Ann. For. Res. 65(1): 3299-3310, 2022
ISSN: 18448135, 20652445

ANNALS OF FOREST RESEARCH
https://www.e-afr.org/

AUTOMATED LAND USE LAND COVER CLASSIFICATION OF SANDUR TALUK, BELLARY DISTRICT, KARNATAKA, INDIA.

Vijayalakshmi Venugopal[1]*, Mahesh Kumar D[1], Veeramani S[2], Prasanna Kumar S C[3]
[1] JSS Academy of Technical Education, Visvesvaraya Technological University, India
[2]Periyar Tiger Conservation Foundation, Kerala Forests & Wildlife Department, India
[3]R V College of Engineering, Visvesvaraya Technological University, India

Abstract: The Land Use Land Cover(LULC) assessment forms the foundation for change detection studies. LULC can be used as an effective and efficient approach in not only monitoring land transformation, natural resources, natural disasters but also in land suitability applications and urban planning and development. This paper contributes in classifying and analyzing multi spectral images with a machine learning approach for the purpose of studying land transformation and change detection. Supervised classification algorithms involve making use of apriori knowledge of the data in order to extract statistical parameters to aid the process of classification. Some of the most popular and efficient supervised classification techniques are Maximum Likelihood Classifier(MLC) and Support Vector Machine(SVM). This paper presents LULC delineation using supervised classification algorithm using the Maximum Likelihood Classifier for the study area Sandur, Bellary District, Karnataka, India. Using QGIS the study area was delineated into six classes viz. water body, agricultural area, forest, built up area, mining area and barren land. The training process was conducted using Google Earth Pro. The overall accuracy of classification for 2001, 2011 and 2021 obtained was 87.5%, 86.3% and 87.32% respectively. The Kappa Coefficient values obtained were 85.01%, 83.43% and 84.8% respectively.
Keywords: Remote Sensing(RS), Quantum Geographical Information System(QGIS), Land Use Land Cover (LULC), Supervised Classification, Maximum Likelihood Classifier(MLC).

1. Introduction

Land, being a non-renewable natural resource, represents one of the unique features of our planet. Land supports human inhabitation as it is the first and most primary requirement for agricultural and cultivational purposes. Population explosion has resulted in an exponential rise in the demand of agricultural products as well as its byproducts leading to overexploitation of non-renewable resources such as land, soil, water etc. In this scenario, Land Use Land Cover(LULC) analysis serves as a means of estimating the changes that have occurred over a period of time, thus supporting planning, management and reclamation activities[1]. While Land Cover(LC) refers to the features present on the earth's surface, Land Use(LU) refers to the utilization of land as a result of human intervention for various purposes. LU, in some applications indicates the depletion of natural resources[2].

An important property of remote sensing data is that they are statistical in nature. The goal of Digital image classification techniques would be to identify patterns on the image datasets giving meaningful insight to the dataset thus forming a description of geoinformatics. Machine learning

based pattern recognition algorithms can be implemented to extract information from remote sensing data which further can help in decision making. The two most widely used classification schemes are supervised and unsupervised. In Supervised classification pixel based grouping takes place depending on spectral characteristics which are similar and which conform to a statistically determined criteria. Unsupervised classification involves determining the number of clusters prior to classification without any knowledge of the data. K-means clustering and ISODATA (Interaction Self-Organizing Data Analysis) are commonly used unsupervised classifiers. Accuracy of classification can be obtained by computing the Kappa Co-efficient and User-Producer accuracy assessment metrics. In general accuracy assessment supports in identifying and selecting an optimal classification algorithm for any application.

Supervised classification technique involves classifying the pixels of the image dataset making use of the training labeled data and then this model could be used for predicting or classifying new images. Photographic sheets, field surveys or topographic sheets are some examples of generating training labeled data. A spectral signature is generated in which pixels are grouped based on similarity criteria. MLC is the most prominent algorithm used for multispectral image classification. Unsupervised Classification technique involves data analysis when apriori knowledge or historical data is not present to training the algorithm. During the process of unsupervised classification, the algorithm chosen itself performs the pattern recognition thus identifying the trends in data. One of the prominent unsupervised classification algorithms used for exploratory data analysis is K-Means Clustering algorithm which works without making use of a training labeled dataset. It can be considered similar to the segmentation phase where pixels are classified based on a predefined criteria. Determining the number of clusters for a given dataset becomes the most critical aspect to achieve classification of optimal accuracy. These clusters are determined and are defined in feature space with respect to the centre of the cluster.

Thus this K-means clustering process can be defined as an iterative process which classifies pixels of unlabeled datasets into distinct clusters based on certain specific homogeneous criteria. This centroid based algorithm takes up an iterative approach to determine an optimal value for K center points.

2. Literature Review

The objective of this paper was to conduct LULC change detection studies via assessment of structural reflectance for the duration between 2005 and 2010. The study area considered was Sandur taluk, in Karnataka state, South of India. An integrated approach using RS and GIS was implemented using ERDAS IMAGINE 9.1. While nearest neighbor and cubic convolution techniques were employed for the geo-registration process, MLC algorithm was used to delineate Land Cover types. It was found that although there was a substantial decrease in the forest area and agricultural area due to mining activity, the percentage of agricultural area remained the same as wasteland was converted into cultivable land. Extensive mining activities to cater to the increased demand of minerals such as iron ore, manganese etc has adversely affected the Land Cover of the study area[3].

LULC was performed for the Narihalla watershed of Sandur taluk, Bellary district, Karnataka using RS and GIS techniques. Visual Interpretation of the LISS III satellite imagery was performed along with the support of ancillary data. Reclamation measures such as trenching and contour furrows need to be implemented for the purpose of water and soil conservation[4].

This research presents a model to identify, evaluate and forecast the trend in LULC along with changes that occurred in the Kodagu District, Karnataka's Harangi catchment. An effort has been made to appropriately record and classify seven LULC classes over time. Each of the seven classes was specifically created for the study period, but with a focus on plantations and urban areas since they show the effects of anthropogenic activities. To do this, the research effort also incorporates accuracy assessment utilizing the Kappa Coefficient to assess three algorithms' performance. Because of its rich plains location and plenty of vegetation, this area is a desirable place to migrate. As a result, there has been significant deforestation in the area, which can be seen in the shrinking amount of woodland and wasteland. On the other hand, from 2007 to 2013, the area falling under the plantation category has significantly risen. For the management and planning of the watershed, this study has offered both qualitative and quantitative changes in the catchment's land use pattern. The Minimum Distance to Mean Algorithm produced lower accuracy while the MLC Algorithm produced optimal classification which was indicated by high accuracy metrics.[5].

For an optimal conservation of the nation's natural resources, a scientific appraisal of our land resources is necessary. Studying changes in land cover and its monitoring has become easier, more accurate and faster due to remote sensing data. The goal of LC planning is to assist decision-makers in deciding on the optimum course of action for particular lands that satisfies human needs while preserving ecosystem services and natural resources. The project uses geospatial techniques for database construction, analysis and information extraction to represent the study area digitally and to monitor the current LULC classification in a scientific manner. Thematic maps of the region of interest were created using satellite photos along with toposheets, maps of forests and wastelands from the Survey of India(SoI). Through the use of NRSC guidelines, implementing an integrated approach which processes the image digitally involving interpretation techniques, an effort has been made to outline the Level-I, Level-II, and Level-III LULC classification system with limited Ground truth checks(GTC). The end results show how geospatial technology may be used to plan and manage natural resource utilisation in an optimal and sustainable manner[6].

Google Earth, an open source software, repository of VHR satellite imagery, has been used in this approach to generate training data for classification as well as test data for validation. Google Earth images have been used to perform Land Cover classification for Urban Bangalore region. The Region of interest(ROI) polygons form the training set whereas the unknown regions form the testing set. The classification involves a procedure in which a pixel becomes a part of a class depending on the Euclidean distance and Average pixel intensity. The generic K-Nearest Neighbour(KNN) has been compared with the proposed Euclidean Distance and Average Pixel Intensity based K-NN classification and the accuracy was found to be higher in the proposed algorithm[7].

The two important indices whose difference can be used in the elimination of water bodies for the purpose of coastline detection are Coal Mine Index(CWI) and Normalized Difference Water Index(NDWI). Detecting changes in the coastline is essential to monitor the effects of climate or other natural phenomena resulting in catastrophic changes. A variation of k-means clustering technique has been implemented where the variances between the clusters determine the number of classes to be differentiated. The Landsat 8 images of the Andaman and Nicobar islands of the Indian subcontinent have been considered for coastline analysis. The green and Near Infrared(NIR) bands are used to compute NDWI, whose higher values indicate the presence of water. Bands I and II of Short Wave Infrared(SWIR) are used to compute the CMI, whose lower values indicate the regions of coal mines. K-Means clustering algorithm has been implemented with two clusters to indicate the land and water bodies significantly. The difference of CMI and NDWI with higher cluster centers are considered as land while the remaining indicates the presence of water. Post the clustering operation, the connected components are identified and contours are computed. This novel and automated approach can be used on any satellite imagery as a precision of 80% has been achieved[8].

Non-overlapping blocks are created from the difference of two multi-temporal input images. Using Principal Component Analysis(PCA) these blocks are projected to create the eigen vector space. Feature extraction is done by projecting the overlapping eigen vectors. K-means clustering algorithm is implemented to generate two clusters. It can be found that the proposed algorithm overcomes the effect of Gaussian and speckle noise[9].

In order to overcome the drawback of lack of training data, unsupervised clustering has been used to segment supervised classification images. Also it has been found that unsupervised classification efficiently classifies homogeneous areas when compared to supervised classification. Once K-means clustering is processed, reclassification is carried out on pixels which are spatially adjacent to one another for which a Weighted Majority Voting(WMV) rule is proposed to handle class separability issues thus improving the classification accuracy. The weight of each pixel is computed considering the relationship that it is inversely proportional to the Mahalanobis distance. The result of this decision based fusion classification methodology has been found to be as effective as object based classification[10].

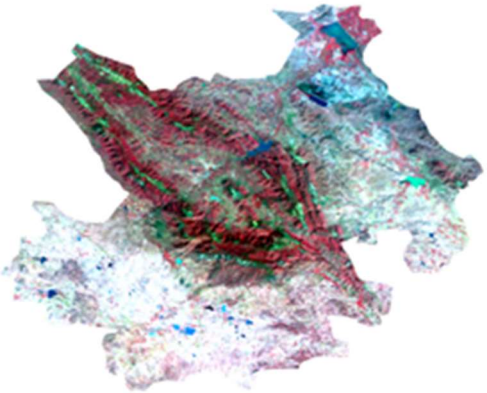
Automatic Unsupervised Classification of water bodies by extracting multiple features has been proposed in this paper. Pixel Region Index(PRI) has been evaluated to assess the smoothness in the local neighborhood of the pixel after which K-Means clustering has been carried out in support of NDWI(Normalized Differential Water Index). Multispectral images of 8m resolution from GF-1 satellite have been used in this study[11].

Object based segmentation of multispectral images is carried out in this paper for forestry applications. In this method, pixels are classified with respect to a particular shape after which Large Scale Mean Shift Segmentation is applied that involves segmenting the image after dividing the image into tiles. Support Vector Machine(SVM) based classification is implemented post segmentation using QGIS[12].

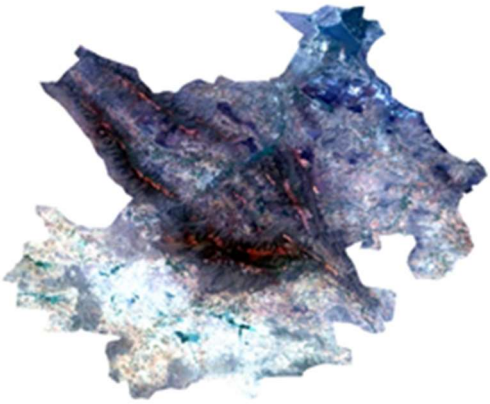
Clustering mainly used in exploratory data analysis can give an insight into the structure of data. It can be used as a means to establish a relationship between the pixels by extracting its features. It can also be used as a compression technique. In this paper clustering has been applied for air pollution studies during 1980 to 2019[13].

3. Study Area and Dataset

(a)



(b)



(c)

Figure.1 Study Area, Sandur, Bellary District: (a) 2001 (b) 2011 (c) 2021

Sandur, is a taluk of Bellary district, Karnataka and known for as a mineral repository such as iron and manganese. It is renowned as the former capital of the famous Vijayanagar Empire. With 15.084°N and 76.5477ºE, it covers an area of 1224.91 sq km. The Naarihalla stream and the Hirehalla stream joined with Kanigana halla stream flow to mark the boundary of the taluka. With a semi-arid type of climate, Sandur valley forms one of the main physical features with hills and vegetation. The Mallappanagudi and Kallahalli gudda ranges together constitute the Sandur hills. With a total geographical area of 94359 Hactres, about 39.29% of Sandur Taluk is cultivable out of which about 14% constitutes the net irrigated area. With the development of ground water irrigation systems, 96% of water is categorized safe whereas the remaining 4% is critical.

4. Materials and Methodology

LULC for three years viz. 2001, 2011 and 2021 has been performed using QGIS. The images for each of the years were downloaded from USGS Earth Explorer. Fig. 1(a) and Fig. 1(b) shows Landsat-7 images were used for 2001 and 2011 years whereas Fig. 1(c) shows Sentinel-2 image was used for the year 2021. Landsat-8 images have a 30m resolution where as Sentinel-2 have a higher resolution of 10m. Each of these images were layerstacked using SCP Plugin and clipped to generate the ROI i.e. Sandur.

For the 2001 and 2011 dataset training operation was performed using Google Earth Pro Satellite image whereas for 2021 dataset training was done using Sentinel -2 LULC ESRI image which has a resolution of 10m. The HCMGIS and SCP Plugins has been used to perform both the training process and LULC. Random stratified sampling was followed where around 10 to 15 polygons were used to generate the training dataset in a vector shape file format. The training process ensured sufficient number of samples have been included to represent all of the classes which would result in a effective and optimal classification. This process resulted in generating a feature set and extraction of spectral signatures for the study area. The study area has been classified into 6 classes viz. Water Bodies, Agriculture Area, Forest Area, Built-Up Area, Mining Area and Barren Land. Using SCP an automated training process with the aid of Google Pro has been adopted in this approach.

Maximum Likelihood Algorithm, which is a pixel based classifier, has been used to classify individual pixels into its corresponding class. This MLC estimates the probability of a pixel belonging to a particular class based on Bayes probability estimation Theorem. A critical constraint of this algorithm would be that the population follows a normal distribution. A multivariate normal form of probability distribution has been assumed. A large number of pixels are required for the training process in order to compute the co-variance matrix.

Data validation was also done using Google Earth Pro. Accuracy assessment and Classification report were generated using Post Processing tool in SCP.

5. Results and Discussions

Accuracy Assessment is basically performed to estimate the quality of classification and to interpret the classification numerically. This is done by correlating the classified pixels with the ground truth. A vector shape file test.shp was generated for each of the classes which contained

the classified pixels. In this work, Google Earth Pro was used in the process of validation where the shape file test.shp was imported into Google Earth Pro and then verified whether the classified pixels did belong to the particular class or not. In this way Confusion matrix was tabulated.

Confusion matrix also called error matrix is an important performance metric used to measure the quality of classification. The confusion matrix represents a contingency table in which the predicted values are compared with the actual values, thus evaluating and grading the classification accuracy.

Confusion matrices were computed for all the three years viz. 2001,2011 and 2021 as shown in Table 1, Table 2 and Table 3 respectively. Overall Accuracy was computed by taking into account the correctly classified pixels represented by the summation of principal diagonal elements in the Confusion matrix and the total number of pixels considered in the classification process. Stratified Random Sampling was adopted in the process of validation where a minimum number of samples were randomly collected in order to assess the accuracy of classification. During the validation process 56 out of a total of 64 samples were correctly classified in 2001, 63 out of a total of 73 samples were correctly classified in 2011 and 62 out of a total 71 samples were correctly classified in the year 2021.

To assess the quality of classification it would be required to correlate the classified image with randomly chosen representative of the population. Stratified random sampling procedure has been adopted in this automated approach to perform validation of the classified image. In this case Google Earth Pro has been effectively utilized as an automated approach to perform the validation operation with which the relevant accuracy metrics were computed. The graph in Fig. 3 represents the percentage of area that has changed during 2001, 2011 and 2021 respectively.

Table 1. Confusion matrix for the year 2001.

Class	Water Body	Agricultural Area	Forest	Built-up Area	Mining Area	Barren Land	User Accuracy
Water body	10	0	0	0	1	0	11
Agricultural area	0	10	1	1	0	0	12
Forest	0	1	9	0	0	0	10
Built-up area	0	2	0	10	0	0	12
Mining Area	0	0	1	0	8	0	9
Barren land	0	1	0	0	0	9	10
Producer Accuracy	10	14	11	11	9	9	64

Table 2. Confusion matrix for the year 2011.

Class	Water Body	Agricultural Area	Forest	Built-up Area	Mining Area	Barren Land	User Accuracy
Water Body	13	0	0	1	0	0	14
Agricultural Area	0	10	1	1	0	0	12
Forest	0	1	9	1	0	1	12
Built-up area	0	2	0	11	0	0	13
Mining Area	0	1	0	0	10	0	11
Barren Land	0	0	1	0	0	10	11
Producer Accuracy	13	14	11	14	10	11	73

There is an increase in Built-up area and Agricultural area from 2.34% to 3.75% and 27.48% to 32.95% respectively. Also a decrease has been found in Water bodies, Forest and Barren Land. This analysis paces the way for detecting changes in the area of study over a period of time. Comparison of area statistics as in Table. 5 gives an estimation of the changes that have taken place thus supporting Land Use planning. The overall accuracy of classification for 2001, 2011 and 2021 images obtained was 87.5%, 86.3% and 87.32% respectively.

Table 3. Confusion matrix for the year 2021

Class	Water Body	Agricultural Area	Forest	Built-up Area	Mining Area	Barren Land	User Accuracy
Water Body	12	0	0	1	0	0	13
Agricultural Area	0	11	0	1	1	0	13
Forest	0	1	10	0	0	1	12
Built-up area	0	2	0	10	0	0	12
Mining Area	0	0	0	1	10	0	11
Barren Land	0	0	1	0	0	9	10
Producer Accuracy	12	14	11	13	11	10	71

The Kappa Coefficient values obtained were 85.01%, 83.43% and 84.8% respectively.

Table 4. Comparison of Accuracy of Classification

Class	2001		2011		2021	
	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy
Water body	90.9	100	92.85	100	92.3	100
Agricultural Area	83.33	76.92	82.33	76.92	84.61	78.57
Forest Area	90	81.81	75	81.81	83.33	90.90
Built-Up Area	83.33	90.90	84.61	90.90	83.33	76.92
Mining Area	88.88	88.88	90.90	88.88	90.90	90.90
Barren Land	90	90	90.90	90	90	90
Overall Accuracy	87.5		86.3		87.32	
Kappa Coefficient	85.01		83.43		84.8	

Table 5. Estimation of Area Statistics for the Land Cover Classes.

Classes	Area in 2001		Area in 2011		Area in 2021	
	Sq Km	%	Sq Km	%	Sq Km	%
Water Body	17.95	1.45	32.91	2.66	25.96	2.10
Agricultural Area	340.24	27.48	408.00	32.95	483.97	39.09
Forest	302.82	24.46	212.20	17.14	200.12	16.16
Built-Up Area	28.95	2.34	46.46	3.75	98.04	7.92
Mining Area	28.33	2.29	26.31	2.13	22.68	1.83
Barren Land	519.47	41.96	511.89	41.35	406.98	32.87

6. Conclusion

This study presents an automated approach to monitor LULC patterns over a period of 30 years where image dataset was generated with a gap of ten years. Landsat-7 and Sentinel-2 images were used for the assessment of Sandur from 2001 to 2021. The results estimates a change in percentage of area over a period of 30 years. It has been found that there is a substantial increase in Built-up area as a result of urbanization which resulted in decrease in Forest cover. Mining area, Water bodies and Barren Land also have been found to be been decreased as a result of correlating the classification with Google Earth Pro.

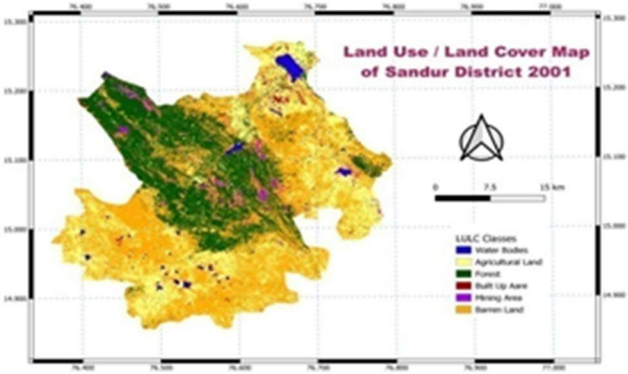


Figure. 2(a)

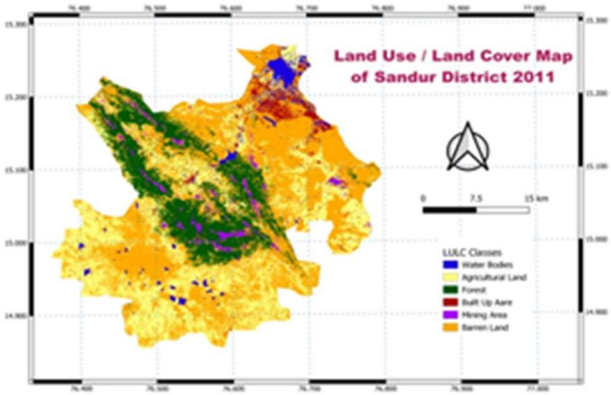


Figure. 2(b)

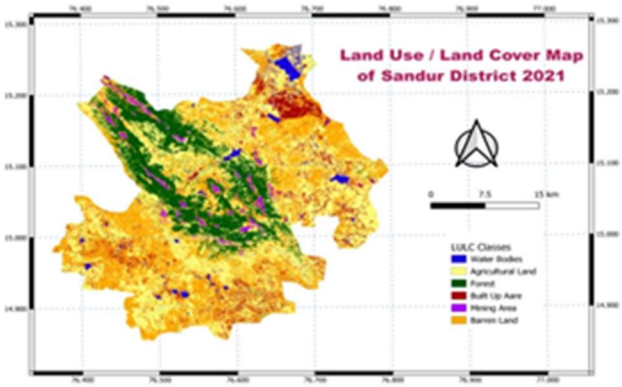


Figure. 2(c)

Figure 2. LULC Map Layouts of Study Area, Sandur, Bellary District: (a) 2001 (b) 2011 (c) 2021

While user accuracy estimates the probability of a pixel assignment to a particular class which is indicated by a higher accuracy value, producer accuracy correlates the classified pixels with their actual class. The feasibility of obtaining field data required for training data and validation where actual ground truth is correlated with the classified image is still a challenge.

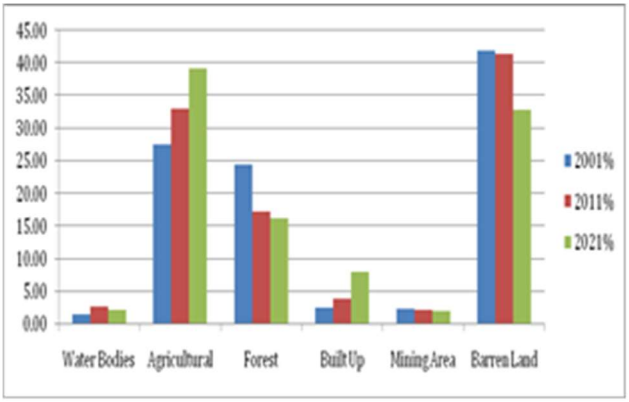


Figure 3. Comparison of LULC Classes of Sandur, for the years 2001, 2011 and 2021

In the absence of field data, an automated approach via Google Earth Pro has been adopted in this case to perform LULC of the study area. An Overall accuracy of 87.5%, 86.3% and 87.32% for the years 2001, 2011 and 2021 respectively.

The objective of this study has been to deploy an automated approach to detect the changes in the area of interest and thus generate a decision support system which can serve as a foundation for change detection studies and in Land use Planning. Also reclamation measures could be further recommended in degraded lands so that these degraded lands could be efficiently utilized.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Dr Mahesh Kumar D suggested the appropriate dataset and system configurations for implementation and processing high resolution images. He has been a constant source of encouragement and actively supported in supervision of the current work.

Mr Veeramani S provided the details of the study area and contributed in data and software procurement.
Dr Prasanna Kumar S C recommended different image processing techniques for the study area.

Acknowledgments
The authors wish to thank USGS and ESA for Landsat-7 and Sentinel-2 for providing open-source imagery to perform this study. We express our thankfulness for ESRI for providing the Sentinel-2 Land Cover map of 10m resolution used in training phase. We also are thankful to Google Earth Pro for providing open access used in Validation phase.

References

[1] Wasteland Atlas of India, 2010.
[2] J.T.M. Lillesand, R.W. Kiefer, J.W. Chipman, "Remote Sensing and Image Interpretation", Wiley International, 2004, 5th Edition
[3] S. Kumar, Chinnaiah, B. V. S. Kumar, "Detection Studies of Land Use/ Land Cover Changes in Sandur taluk, Bellary District, Karnataka, India using Remote Sensing and GIS Techniques", International Journal of Earth sciences and Engineering, Vol 5, 2012, 133-137pp.
[4] Vasanth Patil S.B , Venkataiah C and Basavaraj Hatti, "RS and GIS Application for Land use Land Cover Mapping of the Narihalla Watershed Sandur,Bellary District, Karnataka, India", International Journal of Engineering Research and Technology, Vol 11, 7, 2022.
[5] B. P. Ganasria, G. S. Dwarakisha, "Study of land use/land cover dynamics through classification algorithms for Harangi catchment area, Karnataka State, INDIA", International Conference On Water Resources, Coastal And Ocean Engineering (ICWRCOE 2015).
[6] Manjunatha M.C, Basavarajappa H.T., " Assessment of Land Use Land Cover Classification through Geospatial Approach: A Case Study of Mysuru Taluk of Karnataka State, India," Journal of Environment and Waste Management, Vol 7, June 2020.
[7] Sowmya D. R, V. S. Hegde, Suhas J, R. V. Hegdekatte, P. D. Shenoy, Venugopal K R, "Land Use/ Land Cover Classification of Google Earth Imagery", IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE), 2017.
[8] R. Mondal, J. Mukherjee and J. Mukhopadhyay, "Automated Coastline Detection From Landsat 8 Oli/Tirs Images With The Presence Of Inland Water Bodies In Andaman", IEEE International Geoscience and Remote Sensing Symposium, pp. 5757-5760, 2020.
[9] T. Celik, "Unsupervised Change Detection in Satellite Images Using Principal Component Analysis and k-Means Clustering", IEEE International Geoscience and Remote Sensing Letters, Vol. 6, pp. 772-776, 2009.
[10] H. Yang, Q. Du, B. Ma, "Decision Fusion on Supervised and Unsupervised Classifiers for Hyperspectral Imagery", IEEE International Geoscience and Remote Sensing Letters, Vol. 7, pp. 875-879, 2010.

[11] Y. Zhang , X. Liu, Y. Zhang, X. Ling and X. Huang, "Automatic and Unsupervised Water Body Extraction Based on Spectral-Spatial Features Using GF-1 Satellite Imagery", IEEE International Geoscience and Remote Sensing Letters, 2018.

[12] M. Suneetha, L.N.P Boggavarapu, R. Vaddi, A.R. Raja, R. Gopalakrishnan, Jha C S , "Object based Classification of Multispectral Remote Sensing Images for Forestry Applications", Proceedings, 3rd International Conference on Image and Graphics Processings", 2020.

[13] P.Govender, V. Sivakumar, "Application of k-means and hierarchical clustering techniques for analysis of air pollution: A review (1980-2019)", Atmospheric Pollution Research, 2019.

[14] Chatterjee , J. Saha , J. Mukherjee ,S. Aikat and A. Misra, "Unsupervised Land Cover Classification of Hybrid and Dual-Polarized Images Using Deep Convolutional Neural Network", IEEE Geoscience and Remote Sensing Letters, Vol. 18, 2021.

[15] Luca Congedo, "Semi-Automatic Classification Plugin Documentation", Release 6.0.1.1, Technical Report, 2016

[16] X. Chen, C. Chen, L. Jin, "Principal Component Analyses in Anthropological Genetics", Advances in Anthropology, Vol.1, No.2, 9-14, 2011.

[17] Ahmed, M. Muaz, M. Ali, M. Yasir, S. Ullah, S. Khan, "Mahalanobis Distance and Maximum Likelihood Based Classification for Identifying Tobacco in Pakistan", 2015.

[18] S. S. Rwanga, J. M. Ndambuki, "Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS", International Journal of Geosciences, Vol-8, pp 611-622, 2017.

[19] P. Kumar, A. Rai, S. C. Rai, "Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India", The Egyptian Journal of Remote Sensing and Space Sciences, Vol 23, pp 133–143, 2020.

[20] http://sar.kangwon.ac.kr/etc/rs_note/rsnote/cp11/cp11-7.htm

[21] https://semiautomaticclassificationmanual.readthedocs.io/en/latest/remote_sensing.html#spectral-distance