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Characterisation of chickpea cropping systems in Australia for major abiotic production constraints

Yashvir Chauhan[a,*], Samantha Allard[a], Rex Williams[b], Brett Williams[c], Sagadevan Mundree[c], Karine Chenu[d], N.C. Rachaputi[e]

[a] Department of Agriculture and Fisheries (DAF), 214 Kingaroy-Cooyer Road, Kingaroy, Qld 4610, Australia
[b] DAF, 203 Tor Street, Toowoomba, Qld 4350, Australia
[c] Centre for Tropical Crops and Bio-Commodities, Queensland University of Technology, Gardens Point Campus, P.O. Box 2434, Brisbane 4001, Qld, Australia
[d] The University of Queensland, Queensland Alliance for Agriculture and Food Innovation (QAAFI), 203 Tor Street, Toowoomba, Qld 4350, Australia
[e] QAAFI, University of Queensland, Gatton, Qld 4343, Australia

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ABSTRACT

To develop higher yielding and better adapted chickpeas, various breeding programs currently use a limited number of multi-location trials as a surrogate for the target population of environments (TPE). These TPEs have, however, not been adequately characterised, resulting in some uncertainty about the true representativeness of these surrogate locations as selection environments. We used the Agricultural Production Systems sIMulator (APSIM) model to characterise the Northern Grains Region of Australia, which is a major TPE of chickpea, for drought and thermal regimes. The model was first evaluated for its ability to simulate phenology, dry matter and yield of three new commercially-relevant chickpea varieties including PBA Boundary, PBA HatTrick and PBA Seamer. The model was then used to simulate dynamic changes in water stress quantified through the supply demand ratio, and yield of the highest yielding genotype PBA Boundary from 1900 to 2014 at 45 locations within the region. Water stress, and maximum, minimum and mean temperature patterns were derived through cluster analysis of respective averages computed for every 100 °Cd from 900 °Cd before flowering, to 900 °Cd after flowering. The Northern Grains Region TPE was characterised by four types of water stress patterns and five types each of maximum, minimum and mean temperatures patterns. Ward's cluster analysis of the percentile ranks of simulated seasonal yield resulting from agro-climatic variability of the different locations enabled identification of eight unique agro-ecological regions within the TPE. Locations within each agro-ecological region were geographically contiguous and had highly harmonised annual variability in yield compared to locations of other agro-ecological regions. Overall, the identified agro-ecological regions were fairly homogenous with respect to drought and thermal regimes and could be treated as separate sub-TPEs. We argue that selecting locations within an agro-ecological region should assist breeding for locally adapted genotypes. In contrast, selecting locations distributed across agro-ecological regions could improve the broad adaptation of chickpea.

1. Introduction

With an annual production of 14.2 million tonnes, chickpea is the second most important food legume (FAOSTAT, 2014). The demand of this crop is continuously increasing due to an increase in population and nutritional standards, especially in South Asia and Sub-Saharan Africa where the crop is consumed in significant quantities requiring imports. Import of this crop into these regions has more than doubled between 2004 and 2013 (FAOSTAT, 2014). To cater to this increasing demand, export oriented chickpea industries have been thriving in many developed countries including Australia, Canada and the USA.

In Australia, the establishment of the export oriented chickpea industry coincided with the Green Revolution in South Asia during the 1970s where high yielding wheat varieties were replacing chickpea (Challa and Ramamurthy, 2004). Chickpea was estimated to be grown in over a million ha in Australia in 2016 (www.pulseaus.com.au/marketing/crop-forecast). While considerable research has been directed to take advantage of new opportunities offered by this crop to Australian farmers (Siddique

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* Corresponding author.
E-mail address: yash.chauhan@daf.qld.gov.au (Y. Chauhan).

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et al., 2000), its yield has, however, remained low (~1 t/ha). Chickpea breeding programs have tried to reduce the impact of *Ascochyta* blight, *Botrytis* grey mould and *Phytophthora* root rot; diseases that reduce the yield of this crop in some situations (Knights et al., 2003). However, limited attention has been given to reduce vulnerability of the crop to climatic variability (Whish et al., 2007). Over 90% of the chickpea cropping area in Australia is located within the four million hectares of arable land of the Northern Grains Region. This region, which includes part of southern and central Queensland and northern New South Wales located between 22.7°S to 32.3°S, is sub-tropical in the east to semi-arid in the west (Dang et al., 2015). It is climatically highly variable, exposing chickpea to frequent droughts and extremes of temperature (Knights et al., 2003).

Climatic variability makes the target population environments (TPE), which is defined as a set of conditions to which future-release varieties might be subjected to (Chenu, 2015), quite heterogeneous as well as unpredictable (Dreccer et al., 2008; Windhausen et al., 2012; Heinemann et al., 2015). An obvious implication of this for chickpea breeders is a larger genotype × environment interaction effects than that for genotypes (Berger et al., 2004) which creates considerable uncertainty in identifying superior genotypes, thus slowing the progress in breeding superior varieties. In such situations, characterisation of TPEs can possibly assist in achieving greater gains in yield (Chapman et al., 2000; Chenu et al., 2011; Chenu, 2015). Several approaches have been proposed to determine how uniform TPEs are for their biophysical attributes, including yield, drought, and temperature. These approaches include using geographical information systems, climate analyses (Pollak and Corbett, 1993; Hartkamp et al., 2000) and crop models (Chapman et al., 2000; Heinemann et al., 2008; Sadras et al., 2012; Chenu et al., 2013a,b; Chauhan et al., 2013; Harrison et al., 2014; Lake et al., 2016). The use of crop models to characterise TPEs is becoming common due to the ability of the models to integrate longer term climate, soil, crop, and management information (Chenu, 2015; Heinemann et al., 2015). However, model-based characterisation has received limited attention in grain legumes (Sadras et al., 2012; Chauhan et al., 2013; Lake et al., 2016). The model-based environmental characterisation for mungbean was found to be more informative when used in conjunction with agro-ecological regions (AER) identified on the basis of temporal variability in yield created by different abiotic stresses (Chauhan and Rachaputi, 2014). Identifying sub-regions based on climate, altitude, geography, country, and yield-level, subregions within African TPE enabled larger yield gains in maize compared to combining all multi-environment trials together. Such sub-divisions assisted in dealing with genotype × environment interactions and setting research priorities (Windhausen et al., 2012).

A major requirement for characterising TPEs using a modelling approach is that the model being used should be able to predict crop growth and development reasonably accurately. The Agricultural Production Systems sIMulator (APSIM) is a widely used modelling framework for environmental characterisation (Holzworth et al., 2014). The cereal modules of the model have been tested and applied extensively for breeding and agronomic purposes (e.g., Carberry et al., 1996; Chapman, 2008; Hochman et al., 2012; Chenu et al., 2011). However, the chickpea module of APSIM (Robertson et al., 2002) has had limited testing and application, especially with new commercially-relevant varieties (Whish et al., 2007; Chauhan et al., 2008; Lake et al., 2016); these new varieties have not been parameterised in APSIM. Further, a major limitation in predicting yield by the APSIM Chickpea model could be its harvest index. Harvest index is currently calculated as a linear function of dry matter accumulated during the grain filling period which might be influenced by temperature and drought (Soltani et al., 2005), and the degree of indeterminateness (Siddique and Sedgley, 1985). Currently, these effects are not captured well in APSIM.

The aims of the present study were to (a) parameterise and evaluate the APSIM chickpea model version 7.8 for three commercial varieties; (b) define AERs with similar spatio-temporal variation in simulated yield; (c) characterise the range of drought and temperature regimes that the chickpea crop experiences in the Australian Northern Grain Region, and establish the frequencies of occurrence of these stresses over the entire region and within each AER; and (d) identify locations of relevance to evaluate new breeding lines for the dominant drought and thermal regimes.

2. Materials and methods

2.1. APSIM chickpea module parameterisation and evaluation

2.1.1. Experiment for the chickpea module parameterisation

The major focus of this part of the study was to evaluate the ability of the APSIM model (version 7.8) to predict yield and dry matter of the new chickpea varieties PBA Boundary, PBA HatTrick and PBA Seamer that were to be used in characterisation. As these three varieties had not been parameterised in APSIM previously, especially for phenology, a field trial for this purpose was conducted at Kingaroy (26.5°S 151.8°E) in South East Queensland in 2014.

The above trial was sown on three dates to cover a range of sowing times practiced by farmers in the Northern Grains Region with replications nested within sowing dates (Table 1). These sowings were done at 50 cm row to row spacing, and the varieties were planted at about 30 plants m^{-2} in plots of 3.6 × 12 m with three replications. The soil at the experimental site was a Red Ferrosol holding about 119 mm plant available water at each sowing. The field was given 25 mm irrigation each time a sowing was undertaken. There was little apparent incidence of any disease or pests, and weeds were eliminated with two inter-culture operations and a manual chipping. Flowering and maturity were defined as the timing when 50% of the plants per unit area had at least one open flower, and when over 90% pods were visually dry, respectively (Erskine et al., 1990). At physiological maturity, plants in 4 m (2 m^2) sections of the middle rows in each bed were hand harvested at the ground level and dried at 55 °C for 72 h before weighing. These samples were then threshed in a small thresher and the clean seeds were weighed.

The information collected in this trial was used to update the APSIM chickpea module. The chickpea module of the model has a number of generic and specific parameters. The generic parameters in the module control basic processes of converting light and water to simulate dry matter production and are applied to all varieties, whereas specific parameters are applied to particular varieties. The module provides scope to incorporate calibrated variety specific parameters including phenology, photoperiod sensitivity and partitioning for the new cultivars. We calibrated thermal time from emergence to the end of juvenile phase, which was 515 °Cd for Amethyst – a desi chickpea cultivar grown in Australia in the 1990s to be 425 °Cd for PBA Boundary, 400 °Cd for PBA HatTrick and 410 °Cd for PBA Seamer (Table 2). The other thermal time requirements and photoperiod sensitivity parameters were as those for Amethyst.

The other variety specific parameter we optimised was the potential harvest index. In the original APSIM chickpea model, yield was computed using a linear function of dry matter accumulation and in the model this function (i.e., harvest index (HI)), was 0.01 with the potential HI being 0.5 constant for all varieties irrespective of stress values. Through simulations it was learnt that the potential HI parameter value affected indeterminateness (time up to which yield increase will occur). Under favourable moisture (the