Manaaki Whenua
Landcare Research

Climate change impacts on land use suitability

Prepared for: Deep South and Our Land and Water National Science Challenges

August 2019

The University of Waikato
Te Whare Wānanga o Waikato

Te Pūnaha Matatini
Data ▪ Knowledge ▪ Insight

GNS Science
Te Pū Ao

Plant & Food Research
Rangahau Ahumara Kai

agresearch
āta mātai, mātai whetū

Our Land and Water
Toitū te Whenua, Toiora te Wai
National Science Challenges

The Deep South
Te Kōmata o Te Tonga
National Science Challenges

Climate change impacts on land use suitability

Contract Report: LC3573

Anne-Gaelle Ausseil[1], Tony van der Weerden[2], Mike Beare[3], Edmar Teixeira[3], Troy Baisden[5], Mark Lieffering[2], Jing Guo[1], Liz Keller[4], Richard Law[1], Alasdair Noble[2]

[1]Manaaki Whenua – Landcare Research

[2]AgResearch

[3]Plant and Food Research

[4]GNS Science

[5]University of Waikato

Reviewed by:	*Approved for release by:*
Peter Edwards Researcher Manaaki Whenua – Landcare Research	Suzie Greenhalgh Portfolio Leader – Supporting Business & Policy Manaaki Whenua – Landcare Research

Contents

Summary and highlights

- This project ran for 2 years and was a partnership between two National Science Challenges: Our Land and Water, and Deep South. The common aim was to assist land managers and natural resource planners to assess the resilience of agricultural land uses across New Zealand and to inform decision making for land and water management regarding future climate.
- This project explored the likely impact of climate on the suitability of some primary production activities. It had two aims:
  - to identify the climate attributes influencing the productivity and the impacts on receiving environments,
  - to explore future climate projections to understand the potential impacts of long-term average changes and droughts on production and receiving environments.
- We evaluated a range of simple to complex biophysical models (including climate indices, WATYIELD, Biome-BGC, APSIM) to simulate several production systems (pasture, crop, horticulture) and project into the future the changes in some production attributes and the impacts on receiving environments, in particular nitrate leaching.
- Three spatial scales were tested: point-scale for application of complex biophysical modelling (APSIM) in three regions (Hawke's Bay, Southland, Waikato), regional scale (Hawkes Bay for moderately complex biophysical models (Biome-BGC and WATYIELD) and national scale for simple climate indices.
- Through this modelling exercise and statistical analysis, we identified and ranked some key attributes influencing pasture production:
  - Analysis of the APSIM-based modelling results showed that 82% of the variation in annual pasture production could be explained, with climate attributes accounting for 45% of the variability
  - For the Biome-BGC-based modelling results, a similar degree of variation was explained (89%), with most of this variation explained by the climate attributes.
- We also explored key climate attributes that could influence nitrogen (N) leaching events. A preliminary analysis showed that:
  - the influence of climate attributes varied across soil types and regions. However, one attribute in particular, the Standardised Potential Evapotranspiration index averaged over 3 months from July to September (SPEI3-Sept) showed some consistency in explaining N leaching, pointing to a provisional attribute to consider for further analysis.
- Long-term (mid to end of century) and extreme event impacts for the three studied sectors are summarised in the table below, with key points in the following paragraphs.

	Production	Receiving environments
Pastoral farming	Shift in production towards spring Higher yields with increasing RCP trajectory (3 locations) In the Hawke's Bay: reduction in yield during summer in some locations (West and North), increase in yield in spring everywhere Livestock: higher risk of heat stress for animals, especially in the Waikato, Wairarapa and Canterbury plains	Higher variability in N leaching depending on soil types Higher water demand in the Waikato, no change in Southland In the Hawke's Bay: higher water limitation during spring and summer (especially West of the region)
Arable crops (maize and catch crop wheat)	**Maize:** Earlier sowing date for maize silage across regions, leading to higher catch crop yields No change in maize yield after accounting for earlier sowing date Higher soil N uptake	**Maize:** Higher variability in N leaching (frequency and magnitude) Higher water demand in Waikato, Hawke's Bay More variability in water demand in Southland
Horticultural crops (perennial)	**Wine grape:** Earlier flowering time across New Zealand, leading to higher risk on wine quality	**Kiwifruit:** Higher water demand in the Waikato and Hawke's Bay More variability in water demand in Southland

- Long-term average changes in climate were analysed for pastoral systems.
  - For the 3 locations in Hawke's Bay, Waikato and Southland, using APSIM future yields were greater than present yields, with increasing Representative Concentration Pathways (RCP) trajectory. Increases were greatest and least variable in Southland, and lowest and more variable in Hawke's Bay. More importantly, we showed changes in the projected distribution of pasture growth. Towards the end of the century, the projected growth rates showed a marked increase in late spring/early summer, with a decrease in late summer (January and February) especially in the Waikato and Hawke's Bay case studies. Southland shows a general monthly growth rate increase except during winter.
  - For the Hawke's Bay region using Biome-BGC, results were consistent with the complex biophysical model APSIM. Annual pasture yield increased in all scenarios, with a seasonal shift (more production in spring, and less in late spring-summer). However, the western side of Hawke's Bay looked more affected by the loss of production in summer. Despite the overall increase in yield, there is a trend towards increasing water limitation, which could have implications for irrigation and water demand in a region that is already prone to drought.
- For maize production, the assumed adaptation of sowing dates and maize genotype implied that the two crops experiences different magnitudes of warming during growth due to climate change. For an end of century period, this ranged from 0.2°C in the Hawke's Bay up to 2.1°C for the catch crop wheat in Waikato. Maize crops were sown around 3 weeks earlier for end of century RCP8.5 compared to the baseline. This enables earlier sowing of the next crop (catch crop wheat), which enables longer growth periods and higher yields during winter. Climate change had minimal effects on maize yields except for a slight increase in Hawke's Bay. In contrast, catch crop wheat increased by about 3 t/ha with the highest emission scenario.

- Wine grapes – Maps of flowering dates were produced for the whole country using the Grape Flowering Veraison model. The climate change projections and the increase in average temperature is estimated to shift the flowering date. Results for the sauvignon blanc variety show a shift by up to 2 weeks before the baseline flowering date. The model that was developed is spatially explicit, and can explore different varieties, allowing some future analyses on which variety may be more suitable to grow in the different parts of the country.
- Heat stress index – heat stress is an increased risk for animal health that may be of concern in the future. The risk is more prevalent for RCP8.5 than RCP2.6, with up to two more weeks of moderate heat stress, spread across the country. For severe heat stress, the risk is also increasing for all RCPs, with more pronounced risk towards the end of the century. The change in average days per year for RCP8.5 is more pronounced in regions that are already at risk, in particular: along the coast of the Hawke's Bay and Gisborne areas, mid-Canterbury, central Otago and central North Island.
- We explored the potential consequences of future climate scenarios on nitrate leaching for pasture and maize cropping:
  - Nitrate leaching for the three locations showed that in all cases, nitrate leaching tended to be higher and more variable with increasing RCP trajectory. The most noticeable changes were in Southland where leaching may increase from 5 to 25 kg N-NO3 ha^{-1} yr^{-1}. Variability in results was also due to the soil type. In Hawke's Bay, the Ruataniwha soil tend to have lower leaching level due to an impenetrable pan. In contrast, the Waimakariri soil tended to have the highest and most extreme year-to-year variability.
  - Maize. Estimates of N leaching at 90-cm depth were very variable. The inter-annual variability was shown to be a key metric to consider as N leaching losses could be more affected by extreme events without necessarily large changes in median values.
- Changes in water stress on production due to drought:
  - We tested several drought indices against annual pasture biomass production. The ability of the seasonal SPEI values to explain annual pasture dry matter production was very variable across locations, soil types and Global Climate Models (GCMs). For instance, the seasonal SPEI could explain up to 61% of pasture growth results in the Hawkes Bay soil that did not have an impeded layer.
  - At a regional scale, the modelled pasture production is particularly sensitive to changes in precipitation. The relative soil moisture was used as an indicator of drier-than-average conditions. The indicator varied greatly between GCMs, with some GCMs (e.g. HaGEM-2, GFDL and CESM1) showing drier soil conditions towards the end of the century. However, this indicator did not correlate well with pasture yield, suggesting that other factors (such as CO_2 fertilisation) may dominate the plant response in the model.
  - changes in water stress risk for maize production system differed among locations, crops and soils in the different climate change scenarios. More drought-prone rainfed systems occurred in Hawke's Bay where crops had about 30% of their water demand fulfilled. Catch crops were less affected due to their growth during late autumn/winter.

- The water balance model WATYIELD highlighted an increase in all regions in the Potential Evapotranspiration Deficit (PED), an indicator of water demand for crops. The increase was more prominent in the Waikato and Southland region with increases up to 40% from the baseline. The Hawke's Bay is already a region with high PED, with changes in future climate projection highlighting even more water demand.
- Adaptation can involve tactical, strategic or transformational changes. For dairy farming, short-term tactical changes include bringing in feed or installing irrigation. For sheep and beef farming systems, changes are more difficult in the hill country where topography prevents tactical fertiliser use or irrigation. Strategic changes involve changing a current system to another known system, e.g. changing the ratio of sheep to cattle or increasing lambing percentage and can take many years. All these potential changes may alter the level of impacts on receiving environments. Results for arable crops highlight the relevance of accounting for crop management, which can be seen as a representation of farmer tactic adaptation on climate change impacts. In addition, insights on the importance of soil types, and how they are represented in biophysical simulations, are also key results from our analysis. Some soils will be naturally more prone to the increase in drought conditions, but final outcomes depend on management aspects (e.g. use of irrigation and changes to sowing dates).
- For perennial crops such as wine grapes, the effect of climate change on phenology may require a change in cultivar, with grape varieties adapted to warmer climate. One area of concern is the compressed time for fruit growth and the implications for sugar content and ultimately wine quality. Tactical adaptation may require controlling the vegetative/floral balance through winter pruning, or additional pruning in summer. However, the warmer climate may also open new areas suitable for wine grapes that were previously too cool. The model and script that was developed is spatially explicit, and can explore different varieties, allowing some future analyses on which variety may be more suitable to grow in different parts of the country. With the increased risk of water shortage, especially in regions such as Hawke's Bay, better use of irrigation water will be a necessity.
- Our results highlighted the need to better understand the implications of future climate on receiving environment: preliminary results show that there is a risk of increased water demand that will put pressure on freshwater ecosystems, especially in the Hawke's Bay region. Nitrate leaching events may also be more variable and more extreme with the increase in extreme rainfall events. The soil type is a crucial element that contributes to the likelihood of leaching events. For example, the magnitude and frequency of high N leaching events might increase if high rainfall amounts occur more often before catch crop establishment (early in the autumn/winter season).
- We recommend continuing the work undertaken here through a continued partnership between Our Land and Water and Deep South National Science Challenge, to better understand relative land use suitability in the context of climate change. In particular, future areas of work should include:
    - continuing to explore the influence of climate attributes on nitrate leaching, including timing of extreme events
    - continuing to explore the likely impacts and implications of drought in regions most at risk

- broadening the perspective on receiving environments by looking at the potential impacts on sediment loss, phosphorus loss and faecal contaminants.

Glossary and definitions

AET Actual ET, derived from WATYIELD using NIWA's PET data.

AET-PET Actual ET - potential ET, derived from WATYIELD.

ET – PET The difference between actual evapotranspiration (ET) and potential evapotranspiration (PET) per season. Sourced as an output from the Biome-BGC model

GCM General Circulation Models. Six GCMs have been selected for dynamical downscaling for New Zealand climates

BCC-CSM1.1
CESM1-CAM5
GFDL-CM3
GISSE2-R
HadGEM2-ES
NorESM1-M

GDD (growing degree days) Accumulated heat units above a certain base temperature.

GLF (Growth Limiting Factor – Water) Calculated in APSIM. Water Supply as a Growth Limiting Factor, where 0 = no effect and 1 = high effect (note that this value is the opposite to GLF as outputted by APSIM).

PCP Annual rainfall (precipitation), obtained from NIWA climate data.

PED Potential Evapotranspiration Deficit, defined as the difference between estimated evapotranspiration and rainfall. Values were derived from WATYIELD.

PET Annual potential evapotranspiration, obtained from NIWA climate data.

RAW Readily available water, obtained from S-map.

Relative Soil Moisture Average soil moisture as a fraction of field capacity, presented on a seasonal basis. Sourced as an output from the Biome-BGC model.

SPEI (Standardised Potential Evapotranspiration Index) The Standardized Precipitation Evapotranspiration Index (**SPEI**) is an extension of the widely used Standardized Precipitation Index (SPI). The **SPEI** is designed to take into account both precipitation and potential evapotranspiration (PET) in determining drought (Vicente-Serrano & National Center for Atmospheric Research Staff 2015).

TAW Total available water, obtained from S-map.

1 Introduction and background

Future climate is likely to have a major impact on primary sectors and has the potential to drive major shifts in land use as previously suitable and viable climatic conditions change.

1.1 Production/contaminant losses are important

Sustainable productivity has two requirements, sustained productivity (potentially quantified as yield and/or profitability) of primary enterprises, and sustained achievement of environmental objectives at the site of production and in downstream receiving environments. These two requirements are frequently in conflict and have resulted in undesirable environmental outcomes (Arpaia et al. 2004; Parris 2011; McDowell et al. 2016). To minimise conflicts between productivity and environmental objectives, land-use decisions should be more closely based on information about land suitability, crop and stock requirements, and in particular risks of contaminant loss from land.

The attributes and constraints of climate and land (soil, topography and hydrology) are all primary factors affecting productivity potential under different land uses. Climate and land factors also interact with land use to affect the export of contaminants to adjoining receiving environments (e.g. nitrate leaching to groundwater, sediment and phosphorus losses, faecal contaminants). As climate is an important determinant of the physiological potential of plants to produce biomass and of the risk of losses to receiving environments, it is essential to factor in the added complexity of a changing climate and the suitability of land for certain activities. In the past, research in New Zealand has focused on the long-term effect of climate change on productivity for some key primary sectors including pastoral farming, cropping (maize) and forestry. This was investigated during the Climate Change Impacts and Implications (CCII) research programme (2012–16). A series of outputs included downscaled climate scenarios for New Zealand, based on the latest Global Circulation Models (GCM), biophysical and economic models, and scenarios of New Zealand futures under a range of emissions, policy and socioeconomic pathways. However, the programme had limited in-depth analysis of model outputs and did not focus on extreme events, looking instead at long-term climate change effects on primary production.

1.2 National Science Challenge background

In this context, two National Science Challenges have teamed up to address this issue. The OLW National Science Challenge is charged with the development of tools that assist land managers and natural resource planners to predict the suitability of land for different uses in different environmental settings. The land use suitability (LUS) concept has been defined as a framework for assessing the suitability of land for primary production that acknowledges and accounts for the connections between land use and economic, environmental, social, and cultural impacts (McDowell et al. 2018). These researchers recently expanded the land use suitability concept to include productivity within environmental constraints, with a particular focus on water quality outcomes. Their framework encompasses the productivity potential of land parcels, their contribution of contaminants to downstream receiving environments and the pressure imposed by those contaminants in the receiving environments. There are plans to further develop and refine the LUS concept in Tranche 2 of the OLW National Science Challenge.

The Deep South (DS) National Science Challenge, on the other hand, aims to enable New Zealanders to adapt, manage risk and thrive in a changing climate. Part of this includes understanding the potential impacts and implications of climate change to support planning and decision-making. Primary production is the backbone of New Zealand's economy, and there is an opportunity to bring both challenges together to consider impacts of climate change on land use suitability. Our chief aim is to assess where and how climate change needs to be considered in long-term policy such as the National Policy Statement on Freshwater Management (NPS-FM) and forecasting trends and variability in agricultural production. To achieve this, a project was built as a partnership between the OLW and DS National Science Challenges. The aim is to include the effects of climate change impacts (long-term climate change and extreme events such as droughts) within the land use suitability tools, to assess the resilience of agricultural land uses across New Zealand and to inform decision making for land and water management with regard to future climate.

This report summarises the outcomes from this project that ran from March 2017 to June 2019.

2 Objectives

The primary aim of this research project is to answer the question: 'how will future climate impact on land use suitability?'. In this project, we endeavoured to identify climate attributes that strongly underpin land use suitability, and test how these attributes would change under future climate scenarios, with some conclusions on both biophysical and socio-economic implications. This knowledge will help to fill important gaps by addressing both the impacts of extreme events and effects of longer-term climate change impacts on Land Use Suitability by encompassing impacts on productivity as well as losses of contaminants to receiving environments.

Ideally, complex biophysical models would be applied at any point in the landscape and for various crop systems. However, there is no single model for the different agricultural systems, and the models available in New Zealand are time-consuming to run and are still being actively developed by the research community. We therefore took a tiered approach to fill the knowledge gap in both production and impacts on the environment, by using a suite of simple to complex models and test their utility to inform decision makers on future projections.

This report addresses two main goals:

- Identify climate attributes (both for changes in average seasonal patterns and drought) that may affect production and impacts to receiving environment in selected crops and variables
- Model the impacts of climate change on a selection of production and impact to the environment variables and crops at point, region, national scale.

3 Methods

3.1 Overarching framework

We have investigated a range of metrics that would explain how climate may influence land use suitability in terms of production or impact on receiving environments through simple to complex biophysical models. While complex biophysical models may be closer to reality, they are more demanding for input data and processing time. They offer, however, a better insight into the management adaptation options that might be available to farmers. Simple metrics or bioclimatic models are less demanding and can be run on a larger scale. They do not reflect management practices variation but can inform on generic trends at a sectoral level (Fig. 1).

In our case, we chose to apply the APSIM model that has been extensively developed for pastoral systems and maize cropping. It is a highly complex but well-supported modelling platform in the research space. Because it is data-intensive, we restricted the modelling runs to three locations in the Hawke's Bay, Waikato and Southland region.

For the horticultural sector, limited resources prevented us from using a complex biophysical model such as SPASMO. We therefore developed bioclimatic indices at national scale to inform on the general trends (Figure 1 and Table 1).

Table 1. Model input requirements and level of complexity

Model	Complexity	Process	CO2 fertilisation	Management
APSIM	High	✓	✓	✓
Biome-BGC	Intermediate	✓	✓	✗
WATYIELD	Intermediate	✓	✗	✗
Bioclimatic indices	Low	✗	✗	✗

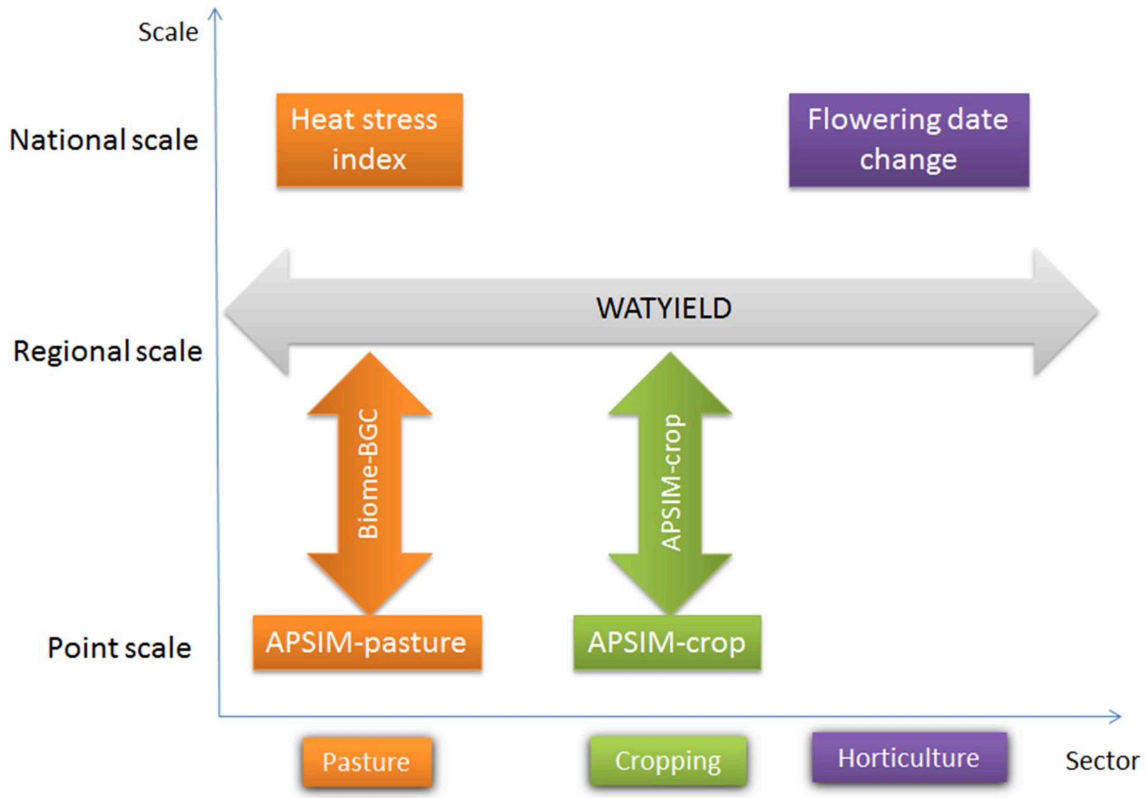


Figure 1. Scope of analyses: scale vs models used per sector.

The future climate will likely impact primary production in terms of changes to the mean climate (temperature, CO_2 concentration and rainfall patterns), but also changes to extreme temperature and drought frequency (Table 2). For long-term changes, we investigated the impact of future climate on production (pasture, maize), phenology (wine grape), and nitrate leaching (pasture maize). For the drought and extreme event issue, this report could not cover all potential impacts in all sectors, but has investigated drought impacts on production (pasture, maize), water demand (pasture, maize, kiwifruit) and looked at the potential impact of heat stress on animals.

Table 2. Scope of impact results

	Production	Receiving environment
Long-term changes to weather patterns	Impact of future climate projections on yield, growth rates (pasture, maize) (section 4.1.1 and 4.1.2) Impact of temperature changes on wine phenology (Section 4.3.2)	Impact on nitrate leaching (pasture, maize) (section 4.1.1 and 4.1.2)
Changes in extreme events (drought, hot days)	Impact of drought events on pasture growth (Section 4.1.1 and 4.2.1) Impact of temperature and humidity changes on heat stress for animals (Section 4.3.1)	Impact of drought events on water demand (Section 4.1.3 and 4.2.2)

3.1.1 Description of biophysical models

3.1.1.1 APSIM – methodology

Pasture parameterisation

The daily time-step Agricultural Production Systems Simulator (APSIM; Holzworth et al., 2014) was used to simulate both pasture and crops. To simulate pasture production under past and future climates, we used the multi-species AgPasture module in APSIM (v. 7.10). APSIM links AgPasture to other modules which provide climate data, soil water and nutrient dynamics, plant and animal organic matter returns, and manipulation of grazing management. The main processes used to simulate plant growth in AgPasture are given in detail in Li et al. (2011); this paper also demonstrates the module's ability to simulate pasture systems in New Zealand accurately across a wide range of soil types and climates. In addition, AgPasture has been validated using data from a long-running free-air CO_2 enrichment (FACE) experiment and has been shown to adequately simulate both intra- and inter-annual variations in response to elevated CO_2 (Li et al. 2013). The effects of increasing atmospheric CO_2 concentration are included in AgPasture by re-parameterising three key functions: plant photosynthesis and respiration, plant N demand and plant stomatal conductance. The parameter values, which depend on the atmospheric CO_2 concentration, were taken from relevant literature (see Li et al. 2013).

For all point locations, the pastures were modelled as a mixed pasture of *Lolium perenne* (perennial ryegrass) and *Trifolium repens* (white clover). Default parameter values for both species were used. For each location two soils were modelled; these were parameterised using APSIM-ready S-map files provided by Manaaki Whenua Landcare Research https://smap.landcareresearch.co.nz/) (section 5.2.1). Pasture management was the same for the three locations: the pasture was grazed when the standing pasture biomass reached 2500 kg DM ha^{-1} for all months except in winter (May, June and July) when the target was set to 2000 kg DM ha^{-1}; The simulated animals were removed when pasture biomass was grazed down to 1400 kg DM ha^{-1} in all months except in winter when it was set to 1700 kg DM ha^{-1}. In all cases the stocking rate was the equivalent of pasture being consumed at the rate of 350 kg DM ha^{-1} d^{-1}. This protocol approximates that used by farmers to maximise both pasture productivity and quality. Simulated nutrient return through deposition of dung and urine was evenly spread across the pasture; note that as is usual for New Zealand hill country farms, the only de novo input of N in the model is from N fixation by clovers. Also, P was not explicitly modelled and was assumed to be non-limiting.

Outputs from APSIM used in this report included daily pasture growth rates and amount of material harvested with the latter being summed on an annual basis. The leaching of NO_3- was also simulated.

Maize/catch crop wheat parameterisation

For crops, APSIM v 7.10 was set up to simulate annual yields of a continuous silage-maize/catch-crop wheat rotation in response to daily weather inputs in each location. Similar to Teixeira et al. (2018), we consider the effect of farmers' tactical adaptation to climate change through two genotype choices (short- and long-cycle hybrids) and movable sowing date in response to temperature. Thermal-time accumulation (degree-days, °C d) from emergence to end-of-juvenile period ("tt_emerg_to_endjuv" APSIM-maize parameter) were set at 130°Cd for the short-cycle hybrids and 250°Cd for long-cycle hybrids. For the adaptation of sowing dates, we assume that farmers prioritize the spring crop (silage maize), so that the sowing and harvest of the winter catch crop are subjected to optimum harvest or termination time of maize crops. Automated sowing rules that assume that farmers sow the maize crop as early as possible from 1 September (early-spring) to 1 January (mid-summer) once the 15-day running mean air temperature is >13°C. These heuristic rules mimic expected farmer's adaptations to changing weather and climate by advancing sowing dates under warmer conditions. Delays in sowing due to excessive soil wetness were captured by constraining sowing on rainy days (> 10 mm rain) or when soils were saturated (i.e. soil moisture 5% higher than plant available water capacity in the top 150 mm). For catch crop wheat (C_3 species), growth rates were assumed to increase with atmospheric CO_2 concentration, adjusted by temperature, by scaling radiation use efficiency (RUE) as per APSIM-wheat default parameterization (O'Leary et al. 2015). In contrast, no CO_2 impact on RUE was considered for silage maize (C_4 species) and RUE is empirically adjusted by air temperature as per APSIM-maize default parameterization. For both crops, transpiration efficiency (TE) was arbitrarily assumed to increase to a maximum of 37% at atmospheric CO_2 concentrations of 700 ppm, in relation to a 350-ppm baseline.

3.1.1.2 Biome-BGC

The Biome-BGC model v4.2 (Thornton et al. 2002, 2005) was used to model point location and regional pasture productivity for New Zealand managed grassland systems under future climate change scenarios. The Biome-BGC model is an ecosystem process model that simulates the biological and physical processes controlling fluxes of carbon, nitrogen (N) and water in vegetation and soil in terrestrial ecosystems. The model includes the CO_2 fertilization effect that enhances both the rate of photosynthesis and reduces water loss in plants under elevated atmospheric CO_2 concentrations. Climate inputs include daily minimum and maximum air temperature, precipitation, vapour pressure deficit, wind, and solar radiation. Soil is modelled as a single layer with site-specific texture and rooting depth inputs. The model runs at a daily time step.

We adapted Biome-BGC to represent two typical New Zealand managed grassland systems: "Sheep & Beef" (low intensity) and "Dairy" (high intensity). Although the Biome-BGC model does not explicitly simulate managed grasslands or animal grazing, we modified and re-interpreted key ecological parameters from the model's built-in C3 grasslands mode to represent the effects of management and the presence of grazing animals on pasture productivity (Keller et al. 2014). Dairy systems receive more N inputs (to simulate more fertiliser use), more grass is eaten (in the form of increased whole-plant mortality), and more animal products (i.e. carbon in milk or meat) are extracted and removed from the system. Irrigation and nitrate leaching are not simulated in either system. Model parameters were calibrated using observations of pasture growth and historic climate at six locations in New Zealand and validated for both dairy and sheep systems (Keller et al. 2014).

For this project, we used the Biome-BGC Sheep & Beef parameterization for all locations and scenarios. This is likely an underestimate of productivity in the areas that are dominated by intense dairy farming. However, our results are given in terms of change in productivity relative to present-day (RCP past), thus minimizing the effect of biases in the absolute levels of pasture growth. This also allows us to better isolate the climate effect on pasture growth without the effect of management interventions. The reference or 'baseline' pasture production for each GCM is an average over the nominal years 1986–2005. For all future scenarios, the model was first 'spun up' to an equilibrium steady state using RCP past climate, and then restarted and run as a transient simulation from 2005 to 2100 using each model- and RCP-specific projected climate.

3.1.1.3 WATYIELD

The Water-Balance model is designed for calculating the water deficit in soil for crop growth. It is developed based on the WATYIELD (a water balance bucket model developed by Manaaki Whenua – Landcare Research (MWLR), FAO-56 (Guidelines for computing crop water requirements) report as well as the SWAT model (developed by USDA) (see appendix 1).

- Soil Moisture Deficit (SMD) – the amount of rain needed to bring the soil moisture content back to field capacity.

The SMD on day i is given by the difference between field capacity and SWC at that day:

$$SMDi = TAW - SWCi \tag{1}$$

When SWC_i is at the field capacity, the minimum value for the SMD_i is 0. At the moment that SWC_i reach WP, the SMD_i will have it maximum value TAW. Therefore, the limits on SMD_i is:

$$0 \leq SMD_i \leq TAW \tag{2}$$

- Evapotranspiration Deficit (ET_cD) - is the total amount of water that is not available for a crop to have an unstressed transpiration process.

The $ETcD$ is the difference between the demand and the available water. It is calculated by comparing the difference between the crop evapotranspiration under standard condition (ET_c) and the actual crop evapotranspiration (AET_c).

$$ET_cD_{\ i} = ET_{c\ i} - AET_{c\ i} \tag{3}$$

The limits on $ET_cD_{\ i}$ is:

$$0 \leq ET_cD_{\ i} \leq ET_{c\ i} \tag{4}$$

The parameterisation of WATYIELD includes the soil properties (TAW and RAW), interception fraction and the crop coefficients. We tested WATYIELD on four land covers: forest, kiwifruit, pasture and maize (Table 3). For kiwifruit, since this perennial crop has deciduous leaves during winter, we only recorded the PED for the period of November to March, when the vine is actively producing.

Table 3. Parameterisation of WATYIELD for selected crop covers

	Pasture	Maize	Kiwifruit	Forest
Crop coefficient (Kc)	1	0.8	1.05 (Nov–March)	0.7
Interception Fraction (IF)	0	0.1	0.15	0.3
Interception Storage Capability (ISC)	0.5	0.5	3	6

3.1.1.4 Bioclimatic indices

Heat stress index

To estimate the potential heat stress on animals, we used the Temperature-Humidity Index (THI) that has long been established (Johnson et al, 1962). THI has been shown to be strongly correlated to reduced milk production and is therefore a useful indicator for farmers for tactical adaptation required in future.

THI was calculated using the formula (NRC 1971):

$$(1.8 * MaxT + 32) - (0.55 - 0.0055 * RelHum) * (1.8 * MaxT - 26.8) \qquad (5)$$

With *MaxT* the daily maximum temperature, *RelHum* the daily relative humidity.

We followed a similar methodology to Nidumolu et al. (2014) in Australia. The THI was defined for:

- Moderate heat stress: where THI is greater than 78
- Severe heat stress: where THI is greater than 82

We then computed raster layers for the current period (1986–2005), mid-century (2046–2060) and end of century (2080–2100) that represent the average number of days per year mild, moderate or severe heat stress per year within the period. Period boundaries are inclusive. This was repeated for each of the four RCPs. Three GCMs were considered (CESM1-CAM5, HadGEM2-ES, and NorESM1-M); the indicators are presented only for CESM1-CAM5. The other GCMS (BCC-CSM1.1, GFDL-CM3, and GISS-EL-R) were unable to be considered due to a lack of relative humidity data.

Phenology change for wine grape

Temperature is known to be a fundamental driver of plant physiology and phenological stages for wine grapes. While there are some process-based phenological models that describe the influence of temperature on the different growth stages of a vine, they are only available on a point basis and require too many input variables.

As an alternative, we used an empirical relationship between cumulative temperature and date of flowering developed by Parker et al (2011). The Grape Flowering Veraison model (GFV) was calibrated and validated in New Zealand. The GFV model is based on the growing degree day model, with the best fit to predict the flowering date (denoted F*) being the summation of degree-days from the 242nd day of the calendar year (typically the 30th of August), with a base temperature (Tb) of 0°C. We created a Python workflow that:

1 calculates cumulative daily mean temperature (ignoring days where mean temperature is < Tb) from NIWA climate data (daily minimum and maximum temperature), for the period 1979–2120, for all RCPs and GCMs, with t_0=242 (corresponding to the 29/30th August) for any given (non-calendar) year.

2 for a set of integer values of F* *[1120, 1411]*°C, calculates annual values of grapevine flowering (expressed as an integer representing the number of days since t_0). The output resolution is identical to the input climate data and covers all of mainland NZ (including Waiheke).

3 for selected periods (early, mid- and late-century), determines the average flowering date across the period, as an integer for each cell, without interpolation. Areas not capable or not suitable for wine production are masked. We therefore removed any land use capability (LUC) class ≥ 6, as well as individual classes 3w, 4w, and 5w). The same mask is used for all periods. This is likely to be a liberal estimate of land that is suitable for viticulture, and certainly represents land that is not currently used for viticulture.

3.1.2 Identification of climate attributes

3.1.2.1 Initial expert consultation

A wide range of key climate variables relevant to climate change impacts on production and the receiving environments, for different agricultural sectors, were initially identified through consultation with experts and stakeholders at a workshop held on 17 March 2017 (Beare et al. 2017). For production, 18 climate variables were identified (e.g. seasonal temperature, number of hot days, seasonal rainfall) (Table 4). In contrast, four climate variables were identified as being potentially relevant to losses to receiving environments (Table 5). At a general level, seasonal variables were of greater value than annual variables when relating climate to production.

Table 4. Range of climate attributes potentially impacting on production, identified through consultation with experts and a stakeholder workshop (see Beare et al. 2017)

Climate variable - general	Climate variable – specific
Temperature	Seasonal mean
	No. hot days/season
	Number of hot nights/season
	Growing degree days/season or year
Rainfall	Seasonal mean
	Increased No. wet days
	Increased No. dry days
Drought	Length of dry season
	Frequency of successive droughts
Extreme wind speed	Seasonal % change
Relative Humidity	Seasonal % change
Solar radiation	Seasonal % change
Plant Available Water (PAW)	= Rain – ET
Vapour pressure deficit	
Hail	
Reliability of water supply	
Temperature and moisture	
Vernalisation	

Table 5. Range of climate attributes potentially impacting on the environment, identified at a stakeholder workshop (see Beare et al. 2017)

Climate variable – general	Climate variable – specific
High intensity rainfall	Seasonal % change
Cumulative drought + cumulative wet/cold	Post drought abruption metric (PDM)
Soil temperature and moisture	
Extreme wind	

Climate variables were further refined to a list of 16 relevant to production and eight relevant to N leaching (Table 6) through a series of project team meetings and data analyses. The degree of complexity for deriving climate attribute values ('Tier', see Table 7) was considered when selecting the final list to be included in the statistical analysis for examining the influence of climate attributes on production and N leaching. Some metrics were simply NIWA outputs (e.g. air temperature) while others were outputs from the process-based models described in section 5.1.1 (e.g. cumulative deep drainage, derived from APSIM).

Table 6. Final list of climate attributes for statistical analysis with modelled yield (above ground biomass production) and N leaching, derived from APSIM and Biome-BGC. Tier value refers to the degree of complexity for deriving values. Y refers to attributes and time scales used for subsequent data analysis

Climate attribute	Tier*	Time scale				Potential Effect (P = production, RE = receiving environment)
		Monthly	Calendar Seasonal	Crop seasonal	Annual	
T annual Air temperature	1		Y	Y		P
GDD (base 7,10)	2		Y	Y	Y	P
Growth Limiting Factor (GLF) – water	3		Y	Y	Y	P
Cumulative deep drainage (mm)	3				Y	P
Number of frost days	1			Y	Y	P
Number of hot days above 25°C	1	Y				P
Total chill hours in winter	1		Y			P
PCP (Annual precipitation)	1	Y				P, RE
PET (Potential evapotranspiration)	1	Y				P, RE
AET (Actual evapotranspiration)	3	Y				P, RE
AET – PET	3	Y				P, RE
SPEI (Standardised Potential Evapotranspiration Index)	2	Y				P, RE
ET-PET	3		Y			P, RE
Relative Soil Moisture	3		Y			P, RE
SoilDev						P, RE
Potential Evapotranspiration Deficit (PED) (mm)	3		Y	Y	Y	P

* see Table 7 for Tier definition

Table 7. Tiers were defined based on the level of input required

Tier	Definition
T1	A raw variable coming from the VCSN (e.g. precipitation or PET)
T2	Bioclimatic indices purely derived from T1 data (e.g. SPEI, growing degree days)
T3	Indices derived from a model that includes dynamic soil and climate characteristics (e.g. Apsim, Biome-BGC or WATYIELD)

3.1.2.2 Statistical analysis

Production

To understand and attribute variance from complex models explained by simpler models, we examined the past plus RCP2.5 RCP4.5 and RCP8.5 in the six soils across the three regions. After regularising the annualised dataset to include periods covered by all models, the past included the years 1971–2003 and the future RCP covered 2006–2098. Stepwise selection of variables was performed in JMP v14.3, SAS Institute, USA. A full suite of available metrics was entered into backwards stepwise regression for selection at stringent p-value of 10^{-15} to minimise the number of and correlation between selected parameters for the final multiple regression. The multiple regression results were used to attribute explained variance.

N leaching

To analyse the variability in modelled N leaching, data was visually assessed to aid with determining which attributes could potentially be applied at a national scale. This was conducted by producing a series of colour-coded plots showing the effect of the eight climate attributes (Table 6) on modelled N leaching from pastures, sourced from the annualised dataset collated for the production analysis (see above).

Results of the visual assessment were to be used for the next phase of the data analysis – development of a generalised mixed effects linear model – to determine the degree of variation that could be explained by the climate attributes, along with other non-climate factors such as year, RCP, GCM and soil. However, due to limited resourcing, this phase of the analysis could not be completed within the current project.

3.2 Case study area

3.2.1 Point location

During the course of the project, it was decided to run the APSIM model, and record results from the other models (Biome-BGC and WATYIELD) in three contrasting regions of New Zealand. The regions of interest were Hawke's Bay, Southland and Waikato.

The three regions would likely have contrasting climate change projections, with the Hawke's Bay region more likely to experience an increased number of drought events. The climate variables were derived from the previous Climate Change Impacts and Implications research programme (Tait et al. 2016). Climate outcomes based on RCPs are modelled via the Coupled Model Inter-comparison Project (CMIP5) using General Circulation Models (GCM). We used six GCMs (BCC-CSM1.1, CESM1-CAM5, GFDL-CM3, GISSE2-R, HadGEM2-ES, and NorESM1-M). The output variables were precipitation, maximum and minimum air temperature, relative humidity, vapour pressure, solar radiation, and wind speed. Each variable was calculated on a regular grid (0.05°, approximately 5 km) using the Virtual Climate Stations (VCS) from NIWA at a daily, monthly, and annual temporal resolution for the 1971–2100 period (Tait & Turner 2005) (Fig. 2).

Figure 2 Study areas (red dots show the three locations chosen for the point-scale case study).

We then chose a VCSN grid point that would include at least two contrasting soils in terms of drainage, with a flat topography that would suit both cropping and pastoral farming, so that the effect of soil could also be analysed (Table 8).

Table 8. Description of soil and VCSN grid used for the point analysis

Region	AGENTNO (VCSN)	New Zealand Soil Classification*			Total Available Water (TAW) (mm)	Readily Available Water (RAW (mm)	Comments
		NZSC Soil group	Family_ Sibling	Drainage class			
Hawke's Bay	31080 lat -39.675 long 176.725	Duric Perch-gley Pallic	Ruataniwha _13a.1	Poorly drained	87	40	
		Weathered Fluvial Recent	Waimakariri _55b.2	Well drained	134	78	
Waikato	29259 lat -37.825 long 175.375	Typic Orthic Gley	Pukehina_8 a1	Poorly drained	220	88	Te Kowhai soil impeded layer
		Typic Orthic Allophanic	Ngakura_8a 1	Well drained	151	61	Horotiu soil: good soil
Southland	10731 lat -46.225 long 168.325	Typic Frim Brown	Waikiwi_30 a1	Well drained	189	61	Edendale soil: rolling deep
		Argillic-fragic Perch-gley Pallic	Pukemutu_ 6a1	Poorly drained	96	37	

*Hewitt, 2010

3.2.2 Regional case study

For the regional-scale analysis, we chose to focus on the Hawke's Bay region. This is in part to complement a concurrent project funded by the SLMACC (Sustainable Land Management, Adaptation and Climate Change) programme from MPI entitled 'Applied adaptation pathways: supporting robust regional decision-making: an application in Hawke's Bay'. This project is looking at the decision-making process and future pathways for adapting agriculture practices and major infrastructure needs in the face of climate change. It is a region of interest also because of the increased risk of drought events, thus giving our project an opportunity to test how production and receiving environments may respond to more frequent drought events.

We examined how some key climatic attributes would vary spatially using WATYIELD and Biome-BGC. Biome-BGC was examined for the whole Hawke's Bay region. The soil in each grid cell was parameterized with percentage clay, silt, and sand sourced from the Fundamental Soil Data Layers (FSL; Landcare Research 2010 https://lris.scinfo.org.nz/layer/48079-fsl-new-zealand-soil-classification/).

For the influence of crop cover on water balance, we used the WATYIELD model for the Karamu catchment within the Hawkes Bay, as this was one of the specific case studies of the

SLMACC project on “dynamic pathways for adaptation” (Fig. 3). The soil information required to run WATYIELD includes TAW and RAW. These values were derived from Smap, using the most dominant sibling within a polygon.

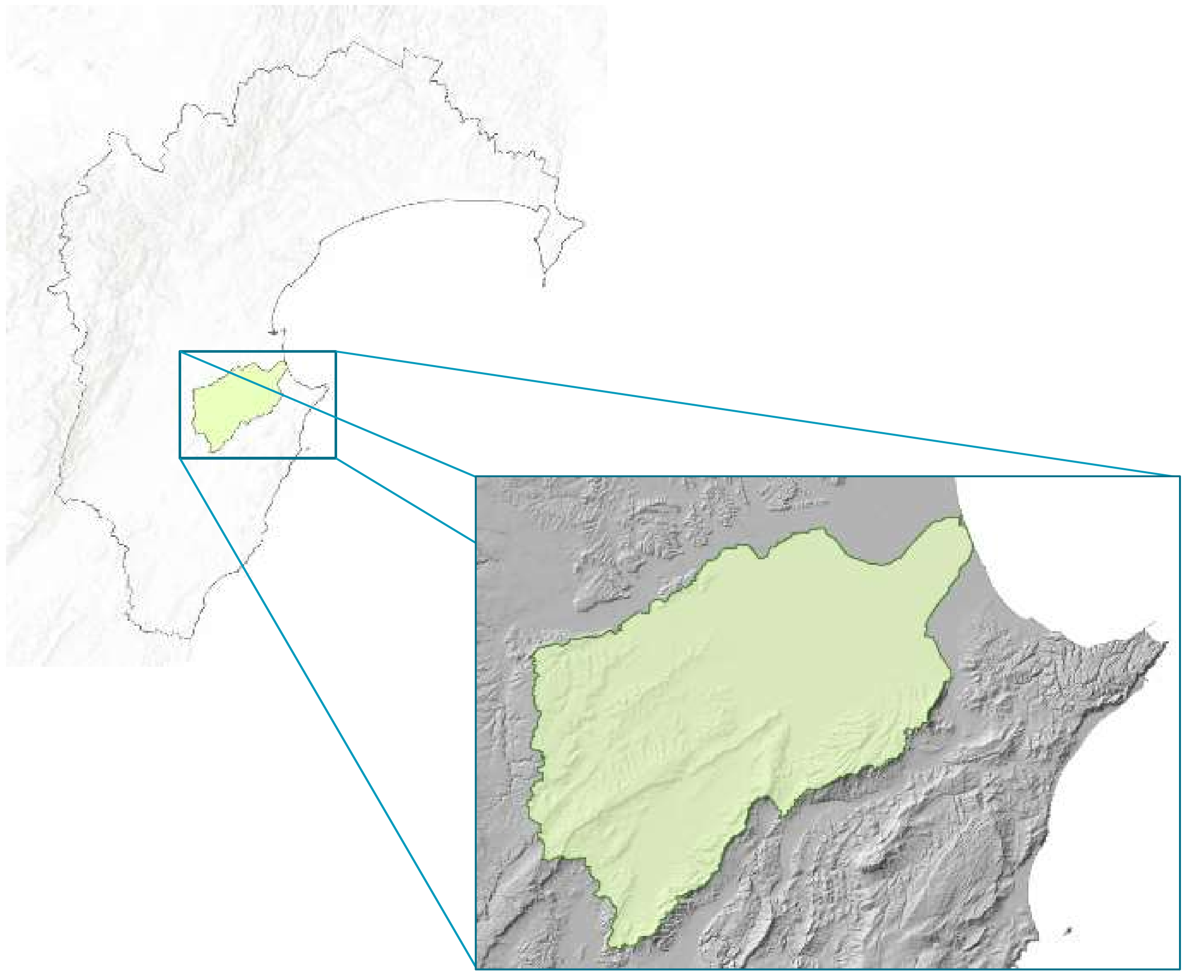


Figure 3. Location of the Karamu catchment for the WATYIELD runs.

4 Results

4.1 Point-based analysis

4.1.1 APSIM results pasture

4.1.1.1 Long-term changes

Figure 4 shows the APSIM modelled dry matter yields for the pastures at the 3 locations x 2 soils and 3 RCPs (plus the present; RCPPa) at mid-century and end of century. In all cases, future yields were greater than the present, with only small differences between the mid- and end-century periods. In most cases, yield increased with increasing greenhouse gas concentration trajectory (RCP). Among the regions, increases in yield were greatest and least variable in Southland and lowest and more variable in Hawke's Bay. However, relative to the median, Southland tended to have more extreme low yields while Hawke's Bay had more extreme high yields.

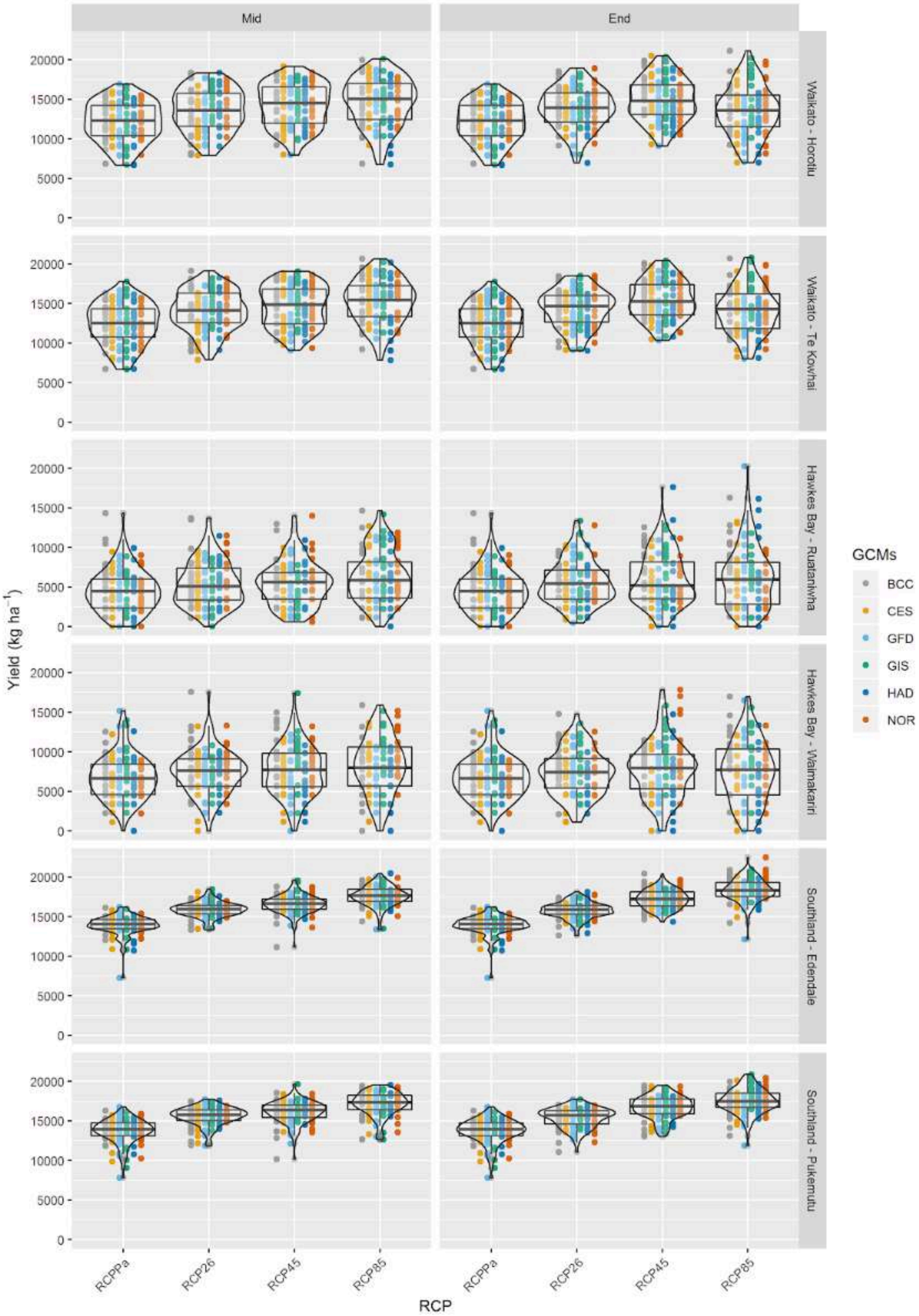


Figure 4. Annual pasture production for the three locations (Waikato, Hawkes Bay and Southland) and the two soils at each location under current conditions (RCPPa) and the three RCPs at mid- and end of the century. Dots represent the six GCMs ("columns") and 20 years ("rows").

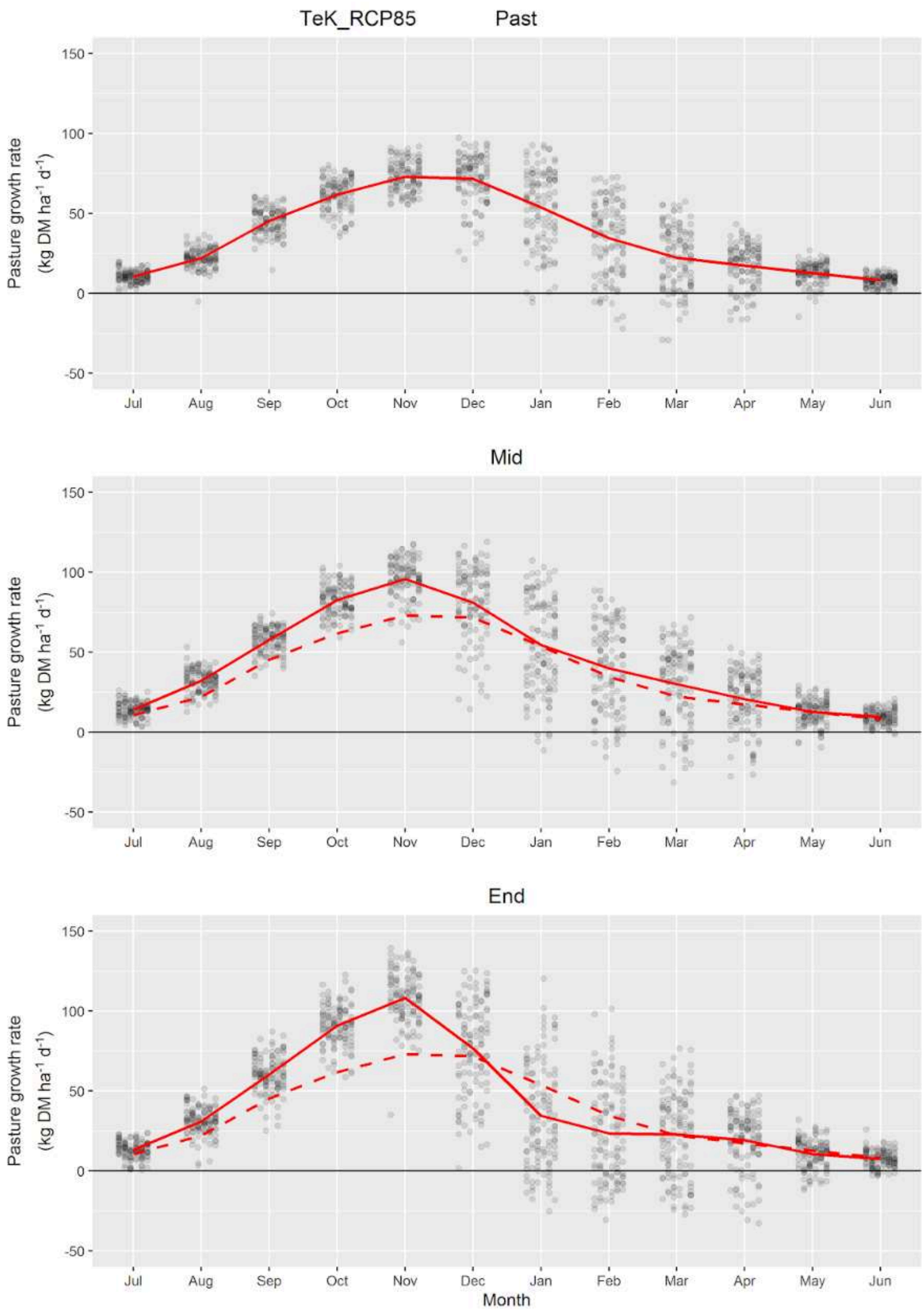


Figure 5. Representative Current (Past), mid-century (Mid) and end of the century (End) monthly pasture growth curve changes in one of the locations/soils (Waikato/Te Kowhai soil) under RCP8.5. Dots represent the six GCMs ("columns") and 20 years ("rows") with no colour coding. Dashed lines in Mid and End panels is the current growth curve.

In addition to changes in projected annual yield, of equal and possibly more importance from the farm system point of view, are the changes in the distribution of pasture growth. To illustrate this impact, we have focused on results for RCP8.5, which represents climate projections under a business-as-usual scenario. As representative of these changes for Hawke's Bay and Waikato modelled, Figure 5 shows the monthly pasture growth curve changes in one of the locations/soils (Waikato/Te Kowhai soil) under RCP8.5 at three time slices ("Past", "Mid" and "End"). The top panel ("Past") shows a typical present-day pasture growth curve with peak growth rates in the late spring and early summer. This curve is shown in the future panels ("Mid" and "End") as the dashed line. As time progresses to the end of century there is a marked increase in the peak growth in late spring/early summer, in this case increasing from about 75 kg DM ha^{-1} d^{-1} to over 100 DM ha^{-1} d^{-1}. Importantly, there is a decrease in growth in late summer (January and February). Of additional significance is the increase in year-to-year variability in growth rates especially in the summer.

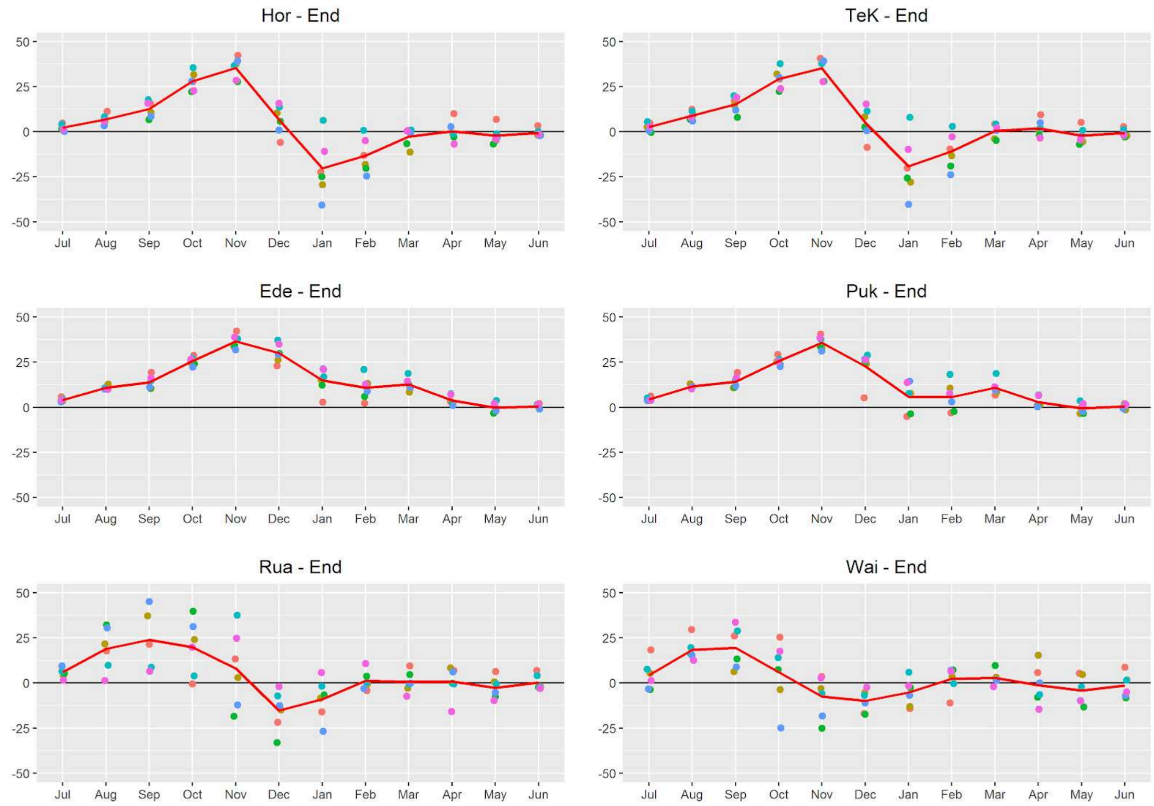


Figure 6. Changes in monthly pasture growth rates at end of century under RCP8.5 for all locations. Dots represent the average 20 years growth rate for each month for the six GCMs.

The changes in monthly growth rates at the end of century for all locations are summarised in Figure 6. For Waikato ("Hor" and "TeK") and Hawke's Bay ("Rua" and "Wai") the changes described above (increased spring and decreased summer growth rates) are clearly evident. For Southland ("Ede" and "Puk"), monthly growth rates are generally increased at all times of the year except in winter. If changes in farm management systems in response to these projected changes are not made in a timely manner, there is the possibility of profound effects on farm financial viability. Some of these tactical, strategic and transformational adaptations are outlined in the discussion.

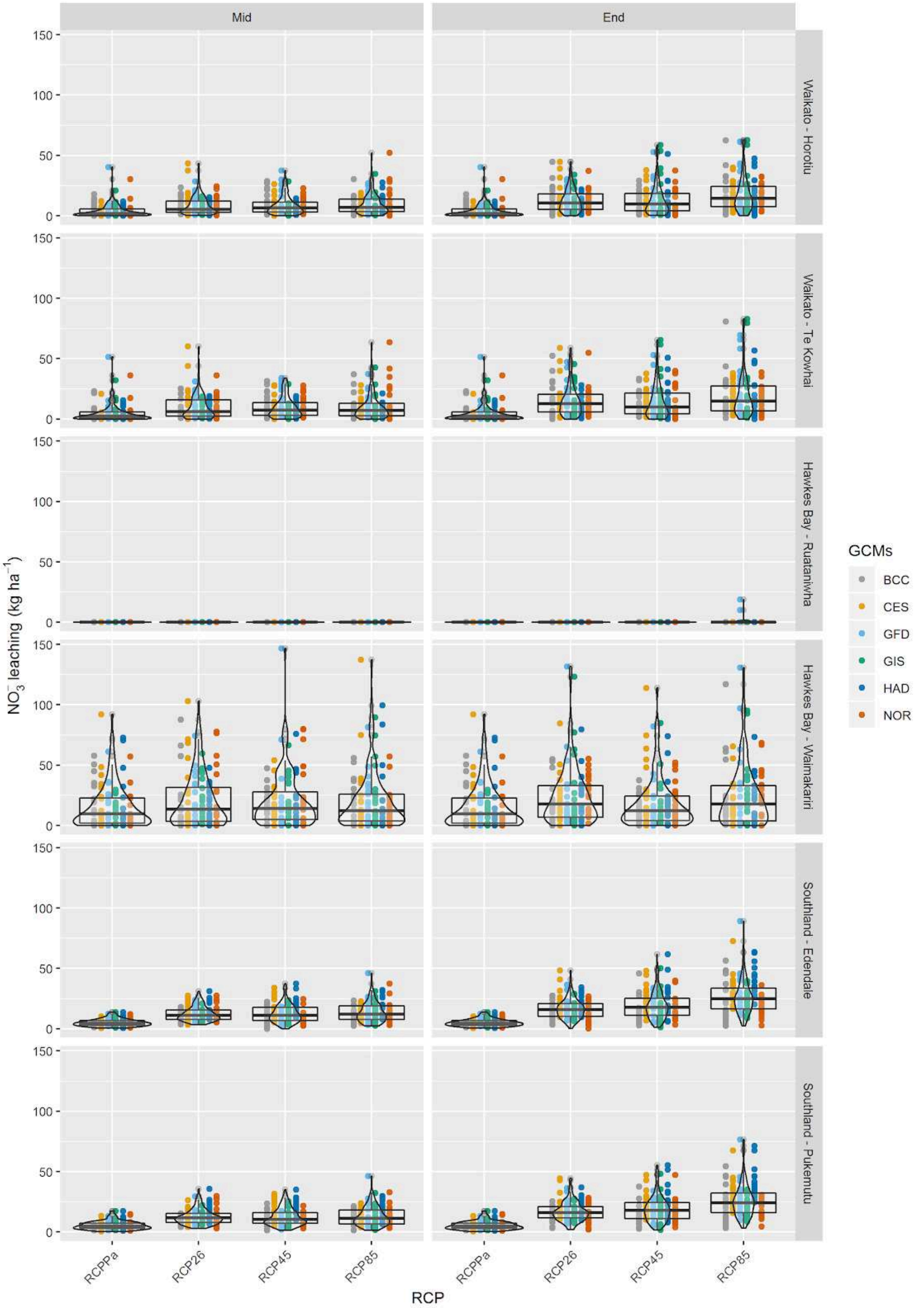


Figure 7. Annual nitrate leaching for the three locations (Waikato, Hawkes Bay and Southland) and the two soils at each location under current conditions (RCPPa) and the three RCPs at mid- and end of the century. Dots represent the six GCMs ("columns") and 20 years ("rows").

Figure 7 shows the changes in nitrate leaching for all locations in a similar fashion to Figure 5. The Rua soil in Hawke's Bay is notable in that leaching levels are very low due to it having an impenetrable pan. In contrast, the Hawke's Bay soil Wai tended to have the highest and most extreme year-to-year variability. In all cases, nitrate leaching was greater both in the future and with increasing greenhouse gas concentration trajectory (RCP). The most noticeable changes with increasing RCP were in Southland whereby the end of the century leaching increased from about 5 to 25 kg $N\text{-}NO_3$ ha^{-1} y^{-1}.

4.1.1.2 Drought impact

We selected GCMs that represented some increasing drought issues in the future in the Hawke's Bay region. These are shown as increasing negative difference from the usual distribution of precipitation and evapotranspiration over time, but to variable degrees (Fig. 8). As for long-term changes (section 5.1.1.1), we have focused on results for RCP 8.5, which represents climate projections under a business-as-usual scenario. For RCP8.5, there is a general negative trend for SPEI that infers less precipitation than normal.

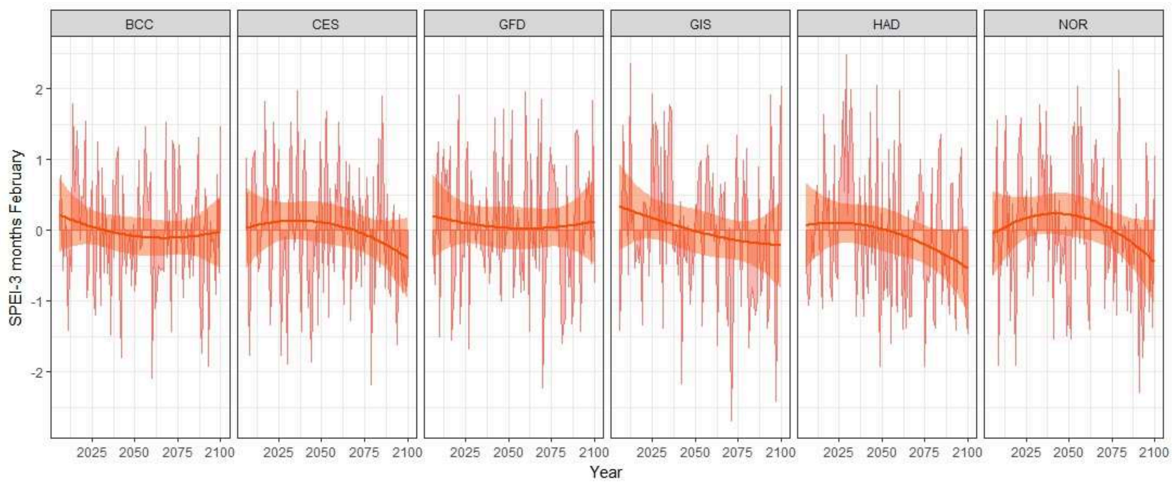


Figure 8. Example of SPEI for different GCMs, Hawke's Bay, cumulated over 3 months before February.

For pastures, we also tried to use the concept of SPEI to see if it could act as a simple predictor of modelled annual pasture dry matter production. To do this, for RCP8.5 for all GCMs and locations from 2006 to 2100, we took the seasonal SPEI3 values for winter, spring, summer, and autumn (corresponding to the SPEI3 values for August, November, February, and May respectively). These values were regressed against modelled annual dry matter production; model selection and multi-model inference were conducted using the R package glmulti. We used multi-model inference as we did not want to make inferences about the importance of the four SPEI3 predictors in terms of a single 'best' model but rather across all possible models (after considering their relative explanatory weights).

Figure 9 shows one of the better models fits: for the Wai soil in the Hawke's Bay using the CES GCM, using the four seasonal SPEI3 values, simulated dry matter production is predicted quite well with an R^2 of about 61%. Conversely, Figure 11 shows a situation (the Puk soil in Southland with the GIS GCM) where the seasonal SPEI3 values could not predict simulated annual dry matter production.

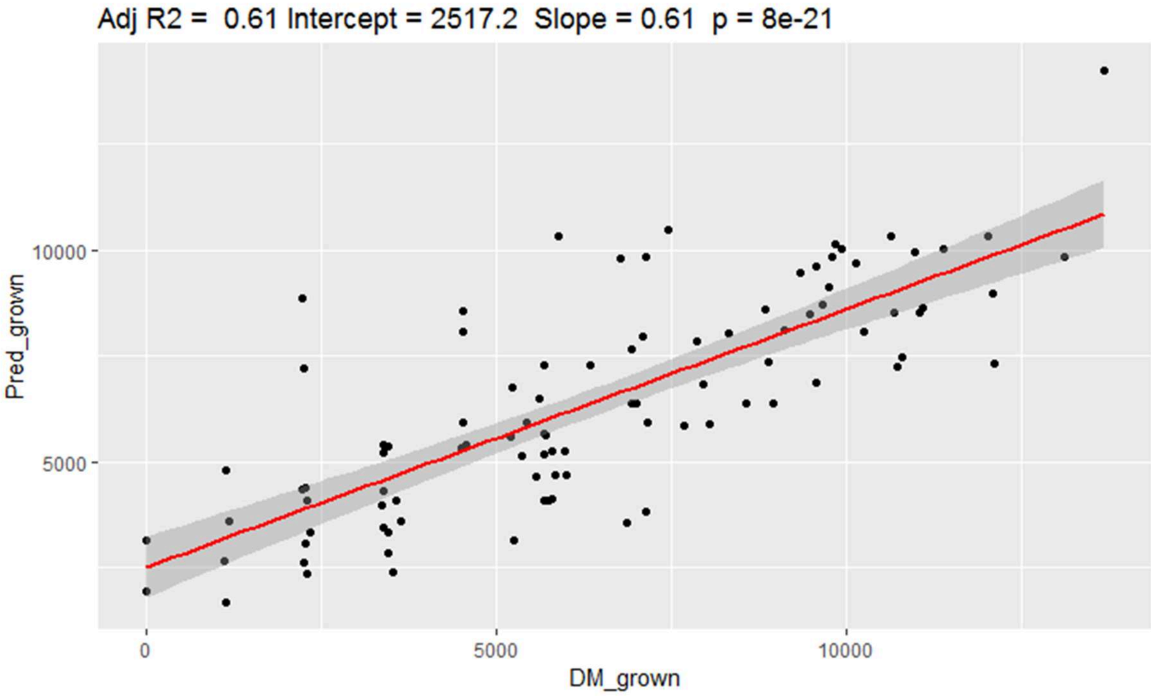


Figure 9. Linear regression between annual dry matter production simulated by APSIM (DM_grown) and that calculated from the multi-model regression (Pred_grown) based on the SPEI3 values for four seasons (winter, spring, summer, and autumn, i.e. SPEI3-August, SPEI3-November, SPEI3-February, SPEI3-May respectively), for the Waimakariri soil in Hawke's Bay, under RCP8.5, GCM CESM1-EM.

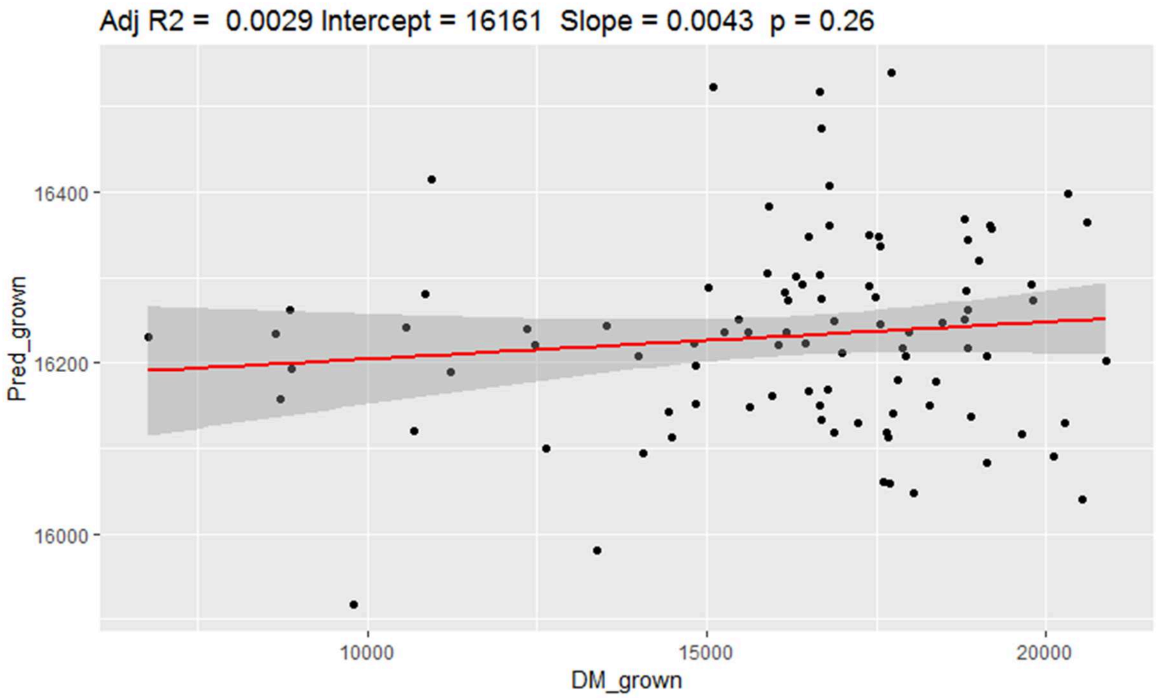


Figure 10. Linear regression between annual dry matter production simulated by APSIM (DM_grown) and that calculated from the multi-model regression (Pred_grown) based on the SPEI3 values for four seasons (winter, spring, summer, and autumn, i.e. SPEI3-August, SPEI3-November, SPEI3-February, SPEI3-May respectively), for the Puk soil in Southland, under RCP8.5, GCM CESM1-EM.

The ability of the seasonal SPEI3 values to predict simulated annual pasture dry matter productions for the different locations and GCMs are summarised in Table 9. There are clear differences between the locations/soils as well as the GCMs. Overall prediction was poor in Southland and intermediate in the Waikato. For Hawke's Bay, the technique worked well for the Wai soil (R2s from 44% to 61%) but not so well for the Rua soil. These differences are likely to be largely to the importance of rainfall to plant growth (e.g. Southland vs Hawke's Bay) though other constraints, such as the impeding pan in the Rua soil affecting the results. There were also marked differences between the GCMs with for example, GIS being ranked lowest in all locations/soils.

Table 9. R^2 values of the best multi-model regression of seasonal SPEI3 values and simulated pasture dry matter production for the six location/soils and six GCMs. Colour coding indicate good (green) to poor (red) fits

		GCM					
		BCC	**CES**	**GFD**	**GIS**	**HAD**	**NOR**
Soil	Hor	0.42	0.32	0.48	0.30	0.54	0.34
	TeK	0.38	0.30	0.44	0.27	0.49	0.33
	Rua	0.35	0.16	0.25	0.09	0.21	0.26
	Wai	0.48	0.61	0.50	0.44	0.52	0.55
	Ede	0.07	0.03	0.11	0.02	0.05	0.04
	Puk	0.09	0.07	0.14	0.00	0.05	0.03

4.1.2 APSIM results maize

The assumed adaptation of sowing dates (i.e. earlier spring sowing during warmer years) and maize genotypes (short- or long-cycle), together with local climate differences, implied that the two crops experienced largely different magnitudes of warming during growth due to climate change. For an end-of-century period, this ranged from 0.2°C for short-cycle silage maize crops in Hawke's Bay (RCP 2.6) to up to 2.1°C (RCP 8.5) for catch-crop wheat following a long-cycle maize in Waikato (Fig. 11). This highlights the importance of interactions between climate change and management decisions (i.e. sowing dates, genotype selection, and crop rotation set up), which together define the degree of exposure of individual crops to climate change.

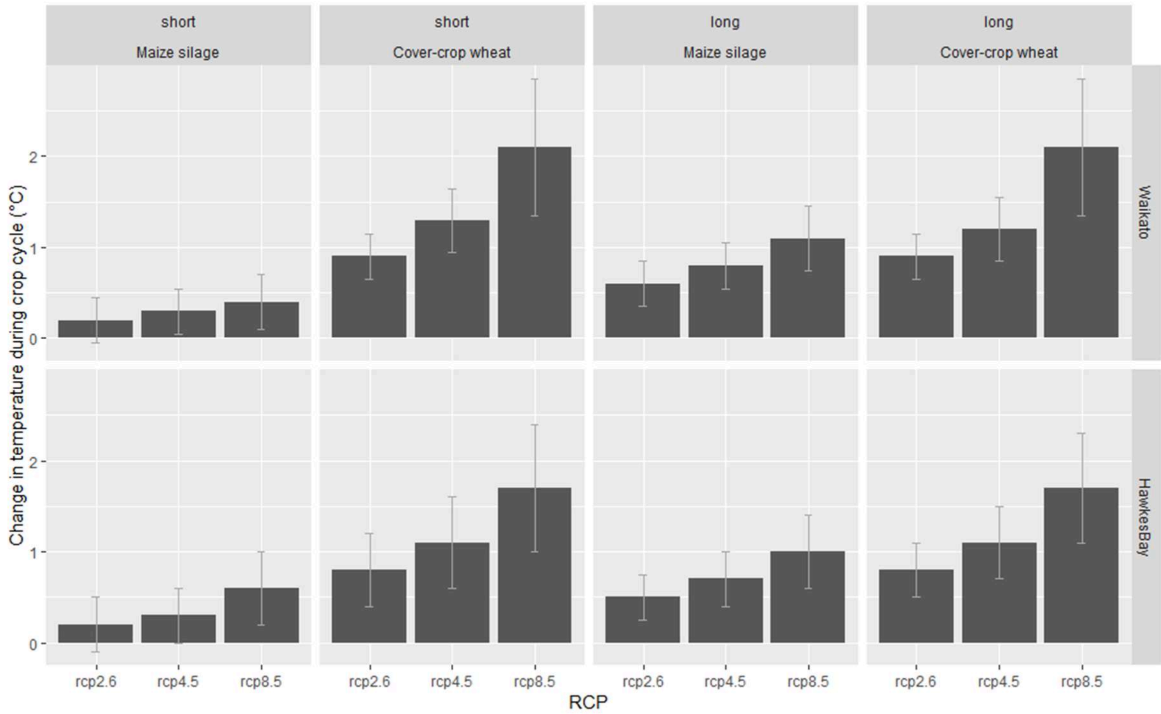


Figure 11. Temperature change experienced during crop growth by different crops in the rotation (silage maize followed by catch-crop wheat) for two maize genotypes (short or long cycle), 3 RCPs during the end-of-century period.

The importance of considering adaptation is illustrated for long-cycle maize crops in rotation (Figure 12). For end-of-century RCP 8.5, maize crops were sown around 3 weeks earlier than for the baseline climate. This enabled also early sowing of the next crop (catch crop wheat) which enables longer growth periods and consequently higher yields during winter.

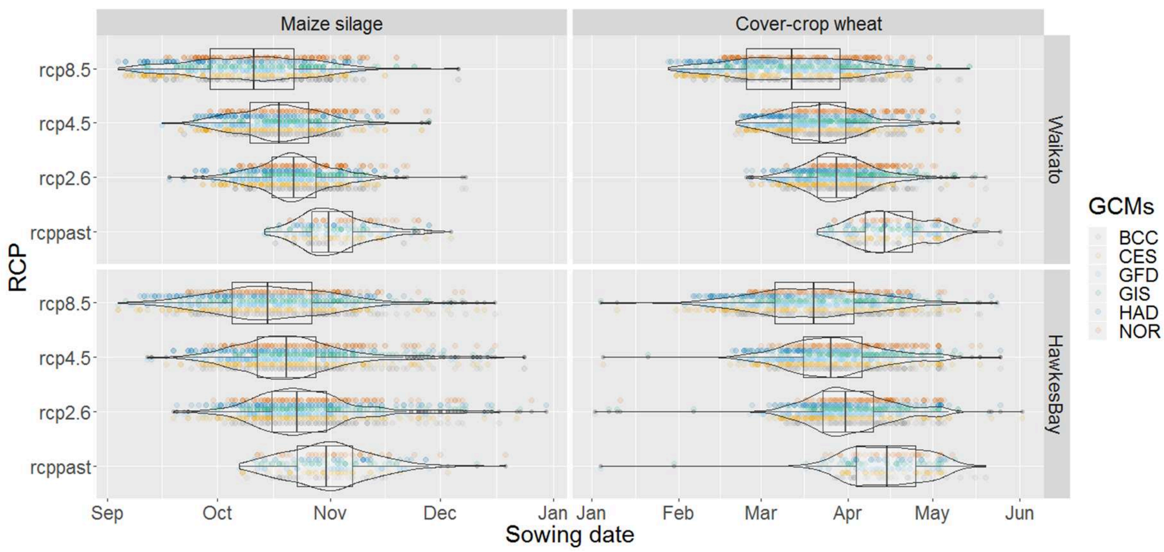


Figure 12. Estimated change in sowing dates for a rotation with long-cycle irrigated silage maize crops followed by catch crop wheat crops for the baseline and end-of-century periods.

Highest baseline irrigated silage yield estimates were approximately 28 t dry matter/ha, with a median of ~20 t/ha in both Hawkes's Bay and Waikato. Irrigation input in maize crop ranged from 0 to 440 mm/year (median of 75 mm/year) depending on the location and soil. Climate change, after accounting for adaptation of sowing dates, had minimal effect on irrigated maize yields, with the exception of slightly increased variability in Hawke's Bay (RCPs 2.6 and 4.5) (Fig. 13). This highlights the importance of accounting for adaptation in managed systems such as arable cropping. Without adaptation, expected impacts of climate change in maize were shown to be negative in the warmer regions of New Zealand (Teixeira et al. 2018). In contrast, for the winter period, catch crop wheat yields increased by ~3 t/ha with the higher emission scenarios. This was a combination of several factors, including the reduction of low temperature limitations during winter, the positive response of C3 crops such as wheat to increasing atmospheric CO_2 and the fact that previous crops (maize) were harvested earlier, enabling the catch crop wheat to be sown earlier and grow for longer periods. Such dynamics highlight the importance of representing crop rotations, not only individual crops, as there is a carryover of effects across sequential crops with possible synergies and trade-offs occurring.

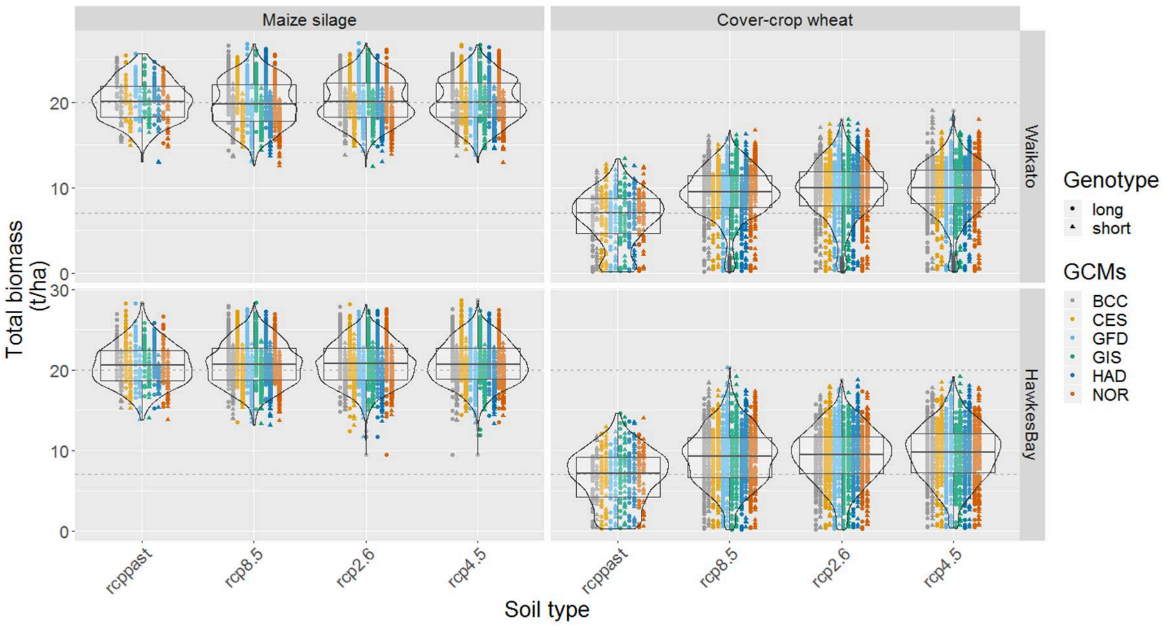


Figure 13. Yield estimates for a crop rotation with irrigated silage maize crops followed by catch crop wheat for different RCPs, six GCMs, for two maize genotypes. Dotted grey lines show baseline median yield for wheat (7 t/ha) and maize (20 t/ha).

For rain-fed systems, changes in water stress risk for the different climate scenarios (i.e. RCPs) represented as a water deficit index (Fig. 14) differed among locations, crops and soils. The more drought prone rain-fed systems occurred in Hawke's Bay for maize crops where crops had ~30% of their water demand fulfilled (i.e. water deficit of 30%). Catch crops, which grow in winter when evapo-transpiration is lower, were less subjected to water stress. As a preliminary analysis, it seems that the effects of RCPs and soils were more evident on the frequency of extreme drought events than median values. Patterns differed with GCMs suggesting the importance of considering climate uncertainty particularly when dealing with drought assessments under climate change. Such responses have CO_2 fertilization effects embedded assuming crops will be more efficient under higher CO_2 (i.e. higher RCP values) and therefore are a conservative measure of drought stress.

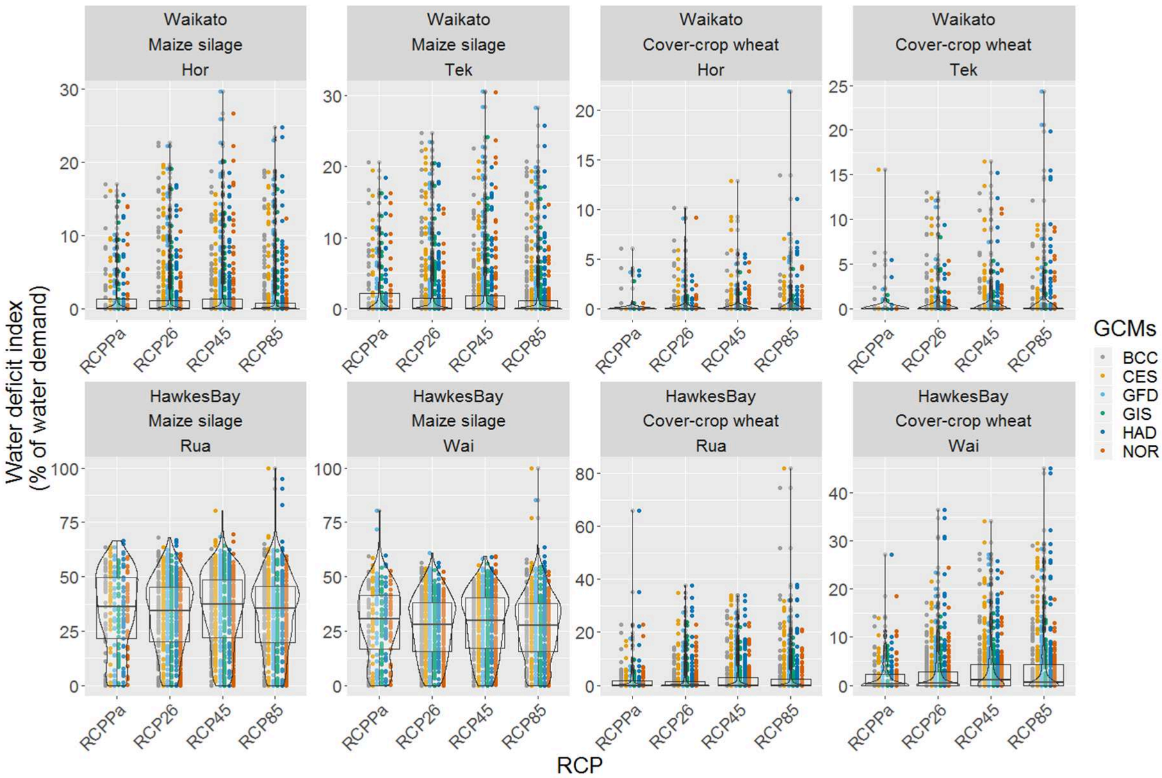


Figure 14. Fractional water deficit as a percentage of total crop water demand for different GCMs, RCPs, soils, crops and locations for rain-fed systems.

The potential of catch crops to uptake residual soil N was largely driven by biomass accumulation (Fig. 15). High emission climate scenarios and late time periods therefore increased N uptake by catch crops from 100 kg N/ha to 150 kg N/ha in response to yield.

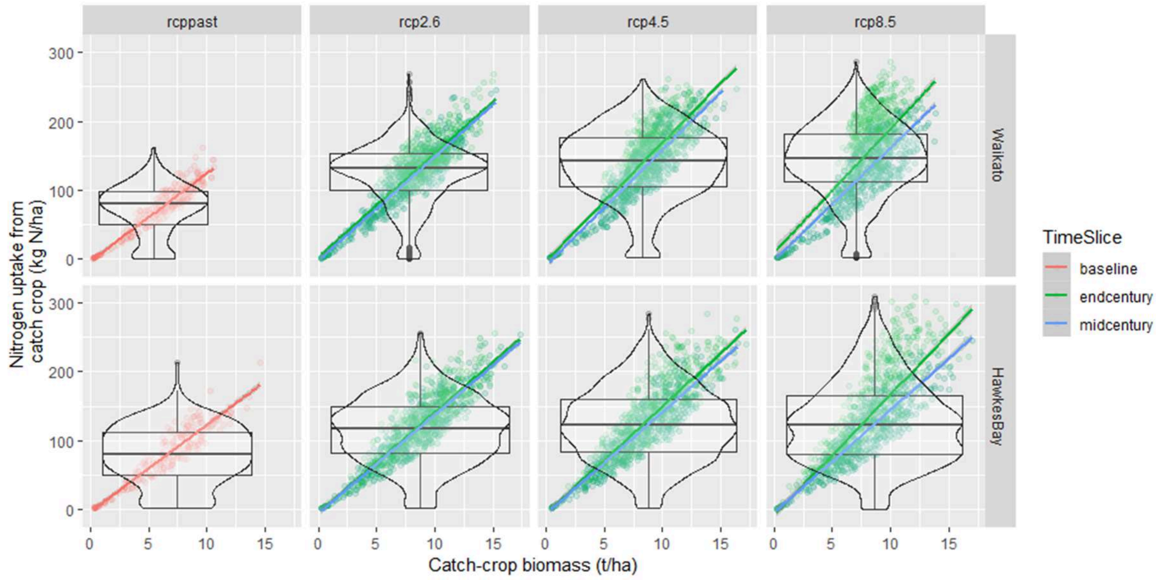


Figure 15. Nitrogen uptake by winter catch crops in response to crop yield during the autumn/winter period. Data pooled across all GCMs and soil types.

Such results indicate that the intensity of N luxury uptake by catch crops, expressed as higher N concentrations, might change under climate change. This implies that catch crops remain an effective adaptation to reduce the risk of N leaching losses under climate change. Nevertheless, catch crops might be slightly closer to their maximum N uptake potential due to a greater N availability in the system with a less than proportional increase in growth rates during autumn/winter. These hypotheses require further testing based on measured data, but our preliminary model results enable identifying these possible patterns of response.

As for impacts on pastoral systems (section 6.1.1), we have focused on results for RCP8.5. Estimates of N leaching at 90 cm depth were largely variable from year to year, as illustrated for RCP8.5 in Figure 16. Soil type was a key determinant of absolute leaching estimates. The impact of climate change on median values was of smaller magnitude than inter-annual variability and the impact of soil type. The "Rua" soil showed less N leaching losses, similarly to the pasture results, likely due to its higher water holding capacity at upper soils layers. The Waimakariri soil in the Hawke's Bay is the only soil that presents potential increased risks with more extreme N leaching events for some GCMs. These results highlight the importance of assessing changes to the frequency and magnitude of extreme leaching events across time periods, GCMs and soil types to sample uncertainty in estimates.

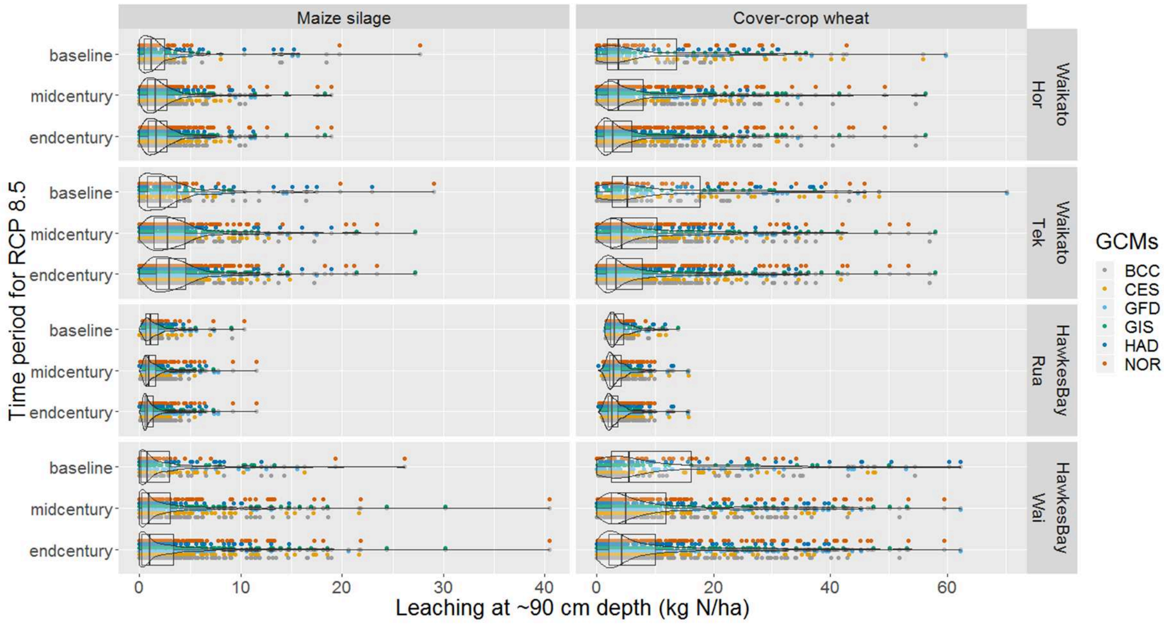


Figure 16. Nitrogen leaching losses at 90 cm depth estimated for RCP 8.5. An irrigated maize silage crop followed by catch-crop wheat over 25 years.

Future analysis will improve the representation of arable cropping systems through a different selection of soil types because the scope of this study required similar soils to be run for both crops and pastures, which might not reflect farmer's choice in crop allocation.

4.1.3 WATYIELD results

We plotted the difference in PED from a nominal pasture cover (Figure 17). For the three locations in Hawke's Bay, Southland and Waikato, the water demand (PED) is higher for maize compared with pasture. Forest is less demanding in water than pasture. Kiwifruit is less demanding in the Hawke's Bay than pasture but has similar PED in the other regions.

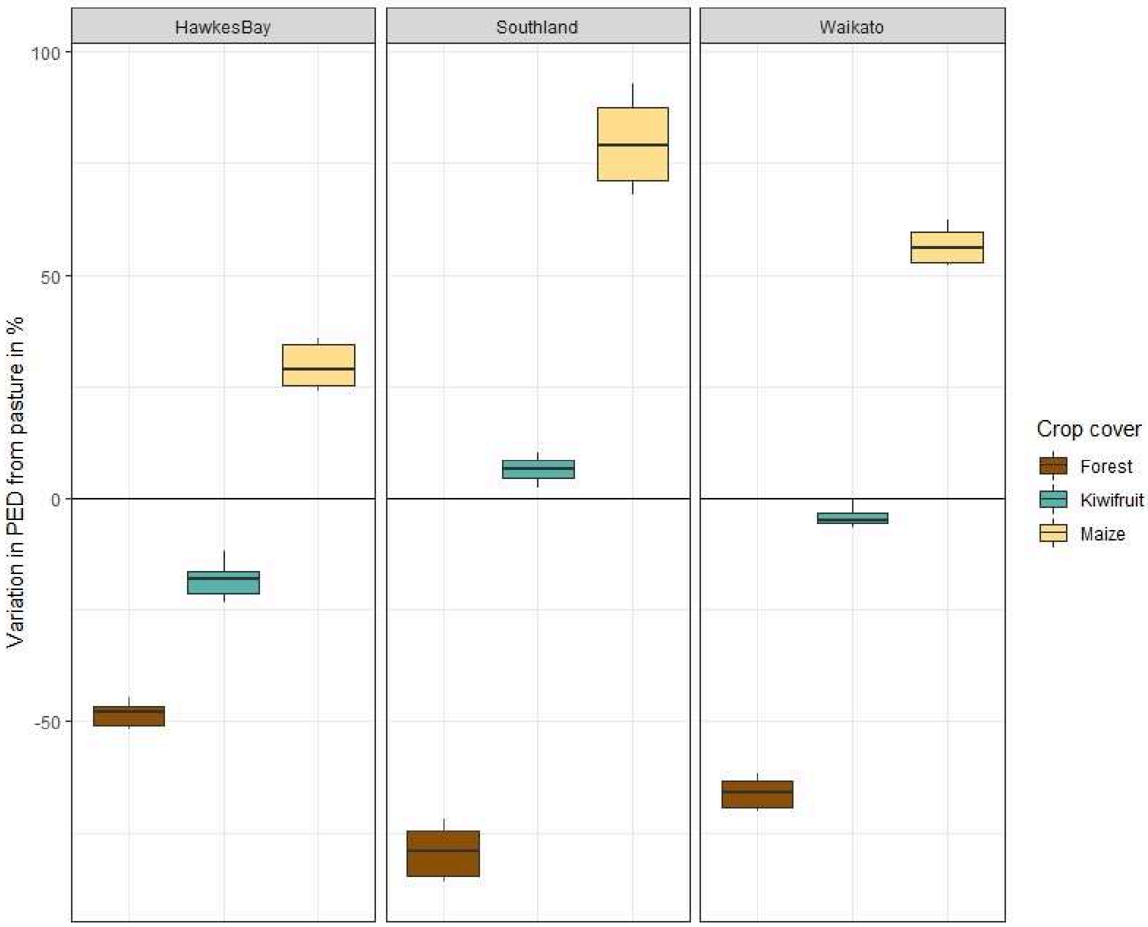


Figure 17. Variation in Potential Evapotranspiration Deficit (PED) from a pasture cover in the three locations in Hawke's Bay, Southland and Waikato.

Looking into the future climate change projections, we estimated that water demand would increase in all scenarios and for the three regions. Results are shown as changes in PED, with more substantial changes in the Waikato and Southland (Fig. 19 and Fig. 20), compared with Hawke's Bay (Fig. 18), which already has high water demand for plants. Changes are more visible towards the end of the century, with 20–30% change in Hawke's Bay, and up to 40% change in Southland for kiwifruit, pasture, and maize. The variability across GCM is shown as larger than the other covers, mainly due to the overall lower PED.

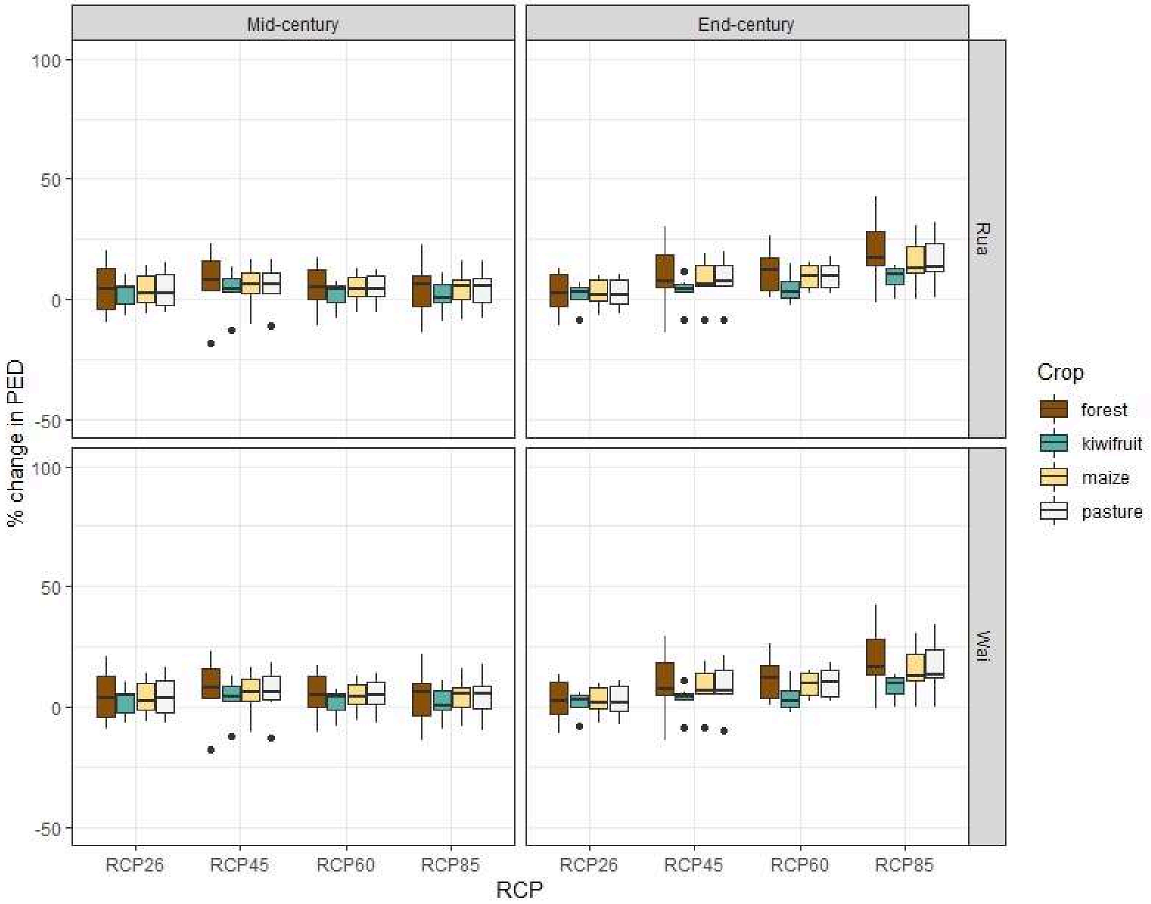


Figure 18. Change in PED for the four RCP (2.6, 4.5, 6.0 and 8.5) in the Hawke's Bay region for two soils (Rua and Wai).

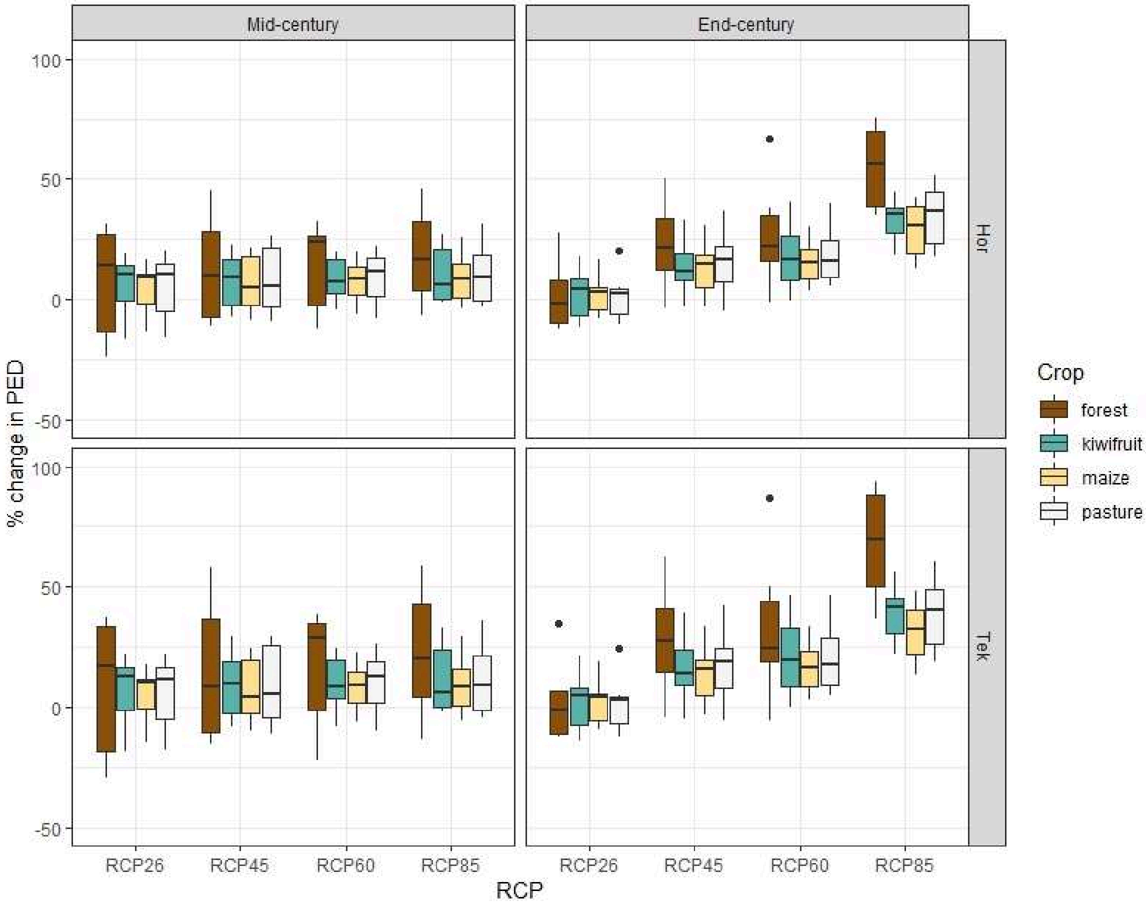


Figure 19. Change in PED for the four RCP (2.6, 4.5, 6.0 and 8.5) in the Waikato region for two soils (Hor and TeK).

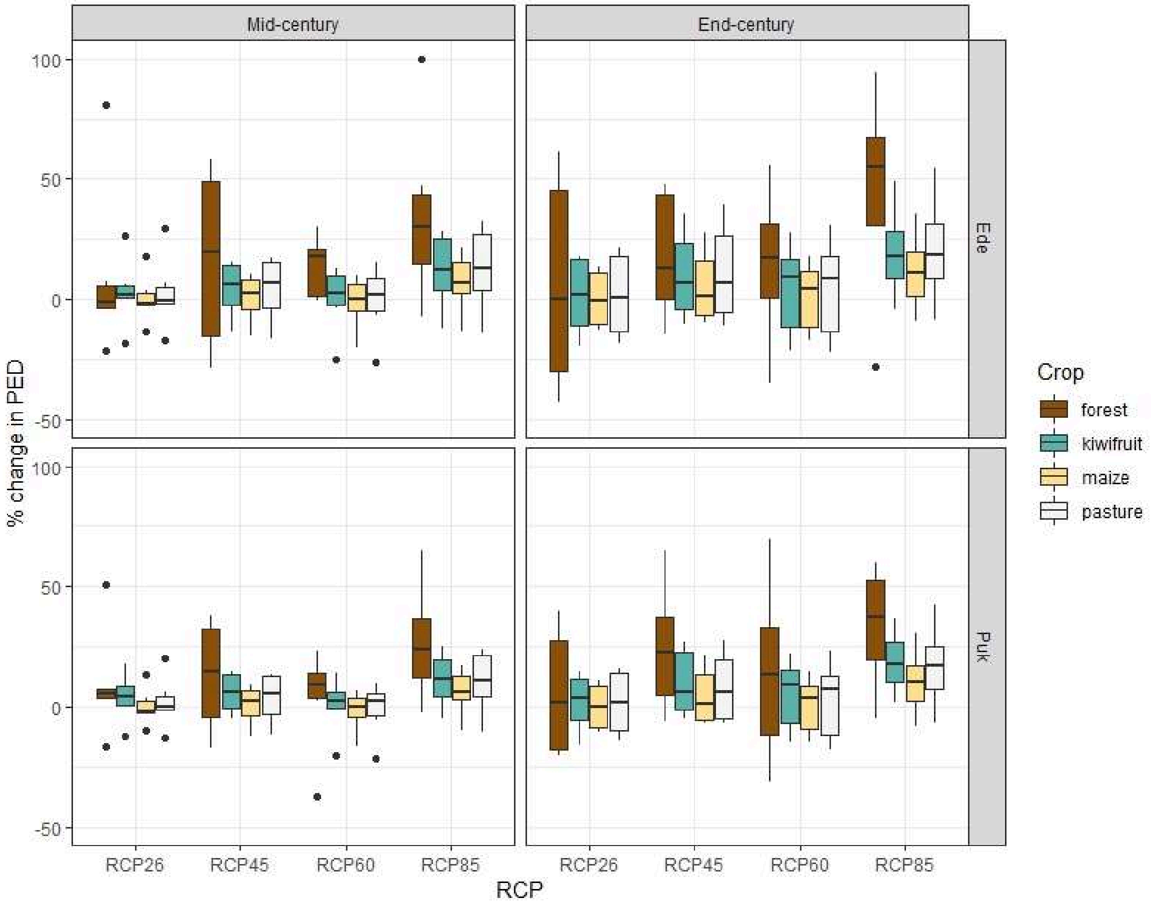


Figure 20. Change in PED for the four RCP (2.6, 4.5, 6.0 and 8.5) in the Southland region for two soils (Ede and Puk).

4.1.4 Statistical analysis

4.1.4.1 Pasture

Production

This project evaluates models ranging from simple (tier 1) to complex (tier 3) as candidate data sources for climate attributes contributing to the evaluation of future land use suitability. For understanding how long-term climate, drought risk, and shifting seasonal patterns can include information about current climate and future climate change, it is useful to have some understanding of the correlations between different models and metrics, and where possible a sense of how variance in annual production from highly complex models can be attributed to simpler metrics. Therefore, we used multiple regression, with which many readers will be familiar for these purposes, treating the output from complex models as independent data.

We compared the proportion of variance in production from the most complex models (APSIM and Biome-BGC) that could be explained by simpler models and metrics representing climate. We evaluated these terms in relation to three other sources of variance. First, we considered variance introduced by the properties of the six soils. Second, we considered the different GCMs. Third, because of an interest in drought and changing seasonal water balances, we specifically asked how much of the variance in production could be explained by indices summarizing water balance in the models. For this analysis we examined the past plus RCP2.5 RCP4.5 and RCP8.5 in six soils in three regions.

Before anything else, it is useful to recognise the correlation between models when examining results. Biome-BGC's pasture production explained 56% of the variance in annual pasture production from the more complex APSIM model. A direct comparison of pasture production is not possible from WATYIELD, but the PED can be compared to the comparable calculation in Biome-BGC: WATYIELD PED explained 91% of the variation in Biome-BGC ET-PET.

A series of highly significant indices selected by stepwise multiple regression explained 79% of the variance in APSIM results. Within this explained variance, 26% could be attributed to the six soils, 4% to the six GCMs, 20% to Tier 1 climate indices, and 29% to water indices derived from Biome-BGC. Of the model derived water indices, Biome-BGC's annual ET-PET was most important (16%). For climate indices, SPEI2 for January was most important (9%).

Stepwise multiple regression identified similar indices that explained 89% of the variance in Biome-BGC annual pasture production. Variance in the 6 soils accounted for 20% of the variance in Biome-BGC production, while variance in the 6 GCMs only accounted for 2%. Water indices within the Biome-BGC model explained 39% of variance in production, with 29% explained by annual ET-PET. Tier 1 climate indices explained 28%, led by SPEI2 for February at 15%.

It is important to note, however, that the water indices were derived from the Biome-BGC model output. These water indices cannot therefore be considered as independent of the Biome-BGC-modelled pasture production. Further regression analysis, with Biome-BGC-derived indices excluded, will be required to explain the variance in production explained by soil, GCM, climate indices and non Biome-BGC-derived water indices. None of the climate variables included in this analysis were derived from the APSIM model.

A limitation of our regression analysis that needs to be acknowledged is the overlapping nature of some of the SPEI2 and SPEI3 attributes. For example, in Table 10, both SPEI2January and SPEI2February have been identified as having some influence on the variation in modelled pasture production. However, both attributes have the month of January in common, as each attribute covers a 2-month period: the month noted in the attribute name and the previous month.

Table 10. Variables explaining APSIM- and Biome-BGC-modelled pasture production

% Variance Explained	APSIM	Biome-BGC
Total	79.0 %	89.1 %
GCM	4.4 %	1.9 %
Soil	26.1 %	19.8 %
Modelled water	28.4 %	39.4 %
Climate Index	20.0 %	28.3 %
Top predictors	Biome-BGC ET Annual Biome-BGC ET Summer SPEI2 January	Biome-BGC ET Annual Biome-BGC ET Summer SPEI2 February

As a preliminary assessment for identifying potential climate attributes for inclusion in the LUS framework, we have focused solely on these attributes and excluded the influence of projection and soil/region related factors. We have excluded 'Tier 3' modelled 'water' variables and assumed, for the purposes of this preliminary assessment, that the remaining variables provide an indication of their relative importance with respect to pasture production. It is also assumed that following removal of the modelled 'water' variable the degree of variation in pasture production explained by the remaining variables is maintained. In reality, however, the multiple regression analysis should be repeated with the revised set of variables. Resourcing did not permit this revision; thus, our exploration of potential climate attributes must be considered as provisional. Climate attributes were ranked and compared between the two models (Table 11).

Results from this preliminary assessment showed that, among the top 8 climate attributes calculated independently from APSIM and Biome-BGC, two were in common: SPEI2.Jan and Nbhotdays25. The SPEI2.Jan variable is the abbreviated name for the *Standardised Potential Evapotranspiration Index,* based on rainfall and PET for the 2 months of December and January. This variable has been classified as a Tier 2 variable, as it can be estimated using climate data available from NIWA. The top contender from the Biome-BGC modelling is also SPEI2, but for February. As noted earlier, data overlap between SPEI2.Jan and SPEI2.Feb. The Nbhotdays25 attribute is classified as Tier 1 as it is directly available from NIWA as a projected climate variable. This attribute relates to the number of days per year where the mean daily air temperature is greater than 25°C.

Table 11. Ranking of top 8 key climate attributes influencing pasture production where production was modelled using APSIM and Biome-BGC. Attributes in bold selected as preliminary variables for consideration in Land Use Suitability framework

APSIM		Biome-BGC	
Climate variable	Degree of variation explained (%)	Climate variable	Degree of variation explained (%)
SPEI2.Jan	**34%**	**SPEI2.Feb**	**48%**
Temp annual	14%	GDD7annual	16%
SPEI3.Nov	11%	SPEI2.Dec	10%
SPEI1.Feb	10%	SPEI3.Jun	9%
Nbhotdays25	**8%**	PCP	4%
GDD10annual	5%	**SPEI2.Jan**	**4%**
PET	5%	Temp autumn	4%
SPEI2.Apr	4%	**Nbhotdays25**	**3%**

N leaching

Visual presentation of the eight selected climate attributes (Table 11) and modelled N leaching data was initially carried out on all 6 soils (Appendix 10.2). However, the dataset did not contain outputs for the Te Kowhai soil, while N leaching losses were zero or close to zero kg N/ha for the Ruataniwha soil. Both soils are poorly drained, and therefore can be considered as low risk' leaching soils. Consequently, for the subsequent data visualisation, both soils were excluded.

Our preliminary assessment of the data suggested some of the climate attributes showed little relationship with N leaching while others show N leaching varies with varying magnitude of the attribute (Appendix 10.2). For example, the influence of 'ET-PETSu' (summer seasonal ET-PET) on modelled N leaching varied according to soil/region, with similar N leaching losses from the Edendale and Pukemutu soils in Southland under different ET-PET conditions (Fig. 21). Similarly, the modelled N leaching losses from the Waimakariri soil in the Hawkes Bay showed large yearly variation. However, the mean N leaching losses could be considered to be not largely different to the average loss from the Southland soils, while the ET-PET Su values are markedly different. The soil/regional variation observed for ET-PETSu diminishes the applicability of this attribute as having national relevance relative to the visual results of SPEI3Sep.

In contrast, the influence of attribute 'SPEI3Sep' (Standardised Potential Evapotranspiration Index averaged over 3 months from July to September) does not appear to be soil/regionally dependent (Fig. 22). The range of SPEI3Sep values are similar for the 4 soil/regional combinations, and for the different RCPs. Furthermore, we can see consistency in the range of SPEI3Sep values within each soil/region/RCP combination. The plot graph shown for SPEI3Sep is like that of other SPEI attributes (Appendix 10.2). These features lend SPEI as a climate attribute that could potentially be applied nationally, making it a provisional attribute to be considered for inclusion in the LUS framework.

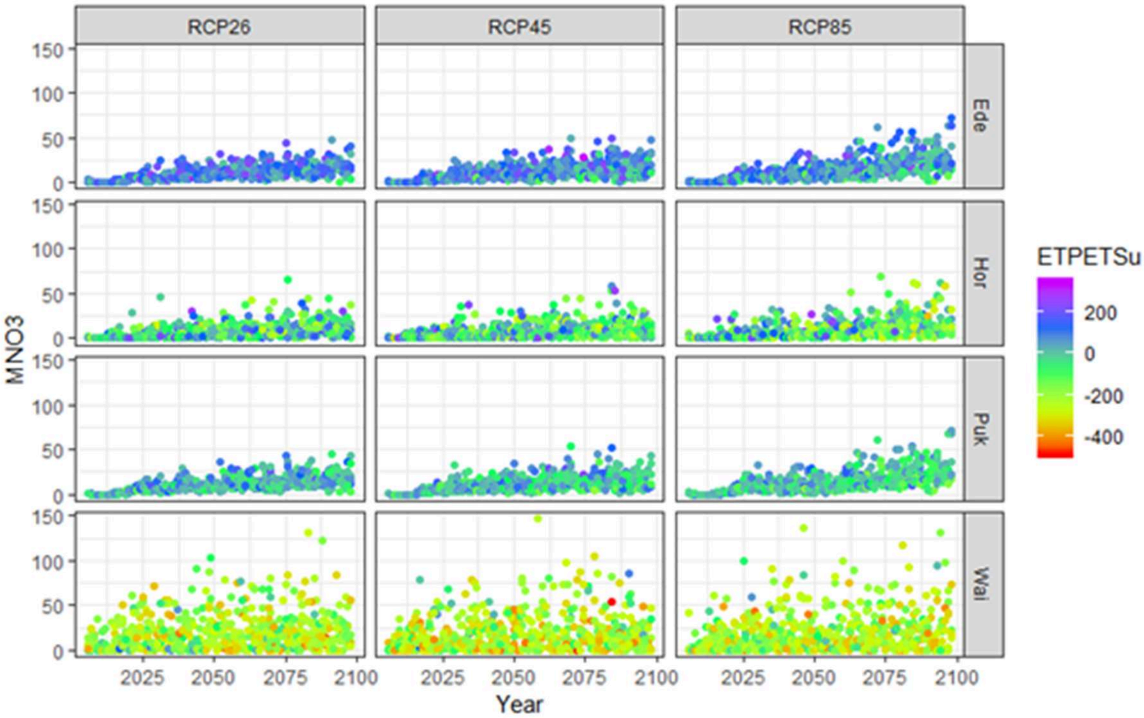


Figure 21. Effect of climate attribute ‘ET-PETSu’ (summer seasonal ET-PET) on modelled N leaching (MNO3, kg N/ha) from 2006 to 2098, for 3 RCPs (2.6, 4.5 and 8.5) and 4 soil/regions (Edendale in Southland, Horotui in Waikato, Pukemutu in Southland, and Waimakariri in Hawke’s Bay).

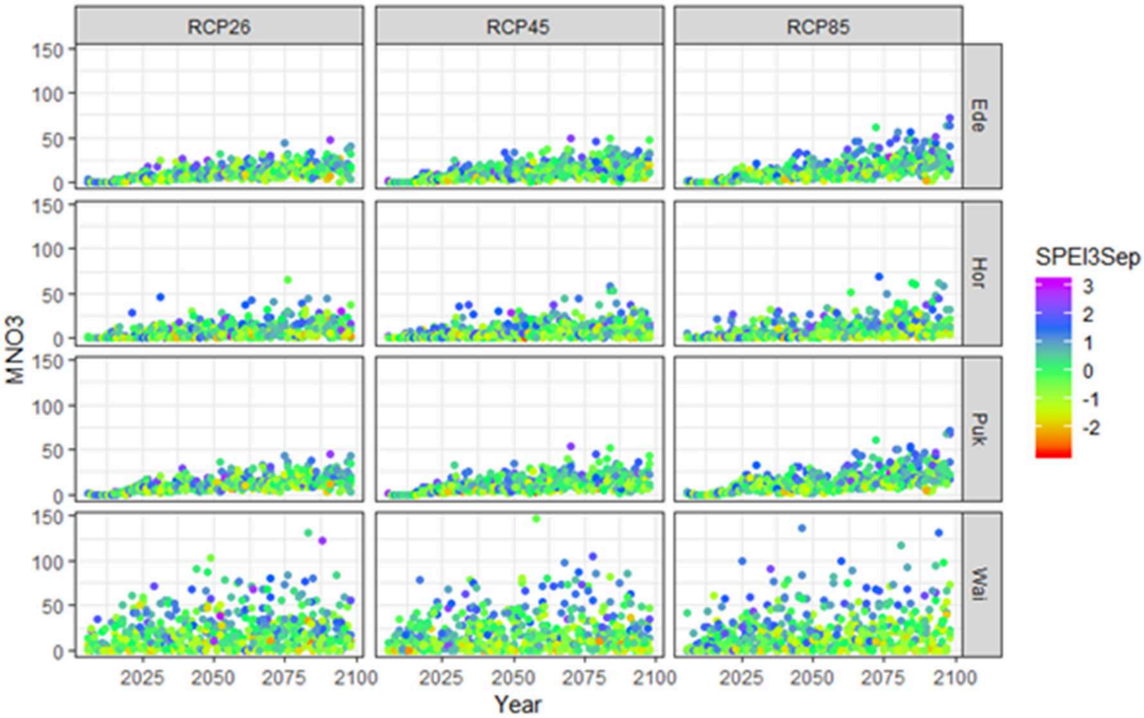


Figure 22. Effect of climate attribute ‘SPEI3Sep’ (Standardised Potential Evapotranspiration Index, 3 month average for July-September) on modelled N leaching (MNO3, kg N/ha) from 2006 to 2098, for 3 RCPs (2.6, 4.5 and 8.5) and 4 soil/regions (Edendale in Southland, Horotui in Waikato, Pukemutu in Southland, and Waimakariri in Hawke’s Bay).

4.1.4.2 Maize

Annual values for each climate attribute and time scale were extracted from the relevant source e.g. NIWA data, output from APSIM. Correlation of each attribute with production, based on a Pearson's correlation analysis, provided a visual means for restricting the list of attributes further. An example with preliminary analysis is shown in Figure 23, where 23 climate variables have been correlated with above ground biomass (RE.TB), for simulations in Hawke's Bay and Waikato.

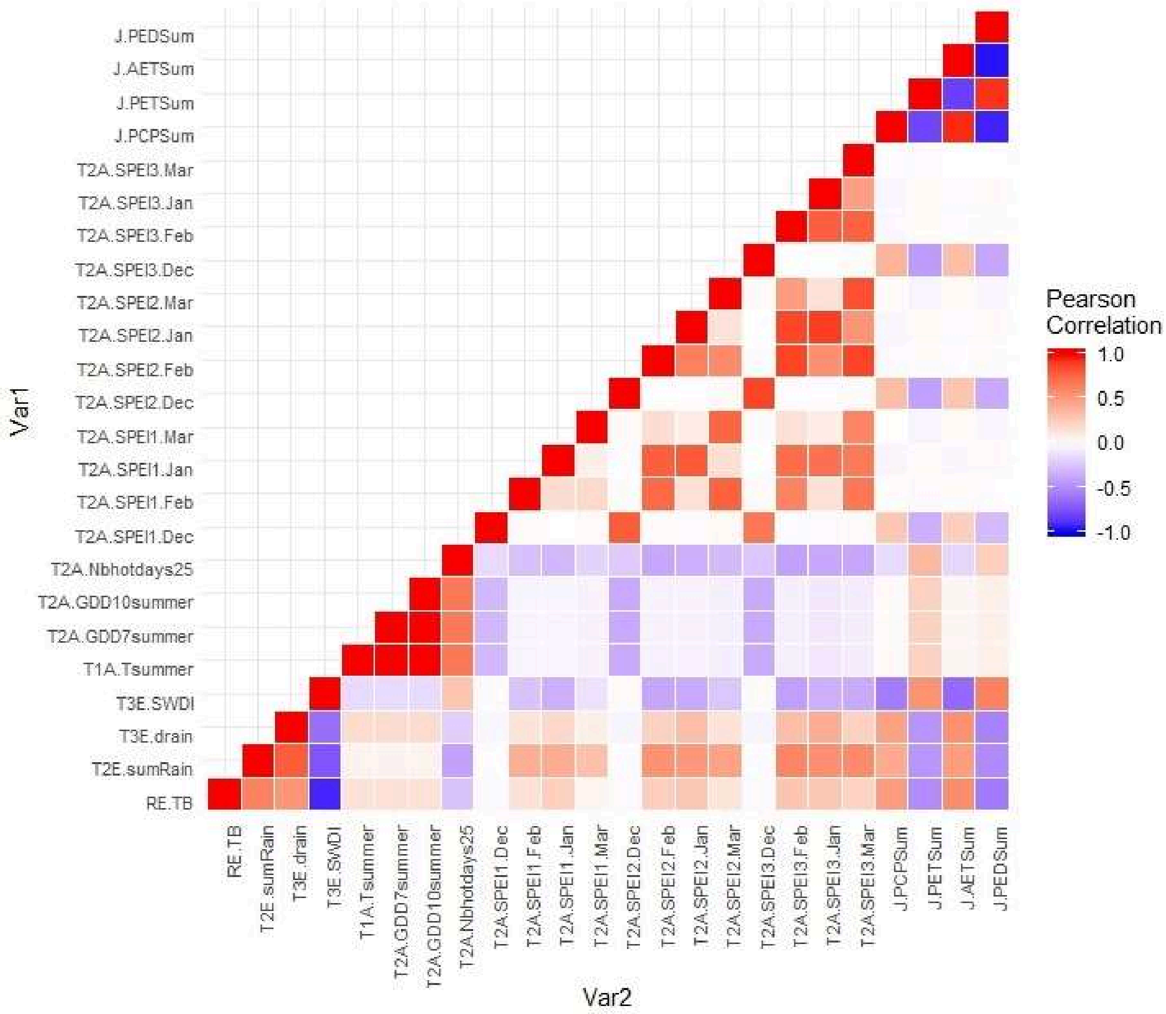


Figure 23. Correlation matrix (Pearson's coefficient) for a selection of climate attributes and Total biomass (RE.TB) for all simulations in the Hawke's Bay and Waikato regions.

As expected for a C4 crop, total biomass was found to have positive correlation with temperature in summer and thermal accumulation. The changes in temperature were in general still within the optimal ranges for the crop. In contrast, extremely high temperature starts reducing biomass as shown by the negative correlation with number of hot days above 25 degrees. For water stress conditions, the analysis highlighted negative correlations between biomass and soil water deficit index (SWDI; the accumulated deficit in relation to crop water demand in APSIM) and also potential evapo-transpiration (PED and PET) that are related to high water demands. From the water supply side, crops with more access to water (e.g. deeper roots and soil profiles) showed high actual evapotranspiration (AET) which is positively correlated with biomass production. These responses show that model responses were sensible, and internally consistent, which is encouraging for further exploration of responses in similar agricultural systems.

As with the pastoral analysis, we performed an exploratory linear regression analysis on a selection of climate attributes related to summer (as we focused on maize, in a rainfed system, for a short genotype) to understand the relative importance of climate vs soil attributes. The results show a high importance of soil (31%), low importance of RCP or GCM (possibly due to the adaptation measures), with the rest of the variables related to climate. The rainfall during the maize growth season was the most influential climate attribute (15%) explaining variation in above ground biomass across these two regions.

Although more analysis is needed to confirm these preliminary results, an example of a multiple linear regression is shown for the Ruataniwha soil in Hawke's Bay (Table 12). In this case, the Hawke’s Bay is a region more sensitive to drought. The water-related attributes were shown as having more influence on the total biomass than temperature-related attributes.

Table 12. Most influential predictors of total above-ground biomass for the Ruataniwha soil, across all RCP and GCM

	Relative importance of predictors
SPEI3.Jan	22%
sumRain	19%
SPEI2.Jan	19%
SPEI3.Feb	15%
SPEI1.Jan	7%
SPEI2.Feb	6%
GCM	4%
Nbhotdays25	3%
SPEI1.Feb	2%
Year	1%
RCP	1%

4.2 Regional scale analysis

4.2.1 Pasture production in the Hawkes Bay region

Overall, the Biome-BGC model predicts that annual pasture yield will increase in the Hawke's Bay region regardless of scenario (Fig. 24). This is primarily due to continued favourable climate conditions and the modelled CO_2 fertilization effect. However, there is a seasonal shift, with warmer temperatures allowing more production in winter and spring throughout the region, and less precipitation in late spring and summer leading to a corresponding reduction in yield in summer. The hill country in the western part of Hawke's Bay is particularly affected, as illustrated for predictions based on RCP 8.5 (Fig. 25).

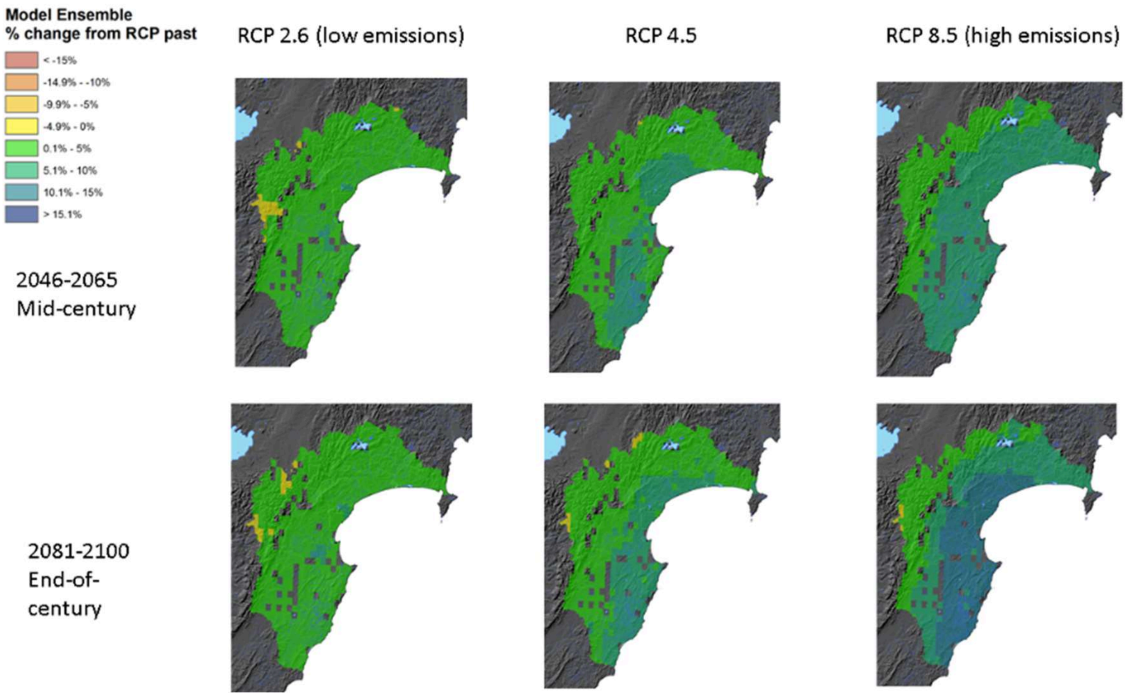


Figure 24. Biome-BGC model ensemble mean annual pasture yield for the Hawkes Bay region, as percentage change from RCP past. Two time slices, mid-century (top: 2046–2065) and end-of-century (bottom: 2081–2100) are shown for RCP 2.6 (left), RCP 4.5 (middle), and RCP 8.5 (right).

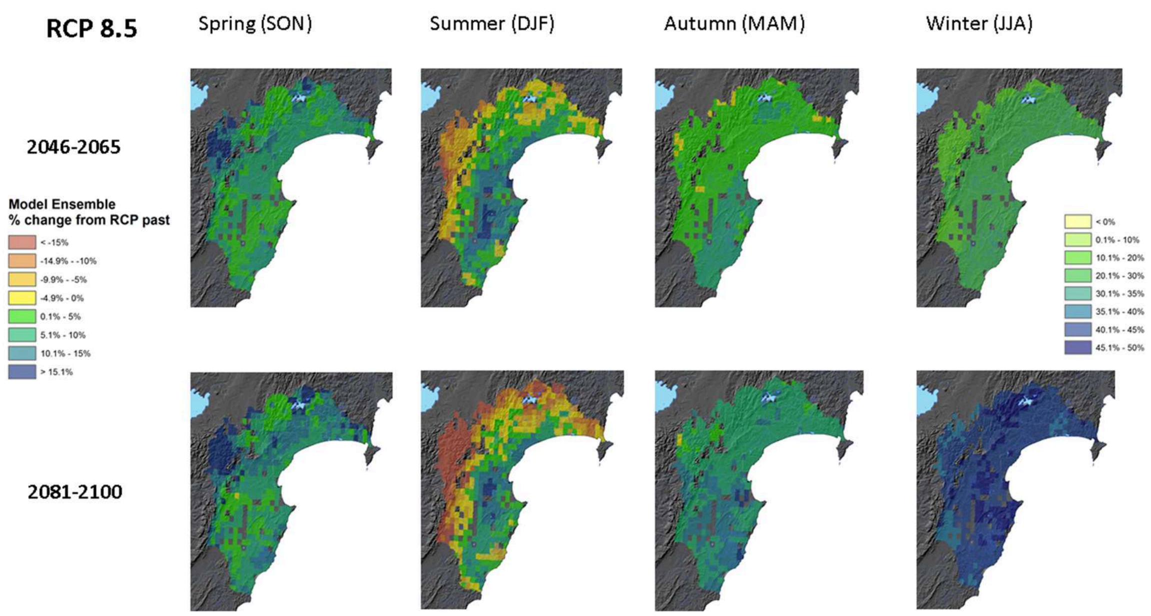


Figure 25. Biome-BGC model ensemble mean seasonal pasture growth rate for the Hawke's Bay region under RCP 8.5, as percentage change from RCP past, for two time slices, mid-century (top: 2046–2065) and end-of-century (bottom: 2081–2100). Note that winter is shown on a different scale.

Despite the overall increase in yield, there is a trend towards increasing water limitation (Fig. 26), as indicated by ET-PET, especially in spring and summer (Fig. 27). This could have implications for irrigation and water demand in a region that is already prone to drought.

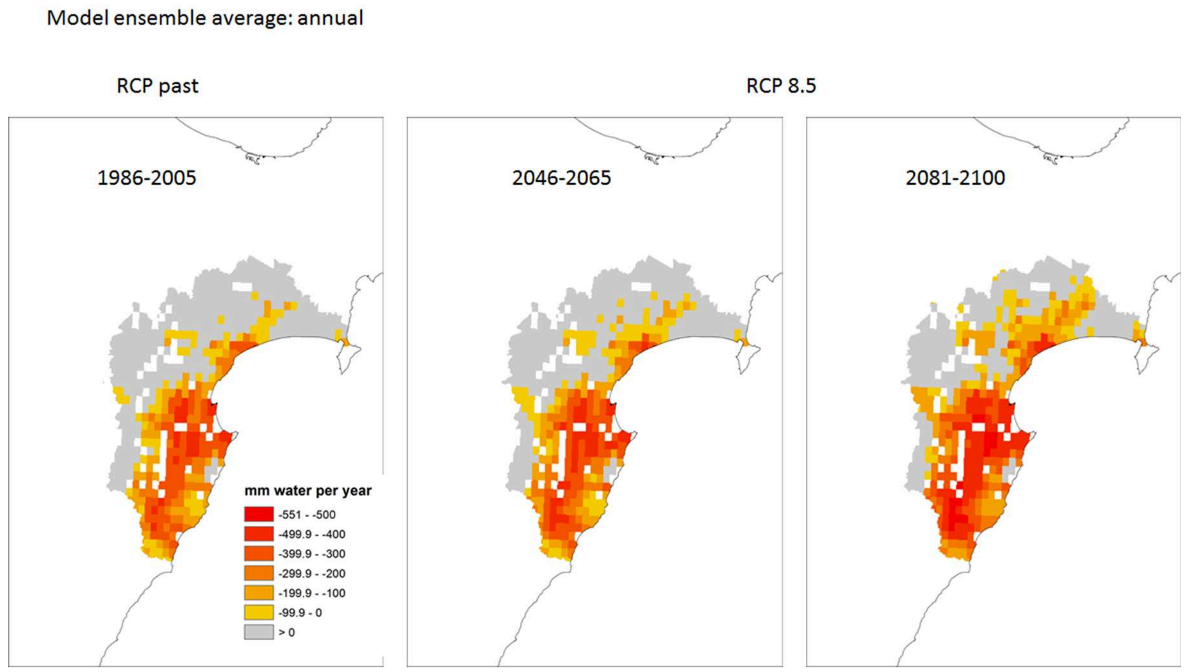


Figure 26. Mean annual cumulative ET - PET (an estimate of water demand; ET calculated from the Biome-BGC model ensemble average) for RCP past (1986–2005) and RCP 8.5 (2046–2065 and 2081–2100). Grey indicates that the plant water demand is met or exceeded.

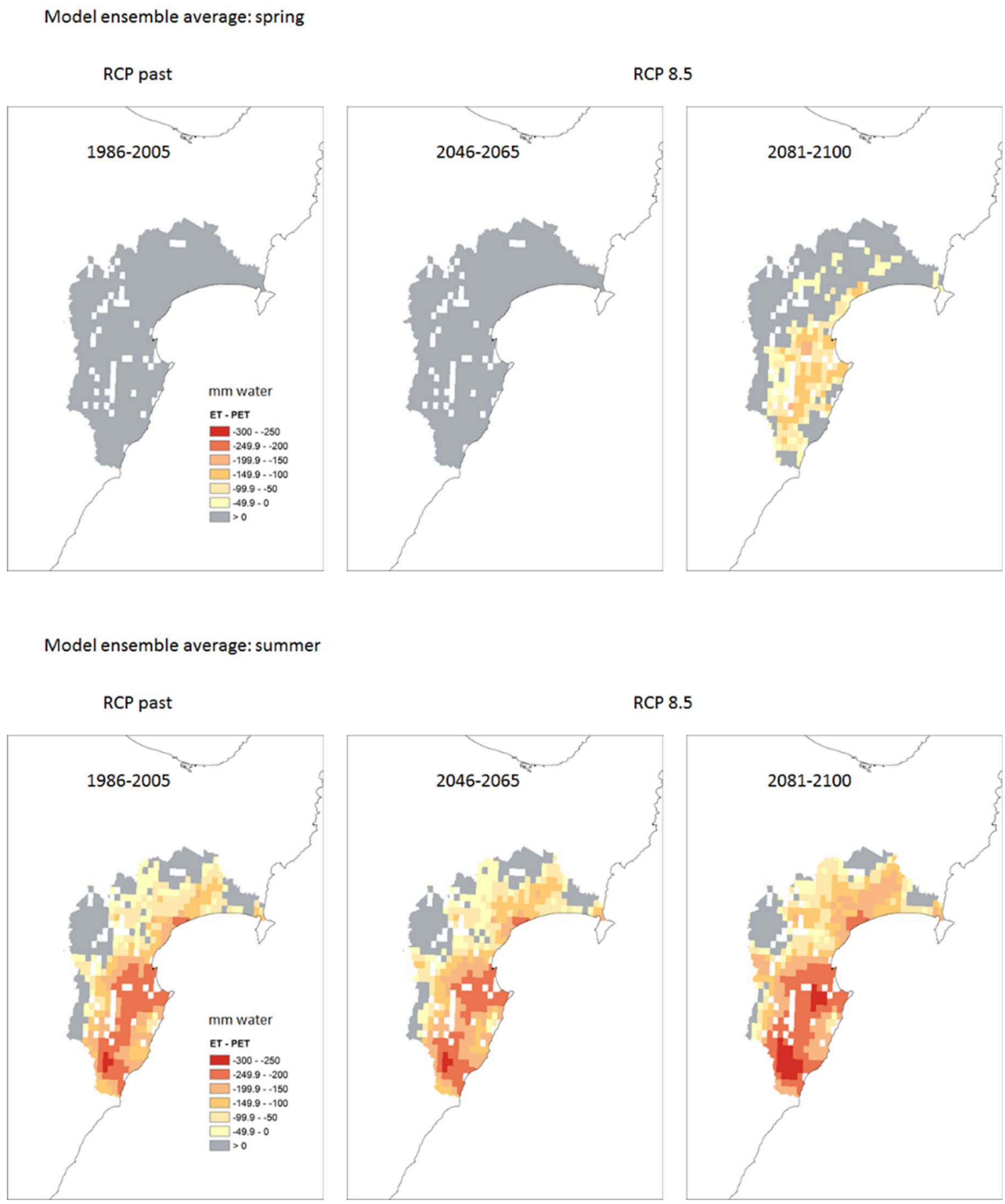


Figure 27 (continued following page). Mean seasonal cumulative ET - PET (an estimate of water demand; ET calculated from the Biome-BGC model ensemble average) for (1986–2005) and RCP 8.5 (2046–2065 and 2081–2100). Grey indicates that the plant water demand is met or exceeded.

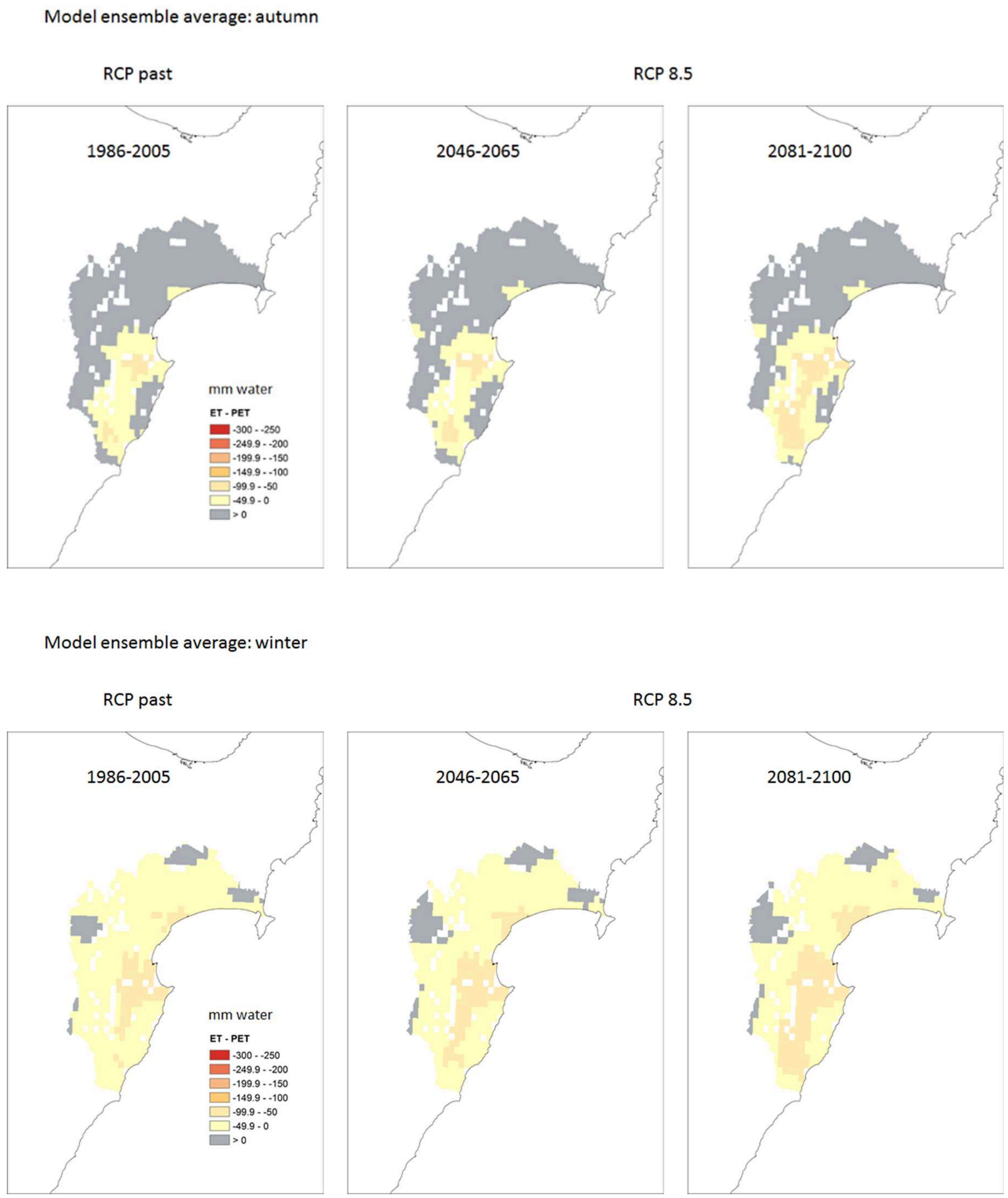


Figure 27(continued). Mean seasonal cumulative ET - PET (an estimate of water demand; ET calculated from the Biome-BGC model ensemble average) for (1986–2005) and RCP 8.5 (2046–2065 and 2081–2100). Grey indicates that the plant water demand is met or exceeded.

The statistical analysis (section 4.1.4.1) revealed that modelled pasture production is particularly sensitive to annual ET-PET and changes in summer PET and precipitation (through the SPEI2.Feb index). Figure 28 shows that the pattern of change in summer pasture production relative to RCP past closely matches changes in precipitation in many parts of the region. While the precipitation in the region as a whole remains relatively low (not shown), even a small increase or decrease has an impact on production. This is especially true when soil moisture is below a certain threshold and ET-PET is negative. This demonstrates the sensitivity of pasture production to precipitation and evapotranspiration and the mitigation potential of irrigation in a water-limited region. However, this might mean additional pressure on a water supply that is already stretched.

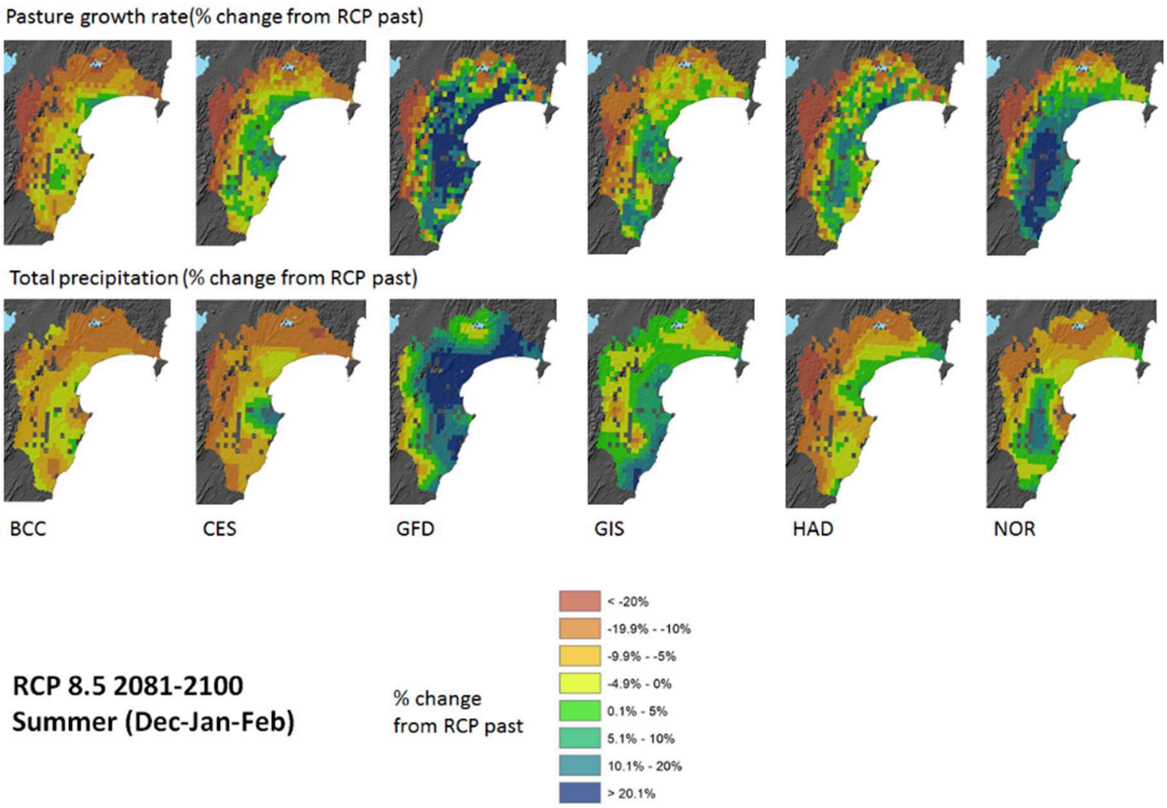


Figure 28. Mean summer (December–January–February) change in pasture growth (top) and total precipitation amount (bottom) in RCP 8.5 at the end of the century (2081–2100), for each of the 6 GCMs modelled (labels at bottom).

We examined regional drought by using relative soil moisture as an indicator of drier-than-average conditions. Figure 29 shows the grid cells with drier conditions in each month of RCP8.5 for each GCM on a normalized scale from 0 to 4, 4 being much drier than historical averages (as defined by RCP past), and 0 indicating average or wetter conditions. Some models, particularly HadGEM-2, GFDL and CESM-1, show notably drier soil conditions in the latter half of the century. The south of the region is particularly affected. However, monthly pasture production is only weakly correlated to this measure of drought, indicating that there are likely other mitigating factors (such as CO_2 fertilization) that dominate the plant response in the model.

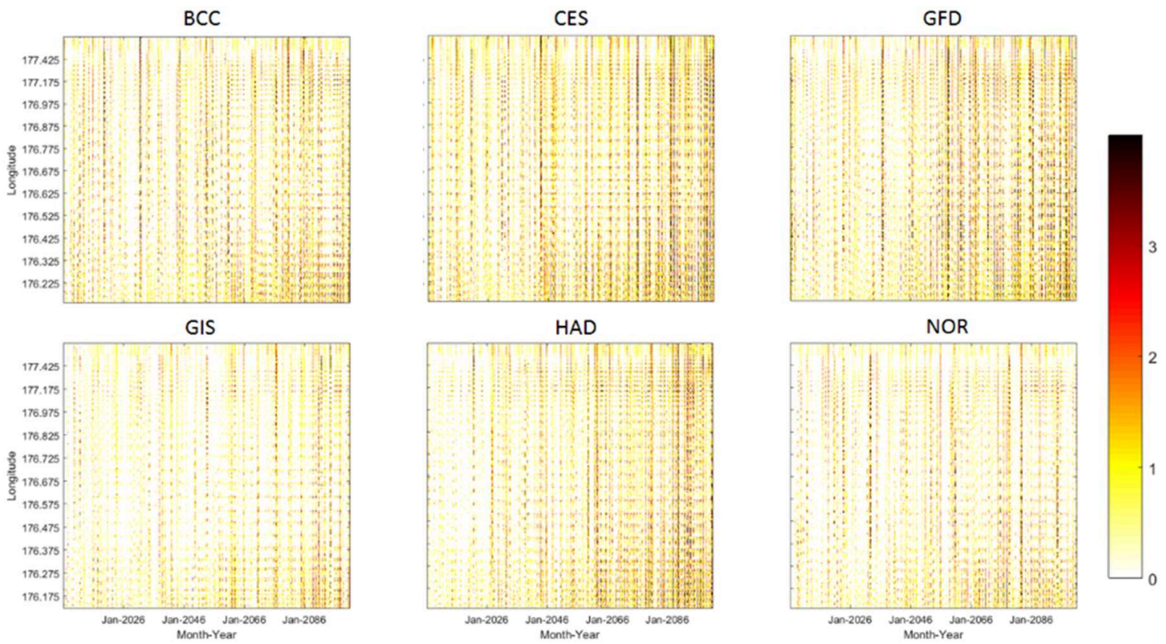


Figure 29. Heat map of drought index (based on relative soil moisture) for each month (x-axis) and grid cell (y-axis) under RCP 8.5, for each of the 6 GCMs modelled. Grid cells are ordered by longitude. Values have been normalised on a scale of 0 to 4; higher index (darker) = drier conditions; 0 indicates soil is at historical average or wetter than average conditions.

4.2.2 WATYIELD results in the Karamu catchment

WATYIELD results show that the Potential Evapotranspiration Deficit (PED) will increase under both RCP2.6 and RCP8.5 scenario. All four vegetation covers have similar temporal patterns of changes of PED (Fig. 30 and Fig. 31). The level of change is much higher under RCP8.5 than RCP2.6 due to the higher PET and decrease in precipitation.

The spatial pattern tends to be driven by vegetation cover as well as climate and soil. For a similar climate and soil, the changes in PED vary for the four vegetation covers. For instance, in the centre of the catchment, forest cover has a relatively higher change rates compared to maize, although this is due to an overall lower PED for forest cover.

The spatial pattern is also driven by soil properties. For example, during a year, the potential evapotranspiration Deficit for a crop is likely to start later in the year for a deep soil with high TAW and high RAW (Fig. 32) (WATYIELD assume soil is at full water holding capacity at the first day of simulation). This is because as more water is retained in the soil, the plant can use it through evapotranspiration for a longer period without rain then shallow soil. However, if the soil water content is too low, it takes longer to refill and meet the evapotranspiration requirement. Therefore, we can see higher PED changes in the south-west catchment where the TAW and RAW are 500 mm and 200 mm respectively.

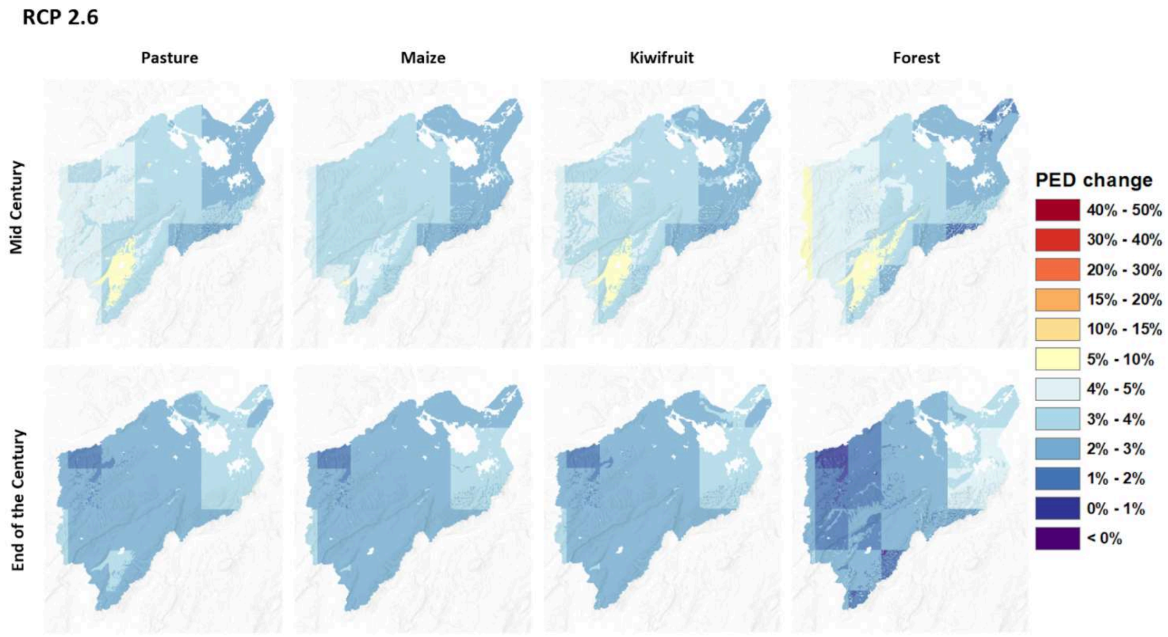


Figure 30. PED change in Karamu (RCP 2.6).

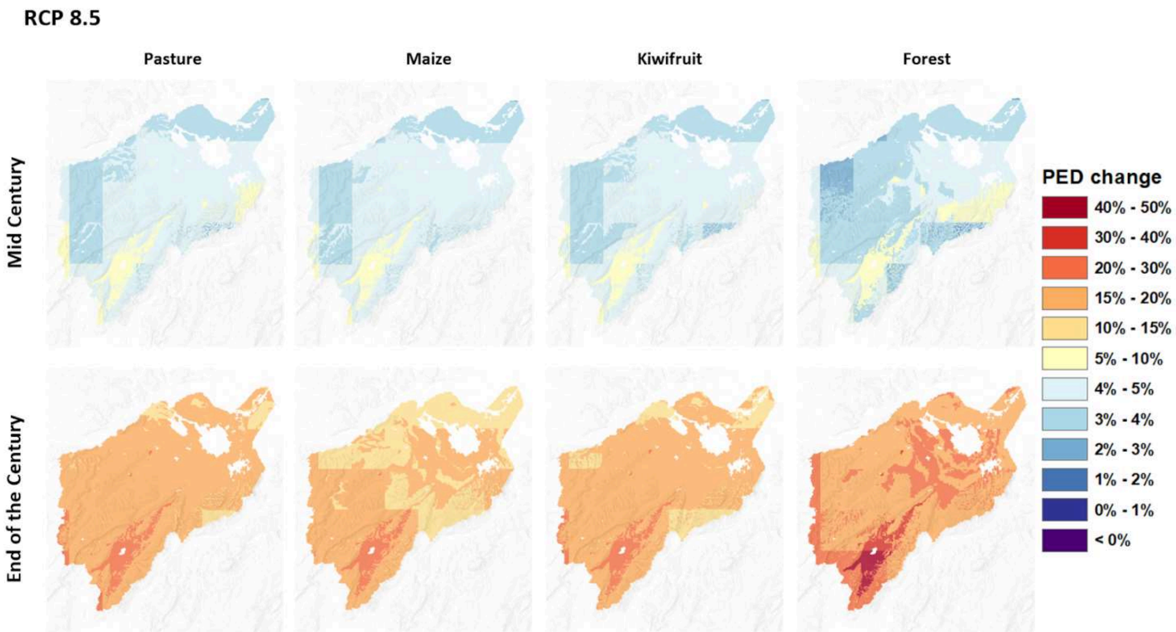


Figure 31. PED change in Karamu (RCP 8.5).

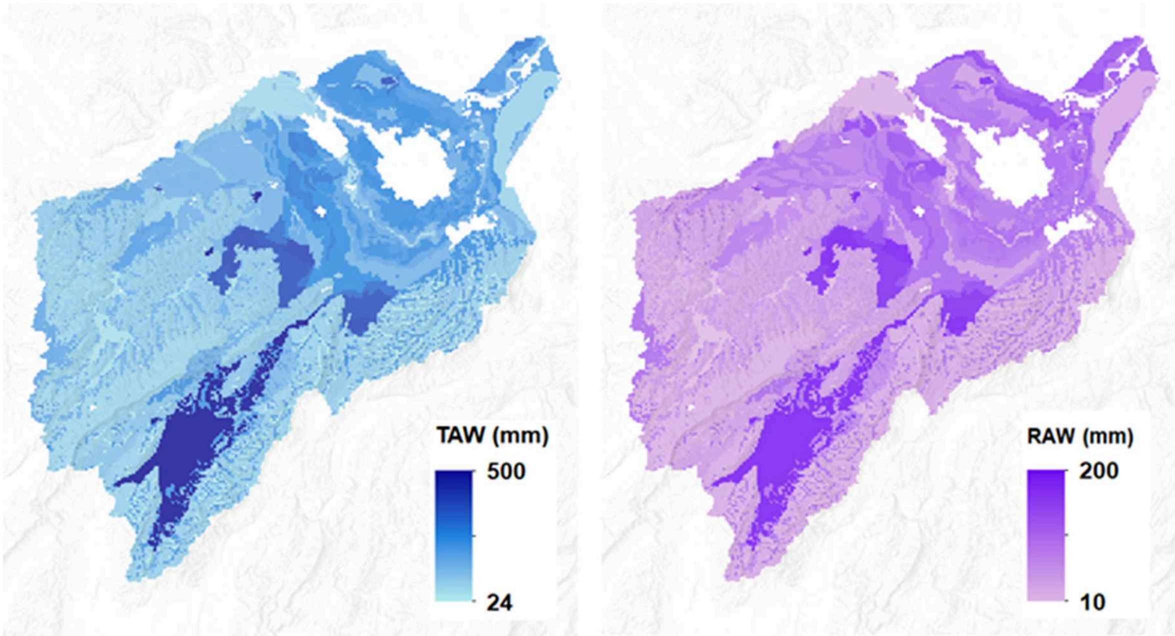


Figure 32. TAW and RAW distribution in Karamu.

4.3 National scale results

4.3.1 Animal heat stress index maps

We mapped the change in numbers of days with mild, moderate and severe heat stress (Figure 33). The baseline shows that regions currently at moderate risk are in the Canterbury, Wairarapa, Hawke's Bay and some parts of the Waikato. Severe heat stress risk is currently spread across the eastern side of the country, with less than 3 days of extreme THI.

Results show that, for all the climate change scenarios, there is an increase in risk of moderate heat stress for dairy cows (Table 13). The risk is more prevalent for RCP8.5 than RCP2.6, with up to two more weeks of moderate heat stress, spread across the country.

For severe heat stress, the risk is also increasing for all RCPs, with more pronounced risk towards the end of the century. The change in average days per year for RCP8.5 is more pronounced in regions that are already at risk, in particular: along the coast of the Hawke's Bay and Gisborne area, mid-Canterbury, central Otago and central North Island.

Note that the THI index does not account for cumulative effects of heat stress events; therefore, it is a conservative estimate of likely heat stress.

Table 13. National average annual number of days with mild, moderate or severe THI under RCP 2.6 to 8.5

		National average annual days of heat stress		
		Mild	**Moderate**	**Severe**
	Present	8.92 (σ 7.86)	2.46 (σ 2.85)	0.48 (σ 0.78)
RCP2.6	2046-2060	15.75 (σ 12.45)	5.00 (σ 4.95)	0.96 (σ 1.37)
	2080-2100	16.25 (σ 12.93)	5.22 (σ 5.22)	0.90 (σ 1.38)
RCP4.5	2046-2060	17.49 (σ 13.82)	5.59 (σ 5.55)	0.96 (σ 1.48)
	2080-2100	22.84 (σ 17.00)	7.91 (σ 7.41)	1.45 (σ 2.06)
RCP6.0	2046-2060	18.13 (σ 13.79)	6.02 (σ 5.78)	1.19 (σ 1.71)
	2080-2100	27.89 (σ 19.38)	10.36 (σ 9.12)	1.94 (σ 2.71)
RCP8.5	2046-2060	21.69 (σ 16.03)	7.18 (σ 6.68)	1.33 (σ 1.86)
	2080-2100	45.18 (σ 27.66)	20.67 (σ 15.48)	4.89 (σ 5.47)

Numbers in brackets are the standard deviations

Lower heat stress categories include higher categories (“mild or worse”, etc.)

GCM: CESM1-CAM5

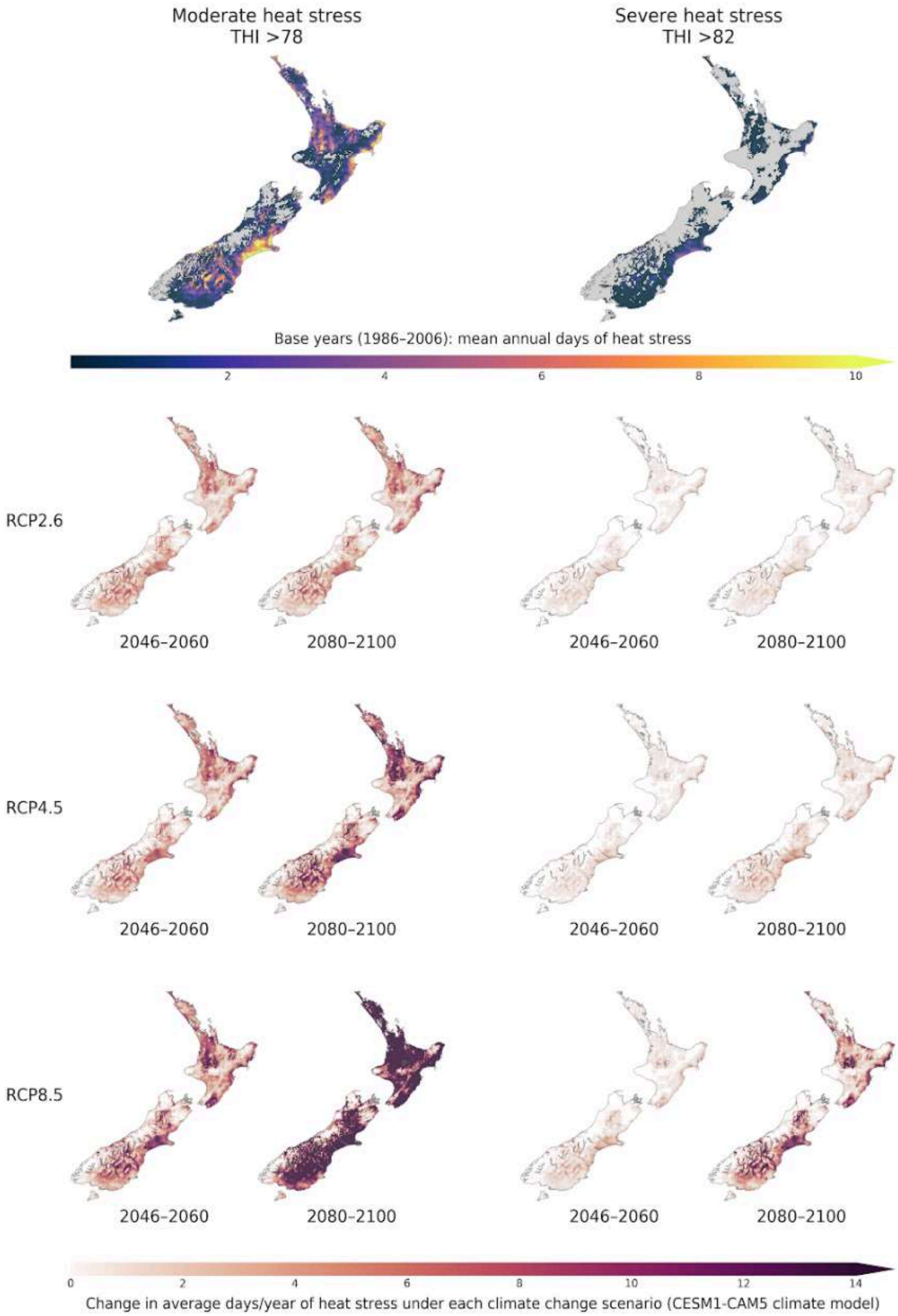


Figure 33. National maps of moderate and severe heat stress (temperature humidity index, THI), and small multiples showing how the average annual number of days of heat stress is predicted to change in the 21st century under different climate change scenarios.

4.3.2 Phenology changes in wine grapes

Maps of flowering dates were produced for the whole country using the Grape Flowering Veraison model (Fig. 34). The future climate change projections and the increase in average temperature is estimated to shift the flowering date. Results for the sauvignon blanc variety show a shift by up to two weeks prior to the baseline flowering date. It is worth noting that parts of New Zealand that were too cool (flowering date beyond mid-December) would reach earlier flowering dates that may become suitable for the wine industry by the end of the century. As such, parts of the South Island that are currently marginally suitable for growing wine grapes may become new areas where the industry could be implemented. However, other climatic factors would need to be taken into account, including the precipitation patterns.

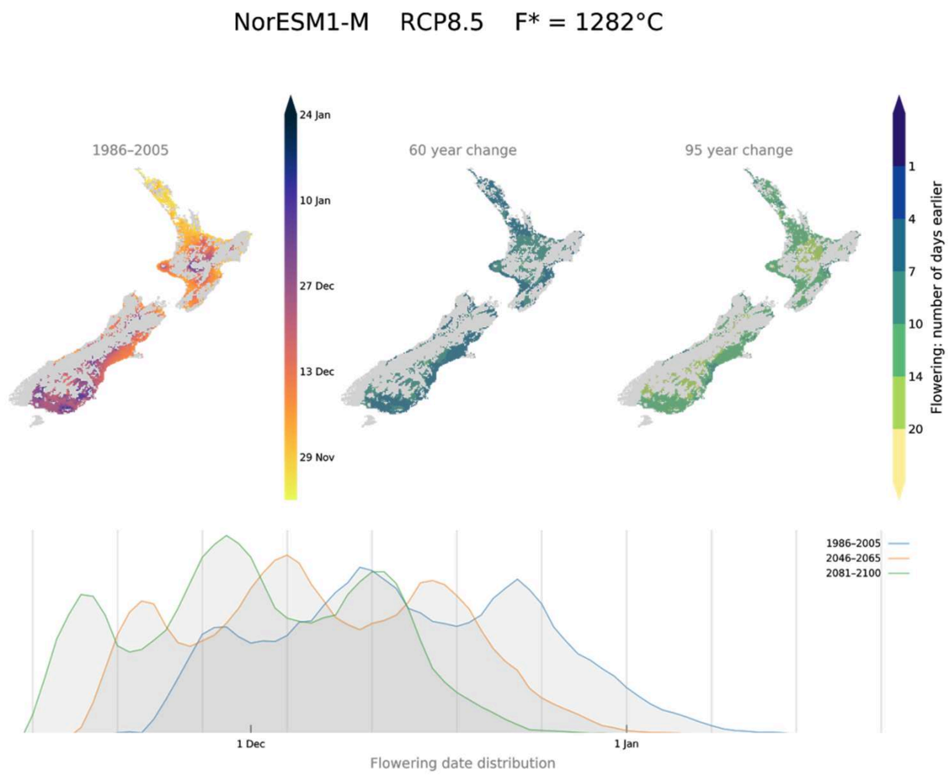


Figure 34. Changes in flowering dates in New Zealand for sauvignon blanc using the GFV model for GCM NorESM1-M and RCP8.5.

Looking more closely in the Hawke's Bay region, the current flowering date for sauvignon blanc is on average around the 8th December, which seems to match broadly with current observations (Agnew et al. 2017) (Fig. 35). The increase in temperature for the worst scenario (RCP8.5) shows that the flowering date could shift by 7 days (mid-century) up to 11 days by the end of the century. Across *all* GCMs, for RCP8.5, the mean change in flowering date for the mid-century period, for Hawke's Bay, is 7 days earlier compared with the present period (standard deviation of 1 day). For the end-of-century period, this value is 14 days earlier (standard deviation of 1.7).

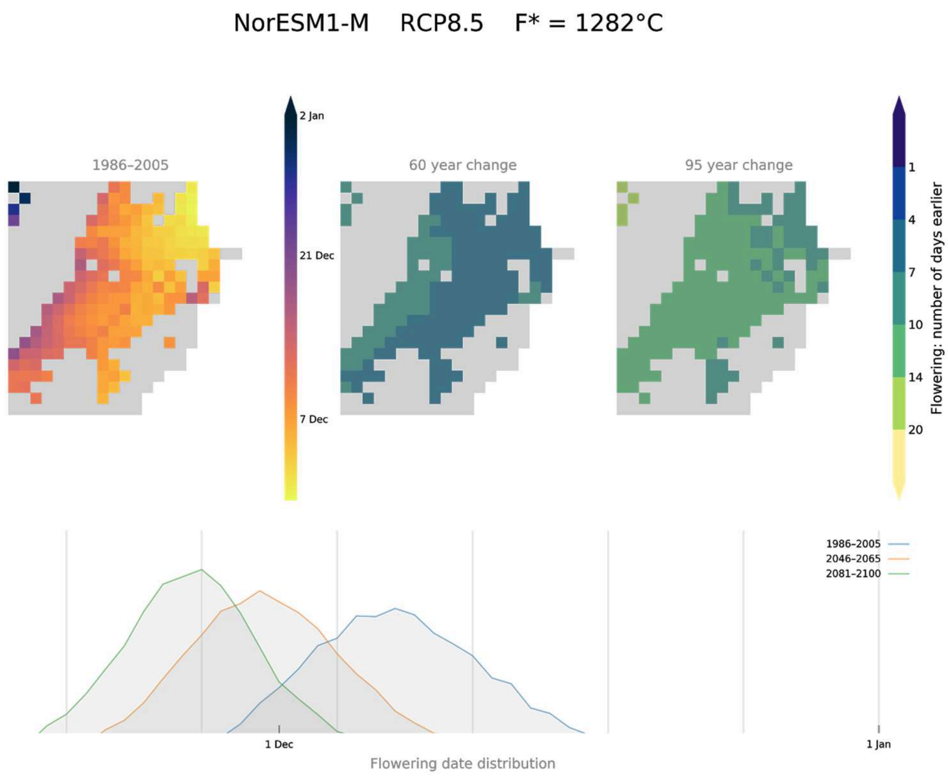


Figure 35. Changes in flowering dates in Hawkes Bay for sauvignon blanc using the GFV model for NorESM1-M and RCP8.5.

The workflow we developed enables us to test the potential phenological changes across grape varieties (Fig. 36). In Hawke's Bay, we projected the changes in flowering dates for two grape varieties grown in the region: pinot noir (F*=1219) and sauvignon blanc (F*=1282). For each of these varieties, the flowering date shifts to be 10 days earlier. The relative varietal difference in flowering date therefore remains approximately the same (4 days) when considering the climatic transition over time. However, there is uncertainty in these changes: see appendix 10.3 for the full collection of results across all GCMs for RCP8.5.

From a varietal change perspective, it is interesting to see that compared to the current pinot noir flowering date, a sauvignon blanc from today that currently flowers a few days later than pinot noir, would actually flower earlier by the end of the century. This means that it would be possible to use the GFV model to select substitutable varieties, i.e. to target flowering in a region at a particular date, to attempt to keep existing temporal patterns same as todays.

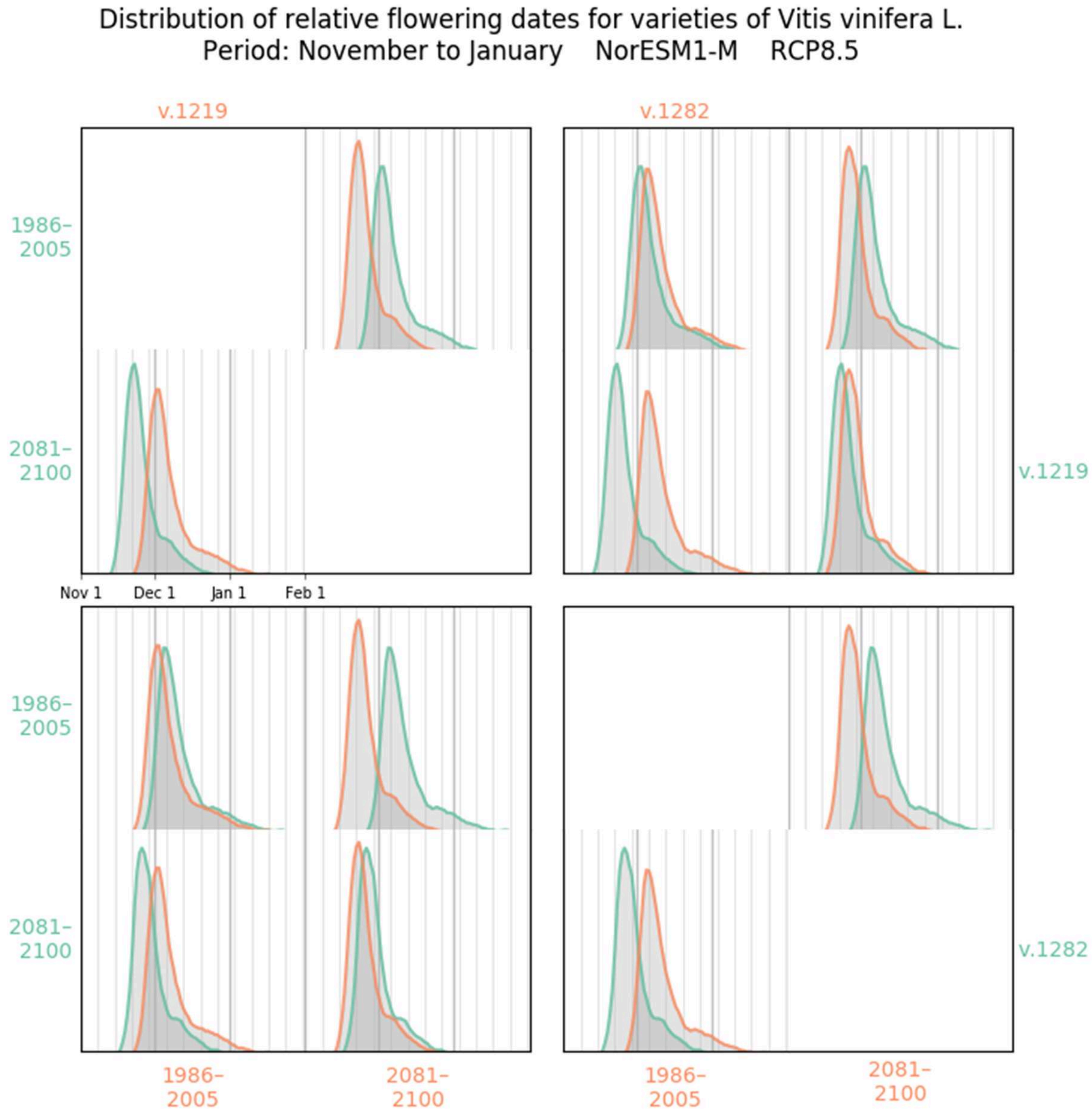


Figure 36. Distribution of flowering dates for two varieties (F* 1219 = pinot noir and F* 1282 = sauvignon blanc) in the Hawke's Bay region (the same regional extent as in Figure 37).

5 Discussion

5.1 Synthesis of impacts of climate change

Table 14 summarises the potential impacts of climate change in the three different sectors that were studied. It shows that impacts are emphasising the increased risk to production (in terms of changes to management, water stress, heat stress) and on receiving environments (increased risk in N leaching and pressure on water demand).

Table 14. Synthesis of effects of climate change on three sectors

	Production	Receiving environments
Pastoral farming	Shift in production towards spring Higher yields with increase RCP (3 locations) In the Hawke's Bay: reduction in yield during summer in some locations (West and North), increase in yield in spring everywhere Livestock: higher risk of heat stress for animals, especially in the Waikato, Wairarapa and Canterbury plains	Higher variability in N leaching depending on soil types Higher water demand in the Waikato, no change in Southland In the Hawke's Bay: higher water limitation during spring and summer (especially West of the region)
Arable crops	**Maize**: Earlier sowing date for maize silage across regions, leading to higher catch crop yields No change in maize yield after accounting for earlier sowing date Higher soil N uptake	**Maize**: Higher variability in N leaching (frequency and magnitude) Higher water demand in Waikato, Hawke's Bay More variability in water demand in Southland
Perennial crops	**Wine grape:** Earlier flowering time across New Zealand, leading to higher risk on wine quality	**Kiwifruit**: Higher water demand in the Waikato and Hawke's Bay More variability in water demand in Southland

5.2 Implications for primary industries

Adaptation can involve tactical, strategic or transformational change. Though it is not the intention to provide an exhaustive list of these, some examples of potential changes are highlighted here for the three sectors studied in this report.

5.2.1 Pastoral systems

To maintain pastoral farm viability adaptations are frequently needed to deal with changes to pasture feed supply – both the total amount grown and its seasonality. Both lower and higher feed availability need to be dealt with. Lower supply means that if there are no changes to stock numbers productivity will decrease while higher supply with no changes in stock number will lead to decreases in grazing pressure decreases and subsequent decline in pasture quality.

Dairy farms are usually more intensive and profitable, and hence short-term tactical changes such as buying in supplementary feed and installing irrigation are able to be introduced. In contrast, for sheep and beef farming systems, especially those on hill country, possible changes are more difficult because the topography is not conducive to intervention-type changes such as tactical fertiliser use or irrigation.

Tactical changes are short- and medium-term adaptations that involve modifying the existing production system using current management options. Typically, these are decisions that are made on short (day–month) timeframes and examples include the buying and selling of stock, buying in supplementary feed, and deciding on the amount of feed to be allocated to different stock classes. Many of these potential changes are already used on a day-to-day basis by farmers to manage changes to potential future (months ahead) pasture growth such as low soil moisture levels coupled with an impeding El Niño event which may lead to a higher risk of drier than normal conditions in eastern areas; in such a situation farmers may pro-actively destock in anticipation of lower feed supply.

Strategic changes are the second level of adaptation: these involve changing a current system to another known production system or making substantive changes to the current system, where practices and technologies are well known. For example, a farmer may change the ratio of sheep to cattle; such systems are known (preferably in New Zealand) and the risks and issues relating to new systems can be anticipated. However, these changes typically take a number of years to implement hence may not have an immediate impact. In addition, other issues need to be considered: for example, changing animal type from sheep to cattle may entail building new infrastructure such as cattle yards and better tracks. Other examples of longer-term strategic changes are increasing the next season's lambing percentage by the better feeding of ewes and changing stock genetics by introducing new, improved genetics. Examples of more wider ranging strategic adaptations may include introducing irrigation or buying additional land in another area to make the existing system more flexible and resilient.

Last, there are transformational adaptations that involve innovation to develop completely new production systems or industries, which may include converting the farm from sheep and beef to a dairying operation or forestry. A prominent recent example in New Zealand is the planting of mānuka plantations.

An important point to note is that when changes to farming systems are made in response to climate change, there are likely to be changes to other impacts to the receiving environment. For example, changing from a sheep system to cattle may increase the potential for nitrate leaching (and nitrous oxide emissions) because of bigger urine patches with higher N loadings.

5.2.2 Arable industry

Results for arable crops highlight the relevance of accounting for crop management, which can be seen as a representation of farmer tactic adaptation, on climate change impacts. For example, the change in timing of crop growth in an agricultural system (e.g. spring crops as maize or winter crops as catch crop wheat) might imply different exposure to seasonal temperature in climate. In addition, insights on the importance of soil types, and how they are represented in biophysical simulations, are also key results from our analysis. Specifically, soil with low water-holding capacity will be naturally more prone to the increase in drought conditions but final outcomes depend on management aspects (e.g. use of irrigation and changes to sowing dates). Finally, inter-annual variability was shown to be a key metric to consider when analysing arable systems because some impact variables, such as N leaching losses, could be more affected by extreme events without necessarily large changes in median values. For example, the magnitude and frequency of high N leaching events might increase if high rainfall amounts occur more often before catch crop establishment (early in the autumn/winter season).

5.2.3 Horticultural industry

For wine grapes, noting the effect of climate change on phenology may require a change in cultivar to grape varieties adapted to warmer climate. One area of concern is the compressed time for fruit growth and the implications for sugar content and ultimately wine quality. Tactical adaptation may require controlling the vegetative/floral balance through winter pruning, or additional pruning in summer (Clothier et al. 2012). However, the warmer climate may also open new areas suitable for wine grape that were previously too cool. The model and script that were developed are spatially explicit, and can explore different varieties, allowing some future analyses on which variety may be more suitable to grow in the different parts of the country.

The preliminary results using a simple water-balance model also suggest that better use of irrigation water will be a necessity, especially in Hawke's Bay where the irrigation resource is already fully allocated.

5.3 Model assumptions and limitations

5.3.1 Drivers of variation in pasture production and N leaching

By testing models with different levels of complexity at a point scale, we were able to analyse the utility and consequences of the level of assumptions from each model. Biome-BGC is simpler than APSIM (one soil layer, does not contain explicit grazing and management modules), yet captures the same trends in yield with climate change. While it was primarily used in this study for regional-scale analysis, ET-PET from Biome-BGC was shown to have significant correlation with yield, so it had enough complexity to provide useful information at the point scale. More general modelling (tier 2) or simpler metrics (tier 1) could be of considerable value where the particular responses to water are needed for a number of sites or for map level analysis. Biome-BGC's ET-PET water indices for the year, or for summer, and

SPEI metrics for the summer months of January and February were very successful predictors in this analysis. WATYIELD outputs were not preferentially selected by the stepwise regression procedure: this may reflect the lack of inclusion of CO_2 fertilisation in WATYIELD. The WATYIELD annualised Potential evapotranspiration Deficit was highly correlated with Biome-BGC's equivalent ET-PET output and may be simpler to deliver. Yet SPEI metrics are simplest of all and performed well.

Pasture production results from the model capable of representing detail in soils and management practices, APSIM, could only partially be explained ($R^2 = 0.56$) by our next most complex model, Biome-BGC. The latter included a detailed daily plant physiology and biogeochemistry representing carbon, water and N, but with only limited representation of long-term average grazing and a one-layer soil. Results showing that less variance in pasture production within APSIM (79%) versus Biome-BGC (89%) can be explained by soil, GCM, water, and climate indices should be understood in the context that APSIM converts detail in soil and management into additional meaningful variation not in Biome-BGC. As a result, variation across the six soils accounted for more of the explained variance in APSIM. Thus, APSIM has considerable value wherever site-level simulations are desirable.

We recognise the overlapping nature of the two SPEI2 January and February metrics. For determining suitable climate attributes for the LUS framework, further analysis of the data will be required. In the meantime, while these results should be regarded as preliminary, they provide a valuable assessment of climate attributes to be considered for the LUS framework.

Our preliminary analysis of the pasture production data has identified two provisional climate attributes that could be considered for the LUS framework. The first is **Nbhotdays25**, given it is independent of other attributes, in contrast to SPEI. This Tier 1 attribute would require relatively little effort to obtain values for the framework, as data are included as one of NIWA's projected climate variables.

The second provisional attribute is **SPEI2**. However, further analysis will be required to determine which SPEI period and what months would be most suitable as a climate attribute explaining current and projected pasture production. This requirement is due to the overlap in monthly data for adjacent monthly SPEI2 (and SPEI3) variables. Regardless, the results strongly suggest that SPEI should be short-listed for inclusion in the LUS framework.

While our data analysis of potential climate attributes aligned to N leaching is not as advanced as that undertaken for pasture production, our preliminary assessment would suggest **SPEI** could potentially be applied nationally, making it a provisional attribute for losses to water (specifically N leaching) to be considered for inclusion in the LUS framework. Given the provisional nature of the data analysis, further detailed analysis will be required to identify whether other climate attributes should be considered. Also, as noted above for production, further work is required to determine which SPEI period (1, 2 or 3 months) and which particular months would be most suitable as a climate attribute explaining current and projected N leaching from pasture systems.

Three useful conclusions can be drawn from this programme. First, the analysis fully confirmed the value of recognising roughly three tiers of complexity in models and indices used to derive outputs relating future production to climate attributes. Second, indices representing water budgets and SPEI metrics both capture considerable variation representing the role of seasonal climate and drought in determining productivity. Third, variation between soils was much more important than variation between GCMs, so that the number of GCMs included in future analysis can be reduced in favour of greater soil or regional diversity. The structure of this analysis may also be relevant to the study of nitrate leaching.

5.4 Future opportunities and knowledge gaps

Our research helped improve our understanding of the importance of climate change impacts on the resilience of agricultural land uses. We see this research helping stakeholders to integrate multiple decision criteria and better understand how to incorporate climate change within decision-making processes, while dealing with soil, water quality, and economic management objectives.

Based on our findings, future research should focus on various aspects:

- The impact of drought on key variables such as production or nitrate leaching should be investigated further. We were constrained by the six GCM projections from previous research. The use of a weather generator to create artificially low precipitations during a certain time of the year, could help by running the biophysical models like APSIM to see how crops may respond. The PFR analysis platform developed during the Discovery Project could enable this complex and demanding task through high performing computers.
- Some of the climate attributes, especially the SPEI that were identified as explaining part of the production outcomes, could easily be mapped for the whole country (similarly to the global drought monitor https://spei.csic.es/map/maps.html), to highlight potential areas affected by droughts as additional indicators to the already available NZDI from NIWA (https://www.niwa.co.nz/climate/information-and-resources/drought-monitor).
- Overall, the structure of the statistical analysis attributing variance in modelled pasture production to candidate climate attributes and other variables was intended to guide the structure of future work, not the specific final selection of climate attributes for the LUS framework. Further data analysis will be required to identify this final selection. However, the work to date has provided valuable information on potential attributes for a more detailed data analysis. This methodology should also be extended to other crops (maize), and other output variables (N leaching, etc.).
- The tiered-approach for the biophysical modelling was explored during this project but would need further scrutiny to make future recommendations on the utility, fit-for-purpose and scale of use of the various approaches against different goals (quantitative projection of biomass change, adaptation options, direction of change, risk profiling) and different end-users (farmers, sector, government).
- Climate is an important determinant of land use and significant biophysical impacts of climate change are expected. However, because climate change impacts are not yet widely considered in land-use decisions, there is still a need to evaluate when, where,

and how to begin factoring emerging climate change impacts into decision contexts and across sectors. This is a starting point for conversation and informing decision making, through an adaptive pathway framework that should be developed further.

6 Acknowledgements

We would like to acknowledge Amber Parker from Lincoln University for useful discussion on the wine phenology model and the implications for the wine growing industry. We would also like to acknowledge Linda Lilburne for provision of Smap data and advice, and Abha Sood for provision of the climate change projections for New Zealand. This project was funding through the Deep South and Our Land and Water National Science Challenges. Thanks to Andrew Tait, Suzie Greenhalgh and Peter Edwards for useful comments on this report.

7 References

Agnew R, Raw V, Grab F, Horner R, Sorensen I, Marshall R, Scofield C, Wood P, Stanley J, Gandell M, Smith J 2017. Grapevine growth stage monitoring for prediction of key phenological events. Progress report to the NZ Wine Grower, 105, 139-141, Aug–Sept 2017. Available at: https://issuu.com/ruralnewsgroup/docs/nzwg_105_aug-sep_2017/139

Arpaia A, Barrios S, Bergmann M, Carone G, Diez Guardia N, Donnay M, Garnier C, Hallet M, Hayden M, Hodson D, Ilzkovitz F, Kuhlmann J, McMorrow K, Mourre G, Nicodeme G, Pichelmann K, Przywara B, Röger W, Salomaki A, Sauner-Leroy J.-B, Stierle M, Thiel M, Verhaeven J, Veuglers R, Watson J, Watson M, Young D 2004. Protecting the environment and economic growth: trade-off or growth-enhancing structural adjustment? In: Commission DGE ed. The EU economy: 2004 review. Brussels, Belgium: European Commission. Pp. 303–342.

Beare M, van der Weerden T, Ausseil AG, Baisden T, Teixeira E, Vogeler I, Keller E, de Klein C. August 2017. Identifying climate attributes that impact on land use suitability. A Plant & Food Research report prepared for Our Land and Water Deep South National/Science Challenges. Milestone No. 73517. Contract No. 34484. Job code: P/442061/01. SPTS No. 15283.

Johnson HD, Ragsdale AC, Berry IL, Shanklin MD 1962. Effects of various temperature-humidity combinations on milk production of Holstein cattle. Missouri Agricultural Experiment Station Research Bulletin 791: 1–39.

Hewitt AE 2010. New Zealand soil classification. 3rd edn. Landcare Research Science Series No. 1. Lincoln, Canterbury, New Zealand: Manaaki Whenua Press.

Holzworth DP, Huth NI, deVoil PG, Zurcher EJ, Herrmann NI, McLean G, Chenu K, van Oosterom EJ, Snow V, Murphy C, Moore AD, Brown H, Whish JPM, Verrall S, Fainges J, Bell LW, Peake AS, Poulton PL, Hochman Z, Thorburn PJ, Gaydon DS, Dalgliesh NP, Rodriguez D, Cox H, Chapman S, Doherty A, Teixeira E, Sharp J, Cichota R, Vogeler I, Li

FY, Wang E, Hammer GL, Robertson MJ, Dimes JP, Whitbread AM, Hunt J, van Rees H, McClelland T, Carberry PS, Hargreaves JNG, MacLeod N, McDonald C, Harsdorf J, Wedgwood S, Keating BA 2014. APSIM – evolution towards a new generation of agricultural systems simulation. Environmental Modelling & Software 62: 327–350.

Keller ED, Baisden WT, Timar L, Mullan B, Clark A 2014. Grassland production under global change scenarios for New Zealand pastoral agriculture. Geoscientific Model Development 7: 2359–2391.

Li FY, Snow VO, Holzworth DP 2011. Modelling the seasonal and geographical pattern of pasture production in New Zealand. New Zealand Journal of Agricultural Research 54: 331–352.

Li FY, Newton PCD, Lieffering M 2013. Testing simulations of intra- and inter-annual variation in plant production response to elevated CO2 against measurements from an 11-year FACE experiment on grazed pasture. Global Change Biology 20: 228–39.

McDowell RW, Dils RM, Collins AL, Flahive KA, Sharpley AN, Quinn J 2016. A review of the policies and implementation of practices to decrease water quality impairment by phosphorus in New Zealand, the UK, and the US. Nutrient Cycling in Agroecosystems 104: 289–305.

McDowell RW, Snelder T, Harris S, Lilburne L, Larned ST, Scarsbrook M, Curtis A, Holgate B, Phillips J, Taylor K 2018. The land use suitability concept: Introduction and an application of the concept to inform sustainable productivity within environmental constraints. Ecological Indicators 91: 212–219. https://doi.org/https://doi.org/10.1016/j.ecolind.2018.03.067

National Research Council – NRC 1971. A guide to environmental research on animals. Washington, DC: National Academy of Sciences. 374 p.

O'Leary GJ, Christy B, Nuttall J, Huth N, Cammarano D, Stöckle C, Basso B, Shcherbak I, Fitzgerald G, Luo Q, Farre-Codina I, Palta J, Asseng S 2015. Response of wheat growth, grain yield and water use to elevated CO2 under a Free-Air CO2 Enrichment (FACE) experiment and modelling in a semi-arid environment. Global Change Biology 21: 2670–2686. doi:10.1111/gcb.12830

Parker AK, De Cortázar-Atauri IG, Van Leeuwen C, Chuine I 2011. General phenological model to characterise the timing of flowering and veraison of Vitis vinifera L. Australian Journal of Grape and Wine Research 17: 206–216. https://doi.org/10.1111/j.1755-0238.2011.00140.x

Parris K 2011. Impact of agriculture on water pollution in OECD countries: recent trends and future prospects. International Journal of Water Resources Development 27: 33–52. https://doi.org/10.1080/07900627.2010.531898

Tait A, Sood A, Mullan B, Stuart S, Bodeker G 2016. Updated climate change projections for New Zealand for use in impact studies. Synthesis Report RA1. Climate Change Impacts and Implications (CCII) for New Zealand to 2100. MBIE contract C01X1225.

Tait A, Turner R 2005. Generating multi-year gridded daily rainfall over New Zealand. Journal of Applied Meteorology 44: 1315–1323.

Thornton PE, Law BE, Gholz HL, Clark KL, Falge E, Ellsworth DS, Goldstein AH, Monson RK, Hollinger DY, Falk M, Chen J, Sparks JP 2002. Modeling and measuring the effects of disturbance history and climate on carbon and water budgets in evergreen needleleaf forests. Agriculture and Forest Meteorology 113: 185–222.

Teixeira E, Ausseil, A, Burgueño E, Brown H, Cichota R, Davy M, Ewert F, Guo J, Holmes A, Holzworth D, Hu W, Ruiter D, Hume E, Jesson L, Johnstone P, Powell J, Christian K, Kong H, Liu J, Lilburne L, Meiyalaghan M, Storey R (in press). A spatial analysis framework to assess responses of agricultural landscapes to climates and soils at regional scale. In: "Landscape Modelling and Decision Support" (Editors: Wilfried Mirschel et al.). Springer book series: "Innovations in Landscape Research" (Series editor: Lothar Mueller) pages 1–22.

Thornton PE, Running SW, Hunt ER 2005. Biome-BGC: terrestrial ecosystem process model, Version 4.2 Final Release. Missoula, MT: Numerical Terradynamic Simulation Group, School of Forestry, University of Montana, available at: http://www.ntsg.umt.edu/project/biome-bgc.php (last access: 31 January 2019).

Vicente-Serrano, Sergio M, National Center for Atmospheric Research Staff eds Last modified 18 Jul 2015. The climate data guide: standardized precipitation evapotranspiration index (SPEI). Retrieved from https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-evapotranspiration-index-spei.

Appendix 1 – WATYIELD Model

The WATYIELD model is designed to calculate the water balance in soil with a certain crop cover. It was developed by Manaaki Whenua Landcare Research (MWLR)), following the FAO-56 Guidelines for computing crop water requirements and the SWAT model (developed by USDA).

The daily soil water balance is calculated by taking the inflow from precipitation to the system and removing water from canopy interception, drainage and evapotranspiration. The daily soil water content (SWC) is obtained from the water balance equation:

$$SWC_i = SWC_{i-1} + PCP_i - I_i - Q_i - E_i \tag{A1}$$

where:

SWC_i	soil water content in the root zone at the end of day *i* [mm]
SWC_{i-1}	soil water content in the root zone at the end of the previous day *i - 1* [mm]
PCP_i	precipitation on day *i* [mm]
I_i	interception on day *i* [mm]
Q_i	drainage on day *i* [mm]
E_i	evapotranspiration on day *i* [mm]

The initial SWC was set equivalent to the Total Available Water (TAW) in soil.

1. Interception

The interception (I) is the free moisture intercepted by the crop canopy. It is determined by the interception fraction (ICF) which is the estimation of total proportion of precipitation lost through interception, and the Interception Storage Capacity (ISC) which is the maximum amount of water can be intercepted by canopy. Both ICF and ISC are obtained from previews study (Rowe, Jackson, & Fahey, 2002). The daily interception is defined by the equation:

$$I_i = \begin{cases} PCP_i * ICF - I_{i-1}, \ IC < ISC \\ ISC - I_{i-1}, \ IC \geq ISC \end{cases} \tag{A2}$$

where I_i is the interception on day *i* [mm], and the $I_{i-1}$is the intercepted water left from the previous day. The I_{i-1}in the first day was set to 0, and then calculated by subtracting the evaporated water from canopy from the interception.

$$I_{i-1} = I_{i-1} - E_{can\ i-1} \tag{A3}$$

The E_{can} is obtained from section 3.

2. Drainage

Whenever the SWC exceed the TAW, water lost through either percolation or runoff. This part of outflow is considered as drainage (Q). It is given by:

$$Q_i = \begin{cases} SWC_i - TAW, & SWC_i > TAW \\ 0, & SWC_i \leq TAW \end{cases} \quad \text{(A4)}$$

Two assumptions were made here. One is that there is no runoff flow form one spatial unit (e.g. pixel cell of raster data) to the other, and the other is that before the soil water reaches the field capacity no drainage occurs.

3. Evapotranspiration

The evapotranspiration consists of three parts, water evaporates from canopy (intercepted water) E_{can}, transpiration from crop and the evaporation from soil. Since transpiration from crop and evaporation from soil are hard to distinguish, they have been considered as a single crop evapotranspiration ET_c.

$$E_i = E_{can\ i} + ET_{c\ i} \quad \text{(A5)}$$

The estimation of evapotranspiration is based on the Potential Evapotranspiration (PET) which is the evaporation climatic demand. Many scientific literatures use another denomination, Reference Crop Evapotranspiration (ET_0) to represent PET. ET_0 is an evapotranspiration rate from a reference surface which is a hypothetical grass reference crop with specific characteristics. It is the evaporative demand of the atmosphere independently of crop type, crop development and management practices. ET_0 can be computed from weather data using Penman-Monteith method (Allen, Pereira, Raes, & Smith, 1998). Although some recent research (Katerji & Rana, 2011; McMahon, Peel, Lowe, Srikanthan, & McVicar, 2013) demonstrated that PET is not equivalent to ET_0, in this study, due to the availability of data, we assume that they are equivalent.

The daily evaporation from canopy, $E_{can\ i}$, is determined by the interception of the day as well as the $ET_{0\ i}$ (the ET_0 on day i)(Liu, Wang, Xue, Singh, & Ma, 2015; Neitsch, Arnold, & Kiniry, 2005).

$$E_{can\ i} = \begin{cases} I_i, & ET_{0\ i} \geq I_i \\ ET_{0\ i}, & ET_{0\ i} < I_i \end{cases} \quad \text{(A6)}$$

Any free water present in the canopy is readily to evaporate, and it contribute to actual evapotranspiration. Thus, we first remove the E_{can} from the ET_0 , to get the remaining, the evaporative water demand for a reference crop(Neitsch et al., 2005).

$$ET'_{0\ i} = ET_{0\ i} - E_{can\ i} \quad \text{(A7)}$$

Once ET'_0 is calculated, we can estimate the crop evapotranspiration under standard condition (crops growth under optimum environment conditions and achieve full production) (ET_c). It is derived from the ET'_0 using Crop Coefficient (K_c) to represent different vegetation types. K_c is determined by a variety of crop characteristics, such as leaf anatomy, stomatal characteristics, aerodynamic properties and albedo. In this study, we use K_c from FAO-56 report (Allen et al., 1998) as well as previous studies in MW, however, the seasonal difference of K_c is not taken into account.

$$ET_c = K_c * ET_0' \quad \text{(A8)}$$

In reality, the optimum environment condition does not always exist for crops growth. As soil dries, the root can initially get enough water from soil to have an evapotranspiration as same as ET_c. However, at a certain point (soil water content below a threshold), the crop can no longer extract enough water through the roots and becomes water stressed, and we call this threshold Trigger Point (TP). Whenever the crop is under this water stress situation, the ET_c start to decrease, and this decreasing rate is described by the water stress coefficient (also called transpiration reduction factor), K_s. Therefore, the actual crop evapotranspiration (under non-standard condition), AET_c, is calculated by:

$$AET_c = K_s * ET_c = K_s * K_c * (ET_0 - E_{can}) \quad \text{(A9)}$$

Since we only focus on the water balance, here we assume factors other than water, e.g. soil salinity, fertility and animal impacts, are under standard condition.

The transpiration reduction factor K_s dependent on three soil water properties:

- Total Available Water (TAW) – the capability of soil to retain water available to plants, and it is the difference between field capacity and permanent wilting point (WP);
- Readily Available Water (RAW) – the fraction of TAW that plants can extract water from the root zone without suffering water stress;
- Soil Water Content (SWC) – the actual amount of water held in soil.

Thus when SWC below the TP, K_s is calculated by the function:

$$K_s = \frac{SWC}{TAW-R} \quad \text{(A10)}$$

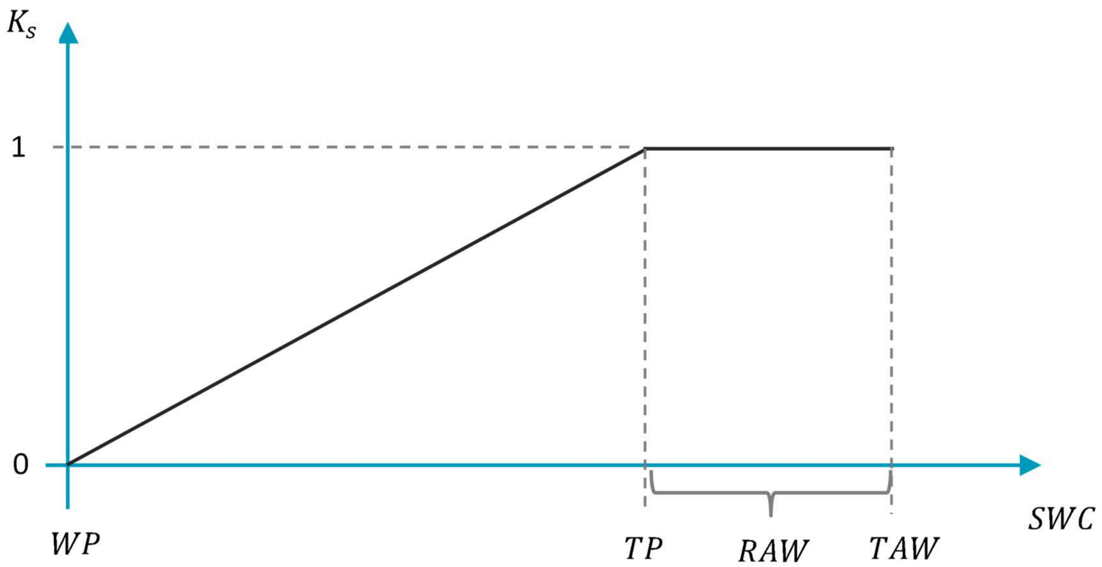


Figure 37. Ks as a function of SWC.

4. Data and parameters

Three types of data are required for setting up parameters in the water balance model, which are climate, soil and crops. The detail of data including source, model used properties and format etc. are listed in the table below.

Table 15. Data sources for WATYIELD

Model Data Parameters		Type	Data	Format	Model used Properties	Source
PCP	Precipitation	Climate	Daily PCP raster	GeoTiff	N/A	NIWA
ET_0	Reference Crop Evapotranspiration (assume it is equivalent to PET)		Daily PET raster			
TAW	Total Available Water	Soil	S-Map	ESRI Shapefile	TAW	MW
RAW	Readily Available Water				RAW	
K_c	Crop Coefficient	Crop	K_c	Text	N/A	FAO, MW
ICF	Interception Fraction		ICF			MW
ISC	Interception Storage Capability		ISC			

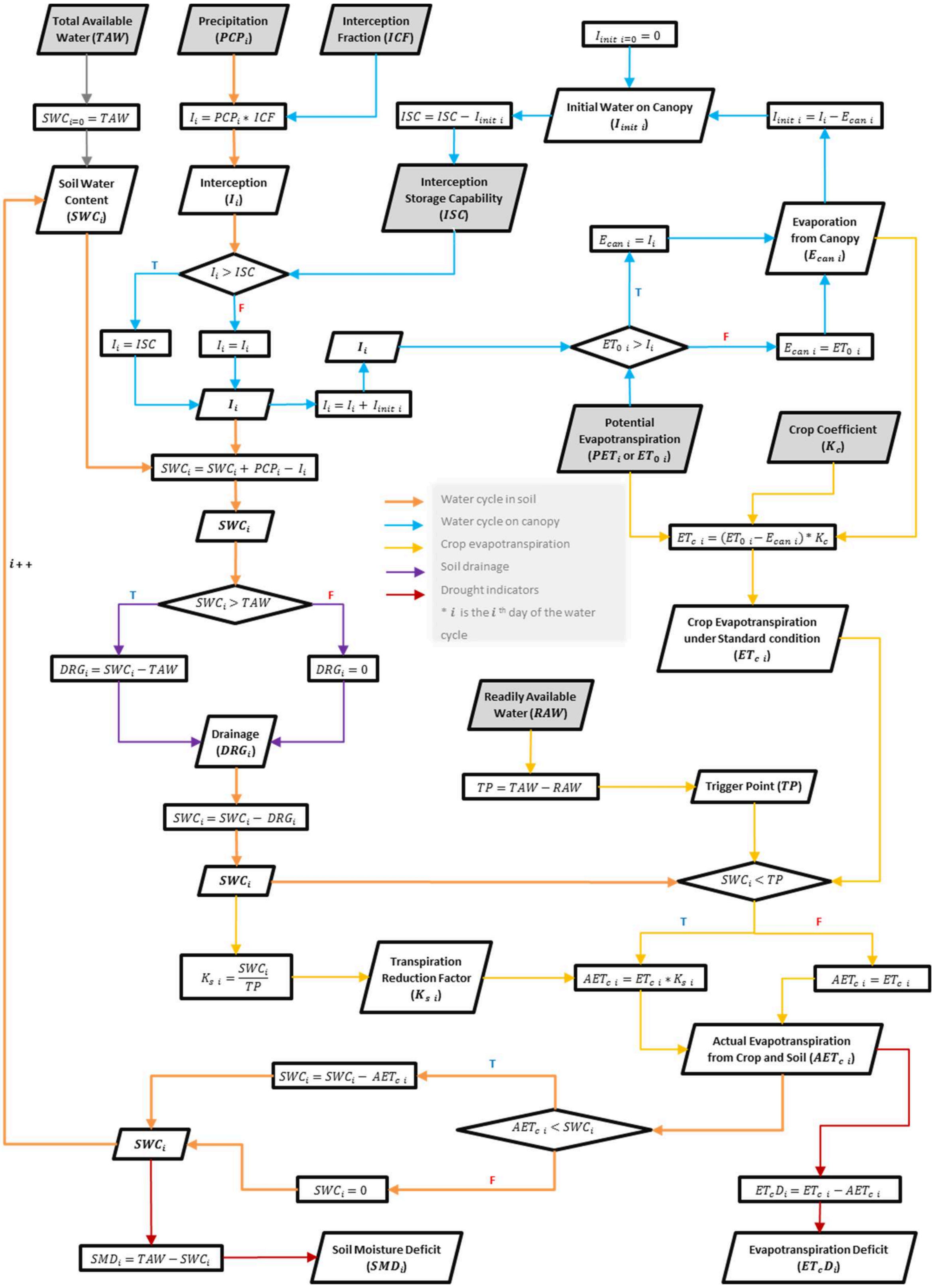


Figure 38. WATYIELD model workflow.

5. References

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). FAO Irrigation and Drainage Paper: Crop Evapotranspiration. *Irrigation and Drainage*, *300*(56), 333. https://doi.org/10.1016/j.eja.2010.12.001

Katerji, N., & Rana, G. (2011). Crop Reference Evapotranspiration: A Discussion of the Concept, Analysis of the Process and Validation. *Water Resources Management*, *25*(6), 1581–1600. https://doi.org/10.1007/s11269-010-9762-1

Liu, X., Wang, S., Xue, H., Singh, V. P., & Ma, W. (2015). Simulating crop evapotranspiration response under different planting scenarios by modified SWAT model in an irrigation District, Northwest China. *PLoS ONE*, *10*(10), 1–21. https://doi.org/10.1371/journal.pone.0139839

McMahon, T. A., Peel, M. C., Lowe, L., Srikanthan, R., & McVicar, T. R. (2013). Estimating actual, potential, reference crop and pan evaporation using standard meteorological data: A pragmatic synthesis. *Hydrology and Earth System Sciences*, *17*(4), 1331–1363. https://doi.org/10.5194/hess-17-1331-2013

Neitsch, S., Arnold, J., & Kiniry, J. (2005). Soil and water assessment tool: theoretical documentation, version 2009. *Texas, …*. Retrieved from http://repository.tamu.edu/handle/1969.1/128050

Rowe, L., Jackson, R., & Fahey, B. (2002). Land use and water resources: Hydrological effects of different vegetation covers SMF2167: Report No 5, *SMF2167: R*, 1–142.

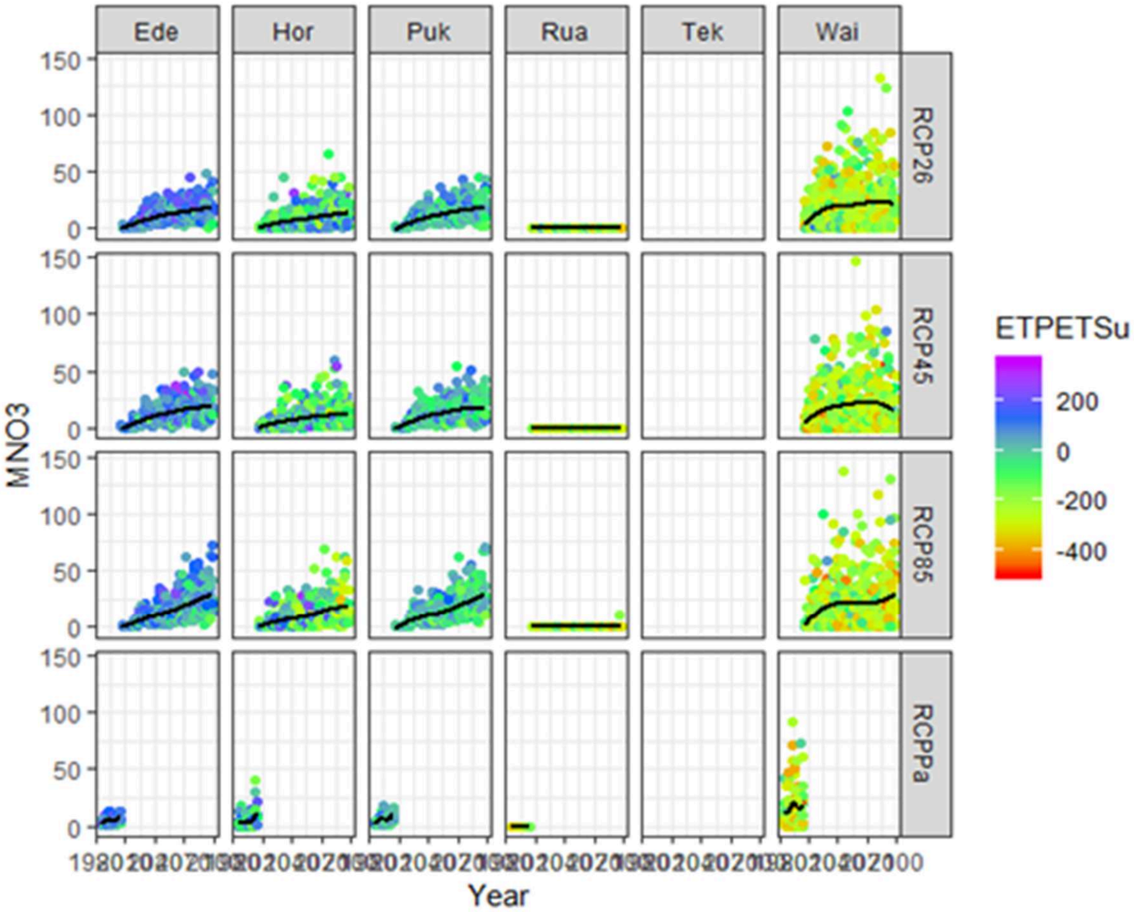
Appendix 2 – N leaching visual plots

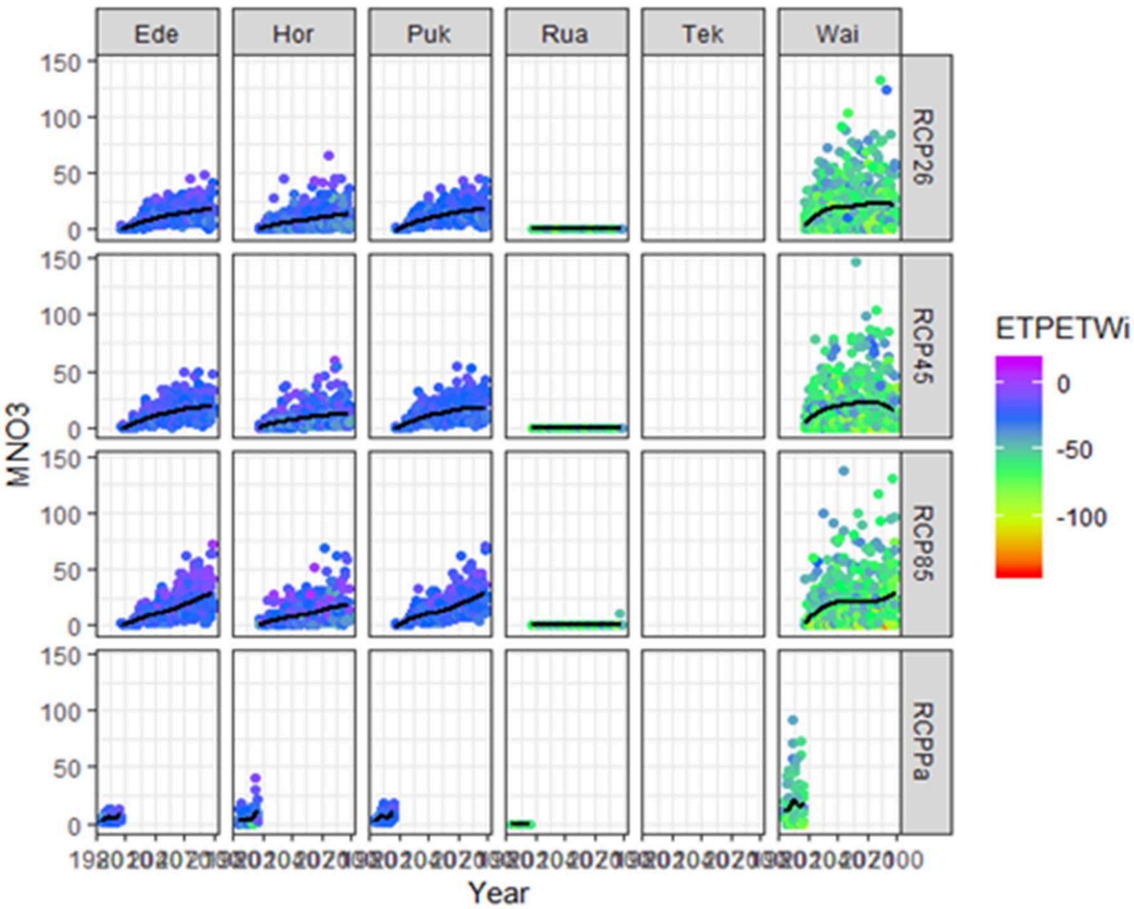
The following figures are visual plots illustrating the influence of the eight selected climate attributes (ETPET, LRelSM, ASoilDev, WYAETPET, PCP, PET, AET and SPEI) and modelled N leaching data (MNO3, kg N/ha) from 2006 to 2098, for 3 RCPs (2.6, 4.5 and 8.5) and the past RCP (from 1990 to 2006) and 6 soil/regions (**Ede**ndale in Southland, **Hor**otui in Waikato, **Puk**emutu in Southland, **Rua**taniwha in Hawke's Bay, **Te K**owhai in Waikato, and **Wai**makariri in Hawke's Bay). Each attribute represents 1 or more different periods. For example, ETPET is presented as an annual value (ETPETAnnSu) or as seasonal values (ETPETAu, ETPETWi, etc.)

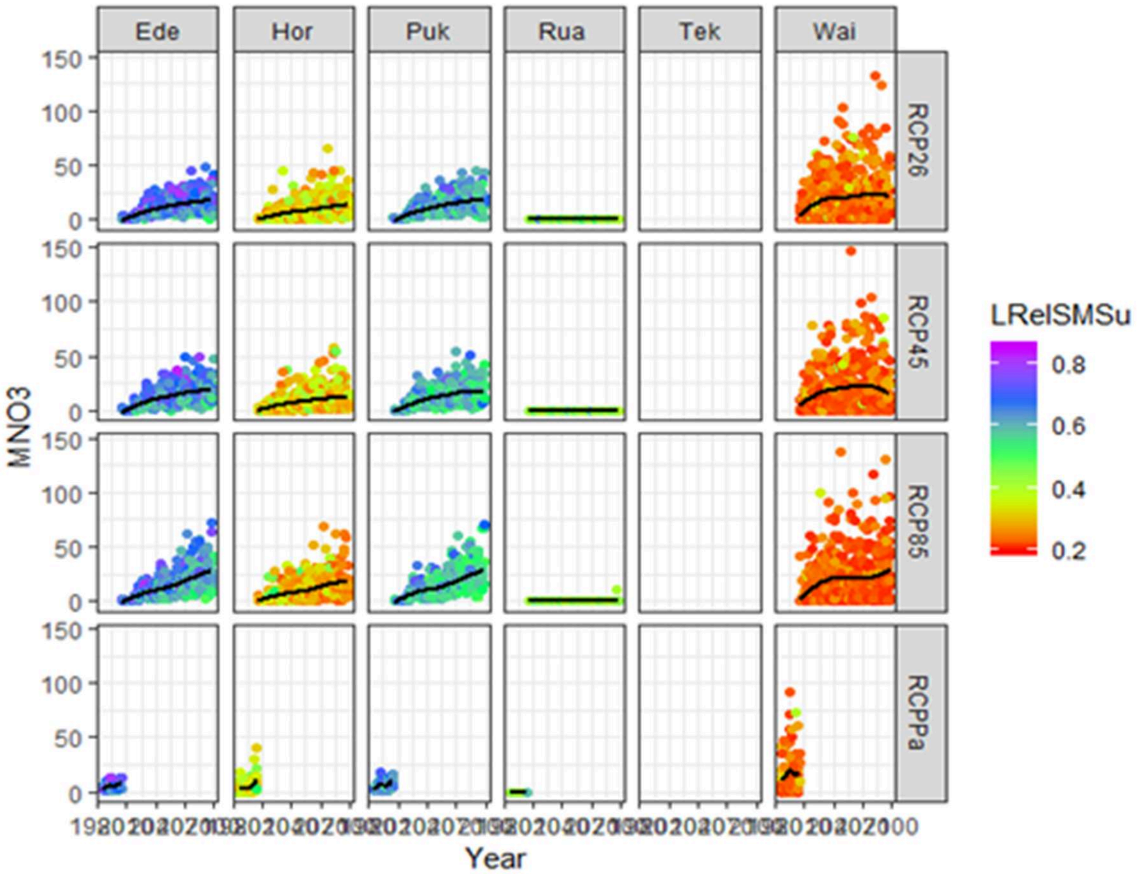
Because the code for the eight climate attributes shown in the figures in this appendix are not identical to those listed in Table 6, a key is provided below:

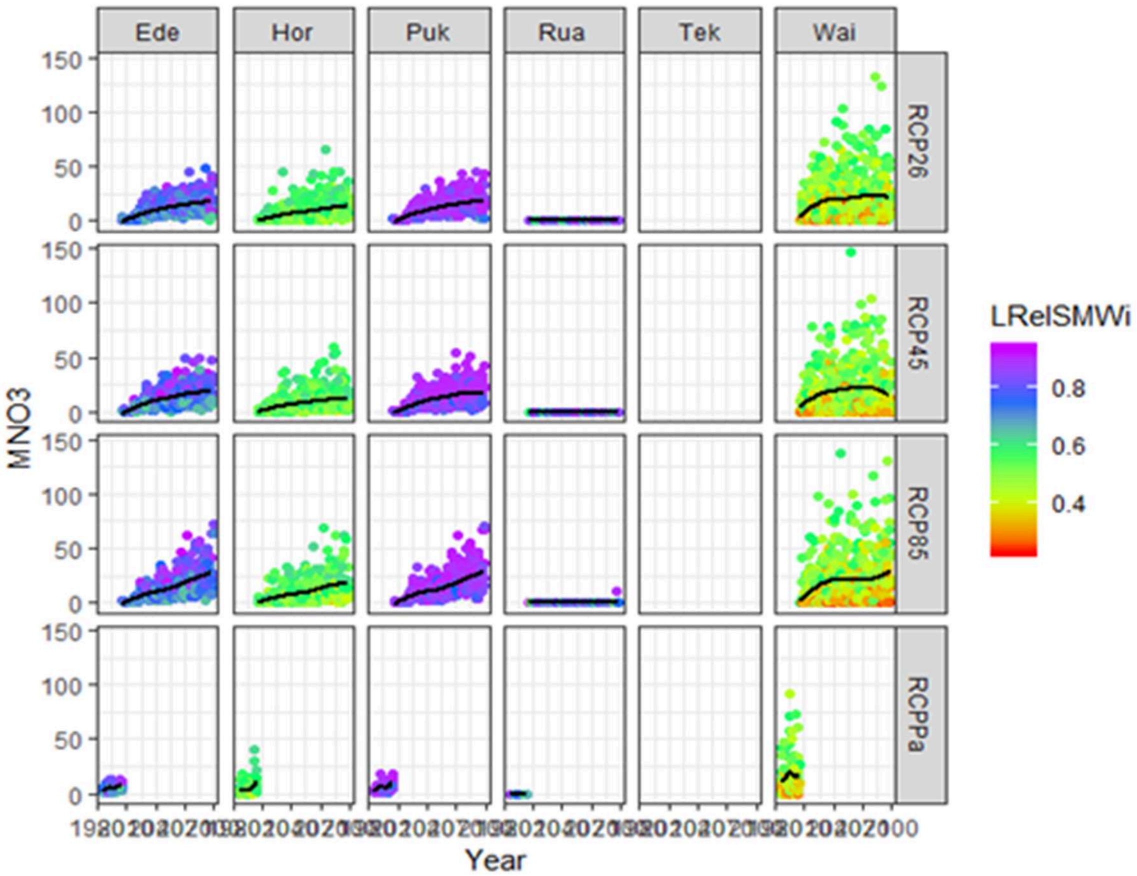
Table 16. Equivalent code used in the appendix figures

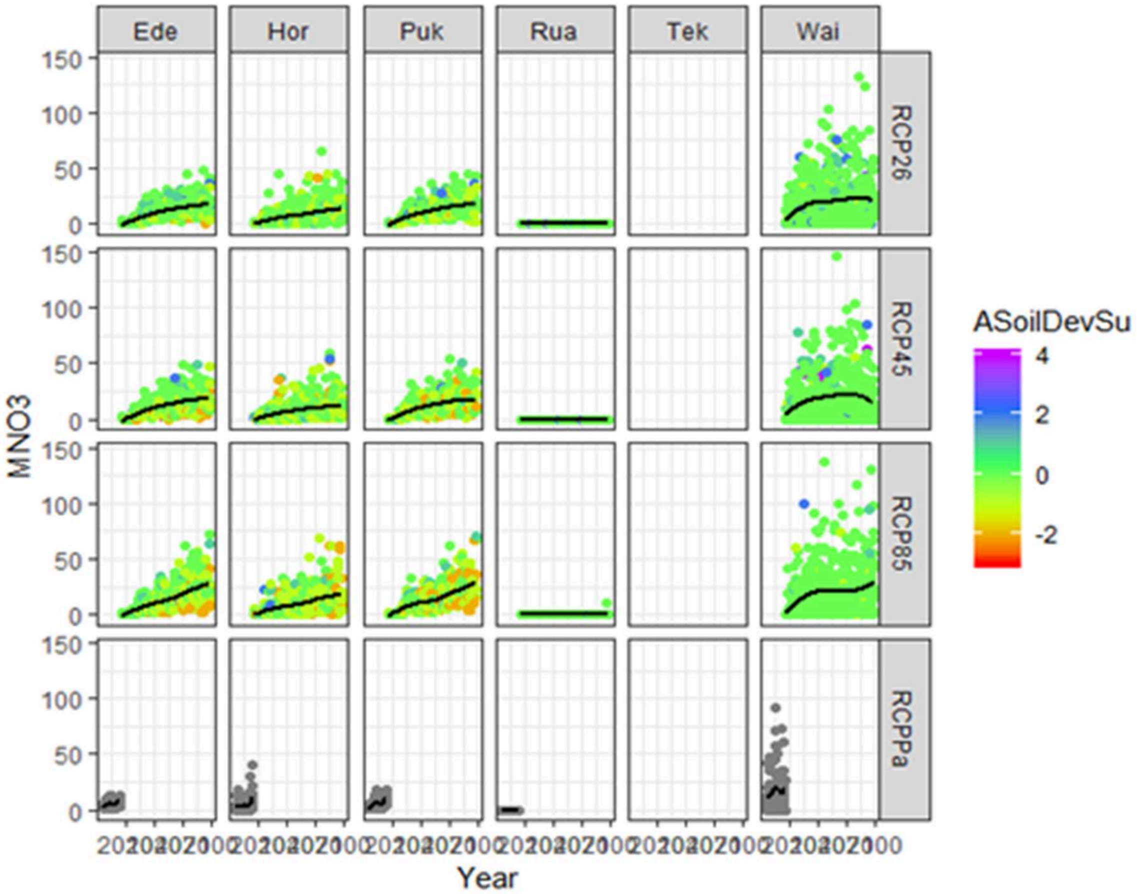
Climate attribute	Code used in figures in this appendix
PCP	PCP
PET	PET
AET	AET
AET - PET	WYAETPET
ET - PET	ETPET
Relative Soil Moisture	LRelSM
SoilDev	ASoilDev
SPEI	SPEI

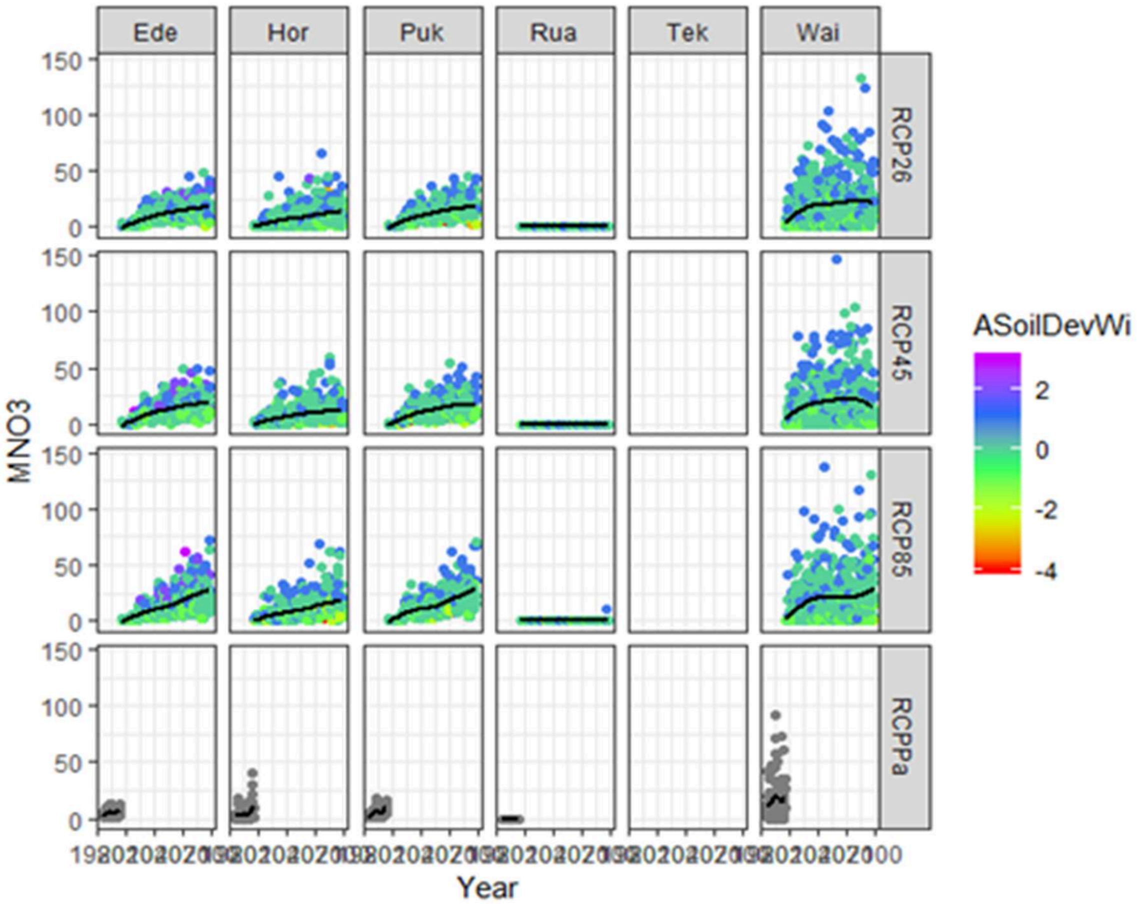

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPa
MNO3
Year
ETPETSu
200
0
-200
-400
150
100
50
0

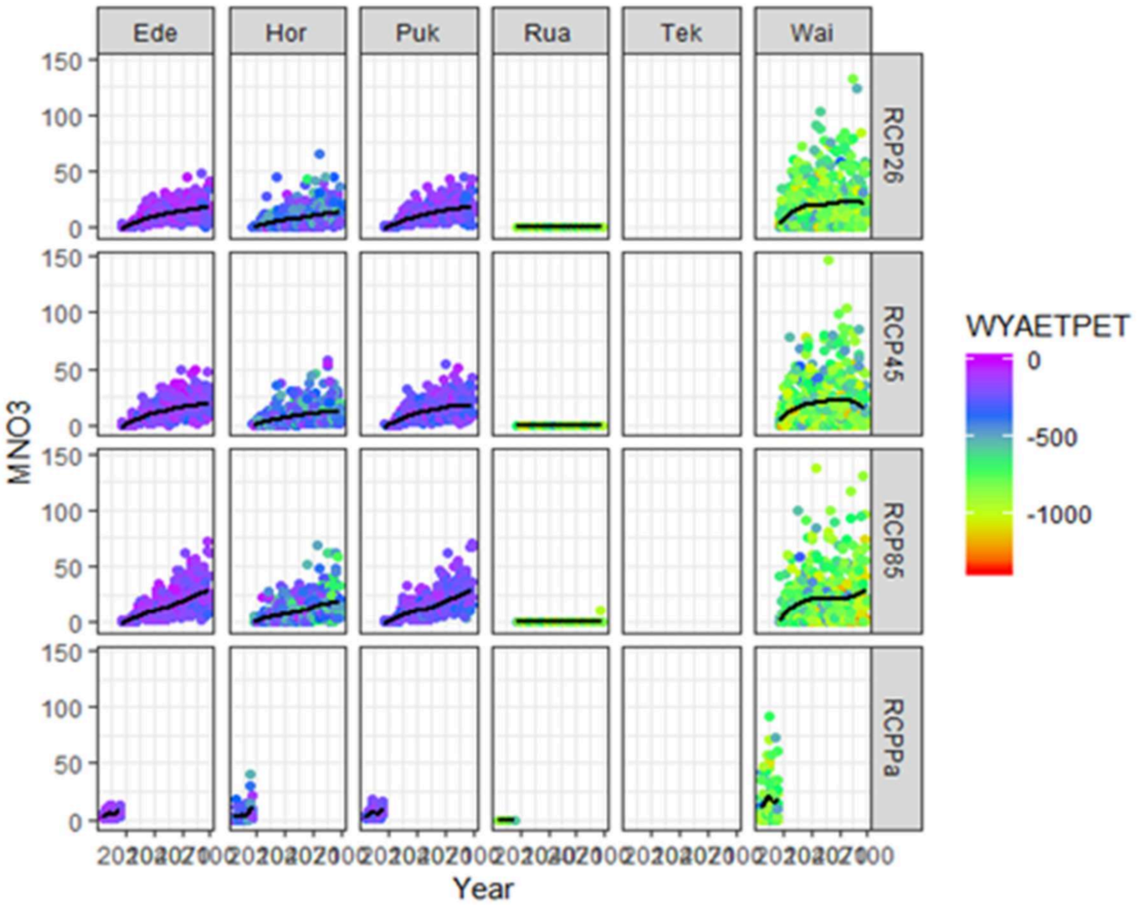

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPa
MNO3
Year
ETPETWi
0
-50
-100
150
100
50
0

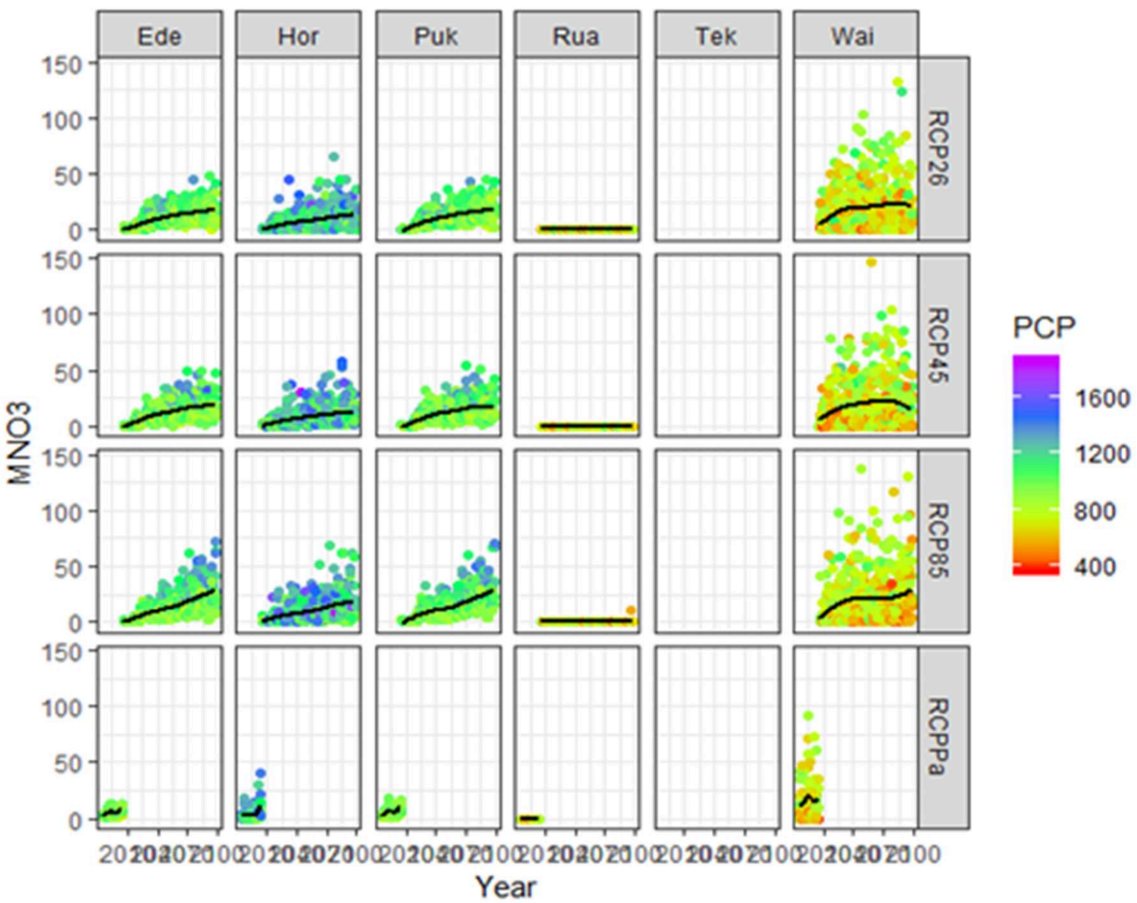

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
MNO3
Year
LRelSMSu
0.8
0.6
0.4
0.2
150
100
50
0

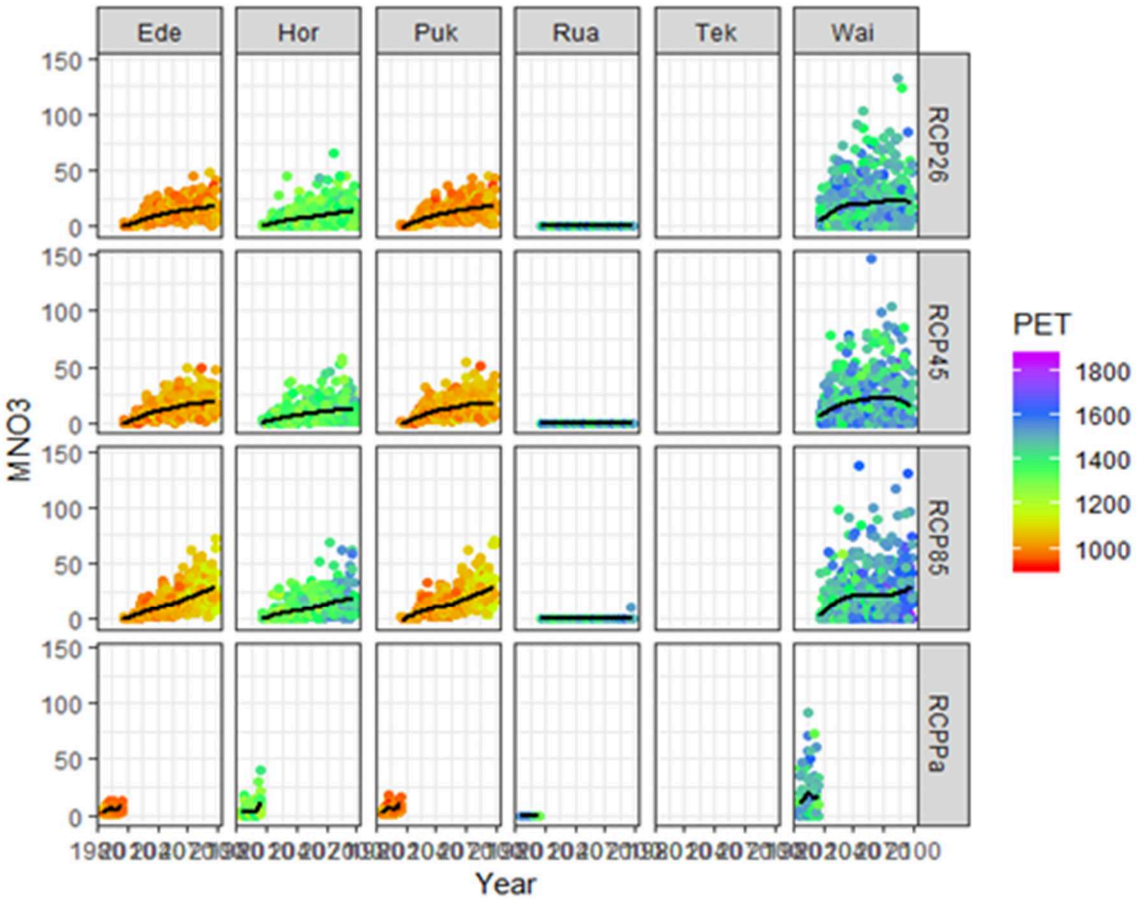

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
MNO3
Year
LRelSMWi
0.8
0.6
0.4
150
100
50
0

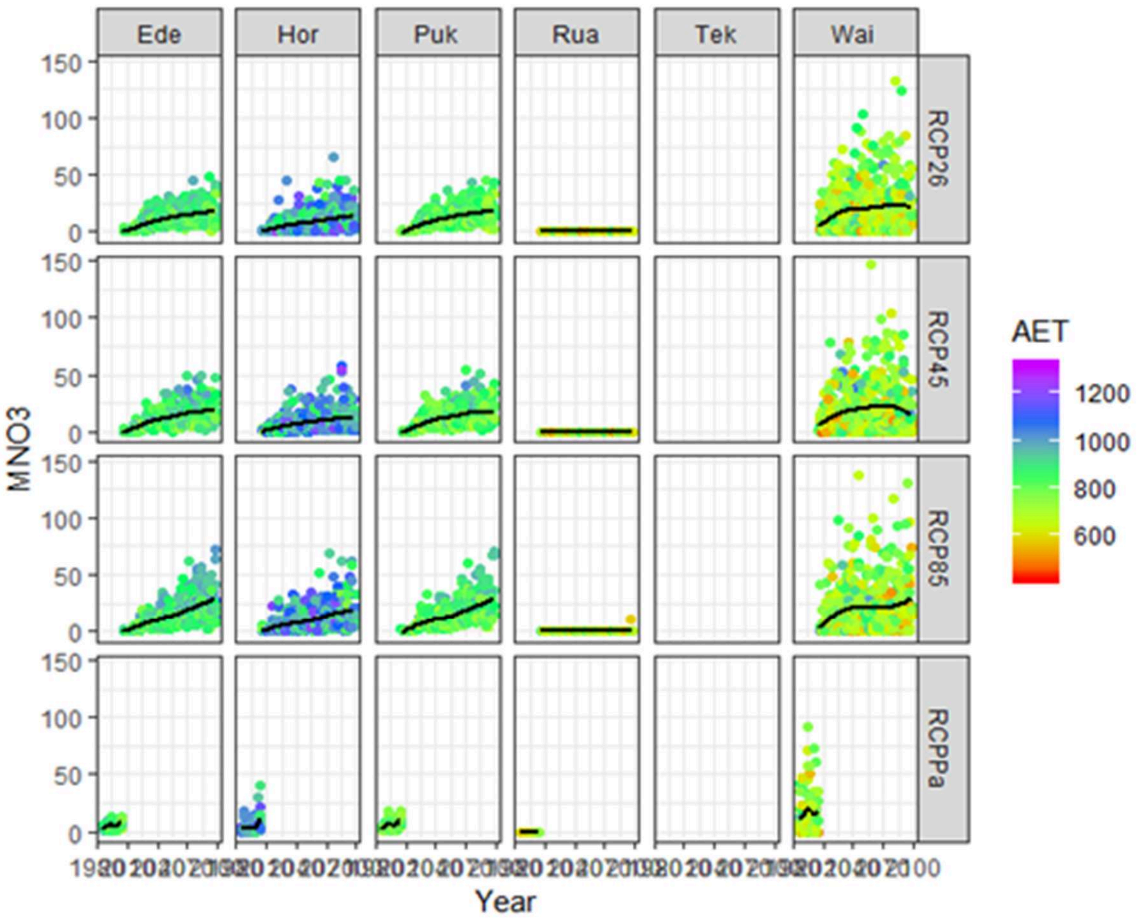

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
MNO3
Year
ASoilDevSu
4
2
0
-2

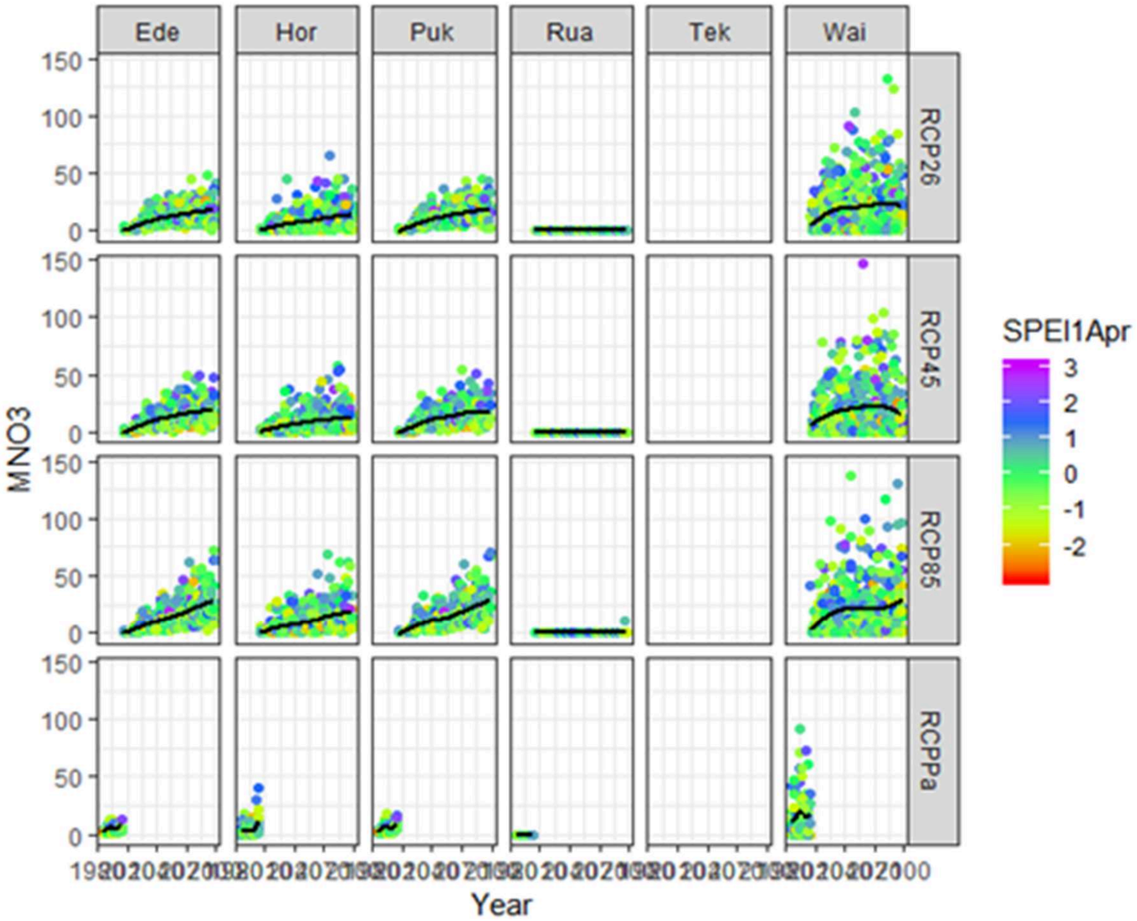

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
MNO3
Year
ASoilDevWi
2
0
-2
-4

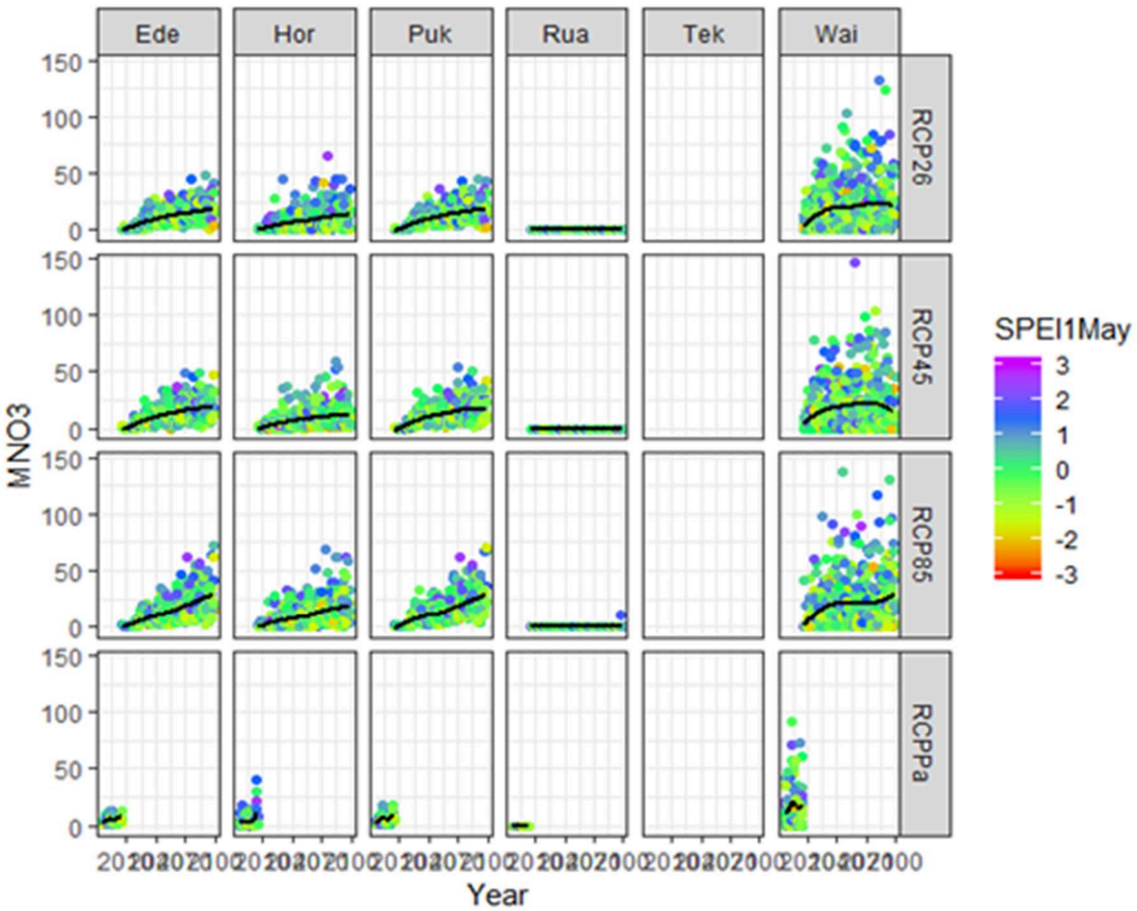

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
MNO3
Year
WYAETPET
0
-500
-1000

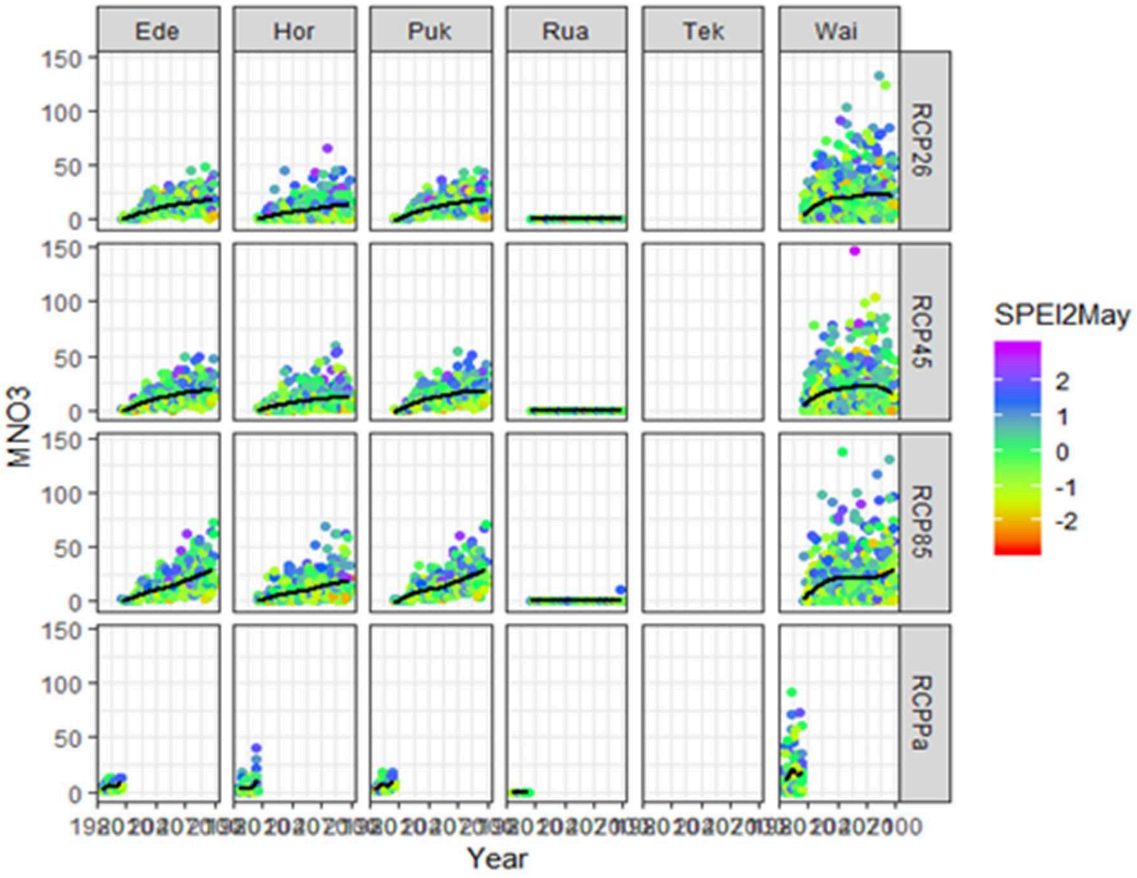

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
MNO3
Year
PCP
1600
1200
800
400

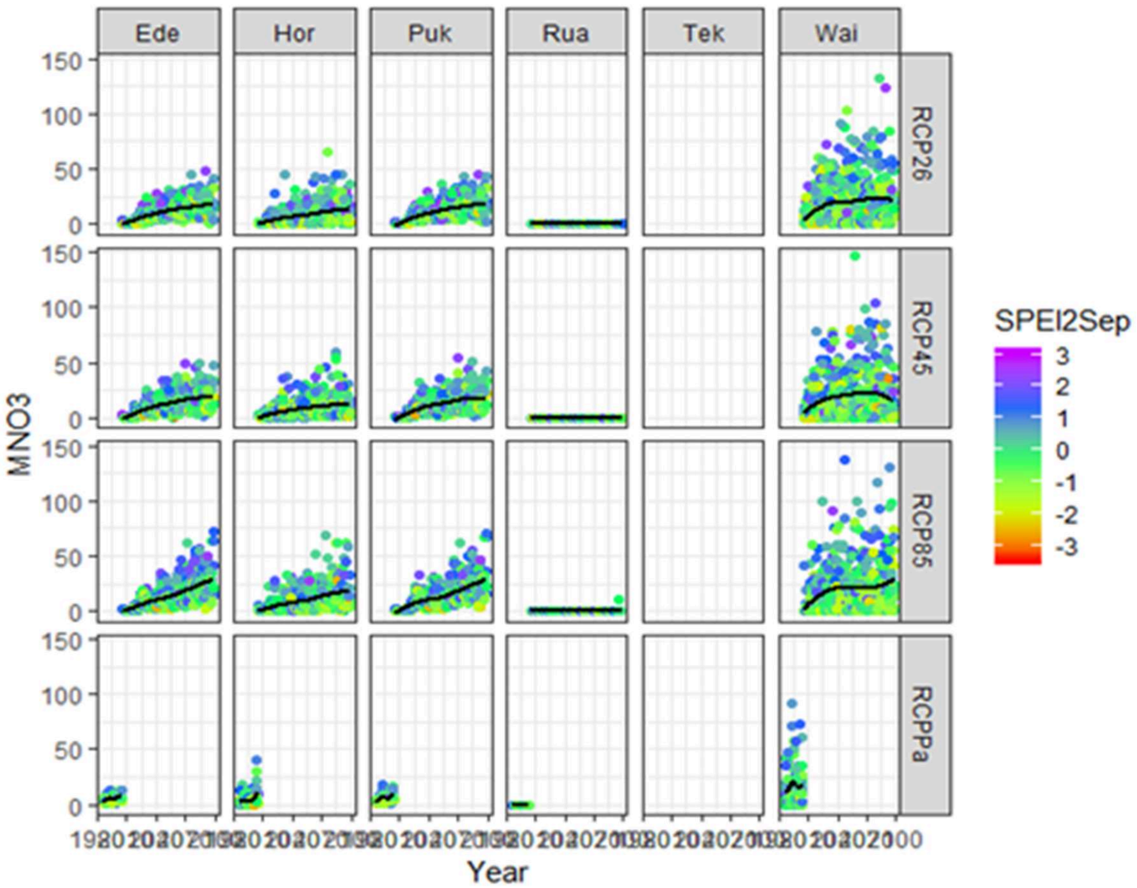

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPa
MNO3
Year
PET
1800
1600
1400
1200
1000

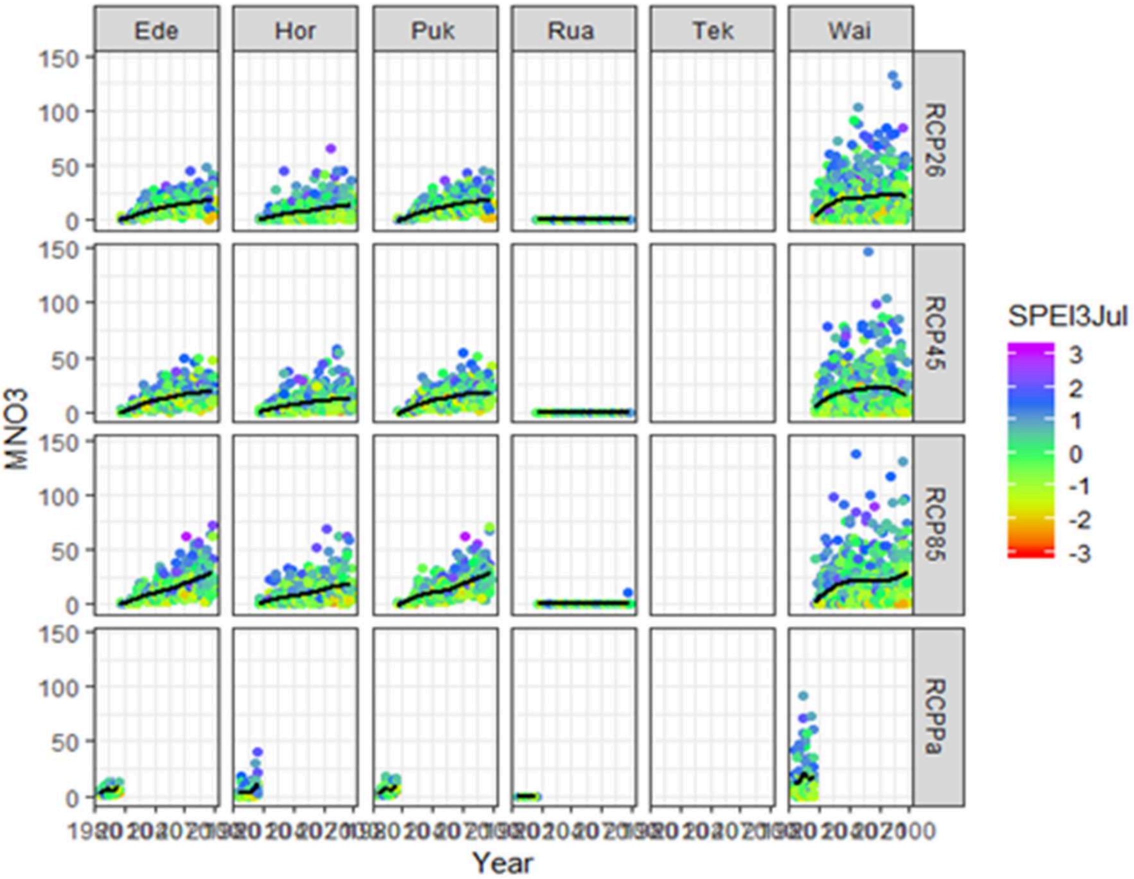

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPa
MNO3
Year
AET
1200
1000
800
600

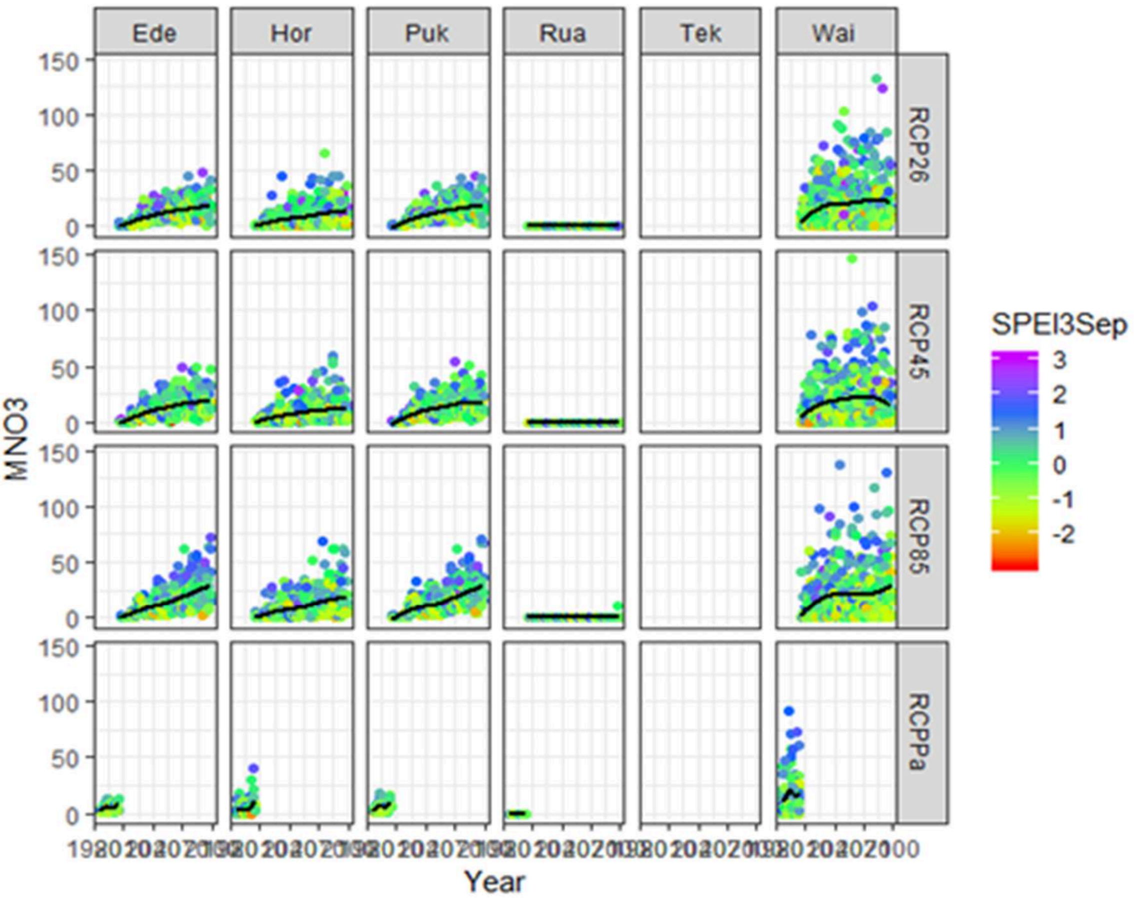

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
150
100
50
0
MNO3
Year
SPEI1Apr
3
2
1
0
-1
-2


Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
150
100
50
0
MNO3
Year
SPEI1May
3
2
1
0
-1
-2
-3


Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
150
100
50
0
MNO3
Year
SPEI2May
2
1
0
-1
-2

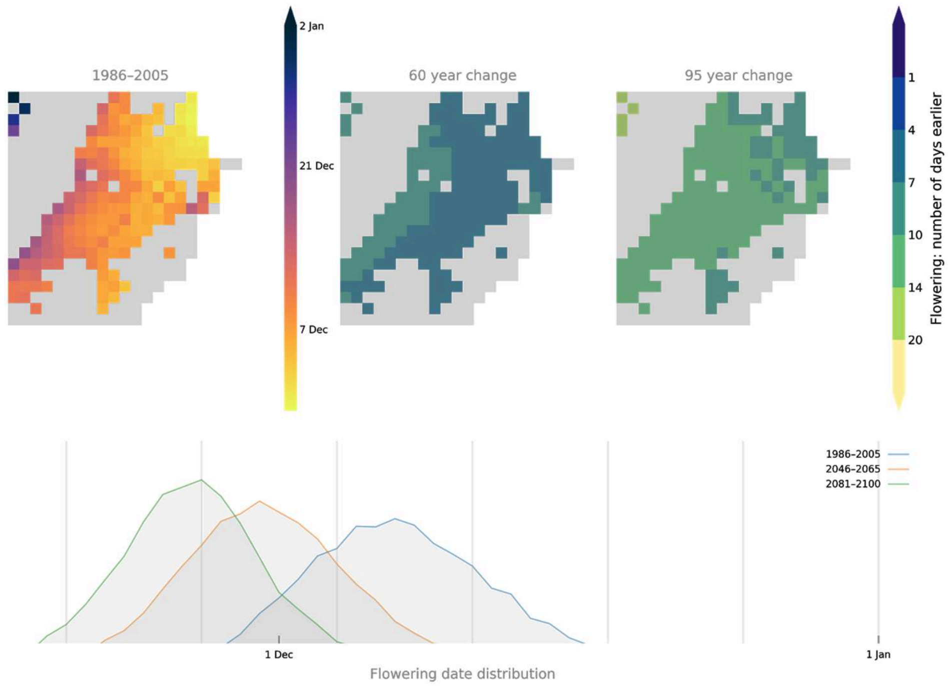

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
150
100
50
0
MNO3
Year
SPEI2Sep
3
2
1
0
-1
-2
-3


Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
MNO3
Year
SPEI3Jul
3
2
1
0
-1
-2
-3

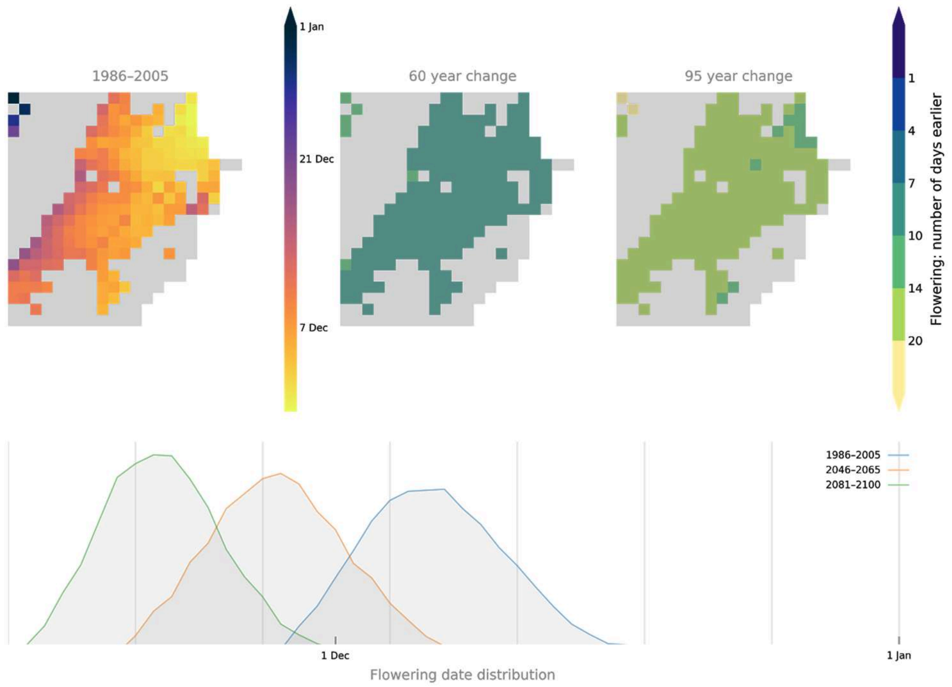

Ede
Hor
Puk
Rua
Tek
Wai
RCP26
RCP45
RCP85
RCPPa
MNO3
Year
SPEI3Sep
3
2
1
0
-1
-2

Appendix 3 – GFV: modelling grapevine flowering dates for a single variety using different global climate models (GCMs)

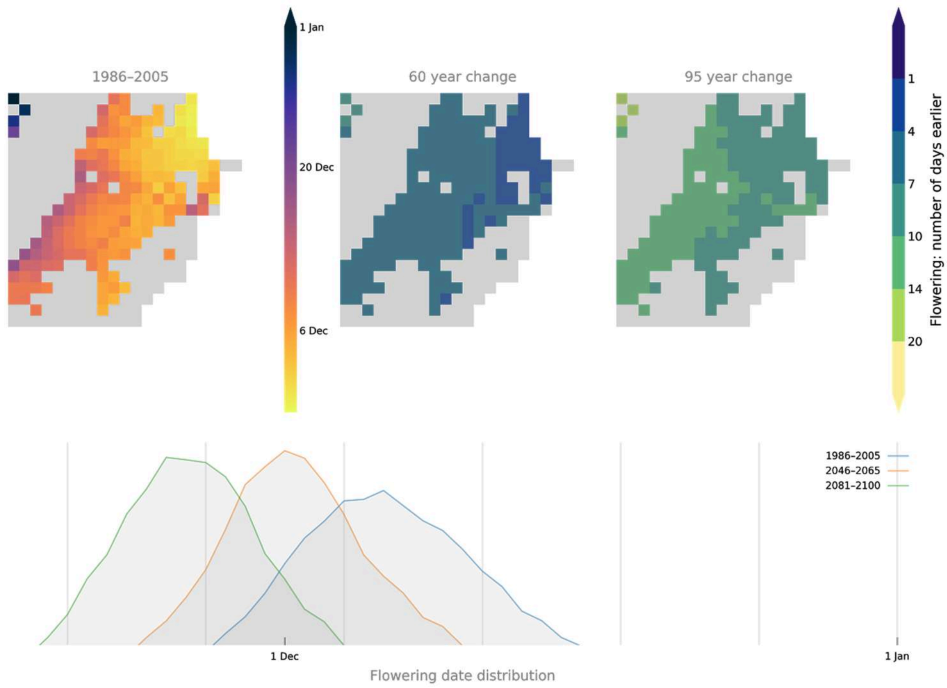
NorESM1-M   RCP8.5   F* = 1282°C



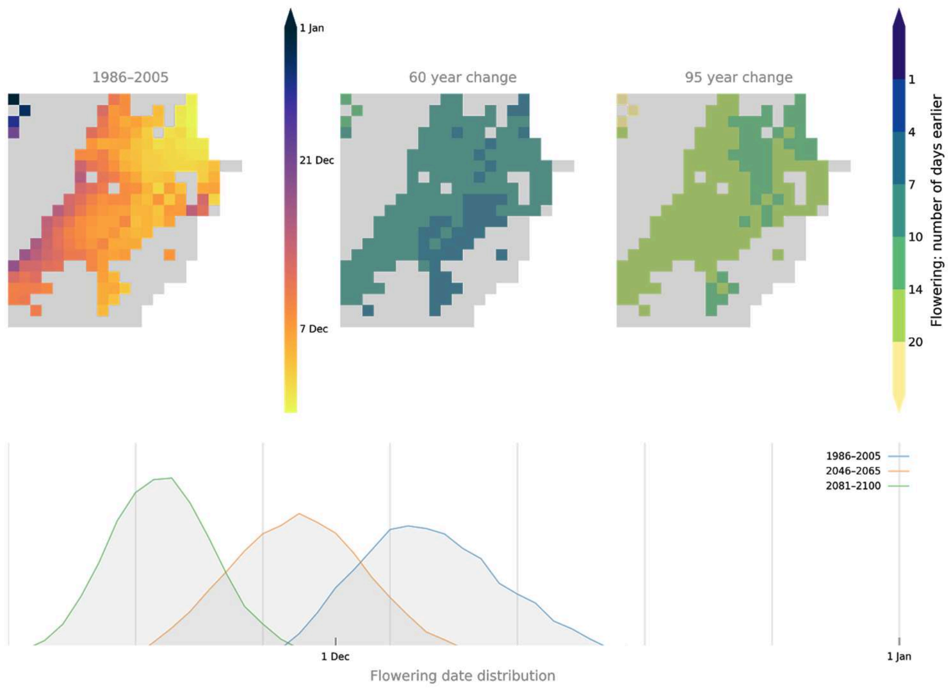
HadGEM2-ES   RCP8.5   F* = 1282°C



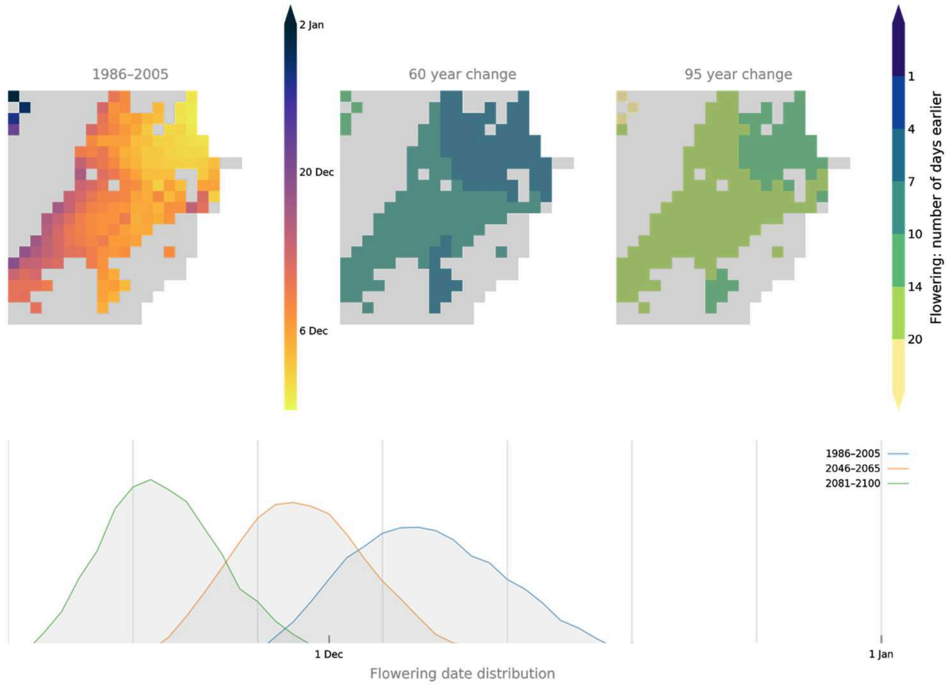
GISS-EL-R RCP8.5 F* = 1282°C



GFDL-CM3 RCP8.5 F* = 1282°C



CESM1-CAM5 RCP8.5 F* = 1282°C



BCC-CSM1.1 RCP8.5 F* = 1282°C