The Queensland land condition monitoring program: up and running

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Abstract. The Queensland Government has begun a cross-agency effort to remotely measure and monitor rangeland condition across the state. The program aims to produce regular map products and information describing the productivity and function of grazing lands aligned with the ABCD land condition framework.

The system is generating large numbers of rangeland condition assessments collected by research and extension staff in the Queensland Government and regional NRM groups using the recently developed Land Condition Assessment Tool (LCAT). More than 1500 LCAT assessments have been collected in the first year of the project. The LCAT data will train a state-of-the-art machine learning model to produce cross-landscape mapping of land condition.

This paper outlines the scope of the program, data collection, plans for user access to the project outputs and opportunities to contribute to the program and assist in the development of robust land condition mapping in Queensland.

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

Introduction

The Grazing Land Management (GLM) land condition framework (Chilcott *et al*. 2003) has been widely adopted by rangeland managers and researchers (e.g. Walsh and Cowley 2016, Scanlan *et al.* 2014). It classes land on a four-point ordinal scale from A (Good) to D (Very poor) and defines grazing land condition as both the capacity to respond to rain and produce useful forage, and how well the grazing ecosystem is functioning (DPI&F 2004). The framework provides a means to measure land condition *in situ*, but we still lack the ability to assess land condition remotely and in a spatially comprehensive and repeatable way.

The Queensland Land Condition program is a multi-agency effort to produce and deliver regular grazing land condition mapping for use by land managers, including stakeholders in the Queensland grazing industry. It offers benefits to industry, government and community through better informed decisions on sustainable land management practices, public funding initiatives, productivity evaluation, property valuation and drought resilience.

The program leverages two recent technological developments that make remote mapping of land condition possible.

- The Land Condition Assessment Tool (LCAT) (Hassett 2020), a digital survey tool that allows simple efficient site-based land condition evaluation suitable for a wide range of users.

- The development of a spatial land condition model (Scarth *et al.* 2020), which is an artificial neural network model, trained by LCAT observations and based on cover metrics derived from remote sensing, and capable of spatially predicting land condition

This paper outlines the Queensland Land Condition Program. We detail the data collection and management, the spatial land condition model, the planned project outputs and opportunities for third parties to contribute to the program.

Data collection and management

LCAT surveys provide a convenient and consistent vehicle to collect site-based land condition data for the program. Users answer a series of questions relating to a site and from these the LCAT algorithms derive multiple site values including an ABCD rating and a numeric (0-100) land condition score. Each survey includes a point location, a set of collected and generated attributes, and up to five site photos. Completed surveys are automatically uploaded to a secure cloud storage platform, then downloaded and packaged locally by the project to train and validate the spatial land condition model.

Over 1500 LCAT surveys were collected in the first year of the program (2020/2021). While the initial sampling was focused on three Great Barrier Reef natural resource management (NRM) regions (Burnett Mary, Fitzroy and Burdekin), approximately one third of the surveys were collected outside those regions. This reflects the longer-term goal of state-wide mapping capacity. Data collection has been led by Queensland Government personnel, but significant contributions have been made by a number of regional NRMs and other agencies.

The spatial land condition model

Scarth *et al.* (2020) developed the neural network multilayer perceptron model as part of a project undertaken for the Reef Water Quality Science Program. The model predicts land condition as a continuous (0:1) variable. It was trained and validated with approximately 1650 historical land condition records from the three focus NRM regions and relies largely on ground cover metrics derived from Sentinel-2 satellite imagery to predict land condition spatially.

The majority of the land condition data used in the first iteration of this model was collected in 2011, several years before the first capture of the Sentinel-2 imagery used by the model for spatial prediction. These older data were used to ensure adequate training / validation dataset sizes, and despite the temporal lag, the spatial model fitted the validation data reasonably well (Figure 1), though with clear overlap of predicted condition scores between GLM condition classes.

The current iteration of the spatial land condition model should be regarded as a prototype, with the primary aim being the development of the modelling framework. However, it offers a number of important advantages for future use. Firstly, it can be further trained as additional site-based land condition data accrues over time, particularly with the continued uptake of LCAT by land managers. Secondly, the Sentinel-2 and similar satellite missions will continue to add to their dense time-series of data. As the time-series lengthens and becomes denser, the cover metrics that are included in the model will become more representative of the full range of seasonal conditions, including intra- and inter-seasonal change, and decadal change associated with drought and wetter periods. Further, the model once trained also predicts efficiently across the landscape, which will reduce production costs and time. New site data can then be used for continuous validation, or for periodic re-calibration (i.e. training) of the model, particularly if new remote sensing variables become available.

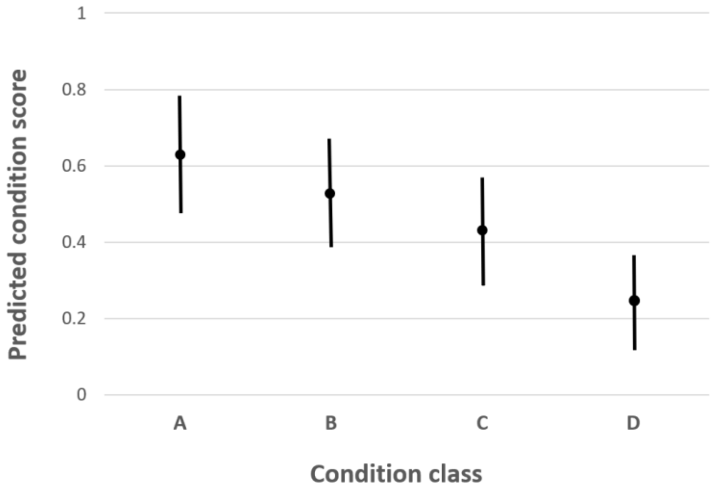

Figure 1. Validation of the continuous land condition score model with predicted land condition scores on the vertical axis compared to observed land condition classes. Points indicate class means and vertical bars show standard errors. Adapted from Scarth *et al.* (2020).

Product delivery

As land condition dynamics are generally relatively slow-changing, and the spatial land condition model depends on dense, longer-term satellite image time series, we plan to generate and release land condition mapping biennially.

The program aims to provide publicly accessible products that allow users to assess land condition at user selected sites or localities. These products will include maps and numeric summaries, and over the longer term, as multiple images become available, also incorporate time series analyses. Upgrades to VegMachine.net (Beutel *et al.* 2019) are planned which will help to address those goals, but other delivery channels will also be investigated, and it is hoped that government and industry will also uptake, use and value-add to these products.

You can contribute

The core requirement of this work is ongoing collection of LCAT data across the state for the next 5-10 years. This will ensure robust prediction by the RP105G model. Interested parties can contribute to better land condition mapping in their region by collecting local LCAT assessments. Those interested can contact our team for further information about LCAT training and coordinating with the broader sampling program.

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References

Beutel, TS, Trevithick, R, Scarth, P & Tindall D 2019, 'VegMachine.net. online land cover analysis for the Australian rangelands', *The Rangeland Journal*, vol. 41, pp. 355-362. https://doi.org/10.1071/RJ19013.

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

DPI&F 2004, 'Stocktake: Balancing Supply and Demand.' Department of Primary Industries and Fisheries: Queensland.

Hassett, R.C. (2020) Land Condition Assessment Tool Reference Guide Version 1.0., Rural Economic Development, Department of Agriculture and Fisheries, Brisbane, Queensland.

Scanlan, JC, McIvor, JG, Bray, SG, Cowley, RA, Hunt, LP, Pahl, LI, MacLeod, ND & Whish, GL 2014, 'Resting pastures to improve land condition in northern Australia: guidelines based on the literature and simulation modelling', *The Rangeland Journal, vol.* **36**, pp. 429–443. https://doi.org/10.1071/rj14071.

Scarth, P, Trevithick, R & 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, Queensland Government. Brisbane.

Walsh, D & Cowley, R 2016, 'Optimising beef business performance in northern Australia: what can 30 years of commercial innovation teach us?', *The Rangeland Journal,* vol. **38**, pp. 291-305. https://doi.org/10.1071/rj15064.