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Cumulative ground cover maintenance: what does it tell us about the grazing landscape and its management?

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Abstract
Two key challenges in rangeland management are determining the sustainability of management practices and the cumulative impact of those practices on the condition / health / productivity of the managed landscape. To this end remotely sensed cover products have been widely used in recent decades as there are no alternative products with a comparable spatiotemporal coverage and resolution.

We trialled a new approach to remotely assess land condition and management sustainability using ground cover data. The method first benchmarks Spring ground cover per pixel against local ground cover values within the land type (regional comparison (RC)). RC is a useful ground cover benchmark because it accounts for impact of land type and rainfall history on ground cover at any site. We then model Spring RC values based on the RC value of the previous Spring and recency of fire (a driver of ground cover not well accounted for by RC). We interpret the predicted quantile of any model prediction (GCM) as an index of how well the RC value has been maintained over that year at the site.

If annual GCM values do indicate how well ground cover has been maintained within the year, it is possible that long term consistency in GCM values (high or low) may highlight the broader sustainability of the management system (e.g. management that maintains ground cover probably also limits erosion and promotes desirable pasture species). Furthermore, more sustainable management systems might indicate places of high and/or improving land condition. This poster explains how the GCM layers were developed and tests the idea that they could be a useful tool to map both the historical sustainability of management systems as well as their impacts on land condition.

Introduction
Two key challenges in rangeland management are determining the sustainability of management practices and understanding their cumulative impact on the condition / health / productivity of the managed landscape. In the Australian rangelands, the sustainability of grazing management practices impacts the landscape through changes in the composition and amount of ground cover present in the landscape. Consequently, remotely sensed ground cover (GC) data – green and non-green cover such as described by the Queensland Government & Joint Remote Sensing Research Program (2022) – has been used widely in

recent decades to track landscape change. Management practice impacts other landscape outcomes as well (e.g. erosion, weed infestation) but there are no analogous remotely sensed datasets with a comparable spatiotemporal coverage and resolution as the existing GC archives to track these outcomes remotely.

One potential geographic identifier of sustainable management practices in grazing land is the consistent maintenance of GC at or above expected (taking into account recent climate and land type) (Beutel & Graz, 2022). If this was the case, and it was possible to quantify and map how well GC was maintained per year, then the cumulative quantum of maintenance could also be mapped and might well indicate the longer-term sustainability of management at any location, at least as far as GC levels are concerned.

Beutel and Graz (2022) trialled this approach by modelling annual change in GC across a section of the Queensland rangelands. That study modelled annual change in ground cover using a large multivariate model and then used the quantile of observed change for any pixel (hereafter GCM: ground cover maintenance score) within its modelled prediction interval to benchmark the observed change for that year. They concluded that cumulative GCM (CGCM) values had some correlation with grazing land condition (Chilcott et al., 2003), but that the GCM model needed to incorporate the impact of fire history and better predict change in GC to fully test the relationship between land condition and CGCM.

Objective

In this study, we developed and tested an alternative approach to generating GCM map layers. The new method models annual change pixel regional comparison (RC) values rather than change in raw ground cover values. Regional comparison values (Beutel et al., 2021) take into account rainfall and land type so were seen as a potentially better target to model than raw GC. The new layer development also incorporates fire recency into GCM calculations. We describe the development of these new GCM layers and their relationship with land condition at a set of sites in Queensland.

Methods and results

Study area

The study area encompasses the Burdekin, Fitzroy and Burnett-Mary catchments, covering around 350,700km^2 in Queensland, Australia (Figure 1). Rainfall in the area is highly variable - between 500 and 1,300 mm annually across the region. Around 175 different land types have been identified in the study area (Department of Agriculture and Fisheries, 2022), many of which are subject to intermittent burning.

Data processing

Our method generated two raster data sets to align with the 30x30m Landsat imagery. We first built seasonal regional comparison (RC) rasters for the study area for each Spring (2014-2023). These images map ground cover quantiles (0 to 100) by comparing cover in each pixel to other pixels in the same land type (Department of Agriculture and Fisheries (2022)) within a 20 km radius. Higher RC pixel values indicate relatively higher levels of ground cover within the land type and local area. Each RC image is thus a point-in-time evaluation of ground cover given the land type, as well as recent local climate and management histories.

We generated a corresponding second set of GCM images to rank annual change in RC values. A quantile random forest model was used to predict RC per pixel for each Spring from two variables: the previous Spring's RC value and the number of months since the most recently mapped fire (fire recency). Fire recency data were based on Collett (2021) and van den Berg (2021), and were included because Beutel and Graz (2022) showed the dramatic impact of fire recency on their GCM images. The model accounted for 51% of the variance in annual RC change, of which <2% was contributed by inclusion of the fire recency data. The resulting GCM image values range from 0 to 100 and we interpret them as indicative of how well ground cover was maintained after fire recency and starting RC values were accounted for.

Analysis

Assuming that each annual GCM image reflects how well ground cover was maintained in that year, we tested whether cumulative GCM values might correspond to longer term management outcomes. We built cumulative GCM images (CGCM) by averaging annual values per pixel for the period 2015-2023. We then extracted mean CGCM pixel values at 2,220 sites where land condition had been assessed in 90x90m plots between 2021 and 2023, and compared the mean CGCM values allocated to different land condition classes. The boxplot of CGCM scores for each land condition class is shown below (Figure 2). It shows that CGCM differentiates the D (very poor) condition class quite well from others, but better condition classes, particularly A and B, are very similar in terms of CGCM scores.

Discussion

This paper outlines the development of a new version of GCM mapping. This version was built using a different approach to Beutel and Graz (2022); GCM values were based here on the regional comparison methodology rather than modelling GC in a complex multivariate modelling process. This new work also considered fire recency, which was absent from the original analysis.

Our test of whether CGCM values might predict land condition showed CGCM has some potential for mapping D condition but does not discriminate other condition classes very well. D condition sites are typically the easiest to identify remotely because they most often have very low GC levels. As such, it is not surprising that D condition sites were easiest to discriminate using CGCM. The approach may have worked better on other condition classes had we used a longer cumulative period than 2015-2023 or had our model accounted for more of the variance in annual RC change. It is possible too though that CGCM can’t discriminate higher land condition classes. Higher classes of condition result more often from change in vegetation composition than GC, and since CGCM is derived from GC imagery, it may lack sufficient capacity to indicate changes in composition.

In this work we were interested in the idea that CGCM might be a tool to map the longer-term sustainability of management practices. We used land condition as a surrogate for management outcomes because these data were available to us. In doing this though we implicitly assumed that more sustainable management systems should have better land condition. This is not always true though. For example, where the management system has recently changed (e.g. through succession or sale) current land condition is likely more due to previous than current management practices, and very poor condition (D) is resistant to most management changes (Chilcott et al. 2003) so may persist through multiple managers and management systems. In summary, land condition may have some relationship to CGCM at the poorer end of the land condition spectrum, but it may not be the best surrogate to test the connection between CGCM and the sustainability of recent management.

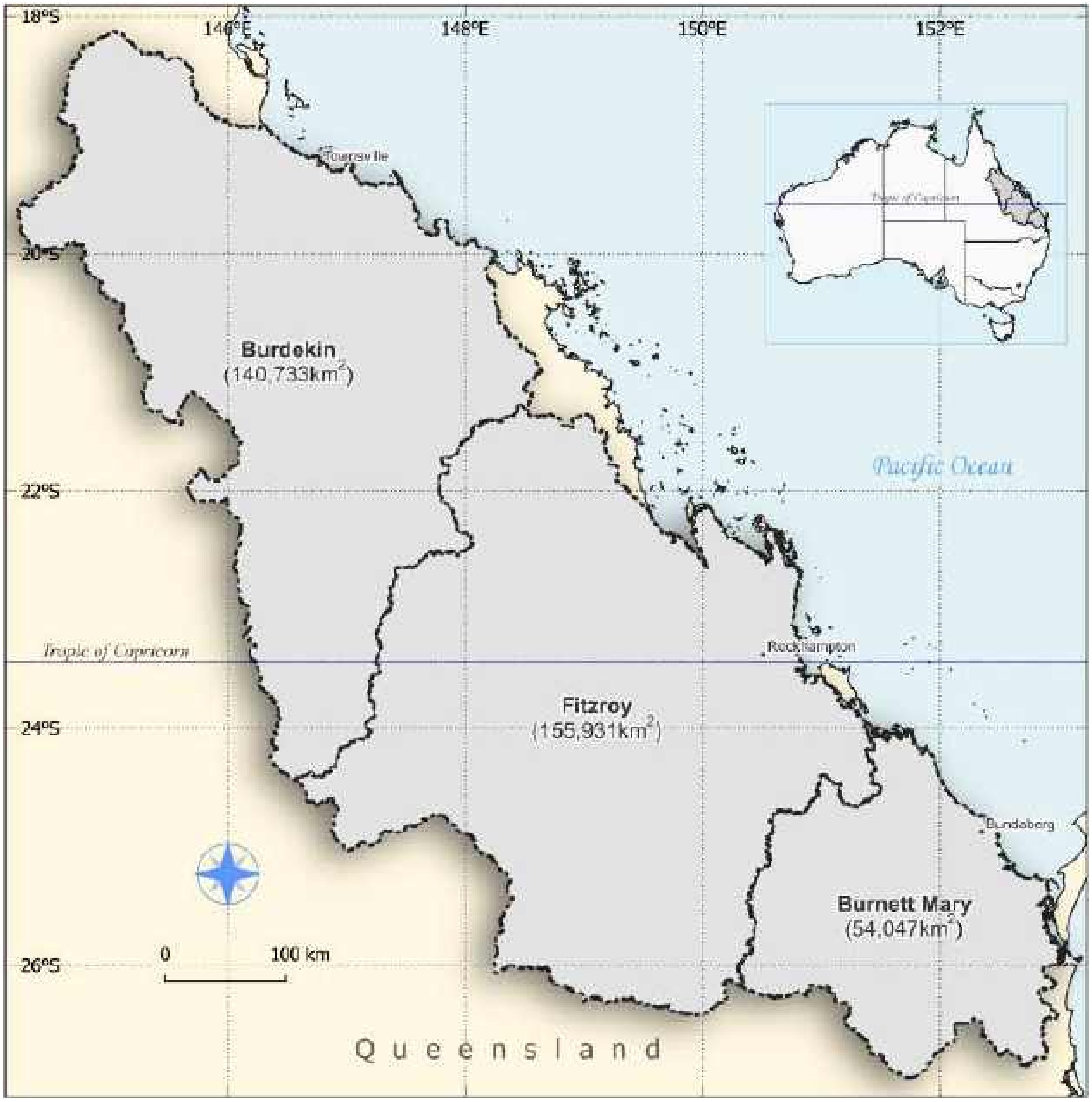

Figure 1. Location of the study area.

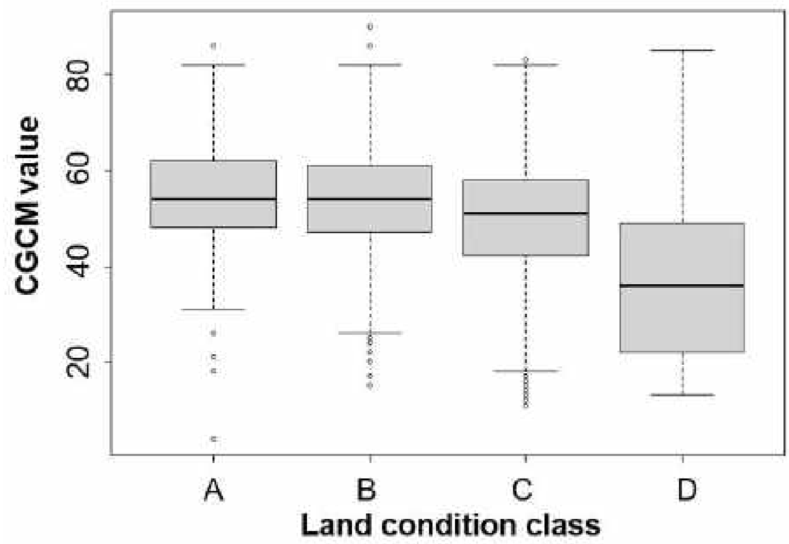

Figure 2. Cumulative (mean) GCM values for different land condition classes on 2220 land condition assessment sites in the study area.

Conclusion

This work is part of a larger project investigating different ways to model Queensland's rangeland health and productivity. This test of the GCM approach suggests that the method may not predict land condition reliably, but we plan several other uses and evaluations of the GCM methodology and products.

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