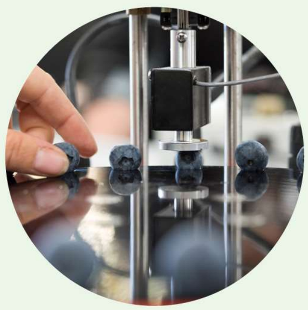







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Potential climate change impacts on myrtle rust risk in Aotearoa New Zealand

Campbell R, Beresford R, Fitzherbert S, Carey-Smith T, Turner R

November 2020

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Contents

Executive summary

Potential climate change impacts on myrtle rust risk in Aotearoa New Zealand

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November 2020

Myrtle rust is of tropical origin and is particularly well adapted to climates that are warmer than the temperate conditions currently predominating in New Zealand. Future climate warming in New Zealand is therefore expected to favour increased activity of the pathogen and consequently more damaging effects from this disease.

In this report the Myrtle Rust Process Model (MRPM), based on *Austropuccinia psidii* responses to climatic variables, was used to explore several climate change scenarios which considered increases in temperature in conjunction with decreases in relative humidity. This included an exploration of the variation and effects of various changes in relative humidity (RH) on the output of the infection risk model. This was necessary because of uncertainty about geographic effects on future reductions in RH associated with climate warming.

The climate change scenarios explored were increases of 1, 2, 3, 4 and 5 degrees Celsius, and corresponding decreases in %RH per degree Celcius.

Infection risk increased with each increased temperature scenario, with largest increases in areas that are currently only marginal suitability for the pathogen with respect to temperature. Latent periods decreased with increasing temperature, resulting in potential for the rust to continue reproducing over winter in many areas, particularly where, under current conditions, cooler winter temperatures slow or halt pathogen development, resulting in overwintering as latent infection..

Future work is recommended to integrate these predictions with host plant distributions and phenology to understand the impact these increased risks could have on the distribution and regeneration of Myrtaceae plant communities.

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1 Introduction

Myrtle rust (*Austropuccinia psidii*; MR) was reported for the first time in Northland, New Zealand in May 2017 (Toome-Heller et al. 2020). The pathogen has a wide host range on Myrtaceae species of which New Zealand has many culturally, environmentally and economically important native and introduced species. MR is of tropical origin and is particularly well adapted to climates that are warmer than the temperate conditions currently predominating in New Zealand. Climate change as a result of global warming is likely to increase the risk of MR in temperate climates through both a shortened *A. psidii* latent period (time from infection to production of new spores) and increased periods of active host growth (Beresford et al. 2020). Alternatively, there may also be interactions with drought and its effect on active plant growth. Periods of active host growth are crucial for myrtle rust development because *A. Psidii* can only infect young expanding plant tissues. Future climate warming of the world (Randers & Goluke 2020), including New Zealand is therefore expected to favour increased activity of the pathogen and consequently result in more damaging effects from this disease.

Predicted weather changes that could potentially influence the severity and regional risk of plant diseases include warmer temperatures everywhere, drier conditions in Northland, Bay of Plenty and Hawke's Bay and increased rainfall in Tasman, Marlborough, Canterbury and Central Otago (MfE 2017). In addition, increased severity and frequency of extreme storm events are expected. For plant pathogens in New Zealand, warming generally implies greater disease risk. Predicted changes in climate are of a magnitude and range to which plant pathogens are highly sensitive. For example, many bacterial and fungal pathogens have an optimal temperature for development between 15-20 ^{o}C. Under our current climate, temperatures are generally suboptimal for infection and reproduction of most pathogens most of the time. Therefore an increase in mean temperature will provide greater frequency of conditions suitable for disease (Beresford & McKay 2012).

Myrtle rust causes damage to its host plants by infecting and destroying leaves, stems, flowers and fruit. Highly susceptible species are impacted by destruction of photosynthetic leaf area, prevention of growth through shoot dieback and prevention of seed production. New Zealand has three native species that have, so far, been observed to be severely attacked by myrtle rust: *Lophomyrtus bullata (ramarama)*, *L. obcordata* (rōhutu, including the natural hybrids between these two *Lophomyrtus* species) and *Metrosideros excelsa* (pōhutukawa). These all have a wide natural distribution within New Zealand and are also used in restoration and amenity plantings and in home gardens. It is likely that other native species will also be found to be affected by myrtle rust as *A. psidii* becomes more widely distributed over time, inoculum loads pass thresholds of susceptibility or *A. psidii* becomes more adapted to NZ conditions.

Climatic risk modelling shows that current climatic conditions in New Zealand are favourable for MR from the northern North Island to the northern South Island and to parts of the west coast of the South Island (Beresford et al. 2018). This is further confirmed by current surveillance data. Specific climatic variables relevant to *A. psidii* have been reviewed by Glen et al. (2007) and the pathogen requires a period of high humidity or leaf wetness and low light for a minimum of 6 h for successful spore germination and infection. Reports on the optimum temperature for infection vary between studies, from 18–21°C down to 15°C (Figure 1). Unpublished New Zealand data suggests an optimum around 16°C (L. Ramos Romero, pers. comm.). Overnight wet periods suitable for infection in New Zealand are currently almost always below the optimum temperature and climate warming would therefore increase the frequency of infection events in most areas and the geographic range of conditions suitable for infection.

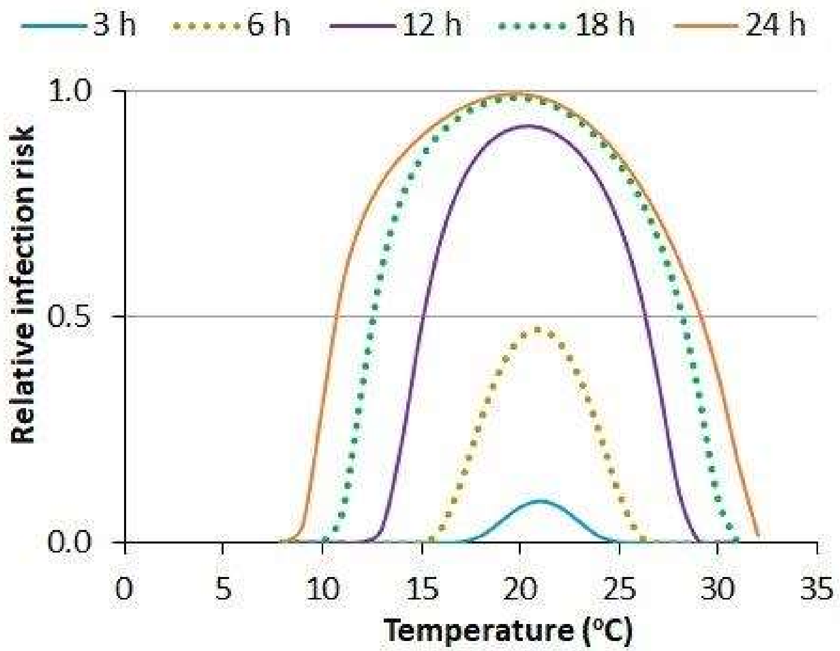

Figure 1. Temperature response curve for infection risk of *Austropuccinia psidii*. Coloured symbols represent the hours of high humidity or leaf wetness, required for successful germination and infection (Figure adapted from Beresford et al 2018).

Another key parameter for MR epidemic development is the generation time between infection and production of new spores, also known as the latent period. A short latent period means rapid pathogen multiplication and high risk of a disease outbreak. Latent development of MR is highly dependent on air temperature, with an optimum of 25–28°C, and can be as short as 5–7 days in New Zealand hosts (Figure 2; Beresford et al. 2020). Latent development slows to zero below about 10°C, arresting development until warmer conditions are returned. Mean daily temperatures under current climatic conditions in the North Island and northern South Island vary between about 7 °C in winter and 23 °C in summer and are therefore generally suboptimal for *A. psidii* latent development. Climate warming will increase myrtle rust risk through a higher pathogen multiplication rate.

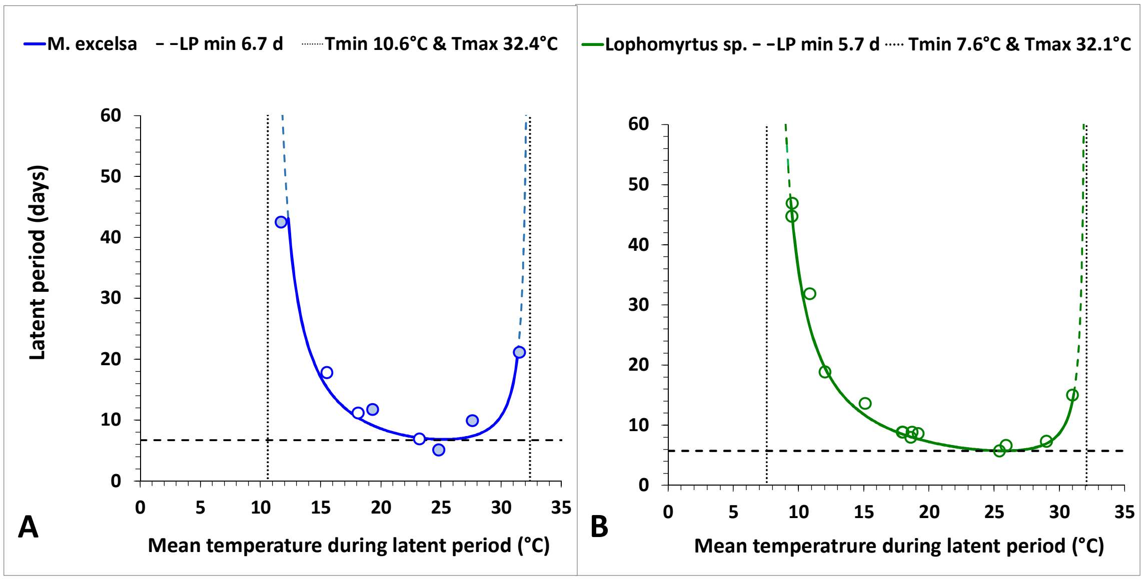

Figure 2. Effect of mean daily temperature on the latent period of *Austropuccinia psidii* on two New Zealand hosts, A, *Metrosideros excelsa* (pōhutukawa) and B, *Lophomyrtus* sp. (ramarama/rōhutu hybrid), as reported by Beresford et al. (2020). Closed symbols are constant temperature data and open symbols are fluctuating shade house or field data. Dashed lines indicate extrapolation of the fitted curves beyond the experimental data points.

Climate change will simultaneously impact the phenological response of plants to climate, as well as infection risk, and spread of plant diseases (Caffarra et al. 2012; Gratani 2014; Tang et al. 2017). For example, bud break and flowering are strongly influenced by spring weather conditions, and are also key plant phenology stages which are susceptible to infection. With predicted warmer spring temperatures, the timing of flower development is also predicted to shift, therefore potentially shifting the susceptible period of infection. An important feature of the interaction between *A. psidii* and its host plants is that infection can only occur on young, actively expanding tissues. Once fully expanded, leaves and stems become resistant to infection; this tissue age related resistance is known as ontogenic resistance. Because ontogenic resistance restricts infection to the actively growing shoots and young tissues, natural epidemics are confined to periods when growth flushes occur. Seasonal growth patterns of Myrtaceae hosts have not yet been quantified, so this study is not able to include host distribution, host density and seasonal growth in the modelling. These interactions need to be understood to effectively predict future disease risk for key plant development periods.

1.1 Climate change scenarios

Climate changes over the next decades are predictable with some level of certainty (MFE 2018). Scenarios known as representative concentration pathways (RCP) are often referred to and are defined by their total radiative forcing at 2100 compared to 1750 (MFE 2018). They represent a mitigation pathway (2.6 W m-2 for RCP2.6), two stabilisation pathways (4.5 W m-2 for RCP4.5; 6.0 W m-2 for RCP6.0) and a pathway with very high green house gas concentrations (8.5 W m-2 for RCP8.5). Global climate model (GCM) simulations are available from the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report, and downscaled for New Zealand future climate predictions (MFE 2018). From these modelled predictions, the mid-range estimate for projected New Zealand temperature change is an expected increase of about 0.8°C by 2040, 1.4°C by 2090, and 1.6°C by 2110 (relative to 1986–2005). Given the different scenario pathways and the different models used, these could range from 0.2–1.7°C by 2040, 0.1–4.6°C by 2090, and 0.3–5.0°C by 2110 (MFE 2018).

Moisture, as rainfall, dew and/or high relative humidity (RH), is a key factor that drives epidemics of most fungal and bacterial pathogens. Dry conditions and increased drought frequency will often decrease disease risk because infection processes generally depend on a period of wetness. (Beresford et al. 2012, Beresford et al 2018). The moisture dependence of plant pathogens presents a challenge for climate change studies because, while temperature changes can be predicted reasonably reliably in climate change datasets, predicting changes in precipitation patterns have much greater uncertainty (Carbon Brief 2018) and rainfall variability is still challenging to predict (Carbon Brief 2018; MfE 2018). Humidity, wind speed, sunshine duration and evaporation, have received even less attention as climatic variables subject to climate change (Zhang et al. 2017). Furthermore, measures of change in RH meaningful to disease risk are also challenging and underdeveloped (MfE 2018). There are however, predictions provided in MFE (2018), for mean annual temperature and precipitation changes across New Zealand, highlighting the differences in predicted values across the country and seasons, for example, increased rainfall in the west (particularly winter and spring), drier conditions in the east and north, and larger increases in temperature in the north compared to the south (Appendix 1).

1.2 Background on current Myrtle Rust Process Model

The Myrtle Rust Process Model was developed in collaboration between The New Zealand Institute for Plant and Food Research Limited (PFR) and the National Institute of Water and Atmospheric Research (NIWA) to assist MPI during the 2017 MR incursion response. Development of the weather-based risk prediction model started in June 2017 and was operational from September 2017 (Beresford et al. 2018). The Myrtle Rust Process Model predicts epidemiological in relation to weather variables (RH, temperature and solar radiation) (Beresford et al 2018). Specific methodology behind the creation of the Myrtle Rust Process Model is documented in Beresford et al. (2018), Beresford et al. (2020) and, for clarity, some details are included here.

The model was developed from published international information on *A. psidii* (Beresford et al. 2018). Since then it has been updated with field and controlled environment data from Australia and New Zealand and continues to be updated as new data are obtained (Beresford et al. 2020). Potential risk predicted by the Myrtle Rust Process Model is based only on climatic factors and does not currently include inputs for host species susceptibility, seasonal availability of susceptible host tissue, or pathogen inoculum. The model's predictions of potential myrtle rust geographic distribution therefore assume susceptible hosts and pathogen spores are present in each area of interest. The model comprises three sub-models that predict daily risk indices representing three epidemiological processes: (1) infection, (2) latent period and (3) spore production. In this study we used only the infection and latent period indices as the key determinants of myrtle rust climatic adaptation. Spore production was not included in the scope of this report because the most important risk factors for the disease spread are the infection risk and the latent period.

The **infection risk sub-model** is a function of wetness, informed by hours of high RH (>=85%), mean temperature during wetness and hourly solar radiation. Spore germination and infection are favoured by wet periods > 6-8 h duration, temperatures > 12°C and low light intensities.

The **latent period** represents the time delay between an infection event and the production of new spores. The period between infection and first appearance of rust symptoms is termed the incubation period and is generally a few days shorter than the latent period. The latent period is used in the risk model because it is epidemiologically more important than the incubation period and is of greater practical use, as it represents the time that symptoms can be visually confirmed to be caused by MR.

For current climate predictions, spatial patterns were predicted using the Myrtle Rust Process Model and the virtual weather grid produced by the New Zealand convective scale model (NZCSM). Daily values of the infection and latent period risk indices were summarised as average daily values period over the previous 7 days (Sunday – Saturday). Calibrations between the modelled weather data and weather stations were conducted. Risk predictions were checked for bias between NZCSM predictions and 100 NIWA climate stations, and time series of NZCSM were also validated against a number of nearest climate stations. Validation from MR surveillance data is difficult because there is no nationally coordinated surveillance programme and MR has not been in New Zealand long enough yet, therefore more data still needs to be collected.

1.3 Objectives

The objective of this research was to extend the Myrtle Rust Process Model to incorporate five potential climate change scenarios to explore what effect these have on predictions of future infection risk and latent period for myrtle rust in New Zealand. To do this we explored temperature and relative humidity (RH) offset scenarios to parametrise the sub-models.

2 Methods

For current MR risk predictions, the virtual weather grid produced by the New Zealand convective scale model (NZCSM) was used to inform the Myrtle Rust Process Model. The risk values are calculated from hourly weather forecast data and the Myrtle Rust Process Model sub-models and summarised for daily means (3pm NZ Standard time). These are then summarised into weekly mean risk (Sunday to Saturday) (Beresford et al. 2018). Output rasters are classified into five classes (described in Table 1) of defined intervals for interpretation of risk and latent period.

Table 1. Infection risk and Latent period classifications, values and risk categories. Latent Period classifications updated from Beresford et al. (2018) with results from Beresford et al. (2020). Longer latency period represents lower risk (longer generation time between infection and secondary inoculum production).

Risk	Values	Risk categories
Infection risk	< 0.2	Very Low
	0.2 - 0.4	Low
	0.4 – 0.6	Moderate
	0.6 – 0.8	High
	0.8-1.0	Very High
Latent period	< 10 days	Very High
	10-15 days	High
	15-30 days	Moderate
	30-50 days	Low
	> 50 days	Very Low

2.1 Climate change scenarios

Using the Myrtle Rust Process Model, national grids of infection risk and latent periods were derived as means for each of four seasons: December, January, February (DJF, Summer); March, April, May (MAM, Autumn); June, July, August (JJA, Winter); September, October, November (SON, Spring).

For the “current” climate scenario, means from the NZCSM for the past 5 years (September 2015 – August 2020) were used. In addition, five future alternative climate change scenarios were explored with change in temperature offsets, where mean temperatures were increased from the “current” period by 1, 2, 3, 4 and 5 ^{o}C (scenarios: T+1, T+2, T+3, T+4, T+5 respectively). These temperature increase scenarios encompass the range of predictions from RCP scenarios and projected time scales tested in MFE (2018, Appendix 1). For example, RCP 8.5 maximum prediction for 2100 is approximately a 5 ^{o}C increase, for 2081-2100 approximately 3 ^{o}C, and by year 2040, the predicted increase in temperature is 1-2 ^{o}C. For RCP 2.6, there is a predicted temperature increase up to about 1^{o}C by 2100 (MFE 2018, Appendix 1).

For each of these five temperature scenarios, RH was also modified, by decreasing %RH per degree C with monthly change in %RH values derived from the RH and temperature relationships outlined in section “2.1.2 Accounting for changes in relative humidity”.

For the “current” scenario and each of the five future scenarios, 12 parameters were calculated (Table 2). These included parameters for the number of days within each season which exceeded an infection risk threshold or were below a latent period threshold (see section 2.1.1 Thresholds). Because the mean risk over each season flattened the high and low risk variation, maximum (infection risk) and minimum (latent period) parameters were also produced for comparison of high risk areas and seasons. The change between the current risk and the future scenario risk was also calculated.

Table 2. Parameters calculated for each of the “current” and five future climate scenarios. Each seasonal value is the mean over the five years of “current” data (September 2015 – August 2020), with each of the climate change scenarios applied to the hourly data. Season is defined as summer (December, January, February; DJF), autumn (March, April, May; MAM), winter (June, July, August: JJA), spring (September, October, November; SON). For “count” parameters, thresholds for infection risk are the mid-point of the “moderate” risk category (>0.5), and the number of days where the latent period was <20 days (moderate risk category).

	Parameter	Description	Units
Infection risk	mean_infection_risk	Mean infection risk over each season	-
	max_infection_risk	Maximum infection risk over season	-
	count_infection_risk	Number of days infection risk > 0.5	Days/season
	mean_infection_risk-change	Difference between mean current and mean predicted scenario infection risk	-
	max_infection_risk-change	Difference between maximum current and maximum predicted scenario infection risk	-
	count_infection_risk-change	Difference between number of days infection risk > 0.5 for current and predicted scenario infection risk	Days/season
Latent period	mean_latent_period	Mean latent period over each season	Days
	min_latent_period	Minimum latent period over season	Days
	count_latent_period	Number of days latent period < 20 days	Days/season
	mean_latent_period-change	Difference between mean current and mean predicted scenario latent period	Days
	min_latent_period-change	Difference between minimum current and minimum predicted scenario latent period	Days
	count_latent_period-change	Difference between number of days latent period < 20 days for current and predicted scenario latent period	Days/season

2.1.1 Thresholds

The latent period calculations are highly sensitive to temperature changes between 10– 4ºC. For the change in seasonal mean of the latent period, there were large magnitude changes when historic climatology had large values for latent period (i.e. over 100 days for the current climate). Thus, the means showed large changes, which may not have been epidemiologically important for the disease (very long “current” latent period, with large changes, but not necessarily resulting in short latent periods). Therefore, the changes in the count of days when the latent period was below a threshold of 20 days, which is the mid-point of the “moderate risk” category for latent period was also calculated. Similarly, for infection risk, changes in the count of days above a threshold where risk was 0.5, the mid-point of the “moderate” infection risk category were calculated. Thresholds were chosen as the mid points of the "moderate" risk categories, and there is growing field evidence that substantial infection occurs above 0.5 risk.

2.1.2 Accounting for changes in relative humidity

Moisture availability is important for the infection cycle of myrtle rust and, therefore RH changes associated with the future temperature scenarios needed to be determined. We reviewed international literature on predicted changes to RH with climate change scenarios, however a consistent and conclusive method was not found. The majority of climate change studies focus on the changes to temperature and precipitation. Humidity, wind speed, sunshine duration and evaporation, have received significantly less attention as climatic variables subject to climate change (Zhang et al. 2017). Dai (2006) concluded that relative humidity has remained nearly constant over the past few decades, with predictions of modest reductions in RH as temperature increased (Simmons et al 2010). Additionally, where increases in precipitation are predicted, RH is likely to increase correspondingly (Oksanen et al 2018). Other models predicting greater warming also predict stronger reduction in RH (Fischer and Knutti 2012), where greater changes are expected in the mid-continental land regions and mid-latitudes associated with greatest predicted changes in heat extremes. Byrne and O'Gorman (2016) predicted a decrease in RH of approximately 1% per degree Celsius increase. However, New Zealand is often under resolved in many of the international models. For New Zealand, RH shows distinct seasonal and geographic patterns for current climate, with eastern regions lower than wetter western regions (MFE 2018). Projections in MFE (2018) showed reduced RH over the majority of New Zealand in all seasons with the largest reductions in inland South Island. The only area of notable exception is a narrow strip down the West Coast, particularly in the winter, reflecting the predicted increase in rainfall in this region (MFE 2018). Over most of New Zealand, the rate of decrease in RH was around 1–2% per degree increase in mean temperature, which is consistent with Byrne and O'Gorman (2016).

This report assessed the change in RH over New Zealand as a function of the temperature anomaly, using monthly mean RH and temperature from NIWA's regional climate modelling programme. NIWA generated six different 130-year climate simulations for each of four representative concentration pathways (RCP; 2.6, 4.5, 6.0, 8.5). For each of these simulations, monthly anomalies of RH and temperature were found relative to the 1986-2005 period. For each RCP, a multi-model mean of these anomalies was taken across the six different simulations. These anomalies were further averaged into four seasons and three 20-year time slices, before the ratio between the RH and temperature anomalies was taken, providing a predicted change in RH per degree of warming (Appendix 2). Consistent with previous findings (e.g. Byrne & O'Gorman 2016; MFE 2018), RH generally decreased with increasing temperature over land, but increased over the ocean (Appendix 2). Additionally, there is a reasonably strong seasonal cycle in the relationship between RH and temperature anomalies with the strongest signal occurring in spring (SON). This seasonal cycle is consistent with the results in MFE (2018) as the data comes from the same regional climate model simulations. A third key result, is that the magnitude and pattern is very similar regardless of the time-slice, which means that this relationship between RH and temperature is not dependent on the magnitude of the temperature anomaly (Appendix 2). Because the change in RH per degree of warming does not vary with the magnitude of temperature anomaly, the RH was averaged over a longer time period to improve our estimate of its true value, over 50 years from 2050 to 2100 for three relative concentration pathways (Figure 3 and Appendix 2). The pattern of relative humidity is consistent across the different RCPs, suggesting that the relationship between RH and temperature anomaly is not sensitive to the magnitude of the climate signal. These predictions still suggest limitations for the predictions for the west coast of the South Island resulting from the coarse resolution of the climate data combined with the strong impact from the ocean due to the predominant weather patterns and air flows for this region.

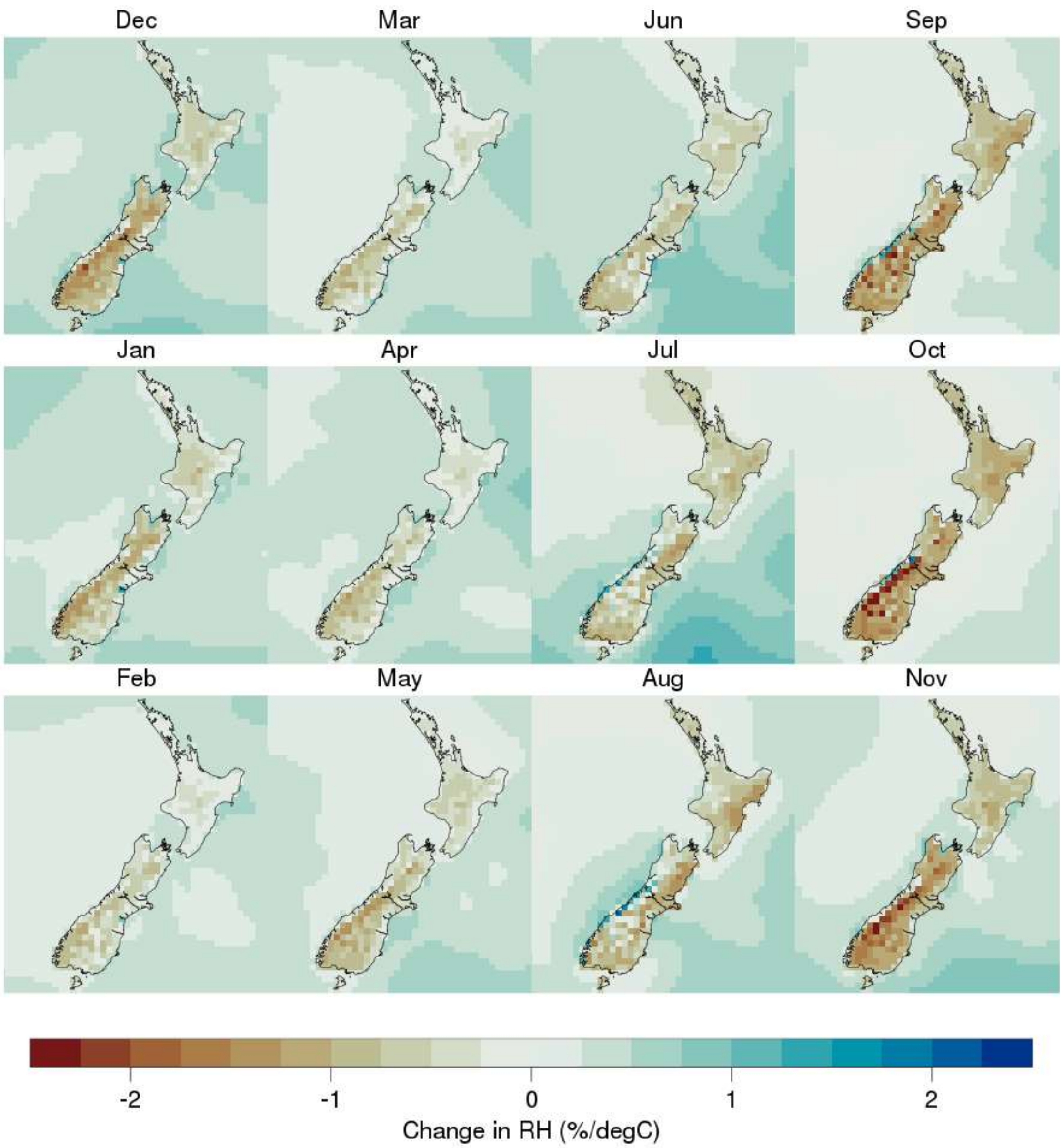

Figure 3. Monthly change in relative humidity per degree of warming for 2050 to 2100, averaged over RCP4.5, RCP6.0 and RCP8.5. Change is percent RH per degree Celsius of warming.

2.1.3 Humidity sensitivity analysis

To investigate the robustness of MR infection risk predictions using the mean RH predictions derived for this report, we ran several additional scenarios using the myrtle rust process model (MRPM) and adjusting the RH parameter. For two seasons (winter, JJA and spring, SON) and one temperature offset (T+3), four additional scenarios (Table 3) were assessed, for three parameters (mean infection risk, maximum infection risk, count of days of infection risk above threshold (0.5)). Only infection risk parameters were looked at since latent period was not affected by RH. The scenarios included RH values reduced or increased from the current NZCSM seasonal means; no change in RH (from current), increased RH by 1% per degree C and decreased RH by 1% per degree C (Table 3) (Appendix 3).

We were particularly interested in the region of the west coast of the South Island, where there is the potential for a different pattern of change in relative humidity with climate change to the majority of the country, with some predicted increases in %RH, rather than decreases, due to predicted increased rainfall.

Table 3. Scenarios used to explore the sensitivity of risk predictions to change in relative humidity. Example seasons were winter (June, July, August; JJA) and spring (September, October, November; SON) were used for the T+3 climate change scenario.

Scenario	Description
myrtlerust_nzcsm-plus3deg.asc	RH reduced by a different % each month (scenario used for the rest of the report)
myrtlerust_nzcsm-plus3deg-minus1rh.asc	RH reduced by 1% per degree of warming (current mean NZCSM - 3% RH)
myrtlerust_nzcsm-plus3deg-plus0rh.asc	No change in RH from mean baseline NZCSM
myrtlerust_nzcsm-plus3deg-plus1rh.asc	RH increased by 1% per degree of warming (baseline +3% RH)
myrtlerust_nzcsm-plus3deg-minus1rh-change.asc	Change in prediction values between baseline RH scenario and – 1%RH/^{o}C
myrtlerust_nzcsm-plus3deg-plus1rh-change.asc	Change in prediction values between baseline RH scenario and + 1%RH/^{o}C

2.2 Incorporating climate change scenarios into the Myrtle Rust Process Model

For the application to the MRPM, the change in RH per degree of warming for the mean over 50 years from 2050 to 2100 for three relative concentration pathways was used. This was further averaged for land areas north of 41.5ºS, to remove the influence of the extreme values over the Southern Alps. The monthly differences were maintained, to represent seasonal variation in the amount of change in RH with each degree of warming (Appendix 2) and these values are shown in Table 4. For each of the five climate change scenarios (delta temperature offsets) the “current” period was modified to increase temperatures by 1 – 5 degrees and relative humidity was decreased relative to the temperature increase using the mean monthly values shown in Table 4. The temperature and relative humidity modifications were applied to the hourly NZCSM “current” data to calculate the means for each season. The change in relative humidity per degree of warming applied to the delta offsets was different for each month. For example, the largest changes occur in October where the relative humidity reduces by 0.93% per degree C. For the T+5 degree scenario, this means that, as well as increasing the temperature by 5 degrees, the relative humidity inputs to the Myrtle Rust Risk model were reduced by 4.65% in October, whereas in March they were only reduced by 0.46%. Only temperature and RH parameters were changed for the scenarios in this report. While solar radiation is predicted to change, and is present in the original MRPM, it was assumed that a change in solar radiation would have a minor effect compared to that of RH and temperature, which are the key drivers of the epidemiology (Beresford et al 2018, Beresford et al 2020).

Table 4. Change in monthly mean % RH per degree of warming (°C) applied to the MRPM for the climate change scenarios tested in this report. Values derived from the monthly mean averaged for 2050 to 2100, averaged over land points north of 41.5°S and averaged over three representative concentration pathways (RCP). For more details see Appendix 2.

Month	Relative humidity adjustment (%/°C)
January	-0.346
February	-0.117
March	-0.091
April	-0.151
May	-0.376
June	-0.447
July	-0.678
August	-0.722
September	-0.843
October	-0.93
November	-0.723
December	-0.449

2.3 Mapping and visualisation

For the current and 5 climate change scenarios (T+1 – T+5), a total of 264 .asc files were generated. These were derived for 12 parameters for 4 seasons for each of 5 climate scenarios, plus 6 parameters for 4 seasons for current climate (change fields for current climate not included). In addition to these, 21 .asc files (3 parameter x 7 (=4 scenarios + 3 change)) were created for the RH sensitivity analysis. Rasters are provided in the coordinate reference system (CRS) EPSG 2193/NZGD2000 Transverse Mercator, cell size 1000 (ncols 1051, nrows 1519).

Figures were drawn from these .asc files in ArcGIS Pro by extracting the values over land (discarding those over the sea) for presentation. National maps of predicted infection and latent period risk categories for the change scenarios were produced by classifying rasters into five classes (Table 1) of defined intervals for interpretation of risk and latent period.

3 Results

3.1 Infection risk

3.1.1 Relative humidity sensitivity analysis

For the spring (SON) and winter (JJA) seasons and T+3 ^{o}C scenario, differences between changes in %RH estimations were investigated for +1%RH per degree C, no change in %RH (from current) and -1%RH per ^{o}C. A reduction in %RH per ^{o}C lead to a decrease in the number of days higher than the 0.5 infection risk threshold. A decrease in RH of 1% per ^{o}C resulted in a decrease of up to 13 days for spring (SON) or 14 days for winter (JJA) days (14% and 15% respectively, of the 3 month seasons) above the 0.5 infection risk threshold (compared with no change in %RH), with a mean decrease of 3 (SON) and 2 (JJA) days (3 and 2% respectively), above the infection risk threshold. The coastal and northern areas experienced the largest changes in infection risk (Figure 4).

For the west coast of the South Island, where rainfall is predicted to increase in certain seasons, there was more uncertainty because of the effects of the assumptions about decreases in %RH with increasing temperature. For spring, the mean increase in days above the 0.5 risk threshold for the +1%RH per degree C assumption was 4.7 days (5%), compared with the -1%RH per degree C assumption where the mean was a decrease of 4.6 days. This resulted in a total difference of up to 9 days (10%) above 0.5 risk between the +1%RH and -1%RH per ^{o}C assumptions (Figure 4). These patterns were similar for the winter scenario, plus or minus 1-2 days difference. For certain areas of the West Coast, the potential outcomes of the assumptions have a more profound effect. The maximum difference was from an increase of 10 days (+1%RH per ^{o}C) compared to a decrease of 9 days (-1%RH per ^{o}C) (10%), resulting in the total potential difference between these two assumption scenarios to be up to 19 days (21%) above 0.5. For spring (SON), the scenarios for the rest of the report (not the sensitivity scenarios) were using the prediction of a decrease in %RH per ^{o}C of between 0.7 and 0.9 % (Table 4), therefore if the West Coast does increase in humidity we could be under estimating the risk for on average 9 moderate-high risk days (6 in winter) and up to 19 days (17 in winter) in areas of the west coast of the South Island (Figure 4).

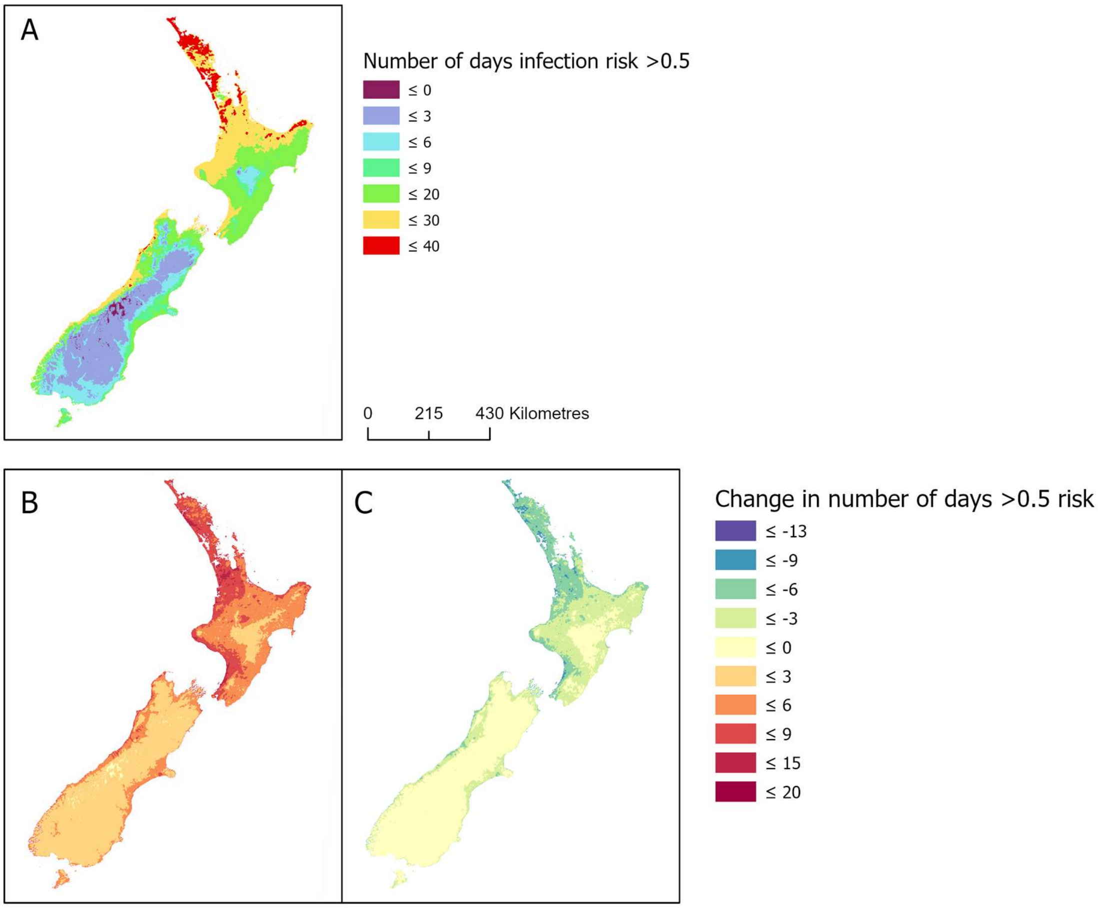

Figure 4. Count of number of days with infection risk >0.5 for spring (SON) for temperature scenario T+3 and no change in RH (A); and changes (relative to A) in number of days with infection risk >0.5, for: RH increasing by 1% per °C (B) and RH decreasing by 1% per °C (C).

3.1.2 Mean infection risk

The mean seasonal infection risk increases from the current climate, progressively through to the more extreme T+5 climate change scenario, particularly in northern, low altitude and coastal regions (Figure 5). So while the decreases in RH decrease the risk, the temperature increases overall mean risk. Mean seasonal risk above 0.4 only occurs in MAM (autumn) and DJF (summer), and for larger areas including the west coast of the South Island and patches in the Marlborough sounds, only from T+2 (summer) and T+3 and above (Figure 5). The increase in land area within the moderate risk category is largest in MAM under the T+4 and T+5 scenarios (Figure 5).

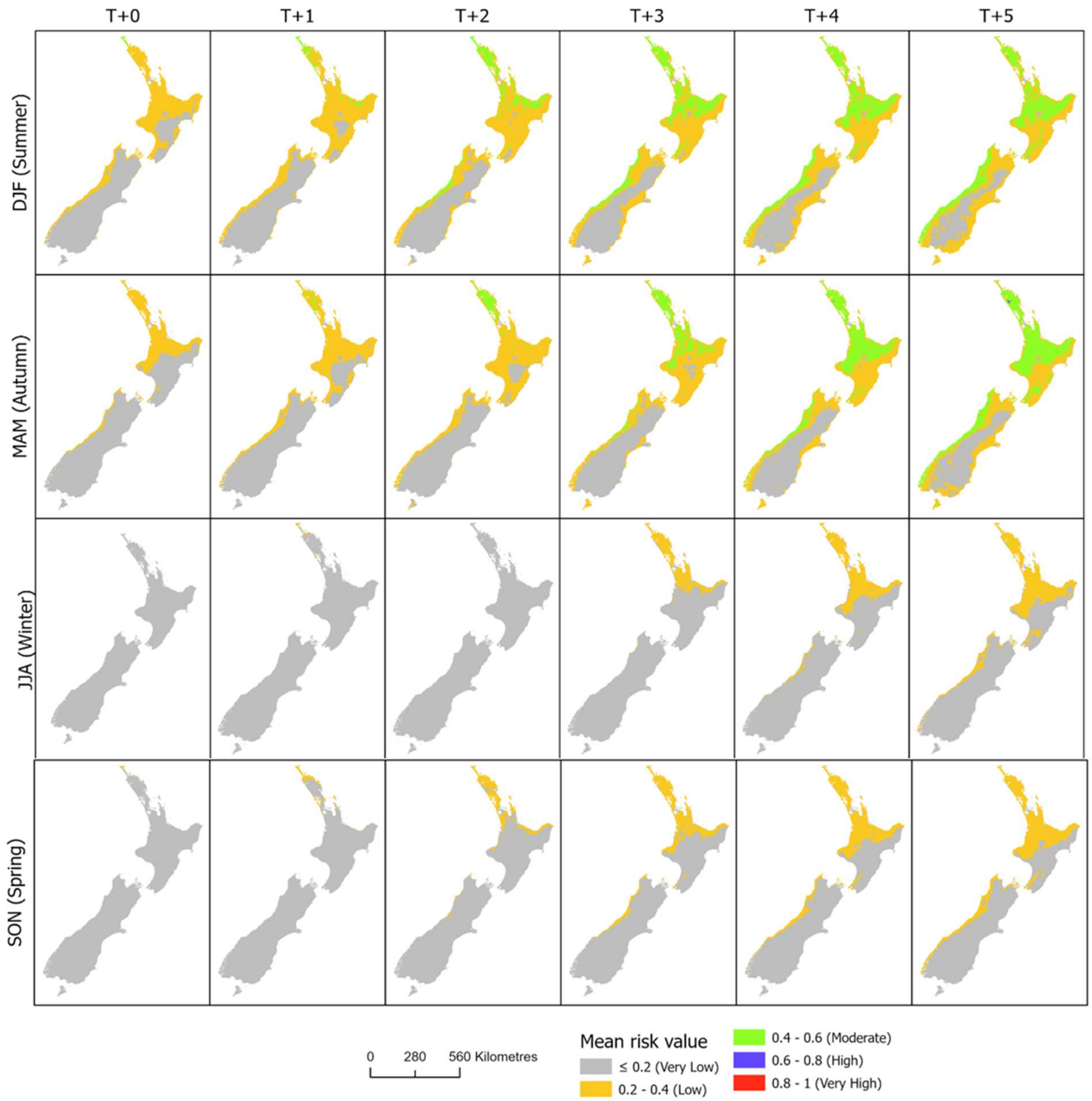

Figure 5. Predicted seasonal mean infection risk for current climate (T+0) and five climate change scenarios (T+1, T+2, T+3, T+4, T+5 ^{o}C). Infection risk derived from the myrtle rust process model with adjusted temperature and RH assumptions. Seasons are DJF = December, January, February (summer); MAM = March, April, May (autumn); JJA = June, July, August (winter) and SON = September, October, November (spring).

3.1.3 Count of days infection risk above threshold

Similarly to the mean infection risk, the number of days where the infection risk was above the 0.5 threshold, increased with increased temperature scenarios (Figure 6). Winter shows areas with no risk above the 0.5 threshold for all scenarios, in areas of higher altitude and areas in the central South Island, similarly for spring, smaller but similar areas are present with no risk above the threshold, in decreasing area from T+0 progressively to T+5 (Figure 6). Similarly to mean infection risk (Figure 5), the number of days above the risk threshold is greater in summer and autumn for all temperature scenarios (Figure 6). Scenarios T+3-5, however have slightly different patterns between summer and autumn, with areas with a greater number of days above the infection risk threshold focused more intensely in Northland for autumn, and more fragmented in summer (Figure 6). In particular, for autumn in parts of Northland, 60–70 days of the season (65–76 % of days) were predicted to be above 0.5 infection risk. In winter, the differences in number of days above the 0.5 infection risk threshold between the north and south are more notable (than the other seasons), with large areas of the North Island predicted to reach 20–40 days above the threshold (22–43 % of days) for the T+3-5 scenarios, while parts of the South Island retained no days above the threshold (Figure 6).

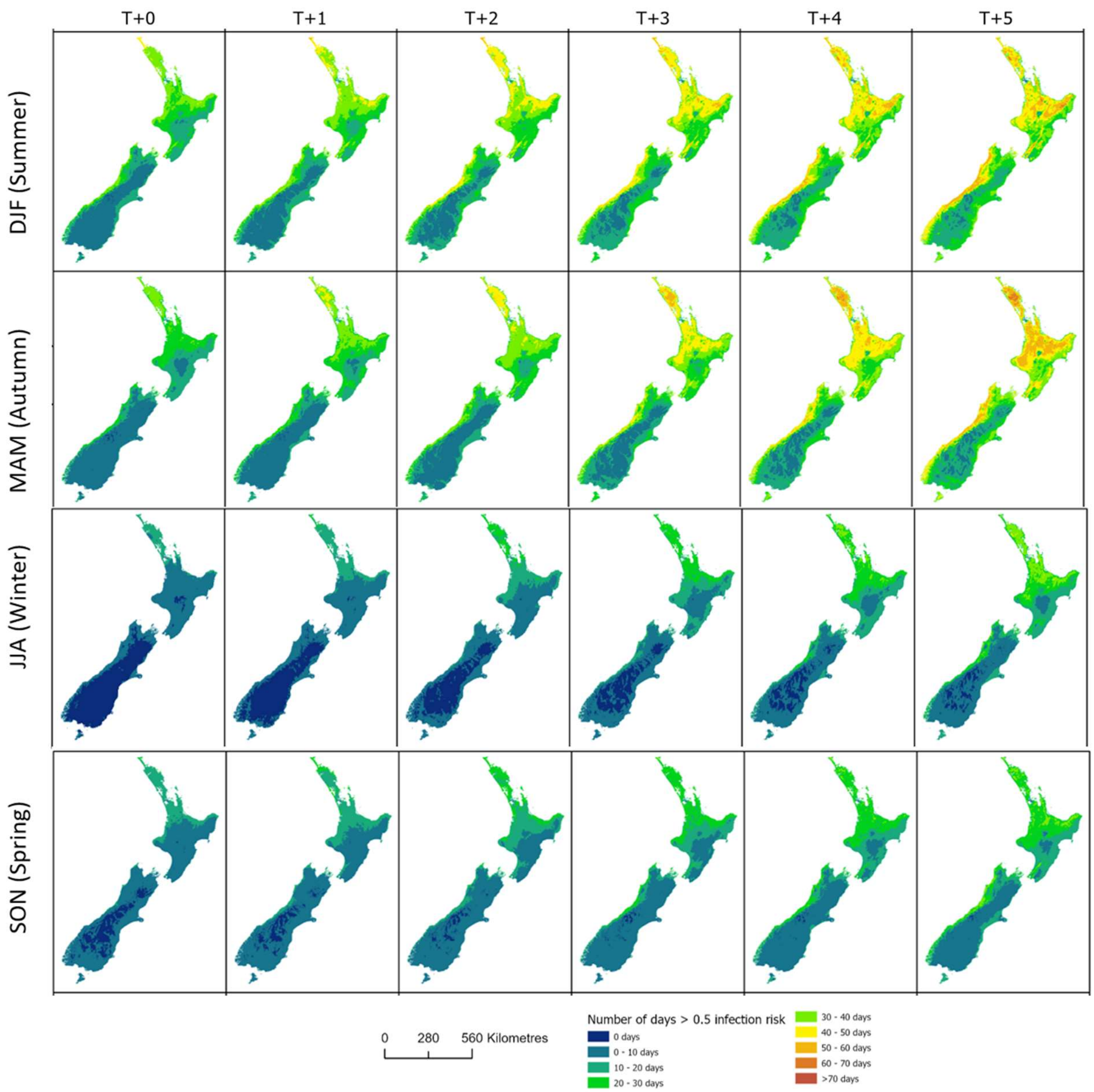

Figure 6. Number of days above the 0.5 (midpoint “moderate” risk category) infection risk threshold for current scenario (T+0) and five temperature and RH change scenarios (T+1, T+2, T+3, T+4, T+5 °C).

3.1.4 Maximum infection risk

While the seasonal mean infection risk shows no areas and seasons within the category “0.8–1, very high risk”, if the maximum infection risk is considered, a large majority of the country for most of the seasons include large areas with a maximum infection risk in the very high risk category, which was smoothed out when averaged across each season.

The change in the maximum infection risk, from current (T+0) to the future scenarios is shown in Figure 7. In Autumn (MAM) and Summer (DJF) scenarios, the change in maximum infection risk for the northern North Island regions has little or no change (maximum infection risk is already at a maximum in these areas for the current climate, and therefore cannot increase for the future scenarios), whereas, in the South Island in winter (JJA) there are large predicted changes in the maximum infection risk, where the change (increase) in maximum infection risk is up to 0.8 (Figure 7). Spring (SON) also shows a lot of change in maximum infection risk, particularly in the South Island T3-5 scenarios. Spring shows more change in maximum infection risk in the central South Island (around the alps), whereas winter shows more extreme change in maximum infection risk in coastal South Island areas (Figure 7).

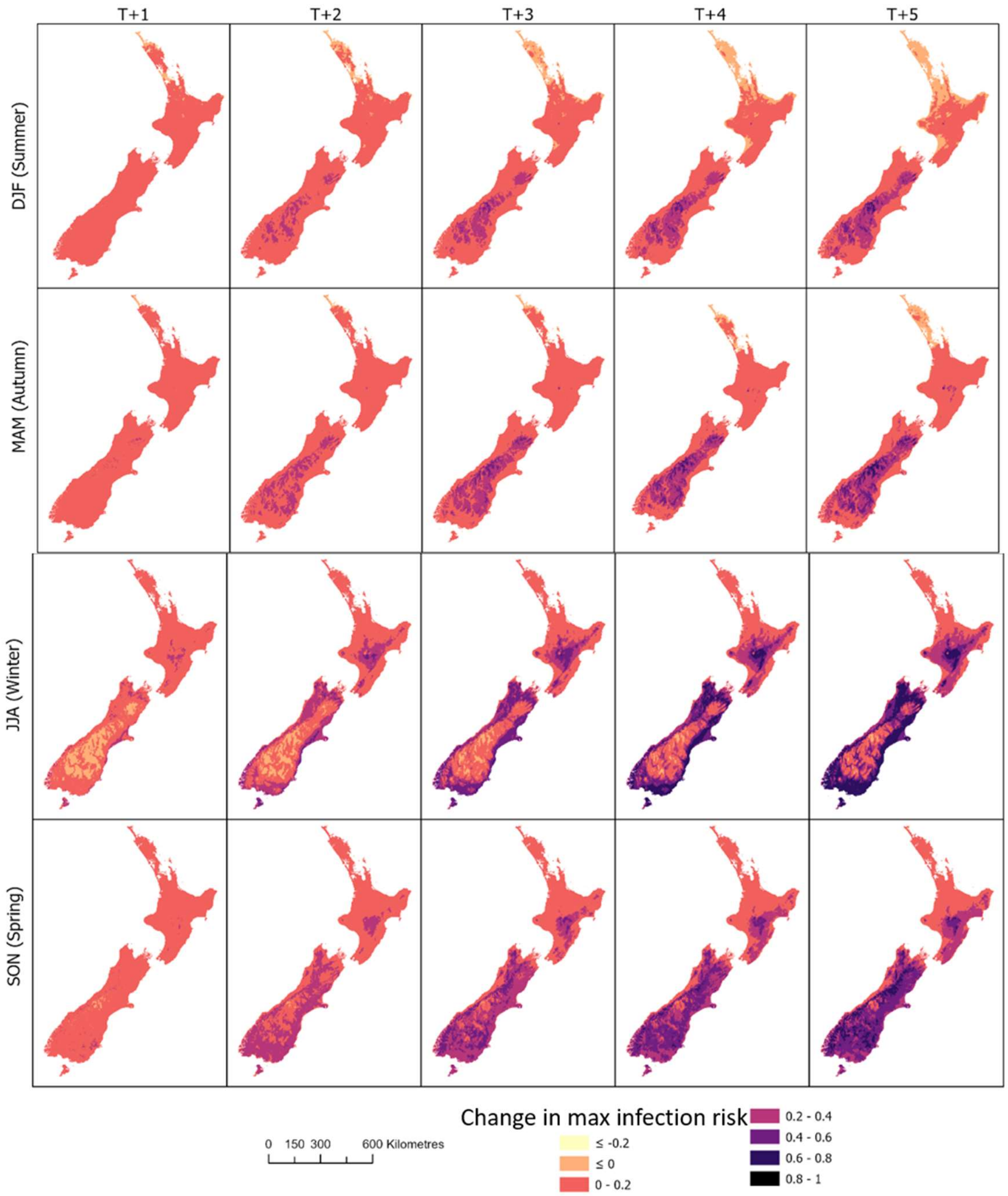

Figure 7. Change in maximum infection risk between current scenario (T+0) and five temperature and RH change scenarios (T+1, T+2, T+3, T+4, T+5 ^{o}C).

3.2 Latent period

3.2.1 Mean latent period

Mean latent period shows obvious increase in risk (decrease in latent period) from T+0 to T+5, driven by the change in temperature (Figure 8). The spatial pattern of decreased latent period is typical of coastal and latitude and altitudinal changes in temperature. Winter still maintains large areas of moderate to low mean risk, under all change scenarios, while for all other seasons, even the change to T+1, increases mean risk in large areas, particularly in the North Island and northern South Island (Figure 8).

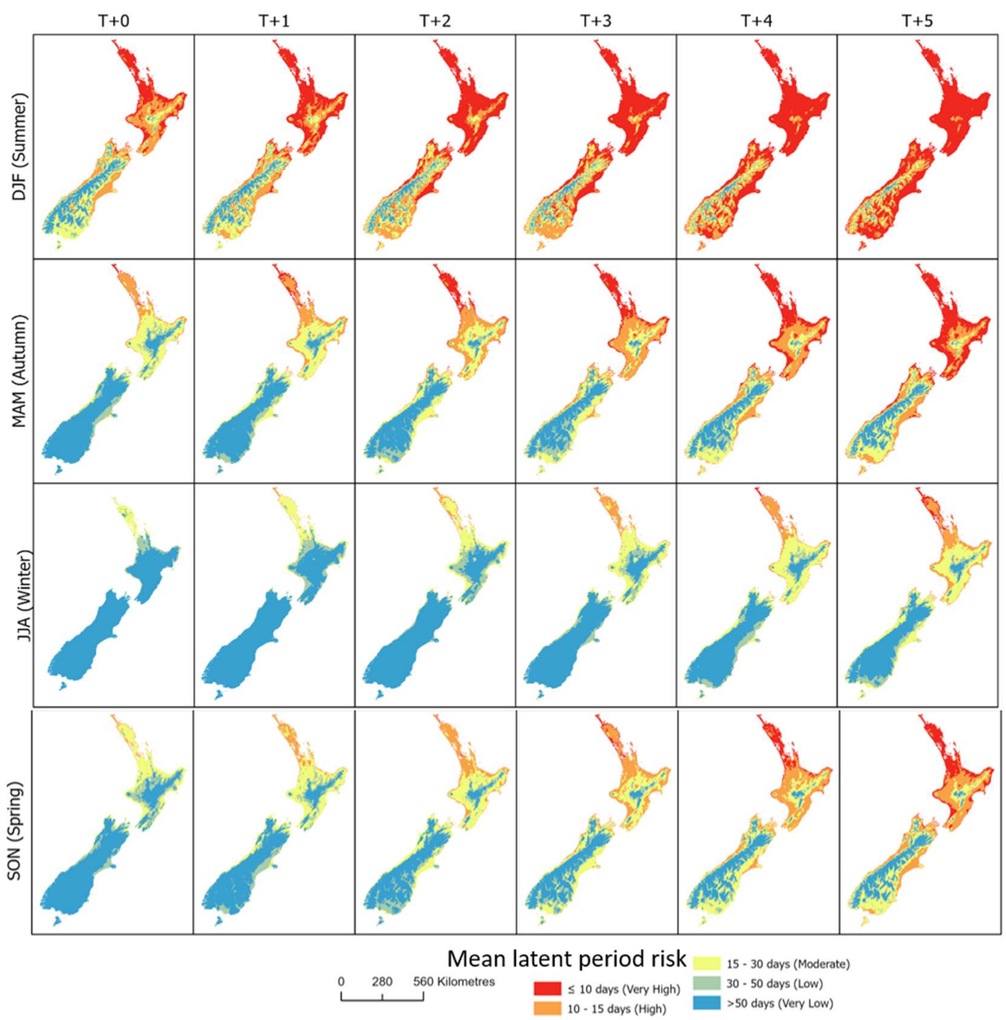

Figure 8. Predicted seasonal mean latent period for current climate (T+0) and five climate change scenarios (T+1, T+2, T+3, T+4, T+5 ^{o}C). Seasons are DJF = December, January, February (summer); MAM = March, April, May (autumn); JJA = June, July, August (winter) and SON = September, October, November (spring).

3.2.2 Count in days latent period below threshold

The threshold used for exploring the changes in latent period was 20 days (within the moderate risk category), and the count of the number of days with risk values below this threshold was quantified. With increasing temperature scenario (from 0 to +5°C), there was a predicted rapid increase in area of more than 70 days (76% of days) below the 20 day latent period threshold for all seasons (Figure 9). The number of days below the latent period threshold is highest in summer, followed by autumn, spring and then winter (Figure 9). From T+3-5, in all four seasons, even winter, there are large areas of the North Island where the latent period is moderate-high risk for much of the season. For all scenarios, summer and autumn have latent periods of moderate to high risk (short latent period) for much of the season in most of the North Island and coastal and northern areas of the South Island.

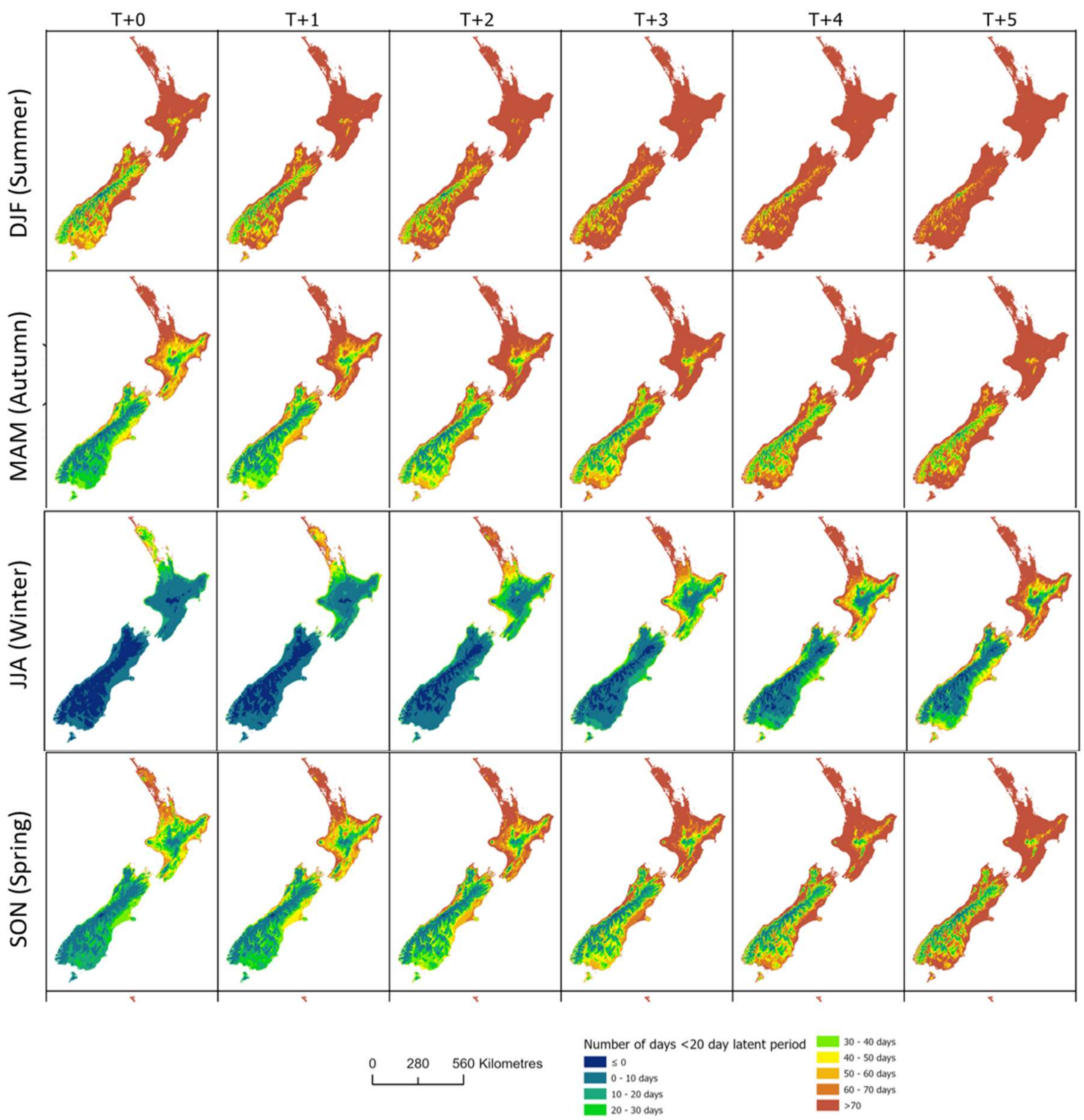

Figure 9. Number of days below latent period threshold (20 days; the midpoint “moderate” risk category), for current climate (T+0) and five climate change scenarios (T+1, T+2, T+3, T+4, T+5 °C). Seasons are DJF = December, January, February (summer); MAM = March, April, May (autumn); JJA = June, July, August (winter) and SON = September, October, November (spring).

3.2.3 Minimum latent period

For much of the country, and all seasons except winter, the minimum latent period (highest risk) in a season is less than 10 days (current and future scenarios), therefore the changes in minimum latent period are mostly around the Southern Alps and high elevation areas which were previously cool enough to lengthen the latent period. The only season where there are marked changes in the minimum latent period is in winter (JJA), where much of the South Island (centered around the high altitude areas) decreases in latent period by often more than 50 days (up to 310 days), in high to mid altitude areas where temperatures are predicted to change the most. While this change is great in magnitude, the mean latent period still remains >50 days, maintaining these areas as very low risk, even for the T+5 scenario (Figure 8).

4 Discussion and conclusions

Both myrtle rust infection risk and latent period risk increased progressively for the five climate change scenarios tested for this report. Changes in risk were most extreme in the currently cooler areas of New Zealand (southern, high altitude) where temperature is currently the limiting factor for both infection risk and shorter latent periods. Changes in winter conditions were particularly important, releasing the rust from some of the seasonal temperature constraints.

Patterns of change for the regional locations were generally consistent, regardless of the parameters measured. For example, mean, count of days above a threshold, minimum, maximum and change, all showed change patterns highlighting the temperature dependencies and predicted temperature change effects such that northern, coastal areas remain high risk, and previously temperature limited areas (high altitude, southern, winter) increase in risk the most.

There was no indication that these scenarios, even the most extreme of T+5, resulted in a restriction to the myrtle rust risk from upper temperature limits or wetness limits i.e. these scenarios do not extend past the optimum temperatures for either infection risk or latent development rate of myrtle rust. The scenarios within each season were still increasing in areas of higher risk. However, the count of days above the infection risk threshold, was greater in autumn than summer under the T+4 and T+5 scenarios, suggesting that summer conditions were less favourable than autumn, either driven by upper temperature or lower moisture limits potentially being approached in summer. Because none of the temperature scenarios predict temperatures above the optimum for the latent period (28 ^{o}C), the latent period does not decline with any of the scenarios. Therefore, the less favourable summer conditions are likely due to a moisture unavailability.

The patterns of change are most interesting in the areas and seasons of marginally suitable conditions, for example, areas which currently experience suboptimal or marginally optimal temperatures for infection, which, with the climate change predictions, steeply approach optimal conditions (the steep edges of the temperature and moisture relationships in Figure 1 and 2). For example the predicted large amounts of change in risk in the regions around the Southern Alps, which are regions also likely to be native estate or conservation land, where susceptible Myrtaceae hosts may be present.

4.1 Infection risk

The largest increases in mean infection risk with increased temperature scenarios were in seasons which were previously temperature limited (winter, spring), bringing them into the favourable temperature range, and these seasons would not typically be moisture limited. There were no detectable decreases in mean infection risk, nor did the mean infection risk reach high – very high even with the most extreme scenario tested, T+5, although there were periods within the season which were in these risk categories for substantial periods of time (up to 76% of days above 0.5 threshold, Figure 6). Thus, highlighting the variability around the mean infection risk, and the number of days above the threshold could be considered a more sensitive risk indication than the seasonal mean.

The largest changes in maximum infection risk were in the currently cooler months, whereas the maximum infection risk did not change for areas already experiencing high risk. While the changes between scenarios were sometimes large in magnitude, these did not always result in risk over the threshold or an increase in the risk category. Thus, there are still areas of the country, even under the most extreme climate change scenario tested here, which could retain seasonal low risk, particularly in the South Island. These areas could be looked at in conjunction with Myrtaceae distribution (and future distribution) to inform infection risk to proposed host refugia areas (McCarthy et al 2020).

4.1.1 Sensitivity and RH

The additional analysis into the impact of changes in RH opened up a number of new questions, particularly around the sensitivity and uncertainty of climate predictions with respect to humidity changes. Moisture availability is important for many pathogen dynamics, and it is poorly understood how the sensitivity of change in RH with temperature and rainfall will be meaningful to future pathogen risk. This is particularly important when understanding the interaction between temperature and moisture on the infection risk, due to their often opposing effects on the infection risk.

These uncertainties around prediction are also likely to be most important in areas of marginal current risk and increased future risk, rather than areas which are already high risk (i.e. much of the north of the North Island). Because the high risk areas remain high, while the marginal risk areas there are uncertainties of the magnitude of change in risk.

Given the investigation into the sensitivity of predictions for the West Coast, with uncertain changes in RH, the risk for the West Coast in this report is potentially underestimated. Because the mean seasonal decreases in RH may not always apply to the West Coast and an increase in moisture in conjunction with the increase in temperatures into optimal temperature ranges would increase the infection risk substantially (Figure 1, Figure 4).

This highlights the need for future predictions of changes in RH to improve accuracy around the areas of the large and variable directions of change in RH around the west coast of the South Island and the Southern Alps (Figure 3). In this report, the mean from Nelson (41.5^{o}S) was taken, where all areas are predicted to have a decrease in %RH with increased temperature. While seasonal differences were incorporated (more change in %RH per ^{o}C for the currently cooler seasons), any potential increases in RH in some seasons for areas such as the west coast were not taken into account. Future work will need to incorporate these subtleties to better address risk areas such as the west coast of the South Island where there are both Myrtaceae present and the potential for increased risk from increased wet conditions.

4.2 Latent period

The greatest changes in the latent period were shown in southern New Zealand, where only a small increase in temperature within the range of 10–15 degrees, results in large decreases in latent period length, as predicted by the latent period and temperature relationships (Figure 2). The changes in the north are less because these regions are often already within the 15–30 day range, which has little variation in latency within these temperatures (already favourable conditions).

The myrtle rust epidemic can progress rapidly when latent periods are around 10–15 days (Beresford et al 2020). Therefore, in some areas, particularly under the T+2-5 scenarios, epidemics could carry on cycling right through the winter, whereas under the current climate only the far north has much of the winter season above the minimum temperature for latent development, with the rest of the country only experiencing a few days above this threshold in winter. The temperature increase scenarios provide an environment where the shorter latent period shifts the disease dynamics to be more like epidemic dynamics observed in Queensland, Australia, with epidemics continuing through the winter season (Beresford et al. 2020). Thus, the host plants have less chance of recovery periods, with no significant break from continuous infection and re-infection cycles. In Queensland, however, hot summer conditions (>30 ^{o}C) limit myrtle rust epidemic development and the most severe disease is observed in the other seasons.

4.3 Host growth, phenology and distribution

Other factors which need to be quantified in the future to assess their effect on risk include host density, host growth and pathogen spore load (Beresford et al. 2018). Ontogenetic resistance is closely linked to leaf expansion which is crucial to explaining the seasonality of MR development in the natural environment, therefore an inclusion of plant phenological stages would be helpful, and the recognition that these periods could also change with climate change scenarios. Climate change will influence plant growth seasons, which in turn will affect actual infection risk. Changes in plant vigour also change the susceptibility of the host (seasonal availability of young growth), therefore factors such as water availability or nutrients may also be important when considering the susceptibility to rust (Beresford et al. 2020). Therefore, for a more detailed approach, when predictions relevant to these factors influencing the disease dynamics are available at a scale meaningful to infection risk prediction, other variables which are predicted to change with climate change scenarios such as Potential Evaporation Deficit, Available Water Capacity and wind may also be important to facilitate understanding of actual risk (MFE 2018).

Furthermore, incorporating a comparison of climatic risk to Myrtaceae host plant distributions, particularly highly susceptible hosts, will be useful, because there are areas within New Zealand where these host plants are not found which is not accounted for in these current risk predictions.

4.4 Limitations

One limitation of the delta temperature offsets approach is that although it provides a good general trend in disease risk with increase in temperature, it does not capture the variability, extreme events, plant stress (or growth) and relative susceptibility or plant damage (from weather events) which could increase infection risk or shorten latent periods.

Using a mean seasonal approach also smooths out aseasonal extreme events, which may have large impacts on subsequent disease dynamics. This is also dependent on the relative risk within the season when extreme events might occur. Tropical cyclones are likely to play a role, particularly in providing more moisture during the warmer months, heightening disease risk conditions.

4.5 Conclusions

In conclusion, for the five climate change scenarios tested in this report, conditions for both shorter latent periods and increased infection risk increase for myrtle rust. These scenarios indicate that increased temperatures have a stronger effect on myrtle rust future predictions than predicted changes in RH, and within these scenarios, the conditions remain and increase optimal conditions for infection and development of myrtle rust. While there are some uncertainties around areas where RH changes are difficult to predict (such as areas of predicted increased rainfall), this effect should be localised and minor compared to the large increases in risk due to temperature increases for the rest of the country. However, more work is needed in the sensitivity of RH, because at optimum temperatures, an increase in moisture availability can have a large impact, therefore high risk areas around the west coast of the South Island are likely to be underestimated in the scenarios explored in this report.

4.6 Recommendations

Future work should address these key points:

- Future work should map uncertainties so that the degree of confidence in predictions for different locations and areas can be visualised.
- The west coast of the South Island is potentially the most interesting region for change in risk for myrtle rust, but also the area with the greatest uncertainty for predicted changes in RH. There are known susceptible plants in this region, but to date, little surveillance information has been available.
- There is scope to improve the understanding of climate change variables relating to disease risk and disease cycles. In particular variables related to moisture availability, plant phenology and host availability/susceptibility.
- Higher resolution RCMs are expected in the next few years (current report used 30 km resolution, next planned available to 12 km resolution), which will improve the resolution of subsequent climate change and risk models.

5 References

Beresford RM & McKay AH, 2012. Climate change impacts on plant diseases affecting New Zealand horticulture. A report prepared for: MPI & MSI; Client Project No. C11X1102. Plant & Food Research: Contract No. 27718; SPTS No. 7532. https://www.agriculture.govt.nz/dmsdocument/4085/direct downloaded 20 April 2020.

Beresford RM, Turner R, Tait A, Paul V, Macara G, Yu ZD, Lima L, Martin R, 2018. Predicting climatic risk of myrtle rust during its first year in New Zealand. NZ Plant Prot 71: 332 – 347.

Beresford RM, Shuey LS, Pegg GS, 2020. Symptom development and latent period of *Austropuccinia psidii* (myrtle rust) in relation to host species, temperature, and ontogenetic resistance. Plant Pathol 00: 1 – 11.

Byrne, MP & O'Gorman PA, 2016. Understanding Decreases in Land Relative Humidity with Global Warming: Conceptual Model and GCM Simulations. Journal of Climate 29.24: 9045–9061.

Caffarra A, Rinaldia M, Eccela E, Rossi V, Pertota I, 2012. Modelling the impact of climate change on the interaction between grapevine and its pests and pathogens: European grapevine moth and powdery mildew. Agriculture, Ecosystems & Environment 148: 89-101. Doi: https://doi.org/10.1016/j.agee.2011.11.017.

Carbon Brief, 2018. https://www.carbonbrief.org/explainer-what-climate-models-tell-us-about-future-rainfall. Accessed 29 April 2020.

Dai A, 2006. Recent climatology, variability, and trends in global surface humidity. Journal of Climate 19(15): 3589 – 3606.

Fischer E & Knutti R, 2012, Robust projections of combined humidity and temperature extremes. Nature: Climate Change: DOI 10.1038/NCLIMATE1682.

Glen M, Alfenas AC, Zauza EAV, Wingfield MJ, Mohammed C, 2007. *Puccinia psidii*: a threat to the Australian environment and economy – a review. Australasian Plant Pathology, 36: 1–16.

Gratani L, 2014. Plant Phenotypic Plasticity in Response to Environmental Factors. Advances in Botany Volume 2014, Article ID 208747, 17 pages http://dx.doi.org/10.1155/2014/208747.

McCarthy JK, Wiser SK, Bellingham PJ, Beresford RM, Campbell RE, Turner R, Richardson SJ, 2020. Using spatial models to identify refugia and guide restoration in response to an invasive plant pathogen. Journal of applied Ecology 00:1 – 10. DOI: 10.1111/1365-2664.13756.

MfE, 2017. Stocktake Report from the Climate Change Adaptation Technical Working Group. ISBN: 978-1-98-852527-3. https://www.mfe.govt.nz/sites/default/files/media/Climate%20Change/adapting-to-climate-change-stocktake-tag-report.pdf.

MfE, 2018. Climate Change Projections for New Zealand: Atmosphere Projections Based on Simulations from the IPCC Fifth Assessment, 2nd Edition. Wellington: Ministry for the Environment. https://www.mfe.govt.nz/sites/default/files/media/Climate%20Change/Climate-change-projections-2nd-edition-final.pdf downloaded 24 April 2020.

Oksanen E, Lihavainen J, Keinänen M, 2018. Northern Forest Trees Under Increasing Atmospheric Humidity. In: Cánovas F., Lüttge U., Matyssek R., Pretzsch H. (eds) Progress in Botany Vol. 80. Progress in Botany, vol 80. Springer, Cham. https://doi.org/10.1007/124_2017_15.

Randers J & Goluke U. 2020. An earth system model shows self-sustained melting of permafrost even if all man-made GHG emissions stop in 2020. *Scientific Reports* 10. https://doi.org/10.1038/s41598-020-75481-z.

Simmons A., Willett K, Jones P, Thorne P, Dee D, 2010. Low-frequency variation in surface atmospheric humidity, temperature, and precipitation: Inferences from reanalyses and monthly gridded observational data sets. Journal of Geophysical Research 115: DOI:10.1029/2009JD012442.

Tang X, Cao X, Xu X, Jiang Y, Luo Y, Ma Z, Fan J, Zhou Y. 2017. Effects of Climate Change on Epidemics of Powdery Mildew in Winter Wheat in China. https://doi.org/10.1094/PDIS-02-17-0168-RE.

Toome-Heller M, Ho WWH, Ganley RJ, Elliott CEA, Quinn B, Pearson HG, Alexander BJR, 2020. Chasing myrtle rust in New Zealand: host range and distribution over the first year after invasion. Australasian Plant Pathology 49:221–230. https://doi.org/10.1007/s13313-020-00694-9.

Zhang P., J. Zhang, and M. Chen, 2017, Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation. Journal of Environmental Economics and Management 83: 8-31.

Appendices

Appendix 1

From MfE, 2018. Climate Change Projections for New Zealand: Atmosphere Projections Based on Simulations from the IPCC Fifth Assessment, 2nd Edition. Wellington: Ministry for the Environment. https://www.mfe.govt.nz/sites/default/files/media/Climate%20Change/Climate-change-projections-2nd-edition-final.pdf downloaded 24 April 2020.

A) Most common temperature and precipitation prediction patterns over 24 and 26 (respectively) models assessed. Temperature in degrees Celsius change (contours every 0.1ºC), precipitation in percent change (contours every 4%) (Figure 5). These images gives an indication of the context for the 1-5^{o}C change scenarios and the relative locations of increased moisture from precipitation.

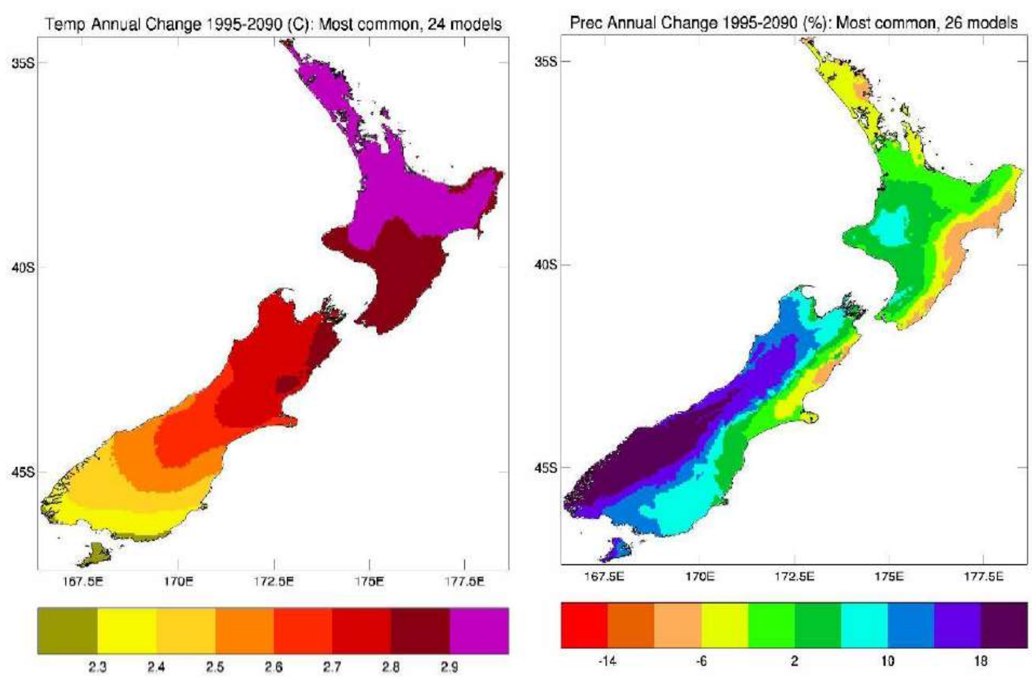

Figure A1. The most common patterns of annual temperatire (left) and precipitation (right) change between 1995 (1986 – 2005) and 2090 (2081 – 2100), as assessed from the statistical downscaling results. The temperature pattern is the ensemble average of 24 models, and precipitation of 26 models (out of 41), for the 2090 projected changes under RCP8.5.

B) Temperature increase scenarios selected for this report (increase of 1, 2, 3, 4, 5 ^{o}C) encompass the range of predictions, RCP scenarios and projected time scales tested in the MFE 2018 report (Figure 7), including the encompassing the levels of uncertainty (Figure 34).

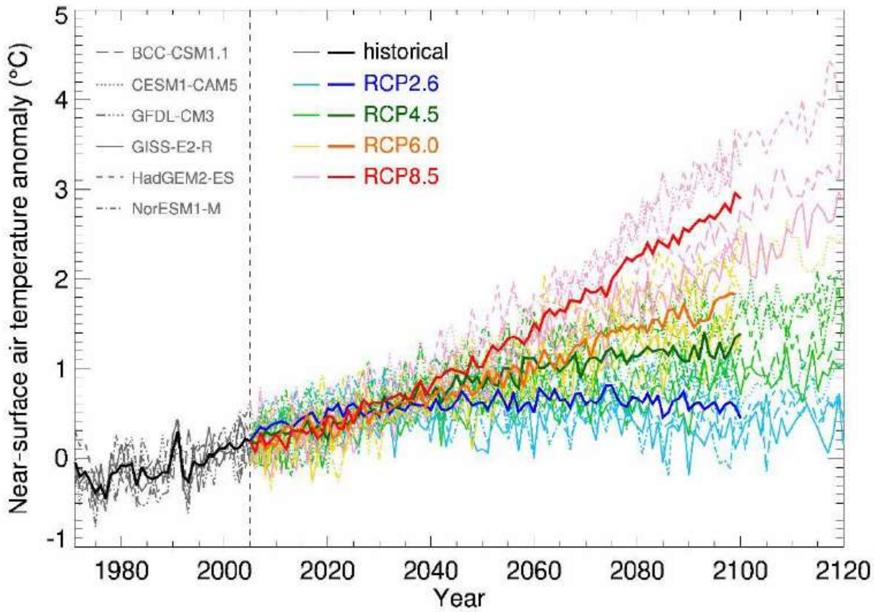

Figure A2. Projected New Zealand-average temperature relative to 1986 – 2005, for six CMIP5 global climate models, and for the historical simulations (here 1971 – 2005) and four future simulations (RCPs 2.6, 4.5, 6.0 and 8.5).

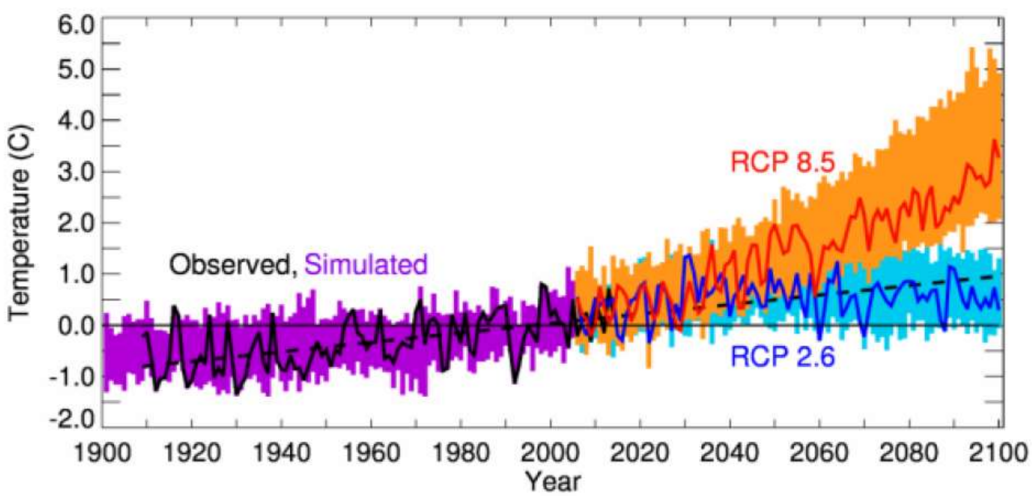

Figure A3. Time series of air temperature anomalies: seven-station series of New Zealand land temperature (black line) and its linear extrapolation to 2100 (dashed black line); historical air temperatures over the New Zealand 'box' for 1900 – 2005 (purple histogram), as simulated by 41 GCMs: simulations of future projected New Zealand box air temperatures for RCP2.6 (blue) and RCP8.5 (orange).

Appendix 2

Myrtle-rust-accounting-for-humidity-changes-discussion.pdf.

This document details literature review and raw methods for how RH changes were accounted for in the climate change scenarios.

Appendix 3

Readme-spring-RH-scenarios_2_SON_JJA.docx.

Notes on methods and files detailing the sensitivity analysis of mean infection risk, maximum infection risk and count of days of infection risk above threshold, including corresponding change files. For two seasons (spring, SON and winter, JJA).

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