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Precision N rates for dryland farming?

Financial analysis of variable-rate Nitrogen (VRN) in the Riverine Plains Region

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Abstract

Collaboration with members of the Riverine Plains Inc. group of farms, near Yarrawonga and Dookie, Victoria in south-eastern Australia, allowed estimates of the financial costs and benefits of precision Site-Specific Nitrogen Applications (also called Variable Rate Nitrogen ,VRN).

Geo-referenced wheat, barley and canola crop yields were matched with growing season rainfalls (GSR) and EM38 survey maps (indicating water-holding and cation exchange capacity), to compare their values for calibrating N application rates given the high spatial and temporal variabilities of productivity in the paddocks sampled.

Tracing the yield-rankings of 90x90m geo-referenced grid areas across several years showed fewer than 5% of grid areas remained in the same yield quartile in four out of five years. EM38 data were positively correlated with grain yield only in years of low to medium GSR. A N-rate trial on high and low EM38 patches on each of two farms produced mixed results in 2017. NDVI (greenness indications) appeared to give better results.

Farm financial risk profiles were determined by simulating long-term effects of VRN on the equity of hypothetical farms. These profiles showed that the costs of VRN would be met by less than one percent increase in yields, or by at least a 70% decrease in applied N. Beginning with no debt and assuming no further benefits of VRN, a low-cost farm showed no risk of loss over random decades drawn from the past 56 years of weather records while a high-cost farm faced risk of loss of 41%, increasing to 44% with the additional costs of VRN.

1. INTRODUCTION

> *... preliminary Site-Specific Nitrogen Application (SSNA) recommendations developed to date have not been held to the same reliability standard as the current regional, whole-field N recommendations diffused by agricultural extension services.* — Liu, Swinton & Miller (2006, p 472). 'Is site-specific yield response consistent over time? Does it pay?' *American Journal of Agricultural Economics*
>
> *Crucial ... to scientifically validating the concept of site-specific crop management is the proposal and testing of the null hypothesis of precision agriculture, i.e. ''Given the large temporal variation evident in crop yield relative to the scale of a single field, then the optimal risk aversion strategy is uniform management.''* — Whelan & McBratney (2000, p 265), 'The null hypothesis of precision agriculture management.' *Precision Agriculture*
>
> *The economics of Precision Agriculture (PA) should be considered in a whole-farm context, just as all other aspects of farm investment. In PA, the analysis of investment outcomes is often confined to* ***a gross margin calculation**** *because it is simple. This approach certainly provides information to support decisions, but it doesn't encompass the broader notion of whole-farm economics.* —Whelan & Taylor (2013, p 175). *Precision Agriculture for Grain Production Systems*, CSIRO Publishing
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> ***bold** words are substituted above for the original**:** "a financial balance sheet" because we need to use the latter term in a very different sense.

The aim of the present paper is to take the economic and financial analysis of precision variable-rate N application a step further by including whole-farm risk analysis to account for temporal variations in weather and prices, as well as spatial variations in farm soils while considering all costs including the cumulative effects of interest over time. Examples of these factors and their analyses were developed in a study done in collaboration with farmers and staff of Riverine Plains Inc. (RPI), in the northern Victoria region around Yarrawonga (36.03° S, 146.03° E) and Dookie (36.37° S, 145.70° E) in south-eastern Australia. We consider the long-term growing season rainfall (**GSR**) histories of both locations from 1880 through 2017 (**Figure 1**).

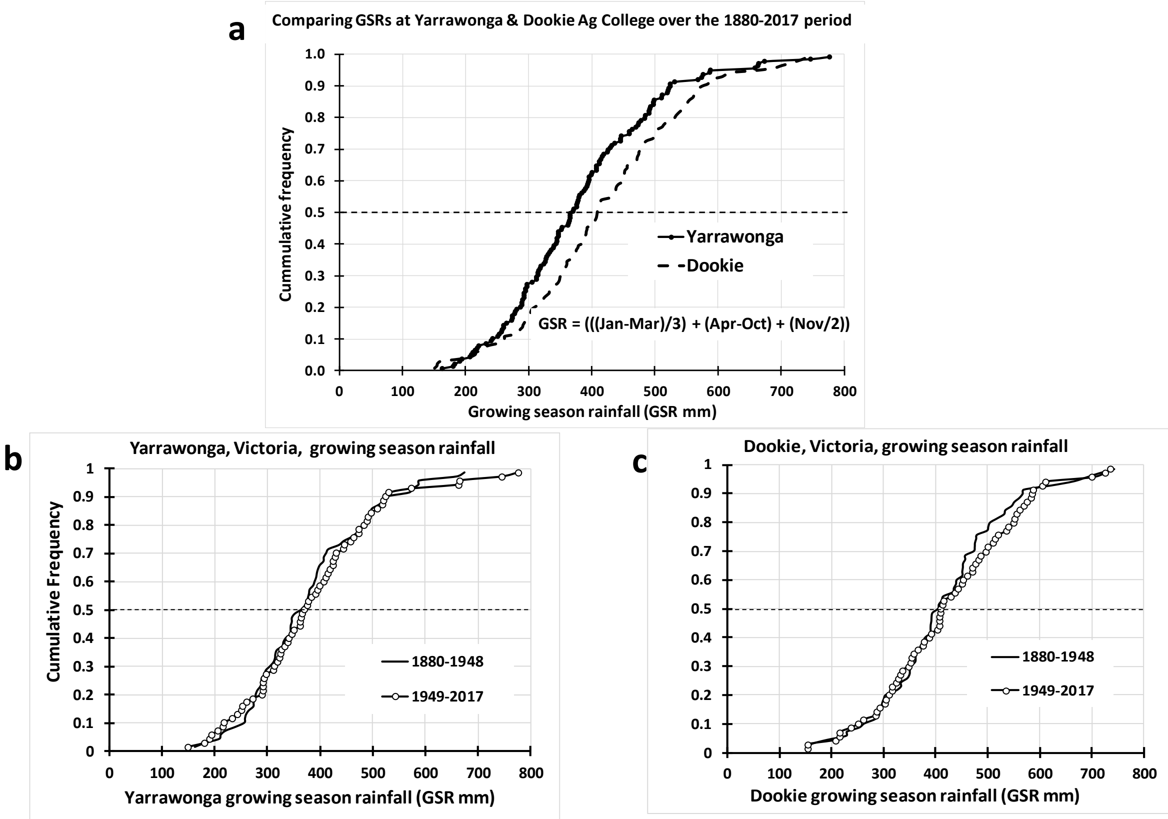


Figure 1. Growing season rainfall (GSR) distributions from 1880 through 2017 for (**a**) Yarrawonga and Dookie based on Bureau of Meteorology monthly rainfall records. Comparisons of the first and second halves of the long-run GSR records for (**b**) Yarrawonga and (**c**) Dookie Agricultural College.

Many studies and extension publications have focused on adjusting best N-fertilizer rates for whole paddocks year by year in response to seasonal changes in rainfall conditions (Nordblom *et al.* 1985). A pair of objections may be raised to these approaches in the case of optimizing N applications**:**

(1) Conditions for yield responses can never be fully anticipated *ex ante*, at the time of application-decisions, but only in retrospect (*ex post*) when the final rainfall and other growing conditions have had their effects, and

(2) Soil conditions are often highly variable within a paddock (particularly, large ones) with respect to relief, soil classes, EM38, waterlogging, acidity, and other factors, such that different parts of the paddock may be expected to respond differently to different growing season rainfalls (GSR), frosts, etc.

The question then remains, can the paddock be divided into zones allowing for more site-specific management over time to increase the whole-paddock profitability compared with treating the entire paddock uniformly?

This paper aims to take the two given sources of risk above into account to answer this question using whole-farm, long-term financial analysis. The first source of risk (unknown final weather conditions affecting yield responses) is incorporated in the financial model which is based on long run local weather records. Dealing with the second source of risk will depend on the satisfactory definition or classification of within-paddock variability. This analysis shows examples of different yield responses to growing season rainfall associated with the different soil magnetic conductivity (EM38) levels identified across paddocks. This was only possible because we had access to several years of detailed yield maps and monthly rainfall data for the same periods as well as detailed EM38 maps of the paddocks (Schefe, Riverine Plains Inc. 2018).

In precision variable-rate nitrogen applications (VRN), the idea is to optimise placement of inputs at the right rates; neither too little nor too much in each target area according to selected criteria at the right time for known and expected conditions. This analysis is based on information on N applications and yields from results of trials in 2017 by Riverine Plains Inc, (Schefe, 2018). The trials were in two farmers' fields, replicating treatments in zones of high and low EM38 readings, associated with water-holding and cation exchange capacity in each field.

Financial risk profiles were then developed for two hypothetical farms, one with low costs and one with high costs, covering the range of farming situations found in the region. Repeated simulation runs with random decades of historical growing season rainfalls (1965-2015) and randomised commodity prices (2010-2015) at the Port of Geelong, were carried out assuming each farm started each iteration with no debt.

In **Section 2** of this paper we review relevant literature on our subject. **Section 3** focusses on methods and measures we use for whole-farm crop yield simulations and within-paddock variability. **Section 4** presents our results on three measures for calibrating VRN: (a) EM38, (b) historical average yields and (c) NDVI. **Section 5** discusses our assessments of farm financial risks attending the adoption of VRN on the two hypothetical farms mentioned above. **Section 6** offers discussion drawing together meanings of the results. **Section 7** concludes the present study cannot reject the null hypothesis that VRN is no more profitable than uniform applications. Ideas and questions for follow-up research are posed.

2. LITERATURE REVIEW

Precision agriculture (PA) today means combining global positioning systems (GPS) and geographic information systems (GIS) for planning, execution and detailed recording of farm operations. Variable-rate-capable equipment is available for integration with satellite-guided auto-steering allowing the widespread adoption of practices such as tramlining and yield-mapping. Comprehensive early accounts of PA technicalities in Australia (GRDC 2006), in the UK (Knight *et al*. 2009; Redman 2016), Canada (Liu *et al*. 2006) and the USA (Lowenberg-DeBoer 2003) are complemented by the accessible CSIRO volume by Whelan and Taylor (2013). These studies foreshadow the need for whole farm financial analysis but do not attempt it, as shown in the following three extracts from the literature. The acronyms VR and VRA, below, refer to site-specific variable rate applications of fertiliser, which we will call VRN.

Lowenberg-DeBoer (2003, p 3) reported: *"In Western Europe VRA seems to be driven mainly by environmental concern and regulation, in particular the limits on use of nitrogen to a total amount per farm. Given that limit some producers are using VRA to make sure the limited quantity of nitrogen goes to the places where yield response is the greatest. In Sweden for example there are 24 custom operators applying VRA nitrogen using the Norsk Hydro greenness sensor.*"

Lowenberg-DeBoer (2003, p 4) noted that: *"partial budgets on VR fertilizer application usually focus on three elements: increased cost of soil sampling information and VR application, the change in cost of fertilizer applied, and the change in revenue due to crop yield. The added information cost is central, yet it is omitted from some studies."*

Lowenberg-DeBoer (2003, p 4) further cited Swinton & Lowenberg-DeBoer's (1998) examination of the profitability-results from nine university field research studies*: "High value crops that responded to VRA of fertilizer tended to do so more profitably than low-value crops, because the yield gains were worth more. VRA of fertilizer on wheat and barley was nowhere profitable, the results for corn were mixed, and VRA fertilizer on sugarbeet was profitable. By contrast, cost savings from reduced fertilizer application were much less important. The fertilizer inputs being managed are fairly low cost and only one study managed more than two of them."*

Environmental concerns over excessive use of N fertilisers are expressed well in reasoning based on social optimality where intensive agriculture intersects with ecologically sensitive land, water and atmospheric resources on which dense human populations depend for health and amenity services. A recent Canadian article by Gourevitch, Keeler & Ricketts (2018) aims to find balances among N management options for net private returns from crop yields against the sum of nine categories of social damage. These are in the form of widespread public exposure to nitrates leached into groundwater, population exposure to air pollution in the form of small particulate matter (PM_{25}) formed from ammonia and nitrous oxide, and climate change mitigation by otherwise avoiding releases of nitrous oxide. The quotation of Lowenberg-DeBoer (2003, p 3) above shows how Western European farmers use site-specific VRN to make efficient use of their reduced allowances of N, which better suit their neighbours.

Smaller paddock areas have often been defined (and fenced) in order to maintain uniform soil conditions and the expectation of uniform responses to inputs. Combined in a larger paddock, such smaller paddock areas might be called ‘zones’ for site-specific targeting of inputs. In place of fences, old boundaries may now be defined in the larger paddock’s GPS map and N-rates altered accordingly during application.

Controlled Traffic Farming or tramlining enables accurately keeping all field equipment wheel-tracks together over the same lines across the ground (such as for inter-row sowing, spreading of fertilisers and soil amendments, shielded-spraying, harvesting, grain carting, etc.) to minimise soil compaction and traffic, prevent overlap or gaps in treatments, and to standardise detailed yield-mapping (Chamen 2015; Kingwell and Fuchsbichler 2011; Robertson *et al*. 2007a). Controlled traffic farming can reduce operator fatigue in addition to the benefits mentioned above.

Monjardino *et al*. (2013) studied the economic issue of apparent underuse of N fertilizer in the low rainfall Mallee region of south-eastern Australia, showing the benefits from different rates for parts of the paddock occupied by dunes, slopes and flats, each of which have different response characteristics. Monjardino *et al*. (2015) studied N management options showing the extent to which the economics of N fertiliser decisions and the farmers’ attitudes to risk can determine N rates in ways that limit closure of apparent yield gaps in the southern Australian wheat belt. Taking a longer-term view that N-rate recommendations based on the average year can lead to early “haying off” and crop failure in a drought year, Robertson, Carberry & Brennan (2009, p801) provide a hypothetical example where increasing a uniform application (from 50 to 70 kg/ha) results in better yield from a high yield-potential zone but 5% lower yield from a low yield potential zone.

Others have reported use of higher-than recommended N rates for corn in high-rainfall Ontario, Canada (Rajsic & Weersink 2008; Rajsic *et al*. 2009). This was shown to make sense if farmers are taking a longer-term, risk-avoiding-view; applying more N than indicated for average conditions because their costs of doing so are low compared to the large yields loss they would suffer with under-application in good years. Rajsic *et al.* (2009, p 233) "*confirm the anecdotal response by farmers who claim they cannot see any losses in the field from applying too much fertilizer but can definitely tell the areas that did not receive enough*."

Extension service recommendations on "optimal" application rates generally consider prices and yield potentials based on deterministic, average conditions so that incorporating locally-known risks (or opportunities) may improve the returns to producers (Rajsic *et al*. 2009, p 223).

Pannell's (2006) '*Flat-Earth Economics'* paper emphasizes the point that yield responses may vary little in a given season over a range of input levels, such that a farmer may expect to capture a majority of the benefits of a calculated economically optimal N application by choosing a lower-than-optimal N rate. The fact that response curves are often quite flat in the vicinity of their maximum values has been known for decades (Jardine 1975a, 1975b; Anderson 1975a; CIMMYT 1988, pp 7, 28 and 52). To be fair, at the time of those writings, no farmer in the world had access to reliable GPS-guided precision equipment. But the advent and perfection of such equipment today has not changed the fact that response curves remain as flat as ever.

Pannell *et al*. (2018, p 2) restate the implication that "*The flatter the curve, and the wider the input range over which it is flat, the lower the benefit from adjusting input rates spatially in response to local conditions*." The same authors show how others (Rogers *et al*. 2016) have contributed to understanding that the degree of within-paddock variability in soil conditions for which response curves are known to differ can be used to determine the expected benefit of site-specific optimal N applications compared to a uniform application.

Specifically, Pannell *et al*. (2018, p 2) suggest adopting "*a strategy of measuring the degree of flatness of payoff curves … to identify situations where the benefits of site-specific crop management are most likely to be high. Information about flatness may contribute to decisions by farmers about their investment in precision technologies, may assist precision-technology researchers to target their efforts to the most promising contexts (e.g. regions, crops or soil types), or may assist technology sellers to target their sales activities to contexts where they are most likely to succeed*."

If the quantitative payoff curves are known and can be weighted by their proportions of the total area of a paddock (ie, 25% low yielding, 50% medium yields and 25% high yielding) then it should be possible to (a) calculate the highest-payoff uniform N rate across all areas, and (b) the highest payoff rates for each of the distinct areas separately. Where the sum of the separate net payoffs in (b) is greater than the net payoffs from the best uniform rate (a) the site-specific rates may be preferred. Pannell *et al*. (2018) demonstrate this will only occur in the most heterogeneous paddocks, which exhibit high variances in response.

Pannell *et al*. (2018) suggest a metric based on the standard deviation of the slopes of site-specific payoff-functions at the optimal **uniform** input rate (SDS). The weighted sum of calculated site-specific maximum payoffs minus the weighted sum of net payoffs at the best uniform rate is a measure of the **net benefit of site-specific applications**. The **relative benefit** of site-specific applications for a paddock is the latter term divided by the weighted sum of net payoffs at the best uniform rate. Across a wide range of hypothetical flat to highly variable example sets of net payoff functions, Pannell *et al*. (2018) illustrate high correlations between their **SDS** criteria and the **relative benefits** of site-specific applications (r = 0.93).

The preceding three paragraphs presume a high level of certainty that the representative payoff functions can be known or predicted with confidence on the day of decision. Of course, under rainfed farming conditions the actual response functions must be expected to shift significantly from season to season (and within seasons). In the 'Methods' section, which follows, we demonstrate that wheat and canola yields in our study area are strongly influenced by growing season rainfall, rising to peaks from low to mid-range GSR, and declining with higher GSR. Associated with each GSR level will be new yield responses to N. In low-rainfall seasons the response can be negative; with added N 'burning off' or 'haying off' the crop. In high-rainfall seasons waterlogging may also reduce the result of an N application.

At the time of sowing, expected responses may differ greatly from those that eventuate as the season progresses. Good rainfalls received by mid-season may be considered to almost guarantee a crop and to justify a follow-up N application. Dry conditions through mid-season may be considered justification for avoiding further N applications. This paper shows that such shifts may not always be uniformly expressed in all parts of heterogeneous paddocks, particularly between low and high rainfall years. One should also expect years with the same GSRs, but different rainfall sequences that produce different outcomes (Kingwell 1994).

Within-paddock management of variations in growth and yield prospects over time is treated by Robertson, Carberry & Brennan (2007a) in Western Australia and by Robertson, Carberry & Brennan (2009) on farms in six case studies across the Australian grain belt. Calculated on a gross-margin basis and averaged over several years these results indicate financial benefits due to the adoption of VRN in most cases.

On the topic of flat response functions, Anderson (1975a, p 195) commented: "*There are many implications of such insensitivity but amongst the most important is the recognition that in pursuing and discussing optimal levels of decision variables, precision is pretense and great accuracy is absurdity*"

This statement from four decades in the past may seem unfairly disparaging given the fact that precision placement of planned rates of N is today routinely achievable with PA navigation and application technologies. However, the inescapable fact remains that rainfed yield responses to N must remain uncertain on the day of application because they depend on ephemeral, poorly predictable, future local weather conditions up to the day of harvest.

The best weather forecasts today for the next 24 hours or weeks and months ahead, must be expressed in probabilistic terms. For the same reason (uncertainty in local weather, further compounded with uncertain international commodity prices), whole-farm financial assessments of site-specific N application must also be expressed in probabilistic terms (Anderson 1975b; Gandorfer, Pannell & Meyer-Aurich, 2011).

Knight & Malcolm (2006, p 41) calculated distributions of gross margins across eight years for a farm in the Victorian Mallee region to analyse the profitability of simulated Site-Specific Crop Management (SSCM) technology and Zone Management for 'fine tuning' applications of nitrogen to rainfed wheat and barley crops. The expected benefits from eliminating gaps and overlaps with satellite-guided steering for sowing and other operations were sufficient to cover the costs of the new SSCM equipment. However, they found the yield differences between zones on their subject farm were too small to justify the extra investments needed for VRN.

Similarly, the likely gains from VRN were insufficient to cover the increased costs of sampling, data analysis, and variable-rate application in Michigan (USA) corn crops (Liu *et al*. 2006, p 481); likewise for corn in Ontario, Canada (Rajsic *et al*. 2009, p 233), and for potato-corn-wheat rotations in Bavaria, Germany (Gandorfer, Pannell & Meyer-Aurich, 2011).

Agricultural economists have long considered Net Present Values of different investment options (the sum of the discounted stream of future benefits and costs at given interest rates) as viewed by a risk averse farmer. Pannell, Malcolm & Kingwell (2000) have most effectively challenged the value of computing risk aversion indices.

Farm financial analysts and banks, on the other hand, view risks in existential terms of likelihood of profitability or insolvency of a farm business over time (Hutchings, 2013); this is the path taken in the present study. Other examples of such financial analyses are given in Nordblom *et al.* (2017 and 2018). Gross margin analyses are not part of a risk analysis, but are provided here only for the single-year analysis of the 2017 RPI field trials.

3. METHODS FOR WHOLE-FARM CROP YIELD SIMULATION

3.1 Whole farm crop yield simulation

Raw geo-referenced header records of crop yields were provided by two co-operating farmers. In one case records were from as early as 2000, and from

2010 in the other case, both for numerous paddocks. Geo-referenced wheat yield (harvester records) from multiple paddocks in each of 19 crop years were provided between the two farms. Canola yield records for 13 years were also provided. There were no continuous wheat or canola records over time because of best-practice use of rotations including barley and, rarely, faba bean, triticale and lentil. Gaps were found in any given paddock's sequence due to drought periods (particularly in the decade from 2001), frosts or other reasons.

Annual growing season rainfalls (GSR) were calculated using the following formula (French-Schultz, 1984) and Bureau of Meteorology monthly rainfall records for Yarrawonga and Dookie Ag College, Victoria, over the 1880-2017 period (**Figure 1**):

$$\textbf{GSR}\text{ mm} = (((\text{Jan to Mar})/3) + (\text{Apr to Oct}) + (\text{Nov}/2)) \qquad \textbf{(1)}$$

Detailed analysis showed that the inclusion of half the November rainfall more accurately predicted crop yield in this area, probably due to the long growing season. Second-degree polynomial (quadratic) functions were fitted to show the relationship between **GSR** and mean yields from all wheat and canola paddocks on a farm in a year from the cooperating farms at Yarrawonga and Dookie. These response curves explained 76% of the variation in wheat yields over 19 years, with GSRs spanning 190 to 550mm. Over a similar span of GSRs, 84% of canola yield variation was explained over 13 years. French-Schultz (1984) limit lines were plotted without contradicting the fitted curves, up to maximum yields at approximately 400mm GSR. The presence of upper limits on yield due to water-logging at high GSR is suggested for both wheat and canola crops in these districts (**Figure 2**).

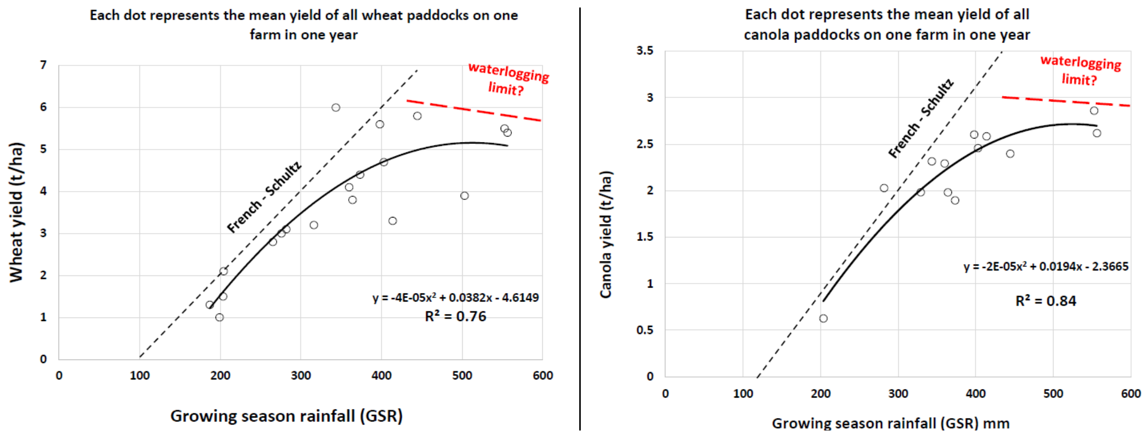


Figure 2. Wheat and canola yield responses to growing season rainfall in the Riverine Plains, Victoria.

3.2 Within-paddock variability

Finding a single paddock with enough years of canola or wheat records to complete a similar set of regressions for within-paddock yields as functions of GSR was challenging, even with the great number of records provided by the cooperating farmers. Two paddocks with enough years of detailed crop yield data were selected for our illustration of within-paddock yield variations associated with GSR (**Figure 3**).

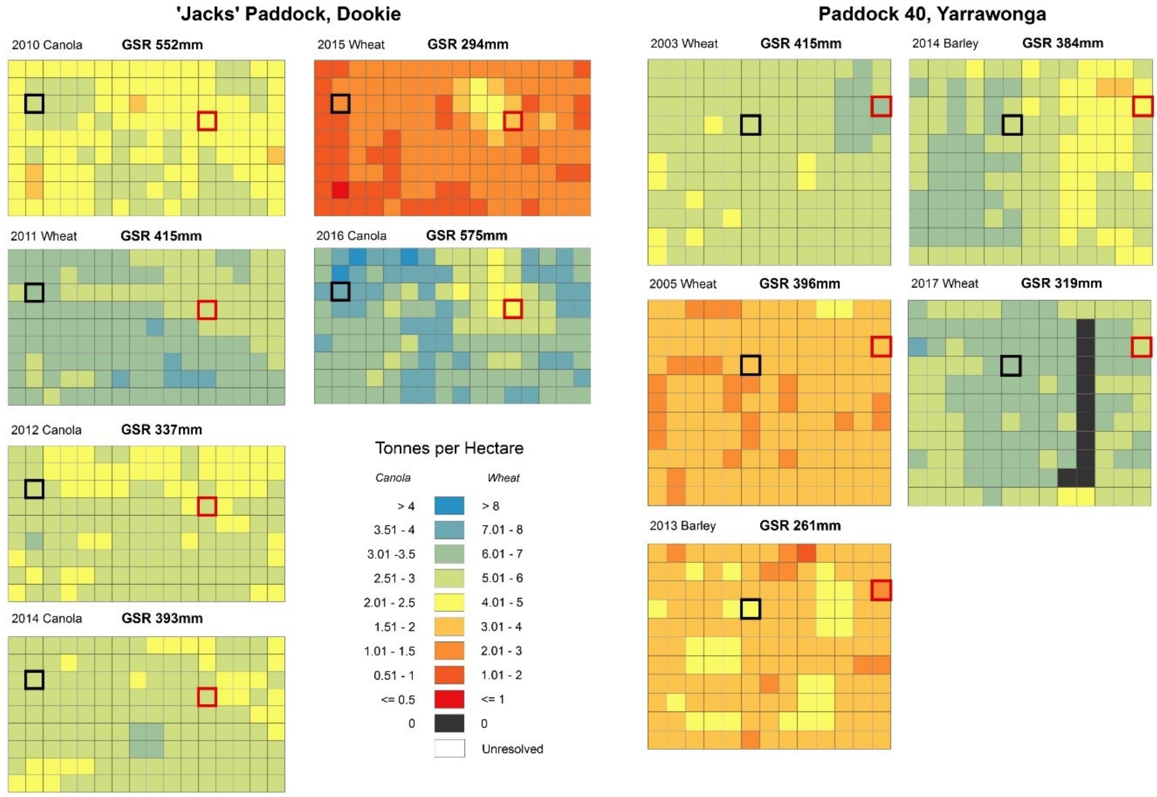


Figure 3. Header yield estimates (t/ha) over six cropping seasons on two Riverine Plains farms. Simulation analyses based on this data are given for 'Jacks' paddock, Dookie, in Figure 4; and Paddock 40, Yarrawonga, in Figure 5. Notice two grid area positions marked in the 'data' maps of each of the two paddocks in the present figure also locate these grid areas in the simulation results.

We estimated grid-area **canola yields** as a function of GSR in one paddock ('Jacks' near Dookie) by combining the detailed georeferenced records of four years of canola yields and two years of wheat, dividing the wheat yields by 1.9, which is the approximate ratio of the wheat yield curve to the canola yield curve across GSRs as mentioned above (Figure 2).

A second paddock ('40' near Yarrawonga) offered detailed records of three years of **wheat yields** and two years of barley. We assumed barley grid-area yields could serve as proxies for wheat; French-Schultz (1984) had assumed similar WUE for barley 21 kg/mm and wheat at 20kg/mm. With the help of CSU's Spatial Data Analysis Network (SPAN), the geo-referenced yield records for the two paddocks mentioned above were summarised in grid areas of 90x90m (0.81 ha) each of which was given a grid address (ie, D6 for row D and column 6 in paddock 40), see Figure 3. These grid areas were considered large enough to act as the focus for VRN applications. Smaller grid areas were considered but increased the complexity of VRN applications, because of the lag in the time taken to adjust the fertiliser rates during application.

The GSR/crop-year specific yield data for each grid area provided the basis for our analysis of **repeatability** of annual yield rankings in quartile bands. The Dookie (canola) and Yarrawonga (wheat) paddocks each cover about 115 ha; thus, each could be mapped as 144 grid areas (see **Figures 4** and **5** respectively).

Quadratic regression analyses were conducted to relate each individual grid-area's yields over the crop years of record to the GSRs in those years, ignoring grid areas with missing data.

$$y = ((\mathbf{a} \times GSR^2) + (\mathbf{b} \times GSR) + \mathbf{c}) \qquad \textbf{(2)}$$

The resulting grid area equations were evaluated individually across ranges of GSRs to illustrate the great variability in water-use efficiency (N response curves) within each paddock.

Readers will notice two particular grid area positions marked in the map of estimated **canola** yields for **each crop year of record** in Jacks paddock (Figure 3). The same two grid areas are marked in the **simulated maps** of yield responses in that paddock (Figure 4) for a rising sequence of GSRs. These were calculated with regression results from equation **2** for each grid area in the map. Notice the thumb-nail chart in the bottom right corner of Figure 4. The dark black curve represents the paddock's expected (average) canola yields at each GSR level. The two other curves represent estimated yield curves of the two marked grid areas in Jacks paddock (Figure 4) selected to illustrate the contrasts in yield performance. A similar sequence of measured and simulated **wheat** yields in paddock 40 is found in Figures 3 and 5, again with marked grid areas chosen to illustrate their contrasts with paddock average performance.

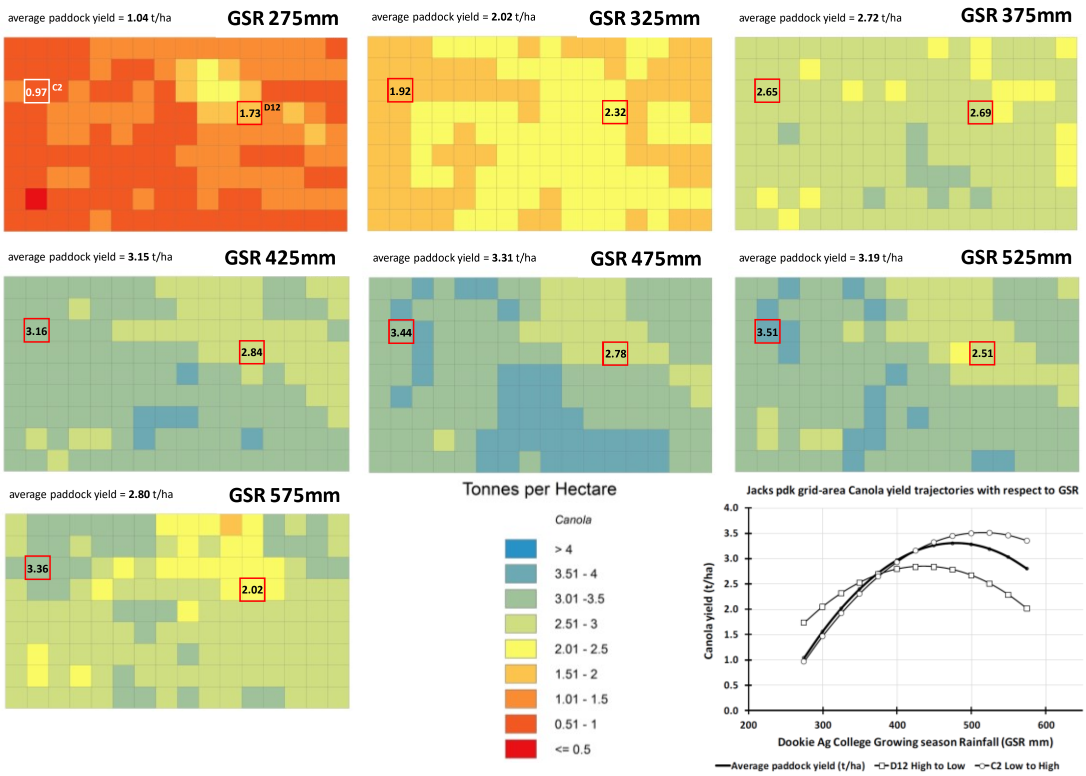


Figure 4. Simulated canola yields for 'Jacks' paddock, Dookie, 275-575 mm GSR, based on grid by grid analysis of yields and GSRs for the six years shown for 'Jacks' paddock in Figure 3.

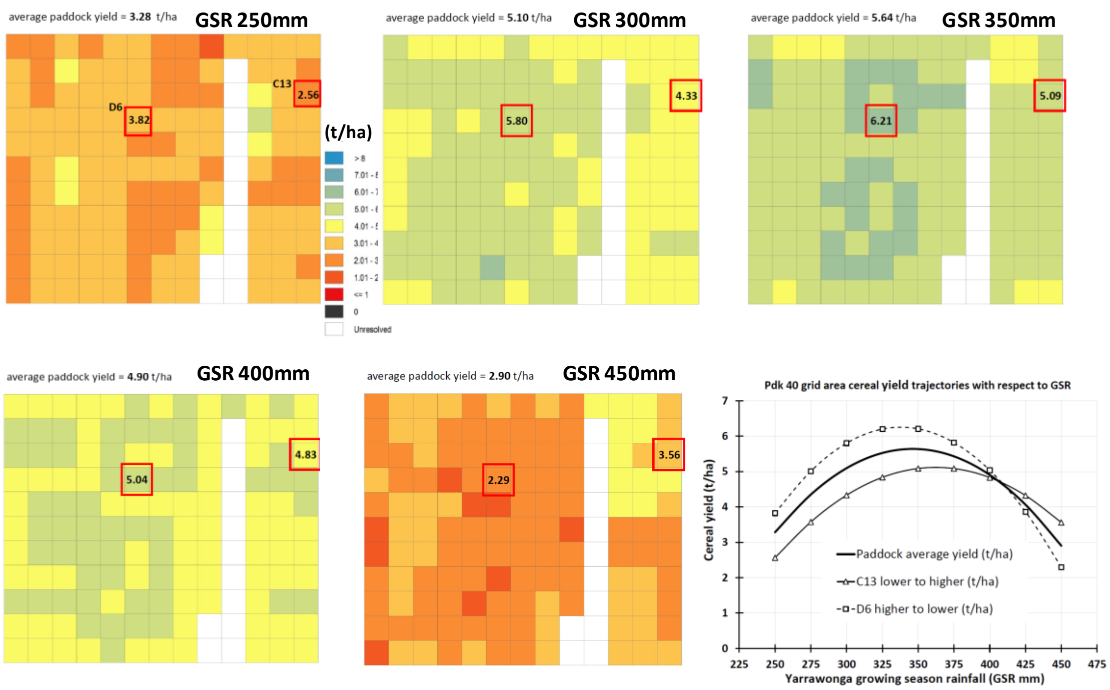


Figure 5. Simulated cereal yields, Paddock 40, Yarrawonga, 250-450mm GSR, based on grid by grid analysis of yields and GSRs for the five years shown for Yarrawonga in Figure 3.

The within-paddock differences in yield responses to GSR may be due to:

1. Variation in soil types, with the soils in some locations being better drained than others.
2. Variation in topography, with runoff accumulating at some sites. This concentration of moisture would result in different response curves to GSR, which is a whole-paddock measurement.

A result of these differing response curves would be that the yield at many sites would respond differently to GSR, which would contribute to the low repeatability of yields between years noted elsewhere in this paper.

4. RESULTS FOR THREE MEASURES OF CALIBRATING VRN

Commonly-used benchmarks for calibrating VRN applications include electro-magnetic conductivity (EM38) measurements, long-term average yields and current NDVI measurements. The accuracy of each of these benchmarks was analysed separately:

4.1 EM38 and yield

Data for Paddock **R1** included detailed EM38 survey records as well as detailed crop yields for the previous four years (**Figure 6**). This presented an opportunity to examine correlations of estimated quadratic (simulated) yield curves (from equation 2) with EM38 data across a rising sequence of GSRs (**Figure 7**) on the same 90x90m grid areas as the maps of crop yield records. The scattered pattern of empty grid areas in Figure 7 had estimated yield functions convex to the GSR axis (ie, lower yields at mid-range GSRs than at the lowest and highest GSRs) and were ignored in the analysis.

Given observed EM38 data for the remaining grid areas in paddock R1, we calculated correlations with the means of the estimated individual simulated yield curves. As a cross-check, within-paddock correlations of actual crop yield and EM38 level were calculated for each GSR level observed in 2011, 2012, 2014 and 2017. These roughly matched the smoothed (simulated) average response curve over the range of GSRs (**Figure 8**).

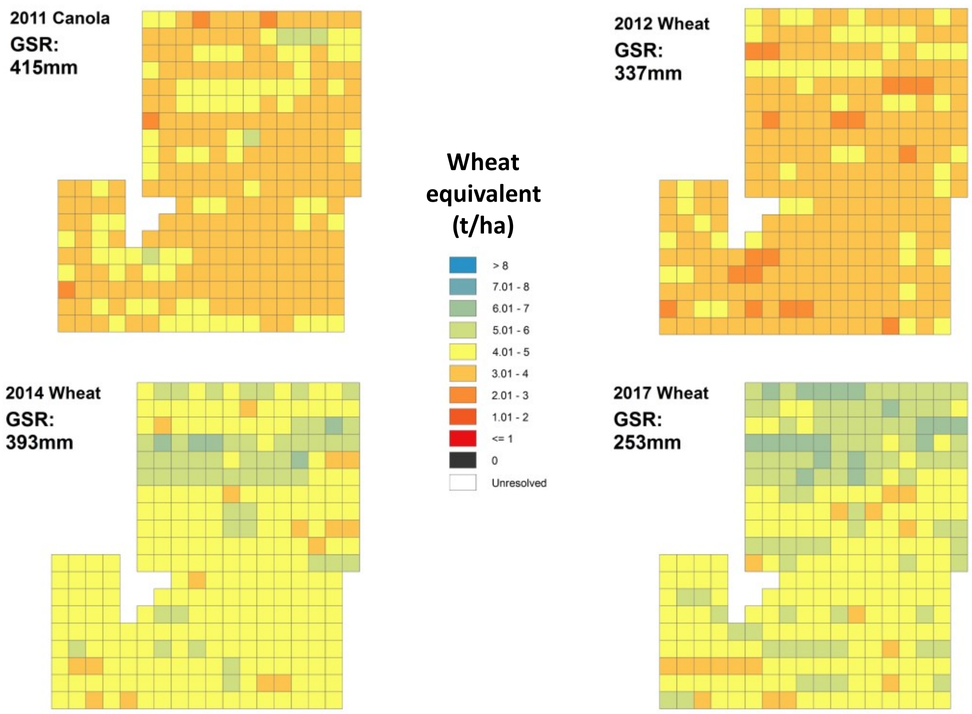


Figure 6. Crop yields in four years, paddock R1, near Dookie. Grid area by grid area analysis of yields associated with GSRs in these four years allowed simulating yields for a range of GSRs (See Figure 7).

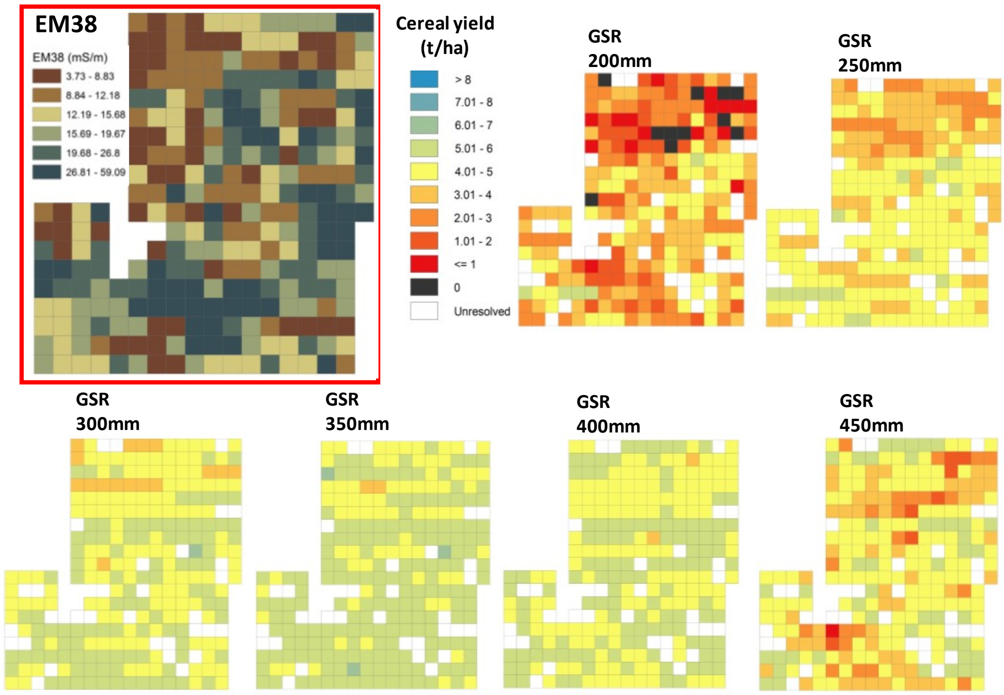
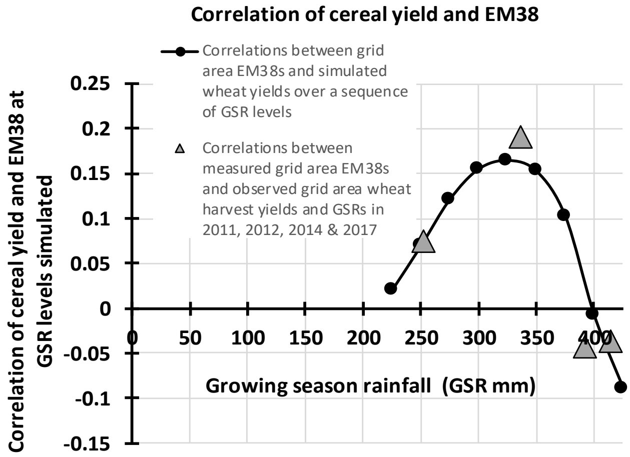


Figure 7. EM38 analysis of paddock R1 (Dookie) and simulated cereal yields at 200-450mm GSR based on analysis of measured cereal yields and GSRs in four earlier years (see Figure 6).



GSR	Correlations between grid area EM38s and simulated wheat yields over a sequence of GSR levels
225	0.019834
250	0.069292
275	0.121349
300	0.155403
325	0.165055
350	0.153059
375	0.102523
400	-0.00799
425	-0.08878

GSR	Correlations between measured grid area EM38s and observed grid area wheat harvest yields and GSRs in 2011, 2012, 2014 & 2017	
253	**0.074152**	correlation of **Wheat 2017** yield and EM38
337	**0.191367**	correlation of **Wheat 2012** yield and EM38
393	**-0.04266**	correlation of **wheat 2014** yield and EM38
415	**-0.03669**	correlation of **Canola 2011** yields and EM38

Figure 8. Correlations of EM38 to cereal yields over a range of GSRs in paddock **R1**, Dookie. Notice, the correlations are most positive in the middle rainfall range, but turn negative under higher rainfalls.

Our observations in (Dookie) Paddock R1 of positive correlation of crop yield and EM38 at low to medium GSR levels and negative correlations at high GSR levels were repeated on the Yarrawonga farm. This was done using limited EM38 measurements with wheat yield data from paddock 40 given four seasons with different GSR levels (**Figure 9**).

Negative correlations of yield and EM38 measures, within a separate single paddock east of Yarrawonga in a single high-rainfall season (2016 with Yarrawonga's GSR = 665mm), were observed in data from a third cooperating farmer. Aggregated to 90x90m grid areas, the within-paddock correlations of wheat yields and EM38 levels were found to be negative (**r = -0.409, Figure 10**) as yields declined with EM38 readings ranging from low to high; perhaps due to waterlogging. The degree of scatter of grid area data points in Figure 10 is indicative of the scatters that would be found around the summary points and curves in Figures 8 and 9.

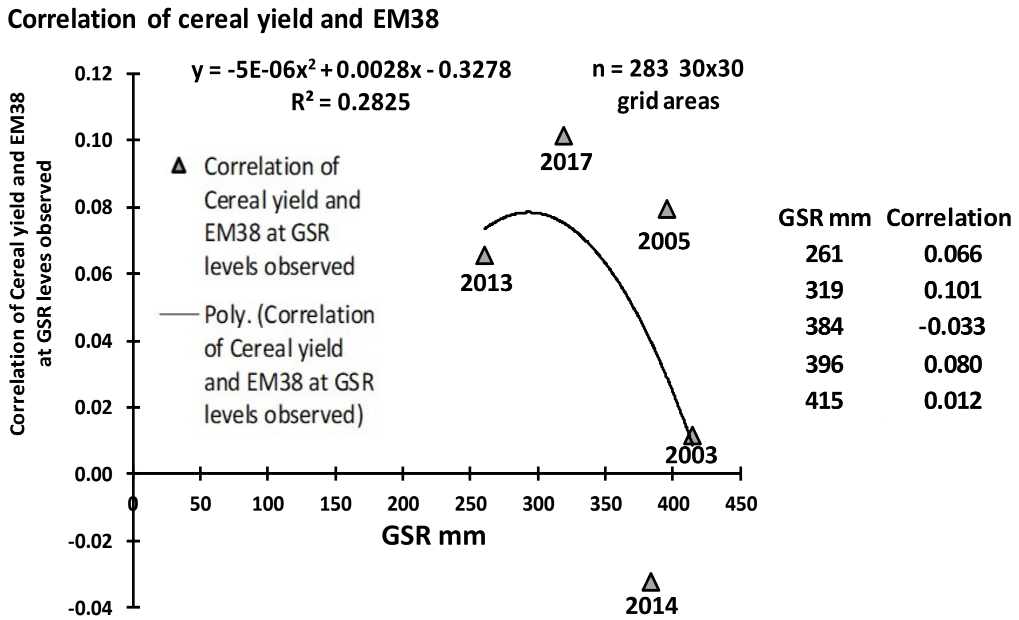


Figure 9. Correlations of EM38 to cereal yields observed GSRs in 5 years on only 22% of paddock **40**, Yarrawonga, outside parts of the paddock involved in the 2017 N-rate trials.

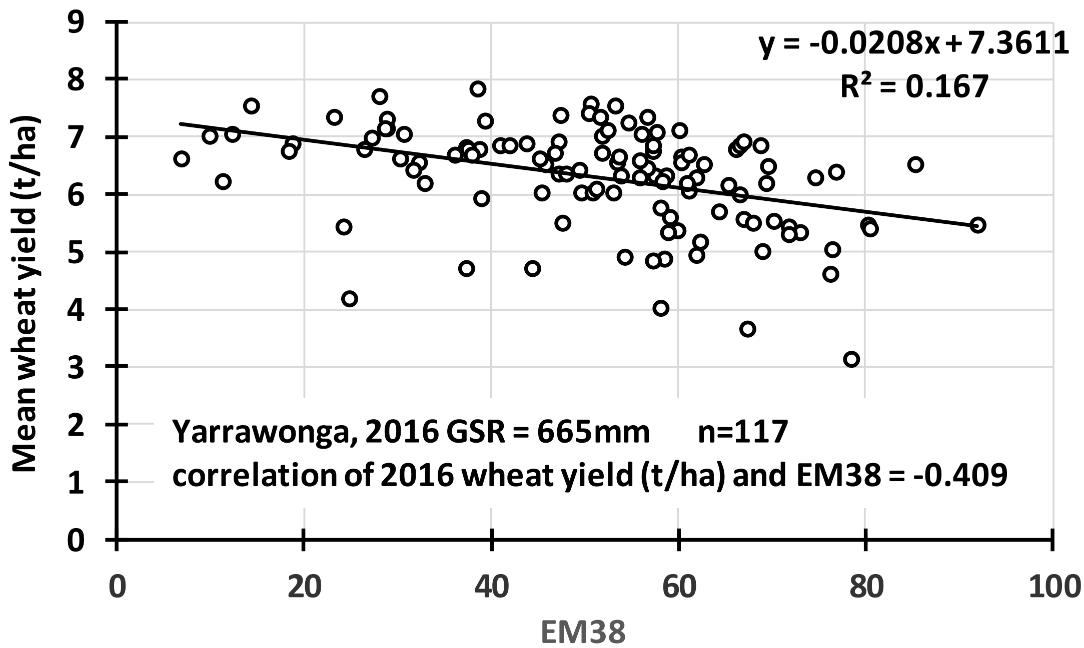


Figure 10. Negative correlation of EM38 and yield within paddock in the high-rainfall season of 2016. This result is from the only paddock and only year for which we had detailed data from header yields and detailed EM38 data from a site East of Yarrawonga, Victoria. Each dot represents one 90x90m grid area in the paddock.

These results justified further analysis of the relationship between GSR, wheat yields and EM38. With all 276 grid areas in paddock R1 divided into 12 EM38 classes, each representing 23 grid areas, the phenomenon noted above comes into clearer focus (**Figure 11**). The highest EM38 class (**L**) shows wheat yields greater than or equal to any other class between 275 and 375mm GSR before falling to yields lower than the lowest-yielding among the other classes at 425mm GSR.

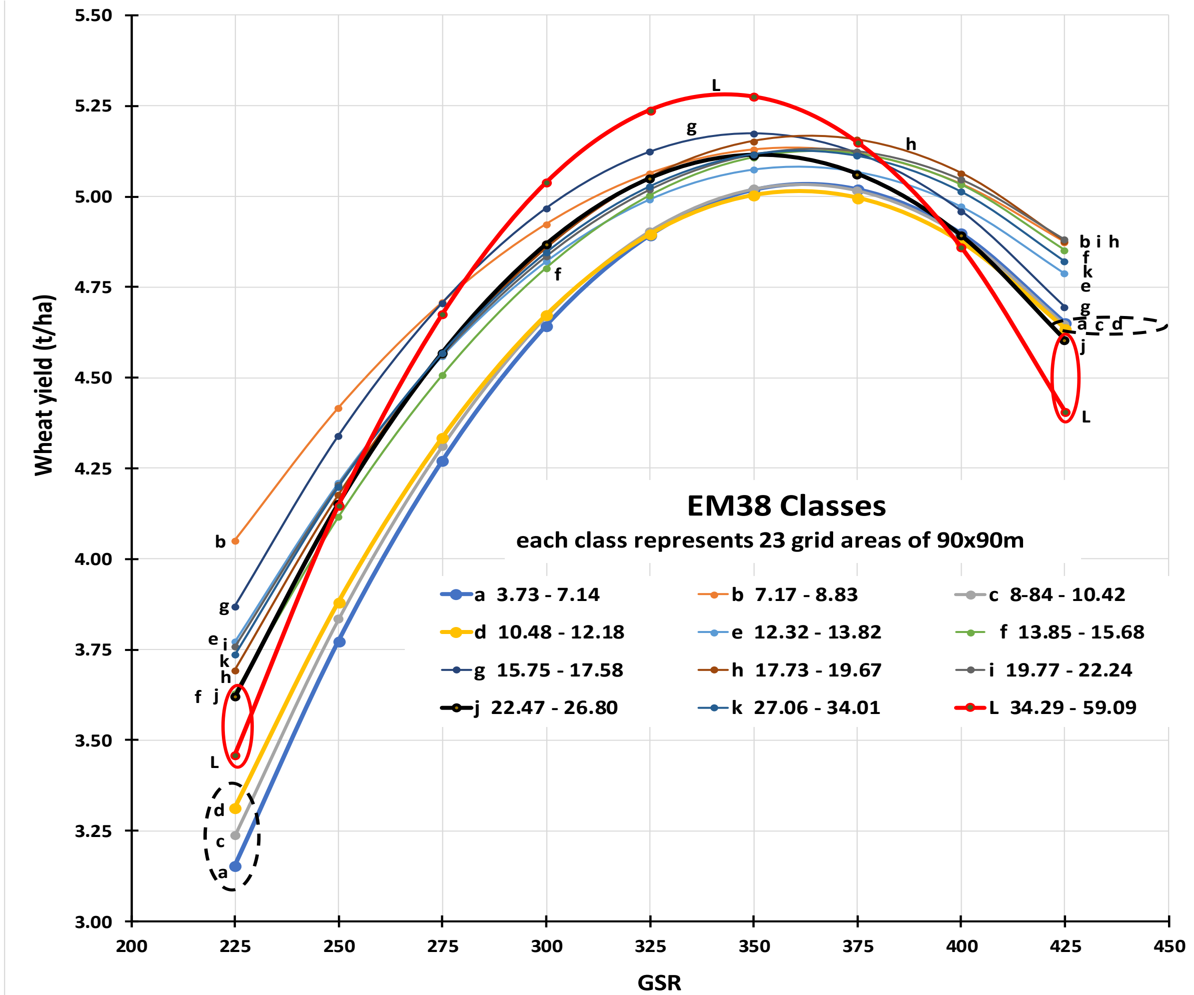


Figure 11. Simulated paddock R1 wheat yield by GSR level sorted into 12 EM38 classes. Note: the highest EM38 class has the highest yields in years with medium rainfalls, but lowest yields in the high-rainfall years.

Three of the four lowest EM38 classes in paddock R1 (**a**, **c** and **d**) show the lowest wheat yields between 225 and 400mm GSR; but beyond 400mm GSR they indicate higher yields than the highest EM38 class (L). If EM38 is a reflection of high clay content and water holding capacity of the soil, the higher GSR amounts could lead to waterlogging conditions in high EM38 soils. These comparisons show the relationship between EM38 measurements and crop yields vary both with location and GSR; EM38 measurements alone are therefore a poor predictor of yields within a paddock.

Highest EM38 levels were associated with higher crop yields at low and medium GSR levels. In the higher rainfall seasons, however, crops may suffer in parts of the paddock with high EM38, while crops in the low EM parts of the paddock perform better. Thus, EM zoning may indicate relative susceptibilities of high EM38 areas in the paddock to waterlogging in high rainfall seasons and drought-proneness of low EM38 areas in the low rainfall seasons.

4.2 Historical average yields: Repeatability

Zoning for VRN is only feasible if the yield ranking of any area within the paddock is repeatable, such that some areas remain high yielding and others remain low yielding in most years. The poor stability of zoning over time is treated by Robertson *et al*. (2007b) in Western Australian wheat crops, and by Liu, Swinton & Miller (2006) on corn crops in Michigan (USA).

In the Riverine plains we could test this for three paddocks where four to five years of yield data were available for each 90m x 90m grid area. The yields all grid areas in a paddock were ranked into quartiles each year, so that the number of years where the yields lay within a given quartile range could be calculated. In this case the number of years (out of five) that the yields lay within a given quartile were plotted (**Figure 12**).

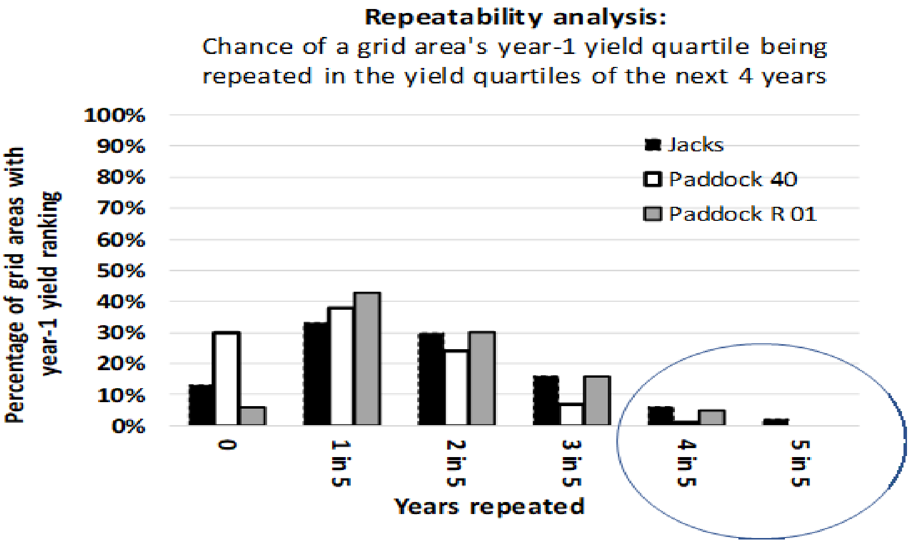


Figure 12. Frequencies of repeatability of yield class suggest recent yield records are an unreliable basis for predicting yield response in a new year. Note, each paddock's columns sum to 100%.

Our analysis shows very low frequencies of quartile rankings any grid areas being repeated in all five years, and less than 5% repeated in four years out of five, which may be considered the minimum useful level of repeatability. This result was consistent for all three paddocks.

4.3 EM38 and yields

The data for Paddock R1 was our key source allowing correlation of grid area yields over several seasons with EM38 survey data. This one-paddock comparison showed low and variable correlation rates between yield and EM38 data as modulated by growing season rainfall (Figures 8, 9, 10 and 11).

The results of the RPI-N rate response trial in 2017 appear to support the finding that EM38 and yield are not always positively correlated. The ranking of the yield response to N applications, based on EM38 zoning, reversed between farms (**Figure 13**). On Yarrawonga paddock 40 the low EM zone showed the higher yields, whereas at Dookie this zone had the lower yields, confirming that the relationship between EM38 readings alone and yields is unreliable.

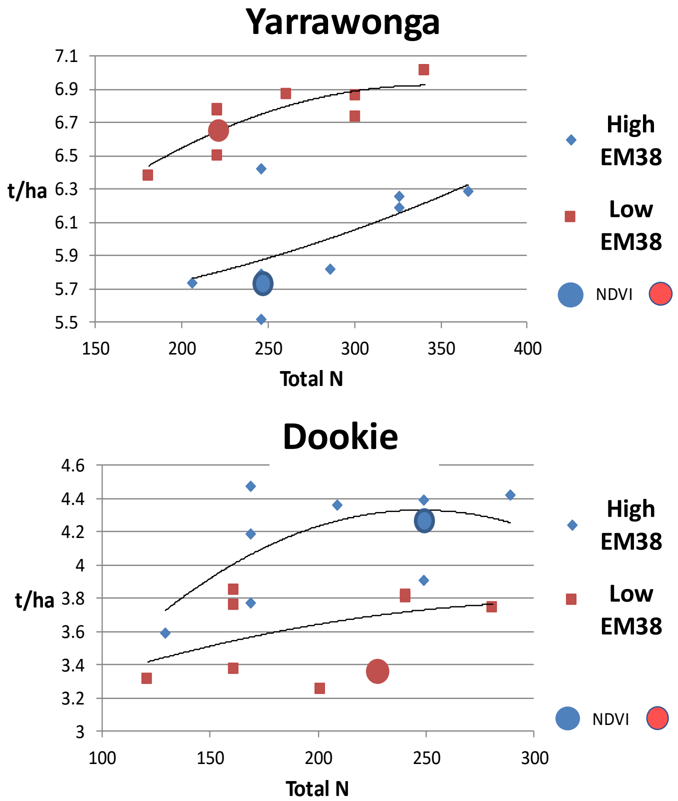


Figure 13. 2017 trial wheat yield responses to N in two paddocks, in High and Low EM38 plots identified in each paddock. Are NDVI results good indicators of yield response regardless of EM38 levels?

Specific grid areas have been identified regarding their yield trajectories over the range of GSRs in 'Jacks' paddock near Dookie (Figure 4) and paddock 40 near Yarrawonga (Figure 5) being different from the average response curves. Do these indicate large differences from the average EM38 levels in their respective paddocks? Access to EM38 survey data of these two paddocks could allow testing these hypotheses.

The above results suggest historical benchmarks alone (such as EM38 and average yields) have little reliability in determining VRN rates from year to year. Furthermore, they question the current practice of dividing paddocks into zones based on historical benchmarks to determine precision application rates in the absence of knowledge or certainty of remaining rainfall for a year.

4.4 Real-time NDVI as guide to VRN versus EM38 and historical yields

Gross margins were calculated based on wheat yields measured in RPI's 2017 variable rate trial. These yields were priced at \$220/t, with a bonus of \$30/t for protein above 11.5%. Urea (priced at \$480/t) and other variable costs typical in these districts were subtracted to give the gross margins calculated in **Table 1**. The gross margins for added N at rates of 0, 40, 80, 120 and 160 kg/ha and 40 kg/ha applications timed by NDVI are given for both Farms (Yarrawonga and Dookie) with results from both high and low EM38 plots on each farm. The effects of the resulting yield differences already seen in Figure 13 are reflected in the gross margins (**Figure 14**) if plotted against added N rather than total N.

Table 1. 2017 trial N (urea) applications, + soil N protein bonus, gross income, costs and gross margins on high and low EM38 plots in paddocks 40 (Yarrawonga) and R1 (Dookie)

Yarrawonga High EM

Added N	Total N	Yield	Protein	Income	Cost N	GM
Kg/ha	Urea + test	t/ha	$30 >11.5%	$220/t	$480/t	$322/ha
0	129	5.7	9.3	$1,254	$0	$932
40	169	6.4	10.2	$1,408	$19	$1,067
80	209	5.8	10.5	$1,276	$38	$916
120	249	6.2	11.5	$1,394	$58	$1,014
160	289	6.3	11.6	$1,416	$77	$1,017
NDVI 40	169	6.0	9.6	$1,309	$45	$942

Yarrawonga Low EM

Added N	Total N	Yield	Protein	Income	ost N	GM
Kg/ha	Jrea + test	t/ha	i0 >11.5%	$220/t	480/t	$322/ha
0	121	6.4	9.4	$1,408	$0	$1,086
40	161	6.5	10.0	$1,430	$19	$1,089
80	201	6.9	10.7	$1,511	$38	$1,151
120	241	6.9	11.1	$1,509	$58	$1,130
160	281	7.0	11.1	$1,542	$77	$1,143
NDVI 40	161	6.8	11.8	$1,485	$45	$1,118

Dookie High EM

Added N	Total N	Yield	Protein	Income	Cost N	GM
Kg/ha	Urea + test	t/ha	$30 >11.5%	$220/t	$480/t	$322/ha
0	206	3.6	10.2	$792	$0	$470
40	246	3.8	10.5	$829	$19	$488
80	286	4.4	11.6	$998	$38	$638
120	326	4.6	11.5	$1,040	$58	$660
160	366	4.4	12.5	$1,002	$77	$604
NDVI 40	246	4.5	11.5	$983	$45	$617

Dookie Low EM

Added N	Total N	Yield	Protein	Income	ost N	GM
Kg/ha	Jrea + test	t/ha	i0 >11.5%	$220/t	480/t	$322/ha
0	182	3.3	11.9	$756	$0	$434
40	222	3.4	13.5	$771	$19	$430
80	262	3.3	14.0	$745	$38	$385
120	302	3.8	14.7	$866	$58	$486
160	342	3.7	14.1	$853	$77	$454
NDVI 40	222	3.8	14.4	$836	$45	$469

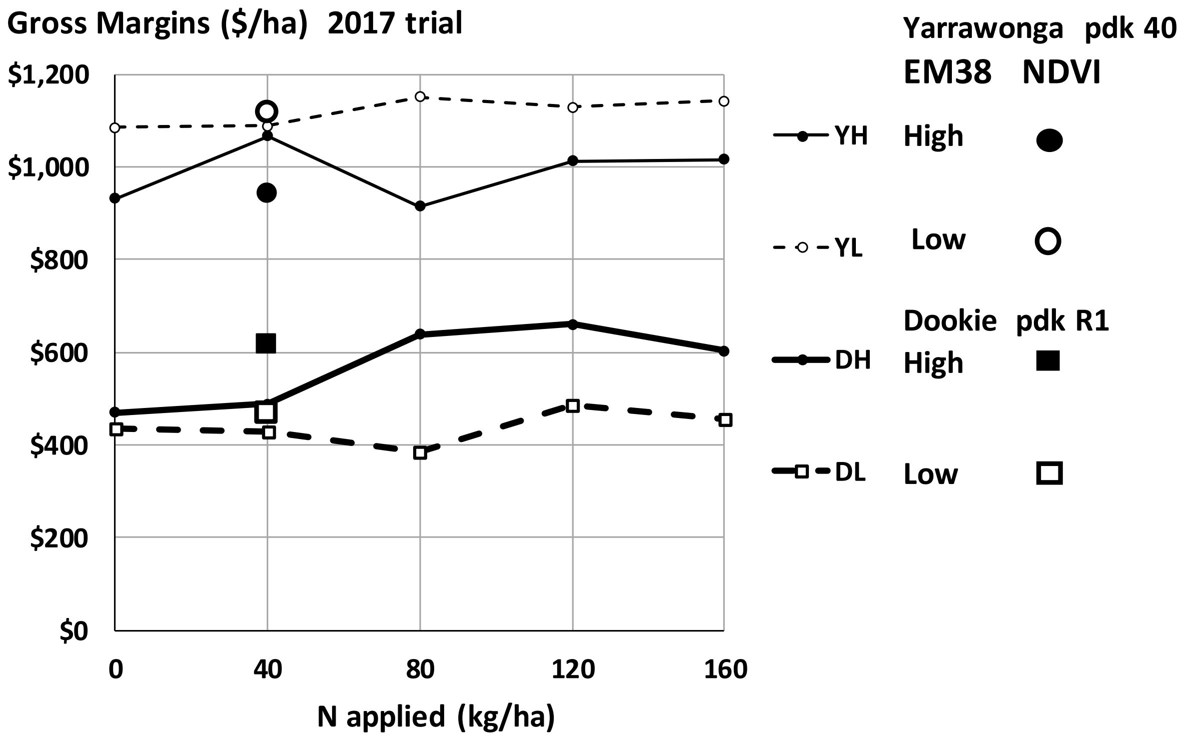


Figure 14. Wheat gross margins for 2017 trial results in paddocks 40 (Yarrawonga) and R1 (Dookie).

These gross margins are difficult to interpret because of the high variability in yields from all four trial sites (Figure 13) and some of the fluctuations in the response curves in Figure 14 may not be significant. It is doubtful that there was profitable response to any rate of N fertiliser at either site on Farm 3, or for the low EM site on Farm 4, due to the high levels of soil N present at the sites at the beginning of the trial. These results may be like those reported on vertisol soils in Spain where high rates of N had routinely been applied by farmers (Lopez-Bellido, *et al*. 2005). The response curve for the high EM site on Farm 4 suggests that there was a significant benefit for applying 80 kg N/ha, but little additional benefit from higher rates. It would be difficult to extrapolate these results to other paddocks in the district, given the extreme spatial and temporal variability of within-paddock crop yields noted in Figures 4, 5, 6 and 7.

The expected superiority of yields in high EM38 in the Dookie site was not seen in the case of the Yarrawonga site, perhaps due to the confounding effect of relatively excess soil water or possible frosting and later sowing at the latter.

The NDVI plots gave results equalling the best gross margins under the conditions, with the exception of the High EM plots on the Yarrawonga farm. Thus, in-crop real-time NDVI technology may show more promise for controlling the application rate of N than the other benchmarks discussed. NDVI control of N applications warrants further research here. It has been in common use in the EU (Lowenberg-DeBoer 2003, p 3).

5. FARM FINANCIAL RISK ASSESSMENTS

Farm financial risk can be expressed as the probability of a range of changes in cash flow measured over time (Hutchings 2013). In this case, simulated 10-year) cashflow budgets were prepared using locally valid variable, fixed and capital costs on two hypothetical farms. These costs included equipment replacement costs, based on typical machinery inventories and farmer-estimated timing of replacements in these districts. The additional costs of VRN equipment were estimated assuming all new machinery will be SS-capable at the time of replacement.

Crop yields were simulated using the regression equations developed for the area (recall Figure 2), based on randomised 10-year historical sequences of GSR between 1960 and 2015. The effects of VRN costs were pursued by simulating wheat and canola yields with our estimated functions across 56 years (1960-2015), from which 47 decades of historical GSR sequences were randomly drawn for combination with randomised weekly price records (from the Port of Geelong, 2010-2015).

Annual gross income for each crop was calculated using the simulated yield sequences, priced using randomised price sequences, as outlined above. The calculated cash flow budgets included all costs, plus interest on the compounding cash balance, which included living costs and income tax. This allowed calculation of the estimated change in the cash balance (equivalent to the ending bank balance) over each decade. @Risk software (Palisade 2017) was used to record the changes in this balance over 10,000 iterations, which allowed estimation of the probability of ranges of these values, representing the risk profile for any scenario for a given farm.

Risk profiles were prepared for each farm before and after including the cost of VRN given the assumption of 100% equity as a starting position.

5.1 FINANCIAL RISK PROFILES

This analysis deals with the effects of implementing variable rate N on whole-farm financial risk over time. Calculating the impact of implementing variable rate N on whole-farm financial risk over time is a more complex matter than shown by a single year gross margin calculation. The sample farms shown are hypothetical but have been developed to show the full range of likely results that may be encountered in the region. One of these farms has higher fixed costs than the other (where costs are judged as a percentage of gross income). A short list of the considerations we applied is given in **Table 2**, which builds upon the factors already described in this paper.

Table 2. Data used for calculation of risk profiles

1. **Ten-year rainfall sequences** selected randomly from 1960-2015 drive simulations of wheat and canola yields over time.
2. **Yields** for each year calculated using yield response curves in Figure 2
3. **Livestock GM** from CSIRO Grassgro model
4. **Prices** based on simulated sequences based on 2011-2016 weekly prices at Port of Geelong
5. **Costs** selected to reflect high and low fixed costs
6. **Cost of soil sampling** for N ($1.50/ha/yr) in the planning of VRN
7. **Debt** standardised at 100% equity
8. **Machinery replacement costs** calculated at expected changeover year (*At changeover variable rate capability expected to be standard fitting*)
9. **10 year cash flows** developed including living costs, taxes and interest.
10. **Output** is change in cash (bank) balance over 10 years, simulated over 10,000 iterations of random prices and decades of local weather (GSR).

The distributions of probabilities of any change in bank balances over 10 years, given price and weather variations, define the 'Risk Profiles' of these two hypothetical farms, with and without variable rate N technology (**Figure 15**). This analysis compares the whole-farm effects of the additional costs (without benefits) of variable rate technologies for N applications on the level of income at any risk percentile.

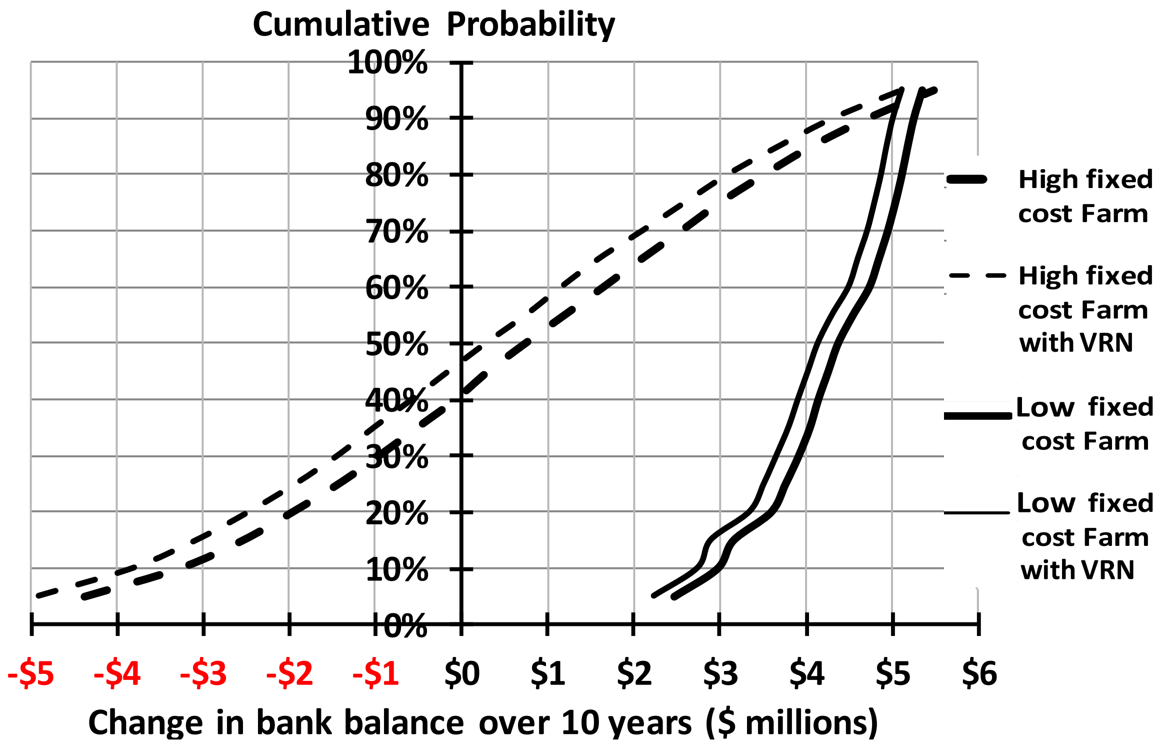


Figure 15. Probabilities of change in bank balances over 10 years, given price and weather variations, define the 'Risk Profiles' of two hypothetical farms distinguished by High or Low fixed costs, beginning with 100% equity with and without variable rate N. Indicated here are only the costs (without the benefits) of VRN. High fixed cost farm may have 3% greater risk of financial loss with VRN; low fixed cost farm has minimal risk.

Financial risk profiles were defined by simulating long-term effects of VRN on the cash balance of each farm. This analysis showed that the added costs associated with VRN could be individually covered by less than 1% increase in yields across all wheat and canola crops or at least 70% decrease in the amount of N applied. This suggests that the additional costs of VRN could easily be met by small increases in yields over multiple years. VRN alone is unlikely to result in the relatively large (70%) reduction in N fertiliser use needed to cover the additional costs. The costs of VRN are more likely to be met by increases in yield (<1%) than by a reduction in N use, which confirms the finding reported by Lowenberg-DeBoer (2003, p. 3).

Comparisons of results for the high and low-cost farms regarding VRN are summarised in **Table 3.** This Table shows the low-cost farm was the most viable, with zero risk of loss. This compares with a 41% risk of financial loss for the high-cost farm without VRN, rising to nearly 44% risk of loss with VRN.

Table 3. Comparisons of risk profiles

	High fixed-cost farm		Low fixed-cost farm	
	No VRN	**+ VRN**	**No VRN**	**+ VRN**
Initial cost of Variable Rate N tech		**$30,963**		**$18,465**
Cost accumulated over 10 years		**$452,721**		**$181,744**
	Change in cash flow needed to cover costs of VRN			
Yield increase (small)		**0.30%**		**0.10%**
Reduced use of N (large)		**68%**		**70%**
Risk of financial loss	**41%**	**44%**	**0%**	**0%**

6. DISCUSSION

> *"Yield monitoring at harvest in the grains industry has been present in Australia agriculture for about two decades, and there is a great opportunity to maximally benefit from this available information to predict crop yields by using bigdata approaches. The size of the dataset and how this affects predictions needs to be further explored. This needs to be done in terms of an expansion of temporal data (more seasons of yield), and an expansion of spatial data (more paddocks/ farms)."* — Filippi *et al*. (2017, p52)

Gross margin results derived with the 2017 trial outcomes were generated with cost information sourced locally, including wheat yields under the various N treatment rates. Using estimated responses of wheat and canola yields to GSR calculated with 65 years of local rainfall data for Yarrawonga and Dookie from the Bureau of Meteorology. These were used to provide a key risk element of high-GSR-sensitivity in yield variations from year to year in our model. This risk environment for estimating yields and gross margins was combined with randomised sets of international agricultural prices from the Port of Geelong in southern Victoria for our simulations of farm financial risk profiles.

The essential element of time and accumulation of debts through periods of good seasons and droughts is a distinguishing feature of the present analysis, which has been absent from the literature on analysis of site-specific crop management. We posed hypothetical cases of two farms that typify conditions in our study area: one constructed as a high-cost farm and the other low-cost. This analysis shows a low repeatability of historical yield rankings over time; similarly, EM38 zoning on its own has proved misleading and a poor predictor of yields. Combining grid-area yield data over several years with GSR levels of those years brings some measure of predictability. Follow-up research to consider these relationships is expected to be fruitful.

As suggested by Filippi *et al.* (2017), many seasons of geo-referenced yield data have been accumulated by farmers in the study area, which can be combined with existing or new EM38 survey maps for the same paddocks. Appropriate public weather records are also available. These data resources allow testing our hypothesis of GSR-modulated rankings of high and low EM38 grid area crop yields over time. High-resolution geo-referenced satellite images of NDVI levels can be accessed for past seasons for analysis in conjunction with high resolution yield records, soil and digital elevation maps to predict production capacities across a paddock over time. Measured or simulated present soil water availabilities and expected near future rainfalls might also be combined to guide follow-up site-specific N applications.

Because prospective zoning for targeted VRN is subject to errors due to unpredictable rainfall, its value may be questioned. Low-cost farms may be able to exploit VRN on a large scale without concern for financial losses, while high cost-farms may face slightly increased chances of financial loss. Real-time NDVI may allow new efficiencies for VRN.

7. CONCLUSIONS

- Paddock zoning based on EM or long-term yields (alone) appear unreliable for guiding VRN.

- NDVI seems to offer an effective way to deal with variability in combination with VRN and does not need zoning.

- Trial results showed little response to increased N due to high soil N levels.

- Based on our initial results for the Yarrawonga and Dookie areas, VRN needs to increase crop yields by less than 1%, or reduce costs of N applied by at least 70%, to break-even over time.
- VRN costs have a relatively small impact on whole-farm risk.
- Main impacts on financial risk are from high fixed costs.
- **Other studies (including CSIRO, 2013 and GRDC, 2006), which depend on gross margin analyses over one or more years have shown positive economic benefits of VRN.**
- **Clear benefits of VRN are not evident from the present study which considers price and weather RISKS over TIME with the effects of cumulative interest.**
- **Therefore, we cannot reject the null hypothesis that precision site-specific nitrogen applications are no more profitable than uniform applications.**

Further research topics

- Expand this form of analysis to more years, soil types and paddocks to test concepts.
- Test the accuracy of EM measurements for zoning applications considering possible negative effects of high EM when GSR is high.
- Trialling real-time, tractor-mounted NDVI for tactical mid-season VRN
- Trialling multiple geo-referenced N-rate strips integrated with sowing operations and NDVI monitoring of test strips for tactical mid-season VRN.

GLOSSARY

Term	Description
Decadal cash margin	The ending cash balance of a farm, counting all costs, after a ten-year period, minus the opening cash balance for that period. The cumulative distribution of such cash balances under a given management plan is referred to as a risk profile, which shows the probabilities of profits and losses
Farm financial risk	Measured in terms of probabilistic gains or losses. This is an existential check for the farm business, indicating its chances of viability or non-viability

Gross-margin	The sum of expected returns for an action or an enterprise minus all variable costs attributable to that enterprise.
GSR	Growing season rainfall, after French / Schultz (1984): **GSR** mm = (((Jan to Mar)/3) + (Apr to Oct) + (Nov/2))
NDVI	Normalised Difference Vegetation Index (greenness indications of crop vigour and development). Satellite or airborne NDVI maps have been in common use. Real-time NDVI with fertilizer spreading or measured by satellite data and mapped to guide same-day VRN, may hold promise.
PA	Precision Agriculture is a broad term encompassing GIS and Differential GPS to allow planning precise positioning of equipment for sowing, fertilizer application, spray applications, harvest recording, etc., as well as recording soil conditions to aid subsequent planning and field operations.
SSCM	Site-Specific Crop Management, includes all PA operations.
SSNA	Site-specific Nitrogen Application, also called Variable-Rate N
Risk profile	The cumulative distribution of decadal cash balances over a range of profits and losses. In a simulation analysis, many randomly drawn decades of actual local rainfall sequences are combined with randomly drawn international commodity prices to produce a range of decadal cash balances defining the risk profile in probabilistic terms.
VRN	Variable-Rate Nitrogen application within a paddock

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We are especially grateful to Craig Poynter, GIS & Remote Sensing, Spatial Data Analysis Network (SPAN), Charles Sturt University; his skilful help has been critical to this study's success in integrating the raw yield, soil and rainfall data and analytic results in the clearest of charts.

Clair Robinson (of Hutcheon and Pearce) assisted our understanding of replacement costs for variable-rate-capable equipment in an era when satellite-guided and GIS-based auto-steer, tramlining and yield-mapping have become the norm. Dr Remy Dehaan, Graham Centre and School of Ag & Wine Science, Charles Sturt University, kindly helped at the early stage, with interpretation of crop-yield map data. We acknowledge Dr Amir Abadi Ghadim, Curtin University, for his inspiration of the partnership which accomplished this work.

The authors alone are responsible for any errors that remain in this report.

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