ConstraintID: a free web-based tool for spatial diagnosis of soil constraints

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Abstract

Better knowledge and understanding of the variation of past crop yields (both spatially across a paddock, and temporally from season to season) can help growers make better management decisions to improve yields in future. Remote-sensing data compiled from earth-observing satellites provide a valuable information source about past crop yields, allowing us to look through multiple years of imagery for consistent patterns through time – that is, spatial patterns of yield variation that repeat season after season. Such consistent patterns might imply the presence of a soil constraint limiting yields in parts of the field. To identify these patterns we have developed a web-based tool, called ConstraintID, to enable growers in the grains growing regions of Queensland and New South Wales (the GRDC Northern Region) to easily look at processed remote-sensing data representing past crop yields in their paddocks, and will show if there are any consistent spatial patterns in the data. The tool also enables the user to input their own local soil data. These data are then compared between the high and low-yielding areas of the paddock (according to the analysed remote-sensing data), which should shed further light on what soil constraints might be driving the within-field yield variation, providing growers with important information for closing yield gaps.

Keywords

ConstraintID, soil constraints, crop yield, decision support tool, remote sensing, Landsat.

Introduction

Within-field spatial variation of crop yields can occur for various reasons, but perhaps the most important driver is the soil. There are different management strategies available to growers to address soil constraints (amelioration, adjusting inputs to match potential, switching to growing tolerant species), but a necessary first step is the identification of affected areas (Dang et al. 2010).

Persistent spatial patterns of yield variation within fields that have otherwise been managed uniformly (spatially) provide an indication that soil constraints are driving variation (Dang et al. 2011). Remotely sensed data from satellites provide a valuable information source for helping with the task of identifying persistent yield patterns (Orton et al. 2018). In particular, the Landsat series of satellites provide a very useful dataset for several reasons:

(i) The long history (we use data from 1999-present), which allows persistent spatial patterns of within-field yield variation (similar patterns repeating season after season) to be identified
(ii) The time between repeated images of the same area (8 days when two of the Landsat satellites are operating), allows growth patterns within a season to be identified
(iii) The large spatial coverage of satellite data (data readily available across the whole region)
(iv) The spatial detail (30-m pixels), which allows within-field patterns to be identified, and
(v) It is freely available.

While Landsat imagery provides an excellent source of raw data, there are a number of processing and analysis steps required to extract useful information. We have developed a free online software tool, ConstraintID (http://constraintid.com.au), to make this task easy for growers, and to present results in a way that is straightforward to interpret. The tool should assist growers with identification of potentially constrained areas, giving them the information to make more informed management decisions.

Methods

The software undertakes spatial analysis within a confined field boundary. It is important that there has been spatially uniform management across the field, otherwise spatial differences due to management could get confused with differences due to soil constraints. The software collates all the remote-sensing data for the field for each year from 1999 to the latest complete season and generates a map of a Crop Yield Index (CYI) representing crop performance. The aim of this index is to show, for any given year, which parts of the field were above average and which parts were below average.

The CYI is based on Enhanced Vegetation Index (EVI) Landsat data from a number of images around the time of peak EVI. The EVI are ranked and then an average ranking over all images calculated for each pixel. This average ranking (standardized to the range 0–100) is used as the CYI for that growing season. This process is repeated for each growing season (1999–2019). For validation, we compared the CYI against yield maps produced from yield monitor data for 53 crops grown between 2001-2016 (Figure 1). To determine how well the CYI was able to model actual crop growth, the concordance correlation coefficient (CCC) was calculated. The CCC provides a measure of agreement between predicted and observed values, with 1 indicating perfect agreement and 0 no agreement. The CCC was calculated for each of the 53 crops, based on the agreement between the CYI and the yield monitor data (with the pixels in the yield monitor data ranked and standardised to the range 0–100 to be comparable with the CYI).

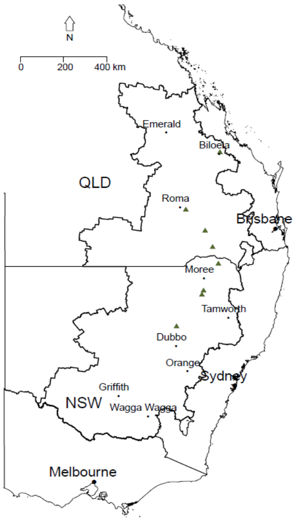

Fig. 1 A map of the GRDC's Northern Region (QLD and NSW) with the locations of the 25 paddocks where 53 analysed crops were grown.

The software tool also allows users to input soil measurement data, which can be used to compare soil characteristics in the high-yielding/unconstrained and low-yielding/constrained areas of the field. Because crop-specific tolerance limits vary between species and between soil constraints (Page et al. 2021), the tool also provides users with guides that allow them to determine whether the soil characteristics present in low and high yielding areas are likely to constrain the growth of 17 crops commonly grown across the region. The tool will thus help growers to choose the crop species most suitable for a particular paddock depending on the most prevalent soil constraints.

Results

Comparison of the crop yield index with yield monitor data: single and multi-year analyses

Over all 53 fields, a median CCC value of 0.64 was achieved, demonstrating reasonable agreement between CYI and the yield monitor data. However, the range of CCC values (0.15–0.89) demonstrated that the index could perform considerably better or worse than the median in particular cases (Table 1). A particular feature of ConstraintID is that remote-sensing data are used from many years (1999–2019), with the hypothesis that results from multi-year analyses will give stronger correlations with soil constraints than results from single years. Therefore, to assess the CYI in a way more suited to its use in ConstraintID, yield monitor data averaged over multiple years were used. In this analysis a much smaller range in the CCC was observed (0.48-0.87) along with a slight improvement in the median value (0.69) (Table 1).

Table 1 Validation statistics (CCC) from different analyses.

Statistics	Single-year analysis	Multi-year analysis
Number of paddocks	25	15
Number of yield maps	53	43
Minimum	0.15	0.48
5th percentile	0.29	0.55

Median	0.64	0.69
Mean	0.59	0.70
95th percentile	0.84	0.86
Maximum	0.89	0.87

Web-based ConstraintID (http://constraintid.com.au/)
The web-based interface of ConstraintID allows farmers and consultants to setup, save and share soil constraint analyses for different paddocks.

An analysis is broken down into six steps presented through the interface:

Step 1: Enter analysis details
Step 2: Define paddock boundary
Step 3: Select soil constraints
Step 4: Import soil test data
Step 5: Select cropping years
Step 6: Review results

For each analysis, the software requires the farmers to trace their paddock boundary over a Google Maps satellite image, using tools provided in Step 2. This then initiates the spatial analysis whereby a time-series of EVI satellite images from 1999 to the present date are extracted (typically up to 20 images per year). The resulting images are then filtered to remove any that might be affected by excessive cloud cover or are indicative of fallow conditions. Finally, the individual EVI pixel values are ranked across the paddock to differentiate between high and low vegetation areas. A single image is then produced for each year, based on averaging the ranked EVI values for that year, which we designate as the CYI. This process typically takes 10-20 seconds.

In the next steps (3 & 4), the user selects which soil constraints they wish to analyse and upload any measured soil test data they have relating to these constraints. In Step 5, the user is presented with a series of paddock images showing the CYI across the paddock for each year. Each image is 'marked' to show whether the software thinks that that year was indicative of a typical cropping year. The user inspects each image to ensure that all typical cropping years are selected, and non-cropping years are de-selected. This calibrates the analysis before generating the final result.

In the final step, all selected cropping years are compiled into a single paddock map of CYI values. A second image is then generated identifying those regions of the paddock that have a consistently high (coloured green) or consistently low CYI (coloured red). The locations of the soil test readings are then overlayed on these regions, allowing a graph of each soil constraint to be generated based on the soil test results, with different lines for high and low yielding areas (Figure 2). These graphs also display critical crop growth limits for one of 17 crops selected by the user.

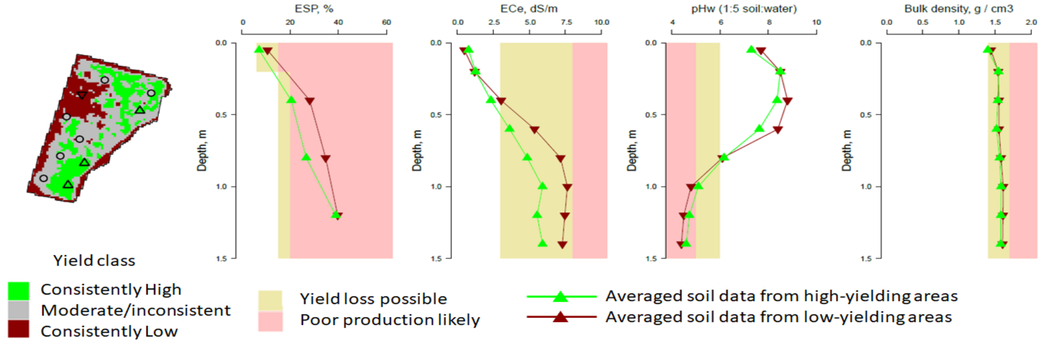

Fig. 2. Soil profiles within the areas with consistently high crop yield index values and consistently low values.

We have developed the ConstraintID tool for use in the grains industry, but similar tools might also be useful to growers in the sugar or cotton industries. Each case would present its own challenges, for instance the adaptation of remote-sensing analyses to be relevant to the different growth patterns of these crops, and the identification of relevant crop-specific critical values of soil constraints. There would also be features that would be common in all cases, such as the comparison of soil data between areas identified as consistently high and low yielding (or unconstrained vs. constrained). These potential extensions of the current work will be looked at in future.

Conclusion

The work presented here provides a snapshot of the ConstraintID web-based tool, which we think should provide growers with a valuable tool for investigating within-field variability and for making more informed management decisions. The maps of the CYI for individual years and the long-term summary maps (identifying areas where the yield index is high or low) should provide growers with valuable insight into the within-field variation and whether or not similar patterns are consistent year after year. Combining these maps together with targeted soil sampling within the high and low (constrained) yielding areas and crop specific critical values could identify potential soil constraints and assist farmers with management decisions.

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