Land Cover Analysis to Determine Areas of Clear-cut and Forest Cover in Olney, Montana

Geob 373 Remote Sensing

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Abstract

Montana's department of natural resources and conservation is interested in evaluating the status of forest in 2002, in an area southwest of Olney. I am tasked to analyse the extent of clear-cut logging within the area, as well as the forest structure and other land cover types within the study area. In order to do this, I rely on Landsat 7 Enhanced Thematic Mapper plus (ETM+) imagery to facilitate the analysis. After obtaining the Landsat images, I performed an unsupervised classification using two hard classifiers CLUSTER and ISOCLUST for analysis, as well as a supervised classification which uses Minimum Distance classification and Maximum Likelihood classification analysis. This allowed me to produce maps with different types of specific land cover classifications to support my analysis and help with the visualization of the study area. The area has an extensive forest cover of dense mature forest, which accounts for approximately 39% of the entire study area. However, clear-cut logging is also quite significant as it accounts for almost 26% of the total area. The area of older logged areas with young regrowth is only 12.5% of the total area, which indicates that logging activities are occurring faster than the regrowth of new vegetation. There are of course errors and uncertainties associated with this study such as the misclassification of classes. However, this study provides a good estimate of the actual forest cover and clear-cut area.

Introduction

The study area is located approximately 15km southwest of Olney. Fig. 1 is a google image that provides an overview of the entire study area. The region comprises of hilly and uneven terrain, and is majority covered by vegetation. The center of the study area appears to be covered by dense mature vegetation. However, it is clear that the area has undergone logging activities, which results in distinct patches of clear-cut lands. There are also some areas of older clear-cut, which is now overlain by the regrowth of younger vegetation cover. There are a couple of lakes located within the study area, and the largest lake is Tally Lake located in the southeast region of the area. Roads network are also evident within the area, which indicates some form of anthropogenic activity such as logging, transport, etc.

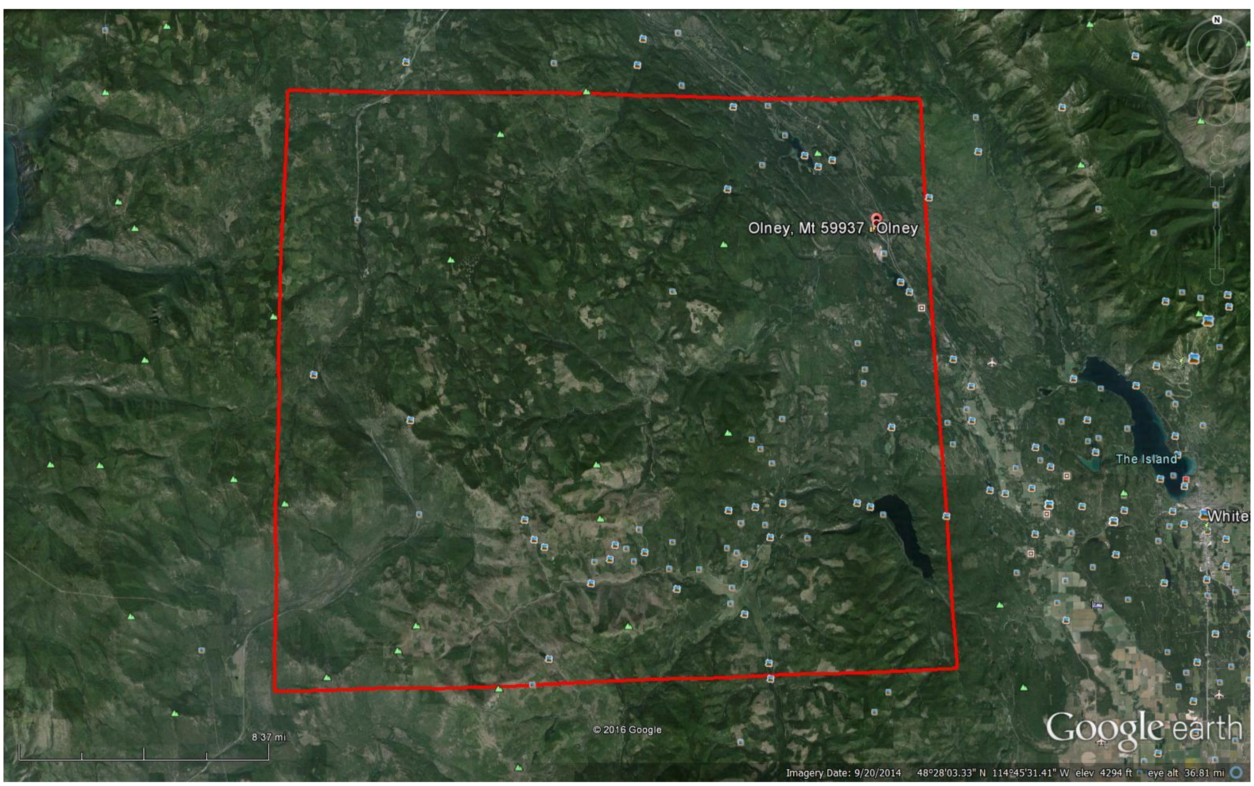

Fig.1. Google earth image of the study area in Montana.

Landsat 7 (ETM+)	Wavelength (micrometers)	Resolution (meters)	
Band 1	0.45-0.52	30	Blue
Band 2	0.52-0.60	30	Green
Band 3	0.63-0.69	30	Red
Band 4	0.77-0.90	30	NIR
Band 5	1.55-1.75	30	MIR
Band 6	10.40-12.50	60 * (30)	TIR
Band 7	2.09-2.35	30	MIR
Band 8	.52-.90	15	panchromatic

Fig. 2. Bands characteristics of Landsat 7 ETM+ sensor

This study relies on Landsat satellite imagery captured in bands 1 to 7 of the Landsat 7 ETM+ sensor. The ETM+ is a eight-band, multispectral scanning radiometer capable of providing high-resolution imaging information of the Earth's surface. Bands 1 to 3 are in the visible band, and can be used for creating a true colour composite image. Band 4 is in the Near Infrared (NIR), and is useful for classifying or analyzing vegetation due to their high reflectance in the NIR. Band 8 is a new feature of the ETM+ sensor, which is a panchromatic band with a 15m spatial resolution. This band can be used for pan sharpening to increase resolution of imagery. However, because band 8 have a resolution of 15m rather than 30m, it will not be used in the various analysis of this study. Fig. 2 shows the different specifications of the bands such as the different wavelength and the spatial resolution.

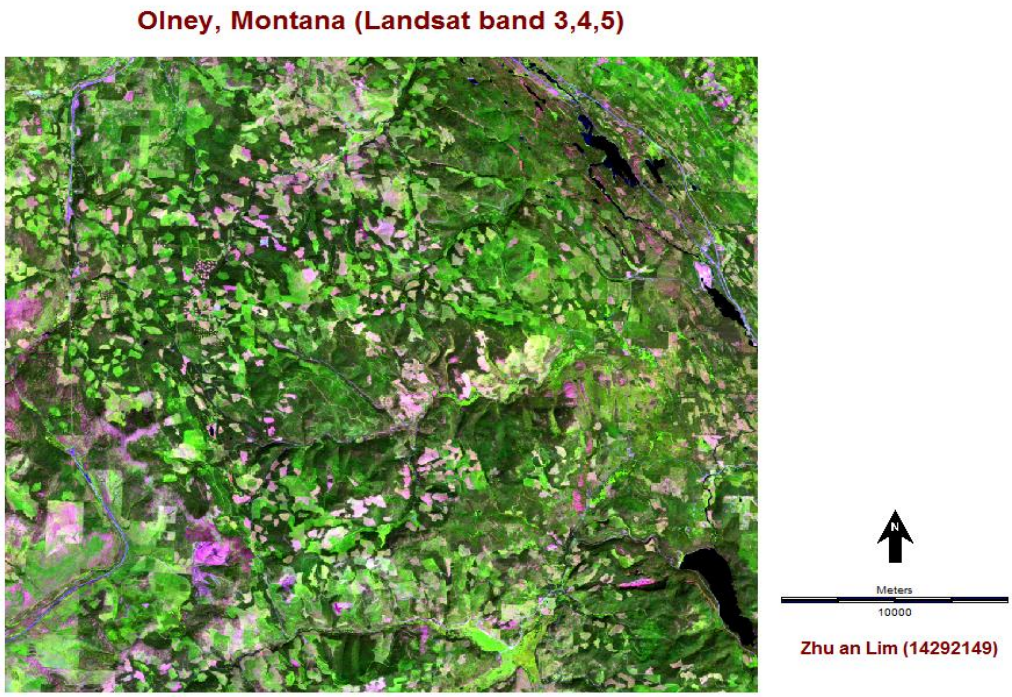

Fig. 3. Colour composite of Landsat band 3, 4, and 5.

Fig. 3 shows a colour composite of Landsat bands 3, 4, and 5. This combination of bands is considered to be most effective in distinguishing the different features within the study area, when compared to other images such as the true colour image (bands 1, 2, 3) and false colour image (bands 2, 3, 4). The allocation of the Near Infrared (NIR) to the green channel allows for the analysis of vegetation "greenness", since healthier vegetation usually has a higher reflectance in the NIR range. This is useful in distinguishing between dense mature forest, younger vegetation regrowth, and recent clear cut areas. Dense mature vegetation appears to be dark green, indicating a healthy and dense forest cover. Lighter green are usually shorter vegetation or younger regrowth. Clear cut ground are distinct patches of lands that are light pink, and are distinct features amongst the vegetated grounds in the image. Water features are also clearly highlighted in this image, and appear to be dark blue to black. Roads appears to be purple in the image, and bare ground are in a lighter shade of purple.

Analysis

Unsupervised classification

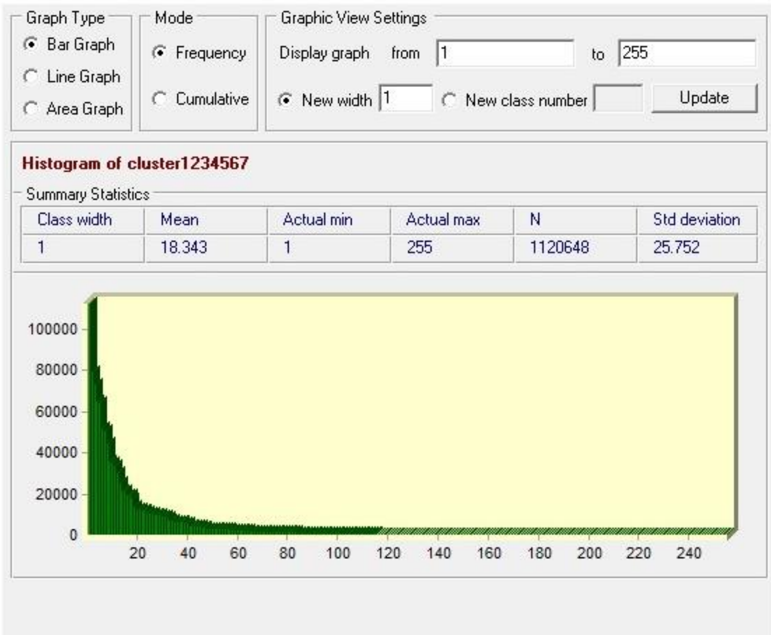

Fig. 4. Histogram of pixels assigned to each class for cluster of landsat band 1 to 7.

Fig. 4 shows the histogram for the number of pixels per cluster for Landsat bands 1 to 7. In order to reduce the number or ‘relevant’ classes used for the analysis, I assume that any class that have a number of pixel of less than 3% of the total number of pixel to be not relevant. This results in a total of 10 classes that is used for the cluster analysis. I then gave appropriate names to the individual classes based on references from the true colour image and false colour image, as well as the help of google image. Fig 5 and 6 are the results of both the CLUSTER and ISOCLUST analysis, with the appropriate names assigned to each class.

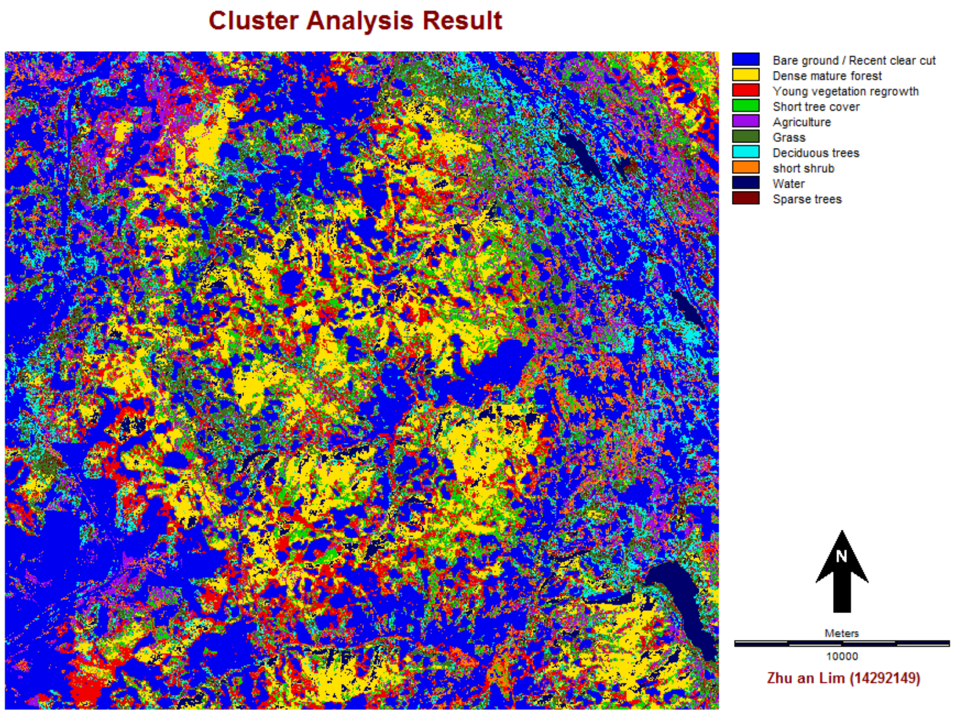

Fig. 5. CLUSTER Analysis for Landsat bands 1 to 7

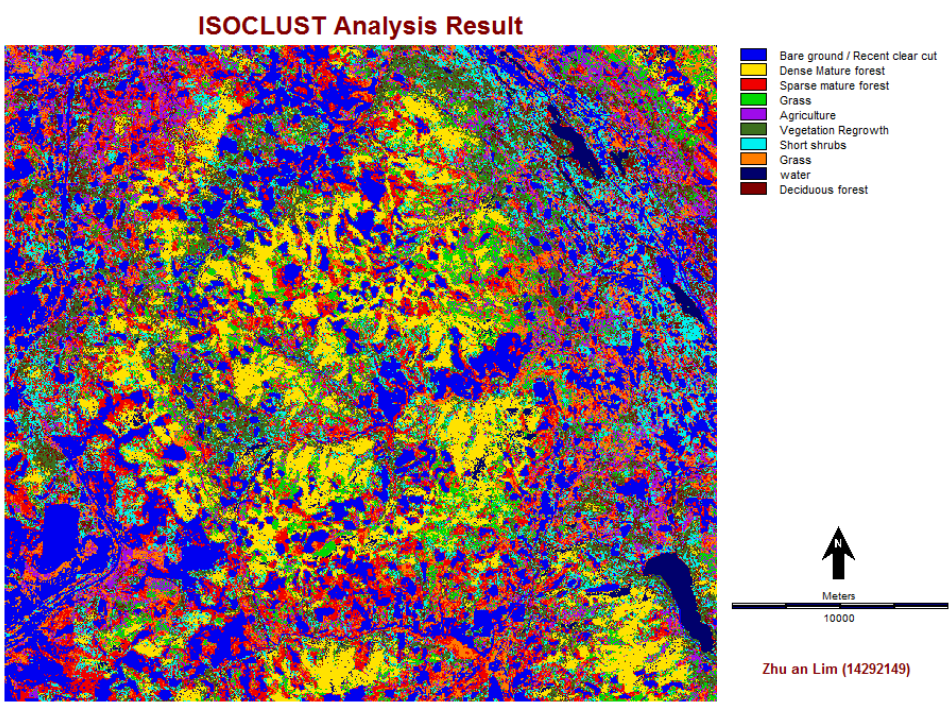

Fig. 6. ISOCLUST Analysis for Landsat bands 1 to 7.

A hard classifier creates a boolean classification scheme (i.e. a pixel is either in the class or not), and is useful when there is no extensive prior knowledge of the region. There is likelihood of human error is minimized, and unique classes can be more easily identified. The unsupervised classification method is effective in distinguishing features with unique reflectance values within the area such as water bodies. For example, water is clearly classified in both CLUSTER and ISOCLUST analysis (fig. 5 and 6) and are quite accurate when compared to the true colour image and google earth. Dense mature vegetation seems to be relatively well classified in both types of analysis as well. However, the CLUSTER analysis tends to misclassify darker shaded slopes with mature vegetation as water. This might be due to the decrease in reflected energy from those surfaces. For ISOCLUST, there is less of this problem where most of the shaded slope areas are classified as mature vegetation.

Both CLUSTER and ISOCLUST seems to be not that effective when it comes to distinguishing between different features with close to similar reflectance value. For example, there is some misclassification of bare ground in both analysis, especially CLUSTER (fig. 5). Land cover with little vegetation or short vegetation might be misclassified as bare ground as the reflectance response of those pixels are quite similar to actual bare ground. For example, in fig. 5, the southwest region has a huge area that have been classified as bare ground, which might not be the case as seen in fig. 6. ISOCLUST seems to better classify bare ground as compared to cluster. It is also difficult to distinguish amongst the open vegetated covers, such as grass, young vegetation regrowth, and short shrubs. They appear to be classified differently in the CLUSTER and ISOCLUST analysis, but it is hard to differentiate them in the true colour image. More background knowledge about the study area is required in order for the analyst to make better decisions for naming the classes. Mismatch between clusters and actual classes could be a potential source of error, and it is also hard to determine how many classes is appropriate to give a good representation of the study area.

Supervised Classification

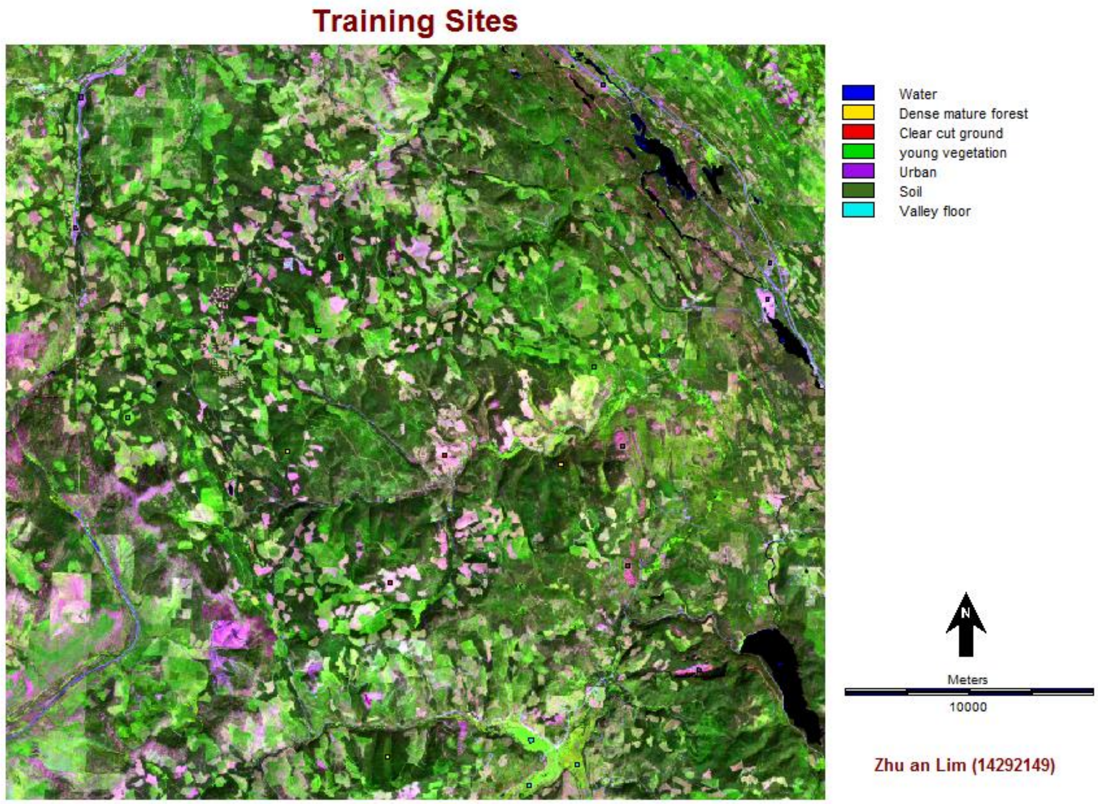

Fig. 7. Training sites for supervised classification analysis

I have defined 7 different class and created training sites with more than 70 pixels each for my supervised classification analysis, which are shown in fig. 7. I named the different classes based on references from the other images and google earth, since I have no prior knowledge of the area. I used fig. 3 as the composite image for my training sites, as the Landsat 345 composite image provides best contrast amongst the different land covers, and allows me to easily distinguish mature vegetation, young vegetation, and clear cut areas.

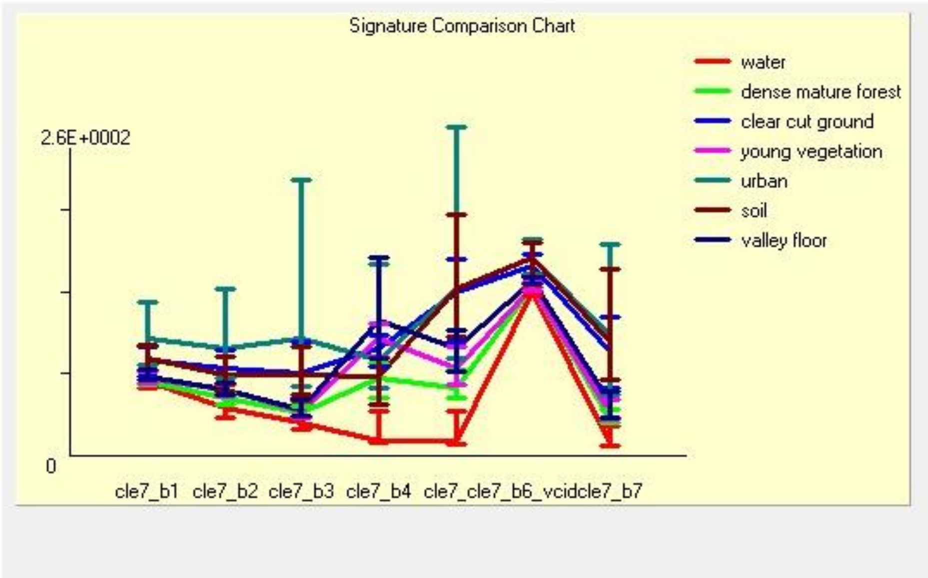

Fig. 8. Spectral response for the different classes for bands 1 to 7

Generally, the spectral response patterns of the different class are distinguishable, although there are some similarities in some of the bands (fig. 8). For example, the different classes seems to be relatively similar for band 6 (TIR), and is hard to distinguish amongst the class. However, band 4 (NIR) seems to provide a good comparison for the different classes. Water has a particularly low reflectance in the NIR, and is easily distinguishable. Young vegetation seems to have a higher reflectance in the NIR than mature vegetation. Urban has high reflectance in band 1 to 3, which is in the visible range. It is quite distinct from the other classes. However, it has close to similar reflectance as soil in band 5 (MIR), which may result in some misclassification.

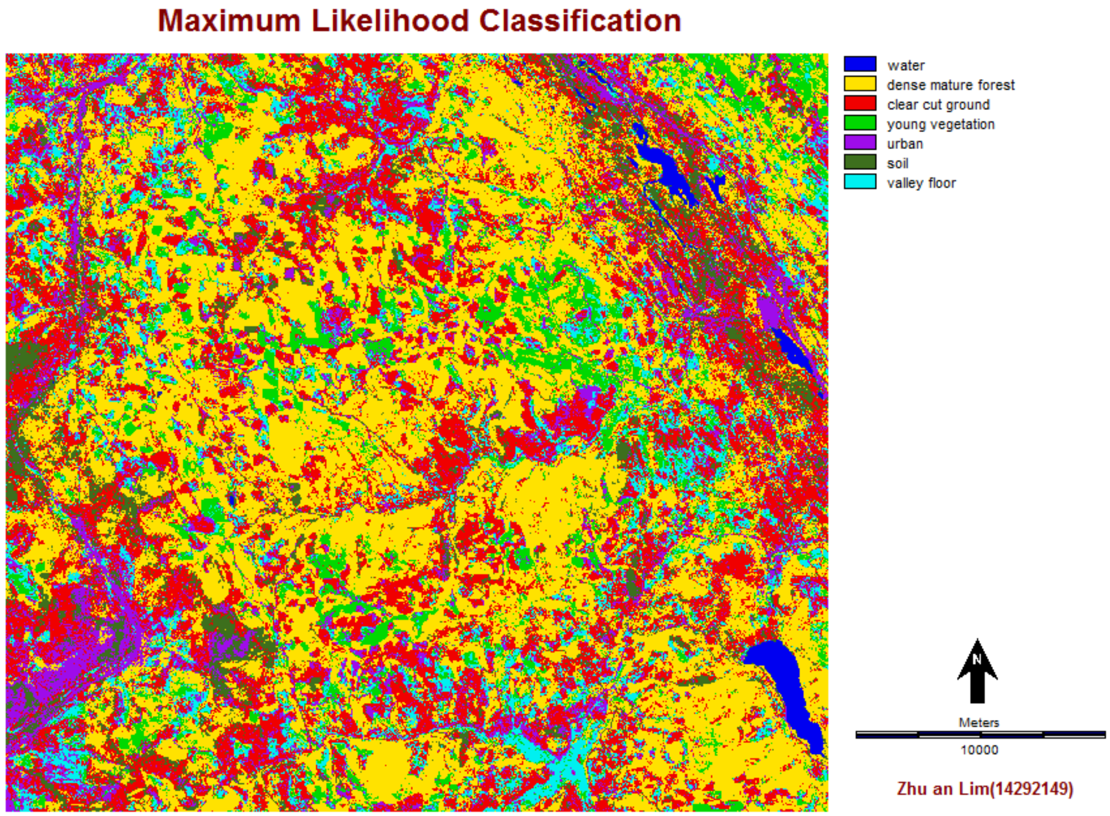

Fig. 9. Maximum likelihood classification map for Olney study area

For the supervised classification analysis, I used a hard classifier rather than a soft classifier, as I have little knowledge on the actual land cover of the study area, and it will be hard to determine which class does a pixel belongs to. I have decided to use the Maximum Likelihood classification rather than the Minimum Distance classification as I have determined that it gives a better representation of the study area, and appears to better correspond with the other images. It seems to have a better classification of the key interests of this study (i.e. mature forest cover, young vegetation, and clear cut), which is an important consideration. The Maximum Likelihood classifier quantitatively evaluates both the variance (internal variability in a band) and covariance (the similarity between bands) of training class pixels and assumes a normal distribution for training classes. This classifier has been most widely used in remote sensing, and typically produces an accurate classification. However, it assumes the most about how the data is distributed.

Fig. 9 shows the results of the classification, and the different types of land cover which I identified. Because I used a hard classifier, it assumes that a pixel must belong to at least one of the land cover classes, and increases the error and uncertainty of mixed pixels. I used a minimum likelihood of 0.0 to reduce the amount of unclassified pixels, but this threshold increases the 'fuzziness' of the classification, and more pixels might be wrong classified. However, it does provide a good estimate of the different land cover, and it reduces the probability of human error as compared to a soft classification.

Conclusion

Overall, the supervised hard classifier provides a relatively representative classification of the land cover and land use in the study area. There is a good classification for dense mature forest, as well as the younger regrowth vegetation from older clear cuts. Dense mature forest was well classified in the image (fig. 9) for most part of the study area. Water features were well defined as well, similar to the unsupervised classification analysis. Young vegetation regrowth was also relatively well classified, especially in the middle region of the image (fig. 9). Roads and urban area were also well defined in this classification. However, there are still some misclassification for recent clear cut and bare ground, most likely due to the similarities in spectral response. Therefore, the results of clear cut lands might be an overestimate since it might include similar features such as bare soil and sand.

Overall, all of the classification analysis seems to have a good classification of water features, such as the lakes in the area. Mature vegetation was also quite well classified, other than the issue of the shaded areas that were misclassified as water as seen in fig. 5. There is more uncertainty with young vegetation. In the unsupervised analysis, they could be separated into different classes such as short shrubs, grass, etc. However, in the supervised analysis, they are grouped together as one class. Clear cut and bare ground are also often misclassified for the different analysis done.

Class	Number of pixels	Percentage over total pixels
Dense mature forest	433918	39%
Recent clear cut	294858	26%
Young vegetation regrowth	139984	12.5%

Fig. 10. Summary for logged areas and current forest structure within study area

For this study, I would suggest to use a hard classifier, in order to reduce the probability of human error since I do not have an extensive knowledge about the study area. The classification of land cover could be improved by having a better spatial resolution, which minimizes the effects of mixed pixels. This would provide a more accurate classification when using a hard classifier. It would also be helpful to have more information with better temporal resolution for the study area, such as aerial photography. This would provide a better overview of the land cover during that specific period of time when the image was captured by Landsat. In terms of accuracy of the different classification methods, I would suggest to use the Maximum Likelihood approach, as I found that it provides the most representative and ‘accurate’ classification of the different land cover types, after comparing it with the true and false colour images.