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Identification of the best viticultural areas by spatial optimisation. Application in New Zealand South Island in the context of climate change

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ABSTRACT

The global winegrowing sector is under pressure due to the effects of global climate change. This is particularly true for New Zealand, where the wine industry is limited to a few regions. This study focuses on the South Island of New Zealand. It uses the Multi-objective Optimisation for Agrosystems (MOA) model to (i) investigate how potential exposure to climate risks and phenological stages will evolve under climate change, (ii) assess the suitability of current vineyards for viticulture in the future, and (iii) investigate potential emerging areas favourable for viticulture.

The results show that a significant shift in the phenological stages of veraison and ripeness can be expected in the future due to the warming of the South Island of New Zealand. The projected phenological stages advancement is around one week in the near term for both Shared-Socioeconomic Pathways studied (SSP2-4.5 and SSP5-8.5) and is more than three weeks and one month in long-term for SSP2–4.5 and SSP5-8.5 respectively. A regional to local increase in frost risk (Canterbury, Otago, and Southland) and a slight increase in disease risk (especially on the coast) are also projected in the future, while the South Island of New Zealand is not expected to be affected by heatwaves. The results show that Marlborough, New Zealand's most important winegrowing region, will continue to be one of the best areas for viticulture in the 21st century. On the other hand, new winegrowing opportunities are expected to emerge inland and southwards.

Overall, this study contributes to the understanding of the impact of climate change on the New Zealand wine industry and emphasises the need to adapt to changing climate conditions. It also provides insights into the future suitability of vineyards and identifies potential expansion areas for the New Zealand viticulture sector.

KEYWORDS: Optimisation modelling, climate change, suitable grapevine growing areas, adaptation, wine grape, mapping

INTRODUCTION

Global climate change is having an impact on regional climates and winegrowing regions around the world (Jones, 2015; Jones *et al*., 2005; van Leeuwen and Darriet, 2016). One of the biggest challenges for the wine industry is the potential impact of climate change in the 21st century. These impacts encompass a range of consequences, from short-term effects on wine quality and style to long-term concerns about varietal suitability and the economic sustainability of traditional winegrowing regions (Morales-Castilla *et al*., 2020; Quénol *et al*., 2014b; Schultz and Jones, 2010).

Climate change, particularly the temperature rise, has profound effects on grapevine phenology and characteristics of grapes and wine (García de Cortázar-Atauri *et al.*, 2017; van Leeuwen *et al.*, 2024; van Leeuwen and Darriet, 2016). One notable effect on grapevine production is an earlier bud break and a shortened growing cycle, which ultimately leads to an earlier harvest (García de Cortázar-Atauri *et al.*, 2017; van Leeuwen *et al.*, 2024; van Leeuwen and Darriet, 2016). In addition, higher temperatures affect the sugar and alcohol content of grapes, which in turn affects the aromas of wines (Duchêne and Schneider, 2005; van Leeuwen and Darriet, 2016; Parker *et al*., 2020). Vines are also exposed to increased climatic risks associated with extreme temperatures. For example, early bud break increases susceptibility to spring frost, while extreme summer temperatures can affect grape quality (Cukierman *et al*., 2021).

The New Zealand winegrowing sector is proving particularly vulnerable to the effects of climate change because vineyards are concentrated in a few regions and rely heavily on a limited number of grape varieties, particularly Sauvignon blanc and Pinot noir in the South Island (New Zealand Winegrowers, 2023). As of 2022, over 80 % of New Zealand's winegrowing regions are located in the South Island and cover 34,304 hectares of vineyards out of a total of 41,860 hectares, including Marlborough, Nelson, Canterbury, Waitaki Valley, and Central Otago (New Zealand Winegrowers, 2023).

A modelling approach offers a means to evaluate the evolving agroclimatic potential of established vineyards and emerging areas in New Zealand, taking into account various climate change scenarios. The approach used not only focuses on studying climate change impacts on vineyards (e.g., Morales-Castilla *et al*., 2020; Ausseil *et al*., 2021) but also aims to determine optimal combinations of exposure levels to different climatic risks (such as frost, heat, and potential pathogenic threats). Moreover, this approach enables the identification of maturity thresholds that align with desired wine styles. The scenario approach allows to define the objectives, constraints, and threshold in collaboration with winegrowers. The solutions provided by the model represent trade-offs between the different objectives and constraints specified by the user in the scenario. This novel approach has been applied to another wine-growing area (Brittany, FRANCE) with a different climate context (Thibault, 2023).

The developed model, known as MOA (Multi-objective Optimisation for Agrosystems), stands as a comprehensive tool that integrates widely used bioclimatic indices and phenological models to investigate viticulture. Furthermore, it allows for consideration of specific constraints and objectives during the modelling process as well as to work at different spatial resolutions thus dealing with the spatial complexity of climate (Neethling *et al*., 2019). The model's outputs consist of the best solutions for existing and emerging vineyards. Thus, the MOA model enables two key capabilities: (i) assessing the most suitable future areas within existing vineyards based on their location and climate projections, and (ii) identifying optimal locations for winegrowing and selecting appropriate grape varieties, according to defined scenarios involving climate projections, objectives, and constraints.

This study specifically focuses on the South Island of New Zealand, given its significant vineyard coverage, to address the following questions:

- How are climatic risks and grapevine phenological stages expected to evolve under current climate change conditions?

- To what extent will Marlborough, the primary winegrowing region in New Zealand, remain suitable for viticulture throughout the 21st century?

- Which presently non-vineyard areas of the South Island in New Zealand have the potential to become favourable for viticulture in the coming decades?

To accomplish this, a comparative analysis is conducted between two climate models. Subsequently, the model that yields the most favourable outcomes for the studied region is selected to run the MOA model, with the outputs being utilised to address the questions.

MATERIALS AND METHODS

1. Climate Data

Climate data used in this study were sourced from the NEX-GDDP-CMIP6 dataset (NASA Earth Exchange Global Daily Downscaled Projections) (Thrasher *et al*., 2022). This dataset offers bias-corrected (Thrasher *et al*., 2012) daily global data derived from CMIP6 simulations (Coupled Models Intercomparison Project phase 6) (Eyring *et al*., 2016), covering the period from 1950 to 2100. The dataset provides a high spatial resolution (0.25° × 0.25°) and encompasses four SSP scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.5, SSP5-8.5) and 35 GCMs (General Circulation Models). For this study, data from the IPSL-CM6A-LR and ACCESS-CM2 climate models were used, specifically for the SSP2-4.5 and SSP5-8.5 scenarios (Bi *et al*., 2020; Boucher *et al*., 2020). SSPs (Shared Socioeconomic Pathways) are scenarios that depict global socio-economic developments constructed based on different climate policies and associated greenhouse gas emission scenarios. The SSP2-4.5 scenario represents a world with intermediate GHG emissions and an average global temperature increase of +2.7 °C by 2100.

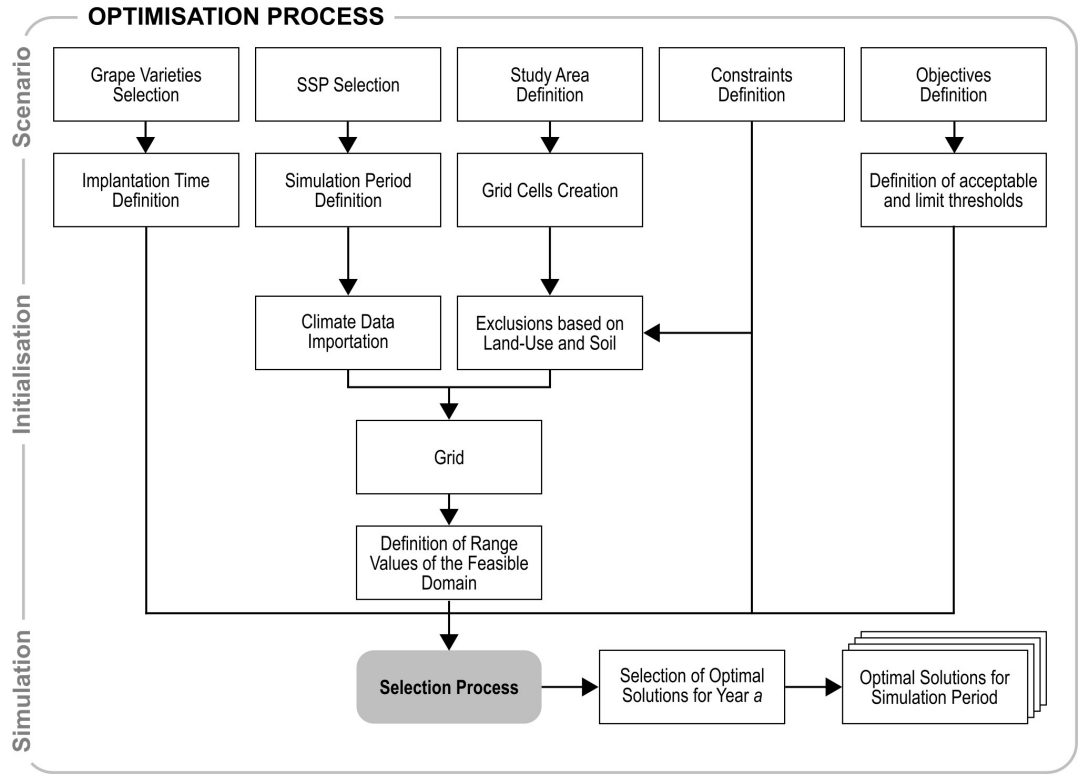


FIGURE 1. MOA Model Process. The three main steps (scenarisation, initialisation, and simulation) of the model are described (Thibault, 2023).

Conversely, SSP5-8.5 is the most pessimistic scenario, portraying a significantly warmer world with very high emissions (>4 °C increase) (Riahi *et al*., 2017). The downloaded and used climate variables include relative humidity, precipitation, wind speed, and mean, maximum, and minimum temperatures.

Observed temperature data from the National Institute of Water and Atmospheric Research (NIWA) website were utilised to assess the performances of both climate models. Temperature data from 82 weather stations across the South Island, available from 2000 to 2014 (i.e., before the "prospective simulation" of climate models), were downloaded. The locations of the weather stations and the corresponding number of years of records are illustrated in SM1.

2. Global Daily Downscaled Projection (GDDP) Statistical Analyses and Comparison

To interpret and discuss MOA outputs, a comparison between the two climate models was conducted. Statistical tests were carried out between the distribution of data from IPSL-CM6A-LR and ACCESS-CM2 models to identify any significant differences. Statistical analyses were conducted with R using a *t-test* over four periods: baseline (1981–2010), near-term (2011–2040), mid-term (2041–2070), and long-term (2071–2100), for each temperature variable (i.e., daily minimum, mean and maximum temperatures) and scenario.

Moreover, the performances of climate models for the temperature variable were also assessed. For this purpose, the IPSL-CM6A-LR and ACCESS-CM2 models' temperature data were compared to observed climate data during a portion (i.e., 2000–2014) of the retrospective simulation of the models which has served as training data in the downscaling process. Daily mean temperatures from the 82 weather stations (SM1) were compared to the grid cell data of both models (IPSL-CM6A-LR and ACCESS-CM2) in which the weather stations were located. In cases where multiple weather stations were located within the same grid cell, the data from the stations were aggregated before the comparison took place. The performance of models was evaluated *via* the linear regression and the mean coefficient of correlation.

3. Multi-objective Optimisation for Agrosystems (MOA) Model

The MOA optimisation model was employed to calculate the bioclimatic index, grape phenological stages, indicators of exposure risk, and winegrowing potential. Subsequently, a concise depiction of the model's structure (Figure 1) was developed, along with an explanation of the parameters encompassing the defined scenario.

3.1. General Structure and Parametrisation of MOA

Using a multi-objective approach, the MOA model has been implemented in the R environment. The integration

of spatial elements provides a significant advantage to the model, as the optimisation based on spatial aspects is not the main objective of traditional methods (Thibault, 2023). MOA has been specifically designed to identify the best areas for viticultural activities in response to different climate change scenarios (Thibault, 2023). By adopting a scenario-based approach, the model allows for the exploration of diverse hypotheses to address a range of questions. These scenarios can be collaboratively developed with winegrowers, incorporating different climate change projections, multiple objectives and constraints, and distinct thresholds for each variable. The model follows a sequential structure comprising three main steps: scenarisation, initialisation, and simulation (Figure 1).

During the scenarisation step, various parameters were defined, including the study area, climate model and projection, simulation period, targeted grape varieties, and duration of implementation. The two grape varieties investigated were Sauvignon blanc and Pinot noir. Scenario definition also involves establishing simulation constraints and objectives. Objectives represent specific goals that are either maximised or minimised based on defined criteria. The first objective was to achieve the technical maturity of 190 g/L sugar for the GSR (Grapevine Sugar Ripeness) before the 15th of April. Objectives related to climate events were also established: minimising heat and frost risks. For both, acceptable and limit thresholds for risk acceptability were defined. Climatic risks (e.g., spring frost, heat waves...) can be interpreted differently in the model based on vineyard vulnerability and exposure frequency. Therefore, depending on the risk and its frequency, the constraint can range from limiting to excluding. Below the acceptable threshold, the solution remained optimal with no considered risk. Beyond the limit threshold, the risk was estimated too high, and the cell was excluded from the optimisation process. Between the acceptable and limit thresholds, the cell's optimisation was limited. In this case, the acceptable and limit numbers of days were arbitrarily set as 4 and 10 days for heat risk and 3 and 5 days for frost risk. The last objective was to minimise disease risk, which was determined as a function of the number of pathogen treatments in vineyards (conventional or organic) using the SEVE model method (Tissot *et al*., 2017). In this study, a conventional vineyard with an average treatment duration of 12 days was assumed. Constraints are conditions that restrict or exclude certain solutions, which can be based on land use, soil aspects, spatial relations, or the historical presence of vineyards. The first constraint was to include cells where the percentage of agricultural land was equal to or above 5 %, reflecting the low resolution of climate data (0.25°) compared to the scale of a vineyard. Spatial relation and winegrowing anteriority constraints were also defined. The spatial relation constraint allows us to consider existing vineyards favouring locations near current winegrowing areas. Thus, direct neighbourhood cells of optimal cells determined by the model were favoured by the spatial relation constraints. In the same way, the anteriority constraint allows one to consider historical winegrowing areas promoting cells with previous viticultural activity. Four levels can be assigned to these constraints: insignificant, weak, moderate, and very important (Thibault, 2023). The different constraint levels in MOA offer a range of options to best adapt to the case study. For example, a very important level for the spatial relation constraint can be considered to explore new opportunities close to existing vineyards. In this application to the South Island of New Zealand, both constraints were set at a moderate level.

In initialisation, the cells were excluded according to scenario constraints related to land use and soil (e.g., percentage of agricultural area per cell). Then, the model defined the feasible domain for the simulation process.

During the simulation step, the phenological stages and the climate risk events were first computed for each cell of the search domain and each grape variety according to the scenario defined. The climate risk vulnerability period extends from the budburst to the ripeness stage. The cells that did not meet the scenario objectives with a given grape variety were then excluded. The requirements to reach the phenological stages are different for each grape variety, thus the same cell could be excluded for one variety and kept for another. At the end of this step, only the solutions that correspond to all cell-variety combinations meeting the objectives remained. An overall score based on the scenario objectives and constraints was associated with each solution. The last phase of the simulation step was the selection of the best solutions. Two types of optimisation were made with MOA, one corresponding to an optimisation by grape variety and the other corresponding to an optimisation between grape varieties. In the latter case, the varieties with the best score were first selected. Then, for the two types of optimisations, the overall scores of the solutions were compared to the values range established during initialisation. The solutions with a better score were considered as the best solutions by MOA. The simulation and selection processes were then repeated for each year of the simulation period.

A noteworthy aspect of MOA is its ability to offer multiple solutions to users. Due to the diversity of objectives, it is rare to find a single solution that satisfies all criteria. Thus, the solutions represent trade-offs between the objectives and constraints. Ultimately, the selection of a solution is left to the user, allowing them to make the final decision at the end of the process (Collette and Siarry, 2003).

3.2. Grapevine Growth Knowledge

The MOA model relies on grapevine growth knowledge to determine phenological stages and compute solutions. To achieve this, two bioclimatic indices and two phenological models were used. Budburst was determined using the Winkler Growing Degree Days (GDD) index proposed by Winkler *et al*. (1974), employing the van Leeuwen *et al*. (2008) method. This method involves calculating the heat summation with a thermal base of 10 °C after the 1st of January for the Northern Hemisphere and the 30th of June for the Southern Hemisphere.

The Grapevine Flowering Veraison (GFV) model, developed by Parker *et al*. (2011, 2013), was employed to determine the flowering and veraison phenological stages. Additionally, the Grapevine Sugar Ripeness (GSR) model was used to determine technical maturity based on the desired sugar concentration (Parker *et al*., 2020). The GFV and GSR models respectively calculate the phenological stages from the 60th and 91st day of the growing season. Grape varieties are assigned threshold values for each phenological stage and sugar concentration (170, 180, 190, 200, 210, 220 g/L) in the GSR model (Parker *et al*., 2020). These models based on grapevine phenology are particularly robust, especially in the context of climate change (Quénol *et al*., 2014a).

In addition, the Huglin Index (Huglin, 1978) was employed to provide supplementary information. It is calculated from the 1st of October to the 30th of April and allows for the classification of winegrowing regions into different climatic categories: very cool (IH ≤ 1,500), cool (1,500 < IH ≤ 1,800), temperate (1,800 < IH ≤ 2,100), temperate warm (2,100 < IH ≤ 2,400), warm (2,400 < IH ≤ 3,000), and very warm (IH > 3,000). All indicators used during the computation of the solution are presented in Table 1.

RESULTS

1. GDDP Models Comparison

The temperature data from the IPSL-CM6A-LR and ACCESS-CM2 climate models are compared in Figure 2. Statistical tests revealed significant differences (*p-value* < 0.05) between the two models for each daily temperature variable (minimum, mean, and maximum temperatures), periods, and SSPs (Table 2). The ACCESS-CM2 model was consistently warmer than the IPSL-CM6A-LR model, with the largest differences observed for maximum temperatures and the smallest differences for minimum temperatures. Over the baseline period (1981–2010), the differences were relatively small, ranging from –0.09 °C for the mean and maximum temperature to –0.10 °C for the minimum temperature. However, the projected differences increased from the near-term period (2011–2040) onwards. For example, the differences in mean temperature reached –0.22 °C and –0.36 °C for SSP2-4.5 and SSP5-8.5, respectively. The differences remained relatively constant or decreased in the mid-term, but they became more significant towards the end of the century (Table 2). In the long term, the differences between the IPSL-CM6A-LR and ACCESS-CM2 models exceeded –0.34 °C for all temperature variables with SSP5-8.5 and ranged from –0.24 °C (minimum temperature) to –0.48 °C (maximum temperature) for SSP2-4.5.

Furthermore, the differences between the two models were not evenly distributed across the study area (Figure 3). The inter-model spread over the region was assessed using the standard deviation of differences for each temperature variable, period, and SSP (Table 2). The general trend was an increase in the inter-model spread over the 21st century for all temperature variables. The standard deviations increased

TABLE 1. Indicators used in the MOA model. They are classified by type of hazards and their calculation period and method are presented.

Type of hazards	Indicators	Calculation period	Calculation method	References
Frost occurrences	Number of frost days	From budburst to veraison	**Fday** = $\sum_{budburst}^{veraison} tmin < -1\,°C$	Poling (2008); Gavrilescu *et al.* (2022); Webb *et al.* (2018)
			Fday = $\sum_{budburst}^{veraison} tmin < -0\,°C$	Gavrilescu *et al.* (2022); Webb *et al.* (2018)
	Advective frost	From budburst to veraison	**AFday** = $\sum_{budburst}^{veraison} tmin < -1\,°C$ AND $wind > 16\,km/h$	Poling (2008)
	Wet frost	From budburst to veraison	**AFday** = $\sum_{budburst}^{veraison} tmin < -1\,°C$ AND $hurs^{a} > 60\,\%$	Gavrilescu *et al.* (2022); Itier *et al.* (1991)
	Last frost date	From budburst to veraison	**LFdate** in Julien Day	Gavrilescu *et al.* (2022)
Heat wave occurrences	Number of hot days	From veraison to maturity	**Hday** = $\sum_{veraison}^{maturity} tmax > 35\,°C$ **Hday** = $\sum_{veraison}^{maturity} tmax > 38\,°C$ **Hday** = $\sum_{veraison}^{maturity} tmax > 40\,°C$	Bahr *et al.* (2021)
	Heat waves	From budburst to maturity	**Hwave** = $\sum_{budburst}^{maturity} hv^{b}$	Fraga *et al.* (2020)
Pathogen occurrences	Potential exposure for organic production systems	From budburst to leaf fall	**Poce** = $\sum_{budburst}^{maturity} pexp^{c}$	Tissot *et al.* (2017); Velasquez-Camacho *et al.* (2022)

[a]relative humidity.

[b]heat wave = (tmax >35 °C) ≥ 5 days.

[c]potential exposure = pr[d] >2 mm and hurs[a] >60 % and wind >2.3m.s^{-1}.

[d]precipitation.

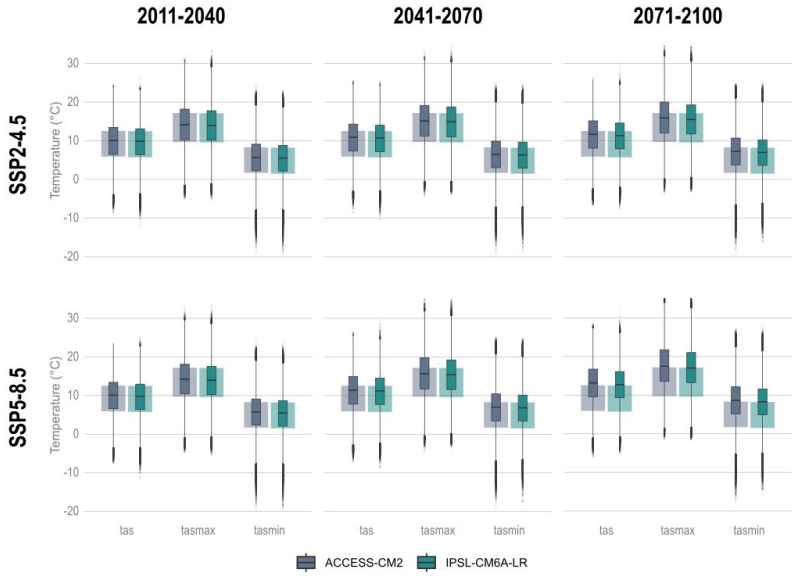


FIGURE 2. Projected minimum, mean, and maximum temperatures for the South Island of New Zealand with ACCESS-CM2 and IPSL-CM6A-LR models in the near term (2011–2040), mid-term (2041–2070), and long term (2071–2100) with SSP2-4.5 and SSP5-8.5. Shaded areas represent the baseline temperatures interquartile range. tas: mean surface temperature; tasmax: maximal surface temperature; tasmin: minimal surface temperature.

from 0.018–0.022 over the baseline period (1981–2010) to 0.069–0.231 in the long term (2071–2100). The increase in the inter-model spread was more pronounced for the minimum temperature variable (0.022 to 0.189 for SSP2-4.5 and 0.231 for SSP5-8.5), while the difference was lower for the maximum temperature (0.019 to 0.069 for SSP2-4.5 and 0.150 for SSP5-8.5). Additionally, the analysis of the difference in the inter-model spread indicated that it was higher for SSP5-8.5 compared to SSP2-4.5 for all temperature variables and periods, and the gap between SSPs widened.

Regarding the performance of climate models, the correlation coefficients of the comparison between cell temperatures and weather station data were relatively low (ranging from 0.29 to 0.59) for both models (SM2). ACCESS-CM2 had higher correlation coefficients for the majority of individual cells (45 out of 69) while IPSL-CM6A-LR presented higher coefficients for 13 cells; 11 cells showed the same correlation

TABLE 2. Projected minimum, mean, and maximum temperature differences between IPSL-CMA6-LR and ACCESS-CM2 models over the South Island of New Zealand in near-term (2011–2040), mid-term (2041–2070), and long-term (2071–2100) with SSP2-4.5 and SSP5-8.5. The minus sign comes from the fact that the differences have been calculated as IPSL-CM6A-LR vs ACCESS-CM2. tas: mean surface temperature; tasmax: maximal surface temperature; tasmin: minimal surface temperature.

		Baseline (1981–2010)	Near term (2011–2040)	Mid-term (2041–2070)	Long term (2071–2100)
SSP2-4.5	tas	–0.09 °C * (sd = 0.018)	–0.22 °C * (sd = 0.047)	–0.21 °C * (sd = 0.093)	–0.36 °C * (sd = 0.115)
	tasmax	–0.09 °C * (sd = 0.019)	–0.26 °C * (sd = 0.040)	–0.28 °C * (sd = 0.074)	–0.48 °C * (sd = 0.069)
	tasmin	–0.10 °C * (sd = 0.022)	–0.18 °C * (sd = 0.061)	–0.14 °C * (sd = 0.127)	–0.24 °C * (sd = 0.189)
SSP5-8.5	tas	–0.09 °C * (sd = 0.018)	–0.34 °C * (sd = 0.053)	–0.23 °C * (sd = 0.126)	–0.44 °C * (sd = 0.177)
	tasmax	–0.09 °C * (sd = 0.019)	–0.36 °C * (sd = 0.053)	–0.33 °C * (sd = 0.126)	–0.53 °C * (sd = 0.150)
	tasmin	–0.10 °C * (sd = 0.022)	–0.31 °C * (sd = 0.060)	–0.14 °C * (sd = 0.144)	–0.34 °C * (sd = 0.231)

*p-value < 0.05.

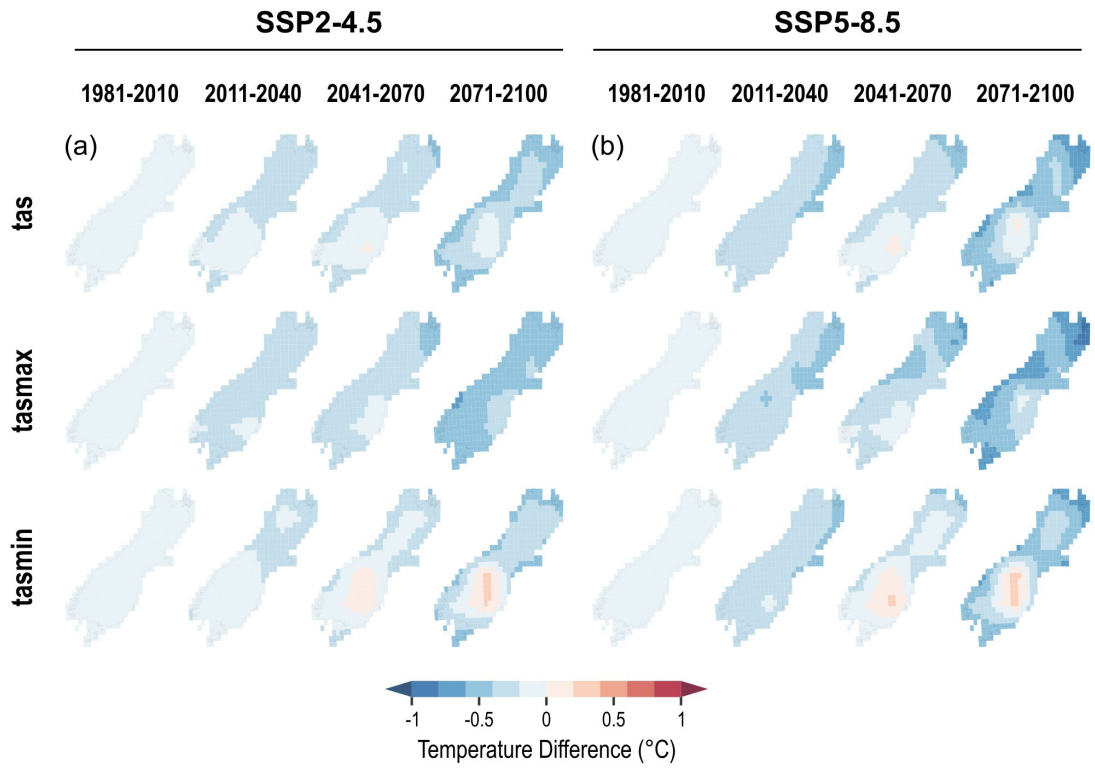


FIGURE 3. Mean temperatures difference between IPSL-CMA6-LR and ACCESS-CM2 models for minimum, mean, and maximum temperatures for the baseline (1981–2010), in the near term (2011–2040), mid-term (2041–2070) and long term (2071–2100) over the New Zealand South Island with SSP2-4.5 (a) and SSP5-8.5 (b). tas: mean surface temperature; tasmax: maximal surface temperature; tasmin: minimal surface temperature.

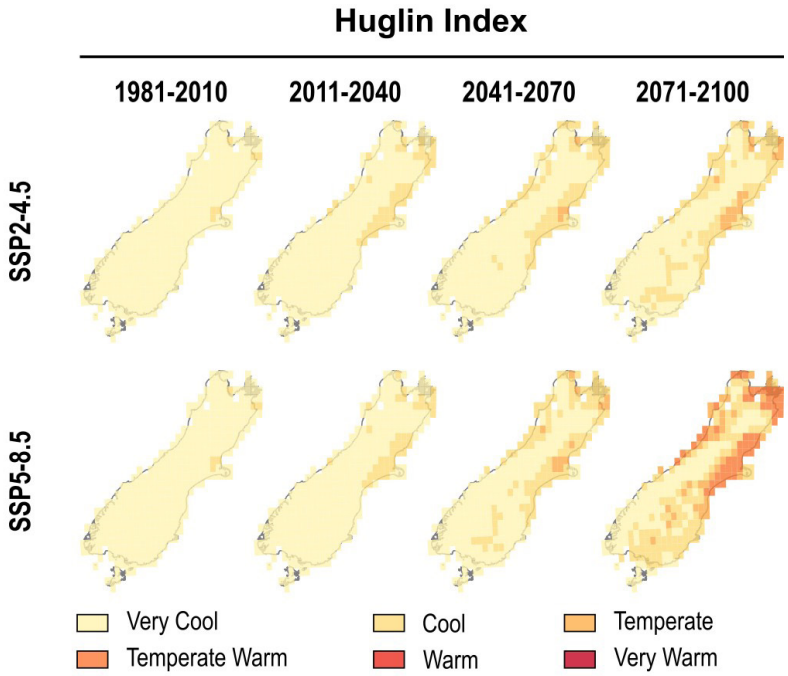


FIGURE 4. New Zealand South Island climate classification according to the mean Huglin Index (IH) for the baseline (1981–2010), in the near term (2011–2040), mid-term (2041–2070) and long term (2071–2100) with SSP2-4.5 and SSP5-8.5. Very cold: IH ≤ 1500; Cold: 1500 < IH ≤ 1800; Temperate: 1800 < IH ≤ 2100; Temperate warm: 2100 < IH ≤ 2400; Warm: 2400 < IH 3000; Very warm: IH > 3000. Results correspond to the inter-model (IPSL-CMA6-LR and ACCESS-CM2) means.

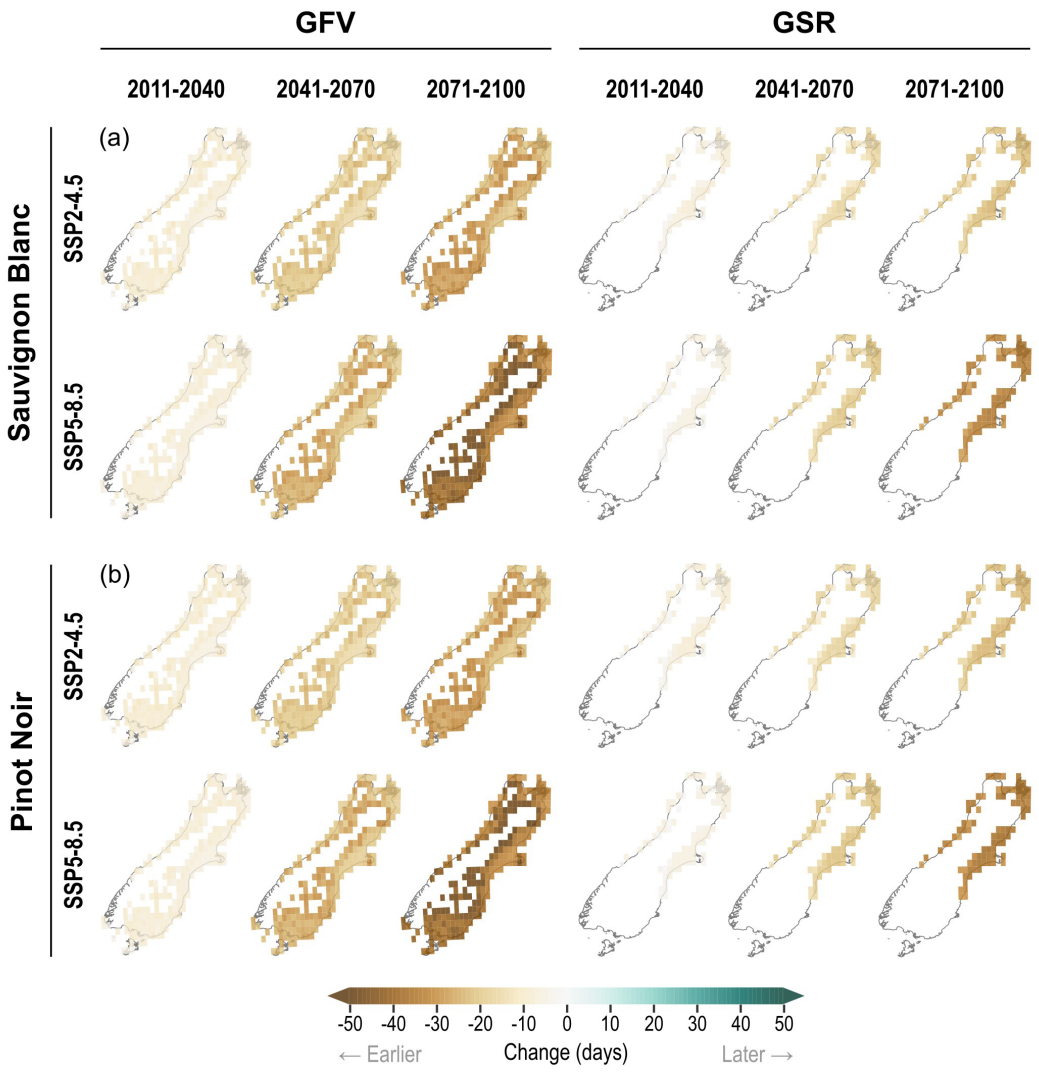


FIGURE 5. Veraison (left panel) and ripeness (time to 190 g/L sugar—right panel) date anomalies compared to the baseline (1981–2010) in near-term (2011–2040), mid-term (2041–2070) and long-term (2071–2100) with SSP2-4.5 and SSP5-8.5 for Sauvignon blanc (a) and Pinot noir (b). Only cells having reached at least once veraison or ripeness, respectively, over the baseline are mapped. Results correspond to the inter-model (IPSL-CMA6-LR and ACCESS-CM2) means.

coefficient for both models. However, significant differences between ACCESS-CM2 and IPSL-CM6A-LR were observed for only 22 cells among which 12 had a higher correlation coefficient with ACCESS-CM2 and 5 with IPSL-CM6A-LR (SM2). The result for the aggregation of all cells with a significant difference between the two climate models (SM3) showed close correlation coefficients for both models (0.40 for ACCESS-CM2 and 0.39 for IPSL-CM6A-LR). Although ACCESS-CM2 tended to have higher correlation coefficients, the comparison with weather station data did not show a strong difference in the performances of both models regarding mean temperature. Thus, climate from both, ACCESS-CM2 and IPSL-CM6A-LR were used to run the MOA model.

2. Bioclimatic Indices, Phenological Models, Climate Risk Exposure Indicators and Winegrowing Potential

2.1 Bioclimatic Indices and Phenological Models

The results presented in this part correspond to the inter-model (ACCESS-CM2 and IPSL-CM6A-LR) mean of MOA outputs. Maps of associated inter-model uncertainty are provided in the Supplementary Material. The climate of the South Island of New Zealand was classified as very cool for the baseline according to the Huglin Index (HI), with only a few exceptions (6 out of 334 cells) classified as cool (Figure 4). From the near-term period (2011–2040) onwards, the climate was projected to warm for both scenarios, with a similar magnitude of change (46 cells moving to a cool class for SSP2-4.5 compared to 38 cells for SSP5-8.5).

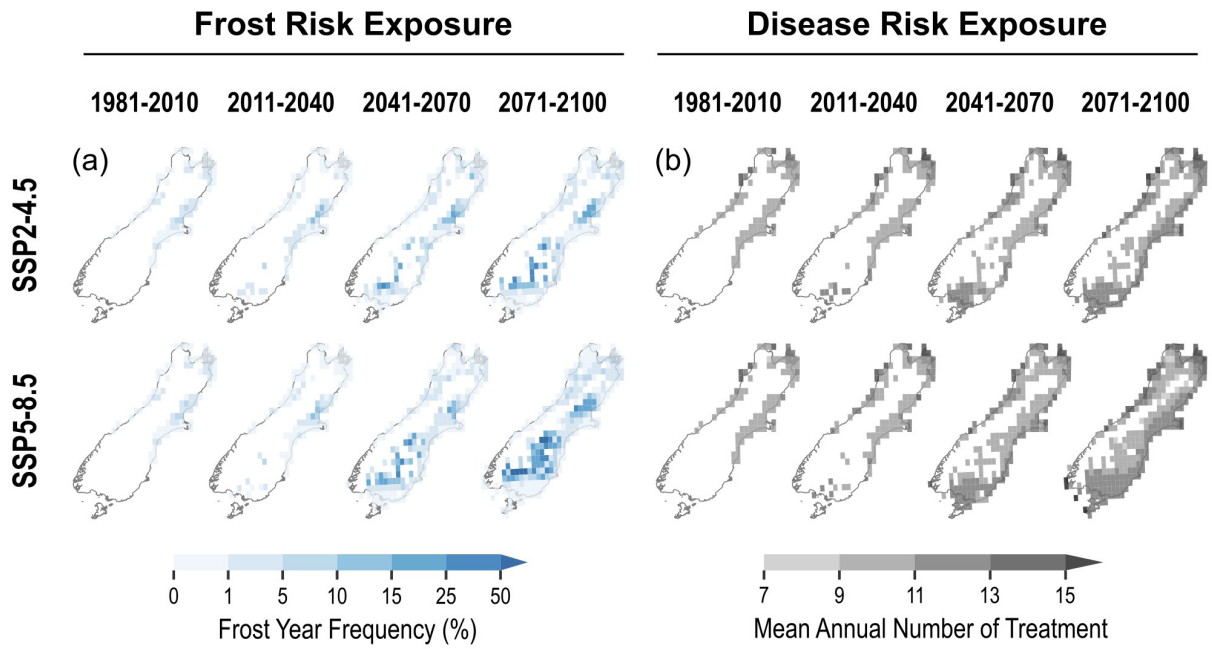


FIGURE 6. Projected frost risk (a—frequency of years with at least one frost event) and disease risk (b—mean number of pathogen treatments per year) exposure for the baseline (1981–2010) in the near term (2011–2040), mid-term (2041–2070) and long term (2071–2100) with SSP2-4.5 and SSP5-8.5 for Sauvignon blanc. Results correspond to the inter-model (IPSL-CMA6-LR and ACCESS-CM2) means.

This warming was particularly pronounced in northern or low-altitude regions such as Marlborough and Canterbury (Figure 4). In mid- (2041–2070) and long term (2071–2100), the warming trend continued, spreading southward and intensifying according to the Huglin Index, with respectively 4 and 12 cells classified as temperate or warmer for SSP2-4.5 and SSP5-8.5 in mid-term, and 19 and 94 cells in long-term. The HI inter-model uncertainty was relatively low over the baseline increasing over the 21st century for both SSPs (SM4) with South Island standard deviation means ranging from 10 (baseline) to 88 HI (long term with SSP5-8.5).

For Sauvignon blanc and Pinot noir, veraison was projected to advance by 8 days in the near term (2011-2040) when simulated with GFV model, by 20 days for SSP2-4.5, and 25 days for SSP5-8.5 in mid-term (2041–2070), and by 27 and 40 days in the long term (2071–2100) (Figure 5). The time to reach 190 g/L sugar was projected to decrease by 5 to 6 days in the near term for both grape varieties and SSPs. The advancement was projected to increase to 14 and 18 days for Sauvignon blanc with SSP2-4.5 and SSP5-8.5 (15 and 20 days for Pinot noir) by 2041–2070. In the long term, the time to reach 190 g/L sugar was projected to reduce by 3 weeks for SSP2-4.5 (22 days for Pinot noir and 20 days for Sauvignon blanc), and under SSP5-8.5 conditions, the advancement was projected to exceed a month (35 and 33 days). The anomalies of these two phenological stages were further investigated in the Marlborough region and the same order of magnitude advancements were also projected (SM5). The values differed by 1 to 2 for the veraison and by –1 to –2 for ripeness at 190 g/L sugar. The uncertainties related to veraison and ripeness are presented in SM6. The average South Island standard deviation mean for veraison was about 2 days in the near and mid-term for both SSPs and increased to 3 days in the long term. For ripeness (time to 190 g/L sugar), slightly higher average South Island inter-model uncertainties were observed, with 3 days for SSP2-4.5 in the near and mid-term, and 5 days in the long term while a constant value of 4 days for all periods was observed for SSP5-8.5.

Although the South Island overall mean of anomalies suggests a lengthening of the period between the veraison and ripeness (time to 190 g/L sugar), the difference between these two phenological stages showed a trend toward a compression of the time (SM7). A significant time compression of 1 to 2 and 2 to 3 days was projected from mid-term (2041–2060) for respectively Pinot noir and Sauvignon blanc with SSP2-4.5. No significant time compression was projected for SSP5-8.5 except in the near term for Pinot noir.

2.2. Climate Risk Potential Exposure

As for bioclimatic indices and phenological models, the results of climate risk potential exposure presented in this part correspond to the inter-model mean and associated inter-model uncertainty maps are provided in the Supplementary Material. For both Sauvignon blanc (Figure 6) and Pinot noir (SM8), the model projected an increase in the area subject to frost events between 98 and 104 cells in the long term for SSP2-4.5 and between 138 and 156 in the long term for SSP5-8.5

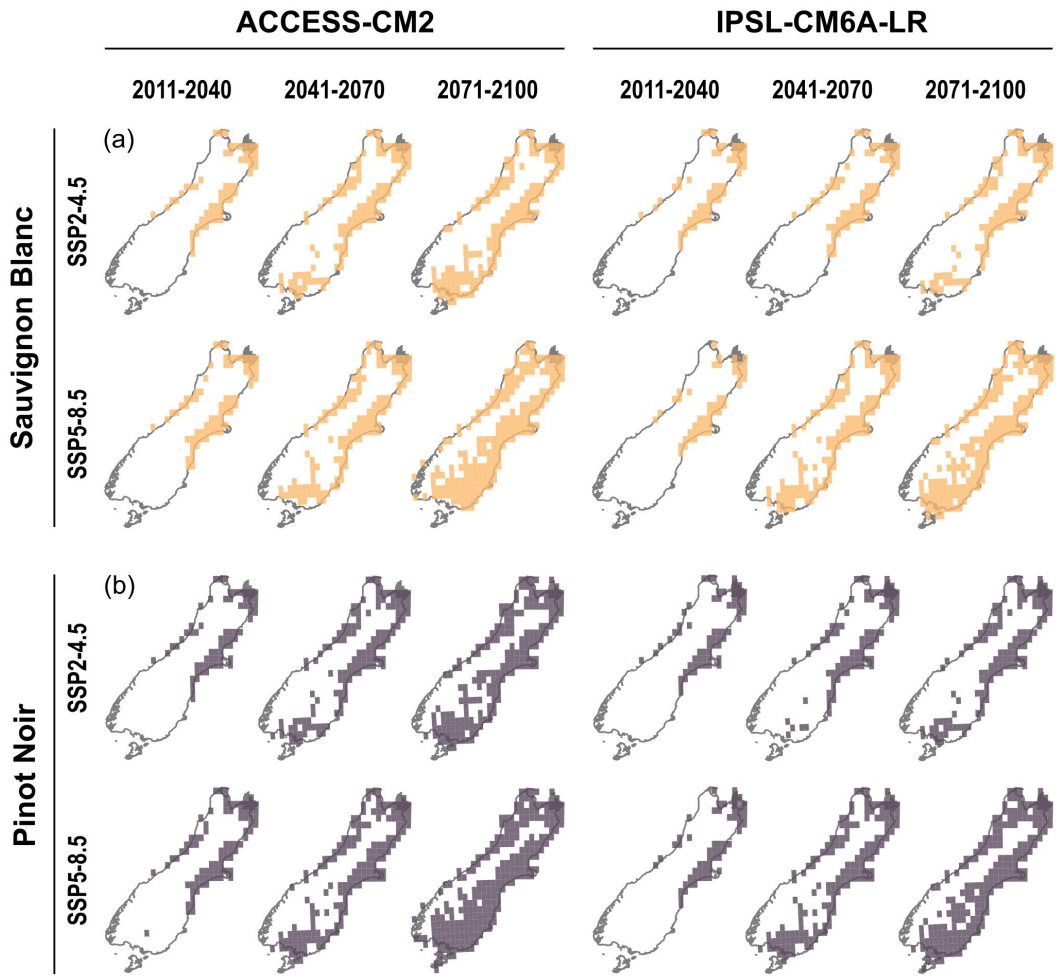


FIGURE 7. Projected best solutions for Sauvignon blanc (a) and Pinot noir (b) with ACCESS-CM2 (left panel) and IPSL-CM6A-LR (right panel) in the near-term (2011–2040), mid-term (2041–2070) and long-term (2071–2100) with SSP2-4.5 and SSP5-8.5.

being affected. While some areas were projected to remain unaffected by frost risk, the frequency of frost events was projected to increase overall. The number of cells experiencing a frost frequency greater than 10 % increased from 0 over the baseline for both cultivars to 2 to 4 cells in the near term for both SSP2-4.5 and SSP5-8.5, to 13 and 24 in the mid-term for Sauvignon blanc, and 18 and 27 for Pinot noir. In the long term with SSP5-8.5, 6 cells for Sauvignon blanc and Pinot noir exceeded a frost frequency of 50 %. Pinot noir showed a slightly more important vulnerability to frost risk than Sauvignon blanc. Moreover, the projected frost risk exposure occurs locally, with greater risk in the middle and South of Canterbury, and in Otago and Southland regions. Additionally, the coast appeared to be relatively unaffected by frost risk, with only 29 to 35 cells along the coast (out of 142) projected to be threatened by frost in the long term for both SSPs and both cultivars, which was proportionally significantly lower than the projections for the South Island as a whole. The inter-model uncertainties to frost risk exposure appeared to be relatively low for both SSPs over the baseline and in the near term, and for most of the South Island in the mid and long term (SM9). However, the uncertainty increased with a higher frost risk exposure ranging from 5 % to 20 % and exceeding 20 % for a few cells in the long term for both SSPs.

The average number of pathogen treatments per year for the South Island showed a relatively stable trend with a slow increase; 10.35 to 11.18 for Sauvignon blanc (Figure 6) from the baseline to the long-term with SSP2-4.5 (10.35 to 11.20 with SSP5-8.5), and 11.69 to 11.53 for Pinot noir (SM8) with SSP2-4.5 (11.69 to 11.44 with SSP5-8.5). On the other hand, the maximum number of treatments was projected to increase from around 14 to around 17 for SSP5-8.5 from the baseline period to the long term for both cultivars. Therefore, the overall trend suggested a small increase in the exposure to pathogens. Pinot noir was also slightly more impacted than Sauvignon blanc by disease risk. The assessment of pathogen threat risk also reveals that the coastline area appeared to be more vulnerable to potential exposure to this risk, as indicated by the higher mean number of treatments. This pattern intensified over the century, particularly evident with SSP5-8.5.

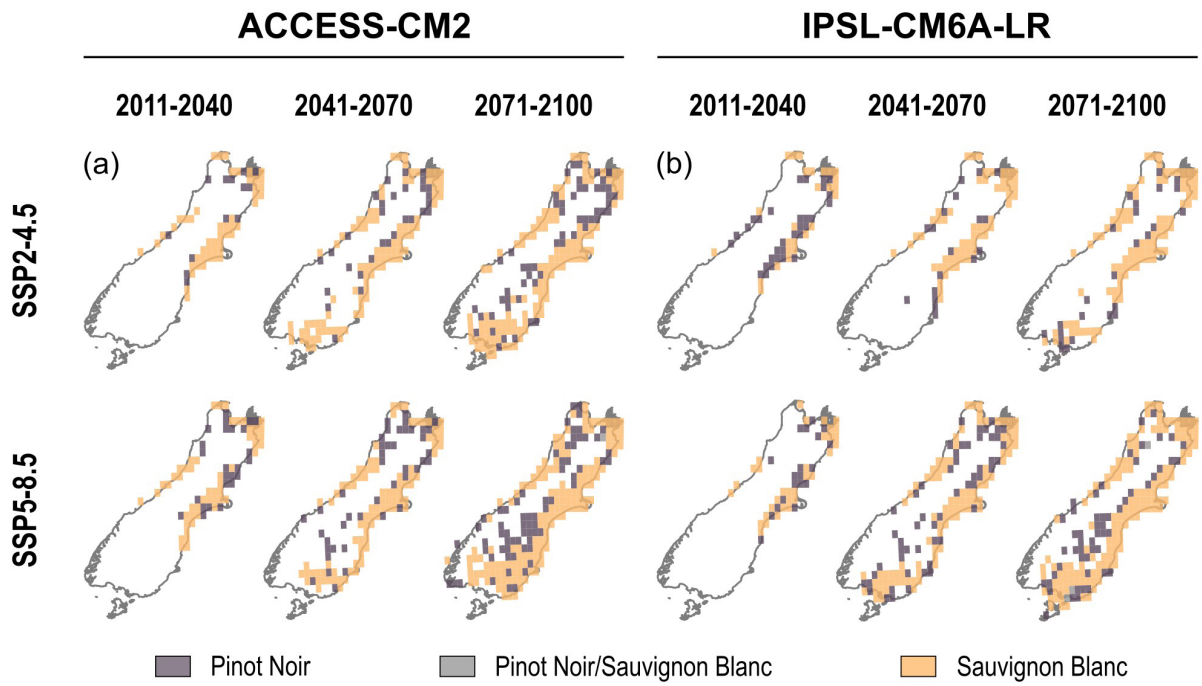


FIGURE 8. Projected best solutions between Pinot noir and Sauvignon blanc with ACCESS-CM2 (a) and IPSL-CM6A-LR (b) in the near term (2011–2040), mid-term (2041–2070) and long term (2071–2100) with SSP2-4.5 and SSP5-8.5.

A very low inter-model uncertainty of disease risk exposure was observed for all periods and all SSPs with values lower than 1 (SM9).

According to the MOA model, the projection of risk exposure indicated that heat waves would not impact the South Island in the near-, mid-, and long-term under both SSPs and grape varieties studied (SM10).

2.3. Future Winegrowing Potential

In the near-term period (2011–2040), the most suitable winegrowing areas (i.e., best solutions of MOA) modelled for Sauvignon blanc occurred predominantly on the coast, specifically in the Marlborough and Canterbury regions, for both SSPs (Figure 7a). The best solutions increased in number in the mid- (2041–2070) and long-term (2071–2100); for Sauvignon blanc, they grew from 60 (56) and 70 (48) cells in the near term for SSP2-4.5 and SSP5-8.5, respectively, to 116 (71) and 130 (136) cells in the mid-term, and 155 (110) and 202 (188) cells in the long term with ACCESS-CM2 (IPSL-CM6A-LR). This expansion occurred inward and southward, encompassing regions such as Otago and Southland in the mid-term and nearly covering the entire South Island (excluding the Southern Alps) in the long term. A similar pattern was observed for Pinot noir, following the expansion described for Sauvignon blanc. However, the modelled expansion of Pinot noir was comparatively more important with the number of best solutions increasing from 67 cells in the near term for SSP2-4.5 (84 cells with SSP5-8.5) to 131 cells (160 cells) in the mid- and 194 cells (246 cells) in the long term with ACCESS-CM2. Although the number of best solutions was higher with ACCESS-CM2, MOA outputs were relatively close to those obtained with IPSL-CM6A-LR. Moreover, for both cultivars and both climate models, the number of best solutions identified MOA was greater with the SSP5-8.5 than with the SSP2-4.5.

Although the projected expansion of best solutions was greater for Pinot noir compared to Sauvignon blanc, a comparison between the two grape varieties (Figure 8) indicated that Sauvignon blanc was the primary option for the South Island of New Zealand for all periods, SSPs and climate models (except in near term for SSP2-4.5 with IPSL-CM6A-LR). In the near term, 13 and 25 cells of best solutions were allocated to Pinot noir compared to 49 and 51 for Sauvignon blanc, respectively with SSP2-4.5 and SSP5-8.5 with ACCESS-CM2; 30 and 43 compared to 93 and 89 in mid-term. By the end of the century (long term), Sauvignon blanc remained more suitable than Pinot noir with 121 cells for SSP2-4.5 and 143 cells for SSP5-8.5, compared to 56 cells and 68 cells for Pinot noir (ACCESS-CM2). Generally, the Pinot noir best solutions tended to be located further inland or at higher altitudes. As for the optimisation by grape varieties (Figure 7), a greater number of best solutions were identified by MOA for SSP5-8.5 than with SSP2-4.5 for the optimisation between grape varieties. Overall, there was an agreement between the two climate models for more than 50 % of the best solutions while the agreement was limited to 27 % of the cells and conflicts were observed for 21 % of the cells (SM11).

DISCUSSION

1. Global Daily Downscaled Projection

The comparison of temperatures between the data from the GDDP IPSL-CM6A-LR and ACCESS-CM2 models underlines the importance of the choice of climate model as input for MOA. Firstly, significant temperature differences were observed between climate models in terms of minimum, mean, and maximum temperatures. For example, such differences were observed between the IPSL-CM6A-LR and ACCESS-CM2 models for all combinations of periods, temperature variables, and SSPs over the South Island of New Zealand and these differences increased over time. Secondly, the spatial distribution of these temperature differences is not uniform. This means that the temperature differences between climate models can be different across regions. The non-uniform spatial distribution of temperature differences can further influence spatial outcomes since MOA provides spatial solutions.

In addition, MOA uses climate indices (Huglin, 1978; van Leeuwen *et al*., 2008; Winkler *et al*., 1974) and phenological models (Parker *et al*., 2011; Parker *et al*., 2020) based on thermal summation to determine solutions. As these indices and models use temperature summations, the temperature differences between the climate models may lead to significant differences in results depending on the climate model that is selected. With these considerations in mind, selecting climate data as input for MOA should be done carefully, considering the specific characteristics and limitations of the climate models used.

The analysis of ACCESS-CM2 and IPSL-CM6A-LR performances over the South Island did not show a strong difference regarding the daily mean temperature. Moreover, it is worth noting that the low correlation values observed (ranging between 0.29 and 0.59) likely reflect that the comparison was made between simulated data representing a 0.25 ° resolution cell and observed data from weather stations located at specific points within this cell. Additionally, the region study is known to be complex to model accurately (Pohl *et al*., 2021; Pohl *et al*., 2023). As a consequence of the close performances of the two climate models, both were used to run MOA.

2. Winegrowing Future in New Zealand South Island

The application of the MOA optimisation model provided insights into the potential impacts of climate change on current vineyards and explored the wine-growing potential of the New Zealand South Island beyond existing wine-growing regions. The observed change in climate, as indicated by the Huglin Index, aligns with the expected warming trends in this area (Ausseil *et al*., 2021; Pearce *et al*., 2018). Although the warming may not be substantial in the near term compared to future periods, the advancement of veraison and ripeness stages demonstrates the high sensitivity of grapevine development to potential future temperatures. Ausseil *et al*. (2021) also investigated the impact of climate change on flowering, veraison, and target sugar ripeness for mid-century (2046–2065) and end-of-century (2081–2100) periods in New Zealand, including Sauvignon blanc. Their findings of advanced veraison and ripeness dates are consistent with the results obtained in this study. However, the authors reported smaller advancements in phenological stages compared to the projections presented in this work; approximately one to two weeks for both stages in the mid-term and intermediate scenarios (i.e., RCP2.5 and SSP2-4.5) in the long term, and around two to three weeks for both stages in the long term with the high GHG emission scenario (i.e., RCP5-8.5 and SSP5-8.5). The compression of time between the veraison and target sugar ripeness projected by MOA is also consistent with their findings. The disparities in results can be attributed to differences in climate data used, including the regional climate models (RCMs) and climate projections (RCPs instead of SSPs), as well as variations in the studied period and scale (regional instead of the entire South Island). Nonetheless, the overall trend of advancing phenological stages is consistent with previous studies conducted in New Zealand and worldwide (Cameron *et al*., 2020; Cook and Wolkovich, 2016; Hall *et al*., 2016; Koufos *et al*., 2020; Ramos and Martínez de Toda, 2020).

While previous studies have examined the changes in grapevine varieties in New Zealand, there has been less focus on integrating the potential exposure to climate risks. This research addressed this gap by considering the climate risks associated with viticulture. Several studies have explored the risk of frost events on viticulture, with some indicating a decrease (Campos *et al*., 2017; Llanaj and McGregor, 2022; Molitor *et al*., 2014), an increase (Mosedale *et al*., 2015), or a combination of both (Meier *et al*., 2018) in frost risk, depending on the specific region and climate projections. The assessment of future potential exposure to climate risks using the MOA model reveals a projected increase in frost risk as a consequence of the earlier budburst, leading to a wider window of vulnerability between the budburst and the last spring frost. The budburst of Pinot noir, an earlier ripening variety than Sauvignon blanc, occurs earlier making it more vulnerable to late spring. Moreover, the projected increase in frost risk is expected to exhibit regional or localised patterns. The parts of the South Island projected to be most threatened by frost risk in the future were the plains and southern regions of Canterbury, Otago, and Southland, while the coastline was projected to be less impacted by frost, as previously demonstrated by Blanco-Ward *et al*. (2007) and Webb *et al*. (2018). Thus, understanding the regional risk of frost frequency is crucial, as parts of the south of the Island and the Canterbury region are strongly impacted by frost events. Grapevine disease risk under climate change has been the focus of a limited number of studies. Salinari *et al*. (2006) conducted simulations suggesting that climate change could increase disease pressure, while Mozell and Thach (2014) suggested that changes in temperature and humidity could contribute to the increased presence of insect-borne diseases. In this study, the assessment of potential exposure to disease risk was based on the number of pathogen treatments.

The results indicated a minor increase in disease risk over the studied periods. Vetharaniam *et al*. (2021) investigated botrytis risk and projected both a minor decrease and a modest increase in disease risk, which aligns broadly with the findings of this study. Additionally, the larger increase in disease risk projected for near-coast areas and with the SSP5-8.5 scenario corresponded to the higher expected humidity in these regions and under this scenario. As for frost risk, Pinot noir was projected to be more impacted by pathogens than Sauvignon blanc as a consequence of its earlier budburst. Regarding heat risk, the results of this study suggested that the South Island is projected to remain unimpacted by heat waves. This finding indicates that heat waves are unlikely to be a limiting factor for winegrowing in the South Island of New Zealand in the future. However, uncertainties and limitations related to this finding are discussed below.

The MOA model provides the best solutions based on the defined scenario and chosen parameters, which represent the optimal combinations of objectives and constraints. Due to the diversity of objectives, it is rare to find a single solution that satisfies all criteria. Thus, the solutions represent trade-offs between the objectives and constraints. Ultimately, the selection of a solution is left to the user, allowing them to make the final decision at the end of the process (Collette and Siarry, 2003). Cells not defined as best solutions by the model do not imply that they are unsuitable for winegrowing, but rather that the objectives/constraints combination is less favourable. Therefore, the figures presented in the study (Figure 5–8) represent only the best solutions, and other areas may still be suitable for winegrowing but are considered less optimal. According to the MOA model, the current vineyards in the Marlborough region are projected to remain among the best areas for winegrowing in the South Island throughout the 21st century for both Pinot noir and Sauvignon blanc, under both SSPs. This finding aligns with the projections of a previous study (Vetharaniam *et al*., 2021). Additionally, Vetharaniam *et al*. (2021) suggested that the suitability for Pinot noir in Marlborough may experience a small decrease, while the suitability for Sauvignon blanc is expected to increase or remain constant. Although this study did not directly assess the degree of suitability, the presence of a significant number of Sauvignon blanc solutions in the Marlborough region (Figure 8) among different cultivars tends to support this projection. However, it's important to note that changes in agroclimatic conditions, such as warming and advancement of phenological stages, may make it more challenging to produce current wine types and lead to changes in wine style in the upcoming decades. Winegrowers may need to adapt by considering alternatives like switching to later-ripening grape varieties or relocating their vineyards further inland and/or southward. The study by Vetharaniam *et al*. (2021) identified Nelson, Marlborough, Canterbury, Otago, and Southland as the most suitable parts of the South Island for winegrowing of both Pinot noir and Sauvignon blanc based on climate scenarios. These findings are consistent with the best solutions identified in our study. Furthermore, the inter-cultivar analysis highlights that Pinot noir tends to be more suitable than Sauvignon blanc in Otago, while the opposite is projected for Canterbury, which aligns with the previous study (Vetharaniam *et al*., 2021).

3. Uncertainties and Limitations

The uncertainties and limitations of this work primarily revolve around the climate data used. The dataset employed in the study consists of downscaled projections derived from General Circulation Models (GCMs). There are inherent assumptions and limitations associated with the bias correction method and downscaling process, as described by Trasher *et al*. (2022). Additionally, the choice of the climate model itself introduces uncertainties. Bias correction is a technique used to address systematic errors in climate models, but it does not guarantee the accuracy of models. One way to address this issue is to employ a multi-model approach by combining different climate models (Thao *et al*., 2022). Several ensemble averaging methods (Massoud *et al*., 2019) exist that aim to enhance the reliability of climate projections by reducing uncertainties among GCMs (Tegegne *et al*., 2020). Research by Tegegne *et al*. (2020) indicates that ensemble approaches yield results closer to observations compared to using a single model. Raju and Kumar (2020) have proposed a method for selecting and combining GCMs in an ensemble. However, it is worth noting that ensemble approaches require more computational resources and time to implement. Additionally, it has been observed that ensemble approaches may struggle to capture different extreme characteristics (Tegegne *et al*., 2020). The spatial resolution of 0.25 ° × 0.25 ° used in this study allows for the examination of climate impacts at local to regional scales. However, it may not capture events occurring at finer levels. Since the study focused on events such as frosts and heatwaves, which can occur at various spatial scales including vineyard and plot levels, some of these events in the future may not be fully captured in the results. For example, while the study projects that the South Island of New Zealand will remain unaffected by heat waves, New Zealand already experiences hot days, thus localised areas within the South Island may experience heatwaves. However, the spatial resolution of the data used in this study may not be sufficient to identify such localised events. Additionally, when identifying new areas favourable for viticulture in the future, coarse spatial resolutions can lead to less precise investigations. In other words, regions with good winegrowing potential may not be identified as the best solutions due to the poor winegrowing conditions within the larger grid cell. Studies employing finer spatial resolutions can address these limitations and provide more detailed insights into localised climate events and suitable viticultural areas. The uncertainty related to the choice of climate data was estimated by separately running MOA with two climate models (ACCESS-CM2 and IPSL-CM6A-LR). The inter-model uncertainties tended to increase toward the 21st century which are consistent with the increasing temperature difference observed between the two climate models. However, their values remained relatively low providing confidence in the orders of magnitude of projected warming, projected

veraison and ripeness date anomalies (GFV and GSR), and projected frost, heat, and disease risk exposure. Regarding MOA winegrowing best solutions, outputs with ACCESS-CM2 and IPSL-CM6A-LR were also very close. The lower number of best solutions identified with IPSL-CM6A-LR is also consistent with the cold bias of this model compared to ACCESS-CM2. The agreement between the two climate models for the optimisation of grape varieties also shows the consistency of the MOA model optimisation process. More robust results could be obtained by coupling MOA to more climate models, especially when using higher-resolution climate data. Indeed, the small difference between climate models at 0.25 ° × 0.25 ° may lead to relatively similar outcomes. However, climate data with a higher resolution may better capture extreme climate events influencing the optimisation process of MOA.

Secondly, there are uncertainties and limitations associated with the MOA model itself, both in terms of the defined scenario and the model's construction. The scenario chosen for the model provides the necessary information and guides how the model computes solutions. Therefore, the results cannot be interpreted without considering the specific scenario and its parameters, such as objectives, constraints, and grape varieties. It should be noted that this study only investigated two grape cultivars, and different results may be obtained with other cultivars.

The construction of the MOA model also introduces uncertainties and limitations to this work. The model is based on various concepts having their inherent limitations (Huglin, 1978; Parker *et al*., 2011; Parker *et al*., 2020; van Leeuwen *et al*., 2008; Winkler *et al*., 1974). While MOA primarily relies on temperature projections, other climate variables, such as rainfall (van Leeuwen *et al*., 2009) and wind (Bonnardot *et al*., 2005), also influence wine development. Neglecting these variables can lead to discrepancies in the results. For example, the MOA model projects some best solutions for viticulture in the future on the West coast of the South Island, which is known for its high rainfall amount. However, based on the expertise of the authors, winegrowing in this area is not considered feasible, even in the context of climate change. Therefore, the MOA model likely underestimates the impacts of precipitation, particularly in areas with very high rainfall. Caution should be exercised when using the MOA model to investigate such areas, and additional considerations should be taken into account. Overall, the uncertainties and limitations associated with the MOA model highlight the need for careful interpretation of results and the consideration of other relevant climate variables and expert knowledge in viticulture.

Therefore, it is important to interpret our results with caution, particularly when examining specific values of variables (e.g., veraison or ripeness date advancement, frost risk frequency...). However, despite this work's assumptions, uncertainties, and limitations, we have confidence that the overall trends and orders of magnitude described here are accurate. Further research will be necessary to validate the presented values and address remaining gaps, such as studying climate risks using data with finer spatial resolution.

CONCLUSION

In summary, we used the MOA optimisation model to investigate the potential impacts of climate change on viticulture in the South Island of New Zealand. The aims were to evaluate the projected evolution of climate risks (frost, heat waves, diseases) and phenological stages (veraison, target sugar ripeness) for two cultivars (Sauvignon blanc and Pinot noir), to assess the suitability of current vineyards for the future and to identify emerging areas favourable for viticulture.

Two climate projection datasets, IPSL-CM6A-LR and ACCESS-CM2, were compared and the results showed significant differences in the minimum, mean, and maximum temperatures in the different scenarios and periods, with a remarkable spatial variability. Both datasets were separately used to run the MOA model.

The findings revealed an overall advancement of veraison and ripeness phenological stages throughout the 21st century, particularly pronounced at higher temperatures. Moreover, a compression of the time between the veraison and target sugar ripeness was also projected. The frost is projected to have more impact on Pinot noir than Sauvignon while it is projected to occur at a regional to local scale, mainly affecting the Canterbury Plains, southern Canterbury, and Otago regions. However, the coastal areas are expected to be less affected by frost. A slight increase in disease risk exposure is expected, with a greater impact along the coast and on Pinot noir. In terms of heatwaves, the study shows that the South Island of New Zealand is unlikely to be affected by this climate risk. Marlborough region is projected to remain an important winegrowing region in New Zealand over the next decades as its vineyards were identified by the MOA model among the best solutions for viticulture in the near, mid-, and long term, for both Pinot noir and Sauvignon blanc grape varieties. For the South Island of New Zealand, MOA modelled that the best solutions for winegrowing would spread inland and southwards, with a faster pace for Pinot noir than Sauvignon blanc.

It is important to consider the limitations and uncertainties associated with the climate data, the scenario used, and the MOA model itself. These factors should be considered when interpreting the results. Further research is needed to confirm our findings and fill the remaining gaps.

MOA model demonstrated its promising usefulness for assessing climate risks, as well as for identifying future winegrowing regions and optimising cultivars. It is a valuable and useful tool to help determine the optimal location of future vineyards and grape varieties based on a range of objectives and constraints.

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