Mapping and spatial analysis of hypertension and diabetes prevalence in the Indian environment: a synthesis of district-level geospatial evidence

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Abstract
Hypertension and type-2 diabetes mellitus are the two most prevalent non-communicable diseases (NCDs) in India and share overlapping environmental, socio-economic and behavioural determinants. This paper synthesizes evidence from district-level geospatial and spatial-epidemiological studies, most drawing on the National Family Health Survey (NFHS-4 and NFHS-5), to map the spatial distribution and clustering of hypertension and diabetes across India. Using narrative synthesis of Moran's I, Local Indicators of Spatial Association (LISA), Bayesian spatial modelling and spatial-scan-statistic findings reported in fifteen peer-reviewed and preprint sources, the review identifies consistent high-burden clusters in the peninsular coastal south (Kerala, Tamil Nadu, coastal Karnataka), the Punjab-Haryana belt and parts of the north-eastern hill states, and low-burden clusters in the north-western arid belt (Rajasthan, Ladakh). Environmental exposures, particularly ambient and household air pollution, alongside urbanization, dietary transition, tobacco and alcohol use, and household-level clustering, emerge as recurring correlates of these spatial patterns. The synthesis is illustrated with two summary tables and two schematic spatial visualizations. Findings support the case for district- and sub-district-level, geographically targeted NCD screening and control programmes rather than uniform national strategies.

Keywords: Hypertension, Diabetes Mellitus, Spatial Epidemiology, India, Non-Communicable Diseases, NFHS

1. Introduction

Non-communicable diseases (NCDs) now account for the majority of deaths in India, and hypertension and diabetes mellitus stand out as the two most prevalent cardiometabolic conditions [1, 3]. National surveys estimate age-standardized hypertension prevalence at roughly 22% of the adult population, with substantial variation across the country's 700-plus districts [3]. Diabetes prevalence, while lower in absolute terms, shows comparable geographic heterogeneity and is projected to rise sharply over the coming decade [8, 11]. Because both conditions are shaped by an interacting set of environmental exposures (air quality, urban form, climate and access to green space), socio-economic conditions, dietary transition and household-level behaviours, aggregate national prevalence figures conceal substantial and policy-relevant spatial heterogeneity.

Spatial epidemiology offers a set of tools, geographic information systems (GIS) mapping, spatial autocorrelation statistics such as Global and Local Moran's I, Local Indicators of Spatial Association (LISA) cluster maps and spatial scan statistics, that can convert individual and household-level survey data into district-level maps of disease burden and statistically significant clusters [1, 7, 8]. Over the past six years, a growing body of Indian research has applied these tools to the National Family Health Survey (NFHS-4, 2015-16, and NFHS-5, 2019-21) and to the Longitudinal Ageing Study in India (LASI), producing district-wise hypertension and diabetes maps for the country [1, 3, 7, 9].

The present paper synthesizes this literature to answer three questions: (i) where are the high- and low-burden clusters of hypertension and diabetes in India located; (ii) what environmental and social determinants are most consistently associated with these spatial patterns; and (iii) what are the implications for geographically targeted NCD policy. Because this paper does not re-analyse primary geocoded microdata, it is presented as a structured narrative synthesis of published spatial-analytic findings, illustrated with an original bar-chart of published state-level prevalence figures and a schematic regional cartogram summarizing the qualitative burden categories reported across studies.

2. Materials and Methods

2.1 Study design

This is a narrative, evidence-synthesis review of peer-reviewed and preprint studies that applied spatial-analytic methods to hypertension and/or diabetes prevalence data in India. It is not a primary geospatial analysis of new microdata.

2.2 Search strategy and eligibility

Studies were identified through targeted literature searches (PubMed/MEDLINE, PMC, Google Scholar and publisher databases including Springer, MDPI, PLOS and JAMA Network) using combinations of the terms "hypertension", "diabetes", "spatial analysis", "GIS", "Moran's I", "LISA", "district", and "India". Eligible studies (i) used district- or sub-district-level Indian data, most commonly NFHS-4, NFHS-5 or LASI; (ii) applied an explicit spatial-analytic method (choropleth/quantile mapping, spatial autocorrelation, LISA clustering, spatial scan statistics, or Bayesian/structured-additive spatial modelling); and (iii) reported hypertension and/or diabetes prevalence or clustering outcomes. Fifteen studies meeting these criteria were retained for synthesis [1-15].

2.3 Spatial-analytic methods used pn the source literature

The synthesized studies predominantly used GeoDa and QGIS software to construct district-level choropleth and quantile maps of prevalence, followed by calculation of Global Moran's I to test for overall spatial autocorrelation and Local Moran's I / LISA cluster and significance maps to identify high-high ("hot-spot"), low-low ("cold-spot") and spatially discordant districts [1, 3, 4, 7]. A smaller subset used SaTScan spatial-scan statistics to detect circular disease clusters [8], Bayesian spatial regression to smooth district estimates while adjusting for covariates [4], or Spatial Autoregressive (SAR)/structured additive regression models to jointly estimate spatial trend and covariate effects [9, 12].

3. Results

3.1 National-level burden and overall spatial pattern

Using NFHS-5 data on 707 districts and over 825,000 participants, age-standardized hypertension prevalence was estimated at 22.4% overall (21.3% among women, 24.0% among men), with prevalence generally higher in western and southern districts than in the north-west [3]. The highest state-level prevalence was recorded in Sikkim (34.5% in women, 41.6% in men) and Punjab (31.2% in women, 37.7% in men), while Rajasthan (15.4%/17.9%) and Ladakh (15.7%/17.4%) recorded the lowest [3] (Figure 1). Multiple independent studies corroborate a peninsular-coastal-south and north-eastern high-burden pattern alongside a north-western low-burden pattern for hypertension [1, 4], with Kerala consistently identified as the state with the single highest hypertension burden [1, 4].

3.2 District-level clustering (LISA) findings

Local Moran's I / LISA analyses consistently identify statistically significant "high-high" clusters of hypertension in coastal districts of the southern peninsula and in several north-eastern districts, and "low-low" clusters in Jammu & Kashmir, western Rajasthan and parts of Gujarat [1]. Marked intrastate heterogeneity, districts of markedly different prevalence sitting adjacent to one another, is most pronounced in central India [1]. A household-clustering analysis covering all 707 districts found that 14.9% of households had hypertension clustering (two or more affected members), accounting for half of all hypertension cases nationally, and 7.7% had diabetes clustering, accounting for 39.3% of diabetes cases; clustering "hot" districts were concentrated in Punjab, Haryana, Kerala, southern Karnataka, western Maharashtra, Chhattisgarh, Jharkhand, Sikkim and Arunachal Pradesh [5], and this pattern overlapped geographically with districts of high tobacco use and overweight/obesity prevalence.

3.3 Spatial patterns for diabetes mellitus

Applying Moran's I and LISA to NFHS-4 and LASI district data, diabetes prevalence showed significant positive spatial autocorrelation among both men (Moran's I = 0.284) and women (Moran's I = 0.554), indicating that high-prevalence districts tend to neighbour other high-prevalence districts [7]; roughly 93 high-burden districts (>30% male prevalence) were spread across the country but concentrated in the southern and western regions [7]. Spatial-scan-statistic analysis of a large demographic-and-health-survey dataset similarly identified significant geographic clusters of diabetes associated with income, alcohol consumption and tobacco smoking, although geographic overlap with tuberculosis endemicity was limited [8]. Among women in their late reproductive years, quantile and LISA cluster mapping across 640 districts found the diabetes burden concentrated in the southern and eastern parts of the country, correlated with obesity, hypertension and urban residence [9], a pattern echoed in district-level analyses of reproductive-age women in southern India [10].

3.4 Environmental correlates of spatial clustering

Beyond socio-economic and behavioural covariates, ambient and household air pollution emerge repeatedly as environmental correlates of the spatial pattern. A national analysis linking NFHS-5 hypertension data with satellite-derived PM2.5 estimates found a spatial association between ambient particulate concentrations and both hypertension and diabetes prevalence [13], while a cross-sectional analysis of young and middle-aged women found that both ambient PM2.5 exposure and household air pollution independently increased the odds of hypertension [15]. Reviews of India's rapid urbanization highlight elevated PM2.5, PM10, NO2 and CO in major cities relative to rural areas as a plausible mechanistic pathway, via insulin resistance, oxidative stress and endothelial dysfunction, contributing to the country's rising type-2 diabetes burden [14]. These environmental findings are broadly consistent with the urban- and western/southern-district concentration of diabetes clustering reported in the survey-based spatial studies above.

Table 1 summarizes the data sources, spatial methods and principal findings of the key studies synthesized in this review; Table 2 aggregates these findings into seven broad macro-regions to give a compact, cross-study regional overview.

Table 1: Summary of district-level spatial-epidemiological studies of hypertension and diabetes in India

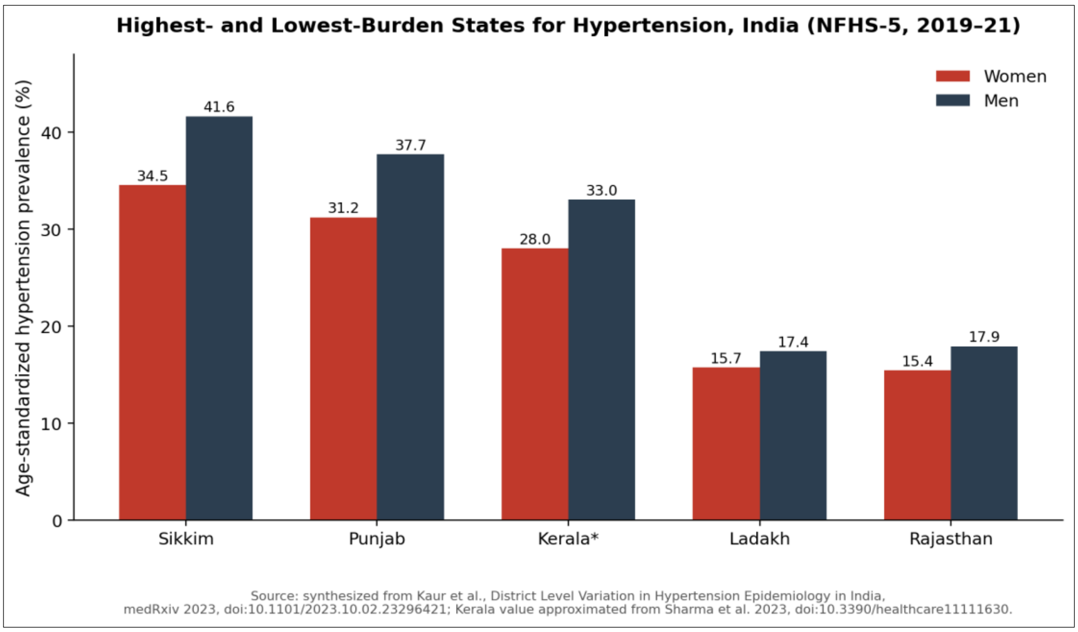
Study (First author, Year)	Data source/period	Spatial method	Key spatial finding	Ref.
Kamath *et al.*, 2023	NFHS-5 (2019-21), 707 districts	GeoDa/QGIS; Global & Local Moran's I, LISA	Highest hypertension burden in coastal peninsular districts and parts of the Northeast; lowest in J&K, western Rajasthan and parts of Gujarat	1
Priti *et al.*, 2025	NFHS-5 (2019-21), 1,551,191 respondents	Spatial autocorrelation (Global Moran's I, LISA)	Significant district clustering in hypertension awareness, treatment and control, with cold-spots concentrated in central-eastern India	2
Gupta *et al.*, 2023	NFHS-5, 707 districts, 825,954 participants	Descriptive + polynomial/multivariate regression by district	Age-standardized prevalence 22.4%; highest in Sikkim and Punjab, lowest in Rajasthan and Ladakh; higher burden in western/southern districts	3
Mani *et al.*, 2025	NFHS-5, South India, 304,420 adults	Bayesian spatial modelling; LISA	Kerala had the highest state prevalence; significant clustering of hypertension with neighbouring-district spillover and co-clustering with diabetes	4
Pedgaonkar *et al.*, 2025	NFHS-5, all 707 districts	District mapping of household clustering + multilevel models	Household clustering of hypertension (14.9%) and diabetes (7.7%) concentrated in Punjab, Haryana, Kerala, southern Karnataka and parts of the Northeast	5
Krishnamoorthy *et al.*, 2023	NFHS-4 (613 districts) & LASI (632 districts)	GeoDa; Moran's I, LISA, spatial regression	Positive spatial autocorrelation for diabetes (Moran's I 0.28-0.55); hotspots concentrated in southern and western districts	7
Hernandez *et al.*, 2020	DHS, 803,164 individuals	SaTScan spatial scan statistic	Significant geographic clustering of diabetes linked to income, alcohol use and tobacco smoking; limited overlap with tuberculosis hotspots	8
Singh *et al.*, 2020	NFHS-4 (2015-16), 640 districts, women 35-49y	Quantile maps; univariate/bivariate LISA; spatial regression	Diabetes burden among women clustered in southern and eastern districts; obesity, hypertension and urban residence were key correlates	9

Table 2: Regional synthesis of reported hypertension and diabetes burden patterns

Macro-region	Representative states/UTs	Hypertension pattern	Diabetes pattern	Refs.
Peninsular coastal south	Kerala, Tamil Nadu, coastal Karnataka	Highest state-level prevalence; strong LISA hot-spot clustering	Highest combined DM burden; hot-spots overlap with HTN clusters	1,3,4,10
North-west arid belt	Rajasthan, Ladakh, parts of Gujarat	Lowest age-standardized prevalence nationally	Comparatively low reported clustering	1,3
North / north-central plains	Punjab, Haryana, Delhi-NCR	High household-level clustering; among highest male prevalence	Elevated urban diabetes clustering	3,5
Himalayan & north-eastern hill states	Sikkim, Arunachal Pradesh and neighbours	Highest reported prevalence among women and men nationally	Moderate, data-sparse	3,5,12
Central India	Madhya Pradesh, Chhattisgarh	Marked intrastate heterogeneity; pronounced household clustering	High clustering linked to tobacco/obesity overlap	1,5
Western India	Maharashtra, coastal Gujarat	Moderate-high, urban-concentrated	High diabetes clustering, particularly urban/peri-urban	7,8
Eastern India	Odisha, Jharkhand, West Bengal	Moderate; overlaps with high tobacco-use districts	Moderate; socio-economic gradient evident	5,9

3.5 Spatial visualizations

Figure 1 reproduces the age-standardized, state-level hypertension prevalence figures reported for the highest- and lowest-burden states in the largest available district-level NFHS-5 analysis, illustrating the roughly two-and-a-half-fold gap between the highest- and lowest-prevalence states.



Source: synthesized from references [1,3]; see figure note for details

Fig 1: Age-standardized hypertension prevalence (%) in the highest- and lowest-burden Indian states, women and men, NFHS-5 (2019-21)

Figure 2 presents a schematic regional cartogram that qualitatively integrates the directionality of findings (high, moderate-high, moderate, or low burden/clustering) reported across the studies summarized in Table 1, to give readers a single, compact visual overview of where India's spatial hypertension-diabetes hot-spots and cold-spots have been reported in the peer-reviewed literature.

Fig 2: Schematic regional synthesis of reported hypertension and diabetes burden/clustering patterns across Indian macro-regions. This is a conceptual cartogram built from the qualitative findings in Table 1 and Table 2 and is not an original GIS-generated choropleth; region boundaries and sizes are illustrative and not drawn to true geographic scale.

4. Discussion

The synthesized evidence points to a remarkably consistent spatial signature for both hypertension and diabetes in India: elevated burden in the peninsular coastal south (particularly Kerala), the Punjab-Haryana belt and parts of the north-eastern hill states, set against comparatively low burden in the north-western arid belt (Rajasthan, Ladakh) [1, 3, 4]. This pattern only partly mirrors classical socio-economic gradients; several of the highest-burden states (Kerala, Punjab, Sikkim) also rank among India's better-performing states on human-development indicators, suggesting that the "double burden" of NCDs in India follows a distinct epidemiological transition pathway in which urbanization, dietary change, tobacco and alcohol use, and, increasingly, environmental exposures such as ambient air pollution outweigh simple poverty gradients as spatial drivers [3, 13, 14].

The consistent identification of significant positive spatial autocorrelation (Moran's I values ranging from roughly 0.28 to

0.55 for diabetes, and comparable or higher values reported for hypertension) across independently conducted studies using different NFHS rounds and different software (GeoDa, QGIS, SaTScan) strengthens confidence that these are genuine, policy-relevant geographic clusters rather than artefacts of a single dataset or analytic choice [1, 4, 7]. The recurring overlap between hypertension/diabetes hot-spots and hot-spots of tobacco use, obesity, and, more recently documented, ambient PM2.5 exposure [5, 13, 15] suggests that district-level NCD control strategies could usefully be co-located with tobacco-control, obesity-prevention and air-quality interventions rather than being planned as parallel, single-disease vertical programmes.

From a health-systems perspective, these findings support three broad implications. First, national NCD targets and resource allocation (for example, under India's National Programme for Prevention and Control of Non-Communicable Diseases) could be weighted toward the specific high-clustering districts identified in this literature rather than applied uniformly. Second, the strong urban-diabetes and coastal-hypertension signal suggests that urban primary health infrastructure and air-quality mitigation (public transport, green space, industrial-emission control) are relevant NCD-prevention levers, not solely traditional lifestyle-counselling programmes. Third, the persistence of low-burden "cold-spot" regions such as Rajasthan and Ladakh, despite comparatively lower health-system resourcing in some of these areas, indicates that environmental and dietary protective factors specific to arid and high-altitude settings merit further investigation.

5. Conclusion

District-level spatial-epidemiological research consistently shows that hypertension and diabetes are not evenly distributed across India: significant high-burden clusters recur in the peninsular coastal south, the Punjab-Haryana belt and parts of the north-east, while significant low-burden clusters recur in the north-western arid belt. These patterns are associated with urbanization, tobacco and alcohol use, obesity, household clustering, and increasingly with ambient and household air pollution. Future research combining primary GIS analysis of the latest NFHS round with fine-grained environmental exposure data (air quality, land-use, green space, climate) at sub-district resolution would sharpen these findings and support more precisely targeted NCD prevention and control policy in India.

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