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Suitability of NDVI AVHRR data for wetland detection. A case study: Kakadu National Park, Australia

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November 2002

supervising scientist

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1 Introduction

1.1 Subject

A wetland inventory is a means of providing managers and decision-makers with base information for wetland conservation tasks (Dugan 1990, Finlayson 1996). A number of compilations on wetland occurrence in Australia have been made (eg Paijmans et al 1985, McComb and Lake 1988, ANCA 1996, Environment Australia 2001). While these provide a broad level of understanding of Australia's wetlands, the specific features of individual wetlands – such as their spatial extent – are still incomplete, and a comprehensive inventory has not been undertaken as yet. Such inventory could be very useful to assess the state of Australia's wetlands, or to establish priorities for wetland management (Spiers and Finlayson 1999, Watkins 1999, Russell French 2001).

The remoteness, inaccessibility and extent of many wetlands in Northern Australia make remote sensing an invaluable tool for inventorying wetlands, and the only feasible way to gather synoptic data on a regular basis in this region (Devonport and Bull 1999). Data from the AVHRR sensor are extensively used for land cover monitoring because of their broad spatial extent, temporal frequency, accessibility, and extensive archives (Benson and McKenzie 1995, Gervin et al 1985). All of these qualities are very desirable for wetland monitoring, and an optimal way to use AVHRR capabilities for that purpose should be found. In addition, the limited funding available for most wetland inventory work makes the low acquisition costs of AVHRR data very attractive.

Various global, continental and regional land cover data sets have been produced using, primarily, NDVI data obtained from the AVHRR sensor, applying diverse classification approaches (eg Tucker et al 1985, 1991, Malingreau 1986, Malingreau et al 1989, Loveland et al 1991, Loveland and Belward 1997, Townshend et al 1991, Townshend 1994, DeFries et al 1995, Cihlar et al 1996, Nemani and Running 1997, Gopal et al 1999). Most of these land cover data sets focus on types of terrestrial vegetation cover. Specific land cover classes, such as wetlands, receive little attention and their extent is usually largely underestimated.

Two global land cover data sets (see Section 2.2) (DISCover Global Land Cover Data Set (DGLC) and Global 4-minute Land Cover Data Set (4mLC)) derived from 1km and 8km NDVI AVHRR data, respectively, were studied. According to Lowry and Finlayson (2001), these data sets did not succeed in identifying wetlands in Australia. In order to see if a more accurate classification can be achieved using the same base data (NDVI AVHRR), an alternative clustering/classification approach was implemented in this study. The metadata of the data sets were also studied to identify limitations in the methodologies applied. Finally, a set of recommendations/suggestions to use NDVI AVHRR data to detect wetlands is given.

1.2 Aims and objectives

Two global land cover data sets (DISCover Global Land Cover Data Set and Global 4-minute Land Cover Data Set) were analysed, manipulated and compared at a regional scale for Kakadu National Park (KNP) in order to investigate the following points:

- To find the limitations in the methodology or approach used in the creation of the data sets that have resulted in the absence or very limited representation of wetlands.
- To find the limitations in the base data utilised for the creation of the data sets that may influence the success in identifying wetlands (eg cloud contamination).
- To propose possible changes in approach that could be made, in order to detect wetlands in KNP by using the same basic data.

Additionally, the data set created by Lovell and Graetz (2001) was also analysed. This is a cloud-filtered version of the same original data utilised to create the 4mLC data set (see Section 2.2.3).

An alternative classification approach proposed by Hastings (1998) (see Section 3.1) is applied to the three data sets. Classification results may show what extent pixel size, clouds and other artefacts, affect the accuracy of the classification.

1.3 Scope and limitations

Although these are global-scale data sets, this work was reduced to study Kakadu National Park (KNP), since very good ancillary data were available to assess the accuracy of the results, and time constrains did not allow studying other regions. Despite the fact the AVHRR has got other bands that may be helpful for wetland detection, the present project was restricted to use only the base NDVI data supplied with the data sets. This was done in order to see if a better classification could be achieved using the same remotely sensed data.

1.4 Report outline

The following report is divided into seven chapters. Chapter 2 describes the study area, gives a brief description of the data sets utilised in this project, and finally defines the Normalised Difference Vegetation Index (NDVI) and its limitations concerning wetland detection. Chapter 3 presents the methodology undertaken in this project. The alternative hierarchical clustering approach implemented in this work is described. The most relevant results and findings of this study are shown in Chapter 4, and they are discussed in Chapter 5. In Chapter 6, the conclusions of this project are presented, and a set of recommendations about using NDVI AVHRR data to map wetlands is given. References are provided in Chapter 7.

2 Background

2.1 Study area

Kakadu National Park (KNP) is located in the Northern Territory of Australia, 120 km east of Darwin. It covers an area of 19,804 km^2 and is the largest terrestrial national park in Australia. KNP extends from the coast of the Timor Sea in the north to the southern hills and basins 150 km to the south (containing the headwaters of the South Alligator and Katherine Rivers), and from the Arnhem Land sandstone plateau in the east (with the headwaters of the East Alligator River), 120km to the wooded savannas and Mary river on the western boundary (figure 1). Sandstone plateau and escarpment, vast areas of savanna woodlands and open forest, billabongs, floodplains, mangroves and swamps are the major landforms and habitats in Kakadu. Lowry and Knox (2002) identified six broad landscape types within the Park that are defined by the geomorphology of the area. The combination of these landforms has created a biological and ecological diversity that is considered both representative and unique (Braithwaite and Werner 1987). In addition to the diversity of landscapes and habitats, KNP is unique in is that it contains a significant large river system – the South Alligator River – entirely within its boundaries.

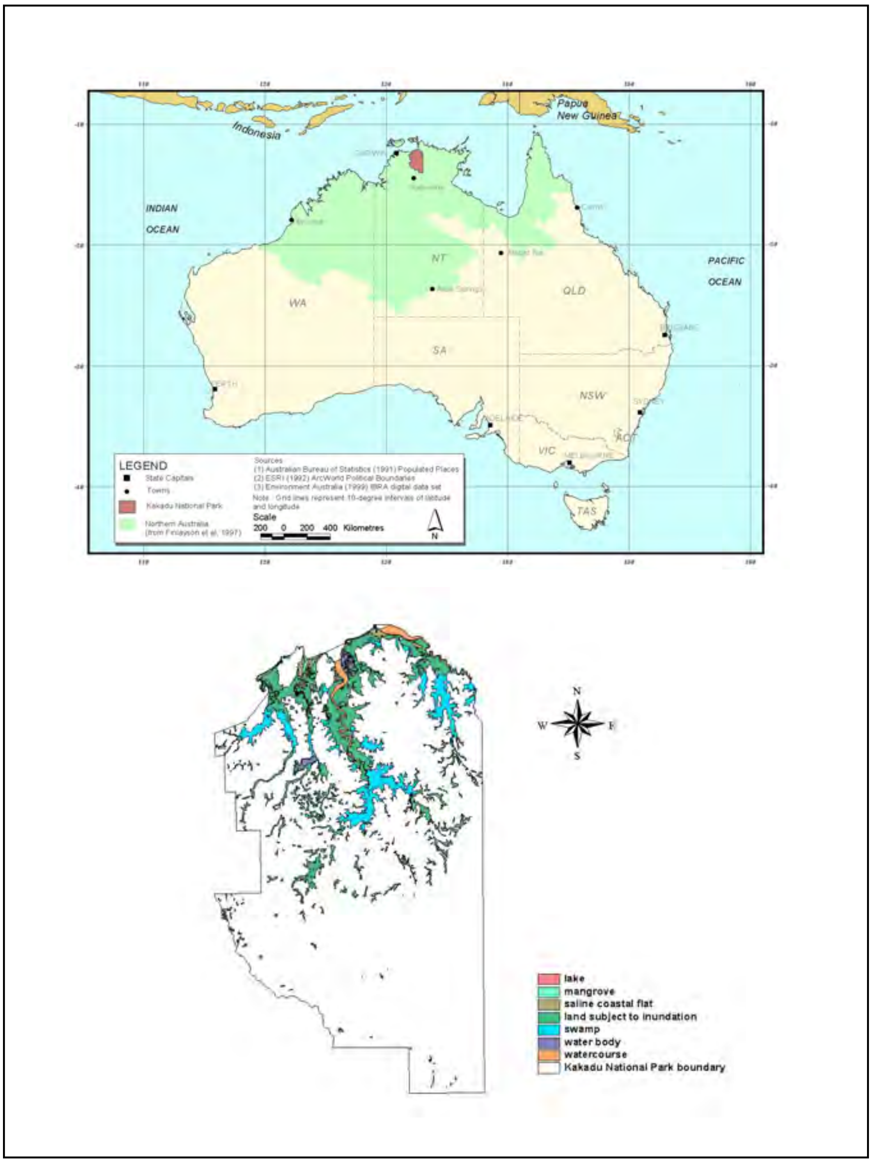


Figure 1 Study area and wetlands location

Seasonally inundated wetlands cover about 13% of Kakadu’s area. Due to their international significance, the park’s wetlands and waterfowl habitats are included in the list of the Convention on Wetlands of International Importance (Ramsar Convention)(Ramsar 2002). The wetlands also have significant cultural value to the indigenous peoples of the area.

The study area is influenced by the monsoons every year and has only two seasons, known locally as ‘the Wet’ and ‘the Dry’. The Wet season begins late in the year (Nov-Dec) and ends three to four months later. Both onset and duration differ from year to year. The Wet season usually brings heavy rain and tropical cyclones that flood a considerable part of the park. During the Dry season very little rain falls, although the precipitation is more variable than during the Wet season (Taylor and Tulloch 1985). The mean annual rainfall for the region varies between 1565 mm in Jabiru to 1300 mm in the south. The temperature is high throughout the year, with mean daily temperature variation between 22.4°C and 34.0°C (Russell-Smith et al 1995).

Although there is no agreement about how wetlands in northern Australia should be classified, several classification systems have been proposed (eg Semeniuk and Semeniuk, 1997, Begg et al 2001). For the purpose of this project, the types of water body described in the AUSLIG 250K topographic map are considered, as it is the ancillary data used. They include 'land subject to inundation', 'swamp', 'lake', 'mangrove', 'saline coastal flat', and 'water body'.

2.2 Data set descriptions

All the NDVI base data of the remote sensing data sets used in this project were obtained from the AVHRR sensor on board NOAA's Polar Orbiting Environmental Satellite (POES) series, which has been operating since 1978 (Hastings and Emery 1992).

2.2.1 DISCover Global Land Cover (DGLC) data set

This is a 1-km spatial resolution data set created by the U.S. Geological Survey's (USGS), Earth Resources Observation System (EROS) Data Center, the University of Nebraska-Lincoln (UNL), and the Joint Research Centre of the European Commission for use in a wide range of environmental research and modelling applications (Loveland et al 2000). It was developed as part of the National Aeronautics and Space Administration (NASA) Earth Observing System Pathfinder program, and the International Geosphere-Biosphere Program (IGBP) Data and Information System activity.

This database was developed on a continent-by-continent basis, and it used 1-km AVHRR NDVI 10-day composites spanning from April 1992 to March 1993, which were combined into monthly composites. Composites representing longer periods of time have been proved to be more suitable for image classification than 1-day images (Zhu and Yang 1996). It results in a decrease of cloud contamination and data volume reduction. The metadata supplied with the data set describe the method used as 'a multi-temporal unsupervised classification of NDVI data with post-classification refinement using multi-source earth science data'. Although NDVI was the base data used for the clustering, the individual bands were also used for post-classification and characterisation of specific landscape properties. Other information, such as key geographic data, elevation data, ecoregions data, and country or regional-level vegetation and land cover maps, were also utilised. However, all this information was not relevant or managed efficiently to detect wetlands in Australia.

The unsupervised classification algorithm used for an initial clustering was CLUSTER, a variation of K-means (see Research Systems 2000) that has been optimised for use with large data sets (Kelly and White 1993). It is an iterative statistical clustering algorithm that defines clusters of pixels with the same NDVI properties. The clustering is controlled by predetermined parameters for number of iterations and number of resulting clusters.

A post-classification stratification was used to separate classes that contained two or more different types of land cover. Two steps were involved in this process: first, to determine the ancillary variables that determine the separation between the classes differentiated by the clustering algorithm. Second, to implement decision rules.

From the final land cover characterisation seven data sets were derived according to the legends of seven land cover classification systems. Wetlands are detected in KNP (just 42 km^2) only when the IGBP legend is used. This is insignificant compared to the known extent of wetlands within the park.

More information about this data set can be found on line at:

http://edcdaac.usgs.gov/glcc/globdoc2_0.html. This data set may also be downloaded from http://edcdaac.usgs.gov/glcc/glcc.html

2.2.2 Global 4-Minute Land Cover (4mLC) data set

This data set was produced by the Centre of Environmental Remote Sensing (CEReS) at Chiba University (Japan), and the Land Cover Working Group (LCWG) of the Asian Association on Remote Sensing (AARS).

The land cover data was derived by using global 8 km 10 days composite AVHRR NDVI data from January 1, 1990 to December 31, 1990, obtained from the NOAA/NASA Pathfinder AVHRR Land (PAL) Data Set (James and Kalluri 1994).

Monthly NDVI composites were generated in order to reduce cloud contamination and remove noise. Land cover classification was derived from clustering monthly NDVI data, ground truth data and a decision tree. The Earth surface was divided into two regions (Asia/Oceania, and the rest of the world) and different methodologies were applied. This is due to the fact that only ground truth data from Asia and Oceania were available and different methodologies were used for each region. The classification for the Asian and Oceanian regions was carried out by combining the following data sources in the same priority order as quoted:

1. Ground truth data. It refers to georeferenced regions where land cover has been identified from maps or field survey.
2. Extended ground truth data.
3. Classified result by decision tree method.

Before extending ground truth data and applying the decision tree, a clustering analysis (k-means) was performed. If a cluster covers a ground truth region, that cluster is considered to have the same land cover class as the ground truth data.

Lastly, the decision tree method is applied based on the clustering results, and maximum and minimum monthly NDVI in twelve months for each pixel.

More detailed information about this data set can be found on line at http:/www-cger.nies.go.jp/grid-e/gridtxt/gflcds.html.

2.2.3 Lovell and Graetz data set (L&G)

Lovell and Graetz (2001) created a filtered NDVI AVHRR data set for Australia, which is derived from the same original type of data that was used for the Global 4-minute Land Cover Data Set. It contains filtered PAL ten-day NDVI composites spanning from mid-July 1981 to September 1994 with a spatial resolution of 8 km.

After examining the PAL NDVI data for the Australian continent they found that obvious cloud contamination remained in the 10-day NDVI composites. They applied the Best Index Slope Extraction (BISE) (Viovy et al 1992) in order to minimise the contamination by cloud and noise in the NDVI time series in the PAL data set. The result was a data set that reduces those effects and improves data consistency and spatial uniformity while preserving seasonal changes. However, the authors suggested that this data set is useful but not definitive.

Since the 4mLC data set did not succeed in showing wetlands in northern Australia or anywhere else in the country, it was thought it would be interesting to compare both data sets and also try to see if this data set could be useful to differentiate wetlands.

This data set was obtained in a CD free of charge from the authors. More information can be found in Lovell and Graetz (2001).

2.2.4 AUSLIG 250K topo map

The hydrological features contained within the digital 1:250 000-scale topographic data sets produced by AUSLIG are currently considered to represent the most consistently reliable source of geographic information about wetlands across northern Australia (J Lowry, pers com). Kakadu National Park falls entirely within AUSLIG Map Sheet SD53-1, and the polygonal water body features from this data set were extracted in the ArcView® desktop GIS environment and used as a reference to assess the accuracy of the earlier wetland classifications. A vector layer representing the boundary of Kakadu National Park was used to define the extent of the study area.

2.3 NDVI and its limitations

The Normalized Difference Vegetation Index (NDVI) is a ratio that provides an estimation of the photosynthetic activity of the land cover (Sellers 1985, Dye 1996). The NDVI was originally developed by Rouse et al (1974) and is defined as follows:

$$NDVI = \frac{NIR - \mathrm{Re}\,d}{NIR + \mathrm{Re}\,d}$$

Where NIR and Red correspond to the AVHRR channels 2 and 1, respectively. The possible NDVI values range from –1 to +1.

Dense vegetation gives a very strong response (high NDVI values), whereas areas with little or no vegetation show low values. This is explained by the fact that chlorophyll in plant leaves absorbs strongly in a portion of visible light, centred at about 0.45µm and 0.67µm (detected by AVHRR channel 1 [0.58-0.68µm]). On the other hand, the structure of the leaves' cells highly reflect and scatter in the near-infrared (NIR) region (detected by AVHRR channel 2 [0.72-1.10µm]) (Gates et al 1965, Lillesand and Kiefer 1994). NDVI also identifies water, ice and snow (low NDVI values).

NDVI has some limitations that can affect the accuracy of image classifications. The most relevant limitations to this project are commented below.

Clouds and fog can obscure the NDVI AVHRR images decreasing the NDVI values. Clouds of sub-pixel size and thin cirrus are difficult to detect with a coarse resolution sensor such as the AVHRR (Kaufman 1987, Henderson-Sellers et al 1987). Other atmospheric factors that can reduce the NDVI values are aerosols (Holben 1986, Holben and Fraser 1984) and water vapour (Chahine 1983). These factors reducing NDVI values can make wetland identification more difficult, as the clustering approach utilised in this project (and others, eg Nemani and Running (1997)) connects wetlands with low NDVI values. This means that pixels with low

NDVI values located in different land covers other than wetlands may be included in the same class as wetlands when a clustering is performed.

As the radiometer scans across the Earth, there is only one point (nadir) exactly under the radiometer. The distance between the radiometer and the ground increases from the nadir. This off-nadir effect causes a reduction in the measured NDVI as the light has to pass through more atmosphere before reaching the sensor (Duggin and Piwinski 1984, Holben and Fraser 1984, Holben 1986). In addition, at large off-nadir view angles the NDVI value can increase with increasing view angle. This is due to the geometric effect of the soil or water being hidden by the vegetation, which, in turn, takes up a higher proportion of the field of view (Robinson 1996).

The illumination and viewing geometry of the sun, sensor and target have a very important effect on the measured NDVI values. The reason is that the spectral response of vegetation depends on the instantaneous angle of view of the sensor relative to the sun and the target (Graetz and Gentle 1982).

The visible wavelengths are more affected by shading than the near-infrared (Graetz and Gentle 1982). That influence is not normalised by the NDVI (Robinson 1996). Large zenith solar angles, directional reflectance and shading tend to reduce the measured NDVI values (Holben and Fraser 1984, Holben 1986, Singh 1988). Again, all these factors reducing NDVI values can cause an overestimation of the number of pixels belonging to wetland classes.

As mentioned above, NDVI can identify water. However, if the water is covered with dense vegetation (such may be the case in some wetlands), the NDVI values will be high and water will not be characterised.

Although it is not an inherent NDVI limitation, it must be kept in mind that vegetation in wetlands is not homogeneous in composition, space and time, and therefore NDVI values can vary greatly within each particular type of wetland at a particular time. Consequently, wetland classification requires meticulous analysis of the available images in order to select the ones that best may represent wetlands.

3 Methodology

3.1 Background

The DGLC and 4mLC data sets used an unsupervised clustering classification method to perform the initial segmentation of the NDVI composites into ‘greenness’ classes. Unsupervised classification techniques are used when there is no previous knowledge about the location and characteristics of specific classes. These algorithms identify pixels with similar NDVI values and group them in clusters (Tou and Gonzalez 1974).

Traditionally (including the studied data sets), when a land cover classification is performed the investigator sets the algorithm to divide the data set into a number of clusters with similar NDVI values. All those clusters then have to be identified and a class has to be assigned. Clusters recognised as containing more than one class have to be split and those that may represent the same class have to be joined (see figure 2). This process can lead to confusion (Hastings 1998) and increases the chances of misclassification.

Hastings (1998) presented a more rational and comprehensive approach for unsupervised classifications. This author suggested building hierarchical sets of clusters, starting with a very simple differentiation and identification of classes, which, in turn, are divided into narrower and more specific classes. For example, first the algorithm can be set to provide three classes, which are studied to understand what type of land cover is represented. Once the land cover of those classes has been identified, a further clustering can be applied within each of the initial classes to sub-divide that generic land cover into more particular ones. Those new sub-classes, in turn, can be split. Figures 3 and 4 illustrate this approach. The process may be extended until the classification requirements are satisfied, or no further differentiation is possible because particular classes are homogeneous or because the spectral resolution is not fine enough for more detailed discrimination.

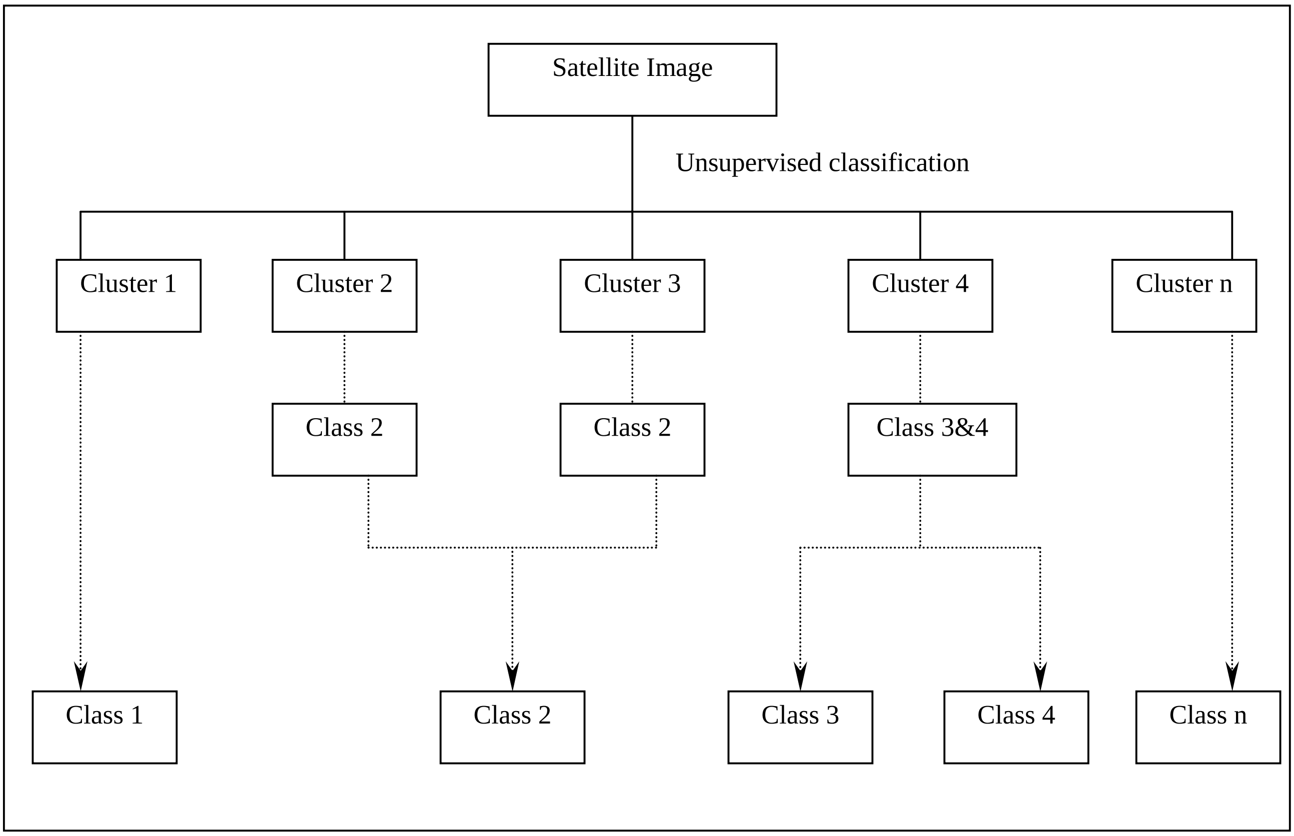


Figure 2 Diagram of a traditional clustering approach

This classification approach could be illustrated with an example at a global scale (see figure 5). As a first step, a two-class clustering may show the desert and non-desert areas of the Earth. In the next hierarchical step, each class would be divided into more classes (eg a two-class clustering in the desert areas may bring up the sub-classes ‘desert with no vegetation’ and ‘desert with sparse vegetation). The number of classes utilised would depend on the researcher’s requirements and the available ancillary data to identify them.

The approach suggested by Hastings (1998) was thought to be a possible alternative to the unsupervised classification methods used in the DGLC and the 4mLC data set. It was implemented in the three data sets (KNP area) in order to detect wetlands.

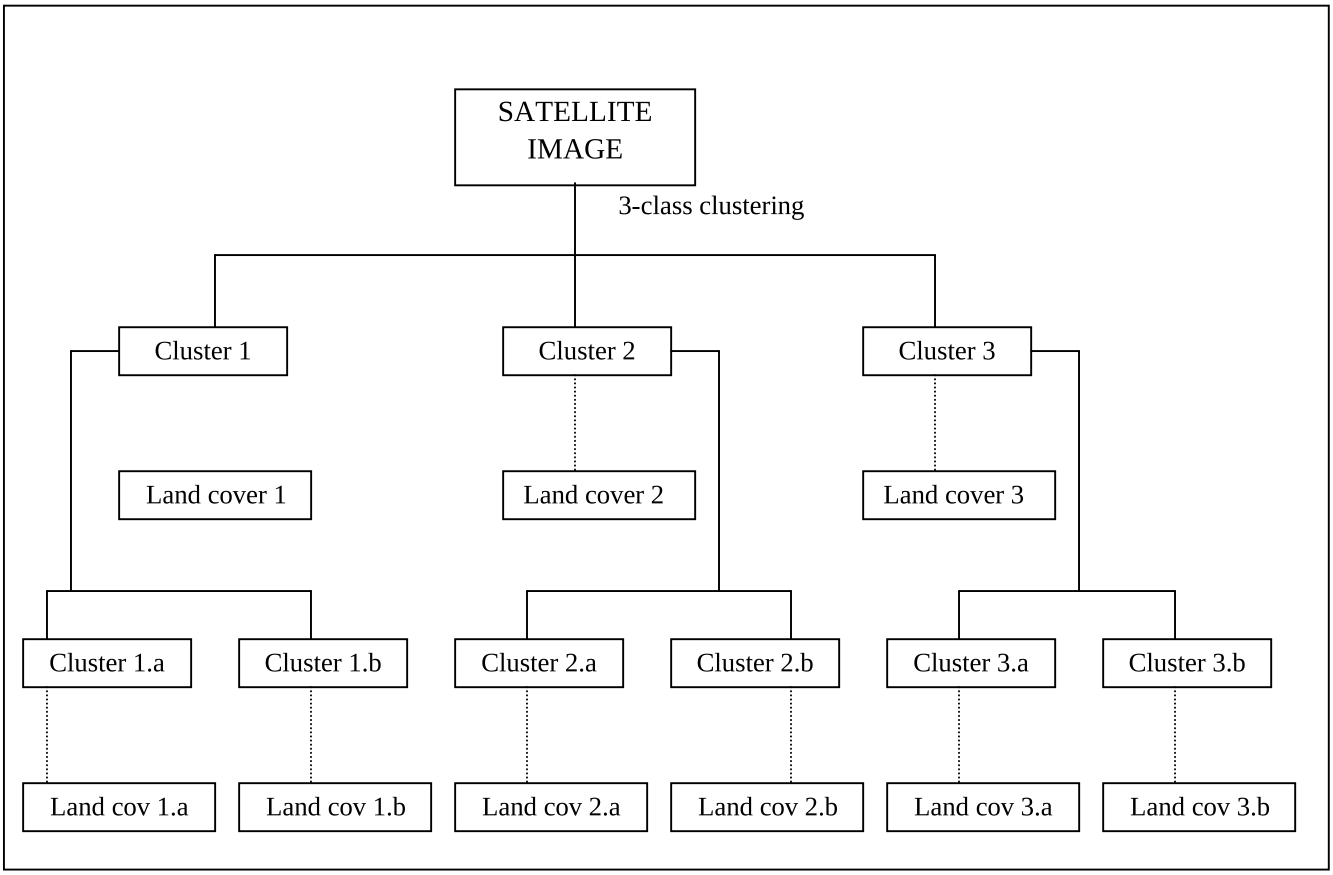


Figure 3 Hierarchical clustering tree. In this example, six classes are identified from the original image. This approach should yield a more accurate classification than applying a 6-class clustering directly.

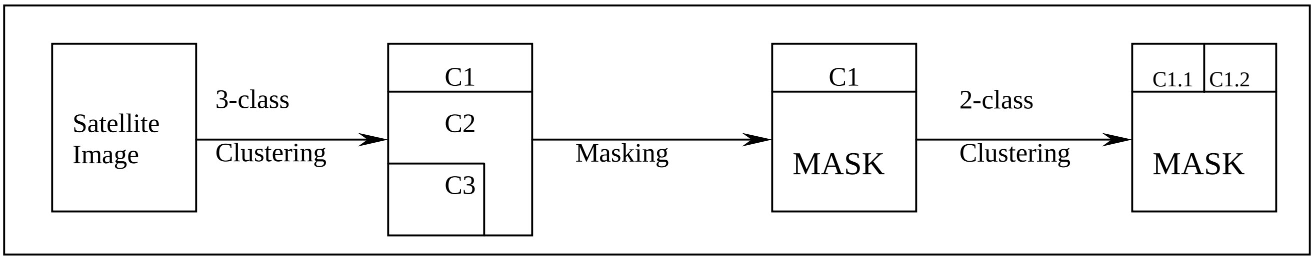
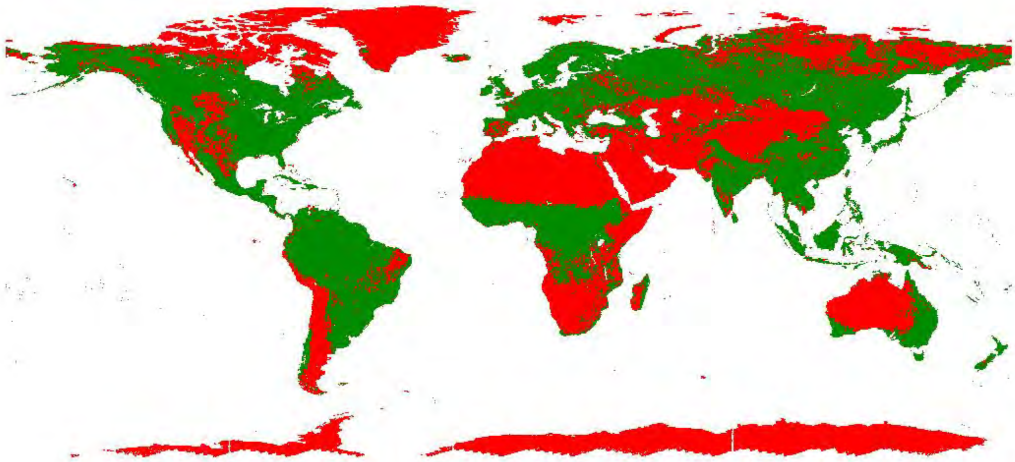
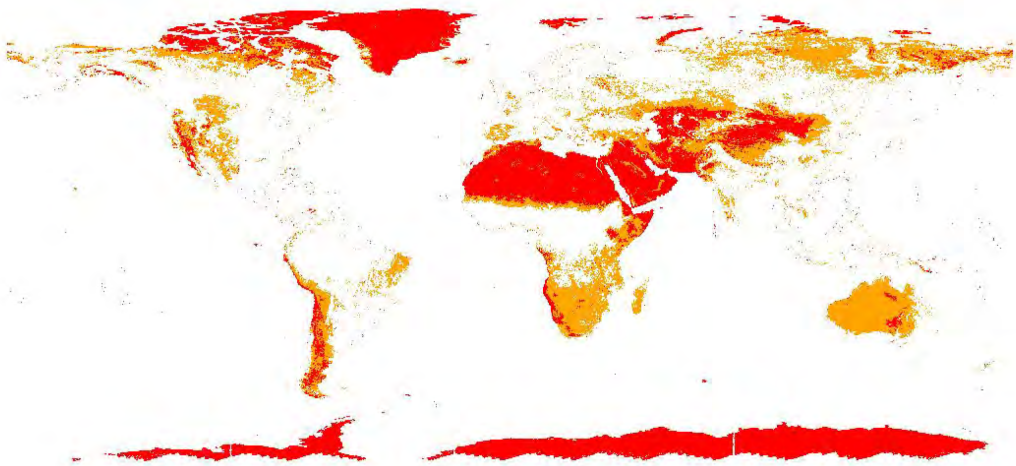


Figure 4 Diagram describing the masking process



a) Two-class clustering showing the desert (red) and non-desert (green) regions of the world



b) Additional two-class clustering within the class ‘desert’ showing desert with no vegetation (red) and desert with sparse vegetation (orange)

Figure 5 Example of hierarchical clustering

3.2 Software

ArcView® 3.2a GIS (ESRI 1999) and ENVI®3.4 (Research Systems 2000) were the two software packages used to manipulate the data. ENVI was used for registration of images, map re-projections, image classification, and image format conversion. ArcView was used for overlaying and spatial analysis. The unsupervised classification algorithm utilised in this project was K-means (Research Systems 2000).

All the NDVI images used from the different data sets were geocoded according to the information supplied in their meta data, and re-projected to the Australian Map Grid (AGD66), Zone 53, using the ENVI tool 'Convert map projection'. This was undertaken to enable integration with the vector data sets representing water bodies extracted from the AUSLIG GeoData set, and the boundary of the study area.

3.3 Clustering

3.3.1 DISCover Global Land Cover Data Set

The monthly NDVI composites were registered in Interrupted Homolosine Goode's projection, and re-projected to the Australian Map Grid (AGD66, Zone 53). An image sub-set was created for KNP. A three-class clustering was generated and a mask was created to keep only the class thought to contain wetlands. Existing knowledge of the region enabled the wetlands to be geographically located within that class. Two and three-class clusterings were produced from that class.

A further analysis was carried out. An annual NDVI composite was created by averaging the twelve monthly composites using the ENVI tool 'Band Math'. It is believed that an annual composite may reduce cloud effects and NDVI seasonal variation (Young and Wang 2001), and therefore wetlands may be characterised more consistently. The same clustering approach was implemented in the annual composite.

3.3.2 Global 4-minute Land Cover Data Set

The monthly NDVI composites were registered in latitude/longitude coordinates, re-projected to the Australian Map Grid (AGD66, Zone 53), and an image sub-set was created for the KNP area from each of the monthly composites. A three-class clustering was applied to the twelve NDVI images, resulting in a class composite that may be interpreted as ocean water, 'wet' region (north) and 'drier' region (south). A mask was created for the class considered to cover wetlands and the pixels of the wet region were clustered again in two classes. Additional clustering was not useful as the number of pixels for each class was small and their range of values was very narrow.

An annual composite was also created for this data set in order to reduce cloud contamination and NDVI seasonal variation. Again, the same hierarchical clustering approach was applied to the annual composite, starting with a three-class clustering.

3.3.3 Lovell and Graetz Data Set

In order to make comparisons with the 4mLC data set and the DGLC data set, monthly and annual NDVI composites were created by averaging ten-day composites from January 1990 to December 1990, and from April 1992 to March 1993, respectively. The operation was performed using the 'Band Math' tool in ENVI. The images were registered in latitude/longitude coordinates, and then reprojected to the Australian Map Grid (AGD66, Zone 53).

A three-class clustering was implemented in the monthly and annual composites. The class corresponding geographically to the wetland area was masked and a new two-class clustering was generated.

3.4 Overlaying and comparisons

The resulting clusters were overlaid with the water body features extracted from the AUSLIG 250K topographic map to visualise and compare the accuracy of the clustering process. Comparisons between data sets were also performed. The classified images from both 4mLC and DGLC data sets were compared with the classified images of the L&G (see figure 6).

To calculate the overall accuracy, the resulting wetland class was overlaid with a layer displaying a specific type of water body for the 1km data (as two types of wetland were distinguished), or with the layer displaying all the water bodies for the coarser data. Next, by intersecting both layers, the wetland area correctly classified was calculated, and then divided by the total area of the class.

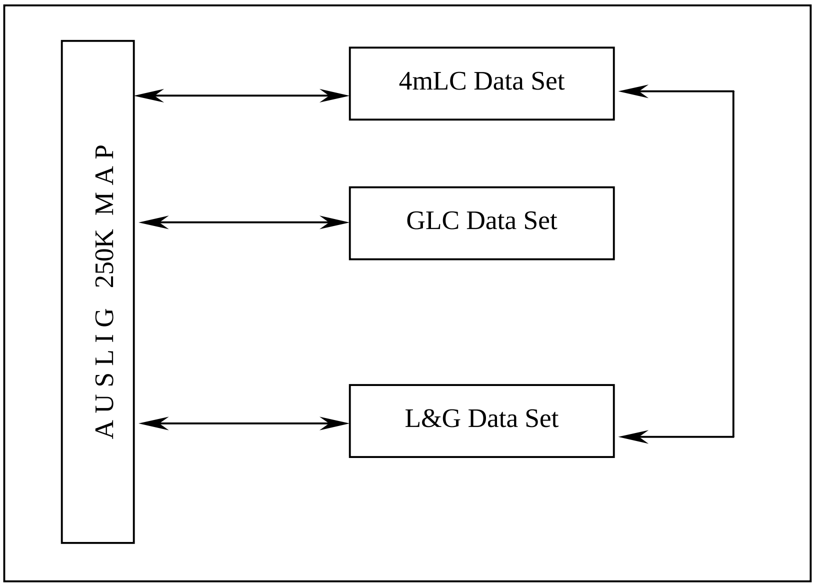


Figure 6 Comparisons made between the different data sets

4 Results

From the classification performed in the DGLC data set it was possible to distinguish the two major types of wetland ('land subject to inundation' and 'swamps') to some extent. The resulting clustering from the monthly composite of September was good at showing the main areas classified as 'land subject to inundation' (figure 7), which is the most important wetland type in KNP in terms of surface area. In the image there was a big contrast between these areas (low NDVI values) and their surroundings (high NDVI values). The surface area of the class considered to represent 'land subject to inundation' was 1710 km^2. In the AUSLIG 250K that class occupies 1572 km^2. The overall accuracy was 30.7%, and 32.4% of the total area of land subject to inundation was identified. On the other hand, swamps (the second most important wetland type, area wise) or any other type of wetland were not discriminated in the image of September.

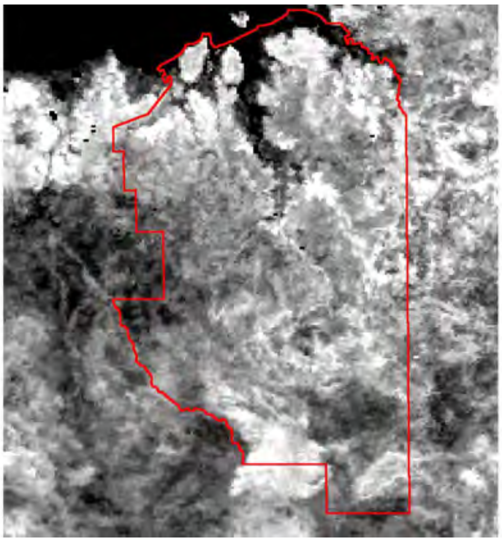
In the image of February it was possible to visualise and discriminate swamps (figure 8). Land subject to inundation could not be delineated from this image, as the NDVI values of these areas were similar to the NDVI values of the surroundings. After clustering was performed, the class including swamps held a total area of 1927 km^2, which is disproportionate in comparison with the 862 km^2 reported by the AUSLIG 250K topo map. The overall accuracy was just 12.6%, and 28.2% of the total swamp area was represented. Although the main regions of swamps were identified, other landscape features (especially in the south of the study area) were also included within the same class. A more selective classification could not be achieved due to the spectral similarity (similar NDVI values) between swamps and the other areas contained in the same class. September and February happened to be the 'extreme' months, where land subject to inundation and swamps were best discerned. September represented the driest period, and February the wettest. The other monthly composites showed the seasonal transition between both extreme states, eg from the lowest NDVI values to highest NDVI values or vice versa. In those transitional months the wetland regions contain high and low-value pixels in different proportions, depending on the month considered. Water bodies other than land subject to inundation or swamps could not be differentiated or were included within one of the mentioned categories. Figure 9 shows the extent of wetlands identified in February and September.

In the 4mLC data set differentiation between different types of wetland was not possible, and only one general wetland category was considered. The composite of October 1990 produced the best results (figure 10). 3437 km^2 were classified as wetlands, and 984 km^2 were correctly classified according to the AUSLIG 250K map (overall accuracy, 28.6%). 32.1% of the total wetland area in KNP was identified.

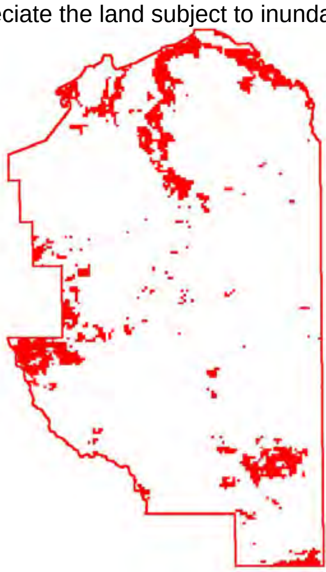
In the L&G data set, the composite of October 1990 showed the most acceptable results (figure 11). The initial three-class clustering was sufficient to extract a possible wetland class that covered the main wetland areas. The area covered by this cluster was 5482 km^2. 1517 km^2 were classified correctly (overall accuracy, 27.6), and 52.6% of the wetland area was covered by this class. A further clustering was applied to this cluster, but the sub-classes did not match the wetland pattern. These results are summarised in table 1.

To compare the L&G and DGLC data sets, the composites for September 93 and February 93 were chosen from both data sets as those months gave the best classification results in the DGLC data set. A visual comparison clearly revealed that there is no similarity in the class distribution pattern after applying the same classification approach (figures 12 & 13).

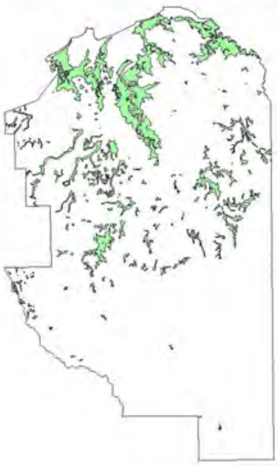
Annual composites did not produce satisfactory results in any of the data sets.



a) NDVI image where it is possible to
appreciate the land subject to inundation

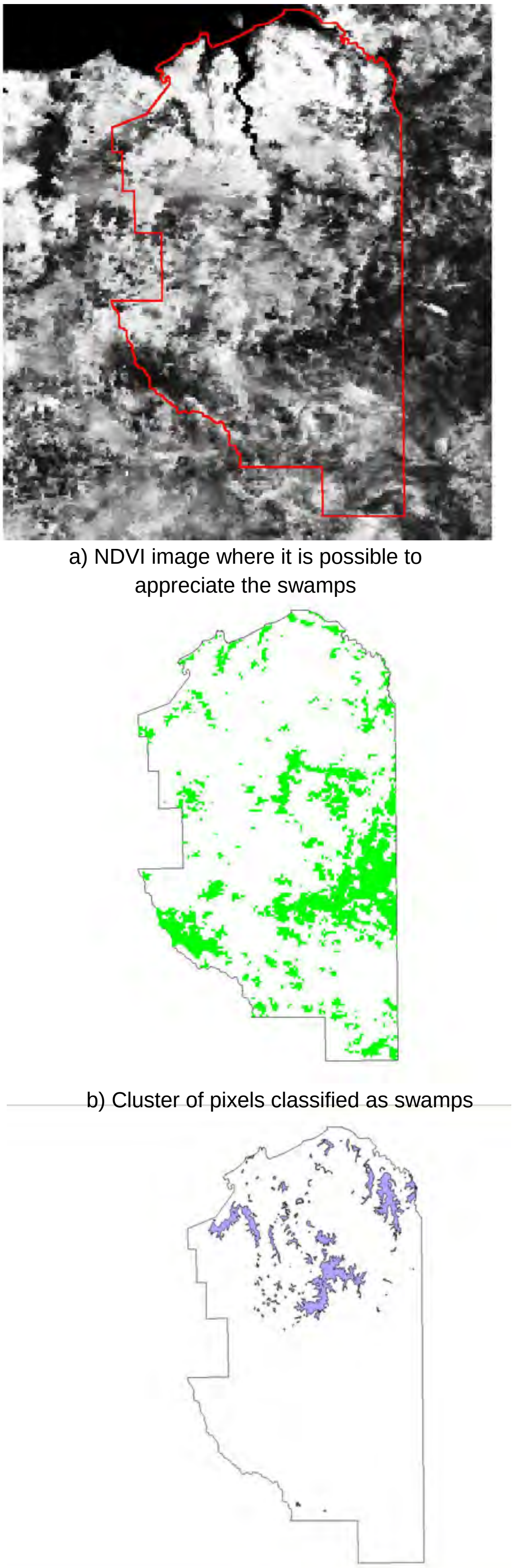


b) Cluster of pixels classified as land
subject to inundation



c) Land subject to inundation from
the AUSLIG 250K topographic map

Figure 7 September 1992, from DGLC data set



a) NDVI image where it is possible to appreciate the swamps

b) Cluster of pixels classified as swamps

c) Swamps from the AUSLIG 250K topographic map

Figure 8 February 1993, from DGLC data set

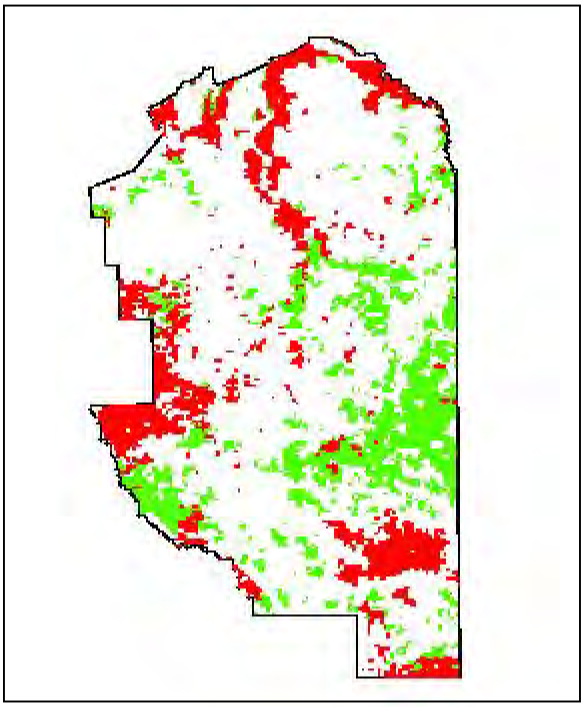


Figure 9 Resulting clusters from September and February 1993 overlaid

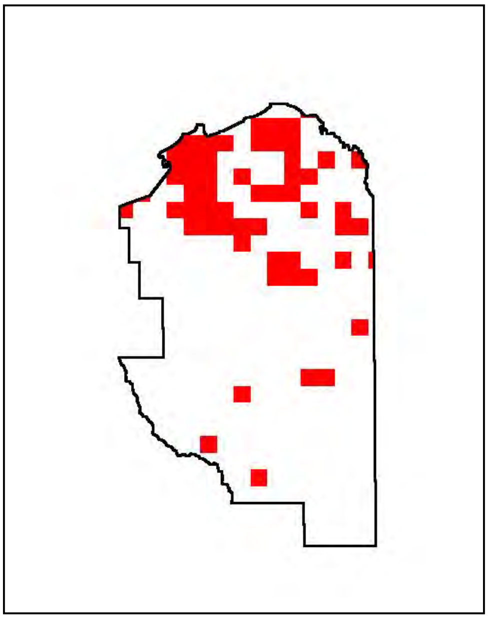


Figure 10 4mLC Data Set. Classification performed in the NDVI composite of October 1990

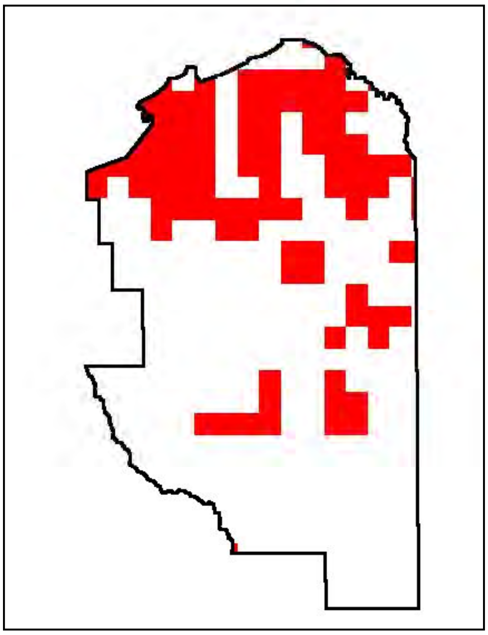
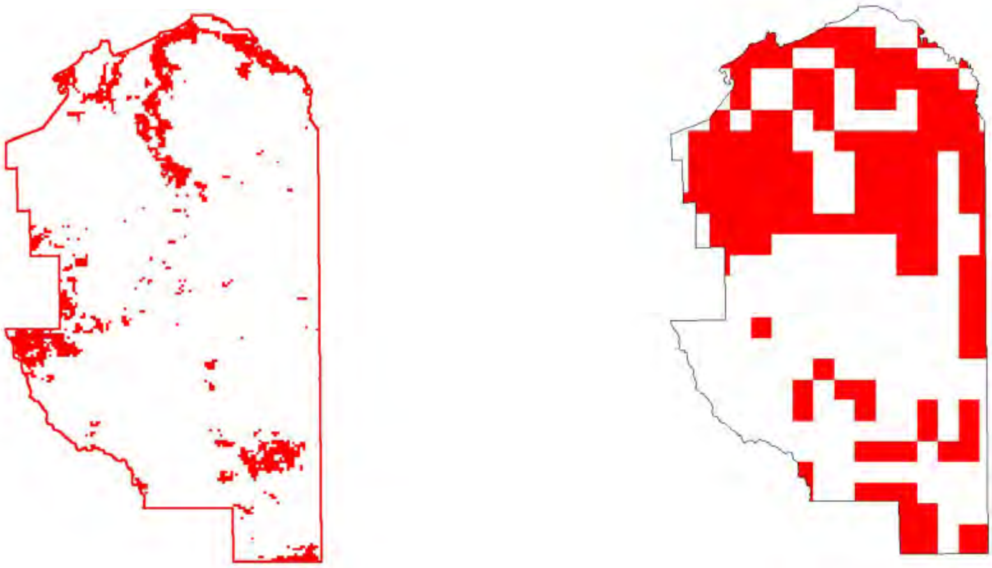


Figure 11 L&G Data Set. Classification performed in the NDVI composite of October 1990

Table 1 Summary of the best classification results for the different data sets

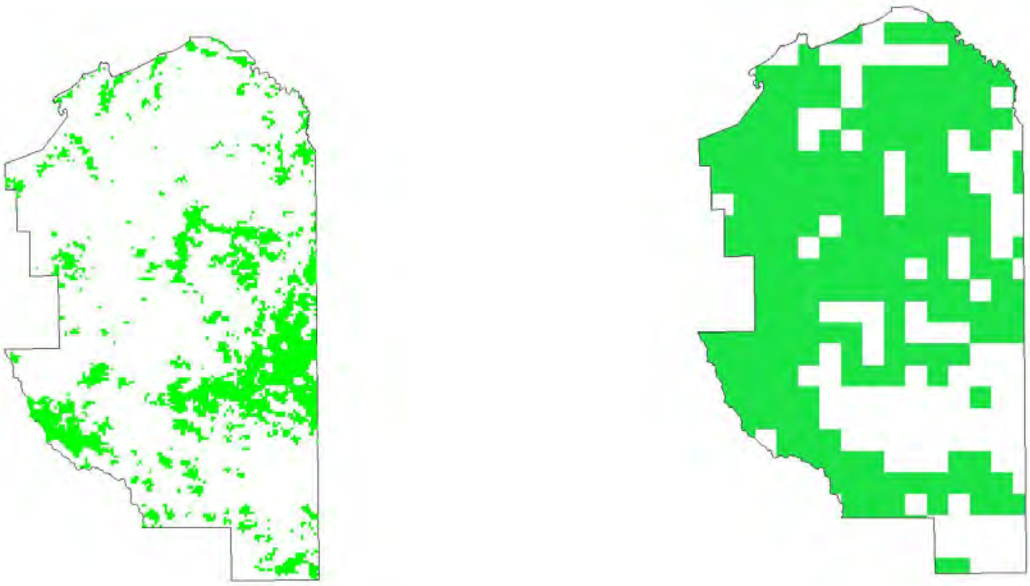
	DATA SET			
	DGLC		4mLC (Oct'90)	L&G (Oct'90)
	Land subj. inund.(Sep'92)	Swamp (Feb'93)		
(1) Total area of the cluster classified as wetland (km^2)	1710	1927	3437	5482
(2) Area of the cluster correctly classified as wetland (km^2)	526	243	983	1517
Overall accuracy (%) ([(2)/(1)] x 100)	30.7	12.6	28.6	27.7
% area correctly classified respect to wetland area	33.4	28.2	34.1	52.6
% area erroneously classified	69.2	87.9	71.4	72.3



(a)NDVI composite of DGLC dataset

(b)NDVI composite of L&G dataset

Figure 12 Comparison of the classifications performed in the September 1992 NDVI composites



February 1993 NDVI composites of DGLC

February 1993 NDVI composites of L&G data sets

Figure 13 Comparison of the classifications performed in the February 1993 NDVI composites

5 Discussion

From the monthly NDVI composites derived from the DGLC data set it was possible to identify and also visualise the strong seasonal changes that occur in the wetlands of KNP, especially in the areas classified as land subject to inundation and swamps (figures 8 and 9).

The NDVI image of September 1993 was best one at showing the areas of land subject to inundation (figure 8). They appeared as very dark areas (very low NDVI values) that contrasted with the bright surroundings (high NDVI values). Although flooding patterns change from year to year, in this case September may have coincided with the peak of the Dry season. According to Finlayson (1993), this time of the year is when the floodplains (land subject to inundation) have mostly dried out and their vegetation gets sparse.

This is when plant communities linked to flooded areas start to disappear and dry-season plants are starting to occur. Consequently, very low NDVI values characterise these areas.

On the other hand, swamps keep water during the Dry season, which allows the associated vegetation to remain during the dry period (Finlayson, pers. comm.). The author has observed that the presence of vegetation in swamps results in higher NDVI values that are similar to the ones held by the surrounding vegetation. In those conditions swamps cannot be differentiated in the NDVI AVHRR images.

The NDVI composite of February 1993 was the most suitable image to identify swamps (figure 8). In this case, swamps appeared as dark regions (low NDVI values), whereas the surroundings kept bright (high NDVI values), allowing rough differentiation. At this stage of the year the Wet season was in its peak and the water level in swamps was higher. As a result, a lot of vegetation that was previously above the water level was now submerged. Thus, the vegetation above the surface is sparser and more water surface is exposed, which results in low NDVI values. On the other hand, land subject to inundation could not be differentiated. At this time of the year these areas have an extensive and dense grass cover started by the water flooding the soil (Milne et al 2000). Consequently, these regions had similar NDVI values (high values) to those of the surroundings, which makes differentiation impossible. [1]

However, the outcome of the clustering operation was a class that contained not only regions of swamps, but other land covers as well (see Chapter 4 and Figure 8). This is due to the fact that other land covers at that point in time had the same range of NDVI values as the swamps. A more selective differentiation was not possible due to the coarse spectral resolution of the AVHRR. When the bands are too wide (red and IR bands in this case) discrimination between some features is not possible, as the spectral differences are not significant enough to be distinguished by the sensor, and consequently, different types of land cover fall into the same class. The inability to differentiate other types of wetland may be due to the same reason. Only land cover types with distinct spectral signatures (eg broadleaf trees vs. coniferous) are able to be distinguished in NDVI AVHRR data.

It must also be taken into account that the NDVI was created to monitor photosynthetic activity, and therefore different types and/or amount of vegetation. This is a very important handicap with respect to monitoring wetlands, as the NDVI may not be able to tell if a dense mass of vegetation is lying on a water body or soil. Still, certain vegetation communities are characteristic of wetlands and their spectral signature should be distinctive. However, if the

[1] Please note that vegetation dynamics in KNP wetlands are complex, and all of the above-mentioned is just a general description of the whole seasonal process (Finlayson, pers. comm.). A detailed description of vegetation changes in floodplains of the wet-dry tropics of Australia can be found in Finlayson (1993).

spectral resolution of the sensor is too coarse (as is the case of the AVHRR sensor), differentiation may not be possible, and wetland vegetation communities may be classified in the same category as other communities that show the same spectral response at that coarse level.

To overcome this problem and to be able to separate spectrally closed land covers by using NDVI AVHRR data, narrower channels in the red and infra-red regions may be necessary.

Additionally, cloudiness may be another reason for low NDVI values in the area (see Section 2.3), as heavy cloud cover, which is common during the Wet season across northern Australia will obscure vegetative cover.

Burnt areas can also influence the quality of the classification, since they appear as dark areas as well. Under current fire management in KNP, floodplain margins are burnt in the early Dry season to reduce the chances of fires exiting from the flood plains later in the season or, conversely entering from surrounding savanna woodlands (Russell-Smith 1995).

The results yielded by the NDVI data from the 4mLC and L&G data sets proved that they are not very suitable for accurate wetland monitoring and mapping. The coarse spatial and spectral resolution of their base data is a major limitation to accurately mapping wetland distribution. The pixel size is too large (about 64 km^2) for accurate ground location (Townshend 1994), and wetland shape and extent can not be accurately represented. This, in turn, leads to mixing-pixel problems, which results in pixels containing more than one type of land cover. Consequently, the spectral signature of a mixed pixel is a combination of the signatures of the different land covers contained in it. This causes inaccuracy in the clustering process.

Other limitations were observed in the methodology applied in the 4mLC data set. This included limited ground truthing of the Asian and Oceanian region. The ground truthing, which did occur, did not include any wetlands in Australia as a whole. To classify the rest of the clusters not covered by a ground truth region or extended ground truth region, a decision tree was used (see Section 2.2.2). Surprisingly, the decision tree described in the metadata does not show any criteria to identify wetlands, even though the legend of the data set has three classes for wetlands. In the final land cover map, the regions of KNP likely to contain wetlands were classified within very broad categories such as ‘vegetation’, ‘grass crops’, or ‘forest’. The only regions classified as wetlands in the whole world were those derived from the ground data (three regions in Asia). Thus, no wetlands were identified in Australia, America, Africa or Europe.

In the Lovell and Graetz data set the results were not much better than in the 4mLC data set, even though the data is filtered for cloud contamination and other artefacts. Despite the fact the wetland class contains 52.6% of the total wetland area, the actual shape and extent of the wetlands cannot be extracted due to the pixel size. Hence, a selection of the pixels that truly cover wetland areas is very difficult. This suggests that pixel size, rather than atmospheric contamination, is a determining factor in the ability to detect wetlands.

It is very useful to compare the images of September 1992 and February 1993 from the L&G study, and the DGLC. Although some resemblance in the results could be expected, it is clearly appreciated that the clustering performed in the images from the L&G data set do not resemble the distribution of either land subject to inundation or swamps (Figure 13). This could be considered the proof that the spatial resolution is the major limitation of both 4mLC and L&G data sets when they are used to identify wetlands.

Overall, the results have suggested that NDVI data from AVHRR imagery is not a very suitable index to map wetlands

Another aspect to take into account is the seasonal variability of wetlands. Since dramatic changes regarding water cover and vegetation communities occur throughout the year, a careful inspection of images from different times of year must be undertaken to select the images that best illustrate the wetlands extent.

6 Conclusions

As outlined in Chapter 1, global land cover data sets derived from AVHRR imagery are not ideal at representing wetlands. This is because the clustering/classification approaches implemented are not suitable to identify wetlands. However, with 1-km data, better wetland classification can be achieved using the same base data, as the present study has demonstrated. In this project it has been found that the 4mLC and L&G data sets are not suitable for wetland identification in KNP. The main limitation encountered in these data sets is the pixel size (8km), as they are too large to accurately identify and map wetlands (see Chapter 5). In general, the shape of the wetlands is too complex and their size usually too small to be adequately covered by an approximately 64 km^2 pixel. This results in mixing pixels, which make land cover identification difficult as the spectral signature is a combination of two or more types of cover in different proportions. It was thought that atmospheric contamination may be an important limiting factor (see Section 2.3), but it has been proved that filtered data does not generate better results when such coarse resolution is used.

Other problems were identified in the 4mLC data set. Its methodology significantly relies on ground truth data, but the authors of the data set have not been able to compile sufficient ground truth data to achieve a better classification (see metadata at www-cger.nies.go.jp/grid-e/gridtxt/gflcds.html). This is proved by the fact that the only regions of wetlands in the world are represented where the ground truth data about wetlands was collected (three places: Vietnam, Bangladesh and Saudi Arabia). Additionally, the decision tree they used to classify all those clusters not identified by the ground truth data (most of the world surface) did not include any criteria for wetlands. The authors of the data set agree that more ground truth data and other quality ancillary information should be collected in the future to achieve a more accurate classification.

The land cover classification from the DGLC also fails to identify wetlands in KNP. However, its base data was found useful. Using an alternative classification approach (see Section 5.1), the two major types of wetlands, area wise, were identified (land subject to inundation and swamps). The shortcoming is that other wetland types are not recognised, and other land covers can be included within those wetland classes. This can be due to the coarse spectral resolution of the AVHRR sensor. To be able to differentiate more types of wetlands, narrower bands may be required. However, these results showed that:

1. 1 km pixels are not too coarse for wetland monitoring.
2. A hierarchical classification approach may generate more accurate land cover classifications.

Although the overall accuracy in the three data sets is fairly similar (see Table 1), the 1-km resolution data set is more suitable:

1. Two different types of wetlands can be distinguished.

2. The areas classified as wetlands resemble their actual shape much better than the 8-km resolution data sets.

It was noticed that the inherent seasonal change of wetlands in KNP makes them 'vanish' and reappear in the NDVI images depending on the season and the type of wetland. Therefore, it is very important to find and select those months were the particular types of wetland are most visible in NDVI images. This feature can be useful to monitor seasonal changes and annual variations.

In summary, it can be concluded that NDVI data derived from AVHRR does not supply sufficient information to accurately monitor wetlands as:

1. Water covered with vegetation cannot be differentiated from land vegetation if both types of vegetation have similar spectral response.
2. Other land covers can have similar NDVI values to those of wetlands. It results in an inaccurate clustering as both wetlands and covers with similar NDVI values are included within the same cluster and further separation is not possible.
3. AVHRR spectral resolution is too coarse to distinguish between some types of wetland vegetation and some types of land cover. This may be the reason why only two types of wetland (land subject to inundation and swamps) were differentiated.

A literature review has shown that wetland detection with AVHRR may yield better results if the thermal bands or band ratios are used in conjunction with NDVI (see Appendix A). This would allow delineating areas with water, regardless if they were covered with vegetation or not. The performance of the thermal bands for wetland detection in KNP could not be tested, as it was beyond the scope of this project because of lack of available data. Research on the utility of these bands in KNP is strongly recommended. However, it has been proved that wetland identification using NDVI AVHRR data can be improved with respect to the studied data sets.

To identify wetlands using NDVI AVHRR data it is recommended that:

1. If wetlands are to be mapped with AVHRR imagery, spatial resolution coarser than 1km should not be used.
2. Seasonal variability has to be taken into account as it affects the extent and differentiation of wetlands, and cloud contamination. Images should be carefully chosen to avoid too much cloud contamination and to find the ones that better show the type/s of wetland/s to be monitored.
3. A hierarchical clustering/classification approach should be used in order to achieve a better discrimination and identification of classes, and,
4. Classification should be supported with as much reliable ancillary data as possible.

7 References

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Appendix A Other approaches for wetland identification

A review of the literature about wetlands and water bodies identification with NOAA AVHRR suggests that other AVHRR bands may be more suitable for this task rather than NDVI data:

1 Travaglia *et al* 1995

The authors used a thermal inertia approach to monitor wetlands for fisheries. It was assumed that water and aquatic vegetation have higher thermal inertia than dry land and non-aquatic vegetation as the former warm up less during the day. Thus, water and aquatic vegetation appear cooler than their surroundings on daytime thermal images. They used AVHRR scenes taken around noon: this is when the thermal contrast between dry and wet areas reaches the maximum (Mason et al 1992). Channel 4 is the most suitable to emphasise that contrast. This is also supported by Gutman and Ignatov (1995), and Liang (2001), who stated that NDVI and channel 4 complement each other to resolve ambiguities when only one of the variables is used. Channel 3 was useful to clarify ambiguities and NDVI was used to highlight vegetation.

They judged that cloudiness is often a problem, either when the area of interest is fully or partially covered, but also when clouds are close to the study area. In this case, the brightness of the clouds saturated the DN values of the sensor, impeding the thermal inertia approach. This is likely to occur during the rainy season in the tropics. Therefore, in KNP and the rest of the tropical regions of Australia this approach is more suitable during the Dry season, which has less cloud cover.

2 Verdin, 1996

The author used AVHRR imagery to monitor ephemeral water bodies in western Niger. The thermal inertia approach was used in this work as well. Cloud-free scenes with the study area near the nadir position of the instrument scan were selected. Visually, little difference was noted between bands 4 and 5 for the images studied, and band 5 was adopted. This work revealed that bands 1 and 2, and the NDVI calculated from them are not especially valuable for monitoring water bodies in the study area.

3 Tamura and Yasuoka, 1998

In this work the authors extracted wetlands in West Siberia using surface temperature and NDVI. Their approach is totally opposite the one Travaglia *et al*. (1995) and Verdin (1996) proposed. Tamura and Yasuoka assumed that higher brightness temperatures (bands 4 and 5) occur in wetlands than in forest. It may be explained by two mechanisms. First, forest may have a greater transpiration rate than wetlands, thus, forests have lower surface temperature in midday due to greater latent heat transfer. Second, forest leaves may be cooled by air until leaf temperatures are in balance with air temperatures (Gate, 1980). On the other hand, wetland plants represented by sphagnum mosses may be less cooled by air because they grow in dense clusters near or at the ground surface.

Surface temperature was computed by the split-window method (Singh, 1984):

$$T_S = 1.764T_4 - 0.764T_5 + 0.78$$

where T_4 and T_5 are radiometric brightness temperatures derived from bands 4 and 5, respectively.

They found a negative correlation between surface temperature and NDVI. The results were verified comparing with classification results from high-resolution satellite images (SPOT/HVR and JERS-1/OPS) and they show fairly good agreement.

4 Sheng et al 2001

This paper shows four different methods that have been used for water body identification in flood monitoring using AVHRR data.

Channel 2 model

Several researchers (Lin, 1989, Sheng et al 1998) have realised that channel 2 is more effective in distinguishing water from land than other channels. This is not very useful if the water is covered with vegetation.

Temperature model

Barton and Bathols (1989) found that nocturnal brightness temperatures derived from channel 4 were effective to monitor the 1988 Darling river flood in Australia. As mentioned above, Verdin (1996) used daytime brightness temperature for water and land discrimination.

Differential model between channel 2 and 1

Xiao and Chen (1987) identified water bodies by using the difference between channel 2 and channel 1.

Ratio model of channel 2 and 1

Sheng and Xiao (1994) created a ratio between channels 2 and 1 (Ch2/Ch1) to enhance the difference between water and land during flood. In the ratio image water has very low value, whereas land has a relatively high value.

The authors consider that, in many cases, the ratio model is the best one as it has got a very good enhancing capability and it is not susceptible to thin cloud contamination. On the other hand, they believe the temperature model usually works well in areas with a great temperature contrast between night and day. However, it may not work during rainy seasons in the summer when there is relatively low or no temperature difference between land and water, and when there are clouds. The latter may be the case in KNP and therefore this approach may not work during the wet months.