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A method for simulating risk profiles of wheat yield in data-sparse conditions

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Abstract

Process-based crop models are a robust approach to assess climate impacts on crop productivity and long-term viability of cropping systems. However, these models require high-quality climate data that cannot always be met. To overcome this issue, the current research tested a simple method for scaling daily data and extrapolating long-term risk profiles of modelled crop yields. An extreme situation was tested, in which high-quality weather data was only available at one single location (reference site: Snowtown, South Australia, 33.78°S, 138.21°E), and limited weather data was available for 49 study sites within the Australian grain belt (spanning from 26.67 to 38.02°S of latitude, and 115.44 to 151.85°E of longitude). Daily weather data were perturbed with a delta factor calculated as the difference between averaged climate data from the reference site and the study sites. Risk profiles were built using a stepwise combination of adjustments from the most simple (adjusted series of precipitation only) to the most detailed (adjusted series of precipitation, temperatures and solar radiation), and a variable record length (from 10 to 100 years). The simplest adjustment and shortest record length produced bias of modelled yield grain risk profiles between −10 and 10% in 41% of the sites, which increased to 86% of the study sites with the most detailed adjustment and longest record (100 years). Results indicate that the quality of the extrapolation of risk profiles was more sensitive to the number of adjustments applied rather than the record length per se.

Introduction

As climate change intensifies, agricultural decision-makers are increasingly interested in the potential impacts such changes will make on crop productivity, and in the level of probability associated with the different impacts. Arguably, the most robust approach for simulating climate impacts on cropping productivity is the use of process-based models. These models account for complex interactions between the climate, soil, genotype and management affecting crop yield (Keating *et al.*, 2003; Stöckle *et al.*, 2003; van Bussel *et al.*, 2011; Grassini *et al.*, 2015; Van Wart *et al.*, 2015). However, meaningful crop model outputs (e.g. crop yield) can only be achieved when the parameters of the model have been appropriately calibrated, crop management options are realistically represented in the simulation, and the input weather data are accurate and reliable (Lamboni *et al.*, 2009; Liddicoat *et al.*, 2012; Grassini *et al.*, 2015). From this list of requirements, the lack of accurate and reliable weather data remains a common problem, particularly in developing countries.

Considerable effort has been devoted to developing protocols for enhancing observed weather data coverage for crop yield-gap analysis, crop yield projections and climate impact assessments (van Ittersum *et al.*, 2013; van Wart *et al.*, 2013; Watson and Challinor, 2013; Grassini *et al.*, 2015; Zhao *et al.*, 2015). There is also an important number of global gridded data sets available, that have been produced using sophisticated methods and validated with a vast number of observations and data derived from remote sensing around the globe (Ruane *et al.*, 2015; Hersbach *et al.*, 2020). However, these data sets cover a limited time period (between 20 and 40 years), and their validity relies on the density of weather stations, on the climate variables measured and record length of the available data, which is spatially highly variable and often low in the tropics, and in remote and rural areas. There is therefore the need to develop methods for reducing the dependency on a dense network of weather stations with high-quality and long-term observations, especially in data-sparse environments.

Regional land-use planning and on-farm management require a solid understanding of the long-term viability of production systems in a variable future climate. In fact, one of the core components of current agricultural decision-support systems is the risk profile – or cumulative probability – of crop yield under different management options (Hunt *et al.*, 2006; Hochman *et al.*, 2009; Hayman *et al.*, 2010b; Hochman and Horan, 2018). The risk profile is particularly useful for reducing climate uncertainty and making better management decisions (Meinke

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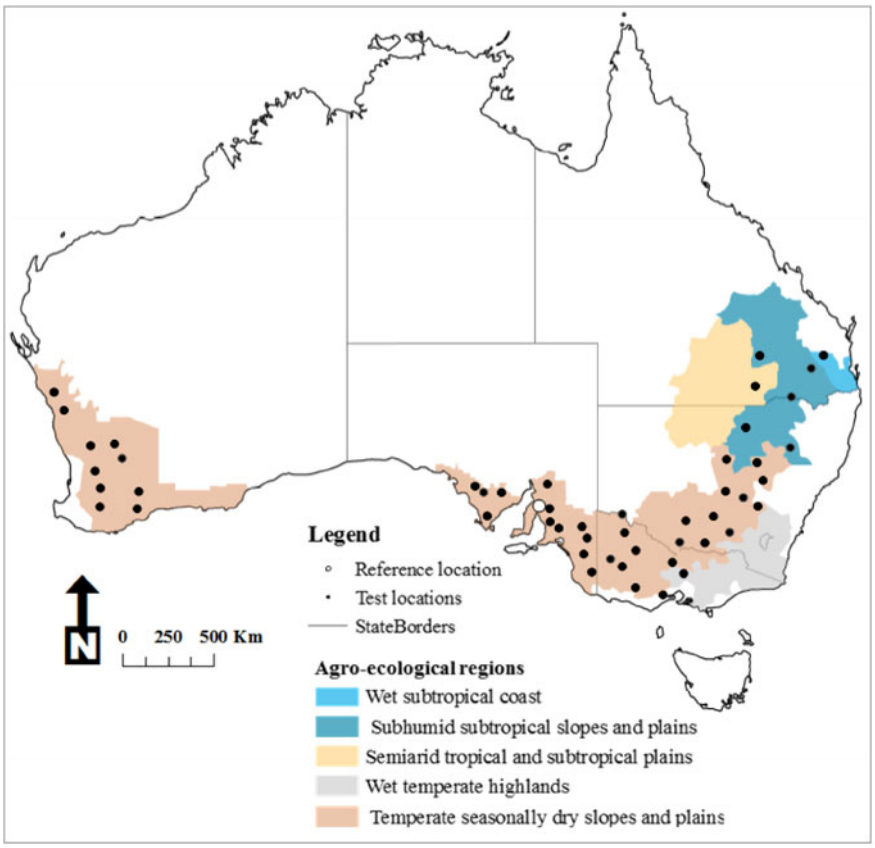


Fig. 1. The Australian grain belt, reference location and test sites considered in this study. Data source: ABARES – BRS (2010).

et al., 1996; Folland and Anderson, 2002; Domsch *et al.*, 2003; Yao *et al.*, 2007; Hayman *et al.*, 2008). Bracho-Mujica *et al.* (2019a) evaluated the dependency of the risk profile on climate record length and found that reliable risk profiles can be generated from short time periods of high-quality data. Furthermore, high-quality long-term rainfall and temperature records can be combined with high-quality temporal data from different locations to produce reliable risk profiles (Bracho-Mujica *et al.*, 2019b). However, in all these studies the averaged climate data used for calculating the adjustment factors covered a long-term period (i.e. >100 years), which opens the question as to the extent to which this method can be used in common situations, where high-quality long-term data are spatially sparse and reliable long-term records to support interpolation or extrapolation are limited.

The goal of this study was to examine the applicability of a simple method of weather data adjustment for climate risk assessment, by testing the effects of short record lengths of averaged climate data on (i) the adjustment factors for precipitation, temperature, and global solar radiation and (ii) on the long-term risk profile of simulated wheat grain yield in the Australian grain belt.

Materials and methods

Study area

The current research focuses on wheat crops in the Australian grain belt. This is due to its importance to the Australian economy (Trewin, 2006; Australian Bureau of Statistics, 2020), its vulnerability to climate variability and change (Hammer *et al.*, 1996; Potgieter *et al.*, 2002) and the availability of one of the best weather data sets suitable for crop modelling (Jones *et al.*, 2009; Trewin, 2013). Previous studies on the assessment and improvement of the method of daily weather data adjustment for modelling risk profiles of simulated wheat yields have been conducted in the same area (Hayman *et al.*, 2010b; Liddicoat *et al.*, 2012; Bracho-Mujica *et al.*, 2019a, 2019b).

A total of 49 wheat-growing test sites within the grain belt were selected (Fig. 1 and Table 1), located in contrasting agro-ecological zones and with high-quality weather data. In addition, one spatial reference site was selected for the current study: Snowtown, in South Australia. The selection was made due to (a) its agricultural importance, (b) its position, located in the middle of the South Australian grain belt, (c) the high-quality long-term weather data required for crop yield simulations are available and (d) it allows for a comparison with previous studies.

Daily precipitation, maximum and minimum temperatures and solar radiation data from these sites were obtained from the SILO patch point database (Scientific Information for Land Owners) (Jeffrey *et al.*, 2001). The period used was 1901–2000, avoiding the bias of the extreme Millennium drought (van Dijk *et al.*, 2013; Verdon-Kidd *et al.*, 2014), which alters the shape of the risk profile.

Adjustment of daily weather data

Risk profiles were derived from the simulated wheat grain yield in two ways: using actual weather data from each study site, and using adjusted weather data from the reference location. 'Adjusted weather data' refers to daily weather series (for precipitation, maximum and minimum temperatures and global

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Table 1. Location of the reference site (italic bold) and 49 test sites ordered clockwise, and agro-ecological zone, mean growing season precipitation (GSPrecip), seasonality, event-size index (τ), growing season maximum and minimum temperatures (GSMaxTemp and GSMinTemp), and global solar radiation (GSSolar)

Agro-ecological zone[a]	Site	Latitude	Longitude	Altitude (m a.s.l.)	GSPrecip (mm)	Seasonality[b]	τ[c]	GSMaxTemp (°C)	GSMinTemp (°C)	GSSolar (MJ/m^2)
Wet subtropical coast	Kingaroy	26.55 °S	151.85 °E	442	300	0.39	2.7	22.0	7.4	16.7
Semiarid tropical and subtropical plains	St George	28.04 °S	148.58 °E	201	223	0.43	2.7	23.6	9.3	17.0
Sub-Humid subtropical slopes and plains	Roma	26.67 °S	148.79 °E	299	241	0.40	2.6	24.0	8.3	17.5
	Dalby	27.18 °S	151.26 °E	344	270	0.40	2.7	22.8	8.0	16.8
	Goondiwindi	28.55 °S	150.31 °E	217	272	0.45	2.8	22.7	8.8	16.8
	Walgett	30.02 °S	148.12 °E	133	235	0.50	2.8	22.4	8.1	16.2
	Gunnedah	30.98 °S	150.25 °E	285	296	0.48	2.9	21.1	6.9	15.4
Wet temperate highlands	Seymour	37.03 °S	145.15 °E	145	402	0.68	3.5	15.8	5.5	11.7
Temperate seasonally dry slopes and planes	Gilgandra	31.70 °S	148.66 °E	282	293	0.52	2.9	20.0	6.0	15.2
	Nyngan	31.55 °S	147.20 °E	173	222	0.50	2.9	21.2	7.4	15.5
	Wellington	32.56 °S	148.95 °E	305	341	0.55	3.1	19.5	5.6	14.5
	Condobolin	33.08 °S	147.15 °E	220	249	0.56	3.0	19.4	6.7	14.6
	Forbes	33.39 °S	148.01 °E	240	300	0.57	3.1	18.8	6.0	14.1
	Cowra	33.80 °S	148.70 °E	360	354	0.58	3.3	17.9	5.6	13.9
	Moombooldool	34.28 °S	146.57 °E	158	261	0.60	3.1	18.7	6.2	13.7
	Hay	34.49 °S	145.25 °E	104	228	0.63	3.0	19.0	6.5	13.8
	Wagga-Wagga	35.05 °S	147.35 °E	219	334	0.63	3.3	17.1	5.9	13.1
	Oaklands	35.56 °S	146.17 °E	145	285	0.62	3.2	17.8	5.9	13.1
	Deniliquin	35.53 °S	144.97 °E	96	255	0.64	3.2	18.2	6.5	13.3
	Elmore	36.50 °S	144.61 °E	130	309	0.66	3.4	16.8	5.7	12.3
	Teesdale	38.02 °S	144.16 °E	106	321	0.62	3.4	15.6	6.8	10.8
	Lake Bolac	37.71 °S	142.84 °E	220	352	0.66	3.5	14.9	5.9	10.8
	Birchip	35.92 °S	142.85 °E	100	240	0.68	3.2	17.8	6.2	12.6
	Ouyen	35.07 °S	142.31 °E	65	217	0.66	3.5	19.0	6.7	13.3
	Mildura	34.18 °S	142.20 °E	54	176	0.63	3.4	19.6	7.2	13.9

(*Continued*)

solar radiation) recorded at the reference location (Snowtown) and later systematically perturbed using adjustment factors (or delta factors). Adjustment factors are variable and site-specific and represent the difference between the reference and a given test site.

To account for the intra-annual variability of the climate variables, adjustment factors were calculated at the seasonal and monthly levels. For the calculation of seasonal adjustment factors, daily climate data – for all climate variables – were averaged from April to October (growing season). Monthly adjustment factors were only calculated for the maximum and minimum temperatures, by averaging daily data for each month within the growing season. The record length used for calculating those averages varied. For the reference site, the full period of weather records was used (i.e. 100 years from 1901 to 2000). For each test site, the record length was 10, 20, …, 100 years in 10-year steps – in order to account for the effect of short climate series on the estimation of adjustment factors and the long-term risk profiles. Adjustment factors calculated with the full record were referred to as the '100-year adjustment factor'. Adjustment factors are listed in Supplementary Tables S1–S5.

Once the average climate data were calculated for the different record lengths and aggregation levels, daily weather data for the reference location were perturbed using adjustment factors summarized in Table 2. The precipitation series were first adjusted with a single factor $\text{Precip}_{s_{AF}}$, which represents the difference in average growing-season precipitation between the test site and the reference location, expressed as a percentage. The adjustment factor for global solar radiation ($\text{Solar}_{s_{AF}}$) was calculated similarly. In the case of maximum and minimum temperatures, two adjustment factors were calculated. Firstly, a seasonal factor ($\text{Temp}_{s_{AF}}$), calculated as the difference in average growing-season temperature between a given test site and the reference location, is expressed in °C. Secondly, a monthly factor ($\text{Temp}_{m_{AF}}$), calculated as the monthly difference in temperature between the reference and a given test site. Weather data were

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Table 1. (*Continued.*)

Agro-ecological zone[a]	Site	Latitude	Longitude	Altitude (m a.s.l.)	GSPrecip	Seasonality[b]	τ[c]	GSMaxTemp (°C)	GSMinTemp (°C)	GSSolar (MJ/m^2)
Temperate seasonally dry slopes and plains	Horsham	36.70 °S	142.20 °E	140	297	0.70	3.6	16.8	5.6	11.9
	Nhill	36.33 °S	141.64 °E	133	289	0.71	3.5	17.2	5.5	12.1
	Naracoorte	36.96 °S	140.74 °E	58	440	0.77	3.8	17.0	6.4	11.3
	Keith	36.10 °S	140.36 °E	29	350	0.75	3.5	18.1	7.1	11.9
	Lameroo	35.33 °S	140.52 °E	99	277	0.72	3.4	18.6	6.4	12.6
	Wanbi	34.78 °S	140.27 °E	77	212	0.68	3.7	19.0	6.1	12.9
	Palmer	34.85 °S	139.16 °E	192	302	0.73	3.4	17.7	6.7	12.4
	Roseworthy	34.54 °S	138.75 °E	103	332	0.75	3.7	18.5	7.8	12.8
	Mintaro	33.91 °S	138.72 °E	418	466	0.78	3.5	16.9	5.7	13.0
	Snowtown	***33.78 °S***	***138.21 °E***	***103***	***305***	***0.73***	***3.5***	***19.0***	***7.0***	***13.2***
	Orroroo	32.73 °S	138.61 °E	428	230	0.68	3.3	17.9	5.4	13.9
	Kimba	33.14 °S	136.41 °E	280	250	0.74	3.7	19.1	7.3	13.5
	Cummins	34.26 °S	135.73 °E	65	346	0.81	3.8	18.7	8.5	12.7
	Kyancutta	33.13 °S	135.55 °E	59	234	0.75	3.8	20.9	6.6	13.7
	Minnipa	32.84 °S	135.15 °E	168	243	0.75	3.7	19.9	8.3	13.8
	Jerramungup	33.92 °S	118.95 °E	300	284	0.74	3.5	18.6	7.4	13.0
	Newdegate	33.09 °S	119.02 °E	300	271	0.77	3.6	19.0	6.8	13.5
	Kojonup	33.83 °S	117.16 °E	305	449	0.85	3.5	17.3	6.9	12.4
	Narrogin	32.93 °S	117.18 °E	338	424	0.86	3.6	17.7	6.8	13.2
	Beverley	32.11 °S	116.92 °E	199	362	0.85	3.4	19.7	6.7	13.9
	Merredin	31.50 °S	118.22 °E	318	234	0.77	3.5	19.9	7.4	14.6
	Wongan Hills	30.89 °S	116.72 °E	283	319	0.84	3.4	20.4	8.5	14.8
	Bencubbin	30.81 °S	117.86 °E	359	238	0.76	3.5	20.4	8.0	15.1
	Mingenew	29.19 °S	115.44 °E	153	354	0.88	3.1	22.4	9.9	15.8
	Yuna	28.33 °S	114.96 °E	270	300	0.85	3.2	22.0	10.0	16.3

Note: Period 1901–2000.
[a]Agro-ecological zones as defined in (Williams *et al.*, 2002).
[b]Seasonality (Walsh and Lawler, 1981).
[c]τ (Sadras, 2003).

then adjusted by multiplying (precipitation and global solar radiation) or adding (temperature) the corresponding factor of every daily record (Table 2).

Adjustment factors calculated with a variable record length (<100 years) were compared with the 100-year adjustment factor. This comparison was established at a test site level using the difference of any given adjustment factor and climate variable from the 100-year adjustment factor.

Step-wise addition of weather data adjustments

Five types of adjustments were applied, resulting from the combination of variables included and level of aggregation (Table 3). For example, the $Precip_s$ consisted of adjusting the daily weather data for precipitation, using a seasonal aggregation, whereas temperatures and solar radiation were unadjusted. $Precip_sTemp_mSolar_s$, was the most complete adjustment, in which all the climate variables from the reference site were adjusted using two different aggregations for the calculation of the average climate data (i.e. seasonal for precipitation and solar radiation, and monthly for temperature).

Crop yield simulations

Wheat grain yield was simulated with APSIM (Agricultural Production Systems Simulator Model) Version 7.8 (Keating *et al.*, 2003; Holzworth *et al.*, 2014). APSIM has been locally calibrated, widely tested and extensively used for climate risk in the study area (Asseng *et al.*, 2002, 2015; Luo *et al.*, 2005, 2009; Robertson *et al.*, 2015).

Observed and adjusted daily weather data calculated for variable periods were used as model inputs. To capture the effects of climate and alternative weather inputs in the current study, the soil type and management practices were kept constant, and assumed no limitation by nitrogen, pests or diseases. To exclude the interaction between the sowing time and climate (Luo *et al.*, 2009; Hayman *et al.*, 2010a), one fixed sowing date was simulated (14 May); sowing density was set to 180 plants/m^2, with a 30 mm

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Table 2. Equations for calculating adjustment factors of weather data

Climate variable adjusted	Aggregation of weather data: seasonal ($_s$)	Aggregation of weather data: monthly ($_m$)	Adjustment factor equations
Precipitation (Precip)	✓		$Precip_{s_{AF}}\ (\%) = \left(\frac{GSPrecip_{ref} - GSPrecip_k}{GSP_{ref}}\right) \times 100$
Maximum temperature (MaxTemp)	✓		$MaxTemp_{s_{AF}}\ (^\circ C) = GSMaxTemp_{ref} - GSMaxTemp_k$
		✓	$MaxTemp_{\mathbf{m_{AF}}}\ (^\circ C) = MaxTemp_{m_{ref}} - MaxTemp_{m_k}$
Minimum temperature (MinTemp)	✓		$MinTemp_{s_{AF}}\ (^\circ C) = GSMinTemp_{ref} - GSMinTemp_k$
		✓	$MinTemp_{\mathbf{m_{AF}}}\ (^\circ C) = MinTemp_{m_{ref}} - MinTemp_{m_k}$ $MinTemp_{m_{ref}} - MinTemp_{m_k}$
Global solar radiation (Solar)	✓		$Solar_{s_{AF}}\ (\%) = \left(\frac{GSSolar_{ref} - GSSolar_k}{GSSolar_{ref}}\right) \times 100$

Note: GSPrecip, GSMaxTemp, GSMinTemp, and GSSolar refer to the long-term average growing season precipitation, maximum temperature, minimum temperature, and global solar radiation, respectively. $MaxTemp_m$ and $MinTemp_m$ refer to the long-term monthly temperature averages for months $m = 4, 5, \ldots, 10$, within the growing season. The terms ref and k refer to the reference location and test sites.

Table 3. Step-wise adjustment applied to the daily weather data at the reference location

Adjustment	Weather variable(s) adjusted	Averaged weather data used for calculating adjustment factors: Seasonal($_s$)	Averaged weather data used for calculating adjustment factors: Monthly($_m$)
$Precip_s$	Precipitation	✓	
$Precip_sTemp_s$	Precipitation and maximum and minimum temperatures	✓	
$Precip_sTemp_m$	Precipitation and maximum and minimum temperatures	Precipitation	Temperatures
$Precip_sTemp_sSolar_s$	Precipitation, maximum and minimum temperatures and global solar radiation	✓	
$Precip_sTemp_mSolar_s$	Precipitation, maximum and minimum temperatures and global solar radiation	Precipitation and global solar radiation	Temperatures

Note: Weather data at the reference site is adjusted by a seasonal adjustment factor for precipitation only ($Precip_s$), seasonal adjustment factors for precipitation and temperatures only ($Precip_sTemp_s$), a seasonal adjustment factor for precipitation and monthly adjustment factors for temperatures ($Precip_sTemp_s$), a seasonal adjustment factor for precipitation, temperatures and global solar radiation ($Precip_sTemp_sSolar_s$), and, a seasonal adjustment factor for precipitation and global solar radiation, and monthly adjustment factors for temperatures ($Precip_sTemp_mSolar_s$)

sowing depth and 250 mm row spacing. Crop parameters used were those from locally adapted varieties, Mace (an early maturing variety) for the winter-rainfall regions of Western Australia, South Australia, Victoria and southern New South Wales; and Gregory (a medium maturing variety) for the summer-rainfall locations of northern New South Wales and Queensland. Crop parameters are summarized in Table 4.

The soil used has a sandy texture, organic carbon content of 0.7% (0–10 cm), rooting depth of 100 cm and 80 mm of plant available water content (PAWC). Key soil characteristics are presented in Table 5. Initial water and nitrogen contents were reset every year on the 1st of April to exclude the effects of previous seasons, as suggested in the literature (Sadras and Rodriguez, 2010; Luo *et al.*, 2013). The initial soil water content was set to full profile, filled from the top layer to ensure crop establishment (Bell *et al.*, 2015), and the initial nitrogen level was set to 100 kg N/ha as urea at sowing.

Risk profiles of modelled wheat grain yields (MWGYs)

Risk profiles were defined as the cumulative probability curve of the annual MWGY for each site, type of weather adjustment (Table 3), and record length. Yields were ranked and corresponding percentiles were calculated. Risk profiles of the MWGYs across the types of adjustments and record lengths were compared using Q:Q plots. Statistics for the comparisons included the root mean squared error (RMSE, Eqn (1)), and the bias (Eqn (2)), overall percentile classes p at each of the 49 test sites j as follows:

$$RMSE_j = \sum_{p=1}^{100} \sqrt{(MWGY_{p,j} - MWGY_{baseline,\,p,j})^2} \quad (1)$$

and

$$Bias_j\ (\%) = \frac{1}{N} \sum_{p=1}^{100} \left(\frac{MWGY_{p,j} - MWGY_{baseline,\,p,j}}{MWGY_{baseline,\,p,j}} \right) \times 100 \quad (2)$$

The bias of the MWGY represents the difference between the risk profiles of MWGY built with weather data adjusted with long-term adjustment factors and those built with data adjusted with shorter record lengths, as illustrated in Fig. 2.

Both indices, RMSE and bias, were mapped for every type of adjustment applied to the reference location, to (i) visualize the spatial variation of the performance indices, (ii) compare the regions and (iii) determine the effect of adjusting a particular set of climate variables on the robustness of the MWGY risk profiles. Construction and statistical analysis of the risk profiles of the

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Table 4. Cultivar-specific parameters for wheat cultivars Mace and Gregory used for the parameterisation of APSIM

Cultivar	Parameter	Value
Mace	Vernalisation sensitivity (vern_sens)	2.3
	Photoperiod sensitivity (photop_sens)	3.2
	Grains per gram stem (grains_per_gram_stem)	25
	Potential grain filling rate (potential_grain_filling_rate, grain^{-1} d^{-1})	0.002
	Potential grain growth rate (potential_grain_growth_rate, g grain^{-1} d^{-1})	0.001
	Maximum grain size (max_grain_size, g)	0.041
	Thermal time from emergence to end of juvenile (tt_end_of_juvenile, °Cd)	400
	Thermal time from end of juvenile to floral initiation (tt_flowering_initiation, °Cd)	555
	Thermal time from flowering to start grain filling (tt_start_grain_fill, °Cd)	545
Gregory	Vernalisation sensitivity (vern_sens)	2.7
	Photoperiod sensitivity (photop_sens)	3.2
	Grains per gram stem (grains_per_gram_stem)	25
	Potential grain filling rate (potential_grain_filling_rate, grain^{-1} d^{-1})	0.002
	Potential grain growth rate (potential_grain_growth_rate, g grain^{-1} d^{-1})	0.001
	Maximum grain size (max_grain_size, g)	0.041
	Thermal time from emergence to end of juvenile (tt_end_of_juvenile, °Cd)	400
	Thermal time from end of juvenile to floral initiation (tt_flowering_initiation, °Cd)	555
	Thermal time from flowering to start grain filling (tt_start_grain_fill, °Cd)	650

Table 5. Key soil characteristics used for the initialisation of APSIM

Depth (cm)	BD (g/cm^3)	AirDry (mm/mm)	LL (mm/mm)	DUL (mm/mm)	SAT (mm/mm)	OC (total %)	Fbiom (0–1)	Finert (0–1)
0–10	1.3	0.044	0.087	0.204	0.459	0.64	0.035	0.4
10–20	1.3	0.096	0.12	0.25	0.459	0.66	0.02	0.6
20–40	1.3	0.175	0.175	0.25	0.459	0.72	0.02	0.7
40–60	1.3	0.18	0.18	0.25	0.459	0.61	0.015	0.7
60–80	1.3	0.18	0.18	0.25	0.459	0.27	0.015	0.8

Note: BD, bulk density; AirDry, Air-dry soil water content; LL, Lower limit of plant available water or permanent wilting point; DUL, drained upper limit of plant available water or field capacity; SAT, saturated soil water content; OC, Organic carbon; Fbiom, fraction of susceptible organic carbon; Finert, fraction of organic carbon that is not susceptible to decomposition.

MWGY were performed using R software (R Development Core Team, 2020) and maps were created using ArcGIS® software (ESRI 2015).

Results

Long-term adjustment factors and weather data record lengths

The calculation of 100-year adjustment factors is based on the difference in the long-term growing-season average of the reference and test sites. Here, we examined the sensitivity of four adjustment factors – for precipitation, maximum temperature, minimum temperature and solar radiation – to the length of the weather record (Figs 3 and 4).

All seasonal adjustment factors were sensitive to the record length, especially for records shorter than 30 years. In the case of precipitation, departures ranged from −14 and 20% for the 10-year series and dropped within the range −10 and 10% with 40 or more years (Fig. 3). Long-term adjustment factors for temperatures were mostly underestimated with shorter records; series of 10 years diverged by −0.9 and 0.3°C for maximum and between −1.2 and 0.5°C for minimum temperature in relation to 100-year series. At most test sites, these departures were reduced to −0.5 to 0.5°C with records longer than 30 years. Solar radiation was the variable with the lowest sensitivity to the record length, with departures ranging between −2.4 and 3%, and with a slight increment at record lengths between 30 and 60 years of weather data.

The effect of record length on the calculation of adjustment factors for maximum and minimum temperatures was stronger at the monthly level (Fig. 4). Particularly, record lengths equal and shorter than 40 years produced the highest departures of adjustment factors from the 100-year factors, independent of the month. However, the departures were higher during the transition months, i.e. April and May for the minimum temperature

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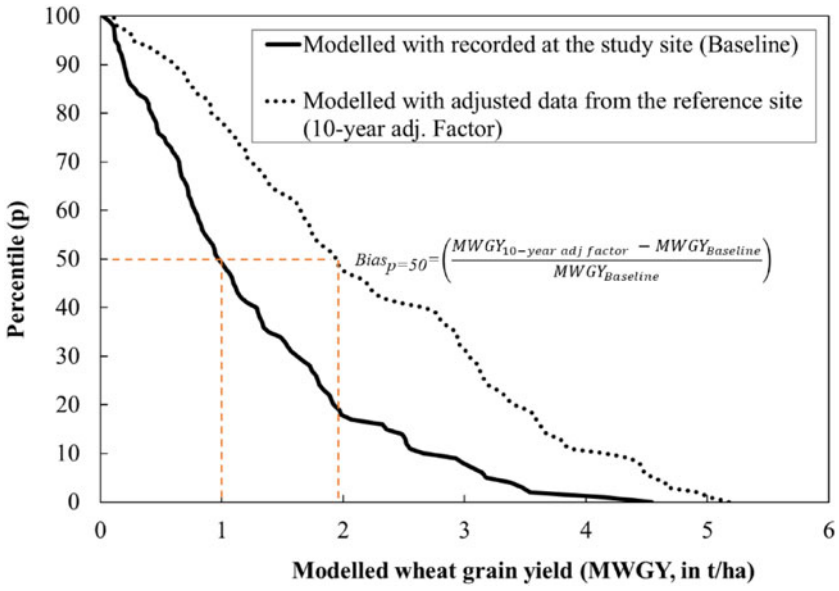


Fig. 2. Comparison of two risk profiles of MWGY, using recorded weather data at the study site Nyngan (NSW, Australia), and using adjusted weather data from a reference site with a 10-year adjustment factor. Bias (normalized) at percentile 50th corresponds to the difference between both MWGY normalized with the mean of the MWGY modelled with observed weather data at the study site.

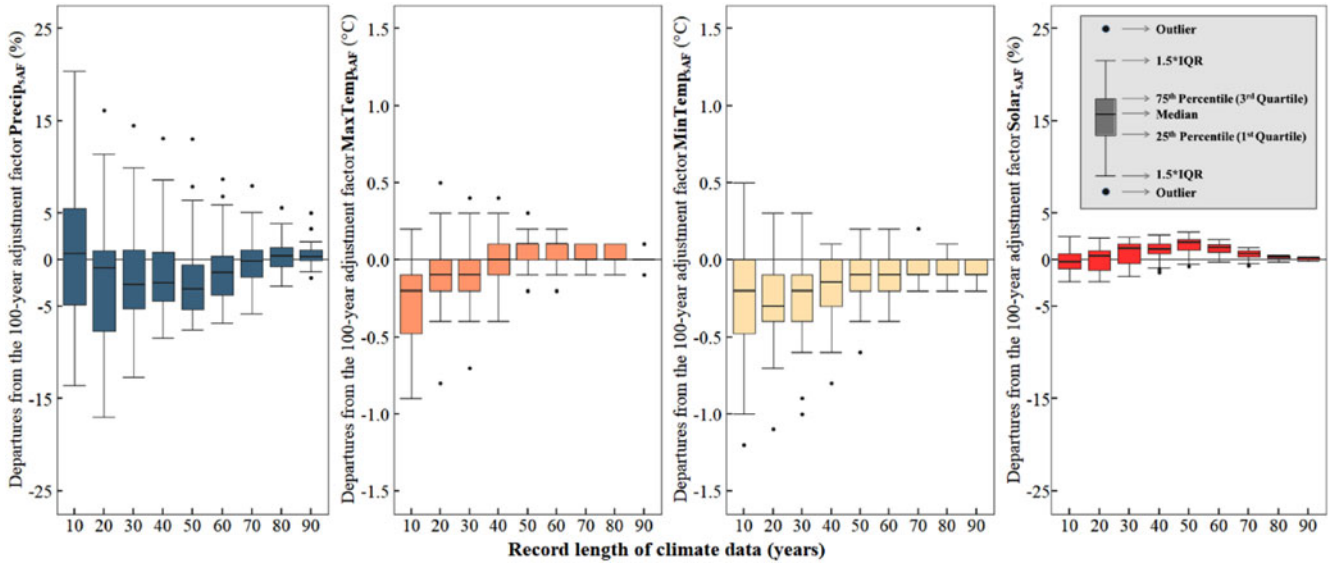


Fig. 3. Departures from the 100-year adjustment factors relative to those calculated with shorter record lengths in 49 locations of the Australian wheat-belt. From left to right weather records of the reference location were adjusted as a function of seasonal precipitation (**Precip$_{sAF}$**), seasonal maximum temperature (**MaxTemp$_{sAF}$**), seasonal minimum temperature (**MinTemp$_{sAF}$**) and seasonal solar radiation (**Solar$_{sAF}$**). IQR refers to the inter-quartile range.

factors, and April and October for the maximum temperature factors. At most test sites, departures were within −0.5 to 0.5°C with records longer than 40 years (Fig. 4).

Long-term risk profiles of MWGY and weather data record lengths

The use of averaged climate data for record lengths shorter than the 100-year period affected the long-term risk profile of MWGY. In Fig. 5, all the test sites are included, but we only present three of the five types of adjustments used in this study (i.e. Precip$_s$, Precip$_s$Temp$_m$ and Precip$_s$Temp$_m$Solar$_s$). The adjustments Precip$_s$Temp$_s$ and Precip$_s$Temp$_s$Solar$_s$ are not shown since lower bias was obtained with the Precip$_s$Temp$_m$ and Precip$_s$Temp$_m$Solar$_s$ adjustments (bias and RMSE values are summarized in the Supplementary Material, Table S6).

The bias of MWGY risk profiles varied spatially (Fig. 5, Table S6). Test sites in the temperate agro-ecological zones with winter-dominant rainfall (Fig. 1) had the lowest biases across all types of adjustments and climate data record lengths (Fig. 5). Long-term risk profiles of MWGY of test sites in wet subtropical coast, subhumid subtropical, and semiarid tropical and subtropical locations were mostly overestimated, with the greatest biases in the study area (Fig. 5). The low matching observed in northern and north-eastern sites is exacerbated by the shortest climate data record lengths. Matching in the −10 to 10% range was only

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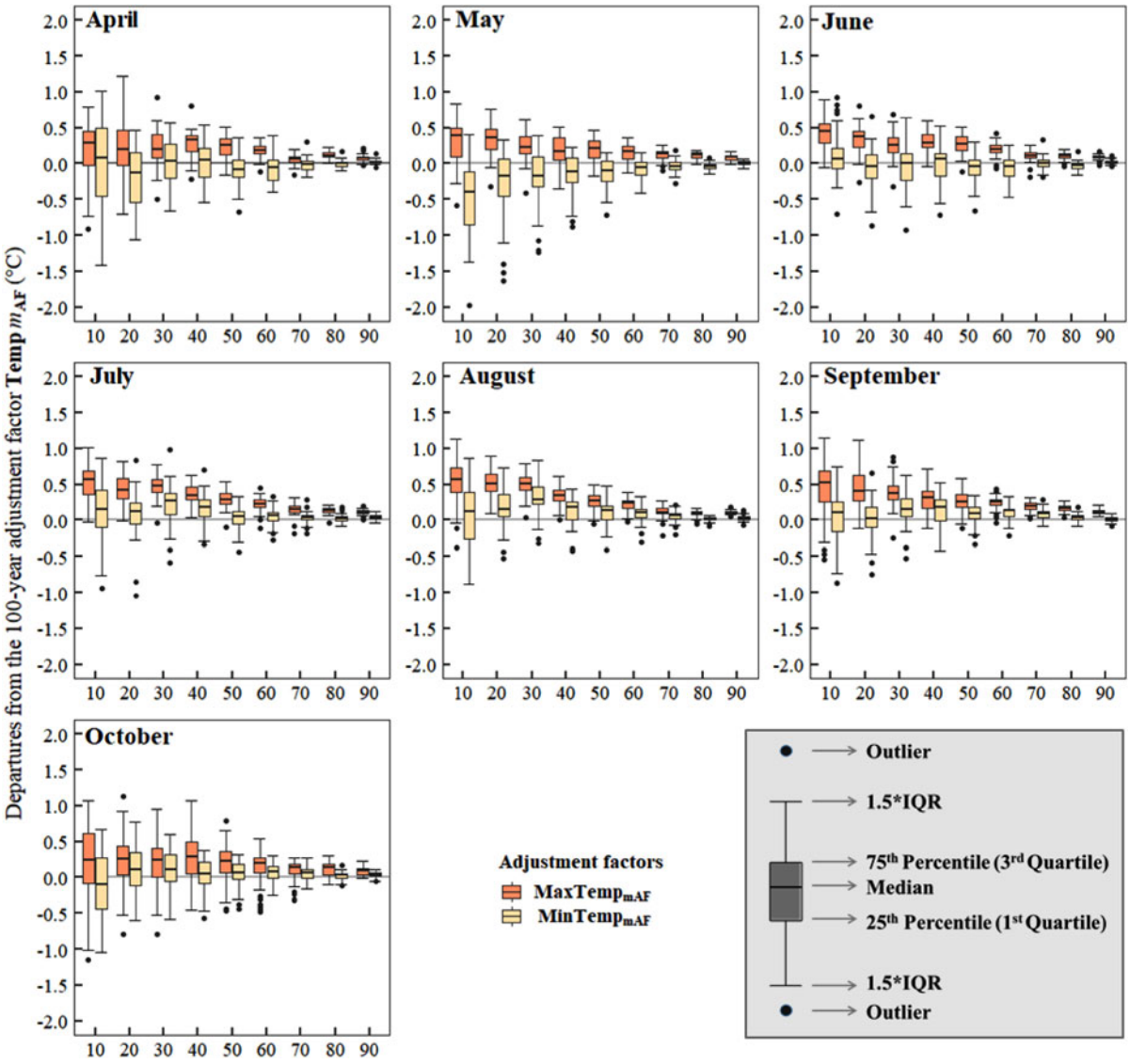


Fig. 4. Departures from the 100-year monthly adjustment factors for maximum and minimum temperatures relative to those calculated with shorter record lengths in 49 locations of the Australian wheat-belt. Weather records of the reference location were adjusted as a function of the monthly maximum temperature (**MaxTemp$_{mAF}$**), and the seasonal minimum temperature (**MinTemp$_{mAF}$**). IQR refers to the inter-quartile range.

achieved in those sites with record lengths of 80 or more years and including all adjustments.

The proportion of test sites in which the long-term risk profiles were estimated within −5 to 5% bias improved with extra adjustments (precipitation, temperature, and solar radiation) and as the record length was increased (Fig. 5, pie charts). Using the shortest record length (10 years) the simplest adjustment (Precip$_s$) produced matching of long-term risk profiles in range −10 to 10% for 41% of the sites, which increased to 49% with the Precip$_s$Temp$_s$ adjustment, 53% with the Precip$_s$Temp$_m$, and up to 60% of the sites with the most complete types of adjustments (Precip$_s$Temp$_m$Solar$_s$). These proportions did not change substantially for record lengths between 10 and 50 years of averaged climate data. However, using averaged climate data for a period of 60 or more years increased the number of sites with bias within −10 and 10%. For example, with the Precip$_s$ adjustment, the number of sites went from 47% (60 years of record length) to 51% (with 100 years of record length), while the use of the Precip$_s$Temp$_m$Solar$_s$ adjustment the number of sites increased from 59 to 86% of the test sites.

Discussion

The effect of limited temporal coverage of averaged climate data on the validity of a method for scaling weather data for extrapolation of long-term risk profiles for simulated crop yields was examined in the current study. This method uses averaged climate data for precipitation, temperature and solar radiation to scale daily weather data from a reference site with long-term records. Scaled daily data are then used for simulating crop yields and building long-term risk profiles, demonstrating that the method tested is able to provide a robust spatial extrapolation of risk profiles, even if the temporal extent of the averaged climate data is limited.

The adjustment factors showed different responses to the record length used for averaging the climate data. As expected, sensitivity to record length ranked precipitation > minimum

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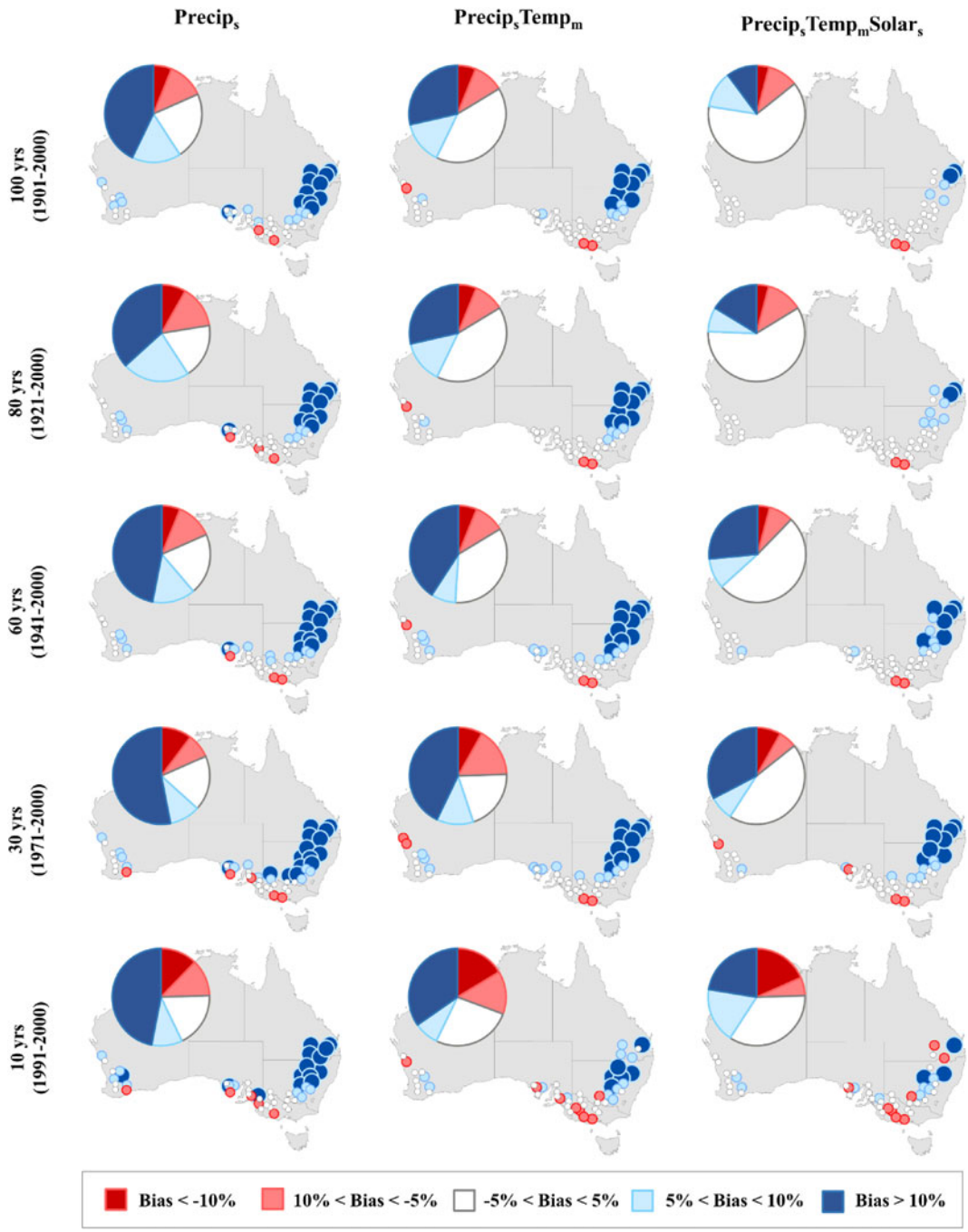


Fig. 5. Bias (%) of the risk profiles of MWGYs built with adjustment factors calculated with variable record lengths of weather data across the different types of adjustments incorporated. Bias compares the risk profiles obtained with weather data observed at the study site for the period 1901–2000, and those obtained with scaled weather data using a variable record length of size n (n = 10, 20, …, 100) for calculating the seasonal adjustment factors for precipitation, maximum and minimum temperatures and solar radiation. The pie charts show the proportion of test sites within different categories of bias.

temperature > maximum temperature > global solar radiation. This response is primarily driven by the natural variability of these climate variables, which is considerably higher for precipitation, and lower for temperature and solar radiation (Jäger, 1988; Von Storch and Zwiers, 1999). Despite this fact, reasonable estimates of the long-term adjustment factors were obtained when using averaged data for shorter time periods. In the case of precipitation, at least 40 years were necessary to obtain departures of the long-term adjustment factor within the range −10 and 10% (Fig. 3). For both, the maximum and the minimum temperatures, a minimum of 30 years at most test sites produced departures spanning from −0.5 to 0.5°C at seasonal level (Fig. 3), and a minimum of 40 years for monthly adjustment factors (Fig. 4). For solar radiation, 10 years records produced departures between −2.4 and 3% (Fig. 3). This finding is relevant for potential future applications of the method in data-sparse environments.

The long-term risk profile of MWGY was also sensitive to the temporal coverage of the averaged climate data (Figs 3–5). However, the number of adjustments applied had a major effect

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on the long-term risk profile. The most complete adjustment ($Precip_sTemp_mSolar_s$) produced acceptable matching of risk profiles in ~60% of the test sites using record lengths between 10 and 50 years. This proportion of sites was higher than the 51% of sites when 100 years of record length was used with only precipitation adjusted. There was also a spatial pattern in the matching of risk profiles. Better results were obtained in winter-rainfall sites, which required fewer adjustments and record lengths, while most summer-rainfall sites required more adjustments and the longest period of averaged climate data. This could be explained by the similarity in climates in the reference location and the western, southern and south-eastern sites, all falling in temperate regions (Williams *et al.*, 2002) with comparable rainfall patterns in terms of amount, seasonality and size of events (Table 1; Williamson, 2007).

The current study uses a simple method for extrapolating risk profiles described in Hayman *et al.* (2010b) and Liddicoat *et al.* (2012) and further developed in Bracho-Mujica *et al.* (2019b), and expand in several aspects. Firstly, the extrapolation method was tested under a non-uncommon situation of having limited daily weather data (in terms of both temporal and spatial coverage) for estimating modelled risk profiles. Secondly, it endorses the incorporation of the monthly adjustment of maximum and minimum temperatures accounting for the role of temperature on crop development (Bracho-Mujica *et al.*, 2019b). Thirdly, it demonstrates the importance of the number of adjustments over the record length of the averaged climate data, which was not tested in previous studies. Fourthly, results from this study allow us to estimate the minimum record length necessary for calculating robust adjustment factors. This enables to produce more robust matching between MWGY risk profiles and illuminate similarities and differences among and across locations on a continental scale.

Crop modellers working in data-sparse environments can use these results to save computational time on climate data, which frees up resources for other factors such as soil types. Farmers and agronomists can use the findings to judge the reliability of simple climate adjustments for risk analysis based on modelled yield. The extensive comparison across the Australian grain belt not only highlights the importance of adjusting the most critical climate variable determining wheat yield, precipitation, but also points to the need to adjust temperature and solar radiation to improve the estimation of the risk profiles of modelled crop yields.

The impact of the temporal coverage of the averaged climate data was explored in the current research, assuming that all climate variables had the same record length. However, another interesting aspect to explore in future studies would be the impact of different temporal coverages across all the climate variables. Nevertheless, these findings provide evidence that temporal coverage is not as important as the type and number of adjustments used for the determination of robust risk profiles of MWGY.

The use of the method for scaling climate data has been rigorously tested across multiple sites and climates within the Australian grain belt, and results demonstrate the power of this simple method for extrapolating the long-term risk profiles of MWGY. However, it is important to note that this method was not intended for estimating year-to-year crop yields but for long-term risk profiles of crop yields. Furthermore, it is important to highlight that the approach used in the current study did not account for the spatial variability of soils and management practices (i.e. sowing dates and nitrogen fertilization), which allowed examination of the maximum impact of climate on the method of extrapolation of risk profiles.

Conclusions

A simple method for adjusting daily weather data for extrapolating risk profiles was tested across the entire Australian-grain belt. Risk profiles based on process-based models could be accurately extrapolated even if only short climate data series were available to compute adjustment factors. The results indicated that although the temporal coverage of the climate data used for adjusting daily records is important, the adjustment of all climate variables (i.e. precipitation, temperatures and solar radiation) produced the most reliable estimations of modelled yield risk across a large area, encompassing a diversity of climates.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S0021859621000253

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Conflict of interest. The authors declare there are no conflicts of interest.

Ethical standards. Not applicable.

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