Land Cover Classification using Random Forest Technique and DEM Auxiliary Data

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Abstract
This article has been written based on findings and results of author's master thesis. Nowadays, every month/year changes occur on the surface of the Earth from a small build ups till large-scale natural disasters that destroyed entire settlements. Observations and analysis using satellite data can help to improve and prevent any natural or anthropogenic disaster, plan and calculate beneficial usage of the land cover. Remote Sensing and Spatial Analysis tools are one of the approaches for them. This study tries to sustain one of the advantageous approaches for extracting information from semi-automatic mapping. Besides, article provides semi-automatic methodology of extracting information from multispectral image for large areas. For that, the Sentinel-2a (S2) optical data with 10 m resolution for Land Cover Classification System (LCCS) classification and as auxiliary data to extract the urban and industrial areas DEM and build up indices were used. Object-based image classification with random forest classification techniques using LCCS classes was done with an accuracy of 88%. Moreover Salzkammergut was chosen as a study area. The Salzkammergut is a historical and recreational area part of Austria, consisting of 52 districts from three federal states and with no official administrative boundaries.

1. Introduction

From time to time, the surface of our planet undergoes various changes. Consequences of land cover transformation can vary depending on the positive or negative outcomes. Remote sensing provides a unique opportunity to obtain valuable information about terrestrial objects and phenomena on a global scale with high spatial and temporal resolution. Recent technological developments in earth observation have improved the quality of data extraction and analyzing techniques. Moreover, rising number of freely available high spatial resolution satellite products develop new opportunities in obtaining spatial information. Using remote sensing and spatial analysis tools it is possible effectively and sustainably manage the land cover and land use areas for different purposes.

2. Study Area

As the study area the Salzkammergut region was chosen for this research. It is a recreational and historical area in Austria in the east of Salzburg, in the federal states of Upper Austria, Salzburg and Styria. The study area was chosen intentionally, because it consists of 52 districts from three federal states and has no an official administrative boundaries. In addition, this region is included in the UNESCO World Heritage List and it is rich for land cover species. The Figure 1 below demonstrates the Salzkammergut region.

3. Materials and Method

The general methodology of this study depicted in Figure 2 below. There are four main parts such as data, pre-classification process, classification and post process, and the results.

3.1 Data Description and Software

For this study data from the *different data sources* were used. In addition, points for accuracy assessment were created by the author. The descriptions of each data implemented are below:

- Sentinel-2 is the latest optical data provider from Copernicus programme of European Space Agency (ESA). For this study the image with 10m spatial resolution with 4 bands, namely b2 (red), b3 (green), b4 (blue) and b8 Near-Infrared (NIR) was used. Furthermore, two Short-Wavelength Infrared (SWIR) bands, b11 and b12 were added. The SWIR bands were resampled from 20m to 10m resolution. The purpose of the usage SWIR bands was to calculate the special indices to increase the quality of image classification. Below, Sentinel-2 image (see Figure 3) clipped to study area.

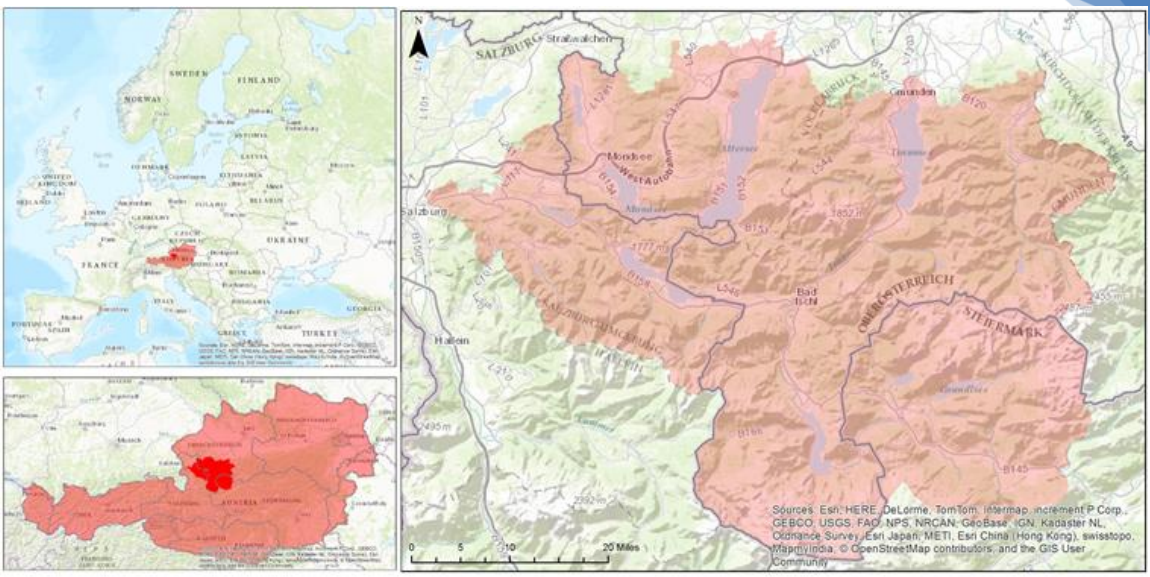

Figure 1: Study area - Salzkammergut region in Austria

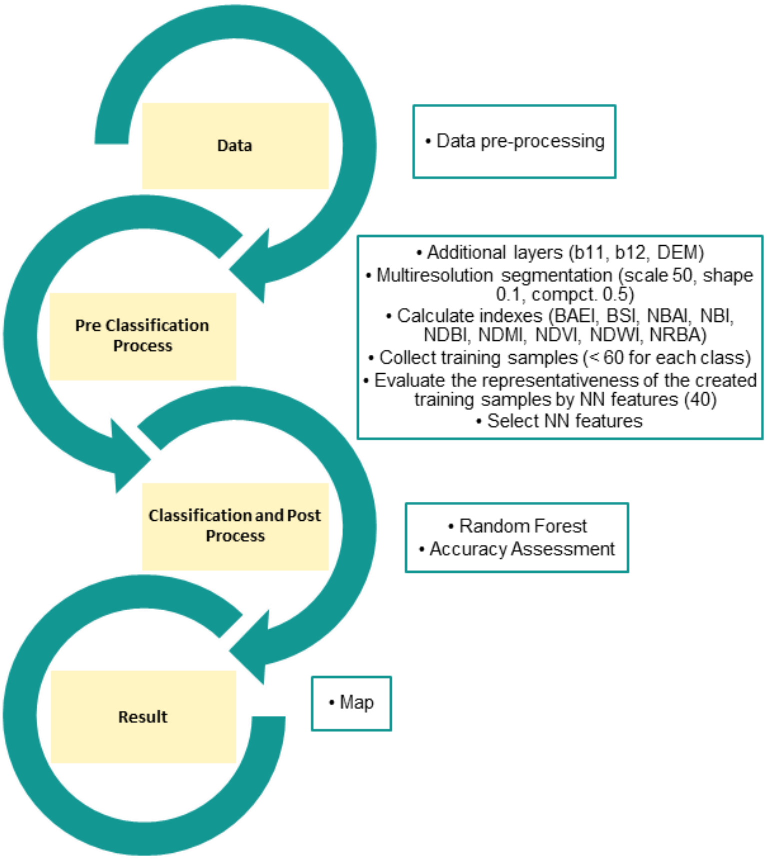

Figure 2: General methodology and overview of this study

• The Digital Elevation Model (DEM) was obtained from the Environmental Systems Research Institute (ESRI) online source and clipped for study area in ArcMap. Besides, it was added as a supplementary data to optimization of classification. The elevation range is between 410 and 2943 meters. It was added to distinguish bare rocks from other bared classes for classification.

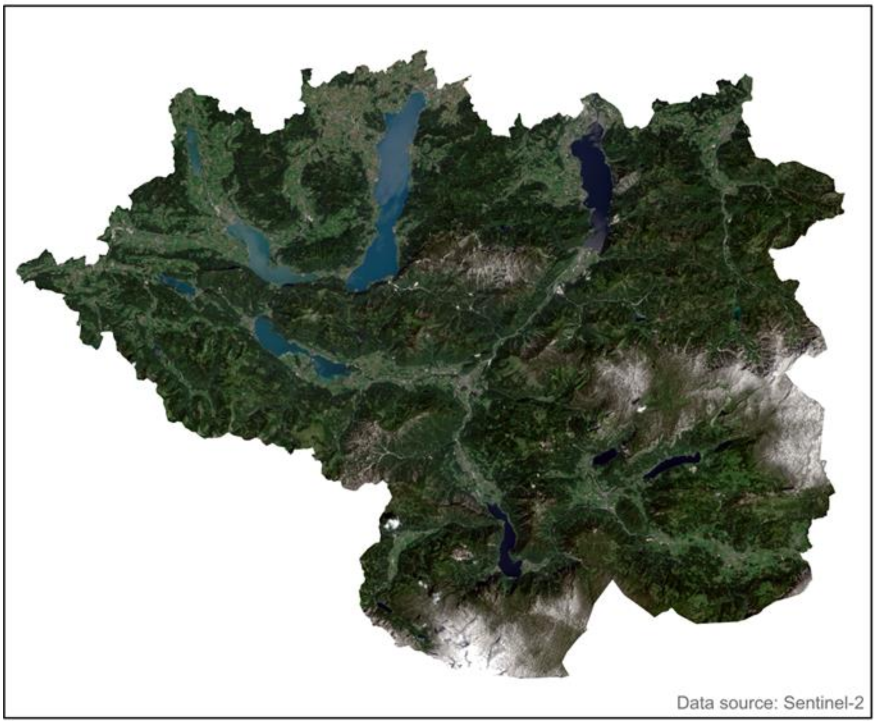

Figure 3: Sentinel-2a optical data

- Polygon shape files were provided from Interfaculty Department of Geoinformatics - Z_GIS and modified to area of Salzkammergut. Polygon shape files were used to clip the satellite image and DEM to extract the study area.

- Points to estimate the classification accuracy were created as a random point in ArcMap. 9000 points were created, counting 500 points for each class. To nominate points with class names CORINE Land Cover (CLC) classification 2012 from Copernicus Land Monitoring Service was used as an auxiliary data.

3.2 Software

To perform the object based classification and accuracy assessment, eCognition Developer software was used. The eCognition Developer is powerful tool developed specifically for OBIA. It is used to develop rule sets for automatic analysis of remote sensing (Trimble, 2017). The second software that was used in this study is ArcGIS for Desktop. Precisely ArcMap is used for all data preparation issues. It is well-known and comfortable software package in GIS environment. To derive class names from LCCS the LCCS application (version 2) were used. Through this application classes were defined and extracted with description.

3.3 Object Based Image Analysis

One of the remote sensing approaches that have been used in this study is object-based image analysis (OBIA). OBIA came up as an “intelligent” approach in delineation of spatial objects by size and shape, texture and saturation (Lang, 2008). OBIA has been built in old concepts of image analysis of remote sensing (Blaschke, 2010). OBIA deal with group of pixels which have the same parameters so called image objects or “geons” (Lang and Tiede, 2007) which are the outcomes of image segmentation. Image segmentation is important part of the OBIA. The usage of image segmentation technique allows to avoid “salt and pepper” (Blaschke and Strobl, 2001, Blaschke 2010 and Lang and Tiede, 2015) effect in image classification. It means that image segmentation regionalize the spatial objects by spectral and spatial behaviour (Lang and Tiede, 2015). Image segmentation parameters can differ depending on the scale, size and many other geometrical parameters. Multi-resolution segmentation starts grouping the neighbor pixels by homogeneity criteria to image objects (Trimble, 2016).

The homogeneity criteria compute color and shape parameters which were specified in advance. Also, scale parameter of multi-resolution segmentation can be assigned in advance. Multi-resolution segmentation produces more homogeneous image objects even in strong textured image data (Baatz and Schaepe, 2000). For this study the pixel level multi-resolution segmentation was done with the scale 10, shape 0.1 and compactness 0.5 as a default. Besides image object level was created using multi-resolution segmentation with the scale 50, shape 0.1 and compactness 0.5 as a default. In this level, sample selection and classification were done. To find proper scale parameter for image segmentation several testing scale sizes, ranging from 20 to 100 were carried out. On this basis, it was decided to stay in the scale size 50 where the image objects are delineatedly comprehensible.

3.4 Random Forest Classification Technique

To extract land cover information from Sentinel-2 the image classification based on OBIA and Random Forest (RF) classification technique was done. Random forest is one of the machine learning techniques and powerful classifier which was adapted for remote sensing image analysis (Chan and Paelinckx, 2008, Li et al., 2016). There is a definition for random forests proposed by one of the founders of RF Leo Breiman (Breiman, 2001): "*Random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest*". So, this method based on construction ensemble of trees, which are mutually independent from each other. Further random forest is mostly often used for land cover classification of multispectral and hyperspectral imagery (Chan and Paelinckx, 2008 and Rodriguez-Galiano et al., 2012). Since random forest classification demonstrated the robustness and functionality in other studies it is recommended to use RF technique in image classification. (Pal, 2005 and Li et al., 2016).

3.5 Land Cover Classification System

For the image classification in this study the LCCS classes were used. The Land Cover Classification System (LCCS) is well-known classification system which has been developed by the Food and Agriculture Organization of the United Nations (FAO) and the United Nations Environment Programme (UNEP) (Di Gregorio, 2005). It is a standardized classification system applicable for specific user requirements and which is created to provide adequate and scalable map. The LCCS can be used in creating any land cover maps all over the world within special predefined characteristic and parameters of existing classifications and legends (Di Gregorio, 2005). To build the list of classes of Salzkammergut region from LCCS the CORINE Land Cover was used. CLC has been employed in terms of the auxiliary data to nominate the class names and the land cover of the study area. Through the CLC 16 classes were extracted. Additionally two classes, "Clouds" and "Shadow" were entered before image classification result. The class "Unclassified" is an outcome of image classification. Since LCCS provide class codes only for land cover areas, classes "Clouds", "Shadows" and "Unclassified" coded by the author as follows (Tables 1).

5.5.1Built-up and vegetation indices

To improve the quality of classification, for properly assign image objects with the class names, the spectral indices were used. The following indices have been modified and adapted to Sentinel-2 spectral bands:

- Normalized Difference Vegetation Index (NDVI) is well known wide spread vegetation index which allows in a quantitative measurement to assess the dynamics of the state of vegetation during the growing season. This method is traditionally used to determine the state of vegetation, its development or death. The NDVI expressed as:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Equation 1

Tables 1: LCCS codes based CLC and author

N	LCCS codes	Name of classes	N	LCCS codes	Name of classes
1	01	Shadow	**11**	5002-3	Roads
2	02	Clouds	**12**	5003-8	Industrial area
3	03	Unclassified	**13**	5003-9	Urban area
4	10001-3781	Broad-Leaved Trees	**14**	6002-1	Bare Rocks
5	10001-5671	Coniferous Trees	**15**	6005	Bare Soil
6	10025	Pastures	**16**	8001-1	River
7	10049	Cultivated Area	**17**	8001-5	Lake
8	20041	Open forbs	**18**	8005	Snow
9	20061	Sparse forbs	**19**	8008	Ice
10	42260-60686	Bogs			

- Normalized Difference Moisture Index (NDMI) was implemented to determine the variation of moisture of land surface (Wilson and Sader, 2002 and Mallick et al., 2012). Other studies show that NDMI has positive effect on accuracy of image classification (Wilson and Sader, 2002 and Lu et al., 2004). Since sample based classification is used in this study, the NDMI helps to determine the training samples of swampy areas. The NDMI formula as:

$$NDMI = \frac{NIR - SWIR1}{NIR + SWIR1}$$

Equation 2

- Normalized Difference Water Index (NDWI) has been used to indicate the vegetation water content and to highlight the water bodies (Gao, 1996 and Chen et al., 2006). The Normalized Difference Water Index is defined as follows:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

Equation 3

- Bare Soil Index (BSI) was used in soil identification and to divide the vegetation with another background (Nandy et al., 2003). BSI was implemented as a supplementary indicator for agricultural land cover areas as:

$$BSI = \frac{(SWIR1 + Red) - (NIR + Blue)}{(SWIR1 + Red) + (NIR + Blue)}$$

Equation 4

- Built-up Area Extraction Index (BAEI) has been used for urban areas mapping of Djelfa city, Algeria with an overall accuracy of 92.66 % (Bouzekri et al., 2015). The BAEI is expressed as:

$$BAEI = \frac{Red + L}{Red + SWIR1}$$

Equation 5

Where: L an arithmetic constant equal to 0.3.

- New Built-up Index (NBI) was proposed by (Bouzekri et al., 2015) to delineate the bare ground areas from built-up areas. NBI based on digital numbers of Red band in bare surface areas (Bouzekri et al., 2015) so the expectancy of bare surface areas depends on high values of indicator. NBI is as:

$$NBI = Red * \frac{SWIR1}{NIR}$$

Equation 6

- Normalized Difference Built-Up Index (NDBI) (Zha et al., 2003) was developed and recommended for mapping urban areas (Chen et al., 2006 and Bouzekri et al., 2015) . In our case, it was beneficial to use NDBI to separately classify urban areas from industrial zone. NDBI as follows:

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR}$$

Equation 7

- Normalized Built-up Area Index (NBAI) and Band Ratio for Built-Up Area (BRBA) are proposed by (Waqar et al., 2012) to extract the built-up areas. Indicators built on the combination of different spectral bands as:

$$NBAI = (\frac{SWIR2 - SWIR1}{Green})/(\frac{SWIR2 + SWIR1}{Green})$$

and, $$BRBA = \frac{Red}{SWIR1}$$

Equation 8

Since above mentioned built-up indices such as BAEI, NBI, NDBI, NBAI and BRBA have been recommended in urban area mapping (Zha et al., 2003, Zhao and Chen, 2005, Chen et al., 2006 and Bouzekri et al., 2015). In this study they were used to improve the extraction of urban area, industrial zone and bare rocks classes in image classification.

3.6 Training Samples

In image (supervised) classification the number of training samples per class should not be less than 50 (Congalton, 1991). Due to the size of the study area it was decided to collect minimum 60 training samples per class. Evaluation of the representatives of collected training samples for classes was conducted by estimating the overlaying of the classes with each other by Nearest Neighbor Features (NNF) in eCognition. After several attempts the training samples were assigned and NNF was chosen. The value of minimum overlay 0.1 and maximum overlay was 0.75.

3.7 Standard nearest Neighbor Features

For this study the standard nearest neighbor features were used to apply for classification. It is standard because valid for all classes (Trimble, 2016). Since classification is object based the usage of spectral features are beneficial (Hall and Holmes, 2003, Leduc, 2004, Pu et al., 2011, Luque et al., 2013 and Li et al., 2016). The NN features were used to improve the classification technique to assign classes by texture, geometry, homogeneity and many other parameters.

As mentioned above, by evaluating the representatives of training samples, the list of applicable NN features were revealed. The predefined NN features were sorted for validation for chosen samples. The predefined lists of features are recommended from other studies (Hall and Holmes, 2003, Pu et al., 2011, Aguilar et al., 2012, Luque et al., 2013 and Li et al., 2016). However, in the end 60 features were obtained. Also the spectral indices for vegetation, moisture, water, bare soil and built-up areas were calculated as well as their mean and standard deviation values. In the Table 2 below features have been listed.

3.8 Classification with Random Forest Technique

After all pre-classification processes are done the object based classification with random forest technique was performed. In eCognition, the classification consists of two parts: train and apply the classifiers. In training part all spectral features and training samples were trained and evaluated appropriateness for the classification. As well as suitability and matching of selected features for classification was assessed. Further, in next part, approved classifiers were implemented and classification process has been launched. The Figure 4 shows the result of classification.

Table 2: Standard nearest neighbor features

1	**Mean**	b2, b3, b4, b8, b11, b12, NDVI, BAEI, BSI, NBAI, NBI, NDBI, NDMI, BRBA,DEM, Max difference, Brightness
2	**Standard deviation**	b2, b3, b4, b8, b11, b12, NDVI, BAEI, BSI, NBAI, NBI, NDBI, NDMI, BRBA, DEM
3	**Extent**	Area
4	**Shape**	Compactness, Density, Roundness, Rectangular fit, Elliptic fit, Asymmetry, Border index, Shape index
5	**Based on polygon**	Area (including inner polygons), Perimeter, Compactness, Number of edges
6	**Based on skeleton**	Number of segments, Avrg. area represented by segments, Std.Dev. of area represented by segments
7	**Texture**	Gray-level co-occurrence matrix (Glcm) homogeneity, Glcm contrast, Glcm dissimilarity, Glcm entropy, Glcm std. Dev., Glcm correlation, Glcm ang.2nd moment, Glcm mean, Gray-level difference vector (Gldv) ang. 2nd moment, Gldv entropy, Gldv mean, Gldv contrast

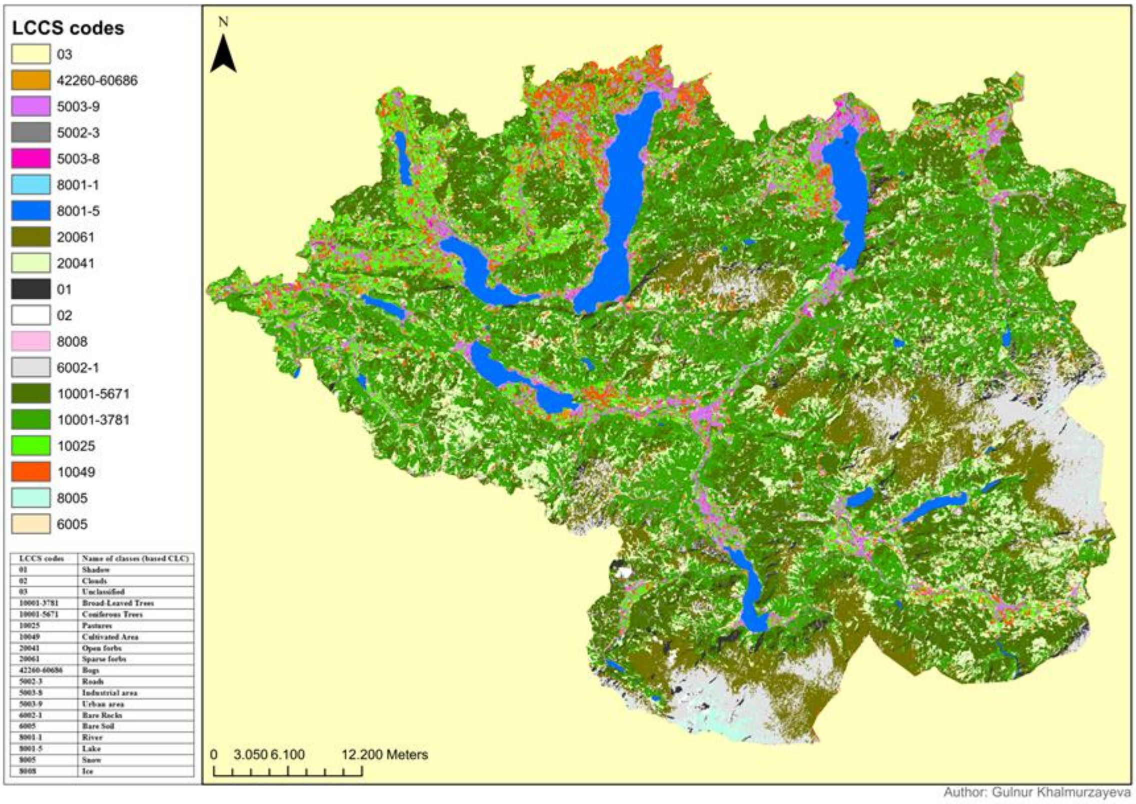

Figure 4: Object based classification with Random Forest technique

3.9 Accuracy Assessment

To perform the accuracy assessment of image classification random points are generated. Due to the size of study area and number of classes it was decided to create 9000 random points in ArcGIS Desktop. However, most of the names of classes were assigned by visual interpretation of the image. Accuracy assessment is the main part of the classification. Successfulness of performed classification, the appropriateness of the methodology that have used depends on accuracy assessment result. The nominated random points added as thematic layer and converted to the samples. Further, the accuracy assessment computed using the Error Matrix. The overall accuracy of performed object based classification is 87.9% (≈ 88%) and Kappa Coefficient is 85.7% (≈86%).

4. Results and Discussion

As Random forest image classification result it was presented a map with class codes. The number of classes was increased for one class. The class “unclassified” is outcome of unclassified areas across the study area. The eCognition software estimated the out zone of study area as class and segmented it. In fact training samples were not collected from out zone segmented objects. According to the accuracy assessment the random forest image classification is properly done for 88% which means that LCCS classes from Sentinel-2 image data has been extracted pretty good. It is clearly seen that the usage of spectral indices and NN features was helpful. The usage of auxiliary DEM was beneficial, training samples of “Urban area” and “Bare rocks” collected in different values of DEM, in different heights, the class object assigned correctly. It seems that not all spectral indices were valuable for this image classification. For instance, NDMI which used to determine the “Bogs” and BSI which is for “Bare soil”, both of the classes showed less accuracy assessment of image classification. However the NN features well served. In sample based classification the author came to idea that the more number of features, especially GLSM and GLDV, the image classification result would be more accurate.

5. Conclusion

This study aims to perform object based image classification for LCCS classes. LCCS class codes were extracted using the LCCS application and object based image classification using the Random forest technique was performed. To improve the quality of image classification spectral indices were calculated; also NN features and DEM were added. From the results it was considered that indices namely NDMI and BSI are not valuable to use in such sample based classifications. However the powerful features like GLSM and GLDV are welcome in implementing and evaluating the training sample selection and providing object based image classification. The quality of sample based classification can be improved using the spectral indices. The number and specification of indices depends on class specification, which is going to determine. The quality of sample based classification can be improved using the auxiliary data as DEM. In some cases, if training samples locates in different values of surface. The quality of sample based classification can be improved using NN features. The choice of NN features depends on number of classes and other requirements of user. But, as it is mentioned above, the more number of features, especially GLSM and GLDV, the image classification result would be more accurate. Moreover the studies presented in this article could be helpful in finding solution in Earth observation challenges.

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