- Current strategies that revolve around protecting New Zealand from fruit flies such as deploying a trapping grid (Stephenson *et al.* 2003) should remain in place. New Zealand biosecurity authorities may need to change the threat profiles of these fruit fly species as a result of climate change.
- Continued research to determine biological relationships between species and climate, particularly to establish species environmental limits and tolerances that will allow more detailed mechanistic modelling.

Appendix A

Supplementary Figures

A.1 Pseudo-absence generation

A.1.1 *B. dorsalis*

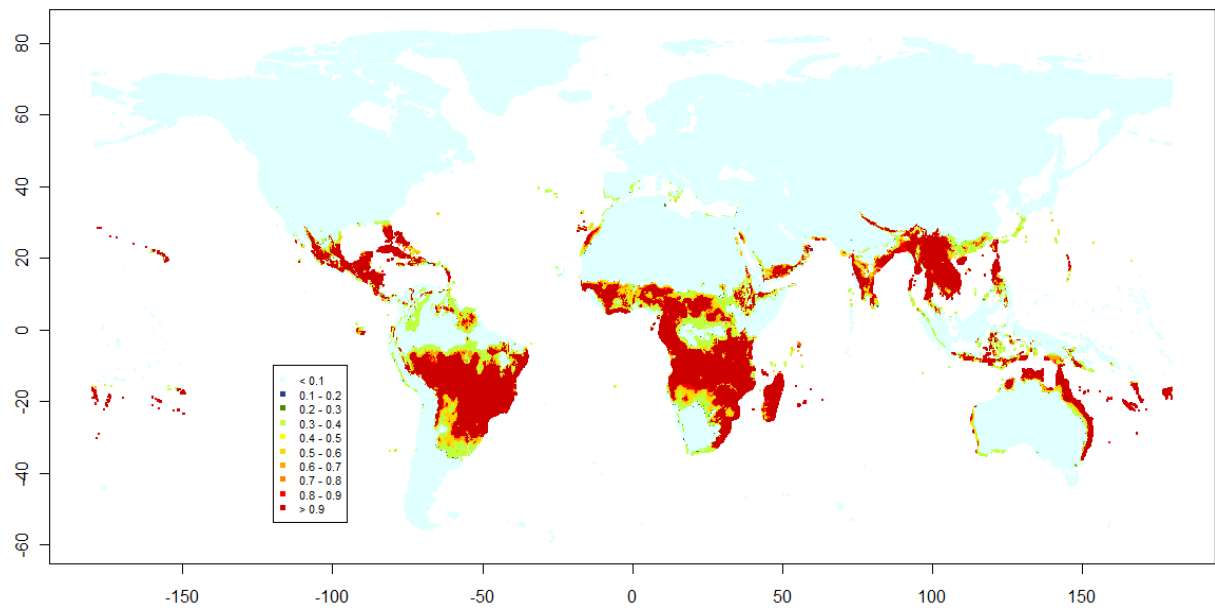


Figure A. 1: Global suitability of the environment for *B. dorsalis* created using an ensemble of SVM replicates. Suitability is indicated by warmer colours. Potential absences are indicated as < 0.1 (cool blue colour).

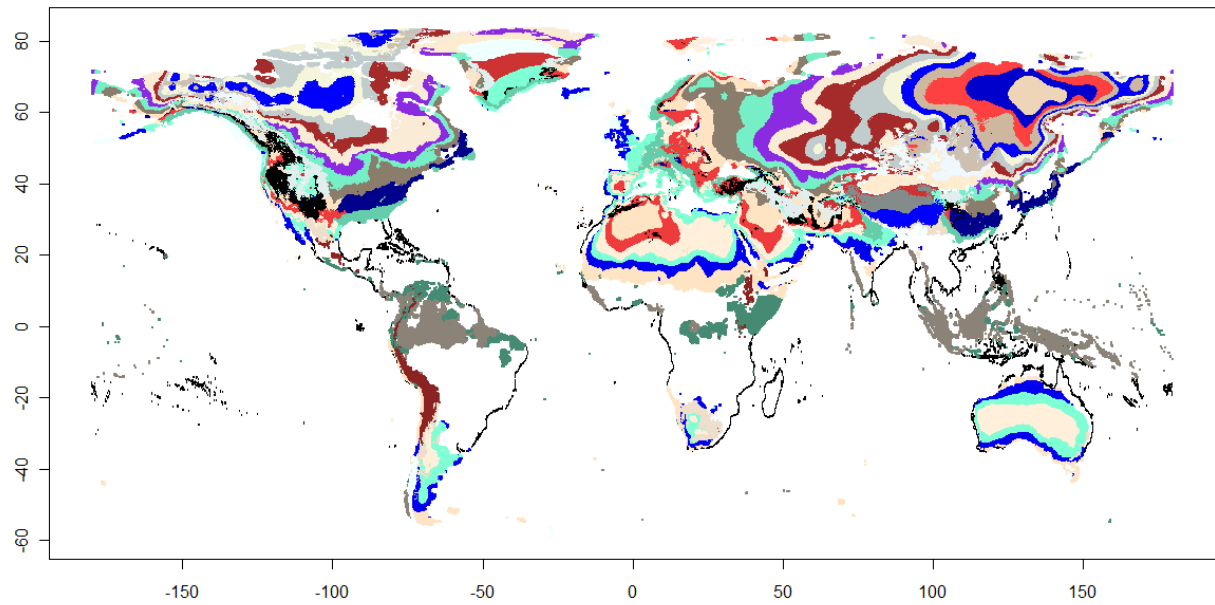


Figure A. 2: Clusters of locations (33) with similar environmental conditions most likely to be unsuitable for *B. dorsalis* establishment and therefore represent absent points. Locations in white represent potential presence points.

B.1.1 B. tryoni

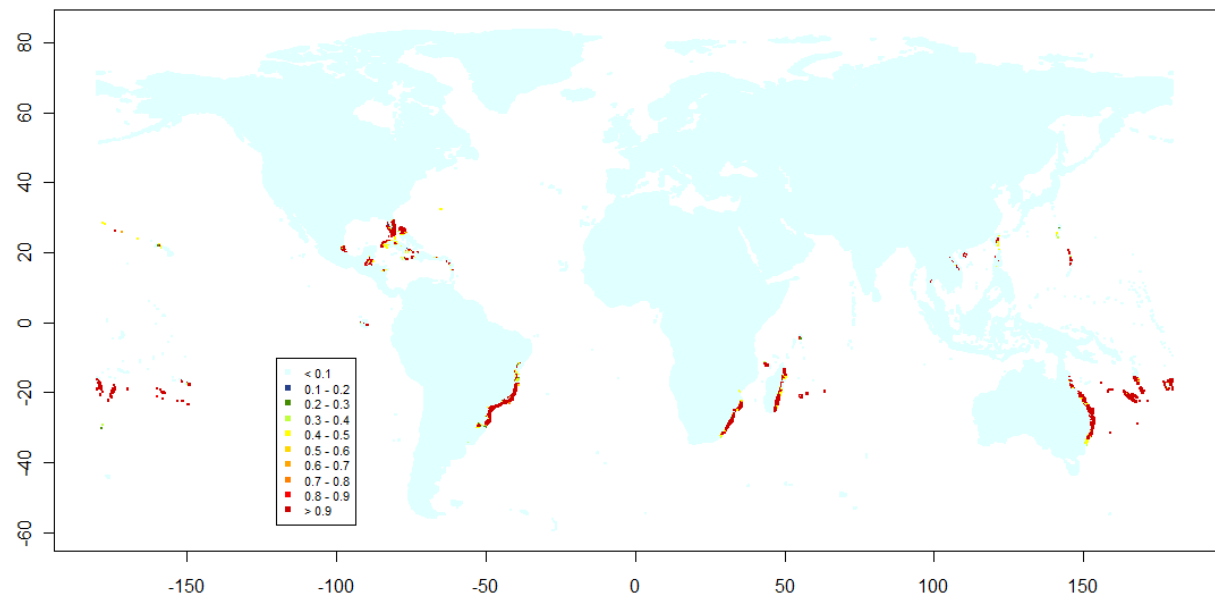


Figure A. 3: Global suitability of the environment for *B. tryoni* created using an ensemble of SVM replicates. Suitability is indicated by warmer colours. Potential absences are indicated as < 0.1 (cool blue colour).

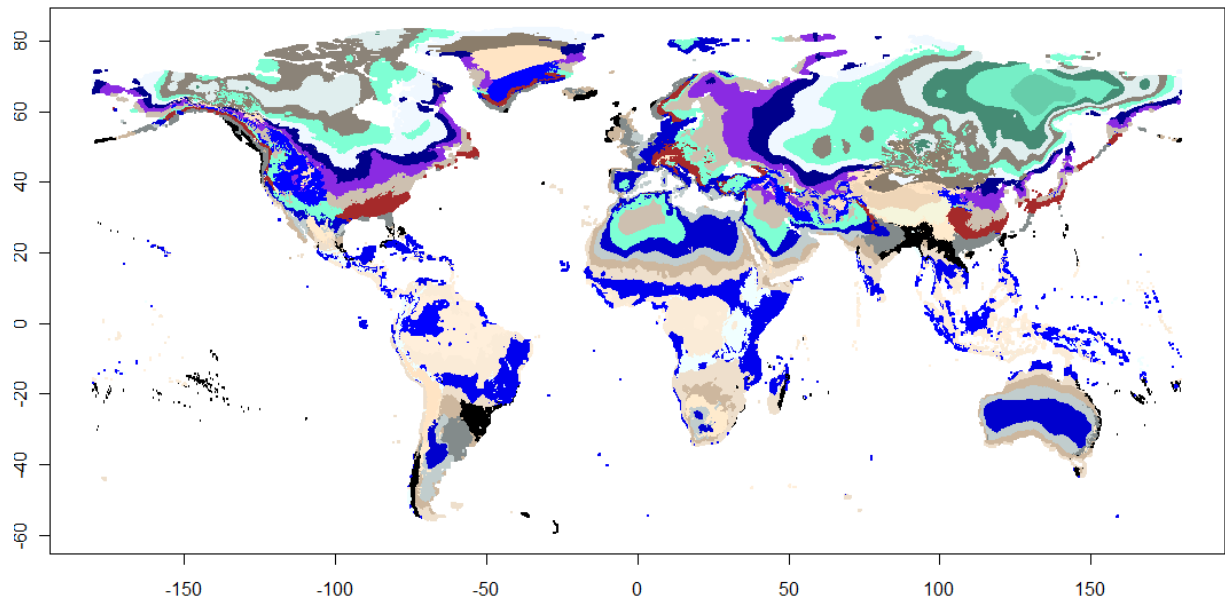


Figure A. 4: Clusters of locations (138) with similar environmental conditions most likely to be unsuitable for *B. tryoni* establishment and therefore represent absent points. Locations in white represent potential presence points.

B.1.2 *B. zonata*

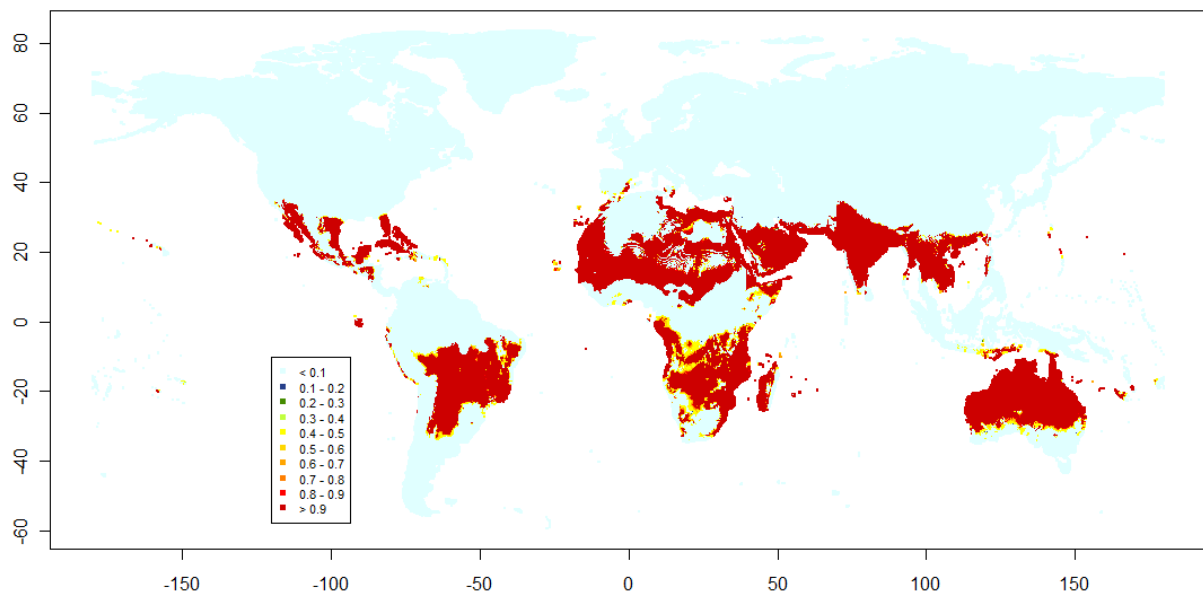


Figure A. 5: Global suitability of the environment for *B. zonata* using an ensemble of multiple SVM replicates. Suitability is indicated by warmer colours. Potential absences are indicated as < 0.1 (cool blue colour).

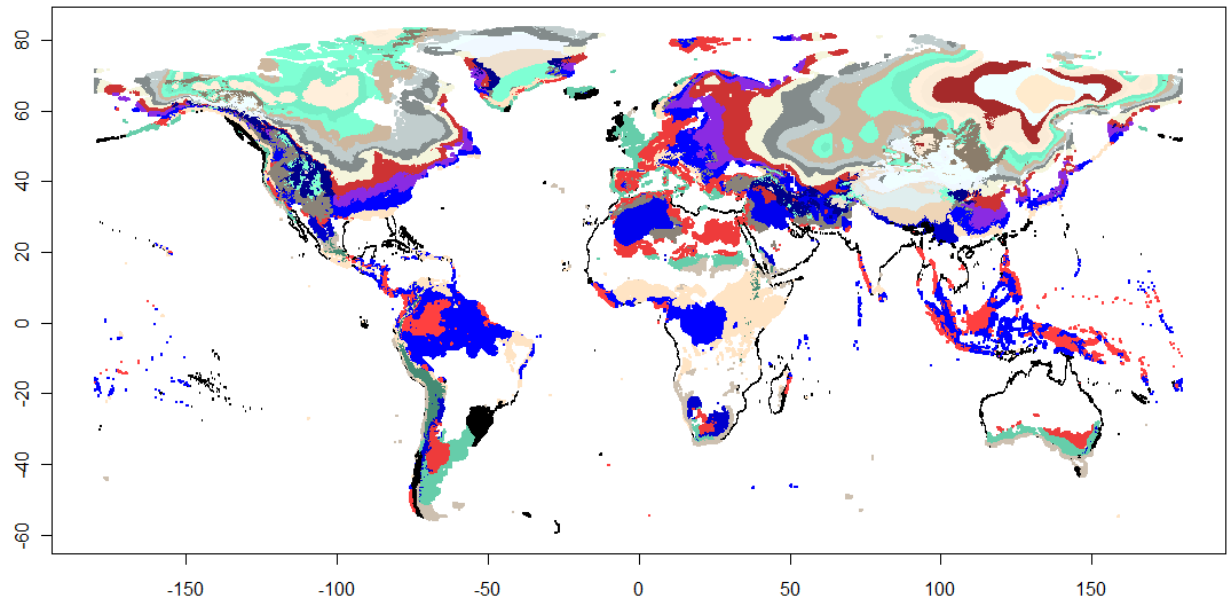


Figure A. 6: Clusters of locations (36) with similar environmental conditions most likely to be unsuitable for *B. zonata* establishment and therefore represent absent points. Locations in white represent potential presence points.

B.1.3 *C. capitata*

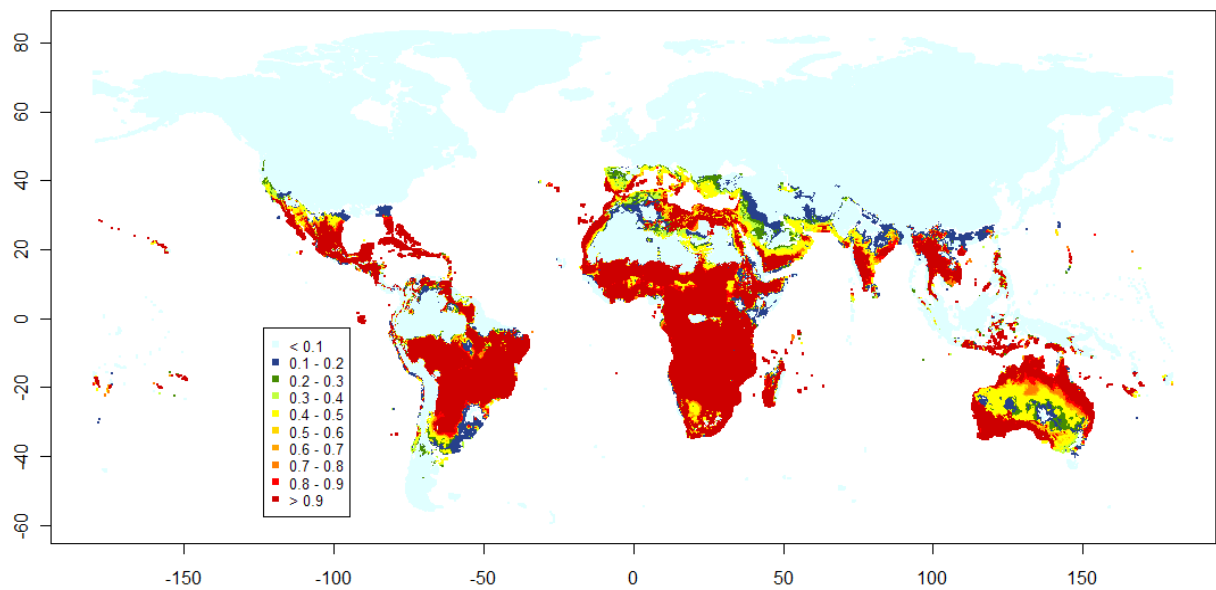


Figure A. 7: Global suitability of the environment for *C. capitata* using an ensemble of multiple SVM replicates. Suitability is indicated by warmer colours. Potential absences are indicated as < 0.1 (cool blue colour).

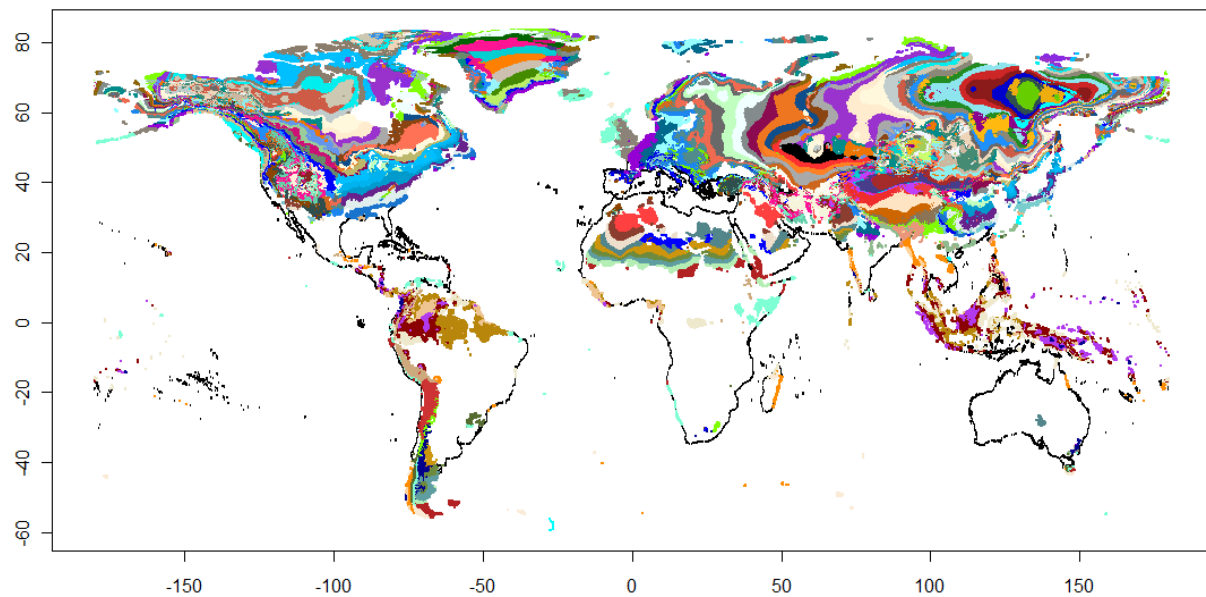


Figure A. 8: Clusters of locations (138) with similar environmental conditions most likely to be unsuitable for *C. capitata* establishment and therefore represent absent points. Locations in white represent potential presence points.

B.1.4 *C. rosa*

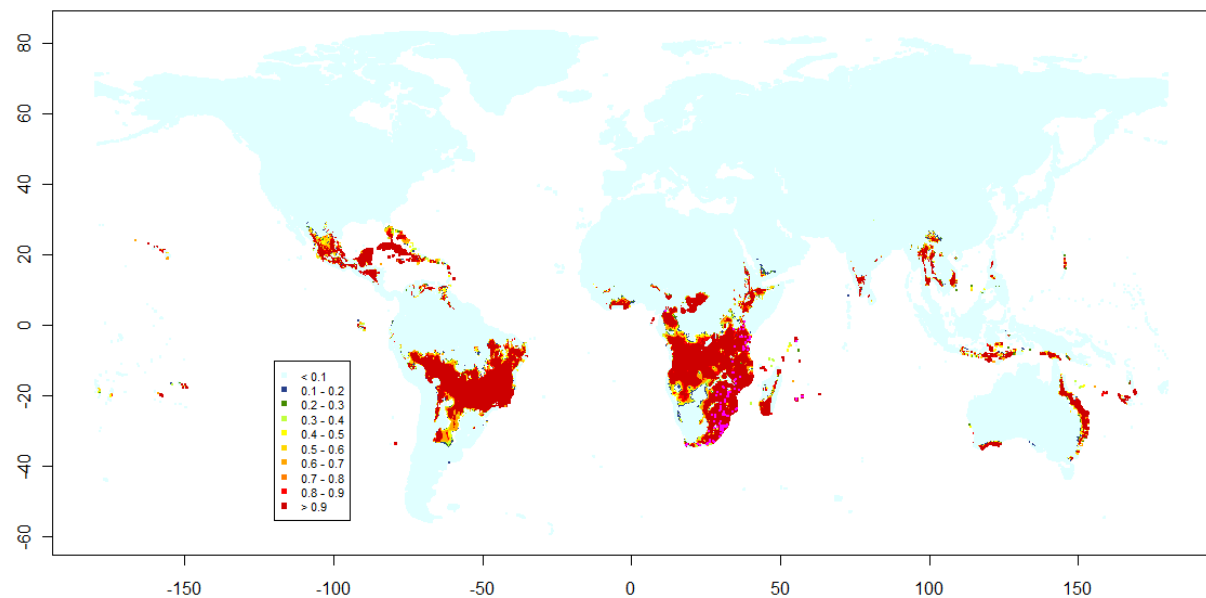


Figure A. 9: Global suitability of the environment for *C. rosa* using an ensemble of multiple SVM replicates. Suitability is indicated by warmer colours. Potential absences are indicated as < 0.1 (cool blue colour).

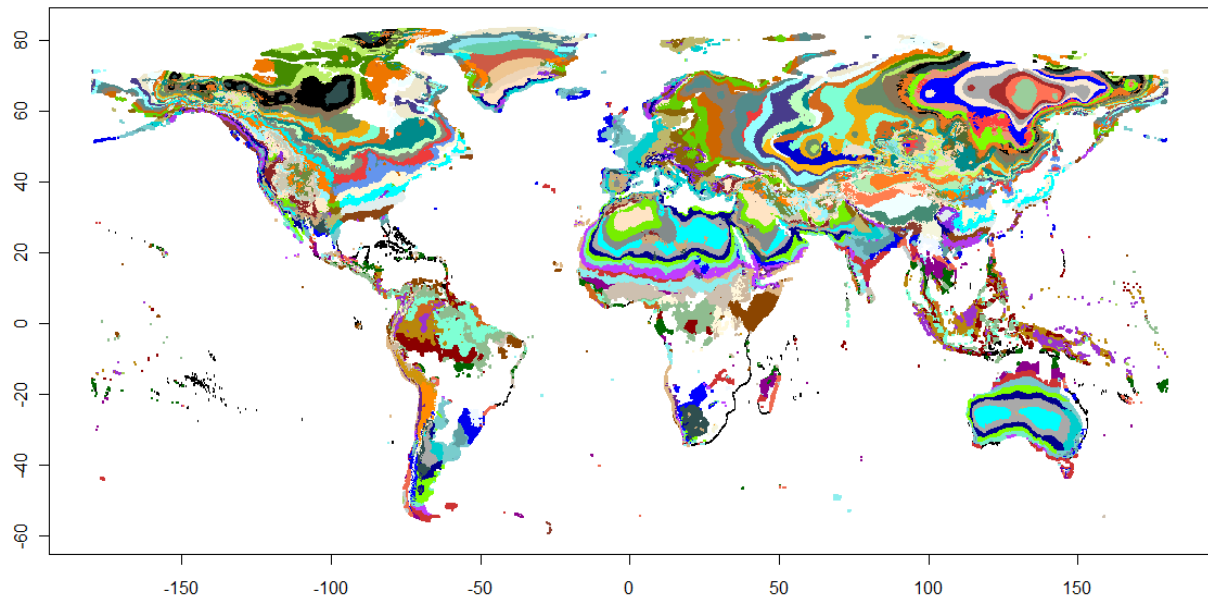


Figure A. 10: Clusters of locations (138) with similar environmental conditions most likely to be unsuitable for *C. rosa* establishment and therefore represent absent points. Locations in white represent potential presence points.

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