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Seasonal climate forecasts provide more definitive and accurate crop yield predictions

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ABSTRACT

As a cropping season progresses yield forecasts become more reliable. Optimal management strategies however rely on early estimates of climate and yield. These estimates are usually derived from the historic range of climate variations applied to current crop conditions. Early in the season these predictions are wide ranging as they incorporate all past historic climate variability and hence a large range of possible yields. Dynamical seasonal climate models offer the opportunity to narrow this range contingent on the models having adequate predictive skill. This study explores the benefits of using a climate model over historical climate to predict wheat yield in the Australian cropping zone throughout the cropping season. We take an ensemble of daily outputs of temperature, radiation and rainfall from a seasonal climate model (POAMA) and apply a simple downscaling and calibration to align with 57 stations across the Australian cropping zone. These data are then used as an input to a crop model (APSIM) to translate seasonal conditions into a yield prediction. Simulations deploy historic weather data up to a date on which forecast data replace measured data. Here we used a range of dates (April to October) through the cropping season for the period 1981 to 2015, to determine where and when the forecast is skilful compared to using the full weather record up to harvest. The forecasts are categorised in three yield categories low (decile 1–3), average (4–7) and high (8–10) and determined to be 'misleading' if they predict low instead of high or vice versa. In the west and south of Australia less than 3 years in 20 give a misleading forecast in April, and less than 1 in 20 years by August. The forecast for east of Australia has less skill primarily due to a strong rainfall bias with the climate model not being able to simulate the correct daily rainfall patterns. Compared to the predictions gained from using the full range of historical climate, POAMA derived forecasts have a narrower prediction range than the climatology driven ones, however this comes at the expense of a higher number of misleading forecasts. Nevertheless, in June (August) the POAMA driven simulations have a greater than 65% (80%) chance of being in the correct or one category out, which was higher than using climatology in each region at the same lead time. The baseline set by this study demonstrates the potential utility of dynamic climate models to predict yield, which should only improve with on-going advances in climate modelling and techniques in downscaling.

1. Introduction

Climate variability is important to global agriculture as it drives production variability, particularly in the dryland semi-arid tropical and subtropical zones of Southern Asia (Bantilan and Anupama, 2002; Meinke et al., 2006; Cooper et al., 2008; Aggarwal et al., 2010; Balaghi et al., 2010; Coe and Stern, 2011) and Sub Saharan Africa (Cooper et al., 2008; Coe and Stern, 2011; Rurinda et al., 2014) as well as for Australia where dryland farmers face extremely variable rainfall (Nicholls et al., 2006; Ash et al., 2007) and thus extreme variation in potential and actual grain production (Anderson, 1979; Hochman et al., 2017).

Being able to forecast climate variability in time to make pertinent cropping decisions could be of considerable value. Current tools use historic climate variability to represent possible futures (e.g. CropARM Nelson et al., 2002 http://www.armonline.com.au/#/ca and Yield Prophet https://www.yieldprophet.com.au/ Hochman et al., 2009). The down side to this approach is that the range of possible futures is wide and so not able to effectively inform management decisions. It is possible to narrow the range of analogue years using indices such as the

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SOI phase system (Stone and Meinke, 2005), however this has been shown to perform more poorly than using the full historical record (Rodriguez et al., 2018). Here we investigate how to narrow this range of future outcomes by instead using a gridded dynamical seasonal climate forecast (POAMA; Hudson et al., 2017) to inform crop models and how this might contribute to on-farm decision making.

The promise of reliable seasonal climate forecasts is that they would enhance a farmer's ability to flexibly adjust investments in farm enterprises by taking full advantage of the few good seasons and by avoiding the risks associated with seasons which ultimately turn out poorly. (Hochman et al., 2009, 2013). Yet, probabilistic seasonal forecasts are a complex technology for farmers and advisers to adopt as an aid to risk management. This is partly because, at current levels of accuracy, clear thinking is required to incorporate imperfect information into planning (Hayman et al., 2007). Further, knowing a rainfall forecast is not necessarily the same as estimating crop yield. This extra step involves incorporating climate models into crop models.

In Australian farming systems information about yield prospects, if available at sowing time in April, can help determine the initial nitrogen application however at this time there is low climate forecast skill. By June the predictability barrier associated with El Niño Southern Oscillation has passed and our climate forecasts tend to become more reliable (Clarke, 2014) and may influence some in-crop decisions such as the level of inputs to control biotic stresses such as weeds, pests and diseases. Climate forecasts in August for the remainder of the cropping season have even higher skill due to the impact of the season to date on yield potential. An August forecast can be used to make the final nitrogen application decisions and, when conditions have been below average, to help decide whether to cut the crop for hay while it is green or to keep the crop in the hope of a more profitable grain harvest.

To address these decisions as the cropping season progresses some agricultural decision support systems (DSS) have integrated seasonal climate information with pre-sowing soil data using crop models including APSIM (Holzworth et al., 2014) and DSSAT (Hoogenboom et al., 2015) to predict production prospects (e.g. grain yield). Using historical climate information to represent the full range of climate variability in these cropping systems provides a probabilistic forecast of potential yields for the year ahead assuming that past climate is the best indicator of future prospects (Hochman et al., 2009). Because this method uses all possible historic climate it necessarily leads to a wide range of possible yields, especially early in the season. A more definitive and accurate forecast would be of greater benefit to farmers in making a decision. In this study we evaluate an alternative method of directly inputting the daily climate model forecasts into the crop model. We then compare the skill of the climate model based yield forecast against the skill of the historic climate based forecast.

There are challenges involved in using a climate model over a local historical weather record or statistical approaches. Outputs from climate models are generated on a coarser grid than what is required for farm-scale crop forecasts and must be locally downscaled and calibrated to reduce inherent biases and overcome the 'connectivity problem' (Stone and Meinke, 2005; Ines et al., 2011; Han et al., 2017; McIntosh and Brown, 2017). Nevertheless, the scientific understanding and skill of dynamic seasonal climate models continues to improve. Studies, such as Charles et al. (2015), suggest that forecasts of seasonal rainfall from dynamic climate models now supersede the previously used statistical techniques. Dynamic model approaches are expected to be superior to statistical methods as they allow for forecasts that incorporate the effects of a number of climate modes, rather than just the Southern Oscillation Index which is not the only driver of climate variability (Brown et al., 2009). It is therefore timely to explore whether these models can be used directly as inputs to force crop models and whether these forecasts provide any advantage over using climatology to inform crop models. We hypothesize that probabilistic predictions of water limited potential wheat yield will be more useful and more skilful when obtained from crop models driven by gridded daily output from seasonal climate models than when driven with the historical climate record.

We answer this question by exploring the yield prediction capability of a system that translates climate forecasts to water-limited yield potential forecasts. In this study we use climate predictions from the Australian Bureau of Meteorology seasonal climate model POAMA (Hudson et al., 2013) as input into the Agricultural Production Systems sIMulator's (APSIM; Holzworth et al., 2014) wheat crop model. APSIM is a farming systems modelling framework that contains interconnected models to simulate systems comprising soil, crop, tree, pasture and livestock biophysical processes

2. Method

2.1. Climate-crop yield modelling system

Running a complex climate model coupled to a crop model is only valuable if it can offer an improvement to the result that would be obtained from simply using historical climatology with a crop model. We explore wheat forecasts over the same time periods and locations to contrast the use of an ensemble of historical weather data with an ensemble of model predictions. Here we use the daily weather output from a dynamic seasonal climate model (POAMA) as the input to a crop model (APSIM) to predict water limited yield potential. The study is conducted for 57 stations over the Australian wheat belt for their growing season from April to October (detailed later in Fig. 5). We assess the performance of the climate forecast by its ability to simulate water-limited yield potential compared to the water-limited yield potential obtained from using observed weather data (SILO; Jeffrey et al., 2001) that drives the same crop model, initialised with the same parameters.

The climate input data is taken to be the observed weather up until the 'start date' when 33 POAMA weather data sets are then concatenated to the observed weather to give 33 possible futures. The start date is taken to be the first of each month over the growing season April to October, and for the years 1981–2015. The climate variables used are daily maximum and minimum temperature, radiation and rainfall. These variables are first calibrated against observed weather using a quantile mapping approach which is available at www.agforecast.com.au (McIntosh and Brown, 2017). At each station we have 35 years of hindcasts with a 33 member ensemble at each of seven start months. This is a total of 1155 APSIM simulations per station, making a total of 460,845 runs across Australia.

The skill of the POAMA-APSIM system is compared with the skill of using historical climatology data as input to APSIM. This climatology approach assumes that the coming year will lie somewhere in the range of what has happened in the last 30 years. Each year's initial conditions are put into APSIM but then 30 runs are conducted using each past year's weather information. This provides a probabilistic outcome comparable to the probabilistic outcome provided by the 33 POAMA ensemble members. Any seasonal climate forecasting system needs, at the very least, to outperform what can be obtained from a climatology analysis.

Water limited yield potential was simulated by running a continuous wheat-fallow system using sowing and nitrogen fertiliser rules that ensured yields were only limited by climate and water conditions. On the east coast of Australia north of Dubbo (latitude -32.244), wheat crops were sown if 15 mm rainfall occurred over 3 days between 26 April and 15 July (the traditional wheat sowing window in the Australian cropping zone) and the soil had at least 30 mm of plant available water in the zone of maximum rooting depth. At all other locations wheat crops were sown if 15 mm rainfall occurred over 3 days between 26 April and 15 July regardless of soil moisture. If the sowing criteria was not met during the sowing window, crops were sown on 15 July. To ensure that nitrogen is non-limiting while avoiding excess