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An evaluation of the effect of terrain normalization on classification accuracy of Landsat ETM+ imagery

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AN EVALUATION OF THE EFFECT OF TERRAIN NORMALIZATION ON
CLASSIFICATION ACCURACY OF LANDSAT ETM+ IMAGERY

BY

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B.S.F. University of New Hampshire, 2002

THESIS

Submitted to the University of New Hampshire
in Partial Fulfillment of
the Requirements for the Degree of

Master of Science

in

Natural Resources: Forestry

September, 2006

UMI Number: 1437615

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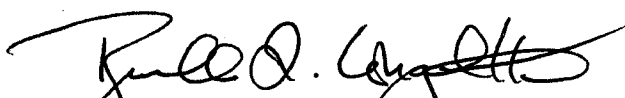
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ACKNOWLEDGEMENTS

I would like to thank Dr. Russ Congalton and Dr. Mimi Becker for considering me for this project, for all of the advice and encouragement provided along the way and for a memorable two-week "family vacation" in New Zealand. I would like to thank Dr. Tom Lee for his guidance at the beginning of my Literature Review and for his constructive comments during the review process.

I would like to thank John Lockley of the University of Waikato for helping me to understand the education system of New Zealand, for all of his help conducting the GLOBE workshops, and for showing me some of the finer points of New Zealand. I must also extend my thanks to his family for their warmth and many tasty meals.

Dr. Daniel Rutledge and the rest of the staff at Landcare Research in Hamilton, New Zealand kindly offered me office space, field equipment, and their expertise in GIS while I was in the country, and for that I am very grateful. Many thanks are due to Robbie Price, and my office-mate, Craig Briggs, for all of their assistance and camaraderie during my stay.

Thanks go to my friends in BASAL and in the Department of Natural Resources for support and encouragement throughout my tenure at UNH. I am indebted to Jen for her friendship, encouragement, insight, and especially for her review of this thesis.

I would like to thank Tina for her support, encouragement, and much needed diversions since her arrival in BASAL. I am especially grateful for her constructive critical reviews of my work and her love of miniature aeronautics.

Finally, I would like to thank my family for all of their support through this whole process. It is truly appreciated.

PREFACE

He rangi ta matawhaiti,
He rangi ta matawhanui'

The person with a narrow vision sees a narrow vision,
The person with a wide vision sees a wide horizon.

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ABSTRACT

AN EVALUATION OF THE EFFECT OF TERRAIN NORMALIZATION ON CLASSIFICATION ACCURACY OF LANDSAT ETM+ IMAGERY

By

Jesse B. Bishop

University of New Hampshire, September, 2006

More than 60% of land in New Zealand has been converted from native forests to residential areas, agriculture, or forest plantations. Settlers brought many species of plants and animals to New Zealand. Many native species were unable to protect themselves from these new predators, causing numerous extinctions. In light of this rapid decline in biodiversity, the New Zealand government has attempted to mitigate the destruction of endemic flora and fauna through both new environmental policies and intensive land management. Land management techniques include the restoration of developed land and the protection of remaining areas of native forest. Monitoring of restoration efforts is important to the government and organizations responsible for this work. Using remotely sensed data to perform change analysis is a powerful method for long-term monitoring of restoration areas. The accuracy of maps created from remotely sensed data may be limited by significant terrain variation within many of the restoration areas. Landcare Research New Zealand has developed a topographic suppression algorithm that reduces the effects of topography. Landsat ETM+ imagery from November 2000 was processed with this algorithm

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to produce two images, an orthorectified image and a terrain-flattened image of a 50-km by 60-km area near Wanganui, New Zealand. Using GLOBE reference data collected on the ground in September/October 2004 and additional reference data photointerpreted from aerial photography, thematic maps were created using unsupervised, supervised, and hybrid classification methods. The accuracy of the thematic maps was evaluated using error matrices and Kappa analysis. The different image processing techniques were statistically compared. It was determined that the topographic-flattening algorithm did not significantly improve map accuracy.

INTRODUCTION

The New Zealand landscape has changed greatly since the arrival of the first humans nearly 1,000 years ago. The once extensive forests have been replaced by agricultural fields, pastures, and built-up areas. Settlers introduced many new species of plants and animals into this mammal-free paradise. These introductions have had devastating effects on the native flora and fauna. Now, the government of New Zealand is focused on restoring damaged ecosystems and creating laws to control the loss of biodiversity. Restoration efforts range from simple tasks such as trapping and poisoning non-native species to monumental undertakings like fencing an entire mountaintop and eradicating all warm-blooded pests from the native forest within the fence. While some of the smaller projects are easy to monitor, the more extensive projects require large scale monitoring that is both costly and time consuming.

Satellite-based remote sensing has been used successfully to assess and monitor environmental conditions in a variety of locations. This technology can reduce the costs of monitoring by providing a synoptic view of the landscape and reducing the number of field observations necessary to understand environmental phenomena. New Zealand offers a unique opportunity to use this technology to monitor the advanced landscape and biodiversity restoration efforts that have been occurring there with increasing frequency.

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This project evolved from an international collaboration between the GLOBE (Global Learning and Observations to Benefit the Environment) Land Cover/Biology Team at the University of New Hampshire and GLOBE New Zealand. GLOBE is an international student-teacher-scientist partnership that measures and reports parameters relating to the atmosphere, hydrology, soils, and land cover. This project combined the remote sensing expertise of the GLOBE Land Cover/Biology team with the enthusiastic students of the GLOBE Program in New Zealand to collect land cover data at five restoration sites in New Zealand.

After initial field visits to the restoration sites, a major problem was discovered. The steep and varying terrain found in some of the study areas would require special processing to extract accurate information from the satellite imagery. Steep terrain affects the interaction of light between the source, the vegetation canopy, and the satellite sensor. To overcome this issue, a number of methods have been used. Dymond and Shepherd (2004) used a method of terrain normalization that they had developed at Landcare Research in Palmerston North, New Zealand to classify indigenous vegetation in the Wellington area of New Zealand. A single restoration area near Wanganui was chosen as a trial site to evaluate the effectiveness of this terrain-flattening algorithm. The team at Landcare Research, Palmerston North prepared two versions of a Landsat ETM+ scene covering the study area near Wanganui. The first was an orthorectified image. The second was further processed with their terrain-flattening algorithm. These images were classified using unsupervised,

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supervised, and hybrid methods in order to compare the accuracy of the maps resulting from the orthorectified image and the maps resulting from the terrain-flattened image. The land cover data collected by the GLOBE students at the Bushy Park Homestead and Forest Park near Wanganui were used as part of the evaluation of the terrain-flattened imagery.

Objectives

The objectives of this study were:

- To develop the best possible land cover classification for an orthorectified image.

- To develop the best possible land cover classification for the terrain flattened image.

- To compare the accuracies of the maps resulting from the classification of each image.

Hypotheses

The general hypotheses for this study were that each classification was significantly better than a random classification and that there is a significant difference in the ability to accurately classify land cover based on the use of the terrain-flattening algorithm. For the first general hypothesis, there are six null hypotheses. They are:

- The unsupervised classification of the orthorectified image is not significantly better than a random classification.

- The supervised classification of the orthorectified image is not significantly better than a random classification.

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- The hybrid classification of the orthorectified image is not significantly better than a random classification.

- The unsupervised classification of the terrain-flattened image is not significantly better than a random classification.

- The supervised classification of the terrain-flattened image is not significantly better than a random classification.

- The hybrid classification of the terrain-flattened image is not significantly better than a random classification.

For the second general hypothesis, there are three null hypotheses. They are:

- There is no significant difference between the unsupervised classification of the orthorectified image and the unsupervised classification of the terrain-flattened image.

- There is no significant difference between the supervised classification of the orthorectified image and the supervised classification of the terrain-flattened image.

- There is no significant difference between the hybrid classification of the orthorectified image and the hybrid classification of the terrain-flattened image.

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CHAPTER I

LITERATURE REVIEW

New Zealand

In order to better understand the impetus for monitoring biodiversity and ecological restoration in New Zealand, it is important to know the histories of the geology, ecology, settlement patterns, culture, and politics of the country. The socio-political climate of New Zealand is a result of both the unique landscape and biota of the country, and the differing cultures and views of the people of New Zealand. The Maori, the original Polynesian settlers of the New Zealand archipelago, generally had a more holistic view of the world than did the European colonialists, who arrived several hundred years after the Maori. Today, the culture of New Zealand can be seen as the result of the intermingling of these views.

Prehistoric New Zealand. New Zealand's geologic evolution began with the deposition of sediments off the shore of Gondwana nearly 600 million years ago. Pressure and volcanic action changed the composition of the sediments before they were lifted from the sea by tectonic action 140 million years ago. This new land was colonized by primitive plants and animals. As Gondwana broke apart and New Zealand shifted to the east, a vast sea grew between the mainland and the New Zealand archipelago. Gradually, connections between New Zealand,

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Australia, and Antarctica were lost. Over the next 80 million years, climatic disturbances and the gradual immersion of four-fifths of the continent resulted in isolated populations, even within New Zealand (Fleming, 1975). As a result of this period of isolated evolution, a majority of the flora and fauna found in New Zealand are unique in the world. The native New Zealand biota contains no land mammals, and therefore, the plant community, along with the various birds, lizards, and tuatara, evolved without browsing pressure or the threat of mammalian predation (Salmon, 1975). Over 80% of the vascular plants in New Zealand are endemic (Anon., 2000). Approximately 20% of vertebrate animals and a majority of invertebrate animals found in New Zealand are endemic (Taylor and Smith, 1997).

History of Settlement. New Zealand was one of the last places in the world to feel the effect of human settlement. When Polynesian settlers arrived 800 to 1000 years ago, 85% to 90% of the land was forested (Holdaway, 1989; McGlone, 1989; King, 2003). The remainder of the landscape was dominated by grasslands, occurring in river terraces and valleys, along cliffs, and atop coastal sand dunes. Wetlands and forested wetlands contributed a small percentage to the landscape (McGlone, 1989). Initial population numbers of the Maori settlers were low, but more settlers arrived and began to change the New Zealand landscape. Although some wildfires occurred naturally in New Zealand, the Maori contributed largely to the burning of the landscape to clear land and to flush game (Salmon, 1975; McGlone, 1989). Indeed, the Maori exploited many large bird species, bringing many near or across the brink of extinction.

The Maori introduced the first destructive mammalian predator, the *kiore*, or Polynesian rat (*Rattus exulans*). Although there were bird species within New Zealand that had evolved to fill the predatory niche that the rat fills elsewhere, their reproductive rate was limited to two broods per year. The *kiore* was able to produce many offspring per year, some of which would begin breeding that same year. The rats exploited the naivety of small native bird species and, with this abundant food supply, grew exponentially. The invasion of the *kiore* in the New Zealand forest has been referred to as a 'grey tide' sweeping across the land (Holdaway, 1989; McGlone, 1989).

Europeans began a period of colonization approximately 200 years ago (King, 2003) and began the process of 'breaking the land' (Sanders and Norton, 2001). Many landholders were legally bound to improve their land as a condition of acquisition. Most often, the land was improved by burning or otherwise removing the native forest to make pastureland. Extensive land reclamation campaigns resulted in the drainage of most of the wetlands in New Zealand. Straight and tall Kauri (*Agathis australis*) trees were removed from the northern forests for shipbuilding and general construction. The combination of overgrazing and forest removal resulted in massive flooding and erosion of the unstable soils (Salmon, 1975). Early settlers brought many species of plants and animals, which were used for both income and convenience (Anon., 2000). New Zealand did not escape the Acclimatization Movement of the late 1800s, during which large numbers of European birds, mammals, and plants were shipped to colonies around the world. The New Zealand Acclimatization Society introduced

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many plants and animals to the country in an attempt to reshape the landscape and provide recreation opportunities similar to what the settlers from Europe were accustomed (Isern, 2002). Rabbits were introduced in 1838 and began the destruction of native vegetation. The Australian brushtail possum (*Trichosurus vulpecula*) was introduced in 1858 with the hope of exporting the luxurious pelts, and soon escaped into the wild. In the late 1800s, weasel, stoat, ferrets, and deer were introduced to New Zealand. The populations of these animals grew with the abundant food provided by the defenseless native flora and fauna (Salmon, 1975). By the 1920s, naturalists were beginning to realize that the introductions of the past century were destroying the native biota (Isern, 2002).

State of the Environment. In the one hundred years following the beginning of intense European colonization, nearly two-thirds of the land area of New Zealand had been converted through human use (Salmon, 1975; Anon., 1997; Norton and Miller, 2000; Sanders and Norton, 2001, Allen et al., 2003). Native forests, once covering 85% of the land area, now cover 23% of the land and occur mostly in isolated fragments and remote areas that have proved difficult to develop or exploit (Anon., 2000; Sanders and Norton, 2001). Lowland forests were cleared for agriculture and timber. Grasslands and shrublands were burned and planted for grazing (Norton and Miller, 2000). Fifty-two percent of the land in New Zealand is currently used for some form of agriculture (Anon, 1997). Lowland areas, such as alluvial floodplain forests, fertile wetlands, and grasslands suffered the greatest destruction (Norton and Miller, 2000). Wetland areas have been reduced by 90% over the last 200 years. The plants and animals brought

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by the settlers of New Zealand have had an incredible impact on the natural landscape. Introduced weeds threaten native plants in almost every community (Sanders and Norton, 2001). Introduced species now outnumber native and naturalized species (Anon., 2000). Forty-five percent of wild vascular plants are introduced species and thirty-two percent of wild terrestrial and freshwater vertebrates are introduced. Of all plants in New Zealand, both wild and cultivated, 84.4% are introduced species (Figure 1) (Anon., 1997). There have been widespread extinctions and many remaining plants and animals are threatened due to habitat destruction, fragmentation, and browsing and predation
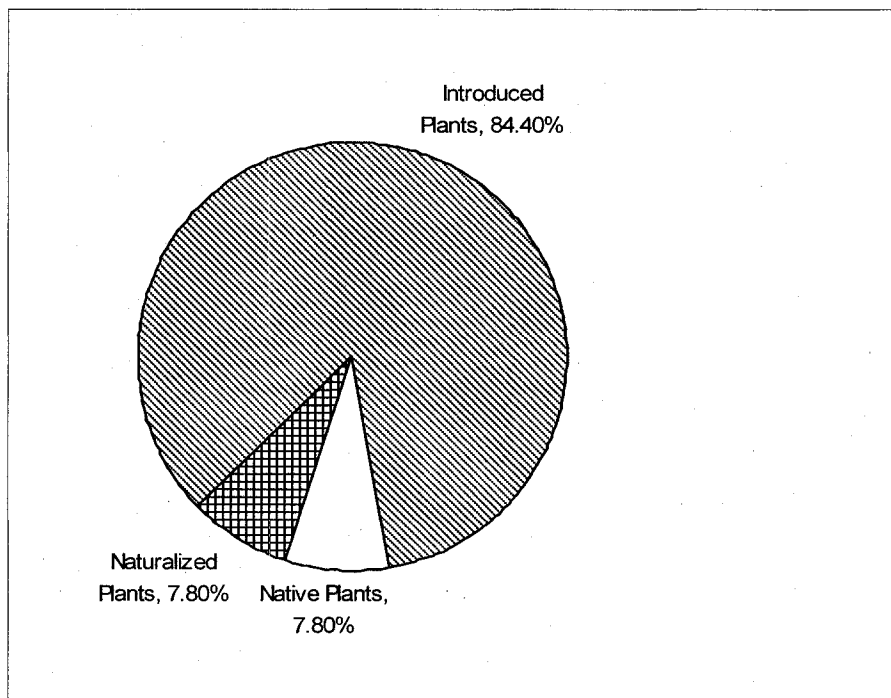
Figure 1: Relative abundance of introduced vascular plants compared to native and naturalized vascular plants (Anon., 2000).

by introduced pests (Norton and Miller, 2000; Sanders and Miller, 2001). Native flora and fauna have been affected by the shifting land use and species composition. Many indigenous species are unable to compete in these modified

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habitats, resulting in small, fragmented populations and widespread extinctions (Anon., 2000). A major problem within the remaining small native forest fragments, which support a limited amount of native biodiversity, is grazing by cattle. Grazing changes the structure of the understory vegetation, reducing the functionality of this important remnant ecosystem (Smale et al., 2005). McGlone (1989) suggests that human activity within the last 1000 years in New Zealand has caused more profound change than natural processes have in the last 3000 years. Without the influence of humans, New Zealand would likely be predominantly forested and would have retained more biodiversity.

Maori Environmental Values. The Maori, the original settlers of New Zealand, have a strong connection with the land. They believe humans share a common *whakapapa*, or ancestry, with plants and animals; therefore, conservation of native biodiversity is very important to them (Anon., 2000). The *tangata whenua*, or people of the land, like many indigenous peoples, have traditionally lived in harmony with their surrounding environment. They believe that the *mauri*, the aura or life force, and *wairua*, the spirit, of natural things must be respected or they will not flourish. Because trees and forests have *mauri*, products created from them must be worthy. Traditional Maori foresters do not believe in timber yards. If they are not the end users of the resource, they know what the final product will be before cutting the timber (Patterson, 1992). Historically, the Maori recognized the need for *kaitiaki*, or stewardship, but often only in areas that had already been depleted (McGlone, 1989; Sanders and Norton, 2001). The Maori use *rāhui*, a form of temporary protection over a

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resource, or *tapu*, the permanent protection of a resource, to protect their environment (Patterson, 1992).

Pre-colonial Europeans did not necessarily respect the beliefs and customs of the Maori and much of their land was taken in the name of the British Crown. The Treaty of Waitangi was signed in 1840 by the new British colonial government and many Maori leaders. This document recognized *rangatiratanga*, or chieftainship, and defined the relation of Maori leaders to the colonial Governor. The document also promised the right of land ownership to the Maori. Unfortunately, until the 1970s, the treaty was largely ignored. Since then, the New Zealand government has attempted to resolve Maori claims against the treaty and return Crown-owned land to the *iwi*, or tribes, to which it originally belonged (Downes, 2000; Menon et al., 2003). This has resulted in a rejuvenation of Maori language and culture (Downes, 2000). Politically, the settlement of Maori claims has been very important in the last 20 years (Menon et al., 2003).

Environmental Policy. Even toward the beginning of the colonial period in New Zealand, leaders realized, in some form, the value of the New Zealand landscape. Scenic reserves were created to protect some of the land (Sanders and Norton, 2001). The creation of Tongariro National Park through the Tongariro National Park Act of 1894 resulted in the fourth such area set aside in the world. Various conservation societies were formed in the urban centers throughout the country. By the turn of the century, these societies had pushed for the creation of additional reserves (Star and Lochhead, 2002). Initially, the

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motivation for these reserves was as much for scenic purposes as for conservation of the native flora and fauna. The economic value of the land was likely the most important factor in whether it would be removed from productivity (Norton and Miller, 2000). Other than some lands that were set aside by the various conservation societies, much of the land in New Zealand was available for development with little regard to planning. This haphazard method of land management continued for the better part of the last century.

In the 1970s, the New Zealand Forest Service focused on protecting timber production through the acquisition of additional land for the government. This resulted in a diversification of Crown land holdings. The Department of Conservation (DoC), formed in 1987 by the Conservation Act, acquired additional lands (Sanders and Norton, 2001).

The international "green movement" reached New Zealand in the 1970s and continued into the 1980s. Growing tired of the history of conservation from an economic point of view, the general inadequate recognition of the value of the environment, and the disregard for Maori environmental values, New Zealanders pushed for changes in government (Gleeson and Grundy, 1997). The Labour party gained control of the Parliament in 1984, pushing aside the National Party, focused on development. The new Labour government broke apart the 'mixed-mandate' agencies and created new, focused, state-owned enterprises that were to function as successful businesses. These included the Department of Conservation and the Ministry for the Environment. Labour began a period of policy review and law reform for all statutes dealing with natural resource

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management. Labour also restructured local government. In 1989, thirteen regional councils were created based on watershed boundaries. Within these regional councils, 74 territorial authorities were established (Gleeson and Grundy, 1997; Wheen, 2002). Regional councils are required to manage water, soil, and geothermal resources and are responsible for pollution control. The territorial authorities, which include district and city councils, control land use through management of subdivisions and noise pollution, and control the surface of water bodies (Gleeson and Grundy, 1997). In 1991, the Resource Management Act (RMA) was passed. It replaced the Town and Country Planning Act of 1977 and the older Soil and Water Conservation Act of 1967, as well as a number of other old and outdated statutes (Gleeson and Grundy, 1997; Norton and Miller, 2000; Wheen, 2002). In addition to the concerns listed above, the older laws were seen to prevent public access to information, yield excessive bureaucratic power, and ignore the rights of the *tangata whenua*, or people of the land. The Town and Country Planning Act, modeled on the British system of local government, regulated the spatial pattern of urban and rural land use. The Resource Management Act instead considers the effects of resource development and does not directly control land use (Gleeson and Grundy, 1997). The purpose of the RMA, as defined by Section 5 of the law is to "promote sustainable management of natural and physical resources." Section 5 of the Act also provides a definition of sustainable management:

> Sustainable management means the use, development, and protection of natural and physical resources in a way, or at a rate, which enables people and communities to provide for their social, economic, and cultural wellbeing and for their health and safety while-

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(a) Sustaining the potential of natural and physical resources (excluding minerals) to meet the reasonably foreseeable needs of future generations; and

(b) Safeguarding the life-supporting capacity of air, water, soil, and ecosystems; and

(c) Avoiding, remedying, or mitigating any adverse effects of activities on the environment (New Zealand Resource Management Act 1991, Sec. 5).

In considering the effects of resource use, the RMA controls externalities arising from development. Any development requires a resource consent application, and most resource consents require an Environmental Impact Statement (EIS) (Gleeson and Grundy, 1997). The RMA recognizes *kaitiakitanga* (the Maori stewardship of the land) and streamlines the government approach to resource claims of the *tangata whenua* (Downes, 2000). The RMA is more sensitive to traditional Maori values and provides for greater participation, predominately at the local level (Gleeson and Grundy, 1997; Downes, 2000). With this new legislation, the New Zealand government has shifted from the traditional spatial land use management model to one focused on ecosystem based resource conservation (Sanders and Norton, 2001).

With this shift in policy, the government has created a method to recognize the intrinsic and economic values of biodiversity. The native flora and fauna represent the unique characteristics of New Zealand (Taylor and Smith, 1997). The numbers of two national icons, the kiwi (a flightless bird) and the silver fern, are decreasing, mainly due to habitat loss and predation. In 1995, tourism was worth approximately NZD$5 billion, nearly a quarter of the overseas earnings of New Zealand (Taylor and Smith, 1997). New Zealand's clean and green image along with the distinct flora and fauna are a major draw for

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international tourists.   Protection and restoration of native ecosystems are important strategies to maintain this growing segment of the economy. The total value of New Zealand's indigenous biodiversity (including both direct economic benefits and intrinsic values) has been estimated to be twice the New Zealand Gross Domestic Product (Patterson and Cole, 1999).   *The New Zealand Biodiversity Strategy* was developed to address the factors contributing to the loss of native biodiversity and to help to protect this valuable resource (Anon., 2000).   This strategy has been implemented throughout the government and strong community support among stakeholders has been evident since its publication in 2000. Today DoC is responsible for the management of a majority of the 8 million hectares of conservation land in New Zealand, representing 30% of the land area of the country. (Taylor and Smith, 1997; Sanders and Norton, 2001). The environmental policies enacted by the New Zealand government reflect the desire to conserve native biodiversity. Because the loss of biodiversity is such a crisis in New Zealand, land managers have found novel ways of studying and protecting the environment there.

Land Management and Restoration. Island biogeography, the study of the geometry of available habitat versus the species distribution in that habitat, has long been studied by land managers.   The concept of island biogeography relates especially well to biodiversity conservation in New Zealand. New Zealand itself is an isolated island amid a vast expanse of ocean. It is also an archipelago of various sized islands having varying degrees of isolation. Within the North and South Islands of New Zealand, a sea of agricultural land surrounds isolated

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forest fragments, home to a majority of the diminishing native biodiversity (Diamond, 1984). Conservation of native biodiversity depends on the protection and management of these forest fragments (Smale et al., 2005). Successful conservation in New Zealand is the mutual interaction between what is ecologically possible, what is economically possible, and the goals of the community (Norton and Miller, 2000).

While the conservation of native fragments is certainly important, whole ecosystem studies have also gained importance in the quest to conserve New Zealand's native biodiversity. The effects of human activities on ecosystems are not yet fully understood (Allen et al., 2003). Studies of natural systems at a whole ecosystem scale, conducted over many years, should give insight into the processes that drive those systems (Hobbs and Norton, 1996; Norton and Miller, 2000; Mitsch and Day Jr., 2004). By not simplifying models to readily illuminate cause and effect relationships, ecosystem scale models can include more pathways and feedback loops. While this method may come at an increased monetary and temporal cost, and may decrease the repeatability of the experiment, complex ecosystem models yield results closer to reality than simplified models (Mitsch and Day Jr., 2004). Whole ecosystem studies have required a shift in thinking from the traditional study of species to species interactions to modeling whole ecological processes, and a shift in scale from specific locational studies to catchment scale and landscape scale studies in order to understand the interactions between and within ecosystems (Sanders and Norton, 2001).

Offshore islands have traditionally been used in New Zealand to protect endangered species from the dangers of predation and development that are found on the main islands. The first recorded use of an offshore island to protect an endangered species occurred in the 1890s. This was considered a key action at the time to protect some of the already dwindling bird populations. The restoration and use of offshore islands as biodiversity reserves for protection became increasingly important through the end of the last century; however, New Zealand's offshore islands cannot continue to be used as a surrogate for mainland habitat in order to protect the country's remaining biota (Sanders and Norton, 2001).

Recently, 'mainland islands,' areas of native vegetation surrounded by other types of landscape (e.g. pastoral, urban) or areas under intensive management within contiguous native vegetation, have been very important tools in the protection of native biodiversity. DoC began using the mainland island concept extensively in 1996-7 when six management areas totaling 10,000 hectares of indigenous forest and grassland were created. While these mainland islands were managed for specific species, positive and negative changes in other species were noticed, including changes in structure and composition. Mainland islands were initially managed for specific species but now tend to have broad, ecosystem-focused goals. Public support for mainland island protection and restoration has been strong, which may be a result of the presence of mainland islands within the community. This accessibility allows sponsors and stakeholders to observe the benefits of protection and restoration (Sanders and

Norton, 2001). Onsite management goals at mainland islands include weed and pest control, management of existing biodiversity, and restoration plantings (Norton and Miller, 2000). The extent of devastation and the broad spectrum of introduced species within New Zealand make it difficult to totally restore an ecosystem to its native structure and function (Hobbs and Norton, 1996; Norton and Miller, 2000).

Protection of native forest fragments within the agricultural landscape is an important first step to protecting native biodiversity. Pest control is critical (Sanders and Norton, 2001). The vegetation must be protected from browsing herbivores and the native birds must be protected from predators. It has been shown that pest populations must be reduced to very low densities for native population densities to increase. Trapping and poisoning are common tools for reducing herbivory and predation. Fencing, perimeter traps, bait station grids, and aerial poison applications are all weapons in the war on invasives (Sanders and Norton, 2001). Once these protective measures are in place, restoration of partially- or non-functioning ecosystems can begin.

Restoration of protected forest fragments can range from minimal management of undisturbed sites to extensive efforts at sites where natural processes are essentially non-functioning (Hobbs and Norton, 1996). Biodiversity rehabilitation through planting of native vegetation in turn provides critical habitat for native birds. Restoration of native vegetation in New Zealand is a very slow process. Reay and Norton (1999) found that it can take 30 to 35 years before the structure and function of the restored system is comparable to a

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natural system. Without protection and restoration plantings, the success of initial colonizing species is inhibited by browsing and the presence of exotic vegetation (Reay and Norton, 1999). Hobbs and Norton (1996) identify seven steps that should be followed to sustainably restore native ecosystems:

1. Identify the processes leading to degradation or decline.
2. Develop a method to reverse or restore degradation or decline.
3. Determine realistic goals for reestablishing species and functions.
4. Develop easily observable measures of success.
5. Develop practical techniques for implementing these goals.
6. Document and communicate techniques.
7. Monitor key system variables (Hobbs and Norton, 1996).

Monitoring ecosystem restoration is a high priority of the government agencies and private land owners who perform the restoration work because of both the importance of the work and the costs involved with the work. A major problem facing these land managers is that there is currently no standardized system to measure and analyze changes in biodiversity (Allen et al., 2003). Hobbs and Norton (1996) suggest that ecosystem health should be estimated by assessing measures of structure, function, and species composition. Collecting these measurement data are made difficult by the small spatial and large temporal scales of whole ecosystem restoration efforts (Sanders and Norton, 2001; Allen et al., 2003). Allen et al. (2003) suggest that the combination of remote sensing and point-based sampling on the ground would solve this difficulty and could be useful for long term biodiversity monitoring. Spatial modeling could then be used to optimize the species composition and stand age distribution of restored forest areas to maximize both the production value of, and biodiversity conservation at, those sites (Norton and Miller, 2000). This may be useful to persuade

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landowners to restore native fragments on their land by providing the opportunity for economic and ecological benefits. Because of the large volume of data needed to monitor biodiversity in New Zealand, the government and land managers enlist the help of volunteers to collect these data. High quality student collected data could be useful to supplement data collected by scientists, land managers, and volunteers.

GLOBE

The GLOBE Program is an international student-teacher-scientist partnership that was founded in 1993, originally coordinated by the Office of the Vice President of the United States, and currently administered by the University Corporation for Atmospheric Research (UCAR). The founders of GLOBE hoped that the program would increase environmental awareness and provide learning opportunities for students that would help them attain higher standards in science and mathematics (Becker et al., 1998). GLOBE schools receive a 15km x 15km subset of a Landsat image, typically centered on their school. In their GLOBE Study Site, students collect data following GLOBE Atmosphere, Soils, Hydrology, Land Cover, and Earth as a System protocols. Data collected by the students are entered into the GLOBE database via the GLOBE website (http://www.globe.gov) and are available to students, teachers, and scientists throughout the world. Currently, there are approximately 31,000 GLOBE-trained teachers from 17,000 GLOBE schools in 109 countries. To this date, over 14 million measurements have been reported.

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The GLOBE Land Cover/Biology team at the University of New Hampshire developed standardized collection protocols that guide students through the process of collecting land cover data. The team also developed pre-protocol learning activities that build the foundation for implementation of the protocols by illustrating the skills and concepts necessary to collect land cover data (Becker et al., 1998). Students use the Modified UNESCO Classification (MUC) system to collect land cover data. The MUC system is suitable in ecosystems throughout the world (Becker et al., 1998; Rowe, 2001). The other GLOBE protocols allow students and teachers to collect data and explore concepts in the four other realms of GLOBE: Atmosphere, Hydrology, Soils, and Earth as a System (The GLOBE Program, 2003). Researchers have illustrated that student collected data are accurate and reliable (Rock and Lauten, 1996; Budd, 1997; Becker et al., 1998; Rowe, 2001; West, 2003).

The GLOBE Program was introduced in New Zealand in 2000 and the first schools were trained in 2001. Presently, there are over 100 schools involved in the GLOBE Program in New Zealand (Lockley, 2002). The GLOBE Program is an important part of the New Zealand Department of Education's goal of integrating biodiversity into the curriculum (Anon., 2000; Lockley, 2002). Nearly 200 students participated in this project in New Zealand, a collaboration between the GLOBE Land Cover team and GLOBE New Zealand. Approximately 60 students were involved in a two-day workshop at the Bushy Park Homestead and Forest Park and their data were used in this project.

Remote Sensing

Lillesand et al. (2004) define remote sensing as "the science and art of obtaining information about an object, area, or phenomenon through the analysis of data that is acquired by a device that is not in contact with the object, area, or phenomenon under investigation." The first remotely sensed data were collected from a balloon outfitted with a camera over Paris in 1858. In 1908, the first aerial photograph was taken from an airplane (Lillesand et al, 2004). Stereoscopic aerial photographs were first used in the 1920s (Botkin et al., 1984). The use of aerial photography heightened during World War II. Following the war, remotely sensed data were collected from V-2 rockets. The CORONA program, a classified military program, collected remotely sensed data from space in the 1960s and 1970s. Photos were taken from manned space missions in the 1960s. In 1973, the Earth Resources Experiment Package (EREP) collected analog and electronic images from the Skylab space station (Lillesand et al., 2004).

Digital space-based remote sensing history was made with the launch of the ERTS-A (Earth Resources Technology Satellites) system in 1972. ERTS was "the first unmanned satellite specifically designed to acquire data about earth resources on a systematic, repetitive, medium resolution, multispectral basis" (Lillesand et al., 2004). The ERTS program was later renamed as the Landsat program. The first widely used imaging instrument, the Multi Spectral Scanner (MSS), collected four channels of data at an 80-meter pixel resolution. With the switch to the Thematic Mapper (TM) instrument on Landsat 4, seven

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bands of data, including a thermal band, were collected at 30 meter resolution for the visible and short wave infrared and 120 meters for the thermal data (Lillesand et al., 2004; Jensen, 2005) (Table 1). The TM bands were specifically designed to capture certain wavelengths that increased the ability to classify natural features (Tucker, 1978) (Table 2). The Enhanced Thematic Mapper Plus on Landsat 7 added a panchromatic band and increased the thermal resolution to 60 meters (Lillesand et al., 2004; Jensen, 2005). Advanced calibration techniques on Landsat ETM+ result in fewer instrument related errors in the data (Vogelman et al., 2001; Lillesand et al., 2004).

Table 1: Characteristics of Landsat sensors (Lillesand et al., 2004).

Sensor	Band	Resolution			
		Spectral (µm)	Spatial (meters)	Radiometric	Temporal
MSS	4	0.5 - 0.6	79 x 79	6-bit	Landsat 1-3: 18 days Landsat 4-5: 16 days
	5	0.6 - 0.7			
	6	0.7 - 0.8			
	7	0.8 - 1.1			
TM	1	0.45 - 0.52	30 x 30	8-bit	16 days
	2	0.52 - 0.60			
	3	0.63 - 0.69			
	4	0.76 - 0.90			
	5	1.55 - 1.75			
	6	10.40 - 12.5	120 x 120		
	7	2.08 - 2.35	30 x 30		
ETM+	1	0.450 - 0.515	30 x 30	8-bit	16 days
	2	0.525 - 0.605			
	3	0.630 - 0.690			
	4	0.750 - 0.900			
	5	1.55 - 1.75			
	6	10.40 - 12.50	60 x 60		
	7	2.08 - 2.35	30 x 30		
	PAN	0.52 - 0.90	15 x 15		

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Table 2: Usefulness of Landsat TM/ETM+ bands (Tucker, 1978).

TM/ETM+	Usefulness
1	chlorophyll and carotinoid concentration
2	chlorophyll and green region characteristics
3	chlorophyll
4	vegetation density and biomass
5	water in plant leaves
6	thermal
7	water in plant leaves

Monitoring land cover and land use over large areas has traditionally been expensive and time consuming using field observation techniques (Tucker, 1978). Resource managers worldwide lack adequate maps to solve resource related problems (Estes and Mooneyhan, 1994). Since the launch of the Landsat program in the 1970s, satellite imagery, having sufficient locational precision, spatial resolution, and a large footprint, has been a cost effective method used to create thematic maps that are utilized to solve natural resource problems throughout the world (Tucker, 1978; Lachowski et al., 1992; Schriever and Congalton, 1995). Some examples of the many uses of satellite imagery include: performing land cover classification, monitoring deforestation, determining wildlife habitat availability, monitoring habitat fragmentation, measuring urbanization, monitoring wetland degradation, characterizing land use, determining resource treatments, monitoring water quality, monitoring forest health, hydrological modeling, risk analysis, and monitoring many other landscape-level phenomena (Adeniyi, 1985; Stehman and Czaplewski, 1998; Vogelman et al., 2001; Fischer and Levien, 2002; Plourde and Congalton, 2003). Data layers generated from remotely sensed data are used as inputs for modeling and decision making (Stehman and Czaplewski, 1998; Plourde and Congalton, 2003).

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The Landsat program has been especially important to land cover mapping in the United States. The spatial and spectral resolutions of the sensor make it particularly useful for vegetation mapping (Tucker, 1978). In 1974, a major remote sensing project, the Large Area Crop Inventory Experiment (LACIE) program, used satellite data to estimate worldwide wheat production. At the same time, remote sensing techniques were being applied to forest inventory and monitoring (Botkin et al., 1984; Fischer and Levien, 2002). More recently, Landsat Thematic Mapper (TM) data, combined with data in a Geographic Information System (GIS), were used to map agricultural crops and other land cover with very high accuracy in the southwestern United States (Congalton et al., 1998). Thematic maps created from digital remotely sensed data can be useful additions to GIS databases, providing that the layers are in the same cartographic projection (Lunetta et al., 1991). Roy and Tomar (2000) describe a methodology to characterize biodiversity using Indian Remote Sensing (IRS) data and ground based biodiversity attribute measurements. Data from high-resolution satellite sensors, such as IKONOS, are now available from commercial providers (Dial et al., 2003). Though this technology allows individual objects to be mapped, the increased resolution also increases within-class spectral variation, or increased scene noise, leading to lower classification accuracies when using traditional per-pixel classification methods (Stenback and Congalton, 1990; Thomas et al., 2003; Lennartz and Congalton, 2004).

Terrain Normalization

Digital remote sensing is dependent on accurately recording the energy reflected and emitted from land cover, thus requiring that radiometric and geometric correction be performed prior to classification (Teillet, 1986). Atmospheric effects and topography have a significant impact on the interaction of light and vegetation, creating difficulty in measuring actual vegetation reflectance (Teillet et al., 1982; Teillet, 1986; Lunetta et al., 1991; Dymond and Qi, 1997; Dymond and Shepherd, 1999; Shepherd and Dymond, 2003). If the changes in reflectance values due to topography are understood, and the extraneous effects are removed, discrimination between land cover classes will be improved (Teillet et al., 1982; Teillet, 1986; Lunetta et al., 1991). In order to correct for the effects of topography, Teillet (1986) suggests that analysts need radiometric calibration data, an atmospheric model, and a target reflectance model. Teillet (1986) warns that all data correction techniques must be performed at the same time to limit perturbation of the original data. The effects of atmospheric conditions, slope, and aspect on incident solar radiation are understood but the effect of slope and aspect on reflectance deserves more study (Dymond and Shepherd, 1999). Development of general correction techniques may be hindered by the land cover class dependent relationship between reflectance and topography (Teillet, 1986). Generally, it is understood that topography causes increased brightness values on slopes facing the illumination source and decreased brightness values on slopes facing away from the illumination source. The exact nature of this relationship is dependent on

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seasonal and temporal variations in illumination in relation to the image acquisition (Gitas and Devereux, 2006). Though Landsat and many other earth-observing satellites are launched into sun-synchronous orbits, where image acquisition occurs at the same time of day on each pass, the orbit does not account for the seasonal variation in sun elevation, which results in differing solar altitude, azimuth, and intensity (Lillesand et al., 2004).

Gu and Gillespie (1998) suggest that the ambiguity created by topographic effects reduces classification accuracy, therefore limiting the ability to notice seasonal variation and decreases in vegetation health. This inhibits land managers' ability to monitor subtle changes in New Zealand's indigenous forests in response to pressures such as browsing by pests (Dymond and Qi, 1997). Many attempts have been made to remove the effects of topography from satellite imagery. It has been difficult to separate topographic effects from the geometric distribution of vegetation (Shepherd and Dymond, 2003). Due to the geotropic nature of vegetation, the relationship between sun angle and crown is independent of the terrain (Gu and Gillespie, 1998; Dymond and Shepherd, 1999; Teillet et al., 1986).

Models that account for vegetation reflectance and terrain effects need to be accurate, simple, and computationally efficient (Gu and Gillespie, 1998; Dymond and Shepherd, 1999). This creates a problem, as highly accurate models based on three-dimensional vegetation canopy modeling and ray tracing require lengthy computations (Dymond and Shepherd, 1999). The often-used Lambertian reflectance model, also known as the cosine model, has proven to be

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too simple in that it only removes the effects of illumination. In addition, vegetative canopies are rarely Lambertian surfaces (Dymond and Shepherd, 1999; Shepherd and Dymond, 2003). The Lambertian model may be effective for scenes with slope angles less than 25° and illumination angles less than 45° (Teillet et al., 1982). Topography can increase the range of illumination to between 0° and 90°. When the illumination angle approaches 90°, the correction factor becomes too strong, resulting in high brightness values. Conversely, when the illumination angle approaches 0°, the correction factor approaches zero or becomes negative, resulting in lower brightness values (Teillet et al., 1982).

Like the Lambertian model, the Minnaert and c-correction models also assume equal reflectance. Additionally, these models account for foreshortening in the direction of the observer (Teillet, 1986). These models tend to oversimplify the photometric model, resulting in inaccurate terrain correction (Gu and Gillespie, 1998). More effective empirical models have been developed that account for illumination and reflection (Teillet et al., 1982). Model parameters must be fit for each situation (Shepherd and Dymond, 2003). Because physical parameters are not used in the model, users must take caution when applying the model in dissimilar situations (Dymond and Qi, 1997; Dymond et al, 2001).

Gu and Gillespie (1998) suggest that bidirectional reflection distribution functions (BRDFs) will remove terrain effects better than simple models. These models account for reflectance as a function of incident and reflected radiation (Teillet, 1986; Lillesand et al., 2004). Complete models are not available and *in situ* models may not be suitable because of the scale dependent nature of

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natural surfaces. BRDFs should be characterized by parameters such as sun zenith angle, sensor zenith angle, their relative zenith angle, terrain slope and aspect angles, tree density, tree height, and crown shape. A model built using these parameters was tested on both a simulated tree canopy and on Landsat TM data (Gu and Gillespie, 1998).

One way that tree canopies can be modeled is as suspended sediments (Dymond and Qi, 1997). Dymond et al. (2001) propose a three-parameter vegetation reflectance model called WAK that outperforms many models that are more complex. Shepherd and Dymond (2003) combine this reflectance model with the Second Simulation of Satellite Signal in the Solar Spectrum (6S) irradiance model for a more complete correction of the topographic effect, which was applied to SPOT data. The SPOT image was processed with an unsupervised classification algorithm that resulted in twelve clusters. The corrected image resulted in lower variation between clusters representing similar vegetation classes. Dymond and Shepherd (2004) applied this correction to 15-meter pan sharpened Landsat ETM+ data of the Wellington Region in New Zealand, collected in 1999 and 2000. These data were used to produce a nine-class land cover map using hierarchical binary split rules. The rules used for mapping were developed iteratively. Manual editing was used to remove errors. Since the binary split rules proved ineffective for delineating planted exotic forests, they were mapped by seeding each forest stand and growing the area to the edge of the forest. The average map accuracy, calculated from 100 randomly generated orthophoto observations, was 95% and was attributed to the

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terrain normalization technique. This level of accuracy may not actually be a result of the flattening algorithm, and further, is highly inflated due to manual editing and poor selection of reference data for accuracy assessment.

Mitri and Gitas (2004) performed a topographic correction of a Landsat TM scene covering the Greek island of Thasos. This image was classified using an image segmentation technique with three land cover classes: burned, not burned, and water. A non-topographically corrected version of this scene was classified using the same methodology. A relative accuracy assessment was performed based on a fire perimeter delineated by the Greek National Fire Service. The relative accuracy of the flattened map was 98.85% and the relative accuracy of the unflattened map was 97.69%. The authors considered this a marginal improvement, but did not include Kappa statistics or a comparison of the accuracy assessment results.

Image Classification

Classification Scheme. Thematic maps are created from satellite imagery using digital classification techniques. These maps are used for specific purposes and use a classification system that categorizes the continuous landscape into a finite set of classes (Gopal and Woodcock, 1994; Steele et al., 1998). Classification systems may have difficulty representing mixed classes, class boundaries, and dynamic systems (Lunetta et al., 1991). A number of characteristics define a good classification system. A classification system should have labels and rules, and should be mutually exclusive and totally exhaustive. Classification systems of a hierarchical nature are often

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advantageous (Congalton et al,. 1998; Congalton and Green, 1999). A hierarchical classification system however, may result in increased classification error (Hord and Brooner, 1976). Sader (1995) suggests that more general classification categories, or the top-level categories in a hierarchical system, may help reduce classification error. Poor definitions will result in inaccurate results (Lunetta et al., 1991).

Reference Data. The digital classification process can be divided into three phases. In the training phase, seed statistics used to generate informational categories are created. Then, pixels not sampled in the training phase are assigned to the informational classes. Finally, the results are assessed for accuracy. The training phase is especially important (Chuvieco and Congalton, 1988). Significant error can result from the selection of misrepresentative training areas, resulting in biased results. Two subsets of reference data must be collected. One is used to relate the variation found within the image to the variation within the landscape in order to complete the training phase. The other is used to compare the thematic map resulting from classification to observed values on the ground in the third phase. Although the data can be collected simultaneously, data used in the training phase should not be used for assessing the accuracy of the map as well.

There are many considerations when choosing a sampling scheme for the collection of reference data. Without proper, statistically-based sampling, accuracy assessment of the thematic map will be invalid (van Genderen, 1977; Congalton, 1988a; Janssen and van der Wel, 1994; Stehman, 1996a; Stehman

and Czaplewski, 1998). Within the natural resources community, there are five commonly used sampling schemes: simple random sampling, stratified random, sampling cluster sampling, systematic sampling, and stratified systematic unaligned sampling (Congalton and Green, 1999). Congalton (1988a) evaluated the sampling schemes in areas of varying spatial complexity, finding that simple random and stratified random sampling performed best. Many researchers suggest that simple random sampling or stratified random sampling are the most appropriate methods (Lunetta et al., 1991; Pugh and Congalton, 2001). Simple random sampling is a statistically sound method which is performed by randomly generating x- and y-coordinates. This technique may result in undersampling of rarely occurring map classes. Stratified random sampling uses prior knowledge of the study area to divide samples into classes. An equal number of points are then randomly distributed within each class (Congalton, 1988a; Congalton and Green, 1999). This methods prevents oversampling common classes and undersampling rarely occurring classes, and is therefore highly recommended (van Genderen, 1977; Ginevan, 1979; Card, 1982; Congalton, 1988a; Janssen and van der Wel, 1994; Stehman and Czaplewski, 1998; Congalton and Green, 1999). The minimum mapping unit must be defined and be the same for the map and the reference data used to assess the accuracy of the map.

Using an appropriate sampling method, a minimum of 50 sample points per class should be collected for accuracy assessment, with additional points to be used for training purposes (Hay, 1979; Stehman, 1996a; Congalton and Green, 1999). The collection of reference data may occur in a number of ways.

Photo- and video-interpretation are commonly used techniques when ground visits are too costly or not possible. Other researchers have made use of local experts, taken notes while flying over the study area, or have done drive-by samples. The most accurate method is to actually visit the reference points on the ground and make notes and measurements, if necessary, to ascertain the land cover according to the classification scheme. Measurements are especially useful for detailed classification schemes that are concerned with canopy cover, dominant species, DBH classes, etc. (Congalton et al., 1983; Congalton and Biging, 1992; Congalton and Green, 1993; Stehman and Czaplewski, 1998). Samples are often located in homogeneous areas to avoid boundary issues and to minimize problems with locational uncertainty. This may artificially inflate the measured accuracy of the thematic map (Todd et al., 1980; Stehman and Czaplewski, 1998; Plourde and Congalton, 2003).

The Global Positioning System (GPS) is often used to locate the reference points for ground-based sampling. Locational uncertainty is a source of confusion in accuracy assessment. While modern GPS technology can minimize locational uncertainty, it cannot be eliminated. Autonomous positioning, using one GPS receiver, has a larger associated locational uncertainty than differential positioning. Differential positioning uses two GPS receivers, one in the field and one fixed at a known location. The differences in the measured position and the actual position at the fixed station are used to correct the measurements taken in the field. There are many sources of error that can reduce the accuracy of using GPS to record reference data locations. These include obstruction of the

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horizon, interference from the forest canopy, interference caused by the atmosphere and ionosphere, poor satellite geometry, errors with the satellite or receiver clocks, or multi-pathing – where the received signal has bounced off another surface (August et al., 1994; Deckert and Bolstad, 1996).

Classification. Having developed an appropriate classification scheme and planned for the collection of reference data, the classification process can begin. Image pre-processing steps such as geo-referencing and the correction of atmospheric and illumination effects are often performed by the supplier of the imagery. These steps require the images to be resampled. Common resampling techniques include nearest neighbor, where the nearest pixel value is used for the new value; bilinear interpolation, which uses the average value of the nearest four pixels for the new value; and cubic convolution, which uses sixteen neighboring pixel values to compute the new pixel value (Janssen and van der Wel, 1994; Cracknell, 1998; Lillesand et al., 2004). Nearest neighbor resampling does not change the data values but may distort linear features. Bilinear interpolation and cubic convolution change the original data values. Lunetta et al. (1991) caution that further study is needed to understand the effects of resampling on the radiometric integrity of the data.

Following the preprocessing step, the remotely sensed data should be extensively explored to better understand the relationship of the variation on the imagery to the variation on the ground. This requires some knowledge of the study area and it is ideal to have collected reference data at this point. Band ratios and other transformations, such as those resulting from Principal

Components Analysis and the Tasseled-Cap transformation, are often used to view the data from another perspective. While these techniques may be useful in better understanding the variability in the data, they do not always result in a better classification. In addition, these techniques may enhance or mask phenomena present in the data that may or may not be of interest to the analyst. Some of the techniques used to explore the data include visual analysis, filtering, histogram analysis, spectral pattern analysis, and bi-spectral plots. These techniques are useful in refining the selection of training areas. Transformed divergence then allows for the selection of the optimum bands to perform a classification (Jensen, 2005). Histogram analysis should always be used following transformations on integer images to ensure that there are no resulting histogram discontinuities. Histogram discontinuities may lead to error in interpretation (Salvador and San-Miguel-Ayanz, 2003).

There are two general classification techniques, each with advantages and disadvantages, that are used to partition remotely sensed data into discrete classes. The unsupervised classification process partitions the image into spectrally similar groups. These groups are then labeled by the analyst according to the classification scheme. In the supervised classification process, training statistics are generated from areas of the image that are numerically representative of the informational categories defined in the classification scheme. These training areas are then used to label the remaining pixels in the image. Spectral clusters generated by unsupervised classification may not match a given informational class. Multiple spectral classes may represent the

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informational classes used in the supervised approach or there may be spectral confusion between two or more informational classes (Duda and Canty, 2002; Lillesand et al., 2004; Jensen, 2005).

A number of techniques have been proposed to overcome the shortcoming of the supervised and unsupervised classification techniques. Hybrid classification, a combination of these techniques, has been used to improve the accuracy of image classification. Chuvieco and Congalton (1988) propose a technique that uses cluster analysis to combine the training statistics from both the unsupervised and supervised techniques to define clusters that are both spectrally and informationally similar. Discriminant analysis is then used to test the groupings. Jensen's (2005) cluster busting technique uses iterations of unsupervised classification to assign informational classes to the image.

One major problem inherent in the classification process is the presence of mixed pixels. A mixed pixel is one in which two or more classes are present. These reduce the probability of correct classification using traditional classification techniques (Botkin et al., 1984; Lunetta et al., 1991; Cracknell, 1998). Another concern found throughout all stages of the classification process is the effect of spatial autocorrelation, or the effect that a characteristic or quality at a location has on the same quality or characteristic at neighboring locations (Congalton, 1988b; Pugh and Congalton, 2001). Natural features tend to have high spatial autocorrelation at low lags. Error within the classification may be a result of the combination of spatial autocorrelation and the sampling scheme

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(Campbell, 1981). Analysts should be cautious of the effects of spatial autocorrelation.

Accuracy Assessment. Historically, little thought was given to assessing the accuracy of maps created from remotely sensed data. When performed, accuracy assessment was an afterthought, and often a cursory look at the final product (Congalton and Green, 1993). Within the last 20 years, the need for accuracy assessment to improve the classification, for quality control, and to report the reliability of the map has been well accepted (Aronoff, 1982; Congalton et al., 1983; Stehman, 1996b). Map error can be the result of classification error, boundary error, or locational error (Hord and Brooner, 1976). The change in scale from reality to the map representing reality is also a potential source of error (Story and Congalton, 1986; Gopal and Woodcock, 1994). The error matrix, a square array of cells with the columns representing reference data and the rows representing the classified data, is now a commonly used tool for expressing map accuracy. The error matrix allows for easy viewing of errors of omission (i.e. when an area is excluded from the class to which it belongs) and errors of commission (i.e. when an area is included in a class to which it does not belong). The sum of the major diagonal divided by the total number of reference points represents the overall map accuracy. Producer's and User's accuracies are computed for each map category (Story and Congalton, 1986). While this information is useful, the error matrix is really a starting point for more advanced discrete multivariate techniques. Kappa analysis is the recommended measure of accuracy (Congalton et al., 1983).

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Kappa analysis is a discrete multivariate technique that results in the KHAT statistic. KHAT is a measure of accuracy that is based on the difference between actual agreement and chance agreement. Kappa analysis is also used to determine if error matrices are statistically different from one another. KHAT values are compared using a two-tailed Z test (Congalton and Green, 1999). Although the often-used stratified random sampling technique does not meet the assumption for the multinomial model, tests have shown that it does not significantly distort the results of Kappa analysis (Stehman, 1996a; Plourde and Congalton, 2003).

Error matrices may also be normalized or marginalized for direct comparison (Congalton et al., 1983; Janssen and van der Wel, 1994). Normalization is an iterative process where the rows and columns are summed to a common value. This eliminates the effect of sample size and includes the effects of errors of omission and commission (Congalton et al., 1983).

CHAPTER II

METHODS

Study Area

Five areas were chosen as potential study sites for the GLOBE
Biodiversity Monitoring project in New Zealand: the Maungatautari Ecological
Island, the Karori Wildlife Sanctuary, the Bushy Park Homestead and Forest, the
Lake Rotoiti Nature Recovery Area, and Tapu Road on the Coromandel
Peninsula (Figure 2).
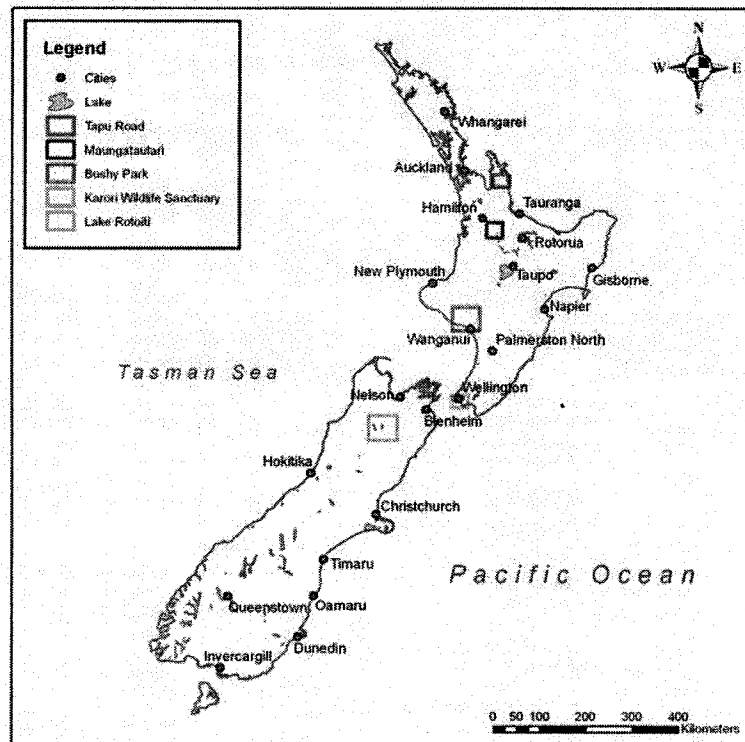
Figure 2: Initial study areas chosen for the GLOBE Biodiversity Monitoring project.

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Maungatautari is a volcanic dome that rises alongside the Waikato River, surrounded by farmland of the central plain of the North Island of New Zealand. A 3400-hectare native forest covers the mountaintop. Construction of a 47 km pest-proof fence that will eventually surround the forested peak has begun. Once the fence is completed, all warm-blooded animal pests will be removed, creating a safe haven for some of New Zealand's most endangered endemic fauna (Maungatautari Ecological Island Trust http://www.maungatrust.org).

The Karori Wildlife Sanctuary is a well-established 252-hectare native forest 2 km from Wellington, the capital of New Zealand. An 8.6 km pest-proof fence surrounds the sanctuary. There have been no breaches of the perimeter fence for over 12 years. Restoration efforts are in progress. Approximately half of the sanctuary will be restored with native vegetation through plantings. The remainder will be allowed to revegetate naturally so that comparisons between the techniques can be made. (Karori Wildlife Sanctuary http://www.sanctuary.org.nz).

Bushy Park is a small, 88-hectare native forest near Wanganui on North Island. Construction of a predator- and pest-proof fence is planned. The forest is part of a homestead donation. The wetland forest is a major attraction for guests staying at the homestead (Bushy Park Homestead http://www.bushypark-homestead.co.nz).

The Lake Rotoiti Nature Recovery area is located in the Nelson Lakes region of the northern South Island. Restoration efforts focusing on 825 hectares of native southern beech (*Nothofagus* sp) forest on the shore of Lake Rotoiti

began in 1997. This area is managed as a mainland island and extensive work has been conducted to eradicate non-native insect species (New Zealand Department of Conservation http://www.doc.govt.nz).

The Tapu Road site on the Coromandel Peninsula is an area of relatively continuous second-growth native vegetation that is not undergoing any active management. This area was to be used as a control in looking at changes over time.

Maungatautari, the Karori Wildlife Sanctuary, Bushy Park, and the Lake Rotoiti Nature Recovery area were used as sites for the GLOBE Land Cover workshops. There were not enough participants to conduct the workshop for the Tapu Road site. In addition, the Bushy Park study site was expanded to be used to evaluate the effectiveness of the terrain flattening algorithm (Figure 3). The data from Maungatautari, Karori, and Lake Rotoiti were not used for this thesis in order to devote additional time and resources to the study of the terrain flattening algorithm.

Bushy Park was chosen as the final study area to evaluate the terrain flattening algorithm for a number of reasons. While this area does not have the largest native forest reserve, other factors, such as the greatly-varied terrain (Figure 4), accessibility, and the variation of land cover, made it the ideal choice. The study area is a 60 km by 50 km rectangular area on the south-west coast of the North Island of New Zealand, lying in the southeastern portion of the South Taranaki District and the western portion of the Wanganui District. The elevation ranges from sea level to 740-meters above mean sea level. The slope of the

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land ranges from 0 degrees to 72.6 degrees. The average slope is 19 degrees. The Wanganui River is a prominent feature of the eastern portion of the landscape, running south through the study area to the Tasman Sea. The Waitotara River flows south through a fertile valley in the western portion of the study area. The largest settlement is Wanganui (population approximately 43,000 in 2001) in the southeastern corner of the study area. The next largest population center is the town of Waverly, in the western zone of the study area. The population of Waverly in 2001 was 903. There are a number of smaller settlements throughout the area with a total population of 4500 in 2001 (Anon., 2001). Precipitation in this part of New Zealand ranges from 800 to 1600 mm per year. The mean temperature range is from 10°C to 18°C (Coulter, 1975).

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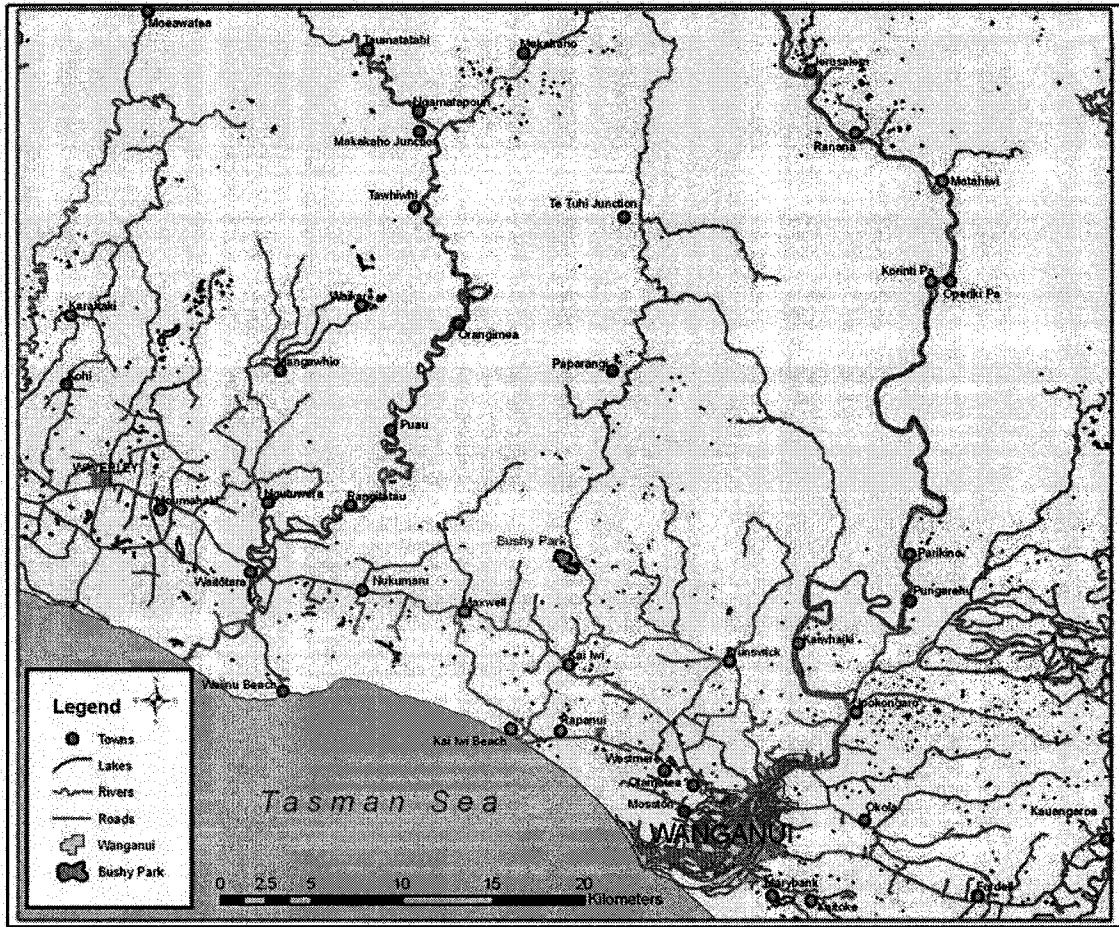
Figure 3: Bushy Park study area (Source: Author).

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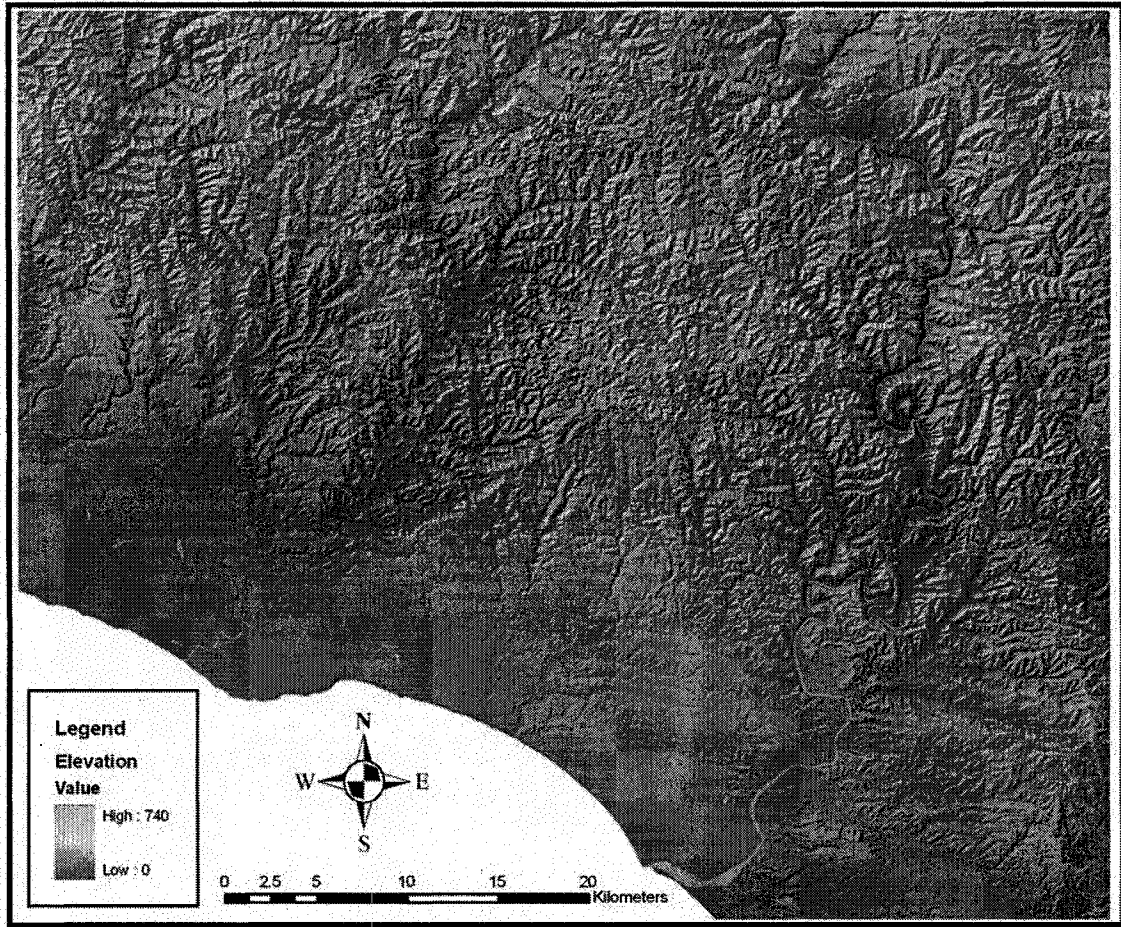
Figure 4: Elevation variation in the Bushy Park study area

Classification System

Since this project had links with the GLOBE Program, the first step in developing a classification scheme was to list all of the possible land cover types that the students may encounter in the study area. Field visits and conversations with local experts were used to determine the MUC codes corresponding to the land cover sites. Since there were many similar land cover types in the initial classification scheme, they were collapsed to seven broad categories: Native Forest, Exotic Forest/Plantation, Shrubland, Agriculture and Grassland, Urban or Developed, Water, and Other. For definitions and percent cover rules, see

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Appendix A. Similar to the GLOBE Program Land Cover Sample Site, the minimum mapping unit for this project was 90 meters by 90 meters (0.81 ha).

Reference Data Collection

A stratified random sampling technique was used to collect reference data within the study area. Due to the large areas without road access, rugged terrain, and thick vegetation, sampling was restricted to within 1 kilometer of roads. The Land Cover Data Base version 2 (LCDB2), an existing land cover classification system, was recoded to reflect the seven classes used in this study. Seven hundred points, one hundred per class, were randomly distributed within the 1-kilometer buffer zone around the roads according to LCDB2 using an ArcView extension from Land Care Research, New Zealand. These points were uploaded into a Garmin 12XL GPS receiver.

In September and October 2004, the land cover values for the reference data points were collected. The points and roads were plotted on a large map to plan collection routes. In most cases, visual confirmation could be made from the road using triangulation. If not, access to the land was sought and the points were visited. Points were accepted if they occurred within a 90 by 90 meter section of homogeneous land cover. A number of points were inaccessible due to washouts following floods in February 2004. Limited 1:50,000 scale orthophoto coverage exists for the southern and western portions of the study area. If aerial photos were available for the unvisited points, the land cover class was determined from photo interpretation. If there was no orthophoto coverage

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or if it was not possible to determine the land cover from the photos, then the reference points were removed.

In October 2004, a GLOBE Biodiversity monitoring workshop was held at Bushy Park. More than 60 students, teachers, and parents collected land cover data following the GLOBE Land Cover and Biometry Protocols. These student-collected data were added to the reference database with no reservations about the quality of the data. A small portion of this reference dataset was randomly extracted and put aside for training purposes (Figure 5).
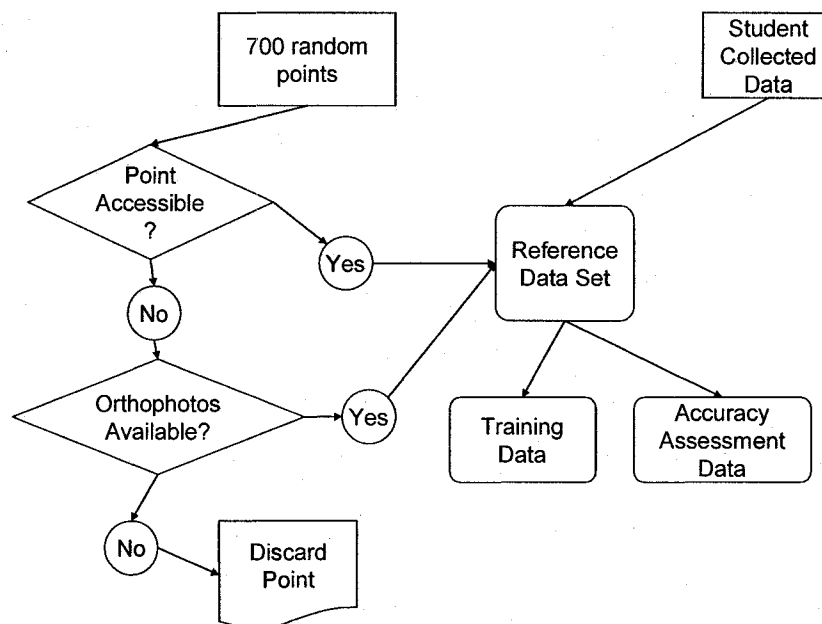
Figure 5: The reference data collection process.

Image Acquisition and Preparation

After the need for terrain flattened imagery was realized, researchers at Landcare Research in Palmerston North, New Zealand were contacted. They prepared two versions of a mosaiced and subset Landsat ETM+ image pair (path

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73, rows 87 and 88) acquired in November 2000. These images include bands 1-5 and 7. The first was an orthorectified scene (Figure 6) and the second was further processed with their terrain flattening algorithm (Figure 7). Both images are pan-sharpened to produce 15 meter by 15 meter pixels resulting in an equivalent scale of 1:50,000. The radiometric resolution of the orthorectified image and flattened image is 8 bits and 16 bits (signed), respectively. The images were registered in Zealand Map Grid (NZMG) coordinates with a reported 10 meter geo-registration accuracy. The images were resampled using cubic convolution.

Figure 6: The orthorectified Landsat ETM+ scene.

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Figure 7: The terrain-flattened Landsat ETM+ scene.

The images were prepared for classification by removing unnecessary data. Feature Analyst for ERDAS IMAGINE was trained to identify areas of clouds and cloud shadows within the images (Visual Learning Systems, 2005). Shapefiles representing these areas were edited in ArcMap for fine details and were then used to create a mask to remove those areas from the orthorectified and flattened images. Since the flattening algorithm does not change ocean pixels, the Tasman Sea was removed from the image to reduce processing time.

Data Exploration

All image processing was done using ERDAS IMAGINE 8.6. The univariate image statistics of each band of data were analyzed for the

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orthorectified and flattened images (Table 3). The histogram of each image band was visually assessed to better understand the dynamic range, shape and distribution of the data (In Appendix B, Figures 23 to 34, show the image band histograms). For band 1 of the orthorectified image, the majority of the data ranged from 54 to 92 and the histogram was positively skewed. For band 2 of the orthorectified image, the majority of the data ranged from 34 to 87. The histogram was bi-modal and positively skewed. For band 3 of the orthorectified image, the majority of the data ranged from 23 to 88 and the histogram was positively skewed. For band 4 of the orthorectified image, the majority of the data ranged from 9 to 176. The histogram was bi-modal and was negatively skewed. For band 5 of the orthorectified image, the majority of the data ranged from 8 to 158. The histogram was multi-modal. For band 7 of the orthorectified image, the majority of the data ranged from 8 to 94. The histogram was bi-modal and positively skewed.

Table 3: Univariate image statistics for both images.

Orthorectified						
Band	Min	Max	Mean	Median	Mode	Standard Deviation
1	27	255	66.946	66	63	6.74
2	17	255	55.162	55	61	9.794
3	1	255	42.946	41	36	11.421
4	1	203	95.982	93	81	29.589
5	1	255	77.736	77	58	28.025
6	1	255	38.65	37	26	15.468

Terrain-Flattened						
Band	Min	Max	Mean	Median	Mode	Standard Deviation
1	1	412	23.75	21	16.5	10.987
2	1	809	46.032	44.563	30.637	16.911
3	1	1069	36.015	31.992	22.395	17.842
4	1	1730	321.515	305.16	232.5	97.468
5	1	2147	152.518	142.57	100.64	56.328
6	1	2059	69.916	60.813	30.406	33.478

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For band 1 of the flattened image, the majority of the data ranged from 3 to 60 and the histogram was positively skewed. For band 2 of the flattened image, the majority of the data ranged from 5 to 100. The histogram was multi-modal. For band 3 of the flattened image, the majority of the data ranged from 0 to 105 and the histogram was positively skewed. For band 4 of the flattened image, the majority of the data ranged from 9 to 588. The histogram was bi-modal and was negatively skewed. For band 5 of the flattened image, the majority of the data ranged from 0 to 319. The histogram was multi-modal. For band 7 of the flattened image, the majority of the data ranged from 0 to 198. The histogram was bi-modal.

The best visual composite for display was chosen. Jensen (2005) states that the best visual composite will generally include one visible band, one longer wave infrared band, and TM Band 4. Indeed, TM Band 7, TM Band 4, and TM Band 2 shown through the Red, Green, and Blue channels of the computer monitor provided easy visual discrimination between the land cover classes (Figure 8). Water appears blue and vegetation retains a green tint. Note that exotic forest plantations appear a deep green color. Indigenous vegetation is a mottled magenta and cyan mixture on the orthorectified image. On the flattened image, indigenous vegetation appears as a mixture of magenta and green (Figure 9). Urban areas are easily distinguished.

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Figure 8: Landsat bands 7,4,2 of the orthorectified image shown through the red, green, and blue channels.

Figure 9: Landsat bands 7,4,2 of the terrain-flattened image shown through the red, green, and blue channels

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Spatial convolution filters were used in an attempt to enhance detail in the images (Jensen, 2005). Edge enhancement filters were used in an attempt to delineate edges around features of interest. This was not a useful method of gaining more information from the data (Figure 10).
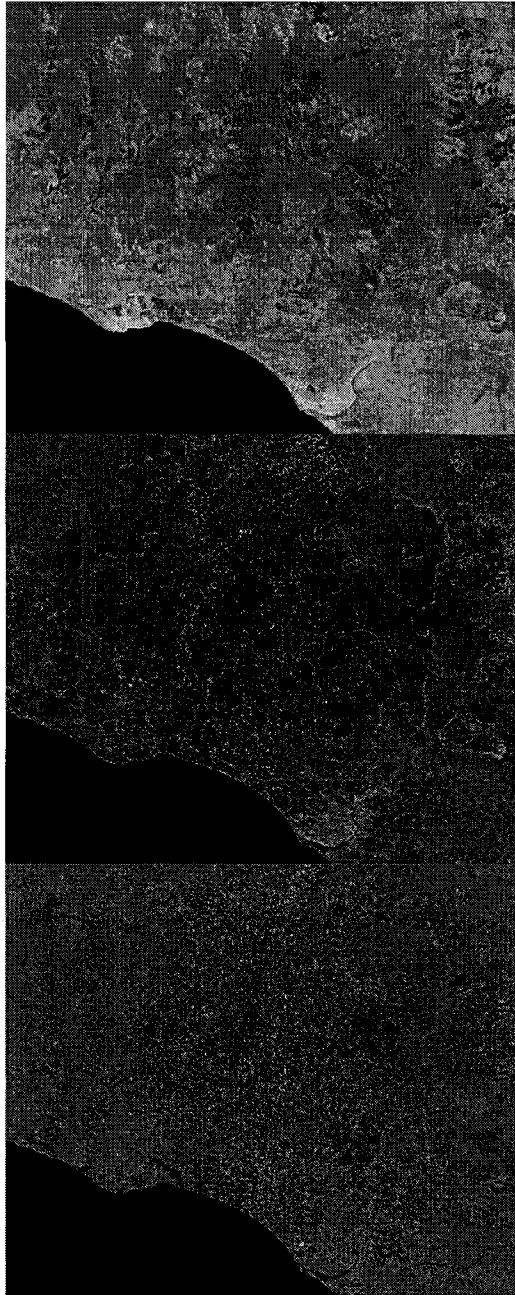
Figure 10: 3x3, 5x5, and 7x7 edge enhancement filters were run on the orthorectified image (from top to bottom).

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Derivative bands were created for both images. Derivative bands can be used to view data in a different perspective, which may help the analyst better understand the variability in the image. However, derivative bands are not always useful in analysis and can obscure other causes of variability, such as terrain effects and shadowing. Principal Components Analysis can be used to reduce the dimensionality of remotely sensed data by creating new coordinate axes in multispectral feature space to maximize the variability in the reflectance values of the image along the first principal component axis. The second principal component axis is orthogonal to the first and each subsequent principal component contains decreasing amounts of variability. A majority of the variability in a Landsat TM image can often be explained by the first three principal components (Ricotta et al., 1999; Jensen, 2005). Band ratios can be used to remove differences in brightness values from identical features resulting from topographic slope and aspect, shadowing, or differences in illumination angle and intensity. Band ratios may also provide unique information not present in individual image bands. Vegetation indices have been used to reduce multiple bands of data to one band with values representing some measure of canopy characteristics (Jensen, 2005). The Tasseled-Cap transformation is a special sequential orthogonalization process that results in three new useful bands and additional bands (with the sum of the useful bands plus the additional bands equal to the total input bands) containing very little information. The useful bands are measures of soil brightness, green vegetation, and wetness, and capture approximately 95% of the variation found in the image (Crist and Kauth, 1986;

Jensen, 2005). Huang et al. (2002) give the coefficients for the Landsat 7 ETM+ tasseled-cap transformation.

The derivative bands created for each image included the first three principal component bands for the six raw bands, tasseled-cap brightness, greenness and wetness bands, the ratio of band4/band3, the ratio of band5/band4, the square root of the ratio of band4/band3 and the Normalized Difference Vegetation Index (NDVI). The first three principal components of each image contained the majority of the variability of the data (Table 4). These derivative bands were rescaled to match the average dynamic range of the raw data bands used to create the ratio for each image and stacked together using the Image Stack command in ERDAS IMAGINE.

Table 4: Variability captured by Principal Components Analysis bands for the orthorectified and terrain-flattened images.

Orthorectified PCA Bands	Variability Captured	Flattened PCA Bands	Variability Captured
1	84.23%	1	90.38%
2	11.85%	2	7.78%
3	3.09%	3	1.45%
4	0.45%	4	0.22%
5	0.28%	5	0.12%
7	0.10%	7	0.04%

Training areas were seeded to generate initial image statistics for both images. These statistics were used to evaluate separability between the land cover classes. Spectral Pattern Analysis was used to visually assess the separability of the land cover classes for the orthorectified image (Appendix C, Figure 35) and the flattened image (Appendix C, Figure 36). Divergence Analysis, a set of measures used to reduce dimensionality and chose the best bandset for the optimum classification, revealed that for both images, the raw

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bands generally provided more separability than the derivative bands (Table 5). Jefferies-Matusita and Transformed Divergence are two measures of divergence and are superior predictors of classification accuracy based on band combinations (Mausel et al., 1990). Additionally, since ratio bands can be used to remove the effects of topographic slope and aspect, using those bands could influence the comparison of the orthorectified to flattened imagery. Thus, it was decided that all further classification would proceed with the raw data.

Table 5: Divergence Analysis results using Transformed Divergence (T-D) and Jefferies-Matusita (J-M) on the orthorectified and terrain-flattened images.

		Orthorectified		Flattened	
		T-D	J-M	T-D	J-M
Best Average Separability		TM 1	TM 2	TM 1	TM 3
		TM 2	TM 3	TM 2	TM 4
		TM 3	TM 4	TM 3	NDVI
		TM 4	TM 5	TM 4	sqrt(4/3)
		TM 5	sqrt(4/3)	TM 7	TCAP-wet

Image Classification

In order to have a fair comparison between the images, the same classification techniques were used on both images; however, to achieve the best classification within each classification technique, different parameters and/or decisions were made (e.g. different training areas for supervised classification, different number of iterations for hybrid classification).

Unsupervised Classification. Four ISODATA (Iterative Self-Organizing Data Analysis Technique) unsupervised classifications were performed for each whole image (i.e. no skip factor), having 200, 250, 300, and 500 classes. The ISODATA algorithm partitions the data into a specified number of clusters basted on statistical similarity. These clusters may be reorganized throughout the process to cluster the data in the best possible way (Jensen, 2005). The

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convergence threshold was set to 0.99, with a maximum of 100 iterations. For all classifications, the algorithm was stopped at the threshold, not the maximum number of iterations. Training data and photo and image interpretation were used to label the unsupervised classes.

Supervised Classification. Training statistics were generated using seed and polygon based Areas of Interest (AOIs) selected using the training data and image interpretation. Spectral pattern analysis (Appendix C, Figures 37-38), contingency analysis, and bi-spectral plots were used to refine the final number of training areas per class (Table 6). A supervised classification was performed for each image using the maximum likelihood algorithm and the appropriate signature file. The maximum likelihood algorithm was chosen because it considers the variability of the land cover classes (Schriever and Congalton, 1995).

Table 6: Distribution of supervised training areas among the land cover classes for each image.

Land Cover Code	Land Cover Name	Supervised Training Data	
		Orthorectified	Flattened
1	Native Forest	20	20
2	Exotic Forest	20	20
3	Shrubland	20	20
4	Agriculture/Field	20	20
5	Urban/Developed	18	20
6	Water	10	10
7	Other	20	20

Hybrid Classification. An additional 100 class ISODATA unsupervised classification was performed for each image. The signature means for both the 100 class unsupervised and the supervised training classes were exported to SAS 9.1 (see Appendix D for SAS code examples for the CLUSTER and TREE commands). Cluster analysis was performed on each image's dataset using the

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squared Euclidean distance and complete linkages. The TREE command was used to produce a dendrogram showing the relationships between the unsupervised spectral groupings and the supervised training classes. The dendrogram was evaluated and an r^2 value of 0.990 was chosen as the minimum value for an acceptable grouping. This value, chosen empirically, represents the threshold where supervised and unsupervised classes are grouped into logical clusters. Unsupervised classes that were statistically linked with homogeneous supervised groupings were labeled according to the supervised class. Unsupervised classes that were linked with a group containing more than one land cover, or those that were linked only with other unsupervised classes, were labeled 'unknown.' The newly labeled unsupervised signatures were merged with the supervised training data. The unknown clusters were used to mask the image that they were associated with. An unsupervised classification was performed on the unclassified portion of the image. 50 classes were used for the orthorectified image and 100 for the flattened image. A second round of cluster analysis was performed using the training signatures and the new unsupervised clusters. The resulting clusters were evaluated and an r^2 value of 0.985 was chosen as the minimum acceptable value for grouping for the second iteration. In this round, logical and informational and spectral groupings occurred at a lower r^2 value. Unsupervised classes that were able to be labeled were added to the training signature set. The training signature files that were created using the hybrid clustering process were used to classify the images using the maximum likelihood algorithm.

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Image Post-processing

All final classification images were recoded to reflect the land cover code used in the classification scheme. A 7x7 neighborhood majority filter was used to approximate the 90 by 90 meter minimum mapping unit.

Accuracy Assessment

The error matrix is a commonly used site specific measure of accuracy. Kappa analysis, a discrete multivariate analysis technique, is used to compare error matrices. Kappa analysis results in KHAT, an estimate of Kappa. KHAT values can range from -1 to +1; however the positive correlation between remotely sensed data and reference data should eliminate negative values. The Z statistic is calculated for the individual error matrix and when comparing error matrices. In the case of an individual error matrix tested at the 95% confidence interval, a value greater than 1.96 indicates that the classification is significantly better than a random classification. When comparing error matrices, again at the 95% confidence level, a value greater than 1.96 indicates that the classifications are significantly different (Congalton and Green, 1999).

Disagreement between the stratified reference data groupings and actual land cover resulted in an uneven distribution among the land cover classes. A random subset of 60 points from each land cover class was chosen from the entire reference data set by an impartial assistant. The 'Extract Values to Points' Tool in ArcGIS Spatial Analyst was used to create a table containing the classified value and reference value for the supervised, unsupervised, and hybrid classifications of each image. Error matrices were generated using pivot tables

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in Microsoft Excel. Kappa statistics were computed using the Kappa Stats program (R.G. Congalton, personal communication). The Kappa statistics for each image were compared for each classification technique.

Difference images were created to compare the orthorectified and flattened images for each classification technique. These were recoded to show differences in black and agreement in white.

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CHAPTER III

RESULTS

Unsupervised Classification

The 300 class unsupervised classification was chosen as the final output for both images (Figure 11). The 200 class unsupervised classifications proved unsatisfactory because of visually evident confusion between classes. Conversely, the 500 class unsupervised classifications were too fragmented to reliably find all of the classes within the image and therefore could not be labeled. The area of each land cover classification changed slightly between the images (Table 7). The greatest shift occurred in the four vegetated classes. There was very little change in total area of water and urban/developed areas classified between the two images.
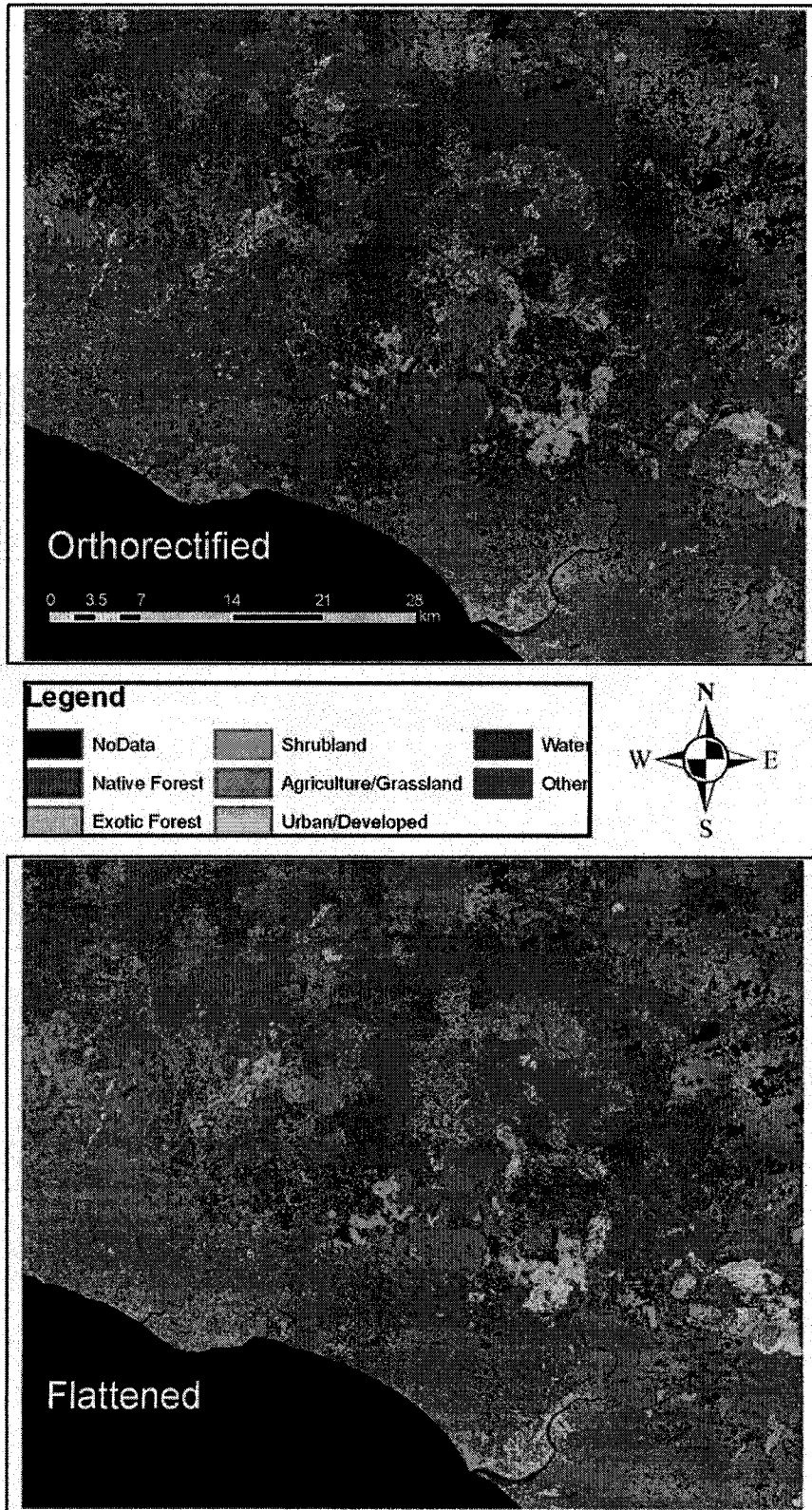
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Figure 11: Thematic maps resulting from the unsupervised classification process.

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Table 7: Changes in areas classified per land cover class by the unsupervised classification method in the orthorectified image versus the terrain flattened image.

	Orthorectified			Flattened			Delta
	Pixels	Area (km^2)	Percent	Pixels	Area (km^2)	Percent	Area (km^2)
Native Forest	4,454,147	1,002.18	39.38%	4,338,153	976.08	38.35%	26.10
Exotic Forest	569,121	128.05	5.03%	718,700	161.71	6.35%	-33.66
Shrubland	1,534,931	345.36	13.57%	1,384,783	311.58	12.24%	33.78
Agriculture/Grassland	4,301,849	967.92	38.03%	4,483,545	1,008.80	39.63%	-40.88
Urban/Developed	178,803	40.23	1.58%	174,733	39.31	1.54%	0.92
Water	61,316	13.80	0.54%	43,089	9.70	0.38%	4.10
Other	211,921	47.68	1.87%	169,085	38.04	1.49%	9.64
Total		2,545.22			2,545.22		

Supervised Classification

The maximum likelihood supervised classification algorithm resulted in a thematic map for each image (Figure 12). The Native Forest, Other, and Shrubland categories changed the most between the images. Water had relatively little change. The remaining classes had a moderate amount of change between them (Table 8).
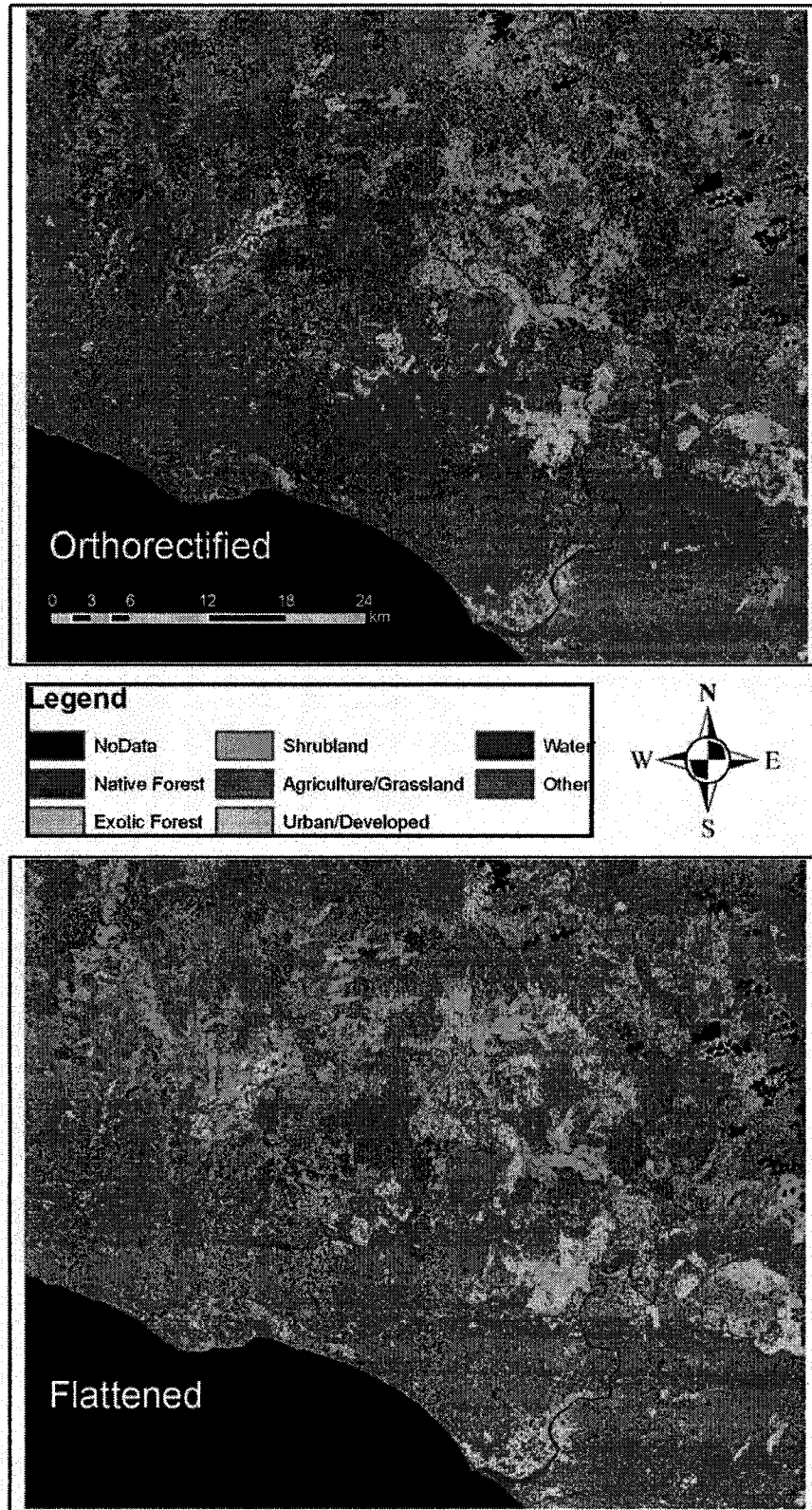
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Figure 12: Thematic maps resulting from the supervised classification process.

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Table 8: Changes in areas classified per land cover class by the supervised classification method in the orthorectified image versus the terrain flattened image.

	Orthorectified			Flattened			Delta
	Pixels	Area (km^2)	Percent	Pixels	Area (km^2)	Percent	Area (km^2)
Native Forest	2,385,777	536.80	21.09%	2,858,160	643.09	25.27%	-106.29
Exotic Forest	1,030,585	231.88	9.11%	853,186	191.97	7.54%	39.91
Shrubland	2,766,265	622.41	24.45%	3,145,912	707.83	27.81%	-85.42
Agriculture/Grassland	3,617,542	813.95	31.98%	3,463,719	779.34	30.62%	34.61
Urban/Developed	462,500	104.06	4.09%	614,724	138.31	5.43%	-34.25
Water	36,053	8.11	0.32%	50,151	11.28	0.44%	-3.17
Other	1,013,366	228.01	8.96%	326,236	73.40	2.88%	154.60
Total		2,545.22			2,545.22		

Hybrid Classification

The improved signature sets created through the hybrid process resulted in a thematic map for each image (Figure 13). The two forest classes and the other class exhibited the most change between the images. Water changed the least. The remaining classes exhibited moderate amounts of change between them (Table 9).
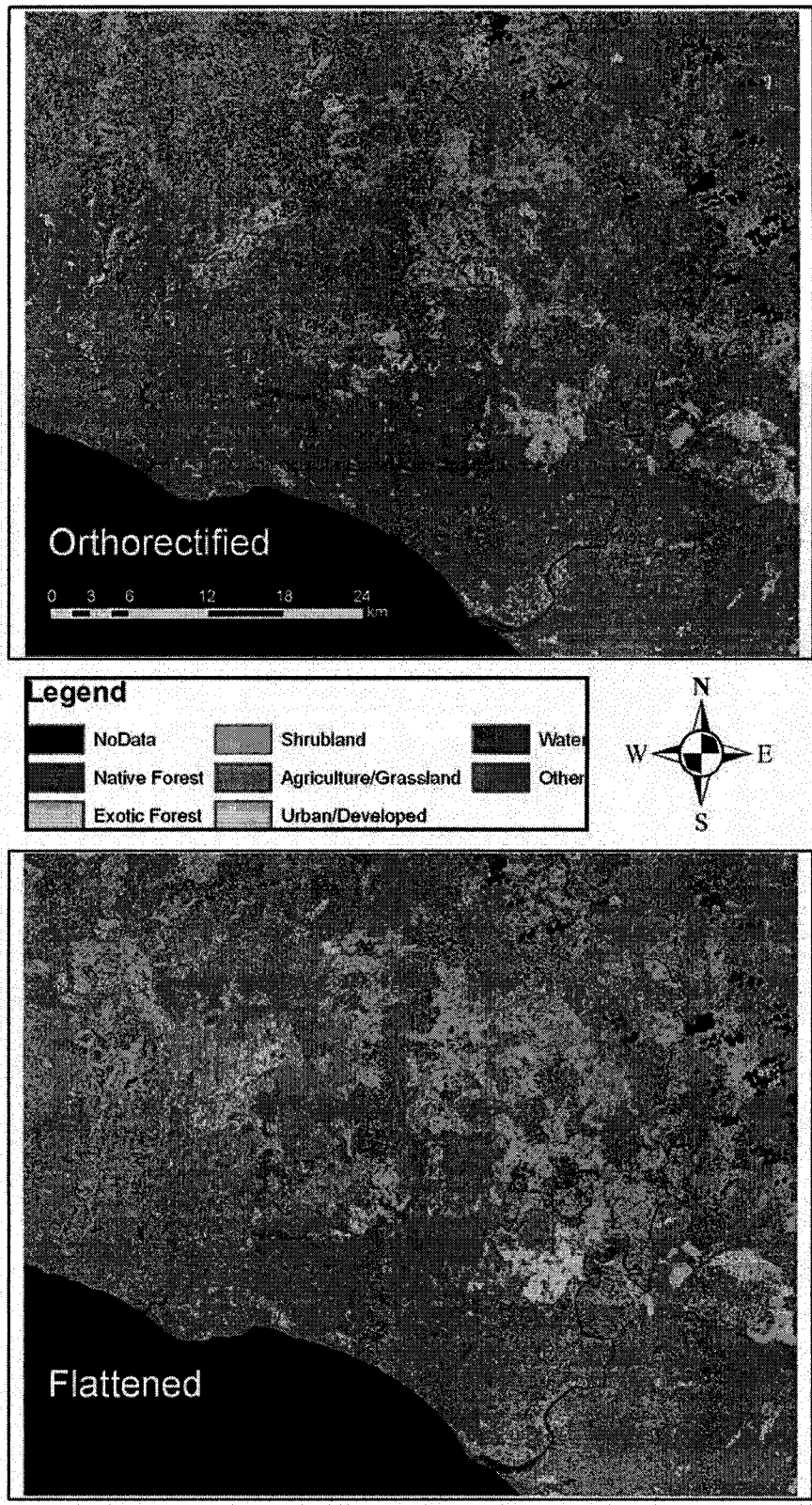
Figure 13: Thematic maps resulting from the hybrid classification process.

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Table 9: Changes in areas classified per land cover class by the hybrid classification method in the orthorectified image versus the terrain-flattened image.

	Orthorectified			Flattened			Delta
	Pixels	Area (km²)	Percent	Pixels	Area (km²)	Percent	Area (km²)
Native Forest	2,147,589	483.21	18.98%	2,846,803	640.53	25.17%	-157.32
Exotic Forest	1,311,422	295.07	11.59%	722,078	162.47	6.38%	132.60
Shrubland	2,976,323	669.67	26.31%	3,208,468	721.91	28.36%	-52.23
Agriculture/Grassland	3,617,833	814.01	31.98%	3,688,505	829.91	32.61%	-15.90
Urban/Developed	343,497	77.29	3.04%	522,913	117.66	4.62%	-40.37
Water	50,747	11.42	0.45%	54,472	12.26	0.48%	-0.84
Other	864,677	194.55	7.64%	268,849	60.49	2.38%	134.06
Total		2,545.22			2,545.22		

Accuracy Assessment

The overall accuracy was slightly higher for the flattened image than the orthorectified image for all classification techniques (Tables 10-15). The classifications were significantly better than random classifications. However, the comparison of the Kappa values within each classification technique shows no significant difference between the orthorectified and terrain flattened imagery (Table 16).

Table 10: Error matrix for the unsupervised classification of the orthorectified image.

Orthorectified - Unsupervised

Classified Data		Native	Exotic	Shrub	Reference Data Ag/Grass	Urban/Devel.	Water	Other	Total	User's Accuracy
	Native	52	17	37	5	1	7	13	132	39.39%
	Exotic	1	29	0	1	0	0	0	31	93.55%
	Shrub	2	7	5	6	11	3	10	44	11.36%
	Ag/Grass	4	7	14	45	7	6	13	96	46.88%
	Urban/Devel.	0	0	1	2	39	2	8	52	75.00%
	Water	1	0	3	0	0	42	5	51	82.35%
	Other	0	0	0	1	2	0	11	14	78.57%
	Total	60	60	60	60	60	60	60	420	Total
	Producer's Accuracy	86.67%	48.33%	8.33%	75.00%	65.00%	70.00%	18.33%		

Overall Accuracy	Lower Limit	K_HAT	Upper Limit	Variance	Z Score
53.10%	39.79%	45.28%	50.77%	0.00078430	16.1677

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Table 11: Error matrix for the unsupervised classification of the terrain-flattened image.

Flattened - Unsupervised

Classified Data		Reference Data							Total	User's Accuracy
		Native	Exotic	Shrub	Ag/Grass	Urban/Devel.	Water	Other		
	Native	47	16	36	3	1	11	12	126	37.30%
	Exotic	2	33	1	2	0	0	0	38	86.84%
	Shrub	3	4	5	2	16	5	9	44	11.36%
	Ag/Grass	8	7	13	50	4	5	13	100	50.00%
	Urban/Devel.	0	0	2	2	39	1	6	50	78.00%
	Water	0	0	3	0	0	37	4	44	84.09%
	Other	0	0	0	1	0	1	16	18	88.89%
	Total	60	60	60	60	60	60	60	420	Total
	Producer's Accuracy	78.33%	55.00%	8.33%	83.33%	65.00%	61.67%	26.67%		

Overall Accuracy	Lower Limit	K_{HAT}	Upper Limit	Variance	Z Score
54.05%	40.88%	46.39%	51.89%	0.00078930	16.5115

Table 12: Error matrix for the supervised classification of the orthorectified image.

Orthorectified - Supervised

Classified Data		Reference Data							Total	User's Accuracy
		Native	Exotic	Shrub	Ag/Grass	Urban/Devel.	Water	Other		
	Native	40	7	14	0	0	3	1	65	61.54%
	Exotic	2	38	2	4	0	0	1	47	80.85%
	Shrub	14	5	26	3	1	2	7	58	44.83%
	Ag/Grass	2	6	12	48	3	7	5	83	57.83%
	Urban/Devel.	0	0	0	3	56	0	9	68	82.35%
	Water	0	0	1	0	0	33	0	34	97.06%
	Other	2	4	5	2	0	15	37	65	56.92%
	Total	60	60	60	60	60	60	60	420	Total
	Producer's Accuracy	66.67%	63.33%	43.33%	80.00%	93.33%	55.00%	61.67%		

Overall Accuracy	Lower Limit	K_{HAT}	Upper Limit	Variance	Z Score
66.19%	55.29%	60.56%	65.82%	0.00072050	22.5597

Table 13: Error matrix for the supervised classification of the terrain-flattened image.

Flattened - Supervised

Classified Data		Reference Data							Total	User's Accuracy
		Native	Exotic	Shrub	Ag/Grass	Urban/Devel.	Water	Other		
	Native	38	4	10	3	0	2	0	57	66.67%
	Exotic	1	40	1	3	0	0	2	47	85.11%
	Shrub	17	10	34	2	0	6	12	81	41.98%
	Ag/Grass	3	6	8	44	4	4	4	73	60.27%
	Urban/Devel.	0	0	2	7	54	1	5	69	78.26%
	Water	0	0	3	0	0	36	2	41	87.80%
	Other	1	0	2	1	2	11	35	52	67.31%
	Total	60	60	60	60	60	60	60	420	Total
	Producer's Accuracy	63.33%	66.67%	56.67%	73.33%	90.00%	60.00%	58.33%		

Overall Accuracy	Lower Limit	K_{HAT}	Upper Limit	Variance	Z Score
66.90%	56.14%	61.39%	66.64%	0.00071770	22.9157

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Table 14: Error matrix for the hybrid classification of the orthorectified image.

Orthorectified - Hybrid

		Reference Data								User's
		Native	Exotic	Shrub	Ag/Grass	Urban/Devel.	Water	Other	Total	Accuracy
Classified Data	Native	34	6	13	0	1	1	0	55	61.82%
	Exotic	5	39	1	4	0	1	2	52	75.00%
	Shrub	17	8	27	2	0	7	11	72	37.50%
	Ag/Grass	3	5	12	48	4	4	6	82	58.54%
	Urban/Devel.	0	0	0	4	52	0	7	63	82.54%
	Water	0	0	3	0	0	40	4	47	85.11%
	Other	1	2	4	2	3	7	30	49	61.22%
	Total	60	60	60	60	60	60	60	420	Total
	Producer's Accuracy	56.67%	65.00%	45.00%	80.00%	86.67%	66.67%	50.00%		

Overall Accuracy	Lower Limit	K_{HAT}	Upper Limit	Variance	Z Score
64.29%	52.99%	58.33%	63.68%	0.00074330	21.3961

Table 15: Error matrix for the hybrid classification of the terrain-flattened image.

Flattened - Hybrid

		Reference Data								User's
		Native	Exotic	Shrub	Ag/Grass	Urban/Devel.	Water	Other	Total	Accuracy
Classified Data	Native	38	7	10	1	1	3	1	61	62.30%
	Exotic	1	38	1	2	0	0	2	44	86.36%
	Shrub	17	11	35	3	4	6	12	88	39.77%
	Ag/Grass	3	4	8	48	7	5	7	82	58.54%
	Urban/Devel.	0	0	2	5	42	0	3	52	80.77%
	Water	0	0	2	0	0	42	5	49	85.71%
	Other	1	0	2	1	6	4	30	44	68.18%
	Total	60	60	60	60	60	60	60	420	Total
	Producer's Accuracy	63.33%	63.33%	58.33%	80.00%	70.00%	70.00%	50.00%		

Overall Accuracy	Lower Limit	K_{HAT}	Upper Limit	Variance	Z Score
65.00%	53.84%	59.17%	64.49%	0.00073890	21.7661

Table 16: Pairwise comparison of the orthorectified and terrain flattened images by classification technique.

method	z-score
unsupervised	-0.2800973
supervised	-0.2197427
hybrid	-0.2164527

Difference Images

Difference images show binary change/no change (Figures 14-16). The supervised and hybrid difference images show similar distribution of disagreement. The unsupervised classification difference image shows much less disagreement than the other difference images.
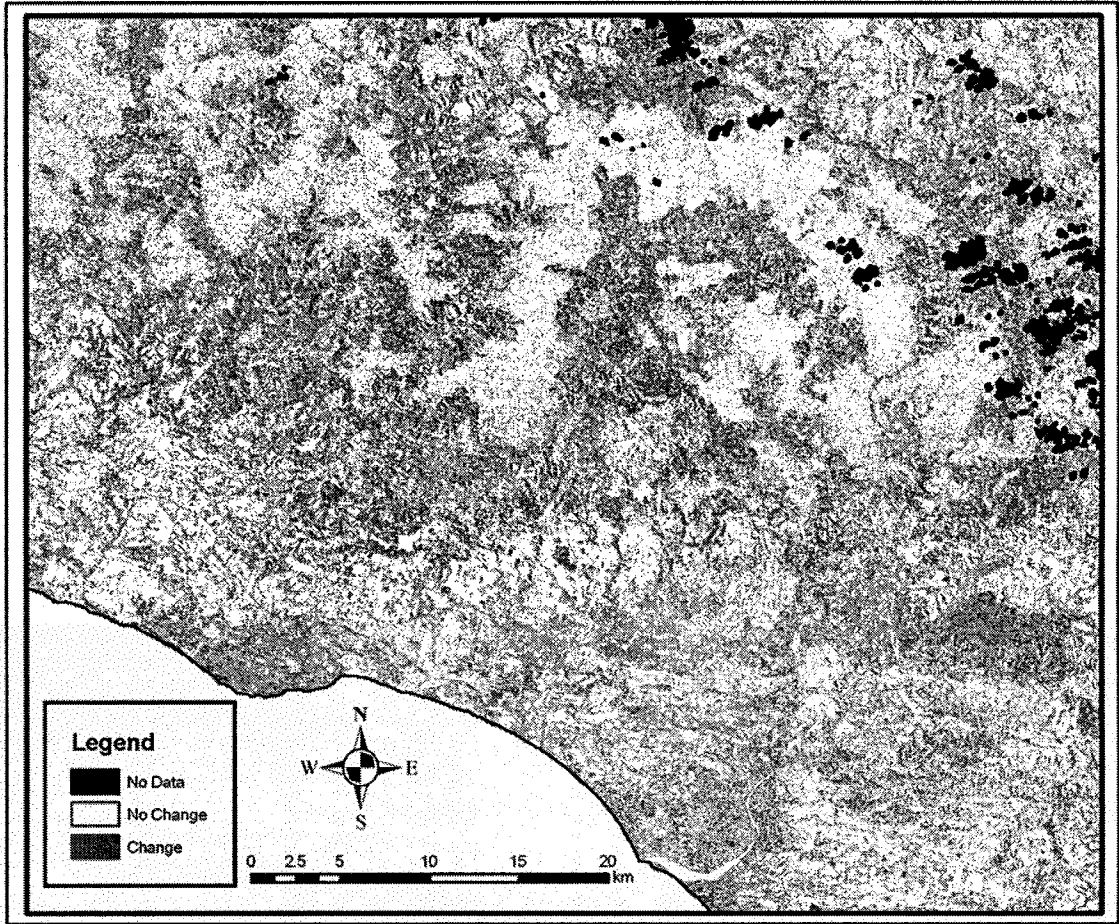
68

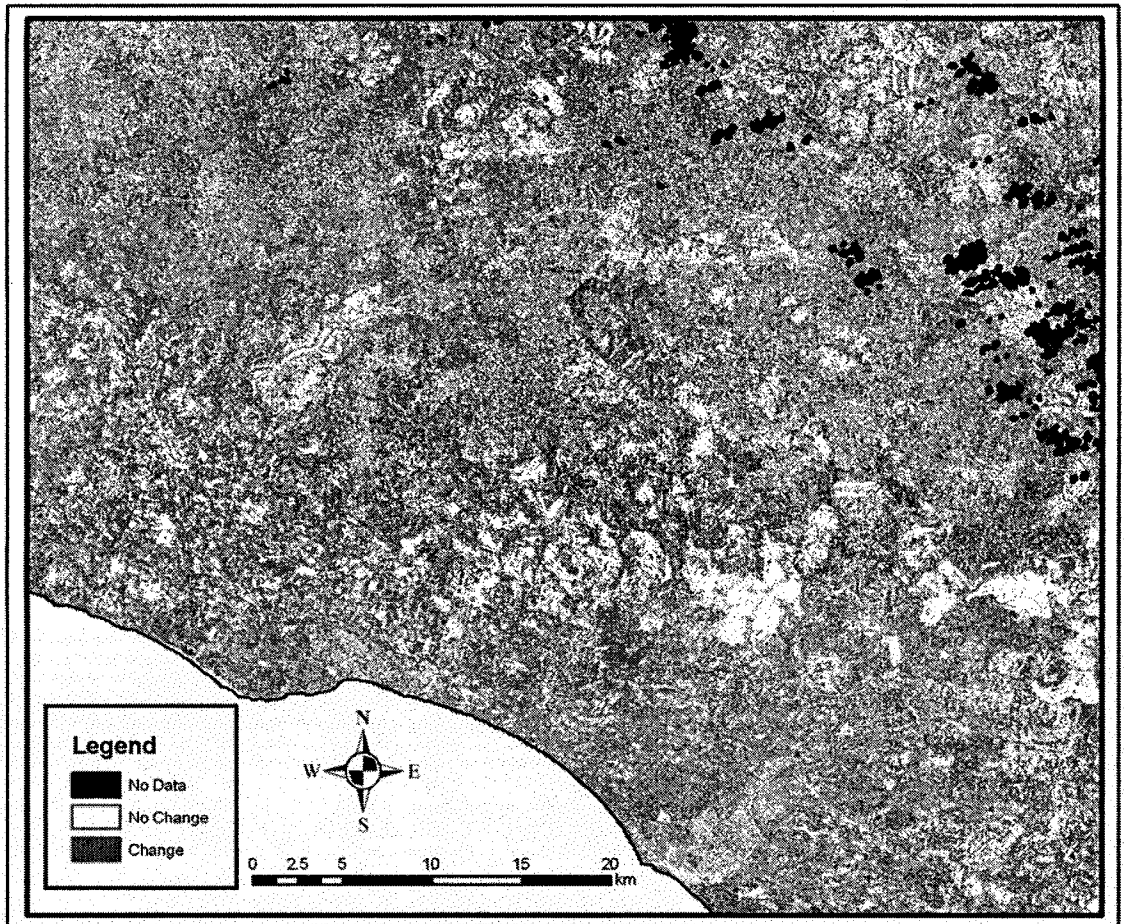**Figure 14: Difference image for the unsupervised classification method.**

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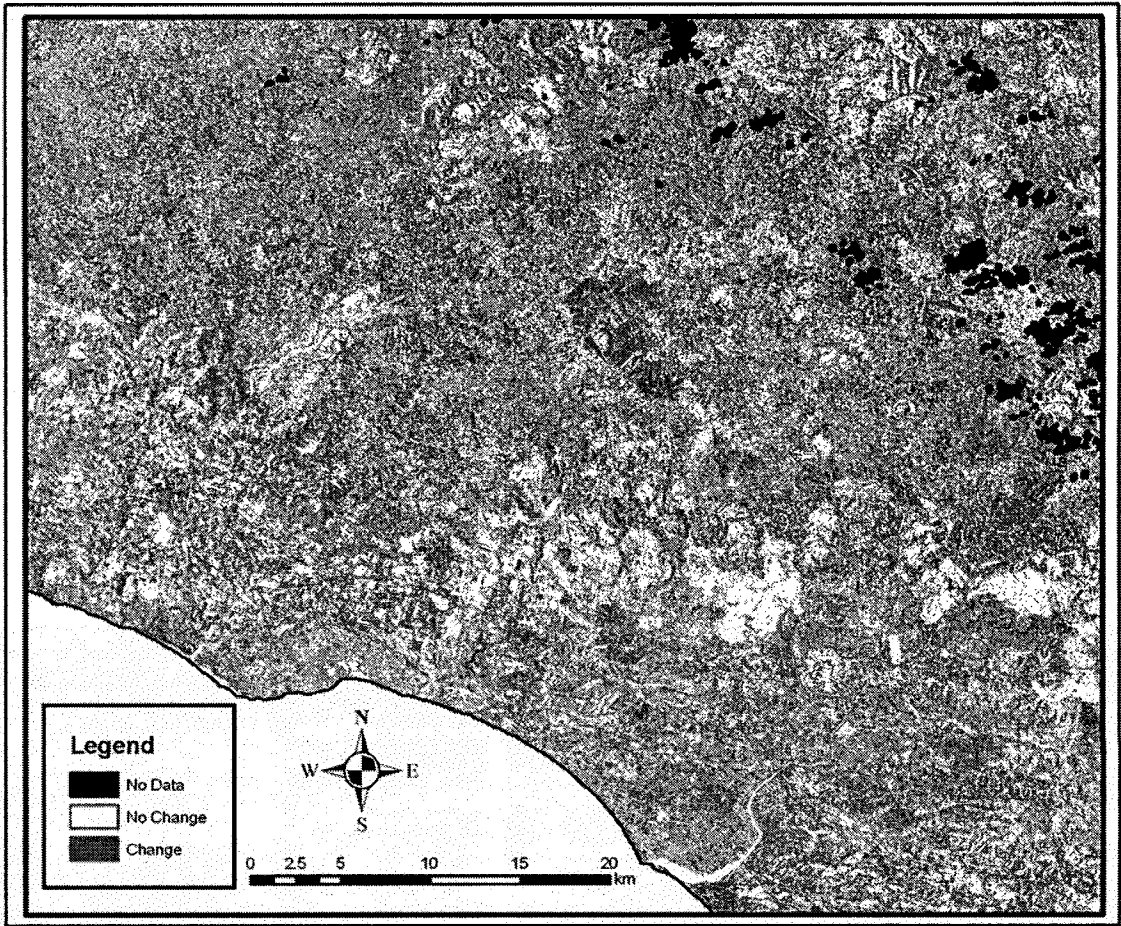**Figure 15: Difference image for the supervised classification method.**

Figure 16: Difference image for the hybrid classification method.

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CHAPTER IV

DISCUSSION

Overall Accuracy of Thematic Maps

The classifications were all significantly better than random classifications. Therefore, the six null hypotheses relating to the three classifications of each image were rejected. The disagreement between the thematic maps and the reference data may be due to a number of factors. The time span between the acquisition of the images in November 2000 and the collection of the reference data in September/October 2004 potentially has allowed a great deal of land cover change to take place within the study area. The rapid growth rate of exotic forest species creates a quick rotation rate for plantations making the potential for change from and to this class very high. Cut areas, and even recently replanted areas, may be dominated by native or exotic shrubs. Exotic forest plantations have grown at a rate of approximately 70,000 ha/year (Taylor and Smith, 1997). Some agricultural land has likely been converted to exotic production forestry. There is also an increasing trend toward gully and riparian restoration among New Zealand farmers. Areas imaged as agriculture may have been fenced and planted with native vegetation. Due to the limited coverage of orthophotos for this study area, only reference data in the western portion of the

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study area were checked against orthophotos acquired in 2000/2001. More recent cloud-free Landsat ETM+ scenes have not been available for this area.

Congalton and Green (1993) list a number of errors other than classification error that may influence classification accuracy. These include registration differences between maps and reference data, data entry error, error in interpretation of reference data, and inconsistencies in human interpretation of heterogeneous vegetation. These factors may account for some of the error in this study.

It is evident from the error matrices that there are high errors of omission in the Shrubland, Exotic Forest, and Other categories resulting in errors of commission in Native, Shrub and Agriculture. This is likely the result of the spectral similarity of these classes.

Using 300 classes for the unsupervised classifications reduced the spectral confusion between land cover classes without reducing the number of pixels per spectral class to a level where they could not be identified on the image. Even so, there was evidence of spectral confusion between some of the land cover classes. Much of the confusion occurred between the Native Forest and Shrubland classes. This resulted in a majority of those confused classes being labeled as Native Forest. There was little ability to distinguish between Native Forest and Shrubland using either the orthorectified or terrain flattened image. The Other category was also subject to low producer's accuracy. Errors omitted from the Other class and committed to the Water class may be the result of positional accuracy. Errors omitted from the Other class and committed to the

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vegetated land cover classes are likely due to changes in land cover between the date of image acquisition and the date of reference data collection.

After many revisions of the supervised training areas, a final set was chosen to best represent the land cover classes present in the study area. From the spectral pattern analysis and the contingency analysis, it was evident that there was still some spectral confusion between the vegetated land cover classes. The spectral variability of the Urban and Other classes resulted in further spectral confusion within the signatures for both the orthorectified image (Figure 17) and terrain-flattened image (Figure 18). This resulted in large errors of omission from the Shrubland class and errors of commission into the Native Forest, Agriculture/Grassland, and Exotic Forest classes for both the orthorectified and terrain flattened images. There were fewer errors of omission and commission between the other vegetated classes.
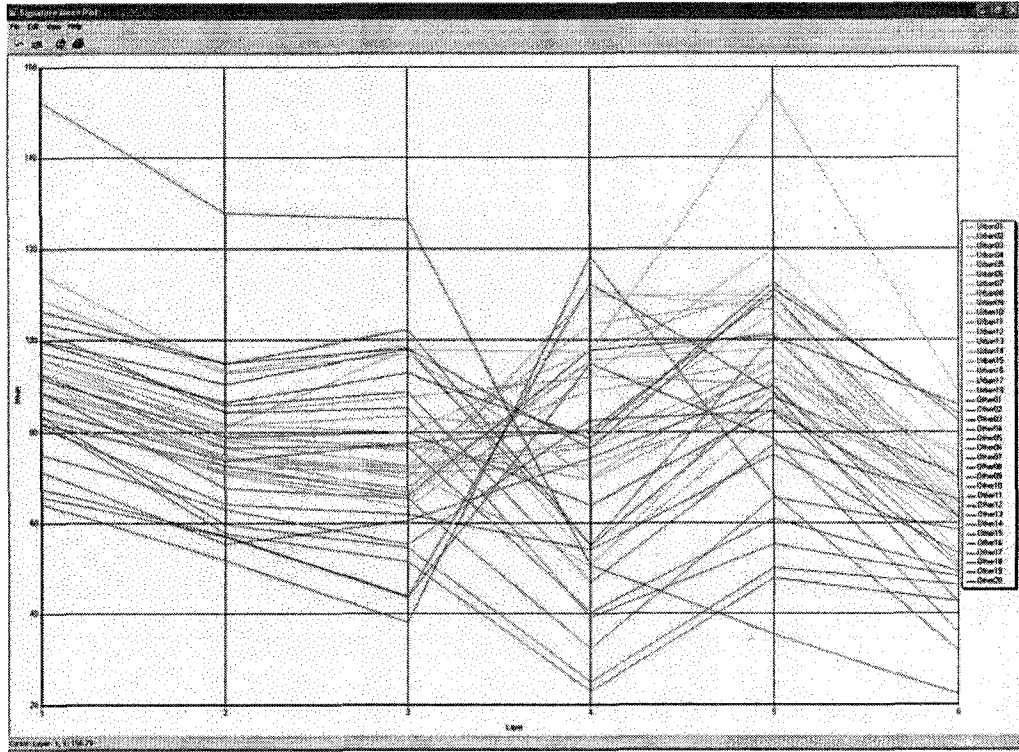
Figure 17: Spectral Pattern Analysis showing confusion between the Urban (cyan) and Other (purple) classes for the orthorectified image.
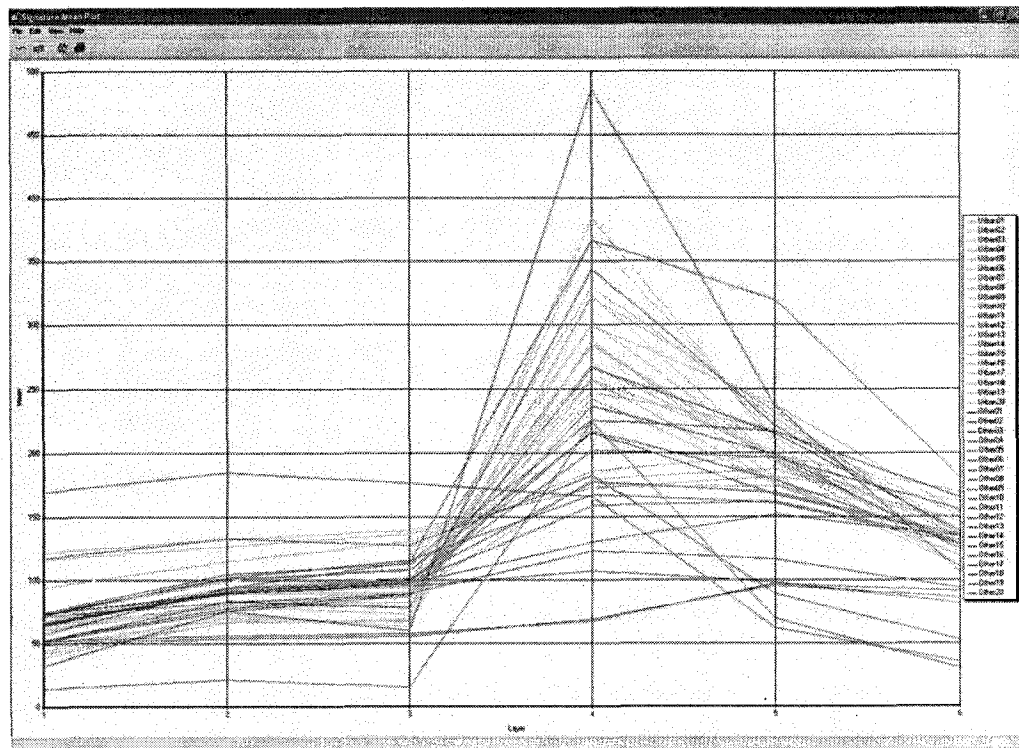
Figure 18: Spectral Pattern Analysis showing confusion between the Urban (cyan) and Other (purple) classes for the terrain-flattened image.

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Although hybrid classification is used to improve training statistics, the overall accuracies for the hybrid classifications were lower (not statistically significantly) than for the supervised classifications. This may in part be due to the spectral confusion that was evident with the unsupervised classifications. Hybrid classification improved the ability to quantify pixels representing the agriculture/grassland class and the water class but did not help or decreased the ability to quantify pixels belonging to the other classes. A hybrid classification using a 300 class unsupervised classification did not yield improved results.

Orthorectified versus Terrain Flattened Map Accuracy

Given the low z-scores for the comparison of the orthorectified and terrain flattened images by classification type, the null hypotheses relating to the comparison of the images are all accepted. Visual assessment of the orthorectified image and the terrain flattened image shows that there is some change within the image that looks as if shadowing has been removed (Figure 19). The unfiltered supervised classification for each image shows some difference in the amount of Shrubland versus Native Forest in this area (Figure 20). According to the Land Cover Data Base 2 (Minimum Mapping Unit = 10000 m2), the center of this image should be classified as continuous native forest. The underlying landform gives some indication as to the source of the misclassification (Figure 21). Valleys are being classified as Shrubland, which may be correct and may have been eliminated from the LCDB2 because of the 100 meter by 100 meter minimum mapping unit. Further field visits would be necessary to confirm this. There is a reduced amount of area classified as

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Shrubland on the hillsides in the terrain flattened image. When the image is filtered to represent the minimum mapping unit, differences between the patches of native vegetation from the orthorectified and terrain flattened images clearly do not correspond to sunlit or shaded slopes (Figure 22). This lack of correlation is evident throughout the extent of the study area.
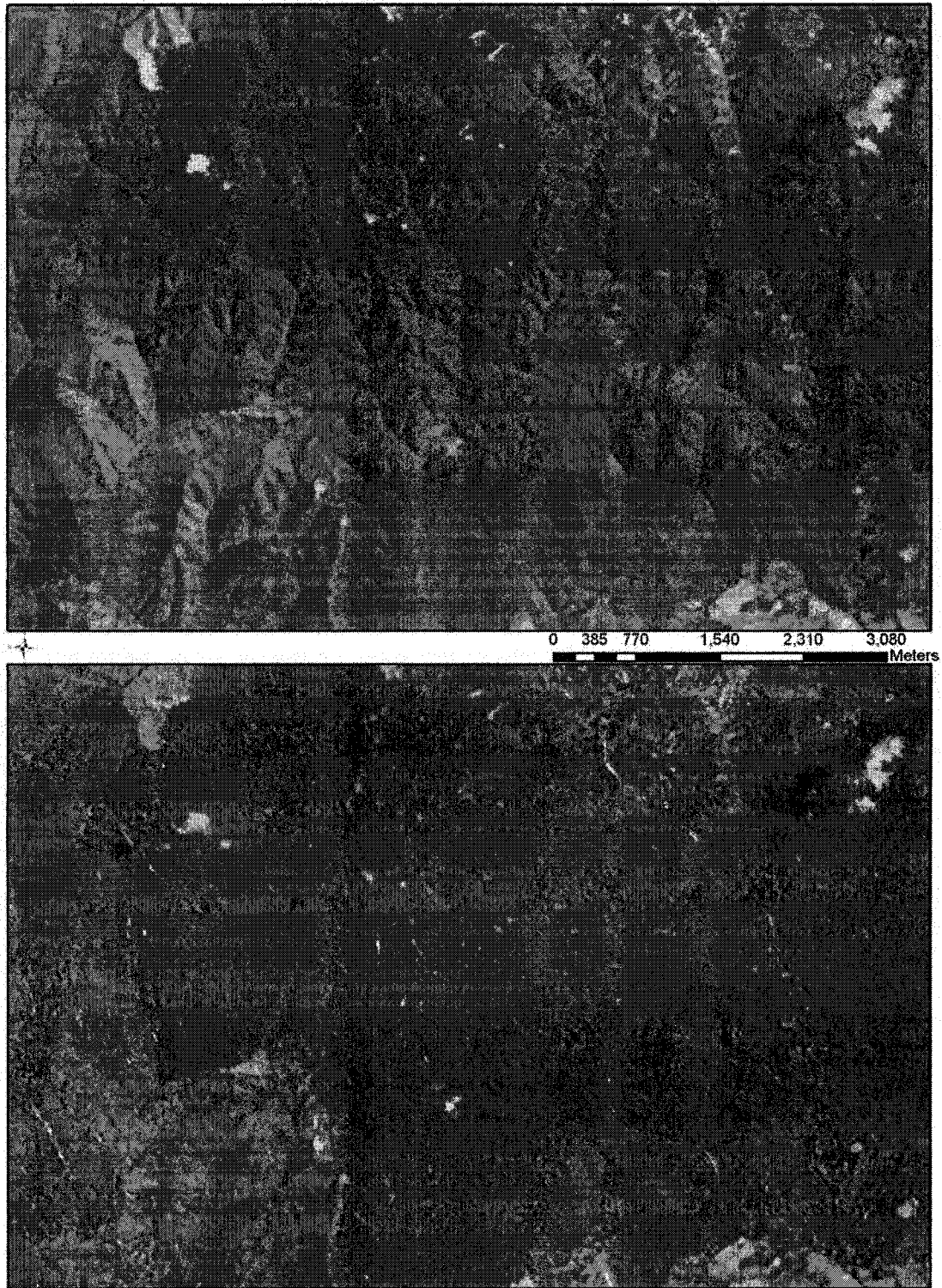
77

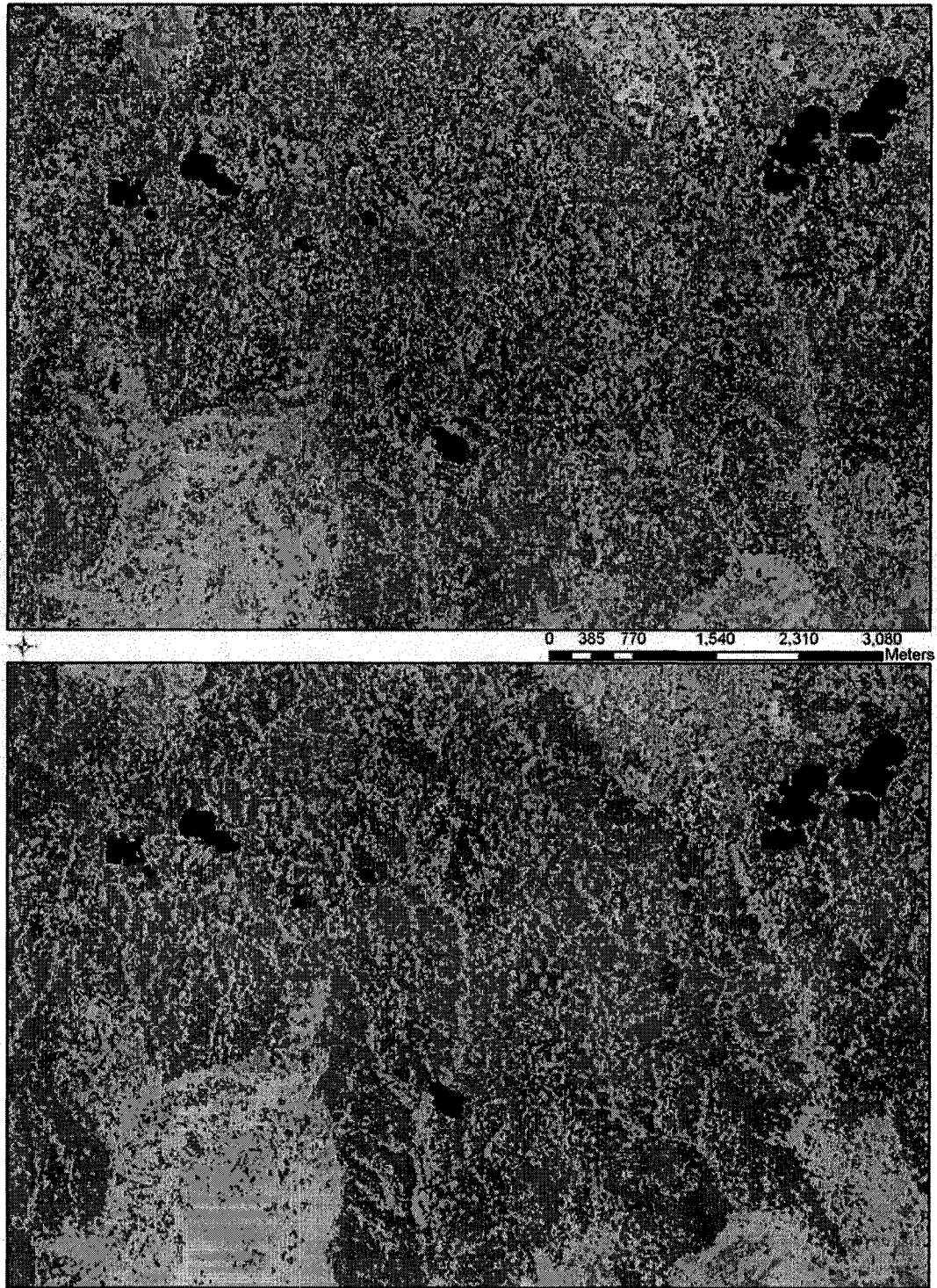**Figure 19: A visual comparison of the orthorectified image (top) and terrain-flattened image (bottom).**

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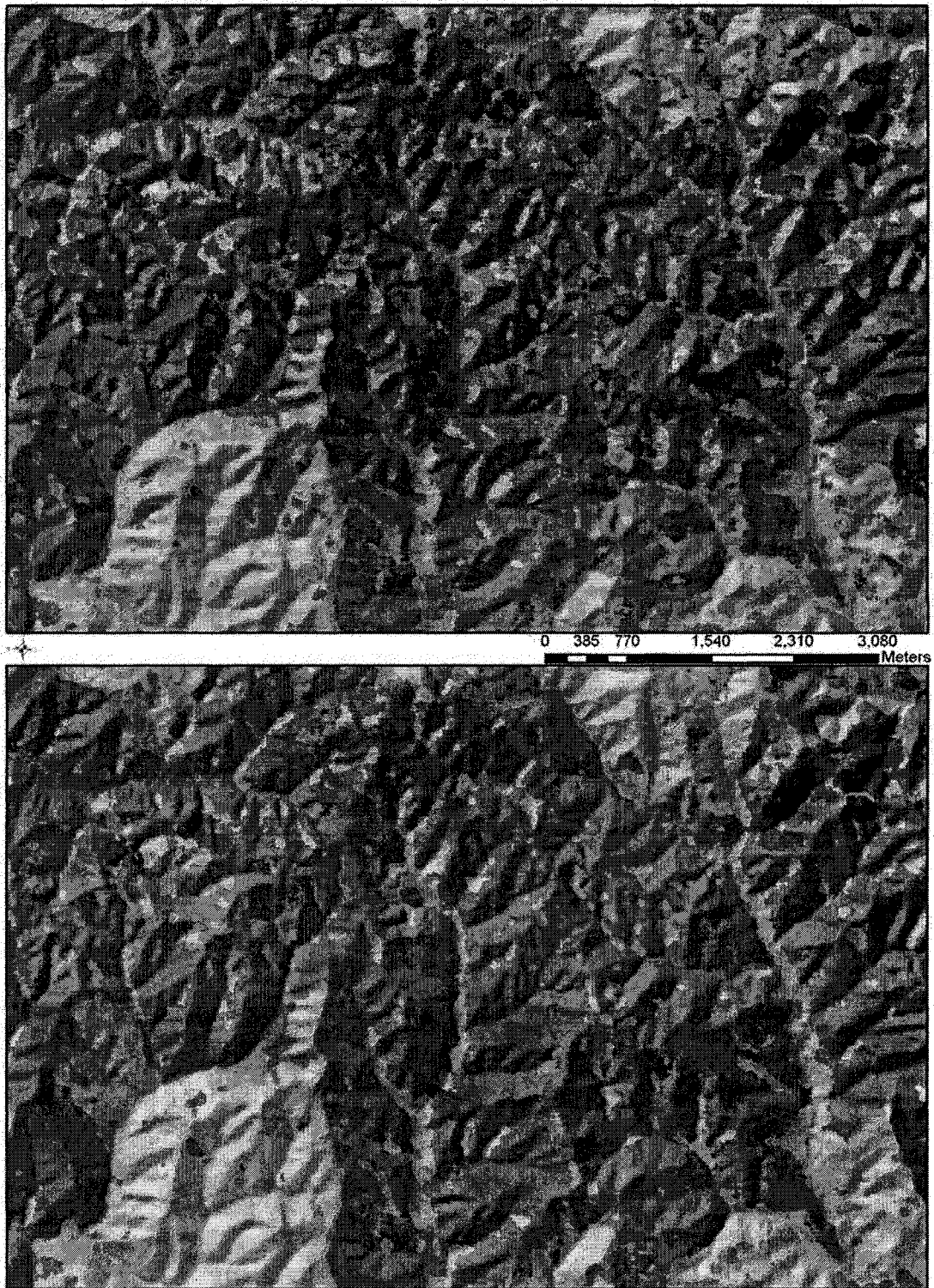
Figure 20: A comparison of the supervised classification of the orthorectified image (top) and the terrain-flattened image (bottom) shows little difference in misclassification in the center area of the image, which should be homogeneous Native Forest (dark green). It is mostly confused with Shrubland (orange) and Exotic Forest (lime green).

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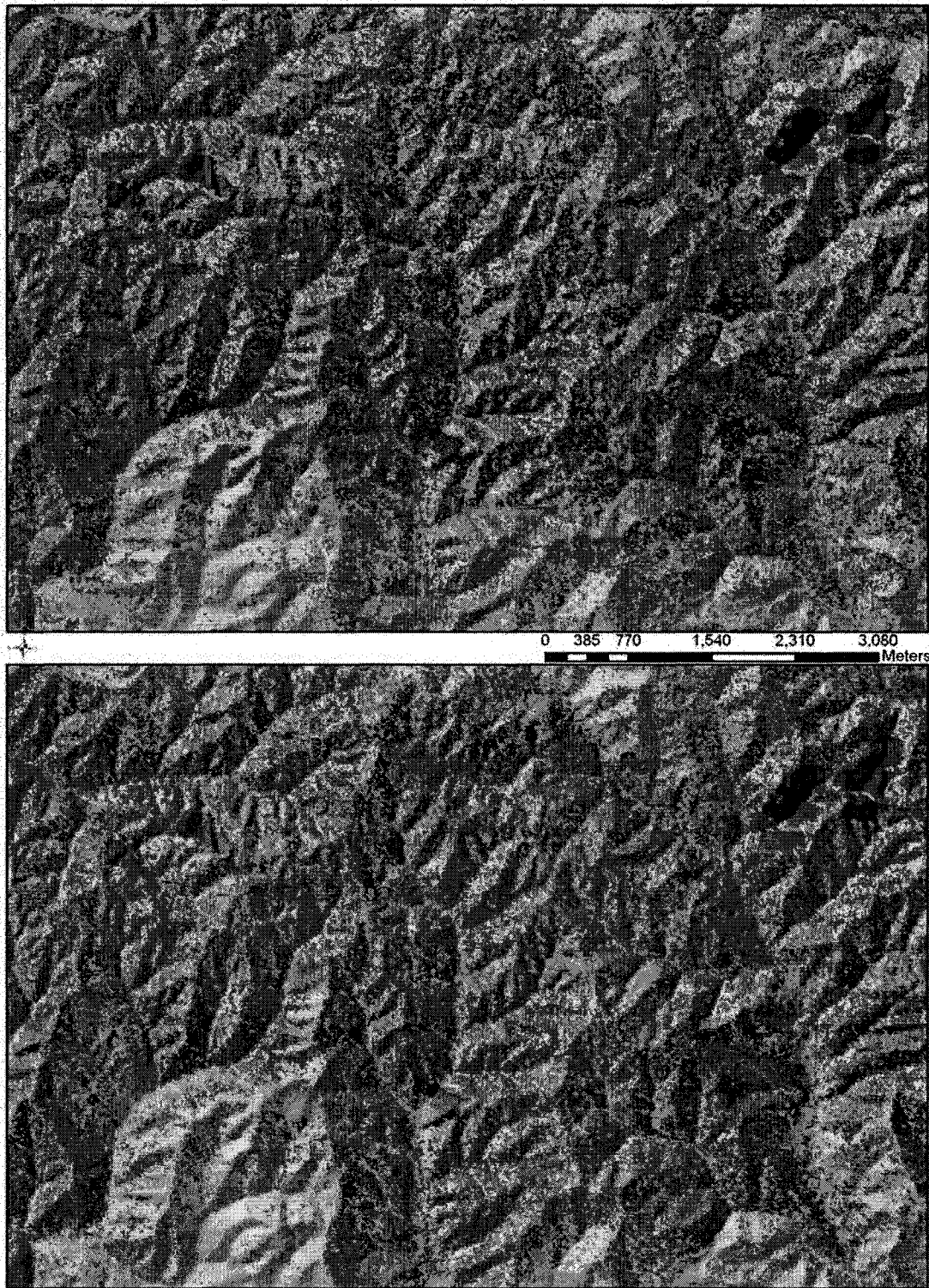
Figure 21: A comparison of the supervised classification of the orthorectified image (top) and terrain-flattened image (bottom) draped over a hillshade layer shows no specific pattern of misclassification related to aspect.

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Figure 22: A comparison of the filtered supervised classification of the orthorectified image (top) and terrain-flattened image (bottom) again shows little relation between the misclassification of homogeneous Native Forest and aspect.

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Conclusions

The high level of accuracy reported by Dymond and Shepherd (2004) was for a map created using hierarchical binary split decision rules and manual editing. The mapping objective was to classify indigenous vegetation, not all land cover. The minimum mapping unit used for the project was 225 m^2, or one pan-sharpened pixel. It is doubtful whether the accuracy of a project with such a small minimum mapping unit can be assessed due to errors associated with positional uncertainty of the reference data, which were also collected on a different scale. Some of these factors, more than the terrain-flattened imagery, may have been responsible for the high classification accuracy. A comparison to unprocessed imagery was never published. The research presented in this thesis attempted to make that comparison using basic classification techniques. The terrain flattened imagery did not significantly improve the classification accuracy in this study.

Further efforts are needed to explore the effect of terrain flattening on image classification accuracy. A more complete set of reference data that is distributed throughout the whole study area would be useful for a more effective comparison. Given the lack of access and the lack of aerial photography however, the feasibility of building a more complete reference data set is questionable. Segment based classification, machine learning algorithms, or other advanced classification techniques might be useful to further increase the accuracy of the thematic maps. Current satellite imagery that matches the date

of reference data collection would be beneficial, but given the questionable status of the Landsat program, this may not be possible in the near future. Like Mitri and Gitas' (2004) study, there was no significant difference using fairly general land cover categories. A more detailed classification could test the ability of the terrain flattening process to produce more accurate maps. This would require a new reference data set with many more land cover points to be collected. Unless a method to sample in the roadless areas could be devised and funded, additional points would have to be added to an already crowded area within 1 kilometer of accessible roads.

The flattening algorithm was not useful in this evaluation and would not likely be useful in any of the study areas proposed for the GLOBE Biodiversity Monitoring project in New Zealand. Other techniques should be explored to improve the accuracy of maps created for that purpose. The map accuracies achieved in this project are certainly not suitable for the change analysis that would be required for tracking changes in biodiversity over time.

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APPENDICES

APPENDIX A

CLASSIFICATION RULES

Native Forest – native woody tree species at least 5 meters tall. The canopy covers at least 40% of the ground.

Exotic Forest – exotic woody tree species at least 5 meters tall. The canopy covers at least 40% of the ground.

Shrubland – native or exotic woody species less than 5 meters tall. The shrub canopy covers at least 40% of the ground

Agriculture and Grassland – herbaceous vegetation covers more than 60% of the ground.

Urban and Developed – areas of residential, commercial, industrial or transportation uses that cover more than 40% of the ground.

Water – the land surface is continually covered by water. The water covers more than 60% of the ground.

Other – this category is used to classify the remainder of the otherwise unclassified pixels.

APPENDIX B

HISTOGRAM ANALYSIS

This section illustrates the histograms of the raw data for both the orthorectified image and terrain-flattened image.
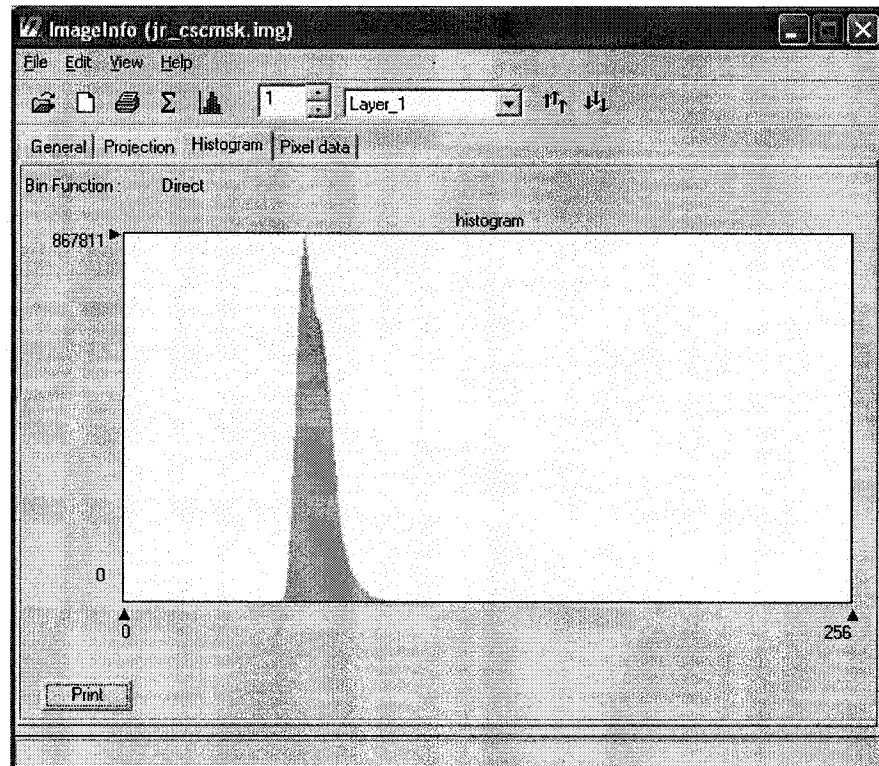
Figure 23: Band one of the orthorectified Landsat ETM+ image.

97
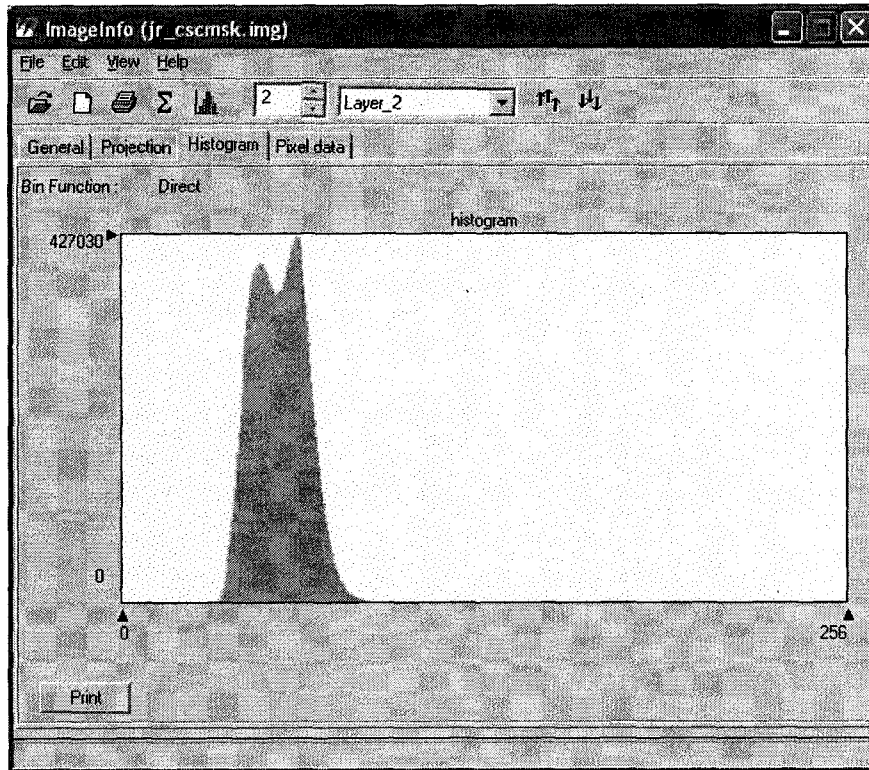
Figure 24: Band two of the orthorectified Landsat ETM+ image.
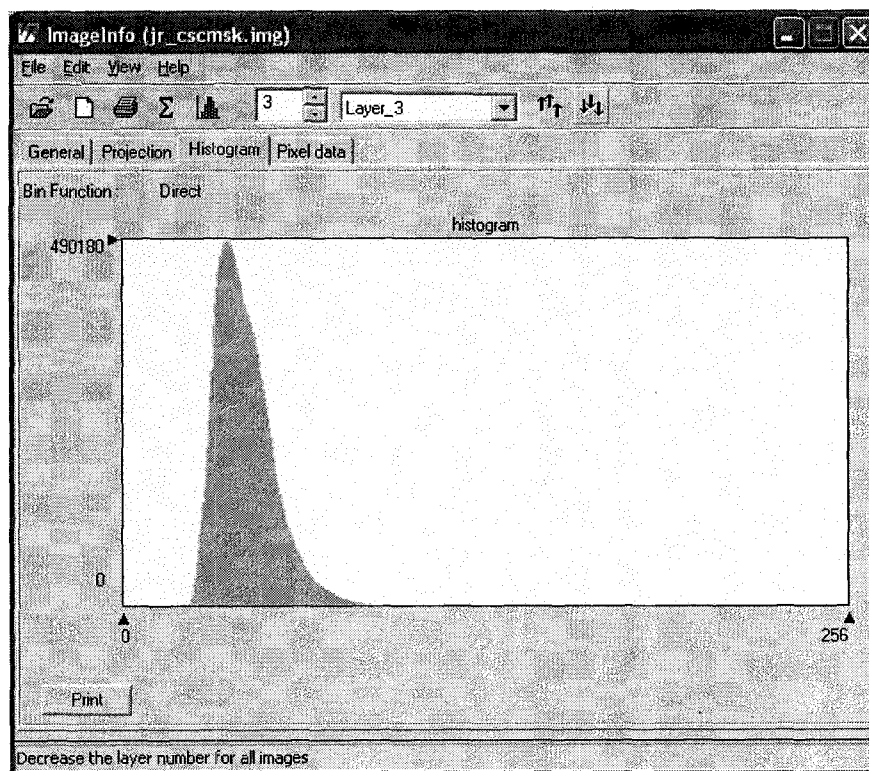
Figure 25: Band three of the orthorectified Landsat ETM+ image.

98
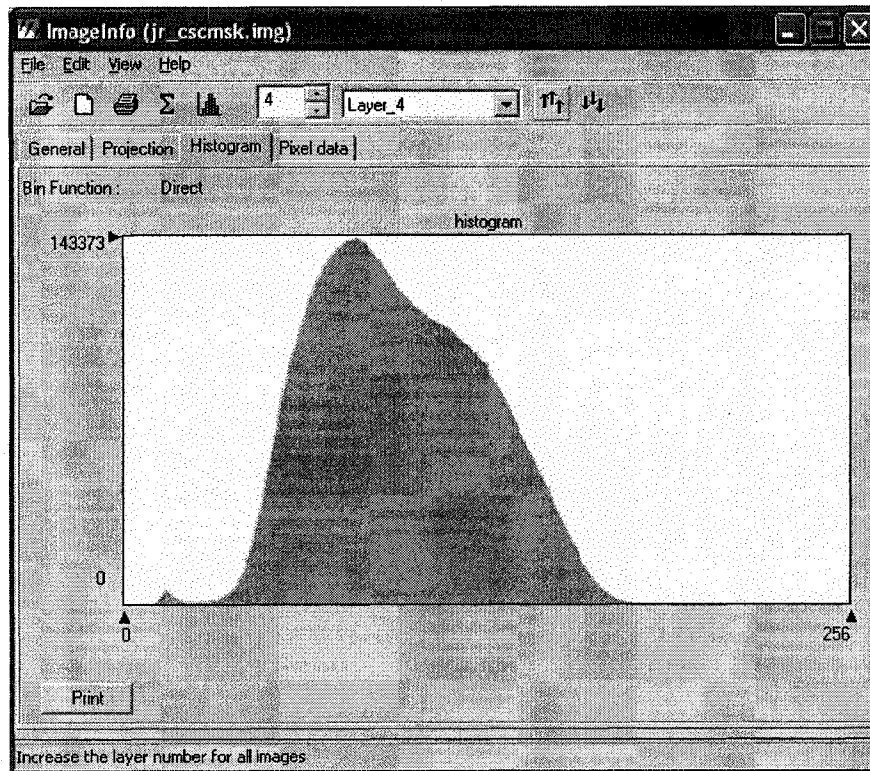
Figure 26: Band four of the orthorectified Landsat ETM+ image.
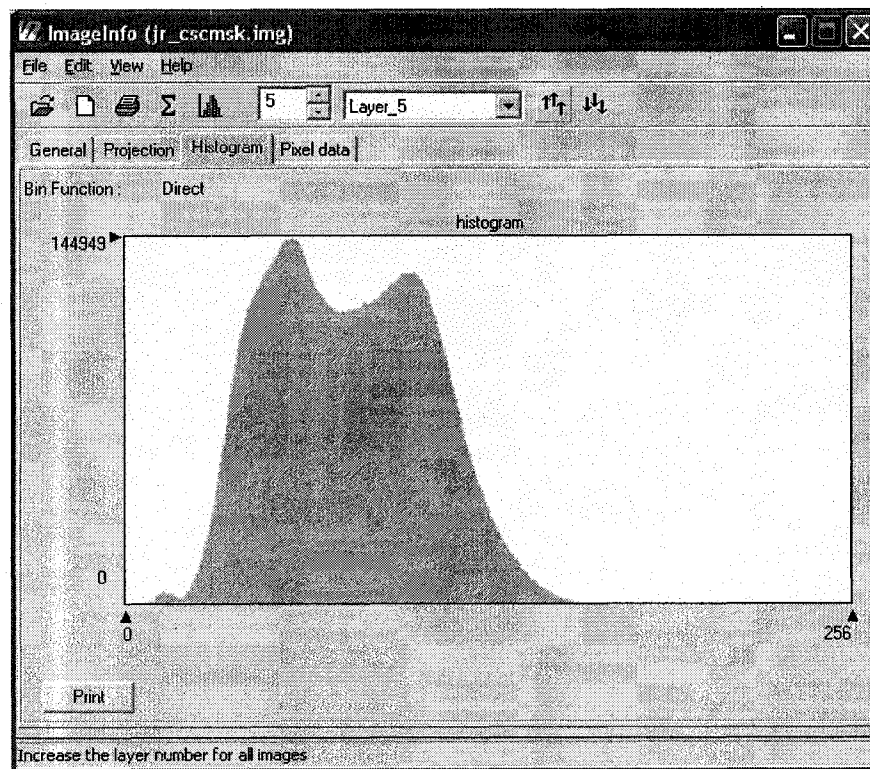
Figure 27: Band five of the orthorectified Landsat ETM+ image.

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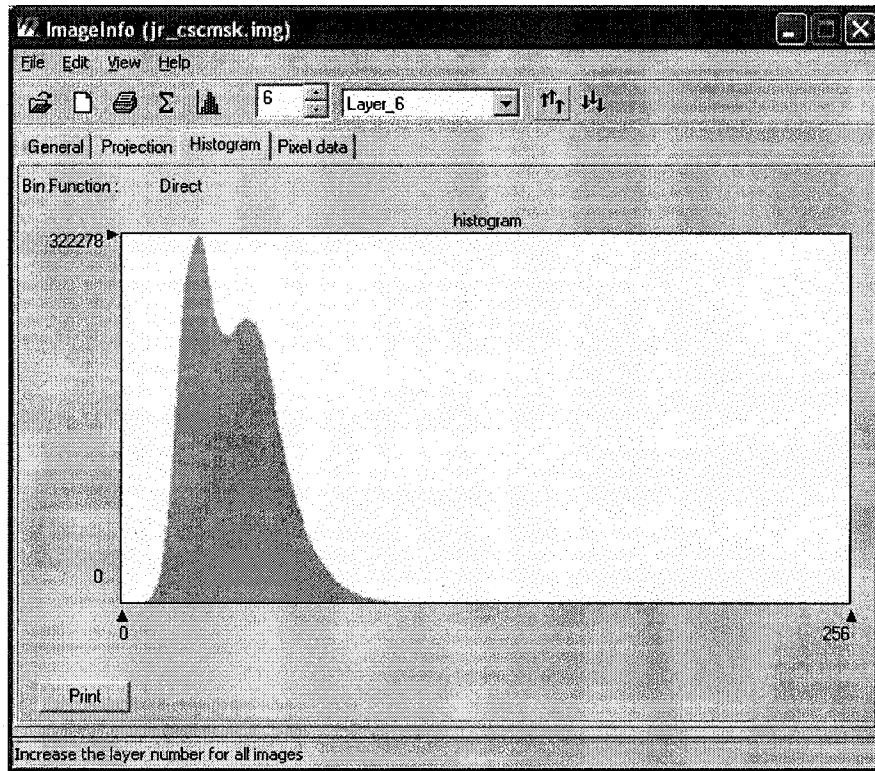
Figure 28: Band seven of the orthorectified Landsat ETM+ image.
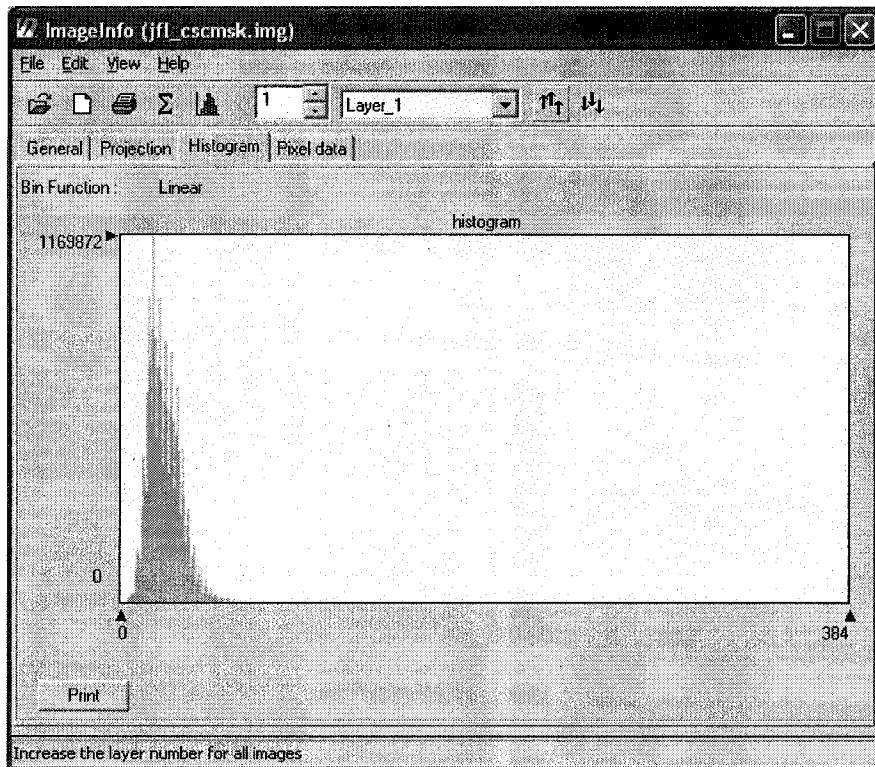
Figure 29: Band one of the terrain-flattened Landsat ETM+ image.

100
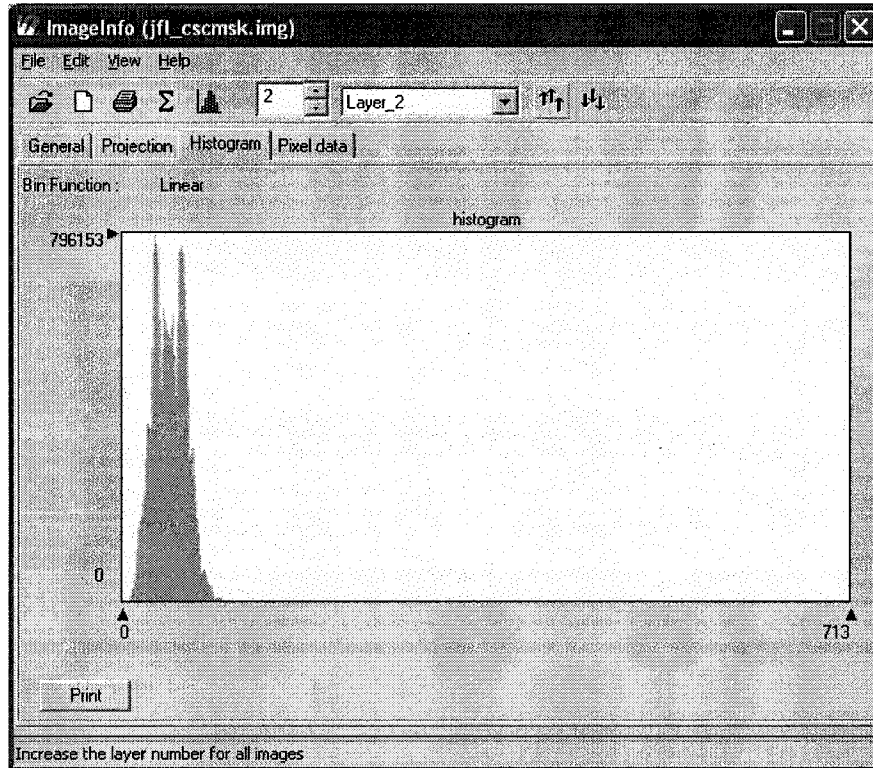
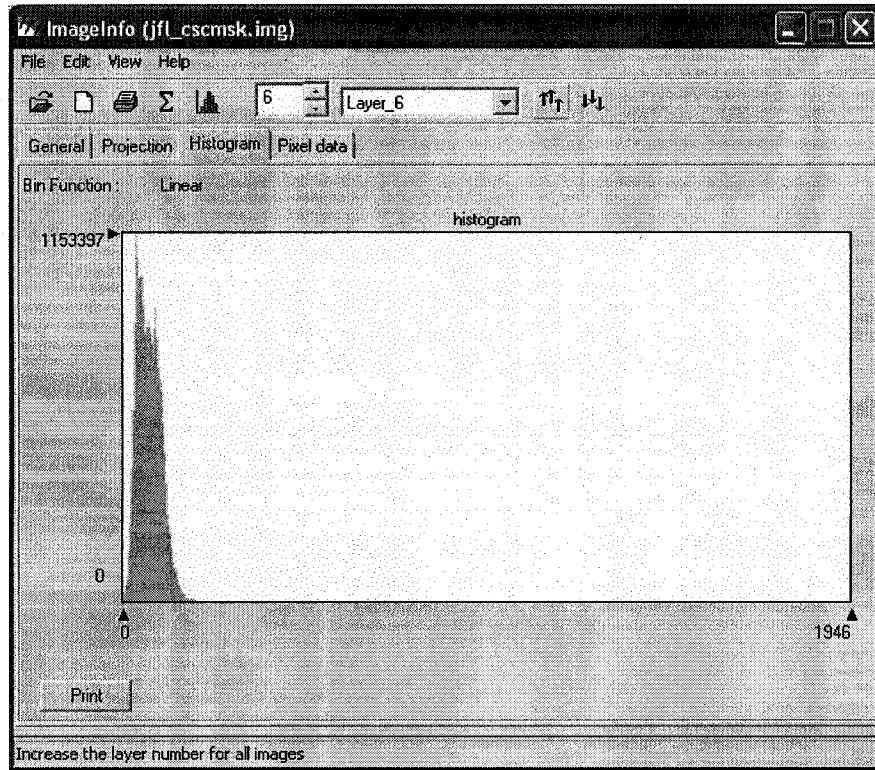**Figure 30: Band two of the terrain-flattened Landsat ETM+ image.**
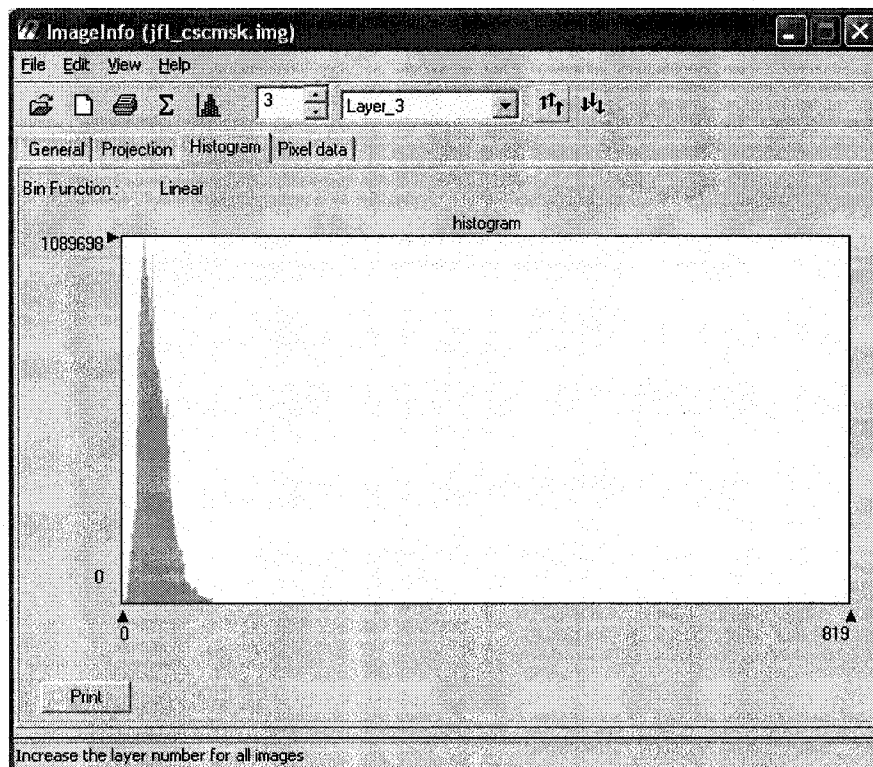
Figure 31: Band three of the terrain-flattened Landsat ETM+ image.

101
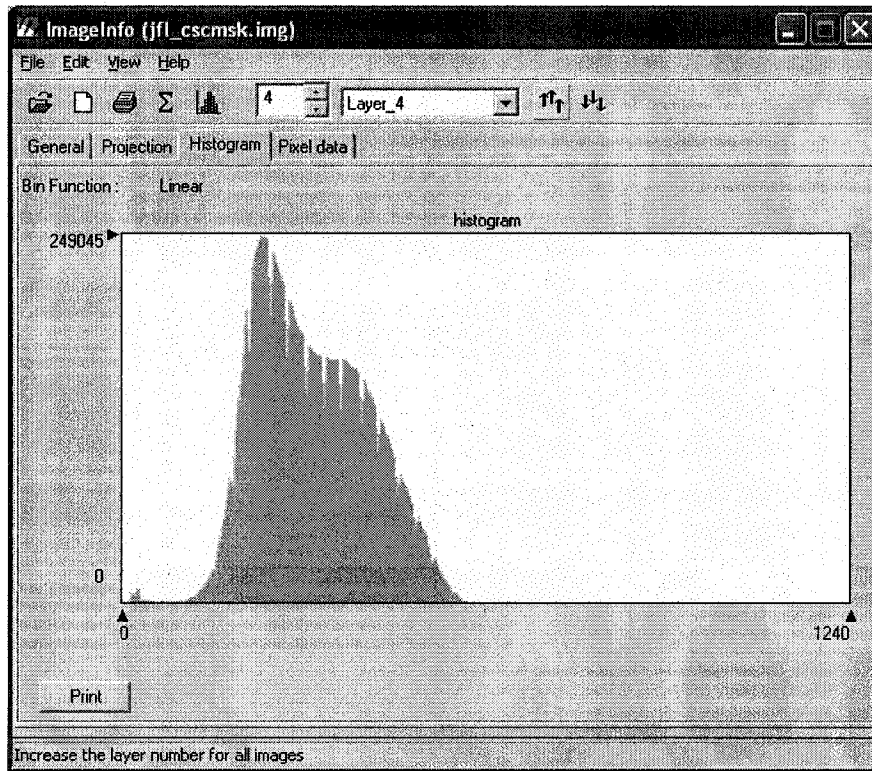
Figure 32: Band four of the terrain-flattened Landsat ETM+ image.
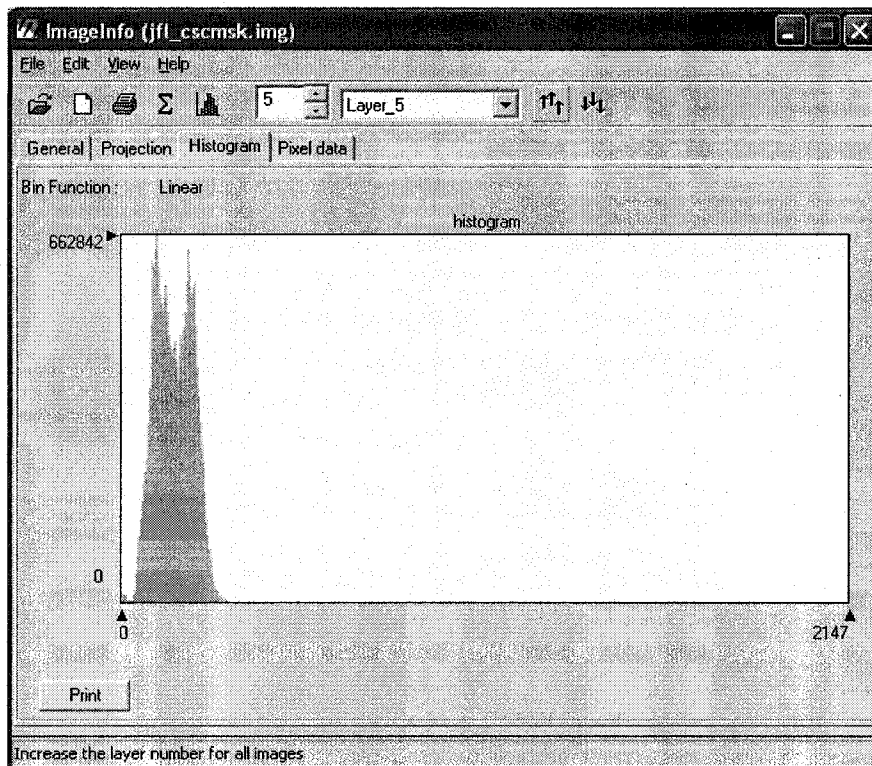
Figure 33: Band five of the terrain-flattened Landsat ETM+ image.

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Figure 34: Band seven of the terrain-flattened Landsat ETM+ image.
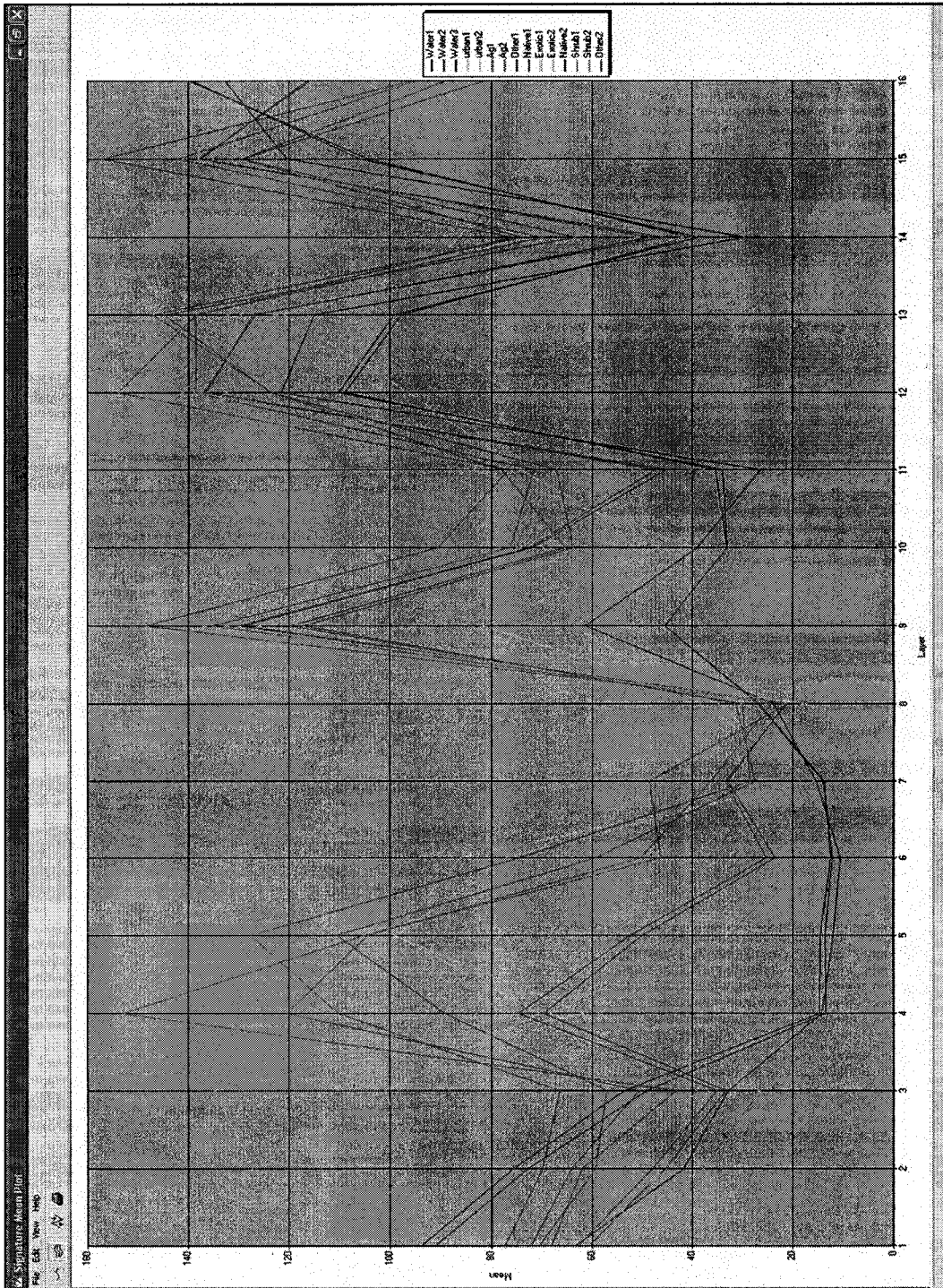
APPENDIX C

SPECTRAL PATTERN ANALYSIS

Figure 35: Spectral Pattern Analysis of the test training areas used to choose bands to classify the orthorectified image. Native Forest (dark green), Exotic Forest (lime green), Shrubland (orange), Agriculture/Grassland (red), Urban/Developed (cyan), Water (blue), and Other (purple).
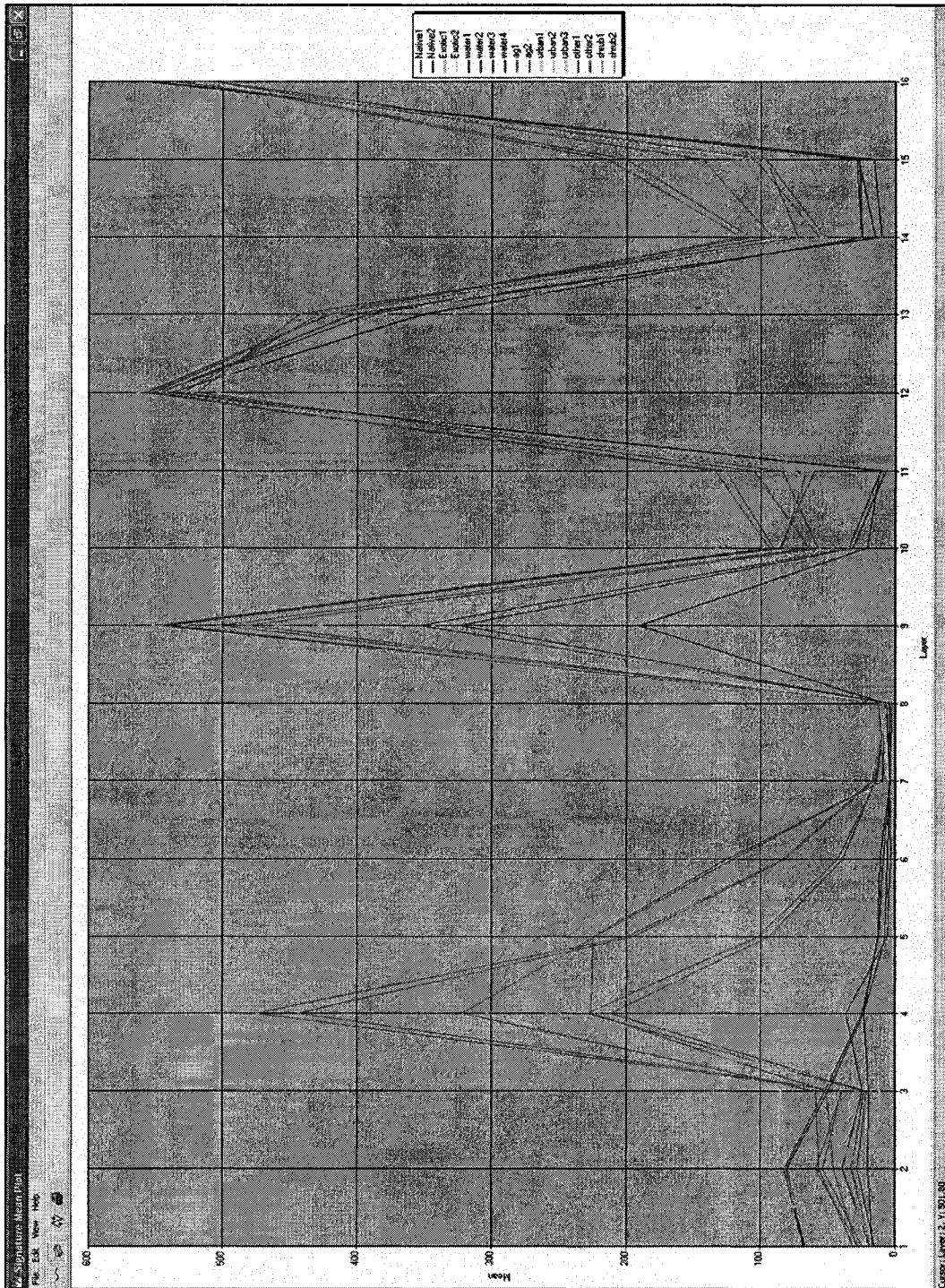
105

Figure 36: Spectral Pattern Analysis of the test training areas used to choose bands to classify the terrain-flattened image. Native Forest (dark green), Exotic Forest (lime green), Shrubland (orange), Agriculture/Grassland (red), Urban/Developed (cyan), Water (blue), and Other (purple).
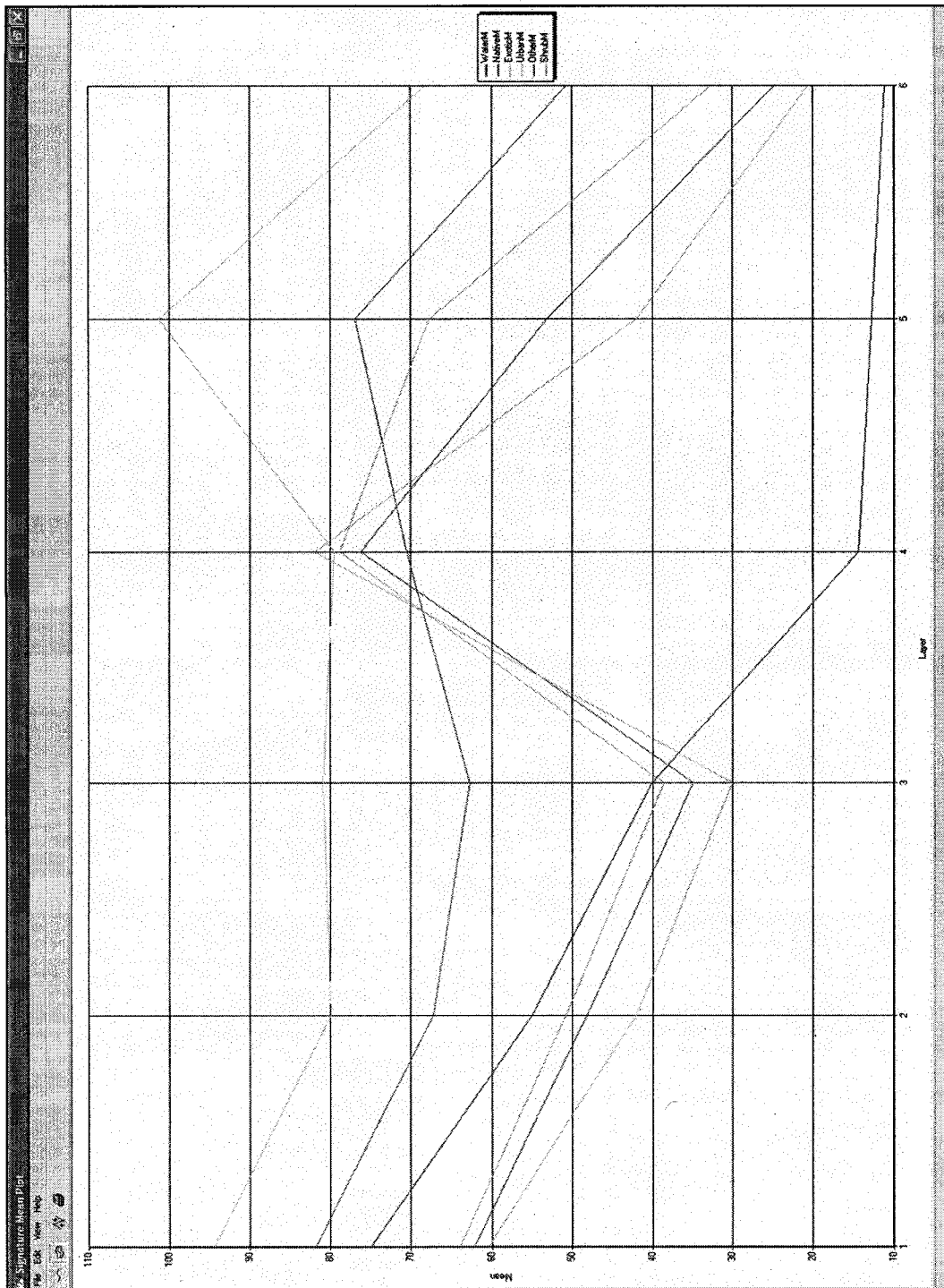
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Figure 37: Merged spectral signatures for the supervised training data used to classify the orthorectified image. Native Forest (dark green), Exotic Forest (lime green), Shrubland (orange), Agriculture/Grassland (red), Urban/Developed (cyan), Water (blue), and Other (purple).
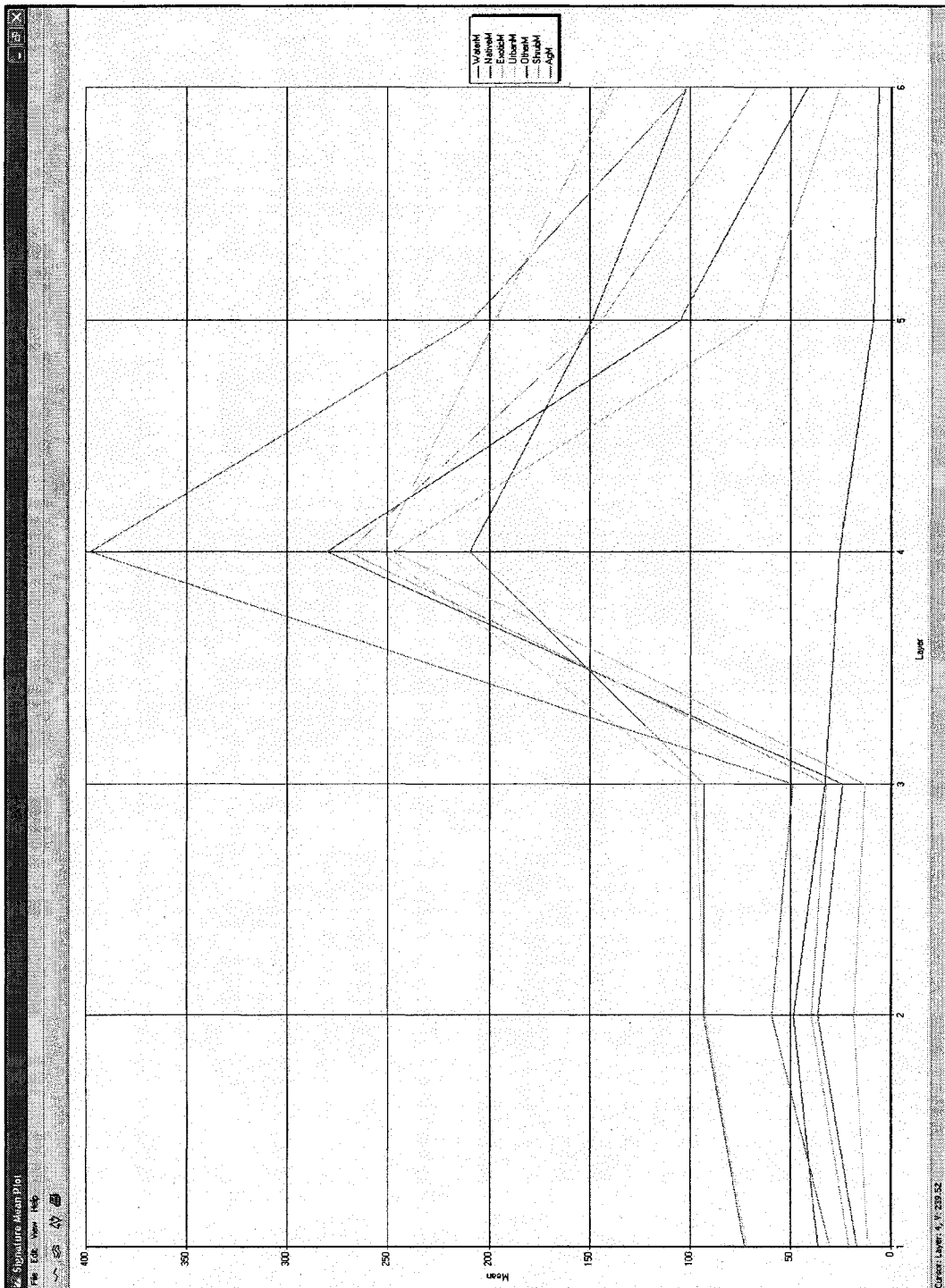
107

Figure 38: Merged spectral signatures for the supervised training data used to classify the terrain-flattened image. Native Forest (dark green), Exotic Forest (lime green), Shrubland (orange), Agriculture/Grassland (red), Urban/Developed (cyan), Water (blue), and Other (purple).

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APPENDIX D

SAS COMMANDS

The code for the hybrid classification for this paper was generated using SAS software, Version 9.1 of the SAS System for Windows. Copyright 2000-2004 SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA

The following commands were used to cluster data for hybrid classification:

```
proc cluster data=WORK.R_01 outtree=R_01_TREE method=complete  ccc
     pseudo;
     var Band1 Band2 Band3 Band4 Band5 Band6 ;
     id Class;
     run;
```

The following commands were used to output a dendrogram for hybrid classification:

```
goptions vsize=10in hsize=7.5in htext=2pt;
axis1 order=(0 to 1 by 0.01);
proc tree data=WORK.R_01_TREE out=New1 nclusters=7 graphics haxis=axis1
horizontal hpages=4 vpages=8;
height _rsq_;
copy Band1 Band2 Band3 Band4 Band5 Band6 ;
id Class;
run;
```

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APPENDIX E

HUMAN SUBJECTS APPROVAL

The Institutional Review Board granted pre-approval for research involving human subjects for this project based on the potential need to interview students regarding the data collected at the GLOBE Biodiversity Monitoring Workshops (Figure 39). There were no interviews or surveys conducted.

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UNIVERSITY *of* NEW HAMPSHIRE

March 10, 2004

Bishop, Jesse
Natural Resources, James Hall
Durham, NH 03824

IRB #:   3162
Study: Monitoring Biodeiversity at Selected Restoration Sites in New Zealand Using GLOBE
Data
Approval Date: 03/10/2004

The Institutional Review Board for the Protection of Human Subjects in Research (IRB) has reviewed and approved the protocol for your study as Expedited as described in Title 45, Code of Federal Regulations (CFR), Part 46, Subsection 110 with the following comments:

- Per the advisors' letter, any instruments or measures involving human subjects developed during the research will be submitted to the IRB for review prior to administration.

Approval is granted to conduct your study as described in your protocol for one year from the approval date above. At the end of the approval date you will be asked to submit a report with regard to the involvement of human subjects in this study. If your study is still active, you may request an extension of IRB approval.

Researchers who conduct studies involving human subjects have responsibilities as outlined in the attached document, *Responsibilities of Directors of Research Studies Involving Human Subjects.* (This document is also available at http://www.unh.edu/osr/compliance/IRB.html.) Please read this document carefully before commencing your work involving human subjects.

If you have questions or concerns about your study or this approval, please feel free to contact me at 603-862-2003 or Julie.simpson@unh.edu. Please refer to the IRB # above in all correspondence related to this study. The IRB wishes you success with your research.

For the IRB

Julie F. Simpson
Manager

cc: File
       Russ Congalton
       Mimi Larsen Becker

Figure 39: IRB approval for this study.