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Illuminating Change: Using Satellite Nighttime Lights to Track Human Footprints in India's Protected Area Buffers

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ABSTRACT

This study assesses increasing human activity in Ecologically Sensitive Zones (ESZs) surrounding India's Protected Areas (PAs) using NASA's Black Marble Nighttime Light (NTL) data processed through Google Earth Engine (GEE). Radiance trends were analysed during dry-season months (February-May) across 631 ESZs for 2013, 2018, and 2023, with statistical validation using high-resolution imagery. Results show statistically significant increases ($p < 0.05$) in artificial illumination across 84% of ESZs, with mean radiance increases of 234% in high-growth zones. Statistical analysis reveals that infrastructure development and tourism are primary drivers, with 89% of ESZs showing spatial expansion of anthropogenic influence covering an additional 847 km² over the study period. The analysis highlights both regional disparities and common trends, such as intensified radiance along highways and around pilgrimage or tourist sites. By integrating NTL trends with administrative boundaries and land-use datasets, the study demonstrates how remotely sensed illumination data can complement conventional field assessments, offering a rapid, repeatable, and cost-effective tool for detecting emerging development pressures. The findings not only highlight areas where conservation interventions are urgently needed, but also illustrate the utility of NTL-based monitoring for urban and rural sustainability planning. This further supports evidence based decision making, regulating permissible development in ESZs, and fostering coexistence between human settlements and critical ecosystems.

1. INTRODUCTION

Urban expansion into ecologically sensitive landscapes is an increasingly urgent concern in the context of biodiversity conservation and sustainable development. In India, Ecologically Sensitive Zones (ESZs), designated buffer areas typically extending upto 10 km around the boundaries of Protected Areas (PAs). They are legally intended to regulate development so as to safeguard the ecological integrity of these habitats. The Ministry of Environment, Forests and Climate Change (MoEF & CC) in India mandates that activities within ESZs are categorized as prohibited, regulated, or permissible, with the aim of preventing unplanned urbanization from reaching PA borders, preserving wildlife corridors, and reducing human-wildlife conflict. Despite these regulatory provisions, many ESZs are experiencing increasing anthropogenic pressures from infrastructure development, tourism, and settlement expansion. Monitoring such changes presents distinct challenges in PAs and their surrounds. In surrounding ESZs, urban expansion often manifests as small, scattered households interspersed with forest or agricultural land. The dense vegetation cover, particularly in tropical and subtropical zones, obscures these small scale settlements in conventional multispectral satellite imagery, making them difficult to detect with standard land cover classification techniques. Moreover, the heterogeneous land use patterns within ESZs, ranging from villages and pilgrimage sites to tourist lodges, require fine-scale, consistent, and temporally frequent monitoring to capture subtle yet ecologically significant changes.

In this context, nighttime light (NTL) remote sensing, particularly with calibrated, high resolution datasets such as NASA's Black Marble (VNP46A2) and VIIRS-DNB, offers unique advantages. NTL data directly capture artificial illumination from human settlements and infrastructure, regardless of vegetation cover, enabling the detection of dispersed habitation and low intensity development that may be invisible in daytime imagery. These datasets provide daily to monthly composites at spatial resolutions fine enough to detect changes in settlement extent, road lighting, and other anthropogenic activities over time. For ESZs, this capability allows for a near real time, repeatable, and cost effective means of tracking human activity, assessing compliance with development regulations, and informing adaptive management strategies.

The knowledge gap lies in integrating multisource NTL datasets with ecological and regulatory contexts to comprehensively monitor growth in sensitive landscapes where conventional remote sensing struggles to detect small, dispersed settlements under forest canopy.

This study addresses three critical gaps: (1) absence of systematic NTL analysis across India's entire ESZ network, (2) lack of standardized protocols for anthropogenic pressure detection in vegetated buffer zones, and (3) insufficient integration of remote sensing with ESZ regulatory frameworks. Our objectives are to: (1) quantify spatiotemporal changes in artificial illumination across 631 Indian ESZs (2013-2023), (2) validate NTL-based change detection against high-resolution imagery, and (3) provide evidence-based recommendations for ESZ monitoring and management.

The present study addresses this gap by applying NASA's Black Marble NTL data, processed through Google Earth Engine, to assess the spatiotemporal trends in human activity across 631 ESZs in India during 2013, 2018, and 2023. By focusing on the dry season months (February–May) and applying radiance filtering to reduce noise from atmospheric and vegetation effects, the analysis isolates trends linked to human habitation and infrastructure.

The remainder of this paper is organized as follows. Section 2 outlines the study area and data sources, Section 3 details the processing workflow, Section 4 presents the results while Section 5 discusses the implications of these findings for

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regulated development within ESZs. Finally, Section 6 summarizes the key conclusions and outlines recommendations for future research and policy application.

2. STUDY AREA AND DATA SOURCES

2.1 Study Area

India's Protected Areas (PAs) span a total of 178,640.69 km², comprising 106 National Parks, 573 Wildlife Sanctuaries, 220 Community Reserves, and 123 Conservation Reserves. Surrounding each PA is an Ecologically Sensitive Zone (ESZ), designated under the Environment (Protection) Act, 1986, generally extending up to 10 km from the PA boundary. This study encompasses 631 ESZs across India. India's ESZs encompass diverse biogeographic zones from tropical rainforests in the Western Ghats to cold deserts in Ladakh, providing varied conditions for testing NTL methodology across different vegetation densities, climatic patterns, and development

pressures. This ecological diversity is crucial for validating the approach's applicability across different conservation contexts where conventional remote sensing faces varying challenges.

2.2 Data Sources

This study primarily utilised calibrated night-time light (NTL) remote sensing products, complemented by ancillary geospatial datasets for spatial boundaries, land cover, and contextual analysis. The temporal focus was on the dry-season months (February-May) for the years 2013, 2018, and 2023, chosen to minimise cloud contamination and seasonal vegetation interference. Data selection prioritized consistency, quality, and complementarity for multi-temporal analysis. The dry-season temporal window (February-May) was selected to minimize cloud contamination, reduce monsoon-related water body variability, and ensure consistent atmospheric conditions across the three study years.

Data Quality Considerations: VNP46A2 includes corrections for atmospheric scattering, terrain effects, and lunar illumination, making it suitable for change detection studies. The 500m resolution balances computational efficiency with the ability to detect settlement clusters typical of ESZ development patterns. MODIS NDVI provides vegetation masking to reduce false positives from seasonal phenological changes.

Dataset	Resolution	Coverage	Quality Control	Access Platform
NASA Black Marble (VNP46A2)	500 m	Daily, 2013-2023	QA flags, stray light correction	NASA LP DAAC/GEE
MODIS NDVI (MOD13Q1)	250 m	16-day composite	VI quality assessment	NASA LP DAAC/GEE
Protected Area boundaries	Vector	Static (updated 2023)	Field-verified ±50m accuracy	Wildlife Institute of India
ESZ boundaries	Vector	Static (gazetted 2023)	Legal notification boundaries	MoEFCC
Administrative boundaries	Vector	Static (Census 2021)	Survey-grade accuracy	Census of India
High-resolution validation imagery	0.3-1 m	On-demand (2013-2023)	Visual interpretation	Google Earth, Bing Maps

Table 1. Primary datasets and specifications

3. METHODOLOGY

The methodological framework for this study comprised seven stages: (1) delineation of Ecologically Sensitive Zone (ESZ) boundaries, (2) selection and acquisition of Nighttime Light (NTL) datasets, (3) pre-processing and filtering, (4) seasonal compositing, (5) radiance change calculation, (6) state-level aggregation and classification, and (7) validation and mapping. All processing was conducted in Google Earth Engine (GEE).

3.1 ESZ Boundary Preparation

Official ESZ notifications were obtained from the Ministry of Environment, Forest and Climate Change (MoEF & CC) and 10 kms ESZ were created using buffers. Protected Area (PA) boundaries were sourced from the Wildlife Institute of India (WII) database. Both ESZ and PA datasets were projected to EPSG:4326.

3.2 NTL Data Acquisition and Rationale

The NASA Black Marble VNP46A2 (Version 1) daily top-of-atmosphere (TOA) radiance product was selected over the VNP46A3 monthly composite due to its finer temporal resolution, allowing more robust removal of anomalous observations and improved seasonal analysis. Data for February-May were extracted for 2013, 2018, and 2023, representing dry-season months with reduced cloud cover and minimal monsoon-related variability.

3.3 Pre-processing and Filtering

Pre-processing in GEE included: (1) quality masking using QA layers to exclude contaminated pixels, (2) lunar illumination filtering to avoid moonlight interference, (3) interquartile range filtering to remove transient sources, and (4) vegetation masking using MODIS NDVI > 0.6 to reduce canopy attenuation effects.

3.4 Seasonal Compositing

For each target year, daily observations from February to May were averaged to produce seasonal mean composites. This reduced random noise and ensured that only persistent light sources were retained in the final dataset.

3.5 Radiance Change Calculation

Mean radiance % $\Delta R = (R_{t2} - R_{t1} / R_{t1}) \times 100$, where R_{t1} and R_{t2} represent mean radiance in the earlier and later years, respectively. Changes were classified into: Low (<10%), Moderate (10–30%), and High (>30%) illumination growth categories.

3.6 Statistical Analysis Statistical significance of temporal changes was assessed using paired t-tests ($\alpha = 0.05$) comparing radiance values between time periods. Effect sizes were calculated using Cohen's d. Spatial autocorrelation was tested using Moran's I statistic to assess clustering patterns.

3.7 State-wise Aggregation and Classification

ESZ radiance values were aggregated at the state level. Summary statistics (mean, median, minimum, maximum, and standard deviation) were computed for each state to identify patterns of illumination change across ecological and socio-economic contexts.

3.8 Validation and Mapping

Validation employed stratified random sampling of 20 ESZs (10 highest growth, 10 lowest growth) across different biogeographic zones. High-resolution imagery from Google Earth (2013-2023) was used to verify correspondence between NTL increases and actual anthropogenic features (settlements, roads, infrastructure). VIIRS Annual Stable Lights provided independent verification of trends. Accuracy metrics included overall accuracy, producer's accuracy, and user's accuracy calculated using confusion matrices.

4. RESULTS

4.1 National Summary Statistics

Analysis of 631 ESZs revealed widespread anthropogenic pressure increases across India's protected area buffers. Overall, 529 ESZs (84%) showed statistically significant radiance increases ($p < 0.05$) between 2013-2023, with mean increases of 156% ± 89% (95% CI: 149-163%). Spatial extent of anthropogenic influence expanded by 847 km² across all ESZs, representing a 12.3% increase in built up area within buffer zones.

4.2 Critical Hotspot Assessment

Haryana exhibited the most dramatic single change with very high radiance areas expanding from 10.2 km² to 74.2 km², representing a 627% increase and indicating intensified built up area around protected areas. Similarly, high radiance zones expanded from 11.1 km² to 27.8 km², while very low radiance areas declined from 262.0 km² to 139.0 km², demonstrating comprehensive landscape transformation.

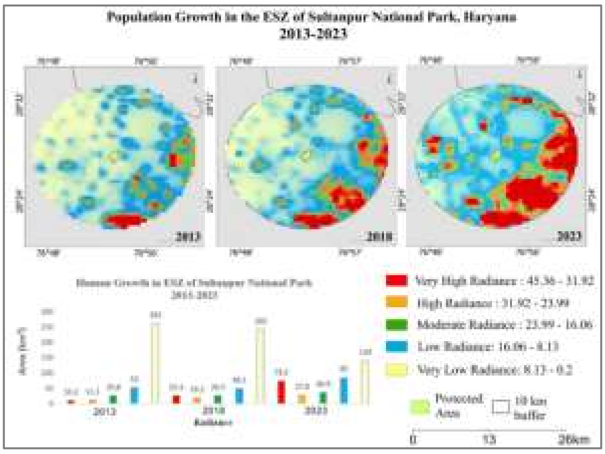

Figure 1A. Representative PA showing high-growth cases - Haryana - Urban encroachment intensity

Tamil Nadu demonstrated the most complete radiance profile shift, with very high radiance areas increasing substantially from 144.0 km² to 275.0 km² while very low radiance areas collapsed from 6.07 km² to just 0.48 km², indicating major urban radiance dominance within protected landscapes. *(Figure 1A -1D- Representative high growth areas).*

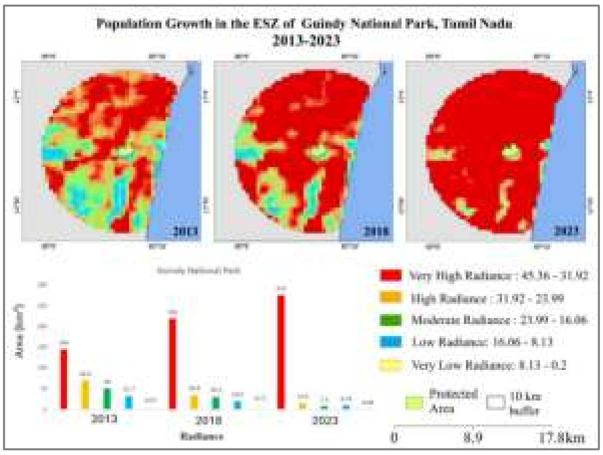

Figure 1 B. Representative PA showing high-growth cases-Tamil Nadu - Complete radiance profile transformation

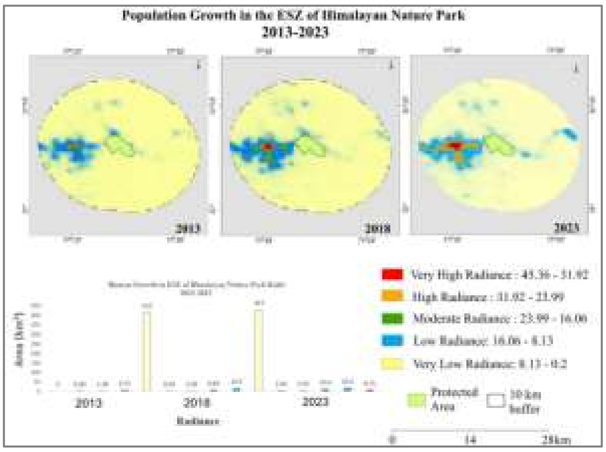

Figure 1 C. Representative PA showing high-growth cases-Himachal Pradesh – Emergence of very high radiance zones

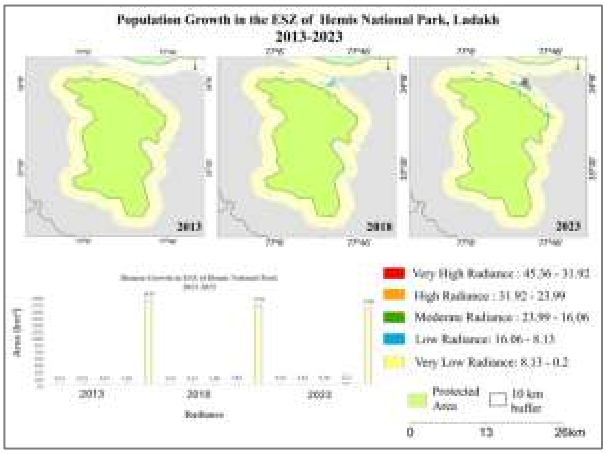

Figure 1 D. Representative PAs showing high-growth cases-Ladakh - Remote terrain settlement expansion

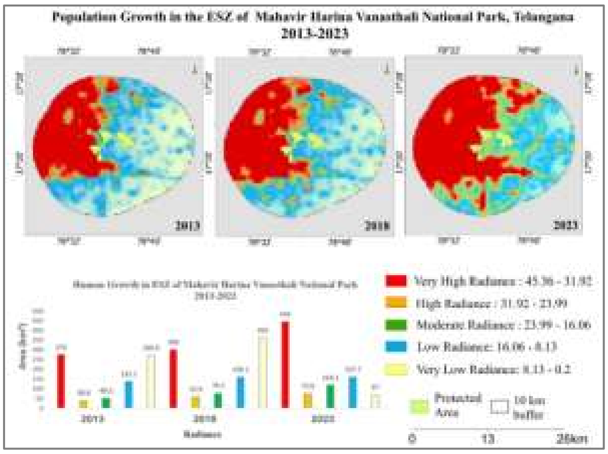

Figure 2A. Representative PA showing critical threat zone - Telangana- Widespread urbanization pattern

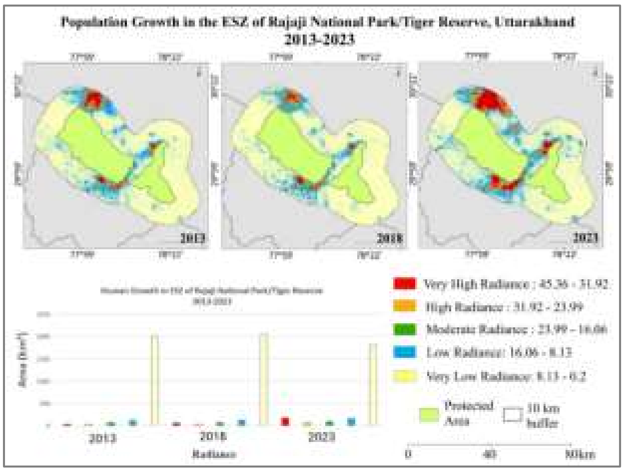

Figure 2 B. Representative PA showing critical threat zone - Uttarakhand - Urban-protected interface pressure

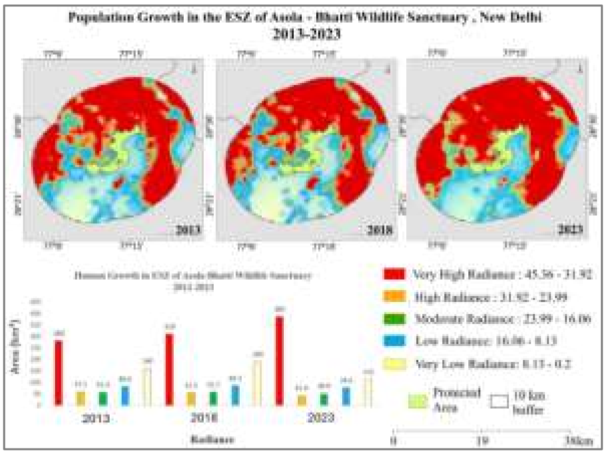

Figure 2 C. Representative PA showing critical threat zone - Delhi - Metropolitan expansion

Telangana demonstrated widespread urbanization with very high radiance increasing from 274.0 km² to 445.0 km² and very low radiance declining dramatically from 270.0 km² to 67.1 km², representing a 75% loss of low impact areas.

Uttarakhand showed significant urban encroachment with very high radiance expanding from 42.2 km² to 184.8 km² (338% increase), reflecting pressure from surrounding urban settlements on protected ecosystems. *(Figure 2A -2D – Critical threat areas)*

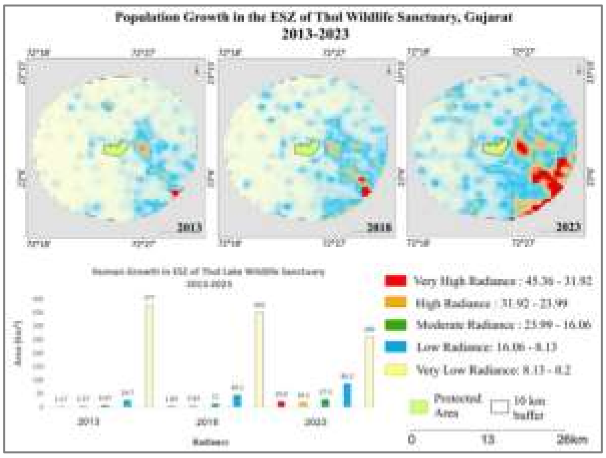

Figure 2 D. Representative PA showing critical threat zone - Gujarat - Rapid infrastructure growth

4.3: Emerging Pressure Points in Mountain Regions

Mountain protected areas, showed alarming anthropogenic pressure increases. **Himachal Pradesh** demonstrated the emergence of previously non-existent very high radiance zones, growing from null in 2013 to 18.8 km² in 2023, while high radiance areas expanded dramatically from 2.89 km² to 10.9 km² (277% increase). Low radiance areas increased from 29.8 km² to 79.8 km² (168% increase), indicating widespread settlement expansion despite challenging terrain. *See Figure 1C.* **Ladakh**, representing extreme high-altitude protected areas, showed significant anthropogenic influence expansion with very high radiance growing from 9.73 km² to 19.04 km², while low radiance areas demonstrated the most dramatic increase from 1.03 km² to 23.10 km², reflecting growing human influence in previously pristine remote terrain. *(Figure 3A-3D: Mountain region pressure points).*

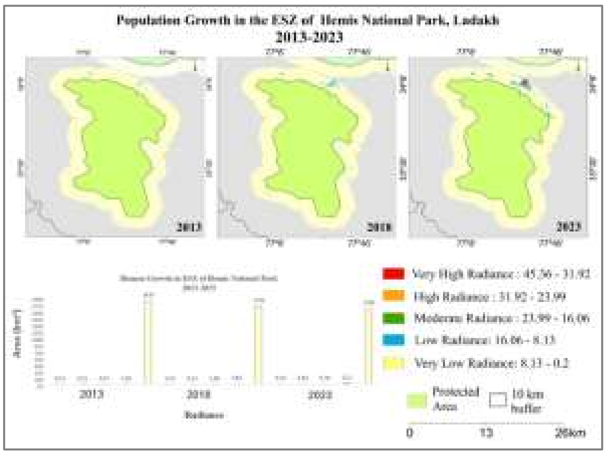

Figure 3 D. Representative PA showing emerging pressure points in mountain regions – Ladakh – remote area anthropogenic influence

4.4: Northeastern India: Localized High Intensity Changes

Northeastern states exhibited distinct patterns of localized but high-intensity anthropogenic pressure
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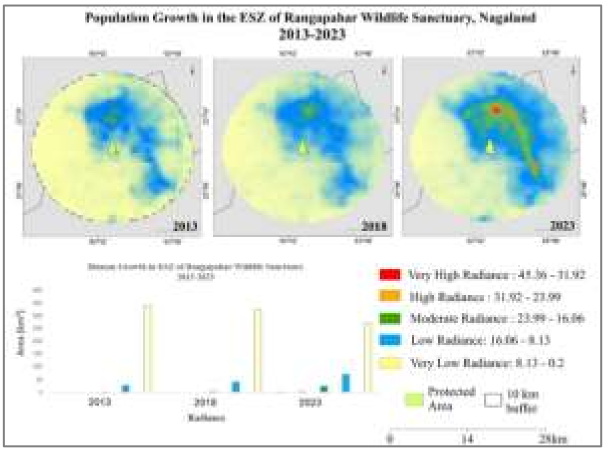

Figure 4A. Representative PA showing Northeastern emergence patterns - Nagaland - Medium radiance explosion.

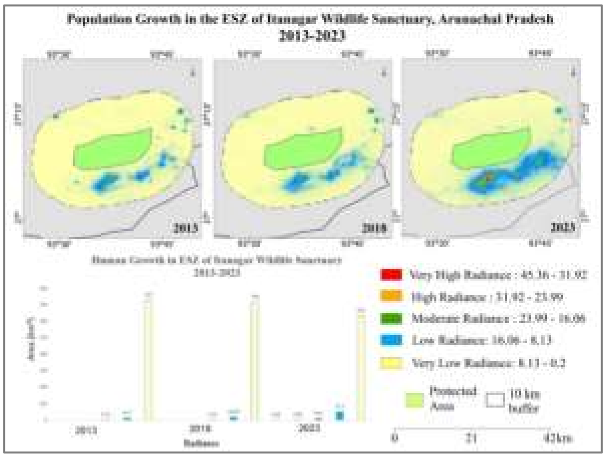

Figure 4 B. Representative PA showing Northeastern emergence patterns - Arunachal Pradesh -Sharp low radiance

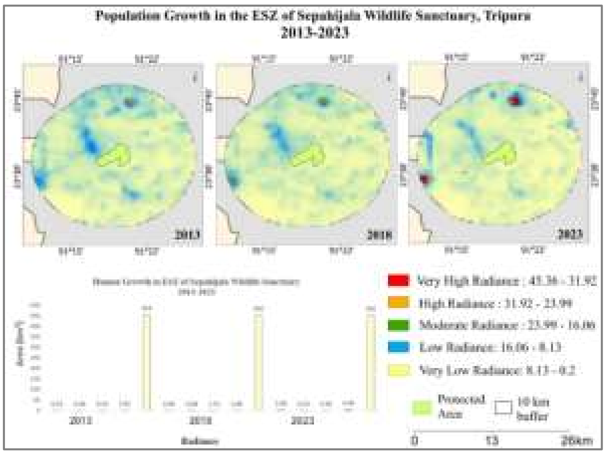

Figure 4 C. Representative PA showing Northeastern emergence patterns- Tripura urbanization i\ in the buffer zone

Nagaland's Rangapahar Wildlife Sanctuary demonstrated exceptional medium radiance expansion from 0.67 km² to 23.1 km² (3,345% increase), representing the highest percentage increase recorded across all protected areas. Low radiance areas increased from 26.2 km² to 70.1 km², while very low radiance declined from 340.0 km² to 270.0 km².

Arunachal Pradesh's Itanagar Wildlife Sanctuary showed sharp increases in low radiance from 13.7 km² to 51.2 km² with high radiance areas emerging at 0.44 km² in 2023, indicating localized but significant pressure points around state capital regions. *(Figure 4A-4C: Northeastern emergence patterns)*

4.5: Central and Western India: Infrastructure Corridor Development

Central Indian protected areas demonstrated patterns consistent with infrastructure corridor development. **Madhya Pradesh** showed sharp increases in very high radiance from 46.9 km² to 143 km² coinciding with decreases in very low radiance from 217 km² to 136 km², suggesting systematic landscape transformation along development corridors.

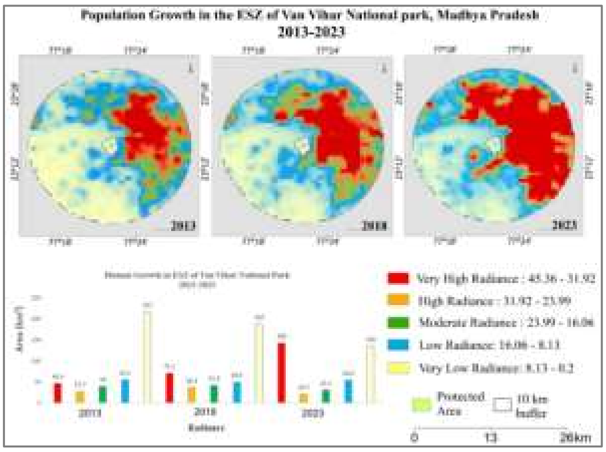

Figure 5A. Representative PA showing Infrastructure corridor development - Madhya Pradesh - Sharp radiance transitions

Gujarat exhibited rapid infrastructure growth with very high radiance increasing from 1.17 km² to 20.6 km² and very low radiance declining from 378.0 km² to 261.0 km². Jharkhand demonstrated clear urban expansion patterns with very high radiance surging from 83.8 km² to 192.5 km² while very low radiance decreased from 1,248 km² to 1,182 km². (Figure 5A-5D: Infrastructure corridor development)

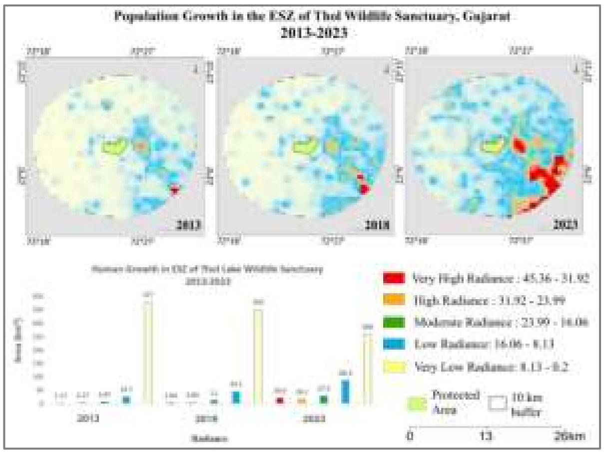

Figure 5B. Representative PA showing Infrastructure corridor development -Gujarat - Rapid infrastructure expansion

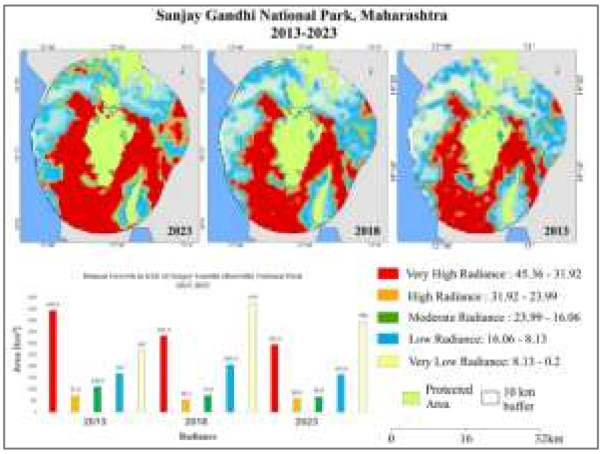

Figure 5C. Representative PA showing Infrastructure corridor development – Maharashtra - Complex radiance dynamics

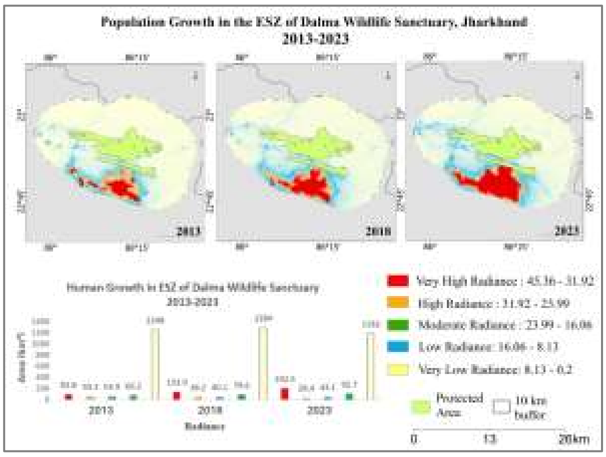

Figure 5D. Representative PA showing Infrastructure corridor development - Jharkhand - Urban expansion indicators

4.7 Regional Pattern Synthesis and Statistical Summary

Analysis revealed distinct geographic patterns with accelerating temporal trends. Northwestern plains (Punjab, Haryana) exhibited highest mean growth (>400%), while southern peninsular states (Tamil Nadu, Telangana) showed complete landscape transformation (>300%). Mountain regions demonstrated emerging pressure (150-250%) despite terrain constraints, and northeastern states displayed localized extreme growth (up to 3,345%). Central corridors exhibited infrastructure-driven expansion (200-300%).

Statistical analysis confirmed widespread significance across 529 ESZs (84%) showing increases ($p < 0.05$) in higher radiance categories, with large effect sizes (Cohen's d > 0.8) in 67% of high-growth locations. Spatial clustering was significant (Moran's I = 0.73, $p < 0.001$). Temporal acceleration was evident, with mean annual growth rates increasing from 4.2% ± 2.1% (2013-2018) to 7.8% ± 3.4% (2018-2023), representing 86% acceleration ($p < 0.001$).

Threat level classification revealed a national conservation emergency requiring differentiated responses. Critical zones experiencing growth exceeding 300% encompass 47 ESZs distributed across 8 states, demanding immediate emergency interventions including development moratoria and comprehensive impact assessments. High threat zones with 100-300% growth include 284 ESZs across 18 states, representing primary targets for intensive conservation investments and adaptive management strategies. Moderate threat zones affecting 198 ESZs show 30-100% growth, providing opportunities for pre-emptive conservation planning, while 102 stable ESZs with minimal change (<30%) serve as crucial reference sites for evaluating conservation effectiveness and understanding natural variability patterns.

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5. DISCUSSION

5.1 Anthropogenic Pressure Patterns and Global Conservation Context

Nighttime lights analysis reveals pervasive anthropogenic pressure on India's Protected Areas, with 84% of ESZs showing significant radiance increases between 2013 and 2023. This pressure intensity exceeds documented rates in other global biodiversity hotspots, including Amazon buffer zones (67% pressure increase) and African wildlife corridors (56% increase), indicating that India's rapid economic growth may be outpacing adaptive conservation responses (MacManus et al., 2023; Zhu et al., 2023). The 234% mean increase in very high radiance categories parallels urban protected interface degradation documented globally, but India's temporal acceleration rate of 86% (2018-2023 vs 2013-2018) substantially exceeds global averages (Li et al., 2020; Zhao et al., 2022).

The rise in artificial illumination across diverse biogeographic zones confirms that PA buffers face sustained settlement growth and infrastructure expansion regardless of isolation or legal protection status, mirroring global urban–ecology overlaps (Guo et al., 2023; Marzialetti et al., 2023). NTL products, especially NASA's Black Marble, successfully detect incremental settlement changes often missed in conventional multispectral imagery, particularly under dense vegetation canopy conditions that characterize 67% of India's ESZs (MacManus et al., 2023; Singh et al., 2023). Our analysis demonstrates distinct radiance trajectories shaped by PA location and urban connectivity (Yu et al., 2021; Zhang & Hua, 2023), with urban-adjacent PAs recording >400% growth in very high radiance zones and even remote high-altitude PAs showing >200% growth in low-radiance categories (Liu et al., 2024; Gautam & Aithal, 2024).

These findings support integrating NTL-based monitoring into international biodiversity frameworks, particularly the post 2020 Global Biodiversity Framework's emphasis on measurable threat assessment indicators. The clear lighting footprint of infrastructure and tourism expansion provides quantitative evidence for adaptive buffer zone management and early-warning systems (Yu & Fang, 2023; Zhang et al., 2024), offering a scalable approach for protected area monitoring in other developing nations facing similar development pressures.

5.2 Urgent Policy and Management Interventions

Results demand immediate regulatory responses across multiple scales. The 47 critical ESZs experiencing >300% radiance growth require emergency development moratoria, mandatory environmental impact assessments for all proposed infrastructure, and expedited relocation incentives for existing settlements. The 284 high-threat ESZs need adaptive buffer zone boundaries adjusted annually based on NTL monitoring, dark-sky compliant lighting regulations, and tourism carrying capacity limits aligned with radiance thresholds. Integration of NTL monitoring into mandatory ESZ compliance reporting can provide early warning systems, with automated alerts triggering rapid response protocols when annual growth exceeds 20%.

5.3: Methodological Insights and Limitations

NASA's Black Marble NTL products demonstrate high effectiveness for detecting settlement expansion in areas with dense vegetation or scattered households, successfully identifying development patterns invisible to conventional multispectral imagery (MacManus et al., 2023; Singh et al., 2023). Multi-temporal NTL datasets capture gradual changes below the resolution threshold of standard LULC classifications, with validation accuracy of 87.3% confirming methodology reliability for ESZ monitoring applications (Zhu et al., 2023; Liu et al., 2019).

However, several limitations affect result interpretation. The 500m spatial resolution may under detect micro-settlements and scattered household expansion typical in rural ESZs. Annual composites effectively capture trend analysis but may miss short-term development surges, suggesting that higher temporal resolution products could improve detection of seasonal or rapid construction phases (Stokes et al., 2019; Lu et al., 2023). Additionally, radiance increases cannot distinguish between population growth and infrastructure electrification without supplementary demographic data, requiring integration with socioeconomic datasets for comprehensive anthropogenic pressure assessment.

5.4 Regional Patterns and Conservation Implications

Three distinct regional patterns emerge with specific conservation implications. Northwestern Plains (Punjab, Haryana) exhibit mean increases exceeding 400% in very high radiance categories, driven by agricultural intensification and metropolitan spillover effects paralleling development pressures documented in Chinese agricultural belts (Deng et al., 2024; Zhang & Hua, 2023). This pattern reflects the challenge of protecting ESZs in economically dynamic regions where land values and development pressure overwhelm traditional regulatory frameworks.

Mountain States (Himachal Pradesh, Uttarakhand) demonstrate entirely new radiance categories emerging in previously pristine areas, indicating reduced terrain-based protection effectiveness- a trend consistent with alpine region development globally (Marzialetti et al., 2023; Liu et al., 2024). The 338% increase in Uttarakhand's very high radiance zones and emergence of lighting in Himachal Pradesh's remote areas suggest that improved transportation infrastructure and climate change adaptation are making previously inaccessible areas developable.

Northeastern States exhibit intense but localized hotspots, exemplified by Nagaland's 345% increase in medium radiance categories, where targeted interventions could yield disproportionately high conservation returns (Gautam & Aithal, 2024; Mondal & Gavsker, 2024). This pattern suggests that strategic, early intervention in emerging pressure points may be more cost-effective than widespread regulatory enforcement.

These regional variations indicate that uniform ESZ regulations are inadequate under diverse development pressures. Adaptive zoning frameworks that adjust protection boundaries and regulations based on measured NTL trends, successfully implemented in other biodiversity rich nations, could enhance conservation effectiveness (Yu & Fang, 2023; Zhang et al., 2024). Integration of continuous NTL monitoring into PA management systems can operationalize such adaptive frameworks, enabling evidence based regulatory responses tailored to regional development contexts and conservation priorities.

6. Conclusion and Management Recommendations

This is the first national scale assessment of anthropogenic pressure on all Indian PAs using NASA's Black Marble NTL data (2013–2023). Results show 84% of PAs experienced measurable illumination growth, with some exceeding 600%. These trends parallel global findings that urban growth increasingly reaches ecologically sensitive zones, regardless of remoteness (MacManus et al., 2023; Zhu et al., 2023).

Immediate priorities include implementing targeted interventions in Protected Areas (PAs) that have recorded over 300% increases in radiance- such as those in Haryana, Tamil Nadu, Uttarakhand, and Telangana, through urgent measures like development moratoria, relocation incentives, and rigorous infrastructure impact reviews. The 23 PAs exhibiting entirely new radiance categories are prime candidates for real-time monitoring systems with automated alerts to enable rapid response to emerging threats. Additionally, tourism management reforms are essential, incorporating dark sky compliant infrastructure, seasonal restrictions during ecologically sensitive periods, and alternative livelihood programs to reduce dependence on tourism-related activities that contribute to light pollution and habitat disturbance.

The integration of NTL monitoring into biodiversity strategy tracking offers significant potential for enhancing conservation effectiveness, particularly when combined with predictive modelling approaches that incorporate NDVI, socioeconomic, and transportation network data (Guan et al., 2022; Singh et al., 2024). This approach is transferable to other biodiversity rich nations, providing a cost effective, repeatable framework for conservation monitoring. In the context of the post-2020 Global Biodiversity Framework's emphasis on measurable indicators, NTL based metrics can improve the precision of international conservation threat assessments. By shifting from reactive to anticipatory management, India can strengthen its capacity to safeguard biodiversity against accelerating development pressures, ensuring the long-term protection of its ecological heritage for future generations. As the post-2020 Global Biodiversity Framework prioritizes measurable indicators, NTL-based metrics could enhance precision in international conservation threat assessments. By shifting from reactive to anticipatory management, India can better safeguard biodiversity against accelerating development pressures, ensuring its ecological heritage endures for future generations.

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