Modelling crop yields and climate risk under limited climate data conditions

Thesis submitted for the degree of

Doctor of Philosophy

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February 2018

Declaration

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Acknowledgements

By the time I received the live-changing notification from the Australia Awards program (formerly Australian Development Scholarships, ADS), indicating that my application was successful I was not able to imagine the amazing opportunities and big challenges waiting for me in Australia. This experience would not be the same without the continuous and kind support provided by my family, supervisors, colleagues, friends, my contact officer for the Australia Awards program and the University of Adelaide.

A special thanks to my beautiful little family (Eduardo y Ernesto) for bravely and happily accompanied me during this challenging journey, and for giving me the energy to try my very best every single day. Thank you boys.

I would like to express my very great appreciation to my principal supervisor, Associate Professor Bertram Ostendorf. I will always be grateful to him for all the encouragement, support and friendship, his always positive attitude towards research inspired me to face the most challenging aspects of consolidating this thesis. I have also learnt from him to look research results from different perspectives and to interpret them in a broader context. Thank you!

Special thanks should be given to my co-supervisor, Dr. Peter Hayman, for giving me the opportunity to work and learn from his invaluable experience over the past 4 years. It was always refreshing and motivating to discuss the issues land managers experience managing climate variability in Australia. I highly appreciate his guidance and motivation to explore important avenues for this thesis.

I would like also to thank Dr. Victor Sadras, for supported me very early in this journey by endorsing my scholarship application, and later in my candidature for providing insightful comments and discussion of my research, that clearly improved my academic writing skills.

I would like to extend my gratitude to my colleagues and friends in the Spatial Information Group, in particular Ken, Adam, Sofanit, Dot, Ingrid and Ramesh. Thank you for the friendship and for sharing your PhD experiences. Your advice, help and encouragement meant a lot to me.

I wish to acknowledge the help of Dr. Margaret Cargill and Alison-Jane Hunter for proofreading this thesis.

To my contact officer Niranjala Seimon for her help and support. I am really grateful to have had a continuous communication with you that really helped me to be able to overcome the personal and academic challenges I experienced during my studies.

I would like to thank my friends in Adelaide, Julio, Cecilia, Sandra, Antonella and Hahn. It was a privilege to share the student experience in Australia with you all. We met as Australia Awards scholars and now I consider you all as part of my family. Thank you.

Finally, I wish to express my gratitude to my family and friends in Venezuela. They encouraged me along the way and gave positive energy to keep pursuing my dreams. Although more than 16.000 km distance separated us, you were always very close to me.

Dedication

Abuela and ***Mamá*** this achievement is for you

Thanks for your endless love and for teaching me the values I appreciate the most: humility, honesty, kindness and loyalty.

Abstract

Agricultural management needs relevant climate information to reduce the climate uncertainty and support crucial management decisions. Risk profiles of modelled crop yields (cumulative probability curves) are effective tools for summarising long-term yield variability, exploring the benefit and limitations of agricultural management decisions and serve to quantify the impact of future climate conditions. However, modelling reliable crop yield and risk profiles requires continuous, accurate, and long-term (>100 years) local weather records for rainfall, temperature, and solar radiation, which are not always available.

This study aimed to systematically assess spatial and temporal factors that limit the accuracy of risk profile of modelled crop yields. The specific objectives were (1) to analyse if and to what degree short time series of weather data can be used to provide reliable risk profiles, (2) to test how simple adjustments of high-quality local data can be used to extrapolate risk profiles across broad climatic regions, and (3) to address a combination of sparse spatial coverage of climate data and short daily weather observations. Here we focused on the Australian grain-belt selected on the basis of the availability to high-quality, long-term climate data, widely used and calibrated process-based crop model (APSIM, Agricultural Production Systems sIMulator).

To examine the sensitivity of risk profiles of modelled crop yields to the temporal coverage of the climate data, 15 wheat-growing sites were selected based on their proximity to weather stations with high-quality daily weather records for the last 100 years (baseline period). Risk profiles were constructed using variable temporal coverages and compared with risk profiles obtained for the baseline period. Results indicated a decline of modelled wheat grain yields, particularly for the last three decades. They also highlight the interactions between model complexity and data demand. The sensitivity of the risk profiles to record length was increased in models accounting for severe frost and heat events.

The second research objective of this study addresses spatial extrapolation and explores to what extent a simple method for adjusting daily weather data using seasonal and monthly factors could produce robust estimates of risk profiles at a continental scale. Adjustment factors were calculated as the difference in long-term average of a given climate variable between 49 test sites and the reference site. Risk profiles modelled with observed weather data were compared with those modelled with adjusted data. Simple adjustments of both precipitation and temperatures produced reliable risk profiles in 80% of the sites. This study implies that for regions with limited availability of high-quality climate data, simple scaling of climate inputs can provide basic climate data for modelling and generating robust spatial patterns of risk profiles of crop yield.

The third objective addresses the realistic scenario of using modern, process-based crop models, which are data hungry, in data sparse environments. Models that can capture combinations of potential climate and management impacts on food production require complex climate data that are either not available or difficult to access at high spatial detail and/or temporal extent for many parts of the world. Here, we assess the sensitivity of the risk profile accuracy to the temporal coverage of the climate data combined with spatial adjustments of daily weather data for risk profile modelling purposes. In this case, adjustment factors were determined using a variable temporal coverage at every study site. Risk profiles were modelled using observed and adjusted weather data covering different periods. Results indicated that although adjustment factors are very sensitive to the record length of the climate data, it was possible to produced reliable risk profiles with only 10-30 years of climate data.

This research has increased our understanding of the sensitivity of risk profiles to the temporal and spatial aspects of climate data availability. It highlights the usefulness of risk profiles to characterise spatial and temporal patterns of yield and will help to improve agricultural management under climate uncertainty.

Publications arising from this thesis

Refereed publications

Bracho-Mujica, G, Hayman, P, Sadras, V & Ostendorf, B 2017, Simple scaling of climate inputs allows robust extrapolation of modelled wheat yield risk at a continental scale, Global Change Biology. Submitted: August 2017.

Bracho-Mujica, G, Hayman, P & Ostendorf, B 2017, Temporal coverage of climate data and its impact on the accuracy of climate risk profiles in the Australian grain-belt, Agricultural and Forest Meteorology. Submitted: November 2017.

Bracho-Mujica, G, Hayman, P & Ostendorf, B 2017, Climate data record length and its impact on a method for extrapolating modelled yield risk. In preparation.

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Chapter 1 : **General Introduction**

1.1. Motivation for the research

Climate variability and uncertainty are key factors influencing performance, adaptation and planning in cropping systems. In fact, more than 30% of the inter-annual variability of the global yield of major crops (i.e. maize, wheat, rice and soybean) has been explained by climate variability, but this percentage can be as high as 60% in the highest productivity areas of the world (Ray *et al.* 2015). Climate variability is a source of uncertainty and risk in agriculture and is likely to increase due to the changes in the magnitude and frequency in extreme weather events (Hartmann *et al.* 2013; Porter *et al.* 2014). Thus, agricultural decision and policy makers are increasingly interested in tools for reducing climate uncertainty and risk.

One simple, valuable tool for understanding and managing climate variability in cropping systems is the risk profile. The risk profile (the cumulative probability curve) of crop productivity allows us to understand the potentialities and limitations of a given cropping system, identify the potential impacts of climate variability and change on crop variability (Domsch *et al.* 2003; Luo *et al.* 2009; Yao *et al.* 2007), support crop insurance programs (Bailey *et al.* 2004; Just & Weninger 1999), and provide a scientific basis for agricultural policy studies (Bailey *et al.* 2004). In fact, current decision-support systems use risk profiles of crop productivity to assist farmers in the management of climate risk. Examples of such systems include Yield Prophet ® (Hochman *et al.* 2009; Hunt *et al.* 2006), the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones *et al.* 2003), and AquaCrop (Raes *et al.* 2009). For these applications, researchers and agricultural advisors have been increasingly using process-based crop models. These models have a strong capability for capturing complex soil-climate-plant interactions and have proved to be invaluable tools for quantifying climate impact on crop productivity and assessing a wide range of farming management decisions and strategies to minimise those impacts.

However, determining comprehensive risk profiles from process-based crop models outputs requires high-quality climate data (i.e. long-term, continuous and accurate daily weather records for precipitation, temperature and solar radiation), which is neither equally available nor equally accessible worldwide, particularly in developing countries and remote areas (Daly 2006; Grassini *et al.* 2015; Hess *et al.* 2002; Jäger 1988; Jeffrey *et al.* 2001; Ruane *et al.* 2015; Saghafian *et al.* 2017; Selvaraju 2012; Watson & Challinor 2013). Whilst this problem could be overcome by using climate data derived from satellite observations, spatial interpolation techniques, reanalyses or stochastic weather generators, these methods restrict the construction of full long-term risk profiles (i.e. based on 100 or more years of climate data). Satellite observations allow scientists to derive climate data for a period of approximately 30 years (NCAR 2014; Schamm *et al.* 2014). On the other hand, spatial interpolation, reanalyses and stochastic weather generators can produce longer climate series; however these methods have mostly been used or validated in temperate regions (Breinl *et al.* 2017; Semenov & Barrow 1997) where dense observational weather networks are located (Ruane *et al.* 2015). Nevertheless, the use of spatial interpolation in combination with a method of climate data adjustment could reduce the dependency on a dense network of weather stations with high-quality observations.

Hayman *et al.* (2010) and Liddicoat *et al.* (2012) used a simple method of scaling weather data to standardise it (i.e. for good spatial coverage, minimal missing daily data and the same record length) for modelling risk profiles of crop yield and developing risk management frameworks along the South Australian grain-belt. However, the question remains of the spatial extent to which this method for scaling daily weather data daily data can be applied for modelling crop yield risk.

Since the lack of high-quality climate data is a very common problem, not restricted to developing countries, which limits long-term climate risk assessments in cropping systems, this thesis aims to (i) examine to what extent the quality of the weather observations (in terms of continuity and temporal coverage of the climate data) impacts on the accuracy of the long-term risk profile of crop productivity; and (b), determine the spatio-temporal validity of a simple method for scaling climate data for modelling long-term risk profiles at continental scale.

1.2. Research objectives

A step-wise approach is used to investigate the sensitivity of risk profiles of modelled crop yield to the quality of the climate data. The study has four objectives:

- review relevant methods for modelling crop yield and long-term climate risk in climate data-sparse environments,
- determine to what extent the long-term risk profile of modelled crop yield changes with variable temporal coverage of climate data (i.e. duration and period),
- examine further implications for long-term risk profiles of modelled crop yield when severe temperature events (i.e. frost and heat) are accounted for, and,
- test the spatio-temporal validity of a scaling method of generating climate data for modelling risk profiles of crop yields when only limited climate data are available.

1.3. Study context

This research was conducted in the Australian grain-belt. The grain-belt was selected as the study area based on three considerations (i) the relevance of the wheat industry to the Australian economy (Trewin 2006); (ii) its growing vulnerability to the natural and anthropogenic climate change (Anwar *et al.* 2007; Asseng *et al.* 2013; Ludwig *et al.* 2008), which underlines the importance of improving and validating climate risk management tools for the region; and (iii) the high-quality climate data available in Australia, which allows testing of limited climate data scenarios to assess the data's effect on the risk profile.

Wheat is the major crop in the grain-belt, covering almost 11.3 M hectares with an estimated gross value of $56 billion AUS for the 2015 – 2016 period (ABS 2017). However, the crop is grown under extremely variable climate conditions (Hammer *et al.* 1996; Nicholls *et al.* 1997), which have impacted on productivity in recent years. Significant declines in precipitation have been observed in much of the grain-belt, from the late 1960s onwards, with further reductions since the mid-1990s in the southwest of Western Australia (Hope *et al.* 2010; Ryan & Hope 2006). The Millennium Drought, also referred to in the literature as the 'Big Dry', lasted from the mid-1990s until early 2010 and is recognised as one the longest droughts since the 1900s, affecting the southwest of Queensland, southern New South Wales, Victoria and the south of South Australia (van Dijk *et al.* 2013; Verdon-Kidd & Kiem 2009).

Wheat management and productivity in the region have also been impacted by the increment in maximum and minimum temperatures since around 1950 and the increased frequency of hotter nights and days since the mid-1970s (Alexander *et al.* 2007; Plummer *et al.* 1999; Trewin & Vermont 2010). The changes in the mean and extreme temperatures have been confirmed with the most robust dataset of high quality temperature data in Australia: The Australian Climate Observations Reference Network – Surface Air Temperature (ACORN-SAT) dataset (Trewin 2013). The declining precipitation and increasing temperatures have had negative impacts on wheat production in Australia. In fact, recent studies have shown that actual wheat yield variability has increased significantly for the 1981 – 2010 period (Toshichika & Navin 2016), along with the stalling of actual wheat yields for the period between 1961-2008 (Ray *et al.* 2012) and a significant decline in modelled wheat yields since 1997 (Hochman *et al.* 2017). Both studies cited above attribute these issues to the recent decline in precipitation and rising temperatures.

The Australian grain-belt is an excellent study area for investigating the sensitivity of the long-term risk profile of wheat yield to the quality of the climate data due to the availability to both long-term, high-quality climate datasets (Alexander *et al.* 2006; Haylock & Nicholls 2000; Jones *et al.* 2009) required for crop modelling, and a carefully calibrated and validated process-based crop model for wheat (APSIM-Wheat) (Asseng *et al.* 2002; Carberry *et al.* 2009; Keating *et al.* (2003); Verburg *et al.* 2003).

1.4. Outline of thesis

This thesis consists of six chapters; two of them have been submitted for publication in a peer-reviewed journal (Chapters 3 and 4). This chapter presents a general introduction to the topic and the motivation for this research, including the general aims, research objectives, study context and outline of the thesis (Chapter 1). The following chapter presents an investigation into the relevant methods for modelling crop climate risk in climate data-sparse environments, by first presenting the current limitations of the world observational network, and then discussing the main advantages and disadvantages of current methods for modelling crop climate risk with limited climate data (Chapter 2). Chapter 3 explores the extent to which the long-term risk profile of modelled crop yield changes with variable temporal coverages of climate data (i.e. duration and period); further implications related to the occurrence of severe temperature events (i.e. frost and heat) have also been considered. Chapter 4 examines how simple adjustments of high-quality local data can be used to extrapolate risk profiles of modelled crop yield across broad climatic regions. Chapter 5 investigates how a combination of sparse spatial and temporal coverages influences the robustness of risk profile extrapolation. Chapter 6 summarises the key findings, limitations and broader implications of the research and the recommendations for further research in the field.

1.5. References

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Chapter 2 : **Literature review**

2.1. Introduction

Cropping systems depend on atmospheric conditions and hence are vulnerable to both natural and human induced climate variability. Precipitation variability, in particular, is one of the major sources of risk in rainfed cropping systems (Hansen 2005; Sivakumar 2011) and the occurrence of extreme weather events (i.e. floods, droughts and heatwaves) also poses an additional threat for most vulnerable cropping systems (Alexander *et al.* 2006; Crimp *et al.* 2013). Unfortunately, state-of-the-art climate models are consistent in predicting that future climates will be more variable and extreme weather events will be more frequent and intense (Collins *et al.* 2013). Under such conditions, it is expected that there will be an increment in the level of difficulty of establishing climate risk management, decision making and planning in cropping systems (Stigter *et al.* 2013). Thus, quantification and effective tools for managing the climate variability and uncertainty are now more than ever fundamental components in frameworks to support farming responses, planning and decision-making.

Management of the climate variability and risk are embedded in crucial and costly decisions farmers make at different temporal scales, requiring specific data, information and tools. Decisions made within the growing season (tactical decisions), such as planting date selections and scheduling fertilisation applications (Meinke & Stone 1997; WMO 2012) can be supported by monitoring of the cropping system (i.e. weather, soil and crop conditions) and the use of summaries of crop yield responses to the (i) long-term climate, (ii) current weather and (iii) predictions of near-future weather conditions (i.e. weather forecasts and seasonal outlooks). The second broad group of farming decisions are those made over a longer period of time (~1 -5 years); strategic decisions (Meinke & Stone 2005; Rodriguez *et al.* 2016; Selvaraju 2012) which include, for example, the selection of crops, varieties and design of irrigation and drainage systems (WMO 2012). Farmers can make informed strategic decisions by considering summaries of crops' yield responses to (i) long-term climate and (ii) projections of future climate conditions. Certainly, summaries of crop yield responses to the long-term climate contain useful information for both types of farming decisions since they (i) allow farmers to understand the impacts of the long-term climate variability and trends on a given cropping system, (ii) provide a reference for establishing comparisons across past, present and plausible future crop responses to climate conditions, and ultimately (iii) help to quantify the long-term crop yield risks.

One of the most robust approaches to linking long-term climate variability and crop responses is the use of process-based crop models. These models are able to simulate complex processes and interactions within the climate-soil-plant system and its responses to management practices and crop genetics (Chenu *et al.* 2017; Keating *et al.* 2003; Semenov & Porter 1995). In addition, crop models are able to run multiple simulations that allow farmers to quantify crop yield responses to climate variability and change over long periods of time (Liu *et al.* 2016). However, the use of process-based crop models is mainly limited by the availability of the input data required by the model (usually high-quality weather data, soil characteristics and crop management), coupled with calibrated and validated model parameters (Challinor *et al.* 2004; Nonhebel 1994b; Ramirez-Villegas & Challinor 2012). Within these requirements, the lack of long-term, accurate and continuous daily weather data for precipitation, temperature and solar radiation remain a common problem within the crop modelling research community (Grassini *et al.* 2015; van Bussel *et al.* 2015; van Wart *et al.* 2015), and for other groups of modellers requiring weather observations at such a temporal scale (i.e. daily), including the meteorological, climatological, hydrological and ecological modelling communities (Ivanov *et al.* 2007; Semenov *et al.* 1998; Wilks & Wilby 1999).

Numerous efforts have been devoted to consolidating fairly long-term, global daily climate datasets (Donat *et al.* 2013; Klein Tank *et al.* 2002; Menne *et al.* 2012; Peterson *et al.* 1997) and methods for completing missing weather data or deriving entire daily weather series. These methods include the derivation of data from satellite observations (Barret & Martin 1981; Huffman *et al.* 2007; Li *et al.* 2013), re-analyses (Balsamo *et al.* 2015; Rayner *et al.* 2006; Rienecker *et al.* 2011), weather generators (Breinl *et al.* 2017; Semenov & Porter 1995; Wilks & Wilby 1999), spatial interpolations (Hancock & Hutchinson 2006; Jeffrey *et al.* 2001), or a combination of all these methods (Hayman *et al.* 2010a; Liddicoat *et al.* 2012; Ramirez-Villegas & Challinor 2012). These notable efforts are certainly steps forward for overcoming the problem of limited temporal and spatial coverage of climate data for multiple agricultural applications at both local and global scales. However, given the need for long-term climate risk assessments for the cropping lands, which requires daily weather data from several decades to a century, it remains unclear whether the current data sets and methods for deriving daily data are suitable for performing robust assessments of long-term crop yield risks in data-sparse environments.

In this context, this article starts by reviewing risk profiles as tools for quantifying the long-term risk of crop yields (Section 2.2). Second, the article describes the role of crop models in assessing long-term crop yield risks (Section 2.3). In the following section, a summary of the main sources of daily weather data is presented, and their applicability in long-term crop modelling is discussed (Section 2.4). A summary of the review and concluding remarks are presented in Section 2.5.

2.2. Managing the climate risk in agriculture: the risk profile

One simple and valuable tool for understanding and managing climate risk and uncertainty in agriculture is the risk profile. In this paper, the term *risk profile* refers to the cumulative frequency curve of crop yields. This tool has been used for understanding and monitoring crop yield variability (Domsch *et al.* 2003; Yao *et al.* 2007), planning resources allocations (Meinke *et al.* 1996), assessing recent climate events (Meinke & Hammer 1995), risk assessment of extreme temperature events in agriculture (Rahimi *et al.* 2007), supporting insurance programs (Bailey *et al.* 2004; Just & Weninger 1999), risk-efficient farm planning (WMO 2012), and for studying climate change impacts (Folland & Anderson 2002; Hayman *et al.* 2010b; Liddicoat *et al.* 2012) and farm policies (Bailey *et al.* 2004; Just & Weninger 1999).

The method for building the risk profile is referred to in the literature as the 'empirical cumulative distribution function' (Rajagopalan *et al.* 2002), 'the quantile function' (Oldford 2016) or as the 'rank method' (Bailey *et al.* 2004). In this paper, the term 'quantile function' will be used. The origins of the quantile function method can be traced back more than 140 years in the literature (Galton 1875, 1899). Galton, in a series of studies, showed how a simple plot of ranked data against their percentile value (or rank position) can be used for determining robust statistical summaries and measures such as the median and the interquartile range, and for obtaining key information about the shape of the data distribution. Extensive reviews of early and current advances in the method for calculating the cumulative frequency curve can be found in Harter (1984), Makkonen (2008) and Oldford (2016).

Applying the quantile method to the long-term risk profile estimation would require the researcher or farmer to rank the simulated crop yields and then estimate their cumulative probabilities. Although there are numerous methods for calculating these probabilities (Harter 1984), the Weibull plotting position function has proved to be an exact function for calculating percentile values of ranked data (Makkonen 2008) by using the following equation:

$$P_m = \frac{m}{(n+1)}$$

where P represents the cumulative probability for the m^{th} rank position, m is the rank number (varies from 1 to n), and n is the sample size or number of observations (i.e. number of years of simulated crop yields).

As the number and quality of the observations (n) increases, it might be expected that the robustness of the risk profile curve would improve. However, there is no recommendation in the literature on the appropriate sample size required for long-term crop yield risk assessments. Nevertheless, for climate applications in general, several authors agree that the strength of the cumulative probability curve will be higher as the sample size increases (Folland & Anderson 2002; Wilks 2011), and recommend 100 or more years of climate data in order to include as much variability as possible in the analysis. This recommendation may also be valid for applications involving long-term assessments of the climate impacts on crop yields, such as the risk profile of crop yields.

A hypothetical representation of the risk profile is presented in Figure 2.1. The curve provides the probability (P) of not exceeding a certain yield value, which helps to inform and discuss climate risk with decision-makers. Although the same information shown in Figure 2.1 can be represented in box plots or summarised in tables, there are advantages with using the full distribution of the risk profile, which include the quantification of a larger number of plausible scenarios and the determination of a more detailed risk analysis.

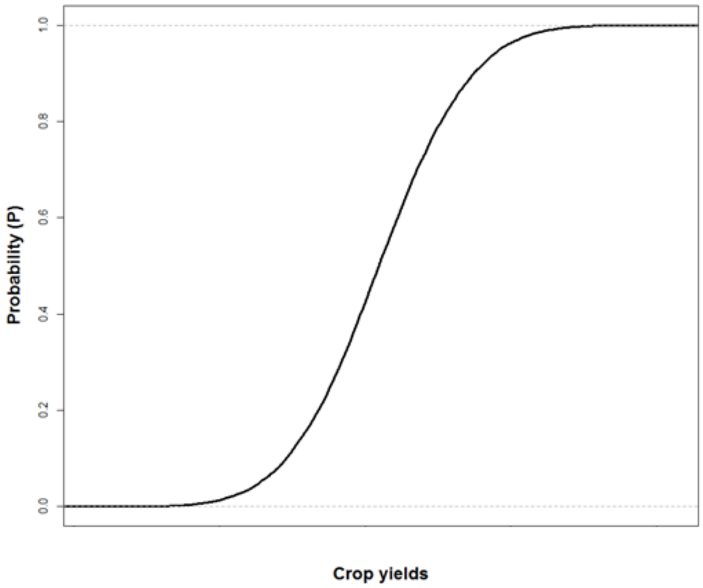

Figure 2.1. Hypothetical risk profile curve of crop yields.

A key feature of the risk profile of simulated crop yields is its versatility. Yields simulated under different weather conditions (past, present and future) and management options, would provide virtually infinite scenarios that can be explored (using a representation as per Fig. 2.1) and used can be used for understanding specific climate-crop-soil-management interactions. Here, process-based crop models play a key role.

2.3. Assessing long-term climate risk in agriculture with crop models

Exploring potential crop systems responses to multiple climate and management scenarios is not possible without crop models. As with any other model, crop models are *representations* of processes and responses of a given system. In this case a representation of the processes, interactions and responses of a given cropping system to the environment. Since the level of detail of crop models varies according to the objectives for which a given model was formulated, crop models have different input data requirements, provide different outputs, and therefore have specific potentialities and limitations.

Crop models can be broadly categorised into two main groups: statistical and process-based models. Statistical or empirical models relate actual crop yields and environmental factors (usually climate variables), and use these crop-climate relationships (Katz 1979; Mavi & Tupper 2004) to predict yields at different levels and combinations of spatial and temporal scales (Lobell & Burke 2010). The applicability of statistical crop models is relatively high, particularly over large spatial scales, since this modelling often involves the use aggregated weather data (i.e. monthly or growing season averages) for the most common climate variables (only precipitation, or precipitation and mean temperature) and historical data of actual crop yields (Peng *et al.* 2004; Prasanna 2014). The main limitations of these models include their inability to account for the element of time, such as the timing of precipitation (Lobell 2013), they are site- and region-specific, valid only for the range of data used (Boote *et al.* 1996), and are not flexible tools for testing different climate, soil and management scenarios.

The second broad group of crop models include process-based models – also referred to as mechanistic or dynamic models. Process-based crop models typically operate at daily time-steps, and have the ability to simulate crop growth, development and yield as a response to daily weather conditions (solar radiation, temperature and precipitation), soil characteristics and management practices (e.g. sowing date, sowing density and depth, and fertilisation) (Soltani & Sinclair 2012). These models are able to depict – at different levels of detail – complex bio-physical processes and interactions in the climate-soil-plant system, using physical and empirical mathematical functions (Chenu *et al.* 2017). In general, most process-based models simulate crop growth as a function of solar radiation, temperature and the leaf area index, while development is usually represented as a function of the thermal time (or cumulative temperature unit), using a specific number of developmental stages and phases according to the crop (Jones *et al.* 2003; Keating *et al.* 2003). Rarely, process-based models are able to account for the effect of diseases and pests on crop yield, however, most of them estimate the effects of water availability, temperature, nutrients and management practices. Based on the common structure of these models, the input data requirement could be very high, and usually include daily weather data for precipitation, temperature and solar radiation, soil characteristics and management choices.

Early process-based models were developed in the mid-1960s (Duncan *et al.* 1967; Monteith 1965); however, in the following years, particularly over the last decades, process-based crop models proliferated. Today, an important number of models have been developed for specific crops, some examples include models for potato (Jefferies & Heilbronn 1991), soybean (Egli & Bruening 1992), cotton (Baker *et al.* 1983; Farahani *et al.* 2009), and cassava (Matthews & Hunt 1994), but there are more models available for the most prominent global crops. For example, recent studies involving multi-model comparisons have reported that there are at least 27 models for wheat (Asseng *et al.* 2013; Martre *et al.* 2015), more than 23 models for maize (Bassu *et al.* 2014) and approximately 13 models for rice (Li *et al.* 2015).

Process-based crop models have also been developed within crop modelling platforms, which encompass models for a variety of crops. Within these platforms, the most widely used include WOFOST (van Diepen *et al.* 1989), EPIC (Kiniry *et al.* 1995), DSSAT (Jones *et al.* 2003), APSIM (Keating *et al.* 2003), CropSyst (Stöckle *et al.* 2003), GLAM (Challinor *et al.* 2004), and AquaCrop (Raes *et al.* 2009; Steduto *et al.* 2009). Process-based crop models and crop modelling platforms have been used extensively to assist both tactical and strategic farming decisions, and to answer fundamental questions related to the impact, mitigations and design of adaptation strategies to the variable and changing climate. However, their applicability is limited by the availability of calibrated model parameters, and the amount of input data required (Boote *et al.* 1996; Lamboni *et al.* 2009; Liddicoat *et al.* 2012; van Wart *et al.* 2013). From these requirements, access to or the lack of high-quality daily weather data remains a common problem faced by the agricultural modelling community worldwide.

The effects of using poor quality weather data (specifically the temporal aggregation) for modelling crop yields have been extensively investigated. One of the pioneer studies addressing this particular issue (Nonhebel 1994a), tested the effect of using averaged weather data (i.e. over a period of 10 days, a month and a season), in wheat crop growth simulations in three different climates (located in the Netherlands, the Philippines and Israel), and found that model outputs were sensitive to the temporal aggregation of the data and obtained different responses in wet and dry years. In a following study, Nonhebel (1994b) was able to discern that even the use of averaged data for temperature and radiation (a factor considerably less variable than precipitation) leads to large biases in simulation results in Wageningen (The Netherlands). van Bussel *et al.* (2011) concurred with these previous studies and in addition demonstrated that as the level of detail of the crop model increases the quality of model outputs decreases due to the temporal aggregation of the weather data across Europe.

The limited access to high-quality daily weather data for research in general has promoted the rescue and digitalisation of data in paper (Rayner *et al.* 2004), homogenisation of available data (Durre *et al.* 2010), as well as the generation of datasets (Balsamo *et al.* 2015; Challinor *et al.* 2005; Fall *et al.* 2011; Rienecker *et al.* 2011). For agricultural modelling in particular, these issues have promoted the development of methods for propagate long-term (i.e. 30 years) daily weather data from a relatively small temporal coverage of the data (van Wart *et al.* 2015), and develop specific climate forcing datasets for completing missing values in weather series (Ruane *et al.* 2015). These important advances reflect the need for better climate data for crop modelling.

In a more general context, Ramirez-Villegas and Challinor (2012) summarised the main issues agricultural researchers face in relation to weather and climate data for climate risk assessments in detail. From their review of more than 205 peer-reviewed publications, these authors concluded that agricultural researchers are more concerned with the spatial scale than the high-temporal resolution data for a limited area. In a similar context, Hayman *et al.* (2010a) used the concept of spatial analogue to determine temporal analogues of potential future impacts of climate on the risk profile. To do so, they simply perturbed daily weather data from one location to then estimate risk profile in neighbour sites, and found encouraging results within South Australia. Later, Liddicoat *et al.* (2012) used a similar approach but this time for obtaining a good spatial and temporal coverage of long-term simulated wheat yield in South Australia, that also reduced the amount of time required for crop modelling.

Overall, there is an important number of studies addressing the problem of limited access to high-quality weather data for crop modelling purposes. However, they primarily focused on the aggregation of the weather data (e.g. daily, monthly, etc.) and standard temporal coverages (e.g. 30-year periods). Furthermore, important advances in methods for improving the temporal and spatial coverages of the weather data have been explored. However, it remains unclear to what extent longer temporal coverages of daily weather data (e.g. 30, 50, 100 years) impacts on the long-term risk assessments of crop yield, and how simple methods reported in the literature could be applied for producing reliable long-term risk profiles of crop yield.

In the following section we provide a list of the most comprehensive daily data sets available and discuss their potentialities and limitations for long-term crop modelling purposes.

2.4. Main sources of daily weather data

Considering the main climate variables required in most process-based crop models, this section presents the main sources of public daily weather data for precipitation, temperature and solar radiation. A distinction has been made between measured daily weather data at surface weather stations (observed weather data), from data generated using a single or a combination of methods (derived weather data) and data available in specific formats required by a given process-based crop model (ready-to-use weather data).

2.4.1. Observed weather data

Daily weather data can be obtained from diverse sources providing global, regional and national climate data sets (GCOS 2015). These datasets are the result of the dedicated and consolidated efforts of numerous regional and international agencies, institutions and organisations (e.g. World Meteorological Organization - WMO, the National Oceanic and Atmospheric Administration - NOAA, and the National Center for Atmospheric Research-UCAR, European Meteorological Services Network-EUMETNET), which have resulted in notable databases for the research community. However, each national meteorological service has the responsibility for the maintenance and expansion of their meteorological network, as well as for the status of their database in terms of format and the quality of metadata and weather observations.

There are three notable sources providing free access to daily data for precipitation and temperature (some include solar radiation) at a global scale (Table 2.1). NOAA has one of the most extensive databases with daily data for precipitation and temperatures, the Global Historical Climatology Network-Daily (GHCN-Daily). This database is quality-controlled and daily checked and include the data from 180 countries and territories (by November 2017, GHCN-Daily version 3.22-upd-2017111905) (Menne *et al.* 2012). Temporal coverage of this dataset is variable, and the longest series are reported in North America, Europa, Australia, predominantly (Donat *et al.* 2013). Access to data is simple, however is limited to the availability of data for the specific site of interest.

Table 2.1. Main sources of daily weather data for precipitation (Precip), temperature (Temp) and global solar radiation (Solar) from surface weather stations.

Database	**Number of stations**			**Temporal coverage**	**Spatial coverage**
	Precip	**Temp**	**Solar**		
GHCN-Daily[1]	~100 000	~30 000	-	Variable Earliest record 1832	Global
GCOS-surface[2]	1 000	1 000	-	Variable	Global
European Climate Assessment (ECA)[3]	195	199	-	Common period: 1961 – 1990; Earliest record 1925	Europe and Middle East
WRDC -World Radiation Data Centre[4]	-	-	~400	Variable	Global

[1] https://www.ncdc.noaa.gov/ghcn-daily-description;
[2] https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ncdc:C00861;
[3] http://www.ecad.eu/dailydata/index.php;
[4] http://wrdc.mgo.rssi.ru/

Another important source of daily data from surface stations is available from the Global Climate Observing System Surface Network (GCOS-surface network). The origin of this database was to create a baseline network containing daily records from stations with a good length and quality of data and a reasonably even spatial distribution (Peterson *et al.*

1997), which resulted in a suit of 1000 weather stations. As expected, the temporal coverage of the data varies from region to region, and from site to site.

None of these three databases (i.e. GHCN-Daily, GCOS-surface network and the ECA) provide solar radiation data. Within the climate variables required for crop modelling, solar radiation is probably one of the most difficult to obtain and different temporal and spatial scales. There are more weather stations measuring precipitation and temperature, in comparison with those with solar radiation data available. For example, the ratio of stations measuring solar radiation relative to those measuring temperature is approximately 1:500 (Badescu 2014). The difficulties with solar radiation are not only related to the amount of stations measuring the variable, but it also limited but the record length and quality of the observations available. One of the best global datasets for solar radiation are available in the World Radiation Data Centre (WRDC) web site (http://wrdc.mgo.rssi.ru/). The WRDC is a laboratory of the Voeikov Main Geophysical Observatory in Russia, sponsored by the WMO. Several measurements related to solar radiation are available within the WRDC database, including (global) solar radiation (in this thesis we use the term solar radiation to refer to global solar radiation) required for crop modelling.

Continuous and important improvements have been made in the global network that are reflected in the increase in the number of stations over the past 60 years (Menne *et al.* 2012). However, since the improvement and maintenance of weather networks is a responsibility of each country, there are substantial differences in the number and quality of the data available in developing and developed countries. The global network of meteorological station is denser over North America, Europe and Australia than over South America, Africa and Antarctica, and the lack of long-term and even recent weather data is still substantial within Africa, Asia and South America (GCOS 2015; Menne *et al.*

2012). Both, the spatial coverage and the temporal coverage of the global network is variable, and has a limited number of sites measuring solar radiation (as briefly illustrated in Table 2.1).

Datasets summarised in Table 2.1 are important sources for multiple research applications. For crop modelling in particular, these datasets facilitate the search and access to high-quality weather data. However, due to the differences temporal coverage of the data (inherent to weather observations) it results difficult to perform uniform comparisons over a long period of time at large spatial scales. Numerous methods for completing or deriving full series of weather data are reported in the literature. In the section 2.4.2 some examples of these methods and datasets derived from them are summarised and briefly discussed.

2.4.2. Derived weather data

Climate data can be derived using a variety of methods to either complete missing values or generate a full series of weather data. Methods include the use of simple empirical functions (e.g. Angstrom equation for estimate solar radiation from sunshine hours), to the most sophisticated methods involving the use downscaled outputs from General Circulation Models (GCMs). These methods include the derivation of data from satellite observations (Barret & Martin 1981; Huffman *et al.* 2007; Li *et al.* 2013), re-analyses (Balsamo *et al.* 2015; Rayner *et al.* 2006; Rienecker *et al.* 2011), weather generators (Breinl *et al.* 2017; Semenov & Porter 1995; Wilks & Wilby 1999), spatial interpolations (Hancock & Hutchinson 2006; Jeffrey *et al.* 2001), or a combination of all these methods (Hayman *et al.* 2010a; Liddicoat *et al.* 2012; Ramirez-Villegas & Challinor 2012). These notable efforts are certainly steps forward for overcoming the problem of limited temporal and spatial coverage of climate data for multiple agricultural applications at both local and global scales. However, the applicability of these methods rely on meteorological observations, and the more sophisticated the method the higher their dependency to in situ observations (e.g. GCMs require measurements of the entire climate system including surface, atmosphere, ocean, land cover and use information).

Derivation of weather data can include the use of one or a combination of methods. The approach used for deriving weather data depend on the objectives for its generation. In some cases, crop modellers require a uniform spatial coverage for a short period of time (1-2 decades). For global studies, data derived from reanalysis also provide a good spatial coverage of the data, however, with important error over regions with low density of weather stations.

For regional applications, data derived from satellite observations could provide continuous daily data even for places where no weather stations are available. For example, the TRMM provide precipitation data covering the latitude band between 50° N and 50°S over the period 1998-2015 (Huffman *et al.* 2007; Liu *et al.* 2012). At point level, a method or a combination of methods can be used for weather data derivation. However, the use of weather generators or interpolation techniques for crop modelling applications are the most widely used methods.

The improvement of GCMs and spatial interpolation techniques has led to the construction of valuable comprehensive gridded datasets for crop modelling (Rienecker *et al.* 2011). There are numerous products available at the moment that can be accessed from numerous web sites. In comparison with the sources of observed data, the temporal and spatial extent of the derived data is better. However, the use of this datasets is limited to regions in which in situ observations required for validation are not available.

So far, this review has shown the main type of weather data available that can be used for crop modelling applications. However, several limitations in these datasets could limit the estimation of a robust risk profile of crop yield in areas with a low density of weather station. In addition, most datasets (not just the list presented in this review) are not ready to be used as input data in a process-based crop model. Therefore, most crop modellers have also to go through quality control routines to verify among other issues missing and impossible values (e.g. a negative value of precipitation), complete gaps in the data, and formatted according to the models' specifications.

2.4.1. Ready-to-use weather data

There a few examples of institutions providing quality-controlled, continuous and formatted weather data for specific crop models. Probably one of the most notable examples is the Australian database SILO (Scientific Information for Land Owners, https://www.longpaddock.qld.gov.au/silo/index.html). SILO provides patched point and gridded daily weather data for the entire country for a range of climate variables and formats suitable for crop modelling applications. This database contains high-quality climate data (Jeffrey *et al.* 2001) from 1889 to present. The data has been carefully quality-controlled and with no missing data. This database has enabled the environmental researchers in general, and most specifically Australian crop modellers to reduce the time invested in checking the quality of the climate data used.

2.5. Summary

Weather data required for modelling long-term risk profiles of crop yield are not always available. The best climate data sets are available for North America (United States and Canada), Europe and Australia, while the spatial and temporal coverage of current weather data is still relatively poor for most regions in South America and Africa.

Notable advances have been made to complete missing values, homogenise and generate climate data sets, provide read-to-use data, but most of them restricted and/or validated for regions with a high density of weather stations. Thus, there is a need for a method or a combination of methods for modelling long-term crop yield risk for environments in which daily wheat data is spatial and temporal limited.

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Chapter 3 : **Temporal coverage of climate data and its impact on the risk profile of modelled wheat yield risk**

Submitted to: Agriculture and Forest Meteorology

Statement of Authorship

Title of Paper	Temporal coverage of weather records and their impacts on the risk profile of modelled crop yields
Publication Status	☐ Published ☐ Accepted for Publication ☑ Submitted for Publication ☐ Unpublished and Unsubmitted w ork w ritten in manuscript style
Publication Details	Agricultural and Forest Meteorology.

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Name of Principal Author (Candidate)	Bracho Mujica, G.		
Contribution to the Paper	Data collection, crop model setting up and yield simulations. Script writing for statistical analysis and mapping. Data analysis and interpretation. Writing of the manuscript. I hereby certify that the statement of the contribution is accurate.		
Overall percentage (%)	90%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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3.1. Abstract

High-quality climate data are critical inputs for modelling climate risk in cropping systems and consist of long-term, continuous, accurate, daily weather records for precipitation, temperature and solar radiation. However, comprehensive weather data often exhibit short record length and missing or inaccurate records, which can lead to inconsistencies.

Risk profiles (cumulative probability curves of crop yield) are effective tools to quantify the performance of agricultural systems under climate variability. The aim of this study was to determine how sensitive risk profiles of modelled wheat grain yield (MWGY) are to temporal coverage of climate data, and additionally to the presence of extreme temperatures.

Here, we examined MWGY risk profiles across the Australian wheat-belt using the highest quality weather records available. To test the effect of the discontinuity and limited record length often found in weather records, risk profiles were constructed using variable temporal coverages (record length and period) and compared with those obtained for a baseline period (last 100 years, 1917 – 2016).

Risk profiles based on more than 40 years showed little bias and small root mean square errors when compared to the baseline, implying that even relatively short climate records can produce reliable long-term performance indicators. Risk profiles able to account for severe frost and heat events required longer climate records (60 years). For most locations in Australia, risk profiles built using data from the last 10-40 years also revealed negative yield trends. Results were consistent across soils and different simulated sowing dates. Findings highlight rainfall as the main climate driver of wheat productivity and the importance of the record length and period considered for extreme weather event analysis in agricultural studies.

Keywords: Climate risk; high-quality climate data; extreme temperature events; frost; heat; APSIM; probability risk assessment

3.2. Introduction

Process-based crop models are able to simulate the complexities of crop growth and development (Asseng *et al.* 2013; Challinor *et al.* 2004; Keating *et al.* 2003; Travis 2016), and are key tools for studying the impact of natural climate variability and change on crop performance (Chenu *et al.* 2017; Jarvis *et al.* 2011; Martre *et al.* 2015; Teixeira *et al.* 2015). To run these sophisticated models for a single season requires a high level of input weather data (i.e. daily, continuous and accurate records for precipitation, maximum and minimum temperatures and solar radiation). In addition, long-term studies of crop performance and response to the climate risk have another requirement – long-term weather records (several decades). Year-to-year climate variability is one of the main sources of uncertainty for decision-makers managing cropping systems (Barnston & Tippett 2014; Hammer *et al.* 2001; Wilby *et al.* 2009), and long-term data allow to capture of as much climate variability as possible, and helps to detect extreme weather events and trends in key climate variables affecting crop performance (Semenov & Barrow 2002). However, these four features of high-quality climate data – fine temporal scale, accuracy, continuity and long temporal coverage – are not always present or publicly available (Christensen & Christensen 2003; Grassini *et al.* 2015; Rosenzweig *et al.* 2013; van Wart *et al.* 2013), limiting the robustness of long-term climate risk assessments in cropping systems at global scale.

Risk profiles of modelled crop yields (cumulative probability curves of crop yield) are effective tools for summarising yield variability and exploring the benefit and limitations of agricultural management decisions, and serve to quantify the climate risk (Day 1965; Dumont *et al.* 2015; Fraisse *et al.* 2006; Hammer *et al.* 1987; Hess *et al.* 2002). However, the limited access to high-quality climate data restricts the number of agricultural regions in which reliable risk profiles can be determined. Although the problem of limited climate data has been addressed in previous crop modelling studies (Grassini *et al.* 2015; van Wart *et al.* 2013; Van Wart *et al.* 2015), the focus of those studies have been on short-term weather records (i.e. few decades). To the best of our knowledge, the issue of how critical long-term climate data is to the risk profile of crop yield has not been specifically addressed to date. This paper examines the sensitivity of the risk profile of modelled crop yields – in terms of bias – to the record length and period covered by the climate data. The objectives of this study were to (a) determine to what extent the long-term risk profile of modelled wheat yield changes with variable record lengths and periods of climate data, and (b) what are the further implications for risk profiles of modelled wheat yield accounting for severe temperature events (i.e. frost and heat).

We found the Australian grain-belt a suitable study area for answering this question. In first place, Australia has one of the best daily weather dataset available (Jones *et al.* 2009; Menne *et al.* 2012) for the climate variables required for modelling long-term crop modelling, and a carefully calibrated and validated process-based crop model for wheat (APSIM-Wheat) (Asseng *et al.* 2002; Carberry *et al.* 2009; Keating *et al.* (2003); Verburg *et al.* 2003). Wheat is the major crop within the grain-belt, covering almost 11.3 Mega hectares with an estimated gross value of $56 billion (Australian dollars) for the 2015 – 2016 period (ABS 2017). The crop is grown under extremely variable climate conditions (Hammer *et al.* 1996; Nicholls *et al.* 1997), which have affected productivity in recent years.

Significant declines in precipitation have been observed in much of the grain-belt, starting from the late 1960s, with further reductions since the mid-1990s in the southwest of Western Australia (Hope *et al.* 2010; Ryan & Hope 2006). The Millennium Drought – also referred to in the literature as the 'Big Dry' – extended from the mid-1990s until early 2010, and is recognised as one the longest droughts since the mid-1900s affecting the southwest of Queensland, southern New South Wales, Victoria and the south of South Australia, (van Dijk *et al.* 2013; Verdon-Kidd & Kiem 2009). Wheat management and productivity in the region have also been impacted by the increment in maximum and minimum temperatures, mostly since 1950, and the increased frequency of hotter nights and days has also increased since the mid-1970s (Alexander *et al.* 2007; Plummer *et al.* 1999; Trewin & Vermont 2010). This has been confirmed using with the most robust dataset of temperature in Australia - The Australian Climate Observations Reference Network – Surface Air Temperature (ACORN-SAT) dataset (Trewin 2013). Clearly, declining precipitation and warming have had negative impacts on wheat production in Australia. In fact, recent studies have shown that actual wheat yield variability has significantly increased for the 1981 – 2010 period (Toshichika & Navin 2016), and actual wheat yields have stalled, with a significant decline in modelled wheat yields since 1997 (Hochman *et al.* 2017). Both studies attributed to the recent decline in precipitation and rise in temperatures.

3.3. Materials and methods

We produced risk profiles of modelled wheat grain yield (MWGY) for 15 sites with long-term and accurate weather records, which allowed us to then systematically degrade the quality of the climate data (i.e. record length and continuity of the records) used for the crop modelling and assess the robustness of the resulting risk profiles. For this purpose, we conducted a series of simulations in APSIM (Agricultural Production Systems Simulator Model) (Keating *et al.* 2003) to produce modelled wheat grain yield (MWGY) using two soils and a range of sowing dates. In addition, we incorporated the impacts of frost and heat using the method proposed by Bell *et al.* (2015) and used by (Flohr *et al.* 2017), producing a total of four simulated time series: MWGY, $MWGY_{Frost}$ (MWGY reduced by frost), $MWGY_{Heat}$ (MWGY reduced by heat) and $MWGY_{Frost|Heat}$ (MWGY reduced by frost and heat). Risk profiles were constructed for the four simulated time series using the last 100 years of weather records (1917 – 2016, also referred in this paper to as the baseline period), by ranking modelled yields and calculating the corresponding percentile values. Figure 3.1 summarises the methods applied for building risk profiles for the baseline period.

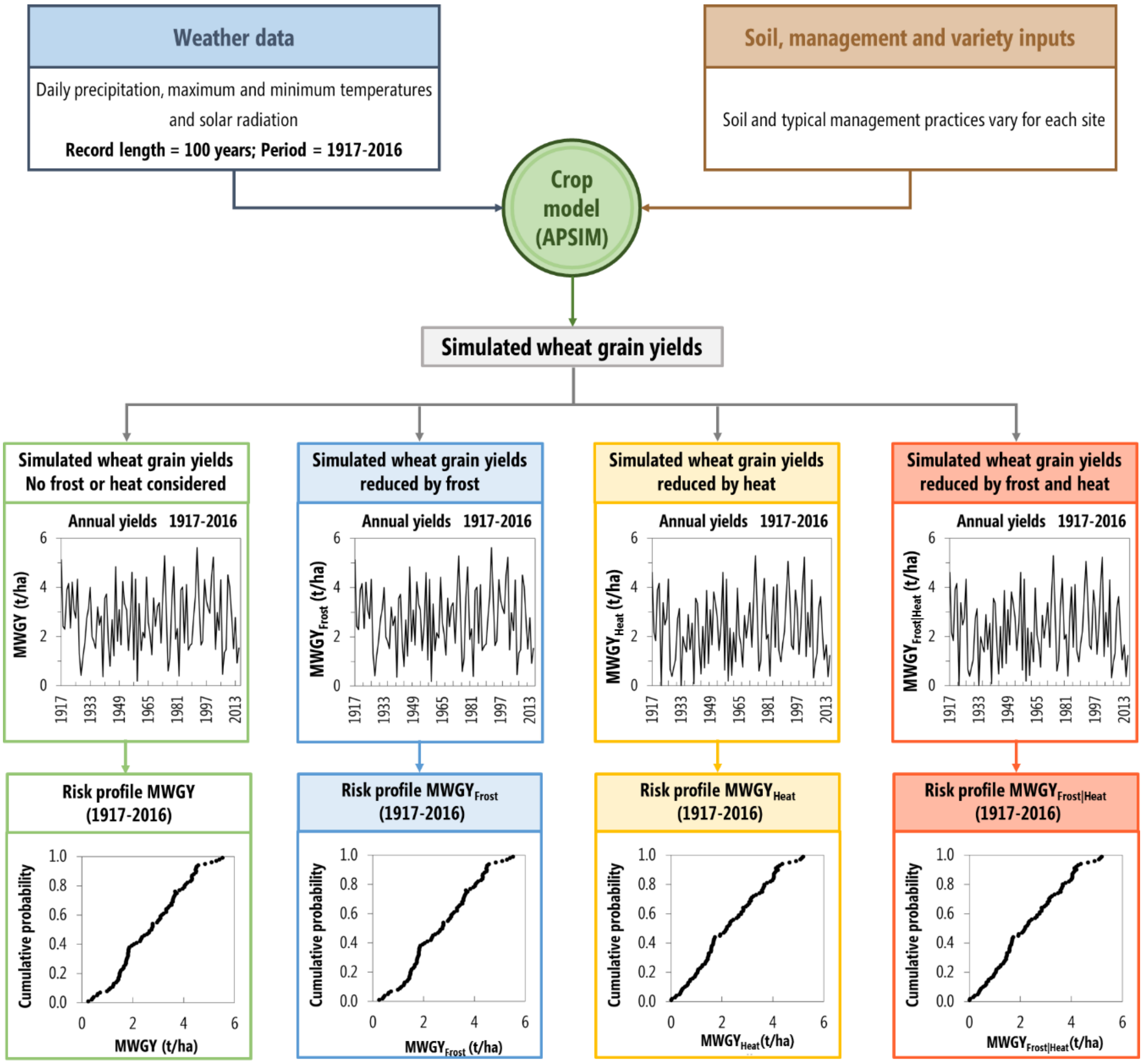

Figure 3.1. Flow chart of the process used to generate risk profiles of modelled wheat grain yield (MWGY) for the baseline period 1917-2016. Risk profiles were generated for the simulation series: MWGY, MWGYFrost (MWGY reduced by frost), MWGYHeat (MWGY reduced by heat) and MWGYFrost|Heat (MWGY reduced by frost and heat). The risk profiles are cumulative probability distributions (percentiles) of yield.

3.3.1. Study area and climate datasets

We selected 15 wheat-growing sites within the Australian grain-belt (Figure 3.2 and Table 3.1), based on their proximity to weather stations with long-term daily records for precipitation, maximum and minimum temperatures and solar radiation. To meet this criterion, we selected weather stations with data digitised within the CLIMARC project (Computerising the Australian Climate Archives) (Rayner *et al.* 2004). These stations have the most complete, accurate and longest temporal coverage of daily weather records for precipitation and temperatures. SILO (Scientific Information for Land Owners, (Jeffrey *et al.* 2001) provides daily patched point data for the CLIMARC sites for the period used in this study (1917-2016). The use of these high-quality climate data sets enabled us to (i) determine long-term risk profiles of MWGY, and (ii) mimic one of the most common problems found in climate data sets, which is the variable temporal coverage (non-continuous data covering different periods of time).

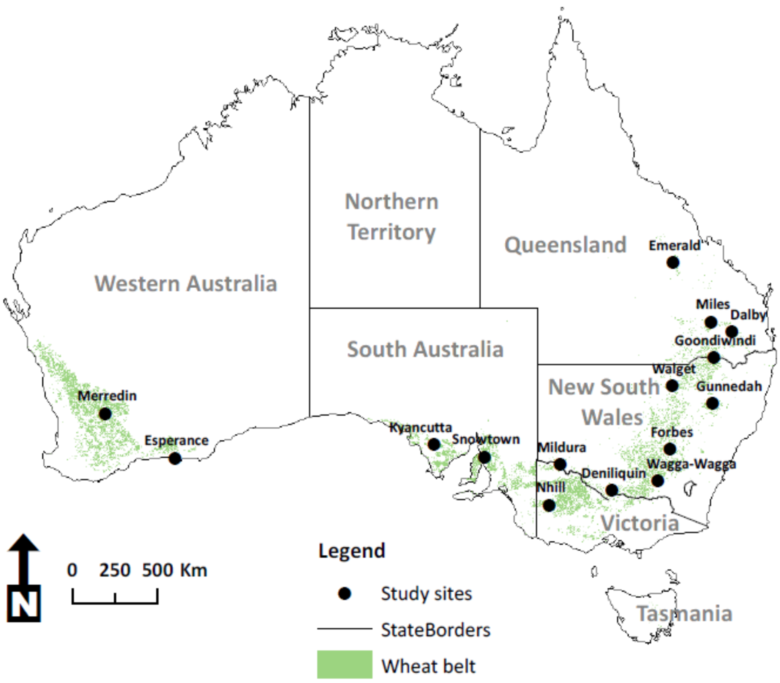

Figure 3.2. Study sites selected (black dots) within the Australian grain-belt. Data sources: ABARES and BRS (2010).

Table 3.1. Study sites and detailed record length available for precipitation and temperature observations within the baseline period (1917 – 2016).

State	Site	Precipitation records			Temperature records		
		Start date	End date	Length (years)	Start date	End date	Length (years)
Queensland	Emerald	Jan – 1917	Jun – 1992	76.5	Jan – 1917	Jun – 1992	76.5
	Dalby	Jan – 1917	Jan – 1992	76.1	Jan – 1917	Jan – 1992	76.1
	Goondiwindi	Jan – 1917	Jun – 1995	79.5	Jan – 1917	Jun – 1995	79.5
	Miles	Jan - 1917	Dec - 2016	100.0	Jan - 1917	Mar – 2005	88.3
New South Wales	Walgett	Jan – 1917	Jun – 1993	77.5	Jan – 1917	Jun – 1992	76.5
	Gunnedah	Jan – 1917	Dec – 2011	96.0	Jan – 1917	Jan – 1992	76.1
	Forbes	Jan – 1917	May – 1998	82.4	Jan – 1917	Jun – 1995	79.5
	Wagga-Wagga	Jan – 1917	Dec – 1975	60.0	Jan – 1917	Dec – 1975	60.0
	Deniliquin	Jan – 1917	Jun – 2003	87.5	Jan – 1917	Jun – 2003	87.5
Victoria	Mildura	Jan – 1917	Dec – 1949	33.9	Jan – 1917	Dec – 1949	33.9
	Nhill	Jan – 1916	Dec – 2008	93.0	Jan – 1916	Dec – 2008	93.0
South Australia	Snowtown	Jan – 1916	Dec – 2001	86.0	Jan – 1916	Dec – 2001	86.0
	Kyancutta	Jan – 1930	Dec – 2016	86.0	Jan – 1930	Dec – 2016	86.0
Western Australia	Esperance	Jan – 1916	Jun – 1969	53.5	Jan – 1916	Jun – 1969	53.5
	Merredin	Jan – 1916	Dec – 2009	94.0	Jan – 1916	Apr – 1985	69.3

It is important to note that the daily weather records used in this study are not 100% complete. However, 13 out of the 15 study sites have more than 76 years of records for precipitation and temperatures. SILO datasets are completed daily series at point level – also known as patched point data, using two interpolation methods: ordinary kriging is used for precipitation, and thin plate smoothing spline for the other climate parameters (i.e. temperature and solar radiation)(Jeffrey *et al.* 2001). Although the SILO interpolation method has the tendency to underestimate the number of wet days at the edges of precipitation events (zeros and high precipitation values, Beesley *et al.* (2009), we could expect that the sites used in this study have the best climate data available, since (a) most study sites are located in high density climate data areas, which is expected to increase accuracy of the interpolations; (b) higher errors for the SILO datasets have been reported for northern areas and high-rainfall zones, not considered in our study and (c) the winter growing season (April to October) tends to have more spatially coherent frontal rain compared to summer rainfall which has a larger component of convective thunderstorms.

3.3.2. Crop yield simulations

The APSIM-Wheat module simulates growth and development of wheat on a daily basis as a response of the crop to solar radiation, temperature, soil water, soil nitrogen and management practices (Keating *et al.* 2003). Within this module solar radiation and temperature determine crop growth rate; temperature affects crop phenology, root expansion, Leaf Area Index (LAI), grain filling rate, nitrogen demand, and the estimation of vapour pressure deficit; and water availability, management practices and mineral nutrients, affects crop response (yield). However, since APSIM is not currently able to model the impacts of severe extreme temperatures on crop yield (Barlow *et al.* 2015; Flohr *et al.* 2017), we externally computed the reductions in wheat grain yield due to frost and heat events.

We used APSIM version 7.8 to simulate wheat grain yields considering two soils at each site, a constant soil and a typical soil. A constant (or artificial) soil was used in order to isolate the impacts of climate on wheat performance. This soil has a sandy texture, 80mm of plant available water content (PAWC), organic carbon content of 0.7% (0 – 10 cm) and a rooting depth of 100 cm. Typical (representative) soils were also used in order to understand the differences across the study area due to soils characteristics. These typical soils are representative for a given study site, and were selected from the APSoil database of APSIM (Dalgliesh *et al.* 2009); characteristics of these soils are detailed in Table A.1 (Appendix A). In all simulations, initial water and nitrogen contents were reset every year on the 1st of April to exclude the effects of previous seasons, as recommended in other studies (Bell *et al.* 2015; Sadras & Rodriguez 2010). Initial soil water content was set to full profile filled from the top layer to ensure crop establishment, and initial nitrogen was set to 100 kg N/ha as urea at sowing.

Locally adapted varieties were selected according to the region. Mace (early maturing variety) was selected for the winter-rainfall regions (Western Australia, South Australia, Victoria and southern New South Wales), and Gregory (medium maturity variety) was chosen for the summer-rainfall sites (northern New South Wales and Queensland). In all cases, sowing density was set to 180 plants/m^2, sowing depth to 30mm and row spacing to 250 mm. Three different sowing dates were simulated to represent early sowing (25th April), typical sowing (20th May) and late sowing (15th June).

Extreme temperature events were incorporated into the MWGY using simple reduction fractions (Table 3.2) as suggested by Bell *et al.* (2015) for frost, heat, and both, frost and heat. Reduction fractions were determined for specific Zadoks-growth stages (Zadoks *et al.* 1974) at which sensitivity of wheat to extreme temperature is very high and likely to impact negatively on yield. These calculations allowed us to generate annual yields of $MWGY_{Frost}$, $MWGY_{Heat}$, and $MWGY_{Frost|Heat}$ over the entire baseline period of 100 years.

Table 3.2. Temperature criteria and approximate yield reductions used for calculating frost and heat stress for specific Zadoks-growth stages as per Bell *et al.* (2015). The criteria use daily values of minimum (Daily MinTemp) and maximum temperature (Daily MaxTemp).

Stress	Level	Criteria	Sensitive stage	Yield reduction per day
Frost	Mild	0 °C ≤ Daily MinTemp < 2 °C	Z60 – 69	10%
	Moderate	– 2 °C ≤ Daily MinTemp < 0 °C	Z60 – 75	20%
	Severe	Daily MinTemp < – 2 °C	Z60 – 69	90%
Heat	Mild	32 °C < Daily MaxTemp ≤ 34 °C	Z60 – 79	10%
	Moderate	34 °C < Daily MaxTemp≤ 36 °C	Z60 – 79	20%
	Severe	Daily MaxTemp >36 °C	Z60 – 79	30%

3.3.3. Degrading of risk profiles

We then segmented the 100-year time series (MWGY, $\text{MWGY}_{\text{Frost}}$, $\text{MWGY}_{\text{Heat}}$, and $\text{MWGY}_{\text{Frost|Heat}}$) into different record lengths (last 10 years, last 20 years, etc., Table 3.3). These segments were then used to generate 'degraded' risk profiles, in other words risk profiles that are based on shorter time periods compared to the baseline. In addition, we tested two additional ways to resample the yield time series; a) by using blocks of continuous years of different length, and b) by randomly selecting individual years from the entire time period (Table 3.3).

Table 3.3. Record lengths and periods for weather data used for 'degraded' risk profiles.

Record length (n, in years)	**Period**	**Specific years**
100	Baseline	1917 – 2016
10	Last 10-years	2007 – 2016
20	Last 20-years	1997 – 2016
30	Last 30-years	1987 – 2016
40	Last 40-years	1977 – 2016
50	Last 50-years	1967 – 2016
60	Last 60-years	1957 – 2016
70	Last 70-years	1947 – 2016
80	Last 80-years	1937 – 2016
90	Last 90-years	1927 – 2016
10, 20, 30, 40, 50, 60, 70, 80 and 90	Continuous n–years	All possible blocks of continuous years of climate data covering a record length of size n (i.e. 90 blocks of 10 years each, 80 blocks of 20 years each, …, 10 blocks of 90 years each)
10, 20, 30, 40, 50, 60, 70, 80 and 90	Random n–years	100 possible combinations of random years of climate data covering a record length of size n

Risk profiles obtained for the baseline period at a given test site were compared with those obtained with shorter record lengths and variable periods. Three resampling periods were considered: last n–years, continuous n–years and random n-years. The last n-years period represents a common characteristic of the temporal coverage of the climate data, which tends to be more complete in recent years. Another period examined was the continuous n-years, which refers to continuous weather records covering recent years or variable periods of time of size n. The third period explored consisted of non-continuous or intermittent weather records of size n, denominated random n-years period. These periods were used for splitting the weather record into record lengths spanning from 10 to 90 years in 10 years blocks (i.e. n = 10, 20, 30, 40, 50, 60, 70, 80, 90 years) as indicated in Table 3.3.

The comparison was performed using a set of statistical metrics: bias (%) and the root mean squared error (RMSE, t/ha). We used 'degraded' risk profiles for the four model types (MWGY, $MWGY_{Frost}$, $MWGY_{Heat}$, and $MWGY_{Frost|Heat}$) at 9 different record lengths (10, 20, …90 years) and 3 different resampling modes (last n-years, continuous n-years and random n-years). To compare the degraded and baseline risk profiles for the different degraded model types, we estimate average bias (eqn. 1) and RMSE (eqn. 2) over all 100 percentile classes p at each of the 15 locations j as:

$$Bias_j = \sum_{p=1}^{100} \left(\frac{MWGY_{p,j} - MWGY_{baseline,p,j}}{MWGY_{baseline,p,j}} \right) \qquad \text{(eqn. 1)}$$

and

$$RMSE_j = \frac{\sum_{p=1}^{100} \sqrt{MWGY_{p,j} - MWGY_{baseline,p,j})^2}}{100}. \qquad \text{(eqn. 2)}$$

Construction and analysis of risk profiles of MWGY were performed using R software version 3.3.3 (R Core Team 2017), and maps were created using ArcGIS® software version 10.3.1 (ESRI 2015).

Initial tests showed consistent results through all types of soil and management practices modelled. For this reason, we present only the results using a low-risk sowing date (20th of May) and representative soils.

3.4. Results

3.4.1. Time series and risk profiles of modelled wheat grain yields

The time series and risk profiles of the four simulated time series for a selected group of representative study sites (Figure 3.3) show a negative trend in simulated wheat yields from the late 1980s onwards, regardless of the model used. The slope of the trend for the period 1980 – 2016 varies from site to site, and is steeper for Wagga-Wagga (–90 kg/ha/year for all four simulated time series) and Nhill (–100 kg/ha/year for the simulated series of MWGY and $MWGY_{Heat}$, and –70 kg/ha/year for $MWGY_{Frost}$ and $MWGY_{Frost|Heat}$). However, slopes for Snowtown and Merredin are considerably less steep (for Snowtown from –20 to –50 kg/ha/year and for Merredin –40 kg/ha/year, for all simulated time series). These trends are reflected in the shift to the left in respective risk profiles, particularly in those estimated using the last 10 and 20 years (periods 2007 – 2016 and 1997 – 2016). Risk profiles built using even the last 40 years of data showed lower simulated yields than those obtained for the baseline period, a result which is consistent across all simulated time series. Differences exist in the magnitude of the underestimation of the long-term risk profiles, as discussed in the following sub-sections.

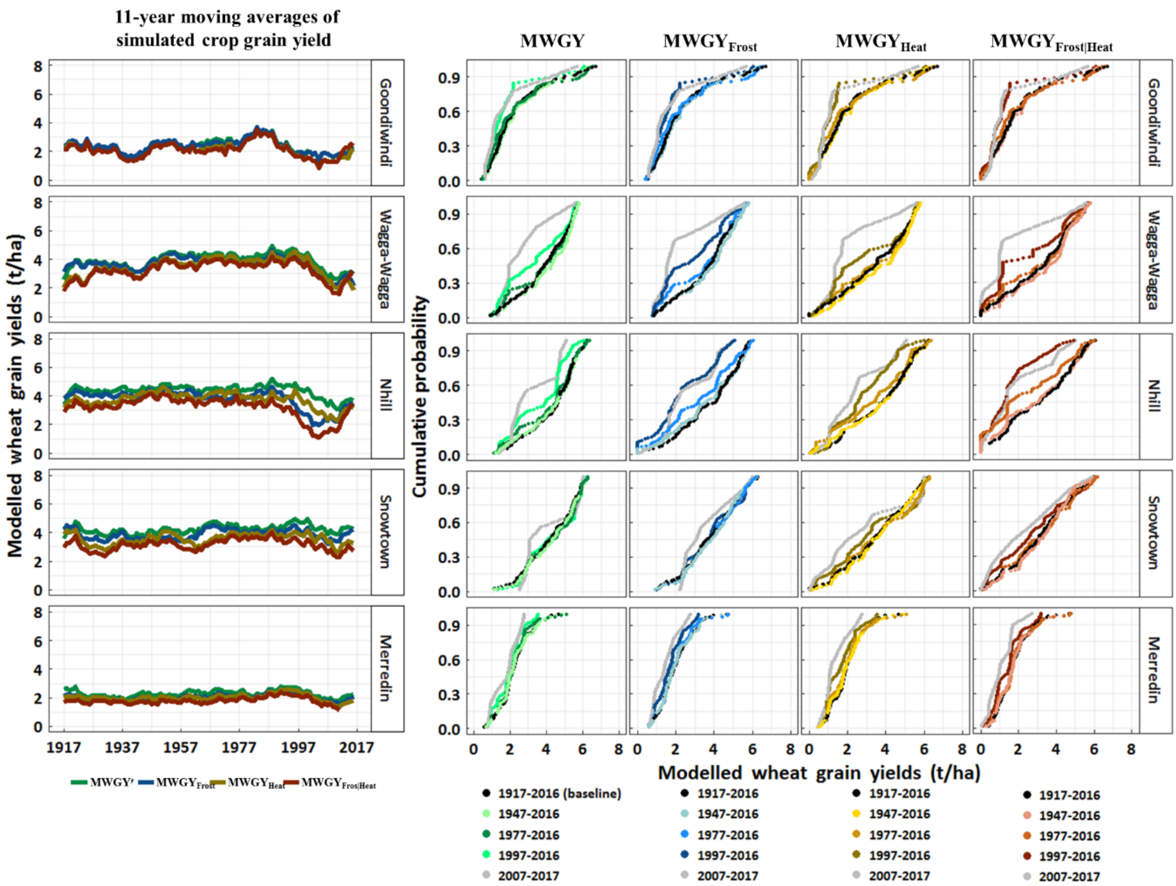

Figure 3.3. 11-year moving averages and risk profiles of modelled wheat grain yield (MWGY) for 5 regionally representative locations. The moving averages cover the baseline period (1917 – 2016), and risk profiles are presented for the MWGY, MWGY reduced by frost (MWGY$_{Frost}$), reduced by heat (MWGY$_{Heat}$), and reduced by frost and heat (MWGY$_{Frost|Heat}$), covering 5 different record lengths. Crop yields were simulated using 20th May as the sowing date and with representative soils.

3.4.2. Temporal coverage of the climate data and its impact on risk profiles

Sensitivity of risk profiles to the temporal coverage of the climate data was further analysed by exploring the full range of record lengths and periods summarised in Table 3.3. In this analysis we looked at the bias obtained with risk profiles built with variable temporal coverages (Fig. 3.4). RMSE plots are presented in Figure A.1 (Appendix A). We have considered that biases within the range of −5% to +5% indicate good match between risk profiles obtained for the baseline period and those using shorter record lengths, and biases spanning the ranges −10% to −5% and +5% to +10% were taken as indicators of acceptable matching between risk profiles. Bias outside of the good and acceptable ranges (either positive or negative) was used to identify high discrepancy between risk profiles.

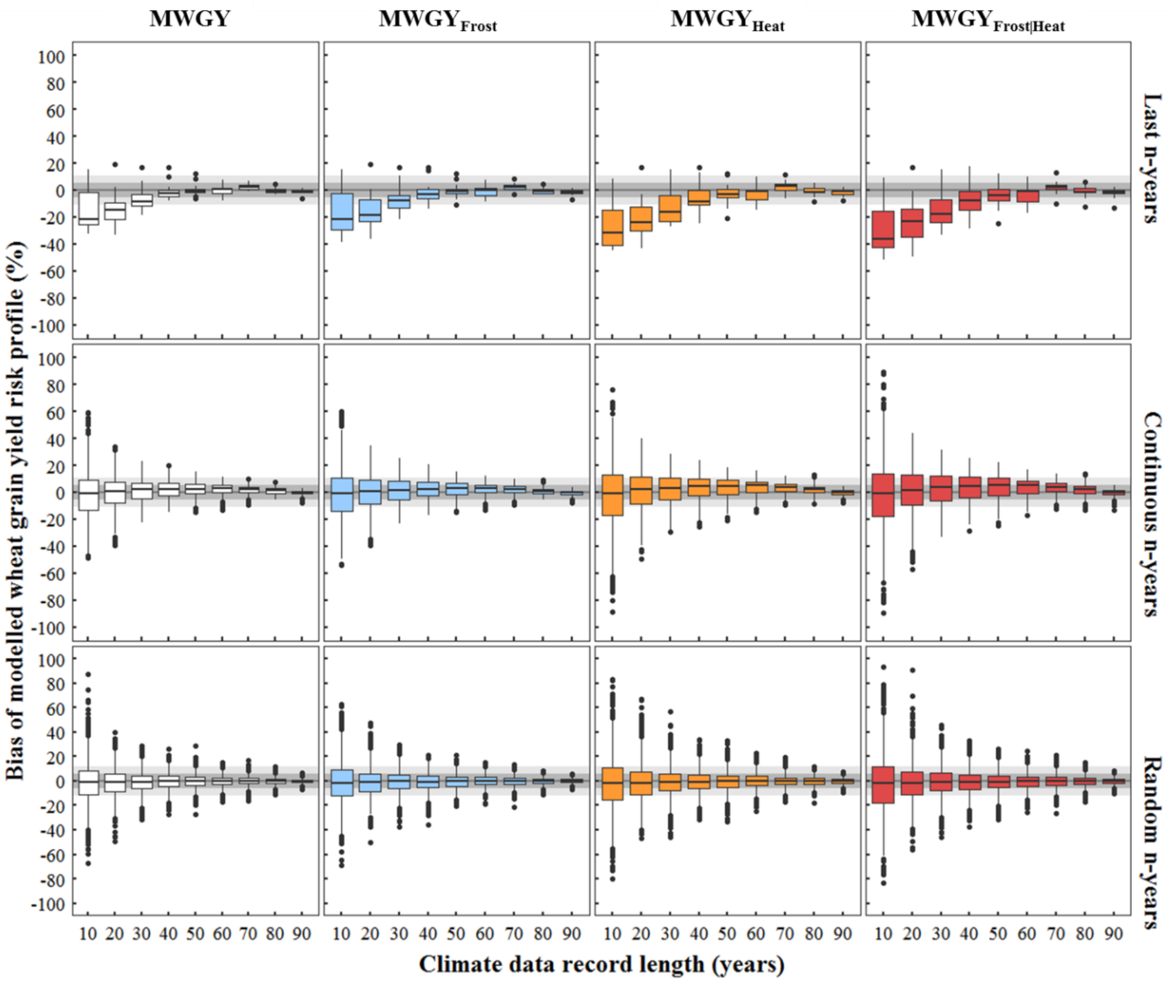

Figure 3.4. Bias (%) of risk profiles of modelled wheat grain yield produced with less than 100 years of climate data. Bias compares risk profiles obtained using 100 years of climate data with those obtained with record lengths of size n (n= 10, 20, …, 90 years). Columns represent the four simulated time series: modelled wheat grain yield (MWGY), MWGY reduced by frost ($MWGY_{Frost}$), MWGY reduced by heat ($MWGY_{Heat}$), and MWGY reduced by frost and heat ($MWGY_{Frost|Heat}$). Rows represent three resampling periods of the climate data (last n-years, continuous n-years and random n-years). Horizontal grey shaded bars highlight the bias within the ranges -5 to 5%, and -10 to 10%. Crop yields were simulated using 20th May as the sowing date and with representative soils. All sites are included in each panel.

Overall, we found a high discrepancy between long-term risk profiles and those built with short record lengths (Figure 3.4), particularly for record lengths shorter than 30 years of climate data. However, there were important differences across temporal coverages tested. The use of the last n-years allowed us to identify that risk profiles determined with the most recent weather records underestimate the long-term risk profile (Fig. 4). This is consistent with a recent drying trend associated with the millennium drought. Taking into account extreme events of heat and frost increased the required record length. At most sites, acceptable matching was obtained for the MWGY model determined with the last 40 or more years of data, while acceptable risk profiles of $MWGY_{Frost}$ required a minimum of 50 years. Risk profiles for the simulated time series accounting for heat ($MWGY_{Heat}$ and $MWGY_{Frost|Heat}$) produced acceptable bias with record lengths of 60 or more years of data.

Resampling periods representing discontinuity of the climate data (random n-years) and the lack of recent continuous weather records (continuous n-years) did not show important differences (Fig. 3.4). However, results for both differed from those obtained with the last n-years period in that neither shoed a clear trend in over- or under-estimation the risk profile. This finding emphasises (a) the underestimation produced due to the use of the recent years of climate data, and (b) the magnitude of the error (bias) using short record lengths.

These results provide the overall picture across the temporal coverage examined in this study. Additionally, we noted the negative trend in modelled yields since 1980s (Figure 3.3), also reflected in the general negative bias of risk profiles built using the last n-years period (Figure 3.4). We therefore took the opportunity offered to further investigated the sensitivity of the long-term risk profile to the recent climate conditions and its spatial variability.

3.4.3. Impacts of recent climate conditions on the long-term risk profiles: spatial aspects

Individual responses – in terms of bias – of the long-term risk profiles to the climate data record length are shown in Figure 3.5. We present only the results obtained using the last 10 to 60 years of climate data, since the bias produced with the last 70, 80 and 90 years was within the acceptable range for the majority of the study sites.

We did not find an obvious pattern in the bias across the study area (Figure 3.5). As expected, at most study sites, the shortest record length tested (10 years) produced the highest discrepancy between the risk profiles in all simulated time series. However, risk profiles for the MWGY and $MWGY_{Frost}$ series produced the highest biases (between -25 and -52%) in most south-eastern sites (i.e. south of New South Wales and South Australia, and Victoria). In contrast, most sites showed the highest values of bias for risk profiles of $MWGY_{Heat}$ and $MWGY_{Frost|Heat}$ built with the last 10 years of climate data.

Although the bias dropped as the climate data record length was increased, acceptable and good match of risk profiles was achieved with different record lengths according to the simulated time series. For the MWGY model 80% of the sites produced acceptable matching with the last 40 years of climate data. However, for the $MWFY_{Frost}$ model good and acceptable matching was obtained in most sites (86%) only with a minimum of 50 years of climate data. Simulated time series accounting for heat were more sensitive to the record length; for these, more than 60 years of data were necessary to obtain good and acceptable matching in 80% of the study sites.

Interestingly, long-term risk profiles at some study sites show minimal sensitivity to the different temporal coverages (Snowtown), or were overestimated (Emerald, Gunnedah and Esperance) across all simulated time series and record lengths.

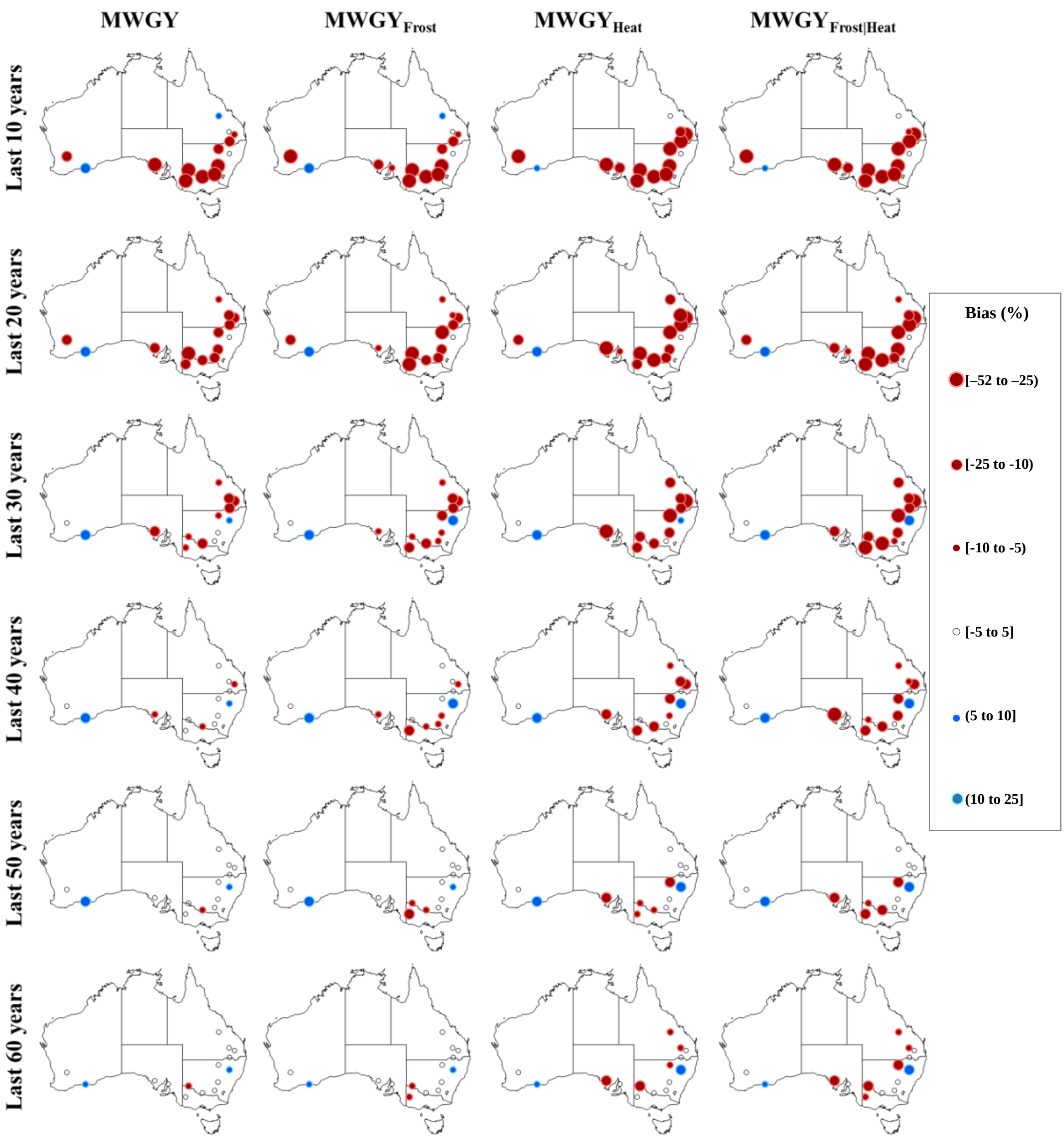

Figure 3.5. Bias (percentage, %) of the risk profiles of modelled wheat grain yield, obtained with a variable record length for the climate data. Columns represent modelled wheat grain yield (MWGY), MWGY reduced by frost ($MWGY_{Frost}$), MWGY reduced by heat ($MWGY_{Heat}$) and MWGY reduced by frost and heat ($MWGY_{Frost|Heat}$). Rows represent the record lengths: 10 years (2007 – 2016), 20 years (1997 – 2016), 30 years (1987 – 2016), 40 years (1977 – 2016), 50 years (1967 – 2016) and 60 years (1957 – 2016).

3.5. Discussion

Different temporal coverages of the climate data changed the shape of the curve of the risk profiles (Fig. 3.3). Especially for risk profiles built with the last 10, 20 and 30 years of climate data, these changes consisted of curves with higher frequency of lower wheat yields. These findings could have important implications for researchers, agricultural consultants and farmers using the risk profile as a decision support tool. They do not necessary translate into a suggestion not to use risk profiles built with the most recent weather records. However, given the expected increment in the frequency of extreme temperature events in Australia (Alexander & Arblaster 2009), we suggest that – whenever possible –both types of risk profiles (the long-term risk profile and those for the last n-years period) be taken into consideration for policy and decision-making purposes in agriculture. This would enable users to reflect on the stability of the risk profile through the different periods, and to take into consideration potential changes in the shape of risk profile curves.

Across all simulated time series and resampling periods, risk profiles showed a consistent response to the record length of the climate data: a higher bias at the shortest record lengths (Fig. 3.4). However, we found important differences in the response of risk profiles to the use of different resampling periods and simulated time series. For example, the last n-years period (especially for record lengths between 10 and 30 years) revealed that risk profiles built with climate records for recent decades will tend to underestimate the baseline risk profile. The continuous and random periods did not show a particular tendency to over/underestimate risk profiles; however, they captured the inverse relationship between bias and the record length. The main difference between simulated time series consisted of higher bias in those accounting for heat ($MWGY_{Heat}$ and $MWGY_{Frost|Heat}$). This finding leads us to suggest minimum record lengths necessary for obtaining a robust estimation of the risk profile for the baseline period (i.e. 40 years for the MWGY time series, 50 years for the $MWGY_{Frost}$ time series, and 60 years for the $MWGY_{Heat}$ and $MWGY_{Frost|Heat}$ time series).

The fact that risk profiles determined with the last 10, 20, 30 and even the last 40 years of climate data underestimate the baseline risk profiles also suggests that modelled wheat yields have declined in recent decades. Since our findings are consistent across simulated time series, soils, crop management and resampling periods for the climate data, we have strong evidence that this decline in wheat yields is mainly precipitation-driven. However, there are important differences across simulated time series – mostly related to the magnitude of the underestimation of the risk profiles rather than the pattern. Combined with the increment in the occurrence of severe temperature events for the last decades, these differences provide evidence that rising temperatures have played a key role in the decline of modelled wheat grain yields. These findings are consistent with those of a recent investigation on the role of climate trends in the stalling of wheat yields (Hochman *et al.* 2017), which revealed that average modelled wheat yield has declined by 27% (1.1 % per year) over the period 1990 to 2015, and determined that 83% of this decline is explained by the reduction in growing-season precipitation, and 17% by the increment in temperatures during the study period (Hochman *et al.* 2017). It is important to note how the Millennium Drought exacerbated the impact of frost and heat (e.g. Nhill in central Victoria).

Although most sites showed a high sensitivity (in terms of bias) to the temporal coverage of the climate data, we found a few sites in which risk profiles were overestimated or had low sensitivity to the temporal coverage. Understanding and reflecting on the natural resilience of these sites to the highly variable climate conditions may help researchers, agricultural consultants, planners and farmers to improve strategies for adaptation to climate change.

3.6. Summary and conclusions

Using the best climate data sets available for Australia, we have examined to what extent the temporal coverage of the climate data affects the robustness of the long-term risk profiles of modelled crop yields. Our results indicate that the long-term risk profile is highly sensitive to both the record length and the sampling period of the climate data, and that this sensitivity is exacerbated when heat events are taken into account in crop yield modelling. We have determined that at most of our 15 study sites in the Australian grain-belt a minimum of 40 years of data is necessary to estimate risk profiles of simulated wheat grain yield with acceptable bias, while risk profiles accounting for extreme events of temperature (frost and heat) require at least 60 years of climate data to achieve acceptable bias levels. In addition, the use of the most recent climate datasets – the last 10 to 30 years – tends to underestimate the long-term risk profiles, which translates to a decline in modelled wheat grain yields for the last three decades in an important number of wheat-growing regions within the Australian grain-belt. Our findings highlight the importance of long-term weather records for the analysis of impacts of extreme temperature events on wheat yields.

3.7. Acknowledgements

GBM is a PhD student supported by the Australia Awards Scholarship (AAS). We thank Margaret Cargill for her assistance in the preparation and proofreading of this paper. We wish to thank Dane Thomas for suggestions to earlier drafts of the manuscript.

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Chapter 4 : **Simple scaling of climate inputs allows robust extrapolation of modelled wheat yield risk at a continental scale**

Statement of Authorship

Title of Paper	Simple scaling of climate inputs allows robust extrapolation of modelled wheat yield risk at a continental scale
Publication Status	☐ Published ☐ Accepted for Publication ☑ Submitted for Publication ☐ Unpublished and Unsubmitted w ork w ritten in manuscript style
Publication Details	Global Change Biology. Submitted 16TH August 2017, manuscript ID: GCB-17-1270.

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Overall percentage (%)	80%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

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4.1. Abstract

Climate change increases variability and uncertainty of crop performance. Process-based crop growth models represent the complex spatio-temporal interactions between plants, atmosphere, and soils and enable realistic climate risk assessments of future crop yield. But they require continuous, detailed daily weather data. Probability distributions of crop model results provide risk profiles of yield and serve to assess long-term climate variability and change. This paper tests to what extent a simple method for adjusting daily weather data using seasonal and monthly factors can produce robust estimates of risk profiles at a continental scale.

We examined the predictability of risk profiles of modelled wheat grain yield across the Australian grain belt. Snowtown, in the middle of the South Australian grains belt (33.8°S, 138.2°E) was selected as the reference site, and 49 wheat-growing sites spaning from 23.5-42.8°S of latitude and 115-151.8°E of longitude were used for testing the adjustments of precipitation, maximum and minimum temperatures and global solar radiation. Adjustment factors were calculated as the difference in long-term average of a given climate variable between a test site and the reference site. For each test site, we compared risk profiles modelled with observed weather data with step-wise adjusted weather data.

Simple adjustments of both rainfall and temperatures produced good matching of risk profiles (root mean square error, RMSE< 0.5 t/ha) in 80% of the sites. Adding the adjustment of the temperatures – with monthly factors – and solar radiation improved the match of risk profiles in the most climate-contrasting sites. In regions with limited availability of high-quality climate data, simple scaling of climate inputs used in this study can provide basic climate data for modelling and generating robust risk profiles of crop yield.

Keywords: spatial analogues; climate risk; crop modelling; APSIM; high-quality climate data; limited climate data; poor-data environments; risk profile

4.2. Introduction

Climate variability is a major cause of risk in dryland farming, and growers have evolved a range of approaches to deal with this (Fujisawa & Kobayashi 2010; Howden *et al.* 2007; Olesen *et al.* 2011; Porter *et al.* 2014). As climate change increases the variability and uncertainty of climate, farmers and policy makers are more and more interested in climate risk assessments (Belay *et al.* 2017; Hammer *et al.* 2001). Crop models are valuable tools for quantifying climate risk and impacts as they capture complex crop responses to climate, soil, management and their interactions (Asseng *et al.* 2015; Liu *et al.* 2016). However, these models require long-term, accurate and continuous daily weather data, which are not always available (Baker *et al.* 2017; Nonhebel 1994a; Ramirez-Villegas & Challinor 2012; van Bussel *et al.* 2015). Considerable effort has been devoted to overcoming this problem of weather data sparseness in the context of agricultural modelling (Grassini *et al.* 2015; van Ittersum *et al.* 2013; van Wart *et al.* 2013; Watson & Challinor 2013; Zhao *et al.* 2015). These studies show notable advances in protocols and strategies to improve weather data coverage for yield-gap analysis, yield projections and climate impact assessments. These methods include the use of data derived from satellites, generated weather data, reanalysis and/or spatial interpolation techniques, which to some extent rely on the availability and length of daily climate records. Nevertheless, the use of spatial analogues in combination with a method for scaling climate data could reduce the dependency on a dense network of weather stations with high-quality observations. It is not uncommon for a region to have a few high–quality stations with daily data in conjunction with well understood spatial patterns of monthly and annual long-term climate averages. This raises the question of the extent to which daily data can be scaled spatially as input for models in the assessment of climate risks.

Spatial analogues are commonly used in climate change studies (Bryan *et al.* 2016; Gao & Bryan 2017; Ramírez-Villegas *et al.* 2011; Wilby *et al.* 2009). Hayman *et al.* (2010a) and Liddicoat *et al.* (2012) used a simple method of scaling weather data for climate risk purposes to complement top-down climate change projections. The scaling method consisted in perturbing historical daily weather data for a reference location (i.e. a location with long-term, accurate and continuous daily weather data available) with a delta factor calculated as the difference in mean precipitation (or temperature) between the reference location and a study site. Crop yield simulated with observed and perturbed weather data was used for generating risk profiles (cumulative probability curves). Risk profiles were visually compared using Quantile : Quantile plots (Q:Q plots) where deviations from the one to one line give a quick visual assessment of the differences (Chambers *et al.* 1983; Natrella 2012). Using Q:Q plots, these earlier studies on the South Australian grain belt showed a close fit between the simulated risk profiles for wheat on the same soil type generated with simply scaled weather data and the actual weather data. The work reported here builds on this earlier work in two ways: spatially by expanding from a portion of the South Australian grains belt to the whole continent, and conceptually by first introducing more rigorous statistics and adjustments at different time scales, and second by adding more climate variables adjusted.

With a focus on modelled wheat grain yield (MWGY) in the Australian grain-belt, this paper tests whether simple adjustments of daily weather data produce robust estimates of the probability distribution of MWGY risk profiles at a continental scale. For this purpose, we applied a stepwise approach to assess the differences in the simulated risk profile between adjusting only precipitation, precipitation and temperature, and adjusting precipitation, temperature and global solar radiation.

4.3. Materials and methods

MWGY risk profiles were estimated as the cumulative probability curve of simulated wheat grain yield in 49 test sites across the Australian grain-belt. We used a simple method of adjusting the historical daily weather data for a single reference location using climate averages for the growing season (April to October). We used three criteria to select Snowtown as reference site: (a) it is agriculturally important and is in the middle of the South Australian grain belt, (b) high quality climate data required for crop yield simulations are available, and (c) it allows comparison with previous studies (Hayman *et al.* 2010a; Liddicoat *et al.* 2012). We then used a stepwise approach to explore the importance of four climate variables (i.e. precipitation, maximum and minimum temperatures and global solar radiation) for the MWGY risk profile. A comparison was established between the MWGY risk profiles obtained with the different adjustments using Q:Q plots and performance metrics. Fig. 4.1 summarises the method.

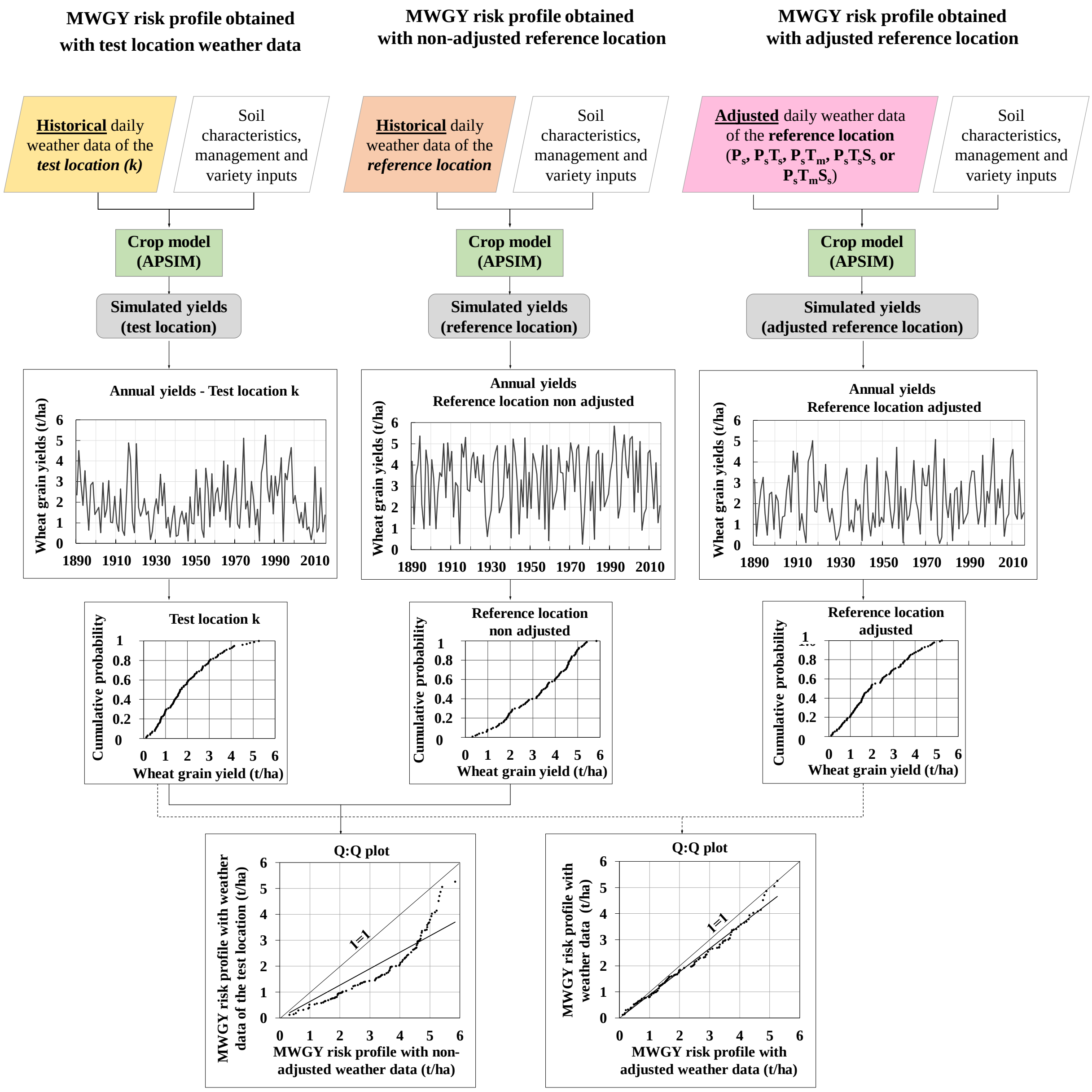

Figure 4.1. Flow chart of the method for modelling wheat grain yield (MWGY) and building MWGY risk profiles for a given test site (k), and for the reference location (ref) using non-adjusted and adjusted weather data, and the Quantile : Quantile plots (Q:Q plots) for comparing MWGY risk profiles. Type of adjustments: $Precip_s$, $Precip_sTemp_s$, $Precip_sTemp_m$, $Precip_sTemp_sSolar_s$ and $Precip_sTemp_mSolar_s$, where Precip is precipitation, Temp is temperature, Solar is global solar radiation and subscripts indicate seasonal (s) and monthly (m) adjustments.

4.3.1. Study area

The study covered the Australian grain-belt (Fig. 4.2 and Table 4.1), selected on the basis of its relevance to the Australian economy (Trewin 2006), its growing vulnerability to the variable and changing climate (Anwar *et al.* 2007; Asseng *et al.* 2013; Ludwig *et al.* 2008), factor which underline the importance of climate risk management in this area. Test sites (49) covered broad climate zones with high quality climate archives included in the region (Jeffrey *et al.* 2001; Jones *et al.* 2009; Raupach *et al.* 2012).

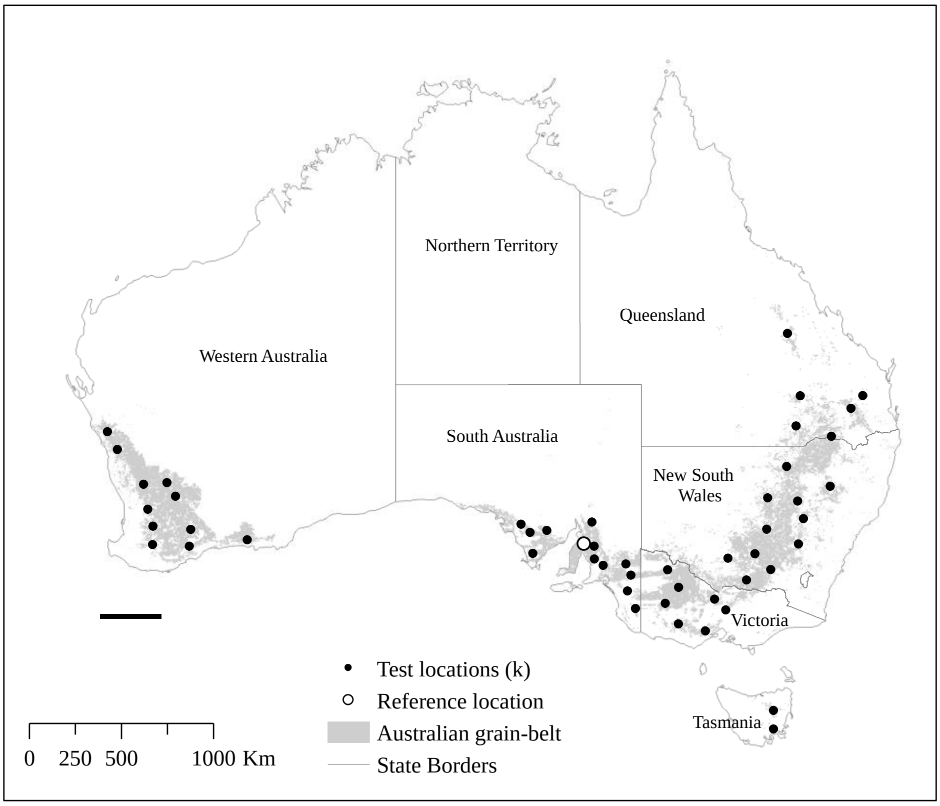

Figure 4.2. The Australian grain-belt, reference location and test sites considered in this study. Data source: ABARES and BRS (2010).

Table 4.1. Location of the reference site (italic bold) and 49 test sites ordered clockwise, and mean annual precipitation (Precip), growing season precipitation (GSPrecip), annual average of wet days (Wet days), seasonality, event-size index (τ), growing season maximum and minimum temperatures (GSMaxTemp and GSMinTemp), and global solar radiation (GSSolar).

State	Site	Precip (mm)	GSPrecip (mm)	Wet days	Seasonality[a]	τ[b]	GSMaxTemp (°C)	GSMinTemp (°C)	GSSolar (MJ/m^2)
Queensland	Emerald	629	210	59	0.33	2.4	26.5	11.4	18.4
	Roma	596	241	58	0.40	2.6	24.0	8.2	17.5
	Kingaroy	773	295	86	0.38	2.7	22.1	7.4	16.7
	Dalby	667	266	69	0.40	2.7	22.9	8.0	16.8
	St George	513	219	55	0.43	2.7	23.6	9.3	17.0
	Goondiwindi	611	269	69	0.44	2.8	22.7	8.7	16.8
New South Wales	Walgett	470	227	57	0.48	2.8	22.3	8.0	16.2
	Gunnedah	617	297	71	0.48	2.9	21.1	7.0	15.4
	Nyngan	442	219	55	0.50	2.9	21.2	7.4	15.5
	Gilgandra	562	292	63	0.52	2.9	20.1	6.1	15.2
	Wellington	615	336	76	0.55	3.1	19.5	5.6	14.5
	Condobolin	440	245	66	0.56	3.0	19.5	6.6	14.6
	Cowra	610	348	85	0.57	3.3	17.9	5.5	13.9
	Moombooldool	433	257	67	0.59	3.0	18.8	6.2	13.7
	Hay	357	221	56	0.62	3.0	19.2	6.5	13.8
	Wagga-Wagga	526	325	95	0.62	3.3	17.3	5.8	13.1
	Oaklands	453	283	75	0.63	3.2	17.9	5.9	13.1
Victoria	Ouyen	328	212	74	0.65	3.5	19.1	6.7	13.3
	Birchip	350	234	70	0.67	3.3	17.9	6.1	12.6
	Elmore	461	303	87	0.66	3.4	17.0	5.6	12.3
	Horsham	422	293	104	0.70	3.6	16.9	5.5	11.9
	Seymour	589	393	99	0.67	3.4	15.9	5.5	11.7
	Lake Bolac	532	349	128	0.66	3.5	15.1	5.8	10.8
	Teesdale	513	320	105	0.62	3.4	15.7	6.8	10.8
Tasmania	Campbell	532	319	122	0.60	3.7	14.0	3.3	10.5
	Cambridge	526	302	131	0.58	3.2	14.9	6.1	10.1
South Australia	Naracoorte	567	428	129	0.75	3.8	17.0	6.4	11.3
	Keith	462	344	112	0.74	3.5	18.2	7.1	11.9
	Lameroo	380	269	99	0.71	3.4	18.7	6.5	12.6
	Palmer	408	298	88	0.73	3.4	17.7	6.6	12.4
	Wanbi	307	209	86	0.68	3.7	19.0	6.1	12.9
	Roseworthy	442	330	94	0.75	3.7	18.5	7.7	12.8
	Mintaro	593	458	104	0.77	3.5	16.9	5.8	13.0
	Snowtown	***413***	***306***	***99***	***0.74***	***3.5***	***18.9***	***6.9***	***13.2***
	Orroroo	336	227	75	0.67	3.3	17.9	5.4	13.9
	Cummins	422	343	109	0.81	3.8	18.7	8.4	12.7
	Kimba	337	247	91	0.73	3.7	19.2	7.3	13.5
	Warramboo	329	249	87	0.76	3.8	20.4	7.1	13.6
	Minnipa	324	243	87	0.75	3.6	20.0	8.4	13.8
Western Australia	Gibson	508	385	120	0.76	3.7	18.9	8.3	13.5
	Jerramungup	381	278	97	0.73	3.5	18.7	7.4	13.0
	Newdegate	348	263	84	0.76	3.6	19.1	6.8	13.5
	Kojonup	526	439	117	0.83	3.5	17.4	6.9	12.4
	Narrogin	490	409	96	0.84	3.6	17.9	6.9	13.2
	Beverley	421	354	87	0.84	3.4	19.9	6.7	13.9
	Merredin	319	243	74	0.76	3.3	19.9	7.6	14.6
	Wongan Hills	378	312	77	0.83	3.4	20.5	8.6	14.8
	Bencubbin	309	229	77	0.74	3.6	20.5	8.1	15.1
	Mingenew	399	345	72	0.86	3.1	22.6	9.9	15.8
	Yuna	351	295	68	0.84	3.2	22.2	10.0	16.3

[a]Seasonality (Walsh & Lawler 1981); [b]τ (Sadras 2003). Both are unit less.

Daily weather data for the period 1890-2015 were obtained from the SILO (Scientific Information for Land Owners) patched point dataset (https://www.longpaddock.qld.gov.au/silo/). SILO is a comprehensive archive of Australian climate data constructed from weather observations for the period 1889 to the present. Missing data values are spatially interpolated at daily time steps using a combination of kriging and smoothing splines methods (Jeffrey *et al.* 2001), providing a consistent characterisation of weather conditions throughout the continent. Detailed percentages of the observations for the period used in this study are presented in Table B.1 (Appendix B).

4.3.2. Adjustment of daily weather data

We derived MWGY risk profiles in two ways: using weather data from the test sites, and using weather data from the single reference location (Snowtown) which were adjusted based on the difference in average climate data between the reference location (ref) and the test site (k). We calculated average climate data for the growing season (seasonal aggregation) and for every month within the growing season (monthly aggregation). The five stepwise adjustments are presented in Table 4.2, showing the two types of data aggregation used for calculating adjustment factors: seasonal or combination of seasonal and monthly.

For each adjusted MWGY risk profile, daily weather data for each climate variable at the reference location was perturbed using an adjustment factor. Each adjustment factor represents the difference in long-term average of a given climate variable between the test site and the reference location on seasonal or monthly scales. The calculation method varied with the variables (Table 4.3).

Table 4.2. Stepwise adjustment applied to the daily weather data at the reference location.

Adjustment	Climate variable(s) adjusted	Averaged climate data used for calculating adjustment factors	
		Seasonal($_s$)	Monthly($_m$)
Precip$_s$	Precipitation	✓	
Precip$_s$Temp$_s$	Precipitation and maximum and minimum temperatures	✓	
Precip$_s$Temp$_m$	Precipitation and maximum and minimum temperatures	Precipitation	Temperatures
Precip$_s$Temp$_s$Solar$_s$	Precipitation, maximum and minimum temperatures and global solar radiation	✓	
Precip$_s$Temp$_m$Solar$_s$	Precipitation, maximum and minimum temperatures and global solar radiation	Precipitation and Global solar radiation	Temperatures

Table 4.3. Equations for calculating adjustment factors of climate data. 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, … , 10, within the growing season. The terms ref and k refer to the reference location and test sites.

Climate variable adjusted	Aggregation of climate data		Adjustment factor equations
	seasonal ($_s$)	monthly ($_m$)	
Precipitation (Precip)	✓		$\mathbf{Precip}_{\mathbf{s_{AF}}}\ (\%) = \left(\frac{\mathrm{GSPrecip_{ref}} - \mathrm{GSPrecip_k}}{\mathrm{GSP_{ref}}}\right) * 100$
Maximum temperature (MaxTemp)	✓		$\mathbf{MaxTemp}_{\mathbf{s_{AF}}}\ (°\mathrm{C}) = \mathrm{GSMaxTemp_{ref}} - \mathrm{GSMaxTemp_k}$
		✓	$\mathbf{MaxTemp}_{\mathbf{m_{AF}}}\ (°\mathrm{C}) = \mathrm{MaxTemp}_{\mathrm{m_{ref}}} - \mathrm{MaxTemp}_{\mathrm{m_k}}$
Minimum temperature (MinTemp)	✓		$\mathbf{MinTemp}_{\mathbf{s_{AF}}}\ (°\mathrm{C}) = \mathrm{GSMinTemp_{ref}} - \mathrm{GSMinTemp_k}$
		✓	$\mathbf{MinTemp}_{\mathbf{m_{AF}}}\ (°\mathrm{C}) = \mathrm{MinTemp}_{\mathrm{m_{ref}}} - \mathrm{MinTemp}_{\mathrm{m_k}}$
Global solar radiation (Solar)	✓		$\mathbf{Solar}_{\mathbf{s_{AF}}}\ (\%) = \left(\frac{\mathrm{GSSolar_{ref}} - \mathrm{GSSolar_k}}{\mathrm{GSSolar_{ref}}}\right) * 100$

Precipitation series were first adjusted with a single factor $\mathrm{Precip}_{s_{AF}}$, which represents the difference between the average growing-season precipitation in the test site (k) and in the reference location (ref), expressed as a percentage (%). We calculated the adjustment factor for global solar radiation ($\mathrm{Solar}_{s_{AF}}$) similarly, also expressed as a percentage. In the case of temperatures, we calculated two adjustment factors. The first, a seasonal factor ($\mathrm{Temp}_{s_{AF}}$), was the simple difference in average growing-season temperatures (maximum or minimum) between a given test site and the reference location, expressed in °C. The second, a monthly factor ($\mathrm{Temp}_{m_{AF}}$), was the monthly difference in temperature (maximum or minimum) between the reference and a given test site. Adjustment factors were then used to estimate adjusted weather data, by multiplying (precipitation and global solar radiation) or adding (temperature) the corresponding factor to every daily record. Table 4.3 presents the equations used for the adjustments, Table 4.4 the seasonal adjustment factors, and Tables B.2 and B.3 the monthly adjustment factors for maximum and minimum temperatures (see Appendix B).

Table 4.4. Distance to the reference location (Snowtown), and seasonal adjustment factors for precipitation ($Precip_{s_{AF}}$), maximum and minimum temperatures ($MaxTemp_{s_{AF}}$ and $MinTemp_{s_{AF}}$) and global solar radiation ($Solar_{s_{AF}}$) for 49 test sites ordered clockwise.

State	Site	Distance (km)	$Precip_{s_{AF}}$ (%)	$MaxTemp_{s_{AF}}$ (°C)	$MinTemp_{s_{AF}}$ (°C)	$Solar_{s_{AF}}$ (%)
Queensland	Emerald	1493	-31.3	7.6	4.5	38.7
	Roma	1293	-21.2	5.2	1.3	32.2
	Kingaroy	1536	-3.7	3.2	0.5	26.1
	Dalby	1449	-13.0	4.1	1.1	27.0
	St George	1177	-28.5	4.7	2.4	28.4
	Goondiwindi	1289	-12.1	3.9	1.8	26.6
New South Wales	Walgett	1025	-25.7	3.5	1.1	22.5
	Gunnedah	1174	-3.1	2.2	0.1	16.2
	Nyngan	878	-28.4	2.4	0.6	17.1
	Gilgandra	1006	-4.5	1.2	-0.8	14.5
	Wellington	1010	9.9	0.7	-1.3	9.4
	Condobolin	835	-19.9	0.7	-0.2	9.9
	Cowra	971	13.7	-0.9	-1.4	4.7
	Moombooldool	774	-16.0	0.0	-0.7	3.7
	Hay	654	-27.7	0.3	-0.4	4.0
	Wagga-Wagga	851	6.2	-1.6	-1.1	-0.8
	Oaklands	755	-7.4	-0.9	-1.0	-1.3
Victoria	Ouyen	403	-30.7	0.3	-0.2	0.7
	Birchip	486	-23.6	-0.9	-0.8	-4.5
	Elmore	655	-0.9	-1.9	-1.2	-7.2
	Horsham	486	-4.2	-2.0	-1.4	-10.5
	Seymour	725	28.3	-2.9	-1.4	-11.9
	Lake-Bolac	604	14.2	-3.8	-1.1	-18.3
	Teesdale	714	4.6	-3.1	0.0	-18.1
Tasmania	Campbell	1216	4.1	-4.9	-3.6	-20.6
	Cambridge	1288	-1.2	-4.0	-0.8	-23.9
South Australia	Naracoorte	420	39.9	-1.8	-0.5	-14.9
	Keith	323	12.6	-0.7	0.2	-9.9
	Lameroo	272	-12.2	-0.1	-0.4	-5.2
	Palmer	147	-2.6	-1.1	-0.2	-6.1
	Wanbi	219	-31.6	0.2	-0.8	-2.4
	Roseworthy	97	7.7	-0.3	0.8	-3.7
	Mintaro	49	49.8	-2.0	-1.1	-1.7
	Orroroo	122	-25.8	-0.9	-1.5	5.2
	Cummins	236	12.2	-0.1	1.5	-4.1
	Kimba	182	-19.4	0.3	0.5	2.2
	Warramboo	250	-18.5	1.6	0.2	2.5
	Minnipa	304	-20.5	1.2	1.5	4.2
Western Australia	Gibson	1522	25.9	0.0	1.4	2.0
	Jerramungup	1780	-9.3	-0.1	0.5	-2.2
	Newdegate	1783	-13.9	0.3	-0.1	1.8
	Kojonup	1946	43.4	-1.4	0.0	-6.3
	Narrogin	1957	33.7	-1.0	0.0	-0.1
	Beverley	1996	15.8	1.0	-0.1	5.2
	Merredin	1885	-20.7	1.1	0.7	10.4
	Wongan Hills	2045	2.0	1.6	1.7	11.9
	Bencubbin	1942	-25.2	1.6	1.2	13.7
	Mingenew	2218	12.7	3.7	3.0	19.3
	Yuna	2295	-3.6	3.4	3.1	23.3

4.3.3. Crop simulations

We simulated wheat grain yield with APSIM (Agricultural Production Systems Simulator Model) Version 7.8 (Keating *et al.* 2003). APSIM accounts for complex spatio-temporal interactions between crops and as a response to environmental drivers (solar radiation intercepted, temperature, soil water availability and soil nutrient dynamics) and management practices. This model has been locally calibrated, widely tested, and extensively used in Australia (Robertson *et al.* 2015) for management of climate risk and understanding of potential impacts of and adaptation alternatives to climate change (Asseng *et al.* 2002; Asseng *et al.* 2015; Holzworth *et al.* 2014; Luo *et al.* 2005; Luo *et al.* 2009).

Wheat grain yield was simulated for the period 1890-2015 using observed and adjusted daily weather data. Although the focus of this study was on scaling precipitation, maximum and minimum temperatures and global solar radiation, vapour pressure deficit (VPD) was also adjusted (indirectly) when temperatures were adjusted. In APSIM, daily mean VPD is estimated as a function of maximum and minimum temperature (Tanner & Sinclair 1983) and is used to correct transpiration efficiency and estimate biomass (Wang *et al.* 2004).

Here we focus on the climate component and how simple adjustments of daily weather data affect the risk profile of modelled wheat yield. For these reasons, we kept soil type and management practices constant except for crop parameters accounting for locally adapted varieties: Mace (an early maturing variety) for the winter-rainfall regions of Western Australia, South Australia, Tasmania, Victoria and southern New South Wales; and Gregory (medium maturity) for the summer-rainfall locations of northern New South Wales and Queensland. The soil used has a sandy texture, an organic carbon content of 0.7% (0-10cm), rooting depth of 100 cm and 80 mm of plant available water content (PAWC). 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 (Bell *et al.* 2015; Luo & Kathuria 2013; Sadras & Rodriguez 2010). Initial soil water content was set to full profile filled from the top layer to ensure crop establishment (Bell *et al.* 2015), and initial nitrogen was set to 100 kg N/ha as urea at sowing. To exclude the interaction between sowing time and climate (Hayman *et al.* 2010b; Luo *et al.* 2009) we simulated four fixed sowing dates (14th, 21st, 25th and 28th of May); sowing density was set to 180 plants/m^2, 30 mm sowing depth and 250 mm row spacing.

4.3.4. Risk profiles of modelled wheat grain yield

Risk profiles were built with the year-to-year wheat grain yield simulated with APSIM. For every site and adjustment, we first ranked yield and calculated the corresponding percentiles (Fig. 4.1). Risk profiles of MWGY built with adjusted weather data (using the specific adjustment(s) factor(s)) was assigned to the corresponding test site. We then compared MWGY risk profiles obtained with adjusted weather data with those obtained with observed data for any given test site (Fig. 4.1). For this purpose, we used Q:Q plots, and calculated a set of statistical indices: the coefficient of determination (R^2), the Nash-Sutcliffe efficiency coefficient (NSE), the root mean squared error (RMSE), and the Ratio of RMSE to the standard deviation of the observations (RSR). These indices were mapped for every type of adjustment applied to the reference location, to (i) visualise the spatial variation of the performance indices, (ii) compare regions, and (iii) determine the effect of adjusting a particular set of climate variables on the robustness of MWGY risk profiles.

4.3.5. Key assumptions

Some assumptions were necessary related to the method of weather data adjustment and crop modelling. The main assumption related to weather data adjustment was that the long-term averages for precipitation, temperatures and global solar radiation were good predictors of their long-term variability. Although it is true that averages are far from representing the interannual variability of the precipitation, this assumption was made for this variable also to test whether a simple average is able to capture the risk profile of MWGY. In relation to wheat yield modelling, we assumed there was no change in soil properties and crop management across the study area, and no limitation caused by pests, disease or weeds. These assumptions were necessary to isolate the climate component, the core objective of this paper.

4.4. Results

In Fig. 4.3 we present a sample of Q:Q plots of MWGY risk profiles obtained for a representative set of locations (for the full set of plots, see Figures B.1 to B.6 in Appendix B). Fig. 4.4 shows the spatial variation and distribution of the error (RMSE), according to the type of adjustment performed to the reference location data. Tables B.4 to B.7 (Appendix B) detail the R^2, NSE, RMSE and RSR according to the sowing date used in the crop yield simulation. We did not find significant differences in MWGY risk profiles due to sowing dates. Hence, we only present results obtained with simulations of MWGY sown on a fixed date 14th of May.

As expected, risk profiles obtained with non-adjusted reference location data did not match risk profiles at test sites. The error (RMSE) varied between 0.15 – 2 .66 t/ha, but it was consistently high across the study area.

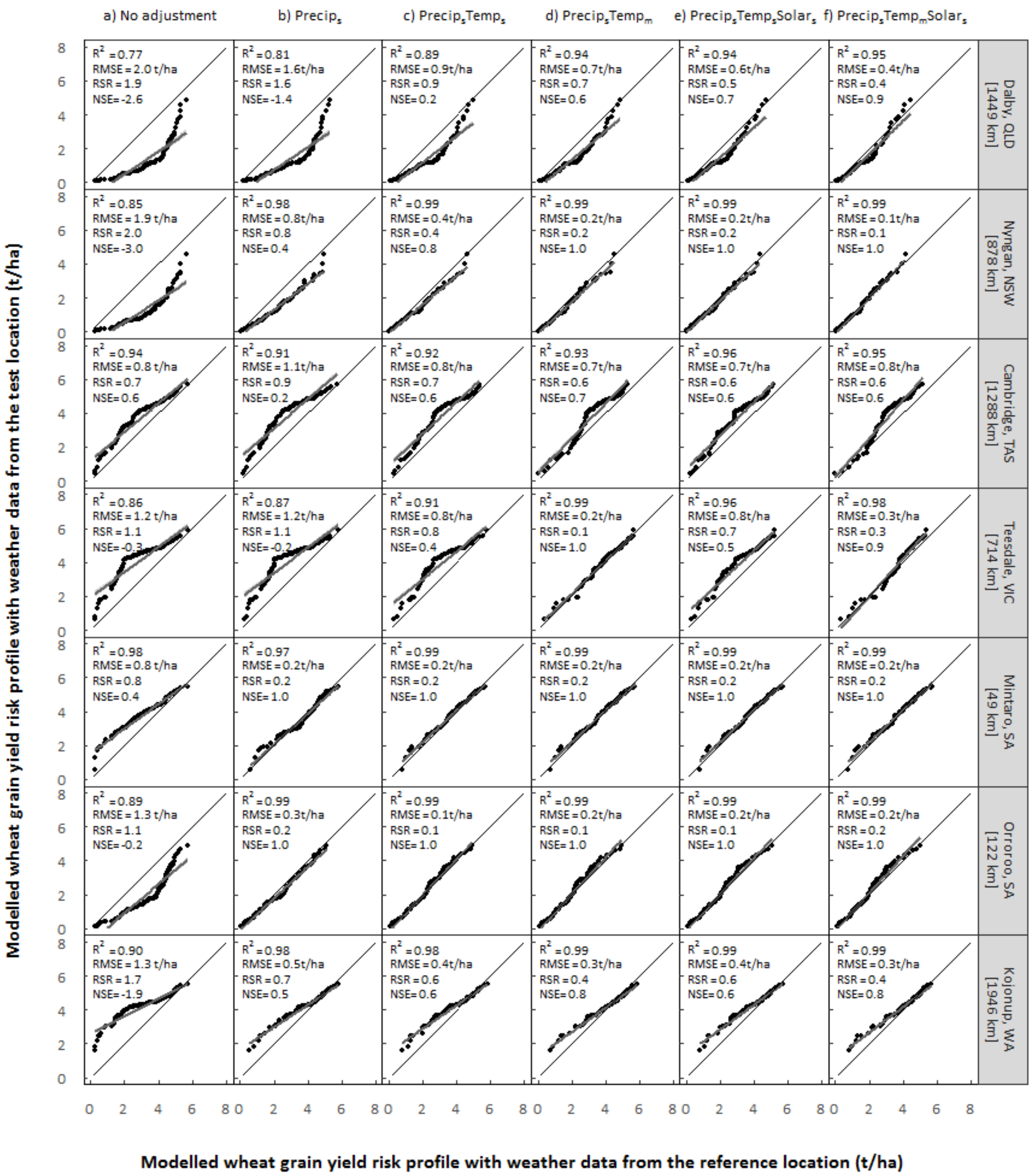

Figure 4.3. Comparison of modelled wheat grain yield risk profiles for five selected test sites in Australia. The six columns represent yield simulated with climate datasets for the reference location with: (a) No adjustment; (b) $Precip_s$, seasonal precipitation adjusted; (c) $Precip_sTemp_s$, seasonal adjustment of precipitation and temperatures; (d) $Precip_sTemp_m$, seasonal adjustment of precipitation and monthly adjustment of temperatures; (e) $Precip_sTemp_sSolar_s$, seasonal adjustment of precipitation, temperatures and global solar radiation; (f) $Precip_sTemp_mSolar_s$, seasonal adjustment of precipitation and global solar radiation, and monthly adjustment of temperatures. Performance metrics are presented in each graph. R^2, RMSE, RSR and NSE refer to coefficient of determination, the root mean square error (in t/ha), the Nash-Sutcliffe efficiency and the ratio of the RMSE to the standard deviation of the observations, respectively. Rows represent the test sites selected as indicated in the right strip which includes the distance to the reference location (Snowtown) in km in brackets.

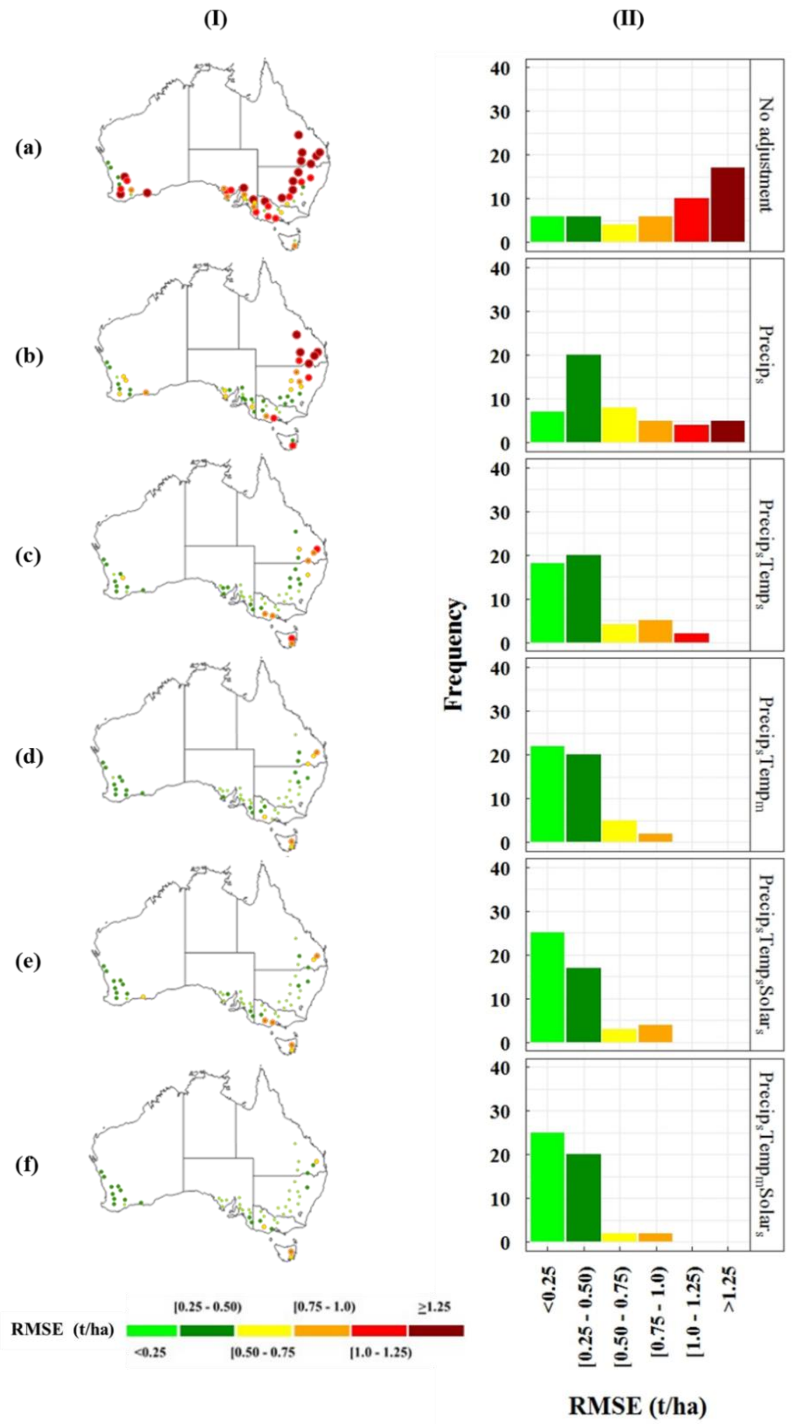

Figure 4.4. Comparison of modelled wheat grain yield risk profiles across the entire study area in terms of root mean square error (RMSE, in t/ha). The columns represent (a) the spatial variability of RMSE and (b) the distribution of RMSE. The six rows represent the different adjustments to the weather data of the reference location: No adjustment; Precip$_s$, seasonal precipitation adjusted; Precip$_s$Temp$_s$, seasonal adjustment of precipitation and temperatures; Precip$_s$Temp$_m$, seasonal adjustment of precipitation and monthly adjustment of temperatures; Precip$_s$Temp$_s$Solar$_s$, seasonal adjustment of precipitation, temperatures and solar radiation; and Precip$_s$Temp$_n$Solar$_s$, seasonal adjustment of precipitation and solar radiation, and monthly adjustment of temperatures.

4.4.1. Effects of estimating MWGY risk profiles with seasonally adjusted precipitation

A simple adjustment of the daily precipitation at the reference location significantly improved estimation of MWGY risk profile at test sites. The RMSE with this adjustment varied between 0.11 – 1.82 t/ha (Table B.4, Appendix B). However, the matching of risk profiles was particularly clear within a latitudinal range from 30° S (Walgett, New South Wales) to 37° S (Seymour, Victoria), which is approximately ±3.5° difference with respect to Snowtown (Fig. 4.4). Despite the variation in precipitation across this latitudinal range (Table 4.1) and the large distances to the reference location (Table 4.4), a seasonal adjustment of precipitation improved the match between MWGY risk profiles (RMSE dropped to 0.11 – 0.76 t/ha, Table S4). This is illustrated in Fig. 4 (compare columns a and b), where the performance indices of MWGY risk profiles obtained with Ps adjustment were better than those obtained with no adjustment, regardless of the distance to the reference location (e.g. 1946 km, Kojonup-Western Australia), and the magnitude of the $P_{s_{AF}}$ (+49.8% Mintaro and -25.8% Orroroo in Australia, Table 4.4).

Overall, the seasonal adjustment of precipitation ($Precip_s$) considerably improved the R^2 and NSE (Fig. 4.3a, b) and reduced the error (Fig. 4.4b). In fact, RMSE was reduced by at least 25% in 30 sites (out of 49 sites); however, the reduction was as great as 80% in southern sites (Table S8). The improvement in matching risk profiles due to the adjustment of precipitation seems to break down in northern locations (Queensland and northern New South Wales) and in a few locations in Victoria (Teesdale and Lake Bolac) and Tasmania (Fig. 4.4, Ib). These locations show a considerable difference in seasonal temperature in comparison with the reference location (Table 4.4). Thus, we added the adjustment of maximum and minimum temperatures and assessed its impact on the robustness of MWGY risk profiles.

4.4.2. Effects of estimating MWGY risk profiles with adjusted precipitation and temperature

Both adjustments in temperatures – using a seasonal ($Precip_sTemp_s$) or monthly factor ($Precip_sTemp_m$) – increased the number of test sites with improved matching particularly in the sites where $Precip_s$ returned the highest error in Queensland, northern New South Wales and in one site in Tasmania (Cambridge) (Fig. 4.4Ib-d).

The range of RMSE dropped from 1.09 – 1.82 t/ha with the P_s adjustment to 0.34 – 1.23 t/ha with $Precip_sTemp_s$ adjustment in Queensland sites, from 0.30 – 1.14 t/ha to 0.19 – 0.73 t/ha in New South Wales, from 1.19 to 0.83 t/ha in Teesdale, and from 1.07 to 0.79 t/ha in Cambridge (Table B.4, Appendix B). The $Precip_sTemp_m$ adjustment further reduced RMSE, which varied across the test sites in New South Wales between 0.14 – 0.48 t/ha, and in Queensland between 0.23 – 0.93 t/ha; it was reduced to 0.15 t/ha in Teesdale and to 0.68 t/ha in Cambridge.

Although the RMSE was reduced across the entire study area, few sites showed poor matching between MWGY risk profiles. These locations included Dalby and Kingaroy (eastern Queensland), Lake Bolac (Victoria) and Campbell (Tasmania) (Table B.4, Appendix B). A closer look showed that average seasonal global solar radiation at these sites is considerably different from the reference location ($Solar_{s_{AF}}$ varies from -20.0% at Campbell up to +27.0% at Dalby, Table 4.4). Thus, we added the global solar radiation adjustment.

4.4.3. Effects of estimating MWGY risk profiles with adjusted precipitation, temperature and global solar radiation

Adding the adjustment of global solar radiation slightly improved the matching of MWGY risk profiles across the study area. In fact, $Precip_sTemp_sSolar_s$ reduced the RMSE to less than 0.50 t/ha in 83% of the test sites (41 sites, see Fig. 4.4IIe and Table A.4 in Appendix A), with a clear improvement in western Queensland, New South Wales and Victoria. Overall, $Precip_sTemp_mSolar_s$ produced the best match of MWGY risk profiles, dropping the RMSE from 2.6 t/ha (No adjustment) to less than 0.8 t/ha ($Precip_sTemp_mSolar_s$ adjustment) (Table B.4), and lowering RMSE below 0.5 t/ha in more than 90% of the sites (Fig. 4.4f). Furthermore, the $Precip_sTemp_mSolar_s$ adjustment was critical at locations showing no improvement with the previous adjustments (Dalby, Kingaroy and Lake Bolac). This highlights the importance of (a) adjusting temperatures and global solar radiation, and (b) considering the monthly variation of temperatures in highly contrasting climates.

It is important to note that some test sites did not show continuous improvement in the matching of MWGY risk profiles as adjustments were added. For instance, in Western Australia, although most sites showed better performance with more adjustments, the improvement was minimal between risk profiles obtained with the successive $Precip_sTemp_s$, $Precip_sTemp_m$, $Precip_sTemp_sSolar_s$ and $Precip_sTemp_mSolar_s$ adjustments. On the other hand, in one location in Victoria (Teesdale) and in both Tasmanian sites we did not find a consistent response in the matching of MWGY risk profiles to the adjustments. In Teesdale, the best matching was obtained adjusting precipitation and temperatures ($Precip_sTemp_m$ adjustment). In Tasmanian sites, a simple adjustment of precipitation was enough to reduced RMSE values to less than 0.35 t/ha in Campbell, but in Cambridge it was necessary to adjust all climate variables ($Precip_sTemp_sSolar_s$) to obtained the lowest RMSE (0.59 t/ha, Table B.4 in Appendix B).

4.5. Discussion

This study shows that a simple method for scaling daily weather data leads to robust risk profiles of simulated wheat yields in the Australian grain-belt. It also highlights the importance of long-term seasonal features for rainfall and temperatures for modelling risk profiles of wheat grain yields.

The stepwise approach enabled us to assess the differences between adjusting a single or all climate variables for simulating wheat yield and their impact on the risk profile. The adjustment of precipitation produced a good match with MWGY risk profiles in test sites within the latitudinal range from 30° to 37°S, which included most sites in southern New South Wales, South Australia, Victoria and Western Australia. Adding the temperature adjustment increased the number of test sites with good matching between MWGY risk profiles, particularly with the use of a monthly adjustment (Fig. 4.3 c, d, and Fig. 4.4c, d). Test sites showing high RMSE values (i.e. more than 1.25 t/ha), with precipitation and temperatures adjustments, were limited to eastern Queensland, Teesdale in Victoria and Campbell in Tasmania. The final incorporation of global solar radiation led to the best matching of MWGY risk profiles at eastern Queensland locations (Fig. 4.4Ie, If).

The agreement between MWGY risk profiles showed a spatial pattern (Fig. 4.4), which disappeared as successive adjustments were added. Overall, the initial pattern is characterised by high matching between MWGY risk profiles in test sites located approximately ±3 latitudinal degrees from the reference site, and by high RMSE in test sites out of this latitudinal range. As adjustments were added, matching of MWGY risk profiles was improved across the entire grain-belt. Although the overall fit was good, there were some outliers. For example, in Western Australia the simple adjustment of precipitation and temperatures produce a close matching of the risk profiles (Fig. 4.4I and Table B.4). This could be due to the similar climates in the reference location and Western Australia sites, both in temperate regions (Williams *et al.* 2002) with comparable rainfall patterns in terms of amount, seasonality and size of events (Table 4.1; (Williamson 2007). On the other hand, Tasmanian sites showed different responses to the adjustments and presented the highest RMSE regardless of the type of adjustment. This could be partially explained by the great differences in maximum temperatures and global solar radiation between Snowtown and Tasmanian sites, but this conclusion has to be considered cautiously as it is based on two sites only.

Our findings concur with those of Hayman *et al.* (2010a) and Liddicoat *et al.* (2012) that a simple scaling method produces robust MWGY risk profiles in the South Australian grain-belt with Snowtown (South Australia) as a reference location, which was the original impetus for this work. Our study expands on their work in several aspects. First, we showed that the method can be extended to the entire Australian grain-belt, despite its great spatio-temporal climate variation (Chenu *et al.* 2013; Meinke & Stone 2005; Murphy & Timbal 2008; Nelson *et al.* 2010; Rodriguez & Sadras 2007) (Table 1). Second, we incorporated the monthly adjustment of maximum and minimum temperatures to acknowledge the importance of seasonal variation of temperature and the large influence on crop development. Third, we added the adjustment of global solar radiation. This enabled us to produce more robust matching between MWGY risk profiles, and illuminate similarities and differences among locations on a continental scale.

Previous studies addressing the issue of limited daily weather data and its impact on crop yield modelling have emphasised on year-to-year assessments rather than comparing cumulative probability curves (risk profiles). However, those studies have recognised aspects also identified in our study, such as the importance of (a) using accurate daily data for precipitation, temperature and global solar radiation for accurate estimation of crop yield (Nonhebel 1994a, 1994b), (b) considering the inter-annual climate variability (Watson & Challinor 2013), and (c) identifying the impact of critical climate variables affecting yield, which included not only precipitation but also temperatures and global solar radiation (Wang *et al.* 2015).

Considering the close agreement between MWGY risk profiles across the Australian continent, the method for scaling weather data used in this study may be generally applicable in regions with limited access to high-quality climate observations. Nevertheless, two main requirements have to be met before applying the method. First, a suitable reference location has to be available, and second, access is needed to long-term averages for precipitation and maximum and minimum temperatures for potential application sites. Long-term averages of precipitation and temperatures can be easily derived from several monthly climate datasets such as the Global Historical Climatology Network (GHCN) (Lawrimore *et al.* 2011; Peterson & Vose 1997), the gridded datasets WorldClim (Hijmans *et al.* 2005) and the CRU TS3.10 (Harris *et al.* 2014). These datasets facilitate application of the scaling method in other agricultural regions with a suitable reference location available.

The minimum record length of the weather data required for estimating robust MWGY risk profiles was not determined in this study. This aspect is not trivial for places where the period of weather record availability is limited to a few years, where observations are plagued with missing and inaccurate values, and where critical climate variables for modelling crop yield are not available (usually global solar radiation). Another important aspect is that although process-based crop models are able to capture complex crop responses and interaction to climate, uncertainties remain due both gaps in the understanding of crop growth and development and due to the structure and parameters of the model (Passioura 1996; Rotter *et al.* 2011; Zhao *et al.* 2014).

Crop modellers working in data sparse environments can use these results to save computational time on climate data which frees up more resources for other factors such as soil type. Farmers and agronomists can use the findings to have increased confidence about simple climate adjustments when interpolating between weather stations. Our 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 for adjusting temperature and radiation to obtain a better estimation of risk profiles of modelled crop yields.

4.6. Acknowledgements

GBM is a PhD student supported by the Australia Awards Scholarships (AAS). We thank Margaret Cargill for her assistance in the preparation and proofreading of this paper. We wish to thank Seth Westra and Pep Canadell for suggestions to earlier drafts of the manuscript.

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Chapter 5 : **Climate data record length and its impact on a method for extrapolating modelled yield risk**

5.1. Abstract

Agricultural decision-makers are increasingly interested in accurate assessments of climate impacts on crop productivity and long-term viability of cropping systems. Process-based crop models are a robust approach to study these impacts. However, these models require high-quality climate data that cannot be always be met. In order to overcome this issue, we examined to what extent a simple method for scaling daily data can be used for extrapolating modelled crop yields in data-sparse environments. To do this, we considered an extreme situation of having one single location with high quality time series combined with several other sites with averaged climate data for the purpose of extrapolating the risk profile.

We focused our study on 50 wheat-growing sites within the Australian grain-belt. Risk profiles were generated using wheat grain yield simulated with daily weather data at each study site, and adjusted the daily weather data. The adjustment of the data was performed using a simple method of perturbation of the daily series with a delta factor. This delta factor (or adjustment factor) was calculated for the climate precipitation, temperature and solar radiation, calculated as the simple difference in averaged climate data between a reference site and any given study site. We selected a single reference site (Snowtown, South Australia) due to the availability of long-term daily weather records for the climate variables of interest. In order to mimic the problem of limited temporal coverage of climate data, adjustment factors were computed using a variable record length (i.e. 10, 20, …, 100 years) for the period 1901-2010. Risk profiles were built using a combination of adjustment from the most simple (adjusted series of precipitation only) to the most detailed (adjusted series of precipitation, temperature and solar radiation).

We found that long-term risk profiles can be generated under data-sparse conditions (short-term records and broad spatial extrapolation). All climate variables were sensitive to the record length of the averaged climate data, particularly to record lengths of 30 or fewer years. However, we found that the quality of the extrapolation is more sensitive to the number of adjustments made, rather than the climate data record length per se, for example, the use of the shortest record length of averaged climate data (10 years) and the most complete produced minimal error (less than 10% of bias) in 60% of the study sites. In contrast, the simplest adjustment calculated with the full record length (100 years) only produced good results in 40% of the sites.

Keywords: climate risk; crop modelling; crop productivity, APSIM; high-quality climate data; limited climate data; climate data-sparse environments; risk profile

5.2. Introduction

As climate change intensifies (IPCC 2014), 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 are able to account for complex interactions between the weather, soil, genotype and soil on crop productivity (Grassini *et al.* 2015), and to assess these interactions for multiple seasons or long-term assessments (Keating *et al.* 2003; Stöckle *et al.* 2003; van Bussel *et al.* 2011; Van Wart *et al.* 2015). However, meaningful crop model outputs (e.g. simulated crop yields) 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 is accurate and reliable (Lamboni *et al.* 2009; Liddicoat *et al.* 2012; van Wart *et al.* 2013). From this list of requirements, access to or the lack of accurate and reliable weather data remains a common problem faced by the agricultural modelling community worldwide. Developing countries in particular face issues with food security and the need for evidence-based decision support.

Considerable effort has been devoted to developing protocols and strategies for enhancing weather data coverage for crop yield-gap analysis, crop yield projections and climate impact assessments (Grassini *et al.* 2015; van Ittersum *et al.* 2013; van Wart *et al.* 2013; Watson & Challinor 2013; Zhao *et al.* 2015). However, the validity of most of the methods used in those studies relies on the density of weather stations, which is spatially highly variable and often low in the remote and rural areas used for agricultural production. Nevertheless, the use of spatial interpolation in combination with a method for scaling weather data could reduce the dependency on a dense network of weather stations with high-quality observations 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 (Hayman *et al.* 2010a; Hochman *et al.* 2009). The risk profile is a particularly useful tool for reducing climate uncertainty and making better management decisions (Domsch *et al.* 2003; Folland & Anderson 2002; Hayman *et al.* 2008; Meinke *et al.* 1996; Yao *et al.* 2007). Bracho-Mujica et al. 2017 (submitted, Chapter 3 this thesis) 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 a different location to produce reliable risk profiles (Bracho-Mujica et. al, submitted, Chapter 4 this thesis). However, in all these studies the averaged climate data used for calculating the adjustment factors covered a long-term period (i.e. more than 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 is spatially sparse and reliable long-term records to support interpolation or extrapolation are limited.

This paper examines the applicability of a simple method of weather data adjustment for climate risk assessment purposes. We first test 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.

5.3. Materials and methods

We examined the applicability of a simple method of weather data adjustment for climate risk assessment purposes in data-sparse conditions. In an ideal, unrealistic situation, a comprehensive spatio-temporal weather dataset would be desirable to compute spatial pattern of risk profiles. Here, we went to the opposite extreme situation: we produced risk profiles based on a high temporal long-term weather record from a single location, combined with averaged climate information at different record lengths from multiple sites for extrapolation. In other words, we used information of intra- and inter-annual climate variability at a single reference site in conjunction with averages as tie-points for extrapolation of risk profiles. One focus of this study is the data quality at tie points to address the common situation that many climate station networks have variable record lengths.

In the first section of this paper, we examined the effect of the record length of the averaged climate data on (i) the accuracy of the adjustment factors used for scaling weather data from a reference site and (ii) the matching of risk profiles of simulated crop yield risk. Forty-nine test sites (tie points) within the Australian grain-belt were selected for a series of simulations of wheat grain yield using two main weather data sets: the observed data at the test site, and adjusted data from the reference site, using adjustment factors calculated with a variable record length for the averaged climate data. The weather data was adjusted with adjustment factors that were calculated as the simple difference of the average for the growing season period (April to October) between the reference site and any test site. The record length for the adjusted weather data varied from 10 to 100 years in 10-year blocks (i.e. n = 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 years). The simulated wheat grain yield, with observed and adjusted weather data (with a variable record length), was used to build the long-term risk profile of the modelled wheat grain yield (MWGY) at site level. Comparisons of the risk profiles were performed using quantile-quantile (Q:Q) plots and statistical performance metrics.

5.3.1. Study area

In this study we focused on the Australian grain-belt, due to the importance of the belt to the Australian economy (ABS 2017; Trewin 2006), the vulnerability of this farming system to climate variability and change (Hammer *et al.* 1996; Potgieter *et al.* 2002), and the availability of one of the best weather data sets required for crop modelling (Jones *et al.* 2009; Trewin 2013). In addition, this study is part of a series of studies conducted in the same study area, related to the assessment and improvement of the method of daily weather data adjustment for modelling risk profiles of simulated wheat yields (Hayman, Wilhelm, Alexander *et al.* 2010; Liddicoat, Hayman, Alexander *et al.* 2012; Bracho-Mujica *et al.* 2017).

We selected 49 wheat-growing test sites within the grain-belt (Fig. 5.1 and Table 5.1), located in contrasting agro-ecological zones and with high quality weather data. In addition, we selected a spatial reference site for this study, Snowtown, South Australia, 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 comparison with the previously mentioned studies. The test sites are located in important wheat growing locations within the grain-belt.

Weather data from these sites were obtained from the SILO patch point database (Scientific Information for Land Owners, (Jeffrey *et al.* 2001). The data provided consisted of daily values for precipitation, maximum and minimum temperatures and solar radiation. The period used for conducting this study was 1901-2000 (100 years), in order to exclude the Millennium drought years (i.e. from approximately the mid-1990s to early 2010 (Verdon-Kidd and Kiem 2009; van Dijk *et al.* 2013), which produce important differences in the shape of the risk profile due to the intensity of the drought (Bracho-

Mujica et. al, submitted, chapter 3 this thesis, Fig. 3.2), and not due to the record length of the weather data.

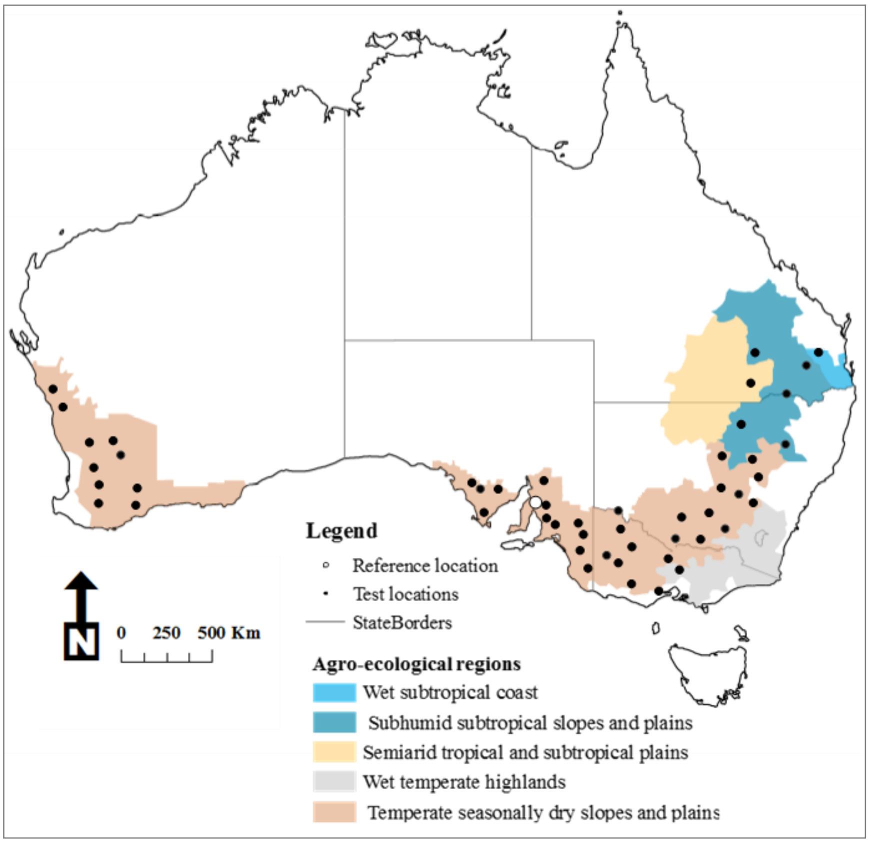

Figure 5.1. The Australian grain-belt, reference location and test sites considered in this study. Data source: ABARES and BRS (2010).

Table 5.1. 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). Period 1901-2000.

Agro-ecological zone[a]	Site	GSPrecip (mm)	Seasonality[b]	τ[c]	GSMaxTemp (°C)	GSMinTemp (°C)	GSSolar (MJ/m²)
Wet subtropical coast	Kingaroy	300	0.39	2.7	22.0	7.4	16.7
Semiarid tropical and subtropical planes	St George	223	0.43	2.7	23.6	9.3	17.0
Sub-Humid subtropical slopes and plains	Roma	241	0.40	2.6	24.0	8.3	17.5
	Dalby	270	0.40	2.7	22.8	8.0	16.8
	Goondiwindi	272	0.45	2.8	22.7	8.8	16.8
	Walgett	235	0.50	2.8	22.4	8.1	16.2
	Gunnedah	296	0.48	2.9	21.1	6.9	15.4
Wet temperate highlands	Seymour	402	0.68	3.5	15.8	5.5	11.7
Temperate seasonally dry slopes and planes	Gilgandra	293	0.52	2.9	20.0	6.0	15.2
	Nyngan	222	0.50	2.9	21.2	7.4	15.5
	Wellington	341	0.55	3.1	19.5	5.6	14.5
	Condobolin	249	0.56	3.0	19.4	6.7	14.6
	Forbes	300	0.57	3.1	18.8	6.0	14.1
	Cowra	354	0.58	3.3	17.9	5.6	13.9
	Moombooldool	261	0.60	3.1	18.7	6.2	13.7
	Hay	228	0.63	3.0	19.0	6.5	13.8
	Wagga-Wagga	334	0.63	3.3	17.1	5.9	13.1
	Oaklands	285	0.62	3.2	17.8	5.9	13.1
	Deniliquin	255	0.64	3.2	18.2	6.5	13.3
	Elmore	309	0.66	3.4	16.8	5.7	12.3
	Teesdale	321	0.62	3.4	15.6	6.8	10.8
	Lake Bolac	352	0.66	3.5	14.9	5.9	10.8
	Birchip	240	0.68	3.2	17.8	6.2	12.6
	Ouyen	217	0.66	3.5	19.0	6.7	13.3
	Mildura	176	0.63	3.4	19.6	7.2	13.9
	Horsham	297	0.70	3.6	16.8	5.6	11.9
	Nhill	289	0.71	3.5	17.2	5.5	12.1
	Naracoorte	440	0.77	3.8	17.0	6.4	11.3
	Keith	350	0.75	3.5	18.1	7.1	11.9
	Lameroo	277	0.72	3.4	18.6	6.4	12.6
	Wanbi	212	0.68	3.7	19.0	6.1	12.9
	Palmer	302	0.73	3.4	17.7	6.7	12.4
	Roseworthy	332	0.75	3.7	18.5	7.8	12.8
	Mintaro	466	0.78	3.5	16.9	5.7	13.0
	Snowtown	***305***	***0.73***	***3.5***	***19.0***	***7.0***	***13.2***
	Orroroo	230	0.68	3.3	17.9	5.4	13.9
	Kimba	250	0.74	3.7	19.1	7.3	13.5
	Cummins	346	0.81	3.8	18.7	8.5	12.7
	Kyancutta	234	0.75	3.8	20.9	6.6	13.7
	Minnipa	243	0.75	3.7	19.9	8.3	13.8
	Jerramungup	284	0.74	3.5	18.6	7.4	13.0
	Newdegate	271	0.77	3.6	19.0	6.8	13.5
	Kojonup	449	0.85	3.5	17.3	6.9	12.4
	Narrogin	424	0.86	3.6	17.7	6.8	13.2
	Beverley	362	0.85	3.4	19.7	6.7	13.9
	Merredin	234	0.77	3.5	19.9	7.4	14.6
	Wongan Hills	319	0.84	3.4	20.4	8.5	14.8
	Bencubbin	238	0.76	3.5	20.4	8.0	15.1
	Mingenew	354	0.88	3.1	22.4	9.9	15.8
	Yuna	300	0.85	3.2	22.0	10.0	16.3

[a]Agro-ecological zones as defined in (Williams *et al.* 2002) [b]Seasonality (Walsh & Lawler 1981); [b]τ (Sadras 2003).

5.3.2. Adjustment of daily weather data

We derived risk profiles of simulated wheat grain yields in two ways: using weather data from the test sites, and using weather data from the single reference location (Snowtown), which were adjusted based on the difference in the average climate data between the reference location (ref) and the test site (k). For every climate variable and site (including both the reference and the test sites), average climate data were calculated for the growing season (i.e. April to October, a seasonal aggregation). Average maximum and minimum temperatures were also calculated at a monthly level for the months within the growing season (a monthly aggregation). However, the record length used for calculating the average climate data varied. For the reference site, the average climate data were calculated using the full span of years available (i.e. 1901-2000, or 100 years), assuming that for future applications of the method the reference location will have been available at least 100 years of climate data (and/or patched data). On the other hand, the average climate data for the test sites were calculated using a variable record length spanning from 10 to 100 years in 10-year blocks (i.e. n = 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 years). Adjustment factors calculated with the full record were referred to as the long-term adjustment factor.

Once the average climate data were calculated for the different record lengths, daily weather data for the reference location were perturbed using an adjustment factor. The calculation method varied with the climate variable (Table 5.2).

The precipitation series were first adjusted with a single factor $\mathrm{Precip}_{s_{AF}}$, which represents the difference between the average growing-season precipitation in the test site (k) and in the reference location (ref), expressed as a percentage (%). We calculated the adjustment factor for global solar radiation ($\mathrm{Solar}_{s_{AF}}$) similarly. It was also expressed as a percentage. In the case of temperatures, we calculated two adjustment factors. The first, a seasonal factor ($Temp_{s_{AF}}$), was calculated as the simple difference in average growing-season temperatures (maximum or minimum) between a given test site and the reference location, expressed in °C. The second, a monthly factor ($Temp_{m_{AF}}$), was calculated as the monthly difference in temperature (maximum or minimum) between the reference and a given test site. Adjustment factors were then used to adjust the weather data by multiplying (precipitation and global solar radiation) or adding (temperature) to the corresponding factor of every daily record. Table 5.2 presents the equations used for the adjustments.

Table 5.2. Equations for calculating adjustment factors of weather data. 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, … , 10, within the growing season. The terms ref and k refer to the reference location and test sites.

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

Adjustment factors calculated with a variable record length were compared with the long-term adjustment factors (calculated using 100 years from 1901-2000). This comparison was established at test site level using the simple departure (difference) of any given adjustment factor and climate variable from the long-term adjustment factor.

5.3.3. Step-wise addition of weather data adjustments

We used five types of adjustments (Table 5.3), indicating the number of climate variables adjusted, and the types of data aggregation used for calculating adjustment factors (i.e. seasonal or a combination of seasonal and monthly). For example, the $Precip_s$ adjustment was performed on the reference site and consisted of adjusting the daily weather data for precipitation only, using a seasonal aggregation for the calculation of the adjustment factors. Therefore, the rest of the climate variables (temperatures and solar radiation) were data non-adjusted from the reference site. The complexity of the adjustment increases as we read down the Table. In fact, $Precip_sTemp_mSolar_s$, was the most complete adjustment used in this study, 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).

Table 5.3. Stepwise adjustment applied to the daily weather data at the reference location.

Adjustment	Climate variable(s) adjusted	Averaged weather data used for calculating adjustment factors	
		Seasonal($_s$)	**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

5.3.4. Crop simulations

We simulated the wheat grain yield with APSIM (Agricultural Production Systems Simulator Model) Version 7.8 (Keating *et al.* 2003). This model has been locally calibrated, widely tested, and extensively used in Australia (Robertson *et al.* 2015) for management of climate risk and understanding of potential impacts of and adaptation alternatives to climate change (Asseng *et al.* 2002; Asseng *et al.* 2015; Holzworth *et al.* 2014; Luo *et al.* 2005; Luo *et al.* 2009).

Wheat grain yield was simulated using observed and adjusted daily weather data calculated for variable periods. Here, we focus on the climate component and the testing of the spatio-temporal stability of a simple method for adjusting daily weather data for extrapolating the risk profile of the modelled wheat yield. For these reasons, we kept the soil type and management practices constant and assumed no limitation caused by pests, disease or weeds. In order to account for the crop parameters of locally adapted varieties we used 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. To exclude the interaction between the sowing time and climate (Hayman *et al.* 2010b; Luo *et al.* 2009), we simulated one fixed sowing date (14th of May); sowing density was set to 180 plants/m^2, with a 30 mm sowing depth and 250 mm row spacing.

The soil used has a sandy texture, an organic carbon content of 0.7% (0-10cm), rooting depth of 100 cm and 80 mm of plant available water content (PAWC). 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 (Bell *et al.* 2015; Luo & Kathuria 2013; Sadras & Rodriguez 2010). 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.

5.3.5. Risk profiles of modelled wheat grain yields

Risk profiles – understood as the cumulative probability curve of the simulated wheat grain yield – were built with the year-to-year wheat grain yields, simulated with APSIM, using observed and adjusted weather data. Risk profiles were built for every site, type of adjustment (Table 5.3), and record length. We ranked the yields and calculated the corresponding percentiles. We then compared the risk profiles of the modelled wheat grain yields (MWGY) across the types of adjustments and record lengths used for calculating the adjustment factors. For this purpose, we used Q:Q plots, and calculated a set of statistical metrics: the root mean squared error (RMSE, Eq. 1), and the bias (Eq.2), over all percentile classes p at each of the 49 test sites j as:

$$RMSE_j = \frac{\sum_{p=1}^{100} \sqrt{MWGY_{p,j} - MWGY_{baseline,p,j})^2}}{100} \qquad \text{(Eq. 1)}$$

and

$$Bias_j = \sum_{p=1}^{100} \left(\frac{MWGY_{p,j} - MWGY_{baseline,p,j}}{MWGY_{baseline,p,j}} \right) \qquad \text{(Eq. 2)}$$

These indices were mapped for every type of adjustment applied to the reference location, to (i) visualise 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. We considered that values within the range of −5% to 5% are indicators of a *good* match between the long-term risk profiles obtained for the period 1901-2000 and those obtained using shorter record lengths, and biases spanning the ranges [−10% to −5%) and (5% to 10%] were taken as indicators of *acceptable* matching between the risk profiles. Bias outside of the good and acceptable ranges (either positive or negative) was used to identify poor matching between the risk profiles.

Construction and statistical analysis of the risk profiles of the MWGY were performed using R software version 3.3.3 (R Core Team 2017), and maps were created using ArcGIS® software version 10.3.1 (ESRI 2015).

5.4. Results

5.4.1. Long-term adjustment factors and weather data record lengths

The calculation of long-term adjustment factors is based on the simple difference in the long-term growing-season average of the reference and test sites. Here, we examined the sensitivity of 4 adjustment factors – for precipitation, maximum and minimum temperatures and solar radiation – to the weather data record length used for calculating the long-term growing season average. This sensitivity was examined in terms of the departure of an adjustment factor calculated with a variable record length, from the one calculated using long-term weather data (Figure 5.2). All the test sites are plotted in Fig. 5.2.

Overall, all the adjustment factors were sensitive to the record length of the averaged climate data, especially when the record length was 30 years or less (Figure 5.2). In the case of the long-term $Precip_{s_{AF}}$, departures ranged from -14 and 20% (using the last 10 years of weather data), which dropped within the range -10 and 10% with 40 or more years of weather data. Long-term adjustment factors for temperatures were mostly underestimated; and this was most noticeable in the last 10 years of weather data ($MaxTemp_{s_{AF}}$ departures were within -0.9 and 0.3 °C, while $MinTemp_{s_{AF}}$ departures oscillated between -1.2 and 0.5 °C). At most test sites, these departures were reduced to a smaller range (i.e. between -0.5 to 0.5 °C) with record lengths of 30 or more years of weather data. The $MinTemp_{s_{AF}}$ showed higher sensitivity than $MaxTemp_{s_{AF}}$. In contrast, solar radiation ($Solar_{s_{AF}}$) was less sensitive to the record length, with departures ranging between -2.4 and 3%, and with a slight increment at record lengths between 30-60 years of weather data.

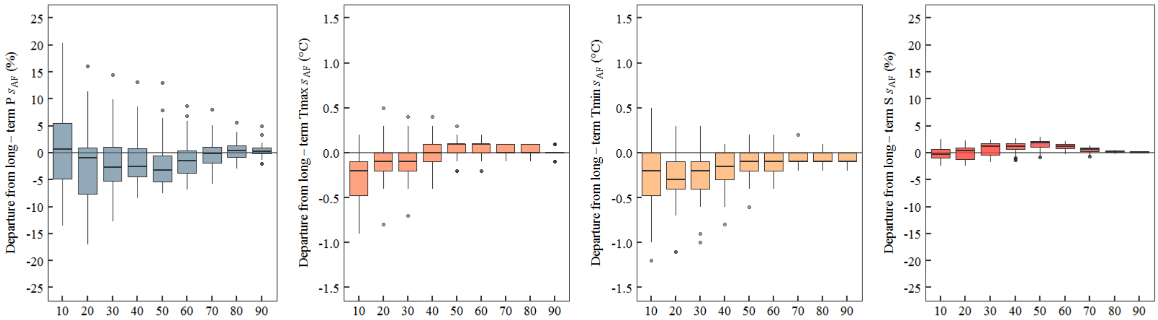

Figure 5.2. Departures from the long-term adjustment factors relative to those calculated with variable record lengths. Climate series for the 1901-2000 period have been used for calculating the long-term adjustment factors. The four columns represent the different adjustments to the weather records of the reference location: $Precip_{s_{AF}}$, the seasonal adjustment factor for precipitation; $MaxTemp_{s_{AF}}$, the seasonal adjustment factor for maximum temperature; $MinTemp_{s_{AF}}$, the seasonal adjustment factor for minimum temperature; and $Solar_{s_{AF}}$, the seasonal adjustment factor for solar radiation.

So far, we have examined the effect of using a short record length for calculating averaged climate data (i.e. for a period shorter than 100 years) on the long-term adjustment factors. Further effects of a limited record length on the accuracy of the long-term risk profile of MWGY are explored in the next section.

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

The use of averaged climate data for record lengths shorter than the long-term period also affected the quality of the long-term risk profile of MWGY (Figures 5.3 and 5.4). 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. In Figs. 5.3 and 5.4 all the test sites are included, but we only present 3 of the 5 types of adjustments used in this study (i.e. $Precip_s$, $Precip_sTemp_m$ and $Precip_sTemp_mSolar_s$). The adjustments $Precip_sTemp_s$ and $Precip_sTemp_sSolar_s$ are not shown due to the similarity in the results obtained with the $Precip_sTemp_m$ and $Precip_sTemp_mSolar_s$ adjustments.

Bias of MWGY risk profiles also varied spatially (Fig. 5.3 and 5.4). Test sites located in the temperate seasonally dry and wet temperate agro-ecological zones (Western Australia, Southern Australia, Victoria and Southern New South Wales) had the lowest biases across all types of adjustments and climate data record lengths (Fig. 5.3). In contrast, long-term risk profiles of MWGY of test sites located in Northern New South Wales and Queensland (wet subtropical coast, subhumid subtropical, and semiarid tropical and subtropical) were mostly overestimated, with the greatest biases in the study area (Figs. 5.3 and 5.4). The low matching observed in northern and north-eastern sites is exacerbated by the shortest climate data record lengths. Good and acceptable matching was only achieved in those sites with record lengths of 80 or more years.

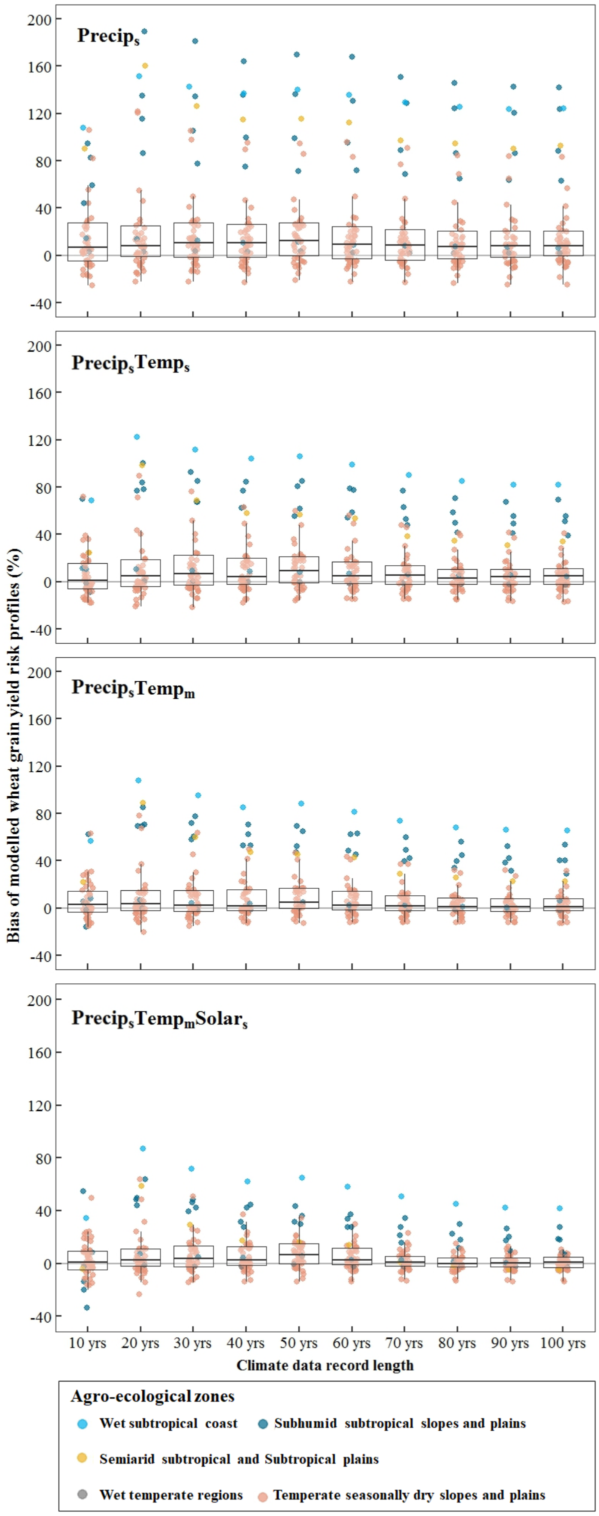

Figure 5.3. Bias (%) of the risk profiles of modelled wheat grain yields built with adjustment factors calculated with variable record lengths of weather data across the different types of adjustments incorporated. Bias compares the risk profiles obtained with weather data observed at the study site 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 of precipitation, maximum and minimum temperatures and solar radiation.

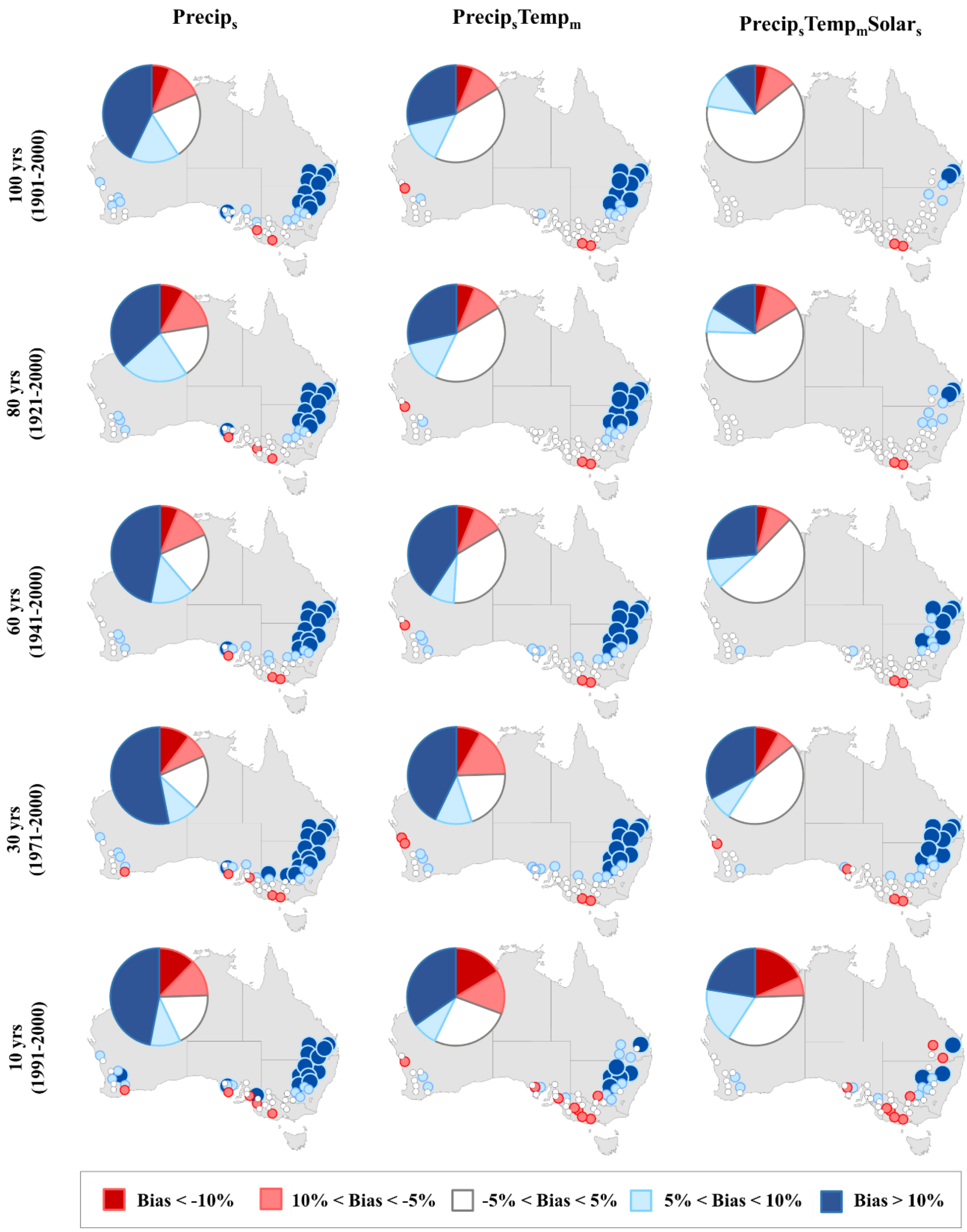

Figure 5.4. Bias (%) of the risk profiles of modelled wheat grain yields built with adjustment factors calculated with variable record lengths of weather data across the different types of adjustments incorporated. Bias compares the risk profiles obtained with weather data observed at the study site 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.

The proportion of test sites in which the long-term risk profiles were estimated reasonably improved as extra adjustments were added (precipitation, temperature, and solar radiation) and as the record length was increased (Fig. 5.4, pie charts). Using the shortest record length (10 years) the simplest adjustment ($Precip_s$) produced good and acceptable matching of long-term risk profiles in 41% of the sites, which increased to 49% with the $Precip_sTemp_s$ adjustment, 53% with the $Precip_sTemp_m$, and up to 60% of the sites with the most complete types of adjustments ($Precip_sTemp_mSolar_s$). These proportions do 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 good and acceptable matching considerably. For example, with the $Precip_s$ adjustment, the number of sites with good and acceptable matching went from 47% (60 years of record length) to 51% (with 100 years of record length), whilst the use of the $Precip_sTemp_mSolar_s$ adjustment went from 59% to 86% of the test sites.

5.5. Discussion

We have examined the effect of a 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. 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 (i.e. 100 years). This scaled daily data is then used for simulating crop yields and building long-term risk profiles. Our findings demonstrated that this method 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. For example, the factor used for precipitation was more sensitive than the rest of the variables tested, while the minimum temperature factor was more sensitive than the maximum temperature factor. The solar radiation factor was relatively insensitive to the changes in the length of the averaged climate data. 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 & Zwiers 1999). Despite this fact, we were able to obtain reasonable estimates of the long-term adjustment factors using averaged data from the test site for a period shorter than the long-term period used in this study (1901 – 2000). In the case of precipitation, we found that at least 40 years were necessary to obtain departures of the long-term adjustment factor within the range -10 and 10% (Fig. 5.2). For temperatures, a minimum of 30 years at most test sites produced departures spanning from -0.5 to 0.5 °C (Fig. 5.2). Solar radiation required the shortest record lengths of averaged solar radiation data (10 years produced departures between -2.4 and 3%, Fig. 5.2). This finding is relevant for potential future applications of the method in data-sparse environments, since, in practice, even averaged climate data for a few years or decades may not be available.

Analogous to the adjustment factors, the long-term risk profile of MWGY was also sensitive to the temporal coverage of the averaged climate data (Figs. 5.3 and 5.4). However, the number of adjustments applied had a major effect 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 identified 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 5.1; (Williamson 2007).

This study expands on previous studies (Bracho-Mujica *et al.* 2017; Hayman *et al.* 2010a; Liddicoat *et al.* 2012) in several aspects. First, we showed that the temporal coverage of the averaged climate data used for calculating adjustment factors and extrapolating risk profiles is relevant for future applications of the method. Second, we endorsed the incorporation of the monthly adjustment of maximum and minimum temperatures to acknowledge the importance of seasonal variations of temperature and their significant influence on crop development. Third, we demonstrated the importance of the number of adjustments over the record length of the averaged climate data. This enabled us 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 more resources for other factors such as soil types. Farmers and agronomists can use the findings to have increased confidence in simple climate adjustments when interpolating between weather stations. Our 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 obtain a better estimation of the risk profiles of modelled crop yields.

In this study, we explored the impact of the temporal coverage of the averaged climate data, 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, our findings provide evidence that temporal coverage is not as important as the type of adjustment 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 our 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 supporting agricultural decision frameworks with the long-term risk profiles of crop yields.

5.6. 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 models could be extrapolated with high accuracy 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.

Acknowledgements

GBM is a PhD student supported by the Australia Awards Scholarships (AAS). We thank Alison-Jane Hunter for the proofreading of this paper.

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Chapter 6 : **Discussion and conclusions**

Risk profiles of simulated crop yield are effective tools for summarising yield variability (Domsch *et al.* 2003; Luo *et al.* 2009; Yao *et al.* 2007) and exploring the benefit and limitations of agricultural management decisions (Hochman *et al.* 2009; Hunt *et al.* 2006; Jones *et al.* 2003). However, modelling long-term risk profiles requires high-quality climate data (daily, continuous and accurate weather records), which are not always available. Poor temporal and spatial coverage of climate data is a very common problem worldwide and may limit the accurate estimation of long-term risk profiles of crop yields. In this thesis the first aim was to determine to what extent the quality of the climate data – in terms of temporal coverage – affects the robustness of the long-term risk profile of crop yields, and the second aim was to test a simple method for scaling climate data inputs for modelling risk profiles of crop yields at a continental scale.

The Australian grain-belt was considered a suitable study area for this investigation, due to its climate diversity, its vulnerability to the natural variability and change of climate, the availability of high-quality climate datasets required for crop modelling, the availability to a extensively calibrated and validated process-based crop model for wheat, and its economic importance. Overall, this study demonstrates that the temporal coverage of the climate data has an important impact on the estimation of the long-term risk profile (Chapter 3); however, this problem was able to be overcome using a simple method of climate data adjustment that was rigorously tested over diverse climates (Chapter 4), variable climate data record length (Chapter 5) producing positive results.

6.1. Key findings

Temporal coverage of climate data affects the risk profile of modelled crop yields

With the best climate data available for modelling wheat crop yield in 15 sites within the Australian grain-belt, Chapter 3 (i) explored to what extent long-term risk profiles of wheat grain yield change with a variable temporal coverage for the climate data, and (ii) examined further implications when reductions in wheat grain yield due to extreme temperature events are considered. This is the first study for the grain-belt in which the impact of frost and heat on wheat grain yield has been simulated using digitised data of temperature of up to 100 years. Previous studies on frost and heat impacts on wheat yield (Bell *et al.* 2015; Crimp *et al.* 2016; Flohr *et al.* 2017; Zheng *et al.* 2015) have used temperature records from 1957 onwards. The most relevant findings of our study were as follows.

- Risk profiles of modelled crop yield are sensitive to the record length and the period covered by the climate data. This is particularly evident in risk profiles built with climate data from the most recent decades (i.e. last 10, 20 and 30 years), producing distinctive risk profiles (Chapter 3, Fig. 3.3). This analysis also highlights the decline in simulated wheat grain yield over the last three decades in the Australia grain-belt, which concurs with findings of a recent study (Hochman *et al.* 2017) exploring the trends in simulated wheat grain yields for the period between 1990 to 2016.
- The effect of limited climate data record length on the robustness of the long-term risk profile deepens when extreme temperature events are taken into consideration, which stresses the importance of rescue, digitalisation of data that remains in paper, and also highlights the importance of maintaining current weather stations recording maximum and minimum temperatures.

Simple scaling of climate inputs allows robust extrapolation of modelled wheat yield risk at a continental scale

A simple method for scaling of daily climate data for modelling risk profiles of crop yield was used for extrapolating risk profiles of modelled wheat grain yield in 49 test sites within the Australian grain-belt. The simplicity of the scaling method is due to the perturbation of historical daily weather data for a reference location (i.e. a location with long-term, accurate and continuous daily weather data available) with a unique adjustment factor per climate variable. Adjustment factors were calculated as the difference in mean precipitation (or temperature or solar radiation) between the reference location and a study site. Risk profiles were later built with wheat grain yield simulated with observed and adjusted weather data series. This method built upon early work (Hayman *et al.* 2010; Liddicoat *et al.* 2012) in two ways: spatially, by expanding the study area from a single region (South Australia) to a continent (Australia); and conceptually by introducing more rigorous statistics and adjustment factors (precipitation, temperature and solar radiation) calculated at different time scales (seasonal and monthly). The key findings for this study were the following.

- Despite the great spatio-temporal climate variation in the study area and the distance from the reference to the test sites (Chapter 4, Table 4.1), this simple scaling method leads to robust long-term risk profiles of simulated wheat yields. This finding indicates that risk profiles of wheat grain yields is a stable tool that respond to the simple difference in averaged climate data between a data-rich site and a data-poor site.
- Reliable long-term risk profiles were obtained in 80% of the study sites (39 sites out of 49 test sites) when only rainfall and temperatures were adjusted (Chapter 4, Figures 4.3 and 4.4). This was particularly noticed across winter-rainfall sites located within a latitudinal range (from 30° to 37°S) covering southern New South Wales, Victoria, South Australia and Western Australia.
- Incorporation of the solar radiation adjustment was crucial for building reliable long-term risk profiles in summer-rainfall regions, particularly for the eastern Queensland sites (Chapter 4, Figure 4.4). This finding reflects the sensitivity of the

model to solar radiation, as well as the significant differences in terms of averaged solar radiation at the reference site and sites located in the north-eastern region of the grain-belt.

A limited temporal coverage of climate data does not limit the applicability of this method for extrapolating modelled wheat yield risk

Poor temporal coverage of the climate data is a common problem faced by crop modellers – and environmental modellers in general. Chapter 5 reports the effect of limited temporal coverage of climate data on the stability and validity of the method discussed above for scaling climate data for modelling risk profiles of crop yield. This study is an extension of the work presented in Chapter 4, and specifically examined the effects of short climate data series on (i) the accuracy of the adjustment factors for precipitation, temperatures and solar radiation, and (ii) the quality of extrapolated risk profiles of modelled wheat grain yield in 49 sites across the Australian grain-belt. The key findings for this study were the following.

- All adjustment factors were sensitive to the record length of the climate data, particularly to record lengths of 30 or fewer years (Chapter 5, Figure 5.1). However, precipitation factors showed the highest inaccuracies, followed by the factors for minimum temperature and maximum temperature. Interestingly, solar radiation factors showed minimal sensitivity to the record length of averaged climate data.
- Despite the effect of the temporal coverage on the accuracy of the individual adjustment factors, this study shows that the type of adjustments considered has a greater impact on the quality of extrapolated long-term risk profiles of modelled wheat yields (Chapter 5, Figures 5.3 and 5.4, from left to right).

6.2. Significance and broader implications

Findings of this thesis demonstrate that the long-term risk profile is a stable tool that can be robustly extrapolated by using a data-rich location (reference location) and averaged climate data for a considerable short period of time.

Since results from the scaling method were robust and consistent across a large area encompassing diverse climates; this study thus provides strong evidence for the effectiveness of the risk profiles of crop yield extrapolation. This finding is especially relevant for using crop models to explore the impacts and interactions of climate change and management factors in data sparse environments (i.e. developing countries with low density, low quality, or short climate data records). However, also in regions with good climate station data, such as our study area, the findings presented here may be of relevance, as this method of climate data adjustment could save important computational time, freeing up resources for assessment of more complex variable interactions including soil conditions or agricultural management decisions.

Given the great climate variability the study area has, we could expect that the requirement of weather data (in terms of temporal coverage) to be lower in regions with less interannual variability. Furthermore, future applications of the methods rigorously tested in this thesis should be made with caution. In first place, the method used for scaling weather data and extrapolate risk profiles was developed for studying the cumulative probability curve of crop yields. Thus, this method would not be suitable for studies involving the estimation and/or prediction of the year-to-year crop yield variability. In addition, the used of the method will necessary involved (i) the use of a reference location with at least 40-60 of weather data (this information can be obtained from the GCOS-surface baseline network (Table 2.1, Chapter 2); (ii) averaged climate data for a period of at least 10-30 years, (iii) a calibrated and validated process-based crop model.

Climate risk assessments of cropping systems over large spatial scales are difficult to perform because of the lack of availability of climate data that has been collected at comparable time periods. The global surface meteorological network has a variable density and inconsistent record lengths and periods. Our results support that simple scaling of climate data can be used to generated risk profiles for comparable periods for spatial analysis.

6.3. Key assumptions and limitations

Some assumptions were necessary related to the crop modelling (Chapters 3, 4 and 5), and method of weather data adjustment (Chapters 4 and 5). Wheat grain yield was simulated with APSIM, a process-based crop model widely validated and calibrated in the Australian grain-belt. Process-based crop models are essential tools for assessing long-term climate impacts on cropping systems, since they are able (i) to capture complex interactions in the plant-soil-climate system, and (ii) to investigate hypothetical scenarios – including climate scenarios. However, uncertainties remain due both to gaps in the understanding of crop growth and development and to the structure, simplifications and parameters of the model (Olesen *et al.* 2011; Passioura 1996; Rotter *et al.* 2011; Zhao *et al.* 2014).

Another important aspect related to the crop modelling was the assumption that there was no change in soil properties or crop management and no limitation caused by pests, disease or weeds (Chapters 4 and 5, in particular). However, these assumptions were necessary to isolate the climate component, the core objective of this thesis.

A second issue related to the method of adjustment was that simple perturbation of daily data for precipitation ignores the intra-annual variability of precipitation as well as the real count of dry and wet spells (Challinor *et al.* 2005). Although it is true that long-term averages are far from representing the inter- and intra-annual variability of the precipitation, these decisions were made for this variable so that testing was possible of whether a simple long-term average is able to capture the long-term risk profile of simulated wheat grain yield, with positive outcomes (Chapters 4 and 5).

6.4. Future research and general recommendations

The importance of daily weather observations cannot be overstated. The environmental research community has demonstrated their interest in improving the data and methods available in order to produce better daily weather databases. This area of research is very dynamic and dependent of the computational advances and our understanding of the processes and interactions occurring in the climate system. Given the current limitations still existing for obtaining reliable climate data in the climate vulnerable cropping regions, expanding and maintaining the current network of meteorological stations is important more than ever.

This research was possible due to the access to an excellent weather database and a widely calibrated crop model for Australian conditions. No testing was conducted in other important cropping regions in the world. Therefore, future research in the field should consider a variety of climates, cropping systems and method of data derivation, in order to improve our understanding of a simple extrapolation method of risk profiles.

For decision support systems applications, this investigation could lead to a future establishment of a database containing a pool of simulation runs and extrapolated risk profiles. This could be a valuable data to support the discussion of climate risk and management of farming systems in data-sparse environments.

6.5. References

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Appendix A

Chapter 3 - Suplementary material

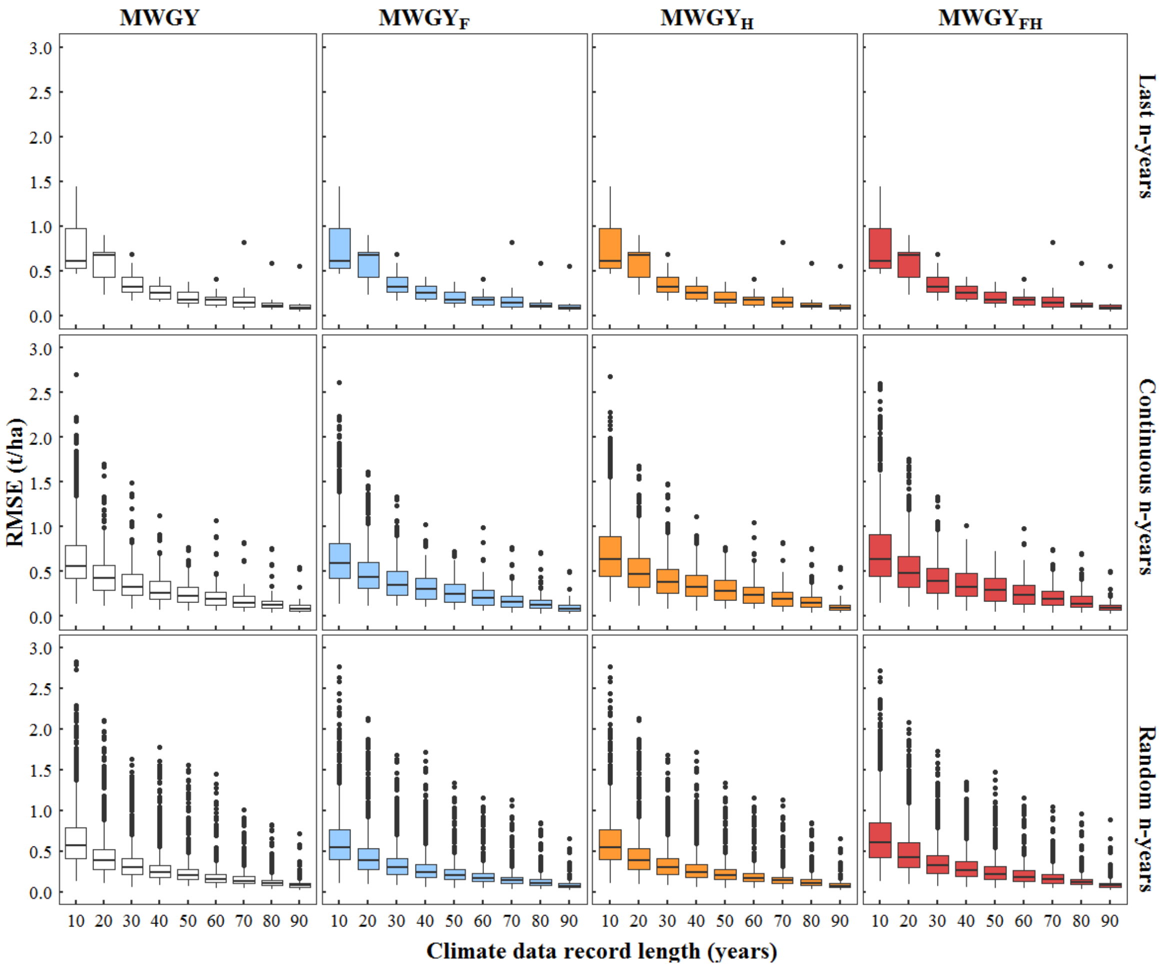

Figure A.1. Root mean square error (RMSE, t/ha) of modelled wheat grain yield risk profiles. Columns represent the four models: water limited modelled wheat grain yield (MWGY), MWGY reduced by frost ($MWGY_{Frost}$), MWGY reduced by heat ($MWGY_{Heat}$), and MWGY reduced by frost and heat ($MWGY_{Frost|Heat}$). Rows represent three resampling periods of the climate data (last n-years, continuous n-years and random n-years). Crop yields were simulated using 20th May as the sowing date and with representative soils. All sites are included in each panel.

Table A.1. Representative soils used in the simulations of wheat grain yield.

Location	APSoil number	General soil characteristics			
		Texture	Rooting depth (cm)	PAWC (mm)	Organic carbon content (%)
Emerald	911	Clay	180	287.3	1.24 (0 - 15 cm)
Dalby	1012	Clay	180	249.5	1.2 (0 - 15 cm)
Goondiwindi	1287	Sandy clay	180	227.1	0.43 (0 - 15 cm)
Walgett	1017	Clay	180	197.6	0.88 (0 - 15 cm)
Gunnedah	1174	Clay	180	210.6	0.89 (0 - 15 cm)
Forbes	546-YP	Clay	150	187.5	1.077 (0 - 15 cm)
Wagga-Wagga	498-GENERIC	-	160	139.5	1.0 (0 - 10 cm)
Deniliquin	181	Sandy clay loam	180	165.2	1.2 (0 - 15 cm)
Mildura	331	Sandy loam	140	134	0.74 (0 - 10 cm)
Nhill	750	Clay	160	148.1	1.05 (0 - 10 cm)
Snowtown	291	Clay loam	150	175.5	1.2 (0 - 10 cm)
Kyancutta	311	Sandy clay loam	120	57.1	0.9 (0 - 10 cm)
Esperance	455	Deep sandy duplex	150	44.2	0.9 (0 - 10 cm)
Merredin	401	Loamy sand	180	87	0.9 (0 - 10 cm)

Appendix B

Chapter 4 - Suplementary material

Table B.1. Percentage of total observations and interpolates daily weather observations over the period 1st Jan of 1890 - 31st Dec 2015. Climate data source: SILO.

State	Location	Percentage of total daily weather observations				Percentage of total observations and interpolated from daily weather observations			
		P	**TMax**	**TMin**	**S**	**P**	**TMax**	**TMin**	**S**
Queensland	Emerald	81	77	78	0	100	97	99	47
	Roma	81	76	76	0	82	77	76	47
	Kingaroy	76	35	35	0	100	47	47	47
	Dalby	81	77	78	0	100	96	97	47
	St George	85	28	27	0	85	32	32	47
	Goondiwindi	80	76	76	0	100	96	96	47
New South Wales	Walgett	88	81	81	0	99	100	100	47
	Gunnedah	97	79	78	0	100	86	86	47
	Nyngan	99	43	43	0	100	47	47	47
	Gilgandra	94	7	7	0	98	47	47	47
	Wellington	97	38	38	0	97	47	47	47
	Condobolin	96	22	22	0	100	47	47	47
	Cowra	86	0	0	0	99	47	47	47
	Moombooldool	90	0	0	0	96	47	47	47
	Hay	74	0	0	0	100	47	47	47
	Wagga-Wagga	61	26	31	0	99	64	65	47
	Oaklands	71	0	0	0	99	47	47	47
Victoria	Ouyen	82	47	46	0	100	47	47	47
	Birchip	93	0	0	0	100	47	47	47
	Elmore	87	0	0	0	100	47	47	47
	Horsham	44	0	0	0	99	47	47	47
	Seymour	93	4	4	0	94	47	47	47
	Lake Bolac	79	0	0	0	98	47	47	47
	Teesdale	88	0	0	0	95	47	47	47
Tasmania	Campbell	10	9	8	0	99	47	47	47
	Cambridge	11	8	8	0	100	53	53	47
South Australia	Naracoorte	88	30	30	0	100	47	47	47
	Keith	86	43	42	0	100	47	47	47
	Lameroo	91	45	45	0	100	47	47	47
	Palmer	87	0	0	0	96	47	47	47
	Wanbi	28	15	15	0	99	47	47	47
	Roseworthy	93	0	0	0	94	47	47	47
	Snowtown	87	72	71	0	98	85	85	47
	Mintaro	87	0	0	0	97	47	47	47
	Orroroo	92	0	0	0	92	47	47	47
	Cummins	73	0	0	0	93	47	47	47
	Kimba	73	35	35	0	98	47	47	47
	Warramboo	68	0	0	0	99	47	47	47
	Minnipa	64	27	27	0	99	47	47	47
Western Australia	Gibson	50	25	26	0	99	51	51	47
	Jerramungup	48	0	0	0	100	47	47	47
	Newdegate	70	0	0	0	98	47	47	47
	Kojonup	85	22	21	0	98	47	47	47
	Narrogin	87	76	76	0	100	81	81	47
	Beverley	88	37	37	0	100	47	47	47
	Merredin	86	39	39	0	100	47	47	47
	Wongan Hills	86	39	39	0	100	47	47	47
	Bencubbin	72	43	43	0	100	47	47	47
	Mingenew	83	7	7	0	97	47	47	47
	Yuna	81	0	0	0	100	47	47	47

Table B.2. Monthly adjustment factors (°C) of maximum temperature for 49 test sites across the Australian wheat belt, for moths m=4, 5,…,10.

State	Location	Position	$TMax_{AF_m}$ (in °C, m=months within the growing season)						
			Apr	May	Jun	Jul	Aug	Sep	Oct
Queensland	Emerald	23.5°S, 148.2°E	6.1	6.7	7.0	7.6	8.5	9.0	8.5
	Roma	26.6°S, 148.8°E	4.5	4.3	4.2	4.6	5.6	6.6	6.5
	Kingaroy	26.6°S, 151.8°E	1.7	2.6	3.1	3.5	4.0	4.2	3.3
	Dalby	27.2°S, 151.3°E	3.2	3.5	3.6	3.9	4.5	5.0	4.7
	St George	28.0°S, 148.6°E	4.3	4.0	3.7	4.0	4.9	6.1	6.2
	Goondiwindi	28.5°S, 150.3°E	3.7	3.3	3.1	3.2	4.0	4.8	5.1
New South Wales	Walgett	30.0°S, 148.1°E	3.4	2.8	2.4	2.5	3.5	4.6	5.1
	Gunnedah	31.0°S, 150.3°E	2.5	1.9	1.4	1.5	2.2	3.0	3.3
	Nyngan	31.5°S, 147.2°E	1.0	0.5	0.1	0.0	0.5	1.2	1.5
	Gilgandra	31.7°S, 148.7°E	1.0	0.4	-0.4	-0.3	0.5	1.4	2.1
	Wellington	32.6°S, 149.0°E	-0.2	-0.9	-1.5	-1.6	-1.1	-0.6	-0.2
	Condobolin	33.1°S, 147.2°E	0.3	-0.3	-0.8	-0.7	0.0	0.5	1.0
	Cowra	33.8°S, 148.7°E	0.4	-0.1	-0.4	-0.4	0.4	1.0	1.3
	Moombooldool	34.3°S, 146.6°E	-0.7	-1.6	-2.2	-2.4	-1.9	-1.4	-0.8
	Hay	34.5°S, 145.3°E	-0.5	-1.1	-1.4	-1.5	-1.0	-0.6	-0.2
	Wagga-Wagga	35.1°S, 147.3°E	0.0	-0.2	-0.2	0.1	0.6	0.8	1.0
	Oaklands	35.6°S, 146.2°E	-1.0	-1.2	-1.3	-1.0	-0.7	-0.7	-0.5
Victoria	Ouyen	35.1°S, 142.3°E	-2.1	-2.0	-2.0	-1.7	-1.6	-2.0	-2.3
	Birchip	35.9°S, 142.9°E	-2.9	-3.0	-2.9	-3.0	-2.6	-2.9	-3.1
	Elmore	36.5°S, 144.6°E	-4.3	-3.7	-3.3	-3.1	-3.2	-4.1	-5.1
	Horsham	36.7°S, 142.2°E	-4.2	-3.1	-2.4	-2.2	-2.3	-3.4	-4.6
	Seymour	37.0°S, 145.1°E	-6.0	-4.9	-4.3	-3.9	-4.1	-4.9	-6.2
	Lake Bolac	37.7°S, 142.8°E	-5.5	-4.1	-3.1	-2.6	-3.0	-4.1	-5.9
	Teesdale	38.1°S, 144.2°E	-2.3	-1.8	-1.3	-1.1	-1.2	-2.2	-3.0
Tasmania	Campbell	41.9°S, 147.5°E	-1.2	-0.8	-0.4	-0.1	-0.3	-0.9	-1.3
	Cambridge	42.8°S, 147.5°E	-0.5	-0.4	-0.2	0.1	0.2	0.0	-0.2
South Australia	Naracoorte	37.0°S, 140.7°E	-1.5	-1.1	-0.9	-0.7	-0.8	-1.2	-1.6
	Keith	36.1°S, 140.4°E	-0.2	-0.2	-0.1	0.3	0.5	0.6	0.5
	Lameroo	35.3°S, 140.5°E	2.4	1.6	1.5	1.3	1.2	1.6	2.0
	Palmer	34.9°S, 139.2°E	1.9	1.4	1.3	1.2	0.7	0.3	0.5
	Wanbi	34.8°S, 140.3°E	-1.0	0.1	0.7	0.8	0.4	-0.5	-1.5
	Roseworthy	34.5°S, 138.7°E	-1.8	-2.1	-2.1	-2.1	-1.6	-1.8	-1.7
	Mintaro	33.9°S, 138.7°E	-0.6	0.4	1.1	1.0	0.5	-0.5	-1.9
	Orroroo	32.7°S, 138.6°E	1.5	1.0	0.6	0.5	1.1	1.8	2.4
	Cummins	34.3°S, 135.7°E	-0.5	0.2	0.8	0.6	0.1	-0.7	-1.7
	Kimba	33.1°S, 136.4°E	0.1	0.1	0.1	0.4	0.5	0.7	0.5
	Warramboo	33.2°S, 135.6°E	-1.1	-1.0	-0.6	-0.6	-1.3	-2.4	-3.1
	Minnipa	32.8°S, 135.2°E	1.7	1.1	1.0	0.8	0.7	1.0	1.4
Western Australia	Gibson	33.6°S, 121.8°E	4.6	4.2	4.1	3.8	3.4	3.1	2.8
	Jerramungup	33.9°S, 119.0°E	0.9	1.0	1.0	1.2	1.2	1.4	1.3
	Newdegate	33.1°S, 119.0°E	-1.8	-2.0	-2.0	-2.0	-2.0	-2.1	-2.0
	Kojonup	33.8°S, 117.2°E	-0.4	-0.6	-0.4	-0.5	-1.1	-1.9	-2.0
	Narrogin	32.9°S, 117.2°E	0.4	0.4	0.7	0.4	0.2	-0.1	-0.2
	Beverley	32.1°S, 116.9°E	2.5	1.8	1.4	1.5	2.3	3.4	4.0
	Merredin	31.5°S, 118.3°E	-0.6	-1.2	-1.4	-1.4	-1.0	-0.5	-0.1
	Wongan Hills	30.9°S, 116.7°E	-0.4	-0.2	-0.1	0.0	-0.2	-0.6	-0.8
	Bencubbin	30.8°S, 117.9°E	1.3	1.4	1.5	1.7	1.7	1.8	1.6
	Mingenew	29.2°S, 115.4°E	2.6	1.9	1.8	1.6	1.2	1.0	1.4
	Yuna	28.3°S, 115.0°E	4.1	4.0	3.9	3.6	3.2	2.6	2.0

Table B.3. Monthly adjustment factors (°C) of minimum temperature for 49 test sites across the Australian wheat belt, for moths m=4, 5,…,10.

State	Location	Position	$TMin_{AF_m}$ (in °C, m=months within the growing season)						
			Apr	May	Jun	Jul	Aug	Sep	Oct
Queensland	Emerald	23.5°S, 148.2°E	6.1	4.2	2.9	2.2	3.1	5.7	7.9
	Roma	26.6°S, 148.8°E	3.1	0.7	-0.6	-1.1	-0.1	2.7	5.3
	Kingaroy	26.6°S, 151.8°E	1.9	0.5	-0.6	-1.3	-0.8	1.3	3.2
	Dalby	27.2°S, 151.3°E	2.6	0.7	-0.3	-0.9	-0.2	2.1	4.2
	St George	28.0°S, 148.6°E	3.8	1.7	0.7	0.2	1.2	3.8	6.0
	Goondiwindi	28.5°S, 150.3°E	3.3	1.4	0.3	-0.2	0.7	2.9	5.0
New South Wales	Walgett	30.0°S, 148.1°E	2.6	0.5	-0.4	-0.9	0.0	2.1	4.3
	Gunnedah	31.0°S, 150.3°E	1.8	-0.1	-1.0	-1.6	-0.9	0.8	2.6
	Nyngan	31.5°S, 147.2°E	-0.1	-1.5	-2.2	-2.7	-2.1	-0.8	0.6
	Gilgandra	31.7°S, 148.7°E	0.8	-0.6	-1.3	-1.6	-0.9	0.4	2.0
	Wellington	32.6°S, 149.0°E	-0.8	-1.8	-1.9	-2.2	-1.6	-1.0	-0.2
	Condobolin	33.1°S, 147.2°E	0.2	-1.0	-1.6	-1.8	-1.1	-0.2	1.1
	Cowra	33.8°S, 148.7°E	0.2	-0.8	-1.3	-1.4	-0.7	0.2	1.3
	Moombooldool	34.3°S, 146.6°E	-0.1	-1.4	-1.8	-2.0	-1.3	-0.8	0.0
	Hay	34.5°S, 145.3°E	-0.5	-1.4	-1.9	-1.8	-1.1	-0.4	0.2
	Wagga-Wagga	35.1°S, 147.3°E	-0.1	-0.4	-0.6	-0.7	-0.2	0.4	0.5
	Oaklands	35.6°S, 146.2°E	-0.6	-0.9	-1.2	-1.2	-0.7	-0.4	-0.2
Victoria	Ouyen	35.1°S, 142.3°E	-1.7	-1.5	-1.6	-1.4	-1.2	-1.0	-1.5
	Birchip	35.9°S, 142.9°E	-1.5	-1.6	-1.8	-1.6	-1.2	-1.0	-1.1
	Elmore	36.5°S, 144.6°E	-1.7	-1.2	-1.0	-0.9	-0.7	-0.8	-1.7
	Horsham	36.7°S, 142.2°E	-0.4	0.0	0.1	0.1	0.2	0.1	-0.5
	Seymour	37.0°S, 145.1°E	-4.0	-4.0	-4.0	-3.6	-3.2	-2.7	-3.5
	Lake Bolac	37.7°S, 142.8°E	-1.1	-1.0	-0.9	-0.7	-0.5	-0.3	-0.9
	Teesdale	38.1°S, 144.2°E	-1.4	-0.6	-0.5	-0.2	0.0	-0.1	-1.1
Tasmania	Campbell	41.9°S, 147.5°E	-0.5	0.1	0.2	0.5	0.6	0.5	-0.2
	Cambridge	42.8°S, 147.5°E	-0.7	-0.4	-0.5	-0.4	-0.2	-0.2	-0.4
South Australia	Naracoorte	37.0°S, 140.7°E	-0.3	-0.3	-0.3	-0.2	-0.2	-0.1	-0.3
	Keith	36.1°S, 140.4°E	-0.8	-0.8	-1.0	-1.0	-0.8	-0.6	-0.6
	Lameroo	35.3°S, 140.5°E	2.8	1.4	1.2	0.9	0.7	0.7	1.2
	Palmer	34.9°S, 139.2°E	1.1	0.0	0.0	-0.1	-0.4	-0.7	-0.9
	Wanbi	34.8°S, 140.3°E	1.5	1.8	1.8	1.7	1.6	1.4	1.0
	Roseworthy	34.5°S, 138.7°E	-1.0	-1.5	-1.7	-1.7	-1.2	-0.8	-0.6
	Mintaro	33.9°S, 138.7°E	1.8	1.6	1.7	1.5	1.4	1.1	0.4
	Orroroo	32.7°S, 138.6°E	0.7	-1.3	-1.9	-2.5	-1.7	-0.2	1.8
	Cummins	34.3°S, 135.7°E	1.1	0.9	0.8	0.8	0.5	0.1	-0.6
	Kimba	33.1°S, 136.4°E	1.1	0.6	0.2	0.0	0.2	0.5	0.7
	Warramboo	33.2°S, 135.6°E	0.3	0.3	0.5	0.4	0.2	-0.3	-1.2
	Minnipa	32.8°S, 135.2°E	2.4	0.9	0.7	0.3	0.0	0.1	0.8
Western Australia	Gibson	33.6°S, 121.8°E	4.7	3.5	3.2	2.6	2.4	2.2	2.6
	Jerramungup	33.9°S, 119.0°E	1.6	1.7	1.4	1.4	1.4	1.5	1.4
	Newdegate	33.1°S, 119.0°E	-1.1	-1.3	-1.2	-1.2	-1.1	-1.0	-1.0
	Kojonup	33.8°S, 117.2°E	0.6	0.2	0.4	0.2	-0.1	-0.4	-1.1
	Narrogin	32.9°S, 117.2°E	0.9	0.2	0.0	-0.1	-0.3	-0.5	-0.8
	Beverley	32.1°S, 116.9°E	2.0	0.1	-0.6	-1.3	-0.4	1.3	3.3
	Merredin	31.5°S, 118.3°E	-1.1	-1.8	-1.9	-1.9	-1.7	-1.1	-0.7
	Wongan Hills	30.9°S, 116.7°E	1.1	1.0	0.9	0.8	0.8	0.6	0.6
	Bencubbin	30.8°S, 117.9°E	0.3	0.2	0.0	0.1	0.0	0.3	0.3
	Mingenew	29.2°S, 115.4°E	3.1	2.1	1.7	1.5	1.3	1.1	1.3
	Yuna	28.3°S, 115.0°E	4.9	3.8	3.6	2.8	2.4	2.2	2.3

Table B.4. Comparison of modelled wheat grain yield (MWGY) risk profiles across the entire study area in terms of coeficient of determination (R^2), root mean square error (RMSE, tn/ha), Ratio of the RMSE to the standard deviation of the observations and the Nash-Sutcliffe efficiency coefficient (NSE). MWGY obtained using the sowing date= 14th of May.

State	Location	No-adjustment				P_s				P_sT_s				P_sT_m				$P_sT_sS_s$				$P_sT_mS_s$			
		R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE
Queensland	Dalby	0.8	2.00	1.90	-2.65	0.81	1.63	1.55	-1.43	0.89	0.93	0.89	0.21	0.94	0.70	0.66	0.56	0.72	0.53	0.56	0.94	0.95	0.39	0.37	0.86
	Emerald	0.7	2.66	4.12	-16.17	0.83	1.45	2.24	-4.08	0.93	0.34	0.53	0.72	0.94	0.23	0.36	0.87	0.94	0.25	0.16	0.94	0.95	0.20	0.31	0.90
	Goondiwindi	0.8	1.74	1.43	-1.06	0.86	1.38	1.13	-0.29	0.90	0.83	0.68	0.53	0.95	0.63	0.52	0.73	0.85	0.38	0.46	0.96	0.97	0.34	0.28	0.92
	Kingaroy	0.8	1.83	1.65	-1.75	0.78	1.82	1.64	-1.72	0.86	1.23	1.11	-0.24	0.92	0.93	0.84	0.29	0.38	0.79	0.87	0.93	0.94	0.59	0.53	0.71
	Roma	0.7	2.31	2.72	-6.48	0.80	1.58	1.86	-2.48	0.90	0.69	0.81	0.33	0.93	0.50	0.59	0.64	0.85	0.39	0.33	0.92	0.93	0.25	0.30	0.91
	St-George	0.7	2.24	2.38	-4.72	0.89	1.09	1.16	-0.36	0.93	0.47	0.50	0.74	0.96	0.32	0.34	0.88	0.95	0.23	0.22	0.95	0.95	0.24	0.25	0.94
New South Wales	Condobolin	0.9	1.31	1.04	-0.10	0.97	0.52	0.42	0.82	0.98	0.34	0.27	0.93	0.99	0.14	0.11	0.99	0.98	0.16	0.20	0.99	0.99	0.11	0.09	0.99
	Cowra	1.0	0.16	0.11	0.99	0.96	0.41	0.28	0.92	0.99	0.23	0.16	0.98	0.99	0.22	0.15	0.98	0.98	0.14	0.20	0.99	0.99	0.23	0.16	0.97
	Gilgandra	0.9	1.02	0.76	0.42	0.95	0.92	0.67	0.54	0.98	0.49	0.36	0.87	0.99	0.31	0.23	0.95	0.95	0.23	0.31	0.99	0.98	0.25	0.19	0.97
	Gunnedah	0.9	1.18	0.95	0.09	0.93	1.14	0.91	0.16	0.95	0.73	0.58	0.65	0.98	0.48	0.38	0.85	0.85	0.38	0.48	0.98	0.99	0.28	0.23	0.95
	Hay	0.9	1.53	1.25	-0.57	0.98	0.33	0.26	0.93	0.99	0.19	0.15	0.98	0.99	0.14	0.11	0.99	0.99	0.12	0.15	0.99	0.99	0.15	0.12	0.99
	Moombooldool	0.9	1.01	0.71	0.49	0.98	0.38	0.27	0.93	0.99	0.21	0.15	0.98	0.99	0.19	0.13	0.98	0.98	0.13	0.18	0.99	0.99	0.22	0.15	0.98
	Nyngan	0.9	1.94	1.98	-2.96	0.98	0.75	0.77	0.41	0.99	0.39	0.40	0.84	0.99	0.22	0.23	0.95	0.97	0.17	0.17	0.99	0.99	0.10	0.11	0.99
	Oaklands	1.0	0.59	0.40	0.84	0.98	0.30	0.20	0.96	0.99	0.22	0.15	0.98	0.99	0.20	0.14	0.98	0.98	0.15	0.22	0.99	0.99	0.20	0.14	0.98
	Wagga-Wagga	1.0	0.20	0.14	0.98	0.98	0.31	0.22	0.95	0.99	0.23	0.16	0.97	0.99	0.20	0.14	0.98	0.97	0.16	0.23	0.99	0.99	0.20	0.14	0.98
	Walgett	0.8	2.01	1.98	-2.97	0.93	0.98	0.97	0.05	0.95	0.48	0.47	0.78	0.97	0.30	0.29	0.91	0.96	0.20	0.20	0.97	0.98	0.18	0.18	0.97
	Wellington	1.0	0.41	0.29	0.92	0.96	0.70	0.50	0.75	0.99	0.34	0.24	0.94	0.99	0.19	0.14	0.98	0.97	0.17	0.24	0.99	0.99	0.19	0.13	0.98
Victoria	Birchip	0.9	1.03	0.73	0.46	0.99	0.14	0.10	0.99	0.99	0.23	0.16	0.97	0.99	0.26	0.19	0.96	0.98	0.14	0.20	0.99	0.99	0.21	0.15	0.98
	Elmore	1.0	0.22	0.16	0.97	0.99	0.15	0.11	0.99	0.99	0.10	0.08	0.99	1.00	0.11	0.08	0.99	0.99	0.09	0.12	1.00	1.00	0.10	0.07	0.99
	Horsham	1.0	0.15	0.10	0.99	0.98	0.26	0.18	0.97	0.96	0.41	0.29	0.92	0.96	0.37	0.26	0.93	0.94	0.25	0.36	0.97	0.98	0.29	0.20	0.96
	Lake-Bolac	0.9	1.18	1.13	-0.29	0.92	0.87	0.83	0.30	0.88	0.86	0.82	0.32	0.91	0.71	0.68	0.54	0.37	0.79	0.83	0.93	0.96	0.67	0.64	0.59
	Ouyen	0.8	1.64	1.27	-0.64	0.98	0.26	0.20	0.96	0.98	0.20	0.16	0.97	0.98	0.20	0.15	0.98	0.98	0.15	0.19	0.98	0.98	0.20	0.15	0.98
	Seymour	1.0	0.52	0.43	0.81	0.99	0.13	0.11	0.99	0.97	0.22	0.18	0.97	0.98	0.20	0.16	0.97	0.97	0.19	0.23	0.98	0.98	0.19	0.16	0.97
	Teesdale	0.9	1.24	1.12	-0.27	0.87	1.19	1.07	-0.17	0.91	0.83	0.75	0.43	0.99	0.15	0.14	0.98	0.51	0.70	0.77	0.96	0.98	0.33	0.30	0.91
Tasmania	Cambridge	0.9	0.80	0.66	0.56	0.91	1.07	0.88	0.21	0.92	0.79	0.66	0.57	0.93	0.68	0.56	0.69	0.65	0.59	0.72	0.96	0.95	0.75	0.62	0.62
	Campbell	1.0	0.25	0.16	0.97	0.99	0.34	0.22	0.95	0.96	1.01	0.66	0.56	0.95	0.86	0.56	0.68	0.57	0.65	0.99	0.96	0.95	0.82	0.54	0.71
South Australia	Cummins	0.9	0.89	0.84	0.29	0.94	0.58	0.54	0.71	0.99	0.26	0.25	0.94	0.99	0.26	0.25	0.94	0.95	0.22	0.24	0.99	0.99	0.23	0.22	0.95
	Keith	0.9	0.83	0.72	0.47	0.94	0.54	0.47	0.77	0.96	0.41	0.35	0.87	0.97	0.34	0.30	0.91	0.90	0.31	0.35	0.97	0.98	0.27	0.24	0.94
	Kimba	0.9	1.04	0.73	0.47	0.98	0.29	0.20	0.96	0.96	0.38	0.26	0.93	0.98	0.25	0.18	0.97	0.95	0.22	0.32	0.97	0.98	0.23	0.16	0.98
	Lameroo	1.0	0.58	0.40	0.84	0.99	0.15	0.11	0.99	0.99	0.15	0.10	0.99	0.99	0.15	0.10	0.99	0.99	0.11	0.15	0.99	0.99	0.15	0.11	0.99
	Minnipa	0.9	0.91	0.63	0.59	0.99	0.11	0.07	0.99	0.99	0.22	0.15	0.98	0.99	0.19	0.13	0.98	0.99	0.11	0.16	0.99	0.99	0.15	0.10	0.99
	Mintaro	1.0	0.78	0.77	0.41	0.97	0.23	0.22	0.95	0.99	0.15	0.15	0.98	0.99	0.15	0.15	0.98	0.98	0.15	0.16	0.99	0.99	0.15	0.15	0.98
	Naracoorte	0.9	1.11	1.20	-0.46	0.94	0.44	0.48	0.77	0.92	0.47	0.51	0.73	0.94	0.35	0.38	0.86	0.76	0.49	0.45	0.95	0.97	0.30	0.33	0.89
	Orroroo	0.9	1.34	1.07	-0.16	0.99	0.26	0.21	0.96	0.99	0.14	0.11	0.99	0.99	0.18	0.14	0.98	0.98	0.13	0.17	0.99	0.99	0.21	0.16	0.97
	Palmer	1.0	0.18	0.14	0.98	0.99	0.27	0.20	0.96	0.99	0.15	0.12	0.99	0.99	0.15	0.11	0.99	0.99	0.09	0.12	0.99	1.00	0.11	0.08	0.99
	Roseworthy	1.0	0.61	0.48	0.77	0.98	0.40	0.32	0.90	0.99	0.20	0.16	0.97	0.99	0.19	0.15	0.98	0.97	0.16	0.21	0.99	0.99	0.19	0.15	0.98
	Wanbi	0.8	1.71	1.48	-1.21	0.99	0.28	0.24	0.94	0.99	0.11	0.10	0.99	0.99	0.10	0.09	0.99	0.99	0.10	0.12	0.99	0.99	0.10	0.09	0.99
	Warramboo	0.9	1.23	0.95	0.10	0.96	0.51	0.39	0.84	0.97	0.28	0.22	0.95	0.97	0.24	0.19	0.97	0.97	0.18	0.24	0.98	0.98	0.21	0.16	0.97
Western Australia	Bencubbin	0.9	1.45	1.35	-0.83	0.96	0.51	0.48	0.77	0.95	0.50	0.46	0.78	0.96	0.45	0.42	0.82	0.89	0.32	0.35	0.97	0.98	0.31	0.29	0.92
	Beverley	1.0	0.38	0.35	0.88	0.98	0.36	0.34	0.89	0.98	0.29	0.27	0.93	0.98	0.32	0.30	0.91	0.92	0.29	0.31	0.99	0.98	0.34	0.32	0.90
	Gibson	0.9	1.35	1.53	-1.35	0.96	0.76	0.87	0.24	0.99	0.49	0.56	0.68	0.99	0.48	0.55	0.70	0.67	0.57	0.51	0.99	0.99	0.48	0.55	0.70
	Jerramungup	1.0	0.23	0.18	0.97	0.99	0.27	0.21	0.96	0.98	0.24	0.18	0.97	0.99	0.26	0.21	0.96	0.97	0.18	0.23	0.98	0.99	0.25	0.20	0.96
	Kojonup	0.9	1.27	1.69	-1.88	0.98	0.52	0.69	0.52	0.98	0.45	0.60	0.63	0.99	0.32	0.43	0.81	0.65	0.59	0.44	0.99	0.99	0.30	0.39	0.84
	Merredin	0.9	1.25	1.24	-0.55	0.96	0.57	0.56	0.68	0.95	0.55	0.55	0.70	0.96	0.48	0.48	0.77	0.80	0.45	0.45	0.97	0.98	0.39	0.39	0.85
	Mingenew	1.0	0.27	0.22	0.95	0.97	0.31	0.25	0.93	0.96	0.49	0.41	0.83	0.96	0.44	0.37	0.86	0.94	0.25	0.30	1.00	1.00	0.32	0.26	0.93
	Narrogin	0.9	1.04	1.18	-0.40	0.98	0.37	0.42	0.82	0.98	0.33	0.37	0.86	0.99	0.27	0.30	0.91	0.85	0.38	0.34	0.98	0.99	0.27	0.30	0.91
	Wongan-Hills	1.0	0.26	0.22	0.95	0.99	0.23	0.19	0.96	0.98	0.23	0.19	0.96	0.98	0.24	0.20	0.96	0.99	0.30	0.25	0.94	0.99	0.30	0.25	0.94
	Yuna	1.0	0.45	0.34	0.89	0.97	0.44	0.33	0.89	0.96	0.34	0.25	0.94	0.97	0.31	0.23	0.95	0.98	0.26	0.20	0.96	0.98	0.27	0.20	0.96
	Newdegate	1.0	0.81	0.74	0.45	0.97	0.47	0.43	0.82	0.98	0.40	0.37	0.86	0.97	0.43	0.39	0.84	0.89	0.33	0.37	0.98	0.98	0.41	0.37	0.86

Table B.5. Comparison of modelled wheat grain yield (MWGY) risk profiles across the entire study area in terms of coeficient of determination (R^2), root mean square error (RMSE, tn/ha), Ratio of the RMSE to the standard deviation of the observations and the Nash-Sutcliffe efficiency coefficient (NSE). MWGY obtained using the sowing date= 21st of May.

State	Location	No-adjustment				P_s				P_sT_s				P_sT_m				$P_sT_sS_s$				$P_sT_mS_s$			
		R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE
Queensland	Dalby	0.84	1.77	1.78	-2.19	0.88	1.39	1.40	-0.97	0.93	0.76	0.77	0.41	0.95	0.55	0.55	0.69	0.80	0.45	0.44	0.95	0.96	0.30	0.30	0.91
	Emerald	0.74	2.43	4.03	-15.37	0.90	1.25	2.08	-3.35	0.95	0.28	0.46	0.79	0.96	0.18	0.30	0.91	0.96	0.19	0.12	0.97	0.96	0.19	0.31	0.90
	Goondiwindi	0.87	1.50	1.28	-0.65	0.91	1.14	0.97	0.05	0.95	0.66	0.56	0.68	0.97	0.46	0.40	0.84	0.91	0.30	0.35	0.97	0.97	0.27	0.23	0.95
	Kingaroy	0.87	1.60	1.51	-1.29	0.84	1.62	1.52	-1.34	0.91	1.07	1.01	-0.03	0.94	0.79	0.75	0.44	0.52	0.69	0.73	0.94	0.95	0.50	0.47	0.78
	Roma	0.75	2.07	2.40	-4.82	0.84	1.34	1.55	-1.44	0.91	0.56	0.64	0.58	0.94	0.38	0.45	0.80	0.91	0.31	0.26	0.94	0.95	0.21	0.25	0.94
	St-George	0.74	2.04	2.24	-4.09	0.89	0.95	1.04	-0.09	0.93	0.42	0.46	0.79	0.95	0.28	0.31	0.90	0.94	0.23	0.21	0.95	0.95	0.24	0.27	0.93
New South Wales	Condobolin	0.94	1.15	0.97	0.05	0.99	0.37	0.31	0.90	0.99	0.20	0.17	0.97	0.99	0.12	0.10	0.99	0.99	0.10	0.12	0.99	0.99	0.16	0.13	0.98
	Cowra	0.99	0.20	0.14	0.98	0.97	0.35	0.25	0.94	0.99	0.21	0.15	0.98	0.99	0.26	0.18	0.97	0.98	0.15	0.22	0.99	0.99	0.29	0.20	0.96
	Gilgandra	0.97	0.85	0.66	0.57	0.97	0.75	0.58	0.66	0.98	0.37	0.28	0.92	0.98	0.24	0.18	0.97	0.96	0.20	0.26	0.98	0.98	0.24	0.18	0.97
	Gunnedah	0.97	0.97	0.81	0.33	0.97	0.94	0.79	0.38	0.99	0.53	0.45	0.80	0.99	0.32	0.27	0.93	0.93	0.27	0.32	0.99	0.99	0.19	0.16	0.97
	Hay	0.87	1.40	1.17	-0.38	0.99	0.21	0.18	0.97	0.99	0.12	0.10	0.99	0.99	0.16	0.14	0.98	0.99	0.10	0.12	0.99	0.99	0.19	0.16	0.98
	Moombooldool	0.94	0.90	0.65	0.57	0.99	0.28	0.21	0.96	0.99	0.20	0.14	0.98	0.99	0.25	0.18	0.97	0.98	0.15	0.21	0.99	0.99	0.28	0.20	0.96
	Nyngan	0.88	1.73	1.81	-2.30	0.98	0.59	0.62	0.61	0.99	0.27	0.28	0.92	0.99	0.14	0.15	0.98	0.98	0.13	0.12	0.99	0.99	0.12	0.12	0.98
	Oaklands	0.97	0.51	0.35	0.87	0.99	0.24	0.16	0.97	0.99	0.22	0.15	0.98	0.99	0.25	0.18	0.97	0.98	0.15	0.22	0.99	0.99	0.24	0.17	0.97
	Wagga-Wagga	0.99	0.17	0.12	0.99	0.98	0.27	0.19	0.97	0.99	0.22	0.15	0.98	0.99	0.27	0.18	0.97	0.98	0.16	0.23	0.99	0.99	0.26	0.18	0.97
	Walgett	0.83	1.80	1.84	-2.42	0.95	0.80	0.82	0.33	0.97	0.33	0.34	0.88	0.99	0.20	0.21	0.96	0.98	0.16	0.15	0.98	0.98	0.16	0.16	0.97
	Wellington	0.99	0.29	0.21	0.95	0.97	0.60	0.43	0.81	0.99	0.24	0.18	0.97	0.99	0.18	0.13	0.98	0.98	0.14	0.19	0.99	0.99	0.22	0.16	0.97
Victoria	Birchip	0.93	0.93	0.69	0.52	0.99	0.22	0.16	0.97	0.99	0.27	0.20	0.96	0.99	0.30	0.22	0.95	0.97	0.18	0.24	0.99	0.99	0.25	0.19	0.96
	Elmore	0.99	0.17	0.13	0.98	1.00	0.10	0.08	0.99	0.99	0.14	0.11	0.99	0.99	0.15	0.11	0.99	0.99	0.09	0.13	0.99	0.99	0.12	0.09	0.99
	Horsham	0.99	0.15	0.11	0.99	0.98	0.29	0.20	0.96	0.96	0.43	0.31	0.90	0.96	0.40	0.28	0.92	0.92	0.28	0.39	0.97	0.98	0.33	0.23	0.94
	Lake-Bolac	0.88	1.28	1.14	-0.32	0.92	0.97	0.86	0.25	0.88	0.94	0.84	0.29	0.91	0.79	0.70	0.50	0.35	0.80	0.90	0.92	0.95	0.74	0.66	0.56
	Ouyen	0.84	1.48	1.22	-0.51	0.99	0.19	0.15	0.98	0.99	0.17	0.14	0.98	0.99	0.19	0.16	0.97	0.98	0.15	0.18	0.99	0.99	0.20	0.16	0.97
	Seymour	0.97	0.60	0.47	0.78	0.99	0.10	0.08	0.99	0.96	0.29	0.23	0.95	0.97	0.26	0.20	0.96	0.95	0.21	0.27	0.98	0.98	0.24	0.19	0.96
	Teesdale	0.85	1.36	1.13	-0.28	0.86	1.31	1.08	-0.19	0.89	0.95	0.78	0.38	0.98	0.26	0.21	0.95	0.48	0.72	0.86	0.94	0.98	0.41	0.34	0.89
Tasmania	Cambridge	0.94	0.92	0.73	0.46	0.90	1.20	0.95	0.09	0.92	0.89	0.70	0.50	0.91	0.80	0.63	0.60	0.60	0.63	0.80	0.95	0.99	0.52	0.41	0.83
	Campbell	0.98	0.39	0.23	0.94	0.97	0.46	0.28	0.92	0.95	0.95	0.57	0.68	0.93	0.85	0.51	0.74	0.69	0.55	0.92	0.95	0.93	0.81	0.48	0.76
South Australia	Cummins	0.91	0.87	0.75	0.43	0.95	0.55	0.47	0.77	0.99	0.21	0.18	0.97	0.99	0.18	0.16	0.98	0.98	0.16	0.18	0.99	1.00	0.14	0.12	0.99
	Keith	0.92	0.84	0.70	0.51	0.95	0.56	0.46	0.79	0.96	0.42	0.35	0.88	0.98	0.32	0.27	0.93	0.91	0.29	0.35	0.98	0.99	0.25	0.21	0.96
	Kimba	0.91	0.98	0.72	0.48	0.97	0.28	0.20	0.96	0.97	0.33	0.24	0.94	0.98	0.24	0.18	0.97	0.95	0.21	0.29	0.97	0.98	0.23	0.17	0.97
	Lameroo	0.97	0.52	0.37	0.86	0.99	0.18	0.13	0.98	0.99	0.22	0.16	0.98	0.99	0.22	0.15	0.98	0.98	0.12	0.17	0.99	0.99	0.16	0.12	0.99
	Minnipa	0.94	0.90	0.67	0.55	0.99	0.15	0.11	0.99	0.98	0.26	0.19	0.96	0.98	0.22	0.16	0.97	0.98	0.14	0.18	0.99	0.99	0.17	0.12	0.98
	Mintaro	0.98	0.79	0.73	0.46	0.99	0.17	0.16	0.97	0.99	0.13	0.12	0.98	0.99	0.13	0.13	0.98	0.98	0.13	0.14	0.99	0.99	0.13	0.12	0.98
	Naracoorte	0.84	1.19	1.19	-0.43	0.92	0.53	0.52	0.72	0.91	0.55	0.54	0.70	0.93	0.39	0.39	0.84	0.75	0.50	0.50	0.95	0.96	0.33	0.33	0.89
	Orroroo	0.92	1.22	1.01	-0.04	0.99	0.17	0.14	0.98	0.99	0.17	0.14	0.98	0.98	0.22	0.19	0.97	0.97	0.18	0.21	0.98	0.98	0.26	0.21	0.95
	Palmer	0.99	0.20	0.16	0.98	0.98	0.28	0.21	0.96	0.99	0.18	0.14	0.98	0.99	0.17	0.13	0.98	0.99	0.11	0.14	0.99	0.99	0.12	0.09	0.99
	Roseworthy	0.97	0.64	0.48	0.77	0.98	0.43	0.32	0.90	0.99	0.20	0.15	0.98	0.99	0.18	0.14	0.98	0.98	0.15	0.20	0.99	0.99	0.18	0.13	0.98
	Wanbi	0.86	1.60	1.48	-1.21	0.99	0.23	0.21	0.95	0.99	0.10	0.09	0.99	0.99	0.10	0.09	0.99	0.99	0.10	0.11	0.99	0.99	0.10	0.09	0.99
	Warramboo	0.89	1.17	0.97	0.05	0.97	0.45	0.38	0.86	0.98	0.23	0.19	0.96	0.98	0.19	0.15	0.98	0.98	0.15	0.18	0.98	0.99	0.16	0.13	0.98
Western Australia	Bencubbin	0.87	1.46	1.53	-1.35	0.97	0.52	0.54	0.70	0.94	0.52	0.55	0.70	0.95	0.47	0.49	0.76	0.86	0.37	0.35	0.97	0.97	0.32	0.33	0.89
	Beverley	0.99	0.32	0.30	0.91	0.97	0.54	0.50	0.74	0.98	0.44	0.41	0.83	0.97	0.48	0.45	0.79	0.85	0.39	0.42	0.99	0.98	0.47	0.44	0.81
	Gibson	0.91	1.32	1.33	-0.78	0.97	0.73	0.74	0.45	0.99	0.45	0.45	0.80	0.99	0.40	0.40	0.84	0.78	0.46	0.46	0.99	0.99	0.40	0.41	0.83
	Jerramungup	0.99	0.25	0.20	0.96	0.99	0.21	0.16	0.97	0.99	0.20	0.16	0.97	0.99	0.28	0.22	0.95	0.97	0.17	0.21	0.99	0.99	0.29	0.23	0.95
	Kojonup	0.92	1.25	1.49	-1.24	0.98	0.51	0.60	0.63	0.98	0.45	0.53	0.72	0.99	0.31	0.37	0.86	0.74	0.51	0.43	0.98	0.99	0.27	0.32	0.89
	Merredin	0.88	1.29	1.41	-1.00	0.95	0.59	0.64	0.59	0.94	0.58	0.63	0.60	0.95	0.50	0.54	0.70	0.75	0.50	0.46	0.96	0.97	0.39	0.43	0.82
	Mingenew	0.99	0.20	0.17	0.97	0.97	0.45	0.38	0.85	0.94	0.29	0.25	0.94	0.95	0.26	0.22	0.95	0.94	0.24	0.29	0.99	0.99	0.30	0.25	0.94
	Narrogin	0.95	0.91	0.93	0.13	0.99	0.28	0.29	0.91	0.99	0.25	0.25	0.93	0.99	0.24	0.24	0.94	0.93	0.26	0.25	0.99	0.99	0.24	0.24	0.94
	Wongan-Hills	0.99	0.24	0.21	0.96	0.98	0.31	0.27	0.93	0.97	0.33	0.28	0.92	0.97	0.37	0.32	0.90	0.99	0.35	0.30	0.91	0.99	0.37	0.32	0.90
	Yuna	0.97	0.57	0.46	0.79	0.97	0.58	0.47	0.78	0.96	0.31	0.25	0.94	0.95	0.32	0.26	0.93	0.98	0.32	0.26	0.93	0.98	0.31	0.25	0.94
	Newdegate	0.96	0.90	0.90	0.17	0.98	0.50	0.50	0.74	0.99	0.44	0.44	0.80	0.99	0.46	0.47	0.78	0.83	0.41	0.41	0.99	0.99	0.44	0.44	0.80

Table B.6. Comparison of modelled wheat grain yield (MWGY) risk profiles across the entire study area in terms of coeficient of determination (R^2), root mean square error (RMSE, tn/ha), Ratio of the RMSE to the standard deviation of the observations and the Nash-Sutcliffe efficiency coefficient (NSE). MWGY obtained using the sowing date= 25th of May.

State	Location	No-adjustment				P_s				P_sT_s				P_sT_m				$P_sT_sS_s$				$P_sT_mS_s$			
		R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE
Queensland	Dalby	0.86	1.65	1.70	-1.92	0.91	1.27	1.31	-0.73	0.95	0.68	0.70	0.50	0.96	0.48	0.50	0.75	0.84	0.40	0.38	0.97	0.97	0.25	0.26	0.93
	Emerald	0.75	2.29	3.79	-13.48	0.92	1.15	1.90	-2.64	0.96	0.24	0.39	0.85	0.97	0.15	0.25	0.93	0.95	0.21	0.13	0.98	0.96	0.20	0.33	0.89
	Goondiwindi	0.89	1.39	1.22	-0.49	0.92	1.03	0.90	0.18	0.95	0.59	0.52	0.73	0.97	0.41	0.36	0.87	0.93	0.27	0.31	0.97	0.97	0.25	0.22	0.95
	Kingaroy	0.89	1.48	1.42	-1.03	0.88	1.49	1.43	-1.06	0.93	0.97	0.93	0.13	0.96	0.70	0.67	0.54	0.60	0.63	0.65	0.96	0.96	0.44	0.42	0.82
	Roma	0.77	1.94	2.28	-4.26	0.87	1.23	1.45	-1.12	0.94	0.49	0.57	0.67	0.95	0.34	0.39	0.84	0.93	0.27	0.23	0.95	0.95	0.21	0.24	0.94
	St-George	0.76	1.93	2.17	-3.77	0.90	0.86	0.97	0.04	0.93	0.37	0.42	0.82	0.95	0.25	0.28	0.92	0.95	0.21	0.19	0.96	0.96	0.23	0.26	0.93
New South Wales	Condobolin	0.95	1.06	0.90	0.18	0.99	0.30	0.26	0.93	0.99	0.15	0.13	0.98	0.99	0.15	0.13	0.98	0.99	0.11	0.13	0.99	0.99	0.20	0.17	0.97
	Cowra	0.99	0.24	0.17	0.97	0.97	0.31	0.22	0.95	0.99	0.24	0.17	0.97	0.99	0.31	0.22	0.95	0.96	0.19	0.28	0.99	0.99	0.35	0.24	0.94
	Gilgandra	0.97	0.76	0.59	0.65	0.98	0.66	0.51	0.73	0.98	0.31	0.24	0.94	0.98	0.22	0.17	0.97	0.97	0.18	0.23	0.98	0.98	0.24	0.19	0.96
	Gunnedah	0.98	0.86	0.73	0.46	0.98	0.82	0.70	0.51	0.99	0.44	0.37	0.86	0.99	0.26	0.22	0.95	0.95	0.23	0.27	0.99	0.98	0.18	0.15	0.98
	Hay	0.89	1.32	1.13	-0.29	0.99	0.17	0.14	0.98	0.99	0.11	0.10	0.99	0.99	0.18	0.15	0.98	0.99	0.11	0.13	0.99	0.99	0.21	0.18	0.97
	Moombooldool	0.95	0.84	0.62	0.61	0.99	0.25	0.19	0.96	0.99	0.22	0.16	0.97	0.98	0.28	0.21	0.96	0.97	0.17	0.23	0.99	0.98	0.31	0.23	0.95
	Nyngan	0.89	1.62	1.72	-1.97	0.99	0.52	0.55	0.70	0.99	0.22	0.23	0.95	0.99	0.11	0.12	0.99	0.99	0.10	0.09	0.99	0.99	0.13	0.14	0.98
	Oaklands	0.98	0.45	0.32	0.89	0.99	0.21	0.15	0.98	0.99	0.22	0.16	0.97	0.99	0.26	0.19	0.96	0.97	0.16	0.23	0.99	0.99	0.25	0.18	0.97
	Wagga-Wagga	0.99	0.16	0.11	0.99	0.99	0.22	0.16	0.98	0.99	0.23	0.16	0.97	0.99	0.28	0.20	0.96	0.97	0.16	0.23	0.99	0.99	0.28	0.19	0.96
	Walgett	0.85	1.69	1.74	-2.07	0.96	0.71	0.74	0.45	0.98	0.28	0.29	0.91	0.99	0.17	0.18	0.97	0.98	0.15	0.14	0.98	0.98	0.17	0.18	0.97
	Wellington	0.99	0.24	0.17	0.97	0.98	0.54	0.39	0.84	0.99	0.21	0.15	0.98	0.99	0.20	0.15	0.98	0.98	0.14	0.19	0.99	0.99	0.25	0.19	0.97
Victoria	Birchip	0.94	0.87	0.65	0.58	0.99	0.25	0.19	0.97	0.99	0.30	0.22	0.95	0.99	0.33	0.25	0.94	0.96	0.21	0.28	0.99	0.99	0.29	0.22	0.95
	Elmore	0.99	0.14	0.11	0.99	1.00	0.09	0.07	0.99	0.99	0.16	0.12	0.99	0.99	0.17	0.13	0.98	0.99	0.11	0.14	0.99	0.99	0.14	0.11	0.99
	Horsham	0.99	0.16	0.11	0.99	0.98	0.29	0.21	0.96	0.97	0.42	0.30	0.91	0.97	0.38	0.28	0.92	0.93	0.27	0.38	0.97	0.98	0.32	0.23	0.95
	Lake-Bolac	0.87	1.34	1.17	-0.38	0.91	1.03	0.89	0.19	0.89	0.97	0.85	0.28	0.90	0.84	0.73	0.46	0.34	0.81	0.93	0.92	0.94	0.78	0.68	0.53
	Ouyen	0.85	1.39	1.16	-0.37	0.98	0.18	0.15	0.98	0.98	0.20	0.17	0.97	0.98	0.24	0.20	0.96	0.97	0.18	0.21	0.98	0.98	0.24	0.20	0.96
	Seymour	0.97	0.65	0.50	0.75	0.99	0.12	0.09	0.99	0.96	0.32	0.25	0.94	0.97	0.29	0.23	0.95	0.95	0.23	0.29	0.97	0.98	0.26	0.20	0.96
	Teesdale	0.85	1.44	1.14	-0.32	0.86	1.39	1.10	-0.23	0.89	1.02	0.81	0.34	0.98	0.33	0.26	0.93	0.45	0.74	0.93	0.93	0.97	0.47	0.37	0.86
Tasmania	Cambridge	0.93	1.01	0.78	0.39	0.91	1.27	0.98	0.02	0.93	0.94	0.73	0.46	0.92	0.86	0.66	0.56	0.56	0.66	0.85	0.95	0.93	0.88	0.68	0.53
	Campbell	0.97	0.46	0.27	0.93	0.97	0.52	0.30	0.91	0.97	0.86	0.50	0.75	0.93	0.81	0.47	0.77	0.77	0.48	0.83	0.97	0.94	0.78	0.45	0.80
South Australia	Cummins	0.93	0.83	0.69	0.52	0.96	0.51	0.42	0.82	0.99	0.17	0.14	0.98	0.99	0.16	0.13	0.98	0.99	0.12	0.14	0.99	1.00	0.12	0.10	0.99
	Keith	0.92	0.84	0.69	0.52	0.95	0.56	0.45	0.79	0.96	0.43	0.35	0.88	0.98	0.32	0.26	0.93	0.91	0.29	0.36	0.98	0.99	0.23	0.19	0.96
	Kimba	0.93	0.94	0.72	0.47	0.98	0.24	0.18	0.97	0.98	0.29	0.22	0.95	0.98	0.20	0.16	0.98	0.96	0.19	0.25	0.98	0.98	0.20	0.15	0.98
	Lameroo	0.98	0.49	0.35	0.88	0.99	0.19	0.14	0.98	0.98	0.25	0.18	0.97	0.98	0.24	0.18	0.97	0.98	0.15	0.21	0.99	0.99	0.18	0.13	0.98
	Minnipa	0.95	0.89	0.70	0.51	0.99	0.14	0.11	0.99	0.98	0.26	0.20	0.96	0.98	0.22	0.17	0.97	0.98	0.14	0.18	0.99	0.99	0.16	0.12	0.98
	Mintaro	0.98	0.80	0.72	0.47	0.99	0.18	0.16	0.97	0.99	0.12	0.11	0.99	0.99	0.13	0.11	0.99	0.99	0.11	0.13	0.99	0.99	0.12	0.11	0.99
	Naracoorte	0.85	1.22	1.17	-0.39	0.93	0.54	0.52	0.73	0.92	0.55	0.53	0.72	0.94	0.39	0.38	0.85	0.77	0.48	0.50	0.95	0.97	0.32	0.30	0.91
	Orroroo	0.94	1.14	0.98	0.04	0.99	0.15	0.13	0.98	0.98	0.19	0.16	0.97	0.98	0.25	0.22	0.95	0.96	0.20	0.24	0.98	0.98	0.28	0.24	0.94
	Palmer	0.98	0.22	0.16	0.97	0.98	0.29	0.22	0.95	0.98	0.20	0.15	0.98	0.99	0.18	0.13	0.98	0.99	0.12	0.15	0.99	0.99	0.11	0.09	0.99
	Roseworthy	0.96	0.65	0.49	0.76	0.98	0.43	0.32	0.89	0.99	0.21	0.15	0.98	0.99	0.17	0.13	0.98	0.98	0.15	0.20	0.99	0.99	0.16	0.12	0.99
	Wanbi	0.88	1.52	1.45	-1.12	0.99	0.19	0.18	0.97	1.00	0.08	0.08	0.99	1.00	0.10	0.10	0.99	0.99	0.08	0.09	0.99	1.00	0.09	0.09	0.99
	Warramboo	0.90	1.13	0.97	0.05	0.97	0.42	0.36	0.87	0.98	0.20	0.18	0.97	0.98	0.17	0.15	0.98	0.98	0.14	0.17	0.99	0.99	0.15	0.13	0.98
Western Australia	Bencubbin	0.88	1.46	1.65	-1.76	0.97	0.54	0.61	0.63	0.95	0.52	0.59	0.65	0.96	0.46	0.52	0.73	0.82	0.42	0.37	0.98	0.98	0.34	0.39	0.85
	Beverley	0.99	0.34	0.33	0.89	0.96	0.63	0.61	0.63	0.97	0.52	0.50	0.75	0.96	0.57	0.55	0.69	0.78	0.47	0.48	0.98	0.98	0.54	0.52	0.73
	Gibson	0.92	1.30	1.24	-0.54	0.98	0.71	0.67	0.55	0.99	0.42	0.40	0.84	0.99	0.36	0.34	0.88	0.83	0.41	0.43	0.99	0.99	0.37	0.35	0.88
	Jerramungup	0.99	0.25	0.20	0.96	0.99	0.20	0.16	0.97	0.99	0.18	0.14	0.98	0.99	0.28	0.22	0.95	0.97	0.16	0.20	0.99	0.98	0.31	0.25	0.94
	Kojonup	0.93	1.22	1.36	-0.87	0.98	0.47	0.52	0.72	0.99	0.39	0.44	0.80	0.99	0.27	0.31	0.90	0.82	0.42	0.38	0.99	0.99	0.24	0.26	0.93
	Merredin	0.88	1.30	1.51	-1.30	0.95	0.61	0.71	0.50	0.94	0.59	0.68	0.53	0.96	0.50	0.58	0.66	0.71	0.54	0.46	0.97	0.97	0.40	0.47	0.78
	Mingenew	0.99	0.23	0.20	0.96	0.96	0.55	0.48	0.77	0.94	0.31	0.27	0.93	0.94	0.32	0.28	0.92	0.89	0.33	0.38	0.98	0.98	0.39	0.34	0.88
	Narrogin	0.97	0.84	0.83	0.30	0.99	0.26	0.26	0.93	1.00	0.23	0.22	0.95	0.99	0.26	0.26	0.93	0.95	0.22	0.23	1.00	0.99	0.26	0.26	0.93
	Wongan-Hills	0.99	0.30	0.27	0.93	0.98	0.39	0.35	0.88	0.96	0.49	0.44	0.81	0.96	0.51	0.46	0.78	0.98	0.43	0.38	0.85	0.98	0.45	0.40	0.84
	Yuna	0.97	0.65	0.57	0.68	0.96	0.66	0.57	0.67	0.94	0.45	0.39	0.85	0.93	0.48	0.41	0.83	0.97	0.42	0.37	0.86	0.97	0.40	0.35	0.88
	Newdegate	0.96	0.92	0.96	0.06	0.98	0.51	0.54	0.71	0.99	0.45	0.47	0.77	0.99	0.47	0.49	0.75	0.81	0.44	0.42	0.99	0.99	0.45	0.47	0.78

Table B.7. Comparison of modelled wheat grain yield (MWGY) risk profiles across the entire study area in terms of coeficient of determination (R^2), root mean square error (RMSE, tn/ha), Ratio of the RMSE to the standard deviation of the observations and the Nash-Sutcliffe efficiency coefficient (NSE). MWGY obtained using the sowing date= 28th of May.

State	Location	No-adjustment				P_s				P_sT_s				P_sT_m				$P_sT_sS_s$				$P_sT_mS_s$			
		R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE	R^2	RMSE	RSR	NSE
Queensland	Dalby	0.89	1.54	1.61	-1.62	0.93	1.17	1.23	-0.52	0.96	0.60	0.63	0.60	0.97	0.43	0.45	0.80	0.88	0.35	0.34	0.98	0.98	0.21	0.22	0.95
	Emerald	0.79	2.19	3.72	-12.96	0.94	1.08	1.82	-2.36	0.97	0.20	0.35	0.88	0.97	0.14	0.23	0.95	0.96	0.19	0.11	0.99	0.98	0.19	0.32	0.90
	Goondiwindi	0.90	1.31	1.16	-0.37	0.93	0.96	0.85	0.27	0.96	0.53	0.47	0.78	0.97	0.38	0.34	0.89	0.94	0.25	0.28	0.97	0.98	0.24	0.21	0.96
	Kingaroy	0.91	1.38	1.34	-0.82	0.91	1.38	1.35	-0.83	0.94	0.89	0.87	0.23	0.97	0.64	0.63	0.60	0.65	0.59	0.60	0.96	0.97	0.41	0.40	0.84
	Roma	0.81	1.83	2.18	-3.80	0.89	1.13	1.35	-0.83	0.95	0.43	0.51	0.74	0.96	0.30	0.35	0.87	0.94	0.24	0.20	0.96	0.95	0.20	0.24	0.94
	St-George	0.79	1.84	2.13	-3.59	0.93	0.80	0.93	0.13	0.95	0.32	0.37	0.86	0.96	0.22	0.26	0.93	0.96	0.20	0.17	0.97	0.97	0.21	0.25	0.94
New South Wales	Condobolin	0.96	0.99	0.84	0.28	0.99	0.25	0.21	0.95	0.99	0.13	0.11	0.99	0.98	0.19	0.16	0.97	0.99	0.11	0.13	0.99	0.99	0.24	0.20	0.96
	Cowra	0.99	0.31	0.21	0.95	0.98	0.27	0.19	0.96	0.99	0.28	0.19	0.96	0.99	0.35	0.24	0.94	0.95	0.23	0.33	0.99	0.99	0.39	0.27	0.93
	Gilgandra	0.97	0.69	0.54	0.71	0.98	0.59	0.46	0.79	0.98	0.28	0.22	0.95	0.98	0.21	0.17	0.97	0.97	0.18	0.23	0.98	0.98	0.25	0.20	0.96
	Gunnedah	0.98	0.77	0.66	0.56	0.98	0.73	0.63	0.60	0.99	0.37	0.32	0.90	0.99	0.21	0.18	0.97	0.96	0.19	0.23	0.99	0.98	0.17	0.15	0.98
	Hay	0.91	1.25	1.09	-0.19	1.00	0.14	0.12	0.99	0.99	0.12	0.10	0.99	0.99	0.20	0.17	0.97	0.98	0.13	0.14	0.99	0.99	0.22	0.19	0.96
	Moombooldool	0.95	0.79	0.59	0.65	0.99	0.24	0.18	0.97	0.99	0.22	0.16	0.97	0.98	0.30	0.22	0.95	0.97	0.18	0.24	0.98	0.98	0.32	0.24	0.94
	Nyngan	0.91	1.52	1.63	-1.69	0.99	0.45	0.49	0.76	0.99	0.18	0.19	0.96	0.99	0.08	0.09	0.99	0.99	0.08	0.08	0.99	0.99	0.15	0.17	0.97
	Oaklands	0.98	0.41	0.29	0.91	0.99	0.18	0.13	0.98	0.99	0.23	0.16	0.97	0.99	0.27	0.20	0.96	0.97	0.17	0.23	0.99	0.99	0.26	0.19	0.96
	Wagga-Wagga	0.99	0.18	0.12	0.98	0.99	0.20	0.14	0.98	0.99	0.24	0.16	0.97	0.99	0.30	0.21	0.96	0.97	0.17	0.24	0.99	0.99	0.29	0.20	0.96
	Walgett	0.87	1.61	1.70	-1.92	0.97	0.67	0.70	0.50	0.98	0.26	0.27	0.92	0.99	0.15	0.16	0.97	0.98	0.13	0.13	0.99	0.99	0.16	0.17	0.97
	Wellington	0.99	0.20	0.15	0.98	0.98	0.48	0.35	0.87	0.99	0.20	0.15	0.98	0.99	0.23	0.17	0.97	0.97	0.16	0.22	0.99	0.99	0.28	0.21	0.96
Victoria	Birchip	0.95	0.81	0.61	0.62	0.99	0.26	0.20	0.96	0.99	0.32	0.25	0.94	0.98	0.35	0.27	0.93	0.95	0.23	0.30	0.99	0.99	0.31	0.24	0.94
	Elmore	1.00	0.10	0.08	0.99	1.00	0.08	0.06	1.00	0.99	0.17	0.13	0.98	0.99	0.19	0.14	0.98	0.99	0.11	0.15	0.99	0.99	0.15	0.12	0.99
	Horsham	0.99	0.15	0.11	0.99	0.98	0.31	0.22	0.95	0.97	0.41	0.30	0.91	0.97	0.37	0.27	0.93	0.93	0.27	0.37	0.98	0.98	0.31	0.23	0.95
	Lake-Bolac	0.87	1.39	1.19	-0.44	0.91	1.07	0.92	0.14	0.89	0.99	0.85	0.27	0.91	0.87	0.75	0.44	0.32	0.82	0.95	0.92	0.94	0.82	0.70	0.50
	Ouyen	0.87	1.32	1.12	-0.27	0.98	0.19	0.16	0.97	0.98	0.22	0.18	0.97	0.98	0.25	0.22	0.95	0.96	0.19	0.23	0.98	0.98	0.26	0.22	0.95
	Seymour	0.96	0.70	0.53	0.71	0.99	0.16	0.12	0.99	0.96	0.34	0.26	0.93	0.96	0.32	0.25	0.94	0.94	0.24	0.31	0.97	0.97	0.29	0.22	0.95
	Teesdale	0.85	1.50	1.17	-0.38	0.86	1.45	1.13	-0.28	0.88	1.07	0.83	0.31	0.97	0.39	0.31	0.90	0.41	0.76	0.98	0.92	0.97	0.51	0.40	0.84
Tasmania	Cambridge	0.93	1.08	0.82	0.32	0.90	1.32	1.01	-0.03	0.93	0.98	0.75	0.44	0.92	0.91	0.70	0.51	0.53	0.68	0.89	0.95	0.94	0.93	0.71	0.49
	Campbell	0.97	0.51	0.29	0.91	0.97	0.56	0.32	0.90	0.97	0.88	0.50	0.74	0.93	0.83	0.47	0.78	0.76	0.49	0.85	0.97	0.93	0.79	0.45	0.80
South Australia	Cummins	0.94	0.80	0.65	0.57	0.97	0.48	0.39	0.85	0.99	0.15	0.12	0.98	0.99	0.18	0.15	0.98	0.99	0.11	0.13	0.99	0.99	0.17	0.14	0.98
	Keith	0.93	0.85	0.69	0.52	0.96	0.56	0.45	0.79	0.97	0.43	0.35	0.88	0.98	0.31	0.25	0.94	0.91	0.29	0.36	0.98	0.99	0.22	0.18	0.97
	Kimba	0.93	0.90	0.71	0.49	0.98	0.22	0.17	0.97	0.98	0.27	0.21	0.95	0.98	0.19	0.15	0.98	0.97	0.19	0.24	0.98	0.99	0.18	0.14	0.98
	Lameroo	0.98	0.45	0.33	0.89	0.98	0.21	0.15	0.98	0.98	0.27	0.20	0.96	0.98	0.26	0.19	0.96	0.97	0.16	0.22	0.98	0.99	0.20	0.14	0.98
	Minnipa	0.95	0.87	0.71	0.49	0.99	0.12	0.10	0.99	0.98	0.26	0.21	0.95	0.98	0.22	0.18	0.97	0.98	0.15	0.18	0.99	0.99	0.16	0.13	0.98
	Mintaro	0.98	0.81	0.72	0.47	0.98	0.18	0.16	0.97	0.99	0.12	0.10	0.99	0.99	0.12	0.11	0.99	0.99	0.11	0.12	0.99	0.99	0.12	0.11	0.99
	Naracoorte	0.87	1.24	1.16	-0.36	0.94	0.55	0.51	0.73	0.93	0.54	0.51	0.74	0.95	0.38	0.36	0.87	0.79	0.46	0.49	0.95	0.98	0.31	0.29	0.92
	Orroroo	0.95	1.09	0.96	0.06	0.99	0.16	0.14	0.98	0.98	0.20	0.18	0.97	0.97	0.26	0.23	0.95	0.95	0.21	0.24	0.97	0.97	0.29	0.25	0.94
	Palmer	0.98	0.24	0.18	0.97	0.98	0.32	0.24	0.94	0.98	0.22	0.17	0.97	0.98	0.19	0.14	0.98	0.98	0.13	0.18	0.99	0.99	0.12	0.09	0.99
	Roseworthy	0.96	0.67	0.50	0.75	0.98	0.45	0.33	0.89	0.99	0.21	0.16	0.97	0.99	0.18	0.13	0.98	0.98	0.15	0.20	0.99	0.99	0.16	0.12	0.99
	Wanbi	0.89	1.45	1.40	-0.98	0.99	0.16	0.15	0.98	1.00	0.09	0.09	0.99	1.00	0.12	0.12	0.99	0.99	0.09	0.09	0.99	1.00	0.11	0.10	0.99
	Warramboo	0.91	1.08	0.94	0.10	0.98	0.38	0.33	0.89	0.99	0.18	0.16	0.97	0.99	0.15	0.13	0.98	0.98	0.13	0.15	0.99	0.99	0.13	0.12	0.99
Western Australia	Bencubbin	0.90	1.43	1.73	-2.04	0.97	0.54	0.65	0.57	0.96	0.53	0.64	0.59	0.97	0.47	0.57	0.67	0.77	0.48	0.39	0.98	0.98	0.36	0.43	0.81
	Beverley	0.99	0.37	0.37	0.86	0.96	0.69	0.69	0.52	0.97	0.58	0.58	0.66	0.96	0.63	0.63	0.60	0.72	0.53	0.53	0.98	0.97	0.58	0.58	0.66
	Gibson	0.93	1.29	1.18	-0.41	0.97	0.69	0.64	0.59	0.99	0.41	0.37	0.86	0.98	0.34	0.31	0.90	0.85	0.38	0.42	0.99	0.98	0.35	0.32	0.90
	Jerramungup	0.99	0.21	0.17	0.97	0.99	0.19	0.16	0.98	1.00	0.13	0.11	0.99	0.99	0.24	0.20	0.96	0.99	0.12	0.14	1.00	0.99	0.28	0.23	0.95
	Kojonup	0.94	1.20	1.29	-0.68	0.99	0.44	0.47	0.77	0.99	0.36	0.39	0.85	0.99	0.26	0.28	0.92	0.86	0.37	0.35	0.99	0.99	0.22	0.24	0.94
	Merredin	0.89	1.28	1.56	-1.47	0.95	0.60	0.73	0.46	0.95	0.58	0.71	0.50	0.96	0.50	0.61	0.62	0.67	0.57	0.47	0.97	0.97	0.41	0.50	0.75
	Mingenew	0.99	0.26	0.24	0.94	0.96	0.61	0.55	0.69	0.93	0.39	0.35	0.88	0.94	0.43	0.39	0.85	0.82	0.42	0.46	0.97	0.97	0.48	0.43	0.81
	Narrogin	0.97	0.79	0.77	0.40	0.99	0.26	0.25	0.94	0.99	0.23	0.23	0.95	0.99	0.30	0.29	0.91	0.95	0.23	0.23	0.99	0.99	0.30	0.29	0.91
	Wongan-Hills	0.99	0.36	0.34	0.89	0.98	0.47	0.44	0.80	0.95	0.60	0.57	0.67	0.95	0.63	0.60	0.64	0.98	0.51	0.48	0.77	0.98	0.53	0.50	0.75
	Yuna	0.97	0.70	0.65	0.57	0.96	0.71	0.66	0.55	0.93	0.57	0.53	0.71	0.92	0.61	0.56	0.68	0.97	0.49	0.45	0.79	0.97	0.48	0.45	0.80
	Newdegate	0.95	0.92	1.00	0.00	0.98	0.52	0.56	0.68	0.98	0.46	0.50	0.75	0.98	0.48	0.52	0.73	0.79	0.46	0.42	0.99	0.98	0.46	0.50	0.75

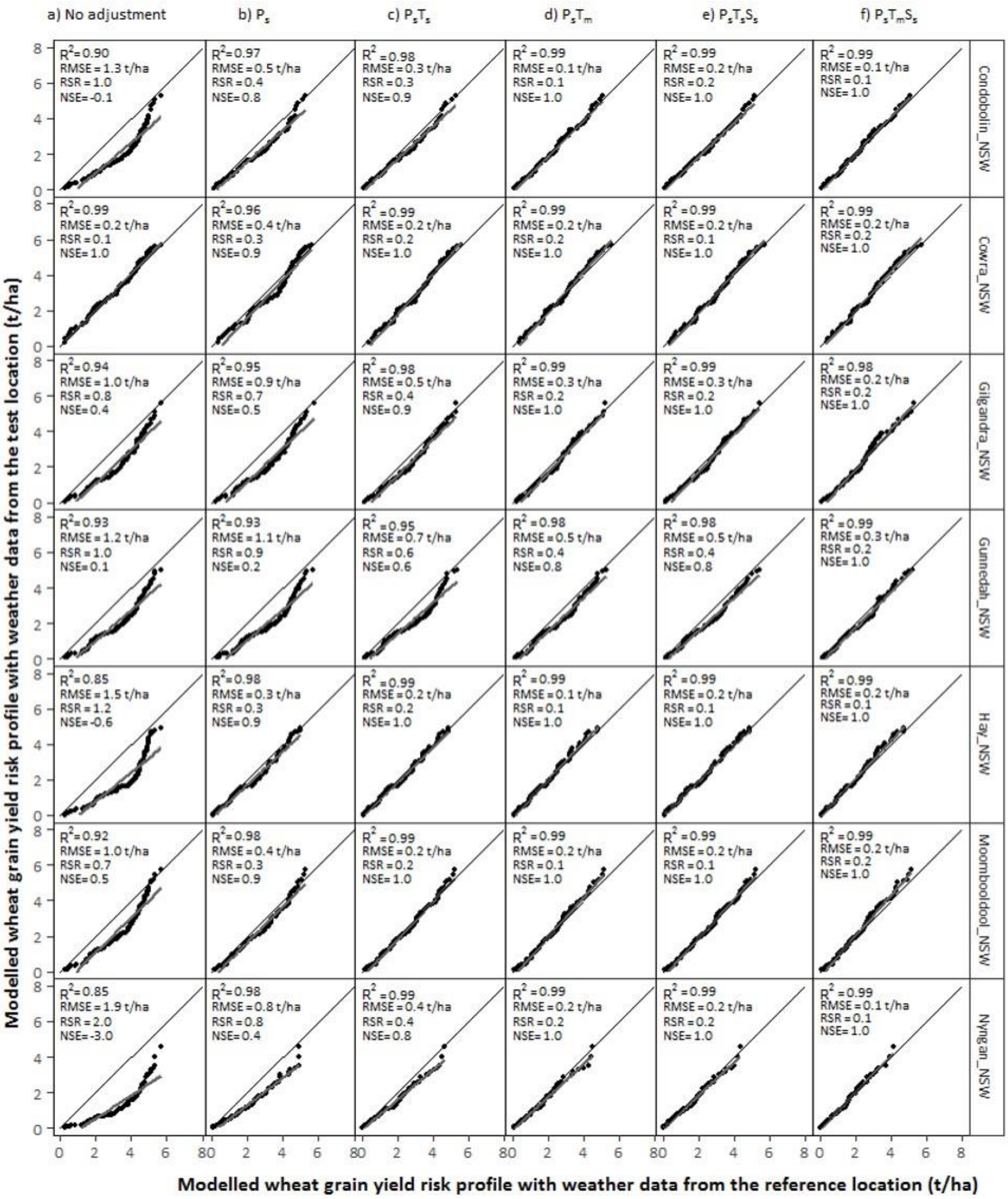

Figure B.1. Comparison of modelled wheat grain yield risk profiles for a selected test sites in Australia. The six columns represent yield simulated with climate datasets for the reference location with: (a) No adjustment; (b) $Precip_s$, seasonal precipitation adjusted; (c) $Precip_sTemp_s$, seasonal adjustment of precipitation and temperatures; (d) $Precip_sTemp_m$, seasonal adjustment of precipitation and monthly adjustment of temperatures; (e) $Precip_sTemp_sSolar_s$, seasonal adjustment of precipitation, temperatures and global solar radiation; (f) $Precip_sTemp_mSolar_s$, seasonal adjustment of precipitation and global solar radiation, and monthly adjustment of temperatures. Performance metrics are presented in each graph. R^2, RMSE, RSR and NSE refer to coefficient of determination, the root mean square error (in t/ha), the Nash-Sutcliffe efficiency and the ratio of the RMSE to the standard deviation of the observations, respectively. Rows represent the test sites selected as indicated in the right strip which includes the distance to the reference location (Snowtown) in km in brackets.

Figure B.2. Same as in Figure B.1. New South Wales and Queensland test sites in Australia.

Figure B.2. Same as in Figure B.1. Queensland and South Australian test sites in Australia.

Figure B.3. Same as in Figure B.1. South Australian test sites in Australia.

Figure B.4. Same as in Figure B.1. South Australian and Victorian test sites in Australia.

Figure B.4. Same as in Figure B.1.Victoria and Western Australian test sites in Australia.

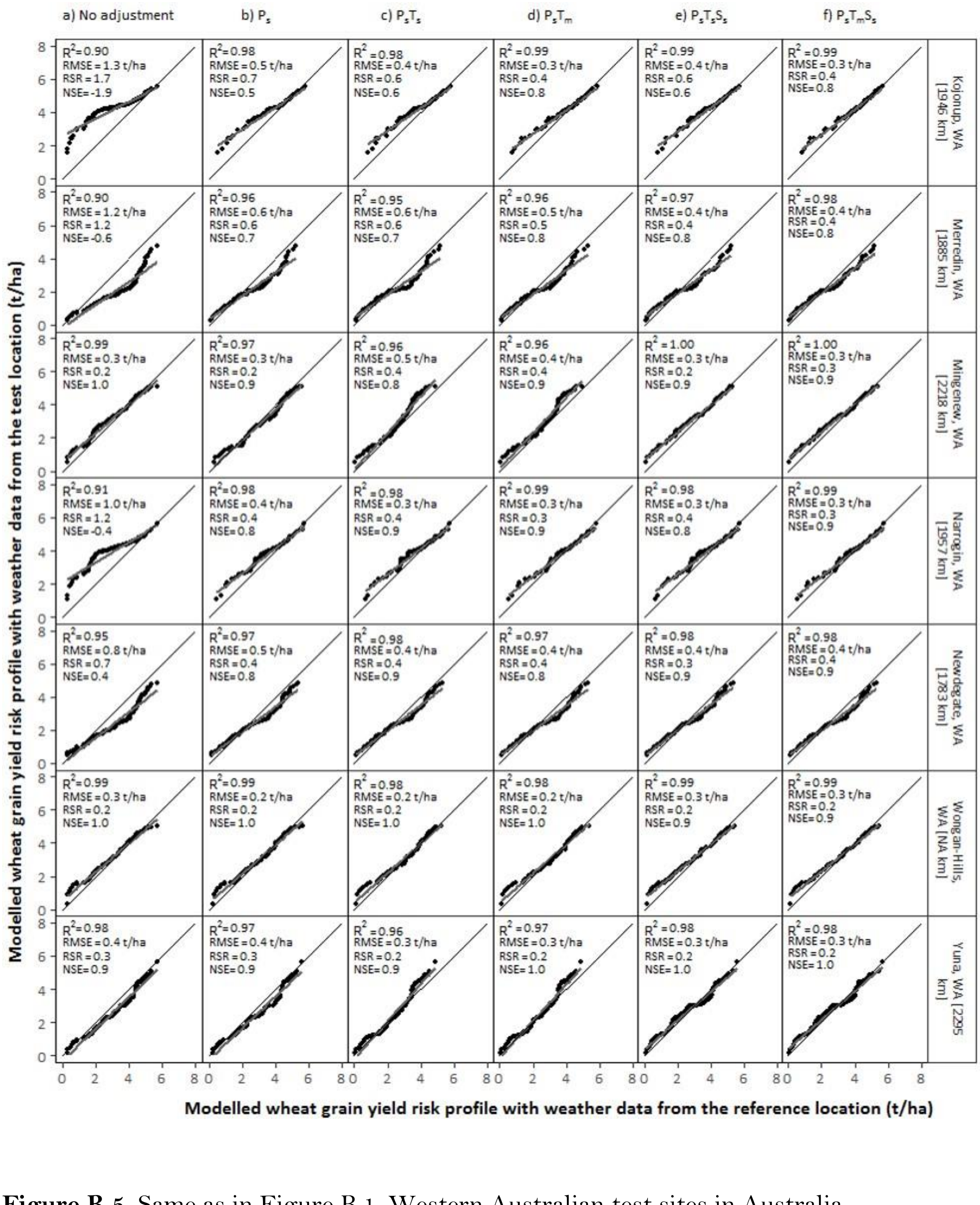

Figure B.5. Same as in Figure B.1. Western Australian test sites in Australia.