XII INTERNATIONAL RANGELAND CONGRESS AUSTRALIA 2025

Mapping the condition of Queensland's grazing lands

Beutel, TS[1]; Graz, FP[1]; Trevithick, R[2] and Hassett, R [1]

[1] Department of Primary Industries, Rockhampton, Queensland; [2] Department of Environment, Tourism, Science and Innovation, Brisbane, Queensland.

Key words: land condition; LCAT; ABCD framework.

Abstract

Grazing land condition is the ability of grazing land to convert rainfall into useful forage and is determined by changes in pasture, soil, and woodland condition. The Grazing Land Management framework defines four condition classes (A, B, C or D), indicating maintenance of 100%, 80%, 50% and 20% of productive potential respectively. The Queensland Government is currently funding a six-year program to map grazing land condition in key Great Barrier Reef catchments. The work incorporates assessment of thousands of grazing land sites using the Land Condition Assessment Tool (LCAT), modelling the ABCD land condition class at those sites and generating modelled land condition maps across the targeted regions. Modelling and mapping land condition across large areas presents some significant challenges. For example, land condition is a multidimensional outcome that can be hard to mathematically fit to a unidimensional scale like ABCD, and spatial data that might predict some of these dimensions is either absent or limited. This has led the project to investigate and trial a number of approaches to delivering land condition mapping. This paper outlines the project's progress and some of our key learnings so far. These include an outline of LCAT sampling to date, an overview of the modelling and validation process and details around the planned rollout of the mapping.

Introduction

One of the key threats to the Great Barrier Reef (GBR) is soil sediment runoff from the GBR catchments, and grazing lands have been identified as a significant contributor to this threat (State of Queensland 2018). The Queensland government currently funds a suite of research and extension projects aimed at protecting the GBR. The Land Condition Monitoring Program is one of these and is tasked with developing maps of grazing land condition for GBR catchments.

Grazing land condition is an established framework for quantifying how well a grazing ecosystem is functioning and is defined as the capacity of grazing land to respond to rain and produce useful forage (Chilcott et al. 2003). Under this framework, sites are classified in one of four classes A (good), B (fair), C (poor) or D (very poor) based on the pasture, soil and woodland condition. Sites in A, B, C and D condition are respectively considered to have maintained about 100%, 80%, 50% and 20% of their original capacity to convert rainfall into useful forage. The system has been used widely in Queensland research, development and extension projects, and has proven a useful tool for engaging land managers around landscape health and productivity.

The Land Condition Monitoring Program involves several activities including upgrading the VegMachine.net website and developing a field guide for identification of important Queensland pasture species. This paper focusses on the land condition mapping component of the program. We outline the process to date for developing land condition layers and discuss several key issues around the work including future directions.

Methods

The project area includes three key Great Barrier Reef Natural Resource Management (NRM) regions (NQ Dry Tropics, Fitzroy Basin Association and Burnett Mary Regional Group). These cover a combined 351 000 km^2. Collection of land condition data in this area began in 2020 and is currently funded to June 2026.

All land condition data in the study were collected using LCAT (Land Condition Assessment Tool (Hassett et al. 2021)), a simple phone / tablet survey tool embedded in the ESRI survey 123 app. LCAT users include field staff of most Queensland NRMs as well as research and extension staff of the Queensland Department of Primary Industries. All users receive LCAT training prior to field use. LCAT users evaluate one hectare grazing land sites, recording data on variables including ground cover, primary pasture species, pasture density, pest species and abundance, woody cover and erosion. The LCAT algorithm then generates a variety of site summaries on-the-fly including a land condition rating (A, B, C or D). These data and summaries are then uploaded to cloud storage where they can be made available for land condition modelling.

The modelling process largely follows that of Scarth et al (2020). The study area is first segmented into polygons with common long term ground cover and woody cover histories. Summary values are then extracted from a large number of existing spatial layers for each segment to serve as the predictors for the land condition model. Where LCAT sites intersect a segment, the summary values for the segment are used in a random forest model to predict the land condition class of the intersecting site. The modelling process generated 30 potential models with varying parameterisations, and a single model was selected by evaluating fit to both holdout and cross-validation data as well as expert evaluation of the mapping on familiar client properties. The final selected model was then used to predict condition in all segments, and these segments were mapped with their predicted land condition class to create the land condition map.

Results

The current iteration of modelling incorporated 4233 land condition assessments, composed of (916, 1268, 1592 and 457 A, B, C and D condition sites respectively. Ten percent of these were randomly assigned to holdout validation data and the remainder used for model training. The final model incorporated multiple spatial predictors, but the most influential related to long term Dynamic Reference Cover Method value (Bastin et al. 2012), historical rainfall, temporal trend in woody vegetation cover, topography and historical ground cover. Table 1 shows the fit of the model to the holdout data. The ordered Kappa statistic for this fit (suitable for ordinal data) was κ=0.52, indicating moderate agreement between observed and predicted land condition class. The model predicts C and D condition relatively well, but fewer A and B condition sites are correctly assigned. Figure 1 shows an example section of the imagery.

Table 1. Confusion matrix for numbers of predicted vs observed land condition classifications from final land condition model for 423 sites in the holdout dataset.

		Predicted			
		A	**B**	**C**	**D**
Observed	**A**	49	20	20	1
	B	12	63	41	4
	C	8	24	134	8
	D	3	4	8	24

Discussion

LCAT has proven a highly effective tool for collecting and collating land condition data in this project. Its key advantage is that it provides a wide set of users with a common set of criteria and rules for consistent assessment of land condition, and the wide user base maximises data available for exercises such as this project. This is a significant improvement on previous land condition studies (e.g. Karfs et al. 2009, Beutel et al. 2021) that relied on multiple datasets from multiple studies, many of which used different methods to arrive at their land condition assessments.

It's worth noting that LCAT data are collected for a number of purposes depending on the collecting organisation. As well as modelling land condition, these purposes include site monitoring, evaluation of sites applying for public remediation funding and assessment of impact by extension providers. This wide use demonstrates the utility of LCAT, but also highlights an important point – that the full LCAT dataset is not a random sample of the landscape. As such the collated points may not represent the true proportion of each condition class in the landscape. This underlines the importance of developing land condition layers that can adequately estimate those proportions for all parts of the landscape.

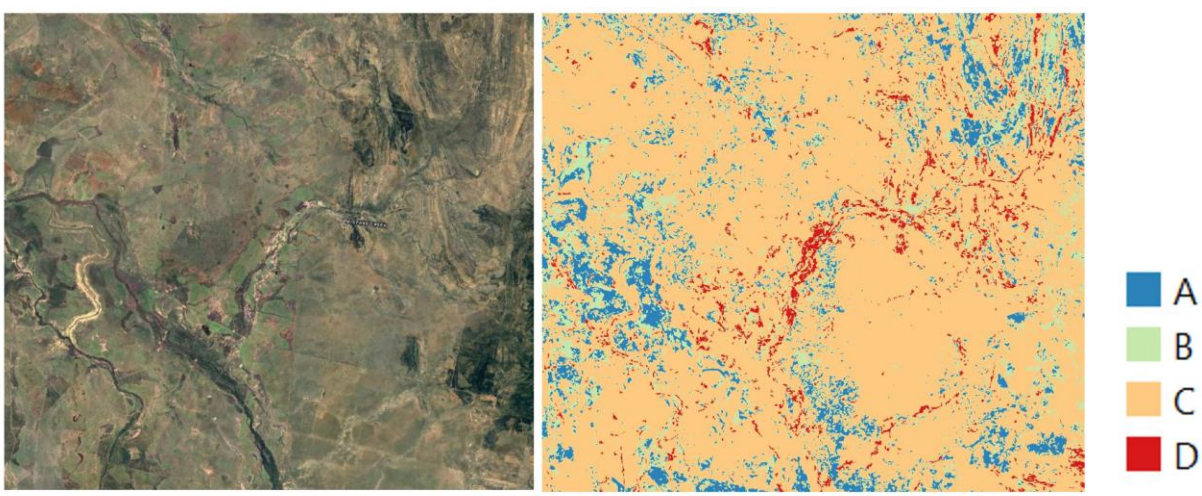

Figure 1. Example section of the current iteration of land condition mapping for a section of the Burdekin region (right) and corresponding RGB image of same area (left).

Table 1 shows the predictive precision of the most recent version of land condition mapping across the entire landscape (we have not yet analysed prediction in subset areas such as individual land types, but work is planned on this topic). While the current model improves on the previous year's iteration (not shown) it also highlights a significant challenge in modelling land condition, and that is the difficulty of correctly detecting high (A and B) condition sites. The current model relies heavily on ground cover related predictors (above), but high ground cover does not necessarily imply good land condition. For example, high coverage of the grass *Bothriochloa pertusa* will produce a C condition rating, at best. We think the model's reliance on ground cover data limits its capacity to distinguish condition classes when cover is relatively high. Conversely poorer condition sites have generally less ground cover than good condition sites, and so the model distinguishes C and D condition sites quite well.

In response to this challenge, we have begun work to model and map the distribution of major pasture species like *B. pertusa*. LCAT surveys include identification of the dominant pasture species so provide a ready data source to map where particular species dominate. If we can map the distribution of such species, these layers could assist in the differentiating condition classes in high cover areas by providing data to the model about pasture composition.

Some of the predictors in our current land condition model are long term (>30 year) ground cover and climatic summary data. These were selected for their predictive capacity, and our thinking is that they may be capturing some of the inherent characteristics of the landscape that have no other surrogates in the predictor set (e.g soil types, climatic zones). Currently it's unclear how long-term predictors will impact our capacity to monitor temporal change in land condition. If these long-term variables mostly describe the context of invariant aspects of the landscape, and shorter-term (≤ 5 years) predictors capture change in condition then its possible long-term predictors will play a useful ongoing role. Ultimately though, the best test of any land condition model's predictive skill is detailed analysis of where and when it does and doesn't predict land condition well, and this is part of the longer term project planning.

The current iteration of the land condition mapping was distributed to a limited audience of extension officers and graziers. These users are providing additional feedback about the mapping. The goal for this work is to publicly distribute future iterations through channels like VegMachine.net once a review of the mapping demonstrates an acceptable level of accuracy and suitable support documentation for users.

Acknowledgements
Funding for the project is provided by the Queensland Reef Water Quality Science Program. We'd also like to thank the numerous land managers and staff in DPI and regional NRM groups who have made this work possible.

References

Bastin G, Scarth P, Chewings V, Sparrow A, Denham R, Schmidt M, O'Reagain P, Shepherd R and Abbott, B (2012) Separating grazing and rainfall effects at regional scale using remote sensing imagery: A dynamic reference-cover method. *Remote Sensing of Environment*, 121, 443-457.

Beutel T S, Shepherd R, Karfs RA, Abbott, BN, Eyre T, Hall TJ and Barbi E. (2021) Is ground cover a useful indicator of grazing land condition? *The Rangeland Journal*, 43, 55-64.

Chilcott CR, McCallum BS, Quirk MF and Paton CJ (2003) Grazing Land Management Education Package Workshop Notes – Burdekin. Meat and Livestock Australia Limited, Sydney.

Hassett R, Beutel T, Brooks E, Graz P, Humphreys P, Northey A and McCosker K (2021) Land condition assessment tool (LCAT)—documenting land resources and condition. In NRM in the Rangelands: shaping our future. Australian Rangeland Society.

Karfs RA, Abbott BN, Scarth PF and Wallace JF (2009) Land condition monitoring information for reef catchments: a new era. *The Rangeland Journal*, 31, 69-86.

Scarth P, Trevithick R and Tindall D (2020) RP105G – Monitoring ground cover patchiness and land condition in the grazing lands of the Great Barrier Reef catchments. Department of Environment and Science, Brisbane.

State of Queensland (2018) Reef 2050 Water Quality Improvement Plan 2017-2022. Queensland Government, Brisbane, Australia.