



Land use Land Cover Classification of Burhner River Watershed Using Remote Sensing and GIS Technique

**J. Himanshu Rao ^{a*}, S. K. Sharma ^a, M. K. Awasthi ^a, S. K. Pyasi ^a
and S. K. Pandey ^b**

^a *Department of Soil and Water Engineering, College of Agricultural Engineering, JNKVV, Jabalpur, Madhya Pradesh, India.*

^b *Department of Horticulture, College of Agriculture, JNKVV, Jabalpur, Madhya Pradesh, India.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/IJECC/2022/v12i730707

Open Peer Review History:

This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: <https://www.sdiarticle5.com/review-history/85237>

Original Research Article

Received 20 January 2022

Accepted 29 March 2022

Published 01 April 2022

ABSTRACT

Information on Land Use Land Cover (LULC) pattern is very important for developing management strategies for land use planning. Remotely sensed satellite data has proved to be an unmatched source of information that can deliver LULC information with good accuracy especially in regions where acquiring LULC information through intensive ground surveys seems to be impractical. The present study aims at performing LULC classification of Burhner river watershed situated in Mandla, Balaghat and Dindori districts of Madhya Pradesh, India by adopting unsupervised classification. It also discusses merits and demerits of using unsupervised classification for a high resolution satellite image along with key factors responsible for using it. Sentinel-2B satellite imagery with spatial resolution of 10 m was used in the present investigation. A total number of 6 LULC classes were identified in the study area namely agricultural land, fallow/open land, forest, habitation, wasteland and waterbodies using ERDAS IMAGINE® 2011. Accuracy assessment of the LULC classified image from reference (ground truth) data using error matrix revealed an overall accuracy of 95.72% with kappa coefficient of 0.94. Furthermore, the error matrix also aided in computing classified image producer's and user's accuracy which were under acceptable limits. The LULC statistics of study area indicated that highest area is covered by forest (53.01%), followed by

*Corresponding author: E-mail: j.himanshuro@gmail.com;

fallow/open land (24%), agricultural land (19.44%) and least area is covered by waterbodies (1.38%) and habitation (0.19%). A major portion of study area under fallow/open land category pointed that underutilized land resource potential exist in watershed. Such land can be further utilized for crop production and plantation purposes in order to maximize output from the available natural resources in a sustainable manner.

Keywords: Land use land cover classification; digital image processing; accuracy assessment; remote sensing, geographic information system.

1. INTRODUCTION

The land surface is used for a variety of purposes. It possesses various characteristics over its spatial extent with a period [1,2]. Land provides vital socioeconomic resources to society, such as food, fuel, fibres and many other ecosystem services that support production functions, regulate risks of natural hazards, or provide cultural and spiritual services [3]. Land surface undergo dynamic changes resulting from natural and human induced activities [4,5]. The human induced activities are attributed to increase in human population, agricultural expansion, and changes in socio-economic well-being of the people which have triggered unsustainable extraction of natural resources [6-8]. Land is becoming a limited resource because of the enormous agricultural and demographic pressure [9]. The ever growing population and limited availability of land necessitates proper utilization of available land through scientific land use planning [10-12].

Land Use Land Cover (LULC) is an important component in understanding the interactions of human activities with the environment [13]. Accurate and timely monitoring of land through LULC mapping plays a critical role in a variety of sectors in the developing world including food security, land use planning, hydrological modeling and natural resources management [14]. LULC information is very important for several planning and management activities concerned with the surface of earth because it constitutes key environmental information for many scientific resource management and policy purposes [15]. LULC classification is a hybrid type of classification [2,16]. The terms land use and land cover have some fundamental differences [17, 18] and thus it becomes essential to define them clearly. Land cover represents the observed biophysical cover of the Earth's surface whereas land use describe the arrangements, activities and inputs people undertake within a particular land type to produce, modify and maintain it [19]. Land use is

an expression of human activity developed for social, economic, cultural and political purposes [20]. Land cover represents the terrestrial component of the Earth's system whereas land use encompass all processes and activities related to the human use of land, including socioeconomic, technological and organizational investments and arrangements, as well as the benefits gained from land and unintended social and ecological outcomes of societal activities [3]. Timely information of LULC and their possibilities for optimal use is vital for the selection, planning and implementation of land use schemes to meet the increasing demands for basic human needs and welfare [9].

LULC monitoring at watershed scale holds a significant role in scientific investigations as it aims to identify the risk associated from land resources degradation, watershed deterioration and ecosystem instability [21]. A watershed is an area from which runoff resulting from precipitation flows past a single point into large stream, river, lake or ocean [22, 23]. Watersheds play a crucial role in natural functioning of Earth thus considered as a core planning unit for sustainable management of natural resources (*i.e.*, land and water) [24].

Advances in remote sensing science and associated technologies have made it possible to obtain the valuable spatiotemporal information on LULC [25]. Remotely sensed satellite imagery and image classification methods provide cost effective and accurate means to derive LULC information [26]. The availability of remote sensing data at very fine spatial resolutions coupled with socio-economic data have revealed multiple patterns of interactions between land managers and terrestrial ecosystems, illuminating important debates on, for example, reconciling food security with nature conservation, whether through land sparing, land sharing, or sustainable intensification strategies [27]. Remote sensing has become a vital source of information for natural resources management including LULC mapping. LULC mapping

involves two types of remote sensing techniques – visual interpretation and digital image analysis [28]. With the advent of remote sensing and Geographical Information System (GIS) technologies, the monitoring of LULC pattern and change detection are now made possible at low cost and with better accuracy [29-31].

Several studies have been successfully conducted in past delivering accurate LULC information using remotely sensed satellite data [18, 25, 32]. Sharma et al., [33] performed LULC classification of Gusuru river watershed situated in Satna and Panna districts of Madhya Pradesh with an overall accuracy of 88.03%. Patle et al., [34] executed LULC classification of Nahra nala watershed situated in Balaghat district of Madhya Pradesh, India with an overall classification accuracy of 95.52% and kappa coefficient of 0.92.

The integrated use of remote sensing and GIS techniques can provide accurate information of LULC pattern with much ease as compared to the traditional ground based surveys [35]. Keeping all such perspectives in mind, the present study aims to perform LULC classification of Burhner river watershed situated

in Mandla, Balaghat and Dindori districts of Madhya Pradesh using unsupervised classification. It also discusses merits, demerits as well as key factors responsible for employing such technique with accuracy assessment of the said classification technique.

2. MATERIALS AND METHODS

2.1 Study Area

The Burhner river rises from the Maikala range, south-east of Gwara village in Mandla district of Madhya Pradesh, India. The Burhner river watershed is geographically located between 80°34'40"E to 81°23'20"E longitudes and 22°49'45"N to 22°31'00"N latitudes coinciding with Mandla, Balaghat and Dindori districts of Madhya Pradesh. The elevation in watershed varies from 393 to 954 m above M.S.L. (Mean Sea Level) with total watershed area of 3959.813 km². The study area receives majority of its rainfall from southwest monsoon from June to September. The normal annual rainfall in watershed is 1647.8 mm/year [36, 37]. The location map of the study area is illustrated in Fig. 1.

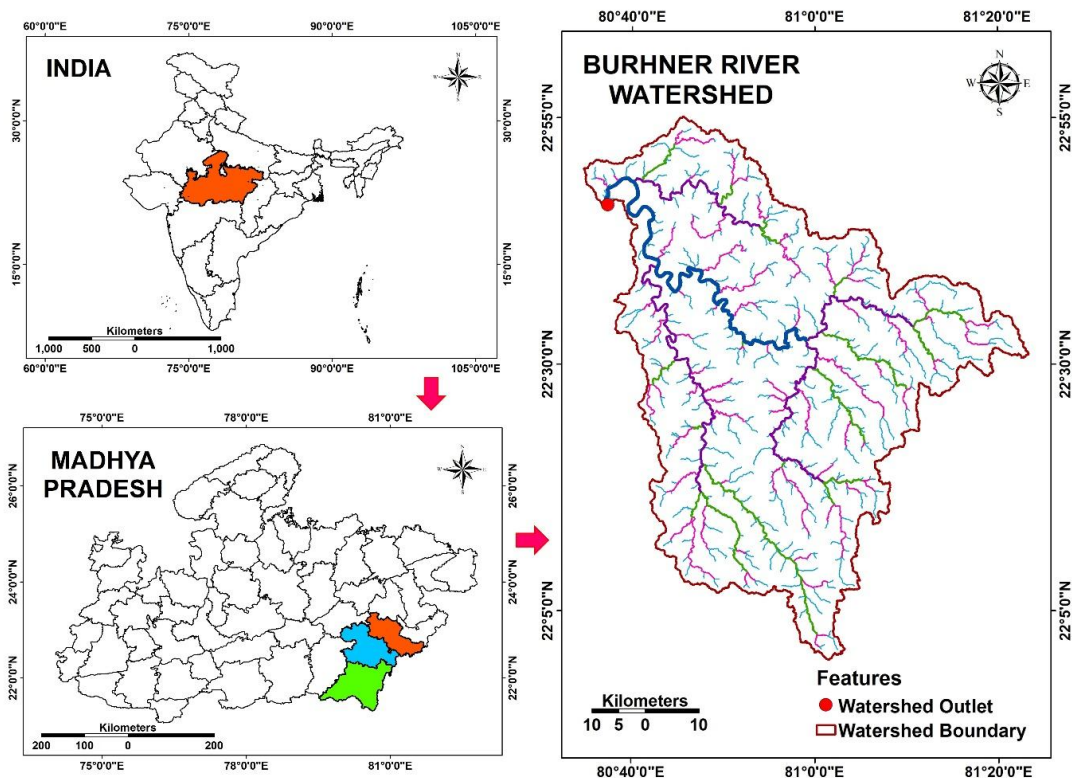


Fig. 1. Location map of study area

2.2 Data Source and Methodology

The digital topographic data used in the present study aided in correct delineation of watershed boundary. The delineation was executed by utilizing CARTOSAT DEM (Digital Elevation Model) of 30 m spatial resolution. The CARTOSAT DEM was acquired from Bhuvan ISRO's Geoportal with its URL as <https://bhuvan-app3.nrsc.gov.in/data/download/index.php>. The delineation was done by using snap pour point methodology in ArcGIS® 9.3 environment. The DEM tiles were initially pre-processed by mosaicking the tiles and were re-projected to a common and widely used UTM (Universal Transverse Mercator) projected coordinate system (Zone 44N) with WGS (World Geodetic System) 1984 as geographic coordinate system. A series of GIS operations such as fill sinks, flow direction, flow accumulation available under spatial analyst tool of Arc toolbox were followed with subsequent designation of watershed outlet so as to obtain the watershed boundary. The resultant watershed boundary was further verified with its base map.

For preparing the base map of the study area, a total number of 14 toposheets coinciding with the

study area were used. Survey of India (SOI) toposheets with toposheets number as 64B/9, 64B/10, 64B/11, 64B/12, 64B/13, 64B/14, 64B/15, 64B/16, 64F/2, 64F/3, 64F/4, 64F/6, 64F/7 and G4G/1 with a scale of 1:50,000 procured from SOI Nakshe Portal (URL: <https://soinakshe.uk.gov.in>) were used.

To prepare the LULC thematic map of the study area, cloud free remote sensing based satellite imagery of Sentinel-2B Level 1C MSI (Multi Spectral Instrument) with spatial resolution of 10 m freely downloaded from United States Geological Survey (USGS) Earth Explorer website (URL: <https://earthexplorer.usgs.gov>) was used. The date of acquisition of the imagery was 18 January 2021 and a total number of 4 tiles with tile name as T44QMK, T44QML, T44QNK, T44QNL together coinciding with watershed boundary were used. The procured tiles were having projected coordinate system as UTM Zone 44N and geographic coordinate system as WGS 1984. The bands of acquired image came with JPEG2000 file extension. Table 1 shows brief information of spatial and spectral characteristics of bands used in Sentinel-2B MSI [34].

Table 1. Brief details of spatial and spectral characteristics of bands used in Sentinel-2B MSI

Band	Spatial resolution (m)	Wavelength (µm)	Description
Band 1	60	0.443	Ultra-Blue-Coastal and Aerosol
Band 2	10	0.490	Blue
Band 3	10	0.560	Green
Band 4	10	0.665	Red
Band 5	20	0.705	Visible and Near Infrared (VNIR) – Vegetation Red Edge 1
Band 6	20	0.740	Visible and Near Infrared (VNIR) – Vegetation Red Edge 2
Band 7	20	0.783	Visible and Near Infrared (VNIR) – Vegetation Red Edge 3
Band 8	10	0.842	Near Infrared (NIR)
Band 8A	20	0.865	Narrow Near Infrared (NNIR)
Band 9	60	0.945	Short Wave Infrared (SWIR) – Water vapour
Band 10	60	1.375	Short Wave Infrared (SWIR) – Cirrus
Band 11	20	1.610	Short Wave Infrared (SWIR)
Band 12	20	2.190	Short Wave Infrared (SWIR)

Source: Gatti and Galoppo [38]

2.3 LULC Classification Approach

At the initial stage, pre-processing technique (*i.e.*, atmospheric correction) was applied to the tiles in order to generate reflectance files using ERDAS IMAGINE® 2011. The band 2 (blue), band 3 (green), band 4 (red) and band 8 (NIR) as obtained after atmospheric correction were further used to prepare the RGB composite image for each tile. The RGB composite image was prepared by using the layer stack tool available in ERDAS (Earth Resources Data Analysis System) IMAGINE® 2011 which is a most preferred and widely used digital image processing software. The RGB composite tiles were mosaicked and further made subset by using vector file of watershed boundary. The change in band combination of RGB composite image successfully yielded FCC (False Colour Composite) image. A false colour composite image is one in which the red, blue and green values do not correspond to the true colours of red, green and blue. The most commonly used FCC image displays the near infrared as red, red as green and green as blue. Thus, FCC can be defined as an artificially generated colour image in which the red, green and blue colours are assigned to the wavelength in which they do not belong in nature. The False Colour Composite (FCC) image of the study area is shown in Fig. 2

The FCC image of the study area aided in preparing the AOI (Area of Interest) files of different LULC classes using on-screen visual interpretation principles (Fig. 3), available ancillary data, prior knowledge-based logic rules, sufficient ground truth (reference) data (Fig. 4) and satellite data of Google Earth Pro. After preparation of AOIs, unsupervised classification was performed using FCC image that yielded broad classes of LULC in the classified image. The unsupervised method of classification typically requires little or no input from the image analyst in developing the output LULC classification [39]. In this method, the classification system, or classifier, uses statistical means and covariance matrices to iteratively assign each pixel to a designated output class based on how spectrally separate each group of clustered pixels are. The k-means clustering approach of unsupervised classification as used in this study, also work in an iterative process. The initial stage includes the build-up of several similar pixel clusters within a range determined

by the analyst. Each resulting cluster is composed of pixel groups consisting of similar spectral values, which likewise occupies a common spectral space [40, 41] that consists of a well-defined mean vector for each class. This operation is followed by a minimum-distance-to-means classification algorithm that determines the final pixel cluster groups. In the k-means operation, pixels are iteratively classified into a predetermined number of clusters with no deletion, splitting, or merging of the clusters between each iteration.

The resultant image obtained after applying unsupervised classification was recoded to prominent LULC classes. These classes were characterized by variations in tone, texture, shape, association, and the pattern of various objects within the satellite data. A total of six prominent LULC classes *viz.*, agricultural land, fallow/open land, forest, habitation, waste land and waterbodies were identified during the classification process. Subsequently, the AOI files were further overlaid on unsupervised classified image to get thematically recoded raster image. At last, area covered by each LULC class covered was calculated. The methodological framework used in the classification approach is shown in Fig. 5.

2.4 Accuracy Assessment

Accuracy assessment or validation is a significant step in the processing of remote sensing data [42]. The most common way to express the accuracy of classified image is by a percentage of the map area that has been correctly classified when compared with reference data or “ground truth” [43]. This statement can be justified by comparing the correctness of the classification generated by sampling the classified data expressed in the form of an error matrix (sometimes also referred as a confusion matrix or contingency table). An error matrix is a square array of numbers set out in rows and columns, which express the number of sample units assigned to a particular class in one classification relative to the number of sample units assigned to a particular class in another classification [44]. The row total in error matrix represents classified data whereas the column total represents reference or ground truth data.

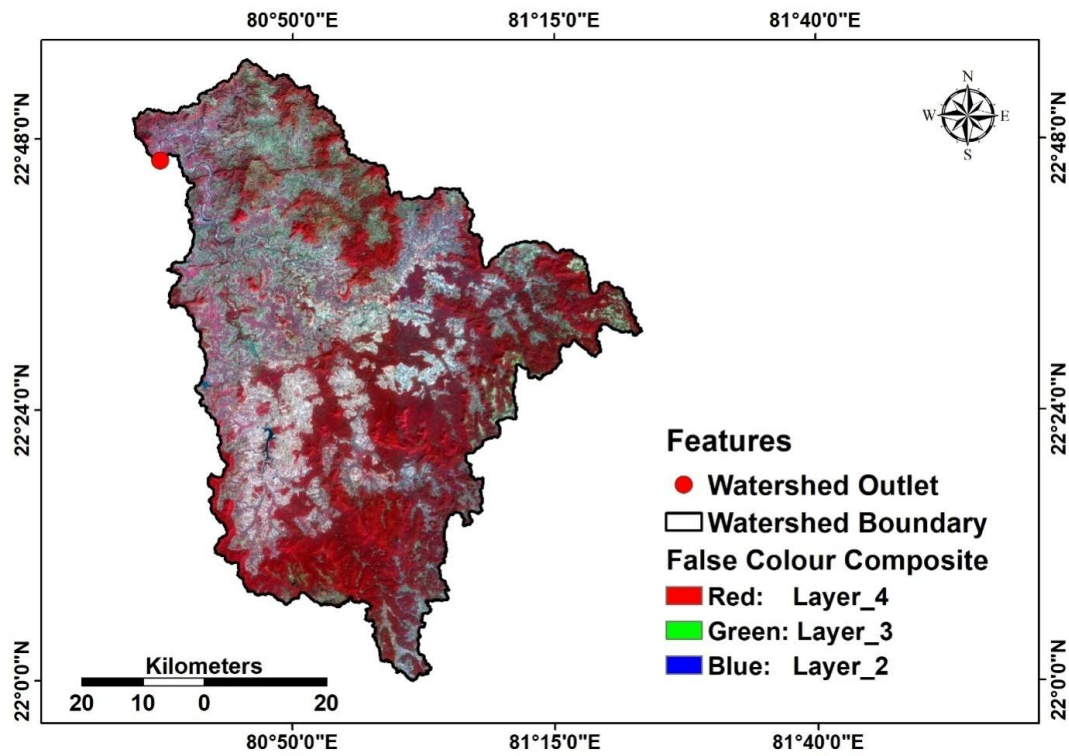


Fig. 2. False Colour Composite (FCC) image of the study area

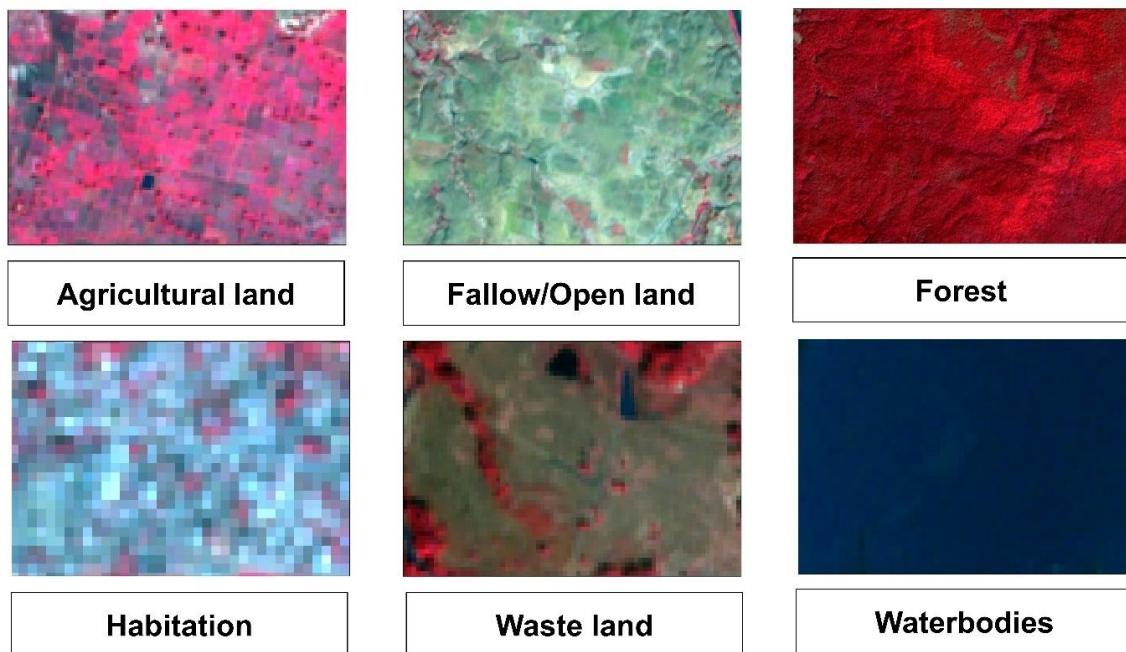


Fig. 3. Details of on-screen visual interpretation principles adopted for different LULC classes

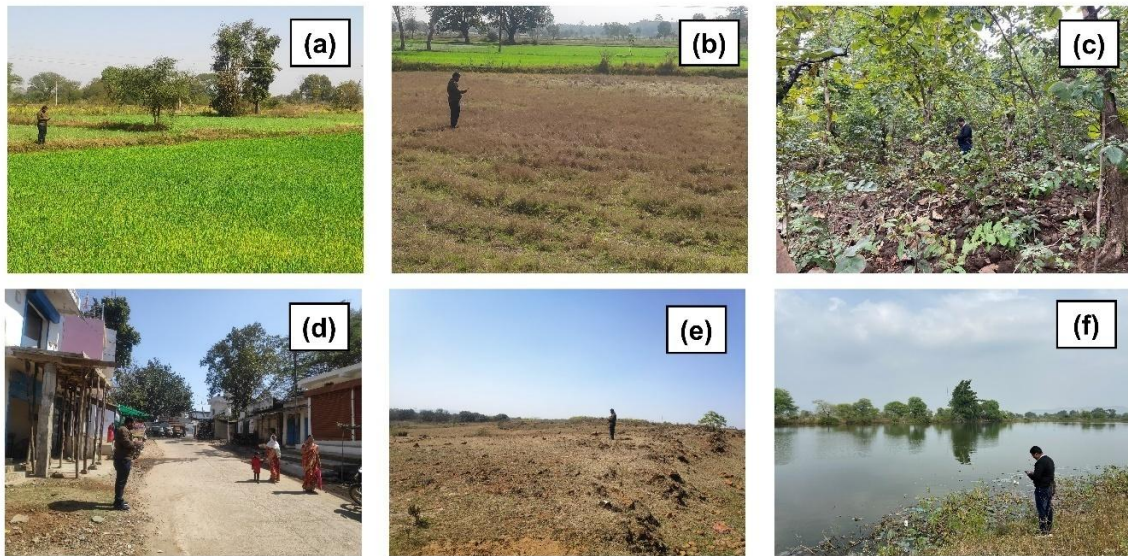


Fig. 4. Collection of reference (ground truth) data for different Land Use Land Cover (LULC) classes covered in Burhner River Watershed: (a) agricultural land, (b) fallow/open land, (c) forest, (d) habitation, (e) wasteland, (f) waterbodies

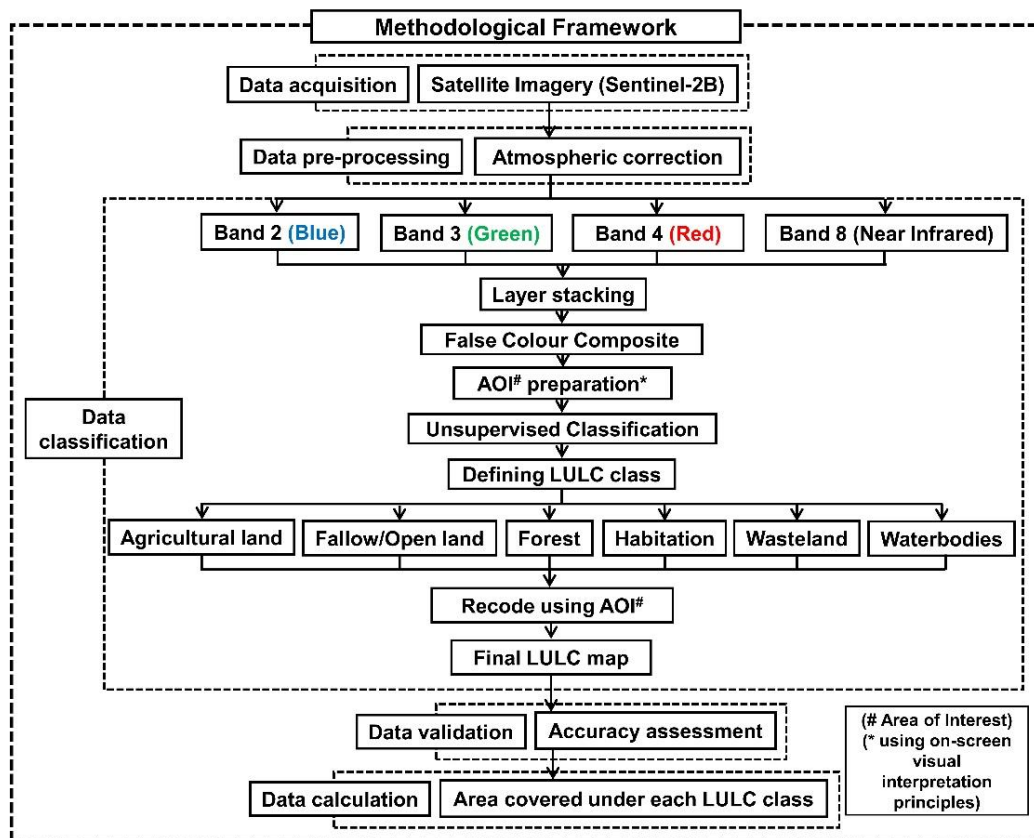


Fig. 5. Methodological framework used in LULC classification approach

An error matrix is a very effective way to represent the accuracy of produced thematic map, because it provides a clear way of deriving the individual accuracies of each class along with both the errors of inclusion (commission errors) and errors of exclusion (omission errors) present in the classification [45]. Commission error is simply defined as including an area into a class when it doesn't belong to that class whereas omission error occurs when an area is excluded from the class in which it truly does belong [44].

Apart from error of commission and error of omission, the error matrix is also used to compute other measures of accuracies such as overall accuracy, producer's accuracy and user's accuracy [43]. The overall accuracy for the image classification can be obtained by dividing the sum of the entries in the "from-to" agreement of the error matrix with the total number of the examined pixels (or sample units) in the classification [46]. Producer's and user's accuracies can be computed to determine the individual class accuracies in addition to computing the overall classification accuracy for the entire matrix. As the name suggests, the producer's accuracy signifies the interest of producer of classification that how well a certain area can be classified [47]. The user's accuracy is indicative of the probability that a pixel classified on the map/image actually represents that category on the ground [43]. The error matrix also aids in generating kappa coefficient values which can be used as another measure of agreement or accuracy [48]. The generation of kappa coefficient (\hat{k}) has become a standard component of almost every accuracy assessment [47, 49, 50] and is a prime tool of most image analysis software packages that include accuracy assessment procedures [44].

For assessing the accuracy of classified map, a total number of 538 randomly distributed points were generated over the entire classified map in ArcGIS® 9.3 environment. The classified data was further compared for agreement with ground truth or reference data obtained from Google Earth Pro satellite data and field visit data (Fig. 4). The ground truth data was obtained from field visits (Fig. 4) by a series of Ground Control Points (GCPs) collected for different LULC classes, using a portable handheld GPS receiver (*i.e.*, Garmin GPSmap76CSx) with positional accuracy of <10 m. For even assessment of accuracy, the GCPs collected were uniformly scattered throughout the classified image. An inventory of collected GCPs were prepared using

MS Excel and were further imported in ArcGIS® 9.3 environment so as to identify agreement between classified image and ground truth (reference) data.

3. RESULTS AND DISCUSSION

3.1 LULC Classification

The land use land cover classification at large watershed scales is a heavy computational task yet is critical to landowners, researchers, decision makers and watershed planners enabling them to make informal decisions for varying objectives [15]. A total of six major LULC classes such as agricultural land (*i.e.*, crop land, agricultural plantation), fallow/open land, forest (*i.e.*, dense/closed and open category of evergreen forest), habitation (*i.e.*, built-up, rural), wasteland (*i.e.*, barren rocky, scrub land) and waterbodies (*i.e.*, streams, ponds, and reservoirs) were identified in Burhner river watershed.

Fig. 6 shows the classified LULC map of the study area. The LULC statistic of Burhner river watershed is shown in Table 2. It indicates that major portion of watershed area is covered by forest (*i.e.*, 53.01%) followed by fallow/open land (*i.e.*, 24%) and agricultural land (*i.e.*, 19.44 %) whereas very small area is covered by waste land (*i.e.*, 1.98%) and waterbodies (*i.e.*, 1.38%) and least area is covered by habitation (*i.e.*, 0.19%).

The percent area covered by different Land Use Land Cover (LULC) classes is represented by a bar chart in Fig. 7. The chart clearly indicates that a large percent of watershed area (*i.e.*, 24% or 950.256 km²) falls under fallow/open land category showing underutilized potential of watershed land resources. Such available land resources can be further utilized for crop production, agricultural plantation, horticultural plantation and forest plantation purposes by watershed managers and local habitats of watershed. However, utilization of such land resources is subjected to a number of constraining factors such as soil depth, topography, accessibility to the area and availability of water and human resources. But by using a proper planned scientific approach use of such land resources can play a key role in uplifting the socio economic conditions of local landowners, small and marginal farmers and local habitats of the study area.

The task of performing LULC classification using a remotely sensed satellite image through unsupervised classification is a complex task. But it also supports in developing better decision making capabilities required in identifying different LULC features while performing classification. Apart from unsupervised classification, supervised classification is also a widely used image classification technique. The LULC classification using these techniques for large terrain is easy when compared with classification performed using exhaustive ground surveys. The choice of training sample data or reference pixels, skills and expertise of the analyst performing classification are the key dominating factors in supervised classification influencing its overall accuracy. Whereas in unsupervised classification, the scheme

automatically recognizes similarity between pixels based on their spectral values and prior expertise of analyst is not required for performing classification. As reference pixels are not chosen in unsupervised classification, thematic recoding of the LULC image further supports in getting more accurate results. It is because each and every terrain feature of the image under investigation is examined by the analyst for further corrections. Such corrections in the classified image are somehow complex and time consuming as LULC classes are rarely internally homogenous and mutually exclusive. But it mitigates the effect of arbitrary or mixed pixels denoting transition zones in geographic space when unsupervised classification is performed using a fine spatial resolution satellite image.

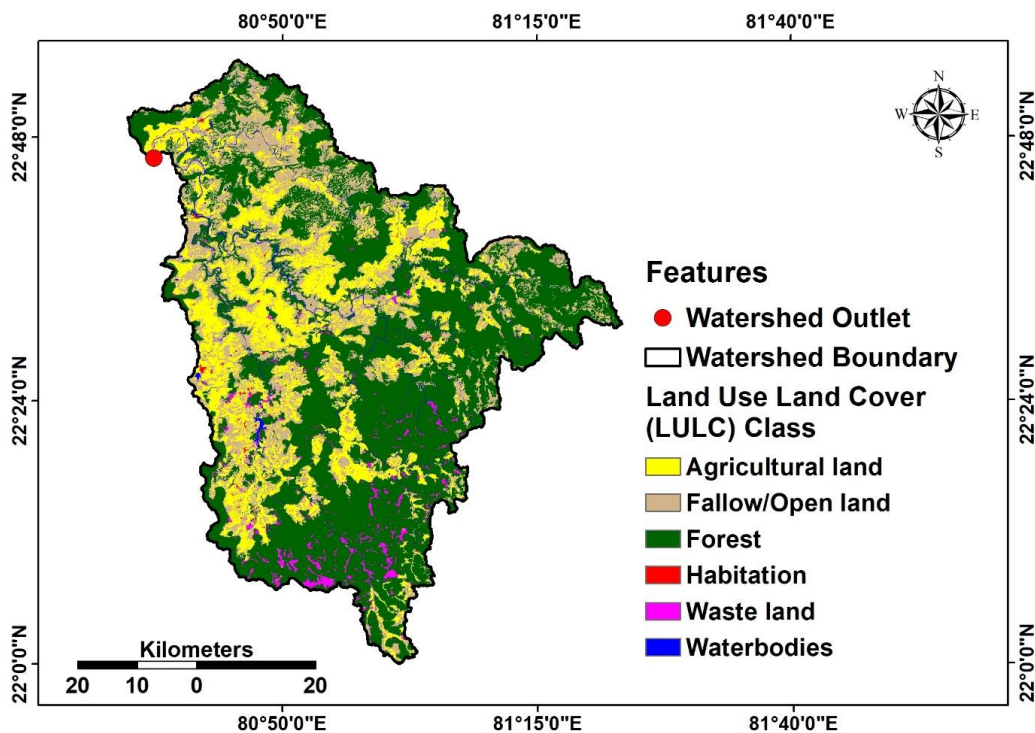


Fig. 6. LULC map of the study area

Table 2. Land Use Land Cover (LULC) statistic of Burhner river watershed

S.No.	Land Use Land Cover (LULC) Class	Area (km ²)	Percent of total watershed area (%)
1	Agricultural land	769.787	19.44
2	Fallow/Open land	950.256	24.00
3	Forest	2099.118	53.01
4	Habitation	7.720	0.19
5	Waste land	78.219	1.98
6	Water bodies	54.713	1.38

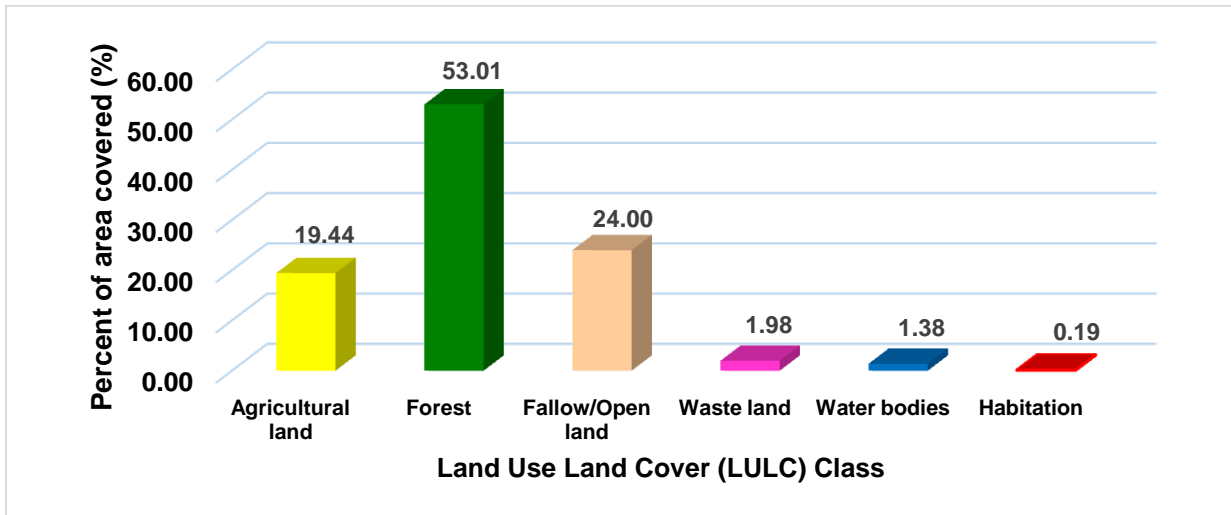


Fig. 7. Percent area covered by different Land Use Land Cover (LULC) classes

3.2 Accuracy Assessment

To obtain the reliability of classified image, error matrix was generated (Table 3). The column section of error matrix represents classified data whereas the row section represents ground truth or reference data as collected from field visits. Out of 538 randomly distributed sample points, 122 points were collected from field visits which assisted in comparing the obtained classified results with the existing land use land cover pattern in the study area. The error matrix aided in assessing the overall accuracy, producer's accuracy, user's accuracy and kappa coefficient of the classified map using reference or ground truth data. The overall accuracy of the classified image was found as 95.72%. The producer's accuracy was calculated by dividing the principal diagonal (the agreement) by total number of sample points in that map class as specified by sum of the reference (ground truth) data (or column total) for that class. Table 3 clearly illustrates the process adopted for calculation of producer's accuracy of each class. The computation of producer's accuracy for different classes of classified image showed that agricultural land producer's accuracy was highest among all the classified classes (*i.e.*, 98.18%). It was further followed by forest (97.82%), habitation (96.42%), waterbodies (95.45%) and wasteland (94.11%). The least value of producer's accuracy was obtained for fallow land (90.07%) indicating a shift in large number of reference data sample points into other classified classes (disagreement) leading to high error of omission. By observing the error of omission (EO) for all the classes, it was evident that EO

was highest for fallow/open land (9.93%), followed by wasteland (5.89%), waterbodies (4.55%), habitation (3.58%), forest (2.18%) and agricultural land (1.82%).

Apart from producer's accuracy, user's accuracy was also calculated for all the produced classes of the classified image (Table 3). The user's accuracy was highest for forest (98.25%), followed by fallow/open land (95.93%), agricultural land (94.73%), habitation (93.10%), waterbodies (87.5%) and wasteland (84.21%). The lower values of user's accuracy in case of waste land and waterbodies was due to the shift of sample points of classified data into other classes (disagreement) leading to high error of commission. A close observance of error of commission (EC) showed highest EC for waste land (15.79%), followed by water bodies (12.5%), habitation (6.90%), agricultural land (5.27%), fallow/open land (4.07%) and forest (1.75%).

The kappa coefficient (\hat{k}) of classified image was found as 0.94. A kappa coefficient value of $\hat{k} = 1$ indicates a perfect agreement between the categories while a value of $\hat{k} = 0$ indicates that the observed agreement equals the chance agreement [48]. A value greater than 0.75 indicates a very good to excellent agreement, while a value between 0.40 to 0.75 indicates a fair to good agreement [51]. A value of less than or equal to 0.4 indicates a poor agreement between the classification categories [52]. On the basis of such criteria, the value of $\hat{k} = 0.94$ in this case indicates good to excellent agreement.

Table 3. Error (Confusion) matrix

Confusion (Error) Matrix								
Reference (Ground Truth) Data								
Classified Data	LULC Class	AL	FO	FT	HT	WL	WB	Row Total
	AL	108	5	0	0	0	1	114
	FO	1	118	4	0	0	0	123
	FT	0	3	225	0	1	0	229
	HT	0	2	0	27	0	0	29
	WL	0	1	1	1	16	0	19
	WB	1	2	0	0	0	21	24
	Column Total	110	131	230	28	17	22	538

Land Use Land Cover (LULC) Class	
Agricultural land	= AL
Fallow/Open land	= FO
Forest	= FT
Habitation	= HT
Waste land	= WL
Water bodies	= WB

Overall Accuracy	
= $\frac{(108 + 118 + 225 + 27 + 16 + 21)}{538} \times 100$	
= $\frac{515}{538} \times 100$	
= 95.72%	

Kappa coefficient	
= $\frac{(538 \times 515) - \{(110 \times 114) + \dots + (22 \times 24)\}}{(538)^2 - \{(110 \times 114) + \dots + (22 \times 24)\}}$	
= 0.94	

Producer's Accuracy		User's Accuracy	
AL = $(108/110) \times 100 = 98.18\%$		AL = $(108/114) \times 100 = 94.73\%$	
FO = $(118/131) \times 100 = 90.07\%$		FO = $(118/123) \times 100 = 95.93\%$	
FT = $(225/230) \times 100 = 97.82\%$		FT = $(225/229) \times 100 = 98.25\%$	
HT = $(27/28) \times 100 = 96.42\%$		HT = $(27/29) \times 100 = 93.10\%$	
WL = $(16/17) \times 100 = 94.11\%$		WL = $(16/19) \times 100 = 84.21\%$	
WB = $(21/22) \times 100 = 95.45\%$		WB = $(21/24) \times 100 = 87.5\%$	

4. CONCLUSION

LULC information is increasingly in demand due to its ability to provide spatial distribution information at higher resolutions, which cannot be achieved by intensive ground surveys especially in regions where harsh topographic conditions pertain. The techniques of remote sensing and GIS thus find its applicability in continuous and precise monitoring of LULC patterns for different sorts of terrain units. The present study carried out in Burhner river watershed aims at performing the Land Use Land Cover (LULC) classification of a high spatial resolution satellite image using unsupervised classification along with its accuracy assessment. It also discusses the merits, demerits and key factors responsible for adopting unsupervised classification technique in the present case. A total number of six LULC classes were prepared during the classification process such as agricultural land, fallow/open land, forest, habitation, wasteland and water bodies. The highest percent of watershed area was covered by forest (i.e., 53.01%) and least area was covered by habitation (i.e., 0.19%). Accuracy assessment was executed by generating error matrix. The classified map yielded an overall accuracy of 95.72%, with kappa coefficient $\hat{k} = 0.94$ denoting good to excellent agreement. The producer's accuracy and user's accuracy also gave acceptable results. The LULC statistic revealed that a

considerable portion of study watershed is covered under fallow/open land category indicating underutilized land resource potential of the watershed. Such land can be used for crop production and plantation purposes which can aid in uplifting the socioeconomic conditions of local habitats. The obtained LULC information can further support in performing spatially distributed soil erosion and hydrological modelling. The results obtained from the study can be used for performing a comparative study between different algorithms of classification techniques such as support vector machine (SVM), random forest (RF), spectral angle mapper (SAM) under supervised classification as well as ISODATA (iterative self-organizing data) under unsupervised classification.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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Peer-review history:
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