Land use/ Land cover classification in the Northern Part of New Zealand

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Abstract

In this project, a supervised classification was applied in a study area in Northern New Zealand. The study was conducted by using Landsat 7 TM (Thematic Mapper) imagery. Through preprocessing, the Landsat image was geometrically corrected using a geo-referenced image. Bands 1, 4, 5 were chosen to apply the classification. Periodical noise was partially removed through Fourier transformation in the three chosen bands. Last step in preprocessing was contrast stretching by using histogram stretch. The supervised classification method was used to apply the classification. 53 training areas were selected as sampling areas. Finally, eight classes were derived by recoding. The overall accuracy was about 86.00%. The urban areas and shadows were hard to classify. Hence, object-based classification was used to find the urban area. Next to supervised classification, unsupervised classification was also adopted as a comparison. In conclusion, we can say that supervised classification is more accurate than unsupervised classification and the defects can be solved by the object-based classification. The result can be more accurate by increasing the training areas in supervised classification and using smaller scale parameter in object-based classification. Future improvement can be considered to remove the noise more effectively and adopt advanced methods like ratio images to improve the accuracy.

Key words

Land use/ land cover classification, Fourier analysis, Accuracy assessment, Pixel-based classification, Object- based classification

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1. Introduction

Since the launch of the first Landsat-1 satellite on July 23, 1972 the Landsat satellite is from great importance for investigating our environment. The Landsat satellites follow a near-polar orbit, and are sun-synchronous. This means that the orbit of this satellite processes the earth at the same angular rate as the earth revolves around the sun (Lillesand et al., 2014). The Landsat satellites fulfills 14 full orbits every day, and with every orbit it displacement is 2875 km to the west. This means that the satellite covers the earth in 16 days (233 orbits). In this study we use Landsat-7 TM data to investigate the different land use types in the Northern part of New Zealand. The sensor on board of Landsat 7 is recording reflection in 7 different bands (table 1.). Band 1-5 and 7 have a spatial resolution of 30m; the thermal band has a spatial resolution of 60m. The different bands can be used to distinguish different features on the ground. Every band has its own special features that it can distinguish. Band 1 is for example useful for selecting cultural features like urban areas, band 4 can be used to map differences in vegetation types and biomass content.

Table 1. Landsat 7 TM has seven different bands, which can be used to classify different features on the ground (journals.lib.unb.ca, 01-11-2016).

Band	Wavelength (μm/microns) R = Reflected E = Emitted	Nominal Spectral Location	Principal Applications
1	0.45 – 0.52 R	Blue (V)	Designed for water body penetration, making it useful for coastal water mapping. Also useful for soil/vegetation discrimination, forest type mapping and cultural feature identification.
2	0.52 – 0.60 R	Green (V)	Designed to measure green reflectance peak of vegetation for vegetation discrimination and vigour assessment. Also useful for cultural feature identification.
3	0.63 – 0.69 R	Red (V)	Designed to sense in a chlorophyll absorption region, aiding in plant species differentiation. Also useful for cultural feature identification.
4	0.76 – 0.90 R	Near Infrared (NIR)	Useful for determining vegetation type, vigour, and biomass content. For delineating water bodies, and for soil moisture discrimination.
5	1.55 – 1 .75 R	Short Wave Infrared (SWIR)	Indicative of vegetation moisture content and soli moisture discrimination, and thermal mapping applications.
6	10.4 – 12 .5 E	Thermal Infrared	Useful in vegetation stress analysis, soil moisture discrimination, and thermal mapping (heat loss, forest fires etc) applications.
7	2.08 – 2.35 R	Short Wave Infrared (SWIR)	Useful for discrimination of certain mineral and rock types. Also sensitive to vegetation moisture content.

As described above, an important application of Landsat images is land use/land cover mapping. This kind of research is important for many planning and management purposes. It is an essential part of understanding and monitoring the system of the earth (Lillesand et al., 2014). In this kind of research there are two important definitions that need to be separated from each other. If we talk about *land cover*, we talk about the type of features on the earth surface. Examples of land cover types are: lakes, forest, concrete buildings etc.

The other definition is *land use.* Land use differs from land cover, because it is using the human activity on the ground. The type of land use depends on the purpose of the particular piece of land. An example of a land use type is a residential area. When classifying Landsat images into land use/land cover map, we can choose between different classification methods. Conventional methods that are used to classify Landsat images are divided into two main methods. First one is unsupervised classification. This method uses an algorithm to classify all the pixels in the image. Depending on how much classes you want, the outcome gives a classified image of the study area. Another approach is called supervised classification. This method starts with selecting training areas, which are used to make spectral signatures. These spectral signatures are used to assign pixels to a certain class (Lillesand et al., 2014).

The aim of this project is to make a land use/ land cover map of Northern New Zealand, by using supervised classification. Because of the high amount of different methods that can be used to classify Landsat images, we also conduct other methods to classify the image. These results are discussed in the discussion. Other methods that are used contain: Object-based classification and NDVI. The structure of this paper follows the IMRAD style. After the introduction part, the method we used is explained. In this so-called method part, different steps like: preparation, correction, preprocessing, classification and post processing are described. All these steps are leading to a final map, which is described in the result chapter. The discussion chapter is as described earlier a comparison between different classification methods. The final chapter is a conclusion chapter, which describes in short the main outcomes and the further application of this research.

2. Methods

2.1 Study area

The study area is located in the Northern part New Zealand region, which is centered at -38.9 latitude and 176.4 longitude, corresponding to the path 072 and row 087 of the Landsat 7 TM data. A big lake called Taupo is located at the upper left of the study area, and the Town Taupo is at the side of the lake. It also covers a part of the Hawke Bay area at the right corner; Most of the area is covered by vegetation. There are two main types of forest: native forest and exotic forest. The mountainous areas are covered with snow and ice and farmlands also covers a large proportion of the region.

2.2 Data

The main data source was a cut out and scaled version of a larger Landsat image with a swath of 185 kilometers. The image to be processed was an .img file with 7 bands and a spatial resolution of 30 meters. This image is originally from the Image courtesy of the U.S. Geological Survey on the date of 2013-10-25-14:47:14. An NIR-IR band image in the .tiff format was used as a reference image to process the rectification. The projection of the reference image is UTM in the UTM zone 60, and the datum is "WGS84".

The band combination that was used in this study was 1, 4, 5. Band 1 is the blue band which records reflectance of wavelengths in the range: 0.45-0.5 μm. This band is used for mapping coastal areas and differentiating between soil and vegetation. It also can be used for forest-type mapping and detecting cultural features. As a result, we decided to use band 1 to detect the urban areas. Band 4 is the near infrared band (NIR) with a wavelength range of 0.76-0.90 μm. It is responsive to the amount of vegetation biomass and crop identification. It also emphasizes soil/crop and land/water contrasts. Accordingly, we decided to use it as a detection of different types of vegetation. Another band we chose was band 5. This middle infrared (MIR) band can distinguish clouds, snow, and ice. Alternative way is to choose band 7 which is used for discrimination of geologic rock type and soil boundaries and discrimination of soil and vegetation content. Here we chose band 5, because it is visually clearer for the needed classifications.

2.3 Geometric correction

To geometrically correct the Landsat image, a reference image was used. The coordinate system of the reference image is UTM in the UTM zone 60, and the datum is WGS84. This georeferencing step is essential to combine the Landsat image with other layers (For example in ArcGIS). To rectify the image, we used 4 control points, spread over the reference image. To conduct this rectification, we used a first polynomial transformation. This first order transformation is used in cases where there is less distortion, and where only simple rotation, scaling and replacement is needed. After rectifying the image, we used the cubic convolution method to resample the pixel values. Reason for choosing this method is the fact that, the nearest neighbor and bilinear interpolation method result in jagged and blurry images. The georeferenced image is displayed in figure1.

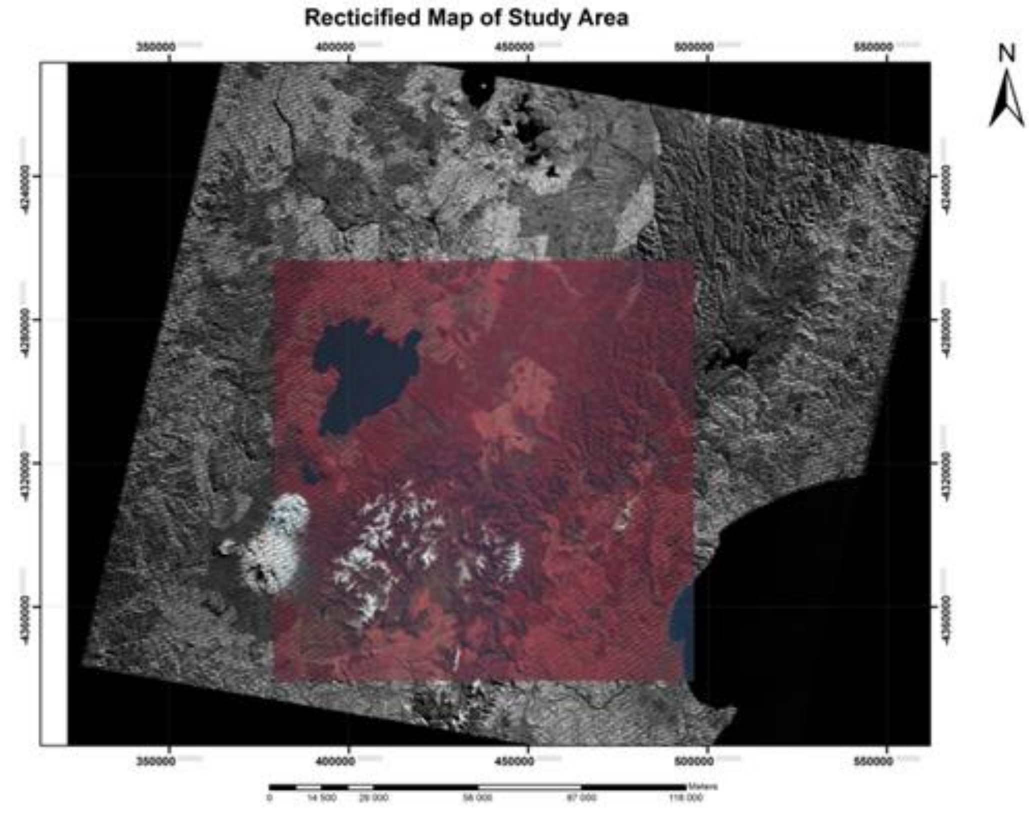

Figure 1. Georeferenced image

2.4 Noise removal

Image noise is the unwanted disturbance in image data that is due to limitations in the sensing, signal digitization, or data recording process. The periodical noise like striping often occurs in satellite images. There are several ways to reduce such noises, like filters to move through the whole image. Another way is Fourier Transformation. Fourier transformation can be used to reduce periodical noise in a frequency domain which will reduce the amount of computation so that the processing speed will be improved. Once an image is transformed from the spatial domain to the frequency domain, the periodic line pattern becomes a radial line. There are two ways provided by the ERDAS software (The Fourier Analysis functions) for reducing noise in images: editing and automatic removal of periodical noise. By editing, we use different shapes of high or low pass filters to cover the radial lines or spots while automatic removal, removes those radial lines or spots according to a removal algorithm. Although it is easy and fast to execute, the result may be degraded afterwards. In this study, we used the editing tool to draw the back-to-back wedge filters in three layers of the Fourier transformed fil. After that we applied the inverse Fourier transformation to derive three noise removed image in bands 5, 4, 1. Finally we utilized the model maker to stack the three layers together.

2.5 Contrast stretching

The goal of image enhancement is to improve the visibility of the objects in the image and improve the contrast between different features so that we can easily distinguish the types of land covers in the classification step. The Image displays and records the information at a range of 256 gray levels (8-bits). Before contrast stretching, the brightness values of the image are often clustered in a narrow range from 0 to 255. As figure 3 illustrated, the histogram shows that in the original image, the brightness levels in the first band of the image are clustered in a limited range from 0 to 149. The remaining values from the 149 to 255 will not be used, resulting in compressed tonal information. It consequently reduces the interpreter's ability to discriminate details in the image. There are three main types of stretching methods: linear stretching simply stretches the digital value to the full range of 0 to255; standard deviation stretches the DN value in the specific defined standard deviations (figure 3, middle). The third method is histogram equalization stretching. It assigns more display values to the frequently occurring portions of the histogram. As a result, the details in these areas will be better enhanced. In this case, we decided to use the histogram equalization stretching, because it is visually more distinguishable for our purposes (figure 2.)

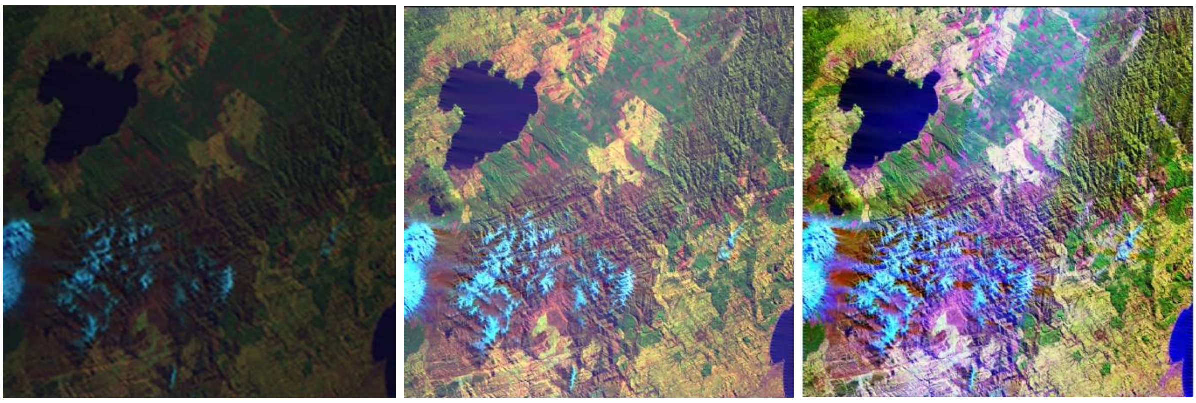

Figure 2. Left: the default stretch histogram. In the middle the standard deviation stretch, and on the right the histogram stretch

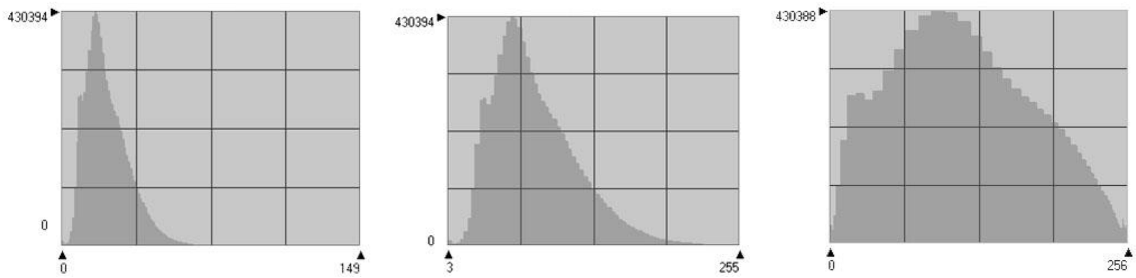

Figure 3. Left: the default stretch histogram. In the middle the standard deviation stretch, and on the right the histogram stretch

2.6 Supervised classification

In this study, supervised classification was used as classification method. The advantage of supervised classification is that the operator can specify the classes and provide sample signatures that will be assigned to that class. Three stages are important: 1) select the training areas to determine how the spectral patterns can be classified in the image; 2) execute classification to group each pixel according to the specific classifier; 3) present the output in a thematic map. In this study, 53 training areas were selected as samples to conduct the supervised classification. 10 for water (including lake and sea classes), 4 for snow and ice, 4 for open areas, 5 for agricultural areas, 4 for the urban areas, 7 for exotic forest, 7 for native forest, 2 for bare soils and 4 for scrubland. We also assigned 6 extra training areas for shadow. Because the shadows are spread over the different land covers, we choose one shadow area for each class. Training samples locations were determined according to the mixed satellite and topographic map from the NZ TOPO Map (topomap.co.nz, 10 January 2016).

It should be noted that scrubland is referring to short and low vegetation. It is a typical land cover in this area (Blaschkei *et al.,* 1981). The traditional maximum-likelihood classifier (MLC) was used to conduct the supervised classification. "MLC classifier assumes that a hyper-ellipsoid decision volume can be used to approximate the shape of the data clusters. For a given unknown pixel, described by a vector of features, the probability of membership in each class is calculated using the mean feature vectors of the classes. The unknown pixel is considered to belong to the class with the maximum probability of membership" (Jia *et al.,* 2014, p.35). The software calculates means and variance of the intensities of all pixels within the training areas for all three bands, so that all pixels are classified. After classification, recoding should be taken. We assigned the new values to the same classes, and assign each types of the shadow to their own classes so that the shadow will be reduced. Unfortunately, the urban area, bare soil and open area are similar spectrally, and they are assigned same values.

2.7 Accuracy assessment

Accuracy assessment utilizes a confusion matrix to infer the classification accuracy (Congalton and Green, 2008). A set of random sampling points in our original image were selected, there should be 256 points in default, but we chose 50 points in order to improve the efficiency. The matrix compared the sampled training pixels we perceived to the pixel actually classified into each land cover category. Finally, the producer's accuracy, user's accuracy and overall accuracy were calculated using reference points. The overall accuracy is computed by dividing the total number of correctly classified pixels by the total number of reference pixels. The producer's accuracy has the similar meaning but it represents in the different categories. In this study, it is quite hard to judge a dark pixel is whether a lake class or simply shadows of each category, we visually assign the most probable class referring to the actual location of the random sample points.

3. Results

3.1 Final map

The result of the supervised classification is shown in figure 4. After recoding, 8 classes were derived. Urban areas were hard to distinguish in the map. This is because they have similar spectral patterns as bare soil and open areas. Therefore the urban areas are included in the open areas. In order to distinguish the urban areas we applied an object-based classification, which is described in the discussion part. The water area is divided into two different classes. The water in the northwestern part of the study area is classified as lake; the water in the southeast part of the study area is classified as sea. A problem with this method is that a salt and pepper effect occurs in the native forest area and in the water area. Because of the stripes in the image, some pixels are misclassified. The shadows in the image are reduced as mentioned before, but there are still some shadows left, which also causes some misclassified pixels.

3.2 Evaluation of the accuracy

To measure the accuracy of the classified map, an accuracy assessment was conducted. The overall accuracy was 86.00%. If we take a look at table 2, we can say that open areas and snow and ice are classified accurately. This is due to the fact that these classes have a spectral signature that is easy to distinguish from other classes. The classes with a low accuracy (scrubland and the forest classes), have a similar spectral signature, which leads to a lower accuracy.

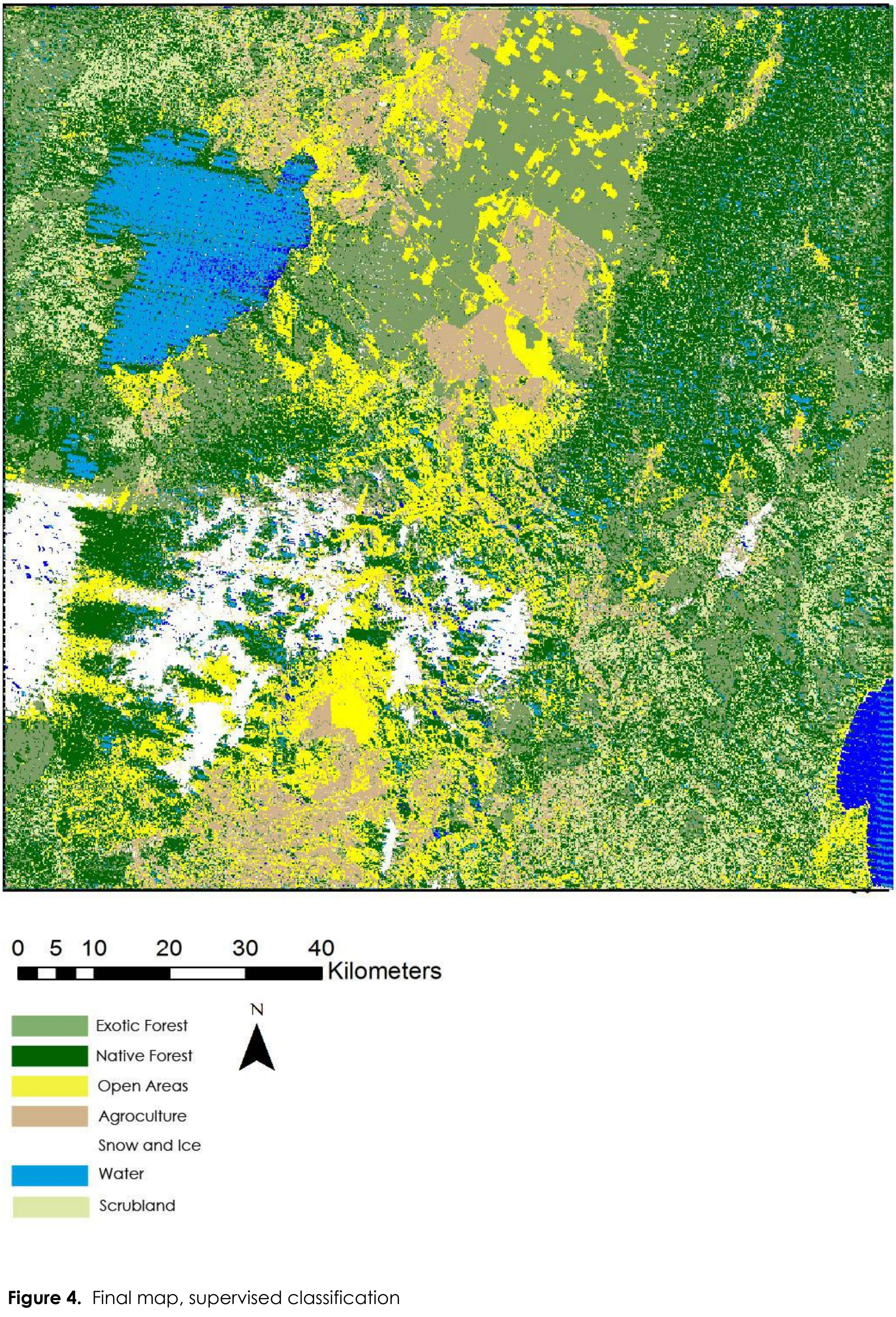

Figure 4. Final map, supervised classification

Table 2. Accuracy assessment

Class	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Lake	7	4	4	57.14%	100.00%
Sea	0	0	0	-	-
Snow and Ice	2	2	2	100.00%	100.00%
Open area	3	3	3	100.00%	100.00%
Agriculture	7	6	6	85.71%	100.00%
Exotic Forest	8	9	8	100.00%	88.89%
Native Forest	18	18	15	100.00%	83.33%
Scrubland	4	7	4	100.00%	57.14%
	Overall accuracy: 86.00%				

4. Discussion

4.1 Comparison with object based classification

The image classification technique used in this study is the so-called pixel-based classification method. Pixel-based classification is a method for image classification that was widely used during the past decades. The basis of this method is the spectrally based decision logic, which is used to classify each individual pixel (Lillesand et al., 2014). The pixel-based classification method categorizes all pixels in the image into classes in an automatically way, and the classes are only based on the spectral information of the pixels in the image (reflectance). Before the introduction of object-based classification, image classification was thus solely based on single pixels and their spectral properties. Object-based classification is different from pixel-based classification, because it is no longer using individual pixels, but objects in the image as processing units (Jawak et al., 2015). The object-base approach became more and more important during the last decade. The problem with the conventional pixel-based method was the application of this approach in high-resolution images. With increasing resolution, the within field spectral variability increases what is resulting in a lower accuracy and a speckled look of the image (Goa and Mas, 2008). The Object-based classification method contains two main steps: 1) multiresolution segmentation and, 2) knowledge based classification on the segments (Jawak et al., 2015). The algorithm that is used in object-based classification divides the whole image into segments of pixels that share the same properties. The user defines some knowledge-based rules for classification (textual, spatial, contextual and spectral) to give each class a description. The last step is to choose a classifier, which assigns each segment to a class.

To see the effect of the object-based approach on the classification result is, we applied this approach to the study area. The result is shown in appendix C. The map shows a homogeneous map of classification areas. Compared to the pixel-based approach the object-based approach has no salt and pepper effect. This is caused by the fact that in object-based classification, the multi-resolution segmentation algorithm is used to create polygons with comparable spectral properties. To avoid too much polygons, a scale parameter of 150 was used. The lower this value is, the smaller the polygons will be. The classification of the polygons was done by using supervised classification. In eCognition a hundred samples were selected to create the new classification map. As mentioned earlier, the map does not show the salt and pepper effect as occurs in the pixel-based method. Because of the high scale parameter that was used, some parts that have to be classified as open areas are classified as exotic forest. For further investigation it will be useful to see what the effect on the classification is if we decrease the scale parameter.

4.2 Supervised vs. unsupervised classification

Within the pixel-based approach it is possible to use two kinds of methods to classify an image. In this study we used the supervised classification method. To compare the result with the unsupervised method, we also conducted an unsupervised classification. Unsupervised classification is different from supervised, because it automatically locates clusters in the data. It is not completely unsupervised because the user has to set the number of classes to a certain amount. In this case we choose 20 classes. By selecting a lot of classes the result of the classification becomes better than when fewer classes are selected. To create the final result, the 20 classes are merged to a number of 9 classes. The resulting map is shown in appendix D. A lot of distortion is visible in the map. At first the shadows are classified as water, especially in the native forest and the snow area this is the case. Secondly, the salt and pepper effect is enormous in this image classification. Compared to the supervised classification the unsupervised method has not a lot of advantages. Maybe the only advantage is the fact that it is not so time consuming as the supervised method, because no training areas have to be selected.

4.3 Further improvements

To further improve the result of the classification other methods can be used. An example of these methods is the Normalized Difference Vegetation Index (NDVI). In this study a band combination of 5, 4, 1 is chosen to conduct the classification. Because it takes a lot of time to remove the stripes with Fourier, the NDVI was created with the striped image. The result of the NDVI image is not very suitable for classification. It is more suitable for mapping the change of the vegetation. This was not the purpose of this study, so this step was not included in the method. To better remove the noise, it can be useful to conduct a more detailed Fourier analysis. The result of the supervised classification, still show some stripes, that causes a lot of misclassified pixels. Finally the shadows can be removed in another way. Auxiliary data like a Digital Elevation Model (DEM) can be used to remove the shadows before the classification.

5 Conclusion

In conclusion, this study presented a supervised classification in the north part of New Zealand using Landsat TM image with the band combination 1,4,5. The results show that the supervised classification is more accurate than the unsupervised. The defects in the supervised classification can be solved by using the object-based method. The object based method can be used to distinguish urban areas from open areas and bare soil. To further improve the classification an object-based approach with a lower scale parameter could give some better results. Other improvements can be found in a more detailed Fourier analysis, image ratio analysis and different approaches for removing shadows.

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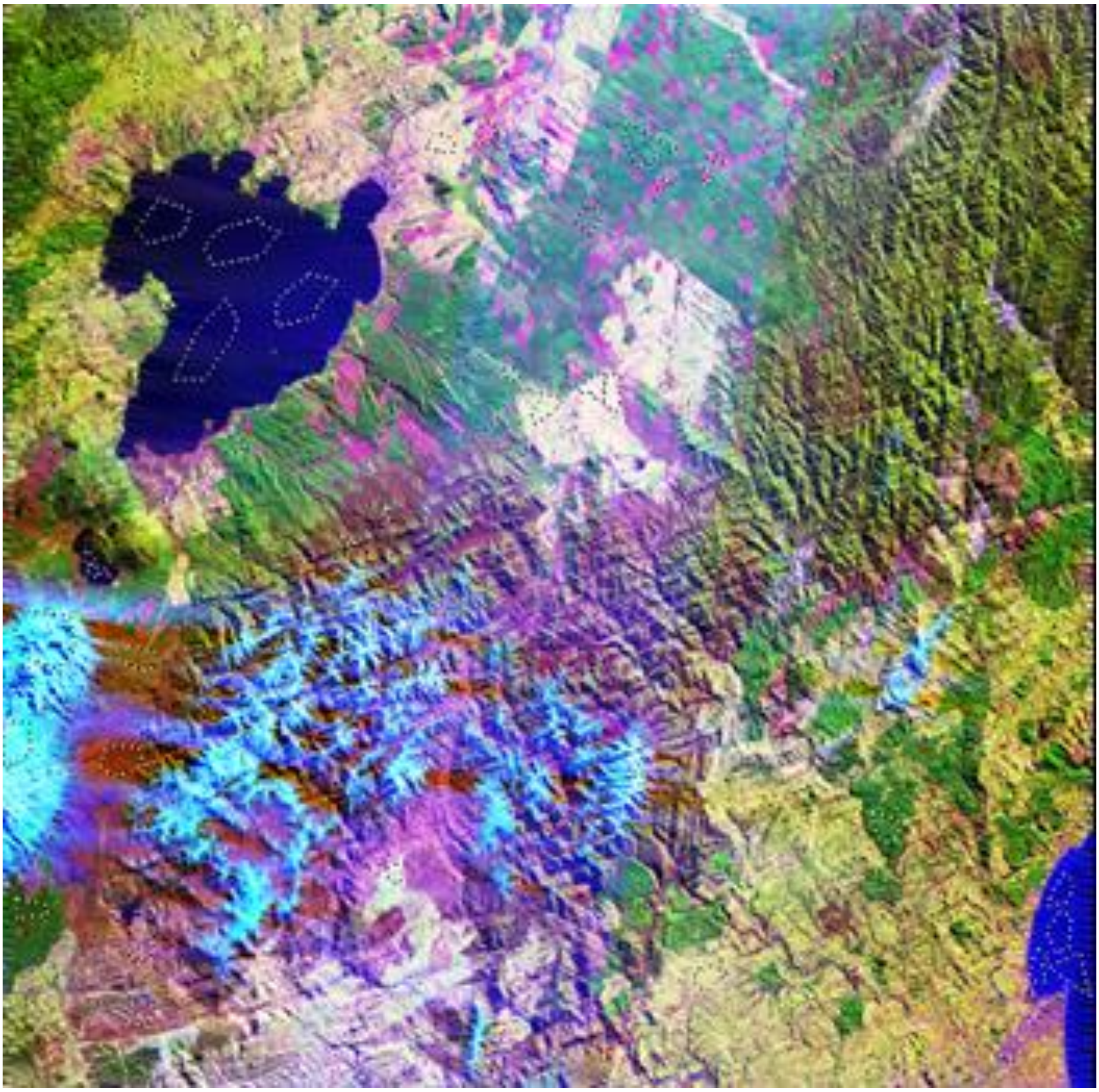
Appendices

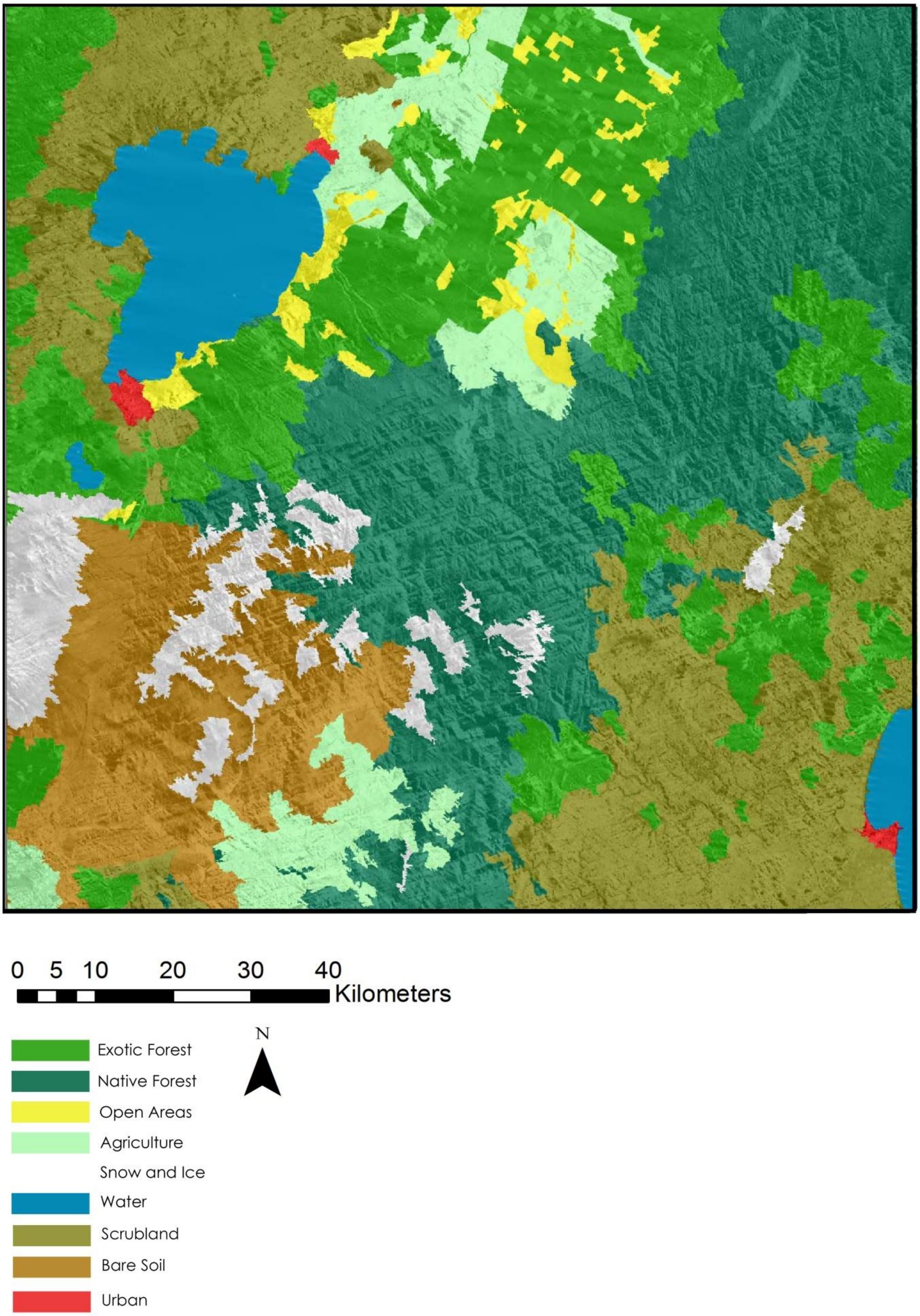
Appendix A, Map of the training areas



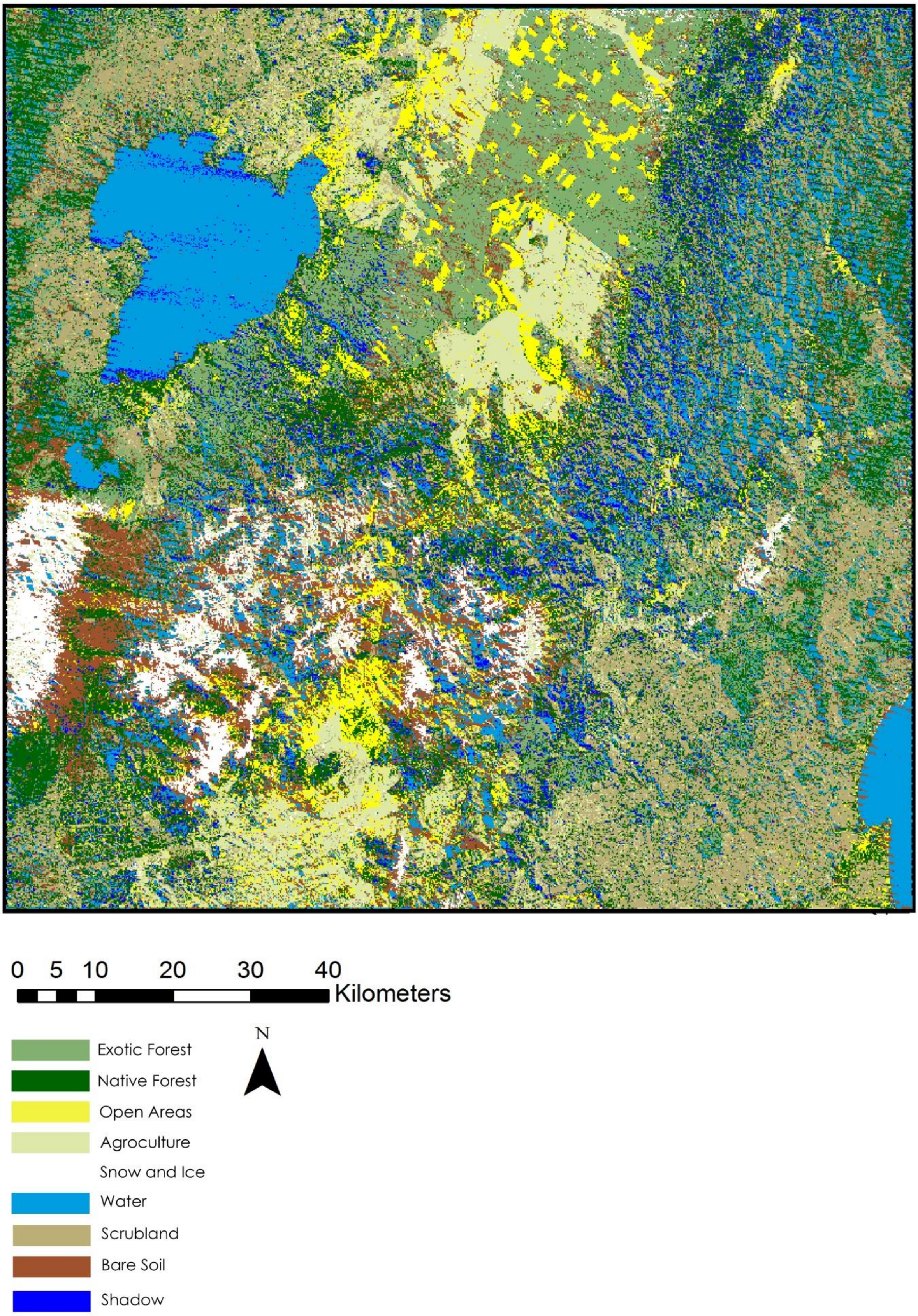
Appendix B, List of the training areas

Class #	Signature Name	Color	Red	Green	Blue	Val
1	Water		0.088	0.087	0.233	
2	Water1		0.104	0.096	0.329	
3	Water2		0.118	0.107	0.392	
4	Water3		0.122	0.117	0.499	
5	Water4		0.124	0.096	0.250	
6	Water5		0.116	0.105	0.183	
7	Sea		0.100	0.100	0.715	
8	Sea2		0.114	0.100	0.703	
9	Sea3		0.111	0.102	0.675	
10	Sea4		0.121	0.109	0.777	
11	Snow1		0.429	0.916	0.928	
12	Snow2		0.181	0.503	0.914	
13	Snow3		0.382	0.796	0.918	
14	Snow4		0.764	0.920	0.929	
15	Open1		0.760	0.380	0.816	
16	OPen2		0.787	0.359	0.821	
17	Open3		0.707	0.374	0.774	
18	OPen4		0.846	0.444	0.798	
19	Agri1		0.903	0.872	0.844	
20	Agri2		0.842	0.864	0.792	
21	Agri3		0.916	0.851	0.865	
22	Agri4		0.796	0.880	0.818	
23	Agri5		0.884	0.824	0.776	
24	Urban1		0.614	0.364	0.663	
25	Urban2		0.703	0.462	0.787	
26	Urban3		0.551	0.300	0.669	
27	Urban4		0.721	0.294	0.855	
28	Ex1		0.343	0.614	0.390	
29	Ex2		0.215	0.333	0.126	
30	Ex3		0.454	0.520	0.650	
31	Ex4		0.581	0.766	0.663	
32	Ex5		0.571	0.873	0.516	
33	Ex6		0.320	0.598	0.623	
34	Na1		0.653	0.750	0.310	
35	Na2		0.775	0.865	0.512	
36	NA3		0.624	0.502	0.337	
37	NA4		0.509	0.275	0.335	
38	NA5		0.536	0.506	0.409	
39	NA6		0.532	0.384	0.153	
40	NA7		0.516	0.223	0.099	
41	BS1		0.660	0.435	0.545	
42	BS2		0.610	0.408	0.487	
43	Ex7		0.283	0.474	0.207	
44	Scrub1		0.793	0.858	0.226	
45	Scrub2		0.774	0.774	0.433	
46	Scrub3		0.824	0.806	0.628	
47	Scrub4		0.673	0.756	0.212	
48	SNa		0.160	0.170	0.151	
49	SNa1		0.116	0.102	0.179	
50	SNA2		0.212	0.181	0.553	
51	SEx		0.169	0.197	0.329	
52	SEx2		0.239	0.296	0.563	
53 ▶	SS		0.123	0.146	0.716	

Appendix C, Object-based classified map



Appendix D, Unsupervised classified map



Appendix E, Map of NDVI