AIRBORNE MULTI-SPECTRAL VIDEO REMOTE SENSING FOR MINE-SITE REHABILITATION ASSESSMENT USING ECOSYSTEM FUNCTION ANALYSIS:

DEVELOPMENT OF AN OPERATIONAL MONITORING PROTOCOL FOR THE ALLIGATOR RIVERS REGION, NORTHERN TERRITORY.

by

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ABSTRACT

Ground based monitoring methods used to evaluate mine-site rehabilitation have been questioned for their ability to effectively measure the ecological 'health' of sites over an appropriate range of spatial and temporal scales. In this context, high-resolution remote sensing potentially can be used to translate ground based survey information into a medium allowing synoptic ecological assessment over multiple scales.

This study evaluated the utility of an airborne multi-spectral video (MSV) system for remote sensing assessment of mine-site rehabilitation and vegetation change in the Alligator Rivers Regions, Northern Territory. As a basis for the evaluation, spatial information requirements for monitoring were identified using concepts of Ecosystem Function Analysis (EFA). Landscape elements were classified based on their 'function' (ability to store, capture, produce and transfer biological resources) or their 'dysfunction' (landscape patches that tend to loose resources). Focus was placed on the ability of MSV to resolve the spatial inter-relationships and contextual arrangement of these elements.

A protocol for the systematic collection, pre-processing, analysis, accuracy assessment and quality control of high-resolution MSV data for multi-temporal monitoring is developed. The constraints on monitoring using optical remotely-sensed data imposed by regional patterns of environmental variation are also reviewed in the context of operational planning and quality control.

MSV data were captured at 0.5m and 0.25m pixel resolution in five narrow bands ranging from visual to near infrared on 26 May 2000 at two abandoned mine-related sites, the El Sherana Airstrip and Guratba (Coronation Hill). Imagery was mosaicked, geo-registered and calibrated to ground reflectance for comparison with contextual ground data.

A hybrid classification strategy was used to develop a classification scheme with maximum accuracy and utility for monitoring purposes. Capability of the classification to resolve key landscape elements was assessed by: 1) Comparison of the spectral reflectance profiles for key surface features; 2) Regression analysis of image classes against geo-referenced ground data for both soil moisture and canopy cover; 3) Calculation of map accuracy statistics derived from cross tabulation of two classifications, each using an independent set of training data; 4) Comparison of supervised classification with unsupervised classification results; and 5) Comparison of imagery collected at two resolutions, 0.5m and 0.25m.

The MSV data provided accurate separation at 0.5m resolution between the key functional groups: perennial grasses; annual grasses and bare-ground; and trees and shrubs. Discrimination within groups was generally less pronounced. However, perennial grass and bare-ground groups separated into distinct sub-classes that are likely to provide good indicators of landscape patch quality. Qualitative comparison between 0.5m and 0.25 m data suggested that the finer grain data further contributed to resolving the pattern of relevant landscape elements.

The utility of data to quantitatively assess cover characteristics of sites was demonstrated using data produced in classifications. At the Airstrip site, this involved a comparison of the disturbed areas with the surrounding 'undisturbed' environment. At the Guratba site a historical comparison was made by conducting a change-analysis against a similar classification derived from co-registered aerial photography data collected in 1990.

High-resolution MSV data complemented ground-based assessment methods using EFA by emulating key indicators. However, it is implicit that EFA ground data acquisition be undertaken concurrently with MSV data to fully realise this potential. It is tacit that monitoring programs integrate both ground-based EFA measurements with remote sensing monitoring techniques. This has significant implications for operational planning and in the coordination of multidisciplinary data-collection for monitoring programs dedicated to evaluate rehabilitation status.

Members of the field team near Guratba (Coronation Hill): from left, Maxi Barowei, Ian Long, James Boyden, Su Rollings and Nick Rollings.

TABLE OF CONTENTS

LIST OF FIGURES

vii

LIST OF TABLES

LIST OF PLATES

MSV   Multi-spectral video

SN   Signal to noise ratio

ICU   Image capture unit

SAV   South Alligator Valley

EFA   Ecosystem Function Analysis is the term that refers collectively to techniques based on a variety of ecological indicators used to assess landscape function, vegetation development and habitat complexity.

LFA   Landscape Function Analysis is the component of EFA used to assess state of environment with respect to the ability of the landscape surface to store, capture, produce and transfer biological resources through ecosystem processes

CCD   The silicon-based Charge-Coupled-Device used as in the ICU sensor array

RS   Remote sensing

GCP   Ground control point

GPS   Global positioning system

FOV   Field of view

EM   Ecosystems Management (Aust.) Ltd. Pty.

BV   Digital brightness value of the image ground sample element (pixel) ranging in value from 0 to 255

PCC   A PATN module that performs multiple linear regression of attributes on ordinations

MCAO   A PATN module that performs Monte-Carlo testing of attributes on ordinations

NDVI   Normalised difference vegetation Index

KIA   Kappa Index of Agreement

KNP   Kakadu National Park

UPGMA   Unweighted Pair Group Method with Arithmetic Mean (UPGMA). An agglomerative hierarchical fusion clustering technique for multivariate classification. UPGMA employs a sequential clustering algorithm, in which local topological relationships are identified in order of similarity, where the classification tree is built in a stepwise manner.

US   Unsupervised multivariate classification technique for image analysis

PC   Principal component

TCC   True-colour composite

FCC   False-colour composite

1   INTRODUCTION

Monitoring systems used to evaluate mine-site rehabilitation have generally been based on ground assessment methods. However, the capability of these methods to effectively measure the ecological state of sites over an appropriate range of spatial and temporal scales is problematic (Corbett, 1999). High-resolution remote sensing offers the potential to translate ground based survey information into a medium that allows for synoptic assessment over a range of scales.

This study focused on developing a monitoring framework that uses high-resolution remotely sensed data in conjunction with spatially referenced ground surveys using Ecosystem Function Analysis (EFA). The capability of a low-cost multi-spectral videography system to emulate ground based EFA indicators was then tested.

A range of studies demonstrate the contribution that remote sensing can make to land management by improving our understanding of ecological processes within landscapes. They used quantitative assessment and habitat mapping in combination with spatial analysis for monitoring of environmental impact and subsequent restoration efforts (Roy *et al.* 1995; Totte, Henquin & Some 1995; Coops & Catling 1997b; DeAngelis *et al.* 1998). Other studies have concentrated on monitoring the impact of mining (Rathore & Wright 1993; Hick *et al.* 1994; Warren & Hick 1996; Farrand & Harsanyi 1997; Mueller *et al.* 1997; Rigol & Chica-Olmo 1998). Although these studies focused on vegetation mapping and restoration, and have used similar concepts for ecosystem assessment, very few published works have specifically studied the application of MSV to provide measurable indicators of ecosystem function at the scale of resolution of 0.25 to 0.5 meters.

Two abandoned mine-sites of the South Alligator Valley (SAV) region, Kakadu National Park (KNP) are subject of this study. Some 18 such sites are located in the region. Despite their relatively small size, the significance of the sites should not be discounted when managing for the conservation of both the biological environment and the natural heritage values within Kakadu. Such sites can detract from the Parks natural heritage and beauty and, if not properly rehabilitated, can act as reservoirs for weed infestation (Randall 1996). Furthermore, isolated pockets of mine-related waste occur at sites that require remediation to prevent dispersal by erosion. Together these factors may contribute indirectly to a decline in the conservation value of the region. This is important when considering the SAV regions high number of endemic species and rich biodiversity (Woinarski *et al.* 1989).

1

Traditional aboriginal owners for the region (the Jawoyn) and the broader public are concerned that these sites be properly returned to their natural state of vegetation and be properly remediated with respect to waste management. Consequently, a mine-site rehabilitation program, of which revegetation is an integral part, has been proposed for these sites by Parks Australia North.

Evaluation of the success of the proposed revegetation program requires assessment of the ecological state of sites with respect to the achievement of a stable and functional ecosystem. This requires measurement of both:

- Vegetation cover at the mine-sites immediately before the program is instigated; and
- Vegetation cover in a historical context, before mining activity began at the sites.

The principle objective of this project is to evaluate the application of a high-resolution airborne multi-spectral video system (MSV) for the ecological assessment and monitoring of mine-site rehabilitation. To achieve this objective, a protocol adapted from Stow, Phinn & Hope (1997), is proposed to ensure optimal application of multi-temporal remote sensing for monitoring change in vegetation form and structure at the scale represented by mine-sites in the SAV region. The framework also provides a basis for assessing the potential of airborne MSV remote sensing techniques to resolve EFA indicators.

The principle aim of the present study is to establish a benchmarking process for the region using high-resolution MSV data. The concepts of the Ecosystem Function Analysis (EFA) developed by Ludwig *et al.* (1997) and Tongway *et al.* (1997) forms the basis for assessing the ecological relevance of information derived by remote sensing and image analysis techniques. A secondary objective is to use this information to conduct a vegetation assessment at mine-sites in the SAV before rehabilitation efforts commence in 2001.

Two mine-sites, Guratba (Coronation Hill) and the El Sherana Airstrip were chosen as demonstration sites for RS-monitoring and development. The general location of these sites within Kakadu National Park is illustrated in Figure 1. In summary the information collected in this study will contribute to the management and planning of revegetation programs in the SAV because:

- It can provide a baseline from which the success of revegetation programs planned for the area in the near future can be quantified;

- It can assist in measuring the extent of specific problem areas that need special attention during rehabilitation;

- It can provide a reference for assessing the vegetation community at mine-sites with respect to 'undisturbed' sites;

- It can assist in developing a methodology for monitoring rehabilitation success that provides synoptic data of an appropriate scale and precision;

- RS can contribute to an understanding of other ecological on- or off-site impacts from mining by identifying the location of 'unnatural' surface features or specific sources of contamination.
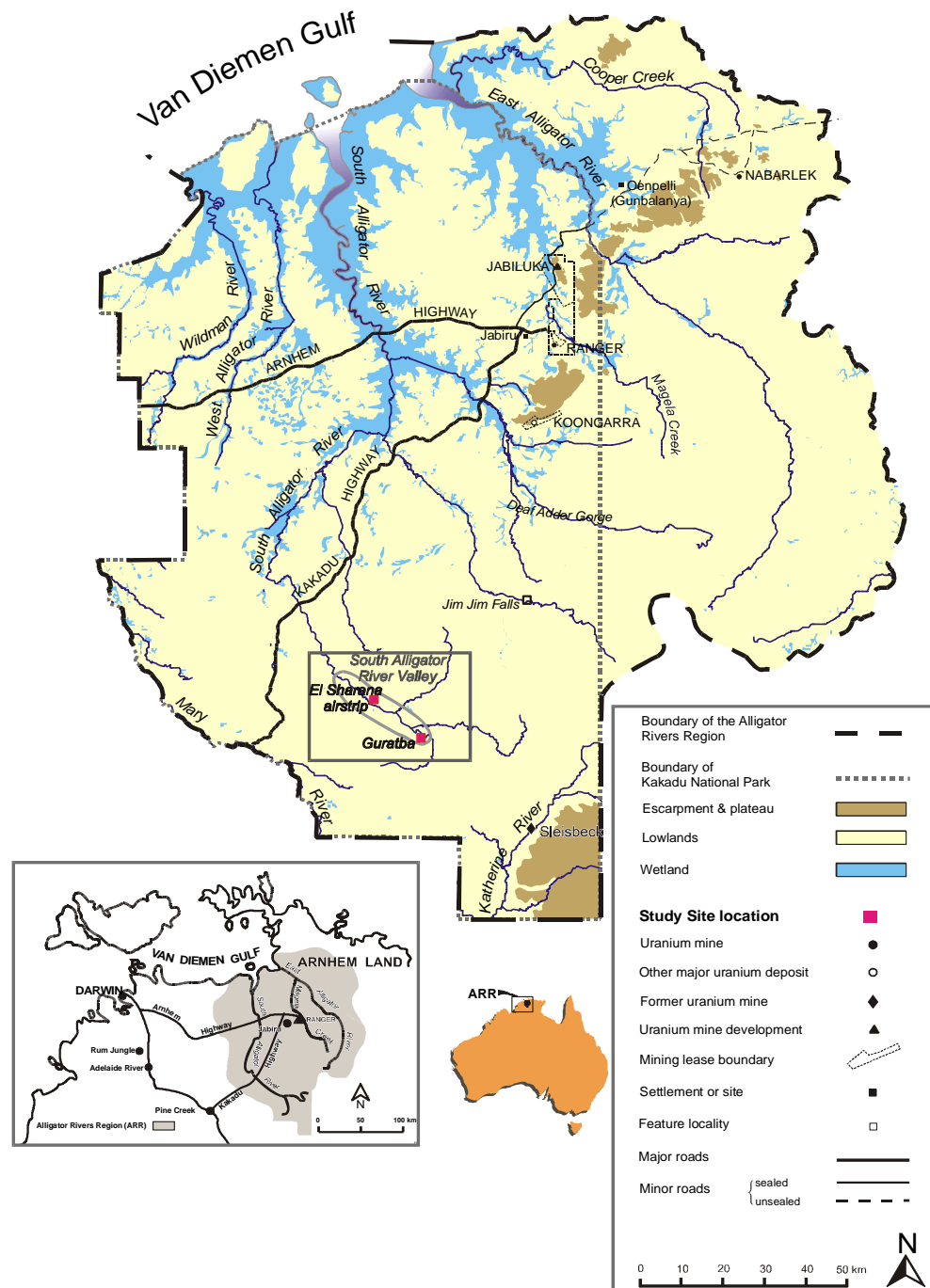
Figure 1. Location of the study sites, Guratba (Coronation Hill) and the El Sherana Airstrip in the South Alligator River Valley of Kakadu National Park, Northern Territory.

1.1 A Framework for Monitoring and Information Evaluation

A central theme to the development of ecological indicators are that measurements be repeatable among independent observations and information be obtained within acceptable levels of precision and accuracy. Only when these criteria is met is the utility of information preserved for monitoring purposes (Ludwig *et al.* 1997).

The factors influencing form, quality, efficiency and utility of information delivered by remote sensing are complex. The analyst must collectively consider the physical and biological environment, the sensor and platform, pre-processing steps and contextual ground information. Consequently a number of authors have proposed protocols designed to optimise the quality, efficiency and utility of remote sensing data for multi-temporal monitoring (Nyquist & Root 1997). Adherence to systematic protocol is essential in the development and quality control of ecological monitoring indicators for rehabilitation assessment.

Stow, Phinn & Hope (1997) provide a general framework for an 'end to end' system for the integrated planning, acquisition of aerial and ground data, quality control and delivery of information for multi-temporal monitoring of detailed vegetation changes. The framework has been adapted for the current study (Figure 2).   This system allows information to be provided to managers in an efficient and cost effective manner, within limits of acceptable error.
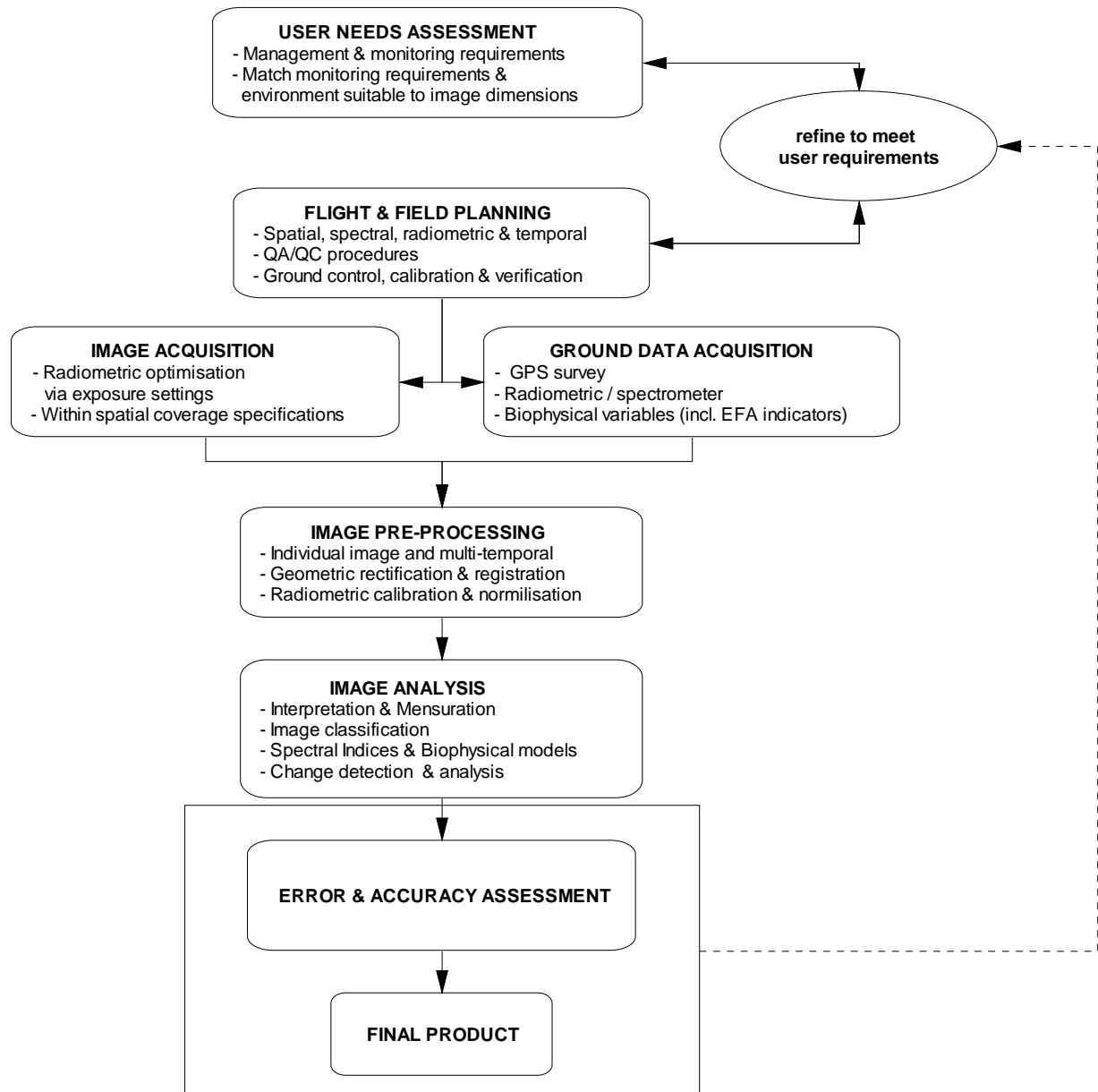
Figure 2. A framework for planning and information flow for an 'end to end' system to monitor environmental disturbance adapted from Stow, Phinn & Hope (1997).

1.1.1 Information Requirements

The first step in the design of a monitoring program is to conduct an analysis of information requirements based on the objectives (Stow, Phinn & Hope 1997). In this context three defining questions arise that guide these requirements:

- At what stage of rehabilitation is the site in becoming a 'functional' and self-sustaining ecosystem?

- How similar is the site to the surrounding 'undisturbed' environment?

- Are there any specific problems that can be identified, such as weed invasion, soil erosion, or areas of mine-related contamination?

5

Strategies for monitoring mine-site rehabilitation must be designed to provide information over a suitable range of scales. Information relating to fine-scale ecosystem processes must be able to be linked in a nested hierarchy to indicators collected at broader scales (Tongway, *pers. com.* 2000). Indicators should be ecologically relevant, quantitative and synoptic. Given that there is a characteristic set of environmental constraints inherent of a given region (be it geological or climatic), any measure of ecosystem health should also be scaled in the context of the 'natural' (pre-disturbance) environment of the site in question (Bell 1996; Corbett 1999). In this context, Corbett (1999) noted the general lack of consistent, repeatable monitoring methods for mine-site rehabilitation assessment that effectively measure, over an appropriate range of spatial and temporal scales, the ecological state of sites.

A conceptual framework for Ecosystem Function Analysis (EFA) has been developed by Ludwig *et al.* (1997) and by Tongway *et al.* (1997). Three interrelated components form this analysis approach where a range of indicators, measured on the ground, have been derived to measure:

1. Basic ecosystem processes (Landscape Function Analysis);
2. Vegetation development (composition, development and density); and
3. Habitat complexity (pattern and structure).

Remote sensing (RS) can potentially improve information relating to these three components of EFA by forming links over a range of scales between scale-dependent elements influencing ecosystem processes (Asner, Wessman & Schimel 1998; Jupp *et al.* 1988; Lobo *et al.* 1998; Tongway *et al.* 1997). This information can potentially relate directly to EFA indicators measured on the ground. Identification of these relationships will allow a synoptic approach to the application of these indicators for assessment purposes using remote sensing.

For this reason the scale of resolution of RS data is a fundamental consideration for designing any monitoring program. The scale at which information is collected should reflect functional divisions based on both ecological criteria and management objectives. These factors are discussed in more detail below.

Landscape Function Analysis

Characteristic patterns and hierarchical organisation of 'patches' evolve within the landscape though basic ecological processes operating over a range of scales. Spatial relationships between distinct elements of a landscape and the interactions among these structural components define

the functional state of an ecosystem at any one time (Bell, Fonseca & Motten 1997; Lobo *et al.* 1998).

The pattern and arrangement of critical patches in the landscape form the basis to Landscape Function Analysis (LFA), which hinges on the **trigger, transfer, reserve and pulse** model shown in Figure 3 (Ludwig *et al.* 1997). The model has inherent spatio-temporal dimensions and, in this sense, remote sensing may provide a means to differentiate patterns relevant to defining the functional state of an ecosystem. The basis of LFA is to measure the spatial arrangement, size and relative distribution of patches (obstructions to runoff) with respect to the distribution of infertile (inter-patch) zones in a landscape as they relate to the down-slope transport of resources by water.
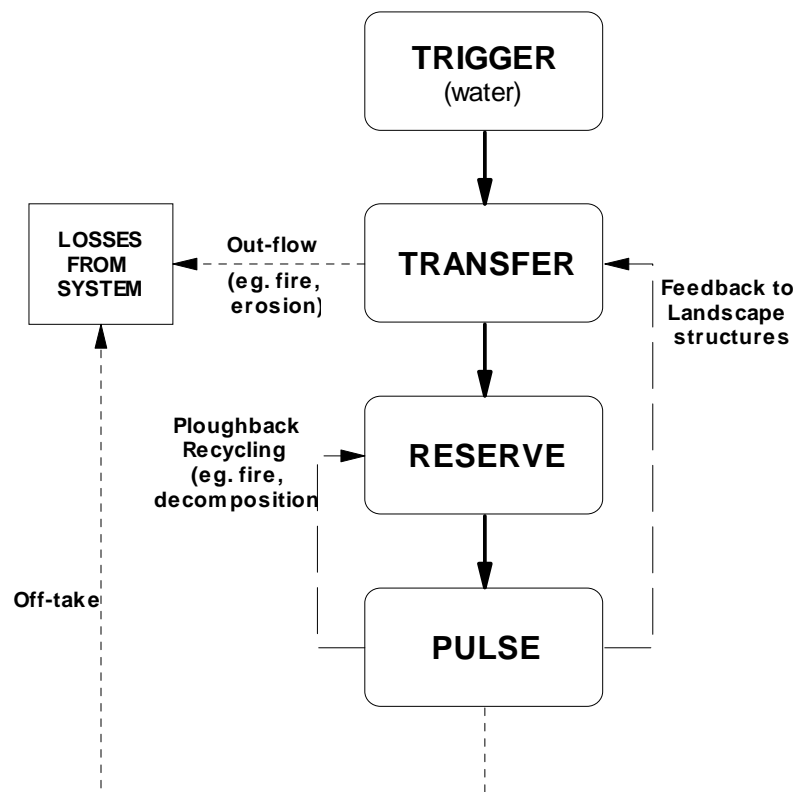
Figure 3. The trigger, transfer, reserve and pulse model proposed by (Ludwig *et al.* 1997) to describe the major spatio-temporal processes related to the functioning of terrestrial ecosystems.

Plants, through the production of foliage, stems, roots and seasonal growth cycle, each respond to -and are constrained by- ecosystem processes (Asner, Wessman & Schimel 1998). In this context, the Wet-Dry tropical climate of the South Alligator Valley strongly influences revegetation of disturbed land, where the ecological cycle of biological production and cycling (conservation and loss) of nutrients limits the establishment of a stable plant community.

Essentially this system is 'water-controlled', where Wet season rainfall between October and April **triggers** biological, physical and chemical activities (Ludwig *et al.* 1997).

Understanding the rate at which materials are **transferred** across a landscape is crucial in determining the functional state of an ecosystem. Water is also the major force driving **transfer** processes through runoff-runon, erosion-deposition and infiltration of water into the soil.

The ecological condition of land may be viewed as a continuum between a fully functional *conserving* landscape and a very dysfunctional, or *leaky*, landscape (Tongway & Hindley 1995). In this context, a well-rehabilitated landscape will be characterised as having:

1. A high level of resource utilisation and control;
2. Low losses to the system through transport processes (runoff and erosion); and
3. Fertile patches where resources are concentrated (Tongway *et al.* 1997).

It follows that the distribution of elements that make up the landscape, especially the number, size, shape, type and spatial arrangement of surface vegetation patches is crucial to the spatio-temporal dynamics driving the **transfer** and **reserve** of scarce resources within the landscape. In this sense, the properties of landscape surface features will govern these processes. By understanding the physical properties for key surface features and by mapping their spatial arrangement an indicator of landscape 'leakiness' may be derived to measures the functional state of the ecosystem. By undertaking comparative measurements, land undergoing rehabilitation can then be scaled in the context of representative pre-disturbance environments.

The spatial arrangement of surface vegetation has been shown to be a key factor in arresting flow of runoff water, allowing for infiltration of water, nutrients and sedimentation as demonstrated in Figure 4 (Tongway & Ludwig 1996; Ludwig *et al.* 1997; Tongway *et al.* 1997; Tongway & Hindley 2000).

GRASSLAND FUNCTIONING

Degraded Grasslands have long, straight fetches, allowing flowing
water to run out of the local ecosystem.

Dense Grasslands cause water flow to be tortuous, with hummocks
absorbing water in transit.
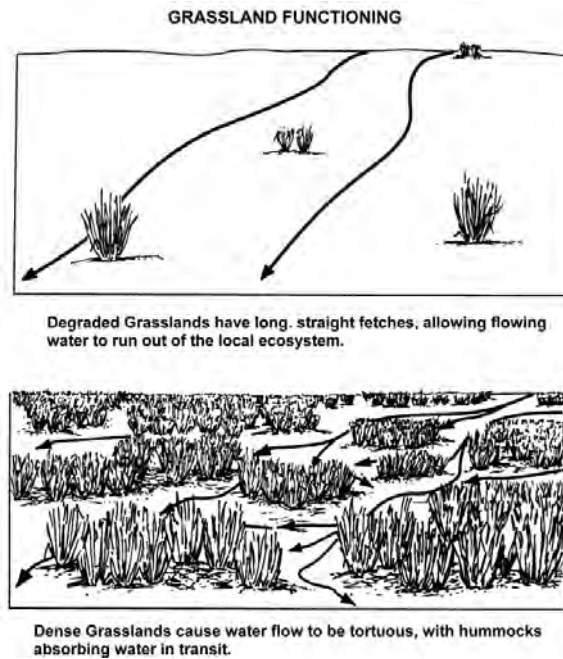
Figure 4. Spatial arrangement of vegetation plays a key role in the regulation and conservation of scarce resources in tropical savannah landscapes by influencing the flow characteristics of surface water (after Tongway & Hindley 1995). Remote sensing may provide quantitative indicators to measure the effectiveness of resource control provided by surface vegetation pattern.

Perennial grasses, in particular, are recognised as being important in facilitating the development of stable and sustainable tropical savannah ecosystems (Ludwig & Tongway 1992; Ludwig & Tongway 1996). Such patches are biologically responsive and provide a feedback loop that is critical to sustaining the quality of fertile patches that, by capturing resources, also respond with a **pulse** of production after a **trigger** event, such as rain. The attributes of grassland patches are further illustrated in figure 5.

Grass hummocks
absorb flowing water.

Saltating soil particles and organic
matter are captured in grass hummocks.
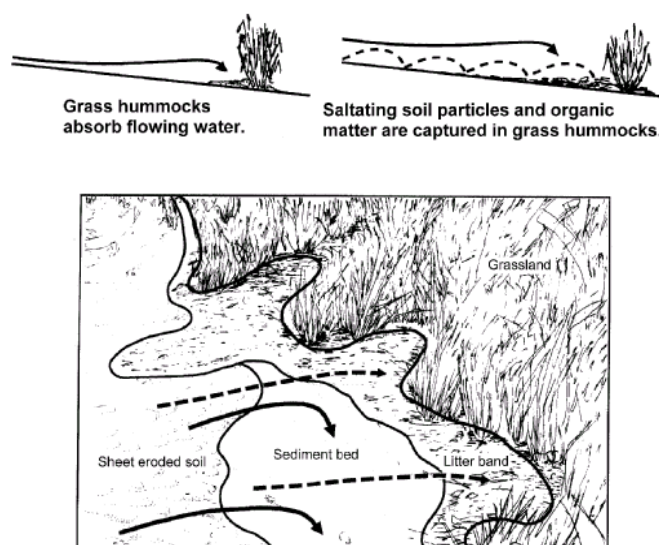
Figure 5 Vegetation patches allow capture of soil and organic matter that may otherwise be lost through erosion (after Tongway & Hindley 1995). Remote sensing may be able to measure the effectiveness of 'resource capture'.

9

Further, it has been demonstrated that distribution of relatively small, fine grained patches at the scale of individual tussock clumps can play an integral role in development of a functional ecosystem, through the conservation of scarce nutrients (Ludwig & Tongway 1992). In fact, many small patches (tussocks) will be more effective at reducing erosive forces of water and wind than having fewer large patches. Therefore, the minimum patch size that provides functional stability with respect these factors can be considered the minimum useful unit in the measurement for LFA and in assessing development towards a sustainable state. In this sense, non-living structures at a scale of 2 to 10 metres wide such as log-hummocks or mounds that obstruct downhill water flow in a local watershed will also facilitate biological activity through the capture of nutrients, litter and seed (Ludwig & Tongway 1992; Ludwig & Tongway 1996).

To refine these indicators further it is also useful to distinguish the quality within each structural component (patch or inter-patch) as the properties of these elements will define the spatio-temporal dynamics of resource capture, storage and loss across a landscape. For example, a grass patch would be considered a more stable obstruction to water flow than a mound of bare soil exposed to erosive forces. Similarly, *perennial* grass provides a far more stable obstruction than that provided by the *annual* grasses, which tends to have a comparably very small basal area and a shallower root system (Tongway & Hindley 1995). The quality of a patch with respect these criteria might be measured by developing indicators that measure 1) vegetation type; 2) vegetation density and 3) vegetation health. Similarly, the quality of inter-patches will vary with respect to factors affecting erosion potential and water infiltration.

The implication here is that RS information should ideally discriminate between these features and should deliver a comparable spatial resolution, where identification of features less than 10cm is desirable. However, if this is not possible, it is still desirable to identify general patterns or clumps of such features in the landscape, at a higher level of hierarchical organisation. A key objective, therefore, is to assess the capability of RS imagery to resolve the distribution and pattern of key patches within the landscape.

Vegetation Development

The restoration of disturbed sites to a 'natural' state with respect to the plant community is an ultimate goal of rehabilitation in a conservation area. In this context, monitoring assessment requires:

1. A reference to the range of plant communities representative of the natural environment and
2. Knowledge of the patterns of recolonisation for different keystone species.

MSV has been has been used successfully to accurately measure change in total and relative vegetation cover (Lonard *et al.* 1999). Furthermore, MSV has been used to discriminate between keystone plant species (Um & Wright 1998; Everitt *et al.* 1999). For example, dominant tree species (*Eucalyptus* spp.), shrubs (*Acacia* spp.) and grasses have mapped to species level, where relative abundances and density can be determined within acceptable error levels (Hick *et al.* 1994; Lyon, Honey & Hick 1994). In some cases, environmental weeds may also be mapped successfully at high spatial resolution.

Habitat Complexity

A measure of habitat complexity will indicate the potential for an environment to accommodate the biological requirements for the range of species known to occur in a given region. Structural components of 'habitat' that may be measured by remote sensing are produced by the combination of all biotic and abiotic in the landscape. Quantitative indicators of habitat complexity have been derived from forest community studies from RS information (Coops & Catling 1997b; Coops & Catling 1997a; Coops *et al.* 1998). These measures essentially are scale-dependent and examine the relative spatial variance among a standardised set of map classes in a given area. Once a thematic map is produced of sufficient accuracy, it is also possible to examine the spatial interrelationships within and between individual classes using spatial analysis techniques. In this context, landscape metrics, such as measures of *contagion* and *fractal dimension* that relate to the context (relationships between classes) and pattern (distribution, size and shape of individual classes), have also been applied by a number of authors (Frohn 1998).

Plant species distribution and density are key elements of habitat complexity. Vegetation-related habitat complexity also has a vertical dimension, which includes tree height, canopy density and crown height. In this context shade is a basic physical element that can be measured by RS that relates to vertical habitat complexity. A shade factor indicator may be derived from remote sensed data once standardised as a function of time of day, associated sun angle and topography. Further information may then be derived relating to the height, width and density of the objects casting the shadow (Campbell 1996).

1.2 Variables Limiting Remote Sensing Capability

The factors that together define the capability of passive optical remote sensing are:

- The *energy source*, (the sun);
- The *transmission path* (atmosphere);
- The *target* (point of interest to be interrogated);
- The *platform*; and
- The *sensor* attached to the platform.

Each factor is critical to overall 'resolving' capability. However, it is ultimately the properties of the *target* and the spatial arrangement of target elements in the context of one another that will determine the ability of remote sensing to resolve between specific elements (Campbell 1996; Zwiggelaar 1998).

The signal to noise ratio (SN) from the target to the sensor determines the resolving power of the sensor. SN is band specific and is temporally and spatially variable with respect to environmental conditions, such as the degree of atmospheric noise, distance of transmission path, or sun angle. For control and assurance of data quality, it is useful for analysts to estimate SN at the time of image acquisition by measuring the ratio of the signal mean to the standard deviation (Curran & Dungan 1988). The deployment of spectrally invariant calibration targets, which allow standardisation of data to ground reflectance measurements (Stow, Phinn & Hope 1997), may assist in providing a standardised calculation of SN.

1.2.1 The Platform

The principle advantage of an airborne platform over satellite platforms is a higher SN ratio from target to sensor. This allows sensors to have higher spectral resolution (narrower bands) and higher spatial resolution (smaller pixel size).   The higher spectral resolution provided by airborne platforms improves potential for fine-resolution diagnostic spectra to be selected for targets of interest (Bork, West & Price 1999; Price 1998). Finer spatial resolution also enhances textural information. For example, components of plant/leaf structure may be used to distinguish between species, or between bare-ground types (Campbell 1996).

Airborne systems also allow greater flexibility over satellite platforms where mission timing, altitude and a range of spectral/spatial resolutions can be easily manipulated. However, aircraft also experience geometric instability that can lead to significant geometric distortion at the edges of the field of view (FOV). This form of displacement is also exacerbated in areas where

topographic relief is significant. Together this can make geometric correction of RS data difficult (Chen, Wang & Lin 1997; Harrison & Jupp 1991). Geometric distortion can be reduced using several techniques including:

- Application of geometric correction algorithms in combination with an adequate number of ground control points (GCPs);

- Allowing appropriate overlap between image frames of a mosaic scene so that peripheral areas where distortion is highest can be removed;

- Use of a gyro-based stabilisation mount to compensate for platform roll pitch and yaw.

1.2.2 The Sensor

The Image Capture Unit (ICU) used in this study was developed by Dr Nick Rollings of the Division of Ecosystem Management at the University of New England. The ICU is designed to carry up to eight precision aligned Sony industrial cameras, each with an independent frame-grabber. A central switch, which is controlled by a PC/104 industrial computer, triggers frame-grabs from each camera simultaneously. Software identifies each frame-grab event where images are then downloaded from frame grabber memory to disk. The entire system is compact, lightweight and can be mounted easily to almost any platform (Rollings 2000a; Rollings 2000b).

The ICU cameras each use a silicon-based Charge-Coupled-Device (CCD) sensor that has a spectral response range between 400 to 1100nm. The high sensitivity of the CCD within this range allows for the use of narrow band filters (Zwiggelaar 1998; Rollings 2000b). Currently 10 spectral filters covering specific regions within the 450-850 nm range are available. This allows considerable adaptability for application-specific spectral configurations (Rollings 2000b).

Such a system has the ability to provide high spatial resolution data in a digital format, which is more easily manipulated than conventional aerial photography (Mumby *et al.* 1998). The spatial resolution of imagery can be manipulated in the range of 0.25m to 5m, depending upon altitude of fly-over. The ICU system combines some of the desirable qualities of satellite imagery and aerial photography; namely the provision of digital data in discreet spectral bands at high spatial resolution.

1.2.3 The Target

Several factors influence reflectance and absorption of electromagnetic radiation by the target. These include target structure, orientation, texture, density and chemistry. With respect to vegetation, physiognomy (leaf morphology, leaf orientation, foliage density, growth form and

phenology) affects the way radiation is *reflected* whereas foliar chemistry affects the way radiation is *absorbed* (Campbell 1996; O'Neill 1996).

Diagnostic narrow-band (±10nm) features have been found that discriminate between a variety of plant and soil types within the 400 to 1100nm range (Skidmore & Schmidt 1996; Warren & Hick 1996; Skidmore *et al.* 1997; Dematte & Garcia 1999). This is despite a large degree of spectrally redundant information within the broader-band blue, green, red and near-infrared region of this spectrum (Baret 1995; Campbell 1996; Price 1998). Spectra that separate between key plant species (e.g. *Eucalyptus* spp.) and soil types also have been found above the CCD-sensor range, between 1100-2400nm (Skidmore *et al.* 1997; Kumar & Skidmore 1998; Zwiggelaar 1998).

1.3 Remote sensing in the South Alligator Rivers Region: The Implications of Environmental Variability.

A requirement of any monitoring program is that the environmental indicators be measured with sufficient accuracy and sensitivity to detect real change. With respect to RS, achieving this aim is complicated by both temporal and spatial variability in the spectral properties of target features. Much of this variability is imposed by regional environmental patterns: climate, geology and topography. Consequently, these factors have important implications for sampling design of both image acquisition and ground sample collection.

1.3.1 Temporal Variability

Appropriate timing of image acquisition is a critical factor influencing environmental data quality. Predictable (seasonal) temporal patterns and stochastic events, such as fire, must be carefully considered with respect to their influence on the spectral response of key surface features as well as on the degree of atmospheric noise (Hick *et al.* 1994).

In the Alligator Rivers Region, remote sensing acquisition for landscape mapping is generally limited to the Dry season period by seasonal cloud cover and rain (Figure 4). Understanding of these conditions assists also in identifying potential problems that may be avoided through careful planning and coordination with land managers. Inter-related factors include:

- Seasonal variation in both climate and vegetation characteristics; and
- Time of day and the specific environmental conditions experienced during image acquisition that influence the quality of data acquisition, such as excessive wind, smoke or cloud-cover, sun angle and shadow effects.
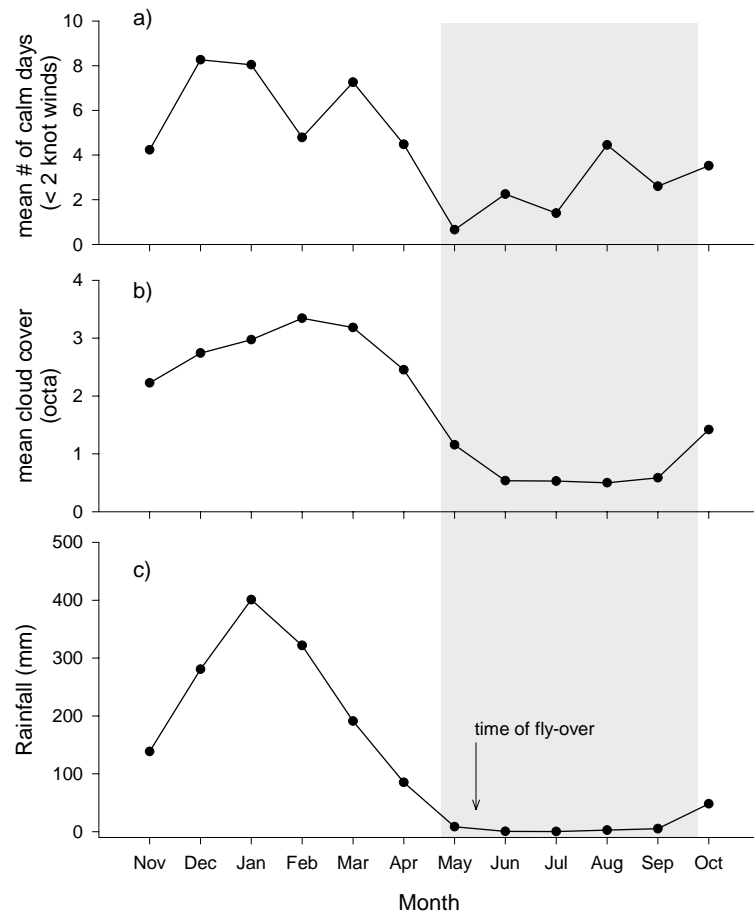
Figure 6. Weather patterns of the Alligator Rivers Region, Northern Territory: a) Mean monthly number of days with calm winds at Oenpelli, NT (< 2 knots); b) Mean monthly low-level cloud cover (< 2600m); and c) mean monthly rainfall (mm) at Mary River Ranger Station, Kakadu, NT. The shaded area indicates a generalised 'window of opportunity' for optical remote sensing data collection based on climatic limitations.

(Data source: Australian Bureau of Meteorology)

Feature definition uncertainty increases as variation in spectral and textural characteristics increases for a particular target. It is therefore important to characterise variation within and between sampling events, to define target discrimination potential. This allows optimal precision and accuracy of feature interpretation. For this reason it is important to have an understanding of the temporal patterns of variation in spectral reflectance *within* and *between* target features - with respect to the spectral profile of specific features of interest.

Vegetation and soils exhibit considerable spectral variation in response to environmental conditions driven by water flux (Muller & James 1885; Roberts *et al.* 1998). This is particularly the case for plants, where physiological and structural changes related to the seasonal growth cycle (phenology) prompt large changes in spectral reflectance (Asner, Wessman & Schimel

1998; Zwiggelaar 1998). Furthermore, soil reflectance can vary considerably in response to changes in moisture content (Baret 1995; Famiglietti *et al.* 1999).

A number of generalisations can be made with respect to the effect of phenological state on spectral and textural response of key plant types. Spectral variation response patterns tend to be consistent with the season for a particular species, but may vary significantly between species (Zwiggelaar 1998). It is therefore useful to determine the time when spectral definition is maximal, given other operational constraints such as cloud cover.

The phenology of plants in the Alligator Rivers Region has been reviewed by Brennan (1996). Although there is considerable temporal variation observed between years in the phenological patterns expressed in plants, the relative sequence of changes within and between species is generally consistent in any particular season. Dominant perennial and annual grasses of the SAV (*Heteropogon* and *Sorghum* spp.) have very different growth cycles. *Sorghum* has fruited and died off by March, while *Heteropogon* spp. continue flowering and fruiting from April to May after which they remain in a dormant growth state (Brennan 1996). Because photosynthetically active vegetation elicits a very different spectral response to senescent vegetation (Roberts *et al.* 1992; Campbell 1996), the phenological difference between perennial and annual grasses during the April/May period may be used to differentiate between these key grass types.

There are other reasons why the early Dry season is considered optimal for RS acquisition and why the later period (June to October) should be avoided. Foliage is a key diagnostic component for plant species discrimination, but several tree species in the SAV region are deciduous in the late Dry season (Brennan *pers. com.* 2000). Data quality is also marred by seasonal fires. The overall burnt area increases over the dry period, where fire either removes surface vegetation or alters its spectral characteristics. Associated smoke also contributes significantly to atmospheric noise.

It is considered that single-date MSV capture during early Dry season yields the maximum spectral contrast between key landscape surface indicators required for EFA, therefore providing the most cost-effective option based on the objectives for monitoring rehabilitation at mine-sites of the SAV region. It should be noted, however, that other studies have utilised within-year multi-temporal RS data to provide further information of ecological significance to monitoring vegetation development or land degradation, by accumulating the differences expressed by particular features over a range of specific times (e.g. Wolter *et al.* 1995; Bohlman *et al.* 1998). For instance, further information might be derived within the ARR in the late Dry season, when

diagnostic phenological characteristics, such as flowering, fruiting, or a growth flush, are expressed by a number of plants (Brennan 1996). Another example may be measuring the degree of feral pig activity on a floodplain, where rutting damage (exposed soil) is maximal in the late Dry Season.

Implications for Operational Planning

In summary, the early Dry season (April/May), appears to be the optimum time to collect RS data for monitoring rehabilitation in the SAV region using EFA indicators. This is because spectrally diagnostic features for major vegetation types are optimal at this time. Data quality is also optimised, as spectral variability within target populations caused by loss of foliage or stochastic events (such as fire), is minimal, while atmospheric visibility tends to be maximal.

As previously stated, the overall area burnt generally increases over the Dry season. In KNP a spate of prescribed 'early' season, burning is conducted. Careful planning and consultation with district landowners and managers will minimise the potential impact of prescribed early-season burning on data quality (Spiers *pers. com.* 2000).

A degree of flexibility should be incorporated into the data acquisition schedule as no amount of planning can account for unpredictable circumstances. Therefore, potential standby costs should be factored into any study. The field and flight team must allow standby time for when conditions are not suitable and be able to respond quickly when conditions become suitable. Therefore it is necessary to have people on the ground the day data acquisition is planned, to notify flight crew of data collection feasibility and to post-pone if necessary. This may seem a costly exercise, but costs are offset by overall improvements to data quality.

Transferability and efficiency of data collection are key considerations in monitoring design and developing accurate indicators of ecosystem processes (Ludwig & Tongway 1992). Adherence to the protocol discussed above will ultimately lead to more accurate and consistent monitoring data.

1.3.2 Spatial Variability

The interrelationship between target spatial heterogeneity and the size of the ground sample unit (pixel) will also determine target discrimination. At too fine a resolution, information can be obscured by introducing noise. On the other hand, coarser scales may obscure the ability to resolve finer scale relationships, which may have diagnostic significance (Hewitt *et al.* 1998).

Spatial variability, or the degree of spectral and textural heterogeneity within a target feature population, has implications for obtaining a representative sample for image classification, particularly over larger regional areas (Pickup, Bastin & Chewings 1994; Baret 1995). Such variability is also influenced by the bi-directional reflectance from surrounding features and is therefore influenced by spatial context between different features (Barrett & Curtis 1992).

However, for monitoring relatively small areas (e.g. mine-sites) that usually display less spatial heterogeneity, the spatial dimension is perhaps not as important as temporal variability. Nevertheless, spatial variation must be considered to aid image interpretation and accuracy assessment (Wade, Foster & Baban 1996). Where spatial variation is observed, sampling efforts should be distributed across the gradient of variation to obtain a representative sample in the most efficient and cost-effective manner (Pressey & Bedward 1991; Campbell 1995).

2   MATERIALS AND METHODS

A generalised outline of the steps involved in pre-flight planning, ground and RS data acquisition, data pre-processing and image analysis are summarised in Figure 5. These steps will be elaborated on under the headings of this section
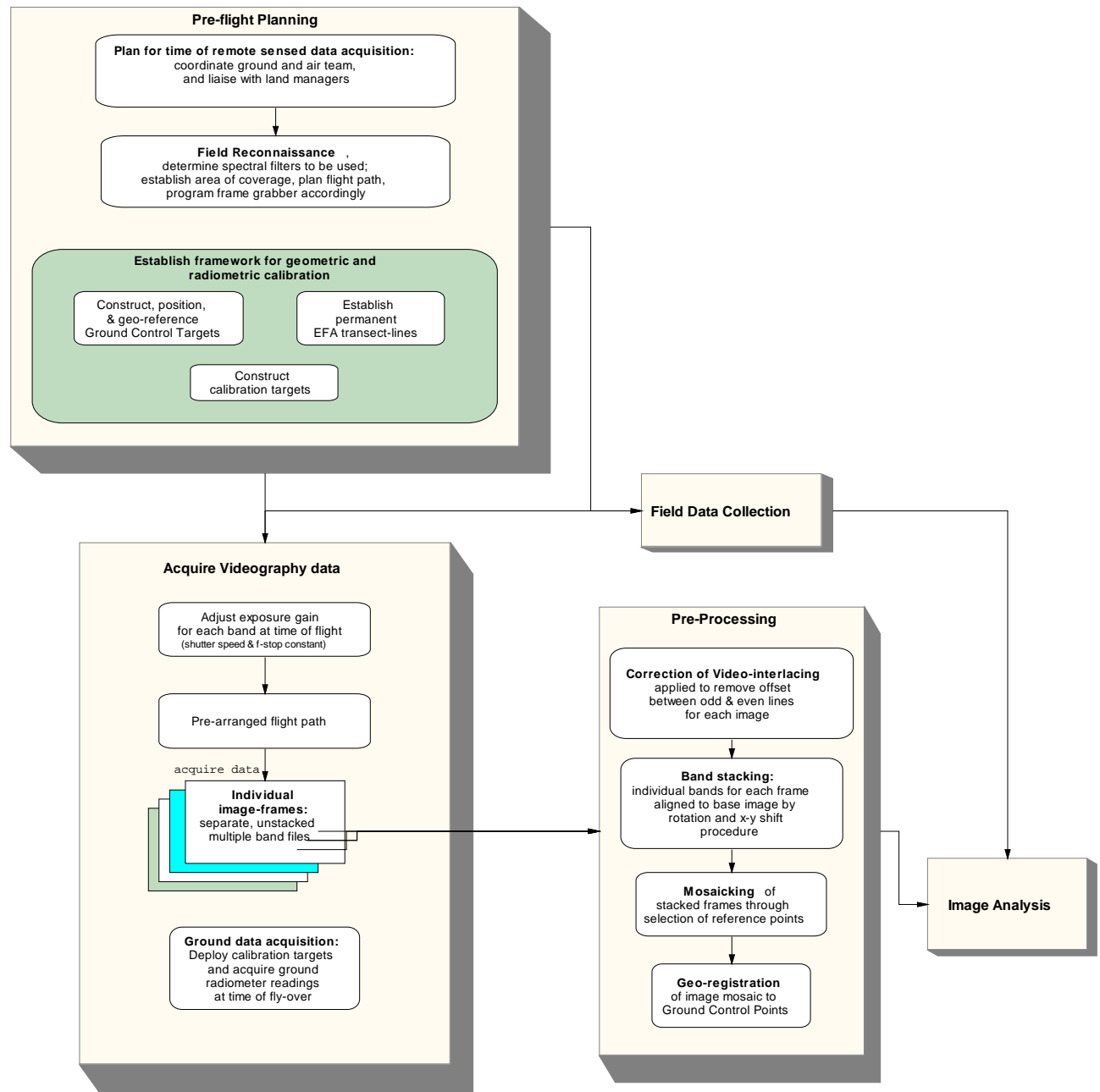
Figure 7.   Outline of steps in pre-flight planning, image acquisition and pre-processing.

2.1 Site Description

The South Alligator River Valley is located at the southern end of KNP (Figure 1). The region has been identified as a unique ecotone between two geologically different landscapes (the Marrawal-Arnhem Convergence), supporting a diverse range of animals and plants of conservation significance (Woinarski *et al.* 1989). Mine-sites in the area tend to be located on the Pine Creek Geosyncline, a geologically complex region consisting of deformed Precambrian sedimentary basin with numerous volcanic intrusions (Anon. 1988). A large range of landforms are represented in the region, with a relief of up to 250 m, ranging from escarpment, plateau, upland and lowland hills and the valley floor (Story *et al.* 1976).

The region has been subjected to a range of human disturbances within the last century- most notably grazing and the possible alteration of fire regimes (over a broad scale), the introduction of a number of exotic species and mining (Graetz 1989; Woinarski *et al.* 1989).

2.1.1 El Sherana Airstrip

The airstrip (Figure 15) was constructed in the 1960s and was in use until the early 1980s (Braithwaite & Woinarski 1990). It is located on a gentle lower slope ($< 5\%$) that experiences seasonal overland water flows and seepage, which has led to development of deep lateritic soils (Stow, Phinn & Hope 1997). The slope drains to a meandering gully that joins the South Alligator River approximately one kilometre from the site. Soil surface texture and particle size characteristics vary according to seasonal geomorphic processes driven by wetness and water flow that are influenced by localised topography (Story *et al.* 1976).

The airstrip is about 50m wide and 1000m long. It was formed by cutting a level surface into the slope, parallel with the slope contour, removing all vegetation and topsoil. Generally, the exposed lateritic sub-soil of the airstrip is compacted, and contains little organic matter as indicated by the lack of vegetation and decomposing surface litter. Since its abandonment, the only other major disturbance has been from excavation of gravel for road works near the north-western end of the airstrip.

Surface soils at the airstrip can be characterised into areas of actively eroding soil (Figure 23), scolded surfaces and several surface depositional classes based on the degree of gravel, sand or clay content (Plate 6). Vegetation colonisation at the site displays a clearly emerging pattern, with some areas being recolonised by perennial grasses (*Heteropogon* spp.) or shrubs (*Acacia* spp.) and other areas by dense to sparse annual grasses. Vegetation is often associated with

localised depressions or obstructions to overland water flow, such as earth mounds or small embankment lines formed from grader earth-works. Significant areas also remain totally devoid of vegetation.

The surrounding area remains relatively undisturbed and consists of Eucalypt woodland dominated largely by *E. foelscheana*, *E. latifolia*, *E. tectifica* and *E. alba*, the latter generally being associated with seasonally waterlogged soils on slopes below the airstrip. Dominant understorey species include *Erythrophleum chlorostachys* and *Buchanania obvalata*. Dense perennial grasses (*Heteropogon contortus* and *H. triticeus*) dominate the herbaceous layer.

2.1.2 Guratba (Coronation Hill)

Guratba is located next to the South Alligator River and has relief of 200m (Figure 30). This site displays greater environmental heterogeneity than the El Sherana site. An upland hill landform pattern is dominant in the area with slopes ranging from 5 to 120%.

Guratba has a history of low-scale mining and extensive exploration activity, which terminated in the early 1980s. The main mining disturbance occurred during the exploration operation when roads and drill platforms were cut into the steep eastern hill-face. There is also a relatively small open-cut mine and a number of adits constructed from earlier mine-workings. Several piles of overburden remain, extracted from adits, the open-cut and the drilling sites.

Geologically, the hill consists of a diverse range of weathered volcanic, metamorphic and sedimentary rocks. On the steeper slopes the surface is often strewn with boulders. These overlie shallow, well-drained skeletal soils with little organic matter (Story *et al.* 1976). Bedrock has often been exposed through construction of drill pads and roads.

Several plant-communities occur. There are three riverine woodland communities: 1) open woodland dominated by *Eucalyptus tectifica* and *Erythrophleum chlorostachys*; 2) open woodland dominated by *Eucalyptus papuana*; 3) and a narrow band of dense riparian woodland dominated by *Syzigium*, *Lophostemon* and *Melaleuca* species. Woodland communities on the upper and lower slopes of the hill are less distinct, but they may be separated into four types: 1) mixed *E. latifolia*, *E. tintannans* and *E. phoenicia*; 2) areas of *E. miniata*; 3) areas of *E. dichromophloia*; and 4) areas of *E. latifolia*, *E. tectifica* and *E. polycilata*.

2.2　Pre-flight Planning

Image coverage was planned to encompass the disturbed site and include a larger portion of the surrounding 'undisturbed' environment. This allowed comparisons to be made between 'disturbed' and 'undisturbed' areas on imagery.

2.2.1　A Framework for Image Geo-registration and Integration of Ground-level Sampling Efforts

A network of Ground Control Points (GCPs) was established at each site to allow potential for future co-registration of multi-temporal imagery for monitoring purposes. In turn this facilitates accurate cross-comparison of ground data with subsequent image interpretation, classification and accuracy assessment.

Ground control targets consisted of 1.5x1.5m sheets constructed of builders' sisalation material. Each was painted a semi-opaque, matt, light-blue colour on one side, while the other side remained a reflective aluminium surface. The blue surface was placed facing upwards (Plate 1). This material also proved durable and fire resistant, a necessary insurance for maintaining the integrity of Dry Season sampling efforts.

Targets were placed at strategic locations (e.g. at either end of permanent transect line monitoring sites) to ensure that the spatial consistency between imagery and the corresponding ground-truth data was maintained. A Trimble™ differential GPS, using an Omnistar™ reference satellite, was used to geo-reference GCPs to sub-meter precision (Plate 1). Geometric correction of the image could then be obtained by assigning real coordinates to targets identified on image.

Permanent transect-lines were established at each site using the procedure outlined by Ludwig & Tongway (1992). A 100m measuring tape was used to accurately mark out each 100m long transect. Transects were positioned along the main slope gradient, representing the direction of water runoff. The end of each transect was marked permanently with a star-picket and aluminium identification tag. GCP targets were placed precisely at the each end of the transect, with the inner edge of the target abutting the outer edge of the transect marker (Plate 1). Where the aerial view of the end of the transect line was obstructed by tree cover a target was also placed centrally along the transect line to validate its position. Positioning transects in this way allowed for accurate measurement of the boundaries between landscape patches/inter-patches required for LFA. Geo-registration of the image to transect lines also allowed ground-based

measurements to be precisely cross-referenced to imagery. This enabled accurate validation of imagery with respect to the different patch/inter-patch classes identified on the ground.

Plate 1. Images were registered to Ground Control Points using a Trimble™ dGPS. GCPs were distributed regularly throughout sites and were also placed at each end of permanent transect lines (Guratba site, lower slopes).

Six replicate transect lines were positioned at both the El Sherana airstrip and at the Guratba site. At the El Sherana site transects intersected the airstrip at about 70m intervals (Figure 16). Approximately 50m of the transect line crossed the airstrip, while the remaining 50m continued onto relatively undisturbed vegetation on either the slopes above or below the edge of the airstrip. Transect lines were systematically interspersed along the airstrip to alternate between slopes above and below the airstrip, allowing equal representation in sampling.

Guratba transects were stratified into three groups to represent the slope gradient of the site on the upper (very steep), middle (steep) and lower (medium) slopes. Two transects were placed in each of these zones. One of these was placed on the north-eastern side of the hill, while the other was placed the south-eastern side of the hill, to account for a change in rock type over the site.

2.3 Ground Data Collection

Collection of suitable ground data is a critical component of image classification, interpretation and subsequent accuracy assessment (Congalton 1991). The complexity of data collection increases as the level of detail required in the image classification increases. This is directly linked to the level of precision and detail required in data collection. In turn, this is influenced by the degree of spatial heterogeneity in the landscape with respect to the independent surface classes that one is attempting to map (Pressey & Bedward 1991).

RS data is generally collected at a scale that is typically greater in both grain and extent than traditional ecological measurements (Sanderson *et al.* 1998). In order to compare imagery on a one to one basis with field measurements, the latter often must be rescaled to match to grain of the image data. Consequently, a two-scale approach was adopted for ground-based sampling to assist in delimiting the effective scales at which EFA indicators may be accurately resolved:

1. A general survey of the key plant species and land surface types identified in initial field reconnaissance was undertaken. Training sites were geo-referenced with a Garmin™ Etrex GPS (at up to ±10m accuracy).
2. Data was collected for soil, canopy cover and patch-boundary analysis along permanent transects geo-referenced to sub-metre accuracy.

Perennial grasses were the primary coloniser that formed stabilised barriers to runoff in disturbed areas. Grass cover could also be nominally classified according to the density and species within disturbed areas.   Bare-ground areas were also a major feature of disturbed sites. These areas could be divided into a number of sub-classes representing ecologically relevant features: earthwork barriers to water runoff; deposition zones; and erosion zones. A typology of these areas and associated vegetation responses is summarised below (Table 1). These patch/inter-patch zones formed the basis for development of a LFA classification scheme.

Table 1. Geomorphic surface-soil groups, associated sub-classes and vegetation response indicators identified at the Airstrip site relevant to LFA classification scheme.

Geomorphic group	Sub-class	Vegetation response
Earth-worked barriers to runoff	Grader-line embankments	Perennial grasses have colonised immediately upslope of some embankments, thereby stabilising these areas, while others embankments have not been colonised. These generally follow the downhill slope rather than the contour.
	Isolated mounds	Earth mounds sometimes stabilised by perennial grasses and/or shrubs allowing hummocks to form.
Active erosion	Rill	Little vegetation; some colonisation by pioneers species at edges of activity (*Acacia* spp and annual grasses)
	Scolds	Compacted skeletal soil; little or no vegetation,
	Pedestalling	Little or no vegetation
Active deposition	Lag gravel	Little or no vegetation
	Sand	Little or no vegetation
	Clay-pans	Little or no vegetation; colonisation at perimeters by some sedges indicating poor drainage

2.3.1 General Survey and Selection of Training Sites

A broad scale approach was adopted for geo-referencing suitable training-site locations for image classification. The relative spatial accuracy of the Etrex GPS had to be taken into account when selecting training site areas. Special attention was given to locating discreet patches in the landscape that would be more easily identified on imagery. GPS points were only logged once a lock of sufficient accuracy (<10m) was obtained.

Although a number of different woodland communities could be discerned at both sites, vegetation was generally very heterogeneous. In addition, some species did not form discreet patches, or only formed very small patches. This made selection of GPS ground-truth points and training site selection difficult. Due to this and time constraints, ground-sampling sizes were not always optimal in providing a representative picture of spectral variability among all key surface features.

Priority was given to sampling dominant vegetation types identified in obvious woodland communities and those specifically associated with disturbed sites (e.g.. *Acacia* spp.). The presence of major sub-dominant species was also recorded opportunistically when within 10m of a sample location.

Training-sites were selected and validated using spatially referenced field notes and by revisiting the site with a registered true-colour composite image of the scene. Geo-referenced digital photographs were taken to represent LFA patch/inter-patch classes (major grass and bare-ground types) and other key surface features (Plates 4 to 11). These were used as an index for the classification scheme adopted. They also provided useful information for image interpretation and training site selection by providing a contextual reference between associated ground features. Photographic referencing is considered an essential aid to ensure repeatability of the classification scheme for standardisation of future monitoring data with baseline information.

Where possible, training site samples for each class feature were distributed evenly over the range in which imagery was captured. This strategy was adopted to account for both: 1) regional variation in spectral characteristics of features; and 2) stochastic variation between frames caused by changes in atmospheric noise, time of day, altitude, and platform role, pitch and yaw. However, the uneven distributions of some features made it impossible to obtain a sufficient sample to account for these two forms of variation, as the features in question only fell within a few frames of the total coverage.

2.3.2 Transect Surveys

Transect surveys were conducted measuring:

1. Canopy cover with a spherical densiometer measured at 10m intervals;
2. Soil moisture content and associated band-reflectance at 1m intervals, where a definite moisture gradient was apparent; and
3. Line intercept boundaries between key patch/inter-patch classes identified using LFA techniques (Tongway & Hindley 1995).

Measurements of Canopy Cover

At the Airstrip site, percentage canopy cover was measured at 10m intervals along each transect line using a spherical densiometer. Sixty-five samples were taken, representing the full range of canopy cover densities. These data were used to perform regression analysis on canopy cover estimates derived from classified imagery (Section 3.2.3).

Measurements of Soil-moisture and Associated Band-reflectance

An area of surface moisture associated with a patch of bare soil was identified on the airstrip. A 30m transect line was positioned to intersect the moisture gradient. To assess the relative

influence of moisture on soil band-reflectance, radiometric measurements were recorded with corresponding soil moisture estimates at one meter intervals along the transect at the time of fly-over. This transect was measured to a known position on one of the permanent transect lines to obtain an accurate spatial reference. This allowed BV reflectance profiles from imagery to be compared with ground measurements for samples sites.

Four replicate samples of surface soil (top 2cm), representing 10 x 10 cm in area were collected systematically from quarters of each $1m^2$ sample area. Samples were immediately sealed in plastic bags to retain moisture content. Wet and dry weights of replicate samples were measured in the laboratory to the nearest 0.01 gram with a Metlar balance. Dry weight was obtained by oven-drying samples for 72hrs at 60^0C. Percentage soil moisture (by weight) was then calculated from these records.

LFA Patch Boundary Measurements

The transect-boundary-intersect between key patch/inter-patch classes was recorded according to the method outlined by Tongway & Hindley (1995). These data have not been fully analysed and will not be explored further in this thesis. However, preliminary results were used for training site validation and classification scheme development.

2.3.3   Radiometric Data Collection

Given the variable spectral response of plants and soils over space and time, simultaneous sampling of ground reflectance with RS data for key targets is an important basis for the interpretation and evaluation of RS image classification strategies (Gamon, Lee & Qui 1992; Milton, Rollin & Emery 1995). Field reflectance measurements were taken with a calibrated 4-channel Exotech™ radiometer configured with blue (450-520 nm), green (520-600nm), red (630-690nm) and near-infrared (800-1100nm) band filters.

Band reflectance profiles for key surface features were taken at locations associated with training sites produced in Section 3.2.1 and from calibration targets. Surface features targeted that were relevant to landscape function analysis were the perennial grasses, annual grasses, dead vegetation and bare-ground classes (Table 1). Given time and equipment constraints, measurements of canopy reflectance for key tree species were not possible. However, measurements were taken in direct sunlight immediately upon obtaining a number of leaf clump specimens for some tree species.

To reduce random error and increase measurement precision, at least five independent measurements of each target type were taken (Milton, Rollin & Emery 1995). The radiometer was held at chest height directly above the area to be sampled, covering a FOV of approximately 25 cm in diameter. Care was taken to ensure that only the surface to be sampled was included in the FOV. Reflectance measurements representing 100% reflectance (assuming a true Lambertian surface) were also taken from clean Reflex™ white paper. Together these measurements were used to derive percentage reflectance from each target.

Use of Calibration Targets

Four calibration targets were placed on the airstrip at the time of image acquisition (Plate 2). Targets were constructed from canvas and measured 3x3m. Each target was painted with separate shade of a uniform, matt, grey paint, together representing a serial range of invariant reflectance values. In this way a linear transform function could be derived from ground reflectance measurements (Section 3.1.2). Ground reflectance measurements were taken from each of the 4 calibration targets and from a 100% reflectance standard within one hour of image acquisition.

Plate 2. Canvas 3x3 m spectral calibration targets were deployed at the airstrip site to allow imagery to be standardised to ground reflectance measurements.

Deployment of calibration targets is considered an important prerequisite for imagery acquired for monitoring purposes. It assists in the standardised comparison with independent multi-temporal remote sensed images. Furthermore, use of calibration targets enabled training site

band profiles derived from imagery to be validated against ground spectral measurements (Phinn, Stow & Zedler 1996; Stow, Phinn & Hope 1997).

2.4 RS Data Collection and Pre-processing

The high relief of the SAV region restricted the use of a fixed wing aircraft for the collection of high-resolution data. Consequently, a Bell Jetranger helicopter was used as a platform for the ICU. A 5-camera ICU array was used in this study (Plate 3). Specifications of imagery and acquisition conditions are summarised in Table 3.

Plate 3. The 5-camera ICU array was fitted to the undercarriage of a Bell Jet-ranger helicopter**.**

Table 2. Image Capture Unit system specifications and acquisition conditions, 26 May 2000.

Sensor type	Focal length	Flying height (pixel size)	Frame size (per band)	Pixel size range	Spectral range (5 bands)	Signal/ Noise ratio
Sony XC-77 monochrome video: 5 silicon CCDs (analogue output)	0.016 m	? (0.5m) ? (0.25m)	512 lines X 512 pixels	0.25 →1m	400→850nm	Better than 50dB

Sensor type:	Image Capture Unit using Sony XC-77 monochrome video
Operator:	Ecosystems Management Pty. Ltd (Australia)
Acquisition date:	26/5/00
Acquisition time:	Airstrip site from 1230-1400 hrs
(Australian Central standard time)	Guratba and other sites from 1400 hrs
Pixel size:	0.25, 0.5, 1.0m coverage's
Band-widths:	Band 1: Blue (450±10nm)
	Band 2: green (550±10nm)
	Band 3 & 4: Red (650±10nm & 625±5nm)
	Band 5: Near -infrared (850±10nm)

CCD= Charge coupled device
FOV= Field of view
ICU= image capture unit

Five ICU spectral filters were assigned within the visible and near-infrared electromagnetic spectrum in areas well known for their ability to discriminate between major vegetation and soil characteristics, such as greenness, moisture content and soil reflectance.

Image pre-processing (video interlacing correction, stacking and mosaicking of 0.5m data) was conducted by Ecosystems Management (Aust.) Ltd. Pty. utilising a Visual Basic program developed by Dr Nick Rollings (the ICU-pre-processing suite). Mosaicking of 0.5m resolution data images was also conducted by EM using ESRI Imagine ™ and by James Boyden with ErMapper ™ version 6.1 for 0.25m resolution data collected from the El Sherana site. Based on redundant control, rectification of the airstrip mosaic was accurate to <0.5m.

3   ANALYSES

Data analysis was divided into a three phases:

1.   Preliminary spectral characterisation of target features and image calibration;
2.   Image classification and accuracy assessment; and
3.   Interrogation of image classes for site evaluation.

These phases are described in detail below.   All maps figures have been projected using Australian Geodetic Datum (1966) and Universal Transverse Mercator in zone 53, south.

3.1   Spectral Characterisation of Surface Features and Radiometric Calibration of Imagery

Ground reflectance data were principally used for spectral characterisation of target features. When possible, corresponding BVs from MSV data were also compared with ground recordings. This involved:

1.   Graphing band profiles for perennial and annual grass types;
2.   Undertaking a non-parametric multivariate classification of radiometric band profiles for all features;
3.   Determining the influence on soil moisture on band reflectance for ground-level measurements and associated BVs sampled from 0.25m and 0.5m resolution data; and
4.   Deriving a Normalised Difference Vegetation Index (NDVI) from ground records to highlight differences with respect to the photosynthetically active potential of vegetation and soil reflectance (Equation 1).

3.1.1   Multivariate Analysis of Band Profiles

The multivariate analysis procedure involved three steps using PATN™ analysis software (Belbin 1994):

1.   A Bray and Curtis dissimilarity matrix was generated for all reflectance band profile measurements;
2.   A 2-dimensional ordination of the matrix was conducted using Semi-Strong- Hybrid- Multidimensional scaling procedure (Belbin 1991);
3.   Finally, a multiple linear regression (PCC) in conjunction with a Monte Carlo permutation procedure (MCAO) was conducted to assess the contribution of each band to ordination space.

3.1.2   Radiometric Calibration of Imagery

Radiometric calibrations of each image band to ground reflectance measurements were performed using each target as a training site for 0.5m resolution data collected from the airstrip

site. For each video band, pixel brightness values (BVs) were sampled from the centre of targets to avoid peripheral pixels and thereby obtain 'pure' pixel samples. A linear regression procedure was then applied using Minitab™ to describe the relationship between BV for each video band against corresponding ground reflectance measurements.

Calibration of imagery to ground reflectance measurements was conducted to utilise information derived from ground reflectance NDVI measurements (Figure 11). This information was used to stratify between major vegetation and bare-ground groups in the unsupervised classification procedure (Section 3.2.2).

Regression analysis produced a highly linear relationship for each band between BV and ground reflectance (Appendix I, Figure 38). Using the derived relationships, linear transforms were applied to each band to convert BV to percentage reflectance. Normalisation of image data in this way enabled a direct comparison between pixel BVs and field reflectance measurements.

3.1.3   Assessing the Relationship between Soil-reflectance and Soil-moisture.

Multiple linear regressions of band reflectance for soil were conducted against $\log_{10}$-transformed values of soil moisture content for corresponding samples collected at 1m intervals along the moisture gradient. Comparative samples were taken for:

1. Ground-based radiometer measurements;
2. Pixel BVs for corresponding 0.25m resolution data; and
3. Pixel BVs for corresponding 0.5m resolution data.

In the latter two cases, individual pixel values were manually interrogated from the image for pixels deemed most central to each corresponding ground-sample point. For each data group, a stepwise regression analysis was performed to determine which band or combination of bands contributed most significantly to the soil-reflectance/moisture relationship.

3.1.4   Use of the Normalised Difference Vegetation Index

An NDVI image was produced from radiometrically calibrated imagery (Section 3.1.2) to represent 'true' NDVI measured on the ground. The NDVI is a useful index because it enhances diagnostic differences between green vegetation and bare-ground. Band ratio measurements also tend to normalise for variations in sun angle, haze and topography. These traits improve utility of data for monitoring as they assist in normalising multi-temporal data (Pickup & Nelson 1984).

32

Equation 1. The Normalised Vegetation Index

$$NDVI = \frac{NIR - R}{NIR + R}$$

where: *NIR*= Near-infrared band

R= red band

3.2 Image Classification

Image classification is a data simplification process in which information contained in the original multi-band image is transformed into a digital thematic map. Image pixels are categorised based on a digital BV ranging from 0-255 units. Delineation of features on the surface is possible when features such as individual plant species, assemblages of species, or soil type produce unique spectral reflectance characteristics as a function of their structure, condition and fractional cover (Phinn, Stow & Zedler 1996).

The classification scheme developed in this project aimed to represent ground features that may contribute to developing indicators of:

1. Landscape Function Analysis;
2. Vegetation development; and
3. Habitat complexity.

In this context, it was uncertain, particularly with respect to finer-grained features (e.g. logs), whether they would classify accurately. This was because the relative scale of features identified on the ground survey varied significantly in patch size and patch distribution pattern, with respect to shape and spatial context with other features. For this reason an iterative approach was applied to image classification, accuracy assessment and interpretation to optimise the utility of the final classification.

A supervised classification approach, in conjunction with conventional accuracy assessment procedures, was the key method adopted to produce a thematic map. Feature classes identified from the initial ground survey, which classified poorly, were either omitted or merged with a higher functional group in the final classification. Unsupervised classification was also undertaken to aid accuracy assessment and image interpretation.

Shaded areas were treated as a separate class in supervised classification. This was because shade can lead to mis-classification if not isolated (Zwiggelaar 1998). Shade is also considered

an important ecological variable with potential value as an indicator. The resulting 'shade' class was also used as a mask in the unsupervised procedure to reduce noise in the classification.

3.2.1 Supervised Classification

The iterative approach adopted for supervised classification aimed to deliver a final product in which classification accuracy was optimised in the context of the key objectives noted above. This process is summarised in the flow chart in Figure 6.

Training sites were digitised for key tree, shrub, grass and bare-ground classes using a geo-registered true-colour composite image as a background. This produces a sample of characteristic spectral band profiles for each surface class. Validation of each training site class was conducted using geo-referenced field notes and photographs. In cases where there was some confusion in the interpretation between field notes and the location of features on imagery, these areas were omitted from the training-site selection process.

The size of training-site patches and degree of replication of patches varied considerably depending on the abundance and density of surface features and the ease at which a 'pure' sample of pixels could be selected. A summary of sampling frequency is provided in Table 6. For training classes depicting single species, care was taken to select polygons sampling only 'pure-pixel' regions from the centre of each class type. The edges between different features were avoided. However, this may not always have been possible for species with small patch area, such as *Acacia holocericia*.

For imagery collected at each 0.25 and 0.5m resolution, a multivariate discriminate function based on training site samples using the 'enhanced' maximum likelihood classified rule in ER-Mapper™ was applied to assign each pixel in the image to an appropriate class.

Preliminary classes were vetted against *accuracy assessment* statistics produced using methods discussed under that subheading, below. Poorly classified classes were either omitted entirely from classification process or merged with a higher functional group. If a high likelihood of an insufficient training sample size was detected, the offending class was omitted. However, if an offending class could be logically merged (in a ecological sense) to a higher functional group, which in turn corresponded spectrally to that group as indicated in Figure 17, the class was then merged with a higher group (e.g. Sorghum + sparse annual grass classes). The classification was repeated iteratively with modified training information and compared against the original accuracy assessment until acceptable level of accuracy was achieved.

SUPERVISED CLASSIFICATION

ground survey
of major vegetation &
'inter-patch' bareground types

Selection of training sites
for each class type

divide training sites
equally into two
independent sample sets

Apply maximum likelihood
classifier for each
training-site sample set
(using bands 1,2,3, & 5)

**PRELIMINARY
ACCURACY ASSESSMENT**

Generate confusion matrix
and accuracy statistics
by cross-tabulating
both classified images

calculate summary statistics
for preliminary classes
(use one classified image only)

Generate Bray & Curtis
dissimilarity matrix of classes
from mean BVs for all bands

Generate classification
dendogram
(HPGMA procedure- Figure 17)

Omit classes with
high level of mis-classification
& insufficient training sample size

Where possible
merge classes types
with poor discrimination into
higher functional group

re-validate training site
class types

Conduct maximum likelihood
classifier for revised
training-site sample sets
(using bands 1,2,3, & 5)

**FINAL
ACCURACY ASSESSMENT
& INTERPRETATION**

Generate confusion matrix
and accuracy statistics
by cross-tabulating
both classified images

Compare with
Unsupervised classes
(refer to Figure 7)

FINAL CLASS MAP

Site evaluation
analysis

Figure 8. Steps used in supervised classification, interpretation and accuracy assessment of 0.5m and 0.25m imagery.
Note: Band 4 (650nm) was omitted from supervised classification procedure, as BVs were saturated (=255) and therefore invariant for a number of class types. This caused ER-Mapper to returned an error when applying the maximum likelihood classifier.

35

Accuracy Assessment

For each classification, a confusion matrix was produced from the two classified images, each utilising an independent set of training-site samples representing the same array of classes (Tables 5 & 7). From these contingency tables four complementary measures were calculated:

Equation 2.   Overall percentage classification accuracy

$$A_1 = \left(\frac{\sum_{l=1}^{r} x_i}{N} \right) * 100$$

Where: A_1= Overall percentage accuracy;
x_i = number of correctly assigned pixels for the *i*th class combination along the confusion matrix diagonal.
r = number of classes (rows) in confusion matrix.
N= total number of pixels assigned in classified image

Equation 3   *Per category p*ercentage accuracy for individual classes in each row

$$\left(\frac{x_i}{r_i} \right) * 100$$

Where: x_i = Number of correctly assigned pixels for class *i*
r_i = Total number of pixels assigned to class *i* over all classes in reference image (i.e. row total)

Equation 4.   Calculation of *Overall* Kappa Index of Agreement (KIA)   (Carsten 1987; Congalton 1988; Congalton 1991; Foody 1992).

$$K = \frac{\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} * x_{+i})}$$

Where: K= Overall KIA
r= number of rows (classes) in cross-classification table
x_{ii}= number of combinations along diagonal
x_{i+}= total observations in row *i*
x_{+i}= total observations in column *i*
N= Total number of pixels in image

$$K_i = \frac{p_i - p_{i+}\,p_{+i}}{p_{i+} - p_{i+}\,p_{+i}}$$

Where p_i=proportion of units agreeing in row i/column i
p_{i+}= proportion of units for expected chance agreement in row i
p_{+i}= proportion of units for expected chance agreement in column i
i= class i

To describe the spectral separation patterns between image classes, a multivariate classification dendogram was also produced for band profiles derived from the preliminary image classification. This allowed individual classes to be compared against each other and determined whether they may be grouped within a functional hierarchy. This was conducted only on the 0.5m resolution image mosaic data for the airstrip (Figure 18) and it involved the following steps, using statistics generated from ER-Mapper™ as an input to the software, PATN™:

1. Mean BVs were calculated for each class across all bands and tabulated;

2. A Bray and Curtis dissimilarity matrix representing the relative differences between classes was produced for these data; and

3. Finally, a classification dendogram (Figure 17) was then generated using an agglomerative hierarchical fusion clustering technique (UPGMA) applied to the dissimilarity matrix (Belbin 1994).

3.2.2 Unsupervised Classification

The objective of performing *unsupervised* classification of imagery was to further interrogate image information in the context of the *supervised* classification. Two questions were asked to guide interpretation:

1. Which *unsupervised* classes strongly associate with the specific training site sample classes used in the *supervised* classification? and

2. Were any *unsupervised* classes formed that were absent from all training-site regions?

The answer to the first question would assist in determining whether there were sub-classes within groups formed in the supervised classification that could provide a higher accuracy for class discrimination. An answer to the second assisted in determining if there is spectral information within the multi-band image that can identify unique features (i.e. a plant species) not targeted in the supervised classification. The appearance of unique *unsupervised* classes may also indicate artefacts caused by classification error.

There were a number of preliminary steps undertaken to reduce noise in the unsupervised classification procedure. First, shaded areas were removed from the classification by using a mask derived from the 'shade' class formed in the supervised classification outlined above. Second, the image was stratified into sub-regions representing two major groups of spectral variation. These were: 1) Bare-ground and annual grasses; and 2) trees, shrubs and perennial

grasses. A Normalised Difference Vegetation Index (NDVI) calibrated to ground reflectance values clearly separated between these two groups, where a threshold NDVI value of 0.35 was used separate the two sub-regions. Once these images had been prepared, Principal Components analysis was applied across all five bands to each sub-image followed by an ISO_class unsupervised classification utilising principal components 1 to 5;

A summary of the steps involved in the unsupervised classification procedure is shown in Figure 7
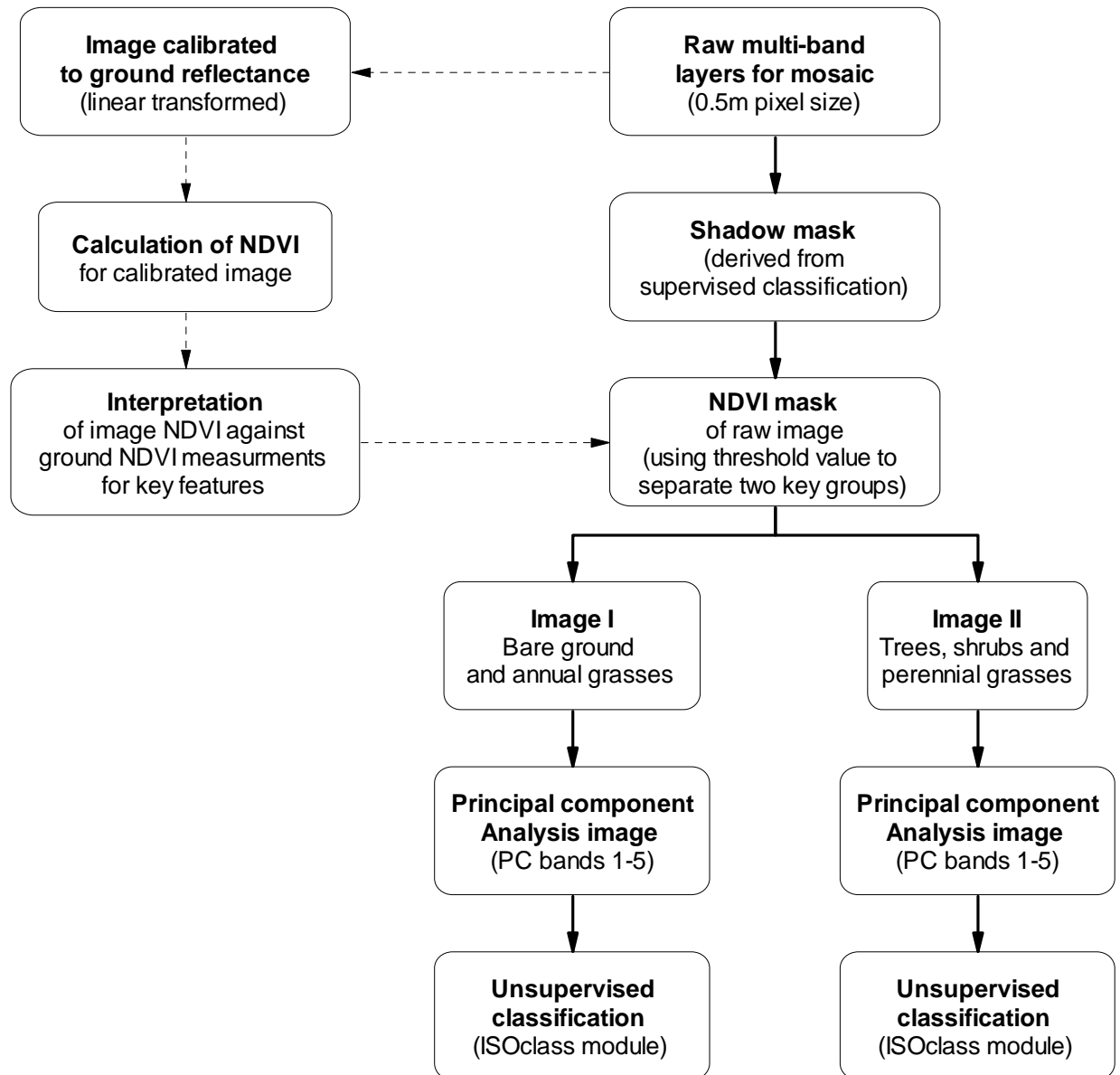
Figure 9. Steps used in unsupervised classification procedure.

3.2.3 Assessment of Canopy Cover Estimates

A linear regression was conducted on percentage canopy cover derived from supervised classification against corresponding spherical densiometer ground measurements using Minitab™ statistical software.   The classified image was sub-sampled along each transect line to correspond to ground sample points by centrally placing 20 m diameter digitised sample regions at 10m intervals along each transect, totalling 65 samples.

3.2.4 Comparison between Disturbed Areas and Analogue sites

The classified image for the El Sherana site was interrogated to compare the disturbed area with surrounding 'pre-disturbance' environment. This was done by sub-sampling two regions: 1) the airstrip proper;   and 2) *analogue* sites selected from 'undisturbed' regions adjacent to the airstrip. Proportional cover of over all map classes was calculated for both these regions and compared.

It was assumed that vegetation communities of *analogue* sites were representative of a 'natural' disturbance history. In this sense, it was tacit that vegetation had reached equilibrium with natural environmental variation, typical geology and topo-climatic patterns of the area.

3.2.5 Assessment of Vegetation Change at Guratba

An evaluation of vegetation change at Guratba, since exploration activities terminated in 1981, was conducted. The two base images used were a 1:7500 aerial photo mosaic taken on June 27 1990 and the current MSV imagery taken on 26 May 2000. Classified maps were derived from each image and co-registered to each other. An additive overlay was then applied between both class maps to detect change. The steps involved in this procedure are summarised in Figure 8.
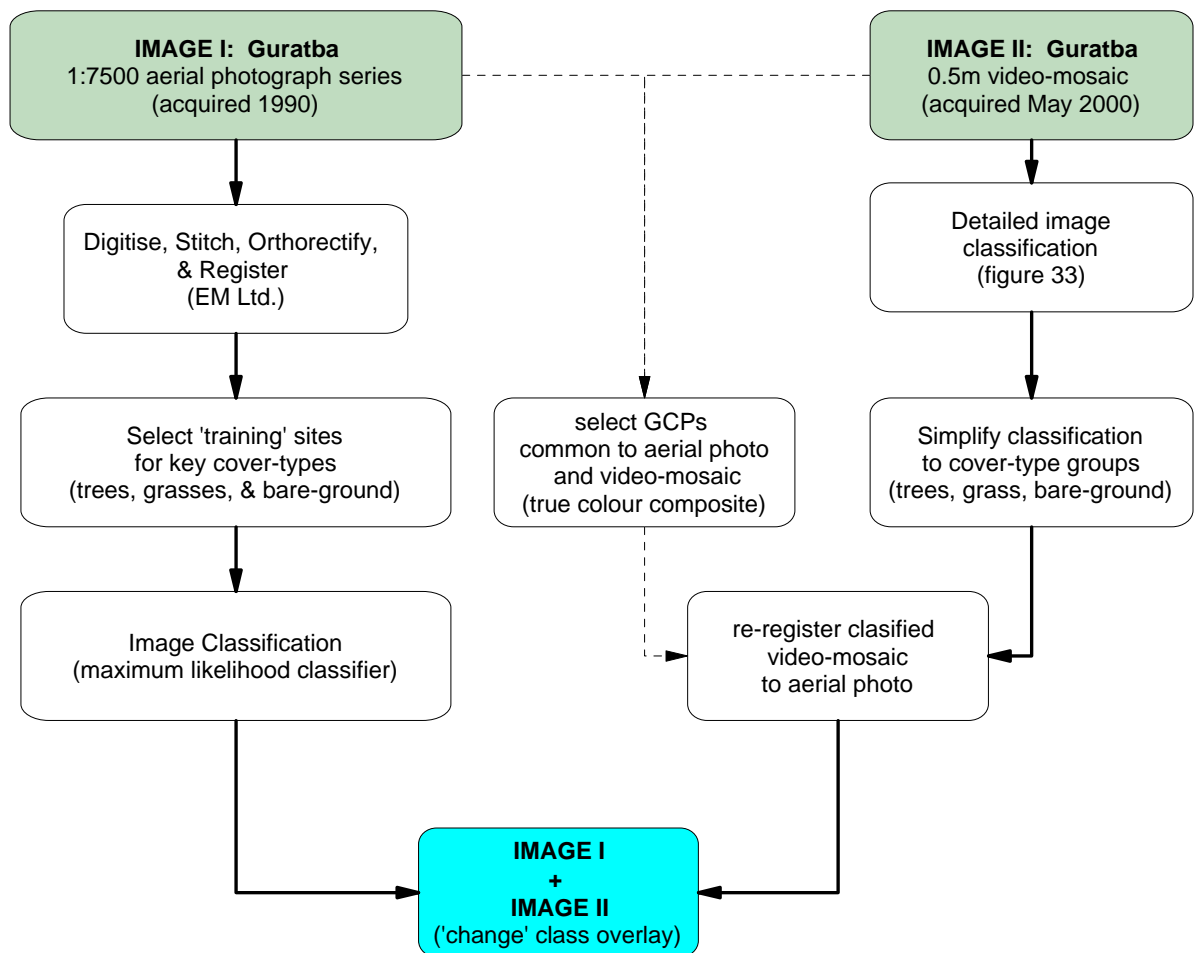
Figure 10. Procedure used to conduct preliminary analysis of vegetation change at Guratba (Coronation Hill).

4 RESULTS

An index of percentage dominance, derived from sampling incidence for upper, middle and lower canopy woody species is shown in Table 3. This provides an assessment of the relative abundance between major species at each site based on sampling effort.

Table 3. Relative dominance of tree/shrub species for each canopy level at both sites, derived from the sampling incidence of species at ground truth survey points.

Canopy level	Tree/ shrub species	Dominance factor for site[1]	
		Airstrip	**Guratba**
Upper	*Eucalyptus latifolia/foelscheana*	*100*	*63*
	E. tectifica	*74*	*100*
	E. alba	*18*	*0*
	E. miniata	*7*	*21*
	E. polycilata	*4*	*25*
	E. tintannans	0	*84*
	E. papuana	0	*68*
	E. dichromophloia	0	11
	Corymbia ptychocarpa	0	2
	Number sampled	*295*	*213*
Middle	*Buchanania obovata*	100	3
	Erythrophleum chlorostachys	39	*100*
	Syzigium eucalyptoides	11	0
	Terminalia ferdinandiana	7	4
	Owenia vernicosa	4	1
	Eucalyptus phoenicia	0	*11*
	Xanthostemon paradoxus	0	5
	E. setosa	0	4
	Number sampled	*45*	*174*
Lower	[2]*Acacia holosericea*	100	4
	[2]*Calytrix exstipulata*	15	34
	[2]*Acacia sp. A*	4	0
	Wrightia saligna	1	2
	Cochlospernum fraseri	1	2
	[3]*Acacia bidwillii var. major (nov)*	0	100
	Terminalia spp.	0	30
	Ficus opposita	0	6
	Pandanus spiralis	0	6
	Brachichiton spp.	0	2
	Grevillia decurrens	0	2
	Number sampled	*90*	*93*

[1] Dominance factor was calculated for a species by dividing its total count by the maximum count recorded for a species in its Canopy group at the site (Upper, middle or lower) and then multiplying by 100
[2] Species almost wholly associated with disturbed regions at the site;
[3] Discreet patch with high numbers of individual plants, otherwise uncommon on site
Numbers in italics indicate that the associated species was used in map classification for the site in question

41

4.1 Spectral Characterisation of Surface Features

Ordination of field radiometric measurements (Figure 9) for key features indicated that there is significant spectral differentiation between several important features, including perennial grasses, annual grasses, a number of different surface soil classes and several dominant tree species. However, separation is not as distinct within certain groups (e.g. trees and shrubs).

Multivariate analysis of ordination pattern indicated that all radiometer bands contributed significantly to differentiation of surface types (Monte Carlo p-value <0.01 for each band). Blue and green bands appearing to contribute to major separation between vegetation and non-vegetation groups, while red and NIR bands produced most separation within vegetation types.

Considerable spectral variation was introduced within vegetation groups by three separate fire episodes in the recent weeks before image acquisition. However, in unburnt areas good spectral separation was apparent between several key features, in particular perennial grasses, annual grasses and bare-ground classes (Figures 10 to 13). Perennial grasses burnt in the first of the fires exhibited rapid regeneration growth and had higher NDVI values than unburnt perennials. Passionfruit vine showed the highest NDVI index indicating some potential for mapping of this weed.

The image resulting from NDVI calculated from video data calibrated to surface reflectance is shown in Figure 12. Calibration of the image allowed image pixel values to be compared directly with the ground based NDVI values (Figure 11).
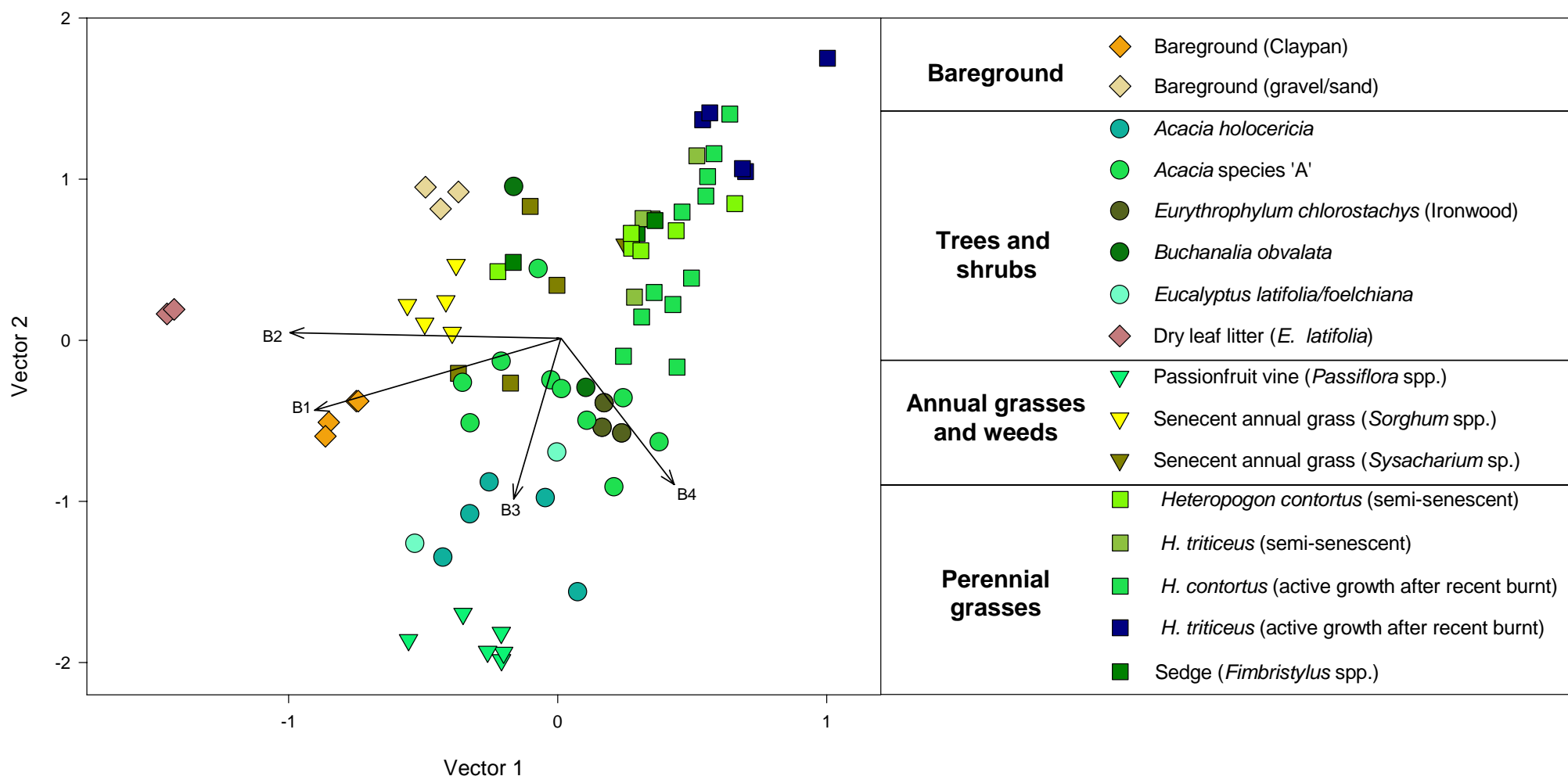
Figure 11. 2-dimendional Ordination of radiometer readings for each recorded ground-feature (using Bray and Curtis dissimilarity and Multi Dimensional Semi-Strong Hybrid ordination technique). Features have been separated into four broad categories of ecological significance (see legend). Each band contributed significantly to ordination space (Monte Carlo simulation probabilities: $p < 0.01$ for bands 1,2,3,4 respectively) with the direction of influence from the origin for each band represented by arrows.
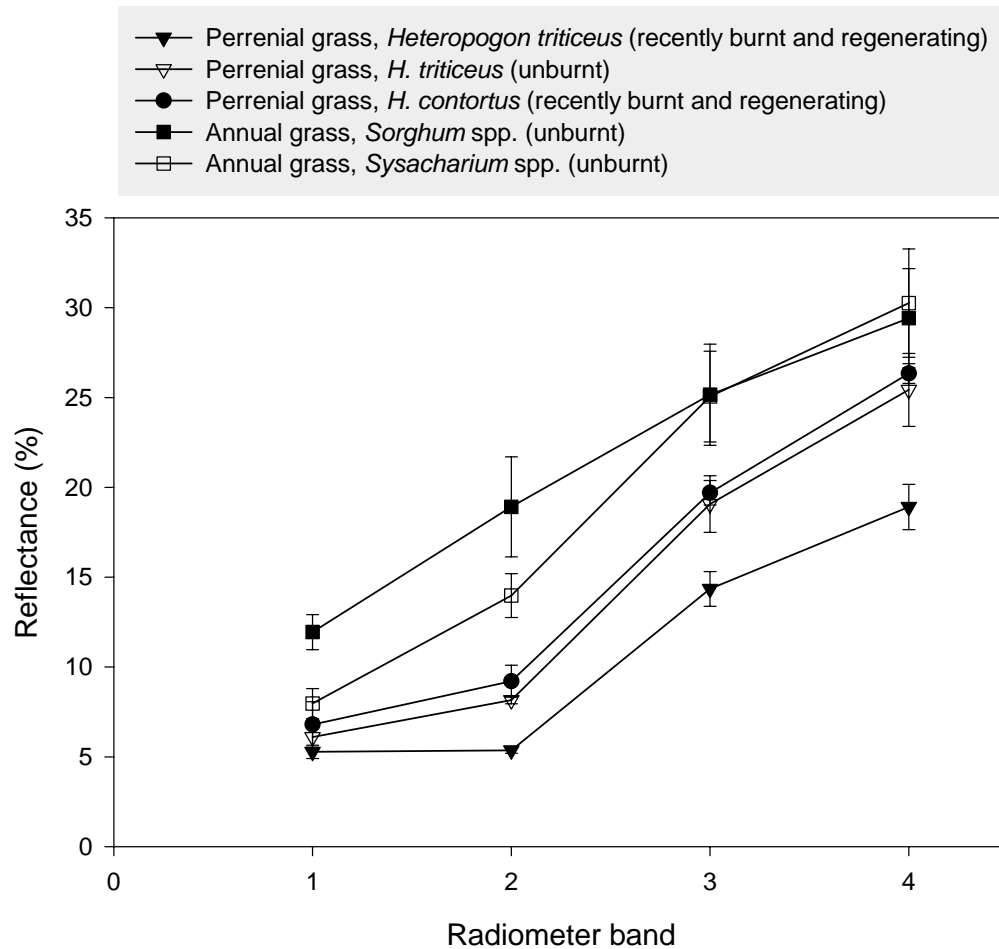
Figure 12. Radiometric band profiles of perennial and annual grass types taken from ground-level measurements. 'Burnt' perennial grass exhibited active regrowth while unburnt grass was in a dormant growth state.
Note: Error bars show Standard Error
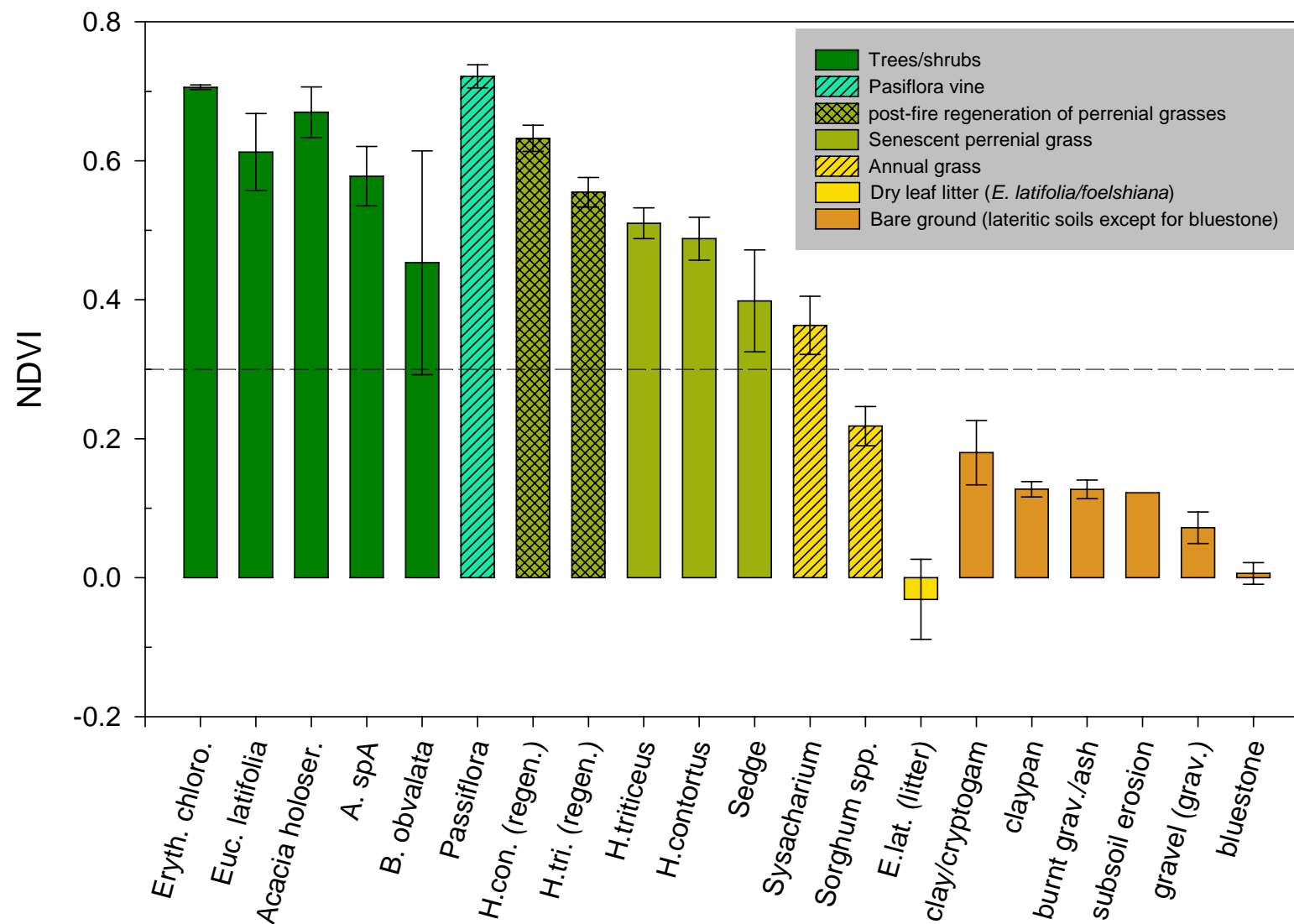
Figure 13. NDVI calculated for key surface features using ground radiometer measurements. The reference line (NDVI=0.35) indicates the threshold that was used to stratify between the annual-grass/bare-ground and the trees/perennial-grass groups each treated independently in unsupervised classification.

Note: Error bars are standard error

45
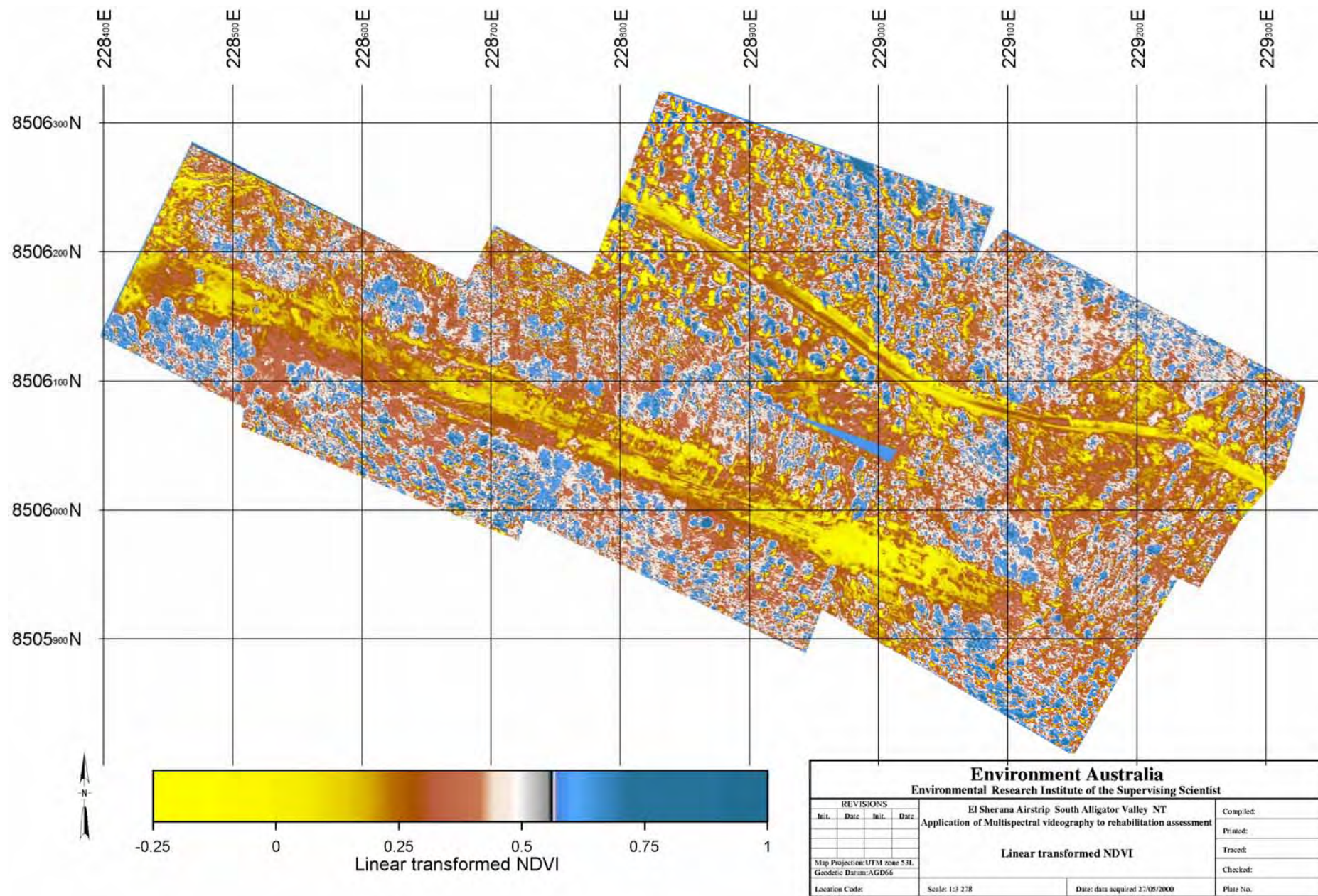
Figure 14. NDVI map, linear transformed to emulate ground radiometer measurements, was used to separate between bare ground and annual grasses from other vegetation in stratified approach to unsupervised classification. Trees (blue and white areas), perennial grasses (dark brown areas), and bare ground and annual grasses (yellow to light brown areas) are clearly distinguished.

4.1.1 Influence of Moisture on Soil Reflectance

A significant linear correlation was produced between ground reflectance (radiometric bands 1, 2, 3 and 4) when regressed against $\log_{10}$-transformed soil moisture. This pattern was emulated in corresponding spectral BVs for both 0.25m and 0.5m resolution data. However, the strength of correlation declined markedly as the scale was increased. These statistical trends are summarised in Table 4, Figure 13 and Figure 14.

A stepwise linear regression of individual radiometer bands and band combinations indicated that Band 2 produced the strongest correlation. Other bands and band combinations did not contribute any further to describing the relationship between soil moisture and reflectance.

Table 4. Summary of R-coefficients and p-values and sample size describing linear regression of reflectance measurements against soil moisture content.

Data source	Scale	Band	R^2		n
Exotech radiometer	Ground	1 (450-520nm)	0.33	0.001	30
		2 (520-600nm)	0.71	<0.001	
		3 (630-690nm)	0.65	<0.001	
		4 (760-1100nm)	0.59	<0.001	
ICU video	0.25m pixel	1 (450±10nm)	0.37	0.043	16
		2 (525±10nm)	0.38	0.008	
		3 (625±10nm)	0.31	0.021	
		4 (850±10nm)	0.35	0.012	
	0.5m pixel	1 (450±10nm)	0.23	0.040	19
		2 (525±10nm)	0.20	0.053	
		3 (625±10nm)	0.27	0.022	
		4 (850±10nm)	0.14	0.115	
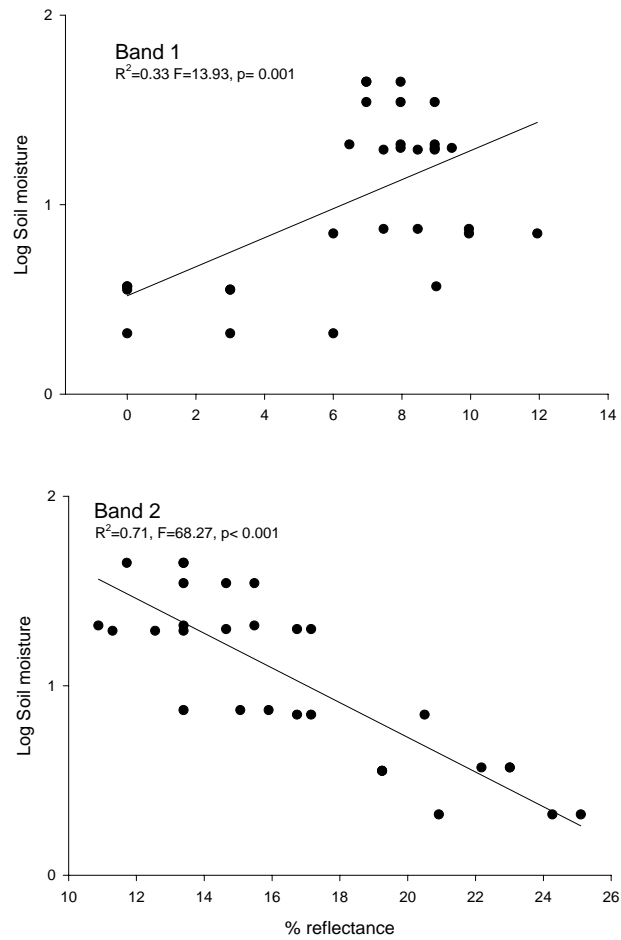
Figure 15. Linear relationships observed between reflectance and soil moisture for ground measurements.
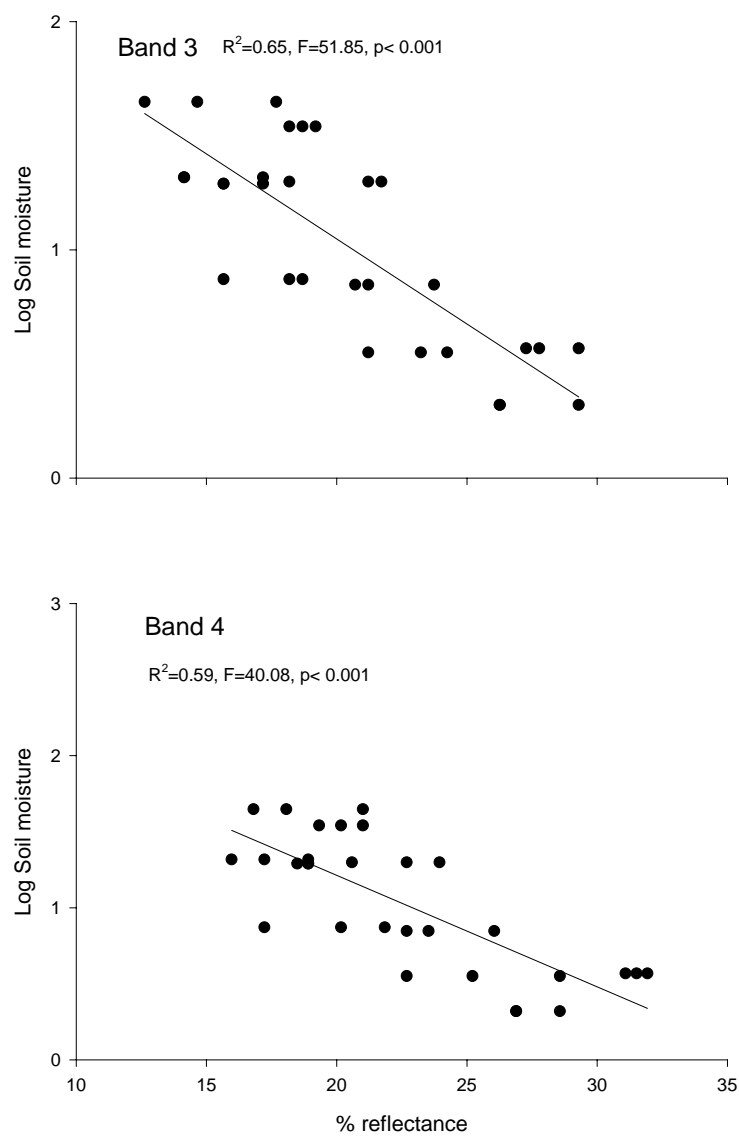
Figure 13. (continued) Linear relationship observed between reflectance and soil moisture for ground readings.
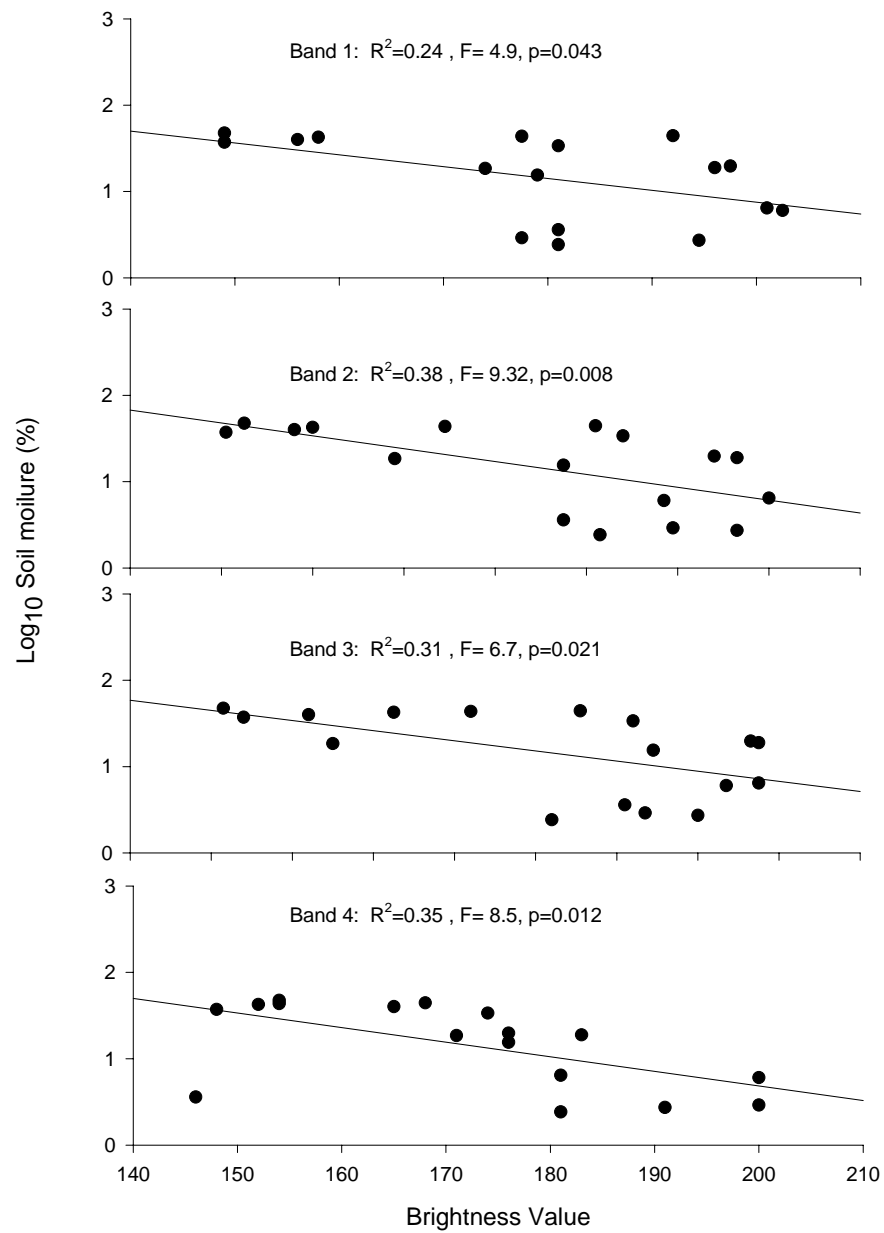
Figure 16. Linear relationships observed between reflectance and soil moisture for video readings at 0.25 m resolution.

4.2 El Sherana Site - Image Classification and Accuracy Assessment
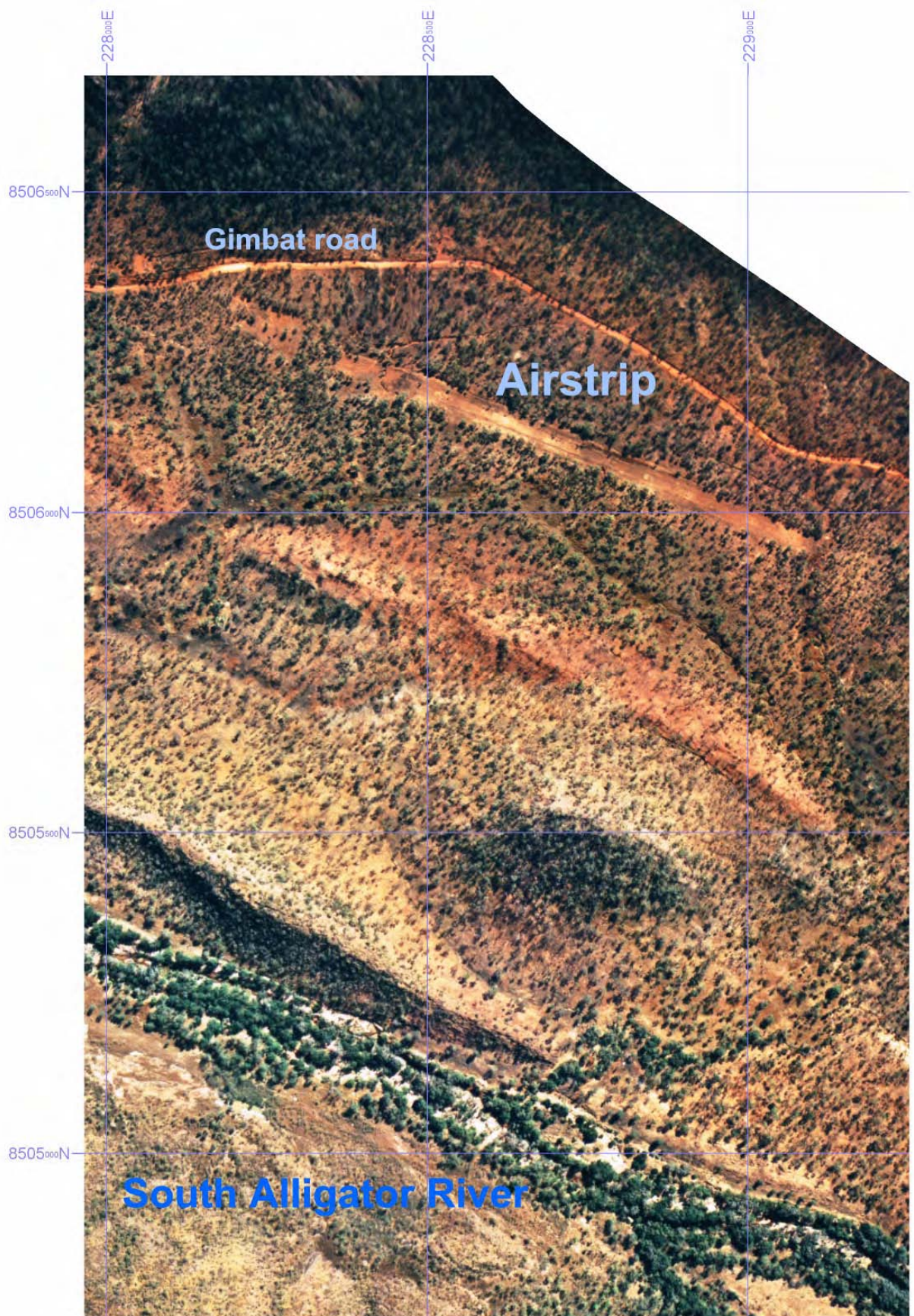
Figure 17. Aerial ortho-photo of El Sharana Airstrip, South Alligator Valley (acquired July 10, 1988), showing the site in the context of the surrounding landscape, and other nearby areas of disturbance (Gimbat road and related erosion).
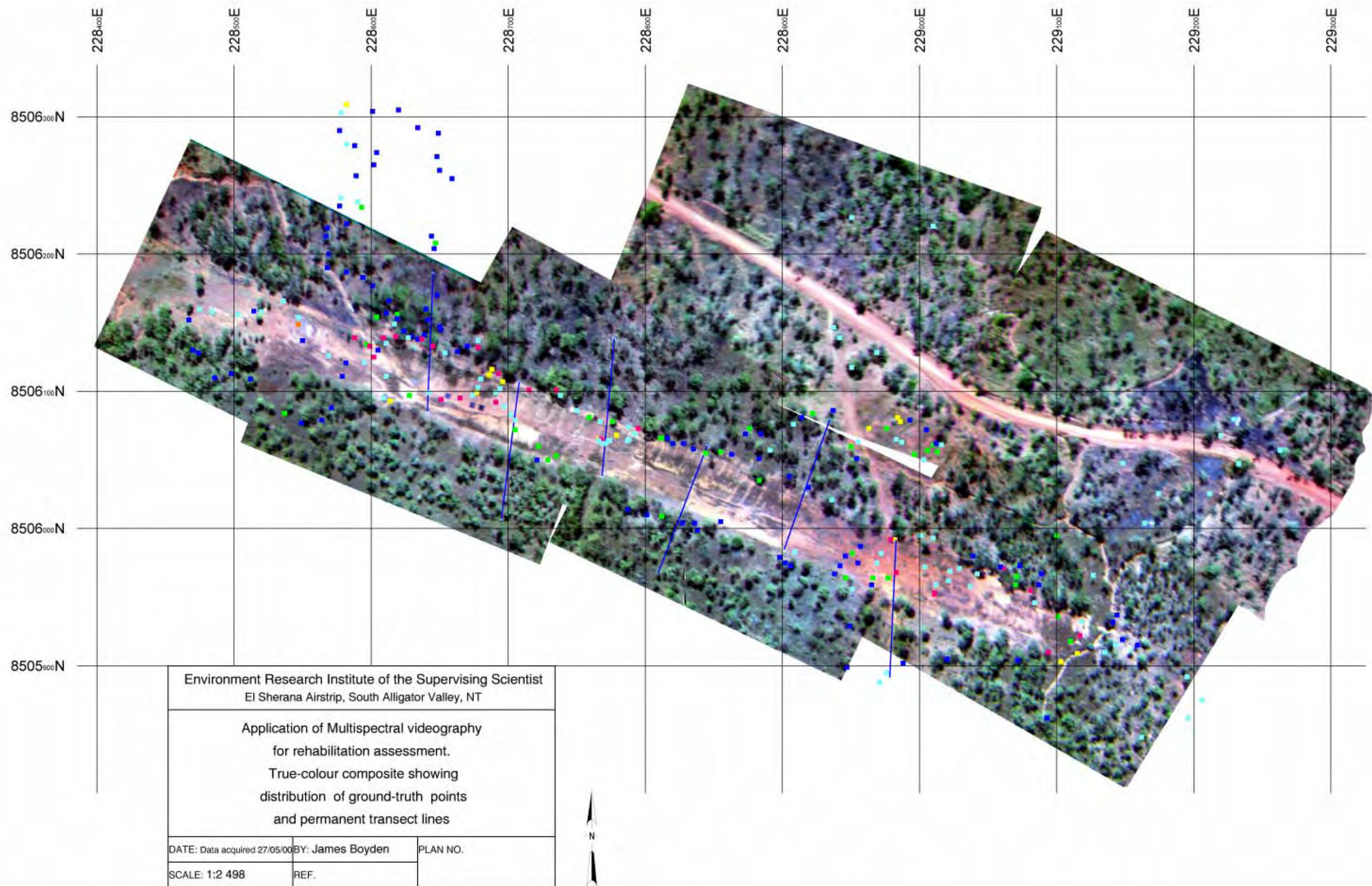
Figure 18. True-colour composite MSV mosaic of airstrip area (0.5m resolution) showing location of permanent transects (blues lines). The distribution of GPS points associated with ground descriptions are shown as colour coded points indicating dominant features of interest at each point: red= *Acacia holosericea*, Blue= eucalypt, green *Buchanania obovata*, light blue= grasses.
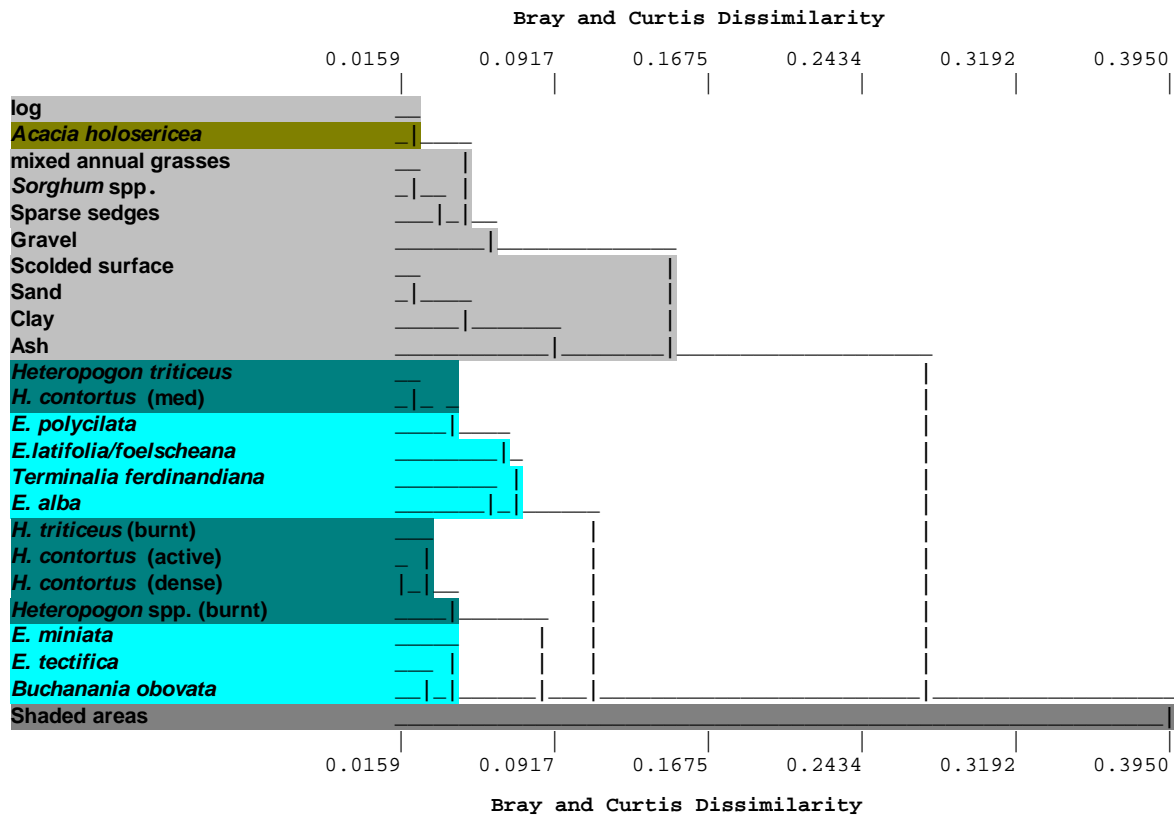
Figure 19. Classification dendogram based on mean spectral separation of classes derived from preliminary supervised classification procedure, before a number of sub-classes were merged or omitted. Major groups are shaded (grey=bare-ground, annual grasses and litter; dark green = perennial grasses; blue= trees; dark grey= shaded areas), where *A. holosericea* is and outlier in this trend. Dendogram produced using UPGMA of Bray and Curtis dissimilarity.

Cluster analysis (Figure 17) indicated that spectral separation between classes formed three functional groups: 1) Bare-ground, annual grasses and litter; 2) Perennial grasses; and 3) trees/shrubs. The shrub, *Acacia holosericea*, was an exception to this rule and fell within group 1. This species, which only occurred as isolated shrubs or small groves with relatively sparse foliage, was nevertheless resolved from the TCC background image in conjunction with contextual ground data, therefore allowing for training site selection.

Accuracy assessment statistics for the final classification scheme adopted are shown in Table 5 and a statistical summary of training site samples is provided in Table 6

54

Table 5. Confusion matrix and accuracy statistics for Airstrip supervised classification generated from cross tabulation of individual classes derived from two independent sets of training site data.

GROUP	Class	Bare ground & Annual Grasses				Perennial Grasses					Trees					Other		Total pixels	% Accuracy: image B	Kappa Index
		G	S	C	AG	HC_1	HC_2	HC_3	HT	BG	EA	EL	EM	EP	ET	BS	S			
Bare ground & Annual Grasses	Gravel (> 50%)	41837	2241	0	5972	0	0	0	7	19	18	0	0	0	0	0	1	50095	84	0.83
	Sand (>50%)	14524	19584	929	7391	72	291	0	77	179	254	52	0	0	39	0	27	43419	45	0.44
	Clay >50%	0	2373	4475	0	0	0	0	0	0	0	0	0	0	0	0	0	6848	65	0.65
	Annual grasses	870	1085	118	145118	3713	508	262	7620	1007	0	0	0	0	124	0	0	160425	90	0.89
Perennial Grasses	*H. contortus _1*	2	0	0	22895	69421	36960	0	14528	584	0	1401	7	0	5251	0	2060	153109	45	0.41
	H. contortus _2	0	0	0	36	24023	44593	5339	5101	3693	0	2	325	0	385	0	7744	91241	49	0.74
	H. contortus _3	0	0	0	1950	398	2175	13934	0	2989	0	0	0	0	168	0	289	21903	64	0.63
	H. triticeus (>50%)	13	0	1	2764	11393	10424	0	150189	380	177	1420	0	159	3849	1	96	180866	83	0.80
	Recently burnt grass	0	0	0	2942	3453	14143	2970	16755	88312	0	0	0	0	2869	0	1147	132591	67	0.64
Trees	*E. alba*	2	0	111	280	3	0	0	444	0	34530	2691	0	152	3572	0	7	41792	83	0.82
	E.latifolia/foelscheana	4	1	36	457	694	4380	0	3083	1256	5247	58825	4060	3316	11429	0	328	93116	63	0.61
	E. miniata	0	0	0	0	1	0	0	0	0	3259	1137	19360	1635	8557	0	0	33949	57	0.55
	E. platycilata	0	0	33	0	0	282	0	13311	7332	3931	722	4462	30795	11421	0	1242	73531	42	0.40
	E. tectifica	0	0	13	20	352	7684	4	3999	5560	1607	2714	21590	5563	128584	0	1534	179224	72	0.68
Other	Bluestone road gravel	0	0	0	0	0	0	0	18	0	0	0	0	0	0	142	0	160	89	0.89
	Shadow	1	0	0	0	82	830	24	1	2339	14	385	7008	178	6801	0	142279	159942	89	0.88
Total pixels		57253	25284	5716	189825	113605	122270	22533	215133	113650	49037	69349	56812	41798	183049	143	156754	1422211		
% Accuracy: image A		73	77	78	76	61	36	62	70	78	70	85	34	74	70	99	91	Over all:	**70**	**0.67**

Table 6. Size and replication of training site samples used in *supervised* classification at airstrip including the number of classes derived from the unsupervised (US) classification with a strong association to a specific field training site class.

Group	Field Training site	# pixels	# sample-patches	mean patch sample size (ha)	Total area sampled (ha)	# of 'US' classes [1]
Trees and Shrubs	*Eucalyptus tectifica*	103055	27	0.065	1.753	1
	Buchanania obovata	92802	4	0.395	1.579	0
	Acacia holosericea	80635	9	0.152	1.372	0
	E. latifolia/foelscheana	58522	50	0.020	0.996	3
	E. miniata	57279	7	0.139	0.974	0
	E. polycilata	53337	3	0.302	0.907	0
	E. alba	27779	4	0.118	0.473	0
Perennial grasses	*Heteropogon triticeus*	141432	14	0.172	2.406	0
	H. contortus (dense)	118096	25	0.080	2.009	0
	H. triticeus (Recently burnt/regen.)	103019	32	0.055	1.752	6
	H. contortus (medium)	92695	23	0.069	1.577	0
	H. contortus (active)	19542	4	0.083	0.332	0
Annual grasses	Mixed annual	74133	7	0.180	1.261	1
	Sorghum spp.	71512	28	0.043	1.216	2
Bare ground	Gravel	38701	9	0.073	0.658	1
	Sand/gravel	25702	17	0.026	0.437	0
	Gravel/clay Scold	9322	5	0.032	0.159	0
	Claypan	5070	9	0.010	0.086	1
Other	Recent burn (no regrown)	31939	19	0.029	0.543	2
	Ash from recent burn	599	2	0.005	0.01	1
	Shadow	150843	87	0.029	2.566	6
	Logs	6933	3	0.039	0.118	0
# of US classes assigned from soil mask		**4**				
# of US classes assigned from vegetation mask		**18**				
Total US classes assigned		**22**				

[1]**A US class was seen as having a 'strong' association with a particular training site class when 80-100% of all pixels in a specific training sample corresponded with the US class**
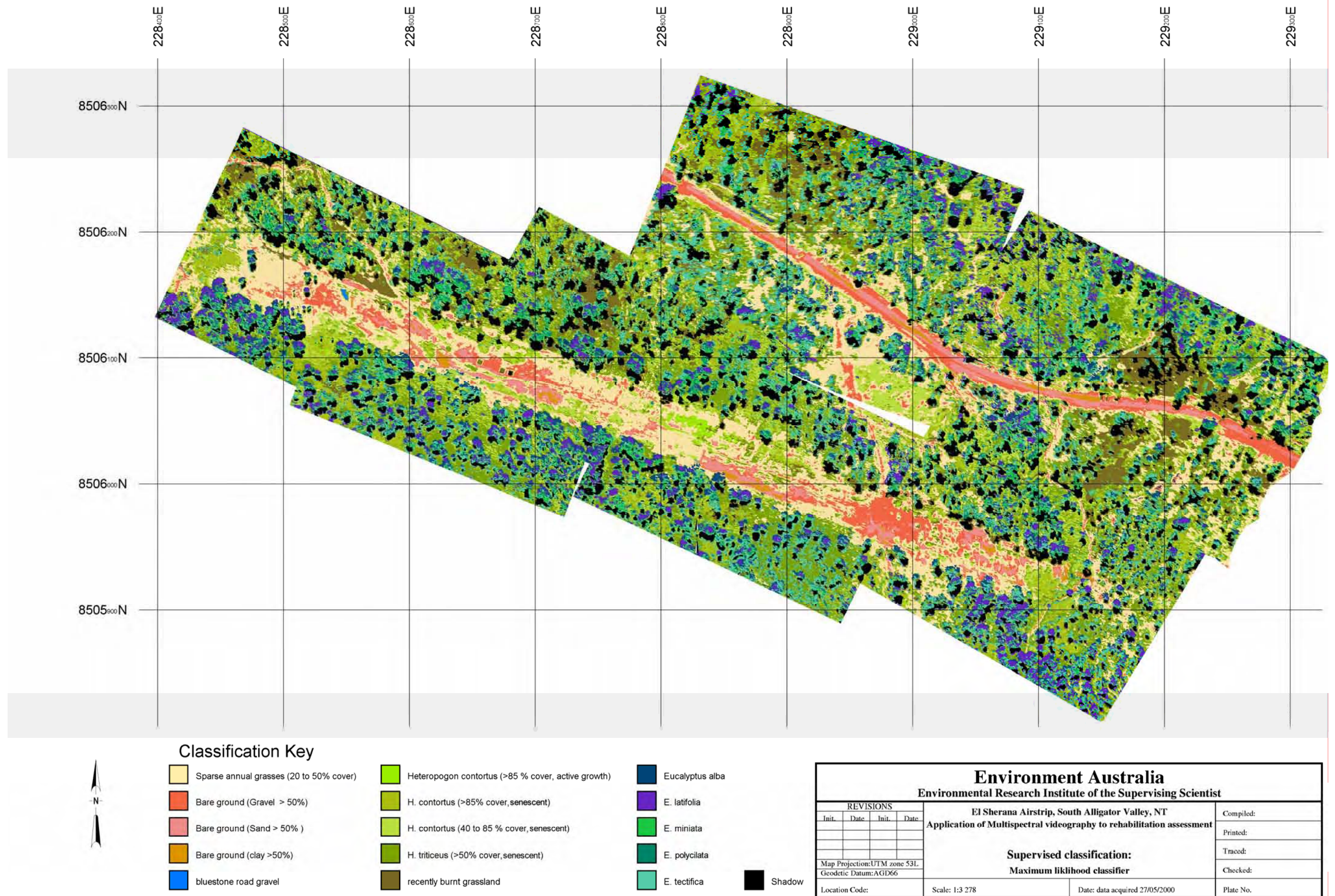
Figure 20. El Sharana site. Map classes derived from final supervised classification of MSV data (0.5m resolution), after training site classes, shown to have poor classification accuracy in preliminary analysis, were either removed or merged.
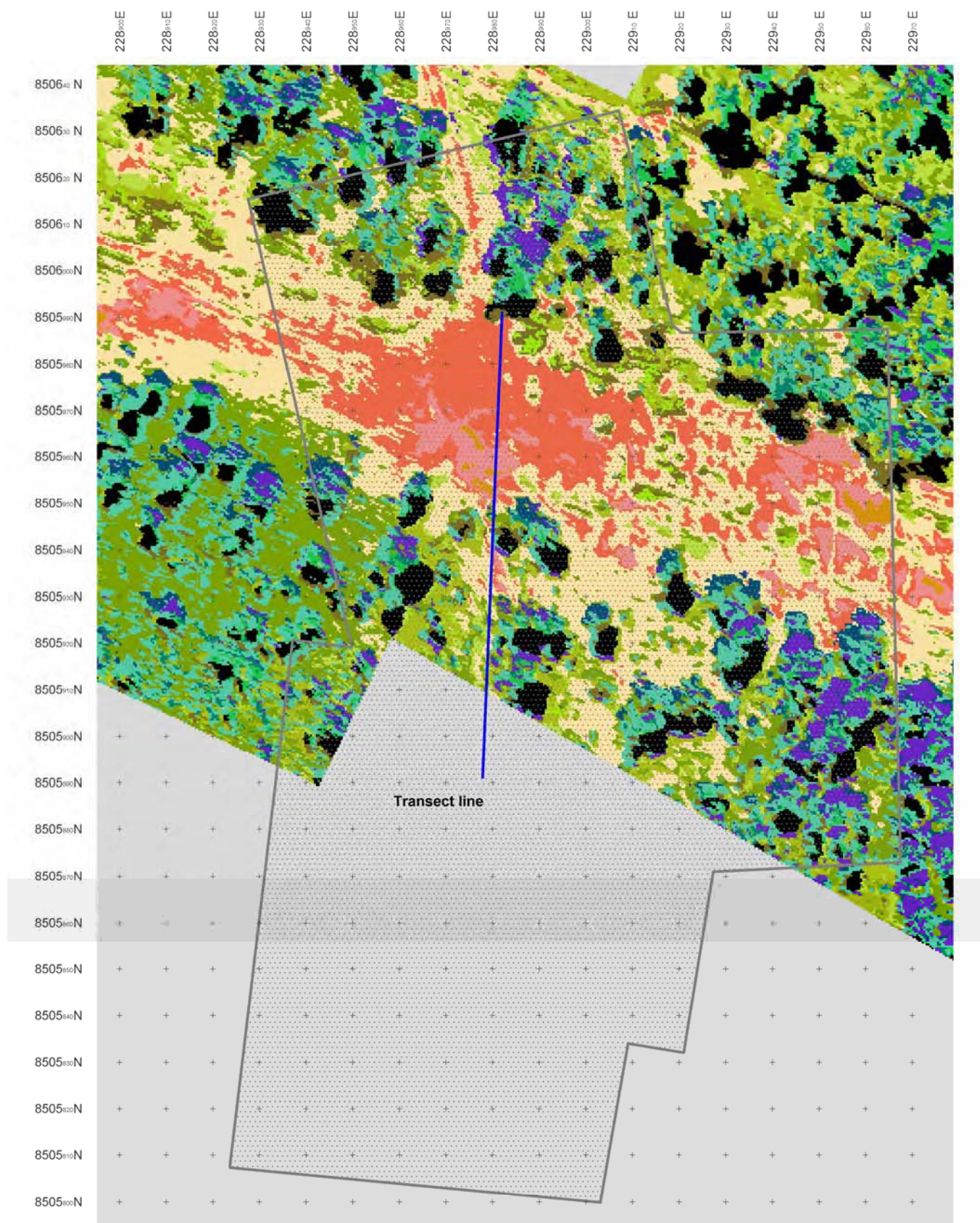
Classification Key (0.5m resolution)

Sparse annual grasses (20 to 50% cover)	*Heteropogon contortus* (>85% cover, senescent)	*Eucalyptus miniata*
Bare ground (Gravel > 50%)	*H. contorutus* (40 to 85% cover, senescent)	*E. polycilata*
Bare ground (Sand > 50%)	*H. triticeus* (>50% cover senescent)	*E. tectifica*
Bare ground (clay >50%)	recently burnt grassland	*H. contortus* (>85% cover, active growth)
		Shadow
		E. alba
		E. latifolia
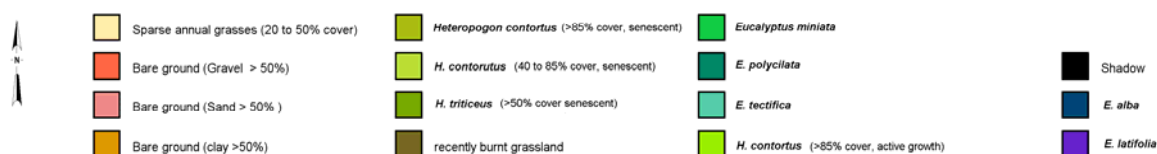
Figure 21. Portion of the classified 0.5m mosaic of the Airstrip showing location of transect 1 (blue line) and shaded region where 0.25m resolution imagery was also captured.

58
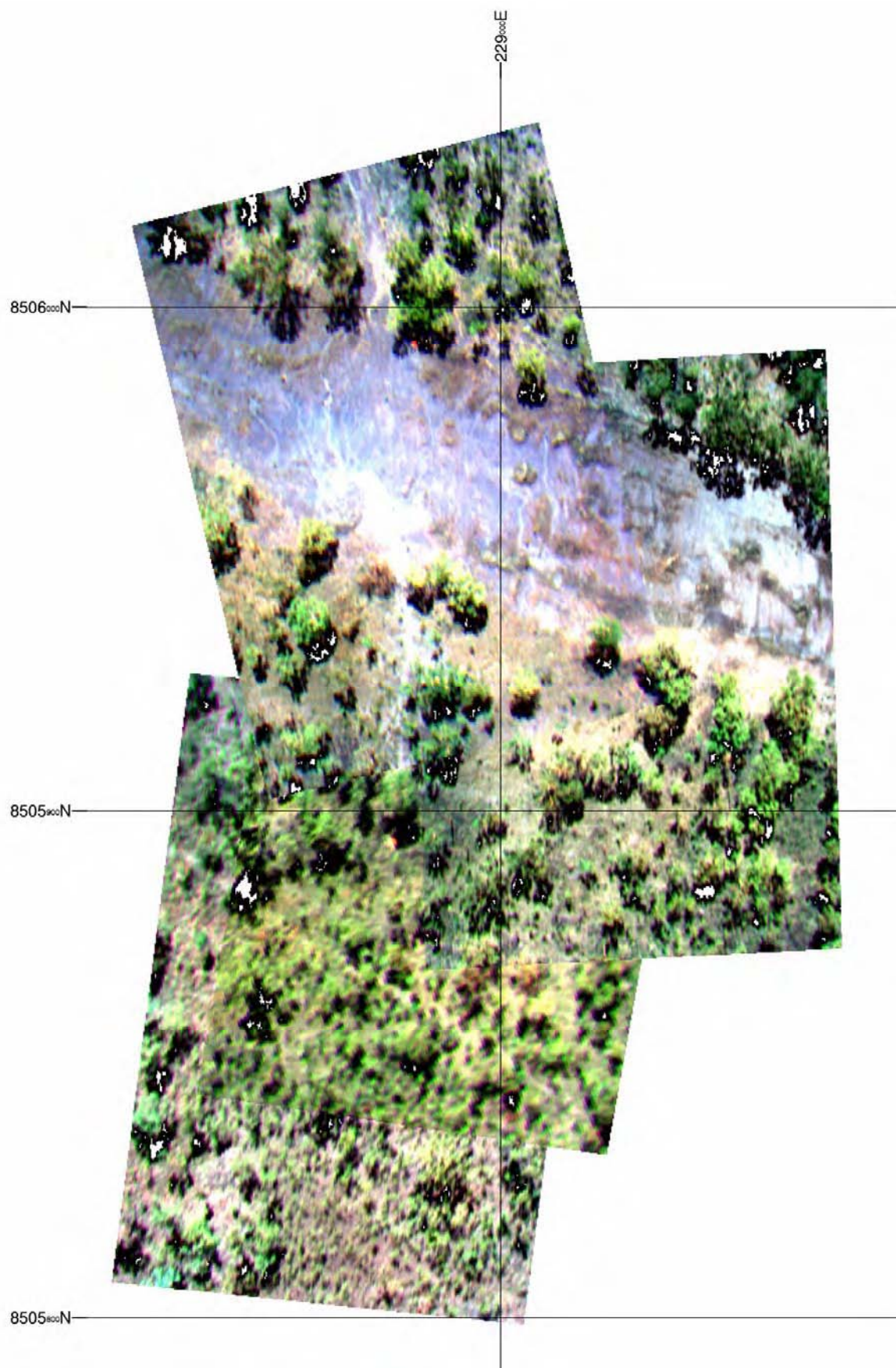
Figure 22. True-colour composite high-resolution (0.25m) mosaic of airstrip at transect 1.

Note: 'white' areas within shade patches indicate zones where BV=0 for at least one band.

Classification Key (0.25m resolution)

Heteropogon contortus (>85% cover, senescent)	Bare ground (gravel > 50%)	Logs (often associated with grasses)
Bare ground (sand >50%)	*Eucalyptus latifolia*	*H. contortus* (>85% cover, senescent)
shadow	Sparse annual grasses (20-50% cover)	*H. triticeus* (>50% cover, senescent)
Bare ground (clay>50%)	*E. tectifica*	*Acacia holosericia* (trees < 3m height)
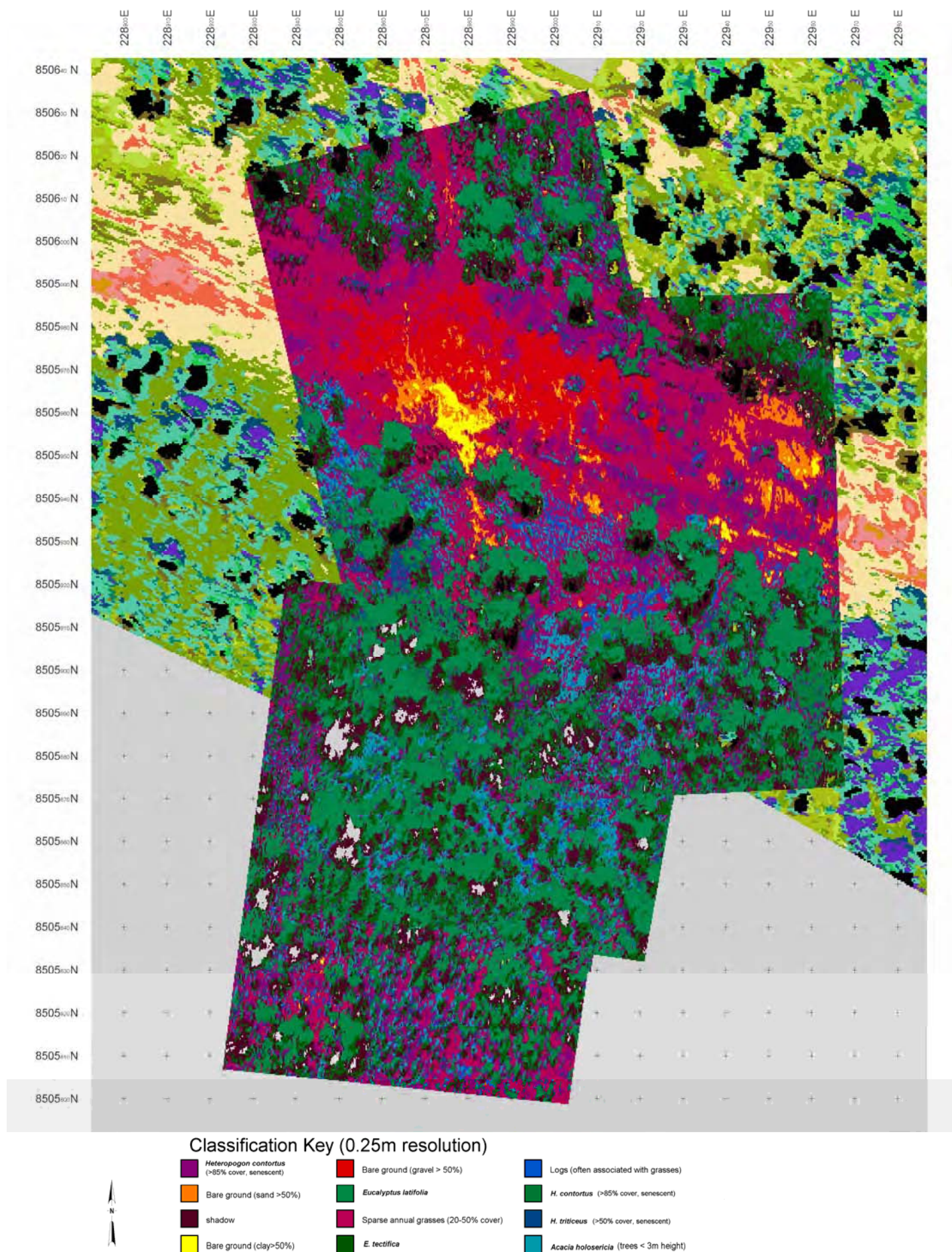
Figure 23. Supervised classification of 0.25m resolution data from transect 1. The same area, classified from 0.5m resolution data, is shown in Figure 19.

60
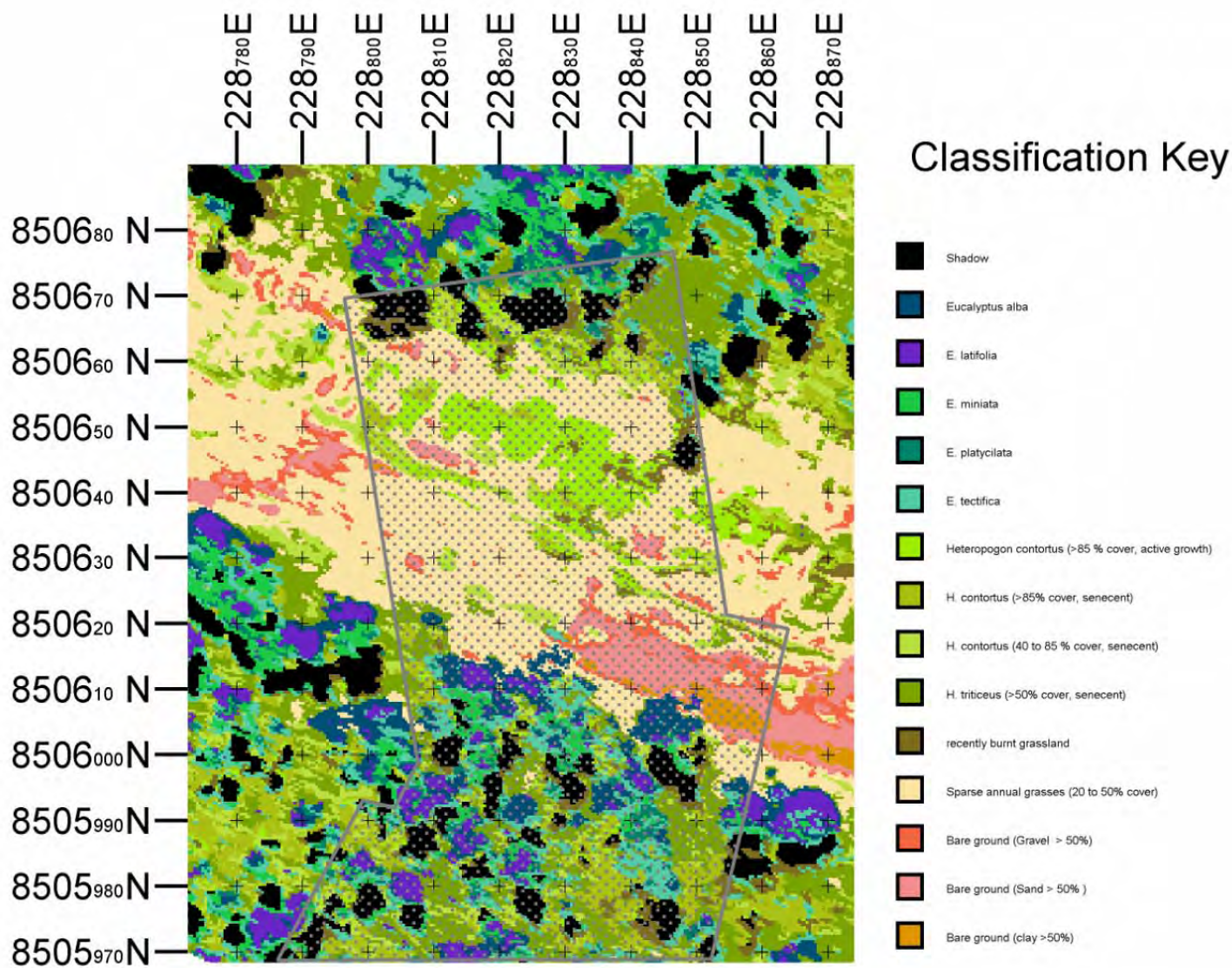
Figure 24. Portion of classified 0.5m mosaic showing shaded region where 0.25m resolution imagery was sampled at transect 3.
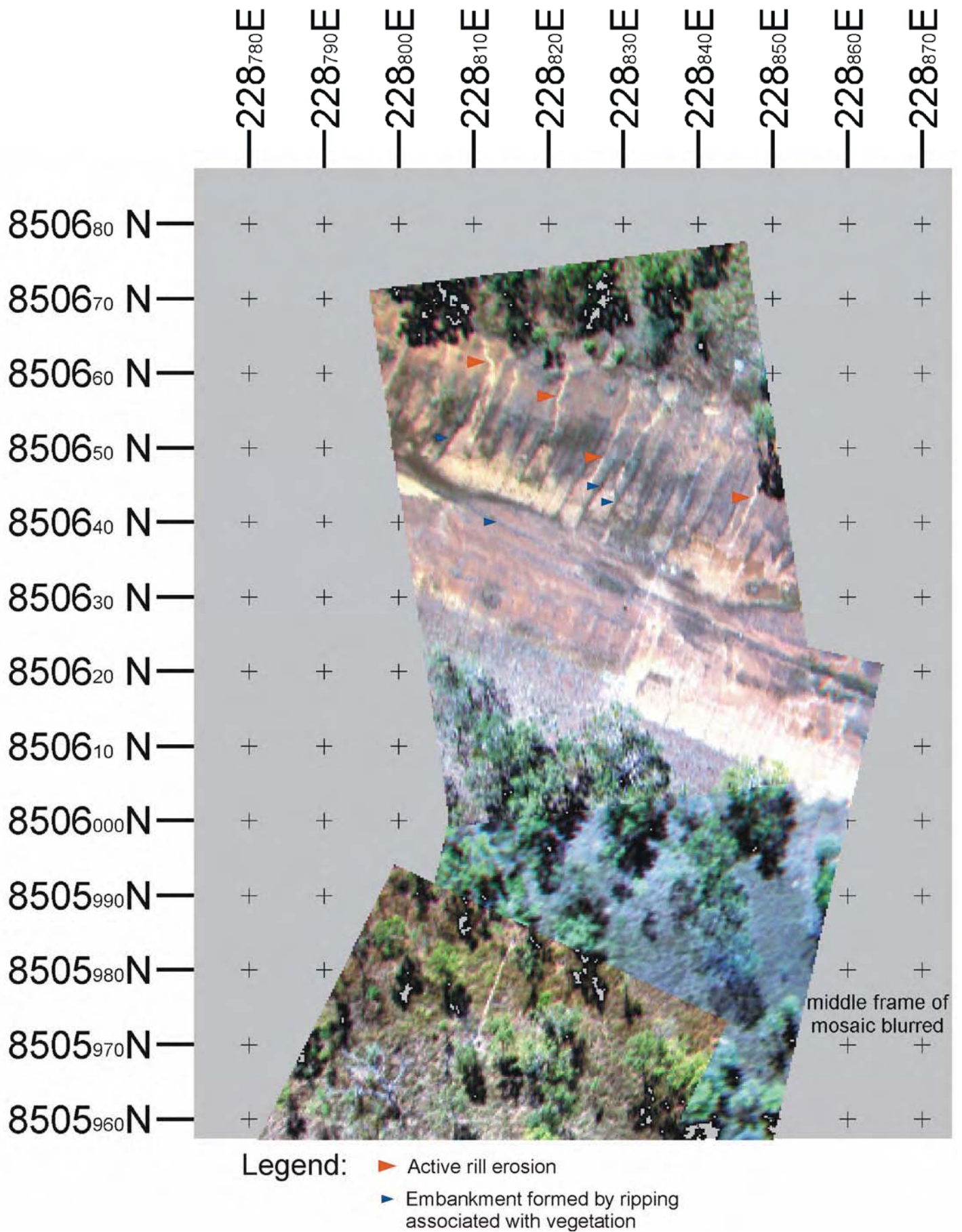
Figure 25. True-colour composite high-resolution (0.25m) mosaic of airstrip at transect 3 showing areas of active rill erosion (orange arrows), and embankments formed by grader-works, now associated with grasses (blue arrows). Image blurring is evident in the middle frame of the mosaic.

Note: Areas of 'grey' associated with shade indicate where BV=0 for at least one of the three bands used in the TCC.
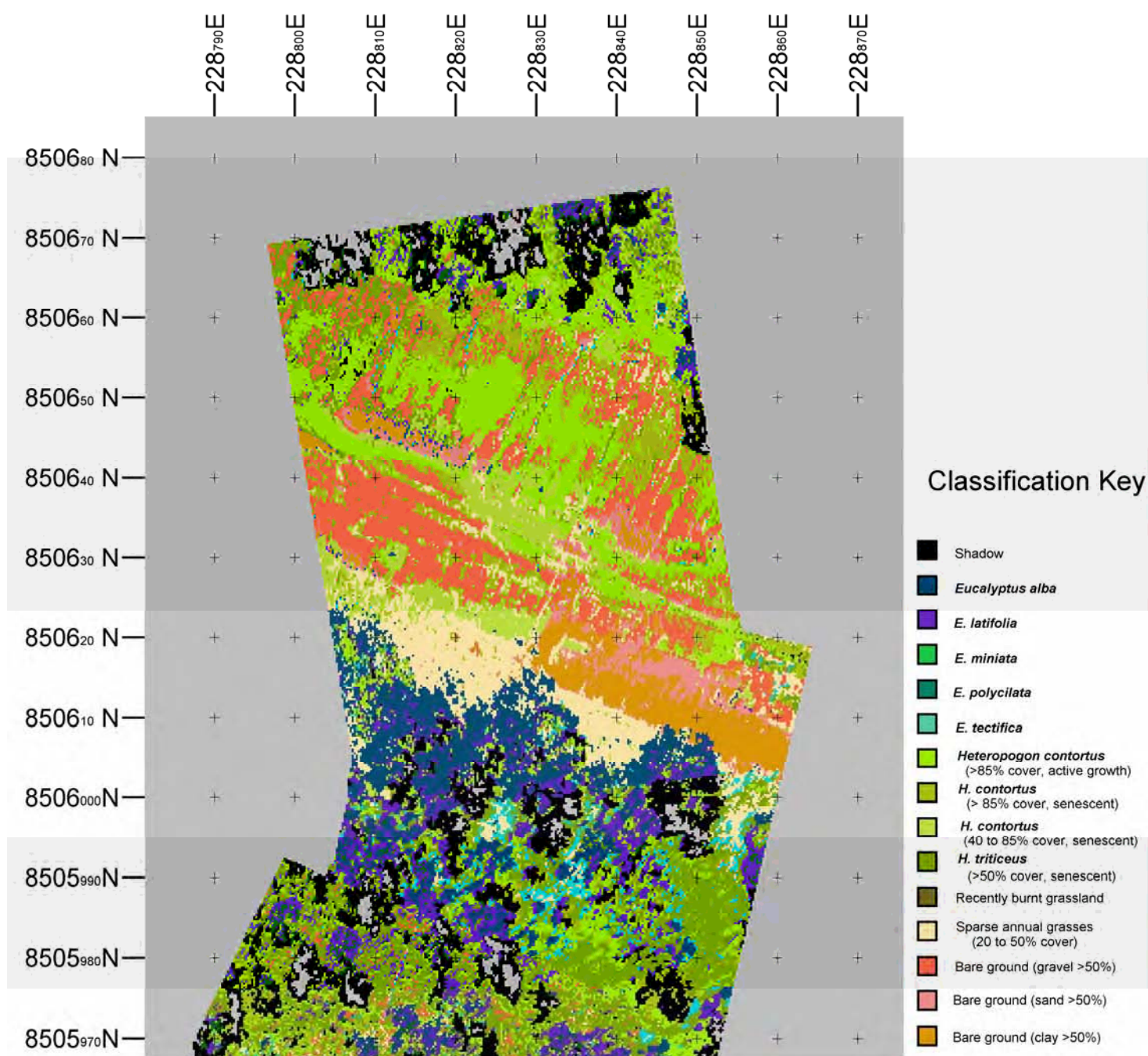
Figure 26. Supervised classification of high-resolution (0.25m) data for transect 3.

Note: Areas of 'grey' associated with shade indicate unclassified areas, where BV=0 for at least one of the three bands used in the TCC.
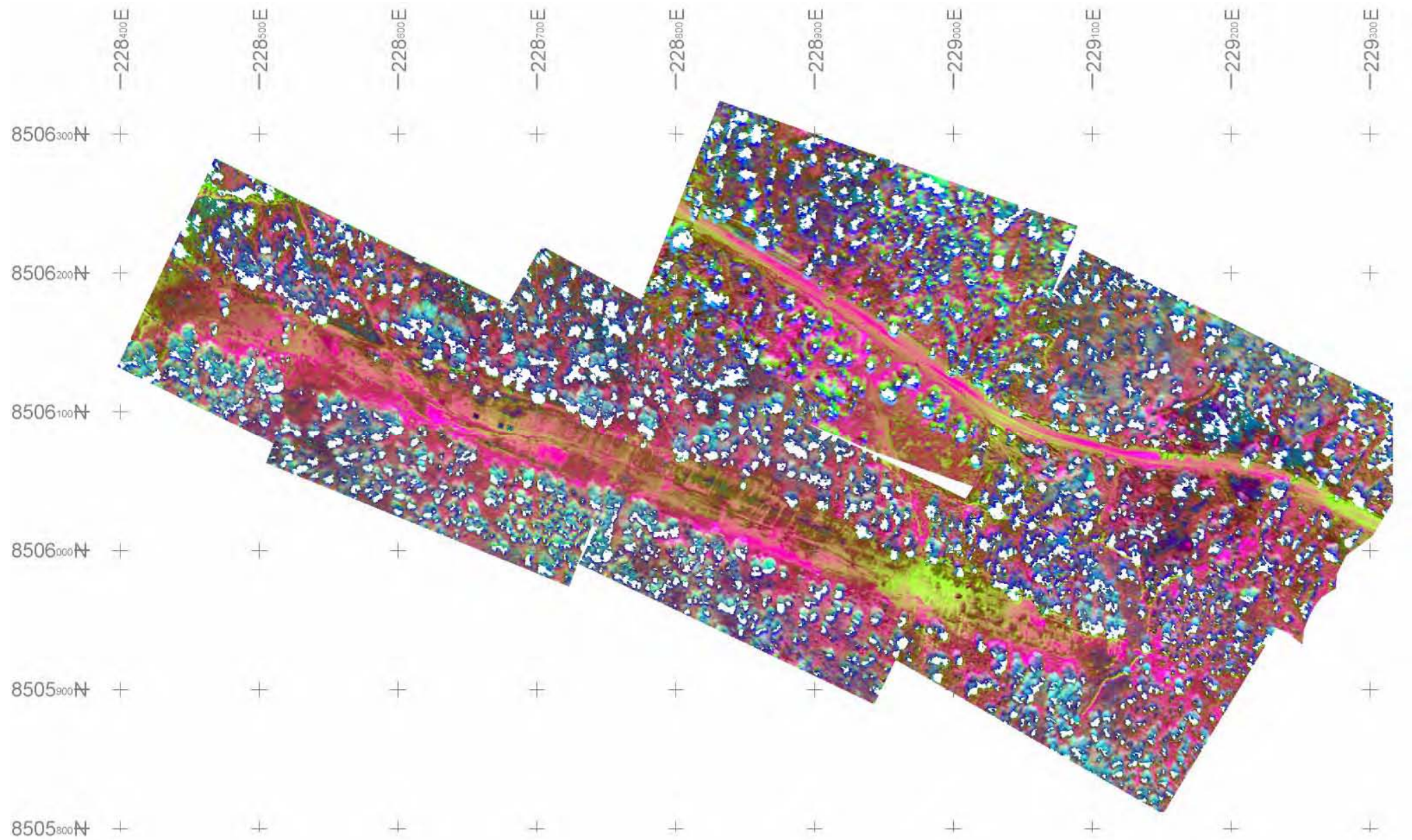
Figure 27. Airstrip site false colour composite of principal components 1,2 and 3. (PC1 =Red PC2=Blue PC3=Green). The PC-calculation was stratified such that the bare-ground region and the vegetation region were calculated independently, before being merging into this image.

Note: White areas (shade) were omitted from calculation as BV=0.
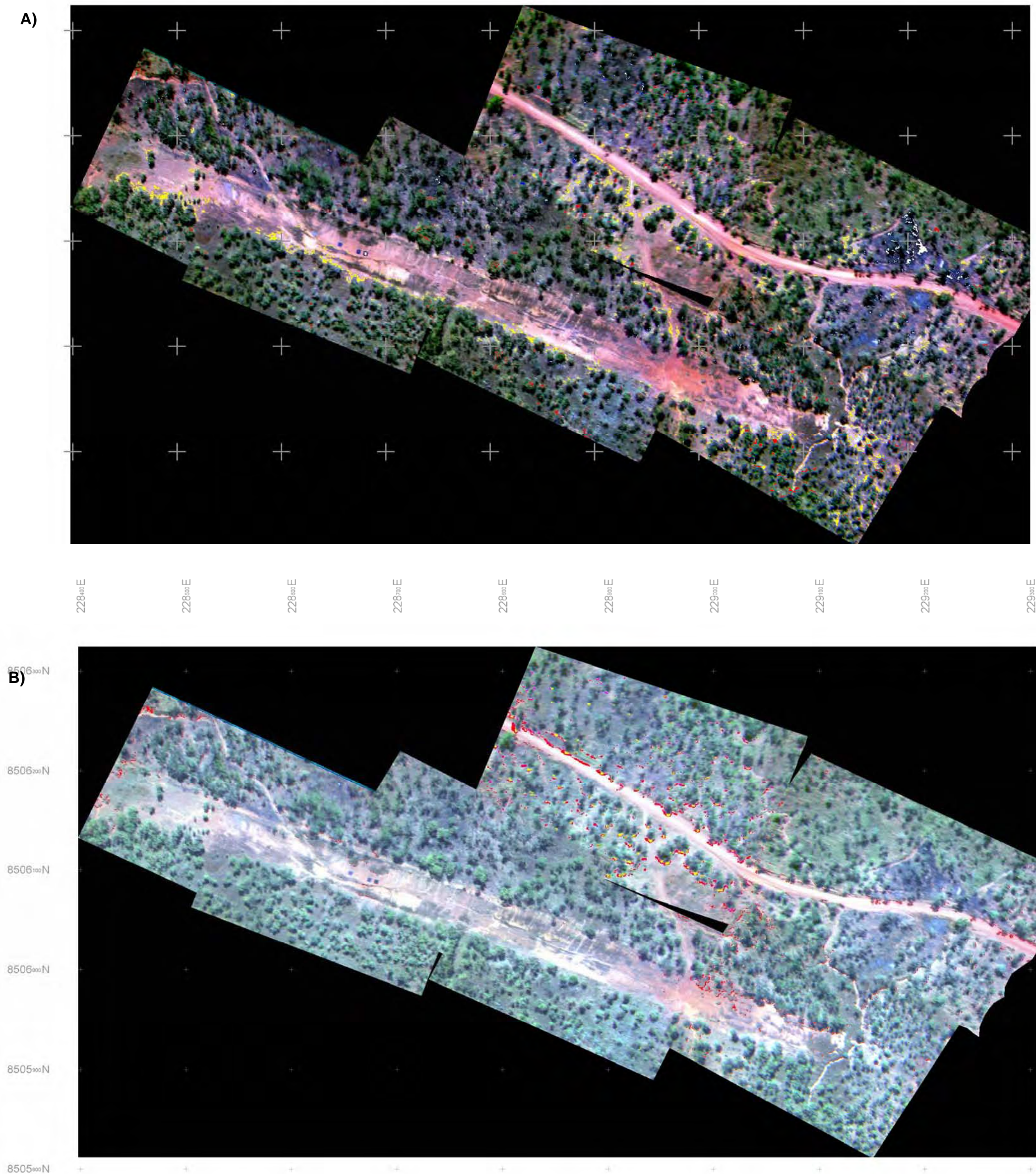
Figure 28. Relationships between classes produced using *unsupervised* procedure and training site region samples used in *supervised* classification procedure: **A)** Classes strongly associated (80-100%) with training region samples. Yellow areas were associated with sorghum annual grass (dense areas), red areas with *Eucalyptus latifolia*, and blue areas with *E. tectifica*. **B)** Classes strongly disassociated (0%) with training region samples used in supervised classification procedure (different classes range from red, orange, light green, and blue. All classes are plotted over a TCC mosaic image.

Plate 4. *Heteropogon contortus* and *H. triticeus* were the dominant perennial grasses at both sites. This picture shows un-burnt *H. contortus* (left) and regeneration (right) after a recent fire (1.5wks).

Plate 5. *Sorghum* was the dominant annual grass at both sites. This 'annual' grass class created for the Airstrip site represents a broad category ranging from sparse to the dense annual grass shown in this photo.

Plate 6.   Gravel, sand and clay were deposited in different regions, disproportionately, relative to runoff/erosive characteristics created by micro-topographical features along the gentle slope of the airstrip.   Sandy areas formed a characteristic zone representing erosion deposits transitional between lag gravel on steeper runoff areas and clay in poorly drained, seasonally waterlogged areas.

Plate 7.   Lateritic clay/silt was typically deposited in poorly drained depressions at airstrip.   These areas were used as training sites from which the 'clay/silt class were formed in the supervised classification procedure.

Plate 8. Scolded surfaces with high clay content were also grouped into the same class by the unsupervised procedure using 'claypan' training sites in Plate 6.

Plate 9. Areas of loose lag gravel were a common feature of runoff area surfaces with little vegetation.

Plate 10. *Acacia holosericea* was a common shrub colonising disturbed areas of the airstrip and erosion gullies, virtually absent in surrounding woodland.

28/5/2000

Plate 11. Mixed open woodland dominated by *Eucalyptus latifolia*, *E. tectifica* and *E. alba* was typical of surrounding 'undisturbed' environment at the El Sherana site.

4.2.1 Comparison of disturbed and non-disturbed sites (El Sherana airstrip)

There were marked differences in vegetation cover and the proportion of bare-ground between the disturbed site and surrounding undisturbed areas (Figure 27). A significant proportion of the airstrip was entirely devoid of vegetation (20%) and a further 42% of the area was dominated by annual grasses. Furthermore, many tree species, occurring on analogue sites appeared to be virtually absent on the airstrip (Figure 28). The proportion of stable vegetation types for analogue sites was far greater and exhibited less than 1% bare-ground and only 3% annual grasses.
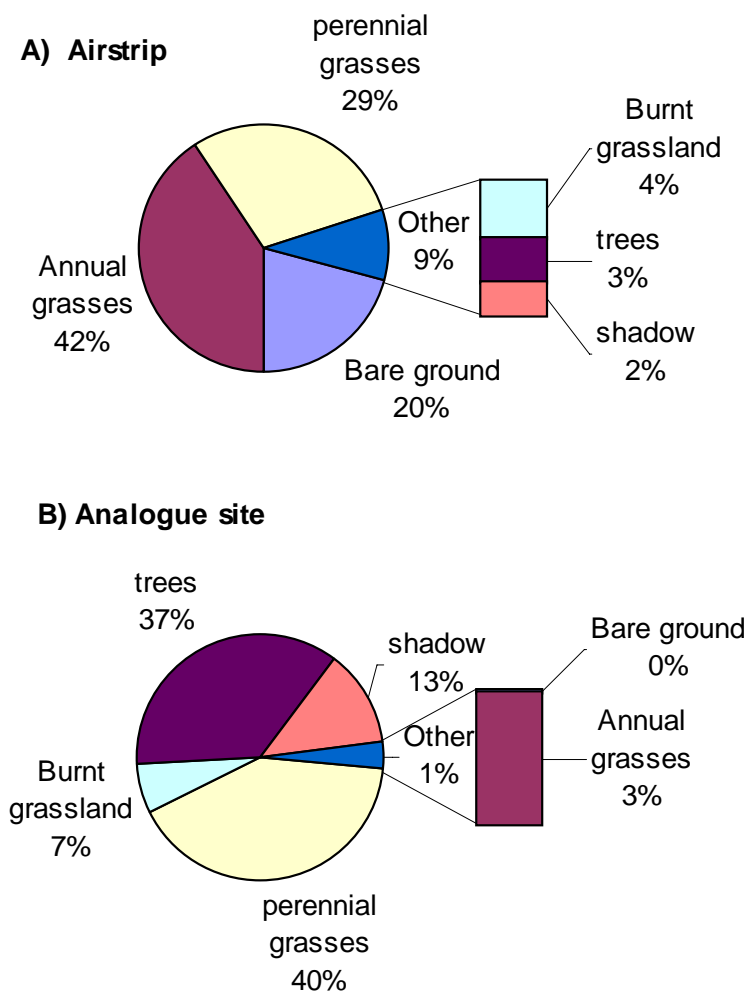
Figure 29. Vegetation and soil cover characteristics compared proportionally between the airstrip (A) and the 'undisturbed' analogue site (B). Area sampled was 4.2 and 10.6 hectares for the Airstrip and analogue sites, respectively.
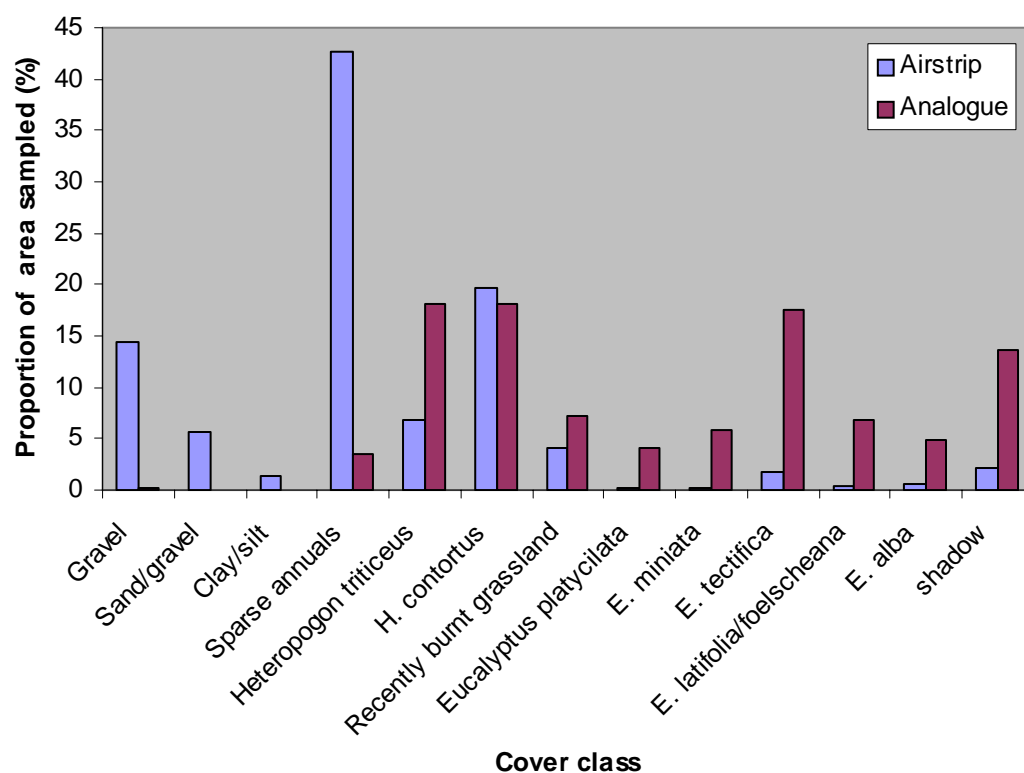
Figure 30. Relative proportion of specific cover classes (within the Tree, Grass and bare-ground categories described in Figure 27 for El Sherana Airstrip and analogue site.

4.2.2 Canopy Cover Assessment

Canopy cover estimates correlated strongly with ground measurements (R^2=0.75) as shown in Figure 29. The map classification tended to over-estimate canopy cover. This is to be expected, because it is likely that smaller trees and shrubs (not measured as canopy on the ground) were classified as trees and, as such, were included in the estimate of canopy area. Application of a filter to remove discreet 'tree' pixel clusters below a certain area (not expected to be included as canopy) may further strengthen this correlation.
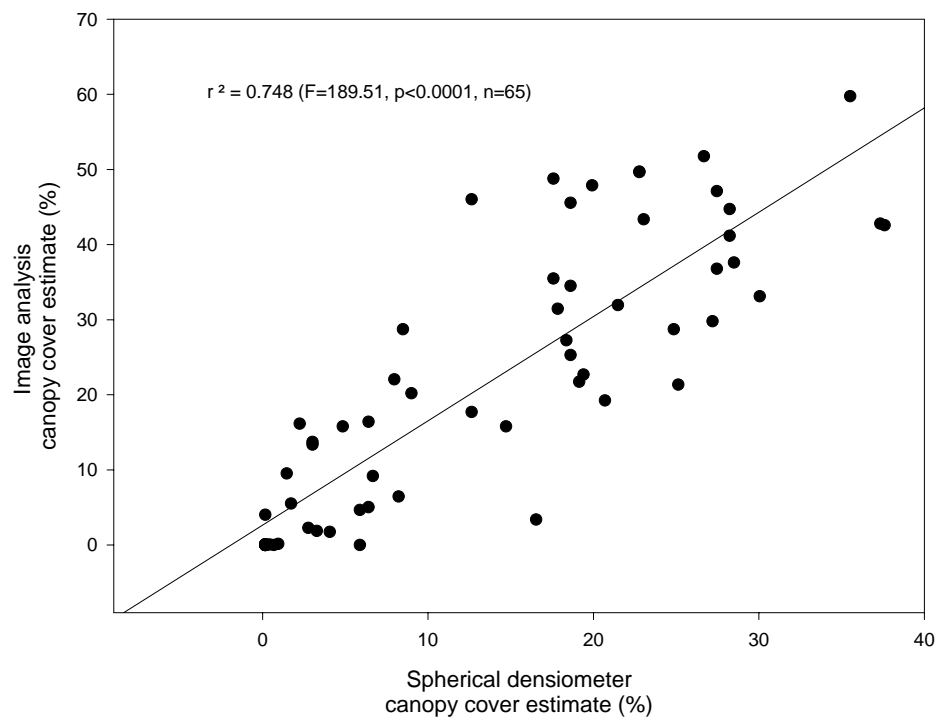
Figure 31. Relationship between percentage canopy cover measured from the ground and tree cover map classes in Figure 18 (n=65).

4.3 Guratba Site - Image Classification and Accuracy Assessment

Figure 32. Guratba site. Aerial ortho-photograph mosaic, June 27, 1990. Shaded region area indicates the video coverage mosaicked from May 2000 at a resolution of 0.5m.
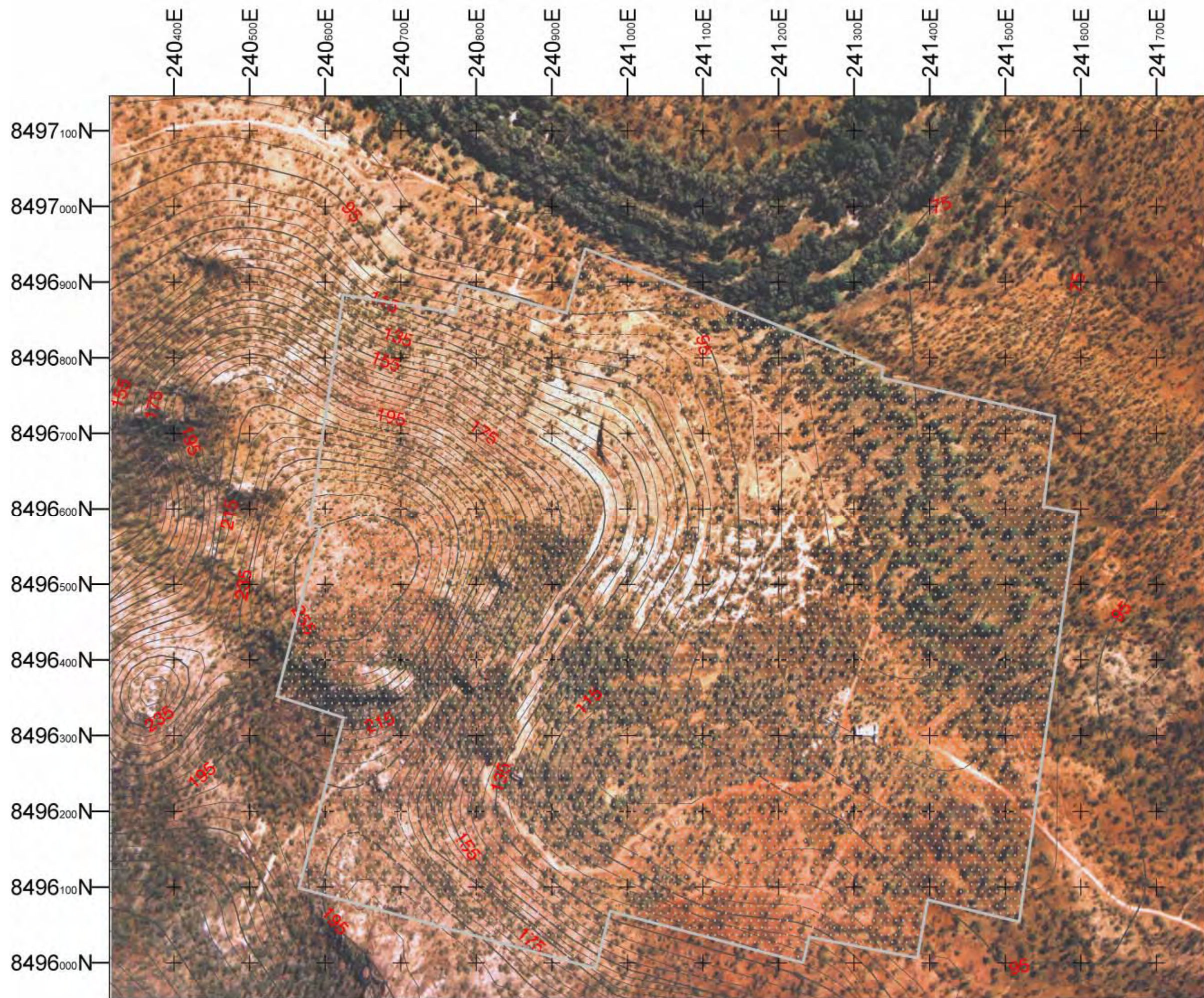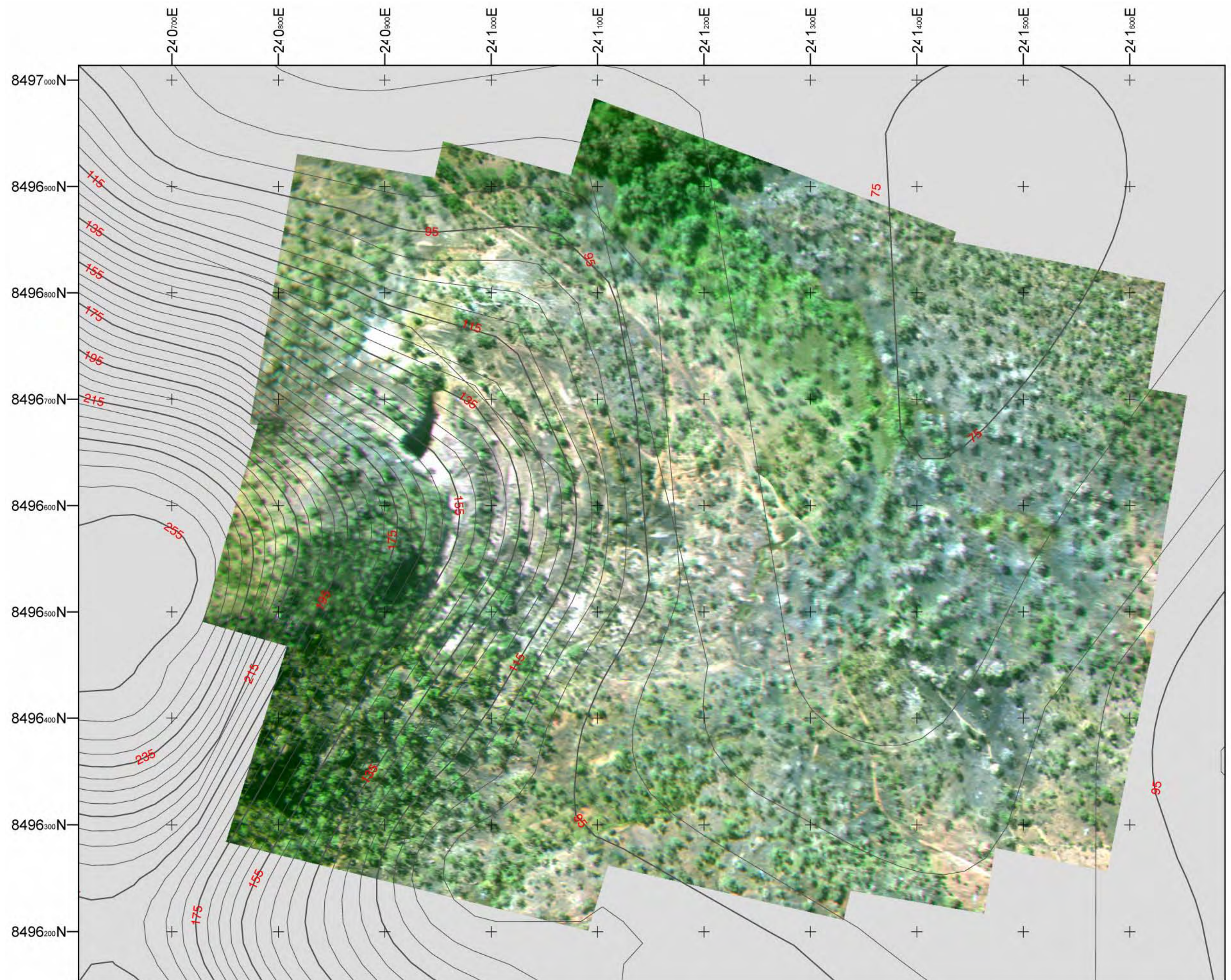
Figure 33. Guratba site true-colour composite video mosaic (May 26, 2000) clearly showing areas of burnt and un-burnt savannah woodland, and bare-ground regions. Scorched tree-crowns, evident in the burnt area in the eastern half, misclassified as areas of bare ground in the supervised classification.
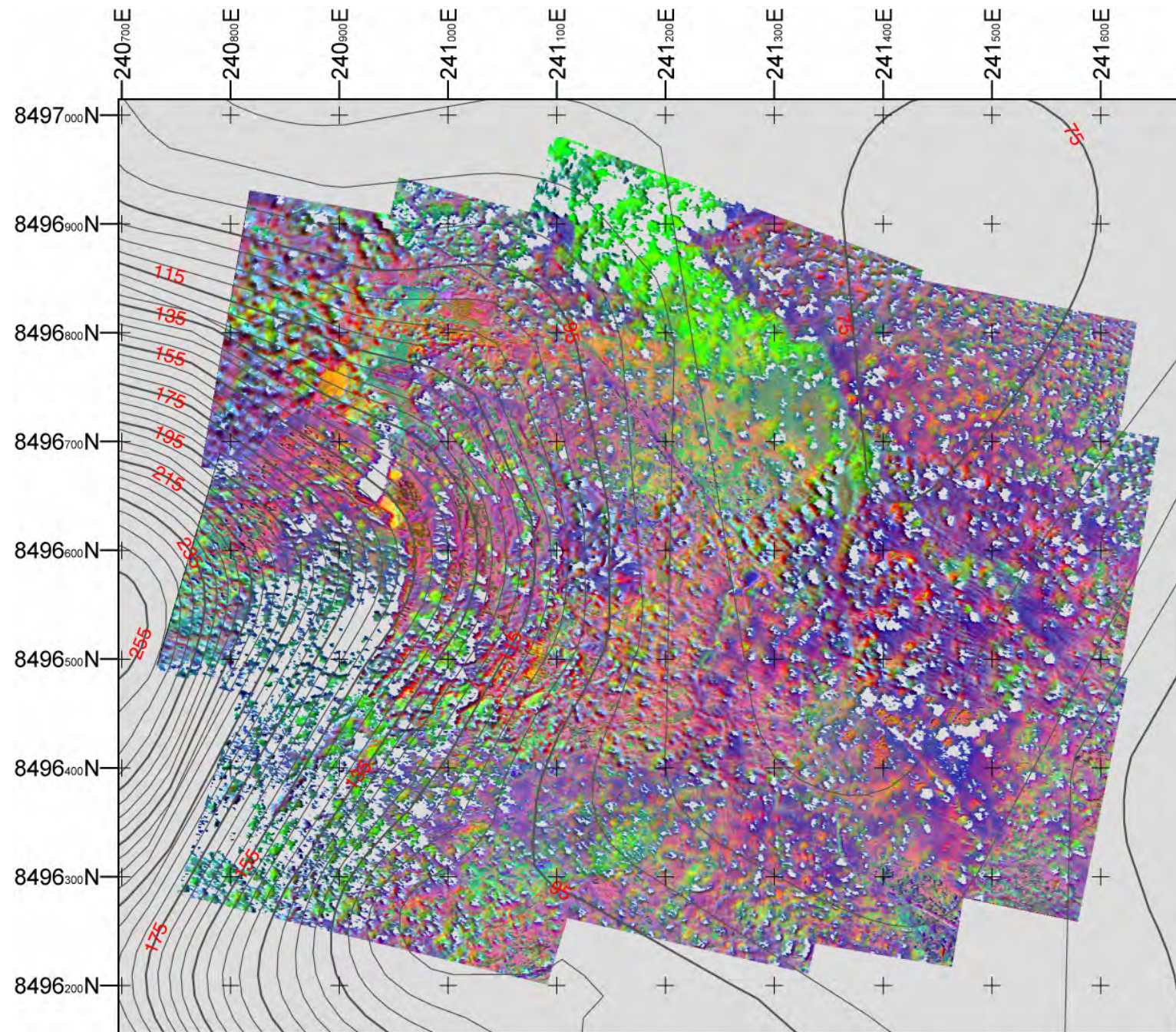
Figure 34. Guratba site, May 2000. False colour composite of principal components 1, 2, and 3 generated from all 5 video bands.

Table 7. Confusion matrix and accuracy statistics for supervised classification generated for the Guratba site from cross tabulation of individual classes derived from two independent sets of training site data.

GROUP	Class	Bare-ground and Annuals				Perennial Grasses		Trees and shrubs									Other		Total pixels	% Accuracy (image B)	Kappa Index
		WG	RG	S.	PV	BG	H	EPh	ET	EM	EPa	EP	ET	ETi	ErC	SC	S	W			
Bare-ground & Annuals	White' gravel	7151	632	18	0	0	0	0	0	0	0	0	0	0	0	296	0	0	8097	88	0.88
	'Red' Gravel	253	53720	6261	564	2002	0	0	0	0	0	0	0	0	0	4134	0	0	66934	80	0.79
	Sorghum spp.	196	6251	56654	0	200	0	0	19	0	0	0	0	4385	0	3647	0	0	71352	79	0.78
	Pasiflora Vine	0	0	231	5446	0	0	804	112	15	226	659	0	0	168	308	0	0	7969	68	0.67
Perennial Grasses	Burnt grassland (mixed)	0	12	214	0	448810	2	0	0	121	0	0	3528	18126	0	4455	14496	184	489948	92	0.88
	Heteropogon spp.	0	0	0	141	14186	71652	136	0	2	14	0	23631	9571	2963	518	0	14	122828	58	0.56
Trees and shrubs	*Eucalyptus phoenicia*	0	0	0	645	3226	0	34804	204	2203	1472	65	7208	21614	284	3063	0	0	74788	47	0.45
	E.latifolia/foelscheana	0	0	51	352	0	444	942	3064	9	235	1798	30	9045	10	392	0	0	16372	19	0.19
	E. miniata	0	0	0	1625	5190	0	820	0	11273	3853	172	2279	678	343	1563	300	0	28096	40	0.40
	E. papuana	0	0	0	112	0	0	1353	347	175	11695	1736	0	2433	1774	358	2	0	19985	59	0.58
	E. polycilata	0	0	0	409	0	465	82	6	489	3201	19806	621	2076	8710	90	2740	0	38695	51	0.50
	E. tectifica	0	0	0	1389	29718	8859	4	0	402	1582	3348	116178	14554	6055	34	50772	4749	237644	49	0.43
	E. tintannans	0	1361	25867	6876	83300	5074	8499	65	1849	104	1056	8987	166790	1190	5870	5853	0	322741	52	0.43
	Erythrophleum chlorostachys	0	0	0	20144	3659	2205	0	0	544	1964	3117	31485	5782	64008	7445	3562	15	143930	45	0.42
	Scorched tree crowns	8	13791	13693	17527	44390	1	580	47	510	174	2	61	41269	978	183034	12144	0	328209	56	0.51
Other	Shadow	0	0	0	0	444	0	0	0	5	1	0	0	3	4	22	21600	0	22079	98	0.98
	Water	0	0	0	0	2994	1183	0	0	0	0	0	4722	33	44	88	1886	13157	24107	55	0.54
	Total pixels	7608	75767	102989	55230	638119	89885	48024	3864	17597	24521	31759	198730	296359	86531	215317	113355	18119	2023774		
% Accuracy (image A)		94	71	55	10	70	80	73	79	64	48	62	59	56	74	85	19	73	Over all:	63	0.57

Classification Key

Heteropogon spp.	E. miniata	
Passiflora sp. (Passionfruit vine)	E. tintannans	Shadow
Eucalyptus papuana	Water	E. polycilata
Burnt grassland	Bare ground ('red' gravel)	E. latifolia
Scorched tree crowns or sparsely burnt grassland	Bare ground ('white' gravel)	E. phoenicia
E. tectifica	Sorghum spp.	Erythrophleum chlorostachys
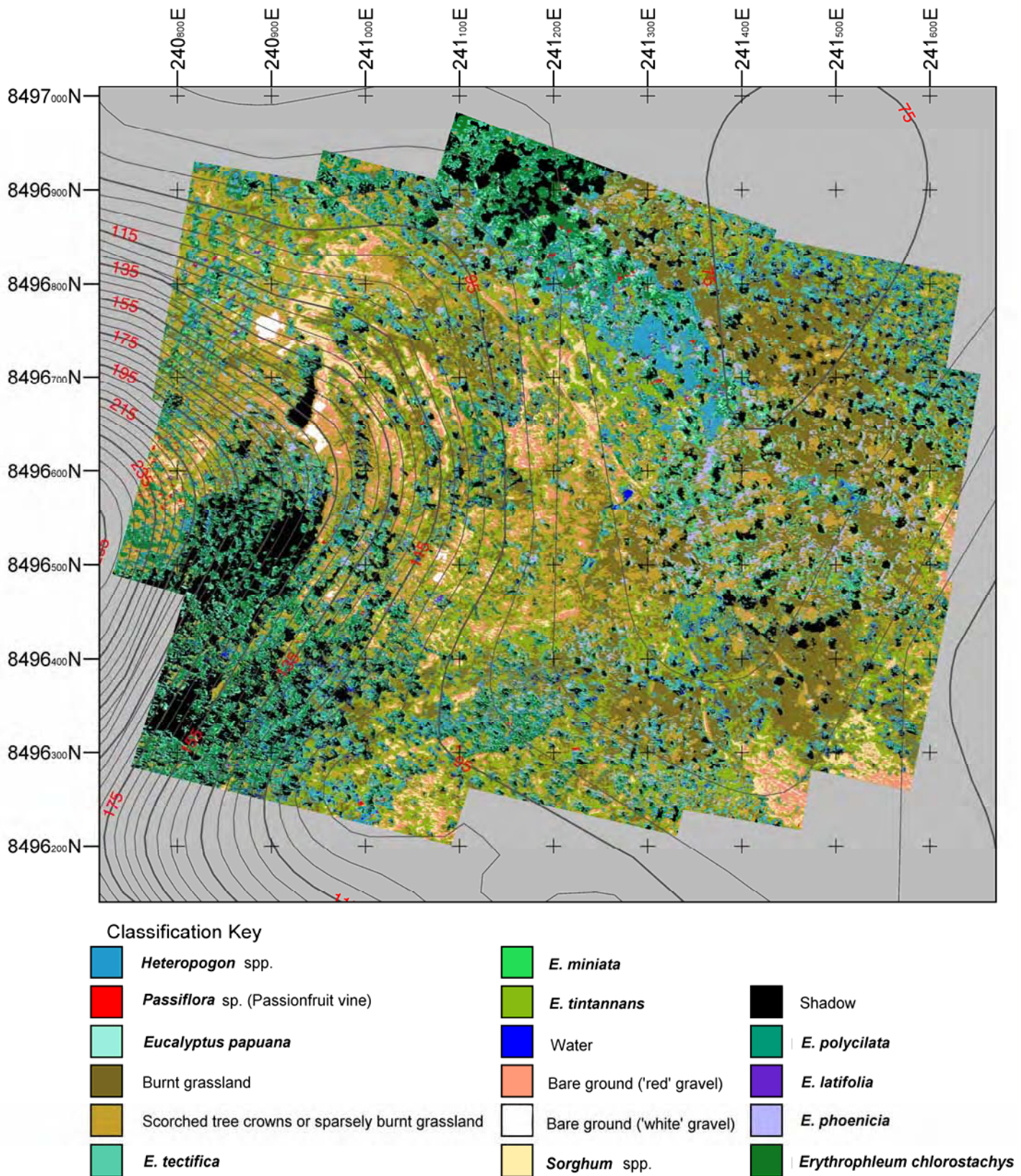
Figure 35. Detailed class map derived from supervised classification approach at Guratba area

Classification Key

- ■ (blue) Trees
- ■ (green) Grass
- ■ (brown) Bare ground ('red' gravel)
- ■ (tan) Bare ground ('white' gravel)
- ■ (magenta) Bare ground ('new')
- ■ (black) Shade

Figure 36. Simplified classification of image used in change analysis .

Classification Key

- ■ (blue) Trees
- ■ (green) Grass
- ■ (brown) Bare ground ('red' gravel)
- ■ (tan) Bare ground ('white' gravel)
- ■ (black) Shade
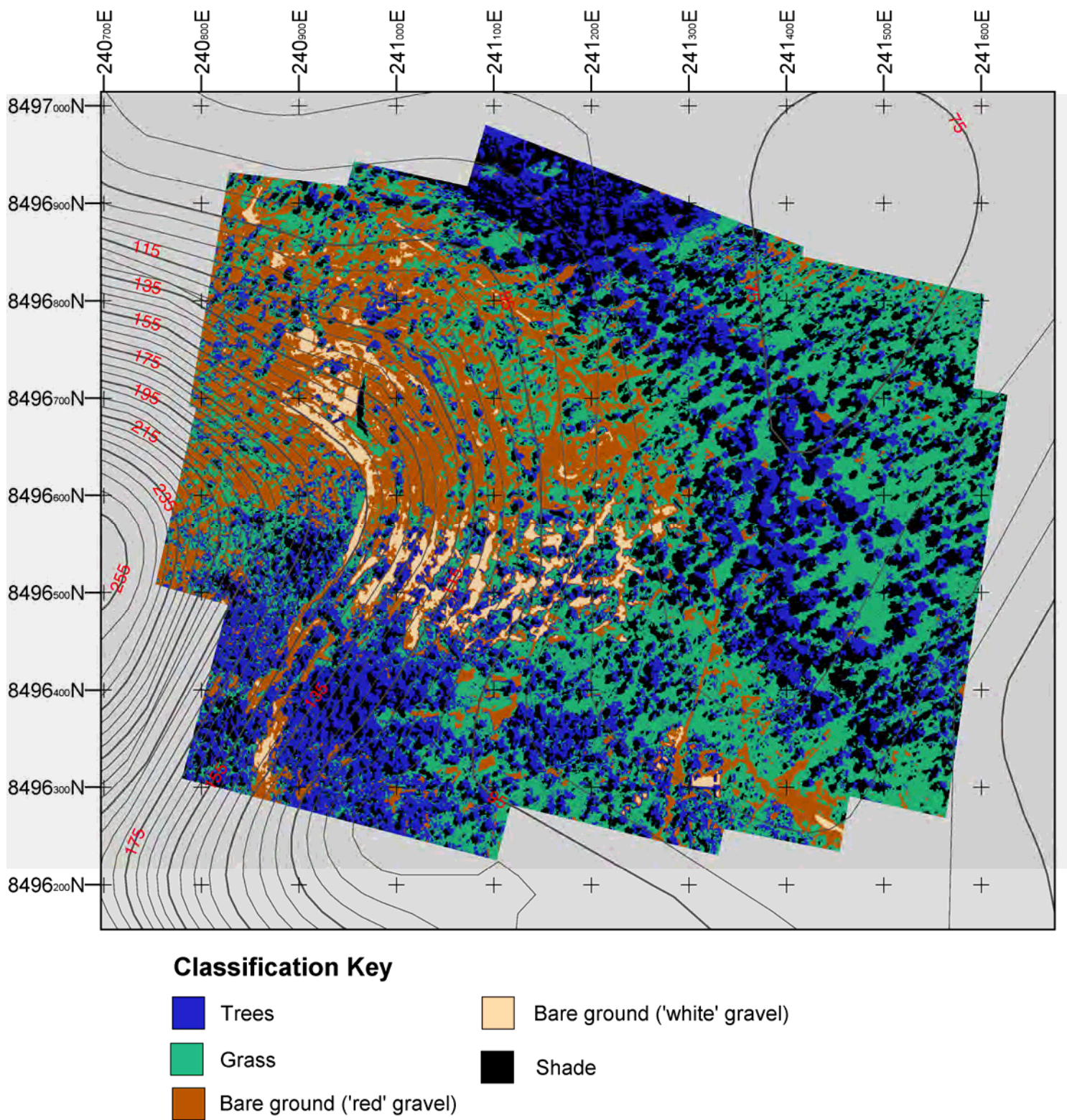
Figure 37. Supervised classification of 1981 aerial photograph (Figure 29) used in change analysis.

4.3.1 Change Analysis between 1981 Aerial Photo and Current Video Imagery

Figure 38. 'Change' analysis classes resulting from additive overlay of class layers derived from May 2000 video mosaic and 1981 aerial photo.

Classification Key

- Remaining original trees
- Absent original trees
- New trees
- Original grassland
- New grassland
- Remaining original bare ground
- Combined shade (unsampled area)
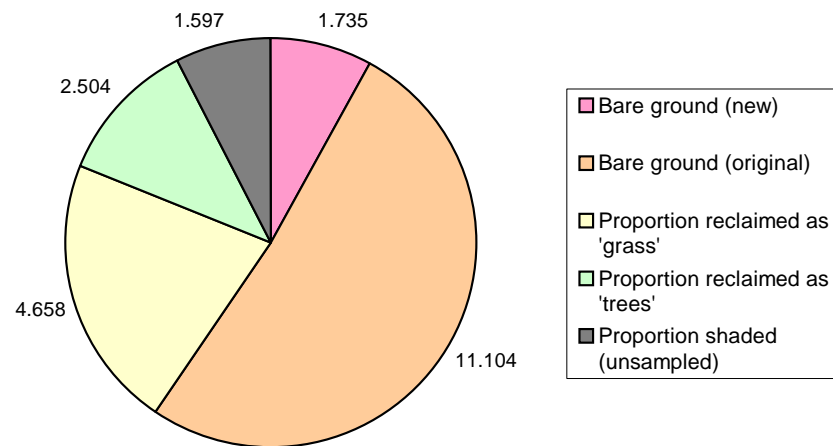
Figure 39. Area summary (ha) of change analysis categories produced from overlay between class layers from 1990 and May 2000 for Guratba. An area of video imagery south east of the Hill, known to have a high level of misclassification due to burning, was masked from this assessment.

5 DISCUSSION

Mine-site rehabilitation may be conceptualised as a number of ecologically relevant phases towards restoration of a 'natural' vegetation community. In the initial phase, a *foundation* for plant colonisation is constructed, sometimes referred to as the 'geotechnical' stage. In this stage the constructed landform typically consists of a fine-grained series of 'banks' and 'troughs' made by deep ripping, forming a series of micro-catchments exerting strong resource control (Tongway & Hindley 2000).

Latter phases (or aims) of the rehabilitation process are: 1) *stabilisation* and abatement of erosion by initial development of vegetation cover; 2) *sustainability*, through establishment of a framework for biological resource control; and ultimately 3) achievement of *biological and functional diversity* in comparison with the undisturbed environment.

Evaluation of rehabilitation status depends upon applying indicators that gauge the progression of rehabilitation in the context of each phase, above. In this sense indicators relevant to each phase, referred to as Ecosystem Function Analysis, are based on: 1) the relative importance of different landscape elements exerting spatial resource control, or LFA; 2) vegetation development and; 3) habitat complexity.

According to Tongway *et al.* (1997; p9), a scientific indicator is "*a single piece of information which acts as a surrogate for an environmental variable to serve a particular use or interest*". In this respect an indicator should be:

- Informative;
- Sensitive and unambiguous;
- Quick, simple and inexpensive;
- Consistent over time;
- Convenient;
- Widely applicable;
- Capable of providing a predictive understanding of ecosystems; and be
- Teachable and transferable between operators.

For the sake of brevity, it will not be possible to discuss each of these criteria in depth. However, the discussion that follows will attempt to evaluate the measurements made by remote sensing in this context, using concepts of EFA and accuracy assessment.

5.1   Indicators of Landscape Function

In the very early 'geotechnical' phase of rehabilitation, it is considered that MSV cannot resolve suitable indicators for LFA assessment. This is because the constructed system of banks and troughs exerting resource control are of relatively homogeneous soil type at this stage. Therefore, no discrimination between these elements can be expected, as they will exhibit similar spectral reflectance profiles. Further, other relatively fine-grained features such as logs, important in resource control dynamics, also discriminated poorly using 0.5m resolution data, although these could be resolved spectrally from other ground features using ground radiometer measurements. Potential for the higher resolution 0.25m data to resolve these fine-grained features could not be determined due to insufficient sample size.

As demonstrated in this study, MSV does appear to separate between relevant landscape patches and inter-patches, such as perennial grasses and bare-ground classes, in the later stages of rehabilitation. This is because geomorphic and biological activity has begun to modify surfaces in these stages. Classification schemes, similar to those developed in this study, have proved useful in providing indicators for spatial modelling to predict erosion potential and landform stability (Post *et al.* 1999). Furthermore, recent studies have demonstrated that quantitative indices of landscape 'leakiness' can be derived from classified imagery (Kinloch, Bastin & Tongway 2000; Bastin *et al.* 2001; Ludwig *et al.* 2001).

Refinement of these indicators is likely by further separation between the *quality* within patch or inter-patch zones of the landscape, as developed in the classification scheme. For example, several geomorphic soil classes could be resolved within inter-patch zones that separate between depositional, stable and erosional surfaces. Furthermore, major vegetation types and cover density classified effectively. Determining a measurable difference in *quality* between individual map-class types using the ground-based indicators developed by Tongway and Hindley (1995) will be necessary to confirm the utility of the classification scheme in distinguishing between the qualities within patch/inter-patch class types.

The classification maps also yielded useful information with respect to the shape, pattern and contextual arrangement of individual patches in the landscape. This allowed the extent of specific problems with respect to rehabilitation at sites to be measured. For example, in some areas at the Airstrip Site embankment microtopography pattern formed by grader-workings was found to be unsuitable for rehabilitation. In these areas, embankments were orientated along the slope instead of in the direction of the slope-contour. This meant that no sinks or troughs were formed to abate the erosive forces of runoff water and allow accumulation of biological

resources. Both true-colour-composite and classified images revealed the location and extent of these problems. In this context, the utility of this information would be enhanced when combined in a GIS environment with a sub-meter scale digital elevation model.

The presence of relatively large homogeneous areas of bare-ground and sparse annual grasses indicated a need to establish a geotechnical foundation for resource control. In the case of the 'clay' surface class, this often indicated an area where surface drainage and water infiltration was poor.

5.2 Vegetation Development Indicators

Reflectance provided by any target (e.g. a tree) is a combination of structural variables (canopy) and optical properties of the leaf and surrounding soil properties (Baret 1995). Considerable evidence has been presented from ground reflectance data to suggest that individual plant species or soil cover types displayed diagnostic spectral profiles. High discrimination between key plant and soil types was also shown in classified imagery. On the other hand, relatively small targets such as *A. holosericea*, classified to group level in the final classification (e.g. trees), were poorly identified to species level. In this sense it would be beneficial to revisit sites, locate these points and measure the relative size of these shrubs/saplings, to determine the degree of misclassification. Peripheral areas of individual tree also tended to misclassify as another tree species. Development of a decision tree algorithm to reclassify peripheral areas may assist in improving overall classification accuracy.

Unsupervised classification indicated regions of tree canopy that had high diagnostic value to species level. However, these features were not distributed consistently among the species population as indicated by cross-tabulation of unsupervised classes against training site pixel samples.

Some vegetation classes in the classification scheme represented broad categories, which nevertheless yielded useful information relating to vegetation development. For example, the 'annual grass' class formed in the supervised classification approach ranged from a mixture of sparse annual and bare-ground (gravel and sand) to dense annual grass (sorghum). Unsupervised classification appeared to separate the dense Sorghum component from this class Figure 26b.

Sorghum may be considered a management indicator species from a number of reasons. In this case, the presence of dense annual grass is likely to indicate a transitional state towards colonisation of perennial grasses, as these patches were often associated with the boundaries between established perennial grasses and more poorly vegetated soils. Sorghum is also often

associated with an environmental disturbance regime. For example, the presence of high Sorghum densities can indicate a regime of frequent annual Dry season burning (Williams *pers. com.* 2000).

5.3   Habitat Complexity Indicators

There is certainly potential to further develop indicators of habitat complexity given that dominant vegetation types and LFA criteria can be accurately resolved using MSV. In this context, shade potential should also be considered a basic component in developing any measure of habitat complexity for open savannah woodland, as shade will relate to moisture conservation in soil and to photosynthetic potential. Although shade will vary with sun angle, it can be standardised, as long as the time of day of data acquisition is known. Furthermore, this provides the potential to estimate canopy depth and tree height, provided the relief is relatively flat, or invariant (Campbell 1996).

Habitat complexity indicators based on spatial variograms between map classes, such as those developed by Coops & Catling (1997a, 1997b) also have potential for rehabilitation monitoring but have not been developed further in the present study.

5.4   Classification Accuracy

The utility of different classes within the classification scheme for conducting EFA is implicitly scale-dependent with respect to the size of different features being monitored. Superimposed upon this dependency are the spectral limitations of surface targets. Together these influence classification accuracy.

Classification accuracy is also influenced by the choice of classification scheme, ground data collection, spatial autocorrelation and sample size (Congalton 1991; Campbell 1995). In the case of supervised classification, the process is dependent upon human judgement and, in effect, is somewhat more subjective than more mechanistic data processing routines (Campbell 1996). However, supervised classification is easily visualised by the analyst and can be standardised and repeatable when based on rigorous ground reference data.

Classification accuracy was improved when a number of preliminary classes were removed from the scheme. Most notably, the coloniser, *A. holosericea*, was shown not to separate well in classification, having a high association with bare-ground classes (Figure 17). Such poor classification is probably the result of a high contribution of background reflectance from bare-ground and boundary errors caused by relatively small training sites. Furthermore, training sites

for this species could only be selected from relatively small patches. This possibly led to a high level of mixed pixels associated with edges. On the other hand, TCC imagery allowed the distribution of *A. holosericea* to be discerned when used in conjunction with contextual ground data.

The hierarchical classification scheme adopted in this study aimed to represent ecologically functional units that contributed in different ways to landscape function analysis, vegetation development and habitat complexity. In this context, it should be noted that the degree of spectral discrimination between key surface features varied (Figure 9 & 11). Consequently, the accuracy of classification between these features also varied. However the separation between major groups in the classification hierarchy was generally pronounced, providing separation between trees & shrubs, perennial grasses, annual grasses and bare-ground/annual grass/litter classes (Figure 15) than separation between sub-classes.

The spectral separation between bare-ground class boundaries was not defined precisely as these classes (e.g. clay, sand and gravel) represented three levels in a continuum based on soil particle size. However, it is useful to distinguish between these groups, since they not only indicate unstable erosion classes (EFA inter-patch zones), but also patterns of water flow, deposition and soil infiltration by water (or lack thereof). Physical soil surface properties have also been shown to be useful ecological indicators for an array of different processes, such as water infiltration potential/water runoff potential, stability to erosion and nutrient cycling state (Tongway & Hindley 1995). Improved precision between classes divisions might be achieved by exploring spectral unmixing analysis methods that attempt to resolve sub-pixel mixture information (Brown, Gunn & Lewis 1999).

Any classification undertaken to generalise patterns of interest will have inherent sources of error. It is imperative, therefore, that the monitoring system incorporates standard accuracy assessment procedures to validate imagery within acceptable levels of error for quality control and assurance.

5.4.1 Mitigation of Potential Error Sources

A number of sources of error are apparent in the data. While some of these sources are unavoidable, others may be reduced. Similarly, a number of preliminary technical difficulties were encountered that, when not recognised, may contribute to information loss and potential error. These problems and some possible ways of overcoming them are summarised in Table 8.

It was evident that significant geometric error was introduced because of aircraft movement (Figure 23). Relative to fixed-wing aircraft, helicopters are more prone to roll, pitch and yaw. Strong winds were encountered during the flyover time, which certainly exacerbated these effects. Recent development of a gyro-based stabilisation mount for the camera array, which compensates for aircraft roll during flight, will substantially reduce this error source. A need to avoid unpredictable weather by exercising a degree of flexibility in the mobilisation/standby time for image acquisition is implicit.

The windy conditions presented a worst-case scenario for the assessment MSV image quality. Although there are a number of frames where noticeable blurring of the imagery is apparent, the majority of frames appear crisp and indeed provide suitable clarity. The windy conditions, however, also caused the flight line of the helicopter for each flight run to be erratic, creating an uneven mosaic of the scene. Originally, it had been planned to obtain 60% overlap between frames to reduce geometric errors. This was not achieved, however.

Table 8. Problems encountered contributing to error or information loss in the acquisition of video data with possible solutions and the operational implications of these 'solutions'.

Problem encountered	Solution	Operational Implications
Radiometric calibration of Guratba image not possible due to large variation between Airstrip and Guratba in reflectance properties	• Deploy calibration targets at individual sites for real time measurements and if necessary deploy multiple sets of targets to over the full range of relief displacement.	• More field resources required: Deployment of field personnel with appropriate equipment (radiometer) at each site to take real time measurements may not be possible.
Geometric error apparent in the co-registration of multiple bands in the frame stacking procedure	• Deploy more GCPs • Ensure artificial GCPs are detectable across the full array of bands to facilitate selection of co registration points • Use multiple GCPs in conjunction with appropriate geometric correction algorithm in co-registration stacking procedure	• More time involved to position more targets over a larger area • Use reflective aluminium surface of builders sisalation material • Labour intensive. Requires to be automated
Geo-registration accuracy of image poor at extremities of mosaic coverage at Guratba	• Deploy a larger network of GCPs to compensate for high relief displacement	• Extra time involved to position more targets over a larger area
Information loss due to saturation (BV= 255), or no detection (BV=0) for certain bands over range of target reflectance conditions	• Develop means to check and adjust gain setting for individual bands. • Consider the need to use neutral density filters for certain bands to assist in adjusting to appropriate sensitivity range	• Need to develop procedure to conduct such adjustments efficiently

Misalignment between overlaying band layers on the image was another source of geometric error apparent in some image frames. This can cause error in multivariate classification procedures utilising multiple bands. Misclassification derived from misalignment error may be revealed at the boundaries between spectrally different features, as it will result in an inappropriate band profile between adjacent features, thereby leading to mis-classification. This was detected in one of the frames using the unsupervised classification procedure of the airstrip mosaic, where a unique class in the boundary region between trees and grasses was formed (Figure 28b). This source of error may also to have contributed significantly to the poor classification of some relatively small features such as *A. holosericea.*

Misalignment error can arise as a result slight optical differences between individual cameras, or through human error in the selection of co-registration points for stacking corresponding band frames. Such errors may be reduced by employing two strategies:

- Using more GCPs in the cross-registration stacking procedure between individual bands for a particular frame;
- Applying a geometric algorithm using multiple GCPs, such as a cubic convolution, to correct geometric distortions between band-frames against a base frame instead of a simple x/y shift procedure to one control point;

The pre-processing stacking method used a simple x-y shift correction to single GCP cross-referenced to a base image frame. Registration between band-frames could have been improved if a larger sample of GCPs were selected then an appropriate geometric correction algorithm applied. As part of quality control of this process, residual errors for each control point and the total 'root mean square' error could be recorded routinely for each registered frame (Wilson *pers. com.* 2001). However, selection of an appropriate number of GCPs can be complicated by lack of identifiable GCPs between bands. Distribution of more artificial GCP targets would have assisted in this respect. Furthermore, target discrimination over the full band-range would have been improved if artificial targets had been placed with the aluminium surface facing upwards, as it was found that the blue surface of the builders sisalation material did not discriminate well in the blue region (450nm).

Together, sources of error due to locational and image blur problems reduce the *actual* area of the ground resolution provided by remote sensing, where it has been suggested that *actual* spatial resolution in data can be as much as 4-6 times greater than the ground resolution element, the pixel (Curran & Williamson 1986). This creates difficulties in selecting training site samples for supervised classification, as the degree of spectral mixing at the boundaries between different features is increased (Curran & Williamson 1986). A representative sample of pixels from relatively small targets, such as *A. holosericea* shrubs, was not possible as is supported by the low per category KIA value for this class (0.14). Reduction of these sources of geometric error will certainly improve classification accuracy of relatively small targets.

Classification of small features was improved by using finer grain data (0.25m) data. For example, while *A. holosericea* was misclassified as gravel, sand or grass classes at 0.5m resolution, the shrubs appeared to classify more often as either *A. holosericea* or a tree class (*E. tectifica*) as shown by comparison of Figure 23 with Figure 21.

5.4.2 Fire

Fire has been identified as a major factor impeding effective collection of EFA monitoring indicators using RS. Image classification accuracy is reduced by adding another dimension of spatial heterogeneity elicited by variable spectral responses of plants to fire (Plate 4 and Figure 31). For example, eucalypts are sometimes prompted to drop their leaves, as is evidenced by the 'scorched' tree crowns at Guratba (Figure 31). .

The process of mine-site rehabilitation may occur over a time frame of 50 years or more. Restricting MSV image collection to in the early Dry Season period is considered a necessary requirement to avoid problems caused by fire and other sources of seasonal variation. Given a sampling frequency of every 3-5 years and the considerable investment of resources in image collection, it would seem possible to plan for such contingencies.

Reiterating, operational monitoring requires good communication with land managers and subsequent cooperation from all parties. Flexibility in the timing of funds allocation for such monitoring projects can also be a useful management option. For instance, when unfavourable conditions arise, such as fire, the possibility of postponing data collection to the following year may need to be considered.

6 CONCLUSION AND RECOMMENDATIONS

The protocols developed above provide a basis for rehabilitation monitoring and assessment of mine-sites in the SAV using high-resolution MSV. The HR data provided synoptic and quantitative indicators useful in ecological assessment. Thematic maps produced by the image classification also presented information in a form that can readily be conveyed to land managers.

It is considered that, the relatively small area encompassed by mine-sites allow for a repeatable supervised classification scheme useful in monitoring. In general small areas have lower spatial heterogeneity and are therefore easily ground-truthed. While the *initial* field sampling to develop a benchmark can be time-consuming and expensive, field survey intensity is reduced once a permanent ground-referenced system and desired map classes are established for a region.

The classification scheme developed was sufficiently accurate to distinguish among key vegetation communities and bare-ground types useful in EFA. Comparison between disturbed sites and undisturbed 'analogue' sites highlighted substantial differences in vegetation communities. Not only was overall vegetation density sparser, species dominance also differed. Some areas remain devoid of vegetation. Classes accurately distinguished within these areas were regions of active erosion, deposition, or poorly drained areas. At the airstrip, embankments formed by deep ripping could also be visualised from TCC imagery, as they were often associated with vegetation. In many cases the arrangement of embankments was found to be inappropriate, as the rip-lines were orientated in the down-slope direction rather than with the slope contour, therefore not providing any protection for the from water runoff, and in some cases it can be considered an erosion.

The utility of the technique for providing repeatable, accurate measurements is very much dependent on adherence to the protocols outlined in this study.   In particular the condition that imagery and ground data be collected concurrently and at a suitable time is important for maintenance of data quality.   This has implications for planning both multidisciplinary data collection and the coordination of field operations. In retrospect, further improvements to data quality and accuracy may also be achieved by implementing a number of minor changes to the

data collection, pre-processing, and analysis procedures. These recommendations are summarised in Appendix II.

Many steps are involved in the pre-processing analysis and delivery of information derived from remote sensing. This can be a resource-intensive and costly exercise. However, there is also considerable scope to improve the efficiency and cost-effectiveness of these steps. Technological advancement in the area of image data acquisition and analysis is developing rapidly. Therefore it is highly possible that improvements in image collection and automated processing techniques will facilitate the provision of cost-effective information (Hick *et al.* 1994; Phinn, Stow & Zedler 1996).

With current technology, processing is more efficient using conventional RBG digital photography. Such a system, with the addition of a NIR band to expand the spectral range required to distinguish between vegetation classes would only need two relatively low-cost camera units; not the five used in this study. This would reduce processing involved in band stacking while also increasing the spatial precision between band layers.

High-resolution MSV (or conventional HR photography) can play an integral role for the monitoring and assessment of mine-site rehabilitation. The information gathered forms a basis for evaluation of the success of the proposed revegetation program for abandoned mine sites in the SAV. It provided a quantitative and synoptic analysis of the status of vegetation and rehabilitation at mine sites in this study, and demonstrated the potential for monitoring using multi-temporal change analysis. Finer scale indicators measured on the ground could be translated to larger scale relationships detected by MSV. In conclusion, an integrated mapping approach, using high-resolution aerial video (or photography) in combination with contextual ground data, can meet the requirements for monitoring revegetation.

APPENDIX I: IMAGE CALIBRATION

Figure 40. Linear relationships for each band between calibration target ground reflectance readings and equivalent video band (pixel brightness values) for 0.5m resolution image data collected from El Sherana Airstrip site. Pixel sample sizes for each target (light to very dark) were 35, 25, 29 and 27 respectively. Error bars are SE.
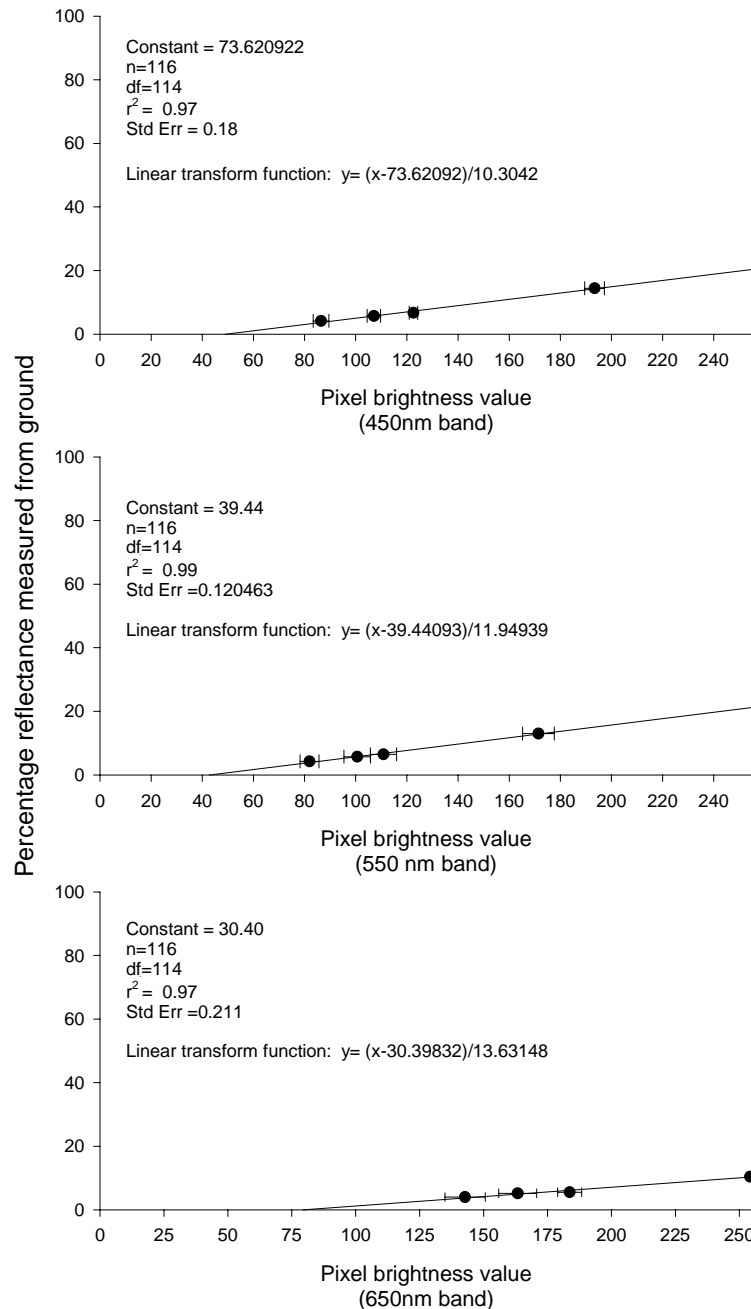
Figure 38. (continued)   Linear relationships for each band between calibration targets ground reflectance readings and equivalent video band (pixel brightness values) for 0.5m resolution image data collected from El Sherana Airstrip site. Pixel sample sizes for each target (light to very dark) were 35, 25, 29 and 27 respectively. Error bars are SE.
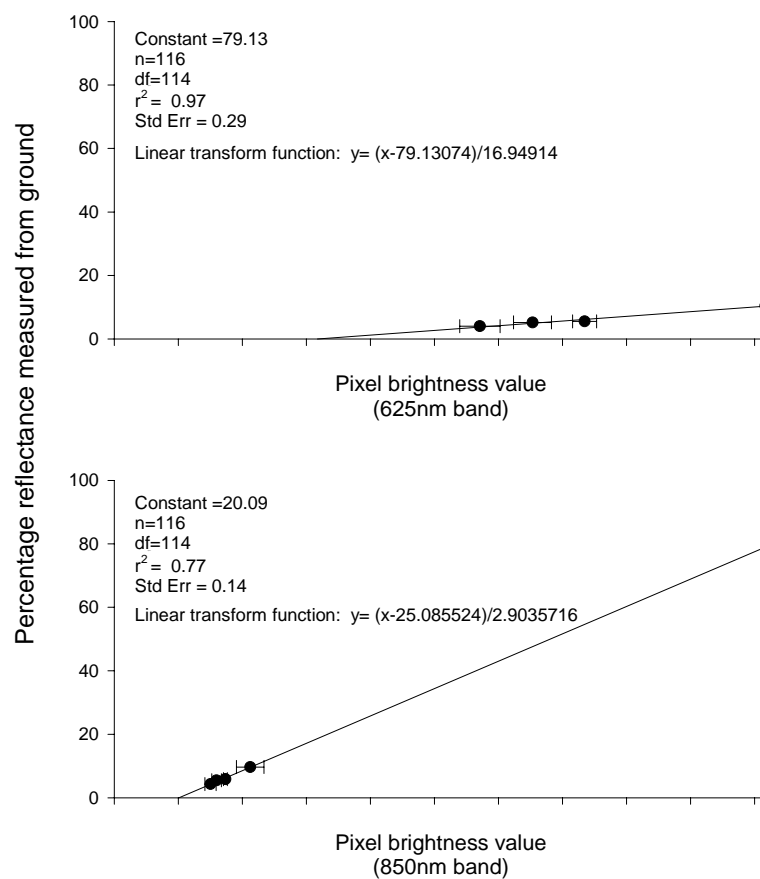
APPENDIX II: RECOMEDNDATIONS FOR PROTOCOL REFINMENT

Recommendation 1.   To maximise   target discrimination, image data collection should be undertaken as early as possible in the Dry season and, where burning of sites before imagery is collected should be avoided.

Recommendation 2.   Deployment of   further artificial GCPs for co-registration purposes would have been beneficial, particularly at the Guratba site, where geometric distortions was exacerbated by the high relief in the area. This will be especially important for minimising error created from multi-temporal change analysis

Recommendation 3.   A more complete collection of Ecosystem Function Analysis data for transect-boundary analysis, with associated measurement of soil surface condition indicators, is necessary. Collection of data at this scale in tandem with high-resolution RS data collection is considered a priority for future research towards refining the monitoring protocol developed here. This would allow a more comprehensive assessment of the precision and accuracy of specific map classes as indicators in EFA. In this regard, the monitoring framework in this study will certainly facilitate any future research efforts at the study site.

Recommendation 4.   A comprehensive spectral library of key vegetation and ground types was not available in this study. Limited time also reduced the ability to collect representative measurements of ground reflectance for key vegetation and surface types. Future monitoring would therefore benefit from a study dedicated to determining the spectrally diagnostic regions between key vegetation types using include sensitive field spectrometry. This knowledge could then be applied to optimise remote sensing multispectral configurations for species discrimination using narrow-band filters. In the Alligator Rivers Region, such a study need only be conducted over the first few months of the Dry season to obtain maximum benefit, as the window of opportunity for mapping to conduct EFA criteria using RS appears to be in the early Dry season.

Recommendation 5.   It is recommended that field validation of classification scheme be undertaken to confirm classification against post-classified data (a method not

pursued in this study due to lack of time). This will assist in further refinement and validation of the classification scheme.

7 BIBLIOGRAPHY

Anon. (1988). Coronation hill gold, platinum and palladium project: Draft environmental impact statement, Prepared for Coronation Hill Joint Venture by Dames and Moore.

Asner, G, C Wessman and D Schimel (1998). Heterogeneity of savannah canopy structure and function from imaging spectrometry and inverse modeling. *Ecological Applications* **8**(4): pp.1022-1036.

Baret, F (1995). Use of spectral reflectance variation to retrieve canopy biophysical characteristics. In: Advances in environmental remote sensing. F Danson and S Plummer. Chichester, West Sussex, England, John Wiley & Sons**:** pp. 33-51.

Barrett, E and L Curtis (1992). *Introduction to environmental remote sensing.*

Bastin, G, J Ludwig, R Eager, V Chewings and A Liedloff (in press). Leakiness index: An indicator of landscape function derived from high-resolution remotely-sensed data. In: *5th North Australian Remote Sensing and GIS Conference(July 2001).* Darwin, Northern Territory University. (proceedings published on CD-Rom).

Belbin, L (1991). Semi-strong hybrid scaling, a new ordination algorithm. *Journal of Vegetation Science* **2**: pp. 491-496.

Belbin, L (1994). Technical reference for PATN: Pattern analysis package, CSIRO: Division of wildlife and ecology.

Bell, L (1996). Rehabilitation of disturbed land. In: Environmental management in the Australian minerals and energy industries. D Mulligan, AMEEF & UNSW Press.

Bell, S, M Fonseca and L Motten (1997). Linking restoration and landscape ecology. *Restoration Ecology* **5**(4): pp. 318-323.

Bohlman, S, J Adams, R Smith and D Peterson (1998). Seasonal foliage changes in the Eastern Amazon basin detected from Landsat thematic mapper satellite images. *Biotropica* **30**(3): 376-391.

Bork, EW, NE West and KP Price (1999). Calibration of broad- and narrow-band spectral variables for rangeland cover component quantification. - *International Journal of Remote Sensing* **20**(18): 3641-3662.

Braithwaite, R and J Woinarski (1990). Coronation hill, Kakadu Stage III - assessing the conservation value. *Australian Biologist* **3**(1): 3-13.

Brennan, K (1996). Flowering and fruiting phenology of native plants in the Alligator Rivers Region with particular reference to the Ranger Uranium Mine lease area, Supervising Scientist Report.

Brennan, K (2000). Personal communication.

Brown, M, S Gunn and H Lewis (1999). Support vector machines for optimal classification and spectral unmixing. *Ecological Modelling* **120**(2-3): 167-179.

Campbell, J (1995). Field data collection for remote sensing analysis: Spot data, Rondonia, Brazil. *International Journal of Remote Sensing* **16**(2): pp. 333-350.

Campbell, J (1996). *Introduction to remote sensing*. NY, London, The Guilford Press.

Carsten, L (1987). A measure of similarity for cellular maps. *The American Cartographer* **4**(4): pp. 345-358.

Chen, N, H Wang and M Lin (1997). Orthographic correction of airborne scanner imagery for mountainous areas. In: *Third international airborne remote sensing conference and exhibition* **Volume II**: pp. 293-299.

Congalton, R (1988). A comparison of sampling schemes used in generating confusion matrices for assessing the accuracy of maps generated from remotely sensed data. *Photogrammetric Engineering & Remote Sensing* **54**: pp. 593-600.

Congalton, R (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment* **37**: pp. 35-46.

Coops, N and P Catling (1997a). Predicting the complexity of habitat in forests from airborne videography for wildlife management. *International Journal of Remote Sensing* **18**(12): pp. 2677-2682.

Coops, N and P Catling (1997b). Utilising airborne multispectral videography to predict habitat complexity in eucalypt forests for wildlife management. *Wildlife Research* **24**: pp. 691-703.

Coops, N, D Culvenor, R Preston and P Catling (1998). Procedures for predicting habitat and structural attributes in Eucalypt forests using high spatial resolution remote sensing. *Australian Forestry* **61**: pp. 244-252.

Corbett, M (1999). Revegetation in the wet-dry tropics of northern Australia: A review. Report to the Alligator Rivers Region Technical Committee.

Curran, P and J Dungan (1988). Zones of information in the AVIRIS spectra. *AVIRIS Airborne Geoscience Workshop*. Electronic source: http://makalu.jpl.nasa.gov/docs/workshops/AVIRIS.proceedings.html

Curran, P and H Williamson (1986). Sample size for ground and remotely sensed data. *Remote Sensing of Environment* **20**: pp. 31-41.

DeAngelis, D, L Gross, M Huston, W Wolff, D Fleming, E Comiskey and S Sylvester (1998). Landscape modeling for Everglades ecosystem restoration. *Ecosystems* **1**(1): 64-75.

Dematte, J and G Garcia (1999). Alteration of soil properties through a weathering sequence as evaluated by spectral reflectance. *Soil Science Society of America Journal* **63**(2): pp. 327-342.

Everitt, J, D Escobar, C Yang, R Lonard, F Judd, M Alaniz, I Cavazos, M Davis and D Hockaday (1999). Distinguishing ecological parameters in a coastal area using a video system with visible/near-infrared/mid-infrared sensitivity. *Journal of Coastal Research* **15**(4): pp. 1145-1150.

Famiglietti, J, J Devereaux, C Laymon, T Tsegaye, P Houser, T Jackson, S Graham, M Rodell and P van Oevelen (1999). Ground-based investigation of soil moisture variability within remote sensing footprints on the southern Great Plains 1997 (sgp97) hydrology experiment. *Water Resources Research* **35**(6): pp. 1839-1851.

Farrand, W and J Harsanyi (1997). Mapping the distribution of mine tailings in the Coeur d'Alene River Valley, Idaho, through the use of a constrained energy minimization technique. *Remote Sensing of Environment* **59**(1): pp. 64-76.

Foody, G (1992). On the compensation for change agreement in image classification accuracy assessment. *Photogrammetric Engineering & Remote Sensing* **58**(10): pp. 1459-1460.

Frohn, R (1998). *Remote sensing for landscape ecology: New metric indicators for monitoring, modeling and assessment of ecosystems*. Lewis Publishers.

Gamon, J, L Lee and H Qui (1992). A multi-scale sampling strategy for detecting physiologically significant signals in AVIRIS imagery. *AVIRIS Airborne Geoscience Workshop Proceedings*. Electronic source: http://makalu.jpl.nasa.gov/docs/workshops/AVIRIS.proceedings.html

Graetz, R (1989). Analysis of land degradation in Stage III of Kakadu National Park, including the Conservation Zone: Phase 1. Canberra, CSIRO division of Wildlife and Ecology.

Harrison, B and D Jupp (1991). *Introduction to remotely sensed data: Part one of the microBrian resource manual*.

Hewitt, J, S Thrush, V Cummings and S Turner (1998). The effect of changing sampling scales on our ability to detect effects of large-scale processes on communities. *Journal of Experimental Marine Biology & Ecology* **227**(2): pp. 251-264.

Hick, P, R Smith, C Ong and F Honey (1994). Vegetation assessment and monitoring using airborne digital multispectral videography: Implications for geobotanical prospecting and quantitative pre and post-mining measurement. *19th Annual environmental workshop, Australian Mining Industry Council*.

Jupp, D, J Walker, B Harrison and P Reece (1988). The effects of vegetation structure in remotely sensed data and its implications for operational monitoring of large-scale changes in Kakadu national park. CSIRO Division of Water Resources.

Kinloch, J, G Bastin and D Tongway (2000). Measuring landscape function in chenopod shrublands using aerial videography. In: *Proceedings of the 10th Australasian Remote Sensing and Photogrammetry Conference*. Adelaide, South Australia, Causal Productions, Adelaide , SA**:** 480-491.

Kumar, L and A Skidmore (1998). Use of derivative spectroscopy to identify regions of differences between some Australian eucalypt species. In: *9th Australian Remote Sensing Photogrammetry Conference*. Sydney, Australia.

Lobo, A, K Moloney, O Chic and N Chiariello (1998). Analysis of fine-scale spatial pattern of a grassland from remotely-sensed imagery and field collected data. *Landscape Ecology* **13**(2): pp. 111-131.

Lonard, R, F Judd, J Everitt , D Escobar, M Alaniz, I Cavazos and M Davis (1999). Vegetative change on South Padre Island, Texas, over twenty years and evaluation of multispectral videography in determining vegetative cover and species identity. *The Southwestern Naturalist* **44**(3): pp. 261-271.

Ludwig, J and D Tongway (1992). Monitoring the condition of Australian arid lands: Linked plant-soil indicators. In: <u>Ecological indicators</u>. D McKenzie, D Hyatt and V McDonald. Essex, Elsevier. **Volume I:** pp. 765-772.

Ludwig, J and D Tongway (1996). Rehabilitation of semi-arid landscapes in Australia. II. Restoring vegetation patches. *Restoration Ecology* **4**(4): pp. 388-397.

Ludwig, J, D Tongway, D Freudenberger, J Noble and K Hodgkinson (1997). *Landscape ecology, function and management: Principles from Australia's rangelands*, CSIRO.

Ludwig, J, R Eager, G Bastin, V Chewings and A Liedloff (2001). A leakiness index for assessing landcape function using remote sensing. *Landscape Ecology*: (in press).

Lyon, R, F Honey and P Hick (1994). Second generation airborne digital multispectral video: Evaluation of a DMSV for environmental and vegetation assessment. In: *First International Airborne Remote Sensing Conference and Exhibition*. **Volume II:** pp. 105-116.

Milton, E, E Rollin and D Emery (1995). Advances in field spectroscopy. In: <u>Advances in environmental remote sensing</u>. F Danson and S Plummer. Chichester, West Sussex, England, John Wiley & Sons**:** pp. 9-32.

Mueller, A, P Strobl, F Lehmann and G Reinhaeckel (1997). Case studies of airborne remote sensing for the assessment of mining impacts. In: *Third International Airborne Remote Sensing Conference and Exhibition*. Copenhagen, Denmark. **Volume I:** pp. 257-264.

Muller, E and M James (1885). Seasonal variation and stability of soil spectral patterns in a fluvial landscape. *International Journal of Remote Sensing* **15**(9): pp. 1885-1900.

Mumby, P, E Green, C Clark and A Edwards (1998). Digital analysis of multispectral airborne imagery of coral reefs. *Coral Reefs* **17**(1): pp. 59-69.

Nyquist, M and R Root (1997). The USGS vegetation mapping program for the national park service: Benchmarking - preliminary results. In: *Third International Airborne Remote Sensing Conference and Exhibition*. Copenhagen, Denmark. **Volume I:** pp. 588-593.

O'Neill, A (1996). Reflectance characterisitics of C3 and C4 grasses in semi-arid Australia. In: *Proceedings of the 8th Annual Australasian and Photogrammetry Conference*. Canberra**:** pp. 231-240.

Phinn, SR, D Stow and J Zedler (1996). Monitoring wetland habitat restoration in southern California using airborne multispectral video data. *Restoration Ecology* **4**(4): pp. 412-422.

Pickup, G, GN Bastin and VH Chewings (1994). Remote-sensing-based condition assessment for nonequilibrium rangelands. *Ecological Applications* **4**(3): pp. 497-517.

Pickup, G and D Nelson (1984). Use of Landsat radiance parameters to distinguish soil erosion, stability and deposition in arid central Australia. *Remote Sensing of Environment* **16**: pp. 195-209.

Post, D, E Martin, J Simanton and E Sano (1999). Use of hand-held radiometers to evaluate the cover and hydrologic characteristics of semiarid rangelands. - *Arid Soil Research & Rehabilitation* **13**(2): pp. 201-217.

Pressey, R and M Bedward (1991). Mapping the environment at different scales: Benefits and costs for nature conservation. In: <u>Nature conservation: Cost effective biological surveys and data analysis.</u> C Margules and M Austin, CSIRO Australia**:** 7-13.

Price, J (1998). An approach to the analysis of reflectance spectra. *Remote Sensing of Environment* **64**: pp. 316-330.

Randall, JM (1996). Weed control for the preservation of biological diversity. *Weed Technology* **10**(2): pp. 370-383.

Rathore, CS and R Wright (1993). Monitoring environmental impacts of surface coal mining. *International Journal of Remote Sensing* **14**(6): pp. 1021-1042.

Rigol, J and M Chica-Olmo (1998). Merging remote-sensing images for geological-environmental mapping: Application to the Cabo de Gata-nijar natural park, Spain. *Environmental Geology* **34**(2-3): pp. 194-202.

Roberts, D, B Nelson, J Adams and F Palmer (1998). Spectral changes with leaf aging in Amazon Caatinga. *Trees-Structure & Function* **12**(6): pp. 315-325.

Roberts, DR, M Smith, D Sabol, J Adams and S Ustin (1992). Mapping the spectral variability in photosynthetic and non-photosynthetic vegetation, soils and shade using AVIRIS. *AVIRIS Airborne Geoscience Workshop Proceedings*. Electronic source: http://makalu.jpl.nasa.gov/docs/workshops/AVIRIS.proceedings.html

Rollings, N (2000a). Development and testing of the image capture unit - multi-spectral airborne video. Electronic source: http://www.ecoman.une.edu.au/Rollings/Icu/paper111arsc9.html

Rollings, N (2000b). Image capture unit. Electronic source: http://www.ecoman.une.edu.au/ibrmsal/icu.htm

Rosenfield, G and K Fitzpatrick-Lins (1986). A coefficient of agreement as a measure of thematic classification accuracy. *Photogrammetric Engineering & Remote Sensing* **52**(2): pp. 223-227.

Roy, PS, SA Ravan, N Rajadnya, KK Das, A Jain and S Singh (1995). Habitat suitability analysis of *Nemorhaedus goral*. A remote sensing and geographic information system approach. *Current Science* **69**(8): pp. 685-691.

Sanderson, E, M Zhang, S Ustin and E Rejmankova (1998). Geostatistical scaling of canopy water content in a California salt marsh. *Landscape Ecology* **13**(2): pp. 79-92.

Skidmore, A, E Knowles, J Delaney, K Bronsveld and F van der Meer (1997). Relationship of Eucalypt vegetation with remotely sensed and digital terrain model data. In: *Third International Airborne Remote Sensing Conference and Exhibition*. Copenhagen, Denmark. **Volume II:** pp. 438-445.

Skidmore, A and K Schmidt Identification of Kenyan rangeland grasses using hyperspectral image data.

Spiers, G (2000). Personal communication.

Story, R, R Galloway, J McAlpine, J Alderick and M Williams (1976). Lands of The Alligator Rivers Area, Northern Territory, CSIRO.

Stow, D, S Phinn and A Hope (1997). An "end to end system" based on airborne multispectral camera image data for monitoring detailed vegetation changes. In: *Third International Airborne Remote Sensing Conference and Exhibition*. Copenhagen, Denmark. **Volume I:** pp. 603-611.

Tongway, D (2000). Personal communication.

Tongway, D and N Hindley (1995). *Manual for assessment of soil condition of tropical grasslands*, CSIRO Australia: Division of Wildlife and Ecology, Canberra.

Tongway, D and N Hindley (2000). Assessing rehabilitation success: A training course to understand, assess and monitor the success of mine rehabilitation using ecosystem function analysis indicators. CSIRO.

Tongway, D, A Kearns, N Hindley and G Barnett (1997). Indicators of ecosystem rehabilitation success and selection of demonstration sites. CSIRO Mine-site rehabilitation program.

Tongway, D and J Ludwig (1996). Rehabilitation of semiarid landscapes in Australia. I. Restoring productive soil patches. *Restoration Ecology* **4**(4): pp. 388-397.

Totte, M, B Henquin and HP Some (1995). Landscape stratification by remote-sensing and characterisation of rural systems in the Bobo-Dioulasso region of Burkina Faso. *Cahiers Agricultures* **4**(2): pp. 113-123.

Um, J and R Wright (1998). A comparative evaluation of video remote sensing and field survey for revegetation monitoring of a pipeline route. *Science of the Total Environment* **215**(3): pp. 189-207.

Wade, SD, IDL Foster and SMJ Baban (1996). The spatial variability of soil nitrates in arable and pasture landscapes - implications for the development of geographical information system models of nitrate leaching. *Soil Use & Management* **12**(2): pp. 95-101.

Warren, P and P Hick (1996). Tracking our performance. Airborne remote sensing at Comalco's bauxite mine, Weipa, North Queensland. In: *3rd International and 21st Annual Minerals Council of Australia Environmental Workshop*. **2:** pp. 67-78.

Williams, R (2000). Personal communication.

Wilson, B (2001). Personal communication.

Woinarski, J, N Gambold, K Menkhorst and R Braithwaite (1989). Wildlife of Kakadu National Park Stage III: Final report to The Australian National Parks and Wildlife Service. Darwin, Division of Wildlife and Ecology, CSIRO Tropical Ecosystems Research Centre.

Wolter, P, D Mladenoff, G Host and T Crow (1995). Improved forest classification in the Northern Lake States using multi-temporal Landsat imagery. *Photogrammetric Engineering & Remote Sensing* **61**: 1129-1143

Zwiggelaar, R (1998). A review of spectral properties of plants and their potential use for crop/weed discrimination in row-crops. *Crop Protection* **17**(3): pp. 189-206.