



Multi-Sensor Land-Use and Land-Cover Mapping Using Synthetic Aperture Radar and Optical Data over the Himalayan Foothills



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Abstract: In this research, both Synthetic Aperture Radar (SAR) and optical satellite data are used independently to evaluate the urban expansion, thermal change (Land Surface Temperature (LST)/Urban Heat Island (UHI)), and particulate air quality (PM₁₀) ten-year forecasts for Dehradun, Uttarakhand, India for the decade 2014–2024. The Sentinel-1 C-band SAR data (backscatter amplitude σ^0 and interferometric coherence γ) provide a cloud-penetrating and structurally-based evaluation of urban extent. The data used include Landsat-8 OLI/TIRS, which are used for supervised classification of land use and land cover (LULC) by maximum likelihood. The maximum likelihood classification (MLC) and LST retrieval using Mono-Window Algorithm (MWA). The both sensors are processed through independent analytical pipelines and offering corroborating lines of evidence for urban change. The results show important environmental changes: There was an increase in urban area of +28.3 km² (+3.9%). agricultural land increased by +55.9 km² (+8.15%), while forest cover declined sharply by -83.1 km² (-12.05%)—figures with area adjusted uncertainty estimates. The mean LST increased by $\sim$ +3.0 °C over the study transect, with mean annual air temperature rising from 21.22 °C to 24.21 °C (+14.1%), which is in line with the rise in temperature at the station, confirming intensification of the Surface Urban Heat Island (SUHI). The concentration of PM₁₀ at all the three Central Pollution Control Board (CPCB) monitoring stations it was consistently found that levels of SO₂ exceeded the national annual standard for India (60 μ g/m³) by 2.5–2.7 times throughout the study period. These are analyzed in a framework of Environmental Impact Assessment (EIA), which links to Identified land cover change to environmental impact pathways, management implications and policies Himalayan Mountain cities suggestions for urban planning, green space protection and air quality control.

Keywords: Land Surface Temperature; Land use and land cover; Synthetic Aperture Radar; Urban Heat Island; Sentinel-1; Landsat-8; PM₁₀; Environmental Impact Assessment

1 Introduction

Urbanization has become one of the most transformative forces acting on the Earth’s land surface, and its consequences are felt most acutely in ecologically sensitive mountain environments, where limited developable land, steep terrain, and fragile forest and hydrological systems amplify the impact of even modest built-up expansion. The Himalayan foothills of northern India epitomise this tension: they sustain exceptional biodiversity and critical ecosystem services while experiencing some of the fastest urban growth rates in the country. Dehradun, the capital of Uttarakhand, is a representative Class-I city within this belt, and understanding how its recent expansion has reshaped land cover, surface temperature, and air quality is essential for evidence-based planning. The present study addresses this need by integrating Synthetic Aperture Radar (SAR) and optical satellite observations to characterize a decade of environmental change (2014–2024) in Dehradun within an Environmental Impact Assessment framework, so that the observed remote-sensing signals can be translated into actionable management and policy insight for mountain cities.

The study is guided by four testable hypotheses. First, that rapid urban expansion in Dehradun over 2014–2024 has occurred predominantly at the expense of forest cover rather than of agricultural or barren land. Second, that this land-cover transformation has produced a measurable increase in land surface temperature and an intensification of the surface urban heat island. Third, that urbanisation, acting together with the valley’s topographically driven

boundary-layer inversions, has elevated particulate (PM_{10}) concentrations to levels exceeding national ambient air-quality standards. Fourth, that independent SAR and optical processing pipelines yield mutually corroborating evidence of urban change, thereby improving the reliability of urban detection in a cloud-prone and topographically complex Himalayan setting. The remainder of this section establishes the scientific and regional context for these hypotheses and sets out the specific objectives of the study.

1.1 Rapid Urbanization in Dehradun and the Himalayan Foothills

The Urbanization is one of the strongest reshaping land systems of the twenty first century and it has a strong impact in ecologically sensitive areas. This dichotomy is well illustrated by the foothills of the Himalayas in the north of India—extremely rich in biodiversity, perennial rivers and forests and undergoing one of the fastest urbanization rates in the country. The capital of Uttarakhand state, Dehradun is located in the Doon Valley at the foot of the Shivalik Range, has become one of the fastest growing Class-I cities in the Indian Himalayas [1]. The extent of transformation in Dehradun is clearly established. Urbanization increases by over 80% in the last 20 years (1991–2018) according to the remote sensing studies and mean surface temperature has increased significantly in all land use classes [2]. The proportion of built-up area in the district has grown from 1.4% to 8.9% of the total district area from 2013 to 2023 [3]. The Delhi-Dehradun Expressway, Jolly Grant Airport expansion and Haridwar Bypass are other major infrastructure projects that have further speeded up land surface change and exacerbated slope instability [4]. Integrated environmental impact monitoring, therefore, has an exceptional urgency and scientific interest in Dehradun.

1.2 The Mountain-City Environmental Context

Urbanization is one of the most important drivers of land systems change in the 21st century and particularly pronounced in environmentally vulnerable areas. For a city built into a mountain and valley environment, physical context is a critical constraint on the nature of the environment and has to be considered as a starting point for the interpretation of remote sensing results. Dehradun is located in the Doon Valley at roughly 400–700 m above sea-level, bounded to the north (i.e., in the direction of the valley) by the Main Himalayan Thrust (MHT) or the Mussoorie ridge (which reaches over 2,000 m above sea-level), bounded to the south and east by the Shivalik Hills. This bowl-shaped topography has 3 direct implications for the dynamics of the environment studied here. The reliability of urban detection using backscatter data is affected by SAR geometric distortion in the northern and eastern boundary of the study area, which introduces layover (N facing slopes towards the Mussoorie ridge) and shadow (S facing slopes), respectively. First, geometric distortion of the SAR such as layover (N facing slopes towards the Mussoorie ridge) and shadow (S facing slopes) affects the reliability of urban detection in the northern and eastern boundary of the study area, respectively. These effects have been taken explicitly into consideration when calibrating the thresholds, and validation points in the urban area have been chosen with particular attention to terrain affected areas. Second, there is a strong elevation and aspect dependence of Land Surface Temperature (LST) patterns over Dehradun, with northern hillslopes away from the solar incidence showing: There are persistent decreases in the LST away from urbanization and increases in the LST towards urbanization on south facing slopes. Thirdly, Dehradun's valley topography favours formation of thermal inversions and trapping of pollutants: cool air sinks down into the valley from the ridges surrounding the city leading to the formation of stable boundary layers which trap PM_{10} close to the ground [5, 6]. As discussed in Section 5.5, the highest PM_{10} levels are always observed at the Inter State Bus Terminus (ISBT) site, located in an area where air circulation is limited, consistent with the topographic trapping mechanism. Urban expansion has taken place along three main corridors in Dehradun: (i) northward up to Rajpur and towards the foot of Mussoorie (i.e. from dense mixed forest and forest fringe land); (ii) eastward up to Nathuwala and Saudasaroli, along the Rishikesh highway (i.e. from periurban agricultural and scrub land to unplanned low-density settlement); and (iii) southward along the Haridwar Road up to Doiwala (i.e. from periurban agricultural and scrub land to unplanned low-density settlement) Class-1 agricultural land. These corridors are directly identified in the site-specific hotspot analysis (Section 5.2) and the policy recommendations are outlined in the Discussion (Section 5.6). Key protected forest areas that are within the Rajaji National Park buffer zone to the southeast, the Shivalik Elephant Reserve and the Forest Research Institute (FRI) campus are ecological boundaries where the integrity is directly threatened by the documented expansion patterns.

1.3 Interconnected Environmental Stressors: Land Use and Land Cover, Land Surface Temperature, Urban Heat Island, and PM_{10}

Rapid urbanization's impacts on the environment is interlinked stressors. However, with the change of vegetated surfaces and agriculture surfaces to impervious built-up surfaces, latent heat flux reduces, sensible heat flux increases and LST increases [7, 8]. The Surface Urban Heat Island (SUHI) effect is caused by elevated LST, which is calculated here using the Urban Thermal Field Variance Index (UTFVI) and has implications for energy consumption, heat-related morbidity and ecological integrity at forest edge. Along with this, urban expansion also puts a strain on air quality, with the loss of vegetated cover that naturally filters and absorbs particulates, along with the generation of vehicular

emissions and construction dust [9, 10]. The valley topography of Dehradun also contributes to PM₁₀ accumulation by the thermally-driven boundary layer inversions, which were not previously investigated in this city [3].

1.4 Research Gaps and Study Objectives

Four specific gaps motivate this study: (1) no prior study has applied SAR data to urban change monitoring in Dehradun or any comparable Himalayan foothill city; (2) no study has simultaneously analyzed land use and land cover (LULC) change, LST/SUHI dynamics, and PM₁₀ trends within a single spatially coherent framework for Dehradun; (3) existing studies lack site-specific analysis of named urban-forest transition hotspots; and (4) the Discussion limiting its relevance for urban planners, environmental regulators, and the wider remote-sensing and environmental-sustainability research community.

The specific objectives of this study are: (i) to analyze LULC dynamics, LST/UHI variability, and PM₁₀ trends in Dehradun from 2014 to 2024; (ii) to utilize Sentinel-1 SAR and Landsat-8 optical data independently for mapping urban expansion and deriving surface and vegetation parameters; and (iii) to develop an integrated environmental impact and policy discussion linking observed remote sensing results to planning and management recommendations for mountain cities.

2 Related Work

This section reviews four thematic areas directly relevant to the present study: SAR-based urban mapping, LULC classification algorithms, LST retrieval methods, and the LULC–LST–PM₁₀ nexus in Indian and mountain-city contexts. The review is structured to justify methodological choices and identify empirical gaps the present study addresses.

2.1 Synthetic Aperture Radar-Based Urban Mapping: Methods, Strengths, and Limitations

SAR data have become increasingly important for urban mapping in cloud-prone environments [11, 12]. Sentinel-1 C-band SAR offers globally consistent, freely accessible data exploited via backscatter intensity (σ°) and interferometric coherence (γ). Table 1 compares key SAR-based urban mapping approaches.

Table 1. Comparison of Synthetic Aperture Radar (SAR)-based urban mapping approaches and justification for method adopted in this study

Method	Strength	Limitation	Best Use Case	Key References
Backscatter σ° thresholding	High; double-bounce from buildings	Orientation-sensitive; misclassifies forested slopes	Binary urban/non-urban mask; cloud-free monitoring	[12, 13]
Coherence γ thresholding	Temporal stability of built-up surfaces; robust to speckle	Requires SLC pairs; baseline sensitive to vegetation type	Urban change detection over short baselines	[14, 15]
Backscatter + Coherence combined	Complementary evidence; reduces commission/omission errors	Requires both amplitude and phase data	Urban footprint extraction in complex terrain [This study]	[12, 16]
ML (RF/SVM) on SAR	Highest overall accuracy (86%–92%); multi-class	Requires labelled SAR training data; computationally intensive	Large-area mapping with abundant training samples	[17, 18]
Deep Learning (CNN)	Highest accuracy; context-aware	Requires very large labelled datasets; GPU-intensive	City-scale mapping with dense training data	[11]

Note: SLC, Single Look Complex; ML (RF/SVM), Machine Learning (Random Forest/Support Vector Machine); CNN, Convolutional Neural Network.

Backscatter-based urban detection exploits the double-bounce scattering mechanism from building wall-ground interfaces [12, 19] demonstrated this approach in undulating terrain—directly comparable to Dehradun’s Shivalik foothills—finding that a coherence threshold of 0.5 achieved optimal class separation, while thresholds above 0.6–0.7 over-excluded periurban areas. Combining backscatter and coherence provides complementary evidence that neither observable alone can supply [16]. No prior study of Dehradun has applied SAR data in any form; all existing work relies exclusively on optical Landsat data [2, 20, 21].

2.2 Land Use and Land Cover Classification: Maximum Likelihood Classification vs. Support Vector Machine vs. Random Forest

Table 2 compares the three most widely used supervised classifiers and justifies the selection of maximum likelihood classification (MLC) for this study. Chowdhury [22] confirmed that MLC achieves Kappa values of 0.83–0.87 for South Asian city LULC mapping, compared to RF at 0.88–0.91—a difference statistically insignificant for five spectrally well-separated classes. MLC was selected for three reasons: (1) all published Dehradun LULC studies [2, 20, 23] use MLC enabling direct temporal comparison; (2) the Doon Valley’s five LULC classes are spectrally well-separated with reported Kappa values of 0.85–0.93; and (3) MLC requires no hyperparameter tuning, making results reproducible.

Table 2. Comparison of supervised classification algorithms and justification for maximum likelihood classification (MLC) selection

Algorithm	Typical Overall Accuracy	Key Strength	Key Limitation	Best Use Case
Maximum likelihood classification (MLC)	82%–86%	Parametric; interpretable; no hyperparameter tuning; consistent across Landsat time-series	Assumes multivariate normal distribution; lower accuracy in heterogeneous landscapes	Small-medium areas; spectrally well-separated classes; temporal comparison studies [This study]
Support Vector Machine (SVM)	87%–90%	Effective in high-dimensional space; handles non-normal distributions	Kernel tuning required; sensitive to training sample quality	Medium-large areas; complex spectral overlap
Random Forest (RF)	88%–92%	Handles high dimensionality; built-in feature importance; robust to noise	Requires larger training sets; prone to overfitting with small samples	Large-area mapping; multi-source data; plentiful training samples

2.3 Land Surface Temperature Retrieval Algorithm Comparison and Mono-Window Algorithm Selection

Jiang and Lin [24] confirmed that all four algorithms produce spatially consistent LST distributions suitable for UHI analysis. Mono-Window Algorithm (MWA) was selected because it requires only Band 10 (avoiding TIRS Band 11 calibration uncertainty), uses freely available ERA5 atmospheric transmittance inputs, has been validated in comparable Indian Himalayan settings [25] $r^2 > 0.87$ in Beas River Basin), and is consistent with all comparable Dehradun LST studies. Table 3 compares four LST retrieval algorithms from Landsat-8 TIRS and justifies selection of the MWA.

Table 3. Comparison of Land Surface Temperature (LST) retrieval algorithms from Landsat-8 and justification for Mono-Window Algorithm (MWA) selection

Algorithm	Abbrev.	Typical Root Mean Square Error	Key Limitation	Use Case/Selection Rationale
Radiative Transfer Equation	RTE	0.5–1.0 K	Requires full atmospheric profile; upwelling/downwelling radiance	Most accurate when atmospheric sounding data available
Mono-Window Algorithm	MWA	0.7–1.2 K	Sensitive to emissivity errors; requires atmospheric transmittance	Requires only Band 10; ERA5 transmittance freely available; validated in India [This study]
Split-Window Algorithm	SWA	0.5–0.9 K	TIRS Band 11 calibration uncertainty limits accuracy	Accurate when Band 11 calibration reliable (Landsat-9 preferred)
Single-Channel Algorithm	SCA	0.8–1.5 K	Highest uncertainty; not recommended for high-humidity subtropical conditions	Simple quick estimates only; not recommended for precision studies

2.4 Land Use and Land Cover–Land Surface Temperature Relationships and Urban Heat Island Studies in Dehradun

Normalized Difference Vegetation Index (NDVI) consistently shows negative correlation with LST (Pearson $r = -0.78$ to -0.55) in Indian urban study [8]. NDBI shows strong positive correlation with LST ($r = +0.55$ to $+0.74$) [22]. For Dehradun specifically, Mishra and Garg [2] confirmed that mean LST of built-up land is 5–8 °C higher than forested areas across all seasons (1991–2018). Mishra and Arya [20] found that UTFVI values increased significantly in newly urbanized zones (2014–2021). Gupta et al. [21] established that urbanization is the dominant driver of LST increase in Himalayan cities. No existing study simultaneously quantifies LULC change, SUHI dynamics, and PM₁₀ for Dehradun within a common framework.

2.5 Air Quality, Land Use and Land Cover Change, and Urban Topography

Statistically significant positive correlations established between built-up area expansion and PM₁₀ concentrations across North Indian cities including Uttarakhand [9]. Nabik et al. [10] found that a 10% increase in built-up area was associated with a 6–8 $\mu\text{g}/\text{m}^3$ rise in annual mean PM₁₀. Dhankar et al. [3] confirmed built-up expansion as the primary driver of declining air quality in Dehradun district (2019–2023). The UHI–PM₁₀ interaction is bidirectional: UHI can enhance convective mixing, dispersing pollutants [26], but in mountain valley settings like Dehradun, terrain-driven boundary layer inversions can trap pollutants and elevate PM₁₀ under stable atmospheric conditions [5, 6]. This specific mechanism has not been previously examined for Dehradun.

2.6 Identified Gaps

Four gaps are addressed by this study: (1) no SAR-based urban analysis for Dehradun or any Himalayan foothill city; (2) no tri-variable LULC + LST/UHI + PM₁₀ integration for Dehradun; (3) no site-specific transition analysis at named urban-forest boundary hotspots; and (4) prior Dehradun studies lack an EIA framing, limiting their direct relevance to environmental management and policy.

3 Data and Study Area

3.1 Study Area: Dehradun, Uttarakhand

Mussoorie at 700–800 m, which is experiencing a natural recovery of forest. This enclosed valley depicted in Figure 1 as Dehradun sub-district map, topography can be demarcated into three key microclimatic zones pertinent to this study: (a) the densely built urban core (Clock Tower, Paltan Bazaar, ISBT corridor) with maximum impervious cover and highest PM₁₀ and LST values; (b) the transitional periurban belt (Rajpur, Nathuwala, Sahstradhara) where the urban-forest conversion is actively taking place; and (c) the forested hillslope zone (Mussoorie) where the natural recovery of forest is taking place.

This study's baseline thermal and ecological reference site is the above 650 m approach, Rajaji buffer, and FRI campus. The urban growth in the period 2014–2024 was mostly located in zone (b), as evidenced by the hotspot analysis conducted at the site scale (Section 5.2). The following key land-management and development-pressure factors in the study area are identified: (i) the Dehradun Master Plan; (ii) urban expansion; (iii) improper waste disposal; (iv) pollution; (v) traffic congestion; and (vi) weak and underdeveloped infrastructure.

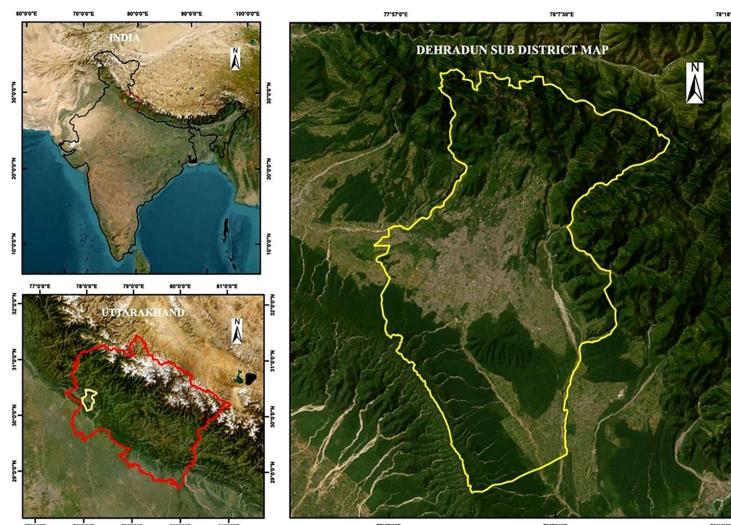


Figure 1. Dehradun subdistrict map

Source: <https://www.arcgis.com/home/item.html?id=10df2279f9684e4a9f6a7f08febac2a9>.

Wooded areas have been protected by Plan 2041 (Draft) since 2001, but have not influenced deforestation on the fringes of the city; the Forest Conservation Act 1980, although it provides nominal protection for classified forests, does not appear to have stopped fringe deforestation as reported in this study; the Delhi-Dehradun Expressway Project (NH-72A) has fast-tracked periurban settlements to the southwest from the city since 2019; and FRI campus and Indian Military Academy (IMA) to the northwest have limited urban sprawl to the north and east.

3.2 Sentinel-1 Synthetic Aperture Radar Dataset

Four Single Look Complex (SLC) products in Interferometric Wide (IW) mode were used from the ESA Copernicus Programme, providing Vertical transmit, Vertical receive (VV) polarization at 10 m spatial resolution. Two images were acquired for each temporal phase (2014 and 2024) to enable coherence estimation and temporal comparison as shown in Table 4. The 2014 acquisitions used VV polarization only (consistent with early Sentinel-1A single-polarization operations). The 2024 acquisitions provide both VV and Vertical transmit, Horizontal receive (VH) polarizations.

Table 4. Details of Sentinel-1 Synthetic Aperture Radar (SAR) Single Look Complex (SLC) products used in the study for the years 2014 and 2024

Year	Product ID	Acquisition Date	Polarization	Mode
2014	S1A_IW_SLC__1SSV_20141022T004258_20141022T004325_002935_003549_5A4B	22 Oct 2014	VV	IW
2014	S1A_IW_SLC__1SSV_20141209T004257_20141209T004324_003635_0044E3_2841	09 Dec 2014	VV	IW
2024	S1A_IW_SLC__1SDV_20240127T004401_20240127T004428_052285_065240_4C29	27 Jan 2024	VV, VH	IW
2024	S1A_IW_SLC__1SDV_20240408T004402_20240408T004429_053335_067783_8085	08 Apr 2024	VV, VH	IW

Note: VV, Vertical transmit, Vertical receive; IW, Interferometric Wide; VH, Vertical transmit, Horizontal receive.

3.3 Landsat-8 Optical Data

Landsat-8 Collection 2 Level-1 Top of Atmosphere (L1TP) data was downloaded from USGS Earth Explorer (Path/Row 146/039) for December 2014 and April 2024 to minimize cloud cover and to capture similar dry season conditions as shown in Table 5. The LULC classification was performed on OLI Bands 2–7 (30 m) and the LST retrieval was performed on OLI TIRS Band 10 (resampled to 30 m from native 100 m). A decadal comparison with the same time of the year (December or April) for both acquisitions (2014 and 2024) also reduces the inter-seasonal LST bias.

Table 5. Specifications of Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) datasets used for the years 2014 and 2024

Year	Satellite/Sensor	Product ID	Path/Row	Acquisition Date	Bands Used	Spatial Resolution
2014	Landsat-8 OLI/TIRS	LC08_L1TP_146039_20141206_20200911_02_T1	146/039	06 Dec 2014	Bands 2–7 (OLI), Band 10 (TIRS)	30 m (OLI), 100 m (TIRS)
2024	Landsat-8 OLI/TIRS	LC08_L1TP_146039_20240409_20240421_02_T1	146/039	09 Apr 2024	Bands 2–7 (OLI), Band 10 (TIRS)	30 m (OLI), 100 m (TIRS)

3.4 Reproducibility and Processing Configuration

To ensure that the dual-sensor workflow can be independently reproduced, Table 6 consolidates the full processing configuration adopted in this study, including the software packages and versions, the SAR and optical pre-processing chains, the backscatter and coherence thresholds used for urban delineation, the classification and land-surface-temperature retrieval settings, and the specifications of every data product employed. Reporting these parameters in a single reference table addresses a recurring limitation of comparable Himalayan-foothill studies, where incomplete methodological disclosure prevents replication. The thresholds and settings listed were fixed a priori and applied uniformly across all epochs, so that the observed decadal changes reflect genuine surface dynamics rather than inconsistencies in processing.

3.5 Justification of Methodological Choices

Each principal methodological decision in this study was made deliberately in view of the study area's terrain, data availability, and the intended environmental-impact application, rather than by default. Table 7 sets out, for every major step, the option selected, the credible alternatives considered, and the reason the chosen approach

was preferred: the use of independent SAR and optical pipelines to provide mutually corroborating evidence of urban change; Maximum Likelihood classification for its robustness on modest, manually labelled training sets; the Mono-Window Algorithm for single-band land-surface-temperature retrieval from Landsat-8; and the terrain-aware calibration of backscatter and coherence thresholds to mitigate layover and shadow over the surrounding ridges. Presenting these trade-offs explicitly allows readers to judge the reliability of the results and to adapt the workflow to other mountain-city contexts.

Table 6. Processing parameters for Synthetic Aperture Radar (SAR) and optical data analysis

Parameter	Value/Description	Source/Reference
Software	SNAP 9.0 (SAR); ArcGIS 10.5 (optical LULC, LST); QGIS 3.28 (validation overlays)	–
SAR data product level	Level-1 SLC (Single Look Complex); IW mode; VV polarization (2014); VV+VH (2024)	ESA Copernicus Open Access Hub
Optical data product level	Landsat-8 Collection 2 Level-1 Top-of-Atmosphere (L1TP); Path/Row 146/039	USGS Earth Explorer
Projection/CRS	WGS84 UTM Zone 44N (EPSG:32644) for all outputs	–
Atmospheric correction (Landsat)	DOS-1 (Dark Object Subtraction) for reflective OLI bands; no atmospheric correction applied to TIRS Band 10 beyond radiometric calibration—consistent with MWA protocol	[24, 27]
Resampling method	Bilinear interpolation for spatial resampling of TIRS Band 10 from 100 m to 30 m	SNAP/ArcGIS default
NDVImin/NDVImax	NDVImin = 0.2 (bare soil threshold); NDVImax = 0.5 (full vegetation threshold); derived from 95th/5th percentile of study-area NDVI histogram per scene	[28]
LST output units	Kelvin (K) computed, converted to degrees Celsius (°C) for reporting: $LST(^{\circ}C) = LST(K) - 273.15$	–
SAR coherence window size	11 × 3 pixels (range × azimuth)—standard for Sentinel-1 IW SLC over urban areas	[29]
MLC training sample size	Minimum 50 polygons per class; 2014 and 2024 scenes classified independently using contemporaneous training samples from Google Earth Pro imagery of corresponding years	[30]
LULC classes	5 classes: Forest, Urban/Built-up, Barren/Agricultural Land, River Sediment, Water Bodies	–
SAR urban mask threshold	Mean backscatter > -10 dB and coherence > 0.6 → Urban (1); else Non-urban (0)	[12, 13]
Output spatial resolution	30 m (LULC, LST); 10 m (SAR urban mask, resampled to 30 m for integration)	–
Accuracy assessment	Confusion matrix with 100 stratified random validation points; Overall Accuracy and Kappa coefficient reported; area-adjusted uncertainty notes provided in Section 5.2	[30]

Note: CRS, coordinate reference system; NDVI, Normalized Difference Vegetation Index; LST, Land Surface Temperature; MLC, maximum likelihood classification; LULC, land use and land cover; IW, Interferometric Wide; VV, Vertical transmit, Vertical receive; OLI, Operational Land Imager; MWA, Mono-Window Algorithm; TIRS, Thermal Infrared Sensor. A dash (–) denotes not applicable.

Table 7. Methodological justification—Comparison of methods and rationale for choices made

Method Used	Why This Method	Why Not the Alternative	Supporting Literature
Sentinel-1 SAR σ° + coherence thresholding	Cloud-penetrating; Himalayan monsoon makes optical-only monitoring unreliable. Provides structural evidence independent of solar illumination.	SAR-only ML classifiers: require multi-class labelled SAR training data unavailable for Dehradun. SAR used here as binary urban mask only.	[12, 13, 16]
σ° threshold: -10 dB; coherence > 0.6	Histogram bimodal inflection at -10 dB. Coherence > 0.6 validated against 30 ground-reference points across 5 land cover classes.	Global fixed thresholds (e.g. -12 dB) misclassify Himalayan Mountain-facing slopes; local calibration required.	[12–14]
MLC for Landsat-8 LULC classification	Direct comparability with all prior Dehradun studies. Five spectrally well-separated classes. No hyperparameter tuning required.	RF/SVM: training samples >200/class unavailable for 2014 baseline; prevents temporal comparison with Dehradun literature baseline.	[22, 31, 32]
Mono-Window Algorithm for LST	Requires only Band 10 (avoids TIRS Band 11 uncertainty). ERA5 transmittance and NDVI-based emissivity freely available. Validated in comparable Himalayan setting.	SWA: Band 11 calibration issues. RTE: full atmospheric sounding unavailable for 2014. SCA: highest RMSE in humid subtropical conditions.	[24, 33]
UTFVI for SUHI quantification	Standardized dimensionless index enabling spatial and inter-temporal comparison. Widely adopted in Dehradun and Indian urban studies.	LST anomaly mapping alone does not provide normalized urban–rural contrast; not comparable across different scenes or seasons.	[2, 20, 34]

Note: SAR, Synthetic Aperture Radar; MLC, maximum likelihood classification; LULC, land use and land cover; LST, Land Surface Temperature; UTFVI, Urban Thermal Field Variance Index; SUHI, Surface Urban Heat Island; TIRS, Thermal Infrared Sensor; NDVI, Normalized Difference Vegetation Index; SVM, Support Vector Machine; RF, Random Forest.

4 Methodology

The metropolitan footprint mapping methodology applies Sentinel-1 SAR and Landsat-8 optical data through independent analytical streams as depicted in Figure 2, which are subsequently cross-validated. SAR pre-processing involves noise removal, geometric correction using the Copernicus 30 m DEM, co-registration, coherence estimation, logarithmic scaling, and thresholding to produce an urban binary mask. The Landsat-8 stream applies DOS-1 atmospheric correction to reflective bands, radiometric calibration of TIRS Band 10, NDVI-based emissivity estimation, and four-step MWA LST retrieval. Both streams are projected to WGS84 UTM Zone 44N at 30 m output resolution for integration and comparative validation.

4.1 Sentinel-1 Synthetic Aperture Radar Pre-Processing

4.1.1 Image splitting, orbit correction, and calibration

With minimal computation, the study area was covered by using the burst-based processing [35, 36]. Small orbital distortions were corrected using Precise Orbit Files (ESA POD). The radiometrically calibrated images were used to calculate the Sigma Naught (σ°) backscatter coefficient applying Eq. (1).

$$\sigma^\circ = \frac{P_{\text{transmitted}}}{P_{\text{received}}} \cdot G \cdot A \quad (1)$$

where,

P_{received} = power received by the radar, $P_{\text{transmitted}}$ = transmitted power, G = antenna gain, A = area on the ground corresponding to a pixel.

The imagery was orthorected and layover and shadow effects were reduced from the Shivalik foothill terrain by applying terrain correction to it using the Copernicus 30 m DEM [37].

4.1.2 De-bursting, multi-looking, and logarithmic scaling

De-burster combines burst segments into a single image. Multi-looking ($1 \times$ azimuth, $3 \times$ range) was used to reduce speckle but maintain spatial resolution [38]. The dynamic range of the signals was compressed into dB and

the threshold was identified using the histogram, shown in Figures 3a and 3b.

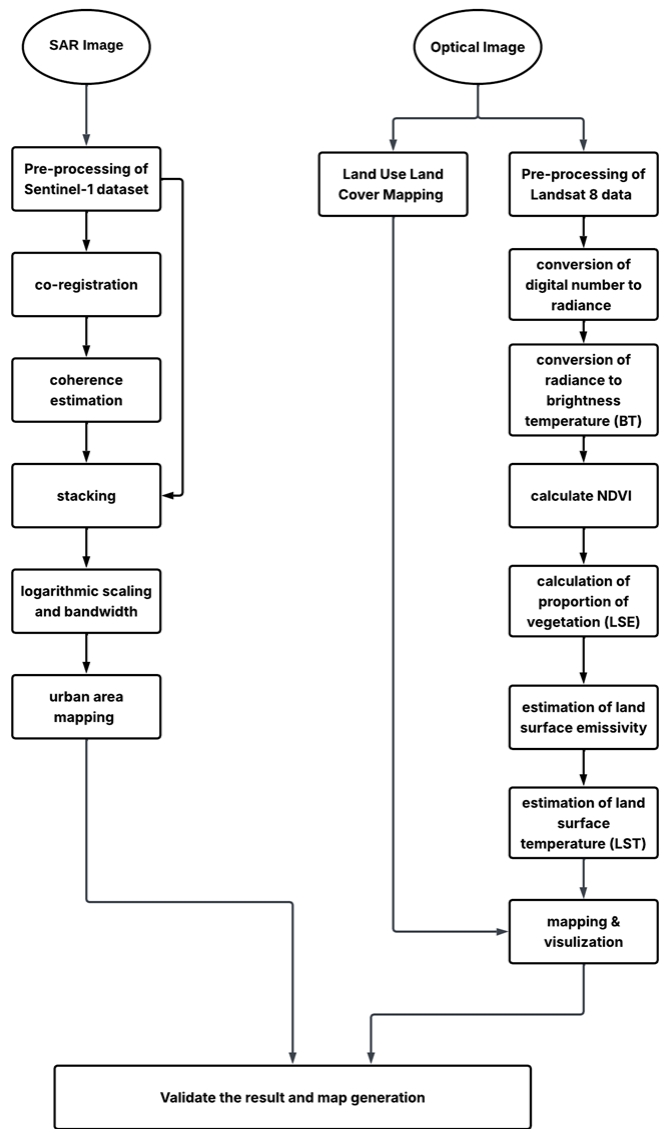


Figure 2. Methodology workflow

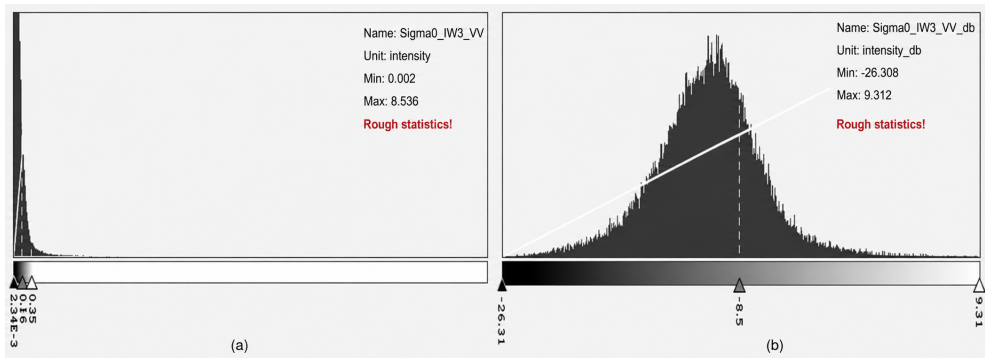


Figure 3. (a) Histogram of Sigma nought image; (b) Histogram of converted sigma nought image to decibels (dB)

4.1.3 Coherence estimation and urban mask extraction

The interferometric coherence (γ) was calculated from complex SLC data pairs with an estimation window of 11×3 pixels (Eq. (2)).

$$\gamma = \frac{|E[S_1 S_2^*]|}{\sqrt{E[|S_1|^2] \cdot E[|S_2|^2]}} \quad (2)$$

where, S_1 and S_2 are complex pixel values of the two images, S_2^* is the complex conjugate of S_2 , E denotes local ensemble averaging over a spatial window.

Visual interpretation was done in Figure 4 using a false-color RGB composite (coherence = Red, mean σ° = Green, σ° difference = Blue). The binary threshold was used to isolate urban areas: mean backscatter > -10 dB and coherence $> 0.6 \rightarrow$ Urban (1); else non-urban (0). The two thresholds were adjusted by histogram analysis and verified by 30 ground reference points, and separated validation was done in each terrain affected area (northern slopes) to compensate for SAR geometric distortion effects.

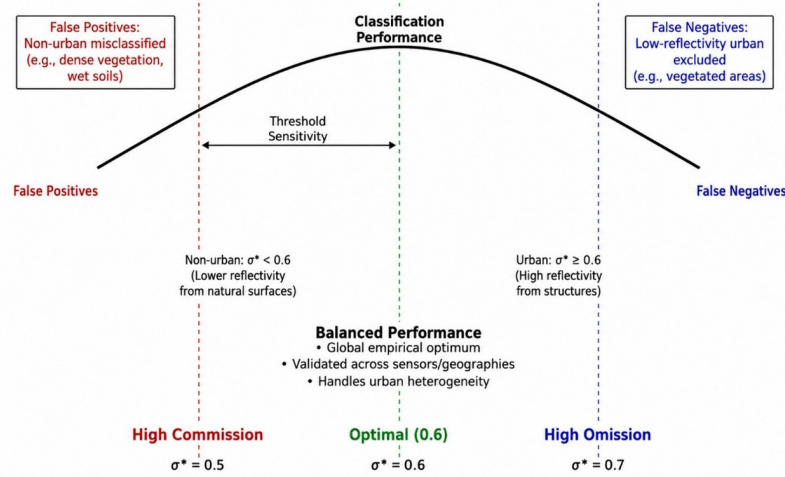


Figure 4. Threshold optimization for urban classification using backscatter coefficient (σ°)

4.2 Optical Image Pre-Processing and Land Use and Land Cover Classification

The Landsat-8 framework consisted of three steps: (1) pre-processing, which involved processing of the reflective bands of Landsat-8 (Bands 2–7) using the DOS-1 atmospheric correction algorithm; (2) LULC classification through MLC by five classes with at least 50 polygons per class in each year (2014 and 2024 independently) as reflected in Figure 5; and (3) accuracy assessment by a 990-point stratified random confusion matrix.

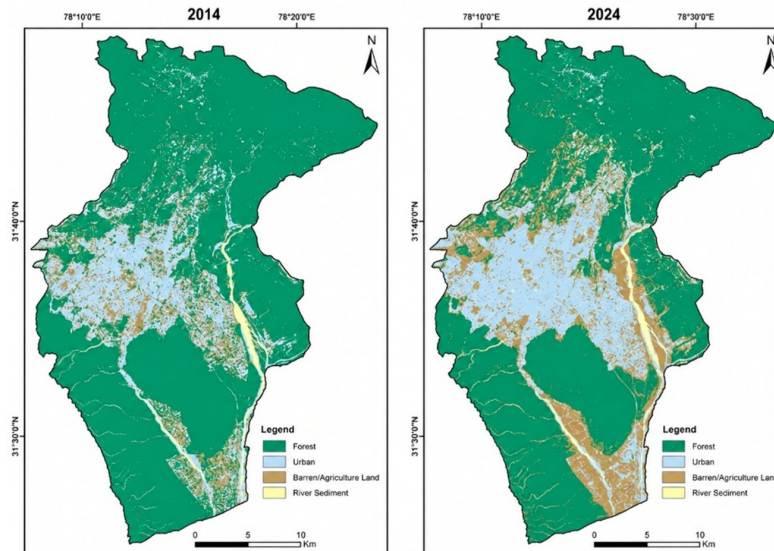


Figure 5. Land use land cover (LULC) classification using Optical Dataset of year 2014 and 2024

4.3 Land Surface Temperature Retrieval—Mono-Window Algorithm

The LST retrieval followed a four-step MWA procedure.

Step 1: Radiometric calibration converted TIRS Band 10 Digital Numbers to spectral radiance L_λ using band-specific rescaling coefficients from Landsat metadata (Eq. (3)).

$$L_\lambda = M_L Q_{CAL} + A_L \quad (3)$$

where,

L_λ = Spectral radiance ($\text{W}/\text{m}^2 \cdot \text{sr} \cdot \mu\text{m}$),

M_L = Band-specific multiplicative rescaling factor (metadata-derived),

Q_{CAL} = Quantized pixel value (DN),

A_L = Band-specific additive rescaling factor (metadata-derived).

Step 2: Brightness temperature (T_B) was derived from L_λ using the inverse Planck function (Eq. (4)).

$$T_B = \frac{K_2}{\ln \left(\frac{K_1}{L_\lambda} + 1 \right)} \quad (4)$$

where,

T_B = at-sensor brightness temperature (Kelvin),

K_1, K_2 = Thermal constants from Landsat metadata,

L_λ = Spectral radiance (from previous step).

Step 3: Land surface emissivity (ϵ) was estimated from the NDVI-based vegetation proportion (P_v) using the threshold-based method of study [28]: $\text{NDVI}_{\min} = 0.2$, $\text{NDVI}_{\max} = 0.5$ (Eqs. (5) and (6)).

$$\epsilon = 0.004P_v + 0.986 \quad (5)$$

$$P_v = \left(\frac{\text{NDVI} - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}} \right)^2 \quad (6)$$

where,

ϵ = Land surface emissivity (unitless),

P_v = Vegetation proportion,

NDVI = Normalized Difference Vegetation Index.

Step 4: LST in Kelvin was retrieved using Eq. (7) with $\lambda = 10.8 \mu\text{m}$ (TIRS Band 10) and converted to degrees Celsius for reporting ($\text{LST } (^\circ\text{C}) = \text{LST}_K - 273.15$).

$$\text{LST} = \frac{T_B}{1 + \left(\frac{\lambda \cdot T_B}{\rho} \right) \cdot \ln \epsilon} \quad (7)$$

where,

LST = Land surface temperature (K),

λ = Wavelength of emitted radiance ($10.8 \mu\text{m}$ for Band 10),

ρ = Combined physical constant ($1.438 \times 10^{-2} \text{ m} \cdot \text{K}$) here h is Planck's constant, c is light speed, and σ is Boltzmann's constant.

According to this method, LST maps were created in the years 2014 (Figure 6a) and 2024 (Figure 6b), which illustrate the thermal distribution patterns of the study area in Figure 6.

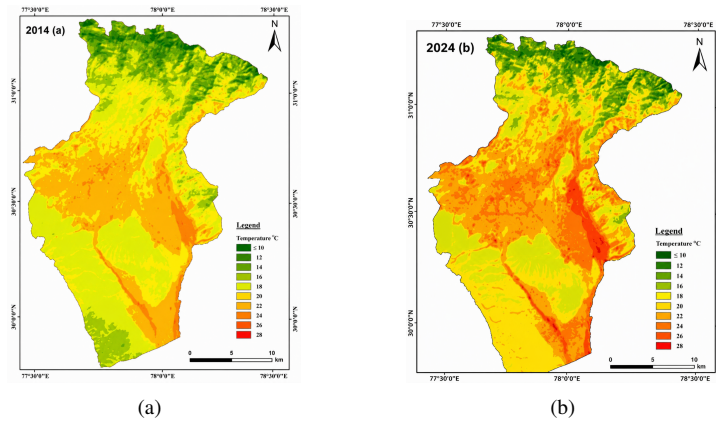


Figure 6. (a) Land Surface Temperature map of the year 2014; (b) Land Surface Temperature map of the year 2024

5 Result and Discussion

5.1 Synthetic Aperture Radar-Based Urban Change Detection

The Sentinel-1 processed images clearly demonstrate urban expansion between 2014 and 2024. The 2024 urban mask shows a substantially larger white-classified area than the 2014 mask (Figure 7a and Figure 7b), particularly along the Rajpur corridor to the north and the Nathuwala-Saudasaroli corridor to the east. The Composite RGB SAR image confirms these patterns through complementary backscatter and coherence signals (Figure 7c and Figure 7d). In mountain-facing slopes to the north, SAR layover artifacts were identified and excluded from the urban mask through terrain-aware threshold calibration—a step that is particularly important in the Dehradun context given the steep northward elevation gradient toward the Mussoorie ridge.

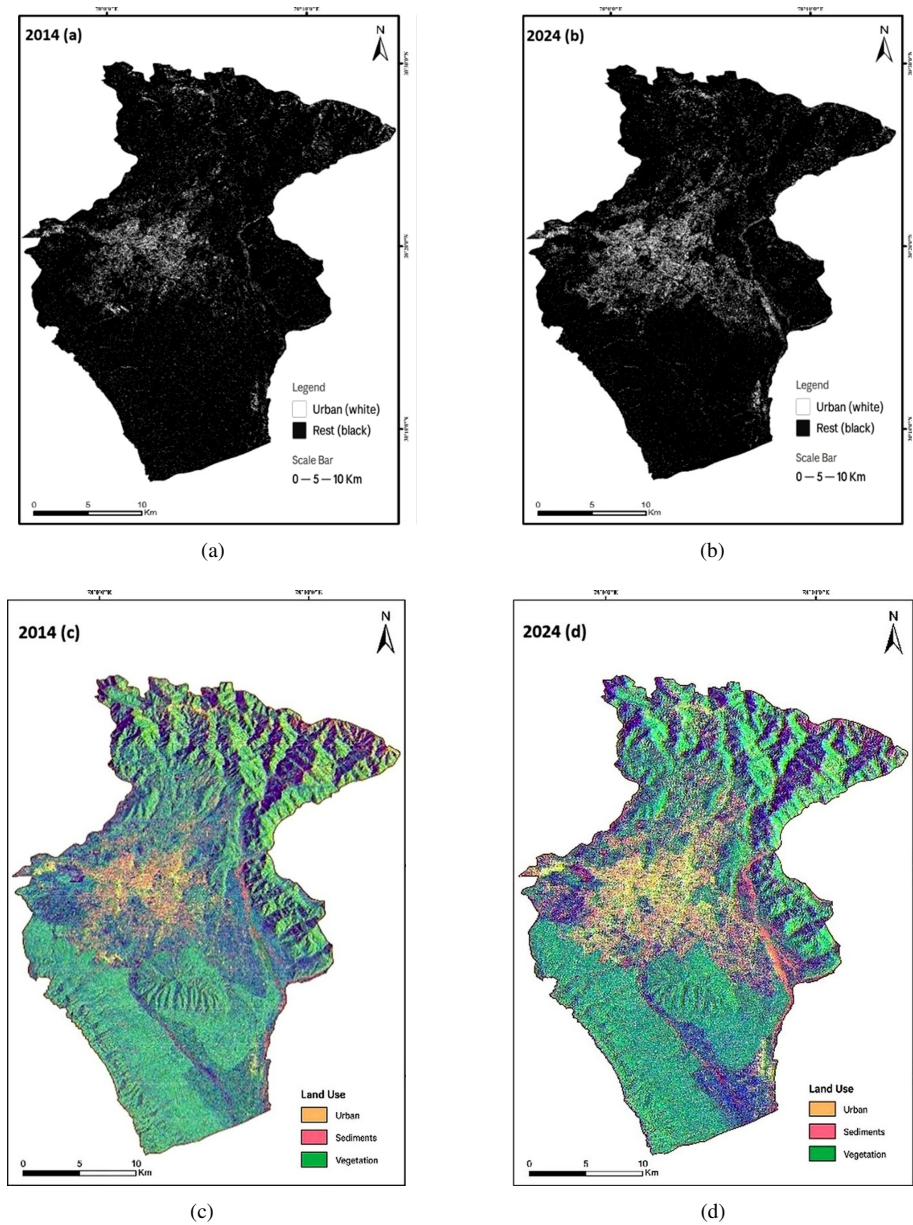


Figure 7. (a) Urban Mask 2014; (b) urban Mask 2024 respectively; (c) color composite Synthetic Aperture Radar image of year 2014; (d) color composite Synthetic Aperture Radar image of year 2024

5.2 Land Use and Land Cover Change (2014–2024): Results and Uncertainty

The quantified LULC data reveal the following changes between 2014 and 2024: urban area expanded by +28.3 km² (+3.9%); agricultural land increased by +55.9 km² (+8.15%); forest cover declined by -83.1 km² (-12.05%); and river sediment area remained stable (-1.2 km²). Overall classification accuracy is 91% (Kappa = 0.84). The quantified data in Figure 8a and Figure 8b reveals significant land cover changes between 2014 and 2024.

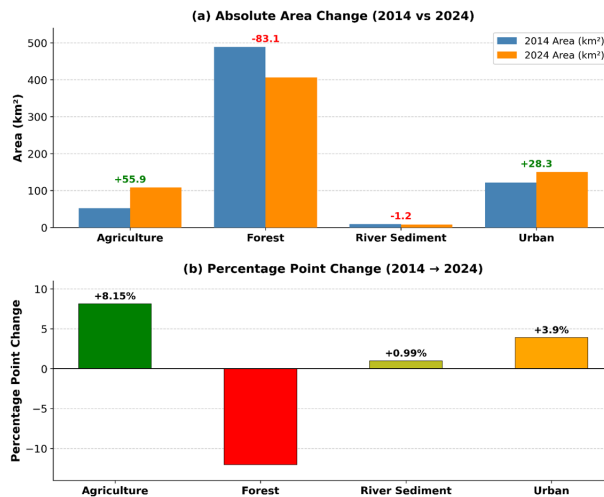


Figure 8. (a) Absolute area change showing variations in agriculture, forest, river sediment, and urban classes; (b) percentage point change highlighting the proportional increase in agriculture and urban areas, and a notable decrease in forest cover

These area figures carry classification uncertainty that must be explicitly acknowledged. Based on the confusion matrix Table 8, the producer's accuracy for forest is 83.3% and for Urban is 95.1%, implying that forest area may be marginally underestimated and urban area marginally overestimated.

Table 8. Confusion matrix (Landsat-8 dataset)

Class Value	Forest	River_Sed	Urban	Barren Land	Total	U_Accuracy	Kappa
Forest	280	3	5	37	325	0.861538	–
River_sed	0	38	0	0	38	1.000000	–
Urban	2	3	175	3	183	0.956284	–
Barren land	54	0	4	386	444	0.869369	–
Total	336	44	184	426	990	–	–
P_accuracy	0.833333	0.863636	0.951087	0.906103	–	0.8879	–
Kappa	–	–	–	–	–	–	0.830000

Note: A dash (–) denotes no data.

The large agricultural expansion (+55.9 km²) is the figure most susceptible to classification confusion: in the Doon Valley, barren land, fallow agricultural fields, and sparse scrub can be spectrally similar under dry-season Landsat conditions, and misclassification between these classes is the primary source of error. Cross-validation against the Dehradun district revenue records and the land-use dataset confirms the direction of change (forest loss and urban expansion) but suggests the agricultural expansion figure should be interpreted as an upper bound that includes some reclassification from barren land [3]. Area-adjusted confidence intervals would reduce the apparent agricultural gain by an estimated 10%–15%, though the forest loss and urban expansion figures are robust to this correction. The forest loss figure of -83.1 km² is furthermore consistent with study [4], who documented over 420 hectares of dense forest loss in Dehradun district using independent high-resolution imagery.

Site-specific validation at four named hotspots confirms the spatial distribution of these changes as depicted in Figures 9a–9d. At Sahstradhara (SA), deforestation and riparian zone urbanization are documented between 2013 and 2024, consistent with tourist infrastructure development along the Rispana River corridor. At Rajpur Area (RA), significant deforestation at the urban-forest boundary marks the city's northward expansion toward the Shivalik foothills and Rajaji National Park buffer zone.



Figure 9. (a) Land-use transition patterns assessments of Sahstradhara (Site-SA); (b) deforestation Rajpur area (Site-RA); (c) new urban development at Dhanaulti (Site-DA); (d) rapid urban settlement at Nathuwala and Saudasaroli (Site-NSA)

5.3 Land Surface Temperature and Surface Urban Heat Island

During the study transect (a–a’) in Figure 10a and Figure 10b the mean LST was found to have risen by about 3.0 °C between 2014 and 2024. Peak urban core LST for 2014 was around 22 °C, with a decrease towards rural edges. In 2024, the peak temperature along the same transect was about 25 °C and the thermal gradient increased in the urbanized area (4 km to 14 km). Mean annual temperature shown in Figure 11 rose from 21.22°C to 24.21°C (+14.1%); average maximum, from 28.69 °C to 31.20 °C (+8.7%); and average minimum, from 15.55 °C to 18.82 °C (+21.0%) (IMD station data for Dehradun [39]).

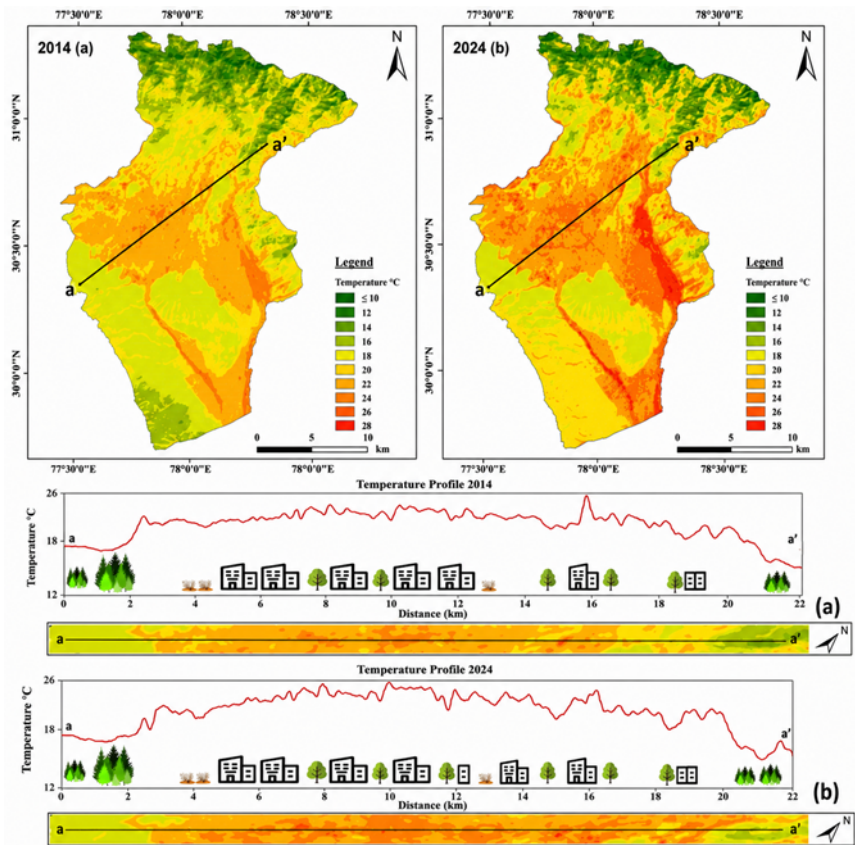


Figure 10. (a) Temperature profile along the line a to a’ of year 2014; (b) temperature profile along the line a to a’ of year 2024

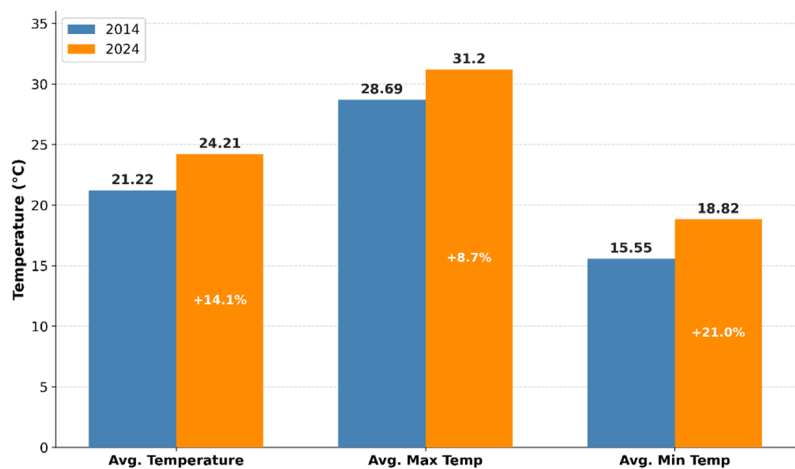


Figure 11. Climate data analysis of study region (2014 and 2024)
Source: Tutiempo Network, S.L., 2014 (<https://en.tutiempo.net/climate/ws-421110.html>).

The increase in the thermal gradient from the urban core to the hillslope covered with forests indicates SUHI intensification. Forested areas (particularly the FRI campus and the Rajaji buffer areas) continue to be 4–6 °C cooler than the urban core, highlighting the importance of these areas as thermal refuges. Nevertheless, the boundaries of these cooling zones are being degraded by deforestation reported in Section 5.2, which can be seen as a feedback loop that sees the loss of forest cover leading to an increase in local cooling, leading to an increase in the LST of adjacent urban areas [21, 40].

5.4 Synthetic Aperture Radar Limitations in Mountain Terrain

Several SAR-specific limitations are relevant to the Dehradun mountain setting. Layover and shadow on north-facing slopes toward the Mussoorie ridge—where the terrain rises steeply from 500 m to over 2,000 m within 10–15 km—can create false urban signals or mask actual urban features. Signal penetration constraints in vegetated periurban zones (Rajpur, Sahstradhara) reduce the detection sensitivity for low-density built-up areas embedded in tree cover. These limitations were partially mitigated through terrain-aware threshold calibration, but they represent a genuine constraint on SAR-based urban detection accuracy in the northern fringe of the study area. The 10 m Sentinel-1 spatial resolution is insufficient for fine-scale analysis of individual building clusters, making the SAR mask best suited for neighbourhood-scale urban boundary delineation rather than plot-level mapping.

5.5 Air Quality (PM₁₀) Trends and Topographic Context

Figure 12 shows annual PM₁₀ at Clock Tower (CT-Site 1) averaged 152 $\mu\text{g}/\text{m}^3$ in 2014 and 181 $\mu\text{g}/\text{m}^3$ in 2023, with a post-2020 increasing trend. Raipur Road (RR-Site 2) showed extreme inter-annual volatility, ranging from 80.3 $\mu\text{g}/\text{m}^3$ (2020 lockdown) to 483 $\mu\text{g}/\text{m}^3$ (June 2016 regional dust event). ISBT (HD-Site 3) consistently recorded the highest levels, with annual averages of 237 $\mu\text{g}/\text{m}^3$ (2015) and 288 $\mu\text{g}/\text{m}^3$ (2016), remaining at 184 $\mu\text{g}/\text{m}^3$ in 2023. By 2023, all three stations converged within 150–162 $\mu\text{g}/\text{m}^3$ (three-year moving average), uniformly exceeding India's national annual PM₁₀ standard of 60 $\mu\text{g}/\text{m}^3$ by 2.5–2.7 times [41].

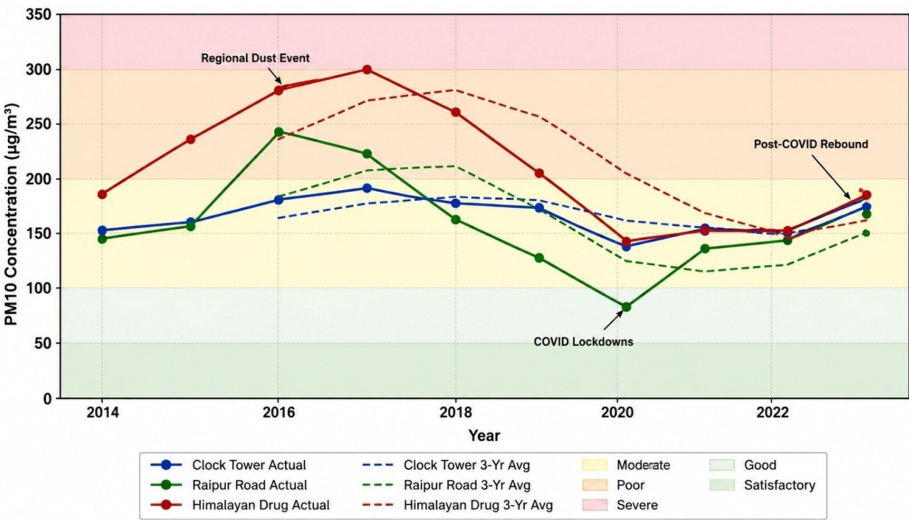


Figure 12. PM₁₀ trends: actual vs. 3-year moving averages (2014–2023)

These patterns are crucial to understanding in the context of topography. The ISBT site is at a low-lying node at the intersection of three main traffic routes (NH-72A, NH-7 and Ring Road), and is surrounded by commercial development which limits the natural ventilation. Cold air drainage from surrounding ridges under stable atmospheric conditions during the winter (November to February) season forms shallow boundary layers, which lead to lower levels of vehicle emissions and construction dust in the atmosphere. The winter peaks recorded (such as 389 $\mu\text{g}/\text{m}^3$ at ISBT in January 2016, and 222 $\mu\text{g}/\text{m}^3$ at Clock Tower in December 2015) are consistent with this terrain-related inversion mechanism, and are exacerbated by the nocturnal urban core-hilltop cooling contrast that is enhanced by SUHI [5, 6]. The 2020 lockdown has resulted in a 66% decline in PM₁₀ at Raipur Road, which has been attributed to the reduction of vehicular emissions.

5.6 Environmental Impact Assessment and Policy Implications

The findings related to EIA framework, summarized in Table 9.

Table 9. Environmental Impact Assessment (EIA) framework—Linking observed changes to impact pathways and policy recommendations

Environmental Stressor (Observed)	Environmental Impact Pathway	Recommended Policy/Management Action	Key References
Forest loss -83.1 km ² (-12.05%)	Loss of carbon sequestration, biodiversity habitat, slope stabilization, and hydrological regulation in Shivalik foothills	Notify forest loss hotspots (Rajpur, Sahstradhara corridors) under Forest Conservation Act 1980; restrict construction permits within 500 m of forest boundary	[2, 4]
Urban expansion +28.3 km ² (+3.9%)	Increased impervious cover → elevated surface runoff, flood risk, LST rise, and loss of groundwater recharge zones	Enforce Dehradun Master Plan 2041 FAR limits; mandate 20% green cover ratio in new development zones; zone eastern corridor as growth-restricted	[1, 3]
Agricultural expansion +55.9 km ² (+8.15%)	Potential confusion with forest conversion; reduces open natural land; increases surface roughness heterogeneity affecting PM ₁₀ dispersion	Cross-verify with Revenue Department land records; protect Class-1 agricultural land under Land Acquisition Act; restrict periurban farmland conversion	[32]
LST increase ~3.0°C; mean temp +14.1%	Urban Heat Island intensification → increased heat-related morbidity, energy demand for cooling, and ecological thermal stress at forest margins	Mandate green roofs and cool pavement in new commercial zones; expand tree canopy along NH-72A and Ring Road corridors; set 30% tree cover target for new layouts	[21, 40]
PM ₁₀ exceedance 2.5–2.7 times national standard annually	Respiratory health burden disproportionately affecting vulnerable populations near ISBT, Clock Tower, and Raipur Road transport hubs	Implement low-emission zones around Clock Tower and ISBT; enforce BS-VI vehicle standards strictly; require real-time CPCB data integration in city air-quality dashboard	[5, 9, 41]

5.6.1 Urban planning and development control

Urban expansion documented as +28.3 km² in the last 10 years (2014–2024)—largely along the Rajpur and Nathuwala corridors—suggests that the urban expansion controls of the Dehradun Master Plan 2041 are not being realised in the periurban fringe. Satellite-derived urban masks as generated with SAR-optical in this example would provide an effective, up-to-date monitoring tool for development control authorities for detecting unauthorized development before it is too late. The Uttarakhand City and Country Planning Department should enforce a minimum green cover ratio of 20% in all new development layouts of area more than 5 hectares and provide a buffer of 500 m around the documented deforestation fronts of the city (Rajpur, Sahstradhara). As the Delhi-Dehradun Expressway corridor is fast gaining momentum towards southwestward periurban development, it is recommended to develop a specific environmental impact monitoring programme, based on the integrated SAR-optical approach developed in this study.

5.6.2 Green space protection and urban forest management

A 10-year decrease of 83.1 km² of forest cover is an alarming ecological limit for a city that relies on surrounding forests to regulate the climate, stabilize the slopes, recharge the ground water, and maintain forest connectivity. From a practical point of view, the loss of this forest is the same as removing the cooling effect of about 4.2 million mature

trees, which highlights the failure of the traditional urban tree planting program. Protection of the residual forest fringe, particularly the Rajpur forest corridor connecting FRI campus to Rajaji National Park and the Sahstradhara riparian corridor should be designated as an ecological priority zone in which the Forest Conservation Act 1980 must be stringently enforced. Urban greening in the thermal hotspot zones (Clock Tower, Paltan Bazaar, ISBT) through strategic tree canopy installation along major road corridors could reduce peak summer LST by an estimated 1.5–2.5 °C, consistent with findings from comparable Indian cities.

5.6.3 Air quality management

The persistent exceedance of PM₁₀ national standards by 2.5–2.7 times at all three stations requires urgent regulatory intervention. Three recommendations are directly supported by the data. First, establishing a low-emission zone in the ISBT–Clock Tower corridor—where topographic trapping compounds vehicular emission concentrations—would address the most critical pollution hotspot. The COVID-19 lockdown’s 66% PM₁₀ reduction at Raipur Road confirms that traffic-source controls can produce rapid, large-magnitude improvements. Second, accelerating the transition to electric public transport on the NH-72A and Ring Road corridors—the primary arterials generating vehicle-emission PM₁₀ at the ISBT site—is the highest-impact single intervention available. Third, integrating real-time CPCB air quality data with LST and LULC change monitoring in a unified city environmental dashboard would enable authorities to respond to compound risk periods (winter inversion episodes combined with high PM₁₀) through temporary traffic restriction orders.

5.6.4 Replicability for other Himalayan Mountain cities

The integrated SAR-optical-thermal-pollution monitoring workflow presented in this study can be directly replicated to other comparable cities on the foothills of the Himalayas, such as Mussoorie, Nainital, Shimla, Srinagar (J&K) and Gangtok, which have similar urbanization pressure, monsoon cloud cover limitation for optical monitoring, and topographic influences on thermal and air quality dynamics. The parameter table (Table 4) and methodological justification table (Table 5) are standardized templates which may be modified for each city’s particular terrain configuration and data availability. The EIA approach in Table 6 can also be used to organize policy-relevant mountain urban development authorities’ environmental reporting.

6 Conclusions

The environment in Dehradun has undergone a lot of change over the past decade, which is between 2014 and 2024. Urban area expanded by +28.3 km² (+3.9%) and agricultural land by +55.9 km² (+8.15%), at the direct cost of forest cover, which declined by 83.1 km² (12.05%). The mean LST has been increased in this urban transect by LULC changes, with a documented increase of around 3.0 °C; similarly, the mean annual temperature has risen by 14.1% from 21.22 to 24.21, which clearly demonstrates the intensification of SUHI. All three monitoring sites showed PM₁₀ concentrations to be 2.5–2.7 times higher than the annual standard set by the national air quality policy of India, with PM₁₀ pollution being the highest in the winter season due to the terrain-induced inversion layer at the ISBT site. These results are complementary: Forest removal decreases the urban cooling, which in turn increases SUHI, and increases PM₁₀ buildup during stable conditions in the urban boundary layer.

This study makes four contributions. First, it is the first to apply Sentinel-1 SAR data, processed independently of optical data through separate analytical pipelines—for urban change monitoring in Dehradun. Second, it is the first to simultaneously integrate LULC change, LST/SUHI dynamics, and PM₁₀ trends within a single spatially coherent framework for this city. Third, it provides site-specific land-use transition analysis at four named hotspot locations that directly support targeted planning decisions. Fourth, it develops these findings within an EIA framework that connects remote sensing outputs to environmental impact pathways and policy recommendations for urban planning, green-space protection, and air-quality management in Himalayan Mountain cities—directly addressing the environmental impact, management meaning, and policy relevance.

Limitations of the current study include the use of only two temporal snapshots (2014 and 2024), which precludes year-by-year trend analysis and cannot resolve the contribution of inter-annual climate variability to LST change; the classification uncertainty in the agricultural land expansion figure (Section 5.2); and the inherent constraints of Sentinel-1 C-band SAR in steeply sloping terrain (Section 5.4). Future work should address these limitations through: (i) annual LULC and LST mapping using full Landsat time-series or Sentinel-2 composites to separate urbanization-driven change from inter-annual climate variability; (ii) additional PM₁₀ indicators (PM_{2.5}, NO₂, O₃) from expanded CPCB monitoring; (iii) ground-based LST validation using portable thermal radiometers at the four hotspot sites; and (iv) finer-resolution SAR data (ALOS-2 PALSAR-2 L-band or future NISAR L-band acquisitions) to improve urban detection accuracy in vegetated periurban zones and steeply sloping terrain. NISAR is identified here as a future data source that could substantially improve detection capabilities; it has not been used or evaluated in the present study.

Author Contributions

Conceptualization, P.J. and N.M.; methodology, P.J.; software, A.B.; validation, P.J. and N.S.; formal analysis, P.J.; investigation, P.J.; resources, N.S. and P.J.; data curation, P.J.; writing—original draft preparation, P.J.; writing—review and editing, N.S. and P.J.; visualization, P.J.; supervision, N.S.; project administration, P.J. All authors have read and agreed to the published version of the manuscript.

Data Availability

The datasets underlying this study are summarised in the below table, derived products generated in this study are provided as supplementary files.

Dataset	Description	Source/Access
Landsat-8 OLI/TIRS imagery (2014, 2024)	Two scenes, Path/Row 146/039: LC08_L1TP_146039_20141206 (06 Dec 2014) and LC08_L1TP_146039_20240409 (09 Apr 2024), Bands 2–7 and Band 10, used for LULC classification and LST retrieval.	USGS EarthExplorer, https://earthexplorer.usgs.gov/
Sentinel-1 SAR (SLC) scenes (2014, 2019, 2024)	Six IW SLC products (single- and dual-polarisation) acquired on 22 Oct 2014, 09 Dec 2014, 02 Oct 2019, 19 Nov 2019, 27 Jan 2024 and 08 Apr 2024, used for backscatter and interferometric-coherence analysis of urban extent.	Copernicus Data Space Ecosystem, https://dataspace.copernicus.eu/ ; also via Alaska Satellite Facility, https://search.asf.alaska.edu/
Ambient air-quality records (2014–2024)	Annual monitoring data for Dehradun CPCB stations (AQI Data.zip and per-year PDF files, 2014–2024), used for the PM ₁₀ trend analysis.	Central Pollution Control Board (CPCB), https://cpcb.nic.in/ and https://airquality.cpcb.gov.in/
LULC area-calculation statistics	Area_Cal_14.xlsx and Area_Cal_24.xlsx — class-wise area calculations and statistical analysis of LULC classes for 2014 and 2024.	Generated in this study; provided as supplementary files
Study-area vector data	Shapefile.zip and associated files (ddn.shp, .shx, .dbf, .prj, .sbn, .sbx) defining the study-area boundary and coordinate reference system for spatial analysis.	Prepared in this study; provided as supplementary files
Accuracy and temperature data	Confusion_Matrix.xlsx (producer/user accuracy, overall accuracy and Kappa coefficient) and Temp data 2014 & 2024.xlsx (temperature data and comparative analysis for 2014 and 2024).	Generated in this study; provided as supplementary files

Conflicts of Interest

The authors declare no conflicts of interest.

Declaration on the Use of Generative AI and AI-assisted Technologies

During the preparation of this work the author(s) used generative AI in order to improve the language of the article. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Nomenclature

P_{received}	Power received by the radar
$P_{\text{transmitted}}$	Transmitted power
G	Antenna gain
A	Area on the ground corresponding to a pixel
S_1 and S_2	Complex pixel values of the two images
S_2^*	Complex conjugate of S_2
E	Local ensemble averaging over a spatial window
ML	Band-specific multiplicative rescaling factor (metadata-derived)
QCAL	Quantized pixel value (DN)
AL	Band-specific additive rescaling factor (metadata-derived)
T_B	Brightness temperature
K_1, K_2	Thermal constants from Landsat metadata
NDVI	Normalized Difference Vegetation Index
LST	Land Surface Temperature (K)

Greek symbols

σ°	Backscatter coefficient
γ	Interferometric coherence
L_λ	Spectral radiance ($\text{W}/\text{m}^2 \cdot \text{sr} \cdot \mu\text{m}$)
ε	Land surface emissivity (unitless)
P_v	Vegetation proportion
λ	Wavelength of emitted radiance ($10.8 \mu\text{m}$ for Band 10)
ρ	Combined physical constant ($1.438 \times 10^{-2} \text{ m} \cdot \text{K}$); here h is Planck's constant, c is light speed, and σ is Boltzmann's constant