

Regional climate change projections for the Tully sugar region

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Abstract: Faced with the challenges of a changing climate, it is imperative that primary industry decision makers have access to climate projections on a local scale. In the Australian sugar industry, changes in maximum and minimum temperature, radiation and rainfall can significantly affect future economic and environmental sustainability. In northern regions an increase in rainfall during the harvest season can lead to crop standover and lower economic returns. Modelling the effects of climate change at a local scale will help develop regional management strategies.

General Circulation Models (GCMs) allow researchers to explore projections of climate variables under a range of possible future emission scenarios. However, current outputs from GCMs are often only available at a coarse resolution (up to 300 km by 300 km). As a result many small scale conditions that can affect climate variables are often not represented in GCM outputs. Sugarcane in Australia is primarily grown in a narrow band on the eastern coast. The Tully region of northern Queensland is situated between the World Heritage Listed Wet Tropics Rainforest and Great Barrier Reef. Topographical changes across the Tully sugarcane-growing region result in climatology varying spatially. Downscaled GCMs can provide a bridge between large scale climate projections and the need for local climate variables. This paper explores climate change projections for maximum and minimum temperature, radiation and rainfall in the Tully sugarcane-growing region at a high spatial resolution.

Temperature and rainfall data were obtained from 11 GCMs for the period 1961 to 2000. Projections for this period were based on 20th century forcings (20C3M) as described by the International Panel of Climate Change (IPCC). GCM projections for the period 2046 to 2065 were also obtained, based on a high emissions scenario (A2). A statistical downscaling methodology was used to downscale daily temperature and rainfall data on a 0.05 by 0.05 decimal degree grid (approximately 5 km by 5 km). Data were downscaled for grid locations known to grow sugarcane within the Tully region. Daily radiation data were not available using the downscaling process. Instead, daily radiation data were generated from downscaled rainfall and temperature data. Equations for daily radiation were parameterised using temperature and rainfall data from a nearby high quality weather station and calculated total solar flux. Estimates were bias corrected to replicate weather station records of radiation.

The projected change in each of the four climate variables was assessed on a regional level for the 11 GCMs and spatial variations within the region were identified. For temperature and radiation variables, the absolute projected change was calculated. For rainfall the projected *relative* change was calculated. The relative change was defined as the percent change from the baseline period (1961 to 2000). Projected changes were analysed at each grid point for summer, autumn, winter and spring. The regional mean change was calculated for each GCM and a 95% bootstrapped confidence interval was produced for the 25th, 50th and 75th percentiles of the paired differences. The percentiles of projected change across the range of GCMs were used to capture the uncertainty between model projections. If the 95% confidence interval of the 50th and 75th (25th) percentile captured only positive (negative) values, an increase (decrease) was considered plausible. An increase (decrease) was considered highly plausible if the confidence intervals for the 25th 50th and 75th all captured positive (negative) values.

For the Tully region, an increase in temperature was considered highly plausible for all seasons under A2 simulated forcings. A projected decrease in radiation was considered highly plausible for winter and spring and plausible for autumn. A relative increase in radiation was plausible for summer and a relative increase in rainfall was considered plausible for spring. However, projected changes in seasonal rainfall varied spatially within the Tully region. An increase in seasonal temperature and rainfall may require changes to traditional management strategies. High resolution climate change projections can help industry decision makers develop localised, robust adaptation strategies. Local adaptations are vital for an economically and environmentally sustainable future.

Keywords: Temperature, radiation, rainfall, GCM, downscale

1. INTRODUCTION

Agricultural industries are highly dependent on climatology for production. Faced with a changing climate it is more important than ever that decision makers within industry have a comprehensive understanding of climatology on a local scale. The modelling community is vital to providing the information necessary for industry to make robust adaptation strategies. In the Australian sugar industry, changes in maximum and minimum temperature, radiation and rainfall can all significantly affect the future economic and environmental sustainability.

The Australian sugar industry is located primarily along the eastern coastline, between mountain ranges to the west and the Pacific Ocean to the east (Figure 1). How climate variables affect the sugar industry can differ between and within regions. Warmer conditions could increase production losses due to higher pest and disease pressure (Park *et al.*, 2010). In northern cane-growing regions excessive rainfall during summer can impede crop growth (Everingham *et al.*, 2003) whereas large rainfall events during the harvest season (winter and spring) can reduce profitability due to crop standover and lower sugar content (Antony *et al.*, 2002). However, models have projected increased cane yields due to higher atmospheric carbon dioxide (CO₂) concentrations (Marin *et al.*, 2013). Robust management strategies will be required to balance the potential risks and opportunities of a changing climate.

Projections from General Circulation Models (GCMs) are available for a range of simulated emission scenarios. These data are available in archives such as the Coupled Model Intercomparison Project (CMIP3) database. The “2007 Climate Change in Australia” technical report documented the 10th and 90th percentiles for rainfall projections from 25 GCMs (Pearce *et al.*, 2007). Pearce *et al.* (2007) considered low, medium and high emissions for 2030, 2050 and 2070. Under a high emissions scenario the report suggested an increase in maximum and minimum temperatures, but no likely change in radiation or rainfall across Queensland, where ‘likely’ was defined as agreement among at least two thirds of the models. Data from GCMs are currently produced at low spatial resolutions (up to 300 by 300 km). In heterogeneous terrain GCMs can fail to capture local climate patterns. By downscaling GCM projections of climate variables it is possible to produce projections at a higher spatial resolution.

Downscaling techniques can be classified as dynamical or statistical (Fowler *et al.*, 2007). Dynamical downscaling techniques model the physical processes of climate variables. Statistical downscaling techniques develop mathematical equations that relate large-scale atmospheric variables to local climate variables. Downscaling techniques have previously been used in Australia to model runoff (Teng *et al.*, 2012) and productivity in wheat (Liu *et al.*, 2011).

In order to develop local adaptation strategies, models of climate variables are needed at a high spatial resolution. The objective of this paper is to investigate downscaled climate change projections for maximum and minimum temperature, radiation and rainfall in the Tully sugarcane-growing region.

2. GENERATING HIGH RESOLUTION CLIMATE DATA

Daily rainfall and temperature data from 11 GCMs (Table 1) were extracted from the CMIP3 database (Meehl *et al.*, 2007). The 11 GCMs were chosen for the availability of daily data in the required region, for current and future projections (Timbal *et al.*, 2009). GCMs were parameterized for 20th century emissions (20C3M) for the period 1961:2000 (20C3M) to represent a climatic baseline (PCMDI, 2002). Projections for the period 2046 to 2065 were produced under the “A2” scenario, representing a future with high population growth, high energy use and high greenhouse gas emissions (Nakicenovic and Swart, 2000).

The analogues statistical downscaling method of Timbal *et al.* (2009) was used to model rainfall and temperature data for the Tully sugarcane-growing region. The statistical downscaling method developed a series of mathematical equations to relate observed daily synoptic patterns to observed daily rainfall, maximum temperature and minimum temperature. The downscaling methodology used rainfall and temperature data from the Australian Water Availability Project (AWAP) on a 0.05 by 0.05 decimal degree

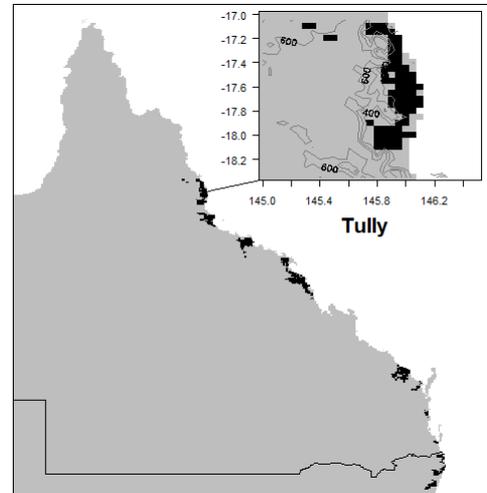


Figure 1. Sugar growing regions in Australia. The Tully region in the north is located between high mountain ranges and the coast.

Table 1. General Circulation Models used in analysis

grid, as baseline climatology. The Bureau of Meteorology (BoM) provided downscaled rainfall and temperature data for each GCM under the 20C3M and A2 scenarios, on a 0.05 by 0.05 decimal degree grid.

Government land use data and advice from industry experts was used to identify the Tully sugarcane-growing region. In total 77 “pixels” of 0.05 by 0.05 decimal degrees were identified

ID number	ID Code	Institute
GCM1	CCM	Canadian Climate Centre
GCM2	CNRM	Metro-France
GCM3	CSIRO	Commonwealth Scientific and Industrial Research Organisation
GCM4	CSIRO2	Commonwealth Scientific and Industrial Research Organisation
GCM5	GFDL1	Geophysical Fluid Dynamics Lab
GCM6	GFDL2	Geophysical Fluid Dynamics Lab
GCM7	GISSR	NASA/Goddard Institute for Space Studies
GCM8	IPSL	Institute Pierre Simon Laplace
GCM9	MIROC	Centre for Climate Research
GCM10	MPI	Max Planck Institute for Meteorology DKRZ
GCM11	MRI	Meteorological Research Institute

(Figure 1). Daily radiation data were not available using the downscaling process. Instead, daily radiation data were calculated from downscaled temperature and rainfall data for each GCM using the methodology of Liu and Scott, (2001). Daily radiation of day (j), ($Q_0(j)$) was calculated by modifying total daily solar flux ($Q_0(j)$) using rainfall for three consecutive days ($R(j)$, $R(j-1)$, $R(j+1)$) and the diurnal range of air temperature. Estimates of daily radiation were bias corrected to maximise the fit to radiation records from a nearby BoM station.

3. METHODOLOGY

3.1. Model validation

The temporal mean $\overline{Y}(season, GCM, scenario, pixel)$ for maximum (\overline{Tmax}) and minimum (\overline{Tmin}) temperature, radiation (\overline{Rad}) and rainfall (\overline{Rain}) were calculated for each $season = \{\text{summer, autumn, winter, spring}\}$, $pixel = \{1, \dots, 77\}$ and $GCM = \{GCM1, GCM2, \dots, GCM11\}$ for 20C3M and A2 scenarios. The spatio-temporal mean $\overline{Y}(season, GCM, scenario)$ was defined as the mean of temporal means across all pixels. Bias was calculated between AWAP spatio-temporal mean radiation, temperature and rainfall and the spatio-temporal means for downscaled GCMs. Radiation from AWAP data were calculated using the same technique as GCMs using AWAP rainfall and temperature data. Spatial patterns of downscaled GCMs and AWAP data seasonal data were also compared.

3.2. Comparing future and historic climate projections

The paired differences in modelled projections were computed between the A2 (2046 to 2065) and 20C3M (1961 to 2000) scenarios. For temperature and radiation, the average temporal mean of paired differences for each season and pixel were plotted spatially. For example, the average temporal mean of paired GCM differences in maximum temperature were calculated as,

$$\overline{\Delta Tmax}(season, pixel) = \frac{\sum_{GCM1}^{GCM11} \overline{Tmax}(season, pixel, GCM, A2) - \overline{Tmax}(season, pixel, GCM, 20C3M)}{11} \quad (1)$$

For rainfall the relative change in the temporal means were calculated as a percentage change from 20th century conditions

$$\overline{\Delta Rain}(season, pixel) = \frac{\sum_{GCM1}^{GCM11} \left[\frac{\overline{Rain}(season, pixel, GCM, A2) - \overline{Rain}(season, pixel, GCM, 20C3M)}{\overline{Rain}(season, pixel, GCM, 20C3M)} \right] \times 100}{11} \quad (2)$$

The change in regional spatio-temporal means for each GCM, were calculated similarly. For example the regional change in spatio-temporal mean rainfall was calculated as,

$$\overline{\Delta\text{Rain}}(\text{season}, \text{GCM}) = \frac{\sum_{\text{Pixel}1}^{\text{Pixel}77} \left[\frac{\overline{\text{Rain}}(\text{season}, \text{pixel}, \text{GCM}, \text{A2}) - \overline{\text{Rain}}(\text{season}, \text{pixel}, \text{GCM}, \text{20C3M})}{\overline{\text{Rain}}(\text{season}, \text{pixel}, \text{GCM}, \text{20C3M})} \right]}{77} \times 100$$

(3)

Downscaled GCMs that produce large positive values in (3) indicate a relative increase (positive change) in rainfall under A2 forcings, when compared to 20th century forcings (20C3M). Downscaled GCMs that produce large negative values indicate a relative decrease (negative change).

Equation (3) represents an independent sample of eleven spatio-temporal mean paired differences in seasonal rainfall. Here it is assumed that the eleven downscaled GCMs are representative of a larger parent population of climate models. The assumption of an independent sample was considered reasonable as the models selected were from a range of the ‘families’ of GCMs identified by Mason and Knutti (2011). Bootstrapped samples (Good, 1997) were used to produce 95% confidence intervals for the 25th, 50th and 75th percentiles of the distribution of paired model differences (Everingham *et al.*, 2013). For example, (3) was used to produce a sample of projected changes to summer rainfall $\{\overline{\Delta\text{Rain}}(\text{summer}, \text{GCM1}) \dots \overline{\Delta\text{Rain}}(\text{summer}, \text{GCM1})\}$. A random re-sample was produced with replacement and the 50th percentile was recorded. The process was repeated to obtain 1000 sample 50th percentiles. A 95% confidence interval was defined from the bootstrapped samples. Similarly confidence intervals were produced for temperature and radiation data.

An increase was considered ‘plausible’ when the confidence interval for the 50th percentile captured only positive values and ‘highly plausible’ if the confidence interval for the 25th percentile captured only positive values. Decreasing rainfall was considered ‘plausible’ (‘highly plausible’) when the confidence interval for the 50th (75th) percentile captured only negative values (Everingham *et al.*, 2013). Our definition of plausible and highly plausible is independent of the magnitude of the change. However the reader can examine the width of the confidence intervals to gauge the variability of the 25th, 50th and 75th percentiles of the paired differences. The authors recognise that definitions for ‘plausible’ or ‘likely’ changes differ within the literature.

4. RESULTS

4.1. Model Validation

Downscaled GCMs underestimated maximum temperature in autumn and overestimated seasonal minimum temperatures. Average daily radiation were underestimated in autumn and winter but were well represented in summer and autumn. Total seasonal rainfall was generally underestimated in summer and overestimated in autumn.

An average across GCMs reproduced spatial patterns of AWAP temperature and radiation data well. A slight north/south difference in bias was evident but not consistent across seasons. A slight decrease in bias magnitude was evident in autumn, winter and spring for radiation data. Rainfall data were the most spatially variable. GCMs managed to reproduce this variability well especially in capturing a small area of high rainfall at approximately -17.4° latitude. Patterns of bias were least consistent for rainfall especially in autumn and spring where southern parts of the region were underestimated while northern regions were overestimated.

4.2. Comparing future and historic climate projections

On a regional scale all GCMs agreed on the direction of change in minimum and maximum temperature under A2 forcings. Projected increases were largest in autumn (maximum) and winter (minimum). For individual GCMs, the projected change under the A2 scenario ranged from 0.5 to 1.5 (degrees C) for maximum temperature. Changes were slightly higher for minimum temperature ranging from 0.6 to 2.3 degrees. Based on bootstrapped 95% confidence intervals, an increase in maximum and minimum temperatures were considered highly plausible for all seasons (Figure 2).

Radiation projections based on downscaled GCMs simulated changes in ranging from -1.7 to 0.9 MJ/m² across all seasons with projected decreases greatest in winter. A projected increase in radiation was considered plausible for summer. A decrease was considered plausible in autumn and highly plausible in winter and spring.

Projections of the relative change in seasonal rainfall had the lowest levels of model agreement. Relative change in projected rainfall ranged from -24.6% (winter) to 64.6% (spring) across seasons. A relative increase in spring rainfall was considered plausible under a high emissions scenario.

Within the Tully region there was little spatial variation in the projected change in radiation and temperature under the A2 scenario (Figure 3). Minimum temperature increases were slightly higher in northern districts for winter and spring. Slight differences in northern and southern districts were also evident for radiation projections in summer and spring. The projected relative change in rainfall for Tully was more spatially variable. In autumn and winter the northern and southern districts of the region projected a small increase (5%), while the centre of the region projected a small decrease (-5%).

5. DISCUSSION

Direct outputs from general circulation models may not truly represent local variability in climate change projections. This is especially true for highly heterogeneous regions such as the Australian sugar industry. In order for industry to make effective adaptation strategies, there is a need to supply projections on a local scale. Use of a downscaling technique can provide projections of climate variables at a high spatial resolution. High resolution projections allow researchers to investigate how climate change may vary between districts within a region.

Projected increases in maximum and minimum temperature (1°C to 2°C) are similar to the results of earlier studies including Pearce *et al.* (2007). Higher minimum temperatures in autumn and winter may translate to a longer growing season. However, crop damage due to diseases may be greater as temperatures increase as many important sugarcane diseases favour warm, moist conditions (Chakraborty *et al.*, 1998). An increase in radiation during summer may translate to higher cane yields. However this may be offset by the projected decrease in radiation during winter and spring. Reduced radiation during winter and spring may restrict crop growth, especially early harvested ratoons and plant cane crops.

An increase in rainfall during the harvest season would cause greater disruptions to harvesting operations, increasing the risk of standover. There may also be significant damage to the cane stool and row profile where attempts are made to maximise the harvest, compromising ratoonability and field drainage (Kingston 2011).

As winter is normally associated with cool, wet conditions, most of the sugarcane in the Tully region is planted during spring. Increased spring rainfall may adversely affect germination and crop establishment, shorten the planting window or in extreme cases sugarcane may need to be replanted. Additional changes to the farming system may be required, such as raised

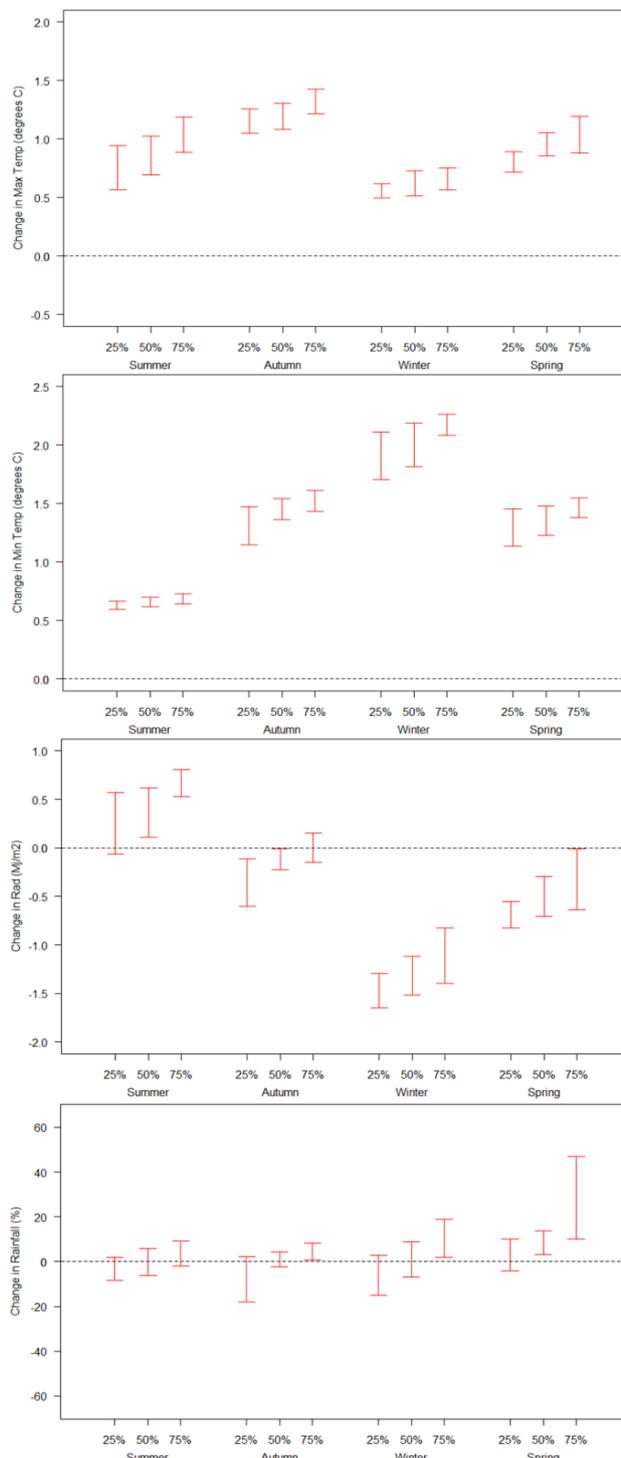


Figure 2. Bootstrapped 95% confidence intervals for the 25th, 50th and 75th percentiles of regional spatio-temporal mean differences for (a) maximum temperature, (b) minimum temperature, (c) radiation and (d) rainfall. Positive values represent a projected increase while negative values represent a projected decrease.

beds, mound planting and better in-field drainage, to reduce the impact of waterlogging on crop growth resulting from increased spring rainfall.

Projected increases in temperature and radiation were relatively uniform across the Tully region. Spatial variability was highest in rainfall projections. Decreases were primarily located in the centre of the Tully mill area while the northern (e.g. Silkwood) and southern (e.g. Murray) districts increased. Although a change was not considered plausible for summer or autumn rainfall on a regional level by our definition (section 3.2), projected differences in district rainfall suggest that targeted adaptation strategies could be developed. For example, districts where rainfall is projected to increase could be harvested before districts with a lower risk of increased rainfall.

6. CONCLUSION

General circulation models allow researchers to identify possible trends in climate variables important to agricultural industries. GCM outputs are produced on a large scale and cannot capture local variability. By using a downscaling technique, spatial variability in projected changes can be assessed within a single region. In this paper we have presented projected changes in maximum and minimum temperature, radiation and rainfall under a high (A2) emissions scenario for the Tully sugarcane-growing region. Uncertainty between models is a major concern in both climate change analysis (Power *et al.*, 2011) and crop simulations (Rotter *et al.*, 2011). By producing confidence intervals on percentiles of model projections, this research aimed to identify the level of uncertainty in climate change projections. It is important to recognise that the GCM projections capture only a subset of future uncertainty. Consequently, measures of future variability such as confidence intervals are conservative.

On a regional scale, increases in maximum and minimum temperature were considered highly plausible for all seasons and an increase in rainfall was considered plausible during spring. Disease (and pest) management will continue to be a priority under these future climatic conditions. Spatial variability in projections of temperature and rainfall suggest that different management adaptations may be required in different districts. For example harvesting and planting operations could be modified to reduce the impact of wet weather and to take advantage of earlier planting opportunities.

Downscaled climate projections could extend crop model research from the regional level down to the district level. This would help develop adaptation strategies for an economically and environmentally sustainable future. However, collaboration between researchers and industry decision makers will remain the most vital step in developing viable adaptation strategies.

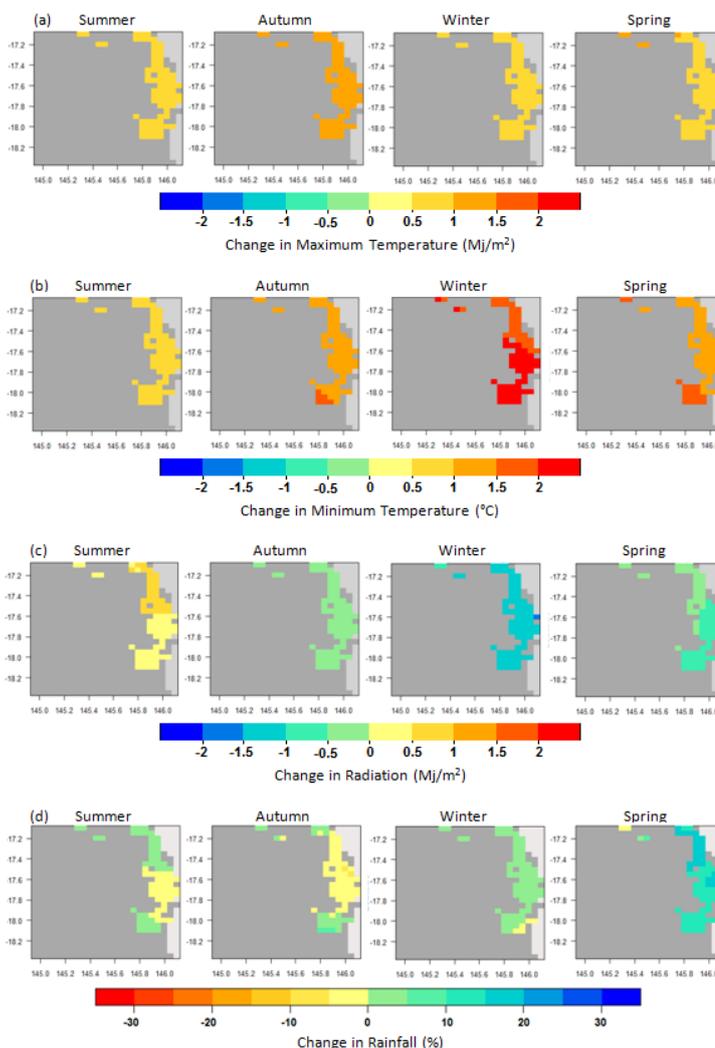


Figure 3. Spatial patterns in average change across 11 GCMs for: (a) maximum temperature, (b) minimum temperature, (c) radiation and (d) rainfall. Rainfall is presented as a percent change relative to the baseline period 1961:2000. Positive values represent a projected increase while negative values represent a projected decrease.

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