Final Report – Volume 1

Remotely sensed and modelled pasture biomass, land condition and the potential to improve grazing-management decision tools across the Australian rangelands

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The content of this report builds on information presented at a MLA and CRC for Spatial Information sponsored workshop held in Brisbane in November 2014 around the science of using remote sensing and modelling, and related technologies for making better decisions on safe carrying capacity. That workshop also considered research priorities for further developing prospective methods for monitoring pasture biomass remotely and adjusting stocking rate accordingly.

Key contributors from the different sectors of the northern beef industry included:

- Gerard Davis, General Manager of Innovation and Technology, Australian Agricultural Company (AACo). This large corporate beef producer is seeking timely data to increase its efficiency as a beef producer while meeting its statutory requirements to maintain the condition of natural resources on its leases and assure the public that it is a socially responsible company.
- Representatives from the production-based and resource-management agencies in Queensland, the Northern Territory and Western Australia.
- Researchers from State Government, universities, CSIRO and the CRCSI. Additionally, TERN AusCover[1] and the Joint Remote Sensing Research Program[2] (JRSRP) have been instrumental in developing remote-sensing methods and capacity relevant to managing natural resource across Australia.
- Enabling agencies: (i) MLA who funded the workshop and otherwise contributed to this report and (ii) the Australian Bureau of Agricultural & Resource Economics & Sciences (ABARES) that contributed significantly to calibrating and validating the MODIS fractional-cover product for Australia.

Gary Bastin, John Carter, Joe Scanlan and Phil Tickle were the major contributors to this report. We would like to thank Cameron Allan in particular, and others that have provided critical comments on this report.

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[1] The AusCover facility provides access to remote sensing data and derived products, associated with land-surface characteristics and biophysical variables derived from satellite and airborne imagery. The facility also provides access to a wide, national network of experts in the field, as well as field methodology protocols and in-situ data for use in ecosystem science and natural resources management. Further information at http://www.auscover.org.au/ (accessed 6 April 2015).

[2] The JRSRP is a collaborative program that combines research, research training expertise and infrastructure from the University of Queensland's Biophysical Remote Sensing Group with remote sensing groups supporting the Queensland, NSW and Victorian governments. The NT Government currently has a formal association with the program. More information at http://www.gpem.uq.edu.au/jrsrp (accessed 6 April 2015).

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Abbreviations and acronyms

3P grasses	Perennial, productive and palatable grasses
AACo	Australian Agricultural Company
ABARES	Australian Bureau of Agricultural & Resource Economics & Sciences
ACRIS	Australian Collaborative Rangelands Information System
AGB	Above Ground Biomass
AGGB	Above-Ground Green Biomass
ALOS PALSAR	Advanced Land Observing Satellite carrying the PALSAR Synthetic Aperture Radar instrument
ANPP	Above-ground Net Primary Production
AOS	Active Optical Sensing
APSIM	Agricultural Production Systems sIMulator
ASRIS	Australian Soil Resource Information System
AussieGRASS	Australian Grassland and Rangeland Assessment by Spatial Simulation
AVHRR	Advanced Very High Resolution Radiometer
BS	Bare Soil
C:N ratio	Carbon to Nitrogen ratio
CRC-REP	Cooperative Research Centre for Remote Economic Participation
CRCSI	Cooperative Research Centre for Spatial Information
CSIRO	Commonwealth Scientific and Industrial Research Organization
CV	Coefficient of Variation
CY	Comparative Yield
DEM	Digital Elevation Model
DM	Dry Matter
DOI	Data Object Identifier
DRCM	Dynamic Reference Cover Method
DSS	Decision Support System
ESA	European Space Agency
EVI	Enhanced Vegetation Index
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
FAT-CHOP	Forage Assessment Tool û Calculating Head On Pasture
FOO	Feed On Offer
FPAR	Fraction of Photosynthetically Absorbed Radiation
FPC	Foliage Projective Cover
GCI	Ground Cover Index
GDM	Green Dry Matter
GEO	Group on Earth Observations
GEOGLAM	Global Pasture and Rangelands Productivity Monitoring
GFOI	Global Forest Observations Initiative
GIS	Geographic Information System
GLAS	Geoscience Laser Altimeter System
GLM	Grazing Land Management
GOFC-GOLD	Global Observation of Forest and Land Cover Dynamics
GPP	Gross Primary Production
GPS	Global Positioning System
GRASP	pasture growth model
GSL	Growing Season Length
hd	head (as in individual beast)
HH	Horizontal-Horizontal radar backscatter
HSC	Herbage Standing Crop
HV	Horizontal-Vertical radar backscatter
IAM	Integrated Assessment Modelling
IBRA	Interim Biogeograpghic Regionalization for Australia
ICESat	Ice, Cloud and land Elevation Satellite
iNDVI	time-integrated NDVI

JAXA	Japanese Aerospace Exploration Agency
JRSRP	Joint Remote Sensing Research Program
LCC	Livestock Carrying Capacity
LCCA	Land Cover Change Analysis
LCC	Livestock Carrying Capacity
LIBRIS	Land Image-Based Resource Information System
LSU	Large Stock Unit
LUE	Light Use Efficiency
LWG	Liveweight Gain
MDA	Mobile Device Application
MLA	Meat and Livestock Australia
MODIS	MODerate resolution Imaging Spectroradiometer
MSS	Multi-Spectral Scanner
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NIR	near-infrared
NIRS	Near-InfraRed Spectrum
NPP	Net Primary Productivity
NPV	Non-Photosynthetic Vegetation
NRM	Natural Resource Management
NSW	New South Wales
NT	Northern Territory
NVIS	National Vegetation Information System
NZ	New Zealand
OPPIS	On-line Property Planning and Information System
PAR	Photosynthetically Active Radiation
PV	Photosynthetic Vegetation
Qld	Queensland
Qld DAFF	Queensland Department of Agriculture, Forestry and Fisheries
Qld DSITI	Queensland Department of Science, Information Technology and Innovation
RAPP	Rangelands and Pasture Productivity
RFID	Radio Frequency IDentification
RLMS	Remote Livestock Management System
RMSE	Root Mean Square Error
SA	South Australia
SGS	Sustainable Grazing Systems
SH	Stubble Height
SLA	Statistical Local Area
SOS	Start of the growing season
SPOT	Satellite Pour l'Observation de la Terre (French-operated earth observing satellite)
SR	Stocking Rate
TERN	Terrestrial Ecosystem Research Network
TIN	Time-integrated NDVI
TLS	Terrestrial Laser Scanner
TM	Thematic Mapper instrument carried by the Landsat series of satellites
TSDM	Total Standing Dry Matter
UAV	Unmanned Aerial Vehicle
UNE	University of New England
USGS	United States Geological Survey
WA	Western Australia
WARMS	Western Australian Rangeland Monitoring System

1 Introduction

A profitable and environmentally sustainable beef industry is critical to the continued socio-economic and cultural well-being of northern Australia (Anon. 2012). Yet recent beef situation analyses conducted for Meat and Livestock Australia (MLA) report that the majority of Northern Beef producers are currently not economically sustainable as they are not able to fund present and future liabilities (McLean et al. 2014). Profit after interest is decreasing, and is mostly negative, as a result of increasing debt with no increase in profits. Clearly, change must occur to improve on this situation and Holmes (2015) argues that “lack of financial literacy and business skill remains the biggest impediment to most pastoralists achieving financial sustainability in their businesses”. Despite this bleak conclusion, both McLean et al. (2014) and Holmes (2015) demonstrate that pastoralists have adopted relevant technology with the latter providing ten examples relevant to herd productivity and a further ten illustrating wider practice-change (e.g. the internet for commerce, satellite phones for communication and “Grazing Land Management research and application that has provided a greater understanding of, and potential to better manage, pastoral landscapes”).

An important component of Grazing Land Management (GLM) extension has been (i) recognition of climate variability (including drought), (ii) the importance of long-term safe carrying capacity (for each productive land type) to assist sustainable management of the natural resource base and (iii) achieving the preceding with shorter term matching of livestock numbers to available forage (seasonal stocking rate) (Chilcott et al. 2005). Estimating both safe carrying capacity and correct seasonal stocking rate has been assisted through the ability to model expected pasture growth from variable amounts of rainfall. As the check on whether grazing management is improving, remote sensing methods are increasingly being used by government agencies to monitor the dynamics of different components of vegetation cover and thereby complement related ground-based methods to monitor land condition. These remotely-sensed products are increasingly being distributed to regional Natural Resource Management (NRM) groups and interested pastoralists (including corporates) with image analysis supported by software and training such as VegMachine (Beutel et al. 2015) and initiatives of the developing NRM Spatial Hub (www.nrmhub.com.au, accessed 28 June 2015).

Essentially, vegetation cover derived from remote sensing provides a two-dimensional view of the earth’s surface. In practice though, including the third dimension (height or bulk) to estimate pasture biomass should assist pastoralists in their stock and pasture management. This could operate at two levels: calculated increase in stocking rate in better seasons (based on known forage availability) and corresponding prudent reduction in stock numbers as forage declines towards threshold levels. An integrated system of modelled and monitored pasture biomass, complemented by adequate ground-truth data, should provide land managers with improved information to better manage their natural resource under continuing climate variability. As of now, we lack the ability to accurately and consistently monitor pasture biomass across the diverse rangelands of northern Australia.

This report assesses the potential for expanding on current capacity to monitor land condition using remotely sensed fractional cover products to improve biomass estimation, animal productivity, pasture growth models and grazing decision tools (e.g. safe carrying capacity) across the Australian rangelands. We focus on northern Australia and include relevant research and implementation from southern Australia where appropriate.

1.1 Characteristics of the northern beef industry

The northern beef cattle industry occupies approximately 60 per cent of the land area across the north and generated an estimated value of production at the farm gate of $3.7 billion in 2009-10 (Gleeson et al. 2012).

Much of the grazed area of northern Australia is rangeland held under pastoral leasehold (Fig. 1-1). There is a large range in regional[3] stocking density (Fig. 1-2) which varies from year to year, particularly with the effectiveness of wet-season (November to April) rainfall and markets (i.e. turn-off). Allowing for this inter-annual variability, cattle numbers have increased appreciably over parts or all of the last three decades in some bioregions (examples shown in Fig. 1-3) and remained relatively stable elsewhere (mainly in the more arid interior and the Kimberley).

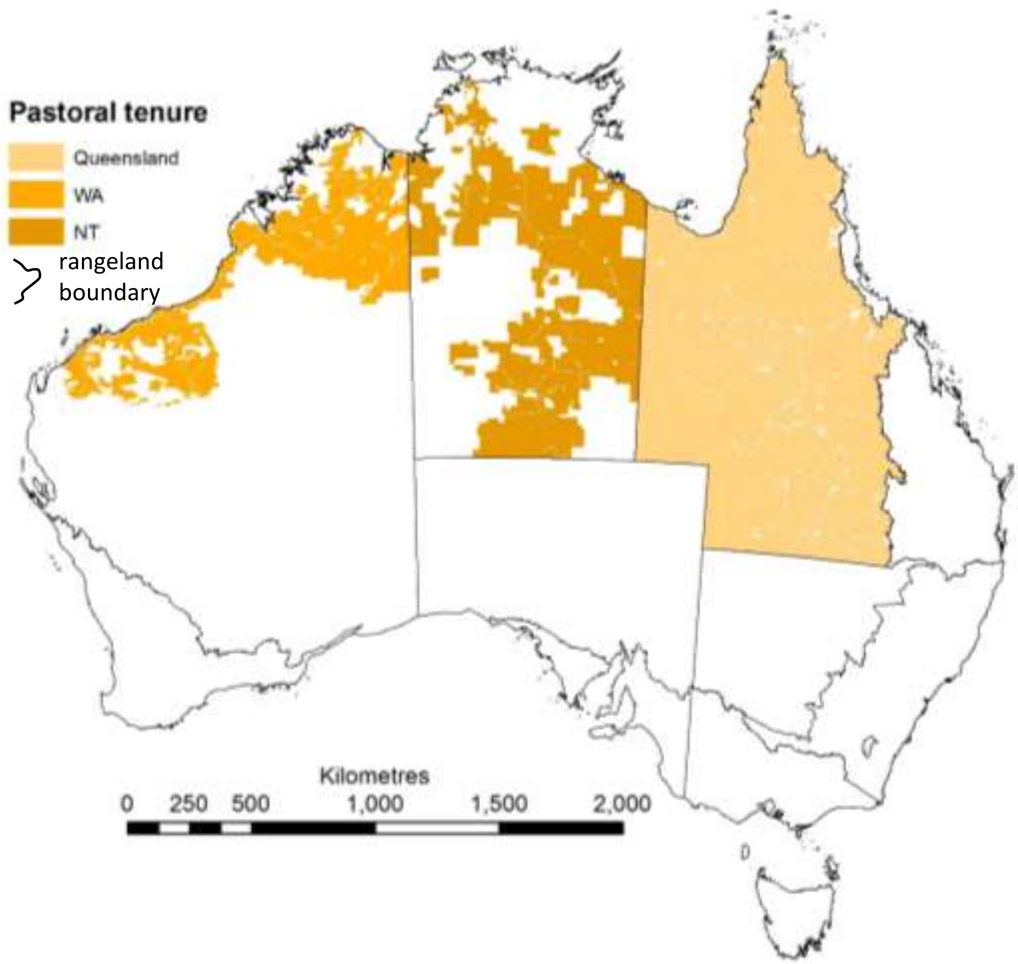
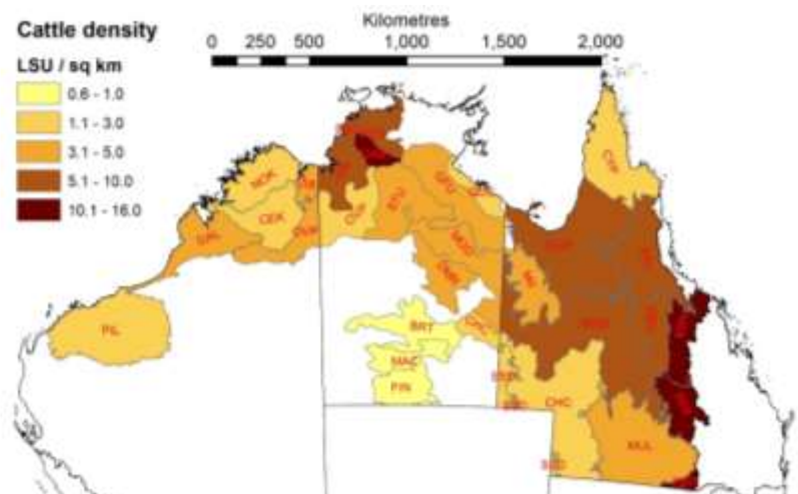


Figure 1-1. Pastoral tenure by state and the Northern Territory in northern Australia. Mapping in Queensland is confined to the rangelands as defined by the ACRIS[4] Management Committee.

[3] Describe and define IBRA as regionalisation – used by ACRIS

[4] ACRIS: Australian Collaborative Rangelands Information System (see http://www.environment.gov.au/land/rangelands/acris, accessed 13 March 2015).



Bioregions

WA	NT	QLD
CEK Central Kimberley	BRT Burt Plain	BBN Brigalow Belt North
DAL Dampierland	CHC Channel Country	BBS Brigalow Belt South
NOK Northern Kimberley	DAB Daly Basin	CHC Channel Country
OVP Ord Victoria Plain	DAC Darwin Coastal	CYP Cape York Peninsula
PIL Pilbara	DMR Davenport Murchison Ranges	DRP Darling Riverine Plains
VIB Victoria Bonaparte	FIN Finke	DEU Desert Uplands
	GFU Gulf Fall & Uplands	EIU Einasleigh Uplands
	GUC Gulf Coastal	GUP Gulf Plains
	MAC MacDonnell Ranges	MGD Mitchell Grass Downs
	MGD Mitchell Grass Downs	MII Mount Isa Inlier
	OVP Ord Victoria Plain	MUL Mulga Lands
	PCK Pine Creek	SSD Simpson Strzelecki Dunefields
	STU Sturt Plateau	
	VIB Victoria Bonaparte	

Figure 1-2. Cattle density (as large stock units, LSU) per northern bioregion based on the 2011 Agricultural Census. Livestock numbers were concorded from Statistical Local Areas (SLA) to corresponding IBRAs by John Carter (Qld DSITI) to facilitate ACRIS reporting of change in livestock density. SLA is the reporting regionalization used by the Australian Bureau of Statistics.

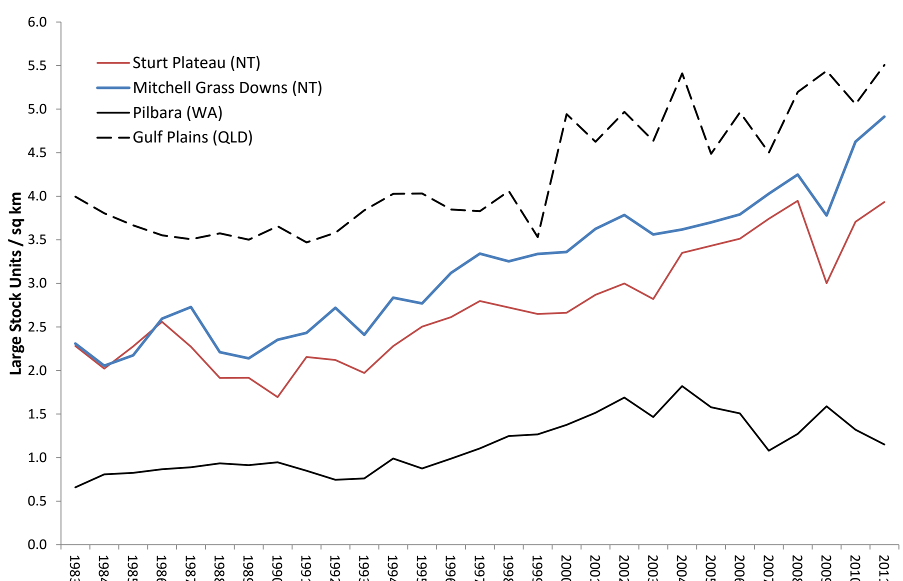


Figure 1-3. Change in cattle density, 1983 to 2011, for example northern bioregions. Data adapted from Agricultural Censuses and surveys conducted by the Australian Bureau of Statistics.

1.1.1 Climate

Regional stocking densities across northern Australia are a function of inherent landscape productivity (particularly that of pastures) and climate variability (mainly rainfall) (Fig. 1-4). Features of annual rainfall relevant to reliable monitoring and modelling of vegetation cover and biomass include:

- Decreasing mean annual rainfall towards the arid interior and in the Pilbara region (Fig. 1-4a).
- Although the variability of rainfall decreases with mean annual amount (Fig. 1-4b) the coefficient of variation has the reverse trend. This pattern is accentuated by mapping the coefficient of variation (CV) against mean annual rainfall (Fig. 1-4c) where most bioregions map on a colour gradient of dark brown (higher mean annual rainfall and low inter-annual variability relative to the mean) to yellow (low mean annual rainfall and high CV).
- Decreasing seasonality of annual rainfall with increasing latitude, mainly related to reduced monsoonal rainfall (Fig. 1-4d).

The components of this figure clearly show that a remotely sensed method for monitoring pasture biomass must be suitably robust to deal with a wide range of probable biomass levels related to the amount of annual rainfall, considerable inter-annual variability in growth and a broad range of phenological conditions (i.e. growth outside of the summer period in inland Australia).

1.1.2 Soils

Based on spatially dominant soil texture of the A horizon, the pastoral lands of northern Australia are predominantly sands, sandy loams and loams (Fig. 1-5). Sandy surface soils predominate in central Australia, the Kimberley, Gulf and Cape York regions. Clay soils predominate In the Mitchell Grass Downs and also occur widely in the Channel Country bioregions. Loamy surface soils characterize the Mulga Lands and Mount Isa Inlier in Queensland, the Pilbara (WA), and Daly Basin, Sturt Plateau and Burt Plain bioregions in the NT. Loamy surface soils also occur extensively in several other NT bioregions (Davenport Murchison Ranges, Channel Country, Finke, Pine Creek, Ord Victoria Plain), the Einasleigh and Desert Uplands, Brigalow Belt North, Channel Country, Cape York Peninsula and Gulf Plains in Queensland and the Ord Victoria Plain bioregion in WA.

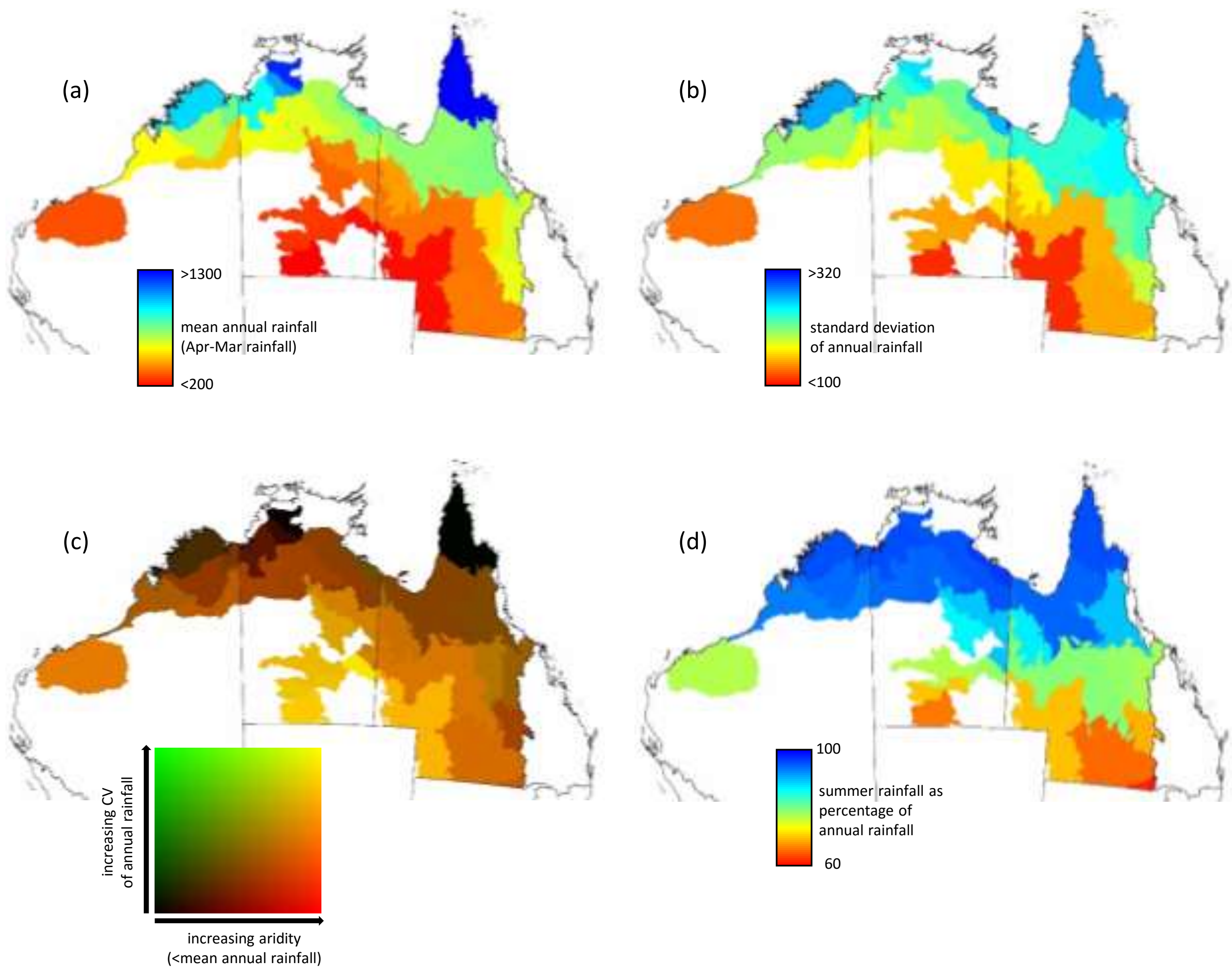


Figure 1-4. Patterns in regional rainfall and its variability and seasonality across northern Australia: (a) is mean annual rainfall for pastoral bioregions, (b) the standard deviation of annual rainfall, (c) the combined mean and CV of rainfall and (d) seasonality. Annual rainfall is April to March to avoid splitting summer wet-season rainfall across two calendar years. Rainfall is spatially averaged for each bioregion. Data source: Bureau of Meteorology.

Using the simple criterion that available nutrients and soil water availability broadly control vegetation growth, the biomass of palatable forage is likely to be greatest where clay soils occur. The supply of palatable pasture probably declines as the surface soil becomes increasingly loamy and then sandy. On this basis, Fig. 1-5 provides a crude approximation of inherent productivity for beef production.

This figure indicates, at broad regional scale, where accurate modelling of pasture biomass could be most beneficial. Separate to this, texture contrast and loamy soils are generally more erodible with Fig. 1-5, again, crudely indicating priorities for regional monitoring activity.

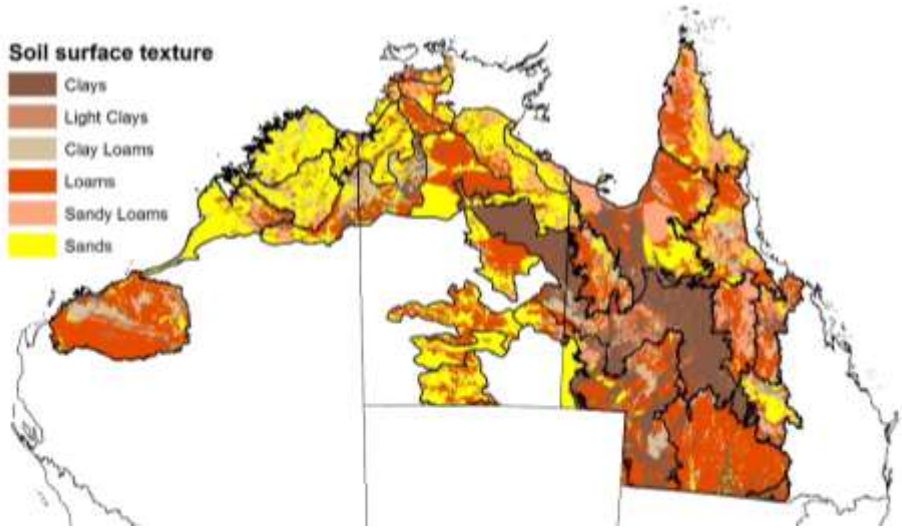


Figure 1-5. Spatially dominant soil-surface texture within northern pastoral bioregions (black lines, see Fig. 1-2 for IBRA names). Source data: ASRIS (the Australian Soil Resource Information System).

1.1.3 Vegetation

Vegetation types across the pastorally important northern bioregions were formed from subgroups of the NVIS[5] Major Vegetation Groups (Fig. 1-6, Table 1-1). Where grasslands dominate, there is broad spatial correspondence between soil surface texture (Fig. 1-5) and vegetation type; i.e. tussock grasses are associated with clay and loam soils, and hummock grasses grow on sands.

In broad terms:

- Tussock grasslands comprise greater than 60% of the area of the Mitchell Grass Downs bioregion and 20-30% of the Ord Victoria Plain, Queensland Channel Country and Gulf Plains, and the Finke bioregion in the southern NT.
- Hummock grasslands occupy 20-50% of the Ord Victoria Plain, Pilbara and Central Kimberley IBRAs in WA, and the Finke, Burt Plain and Channel Country IBRAs in the southern NT.
- Low open woodlands with tussock grasses are a minor component (10-20%) of the Mulga Lands (Qld) and Channel Country (Qld & NT).
- Low open woodlands with hummock grasses are moderately extensive (45% of area) in the WA Dampierland and a minor part (10-20%) of the Pilbara and Ord Victoria Plain (WA) and the MacDonnell Ranges (NT).
- Mulga woodland with tussock grasses covers close to 40% of the Mulga Lands and 13% of the adjoining Channel Country (Qld).
- Other acacia shrublands co-dominate (40-60% of area) in the southern NT (Burt Plain, MacDonnell Ranges and Channel Country IBRAs) and are less common in the Finke (NT) and Pilbara (WA) IBRAs (10-15% of area).

[5] NVIS: National Vegetation Information System (see http://www.environment.gov.au/land/native-vegetation/national-vegetation-information-system, accessed 15 March 2015.

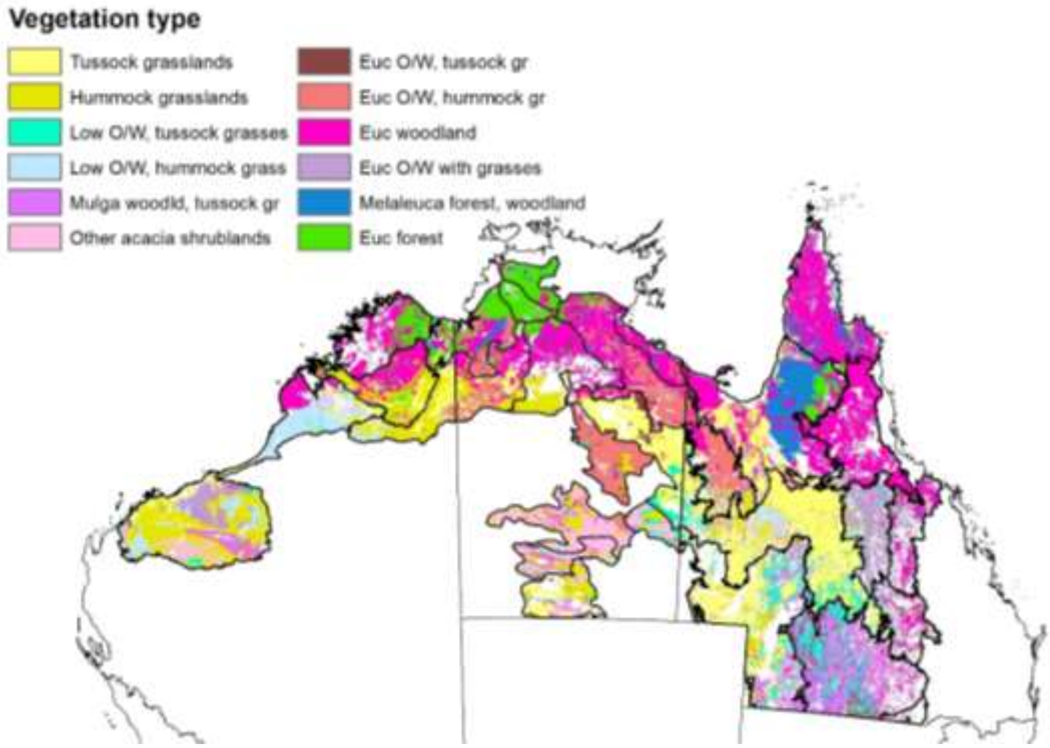


Figure 1-6. Major vegetation types across pastorally important bioregions in northern Australia. Vegetation types were formed from selected sub-groups of the NVIS Major Vegetation Groups (see Table 1.1). Black lines show IBRA boundaries (see Fig. 1-2 for names).

- Eucalypt open woodlands with tussock grasses are a common feature of the Gulf Plains, Qld (~40% of area).
- Eucalypt open woodlands with hummock grasses characterize the Davenport Murchison Ranges (~75% of area) and are also an important component (20-50% by area) of the Mt Isa Inlier (Qld), Gulf Fall & Upland, Victoria Bonaparte, Ord Victoria Plain and MacDonnell Ranges IBRAs in the NT.
- Eucalypt woodlands occur extensively across the savanna region of northern Australia. They comprise 65-70% of the Einasleigh Uplands and Cape York Peninsula IBRAs in Qld and the Gulf Coastal IBRA (NT). Between 20-50% of the area of a further ten bioregions have this vegetation type.
- Eucalypt open woodland with grasses cover 60% of the Desert Uplands bioregion (Qld). The vegetation type is also recognizable in the WA Pilbara (~15% of area).
- Eucalypt forests occur extensively in the NT Top End (occupying 75-80% of the Daly Basin and Pine Creek IBRAs). They are also common (20-40% of area) in the Northern Kimberley (WA) and Victoria Bonaparte regions (WA & NT).
- Melaleuca forest and woodland occupies 12-25% (by area) of the Gulf Plains and Cape York Peninsula IBRAs (Qld).

Table 1-1. NVIS vegetation subgroups combined to form vegetation types.

Vegetation type	NVIS subgroups
Tussock grassland	34 Mitchell grass (Astrebla) tussock grasslands 35 Blue grass (Dichanthium) and tall bunch grass (Chrysopogon) tussock grasslands 37 Other tussock grasslands
Hummock grassland	33 Hummock grasslands
Low open woodlands with tussock grasses	22 Arid and semi-arid acacia low open woodlands and shrublands with chenopods 24 Arid and semi-arid acacia low open woodlands and shrublands with tussock grass
Low open woodlands with hummock grasses	23 Arid and semi-arid acacia low open woodlands and shrublands with hummock grass
Mulga woodland with tussock grasses	20 Mulga (Acacia aneura) woodlands with tussock grass
Other acacia shrublands	21 Other Acacia tall open shrublands and shrublands
Eucalypt open woodlands with tussock grasses	19 Eucalyptus low open woodlands with tussock grass
Eucalypt open woodlands with hummock grasses	18 Eucalyptus low open woodlands with hummock grass
Eucalypt woodlands	8 Eucalyptus woodlands with a shrubby understorey 9 Eucalyptus woodlands with a grassy understorey
Eucalypt open woodland with grasses	48 Eucalyptus open woodlands with a grassy understorey
Eucalypt forests	5 Eucalyptus open forests with a grassy understorey 7 Tropical Eucalyptus forest and woodlands with a tall annual grassy understorey
Melaleuca forest and woodland	15 Melaleuca open forests and woodlands

Mapped vegetation types (Fig. 1-6) viewed in combination with a simple display of soil surface features (Fig. 1-5) and rainfall variability (Fig. 1-4) illustrates that robust methods are required to reliably model and remotely monitor pasture biomass across the diverse biophysical environment of north Australian pastoral regions.

1.2 Pasture biomass, safe carrying capacity and land condition

1.2.1 Definitions

In its simplest sense, **pasture biomass** is the mass (dry weight) of herbage species (pasture) above the ground surface, per unit area (generally, per hectare). This may be of two forms: total standing dry matter (TSDM) or pasture growth for that year (annual growth) or season. The green, photosynthetically-active, component of biomass is generally most nutritious for livestock. Where there is a regular or defined growing season, a derived parameter is the rate at which new pasture accumulates, i.e. growth rate for a defined period.

Long-term **safe carrying capacity** is the number of livestock that an area of land can carry over the long-term (>10 years) without causing a decline in land condition.

Land condition describes the health of grazed rangeland relative to a benchmark or reference area that has been minimally disturbed by past grazing.

1.2.2 Ground-based and modelling approaches to estimating / simulating pasture biomass

1.2.2.1 Ground-based methods

There is a long history of estimating pasture-biomass using ground-based methods in Australia's savanna landscapes. BOTANAL (Tothill et al. 1992) or similarly adapted comparative yield techniques have been most commonly used. Two of the more recent applications include ongoing estimation of pasture biomass by O'Reagain et al. (2009) in ten 1 km^2 paddocks of the Wambiana grazing trial (south of Charters Towers) and, at larger scale, biomass estimation using 2-m square virtual quadrats in 13 paddocks of 9-57 km^2 at Pigeon Hole (NT Victoria River District) (Hunt et al. 2013).

Issues associated with monitoring pasture biomass at paddock-scale using ground-based methods include (Peter O'Reagain[6], pers. comm.):

- Variability within and between soil types.
- Field-based classification of soil types, as a covariate, is difficult (quadrat-scale, local decisions are required, separate to available mapping of soil type at coarser scale).
- Local variability contributes to generally large standard errors around estimated mean yield.
- Consistent operator differences exist, even with rigorous training and cross-calibration.
- There are inevitable differences in the transect path for each year, adding further spatial variation to estimates across years.

The end result is that paddock-scale yield estimates are often inexact due to the realities of spatial variability in land / soil types and associated biomass, and the logistical limit to sampling intensity.

There are promising research results however that indicate that the preceding issues can be addressed and, to some extent, alleviated. Of particular relevance here is collaborative research by partners in the Cooperative Research Centre for Spatial Information (CRCSI) who are developing and testing methods

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[6] Presentation by Peter O'Reagain at the November 2014 Brisbane workshop 'Using Remote Sensing and related technologies for making better decisions on safe carrying capacity – the state of the science, and priorities for future investment'.

that will allow graziers to infer pasture biomass using proximal (near ground) remote sensing. It is intended that the remotely sensed data will be supported by appropriate calibrations to estimate biomass with the service being delivered on mobile devices such as a tablet or palm-top computer.

Currently in the commercial area of extensive pastoralism, more progressive managers are estimating forage availability at the end of the summer growing season to guide paddock-level carrying capacity through the dry season. For example, the Australian Agricultural Company (AACo) employs two rangeland officers (increasing to three in 2015) whose role includes assessment of paddock- and property-scale forage supply at the end of each wet season (Gerard Davis, pers. comm.). These staff then continue to monitor feed availability as the dry season progresses. The various levels of company management use this information to inform paddock-level stocking, inter-station transfers and turn-off to their feedlot and various markets. AACo is moving towards more precise rangeland management including more spatially dense and accurate monitoring of pasture availability.

1.2.2.2 Modelling

Rickert et al. (2000) provide a good overview of modelling pasture and animal production, although this reference is now somewhat dated. Here, we provide some introductory comments then provide more information, in section 3.4, on Australian approaches to modeling pasture biomass – including remote sensing input.

According to Carter et al. (2010), models of savanna and grassland systems in Australia serve two main purposes. Where run in near real-time, the results can assist decision making in applications such as public policy for situation analysis and State of the Environment reporting to climate risk assessments of pasture resources for tactical management of grazing and fire. The second aim is to improve scientific understanding of biophysical processes related to plant growth and disappearance, and to simulate probable long-term outcomes and risks of current management practices for strategic policy and planning purposes.

Models differ from ground-based measurement in both their spatial and temporal scales of application:

- They can provide both a retrospective view of past growth conditions using the historical climate record and the simulated future based on projected climate change.
- Models can be run at paddock scale (e.g. PaddockGRASP, Scanlan et al. 2013, Pahl et al. 2013) through to the whole continent (AussieGRASS, Carter et al., 2003).
- Various components of the vegetation can be simulated, e.g. leaf and stem components of woody vegetation, pasture biomass and cover.
- Model output can be linked to economic models (bio-economic modelling) to explore the financial implications of different management scenarios (e.g. Scanlan et al. 2013, 2014).

Although models allow vegetation dynamics to be investigated over larger spatial and temporal domains than ground-based data collection, good ground data are essential for suitably calibrating and validating most models.

1.2.3 Safe carrying capacity (strategic) and stocking rate (tactical)

Carrying capacity is the number of livestock (as standardized units, e.g. Large Stock Unit, LSU) that can be grazed on an area based on forage availability, the allowed level of pasture utilization and animal feed requirements (intake). That is:

$$\text{Carrying capacity} = \text{pasture} \times \text{utilisation} / \text{intake hd}^{-1} \times \text{area}$$

Long-term **safe carrying capacity** is the number of livestock that an area of land can carry over the long-term (>10 years) without causing a decline in land condition (McKeon et al. 2009). Where this stocking density can be accurately specified, it provides a reference point or benchmark for long-term strategic property planning and helps define a realistic property value.

Short-term (seasonal) carrying capacity is the stocking density that can be safely maintained over a period of months (typically, the dry season in northern Australia) whilst ensuring animal intake requirements are met. It is a tactical management tool to adjust stock numbers based on seasonal forage availability.

1.2.4 Land condition

Land condition is analogous to human health and the rating (or rank) given to an area is often subjective (and contentious). This uncertainty is increased in the arid rangelands where large fluctuations in the amount and timing of rainfall can produce considerable natural variation in the vegetation attributes used to judge condition. As such, it is often difficult to know which parts of the grazed rangelands are remaining stable, improving or deteriorating over time.

More robust approaches to monitoring the health of grazed rangelands use multiple robust indicators that separately, and combined, provide more reliable information from which to judge land condition. To the extent possible, quantitative data should be collected for each indicator.

1.2.4.1 GLM land condition

The Grazing Land Management (GLM) extension program (Department of Agriculture, Fisheries and Forestry 2013) provides guidelines to assist northern beef producers in understanding and better managing their grazing practices. 'Grazing land condition' is defined as "the capacity of land to respond to rain and produce useful forage, and is a measure of how well the grazing ecosystem is functioning" (MLA 2006). There are three components in rating ecosystem functionality:

1. Soil condition – the capacity of the soil to absorb and store rainfall, to store and cycle nutrients, to provide habitat for seed germination and plant growth, and to resist erosion;
2. Pasture condition – the capacity of the pasture to capture solar energy and produce palatable green leaf, to use rainfall efficiently, to conserve soil condition and to cycle nutrients; and
3. Woodland condition – the capacity of the woodland to grow pasture, to cycle nutrients and to regulate ground water.

The GLM package provides criteria for each of component to assess land into one of four condition classes (Table 1-2).

Table 1-2. The GLM 'ABCD' framework for assessing land condition (adapted from Department of Agriculture, Fisheries and Forestry 2013).

Features	Condition class			
	A: excellent	B: good	C: poor	D: very poor
Extent to which features apply	All present	One or more present		
Cover of 3P[7] grasses	Good	Some decline and an increase in less favoured grasses and/or weeds	General decline and large amounts of less favoured species	General lack of any perennial grasses or forbs
Percentage composition of 3P grasses (by biomass)	>80	60-80	10-60	<10
Percentage organic ground cover at the end of the dry season	>50	40-50	20-40	<20
Soil condition	Good	Some decline		
Erosion	Nil	Some signs of previous erosion and/or current susceptibility to erosion	Obvious signs of past erosion and/or high susceptibility to erosion	Severe erosion or scalding resulting in a hostile environment for plant growth
Woodland thickening	Only early signs or none	Some thickening in density	General thickening in density	Thickets of woody plants cover most of area

1.2.4.2 States and transitions

The GLM 'ABCD' land condition framework is a practical application of the state and transition theory developed by Westoby et al. (1989). Here, the singular or variously multiple criteria of soil and vegetation features described in Table 1-2 characterize states (equivalent to condition classes) that remain relatively stable within a range of climate variability, grazing pressure and other forms of disturbance (e.g. fire). An increase in grazing pressure for the same set of seasonal conditions (or maintaining the same stocking rate in a drought) may cause the landscape to transition to a more degraded state, depending on its inherent stability and/or resilience, where the latter is characterized by the ability of vegetation to recover when more favourable conditions return.

Provided landscapes have not crossed a degradation threshold, (typically, C to D condition), reducing the grazing pressure or a sequence of wetter years can facilitate the recovery of B- and C-condition land to an improved state. Recovering D-condition land through manipulating grazing pressure, e.g. wet-season spelling, is more problematic because of extensive erosion or woody thickening. Erosion control often requires earthworks to manage flows of rain water and increase on-site infiltration to restore the water cycle. The potential to use fire for thinning woody thickets is precluded due to limited grass growth and fuel accumulation.

A 1994 special issue of *Tropical Grasslands* proposed a set of state and transition models for pastorally important land types in northern Australia. Ash et al. (1994) provide some commentary on their collective value and limitations. One of their main advantages is in communicating the complexities of vegetation dynamics under a variable climate and stressors (grazing, fire, etc). Because of their

[7] Perennial, productive and palatable grasses.

conceptual nature, the states and transitions framework often fails to adequately deal with the spatial realities of paddock heterogeneity and uneven grazing distribution.

1.2.4.3 Change, rather than condition

While state and transition theory accommodates discontinuous and non-reversible vegetation change and is relevant to many grazed savanna land types, it is inadequate for the more arid and semi-arid regions experiencing highly variable, often episodic, rainfall with consequent non predictable vegetation responses under grazing. At its extreme, this non-equilibrium behaviour of the grazing system has been characterized by Ellis and Swift (1988, also Illius and O'Connor 1999) as having:

- Stochastic or highly variable abiotic patterns which result in variable conditions for plant growth.
- Weak coupling of plant-herbivore interactions.
- Population patterns that are largely density independent. This applies mainly to herbivores but is also true at a higher order in the food web. Thus the carrying capacity of the system is too dynamic for close tracking between the climate and populations. Rather than cycles being limit-driven, they are abiotically controlled.
- As a result, competition is not well expressed and external forces are critical to system dynamics.

The preceding describes the maximum expression of non-equilibrium behaviour and most rangeland ecosystems occupy an intermediate position somewhere between equilibrium and non-equilibrium behaviour, where the former largely conforms to the continuous and reversible principles of vegetation change under Clementsian succession.

Given recent debate about the relevance and suitability of current paradigms for understanding vegetation dynamics in parts of the rangelands (see Briske et al. 2003 for a review), some monitoring systems focus on vegetation **change** over time. This avoids the often fraught process of trying to 'shoe horn' assessments into ill-fitting and often arbitrary condition classes. Causality is a fundamental component of understanding change; in this case, determining the most plausible reasons for observed change, be they climate-related or due to grazing, fire or other forms of disturbance.

The Western Australian Rangeland Monitoring System (WARMS, Watson et al. 2007a, Novelly et al. 2008) is arguably the most recognized and sophisticated site-based monitoring system for reporting regional scale change in perennial vegetation under grazing. WARMS has separate methodologies for monitoring grasslands in northern WA (recent results reported in White et al. 2014) and shrublands in the central and southern WA rangelands (see Watson et al. 2007b for example results and interpretation of change).

1.2.4.4 ACRIS reporting of change

The Australian Collaborative Rangelands Information System (ACRIS) operated between 2003 and 2014 to facilitate collation, analysis and interpretation of change in available data relevant to biophysical and socio-economic attributes in the rangelands. It used data contributed by agency-based monitoring programs (such as WARMS) to report change in ecosystem functioning in the grazed rangelands. This reporting was structured around indicators of:

1. Landscape function as defined and used by Ludwig et al. (1997): i.e. the capacity of land to capture and retain rainwater and soils, and their nutrients—resources that are vital for plant

growth and where in turn plants provide the food and shelter required by animals who provide ecosystem services such as pollination. A critical component of landscape function is the maintenance of an adequate ground cover to protect the soil surface against erosion in dry and drought years.

2. Critical stock forage – the palatable, perennial forage species that maintain (sustain) livestock through the inevitable droughts that characterize the semi-arid and arid rangelands.
3. Tree-grass balance where declining functionality is commonly characterized by woody thickening that usually suppresses long-term pasture growth through competition and, more rarely, by woody loss that may adversely impact landscape stability and supply of ecosystem services.

Confidence in separating grazing effects on vegetation is enhanced where 'slow' variables are monitored and attention is focused on change that is intuitively counter to that caused by variation in climate (mainly rainfall). Examples of slower variables include:

- Basal cover of the herbage layer; it is less affected by short-term variation in rainfall and level of pasture utilization than aerial (or canopy) cover.
- Similarly, the basal area of woody vegetation is a better indicator of long term change than canopy cover as it is less affected by drought and low-intensity fires that can cause considerable leaf fall (i.e. temporary reduction in canopy cover or foliage projected cover).
- The composition (or amount) of perennial pasture species, as distinct from that of all species.

There are practical aspects to technical consideration of monitoring issues though. Passive remote sensing (e.g. the Landsat TM and MODIS sensors) 'see' aerial / canopy cover rather than the basal cover which better protects the soil surface against erosion. Thus, trade-offs are required between the theoretically most desirable vegetation attributes to be monitored and the practical realities of repeatedly doing so across large areas in an efficient and cost-effective manner.

1.2.4.5 Seasonal quality as an aid to understanding change

The seasonal quality matrix used by ACRIS (also WARMS) focused attention on unexpected change (Fig. 1-7). Here, site-level change based on indicators was interpreted with respect to 'seasonal quality'; rainfall above-average, average or below-average prior to the most recent assessment. A decline in indicator value following above-average rainfall or an increase following below-average rainfall strongly suggest non-rainfall related causes. The former is often associated with enhanced fire activity while the latter suggests favourable land management practices.

Notwithstanding the complexity of monitoring land condition, a simple ranking system with its associated guidelines for application does have considerable communication value and can assist pastoralists in broadly understanding and assessing the effects of their land management. This has been well demonstrated in Queensland through the Grazing Land Management training module (e.g. Chilcott et al. 2005) where grazed landscapes are ranked between A (least altered) and D (most impacted) condition based on the amount and composition of palatable perennial forage, evidence of soil erosion and weeds, and woody thickening. Experience has demonstrated that this largely subjective approach to assessing land condition is more robust in the northern rangelands where annual rainfall is higher and more reliable, and palatable perennial grasses are a major component of productive pastures.

Seasonal conditions	Decline	No Change	Increase
Above average	XX	X	~
Average	X	~	√
Below average	~	√	√√

Figure 1-7. Seasonal quality matrix used by ACRIS for summarizing site-level change in condition indicators with respect to rainfall amount. The upper-left and lower-right 'traffic lights' focus attention on those groups of sites showing change counter to seasonal expectations.

1.2.4.6 Event-driven or continuous change; which is the better model for managers?

This question was posed almost 20 years ago by Watson et al. (1996) in regard to the preceding scientific discussion (current at that time) about the appropriate model of vegetation change occurring in Australia's rangelands over decadal and longer time periods– was such change essentially continuous or driven by episodic processes? Given that the evidence pointed to event-driven change in many areas, Watson et al. (1996) posed the question "how should land managers deal with such episodic change"? Parts of the scientific community argued that management must also be event-driven. Watson et al. (1996) cautioned against blind acceptance of this world view concluding that, for management purposes, there should be a balance between the effects of infrequent, unpredictable events and the effects of more continuous processes, measured in timescales of years or less.

They provided this advice on a number of perspectives:

1. Based on WARMS data from monitoring perennial vegetation in the WA arid shrublands, a substantial proportion of total demographic change in shrub populations occurred between events.

2. Pastoralists are best able to devise appropriate management strategies through adaptive management and this can only work if the adaptive cycles have a short return time.

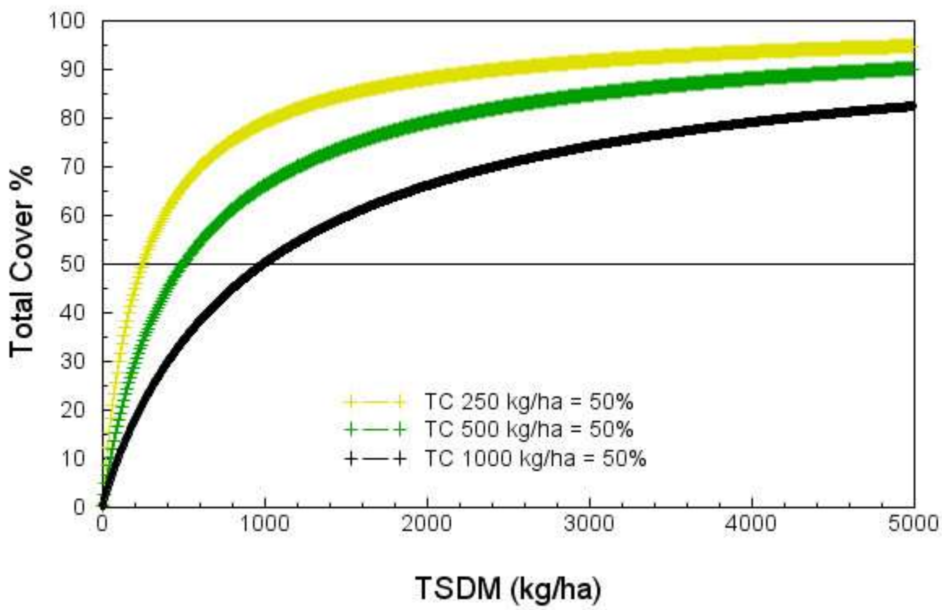
3. It is important that managers think of change as being continuous. Their mental models must acknowledge the value of continuous change. This provides the best opportunity for acquiring knowledge through experience and helps prevent management inertia when faced with an event outside previous experience.

4. Management can take best advantage of a given event by 'conditioning' the resource. An example might be increasing the seedbank which provides the opportunity to alter the otherwise resultant outcome when an event (e.g. post-drought rainfall) occurs.

1.2.5 Required information for land condition and carrying capacity

At the present time (2015), estimating safe carrying capacity and yearly stocking rate is based on pasture biomass; either that present using ground-based sampling techniques or simulated as available from modelling. Land condition monitoring using remote sensing is largely based on ground-cover dynamics (e.g. Pickup et al. 1994, Karfs et al. 2009, Bastin et al. 2012). Established jurisdictional programs based largely on ground data tend to focus on slower attributes of vegetation change (density or demography of perennial vegetation, frequency of perennial grasses; see Appendix in Bastin and the ACRIS Management Committee 2008) and avoid biomass estimation.

Cover-mass functions provide the potential interim link between remotely-sensed ground cover and the third dimension of biomass. One of the earliest of these for the Australian rangelands was developed by Foran (1987). Cover-mass relationships are embedded in the GRASP and AussieGRASS models to estimate cover from simulated biomass (Fig. 1-8). They use asymptotic decay functions to estimate cover based on known (sampled) biomass at 50% and 95% cover. Field data to suitably parameterize these functions for north Australian pastures come from a small set of long-running, well-controlled grazing experiments.



Total Cover = TSDM**$^{0.95}$ / (TSDM**$^{0.95}$ yield_totcov50**$^{0.95}$)

Total cover: cover scaled 0.0-1.0
TSDM: total standing dry matter (kg/ha)
yield_totcov50: biomass at 50% cover (typically 200-4000 kg/ha)

Figure 1-8. Cover-mass functions used in the GRASP pasture growth model. The horizontal line indicates the pasture biomass present at 50% cover for each function.

The accuracy of modelled pasture biomass and cover is likely to be improved where mass-cover relationships are tuned to local conditions. This was demonstrated by Hacker et al. (2007) where they developed improved relationships between total dry matter and the dynamic[8] component of ground cover from field data collected in western NSW. The purpose was to improve calibration of AussieGRASS so as to produce more reliable estimates of TSDM and the dynamic component of cover. The authors concluded that, at regional scales, there was good agreement between average levels of

[8] Grasses, forbs and litter as distinct from the more static components of stones, shrubs and biological soil crusts.

total dry matter and dynamic ground cover produced by AussieGRASS and those obtained from ground based monitoring over 17 years

The potential to adapt cover-mass relationships to estimate biomass over larger areas, and historically, using remotely-sensed fractional cover is being investigated by John Carter (Queensland DSITI) as part of this consultancy. He examined statistical relationships between historic field estimates of biomass in 'Tier 1' grazing trials (Wambiana and Toorak in Queensland, Pigeon Hole in the NT) and contemporaneous fractional cover, particularly the photosynthetic (green) component. The utility and robustness of these relationships will be tested through their ability to reliably estimate pasture biomass (from archived fractional cover):

1. In other paddocks of the same grazing trial – i.e. where different stocking rates or grazing strategies have resulted in different levels of pasture biomass for the same fractional cover.
2. In paddocks of other grazing trials – where different climates, soils and vegetation communities occur and the pasture in each paddock has been grazed in a different way.
3. At 'Tier 2' grazing trials where field data were collected in different ways and with less detail (Galloway Plains, Queensland; Mt Sanford, Kidman Springs and Old Man Plains, NT).

The results of John's work are reported in section 4 of this report.

2 This report

2.1 Background and context

This report has been compiled for Meat and Livestock Australia (MLA) by the Cooperative Research Centre for Spatial Information (CRCSI). The CRCSI has a formal association with the Rangelands NRM Alliance to deliver the first stage of the NRM Spatial Hub. The Australian Government has provided $1.6m in funding to develop tools (a 'dashboard') and training to assist rangeland pastoralists in accessing and using spatial data, including satellite imagery, to better manage their natural resources.

Goals for the first stage of the hub are:

1. Demonstration and evaluation of current best-practice in the use of remote sensing for farm planning and monitoring of productivity and land condition.
2. Training and extension – involving coordination of information delivery and follow-up support.
3. The development and demonstration of a scalable on-line farm planning and information system (OPPIS: on-line Property Planning and Information System).

MLA is co-investing a further $100,000 in the NRM Spatial Hub for this review: specifically to "review and assess the potential for utilising remote sensing of land condition data (at property scale and based on fractional ground cover) to improve biomass, productivity, pasture growth models and grazing decision tools (e.g. safe carrying capacity) across the Australian rangelands".

2.2 Brisbane workshop

The content of this report builds on information presented at a workshop held in Brisbane in November 2014 around the science of using remote sensing and modelling, and related technologies for making better decisions on safe carrying capacity. That workshop also considered research priorities for further developing prospective methods for monitoring pasture biomass remotely and adjusting stocking rate accordingly.

The program for, and attendees at, the Brisbane workshop are provided in Appendix 1 (section 9.1.1).

2.3 Contributing agencies / structures

Key contributors from the different sectors of the northern beef industry included:

- Gerard Davies, General Manager of Innovation and Technology, Australian Agricultural Company (AACo). This large corporate beef producer is seeking timely data to increase its efficiency as a beef producer while meeting its statutory requirements to maintain the condition of natural resources on its leases and assure the public that it is a socially responsible company.
- Representatives from the production-based and resource-management agencies in Queensland, the Northern Territory and Western Australia (see section 9.1.2 for all workshop participants).

- Researchers from State Government, universities, CSIRO and the CRCSI. Additionally, TERN AusCover[9] and the Joint Remote Sensing Research Program[10] (JRSRP) have been instrumental in developing remote-sensing methods and capacity relevant to managing natural resource across Australia.
- Enabling agencies: (i) MLA who funded the workshop and otherwise contributed to this report and (ii) the Australian Bureau of Agricultural & Resource Economics & Sciences (ABARES) that contributed significantly to calibrating and validating the MODIS fractional-cover product for Australia.

Gary Bastin, John Carter, Joe Scanlan and Phil Tickle were the major contributors to this report.

2.4 Scope and content

This report includes:

1. A review of literature relevant to:
   - Land condition assessment (and monitoring) based on remotely sensed vegetation cover,
   - Remote sensing-based methods for estimating vegetation (including pasture) biomass,
   - Cover-mass relationships that support biomass estimation from remotely sensed ground cover, and
   - Linkages between modelled pasture biomass, safe carrying capacity and land condition.
2. Content from the November 2014 workshop that demonstrate key messages from the literature or otherwise support the potential for using remotely-sensed fractional ground cover to estimate pasture biomass and contribute to improved pasture growth models and grazing decision tools across the northern Australian rangelands.
3. A summary of the analysis of biomass – cover relationships from grazing trials in northern Australia by John Carter and colleagues. This work included the potential to improve current modelling of land condition based on the analysis of a subset of the data from the grazing trials.
4. Advice on prospective research areas that will allow improved monitoring of pasture biomass and resource condition at paddock scale and larger using a combination of remote sensing and modelling. The emerging methodology of data assimilation may well be prospective here.

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[9] The AusCover facility provides access to remote sensing data and derived products, associated with land-surface characteristics and biophysical variables derived from satellite and airborne imagery. The facility also provides access to a wide, national network of experts in the field, as well as field methodology protocols and in-situ data for use in ecosystem science and natural resources management. Further information at http://www.auscover.org.au/ (accessed 6 April 2015).

[10] The JRSRP is a collaborative program that combines research, research training expertise and infrastructure from the University of Queensland's Biophysical Remote Sensing Group with remote sensing groups supporting the Queensland, NSW and Victorian governments. The NT Government currently has a formal association with the program. More information at http://www.gpem.uq.edu.au/jrsrp (accessed 6 April 2015).

3 Remote sensing and modelling of land condition and pasture biomass

3.1 Review of relevant literature

This chapter reviews relevant research and applications of remote sensing and modelling to monitoring cover-related rangeland condition and above-ground biomass. It draws on relevant Australian and international literature, including known relevant "grey" sources as available and accessible.

3.2 Remote sensing of land condition

There are three key components to analyzing remotely sensed data for the purpose of monitoring land condition: (i) determining an appropriate index of vegetation cover based on the spectral properties or dimensions of the sensor; (ii) examining spatial pattern in the derived index, including typical summaries (e.g. mean and standard deviation), for stratified areas such as land type / system, paddock or property; and (iii) exploring the temporal dynamics of spatially summarized data.

3.2.1 Spectral indices of vegetation cover

Internationally, the Normalized Difference Vegetation Index (NDVI) is a popular and widely used index of the photosynthetic activity of vegetation (i.e. its greenness). For multispectral scanners, it is a ratio of reflectance in the visible red band to the adjacent near-infrared (NIR) band. Green vegetation absorbs much of the visible red spectrum providing energy for photosynthesis and reflects strongly in the NIR. The NDVI can reliably indicate cover when the vegetation is green and actively growing but its utility declines as the vegetation senesces and decays; i.e. low NDVI may mean low cover or inert / dry vegetation. This is the case for much of Australia's arid and semi-arid regions for extended periods of time and thus NDVI has limited value for monitoring the cover dynamics of our extensively grazed rangelands.

The earliest application of satellite-based remote sensing to pastoral land condition in Australia was the development and demonstration of a land image-based resource information system (LIBRIS) developed by Dean Graetz and colleagues in South Australia in the 1980s (Graetz et al. 1986). Their method used the visible red band of Landsat multispectral scanner (MSS) data, calibrated to ground-based measurement of vegetation cover, to monitor grazing-related changes in sparsely vegetated rangelands of north-eastern SA (Graetz et al. 1988).

Considerable research followed by CSIRO staff in Alice Springs to develop reliable and robust indices of cover from Landsat MSS for the extensive arid rangelands of central Australia (Foran and Pickup 1984, Foran 1987, Pickup et al. 1993). These indices were either ratio based or perpendicular vegetation indices. For the latter, the reflectance values for bare soils of varying colour tend to plot along a "soil line". Dense vegetation (high cover) has much lower reflectance – whether green or dry. One of the more useful central Australian indices was PD54 (Pickup et al. 1993) which estimated cover on the basis of the perpendicular distance of a pixel's reflectance from the soil line in the visible-green – visible red data space compared to the perpendicular distance to the reflectance values of the pixel(s) with maximum vegetation cover. Geoff Pickup and colleagues subsequently used their PD54 index to develop a suite of "grazing gradient" methods for objectively separating grazing effects on vegetation cover from that due to rainfall variability (Pickup et al. 1994).

Over the last two decades, the Queensland Government has contributed substantial resources to remotely monitoring vegetation cover using Landsat TM data. Initial efforts were directed at reliably discriminating the foliage projective cover (FPC) of trees and shrubs to monitor tree clearing and understand regrowth characteristics. This was done using robust regression relationships between field-collected FPC and the multispectral values of Landsat TM (see Danaher et al. 2010 for details). Research then shifted to a reliable index of the amount of bare soil (conversely, ground cover) (Scarth et al. 2006, Danaher et al. 2010). The Ground Cover Index (GCI) used a multiple regression model between field and satellite data, i.e. a similar approach to that used for FPC. The model was applied to mid to late dry season (June-October) imagery to enhance spectral contrast between evergreen tree and shrub canopies and predominantly senescent ground cover. GCI integrated total organic soil surface cover, including senescent and green grasses and forbs, grass and tree litter and cryptogams and had a an accuracy (root mean square error) of approximately ±13% (Scarth et al., 2006).

Initially separate, but then collaborative, research by remote sensing staff in the Queensland Government and CSIRO resulted in a method for discriminating cover components within pixels, both Landsat TM (Scarth et al. 2010) and MODIS (Guerschman et al. 2009). Here, a constrained linear unmixing algorithm was used to estimate the cover-based fractions of photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV) and bare soil (BS) in each pixel. PV is based on the NDVI and NPV is discriminated with a Cellulose Absorption Index. Subsequent validation of fractional cover estimates derived from MODIS and Landsat TM data against rigorously collected field data at greater than 2000 field sites across Australia showed greater accuracy for the Landsat-based estimates compared with MODIS (Guerschman et al. 2015), due mainly to their smaller pixel size (30 m cf 500 m) and improved spatial correspondence with the area measured on the ground. Degrading the Landsat values to the same spatial resolution as MODIS pixels resulted in similar levels of accuracy for each remotely sensed dataset.

In summary, fractional cover estimates (PV, NPV, BS) are now available for all of Australia since 1988 using Landsat TM and since late 2000 derived from MODIS. Landsat TM provides greater spatial resolution than MODIS but lower temporal frequency. The Queensland, NSW and NT Governments produce three-monthly composites of Landsat fractional cover (i.e. mid-season for summer, autumn, winter and spring) with CSIRO generating single-date and 16-day composites of the MODIS counterpart. Geoscience Australia and TERN AusCover are facilitating required standardization of satellite imagery prior to applying the fractional cover algorithm and subsequent delivery of fractional cover products. The former agency (Geoscience Australia) has built a geometrically corrected and radiometrically standardized 'data cube' of all Landsat TM images acquired in Australia. The Landsat fractional cover algorithm has been applied to this data cube to provide a near-continuous record of cover change for most of Australia since 1986.

Depending on fitness for purpose, either Landsat or MODIS fractional cover should provide suitably precise estimates of bare soil / vegetation cover for monitoring purposes in Australia's grazed rangelands (acknowledging that further validation and algorithm refinement may be required in parts of SA and WA where suitable ground data are, as yet, limited).

3.2.2 Methods for monitoring land condition based on remote sensing

The development of LIBRIS (Graetz et al. 1986) and grazing gradient methods (Pickup et al. 1994) as early applications of remote sensing-based monitoring in the arid Australian rangelands was noted above.

Contemporaneous with the application of grazing gradient methods in central Australia (Bastin et al. 1993, 1996, 1998), Jeremy Wallace (CSIRO) worked with colleagues in WA and the NT to develop a "land cover change analysis" (LCCA) method for monitoring grazing effects (Wallace et al. 1994). This method had its genesis from the observation that a major indicator of condition in many grazing regions was the loss of perennials and their replacement by seasonally dependent annuals. In WA's shrublands and grasslands, multi-date Landsat image sequences were used to produce maps of the differential temporal responses of annuals and perennials. This analysis was based on limited ground knowledge but subsequent field validation demonstrated that the maps were useful for interpreting condition. Long-term cover trends from multi-year image sequences also provided information on shrub invasion and cover dynamics from which aspects of condition could be inferred.

The LCCA method was widely tested in the Kimberley (WA), Victoria River (NT) regions and south west Queensland (Wallace and Thomas 1998, Karfs et al. 2004) and subsequently developed into VegMachine (Peel et al. 2006, Beutel et al. 2015). VegMachine is a desk-top PC software package that assists graziers and natural resource management staff in summarising and benchmarking cover change, based on remotely sensed data, over long periods at user-specified locations.

In an unpublished manuscript, Geoff Pickup, Mark Stafford Smith and Gary Bastin compared the above approaches to analyzing remotely sensed data for land condition assessment with the more conventional (at that time) site-based monitoring methods and summarized the overall process as "point, population and pattern". Key attributes of this categorization follow.

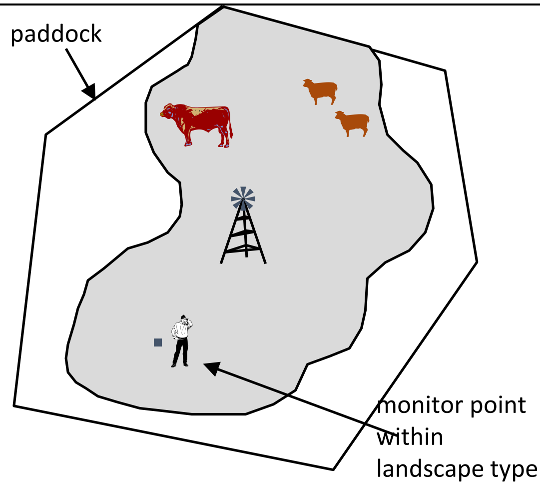
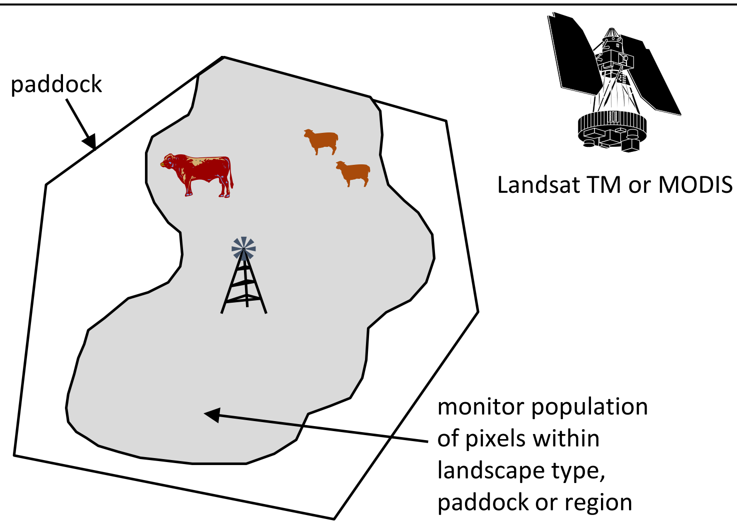
3.2.2.1 Point, population and pattern

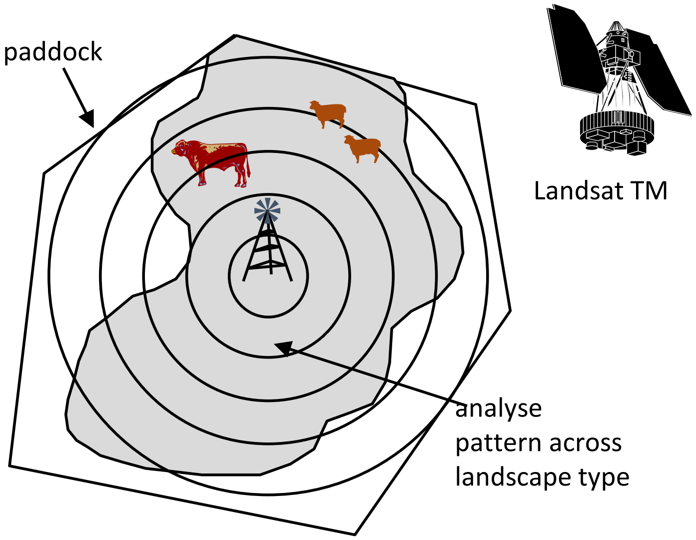
Conventional ground-based techniques for assessing land condition and trend use a limited number of **point**-based assessments at stratified locations within landscapes and paddocks (Fig. 3-1). Remote sensing-based methods analyse the spectral properties of the **population** of pixels within an area of interest with varying levels of sophistication. Methods such as land cover change analysis examine change through time while grazing gradient methods (Pickup et al. 1994) search for systematic **patterns** in vegetation cover that are explicitly related to grazing. All methods may then look for change over time (see, for example, Wallace et al. 2006 and Pickup et al. 1998). All methods also use surrogates as indicators of condition; this is most obvious for remote sensing with its radiometric measures. However, it is also true for any ground-based measures, since it is rarely possible to run a grazing trial to determine whether pastoral productivity has changed at sampling points. Thus all sampling methods should be evaluated for their reliability in genuinely determining land condition (however defined, see Section 1.2.4) and in terms of adequately sampling it over the spatial and temporal scales required.

3.2.3 Ecological basis to remote sensing of land condition

The utility of the "pattern" approach to understanding grazing effects on vegetation cover dynamics (Fig. 3-1) is enhanced where the range in rainfall variability is restricted to either above-average or below-average seasonal conditions (see Fig. 1-7). These two constraints correspond, respectively, with ecological analogues of vegetation resilience and persistence (or stability).

Figure 3-1. Schematic representation of point (ground-based), population (high and low resolution remote sensing-based) and pattern (remotely-sensed grazing gradients) approaches to monitoring condition and trend, and some of their key characteristics.

Approach	Schematic representation of method	Characteristics
point ground-based monitoring		• Small sample area (generally <5 ha per site), and few sample sites (1-2 per paddock or 1 per water point). • Rapid subjective assessment or quantitative and descriptive information about plant species and soil; typically includes information about vegetation composition. • Problems of measurement error and repeatability. • Data can be presented in easily-understood tables/charts. • Data seem readily interpretable (but dependent on the underlying model of landscape change, which may be poorly developed for some ecosystems). • Generally inadequate spatial or temporal sampling for separating grazing from natural (i.e. site) and seasonal effects.
population satellite data and change over time		• General advantages of satellite data: can analyse total area grazed repeat coverage – can acquire data selectively historical archive for both MODIS and Landsat TM data. • Suitable satellite data now freely available. • Lower spatial resolution for MODIS, high resolution for TM • Continental fractional vegetation cover now available as a suitable index; suitably validated for Queensland & NSW rangelands, improved calibration and validation occurring in the NT, caution required in SA and WA rangelands. • Landscape change expressed through differences in fractional cover over time. • VegMachine and developing NRM Spatial Hub tools provide tailored, user-friendly software for analysing time-series data.

		• Inference based on ancillary data generally required to separate grazing effects from natural variation.
pattern satellite data and change over space and time grazing gradient methods		• General advantages as for satellite data above. • Search for systematic change in cover related to grazing, reliably identifying grazing effect but requiring larger paddocks. • Stratification according to landscape type (e.g. land systems) allows separate grazing effects within large paddocks to be monitored. • Uses an explicit definition of land degradation to determine landscape change (i.e. ability of vegetation cover to respond to large episodic rainfall events, when received). • Reasonably complex – results not easily understood or accepted by land managers. • Broadly applicable to rangelands with <500 mm annual rainfall. • Tested by SA and NT Government monitoring agencies through collaborative "technology transfer" projects with developers (CSIRO) but methods not implemented due to various technical and institutional issues.

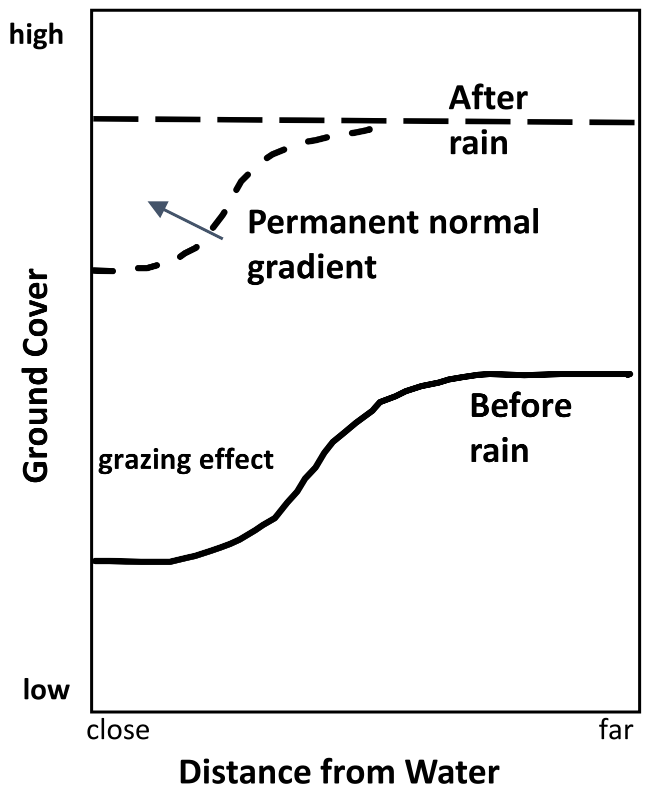


Figure 3-2. Stylised grazing gradient based on remotely sensed ground cover.

3.2.3.1 Vegetation resilience

Vegetation resilience, specifically the response of ground cover to much above-average (and often, episodic) rainfall, underpins the CSIRO-developed grazing gradient methods (Pickup et al. 1994). Grazing gradients of cover develop with increasing distance from water (lower solid line in Fig. 3-2). Water-remote areas provide a guide to expected (reference) cover at any point in time. The extent to which ground cover increases (recovers) after large rainfall events indicates the extent to which the landscape retains its inherent ability (resilience) to respond to such events. The horizontal dashed line in Fig. 3-2 shows the expected average level of ground cover in an undamaged line (i.e. all areas at increasing distance from water have similar cover). Where there is a permanent effect of grazing, the ground-cover response is suppressed (dashed curved line).

3.2.3.2 Stability / persistence of ground cover

Retained ground cover in drier years is critical in minimising the risk of wind and water erosion. It is reasonable to infer that most of the cover present in drier (and drought) years consists of perennial species.

The Dynamic Reference Cover Method (DRCM) automatically calculates an expected (reference) level of ground cover for each Landsat TM pixel in a nominated dry/drought year. The difference between actual and reference cover (cover deficit) indicates the extent to which an area has been modified by past grazing (see Bastin et al. 2012 for further detail on the method and validation of results at a range of scales in north eastern Queensland). Change in cover deficit from one drought period to the next provides an objective and systematic way of determining how ground cover is being managed when its presence is most critical.

3.2.4 Regional application of remote sensing-based methods for monitoring land condition

3.2.4.1 Grazing gradient methods

There are four components to the suite of grazing gradient methods (described in Pickup et al. 1994):

1. Wet Period Average Cover, as illustrated in Fig. 3-2. This method was tested in the southern Alice Springs region (Bastin et al. 1993) and subsequently applied in the Barkly Tableland (McGregor 2000) and northern SA (Bastin et al. 1998). Four types of cover response with increasing distance from water were typically encountered (see Fig. 2 in Pickup and Chewings 1994, also refer Bastin et al. 1993):
   - (i) A temporary normal gradient where vegetation cover was largely restored after a significant wet period (horizontal dashed line in Fig. 3-2).
   - (ii) A permanent normal gradient (the curved dashed line, Fig. 3-2) indicating some degree of grazing-related land degradation.
   - (iii) Composite wet-period gradients where cover initially decreased then increased with distance from water. This response was typically due to proliferation of unpalatable species (often forbs) close to water following rainfall. Cattle avoided this area in their search for more palatable forage further from water. With increasing time since rainfall, this composite gradient reverted to a normal gradient as the largely ephemeral unpalatable cover senesced and decayed.
   - (iv) More rarely, inverse dry-period grazing gradients which recovered to uniform cover (on average) following good rainfall. This counter-intuitive pattern of decreasing vegetation cover with increasing distance from water in dry periods presumably occurred because cattle were forced to forage further from water due to unpalatable vegetation closer to water. Such gradients were usually associated with dams and were due to woody thickening in the run-on areas surrounding these water points. It is unlikely that inverse gradients would occur where ground cover was spatially averaged at increasing distance from water (as distinct from total vegetation cover as analysed by Pickup and colleagues).

2. Wet Period Cover Variance which examines patterns in the variance of cover at increasing distance from water. Such analysis is useful in arid regions where soil and water redistribution is enhanced as grazing and trampling reduce the amount of vegetation cover present and increase the amount of run-off in some areas and run-on in others.

   Over time, vegetation response to rainfall reflects changes in the spatial pattern of soil moisture supply and becomes progressively more variable spatially as the landscape is increasingly polarized into areas of erosion and deposition. This may result in a weak average-cover gradient with distance from water for the mapped landscape (e.g. land system) being analysed. The weak gradient arises because reduced plant growth in run-off and eroding areas is offset by increased growth in run-on and sediment sinks.

   The overall change in cover with distance from water may be small, but there are substantial effects on forage production because of poor vegetation response to rainfall in eroded run-off areas and widespread changes in species composition and shrub increase in run-on areas.

3. The Resilience Method provides location-specific information on the magnitude of vegetation response to rainfall. This can be useful for paddock management, particularly with regard to

infrastructure development including paddock redesign.

4. Cover Depletion provides information on the amount of forage by examining the spatial pattern of cover change during the decay phase of major vegetation pulses. During this phase, vegetation cover decreases because of grazing, consumption by detritivores, conversion to litter, and biological decay. Provided the landscape has been suitably stratified into different land types, consumption by grazing and damage due to trampling should vary systematically with distance from water, whereas other processes of cover loss should, on average, occur at a constant rate across each landscape type. It therefore becomes possible to identify the location and intensity of grazing from the spatially variable component of the pattern of cover depletion over time.

3.2.4.1.1 Applications and limitations

Bastin et al. (1993) analysed 38,000 km^2 of grazed country on all or parts of 16 pastoral leases in the southern NT using the Wet Period Average Cover Method. Land systems containing a high proportion of palatable forage had the most persistent grazing gradients following much above-average rainfall and were assessed as being most adversely affected by grazing. These land systems were generally the most intensively stocked due to their original productivity. In some cases, parts of these land systems had also had a relatively long history of grazing. In a further analysis of these data, Pickup et al. (1998) used a ratio of the cover response close to water (0-3 km) to that further from water (>3 km) following two wet periods (1983 and 1988-89) to report trends in land degradation.

The utility of the Resilience Method for paddock management was tested with a pastoral family near the SA-NT border (Bastin et al. 1996). Products included maps of scaled herbage response to rainfall, herbage response in conjunction with dry period vegetation cover and herbage biomass derived from vegetation cover (based on limited contemporaneous site-based estimation of pasture yield). The cover-based products effectively showed herbage response following a large rainfall event (1989). Much of the spatial variation in response was interpreted as being natural and related to woody cover and soil factors. Some areas with below-average herbage response were attributed to damage caused by previously high rabbit populations. Herbage response on much of the productive grazing country was average to above average indicating good resilience and potential for continued beef production. From a management perspective, the method provided a useful pictorial representation of herbage response across the whole station following one rainfall with the participating pastoralists considering that the Resilience Method would have greater validity when repeated following further significant rainfalls (not tested). Some insights were gained into future property development. However, the technology was difficult to understand and required close liaison between the technician and client. Confusion arose where below-average herbage response could occur in areas of both high and low initial cover when the two areas appeared vastly different and required separate management for beef production and rehabilitation.

The Cover Depletion approach was used to model grazing distribution and resultant defoliation through time by cattle in large (> 100 km^2) paddocks in arid central Australia (Pickup 1994, Pickup and Bastin 1997). Models were based on the inverse Gaussian distribution function with additional model components describing the effects of natural decline in cover over time and the effect of past grazing on the spatial distribution of palatable species. Models were calibrated using an index of vegetation cover derived from Landsat MSS and closely reflected observed cattle distributions where limited validation data were available.

There are some practical limitations to using the grazing gradient methods:

1. The method works best in large paddocks (generally >100 km^2) where water-remote locations exist as suitable reference areas (>8 km from water for cattle).

2. Its use is limited to large rainfall events – approximately decadal in the southern NT, more frequently on the Barkly Tableland (4-6 years) and infrequent (~15 years) in the arid parts of SA.

3. It requires considerable user input to develop and update required GIS layers (particularly fences and waterpoints to calculate distance from water) and interpret results.

The above plus various institutional reasons mean that the methods have not been implemented for routine pastoral monitoring by state-based land management agencies in Australia.

3.2.4.2 Dynamic Reference Cover Method

DRCM has the advantage that cover deficit values are automatically calculated across very large areas, e.g. approximately half of the rangelands in Queensland (640,000 km^2, Bastin et al. 2014). One limitation is that landscape heterogeneity may affect the locations of automatically selected reference-pixel locations and, subsequently, adversely influence the calculated level of reference cover. While this can influence pixel-level cover deficit, indicating condition state, landscape characteristics remain stable over time meaning that change in mean cover deficit between sequences of dry years reliably indicates change due to grazing (i.e. trend).

In the above application, the authors reported that all 34 sub-regions (of bioregions) analysed had similar or increased levels of seasonally-adjusted ground cover at the end of the analysis period (either 2003 or 2005) compared with the base dry year (1988). Allowing for possible landscape heterogeneity effects on assessed condition, the Einasleigh Uplands bioregion was comparatively in a better state and those analysed parts of the Mulga Lands bioregion in poorer state at the first assessment in 1988. Most sub-regions of the Cape York Peninsula, Brigalow Belt North, Desert Uplands, Gulf Plains and Mitchell Grass Downs bioregions lay between these two end-states.

Retrospective validation of the results of remote sensing-based analyses for large areas requires that ground data are suitably extensive and contemporaneous, and options for this are always limited. Simulated levels of pasture utilisation based on AussieGRASS-modelled pasture growth and statistically-based grazing pressure broadly supported the results of the above regional assessment of land condition for parts of the Queensland rangelands (see Fig. 7 in Bastin et al. 2014).

Subsequent to the analysis of state and change for much of Queensland's rangelands, the DRCM method was applied to all of the NSW rangelands between 1992 and 2013 (results not yet published). Calibration and validation of fractional cover to NT environmental conditions now means that similar analysis is possible for the NT pastoral estate.

3.2.4.3 Land Cover Change Analysis / VegMachine

LCCA, as implemented in the VegMachine software, allows the pixel-level analysis of temporal trends in carefully selected Landsat TM-based cover sequences. For example, Fig. 1 in Wallace et al. (2006) illustrated that the cover response from poor condition sites was associated with negative slope (indicating cover loss) and increasing 'seasonal variance' (indicating increased presence of annuals). The authors described both features as being consistent with on-ground understanding of cover responses to grazing-induced condition changes in this East Kimberley environment. Statistics such as the mean, slope and quadratic curvature of the temporal responses for each pixel can be calculated, as well as residual standard errors from linearly fitted trends. Wallace et al. (2006) argued that mapping these trend summaries for selected climatic periods directs attention to areas which are changing differently, and provides evidence of condition and change.

VegMachine has been upgraded since it was first launched in 2002 with an online version currently being developed that will improve access by individual land holders and NRM groups. Beutel et al. (2015) reported that the software had been used across a range of applications (mainly in Queensland) to monitor and interpret rangeland change, engage pastoralists, and assess eligibility for NRM funding. These authors summarized the insights gained from landscape-scale analysis of time-series data in the rangelands as:

1. Natural Resource Management groups have adopted the software very effectively, but largely for project assessment.
2. Grazier adoption has been limited, for reasons of both supply and demand.
3. A simple online form of the tool would dramatically widen pastoralist access and use. This development, however, will require quality support materials and networks.

3.2.4.4 Leakiness index

The Leakiness Index (Ludwig et al. 2007) provides a method for upscaling site-based assessment of landscape function (as described by Ludwig et al. 1997) to hillslopes and small watersheds. The index focusses on the potential of landscapes to lose (i.e. leak) soil sediments due to increased run-off. The spatial arrangement of remotely sensed ground cover is combined with a digital elevation model (DEM) to rank landscapes between fully functional (i.e. resource-conserving) and dysfunctional (completely leaky).

The method was applied to small sub-catchments of the Burdekin River (Bastin et al. 2007) but has not had further regional use.

3.2.4.5 Great Barrier Reef applications

Remotely sensed ground cover has been an important dataset to assessing land condition and associated grazing management practices in the Burdekin and Fitzroy River catchments, Queensland (Karfs et al. 2009, Beutel et al. 2013, Wilkinson et al. 2014). The common aim to most of this work was to equip the regional NRM groups with monitoring data and tools that would encourage improved grazing management, particularly retention of ground cover, and thereby reduce sediment loss to the Great Barrier Reef lagoon. An allied goal was to provide the two NRM groups (North Queensland Dry Tropics and Fitzroy Basin Association) charged with investing public funds in improved NRM with relevant spatial data and analysis tools to better inform their decision making.

Specific products from the work of Karfs et al. (2009) were sub-catchment ground-cover change maps, regional mapping of areas judged to be in very poor condition and stratified site-level summaries of land condition based on rapid ground assessment.

Contributions by Queensland Government agencies under the Reef Rescue initiative (reported by Beutel et al. 2013) included:

1. Catchment-wide fractional cover datasets (including ground cover), with the time series since 1988 packaged and delivered through VegMachine.
2. Spatial mapping of grazing-related land condition validated at 1700+ ground sites.
3. Customized monitoring tools for reef stakeholders.

One component of the project modelled relationships between ground cover, land condition, long-term rainfall and cover deficit (from DRCM analysis) at validation sites. This generated pixel and sub-catchment scale ground cover targets for the two regions, and may be a significant improvement on the blanket 50% ground cover target used in most regions.

Wilkinson et al. (2014) investigated a range of approaches to forage management to help identify practice changes that can reduce offsite impacts of grazing. The purpose of this work was to deliver a regional-scale, ground-truthed assessment of the potential for improved grazing practices to increase forage productivity and reduce erosion. Focus properties were selected across three soil types (Chromosol, red goldfields soil; Sodosol, duplex 'spewy' soils with sodic subsoils; and Vertosol, dark cracking clay soil). One component used DRCM analysis to assess relative differences in historical cover (high, medium and low) and grazing impact. The robustness and limitations of this "cover deficit" approach for property assessment across regions were established, and guidelines developed for its ongoing use. Key findings included:

- Long-term cover is broadly indicative of grazing land processes and function.
- The cover deficit method (DRCM) effectively identified grazing impacts on ground cover across regions.
- Grazing management involves more than ground cover. For example, the widespread dominance of the exotic grass Indian couch (*Bothriochloa pertusa*) in degrading pastures can result in high cover but low productivity and poor soil infiltration capacity.
- Maintaining high ground cover reduces erosion and increases productivity in the long term.

3.2.5 Enabling structures

3.2.5.1 Joint Remote Sensing Research Program

The Joint Remote Sensing Research Program (JRSRP, http://www.gpem.uq.edu.au/jrsrp) formed in 2007 to undertake research and to improve operational monitoring of land cover and land condition attributes, particularly in rangeland environments. This is achieved through research and development of methods which use passive and active remote sensing technologies, field data, process-based modelling, and innovative image processing using open source software and high performance computing facilities.

Membership of the JRRSP includes the University of Queensland, University of NSW, and the Queensland, NSW and Victorian state governments. More recently, the partnership has been enhanced through initiatives such as the Terrestrial Ecosystem Research Network (TERN) Auscover facility and a collaborative research partnership with the Northern Territory government.

The JRRSP has contributed hugely to the collaborative development of Landsat fractional cover across multiple jurisdictions and the application of remote sensing methods more generally. Tindall et al. (2015) provide a recent comprehensive overview of these activities.

3.2.5.2 TERN AusCover

The Terrestrial Ecosystem Research Network (TERN, www.tern.org.au) connects ecosystem scientists and enables them to collect, contribute, store, share and integrate data across disciplines. Collectively this increases the capacity of the Australian ecosystem science community to advance science and contribute to effective management and sustainable use of its ecosystems. TERN has two facilities that directly contribute to ecosystem research in the rangelands: AusPlots and AusCover. AusPlots is a plot-based surveillance monitoring program, undertaking baseline assessments of ecosystems across Australia. The Rangelands program collects critical ecological data in the rangelands.

The AusCover facility (www.auscover.org.au) provides a national expert network and a data delivery service for provision of time-series remotely-sensed data, continental-scale map products, and selected high-resolution datasets over TERN sites. The facility also provides protocols for consistent use of field methods associated with remote sensing.

AusCover has been an important enabling mechanism in developing rangelands remote sensing capacity to its current state. This is well demonstrated with the nationally calibrated archive of Landsat TM imagery (the data cube, section 3.2.1) and derived fractional cover (both Landsat and MODIS based).

3.2.6 Summary: remote sensing of land condition

Remote sensing can contribute to monitoring land condition but does not provide a stand-alone tool for doing so. This is partly because land (or range) condition is a complex issue, meaning different things to different stakeholder groups (see section 1 for further description). From a technical perspective, it is necessary to deconstruct 'land condition' into appropriate functionality criteria and then identify suitably robust indicators that separately, and combined, can build a composite picture of the overall functionality (health) of rangelands under current grazing management.

To the extent that ground cover dynamics can suitably indicate landscape function (as defined by Ludwig et al. 1997), remote sensing capacity can now contribute hugely to this component of monitoring the health (condition) of Australia's grazed rangelands. Landsat TM-based fractional cover has provided wall-to-wall coverage since 1988. The 30-m pixel size provides appropriate resolution because it approximates the size of enhanced patch-grazing effects in savanna landscapes and soil erosion / pasture degradation processes in much of the arid zone.

Methods exist within land management agencies, including NRM groups, for spatially summarizing time-series data to examine trends in cover and, based largely on external information and inference, attribute likely causes to either past rainfall (and its effectiveness), fire or grazing. More sophisticated methods are also available for objectively separating rainfall and grazing effects on ground-cover dynamics, but these have some limitations to their widespread and routine use. Importantly, VegMachine and the developing toolset within the NRM Spatial Hub should increasingly devolve fractional cover datasets to on-ground managers. These data along with simple tools and appropriate training to better understand the cover-based implications of stocking decisions should help lessees in their adaptive management to avoid further significant soil and pasture degradation in the rangelands.

3.3 Remote sensing of biomass

Expanding from remotely-sensed aerial (two-dimensional) measurement of vegetation cover to volumetric (three-dimensional) estimation of biomass is no trivial matter. In the simplest sense, cover is estimated as a relative measure and is constrained between zero and one (or 0 – 100 percent). Biomass is measured (or estimated) in a continuous manner and can rapidly increase as cover approaches 100%, see for example Fig. 1-8. This figure shows generalized mass-cover relationships used in GRASP to estimate pasture cover from modelled biomass.

Vegetation height could be a useful additional variable for estimating biomass and is included in some allometric equations where above-ground woody biomass is predicted from tree basal area (e.g. measured trunk diameter at breast height). For crops and improved pasture situations, instruments such as the rising plate meter are used to measure canopy height as an additional field variable for estimating pasture biomass. Active sensors such as radar and LiDAR provide useful data for remotely estimating tree and shrub heights. The reduced height of pasture swards suggests that these forms of remote sensing will have reduced precision of estimation in a relative sense and therefore contribute greater sources of error in models that predict biomass from cover and height, compared with forests and woodlands. The magnitude of this error source may be greater for altimeters and laser scanners carried on satellites, compared with airborne remote sensing, because of their generally reduced spatial resolution.

A further complicating factor in extending ground cover to herbage biomass is growth form. Erect (bunch and tussock) grasses will have a different cover-biomass relationship to prostrate and stoloniferous species.

The following sections review remote sensing-based approaches to estimating above-ground biomass in forests, woodlands and grasslands.

3.3.1 Forests – a very brief overview

Forests are obviously not a feature of Australia's rangelands. However, an introduction to international activity to remotely sense biomass in forests is included here for two reasons: (i) remote sensing research in forests has probable relevance to estimating pasture biomass in the rangelands and (ii) woodlands are an important component of pastoral northern Australia and it is necessary to understand the impacts of tree basal area and biomass on pasture production in this region.

The use of field-based allometry for estimating the harvestable yield of timber in commercial forests is a well-established science. Beyond commercial interests, vegetation biomass is both an important ecological variable and component of the global carbon cycle. Obviously, most of the carbon in forests, woodlands and shrublands is contained in the woody vegetation and adapted allometric relationships now allow the above-ground biomass to be estimated for defined stands such as environmental plantings (e.g. Paul et al. 2013).

Extrapolating woody biomass estimation beyond plot-scale using allometry remains a challenge, particularly where areas of interest are spatially and structurally diverse (e.g. different species, variable density and height of individuals). Remote sensing should be able to assist up-scaling of woody biomass estimation but, as yet, there is no standardized methodology. A decade old review of the literature (Lu 2006) concluded that biomass estimation remained a challenging task, especially in areas with complex forest-stand structures and environmental conditions. Either optical sensor data or radar data were more suitable for forest sites with relatively simple forest stand structure. At that time, combined use of vegetation spectral response and image texture analysis were considered most prospective for improved estimation of forest biomass.

Two international groups are currently contributing to, and coordinating, remote sensing activity to estimate forest biomass:

1. Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD, www.gofcgold.wur.nl) is a coordinated international effort to ensure a continuous program of space-based and in situ forest and land cover observations to better understand global change, to support international

assessments and environmental treaties and to contribute to management of natural resources.

2. Global Forest Observations Initiative (GFOI, http://www.gfoi.org/) is an initiative of the inter-governmental Group on Earth Observations (GEO) that aims to: foster the sustained availability of observations for national forest monitoring systems; support governments that are establishing national systems by providing a platform for coordinating observations; providing assistance and guidance on utilizing observations, developing accepted methods and protocols and promoting on-going research and development; and working with national governments that report into international forest assessments and the national greenhouse gas inventories.

Both groups, in conjunction with TERN convened a workshop in Brisbane in March 2015 to:

- Discuss the science and technical details behind current methods for remote sensing-based estimation of vegetation biomass, across multiple land-use types, at sub-national, national and global scales,
- Evaluate the current levels of uncertainty against conventional in-situ measurements and models, and
- Evaluate the level of "operational applicability and robustness" of prospective methods for routine use by institutional or governments users.

American, European and Australian (particularly Queensland) researchers are leading players in developing methods for remotely monitoring woody biomass with South Africa also contributing for savanna landscapes.

3.3.1.1 Australia's National Biomass Mapping project

Contributing institutions are the Joint Remote Sensing Research Program and University of Queensland (Richard Lucas, Peter Scarth, John Armston, Tony Gill and Stuart Phinn), Plymouth Marine Laboratory, Aberystwyth University and the Japanese Aerospace Exploration Agency (JAXA) which is contributing radar data.

Major components of the project include:

- Understanding the impacts of surface moisture in annual mosaicked radar (ALOS PALSAR) images for Queensland (e.g. 2009 was a very dry year followed by wet conditions in 2010 and subsequent extensive fires). Spatially and temporally variable amounts and types of vegetation and soil moisture affect radar backscatter in different ways and these need to be partitioned before the backscatter signal can be used to estimate vegetation height (as a proxy for structure and biomass).

- Mapping above-ground biomass for Queensland and NSW.

- Obtaining suitable ground truth data. This has included collating a library of national field-based allometry, terrestrial laser scanning at selected locations and overflying with airborne LiDAR. The Terrestrial Laser Scanner (TLS) is a proving quite valuable for rapidly collecting plot-scale data on the height and density (wood vs leaf) of woody vegetation (Fig. 3-3).

Figure 3-3. Example of terrestrial laser scanning of a woodland community in Queensland. The information collected is a point cloud of spatial (x, y) and return-value (z) coordinates enabling detailed and accurate reconstruction of the three-dimensional structure of the vegetation. A ratio of returned values in the infrared and visible-green wavelengths discriminates denser woody vegetation (trunks and limbs) from leaves and twigs. Image courtesy of the Joint Remote Sensing Research Program.

Research is focused on the height and cover of woody vegetation as the key components for estimating biomass. Woody cover is based on the Landsat “persistent green” product, i.e. the extent to which vegetation is persistently green (photosynthetically active) over time (see http://www.auscover.org.au/xwiki/bin/view/Product+pages/Persistent+Green-Vegetation+Fraction). PALSAR L-band horizontal-horizontal (HH) and horizontal-vertical (HV) backscatter is a promising surrogate for vegetation height (when suitably adjusted for the effects of soil moisture) (Lei et al. 2012). The three images (Landsat persistent green, L-band HH and HV backscatter) have been used to numerically segment the Australian landscape based on the structure of woody vegetation.

At continental and global scale, the ICESat satellite (Ice, Cloud and land Elevation Satellite, http://icesat.gsfc.nasa.gov/icesat/) provided data on topography and vegetation characteristics (as well as ice sheet mass balance, cloud and aerosol heights) between 2003 and 2009[11]. The Geoscience Laser Altimeter System (GLAS) sensor onboard this satellite provided continuous LiDAR coverage of the earth’s surface, albeit at coarse spatial resolution (laser pulses of two wavelengths [infrared, 1064 nm and visible green light, 532 nm] at 40 times per second to illuminate spots [footprints] 70 m in diameter, spaced at 170-m intervals along the Earth's surface). These data have been used to assign a nominal vegetation height to each structural segment defined in the preceding step.

Currently, two vegetation structure maps have been generated: a national vegetation structural map (Fig. 3-4) and a map showing vegetation extent and growth stage in the Queensland brigalow (Fig. 3-5).

Refinement of above-ground biomass mapping is focused on regrowth forests, particularly in the Brigalow Belt bioregion, and mangroves.

Further work in this biomass mapping project will focus on understanding continental variation in vegetation structure and soil moisture as components to improving the Australian biomass – L-band backscatter relationship. Special consideration needs to be given to early-regrowth and flooded forests, low shrublands and mangroves to better estimate biomass using existing satellite data (i.e. L-band radar, ICESat and Landsat). Consistent methods, sampling protocols and direct measurement are required to acquire better validation data. This will likely include airborne LiDAR and terrestrial laser scanning.

[11] ICESat-2 is scheduled for launch in 2017. This will provide the second generation of satellite laser altimetry.

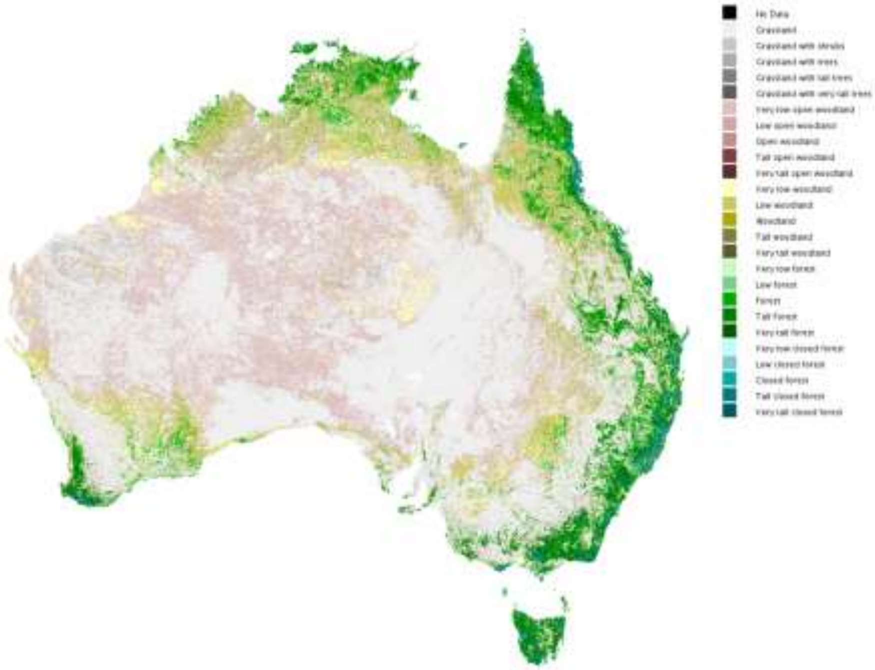
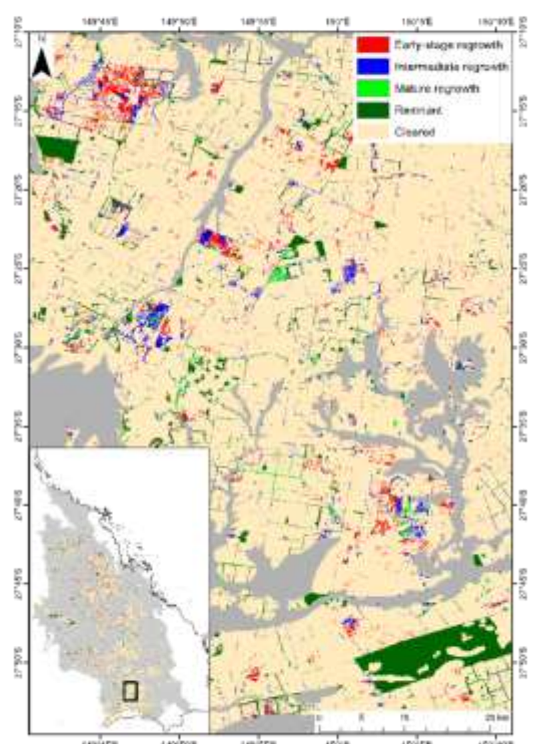
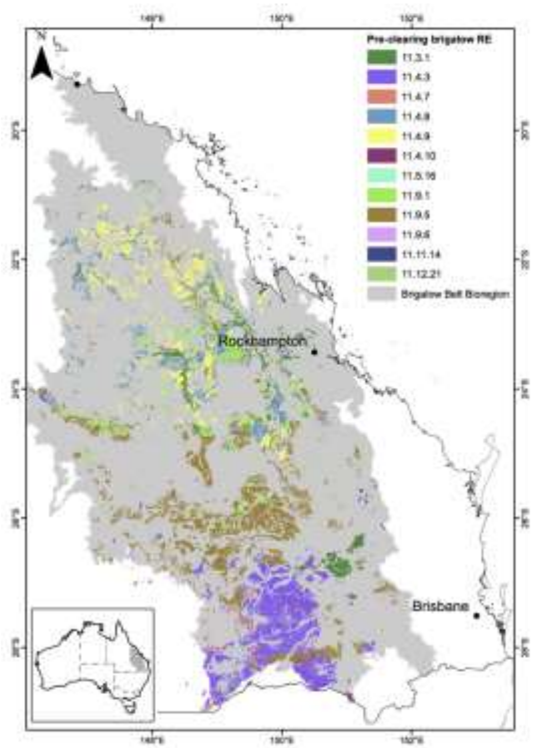


Figure 3-4. Vegetation structural formation map for Australia (25-m resolution) generated from segmentation of the national Landsat Persistent Green product and PALSAR L-band HH and HV backscatter. Map courtesy of the Joint Remote Sensing Research Program.



extent and growth-stage classification



12 mapped Regional Ecosystems for the Brigalow Belt

Figure 3-5. Example map for the "Brigalow Belt vegetation extent and growth stage" product (left) compared with existing regional ecosystem mapping[12]. Map courtesy of the Joint Remote Sensing Research Program.

[12] Regional ecosystems map and describe vegetation communities in a bioregion that are consistently associated with a particular combination of geology, landform and soil. Further information available at http://www.qld.gov.au/environment/plants-animals/plants/ecosystems/about/ (accessed 26 May 2015).

3.3.2 Herbage

Historically, there appears to have been separate, disconnected research initiatives to remotely estimate pasture biomass in Australia and internationally. The more successful of these for Australia, Pastures from Space, resulted in product delivery through a subscription service in parts of south-western WA. There is currently renewed research interest in Australia to estimate herbage biomass from satellite data and it may be that drivers such as the Global Pasture and Rangelands Productivity Monitoring task of GEOGLAM can help achieve coordination and build synergy between currently largely disparate participants.

3.3.2.1 GEOGLAM RAPP

The Group on Earth Observations (GEO) and its Global Agricultural Monitoring (GEOGLAM) initiative are building a dedicated system for observing the condition of pastures and rangeland status (limited information available at http://www.geo-rapp.org/). Australia is leading the development of this Rangelands and Pasture Productivity (RAPP) component, principally through CSIRO.

Proposed elements of the GEOGLAM RAPP include:

- Monitoring of the dynamics, nature and quantity of available plant biomass, including its condition and trends in productivity, as affected by natural and human-induced impacts across the globe.
- Monitoring the nature and quality of the animals that feed on the biomass, including related production of protein.
- Timely and accurate national and sub-national reporting of agricultural statistics.
- Accurate forecasts of declines in the productivity of pastures and rangelands.
- Early warning of pasture decline and related food production shortfalls.

The system will use spatially explicit data describing biomass dynamics and their utilisation, largely based on remote sensing with standardized approaches (across participating countries) to mapping land-cover and biomass. Remote sensing methods will be integrated with ground measurements of above-ground biomass and simulation modelling. These components will need to link to livestock production models and statistical reporting.

Several countries have nominated pilot sites and a prototype “visualization dashboard” has been developed.

Planned near-term input by CSIRO into GEOGLAM RAPP includes:

- Integration of multi-scale soil moisture simulations into the C-Store biomass and productivity model (see section 3.6.1) and evaluation of resultant model performance.
- Developing an Australian and Global Rangeland biomass and cover condition delivery system. This activity will implement the current pre-operational MODIS-fractional cover processing system and the C-Store gross primary production (GPP) model running on high-performance computational infrastructure. Additionally, it will initiate collaborations with key international partners (University of Maryland and NASA) to help run a global MODIS-based rangelands condition monitoring system analogous to the GEOGLAM Crop Monitor system.

- Continued global leadership of GEOGLAM RAPP. Coordination goals include establishing several representative rangeland and grassland pilot/demonstration sites world-wide, comparison of methodologies for biomass production at these sites and linking to indigenous livestock productivity data.

3.3.2.2 Time-integrated NDVI through the growing season

There has been substantial international research into modelling pasture growth from remotely sensed NDVI in regional areas that have a defined growing season (examples listed in Table 3-1). This work is summarized in reverse-chronological order and dates back to the early 1990s. More recent work has included the contribution to standing biomass of non-photosynthetic vegetation (i.e. NPV).

In most cases, rainfall occurrence and/or suitable temperature (for plant growth) define the growing season. The general approach has been to develop a robust regression model between ground-based measurement (or estimates) of pasture biomass and time-integrated remotely-sensed NDVI (or similar vegetation indices) through the growing season. More sophisticated models include a light use efficiency (LUE) component to estimate gross primary production (GPP, see following section).

NDVI is now usually sourced from the 250-m MODIS product (potentially available on a daily basis) with Landsat TM or SPOT substituted where greater spatial resolution is required. Proximal (near ground) and airborne collection of NDVI data may be included for model development and scaling purposes.

Time-integrated NDVI has had limited research and application in Australia, apart from that described in the following sections (3.3.2.2.3 Pastures from Space and 3.3.2.2.4 FAT-CHOP and Rangewatch [i.e. CRCSI research at Liveringa Station in the West Kimberley]). The reasons for this, and particularly in much of the rangelands, include:

- The absence of a defined and regular growing season.
- Tree and shrub canopies contributing to the NDVI signal in most non-grassland environments.
- There is an assumption that light limits photosynthesis during the growing season. This is rarely the case in the arid and semi-arid rangelands where pasture growth is generally restricted by lack of soil water or nutrients.

Table 3-1. International examples of research into, or applications of, time-integrated NDVI through the growing season for monitoring pasture biomass.

Reference	Location	Summary	Key findings
Fu et al. (2014)	Sichuan province, China	This study involved MODIS gross primary production (GPP) and NDVI data (at 1 km^2 resolution). NDVI was used to simulate light use efficiency and the fraction of photosynthetically absorbed radiation (FPAR). A modified GPP was calculated and validated with in situ measured data in 2011. The modified GPP data were shown to be a more accurate indicator for monitoring grassland than previous indicators, and the precision of grass production simulated by the method reached 85.6%.	The authors claim that MODIS data provide an improved indicator for grassland monitoring at regional scale.
Meroni et al. (2014)	Sahel region of northern Africa	SPOT-VEGETATION time series of the Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) related to growing season length (GSL) and timing of the start of the growing season (SOS). The consistency of results was evaluated using field measurements of aboveground herbaceous biomass of rangelands in Senegal.	Demonstrated potential of phenological variables to indicate biomass production but relationships varies geographically, with large scattered areas not showing a statistically significant relationship.
Porter et al. (2014)	Montana (USA) pasturelands allocated to the Conservation Reserve Program	Compare the ability of regression models to estimate biomass - yields and plant spectral responses obtained at different phenological stages over two growing seasons on an 8.1 ha CRP pasture in central Montana. Regression models constructed using NDVI and various band combinations from a hand held Crop Circle sensor and from Landsat satellite images.	Red, red edge and the near-infrared spectral bands were more responsive at boot and peak-growth stages while bands in the short-wave infrared increased model accuracy for the dormant-stage biomass estimations.
Zhao et al. (2014)	Xilingol Grassland, Northern China	Regression models to estimate above-ground biomass using MODIS Net Primary Productivity (NPP) data developed from biomass data collected at 1205 sites between 2005 and 2012.	Linear models based on field survey data and accumulated MODIS productivity (NPP) data provide the optimum model for estimating above-ground biomass.
Zhou et al. (2014)	Grasslands of northern China	This study examined the relationships between nine vegetation indices derived from MODIS and tower-based Gross Primary Production (GPP) at five eddy covariance flux sites over the grasslands of northern China.	The MODIS Enhanced Vegetation Index (EVI) was the best predictor of GPP. Correlation between EVI and GPP declined south to north (in the northern China grasslands), indicating that EVI performed better in more southerly sites where there was higher vegetation cover. Vegetation indices better capture variations in

Reference	Location	Summary	Key findings
			observed GPP in drought when vegetation growth is suppressed.
An et al. (2013)	Tallgrass prairie, Central Great Plains (USA)	Develop a robust model using AVHRR biweekly NDVI values to predict tallgrass above-ground net primary production (ANPP). The optimal period for estimating ANPP using AVHRR NDVI composite data sets was late July.	The Tallgrass ANPP Model (TAM) explained 54% of the year-to-year variation in ANPP. Creation of 1.0 km x 1.0 km ANPP maps for a four-county (approximately 7000 ha) area for years 1989-2007 showed considerable variation in the spatial patterns of annual and inter-annual ANPP, suggesting that complex interactions existed among factors influencing ANPP both spatially and temporally.
Rigge et al. (2013)	South Dakota (USA) mixed-grass prairie	Growing-season NDVI was integrated weekly as a proxy of total annual biomass production, and integrated seasonally to represent annual production by cool- and warm-season species (C3 and C4 vegetation, respectively). Time-integrated NDVI (TIN) decreased with precipitation from east to west; the cool-season percentage of TIN increased from east to west related to the reliability and quantity of midsummer precipitation. Seasonal accumulation of TIN corresponded closely to gross photosynthesis data from a carbon flux tower. Field-collected biomass was strongly related to TIN and cool-season percentage.	Accurate maps of biomass production, cool- and warm-season composition, and vegetation classes can improve the efficiency of land management by facilitating the adjustment of stocking rates and season of use to maximize rangeland productivity and achieve conservation objectives.
Grant et al. (2012)	Southern Alberta (Canada) rangeland	Green biomass estimated with eight vegetation indices (Vis) produced from 20 m SPOT imagery. The Renormalized Difference Vegetation Index and Transformed Vegetation Index provided the best overall prediction (r^2 = 0.68) of the amount of above-ground green biomass production (marginally better than NDVI and other indices tested). Compared with green biomass (current-year growth), the predictive power was lower when non-photosynthetic vegetation (NPV, or carryover of dry, dead matter from the previous year) was included in the analysis.	For regional studies such as this, a variety of VIs should be considered and transformations are recommended to improve statistical predictive capability. Other methods such as spectral mixture analysis may be required to achieve improved results, particularly when including the important NPV component of biomass.
Psomas et al. (2011)	Central Europe	Examined the potential of hyperspectral remote sensing for mapping aboveground biomass in grassland habitats	Spectral regions related to plant water content were the best estimators of biomass. Models

Reference	Location	Summary	Key findings
		along a dry-mesic gradient, independent of a specific type or phenological period	calibrated with narrowband NDVI indices were best for up-scaling field-developed models to the (hyperspectral) Hyperion image. Ratio-based NDVI-type indices were less prone to scaling errors and offered higher potential for mapping grassland biomass using hyperspectral data from space-borne sensors.
Yu et al. (2010)	Alpine Grasslands in Golog Prefecture, China	NDVI correlated with harvested above-ground green biomass (AGGB). A regional regression model developed between MODIS-NDVI and LOG_{10} AGGB was used to calculate maximum carrying capacity (sheep-unit/year/ha). Maximum livestock carrying capacity was then reduced to the theoretical carrying capacity based on slope, distance to water and soil erosion.	Integrating remote sensing and GIS technologies enabled assessment of the spatial and temporal conditions of this alpine grassland. Projected stocking rates could then be forecast for decision making.
Wang et al. (2009)	Grasslands of Chinese Inner Mongolia	AVHRR NDVI data (1.1 km pixel size) and a light-use efficiency (LUE) model adapted to estimate absorbed photosynthetically active radiation and calculate absolute growth rate (AGR) and cumulative absolute growth rate (CAGR) of aboveground biomass in growing seasons between 1986 and 1999.	The LUE model provided sufficiently good simulation accuracy that its use should permit improved livestock feed management in the study area.
Xu et al. (2008)	Chinese grasslands	MODIS NDVI and ground truth data used to estimate grassland (including hay) production for six regions in 2005.	The authors claim that the models based on the six regions are the most suitable for monitoring grass production in China. These results are important for grassland administration, pasture grazing and grassland ecosystem studies in China.
Beeri et al. (2007)	US northern mixed-grass prairie	Quantify the PV and NPV biomass components of pasture using airborne HyMap hyperspectral imagery. Biomass quality, defined as plant C:N ratio, was also estimated using a previously published algorithm.	Total biomass & C:N ratios mapped with 18% and 8% relative error, respectively. Outputs from both models combined to quantify crude protein on a pasture scale. Results suggest synoptic maps of rangeland vegetation mass (both PV and NPV) and quality may be derived from hyperspectral aerial imagery with greater than 80% accuracy.

Reference	Location	Summary	Key findings
Reeves et al. (2006)	Grasslands of western North Dakota (USA)	MODIS net photosynthesis (PSNnet) and above-ground green biomass (AGB); plot-level grassland biomass estimated through the 2001 and 2002 growing seasons and compared with MODIS PSNnet at three times during each growing season.	The relationship between MODIS PSNnet estimates and scaled AGB improved steadily during each growing season and reached a maximum near peak greenness. AGB was more tightly coupled to PSNnet in 2001 because of the relative abundance of green biomass compared with standing dead from the previous year.
Hobbs (1995)	Central Australian rangeland	NOAA-AVHRR data were examined for their potential application in assessing primary productivity in the arid rangelands of Central Australia. Field measurements of herbage biomass were correlated with four indices derived AVHRR NDVI data.	Correlations between temporal sums of NDVI and herbage biomass data are relatively poor and unsuitable for herbage assessment in Central Australia.
Anderson et al. (1993)	Central Plains, north eastern Colorado (USA)	Early research to evaluate the association between spectrally derived (from Landsat) vegetation indices (difference, ratio, NDVI) and dried green vegetation biomass	There was a high degree of association between green biomass and NDVI. This indicated it was possible to predict green biomass levels on semi-arid rangelands using univariate regression models.
Turner et al. (1992)	Tallgrass prairie, eastern Kansas (USA)	Bidirectional reflectance measurements were obtained on grazed, burned ungrazed, and unburned ungrazed tallgrass prairie in eastern Kansas. Observations were also made on experimental plots on which vegetation height and biomass were manipulated by mowing. Foliage biomass and productivity (including off-take estimates) were measured concurrently at all sites.	The productivity of mowed or grazed sites was equal to or greater than that or unmowed or ungrazed sites but individual or cumulative NDVI tended to be positively correlated with biomass, not productivity. The concurrent use of thermal information may have improved this relationship.
Wylie et al. (1991)	Niger, northern Africa	Combined use of NOAA AVHRR data and biomass data, obtained through vegetation sampling of 25-100 km^2 areas, allowed the development of a method for biomass assessment in Niger. Vegetation sampling involved both visual estimates and clipped plots (double sampling). Time-integrated NDVI was regressed against total herbaceous biomass and then used to estimate biomass from the satellite data.	Biomass maps and statistics of the Niger grasslands were produced for the end of each rainy season: 1986, 1987 and 1988.
Williamson (1990)	Australia, improved pasture	Early Australian work to estimate biomass from SPOT-HRV satellite data.	

3.3.2.2.1 Light use efficiency and gross primary production

Net Primary Production (NPP) is an important component of the carbon cycle and a key indicator of ecosystem performance. NDVI is widely used as a surrogate measure of primary production. However, this index only provides an index of photosynthetic potential, or relative vegetation amount. The value of NDVI has been increased by using it to parameterise models that more accurately reflect actual changes in primary production, as well as quantifying its absolute amount (e.g. Seaquist et al. 2003).

NPP represents the net flow of carbon to plants from the atmosphere and defines a balance between gross photosynthesis (gross primary production, GPP) and autotrophic respiration. GPP defines photosynthesis before autotrophic respiration losses, while Net Ecosystem Production is NPP less heterotrophic respiration.

The remote sensing-based LUE model has evolved from Monteith (1972) and is defined as (Seaquist et al. 2003):

$$GPP = \sum_{i=1}^{n} \varepsilon_p \varepsilon (aNDVI + b) PAR$$

where GPP is the Gross Primary Production summed over the growing season (gm^{-2}), ε_p is the maximum biological efficiency of PAR conversion to dry matter ($g\ MJ^{-1}\ m^{-2}$), ε is the environmental stress scalar, NDVI is the (NIR − RED)/(NIR + RED) ratio (unitless), PAR is the incoming photosynthetically active radiation (MJm^{-2}), and *a* and *b* are the regression coefficients.

PAR encompasses the domain of incoming solar radiation between 400 and 700 nm that provides the energy for green vegetation to undergo photosynthesis. It varies as a function of solar zenith angle, cloudiness and the concentration of atmospheric constituents (water vapour and aerosols), but over time-scales of 1 day or longer, its contribution to incoming global radiation fluctuates within a narrow range between 45 and 50% (Frouin and Pinker 1995). The fraction of photosynthetically active radiation (FPAR) denotes the fraction of incident PAR absorbed by plants that is used for photosynthesis and is represented in the LUE as NDVI.

The mathematical representation of LUE provides the pivotal linkage between remotely sensed NDVI and GPP as a measure of photosynthetic potential (Goetz and Prince 1999).

3.3.2.2.2 Mitchell grass – NDVI and biomass through the summer growing season

Noting the limited use of NDVI (and its time-integrated values) for estimating pasture growth in Australia (Section 3.3.2.2), recent exploratory work by David Phelps (pers. comm.) has shown its value in relatively homogenous landscapes that are well understood. It appears that NDVI does have potential for biomass estimation in the Mitchell Grass Downs bioregion near Barcaldine (central Queensland) where two of the above conditions are met (i.e. absence of trees and shrubs, and a semi-regular growing season).

David has established a promising preliminary relationship between field-measured NDVI, using a low-cost hand-held radiometer, and estimated green pasture biomass through the summer growing season (Fig. 3-6). Further, there is a curvilinear relationship between Landsat-derived fractional green cover

(PV) and field-measured green biomass (Fig. 3-7). The potential value of these recent results is increased because the grazing-related ecology of Mitchell grass pastures and associated sustainability issues are well understood. There is generally a direct relationship between cover and biomass where Mitchell grass dominates and this is reversed where Flinders grass and other annuals dominate (i.e. high cover = low biomass).

David intends that further applied work will explore the Landsat fractional cover archive for 'break of season' for potential management advice on when to supplement livestock (and related management advice based on history) and the opportunity for ground truthing remote biomass estimates by end-users, i.e. graziers as 'citizen scientists'.

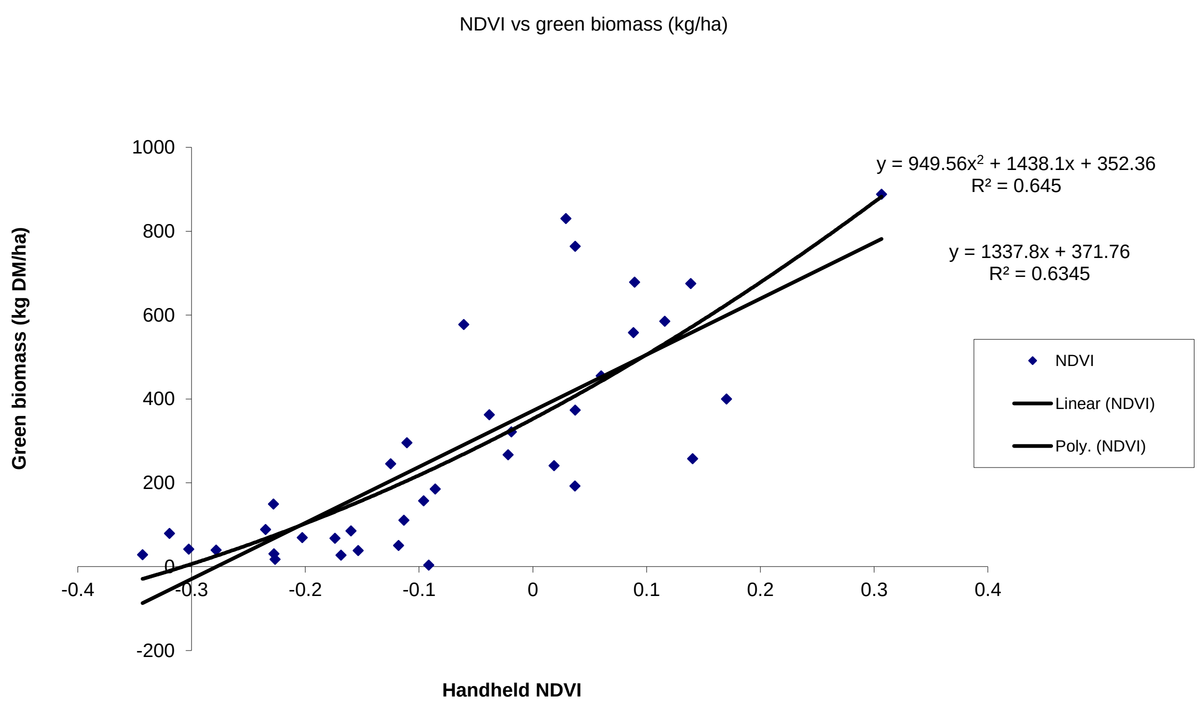


Figure 3-6. Relationship between NDVI of Mitchell grass plots collected with a hand-held radiometer and estimated green biomass. Graph courtesy of David Phelps, Qld Department of Agriculture, Forestry and Fisheries.

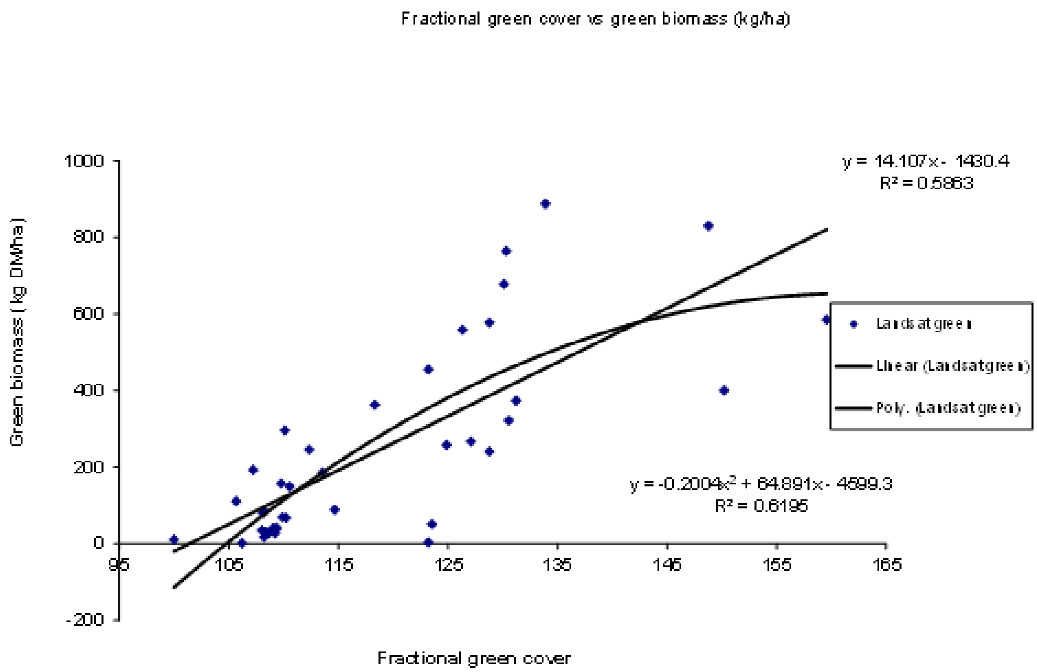


Figure 3-7. Fractional green cover (PV) derived from Landsat TM and corresponding estimated green biomass for Mitchell grass plots near Barcaldine, Queensland. Graph courtesy of David Phelps, Qld DAFF.

3.3.2.2.3 Pastures from Space

Pastures from Space provides near real-time estimates of Feed On Offer (FOO) from MODIS NDVI data to help farmers in the WA agricultural zone in managing pasture utilisation through the growing season (Smith et al. 2011). This is based on the understanding that to better capture the benefits of increased utilization, producers must be able to calculate a feed budget with timely and accurate estimates of pasture biomass and growth rate. The Mediterranean climate and largely annual-based pastures of this south western part of Australia means that NDVI is applicable for monitoring pasture growth through the late winter and spring period.

The Pastures from Space™ project was developed through a partnership between CSIRO and the Western Australian State Departments of Agriculture and Land Information. Pasture biomass (kg DM/ha) and pasture growth rate (kg DM/ha/day) were initially estimated using a range of satellite images including MODIS, Landsat TM and SPOT (Henry et al. 2004). Pasture biomass and growth rate were both derived from NDVI images obtained from satellite data using an empirical relationship between NDVI and actual biomass. Growth rate was estimated by integrating NDVI with coincident climate layers in a light use efficiency model.

Near real-time estimates of pasture biomass were collected from 72 paddocks on 15 farms in south west WA. These data were used to establish an exponential relationship, at field scale, between NDVI provided by MODIS. FOO data were based on the vegetative growth phase for biomass levels between 0 and 2000 kg ha/ha (R^2 = 0.71-0.75). The relationship ceased to have predictive value where FOO was greater than 2000 kg/ha or when the annual pasture species began to senesce. Smith et al. (2011)

reported that near real-time estimates of FOO from MODIS proved useful to farmers despite an apparent standard error of ±300 kg/ha.

3.3.2.2.4 FAT-CHOP and Rangewatch

Participants in the CRCSI (WA Landgate, University of New England, CSIRO) are working with station management at Liveringa Station in the West Kimberley region to increase the precision with which pastures are managed. If successful, one output could be a paddock-scale forage assessment tool for the Kimberley region. As such, it should contribute to the critical decision of how many cattle to return to each paddock following the first muster at the end of the wet season. This goal is called FAT-CHOP (Forage Assessment Tool – Calculating Head On Pasture). It will provide web-based delivery of paddock-scale forage available at the end-of-wet season, taking account of fire effects. The intended delivery platform is called Rangewatch.

Early work is testing the ability of time-integrated NDVI, from MODIS, to estimate green pasture biomass through the wet season across diverse land types in the 263 km^2 test paddock (Donald et al. 2015). MODIS NDVI is being calibrated against field-based NDVI (collected using ground-based radiometry), pasture height (using a rising plate meter) and estimated pasture biomass (Fig. 3-8, also see Mundava et al. 2015 and Donald et al. 2015 for additional explanation and example results).

Fig. 3-8 demonstrates the potential to estimate the green and total pasture dry-matter in this part of the West Kimberley that receives reasonably reliable monsoonal rainfall. Participating scientists recognize that immediate challenges that also need to be solved include (i) scaling field-based estimates of pasture biomass to the size of MODIS pixels and (ii) developing sampling strategies that cope with the variation within and between land systems mapped for the large and diverse test paddock (and, operationally, other paddocks).

Beyond FAT-CHOP, Rangewatch is being developed as a more broadly based decision tool for range management in the region. It is intended that this delivery system will, in time, combine remote sensing with regionally appropriate models of plant growth and a pasture budget calculator.

3.3.2.3 X- and C-band radar for grassland biomass estimation

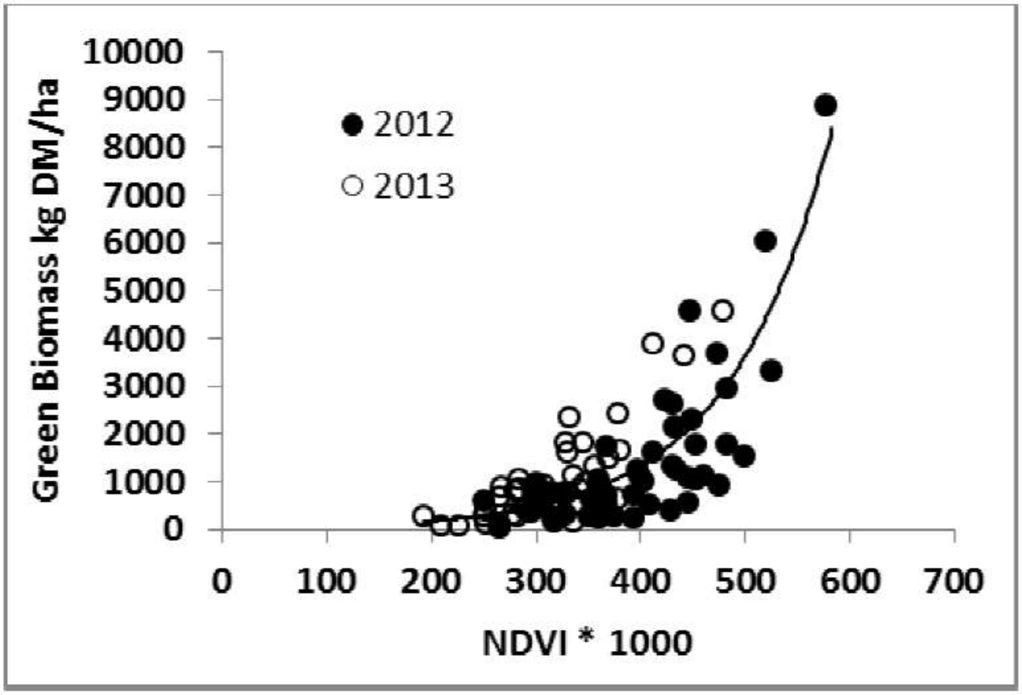
The potential to remotely estimate and monitor pasture biomass is being tested in the Kimberley using a density and volumetric (i.e. physics based) approach, rather than the more conventional spectral approach of greenness (i.e. photosynthetic activity which is related to biochemistry). CSIRO is currently the key player and its research activity builds on the Liveringa work described above. This work is also akin to the use of L-band radar in the National Biomass Mapping project (described in section 3.3.1.1) in that early results show the potential value of corrected C-band horizontal-horizontal (HH) backscatter for predicting herbage biomass (Fig. 3-9).

Further work in this area is based on the premise that operational radar data can contribute to biomass estimation in rangeland / grassland regions, especially in tropical and cloud-affected areas. Boosting this confidence, the recent launch of ESA's Sentinel-1 C-band SAR system and the upcoming Radarsat constellation systems will provide free and comprehensive datasets for wide-area, time-series mapping.

Next steps in developing a method for remotely estimating pasture biomass using radar will include:

- Collecting more field data (standing biomass and cover) across different low-cover types in the rangelands and northern grasslands.

(a)



(b)

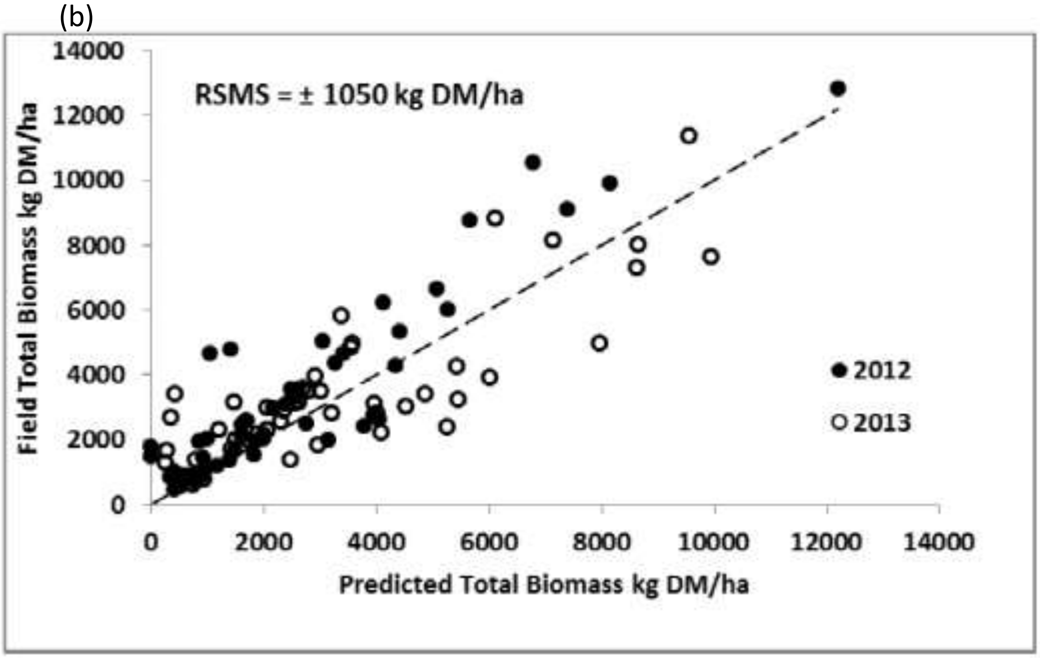
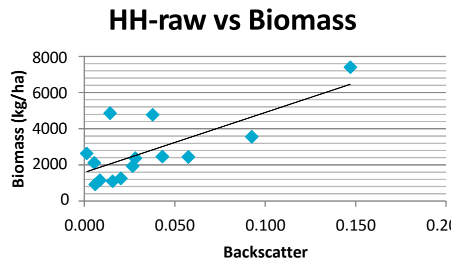
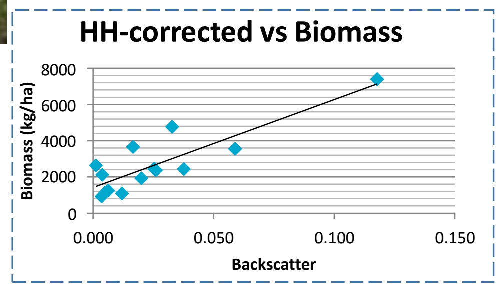


Figure 3-8. Example results from Liveringa Station where MODIS NDVI is being used to predict green pasture biomass. The top graph (a) shows measured green total biomass (from rising plate surveys) against MODIS NDVI (x 1000) for all grass dominant sites for both seasons. (R^2 = 0.65, ± RMSE 825 kg DM/ha). The bottom graph (b) illustrates the accuracy in predicting total pasture biomass from MODIS NDVI for all grass dominant sites and all months in each year. Graphs reproduced from Donald et al. (2015).

- Ensuring coordinated data collection efforts by researchers working in this remote estimation of biomass space (TERN AusCover, CSIRO, the NRM Spatial Hub partners and regional agencies).





$$\sigma_{pq} = f_{pq}(P_1, P_2, \ldots, P_N)$$

where P_i represents one of number bio-physical parameters

	RAW BACKSCATTER	MOISTURE CORRECTED	+ LANDCOVER RATIO CORRECTED	+ VEGETATION DENSITY CORRECTED	+ RVI CORRECTED
CORRELATION	0.5399	0.6689	0.7201	0.7434	0.7549

Figure 3-9. Schematic showing the approach used to estimate grassland biomass in the Kimberley region and indicative results. The graph within the dashed box shows an early-stage useful predictive relationship between corrected HH backscatter from C-band radar and field-based estimation of biomass. Slide courtesy of Alex Held, CSIRO.

3.3.2.4 Importance of ground data and proximal remote sensing

Appropriate ground data are essential for validating remote sensing-based analysis and for both calibrating and validating models. Archived data from earlier field-based studies are often used post hoc for validation purposes and, commonly, may be used for purposes other than what they were collected for. As such, Peter O'Reagain (pers. comm) makes the point that the use of ground data for such external use should be respected with due acknowledgement provided to the source.

Field-based methods for estimating biomass in the Australian rangelands are well established with, for example, BOTANAL being developed as a comparative yield estimation technique to suit savanna and sub-tropical landscapes (Tothill et al. 1992).

Catchpole and Wheeler (1992) provided one of the earlier comprehensive reviews, with recommendations, in using techniques to sample different vegetation complexes such as discrete shrubs or trees, patchy vegetation, homogeneous vegetation, and species-rich inhomogeneous heathland. Further information specific to grasslands is available in Mannetje and Jones (2000).

Axmanova et al. (2012) tested indirect estimation methods for historical vegetation plots where the required biomass variable was missing. Their approach used recorded plant height and cover. Problems arose in dense, structurally diverse vegetation where biomass is unbounded but cover has a fixed upper limit (100%). Actual plant biomass was best predicted using the median of plant heights measured in the field, a technique the authors called "biomass estimate-median method". Biomass can be calculated retrospectively using recorded cover levels and average species' heights according to local floras. The authors proposed their method as a rapid, non-destructive alternative to biomass harvest.

For real time estimation of pasture yield, George et al. (2006) reported that the performance of the comparative yield (CY) method in predicting herbage standing crop (HSC) was not improved by adding stubble height (SH) as an additional factor. Model performance varied with season; models that predicted HSC from CY in summer were weaker than models for winter, early spring, and late spring. They concluded that the CY method can be used with confidence throughout the year.

Proximal (not so remote) sensing can expand the range and value of conventional field data collected without necessarily adding greatly to the work load. Devices that mimic (or mirror) air- and space-borne sensors provide a convenient means for upscaling to the data provided by these more widely used forms of remote sensing.

In an experimental study, Durante et al. (2014) manipulated *Paspalum dilatatum* canopies through different stress treatments (flooding, drought, nutrient availability, and control) and by artificially varying the amount of senescent biomass. They then measured canopy reflectance and constructed simple models, based on either NDVI or selected wavebands, to estimate biomass and two variables related to forage quality: proportion of photosynthetic vegetation and biomass C:N ratio. General models satisfactorily predicted plant properties for the whole set of environmental conditions, but failed under specific conditions such as drought (for estimates of plant biomass), fertilization (for estimates of C:N ratio), and different levels of senescent tillers (for estimates of the proportion of photosynthetic vegetation). Where general models failed, specific models, based on different bands, achieved satisfactory accuracy. Their results indicated that plant biomass and aspects of its quality can be predicted from reflectance information under a broad range of conditions, but not for some particular conditions, where ancillary data or more complex models are probably needed to increase predictive accuracy.

Proximal hyperspectral remote sensing and associated spectral mixture analysis is still in the research domain – but can lead the way to useful and cost-effective public-domain products, as witness the research underpinning Landsat and MODIS fractional cover in Australia. One example of research into forage quantity and quality using field spectroscopy is that of Numata et al. (2008). They used two hyperspectral sensors at two different scales to test their ability to estimate biophysical properties of grazed pastures in Rondonia in the Brazilian Amazon. Using a field spectrometer, ten remotely sensed measurements (i.e., two vegetation indices, four fractions of spectral mixture analysis, and four spectral absorption features) were generated for two grass species, *Brachiaria brizantha* and *B. decumbens*. These measures were compared to above ground biomass (AGB), live and senesced biomass, and grass canopy water content. Water absorption measures between 1100 and 1250 nm had the highest correlations with AGB, live biomass and canopy water content, while ligno-cellulose absorption measures between 2045 and 2218 nm were the best for estimating senesced biomass. These results could improve on current methods for estimating grass measures using spectral absorption features derived from hyperspectral sensors although reported relationships were influenced by grass species architecture.

The value of proximal sensing for efficiently measuring and mapping green herbage mass using remote sensing in Australia has been demonstrated by Trotter et al. (2010). These authors propose that such devices offer substantial potential benefits for improved management of grazed pastures over space and time. In their paper they describe how an active, near-infrared and red reflectance sensor was used to quantify and map pasture herbage mass using a range of derived spectral indices. A common problem in such applications is suitably distinguishing green and senescent plant material. The Soil Adjusted Vegetation Index (Huete 1988) provided the best correlation with green dry matter (GDM), with an RMSE (root mean square error) of prediction of 288 kg/ha. The calibrated sensor was integrated with a Global Positioning System on a 4-wheel motor bike to map green herbage mass. An evaluation of representative, truncated transects indicated the potential to conduct rapid assessments of the GDM in a paddock, without the need for full paddock surveys.

3.3.2.4.1 CRCSI Tools for real-time biomass estimation in pastures

This CRCSI project runs until mid-2017. Partners include the University of New England, University of Canterbury [NZ], Sundown Pastoral Company, Twynam Agricultural Group and NSW Department of Primary Industries. Collectively, they are developing:

- A series of basic regional-, seasonal- and (pasture) species-specific calibrations that graziers can use to infer biomass from active optical sensing (AOS).
- A self-calibration process that allows livestock producers to generate their own location-specific calibrations from data acquired using active optical sensing. Here, the grazier uses AOS to measure NDVI for pastures of interest. He/she also estimates the green biomass (dry weight) and determines NDVI for a sequence of self-calibration quadrats. This calibration is then used to calculate green biomass for the larger area.
- A Mobile Device Application (MDA) that supports active optical sensing for real-time estimation of pasture biomass.
- A computing system that will accept crowd-sourced data from multiple MDAs along with their relevant self-calibration data and, in return, serve algorithm upgrades back to participants.
- Producer training packages around the use of the integrated MDA and sensor system.

Proximal (near ground) active optical sensing reduces the influence of atmospheric effects (cloud, shadow, sun angle) on reflected radiation compared with more conventional passive remote sensing. This in turn reduces the requirement for radiometric correction prior to using the data. In short, active sensing can enhance the signal to noise ratio.

Progress to date is suggesting that separate algorithms are probably required to estimate the dry weight of green pasture biomass from NDVI where different or multiple species are present. The timing of active optical sensing is also important as the NDVI signal decreases as the pasture matures and then senesces (example results in Fig. 3-10). The presence of weedy species with differing phenology and/or growth form (e.g. crumb weed) also confuses the NDVI-biomass relationship. Specific algorithms of the form, species * regional location * time are probably required to deal with these more complex types of interactions. Project participants are optimistic that the self-calibration process to be implemented through the MDA will help control for the variable influences of NDVI on green pasture biomass.

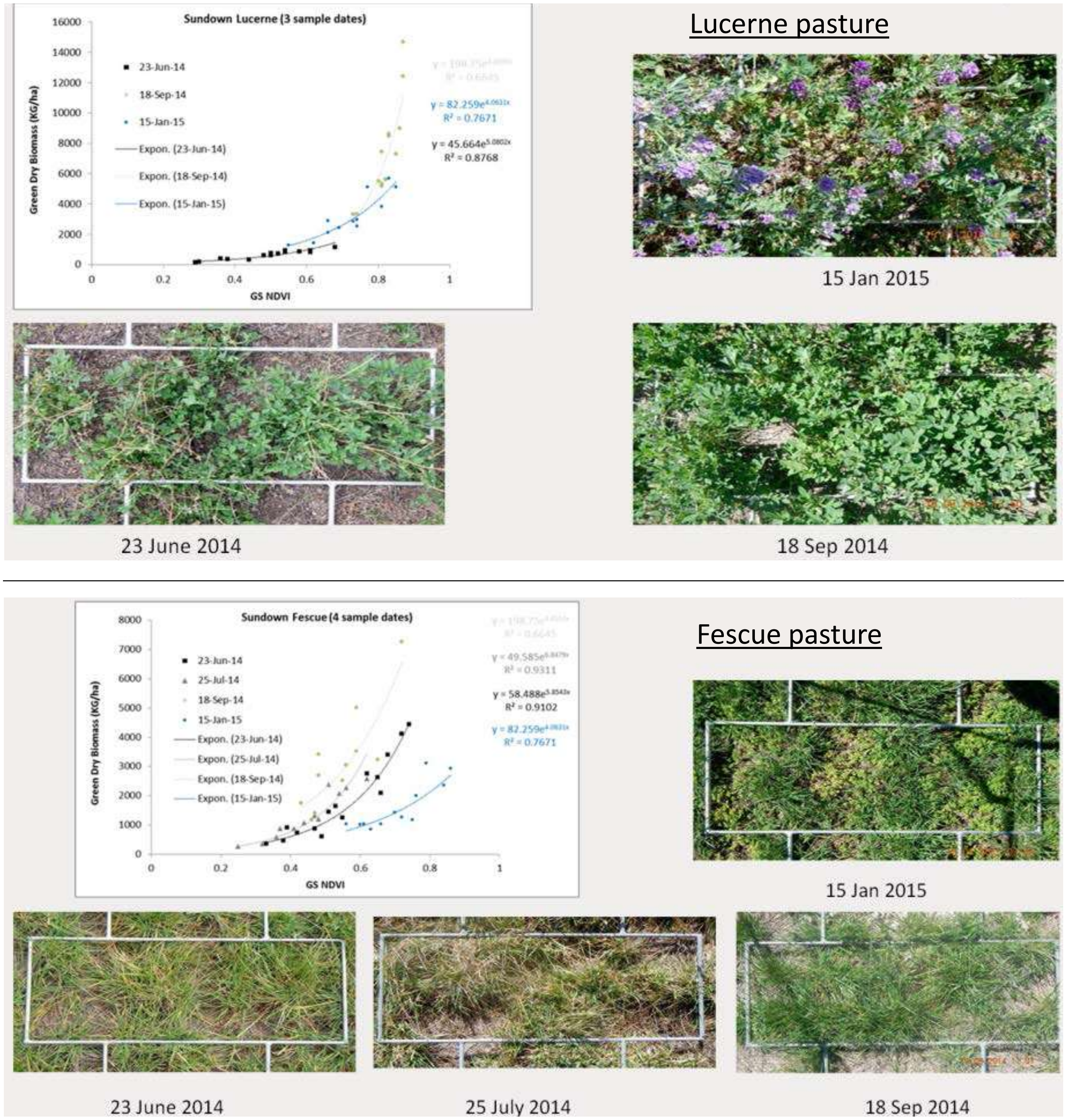


Figure 3-10. The influence of sampling time on the relationship between measured NDVI and producer-estimated GDB (the dry matter of green biomass) for Lucerne (top) and Fescue (bottom) pastures. The calibration curve for Lucerne is independent of sampling time. Different calibration curves are required fescue depending on sampling time. Figure copied from the CRCSI Quarterly Progress Report, Project 4.18: Biomass Business II – Tools for Real Time Biomass Estimation in Pastures.

Recent progress has included testing how well graziers predict ('eyeball') actual dry matter at different stages of pasture growth (Fig. 3-11). Total pasture biomass was consistently under-estimated during the Spring – by up to 50% in late October. Researchers report that this result greatly improved grazier's interest in supporting the research and adopting a 'self calibrating' process. Further work will see the participating graziers undertaking additional field sampling using refined protocols as well as the in-field evaluation of the MDA. This will provide essential information regarding accuracy, usefulness and adoptability of this form of crowd-sourced calibration data for estimating green pasture biomass from proximally sensed NDVI.

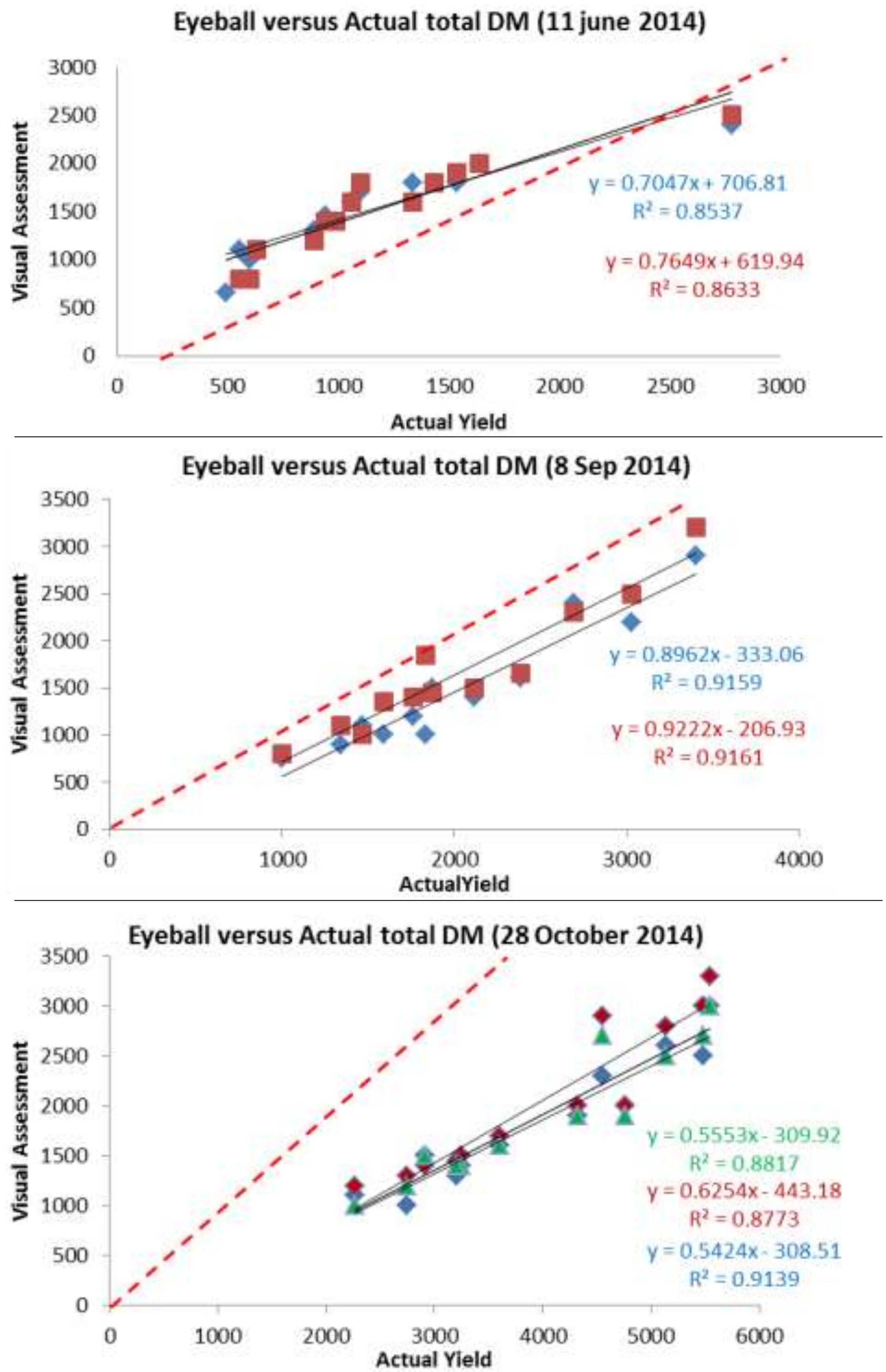


Figure 3-11. Comparison of 'eyeball' predictions versus actual total pasture biomass made by a number of assessors at three times during the year. The red dotted line indicates the 1:1 eyeball / actual. Figure copied from the CRCSI Quarterly Progress Report, Project 4.18: Biomass Business II – Tools for Real Time Biomass Estimation in Pastures.

The value of additional spectral bands (green, yellow and red-edge) and plant parameters for predicting the green and dead fractions of pasture biomass is also being investigated. Initial results indicate the red spectral band (acquired with the Cropcircle instrument) may be correlated to the dead fraction of plant matter whilst the NIR band is better for the green component. The addition of pasture height also greatly increases the relationship of NDVI to pasture biomass.

3.3.3 Cover to biomass relationships

Section 1.2.5 introduced the potential of mass / cover relationships to estimate paddock-scale pasture biomass from remotely sensed ground cover. As described in that section, pasture growth models such as GRASP and AussieGRASS have inbuilt functions to estimate cover from simulated total standing dry matter (TSDM) (see Fig. 1-8).

Section 4 summarizes recent work by Carter et al. (2015) to estimate TSDM from Landsat fractional cover data across three grazing trials in northern Australia. This study was conducted as a possible interim measure to advise land managers on paddock-scale forage availability ahead of an effective remote sensing-based method for monitoring pasture biomass.

Each trial site had a different cover to mass relationship and it was not possible to generate a generic function. At paddock scale within sites, the best relationships had average errors in TSDM estimates, based on contemporaneous Landsat fractional cover, of 13% to 30% (200 – 640 kg/ha). Applying the function from one paddock to other paddocks within the same grazing trial produced considerable error in estimated biomass indicating that even the best function for a grazing trial may degrade significantly when applied to other locations. Carter et al. (2015) provide plausible reasons as to why this occurs but optimistically conclude that "Despite large errors in the estimation of TSDM it may still be useful to make available a Landsat cover estimated dry season TSDM to land managers provided error estimates are supplied with the estimated mean value. This would provide upper and lower bounds for decision making and checks on other methods of biomass estimation at the paddock scale."

3.3.3.1 Regionally customizing AussieGRASS for improved accuracy

AussieGRASS has been widely used to simulate pasture growth and cover at 5-km x 5-km resolution in Australia. This can be done both retrospectively and prospectively; the former based on historic rainfall data and the latter using seasonal climate forecasts. Both have value for improved understanding of the effects of climate variability on livestock production and management of natural resources. Regional confidence in the modelled output is improved where AussieGRASS is calibrated to local conditions. This was demonstrated by Hacker et al. (2007) where they 'tuned' AussieGRASS to the environment of western NSW using long-term monitoring data collected by the Range Assessment Program.

This project developed improved relationships between total dry matter and the dynamic component of ground cover, where the latter included grasses, forbs and litter. At regional scales there was good agreement between average levels of total dry matter and dynamic ground cover produced by AussieGRASS and those obtained from ground based monitoring over 17 years.

Procedures were also developed to combine the static components of ground cover (stone, shrubs and biological soil crusts) with the dynamic vegetation component to estimate total ground cover at regional scales.

3.4 Modelling pasture biomass

Rickert et al. (2000) provide an excellent overview of issues associated with modelling pasture and animal production including basic terminology, principles and constraints associated with modelling, model types and, by way of an example, the generic components of an integrated soil-plant-animal model.

On the international scene, well known models that include simulated above-ground biomass in their output include Century[13] (Parton et al. 1987), PHYGROW (Rowan 1995) and SAVANNA (Coughenour et al. 1984). Such models are often not directly applicable to Australian rangeland environments or, if so, can be difficult to correctly parameterize. This has resulted in both home-grown models and adaptation of international models (e.g. SAVANNA as reported by Ludwig et al. 2001).

Models developed for the Australian rangelands to simulate forage production from rainfall and other environmental factors vary in complexity, application and performance. These include:

- IMAGES (Hacker et al. 1991) is a conceptual model of the pastoral production system within the arid, winter rainfall shrublands of WA. It explicitly explores the effect of herbivores on the condition of the grazing resource. The model was parameterized for five pasture types using data from long term exclosures, grazing trials and rangeland monitoring programs in WA. Validation of model outputs suggested that that the model should be useful in evaluating alternative management strategies, identifying key ecological processes and for setting research priorities.
- Hobbs et al. (1994) developed a simple model of soil moisture balance and herbage production for central Australia. The model required rainfall and potential evaporation as inputs to model daily soil moisture and plant growth. Parameter values were estimated on the basis of pasture biomass data collected from five landscape types over two years, which included up to four major growth events.
- Using an alternative approach, Pickup (1995) described a relatively simple model for estimating herbage production for the same area (central Australia) based on rainfall and evapotranspiration, and its calibration with an index of remotely sensed vegetation cover. This model operated on a one month time step with three calibration parameters: a water-use efficiency term, a cover depletion rate and the percentage of tree and shrub cover present. Model output could potentially show differences in herbage production for particular areas under different rainfall conditions and in response to changes in land condition or level of grazing.
- Also in central Australia, Sparrow et al. (1997) developed an empirical ecosystem model for arid chenopod shrublands that accounted for inherent landscape heterogeneity and temporal variability. This model focused on simple herbage and shrub biomass pools where herbage dynamics were most affected by grazing (as measured by distance from water and average paddock stocking rate, and soil erosion) and shrub dynamics were most sensitive to erosional status. Modelled output corresponded well with the spatial and temporal patterns of a Landsat MSS cover index except on highly erosional sites which appeared more dynamic than predicted.

[13] Century is commonly used for simulating levels of soil organic carbon under different environmental conditions and management regimes (e.g. Allen et al. 2010, Hunt 2014).

- The SEESAW model (Ludwig and Marsden 1995) was designed to simulate the ecology and economics of semi-arid woodlands in the eastern rangelands of Australia. A sub-model within SEESAW computes net primary production (NPP) through time as a function of plant available moisture, available nutrients and temperature. The SEESAW model specifically caters for landscapes with patchy vegetation distribution as a result of run-off and run-on. As these landscapes degrade through inappropriate grazing, the run-off areas expand and have reduced vegetation (NPP) and resources (rain water and soil sediments containing nutrients) are concentrated in confined run-on areas. Ludwig and Marsden (1995) used their model to test the effects of projected climate change versus land degradation on simulated NPP. Their results showed that land degradation reduced landscape-scale NPP by a larger amount than altered rainfall and temperature under projected climate change.
- The GRASP family (WinGRASP, PaddockGRASP) and its spatial implementation at continental scale (AussieGRASS). For several years now, PaddockGRASP and AussieGRASS have been the models of choice for simulating standing biomass, pasture growth, derived animal performance and probable land condition (based on the level of pasture utilisation) in northern Australia (see following section).

Additionally, the appropriateness and performance of models developed for intensive southern Australian grazing systems through the Southern Grazing Systems project (Andrew et al. 2003) are now starting to be evaluated in northern Australia (Doran-Browne et al. 2014).

3.4.1 GRASP and related models

GRASP and its spatially-implemented variants, PaddockGRASP and AussieGRASS, provide both a probabilistic and dynamic implementation of the grazing system as illustrated in Fig. 3-12. PaddockGRASP enables the interactive calculation of paddock stocking rates in workshop environments. AussieGRASS has been used to simulate pasture biomass and cover at much larger scale (regional, state and national) to enhance a broad range of ecosystem understanding. Examples include indicating current and recent seasonal conditions as part of managing for climate variability (www.longpaddock.qld.gov.au/), providing contextual information for improved understanding of past episodes of land degradation (McKeon et al. 2004), modelling carbon dynamics with respect to climate, grazing, and fire (Hill et al. 2005, 2006) and indicating the sustainability of grazing management in the Queensland rangelands (Bastin and the ACRIS Management Committee 2008).

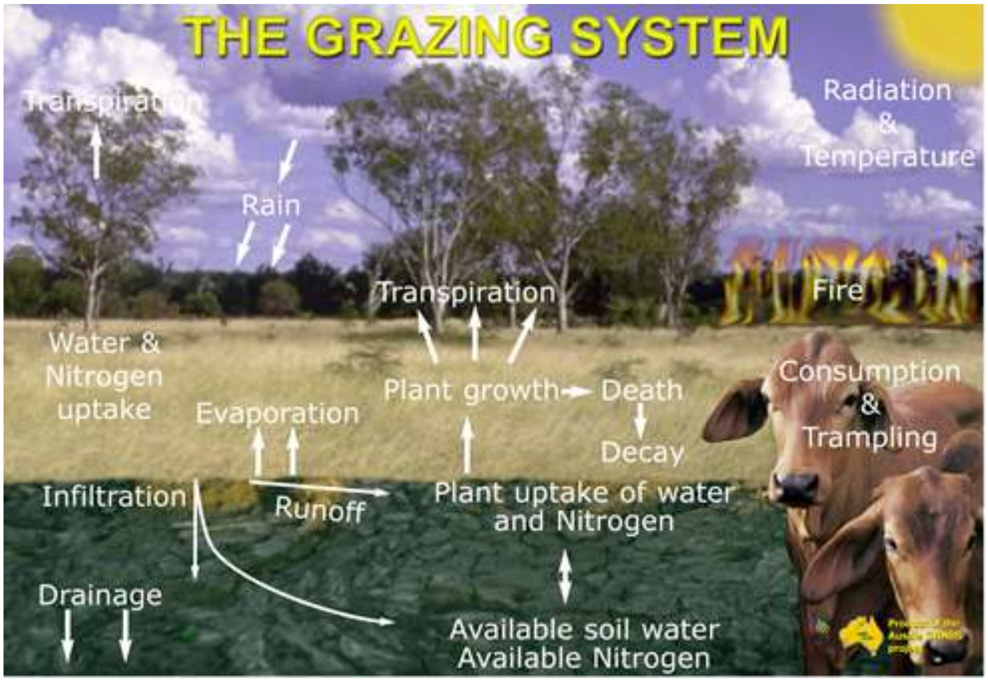


Figure 3-12. Components of the grazing system as implemented in the GRASP suite of pasture growth models. Figure courtesy of Ken Day, Queensland Department of Agriculture, Fisheries and Forestry.

3.4.1.1 Model components

Key GRASP parameters used to describe a land type include:

- Available soil water – based on soil texture and depth;
- Soil and pasture fertility, principally in terms of nitrogen availability;
- Pasture species attributes affecting growth, senescence, detachment, decomposition, trampling, intake and cover;
- Liveweight gain (LWG) and wool production;
- Grass basal area;
- Pasture response to grazing; and
- Tree cover and rooting depth.

GRASP simulates the complexity with which woody vegetation interacts with pastures. Trees can either compete with or benefit pasture growth (e.g. tree micro-climate and tree strip effects) and these effects are highly non-linear. Applications of woody effects include: fragmentation of tree density across landscapes, woodland thickening and episodic tree death and defoliation (such as occurred in a major drought between 1991 and 1994).

3.4.1.2 Role of remote sensing

Remote sensing contributes to calibrating key GRASP parameters and validating simulated output. It provides spatial and temporal information on tree cover and basal area (where aerial photography can precede satellite image archives, e.g. Fensham and Fairfax 2002), and episodic fire and flood as drivers of pasture growth. Remotely sensed green cover (from NDVI), ground cover, soil moisture and atmospheric chemistry (particularly methane emissions) are variously used in both model calibration and validation. Green cover limits interception of solar radiation, resultant photosynthesis and consequent transpiration – as per the light use efficiency algorithm (section 3.3.2.2.1). The GRASP model generates a synthetic NDVI consisting of an understory and woody components. This approach is useful but has its limits, e.g. low growth rate (and low mass to cover) can look the same as high growth rate (high mass to cover).

The Landsat-based bare ground index (now bare-soil fraction) assists calibration of cover where modelled biomass is translated to percentage cover using relationships such as those shown in Fig. 1-8.

3.4.1.3 GRASP applications

The GRASP suite enables:

- Safe carrying capacities to be calculated, e.g. the Stocktake application (Aisthorpe et al. 2014).
- Seasonal forecasts of grazing system components.
- Virtual experiments such as grazing strategies and climate change impacts. Landmark examples are the major works by McKeon et al. (2004) and McKeon et al. (2009). The former provided important contextual information about climate variability for improved understanding of eight major land degradation episodes in different regions of the Australian rangelands (i.e. "learning from history"). The more recent study reviewed approaches for quantifying livestock carrying capacity (LCC); current trends in climate and their effect on components of the grazing system; implications of the 'best estimates' of climate change projections for LCC; the agreement and disagreement between the current trends and projections; and the adequacy of current models of forage production in simulating the impact of climate change. The authors reported the results of a sensitivity study of climate change impacts on forage production across the rangelands and discussed the more general issues facing grazing enterprises associated with climate change, such as 'known uncertainties' and adaptation responses (e.g. use of climate risk assessment).
- Current system state and state relative to history. Within GRASP, the percentage of perennial grasses is used via a non-linear function to indicate pasture 'state' (Fig. 3-13) with state 0 having 90% perennial grass and state 11 having 1% perennial grasses (see Fig. 1 in McKeon et al. 2000). Change in pasture condition state is a function of utilisation percentage where the safe utilisation rate is generally set at 30%. If utilisation is higher than 30% (or as otherwise specified for a particular pasture type), then the simulated state deteriorates. Where pasture utilisation is lower than the safe utilisation, then pasture state improves.

3.4.1.4 Further GRASP development

Potential enhancement of the GRASP suite could include (Ken Day pers comm.):

- Improved parameterization of water infiltration and rainfall intensity effects on runoff (based on Grant Fraser's recently completed PhD).
- Better simulation of daily LWG.

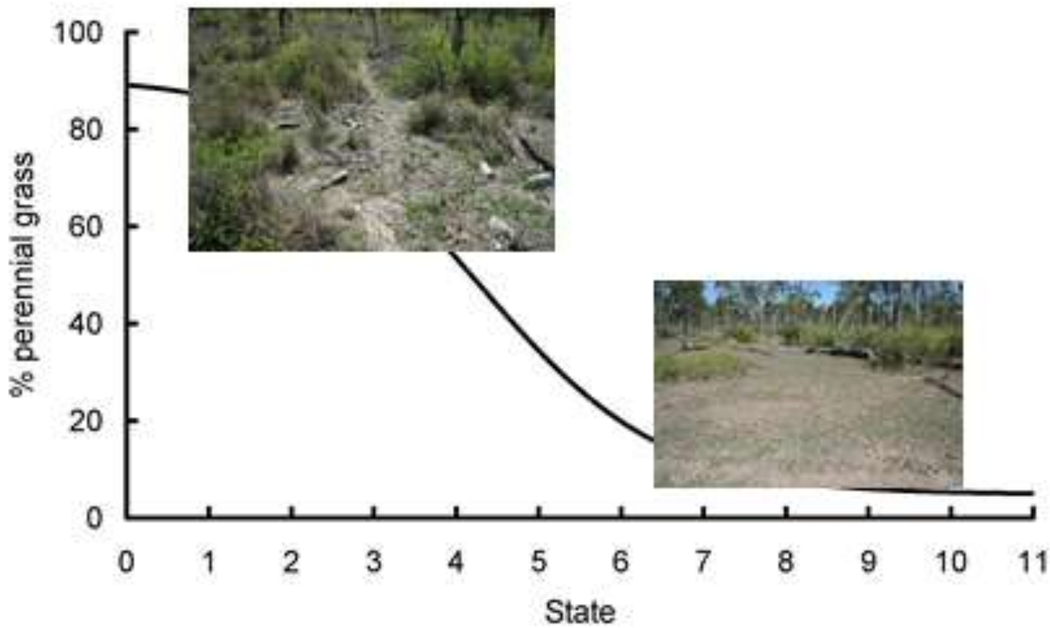


Figure 3-13. GRASP models pasture condition as one of eleven states based on the percentage of perennial grasses. Change in state is largely driven by their level of utilisation.

- An improved set of mass-to-cover functions.
- Use of Landsat fractional cover in point GRASP, Forage and Paddock GRASP applications (for calibration/validation and parameter constraints).
- Parameterizing grazing preference and associated herbivore distribution as a function of simulated pasture growth.
- Improving the utility of the "condition state" component. Currently, GRASP calculates pasture "condition" based on perennial grass composition and level of utilisation (above). The ability to specify actual condition as an input parameter based on remote sensing methods would result in more versatile and dynamic results for modelling stocking rate and carrying capacity simulations (as demonstrated by Scanlan et al. 2013, 2014).

Much of the basic science is in place to enable many of these improvements (Ken Day pers comm.). The challenge is assembling the required resources for software coding, algorithm testing and refinement.

3.4.2 Pasture modelling in southern Australia

There has been extensive research and development into appropriate grazing-system models to assist management of more intensive livestock enterprises in southern Australia. Perhaps the largest and most coordinated was the Sustainable Grazing Systems (SGS) National Experiment that operated across the southern high rainfall zone (annual rainfall >600 mm/year) (Andrew et al. 2003). This large-scale coordinated program combined six diverse research sites into the one integrated experiment. Each site collected a common data set about the productivity and sustainability of grazing systems, so that issues beyond the site could be explored. This required an appropriate database and modelling tools that allowed cross-site issues to be examined by a mix of conventional data analyses and modelling scenarios.

The SGS Pasture Model developed and used in that program is now being evaluated for its effectiveness and utility in modelling more extensively managed northern beef properties with the first application reported by Doran-Browne (2014). A companion paper by Bray et al. (2014) used the model to calculate greenhouse gas emissions for the same production system.

The GRAZ family of grazing-system models may also be suitable for northern Australia following appropriate modification and testing.

3.4.2.1 SGS Pasture Model

The Sustainable Grazing Systems (SGS) Pasture Model is a multi-paddock, biophysical simulation model for livestock systems. Core to the model is gross photosynthesis and respiration. It has a flexible interface for setting up and running simulations and extensive graphical capability for visualizing simulated data output. The software models pasture and animal production in multiple paddocks (up to 30) under different stock management strategies. It works at paddock scale and doesn't have a specific spatial component.

Components of the SGS model include (Johnson et al. 2003):

- A physiological model of pasture species herbage accumulation in response to climatic conditions;
- The water balance including evapotranspiration, run-off (surface and subsurface), infiltration and drainage;
- Pasture utilisation by grazing animals;
- A metabolisable energy-based animal growth model; and
- Organic matter and inorganic nutrient dynamics (for nitrogen, phosphorus, potassium and sulfur) including plant uptake, adsorption, leaching, nitrogen fixation by legumes, and atmospheric nitrogen losses.

A range of grazing options (set stocking, rotational grazing and continuous grazing at a variable rate) is available for different classes of livestock. The main modules (water, nutrients, pasture and animals) are interconnected.

The SGS Pasture Model was developed by Ian Johnson of IMJ Consultants (http://imj.com.au/) in collaboration with MLA and the University of Melbourne. It has been applied to a range of research questions, such as climate variability, drought, business risk, and the impacts of climate change.

For their north Australian application, Doran-Browne et al. (2014) developed new pasture parameter sets within SGS to represent (i) groups of tropical perennial, palatable and productive (3P) grasses and (ii) annual tropical grasses that include both productive and less productive grass species. Fifteen years of data from the long-term Wambiana grazing trial (~70 km south-west of Charters Towers) were used to validate the model. The results showed that SGS is capable of representing northern Australian beef systems with modelled outputs for total standing dry matter and steer liveweight in agreement with the year-to-year variation in measured data over three different soil types and two stocking rates. Recommendations for further model development included incorporating fire, tree growth and the use of urea supplementation as model input. The authors stated that further testing was required to verify that the new pasture parameter sets are suitable for the model to be used in other regions in northern Australia.

3.4.2.2 GRAZPLAN

GRAZPLAN is a decision support system (DSS) for Australian grazing enterprises in the intensive land use zone (Donnelly et al. 1997) that was built from research on grazing systems and then released through a commercial partner. It uses local weather and farm data to test the relevance of different management procedures for individual farms. The main DSS, GRAZPLAN, can be used to evaluate and optimize long-term management decisions in relation to profitability and sustainability. It is quite general in its application and modular in structure. A subcomponent of the DSS, MetAccess, uses the Australia-wide database of climate data to display and analyse daily weather records and provide users with estimates of the probability of specified weather patterns within the range of data from a specified locality.

GRAZPLAN also separate pasture growth and soil moisture sub-models (Moore et al. 1997) and an animal biology model for feed intake, production and reproduction (Freer et al. 1997). These may be relevant to the extensive northern beef industry if, and when, suitably modified and tested.

3.4.2.2.1 GrassGro

The pasture growth module of GrassGro (Moore et al. 1997) is quite general in structure but recognizes four functional groups of pasture plants: annual and perennial species of grasses and forbs. Shoot tissue is classified as live, senescing, standing dead, or litter, and also according to its dry matter digestibility, thus enabling integration with diet selection and feed intake models.

The phenological development of pasture plants is modelled, with the transitions between each stage governed by environmental variables (day length, temperature and soil moisture). Functions predicting net primary production in response to light intercepted, mean daytime temperature, and available soil moisture, and also the process of maturation, are common to all functional groups. Seed and seedling dynamics are modelled for annual species only.

3.4.2.2.2 GrazFeed

GrazFeed (Freer et al. 1997) predicts the intake of energy and protein by grazing ruminants, allowing for selective grazing, and can be linked to the output from GrassGro. When used alone, it caters for supplementary feeding and estimates the use of the diet for maintenance and production, according to current feeding standards. Conception and death rates are predicted from the maturity and condition of the animals. The model is designed to be of general application to any type of sheep or cattle enterprise on any pasture.

The outputs from GrassGro and GrazFeed in combination enable users to analyse simplified grazing systems in terms of pasture and animal production, gross margins, and year-to-year variability of southern improved pastures (e.g. a specified pasture cultivar, or combination of cultivars) at any specified site. The GRAZPLAN package may also be used to simulate forward from current pasture and animal conditions, for assessing the probability distribution of production outcomes, given the historical variability of weather conditions over the specified forward period.

3.4.2.2.3 Potential relevance of GRAZPLAN to the northern beef industry

Attributes of the GRAZPLAN (GrassGro and GrazFeed) approach to modelling pasture growth and associated animal performance that could be attractive for grazing-systems research in northern Australia include:

1. The use of standard input databases such as SILO climate data.
2. Use of a generic approach to modelling that can be applied beyond improved pastures to the more extensively grazed grasslands and rangelands.
3. Established linkages between components – simulated pasture growth from GrassGro is readily input to GrazFeed to predict livestock performance. At enterprise scale, it accommodates multiple paddocks with differing management.
4. The economics (financial implications) of different management decisions are modelled as part of the output.
5. GrassGro:
   - Is based on resource competition for light, water and nutrients (nitrogen and phosphorus); growth dynamics are influenced by phenology; it can be parameterized for vegetation functional types; and handles multispecies vegetation.
   - Models pasture quality as well as biomass dynamics.
   - Has a seedbank sub-model for annual species.
6. The ruminant model (GrazFeed):
   - Is based on the Australian feeding standard.
   - Allows for diet selectivity and feed substitution.
   - Simulates growth, reproduction and mortality.
   - Can deal with both simple and complex animal management systems.
7. The program suite can be run in different modes:
   - The user interface is designed for "what if" analysis. Report templates are available to produce pre-designed charts and tables from the simulated output.
   - In "ecosystem" mode, it can link to the APSIM[14] water balance, soil nutrient cycling and surface residue sub-models. It accesses the APSOIL database of soil attributes. There is a "nutrient-aware" version that responds to nitrogen availability and models soil carbon dynamics.
   - The "Batch GrassGro" program enables large GrassGro analyses to be run where simulations are constructed by describing differences from a library of "farm systems".
8. GrassGro can be coupled to the APSIM cropping models allowing:
   - Analyses of mixed or dual-purpose farming systems (e.g. grain + graze) – this may be useful with the expansion of mosaic agriculture in northern Australia.

[14] APSIM: Agricultural Production Systems sIMulator (APSIM) has a suite of modules which enable the simulation of agricultural systems that cover a range of plant, animal, soil, climate and management interactions (see http://www.apsim.info/)

- Modelling of pasture populations as weeds in cropping systems.

9. "Document"-based simulations can be compiled into larger work flows to build, for example, spatial forecasts. Such simulations use "Simulation Description Markup Language" as command-line programming input. These text-processing algorithms construct large collections of related simulations over large areas, e.g. modelled cropping over much of Australia at 1 km resolution (Zhao et al. 2014)

3.5 Modelling land condition

Modelling of land condition is based on the principle that stocking rate is the key management factor determining pasture condition, livestock production and economic performance in the rangelands (Scanlan et al. 2013). Grazing experiments are usually used to quantify and demonstrate the biophysical impact of grazing strategies and appropriate models provide the means to extrapolate the results of such studies to property and regional scale. As an example, Scanlan et al. (2014) used an extensive literature review and simulation modelling to evaluate the effectiveness of resting pastures to improve land condition in northern Australia.

The Wambiana grazing experiment south of Charters Towers has provided one of the most detailed datasets for developing and calibrating a suitable model of land condition. This study has compared the relative performance of different stocking strategies in managing for climate variability (O'Reagain et al. 2009). The results have provided empirical evidence that strategies such as moderate or seasonally-flexible stocking rates are sustainable while being equally profitable to a higher stocking rate strategy (O'Reagain et al. 2011).

The key steps used by Scanlan et al. (2013) to evaluate the effect of stocking rate on property-level biophysical and economic performance are shown in Fig. 3-14. The analytical flow involved:

1. Using plot-scale data (from the Wambiana trial) to calibrate the GRASP model for the box land type to provide suitable parameters for running GRASP in further simulations. It was assumed that the box land type adequately represented each trial paddock although two other land types were also present. The GRASP model was run over the experimental period from 1998 to 2011 with the results compared with field data for TSDM and LWG of steers at the scale of the paddock. Some calibration of the parameters which drive the change in the percentage of perennial grasses in the pasture was needed, as these parameters could not be derived from the small plot data.
2. Simulations were run for all paddocks to estimate annual pasture utilisation rates and the percentage of green days in the year using paddock stocking rates and rainfall records.
3. Pasture utilisation rates and the percentage of green days were then used as inputs into the general equation to estimate the annual LWG of steers.
4. As the final step, the ENTERPRISE model (MacLeod and Ash 2001) was used to examine property-level economic performance of a breeding-finishing business.

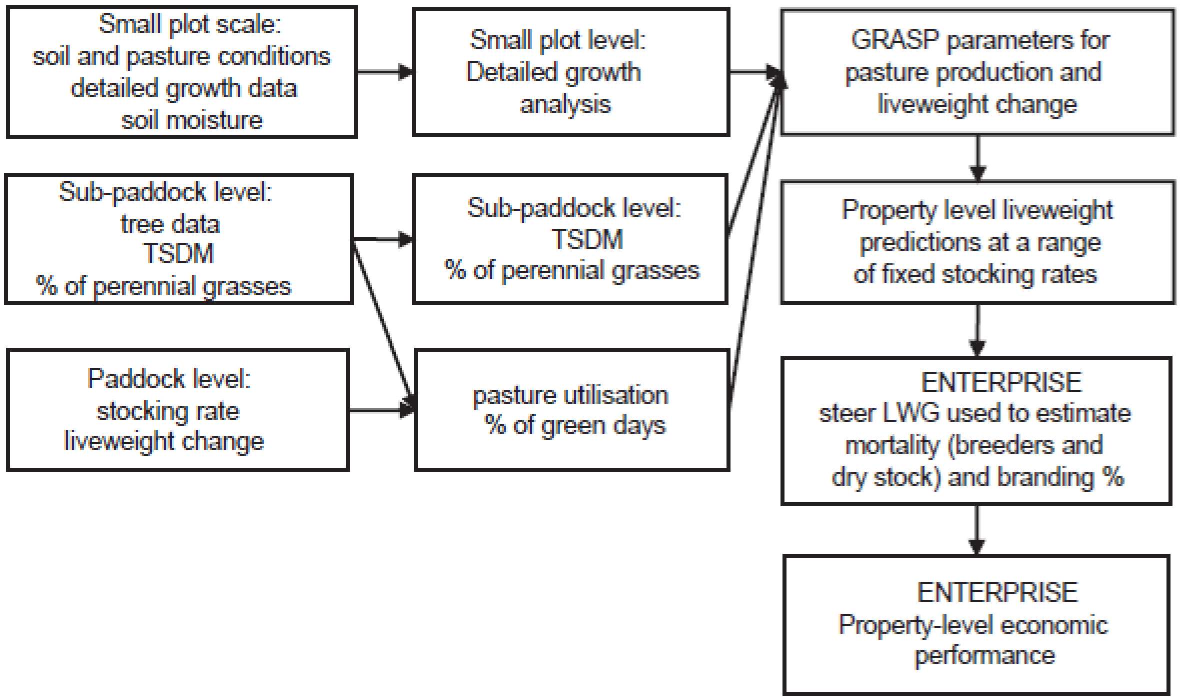


Figure 3-14. Analytical procedure used by to model property-level sustainability and economic performance from plot-scale data collected at the Wambiana grazing trial. Figure reproduced from Scanlan et al. (2013).

3.5.1 Model improvement

Specific improvements to the modelling of Wambiana data (as described in Scanlan et al. 2013) include:

1. Calibrating the model for the three land types present in each trial paddock, not just box.
2. Including the effects of changes in tree cover over time, particularly *Carissa* thickening.
3. Including Landsat fractional cover as part of model calibration. Total ground cover could potentially improve calibration of the runoff component and better parameterize grazing distribution. Including the green component (PV) may improve the current relationship between TSDM and LWG and reduce the occurrence of 'years that don't fit'.

Joe Scanlan (pers. comm.) suggests that, more generally, modelling of land condition (to indicate long term sustainability) and economic performance of northern beef properties could be improved by including spatial and temporal information derived from satellite imagery. Useful additional spatial information includes:

- Patchiness, especially that of trees.
- Identifying and spatially representing consistently different units that relate to livestock performance and management, including degradation effects (e.g. soils; run-on areas). These units may be different to detailed land unit (or regional ecosystem) mapping, e.g. requiring some amalgamation of mapped units.
- Grazing patterns with respect to waterpoints and wind direction.

Temporal components to be improved include detecting the timing and impact of climatic and other environmental effects on vegetation growth: e.g. scattered storm rains, frost, and fire.

3.6 Data assimilation

Wikipedia (http://www.wikipedia.org/) defines data assimilation as "the process by which observations are incorporated into a computer model of a real system. Applications of data assimilation arise in many fields of geosciences, perhaps most importantly in weather forecasting and hydrology. Data assimilation proceeds by analysis cycles. In each analysis cycle, observations of the current (and possibly past) state of a system are combined with the results from a numerical model (the forecast) to produce an analysis, which is considered as 'the best' estimate of the current state of the system. This is called the analysis step. Essentially, the analysis step tries to balance the uncertainty in the data and in the forecast. The model is then advanced in time and its result becomes the forecast in the next analysis cycle."

The C-Store research project currently being conducted by CSIRO illustrates how data-assimilation may be useful for progressing biomass estimation based on linkages between ground data, remote sensing and modelling.

3.6.1 C-Store

C-Store is the project name for CSIRO research that is developing a data integration and modelling system for biomass and carbon assessment. It uses a "diffuse" modelling approach that is based largely on remotely-sensed light interception (FPAR[15]) to estimate gross primary production (GPP) of the woody and herbage vegetation fractions (Fig. 3-15). This is termed the carbon store (upper left box in Fig. 3-16). Modelled output is then combined with observational data through a data assimilation process to refine modelled fractional biomass estimates and calculate associated error surfaces (remainder of Fig. 3-16). Understanding the magnitude and importance of errors is critical as they propagate through the data-assimilation process: they may be additive, variously multiplicative or even cancel each other out.

In summary, C-Store uses a relatively simple, "bottom-up", remote sensing-driven approach that is not overly complex (i.e. not highly mechanistic). The MODIS 250-mm FPAR product is used as input. Data assimilation is important (Fig. 3-16). The biomass of tree and grass fractions are estimated separately for Australia on a monthly basis (example biomass map shown in Fig. 3-17). Simulated output is validated against flux tower data which provide independent data of net carbon exchange between the atmosphere (as CO_2), vegetation and soil. Importantly, output includes initial national error estimates that will help target where additional ground data are required.

[15] FPAR: fraction of photosynthetically active radiation

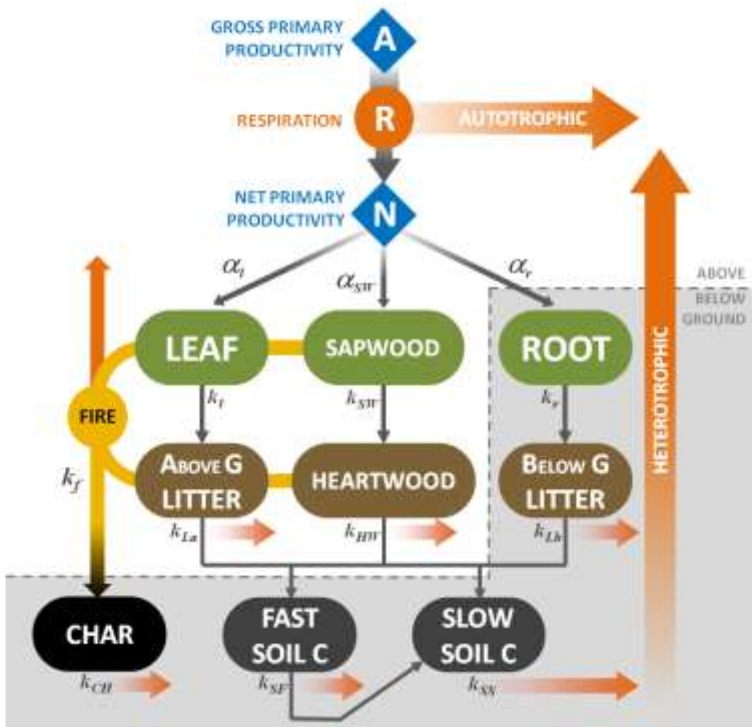


Figure 3-15. C-Store model structure for simulating the woody fraction of vegetation biomass. Estimated GPP is adjusted for respiration to calculate net primary production (NPP). NPP is then partitioned into aboveground components of leaf (which transitions to either sapwood or surface litter) and sapwood (which is converted to heartwood) or belowground root or litter. As a near-final step, the contribution of each component to the fast or slow pools of soil organic carbon is modelled. Fire affects aboveground woody carbon either releasing CO_2 back to the atmosphere or capturing carbon for long periods as char. Figure courtesy of Randall Donohue, CSIRO.

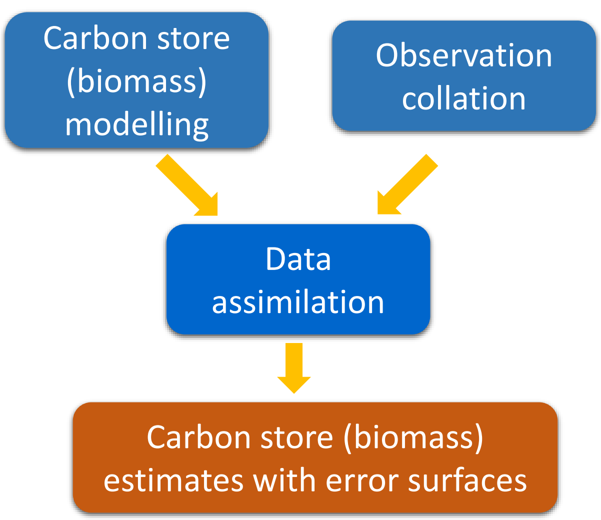


Figure 3-16. Overview of the C-Store approach to estimating vegetation biomass. The method is based on data assimilation and estimates error surfaces as part of the output. Figure courtesy of Randall Donohue, CSIRO.

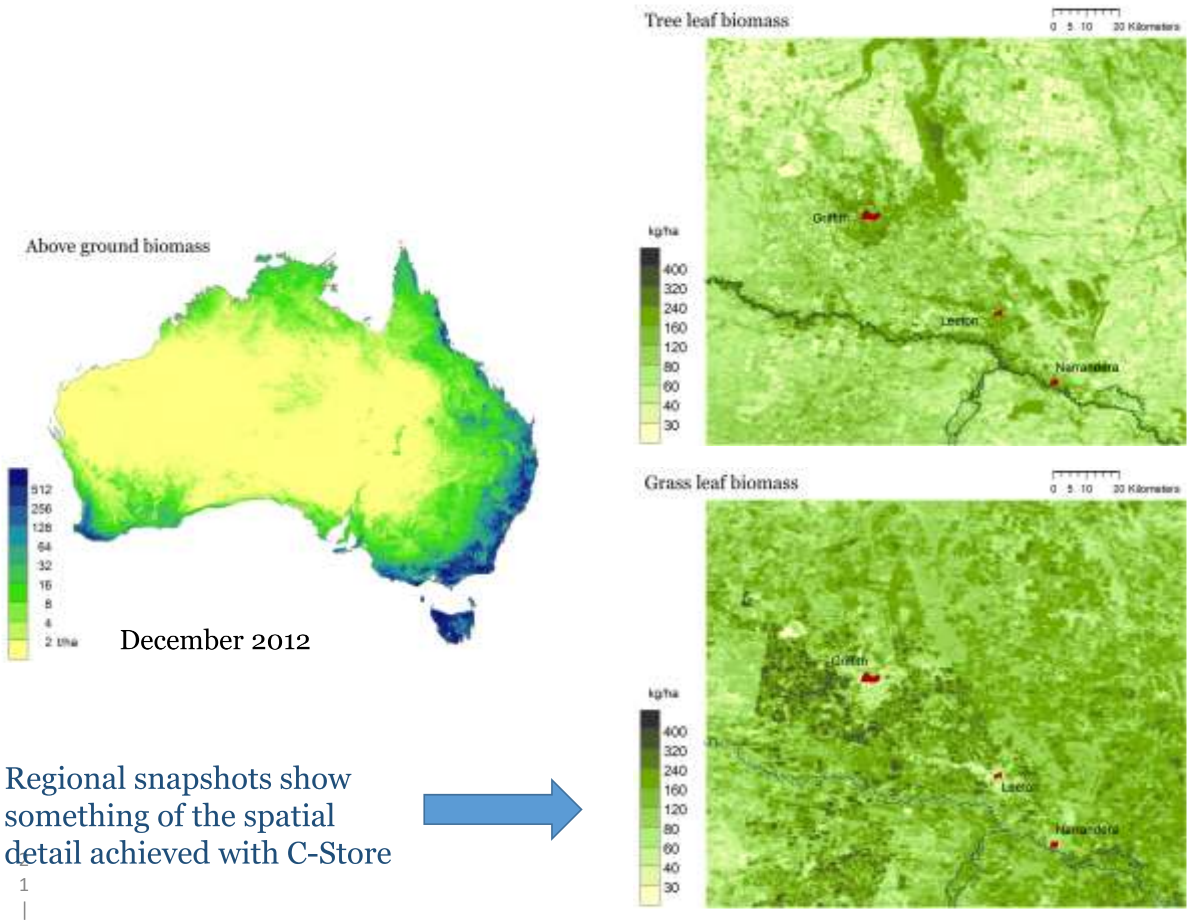


Figure 3-17. A preliminary national estimate of vegetation biomass for Australia in December 2012 generated by C-Store. The images on the right show the tree leaf and grass leaf components for a small part of the continent. Figure courtesy of Randall Donohue, CSIRO.

3.6.1.1 Integrated Assessment Modelling

Integrated assessment modelling (IAM) is often used in more complex areas of the environmental sciences, including policy analysis. The modelling is deemed to be "integrated" because environmental problems do not respect the borders between academic disciplines. Integrated assessment models therefore integrate knowledge from two or more domains into a single framework. Integrated modelling is referred to as "assessment" because the activity aims to generate useful information for policy making, rather than to advance knowledge in its own right. IAM is that part of integrated assessment that relies on the use of numerical models. (This information sourced from Wikipedia, http://en.wikipedia.org/wiki/Integrated_assessment_modelling, accessed 30 May 2015).

IAM may be relevant to a multi-agency approach to developing a robust integrated method for routinely estimating vegetation biomass, particularly herbage, at national scale. Use of IAM may be warranted to ensure that biomass end products are credible, useful and widely adopted for improved livestock production and better management of natural resources at scales spanning enterprise, region, state and national. This includes a broadly based policy component (e.g. surrounding drought). Achieving this outcome requires necessary interdisciplinary and/or transdisciplinary research into the socio-economic requirements of biomass-product development, delivery and effective end-use.

3.7 *Related work*

3.7.1 Precision pastoral management tools

The Precision Pastoral Management project is managed by Ninti One Ltd as part of the CRC for Remote Economic Participation. The CRC's website says that the project is "develop(ing) new management tools that integrate precision animal data with precision spatial data to match livestock performance to environmental conditions, leading to more efficient pastoral management. The project will also encourage adoption of the systems and technologies to remote pastoral enterprises." (http://crc-rep.com/research/enterprise-development/precision-pastoral-management-tools, accessed 30 May 2015)

Existing technologies build on mandatory use of RFID ear tags for cattle and sheep and a walk-over-weighing system that, together, can provide performance data for individual animals (e.g. daily change in liveweight). This technology, including software, can be connected to an auto-drafter to segregate livestock based on liveweight, identity or other criteria. Some of the components derive from the former Desert Knowledge CRC and are currently being commercialized as a Remote Livestock Management System (RLMS).

A component of the CRC-REP project is better understanding the relationship between remotely sensed groundcover and stock performance, including an appropriate adoption pathway for uptake by remote pastoral enterprises. To this end, the project is being conducted in partnership with the WA, NT and Queensland agriculture departments, participating pastoralists in each jurisdiction, other research organisations and businesses in the communications technology, engineering and software sectors.

Little further information is available as the CRC-REP has applied a "commercial-in-confidence" embargo on research results in its bid to ultimately commercialize marketable output products.

3.7.2 Spatially enabled livestock management

The University of New England (UNE), as a research partner in the CRCSI, is researching novel approaches to the rapid and efficient collection of spatial data to improve pasture and livestock management in intensive grazing systems. Some of their developing technologies, including the way in which each is used (i.e. technology fit for purpose), could be appropriate to calibrating and validating methods for biomass estimation in the grazed rangelands.

UNE research areas and their requirements include (see also section 3.3.2.4.1):

- Real-time estimation of pasture biomass using active (rather than passive) remote sensing. Instruments emitting radiation in the visible-red and NIR parts of the electromagnetic spectrum are mounted on quad bikes in conjunction with GPS. This active form of proximal sensing mitigates atmospheric effects (cloud, shadow, sun angle) in passive remote sensing.

- Crowd sourcing of data where participating graziers contribute essential fit-for-purpose calibration and validation data. An example is sufficient calibration data to suitably model pasture biomass from NDVI (above project) because the NDVI – biomass relationship is affected by species composition and the proportion of green and dry matter. Such participatory citizen science encourages and facilitates end-user uptake of developing technologies.

4 Northern grazing trials – mass-cover relationships

Section 1.2.5 introduced the concept of cover-to-mass relationships to estimate paddock-scale pasture biomass from remotely sensed ground cover. As described in that section, pasture growth models such as GRASP have the converse functions (i.e. mass-to-cover) inbuilt to estimate cover from simulated TSDM. The intent in this work conducted by John Carter and colleagues was to develop an interim "work around" to satisfy the increasing demand from the grazing sector for estimates of actual pasture biomass until such time as an integrated approach using remote sensing and modelling can deliver this information.

Section 3.3.3 very briefly summarized recent work to predict TSDM from Landsat fractional cover at a range of scales using data from three well measured grazing trials in northern Australia. This section provides an overview of that work, the main findings and their implications for reliably estimating pasture biomass. For further detail, refer to Carter et al. (2015).

In the rangelands the persistent green fraction corresponds to tree and shrub cover of the "greener" woody species (particularly eucalypts) and this index is designed to show slowly varying (multi-year) changes in tree canopy dynamics. Adjustment of the vegetation cover fraction to account for woody vegetation provides a more reliable estimate of ground cover where trees are present. The current fractional ground cover algorithm (cover under trees) allows ground cover to be estimated up to a persistent green cover of 60% meaning that the product can be used across grasslands, shrublands, woodlands (including most of the savanna region) and open forests.

Grazing trials were used as the source of pasture biomass data because they have been conducted in a systematic manner at a range of scale and at a number of locations across northern Australia. The type, quantity and quality of data available were evaluated and the trials ranked as tier 1, tier 2 or tier 3 (the first two shown in Fig. 4-1).

There are some points of difference between the available biomass data and Landsat fractional cover. The latter includes grass and tree litter cover in the NPV fraction. Pasture biomass (TSDM) was commonly estimated using the BOTANAL technique (Tothill et al. 1992) but this method does not estimate litter mass. Thus there was an immediate miss-match between the two data types for statistical analysis and subsequent modelling purposes. Where ground cover was estimated in addition to BOTANAL, it was quadrat based, which provides a significantly different result to the point intercept method used to calibrate fractional cover. Additionally, the cover estimates did not distinguish between "attached" and "detached" cover with this parameter being an important factor in forage availability.

4.1 Data

Three tier 1 sites were selected as being most appropriate for the initial modelling. TSDM data were assembled for each measurement period for each paddock in each of three grazing trials: Pigeon Hole (Hunt et al. 2013), Toorak (Orr and Phelps 2013) and Wambiana (O'Reagain and Bushell 2011).

The daily BOTANAL records (field data) were matched as closely as possible to their corresponding Landsat image. The latter were downloaded, as available and suitable, from the United States Geological Survey (USGS) archive and processed to fractional cover. Field estimates of quadrat-based ground cover were transformed to a point-intercept basis using the inverse of a function developed by Murphy and Lodge (2002). Ground data were aggregated to paddock scale.

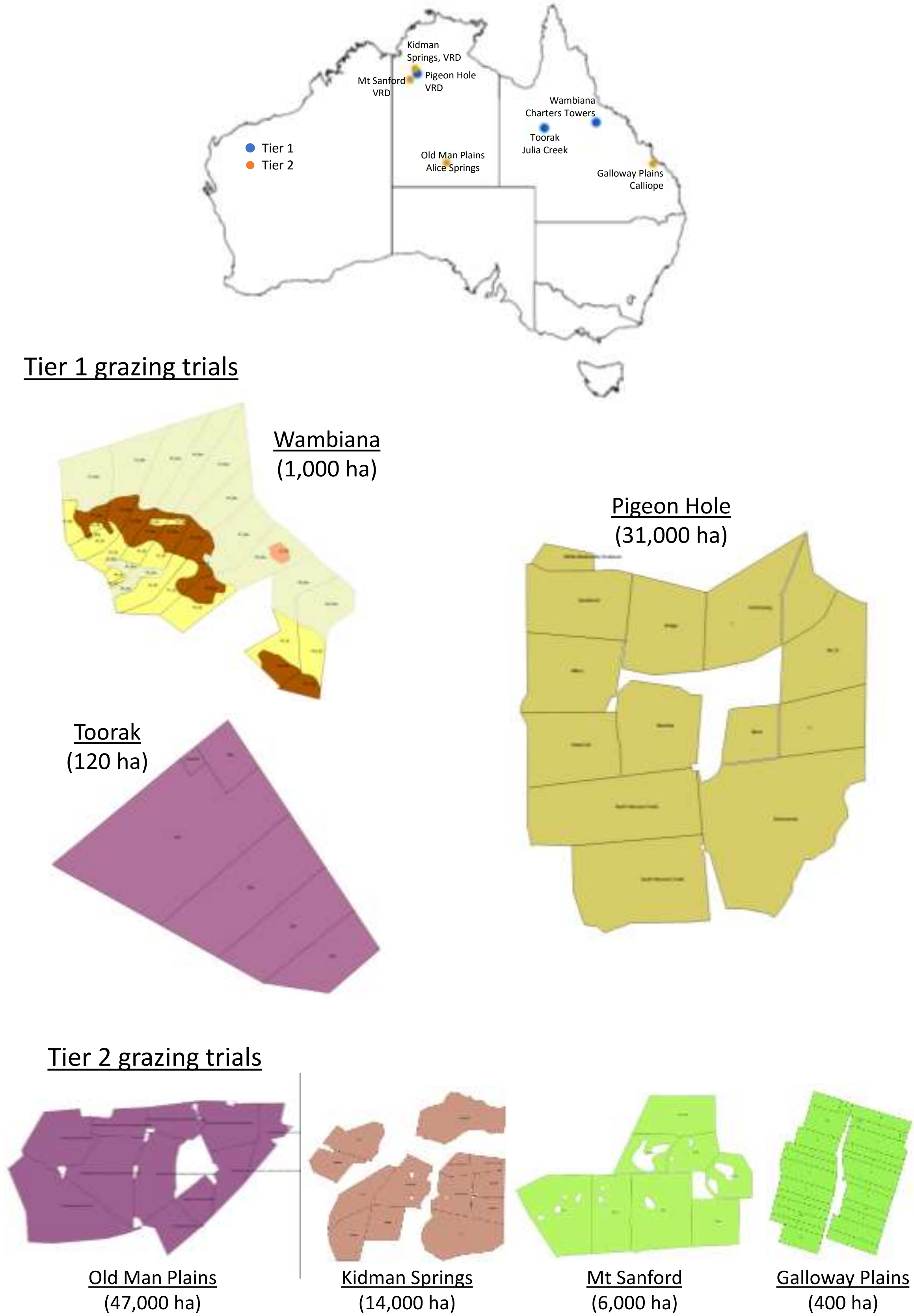


Figure 4-1. Locations of tier 1 and tier 2 grazing trials in northern Australia (top) and their schematic representation (below). Note that the grazing trials are not drawn to scale (see their labelled areas). Grazing trial maps courtesy of John Carter.

Data analysis proceeded from testing for, and then developing, simple relationships between Landsat fractional ground cover and TSDM at a range of scales (paddock, site, all grazing trials so as to partly represent northern Australia) to more complex model components and their interactions, including the importance of the green (PV) component. An example of predicted TSDM based on cover to mass modelling for the Wambiana grazing trial and surrounds is shown in Fig. 4-2.

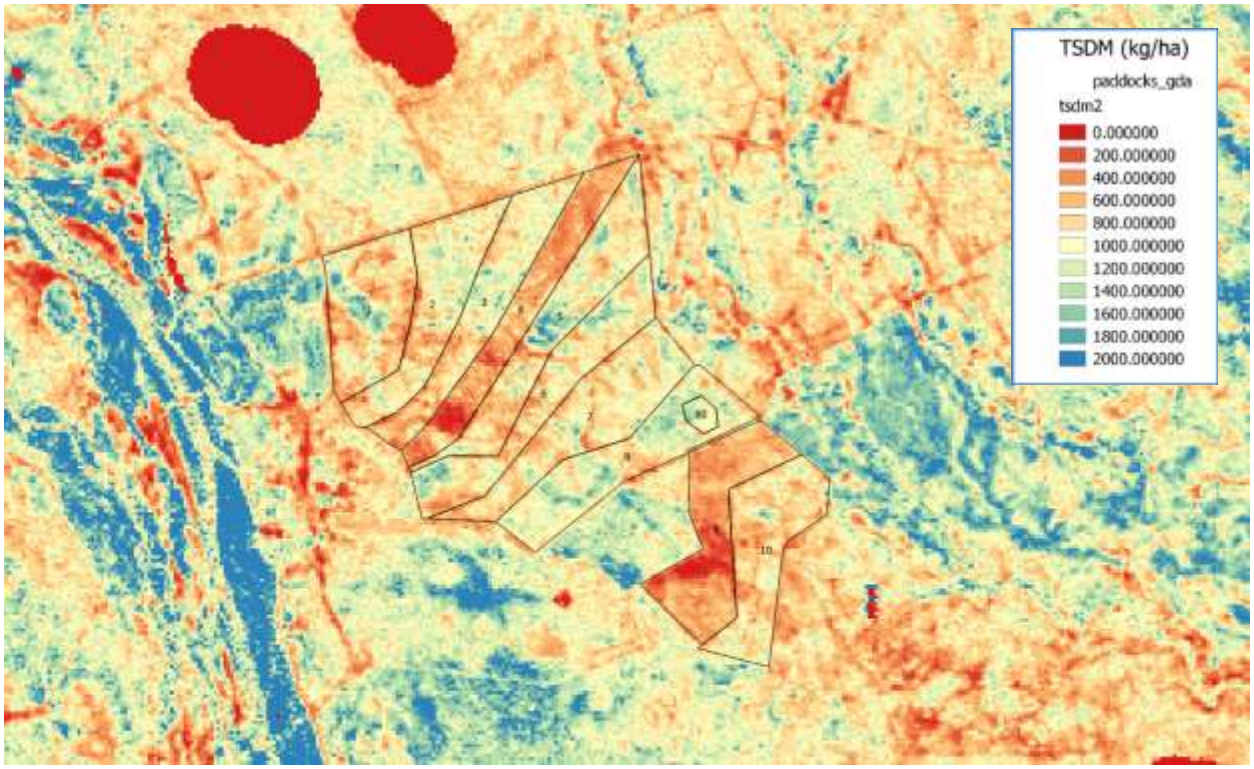


Figure 4-2. Example modelled TSDM product for the Wambiana grazing trial and surrounds. TSDM was predicted from a November 2014 Landsat image of fractional cover. The large red blobs in the top left of the image are masked clouds. Figure reproduced from Figure 19 in Carter et al. (2015).

At its most ambitious level, it was presumed that cover-mass relationships will have value for estimating TSDM from Landsat fractional cover if the relationship for a treatment paddock at one site can usefully predict TSDM at another site under a different grazing treatment, based on its remotely-sensed fractional cover at that time.

To this end, a number of questions about the data and combinations of predictor variables were investigated:

1. How well correlated are the satellite-derived and field-based estimates of cover?
2. If suitably correlated, can simple linear and non-linear regressions be developed for each grazing trial using data from all paddocks and all recording times?
3. Can simple linear and non-linear relationships be developed to predict TSDM using the green and dead fractions, total cover and 12-month average of green cover?
4. Do field data for other variables improve paddock-level regressions between TSDM and total cover?

5. Comprehensive analysis to answer questions relevant to any operational implementation of a model to predict TSDM.
   - Is transforming the data useful? If so, what transformations should be used?
   - How well can TSDM be estimated from Landsat-derived total ground cover with optimum statistical procedures and/or transformations?
   - Are the statistical properties of the data significantly different between grazing trials?
   - Are cover-mass relationships likely to differ between paddocks? Is paddock-scale calibration useful or even possible?
   - Can calibration at one point in time be used for prediction at other times?
   - Does calibration by land type improve paddock-level estimation of TSDM?
6. How to best integrate remotely sensed estimates of cover and modelling. This is partly dependent on prospective model functions for converting Landsat-derived ground cover to biomass. Testing was based on a model of green cover and the Landsat PV (green) fraction at Wambiana.

4.2 Main findings

4.2.1 Comparison of satellite- and ground-based cover estimates

Field-based estimates of total ground cover were, in all cases, less than that of the satellite estimate. When the field data were corrected to a point-intercept basis, the cover values for Toorak and Pigeon Hole were quite close. The Wambiana Landsat mean-cover estimates were about 14% higher than the field estimates which could have been due to bias in either the field or satellite estimates.

4.2.2 Regression analysis

Linear regressions using all data showed that the mass (TSDM) needed for a 1% increase in Landsat-based cover varied with grazing trial. Correcting for the apparent bias in estimation at Wambiana (above), produced a similar value for Pigeon Hole (~60 kg/ha increase in TSDM per 1% increase in fractional cover). The Toorak data suggested about half of this increase (30 kg/ha of TSDM / 1% cover), possibly due to the presence of annual grasses and broad leaved forbs at this grassland site.

While linear fits have some diagnostic value for biological parameters, they were less useful than other functions. Plotting the untransformed data against the linear equations showed large prediction errors at the 95% level of confidence; about 500kg/ha for Pigeon Hole and 1500 kg/ha at Toorak and Wambiana.

The data for all paddocks at each grazing trial showed that the cover to mass relationship was approximately linear at lower cover values and strongly nonlinear at higher cover values (Fig. 4-3), with clear differences between grazing trials. Non-linear fits to the untransformed data slightly improved correlations.

Data analysis for paddock-by-paddock correlations (as opposed to whole grazing trials) indicated that individual paddocks (treatments) could have different mass-to-cover relationships suggesting that calibration at this scale may provide greater precision. Out of 29 paddocks across the three trials, 23 had improved simple linear regressions between satellite cover and field-estimated TSDM compared to analysis at the whole grazing-trial level. In the case of Toorak where the fit was poor, including the percentage of pasture utilized improved the fit to data.

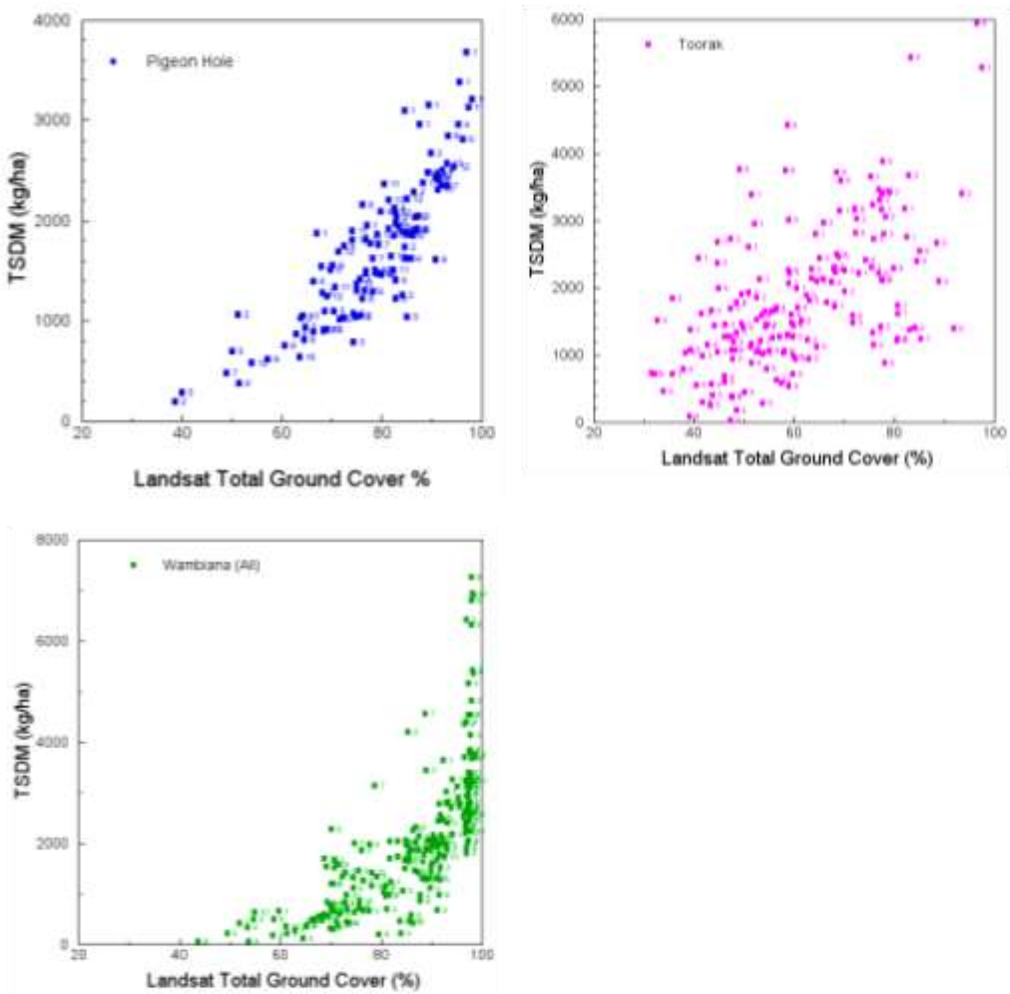


Figure 4-3. Relationships between Landsat-derived ground cover and field-estimated TSDM at three grazing trials: Pigeon Hole (top left), Toorak (top right) and Wambiana (bottom left). Numbers identify paddocks within each grazing trial. Figure adapted from Figure 6 in Carter et al. (2015).

4.2.3 Analysis related to operational implementation

1. Data transformation

   The square root transformation of TSDM considerably improved model fit and reduced prediction error. For cover variables where the unit is percentage, a logit transformation was applied. Where TSDM was predicted using two cover variables, the correlation between the two was investigated and, where appropriate, a log transformation of the ratio between the two used. These transformations improved model fitting (Fig. 4-4).

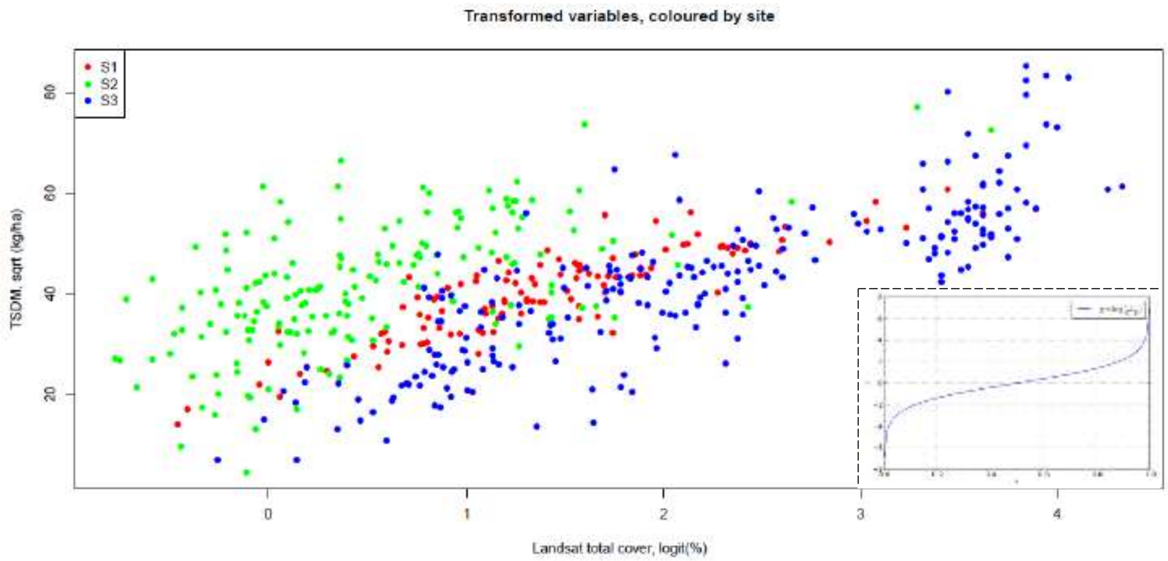


Figure 4-4. Scatterplot of transformed cover and biomass data from three grazing trials: S1 (red) = Pigeon Hole, S2 (green) = Toorak and S3 (blue) = Wambiana. A logit function (dashed inset box) was used to transform the Landsat-derived percentage ground cover. The TSDM data were square root transformed. Figure adapted from Figure 10 in Carter et al. (2015).

2. Using optimal statistical procedures (including data transformation), how well can TSDM be estimated from Landsat total cover?

A very modest fit between satellite ground cover and TSDM was obtained where a global function integrating transformed data from all three grazing trials was applied (Wambiana example shown in Fig. 4-5). Prediction errors were large, often 500-1000 kg/ha too high or 500-2000 kg/ha too low, with the Toorak grazing trial having the poorest results. Additionally, predictions for most paddocks were significantly biased.

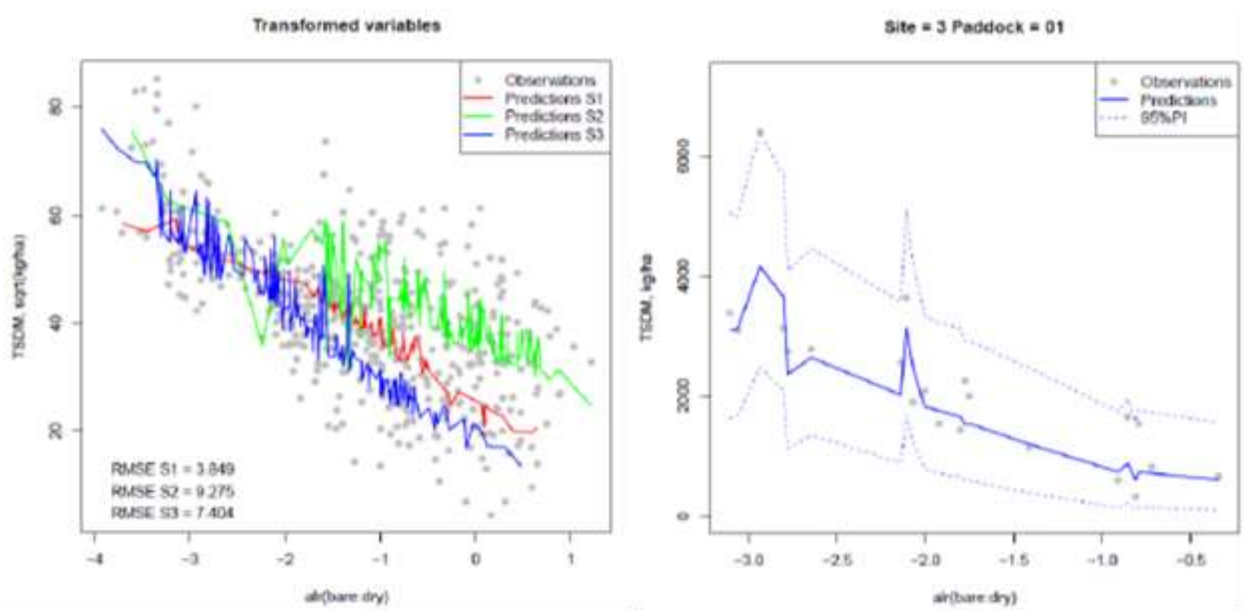


Figure 4-5. Example modelling of TSDM from Landsat-derived ground cover for the Wambiana grazing trial. Left: transformed TSDM as a function of the log (BS/NPV) ratio with the inclusion of average rolling 365-day green cover, persistent green as a measure of woody FPC and interaction terms. Right: the same function applied to Paddock 1 at Wambiana showing overall error limits. Figure reproduced from Figure 13 of Carter et al. (2015).

3. Were the statistical properties of data significantly different between grazing trials?

   Where each grazing trial was treated independently, three statistically different functions emerged. Prediction errors were still large with only Pigeon Hole having a 95% prediction interval of less than 1000 kg/ha.

   Using the green component of fractional cover (PV) as a covariate (to total cover, or its converse, bare soil) generally only provided limited improvement in model fitting. This may have been due to most field data being collected in the dry season.

   Adding variables such as the persistent green (woody) component of vegetation cover and an index of pasture growth (the rolling 365-day mean green cover) along with interaction terms significantly improved the estimates of TSDM at each grazing trial. These approaches also reduced error limits some of the time at individual grazing trials and component paddocks. The approach, however, uses many more variables and requires a large data set for robust calibration. It also has the risk that new unique combinations of input variables may generate spurious results. There was a small range of persistent green values making it risky to apply these functions to more woody locations than that present in the calibration data set. Improving the model to include the persistent green covariate may reflect varying tree-grass competition in different paddocks or the trend in “persistent green” over time, such as seen at Wambiana due to an increase in current bush (*Carissa ovata*).

4. Were the statistical properties of data significantly different between paddocks?

   This was tested by evaluating how well a function developed using data from just one paddock for each grazing trial predicted TSDM for other paddocks of that grazing trial. There was generally a poor result: RMSE values for transformed data indicated a significant decline in skill relative to using all data from the grazing trial. This test is probably a reasonable assessment of field performance on “independent” data as one would expect a decline in predictive skill if the best equations were used at new locations.

5. Can calibration at one point in time be used for prediction at other times?

   Calibrating a statistical model at one point in time is likely risky due to limited data: one data point for each paddock, just six in the case of the Toorak grazing trial. Inter-annual variability in rainfall tends to have an overriding effect which can be much larger than paddock-to-paddock differences. A test was conducted using data from the last set of measurements at each grazing trial, fitting a function between TSDM and the log-transformed ratio of bare soil (BS) and dry vegetation (NPV), and then evaluating the function for preceding annual samplings at each grazing trial. As expected, RMSE values were large (by 2-3 times) than using all data for the test paddocks in each grazing trial.

6. Does calibration by land type improve paddock-level estimation of TSDM?

   This question was answered using the Wambiana grazing trial where data had been collected for three land types of approximately equal area in each of the ten paddocks. A statistical model was constructed for each land type based on TSDM data combined at the paddock level. The TSDM was then predicted for each land type-by-paddock combination and added for each paddock based on the actual area of each land type present. The analysis suggested that there was no overall improvement in TSDM estimates using this approach.

7. Cover and process modelling

    While cover estimates based on remote sensing are not directly used in point-to-paddock scale modelling of TSDM, these data do provide a potential mechanism for model calibration and validation.

    In GRASP, the green and total cover functions (Fig. 1-8) can be parameterized from field data as mass at 50% cover can be potentially estimated from field measurements. The GRASP green-cover function is used to calculate green cover for transpiration and interception of solar radiation. The total-cover function is used to calculate ground cover for estimating erosion risk. The green- and total-cover functions used in GRASP differ in their mathematical formulation and this difference has not yet been fully reconciled. (AussieGRASS uses the same function type for both green and total cover but parameter setting is based on limited data).

    The grazing-trial TSDM data and Landsat fractional ground cover data provided an opportunity to test the efficiency of the two cover model formulations in GRASP. This analysis suggests that the current green cover function is marginally better (but by less than 1%) than the total cover function for estimating total cover. Using the same function for both green and total ground cover would simplify the model (and associated documentation) and allow direct comparison of parameters.

    When comparing simulated ground cover from GRASP with Landsat-derived ground cover, the modelled cover should be adjusted to "point-intercept" form and, ideally, should also use a cover model that explicitly accounts for the litter layer.

    The data from the grazing trials clearly indicated that litter is a required additional cover component if modelling is to match satellite-based measurement.

8. Integrating remote sensed data and modelling at Wambiana

    The Landsat-derived green cover fraction of ground cover (PV) was compared to simulated green cover from the GRASP model for a number of paddocks at Wambiana. In prior work using data from these paddocks, the GRASP model had been well calibrated to the field measurements of TSDM. Green cover is likely to provide greater insight into model performance and be of greater use in parameter adjustment than dry cover as the former is closely connected with pasture growth while total and dry cover are the result of growth plus the additional processes of detachment, grazing, litter formation and litter decay.

    Initial model runs suggested that GRASP green (PV) cover estimates were on average slightly lower than satellite estimates in average and dry years, and too high in the six wettest years. In 2007, estimates were quite poor and much lower than satellite estimates for unknown reasons.

    There may be potential for the green (PV) fraction of Landsat ground cover to better calibrate GRASP simulation of green cover.

4.3 Recommendations

Based on this work to develop generalized relationships between Landsat fractional cover and field-estimated TSDM, Carter et al. (2015) recommend:

1. For field data,
    - More effort in ensuring good operator calibration for field based cover estimates.
    - Influence TERN rangelands monitoring to collect pasture biomass when collecting biodiversity and cover information.
    - Assemble TSDM data for tier 2 locations (Fig. 4-1) and test.
    - Assemble fine scale data from Pigeon Hole and test if calibration can be improved.
    - Capture GIS data for historical grazing trials to enable studies such as that conducted here.

2. Remote sensing
    - Test if pasture growth measured at various “Gunsynd / Swiftsynd” sites can be estimated from an “area under the NDVI or green cover curve” methodology using Landsat and/or MODIS satellite imagery.
    - Improve satellite estimates of NPV and BS for locations with bright soils using the Wambiana data as one of the test locations.
    - Invest effort to identify the causes of occasional spikes and dropouts in the Landsat cover times-series data.
    - Evaluate if a rolling average, median or medoid[16] (Flood, 2013) for cover is superior to single date data (see above).
    - Improve the data extraction system to supply data at points (e.g. 3x3 pixels) as well as polygons.
    - Improve the data extraction procedure to cope with east/west scene boundaries.
    - Investigate if tree canopy removing fires could be included in a variant of the persistent green cover product to improve ground cover estimates.

3. Test requirements for any development of an operational system
    - Use data from the tier 2 grazing trials to conduct a fully spatially independent evaluation of parameters for TSDM estimation selected from the “best matched” of the three calibrated grazing trials and any future satellite-to-biomass models developed.
    - Investigate variations on “average 365 days of green cover” (e.g. add 24, 18, 6 and 3 months as additional independent variables).
    - Assess the level of accuracy required to provide better estimates of TSDM than are currently being used by the grazing industry. For example, the large errors (often under-estimates) at high biomass and cover levels may not be a limiting factor. Would information derived from prediction limits be useful? For example, “there is a 95% chance that TSDM is somewhere between 0 kg/ha and 950 kg/ha”.
    - Assessment of timing requirements including:
        - Is a seasonal mean from composite images good enough or is information required from single date images?

[16] The medoid is a multi-dimensional median. It is used as a way of compositing multi-temporal satellite images over a season (or other time period) to reduce contamination by cloud and other problems (e.g. sensor malfunction). Seasons here are summer, autumn, winter and spring.

    - Is a higher frequency of Landsat fractional cover required?

- What are the prospects for gathering enough quality biomass data to enable calibration at the paddock, property or land type scale (e.g. crowd sourcing, funded large scale sampling campaign etc.)

4. Modelling
    - Inclusion of a new management record data type (Fractional cover) into GRASP functionality.
    - In a new version of GRASP, the runoff cover function is eventually replaced with the function used for green cover.
    - A cover algorithm that accounts for layered cover and litter should be implemented in the future. Modelling where satellite cover data are used in calibration / validation may require modifications to parameters to reflect the differences between quadrat-based and point-intercept based measures of cover.
    - Modelling at the paddock and property scale should take advantage of remote sensed products for validation and possible calibration with due regards to the cover method and model parameters.

5 Safe livestock carrying capacity

The reasons for, and basis of, calculating long-term safe livestock carrying capacity (LCC) and shorter-term, tactical stocking rate (SR) were introduced in sections 1.2.1 and 1.2.3. Long-term (>10 years) carrying capacity is the number of livestock that an area can carry without causing a decline in land condition. Short-term stocking rate is the number of livestock that an area can carry over months (or a season) whilst ensuring that animal intake needs are met.

Factors considered in calculating a safe LCC include:

- Long-term climate variability – which may be addressed by estimating an expected (average or median) level of pasture growth throughout that period.
- A "safe" utilisation level, which varies with land type.
- The limiting effects of tree cover and current land condition on pasture growth. A common approach is to simulate pasture growth for the land type in its natural or undisturbed state and then apply discounts for tree competition and reduced condition.

Knowing the appropriate year-to-year stocking rate assists management in adjusting stock numbers according to seasonal forage availability.

A method for calculating safe LCC for extensively grazed, tropical semi-arid woodlands of north eastern Australia was first demonstrated by Scanlan et al. (1994). Their work built on the developing capacity to reliably simulate TSDM and pasture growth resulting from variable wet-season rainfall. The approach of Scanlan et al. (1994) was then adapted to other regions (e.g. Queensland Mulga lands, Johnston et al. 1996) and subsequently used to systematically investigate the effects of climate variability and projected change on livestock performance (Hall et al. 1998, McKeon et al. 2009). The final step was to model the cumulative effects of highly variable primary and secondary production on enterprise profitability (Scanlan et al. 2013, section 3.5).

The following section is based on the accumulated experience and synthesized knowledge of rangeland scientists who have used the GRASP suite of models (particularly PaddockGRASP) across a wide cross-section of northern Australia to advise pastoralists on safe LCC. The text derives from information provided by Robyn Cowley and Giselle Whish to the November 2014 workshop that preceded this report. Much of the data required to suitably calibrate GRASP for regional applications was collected from appropriately designed grazing trials (Wambiana, O'Reagain et al. [2009]; Pigeon Hole, Hunt et al. 2013; and Toorak, Orr and Phelps [2013]).

5.1 Calculating and using safe carrying capacity

1. Land type and condition
   Currently, the GRASP model is parameterized for the more common, productive land types and its use should be restricted to such. "Land type" depends on definition and the user should check that their intended application matches the described land type that the model has been parameterized for. Extrapolation or expert local knowledge should be used for non-described land types where it is not appropriate to apply the model.

   Current capability allows modelling of a range of tree covers (for parameterized land types).

Pasture growth is simulated for land in ‘A’ condition with percentage discounts then applied for land in lesser condition (B, C or D).

2. Additional factors to consider in translating LCC to actual carrying capacity (stocking rate) include:
   - The period involved (weeks, months, >1 year)
   - Safe levels of pasture utilisation without degrading pastures. Lower levels are advised for more fragile land types. Recommended utilisation rates for NT grazing lands are:
     - 20-25 % for black soil
     - 15 % on red soil
     - 10 %, poor red soil
     - 5 % where spinifex palatable.

3. The area over which LCC is being calculated should be appropriate – account for:
   - Distance from waters (both permanent and semi-permanent sources).
   - Accessibility by livestock.

   Factors currently not well considered in calculating LCC include:

   The grazing preference of cattle for different land types (i.e. patchy grazing).
   Fire in terms of its cumulative effects on modelled pasture growth and more immediate effects on grazing distribution.

4. Grazing system and carrying capacity.
   It may be that the ‘optimal’ grazing system is achieved by combining long-term safe LCC and short-term seasonal stocking rate.

Long-term or “safe” LCC aligns well with a set stocking system where the manager can stock to, or below the LCC for sustainable production. Provision of additional modelled outcomes as percentiles above and below the average (or median) situation could improve understanding of temporal variation in growth (between good and poor seasons, and by how much).

Short term / seasonal stocking rate fits well with variable stocking and rotational grazing systems. A variable stocking strategy has probable increased ecological and financial risks compared with long-term safe LCC.

The combination of long-term safe LCC and short-term / seasonal variation provides a constrained variable stocking strategy. There is a small increase in livestock numbers above the long-term safe LCC in wetter years and a bigger decrease (below the safe LCC) in drier years. This should avoid overgrazing in low rainfall years and achieve increased livestock production in wetter years.

6 Synthesis

This section attempts to summarise and synthesize information that emerged from the Brisbane workshop (November 2014) and subsequent literature review (Chapter 3) that is relevant to (i) monitoring land condition, (ii) estimating pasture biomass at paddock scale using modelling and remote sensing-based methods and (iii) deriving safe LCC.

The synthesis is based on two premises:

1. Pastoralists, as the on-ground managers of natural resources, are the primary client for this information. Land management agencies have a particular interest in land condition and its trend but individual pastoralists determine this outcome through their grazing management decisions; essentially, adjusting stock numbers with regard to seasonal conditions, available forage and some understanding of long-term safe LCC.

2. Providing pastoralists with near real-time information on forage availability should assist them in adjusting stock numbers to better manage grazing pressure and improve land condition.

   With this goal in mind, developing effective and efficient methods for remotely monitoring pasture biomass as an aid to setting and adjusting stocking rate for improved (or maintained) land condition is a complicated, not complex, problem in the context of linked social-ecological systems such as rangeland management. That is, we shouldn't unnecessarily complicate the problem and we should also recognize that we are already some way along the path. This is demonstrated by the present capacity to:

   - Remotely monitor fractional vegetation cover at continental scale,
   - Analyse these data to detect seasonally-adjusted trends (in ground cover) related to grazing,
   - Simulate expected pasture biomass (TSDM) taking account of climate variability, and
   - Calculate safe LCC for some land types.

   Admittedly, some of this expertise is still in the domain of government agencies (including regional NRM groups) and needs to be better devolved to on-ground managers where appropriate. Delivery mechanisms such as VegMachine and the developing NRM Spatial Hub should facilitate this technology transfer.

6.1 Pasture biomass in perspective

The inter-connections between pasture biomass, stocking rate, safe LCC and land condition are illustrated in Fig. 6-1. The appropriate number of livestock in each paddock (Paddock Stocking Rate) for current seasonal conditions is central to the schematic. Setting this number should be a periodic, conscious (tactical) decision by pastoralists based on the calculated, strategic, safe LCC. It should also take account of current land condition. The three components are linked: getting the seasonal stocking rate right can improve land condition over time (provided a threshold of degradation has not been crossed) which, in turn, can increase the safe LCC, based on current land condition. In reverse, prolonged excessive stocking variously degrades landscapes (depending on their inherent stability and resilience) which erodes safe LCC.

In the simplest sense, paddock stocking rate is dependent on the seasonal supply of palatable (and usable) forage. This parameter is a function of pasture species composition (i.e. palatability), grazing preference (land type) and acceptable levels of pasture utilisation (distance from water, etc). Thus it is important to recognize that although we want to model and/or remotely monitor pasture biomass, the value of this attribute for setting (and adjusting) paddock stocking rate is modified by a number of factors that specify actual forage available (Fig. 6-1).

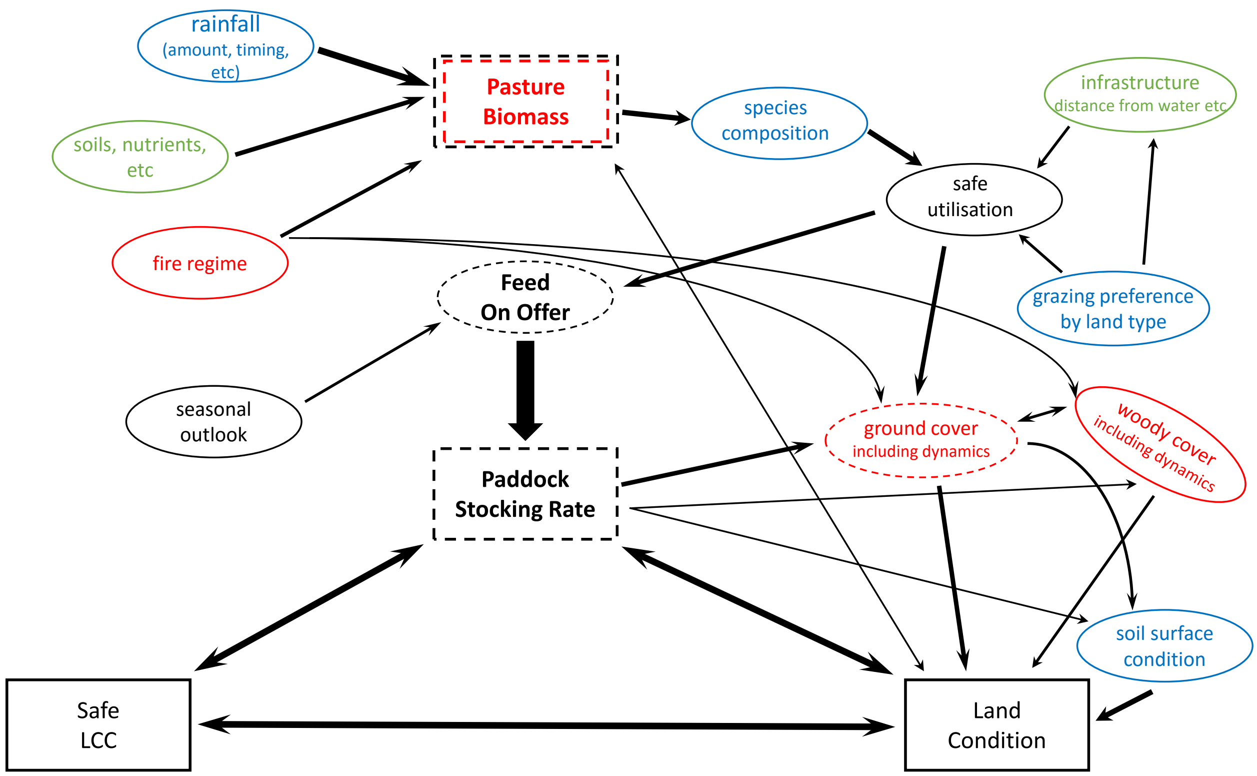


Figure 6-1. Stylized representation of the inter-related components determining paddock stocking rate and land condition. Components within boxes or ellipses with dashed lines represent 'fast' variables and are more commonly associated with tactical decision making. Corresponding shapes with solid lines indicate slower variables and strategic decisions. Blue text and shapes indicate essentially ground-based data, red font and lines are associated with remote sensing, green colouring shows GIS layers and black text / shapes describe mainly modelling components.

At a simple level, pasture growth and resultant TSDM is a function of rainfall and available nutrients (assuming that sunlight is not limiting) – as modelled by GRASP, SGS etc. Fires and herbivores variously consume the biomass which, based on levels of consumption (utilisation), provides a feedback loop between pasture growth and land condition.

Ground cover and pasture biomass can vary by large amounts over short periods in response to rainfall, grazing and fire and are 'fast' variables with limited indicator value for monitoring land condition (section 1.2.4). However, the dynamics of remotely sensed ground cover do have demonstrated value for monitoring land condition (section 3.2.3) and is a preferred attribute (over pasture biomass) for this purpose (Fig. 6-1).

The final feature of this schematic is that we use dashed and solid shapes, respectively, to differentiate the more dynamic components of tactical decision making from the longer-term strategic elements (see figure caption).

6.2 Specifying required data and information

Much information and knowledge already exists with regard to appropriately managing livestock and natural resources for sustained production in the rangelands (Appendix 2, section 9.2). Re-analysis of existing data using new approaches may go some way to supplying additional information to assist pastoralists in this task. However, it is highly likely that new data are required to achieve future aspirational best practice in natural resource management and livestock production (red font in section 9.2).

6.3 Participants

Providing the necessary tools to achieve the near-future, aspirational management described in section 9.2 (i.e. red text) is not a research challenge alone. Rather, it requires a coalition that includes collaborating pastoralists so as to expand the available pool of human resources (“liveware”). Under existing organizational structures, participants would logically include (but are not limited to):

- Industry research and development agencies, particularly MLA, for guidance in developing relevant applied research and as a potential source of funding.
- Research agencies: CSIRO, universities; and enabling structures: relevant CRCs, TERN AusCover (and, perhaps, AusPlots), the Joint Remote Sensing Research Program and international initiatives including GEOGLAM and remote sensing of forest biomass (GOFI, GOFC/GOLD).
- Government agencies, federal and state, with responsibilities for primary industry and natural resource management.
- The Rangelands NRM Alliance and constituent regional groups.
- Interested pastoralists as (i) a conduit to rapid, practical evaluation of emerging technologies and fast tracking their uptake and widespread use (i.e. rapid and effective “pathway to impact”) and (ii) a potential “crowd source” for required validation data.

6.4 What is needed where?

We approach this question by taking stock of what existing technologies and methods can provide now, and into the future, with regard to monitoring land condition, providing reliable paddock-scale estimates of pasture biomass and specifying long-term safe LCC across large areas (Table 6-1). Parts of the table with substantive information are structured under ‘scale’ (spatial and temporal); ‘value’, particularly for on-ground management; ‘delivery’ in terms of landholder accessibility to assist decision making; and ‘further development’ if required. Briefer or more cursory information in other parts of the table is summarized in a less structured form.

As an additional aid to interpretation, parts of the table that provide information directly relevant to the intent of this report are shaded orange. These cells relate to methods for estimating (and monitoring) pasture biomass at the scale of paddocks and larger, and the potential of data assimilation to leverage the information content derived from using remote sensing and modelling approaches separately. Appropriate field data for calibration and validation purposes are also essential but few cells in this part of the table are highlighted because it is anticipated that, in the main, existing data can be re-used or new data will mostly be collected in a fairly standard manner.

Table 6-1. The current and potential future contributions of ground data, remote sensing and modelling to assessing and monitoring the condition of pastoral land, estimating pasture biomass and calculating safe livestock carrying capacity (LCC). Parts of the table shaded orange provide information that is more relevant to the intent of this report.

Component	Parameter		
	Land condition	Pasture biomass	Safe LCC
Ground data - including proximal (near ground) remote sensing			
Site-based monitoring	Scale: paddock to regional and recurrent, although limited replication reduces ability to extrapolate beyond site area. Value: data often strongly influenced by season (rainfall) making it difficult to confidently determine grazing-related trend. Delivery: monitoring results broadly understood - but not always accepted. Further development: mature methods with some scope for proximal remote sensing (using drones or UAVs) to increase efficiency in collecting quantitative data. Likely that most state/NT monitoring programs will continue to decline in the future because of reduced resourcing.	Ground data essential for realistic techniques / methods in estimating pasture biomass. BOTANAL or other Comparative Yield methods commonly used for research purposes at paddock scale. Photo guides provide a viable alternative (to BOTANAL) where lower accuracy of estimates is acceptable, e.g. forage budgeting. Proximal remote sensing using appropriate vehicle- or UAV-mounted instruments may increase the volume of field data and the efficiency with which they are collected for research purposes (e.g. calibrating and validating remote sensing-based products for estimating biomass). Examples include spectral data to sample photosynthetic activity and sward height.	Site-based monitoring data should be suitable for adjusting short-term stocking rate and indicating safe LCC (as part of adaptive management) but are not generally used for calculating LCC. Regional surveys to assess paddock condition, combined with landholder interviews and access to their stocking records, have been used to rigorously estimate safe LCC for specific land types (e.g. Johnston et al. 1996).
Grazing trials	Scale: replicated experimental treatments in small to medium-sized paddocks at limited locations in central & northern Australia. Most trials sufficiently long to capture much of the climatic variation for the region in which they are located. Value: generally high because trials are designed to test the effect of grazing strategy (including stocking rate) on land condition. Extrapolation value may be limited by the small area of treatment paddocks and perceived representativeness of results (required resources does not allow replication at multiple locations). Delivery: conventional means (field days, extension material). Further development: probably limited because costly to establish and operate.	Biomass generally an integral component of the vegetation data collected - generally using BOTANAL or other Comparative Yield methods. These data have contributed significantly to calibrating and validating pasture growth models. As above, proximal remote sensing may contribute useful surrogate data for estimating biomass as suitable methods develop - such as grazing trials are funded into the future.	Grazing trials are often based on the need to establish or demonstrate sustainable stocking rates and long-term safe LCC (e.g. Wambiana and Pigeon Hole). Comments in the 'grazing trials' by 'land condition' cell apply here.

Component	Parameter		
	Land condition	Pasture biomass	Safe LCC
Crowd sourcing	Probably not relevant. Land condition is a human construct. Any voluntary, publically-sourced information is likely to be highly variable and of dubious value.	A latent resource that is yet to be developed and effectively utilised. Scale: potentially, at paddock-level across much of the rangelands and continuing into the future. Value: probably mainly for validating research products and improving their application and utility. The accuracy and/or precision of supplied data may be questionable depending on what is required and the methods used. Delivery: participants will likely have considerable interest in developing products and should provide good advocates / role models for wider uptake. Further development: protocols and techniques for harnessing this resource in the rangelands need to be developed. This includes consideration of human ethics.	Probable limited value. Such data may have contextual value in providing the median and range in values for specified land types at regional scale. If the data are adequately attributed (including a quality tag), it may be possible to specify local "best practice" stocking rates for a range of seasonal conditions.
Dedicated Calibration / Validation missions	Not relevant.	Scale: application in space and time dependent on resourcing. Value: high in technical terms because of purpose-built design. Limited extension value to pastoralists. Delivery: not relevant (data acquired for scientific purposes). Further development: probably small scale and quite specific depending on purpose. Available funding will always be a constraint.	Not appropriate.
Satellite remote sensing			
NDVI and related spectral indices of photosynthesis	NDVI is a poor indicator of vegetation cover across much of the Australian rangelands most of the time. As such, it has little value for remotely monitoring land condition. Further research in this area is not warranted.	There is considerable international literature, including “Pastures from Space”, demonstrating how integrated NDVI through defined and regular growing seasons can be modelled to estimate pasture biomass. David Phelps has shown how this method could have value for an area of Mitchell grassland – further research is required to test and adapt his approach over larger areas of the Mitchell Grass Downs bioregion. Integrated NDVI will likely have limited (or no) value across much of	Not useful for calculating long-term safe LCC. May provide useful information for adjusting seasonal stocking rate in Mitchell grasslands based on preliminary research conducted by David Phelps (and as demonstrated by Pastures from Space in south western WA).

Component	Parameter		
	Land condition	Pasture biomass	Safe LCC
		the rangelands because of (i) highly variable rainfall and episodic / ephemeral growth and (ii) much of the NDVI signal coming from persistently green (woody) vegetation during periods of intermittent pasture growth.	
Fractional cover	Scale: eminently suitable - archived national coverage at fortnightly to three-monthly frequency. Value: scientifically, very high now that methods exist for separating rainfall and grazing effects on ground-cover dynamics. VegMachine can assist pastoralists in visualising and understanding cover change at paddock scale. Delivery: improving through initiatives such as VegMachine and the developing NRM Spatial Hub. Further development: dependent on outcomes from the NRM Spatial Hub.	Cover-mass relationships are variable and there appears to be limited potential for estimating pasture biomass from fractional ground cover. This conclusion is based on the analysis of data from tier-1 grazing trials by John Carter and colleagues within this consultancy. Expansion of this work may be warranted (as recommended by Carter et al., 2015).	Not directly appropriate for calculating safe LCC but very useful for monitoring whether shorter-term stocking rates were appropriate for seasonal conditions experienced (i.e. as part of adaptive management).
Persistent green (woody cover)	Scale: a national-scale Landsat product available. The method used means limited temporal frequency. Value: potentially high for monitoring the dynamics of woody cover and its effect on land condition (e.g. thickening, dieback, changing tree / grass balance) but the current product requires further validation and probable improvement where the woody vegetation is not persistently green (e.g. acacia shrublands). Delivery: accessible via the web (i.e. AusCover portal) to the scientific community but ready access by the grazing industry probably dependent on further validation and product development. At such time, the NRM Spatial Hub should provide a suitable delivery portal. Further technical development required.	Unknown value at this stage. This product, at a minimum, should be useful for stratification and will provide valuable contextual information.	A useful monitoring resource for evaluating whether calculated safe LCC is correct over the longer term. An example is woody thickening and management flexibility to use fire as a control measure in favourable years.
LiDAR	Not relevant.	A prospective area of research. Terrestrial laser scanning (TLS) is providing valuable information for remotely estimating woody biomass in forests and woodlands. Airborne	Not directly relevant.

Component	Parameter		
	Land condition	Pasture biomass	Safe LCC
		laser scanning and altimetry can assist in upscaling this form of proximal remote sensing. Adapted methods should assist in rapidly estimating pasture height and indices of structure in developing volumetric methods for remotely estimated pasture biomass.	
Radar	May have value in the northern tropics, particularly through the wet season, but technical development required to demonstrate the value of this form of active remote sensing for monitoring land condition.	Demonstrated value in remotely estimating forest biomass and similar comments to LiDAR above.	Not directly relevant although may have some value in tropical areas where cloud restricts the utility of passive remote sensing (Landsat, MODIS etc).
Hyperspectral	Not relevant.	Potential value in remotely determining forage quality based on suitable discrimination of chemical attributes that influence palatability, digestibility and nutritive value (e.g. contributions of starch, cellulose, lignin, proteins, etc at the various stages of plant growth). This work still at the research stage.	Not relevant.
Models			
Single purpose - e.g. simulated pasture growth and TSDM	Land condition generally inferred from simulated perennial grass composition (e.g. McKeon et al. 2000) and level of pasture utilisation (John Carter using AussieGRASS at pages 46-48 in Bastin et al. 2008). Simulated, rather than actual, land condition has scientific merit and administrative and policy value at regional scale but probably has limited direct value to pastoralists.	Scale: paddock to continent (e.g. PaddockGRASP and AussieGRASS respectively) and output (including historical) at daily to annual time step based on the climate record. Demonstrated value for range of applications (e.g. drought assessment, seasonal forecasting) based on scientific literature and web applications. Product delivery via well-developed web portals. Further development: probably mainly model refinement to cater for user-specific applications across a broader range of environments (some specific recommendations in Carter et al. 2015).	Simple mathematical functions generally used, as per section 1.2.3 of this report, rather than sophisticated models. Pasture biomass is modelled where appropriate. Additional comments as above for calculating safe LCC using ground data.
Multi-purpose - linked models	Still largely experimental as demonstrated with the Wambiana dataset by Scanlan et al. (2013) and Doran-Browne et al. (2014).	A work in progress based on the derived value of accurately simulating pasture biomass over time (based on seasonal conditions experienced) and for multiple land types (as	No known examples. May become relevant as capacity to remotely monitor pasture biomass increases.

Component	Parameter		
	Land condition	Pasture biomass	Safe LCC
		per examples of Scanlan et al. 2013 and Doran-Browne et al. 2014).	
Assimilation	No known use of data assimilation using remote sensing and modelling approaches to predict or monitor land condition. A useful test could be using remotely-sensed land condition as an input to GRASP and modelling more probable outcomes (likely pasture biomass, derived carrying capacity) rather than the current approach of simulating condition based on predicted perennial composition and pasture utilisation.	Prospective value demonstrated by the C-Store work of Randall Donohue and colleagues (section 3.6.1).	May become relevant when pasture biomass can be reliably monitored across large areas using combined modelling and remote sensing.

Connecting the red text in section 9.2 with the orange cells in Table 6-1, the question of “what is needed where” (see the first paragraph of this section) can be partly disaggregated into:

1. An objective basis for setting stocking rate at critical decision points based on available pasture, determined from remote sensing and well-calibrated models. Contributing components include:
    - Existing ground data (and particularly that obtained from grazing trials), targeted further collections through dedicated calibration / validation exercises and, potentially, crowd-sourced validation data provided by participating pastoralists and others.
    - Proximal and airborne LiDAR to provide proxy data on sward height and vertical structure. Radar data may contribute useful additional information, particularly where cloud is an issue in the tropics. The work of Lucas et al. (2006) and Lei et al. (2012) in the Queensland woodlands provides a lead but the ability of space-borne radar to adequately discriminate pasture height and structure needs to be tested.
    - Expanded research on the utility of radar backscatter at various wavelengths for directly calibrating pasture biomass (section 3.3.2.4).
    - Other forms of optical (passive) remote sensing including defining the grassland boundary and associated environmental conditions, particularly climate, over which integrated NDVI may reliably indicate pasture biomass.
    - Integrating remote sensing and modelling approaches through data assimilation such as that being developed in the C-Store research project (section 3.6.1).

2. Pastoralists should have sufficient quantitative information to clearly understand the effects of their grazing management on ground cover dynamics. This includes historic levels of ground cover at critical decision points. Tools are required to effectively detrend the seasonal (mainly rainfall) component of inter-annual change in ground cover and account for fire effects where necessary.

    Arguably, this is a mature research area – see comments for “satellite remote sensing” (“fractional cover” and “persistent green”) in the “land condition” column of Table 6-2. Considerable investment, however, is still required to suitably devolve the required remote sensing products, software and skills to pastoralists for image visualization and to conduct their own simplified analyses so as better understand the longer term effects of their grazing management on land condition. VegMachine has demonstrated its utility in this space but, as yet, has had limited uptake by on-ground managers. The NRM Spatial Hub in conjunction with the Rangelands NRM Alliance has a longer-term strategy to succeed in this space. It will need continuing funding and further technical development to do so.

3. Widespread use of modelled LCC coupled with paddock-level changes in land condition (from seasonally-detrended changes in ground-cover) as fundamental components for longer term property development and management.

    This is a “work in progress” as demonstrated by the early work of Scanlan et al. (2013) and Doran-Browne et al. (2014) with the Wambiana data set. Their methods need to be up-scaled and tested elsewhere in the rangelands, such as data from other grazing trials allow. Testing additional modelling approaches that can reliably estimate pasture biomass and land condition should increase the value of such integrated analyses. Data assimilation methods seem prospective here based on the future performance of the C-Store approach being developed by Randall Donohue and colleagues (section 3.6.1).

Essentially then, the "what" is *up-scaled and remotely estimated (and monitored) pasture biomass for improved setting of short term (seasonal) stocking rate in each paddock*, with due regard to the calculated long-term safe LCC, and such that land condition is maintained or improved. Providing this information in a timely manner should assist improved grazing management, including land condition. The "where" refers to all pastoral properties but a tractable starting point probably should be the pastorally more productive bioregions in northern Australia.

6.5 Pasture biomass in reality

There are three broadly based approaches to estimating pasture biomass at paddock scale in the rangelands: ground-based, remote sensing and modelling (Fig. 6-2). Each has its strengths and weaknesses. A fourth generic approach, data assimilation, integrates or builds on the strengths of each.

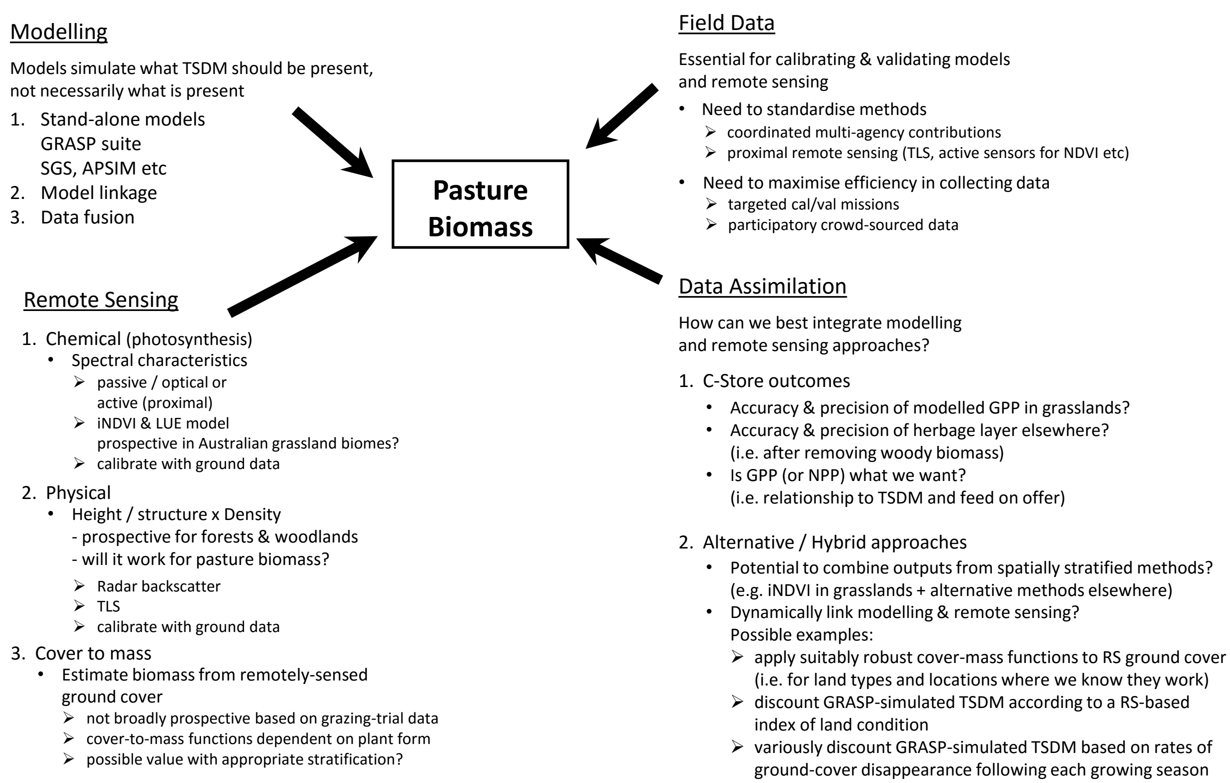


Figure 6-2. Summary categorization of approaches to estimating pasture biomass at paddock scale in the rangelands.

The concluding part of this report (next chapter) suggests the roadmap required to build on the above components (Fig. 6-2) to develop robust methods for efficiently monitoring pasture biomass at paddock scale. This information should then assist broader modelling of safe LCC and tactical manipulation of stocking rates (Fig. 6-1).

7 Roadmap for improved monitoring of pasture biomass

As illustrated in Fig. 6-2, it is anticipated that the development of suitably robust methods for routinely estimating and monitoring pasture biomass across large parts of the pastorally important rangelands will involve various combinations of field-based data, remote sensing and modelling.

Appropriate field data are essential for calibrating and validating remote sensing and modelling approaches. Existing sampling and estimation methods such as BOTANAL provide suitable data for research purposes such as estimating components of pasture biomass (TSDM, green component, etc) in small paddocks. However, these methods are not viable for up-scaling to the larger and more heterogeneous paddocks of commercial grazing enterprises because of the sampling intensity required to obtain sufficiently reliable[17], spatially-integrated estimates of pasture biomass. The need for operator calibration in using indirect (double sampling) methods such as BOTANAL further mitigates against their widespread use in commercial pastoralism. Photo standards can offset this limitation to some extent but need to be prepared beforehand and should be fit-for-purpose. However, correct use of photo standards still requires prior training and periodic refresher exercises to minimize operator error in their use. Where photo standards are used in the commercial sphere to assist biomass estimation, it is generally at site scale (e.g. 1-2 ha) with their locations either fixed or variable in space. Many assessments are required across the range of land types present in larger paddocks to have some confidence in the resultant paddock-scale estimate of pasture biomass.

Grazing systems in some parts of Australia have well developed models for simulating pasture growth and TSDM based on rainfall and soil type (as a proxy for water and nutrient availability). The GRASP suite has been applied in different parts of northern Australia and the SGS model, developed for more intensively grazed pastures in the higher rainfall areas of southern Australia, is now being evaluated in the rangelands where suitable datasets exist (the Wambiana grazing trial at this stage, Doran-Browne et al. 2014). The ability to simulate pasture growth in a variable climate assists the calculation of long-term safe LCC. Further, GRASP allows the effects of grazing strategy, including stocking rate, on land condition to be investigated based on a simple function between simulated pasture utilisation and the probable presence of perennial grasses. This modelling capacity provides a powerful toolset for investigating 'what if' scenarios. However, at the end of the day, most models predict what should happen and this may not necessarily agree with what did happen (or is happening). Including dynamic components such as remotely sensed estimates of pasture biomass at key times and independently assessed land condition (perhaps based on remotely sensed ground-cover dynamics) may increase the functionality of existing modelling approaches. If this is sensible, then it suggests a data assimilation methodology that effectively harnesses the strengths of remote sensing and modelling.

The following sections summarise key points and recommendations for the further development of an integrated approach to reliably estimating pasture biomass at paddock scale.

7.1 Some generic guiding principles

There are some overarching guidelines that provide important context in developing future biomass products:

[17] Reliability of estimated pasture biomass is a combination of accuracy and precision. Accuracy specifies how true (or 'right') is the estimate. Precision describes how close the estimate is to the actual value (e.g. the standard error of the estimate).

1. End-user requirements. As a practical example, for the Australian Agricultural Company (AACo), this is the ability to model forage supply during the current and following season to assist tactical decision making with regard to feed budgeting (Gerard Davis, pers comm.). The company sees potential value in a remote sensing-based biomass product to improve their tactical decision making.

   An allied requirement is timely delivery of the product to coincide with critical decision points (when to sell, destock etc).

2. Product delivery.
   - The pastoral industry must be suitably represented in developing and testing biomass products as it is naïve to simply put a product “out there” and expect end users to embrace it.
   - Meaningful engagement with end users should occur throughout the development and delivery phases as their will be a lag time for many in adopting new technology (i.e. don’t just focus on the ‘now’ in product development and delivery).
   - We need to communicate simple messages to what may well be a complicated problem – i.e. developing suitably precise estimates of remotely monitored pasture biomass.

3. Integrating new information with existing knowledge.
   - In terms of product development and evaluation, we shouldn’t discount the ability of landholders to translate historical biomass products into productivity information (e.g. liveweight gain with respect to feed availability and seasonal quality at the time) based on their experience and accumulated knowledge.
   - Building on a biomass product by linking it to information about:
     - ground cover, including dynamics and inferred land condition;
     - pasture quality, e.g. from near-infrared spectral (NIRS) analysis of dung samples;
     - pasture composition – 3P grasses, other monitoring data as available; and
     - liveweight change, e.g. walk over weighing; etc.

The end-game is to reliably estimate paddock-level pasture biomass in a timely manner to provide a further indicator that assists tactical decision-making on paddock stocking levels. In providing land managers with this tool, it must be within their power to act on it. The reality is that most pastoralists, at least initially, will likely use this additional (biomass) information to supplement their own judgement on feed availability, rather than the desired longer-term outcome of them trusting it as the primary information for such decisions.

7.2 Field based estimation of biomass and utilisation

Recommendations include:

1. Develop and apply nationally consistent, standardized methods / protocols for collecting site-based biomass data for remote sensing purposes. This could be through a suitably adapted form of the methodology used to collect field data for calibrating and validating remotely sensed fractional vegetation cover (Muir et al. 2011).

2. Develop appropriate protocols for adequately dealing with spatial heterogeneity of vegetation, at varying scales, as part of further biomass sampling. Technical issues include:

- Landscape stratification. The recently released Soil Landscape Grid of Australia (at 90 m resolution) should provide useful contextual information with regard to spatial variation in soils to assist sampling design.
- Determining whether heterogeneity is relatively constant or variable across the area to be sampled, and beyond. Remotely sensed data can assist here – e.g. examining the variance (texture) of cover components at increasing spatial scale. Care is required not to confound subsequent data analyses where the same dataset is used for two different purposes. This can occur, for example, where Landsat fractional cover is included as a stratification layer to assist sampling design and then subsequently used to investigate grazing effects.
- Allied with the above, ensuring good operator calibration for field-based estimation of cover and biomass including specifying acceptable levels of precision for each data type collected. In short, what is the tolerance around the standard error of plot-level mean cover and biomass for the acquired data to remain useful?

3. Build on existing agency-based extension programs and national initiatives to facilitate the collection of further biomass data for calibration and validation purposes. For example:
    - There may be potential to leverage off the Grazing Land Management program and its more recent derivatives to increase the geographic range and quantity of contributed field-based biomass data. A critical issue from such an approach will be data quality – which, potentially, can be managed through the application of a national standard (flagged above).
    - Influence the TERN AusPlots rangelands program to include plot-based estimates of pasture biomass when collecting biodiversity and cover information. Note that continued funding of the TERN facility and its AusPlots component is uncertain and this option, if successful, may only provide short-term expediency.

4. Use existing field stations (e.g. Spyglass, Brian Pastures, Kidman Springs) to provide integrated field measurement programs that address knowledge gaps for remote sensing and modelling.

5. Crowd-sourced estimates of pasture biomass could be an asset, perhaps more so for validating biomass products derived from remote sensing (as distinct from their calibration). Again, data quality is an important issue to be managed.

    One immediate prospect here is collaborating with pastoral companies that already monitor paddock-level forage availability for setting seasonal stocking rates and planning turn-off, including inter-property transfers of livestock. Gerard Davis, AACo General Manager, Technology & Innovation, indicated at the November 2014 workshop that such contributions are possible provided their data are not considered commercial-in-confidence.

    A critical allied consideration is the ethical use and representation of such data by the scientific community. Voluntarily contributed data, where fit for purpose, should be highly valued and the contributors duly acknowledged as part of scientific communication. The Data Object Identifier (DOI) is a suitable mechanism for duly recognizing third-party scientific data but this may not extend to less rigorous, crowd-sourced data that is nevertheless contributed in good faith.

6. Include relevant proximal (ground-based) remote sensing technologies in future dedicated programs to collect calibration and validation data for modelling and remotely sensing pasture

biomass. Actual equipment used and data acquired are, of course, dependent on intended purpose but possibilities include:

- Active sensing of photosynthetic activity in the red – near infrared wavelengths (to compute NDVI). Use of near-ground active sensing apparently enhances signal to noise data quality, compared with passive sensing of reflected solar radiation where shadow, cloud, time of day and time of year variously affect NDVI separate to photosynthesis (David Lamb, pers comm.).
- Terrestrial laser scanning to potentially provide proxies for pasture height and sward structure.

7. Facilitate data collation from former grazing trials (and other sources) that have potential value for validating modelled and/or remotely sensed estimates of pasture biomass based on archived satellite data. This will expand on data from the tier 1 grazing-trial sites (Wambiana, Toorak and Pigeon Hole) analysed by Carter et al. (2015) for this report. Tier 2 sites have been identified (Fig. 4-1) and there is an informal list of potential tier 3 sites (the suitability of data for modelling purposes is presumed to decline from tier 1 to tier 3). Further activity could include:
   - Formally specifying and documenting the criteria for each tier (akin to gold, silver and bronze standards) followed by the ranking of known datasets based on their suitability against the criteria.
   - Capturing required GIS data for historical grazing trials to enable spatial analysis such as that conducted for tier 1 sites.
   - Making contact with the data custodians (including data originators where possible) and providing necessary assistance to include all data (particularly textual / descriptive information) in a suitably structured database. A useful guide here, in terms of likely resourcing, is the process recently used to submit data from the Queensland brigalow grazing trials to the TERN EcoInformatics facility.

7.3 Remotely sensed biomass

Remote sensing-based recommendations are grouped into three categories: time-integrated NDVI as a spectral (chemistry-based) index of photosynthetic activity and biomass accumulation; a physical (volumetric and density) based approach to estimating biomass using radar and laser scanning; and limited further work on cover-to-mass relationships to evaluate their feasibility for estimating biomass from Landsat-derived ground cover.

7.3.1 Time-integrated NDVI

1. Test if pasture growth measured at various "Gunsynd / Swiftsynd" sites can be estimated from an "area under the NDVI or green cover curve" methodology using Landsat and/or MODIS satellite imagery.

2. Specify where and how time-integrated NDVI (iNDVI) through semi-regular growing seasons may contribute to remotely monitored pasture biomass in the Australian rangelands.

   Geographically, the intuitive starting point would seem to be the grasslands of northern Australia with reasonably reliable summer rainfall. Results obtained from CRCSI research at Liveringa Station in the West Kimberley (section 3.3.2.2.4) and in the Mitchell grasslands in Queensland (section 3.3.2.2.2) should guide this decision.

If the potential of time-integrated NDVI in summer-rainfall grasslands is confirmed, then systematic field-based estimation of green pasture biomass across much larger areas is required in these biomes (or component bioregions) to develop robust models between iNDVI (probably initially derived from the relatively frequent coverage provided by the 250-m MODIS product) and available field data.

3. Beyond the foundational research required above, the potential geographic range of the method and the environmental conditions within which it is suitably robust need to be defined. Anticipated limitations to the widespread application of iNDVI include:
    - Highly variable, episodic or counter-seasonal rainfall meaning the lack of a sufficiently defined growing season in many rangeland regions.
    - Green trees and shrubs contributing to remotely-sensed photosynthetic activity, thereby weakening statistical relationships between NDVI and green pasture biomass. There is some capacity to spatially mask the NDVI contribution of woody vegetation, e.g. by using the Landsat persistent green product. The ability to do so probably declines in open woodlands and shrublands where woody FPC is quite low but yet may contribute significantly to any satellite-sensed NDVI signal when the pasture is mostly senescent.
    - While the prospects for remotely sensing green pasture biomass using iNDVI in some grasslands would seem to be encouraging, the challenge remains to reliably estimate TSDM, as distinct from green biomass, where the NDVI signal is diluted due to mixed green and dry pasture. This will likely be the case where:
        - There is abundant dry feed throughout the growing season;
        - The growing season is poor, i.e. limited and/or patchy rainfall; or
        - There is a high stocking rate such that livestock consume most of the green pick through the growing season.
    - A further complicating factor is the interaction between the NDVI signal and land condition. For example, the flush of ephemeral forbs, grasses and other weedy species present on degraded land following rainfall will generate high NDVI values and may give the illusion of good ground cover and biomass accumulation when, in effect, both attributes return to low values as the growth quickly matures and then decays. It may be that this problem can really only be overcome by knowing, a priori, what the land condition is and applying a different function to model biomass from iNDVI.
4. It may be possible to assess the spatial and temporal constraints to the feasibility of iNDVI in the absence of systematic field data, e.g. through a 'desk top' analysis of spatially stratified rainfall characteristics (seasonality, reliability, effectiveness for pasture growth, etc), archived NDVI imagery of suitable temporal frequency and spatial resolution (probably MODIS, but only since late 2000) and other GIS layers (woody FPC, land system mapping, etc).

At this stage, iNDVI in grasslands through reasonably well-defined growing seasons appears prospective for remotely monitoring pasture biomass. This is based on a wealth of international literature (examples in Table 3-1), the Pastures from Space program in south west WA, and current research in the Kimberley (Liveringia Station) and the Queensland Mitchell grasslands (David Phelps). There is a need to systematically define the probable geographic extent and associated climatic and other environmental conditions in the rangelands where this method is prospective and then acquire the necessary field data to develop suitably robust models between NDVI and (green) pasture biomass.

7.3.2 Cover – mass relationships

There appears to be limited scope for deriving and applying generalized robust cover – mass relationships such that TSDM can be predicted from Landsat-based ground cover across extensive and diverse landscapes (Carter et al. 2015). However to confirm this, these authors recommend some additional investigation of this modelling approach (see section 4.3). Their recommendations specific to remotely sensed ground cover include:

1. Assemble fine scale data from Pigeon Hole and test if calibration can be improved.
2. Improve fractional cover calibrations for locations with bright soils using the Wambiana data as one of the test locations. Current experience is that bare soil is under estimated and the fraction of non-photosynthetic vegetation over estimated for some bright soils. Additional measurement of the fractional cover components on bright soils is required throughout the rangelands to achieve this improved calibration.
3. Identify the causes of occasional spikes and dropouts in the Landsat fractional cover archive. This 'house keeping' measure should add a further quality flag to the archived fractional cover data and improve efficiency in selecting suitable data for statistical analysis.
4. Evaluate if a rolling average, median or medoid of fractional cover over a specified time period is superior to single-date data. Carter et al. (2015) selected archived image dates which were closest to the dates of field data collection. A flexible selection process may improve statistical relationships between field-estimated TSDM and remotely sensed ground-cover.

   In a similar manner, investigate variants of the "average 365 days of green cover" used for current modelling (e.g. add 24, 18, 6 and 3 months as additional independent variables).
5. Investigate if tree-canopy removing fires could be included in a variant of the persistent green cover product to improve ground cover estimates.
6. Improve the current data extraction system to supply data at points (e.g. 3x3 pixels) for additional analysis. Currently, data are extracted for paddocks (i.e. polygons). Modelling of cover – mass relationships may be improved by better controlling spatial variability (i.e. averaging across small groups of pixels rather than paddocks). However this is counter to the aim of developing generically robust relationships that accommodate acceptable levels of variability.

   Similarly, improve the data extraction procedure to cope with east-west (Landsat) scene boundaries.
7. Use data from the tier 2 grazing trials (Fig. 4-1) to conduct a fully spatially independent evaluation of parameters for TSDM estimation selected from the "best matched" of the three calibrated tier-1 grazing trials and any future satellite-to-biomass models developed.
8. Assess the level of precision needed to allow useful modelling, including the importance of asymmetric error (i.e. large errors in predicted TSDM at close to 100% cover and reduced errors at lower cover values, i.e. the functions cannot return negative TSDM at low cover). This will help determine whether the current 95% prediction limits provide useful information.
9. Assess the level of accuracy required to provide better estimates of TSDM than are currently being used by the grazing industry. For example, the large errors (often under-estimates) at high biomass and cover levels may not be a limiting factor. Would information derived from

prediction limits be useful? For example, “there is a 95% chance that TSDM is somewhere between 0 kg/ha and 950 kg/ha”.

7.3.3 Sward structure and radar

There are encouraging early results to demonstrate statistical relationships between radar backscatter and pasture biomass (Fig. 3-9), sufficient to support the argument for further systematic research in this area. However, it is highly unlikely that a small set of simple universal functions will apply and it is probable that various forms of stratification will be required to develop suitably robust relationships across diverse landscapes. Scientists in the Joint Remote Sensing Research have shown how multivariate analysis of combined GIS and remotely sensed data sets can provide novel forms of stratification to assist biomass estimation in forests (section 3.3.1.1). These methods, suitably adapted, may be transferrable to the rangelands.

Research areas include:

1. Systematic evaluation of the various forms and wavelengths of radar backscatter to determine the most prospective approaches to remotely estimating pasture biomass.

2. As supplementary research to the preceding, investigate the potential for, and best approaches to, landscape stratification to increase the value of preliminary large-area evaluation of radar imagery for biomass estimation.

3. Systematically estimate site-based pasture biomass across pastorally productive (bio)regions in the rangelands to provide comprehensive field data for calibrating and validating the most prospective forms of radar backscatter. This should be a nationally sponsored and coordinated effort, similar in many respects to the recent campaign to collect fractional vegetation cover for calibrating MODIS and Landsat data (Muir et al. 2011). As per recommendation 1 in section 7.2, a nationally consistent, standardized protocol is required at the outset to collect suitable biomass data.

4. Terrestrial laser scanning (TLS) has shown considerable potential to rapidly characterize the structure of woodlands and forests. Its value for similarly characterising sward structure in pastures, and the value of this proxy volumetric information for improving radar-based biomass estimation, should be determined – again, across diverse sward structures (tussock grasses, bunch grasses, stoloniferous mat-forming grasses, etc). If TLS data provide additional value for modelling pasture biomass, then include its routine use in the national campaign to acquire field data on pasture biomass, again using an agreed standardized protocol.

7.4 Modelled biomass and derived value

Recommendations for improved modelling of pasture biomass centre on model improvement per se, possible synergies to be gained from linking models (or appropriate sub-models) and data fusion.

1. Carter et al. (2015) provided specific recommendations for improving parts of the GRASP suite (section 4.3). These are mainly technical ‘in-house’ issues for Queensland Government staff to implement but some of the more complex requirements may require external support.
    - Include remotely-sensed fractional cover as an additional management-record data-type to expand current GRASP functionality.

- In a new version of GRASP, replace the runoff cover function with the function used for green cover. GRASP has separate arithmetic functions for transforming actively growing (green) and total biomass to cover. The green-cover function is used to calculate green cover for transpiration and interception of solar radiation while the total-cover function is used to calculate ground cover for estimating erosion risk. It is likely that the 'green cover' function is suitable for both purposes (as is the case in AussieGRASS).
- Implement a cover algorithm that accounts for layered cover and litter.

  Modelling where satellite cover data are used in calibration / validation may require modifications to parameters to reflect the differences between quadrat-based and point-intercept based measures of cover. The way in which cover is measured (or estimated) matters for calibrating models: quadrat-based estimates differ from point-intercept measurement (Murphy and Lodge 2002).
- Future modelling at paddock and property scale should utilize available remotely sensed products for validation and possible calibration with due regard to the field method used to estimate cover and model parameters.

2. There may be further scope to test the complementarity of existing models in environments external to where they were developed and applied. This has been demonstrated with the SGS model using the Wambiana dataset (Doran-Browne et al. 2014). Further gains may be small and incremental here as there are likely few rangeland datasets beyond the tier 1 set analysed by Carter et al. (2015) that provide the quantity and quality of data required to adequately parameterize, and then effectively test, the performance of alternative pasture growth models. There are probable additional overheads in (i) adapting the software to suitably simulate pasture growth in different rangeland environments and (ii) reformatting calibration datasets to the requirements of alternative models.

3. The power of linking models is well demonstrated, e.g. using simulated pasture growth as input to animal production models and then passing that output to economic models; examples in Scanlan et al. (2014) and Doran-Browne et al. (2014), and a purpose-built feature of the SGS modelling suite (Donnelly et al. 1997). Such bio-economic modelling goes beyond the possible benefits to be gained through model linkage for improved simulation of pasture biomass.

   Applying the functionally of the most appropriate components (sub-models) of broadly different models (GRASP, SGS, GrassGro, APSIM etc) may enhance our ability to reliably simulate pasture growth and derived secondary production over larger areas. The way in which this is done should be directed by what parts of available models best meet specified requirements. This could include, for example:

   - A feed budget calculator that combines simulated pasture biomass with information on species composition (either modelled, inferred or available externally), grazing preference, distance from water, type and class of livestock, etc (i.e. components in the top right of Fig. 6-1) to calculate paddock stocking rate for defined periods.
   - Modelled livestock performance, particularly growth rate, based on simulated forage availability (as above) and dynamic accounting for pasture quality, e.g. based on periodic near-infrared spectroscopy (NIRS) of fecal samples.

4. There are potential benefits to be gained in the modelling sphere based on data fusion[18]. An obvious example is the further inclusion of remotely sensed data and the derived information these data provide, acknowledging that this already occurs in many models (e.g. use of NDVI in GRASP). As a broad distinction, remote sensing quantifies stocks or pools while models simulate flows or transfers among pools.

   Including information on remotely sensed trends in the woody and herbage components of cover as dynamic input variables to modelled pasture growth would seem to be one sensible application of data fusion. This is flagged above for the GRASP model (section 7.3.2). There may be broader potential to include dynamic components of cover in other models.

7.5 Data assimilation

7.5.1 C-Store

The C-Store modelling approach of Randall Donohue and colleagues in CSIRO appeals as an integrated, nationally consistent method for modelling gross primary production (GPP). It is attractive because it uses a relatively simple, but internationally recognized, diffuse modelling approach to estimate GPP based largely on remotely-sensed interception of sunlight by photosynthesizing vegetation. Modelled GPP is adjusted for respiration to calculate net primary production (NPP) which is then partitioned into the woody and leaf fractions, termed the carbon store. This modelled output is then combined with available field data (the assimilation process) to refine the modelled components of NPP. Importantly, the output includes calculated error surfaces for each NPP pool. Understanding the source and magnitude of errors initially assists diagnostic improvement of model components and, when this process is optimized, provides a sound rationale for evaluating the accuracy and precision of modelled output.

Criteria for evaluating whether C-Store adequately simulates pasture biomass nationally include:

- What is the accuracy of modelled grass-leaf biomass (example shown in Fig. 3-17) across the range of pastorally important rangeland (bio)regions? This question is based on the premise that, nationally, C-Store is required to suitably model all carbon pools (Fig. 3-15) across diverse biomes (forests to sparsely vegetated deserts) which, of course, covers a very large range of biomass. The grass-leaf pool (per unit area) also encompasses a large range; just in the rangelands, from tropical tall-grass savanna to arid short-grass pastures. Can C-Store be adequately calibrated to suitably perform, within all carbon pools (Fig. 3-15), across these large ranges of NPP?
- How well can grass-leaf biomass be transformed to our more conventional (or familiar) modelling of pasture biomass, i.e. TSDM, green biomass, etc?
- Are there sufficient field data to suitably model GPP and derived grass-leaf biomass across pastorally productive (bio)regions? This should be apparent from the magnitude of mapped errors and should assist in prioritizing acquisition of further field data.
- Is the spatial resolution and temporal frequency of modelled output (250 m) adequate to assist paddock-scale management? As an initial product for evaluation, the 250-m pixel size

[18] Data fusion is the process of integration of multiple data and knowledge representing the same real-world object into a consistent, accurate, and useful representation (Wikipedia, accessed 25 June 2015).

and monthly time step of C-Store output certainly seem attractive.

The above criteria, to the extent that they are sensible, suggest the following recommendations towards achieving a national C-Store produced pasture-biomass product:

1. Systematically evaluate C-Store output as it becomes available for its efficacy in reliably modelling grass-leaf biomass in the pastorally important (bio)regions of Australia.

2. If necessary, develop quantitative relationships between C-Store modelled grass-leaf biomass and other forms of modelled and estimated biomass (TSDM, green growth, etc).

3. Based on evaluation of the error surfaces generated by C-Store, contribute to a nationally coordinated program to collect targeted field-based biomass data to improve model performance.

4. If necessary (based on the preceding evaluation), consider developing a variant (or sub-model) of C-Store which focuses on improved simulation of the grass-leaf pool to better simulate pasture biomass. Excluding other pools (Fig. 3-15) may be less constraining in suitably parameterizing and calibrating a herbage-specific variant (or sub-model).

7.5.2 Other data assimilation possibilities

1. Investigate potential benefits to be gained from including land condition, based on remotely sensed ground-cover dynamics, as an input to simulated pasture growth and TSDM by such models as GRASP. At present, land condition (in GRASP) is predicted based on the theoretical relationship between perennial-grass composition and pasture utilisation (McKeon et al. 2000). Including actual land condition as a dynamic input variable may improve the accuracy in predicting pasture growth and TSDM, over the current method, for different condition states.

2. Other possibilities of the data-assimilation approach (or, at least, hybrid approaches) are suggested in Fig. 6-2 (repeated below) but we are not yet able to provide firm recommendations for their development. The plausibility of the following suggestions should become clearer as knowledge and capability develops through the C-Store experience.
    - Investigate the value to be gained from using spatially stratified methods that apply the regionally best combinations of modelling, remote sensing and available field data. This represents an optimization approach rather than trying to develop a 'one size fits all' method to biomass estimation in the grazed rangelands. A starting point could be the use of time-integrated NDVI in extensive grasslands that have a semi-regular growing season (section 7.3.1) and estimating pasture biomass from remotely sensed ground cover in other areas where mass-to-cover relationships are suitably robust (section 7.4).
    - Include feedback loops in models of pasture growth that account for spatially and temporally variable rates of pasture biomass depletion (including consumption and trampling by livestock) following significant growth events. This may require the use of high temporal-frequency remote sensing such as that provided by MODIS. Emelyanova et al. (2013) have demonstrated how Landsat and MODIS imagery can be blended to produce a product with the spatial resolution of Landsat TM (30 m) and the temporal frequency of MODIS (potentially daily but, realistically, weekly when mosaicked to remove cloud and other forms or aerosol contamination).

Decay and consumption rates will initially need to be based on remotely-sensed ground cover until suitable methods exist for remotely monitoring pasture biomass. Pickup (1994) and Pickup and Bastin (1997), among others, have demonstrated the potential to model patterns of defoliation. Their approaches may be worth revisiting, in a similar or modified way. It may be that the types of models developed by Pickup and Bastin (1997) can be generalized for known stocking rates on productive land types beyond central Australia. If so, then it may be feasible to include these 'discount' functions in GRASP (or other models) to simulate probable forage remaining at various times since the end of each growing season.

7.6 Maximizing value from knowing pasture biomass

Fig. 6-1 illustrated some of the derived benefits for managing livestock and land from knowing how much pasture is available. Also important is knowledge of the error associated with such estimates; whether derived from ground-based assessment, remotely monitored, modelled or a combination of all methods. Pasture biomass translates to forage availability via parameters such as palatability, accessibility (e.g. distance from water) and safe utilisation level. Resultant feed-on-offer directly informs seasonal stocking rate. Making the correct tactical decision here, year in – year out, within the broader context of long-term safe LCC, current land condition and often high inter-annual variability in rainfall determines management effects on land condition, longer-term profitability and, regionally, longer term sustainability of pastoralism as a land use.

Thus, there is a lot riding on getting biomass estimation right – provided the product is suitably delivered to producers and they choose to use it as part of their routine tactical decision making. Accompanying caveats (e.g. estimation error) need to be part of product delivery. The availability of reliable information about pasture biomass at key decision points has the potential to change paddock stocking levels from being either a continuing art or 'business as usual' to a reasonably precise science. This has benefits for optimizing animal performance, maintaining or improving land condition and assuring longer term business profitability.

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9 Appendices

9.1 Appendix 1: Brisbane workshop, November 2014

9.1.1 Workshop program

	Thurs Nov 20.	
8.15	Transport from Toowong Inn and Suites	
9.00	Workshop Objectives and Introductions	(Phil Tickle and Cameron Allan)
9.20	Industry Primer. An industry perspective on information needs, opportunities and gaps for improving tactical and strategic decision making with regard to forage budgeting, stock numbers and land condition	AACo
9.40	**Field-based estimation of biomass and utilisation**	
	- Review of Plot and paddock scale estimation and grazing trials o Overview of regional setting, paddocks, duration, treatments and measurements o Challenges in estimating pasture biomass o Pasture Utilisation o Scaling and extrapolation issues o Current status of grazing trials and potential to use historic data (post ~1990)	Peter O'Reagain, David Phelps, Robyn Cowley, Paul Novelly
	- Tools for real-time biomass estimation in pastures	David Lamb
10.30	Morning Tea	
10.45	Summary of state of play, gaps, challenges and opportunities.	Facilitator & Group
11.15	**Current Remote Sensing and Modelling of Pasture Biomass** Including: regional application, climate regime, method, precision and scale of results, advantages, limitations, further development	
	- Pastures from Space, Rangewatch and FatChop	David Lamb
(20 mins)	- Global Approaches (GeoGLAM)	Alex Held
	- CSIRO strategic capabilities and directions	Mike Grundy
12.15	**Modelling of Pasture Biomass and Stock Performance**	

(15 mins)	- GRASP/AussieGRASS - SGS Pasture Model - GrassGRO, GRAZPLAN - Others?	John Carter, Ian Johnson Mike Grundy
1.15	Lunch	
2.00	Summary of state of play, model regionalisation, gaps, challenges and opportunities.	Facilitator & Group
2.45	**Current Remote Sensing of Cover**	
	- MODIS and Landsat fractional cover (status and prospects for estimation and modelling of cover and biomass dynamics)	Peter Scarth
	- Radar and data assimilation	Alex Held
	- Outcomes of ABARES ground-cover workshop	Jane Stewart
	- Relating Cover indices to Rangeland Condition – ecological basis	Gary Bastin
3.45	Afternoon Tea	
4.00	Summary of state of play, gaps, challenges and opportunities.	Facilitator & Group
5.00	Wrap-up. Where do we need to get to in the northern and southern rangelands	Facilitator & Group
5.30	Finish for the day	
6.30	Drinks and Dinner	
Friday Nov 21.		
8.30	Objectives for the Day	Facilitator
8.40	**Relationships between Biomass and Cover**	
	- Fundamentals of relating mass to cover (cover and mass components, dynamics, function	John Carter
	- Prospects for modelling grazing trials and land condition using fractional cover	Joe Scanlan
	- Landscape characteristics – what are we trying to model?	Gary Bastin

9.20	**Monitoring of cover / biomass and stock performance**	
	- PaddockGRASP	Ken Day
	- Spatially enabled livestock management – New tools and methods	David Lamb
10.00	Identification of suitable grazing trials and future cal/val needs	Facilitator & Group
10.30	Morning tea	
11.00	**Determining safe carrying capacity and stocking rates** Theoretical aspects versus practical requirements	Robyn Cowley and Giselle Whish
	- Value of current work, what's missing from a science and management perspective	Facilitator & Group
	- Northern versus southern, high/low rainfall grazing systems and models, and the potential for integration	Facilitator & Group
12.30	Lunch	
1.30	**Bringing it together**	Dan Tindall & Group
	- What are the short, medium and long-term opportunities for improving estimation and forecasting of pasture productivity and land condition?	
	- Long-term safe carrying capacity and seasonal stock rates	
	- New sensors, models and methods – What does the "system" need to look like?	
2.30	Afternoon tea	
3.00	Synthesis, key recommendations and a roadmap for future development of tools for determining safe carrying capacity and livestock decisions	Facilitator & Group
4.00	Workshop close	

9.1.2 Workshop participants

Name	Affiliation
Cameron Best	AACo
Gerard Davis	AACo
Jane Stewart	AG Dept Agriculture
Mike Grundy	CSIRO
Alex Held	CSIRO
Michael Schaeffer	CSIRO
Paul Novelly	DAFWA
Gary Bastin	ex CSIRO
Ian Johnson	IMJ Consultants
Cameron Allan	MLA
Linda Hygate	MLA
Jason Barnetson	NT DLRM
Grant Stabin	NT DLRM
Robyn Cowley	NT DPIF
Terry Beutel	Qld DAFF
Chris Holloway	Qld DAFF
Bob Karfs	Qld DAFF
Peter O'Reagain	Qld DAFF
Lester Pahl	Qld DAFF
David Phelps	Qld DAFF
Joe Scanlan	Qld DAFF
Giselle Whish	Qld DAFF
Rob Hassett	Qld Dept Mines & Natural Resources
John Carter	Qld DSITIA
Ken Day	Qld DSITIA
Peter Scarth	Qld DSITIA
Grant Stone	Qld DSITIA
Dan Tindall	Qld DSITIA
Rebecca Trevithick	Qld DSITIA
Kate Forrest	Rangelands Alliance
Phil Delaney	Spatial Information CRC
Phil Tickle	Spatial Information CRC
Megan Woodward	Spatial Information CRC
David Lamb	University of New England
Ben FitzPatrick	University of Queensland

9.2 *Grazing-related decision making by pastoralists*

Data and information available to pastoralists for some components of decision making in managing their livestock and natural resources. Management decisions are made at paddock and property scale on daily to decadal timeframes. The spatial scale may extend to regional for corporate and large family businesses. The black text describes the probable common approach of today (early 21st century) and the red text proposes where most pastoralists could (should) be in 10-15 years.

Spatial scale of application	Temporal domain		
	Immediate (today)	Tactical (weeks to a year)	Strategic (decadal +)
Paddock	Visual assessment of forage available for livestock - taking account of utilisation level, species selection, location of grazing (land type, distance from water), remaining feed, etc. As above, supported by optional access to recent integrated estimates of pasture biomass following the last growing season. Pasture biomass based on remote sensing and modelling.	Stocking rate based on seasonal conditions, experience and the forecast seasonal outlook. In some cases, stocking rate based on modelled livestock carrying capacity. Objective basis to setting stocking rate at critical decision points based on available pasture (determined from remote sensing and well-calibrated models), seasonally interpreted change in liveweight (based on individual animal identification and regular weighing), critical ground-cover thresholds (from remotely-sensed ground cover) and yearly trends in ground cover.	Landscape change based on photos, perhaps at fixed sites and supported by semi-formal ground-based monitoring. This may extend to interpreted land condition taking account of major climatic influences, fire etc. Routine monitoring using historic remotely-sensed ground cover. Tools available to effectively detrend the seasonal / rainfall component of inter-annual change in ground cover and account for episodic to semi-regular occurrence of fire where necessary. Pastoralists should have sufficient quantitative information to clearly understand the effects of their grazing management on ground cover.
	Visual assessment of ground cover to protect the soil surface against erosion and assist infiltration when it rains. Potential access to the most recent remotely sensed image of ground cover.	Liveweight change, assisted in some cases by walk-over weighing. Routine use of walk-over weighing for per-animal data on liveweight change through the dry season.	Above supported in some instances by remote sensing-based cover trends.
	Visual assessment of livestock condition, perhaps assisted by weighing types / classes of livestock when mustered.	Branding percentage. Perhaps also mortality rate.	

Spatial scale of application	Temporal domain		
	Immediate (today)	Tactical (weeks to a year)	Strategic (decadal +)
	Walk-over weighing linked to NLIS tags to track liveweight change of individual animals. Optional automatic drafting available depending on level of property development and the cost of component technologies. Adding GPS capability to NLIS tags will provide real-time locational information for each animal. This will greatly assist mustering and provide additional spatial information for managing pastures.		
Property	As for Paddocks	Assessment of seasonal conditions based on growing-season rainfall, experience and medium-range forecasts.	As for paddocks.
		Turnoff: based on prices (demand) and livestock fit to market specifications, cash flow, tax implications, feed available and the seasonal outlook.	Property planning and infrastructure development assisted by maps, Google Earth, air photos etc.
		Livestock numbers by type and class based on paddock-level information.	In some cases, use of modelled safe livestock carrying capacity (LCC).
		Tactical decision making includes consideration of paddock-level resource condition: livestock performance; feed available at the end of the growing season (from remote sensing and modelling of pasture biomass); past levels of ground cover at critical decision points (using remote sensing); data delivery and analysis via the NRM Spatial Hub dashboard (or similar); recent seasonally-interpreted livestock performance data (individual liveweight change, reproductive performance, etc);	Widespread use of modelled LCC coupled with paddock-level changes in land condition (from seasonally-detrended changes in ground-cover) as fundamental components for longer term property development / management.

Spatial scale of application	Temporal domain		
	Immediate (today)	Tactical (weeks to a year)	Strategic (decadal +)
		improved precision of seasonal climate forecasts; etc integrated with a clear understanding of economic performance.	
Group of properties (corporate and families with multiple holdings)		Inter-property transfers of livestock based on available feed, seasonal conditions, market options and (perhaps) land condition.	Portfolio of properties, property development, managing climate risk (particularly drought) and (perhaps) landscape change (including land condition).
Regional			As above where the group of properties has considerable geographic spread.