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Beyond Daytime Thresholds: Downscaled Population Exposure and Compound Heat Hazard Projections in Andhra Pradesh, India

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Abstract: Extreme heat is intensifying faster than most Heat Action Plans (HAPs) can track. India's frameworks still rely on daytime dry-bulb thresholds that overlook the nighttime warming driving most of the risk. This study develops a novel Compound Heat Hazard Index (CHHI) for Andhra Pradesh, India, from Wet-Bulb Globe Temperature (WBGT)-based heatwave duration, frequency, and total hot days, and anomalies, tracked separately by day and night across a 1991-2020 baseline, a 2015-2026 contemporary period, and a 2027-2030 projection using OLS trend extrapolation. Exposure is mapped at 30 m resolution by downscaling coarse 100 m WorldPop counts through a Population Suitability Index (PSI) and mass-preserving redistribution from Google Earth Engine covariates, correcting for population that coarse products routinely place on riverbeds and open land. Both inputs are validated: the population layer against geotagged field photography at two sites, and ERA5 temperature against IMD gridded observations (R^2 , RMSE, MAE, mean bias). Nighttime heat hazard is intensifying more than daytime heat (Sen's slope estimator 0.116 versus 0.002 days/year for heatwave frequency), a gap that current heatwave declaration criteria do not register. Exposure projections differ by region: Coastal Andhra's risk spreads across its density gradient, while Rayalaseema's sits almost entirely in a few dense urban mandals. Pairing open-source geospatial and statistical tools with pixel- and mandal-level exposure output, this study offers a transferable, low-cost decision-support method for Global South cities where within-city heat and exposure data remain scarce and argues for formally incorporating nighttime heat metrics into built-environment resilience policy.

Keywords: Compound Heat Hazard Index (CHHI), Wet-Bulb Globe Temperature (WBGT), Dasymetric population downscaling, Nighttime heatwaves, Projection

Key Policy Highlights

- Nighttime heatwave frequency in Andhra Pradesh is rising over 50 times faster than daytime frequency (Sen's slope estimator 0.116 vs 0.002 days/year) — a gap current dry-bulb-based HAPs do not register.
- Dasymetric downscaling built entirely from open-source data uses mass-preserving redistribution guided by land-cover (ESA WorldCover v200), spectral indices (NDVI, NDBI, BSI), and settlement (VIIRS, GHSL) covariates to WorldPop data at 100 m to 30 m resolution, an application not previously reported for heat exposure mapping in India. Validated in the transect drawn on Vijayawada, it reduces riverbed and open land overcounts of 170 to 185 persons per pixel to a verified 20 to 30 persons per pixel, along with geotagged field validation.

- Coastal Andhra's heat risk is broad-based across its density gradient; Rayalaseema's is concentrated in a handful of dense urban mandals (notably Kurnool), requiring different intervention strategies.
- Projected High-Risk population exposure grows sixfold between 2015 and 2030, while population grows only 9%, showing that climate change, not demographic growth as the primary driver.

1. Introduction

Extreme heat is one of the most consequential and least visible climate threats of the twenty-first century. Unlike floods, cyclones, or droughts, heat leaves little physical damage, yet the 2023 Lancet Countdown reported that heat-related mortality among people has risen sharply above 1990s levels as heatwaves grow more frequent and severe worldwide (Romanello et al., 2023). South Asia sits at the centre of this risk: several of the world's most populous countries face climate trajectories pushing wet-bulb temperatures toward, and in places beyond, the limits of sustained human tolerance (Raymond et al., 2020). Heat hazard is not a single measurable quantity but a compounding interplay of intensity, frequency, and duration across consecutive days and nights (Mora et al., 2017; Zscheischler et al., 2018). The Compound Heat Hazard Index (CHHI) developed here combines Heatwave Duration (HWD), Heatwave Frequency (HWF), and Total Hot Days (THDs) across day and night into one standardised metric, addressing a problem most hazard indicators ignore: daytime and nighttime warming rates are not uniform. Mukherjee (2018) predicts that day-and-night heatwave occurrences in India will increase sixfold if temperature rises by 2°C, driven by decreasing nighttime cooling. Guirguis et al. (2014) found that in California, heatwaves with abnormally warm nights had a noticeably greater health effect than daytime-only hot spells, since overnight recovery was inhibited. Treating daytime and nighttime heat as equivalent overlooks this physiological dimension.

A second limitation concerns how heat is measured. Although India has officially recognised heatwaves as a natural disaster eligible for disaster response funds under the 16th Finance Commission's recommendations (MHA, 2026), the criteria triggering this recognition remain based on anomalies in the IMD's dry-bulb maximum temperature (Pai et al., 2013). The IMD's experimental "warm night" warnings require daytime temperatures to first exceed 40°C (37°C in coastal areas), creating a structural gap where high marine humidity raises moist enthalpy without pushing dry-bulb temperature above the threshold. Dry-bulb temperature alone cannot indicate whether the body can lose heat: once air nears saturation, sweating stops cooling effectively regardless of temperature (Khambete, 2026). WBGT overcomes this by combining air temperature, humidity, wind speed, and radiant load into one physiologically grounded index (Justine et al., 2023; Liljegren et al., 2008), calculated here using the open-source pywbgt package.

A third limitation concerns population exposure. Gridded global population datasets such as WorldPop (Tatem, 2017), typically at 100 m to 1 km resolution, allocate population evenly regardless of whether cells are inhabited, so riverbeds and open land end up bearing demographic weight they do not deserve. Tuholske et al. (2021) showed this coarseness masks the intra-city variation most relevant to adaptation planning. This study's dasymetric method, based on the mass-preserving principle of Mennis (2003), redistributes coarse WorldPop counts to 30 m using a Population Suitability Index derived from GEE covariates (NDVI, NDBI, Bare Soil Index, GHSL built-up surface/volume, VIIRS nighttime radiance, ESA WorldCover). This study applies that approach to Andhra Pradesh (Section 2), whose sharp intra-state climatic divide and documented heat vulnerability make these three gaps especially consequential. Pixel-specific 90th-percentile WBGT thresholds are established separately for day and night against a 1991-2020 baseline, heatwave episodes from 2015-2026 are assessed against these thresholds, and a linear regression (OLS) model projects the indicators forward to 2027-2030. The hazard layers combine into the CHHI through

a weighted linear combination, with weights set by each component's historical Sen's slope trend, and the resulting surface is overlaid on the 30 m population layer to assess exposure severity down to the Mandal (sub-district) level.

Andhra Pradesh's own Heat Action Plan reflects this measurement gap. The State Disaster Management Authority built one of India's earliest state-level HAPs in 2016 (Press Information Bureau, 2025), structured around daytime dry-bulb advisories and district-level warnings, with no nighttime minimum-temperature thresholds or humidity-adjusted metrics. This gap is not unique to Andhra Pradesh: Khambete (2026) reports a recent national assessment recommending HAPs incorporate nighttime warming, and separately flags a lack of granular, within-city heat and exposure data as a structural problem across India's HAP network. The closest existing comparison is the national Heat Risk Index by CEEW (Prabhu et al., 2025), which scored all 734 Indian districts on 35 hazard, exposure, and vulnerability indicators built from 12 km IMDAA reanalysis over 1982-2022, using expert-weighted AHP criteria. Their central finding, that very warm nights are increasing faster than very hot days across most Indian districts, motivates this study rather than repeating it. This study sharpens that comparison in four ways: a 30 m dasymetric population layer replaces 12 km administrative averages; a single WBGT metric replaces separate dry-bulb and humidity indicators; the retrospective 1982-2022 record extends forward to 2030 through an OLS trend projection; and an empirical CHHI scheme built from each indicator's historical Sen's slope estimator replaces AHP-based expert judgment.

This study attempts to contribute: (i) a compound, day-night-disaggregated heat hazard index based on WBGT rather than dry-bulb temperature; (ii) a trend-weighted, linear regression projection framework for near-term (2027-2030) heat hazard; and (iii) a dasymetrically downscaled, Mandal-level exposure assessment resolving population risk at a resolution relevant for local governance, together establishing the CHHI as a transferable template for compound heat risk assessment across South Asia and beyond.

2. Study Area

Andhra Pradesh, on India's southeastern coast (approximately 12.6°N-19.9°N, 76.8°E-84.9°E), covers approximately 162,970 km² and spans two contrasting climatic regions: the semi-arid Rayalaseema plateau and the sub-humid to tropical Coastal Andhra belt along the Bay of Bengal (Figure 1; Satyanarayana et al., 2023). Maritime humidity along the coast limits nighttime cooling, since water vapour absorbs and re-radiates outgoing longwave energy (Park et al., 2024), even though coastal daytime peaks remain comparatively lower than Rayalaseema's continental extremes. Building India's first country-wide Heat Vulnerability Index, Azhar et al. (2017) established heat as a spatially variable, quantifiable public health risk at district scale. Andhra Pradesh's own 2015 heatwave season, during which the state recorded the country's highest concentration of heat-related deaths (Sarath Chandran et al., 2017), remains among the deadliest on record for the subcontinent. This combination, a sharp intra-state climatic divide alongside a documented history of extreme heat mortality, makes Andhra Pradesh a suitable test case for the compound, day-night heat hazard framework developed here.

Andhra Pradesh, India

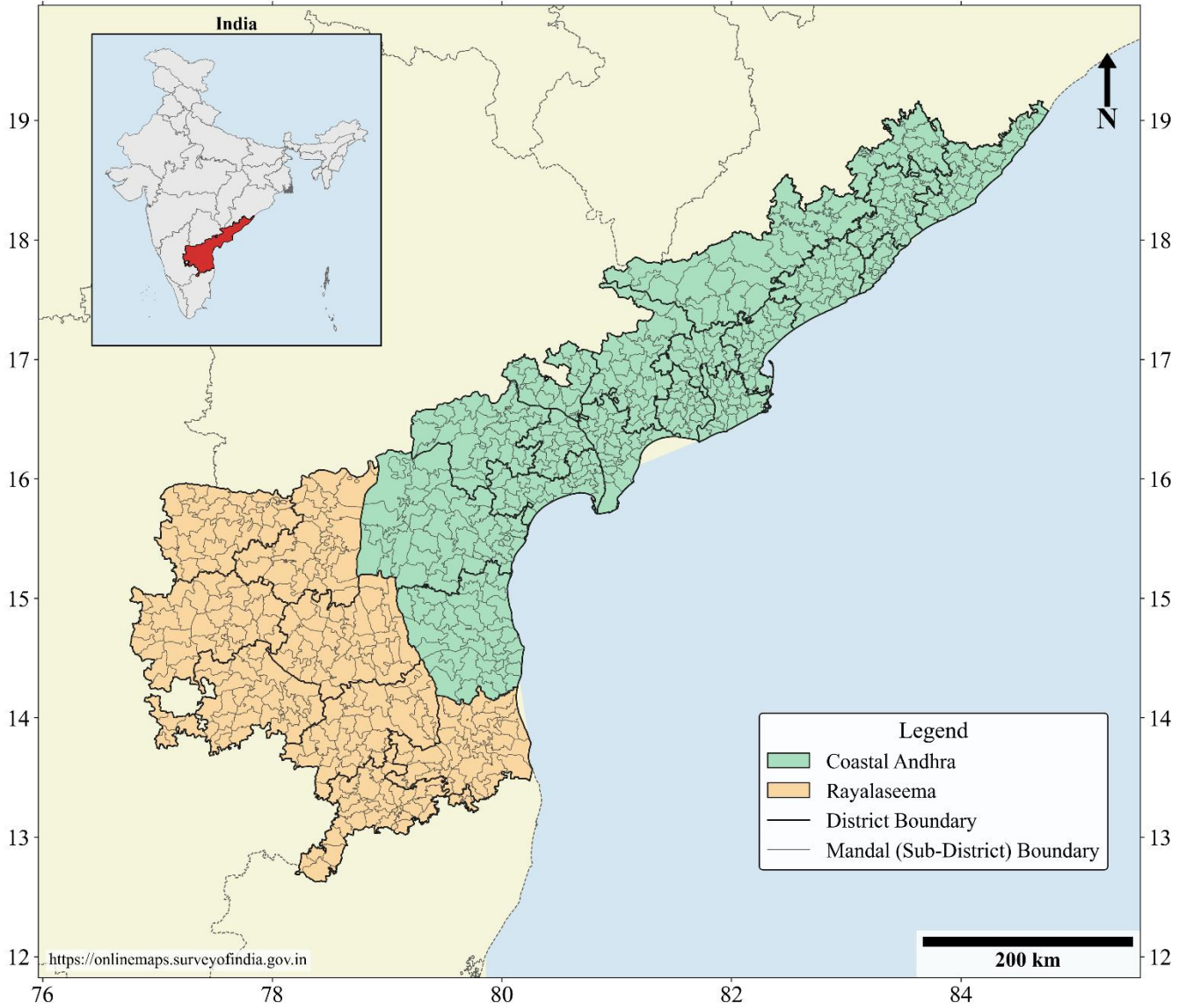


Figure 1: Location Map of the Study Area, Andhra Pradesh

3. Methodology

This study analyses the pre-monsoon summer window (April 1–May 31) across 40 years: a 30-year climatological baseline (1991–2020), a 12-year contemporary period (2015–2026), and a 4-year projected horizon (2027–2030).

3.1. High-Resolution Dasymetric Population Disaggregation (100m to 30 m using Google Colab)

3.1.1. Feature Extraction and Normalisation

Coarse WorldPop counts (100 m; Tatem, 2017) are downscaled to 30 m in Google Colab using a mass-preserving dasymetric weighting engine anchored on a PSI. Continuous covariates are drawn from GEE (Gorelick et al., 2017): Landsat-8/9 Collection 2 Surface Reflectance (cloud-masked, annually median-composited) yields NDVI (Rouse et al., 1974), NDBI (Zha et al., 2003), and Bare Soil Index (Roy et al., 2002); the Global Human Settlement Layer (GHSL P2023A) provides built-up surface area

(GHSLs) and volume (GHSLV) at 5-year epochs (Pesaresi et al., 2024); VIIRS Day-Night Band monthly composites give annual mean nighttime radiance (Elvidge et al., 2017); and ESA WorldCover v200 (Zanaga et al., 2022) is reclassified into a settlement-probability weight (W_ESA) that assigns maximum suitability to built-up pixels and zero weight to open water, dense forest, and barren surfaces. All covariates are min-max normalised to $[0,1]$. The continuous PSI (Eq. 1) is a weighted linear combination:

$$PSI_{cont} = 0.25 \cdot GHSL_{S,norm} + 0.20 \cdot GHSL_{V,norm} + 0.20 \cdot VIIRS_{norm} + 0.15 \cdot NDBI_{norm} + 0.10 \cdot W_{ESA} + 0.10 \cdot (1 - NDVI_{norm}) \quad (\text{Eq. 1})$$

A Boolean mask (Eq. 2) excludes non-inhabited land: a pixel is admitted only where $GHSLS > 10$, $NDBI > 0.0$, or $W_ESA = 1.0$, and Bare Soil Index ≤ 0.1 , clipping PSI to $[0,1]$ within this envelope and zero elsewhere:

$$PSI = clip(PSI_{cont}, 0, 1) \text{ if } \Omega_{control} = True; 0 \text{ otherwise} \quad (\text{Eq. 2})$$

3.1.2. Mass-Preserving Chunk Disaggregation

The domain is discretised into 90 m coarse source blocks (C), each holding a 3×3 grid of 30 m target sub-pixels ($f \in C$) for mass preservation (Eq. 3). Population is redistributed within each block according to each sub-pixel's PSI share (defaulting to an equal $1/9$ split where all pixels score zero), following Eicher & Brewer (2001).

$$w_f = \frac{PSI_f}{\sum_{k \in C} PSI_k}, \text{ if } \sum_{k \in C} PSI_k > 0 \text{ (or) } \frac{1}{9}, \text{ if } \sum_{k \in C} PSI_k = 0; Pop_f = Pop_C \cdot w_f \quad (\text{Eq. 3})$$

where Pop_C is the source WorldPop count within coarse pixel C, and Pop_f is the disaggregated absolute population assigned to target pixel f. Computation runs via out-of-core, low-memory chunk-streaming in *rasterio* using spatial virtual rasters (VRT) and compressed BigTIFF drivers.

3.1.3. Validation of downscaled population

The dasymetric output was validated using two complementary approaches. First, an internal consistency check was performed along a transect drawn over Vijayawada, comparing population density from the native 100 m WorldPop grid against the 30 m dasymetric output at locations including the Krishna riverbed and an adjacent bridge structure. The 30 m output was also aggregated back to its source 100 m grid to confirm mass conservation, verifying that redistribution altered only the spatial pattern of population, not the total count.

Second, the dasymetric output was validated against independent ground observation at two additional locations in Andhra Pradesh: a riverine site near Rajamahendravaram and a peri-urban site at Nidadhavole. At each site, geotagged photographs were captured using the GPS Map Camera application, recording precise coordinates and timestamps, and visually compared against the corresponding 100 m WorldPop and 30 m dasymetric output at the same location to assess whether the downscaled population pattern matched observed land use and settlement conditions on the ground.

3.2. WBGT Modelling

Human bioclimatic heat stress is modelled using the outdoor WBGT calculated via the physical formulation developed by Liljegren et al. (2008), which weights the natural wet-bulb temperature, the black-globe temperature, and ambient air temperature:

3.2.1. Meteorological Inputs and Boundary Forcing

Hourly atmospheric fields at $0.1^\circ \times 0.1^\circ$ spatial resolution are obtained from the ECMWF ERA5-Land Reanalysis product (ECMWF/ERA5_LAND/HOURLY; Muñoz-Sabater et al., 2021). Six primary state variables are extracted: 2 m air temperature

(T_a), 2 m dewpoint temperature (T_d), 10 m eastward and northward wind vectors, surface downward solar radiation, and surface pressure, from which wind speed and irradiance are resolved. These all together construct the natural wet-bulb temperature to feed the

3.2.2. Liljegren Physical Equations

The six ERA5-Land variables listed in Section 3.2.1 serve as the boundary conditions for these energy-balance equations. T_{nwb} , the natural wet-bulb temperature, and T_g , the 50 mm standard black-globe temperature, are each solved from coupled convective, evaporative, and radiative energy-balance equations for a wetted cylinder and a hollow copper sphere, respectively, following the full physical formulation (Eq. 4) of Liljegren et al. (2008). The iterative solution is implemented computationally via the open-source *pywbgt package* (<https://github.com/kwodzicki/pywbgt>, accessed 25 July 2026):

$$WBGT = 0.7 T_{nwb} + 0.2 T_g + 0.1 T_a \quad (\text{Eq. 4})$$

3.2.3. Temporal Disaggregation and Diurnal Segregation

Hourly WBGT is converted to IST. Daytime (06:00–18:00) and nighttime (18:00–06:00) windows each yield a maximum-hourly WBGT metric. ($WBGT_{\text{day,max}}$ and $WBGT_{\text{night,max}}$).

3.2.4. Climatological Baseline and Multi-Criteria Heatwave Characterisation

Using the World Meteorological Organisation (WMO) 30-year baseline (1991–2020; WMO, 2017; $N = 1,830$ daily slices per pixel), a pixel-wise 90th-percentile threshold ($P90$) is set separately for day and night (Eq. 5):

$$P_{90}(x, y) = \inf \left\{ \theta \in \mathbb{R}: \frac{1}{N} \sum_{k=1}^N \mathbb{I}(WBGT_k(x, y) \leq \theta) \geq 0.90 \right\} \quad (\text{Eq. 5})$$

$$E(t, x, y) = I(WBGT_t(x, y) > P90(x, y)) \quad (\text{Eq. 5a})$$

$$L(t, x, y) = \{L(t-1, x, y) + 1, \text{ if } E(t, x, y) = 1; 0 \text{ if } E(t, x, y) = 0\} \quad (\text{Eq. 5b})$$

Where $\mathbb{R}$ is the set of real numbers $\mathbb{I}(\cdot)$ is the indicator function. $E(t, x, y)$ equals 1 if day t 's WBGT at pixel (x, y) exceeds that pixel's 90th-percentile threshold, and 0 otherwise. $L(t, x, y)$ is the length of the current run of consecutive exceedance days ending at day t . It increases by 1 each day the threshold is exceeded, and resets to 0 the moment a single day fails to exceed it. A day exceeding this threshold is flagged as extreme; a Heatwave Spell is ≥ 3 consecutive exceedance days, following Perkins & Alexander (2013).

3.2.5. Validation of ERA5-Land Against IMD Gridded Observations

Understanding between ERA5-Land and IMD observed maximum temperature was assessed using the IMD high-resolution daily gridded temperature dataset ($1^\circ \times 1^\circ$; Srivastava et al., 2009), retrieved via IMDWeb (<https://imdweb.lwcc.in/>) for the summer season, against ERA5-Land April-May maximum temperature rasters exported from Google Earth Engine. Both datasets, along with the calculated WBGT layer, were clipped to the Andhra Pradesh boundary and standardised to a common coordinate system, with missing or non-positive IMD records excluded. NetCDF and TIFF files were processed using xarray and rioarray, respectively, and validation statistics were computed using scikit-learn. To enable grid-level comparison, ERA5 and WBGT were aggregated to the coarser native $1^\circ \times 1^\circ$ IMD grid by computing the spatial mean of constituent pixels within

each cell, with seasonal mean values computed per cell across the full IMD record period. Validation was quantified using the coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and mean bias.

3.2.6. Three-Dimensional Metric Formulation

For each year and diurnal regime, three indices are generated. Heatwave Duration (HWD) days (Eq. 6) is the longest consecutive qualifying heatwave sequence in the season:

$$HWD(x, y) = \max_{t \in Y} L(t, x, y) \quad (\text{Eq. 6})$$

Heatwave Frequency (HWF) days (Eq. 7) is the total cumulative number of days participating in qualifying heatwave spells:

$$HWF(x, y) = \sum_{t \in Y} \mathbb{I}(L(t, x, y) \geq 3) \quad (\text{Eq. 7})$$

Mean Anomaly (MA, °C; Eq. 8) is the departure of the seasonal mean from the 30-year climatological baseline:

$$MA(x, y) = \left(\frac{1}{61} \sum_{t=1}^{61} W BGT_t(x, y) \right) - \overline{WBGT}_{\text{base}}(x, y) \quad (\text{Eq. 8})$$

Linear Regression Projection Framework (2027–2030)

Thermal metrics are projected using an Ordinary Least Squares (OLS) linear regression, fitted independently for each pixel. The OLS regression captures each pixel's 36-year (1991–2026) linear trend (Eq. 9):

$$Y(t) = \beta_0 + \beta_1 t + \varepsilon(t); \hat{Y}_{\text{trend}}(t) = \hat{\beta}_0 + \hat{\beta}_1 t \quad (\text{Eq. 9})$$

These pixel-wise 2027–2030 projections are concatenated with the historical metrics into a complete 40-year raster cube (1991–2030)

3.3. Spatiotemporal Trend, Decadal Shift, and Spatial Clustering Analytics

3.3.1. Mann–Kendall Trend Test & Sen's Slope Estimator

The 40-year series ($n = 40$) is evaluated using the rank-based Mann-Kendall test (Kendall, 1990; Mann, 1945), significant at the 95% confidence level where the test statistic exceeds 1.96 ($p < 0.05$); Sen's slope estimator. (Sen, 1968) gives the rate of change as the median of all pairwise slopes.

3.3.2. Overlap-Corrected Shift Analysis

A one-sample t-test (Hawkins & Sutton, 2012) compares the post-2015 period mean ($ns = 12$ for 2015–2026; $ns = 16$ for 2015–2030) against the 30-year baseline mean per pixel, constrained to pixels with sample standard deviation $> 10^{-5}$ and t-values bounded within $[-20, 20]$.

3.3.3. Spatial Autocorrelation (Getis-Ord G_i^* Hotspot Analysis)

Spatial clustering of Sen's slopes for each metric is mapped using the Getis-Ord G_i^* statistic (Getis & Ord, 1992; Eq. 10) with a 3×3 -pixel ($\sim 27 \text{ km} \times 27 \text{ km}$) spatial weights matrix (w_{ij}):

$$G_i^* = \frac{\sum_{j=1}^n w_{ij} x_j - \bar{X} \sum_{j=1}^n w_{ij}}{S_x \sqrt{\frac{n \sum_{j=1}^n w_{ij}^2 - \left(\sum_{j=1}^n w_{ij} \right)^2}{n-1}}} \quad (\text{Eq. 10})$$

where X_j is Sen's slope at pixel j , M is the number of valid land pixels, $\bar{X}$ is the domain-wide mean slope, and S_x is the global standard deviation. Values of $G_i^* > +1.96$ delineate statistically significant warming-intensification hotspots at the 95% confidence level.

3.4. Calculation of the CHHI

Climate hazard impacts are rarely dictated by a single variable; they are worsened by compounding intensity, frequency, and duration across day and night (Mora et al., 2017; Zscheischler et al., 2018). The CHHI aggregates these into a single, standardised spatial metric using Python libraries (geopandas, raster, and Rasterstats).

3.4.1. Indicator Selection and Normalisation

The index integrates six indicators across 2015–2030: day/night Heatwave Duration, Heatwave Frequency, and total hot days. Nighttime metrics are included because elevated minimum temperatures disproportionately impair physiological recovery (Guirguis et al., 2014). Indicators are Min-Max normalised to [0,1] using global bounds calculated across the full 16-year stack (2015–2030); for pixel i and indicator j (Eq. 11):

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (\text{Eq. 11})$$

where $\min(x_j)$ and $\max(x_j)$ represent the absolute global bounds of the indicator j .

3.4.2. Empirical Weighting and Aggregation

A Weighted Linear Combination (WLC; Malczewski, 2000) sets weights (w_j) by the relative severity of each indicator's historical Sen's Slope estimator, so the fastest-intensifying variables govern the index by construction. The sum of the empirical trend components was 200.8, yielding the proportional weighting matrix in Table 1.

Metric	Time	Sig. Trend (%)	Weight (Wi)	Percentage Weight
HWD	Day	9.8	0.0488	4.9
HWD	Night	14.5	0.0722	7.2
HWF	Day	12.0	0.0598	6.0
HWF	Night	76.8	0.3825	38.2
THDs	Day	27.0	0.1345	13.4
THDs	Night	60.7	0.3023	30.2
TOTAL		200.8	1.000	100

This distribution mathematically reflects the region's pronounced shift toward nighttime heat stress. The overall continuous index for each spatial pixel is defined as (Eq. 12):

$$CHHI_i = \sum_{j=1}^n w_j x'_{ij} \quad (\text{Eq. 12})$$

3.4.3. Risk Classification

CHHI values are split into four equal-interval classes: Low, Moderate, High, and Severe, using the absolute global range across all valid land pixels in the 2015–2030 period (Slocum et al., 2022), so a "Severe Risk" classification represents the same absolute physical magnitude in any year.

3.4.4. Absolute Population Exposure Severity (2030)

Pixel-wise CHHI is multiplied by the 30 m population grid, aggregated to the Mandal level via zonal statistics (rasterstats, Python), and split into four quartile-based severity classes (Low, Moderate, High, Severe; q25, q50, q75). Unlike CHHI, a

bounded index classification (section 3.4.3), population exposure is an unbounded derived product with no fixed physical scale, so quartiles were defined for this study to rank Mandals by relative severity.

3.5. Mandal-Level Zonal Aggregation and Regional Stratification

Boundaries for all 686 Mandals (sub-districts) are ingested via *geopandas* and *rasterstats*, stratified into two domains: Rayalaseema (Kurnool, Anantapur, YSR Kadapa, Chittoor, Sri Sathya Sai, Annamayya, Nandyal, Tirupati) and Coastal Andhra (Srikakulam, Vizianagaram, West Godavari, Eluru, Krishna, NTR, Visakhapatnam, Anakapalli, Kakinada, East Godavari, Bapatla, Prakasam, Dr. B.R. Ambedkar Konaseema, Guntur, Palnadu). Pixel-level values are spatially averaged per Mandal across all 40 years, and Mann-Kendall statistics, Sen's slopes estimator, and shift t-values are computed on each Mandal's aggregated series (methodological framework in Figure 2; dataset list in Table S1).

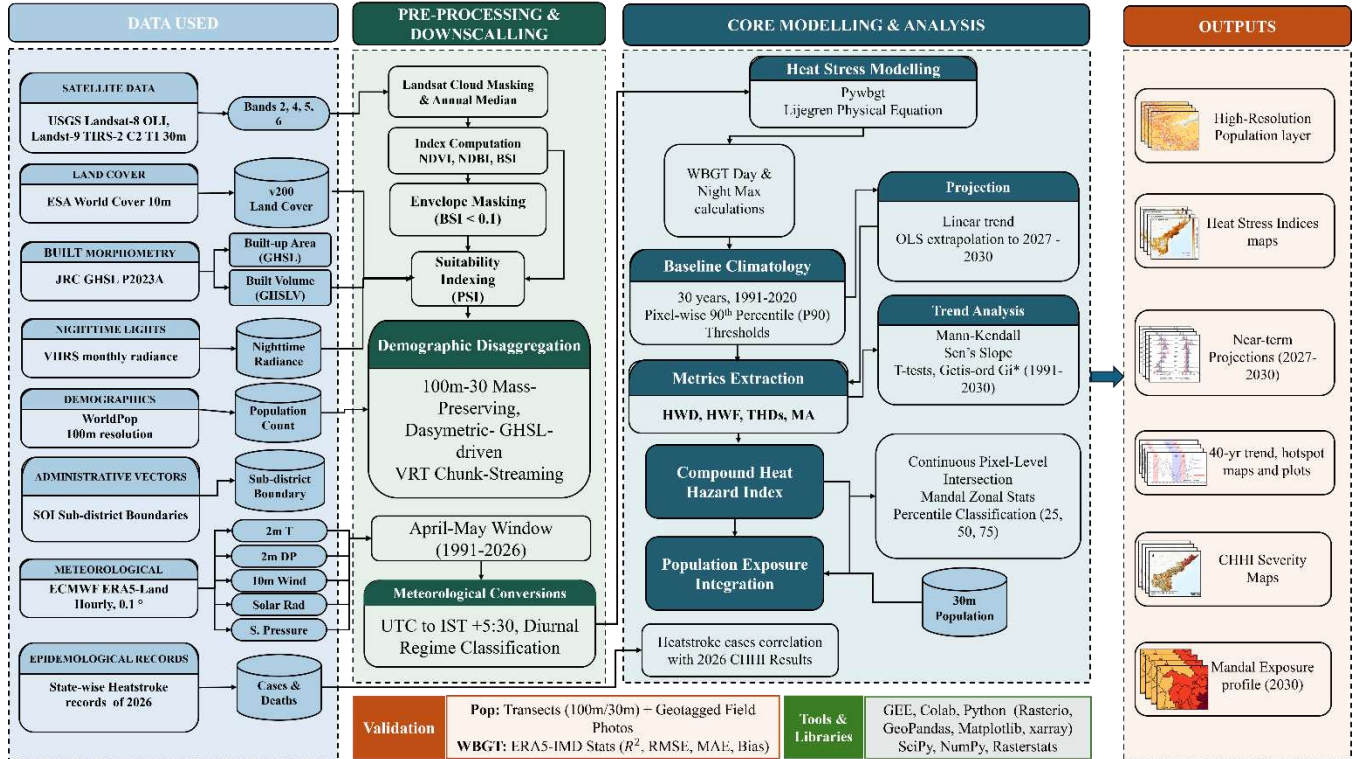


Figure 2: Methodological Framework

4. Results

4.1. High-Resolution Dasymetric Population Allocation and Built-Environment Exposure

Spatial validation of the 30 m dasymetric model shows refined population distribution across complex intra-urban environments. The transect drawn over Vijayawada shows that the native 100 m dataset spreads demographic density across uninhabited features such as the Krishna riverbed and bridge, recording localised peaks of 170–185 persons/pixel; the 30 m dasymetric allocation constrains this mass to the verified built environment, yielding a density range of 20–30 persons/pixel. Aggregating the 30 m output back to the source 100 m grid reproduced the original WorldPop totals with no population loss, confirming that the method redistributes population spatially without altering total counts. This distinction between spatially diffuse and spatially concentrated population estimates is illustrated in Figure 3, which allows for precise observation aligned with heat stress.

At the macro level, the 2026 population most susceptible to heat exposure is concentrated along Coastal Andhra: despite covering 58% of the state's area, it houses approximately 35.6 million people, against 17.8 million in the semi-arid Rayalaseema interior (42% of the landmass). This 30 m demographic layer is the exposure foundation for the climatology sections below.

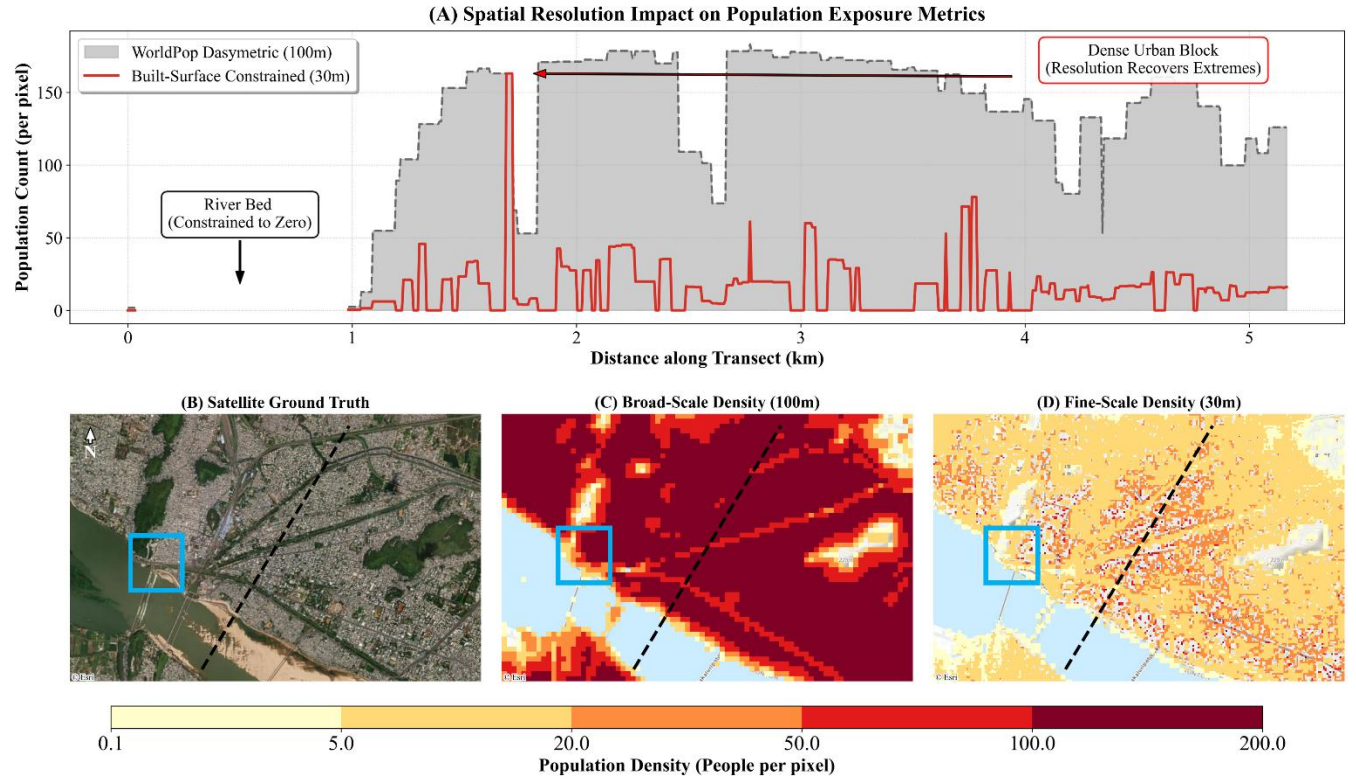


Figure 3: Spatial validation of high-resolution dasymetric population downscaling. Blue bounding boxes highlight a vegetated region where the 30 m built-surface layer (D) prevents the population smearing seen in the 100 m dataset (C).

Ground-truth validation was conducted at two additional locations using geotagged field photography (Figure 4). At the Godavari River site near Rajamahendravaram (16.997696°N, 81.75749°E), the 100 m WorldPop baseline assigns high population density (up to ~40 persons/pixel) across open water and a mid-river sandbar with no permanent settlement; the 30 m dasymetric output removes population entirely from water pixels and reduces density on the sandbar to below 5 persons/pixel, consistent with the field photograph showing largely unsettled riverbed with only sparse informal structures. At the Nidadhavole site (16.905127°N, 81.664777°E), the 100 m baseline shows uniformly high density across a largely vegetated, low-density periphery; the 30 m output resolves this into a finer gradient, with the flagged area (red box) matching the field photograph's sparse, vegetated land cover rather than dense settlement. Both sites support the population smearing correction demonstrated quantitatively in the Vijayawada transect above, extending that validation from a single internal consistency check to independent field observation.

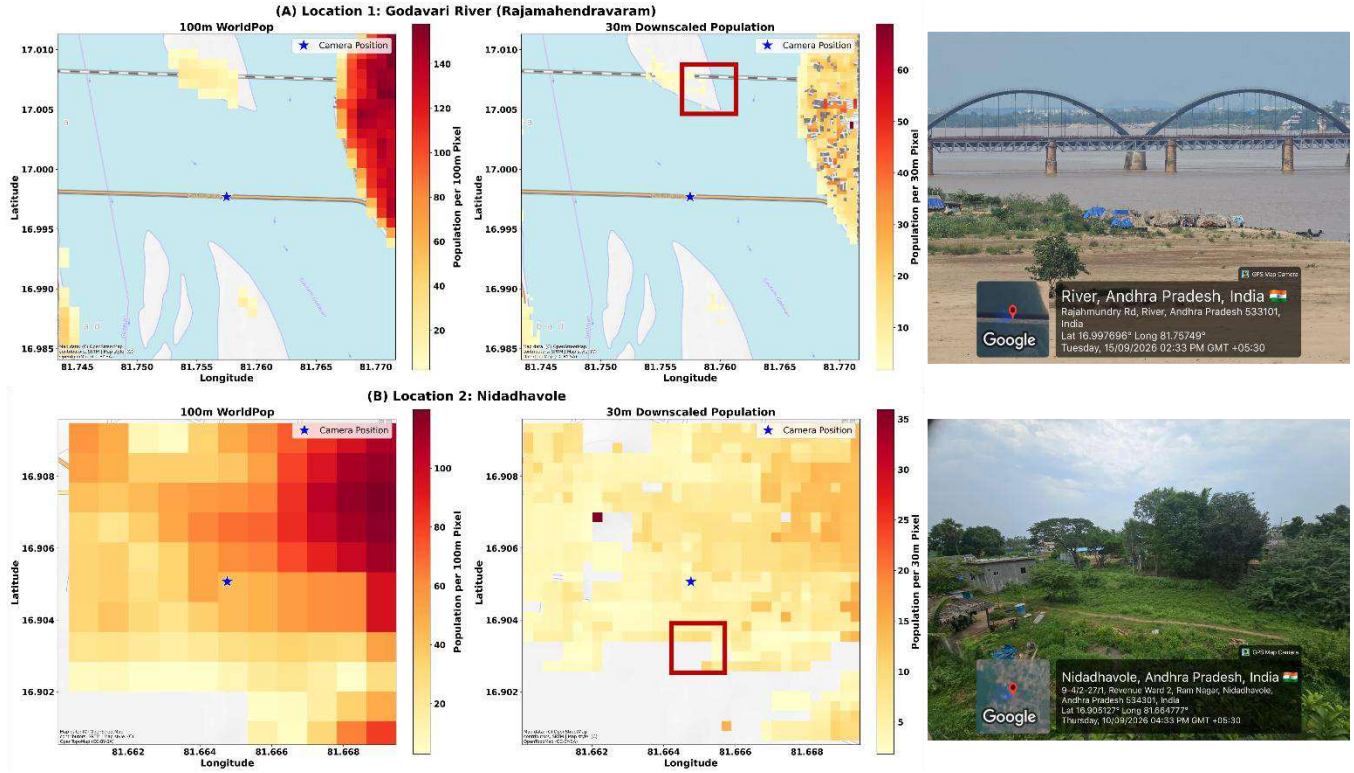


Figure 4: Field validation of Dasymetric population downscaling at two locations of the study area;(A) Godavari River near Rajamahendravaram, (B) Nidadhavole. Blue star represents the camera location, and the red box represents the captured area.

4.2. Validation of ERA5-Land Against IMD Gridded Observations

This study quantified validation using the coefficient of determination (R^2), RMSE, MAE, and mean bias. ERA5-Land shows moderate grid-level agreement with IMD observations at native 1° resolution ($R^2 = 0.530$, RMSE = 1.24°C , MAE = 0.69°C), with a mean bias of -0.44°C indicating a consistent tendency for ERA5-Land to underestimate observed maximum temperature across the domain.

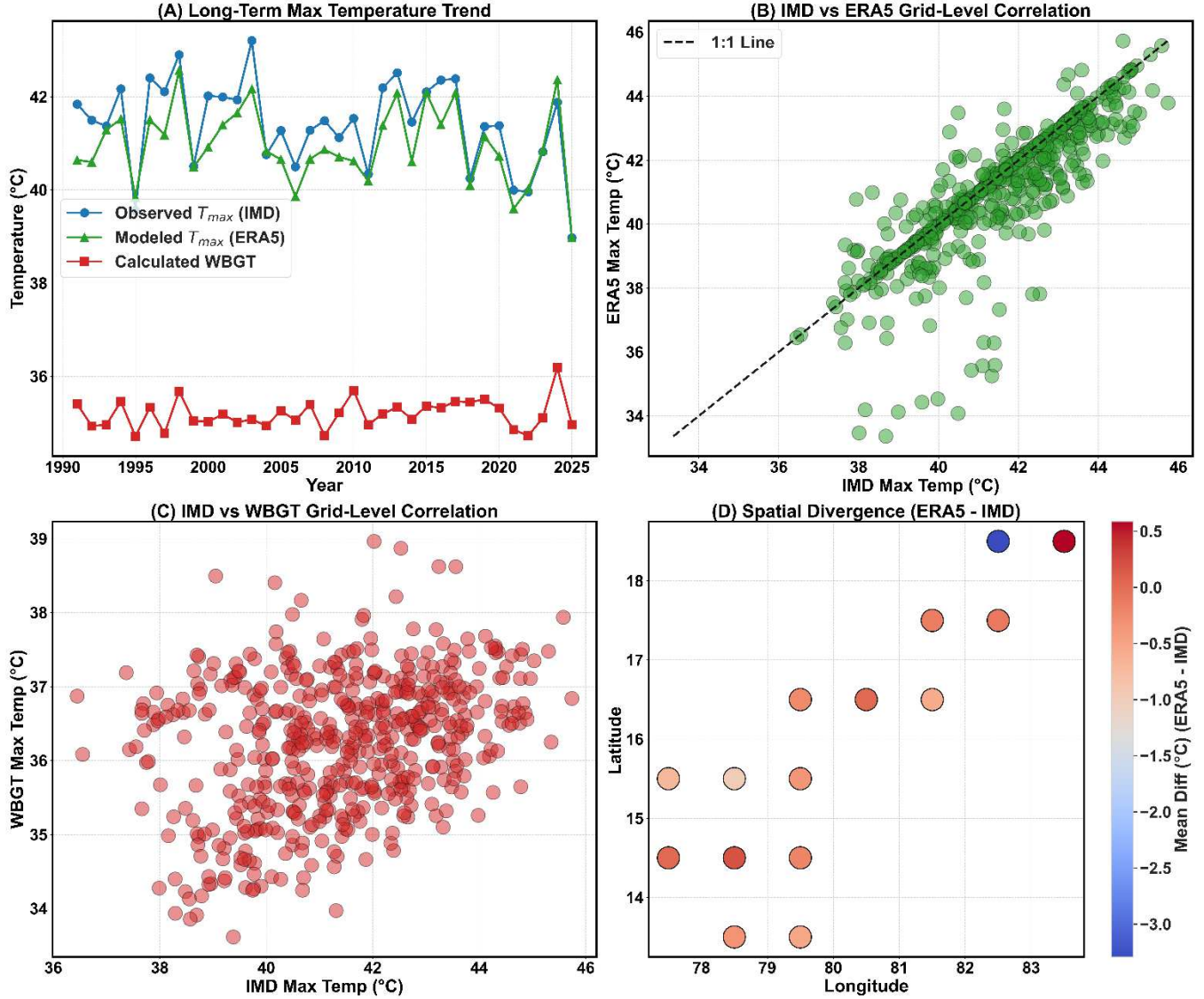


Figure 5: Validation of ERA5-Land against IMD gridded observations (1991-2025). (A) Long-term T_{max} trends: IMD, ERA5, and calculated WBGT. (B) IMD-ERA5 grid-level correlation, with 1:1 reference line. (C) IMD-WBGT grid-level correlation. (D) Spatial Divergence

The long-term trend comparison (Figure 5A) shows ERA5 broadly tracking the interannual pattern of IMD-observed T_{max} across the 1991-2025 record, with ERA5 consistently sitting at or below IMD in most years, consistent with the negative mean bias reported above. Grid-level correlation between IMD and ERA5 (Figure 5B) shows most points clustering near the 1:1 line, with a distinct scatter below the line in the IMD 36-42°C range, where ERA5 underestimates observed temperature by 2°C or more. The IMD-WBGT comparison (Figure 5C) shows a positive but more diffuse relationship, with WBGT values consistently offset several degrees below IMD T_{max} across the full temperature range, consistent with the physical basis of the WBGT formulation. Spatial divergence (Figure 5D) shows most grid cells with a small positive ERA5-IMD difference, but the northeastern corner of the domain departs sharply from this pattern, with mean divergence exceeding -3°C at one grid cell immediately adjacent to a cell showing a positive divergence of similar magnitude.

4.3. Spatiotemporal Climatology of WBGT (1991–2020 Baseline)

The 1991–2020 baseline establishes the localised P90 thresholds used to flag heatwave days in 2015–2030 (Figure 6). Daytime: Coastal Andhra's mean P90 (34.88°C) exceeds Rayalaseema's (33.78°C); the absolute maximum (36.04°C) occurs in Parvathipuram Manyam district; 270 mandals statewide exceed a 35.0°C mean daytime P90. Nighttime: Coastal Andhra's mean P90 (29.41°C) again exceeds Rayalaseema's (28.50°C); the maximum (30.72°C) occurs in NTR district; 247 mandals exceed a 29.5°C mean nighttime P90. These fixed, pixel-specific thresholds are the mathematical baseline against which all subsequent heatwave spells and anomalies are quantified.

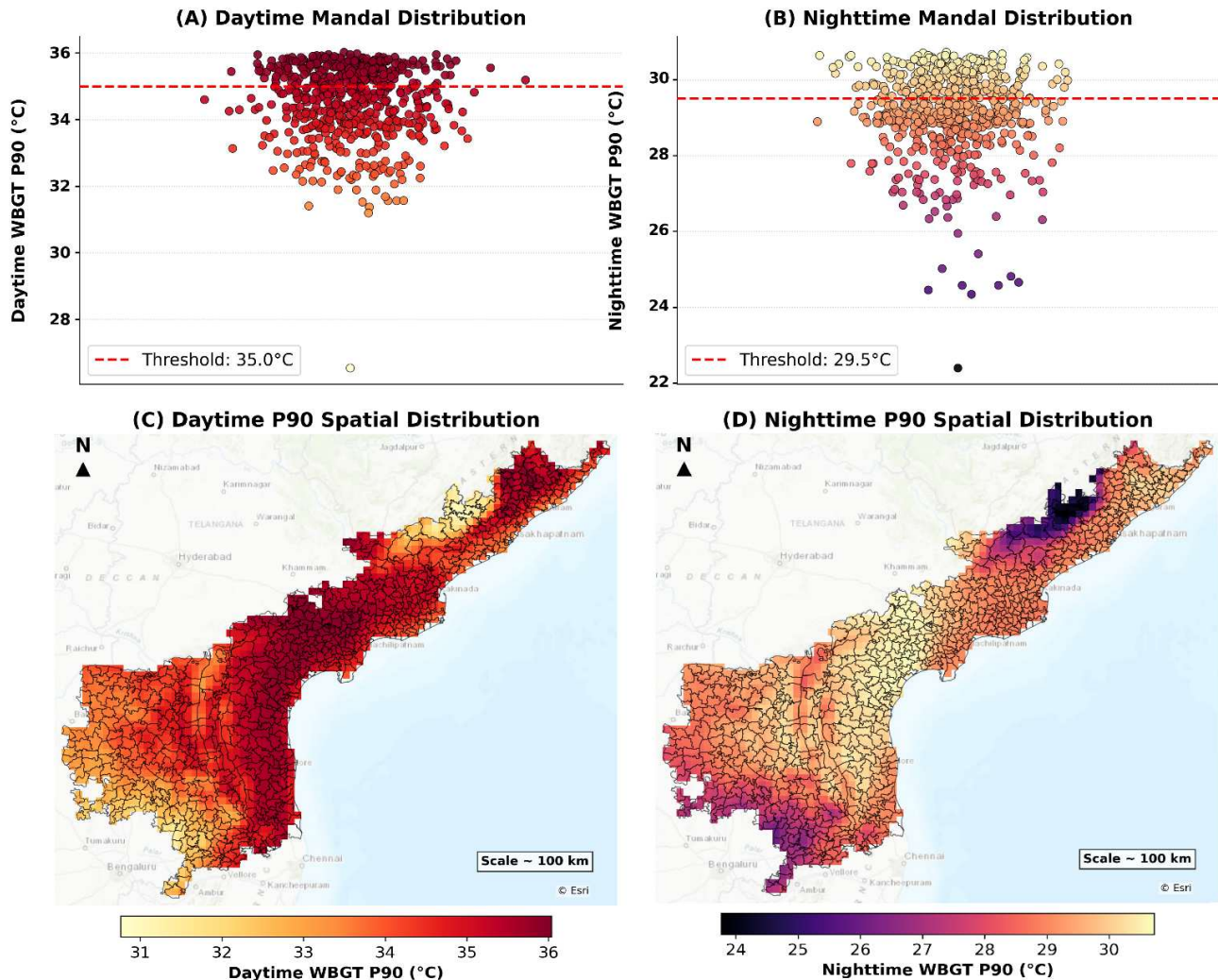


Figure 6: Spatiotemporal distribution of the 1991–2020 WBGT P90 Climatological Baseline

4.4. Contemporary Heatwave Dynamics and Spell Metrics (2015–2026)

Statewide, the 12-year mean nighttime heatwave frequency (4.44 days/year) exceeds daytime (3.22 days/year) (Table 2). Mean nighttime spell duration (3.94 days) similarly exceeds daytime (2.55 days), demonstrating persistent nighttime thermal recovery loss (Figure 7).

Table 2: Summary of statewide average and absolute maximum contemporary heatwave metrics (2015–2026)

Metric	Time of Day	12-Yr Avg	State	Absolute Highest Mandal Avg	Year of Peak	Location of Peak (Mandal, Region)
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HWD	Day	2.55 days	14.00 days	2017	Kottapeta (Coastal Andhra)
	Night	3.94 days	15.50 days	2017	Vepada (Coastal Andhra)
HWF	Day	3.22 days	19.50 days	2016	Kothacheruvu (Rayalaseema)
	Night	4.44 days	17.00 days	2024	Mandasa (Coastal Andhra)
THDs	Day	6.47 days	22.00 days	2016	Kothacheruvu (Rayalaseema)
	Night	6.85 days	23.00 days	2024	Mandasa (Coastal Andhra)
MA	Day	0.07 °C	1.15 °C	2024	Mandasa (Coastal Andhra)
	Night	0.09 °C	1.20 °C	2024	Mandasa (Coastal Andhra)

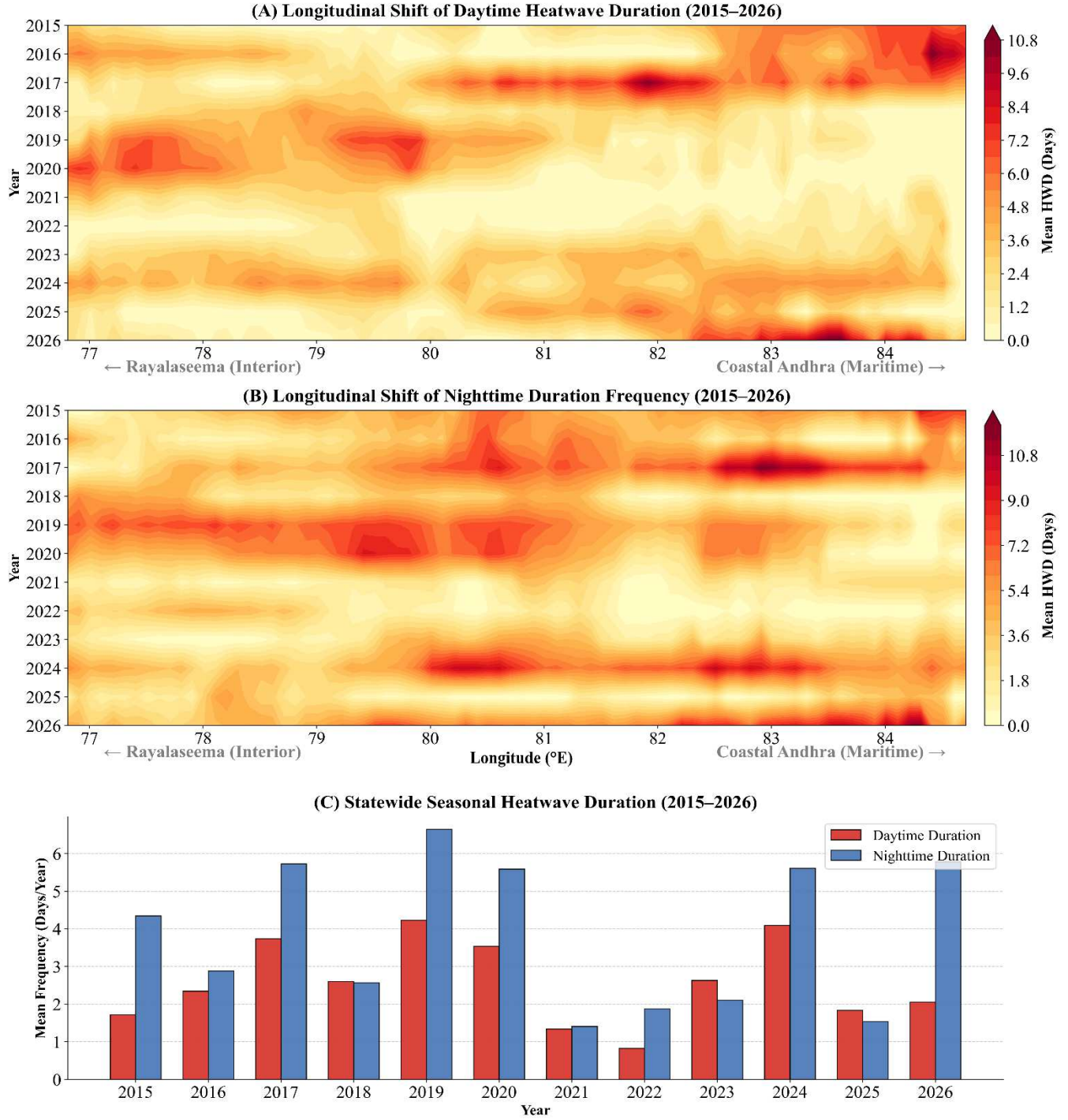


Figure 7: Spatiotemporal and seasonal variability of Heatwave Duration (HWD) across Andhra Pradesh (2015–2026) Benchmark years show sharp localised exceedances: daytime HWF peaked in 2016 at 19.5 days in Kothacheruvu (Rayalaseema); nighttime HWF peaked in 2024 at 17.0 days in Mandasa (Coastal Andhra) (Figure 8). Hot-day exceedances followed the same pattern (22.0 daytime days, Kothacheruvu 2016; 23.0 nighttime days, Mandasa 2024), and the longest continuous spells occurred in 2017 (14.0 daytime days, Kottapeta; 15.5 nighttime days, Vepada).

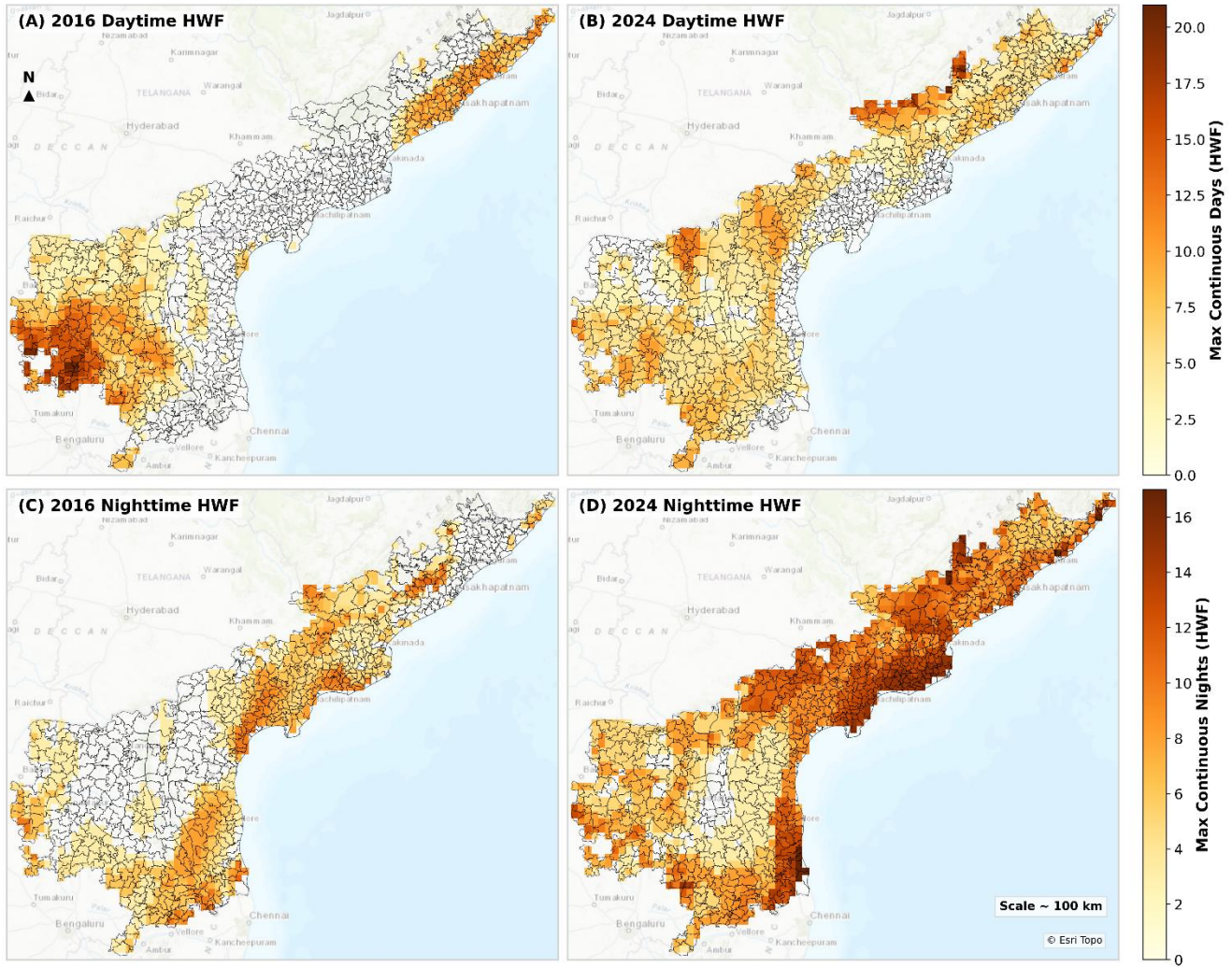


Figure 8: Spatial distribution of localised seasonal Heatwave Frequency (HWF) extremes during benchmark years 2016 and 2024

4.5. Linear Regression Projections of Biometeorological heat stress (2027-2030)

Projected statewide seasonal averages show nighttime metrics consistently exceeding daytime (Figure 9): mean nighttime HWD reaches 5.89 days versus 2.62 daytime; nighttime HWF reaches 7.66 days versus 2.96 daytime; nighttime hot-day exceedances reach 9.11 versus 5.87 daytime.

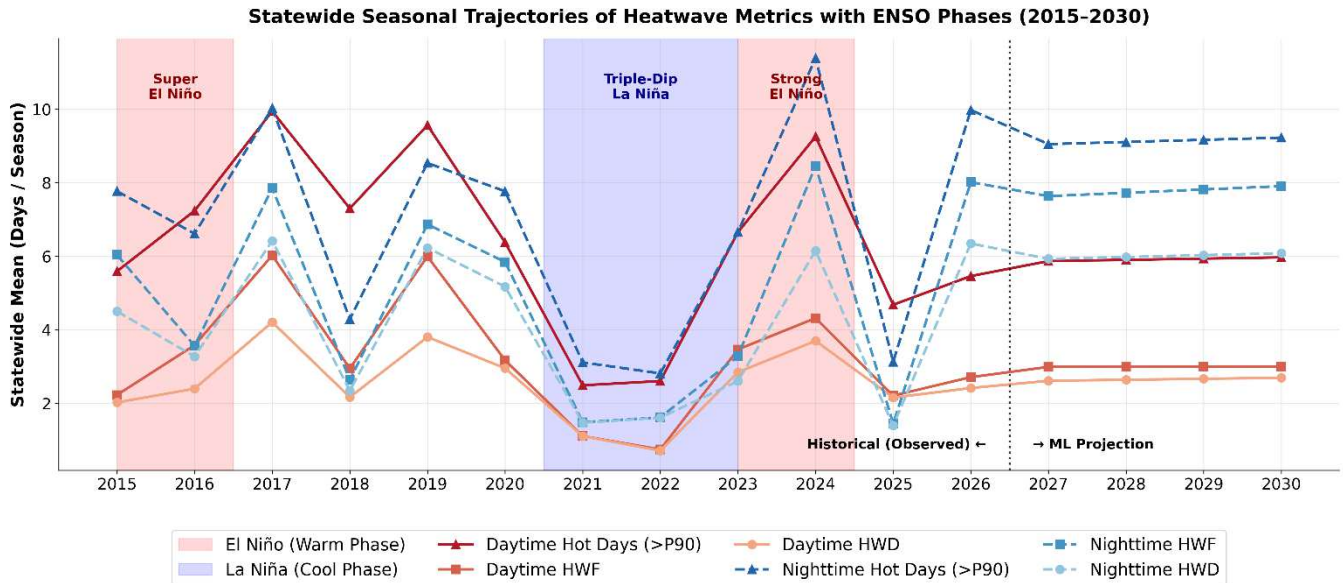


Figure 9: Consolidated interannual trajectories of seasonal heatwave metrics across Andhra Pradesh (2015–2030)

This shows a rightward-shifted mean WBGT anomaly distribution (Figure 10): Projected nighttime mean anomaly (0.20°C) is four times the daytime mean anomaly (0.05°C), an absolute gap of 0.15°C consistent with the broader nighttime intensification pattern in Table 3, where nighttime THDs (0.130 days/year) and nighttime HWF (0.116 days/year) are the two fastest-rising metrics in the 40-year record. Localised 2030 extremes are severe: peak daytime HWD reaches 11.49 days (Seethanagaram, as does peak daytime HWF at 11.34 days); peak daytime hot-day exceedances (13.28) and mean anomaly (0.64°C) occur in Munchingi Puttu.

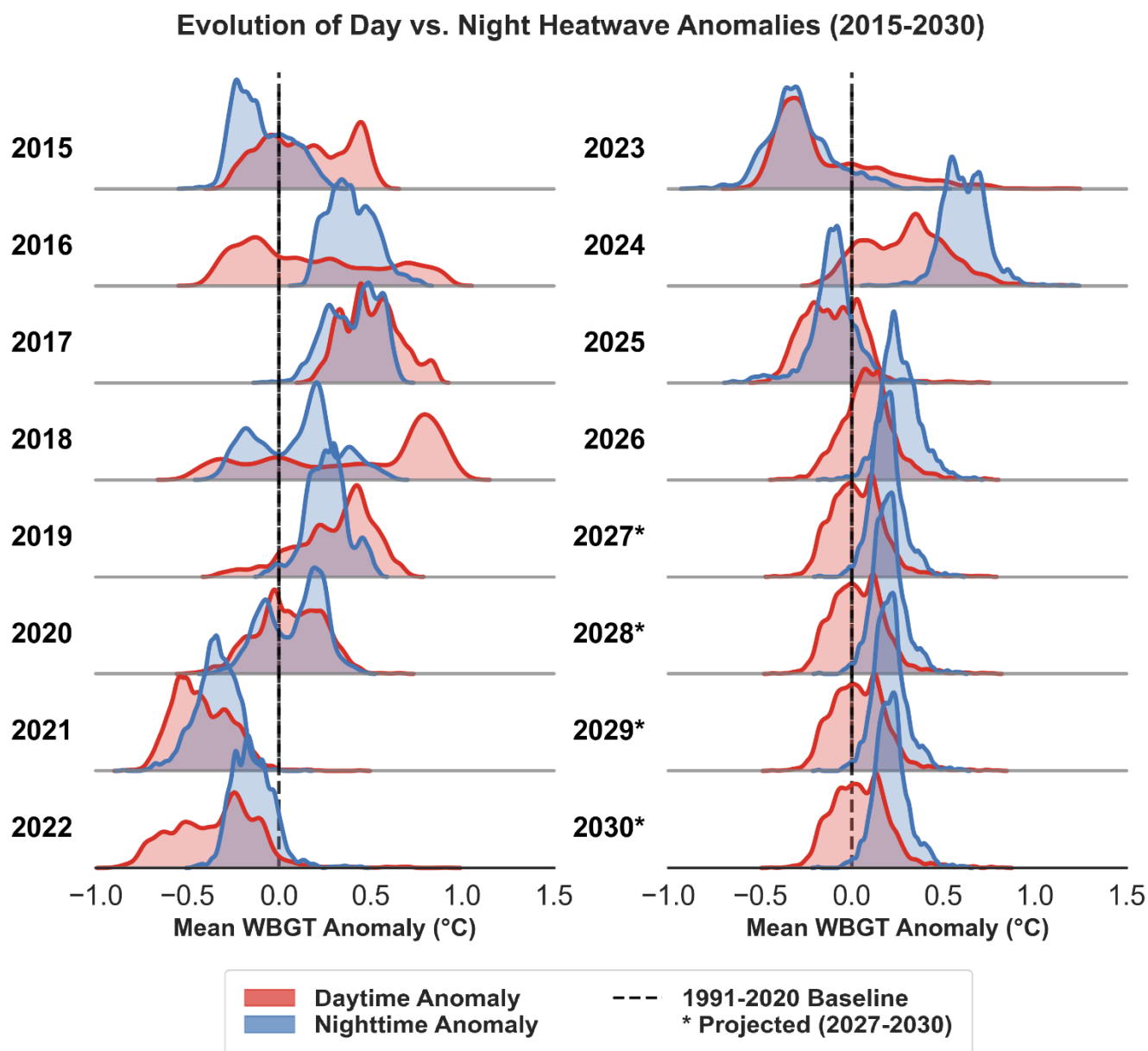


Figure 10: Ridgeline density distributions of Mean WBGT Anomaly (°C). The plot tracks the shifting of localised daytime and nighttime thermal profiles from 2015 to 2030 relative to the historical climatological baseline (1991–2020; dashed line at 0.0 °C).

Nighttime extremes are similarly severe: peak nighttime HWD reaches 12.09 nights (Kondapi); peak nighttime HWF reaches 14.89 days (Jupadu Bungalow); peak nighttime hot-day exceedances (15.78) and anomaly (0.58°C) occur in Pagidyala.

4.6. Long-Term Spatiotemporal Trends and Epochal Shifts

Across 40 years, Mann-Kendall trend tests, Sen's slope estimates, and Getis-Ord G_i^* clustering show statistically significant intensification concentrated overwhelmingly at night (Table 3). Statewide nighttime HWF trends are 0.116 days/year versus just 0.002 for daytime; 76.8% of the state shows significant increasing nighttime HWF versus 12.0% for daytime. Nighttime hot days follow the same pattern (60.7% significant, at 0.130 days/year)

Table 3: Summary of 40-year long-term statistical trends, epoch shifts, and spatial clustering of thermal hazards across Andhra Pradesh.

Hazard Metric	Time of Day	Mean Sen's Slope (Rate/Yr)	Sig. Increasing Trend (%)	Sig. Decreasing Trend (%)	Mean Epoch Shift (t-stat)	Hotspot Clusters (95% CI)
HWD	Day	0.022	9.8%	1.0%	0.844	3
	Night	0.055	14.5%	0.1%	1.609	2
HWF	Day	0.002	12.0%	15.2%	0.122	162
	Night	0.116	76.8%	0.2%	1.718	17
THDs	Day	0.059	27.0%	0.0%	0.811	98
	Night	0.130	60.7%	0.0%	1.441	88
MA	Day	0.009	51.1%	0.0%	1.350	2
	Night	0.010	60.2%	0.0%	1.629	104

Baseline-vs-current t-tests confirm this (Figure 11): mean nighttime HWF ($t = 1.718$) and mean nighttime thermal anomaly ($t = 1.629$) both point to a widespread break from historical norms.

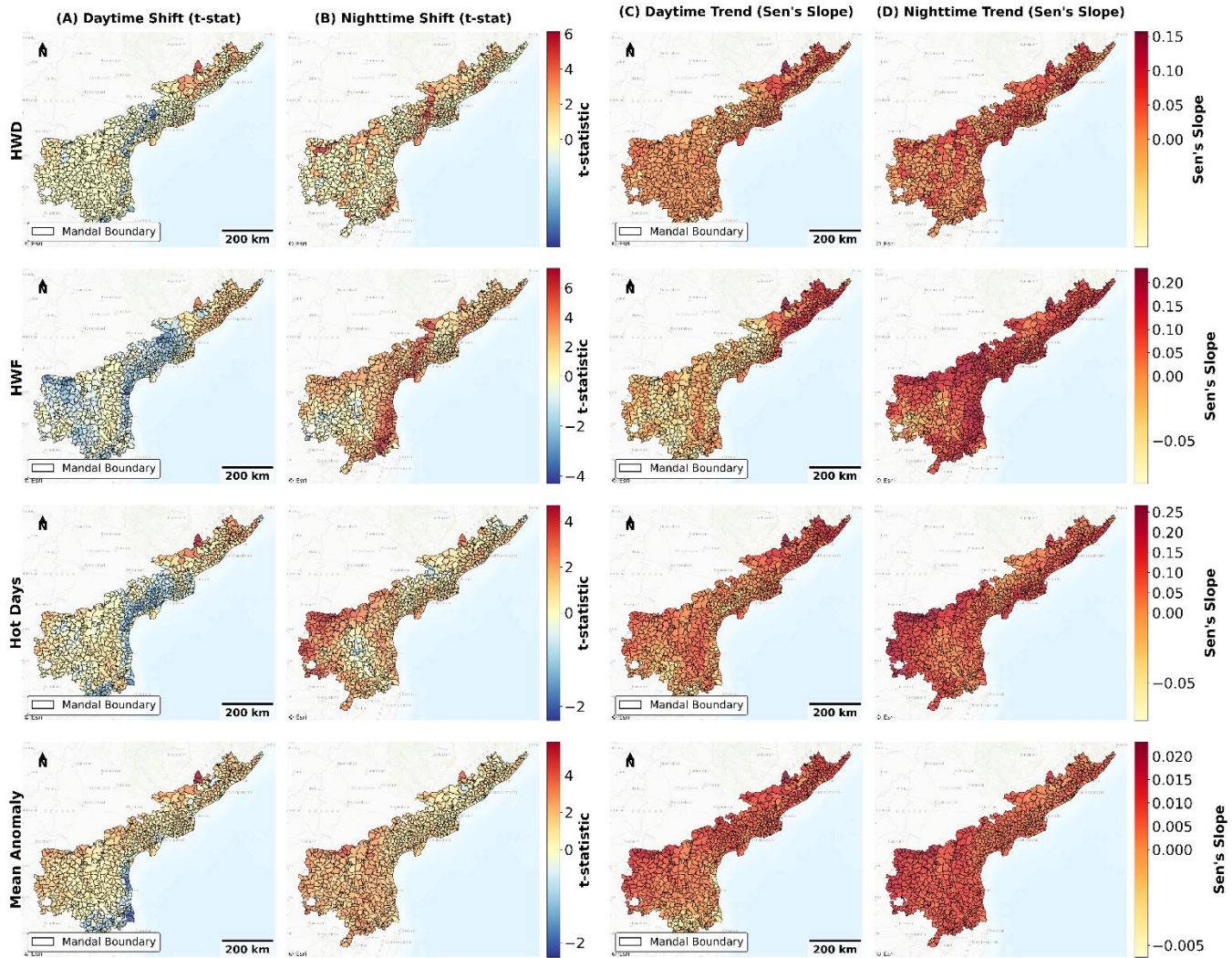


Figure 11: Spatial distribution of long-term climate trends and baseline epoch shifts across Andhra Pradesh. The t-statistic (A & B) represents the epochal shift of the contemporary period (2015–2026) away from the 1991–2020 historical baseline. Figures C & D display the multi-decadal velocity of warming via the Mann-Kendall Sen's Slope estimator.

Daytime trends are lower on average, but Getis-Ord G_i^* still picks up sharp, localised daytime hotspots: 162 for daytime HWF (Figure 12) and 98 for daytime hot days ($>P90$), clustered mainly along the northern coast and a few interior regions. Nighttime warming and its hotspots (104 significant clusters for mean nighttime anomaly) are spread far more broadly; this looks like a statewide loss of overnight cooling, not a few isolated clusters.

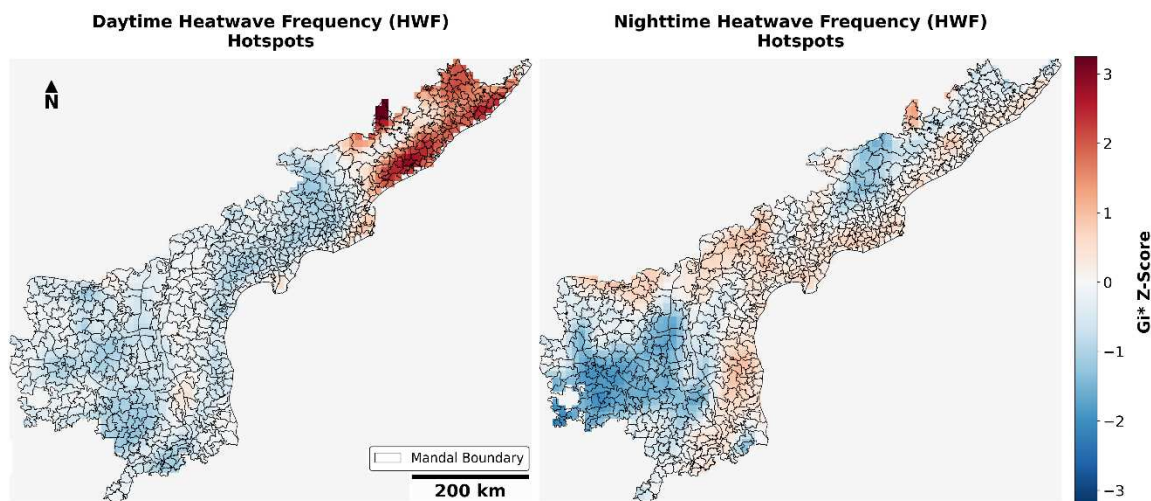


Figure 12: Spatial clustering of long-term Heatwave Frequency (HWF) across Andhra Pradesh using Getis-Ord Z-scores.

4.6.1. Regional Disparities in Long-Term Trends

Coastal Andhra shows the steepest nighttime rise: nighttime HWF there increases at 0.114 days/year, with 71.1% of its mandals showing a significant increasing trend (Figure 13). The three fastest-warming mandals statewide — Munchingi Puttu, Mandasa, and Krosur — are all in Coastal Andhra. Munchingi Puttu (Alluri Sitharama Raju district) dominates regional extremes: the state's highest daytime mean anomaly trend ($+0.0231^{\circ}\text{C}/\text{yr}$), most severe daytime regime shift ($t = 5.7783$), and steepest daytime HWF ($+0.2242/\text{yr}$) and hot-day ($+0.2671/\text{yr}$) trends. Nighttime extremes accelerate too: Gummagatta and Rayadurg show high nighttime warming ($+0.0172$ and $+0.0161^{\circ}\text{C}/\text{yr}$), and Anakapalli shows the sharpest nighttime HWD rise ($+0.1562$ days/yr). Projections carry this forward: the region's mean nighttime HWF roughly doubles, from 3.76 days per season (2015–2026) to 7.78 by 2030.

Rayalaseema exhibits a contrasting pattern: daytime HWF shows no significant long-term trend and is projected to fall (from 2.97 to 1.47 days per season), with peak daytime warming in mandals like Kosigi ($+0.0142^{\circ}\text{C}/\text{yr}$) and Kouthalam ($+0.0139^{\circ}\text{C}/\text{yr}$) staying well below coastal maximums. But its nighttime picture is degrading fast: 67.9% of Rayalaseema mandals show significant nighttime HWF increases, and the region posts the state's sharpest nighttime mean-anomaly shift ($t = 2.200$), above Coastal Andhra's ($t = 1.441$), concentrated in the Nandyal and Kurnool districts. Pagidyala and Nandikotkur show the region's most aggressive nighttime warming ($+0.0197$ and $+0.0189^{\circ}\text{C}/\text{yr}$; regime shifts $t = 4.0843$ and 3.8956), and nighttime hot-day frequency accelerates in Nandavaram ($+0.2632/\text{yr}$) and Guduru ($+0.25/\text{yr}$). Daytime extremes may be stabilising here, but the region is losing its ability to cool down overnight.

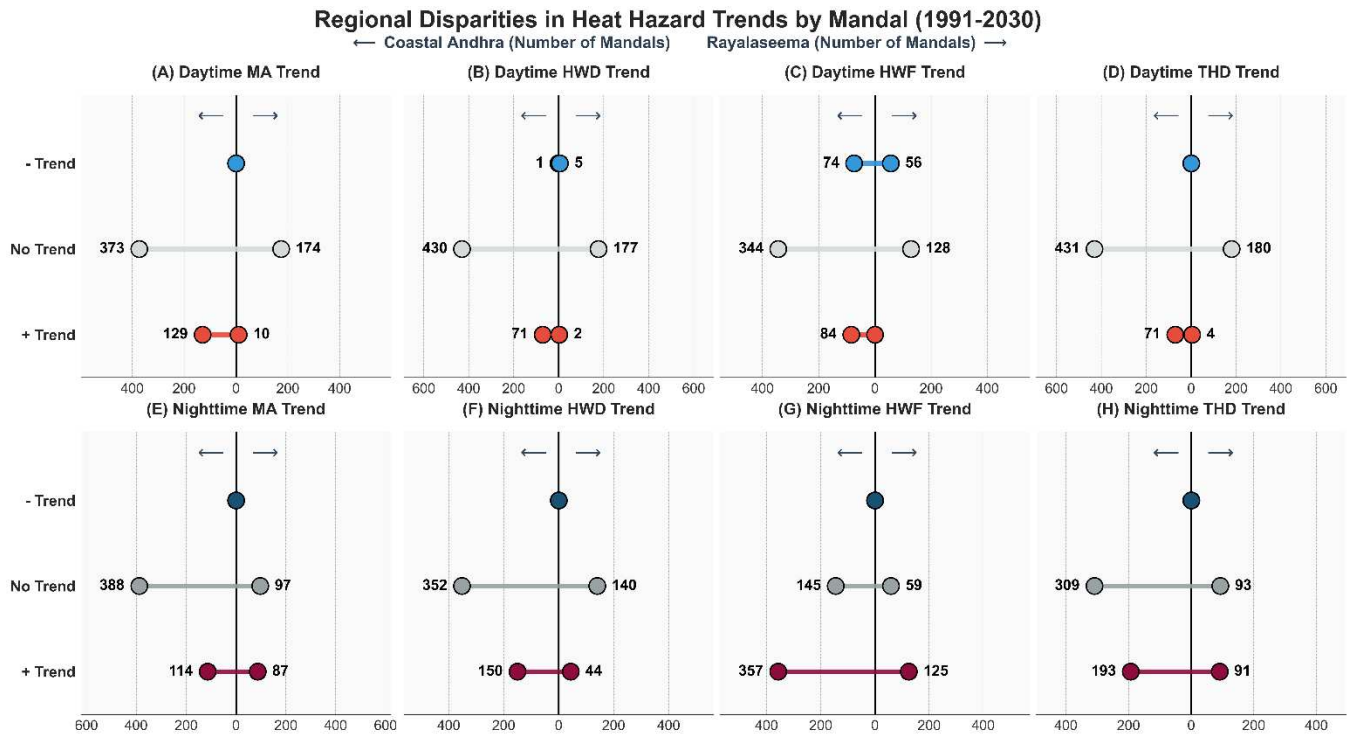


Figure 13: Number of mandals exhibiting significant Heat hazard trends by region (1991–2021). Bilateral lollipop distributions contrast the Mann-Kendall trend significance between Coastal Andhra (left) and Rayalaseema (right). The grid is separated into daytime (top row) and nighttime (bottom row) metrics, including Mean Anomaly (MA), Heatwave Duration (HWD), Heatwave Frequency (HWF), and Total Hot Days (THDs). Nodes indicate the exact count of mandals experiencing significant increasing (+ Trend), significant decreasing (- Trend), or non-significant (No Trend) changes over the 40-years.

4.7. Spatiotemporal Analysis of Population Exposure to Compound Heat Hazards

Intersecting the dasymetric population model with the spatiotemporal climatology metrics lets us quantify both past exposure and projected exposure severity.

4.7.1. Temporal Exposure Dynamics and Health Outcomes (2015–2030)

Statewide annual exposure varies a lot year to year, tracking hazard-season intensity (Figure 14). In the 2015 baseline year, about 2.07 million people (of a state population of 49.73 million) fell into the High-Risk class (0.45–0.65 CHHI) and 0.62 million into Severe Risk (>0.65). 2017 remains the worst year on record: 21.07 million in High Risk and 3.90 million in Severe Risk. 2021 and 2022 sit at the other extreme, with almost the entire population staying below Moderate Risk. The projected period settles into a more stable pattern: by 2030, out of a projected population of 54.25 million, 13.61 million are projected in the High-Risk class and 0.70 million in Severe Risk.

These extremes line up with 2026 health outcomes reported in (Figure 14B). According to the Ministry of Home Affairs' national heatstroke surveillance data (MHA, 2026), Telangana recorded the highest total heatstroke cases nationally (~915), followed by West Bengal (~733), while Maharashtra had the most confirmed deaths (11). Andhra Pradesh ranked fourth nationally in total cases (~540) and second in confirmed deaths (4).

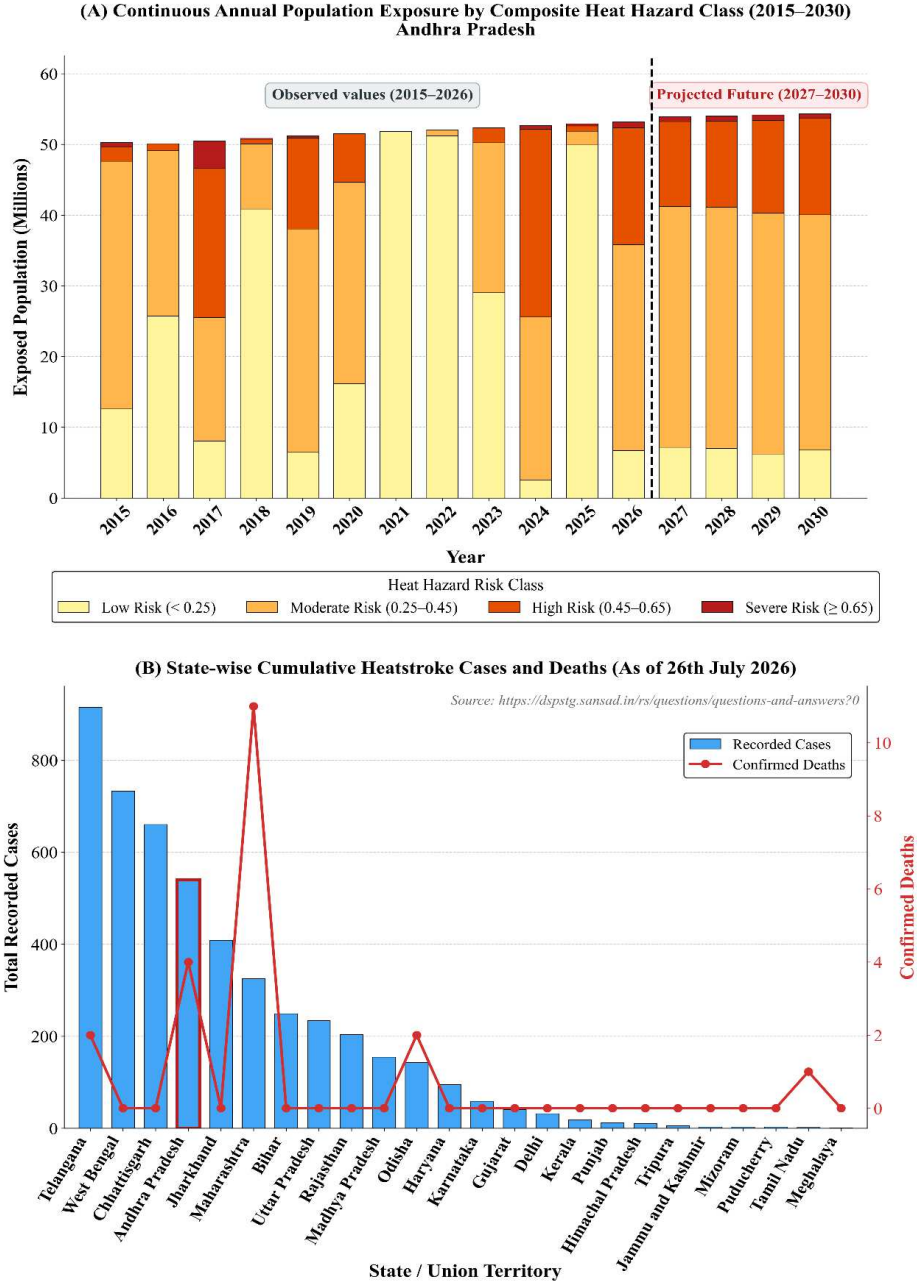


Figure 14: Population exposure to heat hazards and national heatstroke statistics. **(A)** Continuous annual population exposure by heat risk category in Andhra Pradesh from 2015 to 2030. **(B)** Cumulative heatstroke cases and corresponding deaths across Indian states and union territories during the 2026 heat season.

4.7.2. Projected Composite Hazard Exposure and Density Intersection

Mandal-wise CHHI projections show 121 mandals reaching High Risk by 2030, with none reaching Severe Risk (Figure 15); 110 of these (over 90%) sit in Coastal Andhra, whose distribution shifts upward, centred just above the High-Risk threshold, against only 11 mandals in Rayalaseema. Overlaying hazard intensity with population density sharpens the picture: Coastal Andhra's exposure spreads across all density quartiles, while Rayalaseema's high-density areas cluster tightly, well above the rest of the region's distribution.

Table 4: Top 5 critical mandals ranked by the intersection of high projected CHHI and high population density classification per region (2030).

Region	Rank	Mandal (District)	Mean CHHI	Pop. Density (persons/sq km)	Density Class
Coastal Andhra	1	Lakkavarapukota (Vizianagaram)	0.5808	421	High
	2	Kotabommali (Srikakulam)	0.5689	520	High
	3	Kottavalasa (Vizianagaram)	0.5682	572	Very High
	4	Narasannapeta (Srikakulam)	0.5677	694	Very High
	5	Jalumuru (Srikakulam)	0.5553	389	High
Rayalaseema	1	Kurnool Urban (Kurnool)	0.5877	1,950	Very High
	2	Kallur (Kurnool)	0.5191	731	Very High
	3	Yemmiganur (Kurnool)	0.4545	377	High
	4	Nandyal Urban (Nandyal)	0.4479	705	Very High
	5	Nandyal (Nandyal)	0.4223	1,007	Very High

Ranking mandals by mean CHHI within high-density areas turns up the sharpest local hotspots. In Coastal Andhra, high exposure directly overlaps population centers: Lakkavarapukota (Vizianagaram) tops the list at 0.5808 CHHI (High Density), followed by Kotabommali at 0.5689; Kottavalasa (0.5682) and Narasannapeta (0.5677) fall in the "Very High" density band (>572 people/km²). Rayalaseema's risk picture is dominated by one outlier — Kurnool (Urban) — whose mean CHHI (0.5877) is only slightly below Rayalaseema's highest local value, but whose density (1,950 persons/km²) makes it the single most extreme exposure point in the study; the rest of the region's top five stay below the high-risk threshold (Nandyal Urban, for instance, at 0.4479 CHHI), showing dense pockets of exposure exist even outside the high-risk zone.

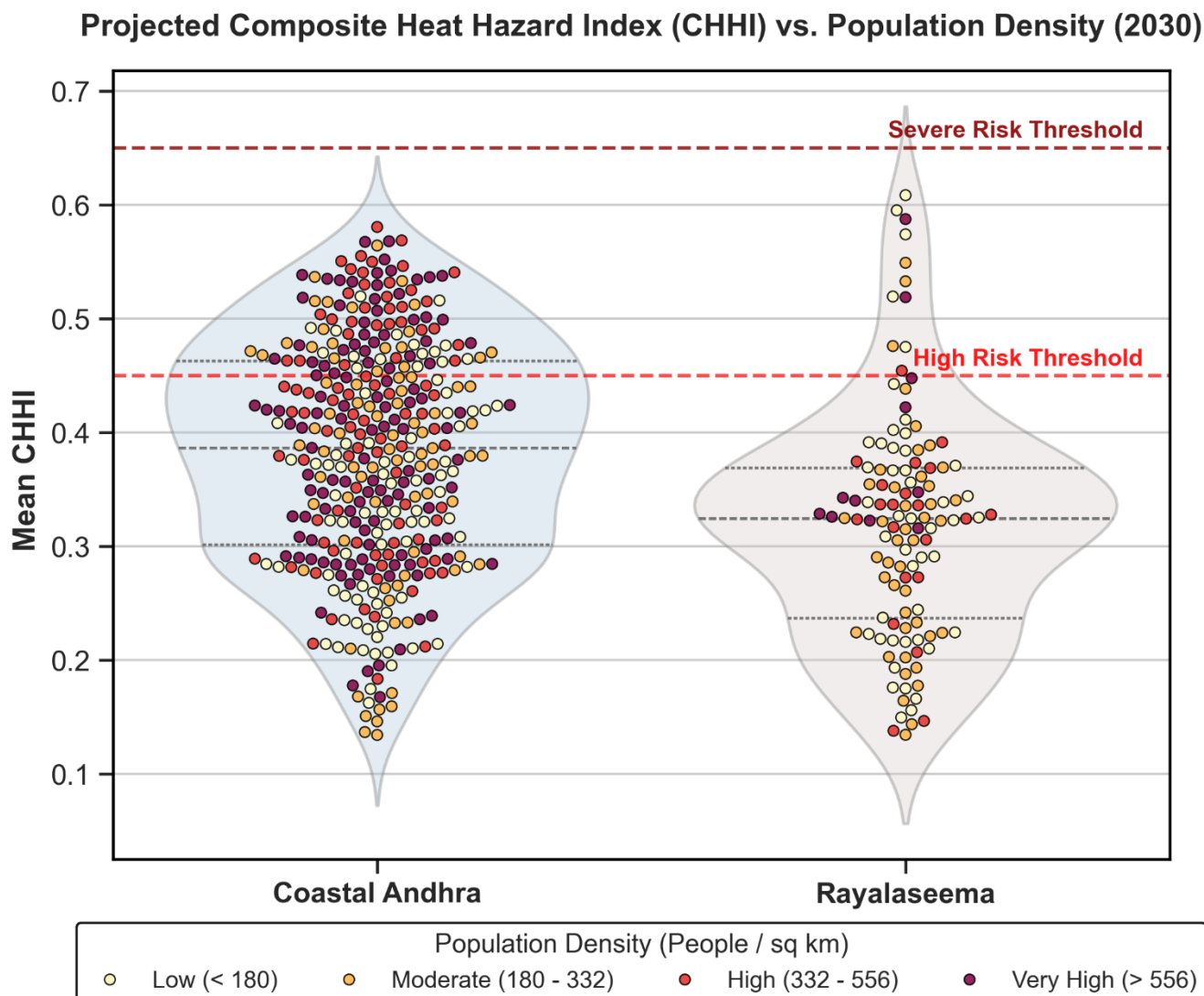


Figure 15: Projected Regional Distribution of CHHI and Population Exposure at the Mandal Level (2030). Mandals are colour-coded by population density quartile (Low to Very High). Dashed lines indicate High (≥ 0.45) and Severe (≥ 0.65) risk thresholds.

4.7.3. Mandal-Level Absolute Exposure Severity (projection of 2030)

The administrative units recording the most acute exposure severity in the 2030 projection are predominantly major urban centres. Nellore (Urban) ranks first statewide, closely followed by Guntur West and Vizianagaram Urban. Additional top-ten hotspots: Tirupati Urban, Gopalapatnam, Pendurti, Rajamahendravaram Urban, and Bhimavaram are all in the Coastal Andhra maritime corridor. In the Rayalaseema interior, absolute exposure is acutely localised: Kallur and Kurnool (Urban) both rank among the most severely exposed administrative units statewide (Figure 16).

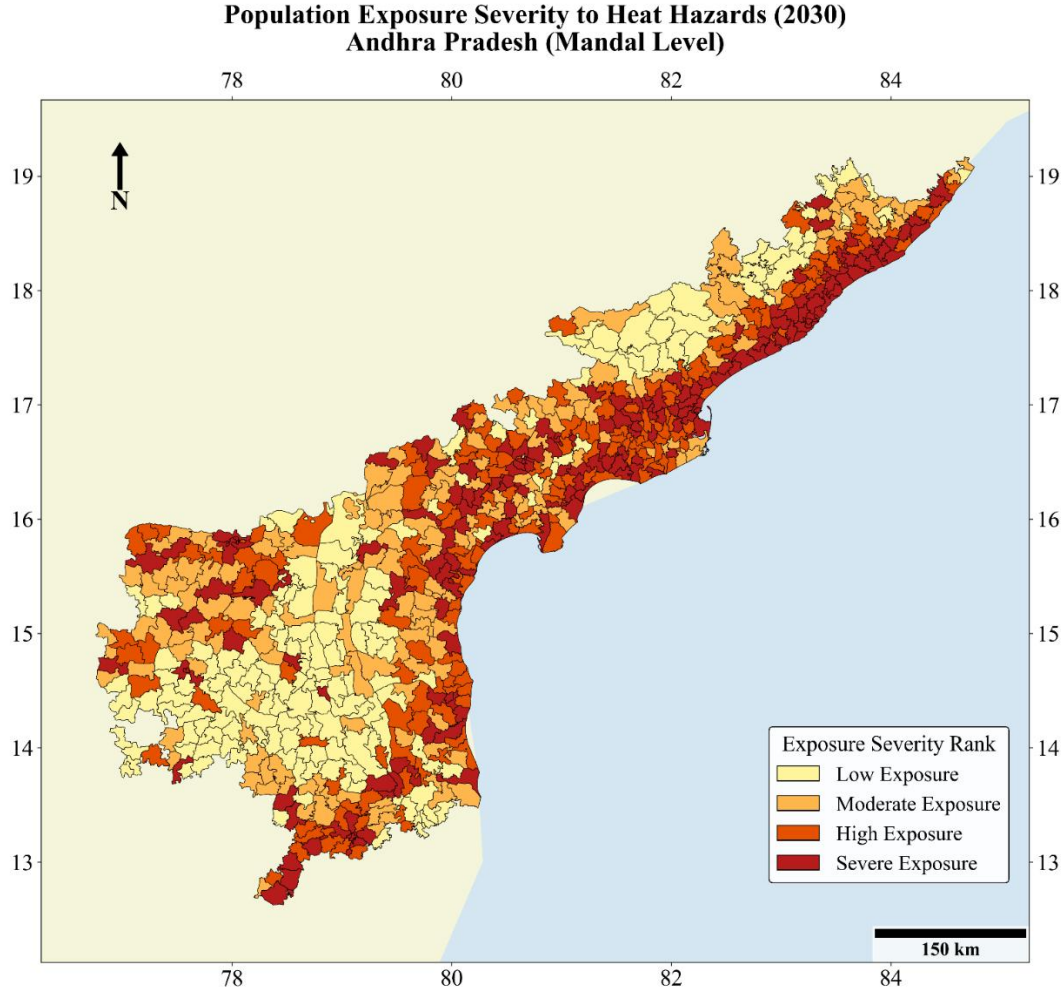


Figure 16: Projected Absolute Population Exposure Severity to Heat Hazards across Andhra Pradesh at the Mandal level (2030)

5. Discussion

5.1. The Nighttime Shift as the Central Signal

Heat hazard in Andhra Pradesh does not rise evenly through the day: nights are heating up far faster than days. Sen's slope estimator for nighttime HWF (0.116 days/year) is more than fifty times daytime's (0.002); 76.8% of the state shows a significant rising trend in nighttime HWF, against just 12.0% for daytime, and nighttime THDs follow the same path (0.130 days/year, 60.7% significance). Mukherjee and Mishra (2018) showed that concurrent day-night heatwave events in India are projected to rise sixfold under 2°C of warming, driven mainly by lost nighttime cooling; the projected near-doubling of Coastal Andhra's mean nighttime HWF (3.76 to 7.78 days by 2030) sits within that trajectory. At the mandal level, the same cluster — Kurnool Rural, Yemmiganur, and Adoni — recurs at or near the top of nearly every nighttime trend metric, showing Rayalaseema's intensification is concentrated in a specific district, not spread evenly across the interior.

5.2. High-Resolution Exposure Mapping and the Value of Dasymetric Downscaling

The transect drawn over Vijayawada for spatial validation (Figure 3) is a direct demonstration of a known problem in exposure modelling: coarse grids spread population over uninhabited land such as riverbeds, bridges, and open ground, over- or under-representing exposure counts. This follows Mennis's (2003) mass-preserving logic, where land-class and development layers

guide dasymetric weighting, and confirms Tuholske et al.'s (2021) finding that coarse-resolution studies miss the finer-scale variation adaptation planning needs most. Baynes et al. (2022) apply a comparable exclude-uninhabited-areas logic to produce 30 m dasymetric population estimates for the conterminous United States, but from Census block data constrained by impervious surface; the present study instead redistributes WorldPop, a globally consistent but coarser input, using a continuous multi-covariate PSI built entirely from open Earth-observation data, making the approach usable in data-sparse contexts where Census-block-level ancillary data does not exist. The 30 m PSI-based allocation, and the resulting 35.6/17.8 million Coastal Andhra-Rayalaseema split, give this study a demographic basis that overlays pixel-level hazard layers along with administrative averages.

5.3. Nighttime Heat and Heatstroke Risk: Why the Weighting Favours Nighttime Indicators

The CHHI weighting matrix assigns 38.2% to nighttime HWF and 30.2% to nighttime THDs — together 68.4% of the total index — against 24.3% combined for daytime (13.4% THDs, 6.0% HWF) and only 12.1% for the two HWD terms. This weighting is based on the fastest trend observed in the 40-year hazard record (Table 3) and is not the result of any design choice; it is in agreement with the health evidence showing that nighttime heat is particularly harmful because thermoregulation (the body's process of maintaining a stable internal temperature) relies on overnight physiological recovery, a process which stops when minimum temperatures remain high. Guirguis et al. (2014) found that heatwaves involving a greater number of nights with high minimum temperatures had more severe health effects than similarly hot days which lacked cooling nights. In a 20-year study of hospitalisations in Hong Kong, Guo et al. (2024) found that excess nighttime heat significantly increased the number of non-cancer hospitalisations — nearly doubling the effect among elderly and low-income patients — and that definitions of hot nights using a single threshold underestimate the real hazard when assessed using a cumulative measure of nighttime heat excess. Liu et al. (2025), in their analysis of 28 East Asian cities, found that compound day-night heatwaves lead to a super-linear increase in mortality risk once a moderate heat threshold is exceeded, whereas single-regime events show a more gradual response — this is the epidemiological reason for constructing the CHHI as a single compound metric rather than as separate additive day and night components.

5.4. WBGT versus Dry-Bulb Temperature: Physiological Measurement and Threshold Design in Current Practice

The nighttime dominance found here would not be captured under India's operational heatwave framework, still largely based on dry-bulb temperature thresholds, with humidity and wind treated as secondary information (Khambete, 2026; Justine et al., 2023). Dry-bulb temperature cannot capture whether the body can shed heat once air nears saturation (Khambete, 2026) — a condition that prevails along the Coastal Andhra corridor and drives its elevated heatstroke risk. WBGT, combining air temperature, humidity, wind, and radiation into one physiological index (Liljegren et al., 2008), captures this compensable-to-uncompensable transition- the point at which sweat evaporation can no longer keep pace with heat gain, that dry-bulb readings cannot. The higher nighttime P90 in Coastal Andhra (29.41°C) versus Rayalaseema (28.50°C), despite Rayalaseema's higher daytime dry-bulb climate, illustrates why a humidity-blind metric would mis-rank the two regions' actual risk. This argues for pixel-wise, climatologically relative thresholds over IMD's blanket subdivision-level criteria, since a fixed threshold cannot register that acclimatised and non-acclimatized populations face different physiological risk.

5.5. Regional Disparities and the Concentration of Compound Hazard

Projected 2030 high-risk exposure concentrates heavily in Coastal Andhra (110 of 121 high-risk mandals, over 90%) against only 11 in Rayalaseema, reflecting the same climatic divide established above, where coastal humidity sustains elevated hazard across a broader area while Rayalaseema's risk remains tied to a small number of dense urban centres. The compound CHHI framing, integrating HWD, HWF, and THDs across day and night (Zscheischler et al., 2018; Mora et al., 2017) and consistent with the super-linear mortality risk Liu et al. (2025) attribute to compound events, captures what a single-variable map would miss: Rayalaseema's risk concentrates in dense urban outliers rather than spreading evenly, showing why fine-grained mandal-level breakdowns matter even where average hazard looks stable.

The Absolute Exposure Severity figure takes this analysis even further. In Coastal Andhra, the intensity of severe thermal hazard (see Figure 15) is widely spread out, whereas the real human impact (see Figure 16) is concentrated in just a few demographic areas: Gajuwaka, Visakhapatnam Rural and Nellore (Urban) feature at the highest levels of severity, with Guntur West, Vizianagaram Urban, Gopalapatnam, Rajamahendravaram Urban and Pendurti also appearing in the top ten, all of them along the coastal area. This aligns with Kacker et al. (2024), who found sharp intra-city risk gradients from built-up density in Delhi, and Tuholske et al. (2021), who showed coarse-resolution studies miss the finer-scale heterogeneity this study's 30 m layer is designed to capture (Section 5.2). It is also consistent with Mandvikar et al. (2024), whose ranking of major Indian cities by Heat Health Risk Index found absolute exposure driven by the interaction of density and hazard intensity, not hazard intensity alone.

In Rayalaseema, the pattern becomes even more pronounced. The Kurnool district is at the top of both the state-level CHHI ranking and the trend analysis (see Table 4 and Figure 11): both Kurnool Rural and Yemmiganur have repeatedly shown the steepest nighttime trends, while Kurnool Urban has the region's highest exposure level. Rayalaseema's risk picture is dominated by one outlier, Kurnool Urban, whose density (1,950 persons/km²) makes it the region's single most extreme exposure point despite a CHHI (0.5877) near the regional maximum; the rest of the top five stay below the high-risk threshold (Nandyal Urban: 0.4479 CHHI), showing dense exposure pockets exist even outside the high-risk zone. This is due to both the density and the locally accelerating nighttime hazard trend, notable given Rayalaseema's smaller total population (17.8 million compared to 35.6 million; Section 4.1). These findings call for different administrative responses: Coastal Andhra needs wide-scale, regional heat measures, given high CHHI overlaps population density across many mandals, while Rayalaseema needs focused, infrastructure-based interventions concentrated in its few severely affected urban centres.

5.6. Population Exposure Trajectories, Mean Anomaly nonlinearity, and the 2026 Heatstroke Record

MA carries the smallest Sen's slope of any metric in this study (0.009°C/yr daytime, 0.010°C/yr nighttime), yet is among the most spatially significant trends recorded (51.1% significant daytime increase, 60.2% nighttime). Mazdiyasni et al. (2017), analysing IMD data from 1960-2009, found that when mean summer temperature rose from 27.0°C to 27.5°C, the modelled probability of a heatwave killing more than 100 people rose from 13% to 32%. Extrapolated across this study's 40-year record, the nighttime MA trend accumulates to approximately 0.40°C, a shift of comparable order to the one Mazdiyasni et al. link to a near-tripling of mass-mortality probability.

Statewide High-Risk exposure (Figure 14A) moved from 2.07 million people in 2015 to 21.07 million in 2017, before falling to near-zero in 2021 and 2022. This variability tracks ENSO phase: the 2017 peak coincides with the tail of the Super El Niño episode, and the 2021-2022 collapse coincides with the Triple-Dip La Niña period. In the projected period, where ENSO forcing is absent from the OLS projection, the trend signal dominates, and High-Risk exposure stabilizes at 13.61 million by 2030, a

sixfold increase against only 9% population growth (49.73 to 54.25 million), confirming climate-driven rather than demographic growth.

Severe Risk exposure barely moves (0.62 to 0.70 million) even as High-Risk exposure grows sixfold, and Section 4.6.2 separately reports zero mandals reaching Severe Risk by 2030 under mandal-level averaging, despite 0.70 million people in that class statewide at the pixel level (Figure 14A). Mandal-level spatial averaging smooths the pixel-level severe extremes the dasymetric model was built to preserve (Section 5.2; Tuholske et al., 2021), the zero-mandal result reflects the resolution of the aggregation step, not the absence of severe exposure. Figure 14B situates these projections against the 2026 heatstroke record: Andhra Pradesh ranked fourth nationally in cases (~540) but second in confirmed deaths (4), behind only Maharashtra, consistent with a compressed nighttime recovery window (Guo et al., 2024; Liu et al., 2025) raising the case-fatality rate of a given exposure event rather than the number of events.

Figure 15 shows a further regional distinction: Coastal Andhra's high-CHHI mandals are distributed across all four density quartiles, while Rayalaseema's cluster is almost exclusively in the Very High-density quartile via the Kurnool Urban outlier. Lakkavarapukota's CHHI (0.5808, 421 persons/km²) is nearly identical to Kurnool Urban's (0.5877, 1,950 persons/km²), yet population exposed per unit hazard is more than four times higher in Kurnool. Romanello et al. (2024) report that global heatwave-day exposure among vulnerable populations (infants, adults over 65) has risen more than threefold since the 1986-2005 baseline; Andhra Pradesh's projected sixfold High-Risk rise by 2030 is of the same order.

5.7. Alignment with Emerging Policy Recommendations

These results consistent with emerging Indian climate policy recommendations. Khambete (2026) reports that a recent CEEW analysis recommends that HAPs move beyond daytime temperatures to incorporate nighttime warming, and separately flags a persistent gap in granular, within-city heat and exposure data. The mandal-level CHHI framework developed here — able to isolate specific high-density hotspots such as Lakkavarapukota and Kottavalasa in Coastal Andhra and Kurnool Urban in Rayalaseema — offers a direct, working answer to that gap, flagging exactly which mandals combine high projected hazard with high population density and elevated heatstroke risk: the level of granularity CEEW and similar assessments have identified as currently missing from national heat policy.

6. Conclusion

This study set out to close three gaps in heat-risk assessment for the built environment: heat metrics that neglect nighttime warnings, exposure data that is too coarse to show where people live, and compound indices weighted on expert opinion rather than observed trends. A 40-year analysis of ERA5-Land-derived WBGT data for Andhra Pradesh (1991-2030) shows nighttime heat hazard intensifying far faster than daytime heat on almost every metric: nighttime heatwave frequency rises across 76.8% of the state against 12.0% for daytime, at a Sen's slope estimator more than fifty times steeper (0.116 versus 0.002 days per year). By 2030, projected nighttime mean anomaly reaches four times the daytime value (0.20°C versus 0.05°C), consistent with nighttime THDs and HWF as the two fastest-rising metrics over 40 years (0.130 and 0.116 days/year). This matters because prolonged nighttime heat closes the window the body needs for physiological recovery and prevents buildings from shedding the heat load accumulated during the day. The exposure model introduces a new methodological feature. Although dasymetric downscaling at a spatial resolution of 30 metres has already been applied to census-based population estimates, this study adapts it to WorldPop by redistributing the counts using a PSI that is entirely based on open-source datasets, an application

not previously reported for heat exposure mapping in India. When checked against the transect drawn over Vijayawada, the technique reduces the overestimations of riverbed and open land by 170 to 185 persons per pixel to a verified level of 20 to 30 persons per pixel, while keeping the total population figures unchanged. This result is reinforced by independent field validation at two additional ground sites, and by ERA5-Land's moderate agreement with IMD gridded observations, which showed a consistent negative bias (-0.44°C) rather than inflation, indicating the hazard estimates reported here are conservative rather than overstated. The regional contrast in exposure calls for spatially differentiated policy responses. In Coastal Andhra, the hazard affects a wide range of areas, covering 110 of the 121 high-risk mandals projected for 2030; in Rayalaseema, it is concentrated in a small number of densely populated mandals, particularly Kurnool Urban (which has a CHHI of 0.59 at a density of 1,950 persons per km^2). However, this difference in patterns is not apparent within India's present heat action plan at the subdivision level, which should adopt WBGT-based nighttime thresholds and mandal-level resolution. The approach transfers to other climatically divided regions of the Global South, offering planners a low-cost, reproducible basis for targeted intervention.

7. Limitations and Future Scope

The study uses ERA5-Land reanalysis data when calculating the WBGT. Validation against IMD gridded observations (Section 3.2.5) shows moderate grid-level agreement for ERA5-Land maximum temperature ($R^2 = 0.530$, $\text{RMSE} = 1.24^{\circ}\text{C}$), with a consistent tendency for ERA5-Land to underestimate observed temperature (mean bias = -0.44°C), most pronounced in the northeastern part of the study domain. This indicates that WBGT-based hazard metrics derived from ERA5-Land in this study likely represent a conservative estimate of true heat hazard intensity. A limitation: in-situ station validation at finer resolution could not be fully resolved within the scope of this study. The evaluation of heat hazard does not take into account socio-economic vulnerability factors such as income, age structure, housing quality, and access to healthcare, factors which influence real health outcomes together with the level of physical exposure. Future work should validate WBGT outputs against ground-based meteorological stations and integrate socio-economic and demographic variables into the CHHI framework to enable a full vulnerability assessment, combining hazard, exposure, and adaptive capacity, rather than hazard-exposure alone, and should use machine learning in projection and link its exposure to hospitalisation or mortality records to empirically test the nighttime-risk mechanism proposed here.

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Author Contributions

Sravanthi K. was responsible for data collection, data curation, formal analysis, visualization, writing of the original draft, software development, resource management, and validation. Dr. Rahul Thapa contributed to the conceptualization of the study and provided critical input through reviewing and editing the manuscript.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process. During the preparation of this work, the authors used the AI assistant Liner to find and organise the most relevant papers and to improve the paper's

language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Data Availability Statement

All data supporting the findings of this study are presented in the supplementary file accompanying this manuscript. The supplementary file includes a comprehensive table detailing each dataset used in the research, along with direct links for access. These datasets are openly available through the sources cited, ensuring transparency and reproducibility of the results.

Declaration of interests

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

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8. Supplementary Files

Table S1: List of Data Sets Used and Related Source Links

Dataset / Product	Source Link	Spatial / Temporal Resolution	Variable(s) Used	Application in Study
WorldPop Global Population	https://gee-community-catalog.org/projects/worldpop/	100 m; annual	Gridded population count	Source population for dasymetric disaggregation
Landsat-8 OLI / Landsat-9 TIRS-2, Collection 2 Tier-1 Surface Reflectance	https://earthexplorer.usgs.gov/	30 m; annual median composite	Surface reflectance Bands 2, 4, 5, 6	NDVI, NDBI, BSI computation for the PSI
Global Human Settlement Layer (GHSL) Data Package P2023A	https://human-settlement.emergency.copernicus.eu/download.php	5-year epochs	Built-up surface area (GHSLs), built volume (GHSLV)	PSI covariates

VIIRS Day-Night Band	https://gee-community-catalog.org/projects/npp_viirs_ntl/?h=viirs+	Monthly composites, averaged annually	Nighttime radiance ($\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$)	PSI covariate (anthropogenic activity proxy)
WorldCover v200	https://gee-community-catalog.org/projects/S2_TSLULC/	10 m	Land-cover classification	WESA settlement-probability weight; non-inhabited land mask
ERA5-Land Hourly Reanalysis	https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=overview	$\sim 0.1^\circ$ ($\sim 9\text{--}11$ km); hourly, 1991–2026	2 m air temperature, 2 m dewpoint temperature, 10 m wind components, surface downward solar radiation, surface pressure	WBGT modeling inputs (Liljegren formulation via pywbgt)
Mandal (sub-district) administrative boundaries	https://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx	Vector polygons; 686 units	Boundary geometry	Zonal aggregation of pixel-level metrics
State-wise heatstroke case and mortality statistics	https://www.mha.gov.in/MHA1/Par2017/pdfs/par2026-pdfs/LS04082026/2541.pdf	State-level; cumulative to 26 July 2026	Recorded heatstroke cases, confirmed deaths	Contextual validation of projected exposure severity