Seasonal Climate Forecasts-An Important Tool in Managing the Risk of Extreme Weather Events in Australia's Wheat Industry

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Abstract
Extreme weather events (EWEs) such as frost, heat stress and terminal drought at reproductive stages are key risk factors in Australian cropping industries and can lead to significant economic losses. This study aimed to investigate the benefits of using a state-of-the-art seasonal climate forecast (SCF) system in managing such risks through contingent decision-making in Australia's wheat industry. Six locations in eastern Australia, three cultivars with varying maturities, and 17 times of sowing were considered. Seasonal hindcasts from the Australian Community Climate and Earth-System Simulator-Seasonal Version 2 (ACCESS-S2), initialized on the 1st of May for the period 1981-2018 were linked with the Agricultural Production System sIMulator (APSIM)-Wheat model (v7.10) to achieve the research aim. Research results showed that (1) ACCESS-S2 showed a more than 10% skill improvement in predicting the occurrence of EWEs and in predicting above/below long-term median wheat yield in most of the cases at a seasonal lead time; (2) 68% of cases had a yield gain using SCF information; (3) across all cases, there was an average yield gain of 281 kg/ha, representing an increase of 13%; and (4) the benefits of using SCF were seen across 69% of predicted wet years, 65% of predicted neutral years and 72% of predicted dry years. Overall, there is a demonstrated benefit in utilizing ACCESS-S2 forecasts in the Australian wheat industry through improved decision-making in managing EWEs. Such a benefit can occur in any climate-year pattern but with dry years being more likely and significant.

Key words
ACCESS-S2, seasonal forecasts, extreme weather events, wheat yield, time of sowings, cultivar maturities.

Introduction
Application of skillful seasonal climate forecast (SCF) information is recognized as one of the most important strategies to manage the risk and/or to capture the opportunity of climate variability through improved farm management. Recent application of SCF has focused on the use of global climate model (GCM)-based SCF information to improve farm management and in predicting crop yield. Rodriguez et al. (2018) reported that SCFs from the Predictive Ocean Atmosphere Model for Australia can be used to increase farmers' profits and reduce risks. Brown et al. (2018), Potgieter et al. (2022) and Iizumi et al. (2018) concluded that the use of GCM-based SCF systems improved crop yield prediction at national, regional and global scale, respectively.

Extreme weather events (EWEs) such as drought, heat stress and frost cause significant economic losses and impact the social fabric of farming communities. Their combined risk on wheat yield can be managed by identifying and adopting the optimal combination of cultivar maturity and time of sowing (TOS). Crop modeling is well suited for this purpose. Using a modeling approach, Luo et al. (2018) identified an optimal combination of wheat cultivar maturities and TOS in managing the risk of EWEs. However, SCF information was not applied for contingent decision-making in managing this risk. The hypothesis here is that timely and skillful SCF will provide benefits in managing the risk of EWEs in Australia's wheat industry. This study aims to assess the forecast skill of a state-of-the-art SCF system, the Australian Community Climate and Earth-System Simulator-Seasonal Version 2 (ACCESS-S2), and to quantify the yield benefits of using SCFs in managing the EWE risk to Australia's wheat industry.

Methods
Study locations
Six wheat production areas in eastern Australia were chosen for this study. The geographic information and growing season rainfall (GSR, Apr.-Oct. inclusive) for each location are given in Table 1.

Table 1 Geographic Information and Growing Season Rainfall (GSR)

Locations	States	Longitude (ºE)	Latitude (ºS)	GSR (mm)	Rainfall areas
Roma	Queensland	148.78	-26.57	236	Lower rainfall area
Goondiwindi		150.30	-28.55	263	Medium rainfall area
Condobolin	New South Wales	147.12	-32.9	243	Lower rainfall area
Temora		147.53	-34.45	308	Medium rainfall area
Ouyen	Victoria	142.32	-35.07	207	Lower rainfall area
Horsham		142.20	-36.70	284	Medium rainfall area

Climate data

Historical daily solar radiation, rainfall, maximum and minimum temperature, evaporation and vapor pressure for the six production areas and for the period from 1981-2018 were sourced from the Scientific Information for Land Owners (SILO) database (Jeffrey et al., 2001) at https://www.longpaddock.qld.gov.au/silo/point-data/. Calibrated daily ACCESS-S2 hindcast data of rainfall, maximum and minimum temperature initialized on the 1st of May each year at a seasonal lead time for the period 1981-2018 were obtained from Australian National Computational Infrastructure (https://dapds00.nci.org.au/thredds/catalog/ux62/access-s2/hindcast/calibrated/atmos/catalog.html). The hindcast data are composed of three burst ensembles and 9 time-lagged ensembles yielding 27 ensemble members in total (Wedd et al., 2022).

The APSIM-Wheat model and its parameterization

The APSIM-Wheat model v7.10 (Holzworth et al., 2014) was used to characterize the occurrence of frost, heat stress and drought events, estimate their combined impact on final wheat grain yield and identify the optimal combination of TOS and cultivar. Detailed management information including sowing is given in Table 2. Soil profile data were accessed from the APSIM APSoil database (https://www.apsim.info/apsim-model/apsoil/). Initial soil water was set at 20% of the plant available water capacity. Soil water, nitrogen and surface organic matter were reset at sowing. Management options considered to mitigate the risk of EWEs included changes in TOS and wheat cultivar maturities. Seventeen TOS were considered starting from 10th April to 31st July at an interval of one week. Three cultivars-*gregory*, *suntop* and *mace* with the characteristics of mid-late maturing, mid maturing and early maturing, respectively, were used. For the skill assessment of ACCESS-S2, simulated results for the period 1981-2018 associated with the 1st of May sowing and cultivar *gregory* were used as the climatological reference.

Table 2 Management information set in the APSIM-Wheat model

Locations	Urea_N at sowing (kg/ha)	Surface Organic Matter (kg/ha)	Cultivars	Sowing Information			
				Time	Density (plant/m^2)	Depth (mm)	Row Spacing (mm)
Roma	80	1000	*gregory, suntop, mace*	10th April - 31st July	100	30	250
Goondiwindi	120	1500					
Condobolin	80	1000					
Temora	120	1500					
Ouyen	80	1000					
Horsham	120	1500					

Skill assessment of ACCESS-S2

The occurrence of EWEs are rare events. One such skill metric that can be used for determining the ACCESS-S2 forecast skill for rare binary events is the Symmetric Extremal Dependence Index (SEDI) score (Cowan et al., 2022). The SEDI skill score is a function of the hit rate (H) and false alarm rate (F). The SEDI is defined in Eq. (1):

$$\text{SEDI} = [\log F - \log H - \log(1\text{-}F) + \log(1\text{-}H)] \,/\, [\log F + \log H + \log(1\text{-}F) + \log(1\text{-}H)] \ldots\ldots(1)$$

H and F are determined from a 2×2 contingency table (Ferro and Stephenson 2011). A SEDI score greater than zero indicates better skill than random forecasts, whereas values less than zero are worse than a random forecast (White et al. 2014). A SEDI score of 0.2 represents a 20% skill improvement over random chance.

For assessing the skill of the ACCESS-S2 in predicting wheat yield, the Brier Skill Score (BSS) was used which is based on the determination of the Brier Score (BS, Eq. 2) for both hindcast and climatology situations. The BSS describes the relative skillfulness of a prediction relative to a reference forecast (Eq. 3).

$$BS = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2 \ldots\ldots(2); \qquad BSS = 1\text{-}BS/BS_{ref} \ldots\ldots(3)$$

Where P_i is the hindcast probability of exceeding the climatological median of the wheat grain yield over the hindcast period, O_i is the observed outcome, N is the total number of hindcasts based on the 1st of May start date (38 years). BS is mean squared probability forecast error, and BS_{ref} is the reference Brier Score.

Data analysis

The 30th and 70th percentile rainfall for the period 1981-2018 based on SILO dataset were quantified across locations and used to classify hindcast climate year patterns as: dry, neutral and wet. A Wilcoxon-test and the one-way analysis of variance (ANOVA) were used to examine whether there is a significant difference in the mean of simulated yield between baseline management and those optimized across all years and the three climate-year patterns, respectively.

Yield benefits of using ACCESS-S2

There are three steps in quantifying the wheat yield benefits: (1) optimal management strategies based on hindcast information were identified, which corresponded to the simulated highest wheat yield; (2) baseline management scenario was determined based on historical climate data, which corresponded to the intermediate mean wheat yield for the study period; (3) the benefits in using SCF for a specific year were calculated as the yield difference between yields driven by optimal management option as informed by SCF- dot point (1) and driven by baseline management as defined in dot point (2).

Results

Skill assessment of ACCESS-S2

Twelve out of 18 cases (three EWEs × six locations) showed a more than 10% forecast improvement over a random forecast in terms of their SEDI score (Fig 1). Among the three EWEs considered, ACCESS-S2 performed the best in predicting the occurrence of soil moisture stress with all locations showing a skill improvement of more than 10%, followed by predicting the occurrence of heat stress and then predicting the occurrence of frost events. In terms of the BSS associated with forecasting wheat yield, ACCESS-S2 showed a skill improvement greater than 10% over a climatological reference at four locations (Fig 2).

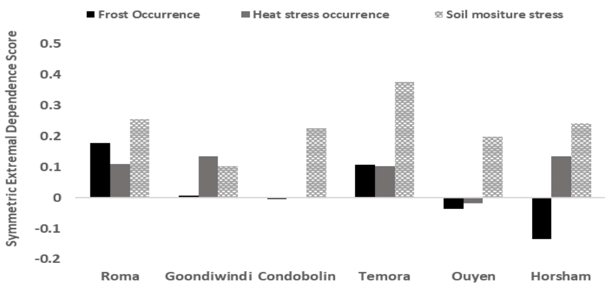

Fig 1 Symmetric Extremal Dependence Index (SEDI) scores for the predicted occurrence of extreme weather events during wheat flowering and grain filling periods at a seasonal lead time.

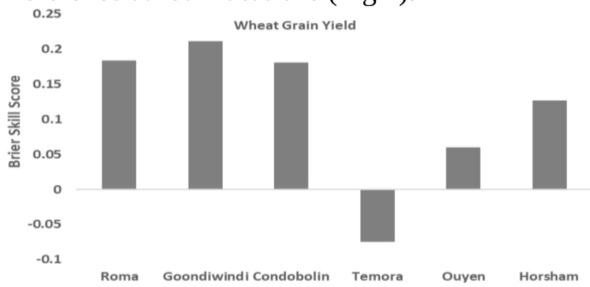

Fig 2 Brier skill score for forecast of above/below long-term median wheat grain yield at a seasonal lead time.

Wheat grain yield

For all years, the magnitude of yield gain under optimized management varied from location to location with the greatest gain at Ouyen (503 kg/ha), and the smallest gain at Horsham (119 kg/ha). Medium rainfall areas such as Horsham and Temora produced the least relative yield gain (4~6%) (Table 3). Wilcoxon test results showed that the difference in the mean of grain yield between optimized and baseline management is significant across all locations except Temora (Table 3). Regarding the three climate-year patterns, yield gain occurred across all locations in dry years ranging from 399 to 1692 kg/ha with a relative increase of 33%-176% (Table 3). However, yield enhancement was only found at half of the locations in neutral years. In wet years, yield gain was found in most of the locations except the medium rainfall sites (i.e. Temora and Horsham) (Table 3). The ANOVA test results showed that yield gain in dry years is significant across all locations except Horsham and non-significant in other climate-year types (Table 3).

Table 3 Changes in mean wheat grain yield between optimized and baseline management scenarios and statistical test results for the period 1981-2018

Locations	All Years[1]		Dry Years[2]		Neutral Years[2]		Wet Years[2]	
	AC[3] (kg/ha)	RC[4] (%)	AC (kg/ha)	RC (%)	AC (kg/ha)	RC (%)	AC (kg/ha)	RC (%)

Roma	150^{**}	20	399^{*}	78	30	4	391	38
Goondiwindi	374^{**}	32	1119^{*}	176	-84	-9	1238	65
Condobolin	340^{*}	13	1613^{*}	87	-223	-9	436	12
Temora	201	6	1692^{*}	93	-190	-5	-737	-15
Ouyen	503^{***}	28	1177^{**}	112	443	26	23	1
Horsham	119^{**}	4	634	33	124	4	-483	-12
All locations	281^{**}	13						

*1: Wilcoxon- test, 2:one-way ANOVA, 3: absolute change, 4: relative change, *: significant at 0.05 level; **: significant at 0.01 level; ***significant at 0.001 level.*

There are 228 cases in total (six locations × 38 years), of which, 154 cases (68%) showed a yield gain arising from optimized management options due to the use of SCFs from ACCESS-S2 (Table 4). The average yield gain across all cases is 281 kg/ha compared with a baseline management situation, which represents a significant increase of 13% (Table 3). Of the 154 cases which had a yield gain, 34, 89 and 31 cases occurred in wet, neutral and dry years respectively, accounting for 69%, 65% and 72% of the predicted wet, neutral and dry years, respectively (Table 4).

Table 4 Summary statistics of wheat grain yield

Case Categories	Number of Cases	Yield gain Cases	Proportion (%)
Total	228	154	68
Wet year	49	34	69
Neutral year	136	89	65
Dry year	43	31	72

Conclusions

ACCESS-S2 showed substantial and consistent skill (over 10% improvement across locations) in predicting the occurrence of soil moisture stress events with the least skill in predicting the occurrence of frost events and intermediate skill in predicting the occurrence of heat stress and in predicting above/below long- term median wheat yield at a seasonal lead (Figs 1-2). There is a demonstrated yield gain across locations with an average of 281 kg/ha and a relative increase of 13%. Yield gain can occur in any climate-year pattern but with dry years being more likely (Table 5) and significant (Table 4). We conclude that the costly impact of EWEs in the Australian wheat industry can be mitigated by combining skillful SCF information such as from ACCESS-S2 with a robust decision-making tool. This will lead to substantial yield gain in the Australian wheat industry especially in drier environments through contingent decision-making.

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