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Trends in wheat yields under representative climate futures: Implications for climate adaptation

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ABSTRACT

Underestimating the impacts of climate change on agricultural production could lead to complacency about the potential adaptation challenges. This study used a Representative Climate Futures (RCF) approach to model projected wheat yields under climate change in Australia. It simulated the range of impacts, resulting from a subset of individual Global Climate Models (GCMs), on wheat production in the major wheat regions of Australia. The study used RCFs that represented 'most-likely', 'best' and 'worst' cases across multiple Representative Concentration pathways (RCPs). Median wheat yields modelled for the South West Australia projected declines between 26% and 38%, under a 'most-likely' case for RCP 4.5 by 2090, and between 41% and 49%, under a 'most-likely' case for RCP 8.5. Median wheat yields declined under RCP 8.5 for the 'most-likely' case across the majority of wheat producing regions, with a range of 1% to 49%. Greater declines were projected under the 'worst' cases of hottest and driest climates. However, the 'best' cases of least warm and wetter climates projected an increase in median wheat yield, a range of 2% to 87%. Variability also changed from the baseline under all projected RCFs and across all regions, with a standard deviation of up to 2.46 t/ha under the 'most likely' case at a site in south-eastern Australia. These likely shifts in the size and reliability of yields, combined with concurrent climate change impacts on other factors, mean that agriculture faces significant adaptation challenges, particularly under some of the 'most-likely' scenarios and all of the 'worst' case scenarios. Further work is required to explore how scenarios in one region relate to those in other regions and thus the overall outcome at the continental scale.

1. Introduction

Australian agriculture has developed to cope with a climate that is highly variable, spatially and temporally. This has influenced the choice of farming systems, management practices, productivity, product quality and costs (Howden et al., 2013). Against a backdrop of longer-term climatic trajectories, the unpredictability of Australia's weather patterns is projected to increase with climate change (CSIRO and Bureau of Meteorology, 2016). While temperatures are projected to increase with climate change, projections in rainfall vary between global climate models (GCMs) (Flato et al., 2013). These changes are projected to vary considerably between regions (CSIRO and Bureau of Meteorology, 2015). Overall, it is highly likely that the agricultural sector will need to increase its level of adaptation if it is to better manage the major uncertainties and other challenges ahead in order to ultimately maintain, or genuinely achieve, more efficient, profitable and sustainable production systems (Stokes and Howden, 2010; Whetton et al., 2012; Vermeulen et al., 2013, Prober et al., 2017).

Many climate change impact studies in agriculture have used either a single GCM (Bassu et al., 2011; Cullen et al., 2009; Anwar et al., 2007) or ensembles of GCMs (Asseng et al., 2013; Vermeulen et al., 2013). These studies incorporated projected climate parameters into agricultural models, which to broadly describe what Vermeulen et al. (2013) call impact approaches. These use statistical or mechanistic models that attach probabilities to possible outcomes under the given range of scenarios. Multi-model ensemble simulations generally provide more robust information than any single model (Randall et al., 2007). However, different GCMs produce different climate projections, presenting a range of plausible future climates. There is considerable disagreement regarding the selection of specific models for future impact

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studies, making it difficult to justify using a reduced sub-set of climate projections (CSIRO and Bureau of Meteorology, 2015).

One approach is to use a small set of best performing GCMs based on their ability to replicate features of the current climate, particularly for specific regions. There are more than 40 Global Circulation Models (GCM) used in the Coupled Model Inter-comparison Project Phase 5 (CMIP5) (CSIRO and Bureau of Meteorology, 2015). The benefits of using a subset selection of GCMs reduces the extraneous computations involved with modelling projected climate change using all of the GCMs used in CMIP5. However, selection can be influenced by bias, leading to inconsistencies across studies and confusion among policymakers (Ruane and McDermid, 2017). Furthermore, the exclusion of GCMs deemed of lower reliability might exclude the consideration of low likelihood, but high impact future regional climates of real significance to adaptation planning. To address these shortcomings, Whetton et al. (2012) developed the Representative Climate Futures (RCF) method in impact and adaptation assessment for the selection of GCMs to represent projected climate change across specified regions. This involved classifying projected changes from the full suite of climate models into classes and assigning relative likelihoods based on the number of climate models falling within those classes (Clarke et al., 2011).

The aim of the present study was to apply the RCF methodology to model the range of climate change impacts across the wheat producing regions of southern Australia, comparing these impacts and variability on future yields between regions and RCFs. The implications of the results for climate change adaptation are discussed.

2. Materials and methods

2.1. Sample sites

The Representative Climate Futures (RCF) approach was modelled at 10 sites within four Natural Resource Management (NRM) regions across southern and eastern Australia. Information on location and agro-ecological zone is presented in Fig. 1 and Table 1. All sites modelled were in the 'Temperate Seasonally Dry Slopes and Plains' agro-ecological zone (Williams et al., 2002), apart from Moree, which was defined as 'sub-humid, subtropical slopes and plains (Williams et al., 2002). Sites were selected on the availability of data and as representative of a region. For example, Charlton was representative of the Murray Basin NRM and Minnipa was representative of the Southern and SW Flatlands (East) NRM. Soil input data for each site was sourced from previous studies by Hunt and Kirkegaard (2011) and Chenu et al. (2011), where they provided input data for multiple sites, including those used in this study, across wheat production areas in Australia.

2.2. Climate data

For each site, historical daily climate data were used for a 31-year baseline period from 1980 to 2010 (SILO database, Jeffrey et al., 2001; http://www.longpaddock.qld.gov.au/silo/). Although the IPCC AR5 used baseline climate data from 1986 to 2005 and centred on the year 1995 (20 years), this study extended this baseline from 1980 to 2010 (31 years with 1995 as the centred year), in order to better capture variability between years for the analysis. Weather data were obtained on a daily time step, with variables consisting of solar radiation (MJ/m2/day), minimum and maximum temperatures (°C), rainfall (mm), evaporation (mm) and vapour pressure (hPa) (Jeffrey et al., 2001). The Representative Concentration Pathways (RCPs) used in this study were sourced from the pathways described in Van Vuuren et al. (2011), being RCP4.5 and RCP8.5. These were selected to represent the highest and lowest (stabilization) impact scenarios.

2.3. Global climate models and the representative climate futures

A set of RCFs was used to describe plausible future climates across the study regions (Whetton et al., 2012). The RCFs formed a typology of selected climate variables (Clarke et al., 2011; Whetton et al., 2012). They were based on a multi-purpose decision-support tool to assist understanding and applying of climate change projections for impact assessment and adaptation planning (Clarke et al., 2011). The RCFs were derived from a web-based tool, hosted by the CSIRO Climate Change in Australia project (www.climatechangeinaustralia.gov.au). They were created in this study via a four step process: the first involving the generation of the RCFs; the second being the examination and application of the model results; the third being the identification of a representative GCM for each key climate future; and the final step involved the application of the results in the impact assessment (Fig. 2).

The individual GCM climate variables consisted of rainfall, solar radiation, maximum and minimum temperature, which corresponded to the inputs required for The Agricultural Production Systems sIMulator (APSIM) model (Keating et al., 2003). The NRM regions selected for analysis were the Southern and SW Flatlands West, the Southern and SW Flatlands East, the Murray Basin and the Central Slopes. The full suite of available GCMs was used and individual GCMs were organised into a 'most likely' case, a 'best' case and a 'worst' case. The 'most likely' case consisted of at least 30% or more of total number of GCMs that were aligned around the changes in relation to the baseline climate. The 'best' case was defined as the climate future resulting in the highest rainfall and 'least-hot'. The 'worst' case was defined as the climate future resulting in the least rainfall and 'most hot' (Whetton et al., 2012). Each GCM was ranked against a multivariate ordering technique according to the mean, minimum and maximum (Kokic et al., 2002). The GCM closest to the multi-model mean of the 'most likely' case was selected, along with the GCMs aligning with the minimum and maximum being selected for the 'best' and 'worst' cases, respectively. The RCF outputs were the smoothed average of the GCM grid cells across each NRM zone. These consisted of monthly percentage changes for rainfall and solar radiation and increases in degrees Celsius for maximum and minimum temperature. These delta change factors were applied across local climate information for each site (Cullen et al., 2009). The year 2090 was used for the analysis, because the climate signal would be strongest under both RCPs. The year 2050 was used as the mid-point of the analysis. Projections under respective GCMs grouped under 'worst', 'most-likely' and 'best' cases for 2090 were assigned the same cases for 2050, irrespective of their respective projections for 2050, so as to keep the GCM selection consistent throughout the analysis.

2.4. Cropping simulations

The cropping systems model APSIM-Wheat (Keating et al., 2003) was used to project the potential effects of the study ensemble on wheat crop productivity at the sample sites (Luo and Kathuria, 2013). APSIM has been validated in several studies that matched modelled yield with observed yield (Asseng et al., 1998, 2004; Probert et al., 1995; Luo et al., 2003). A number of studies have analysed wheat yields and changes under projected climate change for the wheat producing regions used in our study (Hochman et al., 2017), including South Australia (Luo et al., 2005), Victoria (Anwar et al., 2007), southeast Australia (Anwar et al., 2015) and south west Australia (Ludwig and Asseng, 2006).

APSIM contains an array of modules (Keating et al., 2003). The key modules deployed in this analysis were Wheat (wheat crop growth and development), management (setting crop management procedures), Water, Soil Organic Matter, Soil Water (soil water balance), Initial Water (initial water balance), Initial Nitrogen, climate control and daily time step weather data for the period of the simulation. Potential crop water uptake was simulated via relationships with root exploration and extraction potential (Keating et al., 2003). Where water was a limiting factor, above-ground biomass accumulation was the product of available soil water and conversion efficiency in transpiration, which was