# RULE INHERITANCE IN OBJECT-BASED IMAGE CLASSIFICATION FOR URBAN LAND COVER MAPPING

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## ABSTRACT
Mapping land cover in urban areas helps understanding the complexity of the urban landscape and environments. High resolution image data effectively captures such urban complexities and offers great potential for mapping the urban features in detail. The land cover information derived from remote sensing data has proven its usefulness for a wide range of urban applications. The traditional pixel-based classifiers rely on spectral information only, thus unable to capture the complexity and diversity of urban environments inherent in the high resolution image data. On the other hand, the processing at object level with additional spatial and contextual information produces promising mapping results. Urban land cover mapping from high resolution imagery with additional geospatial data using object- based fuzzy image classification techniques produced higher overall accuracy (90%). This paper explores the applicability and transferability of the fuzzy rule set developed over small areas to large areas with similar characteristics. The inheritance of rule set resulted into a slight decrease in overall classification accuracy (5%) that is due to certain new classes not represented previously. However, quickly updated rule set produced improved classification results and reduced processing time considerably.

**Keywords:** Residential buildings, Urban mapping, High resolution image, Object-based image classification

## INTRODUCTION

During the past few years, remote sensing technology has undergone a tremendous improvement for the acquisition of the digital images. Some of the recently launched very high resolution (VHR) space and air borne sensors are capable of acquiring very high spatial (sub meter) and temporal resolution (3-4 days) imagery. These images provide unprecedented levels of spatial information about the earth surface, and specifically increase the quality and the details of the information necessary for producing land cover maps (Walker and Blaschke, 2008). These data contains relevant and ample amount of information necessary for mapping complex spatial patterns within the urban areas and determining their changes (Moller, 2005). It also provides a rapid and cost effective means of collecting latest ground information and appears as an increasingly promising alternative to the traditional field visits and ground surveying. The inherent very fine level of details about the urban features makes possible to map e.g., even a single house, a tree or a parked vehicle. However, at the same time the analysis of such VHR data is more complicated due to high spatial and spectral diversity of the surface materials (Herold *et al.,* 2003). Urban landscapes experienced changes with the rapidly growing urbanization trends, environmental issues and social behaviors. These dynamic changes varies at places to place, with most modern and well planned urban developments in developed countries as oppose to unplanned, sprawls and slum in the developing countries. All these variation depends upon the social, cultural and most prominently economical factors (Antrop, 2005, USGS). Presently available VHR remote sensors capture such variations very effectively, however, mapping these complex urban features and environments pose great challenges. Even the well planned residential neighborhoods compose of houses of various sizes, shapes and roofing. Trees planted along the streets and roads when reaches mature age cover partly the streets, roads and the building or their shadow hides the actual roofs from the imaging sensors. Such occlusions pose difficulty while performing classification based on the spectral features.

To maximize the benefits and to extract the valuable products from VHR data, very efficient image processing and classification techniques are required. Traditional pixel-based classification methods have very limited applications for the processing of VHR data and mostly result in misclassification. However, the object-based classification has proved more useful for processing VHR data and producing more accurate thematic maps (Lu and Weng, 2007; Dehvari and Heck, 2009). Segmentation process creates objects of homogenous spectral properties followed by the classification based on spectral, spatial and contextual features (Blaschke and Strobl, 2001). Selection of appropriate object features to form fuzzy rules requires considerable time and prior knowledge. However, a carefully developed rule set over a small representative area can be transferred to other areas with similar characteristic, thus saving a considerable processing time and analyst's efforts (Lang, 2008).Land cover classification information derived from VHR remote sensing data through object-based classification technique has proven its usefulness for a wide range of urban applications like mapping individual buildings, impervious surfaces, green areas and micro population estimations (Shackelford and Davis 2003, Stow *et al*.2007).

In addition to high resolution image data, a variety of other geospatial data are available, such as high resolution digital terrain model (DTM) and digital surface model (DSM), LiDAR data, roads, buildings, buildings address points data and city zoning maps. Their fusion or integration with the high resolution remote sensing imagery proved extremely useful for land cover classification and mapping land use and urban feature (Shan and Hussain, 2009).

## OBJECT-BASED IMAGE CLASSIFICATION

The availability of VHR data and the limited capabilities of pixel-based classifications for analyzing spectrally heterogeneous data, led to the use of object-based processing. This is a two-step process that starts with segmentation followed by the classification. Initially the image is segmented based on the both the spectral and spatial homogeneity criterion to produces objects that closely resemble the real world structures. The segmentation operates as a heuristic optimization procedure, which minimizes the average heterogeneity of image objects for a given resolution over the whole scene (Baatz and Schape, 2000). With the varying color and shape parameters image objects of different sizes can be created at different levels. The large objects are further segmented to create sub objects which closely resemble the actual ground feature. The objects created at different levels can be linked both to their neighborhood as well as to the objects at lower and higher levels (Baatz and Schape, 2000). The use of objects relationship for the classification better represents the information as compared to individual pixel. The processing with the image objects allows the use of spectral, spatial and contextual characteristics to the classification process.

Popular schemes for object-based classification are supervised fuzzy logic nearest neighbor, and fuzzy membership function approaches (Walker and Blaschke, 2008). The nearest neighbor classifier uses representative training samples for each class and the minimum distance to means for classification. The fuzzy nearest neighbor classifier assigns a membership value between 0 and 1 based on the object's distance to its nearest neighbor. The fuzzy membership function classification is based on the fuzzy logic principles where fuzzy rules are formed for the description of classes. In case of VHR imagery with high spectral variability, fuzzy classification works on the possibility that an object may belong to one or more classes at the same time (Benz *et al*., 2004). It requires selection of appropriate features to develop a rule set, and define membership functions for every class of interest. The classification results depend on these input features and a membership value is assigned to every class. The membership value varies between 0 and 1, and the value closer to one (1) with no or less alternative assignment is considered as better results for a particular class.

Selection of appropriate segmentation parameters is totally trial and error and may require more iteration to achieve the objects of desired size. Also, selection of object features for optimal class separation and development of fuzzy rules need adequate prior knowledge on the characteristics of different ground objects. However, regardless of these limitations, object-based method provides better classification results as compared to processing at pixel level.

## STUDY AREAS AND DATASET

The study areas are parts of the urban area of West Lafayette, IN. Two residential representative areas, Black Bird Farms along Lindberg Road (800m x 415m) and the other on US-52 (415m x 775 m) have been selected for this study. These neighborhoods are relatively similar and comprise of many typical residential land covers, such as residential buildings, grassy areas, trees, roads, parking lots and small lakes. These two areas have been selected with the objective to develop a rule set for land cover classification over one area and then transfer and test it over the other to check its transferability and applicability.

The dataset includes color infra red (CIR) 2005 image data, acquired during leaf off season with ADS-40 push broom sensor. It has three spectral green, red and IR bands with a spatial resolution of 1 meter. The leaf off imagery provides better chance for mapping urban features especially buildings with minimal occlusions from tree cover. DEM and DSM of five (5) feet spatial resolution are also used. The DSM misses information about a number of small buildings; therefore, it cannot be used as the only information for classifying the elevated objects such as buildings, rather used as an aid to the classification process. Subset sample images of the study areas are shown in Figure 1.

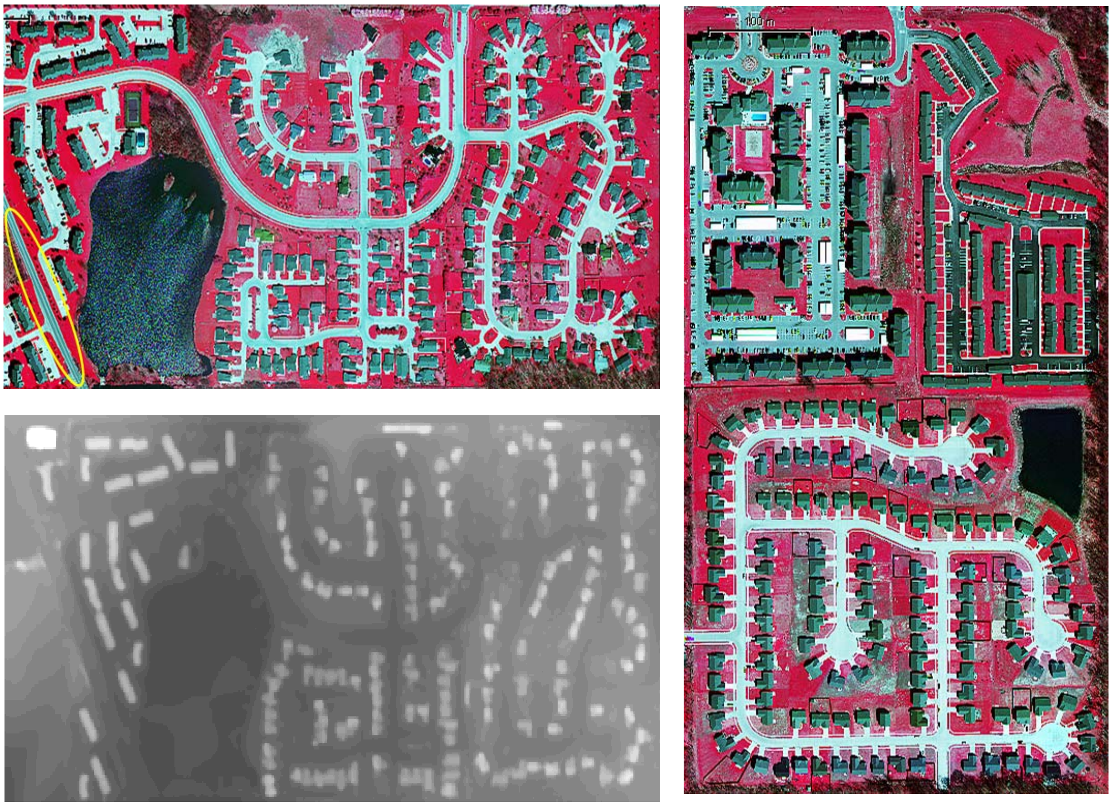

**Figure 1**. CIR images- Black Bird Farms (top left), residential area along US-52, (right) and DSM over Black Bird Farms (bottom left)

## CLASSIFICATION AND ACCURACY

### Pre-processing of the data

As both the DEM and DSM are created from 2005 CIR Ortho-rectified imagery, no further processing was required; however, normalized DSM (nDSM) is produced by subtracting DEM from DSM to obtain the height information.

### Image Classification

The rules based on appropriate class features and object-based fuzzy membership function method are employed for land cover classification. For this study, classification is performed on both the images sequentially and hierarchically, initially with five (5) main classes: Buildings (1, 2), Roads-streets and Parking lots, Shadow, Water, and Vegetation. Building class 1 is obtained based on the height features derived from nDSM and building class 2 for those whose height information is missing from nDSM. Though DEM and DSM are created from the same data, however, due to some processing error at source, height information about some of the buildings is missing from the DSM, as shown in Figure2. Later on parent buildings classes are subdivided into three child classes: 1) Apartments, 2) Single family houses, 3) multifamily houses based on their height and footprints area. Parent vegetation class is subdivided into two child classes as grassy areas and trees. All the roads, streets and parking lots are treated as one single class, and the unclassified objects are kept as "Others". The class hierarchy, object's features used for classification and the resultant classification images are shown in Figure 3, Table 1 and Figure 4, respectively.

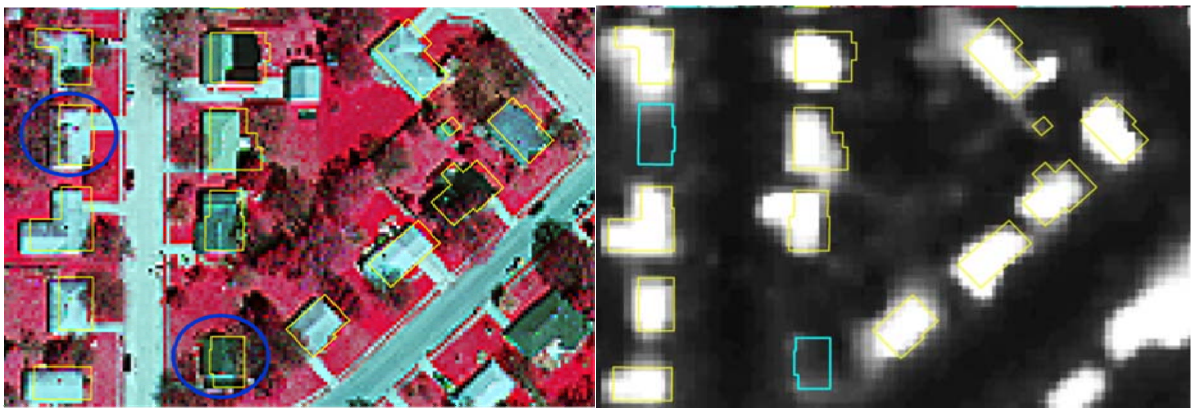

**Figure 2.** Missing Information from DSM, CIR image (left) and DSM (right)

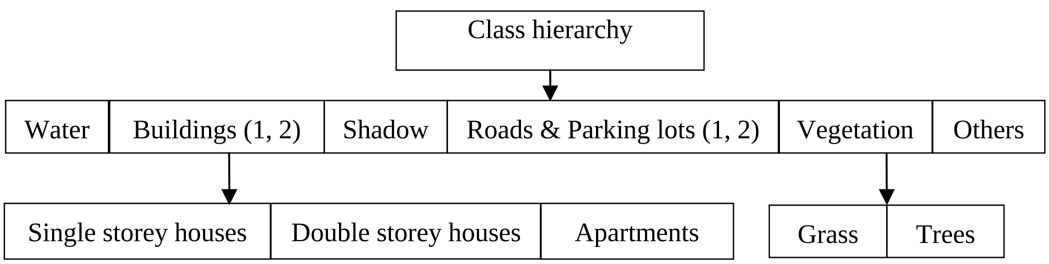


**Figure 3.** Class hierarchies for classification

**Table 1**. Features defined for different classes

| Class | Object features |
|---|---|
| Water | Mean DSM and mean NIR band |
| Buildings | nDSM, footprint area, compactness, length/width ratio |
| Shadow | Means of Red and NIR bands |
| Roads and parking lots | Brightness , Relation( border to existing class) |
| Vegetation | NDVI |
| Others | Unclassified |

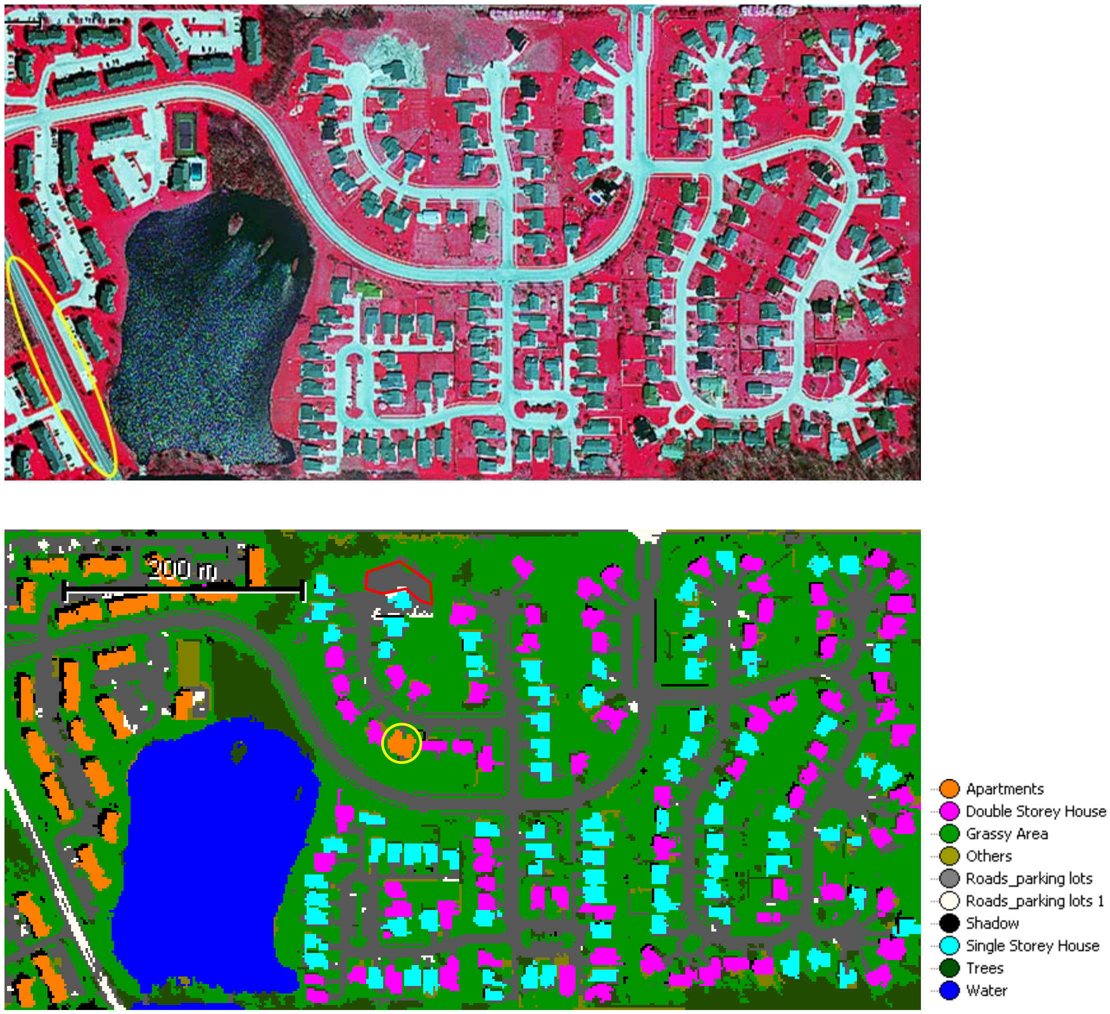


**Figure 4**. Original CIR image (top) and classification map (bottom)

## Classification Accuracy

The accuracy measures of the object-based classification is based on the statistics of the image objects assigned to different classes, as the mean, standard deviation, minimum and maximum fuzzy membership values. The higher the mean and closer the membership values to one (1), the more reliable classification results of a class. Accuracy assessment based on error matrices is also carried out by generating 100 random points over the thematic maps. These error matrices provide statistical information about the classification results, including the user accuracy, producer accuracy, overall accuracy and kappa values. It gives a fair idea about the class separability, class confusion and misclassifications. The statistical and error matrices based classification accuracies are given in Table 2.

Table 2. Quality of classification measured by membership function and random sampling points

| Class | Mean | Membership | | Random Points | |
|---|---|---|---|---|---|
| | | Minimum | Maximum | User Accuracy | Prod Accuracy |
| Water | 0.94 | 0.13 | 1 | 100 | 100 |
| Shadow | 0.60 | 0.14 | 0.98 | 100 | 83.33 |
| Roads and parking lots | 0.92 | 0.10 | 1 | 100 | 83.33 |
| Roads and parking lots-1 | 0.82 | 0.15 | 0.99 | 75 | 100 |
| Single Storey-Single House | 0.70 | 0.11 | 0.97 | 100 | 100 |
| Double Storey-Single House | 0.99 | 0.90 | 1 | 100 | 100 |
| Apartments | 0.80 | 0.15 | 0.98 | 100 | 100 |
| Trees | 0.74 | 0.12 | 0.99 | 100 | 76.92 |
| Grassy Areas | 0.99 | 0.90 | 1 | 90 | 90 |
| Others | 1 | 1 | 1 | 40 | 67 |
| | **Average user's accuracy = 90 %** | | | **Kappa = 0.889** | |
| | **Average producer accuracy = 90 %** | | | **Overall accuracy = 90 %** | |

### Discussion

The statistics of the classification quality measures show the results with higher membership values (mean, min, and max) except for the shadow class. It has a lower mean 0.60, maximum 0.98 of membership values, and 83% producer accuracy in random point assessment (Table 2). Shadow's overall low spectral responses in all the spectral bands and its neighborhood to buildings are used to classify it. Lake water surface with bright reflection effect appears spectrally non homogenous, but is low in elevation as compared to adjacent areas. The use of mean surface values (DSM) and mean NIR band correctly classified the lake water with 100% accuracy (Table 2). Concrete based roads, streets and parking lots appear very bright, but a darker part of (bitumen surface) road with white marking lines (Figure 1, shown in yellow ellipse), and a few parked vehicles appear darker. This variation forced their classification as two classes. Feature based on the mean brightness value correctly classified most of the roads and parking lots but missed a few darker parts of the roads. These unclassified parts were then classified as 'roads and parking lots-1 class using their relationship (relative border) to 'roads and parking lots' class. A bright under construction open area is misclassified as roads and street class (Figure 3, shown in red polygon).The average accuracy of these two roads and parking lots classes is around 90%.

Initially, all the buildings are classified based on their height feature, but it could not pick up all the buildings. For most of the missing buildings, the DSM did show their footprints but with very low surface values. Therefore, additional object features (Table 1) are used to classify the buildings with missing height information. The subdivision of the parent buildings to the detail level classes produced satisfactory results except for one single house (Figure 4, shown in yellow circle). It has been classified as an apartment building based on its larger footprint area and height which are similar to some of the small size apartment buildings. It is observed that due to spectral similarity between roads, parking lots and building roofs, it is hard to separate these classes based on spectral features only. However, with the availability of height information, these classes can be easily separated. Height information coupled with shape features helps to classify buildings at further detail levels, such as single storey, double storey and apartments. Collective use of both height and shape features produced 100% accuracy for the classification of buildings at detail level. Similarly, vegetation classes (grassy areas and trees) are classified using the NDVI, where grassy areas resulted into 90 % accuracy, and trees as 77% mainly due to the leaf off season data with not much of tree canopy and their confusion with shadow. Some of the objects that could not be assigned to above classes are then classified as "others", which produced lower accuracies and ultimately affected the overall accuracy of the classification process.

## INHERITANCE OF CLASSIFICATION RULES

The rule set is a combination of different conditions based on the spectral, spatial and contextual characteristics that an object must meet to be assigned to a class. High resolution images are capable of capturing very fine scale ground details especially in the urban areas. Mapping these ground objects is a complex process due to the presence of spectral similarities and variations both between and within classes. Thus, an accurate delineation of these objects requires use of spectral, spatial and contextual features. The selection and combinations of suitable objects features for different classes of interests consumes lots of processing time and analyst's efforts. The technique of developing a set of rules over a small representative image area may help to minimize these problems. Therefore, the aim of developing a rule set over a small subset image is to test its applicability and transferability to process similar images and large areas so that the time consumed for selection of suitable class features can be minimized and classification process be expedited. Keeping this in mind, rule set is developed while classifying the first study area and then subsequently applied to another subset of the same image. To check the effectiveness of the rule set, the second subset image area has been selected such that it includes classes similar to the previous area, but with a few variations (spectral and structural) to both buildings and roads and certain new classes such as parking sheds. This rule set is applied to the second area for the same classes. Subset image and the classification results based on inherited rule set are shown in Figure 5.

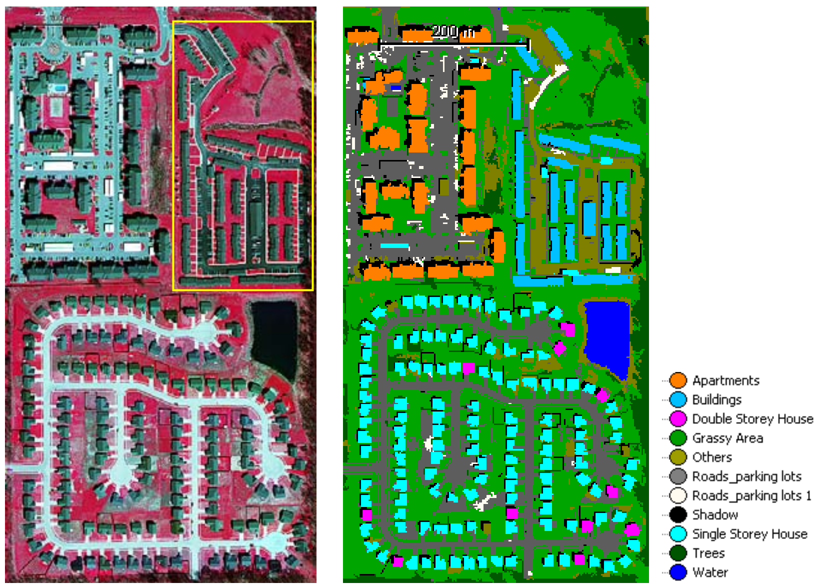

Figure 5. Original CIR image (left), land cover classification results with the inherited rule set (right)

## Classification Accuracy

The accuracy measures of the object-based classification based on the statistics of the image objects and the error matrices based on randomly generated points for this classification are shown in Table 3.

Table 3. Quality of classification measured by membership function and random sampling points (inherited rules)

| **Class** | **Mean** | **Membership** | | **Random Points Accuracy** | |
|---|---|---|---|---|---|
| | | **Minimum** | **Maximum** | **User Accuracy** | **Prod Accuracy** |
| Water | 0.82 | 0.22 | 0.99 | 100 | 100 |
| Shadow | 0.45 | 0.11 | 0.99 | 88.89 | 88.89 |
| Roads and parking lots | 0.87 | 0.10 | 1 | 66.67 | 50 |
| Roads and parking lots-1 | 0.83 | 0.12 | 1 | 88.89 | 100 |
| Buildings | 1 | 1 | 1 | 100 | 100 |
| Single Storey-Single House | 0.88 | 0.24 | 0.99 | 100 | 75 |
| Double Storey-Single House | 0.5 | 0.69 | 0.99 | 100 | 100 |
| Apartments | 0.94 | 0.20 | 0.99 | 100 | 100 |
| Trees | 0.75 | 0.11 | 0.99 | 77.78 | 100 |
| Grassy Areas | 0.99 | 0.17 | 1 | 100 | 75 |
| Others | 1 | 1 | 1 | 11.11 | 33.33 |
| | **Average user's accuracy = 84.85 %** | | | **Kappa = 0.833** | |
| | **Average producer accuracy = 83.84 %** | | | **Overall accuracy = 85 %** | |

## Discussion

Visual analysis of the classification map reveals that the rule set worked partially fine for most of the classes except a few, which are either totally new, spectrally or structurally very different from the one addressed in the initial classification test, e.g. parking sheds and very dark surfaced roads and parking lots. Lake water and shadow classes are correctly classified with accuracies over 90%. Roads and parking lots in this area are spectrally very different, i.e., very bright concrete surface roads in the single houses area, slightly dark in the apartment complex and very dark in the upper right building block (Figure 4, yellow rectangle). Bright to mid bright roads and parking lots are correctly classified, however it did pick up bright roof parking sheds and some of the open/partially grassy areas as roads and parking lots due to spectral similarity. Some of the parked vehicles were classified as roads and parking lot-1 class. It totally missed entire roads and parking lots within the upper right building block. These missed roads and parking lots are spectrally very dark and isolated to this block only. The rules based on spectral and contextual information used for Area-1 roads did not work well for these roads. This misclassifications resulted into low classification accuracy for the two ‘roads and parking lots’ classes which averages about 75% (Table 3). It correctly picked up most of the buildings at parent class level, missed three single houses and almost all the parking sheds being low in elevation and spectrally similar to concrete roads. Classification of parent buildings at the detail categories produced similar good results as for the Area-1, but totally missed the complete upper right building block (shown in yellow rectangle, Figure 5, top right). The buildings in this block are structurally very different from others, e.g. low in height as compared apartments, more footprint area than single houses, and elongated shapes very different from single, double storey single houses or apartments. These building remain classified to as parent building class. Overall, parent vegetation class is mapped very well except a few places where some open area patches with slight vegetation cover are missed. Further subdivision of vegetation class produced reasonable classification accuracy for trees (100%) and grassy areas (75%), with small mutual misclassifications. The places that could not be picked up by the classification rule set were left as unclassified. As class “Others” includes objects from most of the classes, therefore, it considerably affected the over accuracy of this test. The overall classification accuracy for this area is 85%, reduced by about 5% as compared to Area-1(Table-2). However, the use of pre-developed rule set reduced the processing time approximately by about 75% as compared to formulating altogether a new one for every other image.

Most of the classes are correctly classified with the rule set, however, to further improve the results, classification of the same image is performed after quickly modifying the rules, adding a new parking shed class and keeping low height and elongated shape buildings as a separate class “buildings”. Classification with the amended rule set produced qualitatively better results as compared to previous one, shown in Figure 6 (bottom right).

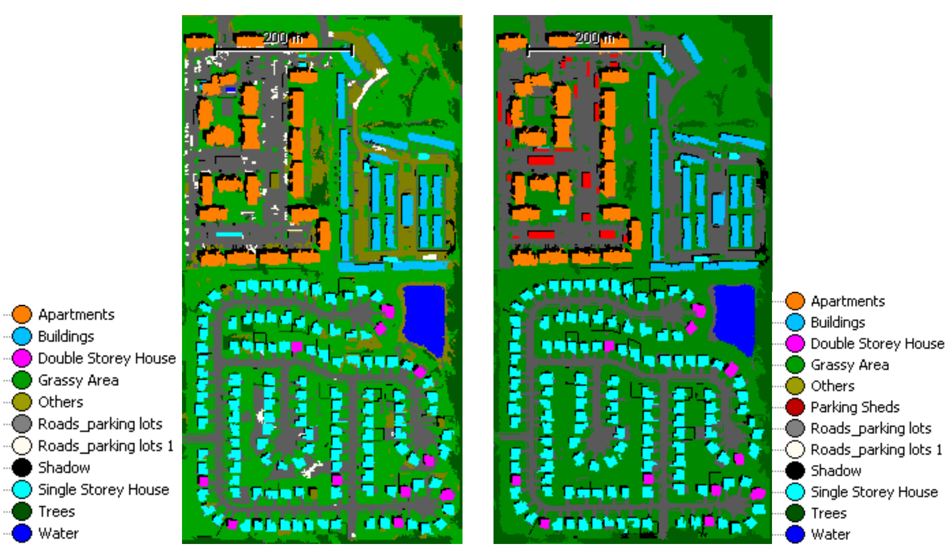


Figure 6. Comparison of land cover classification with the inherited rule set (left) and modified rule set (right)

## CONCLUSIONS

Urban area land cover mapping from high resolution images integrated with elevation data and processing with object based image classification methods resulted in an overall higher accuracies (90%). Supplementary data (nDSM) did help to correctly separate otherwise spectrally confusing elevated and non elevated ground objects. Height information helped to further subdivide classified buildings to detail classes such as single storey houses, double storey houses and apartments. Subdivision of building to such a fine scale can be very useful for many applications such as population mapping, crime and emergency response planning.

It is easy to formulate, test and improve classification rules over a small representative area and then to apply over other parts of the image. Transferred rule set can be run as whole or sequentially for each class. Land cover classification based on the transferability of rule set produced reasonably good results. It is observed that the use of already developed rule set reduced the processing time by about 75% as compared to initial formulation. Such a rule set can be quickly updated, modified and applied over large areas of the similar images for an accurate land cover classification. Detail urban land cover information derived from high resolution (both spatial and temporal) images can be very helpful for quick disaster response, urban planning, development, management and decision making processes.

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