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Research Article

Multi-temporal Satellite Images and Combination of Multi-Classification Approaches for Evaluation of Changes in Forest Cover: A case study

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Abstract: The primary objective of this study is to develop a method to monitor the changes in forest cover using three different techniques, namely Spatial Data Mining (SDM), supervised and unsupervised classification, and Geographical Information System (GIS) overlay processing methods. The secondary objective was to monitor the land use changes using multi-temporal satellite images (Landsat 8 images of 2016 and 2020). The study area is located in Nuwara Eliya, Sri Lanka. The first and second approaches consisted of supervised and unsupervised classification approaches. The use of a combination of two classification mapping approaches provides better results compared with the use of a single classification, which is a novelty of the present study. The GIS overly-processing technique combined the two maps obtained from supervised and unsupervised classifications to develop an improved map for land use changes. The improved map was reclassified and converted into ASCII (American Standard Code for Information Interchange) format, which was then pre-processed to convert the data set into the suitable format for the SDM modeling. The converted format was used to implement SDM modeling with the support of the Clustering-outline detection algorithm. The overall accuracy of the Landsat 8 images was 94.6. Results revealed that the forest cover extent was diminished by 5.28% in the study area between 2016 and 2020. The ground measurement was done with the help of the forest department to verify the results. The study revealed that the forest area decreased, and farming lands increased due to intensive agriculture. Future studies would be necessary to determine the validity and suitability of the developed model for other climatic zones in the country.

Keywords: Classification, Data mining, Forest extent, GIS, Remote sensing

1. Introduction

Forests are one of the world's most essential and valuable natural resources. It plays an important and significant role in maintaining environmental stability balance (FAO and UNEP, 2020). However, this resource is continuously degraded because of careless human interventions, bad political decisions, unacceptable strategies, and poor policymakers. Deforestation means losing trees and destroying the ecosystem and the environment (Lawrence et al., 2022). Declining the forest cover threatens the animals, the plant species, and the sustainability of agricultural production. The rapid decrease in the forest cover extent is mainly caused to the increase in the population, urbanization, expansion of agricultural areas, and industrial development. Depletion of the forest cover is a critical problem for living beings. It has numerous adverse impacts on ecological, social, and economical aspects, including climatic change, water and nutrient cycle breakdowns, soil degradation and desertification, and floods.

Remote sensing technology and the expanding availability of earth observation satellite data with high resolution have already demonstrated the ability to provide in-depth spatial information for identifying and monitoring numerous environmental problems of forest cover at a Spatio-temporal scale (Hufkens et al., 2020). It is considered one of the key methodologies in understanding forest biomass and the various interactions with the atmosphere, biosphere, and carbon cycle (Gamon et al., 2004). Several studies reported important observations using this technology, such as the Leaf Area Index and the fractional cover. A series of earth-observation satellites have recently provided high resolution (0.6–2.5 m) to moderate resolution (15–30 m) images for forest canopy mapping (Bartalev et al., 2003; Carvalho et al., 2006). Remote sensing data from these satellites consists of specific potential for detailed and accurate mapping of the forest areas at various Spatio-temporal scales. The use of remote sensing technology in combination with Geographic Information Systems (GIS) enables monitoring, mapping, and analyzing land changes cost-effectively in a timely manner (Shalaby and Tateishi, 2007).

Remotely sensed images have used the determination of the land use of a given point at a given time. The data obtained must be classified appropriately into categories that represent a set of identified characteristics to be helpful. However, computer-assisted image classifications are still in a poor stage to produce land use/cover maps and statistics with high enough accuracy (Prenzel and Treitz, 2007). Literature provides several image classification techniques that vary from automated to manual digitization. However, the majority of these applications in image processing still rely on the concepts that were developed in the early 70s. Therefore, it is

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argued that they may not be reliably related to spatial concepts (Blaschke et al., 2000). Meanwhile, various studies have derived broad-scale land use types, with some difficulties encountered when trying to characterize the complex land use/cover patterns accurately and precisely (Franklin and Wulder, 2002). A new form of inferential remote sensing technique is required to achieve the full potential of new image data sets for land use mapping. In such cases, Spatial Data Mining (SDM) technique is considered the best alternative methodology for land use mapping (Skidmore et al., 1997). The SDM is known as the process of discovering interesting, previously unknown, and potentially useful patterns from various massive spatial datasets (Wang et al., 2006). The algorithms of the SDM are adept at dealing with issues related to noisy, fuzzy, and incomplete data. Artificial Neural Network (ANN) can be used as the SDM technique (Richard and Lippmann, 1991).

ANNs are a biologically inspired computational technology based on the studies of the brain and the nervous system. This model can learn and train, and after the end of learning, it is very convenient to get results accurately. Therefore, this technology has been applied in research in various fields (Kavzoglu and Mather, 2000). Therefore, ANNs have been applied in various remote sensing applications since the 1980s, with an increase in powerful computers and network topologies (Atkinson and Tatnall, 1997). ANN can combine different data types and prior knowledge about the data (MacMichael and Si, 2018).

Sri Lankan forests are rich in biodiversity and consist of many tree species in a comparatively limited land area. As in many developing countries, forest cover in Sri Lanka has decreased significantly since the beginning of the 20th century. The high rates of population growth and the development projects in Sri Lanka can be considered the key causes for this rapid deterioration in the forest cover and other natural resources. As a developing country, several projects are in progress in Sri Lanka, such as the construction of urban areas, housing schemes, dams, and the development of industrial areas. Moreover, Illegal cutting of forest trees, constant grassland fire, strong wind, and drought have all contributed to the infliction of damage to these rainforests. As a result, many acres of forest areas have disappeared. The natural forest cover in Sri Lanka at the beginning of the 20th century was about 70% of the total land area (Legg and Jewell, 1991). However, the natural forest cover in Sri Lanka declined rapidly during the past century to reach a value as low as 23.9% in 2000 and 22.4% in 2020. Recent findings indicate that forest resources in Sri Lanka are still losing fast; at present, the percentage of forest cover has declined to only 21% of the total land (Geekiyanage et al., 2015). Moreover, some studies reported that, over the period from 1990 to 2015, Sri Lanka showed one of the highest rates of deforestation in the primary forest cover in the world.

Because of the rapid deterioration of the physical forest extent in Sri Lanka, it was identified to be necessary to monitor multi-year forest cover changes together while focusing on mapping past and present situations. The primary objective of this study is to develop a method to monitor the changes in forest cover using three different techniques, namely SDM, supervised and unsupervised classification, and Geographical Information System (GIS) overlay processing methods. The secondary objective was to monitor the land use changes using multi-temporal satellite images (Landsat 8 images of 2016 and 2020). The result would be helpful for managing forest resources and future planning for developing the relevant areas.

2. Materials and methods

This research consisted of four parts.

1. Production of the forest cover map by unsupervised classification.
2. Production of the forest cover map by supervised classification.
3. Combine the maps derived from supervised and unsupervised approaches using the GIS overlay technique.
4. Generation of high accuracy forest extent map using this new map for the SDM analysis. The methodology flow chart for developing a forest cover map is presented in Figure 1.

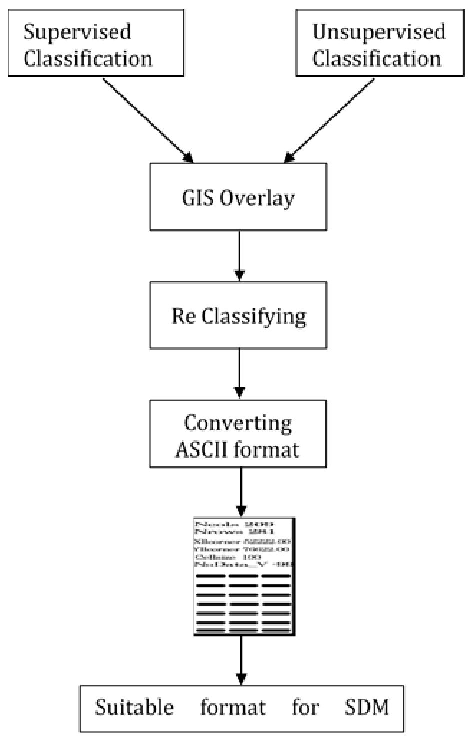


Figure 1: Schematic diagram of developing the classification methodology

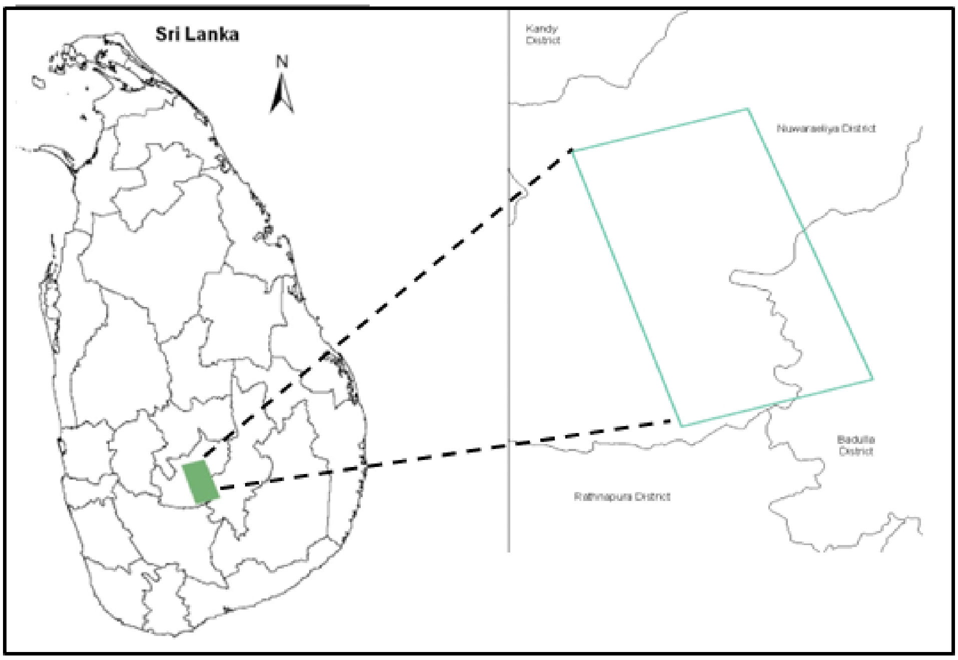


Figure 2: Study area

2.1. Study area overview

The study area of this research is located in Nuwara Eliya, Sri Lanka. Geographically, this area is situated within the geographic coordinates of 6°46'30" to 7°4'20"N latitudes and 80°43'54" to 80°53'51"E longitudes (see Figure 2).

The study area is known to be cloud rainforests. Endemic flora and fauna are two significant features of these forests. Some of the plant and animal species in these lands are endemic. There is dense forest biodiversity in this area. The dense forests are home to Deer, Jackal, Shaggy bear monkey, Sambar, and leopard. However, this forest is currently being declined due to natural and man-made destructive tendencies.

This analysis used two temporal satellite images (2016 and 2020) of Landsat 8.

2.2. Satellite image processing

In Landsat 8, nine-band images were stacked using ERDAS imagine tool, and then Geo-referenced, and re-projection were completed to the stacked image. After that, the study data of the area was extracted (a subset of the image) and then re-sampled. Finally, radiometric, geometric, and topographic corrections were done, respectively.

2.3. Unsupervised Classification

The main advantage of an unsupervised classification algorithm is to map areas such as land use and land cover from remotely sensed images. This classification is known as a computer-automated approach that is lightly similar to object-based image classification. This approach consists of two algorithms, namely, K-means and ISO cluster. Users need to choose the number of classes and pixels of the group based on their spectral value. The ISO algorithm is helpful for iterative optimization to separate cells into the user-specified number of classes. During each iteration, samples are assigned based on the attribute distances between the cells which belong in the cluster. This process is repeated after each iteration, and each pixel is assigned to the closest mean in the attribute space.

ISO algorithm was used for the unsupervised classification of satellite images in both 2016 and 2020 in the ERDAS image-processing application. At first, twenty-five spectral clusters were created to separate the image data into a readable format. These clusters were carefully evaluated with the help of actual ground data (collected during the field visit) and the knowledge of experts in this domain. Then similar classes and the same land cover types were combined. These combined clusters were assessed according to the land use and land cover classes (five classes) listed in Table 1. Finally, a thematic forest cover with land use/cover map was generated after applying a labeling function.

Table 1: Land use/cover classes

Class No.	Class name	Land used
1	Forest	Forest cover
2	Tea	Tea plantation
3	Residential	Houses, buildings, and roads
4	Farmlands	Vegetable, paddy, and irrigated lands
5	Water	Water bodies

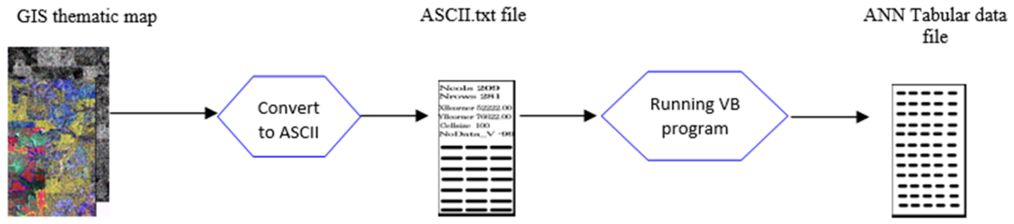


Figure 3: Data preparation for ANN modeling

2.4. Supervised Classification

The supervised approach is based on the concept that a user will be able to select associate pixel values with the relevant land cover classes. Image processing software uses to train these pixel values of the sites as references for the classification of all other pixels in the image. The training site can be selected based on the area's ground experiences and the user's knowledge. Then homogeneous sample pixels are grouped. Finally, the probability distribution is computed using a Maximum Likelihood Estimator (MLE) algorithm. In this study, towel areas were selected as the training samples (Signatures). The land use map of the study area developed by the Survey Department of Sri Lanka (1991) was used as a reference in assigning the training samples, along with the gathered knowledge of field visits. Then supervised classification was done using the parallelepiped non-parametric rule provided by the ERDAS tool. Finally, five classes were generated with a thematic land use/cover map (Table 1).

2.5. GIS overly processing technique

Several classifications are combined to get the best mappings, providing the best results than a single classification. This is the new concept of this study. Therefore, this research proposes using a GIS overlay processing technique that combines and maps the previous supervised and unsupervised classification to generate an improved forest cover map. Firstly, the maps derived from supervised and unsupervised classification were converted to ESRI Grid format. Then, both derived thematic maps were combined (intersecting) with the GIS overlay function in the ArcGIS application.

2.6. Spatial Data mining

The resulting maps of the above three approaches still have some errors. For example, when examining the results map, it was found that some features were left empty, and some pixels were wrong. Therefore, the data mining post-classification technique can be used to eliminate these erroneous pixels. The advantages of the data mining technique are pretty apparent. This will lead to higher product confidence and high flexibility and enable it to be adapted to many scenarios. ANN was used to implement a model for the classification.

The above-created three thematic maps (supervised, unsupervised, and GIS overlay processing) are now in raster format (grid). Then, reclassifying each layer as forest cover area was assigned to 1, and other land use/cover was assigned to 2. After that, derived raster layers were converted into the ASCII format using the raster to ASCII tool in ArcGIS. Then the other unnecessary information, such as the ASCII file's header and no-data values, was removed. This data set was converted to the CSV format, which is suitable for neural network modeling (Figure 3).

This data set was separated into two categories called training point and testing. A randomly selected data set was used to train the ANN model. Other remaining data sets were utilized for testing the network performance. The three-layered LM network (Input layer – hidden layer – output layer) was implemented using TensorFlow. Output values of the network were set to 1 and 0. The back-propagation algorithm was then applied to calculate the weights between these layers. The number of hidden layers and the learning rate (iteration time) were modified during the execution to increase the accuracy (Figure 4).

The hidden layer is the most critical part of ANN modeling. Many hidden elements are different from network to network to obtain the best performance of the final network error, which is used for the classification. The hidden elements were changed from 10 to 30, and the training iteration time of the training samples was changed from 100 to 2000. In this modeling, 0.5 is the initial learning rate, and 0.2 is set as the momentum. As suggested by (Lillesand et al., 2015), adjustments to these parameters were made by analyzing the dynamics errors. The input layer consisted of three inputs corresponding to supervised, unsupervised, and GIS post-processing thematic maps.

In contrast, the output layer consisted of two neurons corresponding to the forest cover and other land use/cover. This study considered two factors to assess the model accuracy: Root Mean Square Error (RMSE) and the Mean Error (ME). According to the prediction, the lowest RMSE and ME were considered the most successful model.

Figure 5 displays the RMSE and ME values of ANN modeling. Figure 4 shows the 3-18-2 network struc-

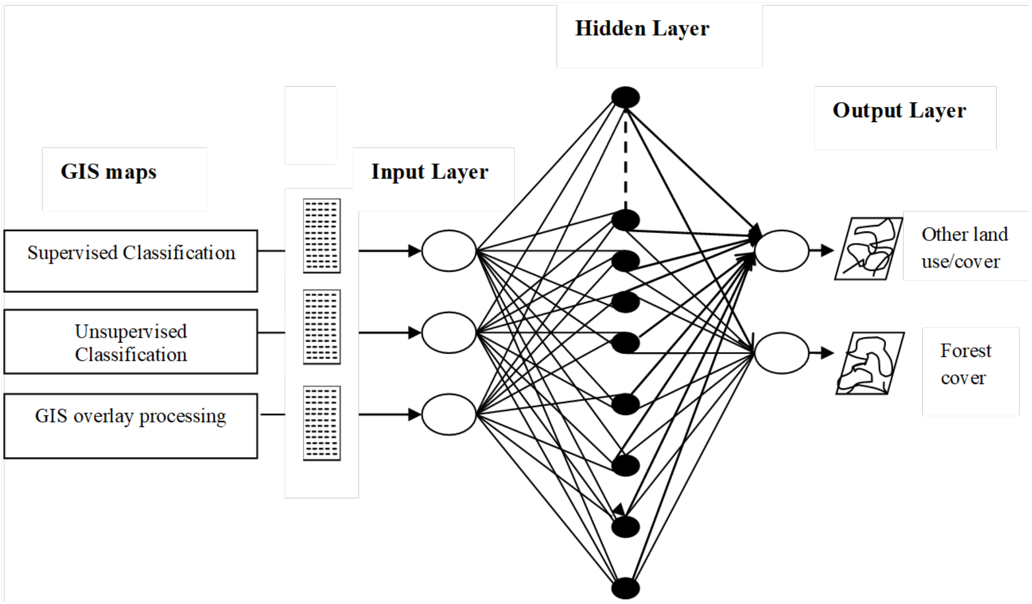
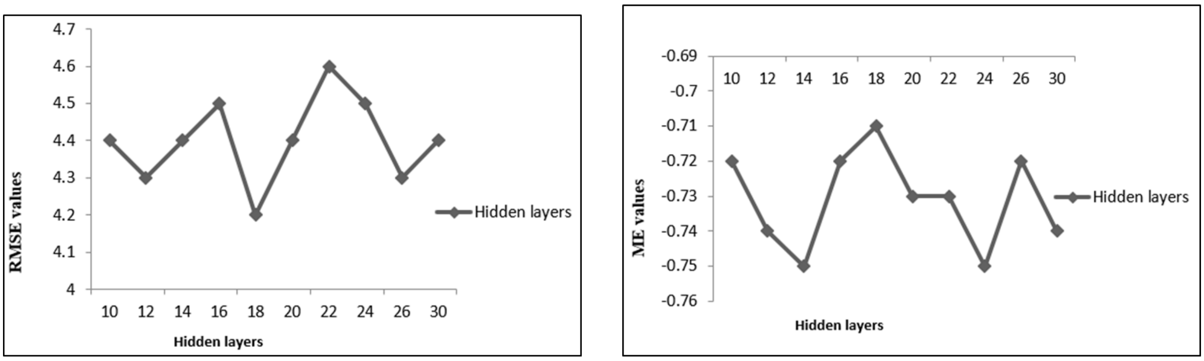


Figure 4: ANN modeling



(a) (b)

Figure 5: (a) RMSE values with the hidden layer, (b) ME values with the hidden layer

ture, which is identified as the lowest RMSE and ME values among the network structures after evaluation. Therefore, the above network structure is the best ANN model for this evaluation. The network size was extremely small; when the volume of hidden layers was less than 18, then the accuracy of the model prediction became low. When hidden layers were greater than 18, the model was over-fitted. In case of the model is over-fitted, the training accuracy could be high, but the prediction accuracy to be decreased.

The next step of the ANN modeling is to identify the relationship between training time and training accuracy. The number of iterations with training accuracy is shown in Figure 6. According to the above graph, it is indicated that a learning rate after 1400 iterations, peak level in training accuracy was reached at a constant level. However, if the iteration time exceeded above1400, the ANN model moved to be over-trained, which is known as another situation of over-fitted. Further, the graph shows when the iteration level at 400 and 1200 accuracy rates are below 40%. This happened due to the conformability of the model structure with the data shape. Therefore, this is not affected by the accuracy of the model.

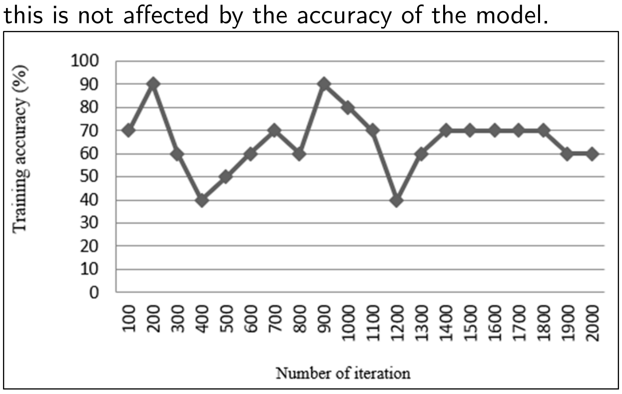
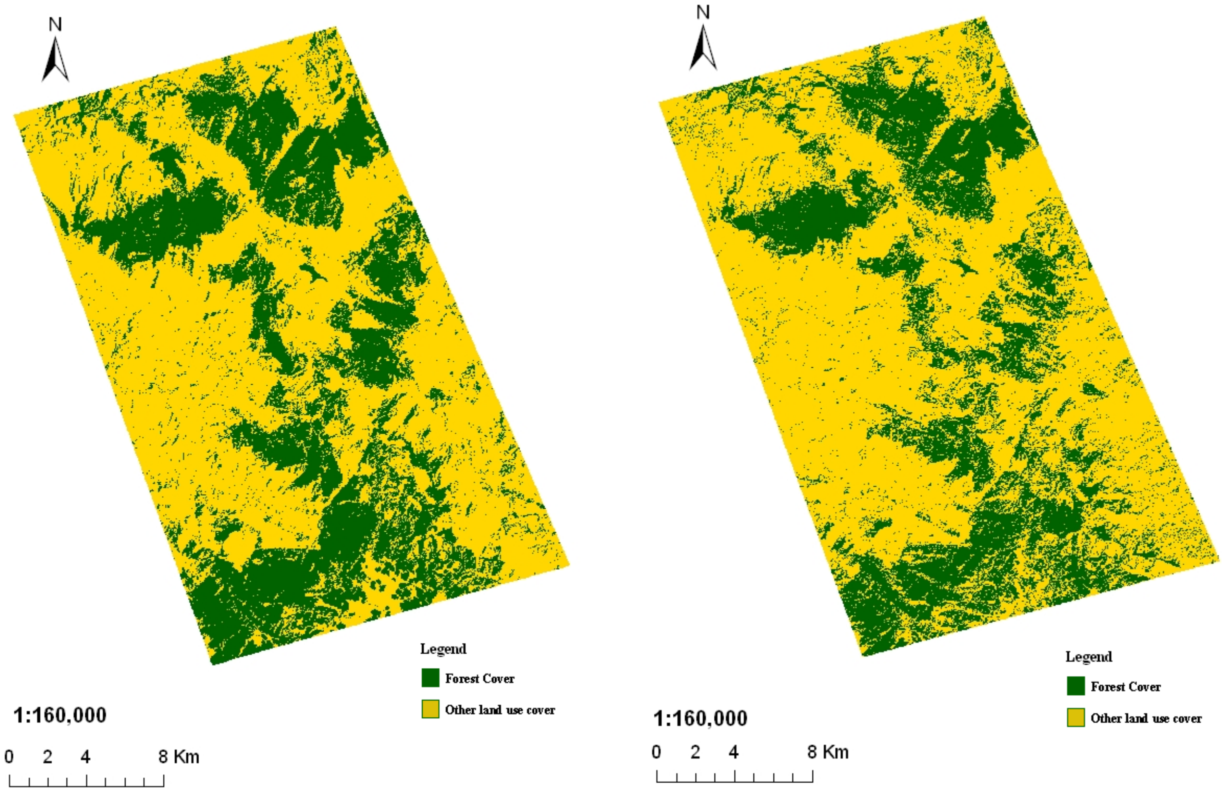


Figure 6: Number of iterations with training accuracy

Based on the above analysis, an appropriate ANN model



(a) (b)

Figure 7: (a) Forest extent map of 2016, (b) Forest extent map of 2020

for this evaluation greatly affected the network structure, training method, and training times. According to the given input criteria, this developed ANN model showed that the 3-18-2 network structure trained at 1400 training times was the best ANN model for predicting forest area cover. The back-propagation algorithm was used to identify the best ANN. The back-propagation algorithm effectively trained the neural network; it does not require prior knowledge (Zhang and Chang, 2015; Heermann and Khazeenie, 1992). Finally, this result was saved in CSV format and then converted this file back to GIS format for the output process. A thematic map was created based on the evaluation result from the ANN modeling. Finally, created thematic image was converted back to ERDAS .img image format for accuracy assessment. These settings were used for the remaining experiments and classification process. Similar procedures were followed for the landsat8 2016 satellite image to produce a forest cover map for 2016.

3. Results and discussions

Field observations, recently published aerial images, and survey results are the most valuable resources to compare the accuracy of thematic maps derived by image classification analyses. Geographical reference data are assumed to be actual for comparing predicted results with accuracy assessment. In this analysis, neighborhood information was incorporated significantly to increase the overall classification accuracy. The overall accuracy was calculated using equation 1 (Congalton, 1991).

$$\text{Overall accuracy} = \frac{\sum_{i=1}^{n} X_{ii}}{\sum_{i=1}^{n}\sum_{j=1}^{n} X_{ij}} \times 100\% \qquad (1)$$

The random sampling method was used to evaluate the accuracy of the classified image. For this purpose, the "Accuracy Assessment" tool in ERDAS was used. Then, 130 points were automatically selected from referenced topographic map. The referenced values were recorded on the "Accuracy Assessment Table" based on the previous land use map of the study area. The classification accuracy was measured by the non-parametric Kappa test, which can provide a more precise evaluation of the classification accuracy. The overall accuracy in 2016 was 96.2, whereas in 2020 was 94.6.

The Kappa statistics for the Landsat 8 2016 and 2020 images were calculated using equation 2 (Congalton, 1991), which were 0.88 and 0.92, respectively.

$$\begin{aligned}\hat{K} &= \frac{\text{overall accuracy} - \text{expected accuracy}}{1 - \text{expected accuracy}} \\ &= \frac{N\sum_{i=1}^{n} X_{ii} - \sum_{i=1}^{n}(X_{i+} \cdot X_{+i})}{N^2 - \sum_{i=1}^{n}(X_{i+} \cdot X_{+i})}\end{aligned} \qquad (2)$$

Finally, these maps were re-sampled in 15x15m resolution, and post-classification smooth was applied for easy analysis. At this stage, one thematic map has only two classes: forest and other land use/cover. The results data were analyzed by MS Excel application. In this approach, two thematic forest cover maps were produced for the years 2016 and year 2020. The methodology described above was applied for both satellite images. The forest extent maps of 2016 and 2020 are shown in Figure 7, respectively. Table 2 presents the results of the forest cover areas and deforestation between 2016 and 2020.

Table 2: Results of ANN modeling

Year	Forest area (ha)	Percentage
2016	19973.97	36.51%
2020	17000.48	31.23%
Forest lost	2973.49	05.28%

According to the results, the forest areas were lost by 05.28% (973.49 ha) in the present study area between 2016 and 2020. The results of the final classified maps showed that the forest cover areas rapidly decreased in the southern part of the study area. Moreover, the forest cover in the northeast area also seemed to be lost. In the southern part of the study area, the residential areas have been proliferating during the last two decades. That might be the main reason for the degradation of forest areas. The other reasons might be the increase of farmlands for cultivation and the natural hazards such as high-speed winds.

Many dense and healthy forests exist in the northeast part of the study area, where the forest extent is almost the same for both years. This area is located at 2000 m above the mean sea level. This area is characterized by enough rainfall throughout the year and a significantly high evaporation rate, along with high moisture content and nutrition in the soil that promotes good growth of forest vegetation. Forest deterioration matters such as man-made and natural hazards are significantly less. Above mentioned reasons might be the reason for the unchanged forest extent for the last four years.

It is known that some satellite images are complicated to classify for various reasons. However, many studies have proven that ANN is one of the best technologies to use for classification. Moreover, many researchers reported that the ANN approach gives higher accuracy for classifying satellite images when compared with statistical methods such as maximum likelihood (MacMichael and Si, 2018); however, ANN requires additional data to be incorporated into the classification process.

4. Conclusion

In the present study, a new methodology for land classification was developed. Multi-year satellite images were used to identify forest extent changes between 2016 and 2020 in Nuwaraeliya, Sri Lanka. Using multi-year satellite data in conjunction with GIS and neural networks provided an opportunity for forest extent monitoring and surveying, which can help monitor deforestation and would be required for future national policy planning, such as forest conservation measures.

The present study supports understanding of the areas where the forests are declined. A strong relationship was observed between forest degradation and an increase in land use change. Remote Sensing is one of the most valuable technologies in mapping and monitoring temporal changes in environmental phenomena over the traditional procedure concerning the cost of effectiveness and availability of information over larger areas. Therefore, satellite images are increasingly available to detect deforestation for biological conservation. It is revealed that some analyses and initiatives have been carried out to some extent; however, updated information is still insufficient. This study shows that the forest that covers the southern part of the study area is still vulnerable, and proper forest management strategies and protection measures would not be applied immediately for conservation. This approach can be applied not only for forest mapping but also for other land use/cover mapping is possible. The results of this study might be helpful for policymakers, researchers, and other interested parties in making and planning decisions on biodiversity management.

Results revealed that the changing process of other land uses/covers increased from 2016 to 2020. That might be related to the development policy and migration, which emphasized the expansion of residential lands and agricultural lands and the development of other infrastructures such as roads. Looking back to the history of these areas, most of the natural forests have been converted into agricultural lands, mainly for tea plantations and vegetable cultivation. A rapid population growth rate resulted in the conversion of forest lands into farmlands. Given the importance of complexity of forest conservation, it requires more advanced evaluations in the future to do with more sophisticated technologies.

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