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GIS and Remote Sensing-Based Assessment of Urban Expansion and Land Use/Land Cover Change in Jamshedpur: A Review

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Abstract

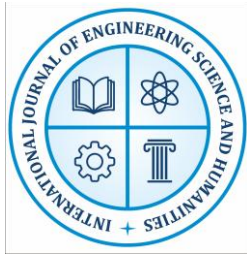
Rapid urbanisation in India has transformed the physical landscape of its cities, and medium-sized industrial centres have experienced some of the most intense land conversions. Jamshedpur, the first planned industrial city of India and a major steel-producing hub in Jharkhand, offers a distinctive setting in which company-led planning, mineral-based industrialisation, forested uplands and two major rivers interact. The application of remote sensing (RS) and geographic information systems (GIS) to the assessment of urban expansion and land use/land cover (LULC) change, with particular attention to Jamshedpur and comparable cities in eastern and central India. The literature is examined under four themes: satellite data sources and pre-processing, image classification and accuracy assessment, measurement of urban expansion and sprawl, and the environmental consequences of land transformation, including forest degradation and rising land surface temperature (LST). The reviewed studies consistently report growth of built-up land at the expense of agricultural land, vegetation, open space and water bodies, alongside a positive association between impervious surfaces and surface heating. Machine learning classifiers, cloud computing platforms and spatial metrics such as Shannon's entropy have improved the reliability of change detection. However, Jamshedpur-specific evidence remains limited, fragmented and largely confined to the peri-urban forest of Dalma. The review concludes by identifying priorities for future work, including high-resolution mapping, predictive modelling, integration of socio-economic data and assessment of urban ecosystem services.

Keywords: Remote sensing; GIS; urban expansion; land use/land cover change; Jamshedpur; land surface temperature; urban sprawl

1. Introduction

1.1 Urbanisation and Land Transformation in India

Urbanisation is one of the most visible forms of human influence on the earth's surface. As cities grow, natural and semi-natural surfaces such as forests, croplands, grasslands and wetlands are progressively replaced by roads, buildings, industrial sites and other impervious surfaces. In



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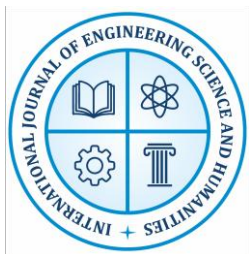
India, the pace of this transformation has accelerated since the economic reforms of the 1990s, and it is no longer confined to the metropolitan cities. Medium-sized cities and industrial towns are now expanding rapidly beyond their administrative limits, frequently in a fragmented and poorly regulated manner (Chettry & Surawar, 2021). Studies of large cities have demonstrated the scale of this process. In Bengaluru, for example, multi-decadal satellite analysis revealed a dramatic increase in paved surfaces accompanied by a sharp decline in vegetation and water bodies, illustrating how quickly urban growth can erode the ecological base of a city (Ramachandra et al., 2015).

Such changes are not merely physical. The conversion of land alters hydrological behaviour, local climate, biodiversity, air quality and the availability of productive agricultural land. For planners and policymakers, accurate and timely information on where, how fast and in what form cities are growing is therefore essential. Conventional ground surveys and cadastral records, while valuable, are expensive, slow to update and rarely capture change across a whole urban region. This gap has encouraged the widespread adoption of satellite-based observation in Indian urban research, ranging from metropolitan centres such as Delhi and Chennai to smaller cities in the Himalayan foothills and the eastern plateau (Aithal & Ramachandra, 2016; Bhat et al., 2017; Tripathy & Kumar, 2019).

1.2 Jamshedpur as a Planned Industrial City

Jamshedpur occupies a special place in the urban history of India. Founded in the early twentieth century around the steel plant at Sakchi, it developed as a company town planned and largely managed by the Tata enterprise, and it is commonly referred to as the Steel City of India. The city is located in the East Singhbhum district of Jharkhand on the Chota Nagpur Plateau, close to the confluence of the Subarnarekha and Kharkai rivers, and is bordered to the north by the forested Dalma hills. Its urban agglomeration, which includes Jamshedpur, Adityapur, Mango, Jugsalai and several census towns, had more than one million residents at the 2011 Census and has continued to grow as an industrial, commercial and educational centre for the region.

The combination of a planned core and unplanned peripheral growth makes Jamshedpur an instructive case. The core areas developed under company management exhibit a relatively ordered pattern with tree-lined roads and parks, while the surrounding municipalities and villages have expanded more informally in response to industrial employment, migration and land demand. The wider region is also affected by mining, forest pressure and shifting cultivation. Research on the Dalma Wildlife Sanctuary, located immediately north of the city, documented a steady loss of very dense forest together with an increase in settlement and bare land between 2009 and 2016, signalling the growing pressure of human activity on the urban fringe (Ranjan et al., 2016). Similar patterns of mining-linked and urban-linked land change have been reported in other industrial regions of eastern India, such as Asansol–Durgapur, which shares many



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physiographic and economic characteristics with the Jamshedpur region (Choudhury et al., 2019).

1.3 Role of Remote Sensing and GIS in Urban Studies

Remote sensing provides synoptic, repetitive and consistent observations of the earth's surface, making it possible to reconstruct the history of land change over several decades. The free availability of the Landsat archive, which extends back to the 1970s, and of Sentinel-2 imagery since 2015, has made multi-temporal analysis accessible to researchers in developing countries. GIS complements these data by providing tools for storing, overlaying, analysing and visualising spatial information, including administrative boundaries, road networks, population data and topography. Together, RS and GIS allow analysts to classify land cover, detect changes between dates, quantify the rate and direction of urban growth and link these changes to environmental indicators (Phiri & Morgenroth, 2017).

Recent technological developments have further expanded these capabilities. Cloud computing platforms such as Google Earth Engine allow thousands of satellite scenes to be processed without local storage or high-end hardware (Gorelick et al., 2017). Machine learning algorithms, including random forest and support vector machines, have improved classification accuracy in complex urban landscapes where spectrally similar surfaces such as bare soil, rooftops and dry fallow fields are easily confused (Belgiu & Drăguț, 2016; Talukdar et al., 2020). More recently, deep learning and artificial intelligence methods have begun to automate change detection at finer spatial scales (Gu & Zeng, 2024).

1.4 Land Use/Land Cover Change as an Environmental Indicator

Land use refers to the purpose for which humans employ land, such as residence, industry or agriculture, while land cover describes the physical material present on the surface, such as vegetation, water or concrete. Changes in LULC are widely regarded as a key indicator of environmental change because they integrate the effects of population growth, economic activity and policy decisions. In urban regions, the most important transitions are typically from cropland, fallow land, scrubland and forest to built-up land. These transitions influence surface energy balance and are closely associated with the formation of the surface urban heat island, as impervious surfaces absorb and re-emit more heat than vegetated or wet surfaces (Mathew et al., 2016; Pal & Ziaul, 2017).

For an industrial city like Jamshedpur, where heavy industry, dense settlements, hills and rivers lie in close proximity, LULC change has direct implications for urban heat, flood risk along the river corridors, forest connectivity with the Dalma landscape and the long-term sustainability of the city. Reviewing the existing body of RS and GIS work therefore helps to clarify what is already known about the city and its region, which methods are most appropriate for its conditions, and where knowledge gaps remain. The following section reviews the literature



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thematically, drawing on studies of Jamshedpur and of comparable Indian cities whose methods and findings are transferable to the Jamshedpur context.

2. Literature Review

2.1 Satellite Data Sources and Pre-processing

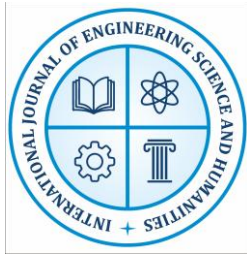
The choice of satellite data is the first and often most consequential decision in any LULC study. Most of the Indian studies reviewed here rely on medium-resolution multispectral imagery, particularly the Landsat series, because of its long archive, free access and consistent 30 m resolution. Landsat Thematic Mapper (TM) imagery is generally used for the 1980s and 1990s, Enhanced Thematic Mapper Plus (ETM+) for the early 2000s, and Operational Land Imager (OLI) with its Thermal Infrared Sensor (TIRS) for the period after 2013. Studies of Dehradun, Chennai, Ranchi and Delhi have all relied on such multi-decadal Landsat sequences to reconstruct urban growth trajectories (Ahmad & Goparaju, 2016; Aithal & Ramachandra, 2016; Bhat et al., 2017; Tripathy & Kumar, 2019).

Higher-resolution data are used where finer detail is required. In the Jamshedpur region, Ranjan et al. (2016) employed high-resolution satellite imagery to assess forest density change in the Dalma Wildlife Sanctuary over five dates between 2009 and 2016, achieving classification accuracy of up to about 95 percent. Indian Remote Sensing (IRS) data, especially LISS-III and LISS-IV, are also used in national and state-level mapping. Sentinel-2, with 10 m resolution in the visible and near-infrared bands and a revisit period of about five days, is increasingly adopted for recent years, although it cannot support long historical analysis. For thermal analysis, the thermal bands of Landsat 5, 7 and 8 remain the primary source for LST retrieval in Indian cities (Choudhury et al., 2019; Sahana et al., 2016).

Pre-processing is essential to ensure that images from different dates and sensors are comparable. Standard steps include selection of cloud-free scenes from the same season, radiometric calibration, atmospheric correction, geometric registration and subsetting to the study area boundary. Seasonal consistency is particularly important in monsoon-affected regions like Jharkhand, where the spectral response of cropland, fallow land and grassland changes considerably between wet and dry seasons. Many researchers select post-monsoon or winter imagery to reduce cloud contamination and to improve separation between vegetation and built-up land (Pal & Ziaul, 2017). Cloud platforms now automate much of this work by offering analysis-ready surface reflectance collections (Gorelick et al., 2017). Table 1 summarises the main data sources used in the reviewed literature.

Table 1: Major satellite data sources used in urban LULC studies

Satellite / Sensor	Spatial Resolution	Period of Availability	Access	Typical Use in Reviewed Studies
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Satellite / Sensor	Spatial Resolution	Period of Availability	Access	Typical Use in Reviewed Studies
Landsat 5 TM	30 m (thermal 120 m)	1984–2012	Free	Historical LULC baselines and early LST estimation
Landsat 7 ETM+	30 m (pan 15 m)	1999–present	Free	LULC mapping for the 2000s
Landsat 8/9 OLI–TIRS	30 m (thermal 100 m)	2013–present	Free	Recent LULC, spectral indices and LST retrieval
Sentinel-2 MSI	10–20 m	2015–present	Free	Fine-scale recent land cover and urban detail
IRS LISS-III / LISS-IV	23.5 m / 5.8 m	1990s–present	Free / paid	National and regional thematic mapping
High-resolution commercial imagery	< 5 m	2000s–present	Paid	Forest density and settlement mapping (e.g., Dalma)

2.2 Image Classification Techniques and Accuracy Assessment

Image classification converts satellite reflectance values into thematic LULC categories. The most common approach in Indian urban studies has been supervised classification using the maximum likelihood classifier (MLC), in which the analyst selects training samples for each class and the algorithm assigns pixels based on statistical probability. MLC has been used successfully in studies of Dehradun, English Bazar and Asansol–Durgapur (Bhat et al., 2017; Choudhury et al., 2019; Pal & Ziaul, 2017). Its main weakness is the assumption of normally distributed class data, which is often violated in heterogeneous urban environments where buildings, roads, bare soil and dry vegetation produce overlapping spectral signatures.

To address these limitations, researchers have increasingly turned to non-parametric machine learning classifiers. Belgiu and Drăguț (2016) showed that the random forest algorithm is robust to noise, handles high-dimensional data well and provides measures of variable importance. In a comparative review, Talukdar et al. (2020) found that random forest and support vector machine classifiers generally produced more accurate LULC maps than traditional methods, although performance depended on the quality of training data. Phiri and Morgenroth (2017) traced the



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broader evolution of Landsat classification from pixel-based statistical methods towards object-based image analysis and machine learning, noting that hybrid approaches often give the best results. Artificial neural networks and multi-layer perceptrons have also been applied, particularly where classification is linked to change prediction (Mishra & Rai, 2016). Most recently, deep learning techniques such as convolutional neural networks have shown promise for automated detection of urban features at fine resolution (Gu & Zeng, 2024).

Accuracy assessment is a necessary part of any credible LULC study. The reviewed works typically report an error matrix from which overall accuracy, producer's accuracy, user's accuracy and the kappa coefficient are calculated, using reference points from field surveys, high-resolution imagery or Google Earth. Overall accuracies above 80 to 85 percent are generally considered acceptable for change analysis. Following classification, change detection is commonly performed through post-classification comparison and cross-tabulation, which produces a transition matrix showing how much land moved from each class to every other class. This technique was used, for instance, to quantify forest-to-settlement and forest-to-bare-land transitions in Dalma (Ranjan et al., 2016). Table 2 compares the principal classification approaches.

Table 2: Comparison of image classification techniques used in LULC studies

Technique	Strengths	Limitations
Maximum likelihood classifier	Simple, widely available in software, well understood	Assumes normal distribution; struggles with mixed urban pixels
Random forest	High accuracy, resistant to overfitting, ranks variable importance	Requires representative training data; less interpretable than simple rules
Support vector machine	Performs well with small training samples and complex boundaries	Sensitive to parameter tuning; computationally demanding for large areas
Artificial neural network / MLP	Captures non-linear relationships; useful for change prediction	Requires careful training; risk of overfitting
Object-based image analysis	Uses shape and texture; reduces salt-and-pepper noise	Segmentation parameters are subjective; best with high-resolution data
Deep learning	Automated feature extraction;	Needs large labelled datasets and



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Technique	Strengths	Limitations
(e.g., CNN)	strong for fine-scale urban mapping	high computing power

2.3 Measurement of Urban Expansion and Urban Sprawl

Beyond mapping land cover, researchers have developed a range of indicators to describe how cities grow. Urban expansion refers to the increase in the area of built-up land, while urban sprawl describes dispersed, low-density and often haphazard growth at the urban fringe. One of the most widely used measures is Shannon's entropy, which indicates whether built-up land is compactly concentrated or dispersed across concentric zones or sectors. Bhat et al. (2017) applied Shannon's entropy to Dehradun and found increasing dispersion of built-up land over time, confirming a sprawling pattern of development. Chetry and Surawar (2021) extended this kind of analysis to eight medium-sized Indian cities, combining entropy with landscape metrics, and showed that sprawl is now a common characteristic of cities in this size class, not only of the metropolises.

Spatial and landscape metrics provide a more detailed description of urban form. Using a gradient and directional approach, Aithal and Ramachandra (2016) demonstrated that urban growth in Chennai proceeded outward along transport corridors and that the urban fringe was becoming increasingly fragmented. Ramachandra et al. (2015) used similar metrics for Bengaluru and linked the city's explosive growth to the loss of lakes and green spaces. In the Jharkhand context, Ahmad and Goparaju (2016) analysed urban sprawl in Ranchi, the state capital, and documented a substantial increase in built-up area accompanied by the conversion of agricultural and open land, a pattern that is broadly comparable to the growth reported around Jamshedpur.

Predictive modelling forms another important strand of the literature. Cellular automata, Markov chain and hybrid models use historical transitions together with driving variables such as distance to roads, slope and existing settlements to simulate future urban growth. Tripathy and Kumar (2019) used cellular automata to model the spatio-temporal growth of Delhi and project future urban extent. Mishra and Rai (2016) combined a multi-layer perceptron with Markov chain analysis to forecast LULC change in Patna district, while Hasnine and Rukhsana (2020) integrated sprawl analysis with prediction of future urban areas for an Indian city. Although such modelling has not yet been applied in depth to Jamshedpur, the methods are directly transferable and would help planners anticipate growth pressures on agricultural land, river corridors and forested hills. Table 3 summarises selected studies relevant to this review.



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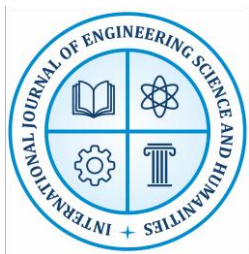
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Table 3: Summary of selected RS and GIS studies relevant to Jamshedpur

Author(s) and Year	Study Area	Data and Methods	Key Findings
Ranjan et al. (2016)	Dalma Wildlife Sanctuary, Jamshedpur	High-resolution imagery, 3S technology, change detection	Annual loss of very dense forest; increase in settlement and bare land
Ahmad & Goparaju (2016)	Ranchi, Jharkhand	Multi-temporal Landsat, sprawl analysis	Rapid built-up growth replacing agricultural and open land
Bhat et al. (2017)	Dehradun	Landsat, MLC, Shannon's entropy	Dispersed sprawl and loss of agricultural and vegetated land
Choudhury et al. (2019)	Asansol–Durgapur region	Landsat TM/OLI, LULC and LST	Industrial, mining and impervious areas recorded the highest LST
Chettry & Surawar (2021)	Eight mid-sized Indian cities	RS, GIS, entropy and landscape metrics	Sprawl is widespread in medium-sized Indian cities
Tripathy & Kumar (2019)	Delhi	Cellular automata, geoinformatics	Simulated future urban expansion for planning
Mondal et al. (2021)	Imphal	Landsat LST and spectral indices	Continuous UHI; strong positive LST–NDBI relationship

2.4 Environmental Consequences of Land Transformation

The environmental effects of LULC change in and around Jamshedpur are most clearly documented for forest cover. Ranjan et al. (2016) reported that very dense forest in the Dalma Wildlife Sanctuary declined by roughly 1.77 square kilometres per year between 2009 and 2016, while settlement and bare land expanded by about 1.69 and 7.37 square kilometres per year respectively. They attributed this degradation primarily to shifting cultivation, forest fires and settlement encroachment. Because Dalma functions as an important elephant habitat and a green buffer for the city, such losses have implications for wildlife movement, human–wildlife conflict and the ecological services that the hills provide to the urban area.



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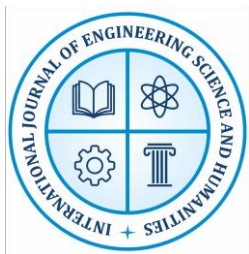
A second major consequence is surface warming. As vegetation and water bodies are replaced by concrete, asphalt and industrial surfaces, land surface temperature increases. In the Asansol–Durgapur Development Region, Choudhury et al. (2019) found that LST rose by about 0.06 °C per year in winter and 0.43 °C per year in summer, with impervious, industrial and coal mining areas reaching around 38 °C while vegetation and water bodies remained near 27 °C. Given its comparable industrial structure, a similar thermal pattern can be expected in Jamshedpur. Pal and Ziaul (2017) observed a close relationship between growth of built-up land and rising LST in the English Bazar urban centre, and Mathew et al. (2016) showed for Chandigarh that the percentage of impervious surface area is a strong determinant of surface temperature.

Spectral indices are commonly used to explain these thermal patterns. The normalised difference vegetation index (NDVI) usually shows a negative relationship with LST, reflecting the cooling effect of vegetation, whereas the normalised difference built-up index (NDBI) shows a positive relationship. Mondal et al. (2021) confirmed these relationships for Imphal over a thirty-year period and identified a persistent urban heat island in the central city. Pandey et al. (2024) compared nine land surface indices and reported that NDBI had a moderate to strong positive relationship with LST in both summer and winter, while all vegetation indices were negatively related. Methodological work on LST retrieval, including comparison of split-window and radiance-based algorithms, has helped standardise these analyses in Indian settings (Sahana et al., 2016).

Other consequences include the loss of fertile agricultural land at the urban fringe, the narrowing of river channels and floodplains through encroachment, and the fragmentation of green spaces within the city. Studies of Bengaluru and Dehradun have linked such changes to the disappearance of wetlands, increased runoff and reduced groundwater recharge (Bhat et al., 2017; Ramachandra et al., 2015). For Jamshedpur, the Subarnarekha and Kharkai river corridors are particularly vulnerable, yet systematic RS-based assessment of riverine land change, wetland loss and green space dynamics in the city is still largely absent from the published literature.

3. Conclusion

This review has examined the use of remote sensing and GIS for assessing urban expansion and LULC change, with a focus on Jamshedpur and comparable cities in India. cost-effective and increasingly sophisticated tools for understanding urban transformation. Multi-temporal Landsat imagery remains the backbone of historical analysis, while Sentinel-2 and high-resolution data provide greater detail for recent periods. Classification methods have evolved from maximum likelihood towards machine learning and deep learning approaches that offer higher accuracy in heterogeneous urban landscapes, and cloud platforms have made large-scale processing widely accessible.



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Across the reviewed studies, a consistent pattern emerges: built-up land is expanding rapidly at the expense of agricultural land, vegetation, forest and water bodies, and this expansion is increasingly dispersed rather than compact. These changes are associated with forest degradation, loss of ecosystem services and rising surface temperatures, with industrial and impervious areas forming the warmest zones. In the Jamshedpur region, the clearest evidence concerns the degradation of the Dalma forest on the northern urban fringe. However, comprehensive city-wide studies of urban growth, sprawl, thermal environment and riverine change in Jamshedpur remain scarce. Addressing this gap is important for a city that combines a historically planned core with rapidly growing and loosely regulated peripheral areas, and whose future depends on balancing industrial growth with environmental sustainability.

4. Future Work

Several directions for future research emerge from this review. First, there is a clear need for a comprehensive, city-wide LULC change assessment of the Jamshedpur Urban Agglomeration covering at least three to four decades, using consistent Landsat and Sentinel-2 data and modern machine learning classifiers. Such a study should include Adityapur, Mango, Jugsalai and the surrounding census towns so that growth beyond the planned core is fully captured.

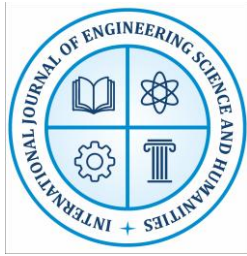
Second, predictive modelling using cellular automata, Markov chain, artificial neural network or hybrid approaches should be applied to simulate future growth scenarios for Jamshedpur. These scenarios would help planners identify areas at risk of conversion, particularly agricultural land, the river corridors and the foothills of Dalma.

Third, the thermal environment of the city deserves dedicated attention. Seasonal LST analysis, combined with NDVI, NDBI and urban thermal field variance indices, could map heat hotspots around industrial zones and dense settlements and evaluate the cooling role of parks and water bodies. Fourth, the integration of socio-economic and demographic data with satellite information would help explain the drivers of change, including migration, industrial investment and land markets.

Finally, future work should exploit emerging technologies such as Google Earth Engine, deep learning, night-time light data and very high-resolution imagery, and should assess urban ecosystem services, flood vulnerability along the Subarnarekha and Kharkai rivers and green infrastructure planning. Such research would provide an evidence base for sustainable and climate-resilient planning in Jamshedpur.

References

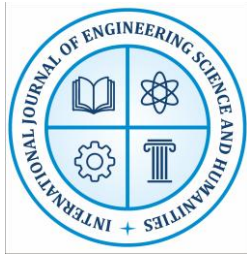
1. Ahmad, F., & Goparaju, L. (2016). Analysis of urban sprawl dynamics using geospatial technology in Ranchi City, Jharkhand, India. *Journal of Environmental Geography*, 9(1–2), 7–13. <https://doi.org/10.1515/jengeo-2016-0002>



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com **ISSN: 2250-3552**

2. Aithal, B. H., & Ramachandra, T. V. (2016). Visualization of urban growth pattern in Chennai using geoinformatics and spatial metrics. *Journal of the Indian Society of Remote Sensing*, 44(4), 617–633. <https://doi.org/10.1007/s12524-015-0482-0>
3. Belgiu, M., & Drăguț, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 114, 24–31. <https://doi.org/10.1016/j.isprsjprs.2016.01.011>
4. Bhat, P. A., Shafiq, M., Mir, A. A., & Ahmed, P. (2017). Urban sprawl and its impact on landuse/land cover dynamics of Dehradun City, India. *International Journal of Sustainable Built Environment*, 6(2), 513–521. <https://doi.org/10.1016/j.ijse.2017.10.003>
5. Chettry, V., & Surawar, M. (2021). Urban sprawl assessment in eight mid-sized Indian cities using RS and GIS. *Journal of the Indian Society of Remote Sensing*, 49(11), 2721–2740. <https://doi.org/10.1007/s12524-021-01420-8>
6. Choudhury, D., Das, K., & Das, A. (2019). Assessment of land use land cover changes and its impact on variations of land surface temperature in Asansol-Durgapur Development Region. *The Egyptian Journal of Remote Sensing and Space Science*, 22(2), 203–218. <https://doi.org/10.1016/j.ejrs.2018.05.004>
7. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
8. Gu, Z., & Zeng, M. (2024). The use of artificial intelligence and satellite remote sensing in land cover change detection: Review and perspectives. *Sustainability*, 16(1), Article 274. <https://doi.org/10.3390/su16010274>
9. Hasnine, M., & Rukhsana. (2020). An analysis of urban sprawl and prediction of future urban town in urban area of developing nation: Case study in India. *Journal of the Indian Society of Remote Sensing*, 48(6), 909–920. <https://doi.org/10.1007/s12524-020-01123-6>
10. Mathew, A., Khandelwal, S., & Kaul, N. (2016). Spatial and temporal variations of urban heat island effect and the effect of percentage impervious surface area and elevation on land surface temperature: Study of Chandigarh city, India. *Sustainable Cities and Society*, 26, 264–277. <https://doi.org/10.1016/j.scs.2016.06.018>
11. Mishra, V. N., & Rai, P. K. (2016). A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. *Arabian Journal of Geosciences*, 9, Article 249. <https://doi.org/10.1007/s12517-015-2138-3>
12. Mondal, A., Guha, S., & Kundu, S. (2021). Dynamic status of land surface temperature and spectral indices in Imphal city, India from 1991 to 2021. *Geomatics, Natural Hazards and Risk*, 12(1), 3265–3286. <https://doi.org/10.1080/19475705.2021.2008023>



International Journal of Engineering, Science and Humanities

An international peer reviewed, refereed, open-access journal
Impact Factor 8.3 www.ijesh.com **ISSN: 2250-3552**

13. Pal, S., & Ziaul, S. (2017). Detection of land use and land cover change and land surface temperature in English Bazar urban centre. *The Egyptian Journal of Remote Sensing and Space Science*, 20(1), 125–145. <https://doi.org/10.1016/j.ejrs.2016.11.003>
14. Pandey, A., Mondal, A., & Guha, S. (2024). Assess the relationship of land surface temperature with nine land surface indices in a northeast Indian city using summer and winter Landsat 8 data. *Cogent Engineering*, 11(1), Article 2382885. <https://doi.org/10.1080/23311916.2024.2382885>
15. Phiri, D., & Morgenroth, J. (2017). Developments in Landsat land cover classification methods: A review. *Remote Sensing*, 9(9), Article 967. <https://doi.org/10.3390/rs9090967>
16. Ramachandra, T. V., Bharath, H. A., & Sowmyashree, M. V. (2015). Monitoring urbanization and its implications in a mega city from space: Spatiotemporal patterns and its indicators. *Journal of Environmental Management*, 148, 67–81. <https://doi.org/10.1016/j.jenvman.2014.02.015>
17. Ranjan, A. K., Anand, A., Vallisree, S., & Singh, R. K. (2016). LU/LC change detection and forest degradation analysis in Dalma Wildlife Sanctuary using 3S technology: A case study in Jamshedpur-India. *AIMS Geosciences*, 2(4), 273–285. <https://doi.org/10.3934/geosci.2016.4.273>
18. Sahana, M., Ahmed, R., & Sajjad, H. (2016). Analyzing land surface temperature distribution in response to land use/land cover change using split window algorithm and spectral radiance model in Sundarban Biosphere Reserve, India. *Modeling Earth Systems and Environment*, 2, Article 81. <https://doi.org/10.1007/s40808-016-0135-5>
19. Talukdar, S., Singha, P., Mahato, S., Shahfahad, Pal, S., Liou, Y.-A., & Rahman, A. (2020). Land-use land-cover classification by machine learning classifiers for satellite observations—A review. *Remote Sensing*, 12(7), Article 1135. <https://doi.org/10.3390/rs12071135>
20. Tripathy, P., & Kumar, A. (2019). Monitoring and modelling spatio-temporal urban growth of Delhi using Cellular Automata and geoinformatics. *Cities*, 90, 52–63. <https://doi.org/10.1016/j.cities.2019.01.021>