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Year Patterns of Climate Impact on Wheat Yields

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Abstract

Rainfall, temperature, and solar radiation are important climate factors, which determine crop growth, development and yield from instantaneous to decadal scales. We propose to identify year patterns of climate impact on yield on the basis of rain and non-rain weather. There are interrelated impacts of climatic factors on crop production within a specific pattern.

Historical wheat yield data in Queensland during 1889-2004 were used. The influence of meteorological conditions on wheat yields was derived from statistical yield data which were detrended by nine-year-smoothing averages to remove the effects of technological improvements on wheat yields over time. Climate affects crop growth and development differently over different growth stages. Therefore, we considered the climate effects at both vegetative and reproductive stages (before and after flowering date respectively) on yield. Cluster analysis was employed to identify the year patterns of climate impact. Five patterns were significantly classified. Precipitation during the vegetative stage was the dominant and beneficial factor for wheat yields while increasing maximum temperature had a negative influence. Crop yields were strongly dependent on solar radiation under normal rainfall conditions. As the effect of rainfall on soil water is relatively long lasting, its beneficial effect in vegetative stage was higher than its effect during the reproductive stage.

The Agricultural Production Systems sIMulator (APSIM) was evaluated using long-term historical data to determine whether the model could reasonably simulate effects of climate factors for each year pattern. The model provided good estimates of wheat yield when conditions resulted in medium yield levels, however in extremely low or high yield years, corresponding to extremely low or high precipitation in the vegetative stage, the model

tended to underestimate or overestimate. Under high growing season precipitation, simulations responded more favorably to reproductive stage rainfall than measured yields.

Key words: Climate pattern, climate variability, yield, model validation, APSIM

1. Introduction

Crop growth, development and grain yields are greatly influenced by climatic factors, including solar radiation, precipitation, and temperature. These factors are closely related and affect yield in different ways. Consequently, understanding the factors that determine crop yield is essential to forecasting regional crop production, improving crop management techniques and adopting feasible strategies to deal with climate change (e.g., Qian *et al.*, 2008; Yu *et al.*, 2008).

Numerous studies have attempted to quantify the crop-climate relationship through the application of statistical regression analysis over the entire and/or critical growing period (Nicholls, 1997; Lobell and Asner, 2003; Lobell *et al.*, 2006, 2007). Nicholls (1997) attributed the increase in wheat yields in Australia to the decrease in frost frequency. Lobell and Asner (2003) reported significant relationships between growing season temperatures and corn and soybean yields based on county level data in the USA. Huff and Neill (1982) concluded that precipitation controlled the corn yields over five Midwestern states in the USA. A number of studies have shown that yields from a variety of crops were linearly related to seasonal crop water use or available water at planting as influenced by precipitation in dry regions (Nielsen, 1997, 1998, 2001; Nielsen *et al.*, 2002, 2006). Large-scale climate events, such as ENSO and Monsoon, also affect crop yields, through alterations in rainfall and temperature regime (Hansen *et al.*, 1998; Podestá *et al.*, 1999, 2002; Potgieter *et al.*, 2005; Sultan *et al.*, 2005). These studies illustrated definitive correlations among crop yields and climatic factors. However, those climatic factors influencing crop yields are often correlated with each other. For example, rainfall increases soil water, but is also associated with decreases in solar radiation and daytime temperature. In humid areas where precipitation is abundant but solar radiation is limited, the latter can be the dominant factor defining crop yield, whereas in dry regions where precipitation is low, yield is mainly limited by water availability (Yu et al., 2001). Furthermore, the limiting climatic factors for crop yield may change with growth stages.

Wheat yield varies from year to year because of the effect of management practices and weather conditions (Thompson, 1969; Baier, 1973). The general increase in yield over time came from technological improvements such as adoption of new cultivars and increase~~changes~~ in nitrogen application and other management options. Through some statistical approaches such as fitting, filtering (Chatfield, 1996; Manly, 1997), the time trend of crop yield due to technological~~y~~ improvements can be approximately eliminated, i.e., detrending, which provided pathways for studying the impact of climate variations on crop yield.

In previous work, crop yields were defined in three general categories: potential, attainable and actual yield levels (Rabbinge, 1993). Potential yield was defined as the crop yield determined only by solar radiation and temperature. When available soil water or nutrients cannot meet the demands of crop growth, potential yield will decline to the attainable yield level. Crop growth can also be affected by pests, diseases, and weeds, resulting in actual crop yield. The gap between actual and attainable yields can be bridged through the use of pesticides, fungicides and herbicides and other effective counter measures. However, climatic factors, such as temperature and solar radiation cannot be controlled by farmers over large areas, and the deficiency in precipitation can only be compensated for if irrigation is applied.

Since the factors limiting crop yields are variable with different climate scenarios (Eghball and Varvel, 1997; Lamb *et al.*, 1997), it is necessary to quantify their relationships separately. Applying cluster analysis to multi-year crop yield data may be an effective means to identify temporal yield patterns (Jaynes *et al.*, 2003). Cluster analysis has been widely adopted to examine crop-climate interactions (Dobermann *et al.*, 2003; Jaynes *et al.*, 2003; Perez-Quezada *et al.*, 2003; Roel and Plant, 2004a, b; Jaynes *et al.*, 2005), including the effects of ENSO on crop yields (Potgieter *et al.*, 2005). It provides a basis to identify the underlying limiting climatic factors for crop yields over long time periods given that non-climatic effect such as improved varieties and management practices can be statistically eliminated.

An alternative to cluster analysis and other statistical methods that can help define relationships between crop yield and climate is the use of crop models, such as APSIM (Keating *et al.*, 2003), CERES (Ritchie *et al.*, 1998), ORYZA (Bouman and Van Lar, 2006), WOFOST (World Food Study, Van Keulen *et al.*, 1986) and RZWQM (Root Zone Water Quality Model, Ahuja *et al.*, 2000). Crop models are designed to describe crop growth and development processes in simple or complex manners, which can help to understand climate constraints on crop growth and yield (Ritchie *et al.*, 1998). As crop models are always a simplification of the real system, they must be validated against experimental data for their suitability under specific climate and soil conditions (Wallach, 2006). Crop models are regularly validated against experimental data over several years, but confidence in the model outputs may be low due to the fact that model validation may not have covered the very large range of weather conditions normally encountered in the long-term weather record.

A key problem in the modeling community is that model validation generally lacks sufficient data over the long term (multi-decadal) to represent all possible climatic patterns in a specific area (Yunusa *et al.*, 2004). Crop models cannot be validated for every climatic condition and also may have limitations with respect to scaling-up to wider climatic conditions. This deficiency of crop models can produce uncertainty with respect to model applications.

Information derived from statistical methods based on cluster analysis and correlation analysis can be useful for evaluating crop models' performance to interpret the interactive effects of climatic factors on crop yields over long time periods. Therefore, the aims of this paper are twofold: (1) to identify the factors which limited winter wheat yields at different growth stages in Queensland, Australia; and (2) to identify interactive effects of climatic factors on wheat yields by validating computer model simulations of wheat yield against long-term historical yield data.

2. Materials and methods

2.1. Climatic data

Well-processed and quality-checked historical climatic data (daily maximum and minimum temperatures, solar radiation, and precipitation) during the period from 1889 to 2004 at Dalby (–27.18º in latitude, 151.26º in longitude), Darling Downs of Queensland, Australia were obtained from Australian Bureau of Meteorology (see the web of SILO at http://www.bom.gov.au/silo/). Each climatic variable during May-Nov. was selected for analysis. This time period represents the growing season length for winter wheat in Queensland, Australia (Hochman *et al.*, 2009). The wheat growing season was simply divided into two stages: vegetative (sowing to flowering stages) and reproductive (flowering to maturity stages), corresponding to the periods of May to Sep. and Oct.-Nov. respectively.

Fig. 1 shows the variation of precipitation during both vegetative and reproductive stages. During the vegetative stage, precipitation ranged from 32 to 450 mm (average, μ=179 mm; standard deviation, σ=82 mm). During the reproductive stage, it fluctuated between 28 and 328 mm (μ =134 mm; σ=69 mm). The precipitation during the vegetative stage was less variable than that during reproductive stage, and no significant trend was found in either stage (Fig. 1).

2.2. Wheat yields

Historical wheat yield data from 1889 to 2004 in Queensland, Australia, were obtained from the Australian Bureau of Agricultural Resources Economics (ABARE, http://www.abareconomics.com). Wheat yield in Queensland varied widely from year to year during the period between 1889 and 2004. The average wheat yield (μ) was 1,133 kg ha^{-1} (σ=436 kg ha^{-1}) (Fig. 2). The yield fluctuated over a baseline of a time trend of yield increase due to technological improvements. The yield trend in the i^{th} year was the average yield over 9~~nine~~-years with respective 4 years before and after the i^{th} year. To eliminate non-climatic effects on yields, the detrended yield was obtained by subtracting trend yield from the actual yield. This 9-year smoothing average ~~method~~ was applied to remove trends in yields.~~assumed to eliminate period variation of climate~~ (Handler and Handler, 1983). Due to higher production in recent decades, the detrended yield varied greatly. So, we divided detrended yield by the average yields to get similar amplitude of yield variation during 1889-2004. In short, the detrended yield is the difference between the actual yield in the i^{th} year (Y_i) and nine-year-smoothing average yield (Y_0). The relative detrended yield is the ratio of detrend~~t~~ed and the average yield, i.e., $(Y_i-Y_0)/Y_0$, which is mainly related to weather conditions.

Since the high-quality and long-term yield data were available at the state level, we choose to use climate data at one site to avoid averaging meteorological variables over space. We selected Dalby to represent the climate of the entire wheat belt of Queensland. Dalby is located in the main producing region of Darling Downs, in Queensland. The wheat yields and planted areas at Darling Downs and the entire state in limited years were compared to justify the method (Fig. 3). A reasonable 1:1 relationship (r^2 = 0.92) existed for wheat yields. Therefore, the yield data of the entire Queensland state correspond well with that of Darling Downs.

2.3. Methods of cluster analysis for year pattern identification

Crops accumulate biomass and develop reproductive apparatus in vegetative growth, which occurs before flowering. After that, crops experience reproductive growth, when part of photosynthate is allocated to seeds and carbohydrate previously stored in leaves and stems is transported to seeds. These two growth stages have diverse assimilate partitioning, which may respond to climate differently (Hay and Porter, 2006). The average values of climatic variables were calculated for each growth stage of a year.

To identify significant climatic factors influencing wheat yield, a two-step procedure was considered. First, we assumed climate determined yield, and grouped rainfall, temperature and radiation into 8 clusters. Second, we tested whether wheat yield distribution in each cluster is significantly different to any other one. Cluster analysis was applied to identify agro-climatological year patterns in Queensland, Australia, based on historical meteorological data. The K-means method of clustering was adopted using SPSS (SPSS 16.0) after maximum and minimum temperatures, precipitation and solar radiation averaged or summed from daily values for both vegetative and reproductive stages were standardized.

The yield and corresponding meteorological variables (rainfall, temperature, and solar radiation) in two periods were used to classify clusters. Different groups (patterns) can be divided with significance and non-significance levels. We applied the Kolmogorov–Smirnov (K-S) tests to ensure each cluster is significantly different from others. Two patterns were aggregated into one, if there is no significant difference between them. The method was repeated until the difference between any patterns was significant.

2.4. APSIM simulations

The APSIM was developed and used for improving risk management under variable climate (McCown *et al.*, 1996; Keating *et al.*, 2003). It is a crop model that is able to simulate crop growth and development, soil water and nitrogen dynamics and the interactions among climate, soil, crop and management practices. These processes are represented as modules which can be readily connected to a central interface engine to simulate cropping systems using conditional rules. The model runs on a daily time-step with daily weather information (maximum and minimum temperature, rainfall and solar radiation). The APSIM version 5.3 was applied to simulate the effects of climatic factors on wheat yields based on long-term historical yield data in Queensland, Australia.

The APSIM has been widely tested against field measurements under a range of growing conditions in Australia (Asseng *et al*., 1998, 2000; Probert *et al*., 1998). In the simulations of this study, specific soil characteristics (i.e., saturated water content, drained upper limit, lower limit, bulk density, and nutrient properties, such as soil organic C, organic C biomass fraction, inert organic C fraction, and nitrate concentration) required for the APSIM model were based on Probert et al. (1998). The crop genetic parameters were obtained from Asseng and van Herwaarden (2003). The parameterized APSIM model was used to simulate wheat yield with the historical climate data from 1889 to 2004. The same wheat variety was used for all simulations, which permits analysis of the impact of only climate variations on crop growth.

3. Results

3.1. Wheat yield-climatic relationships

The relative detrended yields were significantly ($P \leq 0.001$) correlated with maximum and minimum temperatures, solar radiation, and precipitation during the vegetative stage. However, during the reproductive stage, only maximum and minimum temperatures showed significant correlation with the relative detrended yields, not precipitation and solar radiation (Table 1).

These apparent relationships between yield and sole climatic variable may not reflect its actual effect. Rainfall is normally the dominant factor affecting wheat production in this region, but temperatures and solar radiation will affect wheat yields as well, and precipitation is related to both temperature and solar radiation. Fig. 4 shows correlations between temperature and precipitation, and between solar radiation and precipitation averaged over the entire wheat growing period (May–Nov.). Maximum temperature and solar radiation significantly decreased when precipitation increased. Precipitation contributed 44.8% in the variation of maximum temperature and 42.4% in that of solar radiation. Although minimum temperature increased with precipitation, the increase rate was 0.28 degree/100 mm and rainfall only contributed 11.7% in its variation, which is too small to be considered (Fig. 4).

Rain and non-rain weather are two distinct types of meteorological phenomena that interact and influence crop growth. In both vegetative and reproductive periods, high precipitation was usually accompanied by low maximum temperature and low solar radiation (Fig.4, Table 2). Precipitation also showed a close relationship with minimum temperature in the vegetative stage, but it was not significant during the reproductive period (Table 2).

Direct and indirect effects of precipitation on wheat yield are illustrated in the Fig. 5. Precipitation events increase soil water content, and decrease solar radiation and daily temperature. Effects of soil water, solar radiation, and temperature on wheat yield can be positive or negative. Different combinations of these variables contributed to different levels of crop yield. Solar radiation and temperature regularly exert simultaneous effects on crop growth. However, precipitation events are discrete, and have potentially long term-effects on soil water. Therefore, precipitation during the vegetative phase plays the most important role in affecting crop yield among all climatic factors considered.

3.2 Climatic year patterns of wheat yield

After cluster analysis was applied to yield and meteorological variables during both vegetative and reproductive stages and the relative detrended wheat yield data, five climatic year patterns for wheat yield were identified (Pattern A, B, C, D, and E in Fig. 6). The mean of each pattern were –0.384, –0.192, 0.012, 0.196, and 0.376, respectively (Fig. 6).

As shown in Table 1, precipitation during the vegetative stage for the five patterns exhibited large differences, from 96 mm to 337 mm. In the highest precipitation pattern (E), solar radiation was lowest (2248 MJ m^{-2}), the maximum temperature was lowest (20.3 ºC), but the minimum temperature was highest (7.7 ºC). In contrast, solar radiation in the lowest precipitation pattern (A) was larger (2452 MJ m^{-2}), the maximum temperature was highest (22.3 ºC), but the minimum temperature was lowest (6.3 ºC). Solar radiation varied from 2340 to 2470 MJ m^{-2}, and precipitation varied from 96 to 220 mm across the other three patterns (B, C, and D). Greater precipitation during the vegetative stage increased crop yield. Considering all of the climatic variables, precipitation during the vegetative stage is the dominant factor determining wheat yield. This also influences changes of other climate variables. Rainfall decreased maximum temperature and solar radiation, which resulted in their negative correlation with relative detrended yield when rainfall is favorable for wheat in the vegetative stage.

No significant correlation existed between crop yields and precipitation or solar radiation during the reproductive stage (Figs. 7f and 7h). Crop yields were significantly correlated with maximum and minimum temperatures. Maximum temperature during the reproductive stage in Queensland region exceeded the optimal temperature for crop growth and limited yield formation, and minimum temperature is high enough to limit crop yield probably through its impact on respiration.

The direct and indirect impacts of precipitation can be advantageous or disadvantageous to wheat yield, as shown in Fig. 7. Precipitation during the reproductive stage did not show a significant correlation with crop yield. The highest precipitation (178 mm) produced medium yield (Pattern C, Table 1), which is obviously less than the crop yield for the Pattern E where precipitation was 151 mm. This negative impact of precipitation on crop yield may directly come from water-logging due to excessive precipitation, and may also indirectly come from the effects of decreased solar radiation, which was co-varied with the precipitation since the reproductive precipitation was found to be significantly and negatively correlated with maximum temperature and solar radiation (Table. 2). Higher wheat yields were produced under cooler temperatures. Patterns A and D were similar to each other in terms of precipitation (88 mm and 97 mm) and solar radiation (1506 MJ m^{-2} and 1466 MJ m^{-2}), but relative detrended wheat yields were very different (–0.384 and 0.196), indicating that during the reproductive stage crop yields were more influenced by maximum temperature (Table 1 and Fig. 7).

In terms of the total precipitation during the entire growing season, patterns C and D had similar levels of total precipitation (357 mm vs. 317 mm), but the relative detrended crop yields showed large differences. This is mainly due to the difference in the distribution of precipitation between the two growth stages. Pattern B was characterized by low precipitation in the vegetative stage and medium precipitation in the reproductive stage, which led to a low crop yield. This pattern was called “the low vegetative rainfall-medium reproductive rainfall-low yield (LML)”. In contrast, pattern D had high vegetative precipitation and low reproductive precipitation, which contributed to a high crop yield. The pattern was called "high vegetative rainfall-low reproductive rainfall-high yield (HLH)". Pattern C had medium vegetative precipitation and highest reproductive precipitation, which produced a medium crop yield, the MHM pattern (medium vegetative rainfall-high reproductive rainfall-medium yield). For the lowest yield level, the climatic conditions are characterized by lowest vegetative precipitation and lowest reproductive precipitation, termed as the LLL pattern. The highest yield level was associated with the highest vegetative precipitation and higher reproductive precipitation, called HMH. We found that much more precipitation during the vegetative stage contributed to higher crop yield (Patters D and E), while higher reproductive stage precipitation did not (Patterns B and C) (Fig. 7). This demonstrated that vegetative precipitation had the largest impact on final crop yields. For pattern A, due to extremely low precipitation in both growth stages, with a total value of 197 mm during the entire growing season, crop yields were extremely low (–0.384). The total solar radiation during the entire growing period was relatively high (3958 MJ m^{-2}) and the maximum temperature was high (24.8 ºC) in the LLL years (Pattern A). In the HMH years (Pattern E), the cumulative growing season solar radiation (3606 MJ m^{-2}) was considerably low and the maximum temperature was also low (22.4 ºC). For the other three patterns (B, C, and D), the cumulative growing season solar radiation were 3913, 3714, 3829 MJ m^{-2}, respectively, indicating that crop yields increased with cumulative growing season solar radiation and that crop yields are strongly dependent on total solar radiation under normal rainfall conditions (Fig. 7). Solar radiation was not significantly correlated with crop yield during the reproductive stage (Table 1). However, crop yields may increase with increasing solar radiation under conditions when precipitation is not limiting to crop yield.

3.3. APSIM validity against statistical yields

Comparisons were made to investigate whether the APSIM model could interpret the interactive effects of temperature, precipitation and solar radiation, which can be negative or positive, on wheat yield. Modeled yields are not influenced by contributions from agricultural technological advances. There is no significant increasing or decreasing trend for modeled crop yields due to the use of the same cultivar and same practices for all of the simulation years during the period of 1889–2004.

We therefore applied the same normalization method deriving the relative detrended yield to the modeled yields as applied previously to the historical wheat yield data. Fig. 8 showed the comparison between statistical and simulated relative yields for the five climatic patterns. Generally, the simulated yields corresponded well with statistically relative yields for patterns B, C and D (the three intermediate yield levels). However, the model underestimated the yields in the lowest yield level (A) and overestimated the yields in the highest yield level (E). This suggests that the model could be able to account for the effects of temperature, rainfall and solar radiation on wheat yields in majority of years. But for the lowest and highest yield years, corresponding to extremely dry and wet years, especially in the reproductive stage, the model exaggerated the effects of precipitation on wheat yield. The APSIM-simulated leaf area index (LAI) and total biomass was plotted for typical years in each pattern. Simulated LAI and biomass differed much among pattern years. High yield corresponded to high LAI and biomass, and LAI and biomass were low in low yield pattern years (Fig. 9). The coherence between the simulated yield and LAI and biomass indicated that yield is closely related to LAI or biomass, which is well described by the APSIM model.

Fig. 10 shows the average statistically relative yields for the five yield patterns plotted against the modeled relative yields. Although the coefficient of determination for the regression of modeled relative yields against statistically relative yields was high (0.95), the discrepancies in extremely dry and wet years were significant (regression slope = 1.51). The deficiency of the APSIM model is thus characterized as overestimating yield in very wet years and underestimating yield in very dry years.

4. Conclusion and discussion

Climate warming over the last century has ranged between 0.056–0.092 degree/decade (IPCC, 2007). Temperature variability ranged from 3110 to 3763 degree days in the growing season in the study area. For annual crops, this is much higher than the warming trend.

As rainfall in vegetative and reproductive stages exerted different effects on wheat yield, its variation will have significant implication for wheat production. Decreases in rainfall in the vegetative stage and increases in reproductive stage (Fig. 1) reduce wheat production.

Maximum temperature, minimum temperature, and solar radiation were closely correlated with precipitation. These variables had measurable influences on wheat yields in Queensland. However, precipitation is considered to be the most important driving force. Our analysis suggested that the amount of precipitation in May-Sep. can be used to forecast final crop yields in advance of harvest. This will help farmers to better manage their farms prior to and post harvest (i.e. storage, transportation and labor arrangement). Thus, depending on seasonal forecasts, farmers may apply the appropriate nitrogen treatment to meet the demands of crop growth since the peak demand for nitrogen is during the phase when crops grow fastest (Angus, 2001). When total precipitation during the period from May to Sep. is high (≥214 mm), farmers need to apply more fertilizer to obtain higher yields. Otherwise reducing fertilizer rate is necessary to avoid economic loss. During the reproductive stage, increased precipitation may not increase wheat yields, possibly due to lower solar radiation from increased cloudiness in years with high rates of precipitation. The inter-relationship between precipitation and solar radiation makes both of them not significantly correlated with wheat yields during the reproductive stage. Maximum temperature during this stage had a much larger influence. High wheat yields were associated with low daytime temperatures, as reported for rice (Yu *et al.*, 2001), corn and soybean (Lobell and Asner, 2003). A possible reason for this is that high temperatures induce heat injury to the photosynthetic mechanism (Harding *et al.*, 1990; Law and Crafts-Brandner, 1999; Sharma and Singh 1999).

Crop yield is defined by abiotic stresses over time scales of diurnal, daily, seasonal variations of climate and soil conditions. The crop growth modelling is run on daily time step, whereas the year-pattern identification in this study is based on seasonal variation, i.e., two periods of May–Sep. and Oct. –Nov.. The Australian wheat-belt is a region of very high rainfall variability. This characteristic determines distinct year patterns which can be attributed to large scale climate events, such as El Niño and Southern Oscillation (ENSO). Queensland received much more rain in La Niña years and experienced drought in El Niño years (Stone, 1998). Variability in these year patterns of climate will result in rainfall variation at hourly or daily time scales which may impact crop growth. For example, midday depression of photosynthesis due to water stress and extreme high temperature may be more frequent in drought years. Therefore, yield which varies annually within each year pattern may be influenced by the diverse daily variation of climatic factors.

The APSIM model had high capability to estimate wheat yields in years when precipitation was moderate (about 400–500 mm during the growing season). When growing season precipitation was either low or too large, the model significantly underestimated or overestimated wheat yields.

Climatic factors play crucial roles in determining crop yield. To understand crop-climate relations under different climatic scenarios crop models can be very useful for regional crop yield prediction and for determining effective management practices. From the perspective of climate change, understanding relationships between climate and yield can help to predict and monitor crop production and to ensure food security. The results of this paper are valuable for crop modelers and model users. Crop models must be comprehensively evaluated over long time periods so that all possible climatic scenarios can be covered. Once a CSM has been validated over multiple years, it is easy to judge which annual patterns can or cannot be simulated well. With the knowledge derived from regression analysis of crop yield to climatic factors, crop modelers will be able to improve crop models, and model users will be able to judge model accuracy under different climatic scenarios.

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Legends of figures

Fig. 1. Variations of precipitation during the periods of May-Sep. (Precip5-9, solid curve) and Oct.-Nov. (Precip10-11, dash curve) at Dalby in Queensland, Australia.

Fig. 2. Variations of actual yield (solid) and relative detrended yield (dash) during the period of 1889-2004 at Dalby in Queensland, Australia.

Fig. 3. Comparisons of wheat yields (a) and wheat growth areas (b) between Darling Downs and Queensland. The solid line in the top panel (a) represents the linear regression, r is the correlation coefficient, and the dashed lines on each side of it represent the upper and lower 95% confidence limits. The symbol ** indicates statistical significance at 0.01 level.

Fig. 4. Inter-correlations between precipitation (Precip) and maximum (T_{max}) and minimum (T_{min}) temperatures, and solar radiation (R_a) during the wheat growing period at Dalby in Queensland, Australia. The solid line represents the linear trend for each variable. The symbol ** indicates statistical significance at 0.01 level.

Fig. 5. The scheme showing the relationship between precipitation and soil water, solar radiation, and daily temperature, and their effects on crop growth and yield. + indicates positive feedback and – negative. +/- indicates that the impact can be either positive or negative.

Fig. 6. Cluster analysis for the relative detrended wheat yields during the period 1889-2004 in Queensland, Australia. A, B, C, D, and E represent the relative detrended yields, –0.384, –0.192, 0.012, 0.196, and 0.376, respectively. Horizontal bars and upper and lower edges of boxes indicate 10, 25, 75, and 90 percentiles, thick black line and filled circle are the median

and average, respectively. The crosses indicate all the outliers.

Fig. 7. Relationship between relative detrended yield and the maximum temperature (T_{max}), the minimum temperature (T_{min}), precipitation (Precip), and solar radiation (R_a) during the periods of May-Sep. (indicated as 5-9) (a, c, e, and g) and Oct.-Nov. (indicated as 10-11) (b, d, f, and h). A, B, C, D, and E represent the relative detrended yields, –0.384, –0.192, 0.012, 0.196, and 0.376, respectively. Horizontal bars and upper and lower edges of boxes indicate 10, 25, 75, and 90 percentiles, thick black line and filled circle are the median and average, respectively.

Fig. 8. Comparison between statistically and simulated relative yields during the period of 1889–2004 in Queensland, Australia. Five clusters, A, B, C, D, and E represent the relative detrended yields, –0.384, –0.192, 0.012, 0.196, and 0.376, respectively. The solid line is the linear regression equation for the mean values. The dash line indicates the 1:1 line.

Fig. 9. APSIM-simulated biomass and LAI for five patterns of climate impact.

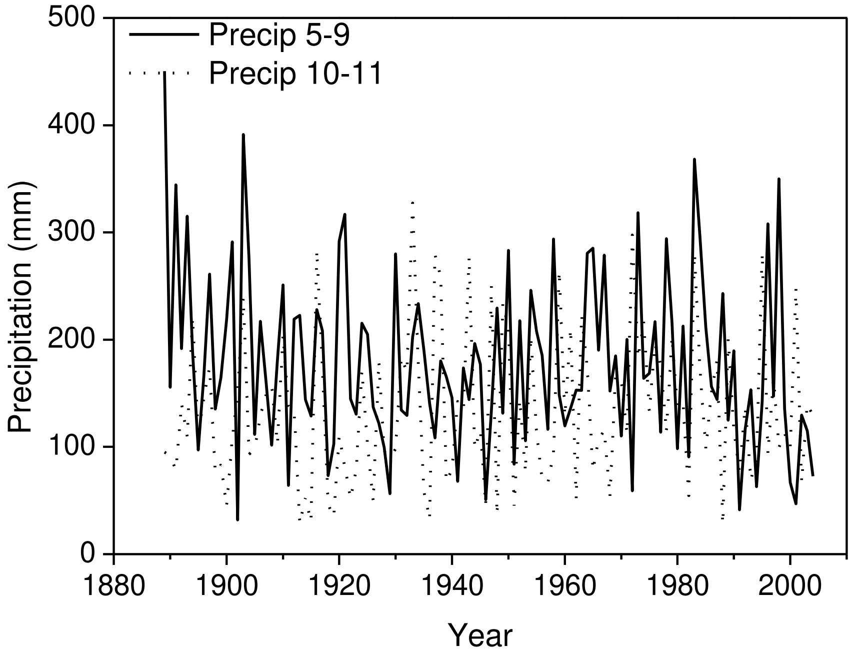
Fig. 10. Comparison between average statistically relative yield and average simulated relative yield by APSIM. A, B, C, D, and E represent the relative detrended yields, –0.384, –0.192, 0.012, 0.196, and 0.376, respectively. The circle inside the box represents the mean yield, and the square inside the box indicates the median yield. The left and bottom edges of the box represent the 5 percentiles, and the right and top edges of the box represent 95 percentiles. The bottom-left and top-right corners indicate 25 and 75 percentiles, respectively. The solid line is the linear regression equation for the mean values. The dash line indicates the 1:1 line.

Table 1. Mean values of the relative detrended wheat yield, the maximum (T_{max}, ºC) and minimum (T_{min}, ºC) temperatures, precipitation (Precip, mm), and solar radiation (R_a, MJ m^{-2}) corresponding to specific cluster during the periods May-Sep. (5-9) and Oct.-Nov. (10-11). The *slope* is the slope of linear regression between the relative detrended wheat yield and meteorological variables for five clusters and *r* is the correlation coefficient. And 'n' is the number of data points for each cluster. The 'Yield' represents the relative detrended yield, which is –0.384, –0.192, 0.012, 0.196, and 0.376 for clusters A, B, C, D, and E, respectively. The symbols *, ** indicate the statistical significance at 0.05 and 0.01 levels.

	n	Yield	Tmax5-9	Tmax10-11	Tmin5-9	Tmin10-11	Precip5-9	Precip10-11	Ra5-9	Ra10-11
R			–0.49**	–0.34**	0.32**	–0.22*	0.56**	0.10	–0.43**	–0.17
Slope			–0.184	–0.068	0.093	–0.078	0.002	0.0005	–0.002	–0.001
A	15	–0.384	22.3	30.9	6.3	14.7	109	88	2452	1506
B	23	–0.192	21.7	29.4	5.0	14.1	96	129	2470	1443
C	38	0.012	21.0	27.6	6.5	13.7	179	178	2340	1374
D	29	0.196	20.8	30.0	6.4	14.1	220	97	2362	1466
E	11	0.376	20.3	27.6	7.7	13.8	337	151	2248	1357

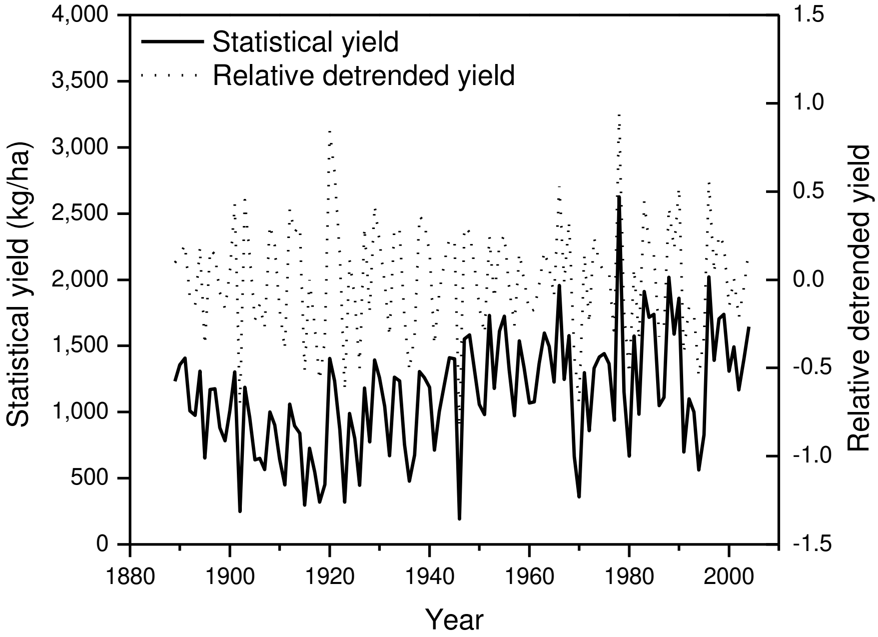
Table 2. Inter-correlations between precipitation (Precip) and maximum temperature (T_{max}, ºC), minimum temperature (T_{min}, ºC), and solar radiation (R_a, MJ m^{-2}) during the periods May-Sep. (5-9) and Oct.-Nov. (10-11). The symbol * indicates the linear relationship between precipitation and other climatic variables significant at 0.01 level, and n.a. represents “not applicable” for correlation.

	Tmax5-9	Tmax10-11	Tmin5-9	Tmin10-11	Ra5-9	Ra10-11
Precip5-9	–0.0058*	n.a.	0.0072*	n.a.	–0.6704*	n.a.
Precip10-11	n.a.	–0.0157*	n.a.	0.0006	n.a.	–0.6465*



Precip 5-9
Precip 10-11
Precipitation (mm)
500
400
300
200
100
0
1880
1900
1920
1940
1960
1980
2000
Year

Fig. 1



585

586 Fig. 2

587

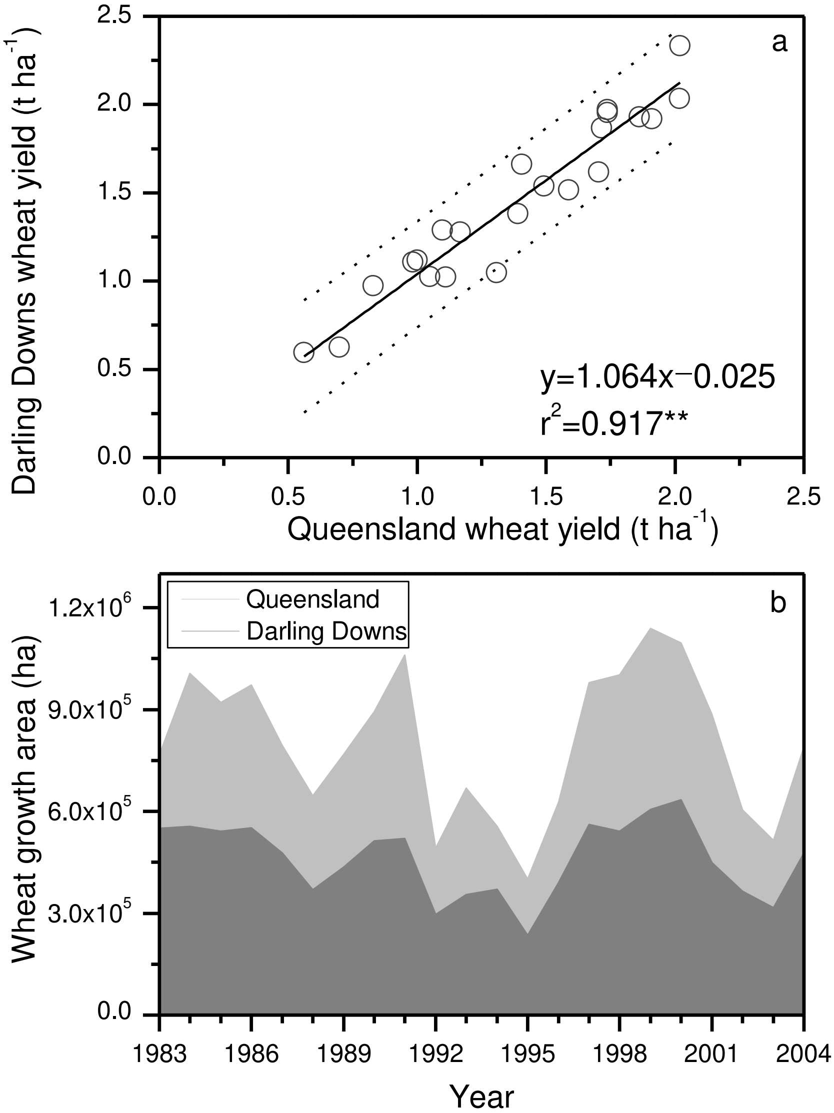
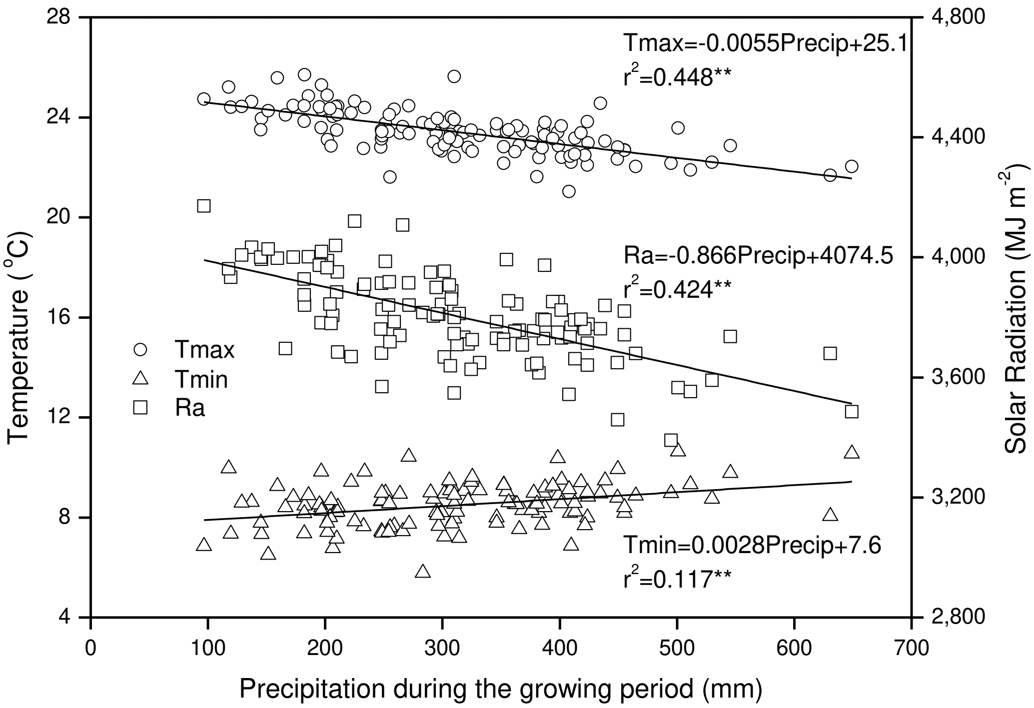

a
Darling Downs wheat yield (t ha^{-1})
Queensland wheat yield (t ha^{-1})
y=1.064x−0.025
r^2=0.917**
0.0
0.5
1.0
1.5
2.0
2.5
b
Queensland
Darling Downs
Wheat growth area (ha)
0.0
3.0x10^5
6.0x10^5
9.0x10^5
1.2x10^6
1983
1986
1989
1992
1995
1998
2001
2004
Year

Fig. 3



28
24
20
16
12
8
4
4,800
4,400
4,000
3,600
3,200
2,800
0
100
200
300
400
500
600
700
Tmax=-0.0055Precip+25.1
r2=0.448**
Ra=-0.866Precip+4074.5
r2=0.424**
Tmin=0.0028Precip+7.6
r2=0.117**
Tmax
Tmin
Ra
Temperature (°C)
Solar Radiation (MJ m-2)
Precipitation during the growing period (mm)

Fig. 4

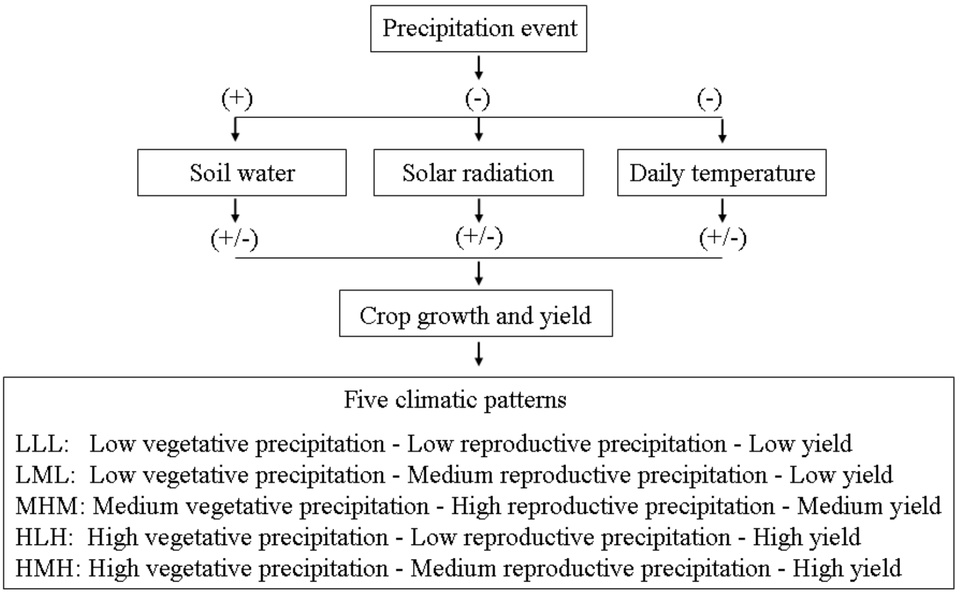
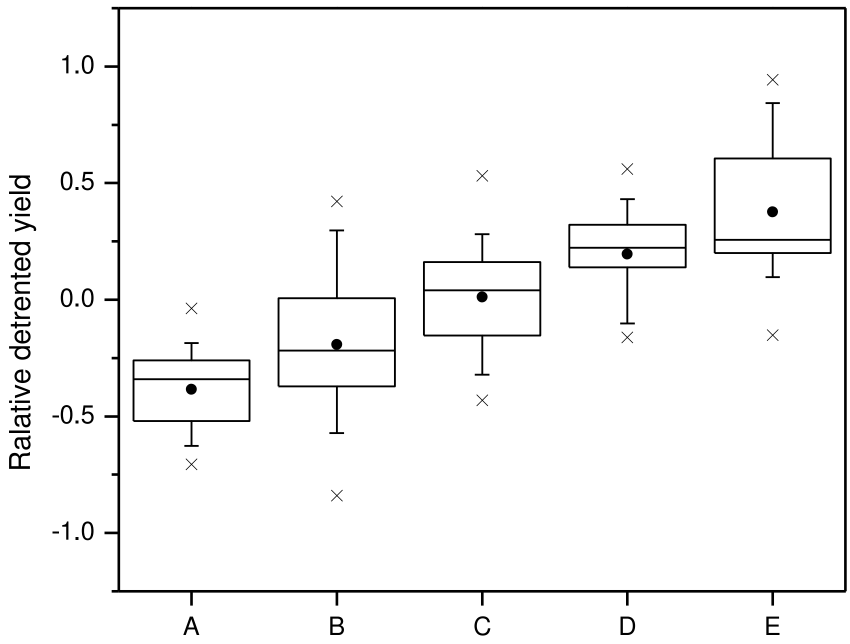

Precipitation event
(+)
(-)
(-)
Soil water
Solar radiation
Daily temperature
(+/-)
(+/-)
(+/-)
Crop growth and yield
Five climatic patterns
LLL: Low vegetative precipitation - Low reproductive precipitation - Low yield
LML: Low vegetative precipitation - Medium reproductive precipitation - Low yield
MHM: Medium vegetative precipitation - High reproductive precipitation - Medium yield
HLH: High vegetative precipitation - Low reproductive precipitation - High yield
HMH: High vegetative precipitation - Medium reproductive precipitation - High yield

Fig. 5



597

598 Fig. 6

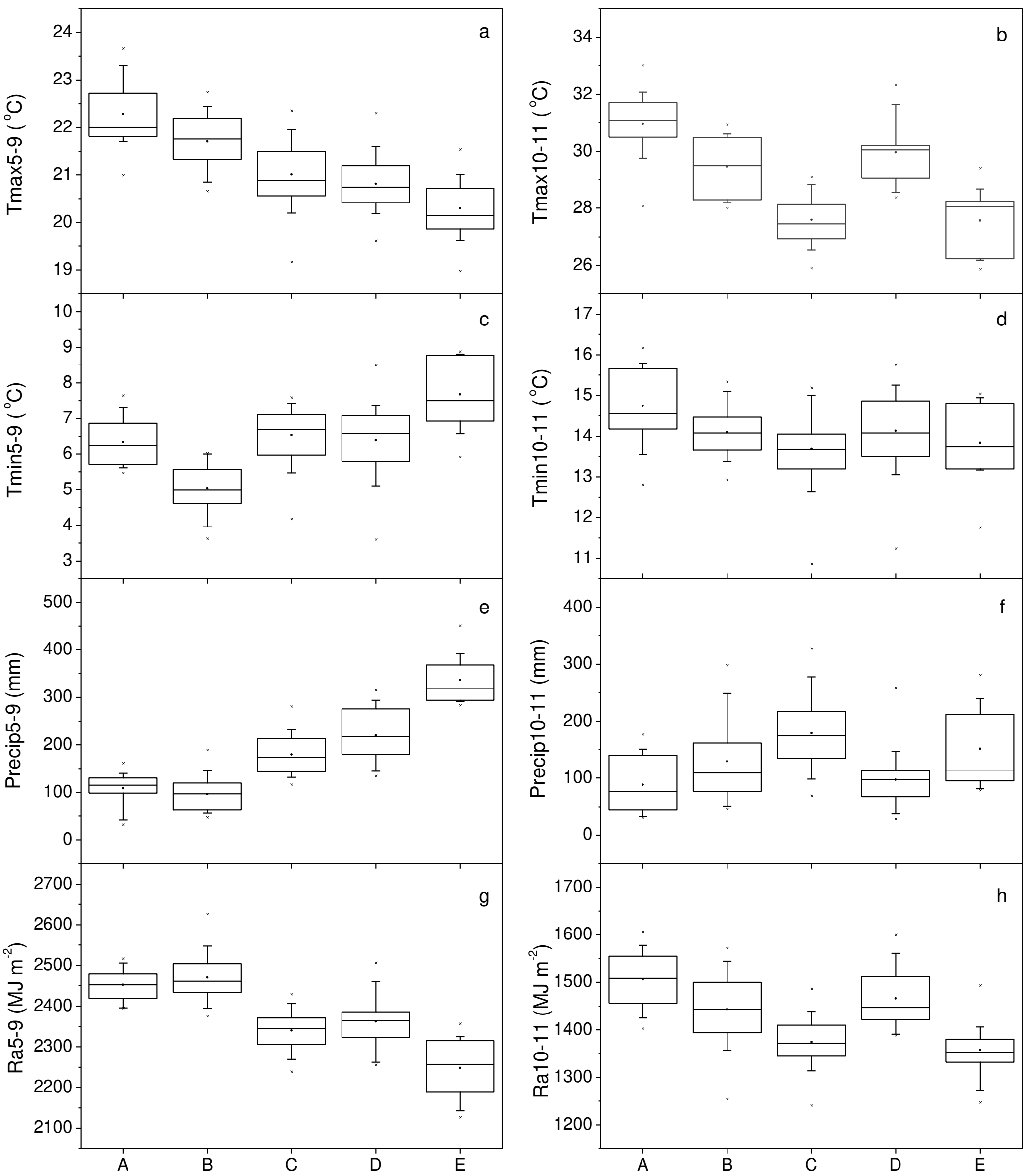

a
b
c
d
e
f
g
h
Tmax5-9 (°C)
Tmax10-11 (°C)
Tmin5-9 (°C)
Tmin10-11 (°C)
Precip5-9 (mm)
Precip10-11 (mm)
Ra5-9 (MJ m-2)
Ra10-11 (MJ m-2)
A
B
C
D
E

Fig. 7

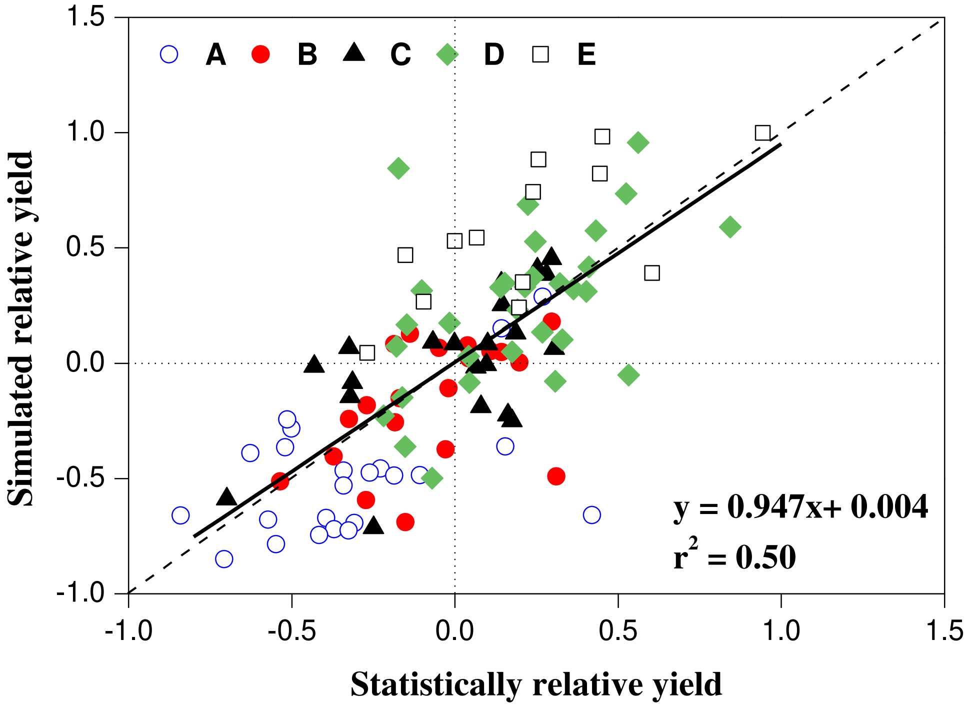
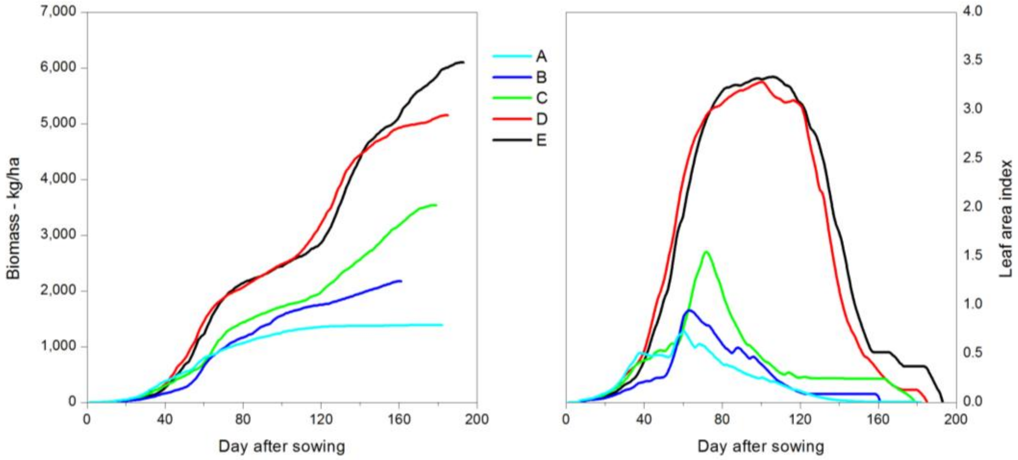

A
B
C
D
E
y = 0.947x+ 0.004
r^2 = 0.50
Simulated relative yield
Statistically relative yield
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.0
-0.5
0.0
0.5
1.0
1.5

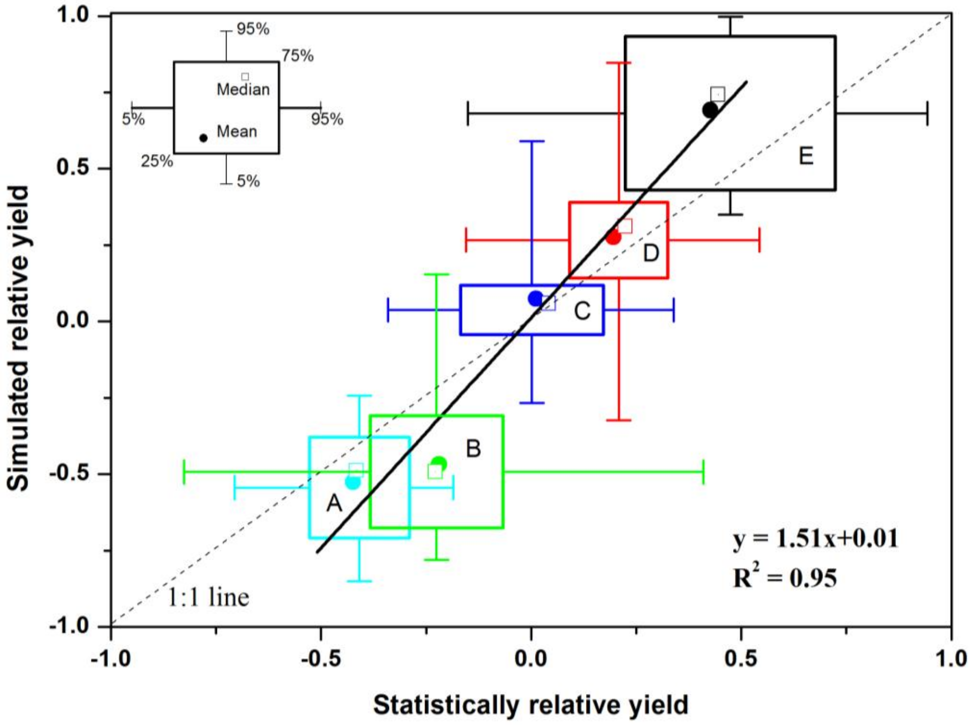
Fig. 8

605



Biomass - kg/ha
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
0
40
80
120
160
200
Day after sowing
A
B
C
D
E
Leaf area index
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0

606 Fig. 9



1.0
0.5
0.0
-0.5
-1.0
-1.0
-0.5
0.0
0.5
1.0
Simulated relative yield
Statistically relative yield
95%
75%
Median
5%
95%
Mean
25%
5%
A
B
C
D
E
y = 1.51x+0.01
R² = 0.95
1:1 line

Fig. 10