Modifying agro-economic models to predict effects of spatially varying nitrogen on wheat yields for a farm in Western Australia

Evans, F. H.[1,2], Andrew, J.[3], Scanlan, C.[4] and Cook, S.[1,2]

[1] Murdoch University, 90 South Street, Murdoch, [2] Curtin University, Kent Street, Bentley, [3] MapIQ, 13 James St, Bassendean, [4] Department of Primary Industries and Regional Development, 3 Baron-Hay Court, South Perth – all Western Australia

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Abstract. *Agricultural research in broadacre farming in Western Australia has a strong history, resulting in a significant public resource of knowledge about biophysical processes affecting crop performance. However, translation of this knowledge into improved on-farm decision making remains a challenge to the industry. Online and mobile decision support tools to assist tactical farm management decisions are not widely adopted, for reasons including: (1) they take too much time and training to learn; and (2) they aren't integrated with the data they need or with each other, making their use too time-consuming.*

Meanwhile, as farmers accumulate more data from their machinery, they find themselves unable to use that data to inform decision making. In an ideal future, variable rate technology (VRT) could be programmed to apply optimal rates of fertilisers. However, the existing suite of models and tools are derived from small-scale controlled field experiments and are not suitable for fine-scale paddock management.

Using 14 years of data from a farm in the eastern wheatbelt of Western Australia, we investigate the calibration and extension of an agro-economic model for spatial prediction of the effects of nitrogen applications on wheat yield and gross return. We use a simple response curve model, NP-Decide, that was developed in Western Australia and remains in common use.

Keywords. *Nitrogen, spatial, modelling, yield potential, spatial, paddock-scale, variable rate.*

Introduction

The wheatbelt of Western Australia (WA) consists of nearly 10 million hectares and contributes more than $4.5 billion to WA's economy each year. The climate is Mediterranean and broadacre cropping relies on winter rainfall in a dryland system. Rainfall is the largest factor affecting wheat yield, which can vary considerably between seasons depending on the amount, frequency and timing of rainfall events. Climate variability explains around 40% of total wheat yield variability in the Australian wheat belt, and in parts of WA that figure can be greater than 60% (Ray, Gerber, MacDonald, & West, 2015).

The south west of WA has experienced a 20% decline in winter rainfall since the 1970s due to southward shifts in rain-bearing synoptic systems (Hope, Drosdowsky, & Nicholls, 2006). This climate change and seasonal variability has seen grain growers improve technical efficiency, largely using existing technologies, to improve productivity despite declining rainfall (Kingwell et al., 2013).

With the continuing pressure of projected future decline in rainfall, decision support tools and precision agriculture (PA) provide a potential means to improve farm profitability. Farmers can improve fertilizer management by either using more inputs to maximize yield when yield prices outweigh fertilizer costs, or by reducing fertilizer use when their costs outweigh the value of the yield. A major unknown part of this equation is in the understanding of how crop responds to fertilizer applications across the farm.

Existing agronomic models were developed for point-scale use, but variability in yield within paddocks can be much larger than the yield response they predict. Understanding and handling spatial variability of yield is essential for PA and variable rate technology (VRT). Technology exists for fine-scale fertilizer application, but the existing models cannot be used as is – they must be calibrated and extended to predict spatially-varying yield response across a paddock.

We investigate the application of an agro-economic model for predicting yield response to fertilizer inputs to determine the potential of extending the model so that can be applied spatially across a paddock. Our hypothesis is that we can use a long-term sequence of yields maps to calibrate the model to a particular location, and make inferences about interactions between seasonal rainfall and local factors causing spatial variability in yield, most importantly soil type and characteristics.

Our vision for this work is to design algorithms that can be used in decision tools, within a framework of on-farm experimentation and even in VRT equipped on farm machinery so that WA grain growers can optimize fertilizer inputs across a paddock to increase yields and or reduce costs.

Data

We use data from a farm in the eastern wheatbelt of Western Australia (Figure 1). This region has an average growing season rainfall of 220mm. Average wheat yields are between one and two tonnes per hectare. 015

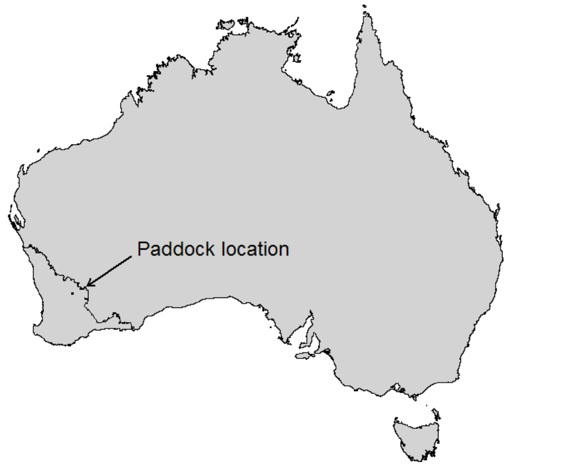

Figure 1: Paddock location in the eastern wheatbelt of Western Australia.

We focus on a single paddock with 14 years of yield monitor records. Years with few yield data points were omitted, leaving eight years in which wheat was grown (Table 1). Figure 2 shows that wheat yields measured across the paddock using a harvester-mounted monitor can vary by up to 1 tonne per hectare from the average paddock yield. $Wavail$, the water available to the crop, or effective rainfall, is defined as one third of summer (November to March) rainfall plus growing season April to October) rainfall.

Table 1: Summary of paddock data (wheat crops)

Year	2004	2006	2007	2009	2012	2013	2015	2016
Crop	Wheat	Wheat	Wheat	Wheat	Wheat	Wheat	Wheat	Wheat
Variety	Caliningiri	Cadoux	Arrino	Wyalkatchum	Mace	Calingiri	Mace/Zen	Mace
Seeding rate	60	50	70	60	45	50	50/30	49
$Wavail$ **(mm)**	264	270	178	225	178	275	224	284
Average paddock units of N applied (kg/ha)	38.1	22.05	36.37	20.4	22.53	21.7	23.35	37.15
Average paddock yield (tonnes/ha)	1.6	1.39	0.68	1.95	0.46	1.81	unrecorded	1.62

100 soil samples were taken across the north east part of the paddock prior to sowing wheat variety Mace in 2016. Soil nitrogen measurements ranged from 0 to 100 mg/ha at 0-10cm depth, with a mean of 17 mg/ha. Soil phosphorus measurements ranged from 0 to 70 mg/ha at 0-10cm depth, with a mean of 15 mg/ha.

The crop was sown on 20 May. Two strip trials were installed in the paddock with high and low rates of MAP fertilizer applied at seeding. MAP was applied to the remainder of the paddock with two rates for zones based on soil type. Forty units of Urea were also applied at seeding, and an additional top-up thirty units of Urea were applied mid-season on 30 July.

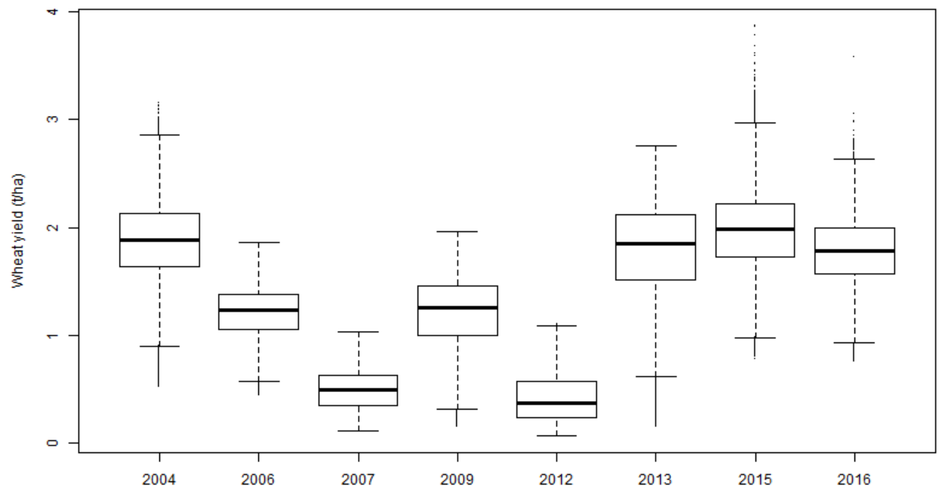

Figure 2: Wheat yield variability by year.

Methods and results

Processing of yield monitor data

Raw yield monitor data were cleaned of outliers by removing values below the 1st percentile above the 99th percentile, prior to kriging to a common 10m grid.

Nitrogen model

The NP-Decide model is a simple response curve model for predicting grain yield given different rates of nitrogen (N) and phosphorus (P) inputs (Burgess, Bowden, & Diggle, 1991). The model is a Misterlich-type model that relies on an estimate of the theoretically-possible potential yield that might be attained by the crop in the absence of fertilizer constraints (Misterlich, 1909). The NP-Decide response curve formula is:

$$Yield = Potential\,Yield\,\left(1 - exp\left(N_{rate}C_{fertN} - N_{st}C_{stN}\right)\right)\left(1 - exp\left(P_{rate}C_{fertP} - P_{st}C_{stP}\right)\right),$$

where $Yield$ and $Potential\,Yield$ are measured in kg/ha, N_{rate} and P_{rate} are the rates of N and P applied (kg/ha), C_{fertN} and C_{fertP} are measures of the responsiveness of the soil to N and P, N_{st} and P_{st} are the measured amounts of N and P in the soil prior to the application (mg/ha 0-10cm) as measured by soil tests, and C_{stN} and C_{stN} calibrate the soil test for the particular soil being tested.

Typical values of these model parameters suited to application in WA are shown in Table 2 (Robertson, Lyle, & Bowden, 2008).

Table 2: NP-Decide model parameters using in WA

Parameter	C_{fertN}	C_{fertP}	C_{stN}	C_{stP}	N_{st}	P_{st}
Values	0.03	0.06	0.05	0.12	Low 10 Standard 30 High 100	Low 5 Standard 20 High 50

Figure 3 shows several response curves for different values of potential yield, and an example pf a 2d response surface from the NP-Decide model.

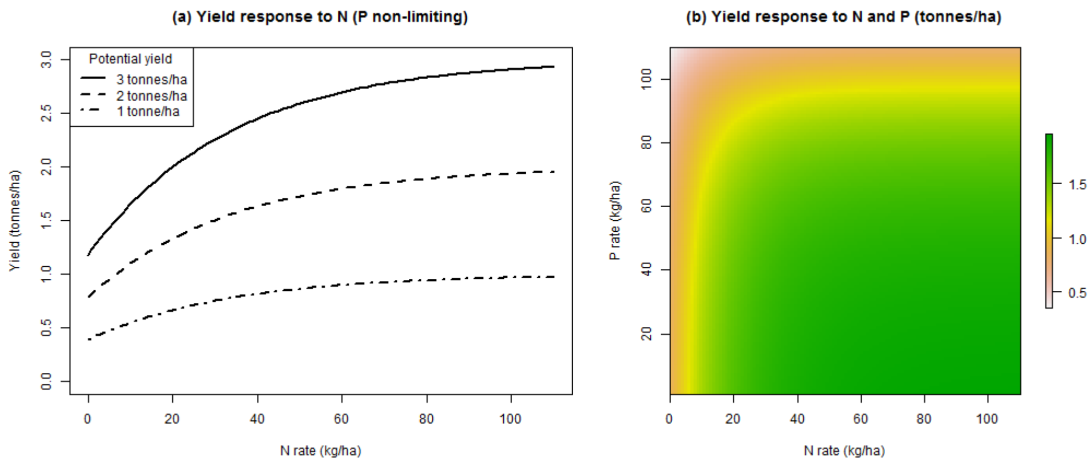

Figure 3. N response curves for different yield potentials and 2-d NP response surface using potential yield of 2 tonnes/ha (using low soil test values of N and P).

Estimation of potential yield

In WA, the largest driver of potential grain yield is the amount of water available to the crop during the growing season. The most commonly used estimate of potential yield, the French & Schultz (F&S) potential yield model, estimates water-limited potential yield by:

$$Yield = WUE\ (Wavail - evaporation),$$

where $Yield$ is measured in kg/ha, $Wavail$, the water available to the crop, is defined to be one third of summer (November-March) rainfall plus growing season rainfall, WUE is an abbreviation for water use efficiency (French & Schultz, 1984). The original definition of the model estimated $WUE = 20$ and $evaporation = 110$ as fixed model parameters; however common use in WA varies the values according to geographic location and rainfall zone. In southern, wetter parts of the wheatbelt, WUE is frequently set higher, and in north and eastern parts of the wheatbelt, lower values are adopted.

Because the F&S model does not account for yield variation due to soil type, another commonly used model, the 'broken stick' model, modifies it by imposing an upper bound to yield potential using a threshold on Wavail that is based on the plant available water capacity (PAWC) of the crop growing in the soil (Oliver, Robertson, Stone, & Whitbread, 2009). Use of PAWC to estimate potential yield using the APSIM crop model has been assessed for use in fertilizer models, showing potential benefits in 30-40% for 31 wheat crops in 2003-2006 (Oliver & Robertson, 2009). However, there can be large variation in PAWC within a soil type as described by the WA soil group classification, and measurement by soil coring is timely and expensive (Oliver, Robertson, & Wittwer, 2006).

Spatial estimation of 'broken stick' potential yield using sequence of yield maps

We present a data-driven method for estimating yield potential using a sequence of paddock yield maps and $Wavail$ data using two different types of the broken stick model with three variants:

1. WUE, $evaporation$ and the threshold on $Wavail$ are fitted from the data (fully flexible model).
2. WUE and the threshold on $Wavail$ are fitted from the data with $evaporation = 110$.
3. Only the threshold on $Wavail$ is fitted from the data with $evaporation = 110$ and $WUE = 20$.

The broken stick models are fitted to the data by iterating through unique values of $Wavail$ and splitting the data set into two parts below and above each value, then estimated in two parts.

The first part fits a quantile linear regression. Quantile regression allows the estimation of conditional quantiles of the response variable instead of the mean (Koenker & Hallock, 2001). In this case, to estimate the upper bound on yield, we fit the line to pass through the 99th percentile of the data. The second part of the model simply fits a horizontal line, with the yield estimated from the first part of the model. The mean squared error (MSE) of the model is calculated, and the value of $Wavail$ that minimizes the MSE is selected as the threshold. The coefficients of the linear regression are then converted to equivalent values of WUE and $evaporation$.

This process is applied spatially to the grid of 10m by 10m cells of interpolated yields. To handle spatial autocorrelation, the model for each individual cell is fitted using data from a window around the cell, with the contribution of cells in the window weighted according to their distance from the central point using Gaussian kernel weights.

(a) radius=1

0.09	0.12	0.09
0.12	0.17	0.12
0.09	0.12	0.09

(b) radius=2

0.02	0.03	0.04	0.03	0.02
0.03	0.05	0.06	0.05	0.03
0.04	0.06	0.07	0.06	0.04
0.03	0.05	0.06	0.05	0.03
0.04	0.03	0.04	0.03	0.02

Figure 4: Gausian kernel weights for moving windows with radius of one and two cells.

Figure 5 shows examples of the fitted models for two paddock locations: one that is higher yielding and one that is lower yielding. The data from the window of cells centered over each location are colored according to their weights, so that the central cell is shown in black and lighter shades of grey indicate cells with lower weights (greater distances from the central cell).

The fitted threshold on $Wavail$ is the same for each location, suggesting that it is driven more by the seasonal rainfall than by differences in soils and their PAWC. However, the potential yield predicted at the threshold varies between the two locations, as would be expected.

The fitted $evaporation$ term from the fully flexible model is considerably higher than the value of 110 that is commonly used (169 for the higher yielding locations and 164 for the lower yielding location), suggesting that more rainfall is required to achieve yield than commonly assumed. The fitted WUE s also higher than the value of 20 that is commonly used (55 for the higher yielding location and 33 for the lower-yielding location. Of course, by the nature of the model, if the $evaporation$ is higher, then the WUE must also be. It is possible that the two years with low seasonal rainfall (2007 and 2012) are biasing the fit of the fully flexible model, and that if data were available or more low-mid rainfall years, then the fitted values of $evaporation$ and WUE might be closer to 110 and 20.

Fixing the $evaporation$ term to 110 does not alter the threshold potential yield, but does suggest higher yield potential for lower values of $Wavail$.

Figure 6 maps the estimated model parameters for the fully flexible broken stick model across the paddock. There are only two detected thresholds (225 and 265mm) on $Wavail$, but a wide range corresponding potential yields at the threshold, and of fitted values of WUE. Fixing $evaporation$ to 110mm alters the fits for WUE but the fitted yield potential at threshold is the same for the fully flexible model (Figure 7). The fitted WUE term appears to be more closely related to soil type than the threshold on $Wavail$.

Use of fixed values or WUE and $evaporation$ reduces the range of potential yield at $Wavail$ thresholds to two values, which underestimates the yield variability in the paddock and is not a useful model for paddock-scale estimation of potential yield.

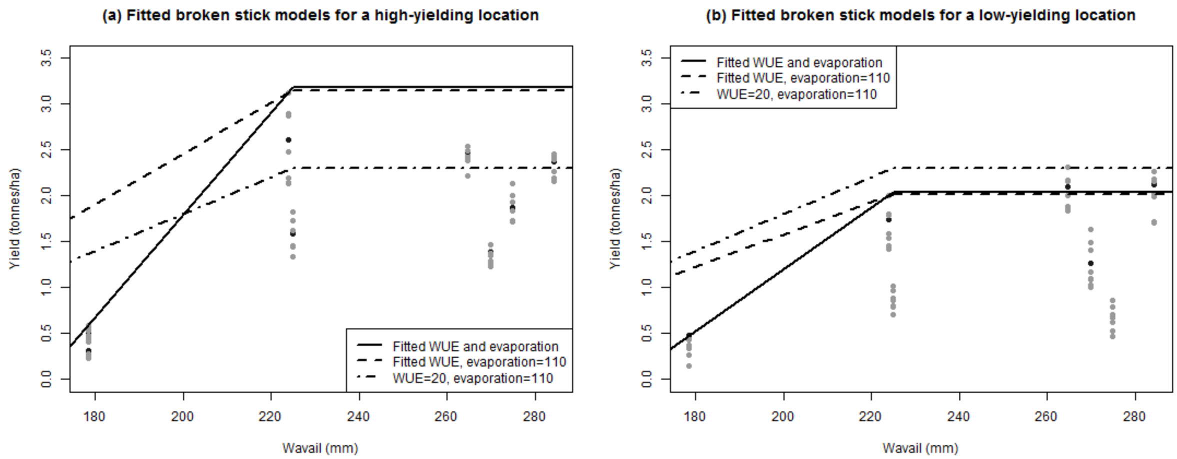

Figure 5: Examples of fitted broken stick models for low and high yielding parts of the paddock.

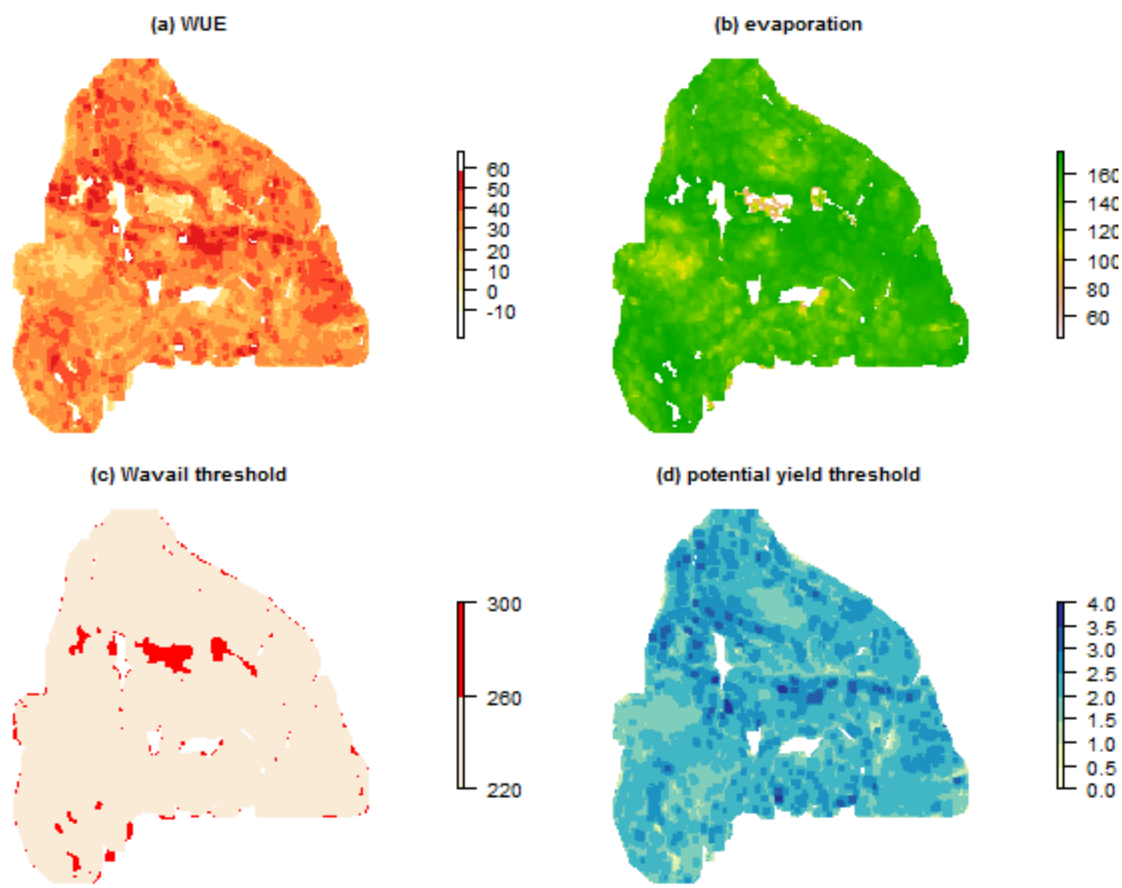

Figure 6: Estimated model parameters for the fully flexible broken stick model.

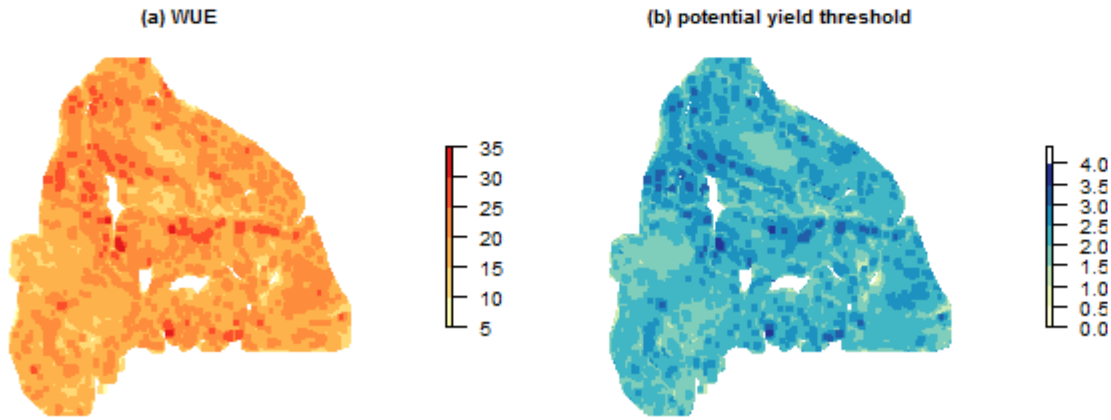

Figure 7: Estimated parameters for the broken stick model with $evaporation = 110$.

Figure 8 shows that the estimated potential yield for 2016 using the broken stick model with fixed $evaporation$ gives much more realistic potential yields than the fully flexible model, which estimates potential yields that are unachievably high.

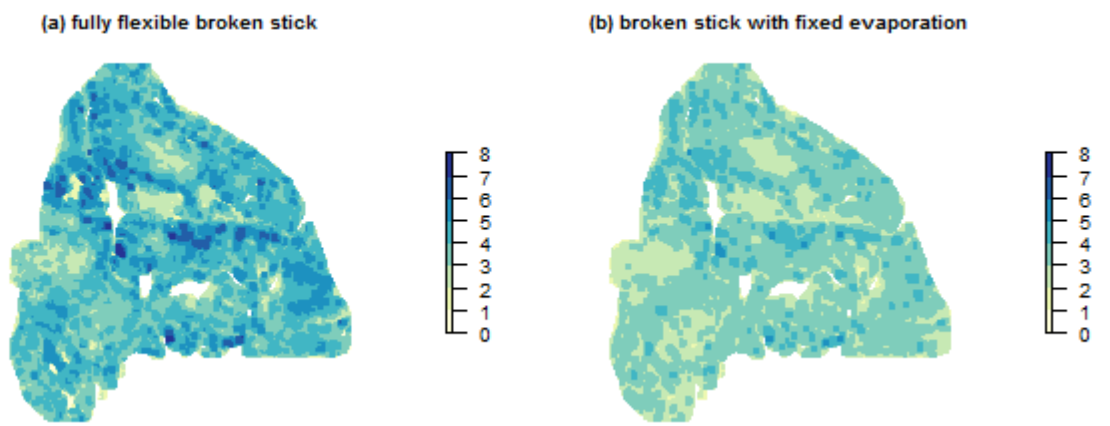

Figure 8: Estimations of 2016 potential yield.

Spatial nitrogen modelling

We applied the NP-Decide model to the 2016 paddock data using potential yield estimated by the broken stick model with $evaporation = 110$ and parameters cited in Table 2 with N_{st} and P_{st} set to the mean values from the soil sample data, 17 and 15 respectively. The resulting yields predicted by NP-Decide were much lower than actual yields by up to 1 tonne/ha.

We then used the yield data in a simple optimization to estimate NP-Decide parameters related to soil type, giving $C_{fertN} = 0.024$ and $C_{fertP} = 0.02$. This gave considerably better results (Figure 9). The predicted yields do not accurately represent all of the spatial variability in the actual yields, but the NP-Decide model is only able to predict response to N and P, and does not account for other factors affecting yield, such as weed, pests and diseases.

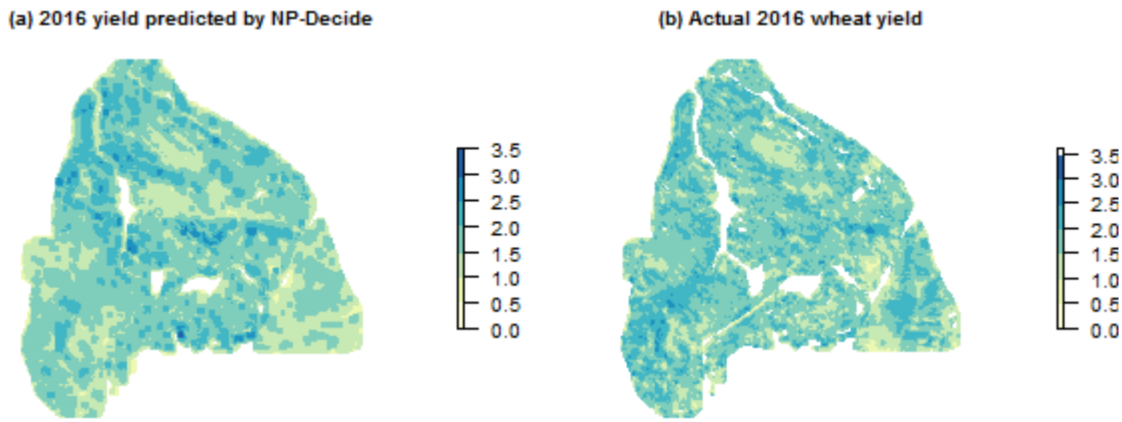

Figure 9: NP-Decide modelled predictions vs. actual yield.

Conclusion

This work investigated the calibration and extension of an agro-economic model for predicting yield and net return from fertilizer inputs, so that the model can be applied spatially across a paddock. Our vision for this work is to design algorithms to help WA grain growers optimize fertilizer inputs across a paddock to increase yields and / or reduce costs.

To extend a model that was develop for point-scale application, we focused on the spatial estimation of one of the primary model inputs, potential yield. Potential yield is commonly required as input to agronomic models and the algorithm described for spatial estimation of potential yield may have wider use.

In this study, we used actual rainfall to estimate potential yield. In the field, actual rainfall is not known at the time when fertilizer decisions need to be made, but our approach can be coupled with seasonal climate forecasts to provide information to the farmer when he or she needs it.

We have made a number of simplifications that require further consideration. We used the broken stick model for potential yield because it is simple and well known in Western Australia, but our adaptation of the model to fit spatially-varying WUE does not fit well with the way the model is usually interpreted. An alternative is to scrap the linear approach completely and use a more modern method like additive quantile models (Fasiolo, Goude, Nedellec, & Wood, 2017).

We used a simple response curve model. It showed potential, but we are yet to compare and contrast the use of more complex models, such as Select Your Nitrogen (SYN), a weekly simulation model that determines root-zone available nitrogen (Bowden et al., 2002), and the crop simulation model APSIM (McCown, Hammer, Hargreaves, Holzworth, & Freebairn, 1996).

This work has shown that there is potential for predicting yield response to fertilizers spatially across a paddock or farm, but we have considered only one paddock and there is considerable more work required to test and further develop the concepts considered here.

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