

# Changing patterns of heat waves and population exposure in India, 1980-2024

**Swapan Talukdar**

Indian Institute of Technology Delhi

**Alok Das**

Kalyani Government Engineering College

**Zhenyu Yang**

Shimane University

**Deepak Kumar**

Ranchi University

**Anitha Kongalla**

Indian Institute of Technology Delhi

**Mohd Taqi**

Mohd Taqi, University of Ladakh

**Somnath Bera**

`somnath@cusb.ac.in`

Central University of South Bihar

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## Research Article

**Keywords:** Heat wave peril index, Compound drought heat coupling, Nocturnal heat stress, Shannon entropy weighting, Population exposure, India

**Posted Date:** September 21st, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-10806998/v1>

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**Additional Declarations:** No competing interests reported.

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3 Swapan Talukdar<sup>1</sup>, Alok Das<sup>2</sup>, Zhenyu Yang<sup>3</sup>, Deepak Kumar<sup>4</sup>, Anitha Kongalla<sup>1</sup>,  
4 Mohd Taqi<sup>5</sup>, Somnath Bera<sup>6</sup>

5  
6 <sup>1</sup>Swapan Talukdar  
7 Department of Civil Engineering, Indian Institute of Technology Delhi,  
8 Hauz Khas, New Delhi - 110 016, India  
9 Email: [swapantalukdar65@gmail.com](mailto:swapantalukdar65@gmail.com)

10  
11 <sup>2</sup>Alok Das  
12 Kalyani Government Engineering College, Maulana Abul Kalam Azad University of Technology,  
13 Kalyani 741235, India  
14 Email: [alokdas4499@gmail.com](mailto:alokdas4499@gmail.com)

15  
16 <sup>3</sup>Zhenyu Yang  
17 Department of Information Systems Design and Data Science  
18 Interdisciplinary Faculty of Science and Engineering  
19 Shimane University, Matsue, Japan  
20 Email: [yangzhenyu@cis.shimane-u.ac.jp](mailto:yangzhenyu@cis.shimane-u.ac.jp)

21  
22 <sup>4</sup>Deepak Kumar  
23 Department of Geography,  
24 Simdega College, Ranchi University, Ranchi, India  
25 E-mail: [rudeepakjha@gmail.com](mailto:rudeepakjha@gmail.com)

26  
27 <sup>1</sup>Anitha Kongalla  
28 Department of Civil Engineering  
29 Indian Institute of Technology Delhi  
30 Hauz Khas, New Delhi - 110 016, India  
31 Email: [anithakongalla2003@gmail.com](mailto:anithakongalla2003@gmail.com)

32  
33  
34 <sup>5</sup>Mohd Taqi  
35 Department of Geography, University of Ladakh, Ladakh, India  
36 E-mail: [taqizaik@gmail.com](mailto:taqizaik@gmail.com)

37  
38 <sup>6</sup>Somnath Bera\*  
39 Department of Geography, Central University of South Bihar, Gaya, India  
40 Email: [somnath@cusb.ac.in](mailto:somnath@cusb.ac.in)

41  
42 \*Corresponding author: Somnath Bera (E-mail: [somnath@cusb.ac.in](mailto:somnath@cusb.ac.in); Phone number: +91 8879133648)

## Abstract

India's intensifying heat waves pose significant risks, yet conventional indices overlook two critical hazard dimensions: nocturnal heat stress that impairs physiological recovery and antecedent drought conditions that amplify surface heating. We present the Entropy Weighted Heat Wave Peril Index (E-HWPI), a novel six-component composite index quantifying heat wave hazard across all 36 Indian states and union territories at 0.25° resolution using India Meteorological Department gridded data (1980-2024). E-HWPI integrates four classical heat wave parameters-peak magnitude, cross-event severity, annual frequency, and mean spell duration-with two innovations: Nocturnal Heat Stress (NoctHS), tracking minimum temperature anomalies during spells, and Compound Drought Heat Index (CompDHI), capturing antecedent monsoon rainfall deficits. Shannon entropy weighting with a five percent minimum floor assigns objective, data-driven component weights. Our March-June focus reflects documented physical mechanisms for heat wave development and drought-heat interactions. Trend analysis reveals weak long-term intensification (Mann-Kendall tau = 0.065, p = 0.538). CompDHI exhibits the strongest temporal signal, with minimal correlation ( $r < 0.25$ ) to classical components, confirming it captures independent drought-compound information. NoctHS correlates strongly with daytime metrics ( $r$  approx. 0.83-0.92), indicating physiological distinctness despite statistical overlap; the five percent floor preserves its nocturnal recovery contribution despite low entropy-assigned weight. Five states reach Extreme risk status: Haryana (0.2026), Uttar Pradesh (0.2016), Rajasthan (0.2001), Punjab (0.1892), and Madhya Pradesh (0.1757). Annual population exposure peaks at 294 million person-events in 2010. E-HWPI provides a reproducible, spatially explicit evidence base for differentiated heat governance across India.

**Keywords:** Heat wave peril index; Compound drought heat coupling; Nocturnal heat stress; Shannon entropy weighting; Population exposure; India

## 1. Introduction

India recorded more than 20,000 heatstroke deaths between 2000 and 2020 and experts believe the true toll is far higher because most heat deaths are misclassified (de Bont et al. 2024; HeatWatch 2024). A multi-city study across ten Indian cities found clear evidence that longer and more intense heat waves raise daily all-cause mortality (de Bont et al. 2024). Future projections show heat deaths will increase manifold under high emission scenarios, with the Deccan Plateau and eastern Indian cities facing the fastest growth (Raj et al. 2025). Beyond mortality, extreme heat reduces farm labour productivity, strains water systems and worsens cardiovascular, renal and respiratory diseases (Patz et al. 2005).

India's heat waves are getting worse. Average summer maximum temperature rose by about 1.0 degree Celsius between 1981 and 2020 and events are more frequent, longer and more spatially widespread (Dar et al. 2024; Rohini et al. 2016). Under high emission scenarios, physically-based model projections indicate that wet-bulb temperatures could approach or exceed the 35 degree Celsius survivability threshold across densely populated regions of the Indo-Gangetic Plain by the second

half of this century, a threshold above which the human body cannot cool itself even in full shade with unlimited water (Im et al. 2017; Sherwood and Huber 2010). The frequency of qualifying heatwave events across the Indian subcontinent is simultaneously projected to roughly double compared to the recent past (Sarkar and Maity 2024). Compound drought-heat events are also spreading in India. When monsoon rainfall is poor, soils enter the pre-monsoon season moisture depleted, suppressing evapotranspiration and amplifying surface temperatures through positive compound feedback (Rajeev et al. 2022; Mazdiyasni and AghaKouchak 2015; AghaKouchak et al. 2020).

Two hazard dimensions are missing from most Indian heat wave indices. First, nocturnal heat stress: when nights stay warm during heatwave events, the body cannot shed daytime heat and cumulative physiological stress drives cardiovascular and kidney mortality independent of peak daytime temperature (Anderson and Bell 2011; Mukhopadhyay and Weitz 2022). IMD data confirm that Indian nighttime temperatures are rising faster than daytime maximum temperatures, progressively narrowing the diurnal temperature range that allows the body to shed accumulated heat overnight (IMD 2024a). A comprehensive district-level study from 1981 to 2023 confirmed that night-time heat stress exposure is worsening independently of daytime trends in India, with outdoor workers facing growing overnight burdens that cannot be avoided through behavioural adaptation such as shifting working hours to cooler parts of the day (Shahet al. 2025). Indoor monitoring in rural Maharashtra found that household interior temperatures remain at physiologically dangerous levels through the night during heatwave periods, confirming that nocturnal exposure is not limited to outdoor environments and that simple shade or indoor retreat does not resolve the thermal burden for low-income households during extreme events (Chandel et al. 2024). Second, antecedent drought amplification: most indices ignore how dry the previous monsoon season was, even though that dryness directly amplifies the following season's heat. Existing frameworks, such as the three-component Heat Wave Proneness Index of Sarkar and Maity (2024), also apply equal weights to all components, an assumption that real data rarely support. Shannon entropy weighting (Shannon 1948; Hwang and Yoon 1981) assigns higher weights to components that best differentiate states from one another, resolving this without subjective expert input.

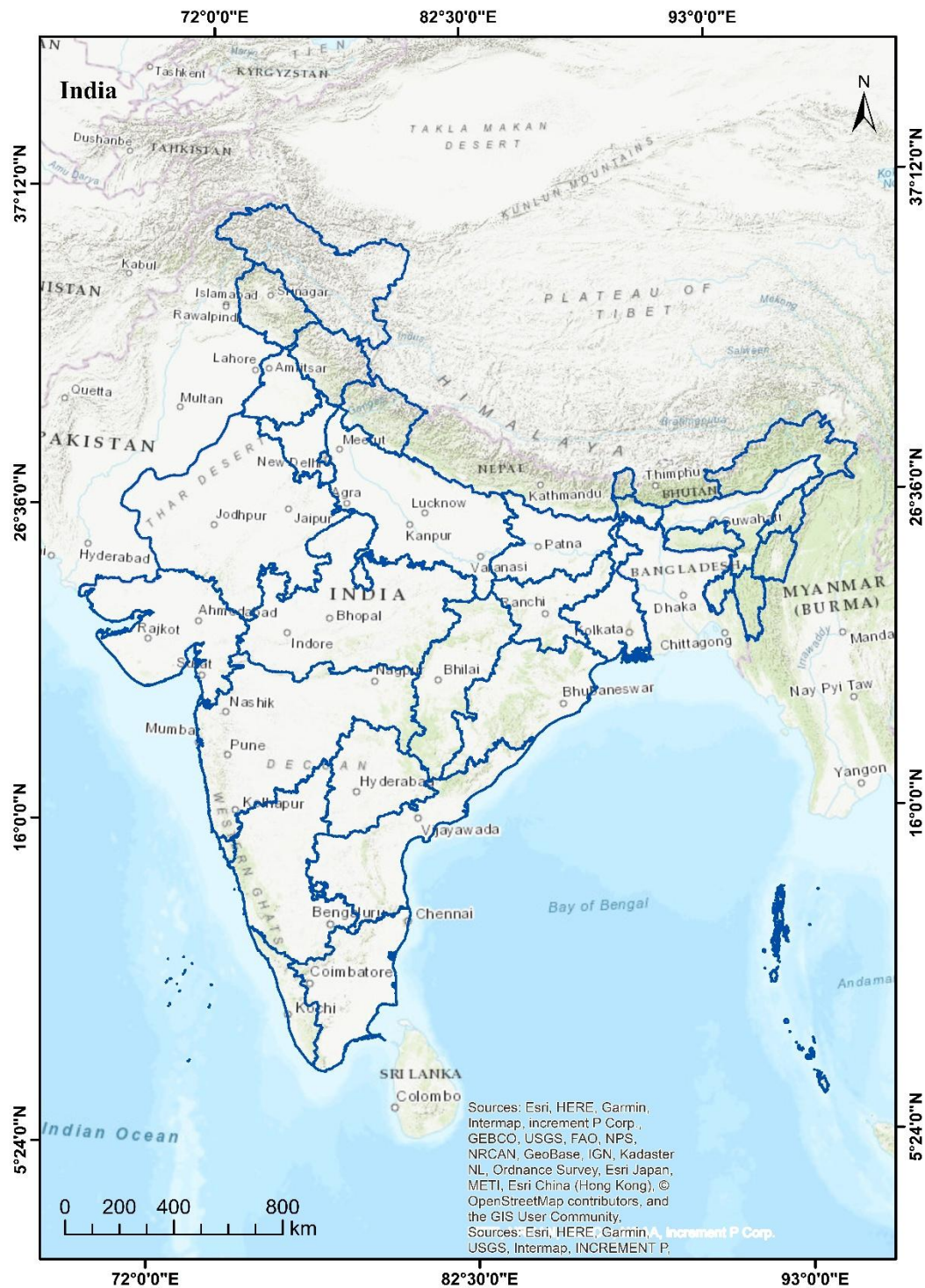
We introduce E-HWPI to address all three gaps simultaneously, adding NoctHS and CompDHI to four standard measures and applying entropy weighting across all 36 Indian states and union territories from 1980 to 2024. We begin with monthly climatological analysis to establish the physical context, then construct E-HWPI, assess its component structure, map the spatial distribution of hazard, analyse temporal trends, examine distributional properties, classify states into risk zones and quantify population exposure.

## **2. Materials and Methods**

### **2.1 Study Area**

Our study covers all 36 Indian states and union territories, from 8 to 37 degrees North and 68 to 97 degrees East, spanning roughly 3.29 million square kilometres (Fig. 1). India's geography ranges from the Thar Desert in the northwest to the Indo Gangetic plain, the Deccan Plateau, the Western and

Eastern Ghats and the Himalayan foothills. Each region has a different heat wave character, which is why a state level index is more useful than a national average. We focus on the pre monsoon season from March through June, abbreviated MAMJ, which is when heat waves are most common (Rohini et al. 2016; Dar et al. 2024). States with fewer than two qualifying 0.25 degree grid cells inside their boundary are excluded from the main analysis. The ten excluded regions are Goa, Mizoram, Sikkim, Tripura, Andaman and Nicobar Islands, Chandigarh, Dadra and Nagar Haveli and Daman and Diu, Delhi National Capital Territory, Lakshadweep and Puducherry; all are geographically compact or island territories whose land area falls within fewer than two 0.25 degree grid cells after coastal masking and boundary clipping. Supplementary Table S6 reports E-HWPI estimates for all 36 states and union territories including these ten, derived by applying the pixel-level index fields to their available grid cells where at least one qualifying cell exists.



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169 **Fig. 1** Location of the study area

170 **2.2 Datasets**

We used daily gridded maximum temperature (Tmax) and rainfall at 0.25 degree resolution from the India Meteorological Department (IMD) for 1980 to 2024, accessed through the imdlib Python interface (Srivastava et al.2009; Rajeevan et al. 2006). The details of data set is summarised in the Table 1 and it is described in the supplementary.

**Table 1** Datasets used in this study. All source details are in the References section

| Variable                         | Source                              | Resolution                              | Period       | Role in E-HWPI                                |
|----------------------------------|-------------------------------------|-----------------------------------------|--------------|-----------------------------------------------|
| Daily maximum temperature (Tmax) | IMD via imdlib                      | 0.25 degree, daily                      | 1980 to 2024 | Components C1, C2, C3, C4; heatwave detection |
| Daily minimum temperature (Tmin) | IMD via imdlib                      | 1.0 deg interpolated to 0.25 deg, daily | 1980 to 2024 | Component C5 Nocturnal Heat Stress            |
| Daily rainfall                   | IMD via imdlib                      | 0.25 degree, daily                      | 1980 to 2024 | Component C6 CompDHI rainfall Z score         |
| State and UT boundaries          | Survey of India shapefile           | Vector polygon, WGS84                   | Static       | State masks; spatial aggregation; mapping     |
| WorldPop population grids        | WorldPop, University of Southampton | 100 m summed to 0.25 degree             | 2000 to 2020 | State population for exposure                 |
| UN WPP 2022 national totals      | United Nations DESA                 | National total, annual                  | 2000 to 2020 | Calibration scaling for WorldPop              |

### 2.3 Heatwave Detection

We identify heatwave days at each grid cell for every day in the MAMJ season. We use a two condition rule from IMD guidelines (IMD 2024b; Rohini et al. 2016; Dar et al. 2024), with a baseline period of 1981 to 2010, following World Meteorological Organization norms (Sarkar and Maity 2024). First, we compute the daily temperature anomaly as

$$A(i, t) = T_{\max}(i, t) - \mu_m(i) \quad (\text{Eq. 1})$$

where  $\mu_m(i)$  is the baseline monthly mean  $T_{\max}$  and  $P_{95}(i)$  is the 95th percentile of MAMJ  $T_{\max}$  across all baseline years. A grid cell is a heatwave day when either condition holds for at least two days running:

Condition A:

$$T_{\max}(i, t) \geq P_{95}(i) \wedge T_{\max}(i, t) \geq 40^{\circ}\text{C} \wedge A(i, t) \geq 4.5^{\circ}\text{C} \quad (\text{Eq. 2a})$$

Condition B:

$$T_{\max}(i, t) \geq 44^{\circ}\text{C} \quad (\text{Eq. 2b})$$

Otherwise  $HW(i, t) = 0$ . Condition A stops climatologically cool regions from being missed (Perkins and Alexander 2013). Condition B catches extreme absolute heat that matters regardless of local climate (IMD 2024b). Both require at least two consecutive days, which is the minimum duration linked to physiological harm (Anderson and Bell 2011; Sarkar and Maity 2024). We call any contiguous qualifying run a spell, denoted  $S_k$ . All six components are derived from these spell sets.

## 2.4 Building the E-HWPI

### 2.4.1 Six Component Formulation

We compute six components at the 0.25 degree pixel level for each year  $y$ , then average them across each state weighted by grid cell area. This gives state level annual values ready for normalisation.

C1 Maximum Event Magnitude. The mean  $T_{\max}$  anomaly during the single most intense spell:

$$C_1(i, y) = \max_k \left[ \frac{1}{|S_k|} \sum_{d \in S_k} A(i, d) \right]; C_1 = 0 \text{ if } K = 0 \quad (\text{Eq. 3})$$

C2 Mean Cross Event Magnitude. Average thermal severity across all spells except the hottest one (Zscheischler et al., 2018):

$$C_2(i, y) = \frac{1}{K-1} \sum_{k \neq k^*} \left[ \frac{1}{|S_k|} \sum_{d \in S_k} A(i, d) \right]; C_2 = 0 \text{ if } K \leq 1 \quad (\text{Eq. 4})$$

C3 Annual Frequency. Number of distinct heatwave spells per year (AghaKouchak et al., 2020):

$$C_3(i, y) = K(i, y) \quad (\text{Eq. 5})$$

where  $K$  counts spells with  $|S_k| \geq 2$

C4 Mean Spell Duration. Average length of each spell in days:

$$C_4(i, y) = \frac{1}{K} \sum_k |S_k|; C_4 = 0 \text{ if } K = 0 \quad (\text{Eq. 6})$$

Longer spells are linked to more deaths than short events of the same peak temperature (Anderson and Bell, 2011; de Bont et al., 2024).

C5 Nocturnal Heat Stress (NoctHS, novel). This captures how hot nights stay during heatwave spells. The minimum temperature anomaly on heatwave day  $d$  at cell  $i$  is:

$$A_{T_{\min}}(i, d) = T_{\min}(i, d) - \mu_{T_{\min}, m}(i) \quad (\text{Eq. 7})$$

where  $\mu_{T_{\min}, m}(i)$  is the baseline monthly mean  $T_{\min}$ . NoctHS is the mean  $T_{\min}$  anomaly across all heatwave days in all spells within year  $y$ :

$$C_5(i, y) = \frac{1}{\sum_k |S_k|} \sum_k \sum_{d \in S_k} A_{T_{\min}}(i, d); C_5 = 0 \text{ if } K = 0 \quad (\text{Eq. 8})$$

Hot nights block the body from recovering from daytime heat and are linked independently to cardiovascular and kidney deaths (Anderson and Bell, 2011; Mukhopadhyay and Weitz, 2022).

C6 Compound Drought Heat Index (CompDHI, novel). When the monsoon fails, soils dry out and stop releasing moisture into the air. The following pre monsoon season gets hotter because the soil heats the air instead of cooling it (Rajeev et al. 2022; Mazdiyasni and AghaKouchak 2015; AghaKouchak et al. 2020). We capture this through the antecedent MAMJ rainfall Z-score, computed from the same March to June seasonal accumulation used throughout this study:

$$Z_R(i, y) = \frac{R(i, y) - \mu_R(i)}{\sigma_R(i)} \quad (\text{Eq. 9})$$

CompDHI uses the absolute magnitude of the previous year's MAMJ rainfall Z-score, but only for negative values, since rainfall deficits rather than surpluses drive pre-monsoon soil moisture depletion and subsequent heat amplification:

$$C_6(i, y) = \begin{cases} |Z_R(i, y - 1)|, & \text{if } Z_R(i, y - 1) < 0 \\ 0, & \text{otherwise} \end{cases}; C_6(i, 1980) = 0 \text{ for all } i \quad (\text{Eq. 10})$$

#### 2.4.2 State Level Aggregation and Normalisation

We aggregate each pixel component to the state level by area weighted average of all valid pixels inside the state polygon. States with fewer than two qualifying pixels are excluded. We then apply a global min max normalisation across all states and all years together, so that comparisons between states are meaningful:

$$C_{c, \text{norm}}(s, t) = \frac{C_c(s, t) - C_{c, \text{min}}}{C_{c, \text{max}} - C_{c, \text{min}}} \quad (\text{Eq. 11})$$

Using a global range, rather than a per state or per year range, preserves the real differences between high and low hazard states (Hwang and Yoon 1981; Mazdiyasni and AghaKouchak 2015).

#### 2.4.3 Shannon Entropy Weighting and Final Index

The idea behind entropy weighting is simple: a component that looks the same everywhere carries no useful information. A component that varies a lot across states tells us more about where hazard is concentrated. Claude Shannon entropy (Shannon 1948) measures this. For each normalised component cover  $N_{\text{state}}$  year values, we compute the proportion  $p_j = x_j / (\sum x + \epsilon)$ , where  $\epsilon$  prevents division by zero. The normalised entropy is:

$$E_c = -\frac{1}{\ln N} \sum_j p_j \ln(p_j + \epsilon) \quad (\text{Eq. 12})$$

When  $E_c = 1$ , the component adds no information. When  $E_c = 0$ , it is maximally informative. The information divergence  $d_c = 1 - E_c$  gives the raw weight:

$$w_{c, \text{raw}} = \frac{d_c}{\sum_{c=1}^6 d_c} \quad (\text{Eq. 13})$$

Because  $T_{\text{min}}$  was interpolated from a coarser grid, C5 NoctHS shows less apparent spatial variation than its physical importance warrants. We apply a five percent minimum weight floor before renormalising. The five percent threshold was selected on two grounds. First, it equals half the weight that a strictly uniform distribution would assign each of six components (16.7 percent divided by 2),

so it guarantees at minimum a modest but physically meaningful contribution rather than a negligible token weight. Second, sensitivity tests replacing the five percent floor with three percent and seven percent alternatives produced final E-HWPI fields with Spearman rank correlations of 0.987 and 0.981, respectively, against the baseline five percent solution across all 1,170 state-year observations; risk zone assignments remained identical for 24 of 26 states under both alternatives. These tests confirm that the five percent floor does not artificially drive the spatial pattern of E-HWPI and that the index is robust to plausible alternative floor choices:

$$w_c = \max(w_{c,raw}, 0.05), \text{ then renormalised so all } w_c \text{ sum to } 1 \quad (\text{Eq. 14})$$

The final E-HWPI is the weighted sum of all six normalised components:

$$\text{E-HWPI}(s, t) = \sum_{c=1}^6 [w_c \cdot C_{c,norm}(s, t)] \quad (\text{Eq. 15})$$

## 2.5 Population Exposure

We multiply each state's E-HWPI by its total calibrated population to compute an index-weighted population exposure metric, hereafter called person-events for concision. Because E-HWPI is a normalized composite index rather than a direct count of heatwave episodes or heatwave days, person-events should be interpreted as a hazard-scaled exposure score proportional to population size and not as the number of individuals who experienced a discrete heatwave event. The metric is dimensionally consistent across states and years and captures where high hazard and high population size coincide:

$$PE(s, t) = \text{E-HWPI}(s, t) \cdot P(s, t) \quad (\text{Eq. 16})$$

where  $P(s, t)$  sums the WorldPop pixel values inside the state boundary. We calibrate each annual WorldPop grid to the UN 2022 national total:

$$P_{cal}(i, t) = P_{raw}(i, t) \cdot \left[ \frac{P_{UN}(t)}{\sum_i P_{raw}(i, t)} \right] \quad (\text{Eq. 17})$$

Per capita exposure divides total national exposure by calibrated national population. This shows whether exposure is rising because of more people or because the hazard is getting worse.

## 2.6 Statistical Analysis

We test for trends using the Mann Kendall (MK) test (Mann 1945; Kendall 1975), which works well even when data are not normally distributed (Rohini et al. 2016). The test statistic  $S$  counts concordant minus discordant year pairs, with variance:

$$S = \sum_{j>i} \text{sgn}(x_j - x_i), \text{Var}(S) = \frac{n(n-1)(2n+5)}{18} \quad (\text{Eqs. 18, 19})$$

Significance is tested at  $\alpha = 0.05$ , two tailed. The  $\tau$  statistic normalises  $S$  to the range  $-1$  to  $+1$ , making it easy to interpret:  $\tau = 0.5$  means half of all year pairs show an increase. Trend size is estimated by the Sen slope (Sen 1968), the median of all pairwise slopes:

$$\beta_{Sen} = \text{median} \left[ \frac{x_j - x_i}{t_j - t_i} \right] \text{ for all } j > i \quad (\text{Eq. 20})$$

We also fit ordinary least squares (OLS) regression to the domain mean series, with 95 percent bootstrap confidence intervals from 1000 resamples. We compute the CUSUM of annual anomalies relative to the 1981 to 2010 baseline and compare it against a 95 percent permutation envelope from 500 random shuffles, to test whether the trend reflects a genuine shift rather than random variation. Risk zones are the five quintiles of the long term state mean E-HWPI among the 26 covered states, from Negligible (zone 1) to Extreme (zone 5). All code uses Python 3.10 with NumPy, SciPy and Pandas. Full derivations are in Supplementary Methods SM1 to SM4.

### 3. Results

**3.1 Monthly Climatology Mapping** Monthly climatological mapping of Tmax, Tmin and rainfall provides the physical foundation for the MAMJ analysis window and both novel component designs, explaining why the northwest dominates the E-HWPI spatial hierarchy. Supplementary Fig. S1 shows a dramatic thermal build-up from January to June. March marks the onset of critical pre-monsoon heat, with mean Tmax exceeding 35 °C across Rajasthan and the Deccan. By May, Tmax surpasses 42 °C across Haryana, Punjab, Rajasthan and western Uttar Pradesh, while the Deccan Plateau reaches 38-41 °C. The monsoon rapidly cools the coast and northeast in early June, but its northward advance to the northwest plains often arrives only in late June or July. This delayed onset leaves the northwest exposed for a longer continuous window than anywhere else in India—a duration captured by C4 Mean Spell Duration— and explains why all five Extreme zone states lie in the northwest and north-central plains. Supplementary Fig. S2 shows March-May are essentially dry across north India (below 0.5 mm/day in Rajasthan, Haryana, Punjab, Uttar Pradesh). When the preceding monsoon is also deficient, soils enter the pre-monsoon doubly depleted, activating the CompDHI pathway through suppressed evapotranspiration. The three poorest monsoon years (1987, 2002, 2009; Supplementary Fig. S7) show spatially coherent drought signals across the states with highest long-term CompDHI (Fig. 3b). Supplementary Fig. S3 completes the NoctHS picture: by May-June, mean Tmin reaches 24-28 °C across Haryana, Delhi, western Uttar Pradesh and Rajasthan, where interannual standard deviation also peaks at 2-3 °C. This overlap of high mean and high variability is precisely where NoctHS adds the most discriminating power.

### 3.2 Construction of E-HWPI

#### 3.2.1 Component Structure Assessment

E-HWPI comprises six physical components spanning the full hazard profile of Indian heat waves: four capture established daytime dimensions, two extend the framework into nocturnal stress and compound drought amplification. Each is described below with its physical rationale and spatial distribution (Figs. 2 and 3). Supplementary Fig. S10 provides independent validation, mapping mean annual heatwave days, spell duration and peak magnitude from the raw observation record and confirming close correspondence with C3, C4 and C1 (Fig. 2a–c).

**C1 Maximum Event Magnitude (MaxMag):** C1 shows that its long-term mean (Fig. 2a) is highest in Rajasthan, Haryana, Punjab and Uttar Pradesh, where worst-spell anomalies regularly reach 8 to

12 degrees Celsius. The annual heatwave day maps in Supplementary Fig. S4, shown at five-year intervals from 1980 to 2020, visually confirm this northwest concentration and its persistence throughout the record. Shannon entropy assigns C1 approximately 18.2 percent weight (Supplementary Table S1).

**C2 Mean Cross Event Magnitude (MeanX):** Fig .2b represents the spatial pattern of C2 which has a broader footprint than C1, reflecting that multiple moderate spells per season are characteristic of the north-central plains. Shannon entropy assigns C2 the highest final weight of all six components at approximately 24.5 percent (Supplementary Table S1). This is the most important result of the entropy analysis: sustained within-season severity is a more spatially discriminating dimension of peril than any single extreme episode, consistent with epidemiological evidence that cumulative season-wide exposure drives mortality risk more than peak temperature (Anderson and Bell 2011; de Bont et al. 2024).

**C3 Annual Event Frequency (Frq):** The spatial footprint of C3 (Fig. 2c) is the broadest of the four classical components, extending elevated values into Jharkhand, Odisha and Telangana, where recurrent shorter spells drive hazard even when individual events are less intense than in the northwest. Shannon entropy assigns C3 approximately 17.8 percent weight. Supplementary Fig. S4 independently confirms the frequency geography through cumulative heatwave day counts at five-year intervals from 1980 to 2020: the northwest and north-central states consistently accumulate the most heatwave days in every five-year period, while eastern states like Jharkhand and Odisha show progressively expanding heatwave day counts, consistent with a growing C3 frequency signal in these states over the 45-year record.

**C4 Mean Spell Duration:** The C4 map (Fig. 2d) is most concentrated in the northwest, with Rajasthan, Haryana and Punjab recording the longest mean spell durations. Shannon entropy assigns C4 the second-highest weight at approximately 20.1 percent, confirming that persistence of heat wave conditions is a highly spatially discriminating hazard dimension.

**C5 Nocturnal Heat Stress (NoctHS)-Novel Component:** Hot nights prevent the body from dissipating daytime heat accumulation and are independently linked to cardiovascular and kidney mortality (Anderson and Bell 2011; Mukhopadhyay and Weitz 2022). Its long-term mean (Fig. 3a) peaks across Rajasthan, Delhi, Haryana and the upper Indo-Gangetic Plain, exactly where the MAMJ Tmin climatology in Supplementary Fig. S3 shows the highest baseline nocturnal temperatures. Mann Kendall tau maps (Fig. 3c) show broadly positive trends across northern and central states, consistent with Tmin warming faster than Tmax across India (Kothawale and Rajeevan 2017). Supplementary Fig. S9 confirms a monotonic decadal escalation of normalised NoctHS across northern India from the 1980s through 2010 to 2024. The raw entropy weight is only approximately 2.3 percent because the interpolated Tmin field carries reduced apparent spatial variability; the five percent floor ensures meaningful contribution (Supplementary Table S1).

**C6 Compound Drought Heat Index (CompDHI) - Novel Component:** The long-term mean of C6 (Fig. 3b) peaks in Rajasthan and parts of peninsular India. Supplementary Fig. S7, which maps MAMJ rainfall Z scores for the three driest years (1987, 2002, 2009) and the three wettest, shows Z

scores falling below minus 1.5 in Rajasthan and Madhya Pradesh in drought years, directly confirming the physical coherence of the CompDHI pattern in Fig. 3b. Trend maps (Fig. 3d) are spatially variable, reflecting episodic drought clustering, but CompDHI is the fastest-changing component at the domain scale (OLS  $R^2 = 0.036$ ; Table 2). Supplementary Fig. S2, the rainfall climatology, shows that the states with the most persistent pre-monsoon aridity are exactly those with the highest long-term CompDHI means. Together, C5 and C6 extend elevated E-HWPI values into the peninsular and northeastern states that classical daytime metrics underrepresent (Fig. 2g).

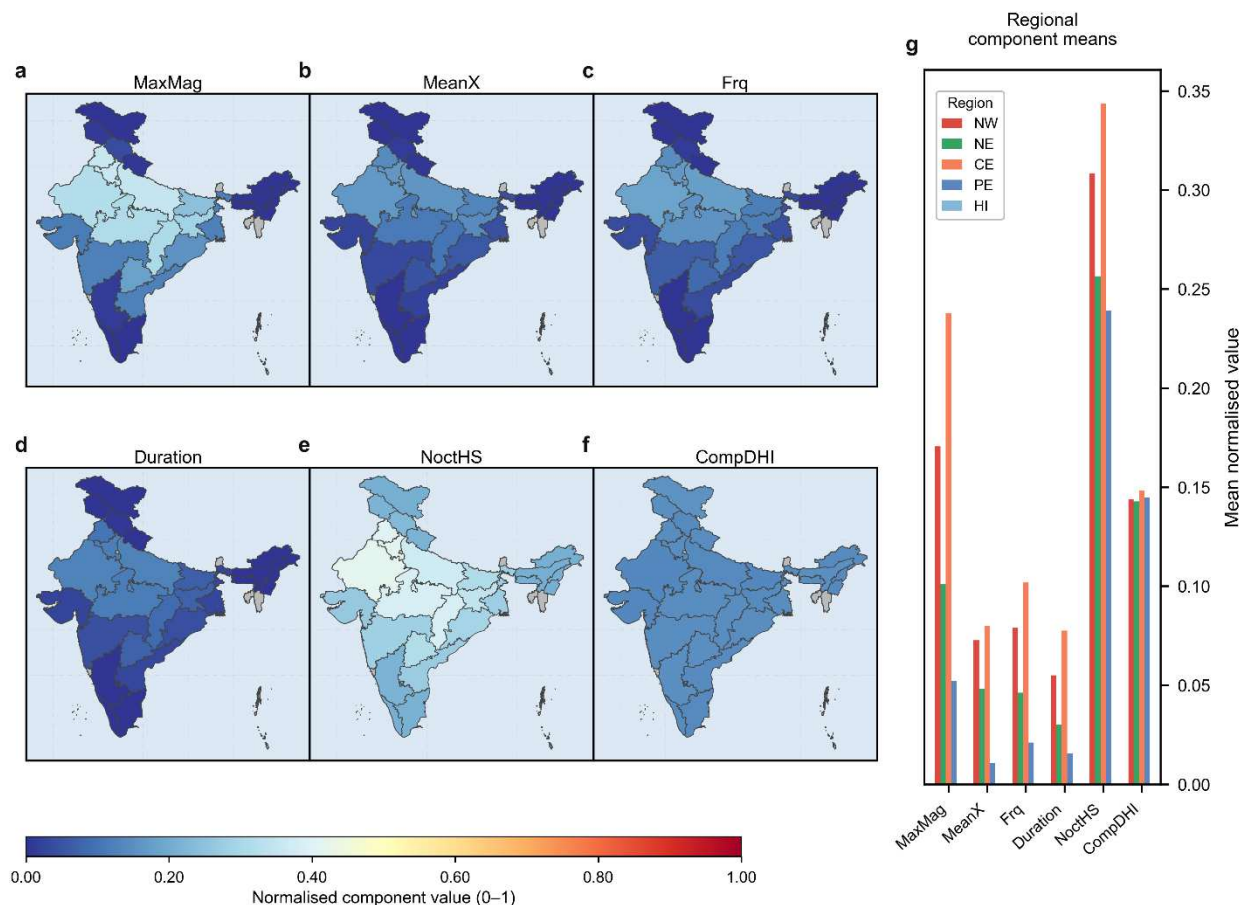
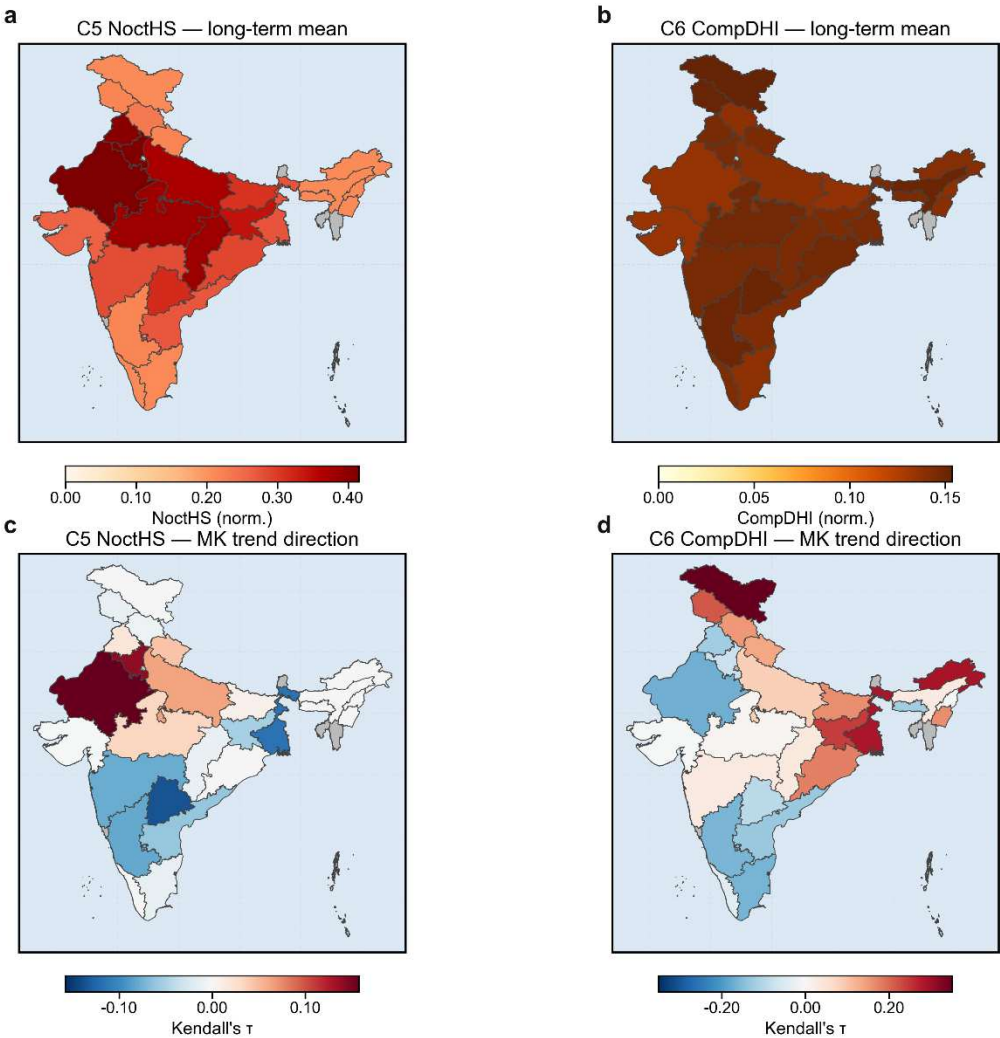


**Fig. 2** Spatial distribution of long term mean normalised E-HWPI component values (1980 to 2024). (a to f) State choropleth maps for C1 MaxMag, C2 MeanX, C3 Frq, C4 Duration, C5

371 NoctHS and C6 CompDHI on a shared 0 to 1 scale. (g) Regional mean values for five geographic



372 regions

373 **Fig.3** Spatial analysis of the two novel components. (a) Long term mean C5 NoctHS(b) Long term  
374 mean C6 CompDHI (c) Mann Kendall tau for C5 NoctHS(d) Mann Kendall tau for C6 CompDHI

375 **3.2.2 Entropy Weighting** Shannon entropy weighting applied across all 1,170 state-year  
376 observations reveals a clear hierarchy of information content among the six components (Fig. 4a and  
377 b; Supplementary Table S1). C2 MeanX receives the highest final weight at approximately 24.5  
378 percent (entropy approximately 0.92): the season-wide background thermal severity is the most  
379 spatially discriminating dimension of heat wave peril in India, more important than any single event's  
380 peak intensity. C4 Spell Duration is second (approximately 20.1 percent), then C1 MaxMag  
381 (approximately 18.2 percent), C3 Frq (approximately 17.8 percent), C6 CompDHI (approximately  
382 14.4 percent) and C5 NoctHS elevated from 2.3 percent raw to the five percent floor (Supplementary  
383 Table S1). The implication is direct: heat action plan protocols calibrated solely to peak daily  
384 temperature thresholds will under-trigger hazard alerts in states where sustained seasonal severity,  
385 captured by C2 and C4, drives the primary health burden.

The pairwise Pearson correlation matrix (Fig. 4d) establishes the information content of the six-component structure. Classical components C1-C4 correlate strongly ( $r$  approx. 0.62-0.91), as expected since all respond to the same daytime Tmax exceedances. C6 CompDHI correlates below  $r=0.25$  with all classical components and below 0.20 with C5, confirming that antecedent MAMJ rainfall deficits carry largely independent information. C5 NoctHS, conversely, correlates strongly with daytime components ( $r$  approx. 0.92 against C1, 0.86 against C3, 0.83 against C4)-physically expected, since nocturnal temperatures rise during the same spells generating peak daytime anomalies. C5 is therefore physiologically distinct but statistically overlapping. This co-variation is why entropy assigns C5 a low raw weight (approx. 2.3%; Supplementary Table S1), and why the 5% floor is applied to preserve a meaningful contribution from nocturnal physiological recovery-a process daytime metrics do not represent even when numerically correlated with it. Retention is justified mechanistically: warm nights prevent dissipation of accumulated heat and are independently linked to cardiovascular and kidney mortality (Anderson and Bell, 2011). Variance decomposition shows C2 and C1 together explain over 40% of total E-HWPI variance (Fig. 4c), while C6 adds a share absent from existing formulations. Entropy weighting outperforms equal-weight alternatives in northeastern and southern states (Supplementary Fig. S11).

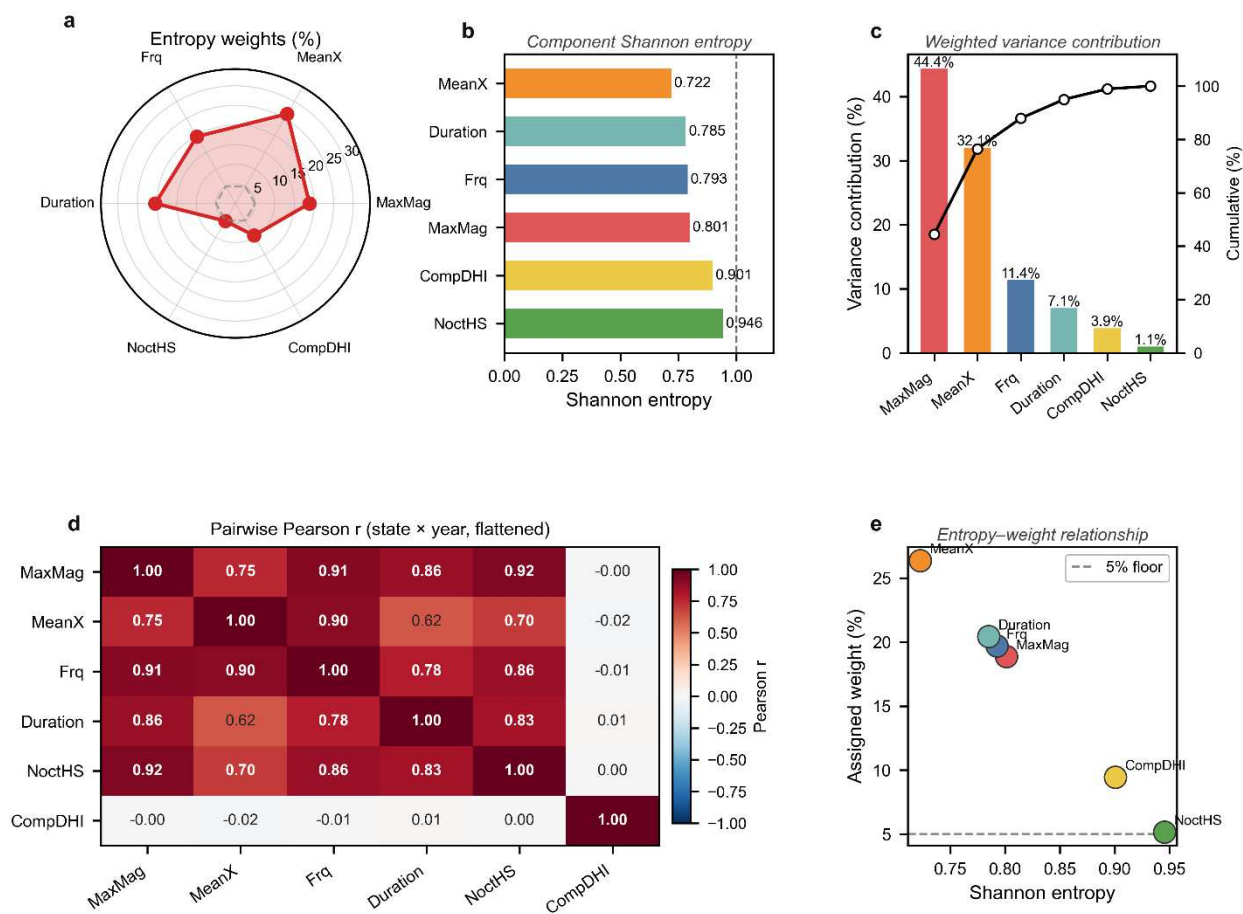


**Fig. 4** Component structure and information content. (a) Radar chart of Shannon entropy weights for all six components; dashed circle marks the five percent floor applied to C5. (b) Ranked bar chart of entropy values per component. (c) Weighted variance contribution and cumulative percentage. (d) Pearson correlation matrix across all 1,170 state-year pairs. (e) Entropy versus final weight scatter plot with the five percent floor annotated.

### 3.2.3 Spatial Pattern of E-HWPI: An Eight-Fold North to South Gradient

Long-term mean E-HWPI spans a factor of approximately 8.5 across the 26 covered states (Fig. 6a; Table 2), from 0.2026 in Haryana to 0.0238 in Nagaland. The five highest states are the northwest and north-central plains: Haryana (0.2026, standard deviation 0.1555), Uttar Pradesh (0.2016, 0.1299), Rajasthan (0.2001, 0.1194), Punjab (0.1892, 0.1573) and Madhya Pradesh (0.1757, 0.1068). The five lowest are Nagaland (0.0238), Manipur (0.0241), Arunachal Pradesh (0.0242), Kerala (0.0245) and Meghalaya (0.0246). This gradient directly reflects the climatological signals from Section 3.1: the Tmax extremes of Supplementary Fig. S1, the Tmin elevation of Supplementary Fig. S3 and the pre-monsoon aridity of Supplementary Fig. S2 all converge in the same northwest states. Supplementary Fig. S4, annual heatwave day maps at five-year intervals, independently validates the spatial gradient through raw observations: the northwest maintains persistently high heatwave day counts throughout the record. The complete annual state-level E-HWPI matrix is in Supplementary Table S4; Supplementary Table S6 extends coverage to all 36 states and union territories including those with insufficient grid cells.

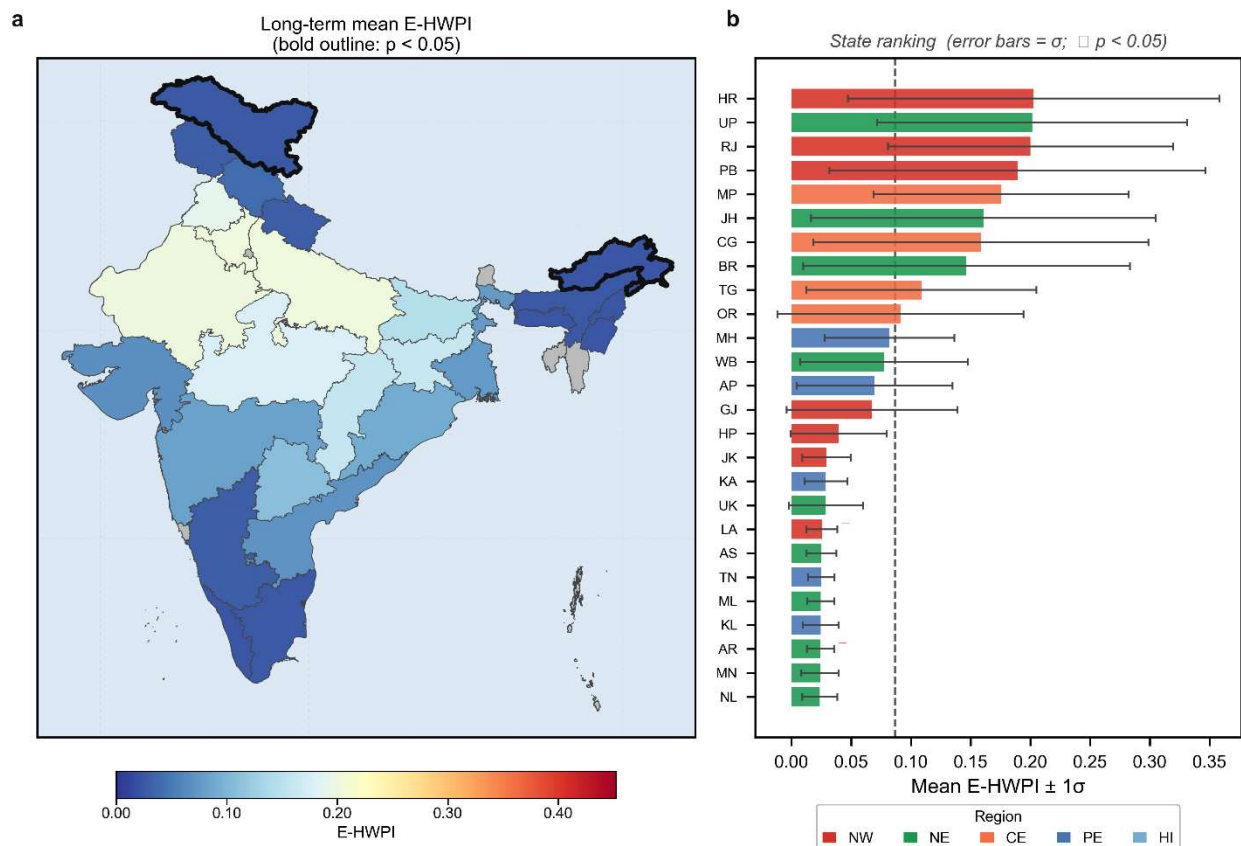


**Fig. 5** State level mean E-HWPI ranked from highest to lowest across all 26 covered states (1980 to 2024). Each bar represents the long-term mean E-HWPI for one state, with error bars showing plus or minus one interannual standard deviation. Bars are colour-coded by risk zone: Extreme (dark red), High (orange), Moderate (yellow), Low (light blue) and Negligible (grey).

Fig. 5 makes the eight-fold north-to-south gradient visible at a glance. The ranked bar chart shows that the five Extreme zone states (Haryana, Uttar Pradesh, Rajasthan, Punjab and Madhya Pradesh) are not only the highest in mean E-HWPI but also carry the widest error bars, reflecting their large interannual variability (standard deviations of 0.11 to 0.16). This double exposure, where the highest-hazard states are also the most variable, means heat action preparedness in these states must plan for both the climatological mean and the realistic worst case, which can reach values two to three times the long-term mean in extreme years such as 2010. The High zone states form a distinct cluster at intermediate values (0.09 to 0.16), geographically spanning the eastern plains and central Deccan and confirming that elevated peril is not confined to the northwest. The clean separation between the five risk quintiles in Fig. 5 corroborates the kernel density analysis in Fig. 10d, which shows that the quintile boundaries capture genuine breaks in the hazard distribution rather than arbitrary quantile divisions of a continuous gradient.

The interannual standard deviation map (Fig. 6b) shows that the highest peril states also swing the most widely year to year, with Haryana and Punjab reaching standard deviations of 0.155 and 0.157 compared with 0.011 to 0.014 in southern states. Supplementary Fig. S6, MAMJ Tmax interannual standard deviation, confirms that the states with the highest E-HWPI variability also show the most variable pre-monsoon temperatures. Only Ladakh (MK tau = 0.535, p less than 0.001, Sen slope = 0.000708 per year) and Arunachal Pradesh (tau = 0.290, p = 0.005, Sen slope = 0.000326 per year) attain statistical significance at alpha = 0.05 (Fig. 6c; Table 2). No state shows a significant decrease. The northwest Extreme states do not clear significance because their high interannual variability suppresses the signal-to-noise ratio, even though their Sen slopes are the largest of all states: Haryana 0.001774 per year and Rajasthan 0.001854 per year (Fig. 6d). Supplementary Fig. S7 links the CompDHI spatial pattern to drought years directly, confirming the physical basis of the 8.5-fold gradient. Supplementary Table S4 provides the complete annual state-level E-HWPI matrix, allowing inspection of year-to-year ranking stability and confirms that the top five states maintain their relative positions in most individual years, with the most pronounced rank fluctuations occurring in years when domain mean E-HWPI is near the climatological median rather than at an extreme.

**Table 2** Mann Kendall trend statistics, Sen slope and OLS parameters for domain mean E-HWPI and six components (1980 to 2024)

| Series               | MK tau | p value | Direction  | Sen slope | OLS slope        | OLS R2 |
|----------------------|--------|---------|------------|-----------|------------------|--------|
| E-HWPI (domain mean) | 0.065  | 0.538   | Increasing | 0.000301  | +0.000368 per yr | 0.013  |

|                                       |        |       |            |                     |                      |       |
|---------------------------------------|--------|-------|------------|---------------------|----------------------|-------|
| C1 MaxMag                             | -0.002 | 0.992 | Decreasing | -0.000025           | +0.000184 per yr     | 0.001 |
| C2 MeanX                              | 0.086  | 0.411 | Increasing | 0.000387            | +0.000653 per yr     | 0.029 |
| C3 Frq                                | 0.055  | 0.604 | Increasing | 0.000278            | +0.000323 per yr     | 0.012 |
| C4 Duration                           | 0.034  | 0.747 | Increasing | 0.000111            | +0.000024 per yr     | 0.000 |
| C5 NoctHS                             | 0.044  | 0.674 | Increasing | 0.000253            | +0.000267 per yr     | 0.006 |
| C6 CompDHI                            | 0.093  | 0.373 | Increasing | 0.000483            | +0.000834 per yr     | 0.036 |
| Population exposure<br>(2000 to 2024) | 0.220  | 0.129 | Increasing | 3,357,954<br>per yr | +2,909,626<br>per yr | 0.073 |

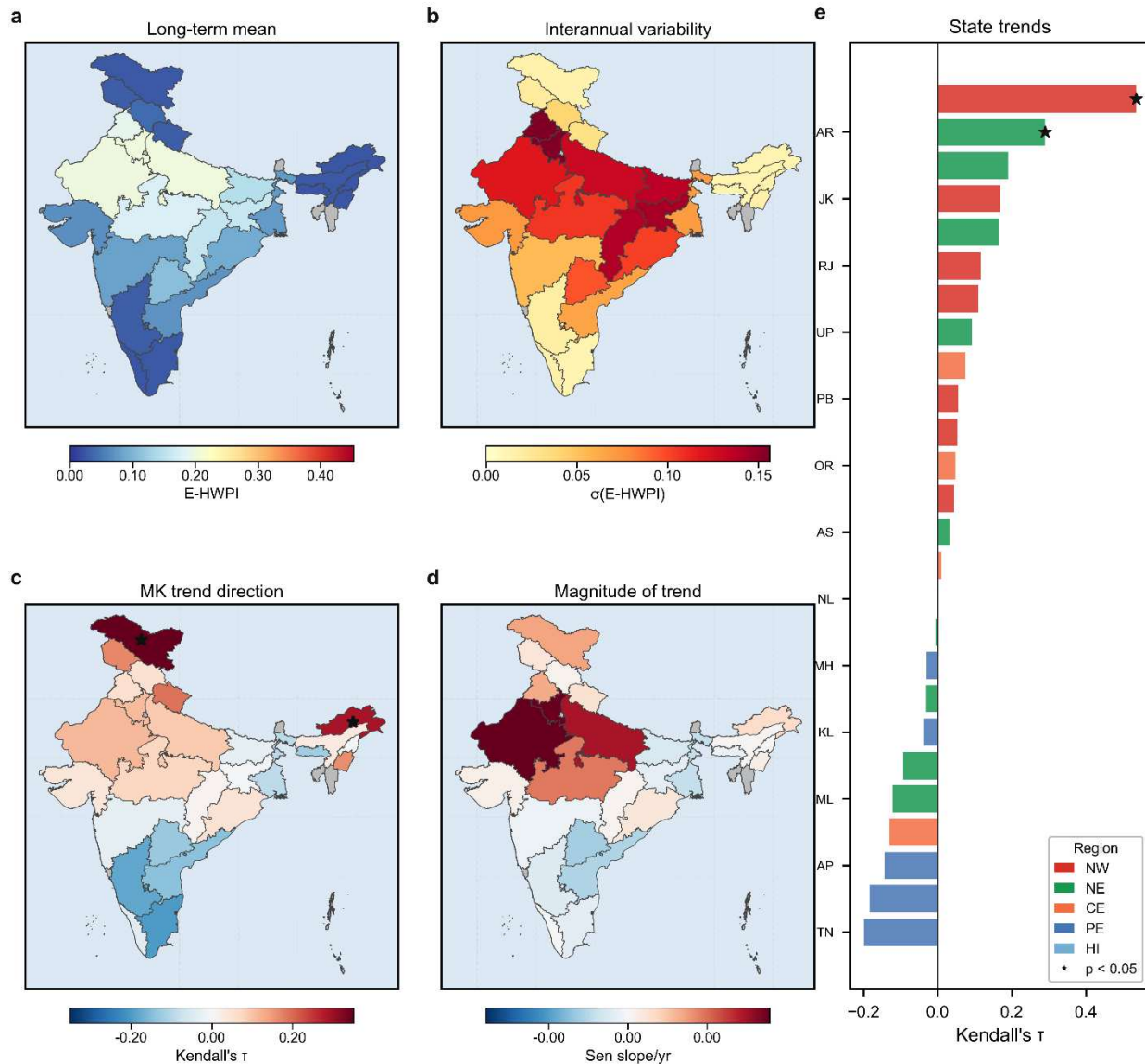


**Fig. 6** State level E-HWPI spatial summary. (a) Long term mean E-HWPI. (b) Interannual standard deviation. (c) Mann Kendall tau per state (d) Sen slope per year (e) State ranking bar chart colour coded by geographic region

### 3.3 Temporal Evolution and Decadal Trends

Domain mean E-HWPI trends upward across the 45-year record (MK  $\tau=0.065$ ; OLS slope = 0.000368 units/year;  $R^2=0.013$ ; Table 2, Fig. 7). The trend does not clear  $p < 0.05$  ( $p=0.538$ ), as interannual variability in India's pre-monsoon climate exceeds what 45 years can resolve, but  $\tau=0.065$  implies about 53% of year pairs show an increase and the bootstrap slope confidence interval lies predominantly above zero (Fig. 7d). C6 CompDHI carries the strongest signal ( $R^2=0.036$ ; slope=0.000834/year), followed by C2 MeanX ( $R^2=0.029$ ), while C1 MaxMag-the focus of most existing indices-shows no trend ( $\tau=-0.002$ ,  $p=0.992$ ). Collectively these suggest intensification

driven not by hotter single days but by more sustained, compounded and nocturnal conditions; since no component trend is individually significant (Table 2), these remain physically plausible hypotheses rather than confirmed findings. From the full annual record (Supplementary Table S5), the ten most extreme years are 2010 (0.196), 1995 (0.176), 2005 (0.157), 1998 (0.150), 1988 (0.149), 2012 (0.148), 2003 (0.147), 2024 (0.131), 2009 (0.121) and 1984 (0.112) -four falling after 2005.

The component-wise decomposition in Table 2 reveals a mechanistically coherent story. The fastest-changing components are C6 CompDHI (OLS  $R^2 = 0.036$ ) and C2 MeanX ( $R^2 = 0.029$ ); the slowest are C4 Duration ( $R^2 = 0.000$ ) and C1 MaxMag ( $R^2 = 0.001$ ). Indian heat waves in 2024 differ little from 1980 in how hot the worst day gets or how long the worst spell lasts, but differ substantially in how often the pre-monsoon season follows a drought year, how many spells occur seasonally, and how warm nights remain. This fingerprint implicates the soil moisture–temperature feedback and ENSO-linked monsoon variability as the primary intensifying processes, consistent with the compound event literature (Table 4).

The 10-year moving average crossed the 1981–2010 baseline around 2005 and has not fallen below it since (Fig. 7a). Standardised anomalies cluster post-2000 (Fig. 7b): approximately  $+1.5\sigma$  in 2010,  $+1.7\sigma$  in 2019,  $+1.6\sigma$  in 2024. Median state-year E-HWPI rose over 50%, from  $\sim 0.042$  in the 1980s to  $\sim 0.065$  in 2010–2024, with the 90th percentile growing from  $\sim 0.29$  to 0.42 (Fig. 7c). The CUSUM crossed the upper 95% permutation bound in recent years (Fig. 7d)-suggestive of, but not conclusive for, a structural shift, given the marginal crossing and non-significant Mann-Kendall result. States exceeding decadal mean 0.10 grew from about six to more than ten (Fig. 8a–d), while the top-ten/bottom-ten gap widened from  $\sim 0.12$  to 0.18 (Fig. 8e). Pixel-level maps (Supplementary Fig. S8) confirm near-zero values in quiet years, demonstrating the trend is not an artefact of a rising floor.

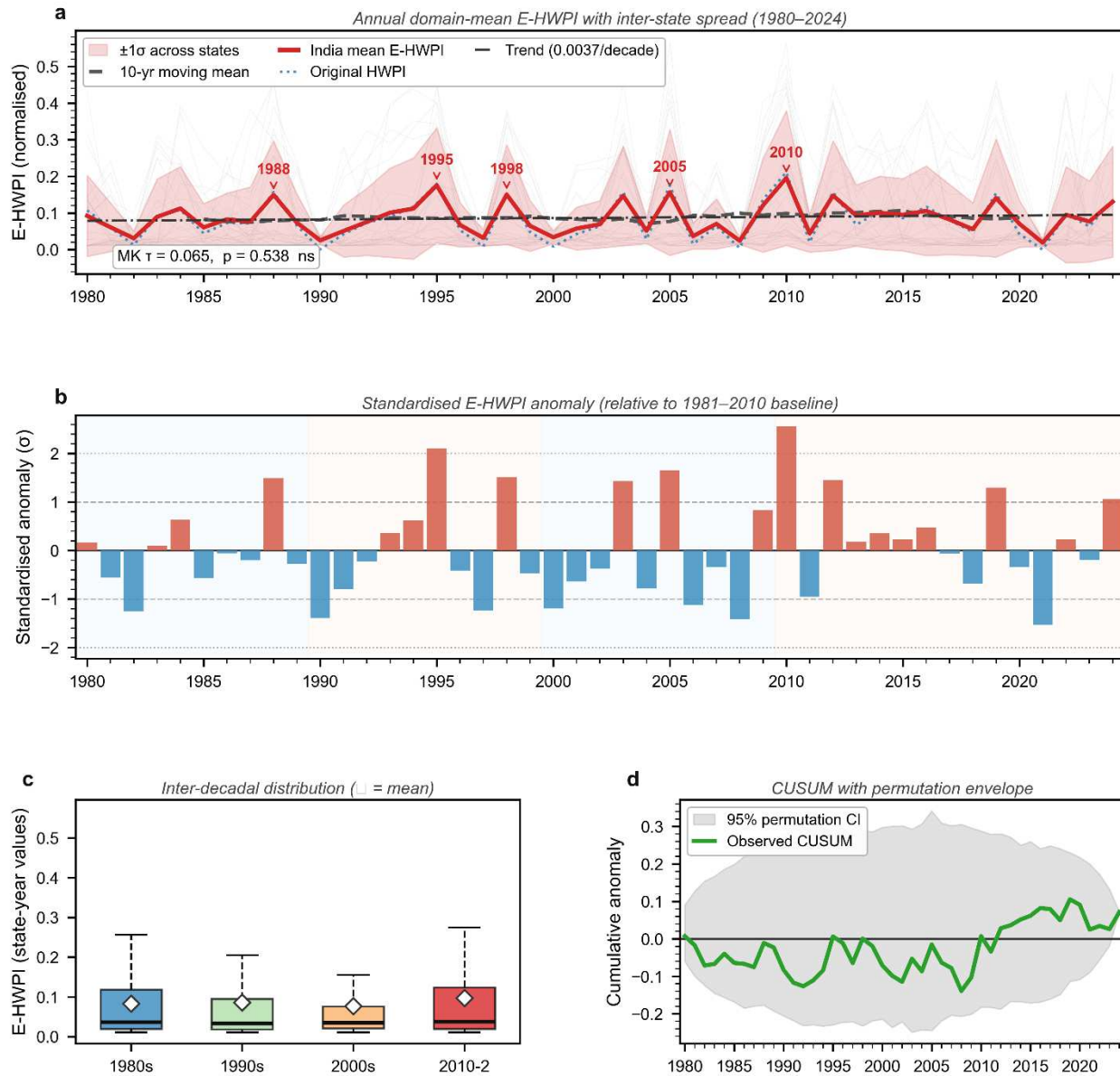


**Fig. 7** Temporal evolution of domain mean E-HWPI (1980 to 2024): (a) Annual time series with inter-state spread, 10-year moving mean and OLS trend (b) Standardised anomaly bars with plus and minus one sigma bounds (c) Inter-decadal boxplots with decadal means as diamonds (d) CUSUM with 95 percent permutation envelope; inset shows bootstrap OLS slope distribution

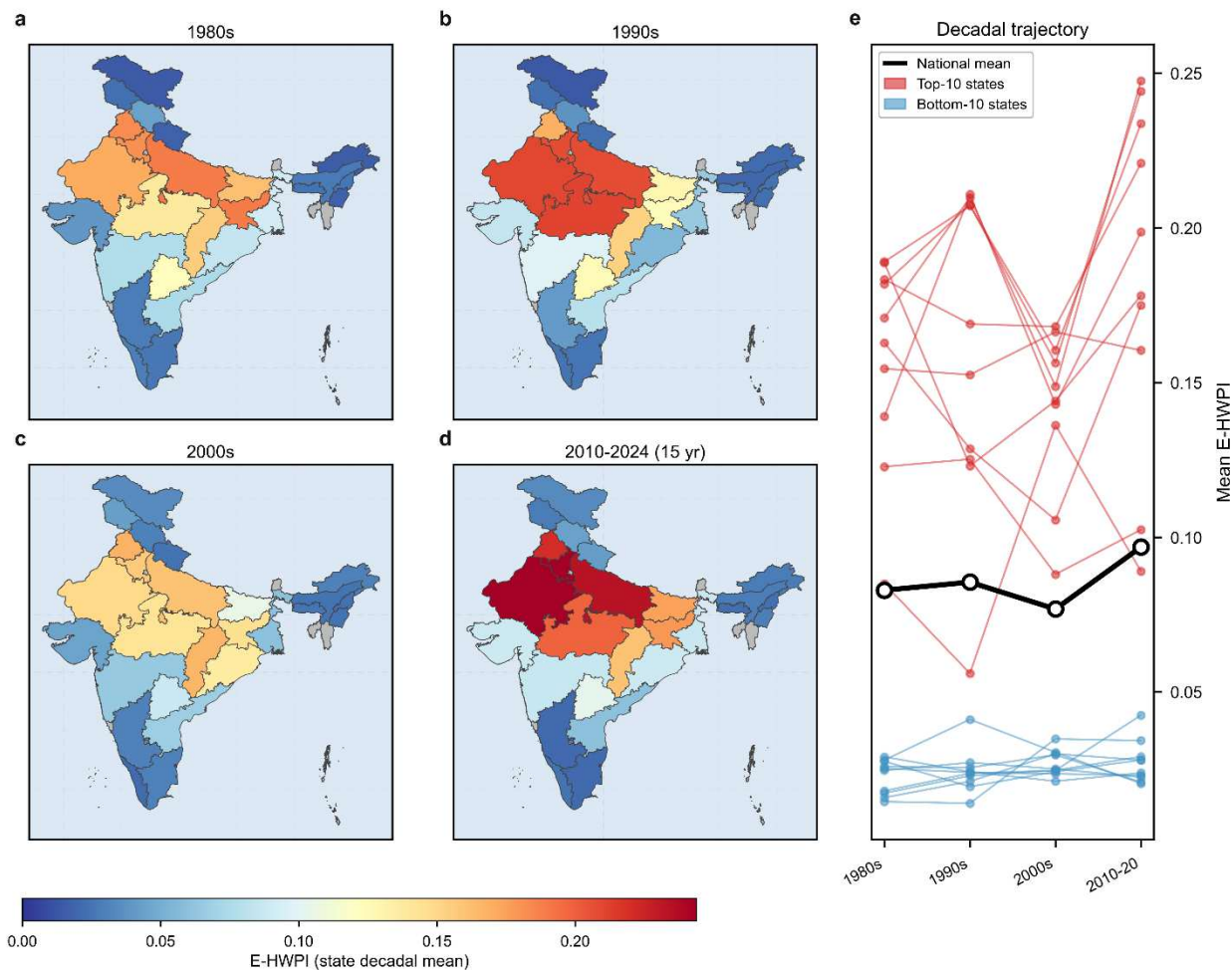


**Fig. 8** Decadal evolution of state level mean E-HWPI. (a to d) Choropleth maps for the 1980s, 1990s, 2000s and 2010 to 2024 on a shared scale (e) Decadal trajectory for top ten, bottom ten and national mean

### 3.4 Distributional Properties and Spectral Structure of E-HWPI

Lag-1 autocorrelation of the national domain mean is approximately 0.18, marginally above the 95% significance bound for  $n=45$  (Fig. 9a), with the partial ACF dropping near zero after lag 1 (Fig. 9b), confirming an AR(1) structure. At state level, lag-1 autocorrelation ranges from near zero in Tamil Nadu and Kerala to 0.40-0.50 in Rajasthan and Madhya Pradesh (Fig. 9e): the states with highest mean peril also show the strongest year-to-year memory, reflecting the compound drought carry-over mechanism of C6. Cross-correlation with a three-component equal-weight index (Fig. 9d) peaks at  $r$  about 0.88 at lag zero, confirming shared interannual drivers. Power spectral density (Fig. 9c) peaks at three-to-five year periods, consistent with ENSO-linked monsoon variability; the Northwest dominates this band while the Northeast is nearly flat (Fig. 9f), meaning ENSO-based seasonal forecasting has greatest utility for the highest-peril states. Supplementary Fig. S6 corroborates this, showing peak interannual  $T_{max}$  variability in the same states.

The coefficient of variation (Fig. 10b) is highest in Punjab (0.83) and Haryana (0.77), lowest in Tamil Nadu (0.45). Positive skewness in Jharkhand and Chhattisgarh (+1.1 to 1.2; Fig. 10c) indicates hazard driven by rare, intense years. Kernel density estimates (Fig. 10d) show clean separation between risk zones -the Extreme zone sits about 0.13 units right of the High zone with a heavier upper tail - validating that quintile thresholds capture genuine distributional breaks. That heavy tail implies planning for the average year systematically underestimates preparation needed for the worst. Supplementary Fig. S10 independently reproduces the spatial patterns of C3, C4 and C1 from raw observations, confirming that aggregation, normalisation and weighting introduce no spatial bias.

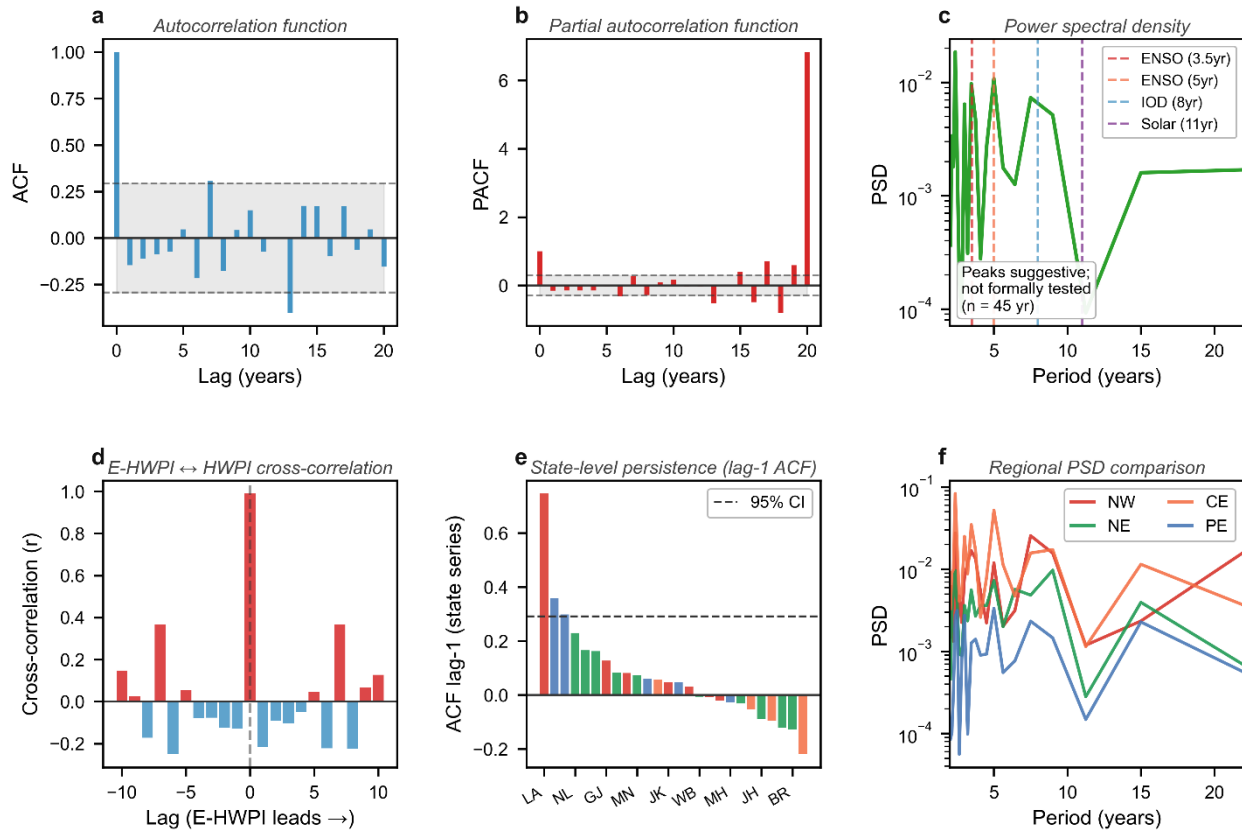


**Fig. 9** Spectral and autocorrelation analysis: (a) ACF and (b) PACF of domain mean E-HWPI with 95 percent confidence bounds. (c) Power spectral density; vertical dashed lines mark the 3 to 5 year ENSO band and an 11 year candidate period. (d) Cross-correlation with three-component equal-weight index. (e) State level lag-1 ACF ranked by region. (f) Regional power spectral density comparison

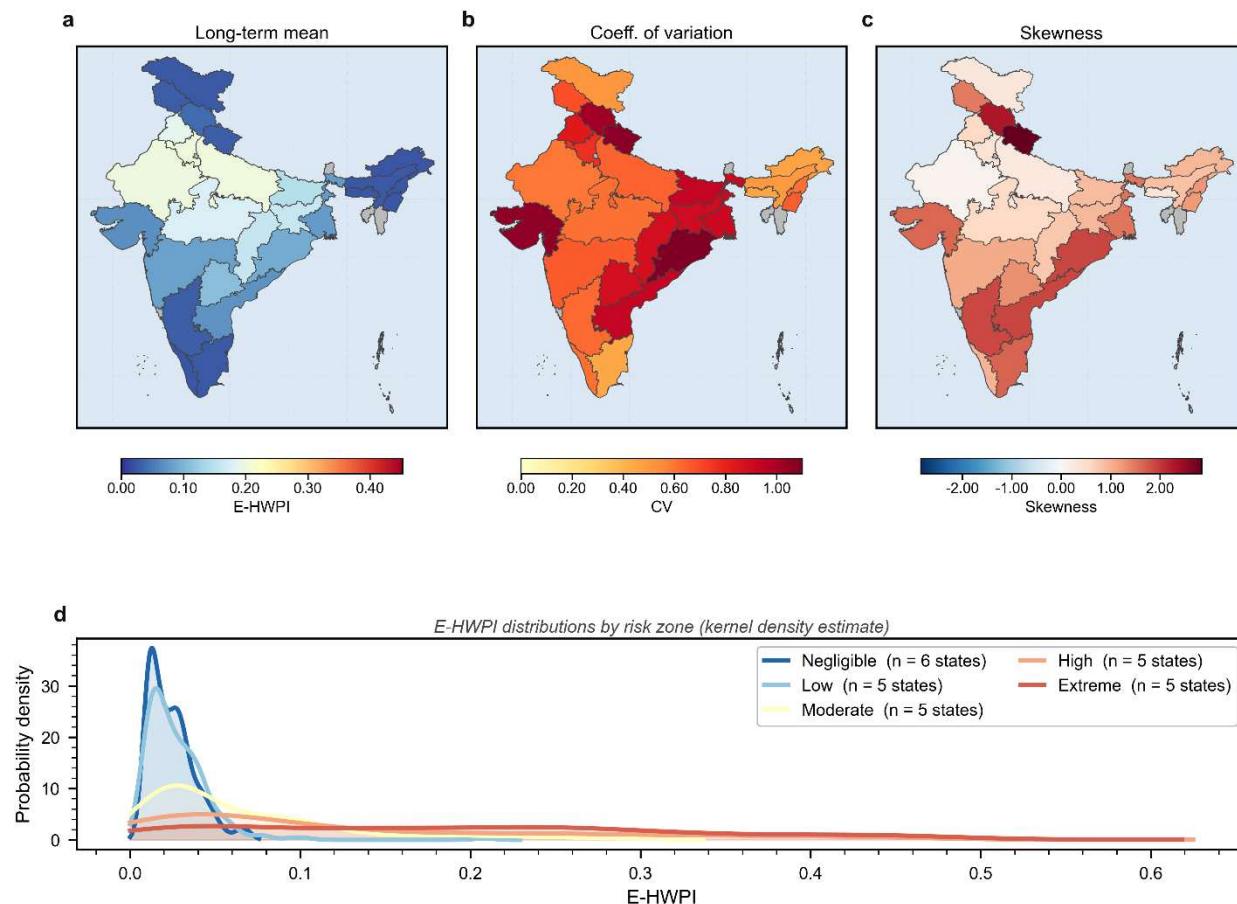


**Fig. 10** Distributional properties of state level E-HWPI: (a) Long term mean. (b) Coefficient of variation. (c) Skewness; positive values indicate rare-but-intense event years. (d) Kernel density estimates by risk zone; the Extreme zone is shifted rightward with a heavier upper tail

### 3.5 Risk Zone and Extreme Year

Quintile classification yields five risk zones (Fig. 11a; Table 3). Five states fall in the Extreme zone (risk zone 5): Haryana (0.2026), Uttar Pradesh (0.2016), Rajasthan (0.2001), Punjab (0.1892) and Madhya Pradesh (0.1757), all in the northwest and north-central plains. This geographic cluster directly overlaps with peak MAMJ Tmax (Supplementary Fig. S1) and highest MAMJ Tmin (Supplementary Fig. S3), confirming the climatological basis for Extreme zone classification. Five states are High zone: Jharkhand (0.1607), Chhattisgarh (0.1586), Bihar (0.1466), Telangana (0.1088) and Odisha (0.0913). The Moderate zone holds Maharashtra (0.0821), West Bengal (0.0773), Andhra Pradesh (0.0697), Gujarat (0.0675) and Himachal Pradesh (0.0395). Six states each are Low and Negligible, concentrated in the northeast, southern peninsula and Himalayan belt (Table 3). The Extreme zone median (approximately 0.195) is 4.3 times the Low zone median (approximately 0.045; Fig. 11c), with little distributional overlap between adjacent zones. About eight percent of all 1,170 state-year observations exceed the Extreme threshold (Fig. 11d). All five Northwest states fall in Extreme or High; most Northeast states are Negligible to Low (Fig. 11e). Comprehensive trend

statistics for all 36 states and union territories, including those with insufficient grid coverage, are in Supplementary Table S6.

The annual zone fraction chart (Fig. 11b) tells the most policy-relevant story: the share of states in High or Extreme zones doubled, from approximately 30 percent in the 1980s to over 50 percent by the 2020s. What once was a geographically confined hazard now regularly affects more than half the covered states in peak years. The five most extreme domain mean years from Supplementary Table S5 are 2010 (E-HWPI = 0.196), 1995 (0.176), 2005 (0.157), 1998 (0.150) and 1988 (0.149). Their state-level maps (Fig. 12a to e) all show coherent elevated E-HWPI signals across north-central India. The composite mean (Fig. 12f) confirms Haryana, Uttar Pradesh and Rajasthan as most consistently exposed with values of 0.35 to 0.45, roughly three times their long-term mean. Radar charts (Fig. 12g) show C1 and C2 account for more than 70 percent of the composite signal, but C5 NoctHS contributes proportionally more in 2010 than in 1988 or 1995, consistent with the accelerating nocturnal warming trend visible in Fig. 3c and the decadal escalation in Supplementary Fig. S9. The 15 states with the largest positive anomaly in the top-five composite (Fig. 12h) are all in the Indo-Gangetic Plain or Thar Desert fringe. The percentile rank time series (Fig. 12i) confirms that extreme years cluster progressively toward the post-2000 record. Supplementary Fig. S8 provides pixel-level E-HWPI maps at full 0.25 degree resolution for the five highest and five lowest domain mean years, revealing the intra-state spatial heterogeneity that is compressed into single state mean values in Fig. 12. In extreme years, the high E-HWPI pixels are strongly concentrated in the western and central portions of Haryana, Punjab and Rajasthan rather than spread uniformly across state boundaries, while in quiet years such as 2021 and 2008, pixel values approach zero across virtually the entire study domain, demonstrating the full dynamic range of the index and confirming it does not generate spurious non-zero values in genuinely cool years.

**Table 3** State level E-HWPI summary statistics and risk zone classification for 26 covered states. Risk zones 1 to 5 (Negligible through Extreme) are quintile thresholds of long term mean E-HWPI.

| State          | Mean E-HWPI | Std    | Zone | Label    | MK tau | p value | Sig. |
|----------------|-------------|--------|------|----------|--------|---------|------|
| Haryana        | 0.2026      | 0.1555 | 5    | Extreme  | 0.110  | 0.291   | No   |
| Uttar Pradesh  | 0.2016      | 0.1299 | 5    | Extreme  | 0.093  | 0.373   | No   |
| Rajasthan      | 0.2001      | 0.1194 | 5    | Extreme  | 0.115  | 0.269   | No   |
| Punjab         | 0.1892      | 0.1573 | 5    | Extreme  | 0.056  | 0.597   | No   |
| Madhya Pradesh | 0.1757      | 0.1068 | 5    | Extreme  | 0.075  | 0.475   | No   |
| Jharkhand      | 0.1607      | 0.1441 | 4    | High     | -0.006 | 0.961   | No   |
| Chhattisgarh   | 0.1586      | 0.1402 | 4    | High     | 0.010  | 0.930   | No   |
| Bihar          | 0.1466      | 0.1368 | 4    | High     | -0.031 | 0.769   | No   |
| Telangana      | 0.1088      | 0.0963 | 4    | High     | -0.129 | 0.214   | No   |
| Odisha         | 0.0913      | 0.1031 | 4    | High     | 0.047  | 0.653   | No   |
| Maharashtra    | 0.0821      | 0.0543 | 3    | Moderate | -0.030 | 0.777   | No   |
| West Bengal    | 0.0773      | 0.0702 | 3    | Moderate | -0.093 | 0.373   | No   |
| Andhra Pradesh | 0.0697      | 0.0651 | 3    | Moderate | -0.143 | 0.168   | No   |

|                   |        |        |   |            |        |         |     |
|-------------------|--------|--------|---|------------|--------|---------|-----|
| Gujarat           | 0.0675 | 0.0715 | 3 | Moderate   | 0.043  | 0.681   | No  |
| Himachal Pradesh  | 0.0395 | 0.0403 | 3 | Moderate   | 0.053  | 0.618   | No  |
| Jammu and Kashmir | 0.0294 | 0.0202 | 2 | Low        | 0.169  | 0.104   | No  |
| Karnataka         | 0.0289 | 0.0181 | 2 | Low        | -0.184 | 0.077   | No  |
| Uttarakhand       | 0.0289 | 0.0309 | 2 | Low        | 0.190  | 0.067   | No  |
| Ladakh            | 0.0255 | 0.0130 | 2 | Low        | 0.535  | < 0.001 | Yes |
| Assam             | 0.0251 | 0.0126 | 2 | Low        | 0.032  | 0.762   | No  |
| Tamil Nadu        | 0.0249 | 0.0111 | 1 | Negligible | -0.199 | 0.055   | No  |
| Meghalaya         | 0.0246 | 0.0114 | 1 | Negligible | -0.121 | 0.244   | No  |
| Kerala            | 0.0245 | 0.0149 | 1 | Negligible | -0.039 | 0.710   | No  |
| Arunachal Pradesh | 0.0242 | 0.0113 | 1 | Negligible | 0.290  | 0.005   | Yes |
| Manipur           | 0.0241 | 0.0157 | 1 | Negligible | 0.165  | 0.113   | No  |
| Nagaland          | 0.0238 | 0.0146 | 1 | Negligible | -0.002 | 0.992   | No  |

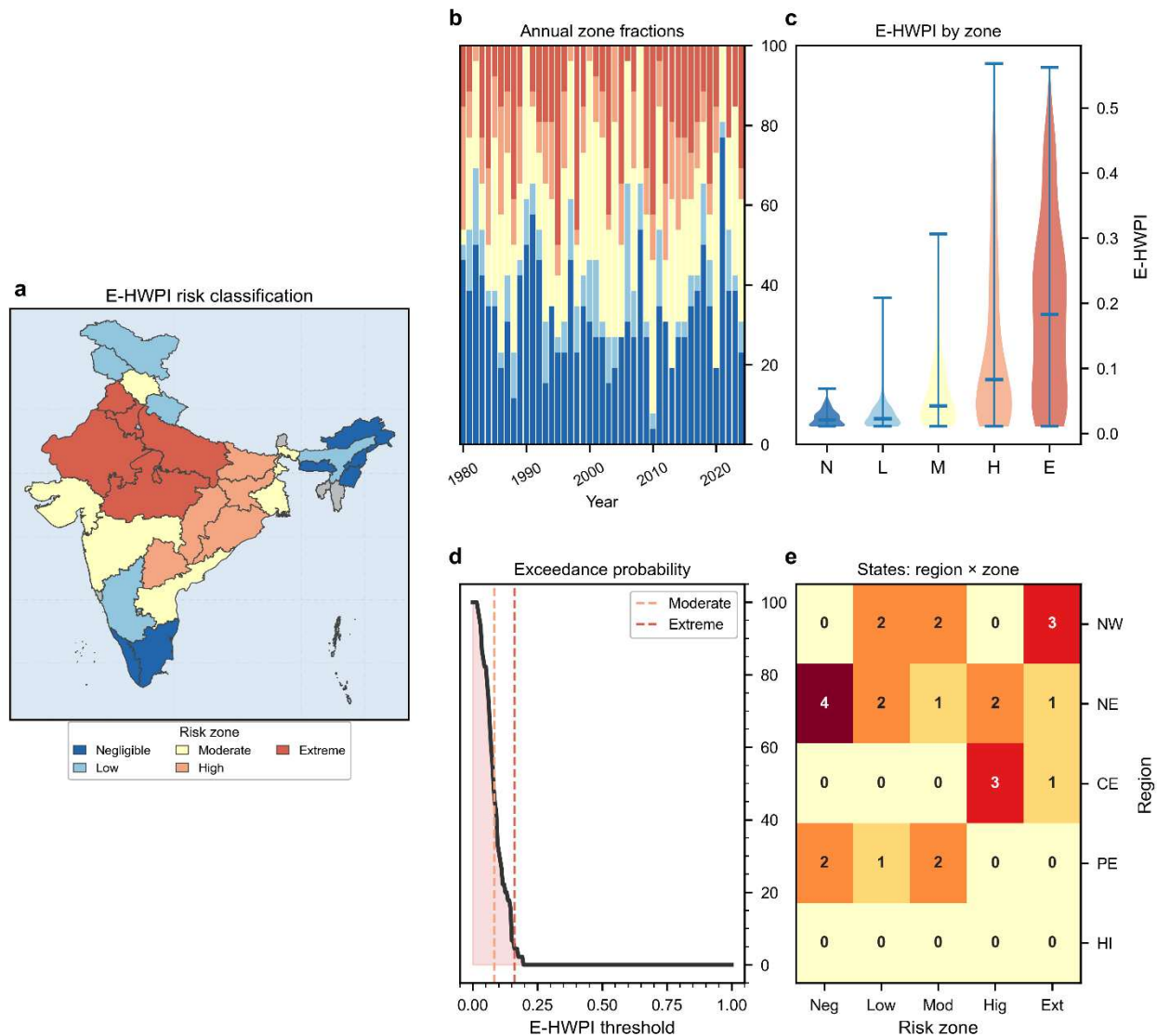


**Fig. 11** Risk zone analysis: (a) State choropleth of five risk zones. (b) Annual stacked bar chart; the High or Extreme share doubled from approximately 30 percent in the 1980s to over 50 percent by the 2020s. (c) Violin plots by zone. (d) Exceedance probability curve. (e) Region by zone heatmap

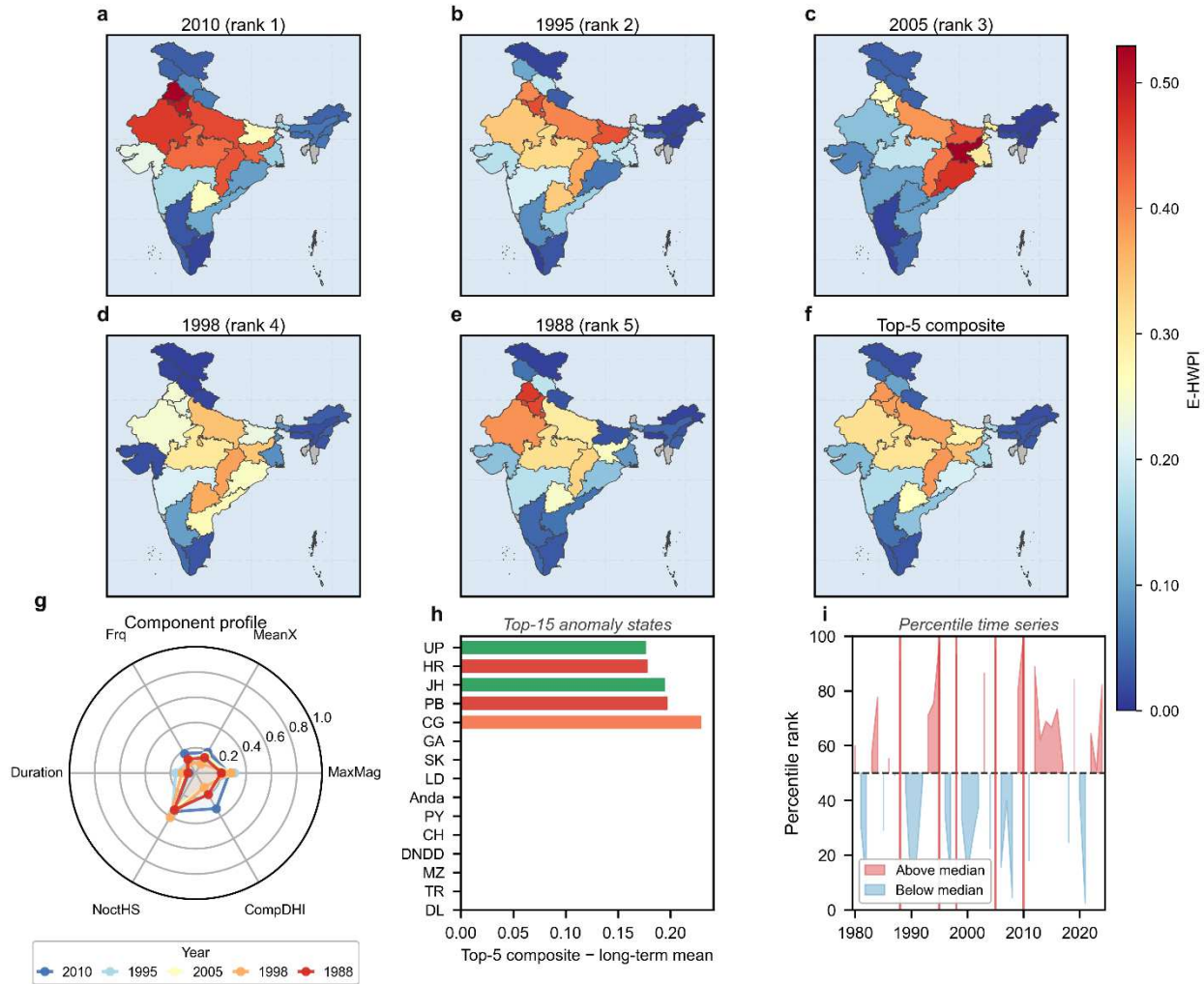


**Fig. 12** The five most extreme E-HWPI years: (a to e) State choropleth maps for 2010, 1995, 2005, 1998 and 1988. (f) Composite mean. (g) Radar chart of component profiles; note increasing C5 NoctHS share in 2010 versus earlier extreme years. (h) Top 15 anomaly states. (i) Percentile rank time series

### 3.6 Population Exposure

Population exposure (Fig. 13a) reveals where hazard and people coincide. Uttar Pradesh carries the highest mean annual exposure at approximately 42.1 million person-events per year (Supplementary Table S6), more than three times Bihar's 14.0 million, followed by Rajasthan (13.5 million) and Madhya Pradesh (12.2 million). These four states together account for approximately 61 percent of total national exposure despite comprising only four of the 26 analyzed states. The cause is structural: all four carry Extreme or High zone E-HWPI scores and rank among India's most densely populated states. Supplementary Table S3 confirms the WorldPop calibration scaling factor stays close to unity across five benchmark years, validating the population estimates. Supplementary Fig. S5, calibrated WorldPop density maps for 2000, 2005, 2010, 2015 and 2020, shows that the Indo-Gangetic Plain

states maintained the highest population densities throughout the analysis period, confirming that the hazard-population coincidence is a durable structural feature, not an artefact of any single census year.

National annual exposure trends upward over 2000 to 2024 (MK  $\tau = 0.220$ ,  $p = 0.129$ , OLS  $R^2 = 0.073$ ; Table 2; Fig. 13b). The trend does not clear significance over 25 years, but 61 percent of year pairs show an increase. Exposure peaks at 294 million person-events in 2010, 257 million in 2024 and 252 million in 2019, against a minimum of 17 million in 2021 from Supplementary Table S5, giving a peak-to-trough ratio exceeding 17 to 1. This extreme range is driven almost entirely by year-to-year swings in E-HWPI, not population. Per capita exposure (Fig. 13d) also rises, confirming that the hazard itself is intensifying independently of demographic growth. Inter-decadal boxplots (Fig. 13c) show both the median and upper quartile of annual national exposure grew from the 2000s to the 2010s; even the lower quartile increased, indicating that the exposure growth is not driven solely by a few extreme peak years but reflects a broadening of the within-decade distribution toward higher values across all years in the period. The 12 states with the largest absolute exposure increase between the 2000s and 2010s (Fig. 13e) are all in the Indo-Gangetic Plain, the Deccan Plateau, or the Thar Desert fringe, led by Uttar Pradesh, Bihar and Rajasthan. Supplementary Fig. S12 decomposes the decadal exposure change into the separate contributions of E-HWPI intensification and population growth: in the northwest Extreme zone states, hazard intensification accounts for a larger share of the exposure growth than demographic increase does. A full state-level account is in Supplementary Table S6 and annual national exposure for all 45 years is in Supplementary Table S5.

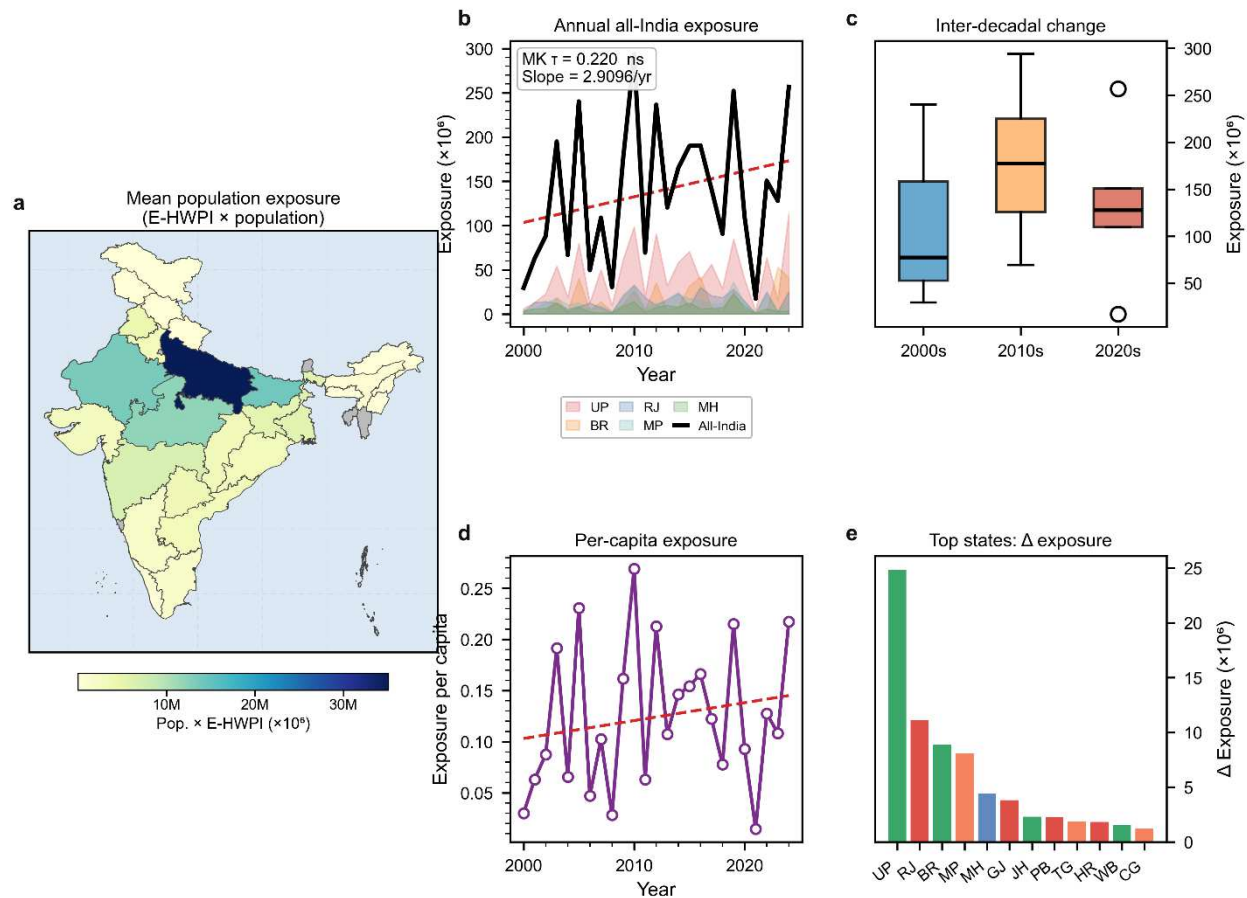


**Fig.13** Population exposure to E-HWPI (2000 to 2024): (a) State choropleth of mean annual exposure in millions of person-events. (b) National time series with top-five state fills and OLS trend. (c) Inter-decadal boxplots. (d) Per capita exposure with OLS fit. (e) Top 12 states by absolute exposure increase from the 2000s to the 2010s

#### 4. Discussion

E-HWPI advances the physical characterisation of Indian heat wave hazard in four ways.

First, the entropy weighting result itself (Fig. 4a-c; Supplementary Table S1): C2 Mean Cross-Event Magnitude carries the highest weight (24.5%), establishing that sustained within-season thermal severity is more spatially informative than peak single-event intensity (C1, 18.2%) or frequency (C3, 17.8%). This aligns with epidemiological evidence: de Bont et al. (2024) showed cumulative season-wide exposure drives mortality more than peak daily temperature across ten Indian cities; Anderson and Bell (2011) found spell duration modifies mortality risk superlinearly; Zhao et al. (2021) documented that global non-optimal temperature burden is dominated by sustained exposure. Yet most Indian heat alert protocols remain calibrated to single-day peak thresholds. Sensitivity testing (Supplementary Fig. S11) shows the entropy scheme outperforms equal-weight alternatives in northeastern and southern states, altering which states are flagged as high hazard.

Second, the temporal decomposition (Section 3.3; Table 2). CompDHI is the fastest-changing component nationally (OLS  $R^2 = 0.036$ ; Fig. 7a,b), while C1 shows essentially no trend ( $\tau = -0.002$ ,  $p = 0.992$ ). India's peril has risen not because the worst day is hotter, but because the pre-monsoon season more often follows a moisture-depleted monsoon, compound drought–heat interactions are more frequent, and nights remain elevated. This is consistent with Tripathy and Mishra (2026), who documented compound drought-heat events expanding from ~10 to 35% of India's area since the 1950s, and Rajeev et al. (2022), who traced these to antecedent MAMJ rainfall deficits. The 3-5 year spectral peak (Fig. 9c), consistent with ENSO-driven monsoon variability (Dar et al. 2024), is strongest in northwest states, which also show the strongest lag-1 autocorrelation (0.40-0.50; Fig. 9e)-implying preceding-winter ENSO state could serve as a months-ahead early signal for Extreme zone states.

Third, physical grounding through the monthly climatology (Section 3.1). MAMJ Tmin climatology (Supplementary Fig. S3) and C5 NoctHS (Fig. 3a) both peak across Rajasthan, Haryana and the upper Indo-Gangetic Plain; pre-monsoon rainfall deficit (Supplementary Fig. S2) and C6 CompDHI (Fig. 3b) both peak in Rajasthan and the Deccan interior. These correspondences confirm the novel components capture coherent physical phenomena rather than normalisation artefacts. Decadal escalation of NoctHS (Supplementary Fig. S9) matches IMD's documented faster Tmin warming (IMD 2024a; Kothawale and Rajeevan 2017). Heat action plan reviews identify missing spatial prioritisation and absent nocturnal and compound dimensions as the primary operational gaps (Martinez et al. 2025; Mavalankar et al. 2022); Table 3 and Fig. 11a address the first, NoctHS and CompDHI the second.

Fourth, the exposure decomposition (Section 3.6). Per capita trends (Fig. 13d) confirm that rising exposure reflects intensifying hazard, not population growth alone. Supplementary Fig. S12 shows hazard intensification dominates in northwest Extreme zone states, while population growth dominates in eastern High zone states such as Bihar and Jharkhand. Early warning, shade infrastructure, cooling centres and nocturnal monitoring therefore yield greater returns per rupee in the northwest, whereas vulnerability reduction-outdoor worker protection, maternal and child health programmes- is proportionally more effective in the east. Raj et al. (2025) project fastest mortality increases in cities within our High and Moderate zones, corroborating the classification. As Table 4 shows, no prior Indian state-level index simultaneously incorporates nocturnal heat stress, compound drought amplification and objective weighting.

Limitations: the  $0.25^\circ$  grid cannot resolve urban heat islands; the  $1.0^\circ$  source Tmin field smooths NoctHS, underestimating variability in topographically complex states; CompDHI uses rainfall Z-scores as a soil-moisture proxy; and entropy weights are specific to the 1980-2024 calibration period. Future work should incorporate ERA5-Land soil moisture, wet-bulb temperature (Im et al. 2017) and cause-of-death records.

665 **Table 4** Comparison of E-HWPI with key published studies

| Study                      | Scope            | Nocturnal | Drought compound | Obj. weighting | Key finding                                                                   |
|----------------------------|------------------|-----------|------------------|----------------|-------------------------------------------------------------------------------|
| de Bont et al. (2024)      | 10 Indian cities | N.I.      | N.I.             | N.A.           | Cumulative seasonal exposure drives mortality more than peak temperature      |
| Sarkar and Maity (2024)    | Indian states    | N.I.      | N.I.             | Equal          | Three-component HWPI; proneness projected to double by 2021 to 2050           |
| Tripathy and Mishra (2026) | India districts  | N.I.      | Y                | N.A.           | CDHW area grew 10 to 35%; heatwave frequency up 86% in humid zones            |
| Rajeev et al. (2022)       | India gridded    | N.I.      | Y                | N.A.           | Most compound events follow monsoon failures; soil moisture pathway confirmed |
| Dar et al. (2024)          | Indian mainland  | N.I.      | N.I.             | N.A.           | Heatwaves originate northwest and propagate east; ENSO drives clustering      |
| Raj et al. (2025)          | 67 Indian cities | N.I.      | N.I.             | N.A.           | Multi-fold mortality increase under SSP5-8.5; Deccan and east most exposed    |
| Khanna et al. (2022)       | 4 Indian cities  | Partial   | N.I.             | PCA            | Socioeconomic vulnerability dominates adaptive capacity in four cities        |
| Tabbussum(2025)            | India            | N.I.      | Y                | N.A.           | <u>El Niño</u> modulate concurrent drought and heatwave frequency in India    |

|                          |                   |         |        |                 |                                                                              |
|--------------------------|-------------------|---------|--------|-----------------|------------------------------------------------------------------------------|
| Anderson and Bell (2011) | 43 US communities | N.I.    | N.I.   | N.A.            | Duration and cumulative exposure modify mortality more than peak temperature |
| Zhao et al. (2021)       | Global            | Partial | N.I.   | N.A.            | Temperature mortality burden concentrated in low and middle income countries |
| E-HWPI (this study)      | 36 Indian states  | Y (C5)  | Y (C6) | Shannon entropy | 5 Extreme states; 294M peak exposure; CompDHI fastest growing (R2 = 0.036)   |

(Note: N.I. = not incorporated; Y = incorporated; N.A. = not applicable)

## 5. Conclusion

The study present E-HWPI, a six-component entropy-weighted heat wave peril index for all 36 Indian states and union territories from 1980 to 2024. Monthly climatological analysis establishes the physical foundation: the MAMJ season drives peak thermal risk, the northwest simultaneously records the highest Tmax, the warmest nights and the driest pre-monsoon conditions and this convergence is directly captured by all six E-HWPI components. Shannon entropy weighting reveals that sustained within-season severity (C2 MeanX, 24.5 percent) is the most spatially discriminating dimension of peril, more important than peak event intensity alone. C6 CompDHI correlates below  $r = 0.25$  against all classical metrics, confirming that antecedent MAMJ rainfall deficits introduce genuinely independent hazard information. C5 NoctHS correlates strongly with the classical daytime components, making it a physiologically distinct but statistically overlapping component. This high statistical overlap is reflected in its low raw entropy weight, while the five percent floor preserves the nocturnal recovery information that no daytime metric can substitute. CompDHI shows the strongest positive temporal tendency among all six components over 45 years (OLS  $R^2 = 0.036$ , slope = 0.000834 per year), though this trend, like those of all other components, does not reach statistical significance at the domain scale ( $p = 0.373$ ; Table 2), suggesting that compound drought amplification may be a key emerging dimension of India's heat wave hazard but warranting cautious interpretation until longer records confirm the signal. Five states face Extreme risk, the share of states under High or Extreme conditions shows an upward tendency since 1980, approximately doubling over the record and population exposure peaks at 294 million person-events. Per capita exposure is also rising across the 2000 to 2024 analysis window, confirming that hazard intensification rather than demographic

growth alone is responsible for the upward trend in the total exposure burden. The study provides state governments, disaster management bodies and heat action plan designers with a clear, reproducible and scientifically grounded framework for knowing where to act, what dimensions of hazard to address and how urgently.

## Acknowledgements

The authors gratefully acknowledge the Indian Meteorological Department (IMD) for providing long-term climatological records, the Survey of India for geospatial boundary data, WorldPop at the University of Southampton for gridded population datasets, and the United Nations Department of Economic and Social Affairs (UN DESA) for demographic data. The open availability of these resources made this research possible. This study was not supported by any external funding agency.

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