The Journal of Agricultural Science

www.cambridge.org/ags

Crops and Soils Research Paper

Cite this article: Anwar MR, Luckett DJ, Ip RHL, Chauhan Y, Graham N, Raman R, Richards MF, Berger J, and Rohan M (2025). Identifying key environmental drivers of chickpea yield and water-use efficiency: a statistical modelling approach. *The Journal of Agricultural Science* **163**, 532–546. https://doi.org/10.1017/S0021859625100270

Received: 12 April 2025
Revised: 4 July 2025
Accepted: 13 August 2025

Keywords:
Abiotic stress; crop growth stages; *Cicer arietinum* L.; exclusive LASSO prediction; shrinkage estimator

Corresponding author:
Muhuddin Rajin Anwar;
Emails: muhuddin.anwar@dpi.nsw.gov.au and 1anwar191962@gmail.com

Identifying key environmental drivers of chickpea yield and water-use efficiency: a statistical modelling approach

Muhuddin Rajin Anwar[1,2], David John Luckett[2], Ryan H. L. Ip[3,4], Yashvir Chauhan[5], Neroli Graham[1], Rosy Raman[1], Mark F. Richards[1], Jens Berger[6] and Maheswaran Rohan[1]

[1]NSW Department of Primary Industries and Regional Development, Wagga Wagga Agricultural Institute, Wagga Wagga, NSW 2650, Australia; [2]Gulbali Institute (Agriculture, Water and Environment), Charles Sturt University, Locked Bag 588, Wagga Wagga, NSW 2678, Australia; [3]Department of Mathematical Sciences, Auckland University of Technology, Auckland, New Zealand; [4]School of Computing and Mathematics, Charles Sturt University, Wagga Wagga, NSW, Australia; [5]Queensland Department of Primary Industries Research Station, Kingaroy, Qld 4610, Australia and [6]CSIRO Agriculture and Food, PMB5, Wembley, WA 6913, Australia

Abstract

Chickpea (*Cicer arietinum* L.) is a vital legume crop with significant global importance, yet its productivity is highly sensitive to environmental variability. This study employed advanced statistical modelling to identify key environmental drivers of chickpea yield and water-use efficiency (WUE). Field trial data from 29 experiments across 10 Australian locations were analysed, focusing on 19 climatic variables across four growth stages: sowing to flowering, flowering to podding, podding to maturity and the critical period around flowering. Using correlation analysis and Exclusive LASSO regression, the study quantified relationships between environmental factors, growth stages and chickpea performance metrics. Key findings identified soil evaporation and soil moisture supply-demand ratio during the sowing-to-flowering stage, along with frost during the critical period, as significant determinants of yield. Frost negatively impacted WUE across multiple growth stages, while mean photothermal quotient during early growth positively influenced transpiration-based WUE. Predictive models developed using daily climate data demonstrated strong performance ($R^2 > 0.68–0.72$) for yield and WUE predictions. The study provides actionable insights for optimising chickpea production under varying environmental conditions, offering practical tools for farmers and agronomists to enhance crop management strategies, supporting sustainable and profitable chickpea farming in Australia and beyond.

Introduction

Chickpea, *Cicer arietinum* L., is a globally significant legume, ranking as the second most important food legume after dry beans (FAOSTAT, 2025). Its prominence stems from its dual role in human nutrition and sustainable agriculture. Chickpeas are a rich source of protein, making them a vital component of diets in many parts of the world, particularly in regions where animal protein is scarce or expensive. Beyond its nutritional value, chickpea plays a crucial role in agricultural systems due to its ability to fix atmospheric nitrogen, which enhances soil fertility and reduces the need for synthetic fertilisers. This nitrogen-fixing capability makes chickpea an ideal rotational crop in cereal-pulse systems, contributing to the sustainability of farming practices (Rani and Krishna 2016; Liu *et al*., 2020; Palmero *et al*., 2022).

Chickpea is predominantly cultivated as a cool-season crop, thriving in climates ranging from Mediterranean to subtropical and tropical regions. The 2023, global chickpea production reached approximately 16.5 million t, harvested from nearly 14.1 million ha (FAOSTAT, 2025). Australia, a major player in the global chickpea market, is the largest exporter of desi chickpeas, the crop ecotype widely used in traditional dishes across South Asia. The crop is well-suited to medium-rainfall regions (300–500 mm), where it exhibits slow growth during the cold winter months, followed by accelerated growth in spring as temperatures rise. The area under chickpea cultivation in Australia has expanded significantly, to 1.039 million ha in 2024-25, driven by favourable grain prices and its role as a profitable break crop in cereal rotations. However, despite its economic and agronomic benefits, the average yield of chickpea in Australia remains relatively low at 1.35 t/ha over the last 10 years (2015-16 to 2024-25), primarily due to challenges posed by diseases and abiotic stresses such as drought, frost and heat stress (GRDC, 2011; ABARES, 2024).

Table 1. Weather data spanning 75 years (1950–2024) for 10 experimental sites (Fig. 1), summarised for both long-term (LT) and short-term (ST) periods (years with experiments). Data covers the growing season (April 1–October 31) and was sourced from SILO (https://longpaddock.qld.gov.au/silo/; Jeffrey *et al*., 2001)

	Number of years for experiments	Mean total rainfall (mm)		Mean daily minimum temperature (°C)		Mean daily maximum temperature (°C)		Mean number of frosts (<= 0°C)	
Site		**LT***	**ST***	**LT**	**ST**	**LT**	**ST**	**LT**	**ST**
Breeza	1	303.7	80.70	6.758	6.122	20.84	23.10	14.36	28.0
Horsham	1	291.5	232.6	5.301	4.675	17.13	17.74	14.31	19.0
Kingaroy	1	303.4	129.6	7.904	7.845	22.29	23.82	14.21	14.0
Leeton	2	291.4	140.0	6.249	6.169	18.52	20.12	15.71	18.5
Narrabri	2	284.7	122.7	7.585	7.871	22.43	23.89	10.95	11.5
Roseworthy	2	312.4	282.2	7.796	7.985	18.75	20.14	2.24	5.0
Tamworth	2	325.0	238.2	5.965	5.812	19.98	21.21	21.59	27.5
Trangie	2	266.8	91.1	7.006	8.074	20.22	22.58	13.09	9.5
Wagga Wagga	3	336.8	249.8	5.710	5.369	17.40	18.51	18.80	30.3
Yanco	1	252.1	88.80	6.746	7.820	18.61	20.48	10.21	6.0

Globally, chickpea yields have stagnated at around 1 t/ha, with productivity gains lagging behind those of other winter crops (Joshi and Rao 2017). Abiotic stresses, particularly drought, are major constraints on chickpea productivity, limiting plant growth, distribution and yield (Garg *et al*., 2016; Saini *et al*., 2022). Drought, exacerbated by climate change, threatens global food security, with chickpea being particularly vulnerable due to its sensitivity to water availability. In Australia, where chickpea is a cornerstone of the pulse industry, the crop's productivity is highly susceptible to climatic variations, especially during critical growth phases. This vulnerability underscores the urgent need for adaptive strategies to mitigate the impacts of environmental stresses and enhance chickpea yields.

Chickpea's sensitivity to environmental variability, including temperature, precipitation and other climatic factors, is particularly pronounced during key growth stages. After germination, temperature, photoperiod and soil moisture availability collectively influence the progression through various phenological stages. Among these, flowering is a critical phase, as the environmental conditions during this period and the length of the reproductive phase significantly affect pod formation and final yield (Lake and Sadras 2014; Peake *et al*., 2020; Graham *et al*., 2022). Understanding and predicting the complex interactions between environmental conditions, crop growth stages and yield outcomes is essential for improving productivity and resource use efficiency. Temperature, solar radiation and water availability significantly influence chickpea yield and water-use efficiency (WUE) (Sadras and McDonald 2011; Siddique *et al*., 2012). These interactions are further modulated by the specific growth stages of the crop, highlighting the need for targeted analyses to identify periods of heightened sensitivity.

Despite significant advancements in agricultural research, there remains a critical knowledge gap in quantifying how combinations of environmental factors and growth stages affect chickpea yield and WUE. Addressing this gap could lead to improved management strategies and adaptive practices, particularly in the face of changing climate conditions. For instance, understanding the impact of cold and heat stress during flowering or the role of soil moisture during podding could inform irrigation schedules, planting dates and varietal selection for mitigating stress and enhancing crop productivity. Therefore, to uncover the most significant drivers of yield and WUE, we split the chickpea growing season phenologically into four intervals: sowing to flowering (sf), flowering to podding (fp), podding to maturity (pm) and critical period (cp) thus isolating the sensitive periods (fp and cp) where the chickpea is prone to pod abortion from sub- and supra-optimal temperatures (Peake *et al*., 2020). In the vegetative phase (sf), the crop accumulates biomass to maximise productivity, while during the seed-filling stage, there is a balance between vegetative and reproductive growth to maximise productivity and WUE.

This study aimed to bridge these knowledge gaps by focusing on four key objectives. Firstly, it sought to quantify the relationships between combinations of environmental factors and chickpea growth stages in relation to grain yield and WUE. Secondly, the study employed correlation analysis and Exclusive LASSO (eLASSO) regression to identify the most influential environmental factors in different growth stages. Thirdly, predictive models were developed to forecast chickpea yield and WUE under varying environmental conditions. Finally, the research aimed to provide a practical tool for farmers and agronomists, enabling informed decision-making to optimise and expand chickpea production.

Materials and methods

Study area and agronomy

The workflow for this investigation – a meta-analysis of nineteen environmental variables across four growth stages of chickpeas – is summarised in Figure S1. Data were collected from 29 field experiments at 10 sites between 2013 and 2019 (with multiple sowing times per year at some sites) in South Australia (SA), Victoria (VIC), New South Wales (NSW) and Queensland (QLD), representing diverse agroclimatic conditions in Australia's chickpea regions (see Table 1 and Figure 1). Detailed information on years, sowing times, cultivars, agronomic practices and experimental designs is available in prior studies (Anwar *et al*., 2022; Chauhan *et al*., 2023). The experiments followed the

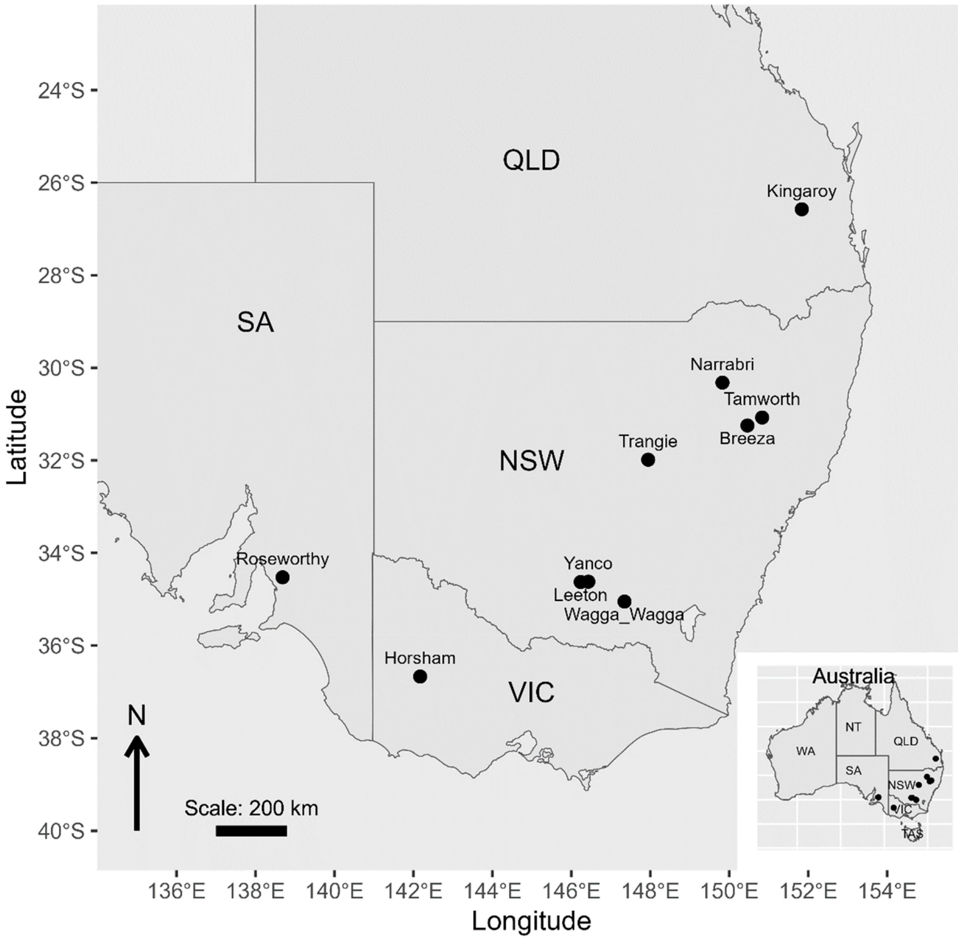

Figure 1. The ten field experimental sites (black dot) in southeastern Australia used in this study.

National Variety Trials (NVT) protocols, including guidelines for crop establishment and pest control (NVT Online, 2025). Although procedures were generally consistent, variations in row spacing, sowing depth, plant density and harvested area were noted. Specific details can be found in Table 1 of Anwar *et al.* (2022).

Phenological stages (flowering and podding) were recorded when 50% of the plants exhibited at least one open flower or visible pod. Yield was measured at physiological maturity via machine harvest and expressed in kg/ha. Daily weather data, including temperature, rainfall and solar radiation, were primarily sourced from the SILO database (https://legacy.longpaddock.qld.gov.au/silo/about.html; Jeffrey *et al.*, 2001), with some locations using on-site climate data. Soil properties for each experimental site are detailed in Anwar *et al.* (2022) and Chauhan *et al.* (2023).

Growing periods and weather indices

The growth stages of chickpea – emergence, flowering, pod set and physiological maturity – are crucial for grain yield and water use efficiency. Abiotic stresses like heat and drought during these stages can significantly affect crop performance (Soltani and Sinclair, 2011; Devasirvatham and Tan, 2018; Bicard *et al.*, 2025). This study defines four key crop growth periods (Lake and Sadras, 2014; Bicard *et al.*, 2025):

a. **SF (Sowing to Flowering)**: The period from sowing to the onset of flowering.

b. **FP (Flowering to Pod)**: The interval between flowering and pod formation.

c. **PM (Pod to Maturity)**: The period from pod formation to maturity.

d. **CP (Critical Period)**: Defined as 300°Cd before flowering to 500°Cd after flowering, based on the thermal time concept.

These growth periods may overlap, requiring careful interpretation. The growth periods were calculated for each genotype based on observed phenology. To assess environmental conditions during these periods, 19 weather indices were calculated, capturing temperature, water availability and solar radiation aspects that influence chickpea growth and yield. Key indices include:

1) **H30**: Number of days with maximum temperatures ≥ 30°C, indicating heat stress.
2) **H35**: Number of days with maximum temperatures ≥ 35°C, representing extreme heat stress.
3) **F**: Frost frequency, measured as the number of days with minimum temperatures ≤ 0°C.
4) **sumTT**: Cumulative thermal time (°Cd), calculated as the sum of daily temperatures above a base temperature.
5) **SE**: Cumulative soil evaporation (mm), representing water loss from the soil surface.
6) **PET**: Cumulative potential evapotranspiration (mm), estimated using the Priestley-Taylor method.
7) **SDR**: Accumulated water deficit ratio, calculated as the ratio of water supply to water demand.
8) **RAIN**: Cumulative rainfall (mm) during the growth period.

9) **ET**: Cumulative crop water use (mm), including both transpiration and soil evaporation.
10) **T**: Cumulative crop transpiration (mm), excluding soil evaporation.
11) **meanVPD**: Mean vapour pressure deficit (kPa), indicating atmospheric demand for water.
12) **meanPTQ**: Mean photothermal quotient (MJ/m²/°Cd), calculated as the ratio of photosynthetically active radiation (PAR) to mean temperature.
13) **meanPTQvpd**: Mean photothermal quotient corrected by vapour pressure deficit (MJ/m²/°Cd/kPa).
14) **meanPAR**: Mean photosynthetically active radiation (MJ/m²/day), derived by multiplying global solar radiation by 0.47 (Pinker and Laszlo, 1992).
15) **DL**: Cumulative day length (hours:minutes).
16) **RADN**: Cumulative solar radiation (MJ/m²/day).
17) **MINT**: Mean daily minimum temperature (°C).
18) **MAXT**: Mean daily maximum temperature (°C).
19) **meanPZT**: Mean temperature corrected for photoperiod (°C).

Vapour pressure deficit (VPD) was calculated from saturated and actual vapour pressure (Zeleke *et al.*, 2023), and the photothermal quotient (PTQ) was derived from cumulative photosynthetically active radiation (PAR) over mean temperature (Fischer, 1985; Soltani and Sinclair, 2011). The PTQ adjusted for VPD (PTQvpd) was calculated by dividing PTQ by mean VPD. The photoperiod-adjusted temperature (meanPZT) was determined using the approach from Gallagher *et al.* (1983) and Verghis *et al.* (1999). The saturated vapour pressure and actual vapour pressure was estimated for maximum (Tmax) and minimum (Tmin) temperatures using the equations provided by Dreccer *et al.* (2018) and Jeffrey *et al.* (2001). Equations to compute VPD, PTQ, PTQvpd and meanPZT, respectively, are given in the Supplementary material.

Soil water balance

Soil water balance is crucial for crop growth and yield as it determines the availability of water for plants. Key components include rainfall, evapotranspiration (ET), runoff and drainage (Unkovich *et al.*, 2018; Unkovich *et al.*, 2023). This study calculates the soil water balance using temperature, rainfall and simulated soil water content at sowing and harvest, following He and Wang (2019).

We used the Agricultural Production Systems sIMulator (APSIM) to simulate soil water dynamics. APSIM is a validated model for crop growth, water cycling and nutrient dynamics (Holzworth *et al.*, 2014; APSIM, 2023). The Soil Water module was parameterised using previous research data (Liu *et al.*, 2014; Zeleke and Nendel, 2019; Wang *et al.*, 2017; Xing *et al.*, 2017; Anwar *et al.*, 2022). To estimate the initial soil water content for the 2013–2019 experimental period, we ran APSIM from January 1, 2000, assuming soil water content was equal to the lower limit of plant-available water (LL15) (He and Wang, 2019).

Total water use (WU) for crops, measured as ET, was determined by the difference between starting soil moisture at planting and final soil moisture at harvest, plus total irrigation and rainfall during the growing season. Water use efficiency (WUE) is defined as crop yield (Y, kg/ha) per unit of water lost through ET (mm). Transpiration (T), which excludes soil evaporation, was calculated similarly (Yang *et al.*, 2016). Equations to compute ET, T and WUE using ET and T, respectively, are given in the Supplementary material.

APSIM also calculates daily potential evapotranspiration (PET) using the Priestley-Taylor method, based on the relationship between crop yield and ET (Paredes *et al.*, 2014; Trout and DeJonge, 2017; Akumaga and Alderman, 2019).

Water supply-demand ratio (SDR)

The APSIM model computes a water-deficit index (Chapman *et al.*, 19193; Chenu *et al.*, 2011), also known as the 'water supply' and 'water demand' ratio, which indicates how well the water extractable by a crop's roots (water supply) meets the crop's potential transpiration needs (water demand). The water supply is calculated for each soil layer with roots, depending on root growth and soil properties. Water demand is estimated daily based on crop growth and atmospheric conditions. The water supply-demand ratio (SDR) ranges from 0 to 1, reflecting water stress levels in plants. An SDR of 1 indicates no stress, while a lower value indicates stress. The water supply-demand ratio (SDR) is the ratio between water supply and water demand, bounded between 0 and 1, which indicates if the plant is water-stressed. Equations 8 and 9 in the Supplementary material describe how SDR and water deficiency was calculated.

Exclusive least absolute shrinkage and selection operator (LASSO)

The technique 'least absolute shrinkage and selection operator' (LASSO) introduced by Tibshirani (1996) is a variable selection method that 'shrinks' some of the regression coefficients to zero during the estimation procedure and aims to retain only the essential features, leading to a more interpretable model. Recent applications of LASSO in agricultural studies include Anwar *et al.* (2024) and Heilemann *et al.* (2024). Since its introduction, LASSO has been extended in various ways to handle different data structures, including situations where the predictor variables can be divided into several groups. For example, a group of indicator variables are often used to represent a multi-level categorical variable collectively. In genomic analysis, for example, several genes may be treated as a group if they belong to the same pathway. Group LASSO (Bakin, 1999; Yuan and Lin, 2006) is used to select the most important groups of variables without focusing on the selection of individual variables. If one is interested in selecting both the important groups and the important variables within the groups, a bi-level selection method such as those proposed by Huang *et al.* (2009) and Breheny and Huang (2009) is needed. A review of group LASSO and bi-level selection methods can be found in Huang *et al.* (2012). Since both group LASSO and bi-level selection methods aim to select the most representative groups of variables, some variable groups may be missing in the final model, which may not be desirable in some circumstances. The method of exclusive LASSO (eLASSO), recently introduced by Campbell and Allen (2017), selects at least one variable from each group, thus maintaining all variable groups in the final model. Campbell and Allen (2017) reported that eLASSO tends to select the correct number of variables even when the explanatory variables within and across groups are correlated. This property is essential since multicollinearity often exists in agricultural studies. Like all other LASSO-based methods, eLASSO seeks to solve a constrained optimisation problem. The objective function involves a penalty term (λ) that governs the number of non-zero coefficients. Under eLASSO, with a sufficiently large λ, there will be exactly one non-zero coefficient per group (that is, only one explanatory variable per group will remain), representing the most parsimonious model possible under such a method. During the shrinking process, biases are inevitably introduced to the regression coefficients. Therefore, the predictive power of eLASSO models may not be as high as that of other models. Yet, eLASSO models offer a unique way for users to identify the most important explanatory variable(s) within and across variable groups.

In this study, the growth periods were considered the variable groups and the 19 weather indices were considered as the explanatory variables. All explanatory variables were standardised by subtracting the mean and further dividing by the standard deviation before analysis. Two eLASSO models were developed for each of the response variables:

- **Model 1**: Selected by minimising the Bayesian Information Criterion (BIC), balancing interpretability and goodness of fit (Schwarz, 1978).
- **Model 2**: Selected using the minimum penalty parameter (λ) that retained one variable from each group, prioritising simplicity and identifying key factors.

The chief intention of including Model 2 was to identify the single most dominant variable per growth stage under the eLASSO constraint, rather than for prediction. The performance of Model 2 also provides a contrast to the more complex but better-performing BIC-selected Model 1.

eLASSO model performance evaluation

We compared the observed and the eLASSO-modelled chickpea yield, water use efficiency based on transpiration (WUE_T) and water use efficiency based on evapotranspiration (WUE_ET) with least square linear regressions, including the coefficient of determination (R^2, the amount of variation explained by the model). We tested the goodness of fit by calculating the Root Mean Square Error (RMSE) (Piñeiro *et al.*, 2008) using Equation 10 given in Supplementary material. Additionally, we expressed the normalised root means square error (NRMSE) as precision parameters given in Equation 11 and the Willmott index (Willmott, 1982) using Equation 12 (Supplementary material).

The analyses were carried out using the ExclusiveLasso package in R (Weylandt *et al.*, 2018). We used R version 4.4.2 (R Core Team, 2024) and the following R packages: correlationfunnel v. 0.2.0 (Dancho, 2020), emmeans v. 1.10.5 (Lenth, 2024), ExclusiveLasso v. 0.0 (Weylandt *et al.*, 2018), ggpmisc v. 0.6.1 (Aphalo, 2024), ggpubr v. 0.6.0 (Kassambara, 2023), glmnet v. 4.1.8 (Friedman *et al.*, 2010; Simon *et al.*, 2011; Tay *et al.*, 2023), grateful v. 0.2.10 (Rodriguez-Sanchez and Jackson, 2023), gt v. 0.11.1 (Iannone *et al.*, 2024), janitor v. 2.2.0 (Firke, 2023), MESS v. 0.5.12 (Ekstrøm, 2023), naniar v. 1.1.0 (Tierney and Cook, 2023), patchwork v. 1.3.0 (Pedersen, 2024), qs v. 0.27.2 (Ching, 2024), remotes v. 2.5.0 (Csárdi *et al.*, 2024), reshape2 v. 1.4.4 (Wickham 2007), tidyverse v. 2.0.0 (Wickham *et al.*, 2019), running in RStudio v. 2024.9.1.394 (Posit team, 2024).

Results

Weather data

Significant variations in ambient temperature and in-season rainfall were observed across ten diverse locations in the south-eastern Australian cropping belt (Table 1, Figure 1 and Supplementary Table S5). Mean maximum temperatures ranged from 15.8°C to 22.7°C, with Narrabri recording the highest, while Wagga Wagga experienced the lowest. In contrast, minimum temperatures varied from 1.3°C to 9.4°C. Rainfall patterns also displayed considerable differences. Breeza, the driest site, received only 71 mm of in-season rainfall. In contrast, Wagga Wagga, the wettest, recorded up to 300 mm. Notably, all experimental sites experienced substantially lower growing-season rainfall during the experimental years compared to their long-term averages. For instance, Breeza's rainfall during the experiment was 80.7 mm, significantly lower than its 303.7 mm long-term average. While minimum temperatures remained relatively consistent between short-term experimental periods and long-term averages, with slight increases of over 1°C at Trangie and Yanco, maximum temperatures showed a clear upward trend in the short term, exceeding long-term means across all sites. Trangie, for example, experienced a temperature increase of more than 2°C. Furthermore, the frequency of frost days was notably higher during the experimental years, particularly at Breeza and Wagga Wagga. These findings collectively suggest that the experiments were conducted during an unusually warm and dry period in the region, characterised by reduced cloud cover, which likely contributed to the increased frequency of frost days. Such climatic conditions could potentially impact chickpea flowering and podding.

Table 2. Descriptive summary statistics for chickpea yield and water use efficiency (WUE) based on two different measures: transpiration (WUE_T) and evapotranspiration (WUE_ET). These data are derived from 438 observations across 29 experiments at ten field experimental sites in southeastern Australia with multiple genotypes per experiment. Some experiments had several sowing times to generate different growing conditions (Anwar *et al.*, 2022). *sd = standard deviation, min = minimum and max = maximum

Response variable	Mean	sd*	min	max
Yield (kg/ha)	1725.3	709.4	113.1	4128.4
wue_T (kg grain/ha/mm)	11.67	4.74	0.85	30.83
wue_ET (kg grain/ha/mm)	6.41	2.45	0.42	16.01

Statistics of response variables

The summary descriptive statistics for chickpea yield and water use efficiency (WUE) based on two different measures: transpiration (WUE_T) and evapotranspiration (WUE_ET) are given in Table 2. These data are derived from 438 observations across ten field experimental sites in southeastern Australia. Yields varied considerably, ranging from 113 to 4128 kg/ha, with an average of 1725 kg/ha. WUE_T ranged from 0.85 to 30.8 kg grain/ha/mm, averaging 11.7 kg grain/ha/mm. WUE_ET showed similar variability, ranging from 0.42 to 16.0 kg grain/ha/mm, with an average of 6.41 kg grain/ha/mm. Standard deviations indicate substantial variability in the dataset.

Correlation analysis of predictor variables

The Pearson correlation coefficients between nineteen weather indices and chickpea yield, water use efficiency based on transpiration (WUE_T), and water use efficiency based on evapotranspiration (WUE_ET) are presented in Table 3 and

https://doi.org/10.1017/S0021859625100270 Published online by Cambridge University Press

Table 3. Pearson correlation coefficients between nineteen weather indices and chickpea yield, water use efficiency based on transpiration (WUE_T), and water use efficiency based on evapotranspiration (WUE_ET) during the critical period (cp). $n = 438$; cp = 300 °Cd before flowering to 500 °Cd after flowering (Lake and Sadras, 2014); Sig= significance levels: *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$; and ns = not significant

	Yield	Sig_Y	WUE_T	Sig_T	WUE_ET	Sig_ET
Chickpea critical period (cp)						
H30	−0.17	***	−0.18	***	−0.22	***
H35	−0.35	***	−0.22	***	−0.32	***
F	−0.43	***	−0.49	***	−0.51	***
sumTT	0.07	ns	0.10	*	0.11	*
SE	0.10	*	0.05	ns	−0.10	*
PET	0.02	ns	0.09	ns	0.01	ns
SDR	−0.02	ns	−0.19	***	−0.08	ns
RAIN	0.03	ns	0.06	ns	−0.15	**
ET	0.09	ns	−0.22	***	−0.20	***
T	0.05	ns	−0.23	***	−0.16	**
meanVPD	−0.17	***	−0.17	***	−0.22	***
meanPTQ	−0.09	ns	−0.04	ns	−0.11	*
meanPTQvpd	0.07	ns	0.09	ns	0.07	ns
meanPAR	0.14	**	0.22	***	0.14	**
DL	−0.18	***	−0.19	***	−0.21	***
RADN	−0.02	ns	0.01	ns	−0.04	ns
MINT	0.35	***	0.43	***	0.40	***
MAXT	−0.04	ns	−0.03	ns	−0.07	ns
meanPZT	0.09	ns	0.22	***	0.07	ns

Abbreviations: **H30** = heat stress, number of days with maximum temperatures > = 30°C; **H35** = number of days with maximum temperatures >= 35°C; **F** = frost frequency, number of days with minimum temperatures < = 0°C; **sumTT** = sum of daily thermal time (°Cd); **SE** = sum of daily soil evaporation (mm); **PET** = sum of daily potential evapotranspiration (mm); **SDR** = accumulated daily water deficit; **RAIN** = sum of daily rainfall (mm); **ET** = sum of daily crop water use (mm); **T** = sum of daily crop transpiration (mm); **meanVPD** = mean vapour pressure deficit (kPa); **meanPTQ** = mean of photothermal quotient (MJ/m^2/°Cd); **meanPTQvpd** = mean photothermal quotient corrected by VPD (MJ/m^2/°Cd); **meanPAR** = mean of photosynthetically active radiation ($MJ/m^2/d$); **DL** = sum of day length (hours); **RADN** =sum of solar radiation ($MJ/m^2/d$); **MINT**= daily mean minimum temperature (°C); **MAXT** = daily mean maximum temperature (°C); **meanPZT** = daily mean temperature corrected for photoperiod (°C).

S1–S3. The results revealed significant relationships between weather indices and chickpea performance, with varying degrees of influence across different growth stages. For instance, during the sowing to flowering (SF) period (Table S1), frost frequency (F) showed negative correlations with yield ($r = -0.33$, $p < 0.001$), WUE_T ($r = -0.27$, $p < 0.001$) and WUE_ET ($r = -0.39$, $p < 0.001$). Sum of daily thermal time (sumTT) and accumulated daily water deficit (SDR) were negatively correlated with yield and WUE. Mean photosynthetically active radiation (meanPAR) and daily mean minimum temperature (MINT) showed positive correlations with yield and WUE. In the flowering to pod (FP) period (Table S2), heat stress indices (H30, H35) had negative correlations with yield ($r = -0.13$, $p < 0.01$; $r = -0.30$, $p < 0.001$) and WUE. Frost frequency (F) continued to affect yield and WUE negatively. Mean vapour pressure deficit (meanVPD) correlated negatively with yield and WUE. The photothermal quotient corrected by VPD (meanPTQvpd) showed positive correlations with WUE_T and WUE_ET.

In the pod to maturity (pm) period (Table S3), sumTT and MINT continued to have positive correlations with yield ($r = 0.44$, $p < 0.001$; $r = 0.25$, $p < 0.001$) and WUE. Frost frequency (F) had a negative impact but was slightly lower than in earlier periods. Mean VPD negatively correlated with WUE_T and WUE_ET.

During the critical period (cp), heat stress indices (H30, H35) negatively correlated with yield ($r = -0.17$, $p < 0.001$; $r = -0.35$, $p < 0.001$) and WUE (Table 3). Frost frequency (F) remained strongly negative across all measures. Mean PAR and MINT had positive correlations with yield and WUE.

These results indicate significant weather influences on chickpea yield and water use efficiency across growth periods. Heat stress, frost and water deficit negatively affect chickpea performance, whereas adequate light and moderate temperatures contribute positively.

Correlation funnels of explanatory variables

The correlation funnels (Figure 2) illustrate the most influential explanatory variables (climate index plus period) for each of the three response variables. For grain yield (kg/ha), of the 10 most influential features, nine are positively correlated with yield while only one is strongly negative ('F_cp' = number of frost days in the 'critical period') (Figure 2A). Of the positive features, six were from the podding-to-maturity ('pm') period; the other three were from the sowing-to-flowering ('sf') period. Four of the influential features involved evapotranspiration ('ET_pm' and 'ET_sf') or transpiration alone ('T_pm' and 'T_sf'). The sum of thermal time for podding to maturity ('sumTT_pm') was the only purely

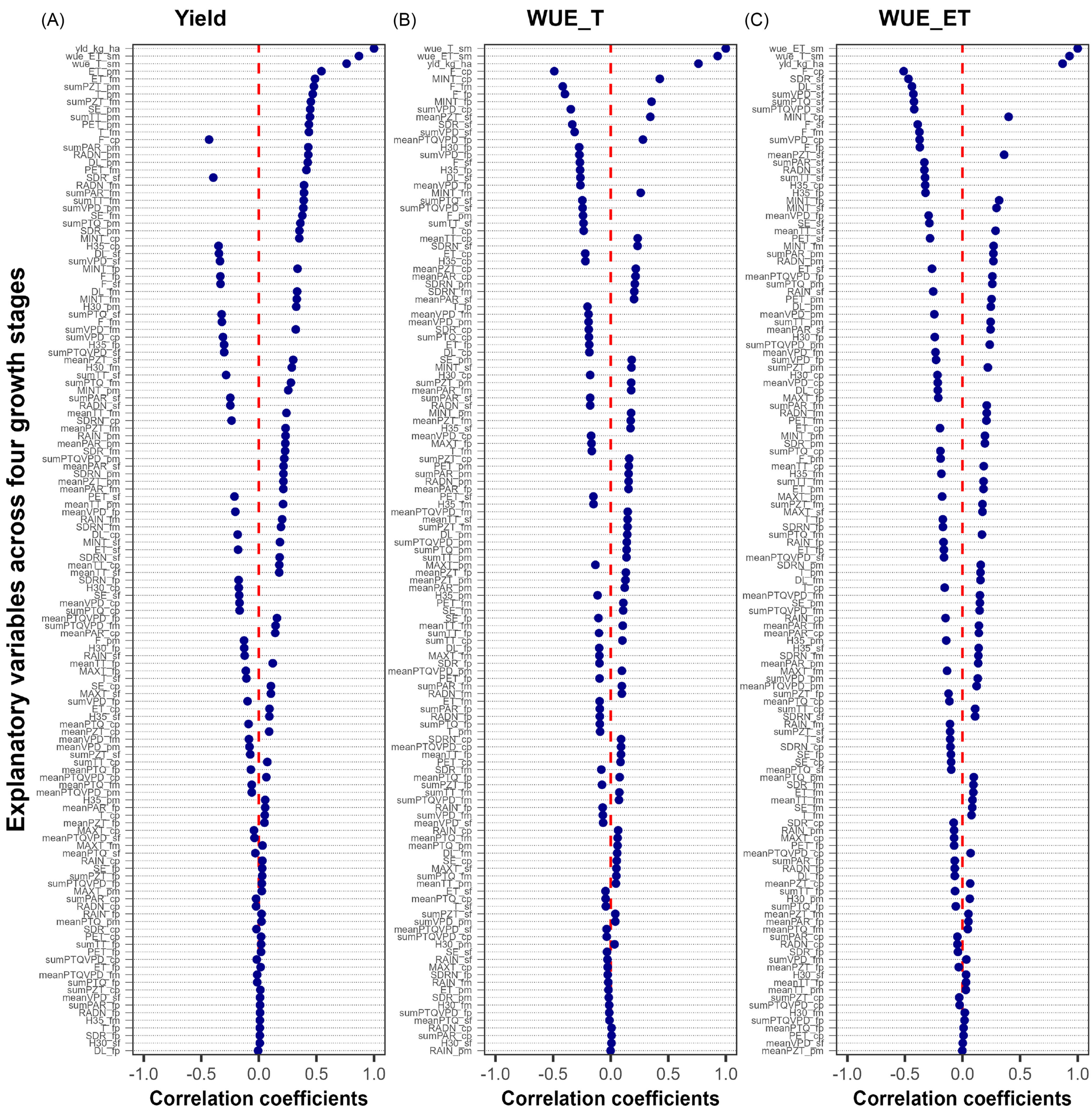

Figure 2. Correlation funnels showing the relationships between response (yield (A), water use efficiency based on transpiration (WUE_T) (B) and based on evapotranspiration (WUE_ET) (C)) and explanatory variables (see text for explanation) across four growth stages (sf =sowing to flower, fp =flower to pod, pm =pod to maturity and cp =critical period). The critical t-test values for these Pearson correlation coefficients ($n = 438$) are: +/- 0.094 (for $0.05 > p > 0.01$); +/- 0.123 (for $0.01 > p > 0.001$); and +/- 0.157 ($p < 0.001$; see Table S1 - S3).

temperature-derived feature present in this top 10. The final two were the sum of PZT in the same periods ('sumPZT_pm') and 'SE_pm'. Another notable negatively correlated point was 'SDR_sf' (soil moisture supply/demand ratio for the sowing to flowering period). Many other interesting observations can be made; for example, while high heat stress at the critical period ('H35_cp') and flowering to podding ('H35_fp') were significantly negatively correlated with yield, the incidence of warm days from podding to maturity ('H30_pm') is positively correlated with yield. We can speculate about the mechanisms for these observations.

When seasonal water-use efficiency for transpiration from sowing to maturity ('wue_T') was examined as the response variable (Figure 2B) it produced a somewhat dissimilar set of most-influential features: in the top 10, four were positively and six were negatively correlated. Low temperatures ('MINT_cp' and 'MINT_fp') were strongly positive while actual frost effects ('F_cp', 'F_sf', 'F_fp') featured strongly on the negative side. The

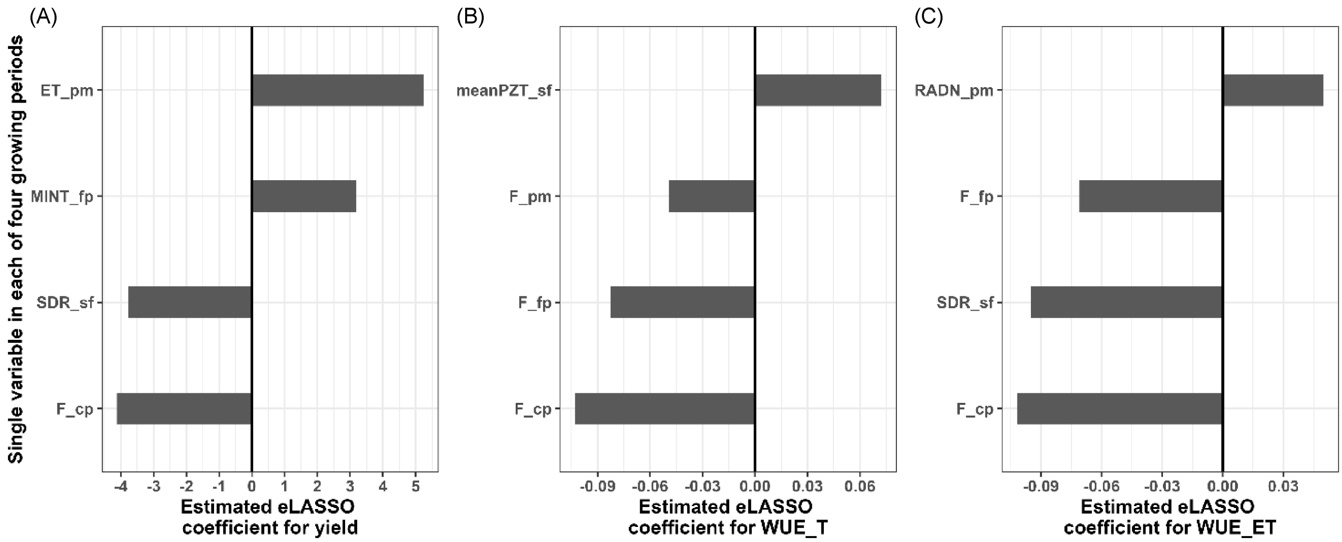

Figure 3. Estimated Exclusive LASSO coefficients based on Model 2 (see text) for chickpea yield (A, Left), water-use efficiency based on transpiration (WUE_T, B_middle) and evapotranspiration (WUE_ET, C_right) in relation to climatic indices across four growing periods (sf = sowing to flower, fp = flower to pod, pm = pod to maturity and cp = critical period).

sum of vapour-pressure deficit for the critical period ('sumVPD_cp') and for sowing to flowering ('sumVPD_sf') were strongly negatively correlated with 'wue_T', along with soil moisture supply/demand ratio in the sowing to flowering period ('SDR_sf'). Finally, 'meanPZT_sf' and 'mean_PTQvpd_fp' made up the positive correlations.

The third response variable (seasonal water-use efficiency for evapotranspiration for sowing to maturity = 'wue_ET') only exhibited one highly positively correlated feature in this top group (Figure 2C), namely 'MINT_cp' (mean daily minimum temperature in the critical period). The other top influencers (features) were all negative: five in the sowing-to-flowering period, plus frost incidence in all three periods involving flowering time ('F_cp', 'F_sf', 'F_fp'). Surprisingly, accumulated day-length in the sowing-to-flowering period ('DL_sf') was strongly negatively correlated with 'wue_ET', in addition to 'SDR_sf', 'sumVPD_sf', 'sumPTQ_sf' and 'sumPTQvpd_sf'.

Exclusive LASSO for Variable Selection

The estimated coefficients based on eLASSO Model 2 for chickpea yield, WUE_T and WUE_ET are presented in Figure 3. Under this model's selection criterion, only one explanatory variable was retained for each growing period. Figure 3 (left panel) reveals that the key factors affecting yield are ET during pm, MINT during fp, SDR during sf and F during cp. Yield increases by approximately 5 kg/ha for every standard deviation increase in ET during these periods, while F during fp and cp and SDR during sf show negative effects on yield.

For WUE_T, Figure 3B (middle panel) shows that mean PZT during sf and frost during other periods (pm, fp and cp) are the key influencing factors. Frost exhibited the most significant effects on WUE_T across these periods, with values ranging from -0.04 to -0.09. In contrast, mean PZT during sf demonstrated a positive effect on WUE_T, with an expected increase of 0.06 for every standard deviation increase in mean PZT. For WUE_ET, the key factors identified include RAND during pm, SDR during sf and frost during fp and cp periods. Among these, only RAND during pm showed a positive effect (approximately 0.03), while all other factors exhibited negative effects ranging between −0.05 and −0.095.

Figure 4 displays the estimated non-zero eLASSO coefficients based on Model 1 for chickpea yield, WUE_T and WUE_ET. For better visualisation of the effects of the explanatory variables, similar enlarged plots showing the complete list of explanatory variables, including those with a coefficient being shrunk to zero, are displayed in Figures S2–S4. This model minimised BIC without restricting the number of explanatory variables. The left panel indicates that ET, SE and mean PTQ during pm and sf periods had the strongest positive effects on yield, while F during cp and mean PTQvpd during sf had the most detrimental effects. For WUE_T (Figure 4, middle panel), SE during sf showed the most positive effects, while F during cp and RAIN during pm had the most negative impacts. Similar patterns were observed for WUE_ET, except that SE during sf had less influence than mean PTQvpd. Detailed eLASSO coefficients based on Model 1 are provided in Table S4.

Predictions of response variables from eLASSO

Figure 5 compares observed and predicted values of yield and water-use efficiency (WUE) in chickpea using two eLASSO models: one based on BIC (Model 1) and the other on the minimum penalty parameter λ (Model 2). Panels A–F in Fig. 5 show predictions versus observations for yield, WUE based on evapotranspiration (WUE_ET) and WUE based on transpiration (WUE_T) for both models.

Each graph displays scatter plots of observed against predicted values, with a black dashed 1:1 line representing perfect prediction and a black solid line indicating the linear regression fit (LR). The insets include key statistical metrics such as the coefficient of determination (r^2), root mean square error (RMSE), normalised RMSE (NRMSE) and Willmott's index (*d*).

For each of the three response variables (yield, WUE_T and WUE_ET) we observed a very similar result within the two eLASSO models (BIC-based and λ-based models) but a large difference between them when plotting observed versus predicted values. The λ-based model fits (see Figure 5B, D and F) had a

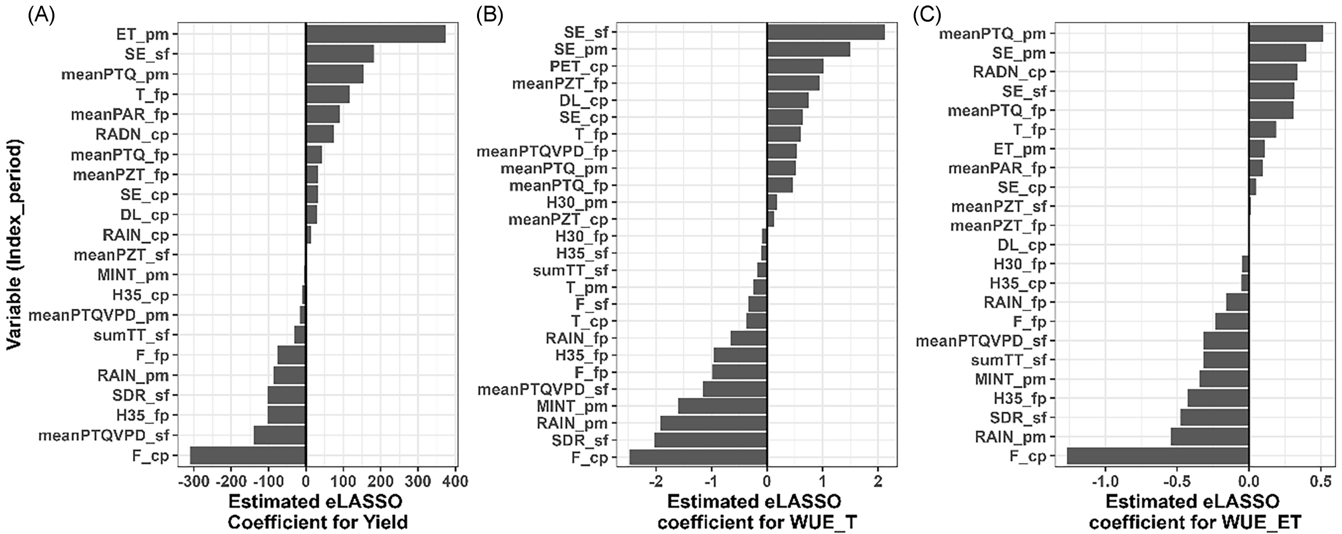

Figure 4. Estimated Exclusive LASSO coefficients based on Model 1 (see text) for chickpea yield (A, Left), water-use efficiency based on transpiration (WUE_T, B_middle) and evapotranspiration (WUE_ET, C_right) in relation to climatic indices across four growing periods (sf = sowing to flower, fp = flower to pod, pm = pod to maturity and cp = critical period).

tighter distribution around the regression lines but much lower R^2s than the BIC-based model fits (Figure 5A, C and E). This was also reflected in their higher RMSE and NRMSE values. However, these λ-based model fits were poorly predictive of the response variables because the model retained only one explanatory variable in each growth stage; hence, the low explanatory and predictive powers reflected by the almost horizontal spread of the points. Predictions of this type would be of little or no utility in the field for predicting crop water use and yield.

In contrast, the BIC-based model fits were much more predictive with much higher R^2 values (all > 0.7) but with a greater scatter about the regression lines (which is also reflected in the lower RMSE and NRMSE statistics). The BIC-based model also fits and estimates a sensible origin (i.e., (0,0)) much more closely for all response variables (actual values not given), so these models perform better across a typical real-world range of yield and water-use scenarios. The λ-based model fits are almost useless for predictive purposes except for the fact that the LASSO procedure uncovered these 'best-fit' solutions. Examination of the range of the predicted values from λ-based model fits illustrates their poor predictive value. For example, predicted λ-based model yields (Figure 5B) range from about 1400 to 2100 kg/ha, whereas the observed yields range from 100 kg/ha to over 4000.

Discussion

The need to improve resource-use efficiency drives agricultural innovation (Sadras and McDonald, 2011; Lorite *et al.*, 2023; Dreccer *et al.*, 2024); understanding the environmental factors influencing crop performance becomes increasingly critical, particularly in the context of climate change and its impact on crop yields (Challinor *et al.*, 2014). This study comprehensively analyses the key environmental drivers, including abiotic stress factors, influencing chickpea yield and water-use efficiency (WUE) under Australian field conditions. By integrating advanced statistical modelling with extensive field data, the research identifies temperature extremes, water availability and solar radiation as critical factors affecting chickpea growth and productivity. The study's use of eLASSO regression (Tibshirani, 1996; Campbell and Allen, 2017) to identify these key drivers represents a significant methodological advancement. Unlike traditional LASSO, which may exclude entire groups of variables, eLASSO ensures that at least one variable from each group is retained, providing a more comprehensive understanding of the factors influencing crop performance. This approach is particularly useful in agricultural studies, where multiple interrelated variables often influence crop outcomes (Kumar *et al.*, 2019). The strong predictive performance of the models developed in this study ($R^2 > 0.7$ for yield and WUE predictions, Figs. 5A, C and E) demonstrates the potential of eLASSO to identify key drivers of crop performance under varying environmental conditions. Despite its advantages, eLasso regression has a notable drawback. Since the algorithm must retain at least one explanatory variable from each group, some of the retained variables may not be important at all. Caution must be applied while interpreting the model, especially when only one variable is selected in any group.

The findings described here offer novel insights into the complex interactions between environmental variables and chickpea performance, which can inform improved agronomic practices and breeding strategies to enhance crop resilience in the face of climate variability (Vadez *et al.*, 2012; Garg *et al.*, 2016; Vadez *et al.*, 2024). This methodology could also be applied to other crops to better understand the complex interactions between environmental factors and crop growth, ultimately leading to more targeted and effective management strategies.

Chickpea yield is highly sensitive to environmental fluctuations, with evapotranspiration (ET) and frost frequency emerging as major determinants (Singh *et al.*, Singh et al., 1993; Berger *et al.*, 2006). The positive correlation between ET during podding to maturity (pm) including sowing to flowering (sf) and yield (Figure 2) underscores the importance of water availability during these stages for biomass accumulation and grain filling. Chickpea is a drought-avoidant crop through plasticity in phenology and employs a deep root system to access subsoil moisture when it cannot escape drought. However, water availability during the reproductive phase is particularly critical, as it supports both pod retention and seed filling (Singh *et al.*, 2008; Comas *et al.*, 2013; Waqas *et al.*, 2019). Inadequate moisture supply during this period

https://doi.org/10.1017/S0021859625100270 Published online by Cambridge University Press

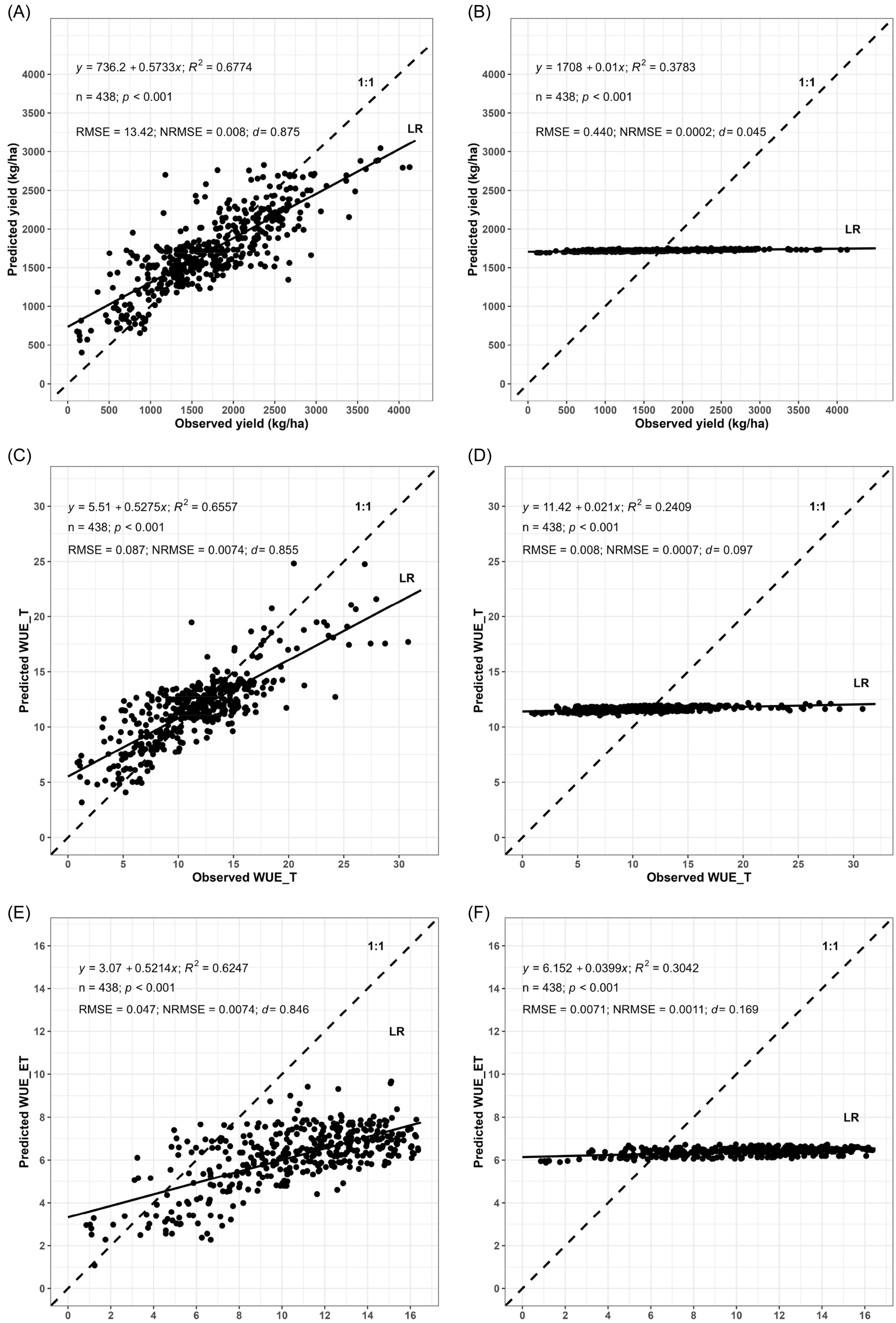

Figure 5. Comparison of observed yield (A and B), water-use efficiency based on transpiration (WUE_T) (C and D) and water-use efficiency based on evapotranspiration (WUE_ET) (E and F). The left panel A, C and E are predictions by exclusive LASSO Model 1 (minimising the Bayesian Information Criterion), and right panel B, D and F are based Model 2 (Minimum Penalty Parameter (λ)). The text inserts show the fitted regression equation, the coefficient of determination of the linear relationship (r^2), the root mean square error (RMSE) and the normalised root mean square error (NRMSE), and Willmott's index (*d*). LR = linear regression (solid black line); 1:1 = the line for a theoretical one-to-one fit (dashed black line).

can lead to increased flower abortion and reduced seed set, ultimately lowering yield potential (Peake *et al.*, 2020). Similar findings have been reported in other crops such as wheat and barley, where post-anthesis water availability significantly enhances grain yield by maintaining assimilate supply to the developing grain (Samarah, 2005; Passioura, 2006; Foulkes *et al.*, 2007). The physiological need for sustained photosynthesis and assimilate translocation to seeds during these stages aligns with ET's observed importance in chickpea's final growth phases (Sadras and McDonald, 2011; Dreccer *et al.*, 2018).

Conversely, frost during flowering to podding (fp) and the critical period (cp) had a strong negative impact on yield (Table 3; Figures 3 and 4), highlighting chickpea's vulnerability to low temperatures during reproductive stages (Lake and Sadras, 2014; GRDC, 2016). Unlike cereals such as wheat and barley, which have a degree of frost tolerance due to protective floral structures and cold acclimation mechanisms, chickpea lacks sufficient protective adaptations (Croser *et al.*, 2003; Barlow *et al.*, 2015; Peake *et al.*, 2020). Frost exposure during flowering causes sterility by disrupting pollen viability, while frost at early podding stages can lead to pod abortion, ultimately reducing the number of harvestable seeds (Clarke and Siddique, 2004; Chauhan and Ryan, 2020). Additionally, frost-induced cellular damage can lead to reduced photosynthetic efficiency and lower carbon assimilation rates, further compounding yield losses (Allen and Ort, 2001; Sage and Kubien, 2007). Frost damage at flowering can lead to flower abortion and reduced pod set, similar to its effects in canola (*Brassica napus*) (Kovaleski *et al.*, 2020). This sensitivity underscores the need for agronomic interventions such as delayed sowing, spatial diversification of planting dates and the development of frost-tolerant chickpea cultivars through breeding efforts (GRDC, 2016; Peake *et al.*, 2020).

Water-use efficiency (WUE) is a key determinant of chickpea productivity, particularly in water-limited environments (Siddique *et al.*, 2012). The study identified mean photothermal quotient (meanPTQ) during sowing to flowering (sf) as a significant positive contributor to WUE_T (Figure 3B), emphasising the importance of early-season radiation use efficiency (Sinclair and Muchow, 1999). PTQ, which represents the ratio of photosynthetically active radiation (PAR) to temperature, measures of the crop's ability to convert solar energy into biomass (Kiniry *et al.*, 1989; Muchow *et al.*, 1990). Higher PTQ values during early growth stages likely promote vigorous vegetative growth, which can enhance the crop's ability to utilise water efficiently during later stages (Richards, 2000). This is particularly relevant for chickpea, as its initial biomass accumulation determines its ability to withstand later-season stresses (Singh and Saxena, 1993; Soltani and Sinclair, 2011). Similar relationships have been observed in other legumes such as lentil (*Lens culinaris*) and faba bean (*Vicia faba*) (Thomson *et al.*, 1997), where high PTQ during vegetative growth enhances biomass accumulation and transpiration efficiency (Siddique *et al.*, 2012).

In contrast, the negative impact of frost on WUE_ET and WUE_T across multiple growth stages (Figure 3B, C) suggests that cold stress not only reduces total water uptake but also impairs physiological water-use efficiency (Chaves *et al.*, 2009; Flexas *et al.*, 2016). This occurs because frost damage to leaves and reproductive structures reduces the plant's ability to fix carbon, leading to an inefficient use of available soil moisture. Moreover, low temperatures can limit root hydraulic conductivity, reducing water uptake even with sufficient soil moisture (Aroca and Ruiz-Lozano, 2012). The correlation between soil moisture supply-demand ratio (SDR) during sowing to flowering (sf) and reduced WUE highlights the significance of early-season moisture availability (Table 3). A low SDR during early growth stages indicates a mismatch between soil moisture supply and crop demand, which can lead to suboptimal biomass development and lower transpiration efficiency (Sadras and Milroy, 1996; Sinclair and Muchow, 2001; Sadras *et al.*, 2015). This aligns with findings in sorghum (*Sorghum bicolour*), where preflowering drought stress leads to inefficient water use and lower yields (Kholová *et al.*, 2014; de Souza *et al.*, 2021). Strategies such as optimising sowing dates, improving soil organic matter content and implementing water-conserving agronomic practices could mitigate these adverse effects in chickpea cultivation (Kumar and Abbo, 2001, Sadras and McDonald, 2011).

Heat stress (H30 and H35) during the critical period (cp) and flowering to podding (fp) was identified as a major constraint, negatively impacting yield and WUE (Table 3; Figure 2). Heat stress accelerates phenological development, shortening the grain-filling period and reducing final seed weight (Vogel *et al.*, 2019; Lorite *et al.*, 2023). Chickpea, as C3 crop, exhibits a decline in photosynthetic efficiency under high temperatures due to increased photorespiration and a reduction in stomatal conductance, which limits CO_2 assimilation (Prasad *et al.*, 2006; Ainsworth and Rogers, 2007). Unlike maize (*Zea mays*), which benefits from a more efficient C4 photosynthetic pathway, chickpea experiences significant reductions in reproductive success under heat stress (Sage and Kubien, 2007; Hatfield and Prueger, 2015). Excessive heat exposure during flowering reduces pollen viability and ovule fertilisation, leading to lower pod set and yield. Interestingly, moderate heat exposure during podding to maturity (pm) had a positive correlation with yield (Figure 2A), suggesting that late-season warmth may facilitate seed development if adequate moisture is available (Devasirvatham *et al.*, 2012; Kaushal *et al.*, 2013; Devasirvatham and Tan, 2018). Similar trends have been observed in soybean (*Glycine max*), where late-season warmth enhances pod filling but excessive heat stress during flowering leads to flower abortion (Hatfield *et al.*, 2011). These findings indicate that chickpea breeding efforts should enhance heat tolerance during flowering while leveraging late-season warmth for improved grain filling.

Chickpea exhibits distinct responses to environmental stressors when compared to other major field crops. While cereals such as wheat and barley demonstrate greater cold tolerance, they are more sensitive to terminal drought stress (Samarah, 2005; Farooq *et al.*, 2017). With its deep-rooting system, chickpea can access subsoil moisture more effectively than shallow-rooted crops like canola and lentil (Kashiwagi *et al.*, 2006; Zaman-Allah *et al.*, 2011). However, its reproductive sensitivity to frost and heat stress limits its adaptation to variable climatic conditions. The negative impact of high vapour pressure deficit (VPD) on chickpea WUE (Figure 3B, C) aligns with observations in maize and sorghum (Sinclair *et al.*, 2005; Lobell *et al.*, 2013), where high atmospheric demand increases transpiration losses without proportional gains in biomass accumulation (Sadras and McDonald, 2011). Unlike sorghum, which can regulate stomatal closure to minimise water loss, chickpea exhibits less efficient stomatal regulation, leading to higher transpiration under high VPD conditions (Koehler *et al.*, 2023). Improving stomatal response traits through breeding and implementing agronomic measures such as mulching and conservation tillage could help mitigate water loss under high evaporative demand conditions (Hatfield *et al.*, 2001; Richards *et al.*, 2010).

A limitation of this study is the absence of simulated biotic stressors such as pests, weeds and diseases, which can significantly impact chickpea yield and water-use efficiency under field conditions. Future research should incorporate these factors to provide a more comprehensive understanding of chickpea performance in realistic agricultural settings.

The findings from this study have important implications for agronomic management and climate adaptation strategies in chickpea production. Optimising sowing dates to avoid frost-prone periods and selecting cultivars with improved heat and drought tolerance are critical for mitigating yield losses. Models are available to achieve this goal (Chauhan *et al*., 2023). Enhancing soil moisture conservation through cover cropping, reduced tillage and organic amendments can improve early-season water availability and WUE. The application of eLASSO modelling offers a robust approach for identifying key environmental drivers and developing predictive tools for chickpea yield and WUE. By integrating climate-responsive agronomic practices with advanced statistical modelling, chickpea production can be optimised for greater resilience under changing climatic conditions. Further research into genotype-by-environment interactions will be essential to develop site-specific recommendations for chickpea growers (Dreccer *et al*., 2018; Bicard *et al*., 2025).

Conclusions

This study provides valuable insights into the environmental factors driving chickpea yield and water-use efficiency, emphasising the crucial roles of water and temperature extremes, particularly evapotranspiration, frost frequency and heat stress during key growth stages. Comparisons with other field crops reveal both advantages and limitations in chickpea's agronomic and physiological traits expressed under varying climatic conditions. Future research should focus on validating these findings across diverse environments and cropping systems, while breeding for improved stress resilience (particularly for climate change adaptation), refining crop management practices and integrating these models into decision-support tools for farmers and agronomists to ensure sustainable and profitable chickpea production in water-limited environments.

Supplementary material. The Supplementary material for this article can be found at https://doi.org/10.1017/S0021859625100270.

Acknowledgements. The authors thank Laney Davidson, Karl Moore, Jessica Simpson and Dr. Asad Assaduzzaman for sowing field trials including data collection, and Dr. Livinus Emebiri for internal review of the manuscript. The authors also would like to acknowledge the APSIM Initiative for providing APSIM software used in this study.

Author contributions. Muhuddin Rajin Anwar (MRA), David J. Luckett (DJL), Ryan H. L. Ip (RHLIp), Yashvir S. Chauhan (YSC), Maheswaran Rohan (MR) contributed to the conceptualisation, investigation, methodology, software and visualisation, writing – original draft and writing – review and editing. Neroli Graham (NG), Mark F. Richards (MFR), Rosy Raman (RR) including MRA and YSC contributed to design the various experiments whose data has been used in the study including writing – review and editing. Jens D. Berger (JDB) contributed to writing – review and editing. MRA wrote the first draft of the manuscript, which all authors subsequently revised.

Funding statement. This research is supported by Grains Agronomy & Pathology Partnership (GAPP), between the NSW Department of Primary Industries and Regional Development (DPIRD) and the Grains Research and Development Corporation (GRDC) under the project BLG111.

Competing interests. None.

Ethical standards. Not applicable.

References

ABARES (2024) Australian crop report. Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra. https://daff.ent.sirsidynix.net.au/client/en_AU/search/asset/1036803/2

Ainsworth EA and Rogers A (2007) The response of photosynthesis and stomatal conductance to rising [CO_2]: Mechanisms and environmental interactions. *Plant, Cell & Environment* **30**, 258–270. https://doi.org/10.1111/j.1365-3040.2007.01641.x

Akumaga U and Alderman PD (2019) Comparison of Penman–Monteith and Priestley–Taylor evapotranspiration methods for crop modelling in Oklahoma. *Agronomy Journal* **111**, 1171–1180. https://doi.org/10.2134/agronj2018.10.0694

Allen DJ and Ort DR (2001) Impacts of chilling temperatures on photosynthesis in warm-climate plants. *Trends in Plant Science* **6**, 36–42. https://doi.org/10.1016/S1360-1385(00)01808-2

Anwar MR, Emebiri L, Ip RHL, Luckett DJ, Chauhan YS and Zeleke KT (2024) Least absolute shrinkage and selection operator regression used to select important features when predicting wheat yield from various genotype groups. *The Journal of Agricultural Science* **162**, 245–259. https://doi.org/10.1017/S0021859624000479

Anwar MR, Luckett DJ, Chauhan YS, Ip RHL, Maphosa L, Simpson M, Warren A, Raman R, Richards MF, Pengilley G, Hobson K and Graham N (2022) Modelling the effects of cold temperature during the reproductive stage on the yield of chickpea (*Cicer arietinum* L). *International Journal of Biometeorology* **66**, 111–125. https://doi.org/10.1007/s00484-021-02197-8

Aphalo PJ (2024) ggpmisc: Miscellaneous extensions to "ggplot2". https://cran.r-project.org/package=ggpmisc

APSIM (2023) SoilWat. Available online from: https://www.apsim.info/documentation/model-documentation/soil-modules-documentation/soilwat/ (Accessed 4 February 2025).

Aroca R and Ruiz-Lozano JM (2012) Regulation of root water uptake under drought stress conditions. In Aroca R (ed.), *Plant Responses to Drought Stress*. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-32653-0_4

Bakin S (1999) Adaptive regression and model selection in data mining problems. Ph.D. thesis. Australian National Univ. Canberra. https://doi.org/10.25911/5d78db4c25dbb

Barlow KM, Christy BP, O'Leary GJ, Riffkin PA and Nuttall JG (2015) Simulating the impact of extreme heat and frost events on wheat crop production: A review. *Field Crops Research* **171**, 109–119. https://doi.org/10.1016/j.fcr.2014.11.010

Berger JD, Ali M, Basu PS, Chaudhary BD, Chaturvedi SK, Deshmukh PS, Dharmaraj PS, Dwivedi SK, Gangadhar GC, Gaur PM and Kumar J (2006) Genotype by environment studies demonstrate the critical role of phenology in adaptation of chickpea (*Cicer arietinum* L.) to high and low yielding environments of India. *Field Crops Research* **98**, 230–244. https://doi.org/10.1016/j.fcr.2006.02.007

Bicard M, Faucon M, Pedas PR, Vequaud D, Pin PA, Elmerich C and Lange B (2025) Unravelling critical climatic factors and phenological stages impacting spring barley yields across Europe. *Field Crops Research* **321**, 109665. https://doi.org/10.1016/j.fcr.2024.109665

Breheny P and Huang J (2009) Penalized methods for bi-level variable selection. *Statistics and Its Interface* **2**, 369–380. https://doi.org/10.4310/sii.2009.v2.n3.a10

Campbell F and Allen AI (2017) Within group variable selection through the Exclusive Lasso. *Electronic Journal of Statistics* **11**, 4220–4257. https://doi.org/10.1214/17-EJS1317

Challinor AJ, Watson J, Lobell D, Howden SM, Smith DR and Chhetri N (2014) A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change* **4**, 287–291. https://doi.org/10.1038/nclimate2153

Chauhan YS, Anwar MR, Richards MF, Lake L, Sadras VO, Luckett DJ, Raman R, Krosch S and Graham N (2023). Effect of soil water on flowering and pod-set in chickpea: implications for modelling and managing frost and heat stress. *Agronomy for Sustainable Development* **43**, 49. https://doi.org/10.1007/s13593-023-00903-x

Chauhan YS and Ryan M (2020) Frost risk management in chickpea using a modelling approach. *Agronomy* **10**(4), 460. https://doi.org/10.3390/agronomy10040460

Chaves MM, Flexas J and Pinheiro C (2009) Photosynthesis under drought and salt stress: regulation mechanisms from whole plant to cell. *Annals of Botany* **103**, 551–560. https://doi.org/10.1093/aob/mcn125

Chenu K, Cooper M, Hammer GL, Mathews KL, Dreccer MF and Chapman SC (2011) Environment characterization as an aid to wheat improvement: interpreting genotype–environment interactions by modelling water-deficit patterns in North-Eastern Australia. *Journal of Experimental Botany* **62**, 1743–1755. https://doi.org/10.1093/jxb/erq459

Ching T (2024) qs: Quick serialization of r objects. Available online from: https://cran.r-project.org/package=qs

Clarke HJ and Siddique KHM (2004) Response of chickpea genotypes to low temperature stress during reproductive development. *Field Crops Research* **90**, 323–334. https://doi.org/10.1016/j.fcr.2004.04.001

Comas LH, Becker SR, Cruz VMV, Byrne PF and Dierig DA (2013) Root traits contributing to plant productivity under drought. *Frontiers in Plant Science* **4**, 442. https://doi.org/10.3389/fpls.2013.00442

Croser JS, Clarke HJ, Siddique KHM and Khan TN (2003) Low-temperature stress: implications for chickpea (*Cicer arietinum* L.) improvement. *Critical Reviews in Plant Sciences* **22**, 185–219. https://doi.org/10.1080/713610855

Csárdi G, Hester J, Wickham H, Chang W, Morgan M and Tenenbaum D (2024) remotes: R package installation from remote repositories, including "GitHub". Available online from: https://cran.r-project.org/package=remotes

Dancho M (2020) correlationfunnel: Speed up exploratory data analysis (EDA) with the correlation funnel. Available online from: https://cran.r-project.org/package=correlationfunnel

de Souza AA, de Carvalho AJ, Bastos EA, Cardoso MJ, Júlio MPM, Batista PSC, Julio BHM, Campolina CV, Portugal AF, de Menezes CB and de Oliveira SM (2021) Grain sorghum under pre-and post-flowering drought stress in a semiarid environment. *Australian Journal of Crop Science* **15**, 1139–1145. https://doi.org/10.21475/ajcs.21.15.08.p3162

Devasirvatham V and Tan DKY (2018) Impact of high temperature and drought stresses on chickpea production. *Agronomy* **8**, 145. https://doi.org/10.3390/agronomy8080145

Devasirvatham V, Tan DKY, Gaur PM, Raju TN and Trethowan RM (2012) High temperature tolerance in chickpea and its implications for plant improvement. *Crop and Pasture Science* **63**, 419–428. https://doi.org/10.1071/CP11218

Dreccer MF, Fainges J, Whish J, Ogbonnaya FC and Sadras VO (2018) Comparison of sensitive stages of wheat, barley, canola, chickpea and field pea to temperature and water stress across Australia. *Agricultural and Forest Meteorology* **248**, 275–294. http://dx.doi.org/10.1016/j.agrformet.2017.10.006

Dreccer MF, Whish J, Delahunty A, Richards M, Graham N, Power S, Clancy l, Rodriguez D, De Voil P and Munford M (2024) Water use and water use efficiency in chickpea during key stages of yield formation. In Lawes R, Flower K, Michael P, Mwenda G, Singh B (eds.), *Adaptive Agronomy for a Resilient Future*. Proceedings of the 21st Australian Society of Agronomy Conference, 21-24 October 2024, Albany, WA. https://www.agronomyaustraliaproceedings.org/images/sampledata/2024/Dreccer_etal_ASA__2024_revised-205-740-Dreccer-Fernanda.pdf

Ekstrøm CT (2023) MESS: Miscellaneous esoteric statistical scripts. Available online from: https://cran.r-project.org/package=MESS

FAOSTAT (2025) Food and Agriculture Organization of the United Nations. Available online from: https://www.fao.org/faostat/en/#data/QCL (Accessed 11 February 2025).

Farooq M, Gogoi N, Barthakur S, Baroowa B, Bharadwaj N, Alghamdi SS and Siddique KHM (2017) Drought stress in grain legumes during reproduction and grain filling. *Journal of Agronomy and Crop Science* **203**, 81–102. https://doi.org/10.1111/jac.12169

Firke S (2023) janitor: Simple tools for examining and cleaning dirty data. Available online from: https://cran.r-project.org/package=janitor

Fischer RA (1985) Number of grains in wheat crops and the influence of solar radiation and temperature. *Journal of Agricultural Science* **105**, 447–461. https://doi.org/10.1017/S0021859600056495

Flexas J, Díaz-Espejo A, Conesa MA, Coopman RE, Douthe C, Gago J, Gallé A, Galmés J, Medrano H, Ribas-Carbo M and Tomàs M (2016) Mesophyll conductance to CO_2 and Rubisco as targets for improving intrinsic water use efficiency in C_3 plants. *Plant, Cell & Environment* **39**, 965–982. https://doi.org/10.1111/pce.12622

Foulkes MJ, Sylvester-Bradley R, Weightman R and Snape JW (2007) Identifying physiological traits associated with improved drought resistance in winter wheat. *Field crops research* **103**, 11–24. https://doi.org/10.1016/j.fcr.2007.04.007

Friedman JH, Hastie T and Tibshirani R (2010) Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software* **33**, 1–22. https://doi.org/10.18637/jss.v033.i01

Gallagher JN, Biscoe PV and Dennis-Jones R (1983) Environmental influences on the development, growth and yield of barley. In Wright GM, Wynn-Williams RB (eds.), *Barley: Production and Marketing*. Agronomy Society of New Zealand Special Publication No. 2. pp. 21–49. https://www.agronomysociety.org.nz/files/SP2_3._Environmental_influences_on_barley.pdf

Garg R, Shankar R, Thakkar B, Kudapa H, Krishnamurthy L, Mantri N, Varshney RK, Bhatia S and Jain M (2016) Transcriptome analyses reveal genotype-and developmental stage-specific molecular responses to drought and salinity stresses in chickpea. *Scientific Reports* **6**, 19228. https://doi.org/10.1038/srep19228

Graham N, Raman R, Warren A and Anwar M (2022) Timing of flowering and pod initiation influences yield potential in chickpeas. GRDC Grains Research Online Update paper, 25 February 2022. Available online from: https://www.icanrural.com.au/documents/Northern%20GRDC%20Grains%20Research%20Updates%20online%202022%20week%202.pdf#page=109 (Accessed 5 February 2025)

GRDC (2011) Choosing rotation crops. GRDC Fact Sheet. Available online from: https://grdc.com.au/__data/assets/pdf_file/0024/223683/grdcfsbreakcropsnorthpdf.pdf.pdf

GRDC (2016) Managing frost risk. Grain Research & Development Corporation, National Frost Initiative. Available online from: https://grdc.com.au/__data/assets/pdf_file/0027/208674/grdc-managing-frost-risk-tips-and-tactics-frost-050216-northen-southern-and-western-region.pdf.pdf

Hatfield JL, Boote KJ, Kimball BA, Ziska LH, Izaurralde RC, Ort D, Thomson AM and Wolfe D (2011) Climate impacts on agriculture: implications for crop production. *Agronomy Journal* **103**, 351–370. https://doi.org/10.2134/agronj2010.0303

Hatfield JL and Prueger JH (2015) Temperature extremes: effect on plant growth and development. *Weather and Climate Extremes* **10**, 4–10. https://doi.org/10.1016/j.wace.2015.08.001

Hatfield JL, Sauer TJ and Prueger JH (2001) Managing soils to achieve greater water use efficiency: a review. *Agronomy Journal* **93**, 271–280. https://doi.org/10.2134/agronj2001.932271x

He D and Wang E (2019) On the relation between soil water holding capacity and dryland crop productivity. *Geoderma* **353**, 11–24. https://doi.org/10.1016/j.geoderma.2019.06.022

Heilemann J, Klassert C, Samaniego L, Thober S, Marx A, Boeing F, Klauer B and Gawel E (2024) Projecting impacts of extreme weather events on crop yields using LASSO regression. *Weather and Climate Extremes* **46**, 100738. https://doi.org/10.1016/j.wace.2024.100738

Holzworth DP, Huth NI, deVoil PG, Zurcher EJ, Herrmann NI, McLean G, Chenu K, van Oosterom EJ, Snow V, Murphy C, Moore AD, Brown H, Whish JPM, Verrall S, Fainges J, Bell LW, Peake AS, Poulton PL, Hochman Z, Thorburn PJ, Gaydon DS, Dalgliesh NP, Rodriguez D, Cox H, Chapman S, Doherty A, Teixeira E, Sharp J, Cichota R, Vogeler I, Li FY, Wang E, Hammer GL, Robertson MJ, Dimes JP, Whitbread AM, Hunt J, van Rees H, McClelland T, Carberry PS, Hargreaves JNG, MacLeod N, McDonald C, Harsdorf J, Wedgwood S and Keating BA (2014) APSIM – evolution towards a new generation of agricultural systems simulation. *Environmental Modelling & Software* **62**, 327–350. https://doi.org/10.1016/j.envsoft.2014.07.009

Huang J, Breheny P and Ma S (2012) A selective review of group selection in high-dimensional models. *Statistical Science* **27**, 481–499. https://doi.org/10.1214/12-STS392

Huang J, Ma S, Xie H and Zhang C (2009) A group bridge approach for variable selection. *Biometrika* **96**, 339–355. https://doi.org/10.1093/biomet/asp020

Iannone R, Cheng J, Schloerke B, Hughes E, Lauer A, Seo J, Brevoort K and Roy O (2024) gt: Easily create presentation-ready display tables. Available online from: https://cran.r-project.org/package=gt

Jeffrey SJ, Carter JO, Moodie KB and Beswick AR (2001) Using spatial interpolation to construct a comprehensive archive of Australian climate data. *Environmental Modelling Software* **16**, 309–330. https://doi.org/10.1016/S1364-8152(01)00008-1

Joshi PK and Rao PP (2017) Global pulses scenario: status and outlook. *Annals of the New York Academy of Sciences* **1392**, 6–17. https://doi.org/10.1111/nyas.13298

Kashiwagi J, Krishnamurthy L, Crouch JH and Serraj R (2006) Variability of root length density and its contributions to seed yield in chickpea (*Cicer arietinum* L.) under terminal drought stress. *Field Crops Research* **95**, 171–181. https://doi.org/10.1016/j.fcr.2005.02.012

Kassambara A (2023) ggpubr: "ggplot2" based publication ready plots. Available online from: https://cran.r-project.org/package=ggpubr

Kaushal N, Awasthi R, Gupta K, Gaur PM, Siddique KHM and Nayyar H (2013) Heat-stress-induced reproductive failures in chickpea (*Cicer arietinum*) are associated with impaired sucrose metabolism in leaves and anthers. *Functional Plant Biology* **40**, 1334–1349. https://doi.org/10.1071/FP13082

Kholová J, Murugesan T, Kaliamoorthy S, Malayee S, Baddam R, Hammer GL, McLean G, Deshpande S, Hash CT, Craufurd PQ and Vadez V (2014) Modelling the effect of plant water use traits on yield and stay-green expression in sorghum. *Functional Plant Biology* **41**, 1019–1034. https://doi.org/10.1071/FP13355

Kiniry JR, Jones CA, O'Toole JC, Blanchet R, Cabelguenne M and Spanel DA (1989) Radiation-use efficiency in biomass accumulation prior to grain-filling for five grain-crop species. *Field Crops Research* **20**, 51–64. https://doi.org/10.1016/0378-4290(89)90023-3

Koehler T, Wankmüller FJP, Sadok W and Carminati A (2023) Transpiration response to soil drying versus increasing vapor pressure deficit in crops: physical and physiological mechanisms and key plant traits. *Journal of Experimental Botany* **74**, 4789–4807. https://doi.org/10.1093/jxb/erad221

Kovaleski S, Heldwein AB, Dalmago GA and de Gouvêa JA (2020) Frost damage to canola (Brassica napus L.) during reproductive phase in a controlled environment. *Agrometeoros* **27**(2), 397–407. http://dx.doi.org/10.31062/agrom.v27i2.26463

Kumar J and Abbo S (2001) Genetics of flowering time in chickpea and its bearing on productivity in semiarid environments. *Advances in Agronomy* **72**, 107–138. https://doi.org/10.1016/S0065-2113(01)72012-3

Kumar S, Attri SD and Singh KK (2019) Comparison of Lasso and stepwise regression technique for wheat yield prediction. *Journal of Agrometeorology* **21**, 188–192. https://doi.org/10.54386/jam.v21i2.231

Lake L and Sadras VO (2014) The critical period for yield determination in chickpea (*Cicer arietinum* L.). *Field Crops Research* **168**, 1–7. https://doi.org/10.1016/j.fcr.2014.08.003

Lenth RV (2024) emmeans: Estimated marginal means, aka least-squares means. Available online from: https://cran.r-project.org/package=emmeans

Liu DL, Anwar MR, O'Leary G and Conyers MK (2014) Managing wheat stubble as an effective approach to sequester soil carbon in a semi-arid environment: spatial modelling. *Geoderma* **214**, 50–61. https://doi.org/10.1016/j.geoderma.2013.10.003

Liu K, Bandara M, Hamel C, Knight JD and Gan Y (2020) Intensifying crop rotations with pulse crops enhances system productivity and soil organic carbon in semi-arid environments. *Field Crops Research* **248**, 107657. https://doi.org/10.1016/j.fcr.2019.107657

Lobell DB, Hammer GL, McLean G, Messina C, Roberts MJ and Schlenker W (2013) The critical role of extreme heat for maize production in the United States. *Nature Climate Change* **3**, 497–501. https://doi.org/10.1038/nclimate1832

Lorite IJ, Castilla A, Cabezas JM, Alza J, Santos C, Porras R, Gabaldón-Leal C, Muñoz-Marchal E and Sillero JC (2023) Analyzing the impact of extreme heat events and drought on wheat yield and protein concentration, and adaptation strategies using long-term cultivar trials under semi-arid conditions. *Agricultural and Forest Meteorology* **329**, 109279. https://doi.org/10.1016/j.agrformet.2022.109279

Muchow RC, Sinclair TR and Bennett JM (1990) Temperature and solar radiation effects on potential maize yield across locations. *Agronomy Journal* **82**, 338–343. https://doi.org/10.2134/agronj1990.00021962008200020033x

NVT Online (2025) GRDC National Variety Trials. Available online from: https://nvt.grdc.com.au/nvt-protocols (Accessed 4 February 2025).

Palmero F, Fernandez JA, Garcia FO, Haro RJ, Prasad PV, Salvagiotti F and Ciampitti IA (2022) A quantitative review into the contributions of biological nitrogen fixation to agricultural systems by grain legumes. *European Journal of Agronomy* **136**, 126514. https://doi.org/10.1016/j.eja.2022.126514

Paredes P, Rodrigues GC, Alves I and Pereira LS (2014) Partitioning evapotranspiration, yield prediction, and economic returns of maize under various irrigation management strategies. *Agricultural Water Management* **135**, 27–39. https://doi.org/10.1016/j.agwat.2013.12.010

Passioura J (2006) Increasing crop productivity when water is scarce—from breeding to field management. *Agricultural Water Management* **80**, 176–196. https://doi.org/10.1016/j.agwat.2005.07.012

Peake AS, Dreccer MF, Whish JP and Hochman Z (2020) Final report to the Grains Research and Development Corporation. Project CSP1904-005RXT: The adaptation of pulses (chickpea and lentil) across the northern grains region. CSIRO Agriculture and Food, Australia. https://doi.org/10.25919/5f1f2438cd4e4

Pedersen TL (2024) patchwork: The composer of plots. Available online from: https://cran.r-project.org/package=patchwork

Piñeiro G, Perelman S, Guerschman JP and Paruelo JM (2008) How to evaluate models: observed vs. predicted or predicted vs. observed? *Ecological modelling* **216**, 316–322. https://doi.org/10.1016/j.ecolmodel.2008.05.006

Posit team (2024) RStudio: Integrated development environment for r. Posit Software, PBC, Boston, MA. Available online from: http://www.posit.co/

Prasad PV, Boote KJ and Allen Jr LH (2006) Adverse high temperature effects on pollen viability, seed-set, seed yield and harvest index of grain-sorghum [*Sorghum bicolor* (L.) Moench] are more severe at elevated carbon dioxide due to higher tissue temperatures. *Agricultural and Forest Meteorology* **139**, 237–251. https://doi.org/10.1016/j.agrformet.2006.07.003

R Core Team (2024) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. Available online from: https://www.R-project.org/

Rani BS and Krishna TG (2016) Response of chickpea (*Cicer arietinum* L.) varieties to nitrogen on a calcareous vertisols. *Indian Journal of Agricultural Research* **50**, 278–281. https://doi.org/10.18805/ijare.v50i3.10749

Richards RA (2000) Selectable traits to increase crop photosynthesis and yield of grain crops. *Journal of Experimental Botany* **51**, 447–458. https://doi.org/10.1093/jexbot/51.suppl_1.447

Richards RA, Rebetzke GJ, Watt M, Condon AG, Spielmeyer W and Dolferus R (2010) Breeding for improved water productivity in temperate cereals: Phenotyping, quantitative trait loci, markers, and the selection environment. *Functional Plant Biology* **37**, 85–97. https://doi.org/10.1071/FP09219

Rodriguez-Sanchez F and Jackson CP (2023) grateful: Facilitate citation of r packages. Available online from: https://pakillo.github.io/grateful/

Sadras VO, Cassman KGG, Grassini P, Hall AJ, Bastiaanssen WGM, Laborte AG, Milne AG, Sileshi G and Steduto P (2015) Yield gap analysis of field crops: Methods and case studies. FAO Water Reports, 41. Available online from: https://digitalcommons.unl.edu/wffdocs/87/

Sadras VO and McDonald G (2011) Water use efficiency of grain crops in Australia: principles, benchmarks and management. Grains Research and Development Corporation, South Australian Research and Development Institute and University of Adelaide. GRDC Project Code: DAS00089; https://www.pir.sa.gov.au/__data/assets/pdf_file/0003/238413/SARDI-Water-Use-Efficiency-Grain-Crops-Australia.pdf

Sadras VO and Milroy SP (1996) Soil-water thresholds for the responses of leaf expansion and gas exchange: a review. *Field Crops Research* **47**, 253–266. https://doi.org/10.1016/0378-4290(96)00014-7

Sage RF and Kubien DS (2007) The temperature response of C3 and C4 photosynthesis. *Plant, Cell & Environment* **30**, 1086–1106. https://doi.org/10.1111/j.1365-3040.2007.01682.x

Saini R, Das R, Adhikary A, Kumar R, Singh I, Nayyar H and Kumar S (2022) Drought priming induces chilling tolerance and improves reproductive functioning in chickpea (*Cicer arietinum* L.). *Plant Cell Reports* **41**, 2005–2022. https://doi.org/10.1007/s00299-022-02905-7

Samarah NH (2005) Effects of drought stress on growth and yield of barley. *Agronomy for sustainable development* **25**, 145–149. https://doi.org/10.1051/agro:2004064

Schwarz G (1978) Estimating the dimension of a model. *Annals of Statistics* **6**, 461–464. https://doi.org/10.1214/aos/1176344136

Siddique KHM, Johansen C, Turner NC, Jeuffroy MH, Hashem A, Sakar D, Gan Y and Alghamdi SS (2012) Innovations in agronomy for food legumes. A review. *Agronomy for Sustainable Development* **32**, 45–64. https://doi.org/10.1007/s13593-011-0021-5

Simon N, Friedman JH, Hastie T and Tibshirani R (2011) Regularization paths for cox's proportional hazards model via coordinate descent. *Journal of Statistical Software* **39**, 1–13. https://doi.org/10.18637/jss.v039.i05

Sinclair TR, Hammer GL and van Oosterom EJ (2005) Potential yield and water-use efficiency benefits in sorghum from limited maximum transpiration rate. *Functional Plant Biology* **32**, 945–952. https://doi.org/10.1071/FP05047

Sinclair TR and Muchow RC (1999) Radiation use efficiency. *Advances in Agronomy* **65**, 215–265. https://doi.org/10.1016/S0065-2113(08)60914-1

Sinclair TR and Muchow RC (2001) System analysis of plant traits to increase grain yield on limited water supplies. *Agronomy Journal* **93**, 263–270. https://doi.org/10.2134/agronj2001.932263x

Singh KB, Malhotra RS, Halila MH, Knights EJ and Verma MM (1993) Current status and future strategy in breeding chickpea for resistance to biotic and abiotic stresses. *Euphytica* **73**, 137–149. https://doi.org/10.1007/BF00027190

Singh KB and Saxena MC (1993) Breeding for stress tolerance in cool-season food legumes. John Wiley & Sons. https://doi.org/10.1002/jpln.19941570222

Singh R, Sharma P, Varshney RK, Sharma SK and Singh NK (2008) Chickpea improvement: role of wild species and genetic markers. *Biotechnology and Genetic Engineering Reviews* **25**, 267–314. https://doi.org/10.5661/bger-25-267

Soltani A and Sinclair TR (2011) A simple model for chickpea development, growth and yield. *Field Crops Research* **124**, 252–260. https://doi.org/10.1016/j.fcr.2011.06.021

Tay JK, Narasimhan B and Hastie T (2023) Elastic net regularization paths for all generalized linear models. *Journal of statistical software* **106**, 1–31. https://doi.org/10.18637/jss.v106.i01

Thomson BD, Siddique KHM, Barr MD and Wilson JM (1997) Grain legume species in low rainfall Mediterranean-type environments I. Phenology and seed yield. *Field Crops Research* **54**, 173–187. https://doi.org/10.1016/S0378-4290(97)00047-6

Tibshirani R (1996) Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society Series B: Statistical Methodology* **58**(1), 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

Tierney N and Cook D (2023) Expanding tidy data principles to facilitate missing data exploration, visualization and assessment of imputations. *Journal of Statistical Software* **105**, 1–31. https://doi.org/10.18637/jss.v105.i07

Trout TJ and DeJonge KC (2017) Water productivity of maize in the US high plains. *Irrigation Science* **35**, 251–266. https://doi.org/10.1007/s00271-017-0540-1

Unkovich M, Baldock J and Farquharson R (2018) Field measurements of bare soil evaporation and crop transpiration, and transpiration efficiency, for rainfed grain crops in Australia – a review. *Agricultural Water Management* **205**, 72–80; https://doi.org/10.1016/j.agwat.2018.04.016

Unkovich M, McBeath T, Moodie M and Macdonald LM (2023) High soil strength and cereal crop responses to deeper tillage on sandy soils in a semiarid environment. *Field Crops Research* **291**, 108792. https://doi.org/10.1016/j.fcr.2022.108792

Vadez V, Berger JD, Warkentin T, Asseng S, Ratnakumar P, Rao KPC, Gaur PM, Munier-Jolain N, Larmure A, Voisin AS and Sharma HC (2012) Adaptation of grain legumes to climate change: a review. *Agronomy for Sustainable Development* **32**, 31–44. https://doi.org/10.1007/s13593-011-0020-6

Vadez V, Grondin A, Chenu K, Henry A, Laplaze L, Millet EJ and Carminati A (2024) Crop traits and production under drought. *Nature Reviews Earth & Environment* **5**, 211–225. https://doi.org/10.1038/s43017-023-00514-w

Verghis BA, McKenzie BA and Hill GD (1999) Phenological development of chickpeas (*Cicer arietinum*) in Canterbury, New Zealand. *New Zealand Journal of Crop and Horticultural Science* **27**, 249–256; https://doi.org/10.1080/01140671.1999.9514103

Vogel E, Donat MG, Alexander LV, Meinshausen M, Ray DK, Karoly D, Meinshausen N and Frieler K (2019) The effects of climate extremes on global agricultural yields. *Environmental Research Letters* **14**, 054010. https://doi.org/10.1088/1748-9326/ab154b

Wang B, Liu DL, Asseng S, Macadam I and Yu Q (2017) Modelling wheat yield change under CO2 increase, heat and water stress in relation to plant available water capacity in eastern Australia. *European Journal of Agronomy* **90**, 152–161. https://doi.org/10.1016/j.eja.2017.08.005

Waqas M, Azhar MT, Rana IA, Arif A and Atif RM (2019) Drought stress in chickpea: physiological, breeding, and omics perspectives. In Wani S (ed.), *Recent Approaches in Omics for Plant Resilience to Climate Change*. Springer. https://doi.org/10.1007/978-3-030-21687-0_9

Weylandt M, Campbell F and Allen G (2018) ExclusiveLasso: Generalized Linear Models with the Exclusive Lasso Penalty. Available online from: https://github.com/DataSlingers/ExclusiveLasso

Wickham H (2007) Reshaping data with the reshape package. *Journal of Statistical Software* **21**, 1–20. https://doi.org/10.18637/jss.v021.i12

Wickham H, Averick M, Bryan J, Chang W, McGowan LDA, François R, Grolemund G, Hayes A, Henry L, Hester J and Kuhn M (2019) Welcome to the tidyverse. *Journal of Open Source Software* **4**, 1686. https://doi.org/10.21105/joss.01686

Willmott CJ (1982) Some comments on the evaluation of model performance. *Bulletin of the American Meteorological Society* **63**, 1309–1313. https://doi.org/10.1175/1520-0477(1982)063<1309:SCOTEO>2.0.CO;2

Xing H, Liu DL, Li G, Wang B, Anwar MR, Crean J, Lines-Kelly R and Yu G (2017) Incorporating grain legumes in cereal-based cropping systems to improve profitability in southern New South Wales, Australia. *Agricultural Systems* **154**, 112–123; https://doi.org/10.1016/j.agsy.2017.03.010

Yang Y, Liu DL, Anwar MR, O'Leary G, Macadam I and Yang Y (2016) Water use efficiency and crop water balance of rainfed wheat in a semi-arid environment: sensitivity of future changes to projected climate changes and soil type. *Theoretical and Applied Climatology* **123**, 565–579. https://doi.org/10.1007/s00704-015-1376-3

Yuan M and Lin Y (2006) Model selection and estimation in regression with grouped variables. *Journal of the Royal Statistical Society Series B: Statistical Methodology* **68**, 49–67. https://doi.org/10.1111/j.1467-9868.2005.00532.x

Zaman-Allah M, Jenkinson DM and Vadez V (2011) Chickpea genotypes contrasting for seed yield under terminal drought stress in the field differ for traits related to the control of water use. *Functional Plant Biology* **38**, 270–281. https://doi.org/10.1071/FP10244

Zeleke K and Nendel C (2019) Growth and yield response of faba bean to soil moisture regimes and sowing dates: field experiment and modelling study. *Agricultural Water Management* **213**, 1063–1077; https://doi.org/10.1016/j.agwat.2018.12.023

Zeleke KT, Anwar MR, Emebiri L and Luckett D (2023) Weather indices during reproductive phase explain wheat yield variability. *The Journal of Agricultural Science* **161**, 617–632. https://doi.org/10.1017/S0021859623000503