

A GIS tool to evaluate climate change impact: functionality and case study

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Abstract: A Climate Change Adaptation Strategy Assessment Tool (CCASAT) for agriculture with integrated GIS capability was described. Historical climate data from 1889 to 2008 and 12 GCMs downscaling scenarios were integrated in the tool. Daily climate change data used were based on state-of-the-art statistical downscaling methods which allow for the description of fine scale structures. Development of GIS functionality within CCASAT involves the selection of mapping projection, boundary allocation, interpolation and a graphical display of the spatial data. Several mapping projections and data interpolation were implemented in CCASAT. All interpolation methods were tested using cross validation and users can review these analyses and select the best interpolation method to plot their data. To demonstrate the GIS functionality in CCASAT, the impacts of climate change on wheat flowering in the NSW wheat belt was investigated as a case study. A non-intercepted spherical equation described well the relationship between the semi-variance in changes of annual long-term hot days (d_h , $T_{max} \geq 28^\circ\text{C}$) and the lag-distance. Cross validations showed that ordinary Kriging methods were the best scheme for interpolation of this index. The results showed that the number of hot days in 2050 during the winter crop growing season (1 May-30 November) would increase by up to 28 days, while frost days ($T_{min} \leq 2^\circ\text{C}$) would decrease by up to 29 days. Predicted changes in the winter-genotype wheat flowering dates ranged from 5 days later in the north-western corner and 10 days earlier in south-eastern corner of the NSW wheat belt. Spring-genotype wheat flowering is projected to be earlier by up to 7 days. The delay in the winter-genotype wheat flowering date is due to the delay in the completion of vernalisation in the warmer conditions. The analysis showed that number of frost days at flowering are not projected to change dramatically in the future, however an increase in hot days during wheat flowering is projected to have serious implications. This case study demonstrates that selecting suitable genotype wheat is the key adaptation strategy for the impacts of climate change on wheat cropping. Spring wheat genotypes are likely to become predominate in future climate, while winter genotype will only be viable in areas where sufficient days of cool temperature exist for completion of vernalisation. Breeding strategies should focus on releasing early-sowing genotypes that do not require vernalisation.

Keywords: *GIS, climate change, modelling, interpolation method, cross validation*

1. INTRODUCTION

In climate or systems modelling, the value of geographic analysis and spatial visualization is well recognised because it is able to improve interpretation of the overall modelling outcomes as single site simulation has limited applicability. Therefore, use of GIS software is widespread, but is not an easy task with many potential users not equipped to take advantage of the comprehensive spatial and visualization analysis features. One possible solution is to develop a simplified task-specific system that can be easily used by non-GIS users. Such a system can either incorporate GIS ActiveX controls (Smakhtin and Eriyagama, 2008) or embed GIS software such as ArcGIS (Panagos *et al.*, 2008; Liu, 2009). These GIS-enhanced systems can be useful for specific tasks. For example, the GIS-based Sediment Assessment Tool for Effective Erosion Control (SATEEC) was developed to estimate soil loss and sediment yield and can be used to identify areas vulnerable to soil loss and to develop efficient soil erosion management plans (Lim *et al.* 2005). However, it is difficult to implement in a portable end-user tool if the database is very large and/or the format of input data differs from the embedded tool.

Studies on potential impacts of climate change on agriculture and/or the environment have rapidly increased in recent years. Understanding the regional impacts of climate change on biophysical systems requires a modelling approach incorporating Global Climate Model data, the cornerstone of the climate change research. However, climate model projections at higher temporal and spatial resolutions are not adapted to describe local effects and thus statistical methods are needed to correct the projections from the GCM using historical climate information.

In particular, many climate and agricultural indices are used to describe the system being investigated and are therefore useful to translate the large-scale climate change information to model the impacts of climate change and develop the appropriate adaptation strategies. A GIS framework provides an enhanced ability to assess the possible responses from a range of adaptation strategies to climate change by integrating the outputs from GCMs and various modelling efforts in agriculture. The purpose of this work was to develop a GIS-based risk assessment tool to utilise the generic output from the GCMs and apply them, through a modelling framework, to assess the specific responses required by each of the major agriculture sectors. As a case study, the impact of climate change on wheat flowering and its implications in term of adaptation strategy are outlined in this communication.

2. DEVELOPMENT GIS FUNCTIONALITY

Development of stand-alone GIS functionality involves four steps: implementation of map projection, determining boundary allocation, data interpolation, and a graphical display of the spatial data. The first three steps for developing a standalone GIS are briefly outlined below.

2.1 Mapping projection

Van Der Grinten projection and Lambert projections were implemented in the Climate Change Adaptation Strategy Assessment Tool (CCASAT). The former was famous when US National Geographic Society adopted it as their reference map of the world from 1992 to 1988 (Snyder, 1993) and the later was used by the NSW Department of Lands (GDA94). As the Van Der Grinten projection is neither equal-area nor conformal, we implemented Lambert conformal conic projection as well as Lambert Azimuthal equal-area projection as an alternative. The two standard parallels for the GDA94 Lambert projection are $-30^{\circ}45'00''$ and $-35^{\circ}45'00''$. The alternative mapping projections are included as the tool has potential for use beyond NSW, Australia.

2.2 Boundary

It is assumed that a boundary dataset is a set of limited points enclosing a geographical area of interest. The boundary is approximated as a set of joined linear lines between each two neighbouring points.

2.3 Interpolation

Inverse Distance Weighted (IDW) and Kriging interpolations are implemented in CCASAT.

IDW Interpolation: IDW is a simple and easy interpolation method for predicting unmeasured values. This method uses the weights directly calculated from the inverse of powered distances.

$$Z_p = \sum_{i=1}^n \left[\frac{d_{i,p}^{-k}}{\sum_{j=1}^n d_{j,p}^{-k}} Z_i \right] \quad (1)$$

Where $k = 1, 2, 3, \dots$, $d_{i,p}$ is the distance between the observed point i and the predicted point p ; Z is the value of the indices. Noticed that if $k = 0$, Eq. (1) becomes an interpolation which is calculated by the simple mean of nearby points. The main disadvantage of this method is the arbitrary definition of the interpolation which is directly related to distances (Mueller *et al.*, 2005).

Kriging Interpolation: In this scheme, interpolation is based on semi-variances which are calculated as

$$\gamma(d) = \frac{1}{2n} [z(x) + z(x+d)]^2 \quad (2)$$

where n is the number of pairs of sample points separated by distance d (called lag distance), $z(x)$ and $z(x+d)$ are the data values at the two paired locations (Bargaoui and Chebbi 2009). The relationships between the semi-variance and the lag distances are often nonlinear. In CCASAT, 13 equations are included for nonlinear regression of the semi-variance relationship. These equations include spherical, exponential, Gaussian models and their derivatives which have no intercept.

For each selection of indices the relationship between semi-variance and lag-distance needs can be evaluated and best fitted relationship are used for interpolation. To assist the selection of the best interception scheme, the Kriging with the best fitted equation and IDW interpolation methods were validated by leave-one-out cross validation (Liu 2007). The power of $k = 0, 1, 2, \dots, 8$ of IDW, ordinary Kriging and universal Kriging interpolations were compared by a number of statistical variables such as correlation coefficient (R^2) or root mean squared errors (RMSE).

To illustrate the validation of the interpolation methods, the change in the long-term annual averaged number of hot days are briefly discussed. The relationship between semi-variance and lag-distance was well described by a modified spherical equation (no intercept), with a R^2 of 0.986 (data not shown). Cross validation showed that the ordinary Kriging interpolation gave the best result of $R^2=0.969$, compared to IDW ($p=3$) with an $R^2=0.968$ which was the best interpolation over all 9 IDW interpolation. It also showed that IDW ($p=0$) gave an $R^2=0.959$, suggesting that even a simple mean of observations can give good interpolation. Similar results were obtained for other climate indices.

3. OVERVIEW CLIMATE CHANGE ADAPTATION STRATEGY ASSESSMENT TOOL (CCASAT)

Statistically downscaled climate data were obtained from the Bureau of Meteorology's statistical downscaling model (BoM-SDM) based on an analogue approach (Timbal and McAvaney, 2001; Timbal *et al.*, 2009). Daily GCM data were extracted from the Coupled Model Intercomparison Project N^o3 (CMIP3) assembled as part of the Intergovernmental Panel on Climate Change (IPCC) 4th Assessment of Climate Change Science released in 2007 (Solomon *et al.*, 2007). Because daily data are required to perform the statistical downscaling, only 12 out of 23 GCMs were used. Daily climate data were available for three time-slices: 40 years from 1961 to 2000 for the 20th century simulations and two 20 year periods from 2046 to 2065 in the middle of the 21st century and from 2081 to 2100 at the end of the 21st century. For future projections, two emission scenarios were considered (out of the 6 recommended by the IPCC (2000): A2, a high emission scenario and B1, a low emission scenario.

To analyse how the climate indices including temperature and rainfall have changed in NSW over the period 1961 to 2000, single site analysis can be undertaken in CCASAT. Plotting the time-series indices over historical record and the model time slices projections is available for any indices selected in any period in the year or season. Prior to examining how these indices may change in the future the user can evaluate the downscaled GCM by comparing results for the time-slice at the end of the 20th century against historical baseline information. Once a satisfactory downscaled GCM was found that provide suitable reproduction of a particular index, the user can evaluate the response of that index to climate change

CCASAT was developed to facilitate the analysis of the impacts of the climate change on a long list of important climate indices for agricultural applications. Wheat flowering was modelled by a phenological model as described by Liu (2007). This model has been included in CCASAT to highlight spatially how different climate change projections will alter flowering dates. Two genotypes (spring and winter) were

parameterized and incorporated in CCASAT. Wheat has been used to demonstrate the tool’s potential, but it has been designed in such a way as to allow a similar analysis for a range of other crops.

As a starting point, single site table allows for plotting of an index as a time series, (any period of the year can be plotted). In a second step, once an index is selected, spatial analysis can be performed to obtain pattern of impact across NSW. The impact of the GCM downscaled projections on that particular index (any combination of GCM, emission scenarios or period of the year) can be displayed. The GIS capacity of the tool is such that the graphics can be processed and displayed within seconds for a resolution of up to 500 m. The combination of the 19 indices and 12 GCMs with two emission scenarios gives 437 cases. In each case, the indices are calculated as cumulative distribution functions and represent either the current climate period 1961-2000 (I_{mc}), hind-casting period 1961 to 2000 (I_{hc}), projections by 2050 (I_{2050}), or 2100 (I_{2100}), change by 2050 (ΔI_{2050}), or 2100 (ΔI_{2100}) and errors (between I_{mc} and I_{hc}). A total of 24 GIS maps are thus created for each case (a total of 10,488 for one period of the year). This number is increased if more than one period, i.e. seasonal rainfall, or different crop varieties, are analysed.

It is well recognised that no single GCM perform better for every climate variables everywhere. Thus, user should evaluate GCMs performances for any specific climate index, and its spatial signature using the GIS mapping tool and comparing the distributions between the indices associated with the hind-casting of the historical record. This allows for the identification of the most suitable GCM for a specific index. In CCASAT, when an index is selected, the performance of all GCMs for the selected index is evaluated. The index calculated based on the GCM simulation of the 1961-2000 time-slice (hind-cast) and based on the historical record for the same period were considered as two populations. Kruskal Wallis test (KW) and the Median Test of Two Population (MT) (Kanji, 1993) were used to test the null hypothesis that the two populations being identical. KW tests were used if the GCMs projections for 1961-2000 and historical recordings for 1961-2000 were from two populations with the same mean, while MT tests were used if they were from two populations with the same frequency distribution.

GCMs were ranked based on the combined rank of the two χ^2 values (Fig 1). GCM performance varies depending on the index selected. MRI-CGCM 2.3.2, CSIRO-Mk 3.5 and GFDL CM2.0 were the overall best performer for averaged annual rainfall, extremes in maximum temperature and annual mean minimum temperature, respectively. The level of performance of the GCM differs according to the variable of interest; in the case of annual rainfall only one GCM performed well ($P < 0.05$ for Kruskal Wallis test and KW test), 8 GCMs were satisfactory according to the same test for mean minimum temperature. The results highlight the importance of GCM selection, a non trivial task as spatial analysis of all available GCMs and appropriate statistics are needed. The innovative design of CCASAT makes this task very quick as only a few seconds of computing time is required for processing these numbers and the results are displayed in an easy to analyse way .

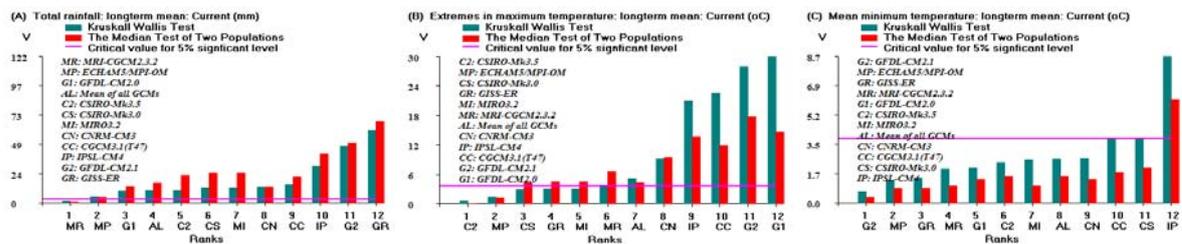


Figure 1. Statistical tests of GCMs performances for impacts of climate change on indices: d_h (A), f , (B) and d_{ff} (C)

4. CASE STUDY

4.1 Indices related the impacts of climate change on wheat flowering

The potential impacts of climate change on crop production is analysed using CCASAT. In order to provide guidance for an adaptation strategy for future wheat cropping systems, simple phenological models for two contrasting wheat genotypes were included. The phenology models and parameterisation procedures are explained in detail in Liu (2007). The climate depend parameters of these models were varied based on the scenario information (either A2 or B1) from the 12 GCMs from the CMIP3 database, downscaled using the BoM-SDM for two time-slices (by 2050 and 2090). These parameters included:

d_h , number of days when $T_{max} > 28.0$ °C, reflecting hot days for winter cropping;

d_f number of days when $T_{min} < 2.0$ °C, reflecting frost days;
 f flowering date, 50% wheat heads flowering .
 d_h and d_f were analysed for the period from 1 May to 30 November and flowering period from $f - 10$ to $f + 10$ days.

4.2 Impacts of climate change on frost days and hot days during winter crop period

With global warming, the GFDL-CM2.0 project that frost days by 2050 will decrease by up to 29 days (Fig. 2A), with a decline in excess of 12 days for almost 80% of the state. During winter crop growing periods, hot days are projected to increase by 2050 by up to 28 days, but 90% of NSW state are projected to have 12-28 days more hot days by 2050 (Fig. 2B). The projected increases in hot days show two distinct regimes: a coastal strip east of the Great Dividing Range (GDR) and the remaining area in-land. Increases in hot days are expected to be less than 16 days along the coastal strip but are projected to be 16 to 29 days in-land.

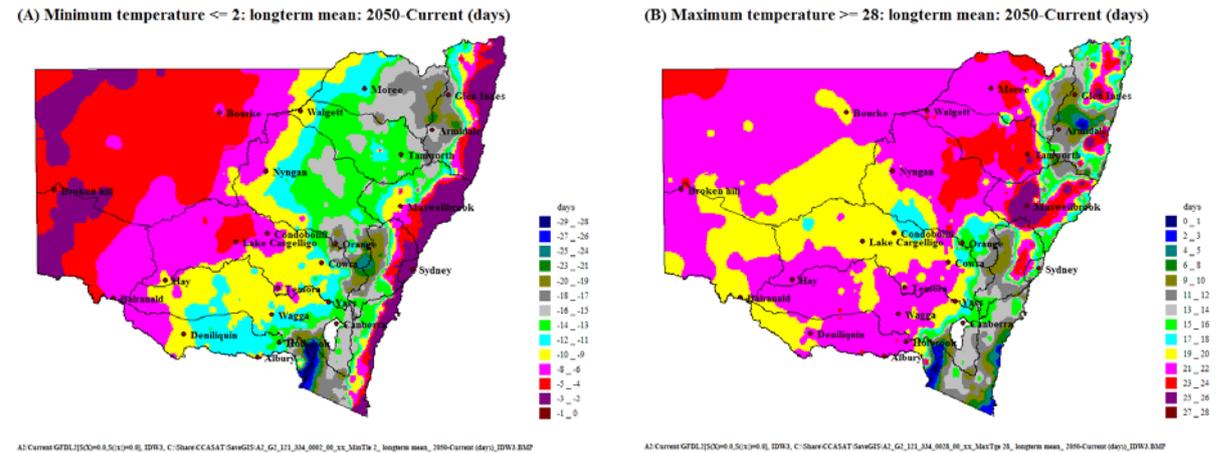


Figure 2. Changes in the number of days when $T_{min} \leq 2^{\circ}\text{C}$ (A) and $T_{max} \geq 28^{\circ}\text{C}$ (B) as projected by GFDL-CM 2.0 in NSW. The changes are the differences between long term means of 2050 (2046-2065) under A2 CO₂ emission scenario and current (1961-2000) during May and November.

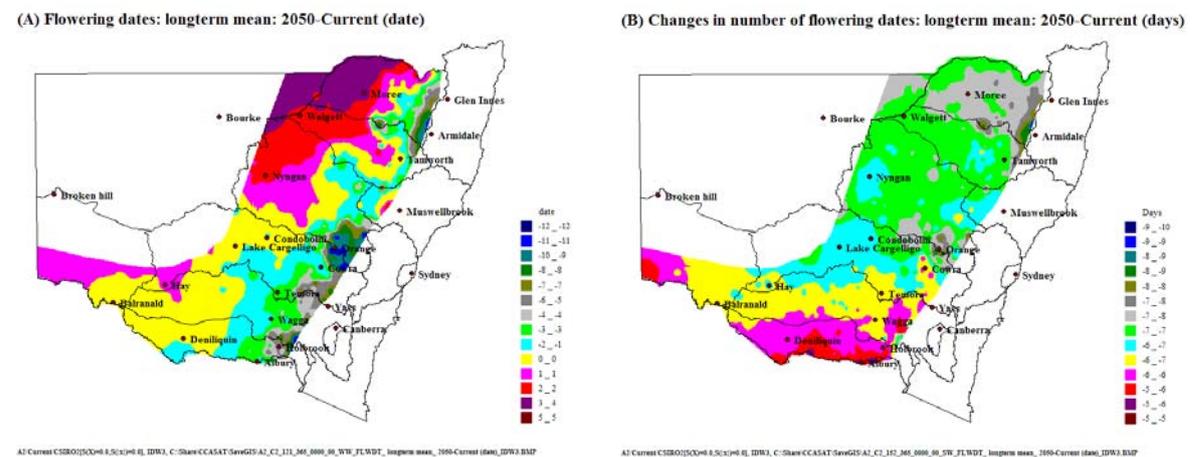


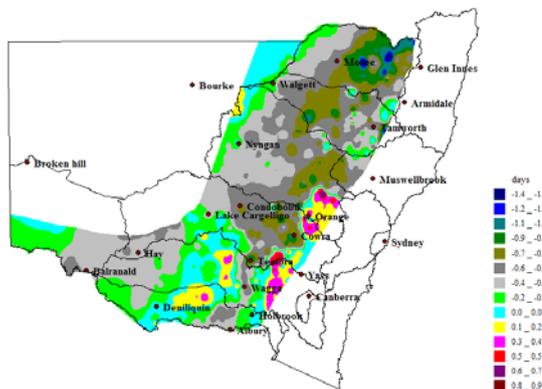
Figure 3. Change on winter genotype wheat flowering (A) and spring genotype wheat flowering (B) projected by CSIRO-Mk 3.5. The changes are the differences between long term means of 2050 (2046-2065) and current (1961-2000) flowering data when winter wheat sown on 1 May and spring wheat sown on 20 June. The projection was based on CO₂ emission scenario.

4.3 Impacts of climate change on wheat phenology

Currently, wheat flowering in NSW wheat belt ranges from mid September in the north-west to mid October in south-east of the NSW wheat belt. The flowering time of the two contrasting genotype wheats was simulated to be well within the current flowering time (data not shown). By 2050 under A2 CO₂ emission scenario projected by CSIRO-Mk 3.5, the flowering time of the winter genotype was to vary from 5 days

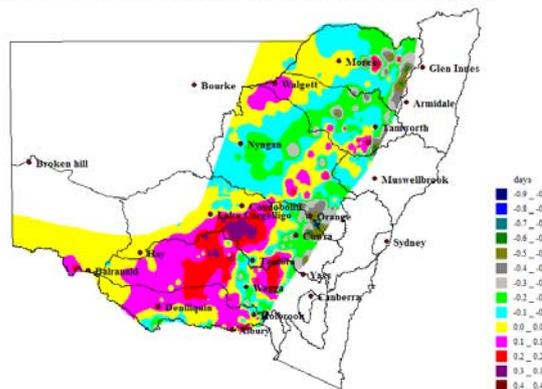
later in the north west to 11 days earlier in the central tablelands (Fig. 3A), while the flowering time of the spring genotype was within 4-7 days earlier than current timing across NSW (Fig. 3B). The winter genotype in the current cool environment will flower earlier as there will still be sufficient cool conditions for completion of vernalisation in projected climates of the future, and the projected warmer conditions would promote crop flowering. However, in the currently warm areas, further warming will result in insufficient periods of cool temperatures for vernalisation and hence flowering time of the winter genotype wheat will be delayed. As spring wheat genotype wheat does not require vernalisation, the warming conditions will make the crop flowering consistently earlier across the whole wheat belt of the state.

(A) No of frost days at flowering: longterm mean: 2050-Current (days)



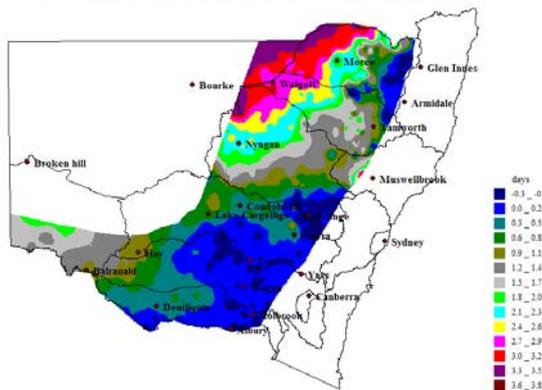
A1 Current CSIRO0000=0.5,CSIO=0.0, IDW3, C:\Share\CCASAT\GeoGIS\A1_CS_131_365_888_06_WW_NoFSTF_inspem_max_1650-Current (days)_IDW3.BMP

(B) No of frost days at flowering: longterm mean: 2050-Current (days)



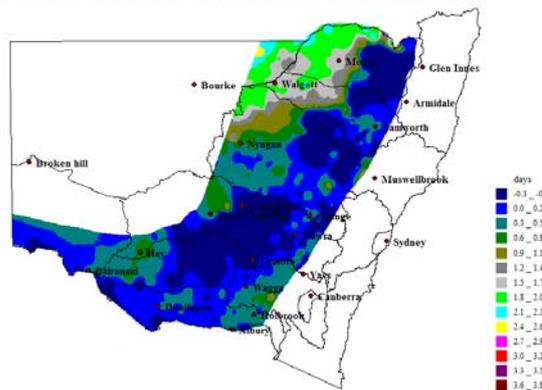
A1 Current CSIRO0000=0.5,CSIO=0.0, IDW3, C:\Share\CCASAT\GeoGIS\A1_CS_131_365_888_06_SW_NoFSTF_inspem_max_1650-Current (days)_IDW3.BMP

(C) No of hot days at flowering: longterm mean: 2050-Current (days)



A1 Current GISSR0000=0.5,CSIO=0.0, IDW3, C:\Share\CCASAT\GeoGIS\A1_GR_131_365_888_06_WW_NoHOT_inspem_max_1650-Current (days)_IDW3.BMP

(D) No of hot days at flowering: longterm mean: 2050-Current (days)



A1 Current GISSR0000=0.5,CSIO=0.0, IDW3, C:\Share\CCASAT\GeoGIS\A1_GR_131_365_888_06_SW_NoHOT_inspem_max_1650-Current (days)_IDW3.BMP

Figure 4. Change in number frost days (A, B) and hot days (C, D) at the flowering time of winter genotype (A, C) and spring genotype (B, D) wheat. Under A2 CO₂ scenario, changes in number of frost days were projected by CSIRO-Mk 3.0, while changes in number of hot days were projected by GISS-ER.

Figure 4 shows that in a future climate under emission scenario A2, the number of frost days in both winter and spring are projected to be slightly changed, ranging between -1.0 and +0.5 day for winter wheat and -0.6 and +0.3 day for spring, on average. CSIRO-Mk 3.0 projection was used as it is the best performance for the changes in number of frost days. However, under the same emission scenario, hot days during flowering time could be up to 5 days more for winter and 2 days more for spring, according to GISS-ER. About 30% of NSW wheat belt is projected to experience ≥ 2 days more hot days on average, which will impact on the winter genotype wheats. However, only 2% of NSW wheat belt is projected to experience ≥ 2 more hot days, on average in the spring, therefore impacting on the spring genotype.

5. DISCUSSION

CCASAT is a simple tool coded in VB6 without inclusion of any ActiveX GIS controls nor embedded external GIS software. It is a stand-alone GIS framework designed in a user-friendly manner for non-GIS skilled users. The tool can be used for analysing climate impacts, identifying the risks and opportunities that will need to be responded to, defining the agricultural and geographical area most sensitive to climate

change and identifying appropriate adaptation responses. Statistical tests of GCMs performances were provided to help users in selecting the most suitable GCMs for their specific indices. The tests were based on a spatial analysis. Such test is beyond the grasp of most commercial GIS software due to computing limitation but with the GIS-enabled CCASAT, it will only take 10 seconds to complete the spatial analysis of all 12 GCMs performances and present the results both graphically and in a tabular format. Since the tool does not rely on any database boundary, it is easily broadened to apply in other geographical areas including other Australia states or overseas.

This paper demonstrated the useful features of GIS-enabled CCASAT. An example analysis using the tool showed that the number of frost days in a future climate is not projected to change dramatically, however projected increases in hot days during wheat flowering time will be a serious problem. Selecting suitable wheat genotypes is the key adaptation strategy for managing the impacts of climate change on wheat cropping. Spring wheat genotypes appears to be more suitable in projected future climate over most area, while winter genotypes is projected to remain appropriate in limited areas where sufficient periods of cool temperature exist for completion of vernalization. Breeding strategies would be likely placed a focus on releasing varieties that do not require vernalization, but can be sown early in the season.

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