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Is ground cover a useful indicator of grazing land condition?

Terrence S. Beutel [A,G,*], *Robert Shepherd* [B], *Robert A. Karfs* [C], *Brett N. Abbott* [D], *Teresa Eyre* [E], *Trevor J. Hall* [F] and *Emily Barbi* [A]

[A]Queensland Department of Agriculture and Fisheries, Parkhurst, Qld 4702, Australia.
[B]Queensland Department of Agriculture and Fisheries, Charters Towers, Qld 4820, Australia.
[C]Queensland Department of Agriculture and Fisheries, Dutton Park, Qld 4102, Australia.
[D]CSIRO Land and Water, Townsville, Qld 4811, Australia.
[E]Queensland Department of Environment and Science, Toowong, Qld 4066, Australia.
[F]Queensland Department of Agriculture and Fisheries, Toowoomba, Qld 4350, Australia.
[G]Corresponding author. Email: terry.beutel@daf.qld.gov.au

Abstract. Remotely sensed ground cover data play an important role in Australian rangelands research development and extension, reflecting broader global trends in the use of remotely sensed data. We tested the relationship between remotely sensed ground cover data and field-based assessments of grazing land condition in the largest quantitative analysis of its type to date. We collated land condition data from 2282 sites evaluated between 2004 and 2018 in the Burdekin and Fitzroy regions of Queensland. Condition was defined using the Grazing Land Management land condition framework that ranks grazing land condition on a four point ordinal scale based on dimensions of vegetation composition, ground cover level and erosion severity. Nine separate ground cover derived indices were then calculated for each site. We found that all indices significantly correlated with grazing land condition on corresponding sites. Highest correlations occurred with indices that benchmarked ground cover at the site against regional ground cover assessed over several years. These findings provide some validation for the general use of ground cover data as an indicator of rangeland health/productivity. We also constructed univariate land condition models with a subset of these indices. Our models predicted land condition significantly better than random assignment though only moderately well; no model correctly predicted land condition class on >40% of sites. While the best models predicted condition correctly at >60% of A and D condition sites, condition at sites in B and C condition sites was poorly predicted. Several factors limit how well ground cover levels predict land condition. The main challenge is modelling a multidimensional value (grazing land condition) with a unidimensional ground cover measurement. We suggest that better land condition models require a range of predictors to address this multidimensionality but cover indices can make a substantial contribution in this context.

Keywords: degradation, grazing lands, ground cover, land condition, remote sensing, rangelands.

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Introduction

A key principle of sustainable landscape management is the need to measure and monitor the state and trend of landscape attributes and processes (West 2003). In Australia, as in other regions, this has driven investment in site-based tools and systems to monitor biophysical change in the rangelands (e.g. Tongway and Hindley 2004; Eyre *et al.* 2006; Thackway and Leslie 2006; Watson *et al.* 2007). These site-based approaches to landscape monitoring vary in both method and the landscape attributes that they target, but generally share the assumption that assessments of the site can be extrapolated to the broader landscape.

The Grazing Land Management (GLM) land condition framework (Chilcott *et al.* 2003) is another example of such tools. It has been widely adopted by managers and researchers in the northern Australian rangelands (e.g. Scanlan *et al.* 2014; Walsh and Cowley 2016) including the Great Barrier Reef catchments along the east Australian coast (e.g. Karfs *et al.* 2009*a*; McIvor 2012; Willis *et al.* 2017). Categorising condition on a four-point ordinal scale from A (Good) to D (Very poor), the GLM framework defines grazing land condition as both the capacity of grazing land to respond to rain and produce useful forage, and how well the grazing ecosystem is functioning (DPI&F 2004). Many users of this framework have assessed condition using various methods and tools from purely visual assessments (e.g. Karfs *et al.* 2009*b*) to detailed site measurements (Aisthorpe and Paton 2004; Abbott and Corfield 2012). However, all take into account simultaneous assessment of soil,

[*]Scopus affiliation ID: 60028929.

Table 1. Description of the GLM land condition classes (modified from Aisthorpe and Paton 2004)

Condition	Description
A (Good)	Good coverage of perennial grasses dominated by 3P species (perennial, palatable, productive) for that land type. Mostly >70% ground cover. Few weeds and no significant infestations. No erosion. No sign or early signs of woodland thickening.
B (Fair)	Similar to A condition but with one or more of the following; some decline in health/density of 3P grasses, increase in other species (less favoured grasses, weeds), mostly 40–70% ground cover, some signs of previous erosion and current signs of erosion risk, some thickening in density of woody plants.
C (Poor)	Similar to B condition but with one or more of the following; general decline in health/density of 3P grasses, large amounts of annuals and less favoured species, ground cover mostly <40%, obvious signs of past erosion and/or current susceptibility to erosion is high, general thickening in density of woody plants.
D (Very poor)	One or more of the following features; general lack of perennial grasses and forbs with mostly bare ground, severe erosion or scalding (resulting in a hostile environment for plant growth), thickets of woody plants cover most of area.

pasture and woodland attributes to deliver a single site condition assessment as per the guidelines of the GLM framework (Table 1). The wide adoption of the GLM framework by multiple research and extension agencies has created a large archive of temporally and spatially diverse land condition records. Note that unless otherwise stated, the terms 'condition', 'land condition' and 'grazing land condition' are used interchangeably throughout this paper and refer specifically grazing land condition as defined under the GLM framework (above).

Another significant feature of rangeland monitoring has been the continued emergence of remote sensing as a tool for rangeland assessment. In the Australian context, this work began more than 30 years ago (Pickup 1989) and has incorporated a range of approaches and objectives (e.g. Pickup and Chewings 1994; O'Neill 1996; Wallace *et al.* 2006; Jafari *et al.* 2007). More recently quantified ground cover measurement (as a proportion of land surface) has been a particular focus for remote sensors (Schmidt *et al.* 2010; Trevithick *et al.* 2014; Barnetson *et al.* 2017). There is now multi-decadal ground cover imagery for the entire continent (Clancy *et al.* 2013; Stewart *et al.* 2014) available for use in monitoring ground cover levels across the landscape and through a variety of tools and programs. Perhaps more interestingly, remotely sensed ground cover data have also assisted in mapping other landscape attributes such as erosion (Ellis and Searle 2013) and land condition (Karfs *et al.* 2009*b*; Bastin *et al.* 2012; Beutel *et al.* 2014). If the targeted landscape attribute correlates with ground cover, this approach offers the significant advantage that ground cover data (which are built in regular, landscape-wide images) provide a useful vehicle to map the targeted attribute through time and space.

Quantifying condition (both as defined under both the GLM framework and other methodologies (e.g. Wallace *et al.* 2006)) has been a particular target for users of ground cover data in Australian rangelands. Consequently, several different indices based on ground cover data have been used to index and map land condition. The most basic of these is a simple summary (e.g. mean, median, trend) of ground cover pixel values on the site of interest (e.g. Wallace *et al.* 2006; Thornton and Elledge 2018; State of Queensland 2019). This approach fundamentally assumes positive correlation between ground cover and a land condition where more cover generally indicates better land condition. While this assumption holds some truth, it does not account for variation in ground cover levels that are unrelated to land condition. For example, this index would assume that two sites with similar ground cover levels are of equal land condition, even if their landscape strata have naturally different levels of ground cover. It would also assume that temporal changes in ground cover level on a site are indicative of land condition change, even though events such as rainfall and fire can impact ground cover but not land condition.

Bastin *et al.* (2012) developed a ground cover index to quantify grazing land condition called the Dynamic Reference Cover Method (DRCM). This approach benchmarks ground cover per pixel by calculating the ground cover difference between the focal pixel and pixels with relatively high ground cover in a surrounding window. Under this model, lower DRCM values equate to poorer land condition. DRCM imagery that maps these values across the landscape are available (TERN AusCover 2020) and can be summarised per site, making the DRCM product an attractive index of landscape health/condition (Bastin and the ACRIS–MC 2008; Wilkinson *et al.* 2014). Bastin *et al.* (2012) used the DRCM in below average rainfall periods only when pixels of resilient cover were more obvious, but others (e.g. Xie *et al.* 2019) have deployed it over a wider range of dates and thus outside very dry periods. A key advantage of DRCM over simple mean or median ground cover is that it accounts for the effect of rainfall on ground cover level and in so doing, provides a more direct evaluation of management impacts on land condition. Similar to simple mean or median ground cover, current versions of the DRCM do not take into account strata such as land type, so that a pixel from one landscape stratum may be benchmarked against a population of pixels largely from other strata. This can result in statistical artefacts in the mapped DRCM product and is most visible where two extensive strata with contrasting cover levels abut. The resulting DRCM imagery for these areas tends to show a halo of low DRCM values in low cover areas immediately around high cover features (where the DRCM benchmark is most inflated by cover in the high cover feature) (Fig. 1). Consequently, the exclusion of landscape strata from DRCM production may incorporate some local biases in its application.

A third approach, called regional comparison, is available through both the VegMachine.net and FORAGE (longpaddock.qld.gov.au) websites for Queensland, with thousands of regional comparison reports delivered to Queensland grazing property managers and associated extension and research personnel in recent years (Zhang and Carter 2018; Beutel *et al.* 2019). Regional comparison ranks median ground cover on the target

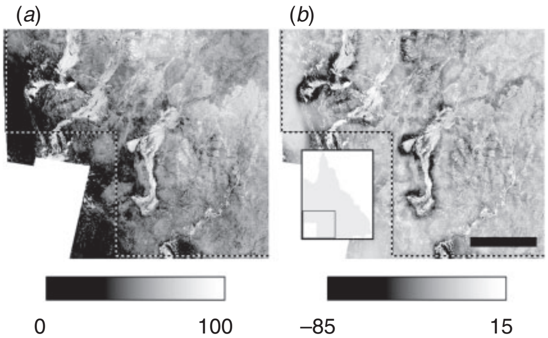

Fig. 1. Corresponding (*a*) TGC and (*b*) DRCM imagery for far south-west Queensland (spring 2019). The respective grayscale ramps indicate the range of values in each image; TGC are measured as percent cover and DRCM as difference in percent cover from a regionally high benchmark (Bastin *et al.* 2012). Where extensive areas of higher ground cover adjoin extensive areas of lower ground cover, a halo of lower DRCM values is often visible in the DRCM imagery around the high cover areas. Black bar (right) length = 200 km.

site among ground cover values from the surrounding region. It is similar to the DRCM approach in that it benchmarks site ground cover against regional ground cover, accounting for rainfall effects to better highlight management impacts on ground cover. Regional comparison also assumes a positive correlation between the benchmarked cover and land condition such that median cover on better condition sites ranks higher against regional cover levels. A key difference of regional comparisons to the other approaches described above is that it also incorporates land type (a landscape stratification based on landform, vegetation and soil features) (State of Queensland 2017). In both VegMachine.net and FORAGE, regional comparisons the ground cover in each of the site's land types is ranked only against cover in the identical regional land types. This ensures more appropriate benchmarking, especially important for sites with land types atypical of the surrounding region. It should also be noted that regional comparison rankings are not typically provided for a single point in time; both VegMachine and FORAGE calculate regional comparisons values for a site each season (1990–present) and display the results in a time series plot. This has several advantages including capacity to retrospectively review management impacts on ground cover, to follow trends in regional comparison rankings rather than one-off measures, and to see short-term fluctuations in a wider historical context.

Equating any of these three remote sensing approaches to land condition makes sense up to a point but ignores the fact that land condition is multidimensional (vegetation composition, ground cover level and erosion severity) while ground cover values are not. Consequently, ground cover indices have a limit as land condition surrogates, and this raises several questions. Perhaps the most important is how reliable are these indices at predicting condition, both in an absolute sense and relative to each other? Prior studies have assessed the relationship between land condition and ground cover indices (e.g. Karfs *et al.* 2009*a*; Bastin *et al.* 2012; Xie *et al.* 2019), but side-by-side comparisons of multiple indices have not been published. Such comparisons offer several benefits, in particular quantifying the absolute

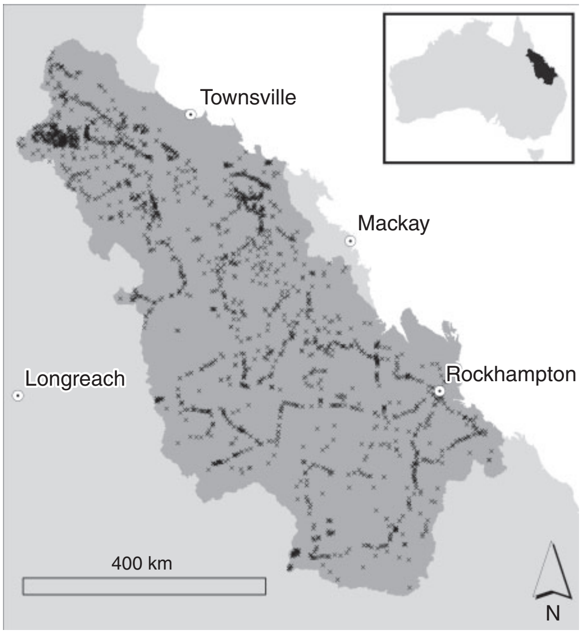

Fig. 2. The study area and centroids of the 2282 study sites.

value of these indices as land condition surrogates and identifying their relative strengths as predictors of land condition.

This paper examines the relationship between grazing land condition as defined by the GLM framework and three remotely sensed ground cover indices at more than 2000 sites in the Burdekin and Fitzroy regions of Queensland, Australia. We compare how well the three indices (median ground cover, DRCM and regional comparison) correlate with land condition. We also test whether averaging these indices over more than one date improves their value as a land condition surrogate. Finally, we build simple models of land condition class (A, B, C or D) using a range of these indices to quantify their power to predict land condition class.

Materials and methods

The study area comprises the combined Fitzroy and Burdekin regions of Queensland, Australia (Fig. 2). The region covers 297000 km^2 in eastern Australia and 70% of the Great Barrier Reef catchment area. It has an average annual rainfall ranging between 2000 mm in the north-east and 500 mm in the south-west. About 83% of the region is grazing land (QLUMP 2017), supporting ~4.6 million cattle (MLA 2019).

Land condition assessments were collected at 2282 sites evaluated during historical studies between 2004 and 2018 (Table 2). For each site, we collated the land condition rating, the date of land condition assessment (one per site when sites were assessed on >1 occasion) and the spatial boundary of the site in a digital shape file. Sites varied in size (Table 2) with the extent of any site determined by the particular goals and methods of the study. All evaluations were made by one or more experienced assessors with a clear understanding of the GLM land condition framework, training in the specific assessment method used (below), and prior experience in field assessment of land condition. All assessments were based on conditions at the single time of assessment.

Table 2. Summary statistics and groupings of grazing land condition datasets used in this study

Source and description	*n*	Site size (ha)	Assessment date(s)	Group
Karfs *et al.* 2009*a*; Beutel *et al.* 2014. Aggregated roadside assessments of land condition in the Fitzroy and Burdekin region.	1508	1	2004–2018	Observe
Unpubl. data. Local expert consensus of property / parcel land condition from 2018 regional workshop. Evaluations took into account expert knowledge of site ground cover, pasture and weed cover and composition, erosion and woody cover levels.	193	25–87055	2018	Consensus
Eyre *et al.* 2011. On site Stocktake (Aisthorpe and Paton 2004) assessment of land condition.	52	1	2006–2009	Measure
Hall *et al.* 2014. Aggregated quadrat assessments of cover, composition and erosion per paddock and land type.	32	1–3240	2009	Measure
Karfs *et al.* 2009*b*. Transect based assessments of cover, composition and erosion. Methods as per Karfs and Beutel 2008.	100	1	2006–2008	Measure
Karfs and Beutel 2008. Transect based assessments of cover, composition and erosion.	43	1	2006	Measure
Beutel *et al.* 2014. Transect based Patchkey (Abbott and Corfield 2012) land condition assessments.	146	1.5	2011–2012	Measure
Unpubl. data. Site based Stocktake (Aisthorpe and Paton 2004) land condition assessments.	208	3	2013	Measure

While all the included studies followed the principles of the ABCD framework to assign a land condition class to a site, they relied on a range of assessment methods varying in terms of both the detail collected and data collection methods. Consequently, we divided all sites into three groups (Observe, Measure and Consensus) based on the methods used at those sites to determine land condition. The Observe group ($n = 1508$) were collected in roadside assessments of grazing land condition from 2004 to 2018. These sites were visually assessed, almost all from the edge of the site (generally from the road corridor boundary looking into the grazed paddock) by experienced land condition assessors. The Measure group ($n = 581$) were collected from 2006 to 2013 and these sites were assessed from within the site boundary using more detailed equipment/methods including line transects, detailed pasture observations and land condition calculators (Aisthorpe and Paton 2004; Abbott and Corfield 2012). The final group (Consensus, $n = 193$) included properties and land parcels where condition was assigned by consensus at a meeting of regional extension and scientific staff in 2018 (T. S. Beutel, unpubl. data). These assessments were thus made off-site and based on assessors' personal knowledge of land condition on those parcels.

In this study, we correlated remotely sensed ground cover indices with land condition ratings at each of the 2282 sites, and we used total ground cover (TGC) imagery (TERN AusCover 2020) to construct these indices. TGC data are derived from a fractional cover algorithm that segments landscape cover at pixel scale into green, non-green and bare ground fractions (Scarth *et al.* 2015). Fractional cover measurements are then adjusted to account for cover under woody vegetation (Trevithick *et al.* 2014) resulting in a fractional ground cover product that is used in areas of <60% woody cover. TGC is the inverse of the bare ground fraction and includes green and non-green vegetation, logs, litter, dung and cryptogams. TGC images have 30 m pixel resolution and are available in seasonal composite (Flood 2013) images (four images per year) from 1990 to present. TGC in the study region generally has highest coefficient of variation in this spring (September to November) (Fig. 3) and grazing impacts on ground cover are easier to observe at this time due to that greater variation. Consequently, we limited our analyses to spring TGC

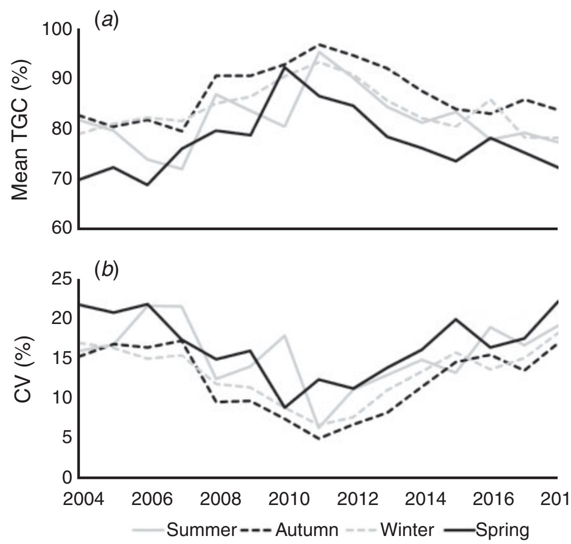

Fig. 3. (*a*) Mean and (*b*) coefficient of variation of remotely sensed TGC values from 2000 randomly selected points in grazed sections of the study area each season (2004–2018). Seasonal TGC tends to be lowest and with a higher coefficient of variation during spring in this region, making grazing impacts more visible at this time of year.

images on the expectation that indices derived from these data would better reflect any relationship between ground cover and grazing land condition.

Three different index types (Type) were compared across all sites; median cover (MC), DRCM and regional comparison (RC) and we also further assessed their relationship with land condition when calculated over three separate time spans (Span; T1, T3 and T5). For a given site and index type, the T1 index was calculated from imagery for the spring image nearest to the date of the land condition assessment. T3 indices were calculated for the T1 season as well as the two preceding springs, then averaged across the three springs to give a single T3 value for the site. T5 index values were calculated as per T3 but averaged over the T1 season plus the four preceding springs to give a single T5 value for the site

Table 3. Calculation methods for ground cover indices used in this work

Index type	Variant	Calculation method	Data required
Median cover (MC)	MC.T1, MC.T3, MC.T5	1. Extract pixel values inside site boundary in the year land condition was assessed. 2. Calculate 50th percentile of these values (MC.T1). 3. Repeat steps 1 and 2 on preceding four years of imagery. 4. Calculate mean of values from steps 2 and 3 for the three years up to and including assessment year (MC.T3). 5. Calculate mean of values from steps 2 and 3 for the five years up to and including assessment year (MC.T5).	1
Regional comparison (RC)	RC.T1, RC.T3, RC.T5	1. Extract pixel values inside each separate land type in the site boundary in the year land condition was assessed. 2. Calculate 50th percentile of these values for each land type. 3. In the same ground cover image as step 1, sample each site land type at 2000 random points in the region (grazing land <20 km beyond site boundary). 4. For each site land type, calculate the proportion of values from step 3 ≤ value from step 2. 5. Calculate the weighted mean of values from step 4. Weight = the land type area within the site. (RC.T1). 6. Repeat steps 1 to 5 with the images of the preceding four years. 7. Calculate mean of values from steps 5 and 6 for the three years up to and including assessment year (RC.T3). 8. Calculate mean of values from steps 5 and 6 for the five years up to and including assessment year (RC.T5).	1, 2, 3
Dynamic reference cover method (DRCM)	DRCM.T1, DRCM.T3, DRCM.T5	1. Extract pixel values inside site boundary in the year land condition was assessed. 2. Calculate 50th percentile of these values (DRCM.T1). 3. Repeat steps 1 and 2 on preceding four years of imagery. 4. Calculate mean of values from steps 2 and 3 for the three years up to and including assessment year (DRCM.T3). 5. Calculate mean of values from steps 2 and 3 for the five years up to and including assessment year (DRCM.T5).	4

[1]TGC imagery. (http://www.auscover.org.au/purl/landsat-seasonal-ground-cover).
[2]Grazing land management land types. (File identifier: 9AB3EE68–039C-40E1–96DF-06E407CD4CCD. http://www.data.qld.gov.au/).
[3]Queensland land use mapping. (https://www.qld.gov.au/environment/land/vegetation/mapping/qlump-datasets).
[4]Seasonal DRCM imagery. (http://data.auscover.org.au/xwiki/bin/view/Product+pages/Seasonal+Dynamic+Reference+Cover+Method).

based on 5 seasons of spring imagery (Table 3). This process produced nine different ground cover index values for each site.

For each Group of land condition sites (Observe, Measure and Consensus), we calculated the correlation between land condition rating and each of the nine ground cover indices using Kendall's rank correlation coefficient (τ), which is appropriate for ordinal data that includes ties. These τ values were compared in a 3×3 (Type $\times$ Span) weighted ANOVA (weighted for Group size) with Groups as replicates to test the effects of Type and Span on the correlation between land condition and cover index.

Finally, we developed several univariate ordinal regression models that predicted land condition rating using individual ground cover indices. For this work, the 2282 sites were randomly split into training ($n = 1597$) and independent test datasets ($n = 685$). All models were developed from the training data and predictive skill summarised from model fit to the independent test data. The aim of this work was to quantify the extent to which

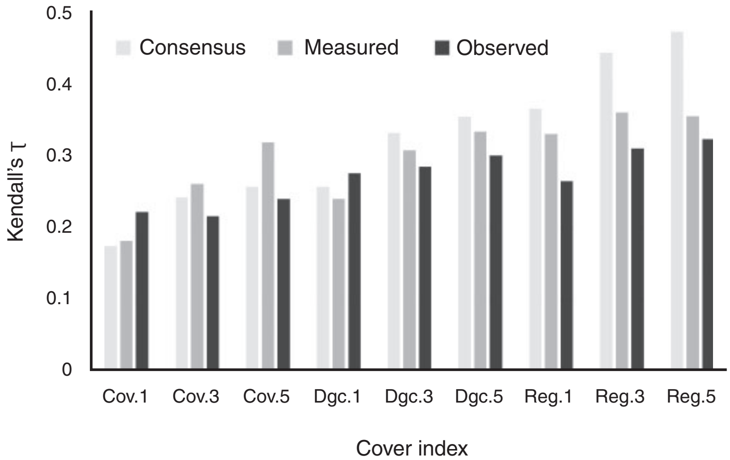

Fig. 4. Kendall's τ_B value for correlation between each cover index and land condition rating in each of the three groups of sites (Consensus, Measured and Observed).

ground cover indices can distinguish different land condition classes in a statistical model. We selected three of the nine indices and for each trialled models with all 16 combinations of:

- four link functions (probit, logit, log, complementary log-log); and
- four index transformations (x, $\sqrt{x}$, log(x+1), 1/(x+1)).

Land condition observations were weighted inversely to the number of cases in each land condition class to compensate for the unbalanced number of sites in each land condition class (Kuhn and Johnson 2013). The final model for each index was selected based on residual deviance and adequate residual plots (Greenwell *et al.* 2018; Liu and Zhang 2018). The three models then classified each site, and their relative predictive success was compared using several metrics.

Results

Fig. 4 shows the Kendall's τ values for correlation between land condition rating and ground cover index for sites in each of combination of Group, Type and Span. Correlation coefficients ranged between 0.17 and 0.47 and all were significantly greater than 0 ($P < 0.001$). The 3×3 (Type × Span) ANOVA indicated significant effects for both index Type ($F_{2,16} = 21.07$; $P < 0.001$) and Span ($F_{2,16} = 6.99$; $P < 0.01$), but not their interaction. Pairwise comparisons (Tukey's range test) of treatment means showed that MC indices correlated significantly less with land condition rating than either the RC ($P < 0.001$) or DRCM ($P < 0.01$) index groups, but DRCM and RC indices were not significantly different. T5 indices also correlated significantly better with land condition rating than single date T1 indices ($P < 0.01$).

Table 4 summarises three ordinal logistic regressions of land condition built with individual ground cover indices as their predictor and applied to independent test data ($n = 685$). The models respectively use the RC.T5, DRCM.T5 and MC.T1 indices at each site to predict land condition rating. The RC.T5 and DRCM.T5 models use the ground cover indices with the most effective combinations of Index (RC or RCM and Span T5). Conversely, the MC.T1 model includes the least effective combination of Type and Span, so together, the three models should represent a range skill to predict land condition. All three models were significant ($68.2 \geq \chi^2 \geq 165.3$; d.f. = 1; $P < 0.001$), clearly outperforming random assignment. The RC.T5 and DRCM.T5 models also outperformed the MC.T1 model on several criteria including better classification in each land condition class, lower rates of large errors (predicted condition >1 condition class from observed condition class), and lower AIC. All three models correctly classified A and D condition sites better than B and C condition sites (Table 4).

Discussion

In the Australian rangelands, remotely sensed TGC data have taken on an increasingly important role in monitoring the grazing landscape and evaluating the impacts of management and investment in those landscapes (e.g. Bastin *et al.* 2009; Wilkinson *et al.* 2014; State of Queensland 2019; Waters *et al.* 2020), facilitated by a growing suite of tools that deliver the data to users in a range of formats and products (Australian Government 2010; Zhang and Carter 2018; Beutel *et al.* 2019). In this context, appropriate and informed use of remotely sensed TGC data and its derived indices is critical. In this paper, we have shown that all tested ground cover indices correlated significantly with observed land condition across our study sites, and we used ground cover indices to predict land condition with a statistically significant skill level. The results show that ground cover indices, and particularly multi-date time ground cover indices, are useful predictors of grazing land condition and support the broader use of remotely sensed ground cover as a metric of rangeland health and productivity. This is not a particularly surprising outcome, but it is the most extensive test so far for the use of ground cover indices as surrogates for grazing land condition and provides important support for the way ground cover data are increasingly used in the Australian rangelands. Future work might look across other regions and finer scaled landscape strata since predictive power may vary across both.

Factors affecting the ground cover–land condition relationship

We identified two strategies to improve the value of ground cover indices in that surrogate role. The first of these is

Table 4. Classification skill of three ordinal regression models that respectively use the MC.T1, RC.T5 and DRCM.T5 ground cover indices as land condition predictors at 685 independent test sites

The 'Random' column indicates theoretical results under random site assignment. 'Predicted | Observed' rows indicate the number of sites in each possible combination of predicted and observed condition class. 'Error' rows show the percent of sites where the predicted condition class was 0 (A|A, B|B, C|C or D|D), 1 (A|B, B|A, B|C, C|B, C|D or D|C), 2 (A|C, B|D, C|A or D|B) or 3 (A|D or D|A) condition classes from the observed condition class. 'Skill' rows show the percent of sites in each condition class that were predicted correctly. 'Fit' rows provide the Chi-square goodness-of-fit and the AIC statistic for each model's fit to the test data

		Model			
		MC.T1	RC.T5	DRCM.T5	Random
Predicted|Observed	A|A	125	134	132	52.75
	A|B	109	99	99	53
	A|C	86	55	59	49.25
	A|D	12	4	8	16.25
	B|A	22	34	31	52.75
	B|B	17	38	30	53
	B|C	22	31	33	49.25
	B|D	5	6	4	16.25
	C|A	39	30	36	52.75
	C|B	51	44	61	53
	C|C	35	57	55	49.25
	C|D	13	14	10	16.25
	D|A	25	13	12	52.75
	D|B	35	31	22	53
	D|C	54	54	50	49.25
	D|D	35	41	43	16.25
Error	0	30.9%	39.4%	38.0%	25%
	1	39.6%	40.3%	41.5%	39.9%
	2	24.1%	17.8%	17.7%	25%
	3	5.4%	2.5%	2.9%	10.1%
Skill	A	59.2%	63.5%	62. 6%	25%
	B	8.0%	17.9%	14.2%	25%
	C	17.8%	28.9%	27.9%	25%
	D	53.8%	63.1%	66.2%	25%
Fit	χ^2	68.2	153.2	165.3	NA
	AIC	4096	3829	3855	NA

benchmarking TGC at the target site against regional levels of ground cover outside the site. The RC and DRCM indices both do this (by slightly different means), and both performed significantly better than the MC indices which are not benchmarked against the surrounding region. Since sites and their surrounding region share a rainfall history, any disparity in their respective TGC levels is unlikely to result from rainfall. This effectively removes rainfall impacts from the index value, making benchmarked indices a better indicator of management impact, which is a key driver of rangeland health (Bastin *et al.* 2012; Beutel *et al.* 2019). This is likely why benchmarked cover indices performed better in this work and will likely perform better elsewhere. RC and DRCM indices performed quite similarly even though only the former benchmarks ground cover within a specific land type. One useful future line of research may look at whether DRCM indices adjusted for land type perform better than the DRCM indices that do not (as was used here). Constructing DRCM imagery is computationally expensive and incorporating landscape strata in its construction would add significant cost and complexity, but it seems a reasonable avenue to improve how well we can predict land condition using ground cover data.

A second strategy to better predict land condition using remotely sensed TGC is to summarise ground cover indices over multiple rather than single dates. This was shown by the T5 indices outperforming the T1 indices. Averaging cover indices over multiple dates dampens the statistical influence of short-term events like fires, heavy grazing and isolated storms that affect ground cover but not necessarily land condition in the year of condition assessment. Consequently, averaging indices over several years removes noise in the ground cover signal that might otherwise confound land condition measurement. We tested spans up to five dates (four years) but averaging over longer periods is possible (e.g. Karfs *et al.* 2009*a*). Predictive skill improved in our work from T1 to T5, and while longer spans may perform better still, presumably skill begins to decline as span extends to the point that the calculated index is more representative of past than present land condition.

These two strategies are also available to users in the Australian rangelands through a variety of channels. Users in Queensland have access to regional comparison analyses through both VegMachine.net and the longpaddock.qld.gov.au websites. While neither of these services explicitly averages regional comparisons over five dates to provide RC.T5 values for a target site, both present RC.T1 data in time series plots that users could visually assess over multiple dates to approximate RC.T5 values. Seasonal DRCM imagery (1990–present) is also available for the Northern Territory and Queensland (TERN AusCover 2020), so users with technical capacity to manipulate this imagery could calculate DRCM.T5 values for sites of interest in these regions. Finally, VegMachine.net can calculate and export median seasonal ground cover (MC.T1) values for any site in Australia, and these exported time series can be converted to MC.T5 values by applying a moving average to the time series. Users should consider these approaches and data sources if their goal is to index land condition using TGC.

Modelling land condition

While the raw correlations discussed above indicate the relative strength of association between each ground cover index and condition class, they do not clearly compare the absolute level of predictive skill in each cover index, and this motivated constructing simple predictive models of land condition, each using a different ground cover index as the single model predictor. It should be noted that these models were developed for comparison purposes only and are not proposed as ready-to-use predictive models. In all models, the correlation between each ground cover index and land condition was significant, but still only moderately predictive. The best models predicted condition correctly for <40% of sites, and while A and D condition sites were correctly classed in >60% of cases, classification of B and C condition sites was worse than random assignment in some cases. The lack of discrimination between B and C condition is particularly unfortunate as the B to C transition delineates relatively healthy/productive areas (fair condition) from land that is clearly degraded (poor condition). Future modelling in this area should pay particular attention to how well intermediate condition levels are predicted. In the interim, users of ground cover indices should be particularly aware that they may not discriminate B and C land condition well. Below, we discuss two potential reasons for limited predictive power to aid interpretation of our results and inform future efforts to model grazing land condition.

One factor that probably limited our capacity to model grazing land condition using ground cover indices is the qualitative nature of the GLM land condition framework. While the framework is an excellent conceptual model for extension and engagement, it can be more problematic as a field assessment tool. We used condition assessments from multiple studies, all collected by trained practitioners. However, even the most rigorous assessments can incorporate subjectivity. This derives from the qualitative nature of the framework descriptors (e.g. some decline vs general decline in health/density of 3P grasses; Table 1) and a corresponding lack of quantitative thresholds that would assist clear cut assessment. For this reason, it is possible for two experienced practitioners to disagree on the exact condition rating of a site. It is likely that some of the challenge that we experienced in modelling grazing land condition was derived directly from the way grazing land condition is defined, and consequently measured in the field. This may be a difficult problem to correct but use of more rigorous field assessment tools (e.g. Aisthorpe and Paton 2004; Abbott and Corfield 2012; Hassett 2020) should provide some benefit, as suggested in our own data where Measured group correlations were generally higher than those for the Observed group ratings (Fig. 4).

As noted above, a second and probably more significant difficulty in modelling condition using ground cover indices is that land condition is multidimensional (Table 1) while TGC is not. This can produce challenging scenarios, such as where ground cover is high but composed of annual or weed species so that condition is poor, or where fire on good condition land reduces cover but does not affect the land condition at the site. An effective land condition model would need to account for dimensions of condition including vegetation composition and erosion severity, and TGC does not appear to do this fully as shown in our results. Since there is an upper limit to how well ground cover indices can explain variation in grazing land condition, it won't be a sufficient predictor for all purposes and users. However, in terms of building better models, we suggest incorporating a wider range of predictors. We built very simple land condition models in this work specifically to compare the predictive skill of several ground cover indices in a modelling context. Realistically though, a concerted effort to map grazing land condition would include more than one predictor, and probably use methods better suited to multivariate data such as machine learning approaches. More complex models could incorporate multiple cover indices and/or other contextual data including land type, climate (e.g. recent and average annual rainfall), soil (e.g. soil order, depth), vegetation (e.g. NDVI, type), spatial arrangement (e.g. spatial autocorrelation) and landscape (e.g. position, slope) layers. There is a wealth of public data suitable for such an exercise (e.g. Jones *et al.* 2009; Grundy *et al.* 2015; Dhu *et al.* 2017) and including a wider range of predictors in models should account for more of the multidimensional variability in grazing land condition. It may also be worth trialling indices based on the separate fractions of TGC (photosynthetic and non-photosynthetic) rather than just TGC alone.

Conclusion

Remotely sensed TGC data are an increasingly important tool for stakeholders in the rangelands of Australia. They are used to engage land managers, assess landscape health and function, and evaluate the impacts of management and investment decisions. This paper provides the largest quantitative analysis so far of their value as a tool to directly measure and monitor ABCD grazing land condition, providing important validation for the way ground cover products are currently being used in tools like VegMachine.net and FORAGE. Our results indicate that remotely sensed TGC correlates significantly with grazing land condition in the Burdekin and Fitzroy regions of Queensland, and more so if ground cover on the target site is benchmarked against the cover in surrounding region and assessed over multiple years. Ground cover indices were also used to create simple land condition models and these suggested ground cover indices are excellent candidate predictors for more comprehensive multivariate models of grazing land condition.

Conflicts of interest

The authors declare no conflicts of interest.

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