03- ACCURACY ASSESSMENT OF LAND USE LAND COVER CHANGE DETECTION IN BURDUR WATERSHED, TURKEY: COMPARING ACTIVE AND PASSIVE REMOTE SENSING.

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Abstract
Remote sensing combined with GIS has been widely used in environmental applications such as land use land cover (LULC) change detection, environmental assessment, landslide mitigation and management, and flood hazard forecasting and assessment. Change detection is one of the most common uses of remote sensing combined with GIS. In passive remote sensing (RS), maximum likelihood classification (MLC) was used to generate a LULC map for the Burdur Watershed using Landsat images of 1990 and 2020. In active remote sensing, random forest (RF) classifier supervised classification was used in change detection analysis using sentinel-1 two date image stack for 2014 and 2020. The classification was pursued using six informational classes including open water, inter-tidal, sandy beach, forest, vegetated and unvegetated areas. Image classification was followed by accuracy assessment. A classification error matrix was prepared for each date stack in both MLC and RF classifier supervised classification results. The results of each classification method were evaluated based on overall accuracy and Cohen's kappa co-efficient (K). The results of the study showed that passive remote sensing had better results compared to active remote sensing in terms of overall accuracy and k values.o Accuracy assessment results illustrated that the overall accuracy and k values were very good (substantial) for 2020 and good (moderate) for year 1990 according to Landies and Koch using passive remote sensing. On the other hand, using active remote sensing, the results were fair for 2014 and 2020. Uncertainties created in the different image interpretation stages impacted the classification accuracy and land-cover class estimation. Primary sources of errors were image acquisition errors, data-processing errors, and errors associated with interactions between instrument resolution and the size of ecological processes on the ground. The results of this study could be used in studies relate to water resources management including hydrological studies and natural resources management in the study area. Moreover, the methodology used in this study could be adopted in any LULC change detection studies in Ireland and the results of the study could be used as input for several studies such as urbanization impact assessment, forestation and deforestation impact on climate change and hydrology of Ireland, change detection in surface area of the lake water bodies.

1. INTRODUCTION

Over the past years, RS has been more widely used in environmental applications. Advances in RS technology, as well as the availability of large amounts of data, have resulted in significant improvements in data analysis, especially when combined with GIS and machine learning (ML) algorithms (Lary et al., 2016, Avtar et al., 2020, Singh et al., 2017). The introduction of new platforms and interfaces, such as graphics processing units, open data sources (e.g., USGS Earth Explorer, Copernicus Data Hub, Bhuvan, Open Topography), and cloud platforms (e.g., Google Earth Engine), has significantly enhanced the mapping and monitoring of environmental changes recently. RS applications have been widely used in environment related applications such as LULC change detection, population change detection, environmental assessment, biodiversity, quality of life, groundwater,

transportation, landslide mitigation and management, mineral resources, and flood hazard forecasting and assessment (Avtar et al., 2020).

Remote sensing is classified as passive and active remote sensing. Since passive sensors provide high-quality satellite imagery, they were more widely used. Passive sensors, such as Multispectral and Hyperspectral technology, were superior in the area of technical observation of the earth. Without the sun or sunlight, satellites that rely on passive sensors will become completely useless.

Remote sensing technology, combined with the use of GIS, has increased the value of LULC change assessment over the last three decades, owing to more frequent and comprehensive changes on the earth's surface. Change detection is one of the most common uses of remotely sensed data from earth-orbiting satellites in remote sensing (Chughtai et al., 2021). Singh (1989) defined change detection as "the process of identifying differences in the state of an object or phenomena by observing it at different times" (Singh, 1989).

1.1 Study Area

Burdur lake watershed is one of those regions that has been heavily experiencing LULC changes throughout the years. One of the most important ecological problems in the Burdur Basin is defined as the decrease in the water level of Burdur Lake. With the effect of precipitation decrease in the basin and the construction of dams and ponds on the streams that feed Burdur Lake, a significant decrease in the lake level has occurred since 1986. The decrease in the water level in Burdur Lake causes a decrease in the living population of endemic fish and plant species, especially waterfowl (Şener et al., 2005, SYGM, 2019).

Burdur Watershed is located in southwestern Turkey. The watershed is located between the waters of Eseler, Monkey Mountains in the west, Kestel, Catak Mountains in the east, Rahat and Koru Mountains in the south, and Boz and Akdag in the north. Burdur, Isparta and some parts of the Antalya provinces are located within the boundaries of the Burdur Watershed (Sener et al., 2005).

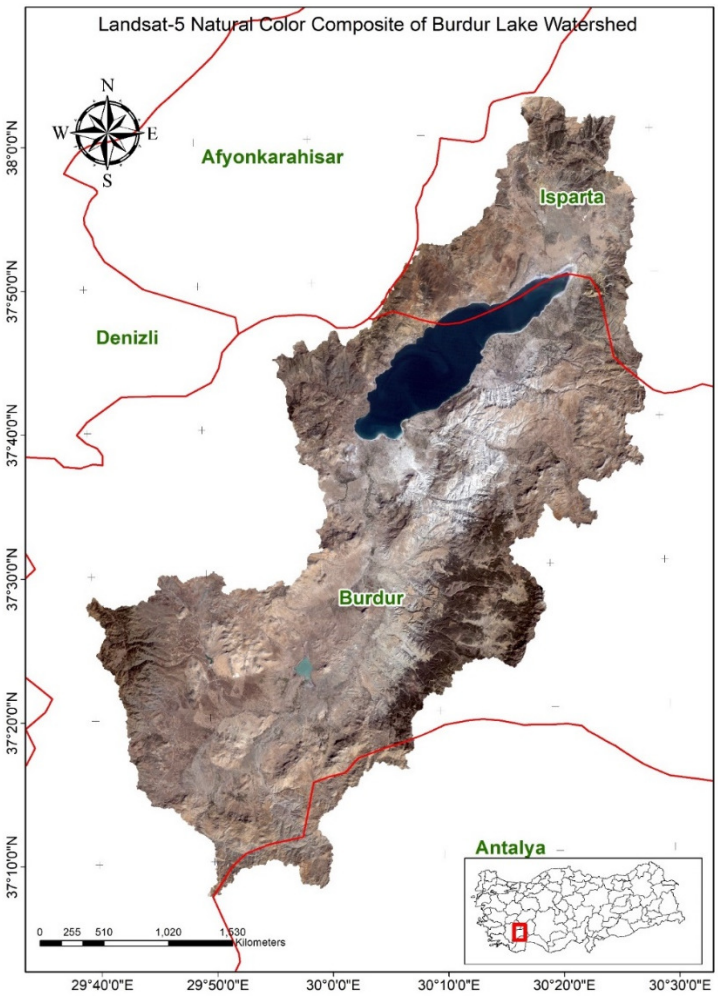

Figure 1: *Study area*

2. MATERIALS AND METHODS

2.1 Data Collection

USGS Earth Explorer and Copernicus Data Hub were used as data collection platforms to create a 2-date image stack. For passive remote sensing, landsat-5 and landsat-8 imageries for 1990 and 2020 years were downloaded using USGS Earth Explorer website (http://earthexplorer.usgs.gov/). For active remote sensing sentinel-1 satellite imageries for 2014 and 2020 years were downloaded using Copernicus Open Access Hub operated by the European Space Agency (ESA) (https://scihub.copernicus.eu/dhus/#/home).

The Landsat 2-date image stack bands were combined in ArcGIS to create a 4-band composite image. Landsat-5 composite image includes 1,2,3,4 bands and Landsat-8 composite image includes 2,3,4,5 bands respectively. Raw Sentinel-1 data were processed and subsets for each date were generated using sentinel application platform (SNAP) (https://step.esa.int/main/download/snap-download/). Prior to classification calibration, speckle filter, terrain correction and radar data enhancements processes were applied to the data.

2.2 Image Classification

2.2.1 Passive remote sensing

Passive remote sensing has been widely used and in particular, Landsat open source data with its high capabilities is popular. Landsat-8 has a spatial resolution of 30 m and a temporal resolution of 16 days. Landsat bands can be enhanced using panchromatic band with spatial resolution of 15 m. The operational land imager (OLI), designed and developed by Ball Aerospace and Technologies Corporation, is the focal point of the observatory. The OLI instrument advances future measurement capabilities while maintaining consistency with historical data by collecting land-surface data with spatial resolution and spectral band parameters compatible with historical Landsat data (Viana et al., 2019, E. D. Chaves et al., 2020, USGS, 2013). Both supervised and unsupervised classification have been applied in LULC analysis using passive remote sensing. In this study, ArcGIS was used to implement a widely used maximum likelihood classifier for LULC classification. The maximum likelihood algorithm measures the variance and covariance of spectral response patterns quantitatively, and each pixel is assigned to the class with the highest likelihood of association (Alawamy et al., 2020, Lu and Weng, 2007). Except for 1990, the training sites for both periods were created using both base map and composite images. Google earth was used in training site creation in 1990. The aim was to create the same training sites for both periods. However, as the surroundings of the lake were continuously changing, the training sites were also changed to prevent any adverse effect on the homogeneity of the six informational classes. Figure 2 shows the map of the training sites with their informational classes alongside the random points that will be used during accuracy assessment in the following section.

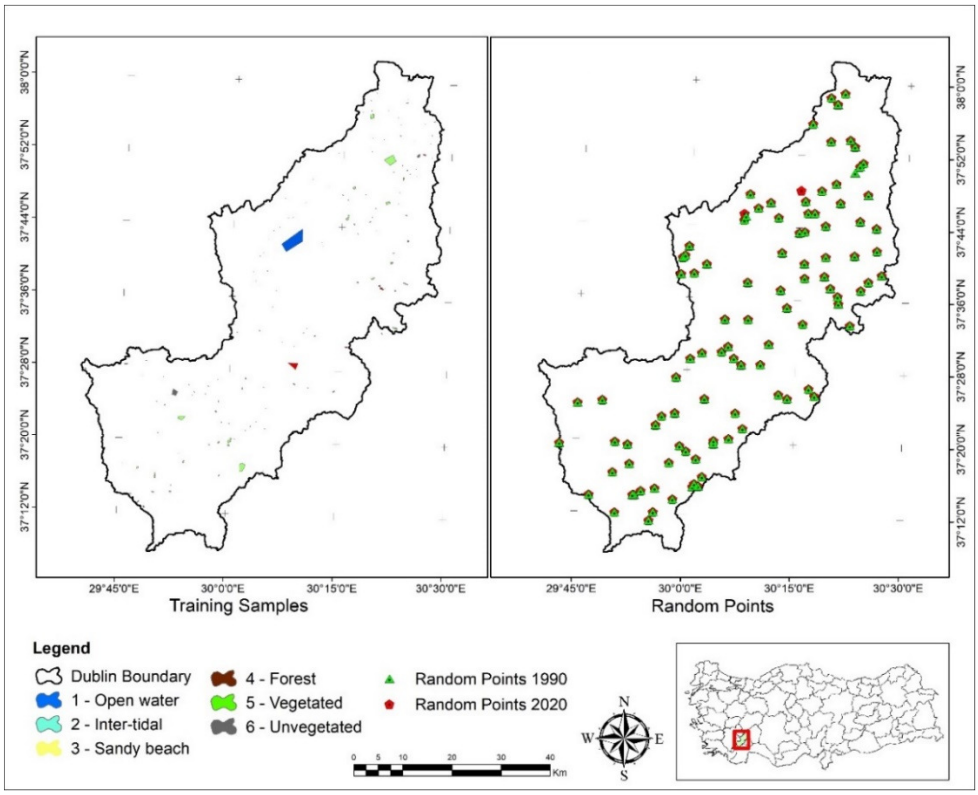

Figure 2: *map of the training sites (left) and random points for accuracy assessment (right).*

2.2.2 Active remote sensing

As data from multiple sensors became available over the last decade, synthetic aperture radar (SAR) data became more extensively applied for LULC change detection. The radar independency from cloud cover and solar illumination, improved spatial resolution, and availability of multiple polarizations and incidence angles have made SAR data being used to a large extent. Previous SAR missions only provided data with a low temporal resolution, making it difficult to establish effective radar based LULC change detection and mapping algorithms over wide areas. These limitations have been greatly reduced since the introduction of Sentinel-1. By integrating datasets acquired during ascending and descending trajectories, the Sentinel-1 could potentially provide images every three days. The ability to detect LULC changes regardless of cloud cover or solar illumination, combined with improvements in sensor characteristics (e.g., dual polarization, improved spatial resolution and incidence angle, precise orbital information), opens up previously untapped possibilities (Belenguer-Plomer et al., 2019, Fakhri and Gkanatsios, 2021). The training sites for Sentinel-1 supervised classification were updated using google earth and composite images. As a supervised classification method, random forest classifier method was performed. The random forest method combines K binary classification and regression trees (CART), where each tree is created by applying an individual learning algorithm to subsets of the input variable sets that were split using the Gini index as one of the attribute values tests. In the division of any node of the decision tree structure, the random forest classification uses a random subset of input predictive variables rather than the optimal ones, reducing the generalization error (Akbari et al., 2020, Rodriguez-Galiano et al., 2012).

2.2.3 Accuracy Assessment

Image classification is a long and time demanding process. As the outcome of image classification will be used as input to other works, research and discipline, it is always important to assess its accuracy. There are several principles and practices currently in use for assessing classification accuracy. One of the widely used practices is the preparation of a classification error matrix (sometimes called a confusion matrix or a contingency table). The error matrix can be used to derive a number of descriptive measures. For example, dividing the total number of correctly classified pixels by the total number of reference pixels yields the overall accuracy. Individual category accuracies can also be determined by multiplying the number of correctly categorized pixels in each category by the total number of pixels in the corresponding row or column. The number of correctly categorized pixels in each category is divided by the number of test set pixels used for that category, yielding producer's accuracies. The number of correctly classified pixels in each category is divided by the total number of pixels classified in that category to assess the user's accuracy (Lillesand et al., 2015, Jensen, 2015).

Another thing to consider when interpreting classification accuracies is that even a totally random assignment of pixels to classes can result in some accurate error matrix values. Indeed, if the number of classes is minimal, a random assignment could produce a remarkably good obvious classification result—a two-category classification could be assumed to be 50% accurate solely by chance. The k ("kappa") statistic compares the real agreement between reference data and an automatic classifier to the chance agreement between reference data and a random classifier. This statistic shows how much of an error matrix's percentage correct values were due to "actual" agreement rather than "chance" agreement. As true agreement (observed) gets closer to 1 and chance agreement gets closer to 0, k gets closer to 1 (Lillesand et al., 2015, Foody, 2020). According to Landies and Koch (1977), k value greater than 0.2 and smaller than 0.4 is considered as fair. Moreover, k value between 0.4 to 0.6 is considered as moderate result and k value between 0.6 to 0.8 is considered as substantial result (Landis and Koch, 1977). Accuracy assessment was performed for each classification using 100 random numbers validated

with google earth. The spatial distribution of random points for the accuracy assessment is given in Figure 2.

3. RESULTS

3.1 Passive remote sensing

The results of the maximum likelihood classification for each period are given in Figure 3. The results emphasised two main subjects including how good the classification was performed and LULC changes throughout the years. Even though, landsat-5 image characteristics is much lower than the Landsat-8, the results indicated that the classification was able to identify 6 major informational classes and especially the Burdur lake surface area. The findings also illustrated the changes throughout the years for different informational classes. The lake surface area has greatly changed throughout the years.

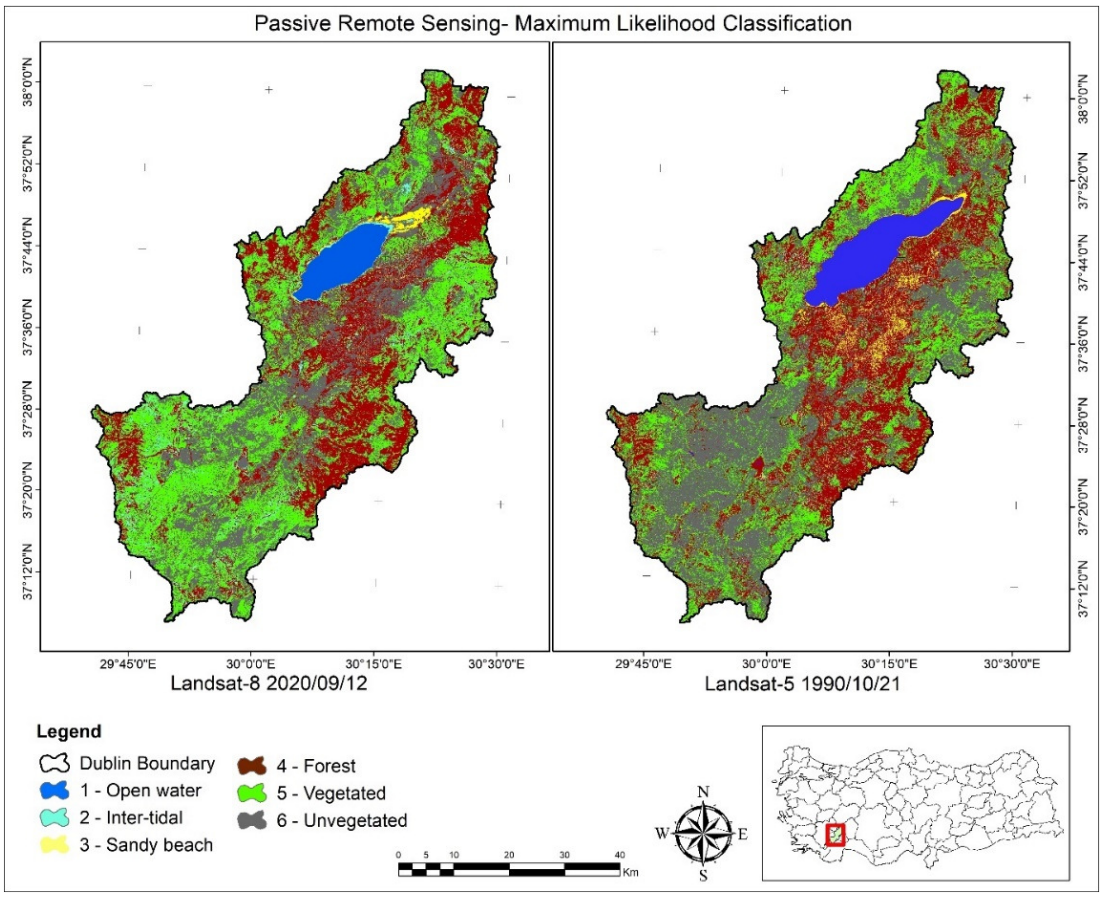

Figure 3: *Passive remote sensing- maximum likelihood classification results.*

3.2 Active remote sensing

The results of the random forest classifier supervised classification for each period are given in Figure 4. For 2014 the edges of the lake were trained as inter-tidal or turbid water to have all six informational classes and mostly the north-east edge of the lake that is mostly getting dry was also trained as turbid water even the area is a mix of plants and water in real situation. However, the findings of 2020 present a better illustration of the real situation, and the lake surface area was accurately identified. In terms of water, vegetation, un-vegetation, and forest informational classes the classification results were better

in representing the real situation. On the other hand, in terms of turbid water and sandy beach informational classes the results were far from real situation.

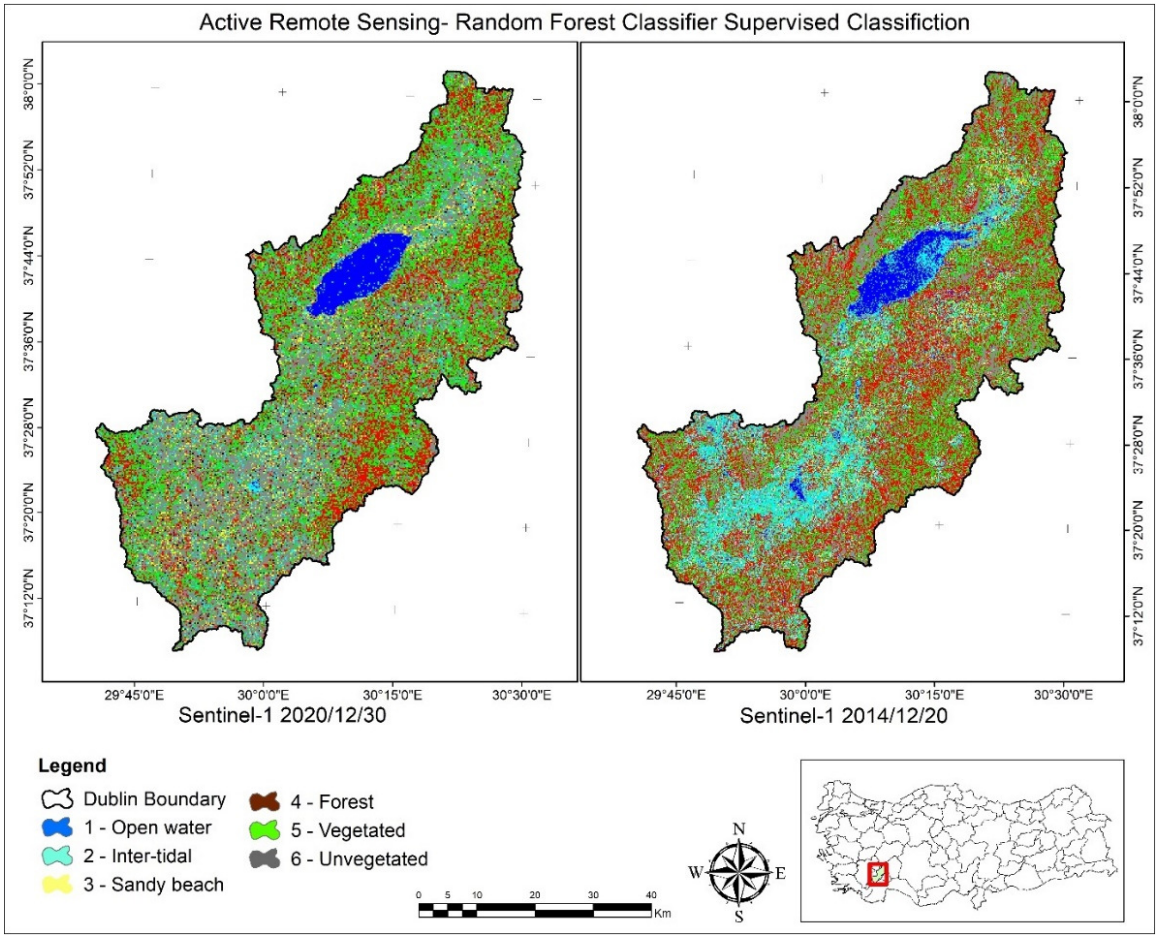

Figure 4: *Active remote sensing- random forest classifier supervised classification results.*

3.3 Accuracy Assessment

Figure 4 shows the random points used for the accuracy assessment. Table 1 illustrates the summary of the accuracy assessment for each classification method. According to the results the overall accuracy and k values were very good (substantial) for 2020 and good (moderate) using passive remote sensing for the year 1990 according to Landies and Koch (1977). On the other hand, using active remote sensing, the results were fair for each period according to Landies and Koch (1977).

Table 1: *Summary of the results for each classification.*

Classification Method	Overall Accuracy	Cohen's kappa co-efficient (K)
MLC 1990	58%	0.43
MLC 2020	75%	0.65
RFC 2014	42%	0.23
RFC 2020	45%	0.24

4. DISCUSSION

In passive remote sensing, majority of the informational classes were identified quite accurately except the informational class 3. Informational class 3 (sandy beach) was seen throughout the watershed even when the watershed was a lake watershed. The main reason behind this was the mining activities

happening in the watershed and they reflected the same wavelength as lake boundary areas. When the results in Table-1 were compared with the literature, similar studies had comparable findings. For instance, Ismail and Jusoff (2008) used a different number of reference data (200 and 388 reference data) to examine the classification accuracy of a classified forest map based on Landsat TM data. This comparison was done using observation (200 reference data), as well as interpretation and observation methods (388 reference data). Classification was pursued using five land cover classes including main forest, logged over forest, water bodies, bare land, and agricultural crop/mixed horticultural. Overall accuracy and the kappa value from 200 reference data were 83.5% and 0.75 respectively. When the number of reference data in the confusion matrix was raised from 200 to 388, the accuracy improved marginally from 83.5% to 89.17%, with the Kappa statistic increasing from 0.75 to 0.80, respectively. Another study that used medium resolution satellite images to map land use on Irish peatlands used a combination of object-oriented image analysis and peatland maps to create land use maps for the period of 2005 to 2006 (Connolly, 2019). The accuracy assessment was performed for each individual study area and the national map. The highest overall accuracy was seen in Limerick, Kerry and Cork which was 86% with a kappa value of 0.78 and the classification in Midlands Upland had the lowest overall accuracy of 66% with a kappa value of 0.76. The overall nationwide map accuracy was 77%.

As radar data are more sensitive to water in comparison to other informational classes, they are better in identification of water bodies. The result of the classification showed that inter-tidal water was seen in areas where no water was found in real situation. The reason behind this was the error happened during training sites identification. The outcomes of the active remote sensing also accentuated the importance of informational classes determination rigorously compared to passive remote sensing. Some of the informational classes used in this study such as inter-tidal and sandy beach classes were not suitable for the investigated area and as a result a misclassification was seen. Due to the abovementioned problems, the results obtained were not comparable to the results in the literature. However, the method adopted demonstrated the importance and applicability of active remote sensing in mapping water bodies and LULC change analysis. Active remote sensing was used in a study investigating the role of Sentinel observations in improving the detection and mapping of surface waters using decision-level image fusion techniques (Bioresita et al., 2019). The method was tested over Central Ireland in 2015–2016 using a time series of 16 Sentinel-1 images and a few Sentinel-2 images and an overall accuracy of above 99% was achieved. Another research employed Sentinel 1 satellite imagery in the investigation of the agricultural impact of the 2015–2016 floods in Ireland (O'Hara et al., 2019). The outcomes of the accuracy assessment of Sentinel 1 flood map versus Copernicus EMS data indicated an overall accuracy of 79.5%. However, when Sentinel 1 and Sentinel 2 maps were combined the overall accuracy increased to 91.0%. From the findings of the studies mentioned above, it could be deduced that active and passive combination might lead to might lead to more accurate results.

Several factors affected the results. The main reason was that supervised classification is highly dependent on the training sites, the ability of the person processing the image, and the spectral distinctness of the classes. The development of training data must be closely monitored in supervised classification. The classification results would be poor if the training data is poor or non-representative. As a result, supervised classification takes more time and resources than unsupervised classification (HSU, 2019, Hasmadi et al., 2009).

Uncertainties created in the different image interpretation stages impact the classification accuracy and land-cover class estimation. For example, the spatial and radiometric resolution limitations of remote sensing data, as well as the atmospheric conditions at the time of image acquisition, can lead to uncertainty in remotely sensed data. Friedl et al. (2001) identified three primary sources of errors: image acquisition errors, data-processing errors, and errors associated with interactions between instrument

resolution and the size of ecological processes on the ground. An error assessment was necessary to identify the type and amount of error in a remote sensing–derived product because it directly affects accuracy assessment. Sources of errors in remote sensing-derived information in the image acquisition includes errors due to sensor system, platform movement, ground control and scene consideration. The errors generated in pre-processing includes errors due to geometric correction, radiometric correction and data conversion (raster-to-vector-to-raster). Image variance was proportional to the scale of ground items in relation to the sensor's spatial resolution. Elements are larger than the resolution cell can be observed directly. Elements smaller than the resolution cells and are undetectable. As the scene's objects shrink in size compared to the resolution cell size, they can no longer be considered individual objects (Jensen, 2015, Friedl et al., 2001, Hasmadi et al., 2009, Fisher, 1997).

5. CONCLUSION

In this study accuracy, assessment of LULC changes was performed using passive and active remote sensing. In passive remote sensing analysis Landsat-5 and Landsat-8 satellites images were downloaded from earth explorer platform. Sentinel-1 data was used for active remote sensing analysis, and it was downloaded from Copernicus Data Hub platform. A 2-date stack of composite images were generated for both remote sensing analysis. Passive remote sensing was used to detect the changes between 1990 and 2020 years. However, change detection analysis for active remote sensing was performed between 2014 and 2020 years. In the following step, image classification was performed for each composite image. For passive remote sensing, maximum likelihood supervised classification was performed using ArcGIS and SNAP open access software was used to perform random forest classifier supervised classification for active remote sensing analysis. As a part of the accuracy assessment, classification error matrix was prepared for each analysis. While passive remote sensing results were substantial and moderate, the results of the active remote sensing were in fair band.

The results of this study could be used in studies related to water resources management including hydrological studies and natural resources management in the study area. Moreover, the methodology of the study could be adopted in any LULC change detection studies in Ireland and the results of the study could be used as input for several studies such as urbanization impact assessment, forestation and deforestation impact on climate change and hydrology, change detection in surface area of the lake water bodies.

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