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Land Use and Land Cover Analysis of Virajpet Semi-Urban Region of Kodagu District using Supervised Fuzzy Classification

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G. S. Sinchana : Conceptualization, manuscript preparation, collection of literature and references;
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Abstract

Identifying and keeping track of the physical traits of various ecosystems, including those in terrestrial, aerated and aquatic environments is a crucial task. Therefore, the categorization of Land Use and Land Cover (LU/LC) using remotely sensed data is an important study in the remote sensing field. Thus, this study aimed to use fuzzy categorization techniques to identify the semi-urban characteristics of land use and land cover (LU/LC) features in Virajpet urban study area of Kodagu district location using both panchromatic data and fused data. For this work, LANDSAT - 8 remote sensing satellite images were acquired during the interval 2017 - 18. The 100, 200, 300, 400 and 500 Training Sample Sites (TS) with 36, 67, 100, 136 and 167 validation points (VS) were collected and examined for semi-urban features of Virajpet using both panchromatic data and fused data. Thus, the experimental investigation showed that for all such training sites and validation points, the total overall classification accuracy (OCA) achieved for panchromatic data was 67.39, 71.01, 76, 80.58 and 84.37 per cent, respectively and kappa Statistics of 0.5430, 0.5581, 0.5733, 0.674 and 0.7054 was obtained. Whereas for the fused data, the OCA obtained was 75, 79.41, 81.37, 85.40 and 87.86 per cent and Kappa Statistics measured was 0.6334, 0.6471, 0.6498, 0.7355 and 0.7981. Therefore, using fuzzy classification can benefit urban planning in the Virajpet taluk as it improves the accuracy and nurtures a deeper knowledge of semi-urban features. Future studies can be carried out by enhancing the urban feature classification accuracy and then performing in-depth investigation of the variables that are influencing the classification performance.

Keywords : Land Use and Land Cover (LU/LC), Remote Sensing, Supervised Fuzzy Classification and LANDSAT - 8 Satellite

Urbanization, or the growth and extension of human settlements in urban areas, is in fact a global process. Cities and towns change the way that land is used and covered significantly as they grow, which influences the ecosystem. Land planning, sustainable development and natural area preservation are necessary to address the problems caused by urbanization and its effects on land usage. Compact urban design, mixed land use, green infrastructure, and the preservation of open spaces are some strategies that can help lessen the detrimental effects of urbanization on land usage and encourage more resilient and sustainable communities (Shobha and Srikantha Murthy, 2023 and Abhilash & Devakumar, 2023).

In the modern era, remote sensing is an essential tool for assessing the dynamic shifts in land use and land cover. By classifying the spectral properties of the land cover, it is used to derive useful information that supports the management of natural resources. However, employing multispectral remote sensing data to categorize LULC based on urban areas, which are highly heterogeneous, presents a considerable barrier. Although land cover and land use analysis are related ideas, they differ significantly. The term 'land use' describes the objective of human activities on the land and reflects choices made for how the land will be used. It includes a variety of human activities, such as farming, urban planning and conservation, that are done to gain goods or advantages from land resources (Ha *et al.,* 2020).

The physical qualities of the land surface, such as the soil, vegetation, buildings, urban infrastructure and water, are referred to as land cover. To ascertain both land use and land cover, remote sensing satellite data, aircraft data and field observations through surveys can be used. Knowing LULC in a particular location requires knowing the differences between land use and land cover since they have different implications for land management and planning (Homer *et al.,* 2020). The three categories of change detection techniques are object-based, feature-based and pixel-based image processing (Abitri *et al.,* 2015). Texture characteristics have demonstrated high discrimination accuracy among various techniques (Azeez *et al.,* 2018).

Classifying such a wide range of land cover classes accurately presents difficulties for conventional parametric classifiers like the Maximum Likelihood Classifier. However, these classifiers may easily integrate supplementary layers because of their nonparametric character, which is appropriate for classifying land use (Bharti, 2004). Although the correlations between vegetation and direct, indirect, and resource gradients may differ across different locations, impacting the quality and accuracy of the datasets, the inclusion of auxiliary characteristics greatly improves classification accuracy overall (Hurskainen *et al.,* 2019).

Land use maps help identify the existing amount of land and track changes over time, while maps of the current terrain are essential for assisting land managers comprehend the current landscape (Islam *et al.,* 2018). Remote sensing presents prospects for improved resource management and the creation of sustainable land use. Landsat data-derived land cover products have shown to be highly accurate at mapping and tracking LULC changes (Ha *et al.,* 2020). This study processed satellite images and evaluated quantitative data using ArcGIS v10.1 and ERDAS Imagine v14 for land use change assessment (Islam *et al.,* 2018). The land cover dataset is being used for a variety of purposes, such as assessing national forest resources, estimating REDD + activity data, combining biophysical and socioeconomic data and evaluating semantic similarity (Jalal *et al.,* 2019).

It is necessary to identify the components and their degrees that influence bias and precision in order to estimate the bias and precision of stratified estimators in the presence of interpretation mistakes. This will make it easier to determine how to lessen the effects of bias (McRoberts *et al.,* 2018). Pre-processing, classification and prediction of time series satellite pictures are some of the procedures involved in the analysis of LU/LC changes using satellite photos (Mohan Rajan *et al.,* 2020). Separate test and training datasets were classified using multispectral Landsat ETM + and hyperspectral DAIS sensors in two different geographic locations to assess the performance of land cover classification. The presumption that data have a Gaussian distribution, though, might not always be accurate (Pal and Mather, 2003).

Cross-validation accuracy, thematic map land cover categorization accuracy and other structural qualities including diagram sizes and variable selection skills were used to evaluate the algorithm's performance. These evaluations were carried out over a variety of time periods and locales (Phiri *et al.,* 2020). According to the study's findings, using temporal data with clearly specified training sites can produce both good overall classification accuracy and accurate individual classification results. With less auxiliary data, AWiFS data has the ability to deliver accurate and timely LULC maps. For regional-level assessment and monitoring, this data can be used for mesoscale mapping of land use and cover (Punia *et. al.,* 2011).

It is possible to classify any place using LULC data from a variety of recently deployed airborne and space-borne sensors, regardless of seasonal impacts (Rao and Kumar, 2019). Improved performance in PA and UA of water and greenhouses by 14.98 and 0.45 per cent and by 5.11 and 38.01 per cent, respectively for urban LULC classification has been shown using a combination of multispectral remote sensing images includes Chinese ZiYuan-3 (ZY-3) high-resolution image, Landsat 8 Operational Land Imager (OLI) multispectral image and Sentinel-1 synthetic aperture radar (SAR) image. Other large data sources, like places of interest (POIs), bus data and taxi data, may be the subject of future research looking at their usefulness (Shi *et al.,* 2019).

By efficiently choosing the data that is most important, minimizing the size of the training set and increasing the model's accuracy in comparison to random sample selection, Active Learning (AL) is a method that improves the development of training sets. Most of the time, classification results utilizing conventional and satellite image analysis approaches have a 90 per cent correlation with official estimations. The findings of the suggested method for estimating sugarcane area are comparable to those of previous methodologies and the model's accuracy might be increased by investigating other vegetation indices (Silva and Romani, 2019).

The main tool for observing land use and land cover (LULC) changes is through multispectral remote sensing imagery. The manner of feature extraction, picture resolution and soft computing algorithms used all influence how LULC is classified and changes are detected from remote sensing images (Thyagharajan and Vignesh, 2019). A knowledge-based tree classifier has demonstrated promising results for differentiating sample points in SAR data, making it useful for various applications like monitoring vegetation and land cover. It does this by utilizing a priori real-time field survey information and four features (backscattering coefficient, scattering mechanism, diffuse scattering and odd bounce scattering) (Verma *et al.,* 2020). The Time-Series Classification Approach based on Change Detection (TSCCD) performs time-series segmentation, classification using the DTW algorithm and Prophet algorithm-based ground-cover change-point detection (Yan *et al.,* 2019). This method has exhibited good sub-sequence classification accuracy, demonstrating its efficacy in resolving actual LULC-TSC issues (Chen *et al.,* 2010).

For studying remotely sensed datasets, fuzzy classification approaches offer a better framework. Despite being a relatively new theory, fuzzy logic has found extensive applicability in a variety of problem domains. In conclusion, remote sensing is extremely important for evaluating LULC changes, particularly in metropolitan settings, together with a variety of classification and analysis methodologies. It provides insightful information for sustainable development, planning and land management (Nedeljkovic, 2004). The rest of the investigated work are considered as trails where in, Section 1 contains the introduction about Land Use/Land Cover with its challenges and requirement of using remote sensing technology, Section 2 includes study area and data products, Section 3 includes proposed methodology of Fuzzy classifier, Section 4 comprises of results based on analyses, Section 5 accomplishes the conclusion drawn from the experimental results.

Study Area & Data Products

Study Area

The Virajpet taluk, which is a part of Karnataka's Kodagu district, is the subject of our study area. The study area is positioned at geographical co-ordinates of 12.19' 50'' North and 75.80' 40'' East. With a 909 meter average elevation (2982 feet), it has distinctive topographic features. Fig. 1, represents the study region in the visual form. It demonstrated an aerial shot that was taken using a visual band.

Data Products

Table 1 gives the specification of image data products used. The data of Landsat-8 satellite was downloaded from Google earth data as shown in fig. 2. Table 2 lists the values and attributes of the dataset used in the study. Table 3 list the bands used in the Landsat 8

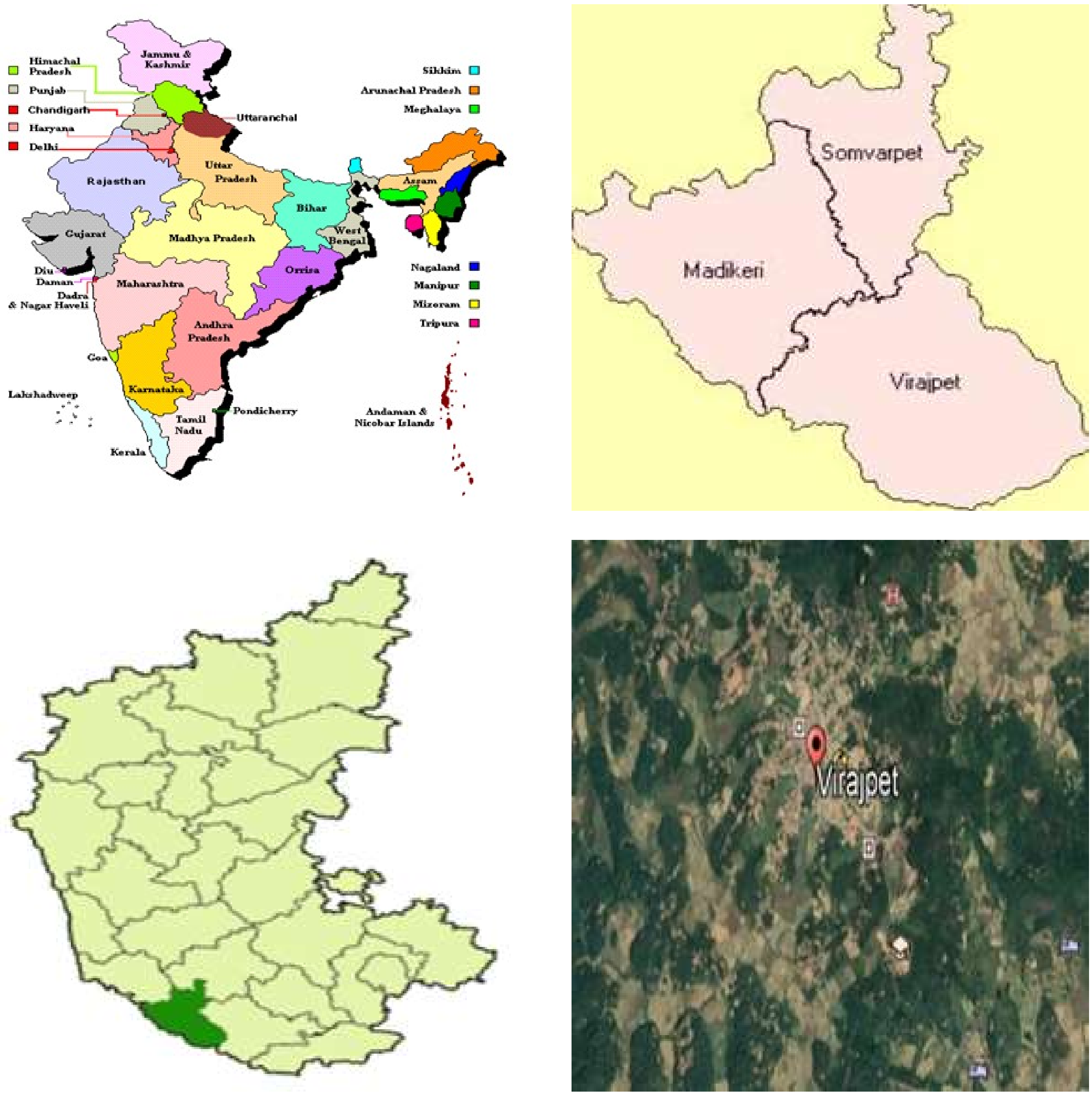

Fig. 1 : Shows the study area of Virajpet, Kodagu district

TABLE 1

Details of the data products used

Satellite and Data type	Date of Acquisition	Spatial Resolution
Landsat-8	2018/10/27	30m
Panchromatic data	2020/08/30	15m

satellite data in detail, including the band name, the range of bandwidth and the relevant spatial resolution.

In this work, the classification of land use and land cover is done using ERDAS software version 9.2. As part of the data collection process, toposheets, Google Earth Pro data, remotely sensed data and

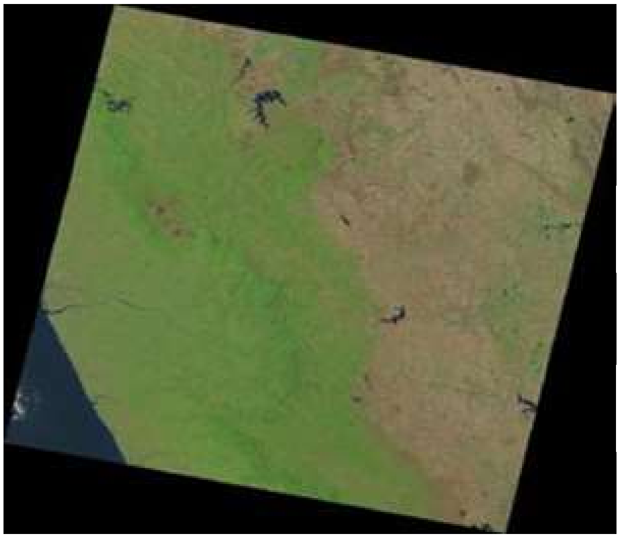

Fig. 2 : Depicts the LANDSAT-8 Satellite Data Image

TABLE 2
List of dataset attributes and its values

Data Set Attribute	Attribute Value
Date Acquired	2018/10/27
Roll Angle	-0.001
Land Cloud Cover	0.00
Scene Cloud Cover L1	0.00
Station Identifier	LGN
Day/Night Indicator	DAY
Ground Control Points Model	885
Ground Control Points Version	5
Data Type L1	OLI_TIRS_L1TP
Datum	WGS84
Ellipsoid	WGS84
Grid Cell Size Panchromatic	15.00
Grid Cell Size Reflective	30.00
Grid Cell Size Thermal	30.00
Panchromatic Samples	15161
Reflective Samples	7581

pre-processed remote sensing image datasets using ERDAS Imagine are all gathered. The characteristics of the urban features in this particular location are analysed using the fuzzy classifier. Furthermore, the CHL-I region is doing a study on the performance

TABLE 3
Details of LANDSAT-8 data

Bands	Band width (mm)	Spatial Resolution (m)
Coastal aerosol	0.433 - 0.453	30
Blue	0.450 - 0.515	30
Green	0.525 - 0.600	30
Red	0.630 - 0.680	30
Near Infrared	0.845 - 0.885	30
SWIR 1	1.560 - 1.660	30
SWIR 2	2.100 - 2.300	30
Panchromatic	0.500 - 0.680	15
Cirrus	1.360 - 1.390	30

evaluation of fuzzy classifiers. By calculating the percentage of land use and land cover areas, this evaluation can assess how well the fuzzy classification approach characterizes the area under study.

Supervised Classification

Based on the values in their data files, multispectral classification divides pixels into distinct classes or groups. The criteria used in this process are what determine which class a pixel is assigned to. Within multispectral classification, supervised training is a regulated procedure in which the analyst is a key player. In this method, the analyst chooses pixels that correspond to recognizable patterns or elements of the land cover. Other sources, such as maps, ground truth data or aerial photographs, may have influenced this choice. It is necessary to have prior knowledge of the desired classes and the data in order to execute supervised classification successfully. While supervised classification often refers to the application of judgment rules, it incorporates a variety of feature extraction techniques. These decision-making guidelines use techniques like Mahalanobis Distance, Minimum Distance and Maximum Likelihood. These guidelines assist in classifying pixels according to their spectral properties and the predetermined standards provided by the analyst.

Stages Involved in Classification

There are three basic stages involved in supervised classification, namely

Training stage

The goal of the training phase is to compile data on the spectral response patterns of each land cover type that will be recognized in the image. For each land cover class, this entails choosing the location, scale, shape and orientation of training samples. The user chooses training samples that correspond to the usual spectral data of the various land cover classes. The training data must be both comprehensive and representative. As a result, training samples must reflect the whole spectrum of spectral variability for each class of land cover.

Classification Stage

The classifier is applied to the image during the classification stage using the predetermined set of training samples and the selected classification algorithm. The spectral properties of the image's pixels are numerically compared to the training samples using common classification techniques or classifiers. The algorithms utilized assign pixels to particular land cover classifications based on these comparisons. The classifiers in pixel-based image analysis are frequently referred to as 'hard classifier's since they give objects a binary membership (1 or 0) indicating whether or not they belong to a certain class.

Accuracy Assessment Stage

An important phase in the categorization process is accuracy assessment. It entails assessing the degree of agreement between the labels given by the classifier and the user-collected ground truth class allocations. The aim of accuracy assessment is to evaluate the suitability of the map for a particular application. There are several methods for evaluating correctness, including topological accuracy, temporal accuracy, thematic accuracy and geographical accuracy.

Fuzzy Classification

Numerous image processing and classification algorithms have been developed and successfully used in the field of remote sensing for a variety of objectives. In order to improve certain aspects, remove noise or make the imagery easier to read and analyze further, image processing techniques are used. Contrarily, classification algorithms concentrate on classifying the imagery's retrieved features or pixels into various groups or categories. The occurrence of mixed pixels, where a single pixel may contain different land cover categories, is a typical problem in remote sensing picture interpretation. Using fuzzy classification approaches, that permit the classification of each pixel into many land cover types, is one way to deal with this issue.

A soft classification technique known as fuzzy classification deals with the ambiguity of class borders and retrieves data from mixed pixels. By using a membership function on remotely sensed images, this is accomplished. Fuzzy classification offers additional details about uncertainty in the picture data as opposed to 'hard' classification, which makes decisive assignments. The classification procedure relies heavily on the fuzzy technique. In this study we classify the satellite images using fuzzy supervised classification as shown in Fig. 3. This method is useful because it aids in mapping geographic data, assessing changes, gauging the degree of uncertainty in class boundaries and dealing with mixed-class pixels. It is practical to interpret the data and extract more complex information from the imagery by using fuzzy categorization techniques.

Results and Discussion

Result Analysis for Fuzzy Classifier

When the imaging sensor is sensitive to a broad variety of light wavelengths, a panchromatic image is produced as shown in Fig. 4. Both thermal infrared and visible light are captured in this kind of image, along with other wavelengths and bands. The term

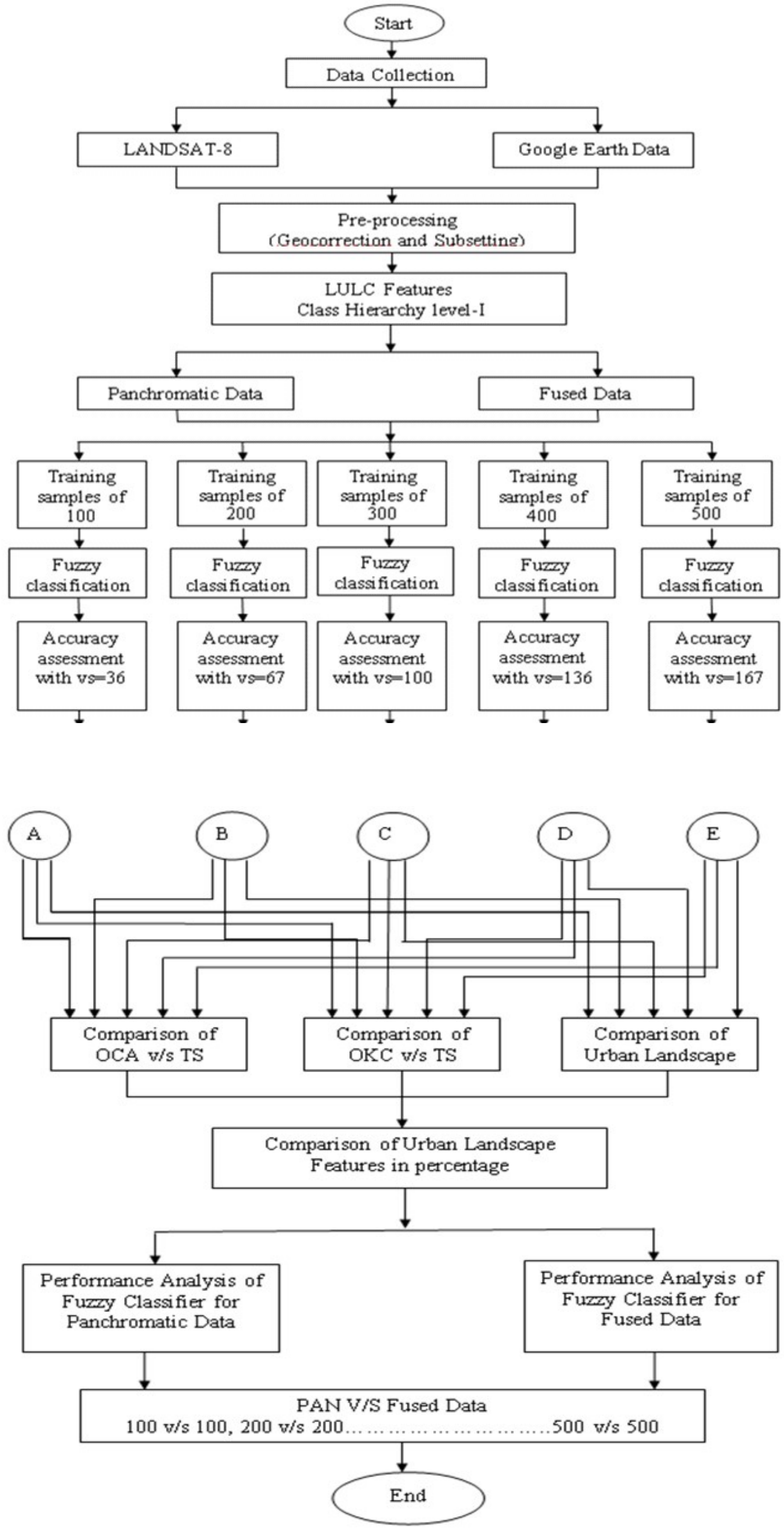

Fig. 3 : Flowchart for Classification of Urban Landscape using Fuzzy Classifier

LANDSAT - 8 Panchromatic Image Classification Using Fuzzy Classifier

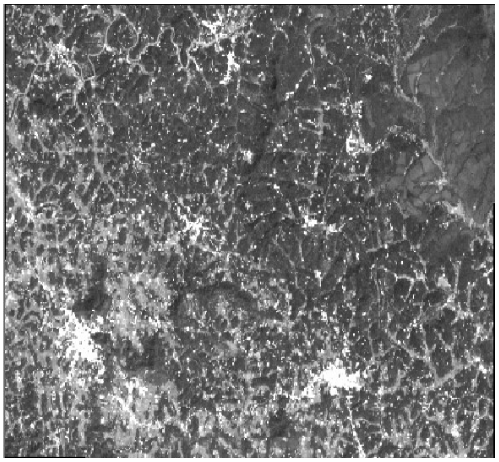

Fig. 4 : Original Panchromatic Image for Fuzzy Classifier

'panchromatic' refers to a thorough portrayal of the scene created by combining several hues. Compared to pictures taken by cameras with a narrow spectral range, panchromatic pictures cover a wider spectrum of wavelengths. Training and validation sets are made in various sizes for each class. We have used sets with 100, 200, 300, 400 and 500 samples, respectively. The associated validation sets also include 46, 69, 100, 139 and 175 samples. These sets are used to identify semi-urban characteristics in the data. The outcomes of this extraction procedure are shown in Fig. 5, 6 and 7. These illustrations show the results of the feature extraction procedure, showing the semi-urban features that were determined depending on the various sizes of the training and validation sets.

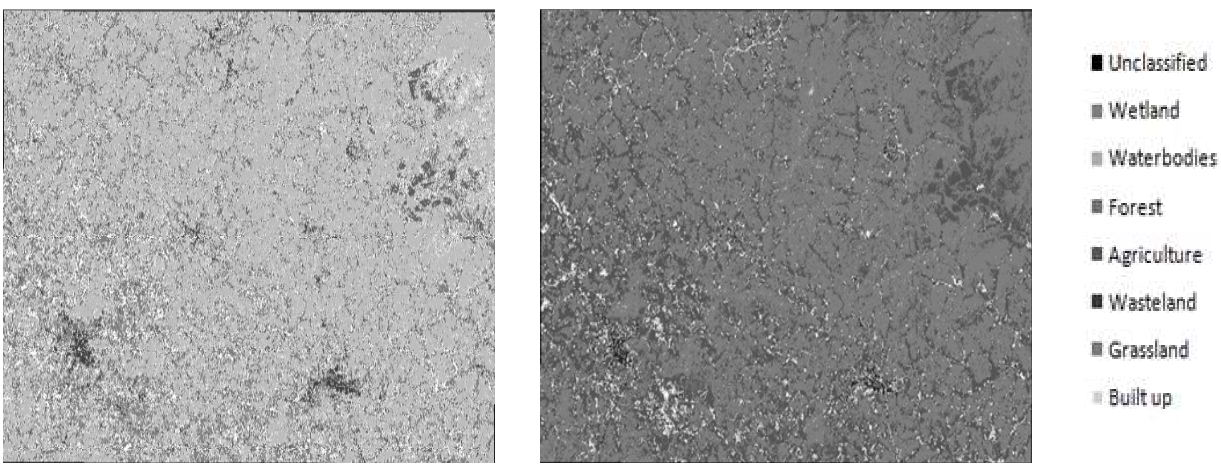

Fig. 5 : Fuzzy Classified LANDSAT-8 Panchromatic Image with TS=100, 200 and VS = 36, 67

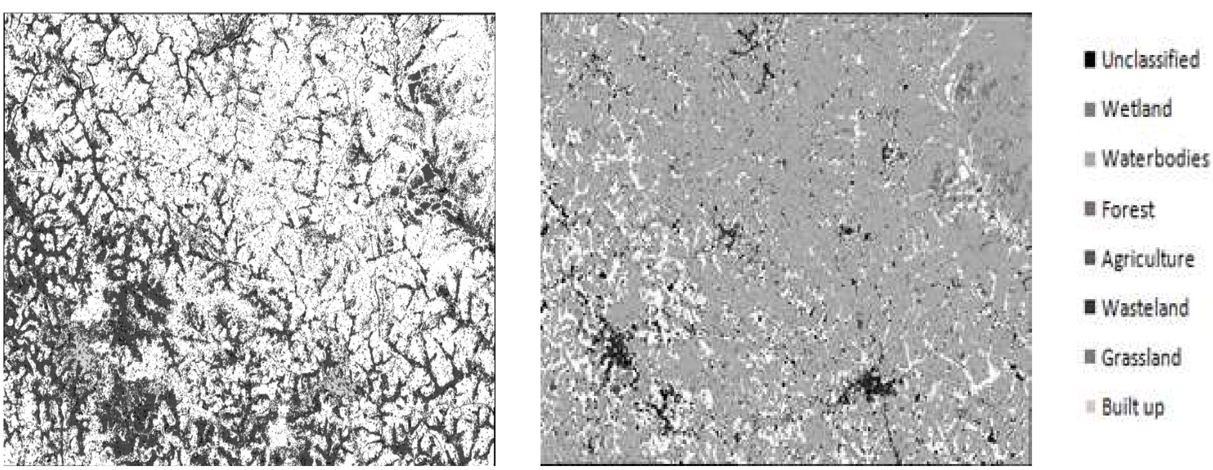

Fig. 6 : Fuzzy Classified LANDSAT-8 Panchromatic Image with TS=300, 400 and VS = 100, 136

It can be interpreted from Table 4, 5 and 6, it interprets that for 100 training samples and 46 validation points, the user accuracies have been classified for seven classes using panchromatic data as 40 per cent of Grassland, 20 per cent of Agriculture, 100 per cent of Wasteland, Waterbodies, Wetland and Built up, 77.27 per cent of Forest, respectively. For 200 training samples and 69 validation points, it is classified as 50 per cent of Wetland, 33.33 per cent of Agriculture, 100 per cent of Grassland, Waterbodies, Wetland and Built up, 87.18 per cent of Forest, correspondingly. For 300 training samples and 100 validation points, it is classified as 50 per cent of Built up, 66.67 per cent of Wetland, 50 per cent of Waterbodies, 56.67 per cent of Agriculture, 100 per cent of Wasteland and Grassland, 86.67 per cent of Forest, accordingly. For 400 training samples and 139 validation points, it is classified as 40 per cent of Wetland, 71.43 per cent of Grassland, 57.14 per cent of Agriculture, 100 per cent

TABLE 4

Confusion Matrix for Fuzzy Classified Panchromatic Image with TS = 100, 200 and VS = 46, 69

Classes	1	2	3	4	5	6	7	RT	UA in %
1	3	0	0	0	0	0	0	3	100
2	0	1	2	0	0	1	1	5	20.00
3	1	3	17	0	0	0	1	22	77.27
4	0	0	0	1	0	0	0	1	100
5	0	0	0	0	2	0	0	2	100
6	0	0	0	0	0	3	0	3	100
7	1	2	3	0	0	0	4	10	40.00
CT	5	6	22	1	2	4	6	46	
PA in %	60.00	16.67	77.27	100	100	75.00	66.67		

Classes	1	2	3	4	5	6	7	8	RT	UA in %
1	1	0	0	0	0	0	0	0	1	100
2	0	7	2	0	0	0	12	0	21	33.33
3	0	2	34	0	0	0	3	0	39	87.18
4	0	0	0	1	0	0	1	0	2	50
5	0	0	0	0	1	0	0	0	1	100
6	0	0	0	0	0	2	0	0	2	100
7	0	0	0	0	0	0	2	0	2	100
8	0	0	0	0	0	0	0	1	1	
CT	1	9	36	1	1	2	18	1	69	
PA in %	100.00	77.78	94.44	100	100	100	11.11			
Kappa	1.0000	0.2333	0.7319	0.4926	1.0000	1.0000	1.0000	1.0000		

TABLE 5

Confusion Matrix for Fuzzy Classified Panchromatic Image with TS=300, 400 and VS=100, 139

Classes	1	2	3	4	5	6	7	8	RT	UA in %
1	1	0	1	0	0	0	0	0	2	50
2	0	17	9	0	0	0	4	0	30	56.67
3	0	3	52	1	0	0	4	0	60	86.67
4	0	0	0	1	0	0	0	0	1	100
5	0	0	0	0	1	1	0	0	2	50
6	0	1	0	0	0	2	0	0	3	66.67
7	0	0	0	0	0	0	1	0	1	100
8	0	0	0	0	0	0	0	1	1	
CT	1	21	62	2	1	3	9	1	100	
PA in %	100.00	80.95	83.87	50	100	66.67	11.11			
Kappa	0.4949	0.4515	0.6491	1.0000	0.4949	0.6564	1.0000	1.0000		

Classes	1	2	3	4	5	6	7	8	RT	UA in %
1	1	0	0	0	0	0	0	0	1	100
2	3	24	8	0	2	2	3	0	42	57.14
3	1	1	74	2	0	0	0	0	78	94.87
4	0	0	0	1	0	0	0	0	1	100
5	0	0	0	0	3	0	0	0	3	100
6	1	1	1	0	0	2	0	0	5	40.00
7	0	1	1	0	0	0	5	0	7	71.43
8	0	0	0	0	0	0	0	2	2	
CT	6	27	84	3	5	4	8	2	139	
PA in %	100.00	77.78	94.44	100	100	100	11.11			
Kappa	1.0000	0.2333	0.7319	0.4926	1.0000	1.0000	1.0000	1.0000		

TABLE 6

Confusion Matrix for Fuzzy Classified Panchromatic Image with TS=500 and VS=175

Classes	1	2	3	4	5	6	7	8	RT	UA in %
1	2	0	0	0	0	0	0	0	2	100
2	2	30	15	0	0	0	0	0	47	63.83
3	0	0	105	0	0	0	3	0	108	97.22
4	0	0	0	2	0	0	0	0	2	100
5	0	1	0	0	2	0	0	0	3	66.67
6	5	0	1	0	0	2	0	0	8	25.00
7	0	0	0	0	0	0	2	0	2	100
8	0	0	0	0	0	0	0	3	3	
CT	9	31	121	2	2	2	5	3	175	
PA in %	22.22	96.77	86.77	100	100	100	40.00			
Kappa	1.0000	0.5604	0.9100	1.0000	0.6628	0.2413	1.0000	1.0000		

Legend : 1 = Built up, 2 = Agriculture, 3 = Forest, 4 = Wasteland, 5 = Waterbodies, 6 = Wetland, 7 = Grassland, 8 = Unclassified, RT = Row Total, CT = Column, Total PA = Producer Accuracy, UA = User Accuracy.

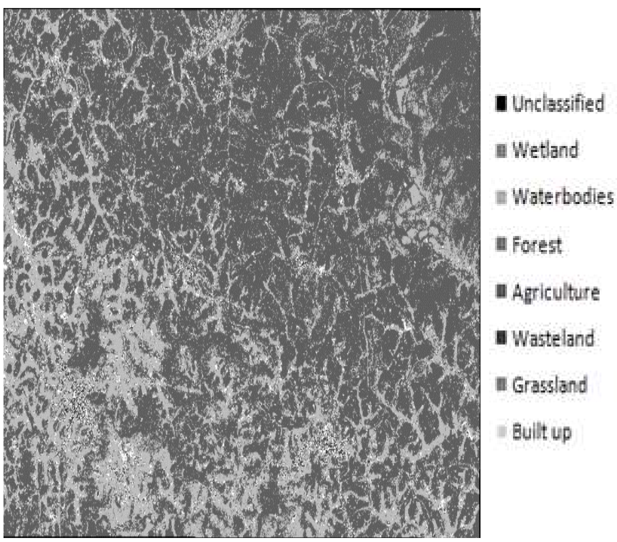

Fig. 7 : Fuzzy Classified LANDSAT - 8 Panchromatic Image with TS = 500 and VS = 167

of Wasteland, Waterbodies and Built up, 94.87 per cent of Forest, in that order. For 500 training samples and 175 validation points, it is classified as 25 per cent of Wetland, 66.67 per cent of Waterbodies, 63.83 per cent of Agriculture, 100 per cent of Wasteland, Grassland and Built up, 97.22 per cent of Forest, appropriately.

From Fig. 8, it was noticed that for 100, 200, 300, 400 and 500 training samples obtained for OCA is 67.39, 71.01, 76, 80.58 and 84.57 per cent and Kappa statistics is 0.543, 0.5581, 0.5733, 0.6745 and 0.7054. This comparison of OCA and Kappa statistics v/s training samples was obtained for LANDSAT 8 panchromatic image. As the training sets were increased, the OCA and Kappa statistics also increased. From Fig. 9, 10 and 11, it interprets that for 100, 200, 300, 400 and 500 training samples, the total area has been classified for panchromatic as 0.90 per cent for all unclassified land, 2.83, 2.92, 3.59, 3.52 and 3.25 per cent of Wetland, 9.38, 1.84, 2.04, 2.26 and 4.34 per cent of Waterbodies, 51.63, 58.52, 59.77, 58.99 and 61.08 per cent of Forest, 0.06, 2.33, 0.81, 0.04 and 0.35 per cent of Wasteland, 13.27, 31.45, 30.45, 23.92 and 28.33 per cent of Agriculture, 19.76, 0.12, 0.66, 8.26 and 0.07 per cent of Grassland, 2.17, 1.92, 1.77, 2.11 and 1.68 per cent of Built-up area respectively.

Table 7, 8 and 9, infers that the total area classified for 100, 200, 300, 400 and 500 training samples is 3065.4 hectares. Out of 3065.4 hectares of land 27.6765 hectares area classified as Unclassified for all training samples. 86.775, 89.517, 110.151, 107.8575 and 99.594 hectares of area are classified as Wetland. 287.49, 56.304, 62.415, 69.147 and 133.032 hectares of area are classified as Water bodies. 1582.6965, 1793.754, 1832.2035, 1808.367 and 1872.399 hectares of area are classified as Forest. 406.809, 964.0545, 933.5235, 733.239 and 868.425 hectares of area are classified as Agriculture land. 1.8525, 71.571, 24.7905, 1.365 and 10.6875 hectares of area are classified as Wasteland. 605.625, 3.642, 20.2335, 253.1475 and 2.235 hectares of area are classified as Grassland. 66.4755, 58.881, 54.4065, 64.6005 and 51.351 hectares of area are classified as Built up area correspondingly.

Image fusion is the process of compiling crucial data from various photos and combining it into a single, consolidated image. Through this consolidation, it is made sure that the fused image has all pertinent and necessary data from the source photos. By utilizing the advantages and distinctive qualities of each input

TABLE 7

Comparison of Urban Landscape Features for Fuzzy Classification of LANDSAT-8 Panchromatic Image for TS=100 and 200

Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %	Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %
Unclassified	18451	68.39	27.6765	0.90%	Unclassified	18451	68.39	27.6765	0.90%
Wetland	57850	214.43	86.775	2.83%	Wetland	59678	221.20	89.517	2.92%
Waterbodies	191660	710.40	287.49	9.38%	Waterbodies	37536	139.13	56.304	1.84%
Forest	1055131	3910.93	1582.6965	51.63%	Forest	1195836	4432.46	1793.754	58.52%
Agriculture	271206	1005.25	406.809	13.27%	Agriculture	642703	2382.23	964.0545	31.45%
Wasteland	1235	4.58	1.8525	0.06%	Wasteland	47714	176.86	71.571	2.33%
Grassland	403750	1496.53	605.625	19.76%	Grassland	2428	9.00	3.642	0.12%
Built up	44317	164.26	66.4755	2.17%	Built up	39254	145.50	58.881	1.92%
Total	2043600	7574.77	3065.4	100.00%	Total	2043600	7574.77	3065.4	100.00%

TABLE 8

Comparison of Urban Landscape Features for Fuzzy Classification of LANDSAT - 8 Panchromatic Image for TS = 300 and 400

Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %	Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %
Unclassified	18451	68.39	27.6765	0.90%	Unclassified	18451	68.39	27.6765	0.90%
Wetland	73434	272.19	110.151	3.59%	Wetland	71905	266.52	107.8575	3.52%
Waterbodies	41610	154.23	62.415	2.04%	Waterbodies	46098	170.87	69.147	2.26%
Forest	1221469	4527.47	1832.2035	59.77%	Forest	1205578	4468.57	1808.367	58.99%
Agriculture	622349	2306.79	933.5235	30.45%	Agriculture	488826	1811.87	733.239	23.92%
Wasteland	16527	61.26	24.7905	0.81%	Wasteland	910	3.37	1.365	0.04%
Grassland	13489	50.00	20.2335	0.66%	Grassland	168765	625.54	253.1475	8.26%
Built up	36271	134.44	54.4065	1.77%	Built up	43067	159.63	64.6005	2.11%
Total	2043600	7574.77	3065.4	100.00%	Total	2043600	7574.77	3065.4	100.00%

TABLE 9

Comparison of Urban Landscape Features for Fuzzy Classification of LANDSAT-8 Panchromatic Image for TS = 500

Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %
Unclassified	18451	68.39	27.6765	0.90%
Wetland	66396	246.10	99.594	3.25%
Waterbodies	88688	328.73	133.032	4.34%
Forest	1248266	4626.80	1872.399	61.08%
Agriculture	578950	2145.93	868.425	28.33%
Wasteland	7125	26.41	10.6875	0.35%
Grassland	1490	5.52	2.235	0.07%
Built up	34234	126.89	51.351	1.68%
Total	2043600	7574.77	3065.4	100.00%

LANDSAT - 8 Fused Image Classification Using Fuzzy Classifier

image, the fusion process rises the overall quality of the final image. The fusion technique seeks to improve contrast and maintain key features from various input images. Thus, the fusion process produces a final image that is more accurate and informative than any individual source image by merging data from various images, often into a single image as shown in Fig. 12.

Training and validation sets are made in various sizes for each class. We have used sets with 100, 200, 300, 400 and 500 samples, sequentially. The associated validation sets also include 40, 68, 104, 137 and 173 samples. These sets are used to identify semi-urban characteristics in the data. The outcomes of this extraction procedure are shown in Fig. 13, 14 and 15.

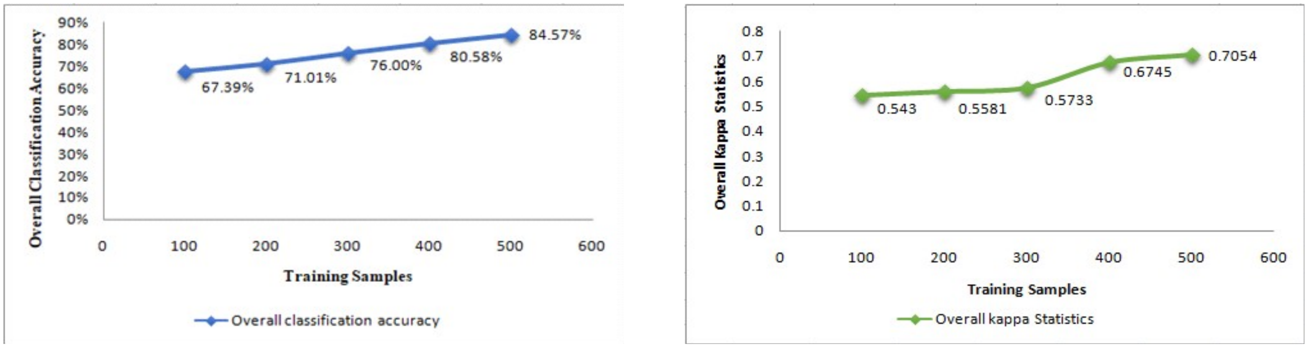

Fig. 8 : Comparison of OCA and Kappa statistics v/s Training Samples

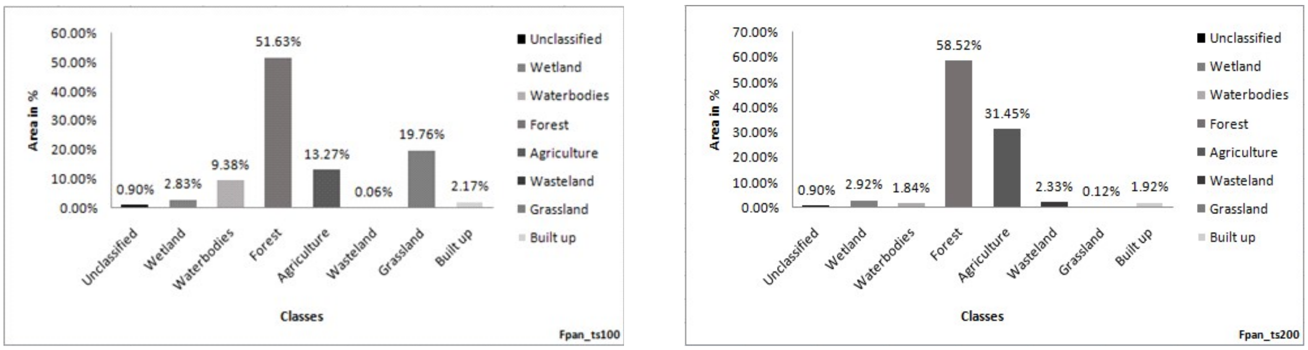

Fig. 9 : Comparison of Area in % v/s Urban Landscape Classes or Features for TS=100 and 200

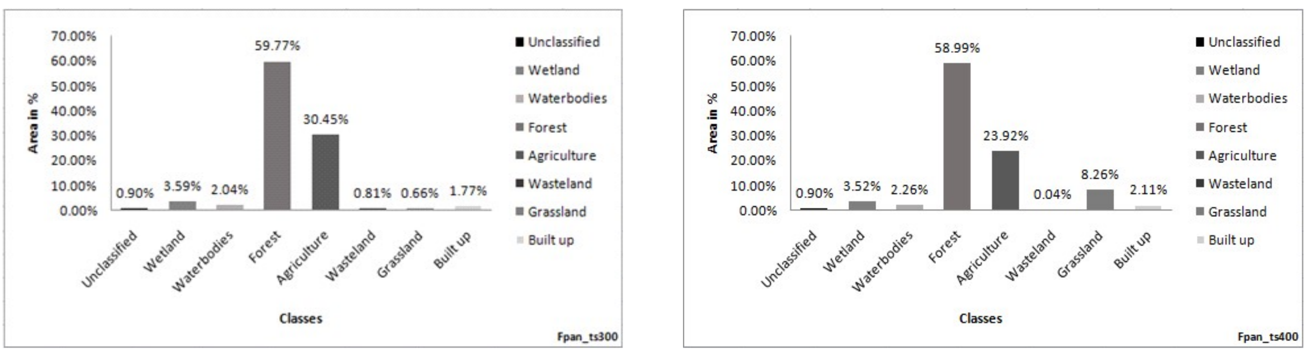

Fig. 10 : Comparison of Area in % v/s Urban Landscape Classes or Features for TS=300 and 400

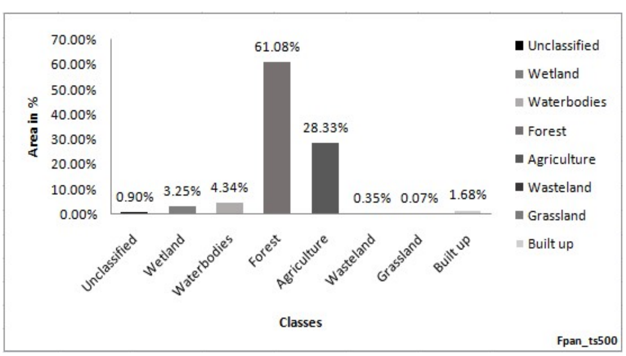

Fig. 11 : Comparison of Area in % v/s Urban Landscape Classes or Features for TS=500

LANDSAT - 8 Panchromatic Image Classification Using Fuzzy Classifier

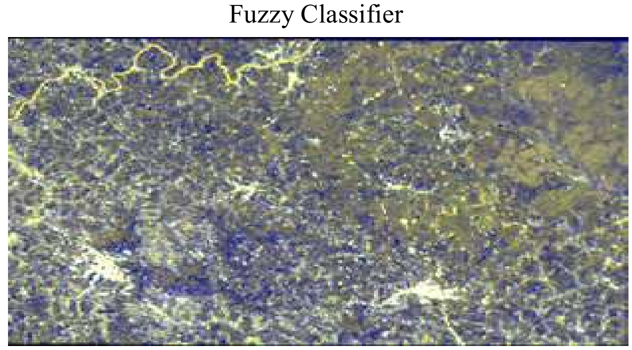

Fig. 12 : Original Fused Image

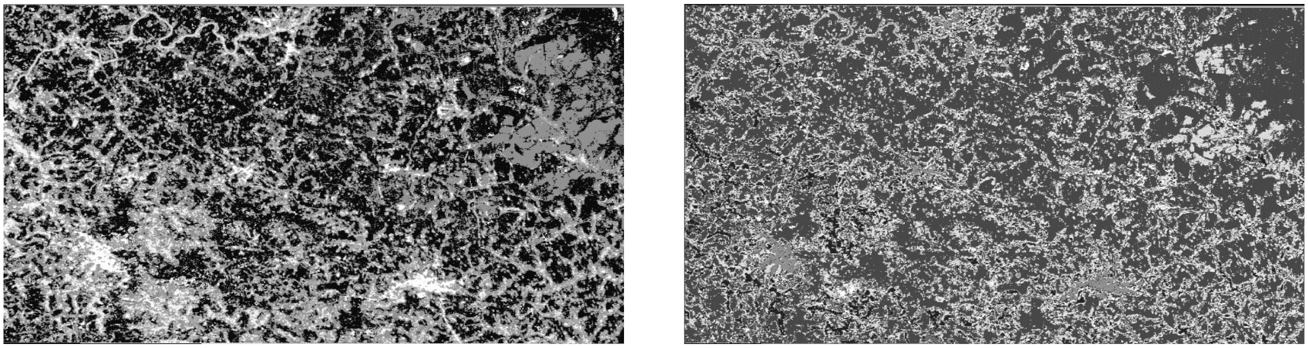

Fig. 13 : Fuzzy Classified LANDSAT-8 Fused Image with TS=100, 200 and VS = 40, 68

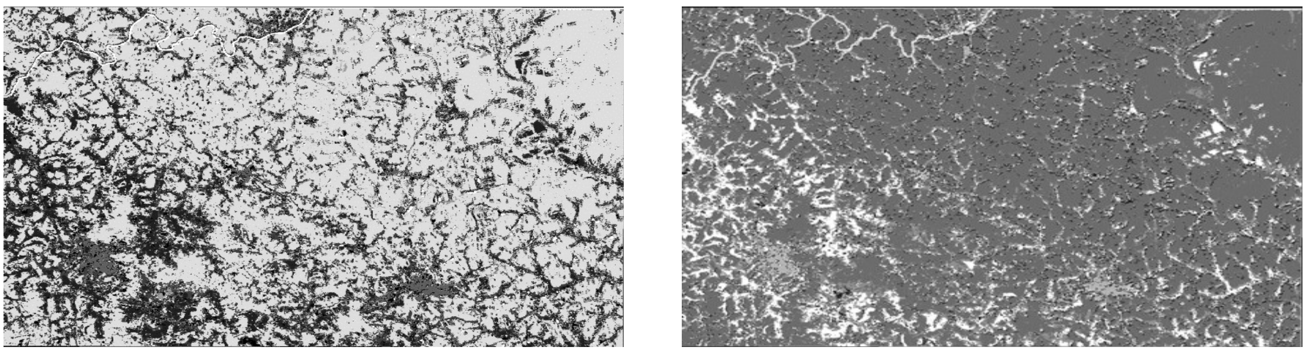

Fig. 14 : Fuzzy Classified LANDSAT-8 Fused Image with TS=300, 400 and VS = 104, 137

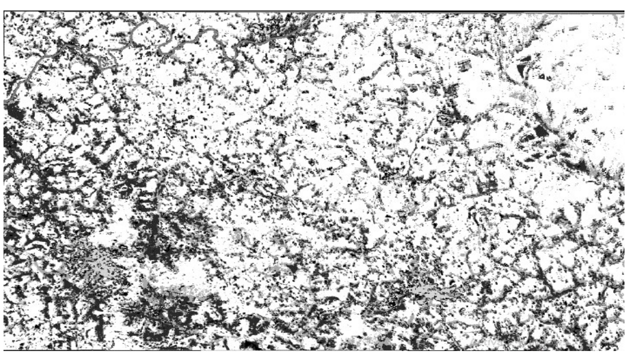

Fig. 15 : Fuzzy Classified LANDSAT-8 Fused Image with TS=500 and VS = 173

Table 10, 11 and 12, indicates that for 100 training samples and 46 validation points, the user accuracies have been classified for seven classes using panchromatic data as 33.33 per cent of Grassland, Wetland and Wasteland, 80 per cent of Agriculture, 100 per cent of Waterbodies and Forest, 66.67 per cent of Built up, respectively. For 200 training samples and 69 validation points, it is classified as 16.67 per cent of the land, 50 per cent of Agriculture and Built up, 100 per cent of Grassland, Waterbodies and Wetland, 97.37 per cent of Forest, respectively. For 300 training samples and 100 validation points, it is classified as 50 per cent of Built up, 18.18 per cent of Wetland, 66.67 per cent of Waterbodies, 90.91 per cent of Agriculture, 33.33 per cent of Wasteland, 60 per cent of Grassland, 98.49 per cent of Forest, respectively. For 400 training samples and 139 validation points, it is classified as 60 per cent of Wetland and Waterbodies, 84.62 per cent of Agriculture, 64.71 per cent of Grassland, 66.67 per cent of Built up and Wasteland, 97.59 per cent of Forest, accordingly. For 500 training samples and 175 validation points, it is classified as 50 per cent of Wetland, 80 per cent of Wasteland, 90 per cent of Agriculture, 73.91 per cent of Grassland, 60 per cent of Built up and Waterbodies, 100 per cent of Forest, correspondingly.

It is clear from Fig. 16 that for 100, 200, 300, 400 and 500 training samples obtained for OCA is 75.00, 79.41, 81.73, 85.40 and 87.86 per cent and Kappa statistics is 0.6334, 0.6471, 0.6673, 0.7355

TABLE 10

Confusion Matrix for Fuzzy Classified Fused Image with TS = 100, 200 and VS = 40, 68

Classes	1	2	3	4	5	6	7	RT	UA in %
1	2	0	0	0	0	1	0	3	66.67
2	0	4	1	0	0	0	0	5	80.00
3	0	0	18	0	0	0	0	18	100
4	0	0	3	2	1	0	0	6	33.33
5	0	0	0	0	2	0	0	2	100
6	0	0	2	0	0	1	0	3	33.33
7	0	0	1	1	0	0	1	3	33.33
CT	2	4	25	3	3	2	1	40	
PA in %	100	100	72.00	66.67	66.67	50.00	100		
Kappa	0.6491	0.7778	1.0000	0.2793	1.0000	0.2982	0.3162		

Classes	1	2	3	4	5	6	7	8	RT	UA in %
1	1	0	0	0	0	0	0	0	1	100
2	0	6	0	0	0	0	0	0	6	100
3	0	1	37	0	0	0	0	0	38	97.37
4	0	0	1	1	0	0	0	0	2	50.00
5	0	0	1	0	1	0	0	0	2	50.00
6	0	0	5	0	0	1	0	0	6	16.67
7	0	2	3	1	0	0	6	0	12	50.00
8	0	0	0	0	0	0	0	1	1	
CT	1	9	47	2	1	1	6	1	68	
PA in %	100.00	66.67	78.72	50.00	100	100	100			
Kappa	1.0000	1.0000	0.9148	0.4848	0.4925	0.1542	0.4516	1.0000		

TABLE 11

Confusion Matrix for Fuzzy Classified Fused Image with TS = 300, 400 and VS = 104, 137

Classes	1	2	3	4	5	6	7	RT	UA in %
1	1	0	0	0	0	0	0	2	50.00
2	1	10	0	0	0	0	0	11	90.91
3	1	0	63	0	0	0	0	64	98.49
4	1	0	1	1	0	0	0	3	33.33
5	0	0	0	0	2	1	0	3	66.67
6	1	0	6	1	0	2	1	11	18.18
7	0	2	2	0	0	0	6	10	60.00
CT	5	13	72	2	2	3	7	104	
PA in %	20.00	76.92	87.50	50.00	100	66.67	85.71		
Kappa	0.4747	0.8961	0.9492	0.3203	0.6601	0.1575	0.5711		

Classes	1	2	3	4	5	6	7	8	RT	UA in %
1	2	0	1	0	0	0	0	0	3	66.67
2	0	11	0	0	0	1	1	0	13	84.62
3	0	1	81	0	0	0	1	0	83	97.59
4	0	0	1	2	0	0	0	0	3	66.67
5	0	0	1	0	1	0	0	0	2	50.00
6	0	0	7	0	0	7	0	0	14	50.00
7	1	1	4	0	0	0	11	0	17	64.71
8	2	0	1	0	0	0	0	2	2	
CT	3	13	95	2	1	8	13	2	137	
PA in %	66.67	84.82	85.26	100	100	87.50	84.62			
Kappa	0.6592	0.8300	0.9214	0.6617	0.4963	0.4690	0.6101	1.0000		

TABLE 12

Confusion Matrix for Fuzzy Classified Fused Image with TS=500 and VS=173

Classes	1	2	3	4	5	6	7	8	RT	UA in %
1	3	1	1	0	0	0	0	0	5	60.00
2	0	18	2	0	0	0	0	0	20	90.00
3	0	0	98	0	0	0	0	0	98	100
4	0	1	0	4	0	0	0	0	5	80.00
5	0	1	1	0	3	0	0	0	5	60.00
6	1	1	6	0	0	8	0	0	16	50.00
7	0	2	3	0	1	0	17	0	23	73.91
8	0	0	0	0	0	0	0	1	1	
CT	4	24	111	4	4	8	71	1	173	
PA in %	75.00	75.00	88.29	100	75.00	100	100			
Kappa	0.5905	0.8839	1.0000	0.7953	0.5905	0.4758	0.7107	1.0000		

Legend : 1 = Built up, 2 = Agriculture, 3 = Forest, 4 = Wasteland, 5 = Waterbodies, 6 = Wetland, 7 = Grassland, RT = Row Total, CT = Column, Total PA = Producer Accuracy, UA = User Accuracy.

and 0.7981. This comparison of OCA and Kappa statistics v/s training samples was obtained for LANDSAT 8 panchromatic image. As the training sets were increased, the OCA and Kappa statistics also increased. From Fig. 17, 18 and 19, it interprets that for 100, 200, 300, 400 and 500 training samples, the total area has been classified for panchromatic as 0.34 per cent for all unclassified land, 6.32, 9.70, 9.06, 7.91 and 8.47 per cent of Wetland, 0.78, 1.65, 1.72, 1.80 and 1.79 per cent of Waterbodies, 40.98 per cent, 57.54, 58.28, 59.10 and 58.01 of Forest, 10.30, 3.31, 2.47, 2.36 and 2.82 per cent of Wasteland, 7.88, 8.09, 10.87, 10.65 and 11.06 per cent of Agriculture, 31.23, 17.15, 14.73, 15.75 and 15.53 per cent of Grassland, 2.17, 2.22, 2.54, 2.09 and 1.98 per cent of Built-up area respectively.

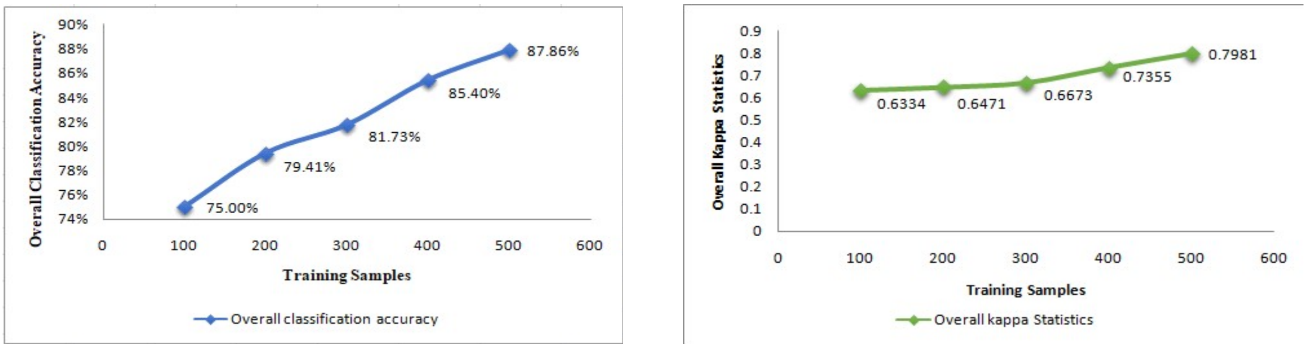

Fig. 16 : Comparison of OCA and Kappa Statistics v/s Training Samples

Comparison of Urban Landscape Features for Fuzzy Classification of LANSAT - 8 Fused Image

Fig. 17 : Comparison of Area in % v/s Urban Landscape Classes or Features for TS=100 and 200

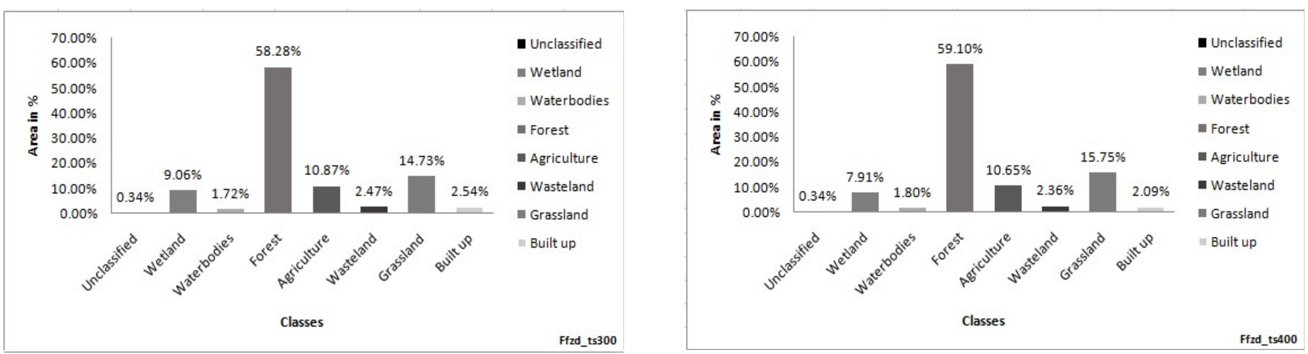

Fig. 18 : Comparison of Area in % v/s Urban Landscape Classes or Features for TS=300 and 400

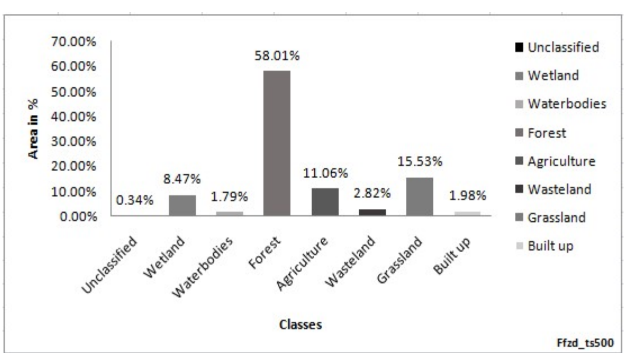

Fig. 19 : Comparison of Area in % v/s Urban Landscape Classes or Features for TS=500

A look at Table 13, 14 and 15, it interprets that the total area classified for 100, 200, 300, 400 and 500 training samples is 6113.838 hectares. Out of 6113.838 hectares of land 20.664 hectares area classified as Unclassified for all training samples. 386.643, 593.217, 554.145, 483.708 and 518.001 hectares of area are classified as Wetland. 47.817, 100.677, 105.186, 110.235 and 109.443 hectares of area are classified as Waterbodies. 2505.282, 3517.755, 3563.22, 3613.296 and 3546.81 hectares of area are classified as Forest. 481.587, 494.796, 664.524,

TABLE 13

Comparison of Urban Landscape Features for fuzzy classification of LANSAT-8 Fused Image with TS=100 and 200

Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %
Unclassified	6888	51.06	20.664	0.34%
Wetland	128881	955.42	386.643	6.32%
Water bodies	15939	118.16	47.817	0.78%
Forest	835094	6190.69	2505.282	40.98%
Agriculture	160529	1190.03	481.587	7.88%
Wasteland	209941	1556.33	629.823	10.30%
Grassland	636407	4717.79	1909.221	31.23%
Built up	44267	328.16	132.801	2.17%
Total	2037946	15107.62	6113.838	100.00%

Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %
Unclassified	6888	51.06	20.664	0.34%
Wetland	197739	1465.87	593.217	9.70%
Waterbodies	33559	248.78	100.677	1.65%
Forest	1172585	8692.56	3517.755	57.54%
Agriculture	164932	1222.67	494.796	8.09%
Wasteland	67416	499.77	202.248	3.31%
Grassland	349518	2591.03	1048.554	17.15%
Built up	45309	335.88	135.927	2.22%
Total	2037946	15107.62	6113.838	100.00%

TABLE 14

Comparison of Urban Landscape Features for fuzzy classification of LANSAT - 8 Fused Image with TS = 200 and 300

Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %
Unclassified	6888	51.06	20.664	0.34%
Wetland	184715	1369.32	554.145	9.06%
Waterbodies	35062	259.92	105.186	1.72%
Forest	1187740	8804.91	3563.22	58.28%
Agriculture	221508	1642.07	664.524	10.87%
Wasteland	50246	372.48	150.738	2.47%
Grassland	300125	2224.88	900.375	14.73%
Built up	51662	382.98	154.986	2.54%
Total	2037946	15107.62	6113.838	100.00%

Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %
Unclassified	6888	51.06	20.664	0.34%
Wetland	161236	1195.27	483.708	7.91%
Waterbodies	36745	272.40	110.235	1.80%
Forest	1204432	8928.65	3613.296	59.10%
Agriculture	216982	1608.52	650.946	10.65%
Wasteland	48104	356.60	144.312	2.36%
Grassland	320957	2379.31	962.871	15.75%
Built up	42602	315.82	127.806	2.09%
Total	2037946	15107.62	6113.838	100.00%

TABLE 15

Comparison of Urban Landscape Features for fuzzy classification of LANSAT-8 Fused Image with TS=500

Classes	Area in pixels	Area in Acres	Area in Hectares	Area in %
Unclassified	6888	51.06	20.664	0.34%
Wetland	172667	1280.01	518.001	8.47%
Waterbodies	36481	270.44	109.443	1.79%
Forest	1182270	8764.36	3546.81	58.01%
Agriculture	225343	1670.50	676.029	11.06%
Wasteland	57446	425.86	172.338	2.82%
Grassland	316571	2346.79	949.713	15.53%
Built up	40280	298.60	120.84	1.98%
Total	2037946	15107.62	6113.838	100.00%

650.946 and 676.029 hectares of area are classified as Agriculture land. 629.823, 202.248, 150.738, 144.312 and 172.338 hectares of area are classified as Wasteland. 1909.221, 1048.554, 900.375, 962.871 and 949.713 hectares of area are classified as Grassland. 132.801, 135.927, 154.986, 127.806 and 120.84 hectares of area are classified as Built up area in that order.

The graph plotted (Fig. 20) interprets that for 100, 200, 300, 400 and 500 training samples, the OCA of panchromatic data is 67.39, 71.01, 76.00, 80.58 and 84.57 per cent and OCA of fused data is 75.00 per cent, 79.41, 81.73, 85.40 and 87.86 per cent. For 100, 200, 300, 400 and 500 training samples, the OKS of

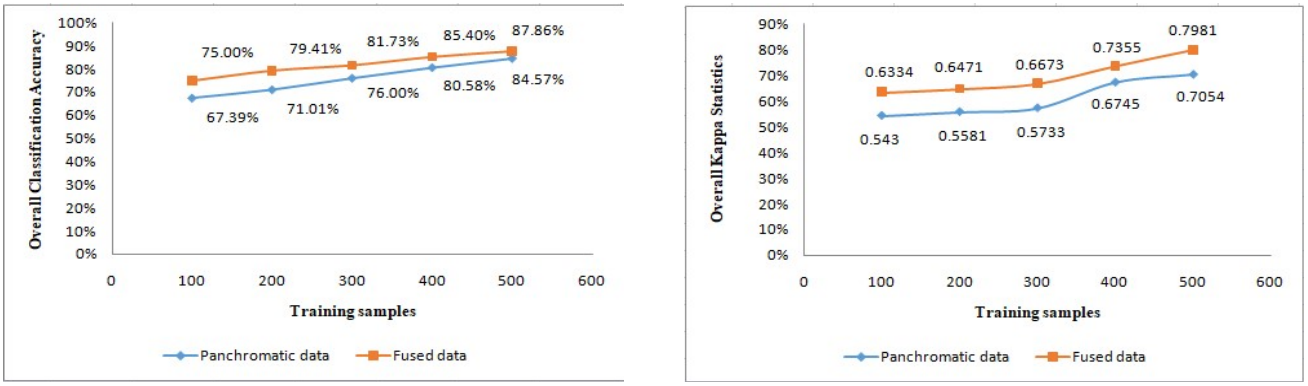

Fig. 20 : Comparison of OCA and OKS v/s Training Samples of Panchromatic Image and Fused Image for Fuzzy classifier

panchromatic data is 0.543, 0.5581, 0.5733, 0.6745 and 0.7054 and OKS of fused data is 06334, 06471, 0.6673, 0.7355 and 0.7981. Therefore, comparatively we can conclude that fused data has high overall classification accuracy and Kappa statistics than the panchromatic data.

For 100, 200, 300, 400 and 500 training samples as depicted from Fig. 21, 22 and 23, it was attained that out of total 100 per cent area, 0.90 per cent of area is unclassified for all panchromatic data and 0.34 per cent of area is unclassified for all fused data. 2.83, 2.92, 3.59, 3.52 and 3.25 per cent of area is classified

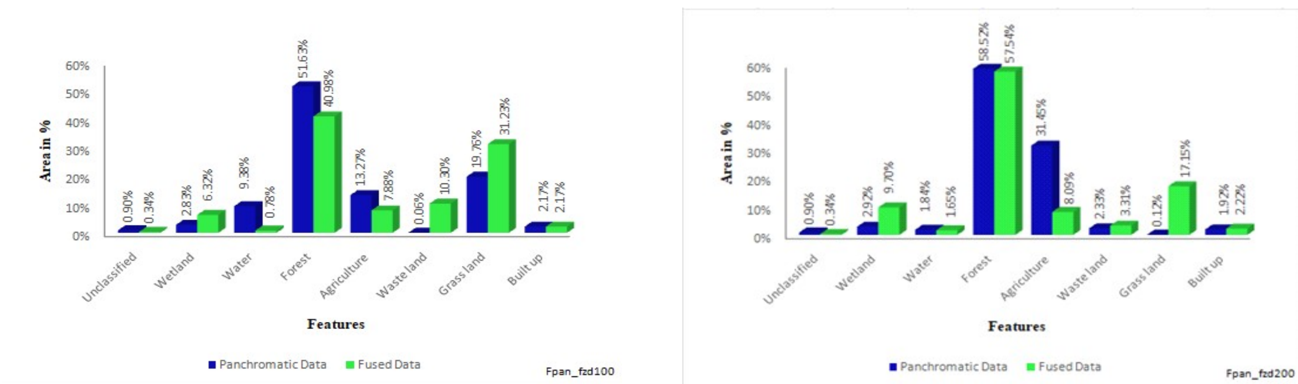

Fig. 21 : Comparison of OCA and OKS v/s Training Samples of Panchromatic Image and Fused Image for Fuzzy classifier

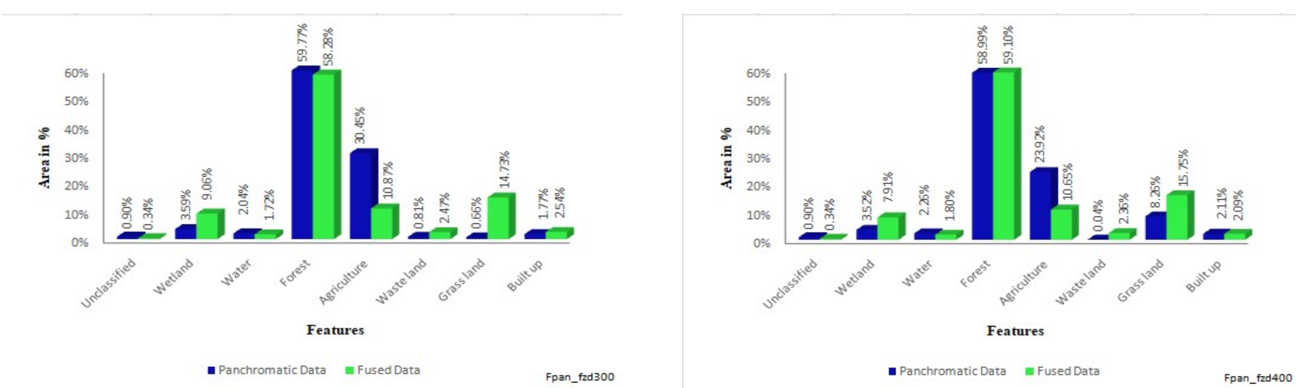

Fig. 22 : Comparison of Urban Landscape Features of Panchromatic Image and Fused Image
for Fuzzy Classifier with TS=300 and 400

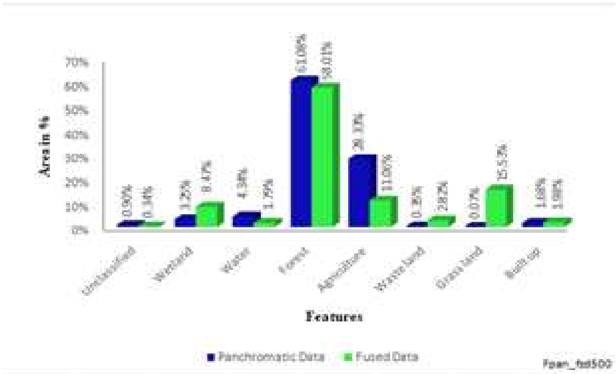

Fig. 23 : Comparison of Urban Landscape Features of Panchromatic Image and Fused Image for Fuzzy Classifier with TS=500

as wetland in panchromatic data and 6.32, 9.70, 9.06, 7.91 and 8.47 per cent of area in fused data, 9.38, 1.84, 2.04, 2.26 and 4.34 per cent of area is classified as waterbodies in panchromatic data and 0.78, 1.65, 1.72, 1.80 and 1.79 per cent of area in fused data, 51.63, 58.52, 59.77, 58.99 and 61.08 per cent of area is classified as forest in panchromatic data and 40.98, 57.54, 58.28, 59.10 and 58.01 per cent of area in fused data, 13.27, 31.45, 30.45, 23.92 and 28.33 per cent of area is classified as agriculture in panchromatic data and 7.88, 8.09, 10.87, 10.65 and 11.06 per cent of area in fused data, 0.06, 2.33, 0.81, 0.04 and 0.36 per cent of area is classified as wasteland in panchromatic data and 10.30, 3.31, 2.47, 2.36 and 2.82 per cent of area in fused data, 19.76, 0.12, 0.66, 8.26 and 0.07 per cent of area is classified as grassland in panchromatic data and 31.23, 17.15, 14.73, 15.75 and 15.53 per cent of area in fused data, 2.17, 1.92, 1.77, 2.11 and 1.68 of area is classified as built up in panchromatic data and 2.17, 2.22, 2.54, 2.09 and 1.98 per cent of area in fused data. Therefore, comparatively fused data is highly classified than the panchromatic data.

In this study, panchromatic data and fused data were used to identify land use and land cover (LU/LC) features using fuzzy classifiers. The goal is to use fuzzy categorization techniques to study the semi-urban characteristics of a certain location. By utilizing fuzzy classifiers and monitoring changes in LU/LC via remote sensing techniques, the strategy seeks to address current issues in LU/LC categorization. The proposed methodology is implemented using ERDAS version 9.2, an image processing program and the experiment is run using an image dataset generated from Google Earth images. The study employs panchromatic (layer 8) data and focuses on semi-urban features.

Semi urban features of Panchromatic data were collected and analysed for five training samples, for 100 training samples, OCA of 67.39 per cent and Kappa Statistics of 0.5430 was obtained; For 200 training samples, OCA of 71.01 per cent and Kappa Statistics of 0.5581 was obtained. For 300 training samples, OCA of 76 per cent and Kappa Statistics of 0.5733 was obtained; For 400 training samples, OCA of 80.58 per cent and Kappa Statistics of 0.674 was obtained; For 500 training samples, OCA of 84.37 per cent and Kappa Statistics of 0.7054 was obtained. Semi urban features of Fused data were collected and analysed for five training samples, for 100 training samples, OCA of 75 per cent and Kappa Statistics of 0.6334 was obtained; For 200 training samples, OCA of 79.41 per cent and Kappa Statistics of 0.6471 was obtained. For 300 training samples, OCA of 81.37 per cent and Kappa Statistics of 0.6498 was obtained; For 400 training samples, OCA of 85.40 per cent and Kappa Statistics of 0.7355 was obtained; For 500 training samples, OCA of 87.86 per cent and Kappa Statistics of 0.7981 was obtained.

Changing the number of training samples produced varied overall classification accuracies (OCA) and Kappa Statistics for panchromatic data. As the quantity of training samples increased, the OCA and Kappa Statistics also increased, suggesting higher classification accuracy. As OCA and Kappa Statistics grew with more training samples for the fused data, this led to further improvement in classification accuracy. Urban planning in the Virajpet taluk may benefit from the fuzzy classification of supervised classification since it improves accuracy and fosters a deeper knowledge of semi-urban features. The study also identifies crucial elements that affect categorization ability, which will aid future studies in this area. Overall, the results show how effective fuzzy classification techniques are in improving classification accuracy as well as their potential use in studying and comprehending semi-urban aspects for the purposes of urban planning.

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