Does the cropping system influence the optimum crop design in sorghum?

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Abstract

Identifying combinations of agronomic management (M) and genotypes (G) to identify crop designs (GxM) that maximise financial gain while minimising risks is an important step in assisting growers to make better informed decisions, particularly in highly variable growing environments (E). Here, an *in-silico* experiment using APSIM-Sorghum investigated whether the crop sequence influences the optimum crop design for grain sorghum across a range of contrasting sites within Australia's northern grains region. The optimum crop design was determined via both the cumulative gross margin and variability (risk). A number of common crop sequences specific to the region were simulated, including (i) continuous sorghum (S-S), (ii) chickpea followed by sorghum (C-S), (iii) chickpea followed by early-sown sorghum (C-ES), (iv) wheat followed by sorghum (W-S), and (v) wheat followed by early-sown sorghum (W-ES), in 3-year crop rotations. Sorghum genetic and management APSIM parameters (*ftn, cultivar, density,* and *rowconfig*) were varied within each crop sequence in a factorial design. Simulation results showed clear and consistent clustering of crop sequences along the efficiency frontier (Pareto ranks 1-3) and that the crop sequence was an important indicator of the probable risk tercile. Systems containing an early sorghum component tended to have a higher Pareto rank than those with a standard sorghum crop and improved optimal gross margin and variability trade-offs. Partitioning revealed that the broadly adapted optimum GxM remained consistent between the simulated dryland crop sequences, and that early maturity and high planting density were important decisions associated with the optimum crop design.

Keywords

APSIM, Pareto rank, simulation, partitioning, agronomy

Introduction

The highly variable and risk-prone nature of dryland cropping in Australia (Chauhan et al. 2013) creates a need to identify strategies that mitigate risks while improving gross margins. Grain sorghum has unique biological and agronomic considerations in the Australian environment by which it is sensitive to water availability and temperature stress throughout the growing season for both the performance and stability of yields (Hammer et al., 2014). The concept of performance landscapes in agriculture was introduced by Messina et al. (2011) and extended in Hammer et al. (2014) to include the interaction of genetic and management components and identification of site-specific optimisation. Pareto optimisation represents a potentially valuable tool for exploring the topography of crop design performance landscapes (Hammer et al. 2014; Rodriguez et al. 2018).

Despite research into the interactions of factors which affect crop performance, the influence of the cropping system on optimum crop designs (i.e., best performing GxM for a given level of risk) has not yet been studied. This study aimed to quantify the influence of the cropping system (crop sequence) on optimum combinations of genetics and management in grain sorghum. A novel *in-silico* approach for analysing crop designs across efficiency frontiers combining crop simulation and the use of Pareto ranking and recursive partitioning was used.

Methods

An *in silico* experiment using the validated APSIM (v. 7.10) Sorghum model (Holzworth et al. 2014) was performed to investigate how the crop sequence influences optimal combinations of genetic (G) and management (M). The effects of interactions between G, M, and the crop sequence on maximising gross margin and minimising variability for a number of crop sequences were analysed across contrasting environments within one of the primary grains growing regions of Australia. Simulation design consisted of multi-year crop sequences containing a grain sorghum component which varied in a number of genetic and management parameters. Tested crop sequences included continuous sorghum (S-S), a chickpea crop followed by sorghum (C-S), a chickpea crop followed by early-sown sorghum (C-ES), a wheat crop followed by sorghum (W-S), and a wheat crop followed by early-sown sorghum (W-ES). The APSIM Sorghum parameters of fertile tiller number (*ftn*), cultivar (*cultivar*), planting density (*density*) and row configuration (*rowconfig*) were varied using through factorial simulations at three levels (a low, medium, and high level for each parameter) for each sorghum crop along with the crop sequence.

Meteorological data was acquired for three distinct weather station sites located at Breeza, Emerald and Dalby using the Australian SILO database. Simulations were run for three-year periods using each year of the climate record as a unique starting point (i.e. 1940-1943, 1941-1944, etc.) with 50 years of climate data. A standard APSIM soil module characteristic of the growing region was used for all sites and simulations. Initial nitrogen at the time of sowing for each crop was set to equal a minimum of 150 kg ha^{-1} within the top 1000 mm of the soil profile via an application of the lacking quantity in the uppermost 50 mm as nitrate (NO_3^-) fertilizer. The soil water profile was set to 100% full at the start of the first crop and rainfed after that, no irrigation was applied. Estimated crop prices and variable costs were acquired from AgMargins (agmargins.net.au). Fertilizer costs were removed from variable cost data and calculated independently using the simulated fertilizer application quantity and a fertilizer cost constant (0.55 \$ kg^{-1}). Mean cumulative gross margins and standard deviations over three-year simulations for each crop sequence were calculated.

Results

Datapoints within the defined range of the Pareto efficiency frontier (ranks 1-3) primarily clustered based on the crop sequence (Figure 1). Although crop sequences clustered within and across risk terciles, clearly defined tercile trends for each were identified. Crop sequences involving an early-sown sorghum component (C-ES and W-ES) largely had lower Pareto ranks (i.e. greater gross margin for a given risk) and were closer to the efficiency frontier than their standard sorghum counterparts (C-S and W-S) within the same risk tercile (Figure 1).

Recursive partitioning results demonstrated considerable similarity in the sorghum crop designs associated with Pareto optimisation for each of the crop sequences. For all crop sequences, cultivar maturity rating was the primary and most common partitioning node and early to medium maturity cultivars were generally associated with lower Pareto rank and late maturity cultivars with higher Pareto rank (Figure 2). Planting density was also commonly associated with clustering although this relationship was less straightforward, where higher planting densities (6 and 8) were associated with lower Pareto ranks in C-ES, W-ES, and W-S crop sequences and higher Pareto ranks in S-S sequences (Figure 2).

Results were largely consistent between the simulated Breeza and Dalby sites, although Emerald differed notably in the greatly decreased optimisation of crop sequences involving early sown sorghum due to high probabilities of heat stress events and low water availability in the critical months (data not shown).

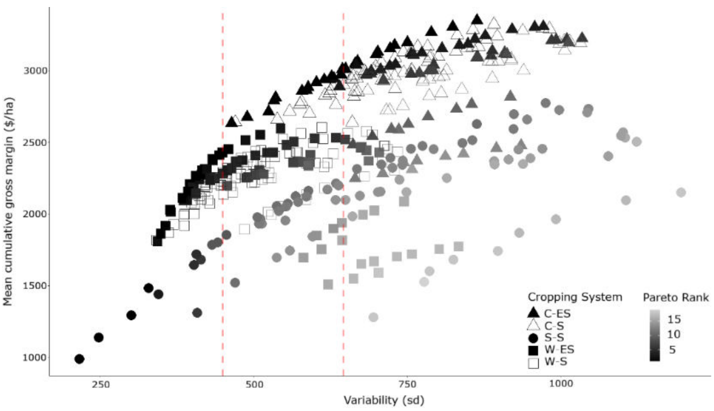

Figure 1. Distribution of cumulative gross margins and standard deviations of GxM and crop sequence combinations for Breeza. The efficiency frontier is determined by data points with a Pareto rank between 1 and 3 and is split into three equal quantiles (terciles) along the x-axis (red dashed lines). Tercile 1 is located on the left extreme of the x-axis and represents 'low risk' strategies, where tercile 2 represents 'medium risk' and tercile 3 represents 'high risk'.

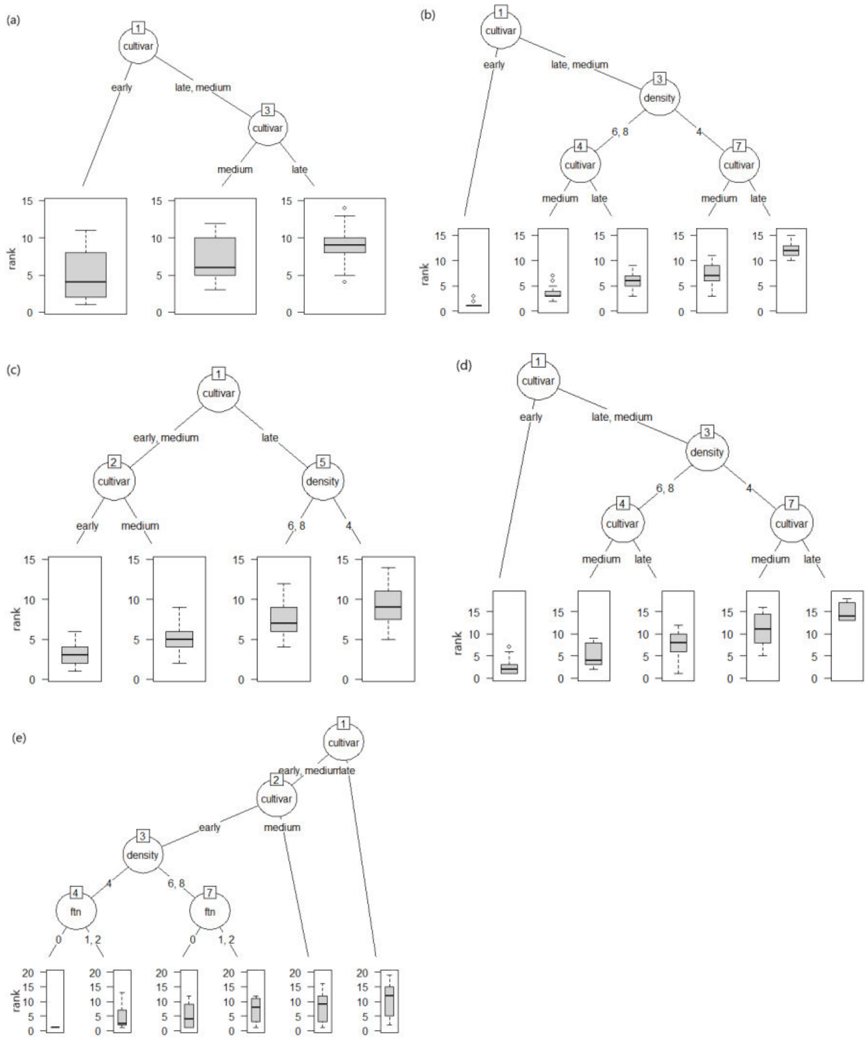

Figure 2. Recursive partitioning trees as a function of Pareto rank for (a) C-S, (b) C-ES, (c) W-S, (d) W-ES, and (e) S-S cropping systems. Shapes (nodes) at a given level of the tree indicate the variable with the highest correlation to clusters in the distribution and the hierarchy of nodes depicts the relative strength of cluster correlation.

Conclusion

We ultimately conclude that the cropping system did not have any significant influence on the optimum sorghum crop design, as the traits associated with optimisation remained consistent across all cropping systems in the simulated dryland Australian environment. The value of the cropping system for decision making was evident as it was strongly associated with both gross margins and risks, but our results suggest that its influence on the optimum crop design did not outweigh the major drivers of performance, such as seasonal temperature stress and rainfall variability, in the Australian Northern Grains Region.

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