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

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ABSTRACT

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. Due to this rapid decline in biodiversity, the New Zealand government has made it a priority to halt this loss. Restoration of developed land and protection of remaining areas of native forest are two important ways to mitigate the loss of biodiversity. 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. However, there is significant terrain variation within many of these areas that may significantly reduce land cover classification accuracy. 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 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 various classification methods. The accuracy of the thematic maps was evaluated using error matrices and the different image processing techniques were statistically compared. It was determined that the topographic algorithm did not significantly improve map accuracy.

INTRODUCTION

This project was the result of a collaborative effort 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. The project was designed to use student collected data to validate land cover maps of restoration areas in New Zealand generated from satellite imagery. After initial field visits to the restoration sites in New Zealand, the researchers realized the need for terrain-flattened satellite imagery. A single restoration site was chosen as a trial site to evaluate the effectiveness of a terrain flattening algorithm developed by researchers at Landcare Research in New Zealand (Dymond and Shepherd, 2004).

New Zealand Ecology

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, 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. 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).

New Zealand was one of the last places in the world to feel the effect of human settlement. Polynesian settlers arrived 800 years ago and Europeans began a period of colonization approximately 200 years ago (King, 2003). Polynesian settlers burned large areas of native forest, exploited many large bird species, and introduced the first destructive mammalian predator, the kiore, or Polynesian rat (McGlone, 1989). In the one hundred years following European colonization, nearly two-thirds of the land area of New Zealand has been converted through human use (Figure 1). 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). Lowland forests were cleared for agriculture and timber. Grasslands and shrublands were burned and planted for grazing. Lowland areas, such as alluvial floodplain forests, fertile wetlands, and grasslands suffered the greatest destruction (Norton and Miller, 2000). Human settlers brought many species of plants and animals, used for both income and convenience, when they settled New Zealand. These species have had an incredible impact on the natural landscape. Indeed, introduced species now outnumber native and naturalized species (Anon., 2000). Effectively, there are now two plant and animal communities within New Zealand; those that evolved there and those that were brought by humans (Taylor and Smith, 1997). Native fauna have been affected by this shifting land use. Many indigenous species are unable to compete in these modified habitats, resulting in small, fragmented populations and widespread extinctions (Anon., 2000).

The New Zealand government has recognized the intrinsic and economic values of biodiversity. The native flora and fauna represent the unique characteristics of New Zealand. The numbers of two national icons, the kiwi - a flightless bird - and the silver fern, are decreasing, mainly due to habitat loss and predation. The Maori, the original settlers of New Zealand, have a strong connection with the land and believe humans have a common ancestry with animals. Therefore, conservation of native biodiversity is very important to them (Anon., 2000). The Department of Conservation (DoC) is responsible for the management of a majority of the 8 million hectares of conservation land in New Zealand. Intensive pest control was carried out on 1.3 million hectares by DoC in 1997 (Taylor and Smith, 1997).

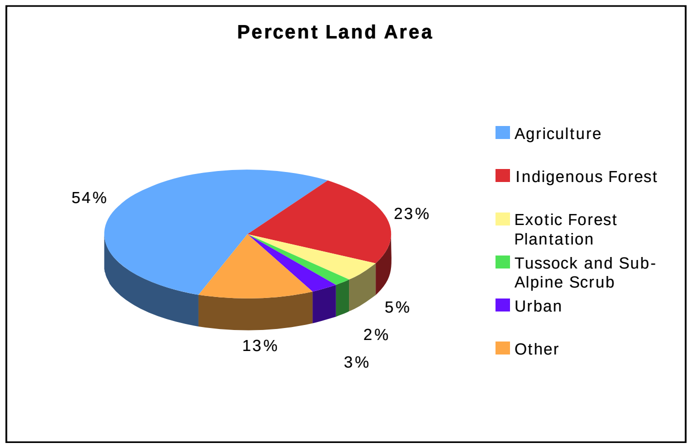

Figure 1. Present day land cover of New Zealand.

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. Recently, 'mainland islands,' either 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 (Sanders and Norton, 2001). This large-area management lends itself to monitoring by remote sensing. Some of these restoration areas were the focus of the GLOBE collaboration.

In 1995, tourism was worth approximately NZD$5 billion, nearly a quarter of the country's overseas earnings (Taylor and Smith, 1997). New Zealand's clean and green image along with the distinct flora and fauna are a major draw for 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 these concerns and help to protect the valuable resource that is biodiversity (Anon., 2000). This strategy has been implemented throughout the government and strong community support among stakeholders has been evident since its publication in 2000.

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 GLOBE Land Cover/Biology team at the University of New Hampshire developed standardized collection protocols that instruct students how to collect land cover data. 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 is accurate and reliable (Rock and Lauten, 1996; Budd, 1997; Becker et al., 1998; Rowe, 2001).

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 throughout 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

Monitoring land cover and land use over large areas has traditionally been expensive and time consuming using field observation techniques. Since the 1970s, satellite-based remote sensing has provided an increasingly affordable opportunity to monitor land cover and land use. 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). 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, leading to lower classification accuracies when using traditional per-pixel classification methods (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. Atmospheric effects and topography have a significant impact on the interaction of light and vegetation, creating difficulty in measuring actual vegetation reflectance (Shepherd and Dymond, 2003; Dymond and Shepherd, 1999; Dymond and Qi, 1997). 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). 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).

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 Lambertian reflectance (cosine) model has proven to be too simple in that it only removes the effects of illumination and vegetative canopies rarely are Lambertian surfaces (Dymond and Shepherd, 1999; Shepherd and Dymond, 2003). The Minnaert and c-correction models tend to oversimplify the photometric model, resulting in inaccurate terrain correction (Gu and Gillespie, 1998). Empirical models have been developed that account for illumination and reflection. 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. Complete models are not available and *in situ* models may not be suitable because of the scale dependent nature of 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. The model built using these parameters was tested on both a simulated tree canopy and on Landsat TM data.

Tree canopies can be modeled in two parts: as suspended sediments and with large shadows cast on the canopy (Dymond and Qi, 1997). Dymond et al (2001) propose a three-parameter vegetation reflectance model (WAK) that outperforms many more complex models. 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. This correction was applied to SPOT data. Dymond and Shepherd (2004) applied this correction to Landsat ETM+ data in the Wellington Region in New Zealand and produced an indigenous forest map using hierarchical binary split rules. The overall map accuracy of 95% was attributed to the terrain normalization technique.

Image Classification

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. In the supervised classification process, training statistics are generated from areas of the image that are representative of the informational categories defined in the classification scheme. The unsupervised classification process partitions the image into spectrally similar groups. Multiple spectral classes may represent the informational classes used in the supervised approach or there may be spectral confusion between two or more informational classes. Conversely, spectral clusters generated by unsupervised classification may not match a given informational class. A combination of these techniques, termed hybrid classification, has been used to improve the accuracy of image classification. Chuvieco and Congalton (1998) 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 used to test the groupings. Jensen's (2005) cluster busting technique uses iterations of unsupervised classification and cluster analysis to assign informational classes to the image.

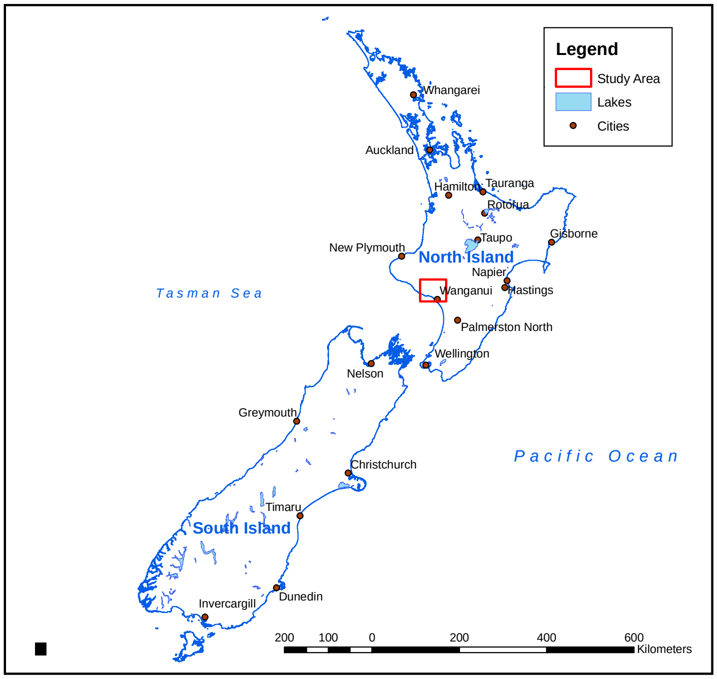

Figure 2. The location of the study site in New Zealand.

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 advantageous. 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. There are many considerations when choosing a sampling scheme for the collection of reference data. Simple random sampling is a statistically sound method but may result in undersampling of rarely occurring map classes. Stratified random sampling uses prior knowledge of the study area to divide samples into classes, resulting in all classes being included in the sample (Congalton and Green, 1999).

Although stratified random sampling does not meet the assumption of the multinomial model, Kappa analysis is an appropriate measure of map accuracy (Plourde and Congalton, 2003).

The error matrix is now a commonly used tool for expressing map accuracy. Kappa analysis is a discrete multivariate technique that is used to determine if error matrices are statistically different from one another. Kappa analysis results in the KHAT statistic, a measure of agreement that is based on actual agreement and chance agreement. KHAT values are compared using a two-tailed Z test (Congalton and Green, 1999).

METHODS

Study Area

The final study area for this project (Figure 2) was chosen from an initial field of five restoration areas throughout New Zealand. While this area does not have the largest native forest reserve, other factors, such as the greatly-varied terrain (Figure 3), 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 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 (NZ Census, 2001). The next largest population center is the town of Waverly, 44 kilometers northwest of Wanganui along the main road through the study area, State Highway 3. The population of Waverly in 2001 was 903 (NZ Census, 2001). There are a number of smaller settlements throughout the area with a total population of 4500 in 2001 (NZ Census, 2001).

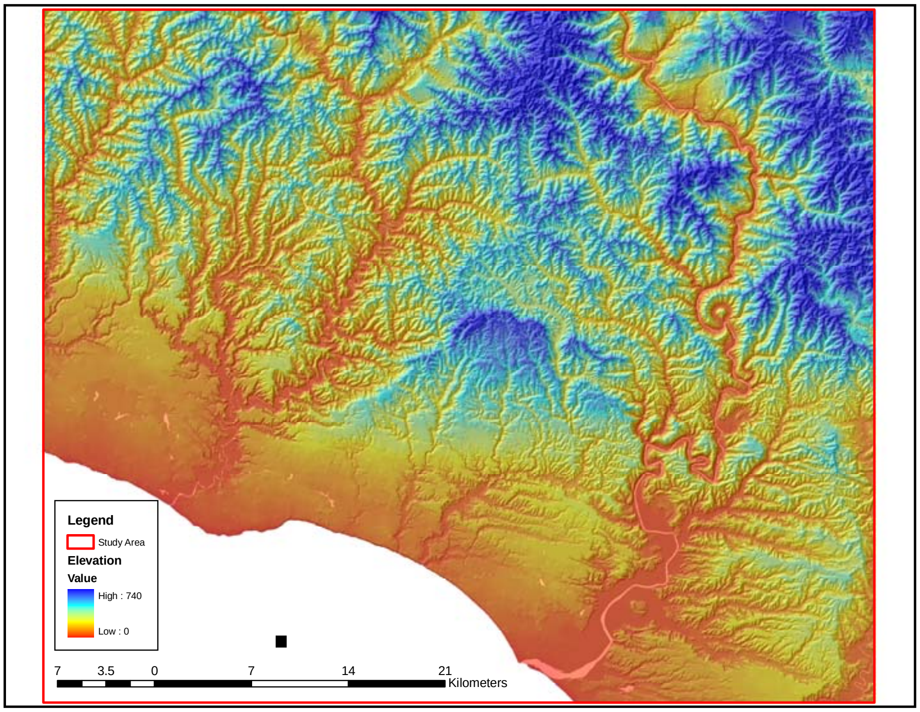

Figure 3. The terrain of the study area is greatly varied.

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 come across in the study area. The MUC codes were listed. 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 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 sampling was restricted within 1 kilometer of roads. The Land Cover Data Base version 2 (LCDB2) 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. These points were loaded into a Garmin 12XL GPS receiver.

In September and October 2004, field sampling was conducted to verify the land cover of these reference points. The points and roads were plotted on 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. A number of points were inaccessible due to washouts following floods in February 2004. Limited 1:50,000 scale orthophoto coverage for the study area exists and if photos were available for the unknown points, the land cover class was determined from photo interpretation if possible. If there was no orthophoto coverage or if it was not possible to determine the land cover from the photos, then the reference points were removed. A small portion of student-collected data was added to the reference database. A portion of this dataset was put aside for training purposes. In addition to the random points, the locations of areas that were deemed exemplary training areas were recorded.

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 Landsat ETM+ image acquired in November 2000. These images include bands 1-5 and 7. The first was an orthorectified scene and the second was further processed with their flattening algorithm. 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, respectively. The images were registered in Zealand Map Grid (NZMG) coordinates with a 10 meter geo-registration accuracy. The images were resampled using cubic convolution.

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. 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. Derivative bands were created for both images. This 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). These derivative bands were rescaled to match the average dynamic range of the raw data bands for each image. Training areas were seeded to generate initial image statistics for both images. These statistics were used to evaluate separability between the land cover classes. Both Spectral Pattern Analysis and Divergence Analysis (Transformed Divergence and Jefferies-Matusita) revealed that for both images, the raw bands provided more separability than the derivative bands. Thus, it was decided that all further classification would proceed with the raw data.

Image Classification

In order to have a fair comparison between the images, the same classification techniques were used on both. 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 unsupervised classifications were performed for each whole image (i.e. no skip factor), having 200, 250, 300, and 500 classes. The convergence threshold was set to 0.99, with a

Table 1. Land cover training data

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

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. The 200 class unsupervised classifications proved unsatisfactory because of confusion between classes that was visually evident. 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 300 class unsupervised classification was chosen as the final output for both images.

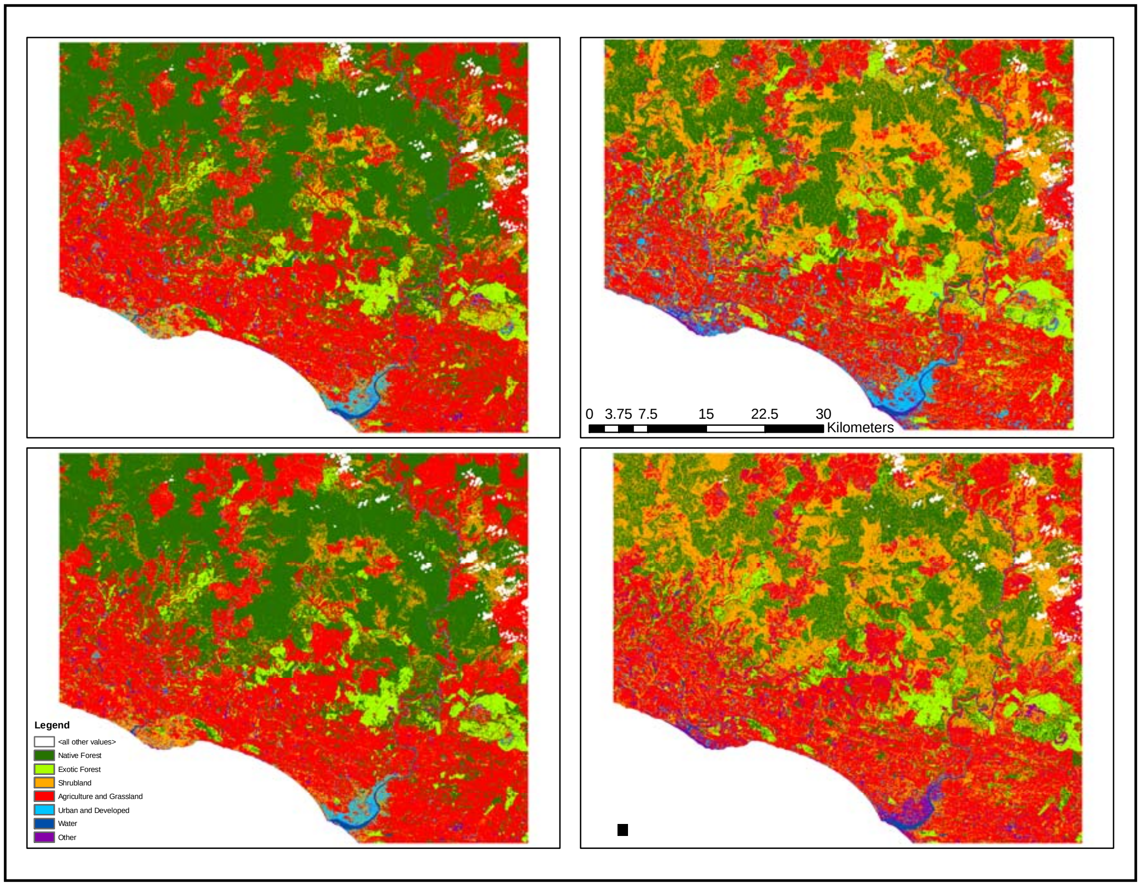

Figure 4. **E**xamples of thematic maps resulting from the classification process. Clockwise from top left: orthorectified unsupervised, flattened supervised, flattened hybrid, flattened unsupervised.

Supervised Classification. Training statistics were developed using seed and polygon based Areas of Interest (AOIs) selected from the training data. Spectral pattern analysis, contingency analysis, and bi-spectral plots were used to refine the final number of training areas per class (Table 1). A supervised classification was performed for each image using the maximum likelihood rule.

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 computed using squared Euclidean distance. These data were exported to SAS 9.

Table 2. Accuracy assessment of the unsupervised classification of the orthorectified image

Orthorectified Unsupervised

Classified	Reference 1	2	3	4	5	6	7	Total	User's Accuracy
1 Native Forest	93	28	59	9	2	9	2	202	46.04%
2 Exotic Forest	1	41	0	1	0	0	0	43	95.35%
3 Shrub	5	13	12	10	21	3	10	74	16.22%
4 Agriculture/grassland	8	15	21	106	15	6	12	183	57.92%
5 Urban/Developed	0	0	2	3	48	2	8	63	76.19%
6 Water	0	0	5	0	1	46	2	54	85.19%
7 Other	0	0	0	6	2	1	16	25	64.00%
Total	107	97	99	135	89	67	50	644	
Producer's Accuracy	86.92%	42.27%	12.12%	78.52%	53.93%	68.66%	32.00%		

Overall Accuracy	KHAT	Variance	Z Score
56.21%	47.58%	0.00053184	20.632

Cluster analysis was performed on each image's dataset using 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 0.985 was chosen as the minimum value for an acceptable grouping. The unsupervised classes were labeled according to the training classes. Unsupervised classes that were not clustered with training statistics were labeled 'unclassified.' The classified areas were put aside and the unclassified areas were used as a mask on the original image. A 100 class ISODATA unsupervised classification was performed on the unclassified area of the original image. The statistics from this classification were merged with the training data. Again, the clustering process was used and a dendrogram was output. For the orthorectified image, these relationships were evaluated and a third iteration of the clustering process was run. For the flattened image, the third iteration did not produce any significant relationships between the unsupervised spectral classes and the informational training classes. Photo and image interpretation were used to label the remaining unlabelled classes. The final classification for each image was then assembled from the partial classifications resulting from each iteration.

Image Post-processing. All final classification images were recoded and dissolved to reflect the land cover code used in the classification scheme. A 3x3 majority filter was used to reduce the speckle in all of the classifications.

Table 3: Accuracy assessment of the unsupervised classification of the flattened image.

Flattened Unsupervised

Classified	1	2	3	4	5	6	7	Total	User's Accuracy
1 Native Forest	90	25	57	10	0	12	2	196	45.92%
2 Exotic Forest	4	52	1	2	0	0	0	59	88.14%
3 Shrub	2	4	13	7	19	6	12	63	20.63%
4 Agriculture/grassland	10	16	22	108	13	5	14	188	57.45%
5 Urban/Developed	0	0	2	4	56	1	6	69	81.16%
6 Water	0	0	2	0	0	41	0	43	95.35%
7 Other	1	0	2	4	1	2	16	26	61.54%
Total	107	97	99	135	89	67	50	644	
Producer's Accuracy	84.11%	53.61%	13.13%	80.00%	62.92%	61.19%	32.00%		

Columns 1–7: Reference.

Overall Accuracy	KHAT	Variance	Z Score
58.39%	50.13%	0.00052812	21.815

Accuracy Assessment

Disagreement between the stratified reference data groupings and actual land cover resulted in an uneven distribution among the land cover classes. For preliminary analysis, no efforts were made to correct the uneven distribution of sample points. The thematic maps resulting from the various classification processes were exported to ESRI GRID files using ArcMap 9.1. Each of these was then evaluated using Jenness Enterprises' Cohen's Kappa and Classifications Table Metrics 2.0 extension for ArcView. The average class value from a 45meter radius circle was used to approximate the 90x90 meter minimum mapping unit in order to determine the map value for each point in the accuracy assessment portion of the reference dataset. The Kappa statistics for each image were compared for each classification technique.

PRELIMINARY RESULTS

The classification process resulted in six thematic maps. Figure 4 gives four examples. The overall accuracy was slightly higher for the flattened image for the supervised and unsupervised classification techniques (Tables 2-5). The overall accuracy was lower for the flattened image for the hybrid classification technique (Table 6). The classifications are significantly better than random classifications. However, the comparison of the kappa values

Table 4. Accuracy assessment of the supervised classification of the orthorectified image

Orthorectified Supervised

Classified	1	2	3	4	5	6	7	Total	User's Accuracy
1 Native Forest	60	9	21	4	0	4	1	99	60.61%
2 Exotic Forest	4	63	3	4	0	0	1	75	84.00%
3 Shrub	32	8	45	7	1	4	0	97	46.39%
4 Agriculture/grassland	2	7	15	98	12	4	7	145	67.59%
5 Urban/Developed	0	0	1	11	74	0	11	97	76.29%
6 Water	0	0	2	0	0	35	0	37	94.59%
7 Other	9	10	12	11	2	20	30	94	31.91%
Total	107	97	99	135	89	67	50	644	
Producer's Accuracy	56.07%	64.95%	45.45%	72.59%	83.15%	52.24%	60.00%		

Columns 1–7: Reference.

Overall Accuracy	KHAT	Variance	Z Score
62.89%	56.26%	0.00049798	25.211

within each classification technique shows no significant difference between the orthorectified and terrain flattened imagery (Table 7).

CONCLUSIONS

The moderate degree of agreement 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 has potentially allowed a great deal of land cover change to take place within the study area. The rapid growth of exotic forests creates a quick rotation rate for plantations. There is potential for much change within this class alone. 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). It is likely that some agricultural land has 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 limited coverage, only reference data in the western portion of the study area was checked against orthophotos acquired in 2000/2001. Recent cloud-free Landsat ETM+ data has not been available for this area.

Table 6. Accuracy assessment of the supervised classification of the flattened image

Flattened Supervised

Classified	Reference 1	2	3	4	5	6	7	Total	User's Accuracy
1 Native Forest	56	10	20	6	0	3	1	96	58.33%
2 Exotic Forest	2	59	2	3	1	0	2	69	85.51%
3 Shrub	43	19	54	12	0	6	2	136	39.71%
4 Agriculture/grassland	4	8	12	92	10	4	6	136	67.65%
5 Urban/Developed	0	0	2	18	76	1	5	102	74.51%
6 Water	1	0	5	0	1	39	0	46	84.78%
7 Other	1	1	4	4	1	14	34	59	57.63%
Total	107	97	99	135	89	67	50	644	
Producer's Accuracy	52.34%	60.82%	54.55%	68.15%	85.39%	58.21%	68.00%		

Overall Accuracy	KHAT	Variance	Z Score
63.66%	57.05%	0.00050585	25.364

It is evident from the error matrices that there are high errors of omission (i.e. when an area is excluded from the class to which it belongs) in the shrub, exotic forest, and other categories resulting in errors of commission (i.e. when an area is included in a class to which it does not belong) in native, shrub and agriculture. This is likely the result of the spectral similarity of these classes.

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

Table 5. Accuracy assessment for the hybrid classifications

Orthorectified Hybrid

Classified	Reference 1	2	3	4	5	6	7	Total	User's Accuracy
1 Native Forest	52	21	22	8	1	5	2	111	46.85%
2 Exotic Forest	8	57	2	3	0	2	1	73	78.08%
3 Shrub	39	9	48	12	0	6	1	115	41.74%
4 Agriculture/grassland	3	6	15	94	17	2	9	146	64.38%
5 Urban/Developed	1	1	2	12	43	1	11	71	60.56%
6 Water	0	0	5	0	0	46	3	54	85.19%
7 Other	4	3	5	6	28	5	23	74	31.08%
Total	107	97	99	135	89	67	50	644	
Producer's Accuracy (%)	48.60%	58.76%	48.48%	69.63%	48.31%	68.66%	46.00%		

Overall Accuracy	KHAT	Variance	Z Score
56.37%	48.45%	0.00053158	21.014

Flattened Hybrid

Classified	Reference 1	2	3	4	5	6	7	Total	User's Accuracy
1 Native Forest	54	32	14	6	1	5	4	116	46.55%
2 Exotic Forest	0	38	0	1	0	0	0	39	97.44%
3 Shrub	47	24	62	16	8	7	1	165	37.58%
4 Agriculture/grassland	5	3	14	97	29	2	13	163	59.51%
5 Urban/Developed	0	0	0	5	5	0	2	12	41.67%
6 Water	0	0	5	0	0	47	2	54	87.04%
7 Other	1	0	4	10	46	6	28	95	29.47%
Total	107	97	99	135	89	67	50	644	
Producer's Accuracy	50.47%	39.18%	62.63%	71.85%	5.62%	70.15%	56.00%		

Overall Accuracy	KHAT	Variance	Z Score
51.40%	42.53%	0.00052532	18.557

account for some of the error in this study.

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. These factors may have been responsible for the high classification accuracy. A comparison to unprocessed imagery was never published. The terrain flattened imagery did not significantly improve the classification accuracy in this comparative study.

Further efforts are needed to improve the overall classification accuracy of this study. Increased care in the selection of training areas may result in more accurate supervised and hybrid classifications. Further classification techniques (e.g. image segmentation using Feature Analyst and eCognition) will be explored and the results compared.

Table 7. Comparison of the KHAT values for the orthorectified and flattened image by each classification method

Pair-wise Comparison	
Classification	**Z Score**
Unsupervised	0.784163
Supervised	0.248712
Hybrid	1.819902

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APPENDIX

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 ore than 60% of the ground.

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