## Generating daily future climate scenarios for crop simulation

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### Abstract

Daily crop simulation models that use rainfall, temperature, solar radiation, evaporation and $CO_2$, can be employed to study the likely effects of climate change on crop production. However, current global climatic models generally operate on a mean-monthly basis and must be downscaled to meet the daily input requirement of the crop models. A method used in Victoria, involves scaling historic daily climate sequences by derived mean-monthly spatial patterns of climate change per degree of global warming. This paper presents a method of generating point-source climate-changed data and the subsequent interpolation of this data across space resulting in daily, gridded, spatiotemporal climate data that can be utilised in crop simulation models. Two methods of applying the climate changed data to analyse crop response are discussed. An application analysing crop response to climate changed data across Victoria is presented. The application has been developed as part of the current Victorian Climate Change Adaptation Programme (VCCAP) using climate generation, crop modelling and hydrological components of the Catchment Analysis Tool (CAT) landscape model.

### Key Words

Climate change, Catchment Analysis Tool (CAT), $CO_2$, crop yield

### Introduction

In an analysis of the impacts of climate change on crop yield, Anwar et al. (2007) demonstrated an approach to downscale global climate predictions resulting in daily climate projections that were used to estimate the impact on crop yield at a point location. The approach removes historic trends from daily climate sequences then scales them so that the mean-annual response matches future climate predictions. As a consequence, there is an identical pattern between the future climates and the detrended set of historical data. Limitations of this approach are well documented in Anwar et al. (2007), the most significant being that it does not try to predict any change in the intensity or frequency of weather events. Whilst acknowledging the limitations, this method of climate generation has two advantages over stochastical climate-models when used to simulate crop-yield at a catchment scale. First, because of the identical patterning between historical and future climate sequences the response of two individual future years can be compared to make a judgment about the impacts of the mean change in climate. Second, the method maintains the historic relationship between rainfall, temperature and solar radiation. The lack of this relationship was identified as a possible limitation of existing stochastic methods by Timbal et al. (2009), "[stochastic] … downscaled predictand series are constructed independently from one variable to another. This is a possible limitation for impact studies that require several predictands (i.e. rainfall and temperature)".

A number of methods exist to spatially scale point-source climate data. The simplest approach involves assigning the point-source data to a localised area around the climate station. More complex methods of spatial interpolation operate on a daily basis and use splining and kriging techniques to account for changes in climate due to elevation (Jeffrey et al. 2001). Our approach combines elements of both of these methods; daily data are assigned to a localised area then given more spatial complexity by scaling each grid point so that the mean-annual response matches an interpolated mean-annual spatial layer. The advantage of this technique is that it provides a relatively simple way to generate smoothed climate sequences across the catchment whilst capturing elevation based changes in the magnitude of rainfall, temperature and solar radiation. Additionally, as the spatial scaling remains fixed for all climate generation we can be assured that any change in crop response under a future climate is not because of a change in the spatial interpolation. In summary, the expectation was that the daily downscaling of global warming projections could be applied spatially across a catchment to show the potential trends in crop yield in a climate changed environment.

## Methods

### *Generation of climate changed data*

In 2001 the International Panel of Climate Change (IPCC) released a series of global warming scenarios describing future emissions of greenhouse gases and aerosols based on different socio-economic assumptions. This resulted in a series of projected global temperatures for the various scenarios. In addition to this, CSIRO developed CCAM, a global atmosphere-only model to account for the regional impacts of climate change by predicting the mean-monthly pattern of change per degree of global warming for temperature, rainfall and solar radiation across Australia. The IPCC Global Warming Factors (GWF) and the CCAM Pattern of Change Data (Pat) were combined in a daily downscaling technique developed by CSIRO Marine and Atmospheric Research and described Anwar et al. (2007). A summary of the method is now detailed.

Daily reference data $r$ for minimum and maximum temperature, rainfall and solar radiation were defined as the historical climate sequences from year $y_1$ to $y_2$ (typically 1935 to 1990). Daily-monthly reference data $r_{m,t}$ were extracted for a given calendar month $m$. A linear regression-line $\Gamma = a \times MA(r_{m,t}) + b$ was fitted to the mean-annual (*MA*) daily-monthly reference data versus the projection year. The daily-monthly data were detrended,

$$s_{m,t} = r_{m,t} - a(y_t - y_1) \quad y_1 \le y_t \le y_2 \quad \textbf{(1)}$$

where $r_{m,t}$ were the daily-monthly reference data, $a$, the gradient of the linear regression line $\Gamma$ and $y_t$, the reference year. The detrended data were centred around zero,

$$u_{m,t} = s_{m,t} - \bar{s}_{m,t} \quad \textbf{(2)}$$

with $\bar{s}_{m,t}$, the mean of the detrended sequence $s_{m,t}$. A baseline value ( $B_m$ ) was calculated for the year 1990 for each calendar month to anchor the projections to the IPCC reference year of 1990.

$$B_m = \bar{s}_{m,t} + a\frac{(y_2 - y_1)}{2} \quad \textbf{(3)}$$

The future maximum and minimum temperature projections were then calculated as a value shifted from the baseline year.

$$x_{m,t} = u_{m,t+y_1-y_2} + B_m + \left(Pat_m \times GWF_{y_t}\right) \quad \textbf{(4)}$$

where $u_{m,t+y_1-y_2}$ were the daily-monthly detrended data between $y_1$ and $y_2$, $B_m$, the baseline value calculated for each calendar month, $Pat_m$, the pattern of change value defined at the co-ordinates of the reference data for month $m$ and $GWF_{y_t}$, the global warming factor predicted by the IPCC for the future year $y_t$. Rainfall and radiation were scaled from the baseline year

$$x_{m,t} = \left(\mu_{m,t+y_1-y_2} + B_m\right) \times \left(1 + Pat_m \times GWF_{y_t}\right) \quad \textbf{(5)}$$

The monthly-daily data were then recombined to form the full daily climate changed sequence.

### *Methods of applying climate changed data*

Two methods of applying the climate changed data were considered in terms of their ability to establish trends in crop yield due to climate change. In method A the annual global warming factor was incrementally increased with each year of the detrended data. In method B one global warming factor for year $y_x$ was applied to the entire detrended trace. For method B the future maximum and minimum temperature projections were effectively calculated as

$$x_{m,t} = \mu_{m,t+y_1-y_2} + B_m + \left(Pat_m \times GWF_{y_x}\right), \quad \textbf{(6)}$$

and the rainfall and radiation projections were calculated as

$$x_{m,t} = \left(\mu_{m,t+y_1-y_2} + B_m\right) \times \left(1 + Pat_m \times GWF_{y_x}\right). \quad \textbf{(7)}$$

### *Spatial scaling of point-source climate data*

The point-source climate data was spatially scaled according to interpolated mean-monthly surfaces generated using the ANUClim software (Hutchinson 2001). The ANUClim software combined a Digital Elevation Model (DEM) and temporal climatic data (1975 to 2005) to generate smoothed mean-monthly rainfall, minimum and maximum temperature, potential evaporation and solar radiation surfaces. The smoothed layers had the same spatial resolution as the input DEM (typically between 10 m and 1 km). To reduce model complexity, filtering tools within the CAT interface allowed for user-specified banding of the ANUClim layers, for example, 10 mm banding for rainfall, with the mean value applied across the band. The ANUClim surfaces were used to generate mean-monthly spatial scaling factors that were then used to scale the point source historic or climate changed data across space on a daily basis. Spatial rainfall, radiation and evaporation scaling factors and temperature shift factors were calculated as

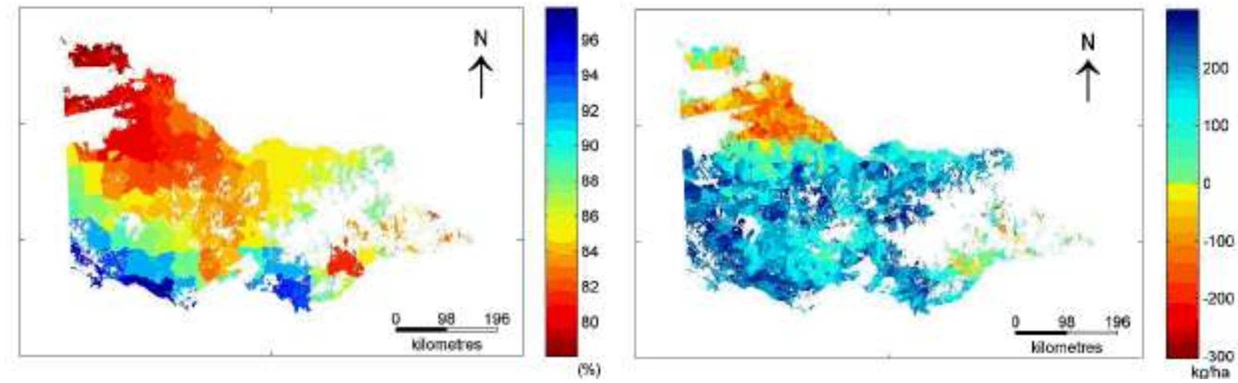
$$r_{rain,radn,evap} = \frac{R_{ANUCLIMbanded,m}}{RBOM_{1975-2005,m,CS}}, \quad r_{temp} = R_{ANUCLIMbanded,m} - RBOM_{1975-2005,m,CS} \quad (8)$$

where $R_{ANUCLIMbanded,m}$ was the banded mean-monthly ANUClim layer for month *m* and $RBOM_{1975-2005,m,CS}$ was the mean-monthly value of the point-source Bureau of Meteorology (BOM) data at the Climate Station (CS).

### Results and Discussion

To demonstrate the use of spatiotemporal climate-change data for crop simulation, point-source climate change data was generated from the historic climate sequences of approximately 700 climate stations across Victoria. The daily historical point-source climate station data was sourced from the Queensland Department of Natural Resources and Environment's SILO 'Patched Point Data' service (Jeffery et al. 2001). The data was generated using the Catchment Analysis Toolkit (CAT) climate change module, CATCLIM which applied the above method in a batch process to generate future climate data files (Weeks et al. 2008). Mean annual global warming factors and $CO_2$ levels were taken from the IPCC A1FI scenario; an extreme-case future scenario reliant on the use of fossil fuels (IPCC 2007). Figure 1 shows the 2050 mean growing season rainfall as a percentage of the 2000 mean growing season rainfall and the difference in mean annual crop yield due to climate change for a slow-developing cultivar type (cv. Mackeller) sown in early July. Crop modelling predicted an increase in yield across most of Southern

Victoria attributed to the warmer winters combined with the beneficial effects of $CO_2$ fertilisation expected under climate change. North Western Victoria had the highest projected percentage decrease in rainfall, which correlated to areas of decreased yield indicating that limited water availability could begin to restrict crop growth in this region. The application demonstrates the ability of the model to spatially represent trends in crop yields across Victoria, showing causal links between rainfall, temperature, $CO_2$ and crop yield.




**a)** **b)**

**Figure 1 a) 2050 growing season rainfall as a percentage of the 2000 growing season rainfall (defined as July to December) and b) Difference in and crop yield under the A1FI climate change scenario for a slow-developing wheat cultivar type between years 2050 and 2000.**

In the crop modelling application the climate data was applied using method B where the year 2050 global warming factor was used to scale the entire detrended trace then an average crop yield was calculated over all the years of the detrended trace. This process was repeated for the year 2000 and the difference in average yield reported. A problem with method A, where the annual global warming factor incrementally increases with each year of the detrended data, is that the year to year variability of climate often far exceeds the shift expected under climate change. To clarify this point, Figure 2 shows the two methods of downscaling temperature data. In method A, each year of detrended data corresponds to the actual years 1990 to 2050. A crop yield could be calculated for each of these years but the difference in yield between any two years could not be attributed to climate change because there is so much variability in the mean climate sequence between years. By using method B, the impacts of climate change are assessed by considering the shift in the distribution of crop yield under a future climate. The application of method B removes error associated with inter-year climate variation by downscaling all historic years using a constant global warming factor then considering the mean crop response over all detrended years.

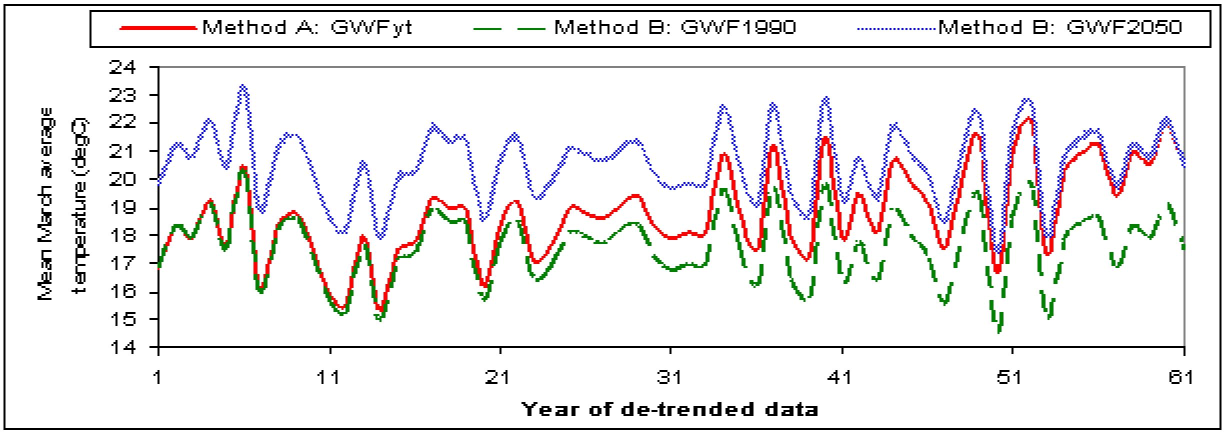



**Figure 2) Example of the downscaled mean temperature for March showing Method A (red line) using an incremental $GWF_{yt}$, where the detrended years correspond actual years 1990 to 2050 and Method B (green and blue lines) that scales the detrended data by the fixed $GWF_{1990}$ and $GWF_{2050}$ respectively.**

## Conclusion

We designed our climate generation method to spatially scale climate data on a daily basis to allow crop simulation models to be applied across catchments and assess the impact of climate change without the confounding of climate variability. We have confidence that we have met these expectations because we have been able to generate climate sequences across all of Victoria and have used these sequences to assess the impact of climate change on crop yield. A major strength of this method is that it retains historic daily climate patterns to allow the causal links between rainfall, solar radiation, temperature, $CO_2$ and crop yield to be determined. Therefore, the implications for crop modelling are two-fold. First, point-scale crop models requiring daily climate inputs can be applied across a whole catchment by using this spatial scaling method. Second, this approach combined with techniques of downscaling global warming predictions allows us to assess the impacts of climate change, accounting for spatial and temporal variability of climate at a catchment scale.

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