Do pulse crops present a greater opportunity for site-specific crop-management than cereals? A national study

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Abstract.

Site-specific crop management (SSCM), a key component of precision agriculture, optimises resource management by adjusting practices based on within-field yield variability. However, quantifying the within-field variability and the opportunity for managing this variability can be challenging. In the Australian context, growers grow pulses more than cereals. Many studies attribute this to pulses exhibiting greater yield variability than cereals. Nevertheless, this has never been comprehensively studied in Australia, and the indicators used have not accounted for the spatial structure of variation within a field. If pulses are more variable than cereals, growers may see greater benefits following the adoption of SSCM. The Yield Opportunity Index (Yi) is an effective tool for assessing the potential and evaluating the adaptability of SSCM. This study quantified within-field variability and opportunities for SSCM using high-resolution yield maps (n = 815 yield maps) from farms in the Australian cropping belt, analysing data from cereals (wheat) and pulses (chickpeas, lentils, and lupin). Despite the perception of greater variability in pulse crops, the results showed that there was little difference between the variability of pulses and cereals based on Yi results. Future research will focus on implementing significance testing and incorporating an economic component into Yi.

Keywords.
within-field variability management, farming systems, yield maps

Introduction

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. By understanding within-field variability in yield, farmers can develop management zones, which represent areas in a field suspected of having similar constraints to achieving yield potential and can then be differentially managed according to their requirements. This approach potentially maximises crop yields and minimises inputs such as fertilisers, and pesticides, leading to more profitable and sustainable farming practices. According to Whelan (2018), SSCM allows farmers to target high- and low-yielding areas better, allowing for better resource allocation and reducing production costs. Throughout the SSCM process, it is necessary to characterise both spatial and temporal variability because the variable input application's impact on yield potential depends on the extent to which yield patterns are expected to be similar in successive years (Whelan & McBratney, 2000). The primary challenge in implementing SSCM is determining if a crop exhibits sufficient variability, both in terms of magitude and distribution, to justify a shift from traditional uniform management practices (Pringle et al., 2003). Therefore, the correct characterisation of within-field variability, especially given its importance in the SSCM process, is critical to justify the application of variable rate inputs (de Oliveira et al. 2007).

The most valuable source for information is the collection of farmer's yield maps, which provide crucial insights into the potential for adopting SSCM. Consequently, the availability of high-resolution yield maps is promising, as it enhances our understanding of yield variability, facilitating more informed decision-making. Most studies report variability as a measure of the statistical distribution of data, with the standard deviation and coefficient of variation (CV) both commonly used. To date, explicit comparisons of variability in cereals and pulses have mostly focused on yield stability over time and have focused on regional or country averages instead of yield monitor data. Eghball and Power (1995) analysed national yield data provided by the United States Department of Agriculture. They concluded wheat and barley had less year-to-year variation than soybean. Cernay et al. (2015) performed a similar analysis on regional time series data across Europe and the United States. Legumes, particularly lupin and soybean, had greater yield anomalies from their observed trend than cereals, but the authors noted that these results varied regionally. However, a recent study that used a scale-adjusted coefficient of variation found that the stability of legume and grain yields was similar across long-term experiments (Reckling et al. 2018). While these studies provide insight into the behaviour of pulse yields relative to cereals over time, a knowledge gap clearly exists in the literature about comparisons made at the field level and also about spatial variability. These time-series comparisons have been made primarily in Europe and North America, with scarce literature specific to the Australian context.

Compared with cereals and oilseeds, growing of pulse crops, such as chickpea, lentil, and lupin, have been declining considerably in Australian fields for the last twenty years (Maaz et al. 2018). This decline is a cause for concern, as cereals cover approximately 76% of Australian cropland, compared to pulses, which cover approximately 9% (Australian Bureau of Statistics 2022). The underutilisation of pulses could threaten the resilience of broadacre croplands in the future, as the inclusion of legumes in crop rotations offers significant benefits. They can 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). These break crop effects have led to yield increases of up to 25% for the subsequent cereal crops (Xing et al. 2017). With producer profitability under consistent pressure from rising input costs, particularly for macronutrients (McLaughlin et al. 2011), pulses are a critical component of improving soil fertility without causing environmental degradation. Pulses are also viewed as an important non-meat source of protein, which is particularly relevant given increased concern about the impacts of intensive and widespread animal production on the environment and human health (Siddique and Sykes 1997, Cheng et al. 2019, Sha and Xiong 2020). However, for pulses to deliver these benefits at scale and aid a global food transition, they must be grown more widely.

The yield opportunity index (Yi)

Considering three hypothetical fields (Figure 2), which all have the same coefficient of variation but have contrasting spatial structures. The left-most 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 right-most field has a clearer spatial structure, and has a greater opportunity for SSCM as management zones can be clearly delineated. Many attempts have been made to develop an indicator that recognises spatial structure and addresses the drawbacks of the more commonly used distribution-based approaches (Han et al. 1994; Cambardella et al. 1994; Tisseyre and McBratney 2008; Roudier et al. 2011). In this study, a yield opportunity index (Yi) was built upon the Opportunity Index (Pringle et al. 2003) (Equation 1), which developed an approach to assess the relative suitability for SSCM of a sample of fields. The Yi ranks fields based on the structure and magnitude of their spatial variation and, uses the structural components of the variogram model (Jowett 1952; Matheron 1963) as inputs.

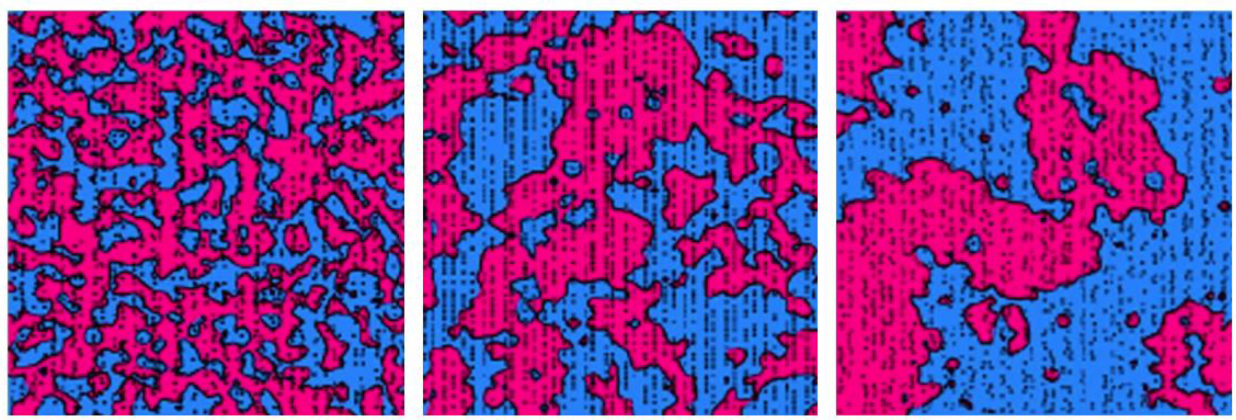

Figure 2. Hypothetical spatial structures of three fields split into a high (blue) and low (red) yielding area. Image sourced from Leroux and Tisseyre (2019).

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

where Mv = magnitude of variation, Sv = spatial structure of variation, CVa = magnitude of autocorrelated (spatially dependent) variation, q50 (CVa) = median magnitude of autocorrelated variation of all fields examined, S = mean maximum correlated distance within the field, s = minimum operable width of available machinery.

The merit of Yi is that it allows a comparison of spatial variability between fields in both space and time. Using the median spatial variation observed in the sample of fields, the index can be used to order fields based on their suitability for SSCM, where fields with higher Y_i values appear more amenable to precision agriculture approaches based on their spatial structure.

Aims

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 located 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.

Methodology

Study area and datasets

This study utilised data from 29 farms, encompassing a total area of 287,000 hectares, and included 815 yield maps collected between 2009 and 2022. These farms are located in the mainland Australian cropping belt (Figure 1). The study area can be segregated into three main regions: Northern, Southern, and Western (Grains Research and Development Corporation 2023). The Northern region encompasses New South Wales and Queensland and receives approximately 500-800mm of annual rainfall (Dang et al. 2010). It is generally more fertile cropland, with clay-heavy soils common, and a diverse range of summer and winter crops are grown in this region (Bramley and Ouzman 2019). The Southern region encompasses Victoria, Tasmania, and South Australia. This region sees approximately 300-700mm annual rainfall (Christy et al. 2019) and is exclusively winter cropping. The Western region covers south-west Western Australia and is the lowest yielding grain growing region (Bramley and Ouzman 2019), largely owing to lighter textured soils and annual rainfall that rarely exceeds 500mm (Christy et al. 2019).

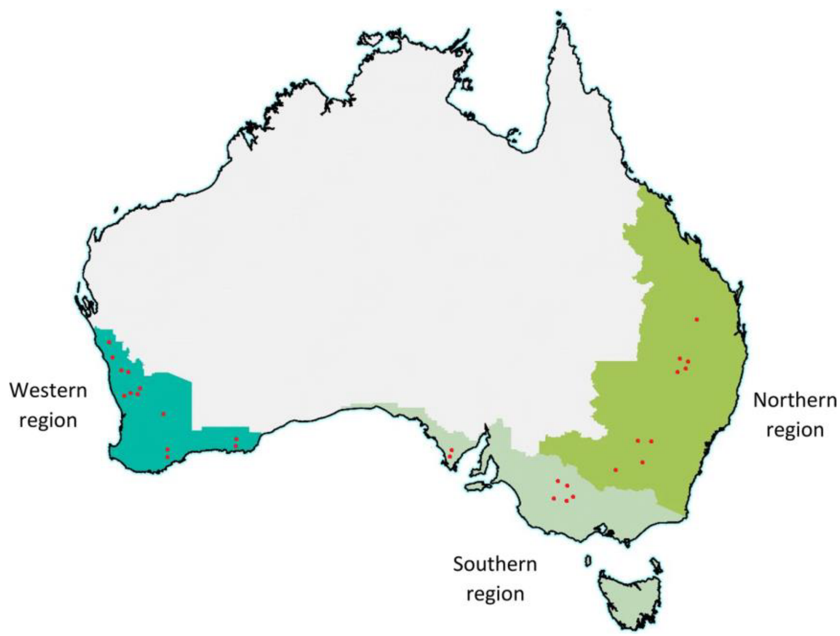

Figure 1. Approximate locations of farms used in the study, marked in red, grouped by Australian grain growing regions. Image sourced from Grains Research and Development Corporation.

Quantifying the within-field variability and SSCM opportunities in cereal and pulse crops

The required inputs for the Yi were extracted after the yield data collection. The experimental variogram 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) (Akaike, 1973). 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 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.

Yield maps were grouped by quartile to classify fields as having low, medium, and high opportunity for SSCM. Using previous literature and research as a guide (Cambardella et al. 1994), fields were grouped into three classes by the 1st and 3rd quartiles in the Y_i 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 2). All crop types had some large outliers, which were typically values greater than 10 (Figure 3). Lupin had the highest mean Yi, 6.13, and lentil had the lowest mean Yi, 4.34 (Figure 3) (Table 2). The mean for chickpea was 5.63 and the median for Wheat was 5.12 (Table 2). Chickpea and lentil had the same mean CV, but had 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 lentil had the lowest Yi (Table 2). Coefficient of variation results showed greater differences between crop types than Yi results (Figure 3).

Table 2. 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)

Across the entire study dataset, pulses and cereals exhibited similar within-field variability as measured by Yi. Lupin was the most variable crop type, with the highest opportunity for SSCM, followed by chickpea, wheat, and then lentil (Figure 3). 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.

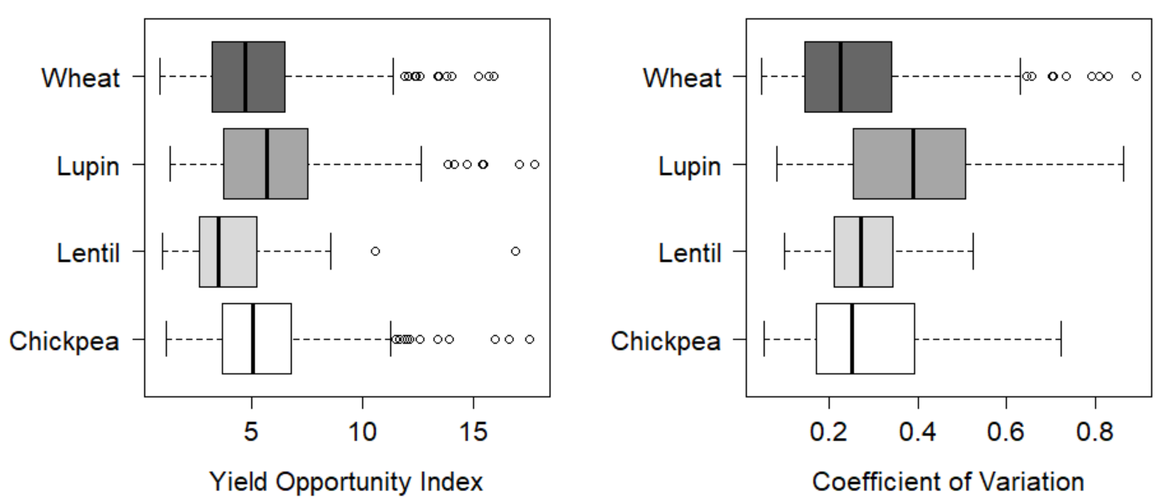

Figure 3. Boxplots of Yi (left) and CV (right) results for all crop types and regions (N = 815).

In their long-term study, Cernay et al. (2015) computed yield trends and then obtained a normalised yield residual for each crop type, finding that lupin was the most variable crop type in three out of the four European regions they analysed. The variance of the trend yield residual was 5–45 times higher for lupin than for wheat. A smaller difference was observed for chickpea and lentil, but both crop types were still significantly more variable than wheat (Cernay et al. 2015). This contrasted to our results, where no definitive differences were found between any of the crop types. Similar findings were observed in another country-level study, which found that, standardised for area, variation in field peas was higher than for wheat (Peltonen-Sainio and Niemi 2012). These studies have attributed these results to the sensitivity of chickpea and lupin to abiotic and biotic stresses (Maqbool et al. 2010; Araujo et al. 2015; Reckling et al. 2018). For example, lupin is less capable of dynamic stomatal control in response to changing environmental conditions than wheat (French and Buirchell 2005). This results in greater photosynthetic activity when the plant is not under water stress, but leaf senescence occurs earlier because wheat can more effectively reduce its transpiration rate to conserve tissue water potential in water stress. These physiological differences are believed to be because of the sensitivity of biological nitrogen fixation to such stress (Aranjuelo et al. 2014). Given the findings in this paper did not find increases in variability, it 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.

These explanations are also problematic for several reasons. They assume that crops are stressed to the same extent in each season, which is especially untrue in the Australian context, which sees large annual variation in the growing conditions for rainfed crops (Shen and Evans 2021). The other reason is that the effects of different crop stresses differ locally. For example, temperature stress above 30°C has been found to threaten wheat across all of the growing regions in Australia, whereas the effects are more localised for chickpea (Dreccer et al. 2018).

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, 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 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 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 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 further demonstrate that the spatial structure of variation in lentils is less pronounced compared to wheat and shows a comparatively weaker pattern in lupins and chickpeas. This suggests that assessments of crop variability could benefit from incorporating measures that consider both the magnitude and the spatial structure of variation to provide a more accurate and nuanced understanding of crop performance across different types.

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