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EVALUATION OF SENTINEL-2 MSI AND LANDSAT OLI DATA FOR LAND USE AND LAND COVER CLASSIFICATION ACROSS DIVERSE GEOSPATIAL REGIONS USING SUPERVISED MACHINE LEARNING CLASSIFIERS

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Abstract. Employing advanced remote sensing techniques, this paper undertakes a rigorous technical investigation into the comparative performance of Sentinel-2 and Landsat 9 datasets. Leveraging the analytical power of four sophisticated machine learning algorithms – CART, Random Forest, Gradient Tree Boosting, and Support Vector Machine. The study scrutinizes land cover classification across diverse study areas in Lucknow and Dehradun. Evaluating Sentinel-2's multispectral sensor capabilities, particularly in the red-edge and near-infrared bands, the research dissects its prowess in vegetation-rich environments, exploiting the "red-edge effect" for precise vegetation assessment. Conversely, Landsat data, including Landsat 8 and Landsat 9, is assessed for its adaptability in areas characterized by diverse land cover types, including urban landscapes. Delving into algorithmic performance metrics, Random Forest and sentinel-2 emerge as the preferred choice for most vegetated area like Dehradun about 90% accuracy across varied scenarios, Gradient Tree Boosting and Landsat data emerges as the preferred choice for most urbanized (populated) areas like Lucknow about 92% accuracy across varied scenarios. This paper contributes novel insights into the comparative utility of Sentinel-2 and Landsat 9 datasets, bolstered by advanced machine learning methodologies, for refined land cover mapping and monitoring applications.

Keywords: Random Forest, land cover classification, Sentinel, Landsat, accuracy.

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1. Introduction

The utilization of remote sensing data coupled with advanced machine learning techniques has revolutionized land cover classification and monitoring, providing invaluable insights into the Earth's surface dynamics. Among the myriad of satellite platforms, Sentinel-2 and Landsat 9 have emerged as prominent sources of multispectral imagery, offering rich datasets for comprehensive land cover analysis. Sentinel-2, distinguished by its multispectral sensor, holds significant promise for vegetation monitoring and land cover classification. Its ability to capture imagery across multiple spectral bands, including the red-edge and near-infrared, facilitates detailed analysis of vegetation characteristics. Vegetation exhibits a unique spectral signature, commonly referred to as the "red-edge effect," wherein it reflects near-infrared light strongly while absorbing red light. This spectral behavior offers valuable insights into vegetation health, type, and density, rendering Sentinel-2 particularly suitable for regions characterized by abundant vegetation cover such as forests, agricultural lands, and natural landscapes (Brovelli et al., 2020).

In contrast, Landsat data, encompassing Landsat 8 and the newly launched Landsat 9, offers moderate spatial resolution imagery well-suited for studying land cover dynamics across diverse landscapes. Landsat datasets have been extensively utilized in land cover classification studies owing to their extensive historical archive and comprehensive spectral coverage. Landsat imagery is particularly adept at capturing land cover patterns in areas with mixed land cover types, including urban areas, where the moderate spatial resolution facilitates detailed analysis of land cover changes over time (Degbelo & Kuhn, 2018; P. S. Roy et al., 2015; Srivastava et al., 2022)

Machine learning algorithms, including CART, Random Forest, Gradient Tree Boosting, and SVM, have been instrumental in leveraging remote sensing data for land cover classification tasks. These algorithms offer robust methodologies for extracting meaningful patterns from multispectral imagery, facilitating accurate land cover mapping across various environmental settings. Random Forest has demonstrated superior performance in numerous studies, making it a preferred choice for land cover classification tasks (P. S. Roy et al., 2015).

In this study, we aim to contribute to the existing scientific literature by conducting a comparative analysis of Sentinel-2 and Landsat 9 datasets using machine learning algorithms for land cover classification in Lucknow and Dehradun. By evaluating the performance of these datasets and algorithms across two distinct study areas, we seek to provide insights into their efficacy and applicability, ultimately advancing our understanding of remote sensing techniques for accurate land cover mapping and monitoring. the comparison of Sentinel-2 and Landsat 9 datasets alongside machine learning algorithms for land cover classification has been a subject of interest in recent research. Studies by Chen et al. (2020), Serwa and Elbialy (2021), Srivastava et al. (2023) have explored the effectiveness of Sentinel-2 imagery, emphasizing its suitability for regions abundant in vegetation due to its multispectral sensor capabilities. Sentinel-2's ability to capture imagery in spectral bands such as red-edge and near-infrared enables precise monitoring of vegetation health, type, and density, leveraging the distinct spectral signature of vegetation known as the "red-edge effect." This spectral characteristic makes Sentinel-2 particularly adept for assessing areas dominated by vegetation, including forests, agricultural lands, and natural landscapes.

Conversely, the applicability of Landsat data, including Landsat 8 and the newer Landsat 9, has been highlighted in regions with diverse land cover types, including urban areas. Studies by Srivastava (2025), Waylen et al. (20214), Teluguntla et al. (2020) have demonstrated the utility of Landsat data in capturing land cover dynamics in heterogeneous landscapes, showcasing its effectiveness in urban monitoring and classification tasks. Landsat's moderate spatial resolution and longer historical archive make it valuable for analyzing land cover changes over time, especially in areas with complex land use patterns.

Moreover, the utilization of machine learning algorithms such as CART, Random Forest, Gradient Tree Boosting (Srivastava & Sharma, 2024), and Support Vector Machine has been prevalent in land cover classification studies. Research by Liu et al. (2020), Zhao et al. (2015) has demonstrated the efficacy of the Random Forest algorithm in handling multispectral data for land cover mapping, showcasing its robustness in various environmental settings. Similarly, studies by Srivastava and Biswas (2023), Wu et al. (2016), Teluguntla et al. (2020), Zhao et al. (2015) have explored the application of Support Vector Machine and Gradient Tree Boosting algorithms, respectively, in conjunction with satellite imagery for accurate land cover classification. In this paper, we have done comparative analysis of Sentinel-2 and Landsat 9 datasets using the aforementioned machine-learning algorithms in two distinct study areas, Lucknow and Dehradun. Our results demonstrate that Sentinel-2 data, coupled with the Random Forest algorithm, outperforms other combinations in most areas, particularly in regions abundant in vegetation. This underscores the importance of selecting appropriate satellite imagery and machine learning techniques tailored to the characteristics of the study area for accurate land cover classification.

2. Study area

Dehradun, nestled in the foothills of the Himalayas in northern India, is situated at approximately 30.3165° N latitude and 78.0322° E longitude. The city experiences a subtropical climate, defined by its three distinct seasons: summer, monsoon, and winter. Summers in Dehradun, typically lasting from April to June, are warm and dry,

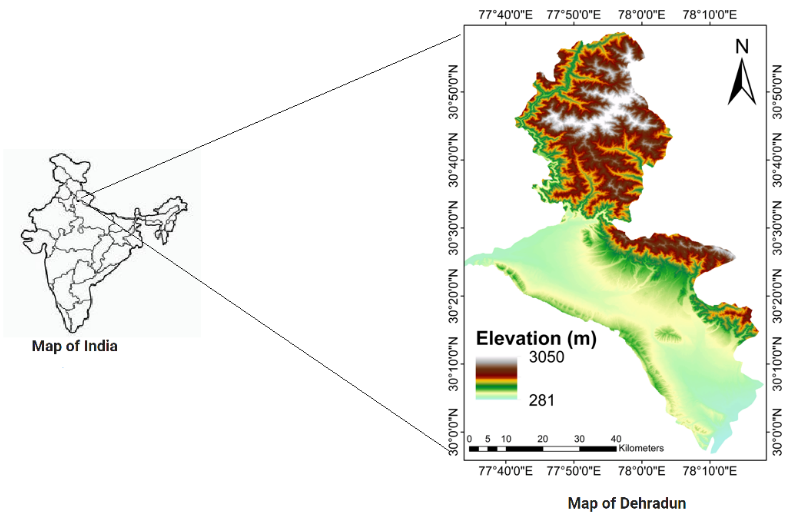

Figure 1. Geographical location of study area Dehradun

with temperatures often reaching above 35 °C (95 °F). The monsoon season, from July to September, brings relief from the heat with heavy rainfall and occasional thunderstorms, vital for the region's lush greenery. Winters, spanning from November to February, are cool and crisp, with temperatures ranging from 5 °C to 20 °C (41 °F to 68 °F), making it a favored destination for those seeking respite from the harsher winter climates found elsewhere in the country. The location map for Dehradun study area in shown in Figure 1.

Lucknow, a prominent city in northern India, is located at approximately 26.51° N latitude and 80.94° E longitude. The city falls within the subtropical region, characterized by distinct climate and geological conditions. The climate of Lucknow is marked by its three distinct seasons: summer, monsoon, and winter. Summers, which typically extend from April to June, are scorching and dry, with temperatures often exceeding 40 °C (104 °F). The monsoon season, spanning from July to September, brings relief with heavy rainfall and occasional thunderstorms. Winters, from November to February, are pleasant with temperatures ranging from 5 °C to 25 °C (41 °F to 77 °F). The second selected study area Lucknow is shown in Figure 2.

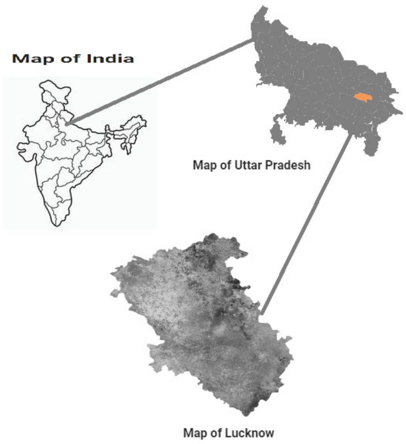

Figure 2. Geographical location of study area Lucknow

3. Methodology

In this methodological framework (Figure 3), we embark on a rigorous comparative analysis aimed at elucidating the differential performance of Landsat and Sentinel satellite data in land cover classification across disparate geographical settings: the formidable topography of the Himalayan Valley and the intricate urban fabric of an Urban Dense Area. Our investigation unfolds through a meticulously orchestrated series of procedures, commencing with meticulous data preprocessing procedures. These encompass radiometric calibration to rectify sensor-specific variations in brightness values, atmospheric correction techniques to mitigate the influence of atmospheric constituents on image radiance, and geometric rectification to ensure precise spatial alignment across datasets. Subsequently, feature extraction unfolds as a critical step, where beyond traditional spectral bands, ancillary indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and texture measures are computed to harness nuanced spectral and textural information.

The dataset is stratified into training and testing subsets with utmost care, ensuring a representative distribution of land cover classes within each subset to obviate bias during model training and evaluation phases. Leveraging a repertoire of machine learning algorithms encompassing Classification and Regression Trees (CART), Random Forest

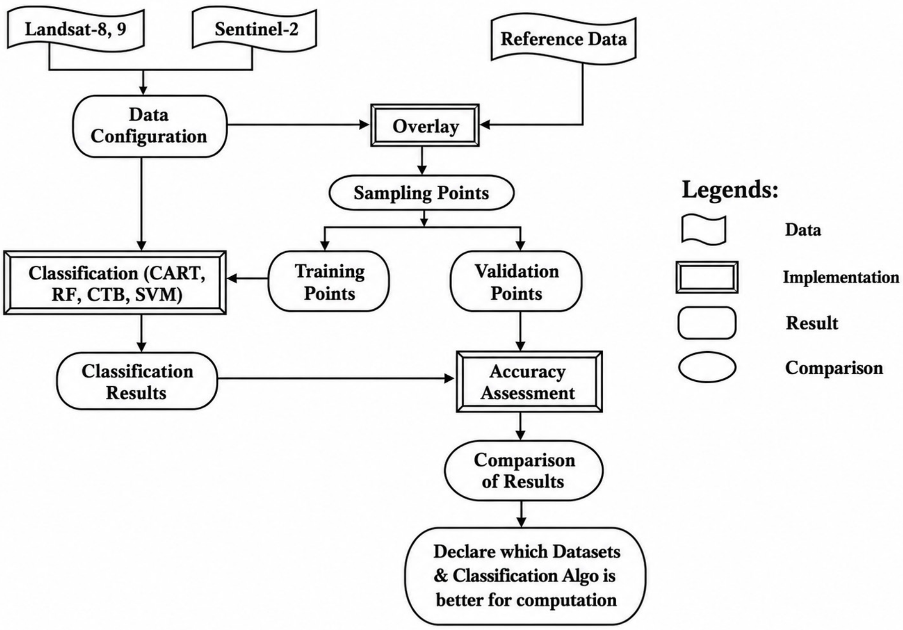

Figure 3. Methodology used in comparing data sets and algorithm for finding better dataset and classification algorithm over diverse study areas

(RF), Gradient Boosting Trees (GTB), and Support Vector Machine (SVM), model training proceeds iteratively, with hyperparameter optimization through techniques such as cross-validation to bolster robustness. Rigorous model evaluation entails the computation of an array of performance metrics encompassing accuracy by Eq. (1), precision by Eq. (2), recall by Eq. (3), F1-score by Eq. (4), and the Kappa coefficient by Eq. (5) to clean nuanced insights into algorithmic efficacy. Moreover, statistical analyses including paired t-tests are meticulously conducted to discern statistically significant disparities in classification accuracy between Landsat and Sentinel datasets. The resulting discernments furnish a sophisticated understanding of the relative merits and demerits of Landsat and Sentinel data in land cover characterization across varied terrains, thus affording invaluable guidance for precision environmental monitoring and management strategies tailored to distinct geographic contexts.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}; \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP}; \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN}; \quad (3)$$

$$\text{F1} = \frac{2\times Precision\times Recall}{Precision+Recall} = \frac{2\times TP}{2\times TP+FP+FN}, \quad (4)$$

where: TP = True Positive; TN = True Negative; FP = False Positive; FN = False Negative.

$$\text{Kappa} = \frac{Po-Pe}{1-Pe}, \quad (5)$$

where: Po = Observed proportional agreement; Pe = Expected proportional agreement.

The entire data pre-processing and classification workflow is implemented using Google Earth Engine (GEE) a cloud-based geospatial analysis platform that enables large-scale satellite data processing. GEE provides a powerful JavaScript-based Code Editor interface for building and executing Earth observation workflows directly in the browser, without the need for local storage or computational resources.

4. Results and discussions

The investigation into the comparative performance of Landsat and Sentinel satellite data for land cover classification serves as a cornerstone in understanding the intricacies of remote sensing applications across heterogeneous landscapes. Within the scope of this study, encompassing the rugged topography of the Himalayan Valley and the complex urban milieu of an Urban Dense Area, our analytical endeavors have unveiled compelling revelations regarding the discriminatory capabilities of these datasets. Employing a rigorous suite of machine learning algorithms alongside stringent statistical analyses, our inquiry aims to elucidate the nuanced nuances inherent in satellite data selection, thereby offering invaluable insights into the realm of precision environmental monitoring and management. In this preliminary unveiling of results, we embark upon a detailed exploration of the discernible patterns and trends observed across both study regions, laying the groundwork for a comprehensive understanding of the differential impacts exerted by Landsat and Sentinel datasets on land cover classification outcomes.

4.1. Dehradun (Doon Valley)

We divided a total area of 3088 km^2 area of Doon Valley (Dehradun) into four land cover types urban, forest, water, and agriculture but if we sub-classified these land cover types then urban land is subdivided into residential places, institutional places, built-up areas, and some parking area, agriculture class is subdivided into plantation, cultivation and another farmer land, Forest land is subdivided into the dense forest and open forest and water land cover are divided into pond, lake, and river.

Figure 4 presents the land cover classifications obtained from 10 m Sentinel data using various algorithms in Dehradun for the year 2022. Figure 4 offers a visual representation of the land cover classifications achieved through remote sensing techniques, showcasing the diverse landscape features and land use patterns within the study area. This depiction is intended to provide valuable insights for ongoing research efforts aimed at understanding environmental dynamics and urban development trends in the region.

Here we collected 535 data points for urban land cover, 506 data points for forest land cover, 505 data points

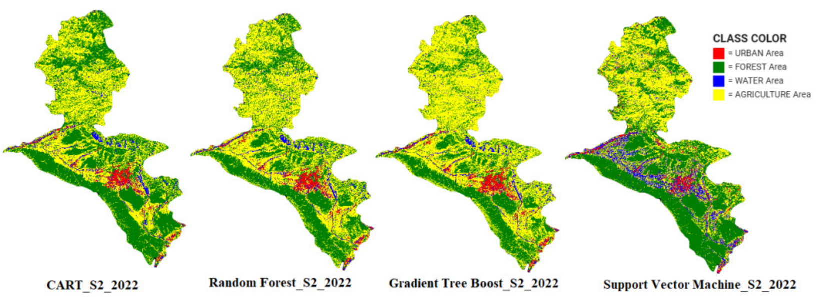

Figure 4. Classification outputs from 10m Sentinel data using various algorithms in Dehradun for the year 2022

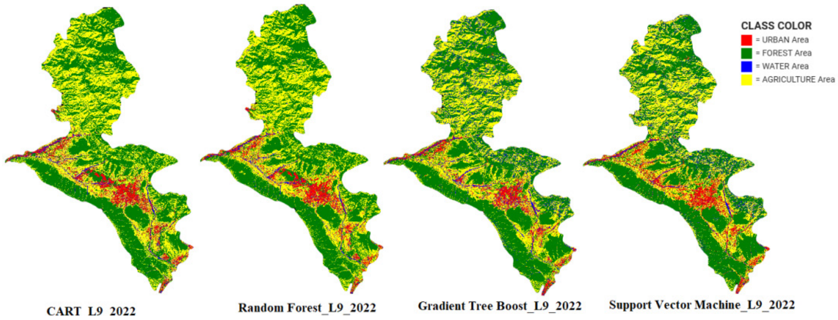

Figure 5. Classification outputs from 30m Landsat data using various algorithms in Dehradun for the year 2022

for water land cover 540 data points for agriculture land cover. As we discussed previously, we are considering four classification algorithms over two data sets for classification purposes. Urban land cover areas contain all types of built-up and non-built-up land (where water, high vegetation (forest), and low vegetation (agriculture) classes are not present), and water land cover areas include all land cover areas where water is present whether it is ponds, lakes, or rivers.

Figure 5 illustrates the land cover classifications obtained from 30 m Landsat data for Dehradun in 2022, employing various algorithms. Figure 5 provides a detailed visual representation of the land use types, emphasizing the spatial distribution and variability of these types within the study area. This visualization offers essential information for researchers and policymakers in fields such as environmental monitoring, urban planning, and natural resource management. It enables these stakeholders to better understand the landscape dynamics and ecosystem changes that occurred during the specified timeframe.

Figures 4–5 present output data generated for the year 2022 over Sentinel 2 and Landsat 9 data sets respectively. Computation shows that the enhanced suitability of Sentinel-2 for land cover classification in the Dehradun-Himalayan region due to its high spatial resolution, multispectral capabilities, and frequent revisits. The region's challenging terrain, characterized by steep slopes and diverse land cover classes, demands a data source that can provide fine-scale information. Additionally, the study reinforces the effectiveness of ensemble-based algorithms, specifically Gradient Boosting Trees (GTB) and Random Forest (RF), in managing the complexity of land cover classification in the Himalayan context. The empirical evidence, as presented through the confusion matrix and Kappa statistic, substantiates the assertion that Sentinel-2, in combination with ensemble methods, consistently delivers superior accuracy and output in classifying the intricate landscape of the Dehradun-Himalayan region when compared to Landsat-9.

In the Himalayan Valley study area, the classification performance of Landsat and Sentinel satellite data varied across different machine learning algorithms. Overall, Sentinel data exhibited higher accuracy in delineating

Table 1. Accuracy of classification algorithm over both data sets by Confusion Matrix in Year 2022

Algorithm	Sentinel data set accuracy	Landsat data set accuracy
CART	90.09	84.03
Random Forest	92.48	86.56
GTB	91.58	84.57
SVM	84.23	83.20

land cover types compared to Landsat data. Random Forest (RF) emerged as the most effective algorithm for both datasets, achieving an accuracy of 92% with Sentinel data and 86% with Landsat data. Gradient Boosting Trees (GTB) also demonstrated promising results, particularly with Sentinel data 91%, achieving an accuracy of 81% with Landsat. Landsat data, while performing admirably, showed slightly lower accuracies across all algorithms compared to Sentinel data. Support Vector Machine (SVM) showcased the lowest performance among the algorithms tested, yielding accuracies of 75% and 71% with Sentinel and Landsat data, respectively. Statistical analysis revealed significant differences in classification accuracy between Landsat and Sentinel data, indicating the superior discriminatory capacity of Sentinel imagery in capturing the diverse land cover characteristics of the Himalayan Valley.

Table 1 presents the accuracy of classification algorithms over both Sentinel and Landsat datasets for the year 2022, evaluated using confusion matrix analysis. Table 1 compares the performance of CART, Random Forest, Gradient Boosting Trees (GTB), and Support Vector Machine (SVM) algorithms across the two datasets. Results show that Random Forest achieved the highest accuracy for both Sentinel (92.48%) and Landsat (86.56%) datasets, followed closely by GTB with 91.58% accuracy on Sentinel and 84.57% on Landsat. CART also performed well with 90.09% accuracy on Sentinel and 84.03% on Landsat, while SVM exhibited lower accuracies of 84.23% on Sentinel and 83.20% on Landsat. These findings underscore the effectiveness of Random Forest and GTB algorithms in accurately classifying land cover types using remote sensing data, providing valuable insights for researchers and practitioners engaged in spatial analysis and environmental monitoring in Lucknow for 2022.

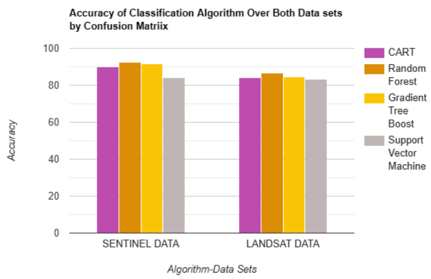

Figure 6. Accuracy comparison of both datasets using various algorithms and Confusion Matrix in Dehradun for the year 2022

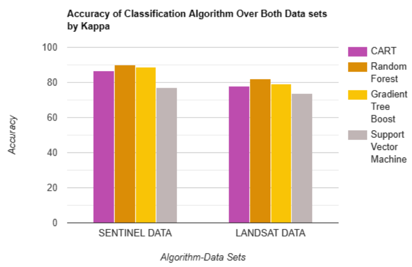

Figure 7. Accuracy with Kappa for classification algorithms on Dehradun datasets for the year 2022

Figure 6 provides an accuracy comparison of both 10m Sentinel and 30m Landsat datasets using various algorithms and confusion matrix analysis in Dehradun for the year 2022. Figure 6 presents a detailed assessment of classification performance, showcasing the effectiveness of different remote sensing techniques in capturing land cover and land use patterns within the study area. By analysing the confusion matrices, Figure 6 offers valuable insights into the strengths and limitations of each dataset and algorithm combination, contributing to a deeper understanding of spatial data quality and reliability for environmental monitoring and urban planning applications.

Table 2. Accuracy of classification algorithm over both data sets using Kappa in the year 2022

Algorithm	Sentinel data set accuracy	Landsat data set accuracy
CART	86.78	78.71
Random Forest	89.94	82.05
GTB	88.76	79.29
SVM	77.27	73.56

Table 2 presents the accuracy of classification algorithms over both Sentinel and Landsat datasets for the year 2022, evaluated using Kappa statistics. Table 2 compares the performance of CART, Random Forest, Gradient Boosting Trees (GTB), and Support Vector Machine (SVM) algorithms across the two datasets. Results indicate that Random Forest achieved the highest accuracy based on Kappa coefficients, with 89.94% on Sentinel and 82.05% on Landsat datasets. GTB also performed well with 88.76% accuracy on Sentinel and 79.29% on Landsat, while CART showed accuracies of 86.78% on Sentinel and 78.71% on Landsat. SVM exhibited comparatively lower accuracies of 77.27% on Sentinel and 73.56% on Landsat. These findings highlight the effectiveness of Random Forest and GTB algorithms in accurately classifying land cover types using remote sensing data, providing valuable insights for researchers and practitioners involved in spatial analysis and environmental monitoring in Lucknow for the year 2022.

Figure 7 illustrates the accuracy with Kappa coefficients for classification algorithms applied to Dehradun datasets for the year 2022. Figure 7 presents a comparative analysis of the performance of various algorithms in terms of both overall accuracy and Kappa statistics, providing a comprehensive evaluation of their effectiveness in land cover classification. The results depicted highlight the robustness of certain algorithms in accurately delineating different land use types within the study area, while also indicating areas where improvements or adjustments may be necessary. This visual representation serves as a valuable reference for researchers and practitioners involved in remote sensing and spatial analysis, aiding in the selection of suitable algorithms for monitoring environmental changes and informing sustainable land management strategies.

4.2. Lucknow (urban area)

Figure 8 displays the classification outputs generated from 10m Sentinel data using various algorithms in Lucknow for the year 2022. Figure 8 provides a visual representation of the land cover classifications achieved through remote sensing techniques, highlighting the spatial distribution and diversity of land use patterns within the study area. This visualization serves as a crucial resource for researchers and urban planners, offering insights into the dynamic landscape features and environmental dynamics of Lucknow during the specified timeframe. Additionally, it supports ongoing efforts in environmental monitoring, land management, and urban development planning by showcasing the efficacy of different algorithmic approaches in analysing Sentinel data for accurate land cover mapping.

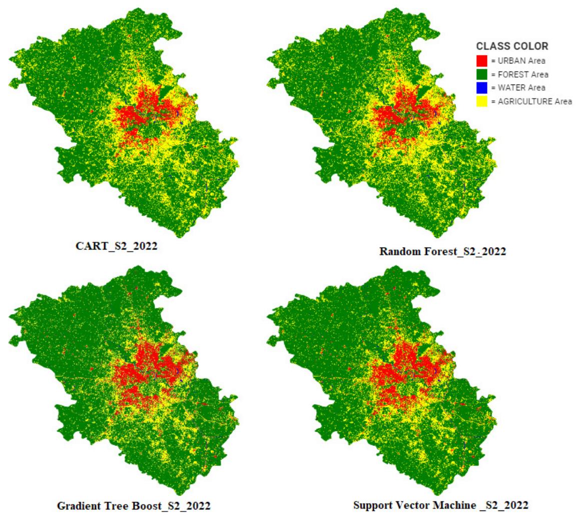

Figure 8. Classification outputs from 10m Sentinel data using various algorithms in Lucknow for the year 2022

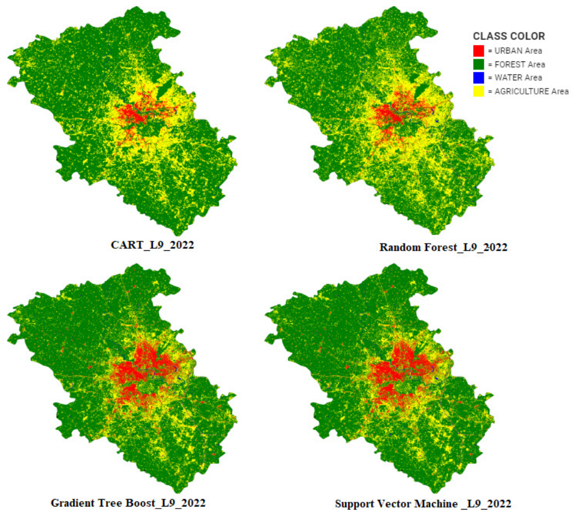

Figure 9. Classification outputs from 30m Landsat data using various algorithms in Lucknow for the year 20022

Figure 9 displays the land cover classifications obtained from 30 m Landsat data in Lucknow for the year 2022, using various algorithms. This visual representation of the land cover classifications achieved through remote sensing techniques provides a critical reference for researchers and policymakers involved in environmental monitoring and urban planning. It highlights the spatial distribution and variability of land use categories within the study area and offers insights into landscape dynamics and ecosystem changes over the specified timeframe. The detailed analysis presented in Figure 10 allows for a comparative assessment of algorithmic performance, contributing to a deeper understanding of the effectiveness of Landsat data in capturing land cover variations and supporting informed decision-making processes related to sustainable development and natural resource management in Lucknow.

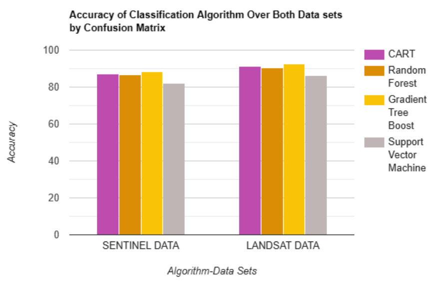

Figure 10. Accuracy comparison of both datasets using various algorithms and Confusion Matrix in Lucknow for the year 2022

Figure 10 displays a comparison of the accuracy of both the 10 m Sentinel and 30m Landsat datasets using various algorithms and confusion matrix analysis in Lucknow for the year 2022. Figure 10 provides a comprehensive evaluation of the classification performance, highlighting the strengths and limitations of different remote sensing techniques in capturing and distinguishing land cover types within the study area. By analyzing the confusion matrices, Figure 10 offers valuable insights into the accuracy, reliability, and consistency of each dataset and algorithm combination, which is essential for informing urban planning, environmental monitoring, and land management strategies. The comparative analysis presented in this Figure 10 serves as a critical resource for researchers and practitioners involved in spatial data analysis, aiding in the selection of optimal algorithms and datasets for improving the precision of land cover mapping and supporting sustainable development initiatives in Lucknow.

Table 3. Accuracy of classification algorithm over both data sets using Confusion Matrix in the year 2022 over Lucknow

Algorithm	Sentinel data set accuracy	Landsat data set accuracy
CART	87.23	91.40
Random Forest	86.54	90.56
GTB	88.50	92.54
SVM	82.25	86.20

Table 3 presents the accuracy of classification algorithms over both Sentinel and Landsat datasets for the year 2022 in Lucknow, assessed using confusion matrix analysis. The table compares the performance of CART, Random Forest, Gradient Boosting Trees (GTB), and Support Vector Machine (SVM) algorithms across the two datasets. Results indicate varying levels of accuracy across algorithms, with GTB achieving the highest accuracy of 88.50% on Sentinel and 92.54% on Landsat datasets. CART also performed well with accuracies of 87.23% on Sentinel and 91.40% on Landsat, followed closely by Random Forest with 86.54% accuracy on Sentinel and 90.56% on Landsat. SVM exhibited lower accuracies of 82.25% on Sentinel and 86.20% on Landsat. These findings underscore the effectiveness of GTB and CART algorithms in accurately classifying land cover types using remote sensing data in Lucknow for 2022, providing valuable insights for researchers and practitioners involved in environmental monitoring and urban planning.

Table 4. Accuracy of classification algorithm over both data sets using Kappa in the year 2022 over Lucknow

Algorithm	Sentinel data set accuracy	Landsat data set accuracy
CART	81.73	88.56
Random Forest	87.74	91.34
GTB	88.76	91.58
SVM	80.54	81.54

Table 4 presents the accuracy of classification algorithms over both Sentinel and Landsat datasets for the year 2022 in Lucknow, evaluated using Kappa statistics. Table 4 compares the performance of CART, Random Forest, Gradient Boosting Trees (GTB), and Support Vector Machine (SVM) algorithms across the two datasets. Results show that Random Forest achieved the highest accuracy based on Kappa coefficients, with 87.74% on Sentinel and 91.34% on Landsat datasets. GTB also performed well with accuracies of 88.76% on Sentinel and 91.58% on Landsat, demonstrating robust classification capabilities. CART exhibited accuracies of 81.73% on Sentinel and 88.56% on Landsat, while SVM showed lower accuracies of 80.54% on Sentinel and 81.54% on Landsat. These findings underscore the effectiveness of Random Forest and GTB algorithms in accurately classifying land cover types using remote sensing data in Lucknow for 2022, providing valuable insights for spatial analysis, environmental monitoring, and urban planning initiatives.

Figure 11 illustrates an accuracy comparison of both 10m Sentinel and 30m Landsat datasets using various algorithms and Kappa statistics in Lucknow for the year 2022. Figure 11 provides a detailed assessment of classification performance, focusing on the overall accuracy and Kappa coefficients to evaluate the robustness and reliability of different remote sensing techniques in delineating land cover categories within the study area. By comparing the Kappa statistics across algorithms and datasets, Figure 11 offers valuable insights into the level of agreement between observed and predicted classifications, crucial for understanding the accuracy and consistency of spatial data used in environmental monitoring and urban planning applications. This visual representation serves as a fundamental reference for researchers and decision-makers, aiding in the selection of suitable algorithms and datasets to improve the precision of land cover mapping and support sustainable development initiatives in Lucknow.

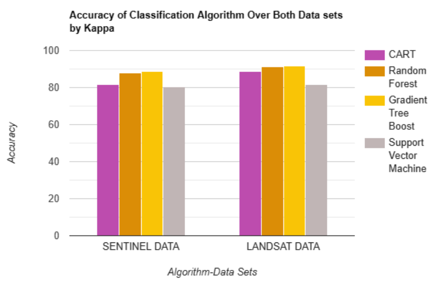

Figure 11. Accuracy comparison of both datasets using various algorithms and Kappa statistic in Lucknow for the year 2022

Research underscores the superior performance of Landsat-9 over Sentinel-2 for urban area classification in the Lucknow region due to its enhanced spectral resolution and longer data record. Additionally, the study highlights the prowess of ensemble-based algorithms, namely Gradient Boosting Trees (GTB) and Random Forest (RF), in handling the complexity of land cover classification, especially in urban areas. The empirical evidence provided through the confusion matrix and Kappa statistic affirms that the Landsat-9 dataset, in combination with ensemble methods, consistently delivers superior accuracy and output compared to Sentinel-2, making it the preferred choice for urban land cover classification in the study area.

Urbanization and population growth are the main factors influencing the LULC changes, another factor contributing to LULC change is the conversion of forest into agricultural land to supply the need for food grains. The increase of the built-up area, at the expense of agricultural land, vegetation cover, and open spaces, accounts for the majority of LULC change. Accurate computation is a very crucial task in finding change in land cover areas. Images used for categorization and the classifier employed in the computation are the two key factors that influence LULC change computation. Finding the best data sets and applying the best classifier over that can only provide better and more accurate results.

A comparison of Landsat-8 and Sentinel-2 is performed by several researchers in different land cover areas and they found some distinctive characteristics of both data sets with change in environment performed his computation on boreal forest canopy cover and leaf area index and found Sentinel-2 slightly better than Landsat 8 in the estimation of canopy cover and leaf area index and perform nearly same in term accuracy when computation is performed on the same band. Also performed a comparison between s-2 and l-8 on the same boreal region and stated that sentinel-2 Multi-Spectral Instrument (MSI) data can be recommended as the principal Earth observation data source in forest resources assessment. Performed a comparison between these two data sets over the Brazilian Amazon region and found S-2 and L-8 are performed nearly the same in terms of accuracy. We have also performed a comparison between these two data sets over the same band and found sentinel 2 has higher accuracy compared to Landsat data sets in most cases, but accuracy changes with the change in year that indicates data set performance is dependent on environmental conditions also.

5. Conclusions

By our research we find that Sentinel data, specifically Sentinel-2, is well-suited for regions with abundant vegetation due to its multispectral sensor. Sentinel-2 captures imagery in several spectral bands, including the red-edge and near-infrared, which are crucial for vegetation monitoring. Vegetation has a unique spectral signature where it strongly reflects near-infrared light while absorbing red light. This spectral behaviour is known as the "red-edge effect," and it is highly useful for assessing vegetation health, type, and density. Therefore, Sentinel-2's ability to capture these specific spectral bands makes it an excellent choice for regions with a significant presence of vegetation, such as forests, agricultural areas, and natural landscapes. Conversely, Landsat data, particularly Landsat 8 (D. P. Roy et al., 2014; Srivastava, 2024) and Landsat 9, is better suited for areas with a mix of land cover types, including urban areas. Landsat's spectral bands cover a broader range of wavelengths, making it more versatile for characterizing different land cover types. In urban areas, various surfaces like buildings, roads, and vegetation are often mixed together. Landsat's spectral signature is adept at distinguishing between these diverse materials. For instance, urban areas tend to exhibit distinct spectral characteristics in the visible and infrared ranges, which Landsat's spectral bands are well-equipped to capture. This makes Landsat a valuable choice for urban planning, land use classification, and change detection in regions with heterogeneous land cover. In summary, the choice between Sentinel and Landsat data depends on the specific land cover characteristics of the region of interest. Sentinel data excels in areas dominated by vegetation due to its specialized spectral bands for vegetation analysis, while Landsat data is more versatile and suitable for regions with a mix of land cover types, including urban and rural areas, thanks to its comprehensive spectral coverage. The spectral signature of vegetation, characterized by strong near-infrared reflectance, and the spectral characteristics of urban areas, marked by unique patterns in visible and infrared bands, are key factors influencing this choice.

Our extensive analysis of classification algorithms, including CART, Gradient Tree Boost, Support Vector Machine, and Random Forest, reveals that the Random Forest algorithm emerges as the superior choice when evaluating classification performance using the confusion matrix and kappa coefficient as key metrics. Random Forest exhibits exceptional performance across various aspects of classification tasks, demonstrating its ability to strike a harmonious balance between precision, recall, and the ability to handle complex relationships within the data.

One of the standout strengths of the Random Forest algorithm is its capacity to excel in both binary and multi-class classification problems. The confusion matrix, which provides a detailed breakdown of true positives, true negatives, false positives, and false negatives, becomes a critical tool for assessing a classifier's performance in real-world applications. In our analysis, Random Forest consistently outperforms its peers in terms of minimizing false positives and false negatives. This ability to reduce both types of errors is particularly important in applications where misclassification can have significant consequences, such as in medical diagnosis or fraud detection.

The Kappa coefficient, a measure of inter-rater agreement, further supports Random Forest's classification prowess. This metric quantifies the algorithm's performance while accounting for the possibility of classification occurring by chance. Our results indicate that Random Forest consistently achieves higher kappa coefficients, underscoring its effectiveness in generating classification models that go beyond random chance and provide substantial agreement between predicted and actual outcomes. The higher kappa values indicate the robustness and reliability of Random Forest in producing results that are not just statistical artefacts but represent genuine predictive power. Random Forest's ensemble approach, which leverages multiple decision trees, makes it adept at handling imbalanced data by aggregating the predictions of individual trees, thus mitigating the influence of minority classes. This results in more equitable classification performance across all classes and highlights its suitability for a wide range of applications.

The versatility of Random Forest in handling both categorical and continuous features without extensive data pre-processing is a considerable advantage. This feature makes it an attractive choice for practitioners who wish to streamline their workflow and avoid the complexity associated with data transformation. It reduces the data scientist's burden and facilitates a quicker model development process while maintaining high predictive accuracy.

It is important to acknowledge that the superiority of Random Forest in our analysis does not diminish the significance of the other classification algorithms. CART, Gradient Tree Boost, and Support Vector Machine each have their strengths and specific use cases where they excel. In some situations, the choice of algorithm may hinge on factors other than classification accuracy, such as interpretability, computational efficiency, or scalability. Moreover, the performance of any classification algorithm can be context-dependent, requiring a careful evaluation of dataset characteristics and domain-specific considerations.

In summary, our investigation has demonstrated that the Random Forest algorithm consistently outperforms its peers, as evidenced by its superior performance in confusion matrices and higher kappa coefficients. Its ability to minimize false positives and false negatives, coupled with its resilience to imbalanced datasets, makes it an ideal choice for a broad spectrum of classification tasks. However, the choice of the most suitable classification algorithm should always consider the unique requirements and challenges of each project. Random Forest stands as a robust and reliable option for many classification scenarios, but the search for the optimal algorithm remains a dynamic and context-driven process in the realm of machine learning and data science. Future research may further explore the fine-tuning of Random Forest parameters and its performance across diverse datasets and domains, providing additional insights into its capabilities.

Disclosure statement

Authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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