State of the paddock: monitoring condition and trend in groundcover across Queensland.

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Abstract

The proposed State Rural Leasehold Land Strategy (SRLLS) is a potential major driver for vegetation condition assessment across Queensland. Pastoral leases cover 85 million ha and within the next 5 years, 60% of these will be up for renewal. Since three quarters of Queensland has a woody foliage cover of less than 20%, methods of monitoring the extent of groundcover (or conversely, bare ground) are required. Monitoring of groundcover is important since it is linked to indicators of soil loss, biodiversity, and pasture production. Ground cover is also an indicator target adopted by regional NRM and catchment management groups.

Ground cover is variable due to both climate and management; both long term and short-term management affects are apparent with those land parcels showing long-term negative trends being of greatest concern. It appears possible to rank one land parcel relative to similar neighbours to identify grazing management related trends. It is possible to detect land parcels that are on a trajectory of increasing cover and others where there is a long-term trend to decreasing cover.

By building on the world-class Statewide Landcover and Trees Study (SLATS) archive of more than 1500 Landsat TM and ETM scenes covering the state with annual coverage or better from 1987, this project will deliver information on the condition and trend of groundcover over the past 20 years at better than paddock scale. By linking these results with climate and pasture growth models, the impacts and ramifications of management decisions on condition indicators can be assessed. This paper will discuss some of the challenges in deriving a robust product that is applicable across the range of cover types encountered in Queensland, and presents some preliminary condition and trend products.

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1. Introduction

Sustainable management of the extensive grazing lands across Queensland would be facilitated by easy access to objective information concerning rangeland condition and trend in condition over time. Queensland's rangelands are subject to high climate variability on seasonal, annual, decadal and longer timescales making management for economic and environmental sustainability difficult. The impacts of climate and management interact to complicate interpretation of data on rangeland condition.

Approximately sixty-five per cent of Queensland is covered by state rural leasehold land. Half of the current pastoral holdings (totalling over 40 million hectares) will expire during the next 15 to 20 years, and their renewal is a major consideration. As custodian of this state rural leasehold land, the government has initiated a review of its future management and use with the purpose of looking at the emerging issues and available options, defining mechanisms to reconcile any conflict between lessees and other stakeholders, and updating the conditions of leases in line with current natural resource management practices. The State Rural Leasehold Land Strategy (SRLLS) is being currently developed to provide a policy framework for achieving sustainable management and use of state rural leasehold land by protecting its environmental, social and economic values, and recognising the various interests held in it. The strategy is based on a stewardship philosophy of state land management, in which the roles and interests of stakeholders are recognised, as is their responsibility for implementing community aspirations and values in a partnership approach. The philosophy underlying the lease agreement is that lessees are the land managers dealing with the care of the land and associated environment on a daily basis.

One of the proposed performance indicators to be used in the SRLLS is groundcover condition and trends. Ground cover is a critical attribute of the landscape affecting infiltration, runoff, water erosion and wind erosion, and as such is a key indicator of land condition (Aust et al., 2003; Booth and Tueller, 2003). However, a reduction is cover does not necessarily correspond to a decline in land condition (Pickup et al., 1998). Ground cover is driven largely by climate and management (Dube and Pickup, 2001). Remote sensing offers one of the few ways to measure groundcover over large spatial extents (Pickup et al., 1993). Frank (1984) completed early work on the change in texture and albedo in response to changes in vegetation cover. Extensive work by Pickup and co-authors (1998; 2000; 1988a; 1988b; 1996; 1993) has pioneered the monitoring of groundcover by remote sensing in Australia. More recent work has focussed on using remotely sensed groundcover to inform landscape leakiness models to better understand the link between cover, patchiness and condition (Ludwig et al., 2006), and the identification of changes in vegetation over time (Wallace et al., 2006).

This research reports on the development of a general cover index that is applicable to monitoring groundcover across Queensland, using both Landsat TM and ETM+ imagery that is available annually in the SLATS Landsat archive. SLATS has used both Landsat imagery to map tree cover and monitor changes in woody vegetation cover throughout the state of Queensland, Australia since 1988 (Goulevitch et al., 1999). Due to the high level of radiometric and geometric correction of the SLATS Landsat archive (De Vries et al., 2004), this imagery is highly suitable for time series analysis.

2. Development of a bare ground index

One of data sets used by SLATS in the process of monitoring annual woody vegetation change is the foliage projective cover (FPC) product derived from Landsat TM/ETM imagery. The FPC product is produced using multiple regression with an extensive set of over 2000 field observations, providing an accurate estimation of woody FPC without the need for image stratification. This product is described in Danaher and Armston (2004) and Lucas *et al* (2006). Multiple regression is a common technique for estimating sub-pixel cover fractions in satellite imagery; however its application is often limited by a lack of field data for calibration and radiometric, spatial and spectral uncertainties in remotely sensed imagery (Salvador and Pons, 1998). In the presence of representative calibration data, multiple regression has been shown to perform as well as more complex non-linear techniques such as regression trees and artificial neural networks (DeFries et al., 1997; Fernandes et al., 2004). Given the performance of multiple regression for modelling FPC, and the availability of a large number (~400) of field calibration sites for groundcover, it was decided to proceed with a multiple regression approach for developing a groundcover index.

Using the same multiple regression approach as that used to develop the woody vegetation index, a generalised bare ground index that can be applied across large areas with different soil backgrounds has been developed. This index does not require the use of ancillary data for the purpose of stratification of areas into similar units. Another important aspect of this generalised index is that, when applied to multiple Landsat scenes, it does not require manual user intervention that could be a source of operator bias. A further advantage of this approach is that when new Landsat imagery becomes available these scenes can be processed in an automated environment, providing information in a timely manner.

2.1 Field data acquisition

At each field site (Figure 1) a range of measurements were taken. These can be separated into two components:

- Collection of discrete point transect sampling data to determine ground cover and the Foliage Projective Cover (FPC) of the overstorey and midstorey woody vegetation;
- Description of general site details, including characteristics such as soil and rock hue value and chroma, tree basal area, dominant species, and soil surface characteristics according to the method described by Tongway and Hindley (1995).

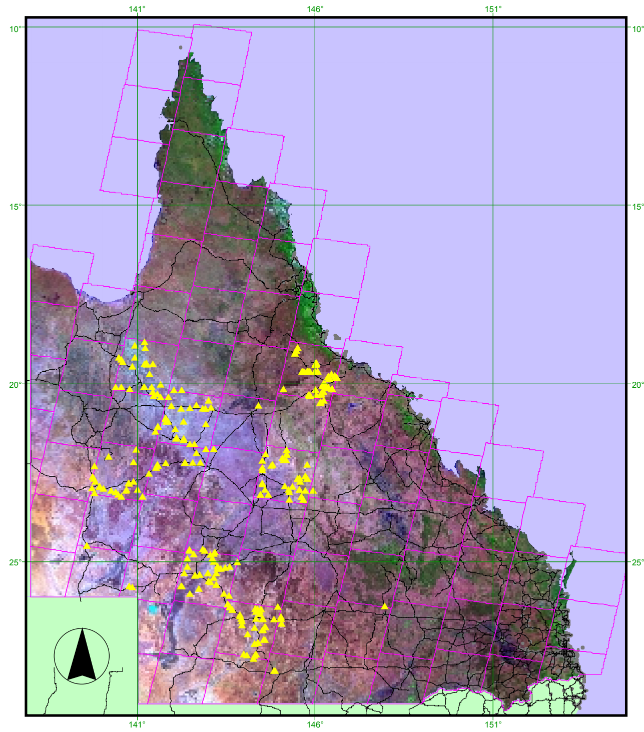

Figure 1 - Distribution of groundcover calibration sites across Queensland shown as yellow triangles. Overlay is areas of standard SLATS Landsat scenes

2.2 Transect sampling

All field data was collected using a modified discrete point sampling method. This transect based sampling approach involved laying out a 100m measuring tape in a north/south orientation. At every metre interval a recording is made of the ground cover, midstorey and overstorey (Brady et al., 1995). It needs to be noted that there are many other field measurement techniques that could have been utilised to measure the amount of ground cover, or its mirror, bare ground. Examples of these include, visual estimates within various size quadrats and continuous measurement along a down slope transect. The discrete point sampling technique was employed because it provided the best compromise between repeatability between different operators without requiring estimation training and regular calibration, and the time taken to measure each site in the field.

A range of characteristics and measurements are recorded at each field site. These include:
A general site description;

- Soil Hue, Value and Chroma measurements. These data are collected for both wet and dry soil and for different soil surface conditions, e.g. soil crust, disturbed soil, windblown surface deposits (sand);

- Rock Hue, Value and Chroma;
- Tree basal area at 5 points using calibrated optical wedges;
- Dominant species by biomass within the ground/midstorey/overstorey layers;
- Soil surface characteristics, such as, erosion features, soil microtopography, surface nature, faunal activity; and
- Evidence of recent site disturbance, e.g., fire, clearing, etc.

And cover recordings:

- Bare soil
- Rock
- Green attached leaf
- Dead attached leaf
- Litter (including all organic litter, tree/grass/dung etc)
- Cryptogam (photosynthetic soil crust)
- Midstorey (woody material 0-2m) recordings of green leaf, dead leaf or branch; and
- Overstorey (woody material > 2m) recordings of green leaf, dead leaf or branch.

After 100 points had been recorded, the measuring tape was laid out in an east/west orientation, with another 100 points recorded. All recording of "hits" was done utilising a palm top computer running Lotus 1-2-3. This program also ran a macro that calculated the running average of percentage bare ground after every 20 points. After an initial 200 points had been recorded, if the last five averages (0-120, 0-140, 0-160, 0-180, 0-200) were within +/- 2 of the final bare ground percentage value, then sampling ceased. If after 200 points had been recorded the criteria had not been met, then the tape was laid out in a northeast/southwest orientation, with another 100 points recorded. Figure 2 shows examples of this approach in two measured field sites.

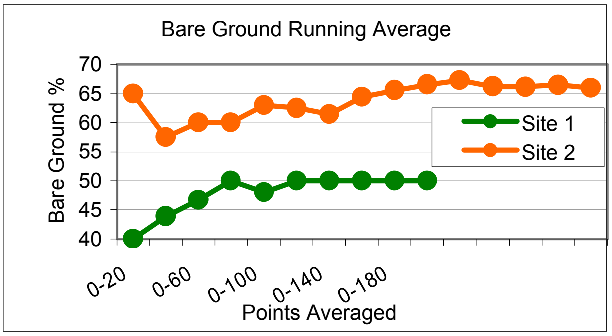

Figure 2 - Example running mean estimates of bare ground. Site 1 stabilised to within ±2% after measuring 200 points, while Site 2 did not adequately stabilise after measuring 200 points. Measurement of an additional 100 points resulted in the bare ground stabilising to an acceptable level

The position of the field site centre was recorded using a backpack mounted differential global positioning system (DGPS). This enabled the accurate location of measured field sites on the Landsat imagery. This also enables accurate re-location of established field sites for repeat sampling at future dates, negating the need for permanent site markings.

2.3 Landsat processing

The Landsat TM and ETM+ images used in this project have been corrected, both geometrically and radiometrically, using methods developed and implemented by the SLATS project (http://www.nrm.qld.gov.au/slats/). Geometric correction is the process used to accurately register satellite images to a ground coordinate system. For the SLATS Landsat archive this has been achieved using ground control points accurately measured by a differential global positioning system (Goulevitch et al., 1999).

When investigating changes over time and across large areas utilising satellite imagery it is imperative that some form of radiometric correction is applied. These corrections account for the variation in sun angle between images and systematic atmospheric effects. All images in the SLATS Landsat archive used in this project have had an rigorous radiometric correction applied (De Vries et al., 2004). The application of this radiometric correction produces a consistent time series of images and wide area mosaics. This allows for the optimal utilisation of field site measurements, as field site spectral signatures collected on a single scene are then representative of areas on multiple scenes that contain similar landscapes in similar seasonal conditions.

2.4 Index Development

To facilitate the regression index development, the percentile bare data was initially transformed to a continuous variable using the hyperbolic function shown in Figure 3. Following the regression analysis, the inverse of this function was used to transform the output back to percent bare running from 0 to 100%.

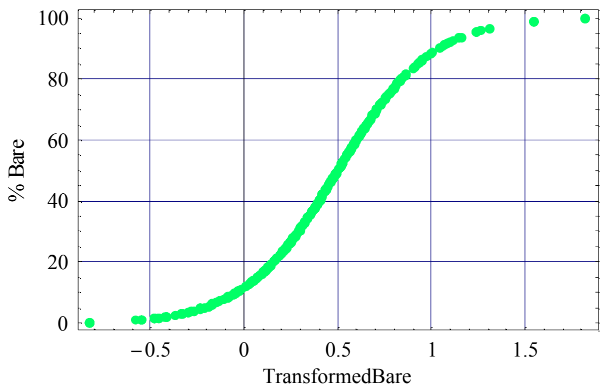

Figure 3 - Hyperbolic function used to transform percent bare data into a continuous space

Signatures for Landsat bands 1 to 7 were extracted for the 3 x 3 pixel mean surrounding the field site location. The 3 x 3 block average provided the best match to the spatial extent of field measurements and also allowed the calculation of the variance within the window. The reciprocal of the variance was used as a weighting in the regression as shown in Figure 4.

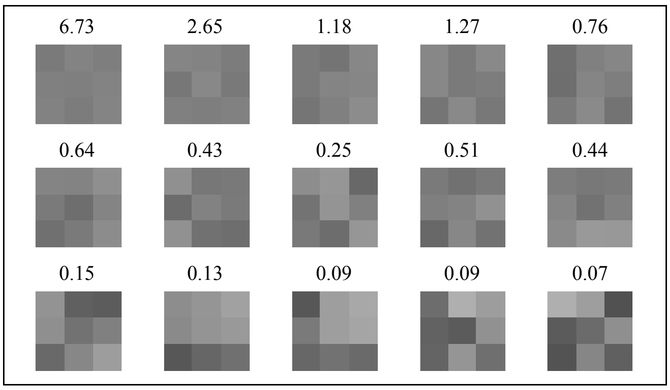

Figure 4 – Example of weighting to reflect the variance in the satellite imagery at the sample location. This is equal to the inverse of the variance of the band digital numbers within the 3 × 3 pixel window.

Signatures were extracted from any image in the database where there was less then 60 days between the groundcover measurement and the image acquisition. The number of day between field and image data was used as a weighting in the regression (Figure 5). The signatures were filtered to remove those affected by cloud or clearing in any image date.

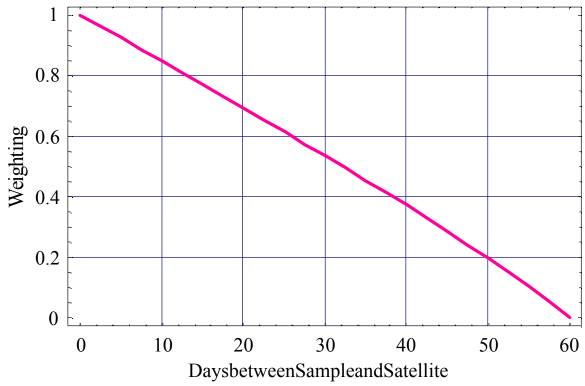

Figure 5 - Weighting to capture the increasing uncertainty of the satellite data to match the field data as the time between capture and sampling increases. This is modelled as an exponential falloff.

A regression index based on truncated singular value decomposition was developed. This method was chosen since it offers greater numerical stability when working with near collinear data and it gives similar results to the often used partial least squares method (Kalivas, 1999). A number of transforms of the Landsat band digital numbers were tested including log, exponential and power functions. To select the optimal number of eigenvalues to retain in each case, a cross-validation approach was used (Figure 6).

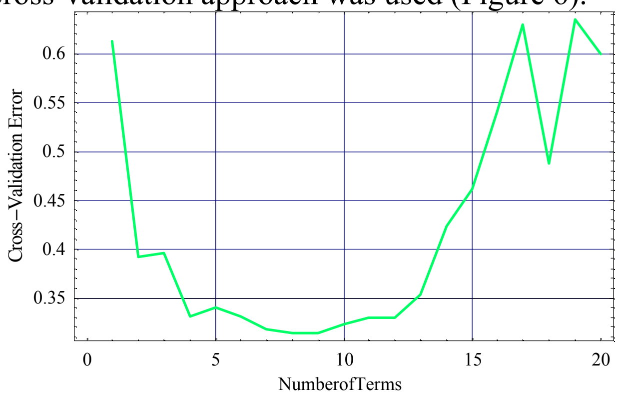

Figure 6 - Example cross-validation plot showing the best prediction accuracy is achieved when retaining nine eigenvalues

This process randomly selected 25% of the data to train the regression. The remaining 75% of the

data was used to validate the output. The root mean square error between the actual and predicted bare ground was calculated for each of 1000 trials for successive eigenvalues.
In developing a multiple regression based index, it is important that the solution delivers an accurate prediction whilst being relatively insensitive to noise in the inputs. This was achieved by optimising the index to use bands and transforms that:

1. Minimised the RMSE between predictions and measured
2. Minimised the sensitivity of the model to extreme values by calculating the mean and maximum of the partial derivatives of each band with respect to the training data.
3. Minimised the effect of quantization “noise” on the prediction. This was calculated using interval analysis by mapping the quantization uncertainty in the Landsat sensor to intervals in the solution.
4. Maximised the reduction in error variance per term added. This requires the product of the response variable with the right hand eigenvectors of the solution to be correlated with the eigenvalues, so the addition of an additional term in the regression will improve the result (Elden, 2004). As an example, the cross validation plot in Figure 6 shows the addition of the third term increasing the error, so this step tries to reduce the occurrence of this, without resorting to partial least squares approaches which have been shown to not be stable in problems with large over-determined data matrices (Elden, 2004; Phatak and De Hoog, 2002).

An exhaustive test of input bands and transformations was conducted systematically leading to the final candidate model This used Landsat bands 3, 5 and 7 only and has an R^2 of 0.93. A plot of the observed verses the predicted transformed bare ground is shown in Figure 7.

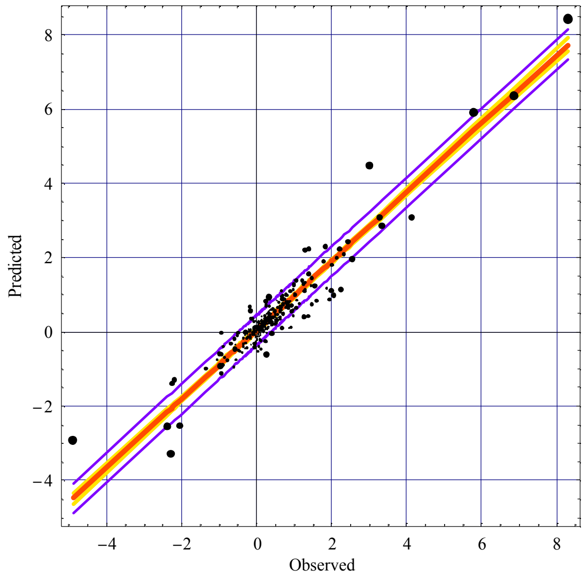

Figure 7 - Plot of measured verses observed hyperbolically transformed bare ground for the best performing model. Dot areas are proportional to the weighting given to each point. Red line is the regression line with confidence in the mean shown as yellow. Purple lines indicate single prediction intervals.

When transformed back into percentage terms the regression has a RMS prediction error of 12.9% and has the form shown in Figure 8.

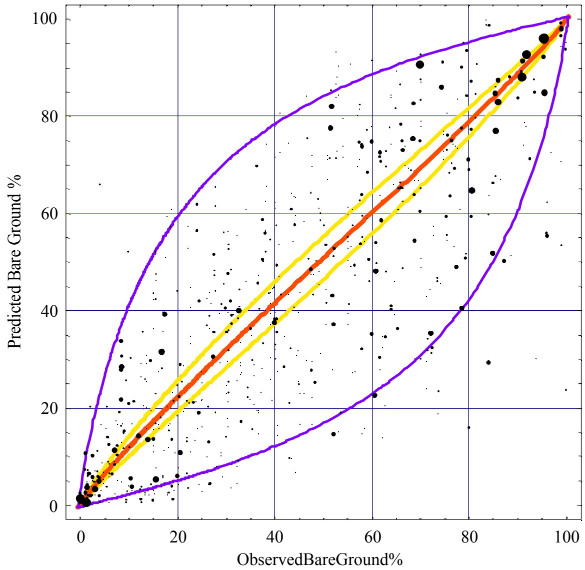

Figure 8 - Plot of observed verses predicted bare ground for the best performing model. Dot areas are proportional to the weighting given to each point. Red line is the regression line with confidence in the mean shown as yellow. Purple lines indicate single prediction intervals.

The sensitivity of the best performing index was evaluated by calculating the partial derivatives of the equation with respect to each band, and then calculating the mean and maximum values from the extracted Landsat data. These are shown in Table 1.

Landsat Band	Mean Sensitivity	Maximum Sensitivity
Band 3	1.1	13.2
Band 5	1.1	7.5
Band 7	1.9	3.9

Table 1 - Mean and maximum partial derivatives of the best preforming model calculated using the training data set.

The best performing model was then applied to the SLATS data archive resulting in almost 2000 groundcover images across Queensland from1986 to the present. An example of this imagery is shown in Figure 9.

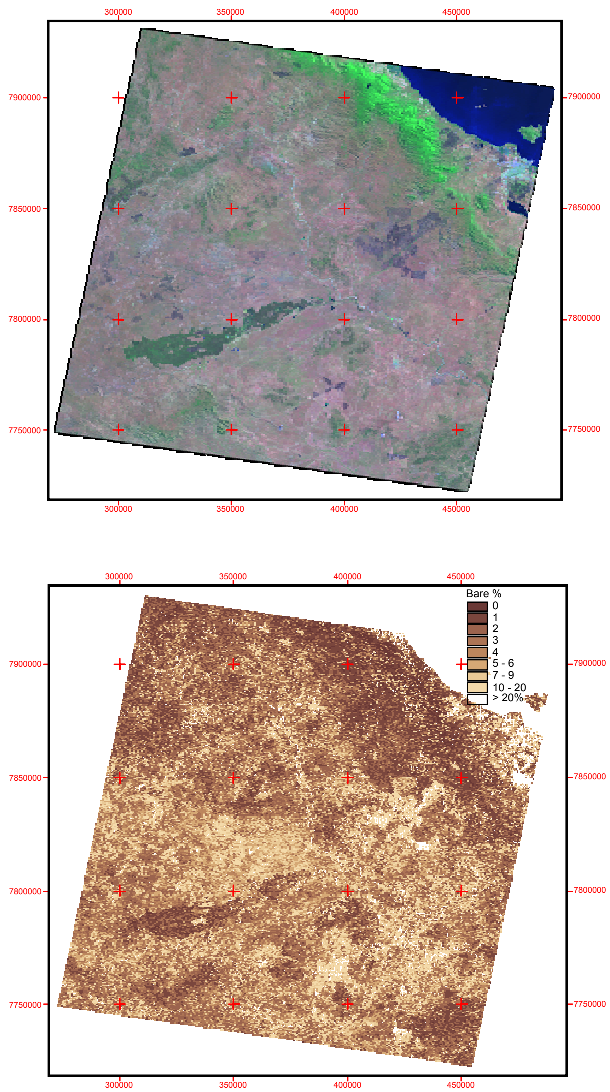

Figure 9 - Bare ground image for the 19 August 2002 Charters Towers scene (top) and associated Landsat image (bottom).

3. Validation

Validation of any remote sensing project is critical so as to be confident in the quality of outputs. The bare ground index has performed well when compared to independently collected, multi-temporal (measured through time) and single date data. This has been the case not only in areas that have had calibration data collected to refine the bare ground index, and areas that have not had calibration data collected. Three validation exercises will be described.

3.1 Cover measurements

Comparisons with independently measured GRASS Check (Queensland. Dept. of Primary et al., 1997) sites across three different woodland land systems (four different land units) within the Desert Uplands bioregion have shown very positive results. The GRASS Check methodology employs a visual estimation, on a per quadrat basis, for a large number of quadrats (100) following a triangular pattern(Queensland. Dept. of Primary, National Landcare et al. 1997). In a study by Booth (2006) it has been shown that visual estimation underestimates ground cover, compared to more objective methods, such as the point intercept technique. Four sites were assessed over three time periods and showed an overall R^2 of 0.91. It needs to be emphasized that calibration data have not been included to refine the bare ground index for this area. These results also demonstrate that, although the model could potentially be “over-fitted” (too many explanatory variables included in the developed model), it is in fact behaving in a stable fashion and producing sensible results for the direction and magnitude of change in ground cover over time. As outlined earlier, the field measurement technique used in the course of calibrating the Landsat data uses a discrete point sampling technique. Other independent comparisons between the bare ground index derived ground cover and ground cover measured at QGraze sites across the Desert Uplands have shown results similar to those achieved for the GRASS Check sites above.

3.2 Mobile observations

Another form of validation of the bare ground index is achieved by comparing mobile visual recordings of pasture utilisation and biomass. These are routinely collected across different areas of Queensland by the CINRS group in the course of calibrating and validating the Aussie GRASS pasture production model (Hassett et al., 2002) and assessing land condition. Comparison with these data provides the opportunity to validate bare ground index derived ground cover for corresponding dates in a relative sense. Figure 10 shows good agreement for areas of lower ground cover (lighter shades of brown) and very low biomass (red crosses). Conversely, there is also strong agreement between areas of high ground cover (darker shades of brown) and higher biomass (green crosses).

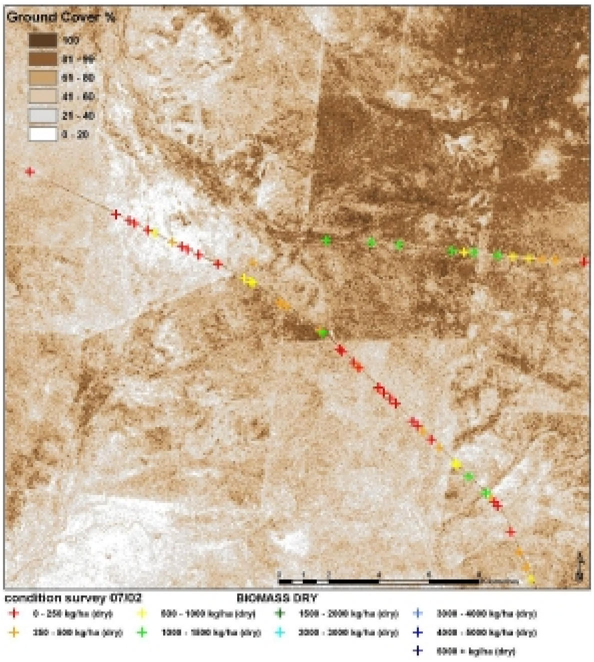

Figure 10 - Comparison of bare ground index derived ground cover for August 2002 and pasture condition observations (dry biomass) collected in July 2002.

Figure 11 shows similar good agreement between remotely sensed ground cover and mobile observations of pasture utilisation, as found for biomass data. This is especially evident across the distinct fence line contrast in the centre of the image. This fence line contrast has been discriminated with the pasture utilisation data. On the low ground cover side (west) the utilisation recordings are in the 40% to 80% range, whereas on the high ground cover side (east) the utilisation recordings are in the 20% to 60% range.

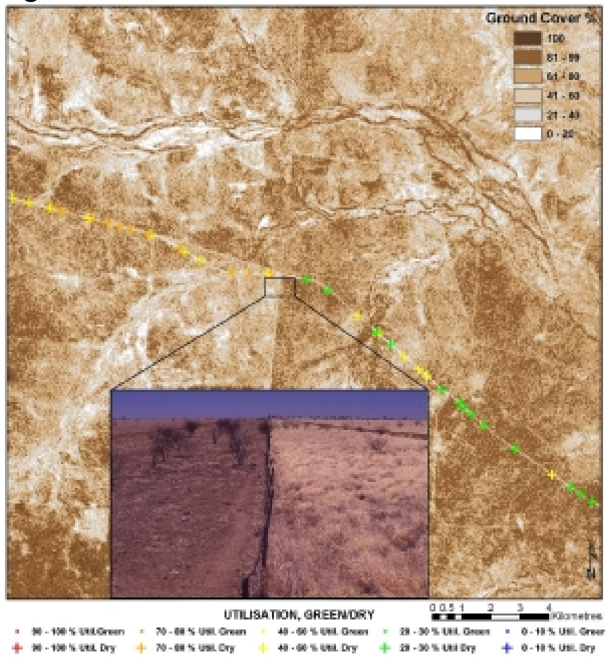

Figure 11 - Comparison of bare ground index derived ground cover for August 2002 and pasture condition observations (pasture utilisation) collected in July 2002. Note: no green biomass was recorded in this area at the time of survey. The photo illustrates the distinct fence line contrast between high cover/ low utilisation (east, right hand side) and low cover/ high utilisation on the western (left) side of the fence. (Photo: R. Hassett July 2002).

The above two comparisons have been taken from Landsat scenes that have not had calibration data collected across them to refine the bare ground index. This again demonstrates the stability of the derived relationship when it is extrapolated into these areas.

3.3 AussieGRASS modelling

The AussieGRASS model (Carter et al., 2000) estimates ground cover from simulated pasture biomass on a daily basis at a resolution of 0.05 degrees. Data from the Landsat bare ground product was up-scaled to the 0.05 degree grid used by removing pixels with significant tree coverage or were on scene edges enabling comparison of identical areas on the date of satellite image acquisition.

There had been little direct calibration of ground cover in AussieGRASS and a subset of the data

(1991-2002) was used to recalibrate a single parameter for about 1/3 of the pasture communities in Queensland to the satellite derived mean cover for the 1991-2002 period.

In a final analysis satellite data for the period 1988- 2005 was used to establish annual means for the entire non-wooded areas covered by Landsat scenes (including most of Queensland and small areas of NT, SA and NSW). Figure 12 shows that the satellite estimate and the model estimated cover time series estimates are similar in magnitude and highly correlated (r2 = 0.98). The year 1991 was the largest outlier for unknown reasons and the range of values observed reflects the influence of climate variability and grazing pressure at a very large scales.

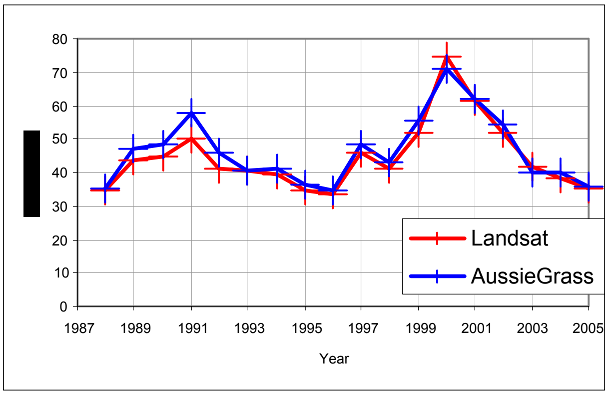

Figure 12 - Temporal plots of Landsat derived and AussieGRASS modelled groundcover for all of Queensland

4. Conclusions

The work presented in this report has resulted in the development of a Landsat image index, the bare ground index, which can be used to derive estimates of ground cover over Queensland across different soil backgrounds and land systems. The bare ground index, at its current stage of development, can be used to quantify the magnitude and direction of ground cover changes over time. The objective and up-to-date ground cover information can be used by producers to support more sustainable management for improved productivity and reduced risk of long-term degradation. The ground cover monitoring system outlined in this research provides a tool that can be used not only to assess condition of a property relative to its neighbours but, at the property level to assess past management decisions and aid future decisions. This tool can be used to objectively assess similar (same land system/unit, etc) areas across a property that are under higher grazing pressure. Assessment of existing property infrastructure (fence lines and water points) and its resultant effect on land condition can be readily undertaken using the ground cover information.

Further research and calibration is ongoing to improve confidence in estimates of absolute ground cover, and to further develop tools to decouple the effects of climate from the trends in the data. Since any given pixel has a bare ground time series that is related to the climate history, the response of the land type to that climate and to the management history, techniques are required to separate these influences. We are currently developing an eigendecomposition of the image based time series to recover and decouple the responses on a scene and statewide scale (e.g. Bretherton et al., 1992; Cherry, 1996) and this work will be reported in a forthcoming publication.

Outputs produced from this project provide information that can be used to:
- Discriminate areas under higher grazing intensities than surrounding areas
- Distinguish climate and grazing management impacts
- Provide spatially continuous, objective information relating to land condition
- Provides a baseline against which future changes can be compared

A critical aspect in the ongoing development of remote sensing techniques for improved management is evaluation and feedback from land managers. The contribution of on-ground knowledge and experience from graziers and extension workers will aid in interpretation of remotely sensed information, refinement of products and improved applicability and value of the tools described in this paper. The availability of timely and spatially explicit information on land condition, will contribute to the capacity of the Queensland Government to enhance the sustainable management of land and water resources across the entire state.

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