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Predicting the spatial distribution of organic rich sediments on the Swan Coastal Plain, Western Australia

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PREDICTING THE SPATIAL DISTRIBUTION OF ORGANIC RICH SEDIMENTS ON THE SWAN COASTAL PLAIN, WESTERN AUSTRALIA

By

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USE OF THESIS

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ABSTRACT

The Organic Rich Sediments (ORS) of the Swan Coastal Plain (SCP) are an important component of the ecosystem, an important source of habitat and refuge for many species of fauna and act as natural fire control mechanisms through edaphic measures within the landscape.

There have been numerous impacts on ORS, with fire now rated as one of the imminent threats to the continued existence and functioning of these entities. Conversely fire is an important tool for land mangers in their efforts to promote biodiversity and manage fuel loads to prevent wildfires, at present many of these ORS are becoming victim to these management practices and other disturbance events due to the lack of adequate information relating to their location. The current inadequacies to the appropriate management of these systems lies in the apparent lack of detailed spatial information relating to the distribution of these sediments, with current practices failing to account for historical sediment deposits and deficiencies with identifying deposits at smaller scales.

Geographical Information Systems (GIS) have been widely used in numerous environmental disciplines to map and predict the spatial distribution of a diverse range of environmental entities from species through to landscapes. The predictive modeling capabilities of GIS were of particular interest to this study and in particular the ability to predict the spatial distribution of ORS based on existing data. Predictive modeling involved the manipulation of existing empirical data relating to the environmental factors that are involved in the formation of ORS on the SCP.

Datasets on wetland type, soil type, slope, aspect and depth to groundwater were compiled to develop a model of ORS on the SCP utilising the weighted overlay model function in Spatial Analyst ArcView 3.2. The predictive capability of the model was ascertained by field sampling while the effectiveness of the model to predict ORS as determined by the calculated organic content of sampled soils was analysed by logistic regression.

Field verification of the model confirmed the predictive capabilities of the model in being able to predict the occurrence of ORS, with correct prediction rates in excess of 50%. It also highlighted the spatial variation which exists between and within deposits which makes predicting the distribution of ORS a very complicated process. Resolution testing showed that the predictive capabilities of the model degenerated at a smaller scale, possibly as a result of limitations associated with the resolution of the model input data.

Key findings of the logistic regression analysis of the predictive model showed that the developed model was robust at the landscape scale. The fit of the model to the data was very strong with SPSS percentage correct values in excess of 80%. Logistic regression highlighted the impact of soil moisture and vegetation type in improving the fit of the model and highlighted the deficiencies associated with using the wetland type variable alone. The logistic regression results showed that the model performed similarly at both sites.

Limitations of the study included restricted sampling methods both in the depth of the sample taken and the regions sample. Navigation using GPS may have led to positional errors with sampling which could have been overcome with the use of Differential Global Positioning System (DGPS) which has a positional accuracy of +/- 1m. Discrepancies in positional accuracy of the input environmental datasets may have resulted in incongruity in the positional accuracies of the output maps, although verification through field sampling and aerial photography interpretation would suggest that this was not the case.

Nevertheless a map of ORS has been produced which can be improved with work in the following areas. A number of remote sensing technologies are available which are available to obtain empirical data relating to soil moisture contents and vegetation types at a landscape level. These include the use of thermal mapping, normalized difference vegetation index (NDVI) and the use of ground penetrating radar.

This study has set the foundation for the development of a vital tool for mangers involved in preserving ORS and their ecological functioning on the SCP and throughout the southwest of Western Australia.

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CHAPTER 1: INTRODUCTION

1.1 General Introduction

Our biological environment is becoming vulnerable to fire particularly with continuing urban expansion. Urban development is leading to the fragmentation of ecosystems, increasing pressure on groundwater supplies and posing a serious threat to the conservation of endemic flora and fauna. Vegetation clearing and fragmentation can lead to changes in seasonal hydroperiods (alternating periods of wet and dry) which, when combined with reduced rainfall associated with climate change, is resulting in extended drought periods(Groom, Froend et al. 2000; Ryder 2000; Salama, Bekele et al. 2002). This has implications for all natural ecosystems within the region including coastal, inland terrestrial and wetland ecosystems.

The destruction of organic rich sediments (ORS) on the Swan Coastal Plain (SCP) has occurred at an unprecedented rate since the establishment of the Swan River Colony, with an estimated 70% loss of the original extent of these systems (Davis and Froend 1999). Early clearing was as a result of the need for market gardens, landfill sites and recreational areas (Bolland 1998) Today the destruction of these sediments is largely due to the threat posed by fire. This threat not only occurs due to the incidence of arson and natural causes such as lightening strikes but also as a result of the use of fire as a management tool for biodiversity and fuel reduction by land management agencies.

This study was convened as a response to the impact of fires on ORS and the systems of which they are a part and the management requirements needed in preventing such fires. Land managers and other government agencies have a need for an integrated and detailed mapping system which can predict with accuracy the occurrence of these soil types and is adaptable to the multi-disciplinary requirements of a broad spectrum of government and non-government agencies.

1.2 Literature Review

1.2.1 Wetlands and Wetland Soils

Organic rich sediments (ORS), also known as 'organosols' or 'peat' (McArthur 1991; Isbell 1996), are characterised by the accumulation of partially decayed organic matter (Ryder 2000). The formation of these soils is not the result of elemental weathering but rather as part of a complex feedback system (Figure 1) whereby the production of organic sediments is influenced by hydrological patterns, vegetation, biological functions, geomorphic settings and climatic conditions (Ryder and Horwitz 1995; V & C Semenuik Research Group and Syrinx Environmental Pty Ltd 2003). The formation of these soils relies on the accumulation of organic matter at a rate faster than its rate of decomposition (Ryder and Horwitz 1995; Horwitz, Judd et al. 2003). The circumstances required for this process are generally found under anoxic conditions, such as those experienced in wetland ecosystems. These conditions are typical of those found in wetlands situated on the Swan Coastal Plain in Western Australia, the region where the present study will be carried out.

Wetland ecosystems are vulnerable to fire where peat is present and where prolonged drying has occurred (Appendix A). Permanent or seasonal drying of organic soils can lead to a decrease or cessation in the production of organic material, which ultimately changes the functioning of the system in which they occur. (Ryder and Horwitz 1995; Ryder 2000; Horwitz, Judd et al. 2003). Indeed, it is these soils that contain high proportions of organic material that are the focus of this study.

The classification of 'peat' (McArthur 1991; Isbell 1996) is restricted to sediments with an organic content of greater than 80%. Deposits on the SCP are known to have significantly lower concentrations of organic matter where the vast majority range from between 15% and 80% (Teakle and Southern 1937), with an organic content of 20% being the minimum concentration for classification as an organic soil (Isbell 1996). Many of these soils still burn in the same fashion as 'peat fires', see Appendix A. Therefore the organic sediments of the SCP, including true peat deposits, will be referred to as Organic Rich Sediments (ORS) for this study, noting the differences in organic contents and the liberal use of the term peat in describing different organic soil types around the world.

In Australia organic rich sediments can be found distributed throughout all states. In Western Australia the distribution of ORS occurs in the tropical regions in the north and the more temperate regions in the southwest of the state, including the expanse of coastal dune systems referred to as the Swan Coastal Plain (SCP).

The wetlands or peat swamps of the SCP are typically surface expressions of unconfined aquifers and as such, many wetlands express seasonality in the amount of soil moisture present (Teakle and Southern 1937; Ryder and Horwitz 1995). This differs from the boreal and tropical peatlands which are maintained as a result of excessive precipitation in relation to evaporation rates (Doyle 1997). Organic soils on the SCP are therefore not as deep as those represented in the tropical and boreal regions. To date, the spatial distribution of organic soils on the SCP has been poorly documented.

There is a relatively large amount of literature relating to the mapping and conservation of peat in Europe (i.e. (Eframova and Eframov 1994; Doyle 1997; Ellis and Tallis 2000; Bauer 2004)), America (i.e.(Smith, Newman et al. 2001; Smith, Gawlik et al. 2003)), Indonesia (i.e. (Rieley, Page et al. 1997; Nuruddin 2002)) and other regions of Australia (i.e. (Pemberton 1987; Horwitz, Pemberton et al. 1998)). There is very little literature however that directly pertains to the nature and distribution of ORS on the Swan Coastal Plain and the southwestern region of Western Australia, as highlighted by papers by Horwitz *et al*, Ryder and a report produced for the Water and Rivers Commission (Department of Environment) (Ryder and Horwitz 1995; Horwitz, Pemberton et al. 1998; Horwitz, Judd et al. 2003; V & C Semenuik Research Group and Syrinx Environmental Pty Ltd 2003).

Mapping for ORS currently utilises wetland maps (Hill, Semeniuk et al. 1996a) for the SCP (pers. comm. L. Mutter, Regional Fire Officer, Department of Conservation and Land Management). Additionally a number of papers (Semeniuk 1987; Semeniuk 1988; Semeniuk, Semeniuk et al. 1990; V & C Semenuik Research Group and Syrinx Environmental Pty Ltd 2003), indicate the lack of sediment mapping associated with wetland classification

1.2.2 Fire and Organic Rich Sediments

Organic soils are unique in the way that they burn. The heat generated by the combustion of organic material can facilitate the movement of fire throughout the soil profile, a combustion process called pyrolysis (Hungerford, Frandsen et al. 1996). This results in fires that can last for extended periods of time, from days to weeks to months. In addition to this, fires in organic soils are difficult to extinguish. Generally fires burn in organic soils until winter rainfall causes an inundation that extinguishes them (Appendix 1). Where an attempt is made to extinguish these fires during very dry periods, for example in autumn, the methods used to extinguish the fire may have adverse side effects for the broader system in which they occur. However, soil moisture present in high enough quantities can prevent the spread of the combustion front by acting as a heat sink during the process of evaporation, thus preventing the spread of the 'fire' (Hungerford, Frandsen et al. 1996; Frandsen 1997a; Subbotin 2003). Studies have shown that the ratio of soil moisture to organic content of soils will influence the point at which they begin to combust. Figure 1 illustrates this fact by showing the ratio of soil moisture to organic content at which soils become susceptible to combustion. When soil moisture values are to the left of the regression line (Figure 1) soils are susceptible to combustion (Hungerford, Frandsen et al. 1996).

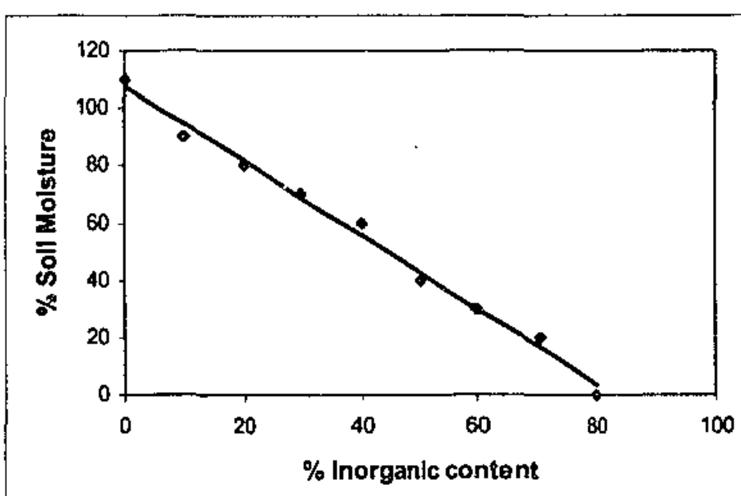


Figure 1 Ignition limit from Frandsen (Frandsen 1997b). The line is the ignition limit for a mixture of peat moss, soil moisture and inorganic mineral soil at an organic bulk density of 110 kg m^{-3}.

1.2.3 Implications of fire in Organic Rich Sediments

Organic soils form an integral part of the systems in which they occur, varying both in spatial and temporal scales. On an ecosystem scale they help to regulate productivity and influence hydrological patterns through interactions with vegetation types (Davis and Froend 1999). On landscape and global scales organic soils act as a sink for carbon and as a refuge for fauna and flora, and an edaphic form of control, during fire events (Horwitz, Pemberton et al. 1998).

Fire occurrence in these ecosystems can have impacts both on the environment and on humans. Fire can destroy these soils reducing their capacity to function and releasing vast amounts of carbon, which is known to contribute to global warming (Hungerford, Frandsen et al. 1996; Horwitz, Pemberton et al. 1998). Disturbance of these sediments due to fire can result in acidification and contamination of underlying groundwater reserves, a significant issue on the Swan Coastal Plain (Appleyard, Wong et al. 2004). Human health implications may result from the release of volatile organic compounds and high particulate emissions in peat smoke (Hinwood, Forrest et al. 2002; Hinwood and Rodriguez 2004).

Despite the large quantity of international literature documenting the adverse impacts on these systems (Pemberton 1988; Eframova and Eframov 1994; Clarkson 1997; Horwitz, Pemberton et al. 1998), fire is deemed to be a necessary management tool for land managers, in Western Australia, whether for fuel reduction or to promote biodiversity. When fires do enter these systems emergency services and environmental managers require knowledge relating to the location, physical state and the capacity of these soils to cope with a fire event so as to manage the situation adequately. The protection of these systems rests with the prevention of fire entering them in the first instance. To this end there is a need to know where ORS occur and therefore a method is required to predict the existence of organic soils in the landscape and to determine the risk they face from fire at any particular time (Horwitz, Pemberton et al. 1998; V & C Semenuik Research Group and Syrinx Environmental Pty Ltd 2003). This information can then be incorporated into fire management protocols for effectively managing these systems for their protection.

The use of Geographic Information Systems (GIS) and remote sensing technologies in mapping ORS, measuring the occurrence and affect of disturbance events on ORS and the detection of characteristics of the systems associated with the occurrence of ORS has been well documented (Ellery, Ellery et al. 1989; Clarkson 1997; Cutler, McMorrow et al. 2002; Nuruddin 2002; Smith, Gawlik et al. 2003; Setiawan, Mahmud et al. 2004). Setiawan *et al* (Setiawan, Mahmud et al. 2004) and Smith *et al* (Smith, Gawlik et al. 2003) in particular have used remote sensing and GIS to map and construct peat fire risk models for tropical peat bogs in Asia and temperate peat deposits in Florida respectively. This has not been done previously in Western Australia.

1.2.4 GIS and predictive modeling

The ability to explain or predict ecosystem behaviour requires knowledge of how ecosystem components are distributed in time and space, and an understanding of the relationships and processes that explain their distribution and behaviour (Allen 1994). The ability to make reliable predictions about ecosystem behaviour requires a knowledge of temporal trends as well as a knowledge of spatial distribution and relationships (Allen 1994; Perez, Telfer et al. 2002).

The ability to be able to predict phenomenon based on a set of individual or interrelated variables has enabled ecologists, conservationists and land managers alike to be able to exploit the GIS capabilities. Over the last decade the increase in spatial information technologies has resulted in a dramatic increase in the use of GIS and remote sensing applications to both explain and predict ecosystem behaviour (Stocks and Wise 2000).

The ecological applications of Geographical Information Systems (GIS) and Remote Sensing (RS) have been well documented. The scope of GIS has extended to forest ecology, vegetation distribution analysis and species and habitat modeling to name but a few (Iverson and Prasad 1998; van Horssen, Schot et al. 1999; Perez, Telfer et al. 2002; Thomas 2002; Harrison and Forster 2003; Flinn, Vellend et al. 2005).

Recent advancements in technology associated with GIS and RS point to the transition from a static modeling and mapping interface to a dynamic system which allows for the

inclusion of data relating to temporal changes that occur within systems and thus increasing the strength of any model developed (Flinn, Vellend et al. 2005).

Generally the development of predictive models in GIS is either inductive or deductive in nature. Inductive models extrapolate the known habitat characteristics of an entity across the entire geographical study region whereas deductive approaches are determined with an *a priori* knowledge of criteria relating to the entity on which predictions about its existence are made (Stoms, Davis et al. 1992). This allows the mapping of wide-ranging areas of land without the requirement for extensive fieldwork.

This study involved the development of a static model predicting the occurrence of organic rich sediments based on a priori assumptions relating to the criteria associated with the formation of these sediments.

1.3 Significance and Aims of the study

Organic Rich Sediments act as a dynamic museum to historical climatic and environmental conditions. They act as an integral component of a system that provides habitat and has the ability to naturally regulate the spread of fire through the landscape. As such they act as refuges for flora and fauna during these events and must act as a source of regenerative material after such events. The wholesale degradation of these sites since early settlement and the undermining of their intrinsic edaphic qualities in fire suppression has led to an increase in the intrinsic value of the relatively few remaining sites. As such every effort should be made to ensure their existence through appropriate management.

The current need to manage fire interactions with these systems along with deficiencies associated with the current practises has led to the demand for a system, which can be adapted to meet the needs of numerous stakeholders. The need for adequate mapping of organic sediments has been highlighted (Horwitz, Pemberton et al. 1998; Horwitz, Judd et al. 2003; V & C Semenuik Research Group and Syrinx Environmental Pty Ltd 2003). GIS technology has a proven track record in predicting the occurrence and risk from fire associated with peat deposits internationally (Smith, Gawlik et al. 2003; Setiawan, Mahmud et al. 2004). Both researchers and industry recognise the need to adequately

map the distribution of these sediments to allow their conservation and to allow the ongoing management of biodiversity with current practises.

This study applies GIS technology and methodology to develop a model to predict the spatial distribution of ORS on the SCP with the aim of it being used by land and fire managers to protect theses systems and also to deal with the ecological consequences of fire. It aims to verify the usefulness of the model with field sampling for variables known to be associated with the presence of ORS. The specific aims of this study were to:

- establish the feasibility of developing a model,
- utilise GIS technologies, which will accurately predict the occurrence of organic rich sediments on the Swan Coastal Plain,
- verify the capability of the predictive model through field sampling,
- analyse field and predictive model variables using logistic regression to determine the significance of the variables used and the goodness of fit of the model to the data.

1.4 Thesis Outline

Chapter 2 provides a description of the focus region and a detailed description of the location, management, soils and vegetation types associated with the two study sites.

Chapter 3 is a detailed description of the methodology used to construct and test the model. Methodology is included for data acquisition and model construction, field verification, resolution testing analysis and logistic regression analysis.

Chapter 4 details the results of the study. Results are included for dataset verification for datasets created as a part of this study, results of field verification sampling, logistic regression analysis and resolution testing analysis.

Chapter 5 discusses the findings of the study in the context of the predictive capability of the model, the feasibility of using GIS to construct the model and implications for fire and land managers.

CHAPTER 2: SITE SELECTION AND FOCUS SITES

2.1 Study Region

The Swan Coastal Plain extends north to Dongara and south to Busselton and is bordered by the Darling and Gingin scarps to the east (Figure 2). The climate is Mediterranean, with hot dry summers and cool wet winters. The soils of the SCP are predominately dune systems. The Quindalup dunes contain unconsolidated sand and shell fragments and are situated nearest to the coast. To the east of these are the Spearwood dunes that are composed of red, yellow and grey sands. These are followed by the Bassendean dunes, which are the oldest of the dune systems and contain highly leached, infertile sands. The Ridge Hill Shelf is a narrow strip of course lateritic ironstone gravel at the base of the Darling Scarp (Bolland 1998). Organic matter accumulates in the lakes and wetlands that form in between the three dune systems, with the wetlands often referred to as peat swamps (Semenuik 1988; Bolland 1998).

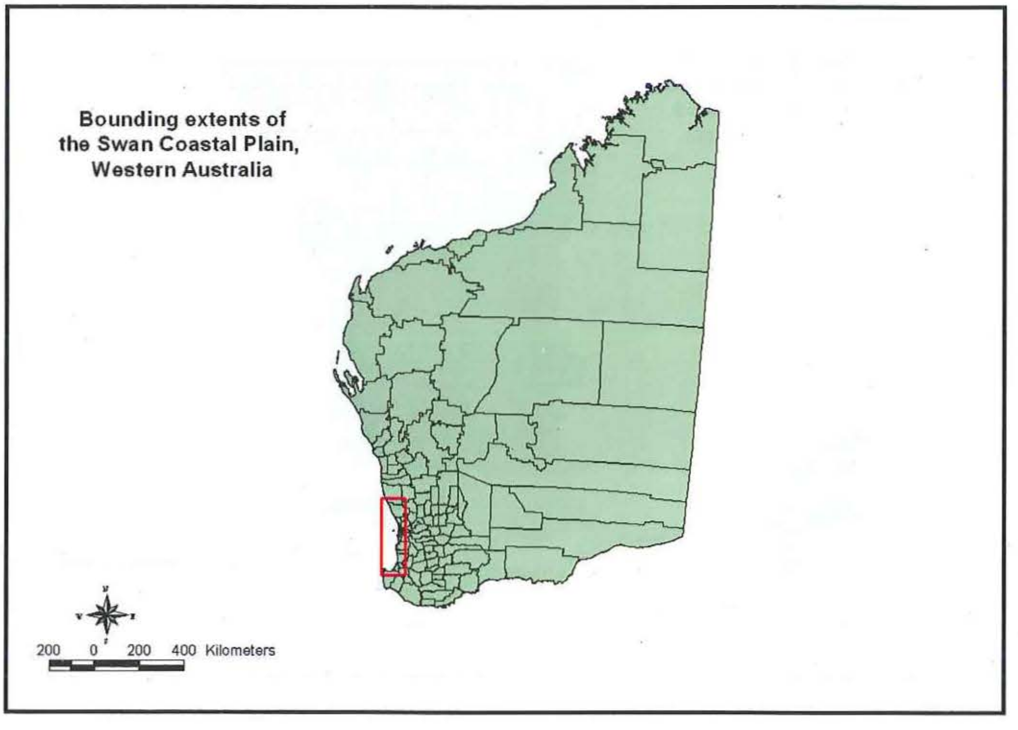


Figure 2 Extent of the Swan Coastal Plain, Western Australia

Two sites were chosen for field verification of the predictive model as part of this study, they included Melaleuca Park and Whiteman Park sites. Sites were chosen due to their reflection of changes in underlying geomorphology and different management regimes. Melaleuca and Whiteman Parks are situated within the Bassendean Dune system. These two sites were chosen as they represented soil representations found on the Swan Coastal Plain and different management regimes and land management practises.

2.2 Melaleuca Park

The Melaleuca Park study site is situated within Melaleuca Park, a conservation reserve vested with the Department of Conservation and Land Management who are responsible for the management of the park. The park is approximately 31km NNE of the Perth Central Area in the locality of Melaleuca. Pine plantations bound the park to the West and the North, whilst Neaves Road intersects the park, running southwest to northeast.

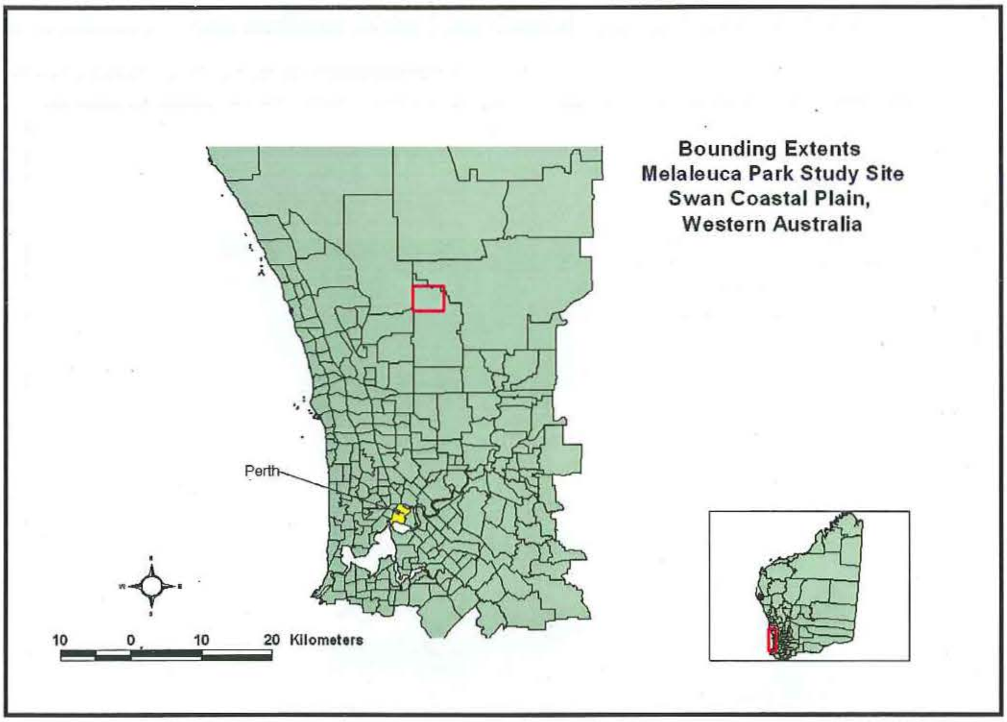


Figure 3 Extent of the Melaleuca Park study site situated within Melaleuca Park on the Swan Coastal Plain, Western Australia

The Melaleuca Park site is situated within the Bassendean Dune System. Soils are characterised by highly leached, infertile and often acidic sands. Any nutrient availability is associated with the presence of organic deposits. Groundwater levels range from near the surface to in excess of 10m below ground level (Bolland 1998).

Vegetation complexes range from varying densities of Banksia woodland over myrtaceous shrubs to stands of *Eucalyptus rudis*, *Melaleuca* sp. and sedges in the wetter areas.

2.3 Whiteman Park

The Whiteman Park study site is situated within Whiteman Park. Whiteman Park is a recreation and conservation reserve. The Western Australian Planning Commission owns the land freehold, with management of the park the responsibility of a management board. The park is approximately 4,000 ha in size and situated approximately 16km northeast of the Perth Central Area, in the City of Swan (Environmental Resources Management 2003).

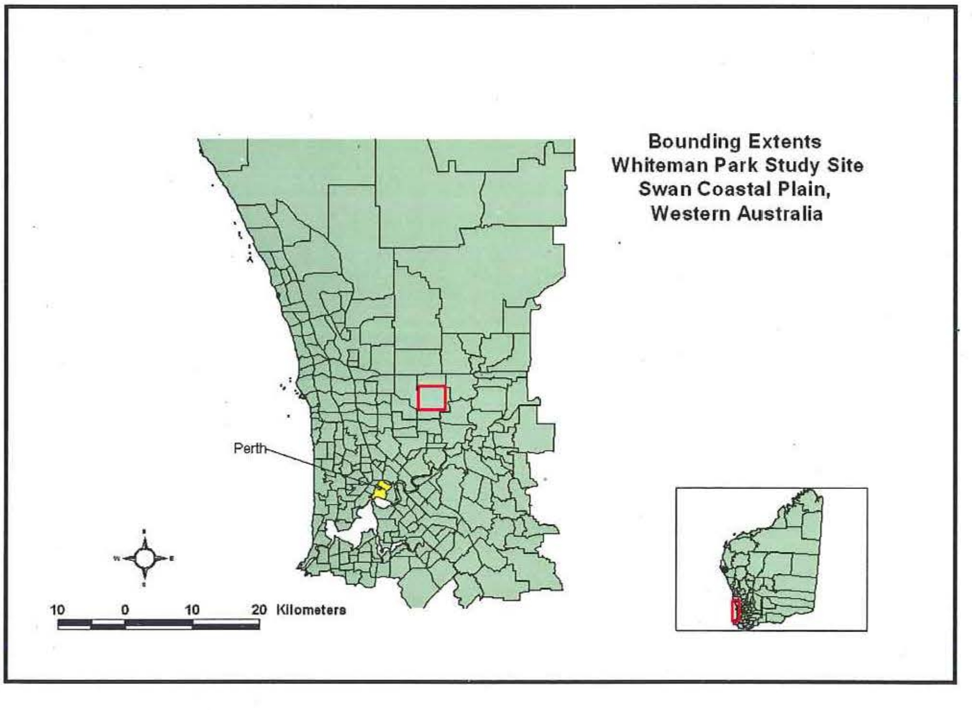


Figure 4 Extent of Whiteman Park study site situated within Whiteman Park on the Swan Coastal Plain, Western Australia.

The soils consist of highly leached, nutrient poor and acidic grey to white sands, typical of the Bassendean Dune system. Clayey soils can be found in the southeast section of the park and the area is interspersed with organic deposits associated with wet depressions in the landscape (Environmental Resources Management 2003).

Vegetation communities in the park range from open woodland of *Banksia* sp., open woodland of *Eucalyptus* sp. through to open woodlands of *Melaleuca* sp. (Mattiske Consulting Pty Ltd 2002). Many parts of the park have been degraded through past grazing practises (Environmental Resources Management 2003).

CHAPTER 3: METHODOLOGY

This section illustrates the methods used to acquire and transform the data prior to constructing the predictive model. It explains the processes used to construct the predictive model and the measures used, both in the field and statistically, to establish the ability of the model in being able to predict the occurrence of ORS.

As part of this study the ability to remotely sense the presence of ORS in the landscape was evaluated. This was done using Thematic Mapper (TM) satellite data. Due to the lack of spatial separation between sample types it was deemed that the results from this analysis are inconclusive and are not reported as a part of this study but rather can be viewed in Appendix 2.

3.1 Data Identification, Acquisition and Description

3.1.1 Data Identification

The first phase in predicting the spatial extent of organic rich sediments (ORS) on the Swan Coastal Plain (SCP) involves identifying environmental factors that can be used as indicators of those conditions that are, or have been favourable for the formation of peat. The indicators used in the study were identified from conceptual models of organic soil formation derived from interpretations of the relevant literature (Figure 5). Analysis of literature indicates that conditions under which the formation and accumulation of these deposits occurs is heavily influenced by vegetation type, hydrological cycles, seasonality of hydroperiods and topography (Semeniuk 1987; Semenuik 1988; Ryder and Horwitz 1995; Davis and Froend 1999; Ryder 2000).

This suggests that data relating to vegetation type and extent, topography, parent soil and groundwater levels are environmental factors that would be suitable indicators to use for predicting the presence of ORS based on the availability of empirical data relating to these variables. Interpretation of the conceptual model led to the development of a set of criteria, which were believed essential for the development of organic sediments (Table 1).

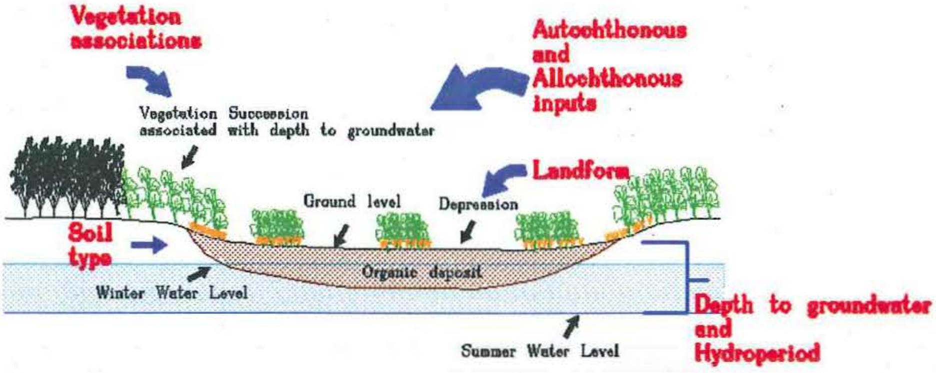


Figure 5 Conceptual diagram of organic sediment formation, indicating the identified criteria.

A search of the Metadata database available on the Western Australian Land Information System (WALIS) website, revealed datasets that met the criteria set out in Table 1.

All available datasets, as a result of the search of the WALIS website, that were deemed to relate to the formation of ORS on the SCP were selected. Those variables found to meet the criteria, the custodian of the dataset and the environmental attributes associated with each dataset were listed in Table 1.

Table 1 Identified criteria, available datasets and their corresponding attributes to be used in construction of model.

Criteria	Dataset	Attributes	Agency
Area subject to permanent/seasonal inundation or waterlogging	Geomorphic Wetland Mapping	Landform, wetland classification, conservation category	Department of Environment (DoE)
Area subject to permanent/seasonal inundation or waterlogging	Groundwater contours	Groundwater height (mAHD)	Department of Environment (DoE)
Soil type indicative of wet soils	Soil-landscape mapping	Landform, soils, geology and vegetation type	Department of Agriculture (DoA)
Low lying areas and blow out depressions within the landscape	Digital Elevation Model (DEM)	Height (mAHD) and positional data	Department of Conservation and Land Management (CALM)
Vegetation types associated with wet soils	Vegetation extent WA	Vegetation extent remnant vegetation	Department of Agriculture (DoA)
Vegetation types associated with wet soils	Taxonomic update and review of Vascular plant species data	Vegetation extent by vegetation type	Department for Planning and Infrastructure (DPI)

3.1.2 Data Acquisition

Datasets were acquired by contacting the relative custodian for each dataset (Table 1). In each instance it was a requirement to complete a non-commercial license agreement with the relevant authority. This allows the transfer and use of digital data between WALIS agencies and the use of information obtained from the state government of Western Australia for non-commercial purposes. Acquisition of all requested datasets took approximately ten weeks.

Five spatial datasets were used to construct a predictive model of the spatial distribution of ORS on the SCP. Datasets include Geomorphic Wetland Mapping (Wetland type), Soil-landscape mapping (Soil type), Groundwater contours (GW), CALM DEM (DEM), Vegetation extent map (vegetation) and vegetation survey map for Whiteman Park (WP veg).

3.1.3 Dataset Description

The wetland dataset is the most comprehensive description of wetlands on the SCP currently available. Coverage extends from Wedge Island to Dunsborough, Augusta to Walpole and the Muir Unicup area (Figure 4). The dataset was created in 1989 and is updated as required (last updated January 2004). The type and extent of each wetland has been recorded according to geomorphic classification standards (Government of Western Australia 2004). The region covering Wedge Island to Mandurah was originally created 1989 – 1991, Pinjarra to Dunsborough 1992-93, Swan Coastal Plain 1993-94 and Augusta to Walpole in 1997. Coverage for each area was created using 1:25 000 topographic maps, orthophotographs, 1:20 000 colour stereo photographs and verified by field evidence (Government of Western Australia 2004). Positional accuracy refers to the vertical and horizontal accuracy of the positions of spatial objects, whilst attribute accuracy is a measure of the degree to which the attribute values of features agree with the information on the source material. Positional accuracy for the wetland dataset is recorded as +/- 50m, there is no record for attribute accuracy (Government of Western Australia 2004).

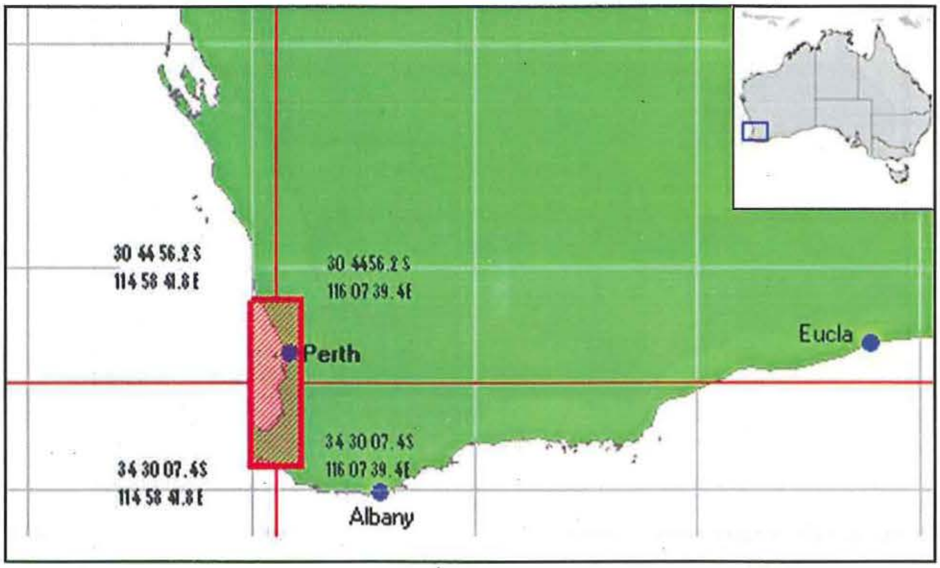


Figure 6: Map showing the spatial extent of the Geomorphic Wetland dataset. Map adapted from WALIS (Government of Western Australia 2004).

The groundwater contour dataset provides groundwater heights, measured as metres above the Australian Height Datum (mAHD). Contours represent the minimum sub-surface level as being derived 3m below maximum sub-surface levels. Coverage includes the whole of the Perth Metropolitan area (Figure 7). The dataset was created from hand drawn interpolations of 1:2 000 map sheets. Weekly, fortnightly and monthly borehole data from 1950 to 1970 was used for interpolations. Verification is carried out on a regular basis using borehole data, with updates carried out as required. Positional accuracy is reported as being + / - 1m (Government of Western Australia 2004). Attribute accuracy is not available.

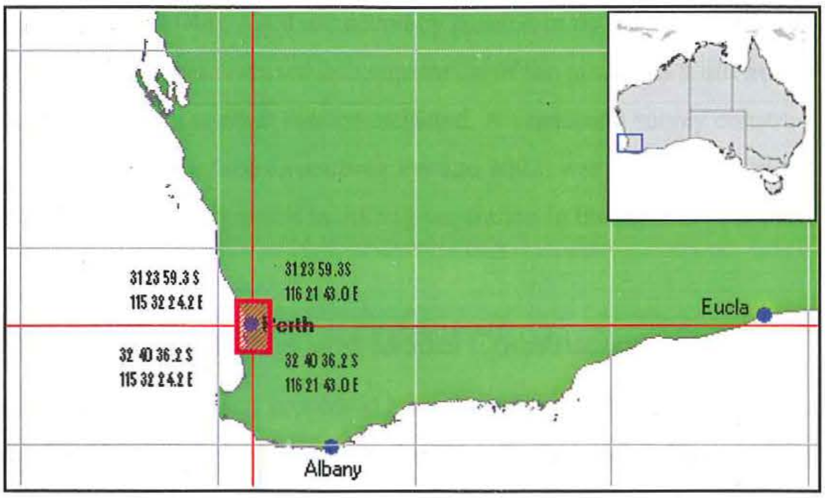


Figure 7: Map showing the spatial extent of the Groundwater Contour dataset. Map adapted from WALIS (Government of Western Australia 2004).

The Department of Agriculture created the soil dataset in 2004 specifically for this project. The coverage stretches from Moore River in the North to the Swan River in the South. Data describes landform, soil-type, geology and vegetation. It also includes the proportion of WA Soil Groups and Supergroups (Schoknecht 2002). Data was created from assorted land resource surveys conducted within Western Australia and descriptive information was compiled from maps and reports. Positional accuracy is reported as +/- 50m. Attribute accuracy is related to the relevant scale of mapping and Natural Resource Assessment Group soil-landscape mapping hierarchy (Government of Western Australia 2004).

The Digital Elevation Model (DEM) was created from aerial photography (date unknown). Coverage includes the state of Western Australia. It was initially created from a 10m pixel (that is a spot height every 10m). This was modified to 25m. The accuracy is reported to be + / - 2m in height (pers com G. Behn, GIS and Remote Sensing Unit, Department of Conservation and Land Management).

The vegetation dataset maps the extent of remnant vegetation in the state of Western Australia (Government of Western Australia 2004). The dataset was produced using Landsat TM satellite imagery and rectified using orthophotographs from between 1996 and 1999. Coverage includes the state of Western Australia. Positional accuracy is

reported as being + / - ~4m. Attribute accuracy is suitable for use at a 1:100 000 scale. Given this the dataset was not used in computation of the model, as it did not match the scale and resolution of the other datasets selected. A vegetation survey constructed by Mattiske Consulting (Mattiske Consulting Pty Ltd 2002) was used for the Whiteman Park site to test the significance of including vegetation in the predictive model.

3.2 Data Transformations and Model Construction

GIS require that the data being processed have the same coordinate system and map projection. The format adopted for this project was the Geocentric Datum of Australia 1994 (GDA94) datum and Universal Trans Mercator, Map Grid of Australia 1994 (MGA94) grid coordinate system.

Transformations were performed using the ESRI ArcView Projection Utility. This is an extension file available with ESRI ArcView (version 3.2). This program facilitates the projection of shapefiles from one coordinate system to another and allows the ability to conduct datum transformations.

Both the Groundwater contour file and the Geomorphic Wetland file required projection from a Lat / Long coordinate system to MGA94 grid coordinate system. Aerial photography for Whiteman Park required datum transformation from Australian Geodetic Datum 1984 (AGD84) to GDA94.

Formatting of data was required prior to the construction of the model. This required processing of data using methods appropriate to the necessary conversion some of the processes involved included the creation of contour files, creation of triangulated irregular networks (TIN), creation of grid files, reclassification of files and the model building process (Figures 8-10).

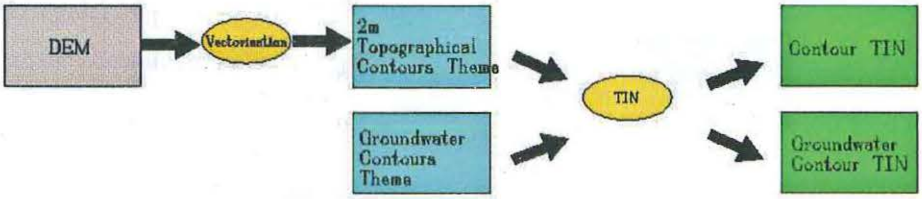


Figure 8 Flow chart showing the process (yellow ellipse) for the creation of contour file from DEM (grey box) and the conversion of vector files (contours) to TIN files (green).

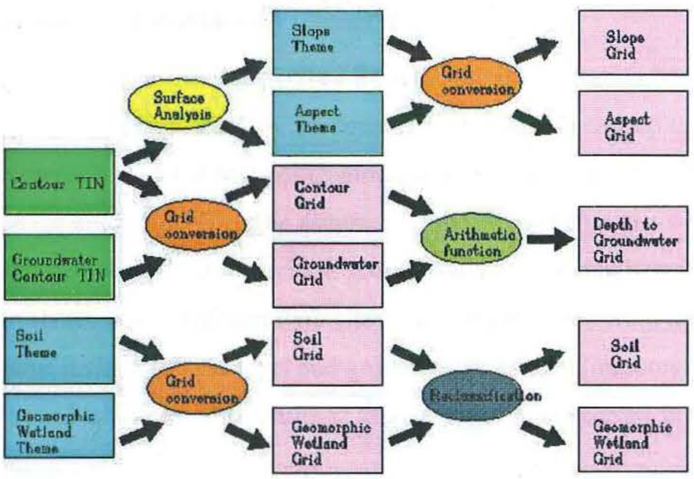


Figure 9 Flow diagram illustrating the processes of surface analysis (yellow ellipse), grid conversion (orange ellipse), arithmetic function (green ellipse) and reclassification represented by the aqua ellipse. Green boxes represent TINs, themes (blue box) and pink boxes represent grid files.

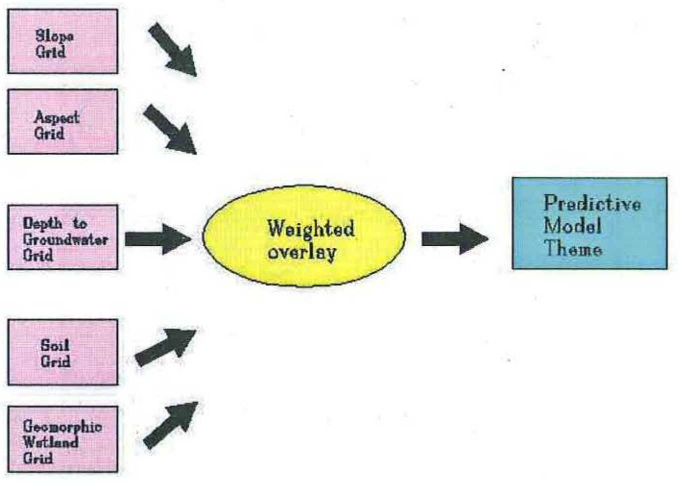


Figure 10 Flow diagram illustrating the creation of the model (blue box) from grid files (pink boxes) by means of the weighted overlay function (yellow ellipse).

3.2.1 Topographical Contour File Creation

The topographical contour file was derived from the Digital Elevation Model (DEM) constructed by CALM (Figure 11). A 2m contour shapefile was created using E.R. Mapper (version 6.0). The ER Mapper Contouring wizard generates contours directly from an image (or algorithm) file. The accuracy of the created contours was verified by comparing with values obtained from DoE groundwater monitoring bores situated within the Melaleuca and Whiteman Park sites. The data obtained from the groundwater monitoring bores include ground level and groundwater heights (measured in mAHD) for the locations of the bores. The results of this verification are shown in section 4.1 of the results chapter

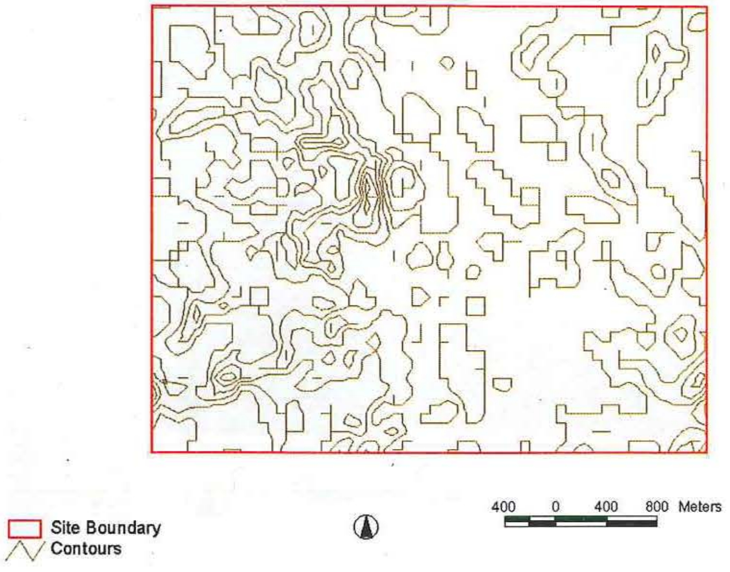


Figure 11: Map illustrating topographical contours for the Melaleuca Park site. Contours were created from CALM DEM using ER Mapper software (Earth Resource Mapping 2003) .

3.2.2 Creation of TIN

Triangulated Irregular Network (TIN) is a surface representation derived from irregularly spaced points and breakline features. Each sample point has an x, y coordinate and a z value or surface value. The area of interest is divided into an evenly spaced grid made of individual cells or pixels. A TIN calculates topological relationships between points and neighbouring triangles and assigns a height value to each individual cell (Environmental Systems Research Institute Inc. 1999a). All vector datasets representing height data required conversion to TIN before being converted to grids.

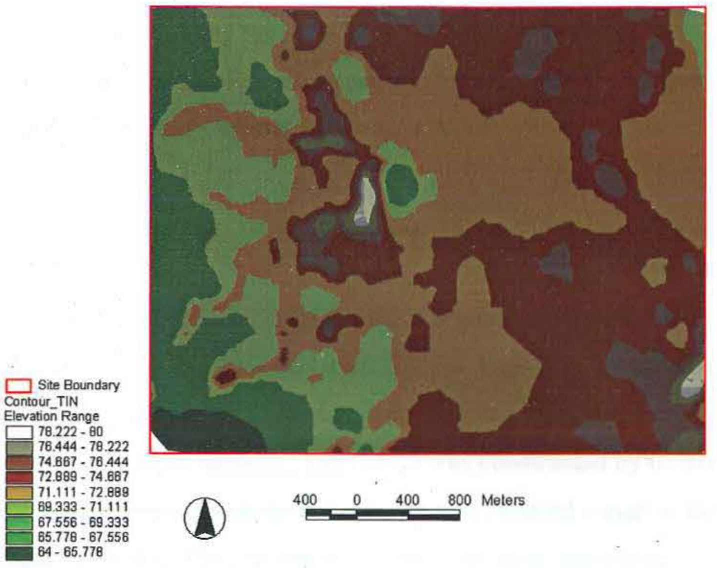


Figure 12 Triangulated Irregular Network (TIN) created using ArcView 3.2 software from 2m contour dataset for Melaleuca Park site.

3.2.3 Depth to Groundwater File Creation

Subtracting groundwater contour values from topographical contour values created a dataset representing the depth of the groundwater table below ground surface (measured in metres). Spatial Analyst module of ArcView 3.2 allows arithmetic functions to be performed on datasets to create a new theme. The area of the study site was divided into a grid each grid was composed of evenly distributed cells or pixels. Each cell was assigned a groundwater and ground height value. For each cell the groundwater height value was subtracted from the ground level height value, which resulted in the depth to groundwater (measured in metres) for each cell of the grid, with an estimated accuracy error +/- 2m (Environmental Systems Research Institute Inc. 1999b).

3.2.4 Creation of Grid

A grid is used to define geographic space as an array of equally sized square cells arranged in rows and columns. Each cell stores a numeric value that represents a

geographic attribute (such as elevation, land use, vegetation type etc) for that unit of space. It is a requirement of constructing weighted models that data is converted into a grid format, thus allowing the calculation of arithmetic functions on each cell (Environmental Systems Research Institute Inc. 1999b). Each dataset was converted into a grid format using Spatial Analyst ArcView 3.2.

3.3 Model Construction

A predictive model for the spatial extent of organic soils on the SCP was developed using ModelBuilder utility in ArcView Spatial Analyst 1.0. ModelBuilder allows the production of a spatial model, which is constructed from the ranking of attributes and the weighting of input datasets. The model was constructed by utilizing the weighted overlay model feature in ModelBuilder, which produced a map of the predicted spatial distribution of ORS. The prediction distributions were categorised from high to low based on the ranking and weighting applied to each attribute and dataset respectively.

Each attribute within a theme (variable) was reclassified into categories with each category assigned a rank. Ranking of attributes converts unrelated variables to a common scale. The ranking used for the predictive model employed a 1-3 system whereby attributes were allocated a rank of between 1 and 3 based on their perceived association with the presence of ORS. One represented no direct association, 2 a possible association and a value of 3 represented a direct association with the presence of ORS (Tables 2 to 4). A restricted rank was assigned when there were data missing for any of the attributes used in the calculation.

Each variable was then weighted. Weights were assigned to reflect the variables perceived strength in indicating the presence of organic rich sediments and are described below.

The initial ranking and weighting of data for Melaleuca and Whiteman Parks (Table 2 to 4) was done through an interpretation of available literature. Landform and hydroperiods are identified by several authors (Semeniuk 1987; Horwitz, Pemberton et al. 1998) as direct influences on the formation of organic sediments. Therefore the wetland dataset was given the greatest weighting. Within the dataset each attribute was

ranked. Sumplands are described as having a more pronounced hydroperiods than damplands, therefore sumplands received a higher ranking than damplands (Semeniuk 1987). No Data, representing areas that were not classified as wetlands, received the lowest rank representing their lack of association with the formation of organic sediments. The same approach was applied to the remaining variables based on their association with the formation of ORS or their perceived strength in predicting their occurrence. Each dataset was then given a percentage weighting to reflect its perceived association with the presence of ORS. From the literature it was evident that the existence of wetlands had a strong association with the presence of ORS therefore the wetland dataset was assigned the greatest weighting. The remaining variables were weighted based on their perceived association with the presence of ORS in relation to that of the wetland variable with all weights totaling 100%.

Multiplying the rank by the weight classifications for each cell, then summing the weighted values to produce an output grid produced the predictive model. The rank and weight matrices for the Melaleuca Park and Whiteman Park sites are shown in Tables 2 to 4).

The inclusion of a vegetation dataset into the predictive model altered the weighting that was applied to different variables (Table 4). The vegetation survey was conducted by Mattiske Consulting (Mattiske Consulting Pty Ltd 2002). Numerous studies (Semeniuk, Semeniuk et al. 1990; Froend, Farrell et al. 1993; Ryder and Horwitz 1995; Davis and Froend 1999) have identified the strong association between vegetation type and the incidence of ORS. The vegetation survey was assigned the greatest weighting to determine its influence on the output of the predictive model. The remaining variables were adjusted accordingly whilst retaining their relative weighting in relation to each other, the sum of weightings for all variables equaled 100%

Table 2: Scaling and weighting matrix for datasets used to develop predictive model for the Melaleuca Park site.

Theme	Attribute	Reclassification	Rank	Weight
Wetland Type	Dampland	1	2	35%
	Sumpland	2	1	
	No Data	No data	Restricted	
Soil Type	Pale deep sands	1	1	30%
	Pale deep sands and semi-wet soils	2	1	
	Semi-wet soil	3	2	
	Wet soils (often peaty w/-diatomaceous earth)	4	3	
	Wet soils (often peaty)	5	3	
	No data	No data	Restricted	
Depth to groundwater (m)	-4.124 - -2.489	1	3	20%
	-2.489 - 0.854	2	3	
	-0.854 - 0.781	3	3	
	0.781 - 2.416	4	2	
	2.416 - 4.051	5	2	
	4.051 - 5.686	6	1	
	5.686 - 7.321	7	1	
	7.321 - 8.956	8	1	
	8.956 - 10.591	9	1	
	No data	No data	Restricted	
Slope (degrees)	0 - 0.852	1	3	10%
	0.852 - 1.704	2	3	
	1.704 - 2.556	3	3	
	2.556 - 3.408	4	2	
	3.408 - 4.260	5	2	
	4.260 - 5.112	6	1	
	5.112 - 5.964	7	1	
	5.964 - 6.816	8	1	
	6.816 - 7.667	9	1	
	No Data	No data	Restricted	
Aspect (degrees)	-1 - 38.756	1	2	5%
	38.756 - 78.512	2	1	
	78.512 - 118.268	3	1	
	118.268 - 158.024	4	1	
	158.024 - 197.78	5	3	
	197.78 - 237.536	6	3	
	237.536 - 277.291	7	1	
	277.291 - 317.047	8	1	
	317.047 - 356.803	9	1	
	No Data	No data	Restricted	

Table 3: Scaling and weighting matrix for datasets used to develop predictive model for the Whiteman Park site.

Theme	Attribute	Reclassification	Rank	Weight
Wetland Type	Dampland	1	2	35%
	Floodplain	2	2	
	Lake	3	3	
	Paluspiain	4	1	
	Sumpland	5	3	
	No Data	No data	Restricted	
Soil Type	Pale deep sands	1	1	30%
	Pale deep sands and semi-wet soils	2	1	
	Semi-wet soil	3	2	
	Semi-wet soil, yellow-brown shallow sands and grey sandy duplexes	4	2	
	Wet soils (often peaty w/- diatomaceous earth)	5	3	
	Wet soils (often peaty)	6	3	
	No data	No data	Restricted	
Depth to groundwater (m)	-3.50 - -1.50	1	3	20%
	-1.501 - 0.00	2	3	
	0.001 - 2.00	3	3	
	2.001 - 3.500	4	2	
	3.501 - 5.500	5	2	
	5.501 - 7.500	6	1	
	7.501 - 9.500	7	1	
	9.501 - 11.500	8	1	
	11.501 - 13.500	9	1	
	No data	No data	Restricted	
Slope (degrees)	0 - 1.605	1	3	10%
	1.605 - 3.21	2	3	
	3.21 - 4.814	3	3	
	4.184 - 6.419	4	2	
	6.419 - 8.024	5	2	
	8.024 - 9.629	6	1	
	9.629 -11.234	7	1	
	11.234 -12.839	8	1	
	12.839 - 14.443	9	1	
	No Data	No data	Restricted	
Aspect (degrees)	-1 - 38.756	1	2	5%
	38.756 - 78.512	2	1	
	78.512 - 118.268	3	1	
	118.268 - 158.024	4	1	
	158.024 - 197.78	5	3	
	197.78 - 237.536	6	3	
	237.536 - 277.291	7	1	
	277.291 - 317.047	8	1	
	317.047 - 356.803	9	1	
	No Data	No data	Restricted	

Table 4: Scaling and weighting matrix for datasets (including vegetation survey) used to develop predictive model for the Whiteman Park site.

Theme	Attribute	Reclassification	Rank	Weight
Wetland Type	Dampland	1	2	20%
	Floodplain	2	2	
	Lake	3	3	
	Palusplain	4	1	
	Sumpland	5	3	
	No Data	No data	Restricted	
Soil Type	Pale deep sands	1	1	20%
	Pale deep sands and semi-wet soils	2	1	
	Semi-wet soil	3	2	
	Semi-wet soil, yellow-brown shallow sands and grey sandy duplexes	4	2	
	Wet soils (often peaty w/- diatomaceous earth)	5	3	
	Wet soils (often peaty)	6	3	
	No data	No data	Restricted	
)epth to groundwater (n	-3.50 - -1.50	1	3	20%
	-1.501 - 0.00	2	3	
	0.001 - 2.00	3	3	
	2.001 - 3.500	4	2	
	3.501 - 5.500	5	2	
	5.501 - 7.500	6	1	
	7.501 - 9.500	7	1	
	9.501 - 11.500	8	1	
	11.501 - 13.500	9	1	
	No data	No data	Restricted	
Slope (degrees)	0 - 1.605	1	3	10%
	1.605 - 3.21	2	3	
	3.21 - 4.814	3	3	
	4.184 - 6.419	4	2	
	6.419 - 8.024	5	2	
	8.024 - 9.629	6	1	
	9.629 -11.234	7	1	
	11.234 -12.839	8	1	
	12.839 - 14.443	9	1	
	No Data	No data	Restricted	
Aspect (degrees)	-1 - 38.756	1	2	5%
	38.756 - 78.512	2	1	
	78.512 - 118.268	3	1	
	118.268 - 158.024	4	1	
	158.024 - 197.78	5	3	
	197.78 - 237.536	6	3	
	237.536 - 277.291	7	1	
	277.291 - 317.047	8	1	
	317.047 - 356.803	9	1	
	No Data	No data	Restricted	
Vegetation Type	CL (cleared)	1	Restricted	25%
	G (Low woodland of Banksia attenuata, manziesii and Eucalyptus todtiana on dry pale sends and slopes and dune crests)	2	1	
	Gd (degraded G community)	3	1	
	H (Low woodland to low open forest of Banksia attenuata, menziesii and illicifolia on deeper pale grey sands, moist at depth)	4	1	
	Hd (degraded H community)	5	1	
	I (Open woodland of Eucalyptus marginata, Corymbia calophylla, Banksia illicifolia and grandis on moist sandy soils with humisold at lower surfaces)	6	1	
	IJ (combination of I and K communities)	7	2	
	IJd (degraded IJ community)	8	1	
	Id (degraded I community, largely a result of past grazing)	9	1	
	J (Open woodland of Corymbia calophylla on moister dark grey humisold soils on flatter lower areas with local additional species reflecting moister soils)	10	2	
	JK (combination of J and K communities)	11	2	
	JKd (degraded J and K community)	12	2	
	Jd (degraded J community largely as a result of past grazing)	13	2	
	K1 (Ranging from low open forest of Melaleuca preissiana, Banksia littoralis to closed heath of Myrtaceae species on seasonally saturated sands and peats of swamp area)	14	3	
	K1d (degraded K1 community largely as a result of past grazing)	15	3	
	K2 (Low open forest to open forest of Eucalyptus rudis and Melaleuca rhaphiophylla on sands and organic silty clays along watercourses and seasonally flooded areas)	16	3	
	No Data	No data	Restricted	

3.4 Field verification

Groundtruthing was performed to test the predictive ability of the model outlined in section 3.3. Soils in the study sites were sampled to determine their organic content. Soil moisture content and vegetation type and density are also good indicators of the presence of organic matter in soil (Froend, Farrell et al. 1993). To enable adequate sampling of all predictive model outcomes a sampling matrix was developed.

Authority was given to sample on CALM lands subsequent to Regulation 4 of the Conservation and Land Management Regulations 2002, license number CE000893.

3.4.1 Sampling Matrix

The study sites were divided into 500m X 500m grids, with four random samples taken per grid. This provided a sampling resolution, which would allow the testing of the strength of the model at an appropriate spatial scale. Two grids running north-south and two grids running east-west were chosen to perform sampling based on the predominance of predicted versus non-predicted sites (Figures 13 and 14).

Sampling was performed by navigating to a predefined site, obtained from the predictive overlay map, using a hand-held Global Positioning System (GPS) with a reported accuracy of +/- 15m (Garmin International). Figures 13 and 14 indicate the correlation between predicted and actual sample sites for Melaleuca and Whiteman Parks. In addition to the predefined sites, random samples were collected based on changes in soil type, vegetation type or topography that were deemed appropriate based on information gained from relevant literature. Eighty one samples were collected for the Melaleuca Park Site and seventy one samples were collected at Whiteman Park. For all samples the vegetation type, resistance, soil moisture and soil organic contents were calculated.

At each sample site the following variables were recorded vegetation type, resistance measurement, soil moisture content and soil organic content. Samples were collected using a hand held auger which was drilled to a depth of 500mm. Samples were analysed at a depth of 100mm and 400mm.

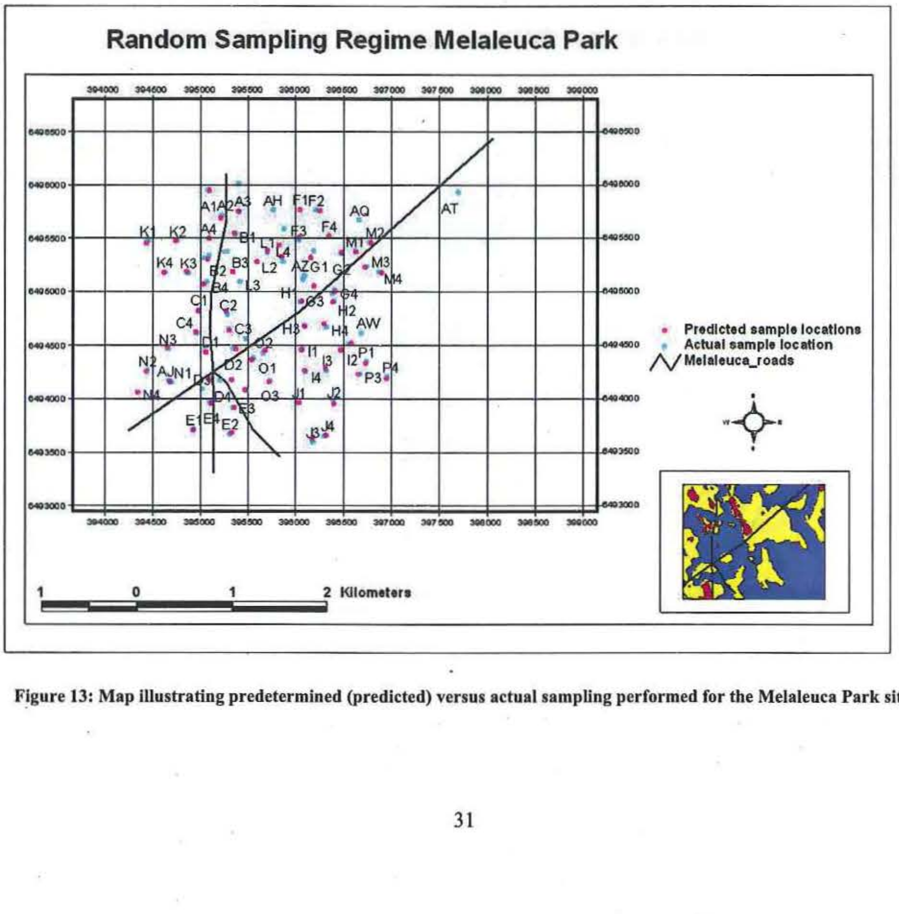


Figure 13: Map illustrating predetermined (predicted) versus actual sampling performed for the Melaleuca Park site.

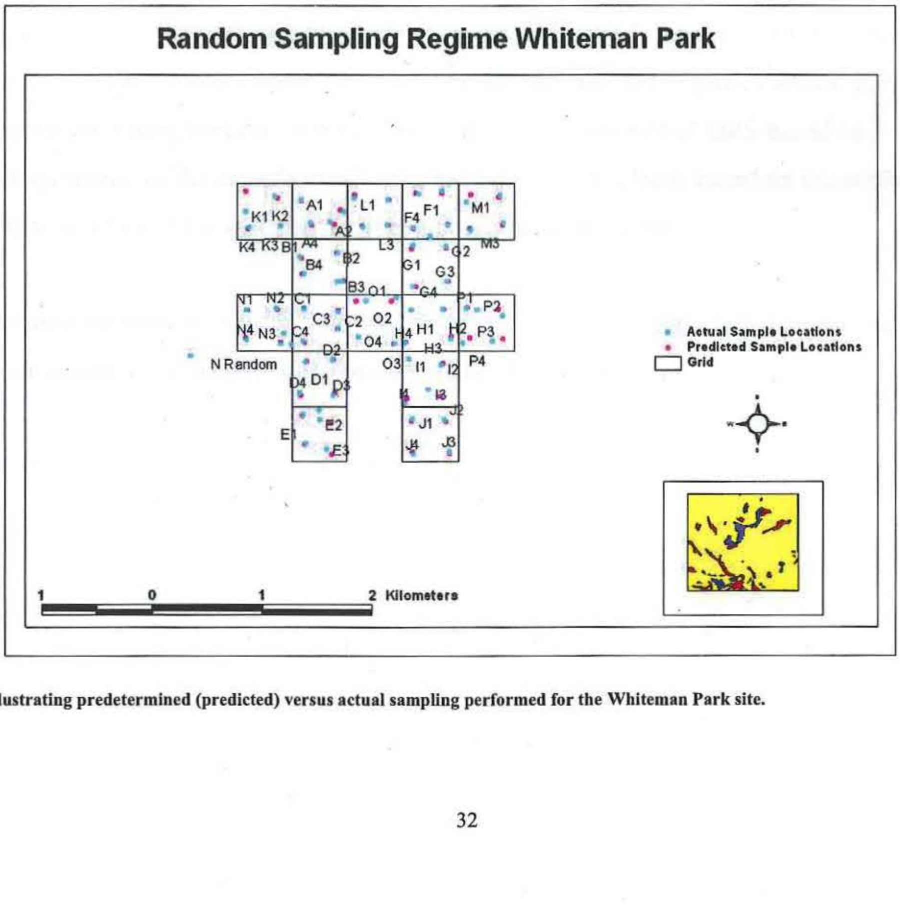


Figure 14: Map illustrating predetermined (predicted) versus actual sampling performed for the Whiteman Park site.

3.4.2 Resolution Testing Analysis

Resolution testing analysis was performed at both Melaleuca and Whiteman Parks to determine the change in performance of the model at a smaller scale and higher resolution. A comparison of the predictions with the actual occurrence of ORS was made through field verification sampling. Analysis involved sampling at 50m intervals (Figures 15 and 17), with 31 and 30 samples collected respectively for each site. A second sensitivity analysis was performed at Melaleuca Park (Melaleuca Park 2) with 10m sampling intervals (Figure 16). A total of 20 samples were collected.

At each sample site the following variables were recorded visual prediction, vegetation type, resistance measurement, soil moisture content and soil organic content. Part of the resolution testing process involved predicting the occurrence of ORS based on a visual interpretation of the sample site. Visual predictions were made based on the surface characteristics of the soil and the vegetation community type.

Logistic regression analysis was used to determine those variables that significantly contributed to the model which provided the best fit for each site.

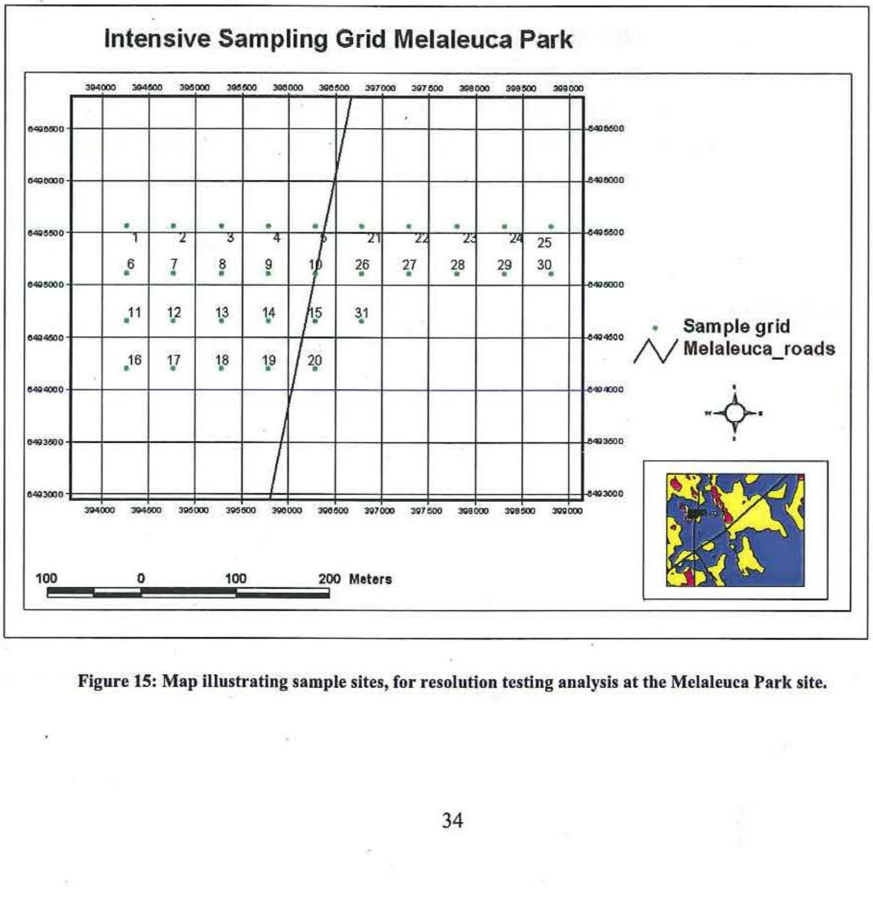


Figure 15: Map illustrating sample sites, for resolution testing analysis at the Melaleuca Park site.

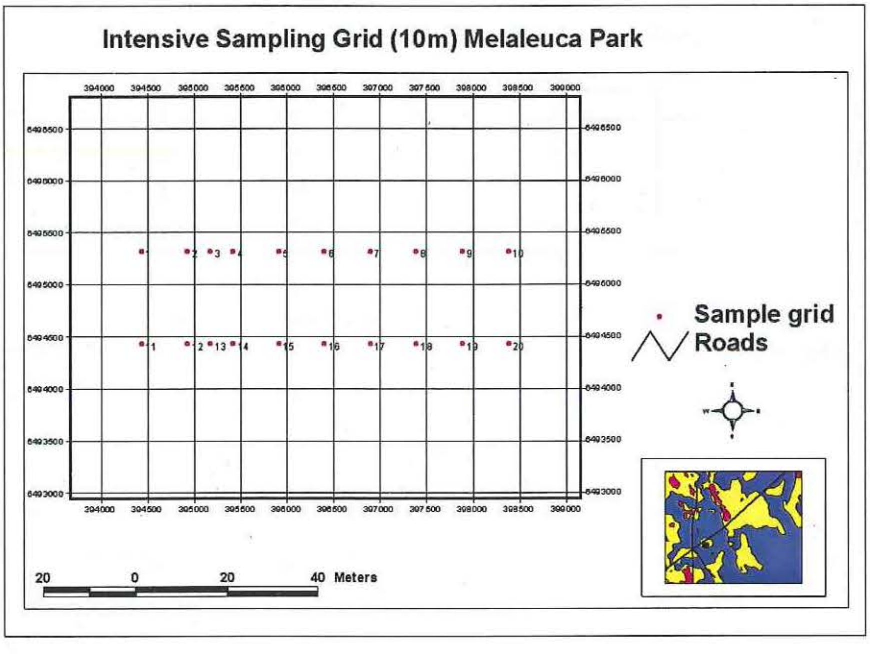


Figure 16: Map illustrating sample sites, for the resolution testing analysis (10m sampling interval) at the Melaleuca Park site.

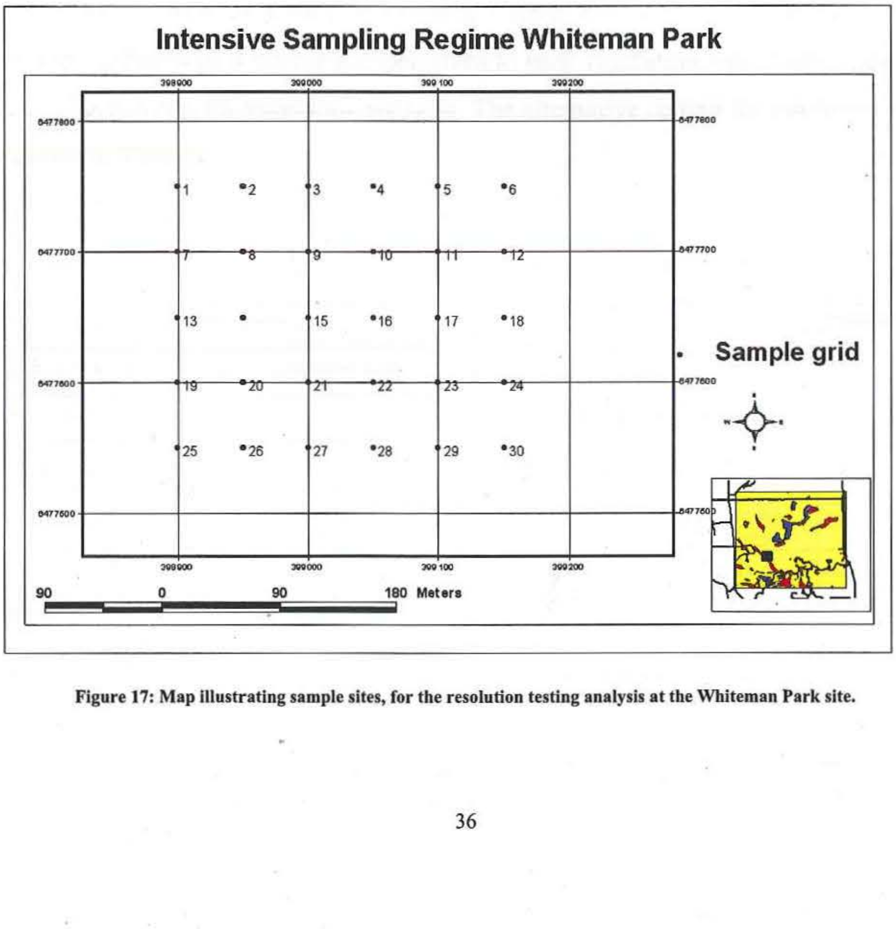


Figure 17: Map illustrating sample sites, for the resolution testing analysis at the Whiteman Park site.

3.4.3 Recorded Variables

3.4.3.1 Vegetation Type

Vegetation type was recorded using the method outlined by McDonald *et al* (McDonald, Isbell et al. 1990) by observing the most dominant species, for the upper, mid and lower strata, vegetation density and canopy cover. An area sparsely covered with a Banksia species over a mixed myrtaceous shrubland would be recorded as Very Open Banksia Woodland (V.O.B.W.). This method of vegetation sampling is in common use in Western Australia and formed the basis for such projects as 'Bushforever' (Western Australian Planning Commission 2000). Vegetation types were then reclassified with a unique number given to each vegetation type. Table 5 indicates the final groupings for vegetation analysis. The alternative coding for resolution testing is shown in Table 6.

Table 5: Vegetation field description, categories and results of reclassification.

Description	Category	Reclassification
Very open *Banksia* sp. Woodland over open mixed heath	V.O.B.W.	1
Open *Banksia* sp. Woodland over open mixed heath	O.B.W.	2
Very open woodland of *Melaleuca preissiana* over open mixed heath	*Melaleuca priessiana*	3
Very open woodland of *Melaleuca priessiana* and *Eucalyptus rudis*	*Melaleuca priessiana / Eucalyptus rudis*	4
Very open woodland of *Melaleuca priessiana* over myrtaceous heath including *Hypocalymma* sp.	*Melaleuca priessiana /* Myrtaceous sp.	5
Closed woodland of *Melaleuca rhaphiophylla*	*Melaleuca rhaphiophylla* thicket	6
Closed shrubland of *Beaufortia elegans*	*Beaufortia elegans* thicket	7
Closed woodland of *Eucalyptus rudis*	*Eucalyptus rudis* woodland	8
Open sedgeland of *Baumea* sp., *Juncea* sp. Or *Typha* sp.	Sedge	9
Open woodland of Corymbia callophylla with occasional Melaleuca sp. over myrtaceous heath	Eucalypt/Melaleuca/Myrtaceae	10
Open woodland of *Eucalyptus rudis* and *Banksia littoralis*	*Eucalyptus* sp./Banksia woodland	11
Vegeation type has been altered by past grazing and/or landuse practises	Grazed / Open plain	12
Open woodland of *Melaleuca rhaphiophylla* and *Agonis* sp. over mixed myrtaceous heath	*Melaleuca* sp. / *Agonis lin*.	13

Table 6: Vegetation field description, categories and results of reclassification, resolution testing analysis.

Description	Category	Reclassification
Very open *Banksia* sp. Woodland over open mixed heath	V.O.B.W.	1
Zone of interaction between Banksia woodland and *Melaleuca* sp. thicket	Border	2
Open thicket region of *Melaleuca* sp.	Open thicket	3
Dense thicket region of *Melaleuca* sp.	Thicket	4

3.4.3.2 Resistance Testing

Resistance to penetration of an object in soil can be indicative of the presence and depth of organic sediments. Inorganic soils tend to offer more resistance to the penetration of an object than do organic soils. Thus it provides a crude but useful field technique for delineating the occurrence of ORS. The method involved inserting a rod (10mm in diameter) into the soil profile under constant pressure. Depth of penetration into the soil profile was recorded to the nearest millimeter. Where organic sediments occurred the point of maximum resistance was defined as the organic-mineral sediment interface.

3.4.3.3 Soil Moisture Analysis

The gravimetric soil moisture (GSM) content of sediments was quantified using the methods as outlined by McDonald *et al* (McDonald, Isbell et al. 1990). GSM measures the amount of moisture contained within a soil, expressed as a percentage of the wet weight of the soil. Each sample received the following treatment

- Pre-weigh all crucibles (weighed to four decimal places and then rounded to two decimal places) on a OHAUS analytical balance
- Approximately ten grams of wet weight sediment was added to each crucible, crucible was reweighed and dried at room temperature for 24 hours.
- Samples were reweighed using analytical balance
- Samples were oven dried at 110^{0}c in a Series 5 Contherm drying oven for 24 hours.
- Samples were cooled in a desiccator and weighed in grams to four decimal places (results rounded to two decimal places)
- Gravimetric soil moisture (GSM) was calculated using the following formula: GSM (%) = 100 x <u>(mass of room temp. sample - mass of oven dry sample)</u>

mass of room temperature sample

3.4.3.4 Soil Organic Content

The organic content of sediments was quantified using the methods outlined by McDonald *et al* (McDonald, Isbell et al. 1990). Each sample was subjected to the process outlined below.

- Pre-weigh all crucibles (weighed to four decimal places and then rounded to two decimal places) on a OHAUS analytical balance
- Approximately ten grams of wet weight sediment was added to each crucible, crucible was reweighed and dried at room temperature for 24 hours.
- Samples were reweighed using analytical balance
- Samples were oven dried at 110^0c in a Series 5 Contherm drying oven for 24 hours.
- Samples were cooled in a desiccator and weighed in grams to four decimal places (results rounded to two decimal places)
- Samples were then ignited in a Furnace Brand muffle furnace for three hours at 550^0c
- Samples were cooled in a desiccator and reweighed in grams to four decimal places (results rounded to two decimal places)
- Loss on Ignition (LOI) as a measure of organic matter (OM) was calculated using the following formula:

$$\text{OM (\% LOI)} = 100 \times \frac{\text{(mass of oven dry sediment} - \text{mass of ignited sediment)}}{\text{mass of oven dry sediment}}$$

The Walkely-Black (wet oxidation) method (Agronomy Society of America 1982) was used to verify the precision associated with using LOI as a measure of the quantitative organic matter content of sampled sediments. The results of this can be seen in section 4.1.

3.4.3.5 Visual Prediction (resolution testing only)

During the resolution testing visual prediction was made for the presence of ORS. Visual predictions were made based on the surface characteristics of the soil and vegetation community type. This visual prediction was then compared with the LOI analysis results to determine the predictive capability of the visual prediction technique.

3.5 Data analysis

Evaluation of the effectiveness of the model was achieved by analyzing the number of correctly predicted outcomes versus the number of incorrect predictions, based on field results. A conservative LOI value of 10% was used as the criterion for the determination of the presence of ORS to allow for errors relating to LOI analysis.

Logistic regression analysis was used to statistically test the fit of the predicted model. Logistic regression was chosen as the method of analysis as it does not require the predictor variables to be normally distributed, linearly related or to have equal variance within each variable set (Tabachnick and Fidell 1996). Logistic regression allows the prediction of a discrete outcome based on a set of predefined variables, which can be continuous, categorical, dichotomous or a mix (Tabachnick and Fidell 1996). Logistic regression models use a logistic function to fit models to data (Bergund 1996).

Logistic regression analysis requires the conversion of categorical data into referenced categories. This enables the impact of each attribute within a variable of the model to be measured. Individual attributes are converted into categories (dummy variables coded as 1) and compared with a reference category (coded as all 0's) (Table 7). The categorical coding tables for all logistic regression analyses can be viewed in Appendix 3.

Table 7 An example of the coding of categorical variables used in the logistic regression for the Melaleuca Park site.

Categorical Variables Codings

			Parameter coding							
		Frequency	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vegetation Type	VOBW	26	.000	.000	.000	.000	.000	.000	.000	.000
	OBW	22	1.000	.000	.000	.000	.000	.000	.000	.000
	Mel. rhaph	1	.000	1.000	.000	.000	.000	.000	.000	.000
	Mel. rhaph/E. rudis	2	.000	.000	1.000	.000	.000	.000	.000	.000
	Mel. rhaph./Hypocalymma	2	.000	.000	.000	1.000	.000	.000	.000	.000
	Mel. rhaph thicket	20	.000	.000	.000	.000	1.000	.000	.000	.000
	B. elegans thicket	3	.000	.000	.000	.000	.000	1.000	.000	.000
	E. rudis thicket	1	.000	.000	.000	.000	.000	.000	1.000	.000
	Sedge	4	.000	.000	.000	.000	.000	.000	.000	1.000
Aspect	Flat	45	.000	.000	.000	.000	.000	.000	.000	.000
	North	3	1.000	.000	.000	.000	.000	.000	.000	.000
	Northeast	1	.000	1.000	.000	.000	.000	.000	.000	.000
	East	6	.000	.000	1.000	.000	.000	.000	.000	.000
	Southeast	6	.000	.000	.000	1.000	.000	.000	.000	.000
	South	3	.000	.000	.000	.000	1.000	.000	.000	.000
	Southwest	2	.000	.000	.000	.000	.000	1.000	.000	.000
	West	6	.000	.000	.000	.000	.000	.000	1.000	.000
	Northwest	9	.000	.000	.000	.000	.000	.000	.000	1.000
Soil Type	PDS	39	.000	.000	.000					
	PDS/Semi-wet	6	1.000	.000	.000					
	Semi-wet	17	.000	1.000	.000					
	Wet-soils/peaty	19	.000	.000	1.000					
Wetland Type	sumpland	19	1.000	.000						
	dampland	12	.000	1.000						
	not	50	.000	.000						

Sequential logistic regression was the method used in this instance. Predictor variables are entered into the model one at a time until the model contains all predictor variables. This involved starting with a constant only model (model with no variables included) and measuring the affect on the model of adding the next least correlated variable with each subsequent step. In a logistic regression model the constant is the predicted log odds when all regressors are set to 0. Thus when only the constant is included in the model, its value is the log of the odds of a positive outcome for the entire data set.

Model chi-square compares the fit of the model with constant and predictors against the constant-only model, Step chi-square compares the fit of the model with the inclusion of the variable added at that step and % Correct gives the number of cases that are correctly predicted by the model for the dichotomous output variable. These values are used to determine the variability between models (groups of variables). Positive changes to step and model chi-square values and an increase in percentage correct values indicate an improvement in the fit of the model to the data. The significance of the effect of individual variables on the strength of the logistic regression model is indicated by the score value. The score statistic is used to determine whether the coefficient is different from zero, based on a change in log-likelihood associated with the effect. A

significant result indicates a predictor that is reliably associated with the outcome (Tabachnick and Fidell 1996).

All analysis was performed using SPSS for Windows version 11.5.0 2002.

CHAPTER 4: RESULTS

The results have been divided into dataset validation, prediction model of the presence of ORS, field verification of the presence of ORS, logistic regression and sensitivity analysis results. Within each section the results are further separated into study sites.

Results for Whiteman Park study site include analysis performed with and without the inclusion of vegetation types as defined by Mattiske Consulting (Mattiske Consulting Pty Ltd 2002), to examine the effect of vegetation data on the strength of the predictive models capabilities.

4.1 Results of Validity Tests for Created Datasets

Correlation between the GIS created topographical contours and the ground height values from the Department of Environment (DoE) groundwater monitoring bores was highly significant as was the groundwater levels (Table 8). The correlation between calculated depth to groundwater values was not significant as shown in Table 8.

Table 8 Correlation matrix showing the relationship between GIS created and Department of Environment groundwater monitoring bore derived values for topographical contour, groundwater contour and depth to groundwater values.

Correlations

		GIS Contour	GIS GW	Contour	GW Contour	Depth to Groundwater 1	Depth to Groundwater 2	Depth to GW adjusted
GIS Topographical Contour	Pearson Correlation	1	.999**	.995**	.998**	.480	.119	.119
	Sig. (2-tailed)	.	.000	.000	.000	.082	.884	.684
	N	14	14	14	14	14	14	14
GIS Groundwater Contour	Pearson Correlation	.999**	1	.996**	.997**	.445	.128	.128
	Sig. (2-tailed)	.000	.	.000	.000	.111	.663	.663
	N	14	14	14	14	14	14	14
Topographical Contour	Pearson Correlation	.995**	.996**	1	.989**	.451	.210	.210
	Sig. (2-tailed)	.000	.000	.	.000	.106	.472	.472
	N	14	14	14	14	14	14	14
Groundwater Contour	Pearson Correlation	.998**	.997**	.989**	1	.482	.084	.084
	Sig. (2-tailed)	.000	.000	.000	.	.081	.826	.826
	N	14	14	14	14	14	14	14
Depth to Groundwater GIS	Pearson Correlation	.460	.445	.451	.482	1	-.146	-.146
	Sig. (2-tailed)	.082	.111	.106	.081	.	.619	.619
	N	14	14	14	14	14	14	14
Depth to Groundwater Monitoring Bores	Pearson Correlation	.119	.128	.210	.084	-.146	1	1.000**
	Sig. (2-tailed)	.684	.663	.472	.826	.619	.	.
	N	14	14	14	14	14	14	14
Depth to GW adjusted 3m	Pearson Correlation	.119	.128	.210	.084	-.146	1.000**	1
	Sig. (2-tailed)	.684	.663	.472	.826	.619	.	.
	N	14	14	14	14	14	14	14

**. Correlation is significant at the 0.01 level (2-tailed).

Although in most instances the results of the Walkley-Black analysis yielded organic content values that were slightly higher than those as a result of the Loss on Ignition analysis, there was a strong linear relationship between the two analyses with an R^2 value of 0.92 (Figure 18).

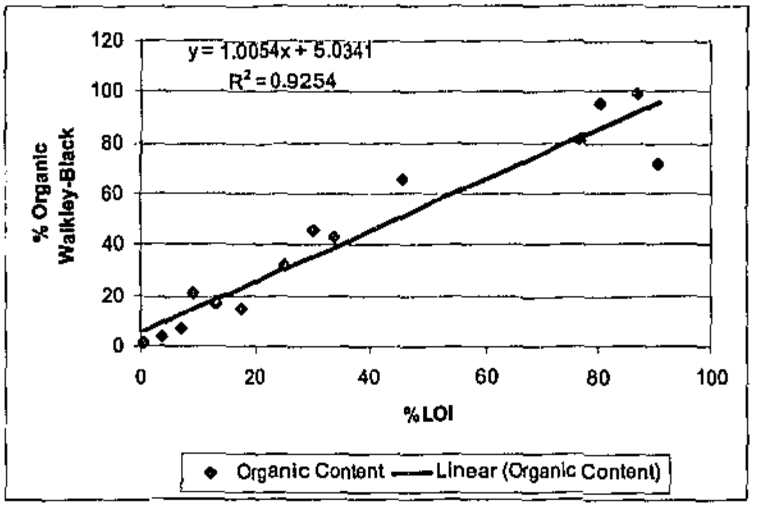


Figure 18 Graph indicating the relationship between loss on ignition (LOI) and the Walkley-Black (wet oxidation) methods for the determination of organic matter content for selected samples from both sites.

4.2 Results of Weighted Overlay Model to Predict ORS

4.2.1 Melaleuca Park

The resultant predictive model from the weighted overlay model can be seen in Figure 19. Red shaded areas represent regions where organic sediments are predicted to occur. This represents 53.34 ha in area and accounts for 3.5% of the total site. The yellow shaded areas represent regions that may contain organic sediments, categorized as medium predictability of ORS occurring, which total 581.83 ha and represent 38.57% of the total site. The blue regions are where the model indicates no organic rich sediments to be present and categorized as low predictability of ORS occurring. They total 867.52 ha in area and account for 57.5% of the total site.

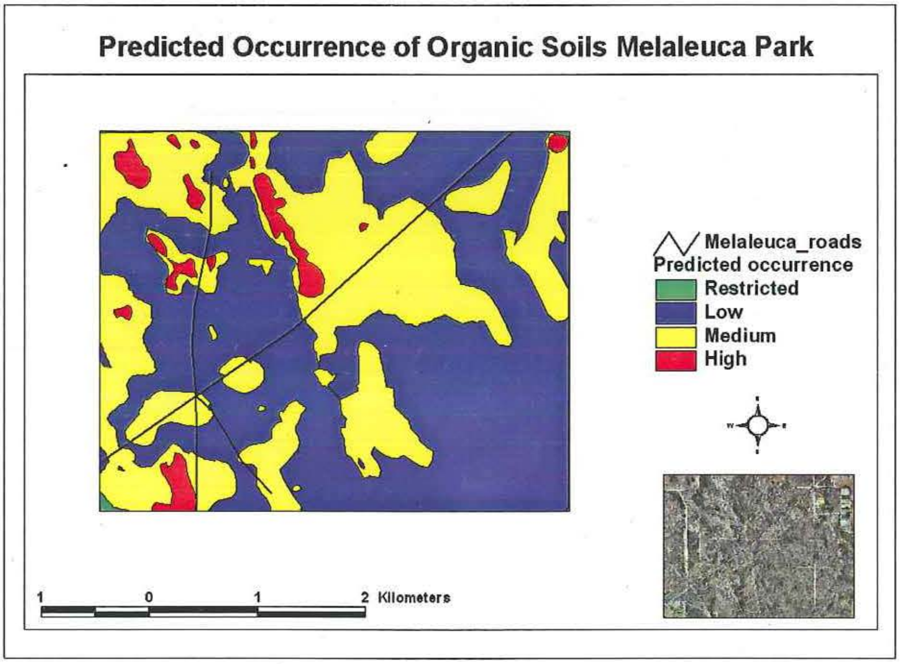


Figure 19 A map of the predicted occurrence of organic rich sediments for the Melaleuca Park site, created from a weighted overlay ArcView 3.2.

4.2.2 Whiteman Park

The predictive model resultant from the weighted overlay for Whiteman Park can be seen in Figure 20. Total area of the site is 1,418.34 ha. Areas predicted to contain ORS (categorized high) account for 5.5% of the total site or 79.19 ha. Areas where there is a possibility of ORS occurring, shaded yellow, account for 90% or 1,282.37 ha. Where the model predicts no ORS to occur, categorized as low, these areas account for less than 5% or 57.09 ha.

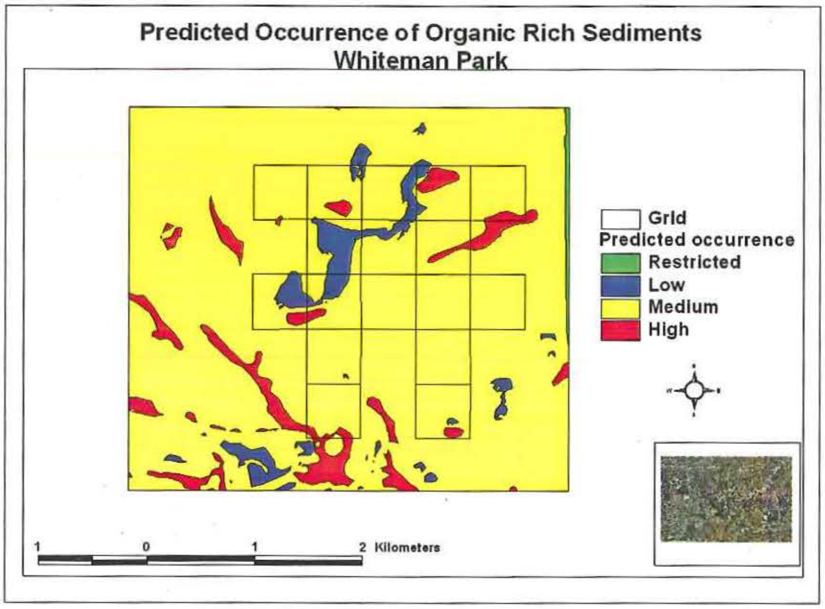


Figure 20: A map of the predicted occurrence of organic rich sediments for the Whiteman Park site, created from a weighted overlay ArcView 3.2.

4.2.3 Whiteman Park (vegetation survey included)

A map showing the predicted occurrences of ORS at the Whiteman Park site as a result of the weighted overlay model, when the vegetation survey dataset was included can be seen in Figure 21. Total area of the site is 1,418.34 ha. Those areas representing regions where ORS are expected to occur total 204 ha and account for 14% of the total site, an increase of ~9%. Areas categorized as medium, regions where ORS may occur, account for 82% of the total area and total 1,166 ha which is a decrease from the predictive model that does not include vegetation data. Those areas not predicted to contain ORS amount to 49 ha and account for less than 5% of the total site.

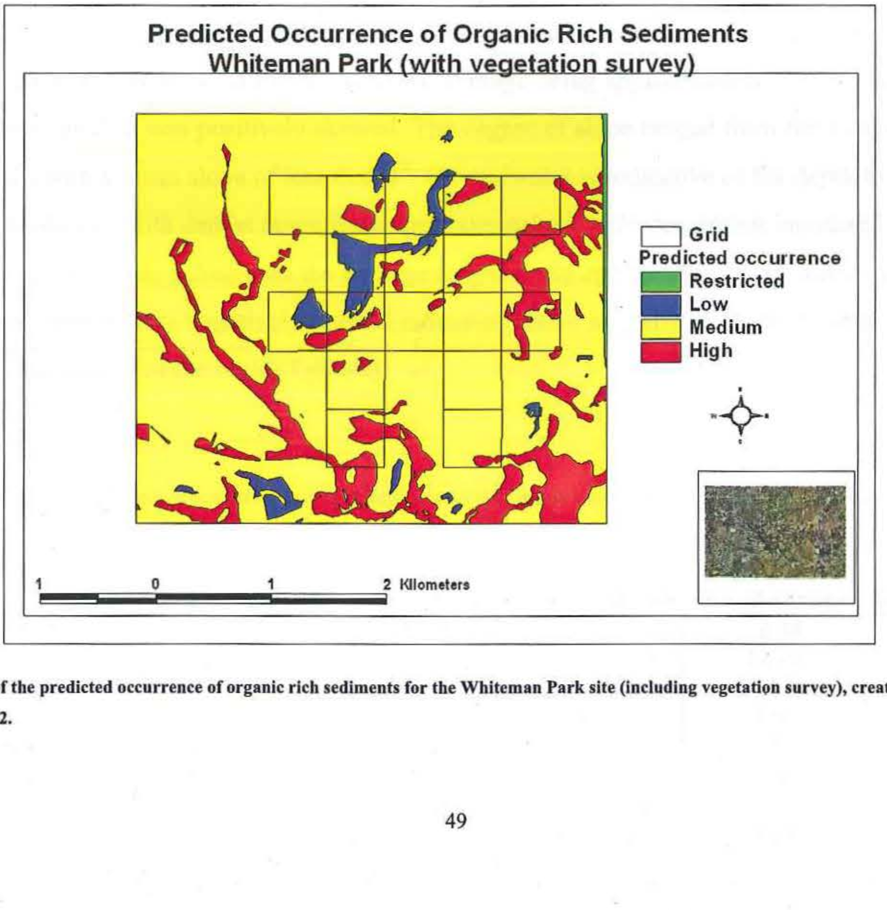


Figure 21: A map of the predicted occurrence of organic rich sediments for the Whiteman Park site (including vegetation survey), created from a weighted overlay ArcView 3.2.

4.3 Field Verification of the Model

4.3.1 Melaleuca Park

The results of field verification for Melaleuca Park as determined by % LOI, percentage moisture, resistance, slope, depth to groundwater, vegetation type, aspect, soil type and wetland type are presented in Tables 9 to 11 and Figure 22.

The range of organic content for the soils sampled at Melaleuca Park ranged from very low (< 1%) to very high (> 90%) and was positively skewed (Table 9). This pattern was repeated with the soil moisture results (Table 9). Resistance readings ranged from < 50cm to in excess of 1.5 meters, with the average being approximately 200cm (Table 9). Again the data was positively skewed. The degree of slope ranged from flat to in excess of 3^0, with a mean slope of less than 1^0. Groundwater is indicative of the depth to groundwater with depths range from approximately -3m (representing inundated areas) to approximately 3.5m, with the average height being approximately 1m below ground level, results were negatively skewed indicating that a majority of values were towards the higher end of the scale (Table 9).

Table 9 Descriptive statistics for field and predictive model variables from the Melaleuca Park site

Variable	N	Minimum	Maximum	Mean	Median	Std. Deviation	Skewness
% moisture	81	0.38	84.48	11.90	3.25	19.14	2.22
% LOI	81	0.96	90.58	12.56	4.41	16.29	2.47
Resistance	81	40	1850	236.79	180	233.02	4.51
Vegetation type	81	1	9	3.41	2	2.55	0.67
Slope	81	0	3.65	0.68	0	0.98	1.44
Aspect	81	1	9	3.32	1	3.04	0.86
GW	81	-2.9	3.46	0.89	0.7	1.54	-0.23
Soil type	81	1	5	2.43	2	1.63	0.62
Wetland type	81	1	5	3.62	5	1.79	-0.58

A Spearman's rho correlation matrix was performed to assess the relationship between variables (Table 10). Correlations are only shown for % LOI, as this was the criterion used to define the existence of organic rich sediments. % Moisture, resistance, vegetation type and soil type variables exhibited highly significant relationships with LOI results. As the organic matter content increases so do the soil moisture levels. Wetland type and depth to groundwater (GW) show highly significant inverse relationships, as organic matter content increases depth to groundwater decreases. Aspect displays a significant relationship whilst slope displays an inverse relationship that is not significant, indicating that the organic matter content of soils is not related to the slope of the land at a landscape scale. This confirms that the amount of soil moisture, vegetation type, soil type and wetland type are important variables in the prediction of ORS.

Table 10: Spearman's rho correlation matrix of field and prediction model variables for the Melaleuca Park site.

Correlations

Variable		% LOI	Variable		% LOI
% moisture	Correlation Coefficient	0.75**	Aspect	Correlation Coefficient	-0.26*
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.02
	N	81		N	81
% LOI	Correlation Coefficient	1	GW	Correlation Coefficient	-0.35**
	Sig. (2-tailed)	.		Sig. (2-tailed)	0.00
	N	81		N	81
Resistance	Correlation Coefficient	0.60**	Soil type	Correlation Coefficient	0.44**
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.00
	N	81		N	81
Vegetation type	Correlation Coefficient	0.75**	Wetland type	Correlation Coefficient	-0.65**
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.00
	N	81		N	81
Slope	Correlation Coefficient	-0.12			
	Sig. (2-tailed)	0.29			
	N	81			

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Ten percent and 15% Organic content categories represent the number of samples categorized as ORS based on 10% and 15% LOI values respectively. The results shown in Table 11 indicate that a large proportion of the results 64 and 71% respectively for the Melaleuca Park site were not classified as ORS.

Table 11 Classification of ORS based on LOI values from field sampling for the Melaleuca Park site

ORS Classification				
Criterion	**LOI Range**	**N**	**Percentage (%)**	**ORS**
10%	< = 10%	81	64.2	No
	> = 10%	81	35.8	Yes
15%	< = 15%	81	71.6	No
	> = 15%	81	28.4	Yes

Field verification analysis compared the prediction outcome with LOI values, utilising a 10% criteria for the positive classification of organic rich sediments. Samples with an LOI value below 10% were classified as inorganic sediments or mineral soils. Results were then compared with model predictions. For the purposes of model validation both the high and medium prediction categories were expected to contain organic sediments with LOI values greater than or equal to 10%, if the LOI value was greater than or equal to 10% then the prediction was considered correct. Sites categorized as low were expected to contain organic sediments with LOI values less than 10%, if this was the case then the prediction was considered correct.

Based on field sampling, areas predicted as containing ORS were correct 87% of the time. Predictions for medium probability areas were 61% correct, and 92% for low probability regions. This provided an overall correct prediction rate of 76% (Figure 22).

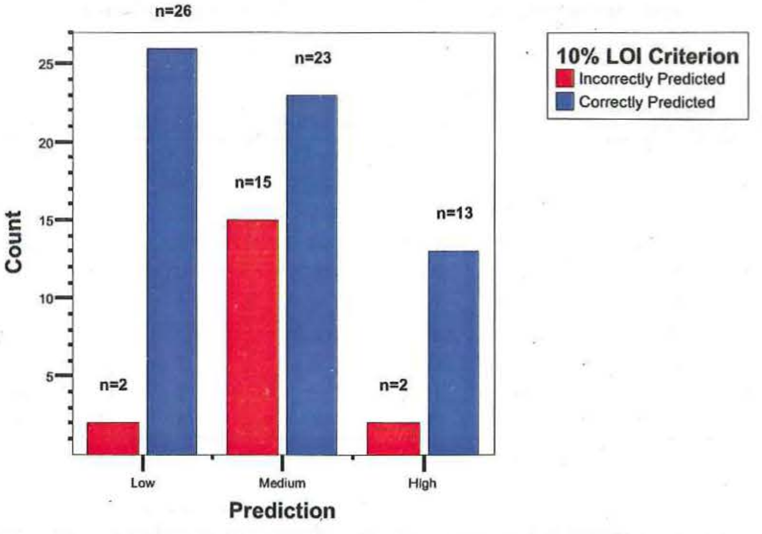


Figure 22: Graph showing number of correct versus incorrect predictions for calculated categories of weighted overlay model for the Melaleuca Park site.

4.3.2 Whiteman Park

The results of field verification for Whiteman Park as determined by % LOI, and other variables such as percentage moisture, resistance, slope, depth to groundwater, vegetation type, vegetation survey, aspect, soil type and wetland type are shown in Tables 12 to 14 and Figure 23.

The range of organic content of soils sampled at Whiteman Park ranged from less than 1% to 30% (Table 12). Soil moisture results range from < 1% to ~ 30% and both organic and soil moisture values were positively skewed (Table 12). Resistance readings ranged from 20cm to 400cm with the average being approximately 100cm. The degree of slope ranges from flat to in excess of 5^0, with a mean slope of ~1^0 (Table 12). Groundwater depths range from approximately -2m (representing inundated areas) to approximately 4.0m, with the average height being approximately 0.5 m below ground level, again results are positively skewed (Table12).

Table 12 Descriptive statistics of field and prediction model variables at Whiteman Park. Vegetation type, Aspect, Soil type and Wetland type are all categorical variables.

Descriptive Statistics							
Variable	**N**	**Minimum**	**Maximum**	**Mean**	**Median**	**Std. Deviation**	**Skewness**
% moisture	71	0.14	88.8	3.97	0.90	11.52	6.20
% LOI	71	0.59	29.81	3.98	2.10	4.84	3.04
Resistance	71	20	470	98.34	80.00	67.13	2.80
Vegetation type	71	1	14	6.73	7.00	4.52	0.19
Slope	71	0	5.88	1.06	0.40	1.55	1.77
Aspect	71	1	8	3.72	5.00	2.37	0.01
GW	71	-2.5	4.15	-0.69	-1.20	1.46	1.71
Soil type	71	1	5	2.73	3.00	1.31	0.16
Wetland type	71	2	5	4.10	5.00	1.29	-0.93
WP Veg	71	1	7	4.61	5.00	1.42	-0.81

A Spearman's rho correlation was performed to assess the relationships between field and predictive model variables and the organic content of soils sampled (Table 13). There was a very significant correlation between the organic content of the soil and the type of vegetation present at the site as evidenced by the results for the W.P. Veg (Mattiske Consulting vegetation survey) variable (Table 13). There was a significant increase in the amount of soil moisture present with increased levels of organic matter as shown by the results for % Moisture (Table 13). The remaining variables did not show significant correlations.

Table 13 Spearman's rho correlation matrix of field samples and predictive model variables for the Whiteman Park Site.

Correlations					
Variable		**% LOI**	**Variable**		**% LOI**
% moisture	Correlation Coefficient	0.72*	Aspect	Correlation Coefficient	-0.02
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.82
	N	71		N	71
% LOI	Correlation Coefficient	1	GW	Correlation Coefficient	0.01
	Sig. (2-tailed)	.		Sig. (2-tailed)	0.91
	N	71		N	71
Resistance	Correlation Coefficient	0.08	Soil type	Correlation Coefficient	0.15
	Sig. (2-tailed)	0.51		Sig. (2-tailed)	0.19
	N	71		N	71
WP Veg	Correlation Coefficient	0.32**	Wetland type	Correlation Coefficient	0.08
	Sig. (2-tailed)	0.01		Sig. (2-tailed)	0.47
	N	71		N	71
Vegetation type	Correlation Coefficient	0.04			
	Sig. (2-tailed)	0.74			
	N	71			
Slope	Correlation Coefficient	0.06			
	Sig. (2-tailed)	0.61			
	N	71			

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

The 10% and 15% organic content category results shown in Table 14 indicate that a large proportion of samples, 91% and 95% respectively, for the Whiteman Park site were not classified as ORS. The results were compared with the model predictions for Whiteman Park. Areas classified as high and medium for the predicted occurrence of ORS were expected to contain ORS, low category predictions were not expected to contain ORS.

Table 14 Classification of ORS based on LOI values from field sampling for the Whiteman Park site.

ORS Classification				
Criterion	**LOI Range**	**N**	**Percentage (%)**	**ORS**
10%	< = 10%	71	91.5	No
	> = 10%	71	8.5	Yes
15%	< = 15%	71	95.8	No
	> = 15%	71	4.2	Yes

Analysis compared the prediction outcome with Loss on Ignition Values (LOI), utilising a 10% criteria for the positive classification of organic rich sediments. Based on field verification sampling the overall ability to correctly predict the occurrence of ORS at Whiteman Park was approximately 14.5% (Figure 23). The ability to correctly predict the occurrence in high probability areas was 25%, in medium probability areas it was 10% and in low probability areas 100% (Figure 23).

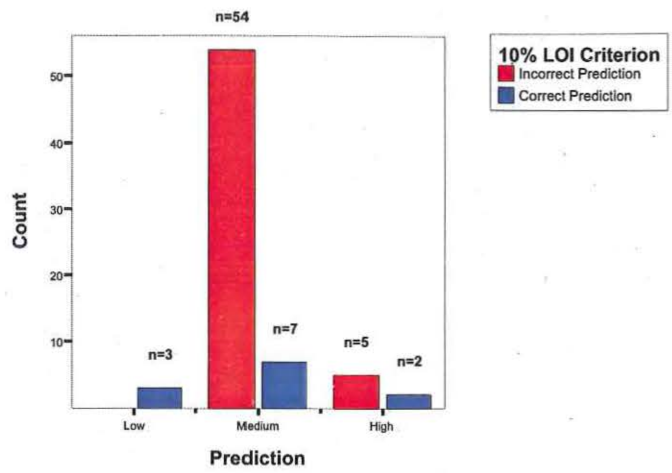


Figure 23 Graph showing number of correct predictions versus incorrect predictions for predicted outcomes of weighted overlay model for Whiteman Park site.

4.3.3 Whiteman Park (with vegetation survey)

Field sampling and analysis compared the prediction outcome from a weighted overlay model with Loss on Ignition Values (LOI), utilising a 10% criteria for the positive classification of organic rich sediments. The results shown in Figure 24 indicated a correct prediction rate of 11% for the prediction of ORS in Whiteman Park, when the vegetation type variable was included in the calculation of the model. There was a 33% success rate for low probability areas, 8% for medium probability areas and 25% success rate for high probability areas.

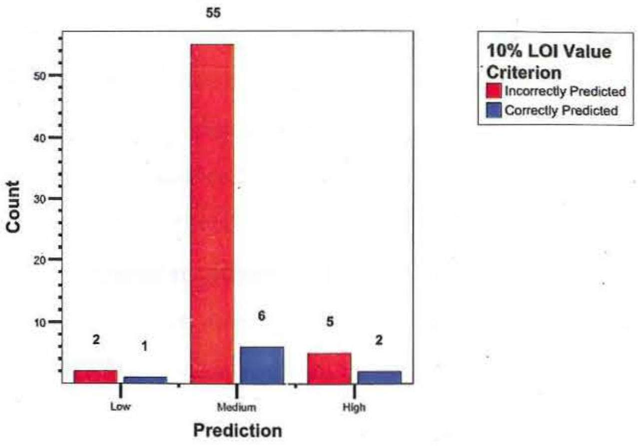


Figure 24 Graph showing number of correct versus incorrect predictions for calculated outcomes of weighted overlay model for Whiteman Park site (including vegetation survey).

4.4 Logistic Regression Analysis

4.4.1 Melaleuca Park

The results of the logistic regression analysis for Melaleuca Park are shown in Tables 15 and 16[ab]. Results are provided for analysis using both field and GIS (predictor) variables and predictor variables alone.

Analysis consists of comparing the significance of individual variables on improving the fit of the model with the data and the influence of different variable combinations improving the fit of the model over a constant only model. In a logistic regression model the constant is the predicted log odds when all regressors are set to 0. Thus when only the constant is included in the model, its value is the log of the odds of a positive outcome for the entire data set.

When comparing models model 1 contains no variables (constant only model). Subsequent models included the addition of the next least correlated variable. The final model represents analysis with all variables included.

The significance of individual variables on the fit of the model for Melaleuca Park is shown in Table 15. The score statistic is used to determine whether the coefficient is different from zero, based on a change in log-likelihood associated with the effect, the greater the value the greater the change in log-likelihood values and indicates an improvement in the fit of the model. % Moisture (Moist), vegetation type (Veg), wetland type (Wet), resistance (Peno), depth to groundwater (GW), and soil type (Soil) are considered to significantly improve the fit of the model. Whilst the vegetation type variable is considered significant only dummy variables 1 (O.B.W.), 5 (*M. rhaphiophylla* thicket) and 8 (sedges) actually contribute to the significance of the variable (Table 15).

Table 15: Logistic regression analysis results for field verification sampling, Melaleuca Park.

		Score	df	Sig.
Variables	MOIST**	28.364	1	.000
	VEG**	58.007	8	.000
	VEG(1)**	9.376	1	.002
	VEG(2)	.565	1	.452
	VEG(3)	.180	1	.672
	VEG(4)	.180	1	.672
	VEG(5)**	33.940	1	.000
	VEG(6)	1.291	1	.256
	VEG(7)	1.816	1	.178
	VEG(8)**	7.545	1	.006
	WET**	27.177	2	.000
	WET(1)**	15.498	1	.000
	WET(2)*	5.838	1	.016
	PENO**	14.403	1	.000
	SLOPE	.046	1	.830
	COMPASS	13.563	8	.094
	COMPASS(1)	1.737	1	.187
	COMPASS(2)	.565	1	.452
	COMPASS(3)	.568	1	.451
	COMPASS(4)	2.686	1	.101
	COMPASS(5)	1.737	1	.187
	COMPASS(6)	1.144	1	.285
	COMPASS(7)	3.614	1	.057
	COMPASS(8)	.812	1	.367
	GW**	7.967	1	.005
	SOIL**	13.895	3	.003
	SOIL(1)	3.614	1	.057
	SOIL(2)	.002	1	.961
	SOIL(3)**	11.491	1	.001
Overall Statistics		64.947	25	.000

Note: * score value significant at the 0.05 level, ** score value significant at the 0.01 level.

When comparing models using only the predictor variables the initial model had a percentage correct value of 64.2 % (Table 16 [b]). There is little change to the model with the inclusion of the slope variable. With the addition of the aspect variable the fit of the model improves as evidenced by the rise in the percentage correct value (Table 16 [b]). An increase in the step chi-square value indicates that the addition of aspect was

significant in improving the fit of the model. A significant increase in the model chi-square value indicated that the improvement in the fit of the model was significant when both slope and aspect were included in the model (Table16[b]). A further improvement in fit occurs with the addition of groundwater (highly significant step and model chi-square values), soil type (significant step and highly significant model chi-square values) and wetland type (highly significant step and model chi-square values) variables. The final model shows excellent fit with a percentage correct value of 84% (Table16[b]).

When a comparison of models was made utilising both field variables and predictive model variables, the initial model had a percentage correct value of 64.1% (Table 16 [a]). This increased by 3.7% with the addition of aspect, indicating an improvement in fit of the model. The step chi-square value is significant indicating that the variable aspect is significant in improving the fit of the model, consequently the model is also considered significant at this stage indicating that a model containing slope and aspect variables is a significantly stronger model than when no variables are used (Table 16 [a]). The improvement in fit of the model with the inclusion of groundwater (depth to groundwater), is highly significant as demonstrated by the step and model chi-square values (Table 16 [a]). The fit of the model is significantly improved with the addition of vegetation, indicating that a model including vegetation type is far stronger than one without (Table 16 [a]). The inclusion of the remaining variables sees small increases in percentage correct and model chi-square values, indicating that the addition of these variables did not significantly improve the fit of the model (Table 16 [a]). The addition of the moisture variable provided a significant increase in the fit of the model, resulting in a percentage correct value of 100% (Table 16 [a]).

Table 16: Results of logistic regression analysis for Melaleuca Park site indicating the model chi-square test, step chi-square test (degrees of freedom [df]) and percentage correct for models analysed using all variables [a] and predictor variables only [b].

[a]All Variables			
Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1 None	19.71 (initial log likelihood)		64.2
Model 2 (+ slope)	0.05 [1]	0.05 [1]	64.2
Model 3 (+ aspect)	18.62* [9]	18.56* [8]	87.9
Model 4 (+ groundwater)	28.62** [10]	9.64** [1]	69.1
Model 5 (+ vegetation)	85.81** [18]	57.56** [8]	92.8
Model 6 (+ soil)	89.08** [21]	3.27 [3]	95.1
Model 7 (+ penetrometer)	89.32** [22]	0.23 [1]	95.1
Model 6 (+ wetland)	93.26** [24]	3.95 [2]	96.3
Model 9 (+ moisture) All Variables	105.67** [25]	12.40** [1]	100

[b]Predictor Variables			
Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1 None	19.71 (initial log likelihood)		64.2
Model 2 (+ slope)	0.05 [1]	0.05 [1]	64.2
Model 3 (+ aspect)	18.62* [9]	18.56* [8]	67.9
Model 4 (+ groundwater)	28.62** [10]	9.64** [1]	69.1
Model 5 (+ soil)	37.50** [13]	9.23* [3]	79
Model 6 (+ wetland) All variables	57.71** [15]	20.21** [2]	86.4

Note: * Chi-square test significant at the .05 level, ** Chi-square test significant at the .01 level.

4.4.2 Whiteman Park

The results of the logistic regression analysis for Whiteman Park are shown in Table 17 and Table 18[ab]. Results are provided for analysis using both field and predictor variables and predictor variables alone.

As part of the logistic regression analysis of the Whiteman Park site the significance of individual variables on the fit of the model (Table 17) as well as the significance of comparing groups of variables on the fit of the model (Table 18[ab]) was considered.

The results in Table 17 show the significance of individual variables on the effect of the model. % Moisture (moist) and resistance (peno) were highly significant at improving the fit of the model at an individual level. The vegetation type (veg) variable was considered significant based on the significance of dummy variables 10 (highly significant) and 6 (significant) (Table 17). The remaining variables were not considered significant.

Table 17: Logistic regression analysis results for Whiteman Park indicating the score, degrees of freedom (df) and significance of each variable used in the analysis.

		Score	df	Sig.
Variables	WET	3.956	3	.266
	WET(1)	.221	1	.639
	WET(2)	.094	1	.760
	WET(3)	3.192	1	.074
	MOIST**	22.866	1	.000
	PENO**	17.850	1	.000
	VEG*	22.990	10	.011
	VEG(1)	1.074	1	.300
	VEG(2)	.951	1	.329
	VEG(3)	.572	1	.450
	VEG(4)	.094	1	.760
	VEG(5)	.342	1	.559
	VEG(6)*	4.592	1	.032
	VEG(7)	.342	1	.559
	VEG(6)	.717	1	.397
	VEG(9)	1.074	1	.300
	VEG(10)**	13.722	1	.000
	SLOPE	1.002	1	.317
	COMPASS	4.122	6	.660
	COMPASS(1)	.190	1	.663
	COMPASS(2)	.572	1	.450
	COMPASS(3)	1.907	1	.167
	COMPASS(4)	.078	1	.780
	COMPASS(5)	.094	1	.760
	COMPASS(6)	.391	1	.532
	GW	2.274	1	.132
	SOIL	1.776	3	.620
	SOIL(1)	.094	1	.760
	SOIL(2)	.064	1	.800
	SOIL(3)	1.593	1	.207
Overall Statistics**		50.971	26	.002

Note: * score value significant at the 0.05 level, ** score value significant at the 0.01 level.

When comparing models using only the predictive model variables the concept only model (no variables included) had an accuracy of 91.5% (Table 18 [b]). An increase of 4.3% in percentage correct value occurred with the addition of the slope variable and a 1.4% increase with the inclusion of the wetland variable (Table 18 [b]). While these results indicate there was a slight improvement in the fit of the model there were no significant improvements in the fit of the model to the data with the addition of variables to the constant only model (Table 18 [b]).

When both field and predictive model variables were considered, the constant only model had a percent correct value of 91.5% (Table 18 [a]). The addition of the vegetation variable significantly improved the fit of the model with a corresponding 4.3% increase in the percentage correct value (Table 18 [a]). Including the resistance variable resulted in a highly significant improvement in the fit of the model with the percentage correct

value increasing to 100% (Table 18 [a]). All remaining variables were not considered to significantly improve the fit of the model with the data.

Table 18: Results of logistic regression analysis for Whiteman Park site indicating the model chi-square test and step chi-square (degrees of freedom [df]) and percentage correct for models analysed using all variables [a] and predictive model variables only [b].

[a]All Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	41.13 (initial log likelihood		91.5
Model 2	(+ groundwater)	1.84 [1]	1.84 [1]	91.5
Model 3	(+ vegetation)	22.84* [11]	20.79* [10]	95.6
Model 4	(+ aspect)	27.79* [17]	5.16 [6]	94.4
Model 5	(+ slope)	28.35 [18]	0.56 [1]	94.4
Model 6	(+ penetrometer)	41.13** [19]	12.77** [1]	100
Model 7	(+ wetland)	41.13** [22]	0.00 [3]	100
Model 6	(+ soil)	41.13* [25]	0.00 [3]	100
Model 9	(+ moisture) All variables	41.13* [26]	0.00 [1]	100

[b]Predictor Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	41.13 (initial log likelihood		91.5
Model 2	(+ groundwater)	1.84 [1]	1.84 [1]	91.5
Model 3	(+ aspect)	8.24 [7]	6.39 [6]	90.1
Model 4	(+ slope)	12.02 [6]	3.78 [1]	94.4
Model 5	(+ wetland)	17.55 [11]	5.53 [3]	95.6
Model 6	(+ soil) All variables	20.17 [14]	2.62 [3]	95.8

Note: * Chi-square test significant at the .05 level, ** Chi-square test significant at the .01 level.

4.4.3 Whiteman Park (with vegetation survey)

Results of logistic regression analysis for Whiteman Park, including vegetation survey data, are shown in Tables 19 and 20[ab]. The significance of individual variables on the fit of the model (Table 19) as well as a comparison of models (Table 20[ab]) was made. Results are provided for analysis using both field and predictive model variables and predictive model variables alone.

Comparison of the effect of individual variables on the model indicated that % moisture (Moist) and resistance (Peno) were considered highly significant in improving the fit of the model (Table 19). W.P. Veg (veg2) was considered significant, with the dummy variable 6 considered highly significant (Table 19). The remaining variables were not considered to have a significant affect on improving the fit of the model.

Table 19: Logistic regression analysis results for Whiteman Park site (including vegetation survey) indicating the score, degrees of freedom (df) and significance of each variable used in the analysis.

		Score	df	Sig.
Variables	SOIL	1.776	3	.620
	SOIL(1)	.094	1	.760
	SOIL(2)	.064	1	.800
	SOIL(3)	1.593	1	.207
	MOIST**	22.866	1	.000
	PENO**	17.850	1	.000
	VEG2*	13.603	6	.034
	VEG2(1)	.497	1	.481
	VEG2(2)	.007	1	.934
	VEG2(3)	.605	1	.437
	VEG2(4)	.988	1	.320
	VEG2(5)	1.312	1	.252
	VEG2(6)**	10.988	1	.001
	SLOPE	1.002	1	.317
	COMPASS	4.122	6	.660
	COMPASS(1)	.190	1	.663
	COMPASS(2)	.572	1	.450
	COMPASS(3)	1.907	1	.167
	COMPASS(4)	.076	1	.760
	COMPASS(5)	.094	1	.760
	COMPASS(6)	.391	1	.532
	GW	2.274	1	.132
	WET	3.956	3	.266
	WET(1)	.221	1	.639
	WET(2)	.094	1	.760
	WET(3)	3.192	1	.074
Overall Statistics**		43.947	22	.004

Note: * score value significant at the 0.05 level, ** score value significant at the 0.01 level.

When only the model predictive model variables were considered (Table 20[b]) the pattern was very similar to that seen when vegetation data was not considered. Increases in percentage correct values are seen with the addition of slope, wetland type and vegetation variables, however no individual variables were considered to have had a significant affect on improving the fit of the model (Table 20[b]). None of the variable combinations were considered to significantly improve the fit of the model from the constant only model.

When both field and predictive model variables were considered, the constant only model had a percent correct value of 91.5% (Table 20 [a]). When the variable slope was added to the model there was a 4.3% increase in the percentage correct value but the increase in step and model chi-square values indicated that the effect on the fit of the model was not significantly different from the constant only model (Table 20 [a]). The addition of the resistance variable was considered highly significant, the model at this stage was considered significantly different from the constant only model (Table 20 [a]). The additions of the remaining variables were not individually considered to significantly improve the fit of the model. The inclusion of the resistance (penetrometer), wetland type, soil type, vegetation survey and moisture variables

resulted in a model that was considered to be highly significant in improving the fit of the model compared with the constant only model, resulting in a percentage correct value of 100% (Table 20 [a]).

Table 20: Results of logistic regression analysis for Whiteman Park site (including vegetation survey data) indicating the model chi-square test and step chi-square (degrees of freedom [df]) and percentage correct for models analysed using all variables [a] and predictive model variables only [b].

[a]All Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	41.13 (initial log likelihood)		91.5
Model 2	(+ groundwater)	1.84 [1]	1.84 [1]	91.5
Model 3	(+ aspect)	8.24 [7]	6.39 [6]	90.1
Model 4	(+ slope)	12.02 [8]	3.78 [1]	94.4
Model 5	(+ penetrometer)	21.46* [9]	6.46** [1]	94.4
Model 6	(+ wetland)	26.24* [12]	4.75 [3]	96.6
Model 7	(+ soil)	31.40** [15]	5.16 [3]	97.2
Model 8	(+ vegetation 2)	41.13** [21]	9.73 [6]	100
Model 9	(+ moisture) All variables	41.13** [22]	0.00 [1]	100

[b]Predictor Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	41.13 (initial log likelihood)		91.5
Model 2	(+ groundwater)	1.84 [1]	1.84 [1]	91.5
Model 3	(+ aspect)	8.24 [7]	6.39 [6]	90.1
Model 4	(+ slope)	12.02 [8]	3.78 [1]	94.4
Model 5	(+ wetland)	17.55 [11]	5.53 [3[	95.8
Model 6	(+ soil)	20.17 [14]	2.62 [3]	95.8
Model 7	(+ vegetation) All variables	26.20 [20]	6.03 [6]	97.2

Note: * Chi-square test significant at the .05 level, ** Chi-square test significant at the .01 level.

4.5 Resolution Testing of the Predictive Model

4.5.1 Melaleuca Park (50m sampling intensity)

31 samples were taken in an analysis of the spatial resolution of the predictive model for the Melaleuca Park site. Sampling was performed by navigating to a predefined set of coordinates, obtained from the predictive overlay map, using a hand-held Global Positioning System (GPS) with a reported accuracy of +/- 15m (Garmin International).

4.5.1.1 Field Verification

Descriptive results for the resolution testing of the predictive model for Melaleuca Park are shown in Table 21. The majority of sites sampled had organic contents less than 10% with a median value of 2.33 and results that were positively skewed (Table 21). This correlated with the low soil moisture values with mean soil moisture content of less than 3%, also positively skewed (Table 21). Wetland type classification was predominately 'not a wetland', while soil type classification indicated predominately 'wet soils often peaty'. Visually more sites were classified as not containing peat.

Table 21: Descriptive statistics results of resolution test analysis (50m sampling intensity) for Melaleuca Park.

	Descriptive Statistics						
Variable	N	Minimum	Maximum	Mean	Median	Std. Deviation	Skewness
% Moisture	31	0.26	12.14	2.98	2.31	2.55	1.80
% LOI	31	0.85	21.11	4.41	2.33	4.46	2.28
Visually Peat	31	0	1	0.35	0.00	0.49	0.64
Resistance	31	75	350	151.61	130.00	64.59	1.31
Vegetation Field	31	1	4	2.13	1.00	1.34	0.56
Slope	31	0	3.36	1.11	1.62	1.10	0.33
Aspect	31	1	8	3.77	4.00	2.86	0.18
GW	31	-0.01	3.7	1.19	0.84	0.91	1.33
Soil Type	31	1	5	4.58	5.00	1.12	-2.43
Wetland Type	31	0	1	0.39	0.00	0.50	0.49

In the Spearman's rho correlation analysis variables were measured against % LOI, as this was the criterion used to define the existence of organic sediments. Analysis resulted in highly significant relationships between the visually peat, percentage

moisture, wetland type, and vegetation field variables when correlated with the organic content of soils sampled (Table 22). The aspect and depth to groundwater variables had significant correlations, which were inversely related, when organic content increased aspect had no influence and depth to groundwater decreased (Table 22). All remaining variables did not exhibit significant correlations with the organic content of the sampled soils.

Table 22 Spearman's rho correlation matrix of field and predictive model variables for the resolution testing of the predictive model (50m sampling interval) for the Melaleuca Park Site.

Correlations					
Variable		**% LOI**	**Variable**		**% LOI**
% Moisture	Correlation Coefficient	0.57**	Slope	Correlation Coefficient	-0.13
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.48
	N	31		N	31
% LOI	Correlation Coefficient	1	Aspect	Correlation Coefficient	-0.36*
	Sig. (2-tailed)	.		Sig. (2-tailed)	0.04
	N	31		N	31
Visually Peat	Correlation Coefficient	0.58**	GW	Correlation Coefficient	-0.41*
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.02
	N	31		N	31
Resistance	Correlation Coefficient	0.24	Soil Type	Correlation Coefficient	0.30
	Sig. (2-tailed)	0.19		Sig. (2-tailed)	0.10
	N	31		N	31
Vegetation Field	Correlation Coefficient	0.48**	Wetland Type	Correlation Coefficient	0.50**
	Sig. (2-tailed)	0.01		Sig. (2-tailed)	0.00
	N	31		N	31

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

A 10% LOI value criterion for the determination of organic soils indicated that a majority of soils were classified as inorganic. An increase in the criterion to 15% led to a 30% decrease in the number of samples classified as organic (Table 23).

Table 23 Percentage of samples classified as ORS based on a 10% and 15% LOI value criterion, for resolution testing (50m sample interval) of the predictive model at the Melaleuca Park site.

ORS Classification				
Criterion	**LOI Range**	**N**	**Percentage (%)**	**ORS**
10%	< = 10%	31	90.3	No
	> = 10%	31	9.7	Yes
15%	< = 15%	31	96.8	No
	> = 15%	31	3.2	Yes

Field verification of resolution testing analysis (50m sampling interval) of the predictive model for Melaleuca Park indicated that the success rate for predicting areas to contain ORS is 27%, predicting medium probability areas was 0% and the prediction of areas not considered to contain ORS was 100%. This led to an overall success rate of the model predicting ORS correctly of approximately 19% (Figure 25). Analysis compared the predicted probability of occurrence with Loss on Ignition Values (LOI), utilising a 10% criteria for the positive classification of organic sediments, with the medium predicted category expected to contain ORS.

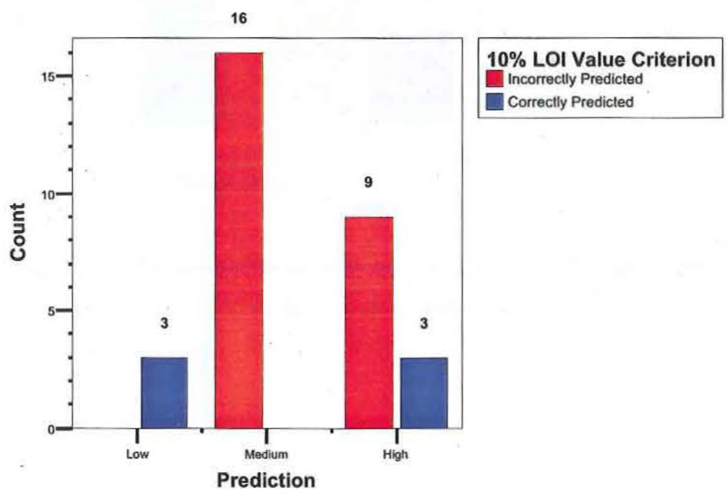


Figure 25: Graph showing the comparison of actual versus predicted occurrence of ORS results for resolution test of predictive model (50m sampling intensity) at the Melaleuca Park Site.

Part of the resolution testing process involved predicting the occurrence of ORS based on a visual interpretation of the sample site. Visual predictions were based on the surface characteristics of the soil and vegetation community type. The ability to correctly predict the occurrence ORS visually in the field was achieved 77% of the time (Figure 26). Where ORS were predicted to occur the prediction rate was correct 36% of

the time, whilst areas predicted not to contain ORS were correctly predicted 100% of the time (Figure 26).

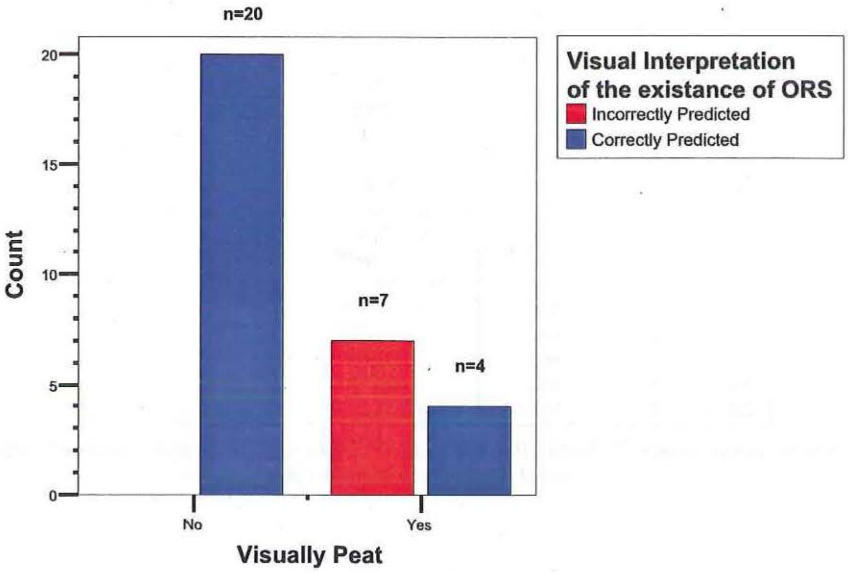


Figure 26: Graph showing the number of correct versus incorrect predictions for the visual interpretation of the presence of ORS at the Melaleuca Park site.

4.5.1.2 Logistic Regression Analysis

When ascertaining the significance of individual variables on improving the fit of the model, both percentage moisture and the third dummy variable for vegetation type were individually considered very significant (Table 24). In addition to this the variable that represents the visual prediction of ORS (visual), and the vegetation type and wetland type variables were considered significant in improving the fit of the model (Table 24). The remaining variables are not considered to have had a significant affect on the model (Table 24).

Table 24: Logistic regression analysis results for resolution testing (50m sampling interval) at Melaleuca Park indicating the score, degrees of freedom (df) and significance of each variable used in the analysis.

		Score	df	Sig.
Variables	MOIST**	6.912	1	.009
	VISUAL*	6.039	1	.014
	PENO	.111	1	.739
	VEG*	8.119	3	.044
	VEG(1)	.492	1	.483
	VEG(2)	.229	1	.632
	VEG(3)**	8.119	1	.004
	SLOPE	.478	1	.489
	COMPASS	3.979	4	.409
	COMPASS(1)	.229	1	.632
	COMPASS(2)	3.693	1	.055
	COMPASS(3)	.492	1	.483
	COMPASS(4)	.356	1	.551
	GW	.132	1	.717
	SOIL	.492	2	.782
	SOIL(1)	.356	1	.551
	SOIL(2)	.492	1	.483
	WETLAND(1)*	5.259	1	.022

Note: * score value indicates significant at the 0.05 level, ** score value indicates significant at the 0.01 level.

When only the predictive model variables were considered the percentage correct value increased from an initial 90.3% to 96.8% with all predictive model variables included, indicating an excellent fit of the model with the data (Table 25[b]). The wetland type variable was considered significant in improving the fit of the model (Table 25[b]). No other predictive model variables significantly improved the fit of the model.

The addition of slope, resistance (penetrometer), soil type and aspect variables into the model did not result in an increase in the overall percentage correct value, with only a small increase in the improvement of the fit of the model (Table 25[a]). The addition of the vegetation variable was considered significant in improving the fit of the model, however the improvement in the fit of the model was not considered significantly different from the constant only model with no variables included (Table 25[a]). The addition of subsequent variables wetland and moisture did not result in a further improvement in the model (Table 25[a]). The fit of the model was not significantly improved from the fit of the constant only model at any stage (Table 25[a]).

Table 25: Results of logistic regression analysis resolution testing (50m sampling interval) for Melaleuca Park site indicating the model chi-square test, step chi-square (degrees of freedom [df]) and percentage correct for models analysed using all variables [a] and predictive model variables only [b].

[a]All Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	19.71 (initial log likelihood)		90.3
Model 2	(+slope)	0.47 [1]	0.47 [1]	90.3
Model 3	(+ penetrometer)	0.55 [2]	0.08 [1]	90.3
Model 4	(+ soil)	2.22 [4]	1.67 [2]	90.3
Model 5	(+ aspect)	5.89 [8]	3.67 [4]	90.3
Model 6	(+ groundwater)	8.65 [9]	2.75 [1]	96.8
Model 7	(+ vegetation)	19.71 [12]	11.06* [3]	100
Model 8	(+ wetland)	19.71 [13]	0.00 [1]	100
Model 9	(+ moisture)	19.71 [14]	0.00 [1]	100

[b]Predictor Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	19.71 (initial log likelihood)		90.3
Model 2	(+ slope)	0.47 [1]	0.47 [1]	90.3
Model 3	(+ soil)	1.75 [3]	1.28 [2]	90.3
Model 4	(+ aspect)	5.86 [7]	4.12 [4]	96.5
Model 5	(+ groundwater)	8.56 [8]	2.70 [1]	96.8
Model 6	(+ wetland)	13.47 [9]	4.91* [1]	96.8

Note: * Chi-square test significant at the .05 level, ** Chi-square test significant at the .01 l

4.5.2 Melaleuca Park 2 (10m sampling interval)

4.5.2.1 Field Verification

Descriptive statistics for the resolution testing of the predictive model with 10m sampling interval for Melaleuca Park are shown in Table 26. Results indicate that a majority of the soils sampled contained organic contents greater than 10%, with a relatively normally distribution (Table 26). The relatively high soil moisture content of the soils sampled corroborates this and results are positively skewed (Table 26). The terrain was relatively flat with a median slope of 0^0, while depth to groundwater was shallow (Table 26). Visually (visually peat) slightly less than half the sites were predicted to contain ORS (Table 26).

Table 26: Descriptive statistics results of sensetivity analysis (10m) sampling for Melaleuca Park. Visually peat, Vegetation field, Aspect, Soil type and Wetland type are all categorical variables.

Descriptive Statistics							
Variable	N	Minimum	Maximum	Mean	Median	Std. Deviation	Skewness
% Moisture	21	0.34	71.96	14.57	2	20.87	1.53
% LOI	21	2.16	87.12	29.64	11.71	32.30	0.93
Visually Peat	21	0	1	0.43	0	0.51	0.31
Resistance	21	20	500	193.71	183	104.77	1.08
Vegetation Field	21	1	4	2.52	2	1.17	0.04
Slope	21	0	1.02	0.10	0	0.31	2.97
Aspect	21	1	4	1.29	1	0.90	2.97
GW	21	0.91	1.13	1.02	1.02	0.05	-0.07
Soil Type	21	3	3	3.00	3	0.00	.
Wetland Type	21	0	2	1.24	2	1.00	-0.53

Spearman's rho correlation of field and predictive model variables revealed highly significant correlations between % LOI values, gravimetric soil moisture content (% Moisture), visual recognition of ORS in the field (Visually Peat), resistance measurements (Penetrometer), type of vegetation (Vegetation Field), and wetland classification (Wetland Type) (Table 27). The remaining variables did not display significant correlations with the organic content of soils sampled (Table 27).

Table 27: Spearman's rho correlation matrix of variables sensitivity analysis (10m) sampling Melaleuca Park site. Variables are measured against % LOI, as this was the criterion used to define the existence of organic sediments.

Correlations					
Variable		% LOI	Variable		% LOI
% Moisture	Correlation Coefficient	0.95**	Slope	Correlation Coefficient	-0.29
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.19
	N	21		N	21
% LOI	Correlation Coefficient	1	Aspect	Correlation Coefficient	-0.29
	Sig. (2-tailed)	.		Sig. (2-tailed)	0.19
	N	21		N	21
Visually Peat	Correlation Coefficient	0.85**	GW	Correlation Coefficient	-0.15
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.51
	N	21		N	21
Resistance	Correlation Coefficient	0.78**	Soil Type	Correlation Coefficient	.
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	.
	N	21		N	21
Vegetation Field	Correlation Coefficient	0.68**	Wetland Type	Correlation Coefficient	0.58**
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.01
	N	21		N	21

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

The 10% organics content category indicated that approximately half the sites were classified as ORS (Table 28). There was only a slight decrease in the number of samples classified as ORS with an increase of 5% in the LOI value criterion (Table 28).

Table 28 Percentage of samples classified as ORS based on a 10% and 15% LOI value criterion, for resolution testing (10m sample interval) of the predictive model at the Melaleuca Park site.

ORS Classification				
Criterion	LOI Range	N	Percentage (%)	ORS
10%	< = 10%	21	47.6	No
	> = 10%	21	52.4	Yes
15%	< = 15%	21	57.1	No
	> = 15%	21	42.9	Yes

The site sampled had a medium predicted probability of containing organic soils. A 52% correct prediction rate was achieved based on field results (Figure 27).

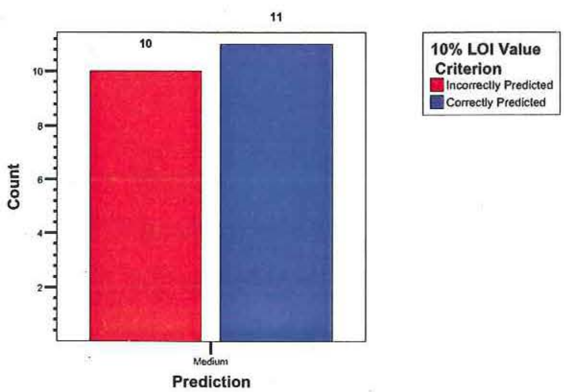


Figure 27: Graph showing the comparison of actual versus predicted occurrence of ORS results for resolution test of predictive model (10m sampling intensity) at the Melaleuca Park Site.

In the field the ability to predict visually the occurrence of ORS correctly was 90% (Figure 28). Predictions were correct 100% of the time for sites predicted to contain ORS, when site was predicted not to contain ORS the correct rate of prediction fell to approximately 83% (Figure 28).

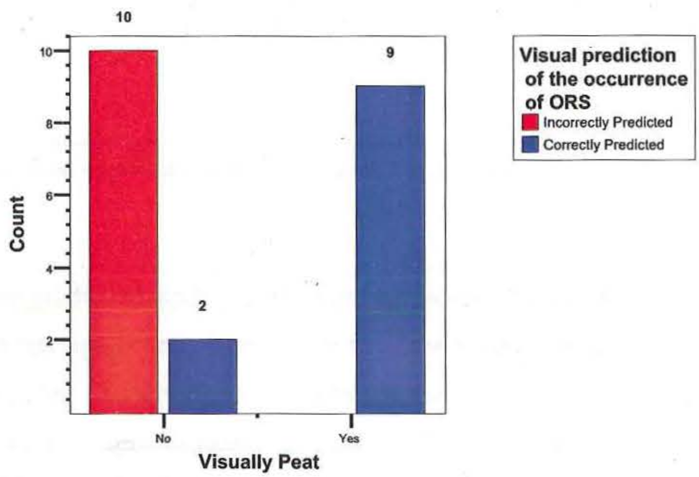


Figure 28: Graph showing the number of correct versus incorrect predictions for the visual interpretation of the presence of ORS, as a result of resolution testing (10m sampling interval) at the Melaleuca Park site.

4.5.2.2 Logistic Regression Analysis

The % soil moisture (Moist), dummy variable 1 for visually peat, vegetation type (Veg, including dummy variable 3) and wetland type (Wetland) variables are individually all highly significant in their effects on the fit of the model to the data (Table 29). Dummy variable 1 for vegetation type (Veg 1) has a significant effect on the model (Table 29). The remaining variables have no significant effect on the fit of the model.

Table 29: Logistic regression results resolution testing (10m sampling interval) Melaleuca Park site indicating the score, degrees of freedom (df) and significance of each variable used in the analysis.

		Score	df	Sig.
Variables	MOIST**	8.620	1	.003
	VISUAL(1)**	14.318	1	.000
	PENO**	6.665	1	.010
	VEG**	11.445	3	.010
	VEG(1)*	4.295	1	.038
	VEG(2)	1.014	1	.314
	VEG(3)**	7.636	1	.006
	SLOPE	2.432	1	.119
	COMPASS(1)	2.432	1	.119
	GW	.798	1	.372
	WETLAND(1)**	8.240	1	.004

Note: * score value significant at the 0.05 level, ** score value significant at the 0.01 level

When only the predictive model variables are considered the inclusion of groundwater and aspect do not significantly increase the fit of the model (Table 30[b]). The inclusion of wetland type has a highly significant effect on the model with an increase in percentage correct of approximately 30% and an overall percentage correct value of 81% (Table 30[b]). The fit of the model to the data at this point is significantly better than a model that does not include the wetland type variable (Table 30[b]).

The constant only model (model 1) yields a percentage correct value of approximately 50% (Table 30[a]). The fit of the model is improved significantly with the addition of the wetland variable, the wetland variable itself is considered highly significant in improving the fit of the model and the resultant percentage correct value is 81% (Table 30[a]). The vegetation variable is considered significant in improving the fit of the model, the model that includes vegetation is considered highly significant from the constant only model, with a percentage correct value of 90.5% (Table 30[a]). The % moisture variable (moisture) is highly significant in its effect on improving the fit of the model, with a resultant percentage correct value of 100% (Table 30[a]). All remaining variables do not significantly impact on the fit of the model.

Table 30: Results of logistic regression resolution testing (10m sampling interval) at the Melaleuca Park site indicating the model chi-square test and step chi-square (degrees of freedom [df]) and percentage correct for models analysed using all variables [a] and predictive model variables only [b].

[a]All Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	29.06 (initial log likelihood)		52.4
Model 2	(+ groundwater)	0.81 [1]	0.81 [1]	71.4
Model 3	(+ aspect)	3.20 [2]	2.39 [1]	61.9
Model 4	(+ wetland)	9.78* [3]	8.56** [1]	81
Model 5	(+ vegetation)	20.82** [6]	11.06* [3]	90.5
Model 6	(+ penetrometer)	20.91** [7]	0.08 [1]	90.5
Model 7	(+ visual)	20.91** [8]	0.00 [1]	90.5
Model 8	(+ moisture)	29.06** [9]	8.16** [1]	100

[b]Predictor Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	29.06 (initial log likelihood)		52.4
Model 2	(+ groundwater)	0.81 [1]	0.81 [1]	71.4
Model 3	(+ aspect)	3.20 [2]	2.39 [1]	81.9
Model 4	(+ wetland)	9.78* [3]	6.56** [1]	81

Note: * Chi-square test significant at the .05 level, ** Chi-square test significant at the .01 level.

4.5.3 Whiteman Park

4.5.3.1 Field Verification

The results of field-testing of resolution analysis for Whiteman Park as determined by % LOI, % soil moisture, resistance and vegetation type as well as the predictive model variables are presented in Tables 31 to 33 and Figures 29 and 30.

The organic content values for soils sampled at Whiteman Park ranged from less than 1% to ~ 30% and are positively skewed (Table 31). Soil moisture results ranged from < 1% to approximately 50%, again results were positively skewed (Table 31). Resistance readings ranged from 35cm to approximately 400cm with the average being approximately 150cm (Table 31). The region is relatively flat with a mean slope of 0.25^0 (Table 31). Groundwater depths range from approximately -2m to – 0.79m (representing inundated areas), with the average depth being approximately 2.0 m below ground level, again results are skewed to the left (Table 31).

Table 31: Descriptive statistics for resolution testing at the Whiteman Park site.

Descriptive Statistics							
Variable	**N**	**Minimum**	**Maximum**	**Mean**	**Median**	**Std. Deviation**	**Skewness**
% Moisture	31	0.19	48.36	5.39	0.59	11.65	2.75
% LOI	31	0.85	33.33	6.95	3.33	8.23	1.95
Visually Peat	31	0	1	0.29	0.00	0.46	0.97
Resistance	31	35	390	149.26	130.00	72.51	1.38
Vegetation Field	31	1	4	2.35	2.00	1.25	0.35
Slope	31	0	1.09	0.25	0.00	0.37	0.99
Aspect	31	1	6	2.48	1.00	2.08	0.77
GW	31	-2.66	-0.79	-2.06	-2.07	0.40	1.05
Soil Type	31	2	5	4.58	5.00	0.99	-2.10
Wetland Type	31	0	3	0.87	0.00	1.38	0.97
W.P. Veg	31	1	4	2.97	3.00	1.20	-0.68

The result of the Spearman's rho correlation analysis for resolution testing at Whiteman Park can be seen in Table 32. Variables are measured against % LOI, as this was the criterion used to define the existence of organic sediments. % Moisture, visually peat, vegetation field, vegetation survey (W.P. Veg) and depth to groundwater are all highly correlated with %LOI (Table 32). Resistance (penetrometer) is significantly correlated, whilst the remaining variables did not display significant correlations (Table 32).

Table 32: Spearman's rho correlation matrix for resolution testing at the Whiteman Park site.

Correlations					
Variable		**% LOI**	**Variable**		**% LOI**
% Moisture	Correlation Coefficient	0.83**	Slope	Correlation Coefficient	-0.14
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.47
	N	31		N	31
% LOI	Correlation Coefficient	1	Aspect	Correlation Coefficient	-0.05
	Sig. (2-tailed)	.		Sig. (2-tailed)	0.79
	N	31		N	31
Visually Peat	Correlation Coefficient	0.56**	GW	Correlation Coefficient	0.49**
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.00
	N	31		N	31
Resistance	Correlation Coefficient	0.43*	Soil Type	Correlation Coefficient	0.21
	Sig. (2-tailed)	0.01		Sig. (2-tailed)	0.26
	N	31		N	31
Vegetation Field	Correlation Coefficient	0.65**	Wetland Type	Correlation Coefficient	0.33
	Sig. (2-tailed)	0.00		Sig. (2-tailed)	0.07
	N	31		N	31
W.P. veg	Correlation Coefficient	0.63**			
	Sig. (2-tailed)	0.00			
	N	31			

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Results for 10% and 15% organic content categories show that a large proportion of the results 80% and 87% respectively for the Whiteman Park site were not classified as ORS (Table 33).

Table 33 Percentage of samples classified as ORS based on a 10% and 15% LOI value criterion, for resolution testing (50m sample interval) of the predictive model at the Whiteman Park site.

	ORS Classification			
Criterion	**LOI Range**	**N**	**Percentage (%)**	**ORS**
10%	< = 10%	31	80.6	No
	> = 10%	31	19.4	Yes
15%	< = 15%	31	87.1	No
	> = 15%	31	12.9	Yes

Analysis compared the predicted probability of occurrence of ORS with the actual occurrence of ORS based on Loss on Ignition Values (LOI), utilising a 10% criteria for the positive classification of organic sediments. Results of ffield-testing have shown that the confidence of the model in being able to predict the spatial distribution of ORS in this instance was approximately 19% (Figure 29). The ability to predict areas that did contain ORS correctly were 22% and 8% for areas predicted as possibly containing ORS (Figure 29).

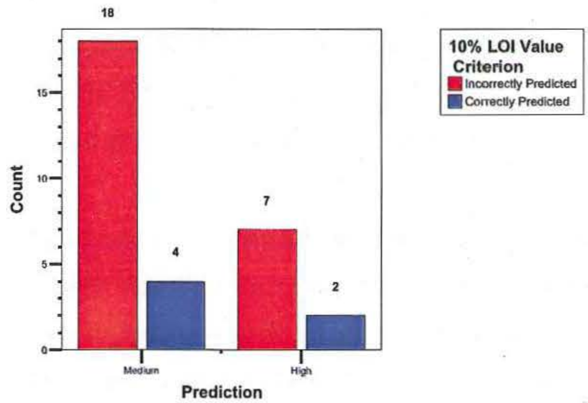


Figure 29: Graph showing the comparison of actual versus predicted occurrence of ORS results for resolution test of predictive model (50m sampling interval) at the Whiteman Park Site.

In the field the ability to predict visually the occurrence of ORS was correct approximately 84% of the time (Figure 30). When the site was categorized as containing ORS correct prediction rate was 55% (Figure 30). When the prediction indicated that no ORS were present the correct prediction rate was approximately 95% (Figure 30).

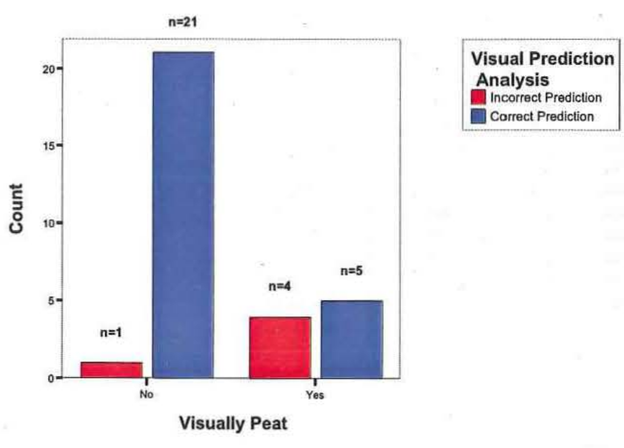


Figure 30: Graph showing the number of correct versus incorrect predictions for the visual interpretation of the presence of ORS, as a result of resolution testing (50m sampling interval) at the Whiteman Park site.

4.5.4 *Logistic Regression Analysis*

The results of the logistic regression analysis for intensive sampling at Whiteman Park are shown in Tables 34 and 35[abc]. Results are provided for analysis using both field and predictive model variables and predictive model variables alone.

Table 34 shows the significance of individual variables in improving the fit of the model. % Moisture (moist), visually peat (visual) and resistance (peno) are considered highly significant whilst vegetation type (Veg) is considered significant, with 'dummy variable' 3 considered highly significant (Table 34). All remaining variables were not considered to have a significant effect on improving the fit of the model with the data.

Table 34: Table indicating the significance of individual variables in improving the fit of the model as a result of logistic regression of resolution testing analysis for Whiteman Park.

		Score	df	Sig.
Variables	WET	3.956	3	.266
	WET(1)	.221	1	.639
	WET(2)	.094	1	.760
	WET(3)	3.192	1	.074
	MOIST**	22.866	1	.000
	PENO**	17.850	1	.000
	VEG*	22.990	10	.011
	VEG(1)	1.074	1	.300
	VEG(2)	.951	1	.329
	VEG(3)	.572	1	.450
	VEG(4)	.094	1	.760
	VEG(5)	.342	1	.559
	VEG(6)*	4.592	1	.032
	VEG(7)	.342	1	.559
	VEG(8)	.717	1	.397
	VEG(9)	1.074	1	.300
	VEG(10)**	13.722	1	.000
	SLOPE	1.002	1	.317
	COMPASS	4.122	6	.660
	COMPASS(1)	.190	1	.663
	COMPASS(2)	.572	1	.450
	COMPASS(3)	1.907	1	.167
	COMPASS(4)	.078	1	.780
	COMPASS(5)	.094	1	.760
	COMPASS(6)	.391	1	.532
	GW	2.274	1	.132
	SOIL	1.776	3	.620
	SOIL(1)	.094	1	.760
	SOIL(2)	.064	1	.800
	SOIL(3)	1.593	1	.207
Overall Statistics**		50.971	26	.002

Note: * score value is significant at the 0.5 level, ** score value is significant at the 0.01 level.

When only the predictive model variables are included in the analysis, the constant only model (model 1) provided a percentage correct value of 80.6% (Table 35 [b]). When the

groundwater variable was included there was an increase in the percentage correct, resulting in an overall percentage correct value of 90.3%, this variable was considered highly significant in improving the fit of the model and the model itself provided a significantly better fit to the data than the constant only model (Table 35 [b]). All remaining variables did not significantly improve the fit of the model with the data.

A logistic regression including both field and predictive model variables had an initial percentage correct value of 80.6% (Table 35 [a]). The inclusion of the slope variable resulted in a 3.3% increase in the percentage correct value and the variable was considered significant in improving the fit of the model (Table 35 [a]). When the groundwater variable was included in the model the percentage correct value increased by 6.4%, this variable was considered significant in improving the fit of the model and the fit of the model was considered significantly improved when compared with the fit of the constant only model (Table 35 [a]). The addition of the moisture variable resulted in a percentage correct value of 100%, again the moisture variable was considered a significant variable in improving the fit of the model, while the improvement in the fit of the model over the constant only model was considered highly significant (Table 35[a]).

The inclusion of the vegetation dataset (Mattiske Consulting Pty Ltd 2002) into the predictive model variables increased the fit of the model resulting in an overall percentage correct value of 93.5% (Table 35[c]). The groundwater variable was still considered more significant in improving the fit of the model than the vegetation type variable illustrated by the decrease in step chi-square value (Table 35[c]). There was a decrease in the significance in the fit of the model with the addition of the vegetation variable although the fit of the model was still considered significant in comparison with the constant only model (Table 35[c]). The remaining variables did not significantly affect the strength of the model.

Table 35: Results of logistic regression analysis for resolution testing at Whiteman Park site indicating the model chi-square test and step chi-square (degrees of freedom [df]) and percentage correct for models analysed using all variables [a], predictive model variables only [b] and predictive model variables only including vegetation survey [c].

[a]All Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	30.46 (initial log likelihood)		80.6
Model 2	(+ aspect)	2.96 [3]	2.96 [3]	80.6
Model 3	(+ slope)	7.97 [4]	5.00* [1]	83.9
Model 4	(+ soil)	11.39 [6]	3.42 [2]	97.1
Model 5	(+ wetland)	11.66 [7]	0.26 [1]	87.1
Model 6	(+ penetrometer)	20.30** [8]	8.64** [1]	83.9
Model 7	(+ groundwater)	24.18** [9]	3.89* [1]	90.3
Model 8	(+ visual)	24.18** [10]	0.00 [1]	90.3
Model 9	(+ vegetation 2)	24.48 * [13]	0.29 [3]	90.3
Model 10	(+ vegetation)	24.48 [16]	0.00 [3]	90.3
Model 11	(+ moisture) All variables	30.46** [17]	5.98* [1]	100

[b]Predictor Variables				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	30.46 (initial log likelihood)		80.6
Model 2	(+ aspect)	2.96 [3]	2.96 [3]	80.6
Model 3	(+ slope)	7.97 [4]	5.00* [1]	83.9
Model 4	(+ soil)	11.39 [6]	3.42 [2]	87.1
Model 5	(+ wetland)	11.66 [7]	0.26 [1]	87.1
Model 6	(+ groundwater) All variables	20.96** [8]	9.30** [1]	90.3

[c]Predictor Variables (with vegetation)				
	Variable	Model Chi-square [df]	Step Chi-square [df]	% Correct
Model 1	None	30.46 (initial log likelihood)		80.9
Model 2	(+ aspect)	2.96 [3]	2.96 [3]	80.6
Model 3	(+ slope)	7.97 [4]	5.00* [1]	83.9
Model 4	(+ soil)	11.39 [6]	3.42 [2]	87.1
Model 5	(+ wetland)	11.96 [7]	0.26 [1]	87.1
Model 6	(+ groundwater)	20.96** [8]	8.30** [1]	90.3
Model 7	(+ vegetation 2)	26.73* [11]	2.77 [3]	93.5

Note: * Chi-square test significant at the .05 level. ** Chi-square test significant at the .01 level.

CHAPTER 5: DISCUSSION AND CONCLUSION

The aim of this study was to evaluate the use of GIS as tool to develop a predictive model of the spatial distribution of organic rich sediments on the swan coastal plain. This study showed that a predictive model developed using GIS with available data was effective in predicting organic rich sediments based on the use of percentage organic matter as an indicator of the presence of ORS.

5.1 Validity of Created Datasets

The validity of the created datasets used to develop the predictive model was assessed to ensure the most accurate model was used and any discrepancy in the data could be interrogated for its impact on the ability to predict ORS.

The correlation between GIS created and values derived from groundwater monitoring bore data for topographical contours indicate that the contours created from a Digital Elevation Model are very close to actual surface levels (Figure 31). The same was observed for groundwater contour mapping (Figure 31). Discrepancies arose in correlation between calculated depth to groundwater values and actual depth to groundwater values, indicating that the calculated values were not representative of actual values (Figure 31). However their relative indication of levels being lower or higher in relation to surrounding areas made it acceptable to use this dataset for its intended purpose as a predictive model variable (Figure 31).

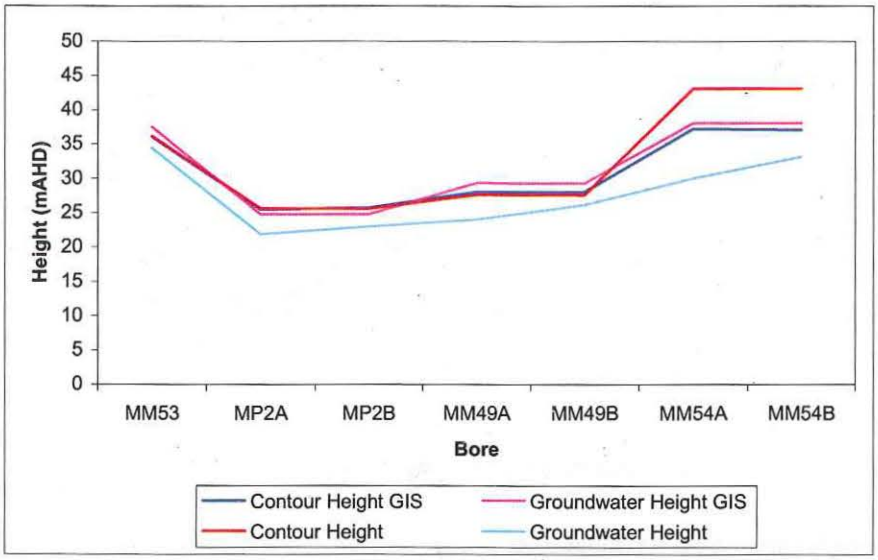


Figure 31 Graph depicting the correlation between created values and observed values for topographical and groundwater contour datasets.

The strong correlation between Loss on Ignition analysis and Walkley-Black analysis of organic content indicated that using LOI as an indication of the organic matter content of sampled soils was adequate. In general the results of the Walkley-Black analysis tended to produce slightly higher organic content values than the LOI results (Figure 32) thus reinforcing the use of 10% LOI values as the criterion for classifying ORS as this is more likely to include specimens with organic contents in the vicinity of 20% which is the recognized criteria for classification of organic soils (Isbell 1996). Discrepancies between the two analyses may be as a result of calcium carbonate ($CaCO_3$), which may be present in some samples. $CaCO_3$ is not consumed due to combustion at temperatures below 750^0c. Therefore samples containing $CaCO_3$ will contain lower organic content values for LOI analysis compared with Walkley-Black results.

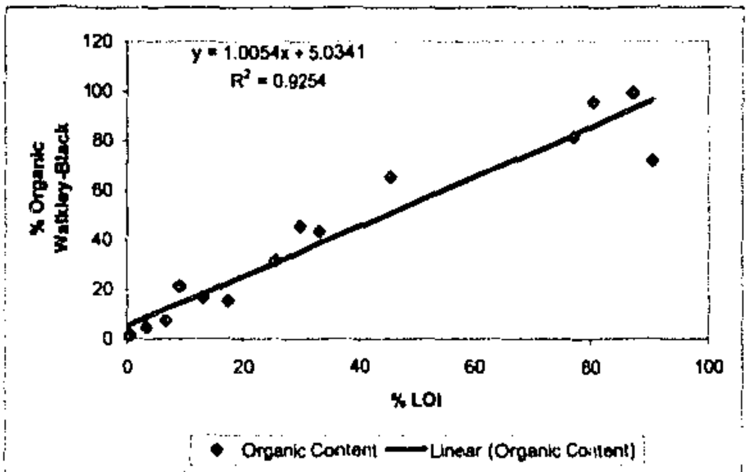


Figure 32 Comparison of LOI and Walkley-Black analysis results for the detection of organic matter content of selected samples from the Melaleuca and Whiteman Park sites.

5.2 Confidence in Predicting ORS at the Landscape Scale

Results of the field verification sampling showed the predictive model developed in this project had a correct prediction rate of 42% when the results from both study sites were combined. Melaleuca Park field investigations revealed that the ability of the model to predict the occurrence of ORS correctly was 76%, while at Whiteman Park the strength of the model was greatly reduced with an overall confidence in predicting the occurrence of ORS of 14.5%. The addition of the vegetation survey dataset (Environmental Resources Management 2003) resulted in a further decrease in the ability to predict the occurrence of ORS with a 11% correct prediction rate at Whiteman Park.

The greatest discrepancy in the ability to confidently predict the occurrence of ORS was as a result of the categorisation of a medium prediction for the presence of ORS determined by the weighted overlay model. At Melaleuca Park a majority of soils sampled in areas predicted as possibly containing ORS were classified as ORS. This pattern was reversed at Whiteman Park with a majority of these soils classified as not being ORS. If areas previously predicted as possibly containing ORS were re-categorized as regions not containing ORS then the ability to correctly predict the spatial occurrence of ORS at Melaleuca Park decreases to 64% whilst at Whiteman

Park it increases to 96%, increasing the overall correct predictive rate of the model to in excess of 70% with combined data. This may indicate a requirement to re-categorize the model into two predictive categories (ORS and Not ORS), as opposed to the current three classifications. It also indicated that there are substantial differences in ORS deposits both on a spatial and temporal scale between sites. The greatest discrepancy in the ability to confidently predict the occurrence of ORS was as a result of the categorisation of a medium prediction of the presence of ORS as determined by the weighted overlay model.

The poor predictive capability of the model as a result of combined data from both sites is heavily influenced by the results obtained at Whiteman Park. Limitations in sampling technique again could account for discrepancies in field verification results. The sampling regime at Whiteman Park failed to adequately sample a representative number of samples from all predictive outcomes, resulting in heavily biased sampling in one particular predictive province. This was due to the accuracy associated with using hand held Global Positioning System (GPS) with a stated accuracy of +/- 15m (possibly up to 50m in some instances), which resulted in discrepancies between targeted sample sites and actual sample sites (Garmin International). This discrepancy could have been rectified through the use of a Differential Global Positioning System (DGPS), which increases accuracy to approximately +/- 1m (Chivers 2003). Financial constraints prevented its use in this study.

As a result of the field verification trials it appears that the predictive capabilities of the model are quite strong when limitations are considered. This suggests that a predictive model using existing data constructed with GIS technologies is a feasible option.

5.3 Results of Logistic Regression Analysis

Logistic regression analysis confirmed the findings of the descriptive analysis indicating that of the predictive model variables for Melaleuca Park aspect, depth to groundwater soil type and wetland type are all significant in improving the fit of the model with depth to groundwater and wetland type being the most significant variables. The fit of the model overall was strong with a percentage correct value of

86%. The inclusion of field variables into the model resulted in the percentage correct value increasing to 100%. This was attributable to the percentage moisture, vegetation type and resistance variables. In this instance analysis dictates that the ability to incorporate the relative soil moisture content and vegetation type as predictive model variables would significantly increase the ability to confidently predict the occurrence of ORS.

The same trend was witnessed for Whiteman Park. Logistic regression analysis showed that when both field and predictive model variables were considered the percentage correct value was 100%, with vegetation type, % moisture and resistance variables again displaying the most significant influence in improving the fit of the model. When only the predictive model variables were considered the percentage correct value decreased to approximately 96%, with no significant improvement in the fit of the model to the data with the addition of any of the predictive model variables. When the vegetation mapping dataset was added to the predictive model the percentage correct value increased to 97%, again the model was not a significantly better fit than the constant only (no variables included) model.

Statistically the feasibility of using GIS to construct a predictive model for ORS on the SCP is confirmed. Again it appears that the use of wetland mapping alone does not provide the same predictive strength as opposed to using multiple predictor variable models. Again it was apparent that the ability to incorporate soil moisture content and vegetation type as predictive model variables would significantly improve the strength of the predictive model. This was further confirmed by the addition of the vegetation mapping dataset by Mattiske Consulting (Mattiske Consulting Pty Ltd 2002) to the Whiteman Park model.

Given the consistency of these results it would suggest that the extrapolation of the model to incorporate the extent of the Swan Coastal Plain would be possible.

Further limitations due to depth of sampling may have decreased the perceived confidence of the predictive model. Sampling concentrated on surface expressions of ORS with sampling depth restricted to the upper 600mm of the soil profile. Therefore buried deposits were not sampled and therefore results may have been negatively

biased due to this. Secondly the natural environment of many sections of the sampling program at Whiteman Park had been altered due to grazing and other historical land use practices at the site, which may have also resulted in negatively biased results.

Three things become apparent from the logistic regression analysis. Firstly the predictive model produced using GIS is a viable option in predicting the spatial distribution of organic rich sediments, given the limitations of sampling and model ranking practices. Secondly the current practice of using wetland mapping alone does not offer the greatest possible solution for identifying the location of these sediments and thirdly soil moisture content and vegetation type empirical data would significantly improve the predictive capacity of the model.

Both soil moisture and vegetation type have been identified by Nuruddin (Nuruddin 2002) and Smith *et al* (Smith, Gawlik et al. 2003) in peat mapping projects performed in Asia and Florida respectively as two of the key variables in confidently predicting the occurrence of peat. There is very little literature however that directly pertains to the nature and distribution of ORS on the Swan Coastal Plain and the southwestern region of Western Australia, as highlighted by papers by Horwitz *et al*, Ryder and a report produced for the Water and Rivers Commission (Department of Environment) (Ryder and Horwitz 1995; Horwitz, Pemberton et al. 1998; Horwitz, Judd et al. 2003; V & C Semenuik Research Group and Syrinx Environmental Pty Ltd 2003). This highlights the importance of this research to the protection and understanding of these soil types and their associated systems.

5.4 Resolution Testing Analysis

Sampling conducted at a smaller scale resulted in a reduction of the capacity of the model to correctly predict the occurrence of ORS both at Melaleuca Park and Whiteman Park. The reduction in predictive ability with the resolution testing (50m sampling interval) at Melaleuca Park could have been attributed to a fire that spread throughout the sampling site in between the field sampling and resolution testing periods. The fire burnt organic sediments thus affecting the results obtained through field investigation. Although the second resolution testing (10m sampling interval) at

Melaleuca Park and the resolution testing performed at Whiteman Park indicate that the loss of predictive capacity is related to issues with scale. The reduction in predictive capacity indicates that the resolution of the predictive model variables may not be suitable for the scale at which sampling took place. Resolution testing field results indicated that the ability to correctly predict the occurrence of ORS at Melaleuca Park fell to 19% (50m sample interval) and 54% (10m sample interval) respectively. At Whiteman Park the ability to correctly predict the occurrence of ORS fell to 19%.

A discrepancy between the logistic regression and field verification results for the resolution testing, further highlight the problems associated with resolution and the appropriate scale of mapping. Logistic regression indicated that the fit of the model was extremely strong with a percentage correct value in the order of 97%, whereas field results point to a correct predictive rate more in the region of 50%.

Resolution testing highlighted the difficulties of prediction at a smaller scale. Deficiencies in the model at smaller localized scales were as a result of the resolution of the predictive model variables. The acquisition of high-resolution data will overcome this deficiency. Such data can be obtained through the use of remotely sensed data which will not only facilitate the strengthening of the predictive model but will also allow for its expansion into a risk assessment model through the inclusion of data which can be used to create risk indices.

Additionally the importance of vegetation mapping to improving the ability to predict the occurrence of ORS was further enhanced. Visual prediction of ORS during resolution testing was predominantly based on the surveying of the surrounding vegetation complex, results showed a correct prediction rate of 90% for Melaleuca Park and 84% for Whiteman Park. Current practise by CALM and FESA officers involves the visual interpretation of the surrounding environment during a fire event to evaluate the likely occurrence of organic rich sediments (pers. comm. L. Mutter, Department of Conservation and Land Management). For personnel with an intimate knowledge of the surroundings in which they are working this can be an invaluable tool. Resolution testing achieved 90% and 84% respectively when predicting the occurrence of organic rich sediments visually. This would result in a powerful

management tool when combined with an accurate map of the spatial distribution of ORS in the area.

5.5 Options for Detecting Soil Moisture and Vegetation Type

There are many options for detecting or inferring soil moisture volumes and vegetation coverage other than the physical collection of data through field sampling. In many instances the detection of these entities is interrelated as the relationship between soil moisture, vegetation type and ground surface temperature are interdependent (Froend, Farrell et al. 1993; Davis and Froend 1999).

One option available is to remotely sense soil moisture content and vegetation type. Remote sensing techniques include thermal mapping, Normalized Difference Vegetation Index (NDVI) and the use of radar and microwave technologies. Due to the expanse of land, which needs to be mapped, namely the Swan Coastal Plain, remote sensing techniques would provide an efficient solution both in terms of time and cost.

Thermal mapping utilizing Landsat thermal infrared imagery has the potential to identify areas containing organic rich sediments (Goward 1989; Kant and Badarinath 2002). During field trials conducted as a part of this study, observations were made as to the difference in temperature associated with areas that contained ORS. This may have been due to the dense vegetation associated with many of these sites or the soil moisture content associated with these sites, or a combination of both. It was noted that during the hottest part of the day certain fauna sought refuge in these areas, supporting the hypothesis that there are temperature differentiations associated with these sights. Numerous studies (Dubayah and Rich 1995; Kant and Badarinath 2002; Li, Jackson et al. 2004; Li, Kustas et al. 2004) have outlined the benefits of utilising the thermal imagery bands of Landsat satellite system to differentiate spatial soil temperature and soil moisture properties at the regional and landscape level. Figure 33 illustrates the use of thermal mapping for the Melaleuca Park site, areas shaded blue are relatively cooler than their surroundings, wetland boundaries have been shown for comparison.

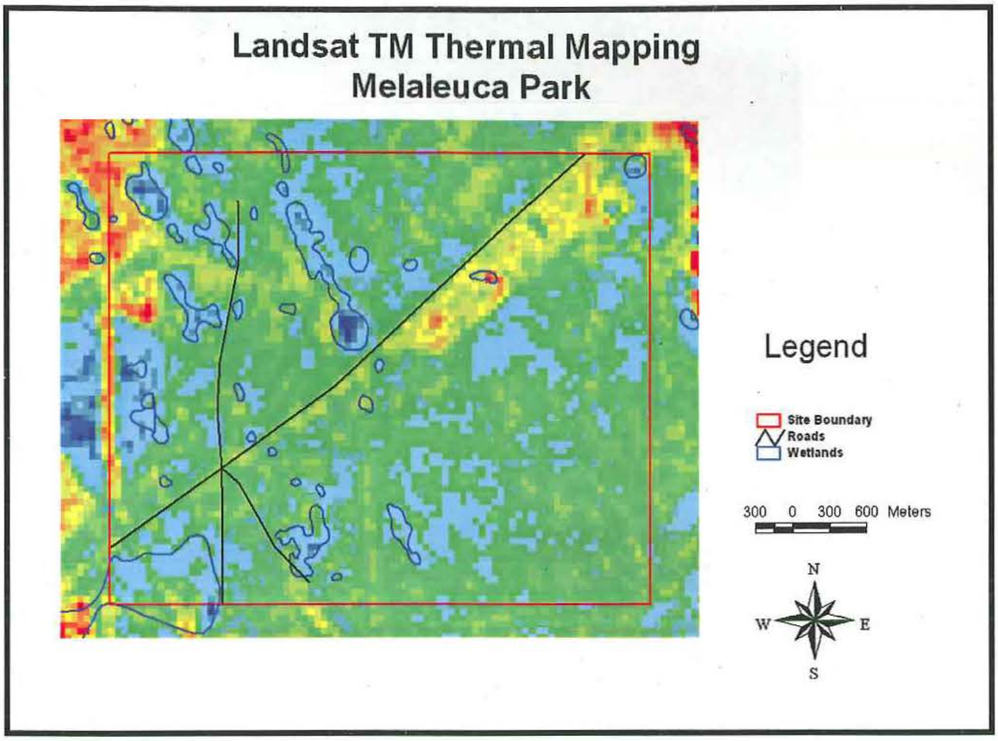
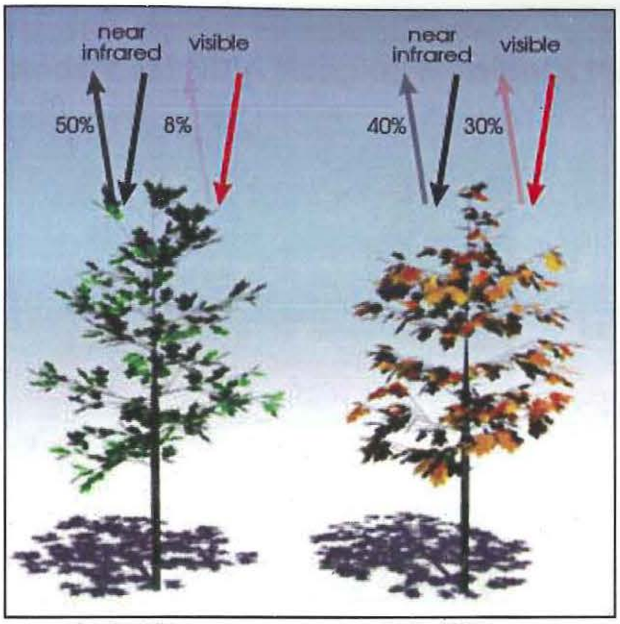


Figure 33: Colour enhanced image of thermal reflectance values using Band 6 Landsat 4 TM for Melaleuca Park site. Areas of low reflectance are coloured blue, areas of high reflectance coloured red. Image provided by G. Behn, Remote Sensing Unit, Department of Conservation and Land Management.

Normalized Difference Vegetation Index (NDVI) allows researchers to determine the density of vegetation on a particular patch of ground (Boer and Puigdefábregas 2003). Vegetation will reflect electromagnetic radiation in the visible and near infrared wavelengths differently depending on the density and health of the vegetation (Carlson and Ripley 1997). Both these variables can be directly correlated with the soil medium that the plants occupy which regulates soil moisture and nutrient availability. NDVI is the result of differences between the reflectance values for the visible and near infrared values emitted by plants (Figure 34). If the difference between visible and near infrared values is small then the vegetation is likely to be unhealthy or sparsely distributed. If the values are high then this is representative of healthy vegetation or densely vegetated areas (Carlson and Ripley 1997).



$$\frac{(0.50 - 0.08)}{(0.50 + 0.08)} = 0.72 \qquad \frac{(0.4 - 0.30)}{(0.4 + 0.30)} = 0.14$$

Figure 34: Example of the theory and formulae behind the calculation of the NDVI value. Image adapted from Robert Simmon (Weier and Herring 1999).

NDVI is a powerful resource that would further enhance the current variables used in the predictive model. It would also facilitate soil moisture analysis by reinforcing findings through association. A colour enhanced NDVI image of the Melaleuca Park site are shown in Figure 35. Regions shaded yellow to red represent vegetation communities that are growing vigorously compared with the surrounding vegetation, wetland boundaries have been included for comparison (Figure 35). While NDVI does not identify species of vegetation it allows the researcher to group patches of vegetation, based on characteristics of the vegetation being mapped. It is useful to differentiate between different vegetation types and for detecting temporal changes associated with plant health or community composition (Boer and Puigdefábregas 2003; Coops, White et al. 2003; Calvão and Palmeirim 2004; Camacho-De Coca, García-Haro et al. 2004; Dilley, Millie et al. 2004).

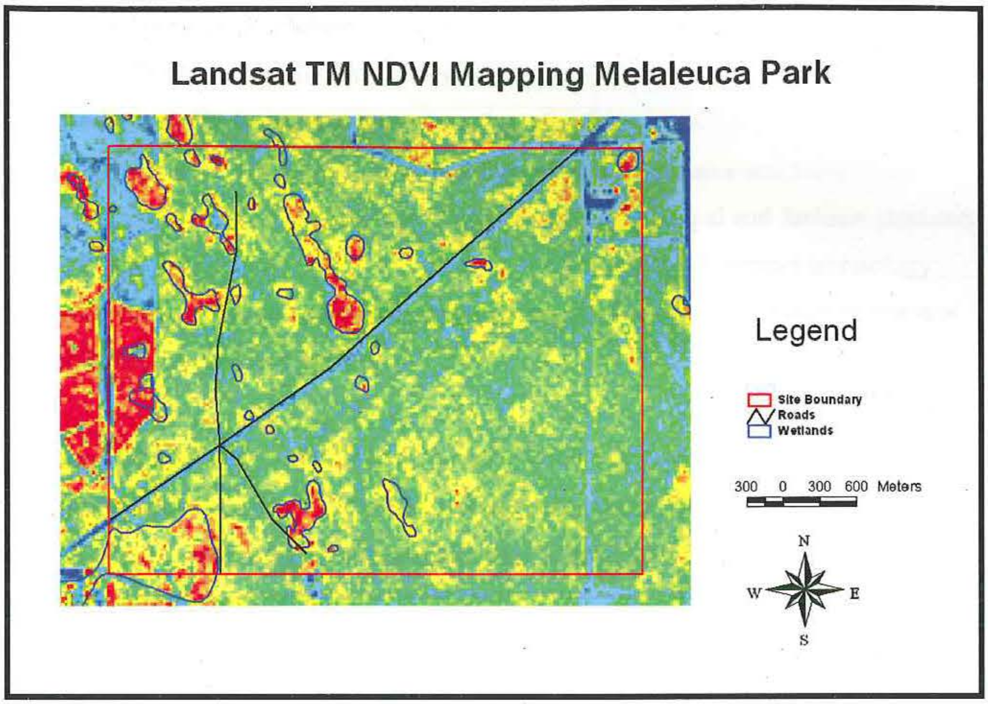


Figure 35: Colour enhanced image of NDVI values for Melaleuca Park site using Landsat 4 TM satellite imagery. Areas coloured red represent healthy or dense vegetation; blue coloured areas represent bare soil or water. Image produced by G. Behn, Remote Sensing Unit, Department of Conservation and Land Management.

Studies evaluating the use of ground penetrating radar and passive microwave techniques for the detection of soil moisture concentrations have been investigated for some time (Engman and Chauhan 1995). Radar is an active system that is able to quantify the amount of soil moisture through detection of variation in backscatter (Boisvert, Pultz et al. 1996; Geng, Gwyn et al. 1996; Moran, Peters-Lidard et al. 2004). Backscatter is the amount of signal returned to the sensor after reflecting of an object therefore it is also susceptible to variations in topography, vegetation and surface roughness. If these are maintained as constants then it stands to reason that the variation will be as a result of variations in soil moisture content. This technology has predominately been used in agricultural and arid land situations where topography and vegetation can be minimized (Boisvert, Pultz et al. 1996; Geng, Gwyn et al. 1996). Whilst topographical variations on the SCP are relatively minimal, there is a large variation in the composition and density of vegetation coverage, for which it may prove difficult to calculate a constant for.

Microwave is a passive technique not dissimilar to that found in active radar detection. There have been numerous studies outlining the benefits and pitfalls associated with this technique in the detection of soil moisture (Engman and Chauhan 1995; Jackson and D.M. 1996; Oldak, Jackson et al. 2002; Burke and Simmonds 2003; Li, Kustas et al. 2004; Jackson 2005; Scipal 2005). Scipal and Jackson (Jackson 2005; Scipal 2005) both purport the advancements made in microwave technology and campaign for its reconsideration in the determination of soil moisture contents at a regional, landscape and local scale.

The above approaches were not considered in this study due to financial and time constraints, as the collection of satellite or airborne remote data is very costly. The cited literature indicates the extensive research being conducted in these areas and warrants further research.

5.6 Improving the Mapping of ORS on the SCP: Options for Environmental Management Agencies

The conservation and management of ORS and their associated systems is vested with a number of government and non-government agencies. From the point of view of emergency response in the case of fire entering these systems both the Fire and Emergency Services Authority (FESA) and the Department of Conservation and Land Management (CALM) are called upon to manage such a situation. In addition to this CALM are also entrusted with the conservation of many of these systems vested in conservation reserves and other CALM managed lands. The Department of Environment (DoE) are entrusted with the conservation of these systems outside of CALM managed lands and in determining the scale of impacts associated with disturbance effects in ORS. Enhancement of the model will be furthered by the addition of remotely sensed data. This will allow the model to become adaptive and moulded to suit the different needs of the relevant agencies.

Current directives and funding from the federal government (Department of Land Information 2005) point to the integration of knowledge and information between agencies to better equip emergency service agencies to coordinate during emergency

events such as bushfire etc. Current research is aimed at the development and implementation of real-time mapping systems which integrates datasets from local, state and federal agencies (Department of Land Information 2005). This study may eventually offer data that can be integrated into such a system. The ability to predict the occurrence of peat soils is a significant aspect of fire management techniques not only on the Swan Coastal Plain but also across the globe. The health implications and the demand on resources in managing fires once they have entered peat soils is astronomically high both in terms of costs to the environment and the costs to the urban community. Thus the ability to prevent fires entering these systems is imperative. Mapping using GIS not only allows for predicting spatial distribution but also provide the capability of being integrated into a real-time mapping system.

5.7 Conclusion

This study confirmed the feasibility of constructing a predictive model using GIS technology. The significant predictors of ORS are soil moisture content, vegetation type, and resistance measures, however all of the data, with the exception of aspect and slope, used in the verification of the model were found to be important in predicting ORS. The model that was developed was statistically relatively strong in being able to predict the spatial distribution of ORS. A map has been produced that can be improved with the inclusion of soil moisture and vegetation type characteristics. It is shown to offer superior performance to the current practice of using wetland mapping alone and offers the ability to be extrapolated to cover the extent of the Swan Coastal Plain subject to further investigation.

This is the first time a map of the spatial distribution of ORS on the SCP has been produced using a range of variables and the first time a predictive model has been produced to aid mangers in dealing with this important problem

Land managers have a swathe of technology available that will enable improved management techniques and mitigation of much of the threat faced by these sediment deposits. To ease the costs associated with the development of such methodologies inter-agency cooperation is imperative. As mentioned previously many government and non-government agencies have a vested interest in the conservation of these

environmental entities. Therefore an inter-agency approach will allow sharing of knowledge and the distribution of costs associated with such projects.

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APPENDICES

APPENDIX 1: CASE STUDY OF PEAT FIRES ON THE SWAN COASTAL PLAIN, WESTERN AUSTRALIA 2004/2005

The summer of 2004 / 2005 has proven to be an extremely disastrous one for the fate of organic sediments on the Swan Coastal Plain. Numerous fires have entered deposits this summer with numerous peat fires still burning in the metropolitan region. CALM have recorded 78 fires this season within the district (SCP) on CALM lands of which 50% of these threatened or impacted on wetlands and their sediments (per com L. Mutter, Regional Fire Officer, Department of Conservation and Land Management).

Whilst the number of fires is down on previous seasons, the intensity of the fires was considered to be much greater (per com. R. Martyn, Department of Conservation and Land Management). This section will outline the events surrounding two peat fires that occurred on CALM lands and one that occurred in Whiteman Park. It will outline the reasons for ignition, the organic and soil moisture content of the soils involved and techniques utilised in the management of the fires.

We begin with geomorphic wetland 8313 which is situated within a conservation reserve in the shire of Swan. Secondly we look at a section of Bennett Brook within Whiteman Park and finally we look at Lake Wilgarup, situated within Yanchep National Park.

Introduction

In July of 2004 the Department of Conservation and Land Management conducted a cool burn to increase biodiversity in a section of the Melaleuca Park Conservation Reserve. As the fire neared the Dampland the fire intensified (pers. comm. R. Martyn, Department of Conservation and Land Management), this allowed the fire to enter the organic sediments associated with this wetland (Plate 1).

In early January 2005 a fire occurred in the southeast region of Whiteman Park which consumed a section of Bennett Brook. The cause of the fire is unknown, although

arson seems the most likely culprit. The fire covered a section of Bennett Brook floodplain (Plate 2).

A fire started in Yanchep National Park on Thursday the 6^{th} of January. The fire was started by arsonists and spread quickly throughout areas of the park, burning approximately 1200ha. The fire entered sediments in Yonderup Lake and Lock McNess as well as Lake Wilgarup (Plate 3 and 4).

Study Sites

Melaleuca Park

Geomorphic wetland 8313 is part of the Melaleuca Park wetland suite. It is situated approximately 8km NE along Neaves Road from the Pinjar / Neaves Road intersection, GDA94 Zone 50, 395 380m east and 6 494 420m north. It is a conservation class wetland. It has been classified as a Dampland, which is considered a seasonally waterlogged basin (Hill, Semeniuk et al. 1996a). It is 0.4ha in size and is bounded by Neaves Road to the south / southeast and Gnangara pine plantation to the north and northwest.

The site in question is situated within the Bassendean Dune system. This system is comprised of an undulating plain, ranging in elevation from ~ 20m to predominately flat terrain, consisting mainly of quartz sand (Semeniuk 1988). The wetland as with many others in the area has formed within the interdunal swales of the aforementioned dune system (Semeniuk and Semeniuk 2001). The vegetation consists of *Banksia illicifolia, Melaleuca preissiana* over a dense thicket of *Melaleuca rhaphiophylla* to approximately 2m in height.

Bennett Brook

The catchment of Bennett Brook is located in the northeast comer of the Perth metropolitan area and is approximately 11, 600 ha in size. The catchment begins in the north, at the Gnangara Pine Plantation and continues to the Swan River in the south and from Ballajura in the west to the Swan River in the east (Western Australian Department of Planning and Infrastructure 1994).

Bennett Brook also has a very rich cultural history being one of the first areas settled by Europeans in the early days of the Swan River Colony. The local Nyungar people had been aware of the value of this area for thousands of years prior to European settlement and still living in the area, retain their connection to this scared site (O'Connor, Bodney et al. 1989).

The Brook itself is 17.5 km long and flows from Whiteman Park to the Swan River in Bassendean. It forms an important wildlife corridor for fauna of the area. Within Whiteman Park Bennett brook travels from the northwest to the southeast section of the park. The brook is at its driest during the summer months (December) with isolated pools of water as opposed to a free flowing brook during the winter months (May / June) (Environmental Resources Management 2003).

Lake Wilgarup

Lake Wilgarup is situated within Yanchep National Park. This park is vested with the National Parks and Nature Conservation Authority and is managed by CALM (Water Authority of Western Australia 1995). It is situated on the eastern side of Wanneroo Road approximately 45km NNW of Perth.

The wetland is classified as a Sumpland, seasonally inundated basin (Hill, Semeniuk et al. 1996b). Lake Wilgarup sits within the Spearwood Dune system. It has formed within an interdunal depression within this system. It is 15.6 ha in area (Hill, Semeniuk et al. 1996a) and the bathymetry of the lake reveals a shallow saucer shaped wetland which is subject to fluctuations in surface water expression (Water Authority of Western Australia 1995). Accounts of surface water levels range from dry in summer to periods of inundation of up to 80cm in depth (Water Authority of Western Australia 1995).

Lake Wilgarup is considered a pristine representation of this type of wetland on the Swan Coastal Plain, yet little is known about the biology of the wetland. Examination of organic sediments revealed true peat's to depths in excess of 2m in some places. Vegetation is classified as Maculiform, heterogeneous with complete coverage, and consists of a closed canopy of *Melaleuca raphiophylla* and occasional *Banksia littoralis*, pockets of sedge including *Baumea articulata* and *juncea* and is surrounded on its upper slopes by stands of *Eucalyptus rudis* (Water Authority of Western Australia 1995).

Methods

Sampling

Soil samples were collected to ascertain the organic matter of soils at each of the sites. The sampling locations can be seen in Figure 1 for Geomorphic Wetland 8313, Figure 2 for Lake Wilgarup and Figure 3 for Bennett Brook.

Soils were sampled using a hand held auger, which was drilled to a depth of 400mm. Two samples were taken per sample site one at the surface (100mm) and one at depth (300mm). Sampling occurred pre-burn and post-burn where possible.

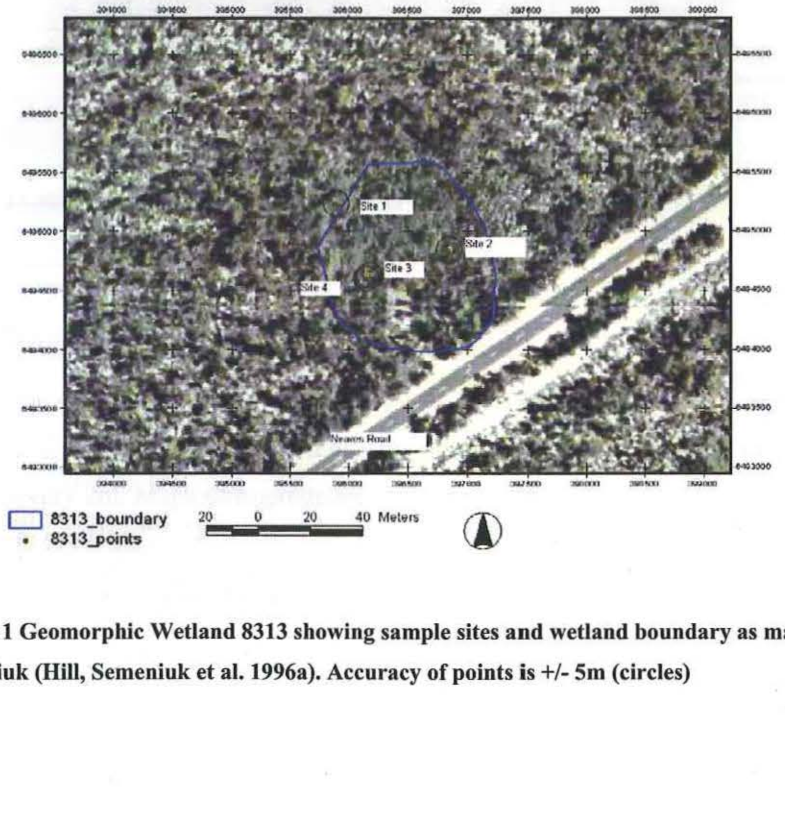

Figure 1 Geomorphic Wetland 8313 showing sample sites and wetland boundary as mapped by Semeniuk (Hill, Semeniuk et al. 1996a). Accuracy of points is +/- 5m (circles)

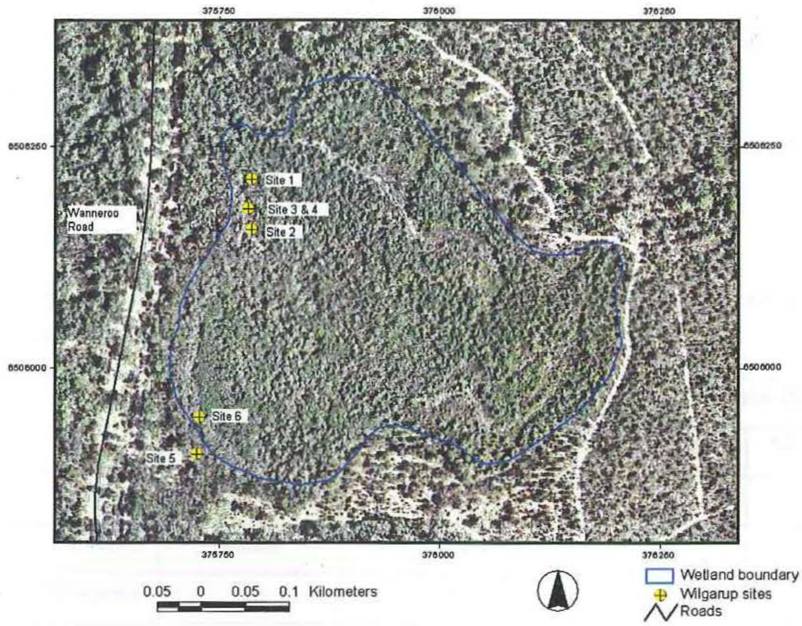

Figure 2 Lake Wilgarup wetland boundary and sampling sites

Fire Boundary Mapping

The extent of each fire was mapped using a Garmin GPS II Plus hand held GPS receiver. The boundary of the burn was traversed by foot and Positional data was logged every 2m. Maps were produced using ArcView 3.2.

Results

At Melaleuca Park sampling occurred pre and post-burn. The results for four sample sites are shown in Table 1. Analysis of sediments pre-burn revealed much higher LOI values equating to higher organic content of the soil and much higher soil moisture values.

Table 1 Pre-burn and post-burn LOI and soil moisture values for four sites sampled in Geomorphic Wetland 8313

	Pre-Burn		Post-Burn	
Site	**% LOI**	**% Soil Moisture**	**% LOI**	**% Soil Moisture**
1 (100mm)	52.09	44.60	X	X
1 (500mm)	43.25	53.84	X	X
2 (200mm)	X	X	38.55	9.35
2 (500mm)	X	X	11.50	14.47
3 (100mm)	X	X	24.17	6.70
3 (300mm)	X	X	9.92	9.67
4 (250mm)	X	X	1.54	1.80

No pre-burn sampling was performed at Bennett Brook. The organic matter content of the soil was far lower than that seen at Melaleuca Park but soil moisture levels remained high (Table 2).

Table 2 LOI and soil moisture values from Bennett Brook sediments

Site	% LOI	% Soil Moisture
1 (100mm)	25.19	40.86
1 (300mm)	11.39	34.83
2 (100mm)	14.04	17.57
2 (300mm)	8.08	12.54
3 (100mm)	17.04	28.45
4 (100mm)	28.51	42.84
4 (300mm)	11.85	33.53

Both pre-burn and post-burn sampling was performed at the site. Table 3 shows the values for LOI and soil moisture for the areas sampled. The post-burn samples were collected from sediment layers directly beneath the ash bed. The ash bed was estimated to be 30-40cm deep in some of the places sampled. The LOI values of the pre-burn sites compared with their soil moisture contents illustrate their potential to ignite during a fire event. Post-burn results indicate why the combustion front has not spread downwards as the ratio of organic to inorganic matter is low, the exception being site 6 with an LOI value of 32.65, this site was still noticeably burning (Table 3).

Table 3 Pre-burn and post-burn LOI and soil moisture values for Lake Wilgarup samples

	Pre-Burn		Post-Burn	
Site	**% LOI**	**% Soil Moisture**	**% LOI**	**% Soil Moisture**
1	87.37	39.08	X	X
2	21.83	9.66	X	X
3	X	X	3.03	1.78
4	X	X	6.04	1.57
5	X	X	5.02	10.72
6	X	X	32.65	6.81

Initial mapping of fire boundary at the end of October 2004 revealed that 22.5% or 0.09ha of the 0.4ha wetland was consumed by fire (Figure 3). A second measurement taken mid November 2004 revealed that a further 0.07ha had been burnt. A further survey at the beginning of January 2005 revealed a further 0.03ha had been burnt. This resulted in a total of 0.19ha or 48% of wetland being burnt as of January 2005 (Figure 3). Subsequent boundary mapping was not possible due to safety concerns regarding the stability of trees in the area, needless to say that the fire is still burning as of mid February 2005.

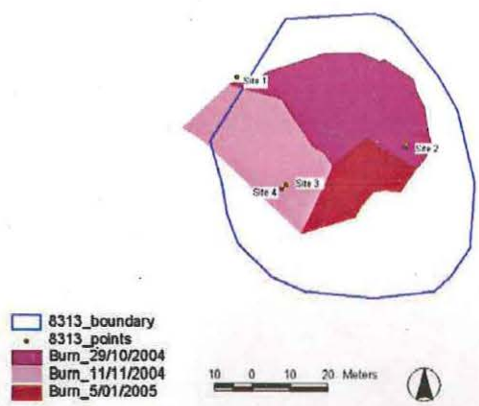

Figure 3 Extent of burn scar for geomorphic wetland 8313

At Whiteman Park the fire occurred in the southwest section of the park. The fire affected a section of Floodplain (6.57 ha) and a section of the Brook itself (0.81 ha). The total area affected by the fire was approximately 19 ha (Figure 4).

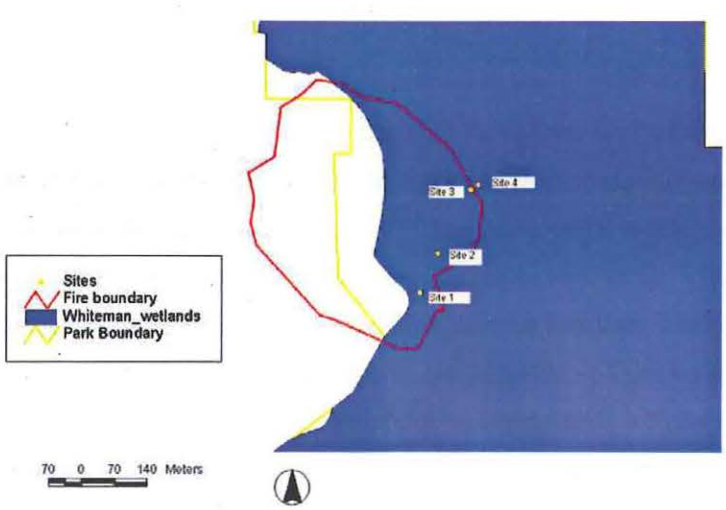

Figure 4 Fire boundary Bennett Brook fire

Approximately 14 ha of the total 15.6 ha of Lake Wilgarup were consumed by fire during the Yanchep National Park fire in 2005.

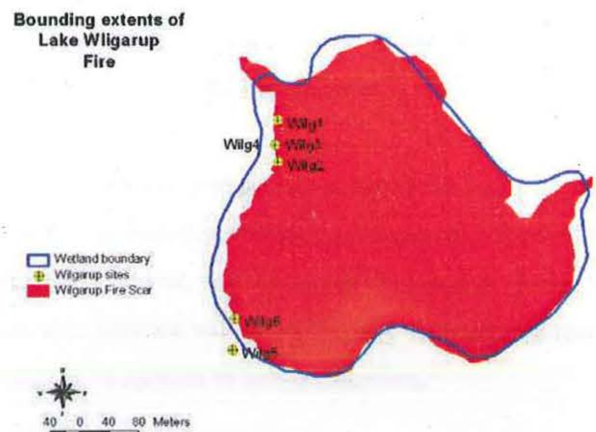

Figure 5 Bounding extent of fire at Lake Wilgarup, January 2005.

Discussion and Conclusions

Melaleuca Park

The fact that the soil at site 1 had not burnt even though the fire had commenced can be explained by the ratio of organic matter to soil moisture. Frandsen (Frandsen 1997a) postulated that soils with approximately 50% inorganic matter would require 40% soil moisture levels or greater to prevent burning. As can be seen at site 1 the combined values lie outside the requirements for ignition to occur therefore it did not initially combust. The ratio of moisture to organic matter would have changed at some stage during the combustion event. A change of soil moisture levels is likely either due to drying by the smoldering front or due to changes in groundwater levels. This would have brought combined values within the ignition range and thus ignition occurred.

Subsequent sampling post-fire beneath the ash-bed revealed a general decrease in LOI values with a much greater decrease in the relative amount of soil moisture. These soils are still continuing to be consumed. This correlates with the ignition rates expected with

these soils considering their soil moisture values. Those sites, which had LOI values less than 10%, did not show indications of being ignited (such as heat / smoke emissions).

CALM made numerous attempts to extinguish the fire subsequent to the ignition of the wetland. This involved using a semi-trailer tanker loaded with water and placing this large volume of water onto the burning site.

The failure of this attempt was probably due to the lack of knowledge about the organic material present. Knowledge relating to the extent of the organic soil deposit both horizontally and vertically, and the spatial distribution of organic concentrations and their relative soil moisture values would have enabled managers to determine required levels of water to be applied to halt combustion.

Bennett Brook

Visual examination of the site indicated that the fire had dried the surface but very little soil organic matter appears to have been consumed due to a lack of ash bed (except sites 3 and 4). The ratio of soil moisture to organic content is considerably high which accounts for the fire not consuming soil organic material. The high soil moisture values may be attributable to the presence of clay as the inorganic component of the soil.

Sights three and four did have a small ash bed ~ 100mm thick. The soil directly below the ash bed showed high soil moisture to organic content ratio's thus preventing further combustion of the soil.

Due to the soil moisture content of the soil, combined with favourable conditions, the fire could be extinguished with minimal environmental damage.

Lake Wilgarup

No attempt has been made to extinguish Lake Wilgarup. Approximately ¾'s of the site has burnt.

Due to the size of the organic deposit and the decreased risk of fire escaping from the site it may be possible that land managers may be waiting for winter rains to extinguish the current combustion process or allowing the fire to naturally extinguish once the organic matter has been consumed.

Conclusion

What is evident from this study is that the nature of the sediments being burnt is vastly different from that seen in other parts of the world. The organic content of the soils on the Swan Coastal Plain are far less than what would normally be classed as peat and yet they still burn in a similar fashion.

Much research is needed into the functioning of these systems, how they recover from fire and ways in which to adequately mange them in a fire situation.

Plate 1 Geomorphic wetland 8313 11/11/2004

Plate 2 Bennett Brook floodplain

Plate 3 Lake Wilgarup (2) August 2004

Plate 4 Lake Wilgarup post-burn 30/1/2005

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Appendix 2: REMOTE SENSING TECHNIQUE FOR THE DETECTION OF PEAT ON THE SWAN COASTAL PLAIN

ANALYSIS OF REMOTELY SENSED DATA

As part of this study it was proposed to utilize remotely sensed data to aid in the identification of spatial distribution of organic soils of the SCP. This process was performed in conjunction with Graeme Behn, Project Leader Remote Sensing Unit, GIS section, CALM. On consultation it was agreed that Thematic Mapper (TM) Band 4 satellite imagery would be used. TM Band 4 data is ideal for detecting near-IR reflectance peaks in healthy green vegetation and for detecting water-land interfaces. The instantaneous field of view (IFOV) for TM band 4 is 30 meters by 30 meters (900 square meters).

IMAGE ANALYSIS

Images for mid-summer (January) were analysed for the years 1994, 1996, 1998, 2000, 2002, 2003 and 2004. Imagery was calibrated to *like values* so that comparisons could be made between the digital numbers from different dates. Imagery was processed using E.R.Mapper 6.3.

IMAGE CLASSIFICATION

Sample sites were selected as a result of a pilot study conducted in July 2004. Sites were categorised based on a visual interpretation for the presence of peat conducted during field surveys. From the acquired data sites were selected and categorised into plantation (4 sites), native vegetation (6 sites), and peat (11 sites).

CANONICAL VARIATE ANALYSIS

Canonical variate analysis was used to determine the spectral separation of the identified sites. Analysis indicated a lack of spectral separation between a number of known peat deposits and natural vegetation sites.

RESULTS

Due to a lack of spectral separation between a number of peat sites and native vegetation sites, it was concluded that it was not possible to remotely sense the occurrence of peat based on the above method.

Appendix 3: LOGISTIC REGRESSION ANALYSIS CATEGORY CODING TABLES

Table 1: Coding of categorical variables used in the logistic regression for the Melaleuca Park site.

Categorical Variables Codings

		Frequency	Parameter coding (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vegetation Type	VOBW	26	.000	.000	.000	.000	.000	.000	.000	.000
	OBW	22	1.000	.000	.000	.000	.000	.000	.000	.000
	Mel. rhaph	1	.000	1.000	.000	.000	.000	.000	.000	.000
	Mel. rhaph/E. rudis	2	.000	.000	1.000	.000	.000	.000	.000	.000
	Mel. rhaph./Hypocalymma	2	.000	.000	.000	1.000	.000	.000	.000	.000
	Mel. rhaph thicket	20	.000	.000	.000	.000	1.000	.000	.000	.000
	B. elegens thicket	3	.000	.000	.000	.000	.000	1.000	.000	.000
	E. rudis thicket	1	.000	.000	.000	.000	.000	.000	1.000	.000
	Sedge	4	.000	.000	.000	.000	.000	.000	.000	1.000
Aspect	Flat	45	.000	.000	.000	.000	.000	.000	.000	.000
	North	3	1.000	.000	.000	.000	.000	.000	.000	.000
	Northeast	1	.000	1.000	.000	.000	.000	.000	.000	.000
	East	6	.000	.000	1.000	.000	.000	.000	.000	.000
	Southeast	6	.000	.000	.000	1.000	.000	.000	.000	.000
	South	3	.000	.000	.000	.000	1.000	.000	.000	.000
	Southwest	2	.000	.000	.000	.000	.000	1.000	.000	.000
	West	6	.000	.000	.000	.000	.000	.000	1.000	.000
	Northwest	9	.000	.000	.000	.000	.000	.000	.000	1.000
Soil Type	PDS	39	.000	.000	.000					
	PDS/Semi-wet	6	1.000	.000	.000					
	Semi-wet	17	.000	1.000	.000					
	Wet-soils/peaty	19	.000	.000	1.000					
Wetland Type	sumpland	19	1.000	.000						
	dampland	12	.000	1.000						
	not	50	.000	.000						

Table 2: Coding of categorical variables used in logistic regression for the Whiteman Park site.

Categorical Variables Codings

		Frequency	Parameter coding (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Vegetation Type	VOBW	9	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	OBW	10	1.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	Mel. rhaph	9	.000	1.000	.000	.000	.000	.000	.000	.000	.000	.000
	Mel. rhaph./Hypocalymma	6	.000	.000	1.000	.000	.000	.000	.000	.000	.000	.000
	Mel. rhaph thicket	1	.000	.000	.000	1.000	.000	.000	.000	.000	.000	.000
	B. elegans thicket	7	.000	.000	.000	.000	1.000	.000	.000	.000	.000	.000
	Sedge	2	.000	.000	.000	.000	.000	1.000	.000	.000	.000	.000
	Eucalypt/Melaleuca/Myrtaceae	7	.000	.000	.000	.000	.000	.000	1.000	.000	.000	.000
	Eucalyptus/Banksia woodland	7	.000	.000	.000	.000	.000	.000	.000	1.000	.000	.000
	Grazed / Open plain	10	.000	.000	.000	.000	.000	.000	.000	.000	1.000	.000
	Melaleuca / Agonis lin.	3	.000	.000	.000	.000	.000	.000	.000	.000	.000	1.000
Aspect	Flat	27	.000	.000	.000	.000	.000	.000				
	North	2	1.000	.000	.000	.000	.000	.000				
	East	6	.000	1.000	.000	.000	.000	.000				
	Southeast	16	.000	.000	1.000	.000	.000	.000				
	South	15	.000	.000	.000	1.000	.000	.000				
	Southwest	1	.000	.000	.000	.000	1.000	.000				
	West	4	.000	.000	.000	.000	.000	1.000				
Soil Type	PDS	20	.000	.000	.000							
	PDS/Semi-wet	1	1.000	.000	.000							
	Semi-wet	39	.000	1.000	.000							
	Wet-soils/peaty	11	.000	.000	1.000							
Wetland Type	dampland	18	1.000	.000	.000							
	floodplain	1	.000	1.000	.000							
	palusplain	8	.000	.000	1.000							
	not	44	.000	.000	.000							

Table 3: Coding of categorical variables used in the logistic regression (including vegetation survey) for the Whiteman Park site.

Categorical Variables Codings

		Frequency	Parameter coding (1)	(2)	(3)	(4)	(5)	(6)
Aspect	Flat	27	.000	.000	.000	.000	.000	.000
	North	2	1.000	.000	.000	.000	.000	.000
	East	6	.000	1.000	.000	.000	.000	.000
	Southeast	16	.000	.000	1.000	.000	.000	.000
	South	15	.000	.000	.000	1.000	.000	.000
	Southwest	1	.000	.000	.000	.000	1.000	.000
	West	4	.000	.000	.000	.000	.000	1.000
WP Veg	G	2	.000	.000	.000	.000	.000	.000
	H	5	1.000	.000	.000	.000	.000	.000
	I	11	.000	1.000	.000	.000	.000	.000
	J	6	.000	.000	1.000	.000	.000	.000
	JK	25	.000	.000	.000	1.000	.000	.000
	K1	21	.000	.000	.000	.000	1.000	.000
	K2	1	.000	.000	.000	.000	.000	1.000
Soil Type	PDS	20	.000	.000	.000			
	PDS/Semi-wet	1	1.000	.000	.000			
	Semi-wet	39	.000	1.000	.000			
	Wet-soils/peaty	11	.000	.000	1.000			
Wetland Type	dampland	18	1.000	.000	.000			
	floodplain	1	.000	1.000	.000			
	palusplain	8	.000	.000	1.000			
	not	44	.000	.000	.000			

Table 4: Coding of categorical variables used in the logistic regression for sensitivity analysis Melaleuca Park site.

Categorical Variables Codings

		Frequency	Parameter coding (1)	(2)	(3)	(4)
Aspect	Flat	15	.000	.000	.000	.000
	East	2	1.000	.000	.000	.000
	South	7	.000	1.000	.000	.000
	Southwest	4	.000	.000	1.000	.000
	West	3	.000	.000	.000	1.000
Vegetation Field	V.O.B.W.	16	.000	.000	.000	
	Border	4	1.000	.000	.000	
	Open thicket	2	.000	1.000	.000	
	Thicket	9	.000	.000	1.000	
Soil Type	PDS	1	.000	.000		
	PDS/Semi-wet	3	1.000	.000		
	Wet (peaty)	27	.000	1.000		
Wetland Type	Not	19	.000			
	Sumpland	12	1.000			

Table 5: Coding of categorical variables used in the logistic regression for sensitivity analysis (10m) Melaleuca Park site.

Categorical Variables Codings

		Frequency	Parameter coding (1)	(2)	(3)
Vegetation Field	V.O.B.W.	5	.000	.000	.000
	Border	6	1.000	.000	.000
	Open thicket	4	.000	1.000	.000
	Thicket	6	.000	.000	1.000
Wetland Type	Not	8	.000		
	Dampland	13	1.000		
Aspect	Flat	19	.000		
	East	2	1.000		
Visually Peat	No	12	.000		
	Yes	9	1.000		

Table 6: Coding of categorical variables used in the logistic regression sensitivity analysis Whiteman Park site.

Categorical Variables Codings

		Frequency	Parameter coding (1)	(2)	(3)
Vegetation Field	V.O.B.W.	10	.000	.000	.000
	Border	10	1.000	.000	.000
	Open thicket	1	.000	1.000	.000
	Thicket	10	.000	.000	1.000
Aspect	Flat	20	.000	.000	.000
	East	2	1.000	.000	.000
	Southeast	5	.000	1.000	.000
	South	4	.000	.000	1.000
Vegetation Type W.P.	I	6	.000	.000	.000
	J	4	1.000	.000	.000
	JK	6	.000	1.000	.000
	K1	15	.000	.000	1.000
Soil Type	PDS/Semi-wet	3	.000	.000	
	Semi-wet	2	1.000	.000	
	Wet (peaty)	26	.000	1.000	
Visually Peat	No	22	.000		
	Yes	9	1.000		
Wetland Type	Not	22	.000		
	Floodplain	9	1.000		