Pulse vs. cereal crop variability: A comprehensive analysis with precision agriculture data across Australia

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Abstract

In Australia, growers tend to cultivate cereal crops more than pulses, and many studies suggest that a key reason for this preference is due to pulses exhibiting greater yield variability compared to cereals. Yet, this has not been thoroughly studied in Australia. Site-specific crop management (SSCM), a crucial aspect of precision agriculture, optimises resource management by tailoring practices to within-field yield variability. However, quantifying this variability and managing it effectively can be challenging. If pulses do indeed exhibit more variability than cereals, growers could benefit more from adopting SSCM. Traditional indicators of variability, such as the coefficient of variation (CV) have flaws as they do not account for the spatial structure of variation within fields. The yield opportunity index (Yi) is a valuable indicator tool for overcoming this issue, and accounts for both the magnitude and spatial structure of variability for assessing the potential for managing this variability. This study quantified within-field variability and SSCM opportunities using a large dataset of high-resolution yield maps (n = 815 yield maps) from farms across the Australian cropping belt, analysing data from cereals (wheat) and pulses (chickpeas, lentils, and lupin). Contrary to the common perception of greater variability in pulse crops, the results indicated little difference in variability between pulses and cereals based on Yi results. The capacity of the Yi to rank fields based on their manageable variability is crucial for guiding growers in implementing variable management practices to address this, which can lead to greater inclusion of pulse crops in rotations.

Keywords

Within-field variability, spatial, temporal, farming systems, yield maps.

Introduction

Including pulses in cropping system rotations comes with a suite of benefits. Legumes are known for their ability to biologically fix nitrogen (Xing et al. 2017), and they can also relieve pest and disease pressure, because the organisms that threaten cereals are generally not hosted by pulses (Kirkegaard et al. 2008). This is particularly important as producer profitability is under consistent pressure from rising input costs, especially for macronutrients (McLaughlin et al. 2011). Pulses are also an important non-meat source of protein, which is particularly relevant given increased concern about the impacts of animal production on the environment and human health. Despite all this, the area sown to pulses in Australia has markedly declined, whereas that of cereal and oilseed crops has increased. Cereals cover approximately 76% of Australian cropland, compared to pulses which cover ~ 9%, and this relative area sown is declining (Maaz et al. 2018).

A primary reason for this decline is the perception from growers that pulse crops exhibit greater spatial and temporal variability than cereals (Cernay et al. 2015). One key reason for this is that legumes are generally more susceptible to yield loss from pests and diseases (Sampaio et al. 2020). Notwithstanding the immediate disadvantages of greater variability in yield, a field characterised by increased within-field variation stands to gain from the variable application of inputs (Pringle et al. 2003). This means that there may be a greater opportunity for site-specific crop management (SSCM) of pulses compared to cereals. Gaining insights into the relative yield variability between pulses and cereals, and the underlying drivers affecting any differences in variability, is pivotal in shaping the resilience of future grain production systems.

Assessing within-field variability is the cornerstone of site-specific crop management (SSCM), as it allows farmers to revise their agricultural practices for specific areas within a field. SSCM allows farmers to target high- and low-yielding areas better, allowing for better resource allocation and reducing production costs (Whelan 2018). Determining if a crop exhibits sufficient variability, both in terms of magnitude and distribution, is crucial to justify a shift from traditional uniform management practices to variable rate management (Pringle et al. 2003; de Oliveira et al. 2007). Yield maps from harvester-mounted yield monitor sensors provide crucial insights into within-field yield variability and the potential for adopting SSCM. These data are now collected by the majority of grain growers in Australia. Most studies report this variability as a measure of the statistical distribution of data, with the coefficient of variation (CV) commonly used. However, the use of CV limits the ability to correctly characterise variation as it is not capable of distinguishing variation arising from spatial dependence (i.e. manageable variation) and variation arising from error (e.g. such as errors in processing yield data). An indicator that overcomes this issue is the yield opportunity index (Yi) as it takes into account both the magnitude, and the spatial structure of variation (de Oliveira et al., 2007). It also allows a ranking of fields, which can be used to prioritise which fields are more suitable for SSCM, where fields with higher Yi values are more amenable to variable management based.

This study aims to address the existing knowledge gap by comprehensively examining within-field variability and opportunities for SSCM in cereals (wheat) and pulses (chickpeas, lentils, and lupin) across Australia. Through the analysis of high-resolution yield maps obtained from multiple farms in the Australian cropping belt, the study intends to compare the spatial variability and consistency of yields across these crop types. Furthermore, the study explores how variations in yield patterns impact the feasibility of adopting SSCM practices for more profitable and environmentally sustainable cropping systems.

Methods

Study area

This study utilised data from 29 farms, encompassing a total area of 287,000 ha, and included 815 individual yield maps collected between 2009 and 2022. These farms are located in the Australian cropping belt, which can be segregated into three main regions: Northern, Southern, and Western.

The yield opportunity index (Yi)

Let's consider three hypothetical fields (Figure 1), which all have the same coefficient of variation but have contrasting spatial structures. The leftmost field has little spatial structure and is dominated by variation that is largely unmanageable due to the finer scale at which high and low-yielding zones occur. In contrast, the rightmost field has a clearer spatial structure, and has a greater opportunity for SSCM as management zones can be clearly delineated. Several attempts have been made to develop an indicator that recognises spatial structure and addresses the drawbacks of the more commonly used distribution-based approaches like CV (Tisseyre and McBratney 2008). In this study, the yield opportunity index (Yi) (Equation 1), is used to rank fields based on the structure and magnitude of their spatial variation. To do this, it uses the structural components of variogram models (models of spatial dependence) as inputs. See de Oliveira et al. (2007) for more detail.

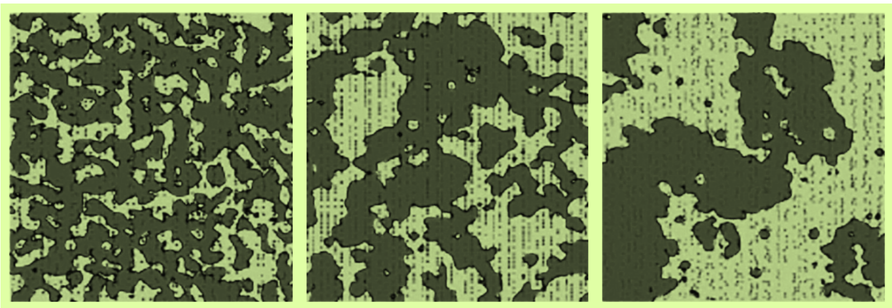

Figure 1. Hypothetical spatial structures of three fields split into a high (light green) and low (dark green) yielding area. Image sourced from Leroux and Tisseyre (2019).

$$Yi = \sqrt{M_v \times S_v} = \sqrt{\frac{CV_a}{q_{50}(CV_a)}} \times \frac{S}{s} \quad (1)$$

The required inputs for the Yi were extracted after the yield data collection. Experimental variograms with 15 bins were created per field. Following this, five variogram models were fitted to the experimental data: Exponential, Spherical, Gaussian, Matern, and Linear. The best model was chosen based on the Akaike Information Criterion (AIC). If none of the models produced a range parameter less than the maximum lag of the experimental variogram, the field was discarded. Once the best model was identified, average total field variation and areal coefficient of variation were calculated. The practical range was subsequently determined based on the model type. The operational machinery constant was calculated using the inputs suggested by Pringle et al. (2003). After collecting the required inputs, the final calculation of Yi (Equation 1) was performed. Using previous research as a guide (Cambardella et al. 1994), fields were grouped into three classes by the 1st and 3rd quartiles in the Yi distribution. Fields below the 1st quartile were classified as low opportunity, fields between the 1st and 3rd quartiles were classified as medium opportunity, and fields above the 3rd quartile were classified as high opportunity. The Yi values at these quartiles were rounded to the nearest 0.5 to provide intuitive threshold values.

Results and discussion

When examining all 815 yield maps, lupin had the highest CV value, and wheat had the lowest (Table 1), indicating lower variability in the latter. All crop types had some large outliers, which were typically values greater than 10 (Figure 2). In terms of Yi, lupin had the highest mean Yi value with 6.13, and lentil had the lowest mean Yi with 4.34 (Figure 2) (Table 1). The mean for chickpeas and wheat were intermediate, being 5.63 and 5.12, respectively (Table 1). Chickpeas and lentils had the same mean CV, but different mean Yi values, and the ordering of the variability between crop types shown by CV was not maintained by the Yi results. For example, wheat had the lowest CV, but lentils had the lowest Yi (Table 1).

Table 1. Count, mean CV, and mean Yi for all crop types and regions in the study (n = 815).

Crop type	No. of yield maps	Mean CV (± SD)	Mean Yi (± SD)
Chickpea	184	0.29 (± 0.15)	5.63 (± 2.87)
Lentil	63	0.29 (± 0.1)	4.34 (± 2.65)
Lupin	148	0.39 (± 0.16)	6.13 (± 3.38)
Wheat	420	0.26 (± 0.15)	5.12 (± 2.73)
All	815	0.29 (± 0.15)	5.36 (± 2.92)

Overall, across the entire study dataset, pulses and cereals exhibited similar within-field variability as measured by Yi. Lupin was the most variable crop type, indicating the highest opportunity for SSCM, followed by chickpea, wheat, and then lentil (Figure 2). Given the skewness of the distributions, greater emphasis was placed on median values, but these generally provided the same rankings of SSCM opportunity as mean values. These results contradict previous findings in the literature regarding the variability of cereals and pulses, suggesting the importance of examining variability within-field instead of using aggregated data and of using an appropriate indicator that recognises both the magnitude and structure of within-field variability. The results also suggest the crop type-dependent nature of variability and that pulses cannot be broadly generalised as having a higher or lower within-field variability than cereals.

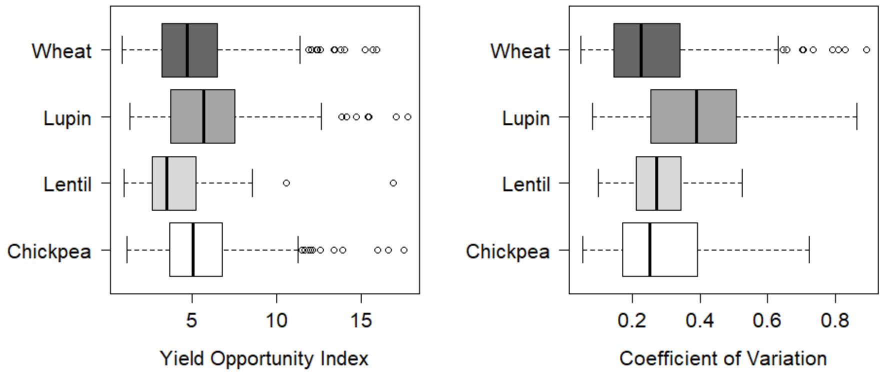

Figure 2. Boxplots of Yi (left) and CV (right) results for all crop types and regions (N = 815).

Cernay et al. (2015) found that lupin was the most variable crop type in three out of four European regions they analysed. A smaller amount of variation was observed for chickpeas and lentils, but both crop types were still significantly more variable than wheat (Cernay et al. 2015), which contrasts with our results. Similar findings were observed in another country-level stud which found that variation in field peas was higher than for wheat (Peltonen-Sainio and Niemi 2012). Neither of these studies used an approach that accounts for both magnitude and spatial structure of variation. These studies have attributed these results to the sensitivity of pulses to abiotic and biotic stresses (Reckling et al. 2018). Given that we did not find increases in variability, this suggests that these stresses either were not consistently greater than the constraints on wheat crops, or that the variability caused by these stresses did not exhibit sufficient spatial structure to lead to a higher SSCM opportunity. The results also indicated noticeable differences between the CV and Yi results. For example, whereas the CV results indicated that wheat was the least variable crop type in the current study, Yi results indicated that lentil was the least variable. This indicates that the CV results, which only consider the magnitude of variation, may have masked the impact of the spatial structure of variation. Relative to the magnitude of variation, the spatial structure of variation appears weaker in lentils compared to wheat, and weaker, but to a lesser extent, in lupins and chickpeas, which validated our initial hypothesis. Reckling et al. (2018) reported similar findings across Northern Europe, where their scale-adjusted CV approach showed a non-significant difference between legumes and cereals in most comparisons, whereas previous approaches have overemphasised the variation apparent in lower-yielding pulse crop types.

Conclusion

This study compared the within-field variability, and subsequent opportunity for site-specific crop management, of key pulse crops compared to wheat. Results were extracted from 815 yield maps across Australian cropping regions. We found that small differences were observed between crop types, but these differences were not as pronounced as in previous studies, which had examined regional and country-level data instead of yield maps. The findings of this study reveal important distinctions between the CV and the Yi results in assessing crop variability. While the CV results highlighted wheat as the least variable crop, the Yi analysis identified lentils as having lower manageable variability. This discrepancy suggests that CV measurements, which focus solely on the magnitude of variation, may overlook critical aspects of the spatial structure of this variation. The results demonstrate that lupins present the greatest opportunity for SSCM, followed by chickpeas, wheat, and finally lentils. The ability of the Yi to rank fields in terms of their manageable variability is a key aspect in guiding growers to implement variable management practices to achieve more sustainable cropping systems and include pulse crops more heavily in rotations.

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