Precision agriculture solutions to underpin profitable land use change for a better environment: A case study in Western Australia

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Abstract

Within Western Australia, yield mapping reveals that wheat yield varies spatially between 0.4 to 4.0 t/ha within the paddock and by applying economic analysis we have shown that some parts of the paddock are consistently operating at a loss. This variability occurs in a farming system characterised by inadequate water use that is responsible for rising saline ground water table. Indeed, some water balance modelling suggests that up to 50% of the wheatbelt landscape might need to be reassigned to an alternative land use having perennial vegetation in order to have a useful impact on salinity. The Dempster-Shafer Weight-of-Evidence model offers a rigorous methodology for assigning land use based on independent lines of evidence. We used this model in a case study at Three Springs to identify areas suitable for cropping and those that might be reassigned to alternative uses. The model used maps of historical gross margins, soil property, drainage values, soil type, remotely sensed biomass and proximally sensed gamma-ray emission as evidence. These maps were then converted to fuzzy sets to include varying degrees of expert judgement and hard data evidence to define which areas are suitable for cropping. By focusing on profits and environmental outcomes, the model has the potential to facilitate the adoption of land use change based on the combined contributions of the grower and discipline leaders.

Key words

Yield variability, Dempster-Shafer, weight of evidence model, fuzzy sets, land use, precision agriculture

Introduction

The productivity of grains / sheep farming in the Mediterranean region of Southern Australia is limited by insufficient rainfall. Paradoxically, the sustainability of this farming system is undermined by insufficient water use leading to raising saline ground water table and the onset of secondary salinity. The reason for this paradox is that the land is occupied for cropping for only half of the year. It remains bare for the rest of the year when water use falls short of that used by native vegetation. A third of the agricultural landscape of Western Australia is at risk and options to solve this problem include engineering and plant-based solutions. Our model estimates suggest that up to half of the landscape may need to be revegetated to perennial plants in order to decrease deep drainage to values comparable with those of native vegetation. This scale of land use change is massive and is unlikely to be adopted unless it is profitable to the farmer. The first question asked is where do we start revegetating the landscape. The answer to this question must include the farmer and be based on a transparent decision process that uses the best lines of evidence on productivity and environmental performance. Both these factors are highly variable spatially. Grain yield ranging from 0.4 to 4.0 t/ha is commonly measured at paddock scale resulting in some areas of the paddock operating at a loss. At the same scale, model values of deep drainage range from 12 to 25 mm due to spatial variability in soil type, water holding capacities and depth of root penetration. This spatial variability offers the opportunity to identify the worst performing areas for re-assignment of land use that is economically and environmentally beneficial. Our aim is to develop a decision process for land use change based on our intimate understanding on the financial performance of the paddock derived from several years of yield mapping and analysis of land suitability for cropping based on different layers of evidence.

The experimental site

The experiment was performed on paddock H10 on Rex Heal's property in Three Springs, WA. The paddock is about 70 ha and had a wheat-lupin-wheat rotation since 1998. The year 2000 was the driest year and 1998 received near to the long-term seasonal average rainfall for the region. Paddock yield was measured on each occasion with an AgLeader yield monitor and was pre-processed and extrapolated to yield maps using the Achiever software. Soil was sampled on the paddock, analysed and maps of potassium, organic carbon content and nitrate release were made using Inverse Distance Weighting interpolation in ArcView. In addition a Normalized Difference Vegetation Index (NDVI) image for mid-August 2000 and a soil map were also available for the paddock. The soil type map was used to estimate deep drainage based on a pedotransfer function developed using the DSSAT model (Zhang and Wong unpublished dada). Proximal sensing was used to map gamma-emission from ^{40}K.

Weighted Linear Combination of Yield and Gross Margin Evidence

Yield varied spatially and from year to year according to seasonal conditions, type of crop grown and the match between the land capability and its use. In spite of these changes, some common themes occurred on the yield and gross margins maps (Figure 1). Since yield depends primarily on available water the map reflects the underlying relationships between water availability and soil types and topographic location in the landscape. Although soil types and topographic locations are fixed, the spatial pattern of yield measured by yield mapping changes every year, which introduces an uncertainty about the boundaries between the good and poor performing areas. The conversion of the yield maps into fuzzy sets allows us to deal with this uncertainty (1). A monotonically increasing sigmoid membership function was used to derive fuzzy sets from the calculated gross margins. The fuzzy gross margin maps show which of the poor performing parts of the paddocks were consistently operating at a loss each year irrespective of the crop grown.

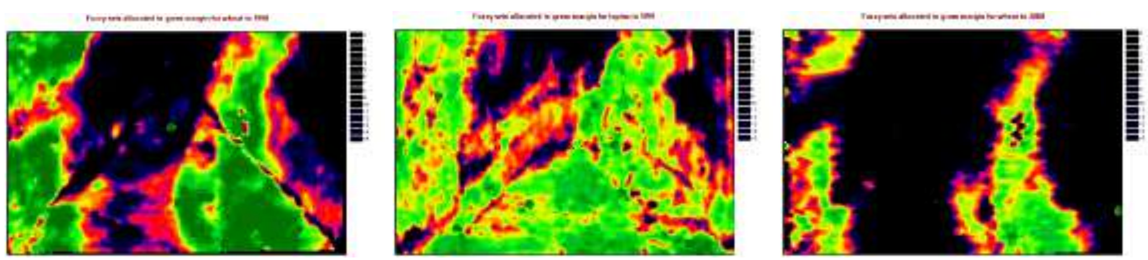

Figure 1. Suitability for cropping based on fuzzy allocations of gross margins. Dark areas are less suitable and green areas most suitable. The maps are for 1998 (left) to 2000.

The fuzzy sets for 1998 and 1999 were then overlayed on that for 2000 in IDRISI using the Weighted Linear Combination technique. The weights used for the different fuzzy sets were derived as Eigenvectors from pair wise comparisons of the fuzzy sets ranked according to how close the seasonal rainfall was to the long-term average (2). Figure 2 shows the result obtained when the worst one third of the land is removed from production. This figure was trimmed to remove areas less than 2 ha since it would be impractical to manage such areas individually.

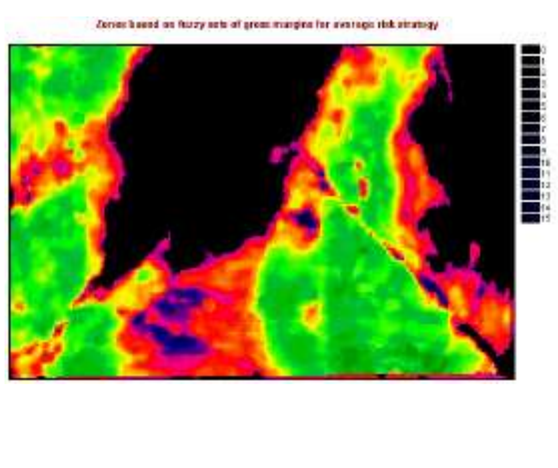

Figure 2. Land classification zones derived from Weighted Linear Combination of fuzzy sets of gross margins for 1998-00. The dark areas have a greater degree of unsuitability for cropping.

Multi-Criteria Evaluation using Dempster-Shafer Weight-of-Evidence method

Past yield performance is not a full indicator of future performance. Including additional evidence, where relevant, could decrease the risk faced by the decision maker. For instance, some of the poor performing areas may simply be suffering from a simple chemical limitation such as local soil acidity or nutrient deficiency that can easily be ameliorated cost effectively. But other zones, such as areas of deep poor water holding sands that may be uneconomic to improve, and would be best reassigned to alternative uses. We used the following evidence in our example to assess suitability for cropping:

1. Fuzzy sets derived from the gross margin maps for 1998 to 2000.

2. Fuzzy sets derived from soil potassium map: In the strongly weathered soils of WA, the majority of topsoil potassium is in the exchangeable form. The amount of potassium increases with the clay content, which in turn gives rise to better water holding characteristics.

3. Fuzzy sets derived from soil organic matter content: It is assumed that soil organic matter content is a controlling variable for soil fertility. Increased organic matter content increases suitability for cropping.

4. Fuzzy sets derived from NDVI maps: It is assumed that higher biomass content is related to more suitable cropping sites since crops operate within a narrow harvest index range under normal seasonal conditions.

5. Fuzzy sets derived from soil type maps: Some soil types for example, deep grey sands are inherently unproductive.

6. Fuzzy sets derived from deep drainage maps: Highly leaky areas are deemed less suitable for current use.

7. Fuzzy sets derived from gamma-emission from K-40. This map is similar to that of topsoil potassium but is cheaper.

The model expert should use input from the farmer and/or agronomist to decide on the relationship between the evidence and its postulated effect. The Dempster-Shafer method (3) allows us to overlay each of these relationships to produce a map of degree of suitability for cropping (Figure 3). In this case, the different lines of evidence for good and poor performing areas were coherent and the potential cropping zones are confidently identified. We are extending this analysis to other paddocks where the balance of evidence is likely to be more complex because recorded yields differed from that expected from independent evidence.

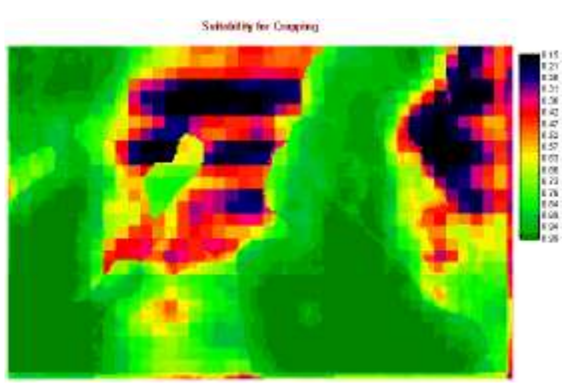

Figure 3. Land use zones derived from the Weight of Evidence model. Green areas have a greater suitability for cropping.

Conclusion

The use of fuzzy sets and weight-of-evidence modelling are powerful tools for rational land use assignment. It allows decisions about land use to be based on best available knowledge and evidence and so reduce the risks for farmers. Although, the method developed here can be extended to include knowledge from more experts and more disciplines, it is important to use the information we have now. We cannot afford to wait for a complete understanding of causal factors inducing within paddock variability to act against our pressing salinity problem.

Acknowledgment

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References

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