# Extracting Terrain Categories from Multi-Source Satellite Imagery

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**Abstract**

*Geoscience Australia has ben conducting a series of national risk assessments for a range of natural hazards such as severe winds. The impact of severe wind varies considerably between equivalent structures located at different sites due to local roughness of the upwind terrain, shielding provided by upwind structures and topographic factors. Terrain surface roughness information is a critical spatial input to generate wind multipliers. It is generally the first spatial field to be evaluated, as it is utilised in both the generation of the terrain and topographic wind multiplier. Landsat imagery was employed to generate a terrain surface roughness product for six major metropolitan areas across Australia. It was necessary to investigate the applicability of multi-sensor approaches to generate a regional/national terrain surface roughness map based on the Australian-New Zealand wind loading standard. This paper presents a methodology to derive terrain surface roughness from various multi-source satellite images. MODIS, Landsat and IKONOS imagery were acquired during 12 September – 26 November 2002 covering a significant portion of New South Wales, Australia. An object-based image segmentation and classification technique was tested for seven bands of MODIS, six bands of Landsat Thematic Mapper, and four bands of IKONOS. Eleven terrain categories were identified using this technique which achieved classification accuracies of 79% and 93% over metropolitan Sydney and rural/urban areas respectively. It was revealed that the object-based image classification enhances the quality of the terrain product compared to traditional spectral-based maximum likelihood classification methods. To further improve the derivation of terrain roughness classification results, an integrated textural-spectral analysis merged Synthetic Aperture Radar and optical datasets. A comparison with results derived from textural-spectral classification showed considerable improvement over the results from earlier classification techniques.*

## 1. Introduction

Terrain surface categories derived from remote sensing data are a primary input for the Geoscience Australia Wind Risk Assessment. The categories have an important role in determining height multiplier characteristics of specific landscapes. In earlier work, Landsat imagery was employed to generate a terrain surface roughness product for six major metropolitan areas across Australia (Forghani et al., 2007). It was necessary to investigate the applicability of multi-sensor approaches to generate a regional/national terrain surface roughness map based on the Australian/New Zealand wind loading standard. The output was incorporated into the local wind multipliers (terrain/height, shielding, and topography) for eight cardinal directions with the return period regional wind speeds (from AS/NZS 1170.2, 2002) on a 25 m x 25 m grid across each study region (Figure 1). The maximum wind value for all directions was then sampled at each grid location and used to assess hazard return period residential damage. The assessments of wind hazard covered both urban areas and adjacent rural regions. It is anticipated that these hazard and risk assessment results will be refined and updated as the understanding of Australian peak wind gusts improves. Peak wind gusts pose risk to a number of Australian communities.

The wind risk product provides the first step towards a national peak wind gust risk assessment level for Australia and represents the first iteration of a continuously improving product (JHD, 2006) and Lin and Nadimpalli (2005). This trend highlights the need for a multi-scale, consistent and seamless terrain surface roughness product at the national level.

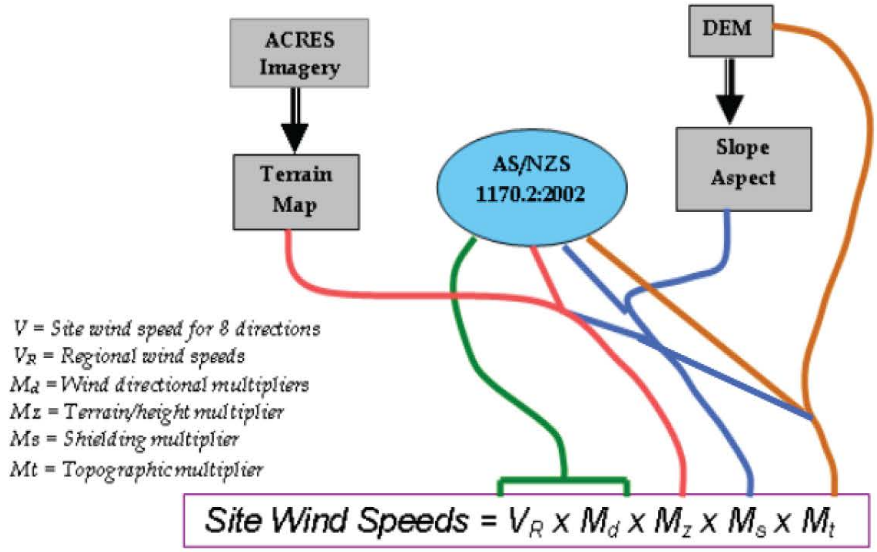


Figure 1: Diagrammatic representation for deriving wind multipliers from topographic and remotely sensed data and the Australian/New Zealand wind loading standard (AS/NZS 1170.2, 2002; Lin and Nadimpalli, 2005)

The 2005 wind modelling workshop at Geoscience Australia highlighted the need for accessing such a terrain product (JHD, 2006). Procedures, protocols, and operational guidelines were subsequently produced that enabled production of a national terrain surface roughness product. The output of the Wind Risk Assessment activity will prove to be of value to government decision-making in managing natural disaster risks, to the wind engineering industry and to the Australia and New Zealand building standards community. Understanding spatially distributed wind fields over complex terrain is important for a variety of applications including pollutant dispersion modeling, fire spread modeling and bush fire risk management (Sharples et al., 2010). The concept behind wind speed simulation from DEM roughness has been previously address in AS/NZS 1170.2 (2002).

Wind multipliers determines the impact of severe wind that varies considerably between structures at various locations due to the geographic terrain, the height of the structure concerned, the surrounding structures and topographic factors. These quantify how the local conditions adjust the regional wind speeds at each location (Lin and Nadimpalli, 2005). There are four wind multipliers; the terrain (roughness) multiplier (Mz), the shielding multiplier (Ms), the topographic (hillshape) multiplier (Mt) and directional multiplier (Md). The relationship between the regional wind speed (VR) in open terrain at 10 m height, the maximum local (site) wind speed (Vsite) and the local wind multipliers is: *Vsite* = *VR* × *Md* × *Mz* × *Ms* × *Mt*. Each of these multipliers is described and also used by other studies (Forghani et al., 2006a, and 2007). Formulas to estimate these wind multipliers for a given location are given in AS/NZS 1170.2 (2002).

Recently, at a local and at a regional level, the terrain surface roughness product was extracted from low and high spatial resolution satellite imagery. The study was carried out over a number of different landscapes of New South Wales region covering an area from Newcastle in the north, Nowra in the south and Bathurst in the west. A terrain surface roughness classification includes information not only about land cover, but also about feature heights that are important in wind modelling. This type of classification must therefore incorporate information from disparate sources to fulfil the requirements of the above mentioned application. The aim of this work was to develop an operational methodology specifically for extracting terrain categories using various remote sensing satellite imagery sources. To date, a number of data sources have been used to derive land cover and terrain surface roughness products, mainly from Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper Plus (ETM+) data.

Data sources such as Landsat TM images can provide basic information at regional scale for compiling forest stand type maps especially classified with an object-based technique (Dorren et al., 2003). However, due to increasing spatial resolutions of data sources, more detailed information is now available and the use of object based segmentation for land cover is becoming increasingly popular (Zhou and Troy, 2008, Kong et al., 2006, Mo et al., 2007 and Yu et al., 2006). Object based segmentation can be improved significantly by the combined use of multispectral and laser data

(Grebby et al., 2010, Maier et al., 2008 and Zhou and Troy, 2008). Grebby et al., (2010) found that the integration of LiDAR-derived topographic variables led to improvements of up to 22.5% in the overall mapping accuracy compared to spectral-only approaches. Using high-resolution digital aerial imagery and LiDAR data Zhou and Troy (2008) presented an object-oriented approach for analysing and characterising the urban landscape structure at the parcel level. They incorporated a three-level hierarchy, in which objects were classified differently at each level, reporting an overall classification accuracy of 92.3%. Chen et al., (2007) also demonstrated the potential of object based classification to map urban land cover for Beijing from ASTER data with a relatively high accuracy. IKONOS images have been used to automatically delineate and classify land-use polygons in Ontario, Canada, within an urban setting, with high overall accuracies, for six- and ten-class maps, with 90% and 86% accuracy respectively (Lackner and Conway, 2008). These increased land classification accuracies contribute towards higher accuracies in predicting the affect of natural hazards such as severe winds.

A number of researchers have attempted to develop operational methodologies for land cover mapping that have been well documented in the remote sensing and GIS literature. For example, Petit and Lambin (2001) developed a scheme for classification and generalization of remote sensing data to extract and generalise land use features using an image classification and database generalisation approach. Their scheme is based on the previous research of Daley et al., (1997). These studies focused on three techniques to control the properties of the generalised data including supervised classification, thematic generalisation, and spatial aggregation. Experience shows that this technique is particularly applicable to the delineation of land cover at the local scale (Moody, 1998). Its applicability at a regional to national scale needs to be explored by examining different image classification techniques (Kazemi et al., 2005). This research examined the hypothesis to derive terrain categories at a regional scale. A review of different image segmentation/classification techniques is beyond the scope of this paper. However, detailed description of several spectral classification techniques and image segmentation is provided in a recent study by Forghani et al., (2006), Haralick an Shapiro (1985), Cufi et al., (2002), Pal and Pal (1993) and Pekkarinen (2002).

## 2. Methodology

A graphic of the project methodology is presented in Figure 2, and key steps are outlined here.

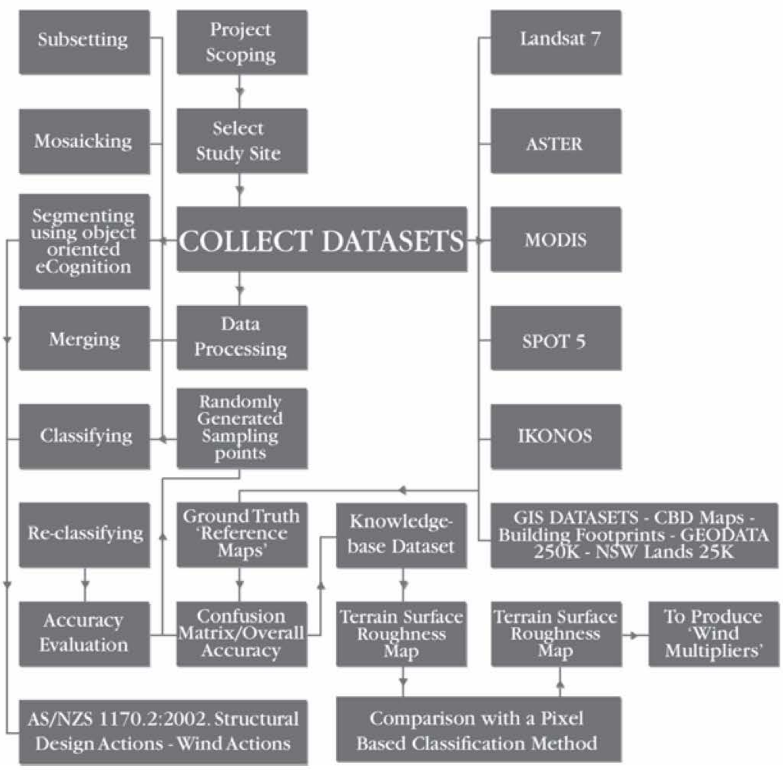


Figure 2: Methodology workflow

*2.1 Study Area*
This study area covers an area of about 81,500 km² in the NSW, Australia and was used to develop and test the proposal of deriving terrain categories at a regional scale in an operational context. The study area provides a mixture of land uses with reasonable levels of built-up areas that are representative of terrain categories at a regional/national scale.

*2.2 Datasets*
Criteria for selection of imagery are temporal coincident, and cloud free. Cloud-free MODIS Bands 1-7, Landsat TM, ASTER, SPOT-5, and IKONOS images were acquired between 12 September and 9 December 2004 over the study area. Geoscience Australia's 1:250 000 topographic data, NSW Department of Lands 1:25 000 topographic maps (Edition, 2006), and a street directory were used as supplementary references.

*2.3 Data Preparation*
The following steps were used to create a multi-resolution satellite image dataset: Projection of images to equirectangular on WGS84 datum and mosaicking. A check was made to ensure the accurate geometric registration o the datasets. A subset of the composite of imagery was generated to cover the study area.

*2.4 Image Segmentation*
The eCognition software was used for image segmentation and object-oriented image analysis classification (Baatz and Schäpe, 2000, Flanders et al., 2003 and Benz et al., 2004). The underlying principle of the system uses a region growing technique, which starts with regions of one pixel in size based on the spectral and spatial characteristics of the pixel that is detailed in Baatz et al., (2004). The local homogeneity criteria are then used to make decisions about merging regions of interest by taking into account the image analyst's expertise. The goal is to build a hierarchical set of image object primitives at different resolutions, the so-called 'multi-resolution segmentation' in which fine objects are subjects of coarse structures. The parameters controlling the algorithm include scale, homogeneity criteria, shape, and colour. These are discussed in detail later.

*2.4.1 Creation of new project in eCognition*
The project dataset was created by loading and importing image layers in eCognition Large Data Handling (LDH) to create the project dataset. It was noted that eCognition LDH allows the handling of over 900 million objects (eCognition, 2013), but is not optimised for performance. The eCognition Enterprise product allows the parallel processing of large datasets and considerably reduces processing times for large datasets, but this product was not available for this project. A multi-resolution dataset was then developed to produce image object primitives by partitioning the whole image into a series of closed objects that coincide with the actual spatial pattern when segmenting the image database (Wang et al., 2004).

*2.4.2 Segmentation parameterisation*
In this study, scale parameter, single layer weights, and the mixing of the heterogeneity criterion about tone and shape of objects were used. The resulting segments (objects) are based upon spectral values of input bands and segmentation parameters defined by the image analyst. As the size of the data set used in the study exceeded the threshold for the number of objects generated, segmentation was done separately for each data set. Visual interpretation and comparison of derived terrain maps using object-oriented image segmentation against pixel-based image classification showed that the image segmentation algorithm enhances the classification outputs, and hence improves the quality of the terrain product but at a significantly increased labour cost.

There was incomplete coverage of IKONOS of study area. Therefore, individual image segmentation was carried out, but using the same training sites within each image. In order to provide an effective visualisation of the image for the segmentation and classification process, the desired band combination e.g. Landsat Bands 3, 2, and 1, was carried out through a layer-mixing function to display the image with a linear stretch. Examination of the image revealed that visually there was a good delineation of urban built-up areas from non-urban and vegetation areas. Three major features need to be incorporated into the image segmentation routine when setting segmentation parameters, namely:

a) Layer weights that assess those layers with more important information about particular features for the segmentation process are given higher weights
b) Scale parameter which measures the maximum change in heterogeneity when merging image objects, and
c) Composition of homogeneity criterion that prioritises the drivers for object creation such as colour has preference to shape.

Consequently, protocols were developed for the use of different scale factors of shape and smoothness/compactness parameters when employing multi source imagery to generate the best desired segmentation results (Table 1). Identifying appropriate parameters maximises the efficiency of the classification routine. The outcome of the segmentation is determined by defining the scale parameter, the single layer weights, and the mixing of the heterogeneity criterion concerning tone and shape.

In summary, a number of iterations regarding the segmentation routine were performed to determine the most appropriate combination of the scale parameter and homogeneity criterion factors. The selection of an appropriate factor was based on trial and error with the segmentation procedure until a satisfactory pattern was found. A number of tools available (eg statistical analysis, creating polygons, etc) in eCognition were used to determine optimum segmentation parameters. The general rule of thumb for setting the scale parameter is that image objects must be smaller than the target features. The delineation of urban built-up area categories relies heavily on spectral differences. The shape parameter is not a significant contributor due to the resolution of such imagery as Landsat. In practice, when determining the optimal segmentation settings, the process of image segmentation involved significant difficulties such as the determination of the optimum segmentation parameters and the number of segmentation levels. It was very complex and therefore time-consuming for an image analyst. In addition, while multiple tools and features embedded in eCognition equips the image analyst to take advantage of textural, contextual and hierarchical properties of image structures, nevertheless the classification with this software demands significantly higher skills, is comparably complex and the development of robust techniques is operator intensive. The comments of Harris and Ventura (1995) also support this observation.

### *2.5 Building Class Hierarchy*

Developing a class hierarchy is one of the important steps for the success of the classification protocol in eCognition. The class hierarchy is considered as the 'knowledge-base' for the classification of the data by containing the sum of all classes with their specific descriptions structured in a hierarchal manner i.e. inheritance, group, and structure. Stored knowledge in the class hierarchy utilises spectral, geometrical, textural, and hierarchical characteristics of the image objects. The classification hierarchy is based on classes supplied by the Australian/New Zealand wind loading standard (AS/NZS 1170.2, 2002). The classification hierarchy structure was performed using multi source imagery supported by GIS datasets.

a) MODIS was utilised to derive the first four categories of broad terrain cover i.e. built up areas, forests, grasslands, and water
b) Landsat-7 and ASTER was used to support deriving suburban classes over selected areas,
c) SPOT-5, 2.5 and 5m resolution data, was used to differentiate the five urban sub-classes i.e. city buildings, high density metropolitan, centre of small towns, and airport runways, and open areas over selected areas eg Sydney, Wollongong and Newcastle, and
d) IKONOS was utilised to differentiate the city buildings from other suburban classes.

### *2.6 Training Set Generation*

A supervised classification using the class hierarchy was conducted. For methodological consistency, all image datasets were classified using an object-based nearest neighbour (NN) classification. The NN classifier was used to produce a set of spectral classes that represents the variation in the image. The candidate training sets were selected in a number of ways to achieve full coverage of the variation. Based on the information collected from the reference GIS data, a number of training areas representative of known terrain cover classes were selected from the raw data to generate detailed training areas. For consistency, all image datasets were classified using an object-based NN technique. *Level 1* represents the basic level of terrain data extraction from MODIS, followed by breaking down this data into sub classes in *Level 2* derived from Landsat 7 data, and then using detailed classification categories in *Level 3* using SPOT-5 and IKONOS imagery. Finally, in *Level 4,* high resolution IKONOS, and QuickBird data, were used to derive detailed urban features such as critical infrastructure. GIS layers assisted in prioritising the choice of particular imagery for selected areas based on terrain land use.

Table 1: Segmentation parameters information

| Imagery | Scale Parameters | Homogeneity Criterion | | Shape Ratio | |
|---|---|---|---|---|---|
| | | Color % | Shape % | Compactness | Smoothness |
| MODIS | 18 | 80 | 20 | 0.5 | 0.5 |
| Landsat | 14 | 70 | 30 | 0.3 | 0.7 |
| IKONOS | 12 | 50 | 50 | 0.4 | 0.6 |

*2.7 Post-Classification Processing*

The earlier iteration of the classification initially grouped pixels into 18 statistical classes. The supervised class samples (signatures) were based on existing GIS and local knowledge. Once desired classes were separated, they were used to create a single thematic dataset. Some of the spectrally similar classes were collapsed into a smaller number that adequately reflected the terrain cover categories. This was performed by evaluating the classified output and the reference data by interactive viewing of the classes on the screen. The aggregation of classes was based on spatial contiguous and spectral similarity. This was achieved through visual interpretation of the spectral classes assessing their spatial patterns and by analysing the spatial similarity of classes using their co-occurrence statistics (Baatz et al., 2004). Spectral classes were aggregated if they were spectrally similar and spatially contiguous. Where spectrally similar classes were spatially different, those classes were kept separate. Finally, a terrain classification map was produced.

**3. Results**

Based on validation and ground information in this study, the object-oriented classification method produces better results over city and metropolitan areas compared to a spectral-based classifier. In addition, vegetation classes can be more easily extracted and separability of built-up regions was evident. The following issues were considered in the process of identification and mapping: *Acquisition date* - the images were not acquired at the same date. Comment can be made on the seasonal conditions at the time of image acquisition and the effect of those conditions on feature interpretability. Therefore, acquisition date has slightly influenced the terrain features that were mapped in this study, and *Detectability* - the resolution of the imagery may prevent identification of all terrain features that are included in the AS/NZS 1170.2 specification. This is particularly relevant in the identification of those problematic features such as airport runways, sandy beaches, cut grass and crops, etc.

*3.1 Evaluation of Classification Accuracy*

The accuracy of the derived terrain map depends on the spatial and spectral resolution as well as seasonal variability in vegetation cover types depicted on input satellite imagery, and access to a detailed reference spatial dataset (Figures 3 and 4). Since this study has been undertaken at a regional scale, well known, seamless and consistent reference data should be used for objective validation. No field validation was performed for this study. However, for accuracy assessment, Geoscience Australia's 1:250 000 topographic data and NSW Department of Lands 1:25 000 scale maps were utilised. The accuracy of the three classified terrain products was assessed by comparison with 20 independent validation sites of known land use classes identified from reference thematic datasets. The test sites contained at least two representative examples of each terrain category. The test data were extracted from the various locations determined from visual interpretation of images within each terrain type, to ensure pure examples of each terrain type were applied in the analysis.

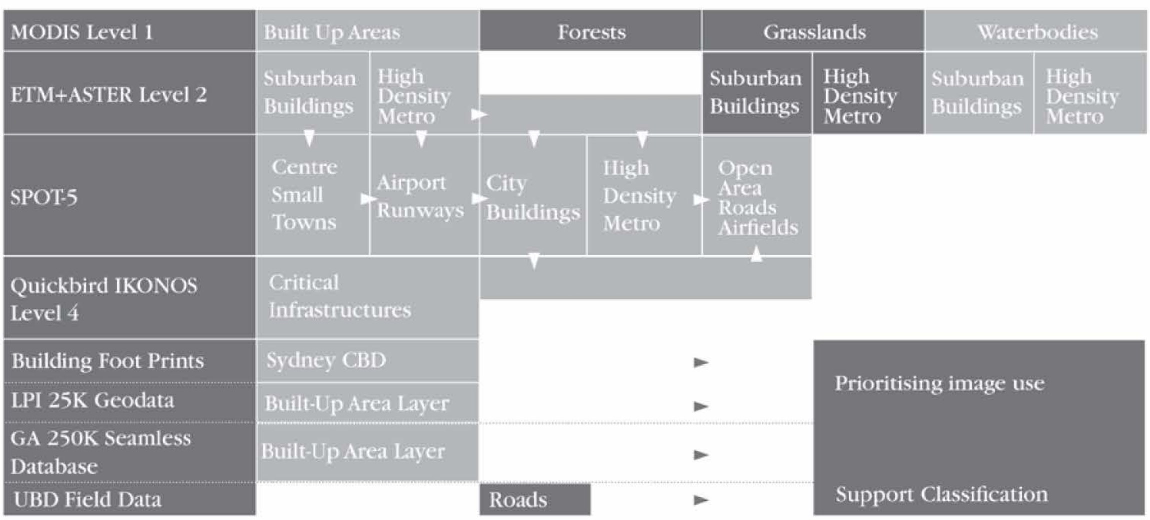


Figure 3: Classification hierarchy structure for land cover/use mapping from various remote sensing data sources

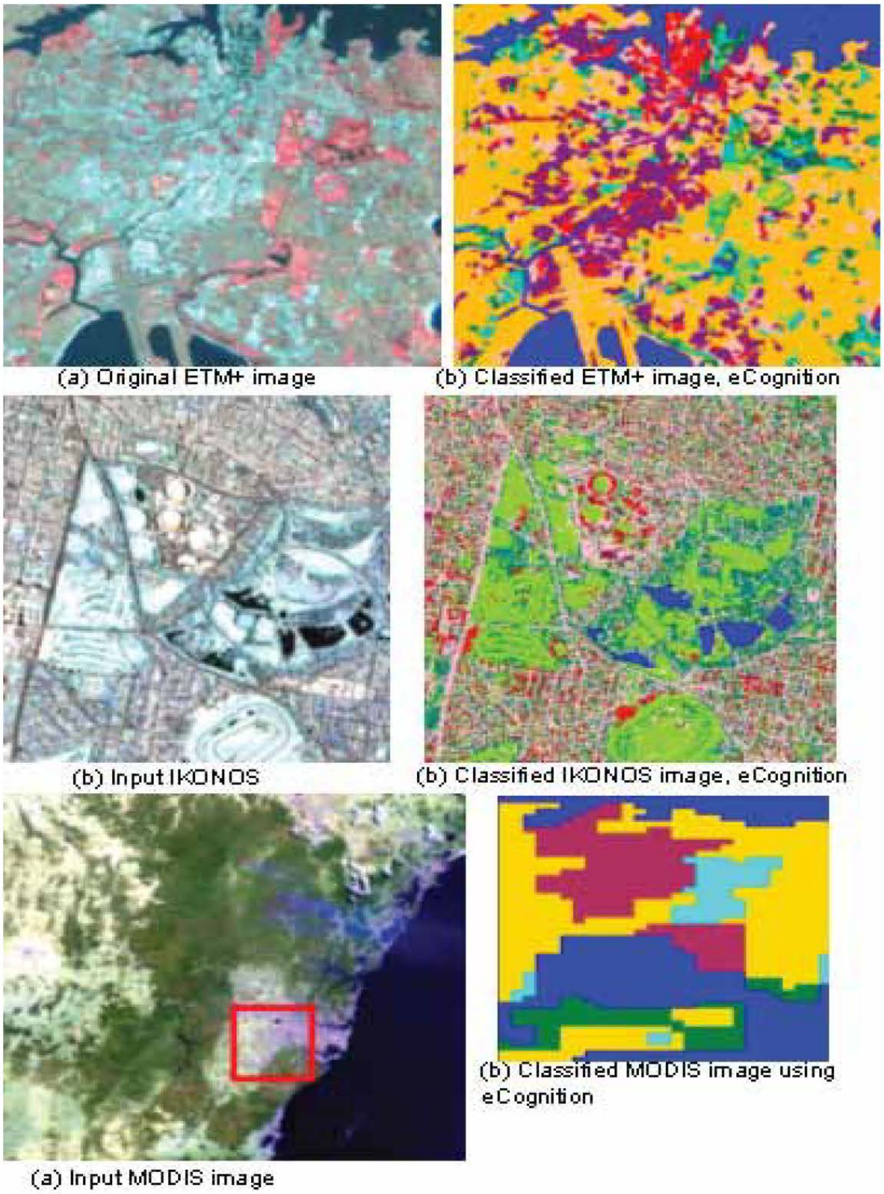


Figure 4: Terrain maps using object-oriented (eCognition) image segmentation for part of Sydney

Table 2: Quantitative accuracy assessment over the test image set of Landsat 7, Sydney. Accuracy measures are for object oriented based segmentation

| **Terrain category** | **Accuracy %** | **Omission %** | **Commission %** |
|---|---|---|---|
| city buildings | 74 | 26 | 22 |
| high density metropolitan | 69 | 31 | 17 |
| centres of small towns | 48 | 52 | 19 |
| Suburban | 92 | 8 | 11 |
| Forests | 88 | 12 | 6 |
| isolated trees and long grass | 83 | 17 | 16 |
| Crop | 76 | 24 | 17 |
| cut grass | 77 | 23 | 7 |
| open areas | 85 | 15 | 18 |
| Water | 98 | 2 | 4 |
| **Total** | **79** | **21** | **13.7** |

Classification accuracy is expressed as the number of correctly classified pixels divided by the total number of pixels in the terrain category. Kappa coefficient expresses the proportionate reduction in error generated by a classification process compared with the error of a completely random classification. A kappa value of 1 indicates perfect agreement, and a value of 0.79 would imply that the classification process was avoiding 79% of the errors that a completely random classification would generate. Applying these measures of omission and commission error is well accepted amongst remote sensing specialists, GIS practitioners Harris and Ventura (1995) and Zhang et al., (2002). Overall classification accuracy for ETM+ was 79 per cent, over Sydney, whereas the commission errors were relatively high at 13.7 percent. This was achieved over one of the most complex areas within the study area (Table 2).

In addition, the accuracy of the classification methodology was estimated to be 94% over rural/urban areas when using the reference data and maps. Thus, the average accuracy over all classes was 86.5%. Overall, we obtained relative improvements in classification accuracy using object based classification when comparing to the spectral based classification results. The improvement was about 9-13% that is discussed in detail by Forghani et al., (2006) (Figures 3 and 4).

## 4. Concluding Remarks

This study developed a terrain cover classification scheme over the Greater Sydney region utilising a four level hierarchical image segmentation scheme. Comparative image classification and segmentation of multi-sensor imagery revealed the following key findings and suggests future recommendations:

- The study attempted the use of remote sensing data to derive eleven categories of terrain information for use at a national scale. Four levels of data were identified for the generation of national terrain surface roughness, including MODIS to derive *Level 1* (areas with no major towns), Landsat/ASTER/SPOT 2/4 to derive *Level 2,* areas with major towns, SPOT-5 to derive *Level 3* areas with capital/major cities, and IKONOS/QuickBird to derive *Level 4,* areas containing significant critical infrastructure.
- Examination of eCognition revealed that the processing of large data volumes of data in the case of Landsat 7, SPOT 5 and IKONOS was slow and time consuming, however it enhances the classification outputs (as demonstrated by Forghani et al., 2006a, 2006b)
- Landsat TM/ETM+ imagery is suited for derivation of 30m and 100m resolution terrain maps based on this study. Thus, it should continue to be used. SPOT-5 should only be employed as a source of ancillary data. It is anticipated that about 120 scenes of Landsat (5 and 7) images are required to map populated Australian regions that mainly cover the eastern part of the country and in limited areas in the west. The proposed methodology in this study would be more successful over areas similar to Australian landscape.

**Acknowledgements**

Assistance of several reviewers who contributed towards development of the content of the paper through reviews, feedbacks and support are gratefully appreciated. The substances of this paper have been presented at the IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2007 23-27 July, Barcelona Spain. The views expressed in this paper are the authors' and not necessarily the views of the organisation.

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