Landslide Classification: An Object-Based Approach

Bryan Zhou

Geog 342: Final Project

Introduction

One type of natural hazard that people are familiar with is landslide. Landslide is a laymen term use to describing the rapid movement of earth material down a slope. A more general term for all landslides is mass wasting. But scientists describe and categorize landslide according to the type of material it transport. For example, a lahar is a landslide that is composed of water, debris, and volcanic material. Not all landslides are involved with liquid (water). One type such as rock fall consists of only large boulders, but contains little or no water at all. Large landslide, especially the ones that occur at the coast can generate large tsunami.

Purpose

- Object-Based mapping of historical or recent landslide in Palos Verdes, Los Angeles, CA using Multi-Resolution Image Segmentation
- Learn eCognition Developer 8.8

Background

eCognition interface offers two types of startup mode: Quick Map and Rule set (Figure 1). In Quick map mode, the classification process has been simplified for the convenience of the user. The Rule set mode allows the user to import or develop their rule sets for image classification. The rule sets represents the algorithms use for analysis of remote sensing data.

The Process Tree window is where the user develops the rule set for image classification (see Figure 3). Image Segmentation and classification algorithms are conducted in the Process Tree window. Headings and sub-heading are added by right-clicking on the window and selecting Append New. Append Child is used for sub-heading or sub-processing. Class types are created in the Class Hierarchy window. The method for adding a class is similar to the Process Tree window. The classes can be grouped together to establish hierarchy and relationship between them.

Materials and Method

The eCognition 8.8 software 64 bit (trail version) was downloaded from the Trimble website. A landslide inventory map of Palos Verdes was obtained from the California government website. The map will serve as a reference guild in identifying landslide for the area. A 2010 orthoimagery of Palos Verdes at 1m resolution was obtained from the USGS Earth Explorer. All pieces of the image had been mosaic in ArcCatalog to form a complete image of the area. The Rule set mode was chosen for this project. The Palos Verdes image was loaded into eCognition and a portion of the area had been chosen for the initial classification using the subset selection tool (Figure 2). In eCognition it is recommended to work with subset image classification, because the computation time of high resolution imagery is tedious.

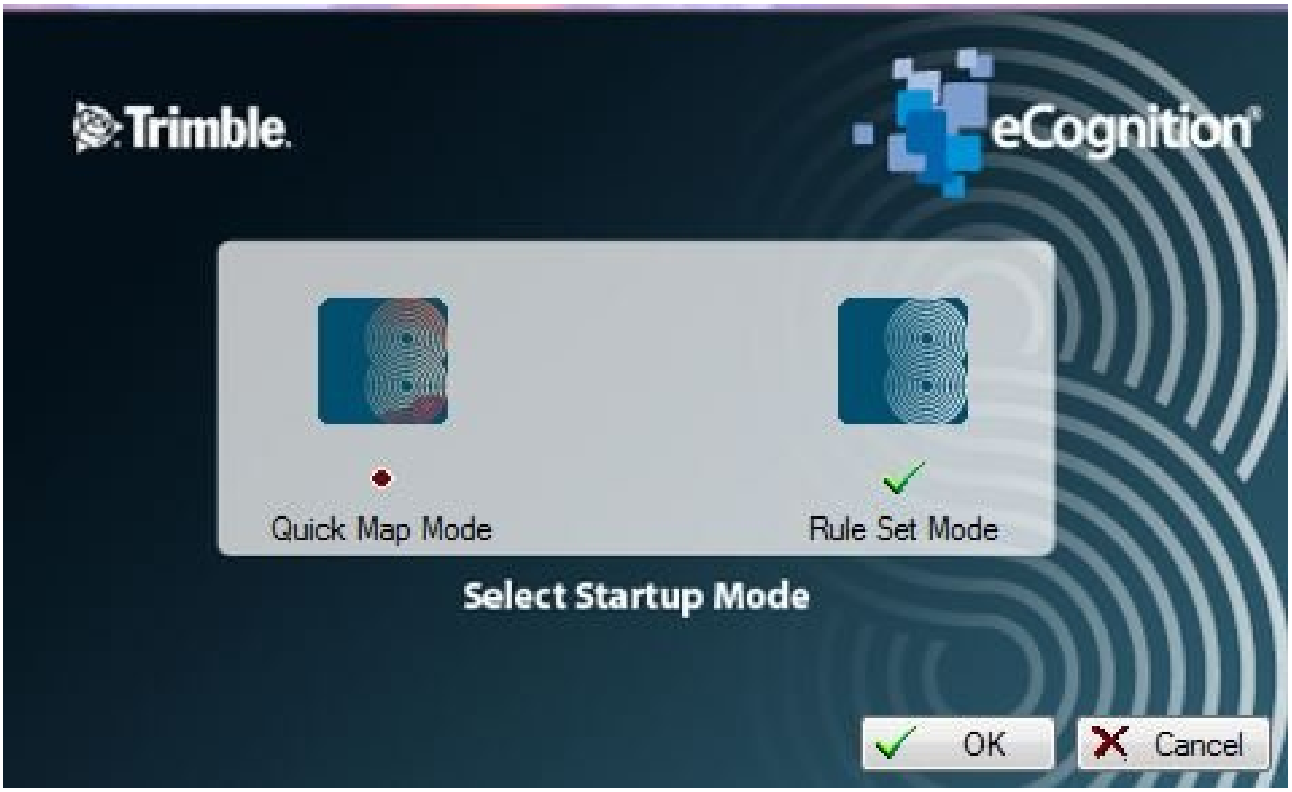

Figure 1: The startup mode

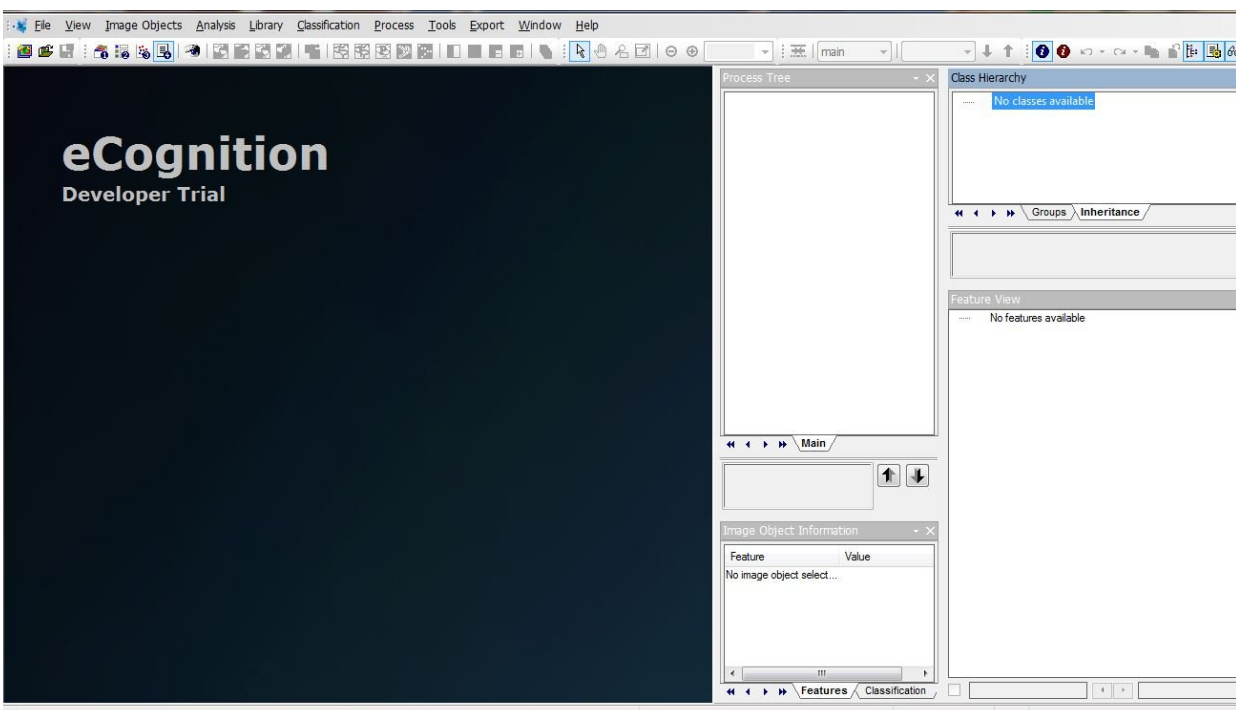

Figure 3: The main components of eCognition

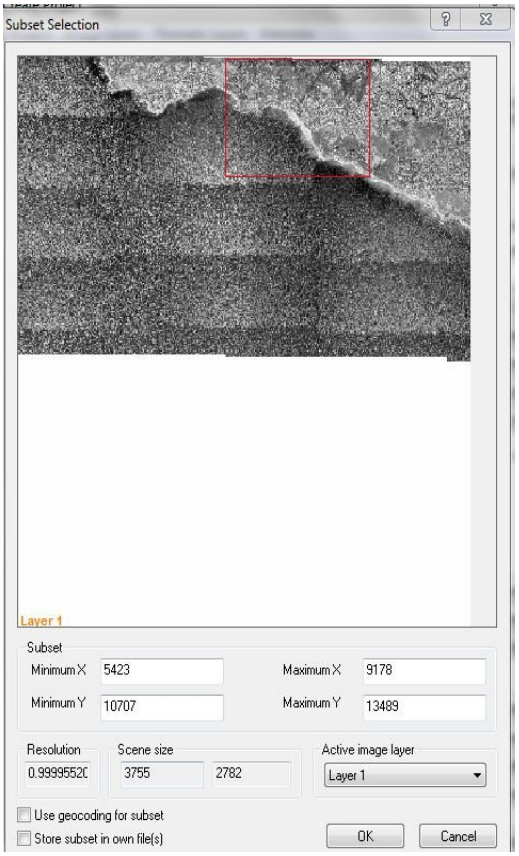

Figure 3: A subset image of Palos Verdes.

Figure 4 shows the basic rule set for this project. Landslide, Non-landslide, and water classes were created in the Class Hierarchy window. For each class, Nearest Neighbor was used for the Class Description, because it is similar to supervised classification (Figure 5). In Supervised classification, training samples are used to guide the software in the classification process

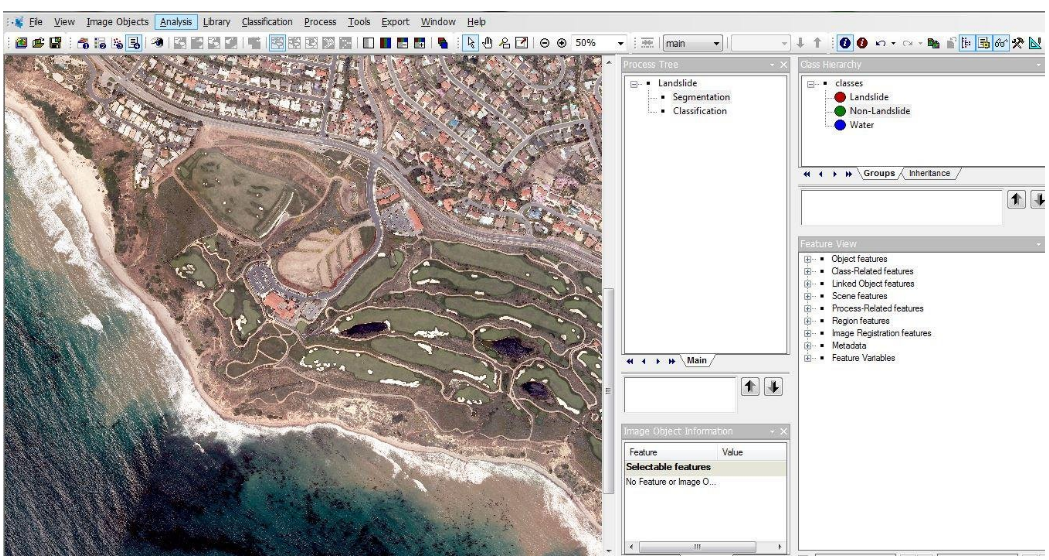

Figure 4: Simple way to organize the workspace.

Multi-resolution segmentation algorithm was run for the image at scale parameter 500, 100, and 70 (Figure 6). Landslide varies with magnitude and frequency (T. Lahousse3, K.T. Chang, and Y.H. Lin). The largest landslide was identified at level 500.

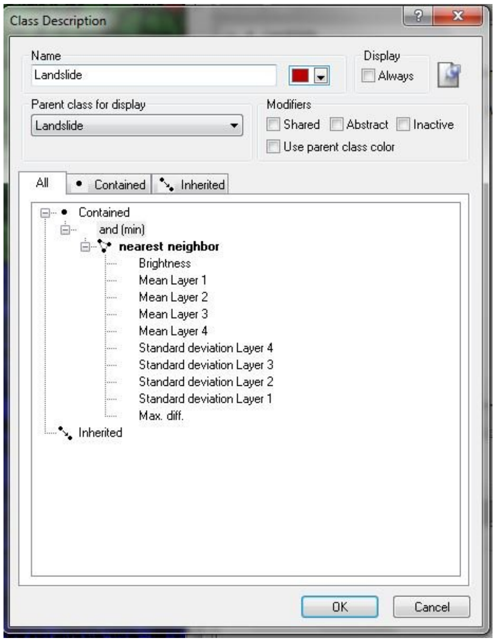

Figure 5: Class Description of Landslide

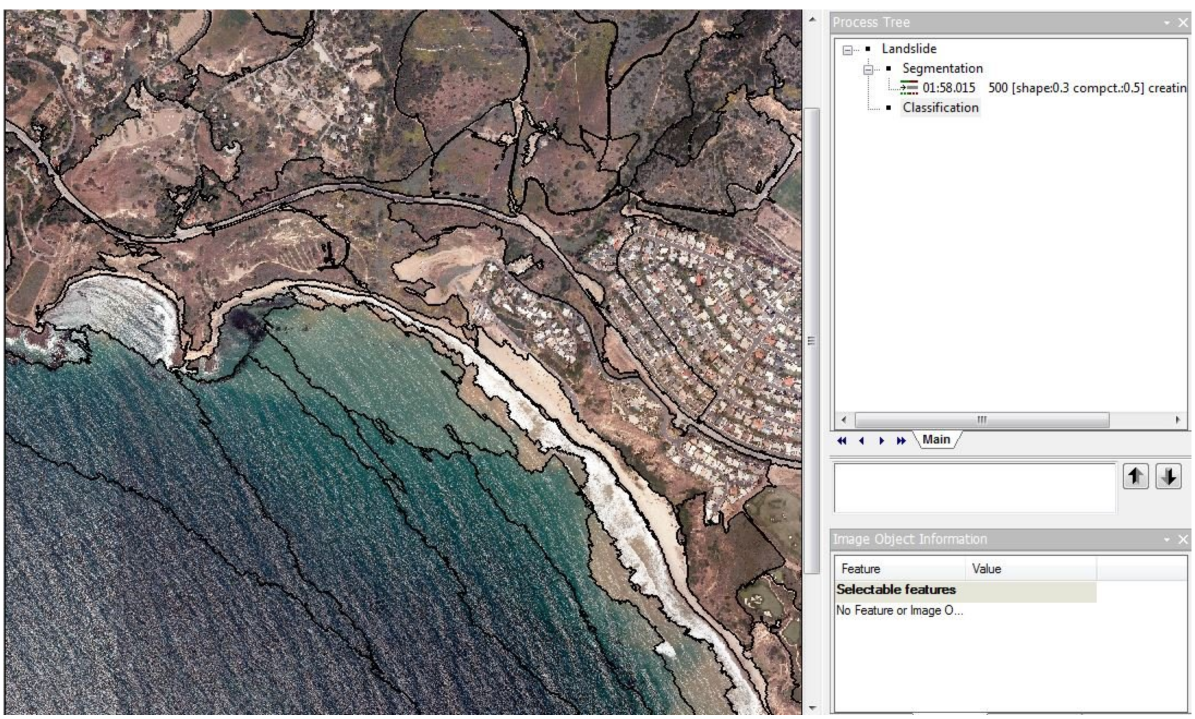

Figure 6: A scale parameter of 500 resulted in large polygons.

Training samples were selected for each class and the classification algorithm was used for the image analysis (Figure 7). All the active classes were selected (Figure 8)and the rest of parameters remained at default. The classification algorithm (see Figure 8) uses the highest value in the class description to classify an object. Figure 9 shows the results at Level 500, the software failed to identify landslide.

The process was repeated for level 100 and 70, but at level 70 more classes were added to the Classification Hierarchy window (Figure 11). At scale parameter of 70, more than 8, 000 objects were created. The results for level 100 (Figure 10) and level 70 (Figure 12). Again, some of the objects were missed classified as landslide, because thresholds were not applied during the classification. Portion of the ocean was classified as sub-urban, because many of sub-urban area have pools. The problem can be fixed with more image segmentation or due away with the ocean with a mask.
I managed to found rule sets for landslide classification at http://www.itc.nl/Pub/OOA-group/Data_and_rule_sets.html. However, the algorithms failed to load properly, because my software was a Trial version. Figure 13 shows what the rule sets look like.

I managed to acquire some of the class description from them and using the threshold values developed by T. Lahousse et al. for my project (see Figure 14). But this time, the Assign class algorithm was used for the classification. The assign class algorithm is most common method for classification and it only load one class compare to the Classification and Hierarchy algorithm. Due to the issue with the algorithms, the results failed to generate.

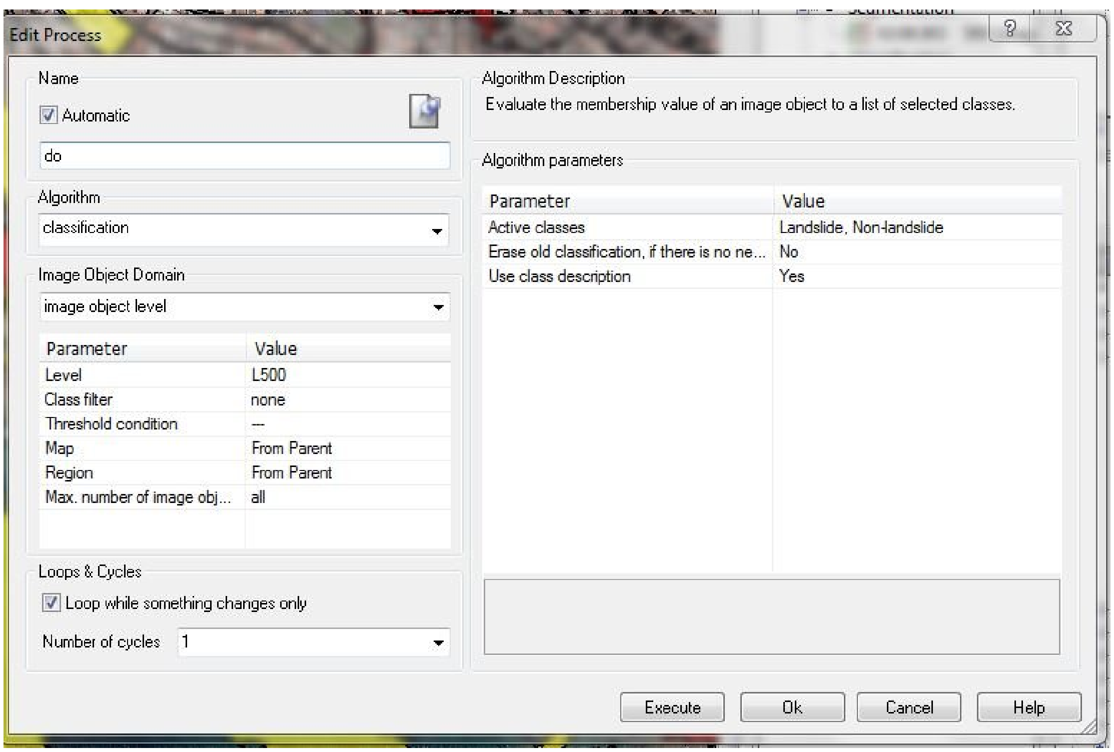

Figure 7: Classification algorithm

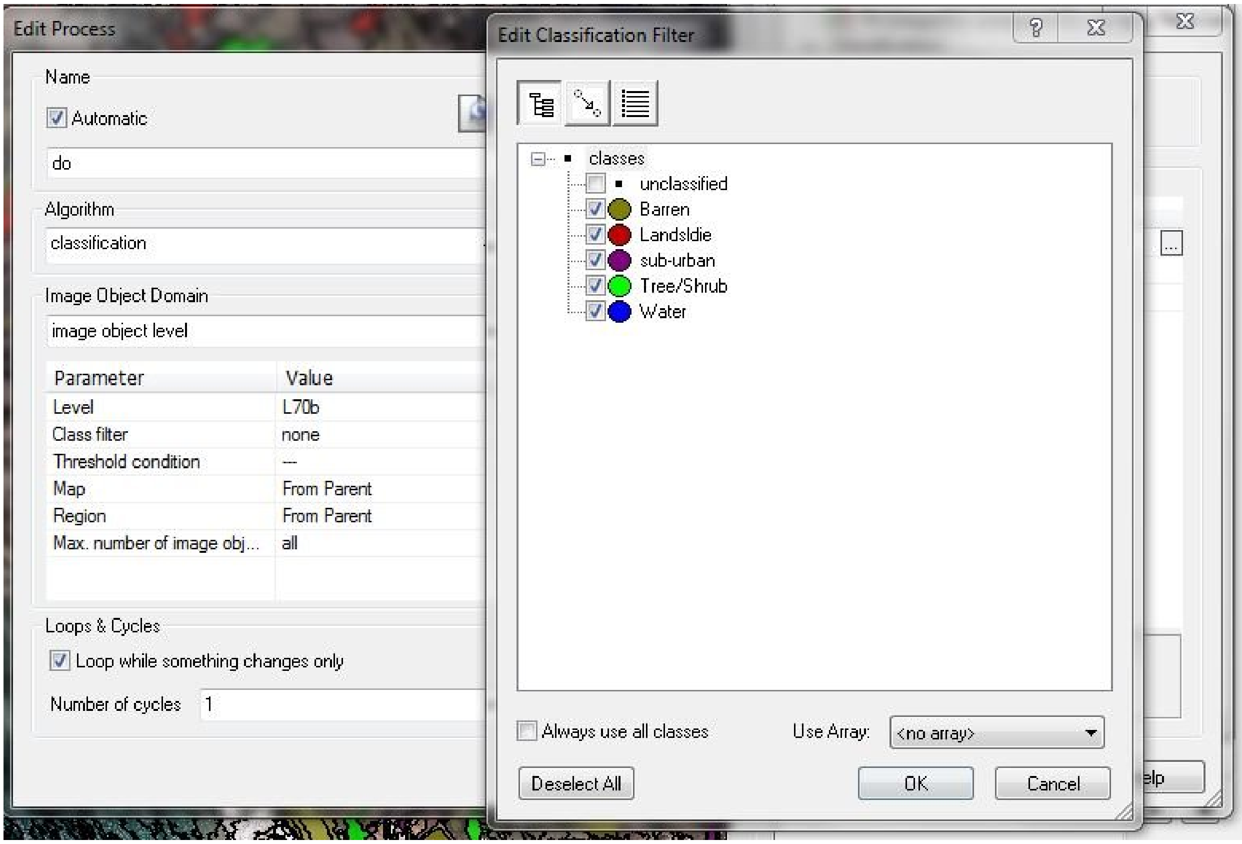

Figure 8: The Active Classes

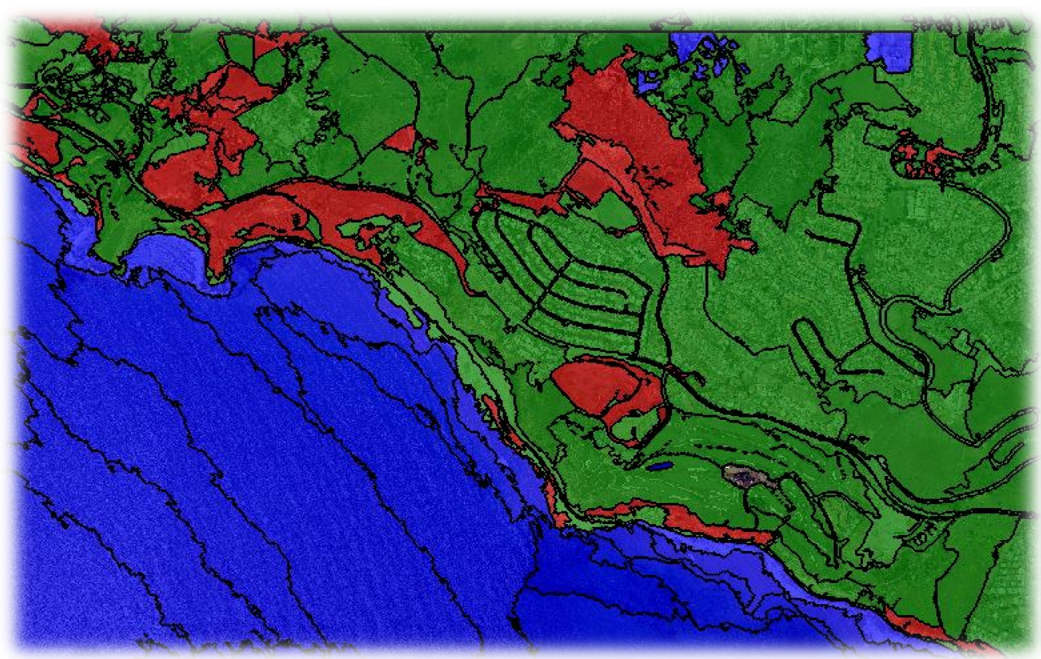

Figure 9: The result from classification process of 500. Some of the area was missed identified as water.

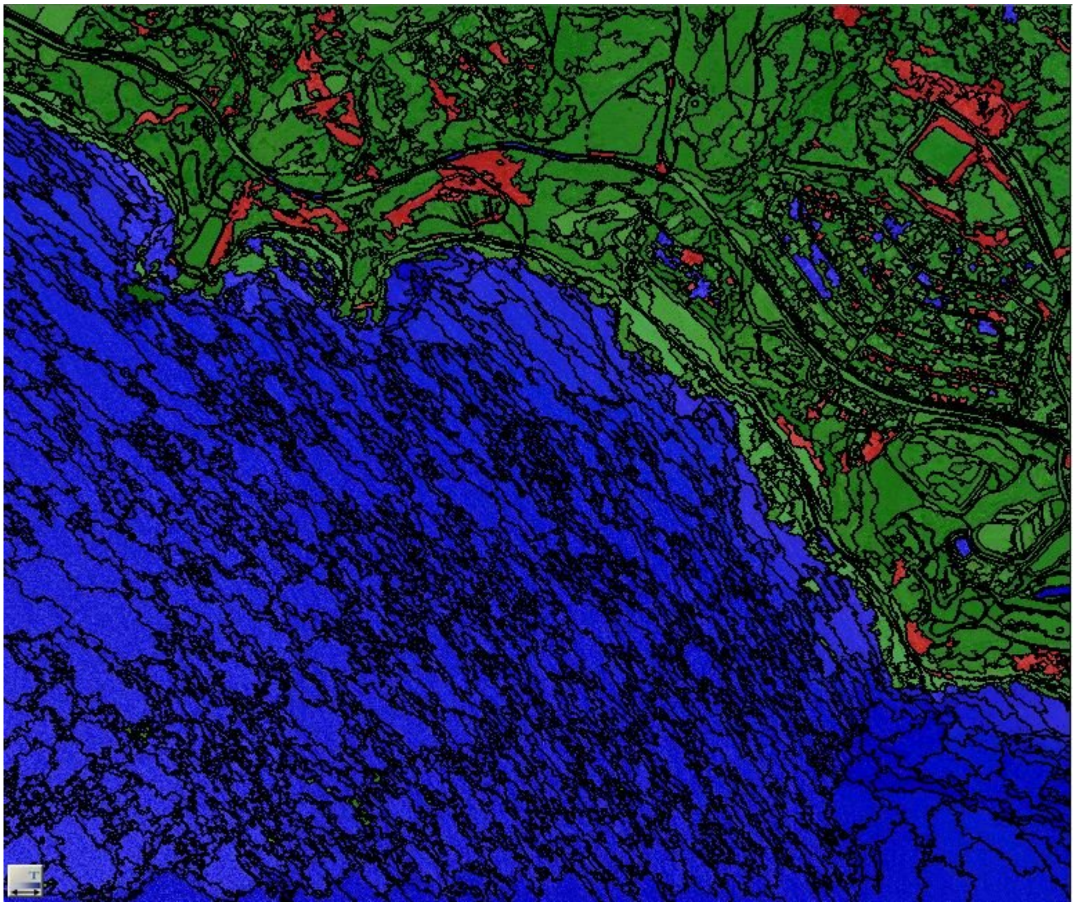

Figure 10: Result from scale parameter at level 100.

Figure 11: Classes for level 70

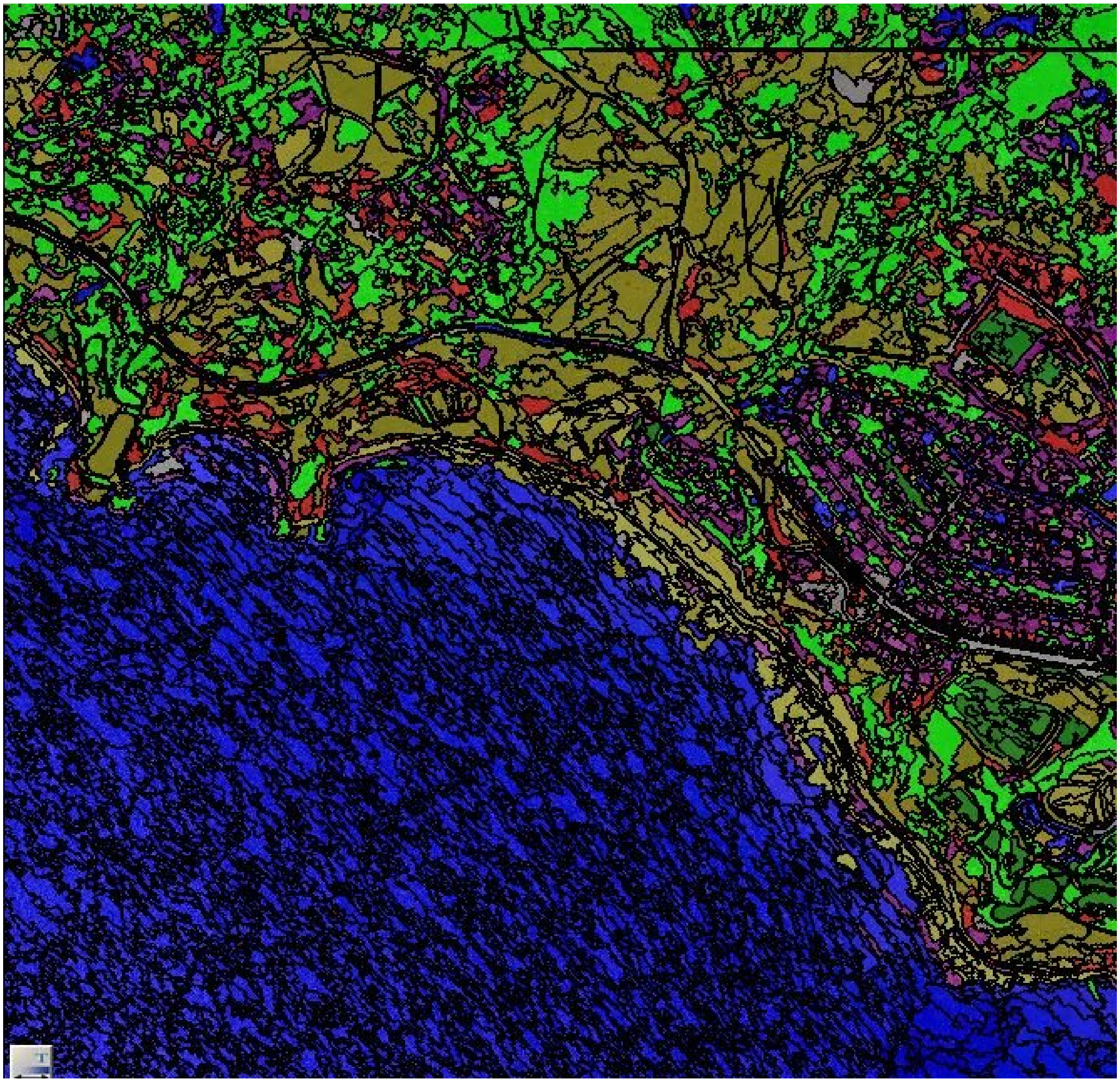

Figure 12: Final Results of scale parameter 70

Discussion

In the beginning, searching for a suitable area for landslide classification was challenging, because most of regions have undergone land development or reclamation. A geologic map was more useful than Google Earth. Another issue was finding a high quality historical imagery of the area. Most of the historical imagery was unavailable due to cost. Accuracy assessment was not conducted for this project, because the software is a trial version. More research was needed for this project, because landslides classification involves multitude of variables including relief, slope, compactness, shape, length, width, pixel values, and texture. The single most difficult part of the project was learning all the algorithms. I managed to learn only few: multi-resolution segmentation, assign, and classification. The user guide and manual was not very helpful, because it does not cover the topic in great detail.

Conclusion

Compare to supervised and unsupervised classification, eCognition has a steep learning curve. Developing proper rule set is the key to success in eCognition. Even the feature analyst (demo) is much easier than eCognition. It will take a semester or two to learn eCognition. I consider eCognition an important asset in land imagery classification. I think need the full version and seek expert advice on landslide.

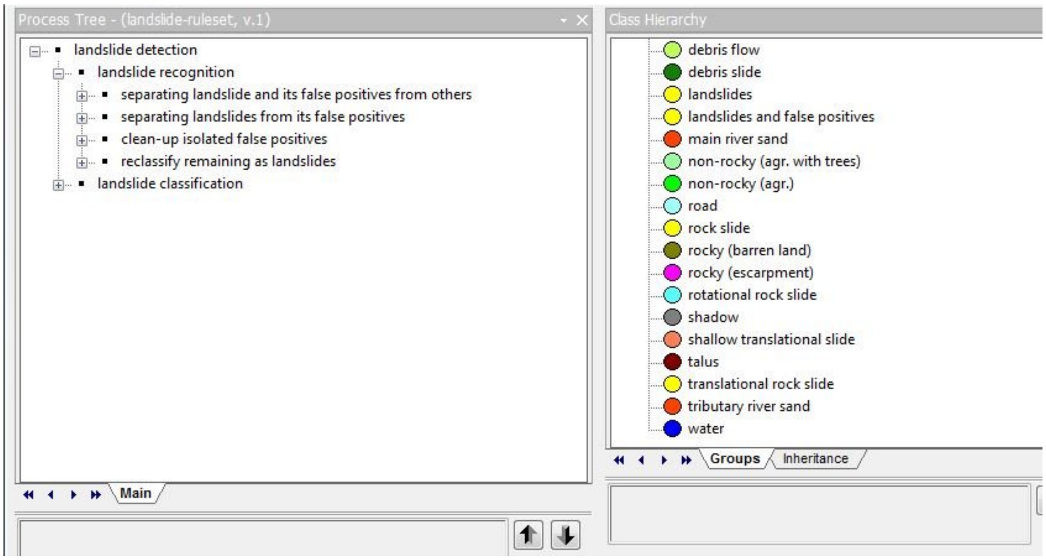

Figure 13: Rule sets from University of Twente

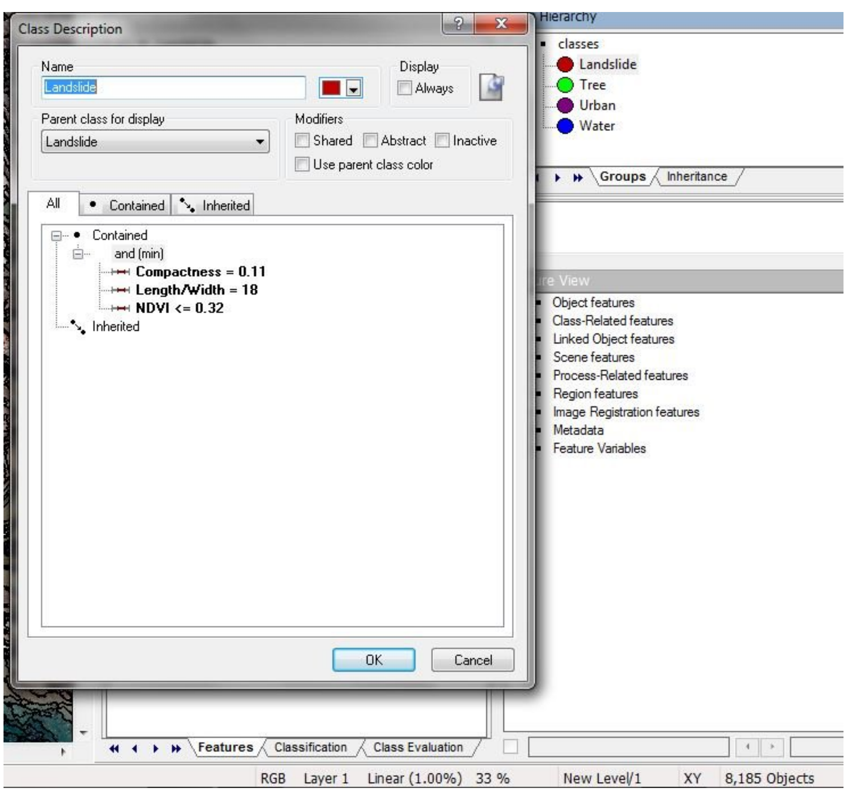

Figure 14: The threshold value for class description of landslide.

References

T. Lahousse, K.T. Chang, and Y.H.Lin., “Landslide mapping with multi-scale object-based image analysis-A case study in the Baichi watershed, Taiwan.” Natural Hazards and Earth System Sciences. 11, (2011): 2715-2726. JOSTOR.Web. 12. March. 2013.