Evaluating Heatwave Forecast Accuracy with NCUM and MODE Tools

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Introduction: The Earth's mean temperature has risen steadily since the late 1970s, leading to more intense and frequent heat waves globally, including in India (IPCC, 2015). Recent heat waves have broken temperature records across the Northern Hemisphere, causing increased mortality, crop failures, wildfires, and infrastructure damage (Vogel et al., 2019). Urbanization in Indian cities like Delhi, Mumbai, Chennai, and Kolkata exacerbates heat waves due to factors such as reduced green cover and heat retention by concrete structures (Kumar et al., 2022). Low rainfall (63% below average) and elevated temperatures have also caused the early onset of heat waves in northwestern India and neighbouring regions (WMO, 2022a).

India's summer season, from March to May, frequently experiences heat wave conditions. According to IMD, heat waves occur when temperatures exceed 40°C in plains, 37°C in coastal regions, and 30°C in hilly areas, with anomalies of 4.5–6.5°C above normal (IMD, 2020). Vulnerable regions include West Bengal, Bihar, Madhya Pradesh, and Uttar Pradesh, as well as coastal Andhra Pradesh and Odisha (Raghavan, 1966; Pai et al., 2004). Atmospheric circulation, soil moisture, and sea surface temperatures significantly influence heat wave formation (Perkins, 2015).

Methodology: This study utilizes the MODE tool, initially developed for rainfall verification (Davis 2006a, 2006b, 2009) to verify heat wave forecasts, marking the first application of this object-based method for heat waves in India. MODE identifies spatially coherent heat wave "objects" by smoothing raw forecasts from NCUM-G and IMD using a convolution radius (R) to merge smaller features into larger ones. A user-defined threshold is then applied to create a binary mask, followed by restoring original data within object interiors. Attributes such as area, intensity, centroid distance, and orientation are calculated for both forecasts and observations. This innovative approach offers a detailed spatial verification framework.

Results: This section analyses heatwave events during MAM (2022–2024) over India (7.5°–37.5°N, 68°–98°E) and evaluates the accuracy of NCUM model forecasts using the MODE tool. To assess forecast performance, attributes such as centroid distance, area ratio, and total interest were computed for Tmax thresholds ≥40°C, ≥43°C, and ≥45°C. For lower thresholds, most forecast objects clustered within 2° of observed locations, though some deviations exceeded 6°, mainly in the northwest-southeast direction. As Tmax thresholds increased, fewer objects were identified, but clustering improved, with deviations under 4° for thresholds ≥43°C and ≥45°C, primarily in the north-south direction. Biases across lead times (Day 1, 3, and 5) were consistent. Overall, the NCUM model effectively predicted regions with higher Tmax values, demonstrating reasonable accuracy in capturing heatwave locations.

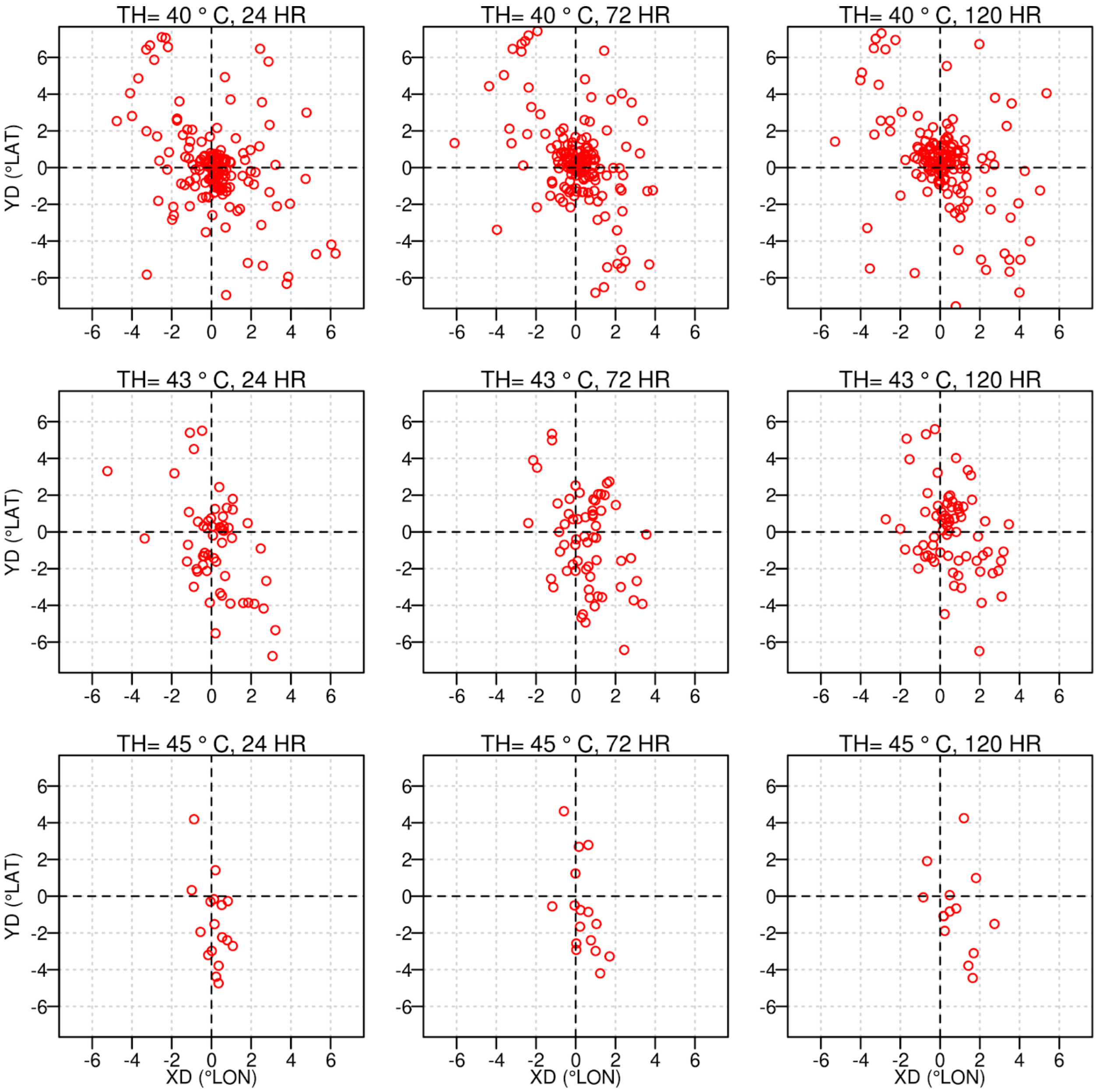

Fig. 1. Scatter plots showing the centroid distance displacement errors (east-west; XD and north-south; YD) for the MAM 2022-2024 in the 24 HR to 120 HR forecasts for three different Tmax thresholds (40, 43, and 45°C) in three columns shown for three rows.

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