Testing a new perspective on remotely sensed ground cover

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Abstract. Remotely sensed ground cover is a widely used metric of landscape health in the rangelands. Users often assume that good management increases ground cover, but changes in ground cover are driven by multiple factors (e.g. rainfall, topography) so that similar management can result in very different changes in total ground cover at different locations.

We used quantile regression to rank ground cover change across the Great Barrier Reef (GBR) catchments and mapped these rankings annually from 2011 to 2020. In theory the resulting cover change quantile images (CCQIs) should allow more nuanced assessment of where, and how significantly, ground cover changes across the landscape. We evaluated our CCQIs at locations of known management history and/or land condition to determine whether they reflect the management practices at those locations.

We identify some of the strengths and limitations of CCQIs, demonstrate their potential use and propose improvements for the next iteration of these products. CCQIs have potential to provide a new perspective on the relationship between management and ground cover resilience, and this has implications for their use as a decision support tool for land managers and investors.

Keywords: Remote sensing, grazing lands, degradation, productivity.

Introduction

Remotely sensed ground cover data are widely used to monitor the status of Queensland's rangelands. Changes in ground cover are driven by the interaction of multiple factors including rainfall, land type, fire and grazing. As a result, similar grazing management strategies can affect very different changes to total ground cover at different locations. This can complicate the task of understanding management impacts on the landscape, particularly if change is slow or nonlinear.

This paper describes a novel approach to benchmarking annual ground cover change. It is premised on the ideas that better management results in better maintenance of ground cover, and that the level of maintenance can be validly compared between sites if seasonal and landscape conditions are taken into account. We outline our methods to benchmark ground cover change, the resulting cover change imagery and provide examples of their use to evaluate management on two sites.

Methods

We developed a quantile random forest model to predict spring *seasonal ground cover* in the combined Burdekin, Fitzroy and Burnett Mary NRM regions. As model input, we generated

125000 random points on grazing land in these regions and at each point obtained the following values:

1. Ground cover in a single randomly selected spring between 1991 and 2010.
2. Ground cover in the year prior to the above spring.
3. 39 other predictor values derived from meteorological and landscape layers – each one particular to the year of prediction.

The model was developed to predict ground cover (1) using prior ground cover (2) and the other predictors (3). Including prior cover (2) in the model accounted for annual change in ground cover for each point, and other predictors accounted for other impacts on annual change in ground cover driven by seasonal and landscape factors. The model was built from 100000 points and validated on the remaining 25000 points.

We then used the final model to spatially predict ground cover for spring 2011 to 2020, generating 10 annual images for the study area. The differences between actual and predicted values were then ranked from 0-100 within all observed differences (i.e., quantiles) and mapped to produce *Cover Change Quantile* images (CCQI).

In effect, pixel values indicate the quantile of ground cover in that pixel relative to the expected cover from the model. Lower values indicate an end-of-year ground cover below expected levels of cover, while higher values are indicative of end-of-year ground cover above modelled levels of ground cover.

As an initial assessment of the results, we compared the mean CCQI value for two sites for each year (2011-2020). The first site is located in the Fitzroy Basin and has been very heavily grazed since 2002, while the second site was a property regarded by local RD&E staff as well managed since approximately 2000.

Results

Our random forest model accounted for 72% of variation in ground cover for the model period (1991-2010). The strongest predictor was ground cover in the preceding season but woody vegetation cover, soil colour and a number of rainfall summary statistics were also influential.

Figure 1 shows the mapped relationship between observed and predicted end-of-year ground cover, and CCQI. In the circled area the observed ground cover exceeds the predicted level and consequently the CCQI values for the area are high. Conversely the rectangle highlights a location where observed values are below predicted values, mapping the area to low CCQI values.

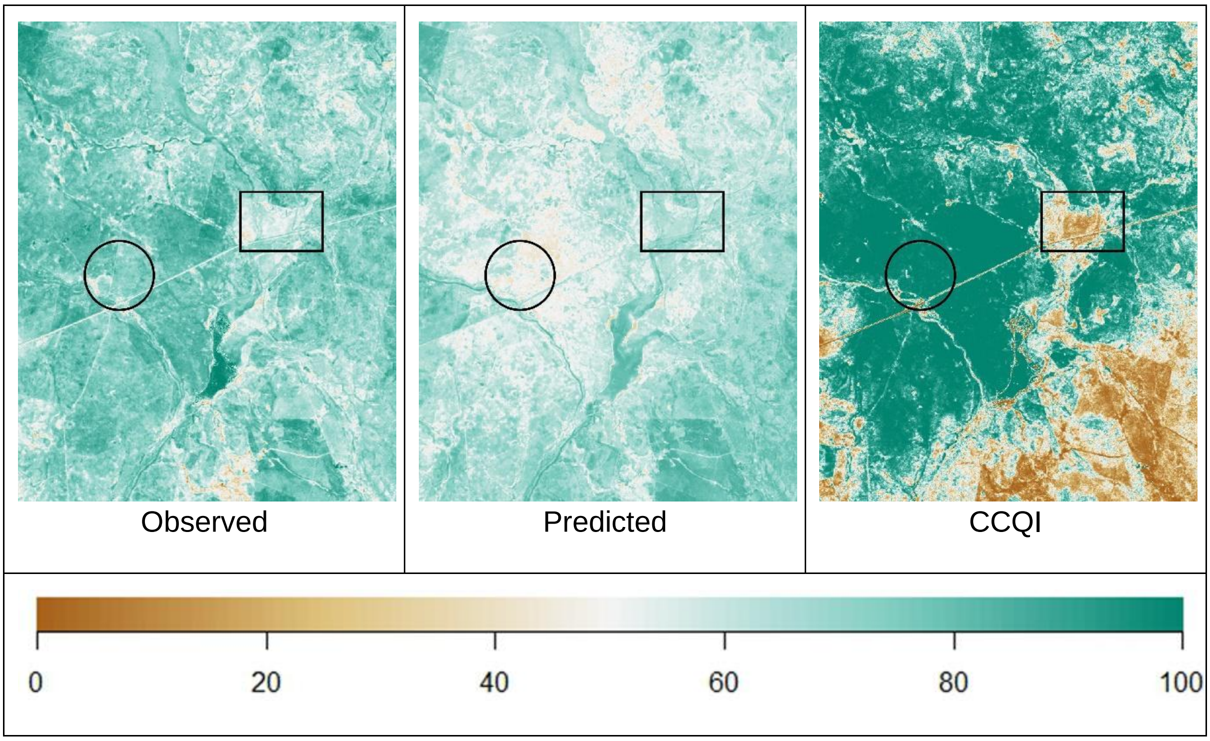

Figure 1. Observed and predicted percent ground cover, and CCQI (quantile) for corresponding sections of the study area in the 2018 layer.

Figure 2 shows the mean CCQI value per year on two test sites, one heavily grazed and another well managed in terms of grazing pressure. It shows the well managed site has a consistently higher mean CCQI value over the period 2011-2020. This aligns with the idea that better management of grazing pressure should result in higher cover change quantiles.

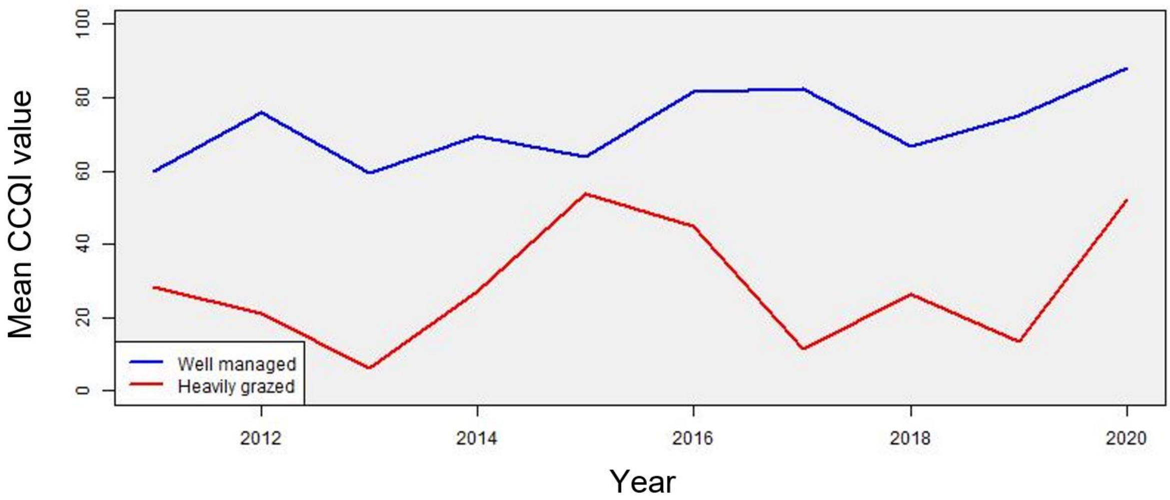

Figure 2. Mean CCQI time series for a heavily grazed site in the Fitzroy and a well-managed property in the Burdekin. The well managed property has consistently higher average CCQI values.

Discussion

CCQIs were developed as a novel approach to remotely evaluating the annual impacts of grazing land management decisions. The random forest approach accounts for the impacts of other factors on annual ground cover change and so isolates the impact of management in the quantile value. The random forest approach also proved useful in that it allowed us to incorporate a wide range of predictors in the analysis.

The test cases shown here suggest that there may be some merit in the use of CCQIs, since the test site values plotted as expected, but testing across a large number of sites is necessary. We also need to further investigate other factors that may impact CCQIs. For example, fires can heavily impact CCQIs (not shown here) and interpretation of their impact on quantile values needs further investigation.

If the method proves to be valid, it may provide a more robust test for the effects of different management strategies across wider areas and assist continuous adaptation of best practice. This would benefit land managers, their support agencies and financiers of grazing enterprises.