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Mapping the spatial and temporal distribution of *Melaleuca* spp on the Magela floodplain between 1950 & 2004, using object-based analysis and GIS

G Staben

June 2008

(Release status - unrestricted)

Mapping the spatial and temporal distribution of *Melaleuca* spp on the Magela floodplain between 1950 and 2004, using object-based analysis and GIS

Grant Staben

Thesis submitted by Grant William Staben, BEnv Sc (CDU), in partial fulfilment of the requirements for the Degree of Bachelor of Science with Honours in the School of Biological, Environmental & Chemical Sciences, Faculty of Science, Information Technology & Education, Charles Darwin University, Northern Territory November 2005

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Declaration

I declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references given.

Grant William Staben, 21 November 2005, Darwin NT

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Abstract

Wetland ecosystems within Kakadu National Park have been recognised for their global significance under the Convention on Wetlands of International Importance. Both natural and anthropogenic factors have been identified that may impact and alter wetland ecosystems in the region. Monitoring natural and human induced environmental change has been identified as a priority. Remote sensing technologies offer an effective way to monitor change in the natural environment at a variety of spatial and temporal scales. Aerial photographs have been identified as a useful resource in floristic studies in wetlands of northern Australia; additionally they provide an important record for assessment of historical landscape change. The spatial and temporal change in the distribution of *Melaleuca* spp on a portion of the Magela floodplain was investigated, using four aerial photographic datasets.

Automated classification of panchromatic and true colour aerial photographs using traditional per-pixel algorithms has been limited due to their fine resolution and reduced spectral properties. Current advances in multi-scaled object-based classification techniques have enabled the successful classification of very high resolution data. The use of a multi-scaled approach has enabled the development of classification methods resembling the way humans interpret an image. In this project, classification of the aerial photographs was undertaken using a semi-automated object-based approach. It was found that environmental conditions at the time of acquisition of the photographs influenced the success of the classification. Estimated accuracy of the four classified datasets ranged between 82% and 90%.

Change analysis was performed on the classified aerial photographs to identify both spatial and temporal change in *Melaleuca* spp canopy cover. The results indicate that there has been little change in canopy cover ($\pm 3\%$) over the 54 year period. However, the results identified that the spatial distribution of *Melaleuca* spp canopy cover has been dynamic across the study area with continual increase in the lower eastern portion of the study area.

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Chapter 1 Introduction

1.1 General Introduction

Kakadu National Park is located in the Northern Territory of Australia. Covering an area of approximately 19 800 km² (Robinson & Whitehead 2003) the park encompasses a diverse range of landscapes and ecosystems, ranging from sandstone plateau and escarpment, to wetland environments associated with coastal and alluvial floodplains. Wetland environments are important to the maintenance and protection of biodiversity and provide services such as water purification and flood mitigation (Keddy 2000). The wetlands of Kakadu have been recognised for their global significance under the Convention on Wetlands of International Importance (Ramsar 2002). For the indigenous owners of Kakadu they are an important social, natural and cultural resource (Brockwell et al 1995). A number of factors have been identified as potentially having detrimental impacts on these wetlands, including exotic flora and fauna (Cowie et al 2000, Walden et al 2004), altered fire regimes (Douglas & O'Connor, 2004), sea-level rise as a result of climate change (Bayliss et al 1997), and anthropogenic activities such as tourism, pastoral and mining industries (Bayliss et al 1997, Storrs & Finlayson 1997). Monitoring natural and human induced environmental change of the wetlands of this region has been identified as a priority (Saynor et al 2001).

This study focuses on mapping *Melaleuca* spp within a section of the Magela floodplain located in Kakadu National Park. The genus *Melaleuca* contains up to 250 species in Australia. All known *Melaleuca* spp are native to Australia with all, but nine, being endemic (Turner et al 1998). In Australia they represent the third most diverse plant genus after *Acacia* and *Eucalyptus* (Turner et al 1998). In the Northern Territory 20 different species of *Melaleuca* occur with varying growth forms from small straggly shrubs to tall trees (Dunlop et al 1995, Riley & Lowry 2002). Whilst not considered endangered in the Northern Territory, *Melaleuca* communities (*M. quinquenervia* and *M. viridiflora*) in coastal areas of northern Queensland have been variously listed as being of concern, vulnerable or endangered (Turner et al 1998). In Florida in the United States of America, *Melaleuca quinquenervia* is considered a major pest, displacing native vegetation communities and reducing suitable habitat for many native fauna (Mack et al 2000, Turner et al 1998).

In September 2001, concerns were raised by the media that the spread of *Melaleuca* spp observed in Papua New Guinea and the Mary River Floodplain in the Northern Territory may be occurring in the wetlands of Kakadu. It was suggested that the spread of *Melaleuca* spp could displace herbaceous vegetation communities in the wetlands of Kakadu (Riley & Lowry 2002). In response to these concerns a remotely sensed project was undertaken by the Environmental Research Institute of the Supervising Scientist (*eriss*). This project used manual interpretation of digitised aerial photographs to investigate the spatial and temporal changes in the distribution of *Melaleuca* spp. The results of the study indicated that there had been an overall decline (21%) in tree density between the years 1975 and 1996 in a 41 km² section of the Magela floodplain. Although the density of *Melaleuca* spp decreased, they found that the distribution of woody vegetation had increased (Riley & Lowry 2002). In their concluding remarks, Riley and Lowry (2002) highlighted that future technological developments in image analysis and classification software may help to overcome problems related to image pre-processing and human error using manual classification methods. The Riley and Lowry (2002) study forms the genesis for this current research project.

The fine-scale of aerial photography is useful in detailed floristic studies of wetland environments (Harvey & Hill 2001). Aerial photographs provide an important resource for studies looking into landscape change over time; as they provide historical data which is unavailable in other forms of remotely sensed images (Lucas et al 2002, Pfitzner 2004). Panchromatic and true colour aerial photographs have been widely utilised for ecological studies; however it has been largely restricted to manual classification methods (Kadmon & Harari-Kremer 1999). The reduced spectral resolution and the increase in pixel heterogeneity of aerial photography have made it difficult to classify using automated approaches (Laliberte et al 2004). In recent times, advancements have been made in the automated classification of very high resolution (VHR) imagery. Object-orientated classification methods have been developed that have enabled imagery to be classified using a multi-scaled approach. This multi-scaled approach enables the development of a classification knowledge base, which is moving towards the way the human mind interprets an image (Baatz et al 2004).

1.2 Aims

There are two primary aims to this project;

To assess the use of object-based classification for distinguishing between *Melaleuca* spp cover and other floodplain communities using aerial photographs.

To identify the spatial and temporal distribution of changes in *Melaleuca* spp cover over the period 1950–2004, for a portion of the floodplain of Magela Creek.

1.3 Thesis outline

This thesis contains six chapters which describe and discuss the methodology used to fulfil the aims of the project; the results are presented and discussed. A brief summary of the content of each chapter follows.

Chapter 1 – Outlines the aims of the research, and gives general back ground to the study including a general overview of the study region.

Chapter 2 – Contains a review of remote sensing of floodplain environments and object-based classification. It contains a review of two previous studies mapping spatial and temporal distribution of *Melaleuca* spp on the Magela floodplain. It also reviews factors identified as possible drivers of environmental change on floodplains of northern Australia.

Chapter 3 – Provides details of the materials and imagery used in the project are given. Image pre-processing steps undertaken are described and results given. Accuracy assessment methods used to assess the final classified images are detailed.

Chapter 4 – Provides detailed descriptions of the object-based approach used to classify each aerial photograph. The results and error assessment for each classified aerial photograph are detailed and discussed, along with issues related to the methods and imagery used.

Chapter 5 – Change analysis methods used are described. Results are presented and discussed in relation to previous studies. Possible drivers of change are identified and discussed.

Chapter 6 – Summarises the thesis and recommendations for further research are detailed.

1.4 Study area

1.4.1 Geographical location

The Magela Creek is located in the Alligator Rivers Region, approximately 250 km east of Darwin in the Northern Territory (Fig 1.1). It is a seasonally flowing tributary of the East Alligator River, consisting of five distinct sections (Finlayson et al 1994, Gardner et al 2002). These sections are described by Finlayson et al (1994) as ‘escarpment channels flowing through deep narrow gorges; braided sand-bed channels with sandy levees; a series of billabongs and connecting channels; a seasonally inundated black-clay floodplain with permanent billabongs; and a single channel that discharges into the East Alligator River’.

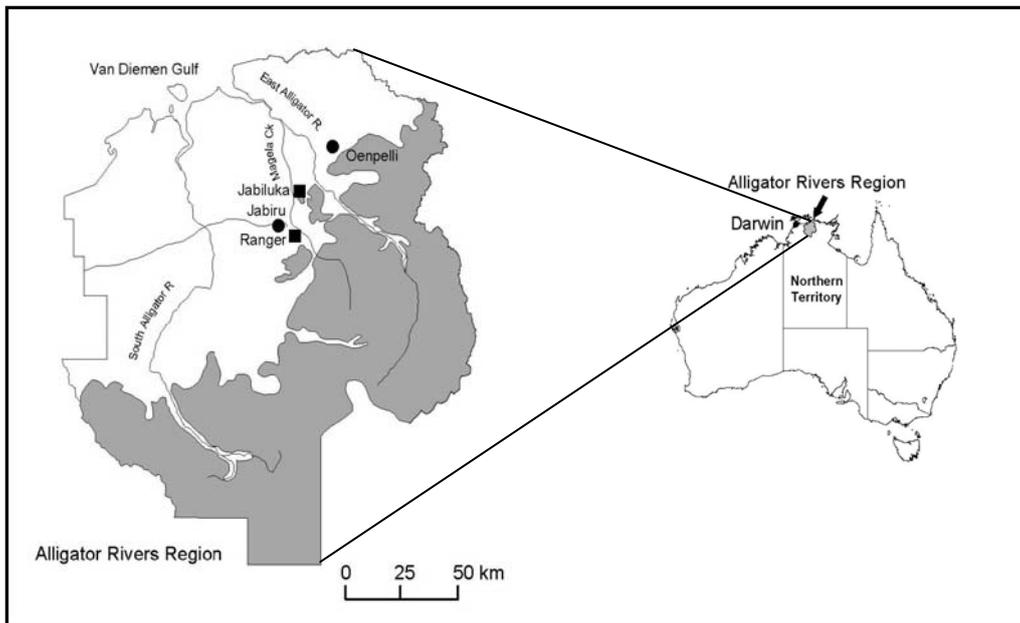


Figure 1.1 Geographical location of the Alligator Rivers Region (ARR) in the Northern Territory, Australia (adapted from Saynor et al 2004)

The study site is a 4.9 km² section of the Magela floodplain, which is located within Kakadu National Park to the north of the Jabiluka Project Area (Riley & Lowry 2002) (Fig 1.2). The study site is a backwater floodplain located at the base of the Ngarradj catchment (Gardner et al 2002). In this study (as with the Riley & Lowry (2002) study) the key assumption is made that all woody vegetation mapped belongs to the genus *Melaleuca*. It is, however, acknowledged that whilst the floodplain consists predominantly of *Melaleuca* spp, the floodplain does consist of other woody species albeit very sparse.

1.4.2 Significance of the study area

Kakadu National Park is proclaimed under the Environment Protection and Biodiversity Conservation Act 1999 (the EPBC Act). The management is a joint relationship between the Aboriginal traditional owners and the Director of National Parks. This arrangement is enshrined in legislation, in lease agreements with the traditional owners and plans of management (KNPPM 1998, Press & Lawrence 1995). Indigenous Australians have occupied the Kakadu region for many thousands of years (Brockwell et al 1995, Morris 1996). They have strong links to the environment and inherited responsibility to protect and maintain the

landscape (Morris 1996). In addition to being an important food source to the indigenous people of the region, the floodplains have significant cultural and heritage values (Brockwell et al 1995).

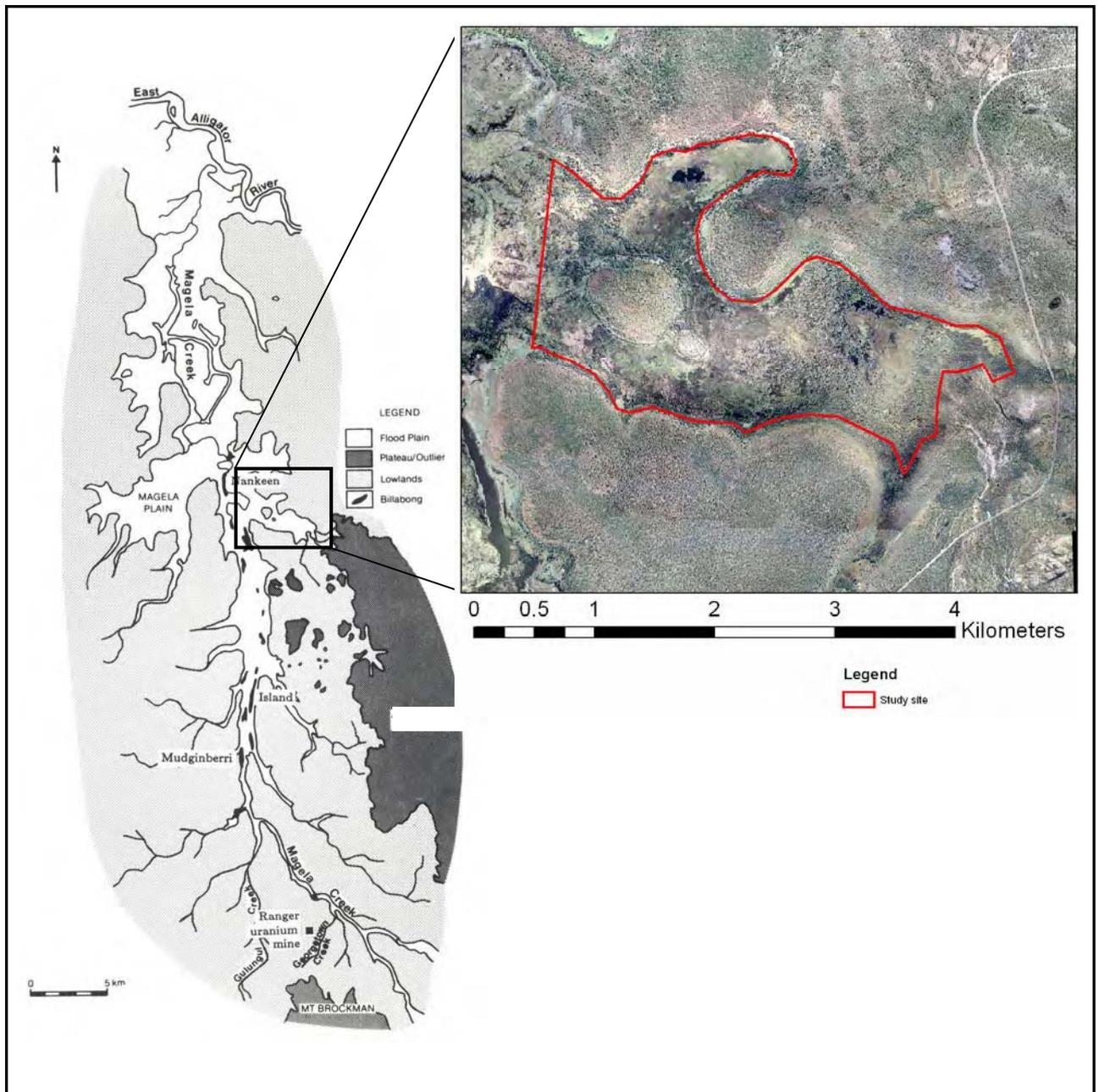


Figure 1.2 Geographical location of the study site in relation to the full extent of the Magela Floodplain. (Full extent of Magela floodplain adapted from Finlayson et al 1989; aerial photograph acquired 2004.)

The Magela floodplain is well recognised for the diversity of wildlife and flora it supports (Gardner et al 2002). It is estimated that during the driest period of the year (August to October) the Kakadu wetlands can support up to two and a half million water birds; with the greatest concentrations located on the Magela and Nourlangie floodplains (Press et al 1995). It is also an important habitat for many mammal, reptile, amphibian and fish species (Gardner et al 2002).

There are several mineral leases within the boundary of Kakadu National Park. Both the Ranger and Jabiluka uranium mines have the potential to negatively impact the Magela catchment (Gardner et al 2002). Of particular interest to this project is the Jabiluka mine located within the Ngarradj catchment. Development of the mine commenced in 1998 subject to a number of environmental requirements, however it is currently in a long term care and maintenance phase (Saynor et al 2004). Discharge from the Ngarradj catchment empties directly into the portion of the Magela floodplain chosen for this study. This section would be one of the first areas affected should any negative impact occur due to mining (Boggs 2001, Gardner et al 2002, Moliere et al 2002). However, mining in the region is only one of several factors identified as having possible negative impacts. To ensure correct land management practices are put in place it is imperative that the reasons behind any negative impact are correctly identified and understood.

1.4.3 Climate

The Magela floodplain is located in the monsoonal tropics, where there are two distinct seasons known as the wet and dry (McDonald & McAlpine 1991). The vast majority of rainfall occurs during the wet season, commencing around November – December and usually lasting for a 3 to 4 month period (Gardner et al 2002). The onset of the wet is seasonally variable and occurs as the monsoon trough approaches the Australian mainland (McDonald & McAlpine 1991). Annual average rainfall for the study area is approximately 1450 mm (Boggs 2001). The wet season is characterised by periods of excessive rainfall which includes thunderstorms, monsoonal depressions and cyclones with periods of occasional showers and lengthy dry spells (McDonald & McAlpine 1991). Annual potential evaporation is very high (approximately 2400–2700 mm) exceeding rainfall most years (Russell-Smith et al 1995). During the dry season May to September there is very little or no rainfall (McDonald & McAlpine 1991).

The wet season is a time of high temperatures and humidity, in contrast to the dry season which experiences relatively cooler temperatures and reduced humidity. The temperature remains high throughout the year with a maximum average temperature ranging between 31°C during June to July to 37.1°C during October (Bayliss et al 1997). The lowest average minimum of 13°C is recorded during July and 24°C during November–March (Gardner et al 2002).

Aboriginal inhabitants in the region identify six seasonal changes reflecting both climatic and ecological changes in flora and fauna (Fig 1.3) (Gardner et al 2002, Morris 1996). The monsoon season occurs during December to March and is known as Gudjewg; Banggerreng is known as the harvest time and occurs during March and May. Yegge is defined by the cool weather period experienced during May to June. June to August is known as Wurrngeng, the early dry season, Gurrung or hot dry season occurs between August and October and Gunmeleng, the pre-monsoon season between October and December (Gardner et al 2002, Morris 1996).

1.4.4 Geology, landforms and soils

The Kakadu region consists of a number of dynamic landforms, ranging from tidal flats, floodplains, lowlands, outliers, a plateau and escarpment complex, and the southern hills and basins (KNPPM 1998). The region is dominated by two main geological formations, the Pine Creek Geosyncline and the Kombolgie Subgroup (Erskine 2003). The Pine Creek Geosyncline extends from Rum Jungle to Oenpelli; it has Lower Proterozoic metasediments deposited under predominantly shallow marine conditions over an Archaean basement.

Forming the resistant plateaus and gorges of the Arnhem Land escarpment is an outcrop of quartz arenite (both ferruginous and non-ferruginous), basalt and tuff known as the Kombolgie Subgroup, this extends from western Milingimbi across the East Alligator River (Erskine 2003).

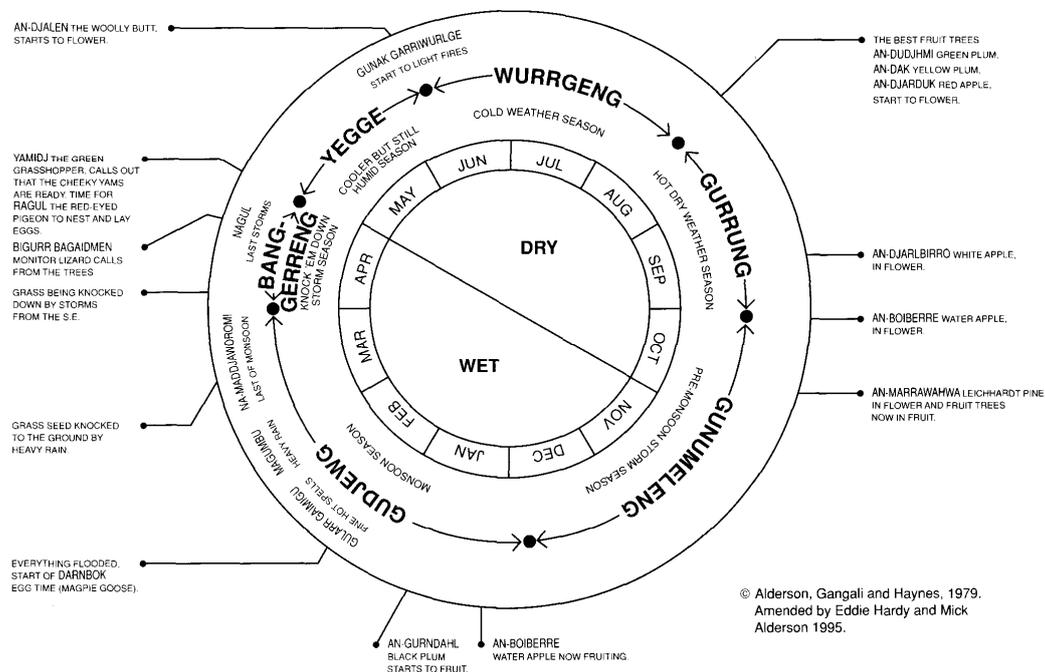


Figure 1.3 The six seasonal changes identified by the Aboriginal inhabitants of the Kakadu region in the Gundjeihmi (Mayali) language (adapted from Brockwell et al 1995)

The Koolpinyah surface consists of gently undulating lowland plain extending from Darwin to the Arnhem land escarpment. Within the study region the sandy plains are a complex of gravels, sands, silts and clays which have been repeatedly weathered, eroded, and redeposited (Russell-Smith et al 1995). A feature of the Koolpinyah surface is the incision of large north flowing river systems, which includes the East Alligator River and the Magela floodplain (Russell-Smith et al 1995), originating from the sandstone formations of the Arnhem Land escarpment. The Magela floodplain is comprised of black organic clays overlying estuarine deposits at shallow depths (Russell-Smith et al 1995). The estuarine deposits occurred when the sea level stabilised within a few meters of its present level about 6,000 years ago. The wetlands have developed within the last few thousand years as mangroves became increasingly confined to tidal sections of the main rivers. Sandy deposits derived from the Kombolgie Subgroup are deposited on the riverbanks and have formed levees that protect the wetlands from tidal saltwater flooding (Russell-Smith et al 1995). The infilling of the trench cut into the Koolpinyah surface forming the Magela floodplain is almost complete (Erskine 2003).

1.4.5 Hydrology

The Magela Floodplain is a seasonally flowing tributary of the East Alligator River flowing into the Van Diemen Gulf (Finlayson et al 1989). There are significant fluctuations in the water regimes in the creeks and rivers of the ARR due to the seasonal nature of the rainfall (Gardner et al 2002). Five major phases have been described to generally represent the rainfall and waterflow cycle in Magela Creek and its floodplains (Gardner et al 2002). These

five phases start with the occurrence of intermittent heavy precipitation which saturates the soil, building up to more consistent rain resulting in creek flow. This turns into widespread flooding as rainfall continues, eventually inundating the floodplain (Gardner et al 2002), and resulting in the floodplain being covered with water up to several meters in depth (Finlayson et al 1989). As the rains stop, the wet season flows diminish, water levels decline, and evaporation eventually dries up most of the floodplain with standing water only found in the few permanent billabongs (Gardner et al 2002).

Stream gauging indicates that catchment storage seeps into the floodplain during the dry season. Most years the floodplain dries up by the end of the dry-season with only a few perennial swamps and billabongs remaining (Williams 1979). The amount of water remaining in the permanent billabongs and the number of waterholes that persist during the dry season varies from year to year (Finlayson et al 1989). Williams (1979) reported that the wet-season rainfall for 1974–75 in the region was up 40%; and almost the entire Magela floodplain was still inundated 10 weeks after the last major rain fell, however he noted that the confluence zone with the east Alligator River was dry.

1.4.6 Flora of the Magela floodplain

A total of 1874 plant species have been recorded in the entire Alligator Rivers Region, with 222 found to occur on the Magela Floodplain (Gardner et al 2002). Vegetation communities located on the upland areas surrounding the floodplain are broadly defined as ‘Eucalyptus open forest’ which is dominated by *Eucalyptus miniata* and *E. tetradonta* with a ground layer consisting of tall grasses *Heteropogon triticeus* and *Sorghum* spp (Russell-Smith 1995a).

The dominant tree species on the Magela floodplain is the genus *Melaleuca* (Williams 1979) which covers approximately 40% of the floodplain (Gardner et al 2002). Williams (1979) undertook the first specific description of the vegetation of the Magela floodplain and identified broad vegetation communities consisting of six units described as; (1) ‘mixed herb-fields’ containing three distinct herbaceous communities; (2) ‘grasslands’ which were described as open swards of aquatic grasses dominated by *Pseudoraphis spinescens*. Unit (3) was defined as ‘undulating annual swamp and grassland’ similar to unit (2) however, it contained undulating surface with hollows that retained water giving an alternation between annual swamp and grassland. Unit (4) was defined as ‘Forest’, described as a dense cover of swamp paperbark trees of the genus *Melaleuca*, species included *M. viridiflora* and *M. nervosa* which were found in seasonally inundated areas, *M. cajuputi* and *M. leucadendron* found in areas subjected to prolonged waterlogging. Areas under water in August but with a depth of less than 40cm, dominated by *Eleocharis dulcis* and *Nymphoides indica* were described as (5) ‘annual swamps’ and (6) ‘perennial swamp’ was defined as areas under water in August with a depth of water greater than 40 cm, with bottom vegetation dominated by alga *Chara* sp Williams (1979) described unit (6) as having water too deep to support tree growth, however on the outer fringe *M. leucadendron* were present. Three emergent herbaceous vegetation types were recorded, *Nelumbo nufcifera*, *Scirpus grossus* and a floating community of grass sedge and juvenile *Melaleuca* which was held to the base of the grass *Hymenachne amplexicaulis*. Williams (1979) interpreted these six vegetation communities as indicators of water depth, due to their topographic relationship with dry season water levels (Fig 1.4) (Gardner et al 2002).

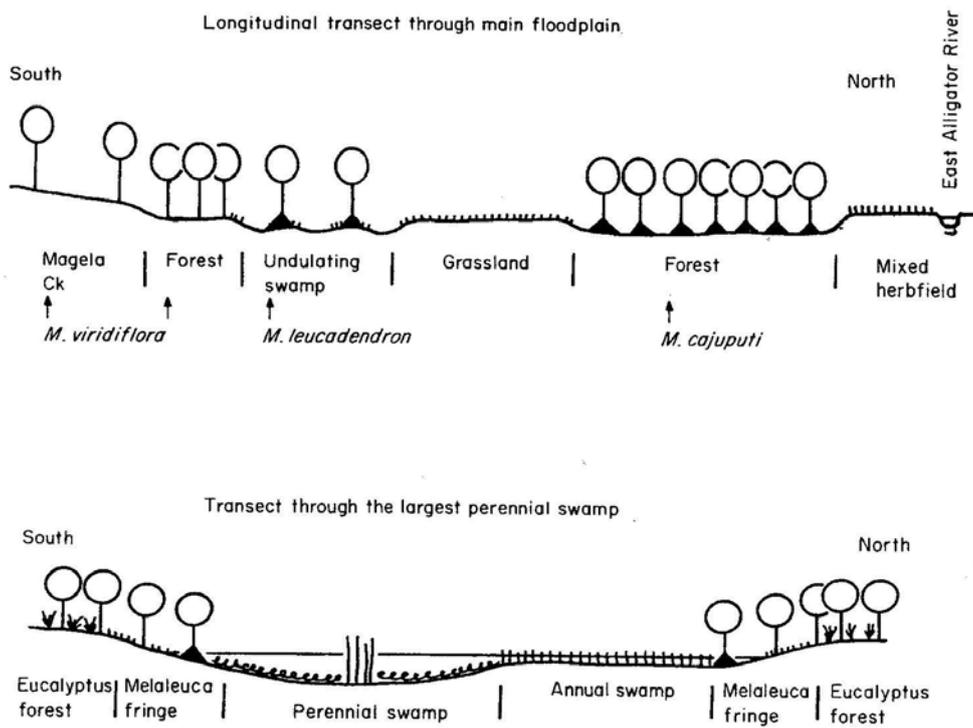


Figure 1.4 Stylised transect representing the topographic relationship between vegetation communities through the Magela plains (adapted from Williams 1979)

Finlayson et al (1989) mapped the vegetation of the Magela floodplain using ten classes that took into account seasonal variations (Fig 1.5). Each of the ten classes were based on several years of peak wet season data with the names used for each class either reflecting the most abundant species at the peak biomass, or a general descriptive name (Table 1.1) (Gardner et al 2002). Finlayson et al (1989) postulated that the major determinant in the composition of flora was related to the duration and period of inundation, with other factors such as water flow velocity and depth also contributing (Finlayson et al 1989).

Table 1.1 The ten different vegetation classes as defined by Finlayson et al (1989) to map the Magela floodplain, along with total cover estimates for each class

Class description	Area ha	% of floodplain
<i>Melaleuca</i> open forest and woodland (canopy cover 10–70%)	7390	34
<i>Melaleuca</i> open woodland (canopy <10%)	1290	6
<i>Nelumbo–Nymphoides</i> herbland	2090	9
<i>Oryza</i> grassland	2730	12
<i>Hymenachne</i> grassland	1930	9
<i>Pseudoraphis</i> grassland	3050	14
<i>Hymenachne–Eleocharis</i> grass-sedgeland	1290	6
Mixed grass–sedge–herbland	1120	5
<i>Eleocharis</i> sedgeland	960	4
Open water community	160	1

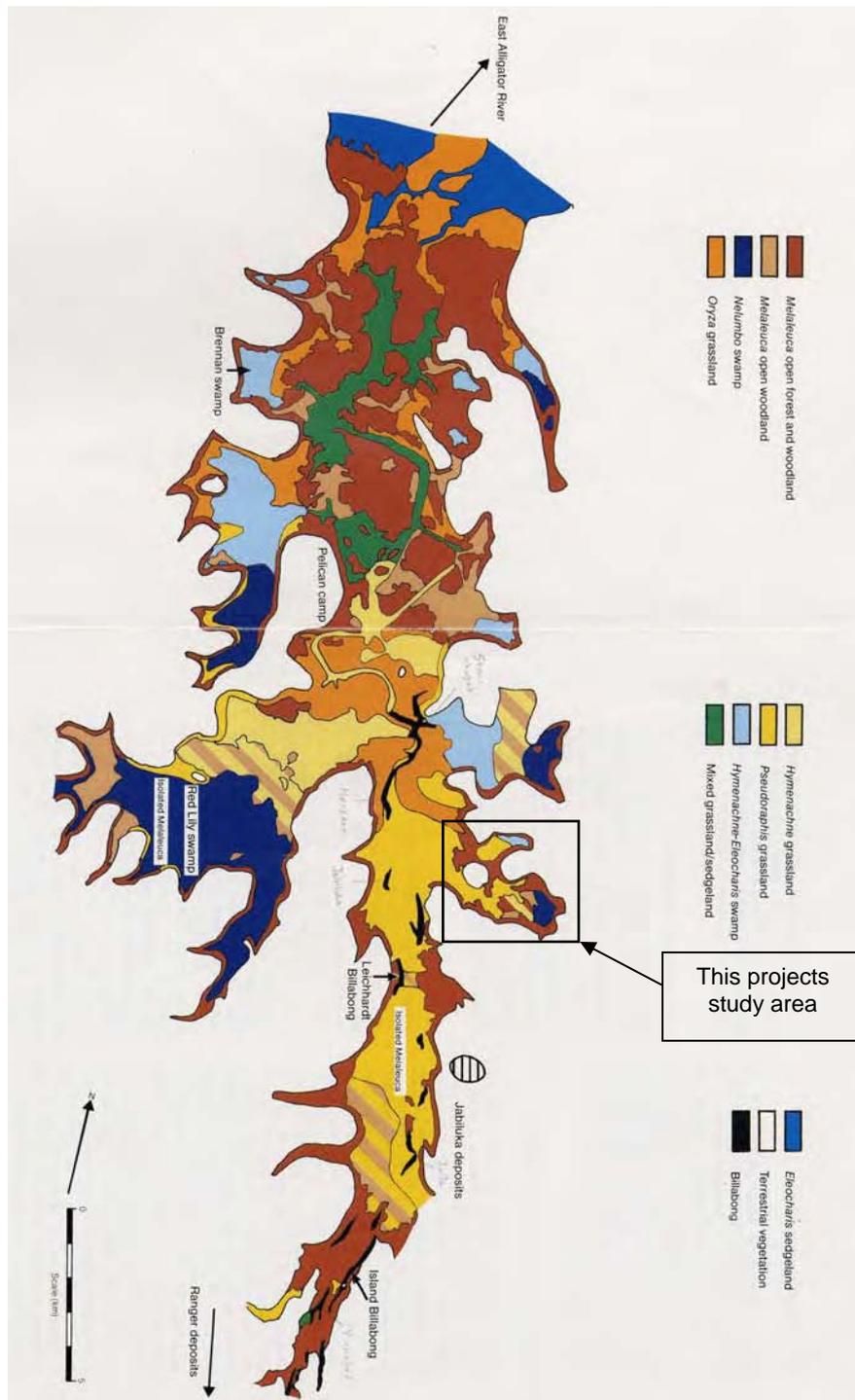


Figure 1.5 Vegetation map produced by Finlayson et al (1989) of the Magela Floodplain (adapted from Finlayson et al 1989)

It was hypothesised that the variation in the vegetation pattern was a function of the flooding and drying phases of the hydrological cycle (Finlayson et al 1989). Of the 222 plant species recorded for the Magela floodplain, the fringe zone was found to contain 100 annual species of which 91 were terrestrial. On the seasonally inundated plain 57 species were recorded while the permanent billabongs and swamps contained 19 and 5 respectively. For the

floodplain the number of different species recorded was 139 annual species, 69 perennials and 14 geophytic perennial species (Finlayson et al 1989).

Litter-fall from *Melaleuca* spp was used as an indirect means to estimate the productivity of the Magela floodplain. Litter-fall from *Melaleuca* spp was dominated by leaf material which appears to fall in a bimodal pattern with peaks during January and June-July (Gardner et al 2002). Annual litter-fall biomass was found to range between 8 to 15 t ha⁻¹ which is equal to or higher than other forests in Australia, indicating the floodplain is highly productive (Gardner et al 2002). *Melaleuca* spp have been identified as good ecological indicators for monitoring the health of the floodplains within the Alligator River Region (Bell et al 2001).

Chapter 2 Literature review

2.1 Remote sensing of floodplain environments and object-based classification

Remotely sensed imagery provides a cost effective method with which to acquire information about the earth's surface. The data and maps produced from this imagery are derived from a wide variety of sensor platforms; as equally as diverse is the spectral and temporal resolution of the images available (Campbell 1996). Remotely sensed information has been an effective tool for monitoring and mapping natural resources (Wang & Moskovits 2001). It has many applications ranging from mapping of wetlands (Roshier & Rumbachs 2004), and mapping of polar regions (Chou et al 1994) to assessing structural damage after natural disasters (Al-Kudhairy et al 2005). It has been widely used at a range of scales, and environments, to map vegetation and landcover types around the world (Cherrill et al 1994, Khwaja et al 2003, Mertes 2002, Muldavin et al 2001, Tommervik et al 2003, Wang & Moskovits 2001).

Remote sensing technologies are particularly suited in northern Australia, due to the low population density, the harsh climate, and vast areas involved (Hill & Carter 1999). Remote sensing applications in northern Australia range from mapping potential feeding grounds of threatened marine turtles (Menges et al 1998), to nesting habitats of saltwater crocodiles (Harvey & Hill 2003). It has been used to map the geomorphology of lowland swamps (Bartolo et al 1999), bushfire history (Bowman et al 2003, Wisell 2001, Zhang et al 2001, Zhang et al 2000), and monitor and assess mine-site rehabilitation (Pfitzner, 2004). (Colley et al 2000) has investigated its application in identifying salt-water intrusion of the Mary River floodplain. It has also been used to map vegetation communities across different northern Australian ecosystems (Ahmad et al 1998, Harvey & Hill 2001, Khwaja et al 2003, Lucas et al 2002, McIntyre et al 2001, McIntyre & Menges 2002, Milne et al 2000).

Mapping the woody weed *Mimosa pigra* has been undertaken in Northern Territory floodplains using a combination of TopSAR (radar) and Landsat ETM+ imagery (McIntyre et al 2001). It was found that *Mimosa* with sparse or absent foliage had a low near infrared reflectance and was not able to be detected using Landsat ETM+ imagery alone (McIntyre et al 2001). However, structural similarity of some vegetation types (eg *Melaleuca* re-growth and *Mimosa*) resulted in misclassification, due to spectral overlap in the radar signature (McIntyre et al 2001). The spatial resolution of the imagery meant that small satellite outbreaks of mimosa were unable to be detected, as the value of a single pixel typically included areas of both mimosa and the surrounding environment (McIntyre & Menges 2002).

Harvey and Hill (2001) assessed the use of Landsat TM, SPOT XS imagery and colour aerial photography (scale 1:15000) in mapping vegetation cover in a northern Australian wetland. Manual interpretation techniques were used to classify the aerial photographs, while the satellite imagery was classified using unsupervised classification techniques. It was found that the detailed information extracted from the very high resolution aerial photography was unable to be replicated using the satellite imagery. To obtain acceptable accuracy levels (> 80%) using the satellite imagery they were required to reduce the classes to three broad land-cover classes (Harvey & Hill 2001). They reported that the ability to incorporate interpretation cues such as context and texture enhanced the delineation and identification capabilities of aerial photographs. This in turn enabled the extraction of a level of floristic detail far superior to the Landsat TM, SPOT XS imagery (Harvey & Hill 2001).

Lucas et al (2002) investigated the temporal dynamics of mangrove communities on the West Alligator River between 1950 and 1991. To map the extent and height of mangrove communities they used a combination of digital orthomosaic and digital elevation models (DEM) derived from panchromatic and colour aerial photographs. The imagery was classified using unsupervised classification techniques, and both the 1950 and 1991 imagery was found to be useful in detecting change between the extent of mangrove communities (Lucas et al 2002). The level of accuracy of the DEM created of the mangrove communities was deemed sufficient in the 1991 colour image to be used as baseline data. However, the accuracy of the DEM created from the 1950 panchromatic imagery was low. The lower quality and spatial resolution of the 1950 imagery was identified as the reason for the reduced accuracy (Lucas et al 2002). Techniques developed by Lucas et al (2002) have subsequently been used to create baseline data maps for all mangrove communities in Kakadu National Park (Mitchell et al 2005).

2.1.1 Object-based analysis

There has been major progress in the extraction of landcover information from remotely sensed imagery over the past decade. Numerous classification algorithms have been developed to extract information from both air and space borne platforms (Devereux et al 2004). Traditional classification algorithms are based on one spatial scale and per-pixel classification in a multi-dimensional feature-space (Blaschke & Hay 2001, Burnett & Blaschke 2003, Wang et al 2004). These traditional methods are based on the concept that semantic information is depicted within single pixels and is well suited to non-complex homogeneous images (Al-Kudhairy et al 2005). Applying traditional per-pixel classification methods to very high resolution (VHR) data such as aerial photographs, satellite images from IKONOS and QuickBird, and radar imagery can create classification problems. This is caused by greater spectral variation within a class due to a smaller pixel size and increased shadow in the image (Laliberte et al 2004, Tuominen & Pekkarinen 2005). There has been significant research into alternative classification methods based on image segmentation (Burnett & Blaschke 2003). Segmentation of an image enables the statistical properties which are based on the pixels within the objects produced to be applied to the classification algorithm. Object-orientated classification methods are able to take into account contextual information such as shape and texture as well as spectral values (Baatz et al 2004, Milne et al 2000). Object based classification methods developed over the past decades can be broken into three broad categories (1) edge finding , (2) region growing and (3) map or knowledge based segmentation (Bock et al 2005, van der Sande et al 2003).

Radar imagery (RADARSAT) was used by Milne et al (2000) to map changes in wetland inundation and vegetation patterns in the Alligator Rivers Region. To overcome the effect of speckle and noise in the radar data, they used an object-based classification approach. This was done using a set of segmentation and clustering procedures specifically developed to classify SAR data at the School of Geography, University of New South Wales (Milne et al 2000). The segmentation and clustering routines were achieved using a Gaussian Markov random field model. This method was successfully used to map the general trends in changes of water extent, and vegetation during the drying phase of 1998 over large areas of the Alligator River Region. AIRSAR-C band data was used to map areas of *Melaleuca* in both dry and wet conditions. A combination of MOMS-2P optical data and SAR radar data was also found to be useful in discrimination between vegetation types. It was reported that the spatial resolution of the SAR data was unable to detect small changes over time (Milne et al 2000).

Halounová (2003) used a combination of object-based classification and image enhancement techniques to classify forest in the Czech Republic, using panchromatic aerial photographs. To enhance the image feature space of the aerial photographs, a number of image processing steps were used to create additional bands, consisting of information derived from median and Gauss filters, and the texture values of the photographs (Halounová 2004). Object-based classification was performed using two scale levels. The ability to classify the image into large regions was found to help reduce spectral overlap. Halounová (2004) reported an overall classification accuracy of 90%. The accuracy of individual classes ranged from 50% to 100%. Class confusion between deciduous and coniferous forest, and very young forest and deciduous forest was reported (Halounová 2003, 2004).

Object-oriented image analysis was used by Laliberte et al (2004) to map shrub encroachment from 1937 to 2003 in southern New Mexico. Classification was performed on a 150 ha area using 11 aerial photographs (consisting of panchromatic, true colour and CIR) and a single panchromatic QuickBird satellite image. A 3x3 smoothing filter was used to reduce the heterogeneity of the image prior to segmentation. The imagery was segmented at two scale levels. The finest scale was used to classify individual shrubs while the coarser scale was used to classify broad classes (eg grass and bare soil) (Laliberte et al 2004). The classification algorithm 'membership function' was used to classify the finest scale level while the 'Standard Nearest Neighbour' algorithm was used to classify the coarser scale. Ground truthing data was used to assess the accuracy of the QuickBird imagery. It was reported that about 87% of shrubs larger than 2 m² were being detected, while only 29% of shrubs below 2 m² were detected, resulting in an underestimation of shrub cover for the classification. They also reported that the varying image quality of the aerial photographs, particularly the 1960 panchromatic image may have also led to over estimation in shrub cover. The ability to perform analysis using a multi scale approach enabled the detection of shrubs present in both dark and light back grounds. This was done by defining a rule base that used relationships between neighbouring objects on the same level, and super objects on a higher level. Laliberte et al (2004) stated that object-oriented analysis enables a classification that comes closer to the ways humans interpret an image.

Until recently the use of object-based classification methods have been restricted to specialised in-house software (Hay et al 2005). With the increased availability of very high resolution imagery and the release of the eCognition software package in 2000, the number of projects using object-based methods has risen. Research has been undertaken using a wide variety of sensors such as Landsat TM (Blake 2004, Crase & Hempel 2005), SPOT (Hall & Hay 2003), ASTER (Whiteside & Ahmad 2005) and IKONOS (Arroyo et al 2005, van der Sande et al 2003, Wang et al 2004). For a comprehensive list see <http://www.definiens-imaging.com/documents/reference.htm>.

2.2 Previous studies mapping spatial and temporal distribution of *Melaleuca* spp on the Magela floodplain

The spatial and temporal distribution of *Melaleuca* spp on the Magela floodplain has been the focus of two previous studies. The first was undertaken by Williams (1984) and the second by Riley and Lowry (2002).

2.2.1 Williams (1984)

Densities of the *Melaleuca* forests were used as an index by Williams (1984) to assess the stability of the Magela floodplain, prior to development of a uranium mine (Ranger) within

the catchment. This was done by comparing *Melaleuca* spp density between two sets of aerial photographs taken in 1950 and 1975. The aerial photographs of the entire floodplain were stratified into areas with homogenous tree cover using a stereoscope (Fig 2.1).

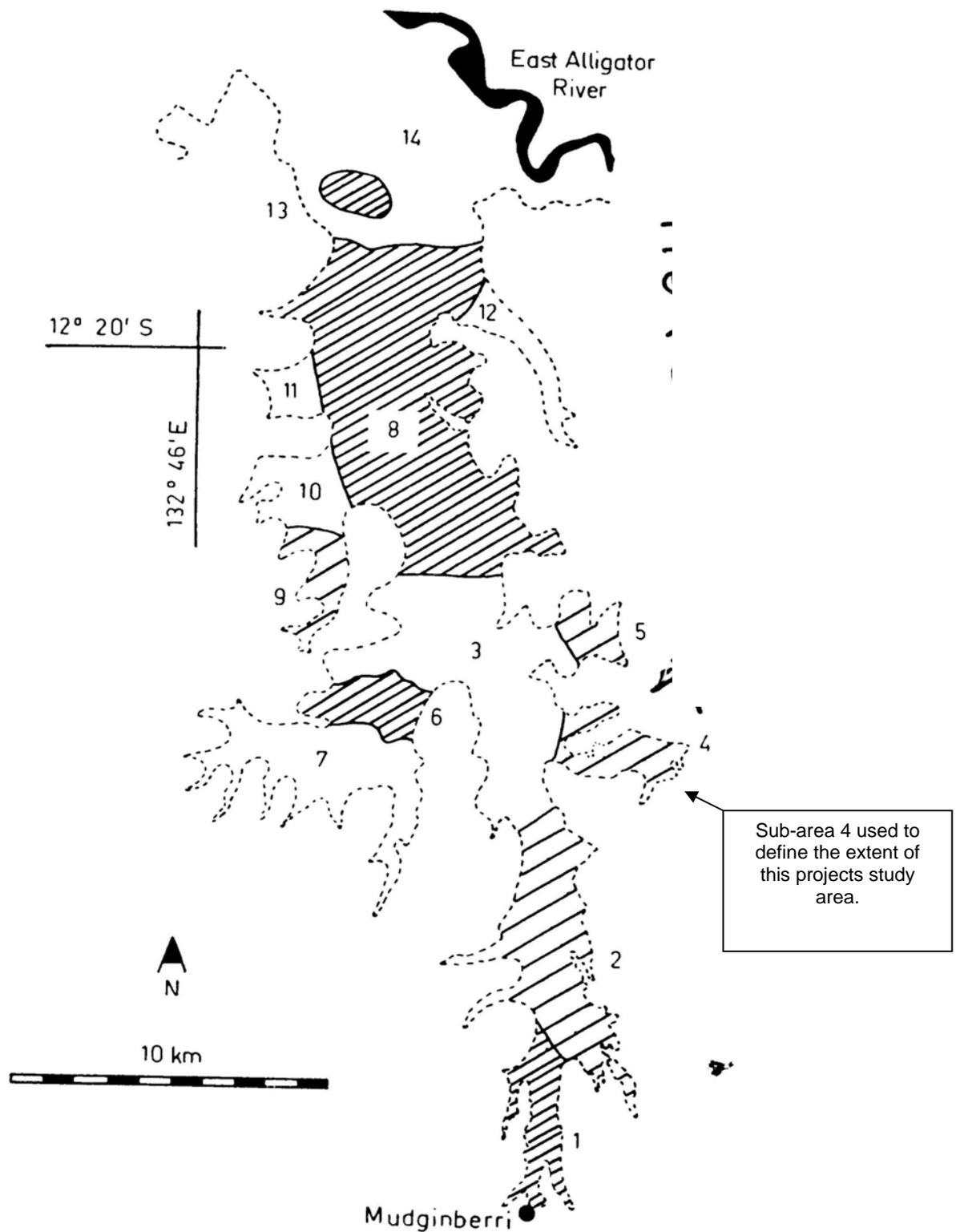


Figure 2.1 The extent of the Magela floodplain and the strata boundaries defined by Williams (1984). Note: Strata 4 (referred to in this study as sub-area 4) was used to define the boundary of this study.

The median density of *Melaleuca* was manually estimated using a closely packed configuration of 10 circles on an acetate overlay of the photo mosaics (Williams 1984). The tree density per km² was then estimated within each circle on a five point scale. The sampling procedures were designed to fulfil the assumptions of the Kolmogorov-Smirnov two sampled test used to test for significant differences between years.

The results show no increase in *Melaleuca* spp density in any stratum between 1950 and 1975, however, significant decreases occurred in stratum 2, 5, 7 and 9. Stratum 7 suffered the largest decline in density. Williams (1984) noted that the quality of the 1950 image was poor in this stratum, and may have led to an overestimation of *Melaleuca* spp. However, it was reported that field observations during 1976 in stratum 7 revealed an accumulation of dead logs, which was also common in other areas in the study suffering similar declines. This was viewed as reinforcing the interpretation of the 1950 aerial photograph. Overall it was found that 38% of the forested areas suffered a significant decrease in tree density.

Williams (1984) concluded that since there had not been an increase in *Melaleuca* between 1950 and 1975 relative to the topography, the successional status of *Melaleuca* was stable. He reported that the topography was stable to the extent that infilling of the floodplain was not observed. It was suggested that factors such as late dry-season fires, strong winds, buffalo and in some instances saltwater intrusion may be responsible for the decline in *Melaleuca* density (Williams 1984).

2.2.2 Riley and Lowry (2002)

Riley and Lowry (2002) also mapped *Melaleuca* spp distribution and density, using a Geographical Information System (GIS) platform. They used two digitised aerial photographic mosaics (1975 and 1996) of a 41 km² section of the Magela floodplain (Fig 2.2). The same 1975 aerial photographs used by Williams (1984) were used in this study. As previously stated in chapter 1, this study was undertaken due to concerns raised by the media in 2001. Riley and Lowry (2002) research endeavoured to follow similar methods to those used by Williams (1984) so comparisons could be made between the two sets of results. This was achieved by stratifying their study area into sub-areas as previously defined by the Williams (1984) study.

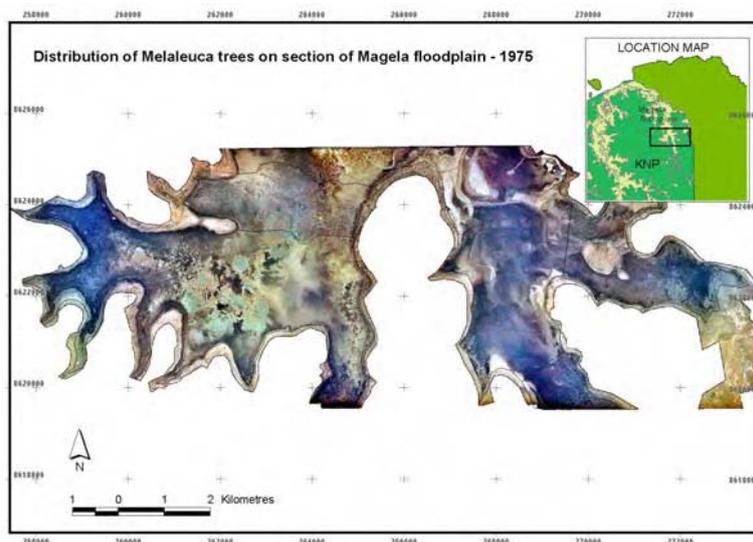


Figure 2.2 Extent of the Riley and Lowry (2002) study area 41 km² section of the Magela floodplain

Manual interpretation of the aerial photographic mosaics was undertaken and single points were generated for every tree within the study area. Multiple points were applied to closed stands where individual trees could not be identified (Riley & Lowry 2002). Tree density was calculated using a minimum of 12 circular sample cells of known area within each of the 5 sub-areas.

From this, it was estimated that tree density across the study area in 1975 was 764 km² while in 1996 it was 601 km². Riley and Lowry (2002) reported a 21% decrease in density of woody vegetation across the study area. Although the density of *Melaleuca* spp decreased, they found that the distribution of woody vegetation had increased between the years 1975 and 1996. In sub-area 7 an increase of 3378 trees was recorded.

Riley and Lowry (2002) compared their density estimates for the 1975 photographs with those of Williams and found that in all but one sub-area (sub-area 6), they had mapped higher densities of *Melaleuca*. It was suggested that the difference between the two studies may be as a result of improvements in calculating precise density estimates generated in the GIS. Or they may be a result of the differences in extent of sub-areas 2 and 3, which did not encompass the same areas as the Williams (1984) study. They reported that while they could not corroborate the density estimates recorded by Williams (1984) in 1975, it was clear that *Melaleuca* had continued to decline in the 41 km² area of the Magela floodplain. Identifying the reasons for change was beyond the scope of their study; however they did refer to the comment made by Williams (1984) that change may be occurring as a result of fire or the presence of feral buffalo. It was suggested that as feral buffalo had been removed from the floodplain, other factors such as fire, and greater periods of inundation during the 1990s compared to the 1980s may be driving the changes observed (Riley & Lowry 2002).

2.3 Drivers of environmental change on floodplains of northern Australia

Ecosystems are in a continual state of flux at a variety of temporal and spatial scales. The causal factors for this change can be either natural, anthropogenic, or a combination of both (Coppin et al 2004). A variety of factors have been identified as influencing the composition and structure of vegetation in wetland environments. These factors range from climate, topography, soil, fire, and introduced flora and fauna (Bayliss et al 1997, Cowie et al 2000, Storrs & Finlayson 1997, Taylor & Dunlop 1985).

Rising CO₂ levels, and global warming, may impact climatic factors such as temperature, total rainfall, and timing of rainfall, thus affecting reproduction and species composition (Osborne 2000). Climate change also has the potential to cause a rise in sea levels which would threaten the low lying floodplains of northern Australia (Bayliss et al 1997, Hennessy et al 2004). Impacts on wetlands of Kakadu National Park would include replacement of freshwater wetlands with saline mudflats, and loss of *Melaleuca* forests (Finlayson 2003). Bayliss et al (1997) identified all wetlands within the Alligator River Region below 4 m in elevation, as being vulnerable to climate induced changes. Rising sea levels have the potential for dramatic ecological effects, leading to reductions in productivity and loss of coastal wetlands (Bayliss et al 1997, Lewsey et al 2004, Nicholls 2004). Hennessy et al (2004) identified salt water intrusion of Kakadu and other freshwater wetlands as a key vulnerability for the Northern Territory. It is thought that the effects of climate change (sea level rise, increase in rainfall) may be contributing to the expansion of tidal creek systems in the lower Mary River since 1940 (Hughes 2003). It is estimated that two creeks in the Mary River wetland have invaded 4 km inland (Stewart 2005). This salt water incursion has had deleterious effects on freshwater

vegetation, resulting in the loss of 17 000 ha of freshwater wetlands of which 6000 ha were *Melaleuca* (Hughes 2003, Mulrennan & Woodroffe 1998).

Floodplain ecosystems, such as in northern Australia are spatially located between both truly aquatic and truly terrestrial systems (Osborne 2000). Over time it can be expected that infilling of the floodplain will occur as sediments deposited from upland areas, aquatic plant remains, and debris increase the soil level (Raven et al 2003). It can then be assumed that a shift in the biological community will result in species more adapted to drier conditions (Osborne 2000). Williams (1984) identified the genus *Melaleuca* as being the probable climax community in successional development in the Magela floodplain. This was based on successional theory which suggests that large, long-lived organisms such as trees will dominate small, short-lived vegetation such as herbs (Williams 1984). It is generally easy to observe and identify early stages of succession. However identifying later stages can be problematic as the expected direction of the succession in mature communities can be reversed, the ultimate outcome may be significantly influenced by the nature of adjoining communities (Raven et al 2003). Climate and environmental factors such as water balances, rates of sedimentation and nutrient availability all contribute to the pace of wetland succession (Osborne 2000). The level of natural or anthropogenic disturbance also plays a role in determining the rate of succession (Beeby 1993, Raven et al 2003).

Water buffalo were introduced between 1822 and 1866, and rapidly formed large feral populations that spread across lowlands and swamps in the Northern Territory (Bowman & Robinson 2002, Levitus 1995, Taylor & Dunlop 1985). Studies suggest they were responsible for considerable change in floristic and vegetation structure on the floodplain (Bowman 2003, Mulrennan & Woodroffe 1998, Taylor & Dunlop 1985, Werner 2005). Feral pigs are also thought to have an impact on floodplain flora; however, the evidence for this is largely anecdotal. Taylor and Dunlop (1985) reported that pigs were much less abundant than buffaloes in the Alligator Rivers Region. However, anecdotal evidence suggests that feral pig numbers have increased with the decline of buffalo populations (Cowie et al 2000, Gardner et al 2002). It has been suggested that the removal of the introduced buffalo from the region has led to an increase in fires in coastal floodplains (Storrs & Finlayson 1997). This link between increase in fires and the removal of buffalo is thought to be due to increased availability of fuel biomass due to the loss of the grazing effect of buffalo (Werner 2005).

Fires are a frequent occurrence across the northern Australian biomes (Rossiter et al 2003, Russell-Smith et al 1998). The occurrences of intense late dry season fires are thought to have increased since the arrival of Europeans to Australia (Anderson et al 1998, Vigilante & Bowman 2004). This increase of fire intensity and frequency can have a detrimental impact on tree and seedling survival (Rossiter et al 2003, Williams et al 1999). Humic fires have been observed to have a detrimental impact on northern Australian floodplains (Russell-Smith 1995b, Williams 1984). Research undertaken by Roberts (1997) looking at the effect of fire intensity on *Melaleuca* spp suggests that a combination of crown scorching and the burning of the humic layer contributed to increased mortality in mature trees. It was reported that the occurrence of fire was found to increase the rate of vegetative recruitment (Roberts 1997). Invasive plants in the floodplains have increased fuel biomass which cause fires of greater intensity which is linked to tree mortality (Douglas & O'Connor 2004).

Invasive weeds such as *Mimosa pigra*, *Salvinia molesta* and *Urochloa mutica* are a significant threat to floodplain environments in northern Australia (Walden et al 2004). Infestations of woody weed *Mimosa pigra* characteristically lead to the development of monospecific communities which replace wet herblands, sedgeland, grasslands and woodlands, greatly reducing biodiversity (Cook et al 1996, Rea & Storrs 1999). The introduced grass *Urochloa*

mutica can occupy a broad array of habitats from permanent waterbodies, swamp forests, *Melaleuca* woodlands and floodplain fringes (Walden et al 2004). They can also form dense monospecific stands out competing native flora, which may reduce hydrological flows thus resulting in greater sediment deposition, leading to a reduction of waterbodies (Walden et al 2004).

Chapter 3 Materials, image pre-processing and methods used to produce accuracy assessment data

3.1 Introduction

Both image pre-processing and accuracy assessment are integral and essential components of any remote sensing project. This chapter describes the different image pre-processing steps and procedures used in this project, including scanning hard copy aerial photographs, image enhancement, geometric correction, creation of mosaics, subsetting of study area, and masking. In addition, the methods used for assessing the accuracy of field data and the classification of aerial photographs are described. Accuracy assessment of the classification method was undertaken to provide credibility to the temporal change analysis of the distribution of *Melaleuca* communities, which is central to this thesis.

3.2 Materials

3.2.1 Imagery

This project used four aerial photographic datasets of a section of the Magela floodplain. The aerial photographs used in the project were taken in 1950, 1975, 1996 and 2004. The 1950, 1975 and 1996 images were acquired as hard copy photographic prints, which are held by the Environmental Research Institute of the Supervising Scientist (*eriss*). The 2004 aerial photographs were acquired in digital format, and are held by the Key Centre for Tropical Wildlife Management, Charles Darwin University on behalf of Parks Australia North (PAN). Also acquired for the project was an orthorectified IKONOS multispectral satellite image held by *eriss*, which was used as a base-map for georectification of the aerial photographs. Details of the images used in the project can be seen in Table 3.1.

Table 3.1 Details of the aerial photographs used in the project

Type	Date	Run No.	Photo No.	Scale	Spectral resolution	Format
Aerial Photo	16/05/1950	7	5015	1:50,000	Panchromatic	hardcopy print
Aerial Photo	22/06/1975	13	3125	1:25,000	True colour	hardcopy print
Aerial Photo	15/06/1996	4	38	1:25,000	True colour	hardcopy print
Aerial Photo	15/06/1996	4	40	1:25,000	True colour	hardcopy print
Aerial Photo	15/06/1996	5	22	1:25,000	True colour	hardcopy print
Aerial Photo	15/06/1996	5	23	1:25,000	True colour	hardcopy print
Aerial Photo	16/06/2004	11	143	1:25,000	True colour	Digital
Aerial Photo	16/06/2004	11	145	1:25,000	True colour	Digital
Satellite	3/06/2001				True colour & NIR	Digital
IKONOS						

Image processing was undertaken at the postgraduate computer laboratory located at Charles Darwin University. The remote sensing and GIS computer programs utilised for the project included eCognition v 4.0, ERDAS imagine v 8.7 and ArcView™ v 9.1. Adobe Photoshop v 4 was used for image enhancement and the aerial photographs were scanned using a UMAX Powerlook 2100XL flat bed scanner. Microsoft Excel 2003 was used for statistical analysis. The global positioning system (GPS) used in the collection of ground truthing data was a Garmin eTrex personal navigator, which has a maximum spatial accuracy of ± 4 meters.

3.3 Image Pre-processing

The steps involved in image pre-processing for this project are summarised in Figure 3.1.

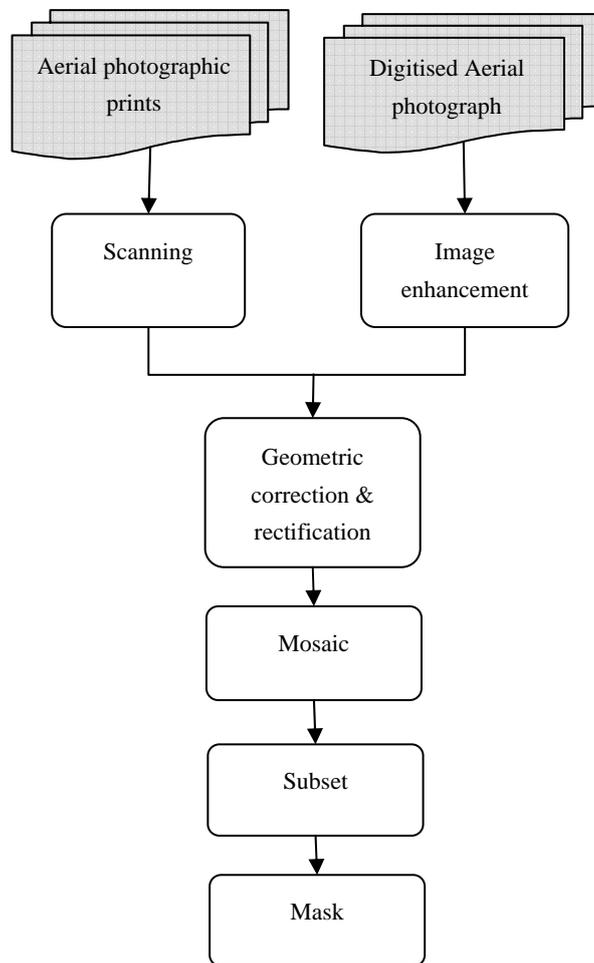


Figure 3.1 Schematic diagrams showing the image pre-processing steps used in this project

3.3.1 Scanning of aerial photographs

A flat bed scanner was used to digitise the 1950, 1975 and 1996 aerial photographic prints. The 1950 image was scanned at 1200 dots per inch (dpi), which at a scale of 1:50 000 is approximately equal to 1 metre in ground resolution. The 1975 and 1996 aerial photographs at a scale of 1:25 000 were scanned at 800 dpi equal to approximately 0.79 meters ground resolution. The 2004 aerial photographs flown at a scale of 1:25 000 were in digital format and had been scanned at 1200 dpi which is equal to a ground resolution of approximately 0.53 meters. The 2004 aerial photographs were scanned by the supplier and contained a yellow hue across each image, to remove this Adobe PhotoShop v 4 was use to enhance each image using the 'auto-adjust colour' function prior to geometric correction.

3.3.2 Geometric Correction

When a vertical aerial photograph is acquired of the earth's surface, it is projected through a perspective centre onto the image plane (Nielsen 2004). This creates relief displacement in the image; objects located at the centre of the photograph will reveal the top of an object while objects moving away from the principle point will show both the sides and top of an object (Fig 3.2) (Campbell 1996). The level of displacement is dependent on the focal length of the camera, flight altitude, the hight of an object, and the distance of the object from the principle point (Campbell 1996). As a result, aerial photographs contain significant geometric distortions (Toutin 2004). To enable further analysis, such as temporal change detection, each image needs to be registered to a map coordinate system (Lu et al 2003). There are various methods available to geometrically correct images, from polynomial functions to rigorous orthorectification procedures (Rocchini & Di Rita 2005).

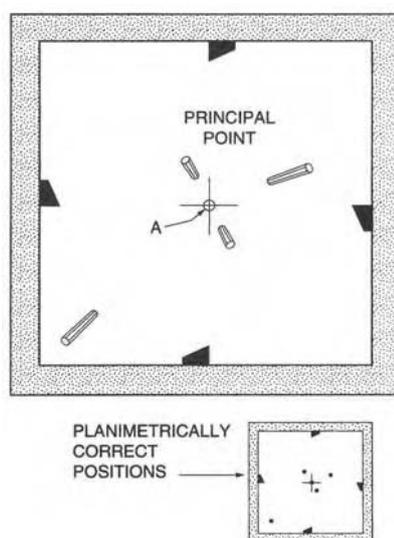


Figure 3.2 Illustration showing the effect of geometric distortions on objects in aerial photographs (adapted from Campbell 1996)

The GIS software ArcView™ v 9.1 was used to geo-rectify the aerial photographs using a 3rd order polynomial transformation. The polynomial method was adopted as there was insufficient information on the camera details needed to perform orthorectification. Polynomial methods however, do not account for ground relief, which contribute significantly to distortions in aerial photographs (Mather 1999, Rocchini 2004). It was assumed that the

flat nature of the terrain in the study area would not greatly affect the accuracy of the georectification of the aerial photographs. Ground control points (GCPs) were selected from the orthorectified IKONOS satellite image to rectify the 2004 aerial photographs. A mosaic of the 2004 aerial photographs was constructed and used as a base-map to rectify the remaining aerial photographs. A minimum of 25 GCPs were selected for each aerial photograph, ensuring their distribution was evenly spread across the image. The total root mean square error (RMSE) for each image was kept below two pixels (Table 3.2). A low RMSE value does not, however, guarantee that an image has high geometric accuracy (Morad et al 1996). In change analysis studies it is critical that image to image registration is precise (Lu et al 2003). By adopting a process of overlaying and visually assessing each image using the GIS, a high level of accuracy was attained. The GPS points (maximum accuracy of ± 4 metres) collected in the field also indicated that the overall georectification of the 2004 image accuracy was high, as single trees on the ground were also spatially correct on the image. All images were projected into the coordinate system GDA 94 MGA Zone 53.

Table 3.2 Number of ground control points (GCPs) and total root mean square error (RMSE) for each aerial photograph

Date	Run No.	Photo No.	No. GCPs	Total RMSE
16/05/1950	7	5015	30	1.79
22/06/1975	13	3125	26	1.56
15/06/1996	4	38	25	1.84
15/06/1996	4	40	25	1.80
15/06/1996	5	22	25	1.78
15/06/1996	5	23	26	1.67
16/06/2004	11	143	27	1.89

All aerial photographs were rectified using a nearest neighbour method. This had the dual advantage of ensuring that the pixel value was not altered, whilst being computationally simple (Harvey & Hill 2001). The 1950 aerial photograph was re-sampled to 1.1 m pixel size, the 1975 and 1996 to 0.89 m and the 2004 image to 0.56 m pixel size. This project did not standardise the spatial resolution of each dataset until the final classification was exported for change analysis. The scale parameter in the multiresolution segmentation process was used at the optimum scale found in each dataset to delineate *Melaleuca* spp

Normalisation of the radiometric properties of the images was not required as object- based classification relies on the contrast between different objects within an individual image, rather than absolute spectral properties of a given target (Laliberte et al 2004).

3.3.3 Mosaics

Mosaics were created using Erdas imagine v 8.7. Image Dodging was used, as this applies a filter and global statistics across each image being mosaicked to smooth out light imbalances (ERDAS 2002). Automatic colour balancing was also applied. The cutlines were user defined and located in the image to minimise obvious differences between each aerial photograph. The feathering function, using a defined 2 m distance was also used to further minimise the effect of the cutline.

3.3.4 Subset of study area and masking

A subset of the study area was created from each aerial photograph mosaic. In order to reduce the chance of class confusion in the classification process (Harvey & Hill 2001), a mask was created to remove upland areas not included in the study (Fig 3.3). The mask was created using the area of interest tool (AOI) in ERDAS Imagine v 8.7, enabling current pixel values in the masked area to be reassigned values of zero (ERDAS 2002). The boundary for the mask followed the boundaries created by Williams (1984) (Fig 2.1), which were also adopted by Riley and Lowry (2002).

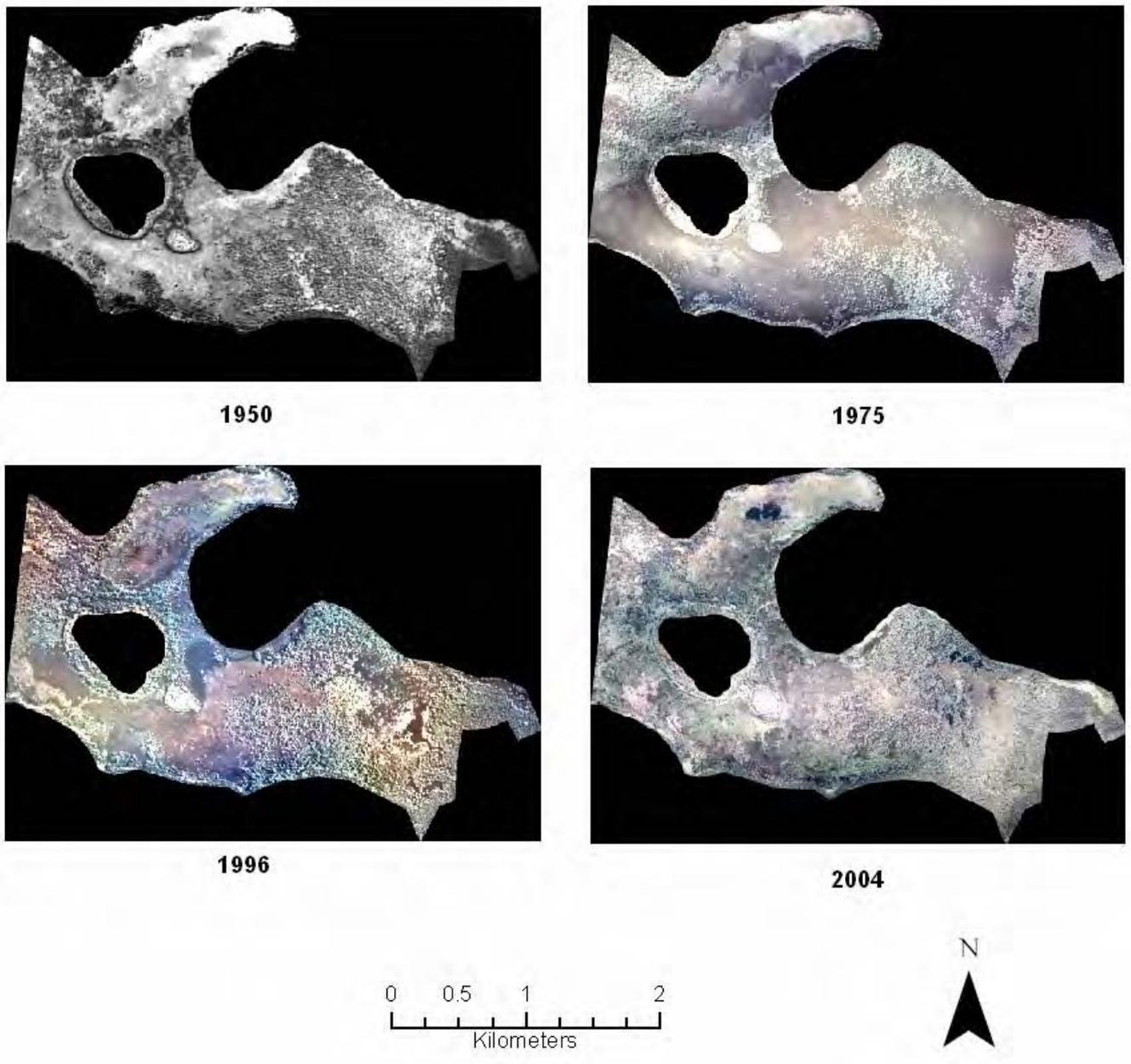


Figure 3.3 Subset and masked aerial photographs used in the project

3.4 Methods used to produce accuracy assessment data

3.4.1 Error matrix

A common method for assessing the accuracy of classified maps produced from remotely sensed imagery is the use of an error matrix (Campbell 1996). An error matrix can be used to obtain a number of different statistics (Congalton 1991). The statistics generated in the error matrices for this project were overall classification accuracy, individual class accuracy, producers and users accuracy, and commission and omission error (Table 3.3) (Campbell 1996).

Table 3.3 Example of a typical error matrix, and the methods used to generate error matrix statistics used in this project. (Adapted from http://rst.gsfc.nasa.gov/Sect13/Sect13_3.html)

Landsat Accuracy Assessment								
Photo/Ground Classes	Landsat Classes				Total Possible	Omissions	Commissions	Mapping Accuracy*
	Corn	Soybeans	Forest	Other				
Corn	25	5	10	3	43	$\frac{18}{43} = 42\%$	$\frac{7}{43} = 16\%$	$\frac{25}{25 + 18 + 7} = 50\%$
Soybeans	2	50	6	5	63	$\frac{13}{63} = 21\%$	$\frac{11}{63} = 17\%$	$\frac{50}{50 + 13 + 11} = 68\%$
Forest	3	4	60	5	72	$\frac{12}{72} = 17\%$	$\frac{18}{72} = 25\%$	$\frac{60}{60 + 12 + 18} = 67\%$
Other	2	2	2	100	106	$\frac{6}{106} = 6\%$	$\frac{13}{106} = 12\%$	$\frac{100}{100 + 6 + 13} = 84\%$
Total	32	61	78	113	284			

Overall Landsat Classification Accuracy = $\frac{25 + 50 + 60 + 100}{284} = 83\%$

*Mapping Accuracy (MA) for any Class X:

COMMISSIONS

→ OMISSIONS

↓

$$MA = \frac{\text{Pixels of } X_{\text{correct}}}{\text{Pixels of } X_{\text{correct}} + \text{Pixels of } X_{\text{omission}} + \text{Pixels of } X_{\text{commission}}}$$

Pixels of X_{omission} = All other classes in X Row

Pixels of $X_{\text{commission}}$ = All other pixels in X Column

Also calculated was the Kappa coefficient (Campbell 1996, Congalton 1991) which accounts for the fact that observed agreement between the classified map and the reference map can be due to chance (Baatz et al 2004). The results of the Kappa statistics range between 0 and 1.0 with 1.0 equal to absolute agreement between the classified and reference map (Campbell 1996, Miller et al 2003). A Kappa coefficient score for example of .85 indicates that the classification accuracy was 85% greater than chance (Miller et al 2003).

Two types of reference datasets were generated to assess the classifications. The first was generated from 250 random points which represented a single pixel each. A reference dataset was created for each aerial photograph. The second was generated using ground truthing data collected in the field.

3.4.2 Ground truthing data

Ground truthing data was collected between the 24th and 26th of August to aid in accuracy assessment of the classified 2004 imagery. It was important that the 2004 classification was validated using ground truthing, as there was no way of collecting ground truthing data for the historical datasets compiled for 1950, 1975 or 1996. Permission was required from the traditional owners and Parks Australia North to access the study area, and a permit (permit No. RK 639) was acquired. The collection of ground truthing data was restricted to the dry areas of the study area, due to logistical and safety issues related to crocodiles. This limited the collection of data to a thin band along the boundary of the study area (Fig 3.4). The 86 sample points were randomly selected at regular intervals whilst traversing on foot.

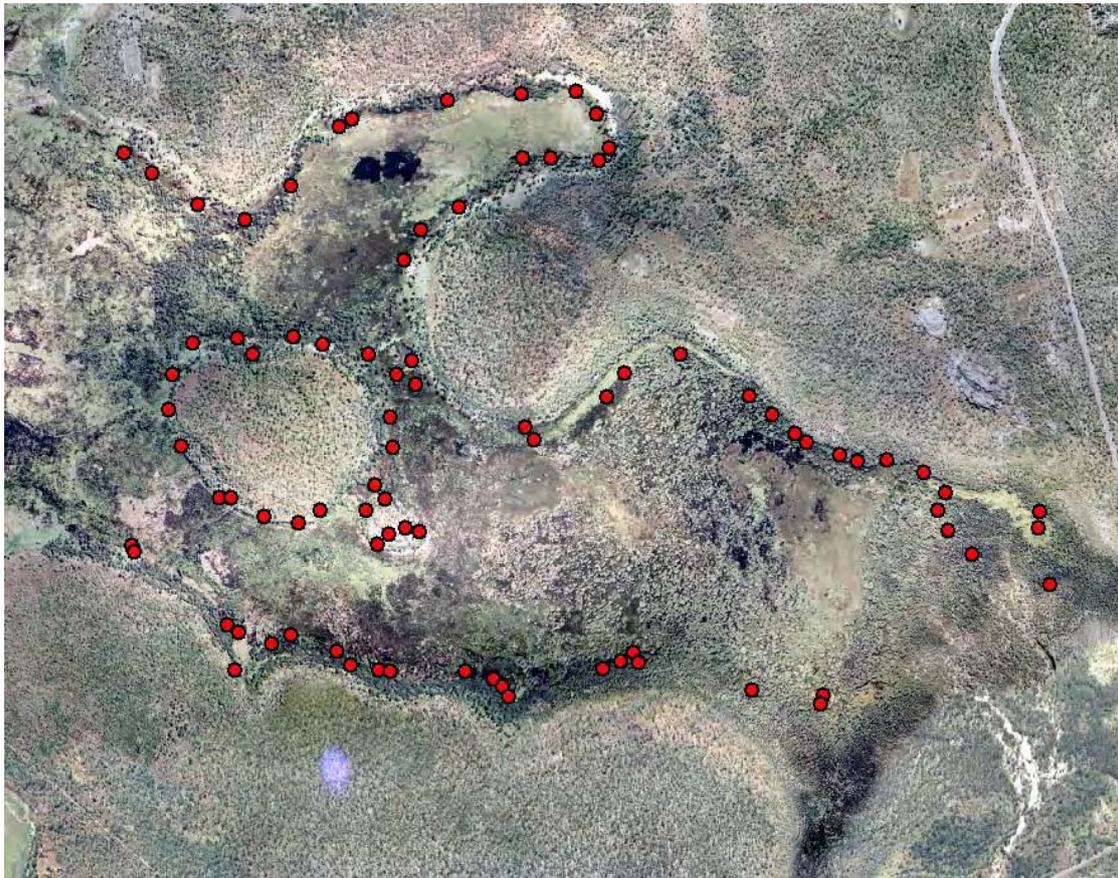


Figure 3.4 Locations of the 86 ground truthing sample points used to assess the accuracy of the 2004 classification

Data recorded at each sample point included:

- GPS readings – four readings were taken at each point to be averaged, this was done to account for the spatial error of the GPS unit (± 4 m).
- *Melaleuca* spp canopy cover was estimated for a 10 m radius, using a spherical densiometer (Lemmon 1956).
- GPS coordinates for individual trees and open areas were recorded.
- Brief descriptions of the upper, mid, and ground stratum were also recorded.
- Several digital photographs were taken at each sample point for later reference.

Canopy cover estimates using a spherical densiometer involve taking estimates of canopy cover at the four cardinal points. These four estimates are then averaged to calculate the overall canopy cover of the given point (Lemmon 1956). The decision to estimate the canopy cover for a 10 m radius was made to account for both the spatial error of the GPS unit and spatial error within the classified dataset.

All GPS coordinates collected at each survey point were downloaded onto an Excel spread sheet and averaged to correct for spatial error. Canopy cover estimates and field notes were also recorded onto the spread sheet which was used to generate an ESRI point shapefile for further analysis using GIS.

Several problems were identified that need to be addressed before the ground truthing data could be used for final accuracy assessment. This included:

- Spatial error in the GPS unit;
- Survey points located on the boundary or not within the study area;
- Adjustment for the different ways canopy cover was represented in the classified maps and recorded using the spherical densiometer;
- Human error in the collection of ground truthing data; and,
- Changes that may have occurred during the 13 month period from when the aerial photograph was taken and field data collected.

To address the aforementioned problems, and determine the level of accuracy of each survey point, the ground truthed points were visually compared to the 2004 aerial photograph. A total of 19 sample sites were removed due to spatial error or human error in canopy estimates, 1 site was removed due to changes that occurred during the thirteen month period. The remaining 66 sample points represented the ground truth data used in the final error assessment.

3.4.3 Digital error assessment methods

Manual interpretation of aerial photographs is a common method employed to assess the accuracy of remotely sensed imagery (Allen 1997, Congalton 1991). Using a GIS platform, manual photointerpretation was used to create reference datasets for each aerial photograph. This was used to evaluate both the automated and final classifications for each dataset.

The Arc-script (Hawth's Analysis tools <http://www.spataleecology.com/htools/>) was used to randomly generate 250 points across the study area in vector file format (Fig 3.5). The 250 point datasets were overlaid onto the individual aerial photographs, and each point was classified as either '*Melaleuca* spp' and given a value of 1, or 'other' and given a value of 3.



Figure 3.5 Location of the 250 random points used to generate reference data for error assessment for the level 1 automated and final classified datasets

Chapter 4 Object based classification

4.1 Introduction

The classification software used in this project has been described by van der Sande et al (2003) as ‘an advanced region-growing and knowledge-based segmentation approach’. This multi-scale segmentation approach allows the extraction of image objects at a variety of scales within the same image (Benz et al 2004). Objects identified at different scales can then be combined into a hierarchical network where each object can know its context, its neighbourhood, and its sub or super-objects (Bock et al 2005). This allows greater flexibility in the methodology developed in the classification process.

This chapter describes the methodology developed to classify each aerial photograph. The results for each classification and accuracy assessment are presented and discussed. It also contains a brief overview of the relevant techniques used to perform classification in this study, using the computer software eCognition. A comprehensive review of classification techniques is described in (Baatz et al 2004). Issues related to the use of panchromatic and true colour aerial photographs in automated classification of floodplain environments are identified and discussed.

4.2 Classification methods

4.2.1 Classification using eCognition

There are two main steps involved in the classification of images using eCognition, they are segmentation and classification (Al-Kudhairy et al 2005).

Segmentation

The first step in the classification process using eCognition is the creation of objects across the image by segmentation (Dorren et al 2003). The segmentation algorithm used by eCognition is a bottom-up region merging technique, starting with single pixel objects (Baatz et al 2004, Benz et al 2004). In numerous proceeding steps, smaller image objects are merged into larger ones, based on the parameters; scale, colour and shape. These parameters define the growth in heterogeneity between adjacent image objects. This iterative process stops once the smallest growth exceeds the threshold defined by the scale parameter (Laliberte et al 2004). The larger the scale parameter the larger the image objects produced (Wang et al 2004). The scale factor is a unitless parameter related to the resolution of the image (Baatz et al 2004). The colour and shape parameter are given a value between 0 and 1, with the shape setting being further divided by smoothness and compactness values also between 0 and 1. The colour value is related to the spectral values of the image bands used, each image band can be given a weighted value between 0 and 1 to be used in the segmentation process. The segmentation process can be performed at different scale sizes, creating different levels of objects within the same image (Fig 4.1) (Hay et al 2005). This allows the development of the classification knowledge base where the different objects can know their horizontal (objects on the same level) and vertical (objects above or below) neighbours.

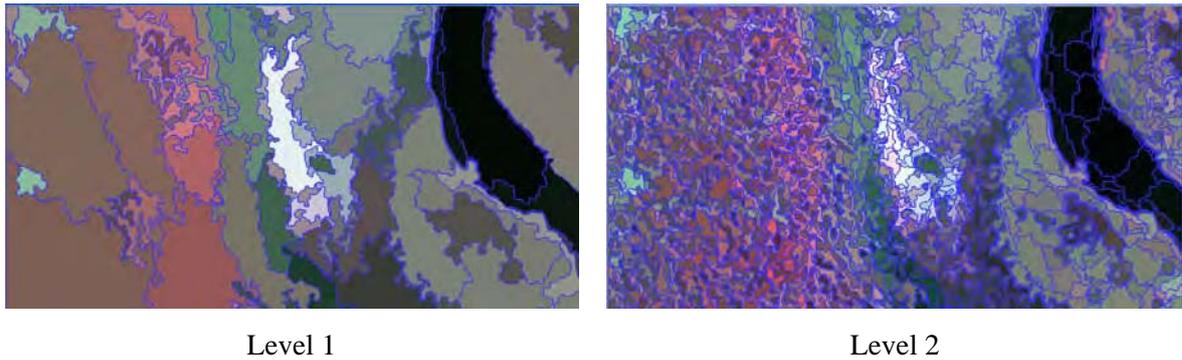


Figure 4.1 Example of the segmentation process at two scale levels across the same scene, level 2 has been used to segment objects into broad classes while level 1 has further segmented objects within those broad classes

The different scale levels can then be combined in a hierarchical network to perform classification of the image (Laliberte et al 2004). Different image objects or information are scale dependant (Baatz et al 2004), and most attributes of an image structure (eg. colour, texture and shape) are also highly scale dependent (Hay et al 2003). This function gives the ability to identify and classify targets in the image at a range of different spectral and spatial scales, adding flexibility and extra information to the classification process. Laliberte et al (2004) reported that a multi-scaled approach enabled shrubs to be extracted from both dark and light backgrounds within the same image by utilising information gained from super-objects created in a different scale level. This was achieved through developing a class hierarchy, which forms the basis of eCognition’s language for creating knowledge for a given classification (Baatz et al 2004). In this project the development of a knowledge base enabled the extraction of individual trees using information inherited from a parent class identified as wooded areas in the image (Fig 4.2).

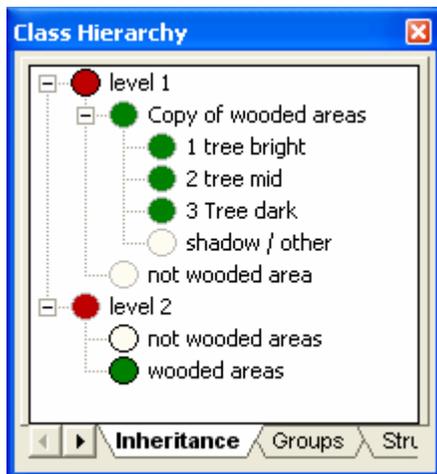


Figure 4.2 An example of a class hierarchy knowledge base developed in this project – classes in level 1 known as ‘child’ classes (eg 1 tree bright) have inherited information passed down from the ‘parent’ classes (eg copy of wooded areas) which in turn became child classes to wooded areas in level two.

Once a level has been classified, the classes generated can also be used in a more advanced classification-based segmentation of the image (Benz et al 2004). This was used by Laliberte et al (2004) to merge their two levels of classified images forming a final combined classification. There are a large numbers of statistics generated from the objects in the segmentation process. These statistics can then be applied to the identification and subsequent classification of the desired classes within the image.

Classification algorithms used in eCognition

There are two classifying algorithms available in eCognition, nearest neighbour and membership function. Both are supervised classification methods based on fuzzy logic, which supports intuitive and transparent editing and handling of complex rule sets (Baatz et al 2004). Fuzzy logic is a mathematical approach used to quantify uncertain statements emulating human thinking, and is able to accommodate linguistic rules (Baatz et al 2004, Benz et al 2004). Fuzzy logic differs from the classic classifiers used in remote sensing which use Boolean logic statements ‘true or false’ to decide if a pixel belongs to a particular class. Using fuzzy logic removes the stiff boundaries associated with Boolean logic and replaces them with values ranging from 0 to 1, with zero equal to false and one equal to true, all values in between represent the transition between true and false (Benz et al 2004). A number of different logical operators such as ‘and’, ‘or’, and ‘mean’, can also be combined to form well structured class descriptions (Baatz et al 2004).

The nearest neighbour classifier is based on selecting image objects generated from the segmentation process that represent the desired class (Benz et al 2004, Laliberte et al 2004). The selected samples are used to automatically develop multidimensional membership functions (Baatz et al 2004). There are two types of nearest neighbour expressions available in eCognition: standard nearest neighbour (SNN) and nearest neighbour (NN). The nearest neighbour differs from the standard nearest neighbour in that in the former case, the nearest neighbour’s feature space can be defined for each class independently, whereas the standard nearest neighbour’s feature space is valid for the entire project. Thus any changes made to the feature space of a class is assigned to all classes using a standard nearest neighbour expression (Baatz et al 2004).

The membership function uses a one-dimensional membership class; it is based on rules defined by the analyst (Baatz et al 2004). The use of the membership function requires that the analyst has a reasonable degree of knowledge of the study area (Baatz et al 2004, Blake 2004). Statistics from a one-dimensional feature space, derived from the objects created in the segmentation process are used to train the membership function for each class. There are various function types that can be defined by the analyst to train the membership function algorithm and can be used to produce either a soft (fuzzy) or hard (Boolean) classification (Fig 4.3).

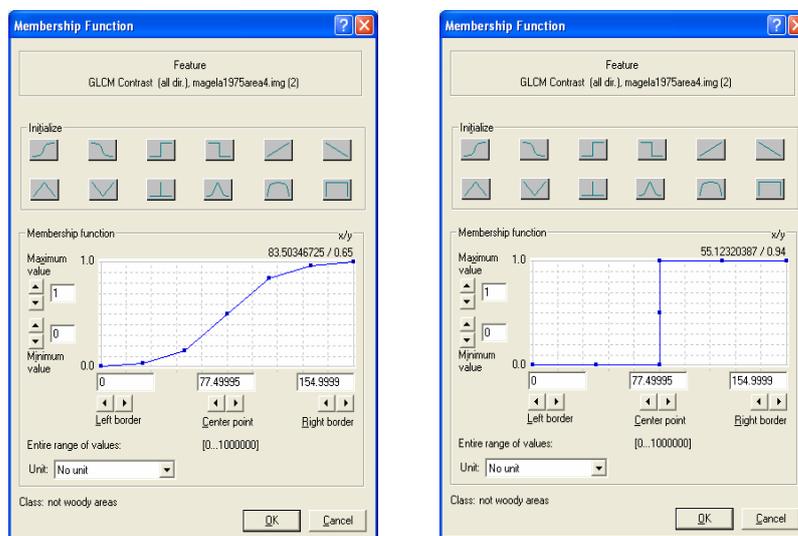


Figure 4.3 Screen shots showing the Membership function dialog box with examples of function form (a) ‘larger than’ using fuzzy logic (b) ‘larger than’ using Boolean logic

Class parameter selection

There are a number of ways to help identify and select the parameters used for generating the classes. Statistical values for objects generated during the segmentation process can be viewed using the ‘image object information’ dialog. The ‘sample editor’ can be used to view the feature signature of a given class (Fig 4.4).

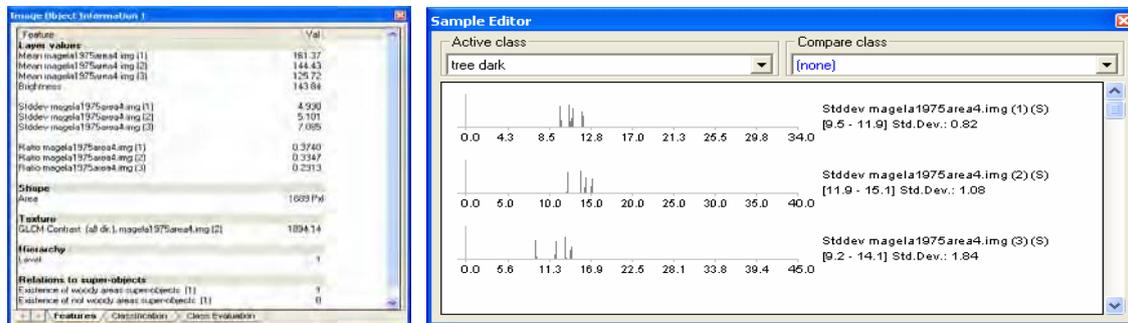


Figure 4.4 Examples of the ‘image object information’ and ‘sample editor’ dialog box used in evaluation of sample selection

The visual effect of a selected features value across the whole image can be assessed using the ‘feature view’ dialog tool. It displays each object across the image in either grey values or a defined range (blue = low values and green = high values). This can be used to distinguish between two classes (Baatz et al 2004). Also available in eCognition is a ‘Feature optimisation tool’, which provides an automated method of assessing and identifying different attributes in feature space that may help distinguish between classes.

There are a large number of statistical values generated for each object these include layer values (eg mean, stdev, ratio...), shape values (eg area, compactness...), and texture values (eg texture after Haralick, Layer value based on sub-objects...) (Baatz et al 2004).

4.2.2 Classification methodology used for 1950, 1975 and 2004 aerial photographs

The classification knowledge base developed for the 1950, 1975 and 2004 images was similar, with variations in parameters used in the segmentation process and values used to define the different classes. The basic image object hierarchy built for each dataset consisted of two levels segmented at different scales. Level 2 contained the coarsest objects which were used to classify areas as either ‘woody’ or ‘not woody’. This was then used as a mask, or parent class for the finer scale (level 1). The finest scale objects were then classified as individuals or stands/clumps of *Melaleuca* spp (Fig 4.5). The classification procedure developed for the 1996 imagery is different and is described below in section 4.2.3.

Segmentation

The decision on the parameters used in the multi-resolution segmentation process varies between different images. It is influenced by the spatial, spectral and radiometric resolution of the image and the scale of the target object (Baatz et al 2004). During the segmentation process all spectral bands available in each image were given equal value. Each image was segmented at a variety of scales, and with different homogeneity parameters. Each segmentation results were visually assessed for representation of the scale of the target objects (eg individual trees and stands of trees – Level 1 woody not woody areas – Level 2). Each segmentation were also assessed for their ability to spectrally represent the target objects, as

attributes of an image structure are also scale dependent (Hay et al 2003). The final scale and composition of homogeneity criterion parameters used for the 1950, 1975 and 2004 image segmentation process are listed in Table 4.1.

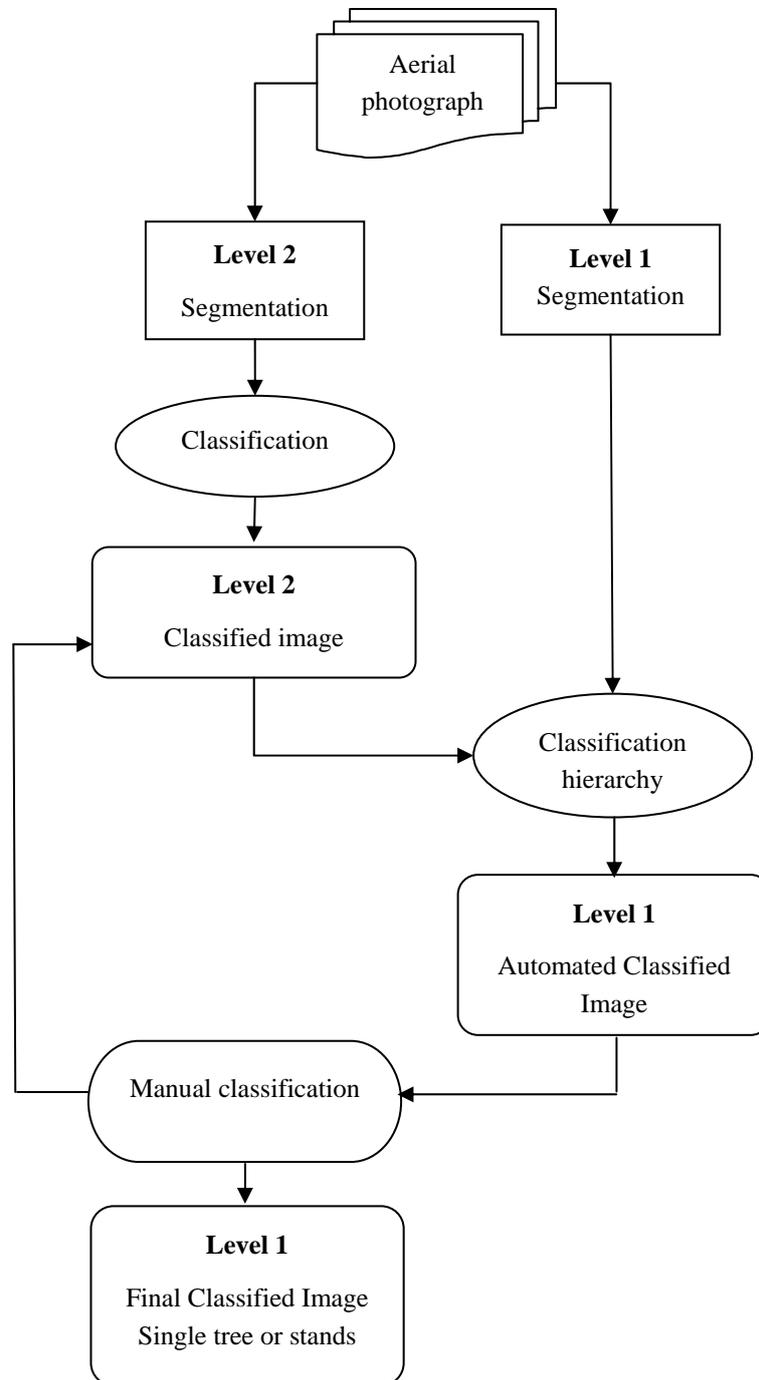


Figure 4.5 Schematic diagram showing the basic steps involved in classifying the 1950, 1975 and 2004 aerial photographs

Table 4.1 Multi-resolution segmentation parameters used for the 1950, 1975 and 2004 aerial photographs

Image	Segmentation level	Scale	Colour	Shape	Shape settings	
					<i>Compactness</i>	<i>Smoothness</i>
1950	Level 1	10	0.9	0.1	0.9	0.1
	Level 2	25	0.9	0.1	0.9	0.1
1975	Level 1	20	0.9	0.1	0.9	0.1
	Level 2	35	0.9	0.1	0.9	0.1
2004	Level 1	30	0.8	0.2	0.7	0.3
	Level 2	200	0.8	0.2	0.5	0.5

Classification Level 2

The classification method chosen to classify the level 2 (woody / not woody areas) in each of the three datasets was the one-dimensional membership function. The function form selected was ‘range’ which is a Boolean logic function. This was chosen as the object factors identified as separating the two classes had very well defined boundaries; in effect a density slice was performed based on the objects statistics. The identification of the object features representing each class was assessed using the feature view dialog tool. The object feature, ‘texture after Haralick GLCM Contrast (all dir) band (2)’ was found to best separate woody and non woody areas for classification of level 2 in both the 1975 and 2004 images. The grey level co-occurrence matrix (GCLM) tabulates how often different combinations of pixel grey levels occur across the scene (Baatz et al 2004). In the 1950 image the object feature ‘mean difference to neighbor (abs)’ was found to best separate the woody and non woody areas. The ‘mean difference to neighbor (abs)’ calculates the averaged absolute layer mean difference for each neighboring object which is computed and weighted in relation to the length of the border between objects (Baatz et al 2004). The value ranges used in the level (2) classifications are shown in Table 4.2. Classification of level 2 was performed and the results were assessed visually on screen. Due to the broad nature of the classes it was clear that areas within the 1950 and 2004 images had been variously under or over classified. Manual classification tools, available in eCognition were used to refine both the 1950 and 2004 classifications.

Table 4.2 Details of the object features and the value ranges used to represent each class in the level 2 classifications for the 1950, 1975 and 2004 aerial photographs

Image	Class	Parameters	Spectral band	Values
1950	Woody areas	Mean difference to neighbour (abs)	panchromatic	0 – 17.4
	Not woody areas	Mean difference to neighbour (abs)	panchromatic	17.41 – 65535
1975	Woody areas	texture after Haralick GLCM Contrast (all dir)	Green 2	155 – 1000000
	Not woody areas	texture after Haralick GLCM Contrast (all dir)	Green 2	0 – 154.99
2004	Woody areas	texture after Haralick GLCM Contrast (all dir)	Green 2	1101 – 1000000
	Not woody areas	texture after Haralick GLCM Contrast (all dir)	Green 2	0 – 1100.99

Classification of Level 1

The development of a class hierarchy in eCognition allows for the grouping of classes between different levels (Baatz et al 2004). This enables information from different levels, upper or lower to be inherited. Copies of the classes in level 2, woody and not woody vegetation were created in level 1. The level 2 classes, woody and not woody areas were then defined as parent classes to their namesakes in level 1. This was done using the membership function and defining the ‘relation to super objects – existence of’ expression (Fig 4.6). This in effect transferred the classification in level 2 through to level 1, restricting the classification of child classes related to woody areas to those defined in the level 2 classification.

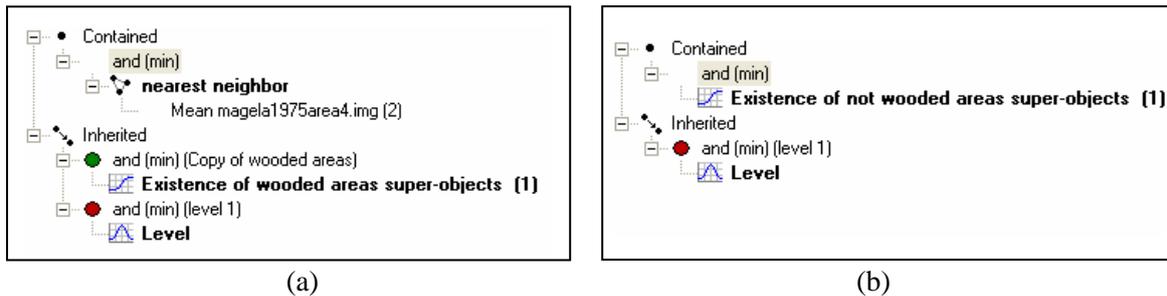


Figure 4.6 Example of class descriptions for level 1, used to build the knowledge base for the class hierarchy for 1950, 1975 and 2004 aerial photographs (a) represents class 1 tree bright which ‘inherited’ information from wooded areas on level 2 and ‘contained’ mean spectral value of objects from level 1 (b) represents class not woody area on level 1 which contained information inherited from the existence of not wooded areas in level 2.

The next step involved developing classes for the final classification. Slight variations in classes were developed. This was necessary to account for the different spectral properties of each aerial photograph; due to environmental and technological factors. Within the ‘woody areas’ super-class, three classes representing *Melaleuca* spp and one representing shadow or anything other than *Melaleuca* spp were created for both the 1975 and 2004 images (Fig 4.7). For the 1950 image, two classes were used to represent *Melaleuca* spp and one class was developed to account for areas not *Melaleuca* spp. All three images contained a class defined as not woody areas.

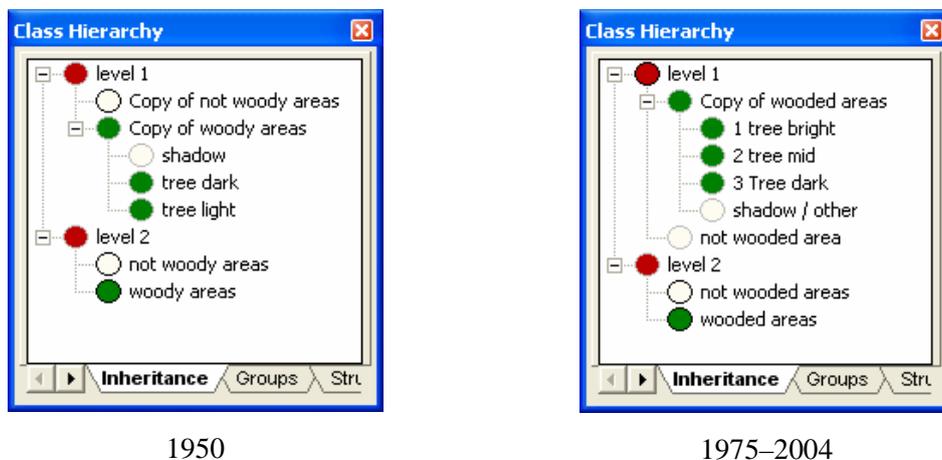


Figure 4.7 Class hierarchies developed for the classification of the 1950, 1975 and 2004 aerial photographs using eCognition

The classification of the level 1 child classes for the 1950, 1975 and 2004 images was performed using the nearest neighbour algorithm. Initial selection of training samples (objects) was undertaken by identifying two or three image objects that best represented each class across the image. This is similar to the selection of training areas used in conventional supervised classification methods (Laliberte et al 2004). The initial selection was based on a one-dimensional feature space. The image object features for 1975 and 2004 were ‘mean of object band (2)’ and for 1950 the parameter used was the ‘mean’ of the object pixels value. In the initial selection of training objects, it is important to only select a few samples for each class, as this ensures the heterogeneous nature of the image is fully considered by the nearest neighbor classifier (Baatz et al 2004). The images were then classified and visually assessed. If objects were not classified, due to their feature space not being represented within a class they were assigned to the correct classes. Also any obvious miss-classified objects were re-assigned or removed as a sample of the particular class. The feature space optimisation tool was also used to identify other attributes that would assist in the separation of classes. This tool evaluates the use of different attributes in multidimensional feature space that best separate the different classes. It was trialed on all three datasets and found to improve the classification of the and 1975 image, however increasing the number of attributes for the classes in the 1950 and 2004 images did not improve their classification. The final parameters used to train the classes in all three images can be seen in Table 4.3.

Table 4.3 Final parameters used to classify the classes in level 1 for the 1950, 1975 and 2004 aerial photographs

Image	class	Parameters	Spectral band
1950	copy woody areas	relation to super-object – existence of	panchromatic
	copy not woody areas	relation to super-object – existence of	panchromatic
	tree	mean	panchromatic
	tree dark	mean	panchromatic
	other	mean	panchromatic
1975	copy of woody areas	relation to super-object – existence of	
	copy not woody areas	relation to super-object – existence of	
	1 tree bright	<div style="border: 1px solid black; padding: 5px; display: inline-block;"> Standard deviation (1) (2) (3) Ratio (1) (2) (3) Mean (2) brightness (1) (2) (3) </div>	
	2 tree bright		
	3 tree bright		
	shadow / other		
2004	copy of woody areas	relation to super-object – existence of	
	copy not woody areas	relation to super-object – existence of	
	1 tree bright	Mean	(2)
	2 tree bright	Mean	(2)
	3 tree bright	Mean	(2)
	shadow / other	Mean	(2)

Due to the nature of the fuzzy logic classifier used by eCognition an object can have more than one membership to a class (Baatz et al 2004). The degree of membership of an object can be evaluated using tools that show graphically and statistically the classification’s

stability and best classification result. These tools and visual assessment were used to initially evaluate and refine each classification.

Manual Classification

Due to the heterogeneity within the imagery, particularly the 2004 image, some objects were classified manually in order to improve the final classification accuracy. This was achieved by selecting the desired class in the class hierarchy, and then selecting the object/s with the appropriate tool; the selected object is then automatically assigned to the selected class. The ease with which objects can be manually classified is a further advantage of the object based approach, allowing classifications to be quickly improved beyond the capability of automated classification techniques.

4.2.3 Classification methodology used for 1996 image

Initial attempts to use the methods developed to classify the 1950, 1975 and 2004 images on the 1996 image failed. In both the 2004 and 1996 images, separation between *Melaleuca* spp and the understory vegetation was difficult due to the highly heterogeneous nature of the imagery. In an attempt to avoid the large manual classification component involved in the 2004 image classification, a new method was developed to classify the 1996 image. The 1996 image was loaded into the remote sensing software ERDAS imagine 8.7, and a low-pass filter applied. Several different kernels were trialed (3x3, 5x5, and 7x7) and visually assessed. The resulting images showed that the 3x3 kernel did not sufficiently reduce the heterogeneity in the image, while the 7x7 kernel resulted in a loss of detail in the image. The 5x 5 kernel was found to be a balance between both, resulting in a smoothing of the image which reduced the heterogeneity whilst retaining sufficient detail of the *Melaleuca* spp (Fig 4.8).

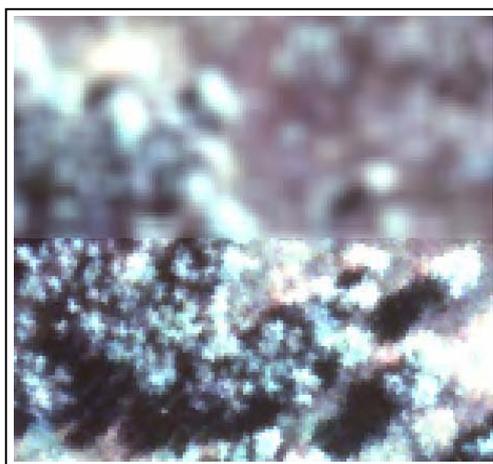


Figure 4.8 Example of the effect of performing a 5 x 5 low-pass filter across the 1996 image. Top half is the low-pass filtered image, bottom half is the raw image.

The classification of the 1996 image was broken into two components, as illustrated in Figures 4.9 and 4.10.

The first step consisted of generating two levels, segmented at scales set at 25 (level 1) and 80 (level 2); the details of the segmentation parameters used in the classification are in Table 4.4. A knowledge base was then defined for the class hierarchy. Classification was performed on level 2 (scale 80) using two broad classes ‘woody’ and ‘not woody areas’. The membership function ‘range’ was used to train the classification of the two classes.

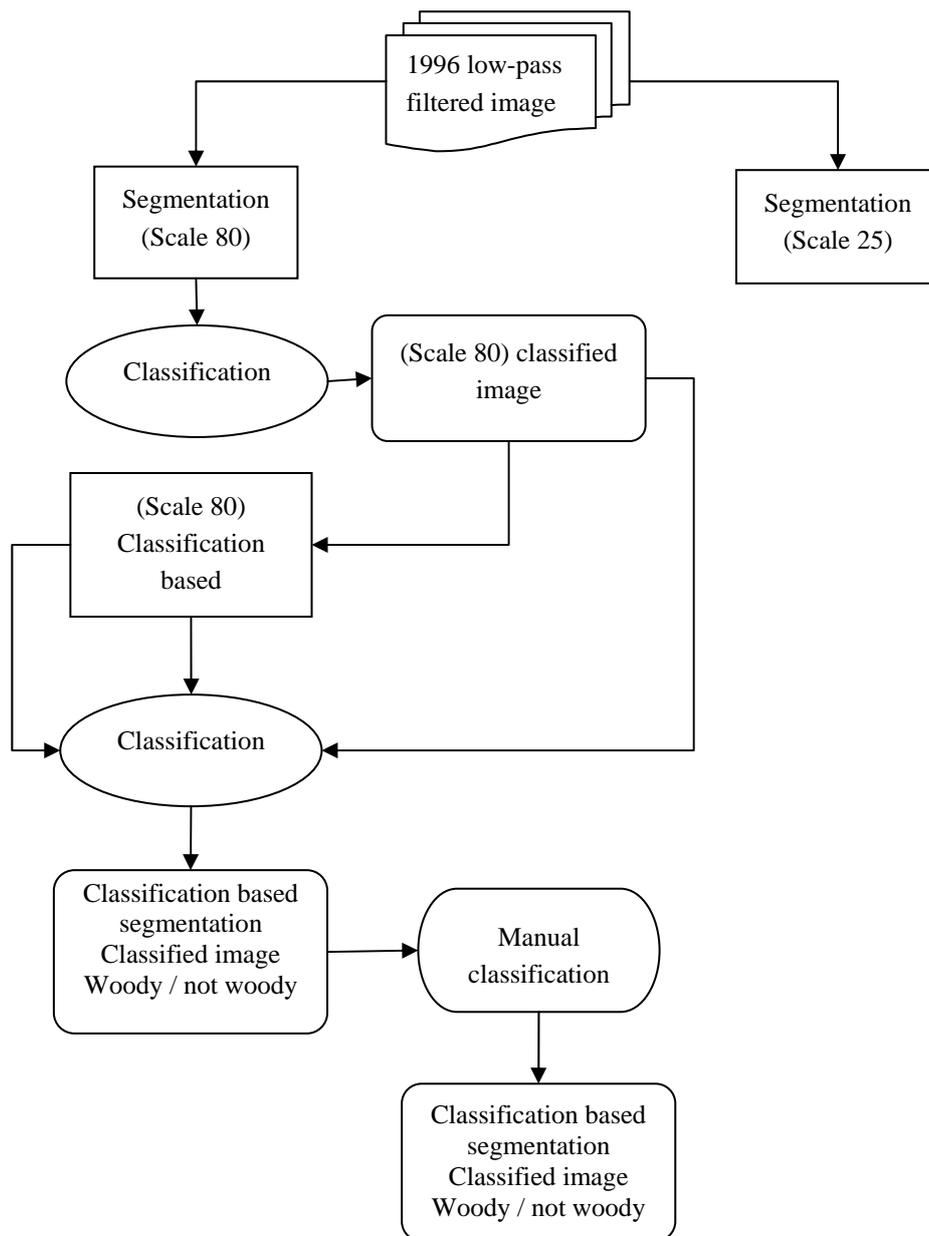


Figure 4.9 Schematic diagram showing steps involved in classifying stage one of the 1996 aerial photographs

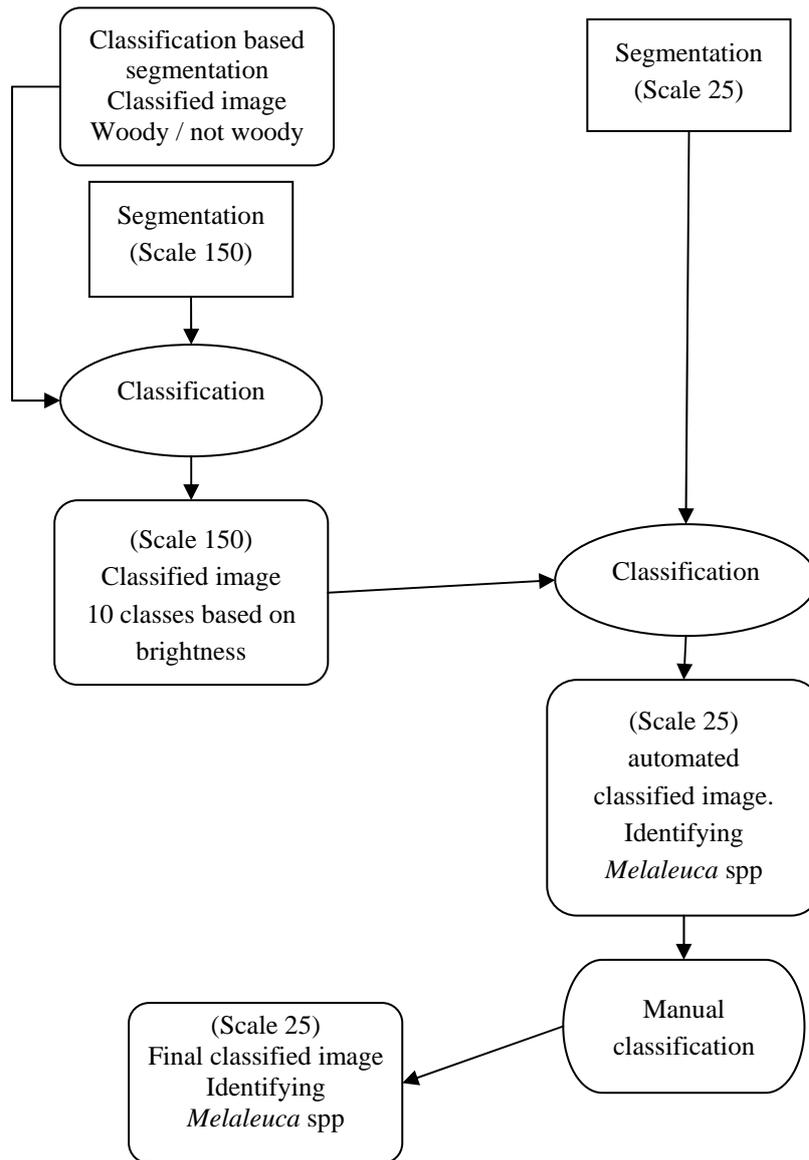


Figure 4.10 Schematic diagrams showing the steps taken in the second stage involved in classifying the 1996 aerial photographs

The feature type identified as best delineating between the two classes was ‘mean diff to neighbours (abs) using band (2)’. The use of the ‘range’ function is analogous to performing a density slice across the image using the feature values detailed for scale 80 in Table 4.5. Classification based segmentation was then performed on the woody, not woody areas classification, creating a new level by merging the image objects based on the two classes.

The project then consisted of three levels. The level 2 classification was then passed through to the classification based segmentation level 3, using the membership function algorithm and inserting the expression ‘class related features – existence of sub-objects’. This ensured that the same areas classified as woody and not woody areas in the level 2 (scale 80) were applied to the same spatial location in the classification based segmentation level 3. The classification was performed and visually assessed for accuracy. There were a small number of areas misclassified in level 2 in both classes which were inherited by level 3, this being rectified using the manual classification tools.

Table 4.4 Parameters used in the segmentation levels developed for the classification of the 1996 aerial photograph

	Segmentation level	Scale	Colour	Shape	Shape settings	
					Compactness	Smoothness
Part 1	Level 1	25	0.9	0.1	0.9	0.1
	Level 2	80	0.9	0.1	0.9	0.1
Part 2	Level 1	25	0.9	0.1	0.9	0.1
	Level 2	150	0.9	0.1	0.9	0.1
	Level 3	0	<i>Classification based segmentation.</i>			

Table 4.5 Parameters used to classify the classes for the 1996 aerial photograph

Level	Scale	Class	Parameter	Values	Spectral band
2a	80	woody areas	Mean difference to neighbour (abs)	30–65535	(2)
2a	80	not woody areas	Mean difference to neighbour (abs)	0–29.99	(2)
3	0	copy woody areas	relation to sub-object–existence of	woody areas	
3	0	copy not woody areas	relation to sub-object–existence of	not woody areas	
2b	150	Tree areas	relation to super-object–existence of	copy woody areas	
2b	150	not trees	relation to super-object–existence of	copy not woody areas	
2b	150	brightness x 10	brightness		(1)(2)(3)
1	25	copy x 10 brightness	relation to super-object–existence of	brightness x 10	
1	25	Trees x 10	Mean		(1)
1	25	other x 10	Standard deviation		(1)
			Ratio		(1)
			Standard deviation to neighbours pixel		(2)(3)
			Compactness of object		

The second stage in the classification process was then undertaken (Fig 4.10). Once the classification based segmentation was classified using the inherited values from the classes in level 2 (scale 80), it was necessary to delete level 2 (scale 80) from the project as it would cause a circular reference to occur in the classification algorithm developed further in the project. Multiresolution segmentation was then performed at scale parameter 150, which then became level 2 in the project. The knowledge base was then further developed for the class hierarchy; this included woody and not woody classes that were related to the super-objects of the same class in level 3. This was done by using the membership function and inserting the expression ‘relationship with super-objects – existence of’ which ensured that the original woody / not woody classes were passed through to level 2. A further ten classes based on brightness levels of the objects in level 2 (scale 150) were created and made child classes of the woody areas class. This was done to account for the bidirectional reflectance distribution function (BRDF) which causes different brightness levels across the aerial photograph. The classification algorithm used was the nearest neighbour and the object features used to define the 10 brightness classes were ‘mean brightness’. The selection of training samples was

undertaken ensuring that the training object selected for each class was within the boundary of the woody class in level 3. This was done by displaying both levels in linked viewing windows. Classification was then performed on level 2, and assessed using the stability and best classification tools.

The final classification was performed on level 1 (scale 25). The knowledge base for the class hierarchy was further developed, and contained 10 brightness classes which inherited information from the 10 brightness classes in level 2 (Fig 4.11).

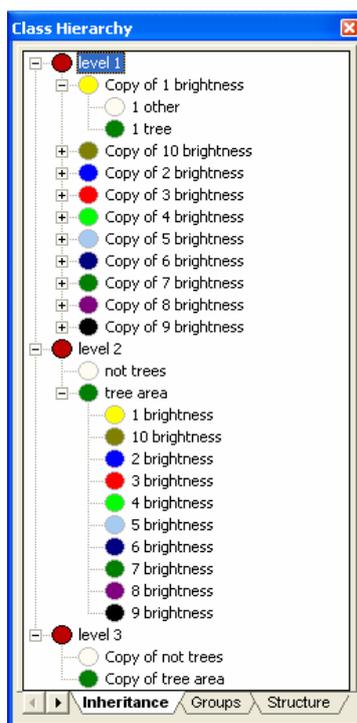


Figure 4.11 Final class hierarchy developed to classify the 1996 aerial photograph

Each of the 10 brightness classes in level 1 became parent classes to two child classes ‘tree’ or ‘other’. The nearest neighbour classification algorithm was used to classify each tree and other class. Training objects were selected using the same technique as level 2 brightness areas, with two linked viewing windows open, ensuring the training objects came from the associated parent class in level 2. Classification was then performed and classes were further refined and evaluated using methods previously outlined. This was undertaken until it was deemed that the automated classification of the image could not be further improved.

Manual Classification

It was clear from visual inspection of the final automated classification of the 1996 image that there were areas not correctly classified. To improve the overall result systematic manual classification of the final classified 1996 image was performed.

4.2.4 Methods used to perform accuracy assessment

Both the automated and manually corrected classified images for each year were exported out of eCognition into Erdas Imagine native format (.img) for accuracy assessment and further analysis using the GIS software ArcView 9.1. An error matrix was developed for both the

level 1 automated and manually classified images for each year. The Kappa coefficient was also calculated for each dataset.

Ground truthing reference datasets

The 2004 classification was assessed using a reference dataset produced from ground truthing data collected in August 2005. The steps used in analysis of the ground truthed sample points is summarised in Figure 4.12. Of the 66 points 47 were defined as being *Melaleuca* spp, while 19 sample points were collected from open areas not occupied by *Melaleuca* spp. Sample points recording individual trees (6 in total) and open areas on the floodplain (19 in total) were visually assessed and assigned as correct or incorrect. In order to calculate the level of accuracy of the mapped canopy cover for the remaining sample points, the percentage of *Melaleuca* spp mapped in a 10 m radius around the ground truth data points was assessed. This was achieved by first buffering each point by 10 m (area = 392.04 m²) and then using zonal statistics to sum the number of pixels in each circle attributed to *Melaleuca* spp in the 2004 classification. The zonal statistics attribute table was then exported to Excel for further analysis. From the zonal statistics the percent canopy cover was calculated for the 2004 classification in each 10 m radius and compared with the spherical densiometer estimates.

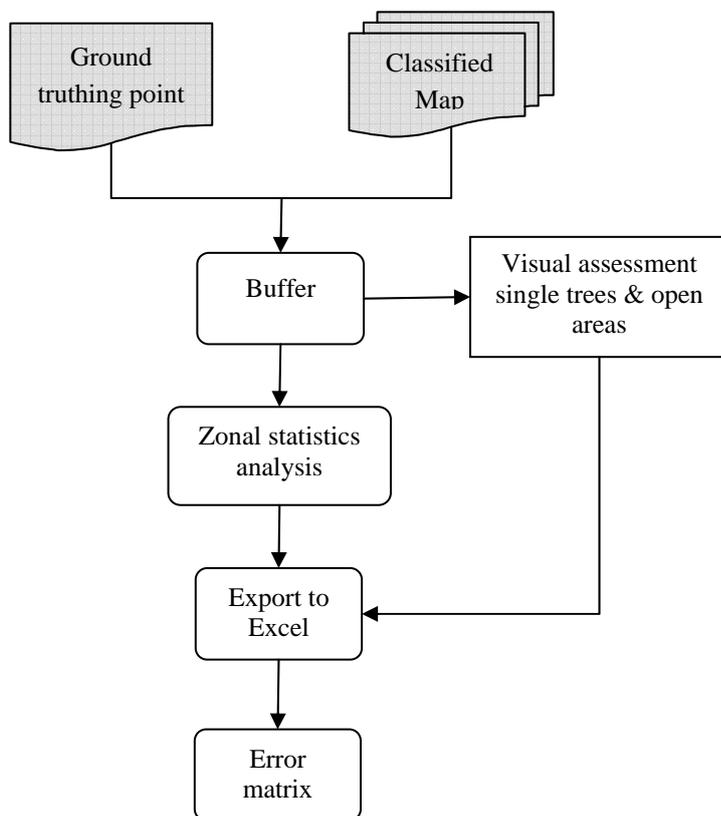


Figure 4.12 Schematic diagram showing steps taken to assess accuracy of the final 2004 classified map, using ground truthing data

From this the number of ground truthing sample points (reference data) that concurred with the classified map could be evaluated. Any canopy cover in the classified map found to be in $\pm 25\%$ agreement with the ground truthing data was considered correct and any greater than $\pm 26\%$ were considered as incorrect.

Photointerpretation reference datasets

All classified datasets were evaluated for accuracy using reference datasets containing 250 randomly generated points, which were manually classified by on screen interpretation of the aerial photographs for each year. The steps used in analysis of the automated and final classifications using the photointerpretation reference datasets is summarised in Figure 4.13. The vector point file datasets (as described in Chapter 3) representing a single pixel were then converted to raster format and used to generate an error matrix for each classified image. The data for the error matrix was generated by changing the values of the two classes in each classified dataset so ‘*Melaleuca* spp’ was equal to 2 and class ‘other’ was equal to 3. The raster calculator was then used to sum both the reference and classified dataset to produce a raster dataset containing attributes used to generate the error matrix (Table 4.6).

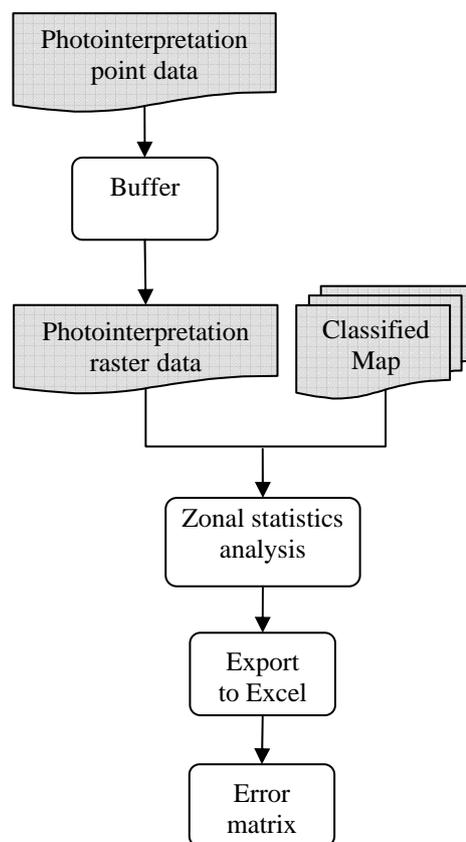


Figure 4.13 Schematic diagram showing the steps used in analysis of the automated and final classified images using the photointerpretation reference datasets

Table 4.6 Results from the error matrix attribute table

Classified map + ref data	= value	No pixels
<i>Melaleuca</i> correctly classified	3	58
<i>Melaleuca</i> classified as other	5	14
Other classified as <i>Melaleuca</i>	4	9
Other class correctly classified	6	169

It must be noted within the methodology used in the 1950, 1996 and 2004 classification, level 2 and 3 have been manually classified and thus the definition of the level 1 classification as automated for these datasets needs to be assessed in this context.

4.3 Results of classification and accuracy assessment

4.3.1 1950

The final classified map showing the distribution of *Melaleuca* spp for the year 1950 is presented in Figure 4.14. The overall accuracy of the 1950 automated classification of level 1 was estimated to be 88% with a Kappa coefficient score of 0.75. Even though the estimation of the accuracy of the automated classification was very good, it was clear from visual inspection that amongst the woody vegetation areas the classification over estimated *Melaleuca* spp coverage. Attempts were made to further train the three classes created as described in the methods. The limitations of the spectral information within panchromatic aerial photographs became evident. It was not possible to successfully separate darker areas surrounding individual trees in some areas. To further improve the classification, manual editing of the classification was performed. This did not alter the overall accuracy with only a slight increase of 89% and a Kappa coefficient score of 0.76. However the producer's accuracy for the '*Melaleuca* spp' class declined slightly, while the accuracy of the class 'other' (not *Melaleuca* spp areas) increased slightly. The overall mapping accuracy for each class in the manual classification increased slightly (Table 4.7). While the improvement was only slight, it was decided to use the manual classification dataset in further analysis over the automated classification.

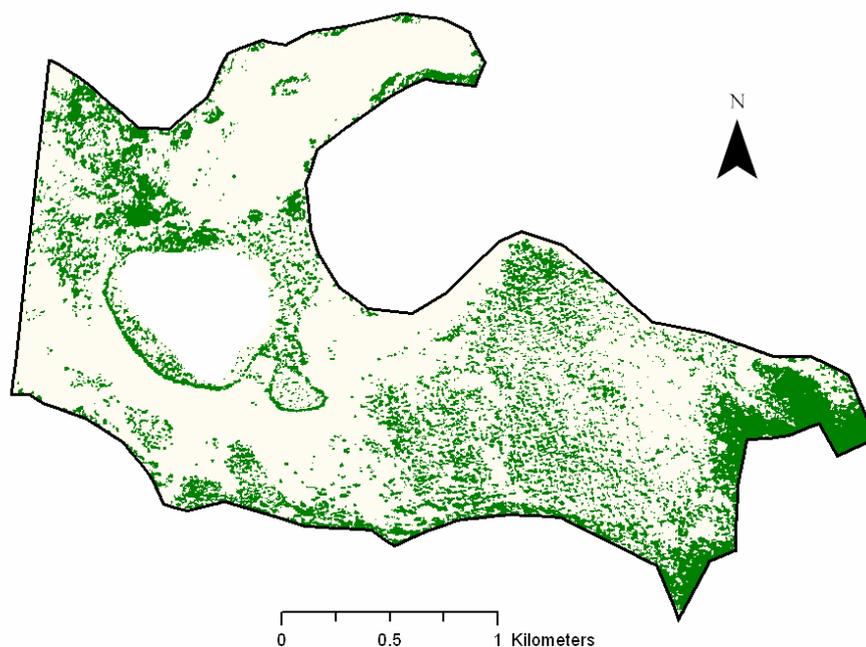


Figure 4.14 Final 1950 classified maps showing the distribution of *Melaleuca* spp across the study area

Table 4.7 Error matrix for the automated and final level 1 classification for the 1950 aerial photograph. Referenced dataset produced from manual interpretation of 250 random points from the 1950 aerial photograph.

Automated level 1

1950 Classification

		Reference data					
		Mel	other	total	OE %	CE %	Mapping accuracy %
classified	Mel	74	12	86	17.8	13.3	72.55
	other	16	148	164	7.5	10.0	84.09
map		total	90	160	250		
		PA %	82.2	92.5			
		CA %	86.0	90.2			
		Overall accuracy =	88.80%				
		k^{\wedge} =	0.75				

PA = producers accuracy, CA = consumers accuracy, OE = omission error

CE = commission error

Final 1950

Classification

		Reference data					
		Mel	other	total	OE %	CE %	Mapping accuracy %
classified	Mel	72	9	81	20.0	10.0	72.73
	other	18	151	169	5.6	11.3	84.83
map		total	90	160	250		
		PA %	80.0	94.4			
		CA %	88.9	89.3			
		Overall accuracy =	89.20%				
		k^{\wedge} =	0.76				

PA = producers accuracy, CA = consumers accuracy, OE = omission error

CE = commission error.

4.3.2 1975

The final 1975 classified map is presented in Figure 4.15. The automated 1975 classification recorded an overall accuracy of 89% and a Kappa coefficient score of 0.73. Mapping accuracy for class '*Melaleuca* spp' was 68%, and 'other' 85% (Table 4.7). The environmental conditions at the time of acquisition for the 1975 image, with much of the floodplain covered by water, reduced the amount of visible not woody vegetation significantly. Despite the

favourable environmental conditions (which enabled clear discrimination between the two classes) and the high estimated accuracy, it was clear that areas of other vegetation were being classified as *Melaleuca* spp. No parameter could be found to separate the overlap between the classes, so areas of other vegetation were then manually classified into the correct class. Error assessment was then conducted and the final 1975 classification had an overall accuracy estimated at 91% and a Kappa coefficient value of 0.77 (Table 4.8). There was only a slight increase in the mapping accuracy of both classes ‘*Melaleuca* spp’ of 71% and ‘other’ 88%.

Table 4.8 Error matrix for the automated and final level 1 classification for the 1975 aerial photograph. Referenced dataset produced from manual interpretation of 250 random points from the 1975 aerial photograph.

Final 1975

Classification

		Reference data					
		Mel	other	total	OE %	CE %	Mapping accuracy %
classified map	Mel	58	14	72	13.4	20.9	71.6
	other	9	169	178	7.7	4.9	88.0
	total	67	183	250			
PA %		86.6	92.3				
CA %		80.6	94.9				
Overall accuracy =		90.80%					
k [^] =		0.77					

PA = producers accuracy, CA = consumers accuracy, OE = omission error

CE = commission error

Automated level 1

1975 Classification

		Reference data					
		Mel	other	total	OE %	CE %	Mapping accuracy %
classified map	Mel	58	9	76	13.4	26.9	68.2
	other	18	165	174	9.8	4.9	85.9
	total	67	183	250			
PA %		86.6	90.2				
CA %		76.3	94.8				
Overall accuracy =		89.20%					
k [^] =		0.73					

PA = producers accuracy, CA = consumers accuracy, OE = omission error

CE = commission error.

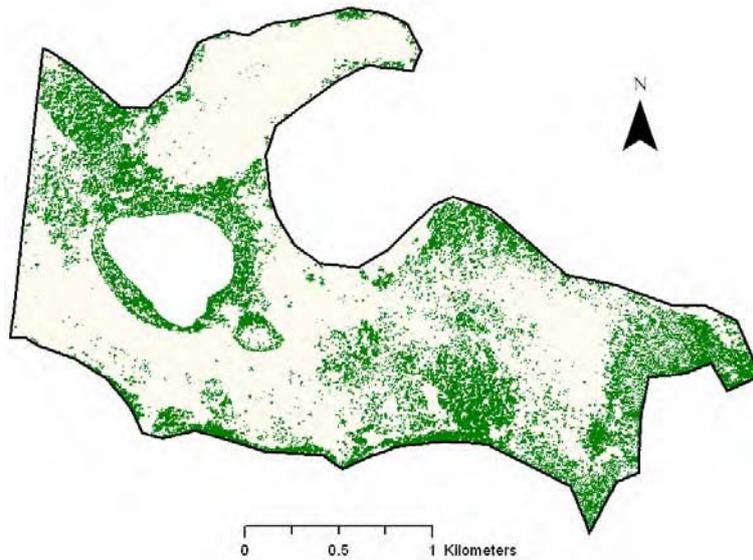


Figure 4.15 Final 1975 classified maps showing the distribution of *Melaleuca* spp across the study area

4.3.3 1996

The error matrix for the automated classification of level 1 indicates that there was an over estimation of *Melaleuca* spp within the image. The commission error for the *Melaleuca* spp class was very high at 86%, indicating that the majority of the error was within the woody vegetation areas. There was spectral overlap between the *Melaleuca* spp and understory vegetation which could not be sufficiently separated using automated classification techniques. The automated 1996 classifications overall accuracy was estimated at 73% with a Kappa score of 0.41. Mapping accuracy of the *Melaleuca* spp class was low at 42% and the class 'other' was 67%. Manual classification was performed to raise the accuracy of the classification. The final classified 1996 image is presented in Figure 4.16 the overall accuracy was estimated to be 82% with a Kappa coefficient score of 0.56 (Table 4.9). The estimated mapping accuracy of each class was *Melaleuca* spp 51% and 'other' 79%.

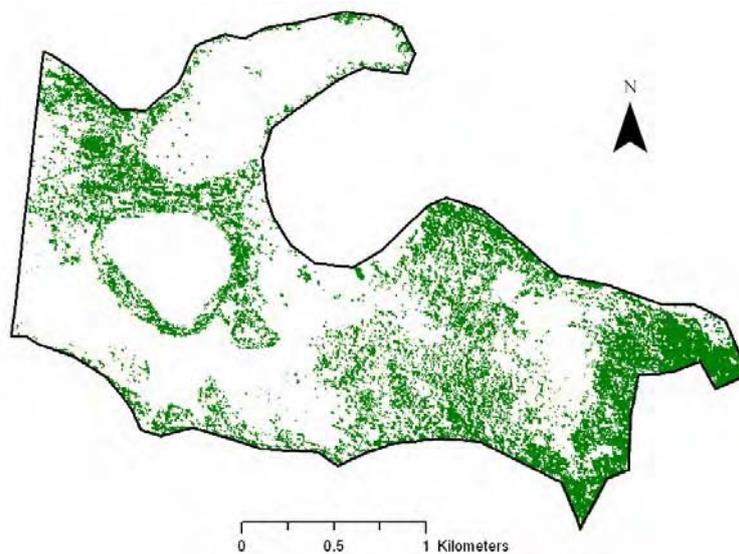


Figure 4.16 Final 1996 classified maps showing the distribution of *Melaleuca* spp across the study area

Table 4.9 Error matrix for the automated and final level 1 classification for the 1996 aerial photograph. Referenced dataset produced from manual interpretation of 250 random points from the 1996 aerial photograph.

Final 1996 Classification

		Reference data								
		Mel	other	total	OE %	CE %	Mapping accuracy %			
classified map	Mel	45	26	71	27.4	41.9	51.1			
	other	17	162	179				13.8	9.0	79.0
	total	62	188	250						
PA %	72.6	86.2								
	CA %	63.4	90.5							
	Overall accuracy =	82.8%								
	\hat{k} =	0.56								

PA = producers accuracy, CA = consumers accuracy, OE = omission error

CE = commission error.

Automated level 1

1996 Classification

		Reference data								
		Mel	other	total	OE %	CE %	Mapping accuracy %			
classified map	Mel	49	53	62	21.0	85.5	42.6			
	other	13	135	188				28.2	6.9	67.1
	total	62	188	250						
PA %	79.0	71.8								
	CA %	48.0	91.2							
	Overall accuracy =	73.6%								
	\hat{k} =	0.41								

PA = producers accuracy, CA = consumers accuracy, OE = omission error

CE = commission error

4.3.4 2004

The error matrix produced to assess the level 1 automated classification shows that there was significant confusion between areas of other vegetation and *Melaleuca* spp. The commission error for *Melaleuca* spp class was very high, 84%. The overall mapping accuracy of the class '*Melaleuca* spp' was very low at 36% and 'other' 58%. Overall accuracy for the automated level 1 classification was poor, estimated to be 66% with a Kappa coefficient score of 0.28. The similar spectral properties of other vegetation and *Melaleuca* spp did not enable discrimination between the classes. Manual classification was performed, which significantly reduced the commission error for the *Melaleuca* spp class to 19% (Table 4.10). The overall accuracy of the final 2004 classification estimated from the 250 randomly generated point

data was 85% with a Kappa coefficient score of 0.64. Mapping accuracy of the ‘*Melaleuca* spp’ and ‘other’ class was 58% and 82% respectively. The final 2004 classification is presented in Figure 4.17. Ground truthing data was also used to estimate the accuracy of the 2004 final classification. The overall accuracy of the final classification was estimated to be 81% with a Kappa coefficient score of 0.59 (Table 4.11). Mapping accuracy for each class ‘*Melaleuca* spp’ and ‘other’ was estimated to be 76% and 57% respectively.

Table 4.10 Error matrix for the automated and final level 1 classification for the 2004 aerial photograph. Referenced dataset produced from manual interpretation of 250 random points from the 2004 aerial photograph.

Automated level 1

2004 Classification

		Reference data					
		Mel	other	total	OE %	CE %	Mapping accuracy %
classified	Mel	48	61	109	33.3	84.7	36.0
	other	24	117	141	34.3	13.5	57.9
map	total	72	178	250			
	PA %	66.7	65.7				
	CA %	44.0	83.0				
	Overall accuracy =	66.0%					
	\hat{k} =	0.28					

PA = producers accuracy, CA = consumers accuracy, OE = omission error

CE = commission error.

Final 2004

Classification

		Reference data					
		Mel	other	total	OE %	CE %	Mapping accuracy %
classified	Mel	50	14	64	30.6	19.4	58.1
	other	22	164	186	7.9	12.4	82.0
map	total	72	178	250			
	PA %	69.4	92.1				
	CA %	78.1	88.2				
	Overall accuracy =	85.6%					
	\hat{k} =	0.64					

PA = producers accuracy, CA = consumers accuracy, OE = omission error

CE = commission error

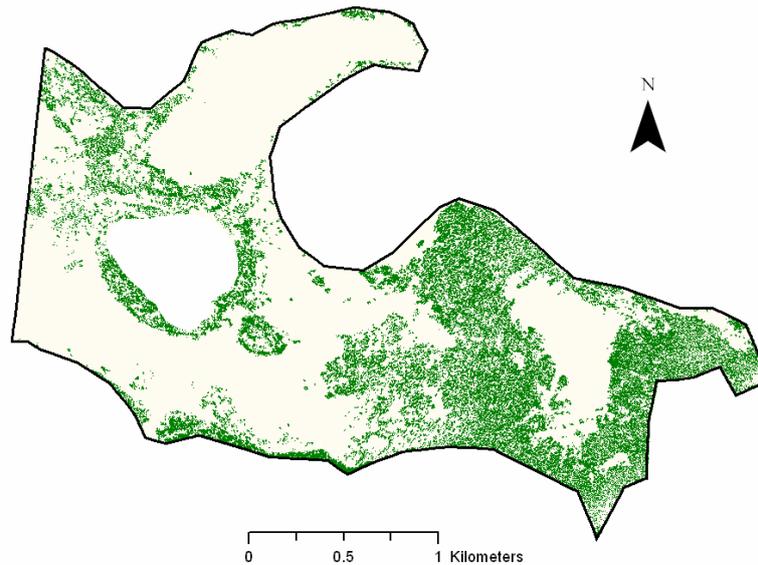


Figure 4.17 Final 2004 classified maps showing the distribution of *Melaleuca* spp across the study area

Table 4.11 Error matrix based on the final classification of the 2004 aerial photograph. Reference map generated from ground truthing data collected during August 2005.

Final 2004

Classification

		Reference data			OE %	CE %	Mapping accuracy %
		Mel	other	total			
classified map	Mel	38	3	41	19.1	6.4	76.0
	other	9	16	25	15.8	47.4	57.1
	total	47	19	66			
	PA %	80.9	84.2				
	CA %	92.7	64.0				
	Overall accuracy =	81.8%					
	\hat{k} =	0.59					

PA = producers accuracy, CA = consumers accuracy, OE = omission error

CE = commission error

4.4 Discussion

Differences in quality and the environmental conditions present within each aerial photograph influenced the ease of classification. Despite the fact that each image was acquired around the same time of year (between May and July), the environmental conditions captured in each photograph were different. This is largely due to the variations of seasonal patterns in climate. While the two distinct seasons known as the wet and the dry in northern Australia are very reliable, the timing and duration of each season can be highly variable (McDonald & McAlpine 1991). This seasonal variation in climate has a great influence on the annual and perennial vegetation of the floodplain environment (Cowie et al 2000, Finlayson et al 1989).

The 1975 image was captured after an above average wet season (Williams, 1979), this is evident in the image as large tracts of the study area were completely inundated, obscuring other vegetation. This is in contrast to the 1996 and 2004 images, where the heterogenous nature of the vegetation in floodplain environments was very apparent. The complexity of the images from 1996 and 2004 made classification for these years extremely difficult, as evidenced by the results of the accuracy assessment for the automated classifications of level 1 for each image. This ‘simplification’ of the imagery also aided the classification process within the 1950 imagery, where objects classified as *Melaleuca* spp were primarily represented by dark pixels.

One reason for the significant commission error in the *Melaleuca* spp class of the automated 1996 and 2004 level 1 classifications was partially due to the inability of the segmentation process to cleanly separate between the *Melaleuca* spp and other vegetation. Multiresolution segmentation of an image derives significant information from the spectral values of individual pixels; it is usually the most important factor in the creation of meaningful objects (Baatz et al 2004). Difficulties arise when the spectral properties of the different classes are similar. Increasing the value of the shape parameter in the composition of homogeneity criterion will reduce the level of influence spectral values have in creating the objects. As can be seen in Table 4.1, the spectral values influence on the segmentation process was reduced in the 2004 image in an attempt to try and enable better separation of the *Melaleuca* spp and other vegetation. The compactness parameter which is part of the shape criterion was also given a higher value as this is able to better discriminate between objects with similar spectral values but different shape (Baatz et al 2004). Whilst it was considered to give a better overall result in the segmentation process it was still not always able to sufficiently separate between the different classes. In this project all spectral bands were evenly weighted in the segmentation process. Walker and Briggs (2005) found that the red and blue bands in their true colour aerial photographs appeared to segment the image best. It is possible that identifying a single or combination of the three spectral bands available from the aerial photographs in the project may have resulted in better separation of the vegetation types.

Typically vegetation studies using automated classification techniques rely heavily on areas of the electromagnetic spectrum such as the infrared region, as it best discriminates between different vegetation species (Ahmad et al 1998, Harvey & Hill 2001). The spectral properties of panchromatic and true colour aerial photographs originate from the visible range of the electromagnetic spectrum (0.30–0.72 μm), which does not differentiate as well between different vegetation types (Figure 4.18) (Campbell 1996).

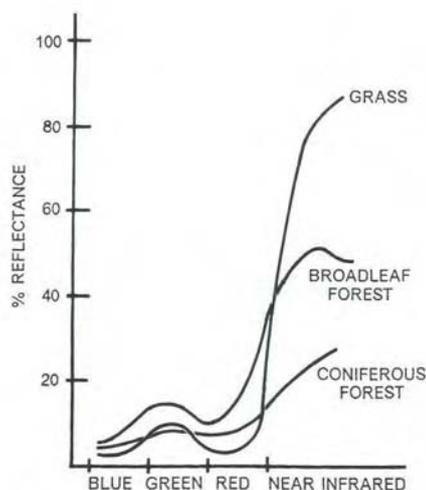


Figure 4.18 Example of the different abilities of the visible (Blue, Green, Red) and near infrared spectrum in discriminating between vegetation types (adapted from Campbell 1996)

Other factors complicating the automated classification of aerial photographs are related to the bidirectional reflectance distribution function (BRDF). BRDF is caused by illumination conditions, viewing geometry, atmospheric conditions, topography, landcover and vegetation types (Pellikka et al 2000, Tuominen & Pekkarinen 2004). BRDF describes mathematically the effect of optical behaviour in relation to the angles of illumination and observation of a surface plane (Campbell 1996) The affect of BRDF is more pronounced in images like aerial photographs which are generally acquired at low altitudes using sensors with wide angle lenses (Tuominen & Pekkarinen 2004). Brightness differences in aerial photographs are also caused by the light exposure fallout effect (Holopainen & Wang 1998). This effect is related to the distance of a point in the image from the image centre, with the exposure at maximum at the principle point and decreasing with radial distance from the centre of the image. This effect is usually compensated for with antivignetting filters (Tuominen & Pekkarinen 2005). As a result of both the BRDF and exposure fallout effects, similar objects (eg *Melaleuca* spp) can have very different spectral properties within the same image (Holopainen & Wang 1998). Attempts to classify the 1996 aerial photograph using similar methods developed for the 1950, 1975 and 2004 aerial photographs was unsuccessful due to the increased BRDF effect. The knowledge base developed for the classification hierarchy for the 1996 image did help to compensate for the influence of BRDF. However the limited spectral properties of the aerial photographs still prohibited separation of understory vegetation.

The aerial photographs used for this project were scanned at a radiometric resolution of 8-bits. Radiometric resolution refers to the number of digital levels used to express the information collected by the sensor (Mather 1999). An image with 8-bit resolution represents data with values ranging between 0-256 grey levels (Campbell 1996). Increasing the bit resolution to 11-bit will increase the possible value range representing the data to 0–2048 grey levels (Laliberte et al 2004). Scanning the original images at a higher radiometric resolution may enable greater discrimination between different vegetation characteristics on the floodplain. Laliberte et al (2004) used a combination of aerial photographs and satellite imagery (QuickBird) to map woody vegetation encroachment. They reported that the panchromatic band of their QuickBird image, which is acquired at a similar spectral resolution as the aerial photographs was able to detect small shrubs missed by the aerial photographs, due to the increased bit resolution (11-bit) (Laliberte et al 2004). Mather (1999) cites (Tucker 1979) who investigated the relationship between radiometric resolution and improved discrimination of vegetation types; it was found that increasing the bit level from 6-bit (64 levels) to 8-bit (256 levels) only led to an improvement of between 2–3%. Increasing the radiometric resolution of the images may help to increase the level of classification accuracy; however, increasing the bit depth may be prohibitive as it will greatly increase the storage requirements and processing time required for each dataset.

While historical aerial photographs provide an insight into the past not available in other forms of imagery (Kadmon & Harari-Kremer 1999), the restrictions on the availability of images acquired at the same spatial and spectral resolution introduces a variety of problems. Differing spatial and spectral resolution and image quality must be taken into account when interpreting the results of data derived from historical aerial photographs (Laliberte et al 2004). It is highly probable that the differing scales and radiometric resolutions of temporal aerial photographs can lead to omission of smaller objects in small scale photographs (Laliberte et al 2004). The reduction in the available detail and quality of the 1950 image was due to a number of factors such as the smaller scale (1:50 000), the use of a single (panchromatic) band, and technological factors related to film and camera quality. These factors may have also led to errors of omission in relation to small *Melaleuca* spp in the 1950

aerial photographs. Also as a result of the 1950 image scale and quality, objects identified as *Melaleuca* spp in some areas may also be tree shadow. The smoothing of the 1996 image may have also led to a reduction in the number of small *Melaleuca* spp detected. Visual inspection between the raw and smoothed 1996 aerial photographs suggests that this was not a problem. However, the high commission error for the *Melaleuca* spp class in the final 1996 classification suggests that areal extent of canopy cover may be over estimated; this needs to be taken into account when interpreting the data.

Despite the obvious high spatial resolution of aerial photographs, the ability to discriminate between objects due to reduced spectral resolution has been a major hurdle in the development of automated classification methods (Tuominen & Pekkarinen 2005). The classification of aerial photographs has traditionally been done using a variety of manual interpretation techniques (Yohay & Kadmon 1998). Humans interpret aerial photographs using a combination of elements which include; image tone, texture, shadow, pattern, association, shape, size, and site (Campbell 1996). A number of these elements such as size, tone, shape, texture and association were incorporated into the development of classification knowledge bases used in this project. One of the main elements used by humans to manually classify aerial photographs is texture (Tuominen & Pekkarinen 2005). An advantage of high resolution aerial photographs is that it enables the ability to use texture as a parameter for automated classification (Hudak & Wessman 1998). Texture was an important feature that enabled the discrimination between the broad classes, woody and not woody areas in the 1975 and 2004 level 2 classifications. It was, however, not a feature used in the level 1 classifications as the finer scale of objects representing *Melaleuca* spp and the other vegetation had similar spectral signatures. This was particularly obvious within the stands of *Melaleuca* forest.

Despite the limited spectral separation between objects this project still relied largely on spectral features (as detailed in Table 4.3 & 4.5) to train the classification algorithms for each class. The shape features of objects were only found to be useful in the 'tree' and 'other' classes of level 1 in the 1996 classification. Walker and Briggs (2005) also found that shape features were not utilised in extraction of arid urban forest using true colour aerial photographs. They reported that the fine scale required in the segmentation process was the likely reason (Walker & Briggs 2005). In this project the only time shape features were used was in the 1996 smoothed image. Laliberte et al (2004) reported that the smoothing of the image using low-pass filters should enable shrubs to be represented by fewer and more homogenous objects. Smoothing the 1996 image may have enhanced the use of shape features of the objects generated in the segmentation process. The level of success in this project was due to the ability to classify different characteristics within the same image. This enabled the development of object associations similar to the way humans would interpret an image. This greatly reduced the impact of spectral confusion caused by BRDF and the limited capabilities of the visible range of the electromagnetic spectrum. Image pre-processing of the 1996 image also helped to improve the classification process.

Halounová (2004) used a combination of image pre-processing methods to enhance signature space in panchromatic aerial photographs. Enlarging the signature space was achieved by running low-pass filters over the images and then using a Haralick function which characterised the different textures of the aerial photograph. The resulting images were then successfully classified using object-orientated methods (Halounová 2004). It is also possible to introduce other spatial data to assist in the development of the classification hierarchy in eCognition (Baatz et al 2004, Bock et al 2005). A combination of different classification methods using per-pixel, and object-based classification algorithms were found to improve

the classification of mangrove species using IKONOS satellite imagery (Wang et al 2004). Exploring different methods of image pre-processing and possibly incorporating unsupervised per-pixel based classification may assist in the automated classification of aerial photographs.

Evaluating the accuracy is an important component in any remote sensing project (Congalton 1991). Statistically the assumption is usually made that the reference dataset created is 100% correct. This is rarely valid, which can lead to a poor assessment of the classification (Congalton 1991). The photointerpretation methods used in this project may have lead to an optimistic or conservative bias in the classification estimates. This bias may have occurred as the same person manually interpreted both the final classified maps and the reference maps used to generate the accuracy assessments. However, there was very little difference between the results of the accuracy assessment of the 2004 final classified image using both the ground truthing and photointerpretation data. This indicates that the photointerpretation methods used did not result in any significant bias in the estimates, and provides confidence that the photointerpreted datasets were valid test datasets for assessing the accuracy of the 1950, 1975 and 2004 classifications.

One prerequisite for ground truthing data collection is to ensure each class is sufficiently represented and survey points cover the entire study site (Congalton 1991). The limited collection of the survey points, due to restricted access to large areas of the study site may have reduced the precision of the accuracy estimate. It was likely that the overall accuracy of the class 'other' was reduced as it was only represented by 19 sample points. Congalton (1991) suggests that a good rule of thumb is to collect a minimum of 50 samples for each class.

4.5 Conclusion

A semi-automated, multi-scale object-based approach was successfully used to classify a portion of the Magela floodplain, using both panchromatic and true colour aerial photographs. The level of manual classification used to produce the final product was related to environmental conditions at the time of capture for each aerial photograph. This resulted in an increase in overall accuracy for the 2004 image from 66% to 85%. Despite the limitations of aerial photographs in automated classification methods, the construction of a knowledge base using a multi-scaled approach enables the development of a method resembling the way humans interpret an image. This increases the ability to classify aerial photographs using automated classification techniques. However, increasing image complexity was found to decrease the accuracy of automated classification techniques. To reduce image complexity, pre-processing using a low-pass filter was found to benefit the overall classification process. The use of advanced pre-processing techniques, a combination of different classification algorithms, and the incorporation of other spatial data may increase the ease of which aerial photographs can be classified using automated techniques.

Chapter 5 Change analysis

5.1 Introduction

Change detection using remote sensing and GIS technology is a process where comparisons are made between two or more datasets with similar spatial and spectral properties (Campbell 1996, Coppin et al 2004, Johnston 1998). A variety of methods have been developed to successfully detect change using a range of sensor platforms and products (Lu et al 2003), including aerial photographs. Aerial photographs are a particularly valuable resource for studies investigating temporal change in the landscape (Yohay & Kadmon 1998) as they provide historical data which is unavailable in other forms of remotely sensed images (Lucas et al 2002). In tropical Australia, aerial photographs have been used to investigate spatial and temporal patterns of exotic (Brown & Carter 1998) and native (Banfai & Bowman 2005, Bowman et al 2001) woody vegetation invasion of grasslands. They have also been used to investigate changes in mangrove (Lucas et al 2002, Lucas et al 2005) and floodplain communities (Freeman 2005, Riley & Lowry 2002, Williams 1984).

The ability to integrate remote sensing and GIS technologies is particularly valuable to agencies or organisations responsible for developing and applying land management and conservation policies, as it provides a means of monitoring the condition and health of an area over a period of time (Campbell 1996, Finlayson & Rea 1999, Lowry & Finlayson 2004). Thus, for many natural resource managers and ecologists concerned with the analysis of spatially referenced data, the use of GIS has become an essential tool (Johnson & Gage 1997). In this chapter the methodology employed, and results acquired from monitoring changes in the spatial and temporal distribution of *Melaleuca* communities on a section of the Magela floodplain from 1950-2004 are described and discussed. In addition, the results from this study are compared with those of two earlier studies by (Riley & Lowry 2002, Williams 1984). While investigating the possible factors that may be driving the observed changes was beyond the scope of the project, several possibilities are identified and discussed.

5.2 Methods

As shown in Figure 5.1, classified datasets were initially exported from eCognition 4.1 into Erdas Imagine (.img) format. As the classes of each individual classification were different, it was necessary to reclassify each dataset so all attributes were equal and suitable for further analysis. This was done using the Spatial Analyst extension in ArcView™ v9.1.

Two classes were created to represent the presence (value of 1) or absence (value of 0) of *Melaleuca* spp across the study area. The pixel size and extent of the classified images were changed to match the 1950 image, which had the coarsest resolution (1950; pixel size 1.1 m).

Calculating the extent of *Melaleuca* spp canopy coverage

To calculate the extent of the two classes (*Melaleuca* spp and not *Melaleuca* spp) for each time period, the sum of pixels attributed to each class were multiplied by the area of a pixel.

$$TA = n \times a$$

where TA = Total area attributed to a class.

and n = number of pixels attributed to a class.

a = area of a pixel (which was 1.21 m²)

Change analysis

There are a wide variety of digital methods used to detect and assess change in remotely sensed imagery (Lu et al 2003, Sunar 1998). The method chosen for this project was image differencing of the classified images. This method subtracts the first date image from the second date image to record differences; it is defined as an image algebra method which applies arithmetic operations to pixels of each classified image (Campbell 1996, Lu et al 2003).

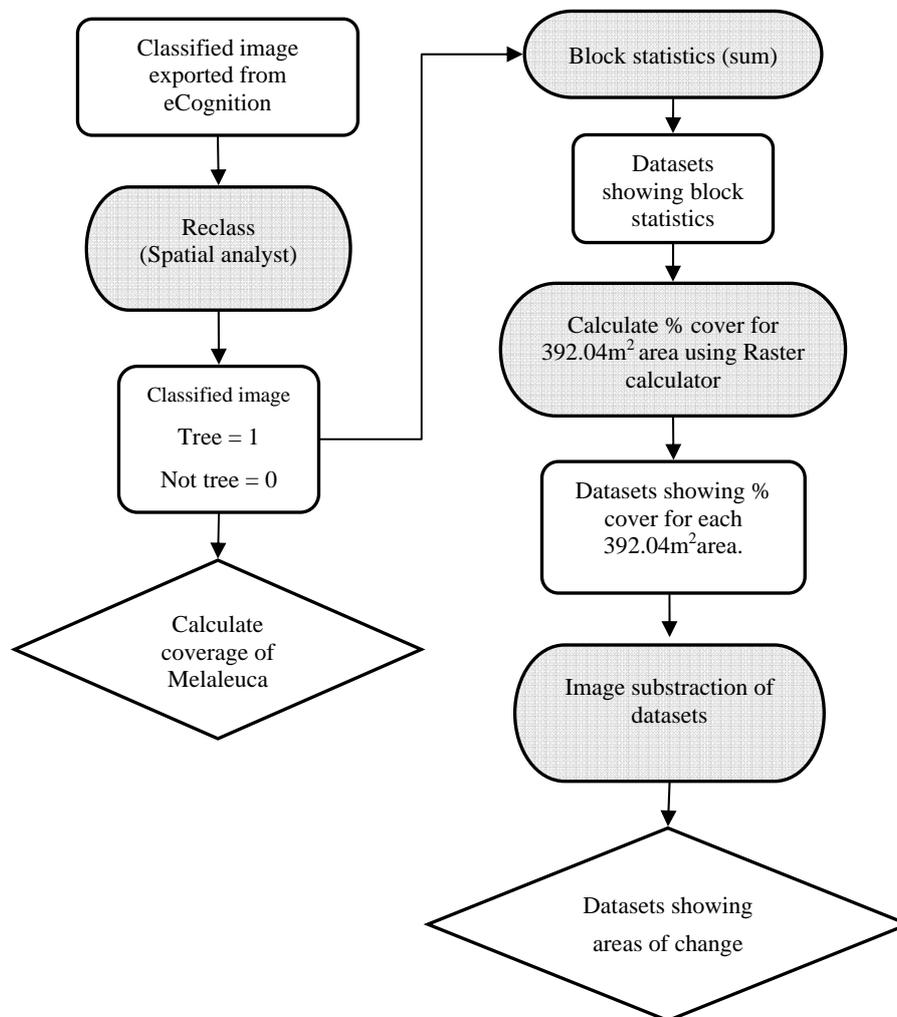
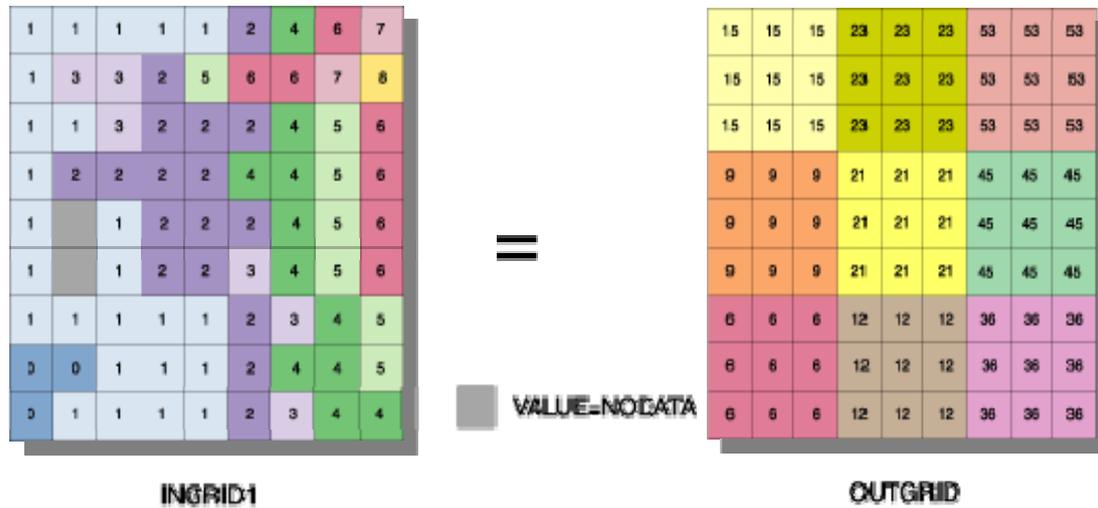


Figure 5.1 Schematic diagram showing the steps taken in the change analysis

Visual inspection of the georectified aerial photographs as described in chapter 3 indicated that miss-registration between the images was low. However, in an effort to compensate for positional error between the datasets caused by geometric distortion, the Block statistics function (available in Arc Toolbox™) was used to generate datasets to assess temporal and spatial change across the three time periods. Block statistics calculate a defined value (eg. maximum, minimum, mean, and sum) for fixed neighbourhoods which do not overlap. This analysis results in the generation of a new raster dataset, where the value generated from the Block statistic is attributed to the extent of the neighbourhood which is defined by the analyst (Fig 5.2). The neighbourhood types available for the Block function are wedge, annulus, circle, and rectangle (ArcGIS Desktop Help v 9.1). The rectangle neighbourhood was used with an extent of 18 x 18 pixels (19.8 x 19.8 meters), representing an area of 392.04 m² per

neighbourhood. This analysis calculated the sum of cells within each 392.04 m² neighbourhood; it then attributed the calculated value to each cell within that neighbourhood. The 392 m² area was selected as it would compensate for the spatial and geometric distortion in the image, while still retaining the fine detail obtained in the classification process.

Figure 5.2 Illustration showing the results of the Block statistics function. (a) Input raster grid (b) output



Expression: BLOCKSUM(INGRID1, RECTANGLE, 3, 3)

raster grid after Block sum (Adapted from ArcGIS Desktop Help v9.1).

As the pixels representing *Melaleuca* spp were given the value of 1 and each cell represents an area of 1.21 m², the Block statistics data were then used to calculate percentage cover value for each 392.04 m² area across each image. This was done using the raster calculator in the Spatial Analyst extension in ArcView™ v9.1. The expression used in the raster calculator was; $(([\text{blockstats_grid}] * 1.21) / 392.04) * 100$

This generated a dataset where each cell within each 392.04 m² neighbourhood was given a percentage of *Melaleuca* spp cover value.

The raster calculator was then used to subtract the earlier (percentage cover estimate) image from the later image to produce datasets showing the spatial patterns of change between the three time periods. The resulting datasets contained ± values, representing the magnitude of change in percentage cover estimated to have occurred at each spatial location for each 392.04 m² neighbourhood.

5.3 Results

Melaleuca spp canopy cover

The total area of *Melaleuca* spp estimated to cover the study area in 1950 was 118.9 ha, representing 23% of the study area. By 1975 the extent of cover had increased by 14.4 ha to 133.4 ha (26%), and in 1996 *Melaleuca* spp cover again increased slightly by 2 ha to 135.4 ha (27%). In 2004 there was a slight decline in cover of 15.4 ha to 120.4 ha (24%) (Fig 5.3 & 5.4).

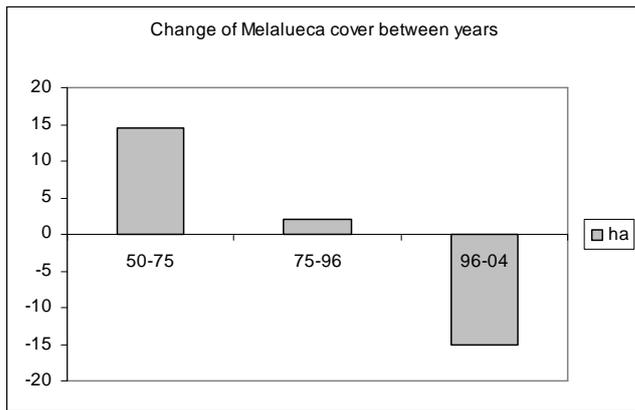


Figure 5.3 Chart showing the level of change in *Melaleuca* spp cover in hectares between the multitemporal datasets

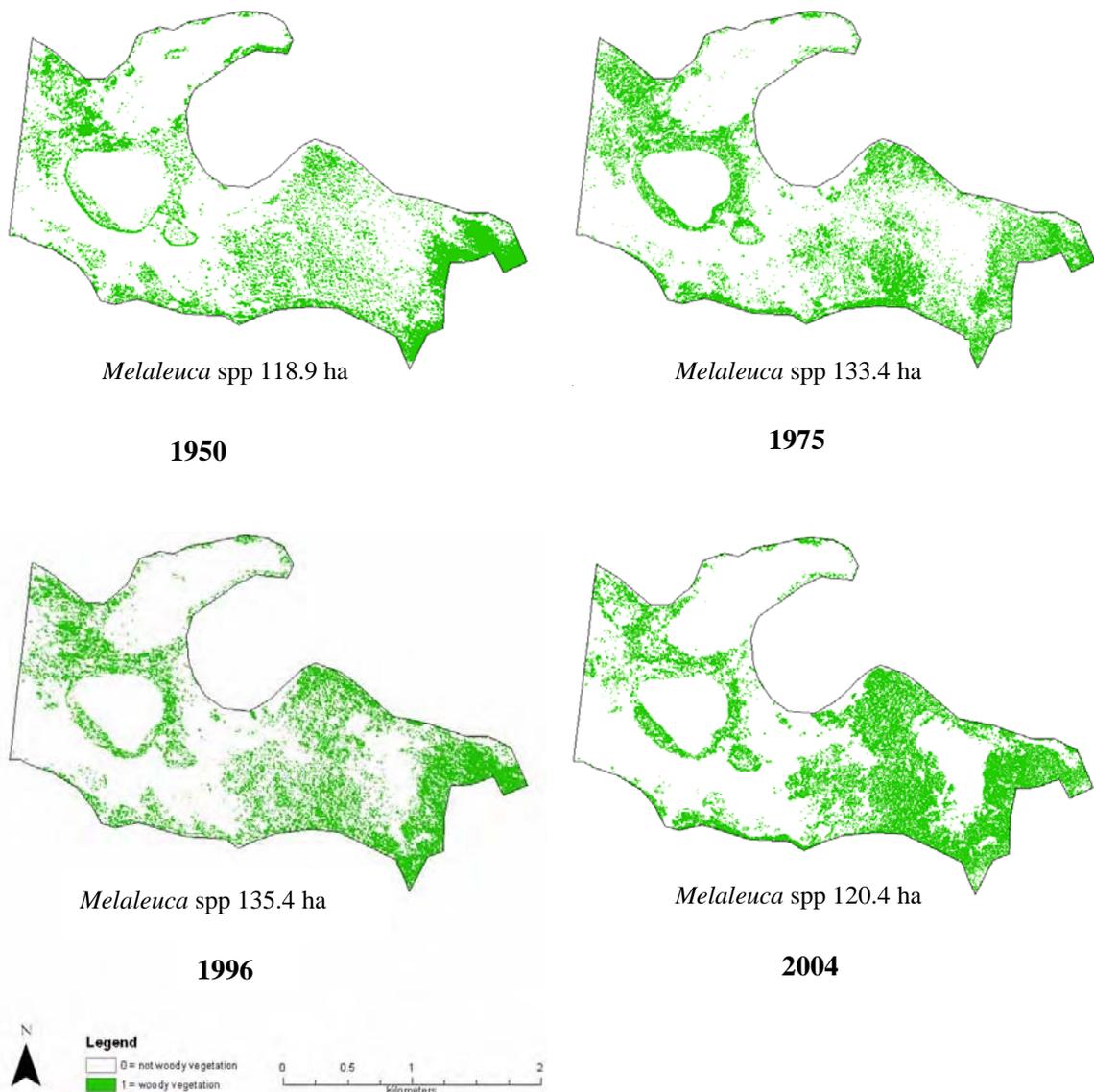


Figure 5.4 Classified images showing the spatial extent of *Melaleuca* spp cover for the study area for each time period

Spatial changes

The datasets in Figure 5.5 show the spatial variability in the percentage of *Melaleuca* spp cover (calculated in 392.04 m² neighbourhoods across the study area). While the quantitative results indicate that the magnitude of *Melaleuca* spp cover change over the 54 year period has not been large (approximately $\pm 3\%$ of the total study area), it is clear from visual assessment of the percentage cover datasets that large changes in the spatial distribution of *Melaleuca* spp have occurred.

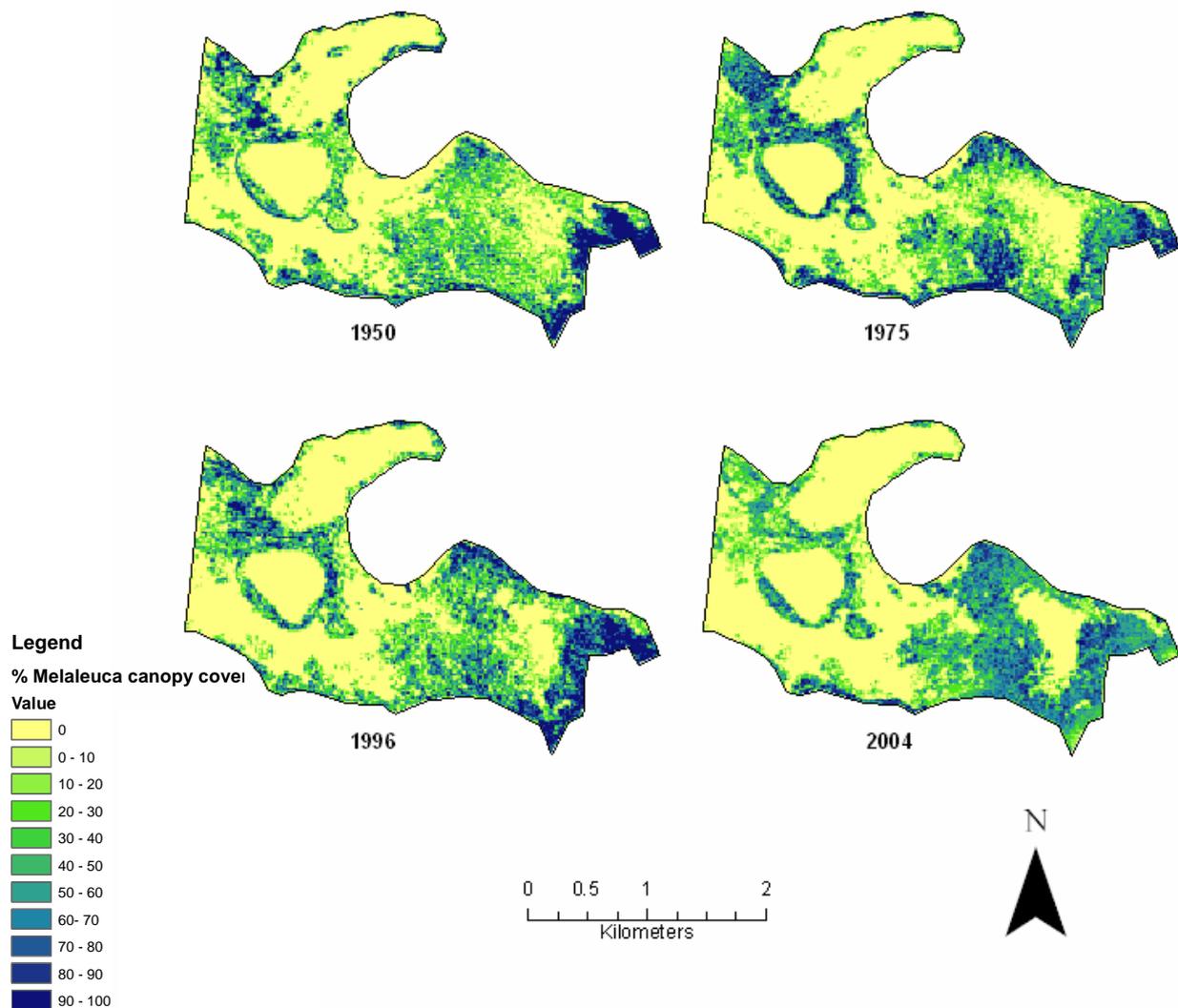


Figure 5.5 Percentage cover datasets created using Block statistics to investigate the multitemporal and spatial changes in *Melaleuca* spp cover

Image differencing between the multitemporal datasets was used to reveal the magnitude and spatial location of *Melaleuca* spp cover change (Fig 5.6). It appears that between 1950 and 1975 the increase was relatively evenly distributed across the study area. During the period 1975 to 1996 the overall *Melaleuca* spp cover increased slightly (2 ha), its distribution however had changed, with the largest increase occurring on the eastern side of the study area. During the eight year period between 1996 and 2004, *Melaleuca* spp coverage declined 15.1 ha. Again, the distribution changed with reductions occurring in patches distributed

across the study area and increases in the eastern side of the study area (Fig 5.6). The image differencing analysis shows that the spatial distribution of *Melaleuca* spp cover across the study area is variable. However, it appears that over the 54 year period increases have consistently occurred in the lower eastern region of the study area.

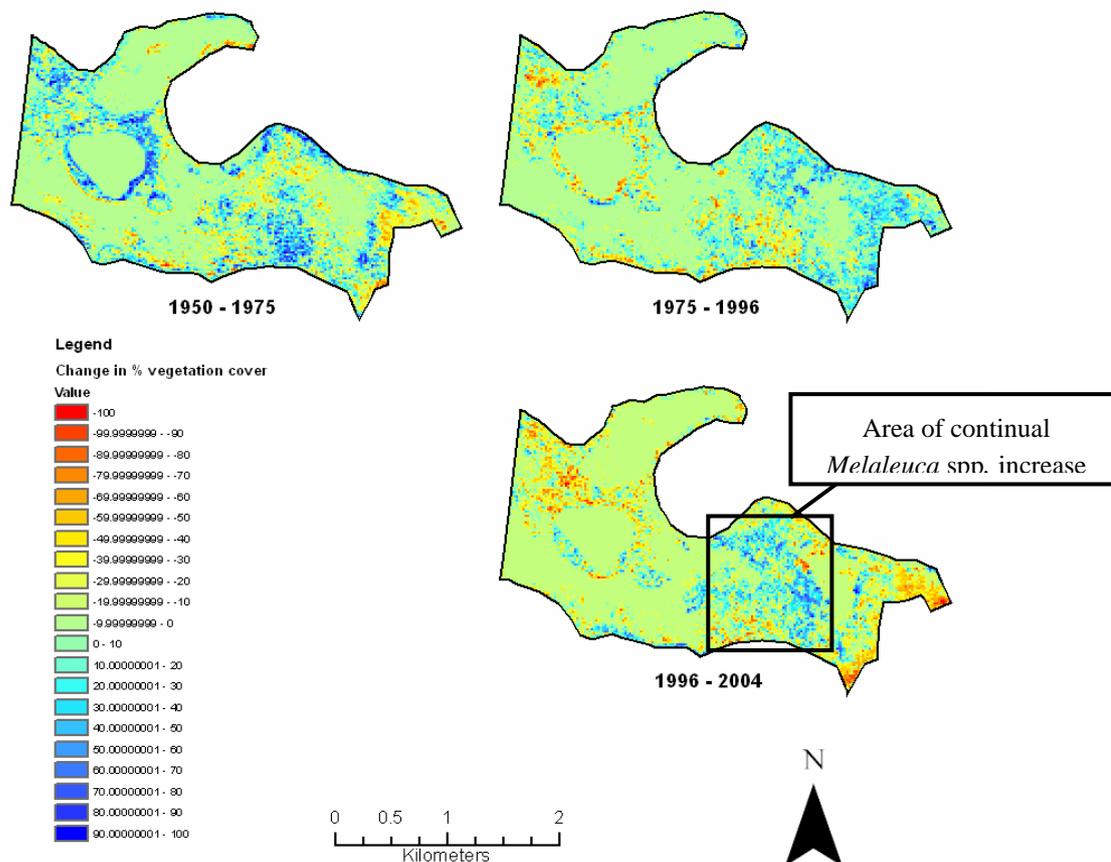


Figure 5.6 Datasets showing the magnitude and spatial location of change that occurred between the multitemporal datasets.

5.4 Discussion

The results of this study suggest that there has been little change in *Melaleuca* spp coverage between 1950 and 2004 in this portion of the Magela floodplain. As reviewed in chapter 2, Williams (1984) investigated the changes in *Melaleuca* forest density between 1950 and 1975 for the entire Magela floodplain. The extent of the study area used in this project was based on the region defined as sub-area 4 by Williams (1984). He reported no significant increase or decrease in density of *Melaleuca* spp in sub-area 4, based on the Kolmogorov-Smirnov two-sample test (Williams 1984). However, there was a decrease in the median density score between 1950 and 1975 from **3** = (1101–1600 trees/ km²) to **2** = (601–1100 trees/ km²) in sub-area 4. Williams (1884) results differ from the current study where a modest increase has been recorded.

A further study undertaken by Riley & Lowry (2002) (also reviewed in chapter 2) assessed the density of *Melaleuca* spp change between 1975 and 1996 for a 41 km² section of the Magela floodplain, including sub-area 4. Their results showed a median density of *Melaleuca* spp in 1975 and 1996 for sub-area 4 of 2600 and 1733 respectively (Riley & Lowry 2002).

Between 1975 and 1996 there was a reduction of 4,249 trees within the sub-area 4, representing a 37% reduction. Riley and Lowry (2002) compared their 1975 median density score results with the results of Williams (1984) and found that their score was higher. Riley and Lowry (2002) suggested the differences between their and Williams (1984) result may be due to the ability of GIS technology to accurately measure area and calculate precise density estimates compared to manual calculations using acetate overlay.

Williams (1984) and Riley and Lowry (2002) both report a decline in the overall *Melaleuca* spp density per km² for their respective studies. These results differ from the current study which suggests that between the periods of 1950–1975 there was a moderate increase (3%) in *Melaleuca* spp canopy cover, and during 1975–1996 there was a small increase (0.4%) over the entire study area of 4.9 km² (Table 5.1).

Table 5.1 Different changes recorded in *Melaleuca* spp in sub-area 4, as reported by Williams (1984), Riley and Lowry (2002) and this study

Different studies			
Time period	Williams (1984)	Riley & Lowry (2002)	Current study
1950–1975	Decrease 50 = (3)* 75 = (2)*		Increase in canopy cover 14%
1975–1996		Decrease (75 = 2600 trees km ²)# (96 = 1733 trees km ²)#	Increase in canopy cover 2%
1996–2004			Decrease in canopy cover 15%

* (3) = Median density score ranging between 601-1100 trees/ km²

* (3) = Median density score ranging between 1101-1600 trees/ km²

Median density of trees / km²

Due to the different methodologies used by Williams (1984) and Riley and Lowry (2002) and the fact that neither study reported any measure of error within their datasets makes it difficult to elucidate the differences between the results. There is always some element of error within any remotely sensed analysis (Hall et al 1991). It is important to recognise that the results of this study are not without error. Differences between the previous studies and this study could be due to artefacts of scale, spatial resolution, image quality, and methods used in image processing. Other potential sources of error are spatial and scale error. This can be caused by a number of factors including; geometric distortion caused by displacement in aerial photographs (Nielsen, 2004), reduction in the quality of the paper print image compared to the original film, or the geometric inaccuracy of desktop scanners (ERDAS 2002, Kadmon & Harari-Kremer 1999). Precise geometrical registration between images is an important prerequisite for any change detection analysis (Lu et al 2003), as misregistration between different images will produce spatial errors (Hall et al 1991). Error can be caused by a misclassification of pixels which can lead to either an underestimation or overestimation of change between datasets (Hall et al 1991). In the 1996 classified image the estimated overall error for the class '*Melaleuca* spp' may have resulted in an overestimation of the extent in canopy cover. Overestimation of canopy cover for 1996 may account for the differences

between the results of this study and Riley and Lowry (2002). Differences may also be due to the fact that this study was measuring actual canopy coverage, whereas the previous studies were calculating tree density, which did not take into account change in spatial coverage. It can be assumed that individual tree growth would have occurred during the intervening 21 year period (Fig 5.7), and as this study is estimating canopy cover, individual increases may have concealed the fact that the overall tree numbers had declined in 1996.

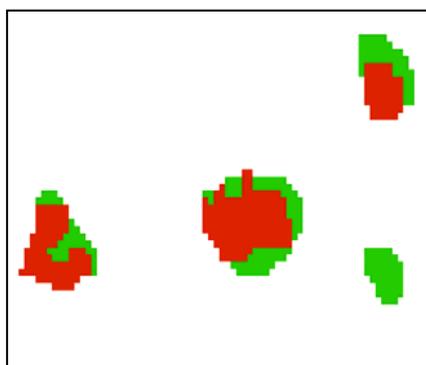


Figure 5.7 Example of changes in spatial coverage of *Melaleuca spp* (detected in this study) due to canopy growth between 1975–1996. Red = 1975. Green = 1996.

Human limitations and instrumental imperfections will always be factors that contribute to error within data (Wolf & Dewitt 2000). Several factors may have contributed to the differences in the results of this study and those reported by Riley and Lowry (2002). The quality of the scanning of the mosaics created for their study, particularly the 1996 dataset was poor due to limitations in equipment used (Riley & Lowry 2002). This may have led to an underestimation of tree points due to an inability to visually detect trees. Also the methodology used to estimate the clusters of points attributed to closed stands of *Melaleuca spp* may have led to an over or underestimation in the 1975 and 1996 dataset respectively. The large scale range used by Williams (1984) and the subjective nature of the method used to calculate the density of *Melaleuca spp* per m² may have also led to errors within his results. Williams (1984) also acknowledged that the scale and quality differences between the 1950 and 1975 aerial photographs may have led to bias in his calculations. As discussed in chapter 4 it is probable that bias due to scale and quality also occurred in this project.

Possible factors driving spatial distribution

The change analysis results reveal the spatial distribution of *Melaleuca spp* canopy cover has varied through time. Identifying the driver/s for this change is beyond the scope of this study. A number of factors have been identified as having possible negative impacts on *Melaleuca* forests specifically within the Magela floodplain. These range from the presence of the introduced water buffalo (*Bubalus bubalis*), and pig (*Sus scrofa*), the increase in invasive weeds, changes in fire regimes and increased periods of inundation (Bayliss et al 1997, 1998, Douglas & O'Connor 2004, Gardner et al 2002, Riley & Lowry 2002, Taylor & Dunlop 1985, Williams 1984). Williams (1984) discounted the effects of plant succession and sediment accumulation on the distribution of *Melaleuca spp* He suggested that strong winds, buffalo, and late-dry season fire were the probable cause. The results of this study suggest that the large stand in the lower eastern region of the study area has been steadily increasing during the past 54 years. Infilling of the wetland may be occurring, as this region of the study area is located at the base of the Ngarradj catchment. The distribution and density of *Melaleuca spp* varies throughout the coastal floodplains of the Northern Territory (Cowie et al 2000). This variation between floodplains cannot be readily explained through differences in

geomorphology. Although differences in species do generally follow distinct patterns of flooding and salinity tolerances (Cowie et al 2000). It is possible that changes identified in this study may be representing intra species changes in the distribution of *Melaleuca* spp, due to changes in rainfall patterns or succession due to sediment accumulation. The general lack of information in Australia to the response of wetland vegetation to changes in water level and sedimentation has been identified as a serious gap in knowledge (Finlayson & Rea 1999).

During the collection of field data evidence of extensive feral pig activity and areas of tree mortality presumed to be due to fire damage were observed; factors which may have an impact on the distribution of the *Melaleuca* spp (Fig 5.8).

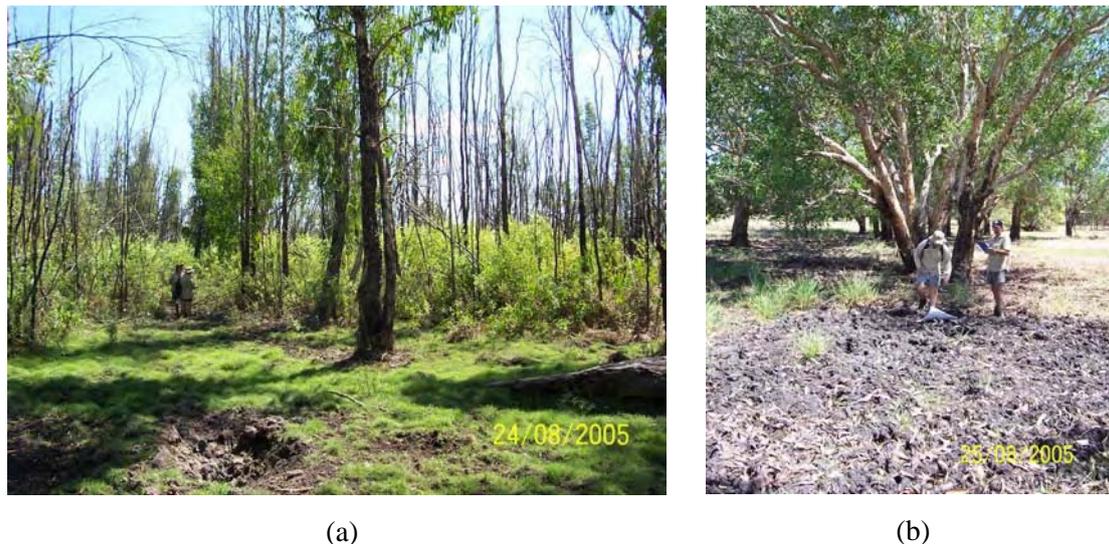


Figure 5.8 Photograph (a) shows area where there has been mortality of *Melaleuca* spp due to fire and subsequent vigorous regrowth of juveniles. Photo (a) and (b) both show damage caused by feral pig disturbance. (photo J Lowry)

Fire occurs regularly throughout the region, and mature *Melaleuca* stands have been identified as fire sensitive communities (Gill et al 2000, Russell-Smith et al 1997). While the floodplain is extensively flooded during the months of January – July (Williams 1979), fire may occur over large areas as it dries (Douglas & O'Connor 2004). Changes in fire regimens and intensity increase the chance of mortality in fire-sensitive woody vegetation (Douglas & O'Connor 2004, Rossiter et al 2003). Late, intense dry season fires may result in the death of *Melaleuca* spp (Cowie et al 2000). The invasive plant Para grass (*Urochloa mutica*) has been implicated in the death of a stand of *Melaleuca* spp on the Magela floodplain, as it has the ability to generate intense fires, due to increased fuel load (Douglas & O'Connor 2004). While *Melaleuca* spp are generally a fast growing pioneer species (Morris 1996) and their seedlings regenerate well in the ash bed of fires (Cowie et al 2000, Roberts 1997), new forests may take between ten and twenty years to develop (Morris 1996). During the collection of ground truthing data, evidence of the destructive nature of fire and the ability of *Melaleuca* spp to rejuvenate was observed (Fig 5.8).

During the collection of ground truthing data, (which occurred on the margins of the floodplain) several large herds of feral pigs were seen, and most areas visited had evidence of pig impact (Fig 5.8). The preferred habitat of feral pigs in the Northern Territory is monsoonal rain forest, floodplain margins, and riparian vegetation, (Caley 1997, DPIE 2003). Caley (1997) reported that water and shade were the probable explanation for the use of riparian vegetation strips in the Douglas-Daly region of the Northern Territory. Feral pigs were observed to play a significant role in the removal of root material from lower portions of

the banks of Magela creek during the dry season of 2002 (Erskine 2003). While it is acknowledged that the impact of feral pigs is detrimental to the environment, there is little quantitative evidence available for the Northern Territory (DPIE 2003, Edwards et al 2004, Russell-Smith & Bowman 1992). The main visual impact of pig damage is related to soil disturbance (Mitchell & Mayer 1997). In south-eastern Australia, pig rooting can change the species composition of native vegetation (Hone, 1995). Outside of Australia they have been shown to modify soil nutrients, reduce plant cover, alter plant species composition, and effect soil erosion (Mitchell & Mayer 1997). Research on the effect of native pigs (*Sus scrofa*) on woody understory vegetation in a lowland rain forest in Malaysia has shown that native pigs play an important role in plant dynamics at the understory level (Ickes et al 2001). Ickes et al (2001) found that the number of seedling recruits within their enclosure plots were three times higher than the unfenced control plots; they also reported that pigs detrimentally affected stem density, species richness, growth and possibly mortality (Ickes et al 2001). Clearly both feral pigs and fire have the potential to disturb ecological function. The results of this study suggest that dynamic changes in distribution of *Melaleuca* spp canopy cover have occurred through time. Identifying and understanding the complex relationships between the various causal factors driving vegetation change is complex and requires further research (Banfai & Bowman 2005).

As the results presented here represent only a small proportion (4.9 km²) of a much larger floodplain system, the findings cannot be used to comment on or extrapolate to the entire floodplain; this requires further investigation.

5.5 Conclusion

The results presented here show that the application of GIS can be successfully used to investigate spatial and temporal changes in *Melaleuca* spp cover within the study area. Although there has been little net reduction in canopy cover over the 54 year period, the use of functions within the GIS platform have enabled the analysis and identification of spatial distribution of canopy cover through time. This study has revealed that the spatial distribution of *Melaleuca* spp canopy cover has been dynamic across the study area with continual increase in the lower eastern portion of the study area. Identification of the causal factors of the changes observed was beyond the scope of this project. However several factors have been identified, namely feral pig, fire and possible changes in intra species distribution may account for the changes observed. The visual impact of both fire and feral pig damage was apparent during the field component of this study. It is clear from literature that the impact and influence of the aforementioned factors are poorly understood in the ecosystems of the wet-dry tropics of northern Australia, this requires further study.

Chapter 6 Summary and Recommendations

6.1 Summary

Kakadu National Park has been internationally recognised for its significant natural and cultural heritage values. The listing of wetlands within Kakadu as sites of international significance by the Convention on Wetlands of International Importance is further recognition of their global significance. The increased awareness of the importance of wetlands to environmental and human health has led to a renewed interest in mapping wetlands (Lowry & Finlayson 2004). Remote sensing technology has been identified as a useful resource for assessing and monitoring the condition and trend of wetland ecosystems in northern Australia (Harvey & Hill 2001, Phinn et al 1999). Further, aerial photographs have been identified as a useful source for both assessing vegetation in the wetland environment and for investigating historical change. However, their use has largely been restricted to manual classification techniques, due to difficulties in automated classification using traditional per-pixel algorithms. Current advances in object-orientated classification techniques have enabled the successful classification of very high resolution data. In this project object-orientated techniques were used to classify four aerial photographic datasets between the years of 1950–2004. Change analysis was then performed using the classified datasets to assess changes in *Melaleuca* spp cover over time for a 4.9 km² area of the Magela floodplain.

Object-based classification

The object-based classification software eCognition was used to classify each aerial photograph using a semi-automated, multi-scale approach. The 1950, 1975 and 2004 images were segmented into objects at two scale levels. The coarsest scale level in the classification hierarchy was classified as either woody or not woody areas, while the finest scale was used to classify individual examples, or stands of *Melaleuca* spp. A classification knowledge base was then constructed utilising both scale levels. A combination of classification algorithms (Nearest Neighbour and Membership function) was used to classify the images. Minimal manual classification was used to refine the final 1950 and 1975 classified images, while the 2004 classified image required greater effort. Accuracy assessment was undertaken using reference datasets generated from digitised manual interpretation of 250 random points across each aerial photograph; additionally ground truthing data was collected to assess the 2004 classification. The final 1950 and 1975 classified images recorded an overall accuracy estimated at 89%, and 90% respectively. The 2004 image was assessed using reference datasets generated from both the digitised and ground truthing data. Estimated accuracy of the final 2004 classification using the digitised referenced data was 85% and for the ground truthing data 81%.

In an attempt to avoid manual classification of the 1996 imagery a different method was developed to classify the image. First a low pass filter was used to reduce the heterogeneity of the image. Four scale levels were used to segment the 1996 aerial photograph. The first step was to classify the image into woody or not woody areas; this classified level was then used to perform a classification based segmentation of the image. A scale level was then generated to classify the area into classes representing the different brightness levels across the image. This was done to account for the BRDF effect in the aerial photograph. The finest scale level was then used to classify the individual trees and stands of *Melaleuca* spp. These different scale levels were combined in a classification hierarchy; the classification algorithms used

were Membership function and Nearest Neighbour algorithms. Adopting the different methodology increased the accuracy of the automated classification of the finest scale level in comparison to the 2004 image. However, to achieve an acceptable level of accuracy, manual classification was still required. The overall accuracy of the final 1996 classification was estimated to be 82%.

Object-based classification was successfully used to map *Melaleuca* spp on the Magela floodplain using a semi-automated approach. It was clear from the results of this study that environmental conditions at the time of acquisition of the aerial photographs influenced the success of the classification. The 1975 image was significantly easier to classify due to the absence of other vegetation, allowing greater contrast between water and *Melaleuca* spp. It was found that the reduced spectral properties of the visible part of the electromagnetic spectrum were not able to discriminate well between *Melaleuca* spp and other vegetation. This was found to affect the quality of the segmentation process, as extraction of meaningful objects (at the scale used in this project) still relies heavily on the spectral properties of an image. Applying a low-pass filter over the 1996 image greatly reduced the heterogeneity of the pixels in the image, and increased the contrast between *Melaleuca* spp and other vegetation types. The combination of smoothing the image and incorporating a scale level classified on the different brightness levels across the image helped to increase the accuracy of the automated classification process. The scale and quality of the 1950 aerial photograph may have led to a bias in the classification process, as small *Melaleuca* spp may have been omitted and tree shadow may have been classified as *Melaleuca* spp. The ability to incorporate objects at different scale levels into a single classification knowledge base increased the spectral information available to classify the image. This helped to compensate for the limited spectral properties of aerial photographs and enhance the overall classification process.

Change analysis

Change analysis was undertaken using a GIS platform. The overall canopy coverage of *Melaleuca* spp was calculated for each year. To identify spatial change in canopy cover over the 54 year time period, datasets representing percent of canopy cover for 392 m² areas across the whole image were produced using the block statistics function and the raster calculator in ArcMap. This was done to compensate for geometric distortions and misregistration between the different aerial photographs which would over estimate the level of change. Image differencing was then performed to produce data revealing levels of \pm % cover change.

The extent of *Melaleuca* spp estimated to cover the study area in 1950 was 118.9 ha, by 1975 the extent had increased by 14.4 ha to 133.4 ha. In 1996 *Melaleuca* spp cover again increased slightly by 2 ha to 135.4 ha and in 2004 there was a slight decline in cover of 15.4 ha to 120.4 ha. These results indicate that the overall canopy cover of *Melaleuca* spp has not varied greatly over the 54 year period. The estimated percentage of canopy cover datasets indicate large changes in spatial distribution of *Melaleuca* spp cover across the study area. However *Melaleuca* spp cover appears to have been expanding in the lower eastern region of the study area over the 54 year period. The results of this study differed from two previous studies (Riley & Lowry 2002, Williams 1984) which also investigated changes in density and distribution of *Melaleuca* spp in the study area. Both these studies reported a decrease in the density of *Melaleuca* spp for their respective assessed time periods. Several factors were identified that may have contributed to these differences. In this study it may be due to bias in the 1950 classification in relation to scale and image quality, this may have resulted in an underestimation of *Melaleuca* spp. It is also possible the level of error in the 1996 classification has overestimated the amount of canopy cover. The observed differences may also reflect

different methodology used in each study, and access to differing levels of technology at the time. Or it may also be a result of error in the estimations of the previous studies.

Identifying the reasons for this change was beyond the scope of this study. However, the impact of fire and feral pigs was very apparent during the collection of ground truthing data in August 2005. It is also possible that changes identified in this study could be representing intra species changes in distribution of *Melaleuca* spp, due to changes in rainfall patterns or succession due to sediment accumulation.

This project has applied both remote sensing and GIS technology to investigate the change in *Melaleuca* spp canopy cover for a 4.9 km² section of the Magela floodplain. While this study shows there has been little overall change in canopy cover in the study area, the change in spatial distribution appears to have been large. The use of historical aerial photographs has enabled the floodplain to be studied at a scale not available in other forms of historical imagery.

6.2 Recommendations

The classification results of the 1975 image demonstrate that object-based analysis can be applied to classification of aerial photographs at a genus scale level. It is considered that object-based analysis could be used to classify other landscapes using aerial photographs, particularly if there is reasonable contrast between the different phenomena in the image. The broad classes extracted from the level 2 classifications suggest that object-based analysis of aerial photographs could be useful in identifying broad vegetation classes within the floodplain, this requires further research.

Applying the classification methods as used in this project to large areas (such as the full extent of the Magela Floodplain) would not be feasible if there is a high level of vegetation present in the ground stratum, due to the time required to manually classify each image. Assessing temporal change in *Melaleuca* cover over a larger area of the floodplain may be feasible by first applying the automated classification procedures as described in this project, and then generating sample plots across the image. These sample plots can then be refined using manual classification methods if necessary.

It is possible that imagery such as CIR aerial photographs and VHR multispectral data, which has a greater ability to discriminate between vegetation types, may enable automated classification of floodplain environment. The biggest disadvantage of this type of data is the limited availability of historical images.

Several factors have been identified in this thesis that may help increase the ability to use automated methods in classifying panchromatic and true colour aerial photographs, including:

- Increasing the radiometric properties (eg 8-bit to 16 bit) of an image may help discriminate between objects.
- Investigating further methods in correcting the BRDF effect.
- Combining unsupervised per-pixel and object-based classification algorithms, and
- Exploring different methods of image pre-processing to enlarge the image feature space.

While the impact of fire is very visual and studies have shown that altered regimes can be detrimental to woody vegetation, the impact feral pigs have on the floodplain is largely a mystery. The level of feral pig activity in the small portion of the Magela floodplain in this study appeared to be high. There level of impact on ecosystem processes in the floodplain environment is one aspect that requires further research.

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