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The National Dynamic Land Cover Dataset

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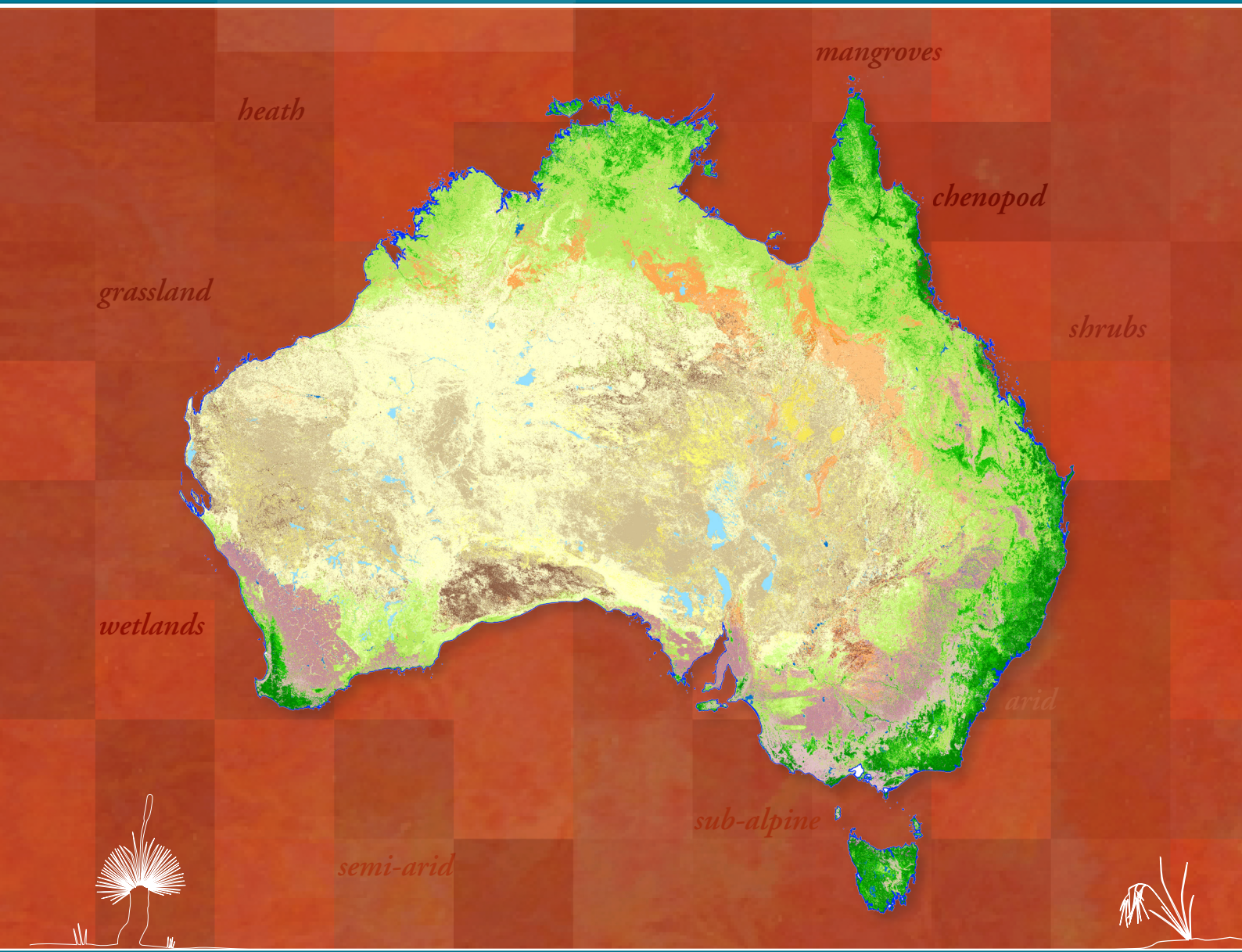

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Leo Lymburner[1], Peter Tan[1], Norman Mueller[1], Richard Thackway[2], Adam Lewis[1], Medhavy Thankappan[1], Lucy Randall[2], Anisul Islam[1] and Udaya Senarath[2].

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Contents

Contents . . . iii
Executive Summary . . . 1
- Introduction . . . 1
- Background . . . 1
- Method . . . 1
- Results . . . 2
- Accuracy assessment . . . 2
- Applications . . . 2
- Feedback and future development . . . 4

Background . . . 7
- Literature review . . . 8
- National coordination for land cover information . . . 9
- Australia's need for land cover information . . . 10
- The National Dynamic Land Cover Dataset initiative . . . 10

Method . . . 11
- Summary of methods . . . 11
- Input data . . . 11
  - Catchment Land Use Maps 2009 . . . 11
  - National Vegetation Information System . . . 11
  - Interim Biogeographic Regionalisation of Australia . . . 12
  - MOD13Q1 Enhanced Vegetation Index product . . . 12
- Pre-processing of the Enhanced Vegetation Index dataset . . . 12
  - Noise removal . . . 12
- Time series coefficients . . . 14
  - Mean . . . 14
  - Standard deviation . . . 14
  - Flatness . . . 14
  - Rate of rise . . . 15
  - Rate of drop . . . 15
  - Global minimum . . . 15
  - Average length of cycle . . . 16
  - Global maximum . . . 16
  - Ratio of the global maximum to the annual maximum . . . 16

Mean timing of the maximum . . . 16
Standard deviation in the timing of the maximum . . . 16
Annual minimum . . . 16
Trend in the annual maximum . . . 17
Trend in the annual minimum . . . 17
Trend in the annual mean . . . 17
Clustering . . . 18
Initial labelling procedure . . . 20
Product validation of DLCDv0 . . . 20
Label revision procedure . . . 24
Comparative assessment of DLCD . . . 25
Results . . . 27
The Dynamic Land Cover Dataset . . . 27
Comparison with independent field data . . . 28
Areas which are well characterised by the DLCD . . . 28
Interpreting the mismatch between the DLCD and the field survey data . . . 28
Thematic emphasis of the field survey data . . . 28
Semantic differences in labelling . . . 28
Land Cover classes which are poorly characterised by Enhanced Vegetation Index (EVI) . . . 28
Systematic class versus canopy continuum . . . 29
Scale and perspective of observation of the field survey data . . . 29
Relationship between the time series coefficients and land cover classes . . . 33
Intercomparison with other land cover and land use datasets . . . 37
Queensland Statewide Landcover And Tree Study (SLATS) Foliage Projective Cover . . . 37
Other National and regional land cover and land use datasets . . . 37
Trend data . . . 42
Interpreting the trend in the annual minimum . . . 43
Interpreting the trend in the annual maximum . . . 43
Interpreting the trend in the annual mean . . . 43
Discussion . . . 47
Assessing an area of interest . . . 47
Identifying unusual behaviour within a specific land cover type . . . 47
Case study 1: Crop dynamics in Western Australia . . . 47
Case study 2: Mangroves in north Queensland . . . 49
Case study 3: Changes in the alpine zone . . . 49
Trends in annual EVI values within the Victorian Alps IBRA sub-region . . . 51
Comparing the Victorian Alps and Snowy Mountains IBRA sub-regions . . . 52
Comparing the changes in the alpine IBRA sub-regions with the rest of Australia . . . 52
Case study 4: Gaining insight into the Mitchell Grass Bioregion . . . 53
Advantages and limitations of the National Dynamic Land Cover Dataset . . . 55
Advantages . . . 55
Consistency in space and time . . . 55
Limitations . . . 57
Thematic . . . 57
Training Data . . . 57

Spatial . . . 57
Green fraction only . . . 58
Single class representation of dynamic behaviour . . . 58
Future developments . . . 58
Crop module . . . 58
Conclusion . . . 61
Acknowledgements . . . 63
References . . . 65
Glossary . . . 67
Glossary for the purposes of ground cover field work . . . 67
Appendices . . . 69
Appendix 1: Detailed description of the relabelling process . . . 69
Error type 1:
Cluster has been incorrectly labelled . . . 70
Error type 2:
Cluster contains more than one land cover type within an Interim Biogeographic Regionalisation of Australia IBRA bioclimatic region . . . 72
Error type 3:
Cluster different land cover types in different Interim Biogeographic Regionalisation of Australia IBRA bioclimatic regions . . . 73
Error type 4:
Cluster contains a valid land cover type and terrain related noise . . . 74
Error type 5:
Cluster contains a land cover type that is poorly represented by Enhanced Vegetation Index (EVI) . 75
Appendix 2: CLUM09 classes . . . 76
Appendix 3: NVIS classes . . . 78
Appendix 4: Comparison of the DLCD with the SLATS FPC data . . . 79
Appendix 5: Comparison with independent spatial data . . . 80
Integrated Vegetation . . . 80
Major Vegetation Groups . . . 83
2005–06 Australian land use data . . . 86
GlobCover . . . 91
Victorian land cover . . . 94

Executive Summary

Introduction

Geoscience Australia and the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) have developed a Dynamic Land Cover Dataset (DLCD) for Australia. The DLCD will allow land managers and decision makers to move beyond snapshot land cover observations. The DLCD's relatively long term observations can be used to assess the land cover dynamics of forests, woodlands, rangelands and cropping systems.

This report describes the DLCD (Figure 1), how the dataset was generated, presents a comparison of the DLCD with independent datasets and examples of how the DLCD classification can be used to analyse trends in the Enhanced Vegetation Index (EVI) and other data sources. The report also compares the DLCD approach to other National and International land cover mapping approaches.

Background

In 2009 the National Committee for Land Use and Management Information identified the need for land cover information to facilitate change detection and improve natural resource management. Existing land cover datasets are composites of State and Territory datasets which have been developed to meet specific legislative needs. This leads to thematic mismatches between different datasets and limits the capacity for meaningful change detection. Nationally consistent and thematically comprehensive land cover information is essential to addressing a range of natural resource challenges. These include sustainable farming practices, management of water resources, air quality, soil erosion and forests, as well as emergency management and urban planning.

Method

The DLCD is based on an analysis of a 16-day EVI composite collected at 250 metre resolution using the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite for the period 2000 to 2008. Currently MODIS imagery is captured by the Aqua and Terra satellites in both the morning and the afternoon, making possible accurate and timely updates of DLCD products. The MODIS time series for each pixel was analysed using an innovative technique which reduced each time series into 12 coefficients based on the statistical, phenological and seasonal characteristics of each pixel. These coefficients were then clustered using a support vector clustering algorithm and the resultant classes were labelled using agreed National data supplied from catchment scale land use mapping and the National Vegetation Information System (NVIS).

The DLCD comprises a major new Australia-wide land cover dataset, poster and maps, a metadata record and supporting technical information. The map products and time series data from the DLCD have been developed with extensive stakeholder input and expert advice from Australian, State and Territory government agencies. Consultation included a National workshop in Alice Springs in late 2009 involving the CSIRO and other relevant agencies and selected universities.

'Nationally consistent and thematically comprehensive land cover information is essential to addressing a range of natural resource challenges.'

The time series data underlying the DLCD is an essential tool box for environmental management at National and regional scales, and can identify trends in vegetation greenness and land management practices.

For example, the DLCD time series data can be used to investigate relationships between vegetation dynamics and land use and management practices. It can be used also to monitor and report on the condition and trend of selected map based features such as the response of tussock grassland following the removal of grazing stock or to compare trends exhibited within regions which share similar vegetation types.

Results

The classification scheme used to describe land cover categories in the DLCD conforms to the 2007 International Standards Organisation (ISO) Land Cover Standard (19144–2), previously the Food and Agriculture Organisation Land Cover Classification (Di Gregorio and Jansen 2000). The DLCD shows Australian land covers clustered into 34 ISO classes. These reflect the structural character of vegetation, ranging from cultivated and managed land covers (crops and pastures) to natural land covers such as closed forest and sparse, open grasslands. Because the DLCD uses the ISO Land Cover Classification, it can be used to develop internationally consistent land cover reporting products, such as changes in land cover types over time for reporting on selected forest and vegetation types and themes, using nominated regions and jurisdictions.

Accuracy assessment

State land and vegetation management agencies provided more than 25 000 field validation sites to assess the accuracy of the DLCD. As land cover classes are not generally clear-cut, but merge gradually from one to the other, a fuzzy logic system (Zhang and Foody, 1998) was used to compare the 34 DLCD classes with the field data on a sliding scale. The classes of the sliding scale are:

- Exact match such as *trees open* versus *trees open*;
- Very similar such as *trees open* versus *trees scattered*;
- Moderately similar as in *trees open* versus *shrubs open*;
- Somewhat similar as in *trees open* versus *shrubs closed*;
- Complete mismatch as in *trees open* versus *irrigated graminoids*.

The match between the 25 817 field validation sites and the DLCD was exact in 30% of cases, very similar in 35% of cases, moderately similar in 10% of cases, somewhat similar in 18% of cases and completely mismatched in 7% of cases. These results show a high degree of consistency between the DLCD and extensive independent field based datasets.

Applications

The DLCD can be used as input into moderate to coarse scale models of:

- Groundwater recharge and discharge;
- Climate;
- Wind and water erosion risk;
- Evapotranspiration;
- Carbon dynamics;
- Land surface processes;
- Inundation.

The DLCD in combination with the trend in annual EVI data can provide insight into the response of land cover to a wide variety of drivers, both natural and anthropogenic. This provides natural resource managers with the capacity to identify emerging patterns of land cover change and provides a broad spatial and historical context within which to interpret that land cover change. This can be combined with ancillary information to assess what, if any, on-ground or policy interventions are required to mitigate the emerging behaviour.

The DLCD can be used as a framework also to analyse other coarse resolution datasets such as 500 metres fractional cover data (Guerschman et al. 2009) and one kilometre fraction of photosynthetically absorbed radiation data (Donohue et al. 2009) thereby providing further insight into land cover change processes.

Using the DLCD as a framework to interpret EVI and fractional cover provides decision makers with additional knowledge to inform target setting, address natural resource management priorities and monitor the outcome of interventions.

An important aspect of the DLCD method is that it is sensor independent and is transferable to other satellites and sensors. This provides a safety net when satellites become redundant or unavailable. A major benefit of this approach is that the method sets the scene for consistent long term environmental monitoring and evaluation, irrespective of the type of satellite or sensor.

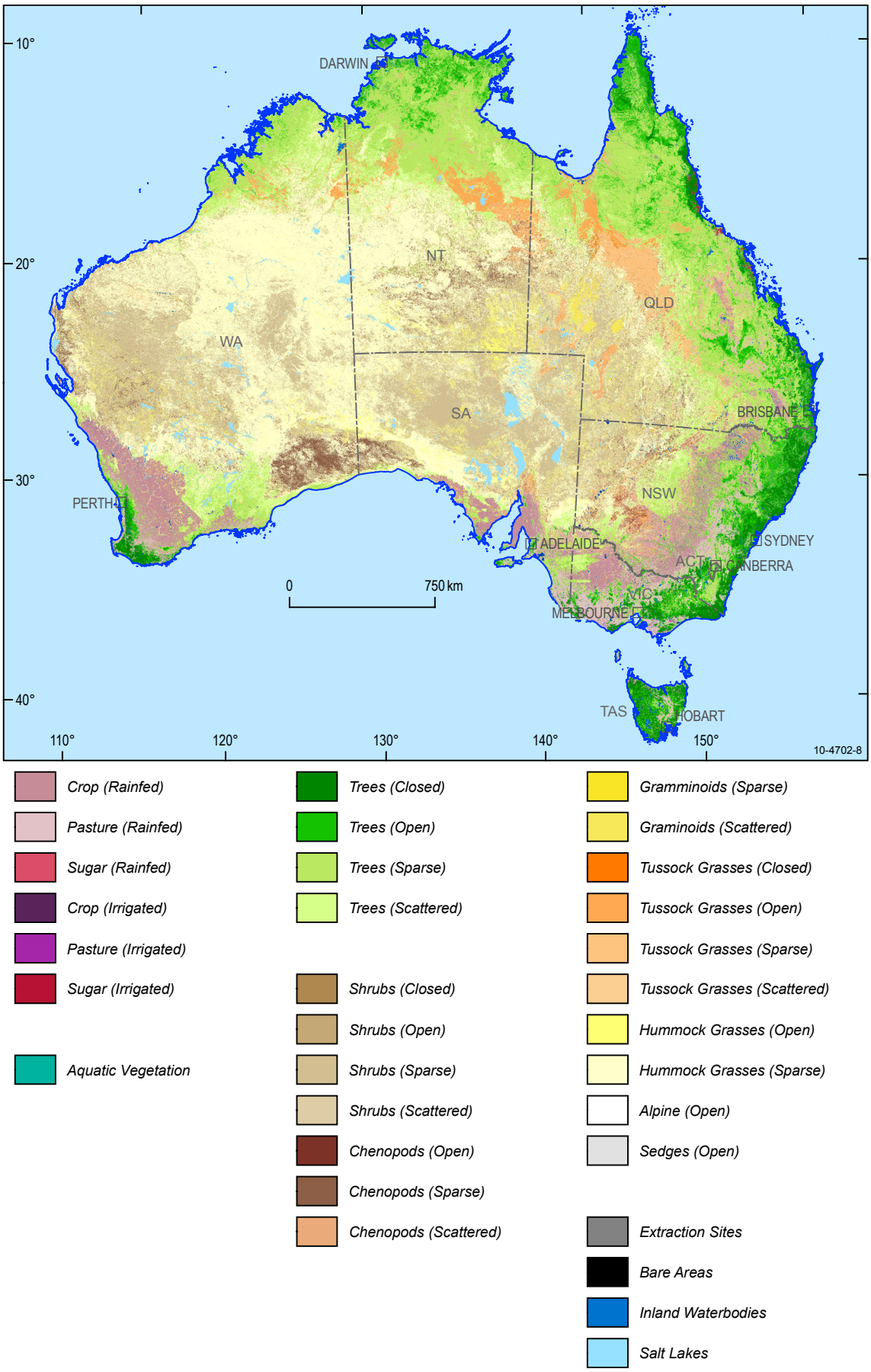

Figure 1: Map compiled from the National Dynamic Land Cover Dataset from 2000 – 2008.

Feedback and future development

If you would like to provide feedback on the DLCD, request a copy of the dataset or view the dataset in 3D please visit: www.ga.gov.au/landcover.

Feedback collected at this website will be used to guide the future development of the DLCD. It is anticipated that in the process of using this map users will identify areas of thematic inaccuracy. There is a form on the webpage for users to identify areas where the map is inaccurate so that these areas can be addressed in the DLCDv1.5. The subsequent DLCDv2 will be based on an annual time step (i.e. there will be a DLCD for each year from 2001 to 2010). This will enable users to analyse year-to-year land cover changes. Future versions may include increased detail about specific land cover types or an application of this method to 25 metre resolution data. The content of the DLCDv3 product suite and subsequent product suites will be determined in response to stakeholder consultation.

Table 1: International Standards Organisation class and equivalent common name conversion table for a subset of the land cover types.

Common Name	ISO descriptor
Closed Tussock Grassland	Tussock – closed
Open Tussock Grassland	Tussock – open
Sparse Tussock Grassland	Tussock – sparse
Very Sparse Tussock Grassland	Tussock – scattered
Open Hummock Grassland	Hummock – open
Sparse Hummock Grassland	Hummock – sparse
Very Sparse Grassland	Graminoids – scattered
Sparse Grassland	Graminoids – sparse
Open Sedgeland	Sedges – open
Dense Shrubland	Shrubs – closed
Open Shrubland	Shrubs – open
Sparse Shrubland	Shrubs – sparse
Very Sparse Shrubland	Shrubs – scattered
Open Saltbush Shrubland	Chenopods – open
Sparse Saltbush Shrubland	Chenopods – sparse
Very Sparse Saltbush Shrubland	Chenopods – sparse
Closed Forest	Trees – closed
Open Forest	Trees – open
Open Woodland	Trees – scattered
Woodland	Trees – sparse

Table 2: Glossary of International Standards Organisation terms.

DLCD Class	Description of equivalent or commonly used cover and vegetation classes
Alpine	Vegetated and rocky areas above the tree-line where the vegetation is covered by snow for several months each year. Includes native tussock grasses and forbs and scattered low shrubs.
Aquatic vegetation	Vegetated areas associated with wetlands, ponds and rivers includes trees, shrubs and grass-like growth forms.
Bare areas	Non-vegetated areas where vegetated cover is absent or could not be detected. Includes naturally bare areas and areas made bare as a result of land management practices.
Chenopods	Native shrubs in the family Amaranthaceae, formerly Chenopodiaceae. The dominant genera include Sclerolaena, Atriplex (salt bush), Maireana (blue bushes, cotton bush), Chenopodium and Rhagodia.
Cropping	Production of plant species usually managed as a monoculture for food and/or fibre. Native vegetation has largely been replaced by introduced species as a result of clearing and sowing new species, the application of fertilisers or the dominance of volunteer species. Dryland and irrigated cropping are defined. Includes production of annual and perennial species.
Forbs	Native and non-native herbaceous flowering plants which are not graminoids. Forbs represent a group of plant communities with broadly similar growth form (e.g. grasses, sedges and rushes). See gramminoids and sedges for further information.
Grassland	Other type of grassland not described by Hummock and Tussock grasslands (may be native or non-native).
Graminoids	Graminoids are native and non-native non-woody plants with narrow leaves growing from the base including the 'true grasses' of the Poaceae (or Gramineae) family, sedges (Cyperaceae) and rushes (Juncaceae). (see forbs).
Hummock	A coarse xeromorphic native grass which has a mound-like form and often is dead in the middle. The main genera are Triodia, Plectrachne and Zygochloa. Forms extensive areas either as the dominant growth form or in association with shrubs and trees.
Mining	A cover class where the vegetation usually is removed to extract the underlying minerals and rocks.
Pastures	Pasture and forage production, both annual and perennial, is based on a significant degree of modification or replacement of the native vegetation. Areas are cultivated or maintained for the production of food for animals, whether harvested or grazed directly. Dryland and irrigated are defined.
Sedges	Herbaceous species, usually perennial, with a tufted habit. Includes the plant families Cyperaceae (true sedges) and Restionaceae (node sedges). See forbs and gramminoids for further information.
Shrubs	Woody plants, multi-stemmed at the base (or within about 200 millimetres from ground level), or, if single-stemmed, less than about 5 metres tall. Not always readily distinguishable from small trees.
Sugar	A cultivated crop comprising tall perennial grass of the genus Saccharum (family Poaceae tribe Andropogoneae). Includes dryland and irrigated practices.
Trees	Native and non-native woody plants more than 2 metres tall usually with a single stem or branches well above the base. Not always distinguishable from large shrubs.
Tussock	Native grass communities and non-native species forming extensive areas dominated by a few species. Family Poaceae with a tufted habit. Tussock communities usually are dominated by particular genera such as Astrebla, Austrodanthonia, Austrostipa, Dicanthium, Eragrostis, Poa, Themeda, Sorghum, Heteropogon, Ophiuros, Oryza, Eragrostis and Spinifex.
Water	Land surface water features include rivers, lakes and ponds. Fresh and saline water bodies are defined. Includes permanent and intermittent water features.

Background

Land cover is the observed biophysical cover on the Earth's surface. This includes various combinations of native vegetation types, soil types, exposed rocks and water bodies as well as anthropogenic elements such as plantations, crop types and built environments. Complementary land information includes land use which involves the purpose to which land cover is committed and land management practices as well as the approach taken to achieve a land use outcome.

Dynamic land cover is a critical information need for National and regional reporting and decision making in Australia (National Land and Water Resources Audit 2007). Many agencies and research institutions collect and interpret a wide variety of land cover data. Increasingly, land cover data with annual or monthly updates is required at National, State and regional levels. with annual or monthly updates. A review of the information required for reporting on Australia-wide indicators identified the need for consistent National information to report on change and trends in the cover of vegetation, the cover extent and its condition against a baseline (Boland and Thackway 2008).

Investment in the development of land cover data and information is not coordinated and Australia lacks consistent and complete nationally agreed standards and protocols for land cover data. Atyeo and Thackway (2006) noted the benefits of the Food and Agriculture Organisation Land Cover Classification (Di Gregorio and Jansen 2000) as a means of translating and compiling existing land cover datasets. The lack of an agreed Australia-wide approach to mapping and monitoring land cover change severely limits the usefulness of available land cover data.

At the *international level* land cover products have been produced by a number of organisations and science communities, mostly based on coarse spatial resolution sensor data. International land cover products include the Advanced Very High Resolution Radiometer (AVHRR) Land Cover (Wilson and Henderson-Sellers 1985), MODIS International Geo-biosphere Program (Friedl et al., 2002), and Globcover (Bicheron et al., 2008). However, the benefits of these internationally produced datasets are limited because:

- Classification schemes and data specifications are driven by the global science community and are unlikely to meet Australian user needs at the National level;
- Ownership and continuity of these data into the future are unknown.

At the *National level* a coordinated land cover initiative was needed to identify common needs. Through improved data collection and interpretation this would improve data quality and quantity for the same expenditure, enabling Australia to align activities to international processes and protocols including International Standards Organisation (ISO) standards on land cover and land cover change. Dynamic land cover information is needed to:

- Evaluate the impact of investments and of resource condition monitoring for issues such as ground cover management, salinity, water, soils, native vegetation extent and types, inland aquatic and native species habitat;
- Report on changes in forest cover and the effect on carbon emissions through the National Carbon Accounting System Land Cover Change program;
- Inform legislated State of the Environment reporting on vegetation condition and extent, as well as the condition of land and soils and of biodiversity;
- Undertake water accounting required by the Bureau of Meterology (BoM) under the Water Act (2007).

At the *State and Territory level*, agencies also need dynamic land cover information for multiple purposes, in most cases, driven by policy or legislative requirements.

At the *regional level* organisations such as natural resource management groups and Catchment Management Authorities require dynamic land cover information, in particular ground cover data to identify areas requiring management action and to monitor the impact of their investment. Dynamic land cover information can help identify and monitor regional natural resource issues such as soil carbon, acidification, salinity, erosion risk, vegetation integrity and water management.

Literature review

This review includes literature describing the use of moderate to coarse spatial resolution, multi-spectral satellite image archives (e.g. MODIS, SPOT and Landsat) to deliver information on land cover types and their extent.

The primary objective of these projects is to identify land and ground cover types and their associated land use management systems (e.g. irrigated areas, land use types, deforestation and regrowth forest) and to discriminate between land cover types over time, or to better understand the dynamics which occurs within particular land cover types.

Hostert et al. (2003) used multi-temporal Landsat imagery to study ecological degradation processes in central Crete, Greece. The authors used spectral unmixing techniques together with the trend analysis to map fractional vegetation cover by analysing nine Landsat TM and four Landsat MSS images from 1977 to 1996. The results highlighted the benefits of using long-term time series datasets to successfully discriminate between vegetation cover types and landscape change over time.

Wesseles et al. (2004) used multi-temporal and single date MODIS image products to discriminate between different vegetation and land use classes and deforestation and regrowth forest. Two study areas were selected, in the Greater Yellowstone Ecosystem, USA and Para State, Brazil. In the USA study, three 250 metre 2-band MODIS images were used (1 August, 26 August and 1 October 2001), while the Brazilian study used a single day (6 August 2001) 500 metre 7-band MODIS image. The multi-temporal USA study facilitated the use of vegetation phenology to identify different vegetation and land use classes. The single image in the Brazil study could be used to identify and differentiate areas of deforestation only, but not regrowth.

Fernandes et al. (2004) used multi-temporal SPOT and Landsat image products to map land cover fractions and continuous fields of vegetation within a landscape mosaic in the Boreal Ecosystem Atmosphere Study (BOREAS) area of Canada. These workers used one kilometre resolution SPOT VEGETATION (fifteen 10-day composites spanning June to August 1999) imagery synthesised with a Landsat TM mosaic. The results showed good discrimination of continuous fields of vegetation within a landscape mosaic.

Xiao et al. (2005) used multi-temporal MODIS land imagery to map paddy rice in 13 provinces of southern China. Three indices were derived including Normalised Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) and Land Surface Water Index (LSWI). These indices were derived from 8-day, 500 metre resolution MODIS surface reflectance data in 2002. The MODIS based paddy rice map was assessed using the National Land Cover Map based on Landsat ETM+ data in 1999-2000 and showed a good agreement between two datasets.

Thenkabail et al. (2005) used multi-temporal MODIS land data among several methods to map irrigated areas in the Ganges and the Indus river basins, India. They used 500 metre resolution 8-day 7-band MODIS land data from 2001 to 2002. This study showed that the MODIS centred at 1240nm produced the most accurate identification of irrigated areas.

Sedano et al. (2005) used multi-temporal MODIS land data among several methods to describe and map agriculture, wetlands, grasslands, thicket, woodland and open forest in the Miombo area of Mozambique. The study used MODIS 500 metre resolution, 8-day, 7-band land data from April 2003 to April 2004. Results of the study showed that classification of the MODIS imagery provided an accurate discrimination between areas of agriculture, wetlands, grasslands, thicket and open forest, while the NDVI analysis was good for discriminating areas of dense forest.

Caccetta et al. (2007) used multi-temporal Landsat imagery to map and monitor the change in extent of Australia's woody perennial vegetation as part of implementing Australia's reporting procedures for

the Kyoto Protocol. Those authors used Landsat MSS, TM and ETM+ covering 15 time periods from 1972 to 2007 as the basis for identifying the presence or absence of perennial vegetation at 25 metre resolution. The results highlight the benefits of using time series archives to accurately map Australia's forest extent and change.

Powell, et al. (2007) used multi-temporal MODIS 500 metre resolution data (November 1 and December 26, 2000) to map 10 types of vegetated and non-vegetated desert landforms in North Africa. These researchers used an approach described as Multiple Endmember Spectral Mixture Analysis (MESMA) to resolve the issue of spatial and spectral variability in mixed pixels and to discriminate between different land cover classes. An assessment of the accuracy of this approach using the landform map of North Africa and Landsat TM data, showed classification accuracies of 54% and 70% respectively, but confusion between sand dunes and sand sheet remained unresolved (Ballantine et al, 2005). Additionally, the MESMA produced much better classification accuracy than the minimum distance and maximum likelihood classifications.

Carrao et al. (2008) used multi-temporal MODIS EVI data to differentiate land cover classes on the Portuguese mainland. They used MODIS 500 metre resolution, 8-day composites acquired during 2000. Their results show that EVI calculated in August provides the optimal month for accurately identifying land cover classes in Australia.

Gao and Mas (2008) compared two land cover classifications for mountainous areas in the central west of Mexico. One land cover classification was developed using a single MODIS 7- band, 500 metre resolution image collected on 8 March 2008, while the other land cover classification was derived from 69 multi-temporal MODIS EVI data collected from January 2001 to December 2003. The authors used an object based image analysis to compare the two land cover classifications. Results showed that MODIS EVI provided greater discrimination of land cover types and produced a more accurate land cover classification.

Guerschman et al. (2009) used multi-temporal MODIS image products to map fractional cover of photosynthetic vegetation, non-photosynthetic vegetation and bare soil in the Australian tropical savannahs. They used 500 metre resolution, 16-day MODIS nadir bi-directional reflectance distribution function adjusted reflectance time series data from 2000 to 2006 and EO-1 30 metre resolution Hyperion data acquired during the 2005 growing season. The data were subjected to linear unmixing based on NDVI and the Cellulose Absorption Index. An evaluation of the results in selected grassy ecosystems in eastern and southern Australia showed that the approach produced good agreement at six of the 10 validation sites.

While the analysis and classification of time series remotely sensed imagery is a relatively new area of research, a wide range of methods continue to be developed to characterise and monitor different land cover types at regional and Australia-wide scales. The general conclusion from this research is that multi-temporal image products are more accurate and informative than single image date products.

National coordination for land cover information

Coordination of land cover information is managed through the Australian Collaborative Land Use and Management Program (ACLUMP). This program promotes the development of nationally consistent information about land use, land cover and land management practices (ACLUMP 2009). ACLUMP is overseen by the National Committee on Land Use and Management Information (NCLUMI), which is a consortium of Australian and State government partners. ACLUMP is sponsored by the Australian Government Department of Agriculture, Fisheries and Forestry under Australia-wide natural resource information coordination arrangements. NCLUMI is the National sponsor for land cover information and has Australia-wide responsibility for technical developments and methods for the acquisition of land cover information (ACLUMP 2009).

ACLUMP promotes the development of a nationally coordinated approach to land cover mapping through participation in a National consortium comprising the *Auscover* initiative, which is led by CSIRO Marine and Atmospheric Research and includes Geoscience Australia through the Terrestrial Ecosystem Research Network. Benefits will include improved imagery resources, an integrated network of reference sites, greater efficiencies in mapping programs and a wider range of enhanced and better integrated land cover products.

The National Dynamic Land Cover Dataset initiative

In late 2007, Geoscience Australia started a project to demonstrate dynamic land cover mapping based on time series analysis of Earth observation data to meet the growing Australian Government need for robust, scientific, baseline environmental information.

Initial results from the Gwydir Catchment in northern New South Wales, which were reported in *AusGeo News* 91*, showed the value of this approach for mapping water body dynamics and for the analysis of agricultural areas to distinguish irrigated and rainfed crops, measure the duration of fallow periods and estimate the fractional cover of soil, vegetation and dry matter.

This approach required calibration and pre-processing of a time series of Landsat and MODIS data to a consistent standard.

As a result of the successful Gwydir Catchment pilot, Geoscience Australia formed a partnership with the Australian Bureau of Agricultural and Resource Economics and Sciences to publish the first Australia-wide DLCD, initially using only MODIS data.

The aim of the DLCD is to provide a nationally consistent dynamic land cover map of Australia based on time series analysis from 2000 to 2008.

Australia's need for land cover information

Prior to 2007 Australia did not have an Australia-wide, consistent and accurate land cover dataset. Land cover mapping for Australia was produced by international organisations and science communities. These products had limited use in Australia because:

- Classification schemes are unlikely to meet Australian requirements;
- The quality and reliability of these products is not generally sufficient for regional needs;
- Levels of classification detail used to describe and map land cover types are insufficient, particularly over populated regions;
- Future ownership and continuity of these data cannot be guaranteed.

The development of an Australia-wide land cover dataset provides the capacity to deliver consistent dynamic land cover information appropriate to needs and at a range of scales. This has been initiated through a partnership between Australia's key science based and land management agencies and is recognised by agencies as a National priority (ACLUMP 2009).

This will contribute to:

- Linking National, State and regional land cover data collation activities and the user community, removing current duplication of effort;
- Identifying National capacity to provide multi-scale, multi-temporal land cover and biophysical data and information products with accuracy and reliability suitable for a wide range of common National, State, regional and local information needs;
- Enhancing efficiency in the development of related land data products changes in land use, land management and vegetation (extent, type and condition) at appropriate scales to inform decision making;
- Providing whole-of-government data coordination arrangements and protocols building on existing land cover land use and land management practices and data collation processes;
- Supporting modelling, monitoring and reporting for National processes such as State of Environment reporting, the National Water Security Plan, and major National policy initiatives in resource management, climate change and emergency management.

* http://www.ga.gov.au/ausgeonews/ausgeonews200812/

Method

Summary of methods

Geoscience Australia and Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) carried out land cover mapping for continental Australia using 250 metre resolution MODIS Enhanced Vegetation Index (EVI) data from 2000 to 2008, consisting of 186 layers of 16-day EVI composites. Every pixel is represented by a time series made up of 186 observations.

Each EVI time series was characterised using a robust suite of statistical, phenological and seasonal factors.

- Statistical
  - Average annual mean
  - Average annual maximum
  - Average annual minimum
  - Average annual standard deviation
  - Global minimum
  - Ratio of the average annual maximum to the Global maximum
- Phenological
  - Average annual rate of rise
  - Average annual rate of drop
  - Flatness
- Seasonal
  - Timing of peak EVI value
  - Standard deviation in the timing of the peak
  - Length of the growing cycle

These factors are referred to as *time series coefficients*. These coefficients were then clustered into groups of pixels and labelled as land cover units. Initially, the clusters were labelled using the National Vegetation Information System dataset and the Catchment Land Use Maps of Australia 2009 (CLUM09) dataset. These initial labels were reviewed and refined at a National workshop in Alice Springs. The labels were refined also by comparing the cluster labels with the information contained in the Fraction of absorbed Photosynthetically Active Radiation (FPAR) dataset (Donohue et. al., 2008) and the Foliage Projective Cover (FPC) dataset produced by the Queensland Statewide Landcover and Trees Study (SLATS) team from the Queensland Department of Environment and Resource Management. They were refined by stratifying the Dynamic Land Cover Dataset (DLCD) using the Interim Biogeographic Regionalisation of Australia (IBRA) dataset. Appendix 1 describes the re-labeling process. Once this refinement process was completed, the DLCD was compared with field datasets provided by State and Territory agencies to allow an overall accuracy assessment.

Input data

Catchment Land Use Maps 2009

The Catchment Land Use Maps 2009 (CLUM09) dataset describes Australia according to the way the land is used, rather than by its cover. The land use data is compiled at a catchment scale from State cadastre, public land databases, fine scale satellite imagery, other land cover and land use data and field data (Bureau of Rural Sciences 2009). The table of land use data values applied in the DLCD analysis is shown in Appendix 2.

National Vegetation Information System

The National Vegetation Information System (NVIS) is a dataset describing the nature and distribution of native vegetation in Australia. NVIS was created from State and Territory data and does not completely cover Australia, with large areas remaining blank. The information contained in the NVIS describes vegetation in terms of its structure and density. The table of NVIS values used in the DLCD analysis is shown in Appendix 3.

Interim Biogeographic Regionalisation of Australia

The Interim Biogeographic Regionalisation of Australia (IBRA) is a dataset dividing Australia into geographically distinct areas with common characteristics such as geology, landform pattern, climate, ecological features and plant and animal communities (Department of Environment, Water, Heritage and the Arts 2009). IBRA contains 85 bioregions and 403 sub-regions, and is used to underpin Australia-wide reporting and protection of native ecosystems.

MOD13Q1 Enhanced Vegetation Index product

NASA makes available a product series derived from the MODIS sensors aboard the TERRA and AQUA satellites. A comprehensive list of these data products can be found at: http://lpdaac.usgs.gov/modis/dataproducts.asp

One of these products is MOD13Q1 which contains both the EVI and the Normalised Difference Vegetation Index (NDVI). The MOD13Q1 product composites 16 sequential days of TERRA MODIS satellite data into a single image. The EVI is a standard product created from the composite data using the following band ratio of 250 metre and 500 metre spatial resolution bands:

$$EVI = G \times \frac{(B2 - B1)}{(B2 + C1 \times B1 - C2 \times B3 + L)}$$

Where

G = gain factor = 2.5
B2 = MODIS 250m band 2: near infra-red
B1 = MODIS 250m band 1: visible red
B3 = MODIS 500m band 3: visible blue
C1 = aerosol resistance term = 6
C2 = aerosol resistance term = 7.5
L = canopy background adjustment = 1

The advantage of EVI over other vegetation indices is that it includes adjustment factors for atmospheric effects and, in the MOD13Q1 product, the 16-day composition process provides a cloud free product. The DLCD uses eight years of EVI data from April 2000 to April 2008. The data were downloaded from the Land Processes Distributed Active Archive Center located at the United States Geological Survey Earth Resources Observation and Science Center: http://LPDAAC.usgs.gov

The EVI data were then formed into a mosaic and remapped using the MODIS Reprojection Tool (MRT) as described in Paget and King (2008).

Pre-processing of the Enhanced Vegetation Index dataset

The dataset was pre-processed by arranging the data in a time series, noise removal and production of time series coefficients. The pre-processing workflow is shown in Figure 4.

Noise removal

After the data had been formed into a mosaic, a preliminary investigation revealed noise within the data. The noise takes the form of large spikes or dips as seen in 2001 in Figure 2.

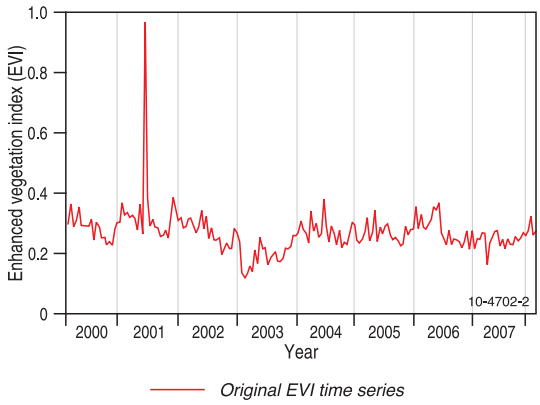

Figure 2: EVI time series for an open forest in the southeast of Australia.

'The advantage of EVI over other vegetation indices is that it includes adjustment factors for atmospheric effects, and in the MOD13Q1 product, the 16 day composition process provides a cloud-free product.'

Spikes and sharp dips in the data have a large impact on many of the time series coefficients and it was necessary to remove these artefacts before further processing took place. The noise removal process is in two stages. In the first step, time series data pass through a spectral filter which removes data points with abnormal values. Such points are defined as points which satisfy both the following conditions:

1. Have a very high or very low value ($\frac{x-\mu}{\sigma} > 2.1$ or $\frac{x-\mu}{\sigma} < -2.1$), where x is the time series value, u is the mean of the time series and σ is the standard deviation of the time series.
2. In the middle of a sudden rise (rate of rise above 95th percentile) and a sudden drop (rate of rise below 5th percentile) or vice versa in the time series.

After the first step, most of the noisy data points are filtered out. However, consecutive noisy data points presented in some time series could not be detected by the spectral filter. Studies (Green et al. 1988) have found that the distribution of noise in remote sensing imagery displays strong local patterns. Hence, a spatial filter is designed to detect noisy elements missed by the spectral filter. The spatial filter detect points satisfying one of following conditions:

1. A large amount of noisy points (>75%) present among the neighbours.
2. Have exceptional high (or low) values ($\frac{x-\mu}{\sigma} > 3.97$) compared to those of neighbours.

The values of thresholds are based on experimental results on training samples provided by remote sensing scientists.

A comparison of the sample time series showing the effect of the noise removal is shown in Figure 3.

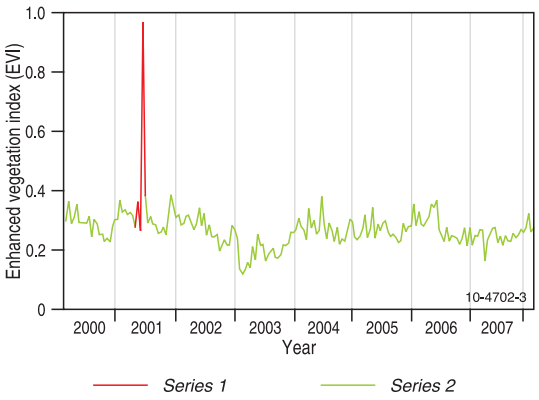

Figure 3: The same EVI time series as shown in the previous figure, with noise removed. Note that new data points have not been interpolated, rather the noisy points have simply been removed from the time series.

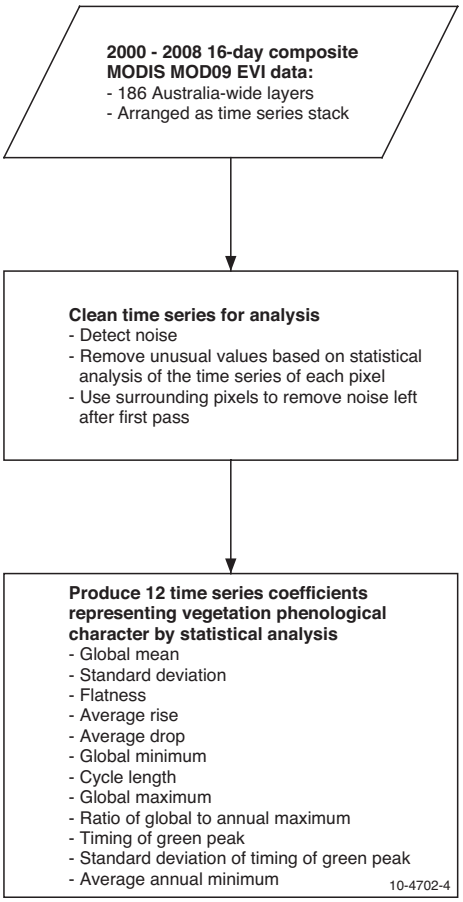

Figure 4: Process flow for pre-processing and production of the time series coefficients.

Time series coefficients

The composite layers were stacked into a time series and a noise filter applied before being statistically analysed to derive a set of 12 time series coefficients which are relatable (Tan et al., 2009) to phenomena such as average greenness, character of the green flush and bare soil duration.

Mean

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Defined as the statistical mean of the time series, where x_i are the values of time series and N is the size of the time series. The mean measures the average level of the time series signals over the long term.

Standard deviation

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i-\mu)^2}{N-1}}$$

It is defined as the statistical standard deviation of the time series. It measures the standard deviation of the time series signals over the long term.

Flatness

Step 1: Sort the time series in ascending order such that $x_i \leq x_j, \forall i < j$

Step 2: Conduct a one-dimensional nearest neighbour clustering on the sorted time series, i.e., find the index C to separate two clusters, such that

$$\arg\min_{C}\left(\sum_{i=1}^{C}(x_i-\mu_1)^2 + \sum_{i=C+1}^{N}(x_i-\mu_2)^2\right),$$

$$\text{where } \mu_1 = \frac{1}{C}\sum_{i=1}^{C} x_i \text{ and } \mu_2 = \frac{1}{N-C}\sum_{i=C+1}^{N} x_i$$

Step 3: Define the threshold $\delta = u_1 - k\,\sigma_1$ where

$$\mu_1 = \frac{1}{C}\sum_{i=1}^{C} x_i\ ,\ \sigma_1 = \sqrt{\frac{\sum_{i=1}^{C}(x_i-\mu_1)^2}{C-1}}$$

and k is a pre-defined constant. The value of k is determined by calculating the flatness of a set of randomly sampled time series from the map with varying values of k. The optimal value of k is the one leading to the maximum of the variance of returned flatness.

Step 4: Find the set of sub-time series $\{S_i\}$ satisfying

$$|S_i| > L_m \text{ and } x > \delta, \forall\ x \in S_i$$

Where L_m is a pre-defined minimum length, which prevents the algorithm from counting random noisy points as time series segments. In this project, the value of L_m is set to four which corresponds to the minimum growth cycle of two months.

Step 5: Calculate the coefficients defined as the ratio of the sum of the lengths of such sub-series against the length of the whole time series

$$\text{Flatness} = \frac{1}{N}\sum |S_i|$$

Rate of rise

Step 1: Define a set of sub time series

$$S = \{S_1, S_2, \ldots, S_M \mid |S_i| \in [L_{min}, L_{max}], i \in [1, M]\}$$

where Lmin and Lmax are the minimum and the maximum of the length of a growth cycle.

Step 2: Calculate the rate of change r_i for S_i. Let $L_i = |S_i|$, x_b and x_e are the first and the last elements in the sub time series respectively, then

$$r_i = e^{\frac{1}{L_i} \log \frac{x_e}{x_b}} - 1$$

Step 3: Find the non-overlapping subset $P \subset S$ with the maximum sum of r_i

$$\arg\max_P \sum_{r_i \in P} r_i \,\Big|\, x \neq y, \text{ given } x \in P_i \text{ , } y \in P_j \;\forall\, i, j$$

Step 4: Calculate the coefficient by averaging the rate of change r_i in set P

$$\text{Rise} = \frac{1}{|P|} \sum_{r_i \in P} r_i$$

Rate of drop

The procedure to calculate the coefficient rate of drop is similar to the procedure described in the above section. However, this time we are interested in the low end of the distribution of r_i.

Step 1: Define a set of sub time series

$$S = \{S_1, S_2, \ldots, S_M \mid |S_i| \in [L_{min}, L_{max}], i \in [1, M]\}$$

Step 2: Calculate the rate of change r_i for S_i. Let $L_i = |S_i|$, x_b and x_e are the first and the last elements in the sub time series respectably, then

$$r_i = e^{\frac{1}{L_i} \log \frac{x_e}{x_b}} - 1$$

Step 3: Find the non-overlapping subset $P \subset S$ with the minimum sum of (negative) r_i

$$\arg\min_P \sum_{r_i \in P} r_i \,\Big|\, x \neq y, \text{ given } x \in P_i \text{ , } y \in P_j \forall\, i, j$$

Step 4: Calculate the coefficient by averaging the rate of change r_i in set P

$$\text{Drop} = \frac{1}{|P|} \sum_{r_i \in P} r_i$$

Global minimum

Step 1: Sort the time series in ascending order so that $x_i \leq x_j, \forall i < j$

Step 2: Calculate the coefficient by averaging the first M elements of the sorted time series. M is a pre-defined constant (in our implementation, M takes the value of the number of calendar years in the time series)

$$\text{GMin} = \frac{1}{M} \sum_{i=1}^{M} x_i$$

Average length of cycle

Step 1: Define a set of sub time series

$$S = \{S_1, S_2, \ldots, S_M \mid |S_i| \in [L_{min}, L_{max}], i \in [1, M]\}$$

that satisfy the following conditions

$$x_m > \mu + \sigma, x_b < \delta \text{ and } x_e < \delta, \ \forall S_i$$

where x_m is the maximum, x_b is the first and x_e is the last element in sub time series S_i. δ is the threshold obtained from Step 3 for calculating Flatness.

Step 2: Calculate the coefficient by averaging the length of the sub time series S_i in the set P

$$\text{Cycle} = \frac{1}{|P|} \sum_{S_i \in P} |S_i|$$

Global maximum

Step 1: Sort the time series in ascending order so that $x_i \leq x_j, \forall i < j$

Step 2: Calculate the coefficient by averaging the last M elements of the sorted time series, M is a pre-defined constant (in our implementation, M is the value of the number of calendar years in the time series)

$$\text{GMax} = \frac{1}{M} \sum_{i=1}^{M} x_i$$

Ratio of the global maximum to the annual maximum

The annual maximum is calculated as the mean of the maximum in each calendar year of the time series. Then the coefficient is the ratio of annual maximum against the Global maximum.

Mean timing of the maximum

Assuming that time series is observed in a regular base, calculate the coefficient by averaging the timing (index) of the maximum element in each calendar year of the time series.

Standard deviation in the timing of the maximum

Assuming that time series is derived from regular observations, calculate the coefficient as the standard deviation of the timing (index) of the maximum element in each calendar year of the time series.

Annual minimum

The annual minimum is calculated as the mean of the minimum in each calendar year of the time series.

Trend in the annual maximum

Step 1: Divide the time series into a sequence of segments, each of which consists of 23 points.

Step 2: Select and keep three points with maximum values in each segment, filtering out the rest of points.

Step 3: Starting from Step 1, assign index numbers to the selected points following the order of the time line.

Step 4: Perform standard maximum likelihood linear regression on the selected points in form $y = cx + b$, where x is the index number and y is the value of EVI (or other time series coefficient).

Step 5: Return the slope of the line 'c' as the value of the trend.

Trend in the annual minimum

Step 1: Divide the time series into a sequence of segments each of which consists of 23 points.

Step 2: Select and keep three points with minimum values in each segment, filtering out the rest of points.

Step 3: Starting from Step 1, assign index numbers to the selected points following the order of the time line.

Step 4: Perform standard maximum likelihood linear regression on the selected points in form $y = cx + b$, where x is the index number and y is the value of EVI (or other time series coefficient).

Step 5: Return the slope of the line 'c' as the value of the trend.

Trend in the annual mean

Step 1: Perform standard maximum likelihood linear regression on annual means in the time series using the form of $y = cx + b$, where x is the time index number and y is the value of the mean of EVI (or other time series coefficient).

Step 2: Return the slope of the line 'c' as the value of the trend.

Clustering

Clustering is used to classify and summarise major patterns in complex datasets. The Support Vector Clustering (SVC) algorithm (Hur and Horn 2002; Yilmaz and Achenie 2007) constructs clusters in which boundaries are defined by a subset of data points. The input data are mapped into a much higher dimensional space using a Gaussian kernel. In the mapped feature space, quadratic programs similar to those used in the SVC algorithm are used to find the smallest sphere to enclose the mapped data image. Data points sitting on the sphere are regarded as support vectors, while the data points outside the sphere are regarded as outliers. The sphere is then mapped back to the original input space, where boundaries of clusters are formed by the support vectors.

In this way, the SVC algorithm implicitly performs density estimation (in the input space) through a single class training process. Compared to conventional clustering algorithms, it has several advantages (Xu and Wunsch 2005) such as being capable of handling arbitrary cluster shapes, having the ability to detect outliers and being insensitive to starting conditions.

However, the running time of the SVC algorithm grows exponentially with the size of the input dataset. It is therefore not feasible to apply the SVC algorithm on the whole dataset. A SVC algorithm operating on spectral subspaces has been proposed to resolve this issue, dividing the spectral space of the input data into a set of overlapping hyper-rectangles. The SVC algorithm is then applied to the data points within each hyper-rectangle independently. Finally, relationships between clusters generated in these hyper-rectangles are determined by evaluating cluster information in the overlapping regions (Tan et al., 2009).

The SVC was applied using the following time series coefficients as input data to generate the first iteration classification of 300 clusters:

- Global mean (mean EVI value for each pixel for the whole time series);
- Standard deviation (standard deviation for each pixel for the whole time series);
- Flatness of the time series (proportion of continuous sub-time series whose values are below a threshold).

The clustering workflow is shown in Figure 5. These three time series coefficients were chosen for a number of reasons. They have a low degree of cross correlation which means they provide good discrimination between classes. They also provide a robust measure of time series behaviour irrespective of whether the land cover shows a consistent annual cycle (as in tropical savannah) or responds to infrequent episodic events (as in desert areas). The mean was chosen because it provides an indication of nett primary productivity. The standard deviation was chosen because it characterises the proportion of rain green versus evergreen vegetation. The flatness of the time series was chosen because it provides a means of characterising periods of near zero photosynthetic activity, thereby capturing fallow periods in cropping regions and periods of low growth in the desert regions.

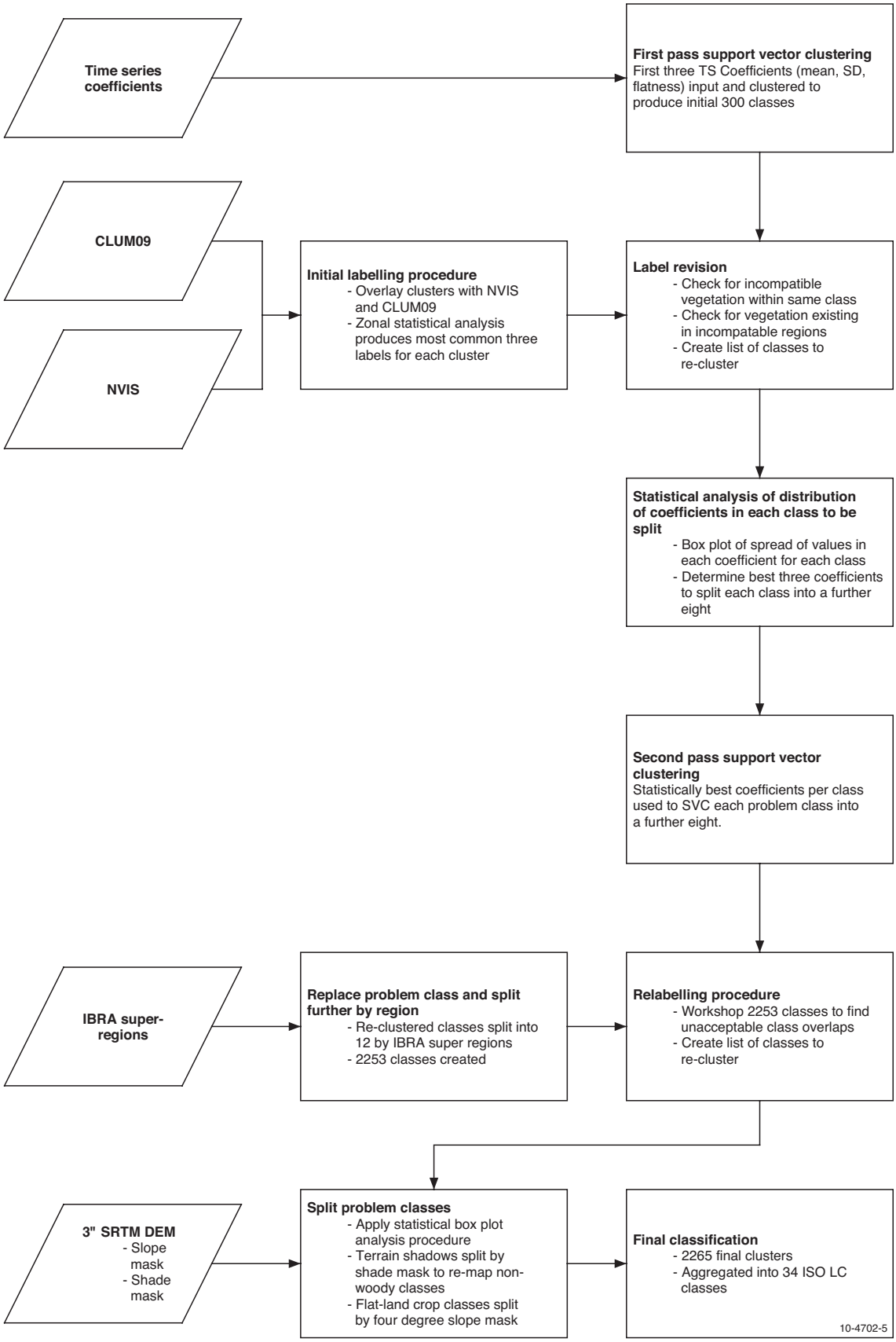

Figure 5: Flow chart of the classification procedure including the labelling, 'feedback' loop and revision.

Initial labelling procedure

The initial clusters were labelled using datasets from the NVIS and the CLUM09 datasets as supplied by ABARES. These datasets were used because of their Australia-wide coverage. However, each dataset focuses on specific thematic areas of interest and includes classes which are incompatible with a land cover classification. DLCD is based on EVI dynamics and therefore is unable to identify land uses which do not have a direct influence on greenness dynamics. Land uses such as defence, communication or Indigenous use will not be detectable because they have no one-to-one relationship with land cover and thereby greenness dynamics. Conversely, cropping regimes have a direct spatial and/or temporal impact on the land cover dynamics and thereby the greenness dynamics. It is the dynamic EVI signature generated by cropping which allows its identification. A breakdown of the International Standards Organisation land cover classes and the datasets used to sort clusters into those classes in the first round of labelling is provided in Table 3.

An automated basis for labelling was created by overlaying the classification with CLUM09 and NVIS datasets. Because each layer has a different spatial resolution and originally was a different projection, the datasets do not match perfectly, leading to up to a two pixel location error (up to 500 metres). Re-projection and re-sampling was done to bring all datasets to the same extent, pixel size and projection as a 50 metre pixel version of the DLCD. To avoid errors associated with re-sampling classifications this was done solely on a pixel split basis, with all layers split down to 50 metre resolution to ensure a 1:1 comparison without the need for aggregation. In the next step a statistical majority method was used to compare each class with CLUM09 and NVIS on a per-pixel basis. The resulting output tables relate each class to the three most common labels derived from each reference dataset and the percentage coverage corresponding to each label. As a result each class can be assessed as to whether it is mostly one label or several and whether the label is applicable in a land cover sense. The most common applicable label was assigned to the classification in a raster attribute table to produce a labelled dataset for discussion and revision by expert stakeholders. The labelling procedure workflow is shown in Figure 6.

The NVIS dataset uses the Specht vegetation structural classification system. The canopy cover thresholds defined in this classification system are:

- Closed (Greater than 70% canopy cover)
- Open (Between 30% and 70% canopy cover)
- Sparse (Between 10% and 30% canopy cover)
- Scattered (Less than 10% canopy cover)

These canopy cover thresholds have been used in the DLCD because they were defined in the primary training data, and they are consistent with the canopy cover guidelines defined in the ISO LC classification (Di Gregorio and Jansen (2000).

Product validation of DLCDv0

Validation of the DLCDv0 products involved State and Territory government agencies and research institutions. The aim of this validation was to obtain direct feedback from science and policy perspectives and from researchers and potential users of the products.

The developers of the DLCD also consulted a range of decision makers to ascertain whether the products (including maps, posters and time series) were useful. For example, did they provide insights about vegetation dynamics, and interactions between vegetation dynamics and land management practices? Did the Australia-wide map product provide additional or better information than existing land cover maps? The developers also assessed what additional data and information products were needed and what would be the best way to provide users with easily accessible products to meet their requirements (e.g. websites, DVDs, posters, databases, spreadsheets).

Table 4 presents a summary of the validation processes which were used to obtain feedback on DLCDv0 prior to revising the data and information products to construct DLCD.

Table 3: International Standards Organisation Land Cover Classes used in the National Dynamic Land Cover Dataset and the data source used to label the clusters during the first labelling procedure.

ISO LC Class	Label Source
Primarily Non-Vegetated Artificial Surfaces and Associated Areas Non Built-Up Extraction Sites	CLUM09
Primarily Non-Vegetated Bare Areas	CLUM09
Primarily Non-Vegetated Waterbodies Water	CLUM09
Primarily Non-Vegetated Waterbodies Water Brine	CLUM09
Primarily Vegetated Cultivated and Managed Lands Herbaceous Graminoids Irrigated	CLUM09
Primarily Vegetated Cultivated and Managed Lands Herbaceous Graminoids Irrigated Pasture	CLUM09
Primarily Vegetated Cultivated and Managed Lands Herbaceous Graminoids Irrigated Sugar	CLUM09
Primarily Vegetated Cultivated and Managed Lands Herbaceous Graminoids Rainfed	CLUM09
Primarily Vegetated Cultivated and Managed Lands Herbaceous Graminoids Rainfed Pasture	CLUM09
Primarily Vegetated Cultivated and Managed Lands Herbaceous Graminoids Rainfed Sugar	CLUM09
Primarily Vegetated Natural and Semi-Natural Aquatic Vegetation	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Forbs Open	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Forbs Sparse	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Closed Tussock Grasses	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Open Alpine	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Open Hummock Grasses	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Open Sedges	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Open Tussock Grasses	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Scattered	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Scattered Tussock Grasses	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Sparse	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Sparse Hummock Grasses	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Herbaceous Graminoids Sparse Tussock Grasses	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Shrubs Closed	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Shrubs Open	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Shrubs Open Chenopods	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Shrubs Scattered	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Shrubs Scattered Chenopods	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Shrubs Sparse	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Shrubs Sparse Chenopods	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Trees Closed	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Trees Open	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Trees Scattered	NVIS
Primarily Vegetated Natural and Semi-Natural Terrestrial Vegetation Woody Trees Sparse	NVIS

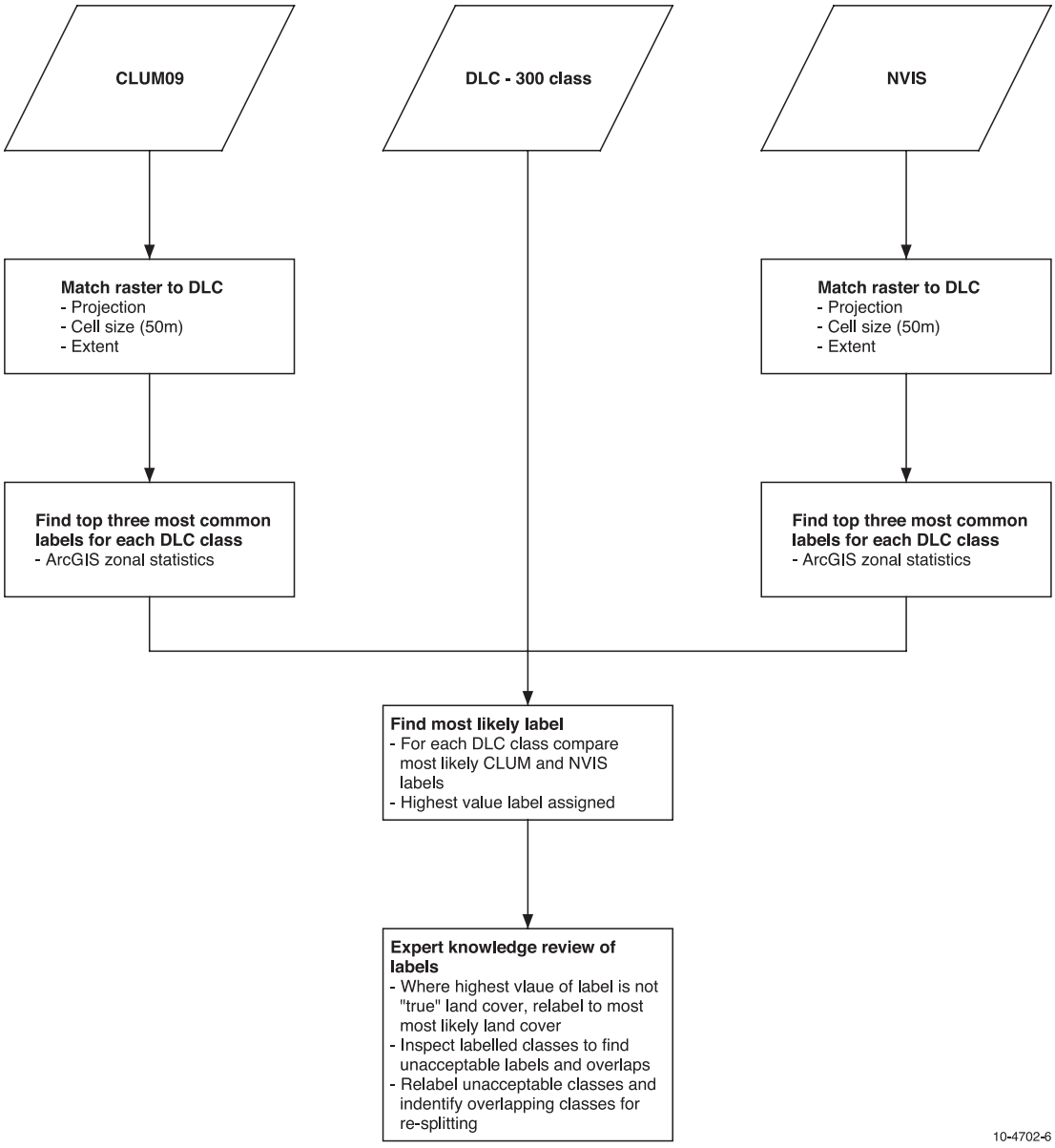

Figure 6: Flowchart describing the labelling procedure and labelling revision.

Table 4: Summary of review mechanisms applied to the DLCDv0.

Description forum/ meeting and title	Type of forum/ meeting	Stakeholder groups represented	Purpose/s	Date	Output
National workshop 'Dynamic land cover mapping' held at Alice Springs.	National technical workshop	Representatives from National and State researchers including government and academic institutions	Structured forum for land cover scientists to review and analyse the data and information available in the DLCDv0	7–9 Sept 2009	A record of the workshop provided to all participants and published on the Bureau of Rural Sciences GovDex land cover website
Teleconference and questionnaire with representatives state and Territory agencies	Teleconference	State and Territory land cover scientists involved in mapping and monitoring of land cover	Structured forum and questionnaire for State and Territory land cover scientists to provide feedback for their jurisdiction	One hour interviews Oct–Nov 2009	Completed questionnaire for each State and Territory
Seminar on 'Insights into the management of natural resources using dynamic land cover' held in Canberra	ABARES seminar series	Australian Government Departments of Environment and Agriculture, Fisheries and Forestry	Provide an overview of the DLCD and its relevance to design and implementation of national policies and programs on land management and monitoring	18 Sept 2009	Seminar loaded onto the ABARES website
Presentations given to SSSI Conference held in Adelaide	International conference Surveying and Spatial Sciences Institute	Representatives from national and state researchers including government and academic institutions	Present underlying methodologies of the DLCD	28 Sept–2 Oct 2009	Abstract in conference papers
Presentations to the Native Vegetation Workshop, held in Hobart	National workshop of Landscape Logic Commonwealth Envionmental Research Facility Hub	State and Territory land cover scientists involved in mapping and monitoring of land cover	Review underlying methodologies and initial results of the DLCD	June 2010	Informal records of meetings
International Society for Photogrammetry and Remote Sensing Workshop	International workshop	International science community	Provide an overview of the DLCD approach and it's capacity to characterise crops	17–18 December 2009	Conference paper
15th Australasian Remote Sensing and Photogrammetry Conference	International workshop	International science community	Provide an overview of the DLCD	13–17 September 2010	Conference paper
34th International Symposium for Remote Sensing of the Environment	International Conference	International science community	Provide an overview of the DLCD	10–15 April 2011	Abstract in Conference Proceedings

Label revision procedure

The results of the initial labelling procedure were assessed by:

- Review by a panel of peers (Alice Springs workshop);
- Comparison with other remotely sensed datasets, including CSIRO Land and Water's Fraction of absorbed Photosynthetically Active Radiation (FPAR) data and the Queensland Statewide Landcover and Trees Study (SLATS) teams FPC data;
- Comparison with the 2007 Landsat 7 mosaic based on visual interpretation;
- Comparison with Google Earth™ based on visual interpretation.

All the clusters which were identified as being wrongly labelled were visually assessed and compared to high resolution imagery. Five different types of mismatch were identified (Table 5). A detailed description of the relabelling techniques is contained in Appendix 1.

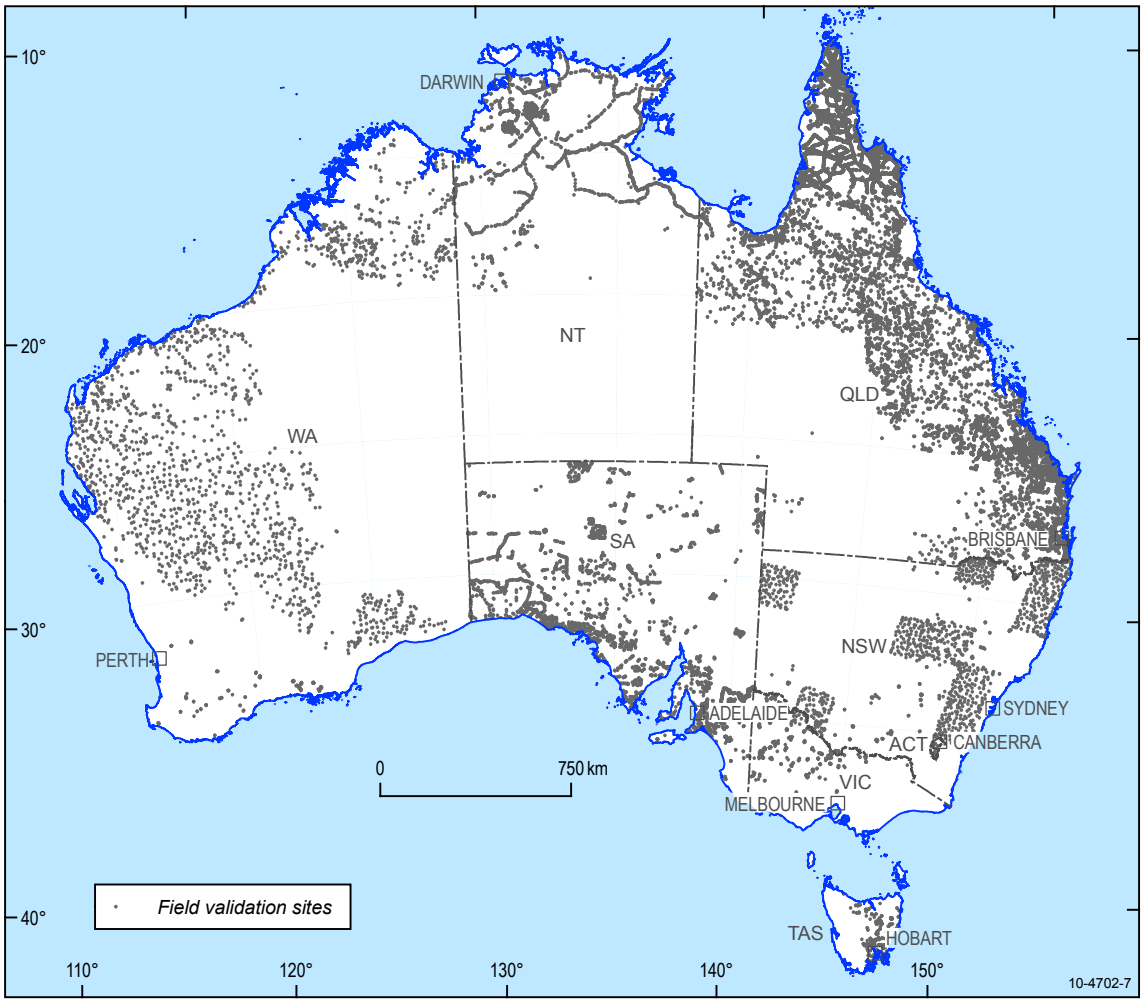

Figure 7: Spatial distribution of field validation sites.

Comparative assessment of DLCD

After each of the five error types had been addressed DLCDv0 was renamed DLCD to denote the completion of the review process. DLCD was then evaluated by comparing it with 25 817 field survey data points captured between 1999 and 2009. Table 6 shows the source data for the field survey data points. The spatial distribution of these points is shown in Figure 7. The field data were provided by agencies from every State and Territory with additional survey information provided by the ABARES.

Because each field survey dataset has its own labelling conventions, a fuzzy logic style comparison system was adopted based on the methods described in Lowry et al. (2007). The approach employs a relative similarity score to compare situations in which the classes are not mutually exclusive and large overlaps may occur, an intrinsic element of land cover. However, when comparing the DLCD to each of the field datasets there are many instances in which there is no direct one-to-one match between the DLCD class and the classification schema used by the field survey team. Given the diversity of classification schemas used by different field survey teams and the large number of classes (>70) in some schema, the DLCD comparative assessment describes the Users Accuracy only rather than Producers Accuracy (Congalton and Green 1999).

Table 5: Mismatch types identified during the review of the initial classification.

Error Type	Procedure
Cluster has been labelled incorrectly	Relabel class
Cluster contains more than one land cover type within an IBRA bioclimatic region	Split class using different TS coefficients and then relabel
Cluster represents different land cover types in different regions	Split class based on the IBRA bioclimatic regions
Cluster contains a valid land cover type and terrain related noise	Apply terrain mask
Cluster contains a land cover type that is poorly represented by EVI	Apply ancillary data mask

To account for diversity of classification schemas used by the field survey teams and to account for the semantic differences between the class names used by the survey teams and the ISO land cover classification (such as the classification used by the DLCD), the fuzzy approach described in Lowry et al. (2007) was modified to allow classes to be labelled as semantically identical between the DLCD and a compared dataset. A relative similarity score matrix was created (see Table 8) for each comparison. This graded the similarity from a value of one (no similarity) to five (exact match) as shown in Table 7.

For example, the Western Australian field survey data contains points classified as Gascoyne bluebush. The Western Australian flora database, FloraBase (http://florabase.dec.wa.gov.au/), identifies Gascoyne bluebush as a chenopod, making it semantically identical to the chenopod classes contained within the DLCD. However, because the structure (open or sparse) is not

Table 6: List of validation datasets used to assess the accuracy of the DLCD.

Data Source	Classification Type	Number of Points
ABARES	Managed Land Covers	1215
Australian Capital Territory Department of Parks Conservation and Lands	Vegetation	19
Northern Territory Department of Environment, Climate Change and Water	Vegetation	1859
New South Wales Department of Environment, Climate Change and Water	Vegetation and Managed Land Cover	882
Queensland Herbarium	Vegetation	16 992
South Australian Department of Environment and Heritage	Vegetation and Managed Land Cover	3450
Tasmanian Department of Primary Industries, Parks, Water and Environment	Vegetation	443
Victorian Department of Sustainability and Environment	Vegetation	20
Western Australian Department of Agriculture and Food	Vegetation	1389

recorded in the field survey, Gascoyne blue bush is rated as a four (very similar) to both open chenopod and sparse chenopod, but not a five (direct match for either). Similarly Notophyll Vine Forest in the Queensland field survey database was taken as a complete match (five) with closed forest. In instances where the class description (e.g. riverine mixed) did not contain sufficient information to clearly identify a comparable class within the DLCD, the sites from that class were omitted from the analysis.

The fuzzy match concept also provides the capacity to characterise the gradually changing nature of woody vegetation structure. There are instances, for example, where dense woodland is indistinguishable from open forest. If the field survey data contains open forest, a pixel containing open forest is counted as an exact match (five). Should the field data be one structural class either side (such as a closed forest or a woodland) then it is counted as very similar (four) and an open woodland or a closed shrubland would be ranked as somewhat similar (two). A rainfed graminoid would be considered a complete mismatch (one).

Table 7: Concepts to rank the similarity between compared classes (Lowry et al. 2007).

Relative Similarity	Explanation	Relative Similarity Score
Complete mismatch	Class descriptions are mutually exclusive	1
Somewhat similar	Compared classes may coexist or be contained within each other	2
Moderately similar	Compared classes are commonly found together	3
Very similar	Compared classes are variations of similar themes but should be discriminable	4
Exact match	Compared classes are semantically the same thing	5

Table 8: Relative Similarity Scores for vegetation structures observed along one of four Northern Territory transects.

DLCD	Melaleuca closed forest	Melaleuca open forest	Melaleuca open woodland	Melaleuca woodland
Aquatic Vegetation	2	2	2	2
Pastures – dryland	1	1	1	2
Shrubs – closed	1	2	1	1
Shrubs – sparse	1	1	1	1
Trees – closed	5	4	1	1
Trees – open	4	5	3	4
Trees – scattered	1	2	5	4
Trees – sparse	2	4	4	5
Tussock – open	1	1	2	1
Tussocks – closed	1	1	1	2
Water – fresh	1	1	1	1

Results

The Dynamic Land Cover Dataset

The classification process identified 34 final International Standard Organisation land cover classes for Australia (Figure 8). The estimated total area of each class across Australia, calculated from the land cover dataset, is shown in Table 9. Grasslands are the dominant feature of Australia's landscapes, covering more than one third of the land area. The combined area of grass-dominated cover types is 2.8 million square kilometres (37.1%). Of this total area 31.5% is represented by hummock grasses and only 5.6% is represented by tussock and tussock-like grasses.

Tree dominated landscapes cover slightly less than one third of Australia's land area. The combined area of tree dominated cover types is 2.5 million square kilometres (32.1%). The majority of this area (25.3%) is comprised of closed, open and sparse tree cover classes. The remaining area (6.8%) is made up of scattered tree cover, much of which changes gradually into a shrub or grass dominated understorey.

Shrub dominated landscapes cover around one fifth of Australia's land area. The combined area of shrub dominated cover types is almost 1.6 million square kilometres (20.7%). Intensive agriculture, including irrigated and rainfed cropping and improved pastures, cover less than 10% of Australia's land area. The combined area of these cover types is more than 650 000 square kilometres (8.5%). Of this total, 8.4% is rainfed and only 0.1% is irrigated cover types. The remaining area of Australia includes fresh and salt lakes, wetlands, forbs and sedges and bare areas which occupy approximately 1.5% of Australia's land area.

Table 9: The estimated total area of each land cover class across Australia

Aggregated Class	Area (sq km)	Percentage
Extraction Sites, Bare Areas and Salt Lakes	91 444	1.19%
Inland Waterbodies, Wetlands, Forbs open and sparse, and Sedges open	30 475	0.40%
Irrigated Cropping, Sugar and Pasture	9 388	0.12%
Rainfed Cropping and Sugar	348 443	4.53%
Pasture – Rainfed	295 002	3.84%
Tussock Grasses – closed and open, Alpine Grasses – open	227 404	2.96%
Grassland and Tussock Grasses – sparse and scattered	201 270	2.62%
Hummock grasses – open	229 311	2.98%
Hummock grasses – sparse	2 190 903	28.51%
Shrubs –closed and open	105 559	1.37%
Shrubs – sparse	1 215 732	15.82%
Shrubs – scattered	61 814	0.80%
Chenopod Shrubs – open, sparse and scattered	210 215	2.74%
Trees – closed	212 201	2.76%
Trees – open	448 772	5.84%
Trees – sparse	1 285 804	16.73%
Trees – scattered	521 936	6.79%
Total	**7 685 676**	**100%**

* The area assessment excludes many small islands, estuaries and bays which are sometimes included in the area of Australia.

Comparison with independent field data

Areas which are well characterised by the DLCD

By determining the relative similarity score for all 25 817 field survey points, then calculating the DLCD accuracy, we obtained the following results:

- **Exact match: 30%**
- **Very similar: 35%**
- **Moderately similar: 10%**
- **Somewhat similar: 18%**
- **Complete mismatch: 7%.**

These summary results can be further broken down on a State and Territory basis (Table 9 and Figure 9) and on a thematic basis (Table 11 and Figure 10).

The State and Territory breakdown reveals a number of features. Firstly the complete match rate is 25% or better in all States except South Australia, and the close matches (combining complete and very similar) are over 60% in all States except South Australia. The thematic breakdown (Table 11 and Figure 10) shows that dryland cropping land cover class is very well represented by the DLCD (75% complete match). The DLCD (Figure 8) also performs well for the open forest, woodland, open woodland and sparse shrubland regions of Australia (>70% close matches). Table 11 also shows themes where the field data do not match well with DLCD. These include irrigated cropping, dryland sugar, irrigated sugar, water (fresh and saline) and mining. None of these land cover types are well characterised by the field data so it is not possible to provide an independent accuracy assessment of these themes in this report. The mismatches seen in Table 11 are the result of a series of factors discussed in the following text.

Interpreting the mismatch between the DLCD and the field survey data

Thematic emphasis of the field survey data

The field survey data used to provide the 25 817 validation points was collected by different agencies for different purposes. Some of the surveys have a botanical emphasis, others have a vegetation structural emphasis and others have a rangelands or land use emphasis. As a consequence, some land cover classes are under represented from a validation point of view in some regions. For example, the Western Australian field survey was rangeland specific so the forest classes are not present in that dataset. None of the field validation datasets focussed on irrigated cropping, irrigated pastures, sugar (either irrigated or rainfed), water or mining. These classes have very few validation points (<10 per class with the exception of the water classes) making it difficult to draw any definitive conclusions about the accuracy of the DLCD for these classes. Different field survey datasets would be required to properly assess this.

Semantic differences in labelling

The different thematic emphases of the various datasets meant that the field survey data labels often were not directly comparable with the ISO standard classes, because they are derived from sources using labelling conventions particular to their own needs. For example, rainfed pasture is an ISO class, but the botanical emphasis of many of the field datasets does not provide an equivalent class to enable direct accuracy assessment. Similarly, the botanical emphasis of many of the vegetation survey data means that many classes are genus or species based rather than common name based. For example a field sample label of *Astrebla* sp. needs to be converted to Tussock Grassland. This is easy to address for the major species, but the level of detail can confound this process. Many classes describe the genus and/or species but not the structural component, making it impossible to identify a complete match. For example, if the density of the *Astrebla* sp. grassland is not specified it can then be assigned a similarity rating of four with all of the Tussock grassland classes, but it is not possible to identify a complete match.

Land Cover classes which are poorly characterised by Enhanced Vegetation Index (EVI)

Some classes within the ISO class nomenclature are not well characterised by EVI (Figure 10). Classes such as an extractive site, which is the ISO land cover term for quarries and mines, are characterised by very low to zero vegetation and are therefore not clearly linked to greenness, resulting in the likelihood that the accuracy of these classes will be poor. Other land cover with little vegetation, such as open tussock grassland and sparse hummock grassland, also

have relatively low complete match or close match. This is because areas with very sparse vegetation which responds to very infrequent and randomly timed rainfall events are difficult to distinguish using EVI. However, these very low density grassland and shrubland areas are rarely a complete mismatch and are more often mislabelled as another very low density vegetation type which falls into the moderately or somewhat similar categories.

Systematic class versus canopy continuum

Within the denser canopy classes (trees closed—trees sparse and shrubs closed—shrubs sparse), there is a low to moderate (12%–49%) complete match rate but a moderate to high (33%–85%) close match rate (Table 11). This reflects the reality that vegetation structural classes are a series of systematic breaks in a continuous change in canopy closure and height, creating examples where dense woodland will look almost indistinguishable from open forest. Similarly there are examples where a tall open forest is very similar to a closed forest. Evaluation of the individual State and Territory datasets reveals a systematic over estimation of canopy closure class within the DLCD, particularly with open forest in the field survey data being classified as closed forest by the DLCD. These errors of over estimation, or producer's error (Congalton and Green 1999), are impossible to report in a consistent fashion because of the sheer diversity of class names used in the field survey datasets.

Scale and perspective of observation of the field survey data

There are locations where the DLCD is likely to completely mismatch field observations. Some areas have sharp environmental gradients such as narrow riparian strips, narrow strips of coastal vegetation and small patches of remnant vegetation in areas which have been cleared for intensive land uses. Other mismatches occur where the information in the training data for an area does not fully characterise the range of greenness dynamics, particularly mining and bare areas. Some of the field survey locations were located in spatial settings which are difficult to resolve with 250 x 250 metre pixels. For example, several vegetation surveys are located in narrow riparian strips, small patches of remnant vegetation or in coastal areas where vegetation communities are narrow strips or associated with fringing mangrove forests and dune-swale complexes. These sites were retained in the analysis because it is important to recognise that there are areas which contain sharp environmental changes where the 250 metre DLCD will not accurately represent the land cover.

Field surveys, particularly botanical and vegetation structural surveys tend to focus on the tallest stratum, with variable levels of detail used to describe the lower stratum. This is consistent with the predominant botanical and structural nomenclatures and with a horizontal or looking out perspective. Earth observation data on the other hand has a vertical or looking down perspective so the influence of the lower stratum on the EVI signal increases rapidly as the upper stratum becomes more open. A field survey site described as low open woodland with no description of the lower stratum may be a low open woodland with open tussock grassland understory. In this scenario a DLCD classification of open tussock grassland would be rated as somewhat similar because there is no description of the lower stratum. As a consequence, the error assessment may under estimate the true accuracy of the DLCD where the field survey lacks a description of the lower stratum.

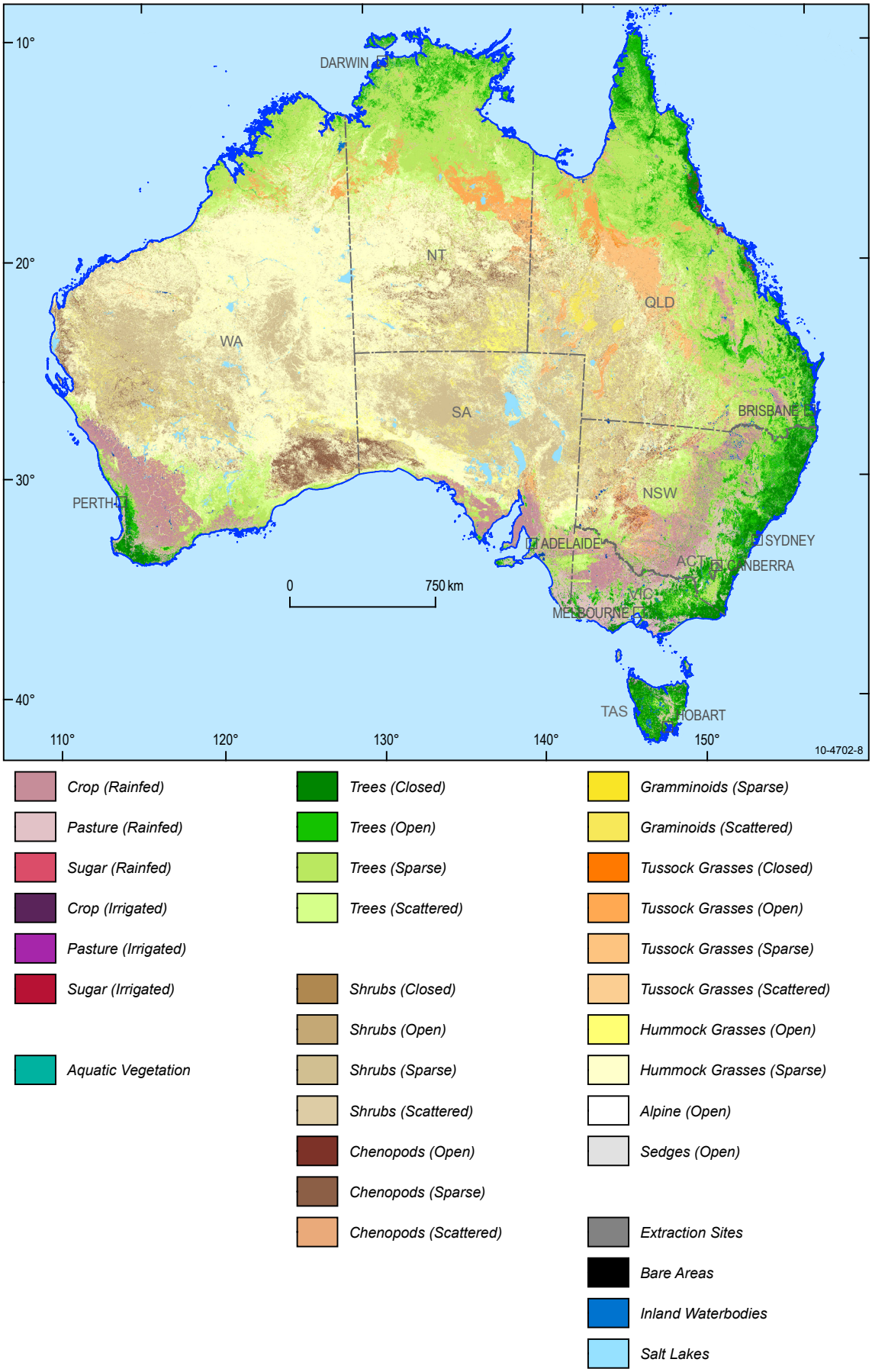

Figure 8: Map compiled from the National Dynamic Land Cover Dataset from 2000 – 2008.

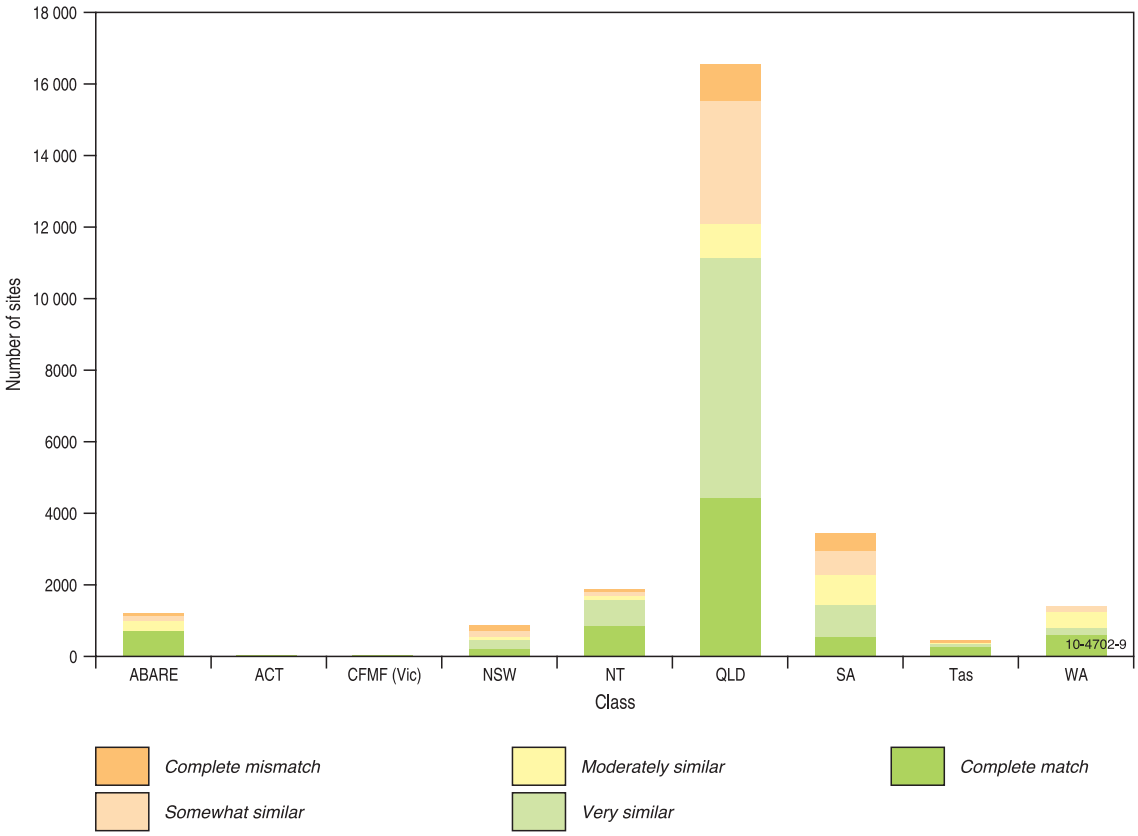

Figure 9: Breakdown of the of the National DLCD accuracy assessment.

Table 10: Thematic breakdown of the National DLCD accuracy assessment.

Data Source	Exact Match	Very Similar	Moderately Similar	Somewhat Similar	Complete Mismatch	Number of Points
ABARES	59%	1%	23%	11%	7%	1215
ACT	37%	53%	0%	11%	0%	19
Vic	35%	55%	0%	5%	5%	20
NSW	26%	26%	11%	19%	18%	882
NT	47%	39%	5%	6%	3%	1859
QLD	26%	40%	6%	20%	6%	16 992
SA	16%	26%	25%	20%	14%	3450
Tas	59%	23%	2%	1%	15%	443
WA	44%	14%	30%	12%	0%	1389

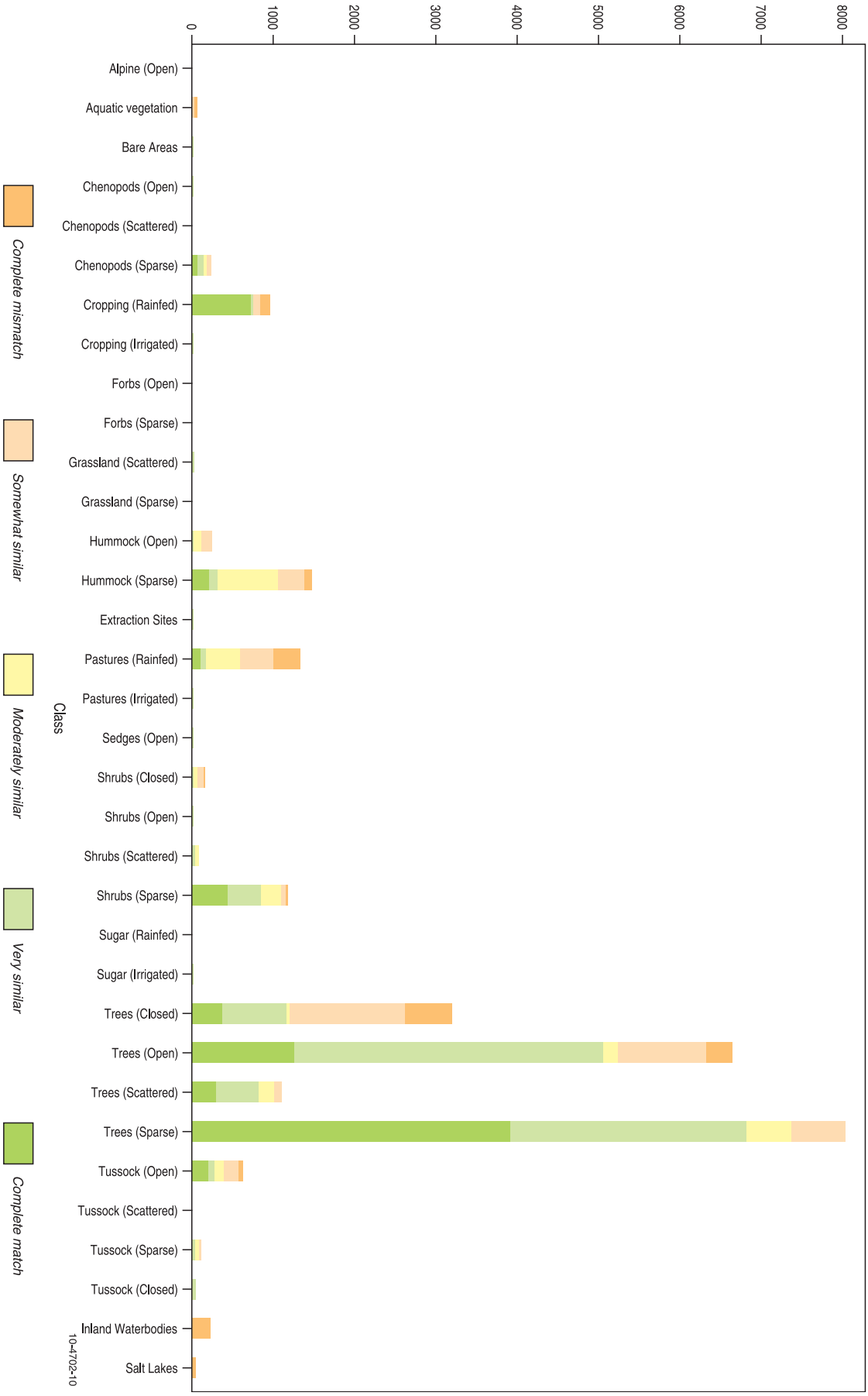

Figure 10: Thematic breakdown of the accuracy assessment.

Relationship between the time series coefficients and land cover classes

The data matrix shown in Table 10 shows the average value of each time series coefficient for the pixels which make up a specific land cover type. For example, the average flatness coefficient for sparse hummock grasses was 0.23. The first three time series coefficients were used to do the initial clustering and problem areas were then split further, using the time series coefficients which provided the best discrimination (see Appendix 1 description for the method of handling type two errors). Figures 11, 12 and 13 show comparisons of statistical, phenological and seasonal time series coefficients for sample land cover classes.

Table 11: The time series coefficients for each of the major land cover classes.

	Mean	Standard deviation	Flatness	Rate of rise	Rate of drop	Global minimum	Avg. length of a cycle	Global Max	Annual max / Global max	Mean timing of maximum	Timing of maximum	Annual minimum
Hummock – sparse	0.12	0.03	0.23	0.14	-0.10	0.08	12.82	0.21	0.87	7.78	6.79	0.09
Hummock – open	0.12	0.03	0.39	0.10	-0.07	0.09	12.66	0.19	0.85	8.33	6.63	0.10
Tussock – sparse	0.15	0.07	0.35	0.29	-0.18	0.08	14.44	0.37	0.81	9.82	8.70	0.09
Tussock – open	0.19	0.09	0.34	0.29	-0.18	0.09	15.41	0.44	0.86	9.03	8.77	0.12
Tussock – closed	0.20	0.08	0.32	0.31	-0.18	0.09	15.75	0.42	0.89	9.94	9.48	0.11
Chenopods – scattered	0.15	0.07	0.35	0.20	-0.13	0.08	10.57	0.38	0.70	8.74	7.44	0.10
Chenopods – sparse	0.14	0.04	0.43	0.13	-0.10	0.10	11.83	0.27	0.77	8.30	6.33	0.11
Chenopods – open	0.15	0.07	0.38	0.19	-0.15	0.09	16.05	0.36	0.73	9.30	4.32	0.10
Shrubs – scattered	0.13	0.02	0.41	0.08	-0.07	0.10	13.41	0.21	0.84	7.74	5.76	0.11
Shrubs – sparse	0.11	0.02	0.33	0.12	-0.09	0.07	13.30	0.17	0.84	7.88	6.03	0.08
Shrubs – open	0.18	0.06	0.21	0.18	-0.14	0.10	9.93	0.33	0.86	8.93	6.05	0.13
Trees – scattered	0.23	0.07	0.26	0.21	-0.14	0.12	14.61	0.41	0.90	9.31	8.04	0.15
Trees – sparse	0.25	0.08	0.24	0.20	-0.14	0.14	15.82	0.43	0.93	9.58	8.26	0.17
Trees – open	0.34	0.10	0.12	0.27	-0.19	0.15	14.64	0.56	0.94	11.32	6.79	0.20
Trees – closed	0.45	0.10	0.07	0.19	-0.14	0.25	13.07	0.66	0.96	11.47	7.52	0.32
Pasture – rainfed	0.36	0.12	0.22	0.23	-0.18	0.17	15.72	0.62	0.90	11.64	4.44	0.22
Cropping – rainfed	0.22	0.12	0.31	0.31	-0.23	0.11	15.06	0.54	0.84	11.21	2.82	0.12
Sugar – rainfed	0.47	0.13	0.13	0.23	-0.17	0.22	16.30	0.74	0.96	9.75	8.98	0.28
Sugar – irrigated	0.42	0.15	0.19	0.27	-0.19	0.18	17.02	0.72	0.94	9.55	8.83	0.23
Wetlands	0.28	0.13	0.19	0.43	-0.25	0.08	15.91	0.57	0.94	9.61	8.51	0.13

Table 12: Thematic breakdown of the National DLCD accuracy assessment.

DLC Class	Complete Match	Very Similar	Moderately Similar	Somewhat Similar	Complete Mismatch	No. of Points
Alpine – open	0%	0%	0%	0%	0%	0
Aquatic vegetation	0%	0%	0%	59%	41%	51
Bare areas	0%	0%	0%	100%	0%	5
Chenopods – open	0%	0%	0%	33%	67%	3
Chenopods – scattered	0%	0%	0%	0%	0%	0
Chenopods – sparse	29%	34%	15%	21%	1%	240
Cropping – dryland	75%	1%	2%	9%	13%	966
Cropping – irrigated	0%	0%	0%	0%	100%	8
Forbs – open	0%	0%	0%	0%	0%	0
Forbs – sparse	0%	0%	0%	0%	0%	0
Grassland – scattered	11%	21%	16%	37%	16%	19
Grassland - sparse	0%	0%	0%	0%	0%	0
Hummock – open	9%	0%	40%	51%	0%	234
Hummock – sparse	15%	7%	50%	22%	6%	1478
Mining	0%	0%	0%	0%	100%	4
Pastures – dryland	8%	6%	31%	31%	25%	1335
Pastures – irrigated	0%	0%	0%	50%	50%	2
Sedges – open	0%	50%	0%	0%	50%	2
Shrubs – closed	1%	19%	21%	52%	7%	162
Shrubs – open	25%	8%	17%	50%	0%	12
Shrubs – scattered	7%	37%	24%	7%	24%	82
Shrubs – sparse	37%	35%	20%	6%	2%	1178
Sugar – dryland	0%	0%	0%	0%	100%	1
Sugar – irrigated	0%	0%	0%	12%	87%	8
Trees – closed	12%	25%	1%	44%	18%	3204
Trees – open	19%	57%	3%	16%	5%	6640
Trees – scattered	27%	48%	17%	8%	0%	1099
Trees – sparse	49%	36%	7%	8%	0%	8040
Tussock – open	32%	12%	19%	29%	7%	621
Tussock – scattered	0%	0%	0%	0%	0%	0
Tussock – sparse	17%	24%	29%	24%	5%	112
Tussocks – closed	7%	32%	32%	20%	7%	40
Water – fresh	1%	1%	0%	0%	98%	232
Water – saline	0%	8%	5%	3%	85%	39

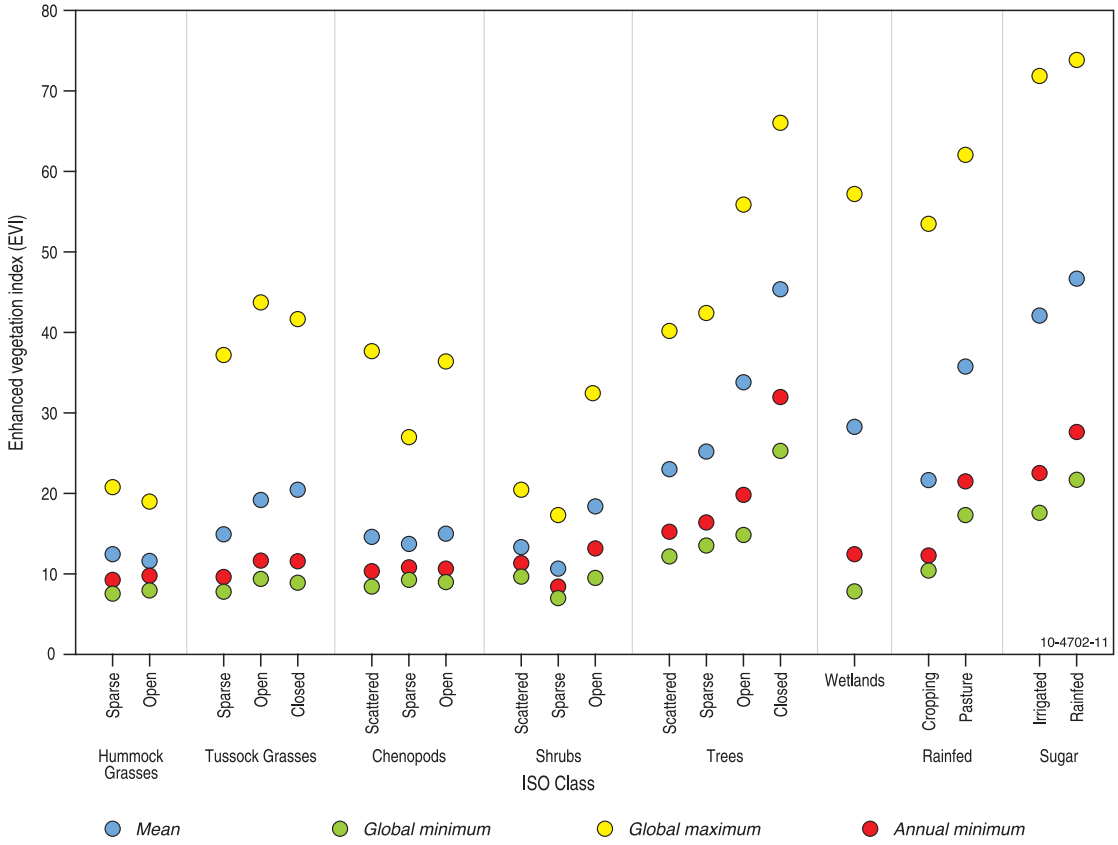

Figure 11: The statistical characteristics of the major land cover classes.

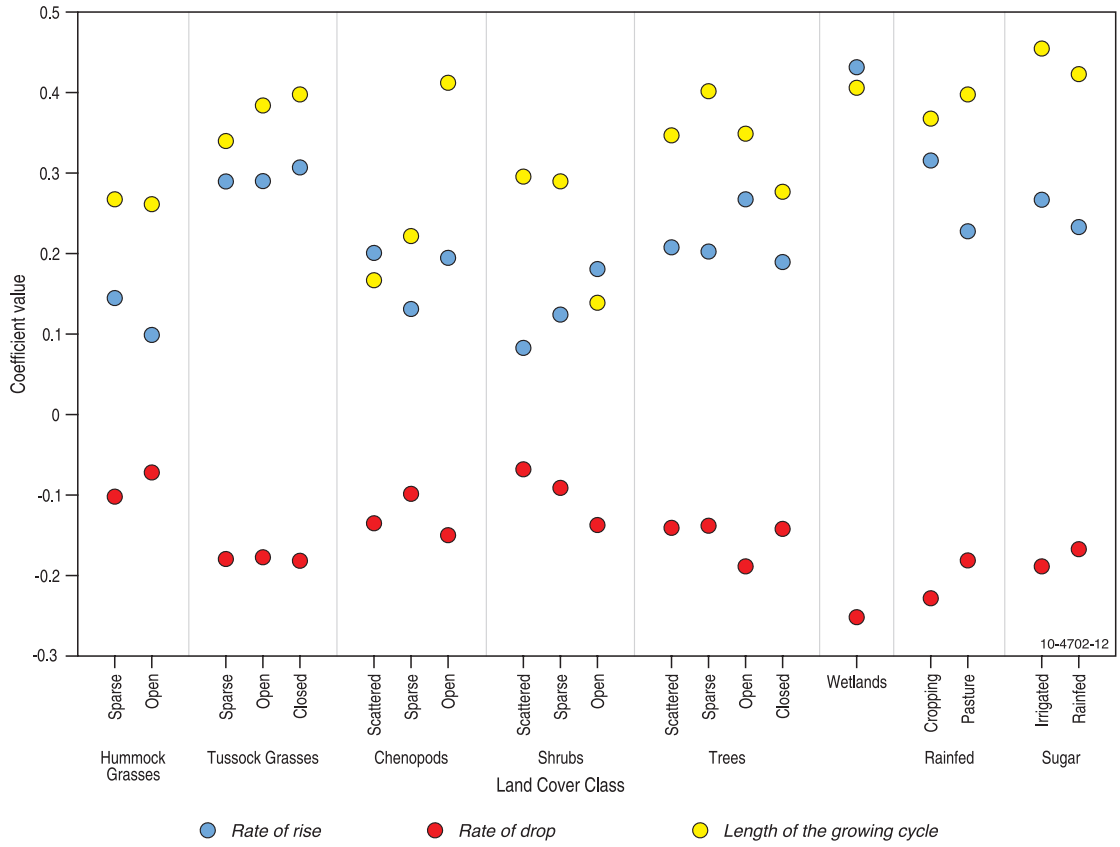

Figure 12: The phenological time series coefficients of the major land cover classes.

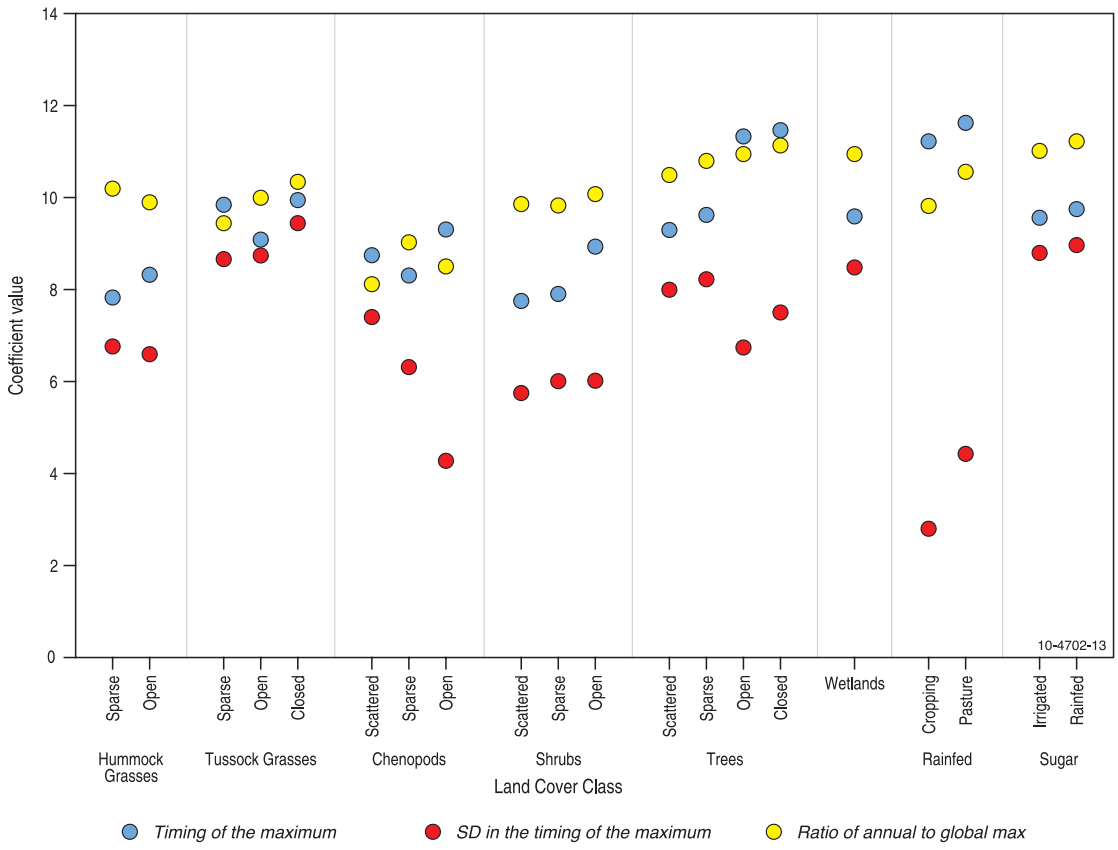

Figure 13: Seasonal time series coefficients for the major land cover classes.

Intercomparison with other land cover and land use datasets

Queensland Statewide Landcover And Tree Study (SLATS) Foliage Projective Cover.

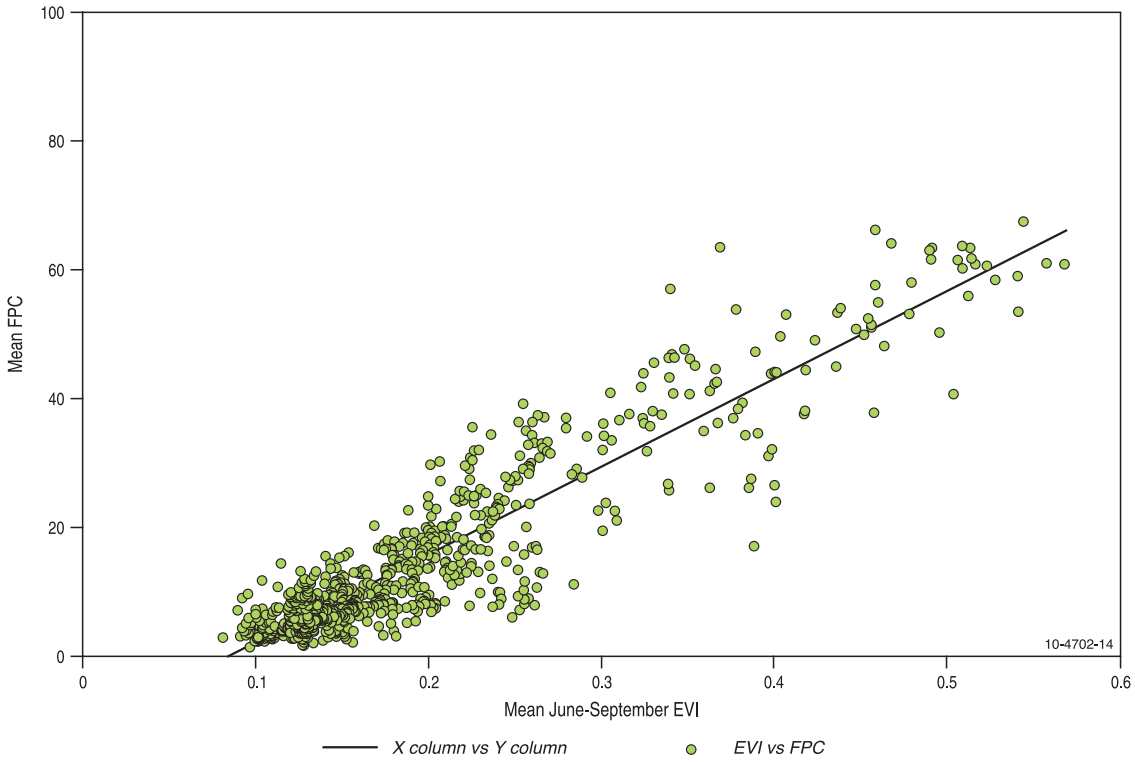

Figure 14: Correlation between FPC and dry season EVI values in Queensland.

A comparison of the Foliage Projective Cover (FPC) and dry season EVI values for the Queensland Statewide Landcover And Tree Study (SLATS) FPC data is shown in Figure 14. A linear regression for this relationship shows an adjusted R^2 of 0.85. The correlation can be characterised based on a linear regression with the equation:

FPC = -11.5 + (EVI x 136.7)

A full statistical description of the relationship is contained in Appendix 4. Applying this equation to the annual minimum values in Table 10 provides a conversion from EVI into a biophysical parameter.

This biophysical parameter has been extensively validated in Queensland for woody vegetation and provides insight into the relationship between FPC and the major land cover classes as shown in Figure 15. These values are based on the linear regression described above and an extensive field campaign would be required to assess the accuracy of these values, particularly for the non-woody classes.

Other National and regional land cover and land use datasets.

A comparison of the DLCD with five independent datasets was done to assess the merits of the DLCD relative to other international, Australia-wide and State level land cover, land use and vegetation datasets.

Comparisons were made between the final land cover classes in the DLCD and five land cover related datasets: GlobCover, Major Vegetation Groups (MVG), Land Use 2005–06 (LU05v4), Integrated Vegetation (IntVeg) and the Victorian Land Cover and Statewide Data 2010 (VicLandCover). Of these five datasets, one provided an international perspective, three gave an Australia-wide perspective and one focussed on the State-wide scale. These are detailed in Bicheron et al. (2008), the Australian Department of the Environment and Water Resources (2007), Bureau of Rural Sciences (2008 and 2009) and the Victorian Department of Sustainability and Environment (2010). The workflow describing the comparison process is shown in Figure 16. A visual

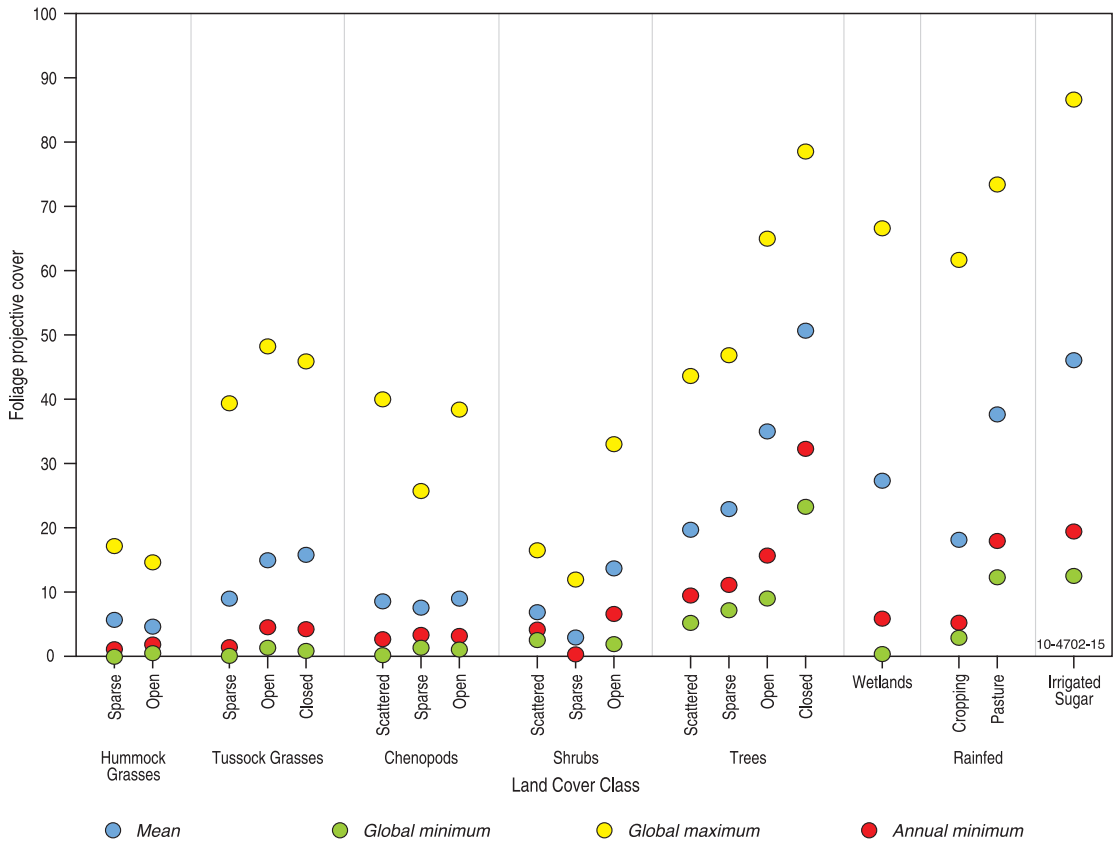

Figure 15: The foliage projective cover characteristics for the major land cover classes.

comparison of the DLCD and the Australia-wide datasets is shown in Figure 17.

To form the comparison, each dataset was converted to the identical projection, datum and cell size as the DLCD before being analysed using the ArcGIS Combine tool. To facilitate this comparison a lookup table of the labels (classification types) of each dataset was created to approximate an equivalent land cover label (classification types) to the DLCD. Reclassifying the labels in an independent dataset to the equivalent label in the DLCD means that comparisons between the datasets are comparing like with like matrices and assumes that sufficient information is available in the metadata for each independent label to be ascribed the most appropriate DLCD label. For example, the 92 labels in the LU05v4 were reclassified to the nearest matching label in the DLCD (i.e. 34 classification types).

The five resulting matrices, DLC-GlobCover, DLC-MVG, DLC-LU05v4, DLC-IntVeg and DLC-VicLandCover represent which class combinations of DLCD and the other datasets exist and in what amounts. A pivot table was produced for each combination approximating a confusion matrix (Table 11) by extracting this information as a set of raster attribute tables.

The cell values of these matrices were then multiplied by the corresponding comparison cell in each relative salinity score matrix to create a fuzzy comparison matrix for each combination of the DLCD and comparison dataset (see Table 8 for an example). For each class a series of statistics in which all matches of the same relative similarity are summed has been created, providing an understanding of the way the DLCD relates to each compared class.

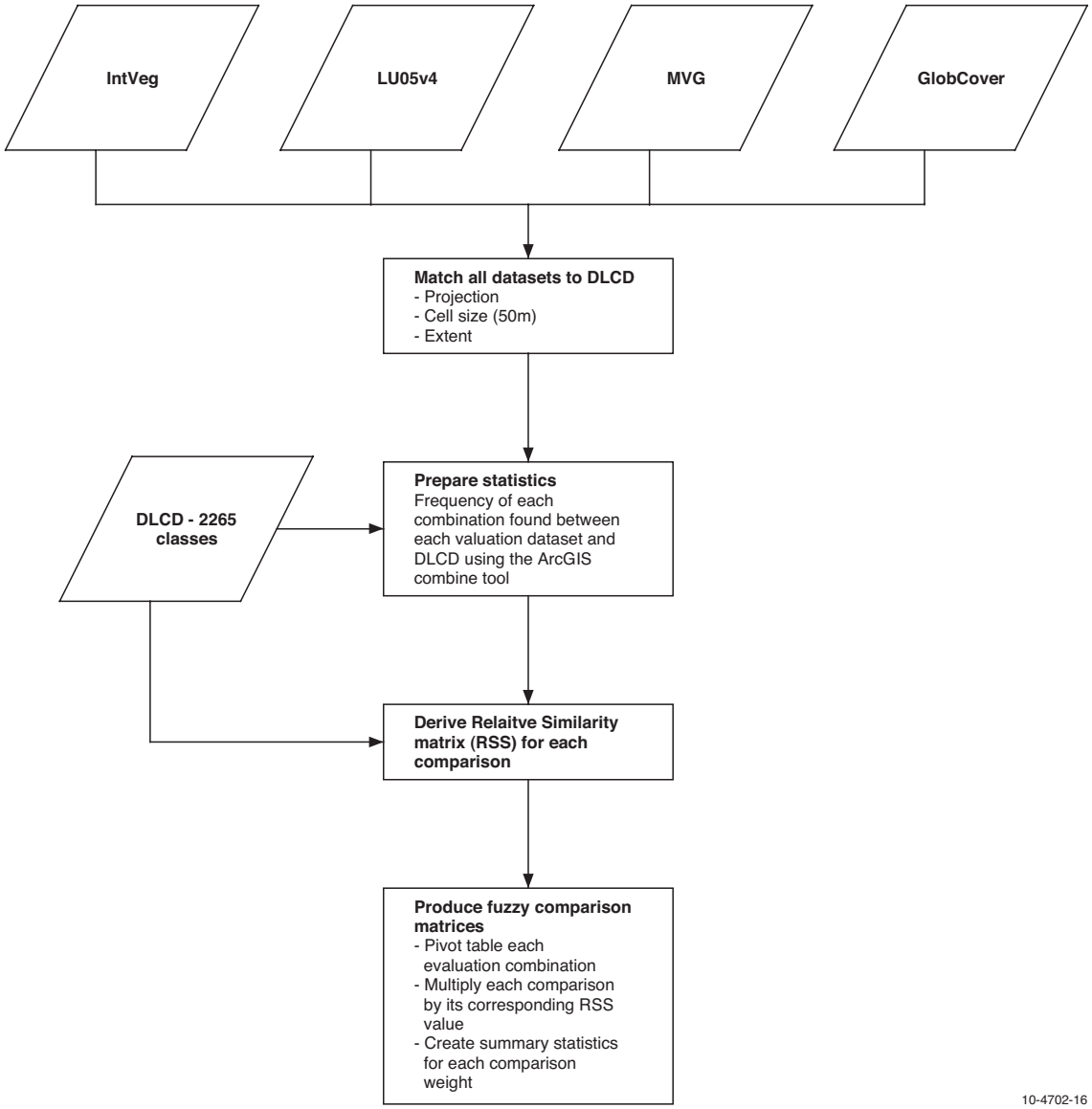

Figure 16: Flow chart describing the process of comparing the National DLCD with IntVeg, LU05v4, MVG and GlobCover.

Table 13: Fuzzy match comparison between the National DLCD and the five comparable spatial datasets.

Compared Dataset	Exact Match	Very Similar	Moderately Similar	Somewhat Similar	Complete Mismatch
LU05/06v4	9%	58%	3%	6%	21%
IntVeg	43%	6%	10%	11%	27%
MVG/MVS	6%	13%	25%	9%	42%
GlobCover	7%	21%	12%	25%	32%
VicLandCover	40%	18%	13%	10%	19%

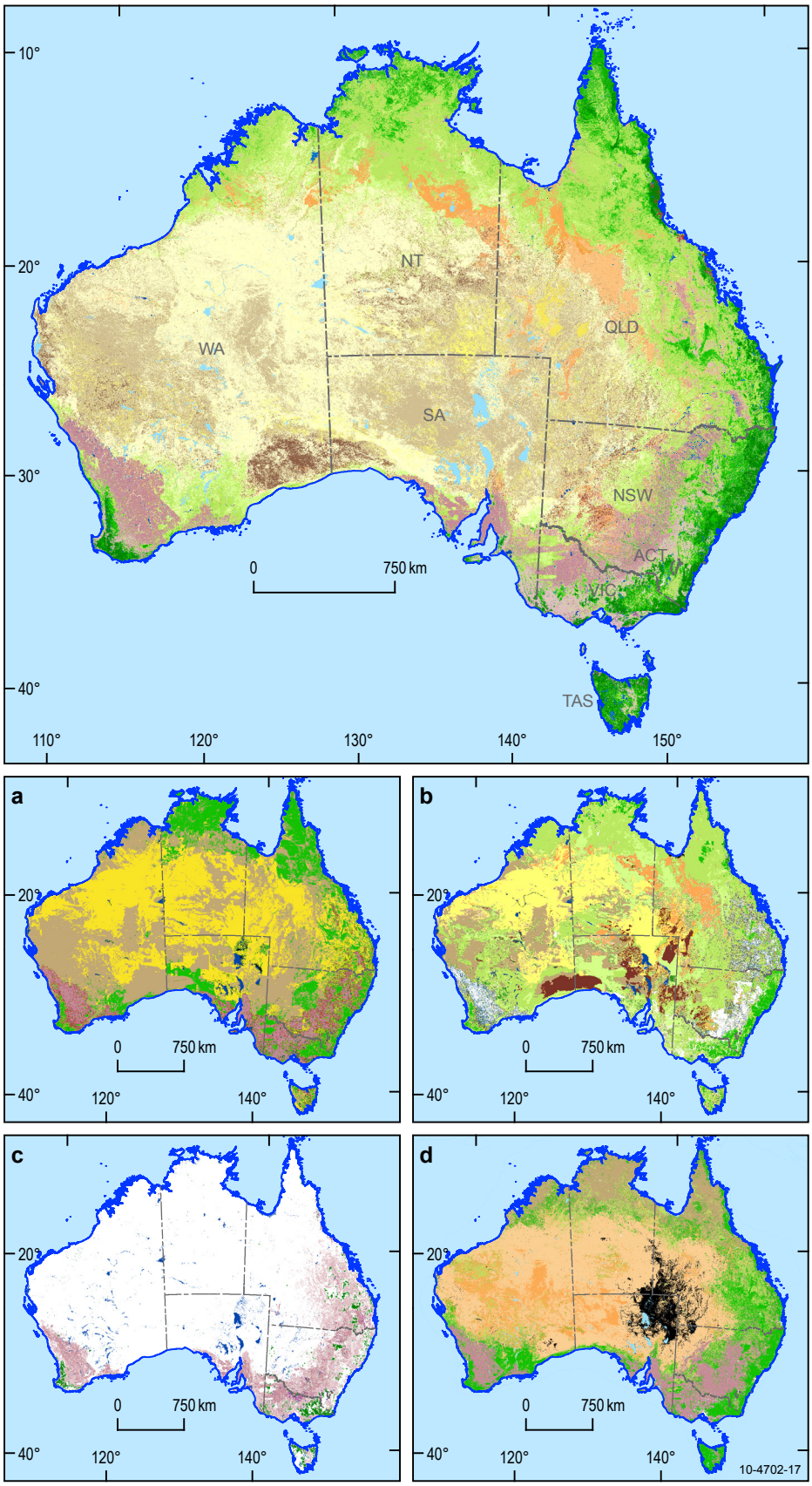

Figure 17: Intercomparison of the National DLCD with IntVeg (a), MVG/MVS (b), LU05/06 (c), and GlobCover (d).

Crop (Rainfed)
Pasture (Rainfed)
Sugar (Rainfed)
Crop (Irrigated)
Pasture (Irrigated)
Sugar (Irrigated)

Aquatic Vegetation

Trees (Closed)
Trees (Open)
Trees (Sparse)
Trees (Scattered)

Shrubs (Closed)
Shrubs (Open)
Shrubs (Sparse)
Shrubs (Scattered)
Chenopods (Open)
Chenopods (Sparse)
Chenopods (Scattered)

Gramminoids (Sparse)
Graminoids (Scattered)
Tussock Grasses (Closed)
Tussock Grasses (Open)
Tussock Grasses (Sparse)
Tussock Grasses (Scattered)
Hummock Grasses (Open)
Hummock Grasses (Sparse)
Alpine (Open)
Sedges (Open)

Extraction Sites
Bare Areas
Inland Waterbodies
Salt Lakes

The per cent match scores for each dataset in Table 12 (page 34) represent average accuracy of all land cover classes for each of the five accuracy classes. The independent datasets which showed largest exact matches with the DLCD included the Integrated Vegetation 2009 dataset with 43% exact match followed by the Victorian Landcover and Vegetation Statewide Data 2010 (VicLandCover) with 40% exact match. It is worth noting that both these datasets were collected and collated by the State and Territory land management agencies from the best available datasets (i.e. highest spatial resolution and most current data), using either a nationally consistent classification system (such as Integrated Vegetation 2009) or a State based classification system.

Combining complete match and very similar to create a close match changes the picture. The LU05v4 dataset now becomes the dataset which most closely matches the DLCD (i.e. 67% accuracy) followed by the VicLandCover dataset and the Integrated Vegetation 2009 dataset (58% and 49% respectively). GlobCover and MVG datasets had the lowest complete matches of all five independent datasets to the DLCD, with 28% and 19% close matches respectively.

The independent datasets which showed largest complete mismatches with the DLCD in order, were the MVG (42%), followed by GlobCover (32%), Integrated Vegetation (2009) (27%), LU05v4 dataset (21%), the VicLandCover dataset (19%). It is worth noting that the MVG represents the current extent of native vegetation types, with all replaced, transformed and adventive vegetation types (Thackway and Lesslie 2008) being classified within three classes:

- cleared, non-native vegetation, buildings;
- unclassified native vegetation;
- regrowth and modified native vegetation.

Consequently, ascribing a matching DLCD label to these three classes proved challenging.

Trend data

The way in which the trend data was calculated is described on page 19. The trend was calculated for the annual minimum EVI values, annual maximum EVI values and annual mean EVI values.

Each of the three trends represents a different aspect of the photosynthetic behaviour of the vegetation within that pixel over a year. It makes sense therefore to interpret each trend independently although there are some caveats which apply to interpreting all trend data.

- Caveat 1: Trend data are easily skewed by extreme values, which is particularly problematic for the minimum and maximum trends that are, by definition, based on extreme values. This means that if an event which causes a major change such as a flood pulse or severe bushfire occurs at the start or end of the time series, it will have a significant influence on the trend in the maximum or minimum. Trend data are of limited use when analysing episodic rather than seasonal systems.
- Caveat 2: Extreme caution should be applied to linking any value judgement to the trend data. If there has been a large green flush on a central Australian floodplain river near the start of the time series and all three trends have been in decline since then, it does not mean necessarily that the river is in 'bad' condition, but may simply mean that there has not been a significant flood event since then. Likewise, an increase in greenness may represent an increase in the presence of invasive weeds rather than any improvement in productivity or condition.
- Caveat 3: Interpretation of greenness dynamics needs to be done within the conceptual framework that acknowledges all factors which may influence greenness in that vegetation community and climatic/landscape setting. This means that the trend data is a very useful tool for flagging areas which are trending upwards or downwards more strongly than similar vegetation types in the same climate and landscape setting. Once these areas are flagged, a more detailed analysis is required to identify which factors (anthropogenic or otherwise) are driving the observed change.
- Caveat 4: In areas where pixels contain little or no vegetative cover such as salt lakes and permanent water bodies the EVI is very noisy and all trend data are meaningless.
- Caveat 5: The trend data for an individual pixel has limited statistical significance. However, if many pixels of the same class show the same trend, particularly if they are collocated, the statistical significance increases rapidly.

Table 14: Factors which drive inter and intra annual changes in greenness dynamics.

Broad scale driver	Specific driver	Human system, Natural system
Plant available water	Timing of rainfall	Natural
	Amount of rainfall	Natural
	Floodplain inundation	Both
	Groundwater expression	Both
	Irrigation	Human
Soil fertility	Soil organic C content	Both
	Soil Nitrogen, Phosphorus, Potassium content	Both
Grazing pressure	Stocking rate	Both
	Stock type	Both
Fire	Fire frequency	Both
	Fire severity	Both
Drought	Curing rate	Natural
Phenology	Leaf bud	Natural
	Leaf drop	Natural
Disease/Plague		Both
Removal of woody vegetation	Land clearing	Human
	Forestry	Human
Vegetation type		Both

Interpreting the trend in the annual minimum

The annual minimum EVI relates to the minimum observed levels of photosynthetic activity for that location in the landscape throughout the year. In environments where the ground cover senesces, or dries out completely the minimum EVI is related to the woody vegetation canopy component.

An example trend in minimum EVI is shown in Figure 18. The trend in the minimum EVI for all Australia is shown in Figure 19. The relationship between dry season EVI and the woody vegetation canopy component of FPC as measured by the Queensland SLATS team is shown in Figure 14. This means that the trend in the annual minimum can be used to estimate the trend in dry season leaf area in these environments. In less water limited environments the minimum EVI can be determined by the green fraction during the driest periods, although the green fraction in these areas may still include a ground cover component, making interpretation of the trend data more difficult. One of the key ways of using the trend data is to compare the trend in the minimum EVI values within one woody vegetation class. The trend in the minimum EVI values can be very strongly influenced by flood and fire events, particularly hot fires which burn the complete canopy and under story.

Figure 20 demonstrates how the DLCD can provide a framework for interrogating the minimum annual EVI trend data. Many of the classes are very close to zero, indicating no strong positive or negative trend. The sugar and trees (closed) land covers are showing a positive trend, while the sparse grassland/shrubland classes and rainfed pasture are showing a negative trend at a National scale. The range of drivers which can influence trends in greenness (Table 13) mean that it is not possible to identify the specific drivers of change without referring to additional datasets.

Interpreting the trend in the annual maximum

The annual maximum EVI value is related to the maximum leaf area, including both canopy cover and ground cover observed at any point during a year. Irrigated summer crops may reach EVI values in excess of 0.8, whereas the maximum EVI over the Nullarbor Plain is around 0.2. An example trend in maximum EVI is shown in Figure 21. The trend in the maximum EVI for all Australia is shown in Figure 22.

The trend in the maximum EVI value is very sensitive to individual good years so can be misleading when applied to systems which are episodic rather than seasonal in nature. The data can be used potentially to assess whether maximum leaf area for a specific area is increasing or decreasing. This is a qualitative rather than quantitative measure (for example the maximum EVI is observed to drop from year to year), but the necessary ancillary data may not be available to link that to an absolute value for change in leaf area index.

Figure 23 demonstrates how the DLCD can provide a framework for interrogating the maximum annual EVI trend data. All classes except sugar and open chenopod shrubland show a negative trend in the maximum EVI value. The range of drivers which can influence trends in greenness (Table 13) means that it is not possible to identify the specific drivers of change using this dataset alone. However, the uniform nature of the negative trends indicates that continental scale drivers such as drought may be impacting on the maximum greenness across a wide range of land cover types.

Interpreting the trend in the annual mean

The trend in the annual mean is the most robust of all three trend data analyses because it incorporates all 23 points in the time series for each year (i.e. every point in the time series). This also makes it a less sensitive tool than the other two trends, as well as a more robust indicator of change. For areas which support vegetation (i.e. not salt lakes and open water bodies), the trend in the mean provides an estimate of how total photosynthetic activity is changing from year to year. A guide on how to interrogate the trend data is provided in the discussion. An example trend in annual mean EVI is shown in Figure 24. The trend in the annual mean EVI for all Australia is shown in Figure 25.

Figure 26 demonstrates how the DLCD can provide a framework for interrogating the mean annual EVI trend data. All classes except sugar show a negative trend in the mean EVI value. The range of drivers which can influence trends in greenness (Table 13) means that it is not possible to identify the specific drivers of change using this dataset alone. However, the uniform nature of the negative trends indicates that continental scale drivers such as drought may be impacting on the mean greenness across a wide range of land cover types.

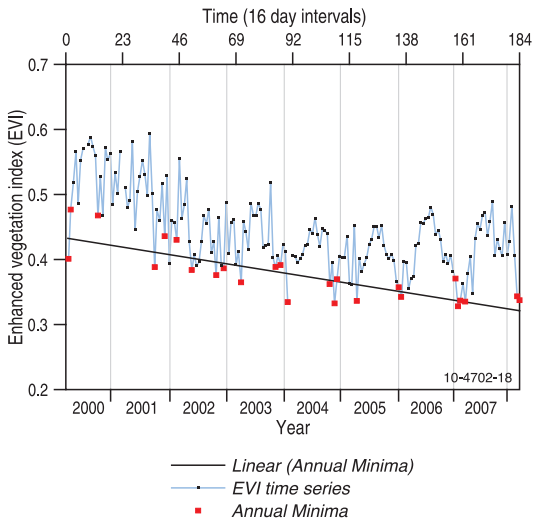

Figure 18: A sample time series that shows how the trend in the annual minimum EVI values was calculated.

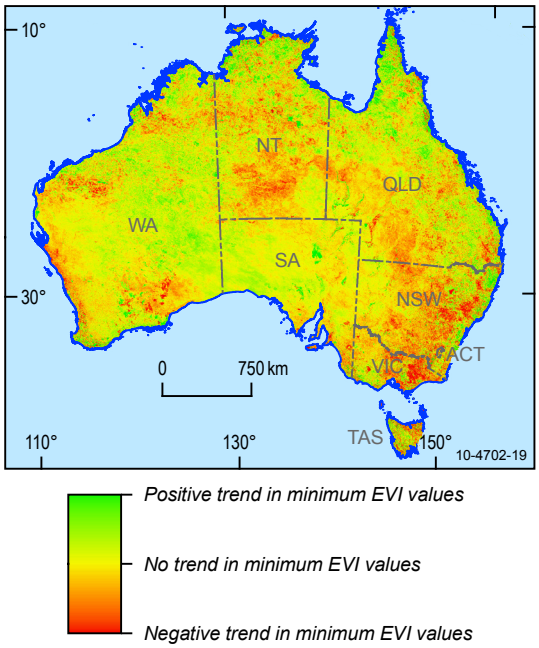

Figure 19: The trend in minimum EVI values across Australia.

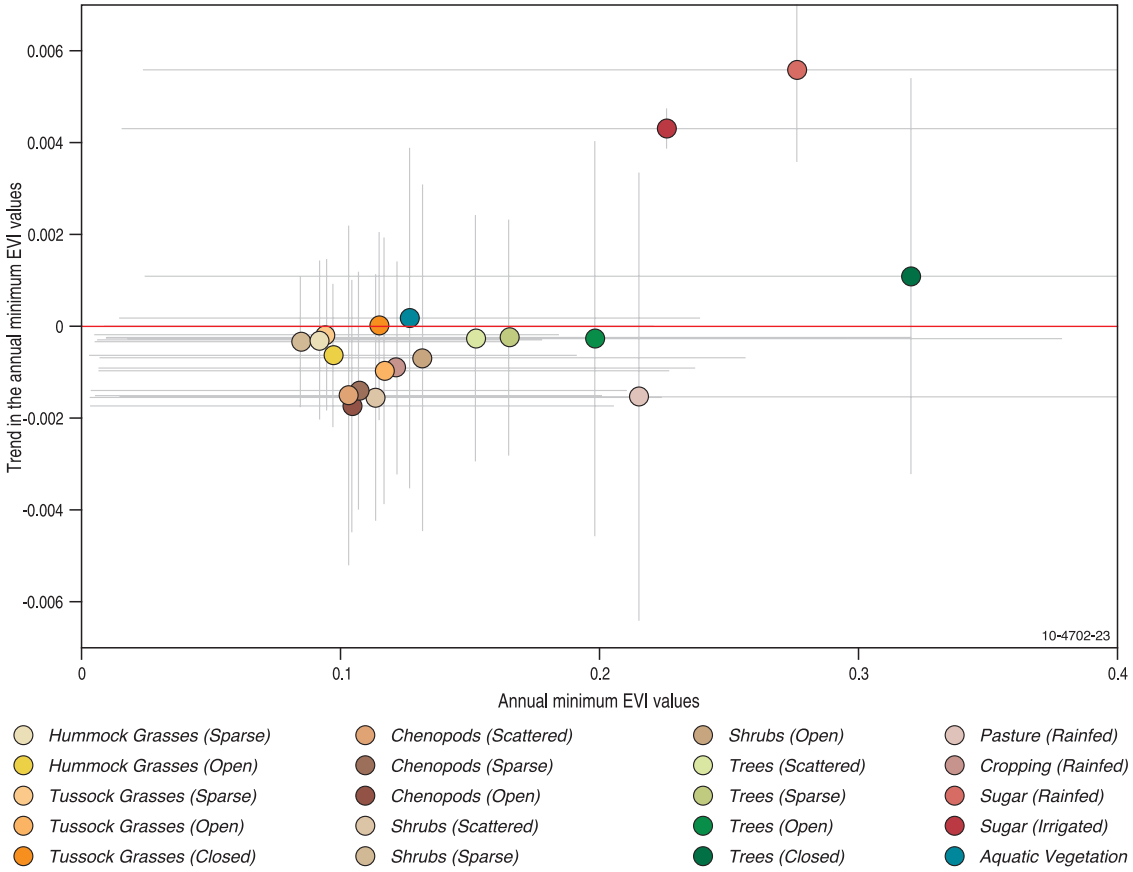

Figure 20: The trend in the annual minimum EVI values for the major land cover types.

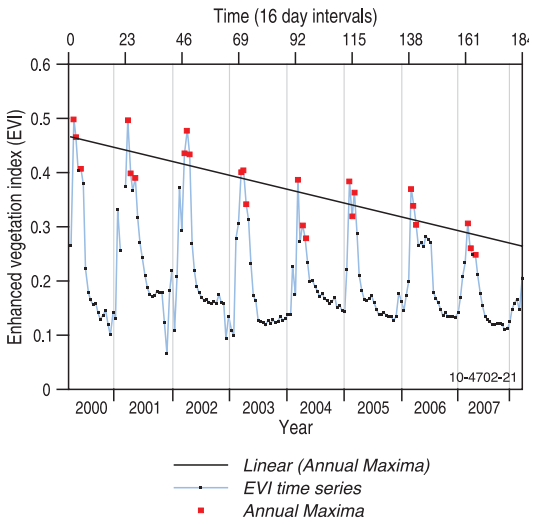

Figure 21: A sample time series that shows how the trend in the annual maximum EVI values was calculated.

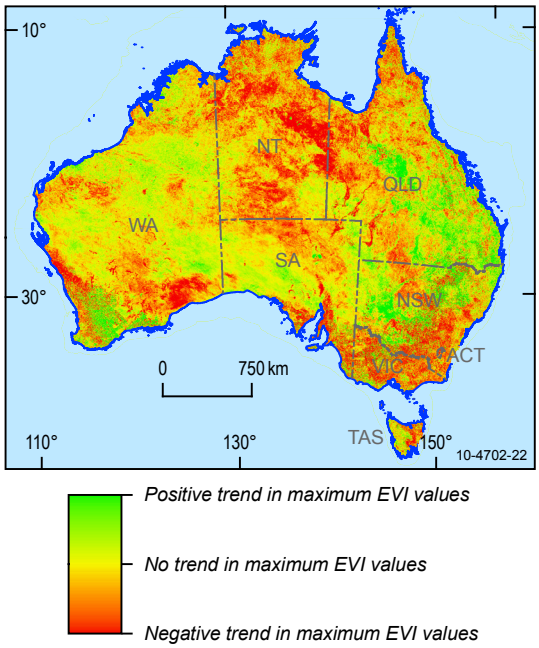

Figure 22: The trend in maximum EVI values across Australia.

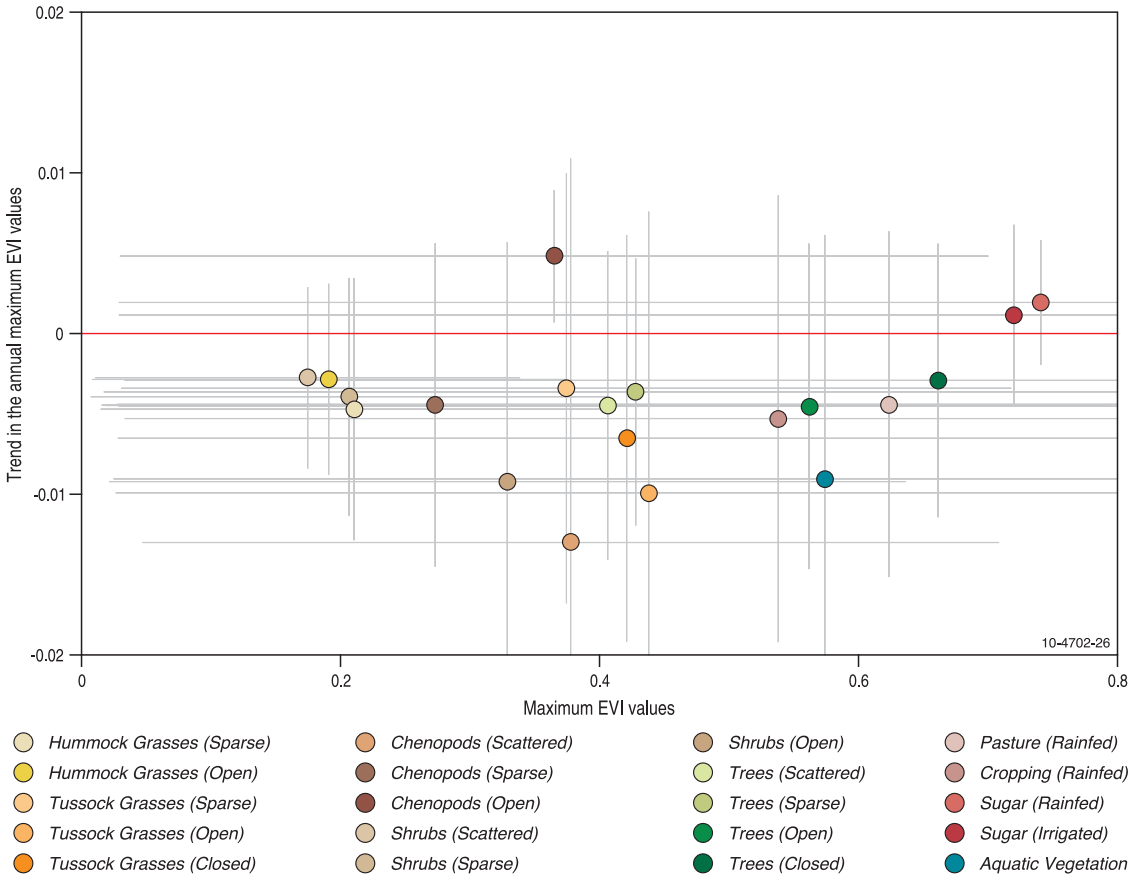

Figure 23: The trend in the annual maximum EVI values for the major land cover types.

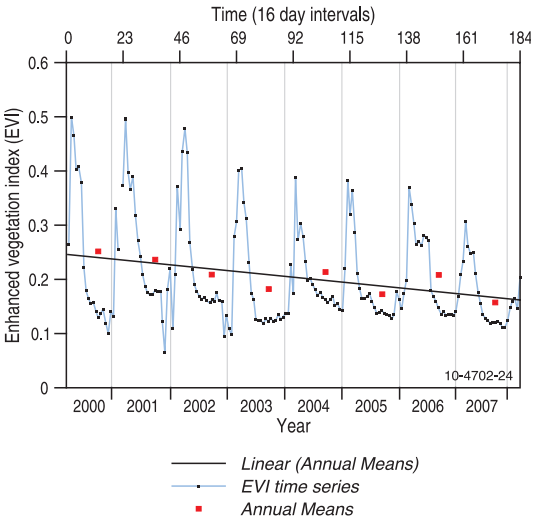

Figure 24: A sample time series which shows how the trend in the annual mean EVI values was calculated.

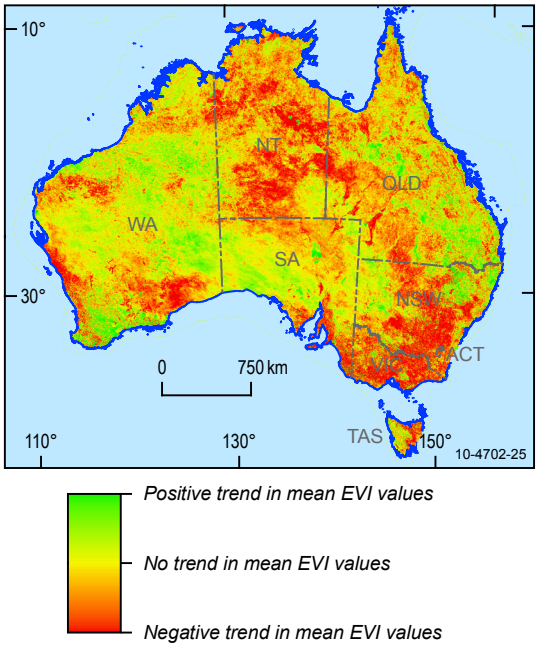

Figure 25: The trend in mean EVI values across Australia.

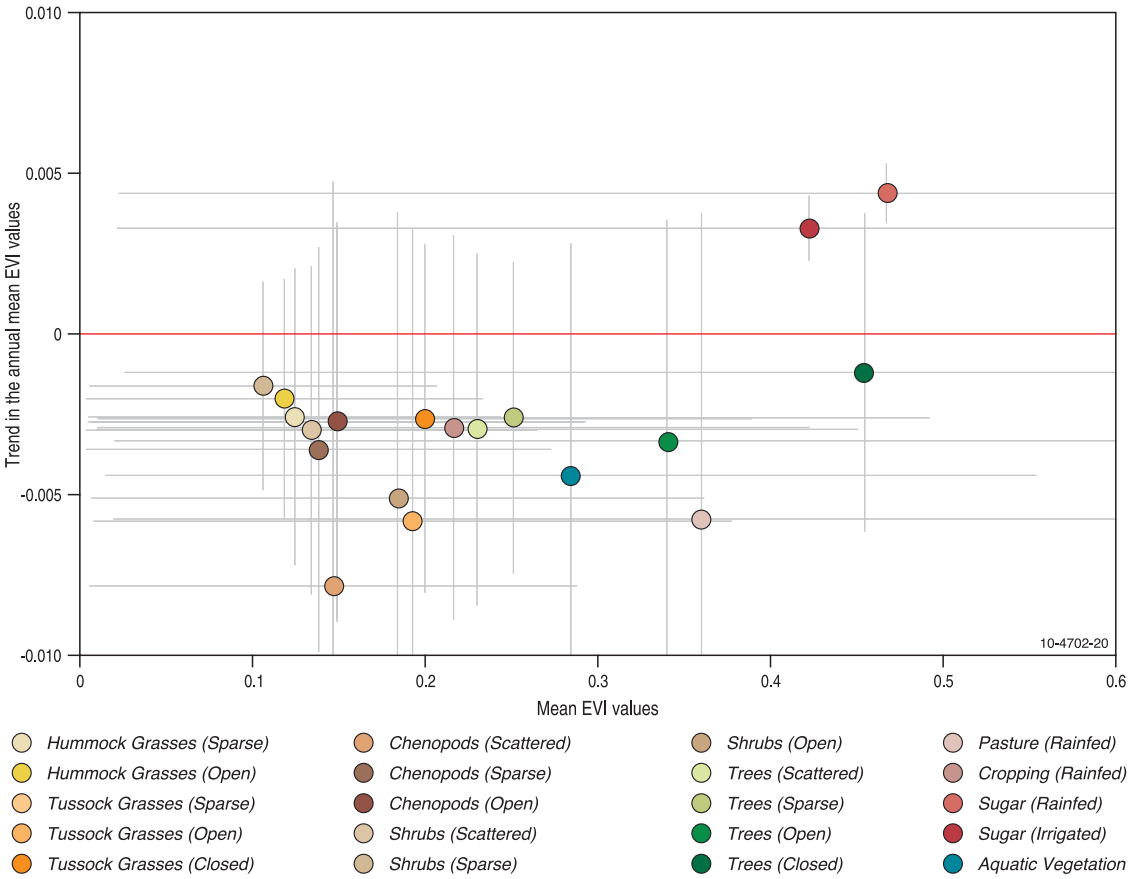

Figure 26: The trend in the annual mean EVI values between 2000 and 2008 for the major land cover types.

Discussion

A key advantage of the National Dynamic Land Cover Dataset is that it provides an Australia wide consistent method for identifying areas which are comparable to one another. This is critically important when it comes to interpreting the Enhanced Vegetation Index time series or other spatial data of comparable spatial resolution because it allows a like-with-like comparison of portions of the landscape which are subject to the same drivers of change in their greenness or fractional cover dynamics. For example, the drivers of change for the greenness over a cropping region are likely to be a combination of land management practice and climate, while the drivers of change over a forest are likely to be climate, bushfire and silvicultural practices. A list of the factors which drive changes in greenness signals is provided in Table 13.

Assessing an area of interest

The DLCD can be used to assess a series of case studies. An area of interest such as a mapped feature or a bioregion may be used to query the trend raster and look at the summary statistics. This is then compared to the trend statistics for that land cover type more generally to assess whether the area of interest is significantly different to the overall land cover type. The alpine areas case study, Mitchell Grass Bioregion case study and the mangrove case study which follow are examples of this style of analysis.

Identifying unusual behaviour within a specific land cover type

This allows assessment of a change in a specific land cover type (e.g. determining which areas of open forest are showing a change reflecting a positive or a negative trend in their annual mean EVI which is significantly different to other open forests). The following Western Australian cropping case study is an example of this style of analysis.

Case study 1: Crop dynamics in Western Australia

Figure 27 (page 48) shows the trend in the annual mean EVI values for the cropping region of Western Australia.The most striking feature is the strong negative trend in the northwest part of the crop region and the positive trend in the southeast. This is consistent with drought in the northwest section of the Western Australian wheat belt from 2002 onwards. In this way the data can highlight specific phenomena within the same land cover type. Figure 28 illustrates time series from a crop and a woodland in the same region. The crop time series shows a strong negative trend. The native vegetation shows a similar downward trend, suggesting that in this particular instance the native vegetation is responding to the same climatic drivers as the cropped areas. The capacity to use the trend layers to highlight areas which are behaving unusually provides a powerful new tool for assessing existing or emerging natural resource management issues. The ability to identify and characterise these issues at a regional and National scale is a fundamental new capability enabled by the DLCD, irrespective of whether a policy response or on-ground response is feasible or logical.

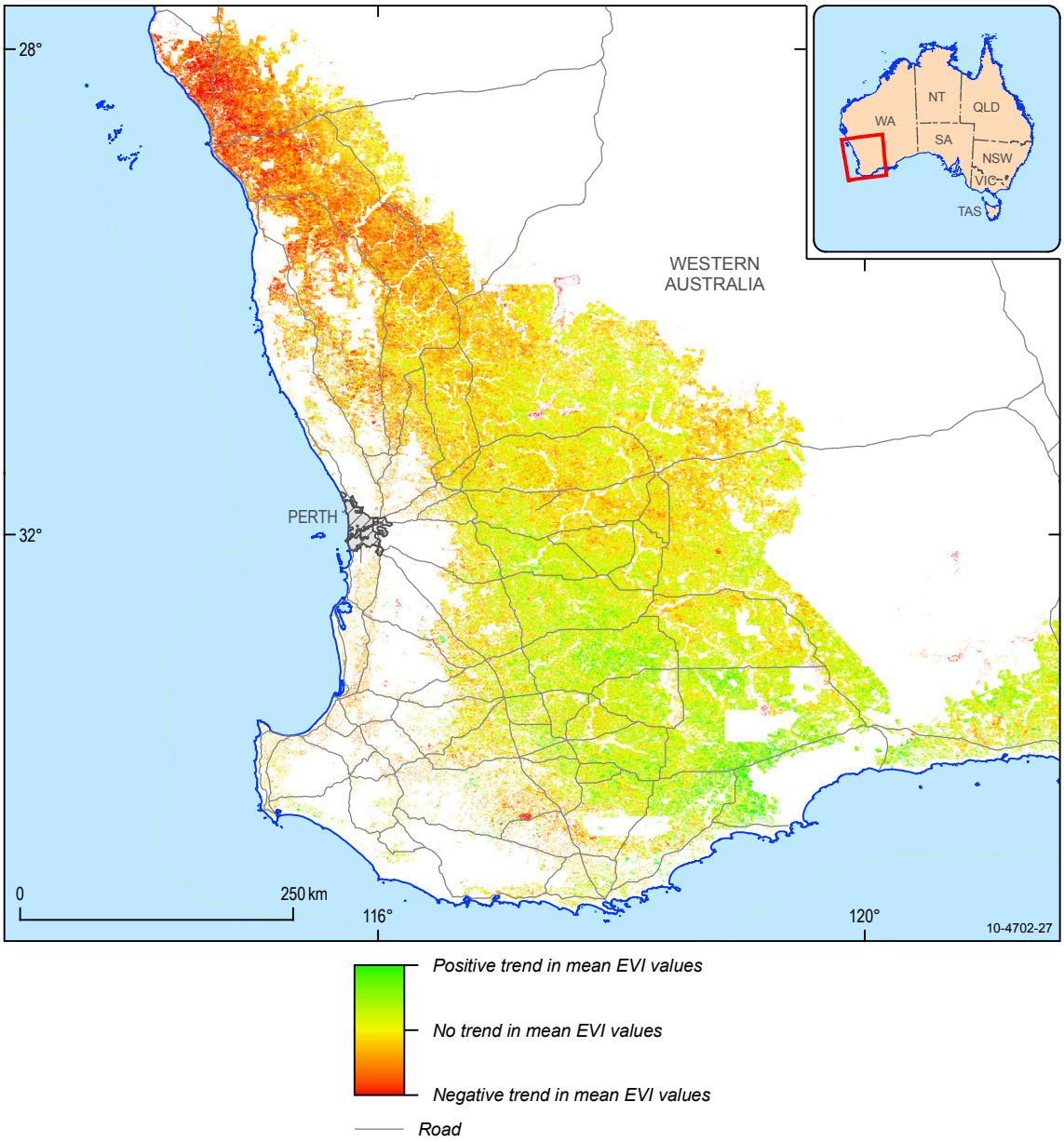

Figure 27: The trend in the mean EVI values for the cropping region in Western Australia.

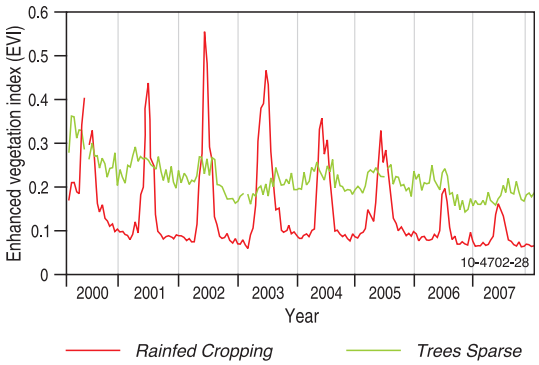

Figure 28: Time series of greenness from a woodland region and a cropping region in the northwest of the Western Australian cropping region.

Case study 2: Mangroves in north Queensland

We compare the mangrove area of the Burdekin delta with other mangroves along the Queensland coast. Mangroves are not a specific theme within the National DLCD, but stands of forest adjacent to the coast and major estuaries were compared with a Landsat mosaic to identify stands of mangroves.

It is clear from Figure 29 (c) (page 50) that all the dense stands of mangroves in the Burdekin delta have undergone a decline in the mean annual EVI. The EVI time series does not provide information on underlying causes, but the DLCD does provide the capacity to highlight specific areas of concern. It also enables comparison of the slope of the mean EVI values for the Burdekin delta mangroves with other mangrove communities.

Illustrating this, Figure 30 shows a series of box plots which represent the range of slopes for the annual mean EVI trend. The red line at zero represents no trend. The mangroves in the Gulf of Carpentaria catchments show a mixture of areas trending up and trending down, consistent with a system in dynamic equilibrium. The mangroves along the wet tropics coast are predominantly trending downwards and the mangroves in the Burdekin delta are exclusively trending downwards. What makes this particularly compelling is that these trends are not present in only one or two pixels, but are present in large areas (133 square kilometres in the Gulf, 133 square kilometres in the wet tropics and 58 square kilometres in the Burdekin delta). Additional data are required to better understand what factors are driving these changes in greenness dynamics, but this example highlights the effectiveness of the DLCD in identifying areas which may be of concern from a state of the environment point of view.

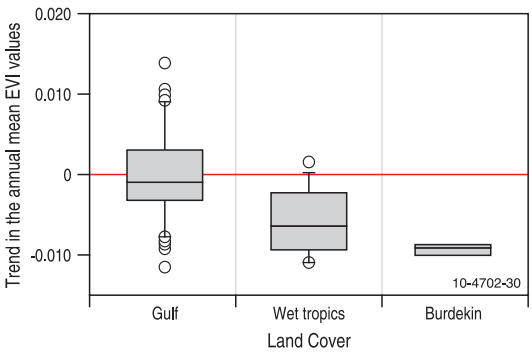

Figure 30: Box plots showing the range of 'slope of the annual mean EVI' values for mangroves communities in north Queensland.

Case study 3: Changes in the alpine zone

This analysis compares the EVI trend data observed in two alpine regions in southeast Australia the Victorian snowfields and the Snowy Mountains. The Interim Biogeographic Regionalisation of Australia (IBRA) sub-regions which contain these two areas, were used to separate the alpine and sub-alpine land cover classes from the rest of Australia. This made it possible to compare woodlands in the Snowy Mountains IBRA sub-region with woodlands in the Victorian Alps and woodlands across Australia.

The analysis suggests that land cover changes may be occurring in the alpine and sub-alpine regions of Australia. However, understanding the nature and drivers of this land cover change requires additional data. The areas contained within the alpine IBRA sub-regions are shown in Figure 32 (page 51) while Figure 31 shows a comparison of the EVI behaviour for two sample areas in the alpine region.

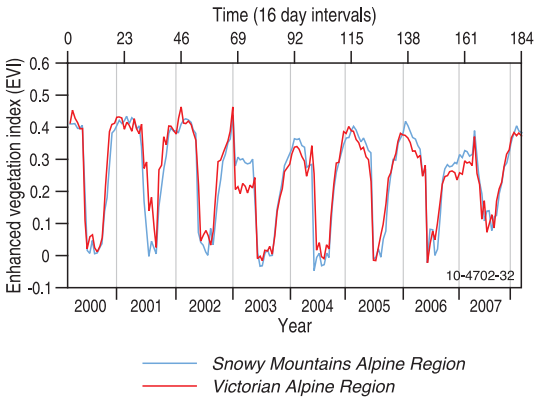

Figure 31: Shows the average time series for the Snowy Mountains alpine (N = 1934) and Victorian alpine (N = 974) regions. Where N is the number of alpine land cover pixels within each IBRA sub-region.

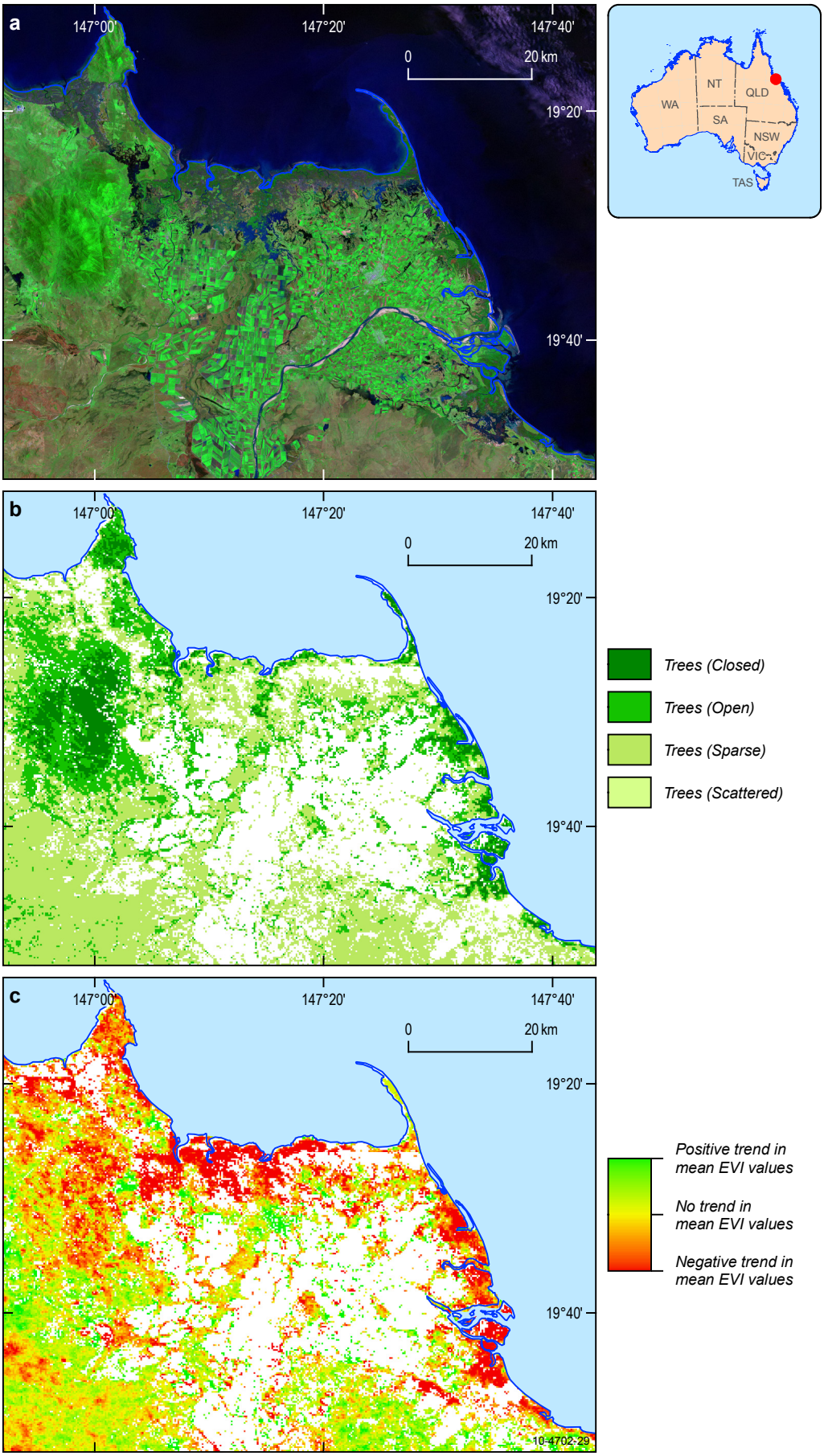

Figure 29: (a.) Landsat image of the Burdekin delta, (b.) DLCD with all non-woody land covers shown as white, increasing green tones represent woody classes from woodland-open to forest-closed, (c.) Trend in the mean annual EVI values.

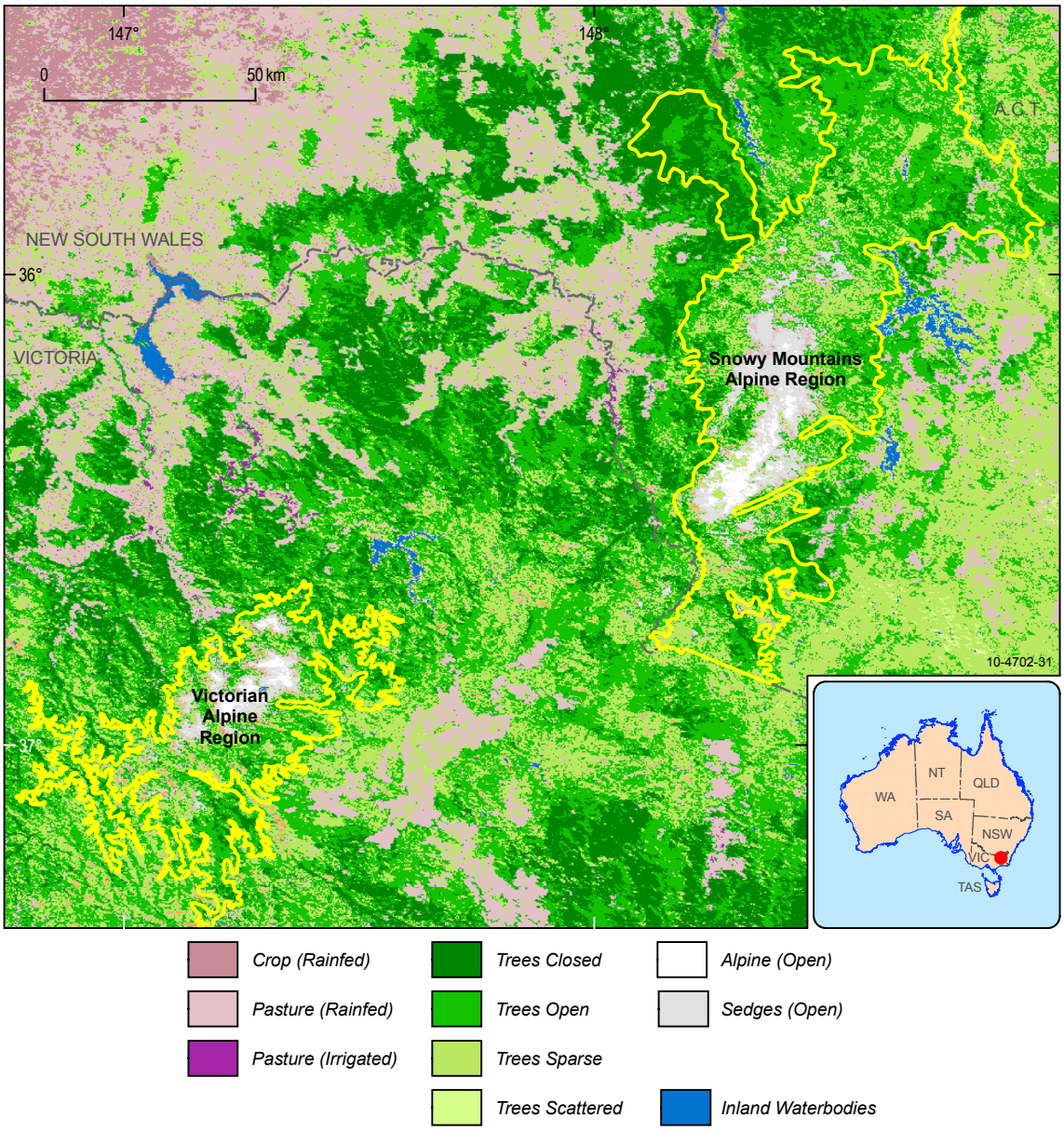

Figure 32: DLCD for the alpine regions.

Trends in annual EVI values within the Victorian Alps IBRA sub-region

The trend in the annual maximum EVI values (Figure 33), annual mean EVI values (Figure 34) and annual minimum EVI values (Figure 35) are all negative with the exception of the trend in the minimum for the alpine class. The trend in the maximum values is most strongly negative for the graminoid/herbaceous dominated land cover types (i.e. alpine, open sedges and rain fed pasture). It is important to note that while these results indicate that changes are occurring in the greenness characteristics of the alpine regions, additional data is required before any inference can be made about change in condition.

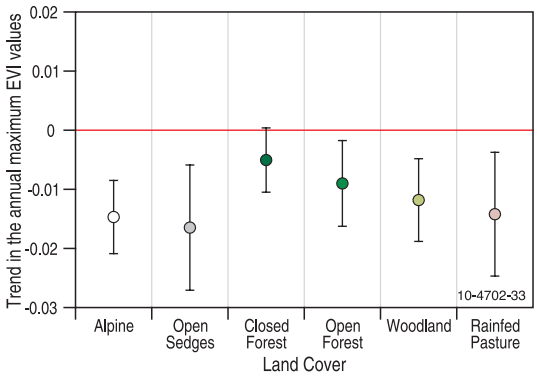

Figure 33: Trend in the annual maximum EVI values for different land covers in the Victorian Alps IBRA sub-region. The dots represent the mean value, with the whiskers representing one standard deviation above or below the mean.

Comparing the Victorian Alps and Snowy Mountains IBRA sub-regions

Figure 36 shows a comparison between the trends observed in the Victorian and Snowy Mountains alpine IBRA sub-regions. The most striking feature is that the trends are more strongly negative in the Victorian Alps IBRA sub-region for all classes other than alpine. This may reflect the differing severity and frequency of major bushfire events within these two sub-regions, or it may reflect the changes in temperature and rainfall associated with the drought in southeast Australia.

Comparing the changes in the alpine IBRA sub-regions with the rest of Australia

Figure 37 compares the trends observed in land cover types which are found in the alpine IBRA regions with those found across a broad range of climatic zones within Australia. There are two points worth noting. Firstly, given the large sample sizes, all of the differences observed in Figure 37 are statistically significant at the 99.9% confidence interval. Secondly the three woody classes show no trend (mean ≈0) at the National scale but show negative trends, particularly in the Victorian Alps IBRA sub-region. These results may reflect the

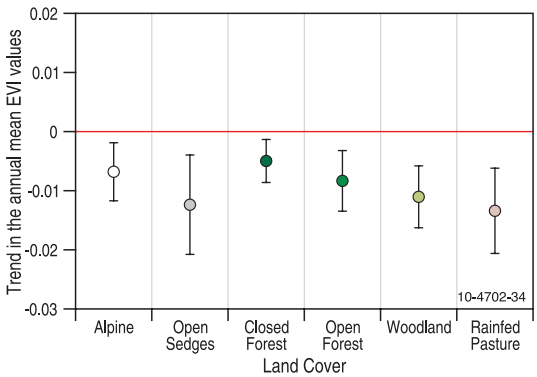

Figure 34: Trend in the annual mean EVI values for different land covers in the Victorian Alps IBRA sub-region.

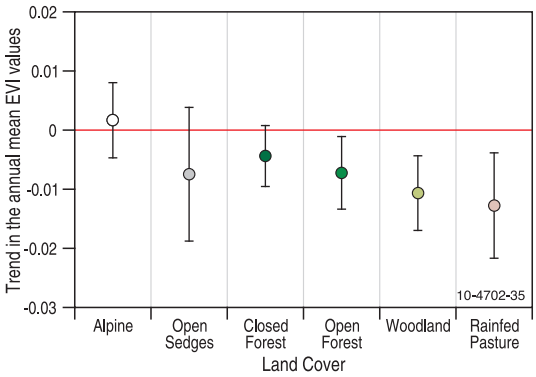

Figure 35: Trend in the annual minimum EVI values for different land covers in the Victorian Alps IBRA sub-region.

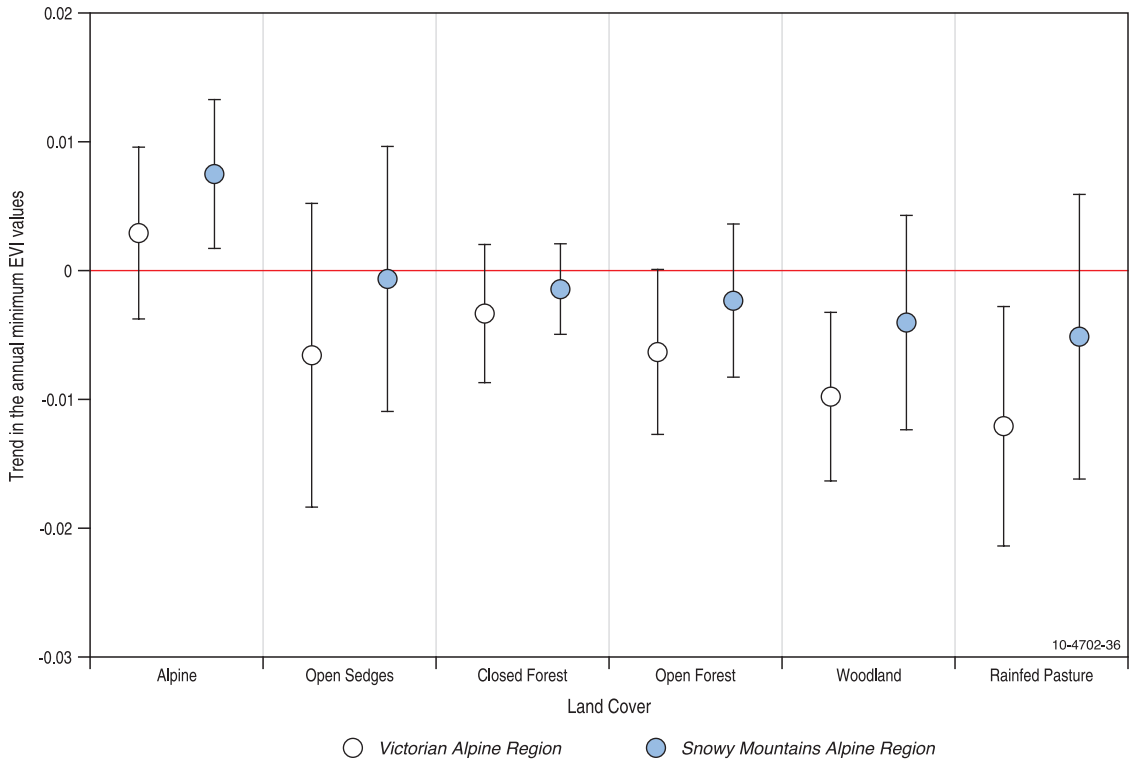

Figure 36: Comparison of the trend in the annual minimum EVI values for different land covers in the Victorian Alps and Snowy Mountains IBRA sub-regions.

differing severity and frequency of major bushfire events within these two sub-regions, or it may reflect the changes in temperature and rainfall associated with the drought in southeast Australia. As with the mangroves example, additional ancillary data are required to understand which factors are driving the change. However, this reinforces the utility of the DLCD to provide insight into the greenness dynamics and identify areas where environmental change may be occurring.

Case study 4: Gaining insight into the Mitchell Grass Bioregion

The capacity which is demonstrated in Figure 38 (page 54) to assess the magnitude and spatial distribution of trends in greenness within a specific land cover type at a range of scales enables critical insight into the different drivers of land cover change which operate at different spatial scales.

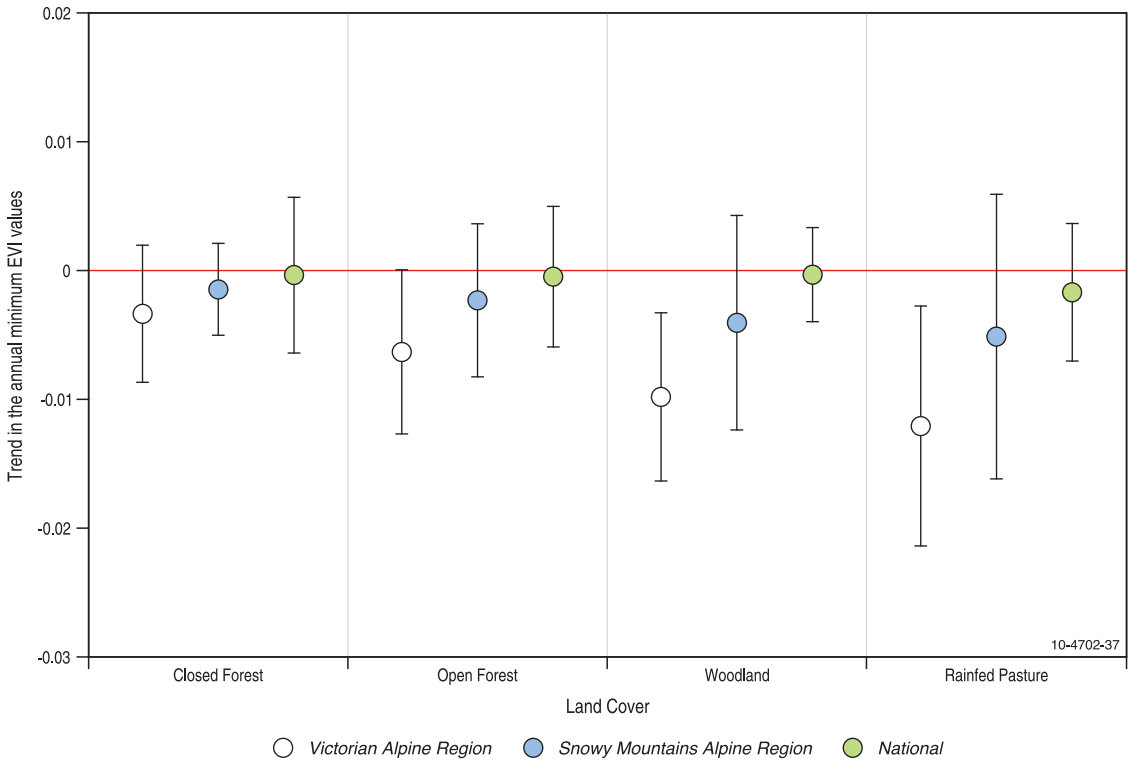

Figure 37: Trend in the annual minimum EVI values for land covers in the Victorian Alps and Snowy Mountains IBRA sub-regions compared to the trends for those land covers at a National scale.

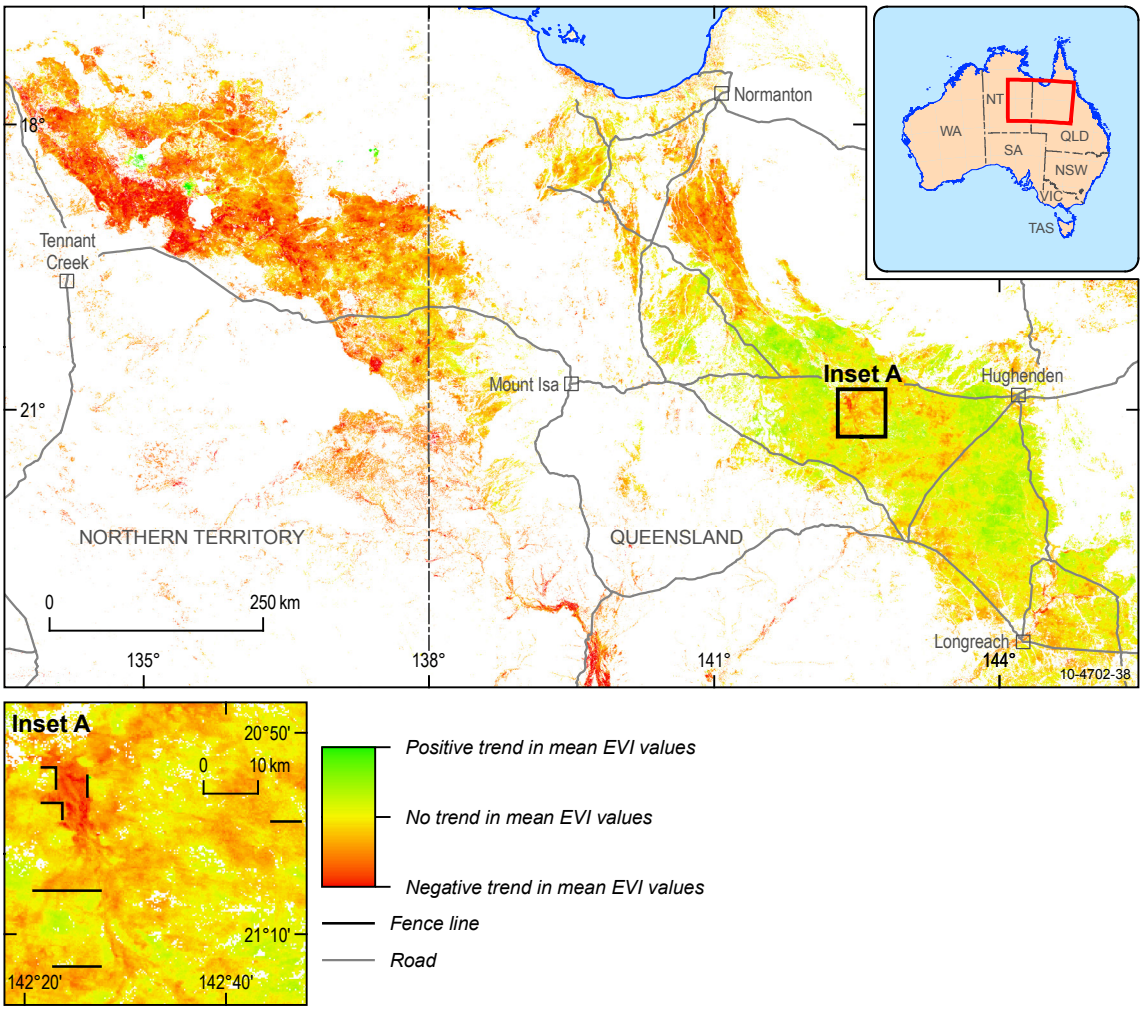

Figure 38: Trend in the annual mean EVI values within the Mitchell Grass Bioregion. The top plate shows the broad scale differences between the Mitchell grass regions in the Northern Territory and those in Queensland, the middle plate shows landscape scale variations in trend and the bottom plate shows fence line contrasts associated with paddock to paddock differences in grazing pressure.

Advantages and limitations of the National Dynamic Land Cover Dataset

Advantages

Consistency in space and time

Key advantages of the DLCD are that it is based on a single consistent data source and it integrates landscape scale greenness dynamics over time. This is important for a number of reasons. It enables meaningful comparisons between land cover types from different areas (e.g. woodlands regions in Western Australia can be compared with woodland regions in New South Wales) and, while the drivers which influence the greenness dynamics might be different for those two regions, both have been observed as behaving like woodlands for the period from 2000 to 2008.

The DLCD enables a more robust and stable land cover classification. For example, areas which are cropped on an opportunistic basis display a very wide range of greenness dynamics, but by observing over an eight year period it is possible to identify areas which are being cropped, even if they are being cropped only very infrequently.

In the DLCD, the dynamics which confound traditional mapping methods become a strength. The use of a single and primary data source with a uniform period of observation avoids the problems encountered with many projects which are compiled GIS datasets from data acquired over different time frames with different thematic emphasis and interpretation.

The DLCD provides a dataset that:

- Enables comparison within and between land cover types, as demonstrated by the previous case studies;
- Enables identification of areas where the greenness dynamics are changing (examples in the previous case studies);
- Provides a context for analysis of other coarse resolution datasets (e.g. the one kilometre resolution recurrent versus persistent Fraction of absorbed Photosynthetically Active Radiation (FPAR) dataset (Donohue et al. 2008) or the 500 metre resolution fractional cover dataset).

The MODIS 500 metre fractional cover dataset (Guerschman et al. 2009) describes each pixel in terms of three variables, green vegetation, bare soil and non-photosynthetic vegetation. The time series of these three fractional covers is shown in a rangeland environment in Figure 39.

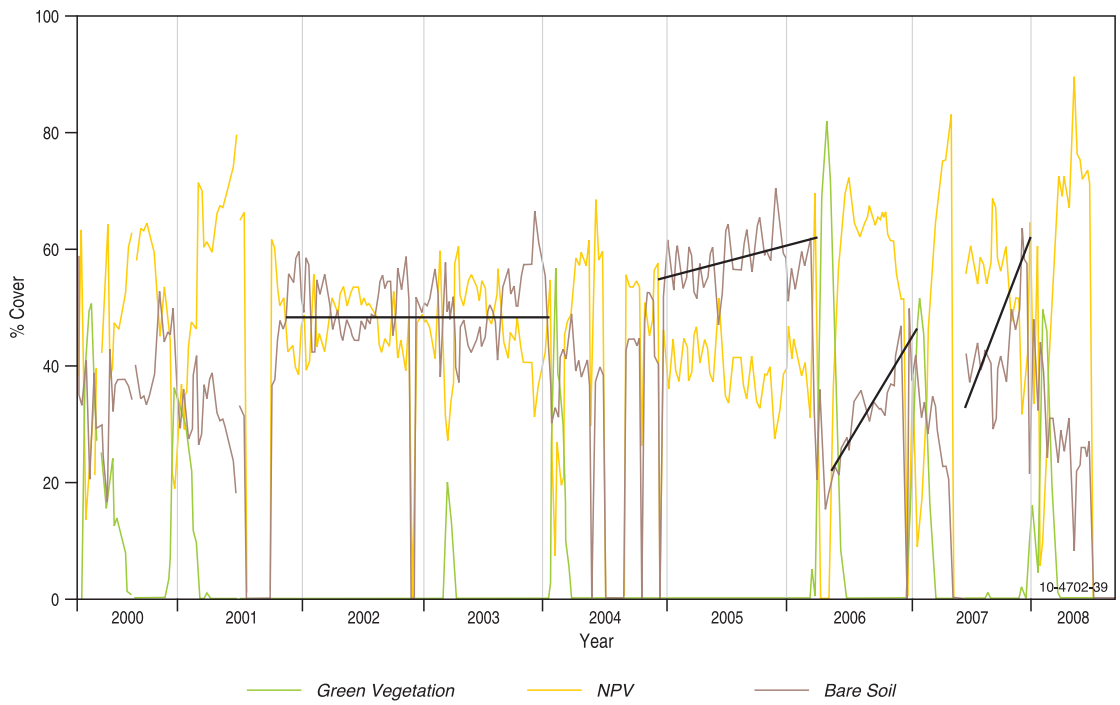

Figure 39: Eight years of 500 metre MODIS fractional cover dynamics for one 500 metre pixel in the Mitchell grass rangelands in the Flinders River catchment in Queensland. The black lines represent low growth periods.

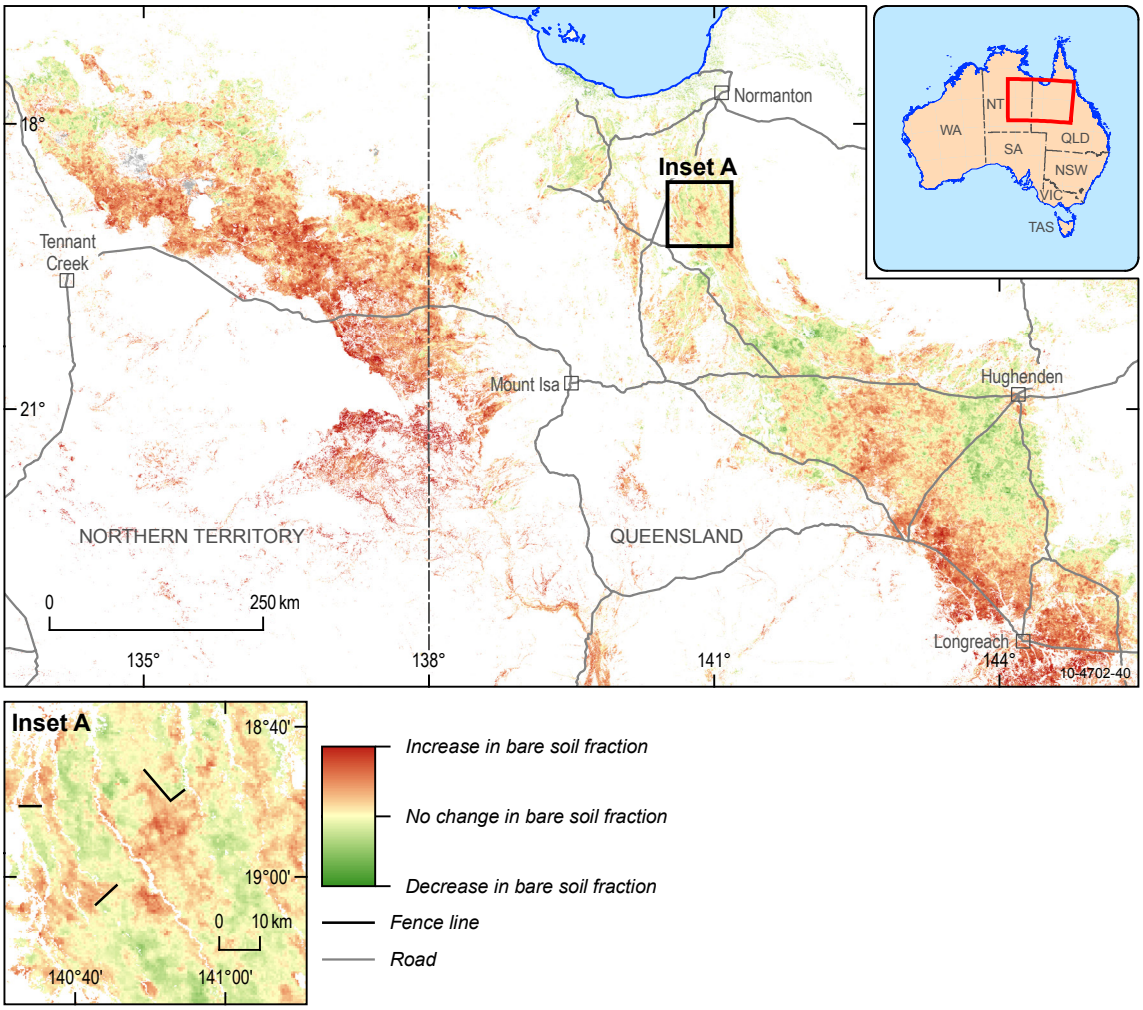

Figure 40: Variations in the trend in the mean bare soil fraction within the Mitchell Grass Bioregion. The top plate shows variations within and between regions, while the bottom plate shows the influence of different grazing pressures on either side of a fence line.

The DLCD provides the context needed for effective interpretation of the time series shown in Figure 39 by providing information about the land cover type from which the fractional cover time series was extracted.

Understanding the relationship between under story and over story density is critical to interpreting remotely sensed estimates of biophysical variables on the Earth's surface. The challenge of discriminating over story signal from ground cover signal has been an ongoing issue for remote sensing. By discriminating areas which have persistent woody vegetative cover from those that do not, the DLCD provides natural resource managers and policy makers with an effective way of addressing this issue. Figure 40 is easier to interpret because areas with a significant proportion of tree cover are being masked out. Furthermore, both products have been generated using the same sensor (MODIS) and are based on the same time frame from April 2000 to mid 2008. The capacity of the DLCD to provide context to other coarse resolution datasets is shown in Figure 40. By combining EVI and fractional cover in the clustering process improved delineation of low cover land cover classes is possible in the rangelands.

By providing a land cover context to the FPAR dataset, Figure 41 provides valuable insight into both the FPAR and DLCD datasets. Without the labelling provided by the DLCD it would be much more difficult to interpret the FPAR data. The FPAR data provide a valuable insight into the woody and non-woody components of the native vegetation classes and into the range of FPAR characteristics displayed by pasture, including irrigated pastures.

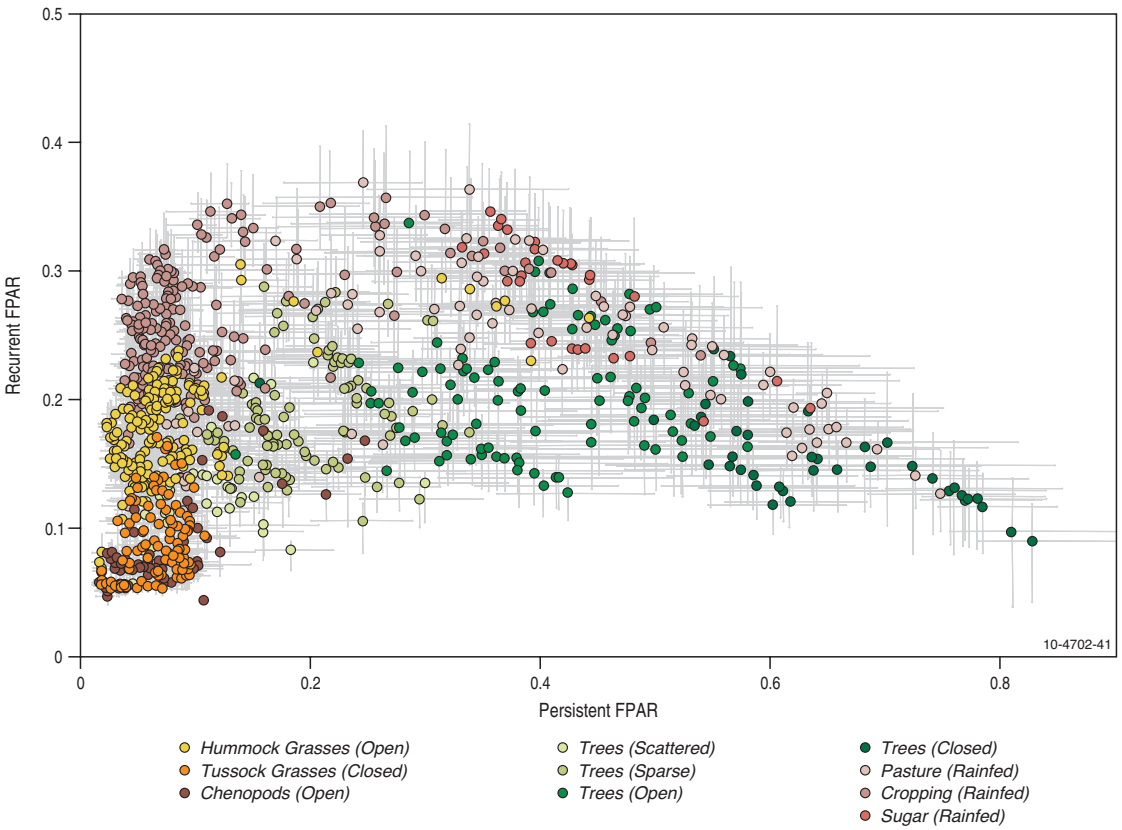

Figure 41: DLCD clusters used to interrogate the persistent versus recurrent fraction of the FPAR (Donohue et al. 2008).

Limitations

Thematic

The level of thematic detail in the DLCD has been determined by a combination of the constraints of the International Standards Organisation (ISO) classification schema and the thematic detail of the input training data. This has the potential to limit the usefulness of the DLCD for users who need additional thematic details such as dominant tree species and height classes. Adoption of the ISO classification schema also precludes land use classes. This is consistent with the use of remotely sensed data which observes changes in land cover rather than land use *per se.* The wide range of greenness dynamics displayed by different irrigated crops in different parts of Australia made it difficult to effectively discriminate between irrigated and non-irrigated cropping. This is further complicated by the year-to-year variation in the irrigation extent. The current DLCD under estimates the extent of irrigation (if an area was found to contain both irrigated and non-irrigated land cover it was labelled as non-irrigated to avoid over estimation). To address this limitation a crop module has been developed to extract information from the time series which is context specific to crops. This is described in the following section.

Training Data

The DLCD is inaccurate in areas where the land cover was poorly represented in the datasets used to label the clusters such as in the shrublands in Tasmania and inter-tidal wetlands. These limitations will be addressed in future versions of the DLCD.

Spatial

The 250 metre spatial resolution represents a fundamental limitation of this remote sensing technique. This is likely to be problematic in areas where variations in land cover occur in small patches such as with vineyards, some irrigated crops, small wetlands, narrow riparian zones, coastal zones with sharp environmental gradients and intensive land cover practices. In areas where, or for projects in which the objects/areas of interest are smaller than 250 metres the DLCD may not provide the level of detail required and an alternate remote sensing or spatial analysis technique is likely to be required.

Green fraction only

The EVI signal is based on the reflectance characteristics of green vegetation. For land cover types which are not well discriminated by their green fraction dynamics such as urban areas and some deserts, the DLCD will present classes which represent the greenness dynamics observed but may not be useful from an analytical point of view. For example, the Sydney central business district behaves like a sparse shrubland from a greenness dynamics point of view and this may be a reasonable representation of how the green fraction appears, although it is not a particularly useful class in this instance.

Single class representation of dynamic behaviour

One of the main limitations of the DLCD is that it is a single value representation of 186 data points and the statistical, phenological and seasonal behaviour of those points. As a result, areas where the land cover type is highly variable are likely to be misrepresented. The best example of this is irrigated areas where the land cover is irrigated cropping in some years, but not in others. For the purposes of the DLCD, if there was any confusion in the class labelling process between irrigated and rainfed, then the cluster was labelled as rainfed.

Consequently the DLCD under estimates the extent of irrigated land cover types. The problem is compounded by the reality that the extent of irrigated land cover within Australia varies from year-to-year because of water availability and land management decisions. As a result it makes sense to characterise irrigation on a year-by-year rather than 10 year average basis. To address this short-coming, a crop analysis tool has been developed to extract specific features associated with EVI time series observed over cropping regions. This crop module will be refined through a stakeholder review process and then applied to all pixels classified as crop within the DLCD. The results will be released as part of DLCDv2.

Future developments

Feedback collected at the land cover website will be used to guide the future development of the DLCD. It is anticipated that in the process of using this map, users will identify areas of thematic inaccuracy. There is a form on the webpage for users to identify inaccurate areas of the map so they can be addressed in version 1.5.

The subsequent version 2 of the DLCD will be based on an annual time step so there will be a DLCD for each year from 2001 to 2010. This will enable users to analyse year-to-year land cover changes. Future versions may include increased detail about specific land cover types, such as the crop module outlined below, or an application of this method to 25 metre resolution data. The content of version 3 of the DLCD product suite and subsequent product suites will be determined via stakeholder consultation.

Crop module

A crop analysis module was developed to better characterise cropping areas using the characteristics of the time series graph and the spatial data (Figures 42 and 43).

The crop analysis module extracts several parameters including:

- Number of peaks;
- Number of fallow events;
- Cumulative duration of fallow events;
- Cumulative area under the curve.

An example of the use of the crop module is shown in Figure 42 while Figure 43 shows examples of three of the outputs of the cropping module for the Namoi and Gwydir catchments in New South Wales. There are a number of key features shown in Figure 43a. The most obvious is the difference in cumulative greenness between the irrigated (predominantly red) and non-irrigated (greens-purples) portions of the two catchments. The other feature is the gradient in cumulative greenness from east (right) to west (left) which reflects the rainfall gradient across this region. These key features are presented from a different dimension in Figure 43b which shows the number of crop cycles over the six year period of observation. Areas which show 12 crop cycles have been double cropped every year. In contrast, some fields on the western edge of the catchment have been cropped only once in the six year period. Figure 43c presents the same features from another perspective illustrating the percentage of time fallow. The intensively irrigated portions of both catchments (those that are double cropped) are fallow for a very short time amounting to less than 20% of the time while the fields in the opportunity cropping regions at the western edges of the catchment are fallow for up to 70% of the time.

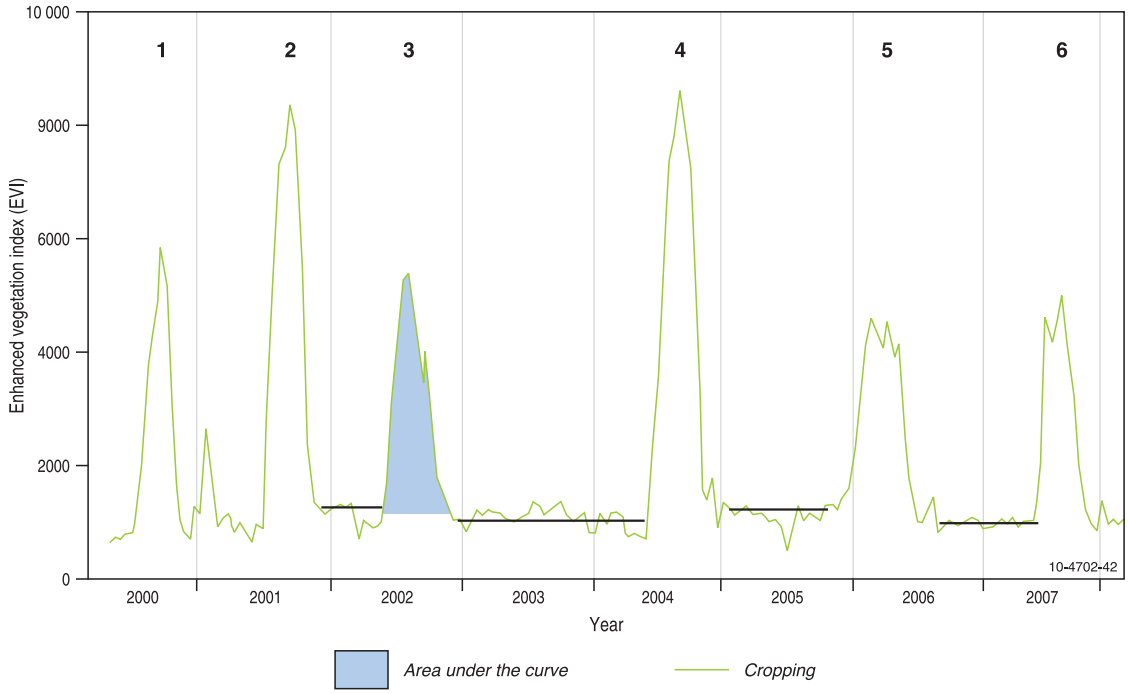

Figure 42: An example of the features extracted by the crop module, including the number of peaks, the number of fallow periods and area under the curve, which approximates the cumulative greenness during the growing season.

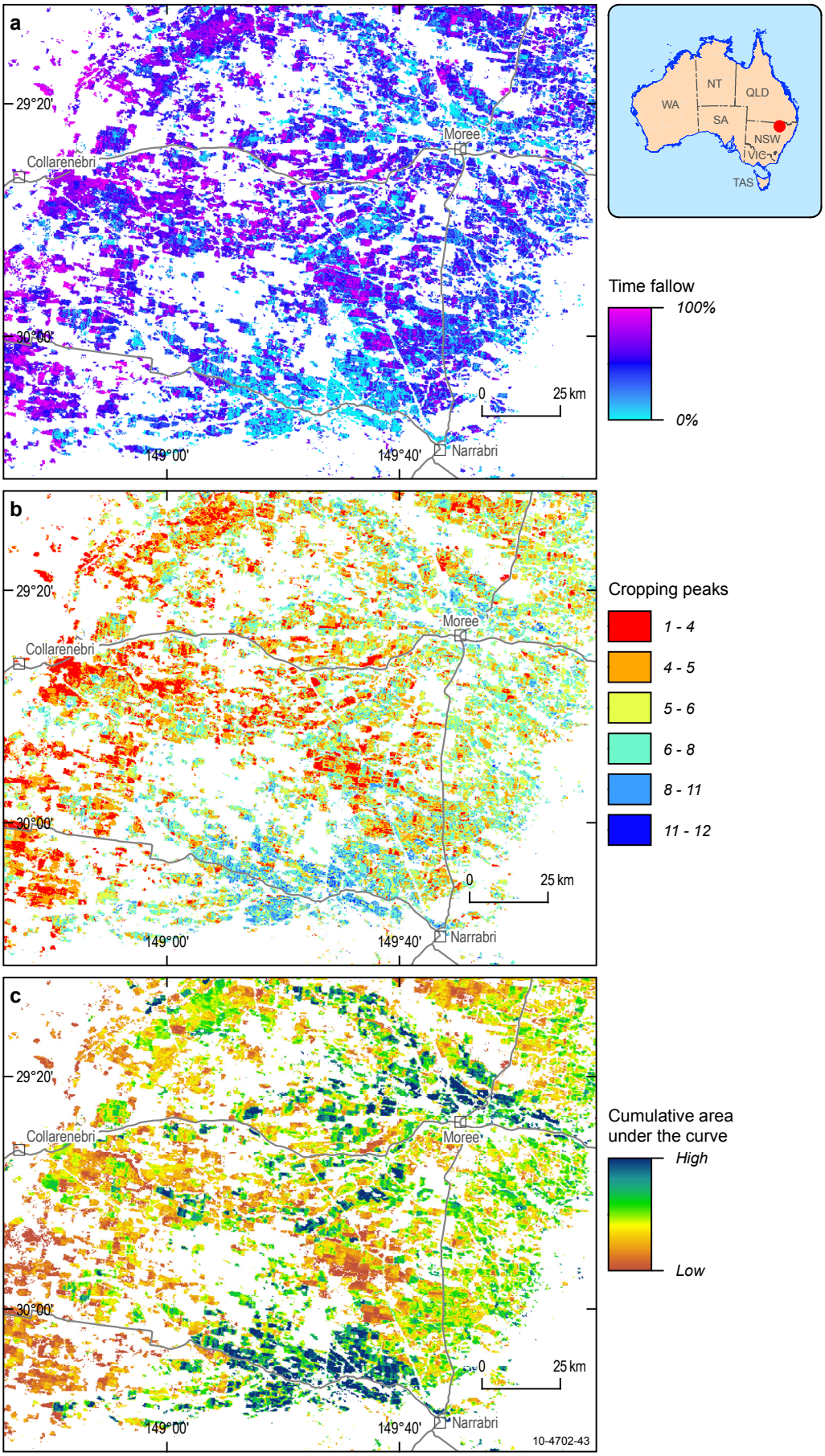

Figure 43: Three of the outputs from the cropping applied to the Gwydir and lower Namoi catchment (a) percentage of time fallow, (b) the number of peaks and (c) the cumulative area under the curve.

Conclusion

The National Dynamic Land Cover Dataset is a consistent complete land cover product for all of Australia. It provides an Australia-wide baseline for land cover analyses and management.

The daily frequency of Moderate Resolution Imaging Spectoradiometer (MODIS) satellite observations provides the DLCD with the ability to be generated at regular intervals aligned with statutory needs, making seasonal and even monthly updates possible. As a result, the DLCD could be used to provide consistent land cover change information. Derivative products from the DLCD such as Enhanced Vegetation Index (EVI) trend analyses have the potential to provide large scale comparisons of the performance of significant environmental features such as mangroves or alpine grasslands. Used as a platform to underpin detailed land cover projects, the DLCD provides a framework to align independent analyses to a common point of comparison.

The development of the DLCD highlights the usefulness of time series analyses in land cover classification and change. The composite MODIS vegetation index approach helps mitigate the effects of clouds and other interferences such as data errors which can make standard satellite image approaches unworkable. The dynamic vegetation index approach provides a consistent reference for every class, hence classes are intercomparable and may be related to biophysical variables such as Fraction of absorbed Photosynthetically Active Radiation (FPAR) and Foliage Projective Cover (FPC).

The 250 metre scale of the DLCD is very advantageous from a regional perspective, allowing an understanding of the big picture rather than delving into the small detail. The DLCD provides a toolbox of useful analytical systems which are applicable to regional comparisons and to understanding the changes in vegetation communities. The DLCD provides an overarching product with the intent of enabling high detail projects to plug into a National standard.

The DLCD can be used as input into moderate to coarse scale models of:

- Groundwater recharge and discharge;
- Climate;
- Wind and water erosion risk;
- Evapotranspiration;
- Carbon dynamics;
- Land surface processes;
- Inundation.

The DLCD in combination with the trend in annual EVI data can provide insight into the response of land cover to a wide variety of drivers, both natural and anthropogenic. This provides natural resource managers with the capacity to identify emerging patterns of land cover change and with a broad spatial and historical context within which to interpret that land cover change. This can be combined with ancillary information to assess what, if any, on-ground or policy interventions are required to mitigate the emerging behaviour.

‘The DLCD is a consistent, complete land cover product for all of Australia. It provides a National baseline for land cover analyses and management.’

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- Executive Steering Committee for Australian Vegetation Information (ESCAVI);
- National Committee for Land Use and Management Information (NCLUMI);
- Queensland Statewide Landcover And Tree Study (SLATS);
- Government Departments of Australia, New South Wales, Queensland, South Australia, Victoria, Tasmania, Western Australia, the Australian Capital Territory and the Northern Territory.

References

Australian Collaborative Land Use and Management Program 2009 (ACLUMP). Status of Land Management Practices, Activities of the Australian Land Use and Management Program. Bureau of Rural Sciences, Canberra.

Atyeo C., and Thackway, R., (2006). Classifying Australian land cover. Bureau of Rural Sciences, Canberra. pp 27.

Ballantine, J., Okin, C., Dylan, G.S., and Roberts, E.P., (2005). Mapping North African landforms using continental scale unmixing of MODIS imagery. *Remote Sensing of Environment, 97*, 470–483.

Bernhard, S., and Alexander, J.S., (2001). Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond, MIT Press.

Bicheron, P., Defourny, P., Brockmann, C., Schouten, L., Vancutsem, C., Huc M., Bontemps, S., Leroy, M., Achard, F., Herold, M., Ranera, F., and Arino, O., (2008). GLOBCOVER – Products Description and Validation Report. Toulouse, France. pp 47. Data download http://193.204.231.21/index.asp

Boland, C., and R. Thackway, R., (2008). *Analysis of the requirements of National Coordinating Committee's for vegetation-related and landcover information.* Bureau of Rural Sciences, Canberra. (https://www.govdex.gov.au/confluence/download/attachments/62981730/landcoveneedsCBoland.DOC). Accessed 16 February 2010.

Bureau of Rural Sciences (BRS), (2006), Final report: 1992/93, 1993/94, 1996/97, 1998/99, 2000/01 and 2001/02 Land Use of Australia, Version 3, Bureau of Rural Sciences, Canberra.

Bureau of Rural Sciences (BRS), (2008). Vegetation cover types. http://adl.brs.gov.au/intveg/ Accessed 22 April 2010.

Bureau of Rural Sciences (BRS), (2009). *2005/06 Land Use of Australia, Version 4. Draft Interim December 2009.* Bureau of Rural Sciences, Canberra.

Bureau of Rural Sciences (BRS), (n.d.). Land Use in Australia – At a Glance. Bureau of Rural Sciences, Canberra. http://adl.brs.gov.au/mapserv/landuse/pdf_files/Web_LandUseataGlance.pdf Accessed 22 April 2010.

Caccetta, P., Furby, S., O'Connell, J., Wallace, J., and Wu, X., (2007). Continental Monitoring: 34 Years of Land Cover Change Using Landsat Imagery. http://www.cmis.csiro.au/rsm/papers/Caccetta_et_al_ISRSE2007.pdf

Carrao, H., Goncalves, P., and Caetano, M., (2008). Contribution of multispectral and multitemporal information from MODIS images to land cover classification. *Remote Sensing of Environment*, 112, 986–997.

Congalton, R., and Green, K. (1999). Assessing the accuracy of remotely sensed data: Principles and practices. Lewis Publishers: New York 137 pp.

Department of Sustainability and Environment (2010). *Landcover and vegetation statewide data 2010. Unpublished dataset 10 May 2010.* Arthur Rylah Institute for Environmental Research, Victorian Department of Sustainability and Environment, Melbourne.

Australian Department of the Environment and Water Resources (2007), *Australia's Native Vegetation: A summary of Australia's Major Vegetation Groups, 2007.* Australian Government, Canberra.

Department of the Environment Water, Heritage and the Arts (DEWHA) Canberra, Australia's bioregions (2009). http://www.environment.gov.au/parks/nrs/science/bioregion-framework/index.html. Accessed 22 April 2010.

Di Gregorio, A., and Jansen, L.J.M. (2000). Land Cover Classification System – Classification concepts and user manual. FAO, Viale delle Terme di Caracalla, Rome. http://www.fao.org/DOCREP/003/X0596E/X0596e00.htm [Accessed on 18 February 2010].

Donohue, R.J., McVicar, T.R., and Roderick, M.L.,(2009), 'Climate-related trends in Australian vegetation cover as inferred from satellite observations. 1981-2006.' *Global Change Biology*, 15, (4), 1025–1039.

Fernandes, R., Fraser, R., Latifovic, R., Cihlar, J., Beaubien, J., and Du, Y., (2004). Approaches to fractional land cover and continuous field mapping: A comparative assessment over the BOREAS study region. *Remote Sensing of Environment*, 89, 234–251.

Friedl, M.A., McIver, D.K., Hodges, J.C.F., Zhang, X.Y., Muchoney, D., Strahler, A.H.,Woodcock, C.E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F., and Schaaf, C., 'Global land cover mapping from MODIS: algorithms and early results' *Remote Sensing of Environment*, 83, (2002) 287–302.

Gao, Y., and Mas, J.F. (2008). MODIS EVI as an ancillary data for an object-based image analysis with multi-spectral MODIS data. *Proceedings of the GEOBIA2008 –Pixels, objects, Intelligence. Geographic object based image analysis for the 21 st century. University of Calgary, Calgary Alberta, Canada*, 1–373.

Green, A.A., Berman, M., Switzer, P., and Craig, M.D. (1988). A transformation for ordering multispectral data in terms of image quality with implications for noise removal. IEEE Transactions on Geoscience and Remote Sensing, 26, 65–74.

Guerschman, J.P., Hill, M.J., Renzullo, L.J., Barrett, D.J., Marks, A.S., and Botha, E.J. (2009). Estimating fractional cover of photosynthetic vegetation, non-photosynthetic vegetation and bare soil in the Australian tropical savannah region upscaling Hyperion and MODIS sensors. *Remote Sensing of Environment*, 113, 928–945.

Hostert, P., Roder, A., and Hill, J., (2003). Coupling spectral unmixing and trend analysis for monitoring of long-term vegetation dynamics in Mediterranean rangelands. *Remote Sensing of Environment*, 87, 183–197.

Huete, A.R., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., and Ferreira, L.G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83, 195–213.

Hur, A., and Horn, D., (2002). "Support vector clustering." *J. Mach. Learn. Res.* 2, 125–137.

Kasetkasem, T., Arora, M.K., and Varshney, P.K. (2005). Super-resolution land cover mapping using a Makov random field based approach. *Remote Sensing of Environment*, 96, 302–314.

Laliberte, A.S., Rango, A., Herrick, J.E., Fredrickson, Ed L., and Burkett, L., (2007). An object-based image analysis approach for determining fractional cover of senescent and green vegetation with digital plot photography. *Journal of Arid Environments*, 69, 1–14.

Lowry, J., Langs, L, Ramsey, R., Kirby, J., and Schultz, K., (2007). A matrix-based approach to fuzzy set accuracy assessment. RS/GIS Lab White Paper, Remote Sensing/ GIS Laboratory, College of Natural Resources, Utah State University.

National Land and Water Resources Audit (NLWRA) (2007). Australian land cover mapping. *Proceedings of a workshop to discuss interest in land cover mapping.* 24 July 2007. National Land and Water Resources Audit. Canberra. http://nlwra.gov.au/files/products/National-land-and-water-resources-audit/pn21311/pn21311.pdf

Paget, M.J., and King, E.A., (2008). MODIS Land data sets for the Australian region. CSIRO Marine and Atmospheric Research Internal Report No. 004.

Powell, R.L., Roberts, D.A., Dennison, P., and Hess, L.L., (2007). Sub-pixel mapping of urban land cover using multiple endmember spectral mixture analysis: Manaus, Brazil. *Remote Sensing of Environment*, 106, 253–267.

Sedano, F., Gong, P., and Ferrao, M., (2005). Land cover assessment with MODIS imagery in southern African Miombo ecosystems. *Remote Sensing of Environment*, 98, 429–441.

Tan, P., Lymburner, L., Thankappan, M., and Lewis, A. (2009). 'Mapping Broadacre Cropping Practices Using Modis Time Series: Harnessing the Data Explosion', in International Workshop on Impact of Climate Change on Agriculture Ahmedabad, India.

Thackway, R., and Lesslie, R. (2008)., Describing and mapping human-induced vegetation change in the Australian landscape, *Environmental Management* 42, 572–590.

Thenkabail, P.S., Schull, M., and Turral, H. (2005). Ganges and Indus river basin land use/land cover (LULC) and irrigated area mapping using continuos streams of MODIS data. *Remote Sensing of Environment*, 95, 317–341.

Verhoeye, J., and De Wulf, R., (2002). Land cover mapping at sub-pixel scales using linear optimization techniques. *Remote Sensing of Environment*, 79, 96–104.

Wessels, K.J., De Fries, R.S., Dempewolf, L.O., Hansen, A.J., Powell, S.L, and Morgan, E.F. (2004). Mapping regional land cover with MODIS data for biological conservation: Examples from the Greater Yellowstone Ecosystem, USA and Para State, Brazil. *Remote Sensing of Environment*, 92, 67–83.

Wilson, M., and Henderson-Sellers, A. (1985). A global archive of land cover and soils data for use in general circulation climate models. *Journal of Climatology*, 5, 119–143.

Xiao, X., Boles, S., Liu, J., Zhuang, D., Frolking, S., Li, C., Salas, W., and Moore, B. (2005). Mapping paddy rice agriculture in southern China using Multi-temporal MODIS images. *Remote Sensing of Environment*, 95, 480-492.

Xu, R., and Wunsch, D., (2005). "Survey of clustering algorithms." *IEEE Transactions on Neural Networks*, 16(3), 645–678.

Yilmaz, Ö., and Achenie, L.E.K. (2007). "Systematic tuning of parameters in support vector clustering." *Mathematical Biosciences*, 205(2), 252–270.

Zhang, J. and Foody, G.M. (1998). A fuzzy classification of sub-urban land cover from remotely sensed imagery. International Journal of Remote Sensing 19(14), 2721–2738.

Zhou, W., Huang, G., Troy, A., and Cadenasso, M.L., (2009). Object-based land cover classification of shaded areas in high spatial resolution imagery of urban areas: A comparison study. *Remote Sensing of Environment*, 113, 1769–1777.

Glossary

Glossary for the purposes of ground cover field work

Table 14: Glossary for the purposes of ground cover field work.

Calibration (Reference) site	A permanent site, or site which is revisited at specific intervals (specific intervals to coincide with land management practices and satellite overpasses). Ground cover at calibration sites needs to be measured with as much accuracy as possible because the data will be used to establish the relationship between reflectance measurements and ground cover fractions. The Queensland Department of Environment and Resource Management methodology for measuring ground cover should be employed at these sites, with appropriate modification for the specific cropping practices (where sites are located in cropping regions) to ensure thorough characterisation. Ideally full range (visible-short wave infra-red) spectral reflectance measurements of end members which represent each fraction (green, non-photosynthetic vegetation and bare soil) should be made each time fractional cover is recorded at the calibration site. Given the limited availability of full range spectroradiometers, the next best scenario is collection of soil from the site so that the soil moisture levels at the time a satellite overpass can be characterised and the soils spectral response to wetting and drying cycles can be established in a laboratory.
Dynamic Land Cover Dataset (DLCD)	The first version of the DLCD is a land cover/land use map based on a characterisation of the Enhanced Vegetation Index (EVI) dynamics from 2000 to 2008. The map is a combination of land use and land cover because the EVI dynamics are driven by land cover in areas which are dominated by remnant/regrowth native vegetation, but are driven by land use practices in the remainder of the landscape.
End member	The spectral reflectance characteristics of a pure cover type (i.e. 100% bare soil, 100% photosynthetic vegetation).

Enhanced Vegetation Index (EVI)	The enhanced vegetation index is defined by the formula on page 15 and the background to the formulation of the EVI is contained in Huete et al. (2002). The EVI has the advantage of being more sensitive to high green biomass targets than the normalised difference vegetation index (NDVI). The inclusion of a blue band within the index also reduces the influence of atmospheric conditions on the EVI values. Both EVI and NDVI provide an estimate of the green fractional cover of a pixel. The green fraction observed by the satellite at any particular point in time is a combination of the FPC and green ground cover fraction.
Evaluation (Monitoring) site	A site with relatively uniform fractional cover characteristics at the time of observation (observations should be made within a week of the satellite overpass, even less if significant rainfall has occurred). These sites need to be characterised to within acceptable error levels of fractional cover (+-10% or similar error bars as determined by the Land Management Practices Technical Working Group), which will allow collection of data using windscreen survey or similar rapid 'over the fence' visual assessment techniques. This allows a much more flexible and rapid data acquisition regime.
Foliage projective cover (FPC)	The green fractional cover of all woody vegetation (typically higher than one metre).
Fractional cover	The fraction of an area (usually a pixel for the purposes of remote sensing) which is covered by a specific cover type such as green or photosynthetic vegetation, non-photosynthetic vegetation (such as stubble, senescent grass, leaf litter) or bare soil/rock. Note that for the purposes of this document, areas which have been burnt resulting in ash/blackened soil are considered as a 'bare soil' cover type.
Ground cover	The fractional cover located within one metre of the ground surface.
Land cover	Land cover in the context of the National Dynamic Land Cover Dataset (DLCD) relates to the observed biophysical features covering the land, such as forest, grassland or water. Land cover does not relate to the way the cover is used, except where the cover and the use are essentially the same thing, such as cropping or pasture.
Land use	Land use is the way that an area of land is used, from a human perspective, such as for transportation, forestry or livestock production. Land use classes and land cover classes overlap where the description of a cover and use are essentially the same, such as cropping or pasture.

Appendices

Appendix 1: Detailed description of the relabelling process

The results of the initial labelling procedure were assessed by:

Review by a panel of peers (Alice Springs workshop):

- Comparison with other remotely sensed datasets included CSIRO Land and Water's recurrent and persistent Fraction of absorbed Photosynthetically Active Radiation (FPAR) data (Figure 44) and the Queensland Statewide Landcover and Trees Study (SLATS) teams Foliage Projective Cover (FPC) data (Figure 45 and Figure 46).
- Comparison with the 2007 Landsat 7 mosaic based on visual interpretation.
- Comparison with Google Earth™ based on visual interpretation.

All the clusters which were identified as being wrongly labelled were visually assessed and compared to high resolution imagery. Observed errors could be broken into five types (Table 15). The following sections detail how errors were rectified after they had been identified. The workflow of the relabelling procedure is shown in Figure 51.

Table 15: Error types identified during the review of the initial classification.

Error Type	Procedure
Cluster has been labelled incorrectly	Relabel class
Cluster contains more than one land cover type within an Interim Biogeographic Regionalisation of Australia (IBRA) bioclimatic region	Split class using different TS coefficients and then relabel
Cluster represents different land cover types in different regions	Split class based on the IBRA bioclimatic regions
Cluster contains a valid land cover type and terrain related noise	Apply terrain mask
Cluster contains a land cover type that is poorly represented by Enhanced Vegetation Index (EVI)	Apply ancillary data mask

Error type 1:
Cluster has been incorrectly labelled

Where clusters had been labelled incorrectly (Type 1) they were relabelled by visual comparison with high resolution imagery. In some instances this was sufficient to relabel that cluster (e.g. a cluster which has been incorrectly identified as forest can be relabelled as cropping based on a visual assessment of Landsat or high resolution Google Earth™ imagery, if that cluster occurs solely within cropping regions). Where visual comparison was insufficient, the recurrent and persistent Fraction of absorbed Photosynthetically Active Radiation (FPAR) for the cluster were graphed and compared to other clusters to find class outliers (Figure 44). Similarly the mean Foliage Projective Cover (FPC) per cluster was graphed against the mean June to September Enhanced Vegetation Index (EVI), providing a second test for outlying clusters (Figures 45). For outlying clusters found in either the FPC or FPAR comparisons, if the high resolution imagery confirmed they were mislabelled they were relabelled according to their persistent FPC or FPAR (e.g. a cluster which had been mislabelled as open forest would be relabelled as a closed forest if it had a persistent FPAR greater than 0.5). Figure 46 shows the result of the relabelling with fewer outliers.

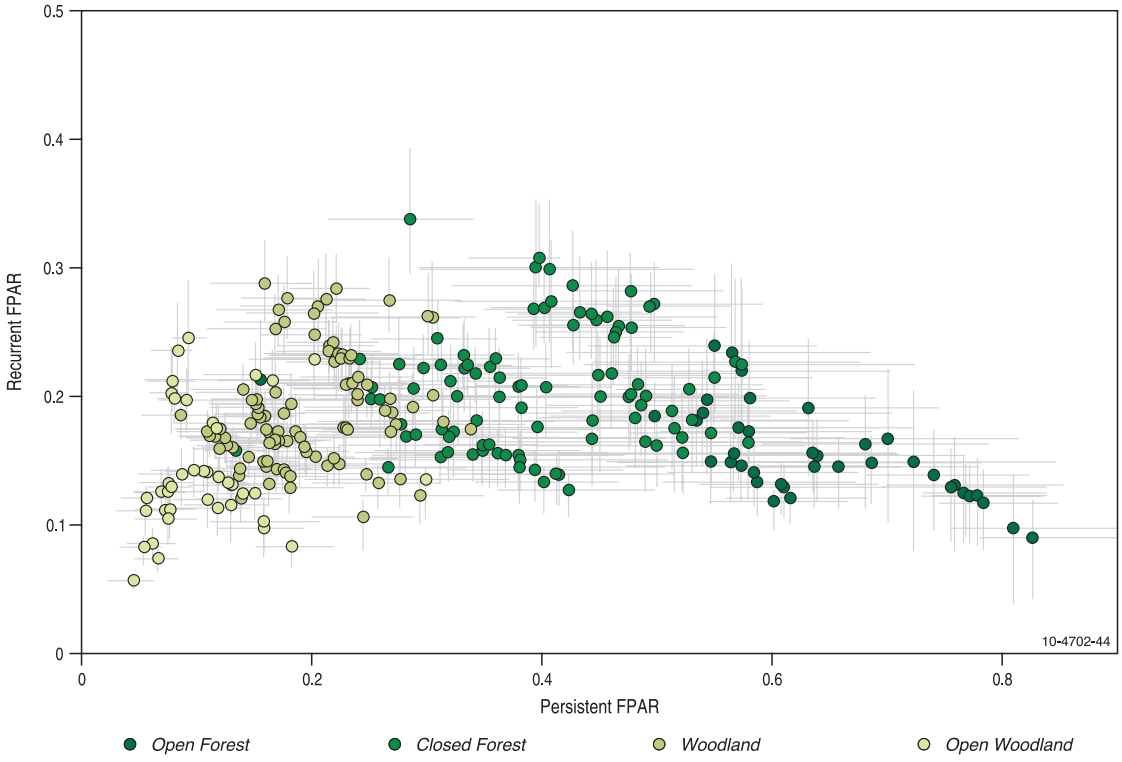

Figure 44: Mean FPAR graphed per cluster of the woody land cover types. Outliers of each cover indicate possible mislabelling.

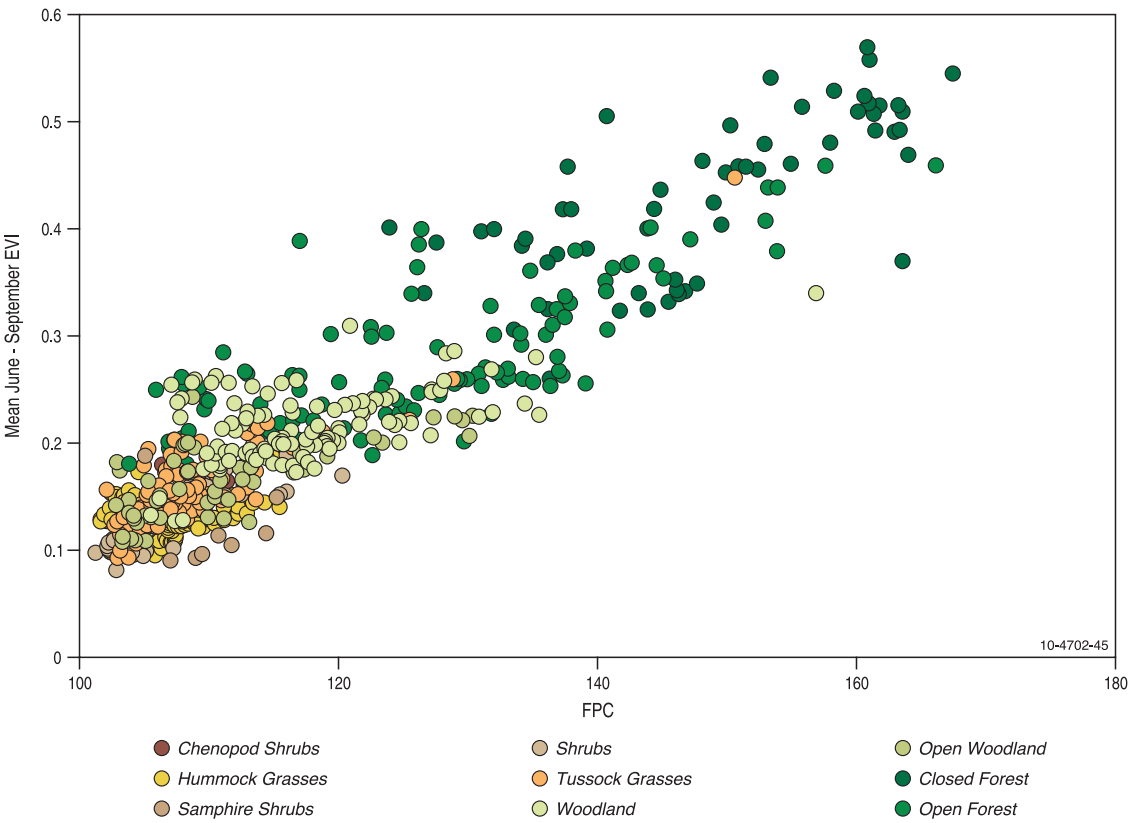

Figure 45: Mean FPC graphed per cluster for natural vegetation cover types. The spread of some covers in comparison to others indicates the broad overlaps which must be addressed in order to form a consistent labelling system. The outliers were identified and corrected as with the FPAR analysis.

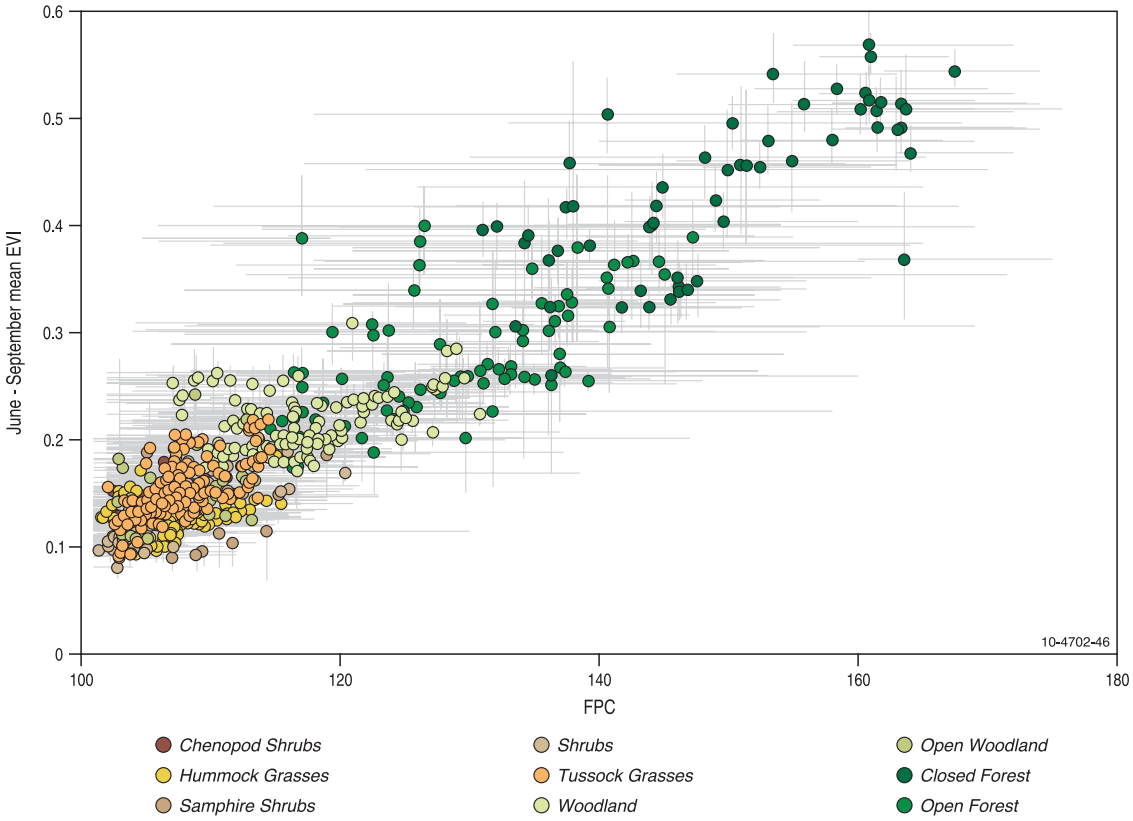

Figure 46: The FPC analysis after correction shows more consistent clustering of cover types, less mislabelling and less overlap between cover types.

Error type 2:
Cluster contains more than one land cover type within an Interim Biogeographic Regionalisation of Australia IBRA bioclimatic region

The Fraction of Absorbed Photosynthetically Active Radiation (IBRA) provides a basis for separating regions of Australia according to similarities in biophysical behaviour. Where a cluster contains more than one cover type, but is localised within a single IBRA region, cluster busting is applied to split the one cluster into several. The cluster busting technique consisted of a series of steps:

1. Identify sample areas of the two different land cover types which have been confused (clustered together) during the first round of clustering (e.g. cropping and wetlands);
2. Extract the statistics for all 12 time series coefficients from each sample area;
3. Plot the results using SigmaPlot 11™ and identify which three time series coefficients provide the greatest discrimination (examples of this process are shown in Figure 47 and Figure 48);
4. Apply the SVM algorithm to the pixels represented using the three time series coefficients;
5. Label the outputs of the SVM algorithm based on the sample areas identified in step one.

In many instances the same confusion occurred across a series of clusters, (e.g. cluster 296 and 294 both contained pastures in high rainfall zones and open forest). Where a series of clusters contained the same class they were all put through step four using the same time series coefficients. In the example given here the pixels from both clusters were analysed by SVM clustering using the time series coefficients, rate of rise, timing of the maximum and annual minimum.

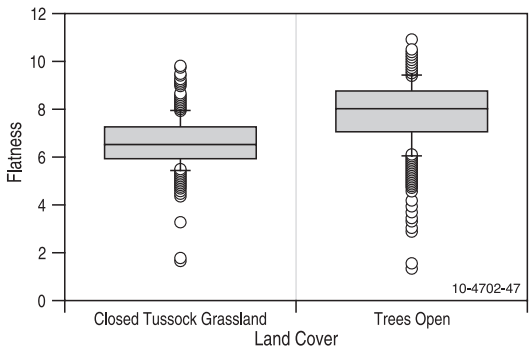

Figure 47: A comparison of two sample class sets showing the overlap of the closed tussock grassland and trees open cover types in the flatness time series coefficient. The boxplot shows a large overlap, indicating that the distributions are sufficiently similar to make it impossible to be discriminated by the flatness, which is one of the three standard inputs to the SVC. As a result, different coefficients are needed to split the classes.

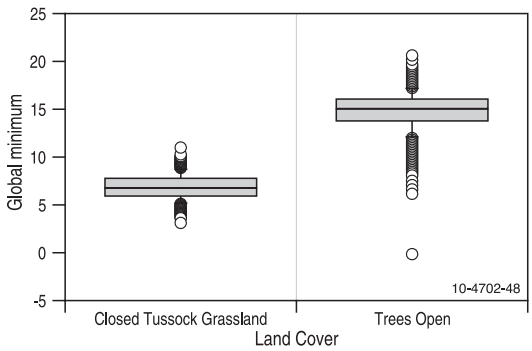

Figure 48: When the two overlapping cover types are examined using a different time series coefficient, the distributions of that coefficient may provide the necessary discrimination to properly separate the cover types. The global minimum time series coefficient can be seen to be a useful discriminator for the closed tussock grassland and trees open overlap because of the difference in the distribution of the coefficient values between the sample sets.

Error type 3:
Cluster different land cover types in different Interim Biogeographic Regionalisation of Australia IBRA bioclimatic regions

The Fraction of Absorbed Photosynthetically Active Radiation (IBRA) provides an underpinning regionalisation for the DLCD. However, IBRA is constructed by the State agencies separately, resulting in the creation of inconsistencies. Some States produced very detailed boundaries while others produced very general boundaries. As a result, the IBRA coverage needs refinement to form a true Australia-wide system. The MODIS time series data provides an extra information layer on Australia-wide biophysical behaviour. Comparison between the IBRA regions and major spatial features of the time series shows good correlation where high detail boundaries were produced and allows adjustment of the low detail boundaries. A large scale segmentation of the time series coefficients was employed to produce an alternative regionalisation of Australia which was then used to consolidate the IBRA coverage into 12 consistent super regions representing major biophysical regions. The workflow for the creation of the revised IBRA super regions is shown in Figure 50. The revised classes addressed most of the incompatibilities within the original classes. However, some issues remained and these were addressed by assigning a unique identifier to each of the 12 IBRA super regions and renumbering classes according to region (Figure 49). All of the revised classes were renumbered by generating a starting class range for each split set and adding a leading digit according to the IBRA identifier. The result was more than 2200 classes instead of the original 300.

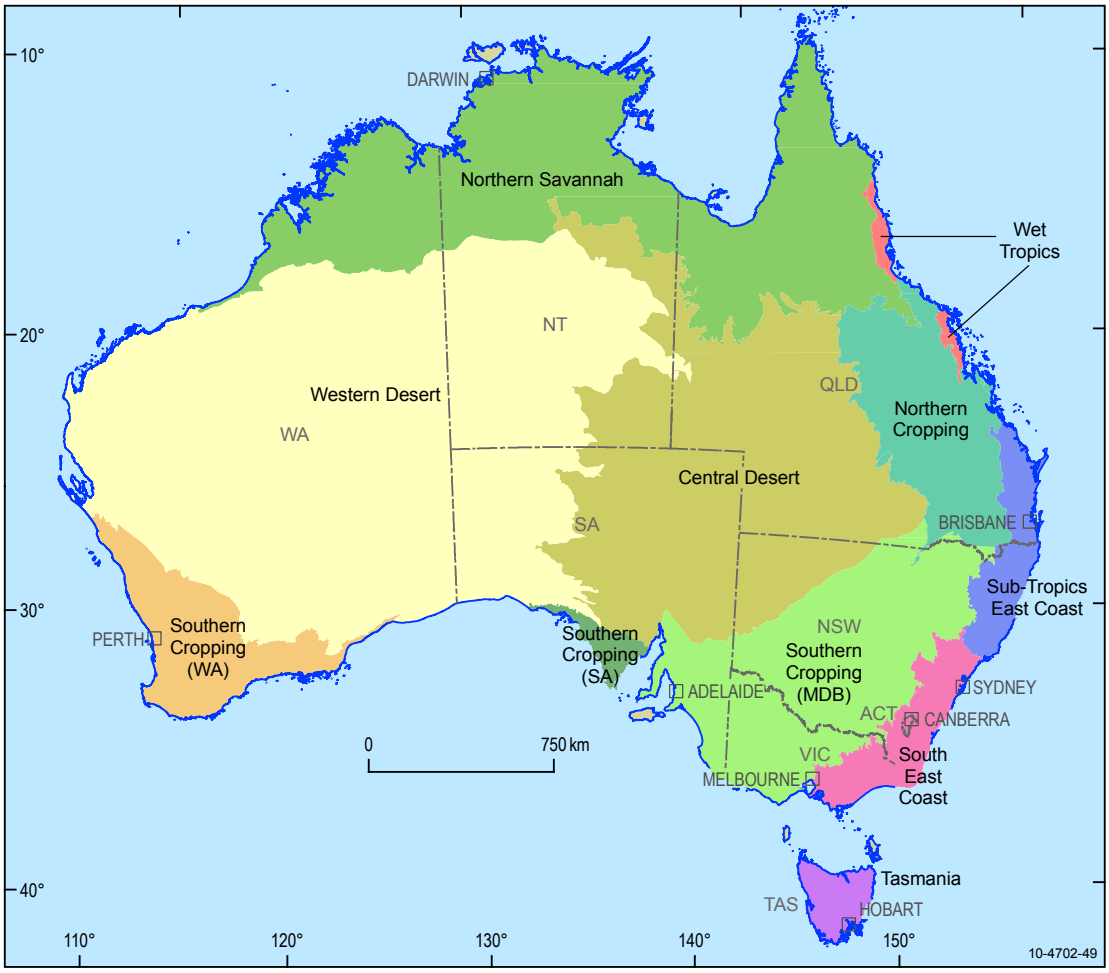

Figure 49: IBRA super regions formed from combining the original IBRA coverage from Australian Bureau of Agricultural Resources, Economics and Sciences (ABARES) with boundaries derived from the MODIS time series coefficients.

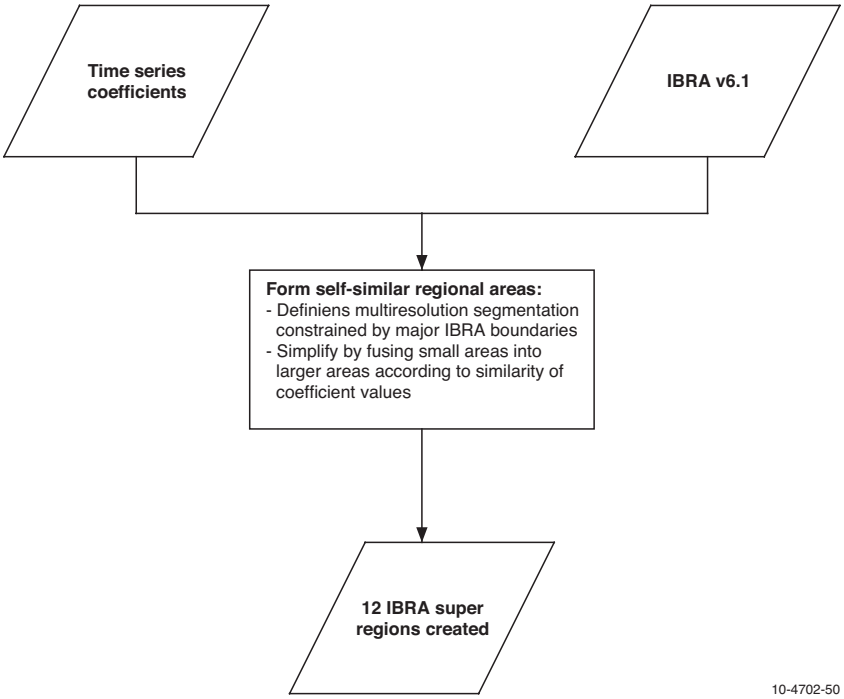

Figure 50: Flow chart describing the creation of IBRA super regions from the original IBRA and the time series coefficients.

Error type 4: Cluster contains a valid land cover type and terrain related noise

The Enhanced Vegetation Index (EVI) time series in high relief areas often contain terrain related artefacts. The problem is particularly obvious on steep southwest facing slopes where winter sun angles produce extensive shading. In forested areas this results in a false seasonality (i.e. the EVI will drop much more for forest on a steep southwest facing slope than for adjacent forests on different aspects). Wet tropics rainforests, which have a stable and high leaf area index, have an EVI signature on southwest facing slopes similar to sugar cane which has seasonally high rather than perpetually high leaf area index. This means that the influence of insolation angle outweighs the influence of on-ground biophysical parameters for certain slopes and aspects. The false seasonality occurring on southwest facing slopes increased the standard deviation and reduced the average annual mean, two of the key time series coefficients in performing the clustering. The problem was most pronounced in very steep terrain, which is typically wooded, and resulted in the presence of non-woody classes in the middle of forests.

A set of rules was developed to re-map problem classes in steep or shadowed terrain in order to obtain the corresponding, fully lit classes. This was done using slope and shade masks generated from the 3 second digital elevation model (3sDEM) generated by the Space Shuttle Radar Topography Mission (SRTM). The slope mask helped separate high productivity cropping such as sugar from dense tropical forest by applying a four degree threshold to cropping. The shade mask was calculated as the equinox solar angle to average the lighting of the terrain and to correct the steep southern slopes. The rules employed slope and shade data derived from the SRTM 3sDEM to provide a final re-classification of a half dozen classes, rectifying crops appearing in mountains and shadowed areas.

Error type 5:
Cluster contains a land cover type that is poorly represented by Enhanced Vegetation Index (EVI)

For some land cover types, specifically those with zero vegetation cover such as water bodies and salt lakes, the Enhanced Vegetation Index (EVI) produces very noisy results and it was necessary to use ancillary data to relabel clusters. The GIS layers used for this purpose were the flats layer and water bodies layer of the TOPO250K National Topographic Database dataset. Because some of these clusters existed both within and outside salt lakes, a contained within rule was applied so that where cluster value x was contained within a salt lake polygon it was relabelled as a salt lake. The same approach was taken with water bodies. Given the variability of EVI time series associated with mines and extraction sites in general and the low variable nature of vegetation in these settings, these areas also may be masked in future versions of the DLCD.

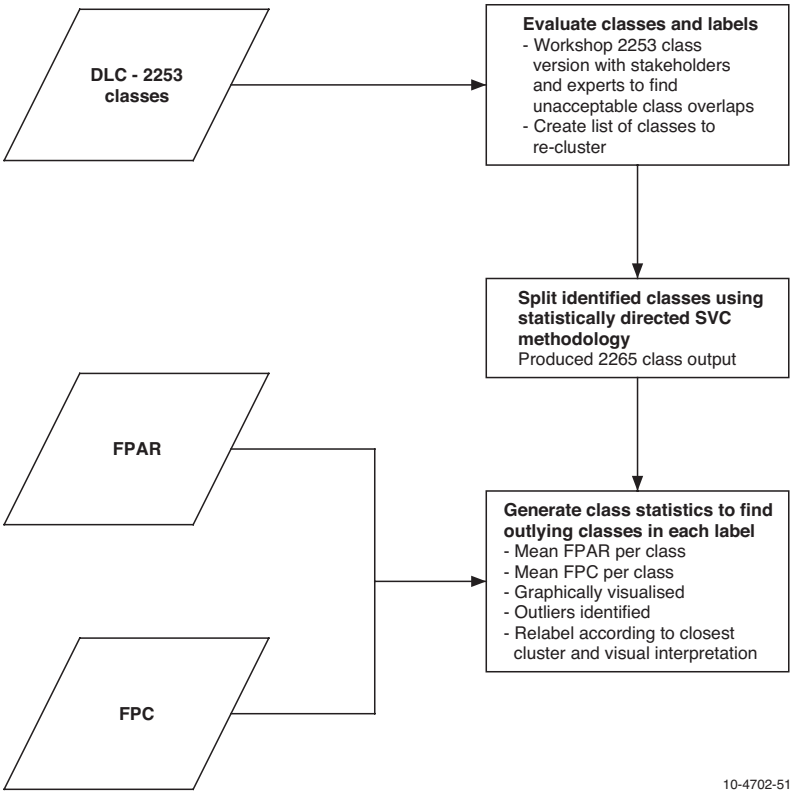

Figure 51: Flow chart describing the relabelling procedure after the workshop review and identification of problem classes.

Appendix 2: CLUM09 classes

Table 16: CLUM09 classes.

CODE	DESCRIPTION
110	1.1.0 Nature conservation
111	1.1.1 Strict nature reserves
112	1.1.2 Wilderness area
113	1.1.3 National park
114	1.1.4 Natural feature protection
115	1.1.5 Habitat/species management area
116	1.1.6 Protected landscape
117	1.1.7 Other conserved area
120	1.2.0 Managed resource protection
121	1.2.1 Biodiversity
122	1.2.2 Surface water supply
123	1.2.3 Groundwater
124	1.2.4 Landscape
125	1.2.5 Traditional indigenous uses
130	1.3.0 Other minimal use
131	1.3.1 Defence
132	1.3.2 Stock route
133	1.3.3 Residual native cover
134	1.3.4 Rehabilitation
200	2.0.0 Production from relatively natural environments
210	2.1.0 Grazing natural vegetation
220	2.2.0 Production forestry
221	2.2.1 Wood production
222	2.2.2 Other forest production
300	3.0.0 Production from dryland agriculture and plantations
310	3.1.0 Plantation forestry
311	3.1.1 Hardwood production
312	3.1.2 Softwood production
313	3.1.3 Other forest production
314	3.1.4 Environmental
320	3.2.0 Grazing modified pastures
321	3.2.1 Native/exotic pasture mosaic
322	3.2.2 Woody fodder plants
323	3.2.3 Pasture legumes
324	3.2.4 Pasture legume/grass mixtures
325	3.2.5 Sown grasses
330	3.3.0 Cropping
331	3.3.1 Cereals
332	3.3.2 Beverage and spice crops
333	3.3.3 Hay and silage

CODE	DESCRIPTION
334	3.3.4 Oil seeds
335	3.3.5 Sugar
336	3.3.6 Cotton
338	3.3.8 Legumes
340	3.4.0 Perennial horticulture
341	3.4.1 Tree fruits
342	3.4.2 Oleaginous fruits
343	3.4.3 Tree nuts
344	3.4.4 Vine fruits
345	3.4.5 Shrub nuts fruits and berries
346	3.4.6 Flowers and bulbs
347	3.4.7 Vegetables and herbs
350	3.5.0 Seasonal horticulture
351	3.5.1 Fruits
352	3.5.2 Nuts
353	3.5.3 Flowers and bulbs
354	3.5.4 Vegetables and herbs
360	3.6.0 Land in transition
361	3.6.1 Degraded land
362	3.6.2 Abandoned land
363	3.6.3 Land under rehabilitation
364	3.6.4 No defined use
400	4.0.0 Production from irrigated agriculture and plantations
410	4.1.0 Irrigated plantation forestry
411	4.1.1 Irrigated hardwood production
412	4.1.2 Irrigated softwood production
413	4.1.3 Irrigated other forest production
414	4.1.4 Irrigated environmental
420	4.2.0 Irrigated modified pastures
421	4.2.1 Irrigated woody fodder plants
422	4.2.2 Irrigated pasture legumes
423	4.2.3 Irrigated legume/grass mixtures
424	4.2.4 Irrigated sown grasses
430	4.3.0 Irrigated cropping
431	4.3.1 Irrigated cereals
432	4.3.2 Irrigated beverage and spice crops
433	4.3.3 Irrigated hay and silage
434	4.3.4 Irrigated oil seeds
435	4.3.5 Irrigated sugar
436	4.3.6 Irrigated cotton
437	4.3.7 Irrigated tobacco

CODE	DESCRIPTION
438	4.3.8 Irrigated legumes
440	4.4.0 Irrigated perennial horticulture
441	4.4.1 Irrigated tree fruits
442	4.4.2 Irrigated oleaginous fruits
443	4.4.3 Irrigated tree nuts
444	4.4.4 Irrigated vine fruits
445	4.4.5 Irrigated shrub nuts fruits and berries
446	4.4.6 Irrigated flowers and bulbs
447	4.4.7 Irrigated vegetables and herbs
450	4.5.0 Irrigated seasonal horticulture
451	4.5.1 Irrigated fruits
452	4.5.2 Irrigated nuts
453	4.5.3 Irrigated flowers and bulbs
454	4.5.4 Irrigated vegetables and herbs
460	4.6.0 Irrigated land in transition
461	4.6.1 Degraded irrigated land
462	4.6.2 Abandoned irrigated land
463	4.6.3 Irrigated land under rehabilitation
464	4.6.4 No defined use (irrigation)
500	5.0.0 Intensive uses
510	5.1.0 Intensive horticulture
511	5.1.1 Shadehouses
512	5.1.2 Glasshouses
513	5.1.3 Glasshouses (hydroponic)
520	5.2.0 Intensive animal production
521	5.2.1 Dairy
522	5.2.2 Cattle
523	5.2.3 Sheep
524	5.2.4 Poultry
525	5.2.5 Pigs
526	5.2.6 Aquaculture
530	5.3.0 Manufacturing and industrial
540	5.4.0 Residential
541	5.4.1 Urban residential
542	5.4.2 Rural residential
543	5.4.3 Rural living
550	5.5.0 Services
551	5.5.1 Commercial services
552	5.5.2 Public services
553	5.5.3 Recreation and culture
554	5.5.4 Defence facilities
555	5.5.5 Research facilities

CODE	DESCRIPTION
560	5.6.0 Utilities
561	5.6.1 Electricity generation/transmission
562	'5.6.2 Gas treatment, storage and transmission'
570	5.7.0 Transport and communication
571	5.7.1 Airports/aerodromes
572	5.7.2 Roads
573	5.7.3 Railways
574	5.7.4 Ports and water transport
575	5.7.5 Navigation and communication
580	5.8.0 Mining
581	5.8.1 Mines
582	5.8.2 Quarries
583	5.8.3 Tailings
590	5.9.0 Waste treatment and disposal
591	5.9.1 Stormwater
592	5.9.2 Landfill
593	5.9.3 Solid garbage
595	5.9.5 Sewage
600	6.0.0 Water
610	6.1.0 Lake
611	6.1.1 Lake – conservation
612	6.1.2 Lake – production
613	6.1.3 Lake – intensive use
620	6.2.0 Reservoir/dam
621	6.2.1 Reservoir
622	6.2.2 Water storage – intensive use/farm dams
623	6.2.3 Evaporation basin
624	6.2.4 Effluent pond
630	6.3.0 River
631	6.3.1 River – conservation
632	6.3.2 River – production
633	6.3.3 River – intensive use
640	6.4.0 Channel/aqueduct
641	6.4.1 Supply channel/aqueduct
642	6.4.2 Drainage channel/aqueduct
650	6.5.0 Marsh/wetland
651	6.5.1 Marsh/wetland - conservation
652	6.5.2 Marsh/wetland - production
660	6.6.0 Estuary/coastal waters
661	6.6.1 Estuary/coastal waters – conservation
662	6.6.2 Estuary/coastal waters – production
663	6.6.3 Estuary/coastal waters – intensive use

Appendix 3: NVIS classes

Table 17: NVIS classes.

CODE	DOMINANT LAYER
6	G chenopod shrub i
11	G forb c
13	G forb i
15	G heath shrub c
16	G heath shrub i
17	G hummo
19	G hummock grass
21	G hummock grass c
23	G hummock grass i
34	G samphire shrub bc
36	G samphire shrub i
37	G samphire shrub r
40	G sedge c
44	G shrub c
45	G shrub i
46	G shrub r
52	G tussock grass c
53	G tussock grass d
54	G tussock grass i
55	G tussock grass r
60	M chenopod shrub i

CODE	DOMINANT LAYER
69	M samphire shrub r
70	M shrub bc
72	M shrub c
73	M shrub d
74	M shrub i
75	M shrub r
77	M tree c
78	M tree d
79	M tree i
80	M tree mallee d
82	M tree r
86	U chenopod shrub c
87	U chenopod shrub i
91	U mallee shrub c
92	U mallee shrub i
102	U shrub c
105	U shrub r
107	U tree c
108	U tree d
109	U tree i
111	U tree r

Layer descriptors are:

U = an upper layer
M = a mid layer
G = a ground layer

Cover classes are:

d = 70-100%
c = 30 -70
i = 10-30
r < 10%
bi ~0 scattered
bc ~0 clumped

Appendix 4: Comparison of the DLCD with the SLATS FPC data

The Queensland Statewide Landcover and Trees Study (SLATS) Foliage Protective Cover (FPC) data was used to produce mean FPC per cluster. This was compared with the mean June to September EVI for the clusters to derive a transform relating EVI to FPC. The graph of the relationship is shown in Figure 52, and the regression parameters detailed below.

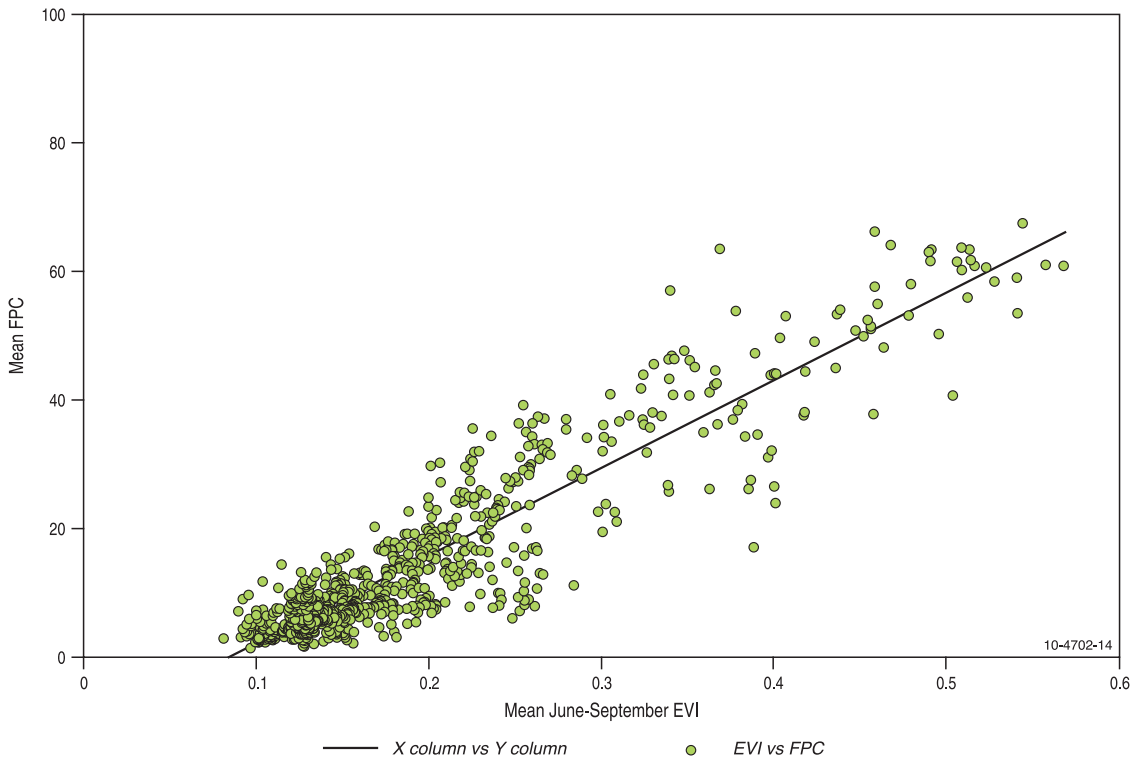

Figure 52: Shows the correlation between dry season foliage projective cover and dry season EVI.

Statistical Tests:

Normality Test (Shapiro-Wilk)	Failed (P = <0.0001)
W Statistic = 0.9704	Significance Level = 0.0500
Constant Variance Test	Failed (P = <0.0001)

Fit Equation Description:

[Variables]

x = col(1)
y = col(2)
reciprocal_y = 1/abs(y)
reciprocal_ysquare = $1/y^2$
Automatic Initial Parameter Estimate Functions
F(q) = ape(x,y,1,0,1)

[Parameters]

y0 = F(0)[1] Auto {previous: -11.5764} {MinRange: -12.3} {MaxRange: 36.9}
a = F(0)[2] Auto {previous: 136.679}
{MinRange: -4.5} {MaxRange: 1.5}

[Equation]

$f = y_0 + ax$

Appendix 5: Comparison with independent spatial data

Integrated Vegetation

Table 18: Comparison of the Integrated Vegetation dataset with the National DLCD.

Integrated Vegetation	Exact Match
Intensive uses includes urban, defence, research stations, mining, peri-urban, etc.	0%
Perennial crops	28%
Bare	0%
Horticultural trees and shrubs	61%
Plantation – hardwood	64%
Native shrublands and heathlands	37%
Annual crops and highly modified pastures	70%
Ephemeral and permanent water features	71%
Native grasslands and minimally modified pastures	61%
Native forests and woodlands	81%
Plantation – softwood/mixed	89%

Figure 53 shows a visual comparison of the Integrated Vegetation (IntVeg) coverage and the DLCD using the DLCD class colour scheme. Table 18 compares the IntVeg with the DLCD showing the degree of complete match with the IntVeg classes. Table 19 compares the DLCD with the IntVeg showing the degree of similarity with the DLCD classes using the relative similarity score method (see Table 7).

Nine of the 11 IntVeg classes consistently matched classes described in the DLCD. Only two of the 11 IntVeg classes are not represented in the DLCD. They are bare and intensive uses and include urban, defence, research stations, mining, peri-urban, etc. These two IntVeg classes are expected to have zero or very low occurrences of green vegetation, either seasonally or annually, or during the period from 2000 to 2008.

The intensive uses class is not a land cover but a land use class encompassing numerous covers, including those which are bare and those having some vegetation. The bare class within the integrated vegetation dataset shows a zero complete match with the DLCD. An overall observation of the correspondence between the IntVeg and DLCD datasets is that they share similar land cover classes and the relative proportions of these classes.

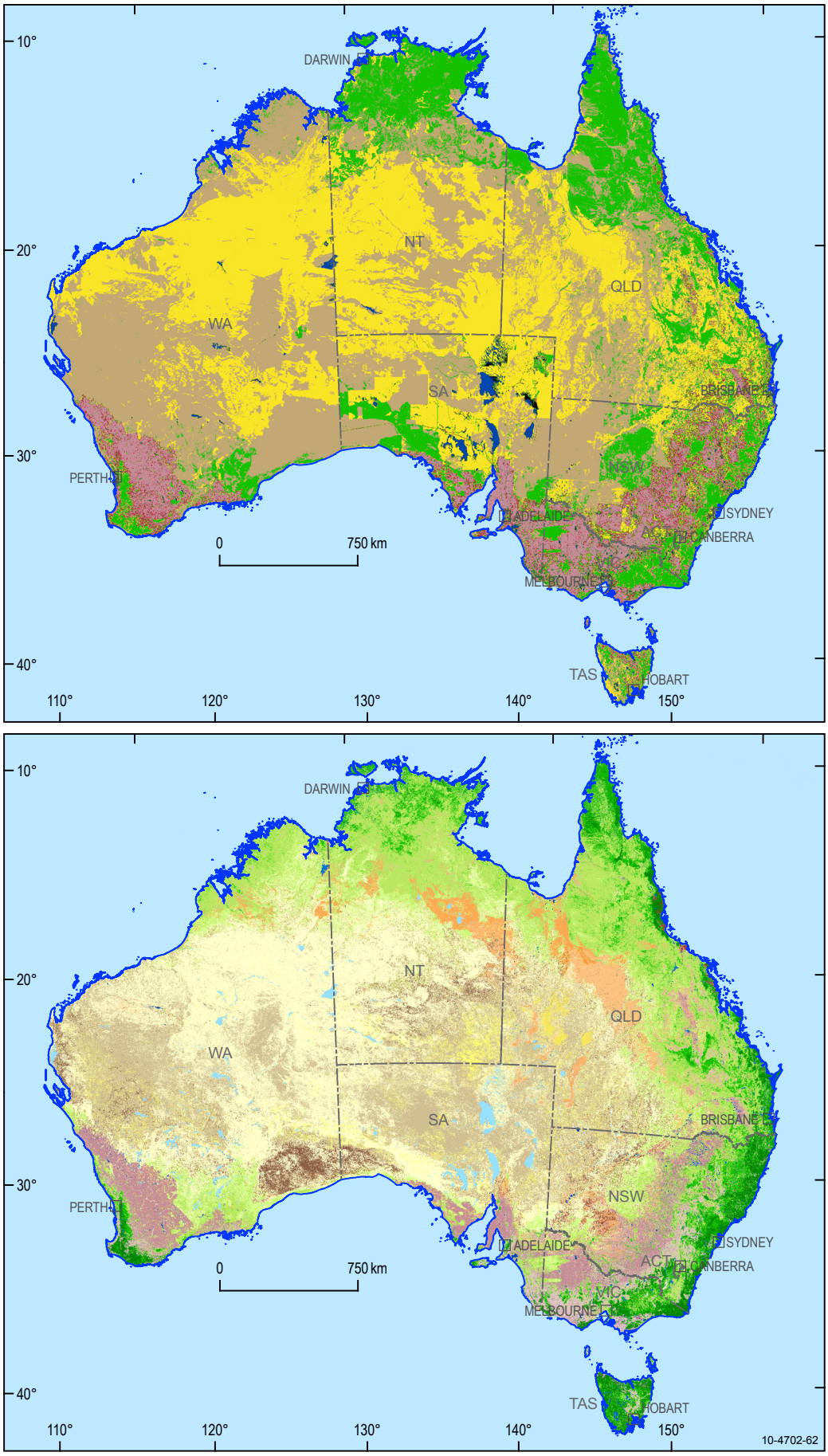

Figure 53: A visual comparison between IntVeg (top) and the map compiled from the National Dynamic Land Cover Dataset (bottom) with the IntVeg classes coloured to match the closest comparable label in the DLCD.

Table 19: Comparison of the National DLCD with IntVeg dataset using the relative similarity score method (see table 7).

DLCD	Exact Match	Very Similar	Moderately Similar	Somewhat Similar	Complete Mismatch
Alpine – open	3%	34%	0%	0%	63%
Aquatic Vegetation	0%	3%	62%	31%	4%
Bare	1%	1%	0%	9%	90%
Chenopods – open	60%	0%	29%	0%	10%
Chenopods – scattered	53%	43%	0%	3%	1%
Chenopods – sparse	75%	0%	21%	3%	1%
Cropping – dryland	82%	0%	0%	11%	7%
Cropping – irrigated	37%	2%	4%	0%	57%
Forbs – open	0%	0%	22%	0%	78%
Forbs – sparse	0%	0%	11%	0%	89%
Grassland – scattered	75%	0%	1%	22%	2%
Grassland – sparse	46%	0%	0%	45%	8%
Hummocks – open	48%	0%	0%	47%	5%
Hummocks – sparse	55%	0%	0%	38%	7%
Mines	2%	19%	0%	2%	76%
Pasture – dryland	57%	17%	0%	8%	19%
Pasture – irrigated	75%	0%	0%	1%	25%
Sedges – open	16%	0%	0%	1%	82%
Shrubs – closed	52%	0%	13%	35%	1%
Shrubs – open	37%	0%	38%	1%	24%
Shrubs – scattered	72%	20%	0%	6%	2%
Shrubs – sparse	61%	0%	35%	3%	0%
Sugar – dryland	25%	0%	39%	0%	36%
Sugar – irrigated	10%	0%	53%	2%	35%
Trees – closed	79%	0%	0%	0%	21%
Trees – open	70%	0%	0%	10%	20%
Trees – scattered	29%	69%	0%	0%	2%
Trees – sparse	49%	0%	28%	15%	9%
Tussock – open	57%	0%	0%	24%	20%
Tussocks – closed	60%	0%	0%	32%	9%
Tussocks – scattered	63%	0%	0%	8%	29%
Tussocks – sparse	69%	0%	0%	25%	6%
Water	36%	0%	1%	2%	62%
Water – saline	49%	1%	0%	0%	50%

Major Vegetation Groups

Table 20: Comparison of the MVG dataset with DLCD.

MVG	Exact Match
Unknown/no data	1%
Naturally bare - sand, rock, claypan, mudflat	0%
Casuarina forests and woodlands	3%
Cleared, non-native vegetation, buildings	0%
Sea and estuaries	20%
Low closed forest and tall closed shrubland	15%
Heath	0%
Acacia forests and woodlands	11%
Acacia shrublands	2%
Acacia open woodlands	3%
Mallee woodlands and shrublands	38%
Eucalyptus open woodlands	20%
Other grasslands, herblands, sedgelands and rushland	3%
Chenopod shrublands, samphire shrubs and forblands	14%
Other shrublands	2%
Unclassified native vegetation	0%
Regrowth, modified native vegetation	0%
Callitris forests and woodlands	37%
Other forests and woodlands	49%
Mangroves	52%
Tussock grasslands	34%
Eucalyptus woodlands	48%
Inland aquatic – freshwater, salt lakes, lagoons	76%
Eucalyptus low open forest	44%
Eucalyptus open forest	40%
Eucalyptus tall open forest	22%
Rainforest and vine thickets	58%
Melaleuca forests and woodlands	80%
Tropical eucalypt woodlands/grasslands	69%
Hummock grasslands	74%

Figure 54 shows a visual comparison of the Major Vegetation Groups (MVG) coverage and the DLCD using the DLCD class colour scheme. Table 20 compares the MVG with the DLCD showing the degree of complete match with the MVG classes while Table 21 compares the DLCD with the MVG showing the degree of similarity with the DLCD classes using the relative similarity score method (see Table 7). Five MVG classes had zero scores for exact match:

- naturally bare – sand, rock, claypan, mudflat;
- cleared, non-native vegetation, buildings;
- heath;
- unclassified native vegetation;
- regrowth, modified native vegetation.

This result is consistent with the DLCD representing vegetation greenness where these five MVG classes are expected to exhibit very low or zero occurrences of green vegetation with the DLCD dataset. This would suggest that there are no equivalent classes for these covers in the MVG and DLCD datasets and that there is a wide spread of DLCD classes for each MVG class.

An overall observation of the correspondence between the MVG and DLCD datasets is that they do share numerous similarities between their classes, producing a reasonable match between the relative proportions of these classes in the two datasets.

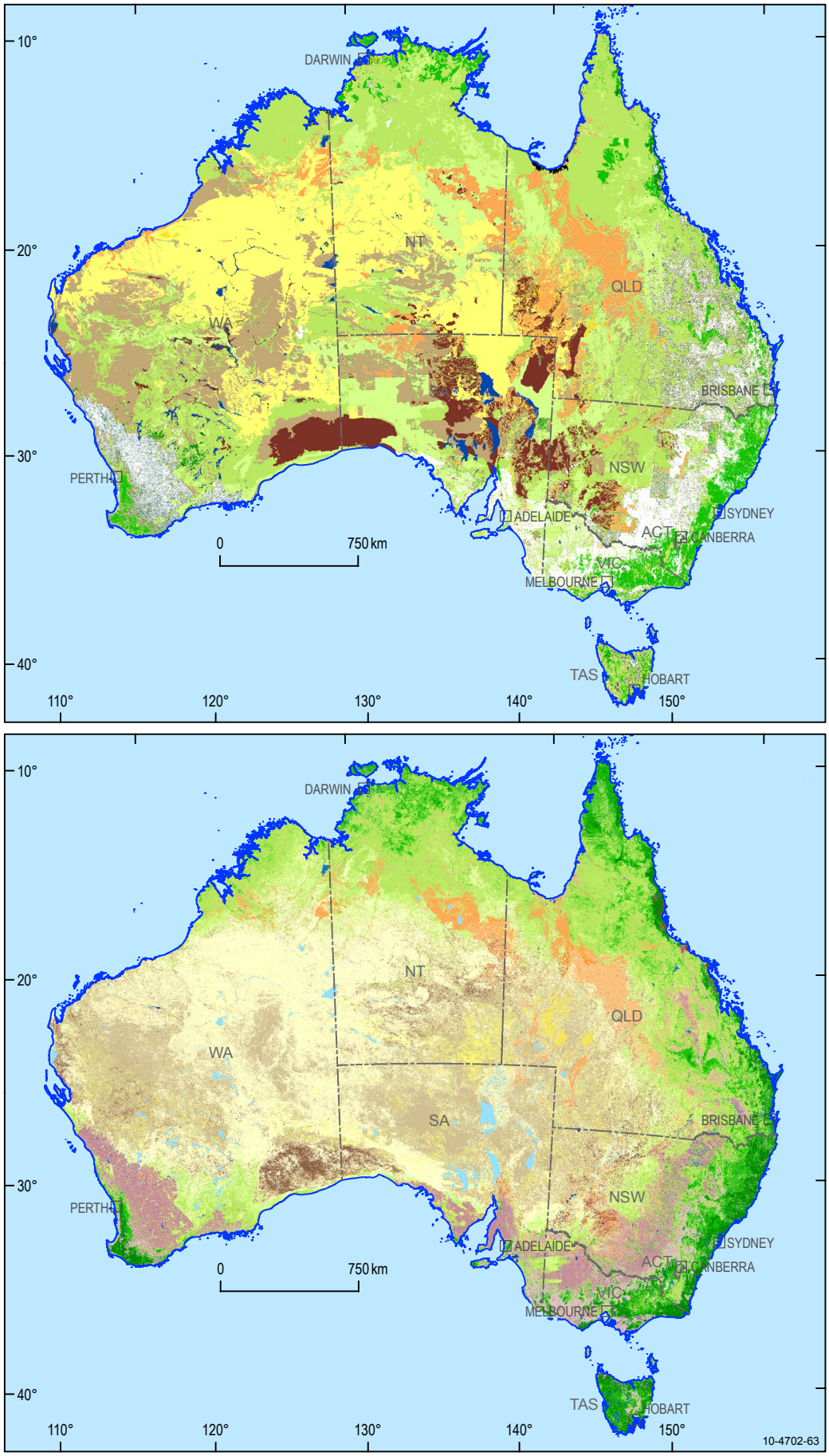

Figure 54: A visual comparison between MVG (top) and the map compiled from the National Dynamic Land Cover Dataset (bottom) with the MVG classes coloured to match the closest comparable label in the DLCD.

Table 21: Comparison of the 30 classes in the MVG dataset with equivalent 34 land cover classes in the DLCD dataset using the relative similarity score method (see table 7).

DLCD	Exact Match	Very Similar	Moderately Similar	Somewhat Similar	Complete Mismatch
Alpine – open	3%	0%	88%	0%	9%
Aquatic Vegetation	0%	6%	10%	0%	82%
Bare	0%	9%	0%	0%	90%
Chenopods – open	0%	12%	42%	6%	38%
Chenopods – scattered	6%	5%	29%	20%	40%
Chenopods – sparse	1%	25%	20%	27%	27%
Cropping – dryland	0%	0%	75%	0%	18%
Cropping – irrigated	0%	0%	3%	0%	96%
Forbs – open	29%	0%	0%	0%	71%
Forbs – sparse	8%	0%	0%	0%	92%
Grassland – scattered	11%	54%	3%	8%	23%
Grassland – sparse	20%	6%	3%	21%	51%
Hummocks – open	3%	31%	5%	20%	41%
Hummocks – sparse	4%	42%	8%	15%	30%
Mines	0%	1%	0%	0%	98%
Pasture – dryland	0%	0%	52%	0%	41%
Pasture – irrigated	0%	0%	1%	0%	90%
Sedges – open	0%	2%	3%	44%	49%
Shrubs – closed	17%	29%	42%	7%	5%
Shrubs – open	13%	14%	51%	6%	15%
Shrubs – scattered	0%	35%	24%	27%	13%
Shrubs – sparse	0%	40%	29%	16%	14%
Sugar – dryland	0%	0%	0%	0%	98%
Sugar – irrigated	0%	0%	0%	0%	98%
Trees – closed	0%	20%	65%	3%	10%
Trees – open	33%	38%	16%	5%	6%
Trees – scattered	5%	57%	25%	0%	11%
Trees – sparse	56%	14%	17%	10%	1%
Tussock – open	0%	3%	65%	4%	26%
Tussocks – closed	0%	4%	63%	2%	31%
Tussocks – scattered	0%	0%	81%	0%	9%
Tussocks – sparse	0%	3%	68%	7%	22%
Water	14%	0%	0%	0%	77%
Water – saline	0%	0%	0%	58%	41%

2005–06 Australian land use data

Figure 55 shows a visual comparison of the 2005– 06 Australian Land Use (LU05v4) coverage and the DLCD using the DLCD class colour scheme. Table 22 compares the LU05v4 with the DLCD showing the degree of complete match with the LU05v4 classes while Table 23 compares the DLCD with the LU05v4, illustrating the degree of similarity with the DLCD classes using the relative similarity score method (see Table 7).

Thirty-one of the 92 LU05v4 classes had a zero score for the complete match. These land use classes include:

- managed resource protection such as traditional indigenous uses and surface water supply;
- cropping of legumes and hay and silage;
- nature conservation;
- plantation forestry for softwood and hardwood production;
- perennial horticulture of vine fruits and tree nuts.

This would suggest that there is no equivalent between these classes in the LU05v4 and Dynamic Land Cover datasets and that there is a wide spread of DLCD classes for each LU05v4 class.

Thirty-six of the 92 LU05v4 classes had zero score for complete match, indicating that the DLCD had no equivalent classes which corresponded to the LU05v4. Examples include:

- intensive horticulture such as shadehouses and glasshouses;
- intensive animal production;
- urban and rural residential;
- transport and communication;
- waste treatment and disposal.

This result is consistent with the DLCD representing vegetation greenness where these 36 LU05v4 classes are expected to exhibit very low or nil occurrences of green vegetation with the DLCD dataset.

An overall observation of the correspondence between the LU05v4 and DLCD datasets is that they do not share similar classes so there is a relatively poor match between the comparative proportions of these classes in the two datasets.

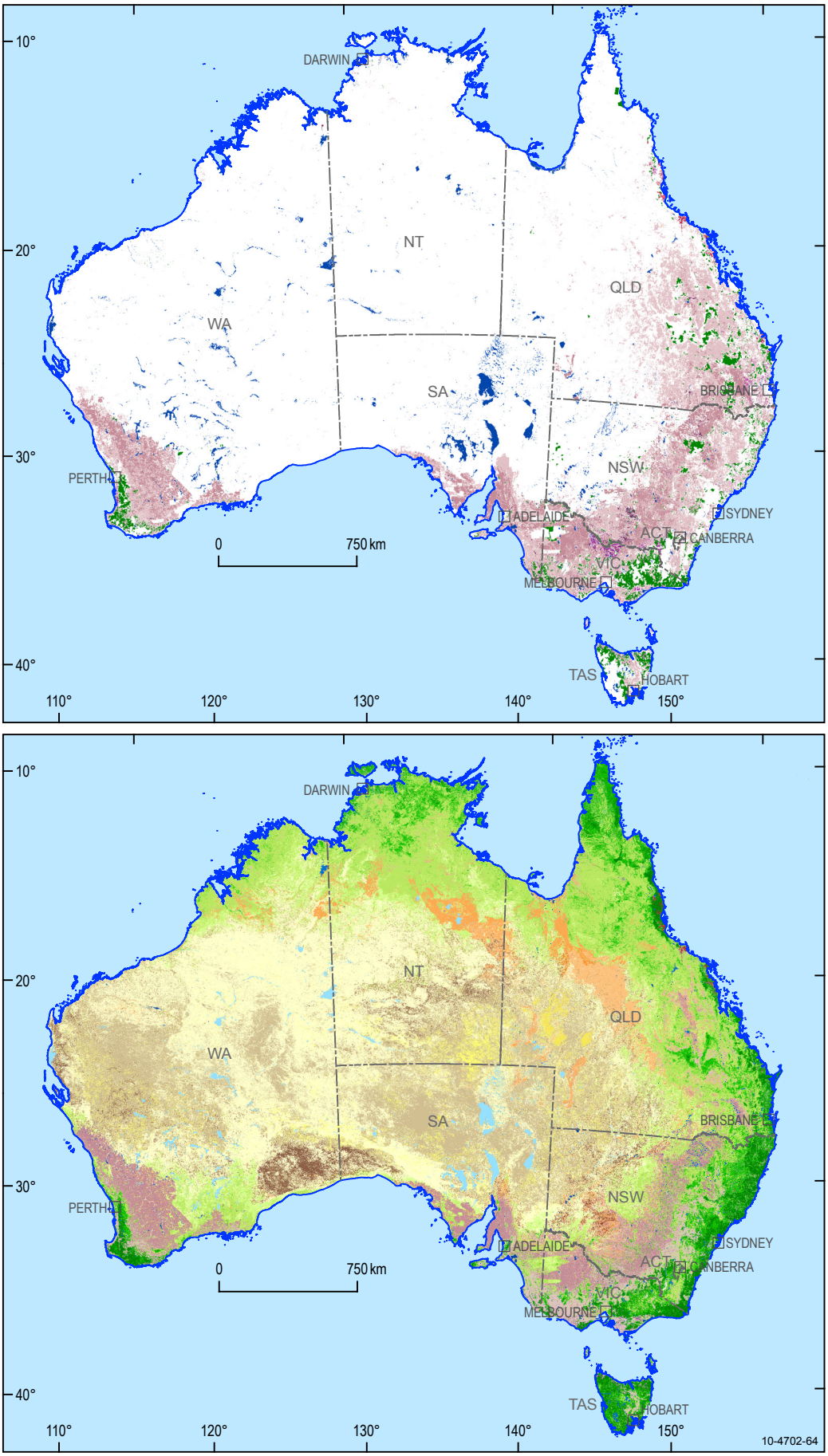

Figure 55: Comparison between LU05v4 (top) and the map compiled from the National Dynamic Land Cover Dataset (bottom) with the LU05v4 classes coloured to match the closest comparable label in the DLCD.

Table 22: Comparison of the 2005–06 land use data with DLCD.

Land Use Description	Land Use Detail	Exact Match
Shadehouses	Intensive horticulture	0%
Glasshouses	Intensive horticulture Intensive animal production	0% 0%
Dairy	Intensive animal production	0%
Cattle	Intensive animal production	0%
Poultry	Intensive animal production	0%
Pigs	Intensive animal production	0%
Aquaculture	Intensive animal production Manufacturing and industrial Residential	0% 0% 0%
Urban residential	Residential	0%
Rural residential	Residential	0%
Rural living	Residential Services	0% 0%
Commercial services	Services	0%
Public services	Services	0%
Recreation and culture	Services	0%
Defence facilities	Services	0%
Research facilities	Services Utilities	0% 0%
Electricity generation/transmission	Utilities	0%
Gas treatment, storage and transmission	Utilities Transport and communication	0% 0%
Airports/aerodromes	Transport and communication	0%
Roads	Transport and communication	0%
Railways	Transport and communication	0%
Ports and water transport	Transport and communication	0%
Navigation and communication	Transport and communication Mining Waste treatment and disposal	0% 0% 0%
Landfill	Waste treatment and disposal	0%
Solid garbage	Waste treatment and disposal	0%
Sewage	Waste treatment and disposal	0%
Tailings	Mining	1%
Quarries	Mining	0%
Mines	Mining	0%
Irrigated vine fruits	Irrigated perennial horticulture	0%
Estuary/coastal waters - conservation	Estuary/coastal waters Marsh/wetland Estuary/coastal waters	9% 4% 12%
Vine fruits	Perennial horticulture	0%
Irrigated vegetables & herbs	Irrigated seasonal horticulture	0%
Vegetables & herbs	Seasonal horticulture River	0% 19%
Sugar	Cropping	7%

Land Use Description	Land Use Detail	Exact Match
Effluent pond	Reservoir/dam	35%
Irrigated cotton	Irrigated cropping	0%
Marsh/wetland – conservation	Marsh/wetland Irrigated plantation forestry	5% 0%
Irrigated legumes	Irrigated cropping Land in transition	1% 0%
Irrigated oil seeds	Irrigated cropping Reservoir/dam	0% 42%
River – conservation	River	42%
Irrigated cereals	Irrigated cropping Grazing modified pastures	0% 25%
Irrigated hay and silage	Irrigated cropping	1%
Hardwood production	Plantation forestry	0%
Irrigated sugar	Irrigated cropping Lake	41% 12%
Irrigated tree fruits	Irrigated perennial horticulture	0%
Tree fruits	Perennial horticulture	0%
Evaporation basin	Reservoir/dam Irrigated modified pastures Plantation forestry	51% 51% 0%
Irrigated tree nuts	Irrigated perennial horticulture	0%
Hay and silage	Cropping	30%
Cotton	Cropping	62%
Tree nuts	Perennial horticulture	0%
Lake – conservation	Lake	5%
Softwood production	Plantation forestry	0%
Natural feature protection	Nature conservation Production forestry	0% 0%
Other conserved area	Nature conservation	0%
Oil seeds	Cropping Other minimal use	63% 0%
Cereals	Cropping	70%
Protected landscape	Nature conservation	0%
Defence	Other minimal use	0%
Habitat/species management area	Nature conservation	0%
National park	Nature conservation Grazing natural vegetation	0% 1%
Residual native cover	Other minimal use	0%
Strict nature reserves	Nature conservation	0%
Surface water supply	Managed resource protection	0%
Wilderness area	Nature conservation	0%
Traditional indigenous uses	Managed resource protection	0%
Legumes	Cropping	77%

Table 23: Comparison of the 92 classes in the LU05v4 dataset with equivalent 34 land cover classes in the DLCD dataset.

DLCD	Exact Match	Very Similar	Moderately Similar	Somewhat Similar	Complete Mismatch
Alpine – open	0%	100%	0%	0%	0%
Aquatic Vegetation	5%	80%	6%	0%	9%
Bare	0%	0%	0%	2%	96%
Chenopods – open	0%	80%	0%	10%	11%
Chenopods – scattered	0%	96%	0%	2%	2%
Chenopods – sparse	0%	97%	0%	2%	1%
Cropping – dryland	47%	38%	2%	0%	13%
Cropping – irrigated	1%	3%	53%	0%	42%
Forbs – open	0%	19%	0%	5%	76%
Forbs – sparse	0%	5%	0%	1%	92%
Grasslands – scattered	0%	99%	0%	0%	1%
Grasslands – sparse	0%	98%	0%	0%	2%
Hummocks – open	0%	100%	0%	0%	0%
Hummocks – sparse	0%	98%	0%	1%	1%
Mines	0%	0%	0%	0%	100%
Pasture – dryland	70%	3%	12%	0%	14%
Pasture – irrigated	74%	0%	2%	0%	23%
Sedges – open	0%	85%	0%	5%	10%
Shrubs – closed	0%	95%	0%	4%	0%
Shrubs – open	0%	72%	0%	11%	15%
Shrubs – scattered	0%	94%	0%	2%	4%
Shrubs – sparse	0%	99%	0%	0%	1%
Sugar – dryland	39%	8%	0%	1%	51%
Sugar – irrigated	21%	0%	0%	25%	54%
Trees – closed	0%	69%	0%	19%	11%
Trees – open	0%	50%	31%	0%	19%
Trees – scattered	0%	89%	0%	9%	1%
Trees – sparse	0%	81%	0%	0%	19%
Tussock – open	0%	75%	0%	18%	7%
Tussock – scattered	0%	45%	0%	34%	22%
Tussock – sparse	0%	91%	0%	7%	2%
Tussocks – closed	0%	86%	0%	1%	13%
Water	49%	0%	0%	25%	25%
Water – saline	0%	74%	0%	12%	14%

GlobCover

Figure 56 shows a visual comparison of GlobCover coverage and the DLCD using the DLCD class colour scheme. Table 24 compares the GlobCover with the DLCD and shows the degree of exact match with the GlobCover classes, Table 25 compares the DLCD with GlobCover and shows the degree of similarity with the DLCD classes using the relative similarity score method (see Table 7).

Table 24 shows that only five classes had any amount of complete match with the DLCD. Table 25 shows that while 27 DLCD classes had scores of zero for complete match, several of these classes had significant scores for the similar matches with the GlobCover dataset. Seven of these 27 DLCD classes had significant scores for complete mismatch indicating that, for these classes, the DLCD had no equivalent classes corresponding to the GlobCover, including:

- rainfed shrub or tree crops (e.g. cashcrops, vineyards, olive tree, orchards, etc.);
- permanent snow and ice;
- artificial surfaces and associated areas (urban areas more than 50%).

This result is consistent with the DLCD representing vegetation greenness where these seven GlobCover classes are expected to exhibit very low or no occurrences of green vegetation with the DLCD. The remaining seven DLCD classes had a wide range of similarity per cent scores, indicating the DLCD had numerous land cover classes which were not unique to the GlobCover classes.

An overall observation of the correspondence between the GlobCover and DLCD datasets is that they do not share similar classes so there is a relatively poor match between the relative proportions of these classes in the two datasets.

Table 24: Comparison of GlobCover and the DLCDMv1.

GlobCover	Exact Match
Rainfed shrub or tree crops (cashcrops, vineyards, olive tree, orchards)	0%
Permanent snow and ice	0%
No data	0%
Artificial surfaces and associated areas (Urban areas >50%)	0%
Closed (>40%) broadleaved deciduous shrubland (<5m)	0%
Post-flooding or irrigated shrub or tree crops	0%
Bare areas	0%
Closed to open (>15%) grassland or woody vegetation on regularly flooded or waterlogged soil, fresh, brakish or saline water	0%
Closed to open (>15%) broadleaved forest regularly flooded (semi-permanently or temporarly), fresh or brakish water	0%
Closed to open (>15%) (broadleaved or needle-leaved, evergreen or deciduous) shrubland (<5m)	0%
Closed to open (>15%) broadleaved deciduous shrubland (<5m)	0%
Rainfed croplands	40%
Water bodies	32%
Mosaic vegetation (grassland/shrubland/forest) (50-70%) / cropland (20-50%)	0%
Closed (>40%) broadleaved forest or shrubland permanently flooded, saline water	0%
Closed to open (>15%) herbaceous vegetation (grassland, savannas or lichens/mosses)	0%
Mosaic cropland (50-70%) / vegetation (grassland/shrubland/forest) (20-50%)	0%
Mosaic grassland (50-70%) and forest or shrubland (20-50%)	0%
Mosaic forest or shrubland (50-70%) and grassland (20-50%)	22%
Sparse (<15%) vegetation	0%
Cultivated and managed areas	0%
Open (15-40%) broadleaved deciduous forest/woodland (>5m)	67%
Closed to open (>15%) broadleaved evergreen or semi-deciduous forest (>5m)	84%

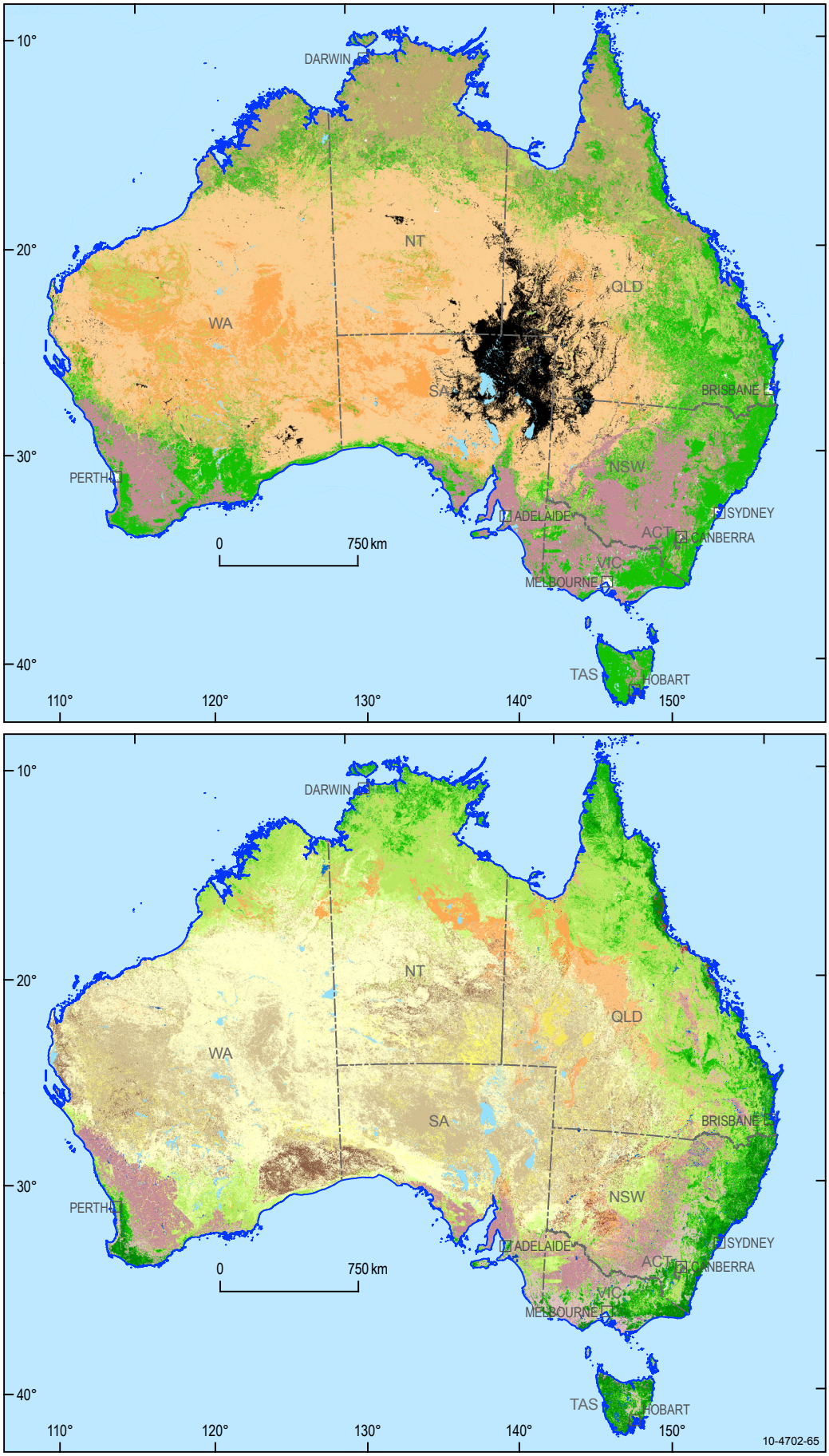

Figure 56: Comparison between GlobCover (top) and the map compiled from the National Dynamic Land Cover Dataset DLCD (bottom) with the GlobCover classes coloured to match the closest comparable label in the DLCD.

Table 25: Comparison of the 23 classes in the GlobCover dataset with equivalent land cover 34 classes in the DLCMv1 dataset.

DCLD	Exact Match	Very Similar	Moderately Similar	Somewhat Similar	Complete Mismatch
Alpine – open	0%	12%	0%	10%	77%
Aquatic Vegetation	0%	9%	1%	0%	90%
Bare	0%	15%	0%	6%	79%
Chenopods – open	2%	10%	12%	64%	11%
Chenopods – scattered	0%	44%	14%	3%	38%
Chenopods – sparse	0%	1%	84%	0%	15%
Cropping – dryland	0%	6%	2%	0%	92%
Cropping – irrigated	0%	13%	0%	47%	40%
Forbs – open	0%	1%	0%	0%	98%
Forbs – sparse	0%	0%	3%	3%	92%
Grassland – scattered	0%	13%	0%	82%	5%
Grassland – sparse	0%	0%	30%	68%	1%
Hummocks – open	0%	0%	54%	7%	39%
Hummocks – sparse	0%	52%	7%	39%	1%
Mines	0%	0%	0%	0%	0%
Pasture – dryland	0%	81%	0%	0%	18%
Pasture – irrigated	0%	9%	2%	0%	88%
Sedges – open	0%	1%	13%	74%	12%
Shrubs – closed	0%	73%	6%	21%	1%
Shrubs – open	3%	23%	0%	73%	1%
Shrubs – scattered	0%	1%	5%	91%	3%
Shrubs – sparse	0%	70%	5%	24%	1%
Sugar – dryland	0%	59%	2%	0%	38%
Sugar – irrigated	0%	53%	12%	0%	34%
Trees – closed	0%	1%	92%	4%	4%
Trees – open	74%	4%	1%	4%	17%
Trees – scattered	50%	2%	3%	6%	40%
Trees – sparse	19%	29%	7%	44%	1%
Tussock – open	0%	0%	3%	49%	48%
Tussocks – closed	0%	5%	32%	16%	47%
Tussocks – scattered	0%	68%	1%	31%	0%
Tussocks – sparse	0%	66%	21%	11%	1%
Water	2%	0%	0%	29%	64%
Water – saline	81%	0%	0%	2%	14%

Victorian land cover

The accuracy of the DLCD was assessed relative to the Victorian land cover 25 metre dataset by adding per cent scores together for the complete match and very similar. Table 26 shows that the complete match between the DLCD and the Victorian land cover was very poor, with only dryland crop and exotic pasture having a greater than 50% match. Table 27 shows that the most accurate DLCD classes (complete match scores greater than 75%) included two classes: pastures – irrigated and trees – open. DLCD classes with 50% to 75% accuracy included four DLCD classes, trees – closed, cropping – dryland, water – saline and pastures – dryland.

Complete mismatches were observed between 12 DLCD classes and the Victorian land cover, where scores ranged between 75% and 100%.

Table 26: Comparison of the Victorian land cover raster and DLCD.

Victorian Land Cover	Exact Match
Bare Areas – (sandunes/firescars/saltpans etc)	0%
Chenopod Shrubland	4%
Dryland crop	63%
Eucalypt Forest	36%
Eucalypt Woodland	21%
Eucalypt Woodland sparse (scattered)	9%
Exotic Tree Plantation	0%
Exotic Pasture	64%
Heathland (Banksia as an emergent)	0%
Heathland (various)	0%
Irrigation	14%
Mallee (dense)	0%
Mallee Open	0%
Native Pasture (dense)	49%
Non-Eucalypt Forest (dense)	16%
Non-Eucalypt Shrubland	0%
Non-Eucalypt Woodland	25%
Rocky outcrop	0%
Rough Pastures (derived chenopod shrubland)	1%
Rough Pastures (derived Native Pasture) high cover	0%
Rough Pastures (derived Native Pasture) Moderate cover	0%
Rough Pastures (derived Native Pasture) sparse	0%
Samphire/saltmarsh	0%
Urban/built	0%
Water Wetland	1%

Table 27: Comparison of the 25 classes in the Victorian land cover dataset with the equivalent 34 land cover classes in the DLCD dataset using the relative similarity score method (see table 7).

DLCD	Exact Match	Very Similar	Moderately Similar	Somewhat Similar	Complete Mismatch
Alpine – open	0%	24%	0%	0%	76%
Aquatic Vegetation	35%	0%	10%	0%	54%
Chenopods – open	16%	0%	1%	1%	83%
Chenopods – sparse	16%	0%	0%	0%	84%
Cropping – dryland	68%	0%	22%	1%	9%
Cropping – irrigated	4%	0%	23%	1%	71%
Forbs – open	0%	1%	0%	0%	99%
Forbs – sparse	0%	0%	0%	9%	91%
Hummock – open	0%	0%	0%	5%	95%
Hummock – sparse	1%	0%	0%	37%	62%
Mining	0%	0%	0%	0%	100%
Pastures – dryland	58%	0%	17%	14%	11%
Pastures – irrigated	42%	37%	0%	3%	18%
Sedges – open	0%	0%	13%	1%	86%
Shrubs – closed	8%	0%	33%	24%	36%
Shrubs – open	11%	0%	2%	13%	74%
Shrubs – scattered	0%	10%	0%	9%	81%
Shrubs – sparse	1%	2%	30%	1%	66%
Trees – closed	0%	75%	0%	17%	8%
Trees – open	45%	34%	0%	0%	20%
Trees – scattered	1%	19%	0%	63%	17%
Trees – sparse	16%	16%	21%	7%	40%
Tussock – open	0%	3%	3%	12%	81%
Tussock – sparse	0%	0%	3%	19%	77%
Water – fresh	0%	0%	0%	0%	100%
Water – saline	64%	0%	0%	0%	36%

mangroves
grassland
chenopod
shrubs
wetlands
sub-alpine
semi-arid

GA10–4689