Incorporating Climate Futures into Enterprise Suitability Mapping

Technical report

JULY **2015**

Department of
Primary Industries, Parks, Water and Environment

Tasmanian Government

Caution and Disclaimer

The Enterprise Suitability information and material contained in this report and displayed in LIST*map* are based on computer modeling of the potential suitability of specific agricultural enterprises to a given area and, as such, there are inherent uncertainties in the results. Climate Futures Tasmania (CFT) data has been used as the basis for climate projections. CFT data was derived from climate change scenarios and projections by the Antarctic Climate & Ecosystems Cooperative Research Centre. This data was also based on computer modelling. Modelling involves simplification of real physical processes that are not fully understood and which must be anticipated.

The rules on which the Enterprise Suitability outputs are modelled were developed by the Tasmanian Institute of Agriculture (TIA).

While every effort has been made to ensure the material is accurate, the Crown in Right of Tasmania ("Crown") and the TIA provide no warranty, guarantee or representation that the material is accurate, complete, up to date, non-infringing or fit for a particular purpose.

Furthermore, the Crown and TIA expressly disclaim all and any legal liability and responsibility whatsoever arising from or connected with:

(a) the accuracy, reliability, validity, currency or completeness of the material;

(b) the consequences of anything done or omitted to be done by any person, either in whole or in part, in reliance of the material.

The material does not take into account personal circumstances. The material is made available on the understanding that the Crown and TIA are not providing professional advice and that users of this material should undertake site-specific investigations and research and obtain appropriate professional advice relevant to their particular circumstances.

The relevant maps that form part of the material have been prepared at 1:50,000 scale. These maps consider only physical soil, topographic and climate constraints and do not take into account other parameters or any legislative, regulatory and/or policy requirements of Federal, State or Local Governments that apply to the land in question and/or which could affect the proposed land use or agricultural enterprise.

Citation

Webb, M (2015) *Incorporating Climate Futures into Enterprise Suitability Mapping - Technical report*. Department of Primary Industries, Parks, Water and Environment. Launceston, Tasmania.

The methodology outlined in this document is a prelude to a formal scientific paper currently in preparation:
Webb M, Kidd D, Minasny, B (2015) *Incorporating regional climate models within the crop suitability framework to assess future land suitability change.* <Manuscript in preparation>

Executive Summary

This report was commissioned by the Tasmanian Climate Change Office to identify likely impacts of predicted climate change scenarios on the suitability of Tasmanian agricultural areas for a range of commercial crop enterprises.

The Department of Primary Industries, Parks, Water and Environment (DPIPWE) have generated significant capacity to model the suitability of crops for Tasmanian soil and climatic conditions. The work is based on digital soil and climate mapping validated by extensive field sampling and monitoring. Through application of known soil, landscape and climate preferences for specific crops (crop rules) it is possible to predict the suitability of such crops to farming land in the state.

Tasmania has available high standard climate change projections developed through the Climate Futures Tasmania (CFT) project. This work provides comparable information on likely change to climate variables modelled by DPIPWE for crop suitability.

This report outlines the steps undertaken to integrate these two predictive tools to map the potential suitability of five crops comprising of Barley, Poppies, Potatoes, Wine grapes (Sparkling and Table wine) and Wheat to changing climate. Climate Futures Tasmania (CFT) projections were incorporated into the enterprise suitability modelling framework to identify land areas most prone to change under a lower (B1) or higher (A2) emissions scenario.

The analysis highlights areas that are likely to become more suitable or less suitable for cropping in response to changes in climate regimes, particularly in relation to frost risk and Growing Degree Days (GDD).

The Report finds that in comparison with the current enterprise suitability for the five crops studied, suitability is projected to become in general more favourable in Tasmania under either emissions scenario.

Key findings are:

- Frost risk is expected to become generally less severe for all of the five crops investigated.
- Areas of greatest change with regard to less severe frosts include the upper Derwent Valley and lower highland areas as well as areas of the Midlands Region.
- Table wine grape production is expected to benefit from increased growing degree days (GDD) during the growing season. This is especially notable for the eastern of half of the state with new areas gradually becoming more suitable over time.
- Sparkling wine grape production may be adversely affected, particularly for areas on the East coast and Midland areas under a higher emission scenario at year 2050, where GDD may exceed 1200 more regularly.
- Heat risk for potatoes is also expected to increase in probability, resulting in a marginal decrease in suitable land for potatoes around the coastal and Midland areas of the state. However, this is negated by the decrease in frost prone areas resulting in an overall increase in suitable land.

The report demonstrates the potential for using the developed models and tools for a wider range of crops and climate change scenario's, it demonstrates potential to aid long term investment strategy for a range of agricultural enterprises.

Contents

1. Introduction

In December 2012, the Department of Primary Industries, Parks, Water and the Environment (DPIPWE) completed a pilot project to identify the 'suitability' of 20 crops within two contrasting areas: 45,000 ha of the Meander Irrigation Scheme and 27,000 ha of the Midlands Water Scheme around Tunbridge. This pilot demonstrated the potential for using models of soil and climate variables to match crop viability with specific areas of the landscape.

The pilot project produced enterprise suitability modelling for 20 crops across the study areas, and provided component data such as soil and climate attributes that identified potential limiting factors for a crop on a particular piece of land. This information was generated at a 30m grid, and there was an underlying assumption that water availability was not an issue as the pilot project was undertaken in the context of the new Tasmanian irrigation schemes. Current outputs can be accessed from the following URL:

http://dpipwe.tas.gov.au/agriculture/investing-in-irrigation/enterprise-suitability-toolkit/enterprise-suitability-maps

In 2013-14, DPIPWE's Sustainable Landscapes Branch undertook a desktop analysis and mapping exercise to test the feasibility of incorporating 'Climate Futures for Tasmania' (CFT) climate change projections with the enterprise suitability modelling. Focusing on poppies, a single climate model, carbon emission scenario and time period were applied to areas of the Meander region and the southern Midlands.

This test project was successfully completed and it was proposed to apply the methodology more broadly, and undertake State-wide enterprise suitability mapping of five crops: poppies, wheat, potatoes, grapes (wine) and barley. These crops were selected based on advice from AgriGrowth Tasmania. Wheat was also specifically requested by the Tasmanian Institute of Agriculture.

This report outlines the steps undertaken that mapped the selected crops at an 80m grid scale using all available CFT climate models for the A2 (higher emission scenario) and B1 (lower emission scenario) simulations and for the 2030 and 2050 timeframes. A summary of the main findings are given in section 3 of this document.

Table 1. Enterprise suitability rules for Barley, Poppies, Potatoes, Wheat and Wine grapes.

Crop	Suitability rating	Soil depth (cm)	Depth to sodic layer (cm)	pH (0 - 15cm)	Ecse dS/m	Clay content % (0 - 15cm)	Drainage classification	Stoniness % (0 - 15cm)	Slope %	Climate rule1	Climate rule1	Climate rule1	Climate rule1	Climate rule1
Barley										*Frost risk: Chance (%) of having a day with Tmin <0°C in December*				
	Well suited	>40cm	>30cm	>=6	<4	>8.5%	Moderate to excessively well drained	<10%	<5%	<20% of years	NA	NA	NA	NA
	Suitable	>40cm	20 - 30cm	5.5 - <6	4 - 8	>8.5%	Imperfectly drained	10 - 20%	5 - 25%	20 - 30% of years	NA	NA	NA	NA
	Marginally suitable	>40cm	<20cm	5 - <5.5	8 - 16	<8.5%	Imperfectly drained	10 - 20%	5 - 25%	30 - 40% of years	NA	NA	NA	NA
	Unsuitable	<40cm	<20cm	<5	>16	<8.5%	poor to very poorly drained	>25%	>25%	>40% of years	NA	NA	NA	NA
Poppies										*Frost risk: Chance (%) of having a day with Tmin < -1°C (15 Nov. to 15 Dec.)*	*Frost risk: Chance (%) of having a day with Tmin < -1°C (1 - 15 Nov.)*			
	Well suited	>40cm	>30cm	>=6	NA	>10%	Moderate to moderately well drained	<10%	<5%	<10% of years	<10% of years	NA	NA	NA
	Suitable	>40cm	>30cm	>=6	NA	>10%	Imperfectly/excessively well drained	10 - 20%	5 - 20%	10 - 20% of years	10 - 20% of years	NA	NA	NA
	Marginally suitable	>40cm	15 - 30cm	5.3 - <6	NA	5 - 10%	Imperfectly/excessively well drained	10 - 20%	5 - 20%	20 - 40% of years	20 - 40% of years	NA	NA	NA
	Unsuitable	<40cm	<15cm	<5.3	NA	<5%	poor to very poorly drained	>20%	>20%	>40% of years	>40% of years	NA	NA	NA
Potatoes										*Frost risk: Chance (%) of having a day with Tmin < -0°C (1 Nov. to 28 Feb.)*	*Heat risk: Chance (%) of having a day with Tmin > -20°C (1 - 15 Nov.)*			
	Well suited	>25cm	NA	>5	<1.2	>5%	Well drained	<2%	<10%	<20% of years	<20% of years	NA	NA	NA
	Suitable	>25cm	NA	>5	1.2 - 2	>5%	Moderate/excessively well drained	2 - 10%	10 - 25%	20 - 40% of years	20 - 40% of years	NA	NA	NA
	Marginally suitable	15 - 25cm	NA	>5	2 - 4	<5%	Imperfectly drained	10 - 20%	10 - 25%	40 - 60% of years	>40% of years	NA	NA	NA
	Unsuitable	<15cm	NA	<5	>4	<5%	poor to very poorly drained	>20%	>25%	>60% of years	>40% of years	NA	NA	NA
Wheat	Wheat									*Frost risk: Chance (%) of having a day with Tmin < -0oC (1 - 15 Nov.)*				
	Well suited	>40cm	>30cm	>=6	<3	>8.5%	Moderate to excessively well drained	<10%	<5%	<20% of years	NA	NA	NA	NA
	Suitable	>40cm	20 - 30cm	5.5 - <6	3 - 6	>8.5%	Imperfectly drained	10 - 20%	5 - 25%	20 - 30% of years	NA	NA	NA	NA
	Marginally suitable	>40cm	<20cm	5 - <5.5	6 - 12	<8.5%	Imperfectly drained	10 - 20%	5 - 25%	30 - 40% of years	NA	NA	NA	NA
	Unsuitable	<40cm	<20cm	<5	>12	<8.5%	poor to very poorly drained	>25%	>25%	>40% of years	NA	NA	NA	NA
Wine grapes										*Frost risk: Chance (%) of having a day with Tmin < -2°C (15 Sep. to 15 Oct.)*	*Frost risk: Chance (%) of having a day with Tmin < -2°C (15 Oct. to 15 Nov.)*	*Growing Degree Days: Oct. to Apr. with a base temp. of 10°C*	*Chill hours: Mean July temperature (°C)*	*Annual Rainfall (mm)*
	Well suited	>40cm	>100cm	>5.6	<1.5	NA	Well drained	NA	3 - 10%	<20% of years	<10% of years	[Sparkling wine: 900 -1085], [Table wine: >1150]	<12°C	<700mm
	Suitable	20 - 40cm	50 - 100cm	>5.6	1.5 - 2.6	NA	Well drained	NA	<3%, 10 - 15%	20 - 50% of years	10 - 20% of years	[Sparkling wine: 850 - 900, 1085 - 1150], [Table wine: 1000 - 1150]	<12°C	700 - 900mm
	Marginally suitable	10 - 20cm	30 - 50cm	5 - 5.5	2.6 - 4.1	NA	Moderately well drained	NA	15 - 20%	50 - 100% of years	20 - 50% of years	[Sparkling wine: 800 - 850, 1150 - 1200], [Table wine: 800 - 1000]	<12°C	900 - 1200mm
	Unsuitable	<10cm	<30cm	<5	>4.1	NA	Imperfect to very poorly drained	NA	>20%	>1 per year	>50% of years	[Sparkling wine: <800, >1200], [Table wine: <800	<12°C	>1200mm

2. Methods

2.1 Background

The current structure of the enterprise suitability maps are derived from a combination of digital soil mapping (DSM) and localised climate data which are guided by individual crop rules (refer to: http://dpipwe.tas.gov.au/agriculture/investing-in-irrigation/enterprise-suitability-toolkit). The soil attributes such as pH, soil depth, stoniness and drainage are combined with climate parameters such as frost risk, growing degree days (GDD) and chill hours (refer section 2.1). Each input layer is categorised into well suited, suitable, marginally suitable or unsuitable according to a set of enterprise suitability rules (Table 1) where the layer with the least suitable rating determines the overall suitability rating for any particular area. This is known as the most limiting factor approach (Klingebiel and Montgomaery et al, 1961). Currently this method of determining suitability is being carried out for the agricultural areas of Tasmania at 80m resolution and the outputs due to be released at the end of July 2015 (Kidd, Webb et al, 2015).

2.1.1 Production of the current (1994 to 2013) state wide climatic models

Climate variables to feed into the state wide enterprise suitability framework have been recently produced (along with the soil attributes detailed in Kidd, Webb et al, 2015). The climate parameters were determined from short-term temperature logger data which were calibrated to long-term Bureau of Meteorology (BoM) weather station data (refer to Webb, Hall et al, 2015). The current arrangement of DPIPWE logger locations were relocated from their original study areas (in the Meander and Southern midland regions) and placed in strategic areas around the state in June, 2013 (Figure 1). As similarly performed in Webb, Hall et al (2015), loggers were dispersed according to a stratified random sampling regime to take into account the major topographical characteristics of Tasmania. Having optimally placed loggers enables optimisation of the climatic models that are produced by data mining algorithms such as regression trees (Quinlan 1986) or random forests (Breiman 1996). In other words, they can be trained sufficiently from temperature estimates derived from loggers placed in a range of vastly different landscapes which help to account for the variability associated with topography and climate. In addition to these, temperature datasets with at least 12 months of continuous recordings were sourced externally from sources including Gunns Ltd (Weather station data), Hydro Tasmania (Weather station data) and Ag Logic consultancy (temperature logger data). This added additional datasets to the modelling process and helped improve overall model certainty.

The loggers were programmed to record temperature half hourly for a minimum of 1 year (e.g. June 2013 to June 2014). After this period the temperature data were manually downloaded and calibrated to long-term BoM station data. The calibration method initially involved geostatistical mapping of long-term BoM data to produce uncalibrated temperature estimates of long-term data at each logger site. This dataset then underwent linear least square regression with the actual logger site recordings for concurrent recording days (e.g. June 2013 to June 2014) to produce a set of calibration equations. Historical data then can be inferred upon the logger sites by using the newly established calibration equations and the long-term uncalibrated temperature estimates (prior to the logger recording period) as the *x* factor in the linear equation.

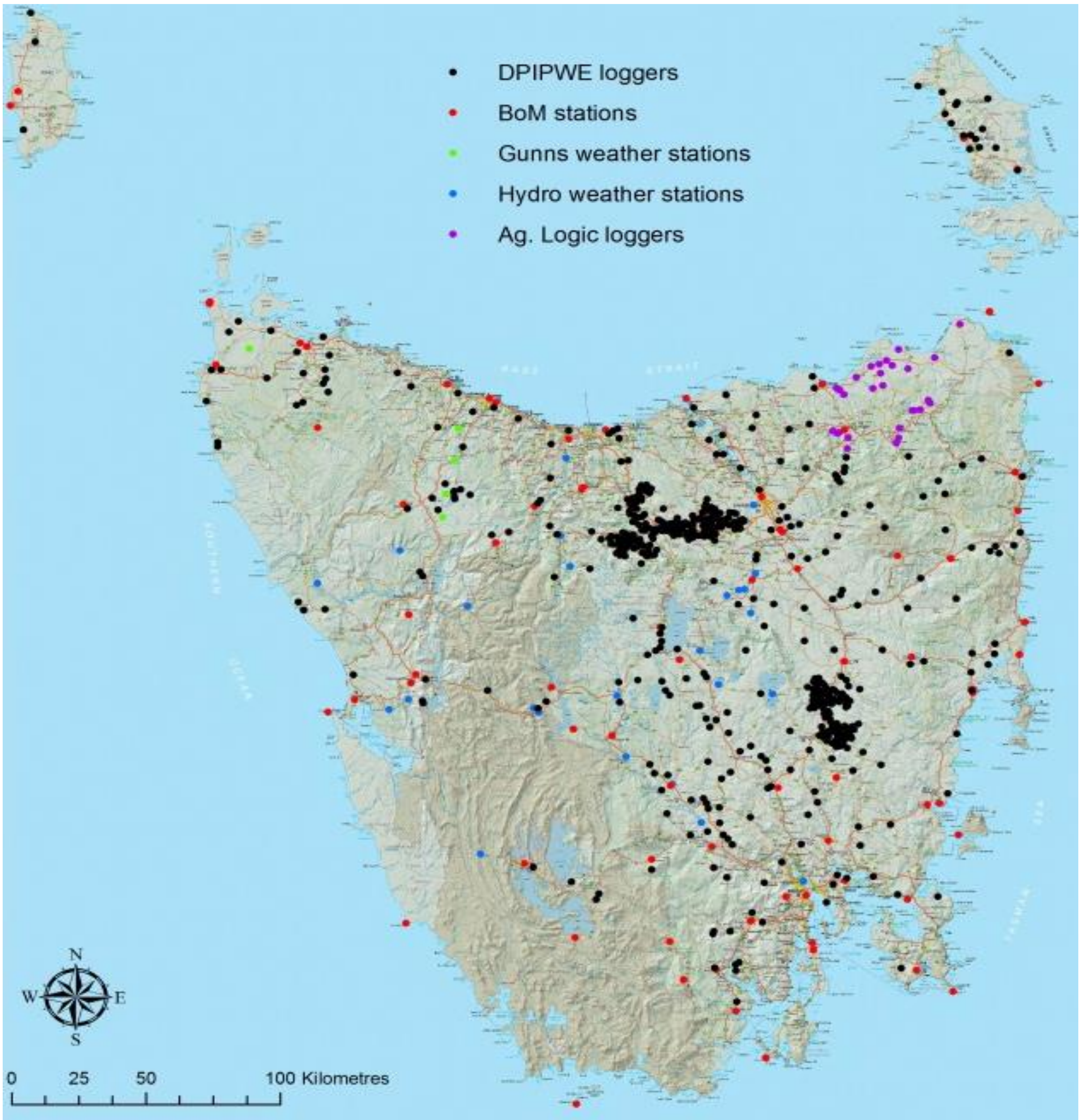


Figure 1. Location of historic and current temperature logger/weather stations used in the modelling process. (Base image by TASMAP, © State of Tasmania)

The results are individual calibrated temperature datasets for each logger/weather station encompassing 20 years (1994 – 2013) of daily minimum and maximum temperatures. Using a K-fold cross validation technique (Hastie, Tibshirani et al 2013), tests confirmed that the estimates were within the acceptable error range of climate mapping with mean absolute error of around 0.5°C or below for most of the logger/weather station sites.

Using the newly derived long term logger calibrated temperature estimates it was then possible to produce the climatic variables such as frost risk, extreme heat risk, chill hours and GDD (refer to section 2.2.3 for calculation example). Each variable could then be spatially interpolated from the logger/weather station sites using data mining techniques such as random forests (Breiman 1996).

When combined with predictor variables or covariate datasets to explain the climatic variability, accurate climate models could be produced based on the values of each climate variable at the logger/weather station sites. In order to assess the accuracy of the resulting outputs generated from the random forest model, a K-fold cross validation was undertaken. Specifically, the training dataset (i.e. climate variable estimates from the logger/weather stations) was split into K equal sized parts by random sampling. For each fold, the K-th part was kept for validation and the remaining parts (K – 1) combined for modelling using random forests. The process was repeated K times (folds) where each K subsample was used once to validate each K - 1 model (Hastie, Tibshirani et al 2013). For this study, K = 10 was specified and at the conclusion of the K-folds all outputs were averaged to arrive at the final interpolated prediction values. At each k-fold, cross validation measures comprising the Root mean square error (RMSE), coefficient of determination (R^2) and concordance coefficient (used to quantify the agreement between paired readings that fall on the 45^o line through the origin, a high rating close to 1 indicates strong agreement (Lin 1989)) were derived to statistically give an indication of prediction accuracy. They were averaged at the conclusion of the K-folds to get an overall measure of model performance (Table 2).

On the whole, the climatic variables were validated to an acceptable level, with good agreement between the predicted values and the held back validation set. The GDD and mean temperature output tended to produce the most accurate results which was consistent with that found in Webb, Hall et al (2015). The least accurate output was exhibited by Potatoes concerning frost risk, however, with an RMSE of below 15%, this was generally acceptable.

The climate outputs for poppies, wheat, potatoes, grapes (wine) and barley based on the modelling are shown in figure 2.

Table 2. Validation statistics showing coefficients of determination (R^2), concordance coefficient (P_c) and root mean square error (RMSE) for each climate variables based on interpolating the calibrated logger/weather station data (using random forests) for the period 1994 – 2013.

Climate variable	*RMSE*	R^2	P_c
Frost risk (%) at flowering – Barley	10.3	0.7	0.8
Frost risk (%) at flowering – Poppies	9.3	0.8	0.8
Frost risk (%) at late hook stage – Poppies	9.3	0.8	0.8
Frost risk (%) – Potatoes	14.3	0.8	0.9
Heat risk (%) – Potatoes	7.5	0.4	0.5
Frost risk (%) Oct. to Nov. – Wine grapes	10.6	0.8	0.8
Frost risk (%) Sep. to Oct. – Wine grapes	13.8	0.7	0.8
Frost risk (%) – Wheat	11.6	0.8	0.9
Growing Degree Days (GDD) – Wine grapes	91.2	0.9	0.9
Hourly mean temperature (^{o}C)– Wine grapes	0.4	0.9	0.9

RMSE, Root Mean Square Error*; R2,* coefficient of determination; *Pc*, concordance coefficient. RMSE units for frost risk, GDD and hourly mean temperature are % (of years), days and ^{o}C, respectively.

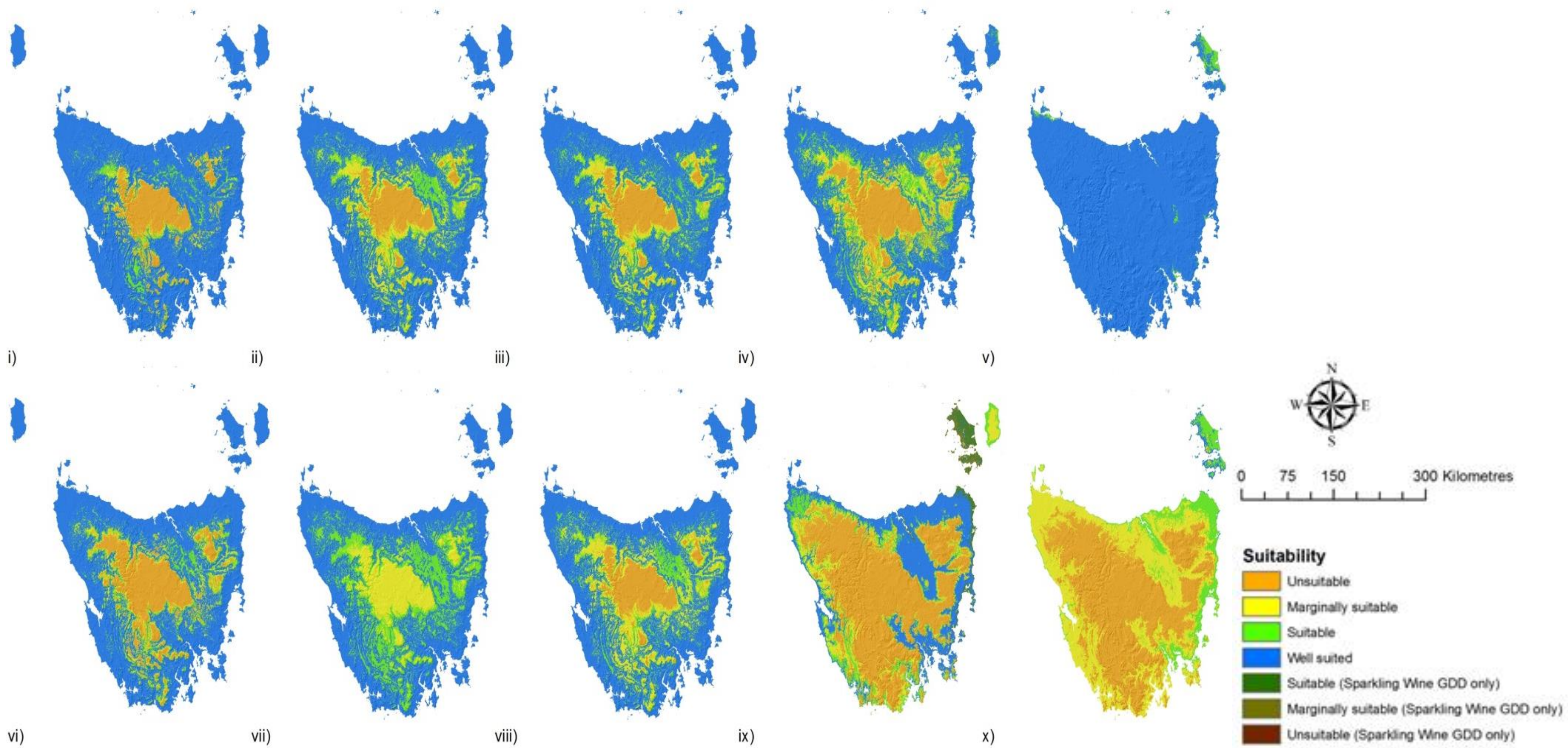


Figure 2. Climate outputs based on calibrated logger/weather station data for the period 1994 – 2013. i) Frost risk at flowering – Barley, ii) Frost risk at flowering – Poppies, iii) Frost risk at late hook stage – Poppies, iv) Frost risk – Potatoes, v) Heat risk – Potatoes, vi) Frost risk – Wheat, vii) Frost risk Sep. to Oct. – Wine grapes, viii) Frost risk Oct. to Nov. – Wine grapes, ix) Growing Degree Days (GDD) – Sparkling wine grapes, x) Growing Degree Days (GDD) – Table wine grapes. Refer to table 1 for formal rule definitions.

2.2 Incorporating CFT projections

CFT projections were applied to the climatic variables at each logger site to provide daily minimum and daily maximum temperature datasets for two twenty year periods: 2011-2030 and 2031-2050. Ideally, it would be preferable to provide 30 year climatic ranges (i.e. 2001 – 2030 and 2021 – 2050) and is generally accepted for determining long-term climate trends (Corney, Katzfey et al, 2010; Dèquè 2007). However, given the original climate mapping method involved determining the climatic variables for the 20 year period (1994-2013) the decision was made to consistently use this period length for the projected climate variables. Note that the original climate mapping project attempted to determine climate between 1984 and 2013 to provide a 30 year climate dataset. However, due to the sparseness and irregularity of existing BoM recordings prior to 1994, it was not possible to produce accurate long-term climate grids (uncalibrated) that best represented temperature in the prior decade.

Incorporating climate projections into the enterprise suitability framework involved five main processes: Initial downscaling of the CFT grids using regression trees; Calibration of the downscaled CFT data to the logger/weather station sites; Climatic variable estimation for the projection periods; Interpolation of the climatic variable estimates; Incorporation of the projected climatic grids into the enterprise suitability models.

2.2.1 Initial downscaling of the CFT grids using regression trees (Cubist)

In its raw format each CFT model (x6) data are stored as 10x10km netCDF grid files as a time series of simulated daily minimum/maximum temperatures from 1961 through to 2100 (as either the A2 = higher emission scenario; or B1 = lower emission scenario). The simulations are based on Global Climate Model produced by CSIRO in Australia (CSIRO-Mk3.5), Max Planck Institute in Germany (ECHAM5/MPI-OM), Geophysical Fluid Dynamics Laboratory in the USA (GFDL-CM2.0 & GFDL-CM2.1), The University of Tokyo (MIROC3.2 (Medres)), and the Met Office in the UK(UKMO-HadCM3) (Corney, Katzfey et al, 2010).

Simply intersecting the datasets at the 10x10km resolution with the locations of the loggers/weather stations does not take into account the possible topographic characteristics that strongly influence temperature at the required 80m resolution. To account for this, an initial statistical downscaling method was employed, similarly to that explored by Poggio and Gimona (2015), however, instead of using a geostatistical approach, regression trees was employed in this study due to its comparatively more efficient computational performance. The regression tree algorithm which is performed using the software Cubist© (Quinlan 2012) is able to statistically relate topographic predictors such as a digital elevation model (DEM) and related derivatives (i.e. slope and aspect) to the response variable such as temperature. In its simplest form, the algorithm forms a series a rule based partitions based on a training set of pre-classified cases which is empirically based on their relationship with the predictor variables. These groups are then modelled using linear equations to arrive at a predicted value. For this exercise, this process was implemented for every day in the CFT data series up to 2050 for each of the 6 CFT models. To relate the daily values from the CFT temperatures grids, the predictor variables of the 3 second SRTM Digital Elevation Model (DEM) (Gallant, Dowling et al 2011), a distance (km) to sea index (derived using the Euclidean Distance Spatial Analyst tool in ESRI 2013 ArcGIS Desktop: Release 10.2 Redlands, CA: Environmental Systems Research Institute) and the SAGA wetness index (Boehner, Koethe et al 2002; Böhner and Conrad 2007; Grabs, Seibert et al. 2009) was used and up-scaled to the CFT grid resolution of 10x10km. These predictor variables were chosen due to their strong relationship with temperature and their ability to account for temperature lapse rates associated with topography (Webb, Hall et al, 2015; Jarvis and Stuart 2001a & 2001b). To upscale the predictor variables to the cell resolution of the CFT grids, the cell values of the 80m predictor values of the DEM and SAGA wetness index that collectively fell within each 10x10km CFT grid cell were averaged to represent the overall predictor value at each 10x10km grid cell. For the distance to sea index, the 80m cell value that fell within the centre of each 10x10km CFT grid cell was taken as the overall 10x10km grid value. A cubist model was, thus, formed for every day in the CFT data series up to 2050 (for daily maximum/minimum temperatures) at the CFT grid resolution using the up-scaled predictor variables. Because we have the predictor variables at 80m resolution, the Cubist established model for each day at the 10x10km CFT grid resolution could therefore be applied to the predictor dataset at the desired 80m resolution. This presented an uncalibrated set of daily CFT temperature grids (up to 2050) at 80m resolution which were then intersected with the geographic locations of the logger/weather station sites to result in individual uncalibrated CFT datasets (per each of the 6 CFT models) at these sites.

2.2.2 Adjustment of the CFT data at the logger/weather station sites

The dataset derived from the initial downscaling exercise underwent further adjustment to eliminate inherent bias that may still exist. According to Poggio and Gimona (2015), Corney, Katzfey et al (2010), Dèquè (2007) systemic error (or bias) is a consistent error that can be caused by the lack of resolution of regional climate models, in this case, the CFT grids at 10x10km resolution. Even though we may have eliminated some of it using the initial Cubist downscaling method, another method was required to completely remove it at each logger/weather station site. As similarly employed by Corney, Katzfey et al (2010), Dèquè (2007) and Sansom and Tait (2004) a percentile adjustment method was utilized in this project to ensure the current CFT estimates (i.e. 1994 to 2013) at each logger/weather station site matches the 'actual' estimates of the logger/weather station (1994 to 2013) over the entire probability distribution. The discrepancy between the two datasets can then be applied in each quantile of the probability distribution into the future period. Hence, any consistent error or bias, which is likely to be topographic related, can be removed and the dataset more representative of temperatures likely to be exhibited by the logger/weather station sites within each CFT climate simulation.

Prior to applying the adjustment method both datasets for the period in question was de-trended using a linear regression model to remove effects of any long term change in the climate (but not to remove the 20-year mean of the modelling output). As discussed by Corney, Katzfey et al (2010), the de-trending of the simulations was necessary to ensure that both datasets were normally distributed and therefore any climate change signal did not affect the percentile rankings. For instance, a 50thpercentile day in the period 1994-2003 should be grouped with a 50thpercentile day from the period 2004-2013.

The bias-adjustment process can be broken into two stages. The first stage compares the distributions of the downscaled CFT estimates and the 'actual' estimates at the logger/weather station site (refer section 2.1.1) over the period of time that both datasets exist (1994 to 2013), and calculates an adjustment factor for each percentile bin. In this analysis, comparisons were made across the seasons which ensured that days of similar temperatures are driven by the same processes (Corney, Katzfey et al, 2010). Percentile bins of 10 (i.e. every 10th percentile) was also used to compare the entire seasonal distribution between datasets. Percentile bins of 1% was considered

(Corney, Katzfey et al, 2010), however, due to computation limitations that would otherwise considerably slowed the adjustment process, bin sizes of 10% was seen as a reasonable compromise.

The second stage applies this adjustment factor to each percentile bin over the full period, i.e. up to 2050 and accounting for the seasons. To mitigate any inaccuracy of the tales at the distributions (i.e. at the extreme temperatures) values below the 10^{th} and above the 90^{th} percentiles were averaged to become the 0 and 100^{th} percentile values, respectively. This prevented any CFT temperatures below the 10^{th} or above the 90^{th} percentiles from being adjusted at the extreme temperature estimates of the logger/weather station data that would have otherwise given consistently unrealistic values. Figure 3 and 4 illustrates an example of the adjustment process whereby the original CFT estimate is adjusted to more closely resemble the actual records of the logger site.

The end result of the adjustment process is a calibrated dataset of CFT simulation models specifically catered to each logger/weather station sites spanning from 1994 to 2050 of daily minimum/maximum temperatures.

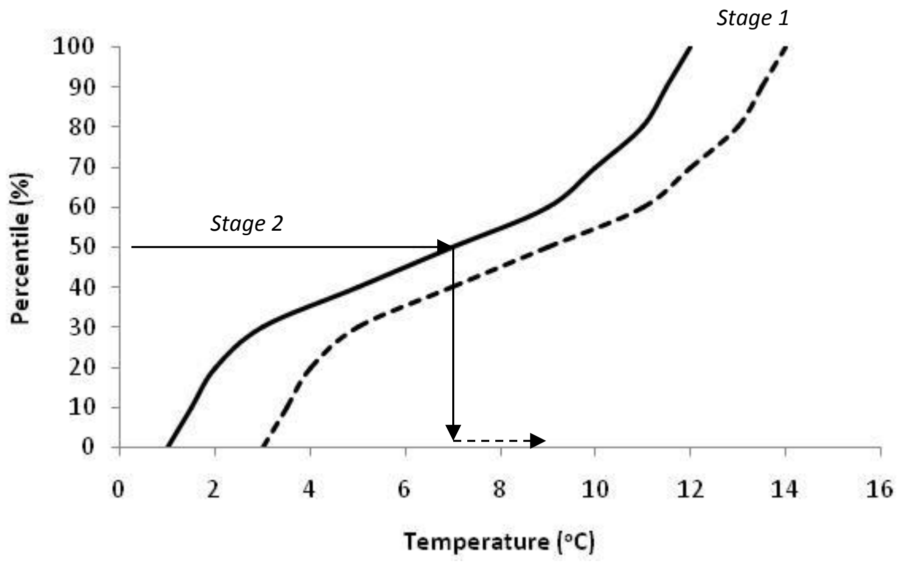


Figure 3. Schematic diagram that shows the two stages involved in the adjustment of the down scaled CFT deciles to the 'actual' deciles at the logger/weather station sites for the period 1994-2013. The thick solid curve is the estimation of the temperature distribution at a logger site based on data from the downscaled CFT data. The dotted curve is the solid curve shifted to the right by the difference between the actual temperature values and downscaled CFT temperature values. Figure is adapted from Samson and Tait (2004)

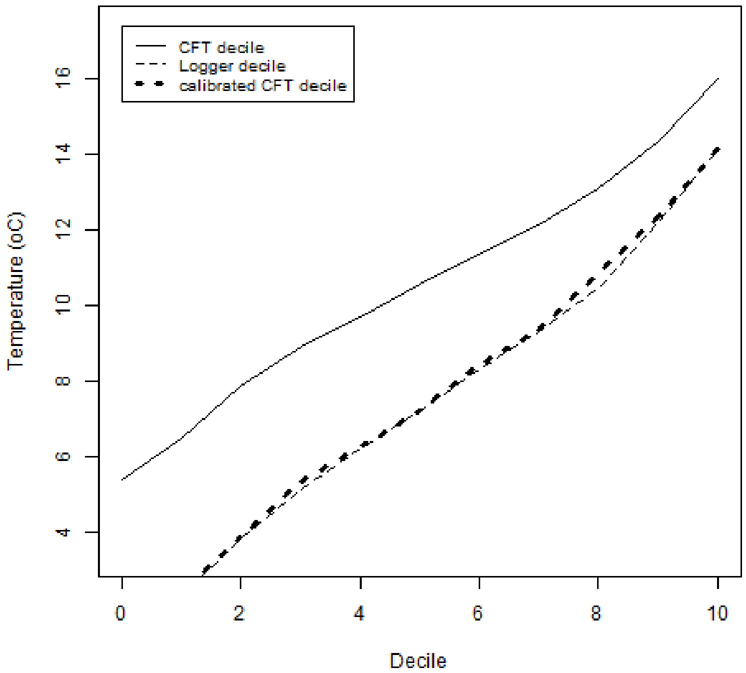


Figure 4. The result of the adjustment method being applied to a temperature logger site located in the Southern Midlands region of Tasmania. The solid line represents the unadjusted downscaled CFT decile, the thin dashed line represents the 'actual' logger decile and the thick dashed line represents the CFT decile after the adjustment procedure.

2.2.3 Climatic variable estimation for the projection periods

From the adjusted CFT dataset, it was possible to calculate the climate variables at the specified climate periods (2011 to 2030 and 2031 to 2050), similarly to that conducted in Webb, Hall et al (2015). For example, for frost risk, a typical rule would constitute the following (using the frost risk rule for wine grapes as an example).

The frequency of years for which a value of less than -2°C occurs for Tmin, the minimum air temperature at 1.2 m above the ground, in the period 15 September to 15 October, determines the level of frost risk for wine grapes.

Frost risk frequency was determined for each temperature logger/weather station by counting years that had at least one day of frost occurring at less than -2°C (for days between 15 September to 15 October) for the two 20 year projection periods (i.e. 2011 to 2030 and 2031 to 2050). This count was summed and divided by the total number years (i.e. 20) to derive the average value.

GDD was calculated by taking the average of the daily maximum and minimum temperatures compared to a base temperature, T_{base}. This is in the form:

$$GDD = \frac{T_{\max} + T_{\min}}{2} - T_{base}$$

For each temperature logger/weather station the average per annum GDD totals were calculated by adding the GDD tally of each year and then averaging the total after the 20 year period. *For the successful propagation of wine grapes, a base temperature of 10°C was used to model GDD from October through to April.*

To calculate chill hours, which was only required for wine grapes, the *mean hourly temperature in the month of July* was determined. Considering that hourly temperature was not an output available from the 6 CFT models, an alternative method was adopted to account for the hourly values. As a surrogate, mean hourly temperature were calculated by taking the average of the daily maximum and minimum temperatures. This has been done simlarly by Dall'Amico and Hornsteiner (2006), who used daily minimums/maximums to calculate mean temperatures with acceptable accuracy. As such, for each temperature logger/weather station mean July temperatures were calculated by adding the daily mean value of each day (calculated as: $T^i_{avg} = (T^i_{min} + T^i_{max})/2$) and then averaging the total after the 20 year period.

2.2.4 Interpolation of the climatic variable estimates

For the climate variable estimates representing each CFT model (CSIRO‐Mk3.5, GFDL‐CM2.0, GFDL‐CM2.1, ECHAM5/MPI‐OM, MIROC3.2 (medres), UKMO‐HadCM3), emission scenario (A2 and B1) and climate period (2030 and 2050) interpolation was carried out using the Random forests algorithm (Breiman 1996). The algorithm is similar to regression trees (Breiman and Cutler 2012), except random forests has greater stochasticity, where many weak trees can be grown (trained) independently. In order to assess the accuracy of the resulting outputs generated from the random forest model, a K-fold cross validation was undertaken, similarly to that undertaken when assessing the accuracy of the original climate outputs (refer to section 2.1.1). Table 3 summarises the validation statistics generated from this procedure for each climate variable. Much of the statistics suggest that the models were relatively accurate in their predictions. The most accurate tended to be models generated for GDD whereas the least accurate was exhibited by Potatoes concerning frost risk, however, with an RMSE of below 15%, this was generally acceptable. Interestingly, these results were similar to that found in section 2.1 (Table 2), which indicate that the models maintained consistency regardless of the climate model, emission scenario or climate period that was modelled.

Table 3. Validation statistics from the random forest models that interpolated each of the climate variables that relate to each CFT model, emission scenario (A2 and B1) and climate period (2030 and 2050). The statistics are based on averaging the validation outputs produced from each of the six CFT models.

	2030						2050					
	A2			B1			A2			B1		
Climate variable	*RMSE*	R^2	P_c	*RMSE*	R^2	P_c	*RMSE*	R^2	P_c	*RMSE*	R^2	P_c
Frost risk (%) at flowering – Barley	9.1	0.7	0.8	9.2	0.7	0.8	7.9	0.7	0.8	8.8	0.7	0.8
Frost risk (%) at flowering – Poppies	7.4	0.8	0.8	7.5	0.7	0.8	6.1	0.7	0.8	6.9	0.7	0.8
Frost risk (%) at late hook stage – Poppies	7.5	0.8	0.9	8.3	0.7	0.8	6.5	0.8	0.9	7.3	0.8	0.8
Frost risk (%) – Potatoes	13.2	0.8	0.8	14.0	0.8	0.8	11.1	0.8	0.8	13.0	0.8	0.8
Heat risk (%) – Potatoes	8.9	0.5	0.7	8.8	0.6	0.7	11.4	0.6	0.7	9.3	0.6	0.7
Frost risk (%) Oct. to Nov. – Wine grapes	8.0	0.8	0.8	8.8	0.8	0.8	6.9	0.8	0.9	8.3	0.8	0.8
Frost risk (%) Sep. to Oct. – Wine grapes	14.5	0.7	0.8	15.2	0.7	0.8	12.5	0.7	0.8	14.2	0.7	0.8
Frost risk (%) – Wheat	9.6	0.8	0.9	10.6	0.8	0.9	8.7	0.8	0.9	9.8	0.8	0.9
Growing Degree Days (GDD) – Wine grapes	92.5	0.9	0.9	92.1	0.9	0.9	94.2	0.9	0.9	93.1	0.9	0.9
Hourly mean temp. (°C)– Wine grapes	0.4	0.9	1.0	0.4	0.9	1.0	0.4	0.9	1.0	0.4	0.9	1.0

RMSE, Root Mean Square Error*; R2,* coefficient of determination; *Pc*, concordance coefficient. RMSE units for frost risk, GDD and hourly mean temperature are % (of years), days and °C, respectively.

2.2.5 Incorporation of the projected climatic grids into the enterprise suitability models.

In order to reduce considerable computation, each projected climate variable surface produced from the 6 CFT climate models (CSIRO‐Mk3.5, GFDL‐CM2.0, GFDL‐CM2.1, ECHAM5/MPI‐OM, MIROC3.2 (Medres), UKMO‐HadCM3) was averaged to produce a 6 model mean surface of each climate variable. The six model mean display of the climate outputs are consistent with maps similarly portrayed on the LIST:

http://www.dpac.tas.gov.au/divisions/climatechange/adapting/climate_futures/?a=139608).

The 6 model mean of the climate grids were assimilated with the digital soil attribute surfaces to inform on enterprise suitability for the chosen enterprise crops. Using the statictical software package "R" (R Development Core Team 2012), enterprise suitability models were constructed to identify the suitability boundaries according to the enterprise suitability crop rules (Table 1). Specifically, the model delineates land areas pertaining to "well suited", "suitable", marginally suitable" or "unsuitable" for crop propagation and uses a most limiting factor approach to identify the overall suitability category for any particular area. The original state wide enterprise suitability outputs (version 1.0) using this classification system can be viewed in figure 5. These outputs are based on climatic variables using temperature estimates from the 1994 to 2013 period (Figure 2, section 2.1.1) in conjunction with soil attributes produced by Kidd, Webb et al, 2015.

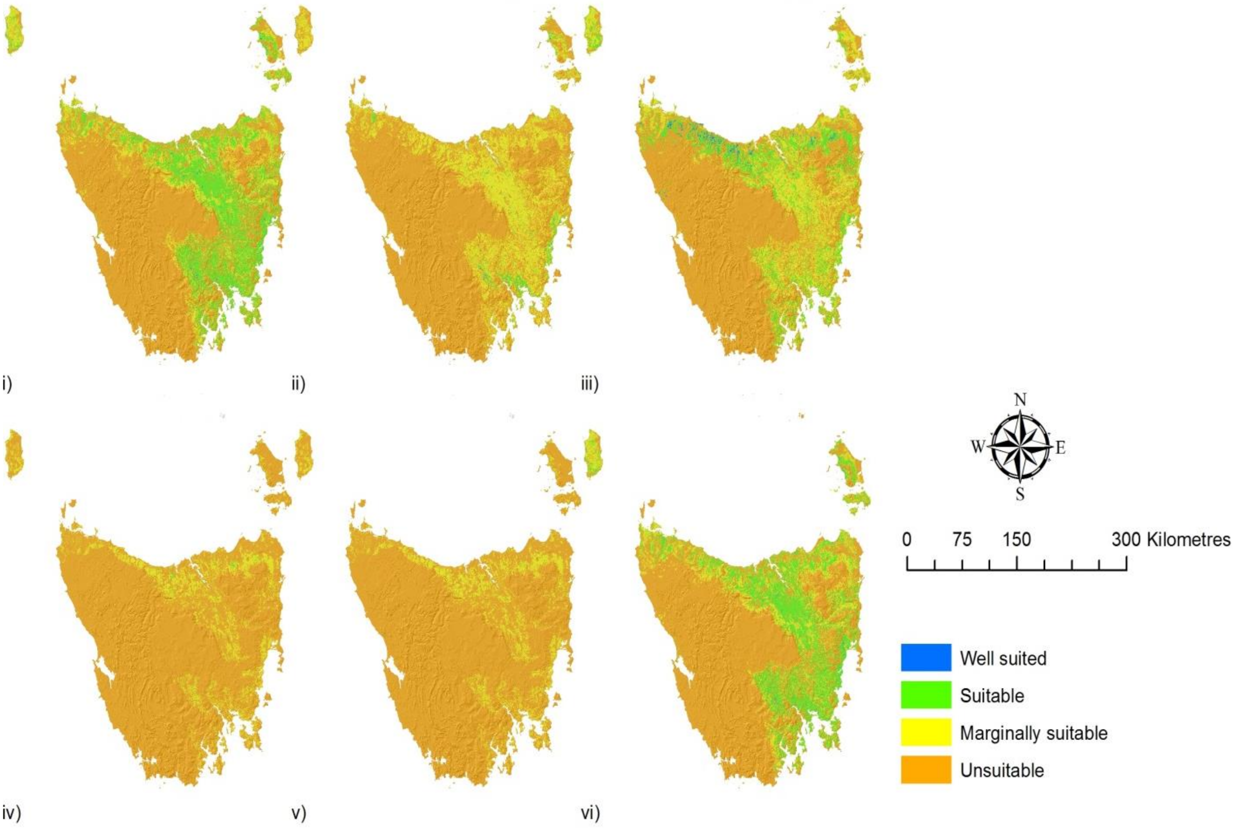


Figure 5. Enterprise suitability outputs (version 1.0) for: i) Barley, ii) Poppies, iii) Potatoes, iv) Sparkling wine grapes, v) Table wine grapes, and vi) Wheat

To portray the enterprise suitability outputs based on the projected climate grids, the enterprise suitability models was implemented for each emission scenario (A2 or B1) at each time frame (2030 & 2050) using the climate variables (based on the six model mean) equal to these scenario and time frames. This resulted in four final enterprise suitability outputs for each crop (Barley, Poppies, Potatoes, Wheat and wine grapes (Table wine and Sparkling wine)), constituting climate variables derived from:

1. A2 simulation at 2030
2. A2 simulation at 2050 } Higher emission scenario
3. B1 simulation at 2030
4. B1 simulation at 2050 } Lower emission scenario

The outputs of these models can be viewed in figures 10, 17, 25, 31, 43, 44.

Note that all outputs will be publicly available by end of July 2015 and can be accessed via the Tasmanian Government web mapping portal: http://www.thelist.tas.gov.au/. The online mapping system allows interactive interrogation of each enterprise suitability layer at any geographic location and gives the underlying information that determines a suitability rating based on the most limiting factor approach.

3. Summary and major findings

The following section reports upon the major changes encountered after incorporating the CFT projections into the enterprise suitability mapping framework. Using the baseline period, or more specifically, the current enterprise suitability model as of 2015 (version 1.0) that included logger estimations describing actual climate between 1994 and 2013 (refer section 2.1.1) - it was possible to determine potential suitability change with respect to the emission scenarios (A2 & B1) at 2030 and 2050. Note that the following analysis on each crop are focussed specifically on how suitability may change with climate and its influence on Frost risk, GDD and mean temperatures with the assumption that soil properties remain static (i.e. are not influenced by climate change processes). In addition, areas that are currently designated as protected/conservation and urban zones as well as areas of major water bodies are assumed to remain static in the future and as such have been automatically classified as 'unsuitable' in the final outputs. Note that such areas are not included in the calculations detailed in the section below and are therefore based on land areas that are currently under private land tenure as of June, 2015. These areas are displayed in figure 6.

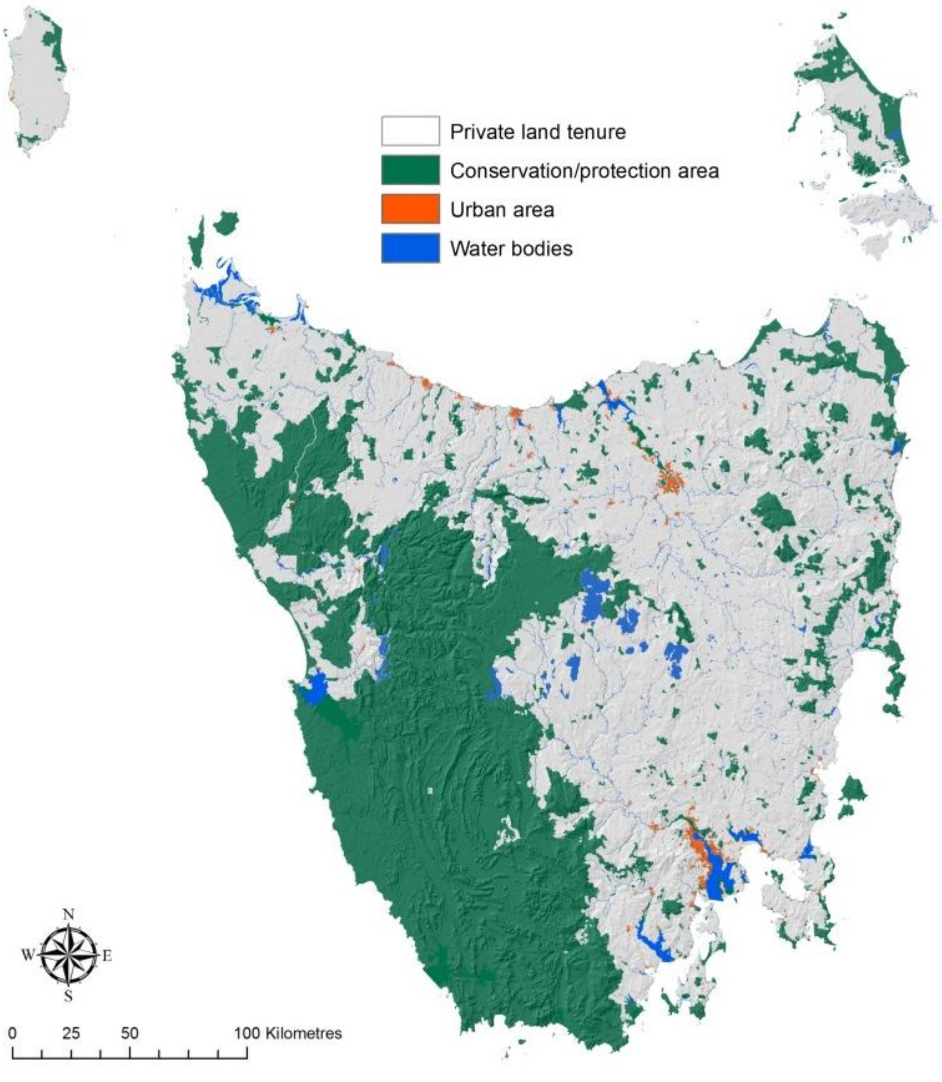
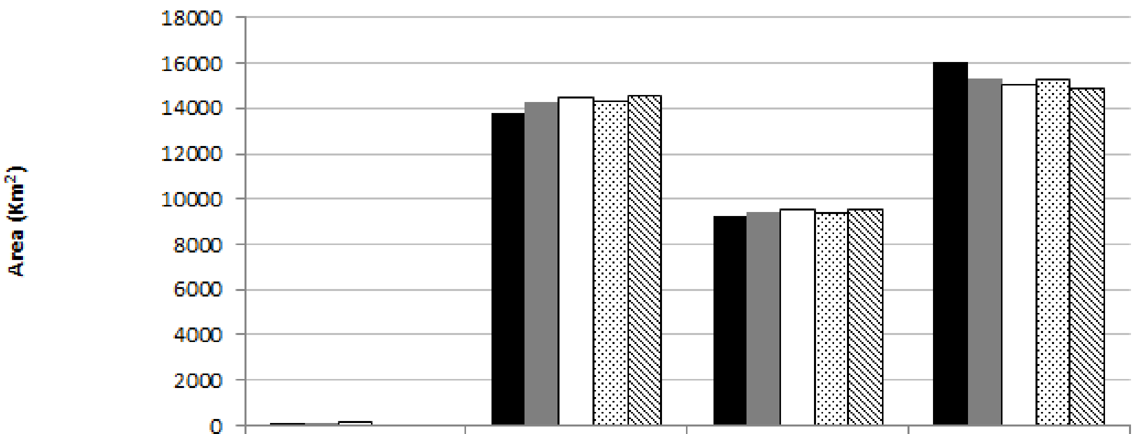


Figure 6. Land areas excluded from analysis and defined as 'unsuitable' for production include conservation/protection areas, urban areas and water bodies.

3.1 Barley

Projected land area changes with respect to Barley suitability are shown in figure 7. Both the A2 and B1 emission scenarios indicate a potential increase in suitable land when compared to the current suitability estimations, with most change exhibited at 2050 under the A2 scenario. Most notably, unsuitable land is expected to decrease by at least 4% (B1 scenario at 2030) and by as much as 7% (A2 scenario at 2050) when compared to the current estimations. The greatest areas of change appear to be around the Upper Derwent/lower highlands area (highlighted by the dashed frame in figure 10).

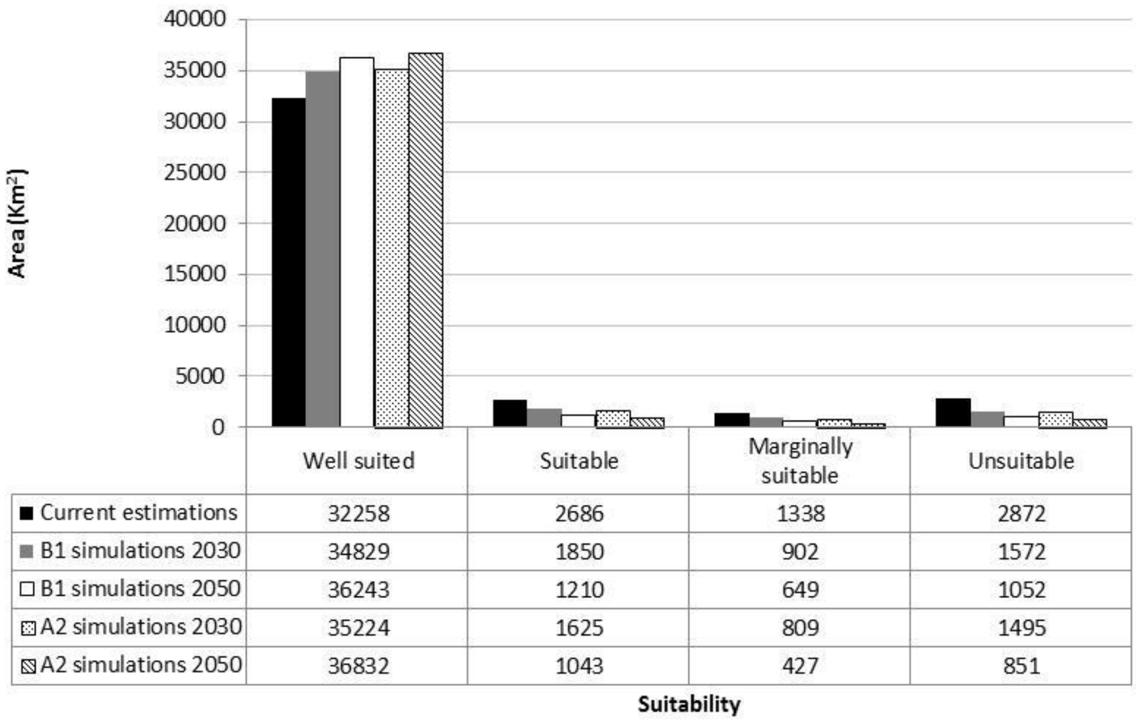
When analysing the frost models alone (i.e. removing all soil modelling components - figure 8), it can be seen that over time frost risk gradually reduces in severity, and as expected, the A2 scenario at 2050 is particularly less prone. This is reflected in figure 11, that is, if soil analysis were excluded from the enterprise suitability models, the gradual reduction of frost risk up to 2050 effectively equates to a substantial increase of land area becoming more suitable to Barley production. Most notably, well suited areas with respect to frost risk become more widespread with a distinct decrease in unsuitable areas (figure 9).



	Well suited	Suitable	Marginally suitable	Unsuitable
Current estimations	120	13743	9257	16034
B1 simulations 2030	126	14259	9437	15332
B1 simulations 2050	126	14476	9525	15027
A2 simulations 2030	126	14315	9415	15297
A2 simulations 2050	126	14601	9527	14899

Suitability

Figure 7. Enterprise suitability area (Km^2) change for barley with respect to each suitability comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050 (i.e. frost risk simulations). Refer figure 10 to view maps.



	Well suited	Suitable	Marginally suitable	Unsuitable
Current estimations	32258	2686	1338	2872
B1 simulations 2030	34829	1850	902	1572
B1 simulations 2050	36243	1210	649	1052
A2 simulations 2030	35224	1625	809	1495
A2 simulations 2050	36832	1043	427	851

Figure 8. Area (Km^2) change with respect to frost risk for Barley (without the soil parameters as a model constraint – refer figure 11) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for barley is defined as the risk of having a day where Tmin <0^o C in December - classified to their suitability categories: <20% = Well suited, 20-30%= Suitable; 30-40%= Marginally suitable; >40%= Unsuitable]

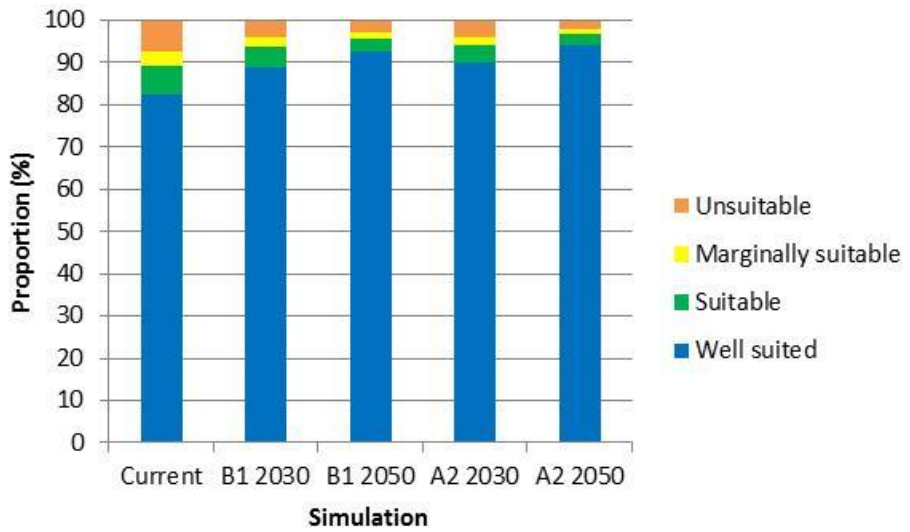


Figure 9. Proportion (%) of land area change with respect to frost risk for Barley (without the soil parameters as a model constraint – refer figure11) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for barley is defined as the risk of having a day where Tmin <0^o C in December - classified to their suitability categories: <20% = Well suited, 20-30%= Suitable; 30-40%= Marginally suitable; >40%= Unsuitable]

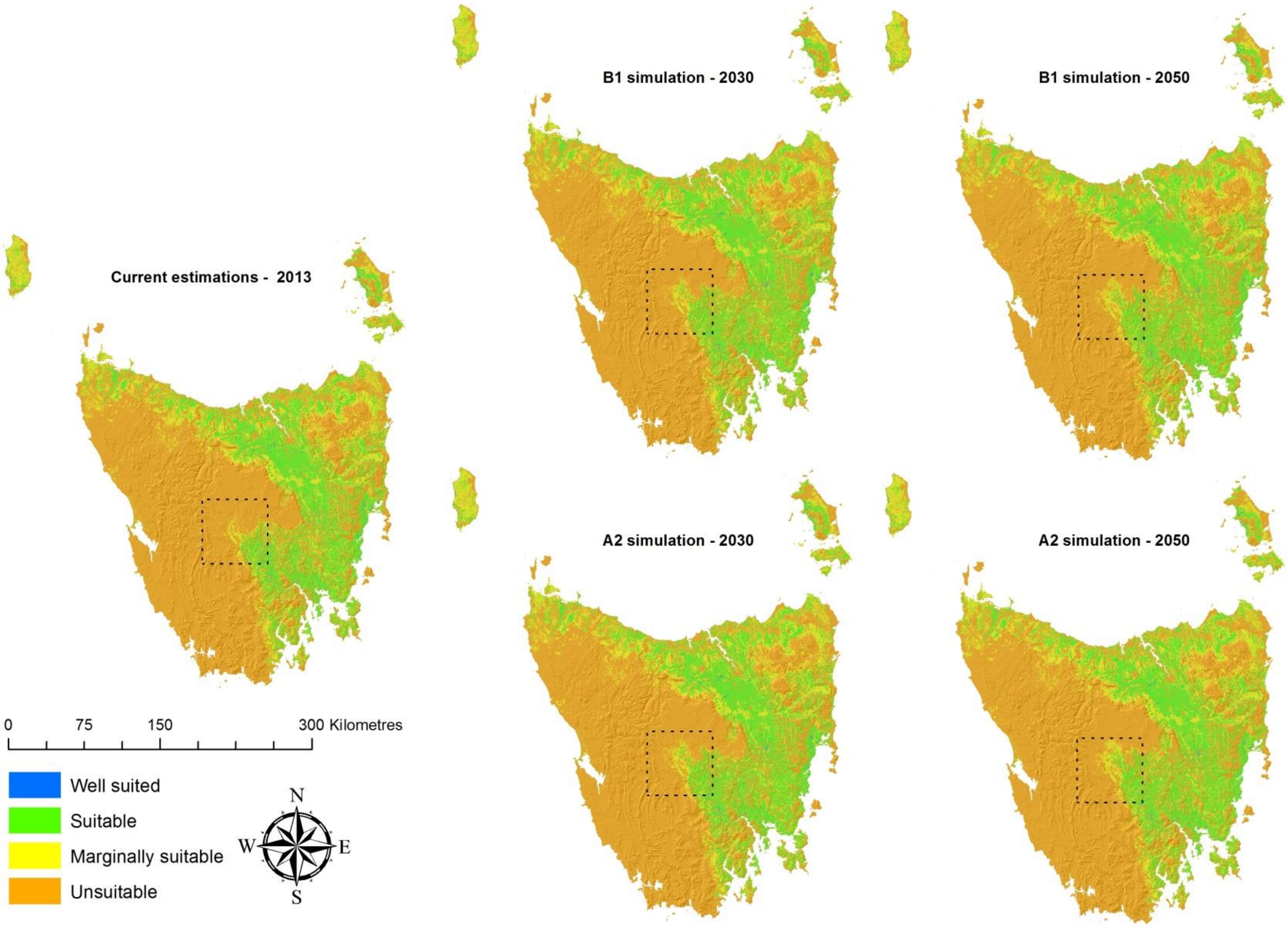


Figure 10. State wide enterprise suitability maps for Barley comparing the current enterprise suitability model outputs versus outputs incorporating the B1 and A2 emission scenarios (i.e. frost risk) at 2030 and 2050. Dashed frame highlights potential area of pronounced change.

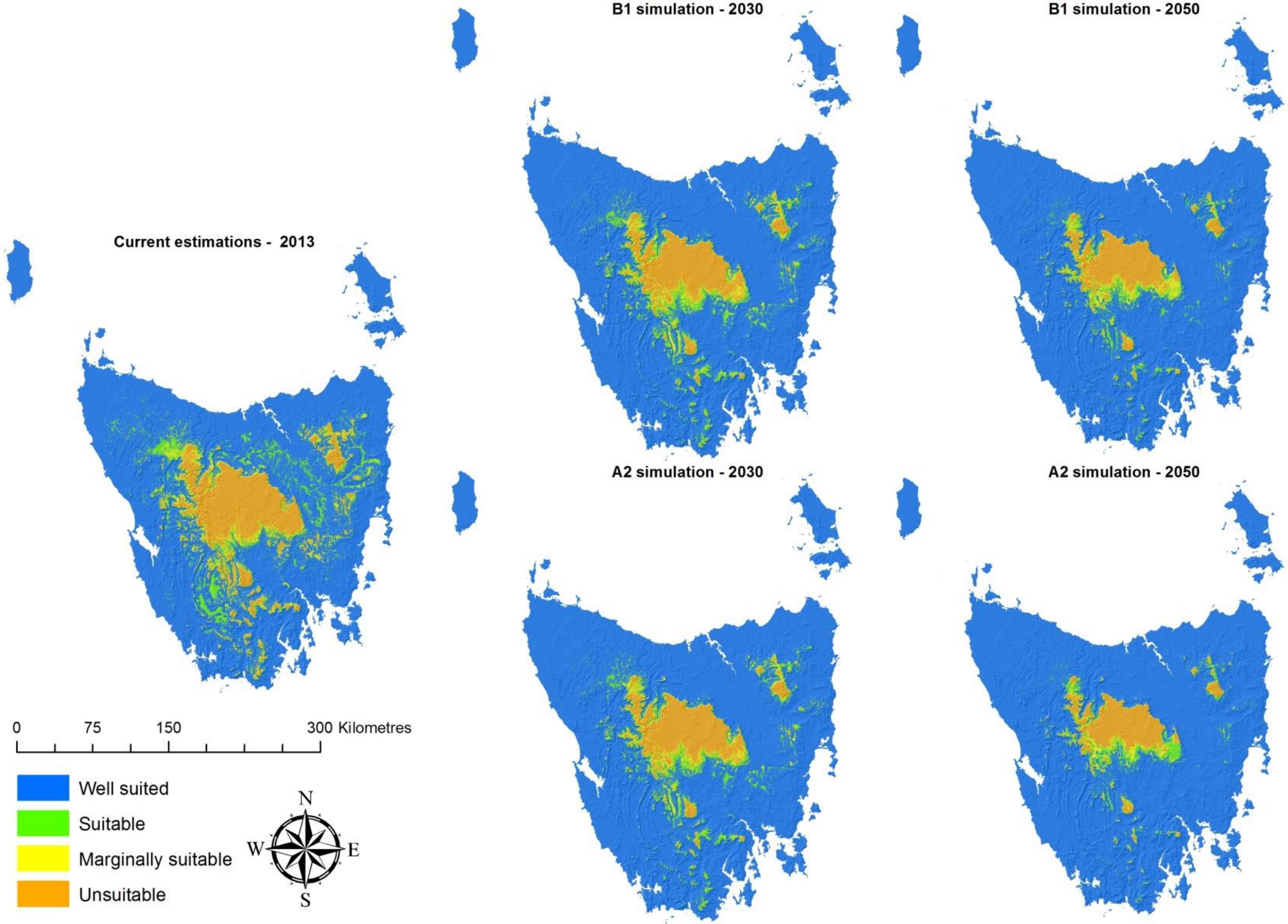
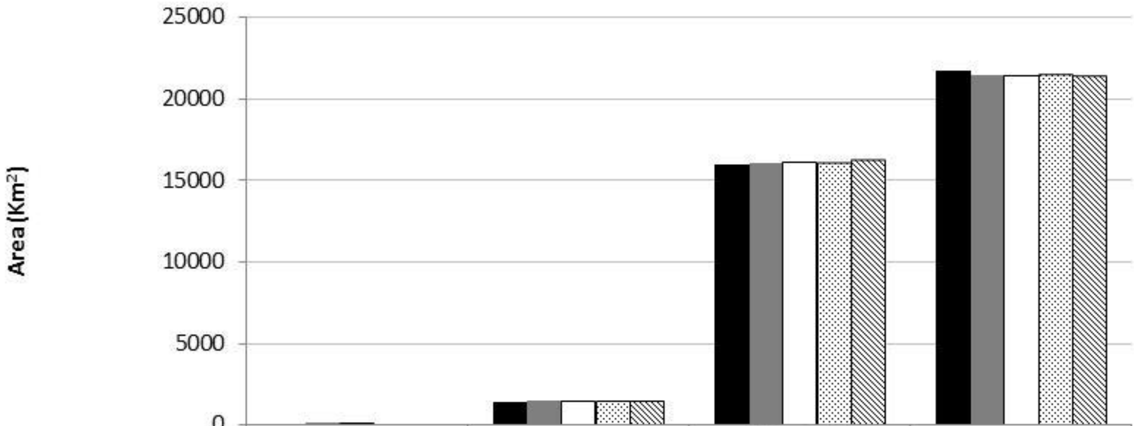


Figure 11. State wide frost risk maps for Barley comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for barley is defined as the risk of having a day where Tmin <0° C in December - classified to their suitability categories: <20% = Well suited, 20-30%= Suitable; 30-40%= Marginally suitable; >40%= Unsuitable]

3.2 Poppies

Projected area changes with respect to Poppies suitability are shown in figure 12. When compared to the current suitability estimations, both the A2 and B1 emission scenarios indicate a slight increase of suitable land available for Poppy production; most change is expected to occur in 2050 under the A2 scenario. Under the emission scenario's, unsuitable land is expected to decrease by at least 1% (B1 scenario at 2030) and by no more than 2% (A2 scenario at 2050) when compared to the current estimations. The greatest areas of change tend to be around the Upper Derwent/lower highlands area (highlighted by the dashed frame in figure 17).

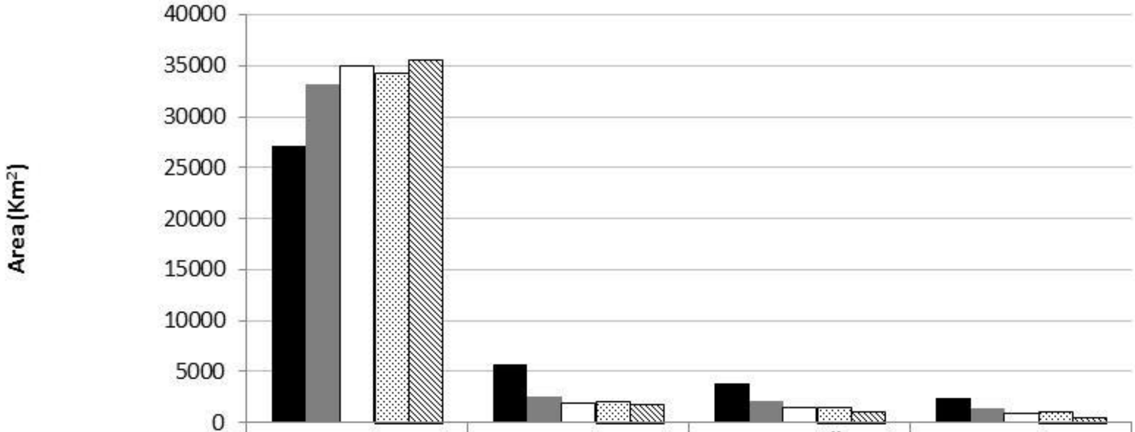
When viewing each of the frost outputs in isolation (i.e. removing all soil modelling components - figure 13& 14), it can be seen that over time frost risk gradually reduces in severity for both frost risk at flowering and late hook stage. As expected, the A2 scenario at 2050 is particularly less prone for both frost variables, more so for frost risk at flowering. Again, the gradual reduction of frost risk up to 2050 effectively equates to a substantial increase of land area becoming more suitable to Poppy production. Most notably, well suited areas with respect to frost risk become more widespread with a distinct decrease in unsuitable areas (figure 15, 16, 18& 19).



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	98	1428	15931	21697
■ B1 simulations 2030	116	1469	16074	21495
□ B1 simulations 2050	117	1470	16134	21432
⊠ A2 simulations 2030	117	1469	16098	21470
▨ A2 simulations 2050	117	1471	16211	21354

Suitability

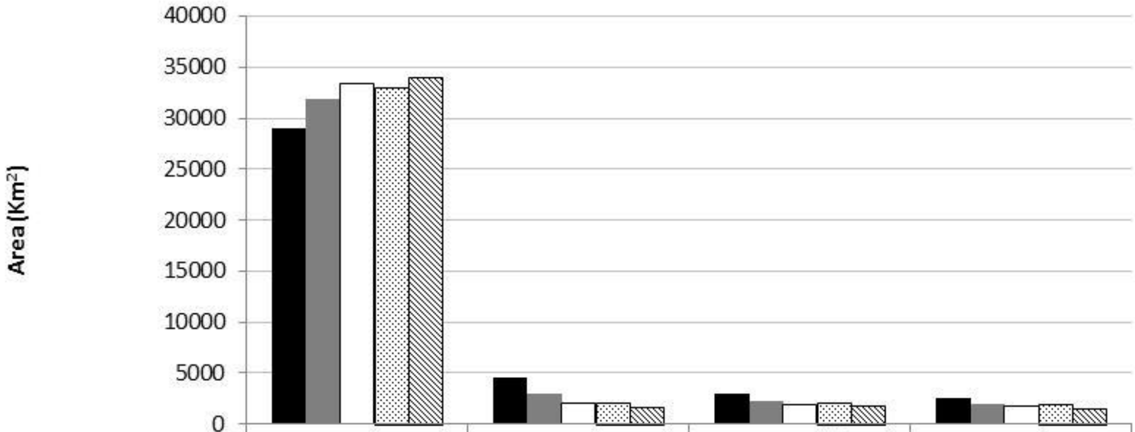
Figure 12. Enterprise suitability area (Km^2) change for poppies with respect to each suitability comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050 (i.e. frost risk simulations). Refer figure 17 to view maps.



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	27174	5657	3890	2433
■ B1 simulations 2030	33217	2542	2055	1339
□ B1 simulations 2050	34998	1846	1475	835
⊡ A2 simulations 2030	34343	2129	1497	1183
⧅ A2 simulations 2050	35582	1821	1187	563

Suitability

Figure 13. Area (Km^2) change with respect to frost risk for Poppies at flowering (without the soil parameters as a model constraint – refer figure 18) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Poppies at flowering is defined as the risk of having a day where Tmin<-1^o C (15 November to 15 December) - classified to their suitability categories: <10% = Well suited, 10-20%= Suitable; 20-40%= Marginally suitable; >40%= Unsuitable]



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	28988	4504	3039	2623
■ B1 simulations 2030	31893	2979	2265	2017
□ B1 simulations 2050	33459	2030	1864	1802
⊡ A2 simulations 2030	32963	2114	2131	1946
⧅ A2 simulations 2050	34056	1744	1806	1548

Suitability

Figure 14. Area (Km^2) change with respect to frost risk for Poppies at late hook stage (without the soil parameters as a model constraint – refer figure 19) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Poppies at late hook stage is defined as the risk of having a day where Tmin <-1^o C (1-15 November) - classified to their suitability categories: <10% = Well suited, 10-20%= Suitable; 20-40%= Marginally suitable; >40%= Unsuitable]

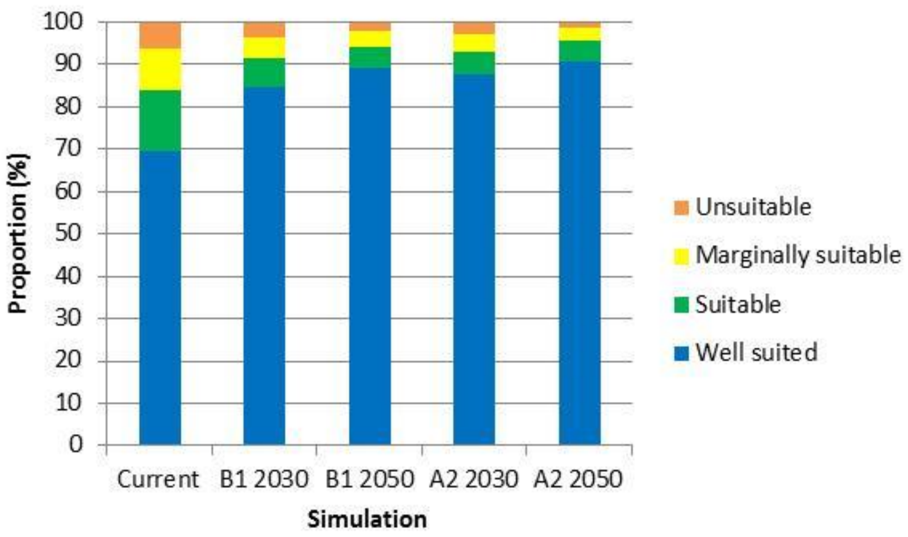


Figure 15. Proportion (%) of land area change with respect to frost risk for Poppies at flowering (without the soil parameters as a model constraint – refer figure 18) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Poppies at flowering is defined as the risk of having a day where Tmin <-1° C (15 November to 15 December) - classified to their suitability categories: <10% = Well suited, 10-20%=Suitable; 20-40%= Marginally suitable; >40%= Unsuitable]

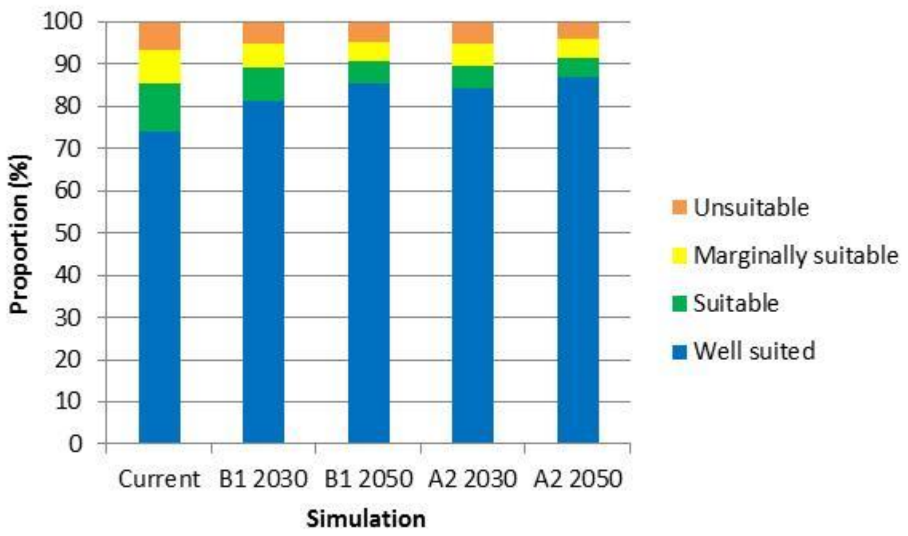


Figure 16. Proportion (%) of land area change with respect to frost risk for Poppies at late hook stage (without the soil parameters as a model constraint – refer figure 19) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Poppies at late hook stage is defined as the risk of having a day where Tmin <-1° C (1-15 November) - classified to their suitability categories: <10% = Well suited, 10-20%= Suitable; 20-40%= Marginally suitable; >40%=Unsuitable]

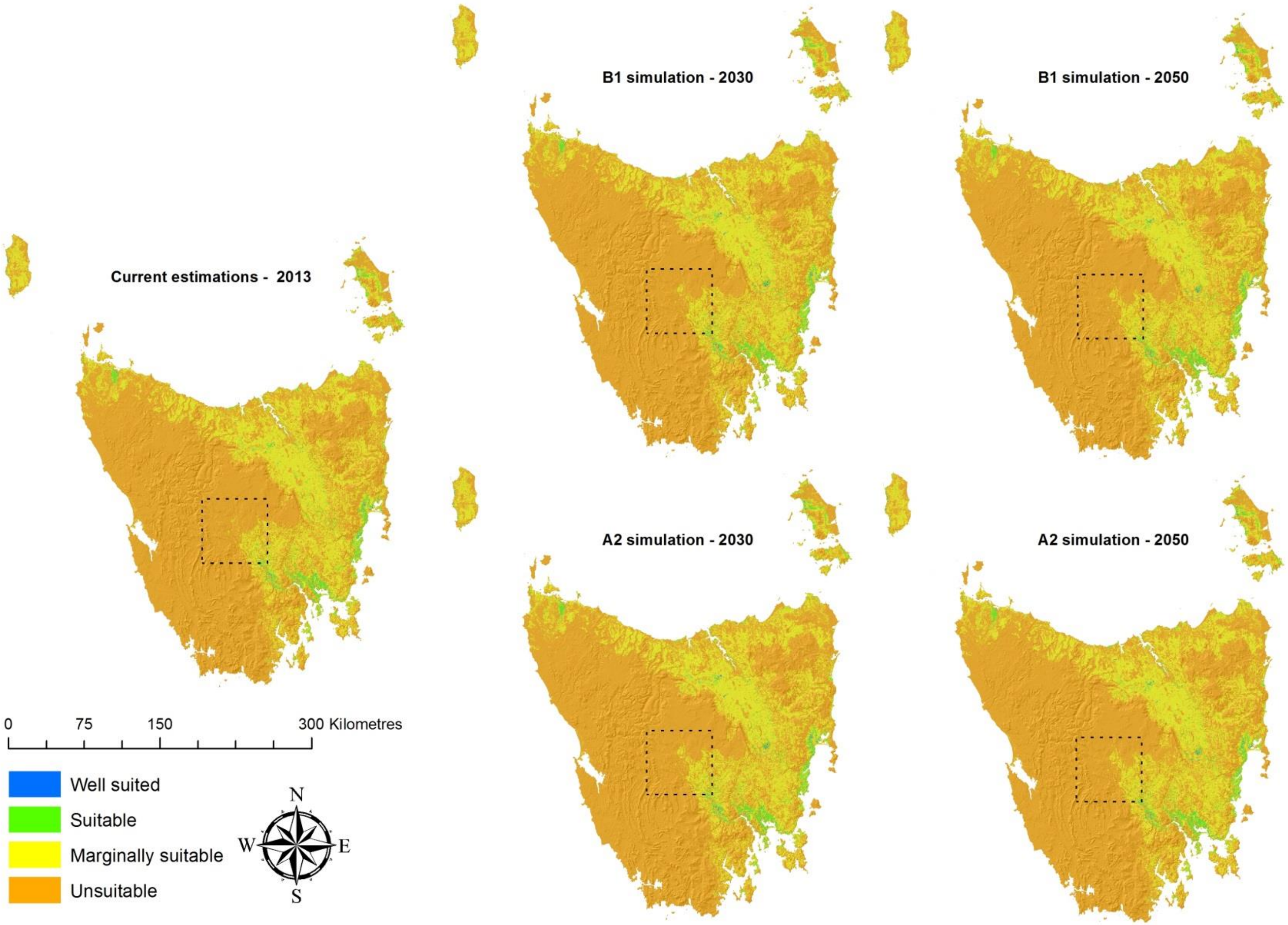


Figure 17. State wide enterprise suitability maps for Poppies comparing the current enterprise suitability model output versus outputs incorporating the B1 and A2 emission scenarios (i.e. frost risk) at 2030 and 2050. Dashed frame highlights potential area of pronounced change.

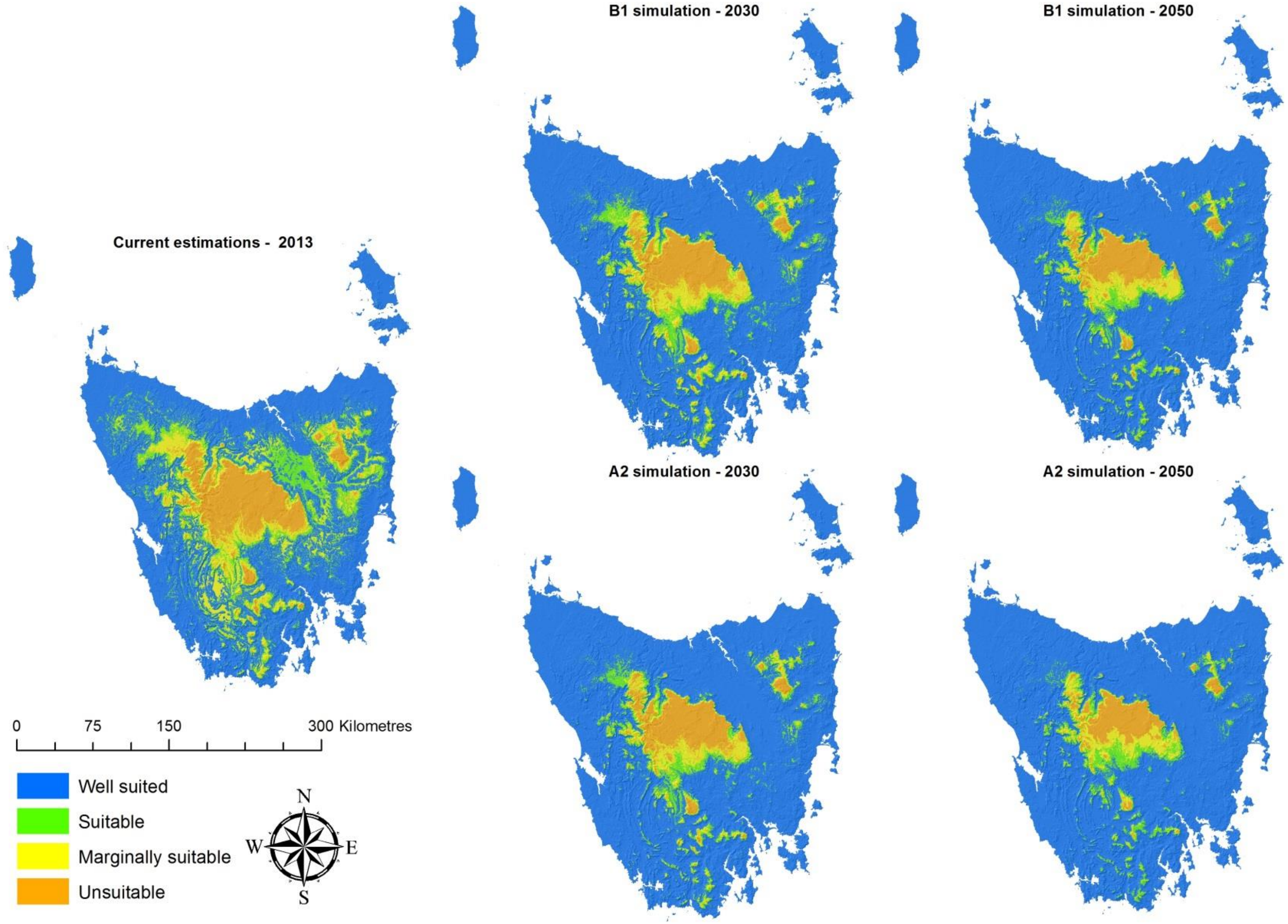


Figure 18. State wide frost risk maps for Poppies at flowering comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Poppies at flowering is defined as the risk of having a day where Tmin <-1^{o} C (15 November to 15 December) - classified to their suitability categories: <10% = Well suited, 10-20%= Suitable; 20-40%= Marginally suitable; >40%= Unsuitable]

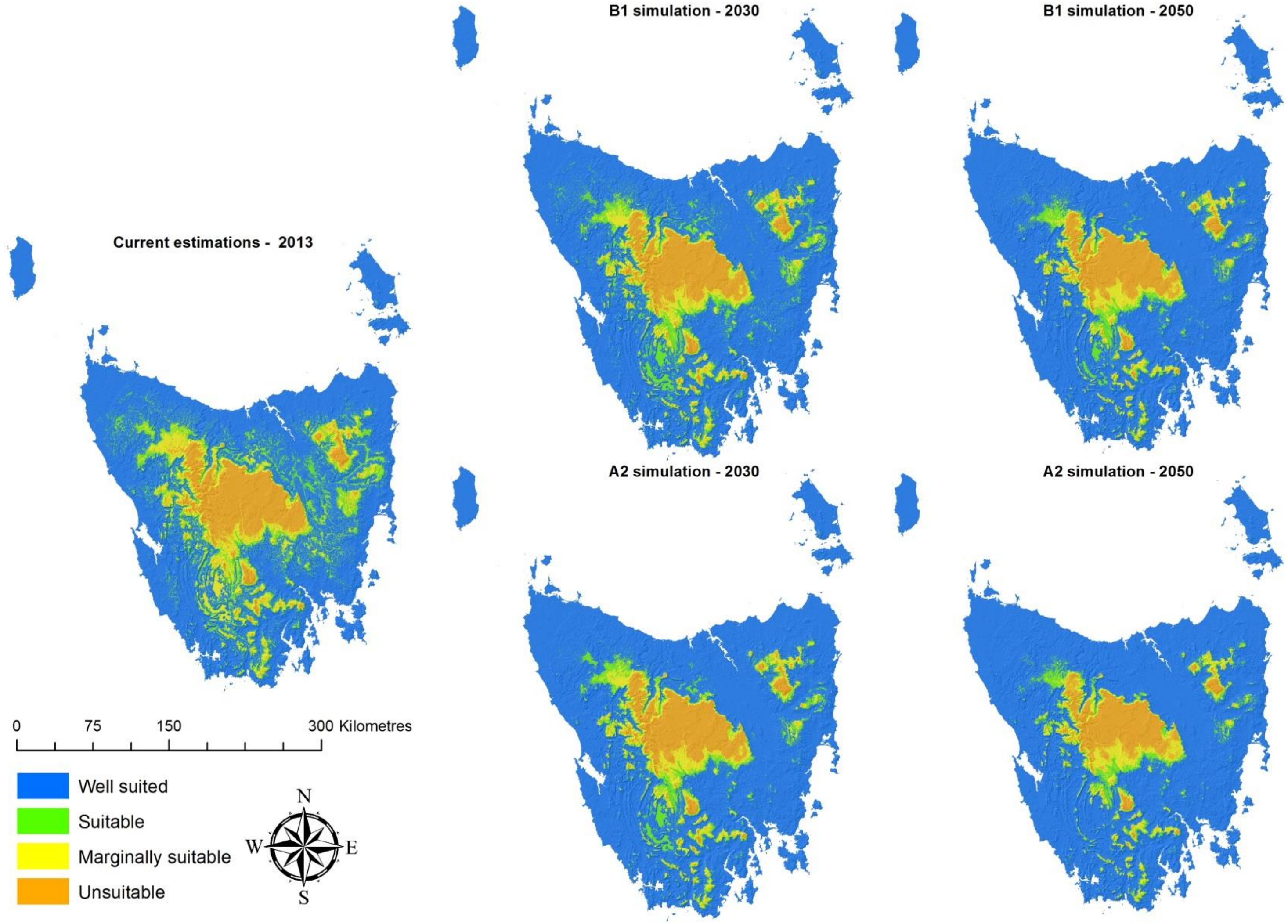
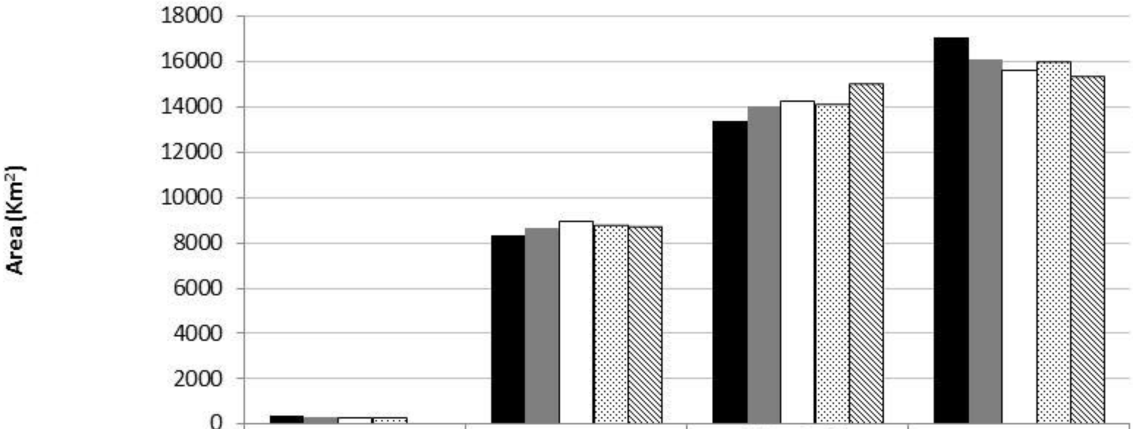


Figure 19. State wide frost risk maps for Poppies at late hook stage comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Poppies at late hook stage is defined as the risk of having a day where Tmin <-1° C (1-15 November) - classified to their suitability categories: <10% = Well suited, 10-20%= Suitable; 20-40%= Marginally suitable; >40%= Unsuitable]

3.3 Potatoes

Projected area changes with respect to Potatoes suitability are shown in figure 20. When compared to the current suitability estimations, both the A2 and B1 emission scenarios indicate a marked increase of suitable land available for Potato production with most change to occur in 2050 under the A2 scenario. Hence, unsuitable land is expected to decrease by at least 6% (B1 scenario at 2030) to 10% (A2 scenario at 2050) when compared to the current estimations. Again, the areas with most pronounced change tend to be around the Upper Derwent/lower highlands region (highlighted by the dashed frame in figure 25).

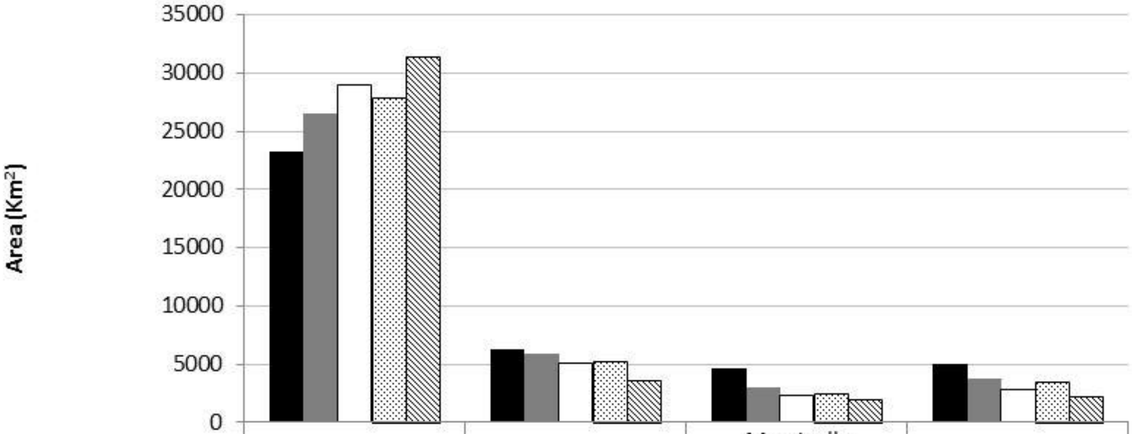
When viewing the frost outputs in isolation (i.e. removing all soil modelling components - figure 21, 23 & 26), it can be seen that over time frost risk gradually reduces in severity and with that, a notable increase in suitable land. However, when viewing the second climate variable for Potatoes (figure 22 & 24), the projected increase of having a higher proportion of minimum temperature days above 20^{o}C (November through to February) results in land areas gradually becoming less suitable, particularly under the A2 scenario at 2050 (figure 27). Of particular note, areas on King and Flinders Island as well as some areas throughout the midland regions of the state are projected to become more marginally suitable for Potato production (NB: there is no unsuitable category for this climate variable). As a whole however, the decrease in frost severity is expected to outweigh the increase in prolonged warming in late spring/summer to result in areas becoming more suitable under either emission scenario.



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	344	8321	13403	17086
■ B1 simulations 2030	334	8672	14030	16117
□ B1 simulations 2050	288	8956	14277	15632
⊡ A2 simulations 2030	330	8775	14062	15987
⧅ A2 simulations 2050	132	8706	15016	15299

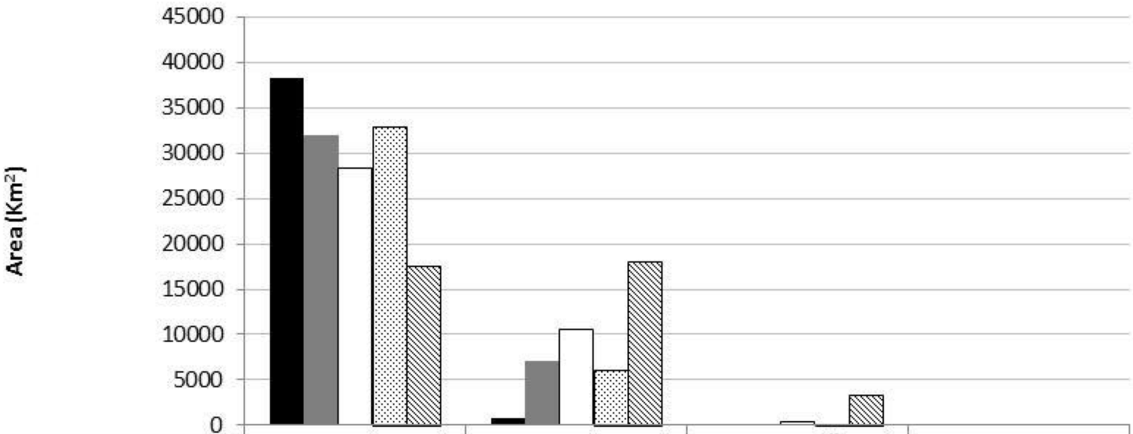
Suitability

Figure 20. Enterprise suitability area (Km^2) change for potatoes with respect to each suitability comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050 (i.e. frost risk and heat risk simulations). Refer figure 10 to view maps.



	Well suited	Suitable	Marginally suitable	Unsuitable
Current estimations	23254	6283	4647	4970
B1 simulations 2030	26552	5863	3036	3703
B1 simulations 2050	28974	5042	2346	2792
A2 simulations 2030	27919	5282	2454	3498
A2 simulations 2050	31379	3637	1923	2215

Figure 21. Area (Km^2) change with respect to frost risk for Potatoes (without the soil parameters as a model constraint – refer figure 26) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Potatoes is defined as the risk of having a day where Tmin <0° C (1 November to 28 February) - classified to their suitability categories: <20% = Well suited, 20-40%= Suitable; 40-60%= Marginally suitable; >60%= Unsuitable]



	Well suited	Suitable	Marginally suitable	Unsuitable
Current estimations	38317	834	3	0
B1 simulations 2030	31986	7119	48	0
B1 simulations 2050	28275	10579	300	0
A2 simulations 2030	32902	6162	89	0
A2 simulations 2050	17592	18130	3431	0

Figure 22. Area (Km^2) change with respect to heat risk for Potatoes (without the soil parameters as a model constraint – refer figure 27) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Heat risk for Potatoes is defined as the risk of having a day where Tmin >20° C (1 November to 28 February) - classified to their suitability categories: <20% = Well suited, 20-40%= Suitable; >40%= Marginally suitable]

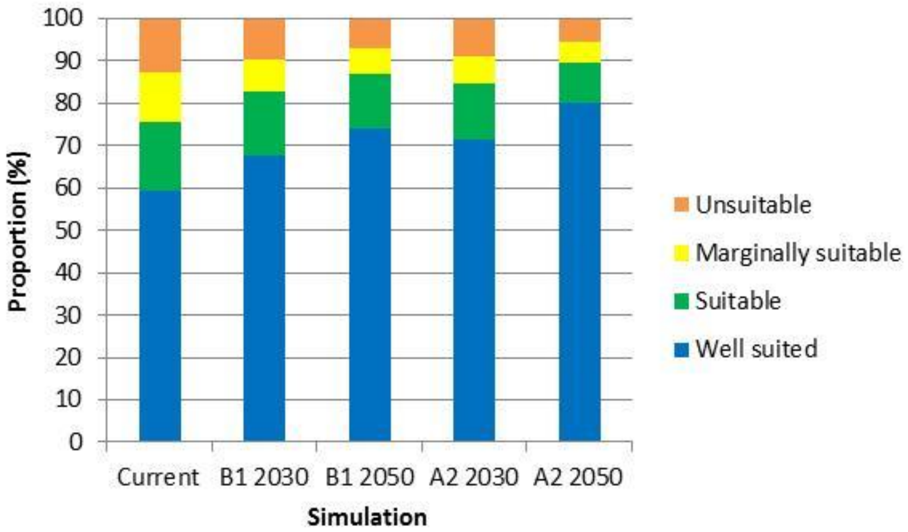


Figure 23. Proportion (%) of land area change with respect to frost risk for Potatoes (without the soil parameters as a model constraint – refer figure 26) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Potatoes is defined as the risk of having a day where Tmin <0^{o} C (1 November to 28 February) - classified to their suitability categories: <20% = Well suited, 20-40%= Suitable; 40-60%= Marginally suitable; >60%= Unsuitable]

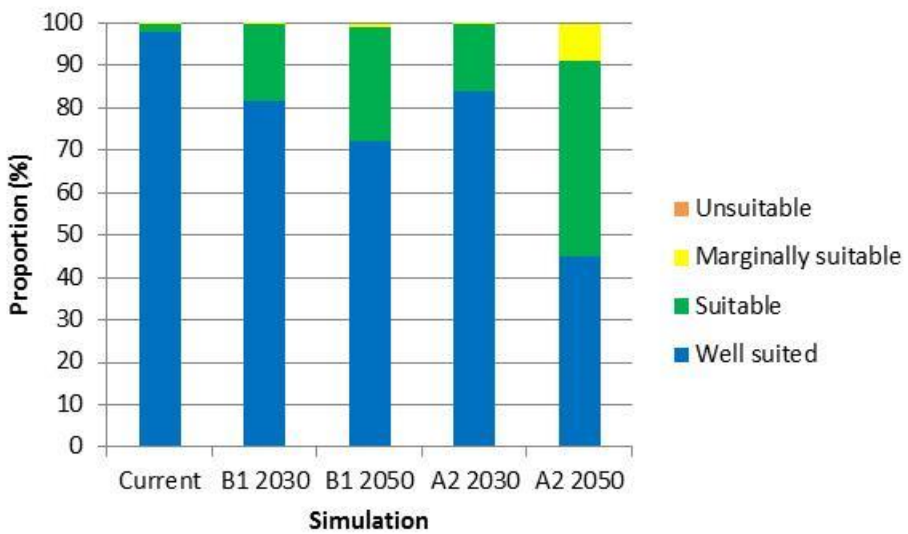


Figure 24. Proportion (%) of land area change with respect to heat risk for Potatoes (without the soil parameters as a model constraint – refer figure27) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Heat risk for Potatoes is defined as the risk of having a day where Tmin >20^{o} C (1 November to 28 February) - classified to their suitability categories: <20% = Well suited, 20-40%= Suitable; >40%= Marginally suitable]

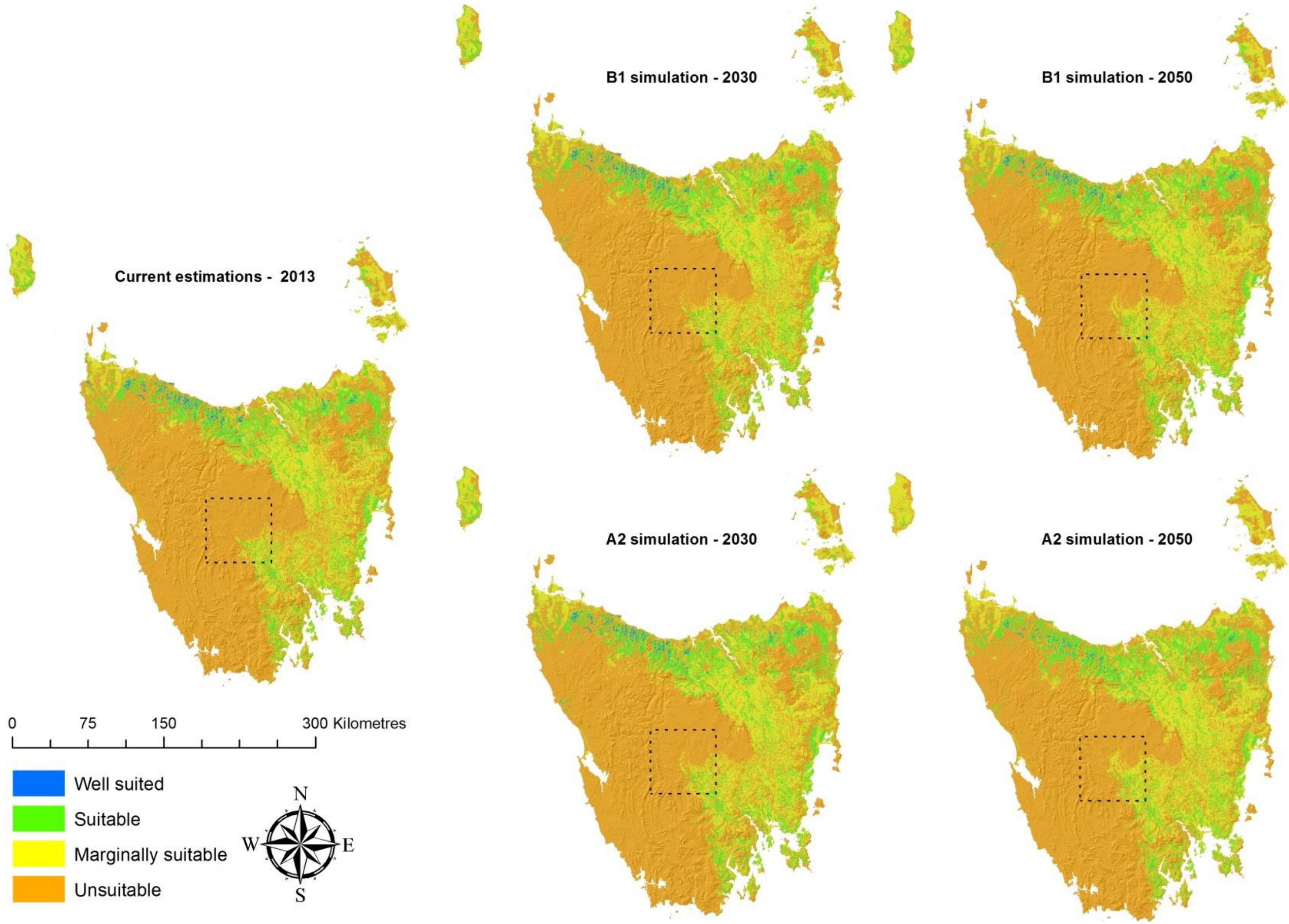


Figure 25. State wide enterprise suitability maps for Potatoes comparing the current enterprise suitability model output versus outputs incorporating the B1 and A2 emission scenarios (i.e. frost risk and heat risk) at 2030 and 2050. Dashed frame highlights potential area of pronounced change.

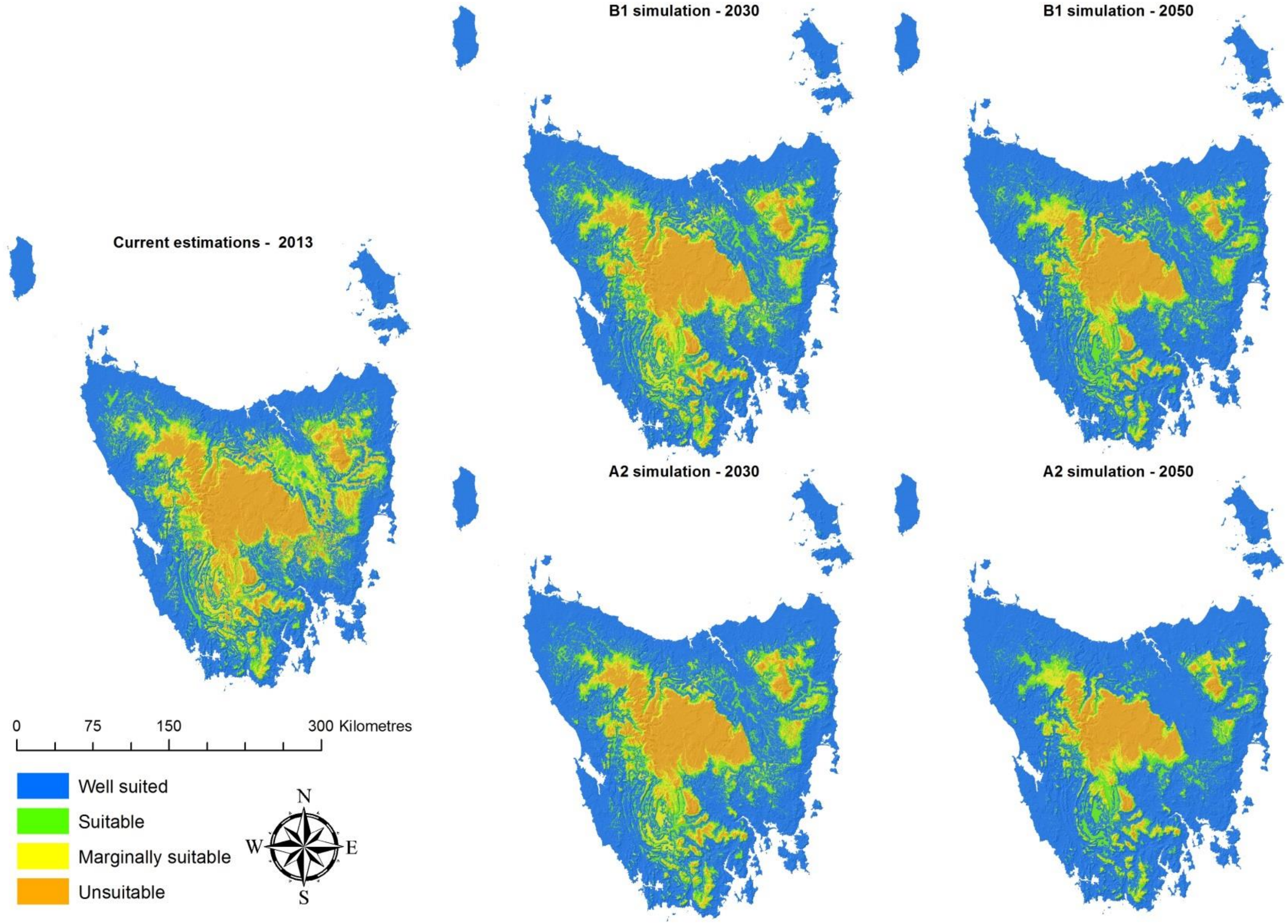


Figure 26. State wide frost risk maps for Potatoes comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Potatoes is defined as the risk of having a day where Tmin <0^{o} C (1 November to 28 February) - classified to their suitability categories: <20% = Well suited, 20-40%= Suitable; 40-60%= Marginally suitable; >60%= Unsuitable]

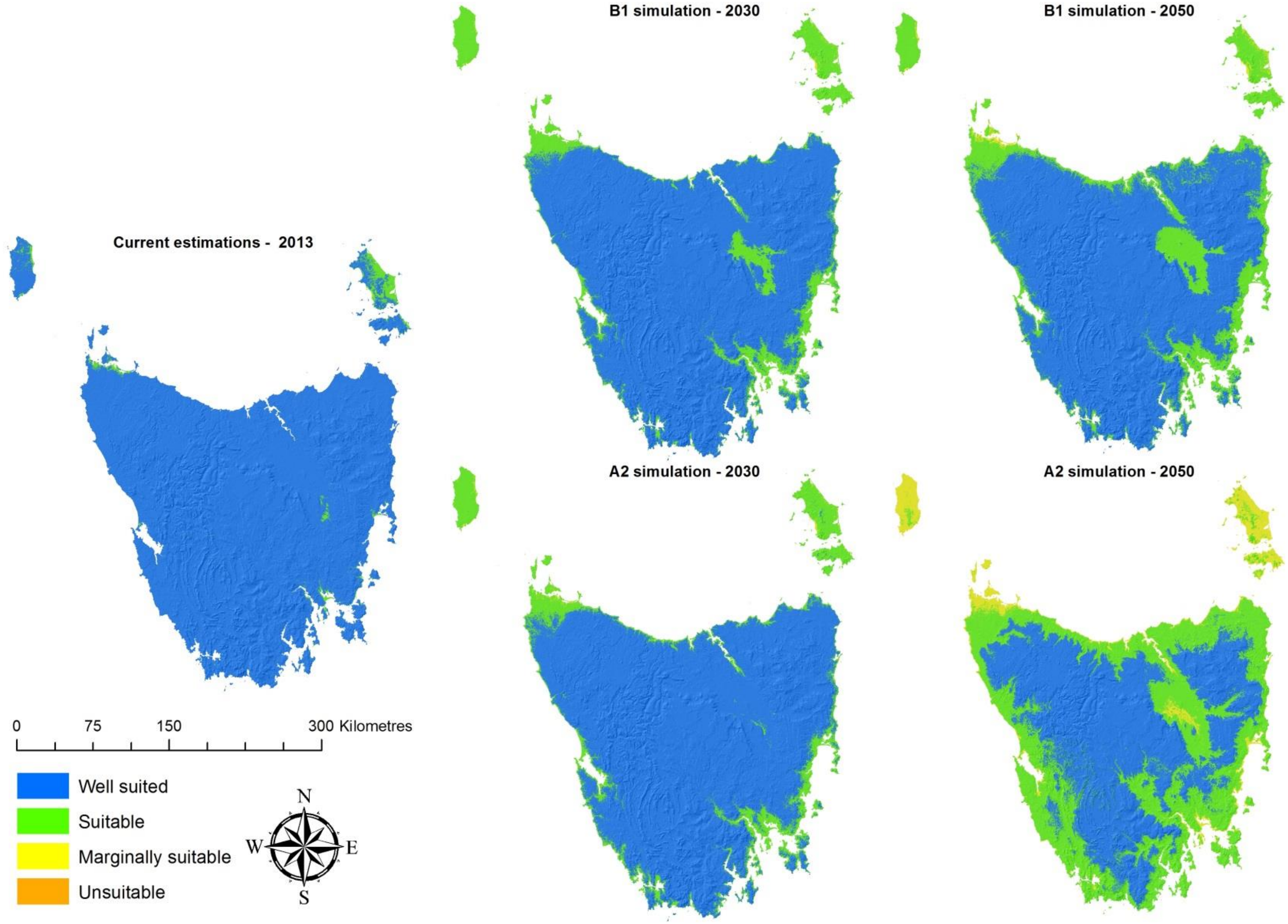
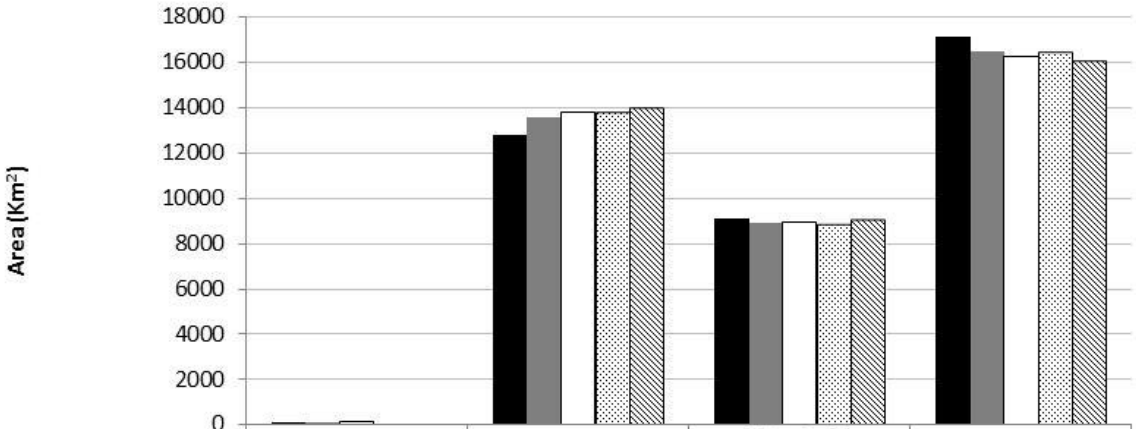


Figure 27. State wide heat risk maps for Potatoes comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Heat risk for Potatoes is defined as the risk of having a day where Tmin >20° C (1 November to 28 February) - classified to their suitability categories: <20% = Well suited, 20-40%= Suitable; >40%= Marginally suitable]

3.4 Wheat

Projected area changes with respect to Wheat suitability are shown in figure 28. Both the A2 and B1 emission scenarios indicate a potential increase in suitable land when compared to the current suitability estimations, with most change exhibited at 2050 under the A2 scenario. Most notably, unsuitable land is expected to decrease by at least 4% (B1 simulation at 2030) and by as much as 6% (A2 simulation at 2050) when compared to the current estimations. The greatest areas of change appear to be around the Upper Derwent/lower highlands area (highlighted by the dashed frame in figure 31).

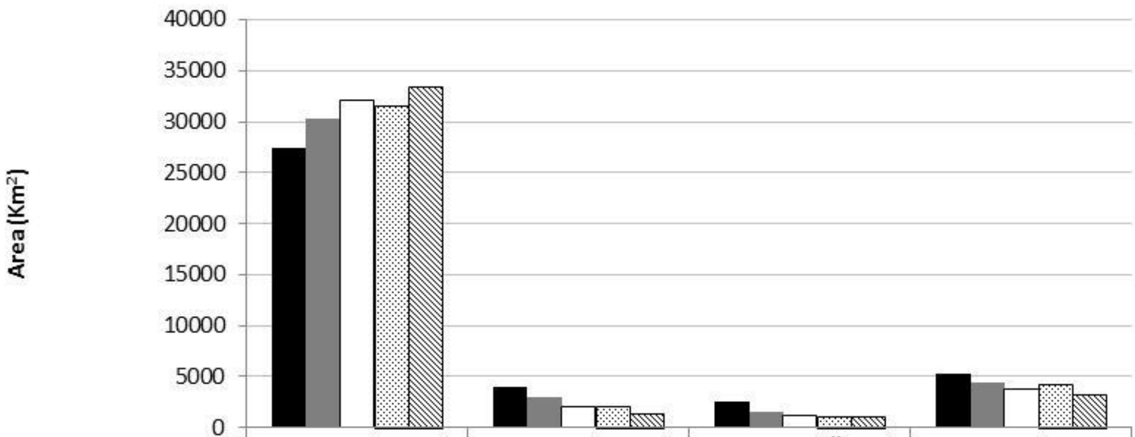
When viewing the frost models alone (i.e. removing all soil modelling components - figure 29), it can be seen that over time frost risk gradually reduces in severity, and as expected, the A2 scenario at 2050 is particularly less prone. This is reinforced in figure 32, that is, if soil analysis were excluded from the enterprise suitability models, the gradual reduction of frost risk up to 2050 effectively equates to a substantial increase of land area becoming more suitable to Wheat production. Most notably, well suited areas with respect to frost risk become more widespread with a distinct decrease in unsuitable areas (figure 30).



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	110	12768	9136	17139
■ B1 simulations 2030	122	13599	8932	16499
□ B1 simulations 2050	124	13813	8965	16252
⊡ A2 simulations 2030	124	13742	8862	16426
▧ A2 simulations 2050	124	13965	9034	16031

Suitability

Figure 28. Enterprise suitability area (Km^2) change for Wheat with respect to each suitability comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050 (i.e. frost risk simulations). Refer figure 31 to view maps.



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	27426	4006	2501	5221
■ B1 simulations 2030	30249	2986	1534	4385
□ B1 simulations 2050	32110	2061	1207	3776
A2 simulations 2030	31553	2167	1180	4254
A2 simulations 2050	33435	1380	1055	3284

Suitability

Figure 29. Area (Km^2) change with respect to frost risk for Wheat (without the soil parameters as a model constraint – refer figure 32) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Wheat is defined as the risk of having a day where Tmin <0^o C (1-15 November) - classified to their suitability categories: <20% = Well suited, 20-30%= Suitable; 30-40%= Marginally suitable; >40%= Unsuitable]

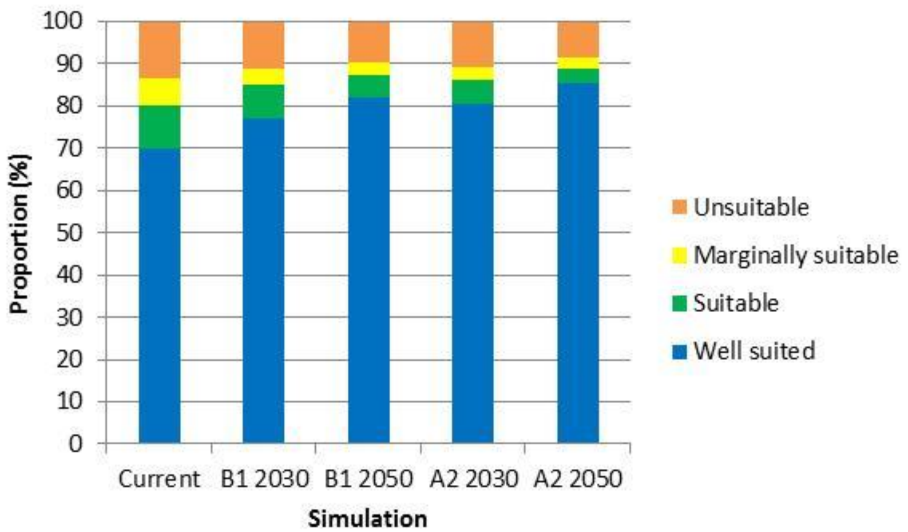


Figure 30. Proportion (%) of land area change with respect to frost risk for Wheat (without the soil parameters as a model constraint – refer figure 32) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for Wheat is defined as the risk of having a day where Tmin <0^o (1-15 November) - classified to their suitability categories: <20% = Well suited, 20-30%= Suitable; 30-40%= Marginally suitable; >40%= Unsuitable]

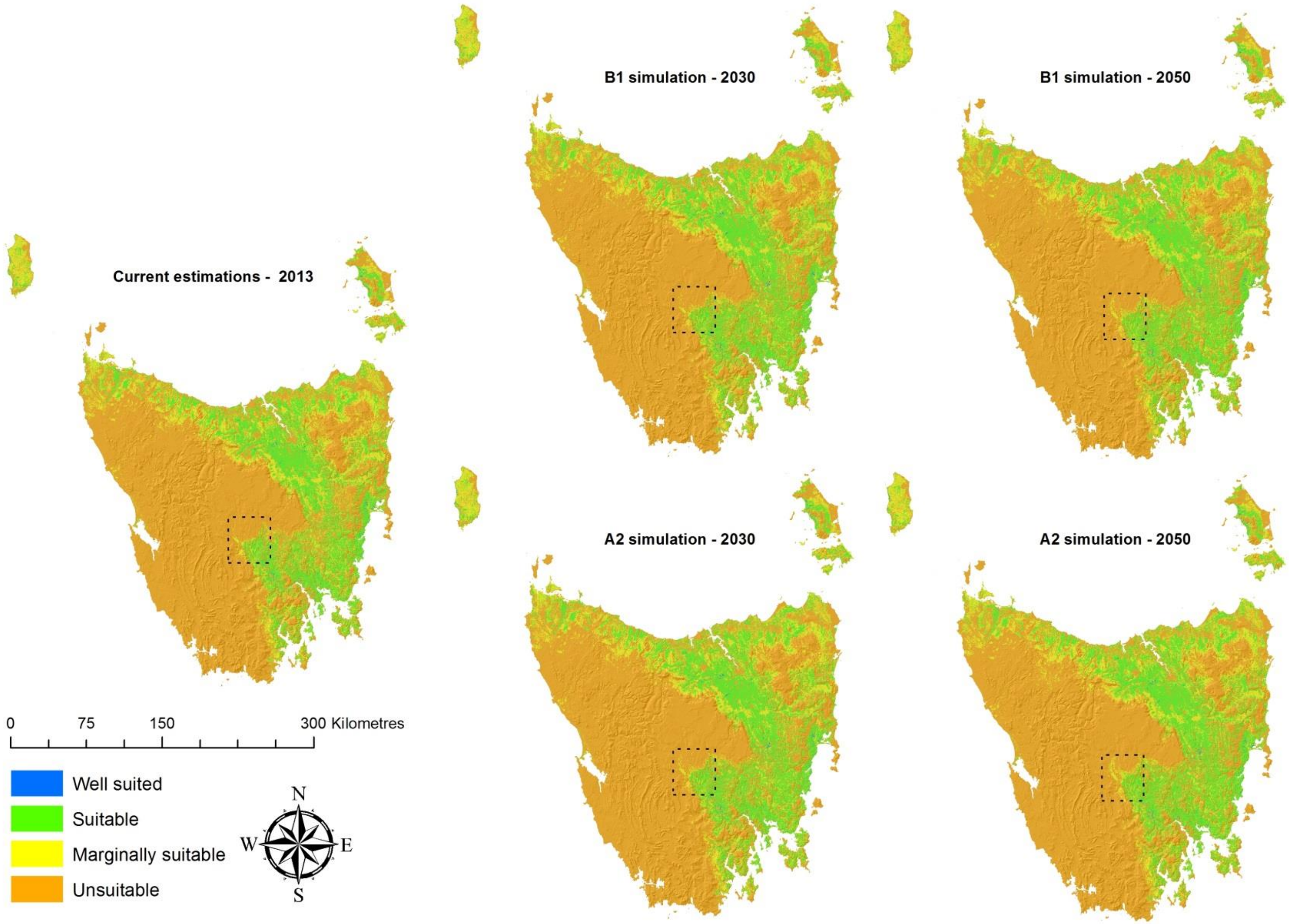


Figure 31. State wide enterprise suitability maps for Wheat comparing the current enterprise suitability model output versus outputs incorporating the B1 and A2 emission scenarios (i.e. frost risk) at 2030 and 2050. Dashed frame highlights potential area of pronounced change

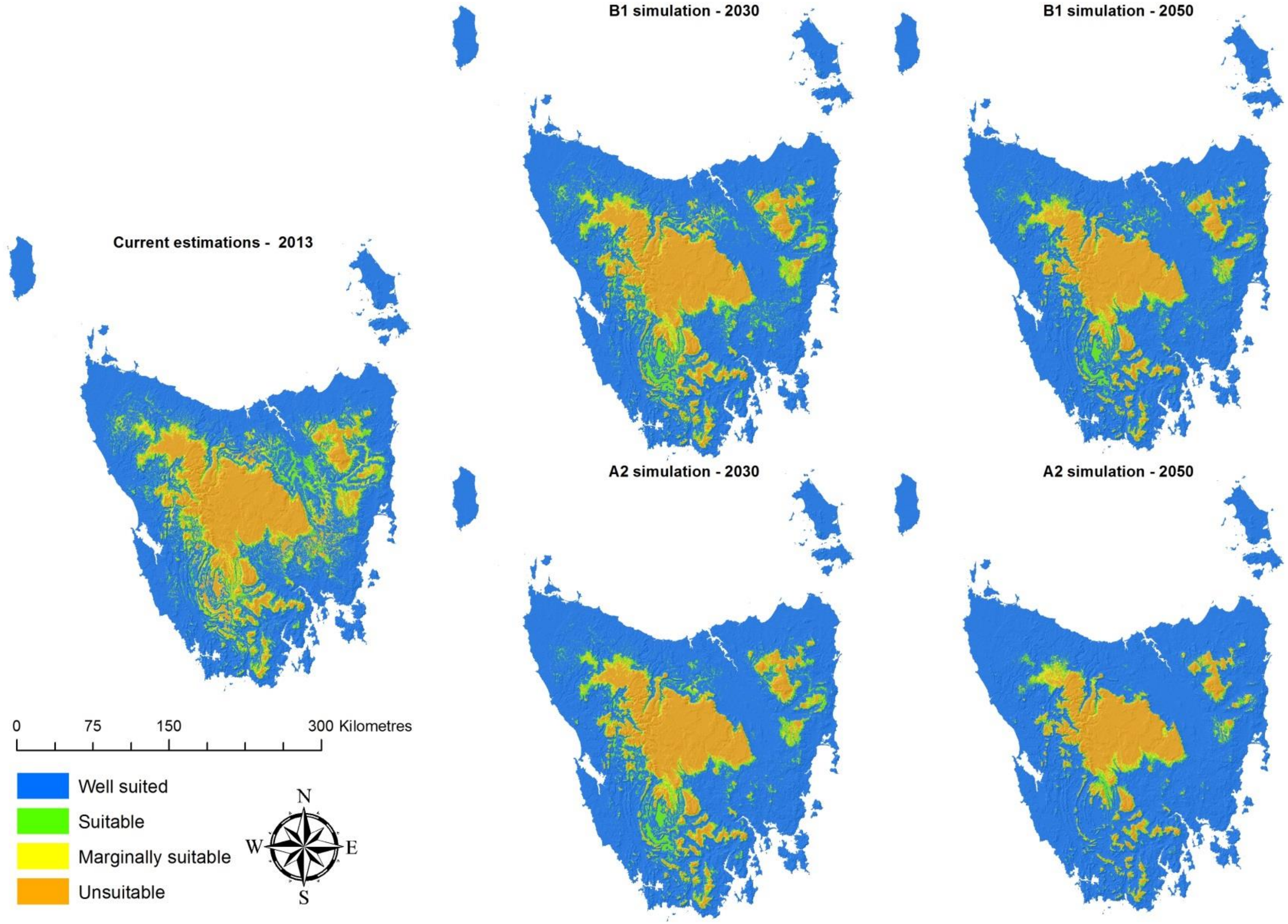


Figure 32. State wide frost risk maps for Wheat comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050 [Frost risk for Wheat is defined as the risk of having a day where Tmin <0^{o} (1-15 November) - classified to their suitability categories: <20% = Well suited, 20-30%= Suitable; 30-40%= Marginally suitable; >40%= Unsuitable]

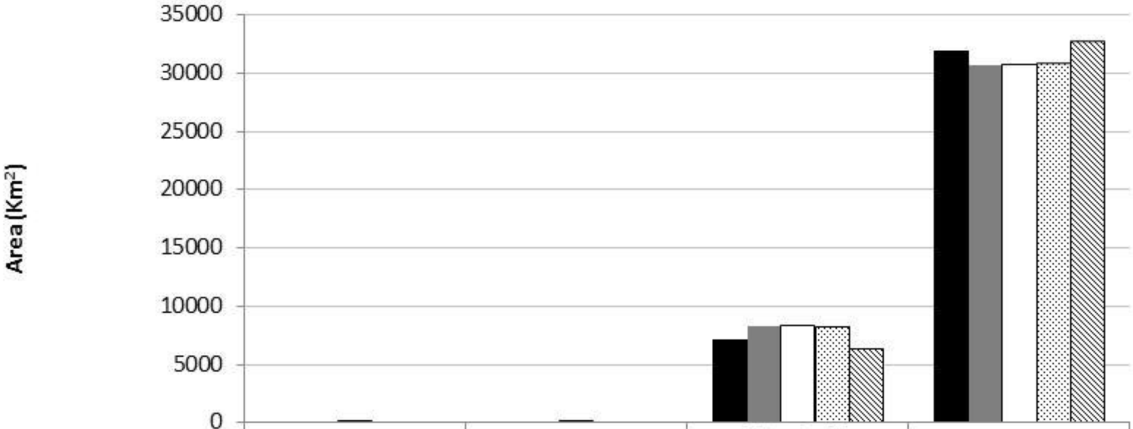
3.5 Wine grapes

Projected area changes with respect to Wine grape suitability are shown in figure 33 & 34. For Table wine, both the A2 and B1 emission scenarios indicate a potential increase in suitable land when compared to the current suitability estimations, with most change exhibited at 2050 under the A2 emission scenario. Most notably, unsuitable land is expected to decrease by at least 5% (B1 scenario at 2030) and by as much as 7% (A2 scenario at 2050) when compared to the current estimations. Much of the change is expected to occur sporadically around certain areas of northern and north-eastern Tasmania, namely around Scottsdale and Sassafras regions (figure 44).

Similarly, Sparkling wine suitability is also expected to become more favourable (figure 33). Notably, unsuitable land is expected to decrease by at least 4% (B1 scenario at 2030). However, under the A2 scenario at 2050, suitability could become less favourable. This compares to a slight increase in unsuitable land of 2% when compared to the current estimations. When viewing figure 43, the midlands region of the state is expected to become less favourable under this emission scenario.

When analysing both of the frost models in isolation (figure 35, 36, 39 & 40- note that both frost models apply to both Table wine and Sparkling wine enterprise suitability models) it can be seen that over time frost risk gradually reduces in severity, and as expected, the A2 scenario at 2050 is particularly less prone; more so, regarding frost risk for days between September and October (figure 35 & 39). On the other hand, there is a contrast between Growing Degree Days (GDD) comparing between the wine grape varieties (note that GDD's are reclassified differently as input variables in either wine grape suitability models – refer figure 47 & 48). For instance, GDD's for Table wine is expected to become more favourable across both scenarios (figures 38 & 42). The opposite is true concerning GDD's and Sparkling wine (figures 37 & 41); particularly for A2 scenario at 2050 where the increased number of GDD's may actually be detrimental to Sparkling wine production. Specifically, GDD's above 1200 for the period between October and April may encroach further inland, especially throughout the midlands area of Tasmania and simultaneously become undesirable for Sparking wine production (figure 48). Interestingly, GDD's <800 (also unsuitable for Sparkling wine production) would increasingly become less prominent in higher elevation areas and therefore become more suitable. However, this would not be sufficient to negate the higher GDD's (>1200) likely to be encountered in lower elevation areas including those areas on the North-east to east coast of Tasmania.

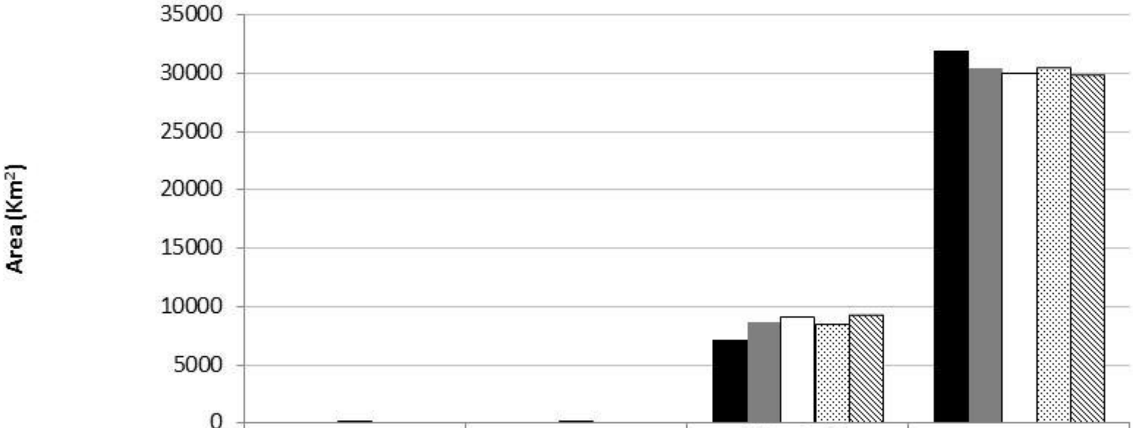
It should be noted that mean hourly temperature did not exceed the threshold suitability limit of 12^{o}C in any of the simulation models (NB: >12^{o}C would represent unsuitable for wine grape production, <12^{o}C well suited). As such, this output was excluded from further analyses.



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	1	140	7079	31934
■ B1 simulations 2030	1	144	8314	30695
□ B1 simulations 2050	1	93	8304	30756
⊠ A2 simulations 2030	1	145	8282	30726
▧ A2 simulations 2050	0	68	6415	32671

Suitability

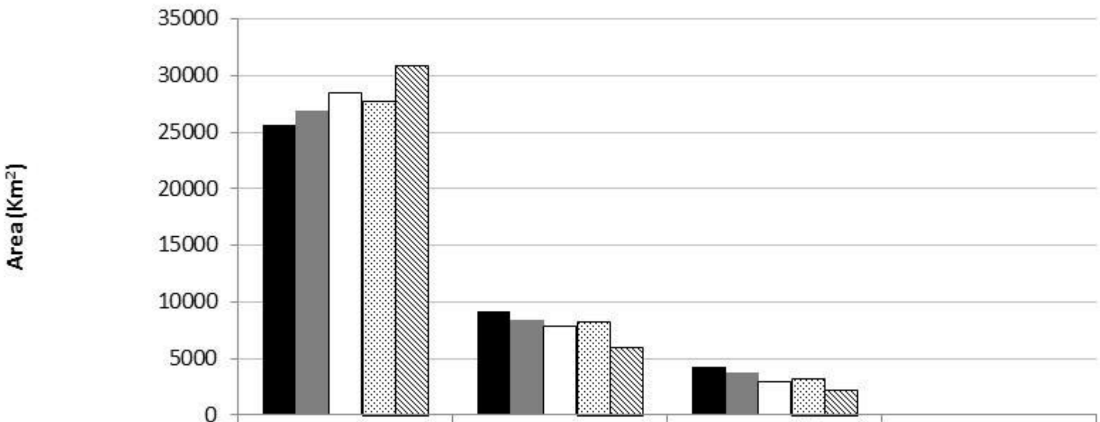
Figure 33. Enterprise suitability area (Km^2) change for Sparkling wine with respect to each suitability comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050 (i.e. frost risk simulations). Refer figure 43 to view maps.



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	0	49	7195	31909
■ B1 simulations 2030	1	120	8622	30411
□ B1 simulations 2050	1	144	9062	29946
⊠ A2 simulations 2030	1	118	8564	30471
▧ A2 simulations 2050	1	156	9267	29729

Suitability

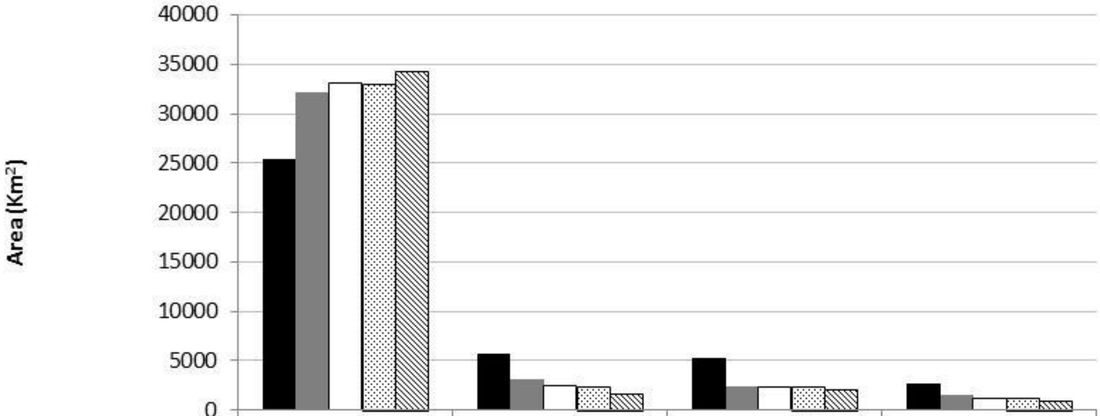
Figure 34. Enterprise suitability area (Km^2) change for Table wine with respect to each suitability comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050 (i.e. frost risk simulations). Refer figure 44 to view maps.



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	25689	9205	4259	0
■ B1 simulations 2030	26908	8453	3793	0
□ B1 simulations 2050	28502	7774	2877	0
⊡ A2 simulations 2030	27727	8218	3209	0
▧ A2 simulations 2050	30865	6053	2235	0

Suitability

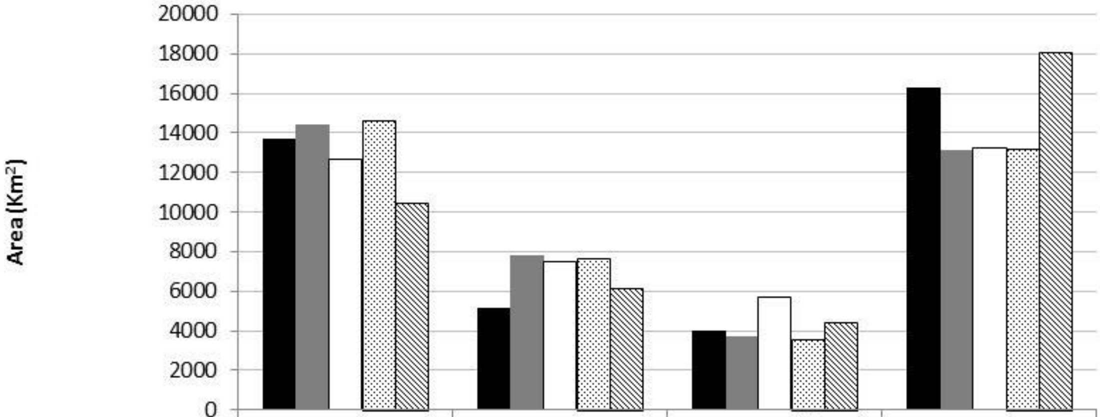
Figure 35. Area (Km^2) change with respect to frost risk for wine grapes from September to October (without the soil parameters as a model constraint – refer figure 45) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for wine grapes for this period is defined as the risk of having a day where Tmin <-2°C (15 September-15 October) - classified to their suitability categories: <20% = Well suited, 20-50%= Suitable; 50-100%= Marginally suitable; >1 frost per year= Unsuitable]



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	25392	5674	5356	2731
■ B1 simulations 2030	32135	3072	2456	1492
□ B1 simulations 2050	33109	2432	2358	1254
⊡ A2 simulations 2030	33024	2458	2423	1249
▧ A2 simulations 2050	34292	1757	2149	955

Suitability

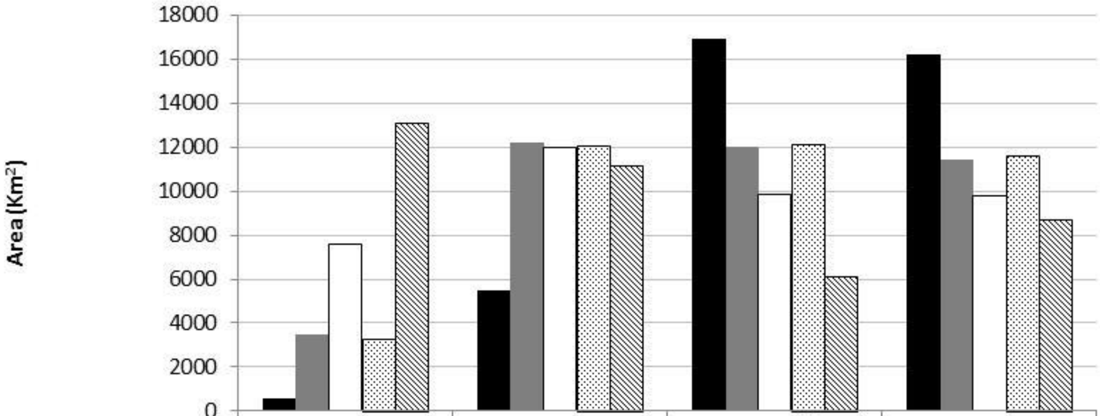
Figure 3. Area (Km^2) change with respect to frost risk for wine grapes from October to November (without the soil parameters as a model constraint – refer figure 46) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for wine grapes for this period is defined as the risk of having a day where Tmin <-2°C (15 October -15 November) - classified to their suitability categories: <10% = Well suited, 10-20%= Suitable; 20-50%= Marginally suitable; >50%= Unsuitable]



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	13689	5143	4028	16293
■ B1 simulations 2030	14416	7838	3737	13163
□ B1 simulations 2050	12703	7510	5727	13213
⊡ A2 simulations 2030	14666	7665	3603	13219
▧ A2 simulations 2050	10447	6152	4468	18086

Suitability

Figure 37. Area (Km^2) change with respect to Growing Degree Days (GDD) for Sparkling wine grapes (without the soil parameters as a model constraint – refer figure 47) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [GDD for Sparkling wine grapes is defined for the period October through to April with a base temperature of 10^{o}C - classified to their suitability categories: 900-1085 = Well suited, 850-900 & 1085-1150 = Suitable; 800-850 & 1150-1200 = Marginally suitable; <800 &>1200= Unsuitable]



	Well suited	Suitable	Marginally suitable	Unsuitable
■ Current estimations	538	5482	16911	16223
■ B1 simulations 2030	3501	12192	12009	11452
□ B1 simulations 2050	7586	11959	9833	9776
⊡ A2 simulations 2030	3258	12099	12170	11628
▧ A2 simulations 2050	13097	11168	6150	8738

Suitability

Figure 38. Area (Km^2) change with respect to Growing Degree Days (GDD) for Table wine grapes (without the soil parameters as a model constraint – refer figure 48) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [GDD for Table wine grapes is defined for the period October through to April with a base temperature of 10^{o}C - classified to their suitability categories: >1150 = Well suited, 1000-1150= Suitable; 800-1000= Marginally suitable; <800= Unsuitable]

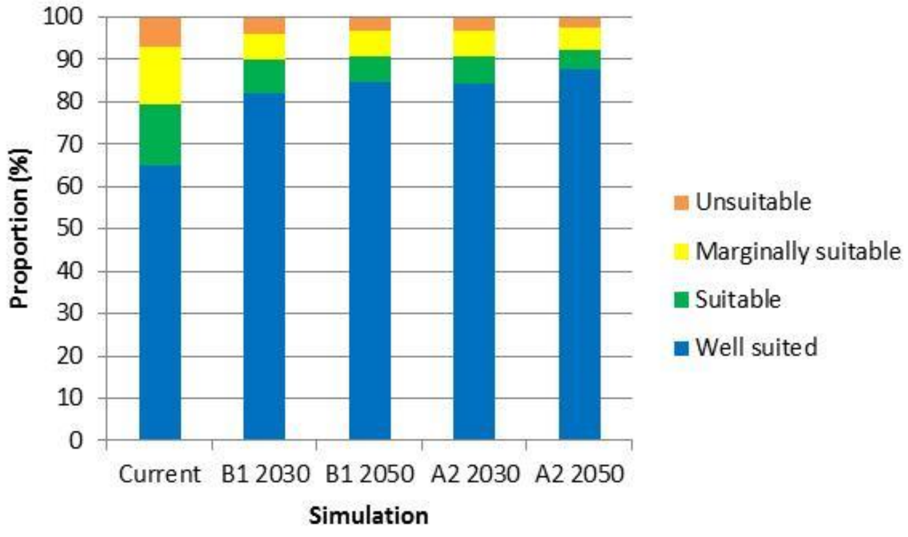


Figure 39. Proportion (%) of land area change with respect to frost risk for wine grapes from September to October (without the soil parameters as a model constraint – refer figure 45) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for wine grapes for this period is defined as the risk of having a day where Tmin <-2°C (15 September-15 October) - classified to their suitability categories: <20% = Well suited, 20-50%= Suitable; 50-100%= Marginally suitable; >1 frost per year= Unsuitable]

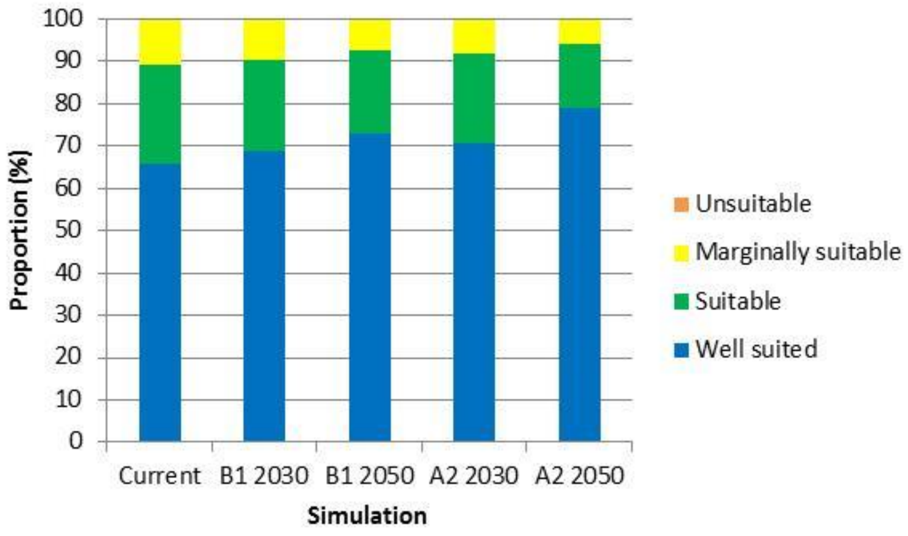


Figure 40. Proportion (%) of land area change with respect to frost risk for wine grapes from October to November (without the soil parameters as a model constraint – refer figure 46) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [Frost risk for wine grapes for this period is defined as the risk of having a day where Tmin <-2°C (15 October -15 November) - classified to their suitability categories: <10% = Well suited, 10-20%= Suitable; 20-50%= Marginally suitable; >50%= Unsuitable]

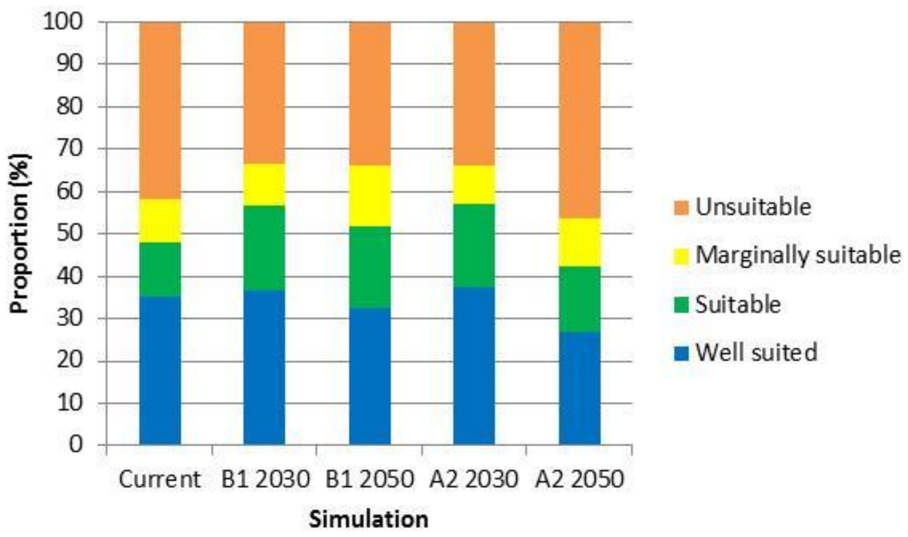


Figure 41. Proportion (%) of land area change with respect to Growing Degree Days (GDD) for Sparkling wine grapes (without the soil parameters as a model constraint – refer figure 47) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [GDD for Sparkling wine grapes is defined for the period October through to April with a base temperature of 10°C - classified to their suitability categories: 900-1085 = Well suited, 850-900 & 1085-1150 = Suitable; 800-850 & 1150-1200 = Marginally suitable; <800 &>1200= Unsuitable]

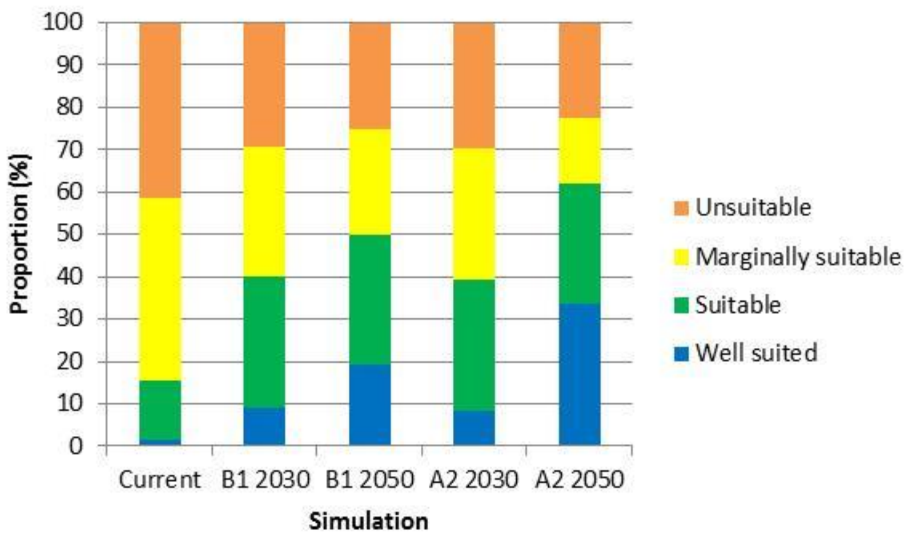


Figure 42. Proportion (%) of land area change with respect to Growing Degree Days (GDD) for Table wine grapes (without the soil parameters as a model constraint – refer figure 48) comparing current model estimations versus models incorporating the B1 and A2 emission scenarios at 2030 and 2050. [GDD for Table wine grapes is defined for the period October through to April with a base temperature of 10°C - classified to their suitability categories: >1150 = Well suited, 1000-1150= Suitable; 800-1000= Marginally suitable; <800= Unsuitable]

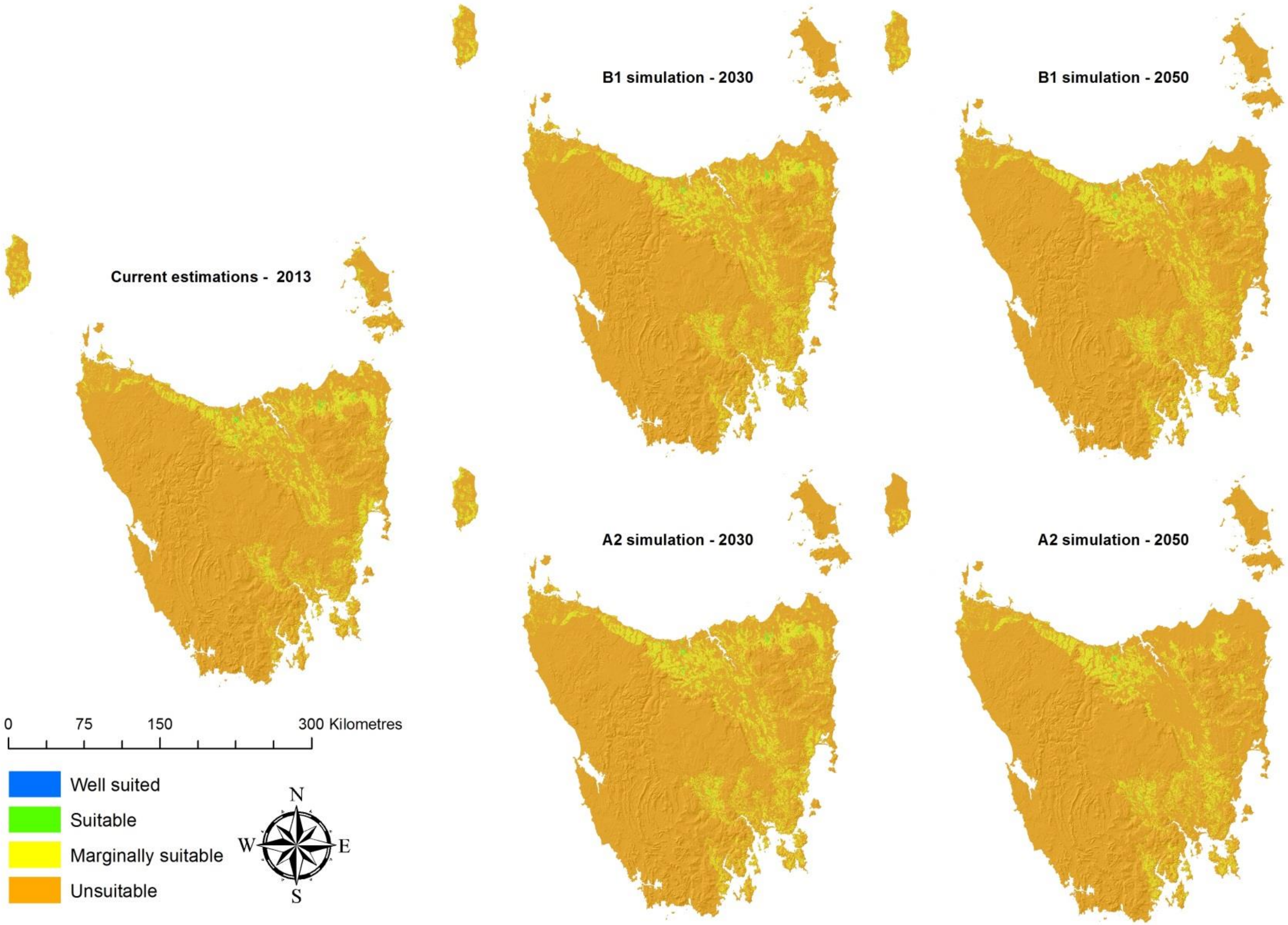


Figure 43. State wide enterprise suitability maps for Sparkling wine grapes comparing the current enterprise suitability model output versus outputs incorporating the B1 and A2 emission scenarios (i.e. frost risk, GDD and hourly mean temperature) at 2030 and 2050.

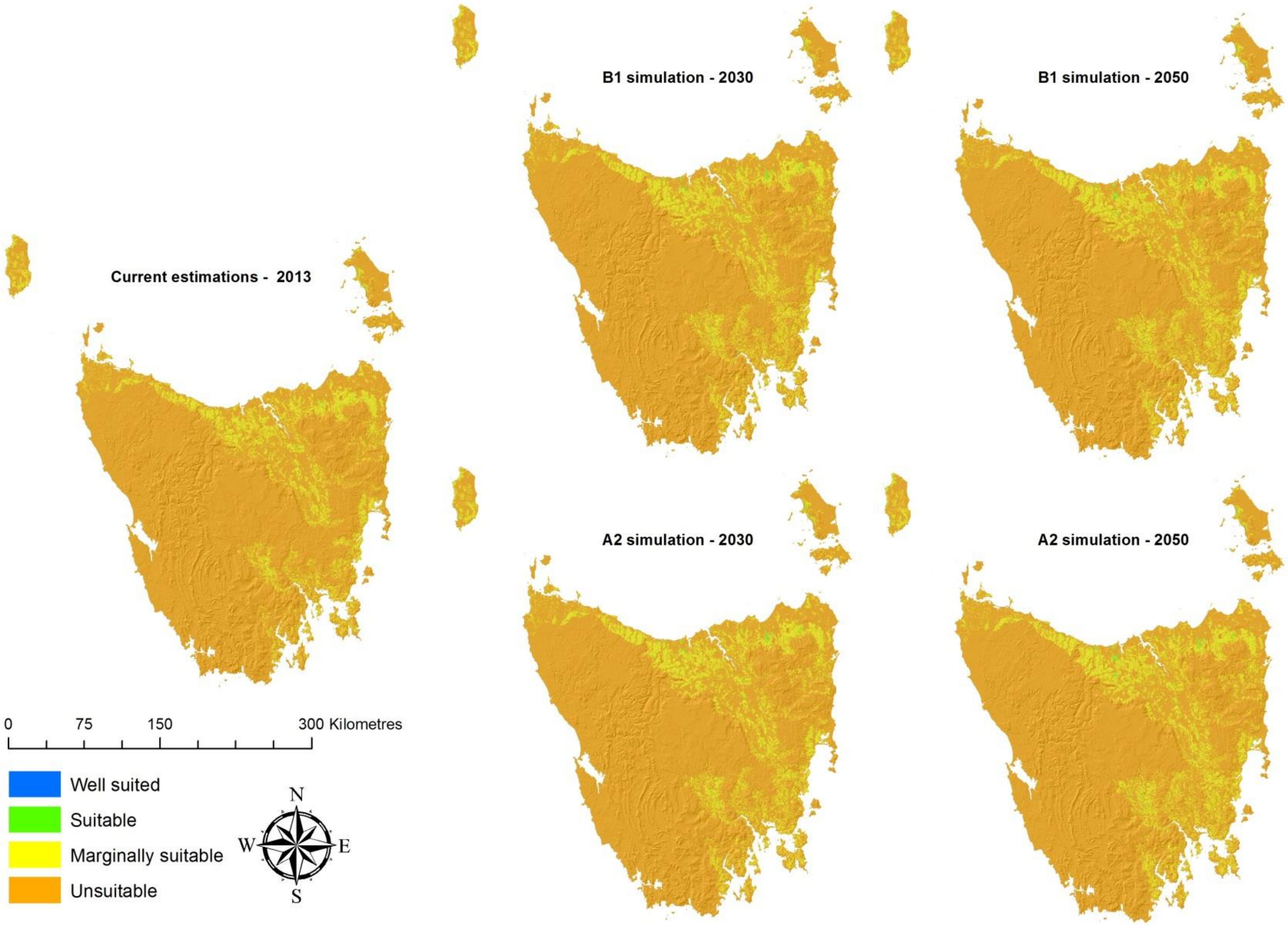


Figure 44. State wide enterprise suitability maps for Table wine grapes comparing the current enterprise suitability model output versus outputs incorporating the B1 and A2 emission scenarios (i.e. frost risk, GDD and hourly mean temperature) at 2030 and 2050.

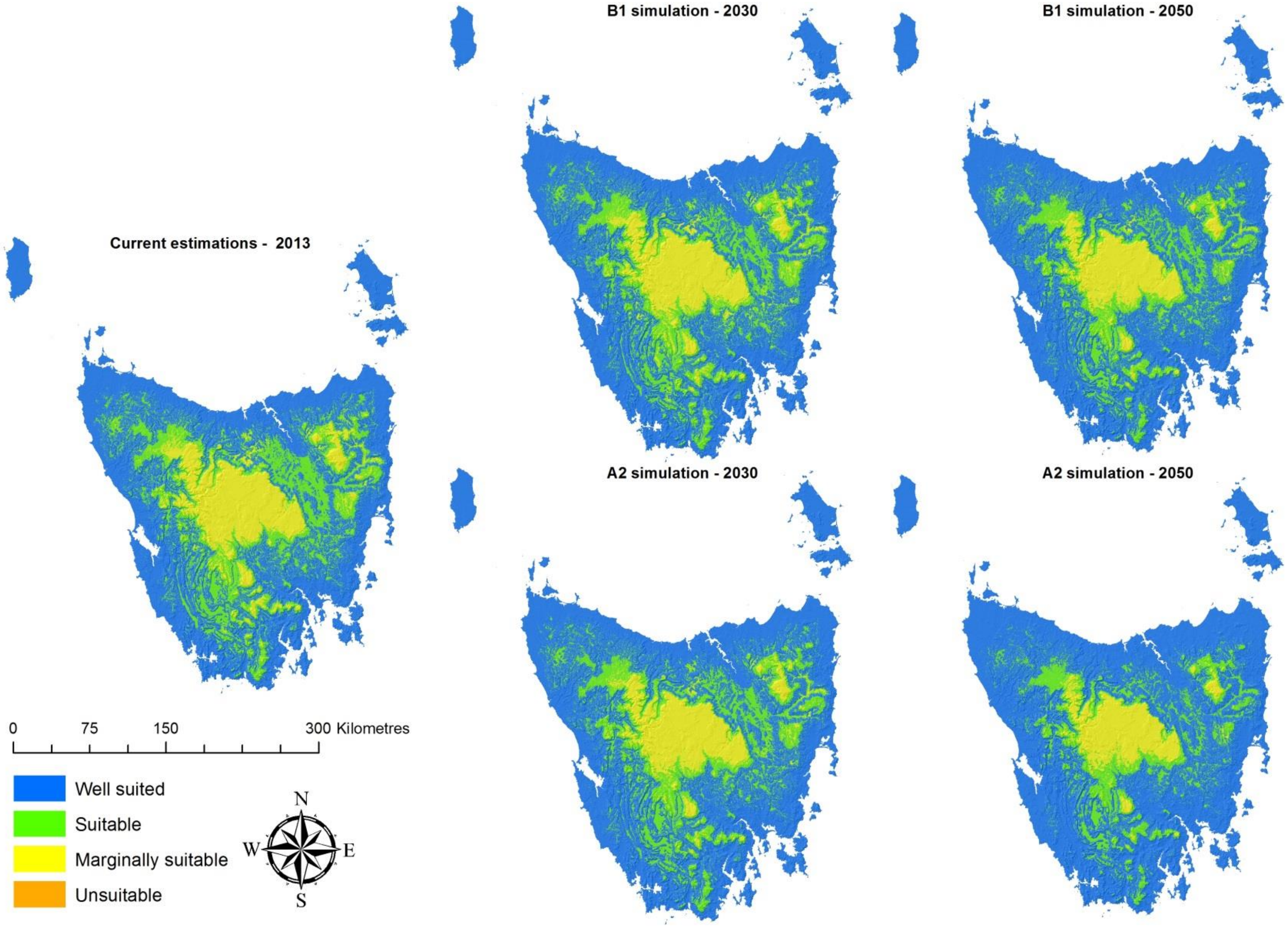


Figure 45. State wide frost risk maps for wine grapes (September to October) comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050 [Frost risk for wine grapes for this period is defined as the risk of having a day where Tmin <-2^{o}C (15 September-15 October) - classified to their suitability categories: <20% = Well suited, 20-50%= Suitable; 50-100%= Marginally suitable; >1 frost per year= Unsuitable]

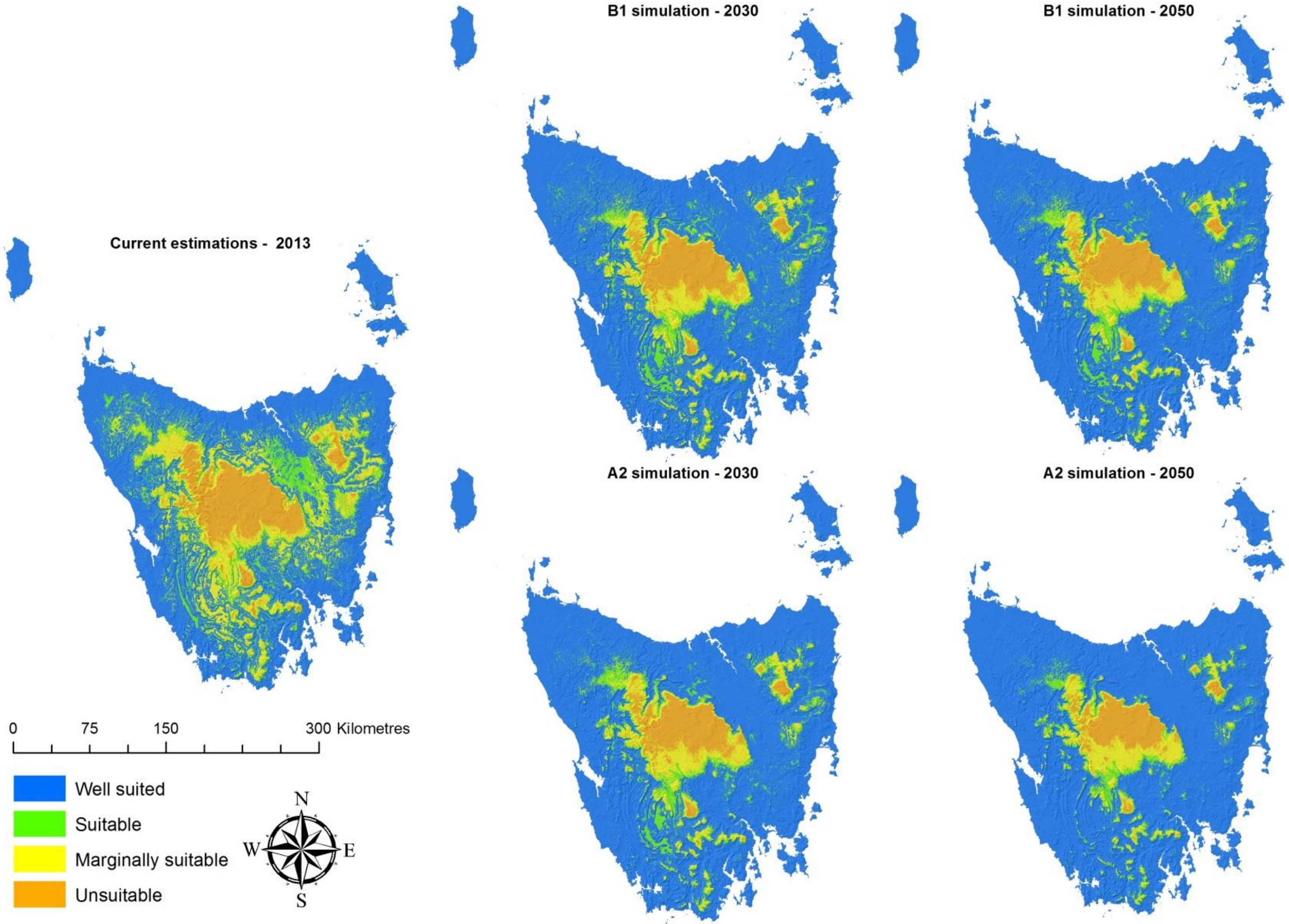


Figure 46. State wide frost risk maps for wine grapes (October to November) comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050 [Frost risk for wine grapes for this period is defined as the risk of having a day where Tmin <-2°C (15 October -15 November) - classified to their suitability categories: <10% = Well suited, 10-20%= Suitable; 20-50%= Marginally suitable; >50%= Unsuitable]

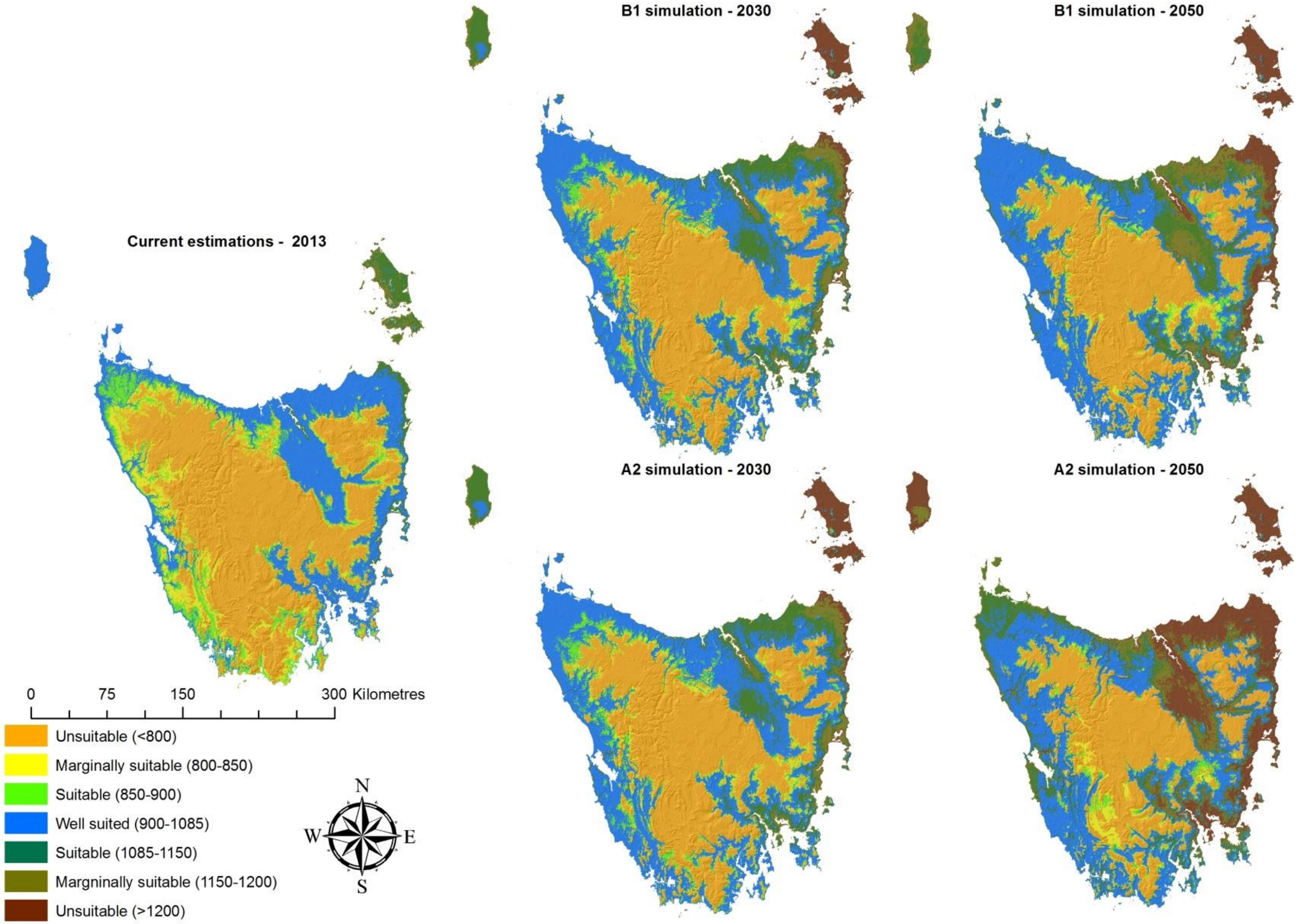


Figure 47. Growing Degree Day (GDD) maps for Sparkling wine grapes comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050 [GDD for Sparkling wine grapes is defined for the period October through to April with a base temperature of 10^{o}C - classified to their suitability categories: 900-1085 = Well suited, 850-900 & 1085-1150 = Suitable; 800-850 & 1150-1200 = Marginally suitable; <800 &>1200= Unsuitable]

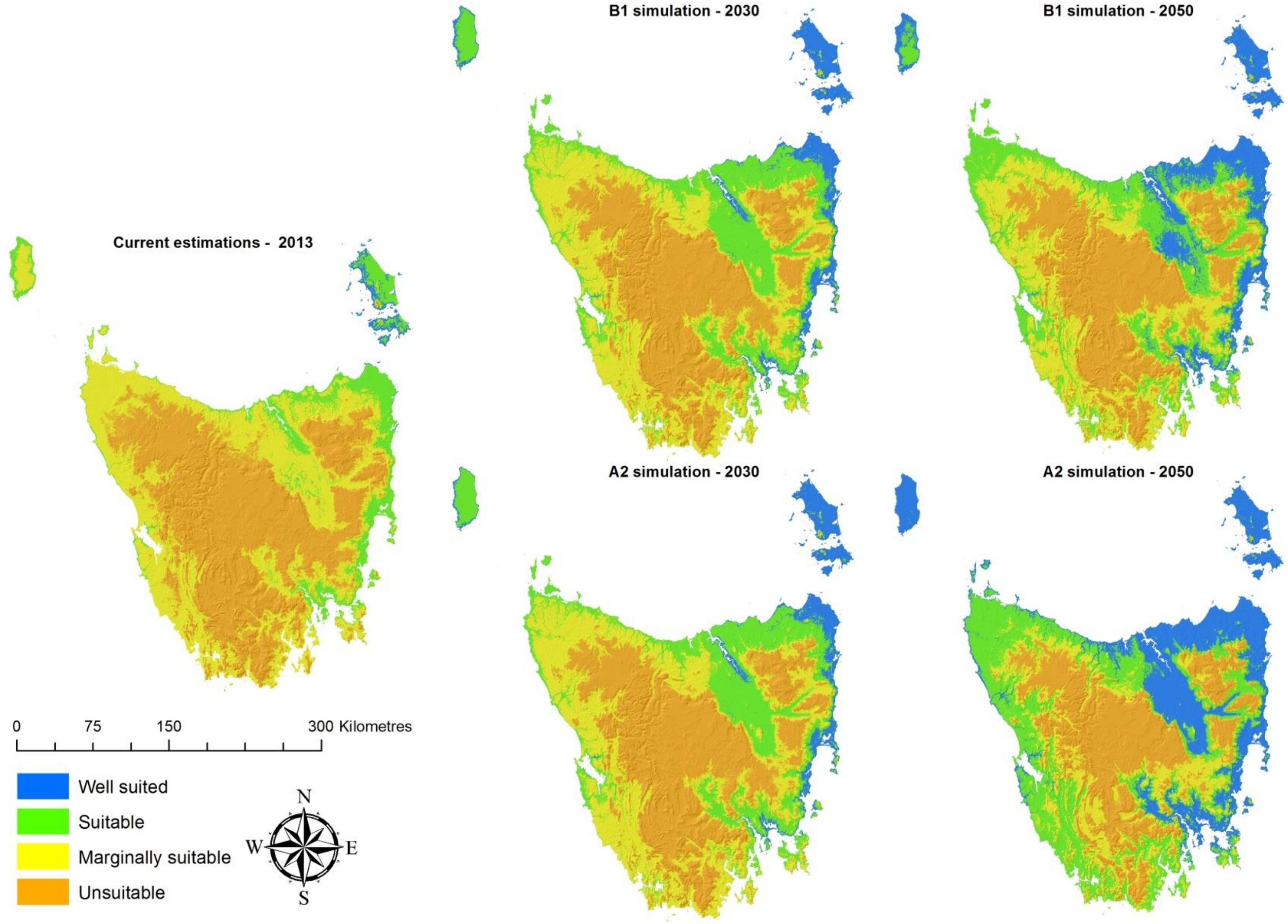


Figure 48. Growing Degree Day (GDD) maps for Table wine grapes comparing the current output versus outputs incorporating the B1 and A2 emission scenarios at 2030 and 2050 [GDD for Table wine grapes is defined for the period October through to April with a base temperature of 10°C - classified to their suitability categories: >1150 = Well suited, 1000-1150= Suitable; 800-1000= Marginally suitable; <800= Unsuitable]

4. Appendix

4.1 Data Inventory

The following table lists the datasets produced from the analysis and are available for further use in a GIS.

File name	Description	Type of mapping	ESM Crop
Barley_2030_A2_sixmodelmean.gdb	Enterprise suitability output for Barley where the climate inputs are based on the A2 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Barley
Barley_2050_A2_sixmodelmean.gdb	Enterprise suitability output for Barley where the climate inputs are based on the A2 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Barley
Barley_2030_B1_sixmodelmean.gdb	Enterprise suitability output for Barley where the climate inputs are based on the B1 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Barley
Barley_2050_B1_sixmodelmean.gdb	Enterprise suitability output for Barley where the climate inputs are based on the B1 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Barley
Poppies_2030_A2_sixmodelmean.gdb	Enterprise suitability output for Poppies where the climate inputs are based on the A2 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Poppies
Poppies _2050_A2_sixmodelmean.gdb	Enterprise suitability output for Poppies where the climate inputs are based on the A2 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Poppies
Poppies _2030_B1_sixmodelmean.gdb	Enterprise suitability output for Poppies where the climate inputs are based on the B1 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Poppies
Poppies _2050_B1_sixmodelmean.gdb	Enterprise suitability output for Poppies where the climate inputs are based on the B1 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Poppies
Potatoes_2030_A2_sixmodelmean.gdb	Enterprise suitability output for Potatoes where the climate inputs are based on the A2 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Potatoes
Potatoes _2050_A2_sixmodelmean.gdb	Enterprise suitability output for Potatoes where the climate inputs are based on the A2 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Potatoes
Potatoes _2030_B1_sixmodelmean.gdb	Enterprise suitability output for Potatoes where the climate inputs are based on the B1 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Potatoes
Potatoes_2050_B1_sixmodelmean.gdb	Enterprise suitability output for Potatoes where the climate inputs are based on the B1 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Potatoes
Sparklingwine_2030_A2_sixmodelmean.gdb	Enterprise suitability output for Sparkling wine where the climate inputs are based on the A2 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Sparkling wine
Sparklingwine _2050_A2_sixmodelmean.gdb	Enterprise suitability output for Sparkling wine where the climate inputs are based on the A2 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Sparkling wine

Sparklingwine _2030_B1_sixmodelmean.gdb	Enterprise suitability output for Sparkling wine where the climate inputs are based on the B1 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Sparkling wine
Sparklingwine _2050_B1_sixmodelmean.gdb	Enterprise suitability output for Sparkling wine where the climate inputs are based on the B1 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Sparkling wine
Tablewine_2030_A2_sixmodelmean.gdb	Enterprise suitability output for Table wine where the climate inputs are based on the A2 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Table wine
Tablewine _2050_A2_sixmodelmean.gdb	Enterprise suitability output for Table wine where the climate inputs are based on the A2 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Table wine
Tablewine _2030_B1_sixmodelmean.gdb	Enterprise suitability output for Table wine where the climate inputs are based on the B1 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Table wine
Tablewine _2050_B1_sixmodelmean.gdb	Enterprise suitability output for Table wine where the climate inputs are based on the B1 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Table wine
Wheat_2030_A2_sixmodelmean.gdb	Enterprise suitability output for Wheat where the climate inputs are based on the A2 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Wheat
Wheat _2050_A2_sixmodelmean.gdb	Enterprise suitability output for Wheat where the climate inputs are based on the A2 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Wheat
Wheat _2030_B1_sixmodelmean.gdb	Enterprise suitability output for Wheat where the climate inputs are based on the B1 emission scenario at 2030 using the six model mean of the CFT climate models.	Enterprise suitability	Wheat
Wheat _2050_B1_sixmodelmean.gdb	Enterprise suitability output for Wheat where the climate inputs are based on the B1 emission scenario at 2050 using the six model mean of the CFT climate models.	Enterprise suitability	Wheat
fr_lt0_0112to3112_x.tif	Risk (%) of having at least one day of <0oC for the period: 1 to 31 December. “x” denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Frost	Barley
fr_ltm1_1511to1512_x.tif	Risk (%) of having at least one day of <-1^{o}C for the period: 15 November to 15 December. “x” denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Frost	Poppies

fr_ltm1_0111to1511_x.tif	Risk (%) of having at least one day of <-1^{o}C for the period: 1 to 15 November. "x" denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Frost	Poppies
fr_lt0_0111to2802_x.tif	Risk (%) of having at least one day of <0^{o}C for the period: 1 November to 28 February. "x" denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Frost	Potatoes
min_mt20_0111to2802_x.tif	Risk (%) of having at least one day with a minimum temperature of >20^{o}C for the period: 1 November to 28 February. "x" denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Minimum temperature	Potatoes
fr_ltm2_1509to1510_x.tif	Risk (%) of having at least one day with a minimum temperature of >20^{o}C for the period: 1 November to 28 February. "x" denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Frost	Wine grapes
fr_ltm2_1510to1511_x.tif	Risk (%) of having at least one day with a minimum temperature of >20^{o}C for the period: 1 November to 28 February. "x" denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Frost	Wine grapes

ch_avg_0107to3107_x.tif	Risk (%) of having at least one day with a minimum temperature of >20°C for the period: 1 November to 28 February. "x" denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Chill hours	Wine grapes
gdd_bt10_0110to3004_x.tif	Number of growing degree days (Base temperature of 10 °C) for the period: 1 October to 30 April. "x" denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Growing degree days	Wine grapes
fr_lt0_0111to1511_x.tif	Risk (%) of having at least one day of <0°C for the period: 1 to 15 November. "x" denotes the available separate model outputs: echam5_A2, echam5_B1, gfdlcm20_A2, gfdlcm20_B1, gfdlcm21_A2, gfdlcm21_B1, miroc3_2_medres_A2, miroc3_2_medres_B1, Mk3.5_A2, Mk3.5_B1, ukhadcm3_A2, ukhadcm3_B1, sixmodelmean_A2, sixmodelmean_B1, sixmodelmax_A2, sixmodelmax_B1, sixmodelmin_A2, sixmodelmin_B1	Frost	Wheat

5. References

Böhner J, Conrad O (2007) System for Automated Geoscientific Analyses, software, version 2.08. SAGA User Group Association. Hamburg, Germany

Böhner J, Koethe R, Conrad O, Gross J, Ringeler A, Selige T (2002) Soil Regionalisation by Means of Terrain Analysis and Process Parameterisation. In: Micheli E, Nachtergaele F, Jones R, Montanarella L (ed) Soil Classification 2001, European Soil Bureau , Hungary, pp 213-222

Breiman L (1996) Random forests. Mach Learn 24:123-140

Breiman L, Cutler A (2012) Random Forests – manual. http://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm. Accessed 14 August 2012

Corney S, Katzfey j, MeGregor J, Grose M, Bennet J, White C, Holz G, Gaynor S, Bindoff N (2010) Climate Futures for Tasmania: climate modelling technical report, Antarctic Climate and Ecosystems Cooperative Research Centre, Hobart, Tasmania.

Dall'Amico M and Hornsteiner M (2006) A Simple Method for Estimating Daily and Monthly Mean Temperatures From Daily Minima and Maxima. Int J Climatol 26:1929-1936

Dèquè (2007) Frequency of precipitation and temperature extremes over France in an anthropogenic scenario: Model results and statistical correction according to observed values. Global Planet Change 57: 16-26

Gallant J, Dowling T, Read A, Wilson N, Tickle P (2011) 1 second SRTM Derived Digital Elevation Models User Guide, Geoscience Australia, Canberra

Grabs T, Seibert J, Bishop K, Laudon H (2009) Modeling spatial patterns of saturated areas: A comparison of the topographic wetness index and a dynamic distributed model. J Hydrol 373:15-23

Hastie T, Friedman J, Tibshirani R (2009) The Elements of Statistical Learning (2nd edition). Springer-verlag, New York

Jarvis C, Stuart N (2001a) A Comparison among Strategies for Interpolating Maximum and Minimum Daily Air Temperatures. Part I: The Selection of Guiding Topographic and Land Cover Variables. J Appl Meteorol 40:1060-1074

Jarvis C, Stuart N (2001b) A Comparison among Strategies for Interpolating Maximum and Minimum Daily Air Temperatures. Part II: The Interaction between Number of Guiding Variables and the Type of Interpolation Method. J Appl Meteorol 40:1075-1084

Kidd D, Webb M, Malone B, Minasny B, McBratney A (2015b) Digital Soil Assessment of Agricultural Suitability, Versatility and Capital. Geoderma Regional (in Review). Submitted June 30th, 2015.

Klingebiel A and Montgomery P (1961) Land Capability Classification. Agriculture Handbook N. 210. U.S.D.A., Soil Conservation Service, Washington.

Lin L (1989) A concordance correlation coefficient to evaluate reproducibility. Biometrics 45:255-268

Sansom J, Tait A (2004) Estimation of Long-Term Climate Information at Locations with Short-Term Data Records. J Appl Meteorol 4: 915-92

Poggio L, Gimona, A (2015) Downscaling and correction of regional climate models outputs with a hybrid geostatistical approach. Spatial Statistics. <Article in press: http://dx.doi.org/10.1016/j.spasta.2015.04.006>

Quinlan J (1986) Induction of decision trees. Mach Learn 1:81-106

R Development Core Team (2012) R: A language and environment for statistical computing. R Foundation for Statistical Computing. http://www.R-project.org/

Webb M, Hall A, Kidd, D, Minasny B (2015) Local-scale spatial modelling for interpolating climatic temperature variables to predict agricultural plant suitability. Theor Appl Climatol 1-21