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Evaluation of MODIS for groundcover & biomass/feed availability estimates in tropical savannahs system

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Queensland Government
Department of Primary Industries and Fisheries

Abstract

This project has developed a remote sensing index for monitoring bare ground[1] in all seasons over tropical savannah grasslands at a spatial resolution of 1 km.

The MODIS bare ground index (ModBGI) was developed over the Charters Towers Landsat –TM scene area. It uses data from combined AM and PM overpasses of the MODerate Resolution Imaging Spectroradiometers (MODIS) on board the Terra and Aqua satellites and was established using a Landsat –TM ground cover product. The ModBGI model is sufficiently robust and stable to return meaningful results in all seasons. At 1 km the ModBGI index is useful at a catchment and regional planning scale but is of limited use at the paddock/property scale.

The project has made use of the Bi-directional Reflectance Distribution Function (BRDF) parameters of MODIS in combination with semi-empirical models to standardise a time series of MODIS image data. Standardising MODIS data to a common sun angle has reduced seasonal variability within data captured at different times of the year and enabled derivation of a biomass model. The biomass model was developed using field data collected from 31 sites during April 2004/5/6 and October 2004/5 and sun angle corrected MODIS data. The biomass model requires more field validation to properly assess its accuracy and suitability to provide stand alone products. It is of interest from a research perspective and with further development could become a source of calibration for existing models such as AussieGRASS.

[1] *The terms ground cover and bare ground are used interchangeably in this report — ground cover is assumed to be 1 minus bare ground.*

Executive Summary

Frequent and reliable information about the trends in amount and condition of pastures can assist producers to better plan and adjust their grazing management, especially in more extensive areas with large paddock sizes. Collecting data frequently in a consistent format over such a wide area requires the use of satellite remote sensing. Satellite remote sensing provides reliable and repeatable data that can be used in conjunction with site specific field measurements to derive estimates of ground cover, pasture condition and trend across large diverse ecosystems.

The high temporal resolution and multiple look angle characteristics of the MODerate Resolution Imaging Spectroradiometers (MODIS) on board both the Terra and Aqua satellites are an attractive option for remote sensing research and product development worldwide. While MODIS data is relatively inexpensive, its spatial resolution is coarse (250m, 500m and 1 km compared with Landsat –TM's spatial resolution of 30m). The purpose of this project was to determine the capability of MODIS imagery for providing frequent and useful information on pasture cover and biomass at paddock to property scales.

The project has successfully derived a MODIS bare ground index (ModBGI), developed using logistic regression to account for non-linearity in the data. The model is robust and highly significant (L.R. 9730.16, chi pr. < 0.001), and we are therefore very confident about the ability of MODIS to predict scaled-up Landsat bare ground data.

At a catchment scale the ModBGI compliments existing Landsat –TM based ground cover monitoring; particularly at times when Landsat –TM is either unavailable or cloud affected. It is unlikely that MODIS resolution bare ground data could ever stand in for Landsat –TM derived products; however, the ability of MODIS to provide composite images every 16 days (i.e. compiled from cloud free days within a 16 day period) makes it useful for time series analysis. Monitoring trends is a primary application for the ModBGI derived as part of this project. MODIS data is too coarse to be used effectively as a stand alone product at the paddock or property scale in most cases, but it can provide useful time series trend information that compliments the higher spatial resolution Landsat –TM ground cover products.

The project has been able to define statistical relationships between field measurements of pasture biomass and MODIS but only after we identified an effective means of standardising a time series of MODIS data. Standardising the time series data was required to reduce seasonal effects within the imagery, thereby permitting detection of more subtle changes. The biomass model had a regression value (r^2) of 0.54 and a standard error of prediction of +/- 453 kg/ha. This model will therefore require further development and validation before it is suitable for assisting grazing management. There has also been some preliminary investigation of relationships between MODIS imagery and In-vitro Dry Matter Digestibility (IVODMD %) measurements of pasture.

The ModBGI was successfully applied to a time series of 1 km MODIS data and further work is continuing to derive a 500m resolution product for both ground cover and pasture biomass. The 250m MODIS data does not cover the same spectral range, nor come with the BRDF parameters required to standardise a time series. The 500m product, complete with all parameters, has only recently been made available by NASA.

By September 2008 NASA will have reprocessed its 500m spatial resolution MODIS archive to a stage where the data includes all of the parameters required for application of the ModBGI and biomass models developed as part of this project.

It will then be possible to apply ModBGI at a spatial resolution of 500m to a statewide coverage acquired every 8 days. The biomass model derived here at 1 km will be recalibrated and re-evaluated to a spatial resolution of 500m as soon as data becomes available. Work is on-going under the auspice of both the Statewide Rural Leasehold Land Strategy (SRLLS) and Statewide Landcover and Tree Study (SLATS).

Contents

1 Background

1.1 Requirements for biomass and ground cover data

Planners and land managers interested in issues such as soil erosion, water quality, stocking rates, feed availability and the sustainable management of grasslands require timely ground cover and biomass information at an appropriate scale over all seasons. To date there has been neither a system nor a dataset suitable for near real time monitoring of groundcover or biomass over tropical savannah grasslands in northern Queensland.

The aim of this project was to develop indices from MODIS imagery that could provide regular groundcover and biomass/yield information to producers with respect to their individual properties. It was hoped that this information would provide valuable decision support on the impact of seasonal variability and the implications of different pasture management regimes in tropical savannah systems.

All satellite data has limitations of spatial, spectral, radiometric and temporal resolution. For example, Landsat –TM with a spatial resolution of 30 meters is ideal for monitoring ground cover, pasture condition and trend but can only be obtained over the same area every 16 days. During the wet season, where several 16 day Landsat –TM cycles may be cloud affected, the Landsat time series loses its ability to effectively monitor tropical savannah grasslands. SPOT has a higher spatial resolution and is potentially more frequent but requires more scenes to cover the same area and is expensive. All satellite sensors are limited by radiometric effects that are a function of viewing geometry and variable atmospheric conditions. The advantage of MODIS over other sensors is that there are MODIS instruments on two satellites (one with a ‘morning’ overpass and one with an ‘afternoon’ overpass) and it has a unique ability to view the same piece of ground from several different angles, enabling more comprehensive correction for radiometric variability. It also has a high temporal resolution enabling users to more reliably obtain cloud free imagery. The limitation is that the spatial resolution of MODIS is coarse (250 m, 500 m and 1km). The BRDF data that enables more comprehensive correction for radiometric variability is limited to a spatial resolution of 1 km (although NASA is currently reprocessing archives to produce a full suite of BRDF parameters at a spatial resolution of 500 m).

The temporal frequency of MODIS and its multiple look angle capability enable a bare ground image to be derived from MODIS data more often than from Landsat –TM data, particularly during periods of seasonally high cloud cover, albeit at a lower spatial resolution of 1 km (i.e. Landsat –TM 30 m). While MODIS imagery is available at higher spatial resolutions of 500 m and 250 m the index derived here relies on unique Bi-directional Reflectance Distribution Function (BRDF) parameters which were only available at 1 km resolution when the analysis was done. NASA has commenced reprocessing its archive of 500 m resolution MODIS data to include BRDF layers, but to date 500 m BRDF layers for the period 2004–2007 are not available over Charters Towers.

Sustainable management of tropical savannah grasslands would be enhanced by easy access to objective information concerning land condition and trend over time. Tropical savannah grasslands are subject to high climate variability making collection of meaningful land management information at suitable spatial and temporal scales difficult. The impacts of climate and management interact to complicate interpretation of data on land condition and trend (Scarth *et al*., 2006).

Groundcover (or conversely bare ground) is a critical attribute of the landscape affecting infiltration, runoff, water and wind erosion, and as such is a key indicator of land condition and trend (Aust *et al*., 2003; Booth and Tueller, 2003). However, a reduction in cover does not necessarily correspond to a decline in land condition (Pickup *et al*., 1998). Ground cover is driven largely by variability in climate and management (Dube and Pickup, 2001) and remote sensing offers one of the few ways to measure groundcover frequently in a consistent format over large spatial extents (Pickup *et al*., 1993).

One of the limitations to effective use of coarse scale MODIS imagery is that the natural variability that occurs within a 1 km pixel is very difficult to quantify at a field site scale (100 m x 100 m). The issue of scale using coarse spatial resolution remotely sensed imagery is not unique to tropical savannah grassland ecosystems; Dengsheng Lu (2006) states,

> "*Overall, the AGB* [Above Ground Biomass] *estimation using coarse spatial-resolution data is still very limited because of the common occurrence of mixed pixels and the huge difference between the size of field-measurement data and pixel size in the image, resulting in difficulty in the integration of sample data and remote sensing-derived variables.*"

This research was commissioned by MLA to investigate the possibility of using relatively inexpensive coarse scale satellite imagery from MODIS sensors aboard the Terra and Aqua platforms to monitor groundcover and provide pasture biomass/yield estimates to producers.

1.2 Moderate Resolution Imaging Spectroradiometer (MODIS)

MODIS is a key instrument aboard both the Terra and Aqua satellites. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. Terra MODIS and Aqua MODIS view the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands, including ultra-violet, visible infrared and shortwave infra-red. The MODIS instrument captures imagery at 250 m, 500 m and 1 km resolutions.

In the early stages of this project data from the Terra platform alone was used in analysis, however in later stages of the project models have been redefined using a combined 1 km product derived from both the Terra and Aqua satellites. The combined Terra/Aqua product provides the highest probability for quality input data due to the additional passes available.[2] The MODIS BRDF/Albedo product used here is derived using an algorithm based on multidate, atmospherically corrected, cloud-cleared data. A semi empirical kernel-driven bidirectional reflectance model was used to determine a set of parameters describing the Bi-directional Reflectance Distribution Function (BRDF) of the land surface measured over 16–day periods.[2] These 1 km gridded parameters are then used to determine directional hemispherical reflectance ("black–sky albedo"), bi-hemispherical reflectance ("white–sky" albedo), and nadir BRDF–adjusted reflectance (NBAR) for seven narrow spectral bands and three broad bands[2]. Since the parameters of the simple kernel–based BRDF model (Ross Thick–Li Sparse) are also provided with MODIS data, along with extensive quality information, the combined Terra/Aqua MODIS BRDF/Albedo product offers additional flexibility to derive reflectance measures particularly suited to specific applications[2]. Of particular interest to this project has been use of BRDF parameters and kernel–based BRDF models to standardise a time series of MODIS data to a common solar zenith angle, thus reducing seasonal effects within the imagery.

[2] http://edcimswww.cr.usgs.gov/pub/imswelcome/

The 1 km resolution MODIS derived from data captured by the Terra and Aqua satellites over a 16–day period contains the most comprehensive array of BRDF parameters. NASA has recently begun to provide the full suite of BRDF parameters at a spatial resolution of 500 m; however imagery over Charters Towers region for the period of this study is not yet available at 500 m. At this time BRDF parameters are not available over the full spectral range of 250 m resolution MODIS.

1.3 Monitoring biomass using vegetation indices

Tropical savannah pastures are characterised by a significant senescent component during each dry season, and can exhibit a mixture of green and senescent components at any time of the year. In tropical savannah grasslands pasture becomes green quickly following rainfall and conversely dries off quickly at the onset of the dry season. Greenness indexes such as NDVI are based on the red (sensitivity to the presence of chlorophyll pigment in leaves) and NIR (sensitivity to plant cell structure) portions of reflectance. Rapid changes in ephemeral greenness and significant amounts of standing dry matter in tropical savannah pastures can cause problems when using an NDVI based index. As it ‘greens up’ NDVI values are too high and in senescence too low to maintain consistency with actual ground cover and pasture biomass.

In support of this argument Huete *et al.* (1994) comments that NDVI is suboptimal for environments containing particularly sparse, discontinuous semiarid canopies. Those land cover types which demonstrate a defined period in which they are totally green (e.g., grain crops prior to senescence) are examples of groundcover which can be successfully monitored using NDVI. To capture the diversity of pasture growth in tropical savannah ecosystems requires a model that is sensitive to standing dry matter, structure and height rather than greenness.

In remote sensing multiple regression models are commonly employed to estimate sub–pixel cover fractions in satellite imagery; however 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). MODIS BRDF parameters generated by multiple look angles offer a unique opportunity to remove noise in remotely sensed data; to provide a more radiometrically ‘correct’ product. While the spatial resolution of MODIS is poor for ground cover and biomass monitoring at a property scale (i.e. when compared with Landsat –TM) the MODIS signal is potentially cleaner and more likely to be able to differentiate groundcover and biomass based on structural characteristics of vegetation.

The advantage of a multiple regression index is that it does not require the use of ancillary data for the purpose of stratification of land areas into different soil types or sub–ecosystems (Scarth *et al.*, 2006). It can also be applied to a time series of MODIS in an automated environment to provide data and imagery in a timely manner (Scarth *et al*., 2006).

Multiple regression techniques were used here to develop ModBGI, non-linearity in the distribution of data led to refinement of the ModBGI using a *generalised linear model*. Preliminary models for estimation of biomass (kg/ha) and IVODMD (%) are derived using multiple regression at this time, within that framework further research using different types of generalised linear models is on-going.

1.4 Use of BRDF parameters in pasture ground cover / biomass modelling

MODIS bands and BRDF parameters are sensitive to both the spectral and structural characteristics of the pasture sward; so it may be possible to use MODIS to overcome problems with greenness in application of NDVI based indices. The concept is to use information contained in MODIS to compliment and further develop existing models and methodologies for monitoring ground cover and biomass in diverse tropical savannah systems. A significant portion of MODIS research is devoted to use of BRDF parameters in the search for a relationship between the structure of ground cover and BRDF statistics generated by multiple view angles of the sensor.

Vegetation canopies scatter and reflect light unequally; they are anisotropic scatterers as apposed to isotropic surfaces that scatter light equally in all directions. The unequal distribution of reflectance from vegetation canopies is to some extent captured in a BRDF, which is related to both the spectral and structural characteristics of ground cover. Figure 1 is analogous to overpass of MODIS and its acquisition of images at a range of viewing angles, with a *constant sun angle*.

MODIS accumulates sequential angular views over a period of hours or days. These directional observations are subsequently coupled with semi-empirical models to describe the BRDF (Schaaf *et al.*, 2002).

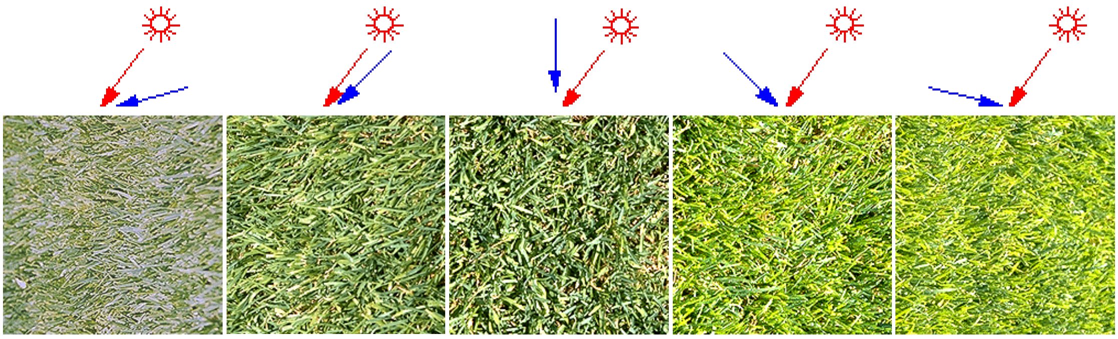


Figure 1: Bidirectional reflectance effect on a grass lawn, observed under different viewing angles from a mounted camera in the solar principal plane. The BRDF effect is most pronounced in the so-called solar principal plane where the source of illumination, target and sensor are in one plane. Solar zenith angle is 35°, indicated with red arrows. The view directions are given in blue. The camera keeps aperture, exposure time and focal length constant (k=16, t=1/15, f=135mm). (http://www.geo.unizh.ch/econo/research).

Reflectance values based on 1 km MODIS data are compiled over a 16-day period from multiple images of the same area at different angles. These data are used to calculate BRDF parameters for each pixel. BRDF parameters are then used to derive a 16-day composite reflectance value for each pixel using equation 1 below.

(1) MODIS Reflectance = isotropic parameter + (volumetric parameter * semi-empirical model) + (geometric parameter * semi-empirical model)

The isotropic/volumetric/geometric parameters are calculated for each band using 1 km resolution MODIS imagery from multiple look angles. There are several semi-empirical models that can be employed in the equation above, deciding which models are best suited to model the volumetric and geometric characteristics of scatter for particular ground cover types is an entire research question in itself and is beyond the scope of this project (see Wanner *et al.*, 1995). This study has adopted MODIS semi-empirical models referred to as the Ross-thick (volumetric component) and Li-Sparse (geometric component) models. A standard MODIS 16-day reflectance product is corrected to NADIR view angle and uses the mean solar zenith angle for each pixel over that 16-day period. Within the semi-empirical model equations solar zenith can be adjusted to any angle, and for the biomass portion of this study a standardised solar zenith angle of 45 degrees has been applied to a MODIS time series. For ModBGI development a mean solar zenith angle over the 16 day period is used[3].

A clear advantage of MODIS over other sensors is the relative simplicity with which remote sensing practitioners can adjust a time series of data, in this case extending over wet and dry seasons, to a common solar zenith angle. For those interested in the mathematics behind the concepts — the Ross-thick and Li-sparse semi-empirical model equations are listed in Appendix 9.2.

[3] Further BRDF corrections to Landsat –TM data used in generation of bare ground products will lead to the use of sun angle corrected MODIS for ModBGI development in the future

2 Project Objectives

1. Develop relationships for ground cover and pasture biomass/feed availability between field measurements and MODIS indices.
2. Provide guidelines for the use of MODIS data in the estimation of groundcover and biomass/feed availability at a range of scales.
3. Provide participating producers with the tools and techniques for collecting field data for property/paddock based calibration in support of prototype estimates of ground cover and pasture biomass/feed availability.
4. Develop a prototype framework for the automated delivery of prototype remote sensing products of groundcover and pasture biomass and report on the requirements for operational and near-real time delivery.

3 Methodology

3.1 Acquisition and Sampling of Field data

Two study sites were selected for sampling groundcover and biomass (Figure 2). Charters Towers was the principal site, located in the Dalrymple Shire, Queensland. An additional site was established in the Brisbane Valley, near Wivenhoe Dam.

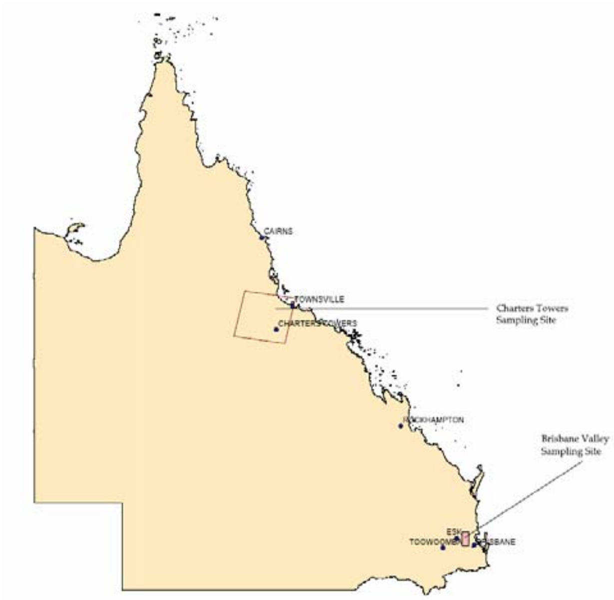


Figure 2: Charters Towers and Brisbane Valley study sites

3.1.1 Study site characterisation

3.1.1.1 Charters Towers

The Dalrymple Shire, encompassing the Charters Towers Landsat –TM scene, is characterised by savannah woodlands dominated by eucalypts (bloodwoods, ironbarks and box). Average annual rainfall ranges from 500–700 mm and is strongly seasonal, with 70–80% occurring as summer rainfall between November and April. However, extreme variation of annual rainfall exists between years. A semi-arid climate prevails over the shire, with warm sub-humid conditions, highlighted by hot, wet summers and dry, warm winters.

Grazing is the predominant land use within the region and, as a result, much of the native woodland has remained intact. However, the above described variability in rainfall combined with soil type differences produces conditions which are more diverse and complex than those encountered in other areas of tropical savannah, such as the Mitchell Grass Downs or Gulf Country.

3.1.1.2 Brisbane Valley

The Brisbane Valley sites are located on land controlled by SEQ Water. The sites were selected on shallow granite/gravely soils and heavier loams with the aim of some similarity in soil type and dominant grass species so as to be comparable with sites selected in the Charters Towers Landsat –TM scene area. Common species at both sites include Black Spear Grass (*Heteropogon contortus*), Barbed Wire Grass (*Cymbopogon refractus*) and Wire Grasses (*Aristida sp.*). Other grasses represented in both areas, while different genera, are sufficiently similar in both form and growth habit that comparison was thought to be valid for ground cover and biomass predictive models (at a MODIS scale). For example, Charters Towers sites of Indian Couch (*Bothriochloa pertusa*) may be comparable, from a remote sensing perspective, with sites of Couch (*Cynodon dactylon*) within the Brisbane Valley as both share stoloniferous low growing form and habit. Taller tussock grasses are represented in both areas by species such as Forest Blue Grass (*Bothriochloa bladhii*), Pitted Blue Grass (*Bothriochloa decipens*), Blugrasses (*Dichanthium sp*.), Balck Spear Grass (*Heteropogon contortus*), Kangaroo Grass (*Themada triandra*), Barbed Wire Grass (*Cymbopogon refractus*) and Red Natal Grass (*Melinis repens*).

The Brisbane Valley sites were monitored monthly to gain insight into more subtle temporal changes not captured in the bi-annual field data capture from the Charters Towers study region.

The full value of data captured from the Brisbane Valley sites is yet to be realised as the sites are located too close to Wivenhoe dam to be used with confidence at the 1 km spatial resolution. Slight misregistration at 1 km can result in water contamination of the signal. The data are useful for inclusion in existing Landsat –TM bare ground modelling and will be incorporated when NASA releases a MODIS 500 m product inclusive of all BRDF parameters.

3.1.2 Groundcover Survey

A stratified sampling methodology was employed for the selection of primary sampling plots across Landsat –TM scenes for both study areas. Site information relating to slope, tree basal area, roads, urban areas and property boundaries were input into a GIS. On the basis of a number of decision rules (slope <10%, tree basal area <10 m^2/ha, vicinity of road), plot locations were generated (Figure 3). A tree basal area less than 10 m^2/ha is arguably a threshold between areas where a satellite sensor detects a response predominantly influenced by pasture attributes as opposed to above 10 m^2/ha where the spectral and BRDF related responses detected by a sensor begin to be more influenced by tree cover. This study aims to measure and monitor attributes of cover and biomass related to pasture rather than tree cover. Figure 4 is a frequency distribution of sampled sites by basal area with the majority of sites selected having a basal area less than 3 m^2/ha.

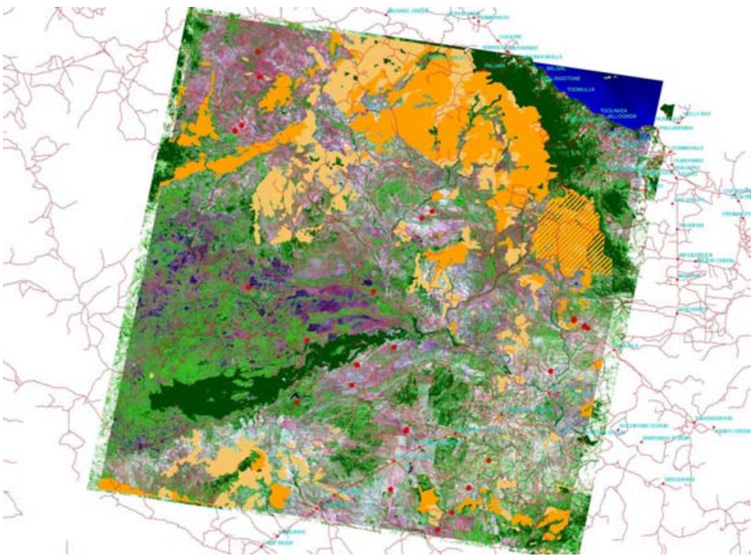


Figure 3: Stratified random sampling technique employed for the selection of sampling sites across the Charters Towers scene

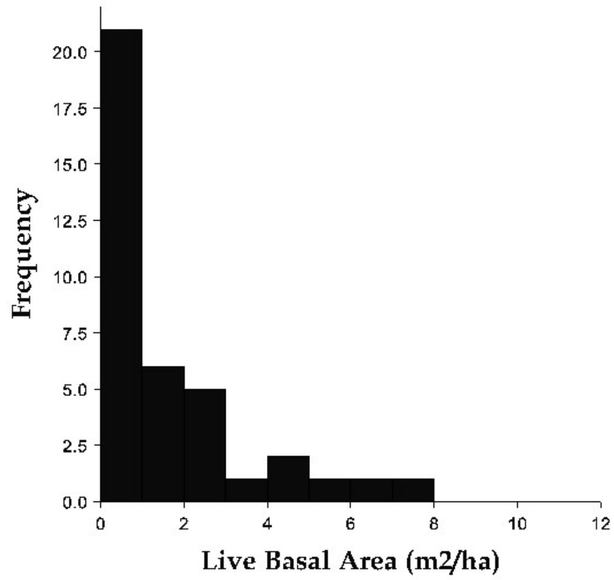


Figure 4: Frequency distribution of sampling sites according to basal area

Thirty one sites were established across the Charters Towers Landsat –TM scene and 6 within the Sunshine Coast Landsat –TM scene (which encompasses the Brisbane Valley site). Groundcover measurements were undertaken at both study sites and involved the collection of FPC, tree basal area, groundcover and site characteristics.

FPC measurements were acquired along a minimum of two 100 m transects, laid in the north-south and east-west directions, forming a cross (Figure 5a). The centre of each plot located at the intersection of the cross, as determined using a sub-metre differential GPS unit. Ground layer, mid-storey and over-storey strata attributes were recorded at each metre along the north-south and east-west transects, and subsequently entered into a palmtop computer in-situ. A running mean was established; calculated on 20 point blocks. The running mean provides an indication of stability (i.e., homogeneity) of the plot. The methodology for dealing with heterogeneous sites is described in more detail in Appendix 9.5. Tree basal area measurements (using a calibrated optical wedge) were acquired from the centre of each plot and 25 m to the north, south, east and west (Figure 5b).

In addition, the floristic attributes for three strata, topographic features, soil colour and photographs were taken at each of the plots.

3.1.3 Destructive Biomass Harvesting

Biomass was harvested at both study sites; however, a more intensive campaign was undertaken at the Brisbane Valley plots, whereby biomass was collected at more frequent intervals throughout the year. The biomass was harvested using 0.5 m x 0.5 m quadrats, randomly distributed within the 100 m x 100 m area, enclosed by the ground-cover transects. Five quadrats were randomly sampled within each of the four 50 m x 50 m areas (Figure 5c). Prior to harvesting, a visual green biomass to senescent biomass ratio and total cover estimate was established for each quadrat. Total biomass and sub samples were weighed in the field and the sub samples were taken back to Brisbane for drying. Samples were ground and submitted for chemical analysis including measurements of In-vitro Dry Matter Digestibility (IVODMD%).

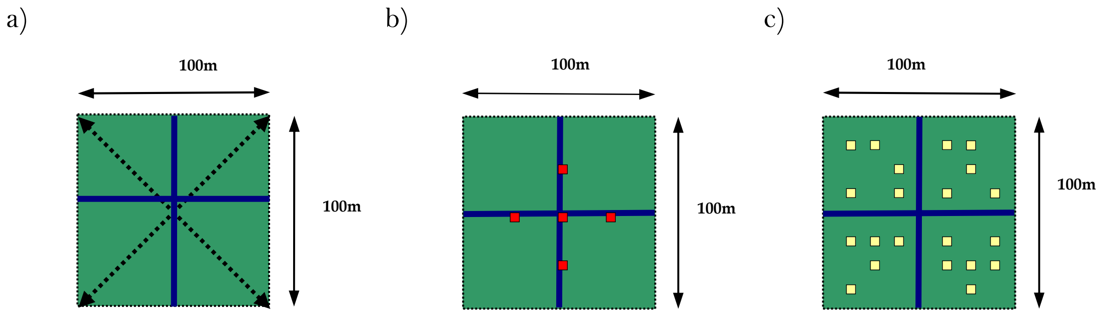


Figure 5: a) Groundcover and FPC measurements acquired along blue transects and in diagonal directions according to a running mean b) Tree basal area recorded at the centre of the plot and in the four directions 25 m from the centre and c) random distribution of five biomass quadrats within each 50 m x 50 m

3.2 Acquisition and Pre-processing of Remotely Sensed Data

3.2.1 Moderate Resolution Imaging Spectroradiometer (MODIS)

The following MODIS data products were obtained for the period February 2000 to October 2005, through the NASA-DAAC EROS Data Centre, Sioux Falls SD,

a) MODIS Nadir BRDF Adjusted Reflectance (MOD43B4), 16-day composite, provided as a level-3, 1 km resolution product in sinusoidal projection;
b) MODIS BRDF/Albedo Model parameters (MOD43B1), 16-day composite, provided as a level-3, 1 km resolution product in sinusoidal projection;
c) MODIS Vegetation Indices (MOD13Q1), 16-day composite, provided as a level-3, 250 m resolution product in sinusoidal projection;
d) MODIS Leaf Area Index/FPAR (MOD15A2), 8-day composite, provided as a level-4, 1 km resolution product in sinusoidal projection.

Five tiles for each date and each dataset were ordered, which encompasses the entire state of Queensland (and the northern part of the Northern Territory). Preliminary data processing for geometric, radiometric and atmospheric correction was performed by NASA-DAAC. On receipt of the MODIS data, it was mosaiced and then reprojected from its native sinusoidal into geographic projection. All pre-processing was undertaken using ERDAS Imagine software.

Further research during the early part of 2006 raised questions about the potential to correct MODIS imagery for seasonal sun angle effects using BRDF parameters and the Ross-thick and

Li-sparse semi-empirical models previously described. It was anticipated that a better result would be possible using sun angle corrected data derived from both AM (Terra) and PM (Aqua) MODIS over passes.

Subsequently more data was acquired. The products used in current ModBGI and biomass models are as follows,

e) MODIS Nadir BRDF Adjusted Reflectance (MCD43B4), 16-day composite, provided as a level-3, 1 km resolution product in the sinusoidal projection;

f) MODIS BRDF/Albedo Model parameters (MCD43B1), 16-day composite, provided as a level-3, 1 km resolution product in the sinusoidal projection.

An archive of both products was acquired via an ftp protocol. Table 1 lists wavelengths of the seven MODIS bands (i.e. 7 x AM overpass, 7 x PM overpass) supplied with the MCD43B4 product. The MCD43B1 product contains more than 40 bands, 30 of which (Table 2) are BRDF parameters used in equation 1 (page 11).

Table 1: MODIS bandwidths for MCD43B4 imagery (1 km)

BANDS	**AM / PM**	**BANDWIDTH**
1	both	620 to 670 *u*m (Red)
2	“	841 to 876 *u*m (NIR)
3	“	459 to 479 *u*m (Blue)
4	“	545 to 565 *u*m (Green)
5	“	1,230 to 1,250 *u*m (IR)
6	“	1,628 to 1,652 *u*m (SWIR)
7	“	2,105 to 2,155 *u*m (SWIR)

Table 2: MODIS BRDF parameters supplied with MCD43B1 product (1 km)

BANDS	**PARAMETER**	**AM / PM**	**BANDS / BANDWIDTH**
1 — 10	Isotropic	Combined	1 – 7 (As in Table 1, bands 1–7) 8 – 0.3 to 0.7*u*m 9 – 0.7 to 5.0*u*m 10 – 0.3 to 5.0*u*m
11 — 20	Volumetric	Combined	11 – 17 (As in Table 1, bands 1–7) 18 – 0.3 to 0.7*u*m 19 – 0.7 to 5.0*u*m 20 – 0.3 to 5.0*u*m
21 — 30	Geometric	Combined	21 – 27 (As in Table 1, bands 1–7) 28 – 0.3 to 0.7*u*m 29 – 0.7 to 5.0*u*m 30 – 0.3 to 5.0*u*m

3.2.2 Landsat TM and ETM+

The Landsat –TM and Landsat–ETM+ imagery were obtained through the Statewide Landcover and Trees Study (SLATS), with geometric correction applied using the techniques outlined by Armston *et al*. (2002). All scenes were registered to Universal Transverse Mercator (UTM) Coordinates (Zone 55 South) using the Geodetic Datum of Australia 1994 (GDA94).

SLATS use both Landsat–7 ETM+ and Landsat–5 TM imagery to monitor short-term woody vegetation changes throughout Queensland (de Vries *et al*., 2006). Danaher *et al.* (2006) state that,

> *"In order to analyse more subtle long-term vegetation change, time-based trends resulting from artefacts introduced by the sensor system must be removed."*

As part of SLATS, a reflectance-based vicarious calibration approach using high-reflectance, pseudo-invariant targets in western Queensland was developed (de Vries *et al.*, 2006). The radiometrically corrected Landsat –TM data generated by SLATS underpins the Landsat –TM bare ground product and in turn the ModBGI developed as part of this study.

As an aside, it is interesting to note that correction of MODIS imagery to a common solar zenith has prompted some revision of BRDF related corrections to Landsat –TM within SLATS. Synergies between standardisation of MODIS for solar zenith angle and revision of calibration of Landsat –TM are on-going within SLATS.

3.3 Analysis of Remotely Sensed Data

3.3.1 Standardising solar zenith angles within a MODIS time series

A model to standardise all MODIS bands for all image dates to a reflectance based on a common solar zenith angle of 45 degrees was applied. This was done to aid the search for a relationship between MODIS and field measurements of biomass. It was done using the semi-empirical model equations listed in Appendix 9.2 in combination with BRDF parameters supplied with MODIS imagery. Both the parameters from the imagery and output from the equations were applied as described in equation (1).

Figure 6 compares the MODIS signal before (solid line) and after (dashed line) correction to a common solar zenith angle of 45 degrees. In this example a time series of red reflectance (Band 1) is plotted for a single pixel with an FPC of 40% (Figure 6). The spectral response for a pixel with an FPC of 40% is primarily influenced by over story vegetation and would be expected to be reasonably stable over time. Figure 6 shows the new standardised reflectance values for the pixel over the time period (dashed line) are lower due to the fact that the sun is effectively lower in the sky. In addition, variability over seasons has been reduced to some extent (i.e. the dashed line is 'flatter' through time). A 45 degree sun angle has been adopted here based on earlier work with Landsat –TM completed by SLATS scientists. Determining the optimal sun angle for ground cover and biomass modelling is a research question beyond the scope of this project.

By standardising all MODIS image dates to a solar zenith angle of 45 degrees the variability that can be attributed to seasonal change within a MODIS time series is reduced (not eliminated). For this study, the use of a standardised time series has improved the statistical relationship between biomass field measurements and MODIS.

For ModBGI a slightly improved result is obtained using a mean solar zenith angle (i.e. no sun angle correction). This occurs due to the fact that the equation to derive ModBGI uses Landsat –TM as a response variate (i.e. MODIS predicting Landsat –TM bare ground). Seasonal sun angle effects influencing Landsat –TM equally affect MODIS data. When MODIS data is corrected to a standardised solar zenith of 45 degrees and the Landsat –TM data are not similarly corrected then the ModBGI model returns poorer results. Landsat –TM products do not have the extensive range of BRDF parameters and associated models afforded to MODIS. By contrast to the ModBGI model, the biomass model does not rely on Landsat –TM data, the response variate in its case is actual field data measurements independent of any satellite sensor. So, for biomass modelling, removal of seasonal sun angle variability within MODIS improves the end result.

It may be possible to use MODIS BRDF parameters and sun angle correction to radiometrically refine Landsat –TM seasonal variability in the future, work is on going within SLATS.

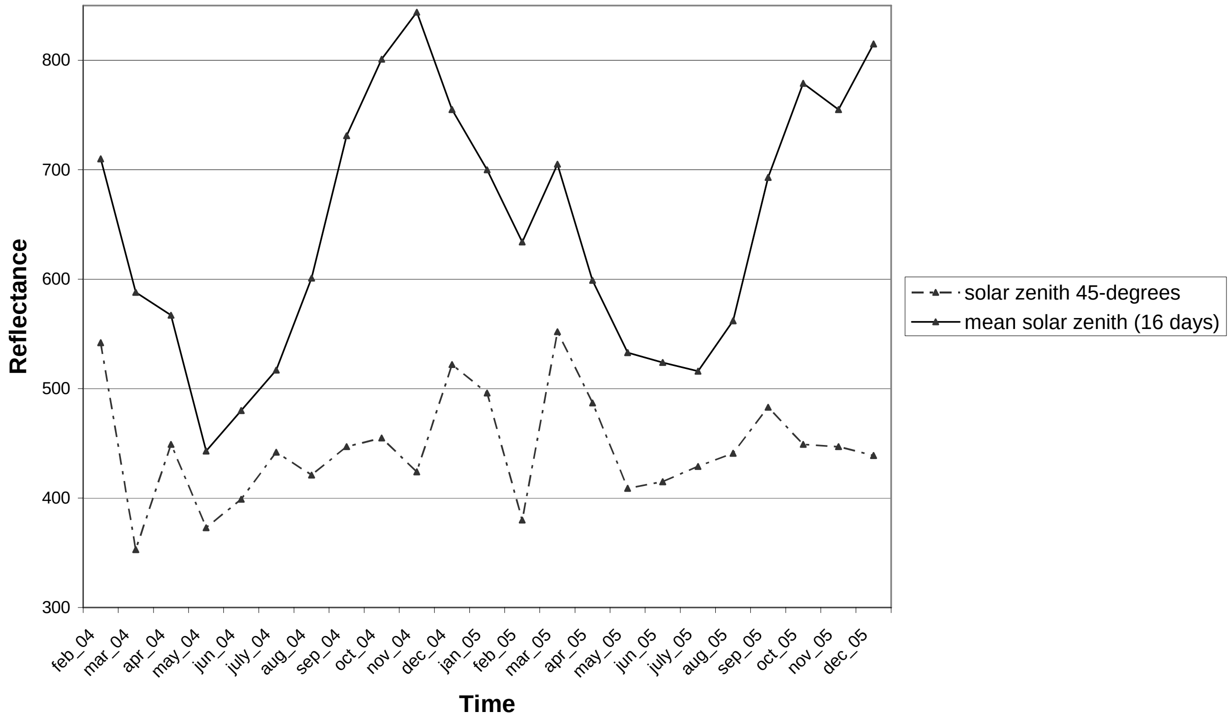


Figure 6: Time series reflectance for a single pixel with a Foliage Projective Cover (FPC) of 40 before and after correction to a common solar zenith angle.

3.3.2 Developing a MODIS Bare Ground Index (ModBGI)

The concept of a ModBGI has its origin within SLATS image processing methodology. SLATS use a multiple regression index to map foliage projective cover (FPC) as part of its annual monitoring of woody vegetation change (Scarth *et al.*, 2006). The FPC product is derived from Landsat –TM imagery using multiple regression techniques and an extensive set of over 2000 field observations. It provides an accurate estimation of woody FPC without the need for image stratification (Scarth *et al.*, 2006). The FPC product is described in Danaher *et al*. (2004) and Lucas *et al.* (2006).

At the outset, multiple regression techniques were preferred in this study because it 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). Scarth *et al* (2006), with reference to development of the Landsat –TM multiple regression bare ground index comments that,

> *"In the presence of representative calibration data, multiple regression has been shown to perform as well as more complex nonlinear 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."*

The analysis presented here used the latest available Landsat –TM MRBGI product from SLATS as a response variate in regression analysis. At first the analysis to derive a ModBGI was done using a general linear model, but the final product uses a *generalised* linear model to account for non-linearity in data distributions. Iterative analysis using multiple bands of MODIS (including BRDF parameters) was done to find the best combination of explanatory variates and derive a ModBGI at a spatial resolution of 1 km. During analysis, explanatory variates such as MODIS spectral bands, products of bands, logarithms of bands and a full range of BRDF parameters were evaluated. Each iterative analysis commenced with a large number of explanatory variates and by process of elimination arrived at a model that has as few terms as possible but still provides the maximum amount of information. Further, cross-validations using subsets as training data and calculating prediction root-mean square errors (RMSE) were used to determine the optimal number of terms for both the ModBGI model and biomass models. This is explained in more detail in the results section of this report. Cross validation methods were used to refine both the ModBGI and biomass models. Cross validation identified the need to use a *generalised* linear model for final derivation of ModBGI. The biomass model was derived using a general liner model; however research using *generalised* non-linear algorithms is on-going. In both the ModBGI and biomass models cross validation feedback resulted in a reduction of the number of explanatory variates used to avoid over fitting and redundancy.

The first step in the methodology for ModBGI derivation was to scale up the Landsat –TM bare ground data so that it could be used coincidently with 1 km MODIS imagery. In scaling up, a mean value for Landsat –TM bare ground was calculated to coincide with the extents of each 1 km MODIS cell. Landsat –TM image dates were selected as close as possible to MODIS image acquisition dates. A standard deviation about the mean was also calculated from Landsat –TM bare ground data for each 1 km cell. The standard deviation is useful in determining which 1 km cells are likely to have more homogeneous ground cover. That is, scaled up cells that have small standard deviations are those where Landsat –TM pixels are least variable within that particular 1 km. Conversely, those 1 km cells with a high standard deviation are where Landsat –TM bare ground is most variable, therefore a more heterogeneous cover within the cell. Consideration of frequency distributions within 1 km cells is on-going and is described in Appendix 9.8. Scaled up Landsat –TM bare ground image dates and corresponding MODIS image dates used to derive the preferred ModBGI are listed in Table 3.

Table 3: Image dates used in derivation of ModBGI

Landsat –TM MRBGI image (Scaled up to 1 km)	**MODIS MCD43B4 and MCD43B1 imagery**
15/07/2003	12/07/2003
12/04/2004	06/04/2004
18/08/2004	12/08/2004
22/10/2004	15/10/2004
16/04/2005	23/04/2005
09/10/2005	16/10/2005

Following iteration using combinations of spectral bands, products of bands, logarithms of bands and BRDF parameters through multiple regressions, the preferred ModBGI model was selected based on statistical criteria including R^2, standard error and level of significance. Later, cross validation was used to select the smallest number of significant terms for inclusion in the model. During the cross validation, significant non-linearity between observed and predicted values led to the adoption of a generalised linear model and an improved result.

The preferred model is based on a sample size that is representative of both the spatial extent and temporal sequence of data available. The preferred ModBGI model presented here has been derived from 66,705 observations inclusive of approximately 55% of the spatial and temporal sequence listed in Table 3 (i.e. poor quality data and areas with an FPC of greater than 20% are not included in the analysis, no other masks are applied). The model is representative of tropical savannah grasslands and has been applied to a time series and mapped (Appendix 9.1).

GenStat ™ was used for all statistical analysis.

3.3.3 Developing MODIS Multiple Regression Biomass and In-Vitro Dry Matter Digestibility Indices

Total Standing Dry Matter (TSDM) (kg/ha) was measured from pasture harvested at Charters Towers field sites during April 2004, October 2004, April 2005, October 2005 and April 2006. All samples have been ground and analysed for Ash (%) and In-vitro Dry Matter Digestibility (IVODMD) (%).

Relating field measurements to 1 km MODIS cells in which they reside raises issues of whether or not the field site (100 m x100 m) is truly representative of the 1 km MODIS cell. Each field site is one one–hundredth of the area of its corresponding MODIS cell. The difference in scale between images and site measurements is a major limitation when using MODIS data in combination with field measurements. Regardless of the field methodology employed there is inherent variability with a 1 km cell due to grazing pressure, soil changes, slope, tree cover, roads, dams etc… that is very difficult to sample.

The methodology used in this research to redress this issue involves weighting an observation based on a ratio between scaled up Landsat –TM bare ground data at 100 m x 100 m (the field site area) and scaled up Landsat –TM bare ground at the MODIS 1 km pixel resolution. That is, a 100 m x 100 m cell is created around each field site and statistics extracted from Landsat –TM bare ground data to calculate a mean bare ground for each field site. A mean bare ground value is also calculated for the 1 km MODIS cell that the site is located within. With a mean Landsat –TM bare ground measurement for both the 100 m x 100 m site and its corresponding 1 km MODIS cell it is possible to calculate a ratio between the two measurements that relates each field site to the MODIS pixel in which it resides. Subsequently the ratio is used as a weight in multiple regression analysis. That is, where the Landsat –TM bare ground mean for a 100 m x 100 m site is not similar to the Landsat –TM bare ground mean for its surrounding 1 km cell the site is weighted lower during analysis. Conversely, where strong agreement exists between the field site and the surrounding 1 km the measurement from that site has a higher weight in the analysis and more influence over the final biomass and IVODMD (%) models.

In the future this methodology could be employed during site selection to only select field sites that have a high likelihood of being representative of the MODIS pixel in which they reside.

The preferred MODIS biomass and IVODMD (%) models presented in this report have been selected based on statistical criteria including R^2, standard error and level of significance. An effort has been made to use all field sites; however data was lost where corresponding MODIS imagery is poor quality or cloud affected. As with ModBGI development, cross validation involved calculation of prediction RMSE and formed the basis of optimising explanatory variates to include in the model. The cross validation methodology is explained in more detail in the results section of this report.

The biomass and IVODMD (%) models incorporate different combinations of MODIS reflectance and BRDF parameters; they have been derived independently of each other.

3.3.4 Validation of the ModBGI and biomass models

Prediction of bare ground using the ModBGI model is based on scaled up Landsat –TM MRBGI data. Hence, the accuracy of the ModBGI output is limited by accuracy of Landsat –TM bare ground products. There is additional loss of information in ModBGI product compared to Landsat –TM bare ground imagery due to differences in scale (i.e. Landsat –TM 30 m, MODIS 1 km). Comparison of the original Landsat –TM bare ground imagery and output from the ModBGI model shows the diluting effect of scale. High variability in cover observed at the Landsat –TM scale becomes generalist at 1 km, resulting in a loss of information at the paddock/property scale (Appendix 9.3).

Cross validation of ModBGI and biomass models has been done by taking a random sub–sample of input data, deriving a new model from the sub-sample and applying that model to the remainder. This is done iteratively using progressively more explanatory variates while observing root mean square errors (RMSE). The RMSE analysis described in the results section of this report was used to optimise the number of explanatory variates and avoid over fitting of the data.

Further evaluation of the biomass model was done using mobile visual estimates taken across the Charters Towers scene in April and October 2005. The mobile observations are independent data sets available for use in evaluation of output from the biomass model. Using a similar methodology that was used to scale up Landsat –TM bare ground data, the mobile estimates of biomass (Figure 7a) were scaled-up to 1 km MODIS resolution. For MODIS grid cells in which more than one mobile biomass measurement is recorded (Figure 7b), a mean and standard deviation were calculated. To evaluate the output from the biomass model, the mean per 1 km cell was plotted against the TSDM (kg/ha) output from the model. Further, both datasets were scaled up to 5 km cells to compare confidence in means for both model output and mobile estimates. The analysis highlights the issues of scale between ‘local’ field measurement and ‘generalised’ MODIS imagery.

Evaluation also included categorising output from both the scaled-up mobile estimates and biomass predictive model into ranges (i.e. 0-1000, 1000-1500……..4000-4500 kg/ha TSDM). The results were plotted in an accuracy assessment matrix and a ‘KHAT’ statistic calculated to determine the level of agreement or otherwise between the two independent data sets. This analysis was also done over an area of Mitchell Grass Downs to determine whether or not the biomass model was more effective in more homogeneous swards.

In addition, histograms of both scaled-up mobile estimates and biomass TSDM (kg/ha) model output were compared to give an overall indication of agreement between modelled and independent mobile estimates. Mobile estimates were also mapped in overlay with biomass model output (Appendix 9.4). While outside the scope of the objectives of this study additional work has been done to consider a role for MODIS data in AussieGRASS (Appendix 9.7). Appendix 9.7 summarises results using the GRASP model in it CEDAR and AussieGRASS implementations to predict MODIS NDVI.

a)

b)

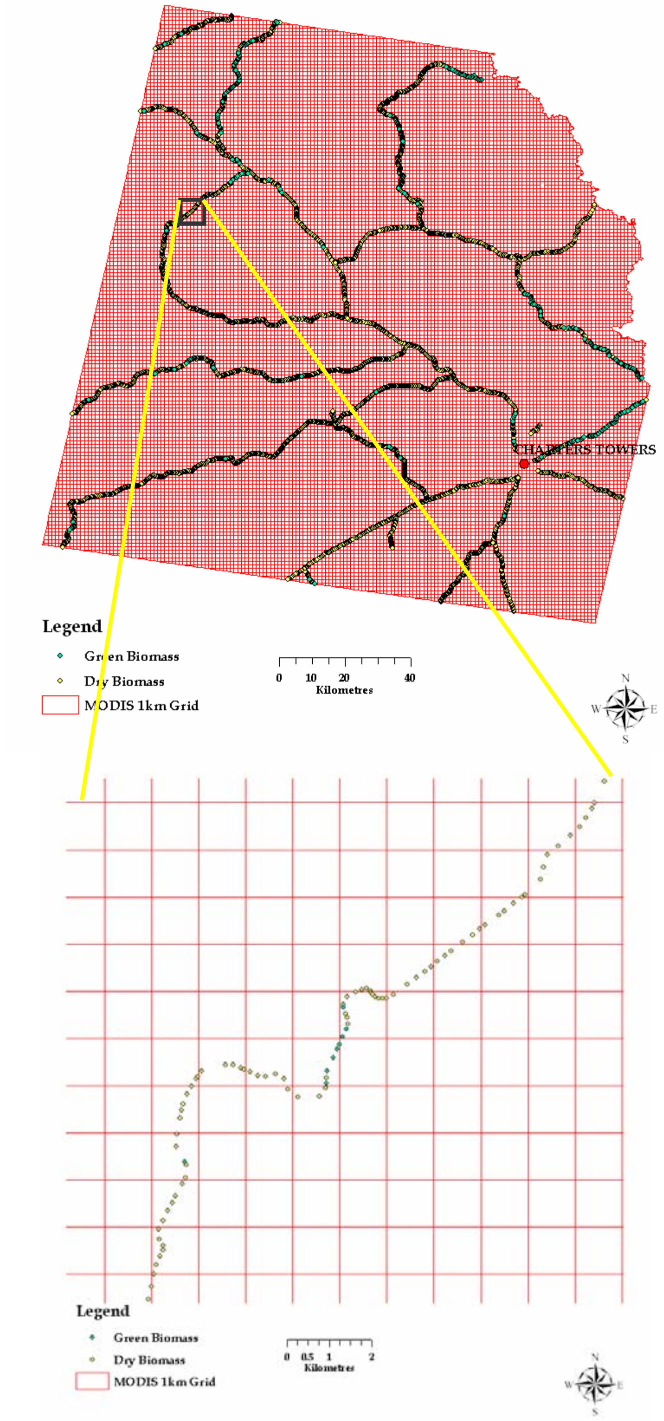


Figure 7: Visual biomass estimate acquisition across the Charters Towers Landsat scene a) full extent and b) example of multiple estimates within a single MODIS 1 km grid cell

4 Results and Discussion

4.1 Objectives 1 and 2

4.1.1 Groundcover model

Following an iterative approach, MODIS reflectance bands, products of bands, logarithms of bands and BRDF parameters were tested as explanatory variates to predict Landsat –TM bare ground (response variate). A preferred model was developed that is robust and representative of the spatial extent of the study area. The most important aspect of ModBGI is in its ability to reliably predict bare ground with high temporal frequency in wet and dry years across all seasons. If so, it can compliment higher spatial resolution Landsat –TM bare ground products. If the model is sufficiently robust for all seasons then there is some prospect for it to be used in its own right as a high temporal resolution broad scale monitoring tool.

To cross validate and test ModBGI the prediction root mean square errors (RMSE) for every candidate model (5 for each subset size) was calculated as the average of the RMSE resulting from 1000 cross-validation runs.

$$RMSE = \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right) \Big/ \left(n - m \right)$$

where n is the number of observations, m is the number of explanatory variates, y_i is the observed value of *total standing dry-matter* (TSDM) and $\hat{y}_i$ is the independently predicted value. This measure penalises for extra explanatory variates included in the model.

For each run, 1% of the observations were randomly sampled to train the model and the remaining 99% were used to validate. The training and validation datasets were uniformly sampled across the range of the response variable (scaled-up Landsat –TM bare ground) so that they were balanced (i.e. their histograms looked approximately the same). Validation involved observation of the prediction root mean square errors (RMSE) iteratively as more explanatory variates were added, this was done to determine the best number of most significant explanatory variates to include in the model. The final ModBGI model has been derived using feedback from the validation process.

Table 4 and Figure 8 define the preferred ModBGI model. The preferred model includes 66,705 observations which is inclusive of 55% of the spatial and temporal sequence listed in Table 3 (i.e. poor quality data and areas with an FPC of greater than 20% were not included in the analysis, no other masks were applied).

The preferred ModBGI model used both derived reflectance and BRDF parameters as explanatory variates. It performs well across seasons because it has some sensitivity to the structure of groundcover and is less sensitive to ephemeral greenness (or lack of) in tropical savannah grasslands at different times of the year. In the preferred model, MODIS BRDF parameters from red reflectance and longer wave infra-red bandwidths were included, the result is a model that is less sensitive to greenness and more sensitive to the structure of the pasture sward.

Importantly, the model does not use NDVI; rather it uses MODIS reflectance and BRDF parameters that are theoretically more sensitive to variables such as pasture height and physical structure of ground cover.

Table 4: Summary statistics for the preferred ModBGI model.

Regression analysis

Response variate: MEAN_BG
Weight variate: weight_fpc
Fitted terms: Constant, Band_1, Band_2, Band_6, Band_7, Band_7_iso, Band_1_geo, Band_6_geo, Band_7_geo, prod_1_6, prod_2_6, prod_6_7, MEAN_FPC

Summary of analysis

Source	d.f.	Deviance	Deviance	ratio	chi pr.
Regression	12	116762	9730.1571	9730.16	<.001
Residual	66693	31668	0.4748		
Total	66705	148430	2.2252		

Estimates of parameters

Parameter	estimate	s.e.	t	t pr.
Constant	6.766	0.124	54.37	<.001
Band_1	0.012919	0.000141	91.4	<.001
Band_2	-0.0036788	0.0000745	-49.4	<.001
Band_6	-0.0031566	0.0000217	-145.7	<.001
Band_7	-0.0029750	0.0000635	-46.86	<.001
Band_7_iso	0.018716	0.000145	129.25	<.001
Band_1_geo	-0.009337	0.000268	-34.90	<.001
Band_6_geo	0.009734	0.000143	67.87	<.001
Band_7_geo	-0.021265	0.000195	-109.28	<.001
prod_1_6	-2.93E-06	3.95E-08	-74.27	<.001
prod_2_6	1.13E-06	2.00E-08	56.82	<.001
prod_6_7	7.95E-07	1.64E-08	48.57	<.001
MEAN_FPC	-0.048645	0.000941	-51.72	<.001

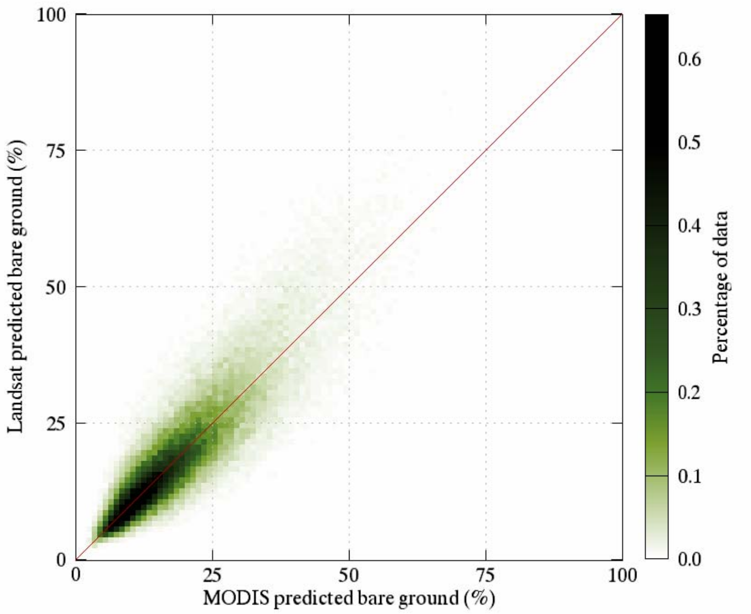


Figure 8: Graphical representation of the preferred ModBGI model statistically summarised in Table 4

4.1.1.1 Cross-validation of the ground cover model

The root mean square error (RMSE) analysis is summarised in Figure 9. In Figure 9 the x–axis shows the number of explanatory variates used in iterations of a model. The y–axis shows the cross-validated RMSE (%). For each number of explanatory variates, the line shows the average prediction RMSE for the best fitting model. The upper and lower error bounds (the shaded area) show the maximum and minimum prediction RMSE from the 1000 runs for that model. The results show that the high number of observations is a reasonable safeguard against over-fitting. Even though the maximum and minimum cross-validated RMSE is variable, with a higher number of terms, it is within 1%.

Based on Figure 9, twelve explanatory variates provides the best trade-off between RMSE and range (the prediction RMSE has levelled off and the minimum/maximum RMSE range is small). Anything with greater than fourteen terms is unnecessary and merely incorporates more highly correlated data without capturing any more information. Based on the results, the preferred model uses the following twelve terms (CV RMSE = 6.78961): Band_1, Band_2, Band_6, Band_7, Band_7_iso, Band_1_geo, Band_6_geo, Band_7_geo, prod_1_6, prod_2_6, prod_6_7, MEAN_FPC.

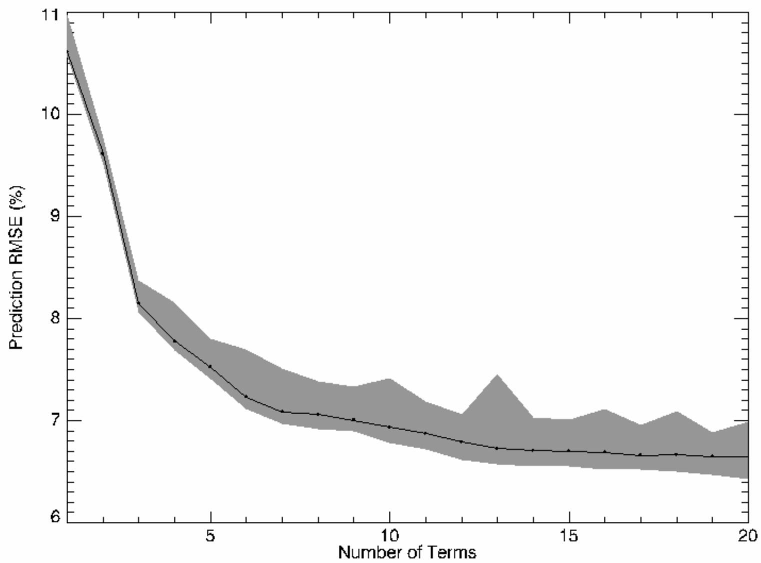


Figure 9: Prediction Root Mean Square Error (RMSE) by number of explanatory variates.

4.1.2 Biomass model

Similar to bare ground modelling, with regard to biomass the aim is to find an index that can exploit the multiple look angle characteristics and associated BRDF parameters particular to MODIS and model biomass accurately across wet and dry years/seasons.

Prior to the correction of a MODIS time series to a common solar zenith of 45 degrees, there was no discernable relationship between MODIS and the TSDM (kg/ha) measurements taken at selected field sites, at different dates, across the Charters Towers study area. However, once corrected to a standardised solar zenith angle a statistical relationship between measured biomass at selected sites and standardised MODIS data emerged (Tables 5 and 6, Figures 10 and 11).

Using feedback from cross validation two biomass models were derived, one uses 3 explanatory variates (Table 5 and Figure 10) and one 8 explanatory variates (Table 6, Figure 11). Cross validation revealed that while 3 explanatory variates capture most of the information contained within the imagery up to 8 explanatory variates improves the fit of the model. However, by including more than 3 explanatory variates there is some risk that the improved fit is coming at the expense of accuracy. Certainly more than 8 explanatory variates improved the fit of the model further but the predictive accuracy is compromised (i.e. fitting to the ‘noise’). Both models are presented here and throughout the remainder of the report the model using 8 explanatory variates is presented. The biomass image included in Appendix 9.4 has been derived using 8 explanatory variates listed in Table 6. Research into use of non-linear models to help determine the optimal number of explanatory variates is on-going.

Table 5: Statistical summary of the ‘3 explanatory variate model’ to predict biomass (kg/ha TSDM) from MODIS imagery.

Regression analysis

Response variate: TSDM
Weight variate: weight
Fitted terms: Constant, Band_6, Band_9, Band_2_6

Summary of analysis

Source	d.f.	s.s.	m.s.	v.r.	F pr.
Regression	3	26250450.	8750150.	37.60	<.001
Residual	116	26996024	232724		
Total	119	53246474	447449		

Percentage variance accounted for 48.0
Standard error of observations is estimated to be 482

Estimates of parameters

Parameter	estimate	s.e.	t(116)	t pr.
Constant	15317.	1809.	8.47	<.001
Band_6	-1.806	0.338	-5.34	<.001
Band_9	-9.55	1.41	-6.76	<.001
product_2_6	0.001838	0.000329	5.58	<.001

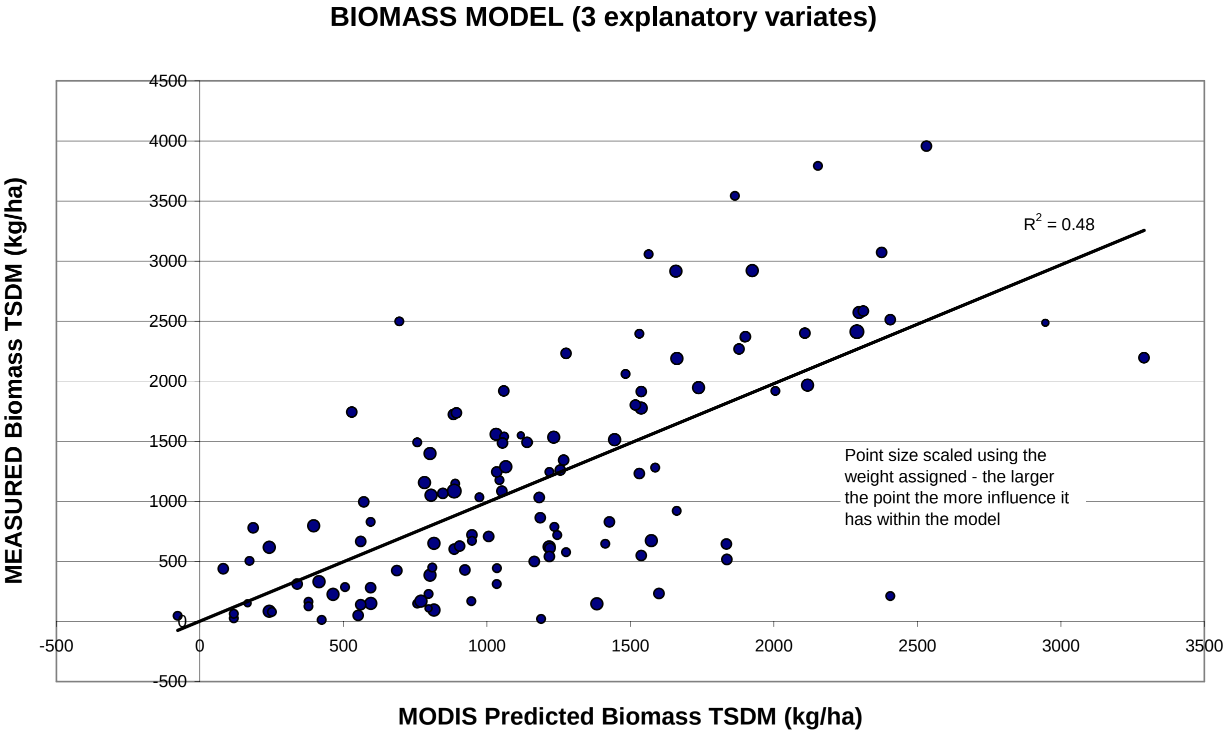


Figure 10: Predicted TSDM (kg/ha) versus Measured TSDM (kg/ha), using 3 explanatory variates, Charters Towers

Table 6: Statistical summary of the '8 explanatory variate' model derived to predict biomass (kg/ha TSDM) from MODIS imagery.

Regression analysis

Response variate: TSDM
Weight variate: weight
Fitted terms: Constant, Band_1, Band_5, Band_6, Band_8, Band_9, product_2_6, Band_2_vol, fpc_mean

Summary of analysis

Source	d.f.	s.s.	m.s.	v.r.	F pr.
Regression	8	30479610.	3809951.	18.58	<.001
Residual	111	22766864.	205107.		
Total	119	53246474.	447449.		

Percentage variance accounted for 54.2
Standard error of observations is estimated to be 453

Estimates of parameters

Parameter	estimate	s.e.	t(111)	t pr.
Constant	17503.	2426.	7.21	<.001
Band_1	-3.45	1.48	-2.33	0.022
Band_5	2.440	0.714	3.42	<.001
Band_6	-2.193	0.500	-4.39	<.001
Band_8	6.94	2.51	2.77	0.007
Band_9	-12.84	1.81	-7.08	<.001
product_2_6	0.001833	0.000340	5.39	<.001
Band_2_vol	1.540	0.830	1.85	0.066
fpc_mean	-27.0	12.9	-2.09	0.039

Tables 5 and 6 and Figures 10 and 11 outline the statistical relationship derived from field site biomass measurements taken across the Charters Towers scenes in April 2004, October 2004, April 2005, October 2005 and April 2006, and coincident MODIS imagery.

In Figure 11 sites 18 and 19 (red points intersected by a dashed vertical line) are actually located within the same MODIS pixel, a paired site; therefore the biomass model returns the same predicted value (x-axis) for TSDM (kg/ha) at each site. In fact the sites are located on separate properties of which one is heavily grazed and one is managed with lower stocking rates. Herein lays the difficulty in modelling biomass at the MODIS scale. The actual measured biomass (y-axis) within the same MODIS pixel on the same date is 212 kg/ha for site 18 and 2,511 kg/ha for site 19 (i.e. large difference between the two sites for measured TSDM). Photos of these two sites are included in Figure 12.

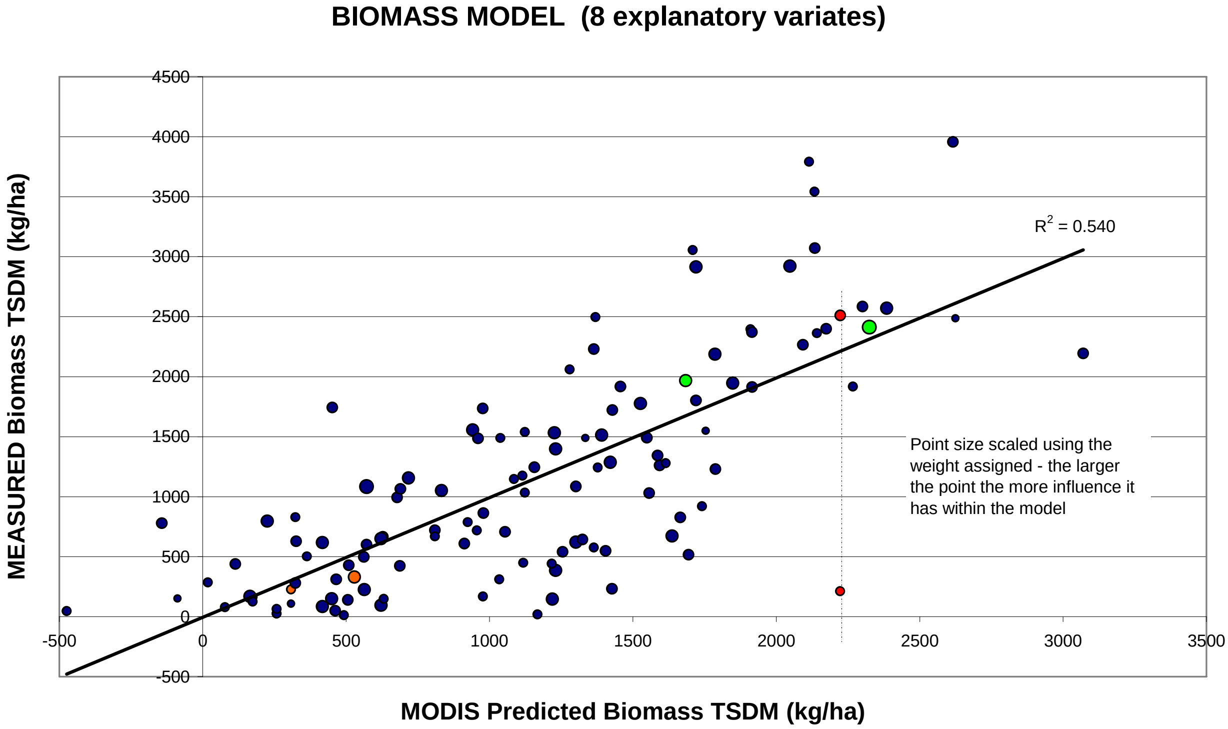


Figure 11: Predicted TSDM (kg/ha) versus Measured TSDM (kg/ha), using 8 explanatory variates, Charters Towers

Site 18 and 19 each represent one one–hundredth of the area of the 1 km MODIS pixel in which they reside. So, in the example above, it is difficult to determine which site is more representative of the MODIS pixel. As discussed in the methodology section of this report a weight for each observation was derived by scaling up Landsat –TM bare ground to each 100 m x 100 m field site and its corresponding 1 km MODIS scale pixel. A spatial statistic derived from a ratio of the two scaled up means was employed as a weight in the regression analysis summarised in Figures 10 and 11. The size of the points in Figures 10 and 11 are an indication of each points influence in the analysis, larger points are those with higher weights. That is, a larger point is where scaled-up Landsat –TM bare ground for the field site (100 m x 100 m) is similar to scaled-up Landsat –TM bare ground for the surrounding MODIS 1 km pixel. Site 18 has quite a low weighting (0.43) therefore the site is likely to not be as representative of the MODIS pixel as Site 19, which has a slightly higher weight (0.52). While site 19 is better placed with regard to the regression line its weight is still not particularly high — the weighting system employed provides a logic, and does improve fit and summary statistics for the biomass models, however there remains many unknown and unresolved issues when relating biomass measurements to 1 km MODIS. For example, what effect are the trees having at each site with regard to volumetric and geometric components of scatter, that is, trees and low biomass pasture at site 18 compared with trees and high biomass pasture at site 19? Weighting observations based on a spatial relationship between Landsat –TM mean bare ground (at the field site scale) and the same at MODIS scale improved the predictive biomass models but it is still only a partial solution. More field sampling of targeted sites is required to develop a more comprehensive understanding of relationships between biomass and MODIS.

SITE 18 April 2004	SITE 19 April 2004
	

Figure 12: Paired site 18 and 19 April 2004

The most interesting phenomenon of the biomass models is the fact that sites that have both a low measured biomass and are ephemerally green are generally falling at the low biomass end of the model (Figure 11 [larger orange point], Figure 13 – photo site 31, April 2006). This is in contrast to where these sites would fall in an NDVI based model – an ephemerally green site with low biomass would tend to be over estimated by an NDVI based index. Consider site 28, October 2005 (Figure 11 [smaller orange point], Figure 13) which lies in a similar position but is bare and dry. The model appears more sensitive to height and structure of the pasture sward than to its greenness.

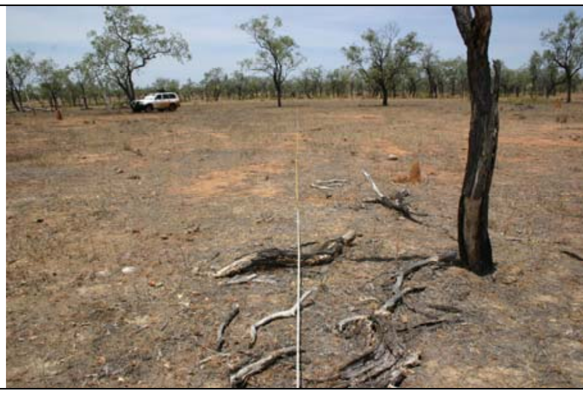
SITE 31 April 2006	SITE 28 October 2005
	

Figure 13: Green and dry sites falling at the low end of predicted biomass (kg/ha TSDM)

There is potential to compliment existing models such as AussieGRASS by providing biomass predictions based on height and structure rather than greenness. For example, site 11 (Figure 11 [green points], Figure 14) in both the wet and dry seasons is accurately predicted by the model. Both measurements have particularly high weights indicating that at both times of the year this site is likely to be representative of the larger 1 km MODIS pixel in which it resides. With ‘20-20 hindsight’ it would have been interesting to have had field sites where there is 90-100% agreement between the bare ground mean at field site scale and at the MODIS 1 km scale, as is the case with site 11.

SITE 11 April 2006	SITE 11 October 2005
	

Figure 14: Green and dry site both assigned a high weight in regression analysis – accurately predicted by the biomass models.

4.1.2.1 Pasture species within statistical space of the biomass model

To consider in more detail the notion that the biomass models derived are more sensitive to pasture sward structure than to greenness it is worthwhile considering where various species are located along the regression line.

Bothriochloa pertusa and *Urachloa sp.* are both low growing prostrate species and as expected are located toward the lower end of the biomass model, by contrast the more upright growing and ‘tussock like’ sites that include *Bothriochloa decipiens* (some sites are a mix of *Bothriochloa decipiens, Bothriochloa ewartiana* and *Bothriochloa bladhii*) are located at the higher biomass end of the regression line, as are sites dominated by *Cenchrus ciliaris* (Figure 15). Examples of these sites are displayed in Figure 16. On the left side of the Figure; sites 31, 28 and 15 are ‘lawn like’ in contrast to sites 4, 11 and 27 that are more ‘tussock like.’

Tree basal area at all sites are displayed in Figure 16 and are quite low — the spectral response is more influenced by pasture sward than trees at each site.

There appears to be an anomaly when we consider the position of sites dominated by *Bothriochloa ewartiana.* Figure 17 shows sites dominated by *Bothriochloa ewartiana* falling along the full length of the regression line (both orange and blue points). This is contrary to what is expected, given the growth habit of *Bothriochloa ewartiana* it would be expected that all sites would be located at the higher end of the model. These sites are scattered throughout the statistical space of the model. However, upon closer scrutiny observations falling in the middle to lower end of the model all emanate from two sites, 10 and 22 (Figure 17 [orange points]). Sites 10 and 22 have live tree basal areas greater than 4.0, while those *Bothriochloa ewartiana* observations falling in the middle to top end of the biomass model are located at sites 17 and 19

(Figure 17 [blue points]). At sites 17 and 19 live tree basal areas are less than 1.0. Figure 18 shows photos of sites 10 and 17 taken during April 2006. The measured biomass at site 10 is 1,557 kg/ha TSDM, lower than the 2,600 kg/ha TSDM measured at site 17. At site 10 there are more live trees and less pasture (orange points), at site 17 fewer live trees and more pasture (blue points). Infact the *Bothriochloa ewartiana* sites provide further confirmation that the biomass model presented here is sensitive to structure of pasture sward, that is, sites with higher live tree basal area and lower measured pasture biomass (sites 10 and 22) are falling in the lower end of the statistical space, by contrast, sites with fewer trees and higher yields of 'tussock like' pasture are falling in the higher end of the model (sites 17 and 19). It is the sward not the trees that are influencing the position of a site within the statistical space of the model. Where there are more live trees there is less 'tussock like' grass. It is interesting to note that scattering from live trees that might be expected to 'push' a site up the regression line in fact does not appear to be influencing the position of the *Bothriochloa ewartiana* sites within the model.

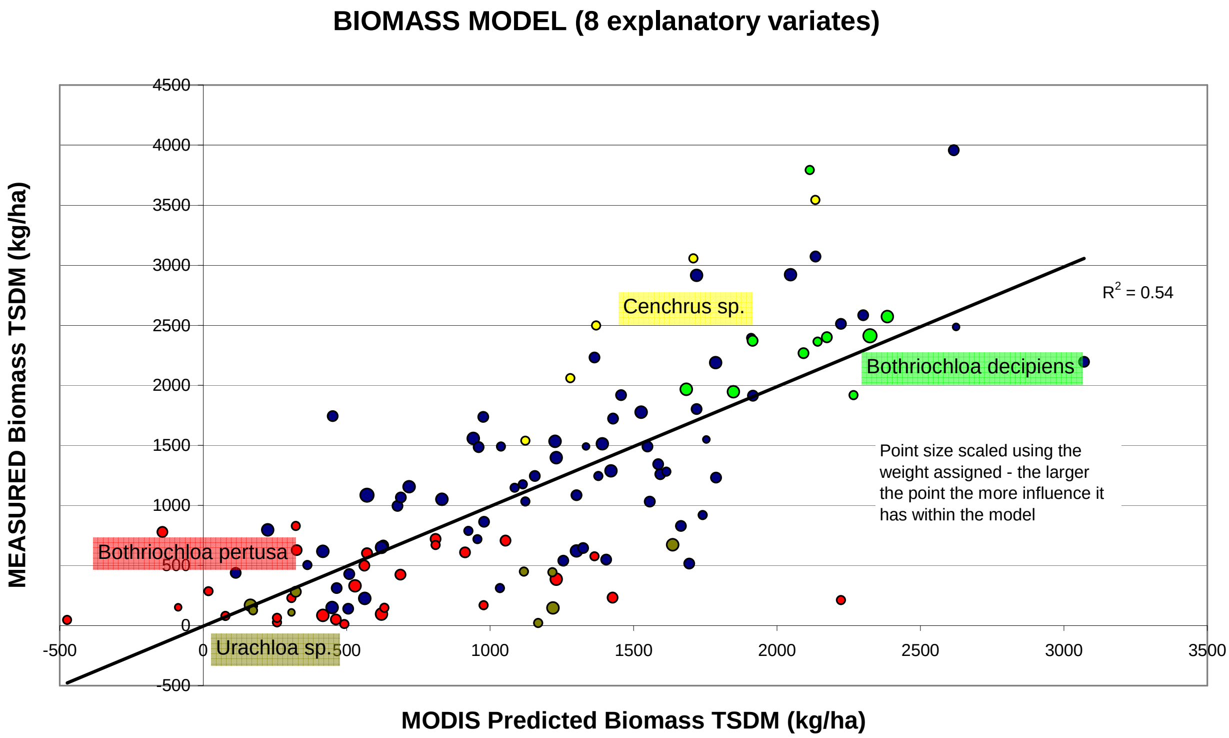


Figure 15: Biomass model displaying relative position of *Bothriochloa pertusa* (red points), *Urochloa* sp. (*brown points*), *Bothriochloa decipiens* (green points) and *Cenchrus ciliaris* (yellow points).

The best illustration of sensitivity of the biomass models to structural characteristics of pasture sward can be seen by observing those sites that fall along the trendline (Figure 19). Figure 19 shows the measured TSDM (kg/ha) for each site depicted along the trendline. That is, by looking at photos and TSDM measurements at the bottom end of the trendline and working through to the top end it becomes clearer what is being captured by the model.

Figure 16: 'Lawn like' and 'Tussock like' pasture swards positioned at opposite ends of the biomass model regression line

SITE 31 April 2006 (*B. pertusa*) – 'lawn like' Live Tree Basal Area = 1	SITE 04 April 2006 (*Cenchrus ciliaris*) – 'tussock like' Live Tree Basal Area = 0
	
SITE 28 April 2006 (*B. pertusa* and *Urochloa sp*.) – 'lawn like' Live Tree Basal Area = 1.4	SITE 11 April 2006 (*B. decipiens* and *B. ewartiana*) – 'tussock like' Live Tree Basal Area = 1.8
	
SITE 15 April 2006 (*B. pertusa*) – 'lawn like' Live Tree Basal Area = 0.3	SITE 27 April 2006 (*B. decipiens* and *B. bladhii*) – 'tussock like' Live Tree Basal Area = 2.7
	

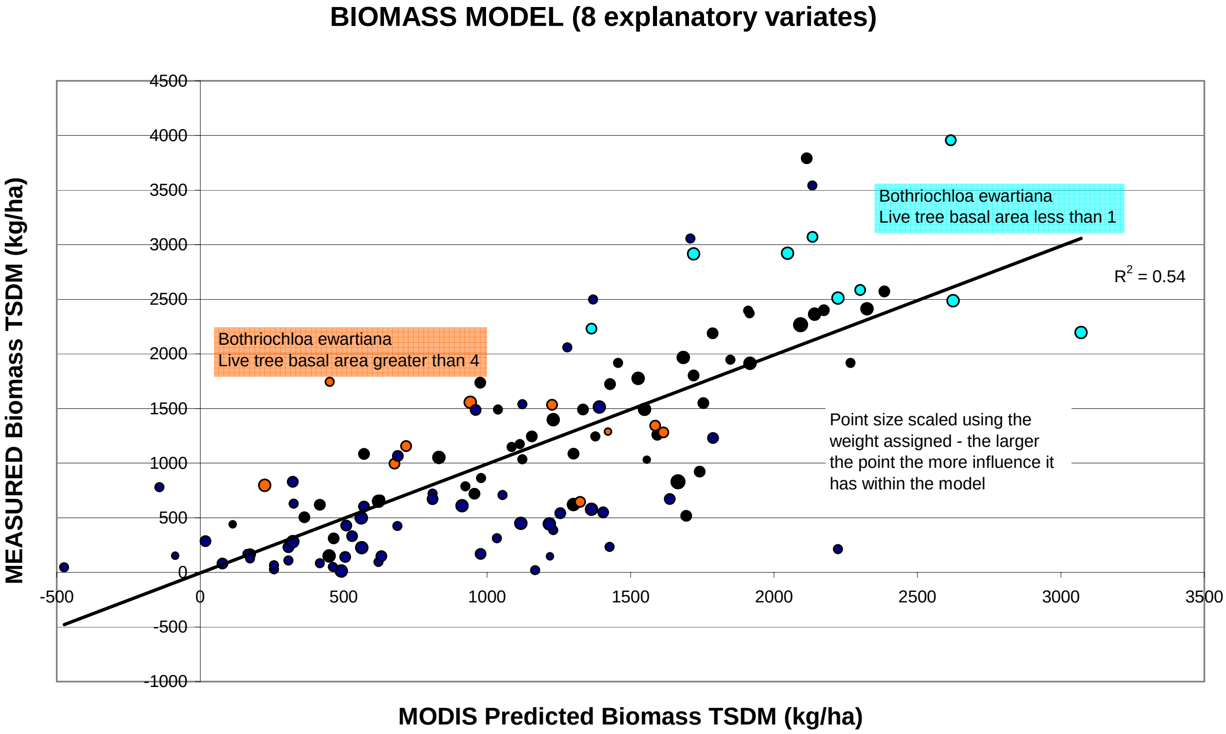


Figure 17: Biomass model displaying relative position of *Bothriochloa ewartiana* sites where the tree basal area is less than 1.0 (blue points) and *Bothriochloa ewartiana* sites where the tree basal area is greater than 4.0 (orange points).

SITE 10 April 2006 Live Tree Basal Area = 4.8	SITE 17 April 2006 Live Tree Basal Area = 0.6
	

Figure 18: *Bothriochloa ewartiana* sites with contrasting tree basal areas

It is quite evident that along the trendline the model is more sensitive to the shape and structure of pasture swards rather than ephemeral greenness. Several green sites are located along the trendline in relatively logical positions with regard to measured biomass, despite being far greener than other sites with similar measured biomass. By observing photos of sites along the trendline it is possible to visualise what the model is capturing in statistical space.

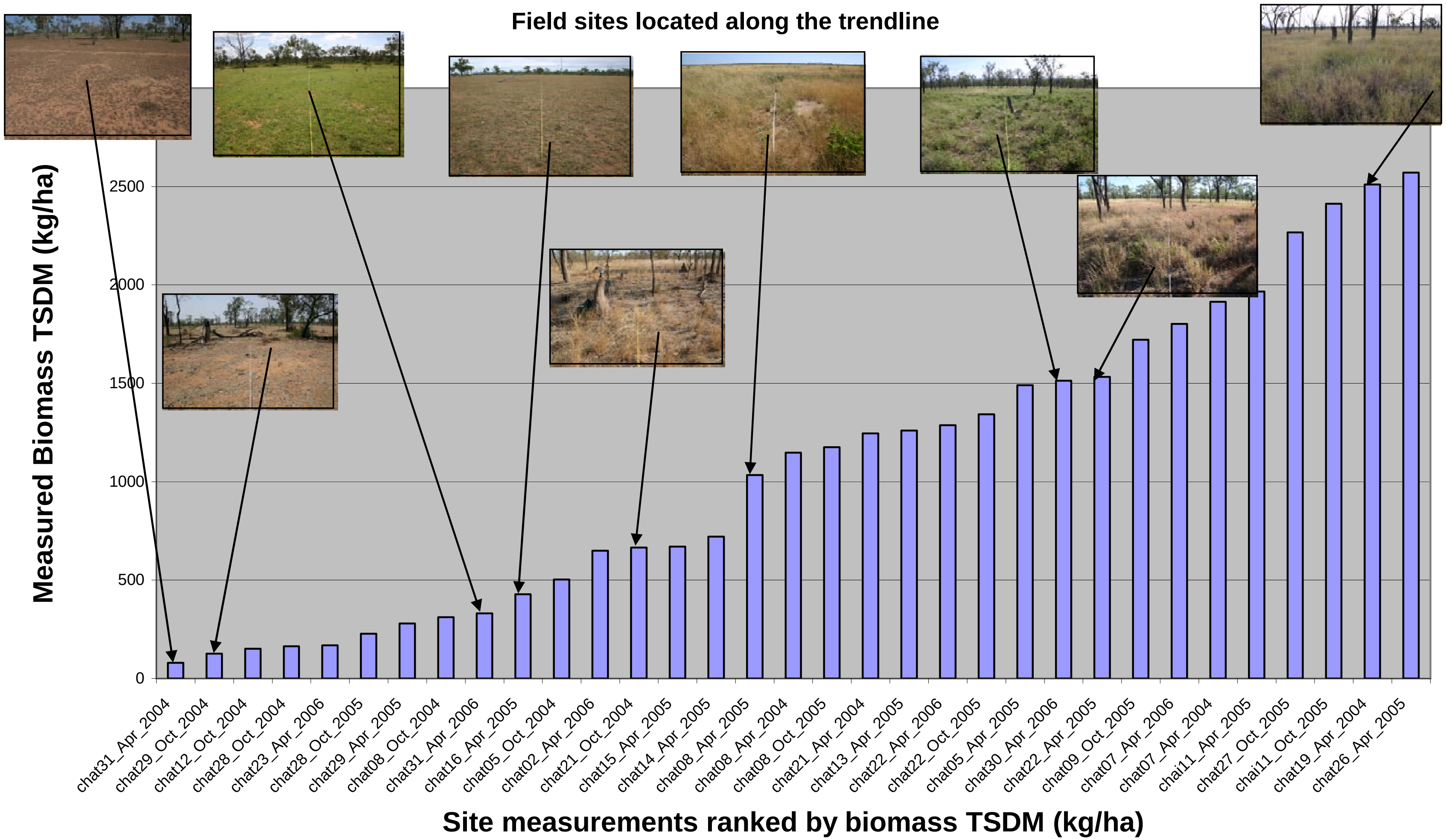


Figure 19: Analysis of field sites located along the trend line of the biomass model

4.1.2.2 Cross-validation of the biomass model

The prediction RMSE for every candidate model (5 for each subset size) was calculated as the average of the RMSE resulting from 1000 cross-validation runs,

$$RMSE = \sum_{i=1}^{n}\left(y_i - \hat{y}_i\right) \Big/ \left(n-m\right)$$

where n is the number of observations, m is the number of explanatory variates, y_i is the observed value of *total standing dry-matter* (TSDM) and $\hat{y}_i$ is the independently predicted value. This measure penalises for extra explanatory variates included in the model.

For each run, 90% of the observations were randomly sampled to train a multiple linear regression model and the remaining 10% were used to validate. Each observation was weighted by a ratio of % bare ground at the field plot and MODIS scales. The training and validation datasets were uniformly sampled across the range of the response variable so that they were balanced (i.e. their histograms looked the same).

The training/validation sample size ratio was different to the one used for the bare ground model (1/99%) due to the much smaller number of observations (120). Several iterations were run, each time reducing the size of the ratio. The optimum number of terms fluctuated, suggesting that a ratio less than 90/10% was creating unbalanced datasets.

Figure 20 shows the results of the cross-validation.

Divergence between the model and prediction RMSE (dashed line and solid line) steadily increases after 3 explanatory variates, with a rapid increase after 8 explanatory variates. This suggests the predictive capability of the model is quite poor regardless of the number of explanatory variates. After 8 explanatory variates, the model is over-fitted (the extra explanatory variates are just fitting to noise).

The minimum prediction RMSE is 674.9 TSDM, which is 17% of the entire range used to train the model. This shows the high level of noise in the dataset. It has not been determined how much of the noise is explained by measurement error.

Based on Figure 20, either the 3 or 8 explanatory variate models could be justified. A 3 explanatory variate model is more stable (much closer to the model RMSE) and only 21.5 TSDM greater than the 8 explanatory variate model. The 8 explanatory variate model gives the best cross-validation result and is the model adopted as part of this study, however, the potential for over-fitting is acknowledged. Indeed anything with greater than 8 explanatory variates is just fitting to noise and giving spurious predictions.

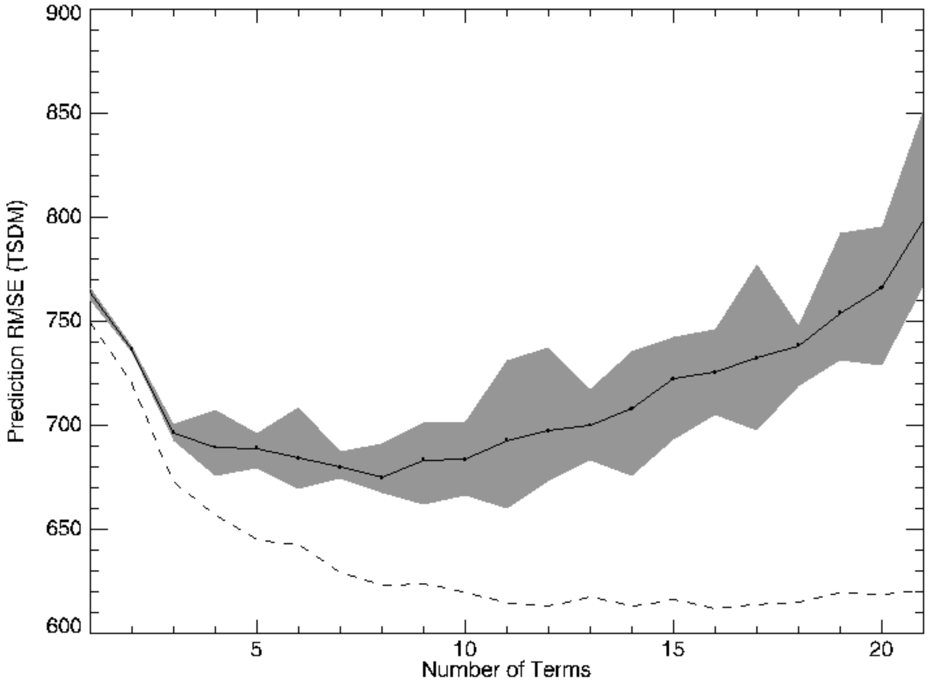


Figure 20: Mean prediction RMSE of the best model for each number of explanatory variates. The upper and lower error bounds (the shaded area) shows the maximum and minimum prediction RMSE from 1000 cross-validation runs. The dashed line shows the corresponding model RMSE.

Table 7: The change in prediction RMSE and the predictors of the best-fitting models are shown. The best-fitting model for each number of explanatory variates was determined by cross-validation.

Explanatory Variates	RMSE Change	Predictors
1	0.0	Band_10
2	27.6	Band_9, Band_2_vol
3	40.1	Band_6, Band_9, product_2_6
4	7.0	Band_5, Band_6, Band_9, product_2_6
5	0.4	Band_2, Band_6, Band_7, product_2_6, Band_2_vol
6	4.7	Band_4, Band_5, Band_6, Band_9, product_2_6 , fpc_mean
7	4.3	Band_3, Band_5, Band_6, Band_9, product_2_6, Band_2_vol, fpc_mean
8	5.1	Band_1, Band_5, Band_6, Band_8, Band_9, product_2_6, Band_2_vol, fpc_mean
9	-8.5	Band_1, Band_3, Band_5, Band_6, Band_9, product_2_6, Band_2_vol, Band_3_iso, fpc_mean

This analysis has assumed that a multiple linear regression approach is the best regression technique for the prediction of TSDM. Previous work by SLATS has shown it to be a robust technique. However a *generalised* linear model may result in a more sensible fit to the data because it can account for statistical properties of the response variable and non-linearity in relationships with the predictors. Further analysis is on-going into the improved fit potentially provided by generalised linear models.

4.1.2.3 Scale issues for field data and MODIS

It is difficult to overcome the problem of scale at which field based measurements (or in this case mobile field observations) are made by contrast with the scale of MODIS. Figure 21 is a cross plot of mobile field observations and biomass model output (kg/ha TSDM) scaled up to 5 km x 5 km. There is a weak statistical relationship between the two independent data sets. At 1 km and 10 km the result is very similar to that obtained at 5 km. Five kilometre resolution was chosen to enable comparison of confidence in means for both scaled-up model output (Figure 22) and scaled-up mobile field estimates (Figure 23). The variability within 5km cells, for both the model output and mobile estimates, is captured by plotting confidence in means, which is a function of standard deviation, confidence limits and the number of observations per 5km cell. Figure 23 demonstrates the limitations of scale. There is wide variability about the mean for mobile field estimates within most MODIS cells. As the observer drives through each 5 km cell (or 1 km cell or 10 km cell) the landscape varies and land cover is constantly changing. Obtaining a meaningful average for each cell is very difficult. It is not that there is any problem with the observations made, the problem comes back to how can an accurate and reliable measure of biomass for a 1 km, 5 km or 10 km cell be made?

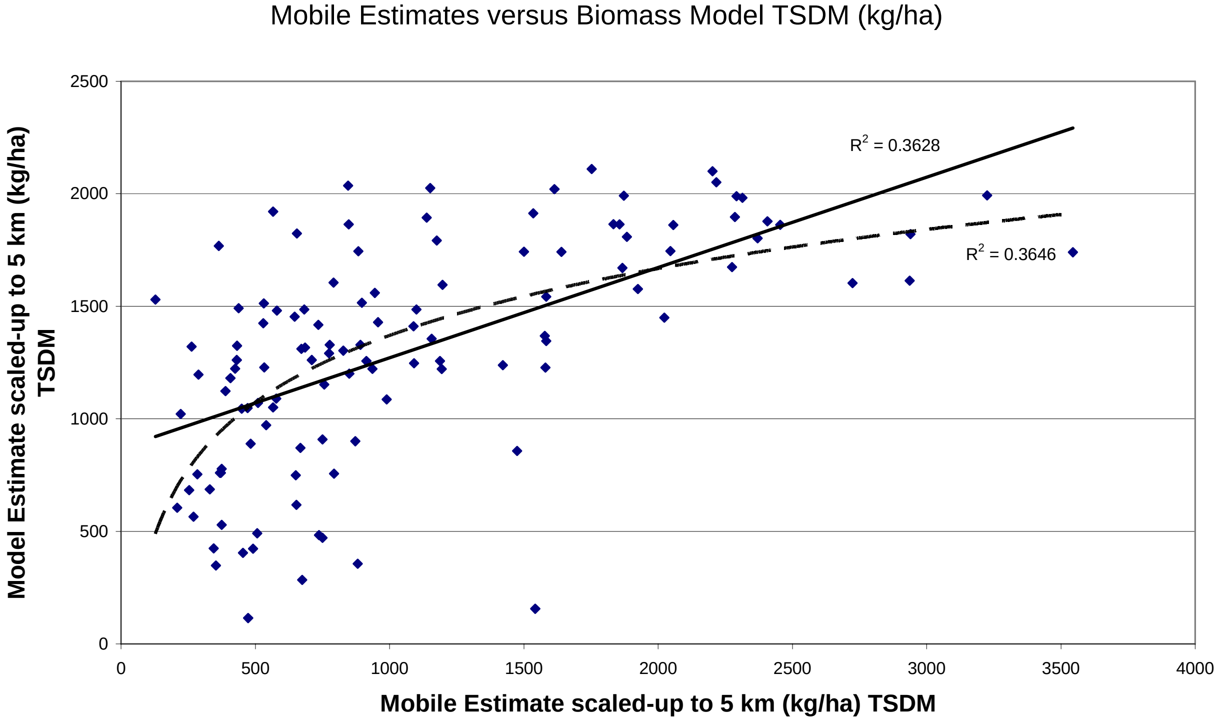


Figure 21: Mobile estimates versus biomass model predictions (kg/ha TSDM) – scaled-up to 5 km grid cells

The confidence in means plotted for mobile estimates (Figure 23) show that at low biomass 5 km cells have less variability and the mean per cell is more reliable. This is most likely due to the fact that low yielding bare areas are often (not always) a result of periods of low rainfall and can often be wider more homogeneous areas, hence a more stable mean for lower estimates. However, as surrounding areas increase in kg/ha TSDM so does the variability about the mean. The variability within a large cell (MODIS) across tropical savannah grasslands is essentially why the relationship between model estimates and mobile field observations is weak (Figure 21).

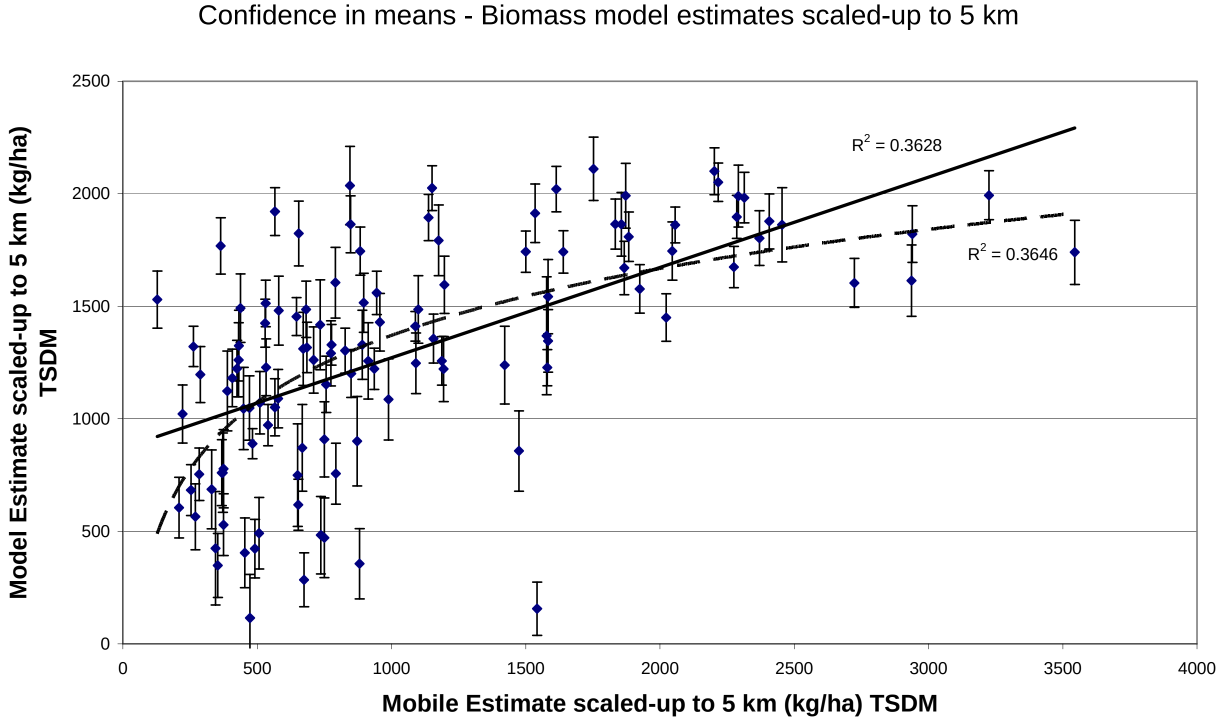


Figure 22: Confidence in Means for biomass model predictions

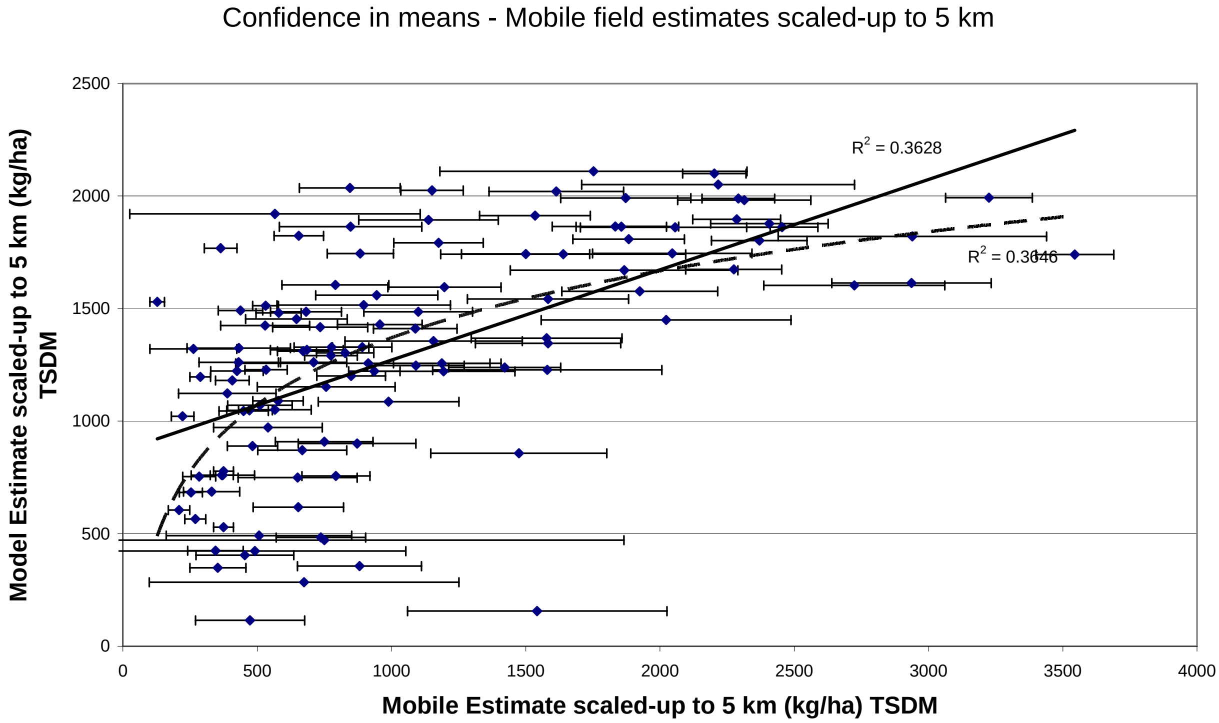


Figure 23: Confidence in Means for mobile field estimates

Both the model output and mobile field observations were grouped into ranges and histograms were plotted (figures 24 and 25). Figures 24 and 25 demonstrate a shift that exists between model estimates and mobile field observations. It also shows some difference between the biomass models. The model that uses 3 explanatory variates captures the higher frequency of low TSDM (kg/ha) measurements, while the 8 explanatory variate model is smoother overall.

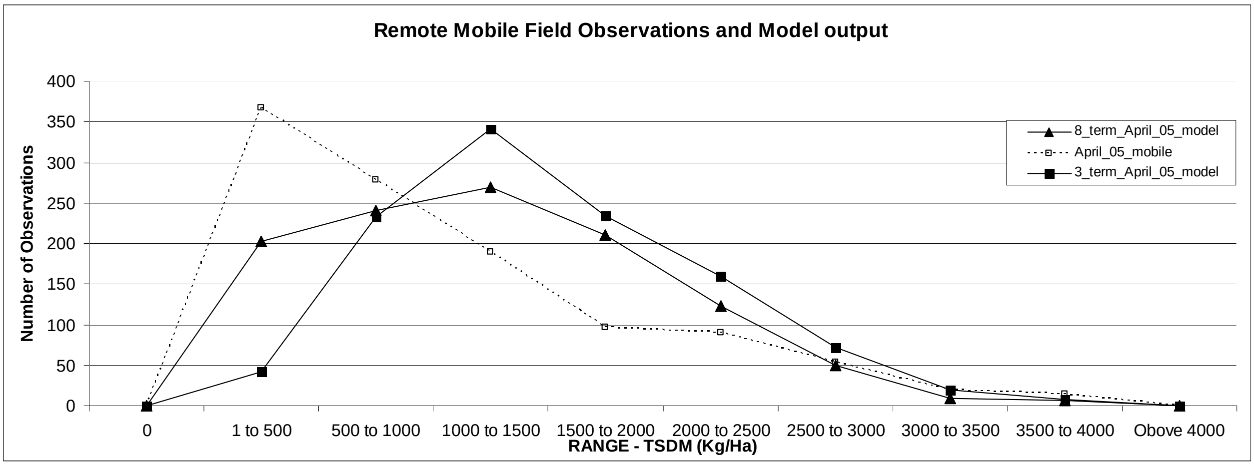


Figure 24: Number of observations by TSDM (kg/ha) for model output and scaled-up (1 km) mobile field estimates, April 2005, Charters Towers study region

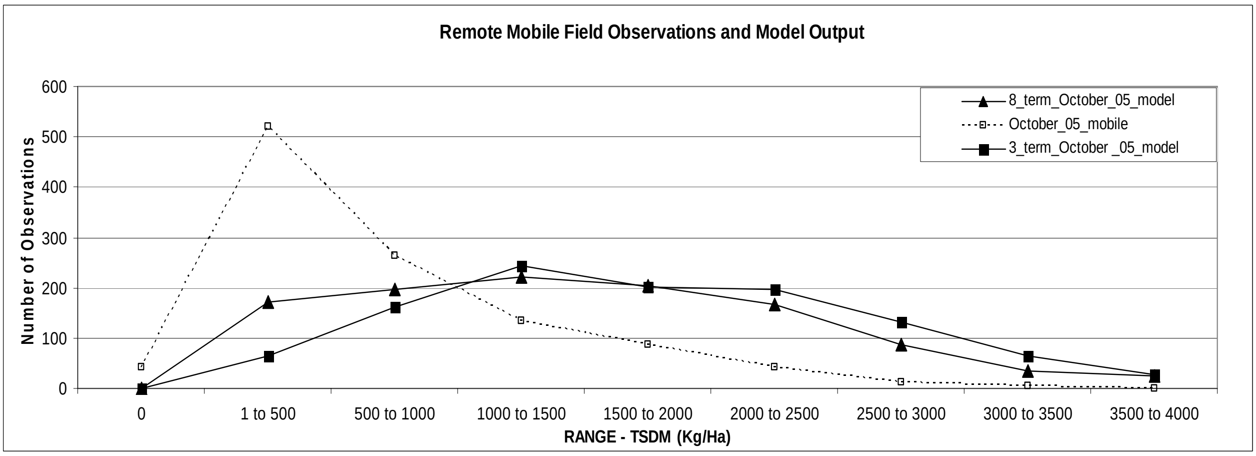


Figure 25: Number of observations by TSDM (kg/ha) for model output and scaled-up (1 km) mobile field estimates, October 2005, Charters Towers study region

In both April and October 2005 the model estimates of biomass are over predicted in relation to scaled-up (1 km) mobile field observations. The biomass models are more in agreement with mobile field estimates above 1,000 kg/ha than below 1,000 kg/ha.

This phenomenon is also apparent when an accuracy assessment methodology is applied to the data. Using an accuracy assessment methodology a matrix was constructed to show where there is agreement between the data sets. The results are presented here for both the Charters Towers study area and over an area of Mitchell Grass Downs (Tables 8, 9, 10 and 11).

4.1.2.3.1 Accuracy Assessment – Charters Towers and Mitchell Grass Downs

An accuracy assessment using biomass model output (1 km) and scaled-up mobile field estimates (1 km) for the Charters Towers study area and over an area of Mitchell Grass Downs returns a weak correlation between biomass model estimates and mobile field observations. Results of the accuracy assessment matrix for each date are summarised in Tables 8, 9, 10 and 11.

The diagonal line shaded in each matrix represents the number of pixels where both the model estimates and the scaled up mobile field estimates are within the same range. So, for Charters Towers study region in April 2005, 301 pixels (Table 8) had both model and mobile estimates of between 0 and 1000 kg/ha TSDM. While for 206 pixels the model over predicts in relation to the mobile estimates; 1,000 to 1,500 kg/ha compared with mobile estimates of 0 to 1,000 kg/ha TSDM. This result is consistent with the histogram in Figure 24. A common result through all of the accuracy assessment matrices is where the model over predicts at the lower end of ranges (Tables 8 through 11). While there appears to be some level of agreement along the diagonal lines, to properly evaluate the results a 'KHAT' statistic was calculated for each matrix (Lillesand and Kiefer, 1994). Conceptually 'KHAT' can be defined as,

KHAT = *observed accuracy – chance agreement* / *1 – chance agreement*

Lillesand and Kiefer (1994) state,

> *"This statistic serves as an indicator of the extent to which the percentage correct values of an error matrix are due to 'true' agreement versus "chance" agreement."*

As true agreement (observed) approaches 1 and chance agreement approaches 0; KHAT approaches 1 (Lillesand and Kiefer, 1994). KHAT ranges between 0 and 1, a value of 0.8 can be considered as an indication that an observed classification is 80% better than one resulting from chance (Lillesand and Kiefer, 1994). KHAT of zero indicates that the matrix is no more than a random assignment of pixels (Lillesand and Kiefer, 1994).

So, while there appears to be agreement between the two data sets along the diagonal line of each matrix, the result for Charters Towers in April 2005 has only a 15% chance of being anything other than random agreement. In October (2005) the result is worse at 8%. For Mitchell Grass Downs the level of agreement is better with the relationship between the two data sets for April and October (2005) of 24% and 19% respectively. This is quite a reasonable result given that the model has been derived from field data collected in the Charters towers region, there has been no field measurement included from Mitchell Grass Downs. That fact that the model output is more consistent with mobile estimates from Mitchell Grass areas is not surprising given the relative homogeneity of Mitchell Grass compared with diversity within the Charters Towers study area.

In the future it may be possible to locate more field sites on Mitchell Grass Downs in an effort to better define and refine the biomass model.

The accuracy assessment matrices have been prepared using 1 km data and the confidence in means tests (Figures 22 and 23) using scaled up 5km data. Scaling up beyond 5 km in search of correlation is not really feasible as the number of cells available for analysis is greatly diminished within the Charters Towers study area (i.e. pixels run into wooded areas). It also becomes counter intuitive as the clients (MLA and producers) are not interested in whether or not the biomass model is accurate at a whole of Queensland scale; they want to know whether or not

MODIS can be used to predict biomass at the paddock/property scale. At this stage it cannot be used effectively for that purpose. Poor correlation with mobile field estimates bears this out (Figure 21).

TABLE 8: Charters Towers April 2005. Mobile field estimates versus biomass model predictions TSDM (kg/ha) (1,108 1 km pixels)

		BIOMASS MODEL TSDM(kg/ha)								
		0-1000	**1000-1500**	**1500-2000**	**2000-2500**	**2500-3000**	**3000-3500**	**3500-4000**	**4000-4500**	**TOTAL**
MOBILE ESTIMATE TSDM(kg/ha)	**0-1000**	301	206	98	27	2	0	0	0	634
	1000-1500	44	66	51	20	1	0	0	0	182
	1500-2000	11	42	35	16	1	0	0	0	105
	2000-2500	7	17	43	19	3	0	0	0	89
	2500-3000	4	11	29	13	2	0	0	0	59
	3000-3500	2	4	9	9	0	0	0	0	24
	3500-4000	1	2	7	3	0	0	0	0	13
	4000-4500	0	1	1	0	0	0	0	0	2
	TOTAL	370	349	273	107	9	0	0	0	**1108**

KHAT Statistic

A = 301+ 66 + 35 + 19 + 2 + 0 + 0+ 0 = 423

B = (634*370) + (349*182) + (273*105) + (107*89) + (9*59) + (0*24) + (0*13) + (0*2) = 336,817

KHAT = $\{(1108 * A) – B\} / \{(1108)^2 – B\}$ = 0.15 (15%)

TABLE 9: Charters Towers October 2005. Mobile field estimates versus biomass model predictions TSDM (kg/ha) (1,092 1 km pixels)

		BIOMASS MODEL TSDM(kg/ha)							
		0-1000	**1000-1500**	**1500-2000**	**2000-2500**	**2500-3000**	**3000-3500**	**3500-4000**	**TOTAL**
MOBILE ESTIMATE TSDM(kg/ha)	**0-1000**	251	261	221	69	3	0	0	805
	1000-1500	9	27	62	30	4	0	0	132
	1500-2000	6	13	35	22	11	0	0	87
	2000-2500	4	4	20	15	5	1	0	49
	2500-3000	1	2	1	3	5	2	0	14
	3000-3500	0	0	0	1	2	1	0	4
	3500-4000	0	0	0	1	0	0	0	1
	TOTAL	271	307	339	141	30	4	0	**1092**

KHAT Statistic

A = 251+ 27 + 35 + 15 + 5 + 1 + 0 = 334

B = (805*271) + (132*307) + (87*339) + (49*141) + (14*30) + (4*4) + (1*0) = 295,217

KHAT = $\{(1092 * A) – B\} / \{(1092)^2 – B\}$ = 0.08 (8%)

TABLE 10: Mitchell Grass Downs April 2005. Mobile field estimates versus biomass model predictions TSDM (kg/ha) (477 1 km pixels)

		BIOMASS MODEL TSDM(kg/ha) 0-1000	1000-1500	1500-2000	2000-2500	2500-3000	TOTAL
MOBILE ESTIMATE TSDM(kg/ha)	0-1000	377	48	7	0	0	432
	1000-1500	12	12	1	0	0	25
	1500-2000	8	5	2	0	0	15
	2000-2500	0	3	0	0	0	3
	2500-3000	0	2	0	0	0	2
	TOTAL	397	70	10	0	0	**477**

KHAT Statistic
A = 377+ 12 + 2 = 391
B = (397*432) + (70*25) + (10*15) + (0*3) + (0*2) = 173,404
KHAT = $\{(477 * A) – B\} / \{(477)^2 – B\} = 0.24$ (24%)

TABLE 11: Mitchell Grass Downs October 2005. Mobile field estimates versus biomass model predictions TSDM (kg/ha) (464 1 km pixels)

		BIOMASS MODEL TSDM(kg/ha)					
		0-1000	1000-1500	1500-2000	2000-2500	2500-3000	TOTAL
MOBILE ESTIMATE TSDM(kg/ha)	0-1000	410	10	0	0	0	420
	1000-1500	17	5	0	0	0	22
	1500-2000	7	1	0	0	0	8
	2000-2500	3	0	0	0	0	3
	2500-3000	1	0	0	0	0	1
	TOTAL	438	16	0	0	0	**454**

KHAT Statistic
A = 410 + 5 + 0 + 0 + 0 = 415
B = (438*420) + (22*16) + (8*0) + (3*0) + (1*0) = 184,312
KHAT = $\{(454 * A) – B\} / \{(454)^2 – B\} = 0.19$ (19%)

4.1.3 In-vitro Dry Matter Digestibility model

Dry matter digestibility is a term used to describe the condition and value of pasture as fodder for grazing animals; it is a rating that is applied to fodder, determined by chemical analysis, to describe the actual portion that is digested and not excreted by the animal. The higher the digestibility rating, the more can be utilised by the animal for metabolic processes, conversely, the lower the rating of digestibility, the greater the amount will be passed out in the faeces (Stone G. *et al*, 2006).

In-vitro Dry Matter Digestibility (IVODMD) (%) has been measured from pasture samples dried and ground from each Charters Towers field site. As with biomass modelling MODIS + BRDF parameters have been used in multiple regression analysis to predict IVODMD (%). A summary of the model is included here (Figure 26 and Table 11).

The model is almost the inverse of biomass with *Bothriochloa pertusa* sites falling toward the high digestibility end and the more 'tussock like' swards (*Bothriochloa decipiens, Bothrichloa ewartiana and Cenchrus ciliaris*) falling at the lower digestibility end of the model (Figure 26).

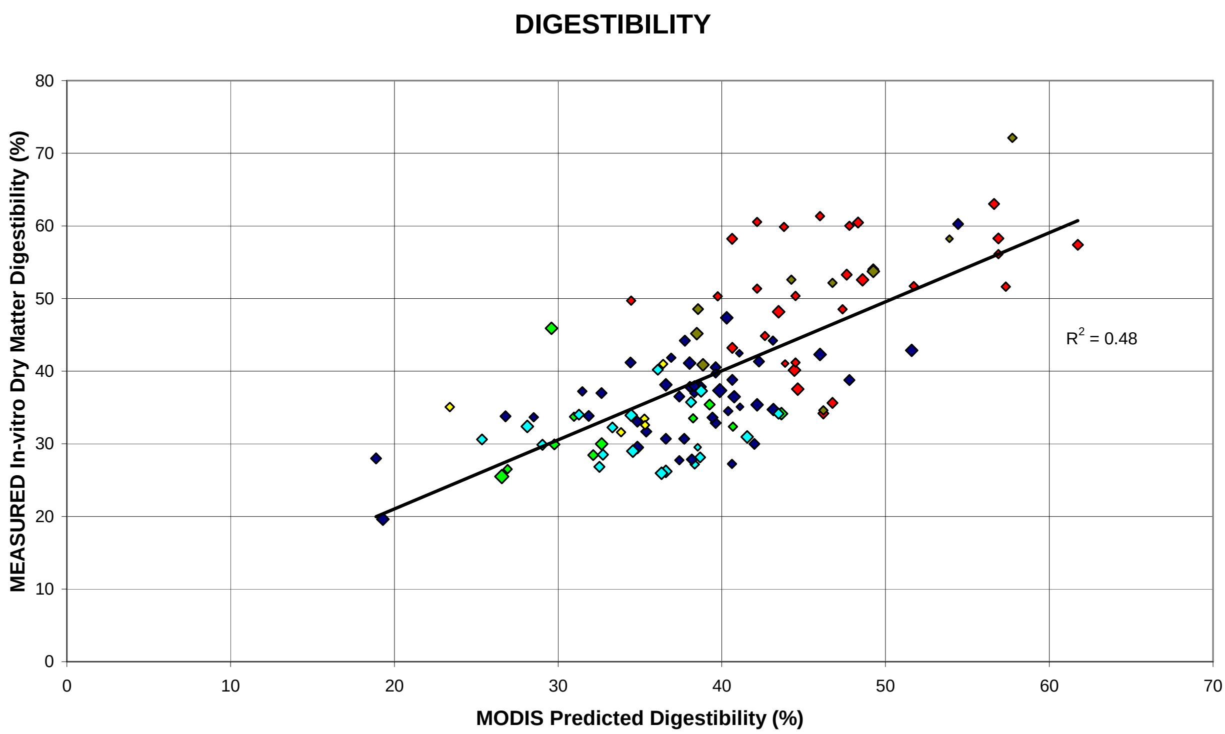


Figure 26: In-vitro Dry Matter Digestibility model displaying relative position of *Bothriochloa pertusa* (red points), *Urochloa* sp. (*brown points*), *Bothriochloa decipiens* (green points), *Bothrichloa ewartiana* (blue points) and *Cenchrus ciliaris* (yellow points).

The model (Table 11) has a much lower standard error than the biomass model, however, care needs to be taken in interpretation of the results. IVODMD (%) range from 0% to 100% whereas biomass can be anything from 0 to 4,500 kg/ha, the digestibility range is likely to be more uniform and consistent hence easier to predict using multiple regression techniques.

The position of pasture species along the regression line provides further evidence of the fact that this MODIS index has some sensitivity to structure of the pasture sward as opposed to its greenness, with ‘tussock like’ swards of lower digestibility at the lower end of the model and conversely ‘lawn like’ pastures with less cellulose at the higher end of the model.

An area of further research may involve using both biomass and IVODMD (%) models to determine coincident areas of low biomass and high digestibility, high biomass and high digestibility, high biomass and low digestibility etc… Currently there is continued effort to determine whether or not the IVODMD (%) model is actually providing new information or is simply the inverse of biomass.

Table 11: Statistical summary of a model derived to predict In-vitro Dry Matter Digestibility (%) from MODIS

Regression analysis

Response variate: IV_O_DMD
Weight variate: weight
Fitted terms: Constant, band_1, band_2, band_4, band_7, product_2_6, b5_geo, b8_geo, b10_geo, b2_vol, b5_vol, b6_vol, b7_vol, b9_vol

Summary of analysis

Source	d.f.	s.s.	m.s.	v.r.	F pr.
Regression	13	4008.	308.33	9.45	<.001
Residual	106	3458.	32.62		
Total	119	7466.	62.74		

Percentage variance accounted for 48.0
Standard error of observations is estimated to be 5.71.

Estimates of parameters

Parameter	estimate	s.e.	t(106)	t pr.
Constant	-20.4	12.6	-1.61	0.110
band_1	0.0530	0.0121	4.38	<.001
band_2	0.05129	0.00720	7.12	<.001
band_4	-0.1517	0.0194	-7.80	<.001
band_7	0.03259	0.00668	4.88	<.001
product_2_6	-0.00000726	0.00000228	-3.19	0.002
b5_geo	-0.1520	0.0695	-2.19	0.031
b8_geo	-0.551	0.191	-2.88	0.005
b10_geo	0.526	0.191	2.75	0.007
b2_vol	2.49	1.09	2.28	0.025
b5_vol	0.636	0.272	2.34	0.021
b6_vol	0.2287	0.0955	2.40	0.018
b7_vol	1.218	0.512	2.38	0.019
b9_vol	-4.62	2.01	-2.30	0.023

4.2 Objective 3

An aim of the project was to create positive links between Department of Natural Resources and Water (NRW) staff, the Dalrymple Landcare Group and interested producers. A liaison group was set up by members of the Dalrymple Landcare Group to keep producers informed of progress during project implementation. Primary sources of contact for NRW staff have been Mr. Bob Shepherd at Charters Towers Department of Primary Industry and Forestry (DPI&F) and individual producers during bi-annual field trips to the region. Members of the liaison group are listed in Table 12.

An example of the type of documentation prepared for the liaison group and other interested producers is included in Appendix 9.6.

Table 12: Dalrymple Producer Liaison Group

Producer Name	Property Name
Alistair and Catherine Gordon	Allensleigh, Cargoon
Mike and Noeline Dore	Cuba Plains
Ray and Chris Whitney	Fanning River
Keith and Alma Atkinson	Camel Creek
Doug and Denise Hamer	Glen Dillon
Peter Pemble	Myrrulumbing
David Nicholas	Paynes Lagoon

The document contained in Appendix 9.6 was mailed out to participating producers in early 2005. It was prepared to inform producers of the MODIS project, its objectives and what was involved. This was particularly important as it reinforced producer involvement in the project and helped bring those whose properties encompassed actual field sites up to date with what was planned. The document was also sent to a number of producers that were not involved but wanted more information regarding the project.

It was originally proposed that six producers within the Charters Towers study area would be involved in frequent (2 to 4 weekly) collection of cover and biomass data which would contribute to (a) calibration and validation of MODIS products; and (b) assessment of value and acceptance of products for improved land management. Achievement of Milestone 2 in the contract for NBP.330 included training producers within the study area in the collection of property/paddock based field data. It was proposed that these producers be selected in consultation with regional organisations and MLA.

Producer involvement in data collection sought to provide a higher sampling frequency than the information collected by NRW officers and would be used to “fine-tune” the calibration of cover indices and to contribute to the development of MODIS biomass relationships. The optimal sampling frequency was determined to be approximately every two to four weeks within the growing season, extending to four to six weeks during senescence. However, it was intended to determine a practical field data collection program taking into consideration the availability of producers to make a substantial time commitment, and the options of sampling being done either independently by producers or with the support of an experienced local field officer.

Assistance was sought from representatives of the DPI&F, Charters Towers, to liaise with producers and identify interested and suitably-located participants. Despite widespread interest and support for the MODIS project by local producers, none were able to commit to sample pasture biomass and groundcover at the frequency required to be of most value for the calibration stage of the project. Investigations were subsequently made into data being collected in the study area by a local field officer contracted on a casual basis. However, attempts to engage a suitably experienced person able to make a commitment to the sampling intensity were unsuccessful.

The objectives of producer involvement were to obtain a time-series of biomass data and evaluate how well MODIS imagery can be tuned to local conditions and to gain greater acceptance through producer participation in all stages of the project. The original expectation of time commitment by producers was, in hindsight, unrealistic. The difficulty in getting producers directly involved in field data capture is a function of their time available but more importantly has been compromised by the lack of a suitably qualified field officer based in Charters Towers and assigned to the project. From an agricultural extension perspective, to expect the level of producer involvement implied in objective 3, that is, producers actively involved in data capture to coincide with satellite overpass requires a very high level of facilitation and coordination. It also requires a considerable effort in training, data quality control and management. It is not a simple task. It is unrealistic to expect that this level of producer involvement would be possible without an experienced extension specialist involved at the project site.

The documentation provided to producers and efforts of project staff to keep producers informed has been commendable given the fact that the staff are based in Brisbane not Charters Towers.

In hindsight the project designers have been overly optimistic with objective 3. It is not realistic to assume a high level of producer involvement without assigning a competent coordinator / facilitator in the field.

4.3 Objective 4

The Reviewer's Report, Meat and Livestock Australia (MLA), Northern Beef Program Resource Management Projects (Scanlon and Stafford Smith, 23/06/2005) is clear in that this project *'…is more a technique–development than end-user project, so producer involvement is probably very secondary and aimed at setting priorities for the quality/precision of analysis outputs that would be needed to give them value (hence meeting load on producer collaborators should reflect this).'*

A meeting with John Childs in late January / early February 2006 reinforced the point that producers are interested to know whether or not it is possible to use MODIS imagery as an information source for successful monitoring and management of tropical savannah grasslands. Until the scientific parameters are adequately understood and tested to a level of precision and reliability it is not possible to determine the appropriateness or otherwise of various MODIS based products for producers.

Meetings with Bob Shepherd, Department of Primary Industries and Fisheries (DPI&F) and two members of the Dalrymple Landcare Group — Mr. and Mrs. Keith and Alma Atkinson (Camel Creek Station) and Mr. Doug Hammer (Glen Dillon) — during the April 2006 field trip to Charters Towers, indicated a clear understanding of the research nature of this project. There does not appear to be any unrealistic expectations nor any particular anticipation of producer based products emerging at this stage.

The scientific validation and on-going calibration of data that may result in the development of stable remote sensing indices of groundcover and pasture biomass has been the main focus of this project.

At project completion the relationship between biomass measurements and MODIS is not sufficiently robust to be used to prepare products for producers; however, the ModBGI was applied to a time series of MODIS imagery and may be of interest to planners at a catchment or regional planning scale. It is not relevant at a property scale. Given involvement of producers in catchment management, increasing interest in broader land management / erosion / downstream and environmental issues relevant to tropical savannah; a bi-monthly bare ground product at 1 km scale will contribute as a broad scale monitoring tool. As discussed earlier MODIS imagery and BRDF parameters are being made available at a 500 m resolution. A 500 m bare ground image — available twice per month, or every 8 days — will be a useful monitoring tool for those interested in ground cover at the catchment and regional planning scale.

Figure 27 outlines a framework for automated delivery of MODIS groundcover products. While the poor spatial resolution of MODIS at property scales is a major limitation to its usefulness and relevance, when it comes to the issue of data transfer fewer pixels result in a much smaller and more manageable file size compared with Landsat –TM products. The Charters Towers area bare ground images displayed in Appendix 9.1 are 52 kilobytes each. A state-wide data set is 1,800 kilobytes (or 1.8mb). The conceptual model (Figure 27) proposes a simple system where data processing is automated in Brisbane and files are emailed to Charters Towers DPI&F for printing and distribution to interested producers, local authorities etc... As products derived from MODIS data become more refined (i.e. 500m and input from more field data, calibration etc...) it is envisaged that the level of interest from producers would increase.

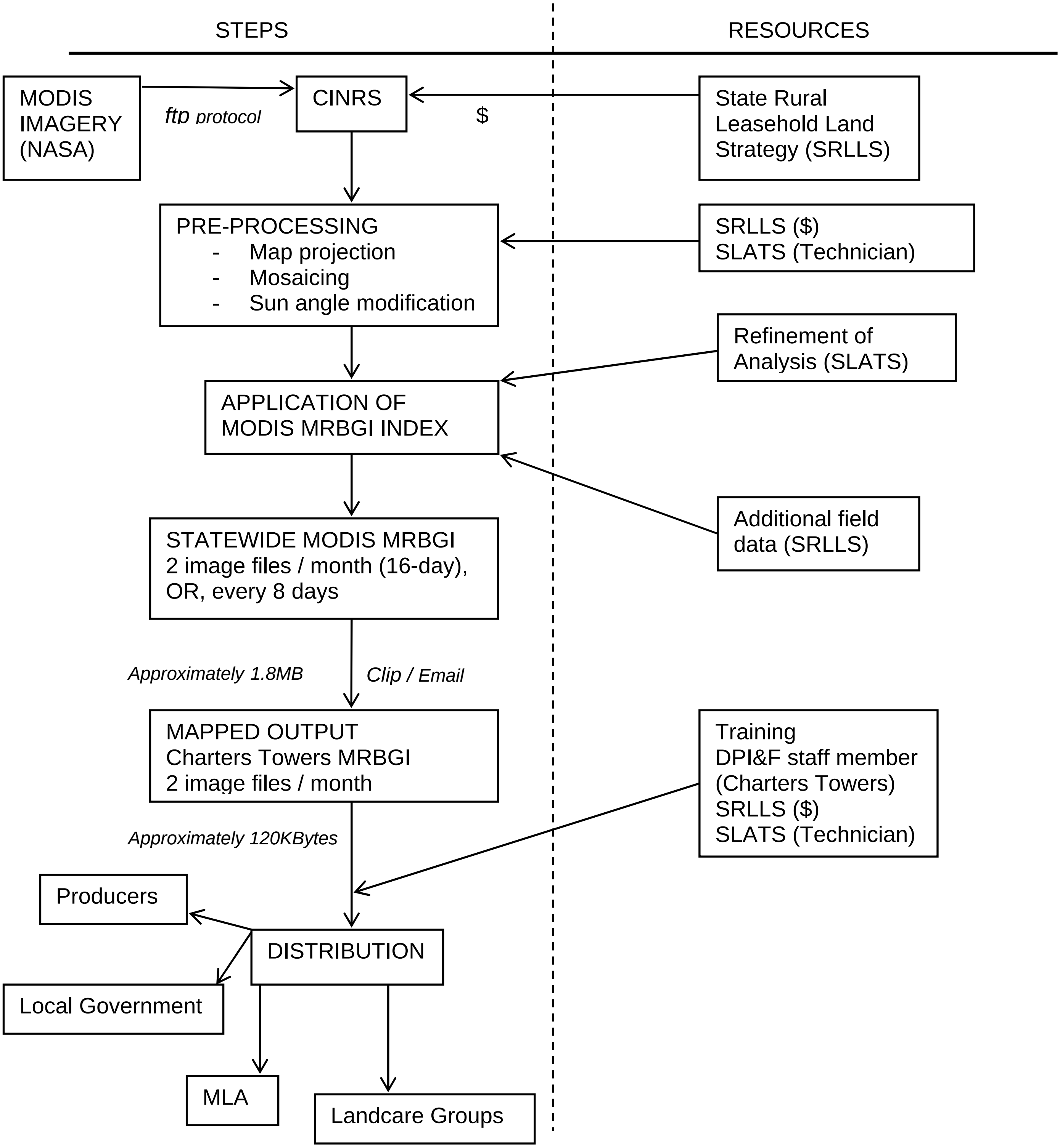
The concept outlined in Figure 27 assumes that supply of MODIS bare ground products would come under the auspice of on-going State-wide Rural Leasehold Land Strategy (SRLLS) initiatives with technical input from SLATS.

To be utilised effectively and supplied to interested producers, regional catchment groups and local government planners there must be adequate training given to a nominated officer of DPI&F in Charters Towers. Without some technical support at the local level it is unlikely that MODIS based products would be distributed or utilised effectively.

MLA's initiative to explore and develop MODIS products for monitoring bare ground and biomass over tropical savannah has the potential to expand into SRLLS and other government initiatives such as QScape. This requires synergies between SLATS, SRLLS and QScape initiatives in the form of technical support and funding.

Through funding this project MLA has laid the groundwork for continued effort and made a significant contribution to research in monitoring land condition and trend.

FIGURE 27: Conceptual model for the supply of prototype MODIS products to producers



5 Success in Achieving Objectives

Project achievements for objectives 1 and 2 have been beyond expectation and provide a foundation for continuance of MODIS work within NRW programs including; the Statewide Rural Leasehold Land Strategy (SRLLS), Statewide Landcover and Tree Study (SLATS) and QScape. While objectives 3 and 4 encountered more difficulty during the project cycle, it is very likely that elements of objectives 3 and 4 will continue to be met under the auspice of SRLLS, SLATS and QScape. MLA's MODIS initiative is currently dovetailing into both SRLLS and SLATS and there may be opportunities to use ModBGI output with Landsat –TM bare ground imagery in QScape modelling.

5.1 Objective 1

Develop relationships for ground cover and pasture biomass/feed availability between field measurements and MODIS indices.

The project has been successful in quantifying statistical relationships between Landsat –TM bare ground data and MODIS imagery. This has resulted in development of a statistically significant empirical relationship and subsequent index – referred to as the MODIS bare ground index (ModBGI). ModBGI makes use of both MODIS reflectance data and Bi-directional Reflectance Distribution Function (BRDF) parameters. The model has been applied to a time series of 1 km resolution MODIS imagery and is being further developed using 500m resolution imagery. Progress is limited by the speed at which NASA reprocesses its 500m archive to include all parameters the model requires. The current goal is to develop a statewide 500m ModBGI product that will be available every 8 days.

The development of ModBGI required the scaling up of Landsat –TM based ground cover products to a coarser MODIS resolution during analysis. This approach has been innovative and successful, enabling existing calibrated ground cover products to be used to derive a relationship with data from a coarser spatial resolution sensor consistently and in a repeatable format.

Application of algorithms to standardise a MODIS time series has been a key element in development of a biomass model. Using the BRDF parameters supplied with MODIS it is possible to reduce seasonal fluctuation caused by changing solar zenith angles in a time series of imagery. With seasonal sun angle effects reduced, MODIS bands are more readily correlated with field measured changes in biomass. Using a time series of data corrected to a common solar zenith angle of 45 degrees it was possible to derive statistically significant models between field measurements of biomass and MODIS. Without standardising for sun angle a relationship between biomass measurements and MODIS was not observed. When NASA has processed 500m imagery (including all BRDF parameters) it will be possible to test the level of improvement that can be gained from application of a standardised 500m time series. Biomass estimates at 1 km are of limited value at the paddock/property scale, however at 500m, particularly if the resolution allows for improvement in predictive accuracy the biomass model; output may become useful at the paddock/property scale.

5.2 Objective 2

Provide guidelines for the use of MODIS data in the estimation of groundcover and biomass/feed availability at a range of scales.

The research completed to date has been innovative in that it has sought to deal with scale issues associated with linking field calibration data to coarse spatial resolution imagery. Ground cover and biomass estimations are normally limited with MODIS scale imagery because of the common occurrence of mixed pixels, and the huge difference between the size of field-measurement data and pixel size in the image, resulting in difficulty in the integration of sample data and remote sensing-derived variables (Dengsheng Lu, 2006).

To partially redress this issue the project has developed a system for weighting site data used in the development of the biomass model. Landsat –TM bare ground imagery was scaled up to both the field site and MODIS scales to derive a spatially weighted statistic. That is, field sites were weighted during analysis based on the similarity or difference in bare ground mean between the site and its surrounding MODIS pixel. The methodology developed has potential to be used at the site selection stage should there be an opportunity to collect more field calibration or validation data.

Scale issues are important when we consider use of output from the ground cover and biomass models. It is likely that 1 km output from ModBGI will be useful at a catchment scale but will be of limited value at the paddock or property scale. Similarly, output from the biomass model is of limited value at the paddock/property scale (except perhaps for larger pastoral holdings) but is of interest to scientists involved in development of models such as AussieGRASS. There will be considerable interest in development of a biomass model at a spatial resolution of 500m. The scale issues described above are obviously reduced when the spatial resolution of MODIS imagery is reduced from 1 km to 500m. There is also a possibility that the statistical relationship between field measurements and the 500m imagery will be improved. As soon as data becomes available both the ModBGI and biomass models will be recalibrated to 500m.

5.3 Objective 3

Provide participating producers with the tools and techniques for collecting field data for property/paddock based calibration in support of prototype estimates of ground cover and pasture biomass/feed availability.

A producer information document prepared and distributed by the project is attached as Appendix 9.6. There has been considerable advancement within objectives 1 and 2 since the distribution of the producer information booklet. It is recommended that once this report has been approved by MLA a new summary for participating producers be prepared and distributed. This would also be an opportunity to provide some prototype ModBGI and biomass products to key producers and DPI&F staff as an example of output from the project and to gain feedback on accuracy and appropriate/potential use. The feedback will be useful to guide use of MODIS in SRLLS, SLATS and QScape.

In early stages of the project it was suggested that producers could be involved in site sampling and data collection. As discussed in the results section of this report, it was originally proposed that six producers within the Charters Towers study area would be involved in frequent (2 to 4 weekly) collection of cover and biomass data which would contribute to (a) calibration and validation of MODIS products; and (b) assessment of value and acceptance of products for improved land management. Assistance was also sought from representatives of the DPI&F, Charters Towers, to liaise with producers and identify interested and suitably-located participants.

Regrettably no local producers were able to commit to routine sampling of pasture biomass and groundcover. Attempts to arrange data capture by a local field officer contracted on a casual basis also failed.

The documentation provided to producers and efforts of project staff to keep producers informed has been commendable given the fact that the staff are based in Brisbane not Charters Towers.

In hindsight the project designers have been overly optimistic with objective 3. It is not realistic to assume a high level of producer involvement without assigning a competent coordinator / facilitator in the field. However, the achievements within objectives 1 and 2 auger well for continuance of MLA's MODIS initiative and it is likely that objectives 3 and 4 will be further persued within SRLLS, SLATS and QScape.

5.4 Objective 4

Develop a prototype framework for the automated delivery of prototype remote sensing products of groundcover and pasture biomass and report on the requirements for operational and near-real time delivery.

A meeting with John Childs on 2^{nd} February 2006 reinforced the point that producers are interested to know the feasibility of using MODIS imagery as an information source for successful monitoring and management of tropical savannah grasslands. For this reason the project has kept a focus on objectives 1 and 2 that are related to unravelling the complexity of MODIS in relation to both ground cover and biomass monitoring. At project completion the scientific parameters related to MODIS bare ground monitoring were adequately understood and tested to be able to provide products at a catchment scale. The same cannot be claimed for the preliminary biomass models developed as part of this project; the level of certainty, precision and reliability it is not completely understood and requires further validation.

While the project has not reached a stage where it is able to automate delivery of products to producers a framework for delivery is outlined in Figure 27. Some preliminary work to provide a statewide 500m ModBGI product via Framework for Online Report Generation (FORAGE) is currently under consideration. Again, the involvement of local extension specialists would facilitate interpretation and interest in MODIS products. It is perhaps too optimistic to assume that just making products available will result in use of the product. For a ModBGI product to be utilised effectively there must be adequate training given to a nominated officer of DPI&F in Charters Towers. Without some technical support at the local level it is unlikely that MODIS based products would be distributed or utilised effectively.

In summary, objectives 3 and 4 have been more difficult, partly because it is only when objectives 1 and 2 are met that objectives 3 and 4 can meaningfully commence, and partly, because the distance between Brisbane (project staff) and Charters Towers (producers) greatly reduces the opportunity for producer involvement. However, to the credit of the project staff and an interested core of local producers in-roads were made with regard to objectives 3 and 4. A lesson learnt from this project is that if producers are to be meaningfully included and involved in project development and implementation then an agricultural extension specialist is required at the project site to facilitate their involvement. Objectives 3 and 4 are do-able; however without an on-the-ground facilitator this project has not been able to progress with objectives 3 and 4 to the extent envisaged by the project design team.

It is recommended that at the completion of this report (i.e. when it has been approved by MLA) producers and key stakeholders be provided with a summary of results. This would be complimentary to on-going work within SRLLS, SLATS and QScape.

6 Impact on the Meat Industry — now and in five years time

The aim of this project was to put a methodology in place to provide regular groundcover and biomass/yield information to producers with respect to their individual properties. It was hoped that this information would provide valuable decision support on the impact of seasonal variability and the implications of different management regimes.

The project has developed an index that can be reliably applied to MODIS imagery to monitor bare ground (i.e. ground cover). While the data can be made available frequently its spatial resolution is too coarse to be of significant use at the property scale. However, the meat industry is increasingly more accountable for land management at a catchment or regional scale. As an industry that is concerned with sustainable land management outcomes it would be advantageous to have an up to date monitoring system that provides information relevant to environmental concerns such as soil fertility, runoff and erosion. Meat industry representatives may wish to seek clarification of ground cover in response to long term production related issues at a regional scale. They will be better served if they have up to date imagery in a temporal sequence to monitor seasonal trends.

Producer knowledge of the broader scale impacts of their land management is important; the information products derived here along with the prospect of improvement and continued development of these products provides longer term outcomes and benefits to the meat industry. MODIS as a bare ground monitoring tool provides an opportunity for producers to improve their understanding of issues relating to managing for climate variability and addressing environmental concerns.

The project has given substantial insight into the complexity and dynamics of relating field measurements of biomass (kg/ha) and In-vitro Dry Matter Digestibility (%) to data captured by MODIS. While the information derived is of limited benefit at the paddock/property scale, with the availability of higher resolution data from MODIS, more field work through SRLLS and refinement from expertise within SLATS there is considerable potential. The project has not achieved a result with regard to biomass estimation objectives sought at the outset. However, the ecosystem dynamics of tropical savannah grasslands could become easier to monitor through the application of ModBGI along with local knowledge of pasture quality, quantity and response. The work with biomass and in-vitro dry matter digestibility (%) has generated enough interest for it to be pursued through SRLLS initiatives and SLATS. To that extent both MLA funds and NRW staff have made a contribution toward developing products for those interested in monitoring biomass/feed availability in tropical savannah systems. If elements of the work completed to date are taken on board by SRLLS, SLATS and QScape then MLA may well regard this as a favorable outcome for its project.

7 Conclusions and Recommendations

7.1 Conclusions

- MODIS imagery can be used to monitor bare ground at regional planning scales.
- A MODIS bare ground index developed as part of this project is sufficiently robust to deliver meaningful results for bare ground estimates at a spatial resolution of 1 km in all seasons.
- As NASA continues to process 500 m MODIS imagery complete with all BRDF parameters and associated information it will be possible to develop a 500 m ModBGI.
- Empirical relationships between biomass and satellite imagery are elusive. Progress has been made during this project by exploring the effect of standardising a time series of MODIS imagery to a common sun angle. In addition, a spatial statistic (derived from Landsat –TM bare ground data) has been derived and used as a weight in multiple regression analysis and subsequent index development. The index requires further development and validation before it can be used to generate products for producers.
- Preliminary MODIS based indices have been developed to predict both IVODMD (%) and biomass (kg/ha) although care must be taken in interpreting the results. The results lack comprehensive and rigorous field validation. Partial validation indicates that the derived biomass index tends to over predict TSDM (kg/ha) within the 0 to 1,500 kg/ha range.
- The unique BRDF parameters of MODIS allow remote sensing algorithms to begin to model the structure of pasture swards and lessen the effect of ephemeral greenness which can be problematic in NDVI based biomass modelling. This observation warrants further investigation and research in relation to both ModBGI and biomass predictions.
- ModBGI imagery is low spatial resolution (1 km) and as a result a single layer bare ground image which coincides with the Charters Towers Landsat –TM scene area can be saved as a small digital file and easily transferred by email.
- It is not possible to obtain meaningful producer involvement in projects of this nature without an experienced extension officer based in the field.
- Benefits to the Meat Industry from this research are longer term and are likely to be realized as higher resolution MODIS data becomes available and results are reworked and refined as an integral part of SRLLP and SLATS.
- Meat Industry representatives should view ModBGI as a broad scale monitoring tool useful in catchment management and land planning at a regional scale.

7.2 Recommendations

7.2.1 Groundcover

- Continue to refine ModBGI with each iteration and refinement of Landsat –TM MRBGI.
- Develop a 500 m ModBGI as MODIS imagery and BRDF parameters become available. Some of this data is already available.

- Incorporate all statistical analysis into relevant initiatives within SRLLS and SLATS.

7.2.2 Biomass

- Continue to refine and explore the relationship between MODIS and biomass with particular emphasis on modelling structure of the sward.

- Collect more field data.

- Identify potential field sites using scaled-up Landsat –TM bare ground to select sites that at the field site scale are representative of the 1 km and/or 500 m MODIS pixels in which they reside.

- Expand the study region to include flatter terrain and wide homogeneous areas such as Mitchell Grass Downs using 500 m data.

- Promote the concept of state-wide biomass modelling using MODIS and further integrate output coverage into models such as AussieGrass.

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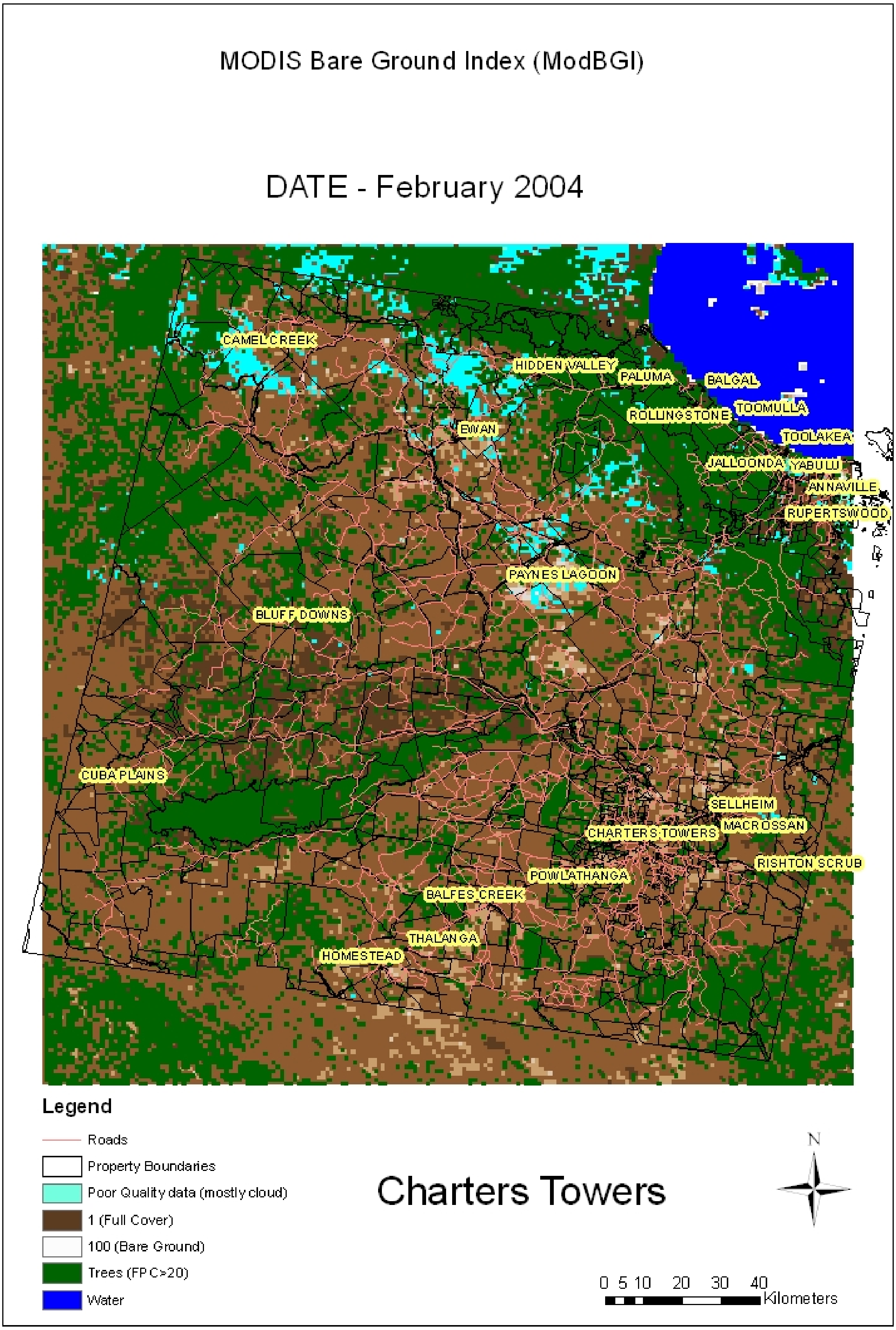
9 Appendices

9.1 ModBGI Time Series (2004-2005)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TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
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Property Boundaries
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Charters Towers
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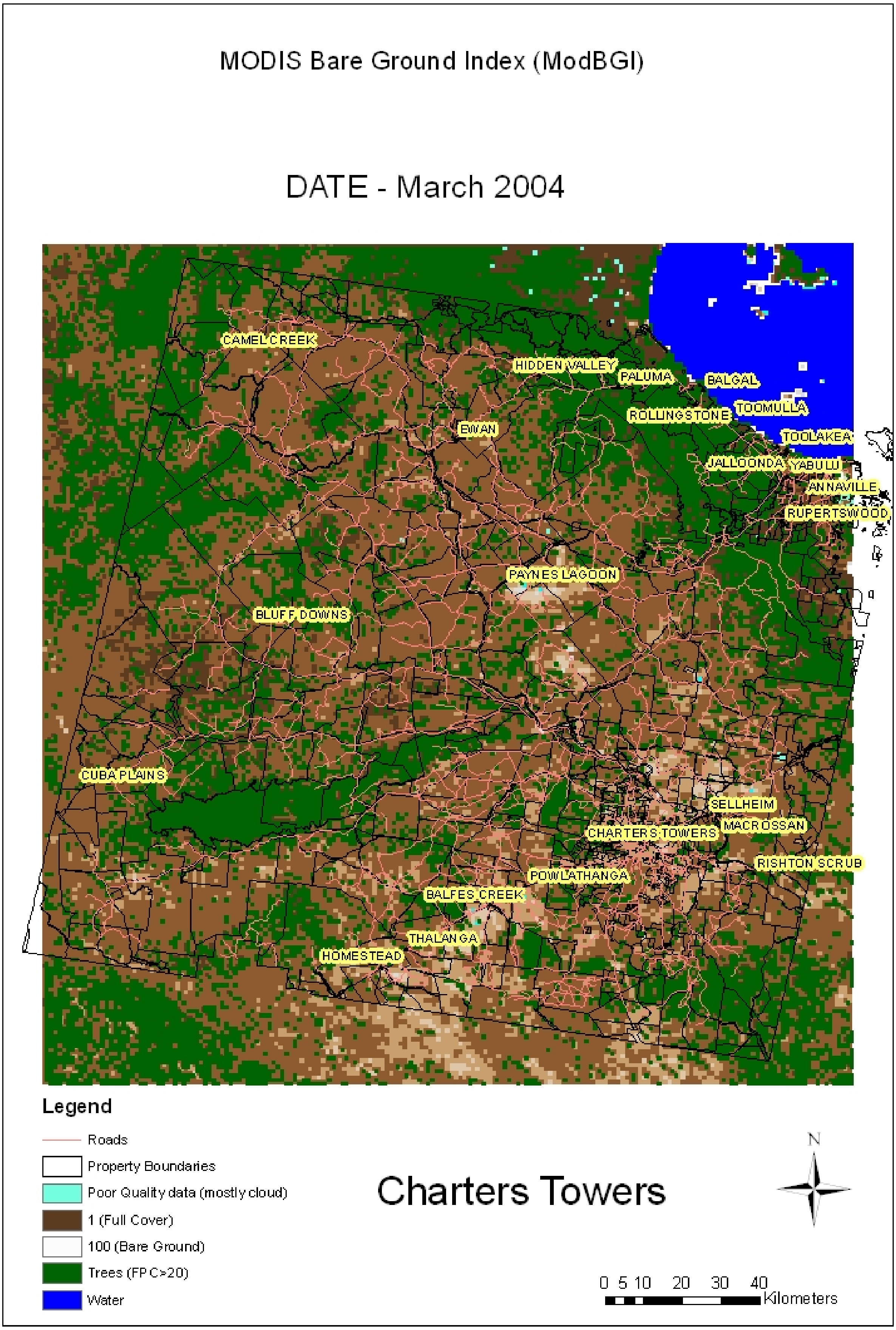
Kilometers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TOOLAKEA
JALLOONDA
YABULU
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PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
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HOMESTEAD
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Roads
Property Boundaries
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Trees (FPC>20)
Water
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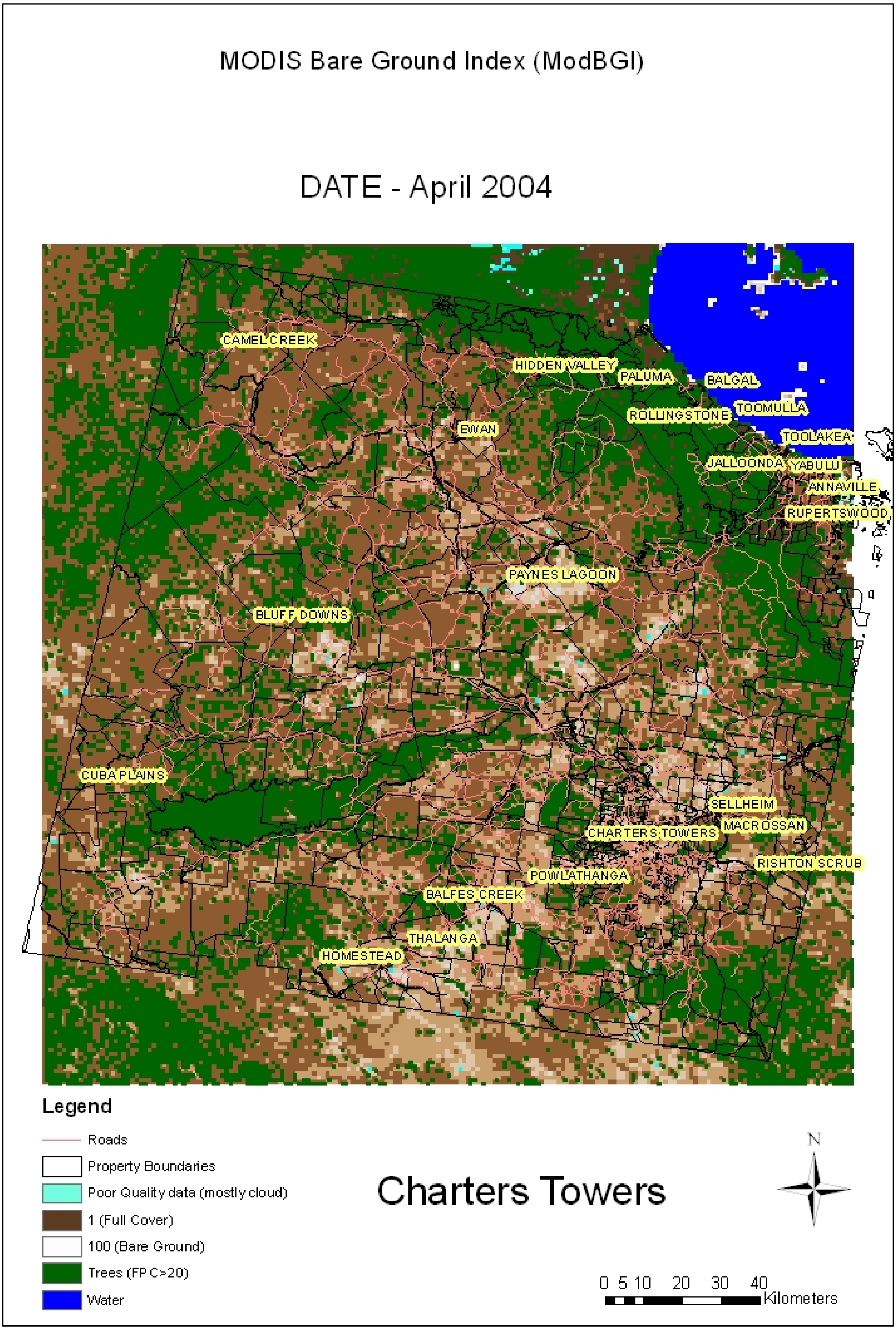
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EWAN
TOOLAKEA
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Charters Towers
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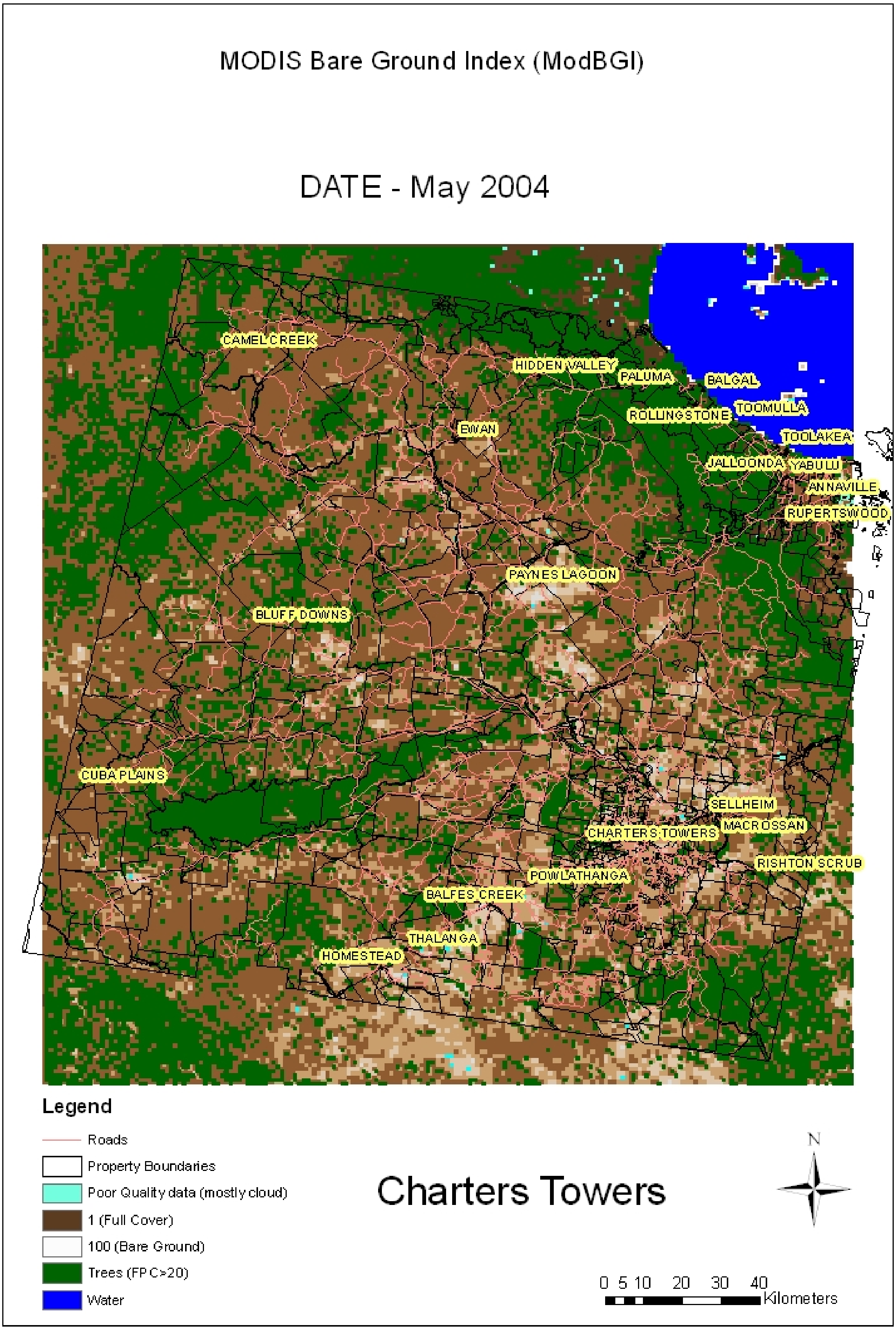
Kilometers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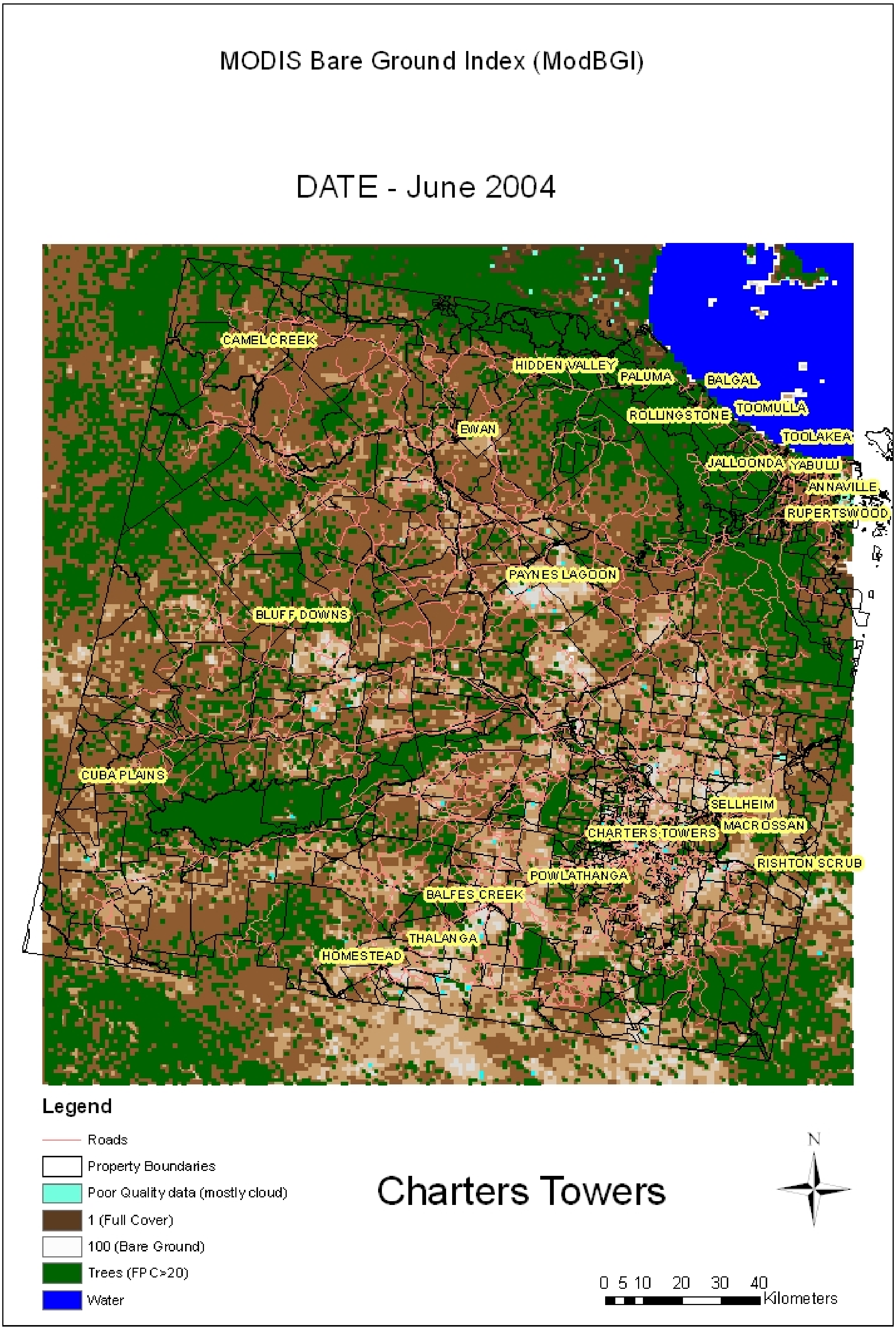
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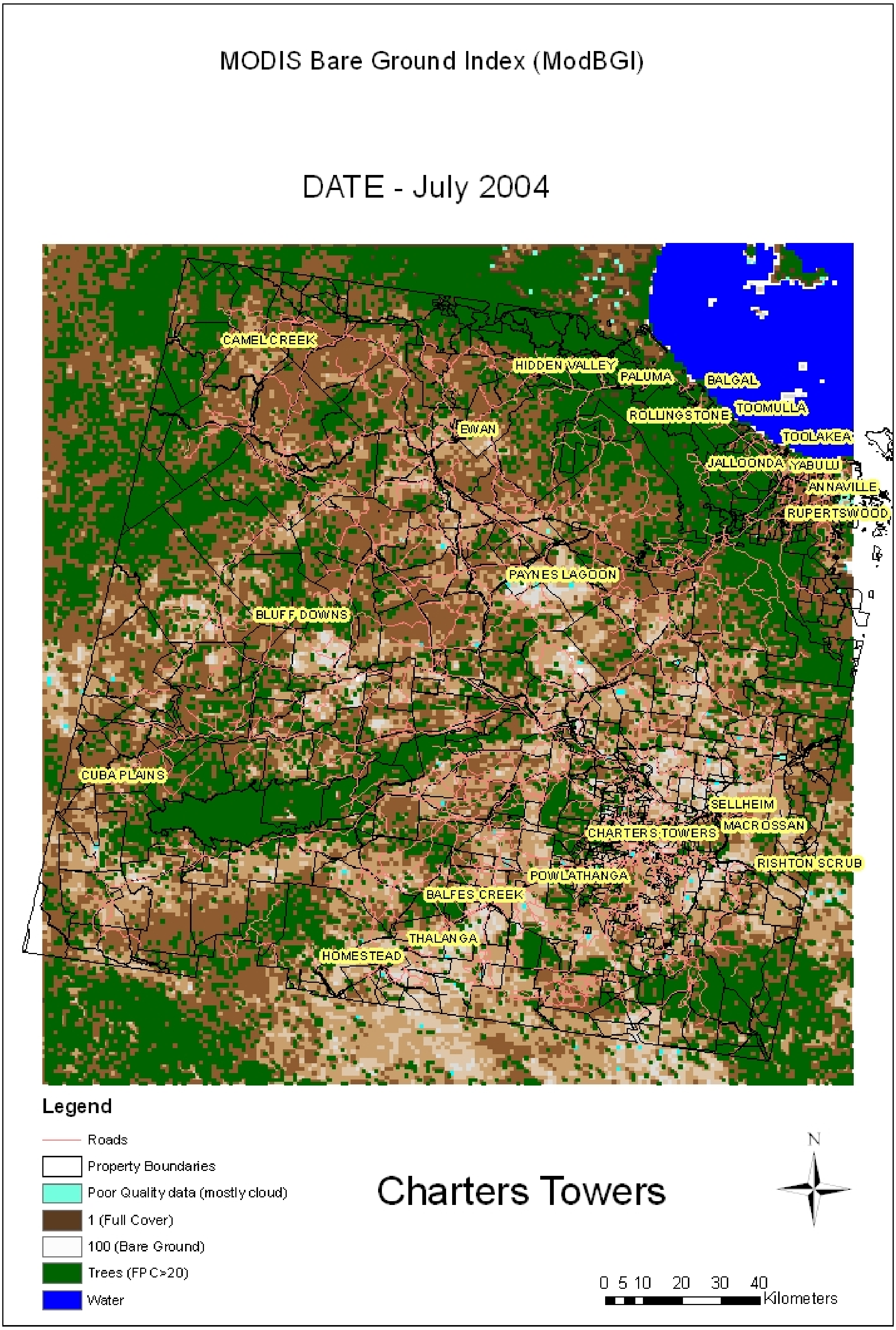
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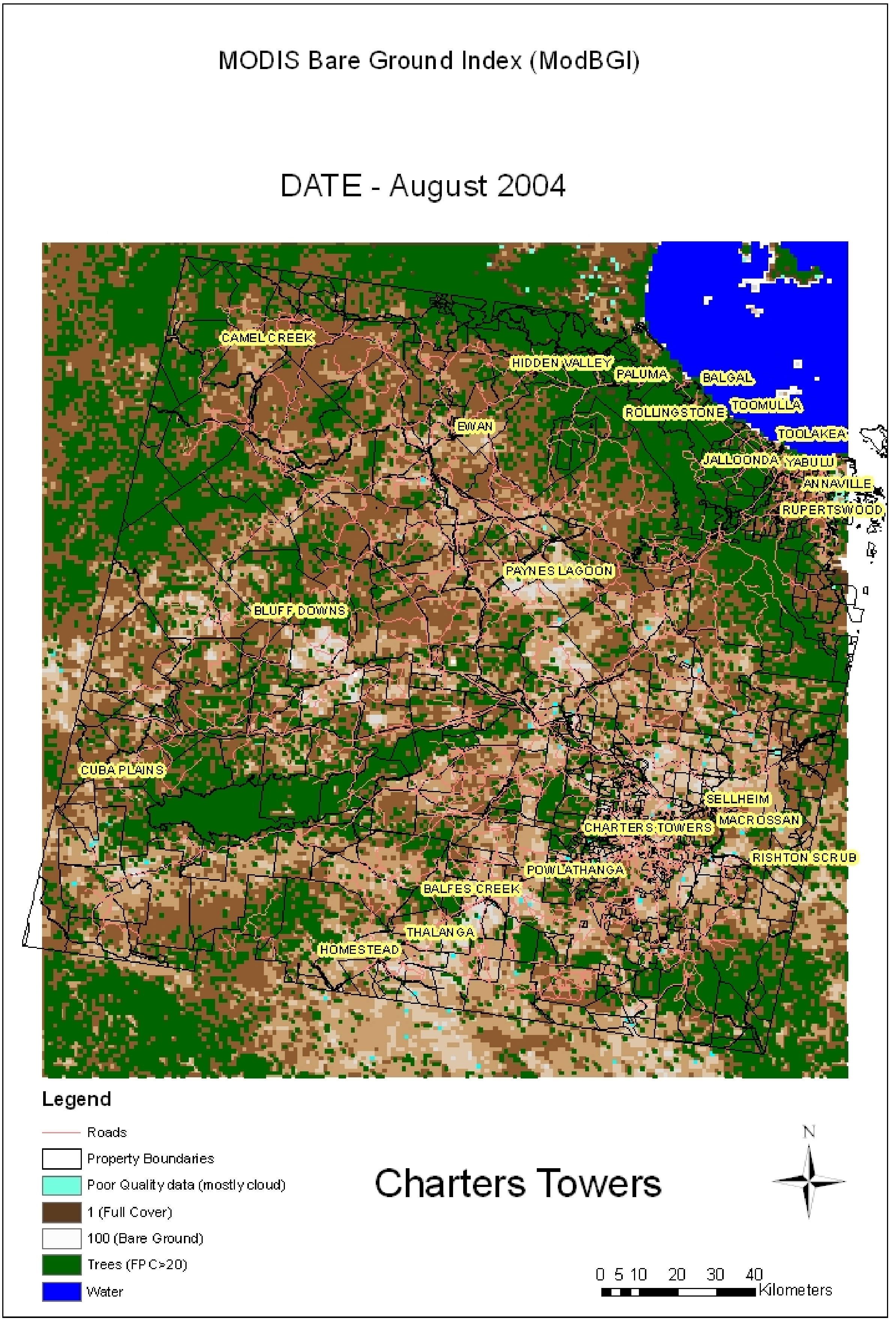
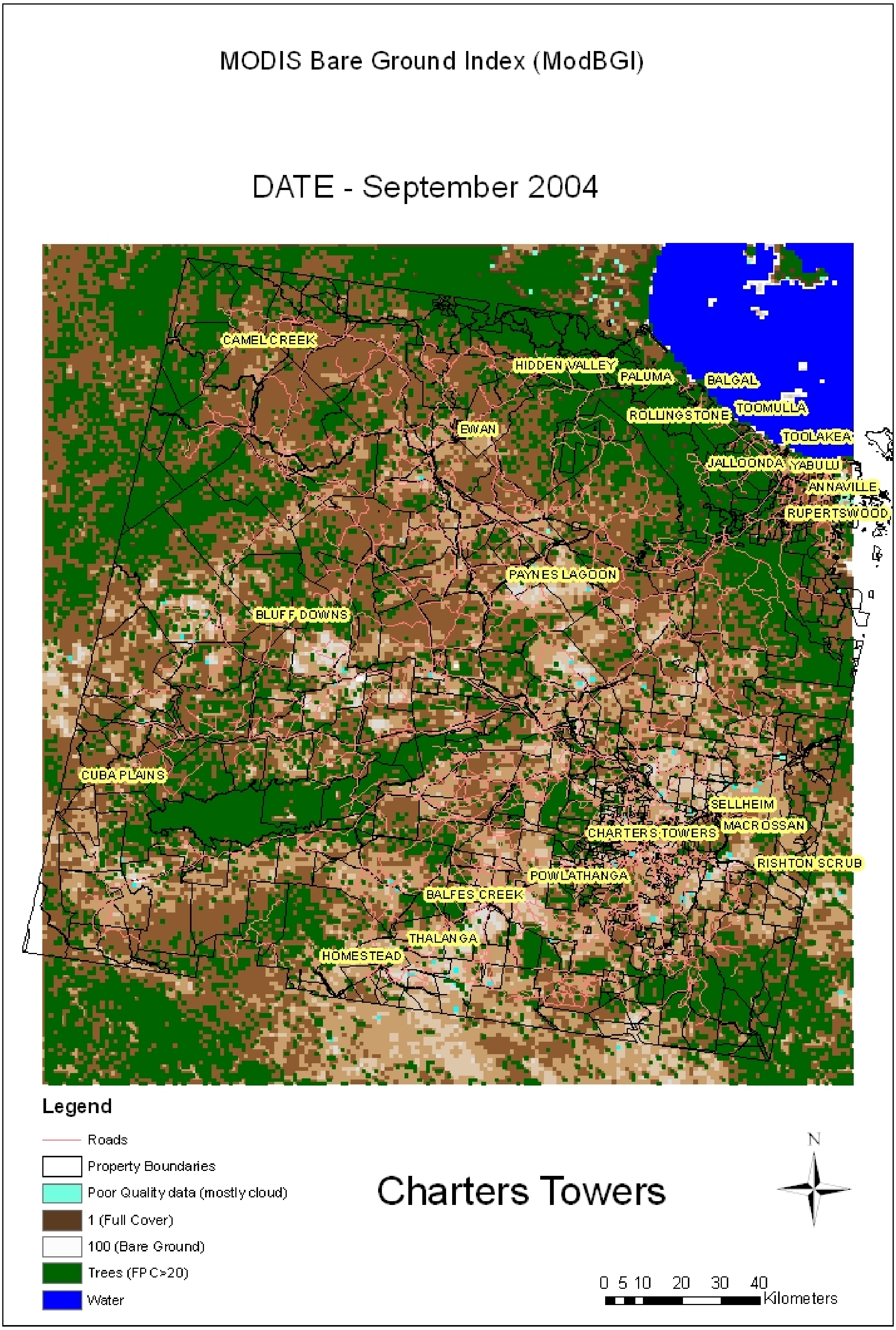
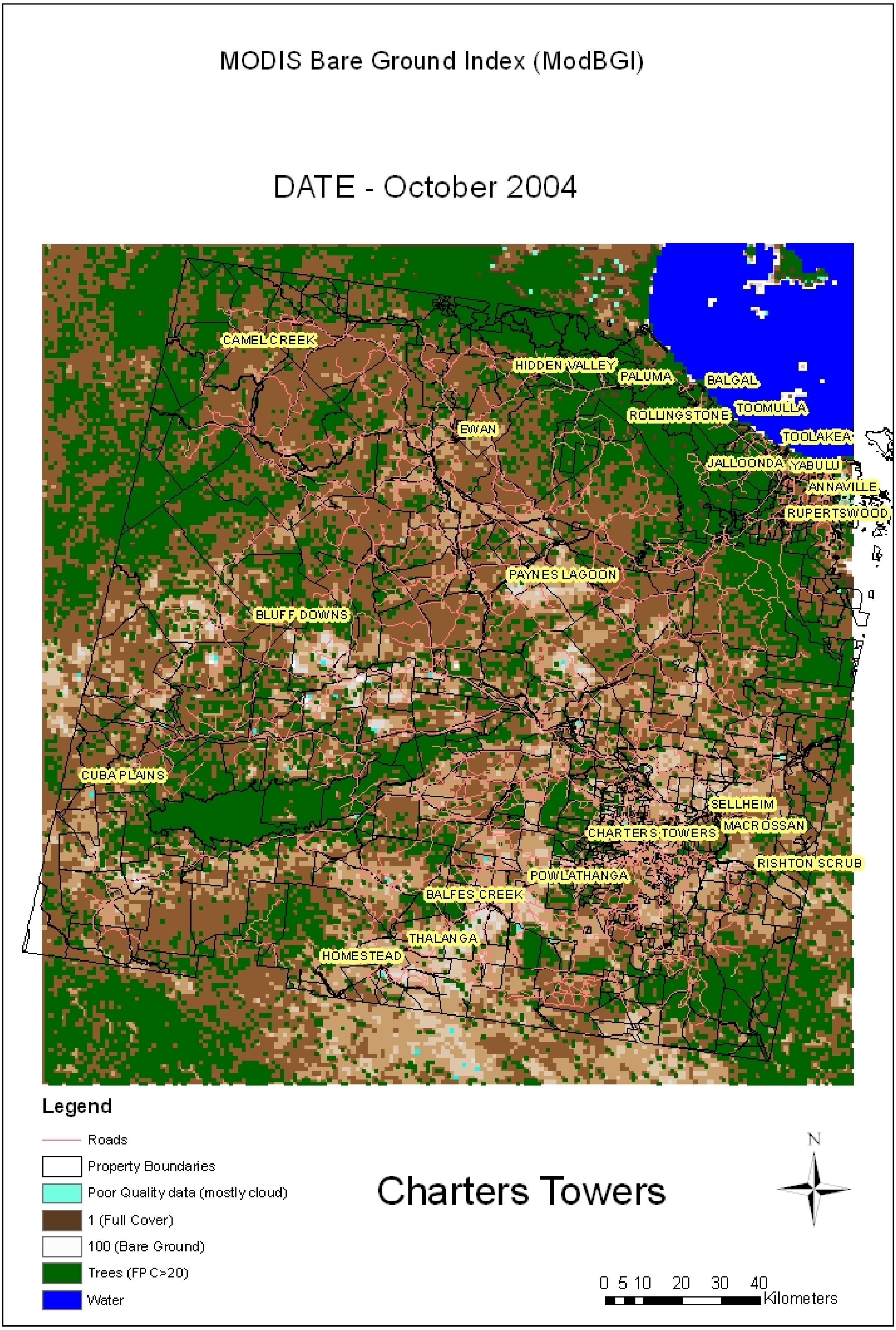
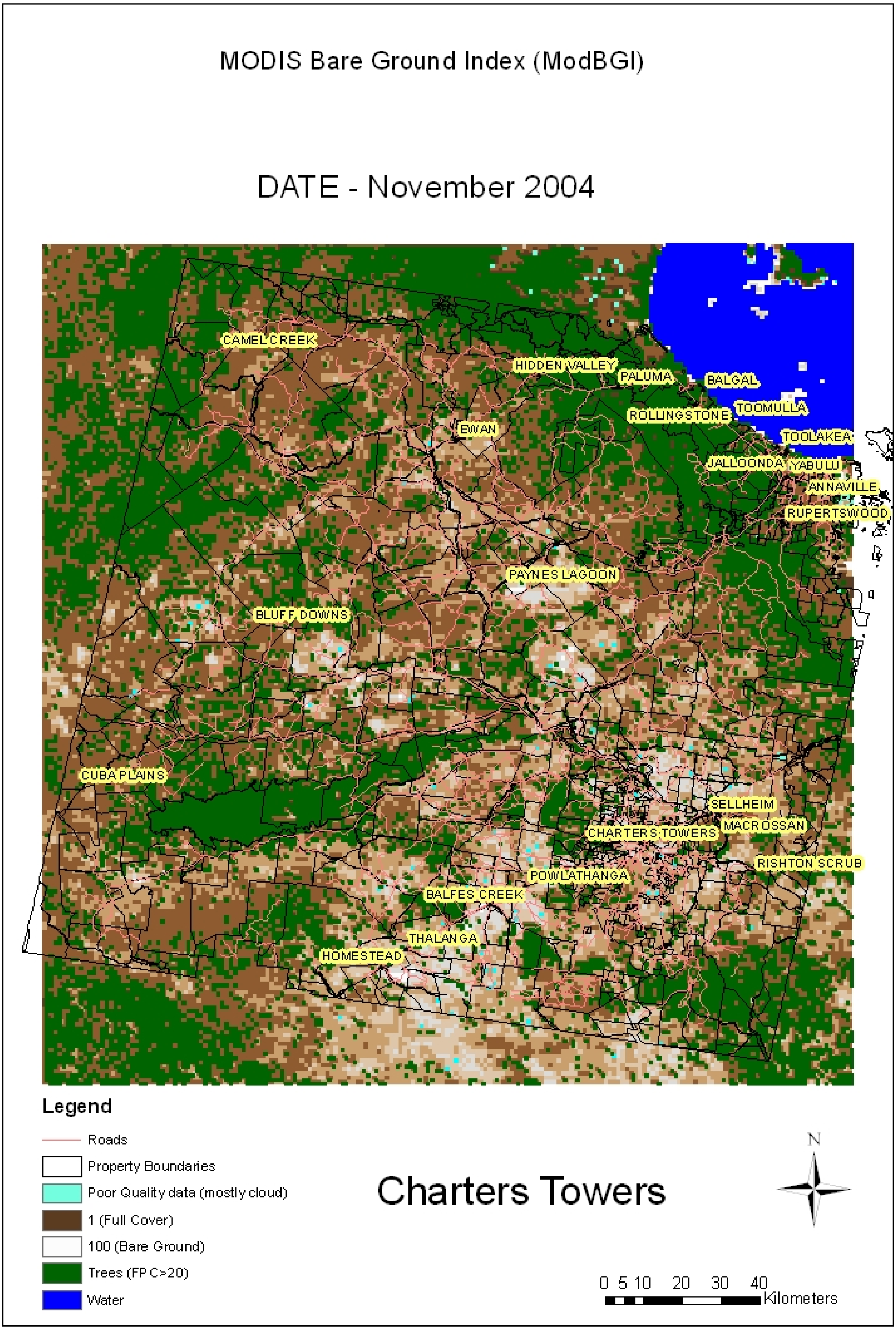
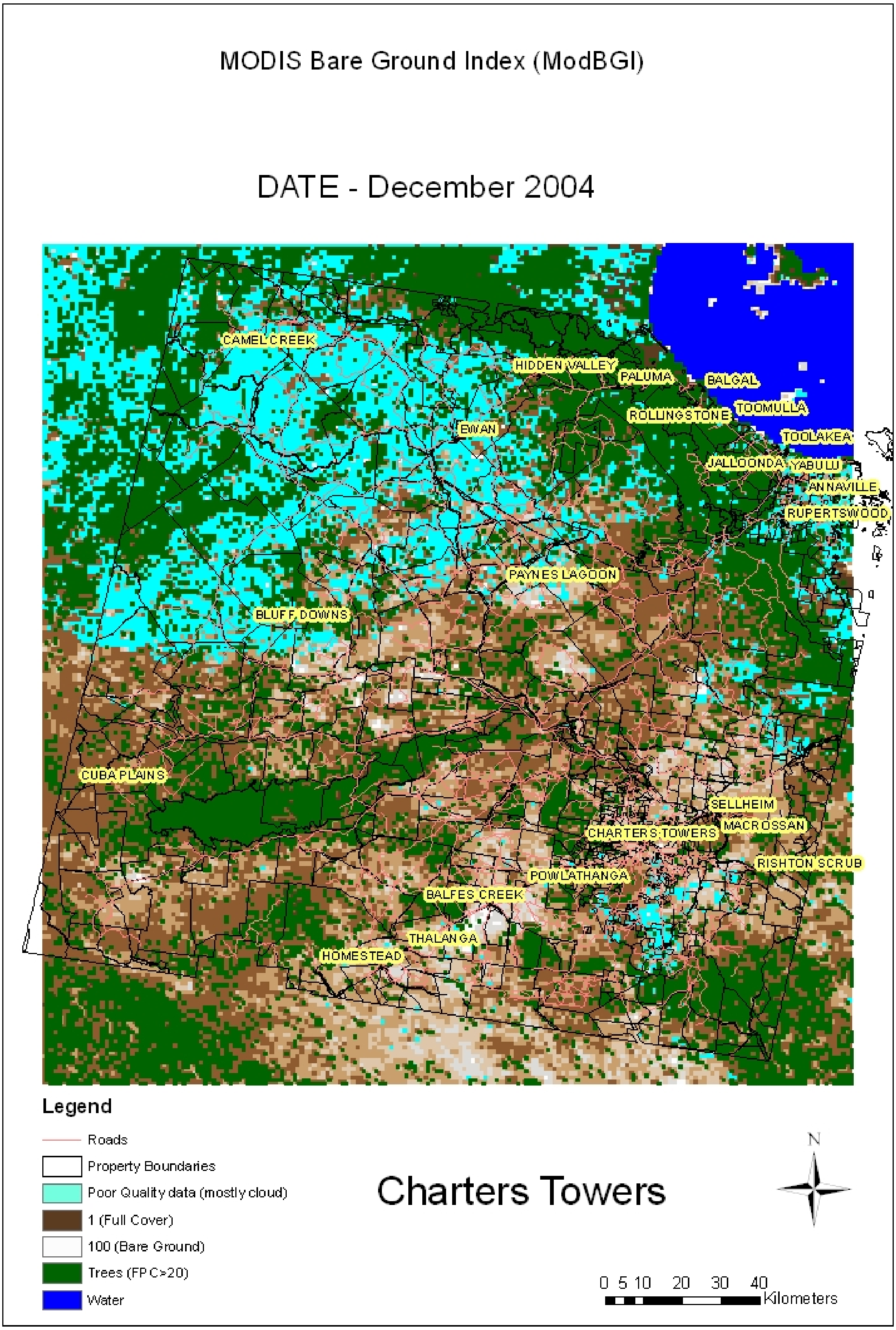
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

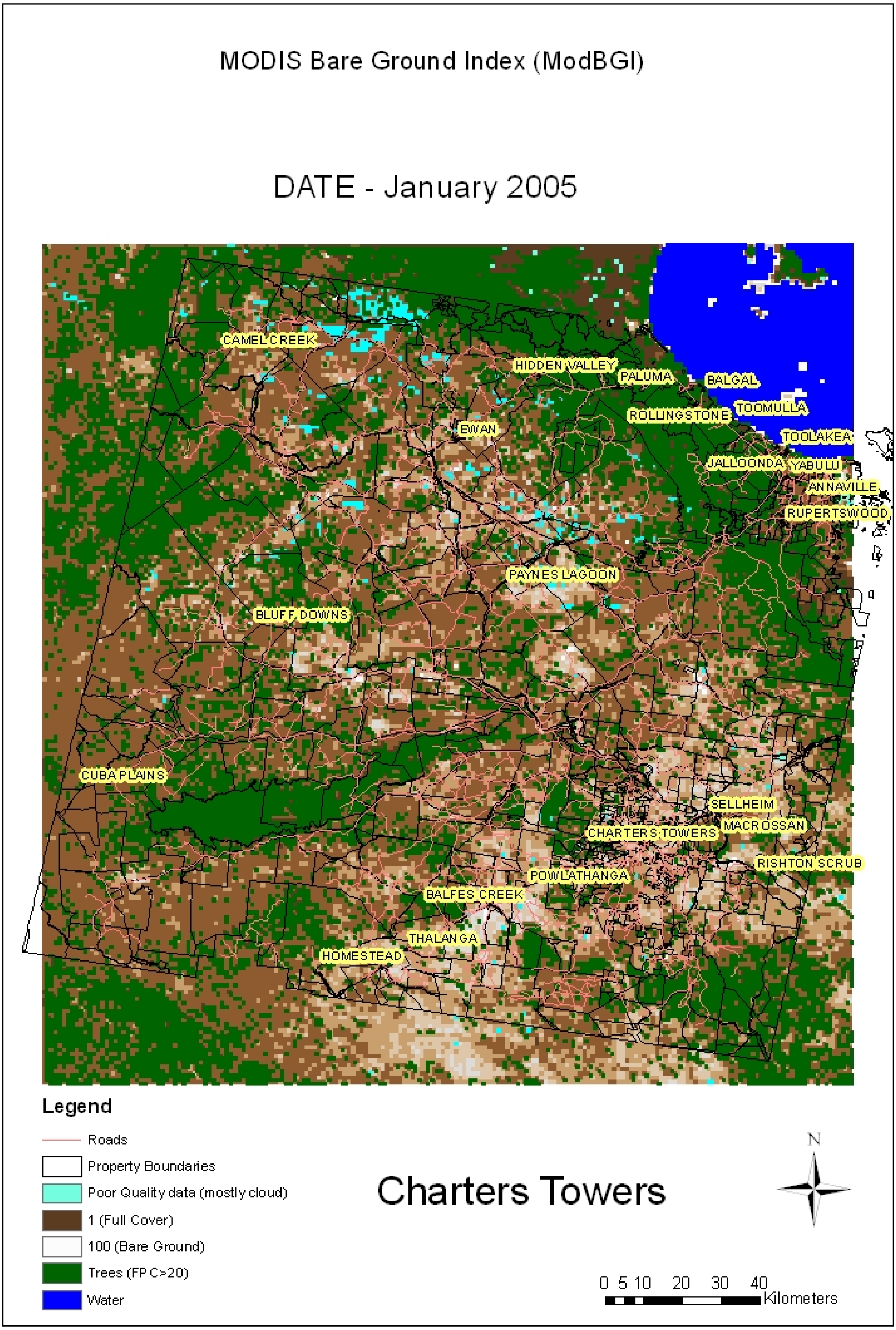

MODIS Bare Ground Index (ModBGI)
DATE - August 2004
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

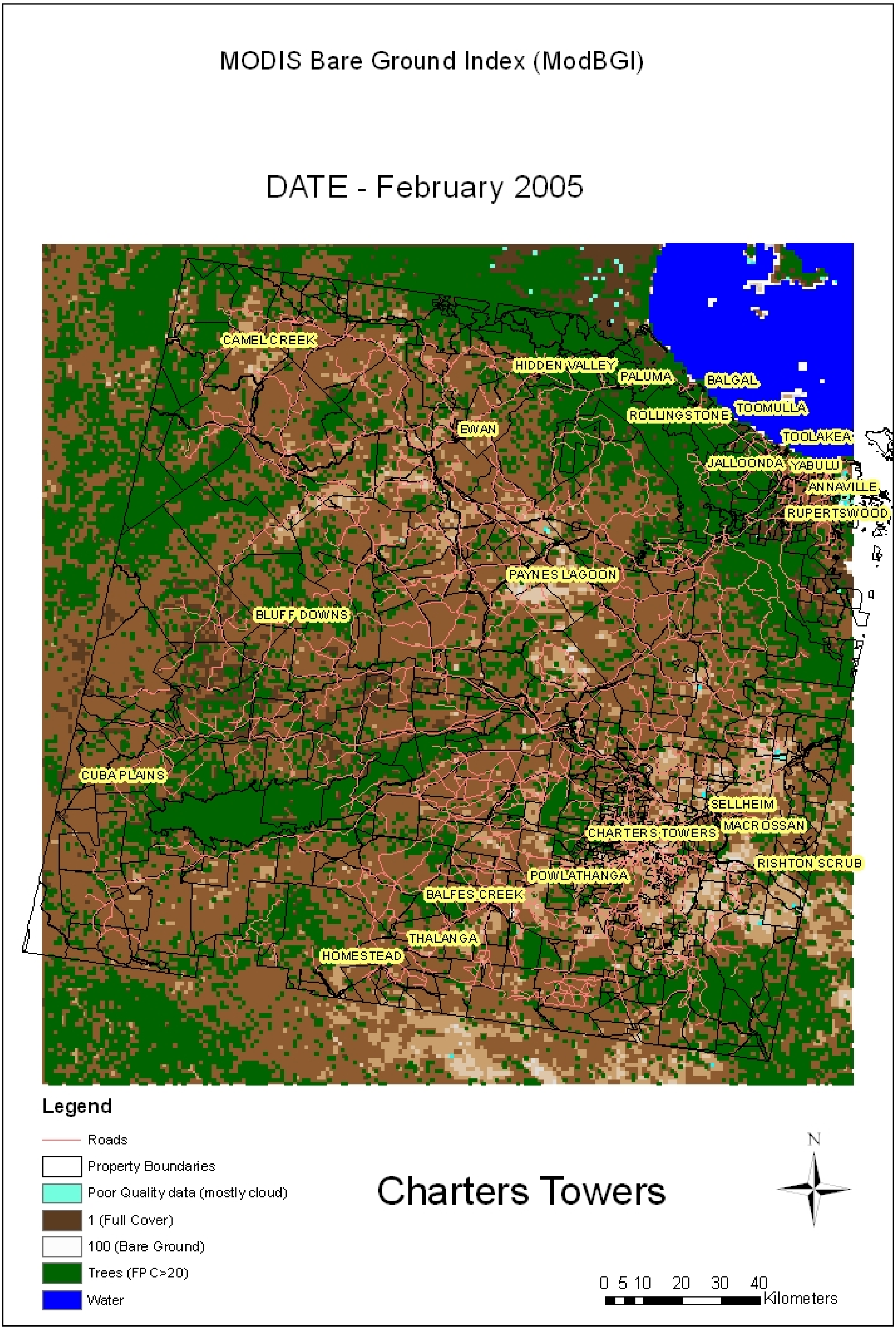

MODIS Bare Ground Index (ModBGI)
DATE - September 2004
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

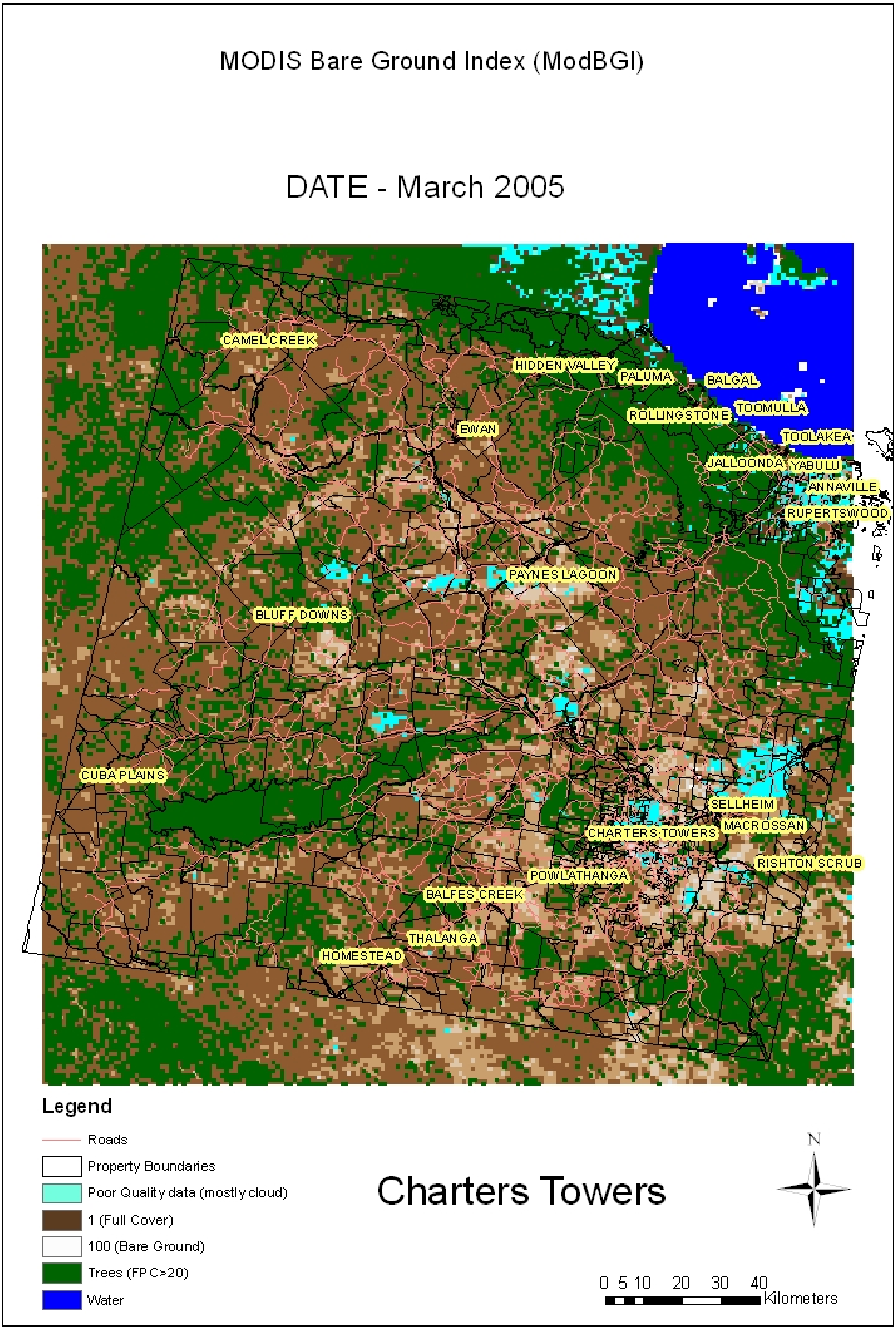

MODIS Bare Ground Index (ModBGI)
DATE - October 2004
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

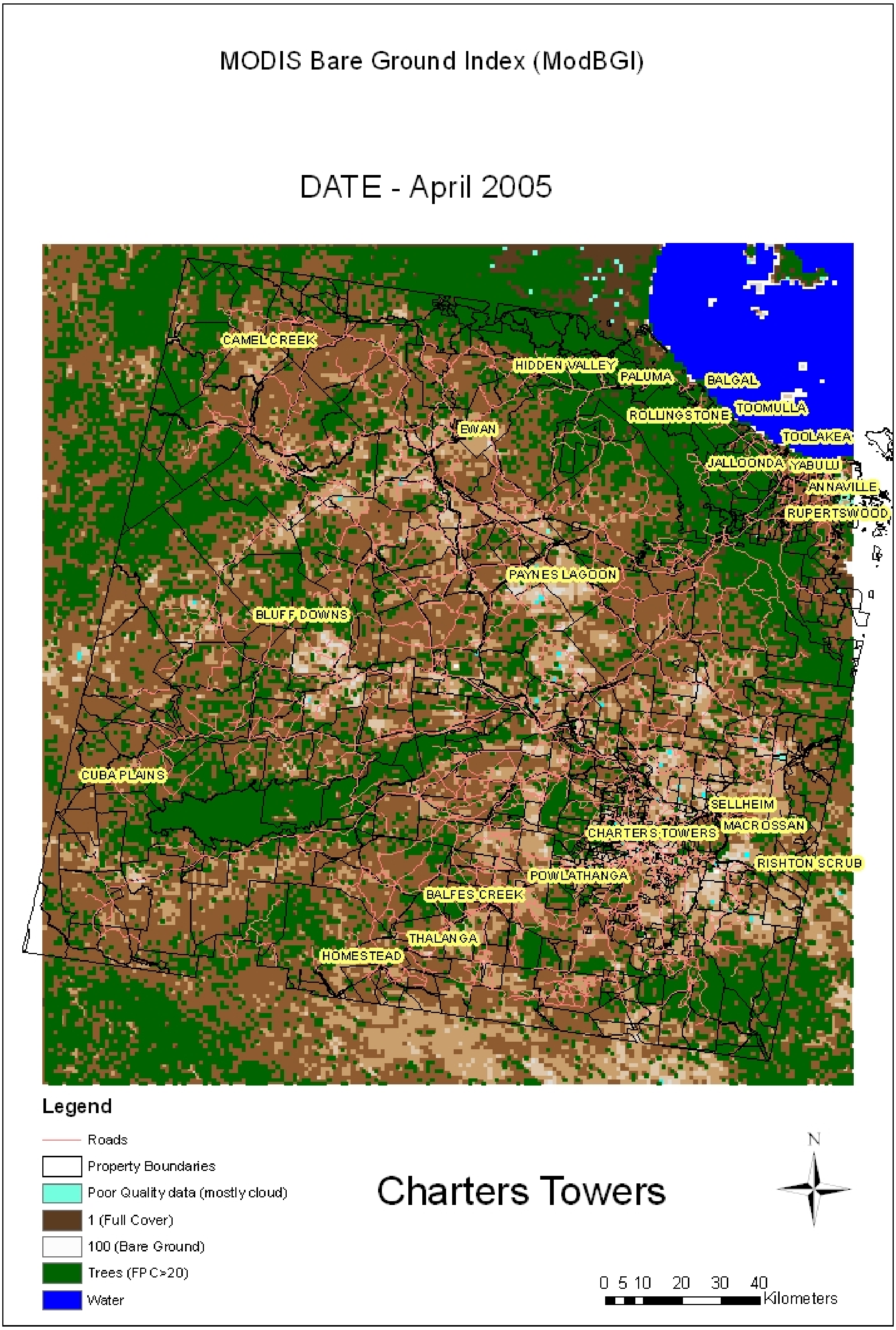

MODIS Bare Ground Index (ModBGI)
DATE - November 2004
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

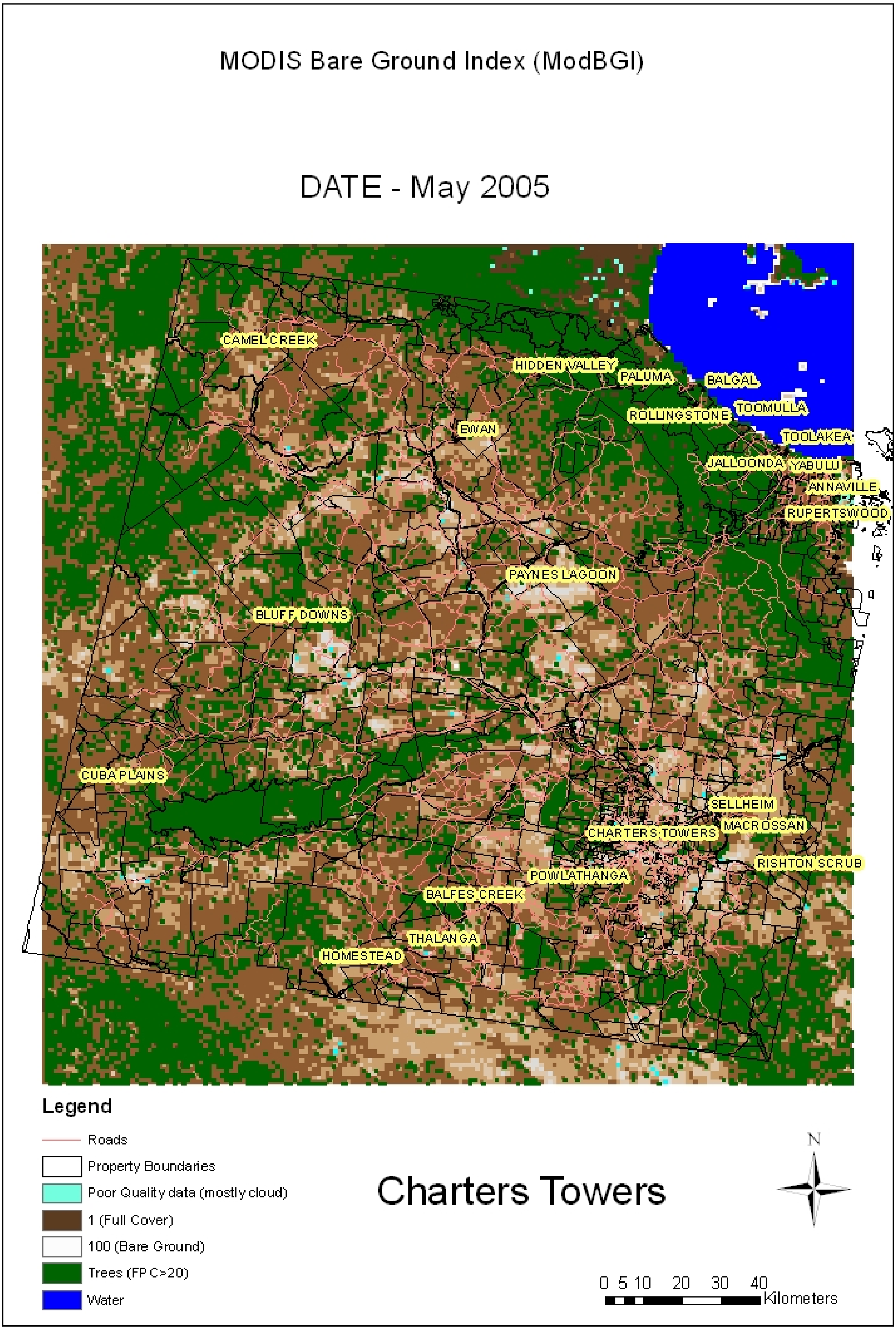

MODIS Bare Ground Index (ModBGI)
DATE - December 2004
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

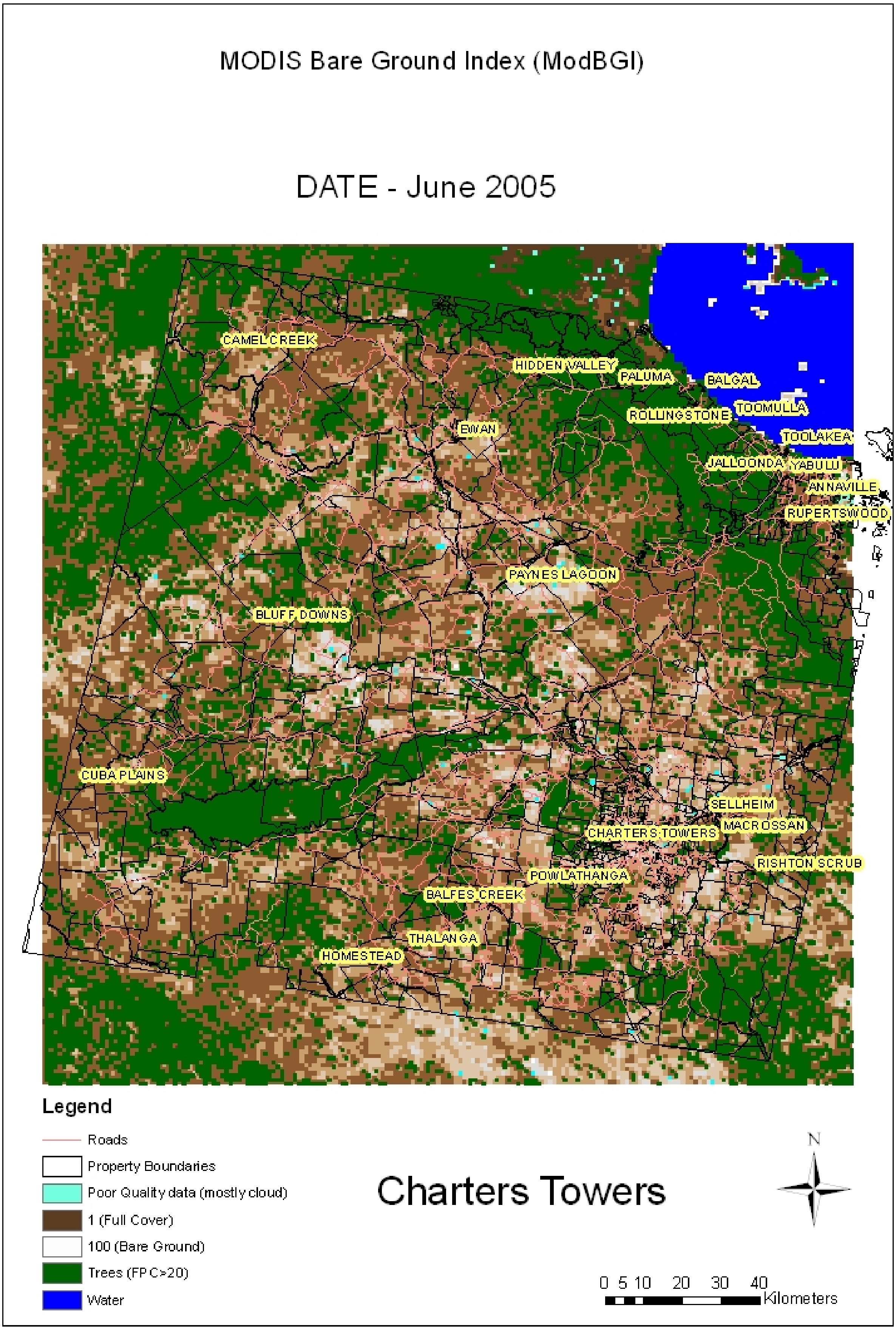

MODIS Bare Ground Index (ModBGI)
DATE - January 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

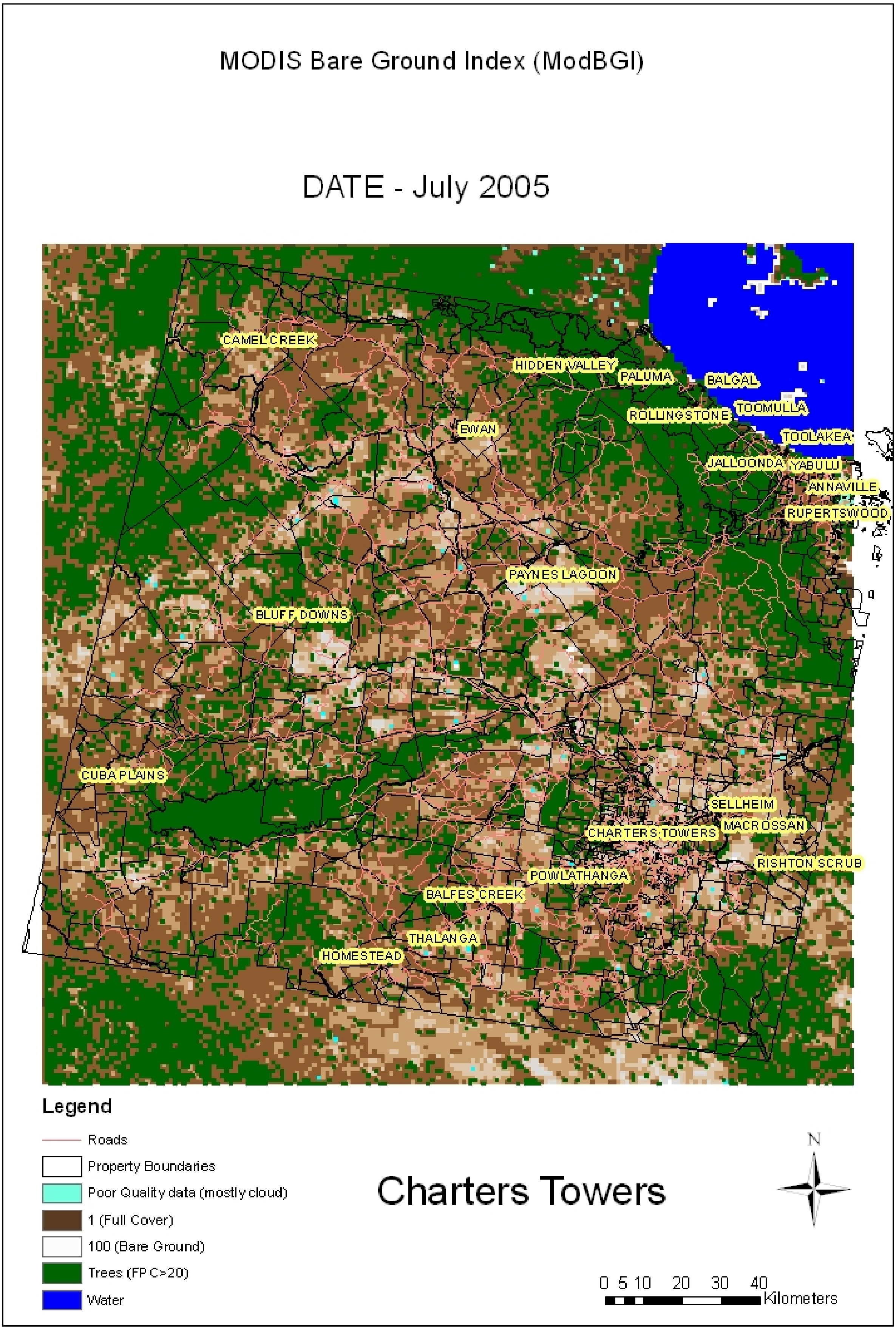

MODIS Bare Ground Index (ModBGI)
DATE - February 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

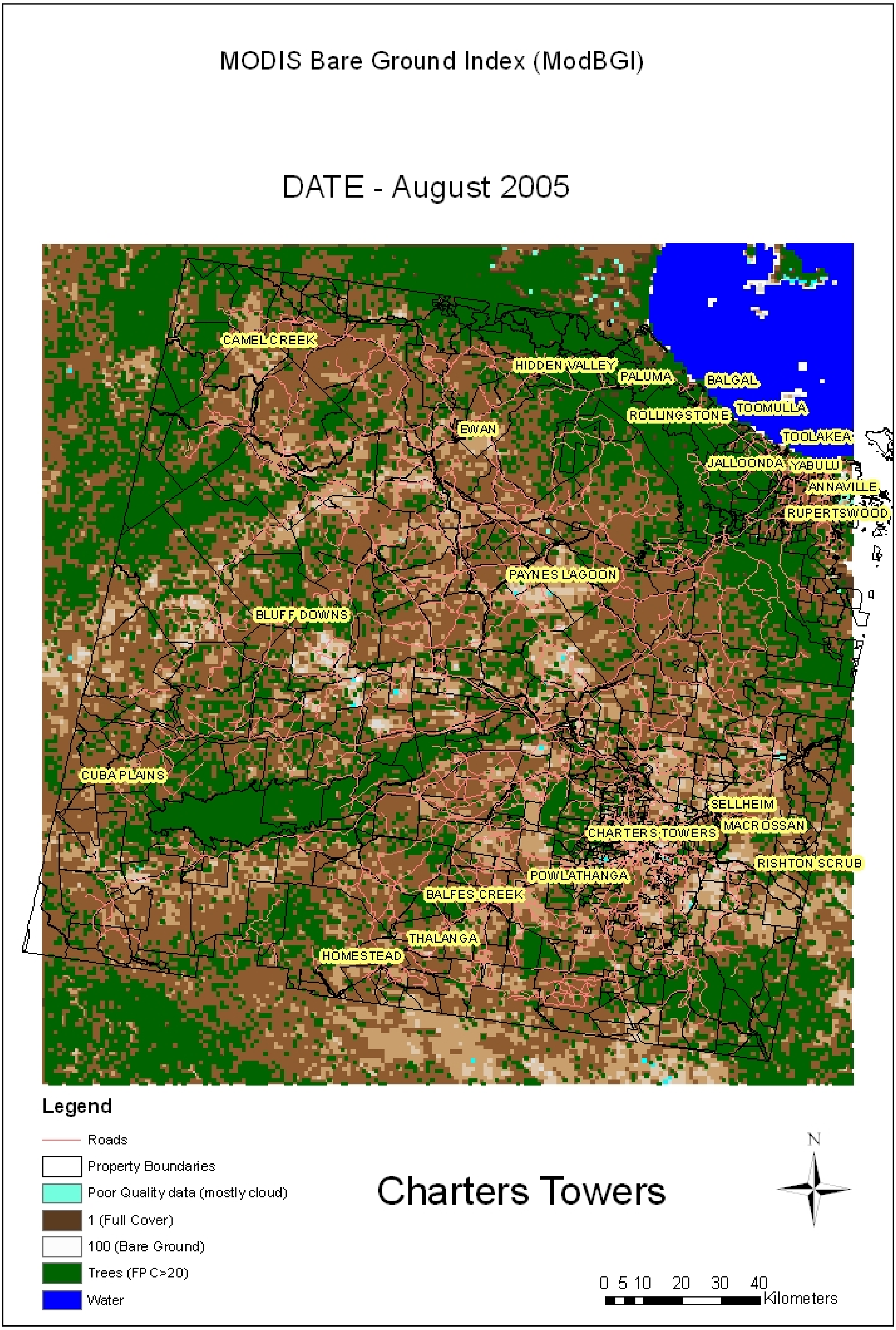

MODIS Bare Ground Index (ModBGI)
DATE - March 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

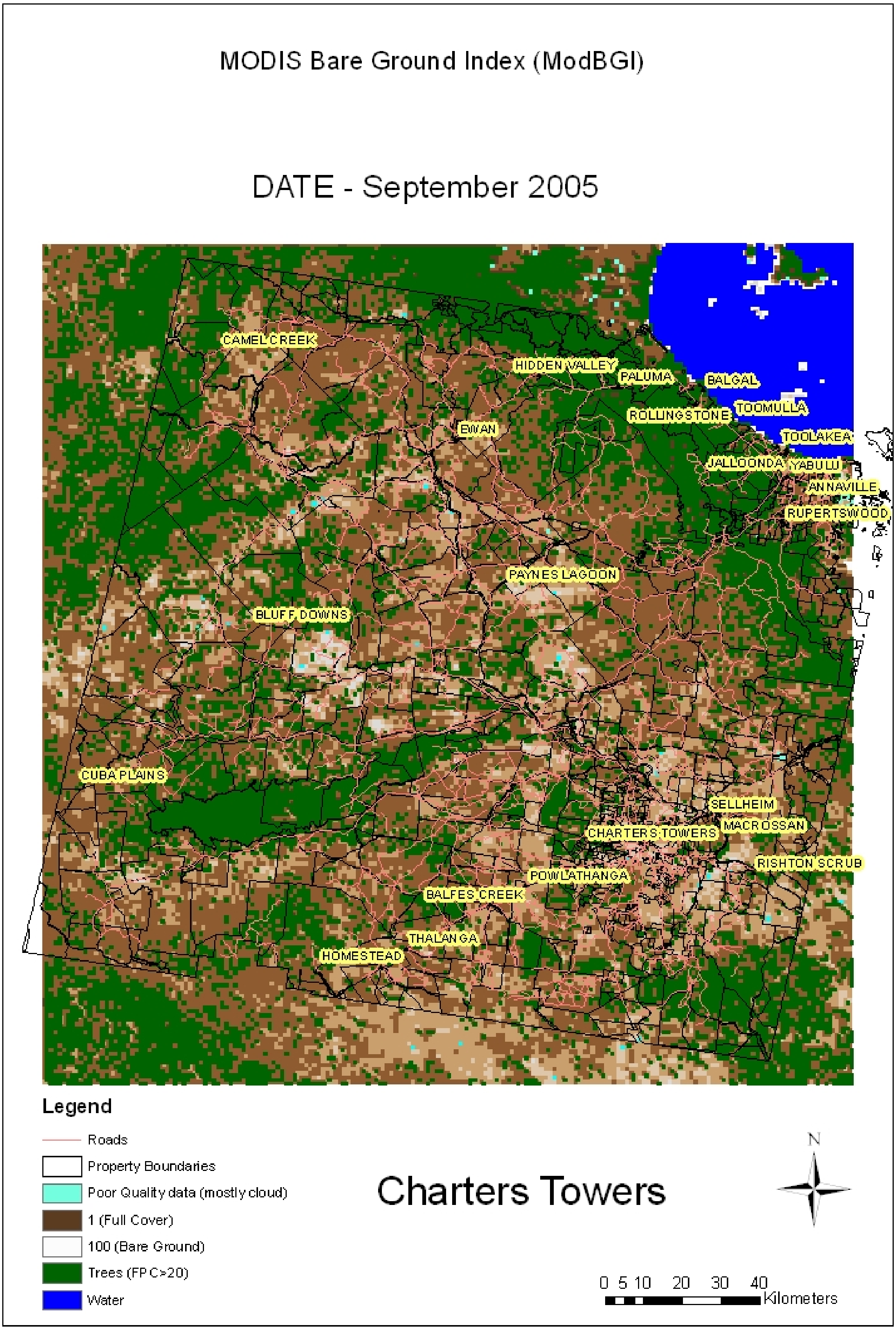

MODIS Bare Ground Index (ModBGI)
DATE - April 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

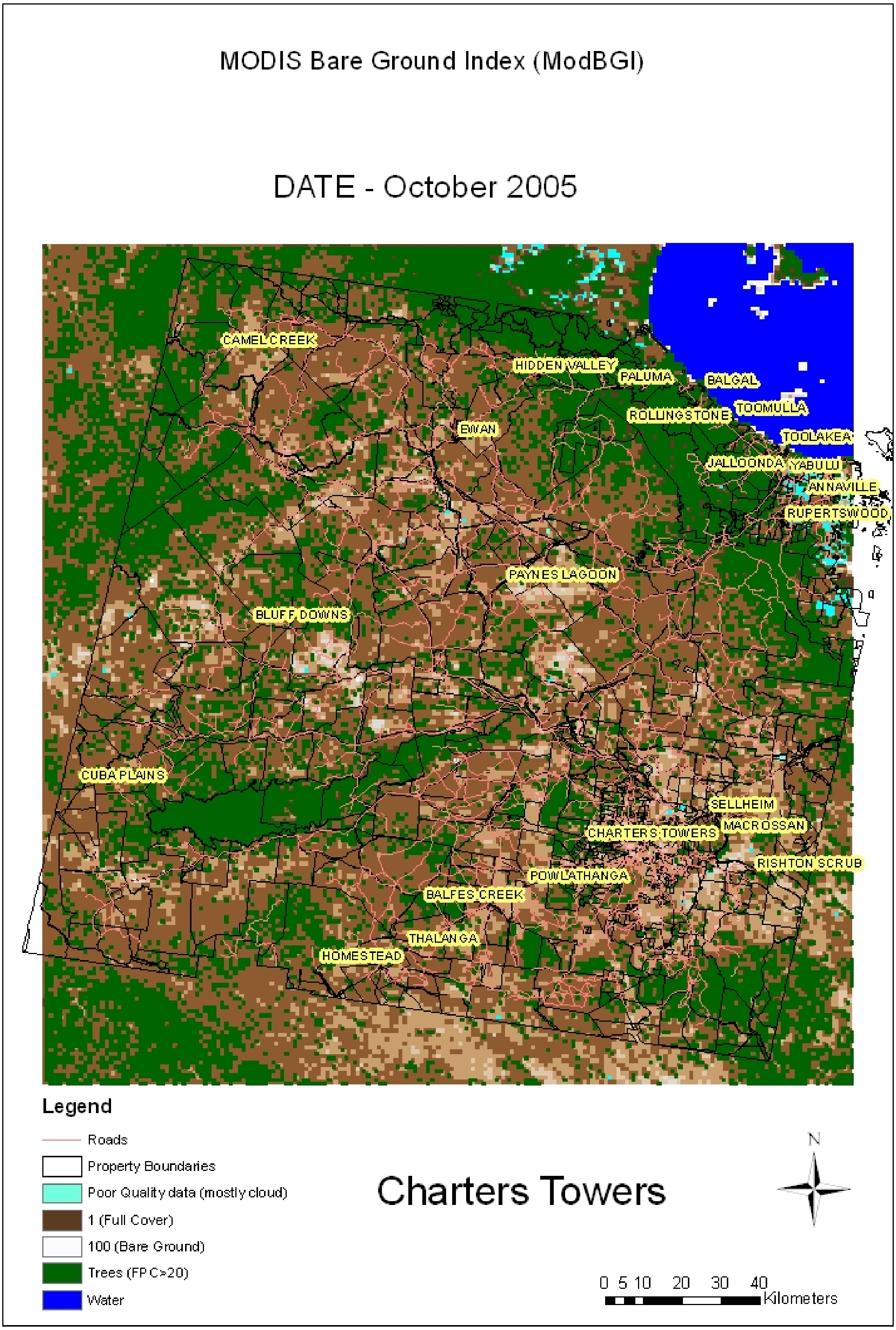

MODIS Bare Ground Index (ModBGI)
DATE - May 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

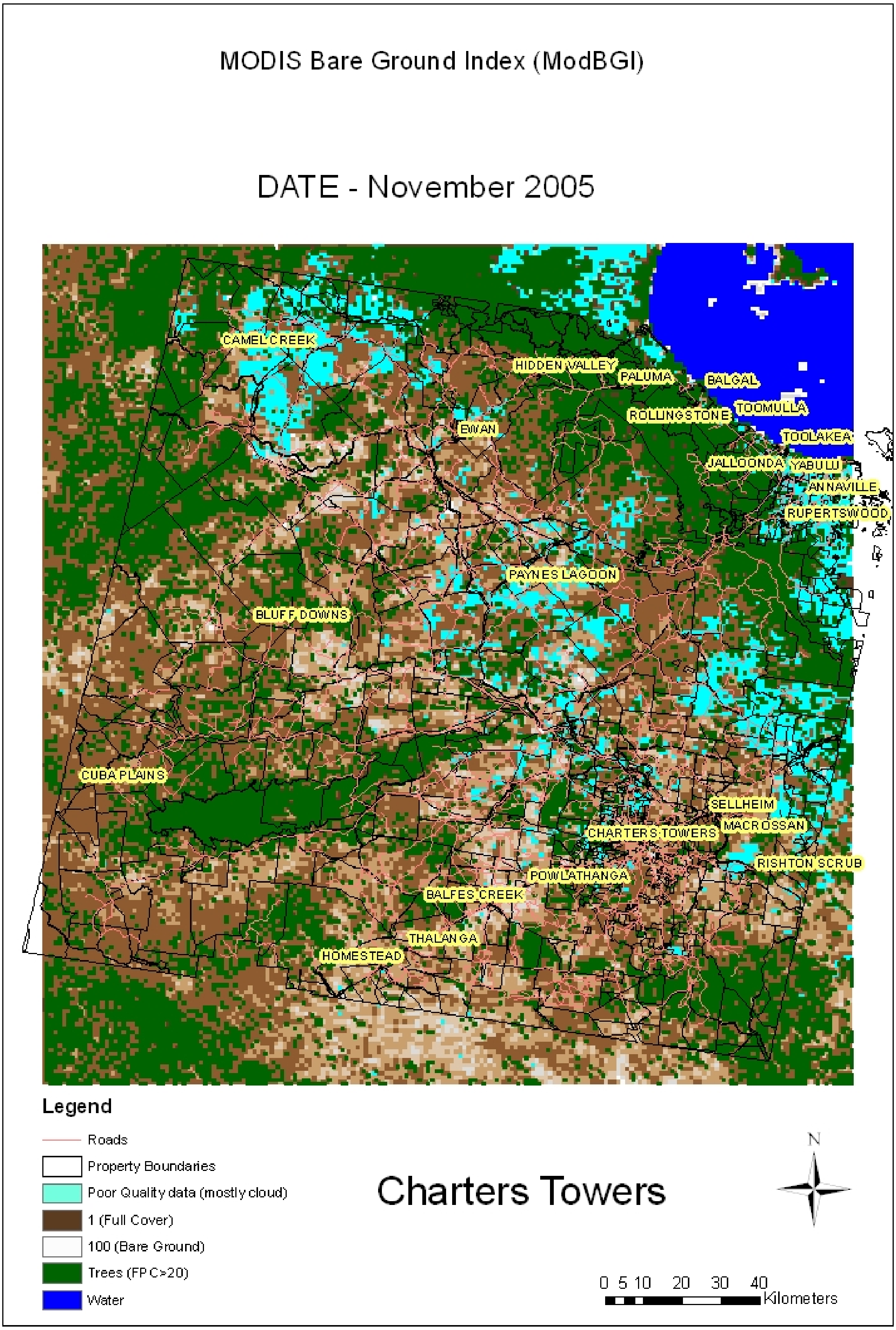

MODIS Bare Ground Index (ModBGI)
DATE - June 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

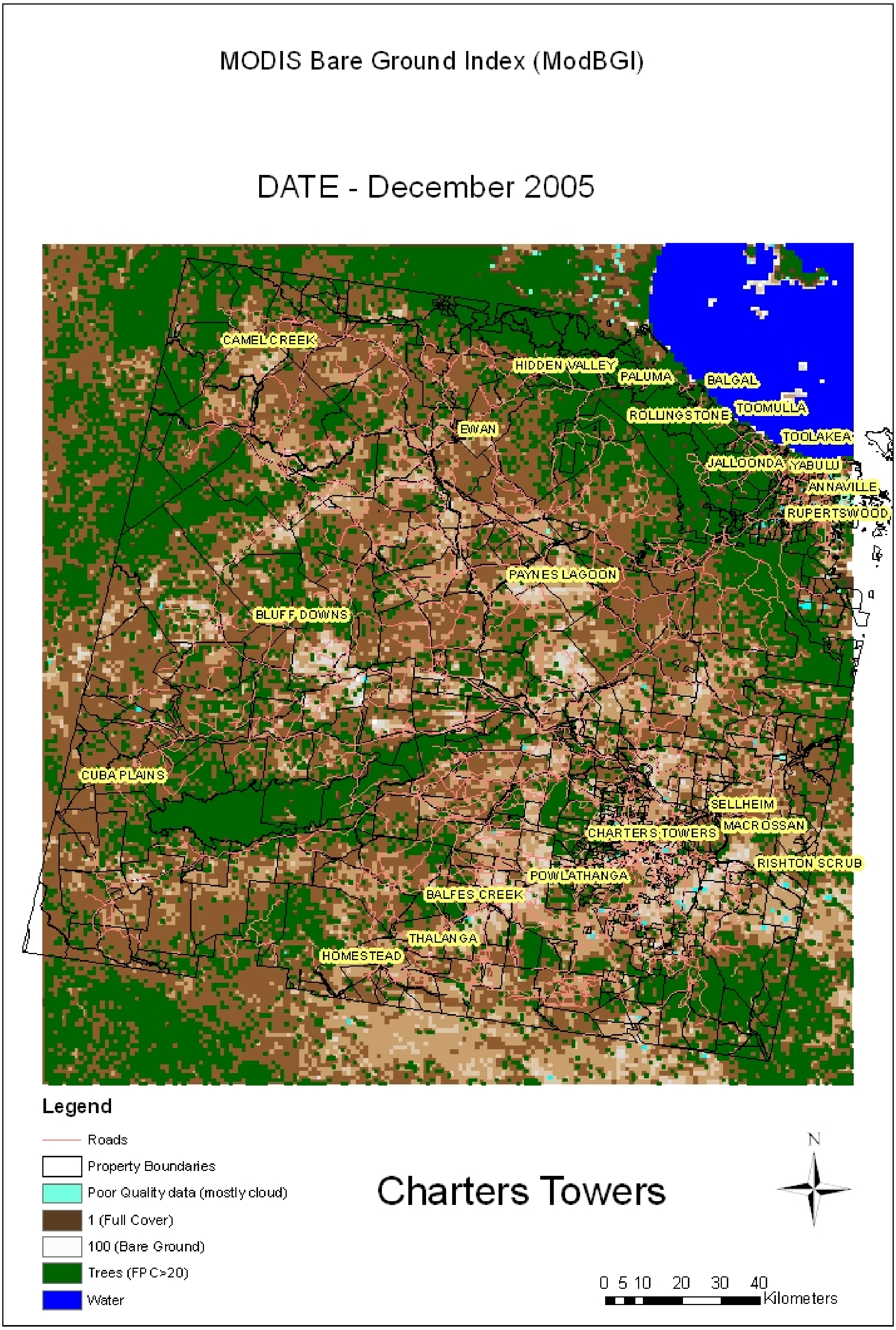

MODIS Bare Ground Index (ModBGI)
DATE - July 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers


MODIS Bare Ground Index (ModBGI)
DATE - August 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
CHARTERS TOWERS
MACROSSAN
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers


MODIS Bare Ground Index (ModBGI)
DATE - September 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers


MODIS Bare Ground Index (ModBGI)
DATE - October 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers


MODIS Bare Ground Index (ModBGI)
DATE - November 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers


MODIS Bare Ground Index (ModBGI)
DATE - December 2005
CAMEL CREEK
HIDDEN VALLEY
PALUMA
BALGAL
TOOMULLA
ROLLINGSTONE
EWAN
TOOLAKEA
JALLOONDA
YABULU
ANNAVILLE
RUPERTSWOOD
PAYNES LAGOON
BLUFF DOWNS
CUBA PLAINS
SELLHEIM
MACROSSAN
CHARTERS TOWERS
RISHTON SCRUB
POWLATHANGA
BALFES CREEK
THALANGA
HOMESTEAD
Legend
Roads
Property Boundaries
Poor Quality data (mostly cloud)
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Charters Towers
N
0 5 10 20 30 40
Kilometers

9.2 Ross-thick and Li-sparse semi-empirical model equations

Ambrals.nb 1

Ambrals Equations

```
In[9]:= ξ := ArcCos[Cos[i] Cos[v] + Sin[i] Sin[v] Cos[Φ]];
        rossthick := ((π/2 - ξ) Cos[ξ] + Sin[ξ]) / (Cos[i] + Cos[v]) - π/4;
        rossthin := ((π/2 - ξ) Cos[ξ] + Sin[ξ]) / (Cos[i] Cos[v]) - π/2;

        br = 1;
        hb = 2;
        it := ArcTan[br Tan[i]];
        vt := ArcTan[br Tan[v ]];
        ξt := ArcCos[Cos[it] Cos[vt] + Sin[it] Sin[vt] Cos[Φ]];
        d := Sqrt[Tan[it]^2 + Tan[vt]^2 - 2 Tan[it] Tan[vt] Cos[Φ]];
        t := ArcCos[Min[{1, hb Sqrt[d^2 + (Tan[it] Tan[vt] Sin[Φ])^2] / (Sec[it] Sec[vt])}]];
        o := (t - Sin[t] Cos[t]) (Sec[it] Sec[vt]) / π;
        lisparse := o - Sec[it] - Sec[vt] + (1 + Cos[ξt]) Sec[vt] / 2;
        lidense := (1 + Cos[ξt]) Sec[vt] / (Sec[it] + Sec[vt] - o) - 2;

        General::spell1 : Possible spelling error: new symbol name "ξt" is similar to existing symbol "ξ". More…
```

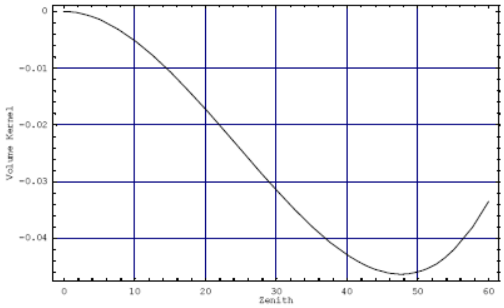
Values at 45 Degrees

```
Simplify[rossthick //. {v → 0, i → 45 Degree}] // N
Simplify[(lisparse) //. {v → 0, i → 45 Degree}] // N

Out[35]= -0.045862

Out[36]= -1.56066
```

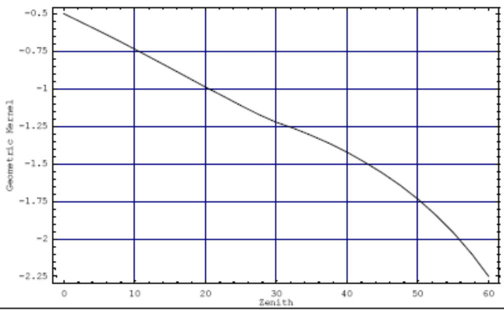
Ambrals.nb 2

Values at different Zenith Angles

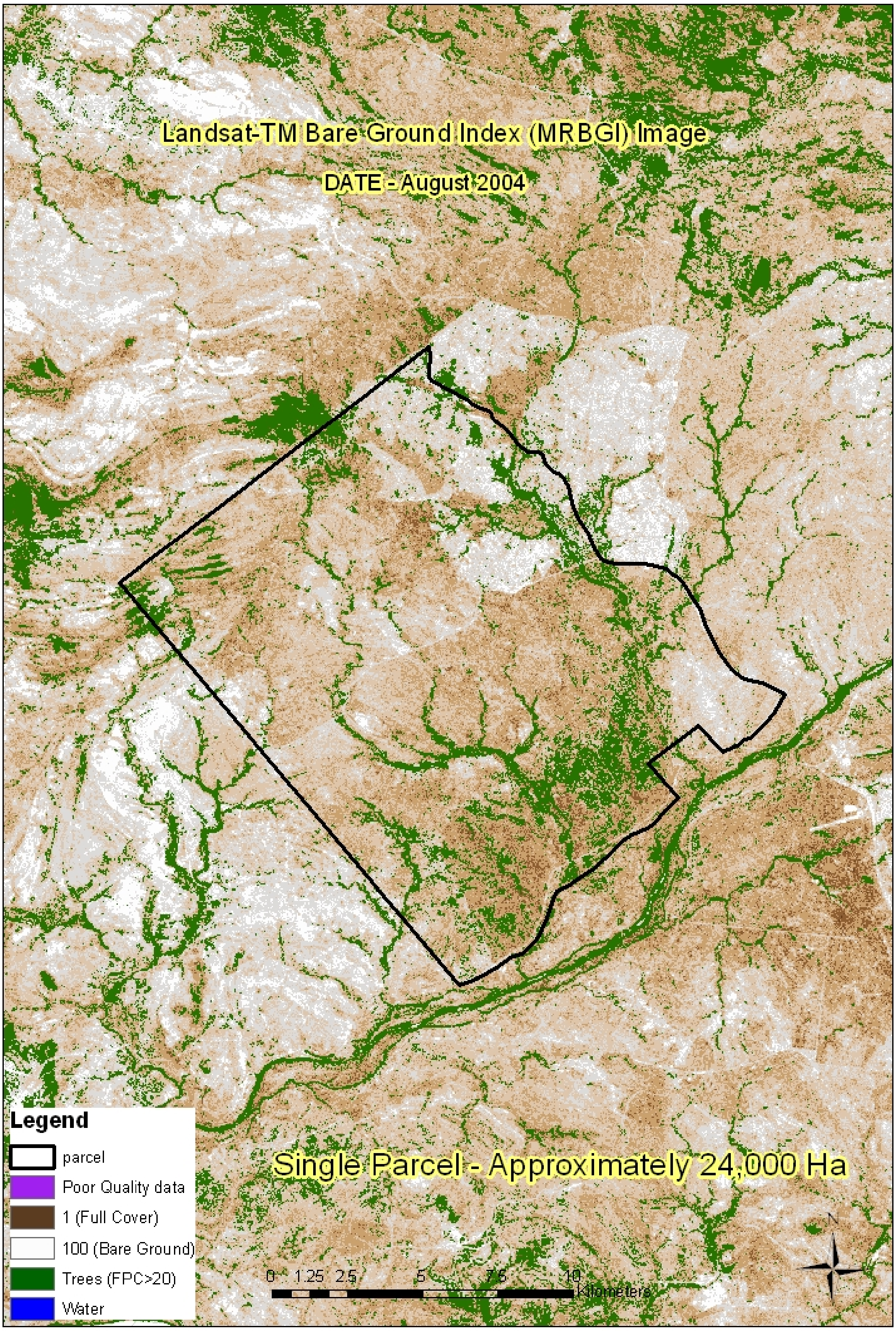
```
In[53]:=
Plot[rossthick //. {v → 0, i → id Degree}, {id, 0, 60}, GridLines → Automatic,
 Frame → True, FrameLabel → {"Zenith", "Volume Kernel"}]
Plot[lisparse //. {v → 0, i → id Degree}, {id, 0, 60}, GridLines → Automatic,
 Frame → True, FrameLabel → {"Zenith", "Geometric Kernel"}]
```

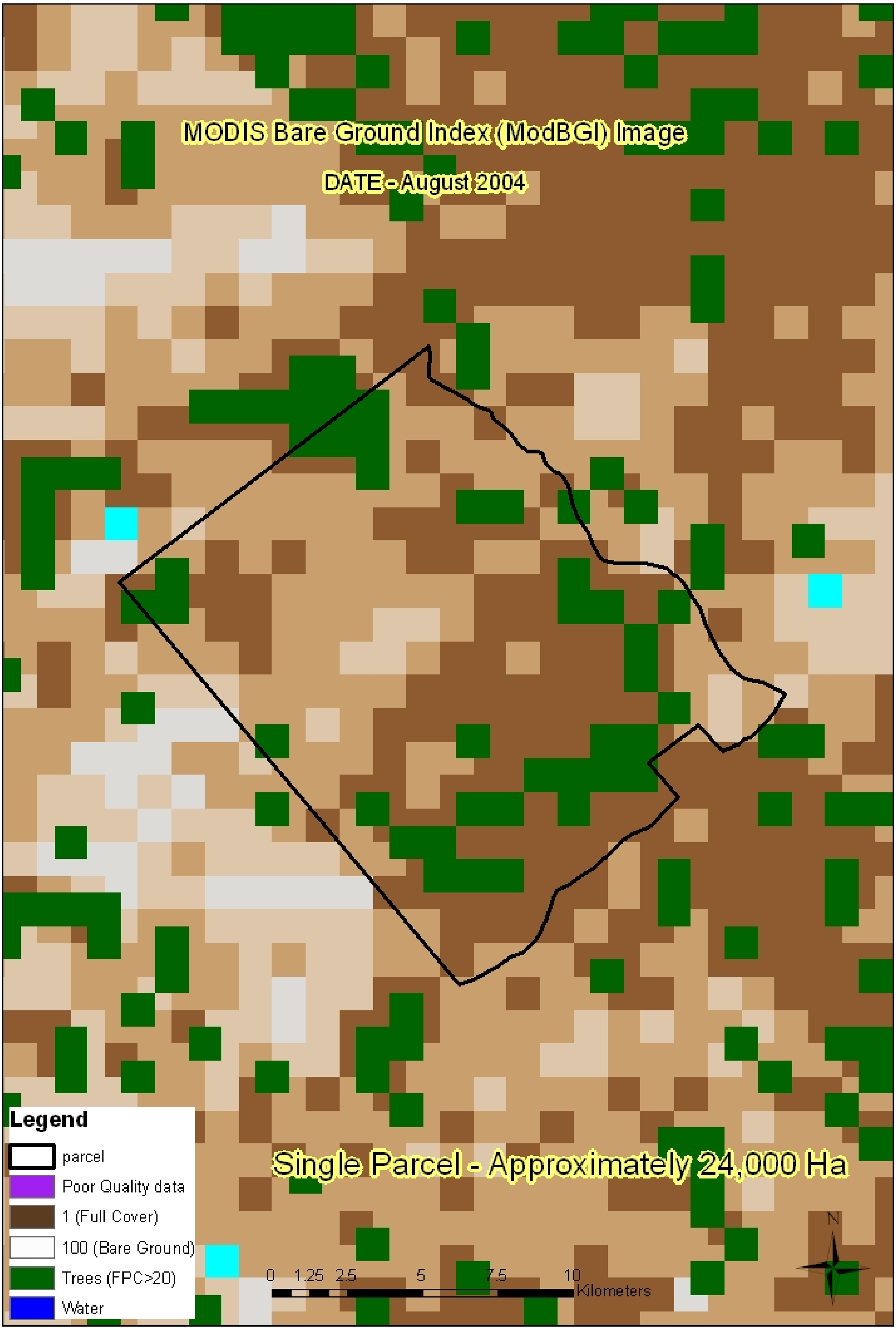


Out[53]= - Graphics -

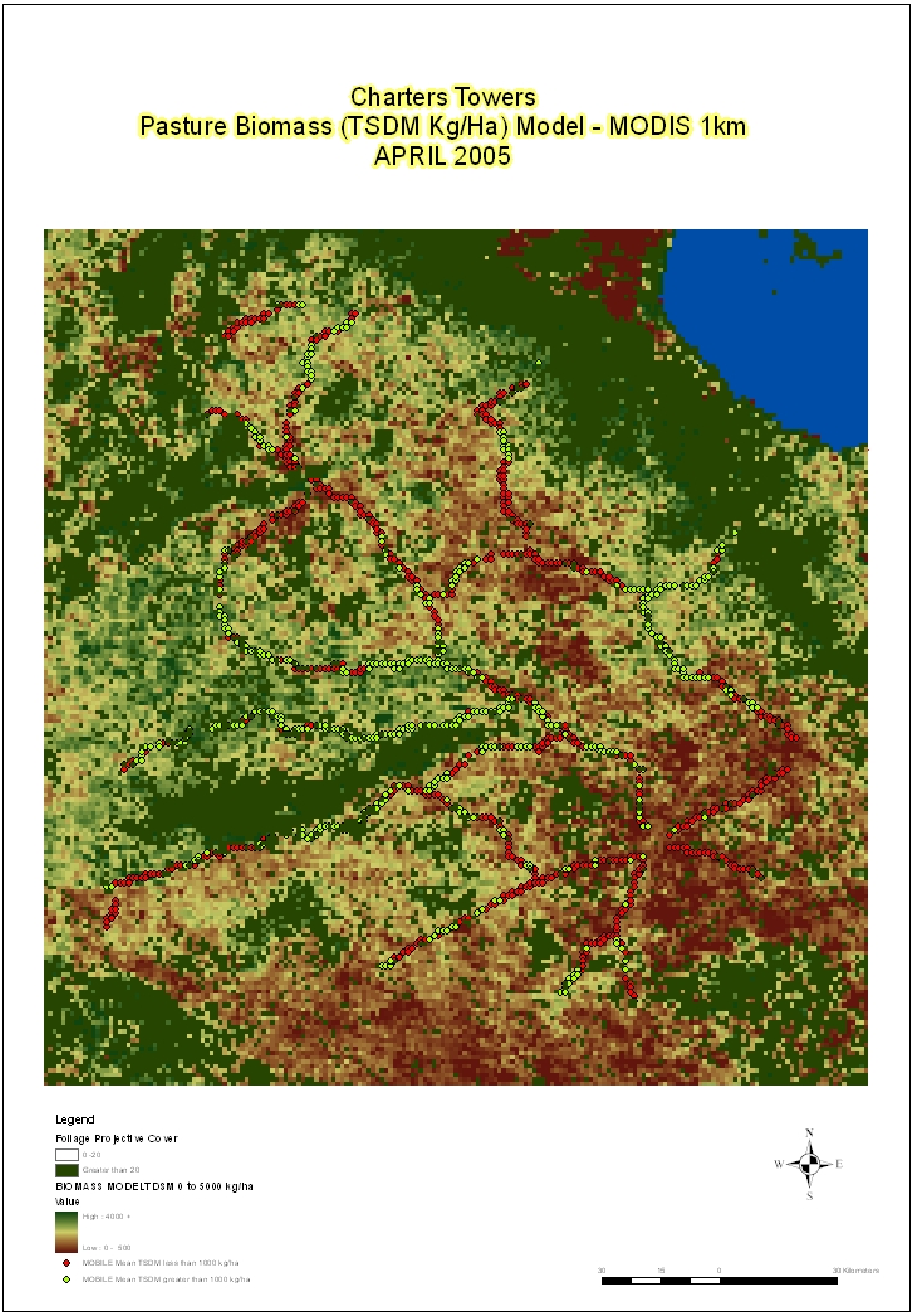


9.3 Landsat –TM versus ModBGI at the property scale


Landsat-TM Bare Ground Index (MRBGI) Image
DATE - August 2004
Legend
parcel
Poor Quality data
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Single Parcel - Approximately 24,000 Ha
0 1.25 2.5 5 7.5 10
Kilometers
N


MODIS Bare Ground Index (ModBGI) Image
DATE - August 2004
Legend
parcel
Poor Quality data
1 (Full Cover)
100 (Bare Ground)
Trees (FPC>20)
Water
Single Parcel - Approximately 24,000 Ha
0 1.25 2.5 5 7.5 10
Kilometers
N

9.4 Mapped output from biomass model


Charters Towers
Pasture Biomass (TSDM Kg/Ha) Model - MODIS 1km
APRIL 2005
Legend
Foliage Projective Cover
0 -20
Greater than 20
BIOMASS MODELTDSM 0 to 5000 kg/ha
Value
High : 4000 +
Low : 0 - 500
MOBILE Mean TSDM less than 1000 kg/ha
MOBILE Mean TSDM greater than 1000 kg/ha
N
W
E
S
30
15
0
30 Kilometers

9.5 Field measurement protocols

An analysis by Robert Denham[4] of the protocol for transect sampling of pasture variables for developing relationships with satellite imagery.

Aim
To establish flexible stopping rules for determining how many transects are necessary when the distribution of bare ground is heterogeneous or patchy.

Transects
A transect layout (north-south, east-west) is acceptable when the distribution of bare ground is homogeneous. In reality most areas are heterogenous. Figure A6 illustrates a range of patchiness in 1 ha blocks, each with a density of 0.05, but distributed quite differently. The problem with using radial transects is that a higher density of points is sampled closer to the centre of the circle (Figure A7). This gives a weighted sample of the density, with more weight towards the centre of the area. This provides both positive and negative features.

Positive – In relating the transect data to the imagery, this weighting should be replicated, e.g. by using a 3 x 3 or even 5 x 5 window of pixels, and weighting centre pixels higher.

Negative – The transect layout needs to be changed to a parallel layout or alternatively the points should be re-weighted with the centre points down-weighted to give a good estimate of the density of the site as a whole.

Stopping Rules
In general, the patchier a site the more transects will be required. Density of a site also has an effect but not as great. The patchiness can be characterised by the mean run length, where a run is a series of consecutive cover hits. Patchier sites will have a higher mean run length. Figure B3a shows an example with a low density (0.05) and a series of patchiness. The first is evenly distributed, the final, with a scale of 100 consists of large patches. The number of transects and the estimates are given in each panel. As the number of transects increases, the standard error obviously decreases, but there is a need for more transects in the patchier sites. Thus, there is a relationship between patchiness, density and number of transects required. As the run length increases, more transects are needed, particularly when the cover is low.

Estimating patchiness
A measure of patchiness would allow estimation of the number of transects required.

Possible ways of quantifying patchiness include:
1. An indication of the degree of patchiness may be obtained from imagery hence giving an indication of the number of transects necessary.
2. In the field, a cumulative mean of the run length at the completion of the second transect will provide a basis for deciding how many transects are needed. Ongoing updates can be computed as in the ‘stopping rule’ used previously for field sampling.
3. A visual estimate of the patchiness could be made before commencing a transect.

[4] Robert Denham is a biometrician with the CINRS group of Queensland NR&W.

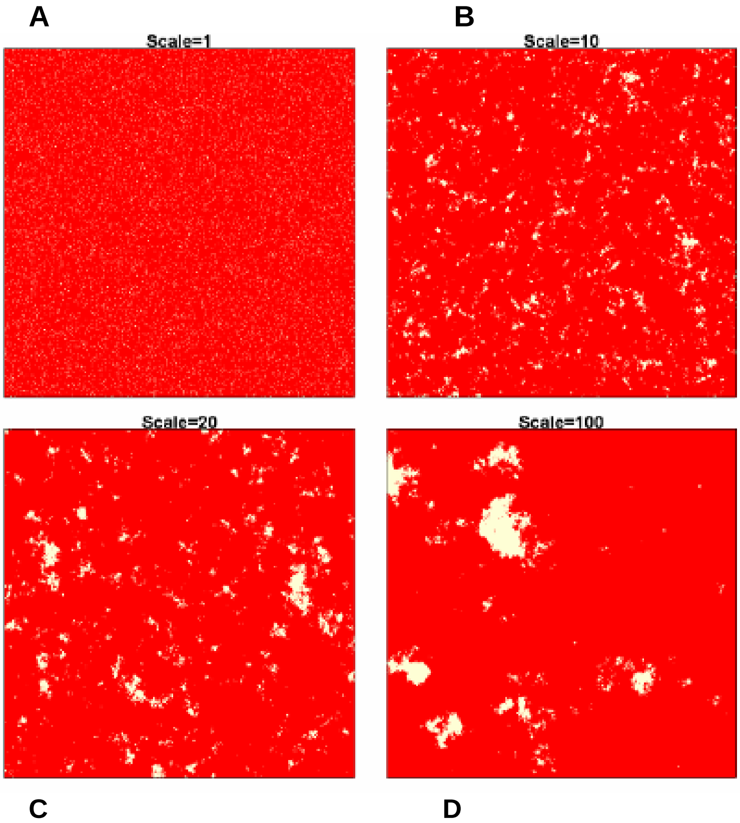


Figure A6 Different levels of patchiness in a 1 ha block, each with an overall density of 0.05 illustrate the problems associated with radial sampling when cover is heterogeneous. Each 1ha block contains the same amount of cover. The white clumps represent bare ground. Block A is the most homogeneous. If radial sampling were undertaken on Block A, the minimum number of transects would be required in order to obtain an unbiased estimate of cover. However, where bare ground is clumped (Block D), a larger number of transects is required to obtain an unbiased estimate.

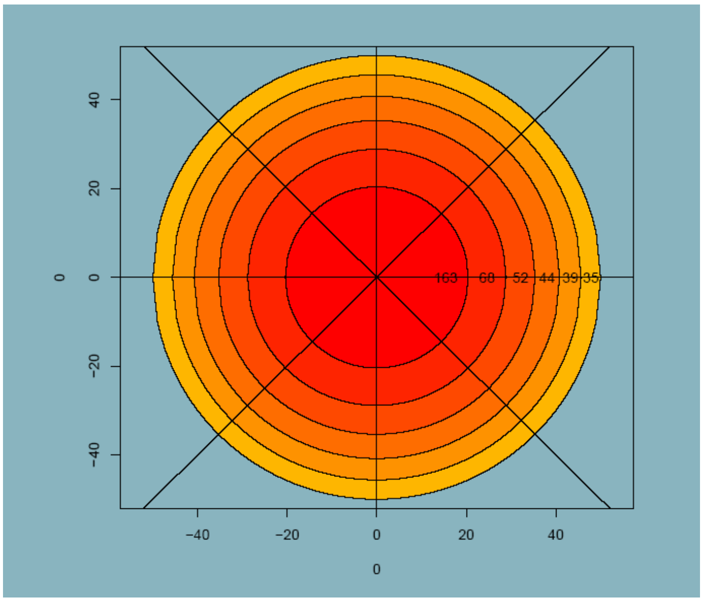
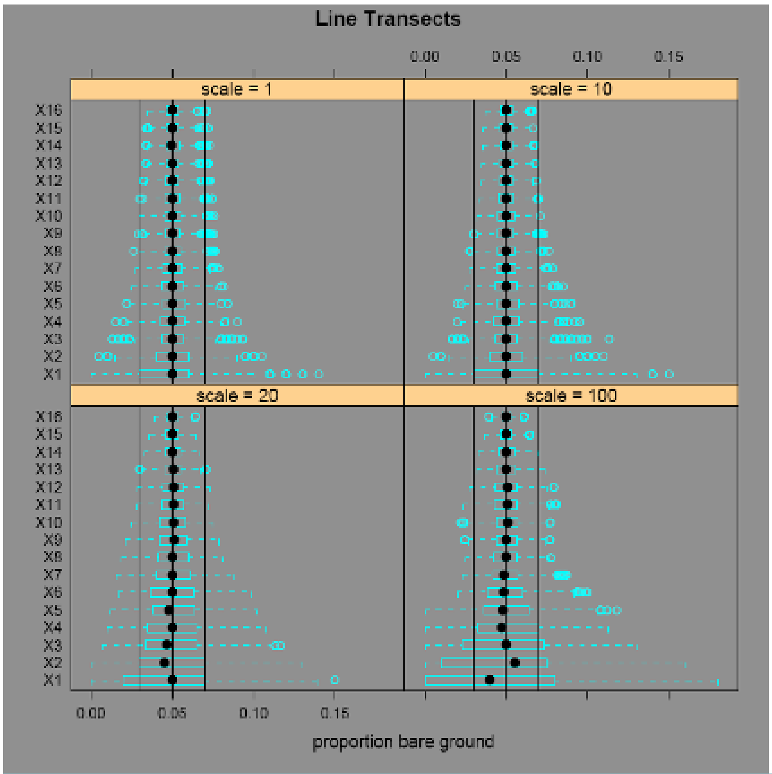


Figure A7 Analysis of radial sampling: Each ring has the same area; the number of points within each ring is shown. If a large bare patch was present in the centre of a 1ha block and was sampled using the above radial method, the bare patch would weight the estimate to the centre, which is not representative of the whole area. When the area being sampled is homogeneous, radial sampling doesn't affect the overall estimate.

Alternative Procedures

There are a number of alternative sampling techniques that can be employed. These include grid sampling, shorter transects and transect intercepts. Grid sampling is time intensive and isn't a feasible alternative. However, the option of a larger number of shorter transects hasn't been considered fully. Further investigation is underway regarding these alternative techniques.

a)



b)

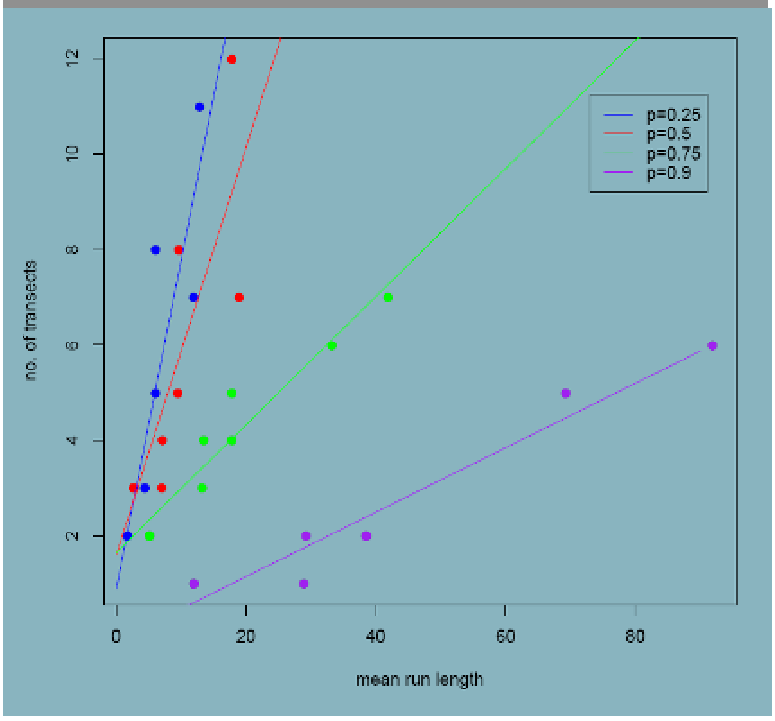


Figure A8 a) Relationship between sampling variability, number of transects, and patchiness. The top left is not patchy at all, while the bottom right is very patchy b) Relationship between mean run length and number of transects, indicating that the greater the mean run length, the less number of transects which need to be undertaken.

9.6 Producer Information Document

Evaluating the use of MODIS Imagery to monitor groundcover and estimate biomass in the tropical savannah ecosystems of Queensland

Research funded by Meat and Livestock Australia (MLA)

Undertaken by:
Climate Impacts and Natural Resource Systems
Department of Natural Resources and Mines
80 Meier's Road, Indooroopilly QLD 4068.

Introduction

This paper provides an update on the Meat and Livestock Australia (MLA) project which is evaluating the potential of MODIS satellite imagery to provide information on pasture condition to assist with greater productivity and sustainability of northern Australian grazing properties. Grazing properties are managed against a background of high climate variability and an improved capacity to monitor ground cover and feed availability would enhance climate risk assessment in turn reducing the risk of degradation with long-term loss of productivity.

Your role as producers involved in this pilot study in the Charters Towers region is vital to the success of the project in terms of providing:

1. Assistance in the validation of preliminary estimates of cover and feed availability; and
2. Advice on the usefulness of products and how to maximise the benefits from the project

We would encourage you to provide feedback or ask questions at any stage, either in person when we are undertaking field work (usually in April and October) or via email, phone or post. In particular we would appreciate your critical evaluation of the accuracy and usefulness of prototype products and information on property-specific conditions or needs.

Aims of Project

This is a Meat and Livestock Australia (MLA) funded project. The Queensland Department of Natural Resources and Mines is working in conjunction with MLA to provide timely and accurate information regarding ground cover and pasture biomass/feed availability. This information has the potential to provide decision-support to land managers for improved productivity and sustainability in the grazing lands in Queensland. The goal of the project is to investigate the feasibility of providing this information utilizing the unique sensor attributes of the Moderate Resolution Imaging Spectroradiometer (MODIS) for a pilot study in the Charters Towers region of north Queensland.

The project objectives are outlined below.

1. Develop relationships for ground cover and pasture biomass/feed availability between field measurements and MODIS indices.
2. Provide guidelines for the use of MODIS data in the estimation of groundcover and biomass/feed availability at a range of scales.
3. Provide participating producers with the tools and techniques for collecting field data for property/paddock based calibration in support of prototype estimates of ground cover and pasture biomass/feed availability.
4. Develop a prototype framework for the automated delivery of prototype remote sensing products of groundcover and pasture biomass and report on the requirements for operational and near-real time delivery.

Potential Industry Benefits

This project aims to put a methodology in place, which can provide regular groundcover and biomass/yield information to producers with respect to their individual properties. It is hoped that this information will provide valuable decision support information on the impact of seasonal variability and the implications of different management regimes.

The ecosystem dynamics of the tropical savannah may also become better understood through the availability of such information, particularly when it is used in conjunction with your knowledge of pasture quality/quantity and pasture response and other datasets such as climate information, on-ground monitoring and simulations of pasture biomass and growth such as provided on the Queensland government website through the AussieGRASS project (www.longpaddock.qld.gov.au). This union of scientific and grazier knowledge is a great opportunity to improve understanding of issues relating to managing for climate variability and addressing environmental concerns relating to soil fertility, runoff and erosion events.

This project will also link with other programs, particularly the Grazing Land Management Education Program developed by DPI&F and supported by MLA to evaluate options for delivery of remote sensing information to land managers.

Description

The primary focus of this pilot project is the Charters Towers Landsat scene, which is a 185km x 185km area, depicted in Figure 6. The life of the project is three years, spanning from January 2004 to December 2006. During this time, field data (i.e., groundcover and biomass information) will be collected in April and October of each year from 100m x 100m sites established across the scene. These data will be used in conjunction with Landsat satellite imagery at 25m x 25m scale to calibrate the MODIS imagery for cover. Due to the high variability within MODIS scenes (1km x 1km), we will also use mobile visual observations of pasture biomass and cover to validate products. Typically more than a thousand observations are recorded to assess grazing land condition in trips also conducted in April and October. Furthermore, the project will involve close consultation with selected producers, particularly in the later stages when validation is required. Your involvement will also be fundamental in shaping the form and delivery of the resultant information products.

The operational aspect is also a key feature of this project. Once the MODIS products have been developed and validated, their automated delivery to you is essential. It is envisaged that a prototype for automated web/email based delivery will be developed to facilitate rapid transfer of this information. For those of you who do not have internet/email access, these products may be sent to you via regular post or fax.

What is MODIS?

MODIS is an acronym for Moderate Resolution Imaging Spectroradiometer. It is an instrument on board the Terra satellite. The Terra satellite was launched in December 1999 and currently provides near-daily coverage of Australia.

Data are acquired in 36 spectral bands. These data provide the capacity to investigate land surface processes such as pasture growth and condition.

MODIS provides the opportunity for near real-time information delivery. Another advantage is that the data are freely available. Further information regarding MODIS can be found at http://modis-land.gsfc.nasa.gov/

The MODIS data are ordered from the U.S. on DVD. It arrives in a raw format and subsequently, there are a number of pre-processing steps involved prior to any analysis being undertaken. These include importing, reprojecting and mosaicing of the imagery.

Methods and Preliminary Results

We have acquired MODIS data over the entire state of Queensland. Due to its coarse resolution of 1km x 1km pixels, it is impossible to effectively sample ground information and directly relate it to the MODIS data. In order to overcome this disparity between the resolution at which the field data is sampled and that of the MODIS sensor, an intermediate step is used, which involves Landsat data (25m x 25m pixels), to scale up the field measurements.

This MODIS project is therefore able to build on research to monitor groundcover using Landsat imagery to map bare ground. Bare ground is the reciprocal of groundcover and thus this method provides an indication of the distribution and amount of ground cover. The MODIS project aims to implement a similar methodology to monitor cover.

There is a larger proportion of green cover at the end of the wet season than at the end of the dry. Green grass and dry (senescing) grass have different spectral signatures (that which makes them visible to an optical satellite, such as MODIS). This is demonstrated in Figure 1.

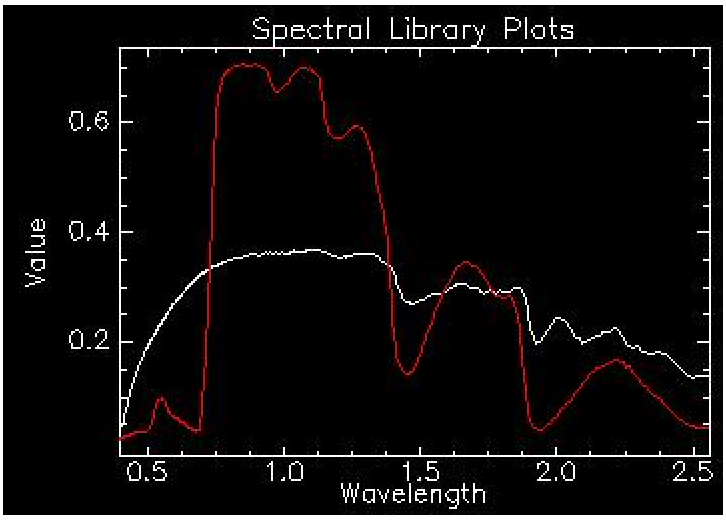


Figure 1: Spectral signature of dry grass (white line) and green grass (red line)

Green vegetation (Figure 2) can be effectively and accurately estimated by MODIS via an index known as the Normalised Difference Vegetation Index (NDVI). NDVI is based on the red (sensitive to the presence of chlorophyll pigment in leaves) and Near Infra Red (NIR) (sensitive to plant cell structure) portions of the spectra. However, it is considerably more difficult to detect senescing vegetation (dry cover; Figure 10) using MODIS (or any satellite for that matter).

Figure 2: Plot 27 sampled in April 2004

Figure 3: Plot 27 sampled in October 2004

A strong correlation exists between NDVI and rainfall estimates. Average monthly rainfall estimates for each of the 31 sites were obtained from the SILO webpage (http://www.nrm.qld.gov.au/silo/silo2/). Rainfall results in greening of the landscape, which is subsequently accurately detected by the NDVI. This is demonstrated in Figure 10.

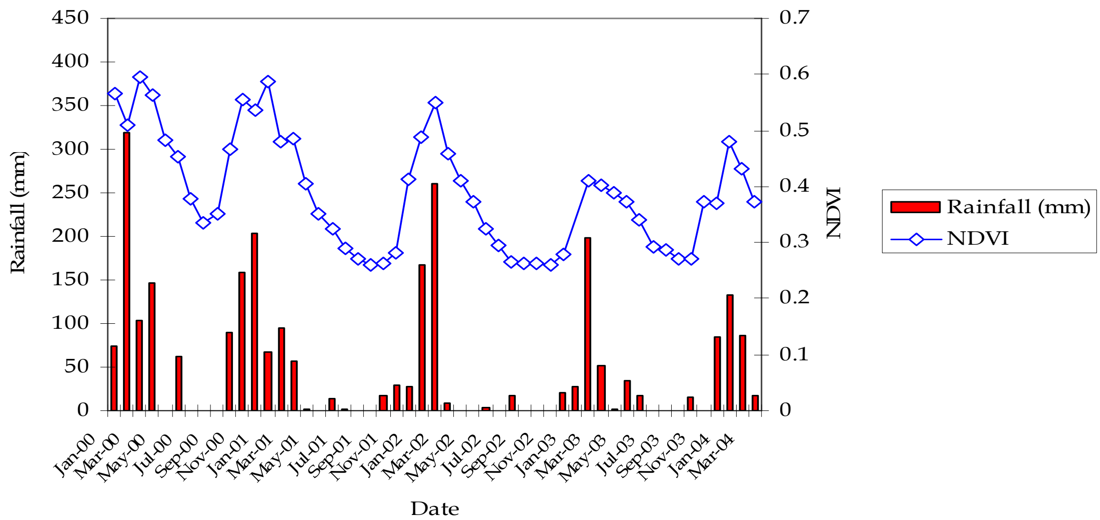


Figure 4: Relationship between monthly rainfall and NDVI

In terms of the biomass component of the project, the NDVI can be applied to the MODIS time series (image archive from 2000-2004). Time-series NDVI data show the green-up and senescence (drying) cycle of vegetation (Figure 5). The behaviour of NDVI across the year can be used to indicate pasture growth, and hence be used as a surrogate for biomass/yield. The senescent component is needed to give total biomass/ feed availability.

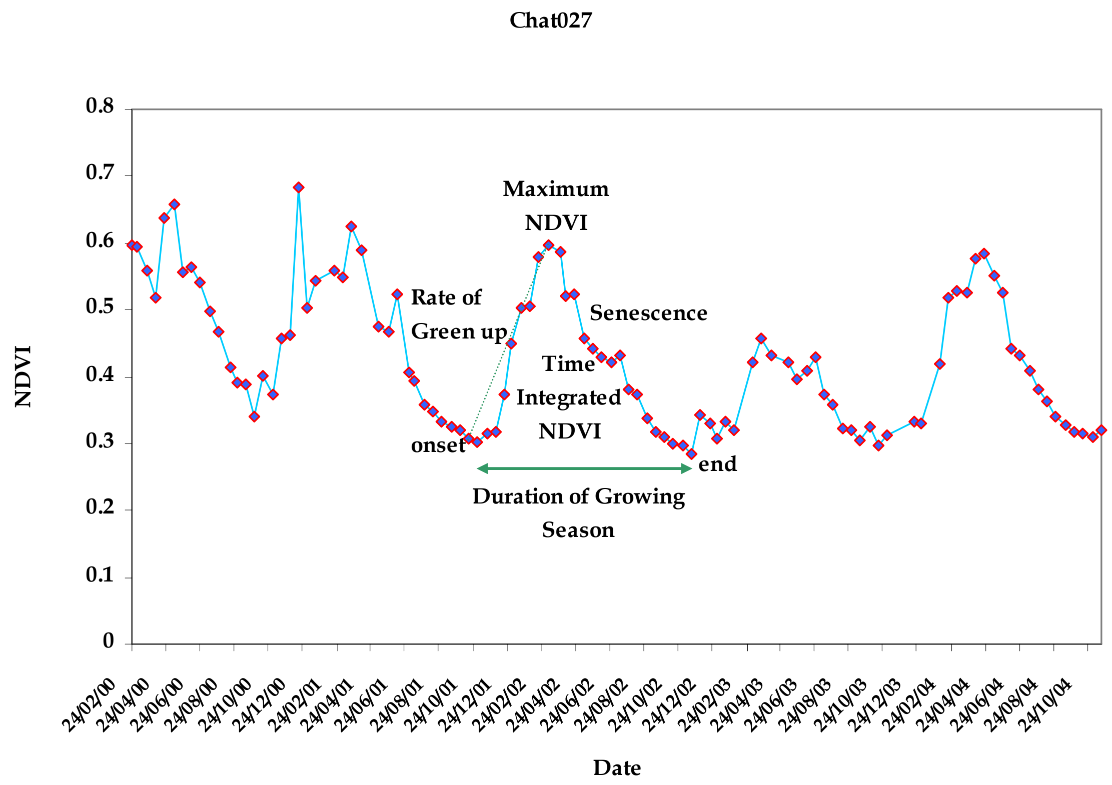


Figure 5: Time Integrated NDVI curve demonstrating the duration of greenness, the onset and end of greenness, the rate of green up, maximum greenness (NDVI) and senescence over a single season

Participating Producers

During field sampling undertaken in October 2004, we spoke to six producers about the research, sampling and the opportunity to become involved in terms of participating in the pilot study through validating results, having early access to prototype products and having an opportunity to have input into the final format of information for producers.

31 plots have been established across the Charters Towers Landsat scene. Some of these plots fall within the area of the properties outlined in Figure 10, however, the majority don't. The main opportunity is to validate results that shall be applied across the entire region. Preliminary results should be available to you mid-2005, and we would welcome your feed-back on the usefulness and accuracy of these products.

Field work is planned to be undertaken during the first half of April 2005. I am looking forward to catching up with each of you again, and hope that if there is any thing you need answered regarding the MODIS project, you will take this opportunity to do so.

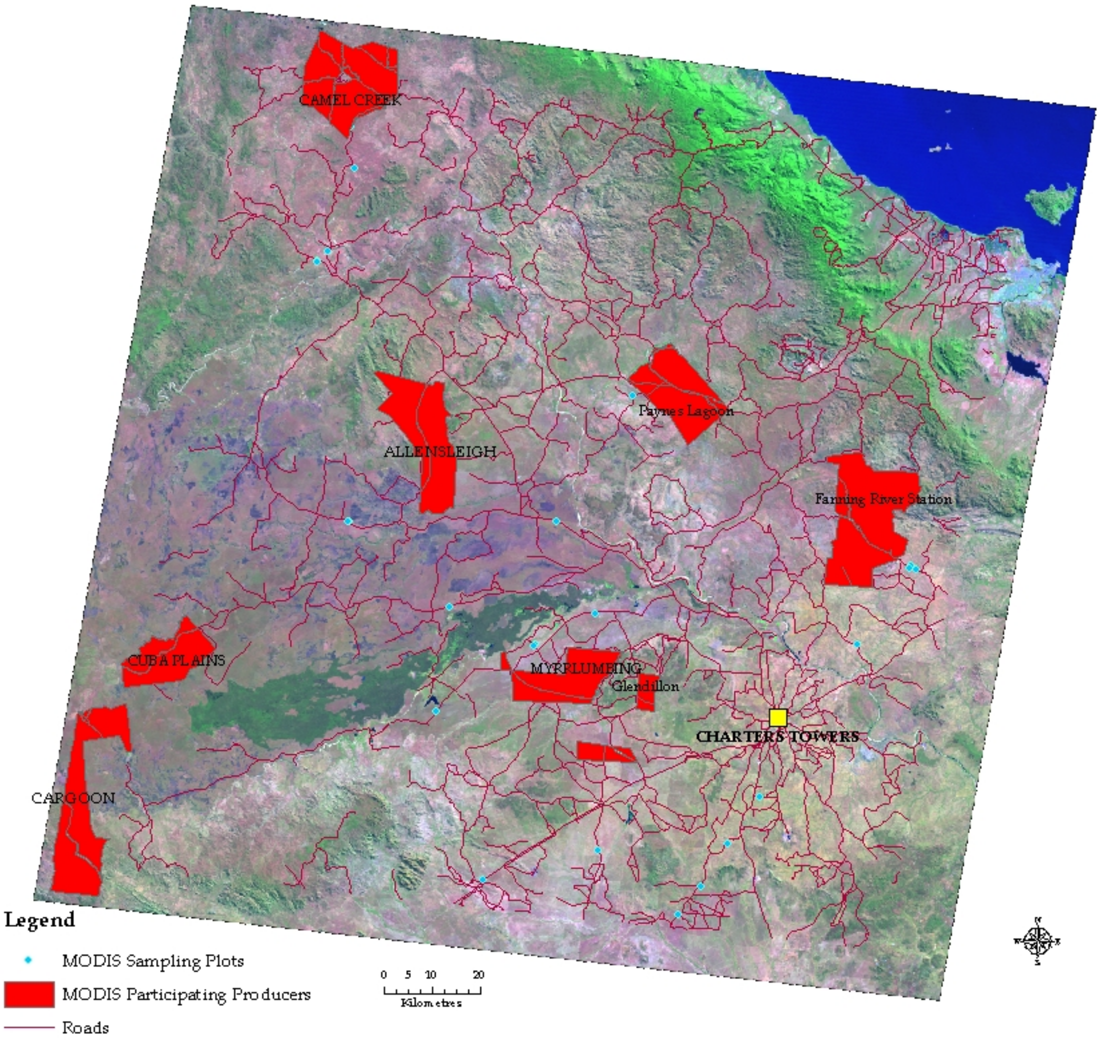


Figure 6: Distribution of participating producer properties across the Charters Towers Landsat scene

Field Sampling

In April 2004, 31 plots were established across the Charters Towers Landsat scene (Figure 7). These sites will be revisited each April and October, corresponding to the end of the wet and dry season, respectively, until the completion of the project in December 2006.

The selection of these plots was based on a stratified sampling methodology, whereby variables such as slope, tree basal area and distance to infrastructure (e.g., roads, fences) are taken into account. For example, the accuracy of the satellite information is reduced when the slope is too great. Furthermore, if the tree cover is too dense, then the satellite will be recording the response from the tree foliage rather than from the groundcover. Logistics also play an important role in the selection and number of field plots. For example, plots have to be located within relatively easy access of roads, due to the equipment required to sample (i.e., GPS, tapes, camera, and quadrats). It is not feasible to carry this equipment over great distances, in addition to the harvested material that is subsequently collected from the plot.

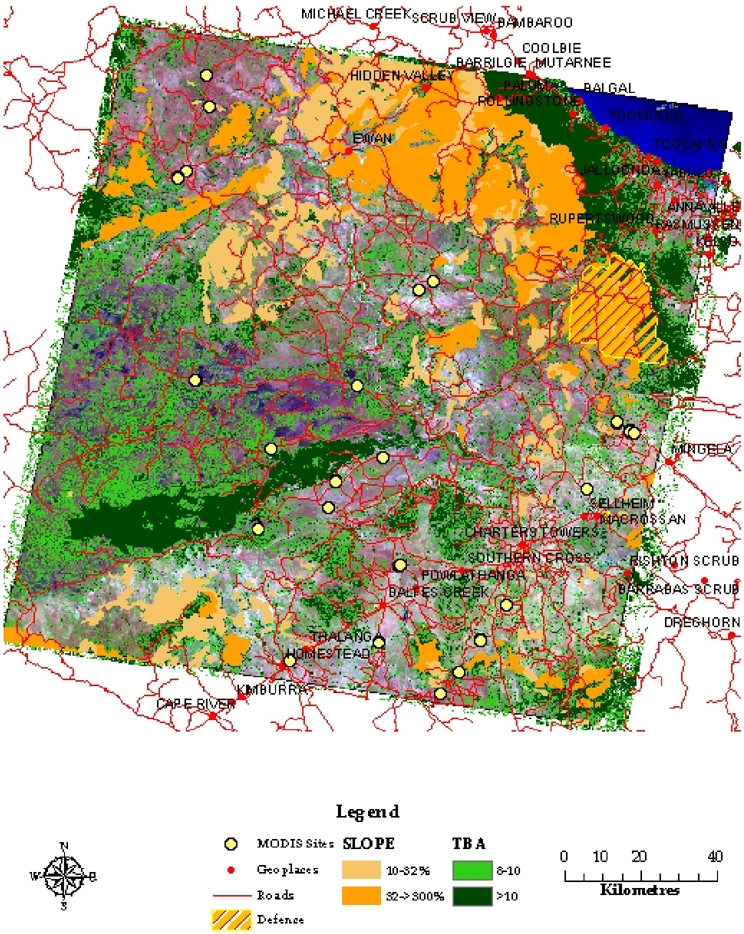


Figure 7: Distribution of MODIS sampling sites across the Charters Towers Landsat scene based on stratification of sampling with respect to Tree Basal Area (TBA) and Slope

There are two components to the field sampling (i) groundcover and (ii) biomass. The methodologies for each of these components are outlined below.

Groundcover

For each plot established:
(i) A minimum of two 100m transects are laid in the north-south and east-west directions (Figure 8), forming a cross. The centre of each plot is located at the intersection of the cross, as determined using a sub-metre differential GPS unit.
Each time these sites are revisited, the differential GPS unit can relocate the exact centre of the plot, within a 0.5m accuracy. On most occasions, we are able to find the hole where the peg was hammered in.

(ii) Ground layer, mid-storey and over-storey attributes are recorded at each metre along the north-south and east-west transects, and subsequently entered into a palmtop computer in-situ. A running mean is established, which provides an indication of the homogeneity of the plot.

At each metre along the transect, groundcover attributes, such as green leaf, dead leaf, bare ground, rock, disturbance and cryptogams are recorded. Mid-storey and over storey attributes are also recorded at each metre and these include green leaf, dead leaf and branch. Later, the groundcover data obtained from these measurements are input into an algorithm with the MODIS data to calculate an index for bare ground.

The amount of green material in relation to dead material (on the ground) is important as this is significantly affected by the seasons.

(iii) Tree basal area measurements (using a calibrated optical wedge) were acquired from the centre of each plot and 25m to the north, south, east and west (Figure 9).

The tree basal area measurement is critical, given that it is a determining factor in whether the satellite can 'see' the ground and hence is used in the stratification of data at a number of levels in the methodology.

(iv) Other site observations including photographic record, soil colour, rock colour and species composition relevant to developing a relationship between satellite imagery and ground cover or biomass are collected.

Species information on the composition and type (i.e., annuals or perennials) of pasture is collected. Soil and rock colour is important, as this is what the satellite will be observing when there is no cover. Site photographs provide a valuable record and an indication of seasonal and inter-annual variation in the site.

Biomass

(i) Biomass is harvested from 0.5m x 0.5m quadrats
In areas where cover is sparse, hand shears are used. Electric shears are used for high cover/high biomass sites.
(ii) Five quadrats are randomly sampled within each of the four 50m x 50m areas within the

100m x 100m plots (Figure 10)
(iii) Prior to harvest, a visual green to dry biomass ratio and total cover estimate (%) is established for each quadrat
(iv) Total biomass and sub-samples are weighed in the field and sub-samples are taken back to Brisbane for drying and then re-weighing.

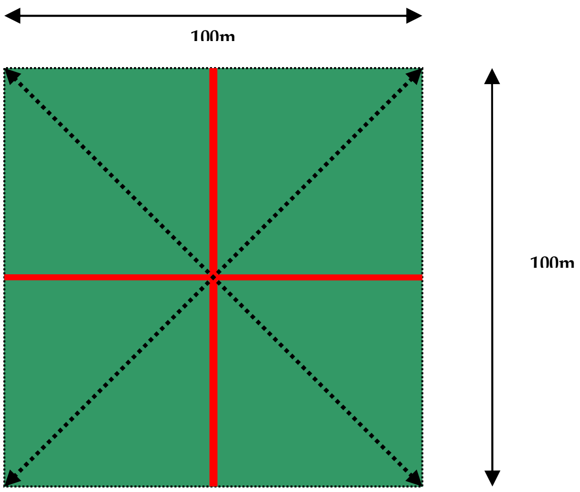


Figure 8:
Transect directions within the 100m x 100m plot

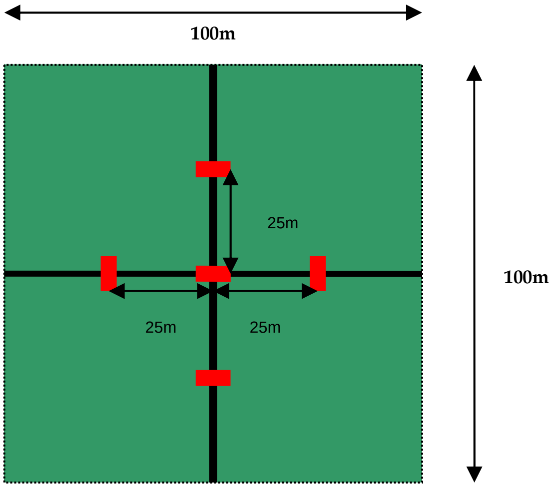


Figure 9:
Positions for the record of tree basal area

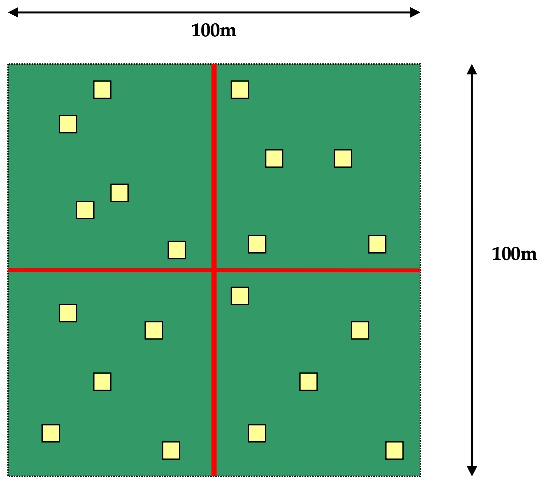


Figure 10:
Harvest of 20 biomass quadrats within the 100m x 100m plot

Any Questions

This MLA project provides a valuable opportunity to investigate a new technology and to develop prototype products to support producers in decision-making for more productive and sustainable use of grazing lands in northern Australia. Your participation in this study is appreciated and we look forward to working with you to ensure that the project is successful in providing you with useful products.

If you have any questions or if there is anything that you would like to discuss regarding the MODIS project, please contact myself (MODIS Project Officer) via the below details.

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Climate Impacts and Natural Resource Systems
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Indooroopilly QLD 4068.
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9.7 Integration of MODIS data and existing models

Estimating NDVI from Green Cover

1. MODIS and Landsat NDVI estimated from Tree and Grass cover

The GRASP model in its CEDAR and AussieGRASS implementations require data for calibration. Greenness as observed satellite provides a potential tool for model calibration. To date only data from the Pathfinder project has been used to calibrate AussieGRASS at the pasture community scale. The Pathfinder data suffers from a range of problems but in particular the data is only available at an 8km scale and it is not fully corrected for BRDF and atmospheric effects. This means that at individual points the data is not reliable enough for model calibration and validation. The MODIS instrument is well calibrated and products corrected for atmospheric effects and BRDF are available every 8-16 days (subject to cloud cover) since the year 2000. This potentially provides up to 160 observations of greenness at any point in the landscape at the 1km scale (depending on cloudiness). The greenness observed is from a maximum value composite so the greenest observation from the 16 day period is incorporated into the image. In the MODIS data the date of pixel acquisition within the 16 day window is not specified for the 1km product.

The GRASP model calculates a synthetic NDVI from its internal estimate of green cover which is in turn calculated from pasture green biomass. Field observations from Dalrymple scaled up using Landsat (for areas where tree basal area were < $10m^2$/ha) were used to produce an equation that estimated MODIS NDVI as a function of pasture green cover and tree basal area (Figure 1). This simple function was coded into the CEDAR version of GRASP for testing at individual points and ancillary code was developed to store NDVI values in the MRX files and provide access to observed and predicated data in the CALIBRATOR.

In reality the formulation of this equation is an over simplification and does not functionally represent the case where trees canopy exists over green pasture and or where tree shadow occurs over pasture and therefore can only be used where tree basal area is low. Like wise equation relating green cover to NDVI for LANDSAT was developed for treeless areas. (Different sensors produce different estimates of NDVI because of wider or narrower spectral bands from the various sensing systems.

Synthetic NDVI (MODIS) $r^2 = 0.781$

<u>For areas with tree basal area < 10.0 m^2/ha</u>

```
out%syn_MODIS_NDVI = 0.2227 + 0.003364 * (ratio%rad_cover*100)      &
 -0.000002367 * (ratio%rad_cover*100)**2 + 0.00377 * state%tree_BA
```

<u>For areas with no trees</u>

```
out%syn_MODIS_NDVI = 0.2092 + 0.00459 * (ratio%rad_cover*100)
out%syn_LANDSAT_NDVI = 0.042 + 1.1 * ratio%rad_cover
```

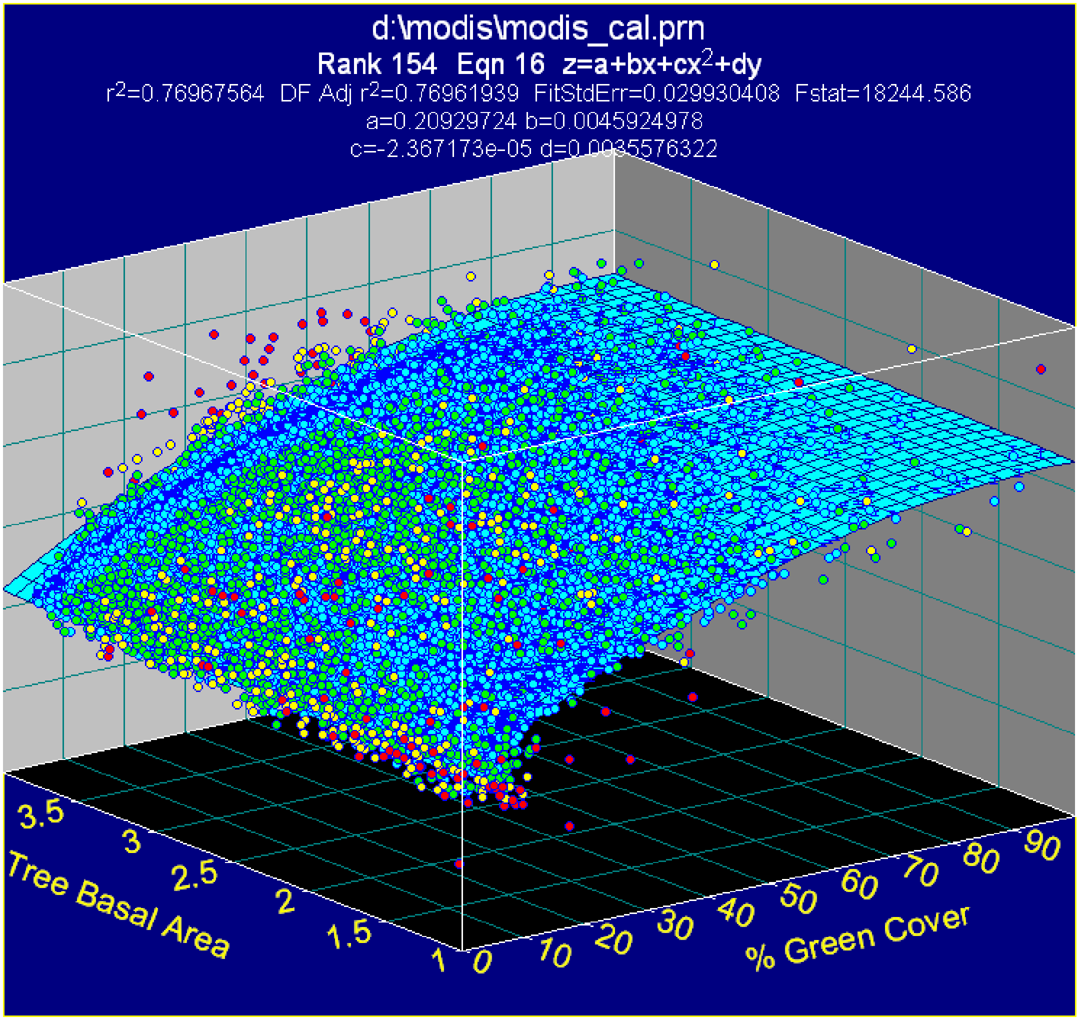

Figure 1: MODIS NDVI as a function of pasture green cover and tree basal area.

MODIS data can be extracted from a series of images for a given location (MODIS calibration site 08) to produce a tabular time series that is inserted into the model management records file (MRX). Similarly a climate data time series can be extracted for the same location. The model can then be run to estimate simulated NDVI for each satellite observation in the MRX file. For each observation an error estimate for satellite observed – model simulated NDVI can be determined and accumulated over all observations. A genetic algorithm can then be used to adjust a range of parameters (e.g. soil water index at which growth stops) such that the total error for the time-series is minimised.

An example of the outcome of this process is demonstrated in Figure 2, where there has been an attempt to match observed and predicted NDVI. This attempt was only moderately successful. Examination of the model outputs suggests that mapping of rainfall at fine scales was inadequate as soil water estimates suggest that some falls are missed or underestimated and others are smeared (Figure 3). The scale at which such optimisations can successfully be preformed will depend on rain station density. Future developments needed to make this technique more useful are:
- Satellite data drill developed to give average data at a range of scales
- Green cover to NDVI algorithm that accounts for tree basal areas > 10
- Parameter constraints developed to better limit optimisation outcomes

- Spatial layers of greenness from MODIS calculated from multiple bands
- Total cover estimates incorporated in addition to green cover estimates

At this stage the integration between modelling will not progress beyond the “proof of concept” phase. However further investigation (3) of greenness to NDVI equations is likely to proceed.

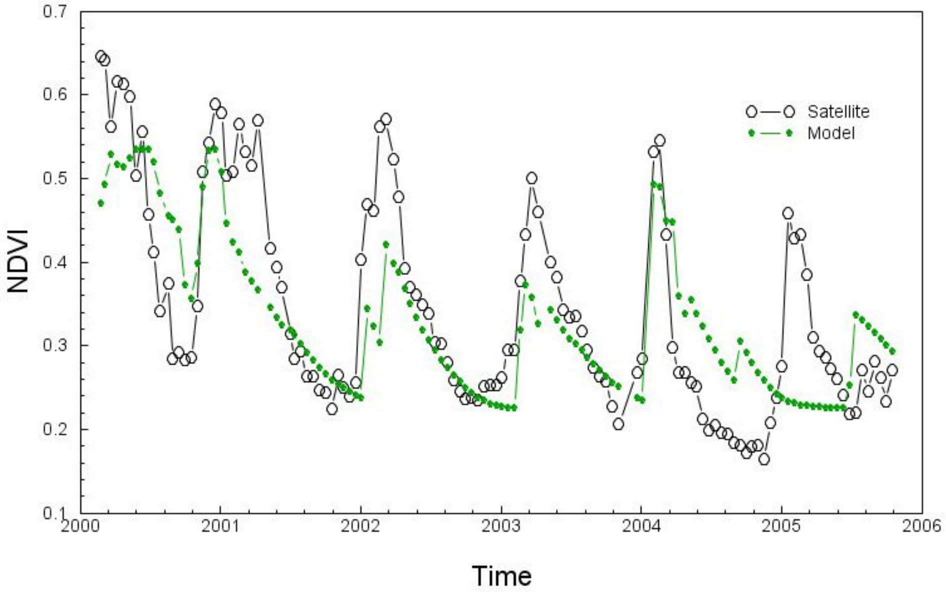

Figure 2: NDVI from MODIS for a single pixel and NDVI simulated from CEDAR

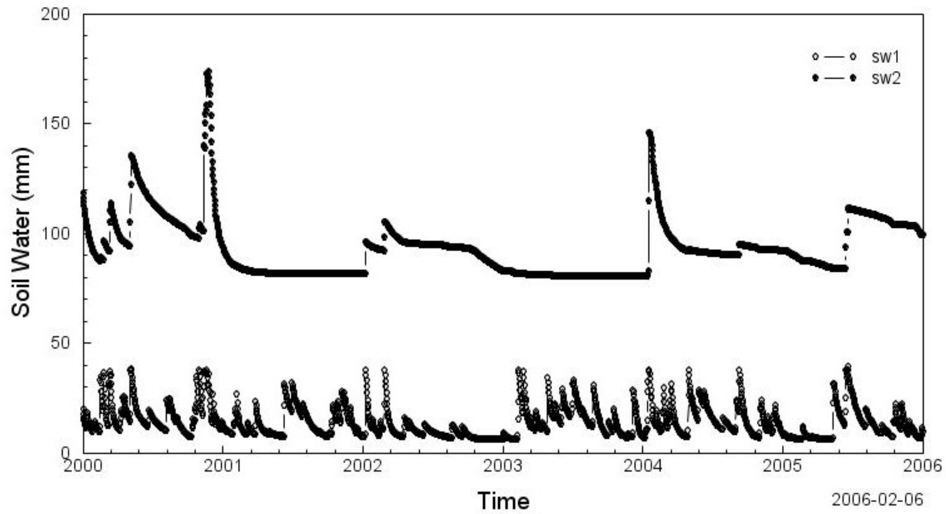

Figure 3: Soil water layers 1 and 2. Time series indicates missing and smearing of rainfall at this analysis scale

2. LANDSAT Ground Cover and AussieGRASS.

As part of this project LANDSAT BGI has been up-scaled to 5km and masked for tree cover, water cover and at the edge of the scene. An automated process has been developed to upscale several thousand LANDSAT scenes covering the 1987 to 2007 period and convert them to files that can be used in AussieGRASS.

Initial testing at large scales shows that the model and LANDSAT cover estimates are quite similar and show significant dynamics Figure (4).

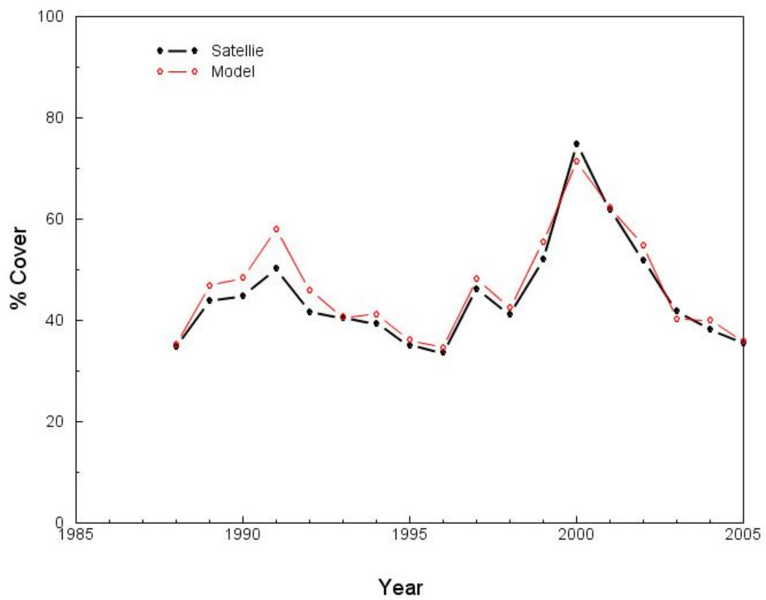

Figure 4: Ground cover estimated from Landsat and AussieGRASS, some calibration of AussieGRASS pasture communities using the mean cover for 1990 to 2002 was necessary.

9.8 Prospects for downscaling MODIS 1km ground cover data

Statistical downscaling

It is possible to view the landsat ground cover estimates that make up a 1km MODIS pixel as a frequency distribution in either a raw (Figure 1) or accumulated form (Figure 2) . While there is a range of distribition shapes most can be converted to a cumulative frequency distribution described by a 3 parameter sigmoid equation. The three parameters represent the mean, a shape parameter and a maximum value (usually 100%). The mean has already been predicted by MODIS but there is potential to estimate the shape parameter using independent equations derived from MODIS that decribe something about the patchyness of the pixel. Potentially a MODIS cover product could contain information on the mean and distribution of cover estimates. An alternative and untested method may be to “bump” or apply a trend to the landsat cover estimates using MODIS layers in time, so the LANDSAT view of underlying patern of cover is preserved.

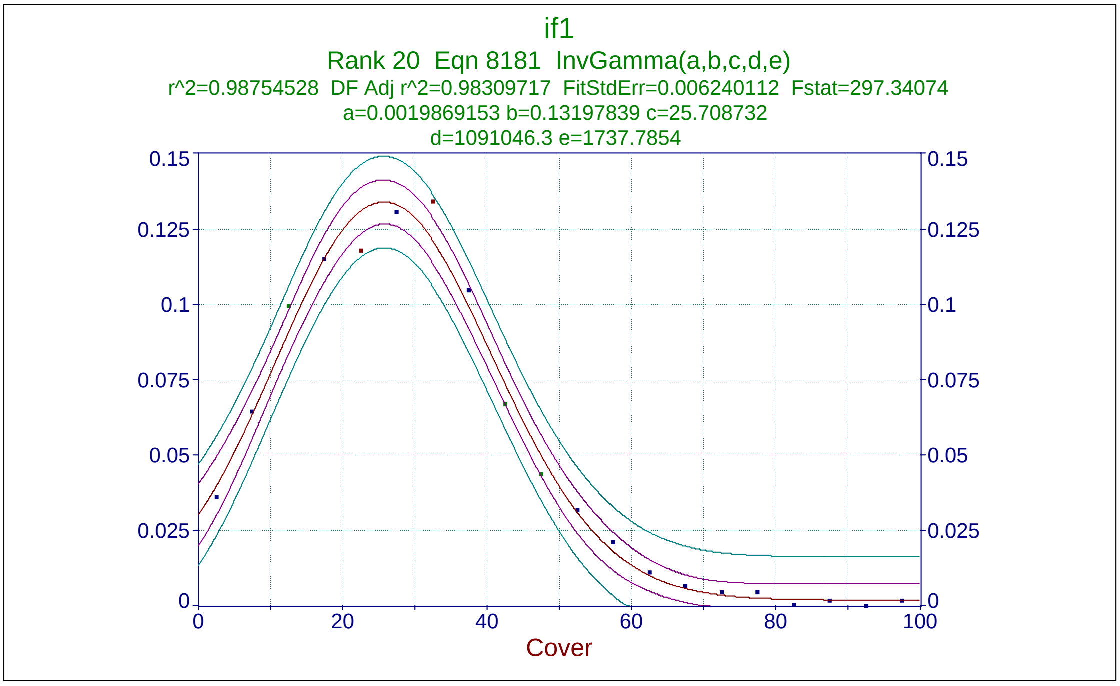

Figure 1: Raw frequency as a percentage for bare ground, the most common bare ground amount is about 24% (Site 31 June 2003)

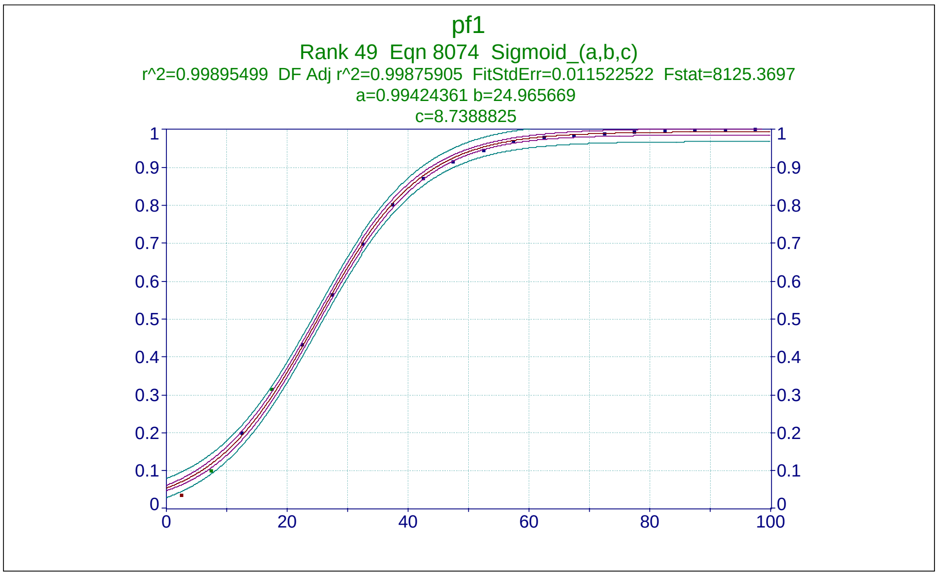

Figure 2: Cumulative frequency as a percentage for bare ground (Site 31 June 2003), 100% of LANDSAT pixels have 100% cover or less, 20% of LANDSAT pixels have a cover of 33% or less.

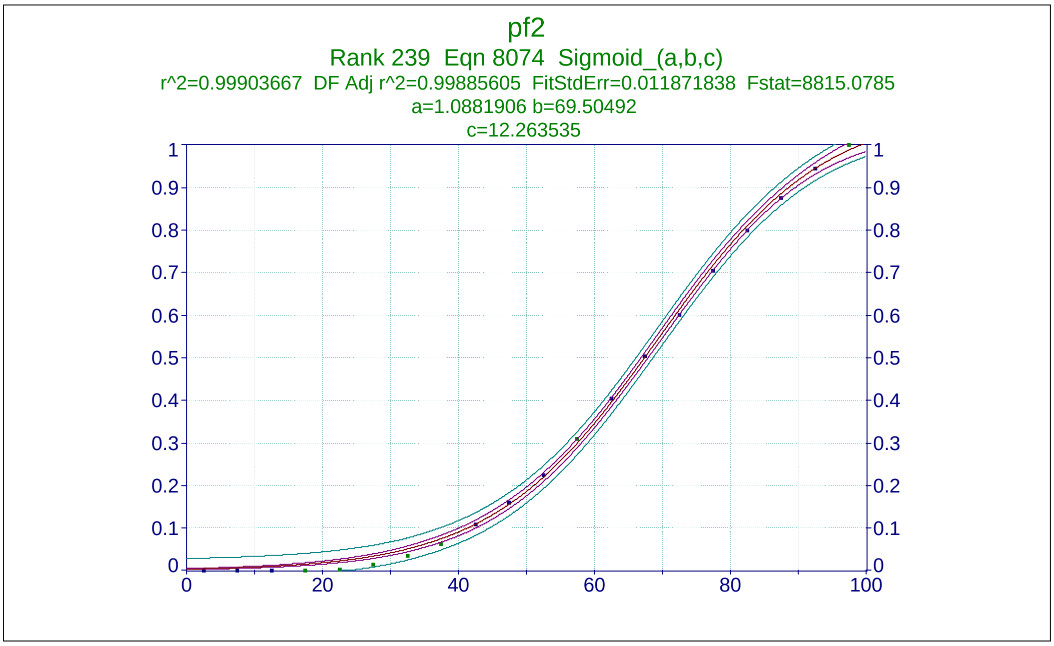

Figure 3: Cumulative frequency as a percentage for bare ground (Site 31 July v2003)

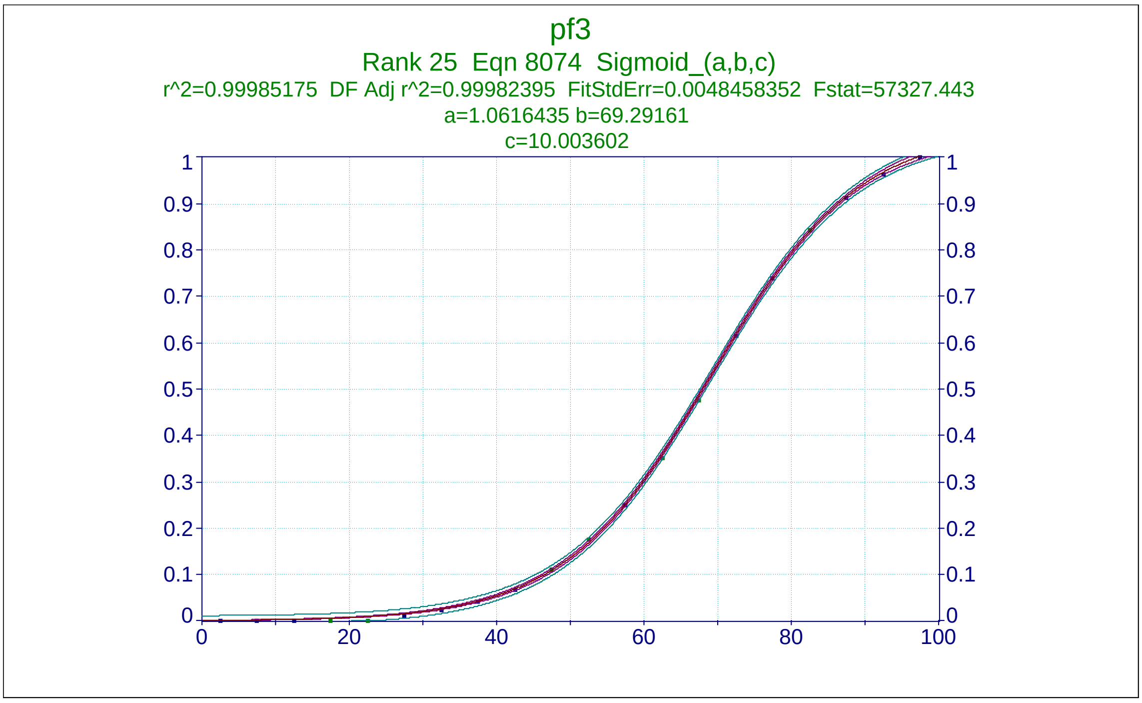

Figure 4: Cumulative frequency as a percentage for bare ground (Site 31 April 2004)

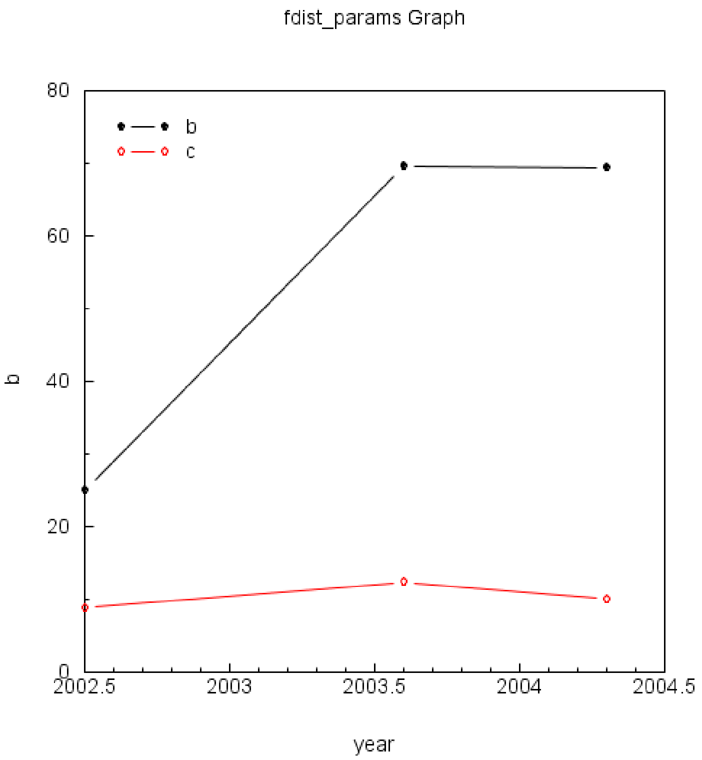

Figure 5: Change in parameters over time, (b mean cover) and c shape parameter for MODIS site 31