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Evaluation of Multi-Sensor Satellite Data Accuracy for LU/LC Classification: Insights from Cartosat-1 and Liss-Iv Imagery In 2021

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ABSTRACT

Aims: Due to increasing flaws in digital satellite images, land-use and land-cover (LU/LC) must be classified accurately. It is essential to assess the accuracy of Cartosat-1 and LISS-IV data, concentrating on how well-suited these data sets were for mapping and tracking land-use and cover. The study aimed to evaluate how well these datasets distinguished between various land-cover categories.

Material & Methods: A supervised classification method was followed to classify the study area into ten LU/LC classes: agriculture, built-up, canal, degraded forest, dense forest, drainage, moderately dense forest, transport, wasteland, and waterbody in ArcGIS. Supervised classification uses known samples to train classification algorithms, enabling detailed analysis, decision-making, and distinguishing subtle spectral variations. A total of 200 points were randomly selected in the study area using stratified random selection methodology for accuracy assessment, which was verified using Google Earth.

Findings: The results of the study show that the overall accuracy for LU/LC classification of Cartosat-1 and LISS-IV for the year 2021 was obtained as 92% and 88.50%, respectively, with corresponding kappa coefficient values of 0.90 and 0.86, which proves that data from Cartosat-1 is more accurate as compared to LISS-IV for LU/LC classification. It was also found that LU/LC classes belonging to both classified data of Cartosat-1 and LISS-IV data showed variability in their areas. Due to the high spatial resolution of Cartosat-1 data, LULC classes edge-to-edge classification results have been obtained. Different features have been purely identified and classified. Resolutions of both the satellite data might have played crucial roles in image interpretation and in conducting an accurate assessment of the classification of both the satellite imageries.

Conclusion: Cartosat-1 gives the best classification accuracy and kappa value. Due to its high spatial resolution, the Cartosat-1 dataset is better than the LISS-IV dataset for detailed LU/LC classification.

Keywords: Accuracy Assessment; Cartosat-1; LISS-IV; LU/LC; Supervised Classification.

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Introduction

Land-use and land-cover (LU/LC) data is crucial for several applications, including modeling atmospheric and hydrological processes, making decisions, and choosing, organizing, and implementing various plans for managing and protecting natural resources. Engidahttps://orcid.org/0000-0001-7867-6201 et al., 2021 found that the seasonal variability of stream flow caused by the LU/LC was evaluated, and comparisons were made regarding the contributions of groundwater flow, lateral flow, and surface runoff to stream flow. Since high-resolution data is not publicly available, obtaining it is cost-effective. Additionally, researchers can use multi-temporal data from remote sensing satellites to develop information about LU/LC for various years based on their study interests and goals [1, 2]. Although they have different meanings, land-cover and land-use are related. Land-cover, for example, describes the physical state of features found on the earth's surface, such as wetlands, grasslands, and forests [3]. In contrast, land-use refers to how humans use land to suit their needs, such as through residential, commercial, industrial, or agricultural zones [4, 5].

LU/LC is directly proportional to each other as land-cover includes land-use features and can be represented on different scales. Although "land-use" and "land-cover" are sometimes used synonymously, they have slightly distinct connotations in reality. The term "land-cover" often refers to characteristics visible from a distance using remote sensors and found on the earth's surface, such as forests, grasslands, and bodies of water. These features can be man-made, natural, or semi-natural. Conversely, land-use describes a variety of human endeavors involving a particular plot of land, such as commercial, industrial, residential, agricultural, and recreational operations. The data related to the LU/LC of an area can be used as input by watershed management planners. By examining these data sets, planners can identify patterns of human activity within the watershed, from forestry and conservation initiatives to urbanization and agricultural activities. With this knowledge, they can evaluate how different land-uses affect ecosystems' quantity, quality, and general health. Additionally, planners may model and anticipate future land-use changes using geographic information system (GIS) techniques. This allows for proactive planning for conservation and infrastructure development projects. [6, 7]. A watershed is a geographical area from where the entire rainwater running off the land gets drained to a single outlet, and the outlet may be a stream, river, wetland, or lake. [8, 9]. Geographic Information Systems (GIS) and remote sensing are time-saving methods, and satellite data, with its wide field of view, real-time information, and frequent coverage, has shown to be highly beneficial in generating LU/LC information at certain times. When combined with geographic information systems, satellite remote sensing can allow researchers to examine changes in land-use and cover more ground quickly and more accurately. One of satellite imagery's main benefits is its capacity to record data on a temporal scale, making it possible to identify changes in land-use and cover patterns over time [10, 11]. The ongoing use of remote sensing data has made image analysis rapid, simple, and effective; nevertheless, this increased use has also led to complexity, which increases the possibility of analysis error [12, 13].

Remote sensing and GIS analysis depend on accurately classifying land-use and land-cover (LU/LC). However, many obstacles must be overcome for the classification process to be successful. Mixed pixels are a common problem where accurate classification is complicated by multiple land-

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cover types within a single pixel. Spectral confusion occurs when different land-cover types have similar spectral signatures, and it is hard for algorithms to distinguish between them. Furthermore, temporal variability is problematic because it can result in out-of-date classification results. After all, land-cover varies over time due to human activity or natural processes. Scale dependency is an additional issue where the accuracy of classification is impacted by the spatial resolution of the imagery, with features becoming less discernible at finer resolutions. Spectrum misinterpretation or confusion between related classes can lead to misclassification errors. In order to address these issues and assess the quality of LU/LC classification results, trustworthy accuracy assessment techniques are necessary. Validating classification results with ground truth data obtained from field surveys or high-resolution aerial imagery is crucial [16, 17, 18].

Conventionally, the accuracy assessment of image classification has yet to be followed because it was believed that the image interpretation is 100% correct. So, these assumptions need to be more frequently valid, leading to poor LU/LC classification assessment and less accurate information [14]. Accuracy assessment is the evaluation of classification with ground truth data to elevate how well the classification represents the real world, and an error matrix is the most common form of expressing the accuracy of classification [1, 15, 22]. Assessing accuracy involves evaluating three key factors: producer, user, and overall accuracy. Producer accuracy typically refers

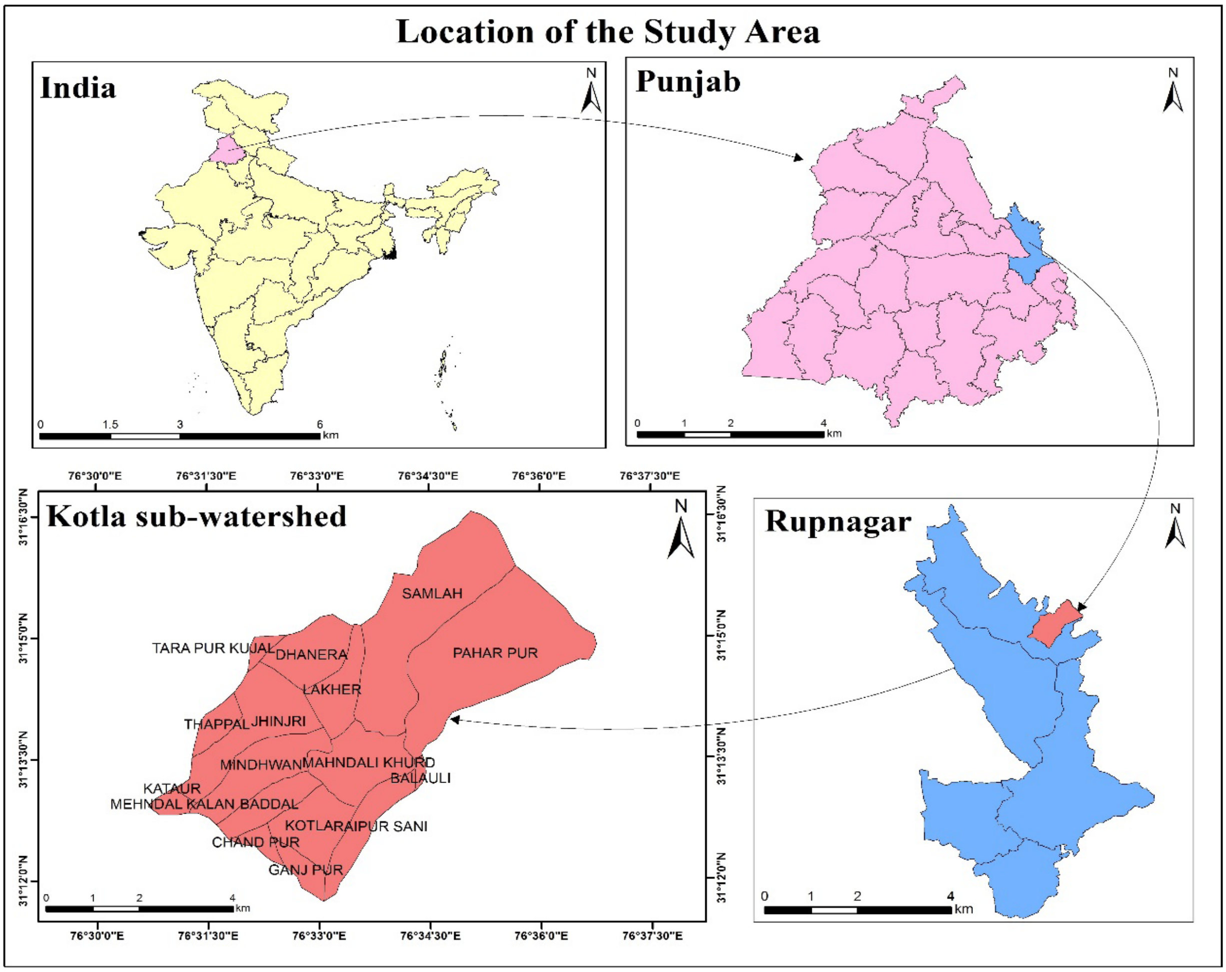

Figure 1) Geographical location of the Kotla sub-watershed.

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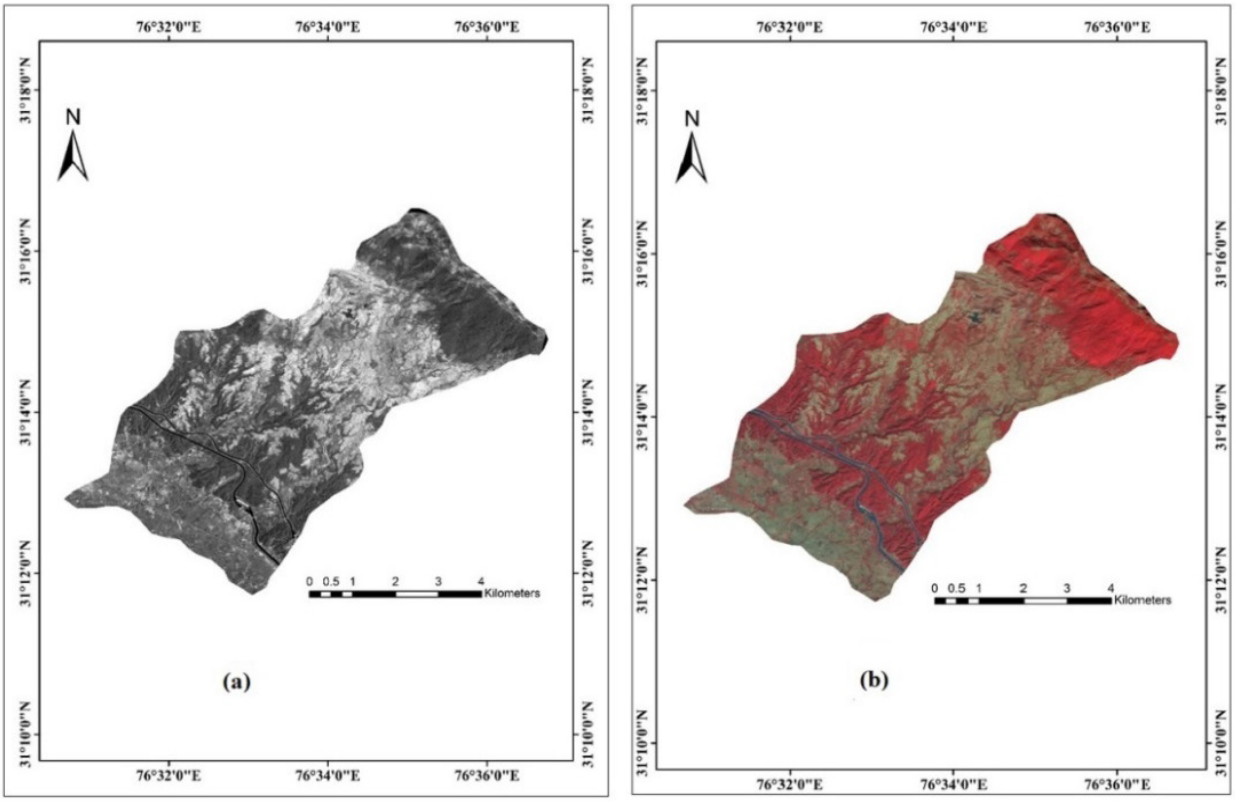

Figure 2) Satellite images from (a) IRS-P5 Cartosat-1 and (b) IRS-P6 LISS-IV for the year 2021.

Table 1) Specification of satellite data.

Satellite	Sensor	Bands	Band Wavelength (µm)	Resolution (m)	Path/Row
IRS-P5	Cartosat-1	PAN (Panchromatic)	0.5-0.85	2.5	517/254
IRS-P6	LISS-IV	Green (B2)	0.52-0.59	5.8	94/49
		Red (B3)	0.62-0.68		
		NIR (B4)	0.77-0.86		

to how well-referenced points of a particular ground cover type are classified. In contrast, user accuracy measures the likelihood that a point classified into a given class belongs to that class on the ground. The most common and straightforward way to measure accuracy is overall accuracy; however, the kappa coefficient, whose value ranges from 0 to 1, is a significant technique used to assess the statistical accuracy of error matrices. The higher the kappa value, the more accurate the classification [16, 17, 18].

LISS-IV gives multispectral imaging at a medium spatial resolution (5.8 meters), while Cartosat-1 offers more excellent spatial resolution (2.5 meters). Depending on the application's particular needs, one may choose between these datasets; Cartosat-1 is better suited for applications needing extreme detail, while LISS-IV is better suited for larger-scale analysis where less resolution is acceptable but multispectral capabilities are required. Understanding the relative advantages and disadvantages

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of LISS-IV and Cartosat-1 sensors for use in remote sensing applications requires comparing their accuracies. LISS-IV's multispectral capabilities provide insightful information on vegetation health and land-cover classification, while Cartosat-1's high-resolution panchromatic imagery is ideal for tasks involving detailed mapping and urban planning. By evaluating their accuracy, stakeholders can make well-informed decisions about data quality assurance, resource allocation, and sensor selection. Furthermore, by making this comparison, researchers can improve methodology and the dependability of analyses in areas like environmental monitoring, disaster management, and agriculture. It also helps to validate remote sensing data scientifically. The primary purpose of this study is to evaluate and compare the classification accuracies of two different satellite sensor data, i.e., Cartosat-1 and LISS-IV, for the year 2021. Maximum likelihood was applied to multi-sensor data to classify ten LU/LC classes. In the recent literature, no such comparison has been experimented with, especially between Cartosat-1 and LISS-IV data, to check the accuracy. The current study was conducted on the accuracy assessment of the LU/LC classification of the Kotla sub-watershed, keeping all the factors mentioned above in mind.

Materials & Methods

Study Area

Kotla is the study area located in Indian Punjab. It lies between latitudes 31°11'36" N - 31°16'40" N and longitudes 76°30'51" E - 76°36'57" E, as shown in Figure 1. The study area has a total of 17 villages, covering 3522.55 hectares. The Kotla sub-watershed is almost entirely covered in forests. The northeastern border of the study area is shared with Himachal Pradesh. The temperature of the study area varies from 4°C to 45°C with 700-800 mm average rainfall. Soil texture varies from loam to silt clay loam. The study area has different landscape characteristics and diverse land-use, and it covers categories such as forest, agricultural areas, plantation, built-up, waterbodies, and drainage. The study area consists of several types of land-cover and land-uses, some of which are mentioned above. This study identifies the most important LULC classes, which can give a more accurate comparison between two different satellite sensors.

Acquisition of Satellite Data

This study completed the objectives using IRS-P5 Cartosat-1 and IRS-P6 LISS-IV satellite data for 2021 (Figure 2). The Punjab Remote Sensing Centre (PRSC) provided the satellite data in Ludhiana, Punjab, India. Table 1 gives detailed information on satellite images.

Satellite Data Pre-Processing

Pre-processing images is one of the essential procedures that need to be done. Developing a closer connection between collected data and the biophysical phenomena is vital. Using ArcGIS and ERDAS Imagine, images were pre-processed for mosaicking, georeferencing, and sub-setting according to the study region. After the pre-processing, pre-processed image pixels were assigned to classify LU/LC classes through the image classification process. The flow chart of the methodology used in this study is shown in Figure 3.

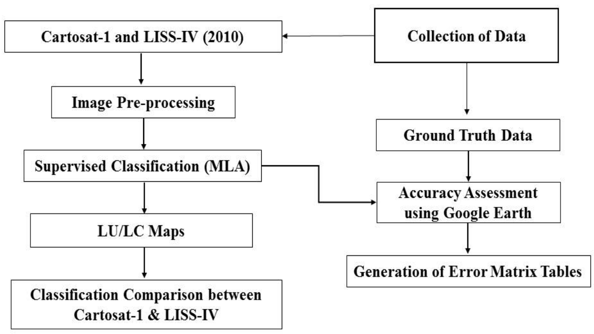

Figure 3) Overall flow chart of methodology.

LU/LC Classification

The maximum likelihood algorithm used for supervised classification in the present study is to prepare LU/LC classification maps for

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Table 2) Statistical analysis of the area under LU/LC of Cartosat-1 and LISS-IV for the year 2021.

LU/LC Classes	Cartosat-1, Area (ha)	LISS-IV, Area (ha)	Area (ha) Dissimilarities (Mode Value)
Agriculture	1409.28	1398.38	10.9
Built-up	108.26	106.08	2.18
Canal	37.33	36.42	0.91
Degraded Forest	312.24	301.12	11.12
Dense Forest	1365.09	1351.11	13.98
Drainage	41.23	94.79	-53.56
Moderate Dense Forest	189.18	177.11	12.07
Transport	35.31	35.55	-0.24
Wasteland	16.12	14.77	1.35
Waterbody	8.26	6.97	1.29

Table 3) Error Matrix table of LU/LC classification of Cartosat-1 (2021)

Reference	Agriculture	Built-up	Canal	Degraded Forest	Dense Forest	Drainage	Moderate Dense Forest	Transport	Wasteland	Waterbody	Grand Total	Producer's Accuracy (%)	User's Accuracy (%)
Agriculture	33	1									34	89.19	97.06
Built-up		29									29	93.55	100.00
Canal			17								17	100.00	100.00
Degraded Forest				24	1					1	26	96.00	92.31
Dense Forest	4	1		1	20	1	1		1	3	32	95.24	62.50
Drainage						19					19	95.00	100.00
Moderate Dense Forest							10			1	11	90.91	90.91
Transport								15			15	100.00	100.00
Wasteland									6		6	85.71	100.00
Waterbody										11	11	68.75	100.00
Grand Total	37	31	17	25	21	20	11	15	7	16	200		
Overall Accuracy = 92%													
Kappa Coefficient = 0.90													

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Cartosat-1 and LISS-IV for 2021 [20]. Because of their high accuracy, controllability over the classification process, interpretability, and capacity to accommodate spectral variance, supervised classification methods are essential for Land-Use/Land-Cover (LU/LC) classification. It uses labeled training data to train algorithms to identify patterns, which leads to accurate segment or pixel categorization. The main LU/LC types identified in the study region include agriculture, built-up areas, canals, degraded forests, dense forests, drainage, moderate thick forests, transportation, wasteland, and waterbodies. The following steps have been followed to classify the LU/LC categories:

Step-1: Identified sample areas representing different land-cover types. Created polygons or ROIs for each land-cover class. Assign each ROI to a specific land-cover class.

Step 2: Load the pre-processed imagery into ArcGIS and access classification tools from the Classification toolbar. The Maximum Likelihood technique has been chosen. Train the model using the ROIs to classify the image into predefined land-cover classes.

Step 3: Validate the classified map with reference data and calculate statistical measures like overall accuracy, producer's/user's accuracy, and kappa coefficient to know the classification accuracy.

Accuracy Assessment

After the LU/LC maps were prepared, the accuracy assessment of both classified imageries was assessed based on the error matrix table. LU/LC categories based on 200 points were selected using a random sampling method in ArcGIS, which is spatially distributed to assess accuracy. We converted that point shape file into KML format to overlay it on Google Earth. Historical Google Earth images of 2021 have been used as reference data to validate our LU/LC classifications. Out of those 200 points, the ground truth data was also collected for some of the accessible locations by visiting the study area, as shown in Figure 4. The confusion matrix calculates the overall accuracy of the categorized image. Four statistical measures were used to evaluate the accuracy, following Eq. 1, 2, 3, and 4, as given below: overall accuracy, user accuracy, producer accuracy, and Kappa coefficient. The Overall Accuracy measure describes how well the classifier performed for each class in the categorized image. Kappa statistics takes into account adjusting for accuracy depending on chance. All the randomly selected points were verified using historical data on Google Earth (Reference data), as shown in Figure 5, by viewing a satellite image for 2021. Ground verification by visiting the field was also performed on some of the selected features (Figure 4). This assessment was carried out using an error matrix.

where, x_{i+} and x_{+i} are the marginal totals for row i and column I, x_{ii+} number of

$$\text{Producer's Accuracy} = \frac{\text{Total no. of correct points in each class}}{\text{total no. of points used for that class (Classified Total)}} \quad \text{Eq. (1)}$$

$$\text{User's Accuracy} = \frac{\text{Total no. of correct points in each class}}{\text{total no. of points used for that class (Reference Total)}} \quad \text{Eq. (2)}$$

$$\text{Overall Accuracy} = \frac{\text{Total no. of correct points}}{\text{total no. of selected points}} \quad \text{Eq.(3)}$$

$$\text{Kappa (K) coefficient} \quad \hat{K} = \frac{N\sum_{i=1}^{k} x_{ii+} - \sum_{i=1}^{k}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{k}(x_{i+} * x_{+i})} \quad \text{Eq. (4)}$$

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Figure 4) Pictures collected during the field visit.

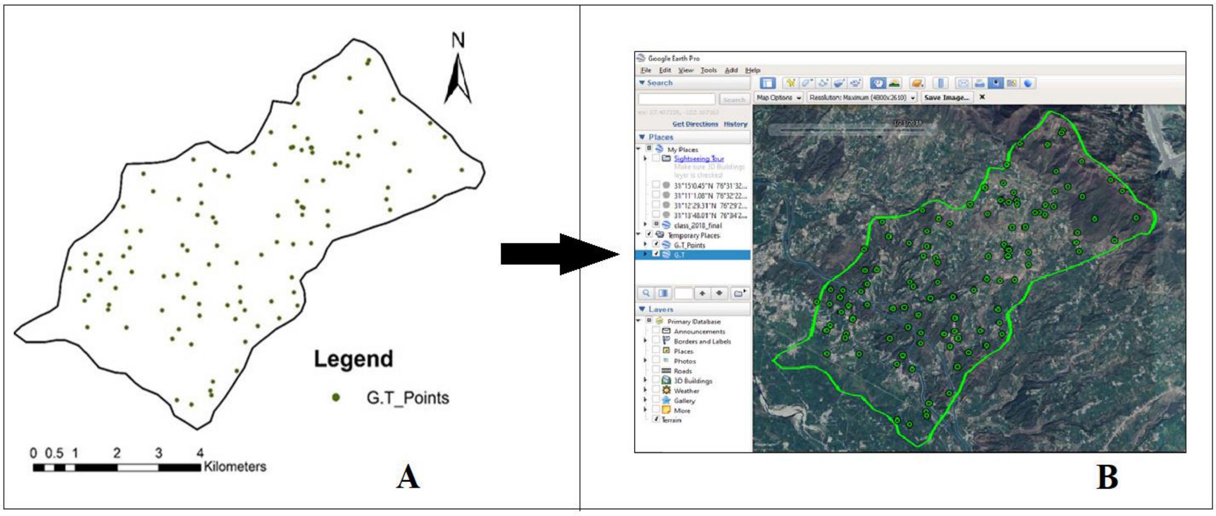

Figure 5) Verification of selected points using Google Earth.

observations in row i and column I, and N is the total number of observations.

Findings

LU/LC of Cartosat-1 for the Year 2021

All the identified and mapped LU/LC classes and percentage areas of Cartosat-1 for the year 2021 are shown in Figure 6. Table 2 shows that the significant area in the sub-watershed was covered by agricultural land by 1409.28 ha, which accounts for 40.01% of the total area, followed by dense forest, which attained second position in area coverage after agriculture. The area covered by dense forest was 1365.09 ha, which accounts for 38.76% of the total area of the sub-watershed.

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The other LU/LC classes, i.e., built-up, canal, degraded forest, drainage, moderately dense forest, transport, wasteland and waterbody, covers an area of 108.26 ha, 37,33 ha, 312.24 ha, 41.23 ha, 189.18 ha, 35.31 ha, 16.12 ha and 8.26 ha respectively which accounts 3.07%, 1.06%, 8.86%, 1.17%, 5.37%, 1%, 0.46% and 0.23% of total area respectively (Figure 12).

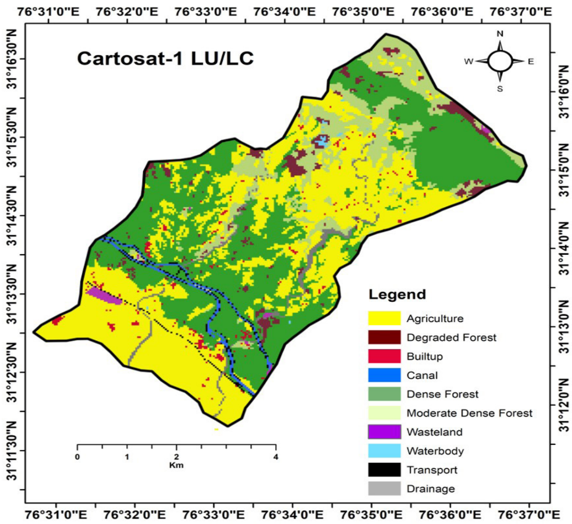

Figure 6) LU/LC classification using Cartosat-1 for the year 2021.

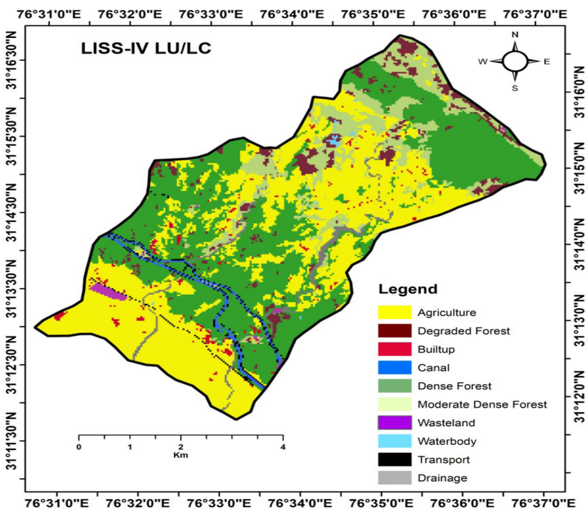

Figure 7) LU/LC classification using LISS-IV for the year 2021.

LU/LC of LISS-IV for the Year 2021

The LU/LC map of LISS-IV for the year 2021 is shown in Figure 7, and the percentage area under all ten classes can be seen in Figure 8. According to the data in Table 2, dense woodland covered an area of 1351.11 ha, or 38.36% of the whole sub-watershed area, whereas agricultural covered the majority of the Kotla sub-watershed, with 1398.38 ha, or 39.70% of the total area. A total of 106.08 ha, 36.42 ha, 301.12 ha, 94.79 ha, 177.11 ha, 35.55 ha, 14.77 ha, and 6.97 ha are covered by the other classes, which include built-up, canal, degraded forest, drainage, moderately dense forest, transport, wasteland, and waterbody. These areas account for 3.01%, 1.03%, 8.55%, 2.69%, 5.03%, 1.01%, 0.42%, and 0.20% of the total sub-watershed area, respectively (Figure 8).

To assess classification accuracy, the analysis of Cartosat-1 was compared with the results obtained from LISS-IV satellite data. This particular objective was to determine the quality of information derived from the LU/LC classification of satellite imageries. The area under LU/LC classes showed variability when comparing both classified data of Cartosat-1 with LISS-IV for the year 2021, as shown in Table 2. In such a case, it becomes crucial to compare the two datasets to understand the accuracy better. In the case of agriculture, built-up, canal, degraded forest, dense forest, drainage, moderately dense forest, transport, wasteland, and waterbody about 10.9 ha, 2.18 ha, 0.91 ha, 11.12 ha, 13.98 ha, 53.56 ha, 12.07 ha, 0.24 ha, 1.35 ha, and 1.29 ha area difference were identified and spatial resolution of both the datasets have plaid crucial role in this. In the case of drainage, a considerable difference in the area has been observed, which may be due to the spatial resolution of the sensors and the better identification of its boundaries. In the case of dense forests, a 13.98 ha area difference has been observed, which may be due to the spectral and spatial resolution of both sensors.

Classification Accuracy Assessment

An accurate assessment of the resulting

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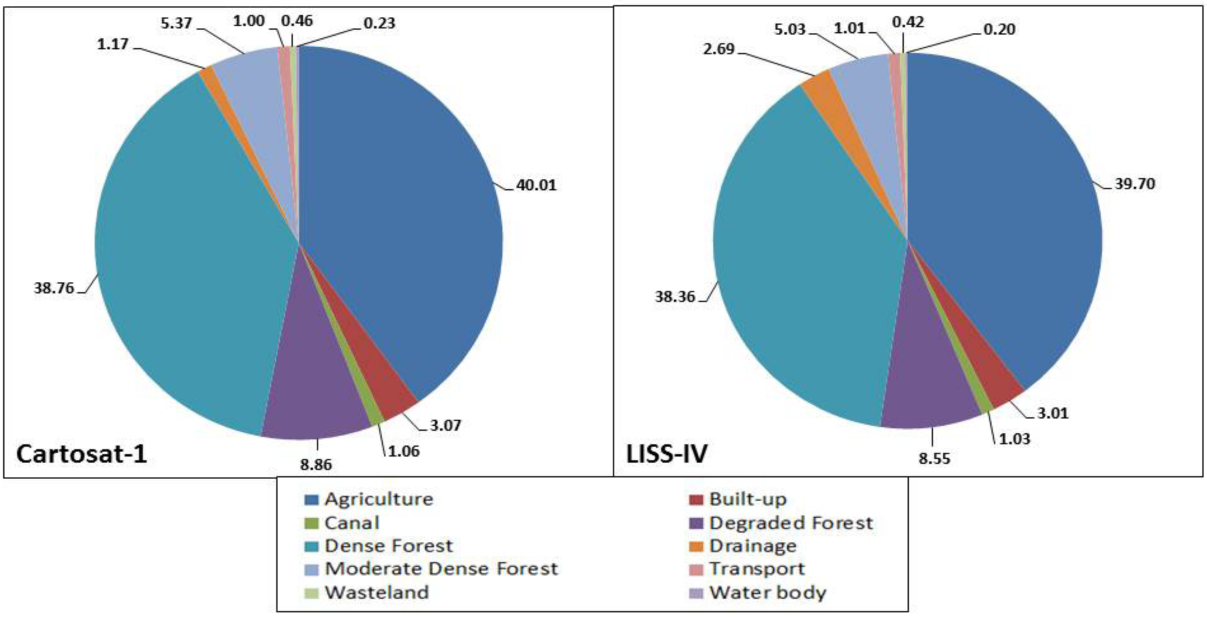

Figure 8) LU/LC classes area distribution (%) from Cartosat-1 and LISS-IV.

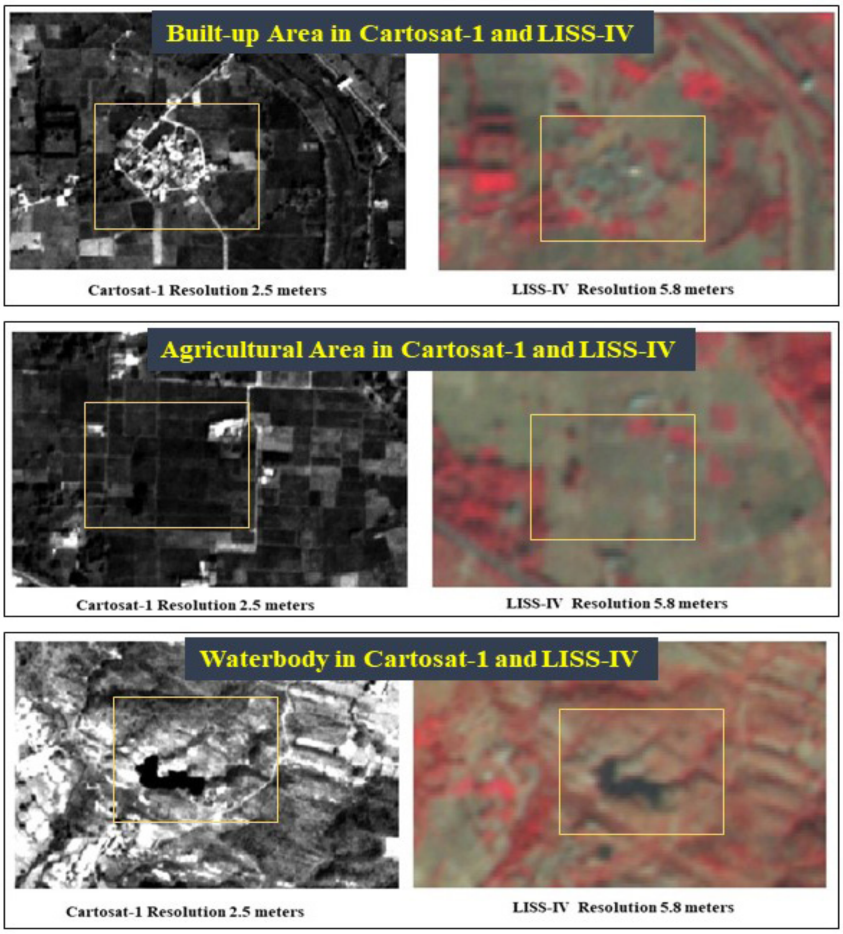

Figure 9) Visual comparison of built-up, agriculture, and waterbody using Cartosat-1 and LISS-IV satellite data.

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Table 4) Error Matrix table of LU/LC classification of LISS-IV (2021).

Reference	Agriculture	Built-up	Canal	Degraded Forest	Dense Forest	Drainage	Moderate Dense Forest	Transport	Wasteland	Waterbody	Grand Total	Producer's Accuracy (%)	User's Accuracy (%)
Agriculture	30	1		1			1				33	83.33	90.91
Built-up	6	26			2		1				35	96.30	74.29
Canal			17								17	100.00	100.00
Degraded Forest				23	1					3	27	88.46	85.19
Dense Forest				1	20		1		1	1	24	83.33	83.33
Drainage					1	19					20	100.00	95.00
Moderate Dense Forest							10			1	11	76.92	90.91
Transport								15			15	100.00	100.00
Wasteland									8		8	88.89	100.00
Waterbody				1						9	10	64.29	90.00
Grand Total	36	27	17	26	24	19	13	15	9	14	200		
Overall Accuracy = 88.50%													
Kappa Coefficient = 0.86													

classified satellite imageries, namely Cartosat-1 and LISS-IV for 2021, was estimated to ascertain the quality of information obtained from the satellite data. The investigation produced data demonstrating that, for 2021, the total LU/LC classification accuracy for Cartosat-1 and LISS-IV was 90% and 88.50%, respectively, with corresponding kappa coefficient values of 0.90 and 0.86. The error matrix, producer, user, overall accuracy, and kappa coefficient data for Cartosat-1 and LISS-IV for the year 2021 are displayed in Tables 3 and 4. The accuracy of both classifications was based on the spatial resolutions of both sensors. As we all know, Cartosat-1 has a better resolution than LISS-IV, so the feature identification was better and very close to their actual feature boundaries.

Discussion

The multi-sensors data, i.e., Cartosat-1 and LISS-IV for the same year (2021), has been used to map different LU/LC classes, but in the result, it was found that LU/LC classes show variability in their areas as shown in Table 2. Drainage showed a significant difference in the area, which is 53.56 ha. In contrast, other LU/LC classes such as agriculture, built-up, canal, degraded forest, dense forest, moderate dense forest, transport, wasteland and waterbody showed 10.9 ha, 2.18 ha, 0.91 ha, 11.12 ha, 13.98 ha, 12.07 ha, 0.24 ha, 1.35 ha and 1.29 ha classification differences respectively when compared LU/LC classification of Cartosat-1 with LISS-IV (Table 2). In the case of drainage, a considerable difference in the area has been observed, which may be due to the spatial resolution of the sensors and the better identification of its boundaries. In the case of dense forests, a 13.98 ha area difference has been observed, which may be

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due to the spectral and spatial resolution of both sensors. Resolutions of both satellite data might have played crucial roles in image interpretation and accurately assessing both satellite imageries' classification [21]. Cartosat-1 has a high spectral resolution of 2.5 m compared to LISS-IV spectral resolution, which is 5.8 m, due to which LU/LC features in Cartosat-1 data were more transparent and more accessible to interpret than LISS-IV data. Built-up area (situated at Latitude 31°13'0.04" and Longitude 76°31'56"), agricultural area (situated at Latitude 31°13'27" and Longitude 76°31'49"), and waterbody (situated at Latitude 31°15'28" and Longitude 76°34'18") are shown in Figure 9 which shows the clear view of features in Cartosat-1 satellite image as compared to LISS-IV.It was found that the Cartosat-1 satellite data is more accurate, as it showed an overall accuracy of 92%, compared to the LISS-IV satellite data, which showed an overall accuracy of 88.50%, with kappa coefficient values of 0.90 and 0.86, respectively (Tables 3 and 4). Topaloglu et al. (2016) also reported differences in the results of the LU/LC from two satellite sensor data in the same year.

Conclusions

The remote sensing technique is crucial in LU/LC mapping, and GIS software is a well-developed tool for satellite image classification. In the present study, an accuracy assessment was performed using Google Earth imagery and two sensors. Google Earth data has a high resolution (approximately 0.5 meters) and is a good source of detailed information to verify image classification with low-resolution data. Kotla, situated in the Rupnagar district of Punjab, India, was used for this study. Two satellite sensors, i.e., Cartosat-1 and LISS-IV, for the year 2021, have been used for LULC classification by applying the Supervised classification technique. It has been observed that Cartosat-1image produced 92% of classification accuracy compared with LISS-IV data, which has 88.50% overall accuracy. The area under LU/LC classes showed variability when comparing both classified data of Cartosat-1 with LISS-IV for the year 2021 with each other. Cartosat-1 gives the best classification accuracy and kappa value. So, the Cartosat-1 dataset is better than the LISS-IV dataset for detailed LU/LC classification due to its high spatial resolution. Although LISS-IV is also very useful for interpretation, if Cartosat-1 data is available for the same period, it can be preferred over LISS-IV data.

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