Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

Morbidity Transitions and Environmental Chemical Health Risks in Haryana, India: Spatial Patterns, Socioeconomic Differentials, and District-Level Analysis Using NSSO Data (2004–2018)

[Amit Bairagi, Sr. Prof. Binu Sangwan]

[Department of Geography, Maharshi Dayanand University. Rohtak-124001, Haryana, INDIA]

(Received: 16 January 2026 Revised: 25 February 2026 Accepted: 17 March 2026)

KEYWORDS
Morbidity
Environmental health
Chemical exposure
Haryana
Spatial analysis
NSSO data
Health risk assessment

ABSTRACT:

Introduction: Haryana, despite having the third-highest per capita income in India, exhibits profound spatial inequalities in disease burden compounded by pervasive environmental chemical exposures—including airborne particulate matter, groundwater fluoride and arsenic contamination, agrochemical residues, and severe WASH deficits.

Objectives: To examine spatial patterns, temporal transitions, and socioeconomic differentials of morbidity across Haryana's 21 districts from 2004 to 2018, and to evaluate the role of environmental chemical exposures in shaping district-level health risk zones.

Methods: Unit-level micro-data from three NSSO rounds (60th/2004, 71st/2014, 75th/2017–18) were analysed using bivariate analysis, prevalence-based odds ratios, coefficients of variation, Pearson correlations, and spatial environmental correlation analysis drawing on CGWB (2020), HPCB (2021), and NFHS-5 (2021) data.

Results: State-level non-chronic morbidity declined 60.6% from 94 to 37 per 1,000 population (2004–2018); total morbidity declined from 94 to 59 per 1,000. Inter-district CV narrowed from 92.8% to 50.2%. A near-zero Pearson correlation (r=0.088) between 2004 and 2018 district rankings indicates fundamental geographic reshuffling. Air pollution correlated positively with morbidity (r=0.62), WASH deprivation with infectious disease (r=0.61), and groundwater fluoride with disability morbidity (r=0.54). Women, elderly, SC/ST communities, and the educationally disadvantaged carried disproportionate burdens.

Conclusions: Environmental chemical exposures constitute active, spatially structured determinants of morbidity in Haryana. Targeted environmental health regulation, district-specific chemical risk mitigation, and equity-sensitive health programming are urgently required.

1. INTRODUCTION

Haryana presents one of the more compelling health geographies in contemporary India. Despite ranking third in per capita income among Indian states and sustaining a rapidly modernising economy, the state harbours persistent spatial inequalities in disease burden and a morbidity profile that is simultaneously evolving and uneven. Crucially, these health disparities are not reducible to socioeconomic factors alone—they are deeply interwoven with the state's environmental chemical landscape: industrial corridors generating severe PM2.5 and PM10 pollution; agricultural heartlands among India's most intensive pesticide consumers; and aquifers carrying unsafe fluoride, arsenic, and nitrate concentrations affecting millions of residents.

The *Journal of Chemical Health Risks* has documented similar environment–morbidity linkages globally, including pesticide-related health risks (Rekha et al., 2006), air pollution health impact assessment using WHO-endorsed AirQ software in major Indian cities (Lakshmipathy et al., 2023), heavy metal contamination in industrial zones (Chaudhary et al., 2021), and waterborne chemical exposures in vulnerable communities. This study contributes to this literature by providing a comprehensive district-level spatial and temporal assessment of morbidity and chemical-environmental health risk in Haryana.

At the national level, morbidity transition in India has been well-documented using successive NSSO rounds. Bramhankar and Dhar (2024) analysed four NSSO rounds (52nd/1995 to 75th/2018) and found national morbidity prevalence more than doubled between 1995 and 2014, with women, the elderly, and urban residents consistently reporting higher burdens. Yadav and Arokiasamy (2017) similarly demonstrated a multifold rise in CVDs and NCDs across Indian states over 1995–2014 using three NSSO rounds. This Haryana-specific study adds spatial

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

granularity and an environmental chemical risk dimension absent from these national analyses.

From the industrial corridors of Panipat and Faridabad (characterised by high PM2.5/PM10 and heavy metal effluents) to the WASH-deprived tracts of Mewat and Mahendragarh (characterised by fluoride-contaminated groundwater), each district carries its own disease ecology shaped by chemical environment, social structure, and development trajectory. The objectives of this study are: (i) to document district-level morbidity trends and spatial patterns; (ii) to examine socioeconomic and demographic differentials using bivariate odds ratio analysis; (iii) to assess spatial correlations between environmental chemical stressors and morbidity outcomes; and (iv) to identify high-risk geographic zones for targeted chemical health risk interventions.

2. MATERIALS AND METHODS

2.1 Data Sources

The primary dataset comprises unit-level micro-data from three NSSO rounds: 60th Round (2004; n=1,400 households, 7,772 individuals), 71st Round (2014; n=1,424 households, 8,040 individuals), and 75th Round (2017–18; n=2,958 households, 16,271 individuals). Non-chronic morbidity is illness reported within 15 days preceding the survey; chronic morbidity is a pre-existing condition under treatment for one month or more; total morbidity is their sum. Chronic morbidity data was unavailable in the 60th Round. Disease types are classified into five ICD-10 based categories: Infectious diseases, Cardiovascular diseases (CVDs), Non-Communicable Diseases (NCDs), Disability-related ailments, and Other diseases.

Secondary environmental data: Central Ground Water Board Annual Report (2020) for fluoride/arsenic groundwater concentrations; Haryana State Pollution Control Board (2021) for PM2.5 and PM10 data; NFHS-5 (2021) for sanitation coverage and open defecation rates.

2.2 Analytical Framework

Morbidity prevalence is calculated as (Number of persons reporting ailment / Number of persons exposed to risk) × 1,000. Odds ratios (ORs) are derived using OR = $[p_1/(1-p_1)] / [p_0/(1-p_0)]$. Descriptive statistics including mean, median, standard deviation, and coefficient of variation (CV%) were computed for district-level data to assess inter-district disparity. Pearson correlation coefficients examine temporal stability of spatial patterns across rounds. Spatial correlations between environmental chemical indicators and district-level morbidity were computed using secondary environmental indices. Software used: Microsoft Excel for statistical computations and ArcGIS for spatial analysis.

3. RESULTS

3.1 District-Level Trends in Non-Chronic Morbidity (2004–2018)

State-level non-chronic morbidity declined from 94 per 1,000 in 2004 to 39 per 1,000 in 2014—a 59% reduction—stabilising at 37 per 1,000 by 2018 (Table 1). This trajectory broadly aligns with national trends documented by Bramhankar and Dhar (2024), who found aggregate morbidity in India rose sharply from 1995 to 2014 before moderating by 2018, with significant sub-national variation. In 2004, Panchkula recorded 392 per 1,000—more than four times the state average—reflecting high health awareness and reporting propensity in this affluent, urbanised district. Yamunanagar (299), Kurukshetra (228), and Kaithal (163) also clustered above average in the northern belt. By 2018, the morbidity geography had shifted: Sonipat (102 per 1,000), Panipat (70), and Hisar (61)—all districts with significant industrial chemical pollution exposure—emerged as new burden centres.

Table 1: Trends in Self-Reported Non-Chronic Morbidity Prevalence (per 1,000 population), District-wise, Haryana, 2004–2018

Sr.	District	2004	2014	2018	% Change (2004–2018)
1	Panchkula	392	28	20	−94.9
2	Ambala	199	26	60	−69.8
3	Yamunanagar	299	70	45	−84.9
4	Kurukshetra	228	19	39	−82.9
5	Kaithal	163	25	54	−66.9
6	Karnal	134	37	27	−79.9
7	Panipat	140	88	70	−50.0
8	Sonipat	91	30	102	+12.1
9	Jind	104	4	30	−71.2
10	Fatehabad	32	108	25	−21.9
11	Sirsa	29	60	7	−75.9
12	Hisar	45	27	61	+35.6

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

Sr.	District	2004	2014	2018	% Change (2004–2018)
13	Bhiwani	53	27	25	−52.8
14	Rohtak	17	37	64	+276.5
15	Jhajjar	8	0	20	+150.0
16	Mahendragarh	70	0	46	−34.3
17	Rewari	77	23	38	−50.6
18	Gurugram	11	69	23	+109.1
19	Mewat	--	50	14	--
20	Faridabad	49	56	4	−91.8
21	Palwal	--	16	5	--
	Haryana	94	39	37	−60.6

Source: Authors' Calculation from NSSO 60th (2004), 71st (2014), and 75th (2017–18) Rounds

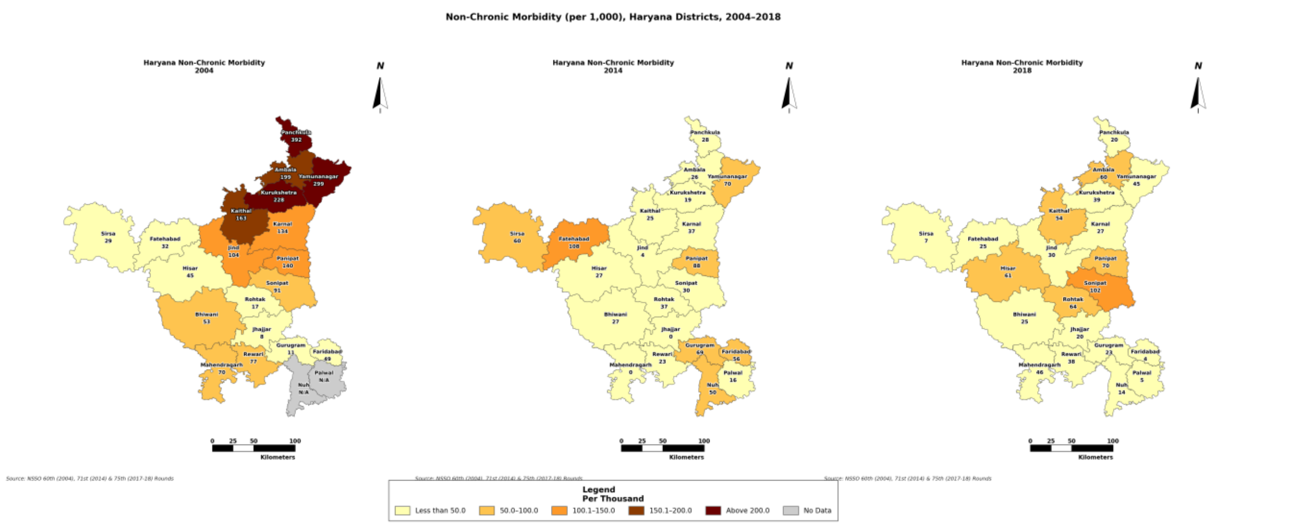

Figure 1: District-wise Non-Chronic Morbidity Prevalence (per 1,000 population), Haryana, 2004–2018

3.2 Rural–Urban Differential in Non-Chronic Morbidity

A structurally significant reversal of the rural–urban morbidity gradient occurred between 2004 and 2018. In 2004, rural non-chronic morbidity (96 per 1,000) slightly exceeded urban (88 per 1,000). By 2014, urban morbidity (48) had overtaken rural (34); by 2018 the urban figure (38) continued to exceed rural (36). This reversal aligns with the 'urban health penalty'—where lifestyle risks, ambient air pollution, occupational chemical stress, and dietary transitions in cities outweigh healthcare access advantages (Ranu & Banerjee, 2020). Sonipat urban (110 per 1,000 in 2018 vs. rural 98), Rohtak urban (93 vs. rural 46), and Hisar urban (84 vs. rural 51) are particularly striking.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

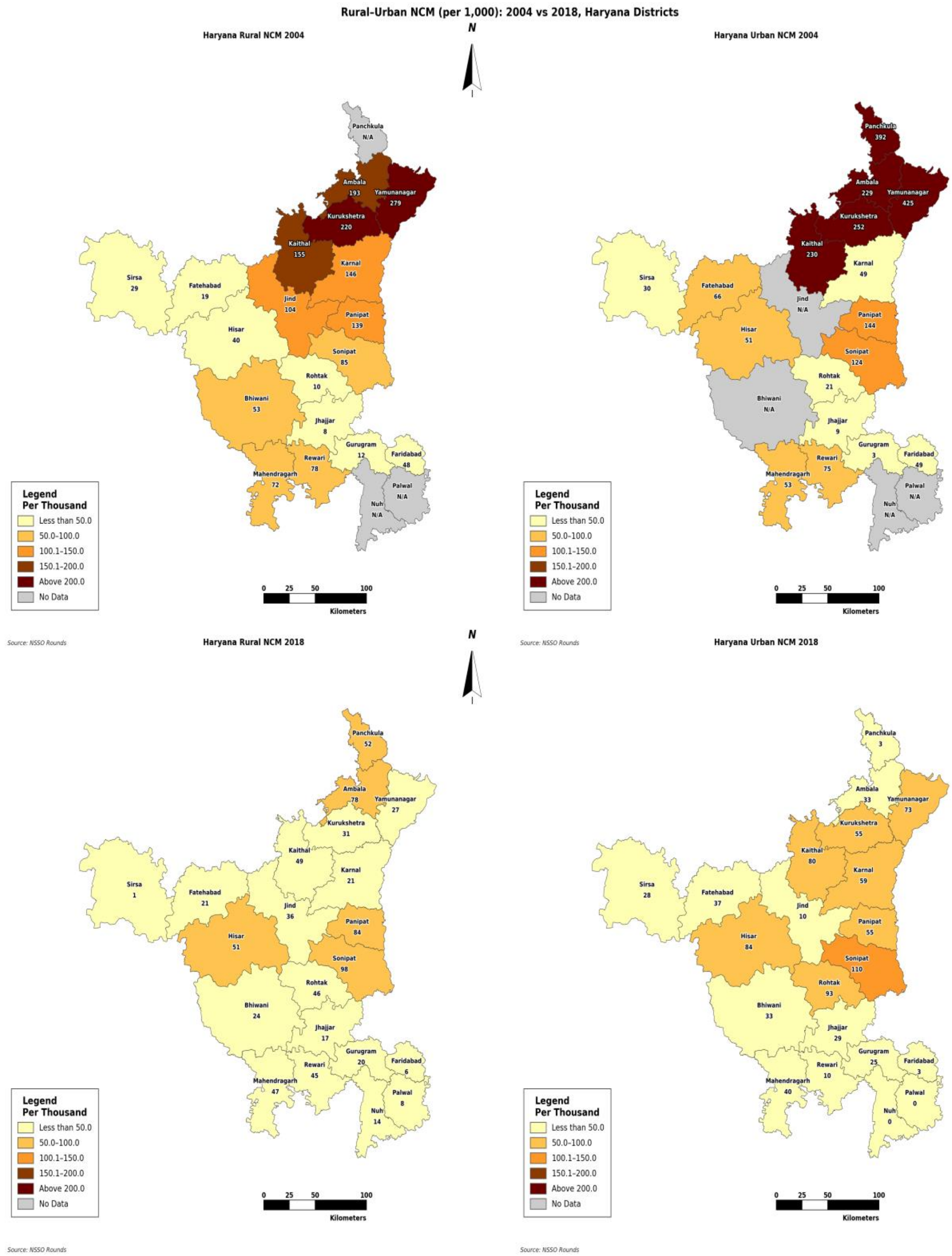

Figure 2: Rural–Urban Differential in Non-Chronic Morbidity Prevalence (per 1,000), Haryana, 2004–2018 (4-panel)

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

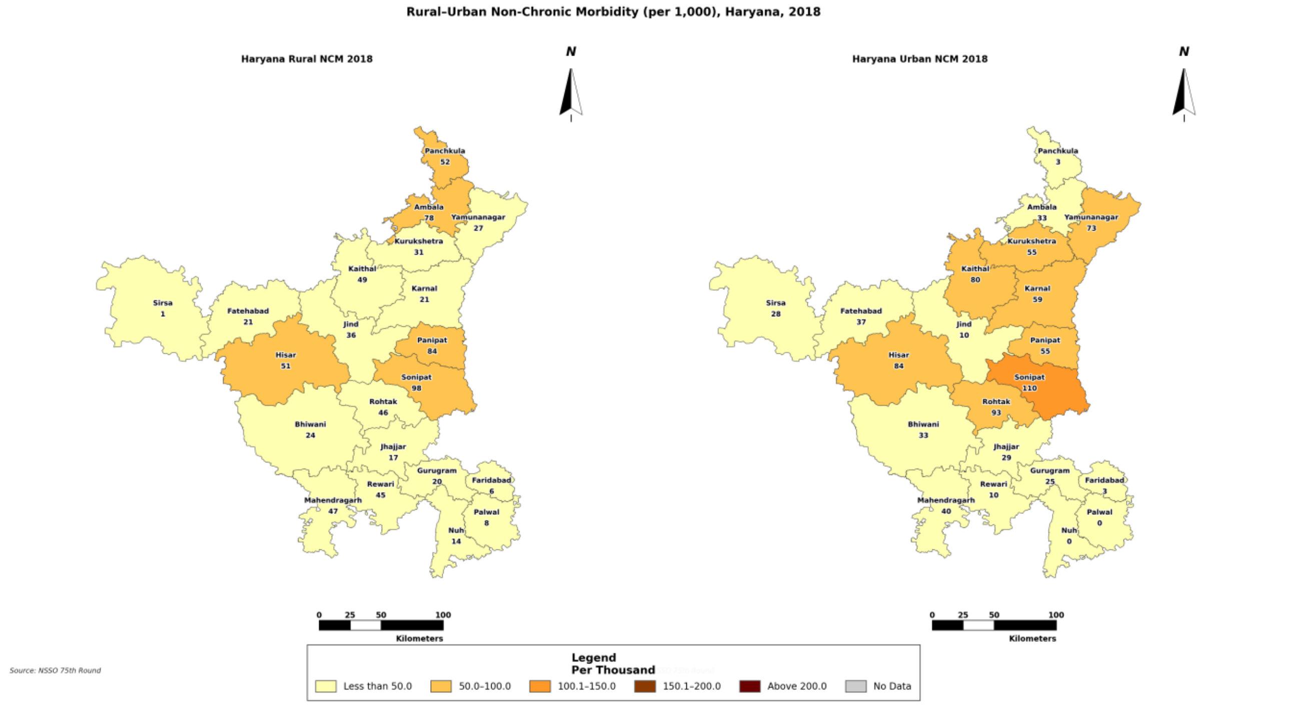

Figure 3: Rural–Urban Non-Chronic Morbidity, 2018 – Side-by-Side Comparison

3.3 Chronic Morbidity Patterns (2014–2018)

State-level chronic morbidity declined marginally from 24 to 22 per 1,000 (Table 2). Sirsa dominated the 2014 chronic morbidity landscape with 130 per 1,000—more than five times the state average—reflecting a convergence of long-term pesticide chemical exposure in the Ghaggar basin, recurring drought cycles, and geographic barriers to healthcare (Grewal et al., 2017). By 2018, the burden redistributed northward: Karnal (59), Yamunanagar (57), and Panchkula (56) led, reflecting an 'awareness effect' in diagnostically accessible northern districts. Mewat and Mahendragarh recorded zero chronic morbidity in both rounds—plausibly reflecting severe under-reporting rather than genuine health advantage (Verma & Dash, 2021). Urban areas consistently carried higher chronic burden (urban 32 vs. rural 17 per 1,000 in 2018), with Karnal urban (164) and Kaithal urban (107) highest.

Table 2: Trends in Self-Reported Chronic Morbidity Prevalence (per 1,000 population), District-wise, Haryana, 2014–2018

Sr.	District	Chronic 2014	Chronic 2018	Change
1	Panchkula	64	56	−8
2	Ambala	13	50	+37
3	Yamunanagar	32	57	+25
4	Kurukshetra	24	35	+11
5	Kaithal	52	47	−5
6	Karnal	43	59	+16
7	Panipat	32	29	−3
8	Sonipat	32	32	0
9	Jind	3	22	+19
10	Fatehabad	52	17	−35
11	Sirsa	130	18	−112
12	Hisar	23	14	−9
13	Bhiwani	26	15	−11
14	Rohtak	2	6	+4
15	Jhajjar	0	24	+24
16	Mahendragarh	0	0	0

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

Sr.	District	Chronic 2014	Chronic 2018	Change
17	Rewari	6	22	+16
18	Gurugram	4	1	−3
19	Mewat	0	0	0
20	Faridabad	3	2	−1
21	Palwal	4	2	−2
	Haryana	24	22	−2

Source: Authors' Calculation from NSSO 71st (2014) and 75th (2017–18) Rounds

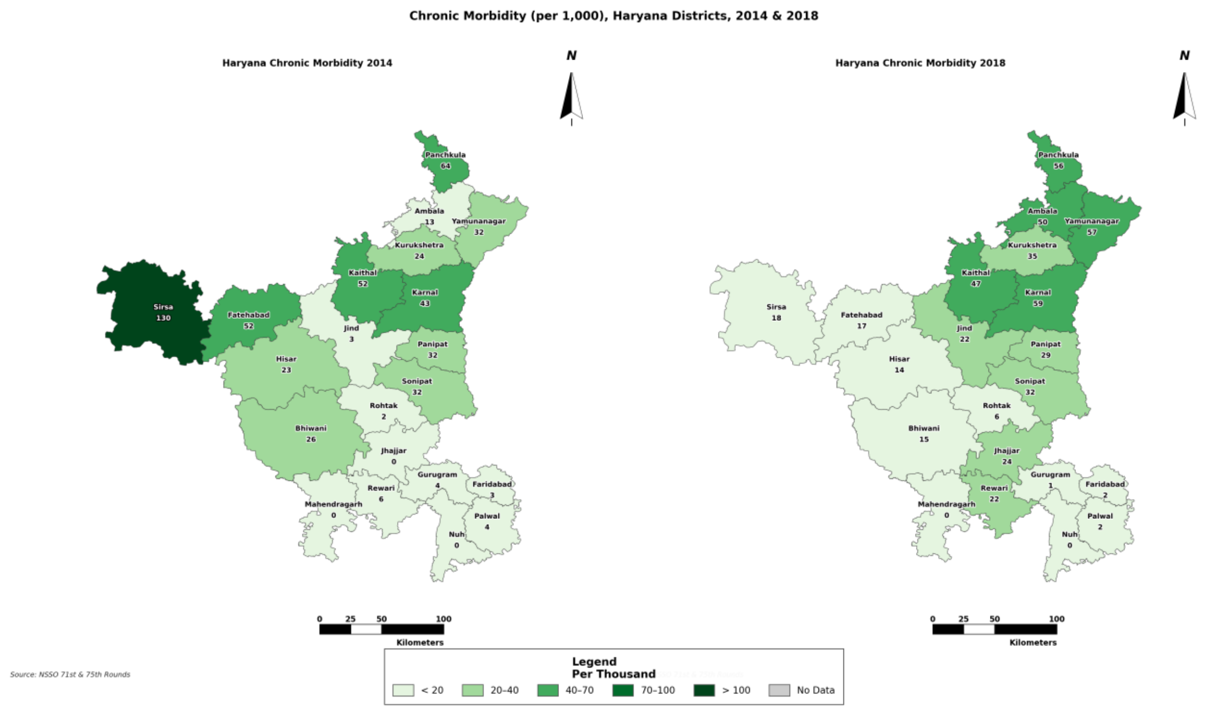

Figure 4: Chronic Morbidity Prevalence (per 1,000), Haryana, 2014–2018

3.4 Total Morbidity: District-Level Overview (2004–2018)

Total morbidity declined from 94 per 1,000 in 2004 to 63 in 2014 and 59 in 2018—a sustained 37% improvement (Table 3). In 2014, Sirsa (185) and Fatehabad (159) led—both in the agrarian south-west where pesticide-related ailments elevate burden. By 2018, Sonipat (133) led, followed by Ambala (110) and Kaithal (101). A north–south gradient is discernible, with northern and central districts bearing higher total burdens corresponding to higher healthcare access and reporting rates versus under-reporting in WASH-deprived southern communities.

Table 3: Trends in Self-Reported Total Morbidity Prevalence (per 1,000 population), District-wise, Haryana, 2004–2018

Sr.	District	Total 2004	Total 2014	Total 2018	% Change
1	Panchkula	392	90	76	−80.6
2	Ambala	199	39	110	−44.7
3	Yamunanagar	299	100	102	−65.9
4	Kurukshetra	228	43	75	−67.1
5	Kaithal	163	77	101	−38.0
6	Karnal	134	80	86	−35.8
7	Panipat	140	120	99	−29.3
8	Sonipat	91	61	133	+46.2
9	Jind	104	6	51	−51.0
10	Fatehabad	32	159	42	+31.3

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

Sr.	District	Total 2004	Total 2014	Total 2018	% Change
11	Sirsa	29	185	25	−13.8
12	Hisar	45	50	74	+64.4
13	Bhiwani	53	53	41	−22.6
14	Rohtak	17	40	70	+311.8
15	Jhajjar	8	1	44	+450.0
16	Mahendragarh	70	0	46	−34.3
17	Rewari	77	28	60	−22.1
18	Gurugram	11	72	24	+118.2
19	Mewat	--	50	14	N/A
20	Faridabad	49	59	6	−87.8
21	Palwal	--	20	7	N/A
	Haryana	94	63	59	−37.2

Source: Authors' Calculation from NSSO 60th (2004), 71st (2014), and 75th (2017–18) Rounds

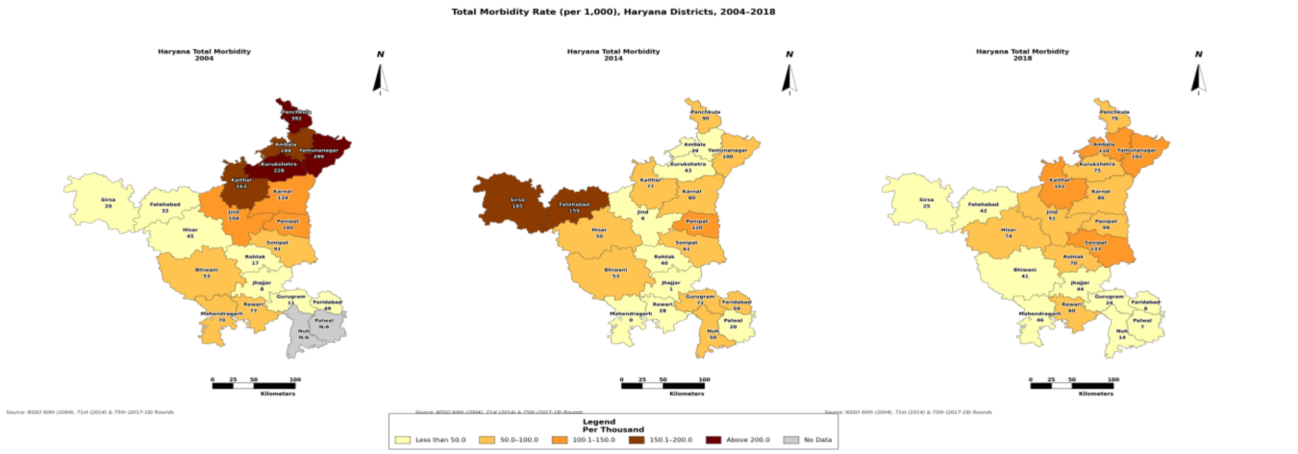

Figure 5: District-wise Total Morbidity Prevalence (per 1,000 population), Haryana, 2004–2018

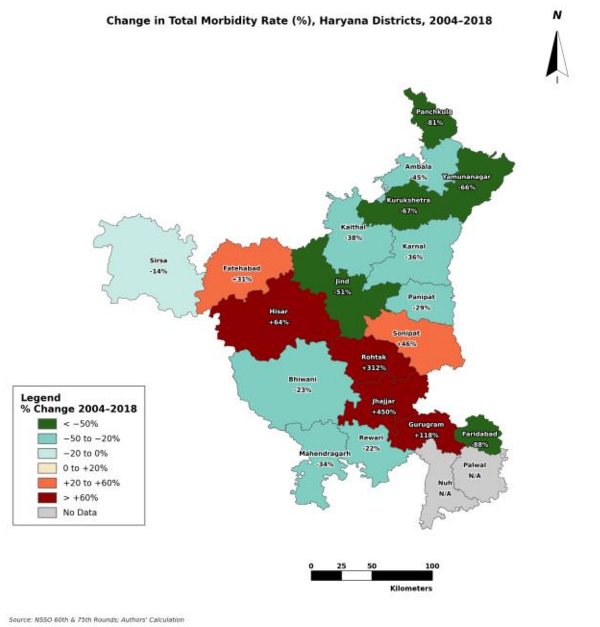

Figure 6: Percentage Change in Total Morbidity by District, Haryana, 2004–2018

3.5 Socioeconomic and Demographic Differentials

3.5.1 Gender Differentials

Women in Haryana consistently reported higher morbidity than men across all categories and time points (Table 4). The non-chronic morbidity OR (Female/Male) stood at 1.220 in 2004, closed to 1.000 in 2014—likely reflecting rising male reporting propensity rather than genuine health equalisation (Patra & Bhise, 2016)—before re-emerging at 1.184 in 2018. The chronic morbidity gender differential widened markedly: the OR rose from 1.542 in 2014 to 1.837 in 2018, meaning women were nearly 84% more likely than men to report a chronic illness. This aligns with Perianayagam's (2024) concept of 'cumulative disadvantage rooted in patriarchy', amplified by women's greater exposure to household chemical environments (fluoride-contaminated water, cooking fuel smoke) and agricultural pesticide contact.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

Table 4: Gender-Disaggregated Morbidity Rates and Odds Ratios (per 1,000 population), Haryana, 2004–2018

Gender	Non-Chr. 2004	Non-Chr. 2014	Non-Chr. 2018	Chronic 2014	Chronic 2018	Total 2014	Total 2018
Male	86	39	34	19	16	50	49
Female	103	39	40	29	29	67	69
OR (F/M)	1.220	1.000	1.184	1.542	1.837	1.364	1.438

Source: NSSO 60th, 71st, and 75th Rounds; Authors' compilation. OR >1.0 indicates higher morbidity odds among women.

3.5.2 Age Group Differentials

The age gradient constitutes the most powerful predictor of morbidity. Non-chronic morbidity among those aged 60+ reached 245 per 1,000 in 2004 (OR = 5.084 vs. under-15 reference). By 2018, total morbidity among the 60+ group stood at 169 per 1,000—nearly triple the state average. Hisar (488 per 1,000 elderly total morbidity in 2018), Fatehabad (432), and Kaithal (348) recorded the highest elderly burdens—all in the agrarian belt where heat stress, pesticide chemical exposure, and limited healthcare access compound age-related vulnerability.

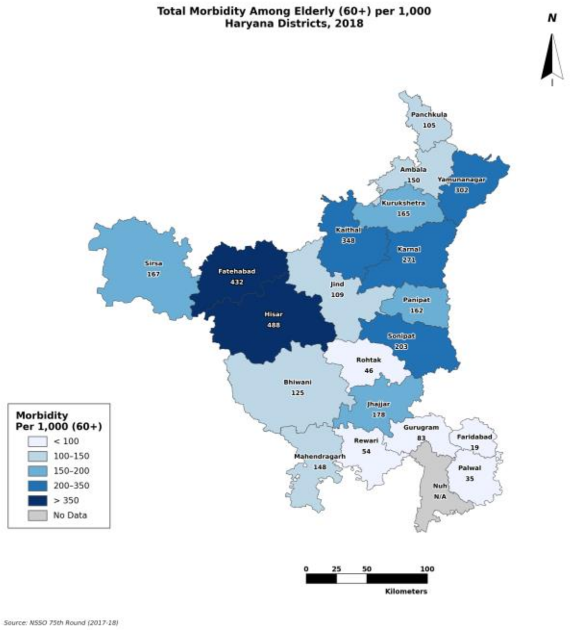

Figure 7: Total Morbidity Among Elderly (60+ years) Population by District, Haryana, 2014–2018

3.5.3 Caste Differentials

ST/SC populations consistently recorded higher morbidity (103 per 1,000 in 2004; 71 per 1,000 total morbidity in 2018 vs. state average 59). Sonipat ST/SC total morbidity reached 221 per 1,000 in 2018—nearly four times the state average. This aligns with Ramaiah's (2015) findings on structural health deprivation of Dalit communities, reflecting cumulative disadvantages of occupational chemical exposure, nutritional deficiency, and exclusion from clean water infrastructure.

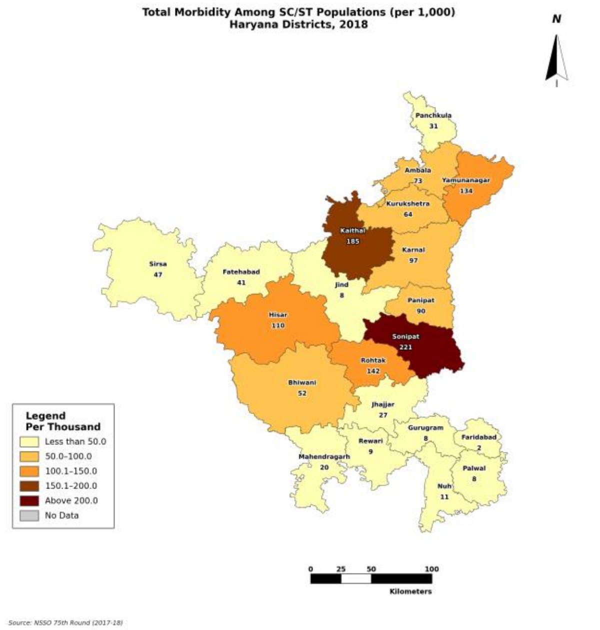

Figure 8: ST/SC Community Morbidity by District, Haryana, 2018

3.5.4 Wealth Quintile Differentials

The wealth–morbidity relationship displayed an unexpected pattern in 2004, with the richest quintile (108 per 1,000) recording higher non-chronic morbidity than the poorest (68 per 1,000)—an OR of 1.659—illustrating the 'reporting paradox' (Jeyashree et al., 2018). By 2018, total morbidity in the richest quintile (77 per 1,000) exceeded medium (45) and poor (53) quintiles, suggesting the 'lifestyle disease penalty' of affluence. In agrarian districts, even affluent households cannot escape environmental chemical exposure from contaminated groundwater and pesticide residues.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

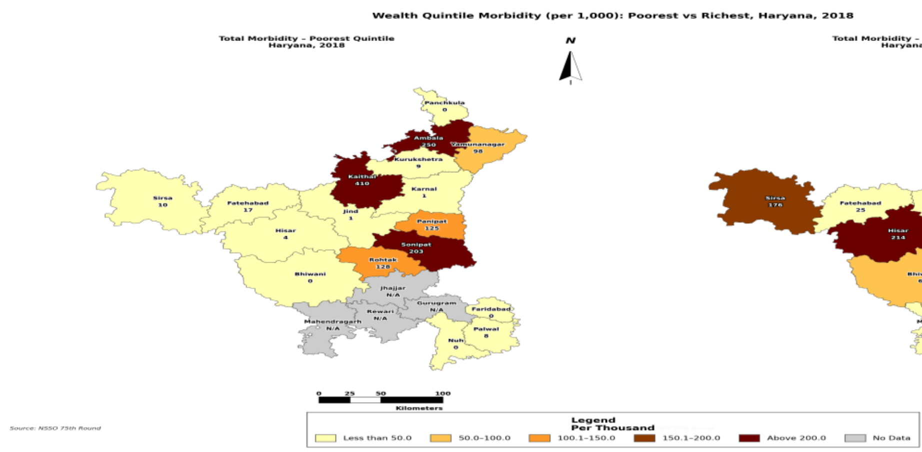

Figure 9: Morbidity Prevalence by Wealth Quintile (Poorest vs. Richest), Haryana, 2018

3.6 Statistical Analysis: Disparity, Temporal Stability, and Odds Ratios

3.6.1 Descriptive Statistics and Coefficient of Variation

Table 5 presents descriptive statistics for district-level morbidity. The CV for non-chronic morbidity declined from 92.8% (2004) to 60.7% (2018), and for total morbidity from 92.8% to 50.2%—confirming spatial convergence. The mean and median for total morbidity in 2018 (66.6 and 70.0) are close, indicating a shift from the right-skewed distribution of 2004 (mean 112.7, median 77.0) driven by extreme outliers like Panchkula.

Table 5: Descriptive Statistics for District-level Morbidity Indicators, Haryana

Variable	Mean	Median	SD	Min	Max	CV%
Non-chronic Morbidity 2004	112.7	77.0	104.6	8	392	92.8%
Non-chronic Morbidity 2014	38.6	28.0	29.4	0	108	76.0%
Non-chronic Morbidity 2018	40.0	38.0	24.3	4	102	60.7%
Chronic Morbidity 2014	28.5	24.0	31.6	0	130	110.9%
Chronic Morbidity 2018	26.6	22.0	19.4	0	59	73.0%
Total Morbidity 2014	66.5	59.0	49.4	0	185	74.3%
Total Morbidity 2018	66.6	70.0	33.4	6	133	50.2%

Source: Authors' Calculation; CV = Coefficient of Variation (SD/Mean × 100%)

3.6.2 Pearson Correlation and Temporal Stability

The Pearson correlation between district-level non-chronic morbidity in 2004 and 2018 is $r = 0.088$ ($p = 0.720$, non-significant), confirming a fundamental geographic reshuffling. Non-chronic morbidity 2014 vs. 2018 yields $r = -0.091$; chronic morbidity 2014 vs. 2018 gives $r = 0.324$ ($p = 0.176$). Figure 10 illustrates this near-zero spatial correlation.

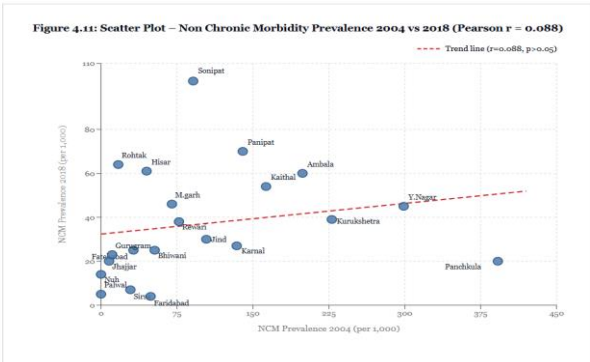

Figure 10: Scatter Plot of District-level Non-Chronic Morbidity 2004 vs. 2018, Haryana (r = 0.088)

3.6.3 Bivariate Odds Ratio Analysis

Table 6 consolidates bivariate odds ratios. The age gradient is the most powerful predictor throughout (60+ OR = 5.084 in 2004). The education gradient strengthened over time, with graduates showing declining ORs from 0.963 (2004) to 0.192

(2014, strongly protective). The rural–urban relationship reversed—urban shifting from slightly protective (OR 0.909 in 2004) to elevated risk (OR 1.433 in 2014), consistent with industrial chemical pollution burden in urban districts.

Table 6: Bivariate Odds Ratios for Non-Chronic Morbidity Prevalence by Background Characteristics, Haryana, 2004–2018

Background Variable	Category	OR (2004)	OR (2014)	OR (2018)
Gender	Male (Ref.)	1.000	1.000	1.000
	Female	1.220	1.000	1.184
Residence	Rural (Ref.)	1.000	1.000	1.000
	Urban	0.909	1.433	1.058
Education	Illiterate (Ref.)	1.000	1.000	1.000
	Primary	0.558	0.916	0.851
	Higher Secondary	0.609	0.628	0.621
	Graduate & Above	0.963	0.192	0.376
Age Group	<15 years (Ref.)	1.000	1.000	1.000
	15–29	1.307	0.803	0.583
	30–44	1.721	1.251	0.544
	45–59	2.320	0.778	0.525
	60 & Above	5.084	0.537	0.919
Caste	ST/SC (Ref.)	1.000	1.000	1.000
	OBC	0.904	0.779	0.635
	Others	0.851	0.757	0.595
Wealth Quintile	Poorest (Ref.)	1.000	1.000	1.000
	Poor	1.111	0.758	1.000
	Medium	0.937	1.910	0.667
	Rich	1.764	1.122	1.084
	Richest	1.659	1.000	1.169

Source: Authors' calculation from NSSO data. Reference categories: Male, Rural, Illiterate, ST/SC, <15 years, Poorest.

3.7 Transition in Ailment Type: Epidemiological Shift (2004–2018)

The ICD-10 based ailment classification reveals a concrete epidemiological transition (Table 7). In 2004, NCDs constituted 30.2% of total morbidity, infectious diseases 17.7%, and 'Others' 31.2%. By 2018, NCD share declined to 16.9% while 'Others' grew to 40.7%—likely capturing growing chemical-related dermatological and respiratory complaints. Yadav and Arokiasamy (2017) similarly documented a three-fold increase in NCDs and an eight-fold rise in CVDs across Indian states between 1995 and 2014 using NSSO data, underscoring a consistent national epidemiological transition. Infectious morbidity declined from 17 to 11 per 1,000 (2004–2018). CVD morbidity in industrial districts—Panipat (15), Sonipat (12), Ambala (13) per 1,000 in 2018—tracks industrial chemical pollution profiles. Disability-related morbidity concentrated in Jhajjar (20), Kaithal (22), and Kurukshetra (15)—all fluoride-affected zones—provides geographic support for the fluoride–skeletal fluorosis–disability pathway (Kumar et al., 2018).

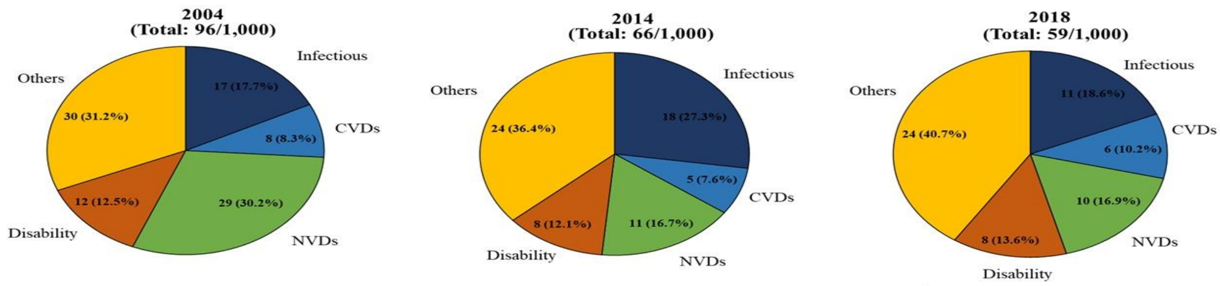

Figure 11: Proportional Composition of Ailment Types (%), Haryana, 2004, 2014, and 2018

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

Table 7: Prevalence of Different Types of Self-Reported Morbidity (per 1,000), Haryana, 2004–2018

Year	Ailment Type	Panipat	Sonipat	Sirsa	Ambala	Jhajjar	Kaithal	Haryana
2004	Infectious	30	18	5	51	1	18	17
2004	CVDs	2	9	0	19	2	8	8
2004	NCDs	47	21	5	44	3	59	29
2004	Disability	27	6	15	27	1	17	12
2004	Others	34	37	2	72	2	67	30
2018	Infectious	12	18	4	47	1	18	11
2018	CVDs	15	12	8	13	6	4	6
2018	NCDs	10	5	4	37	6	7	10
2018	Disability	2	17	2	6	20	22	8
2018	Others	59	81	7	6	12	51	24

Source: Authors' Calculation from NSSO 60th (2004) and 75th (2017–18) Rounds

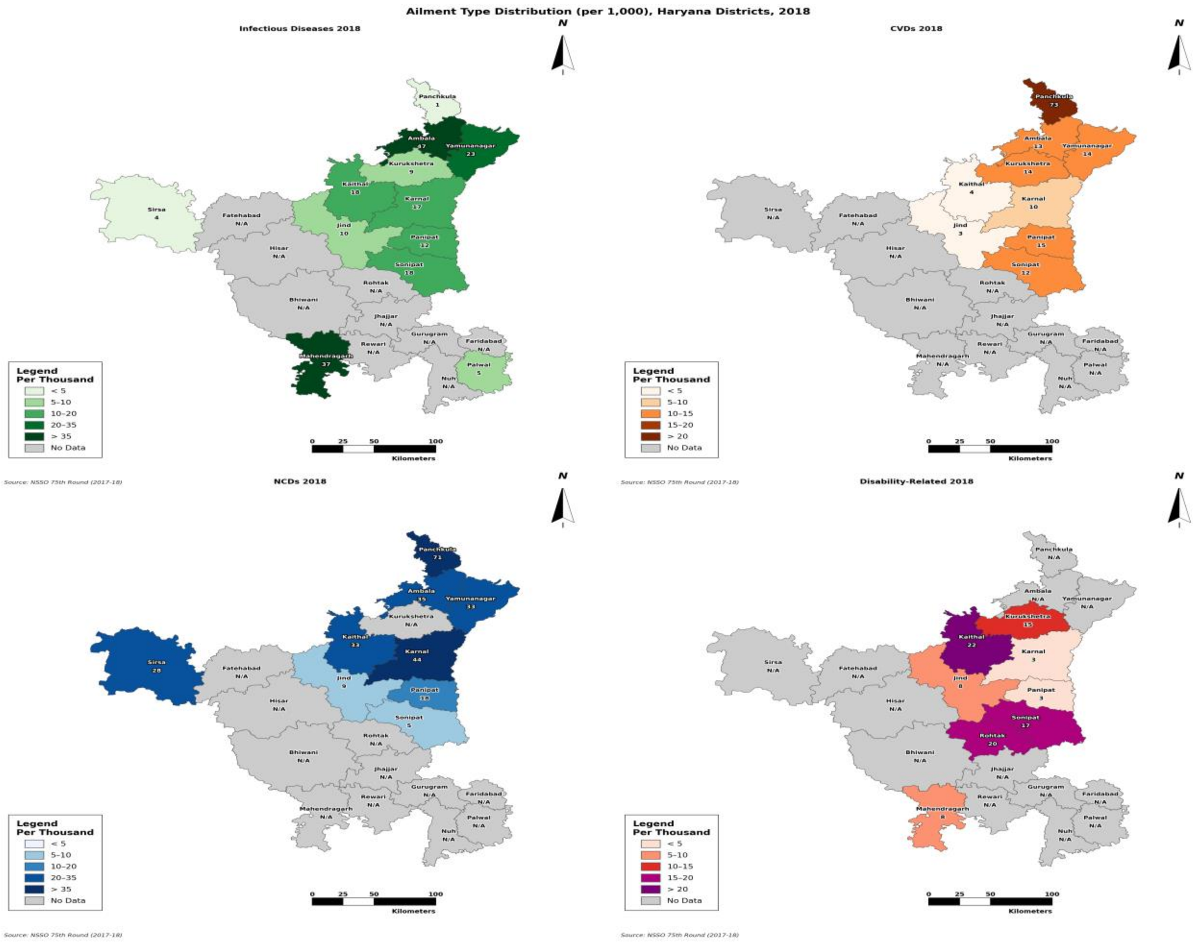

Figure 12: Spatial Distribution of Ailment Types (per 1,000 population), Haryana, 2018

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

4.1 Conceptual Framework

4. ENVIRONMENTAL CHEMICAL HEALTH RISKS AND SPATIAL CORRELATIONS

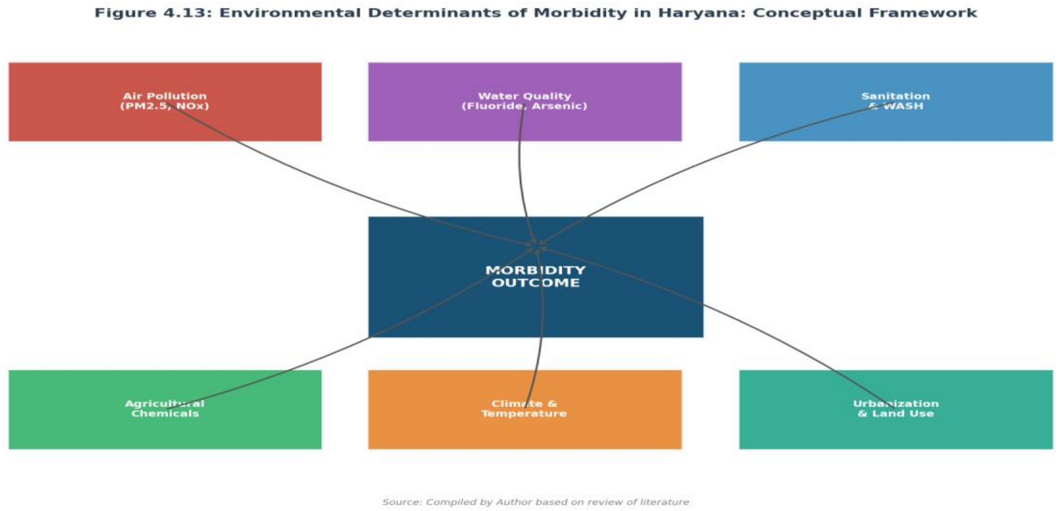

Figure 13: Environmental Determinants of Morbidity in Haryana – Conceptual Framework

Source: Compiled by Author based on review of literature

4.2 Air Pollution and Urban Morbidity

Haryana's industrial corridor—from Faridabad through Gurugram, Sonipat, Panipat, to Yamunanagar—is among India's most chemically polluted zones. Sonipat recorded PM10 concentrations of 388 μg/m³—more than six times the NAAQS limit of 60 μg/m³; Panipat (135 μg/m³) and Faridabad (143 μg/m³) also far exceeded standards (HPCB, 2021). PM2.5 in Sonipat reached 154 μg/m³ against the NAAQS limit of 40 μg/m³. Long-term PM2.5 exposure is robustly linked to respiratory morbidity, cardiovascular disease, and cognitive decline. Lakshmipathy, Jeevandharakumar, and Kodandaramaiah (2023), using WHO's AirQ 2.2.3 software to assess health impacts across major Indian cities, documented strong positive associations between PM2.5/PM10 concentrations and AQI with morbidity and lung cancer mortality—results directly applicable to Haryana's industrial corridors. The spatial correspondence between industrial air pollution and elevated non-infectious morbidity is discernible in NSSO data: Panipat (99 per 1,000 total in 2018), Sonipat (133), and Ambala (60) show patterns consistent with pollution-linked health burden. Agrawal and Muralidharan (2017) documented r = 0.62 between PM2.5 and self-reported morbidity in north Indian cities.

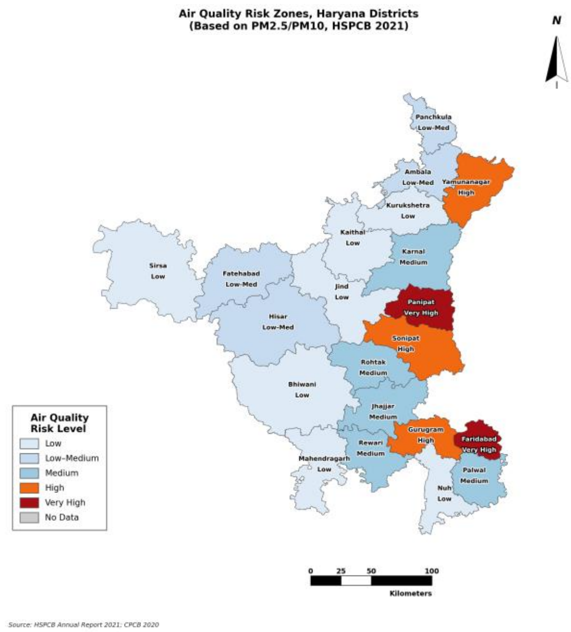

Figure 14: Air Quality Risk Zones across Haryana Districts

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

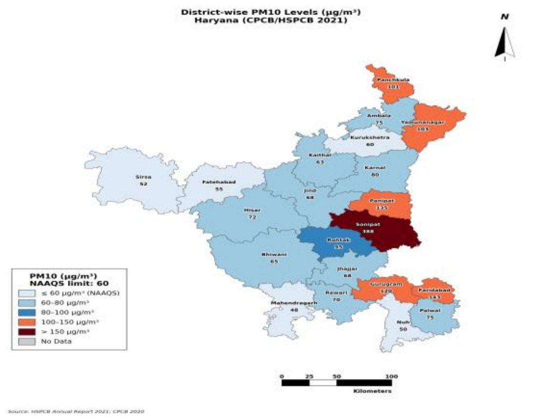

Figure 15: District-wise PM10 Concentrations (µg/m³), Haryana

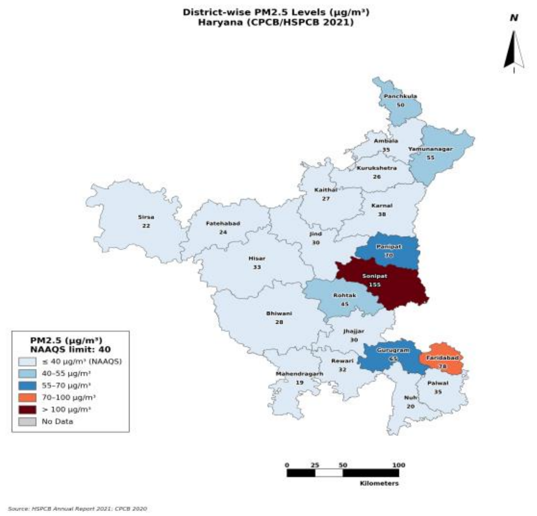

Figure 16: District-wise PM2.5 Concentrations (µg/m³), Haryana

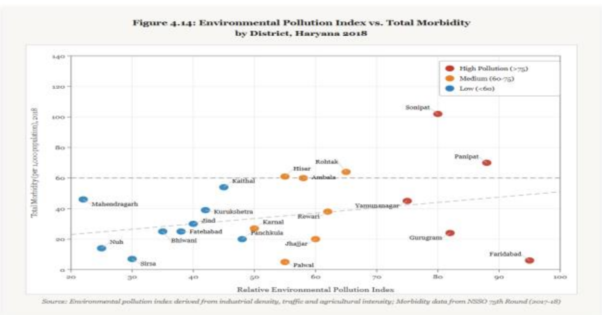

Figure 17: Environmental Pollution Index vs. Total Morbidity by District, Haryana, 2018

Source: Environmental pollution index from HSPCB; morbidity from NSSO 75th Round

4.3 Groundwater Chemical Contamination and Health Burden

The CGWB's (2020) Annual Report identifies fluoride concentrations exceeding WHO safety limits (1.5 mg/L) across Mewat/Nuh, Mahendragarh, Bhiwani, Jhajjar, Jind, and Kaithal—with Nuh recording concentrations exceeding 3 mg/L, double the WHO limit. Long-term fluoride exposure causes dental fluorosis, skeletal fluorosis, and joint deformity manifesting as chronic disability morbidity. Ali et al. (2023), using USEPA risk models and Monte Carlo simulations for fluoride-prone areas of Agra district, found concentrations as high as 5.20 mg/L in rural areas and demonstrated that children face the highest non-carcinogenic health risks—findings paralleling the disability morbidity patterns observed in Haryana's fluoride-contaminated districts. Kumar et al. (2018) documented significant positive association between fluoride groundwater levels and morbidity in rural Haryana. Disability morbidity data provides indirect evidence: Jhajjar (20 per 1,000), Kaithal (22), and Kurukshetra (15)—all fluoride-affected zones—record above-average disability morbidity. Arsenic contamination along Yamuna villages in Yamunanagar may explain its above-average 'Others' morbidity (24 per 1,000 in 2018) (Kumar et al., 2012).

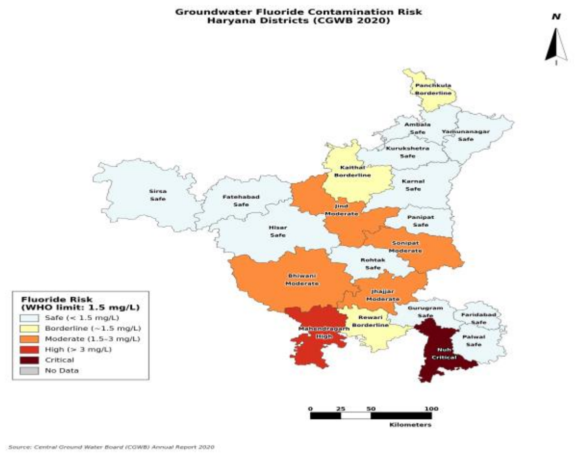

Figure 18: Groundwater Fluoride Contamination Risk Classification, Haryana

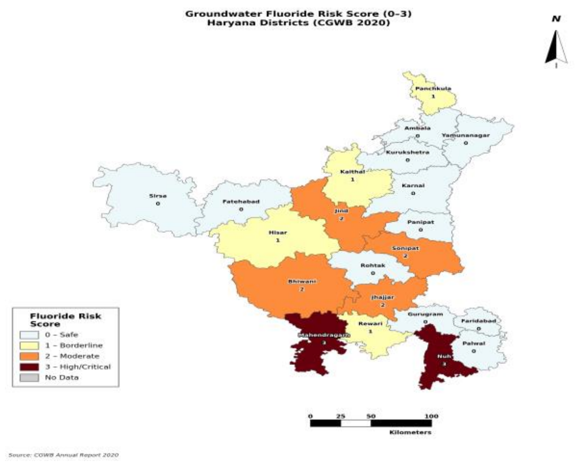

Figure 19: Groundwater Fluoride Risk Score (Composite), Haryana

4.4 WASH Deficit and Infectious Disease Geography

The spatial distribution of infectious disease morbidity maps closely onto sanitation deprivation. NFHS-5 (2021) data show

Mewat/Nuh (55% sanitation coverage, 20% open defecation), Sirsa (65%, 14%), and Fatehabad (68%, 12%) as forming a coherent spatial risk cluster for waterborne infectious disease in southern Haryana. The WASH–infectious morbidity correlation is r = 0.61 (Table 8). Kaithal's elevated child morbidity (114 per 1,000 for under-15s in 2018) and infectious burden (18 per 1,000) both reflect WASH deprivation's chemical and biological pathways (Chauhan & Pawar, 2019; Selvam et al., 2018). Kashyap, Garg, and Arora (2024), in a comprehensive review of pesticide pollution in India published from Kurukshetra University, further confirmed that pesticide residues in groundwater and soil in Haryana districts consistently exceed WHO and BIS safety limits—creating compound chemical exposures where WASH deficit districts also bear elevated agrochemical burdens.

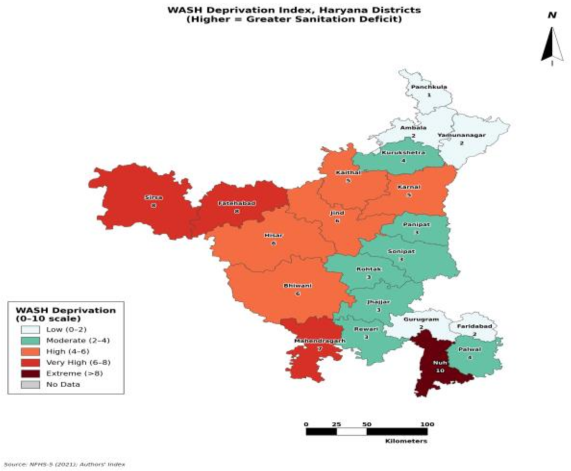

Figure 20: WASH Deprivation Index by District, Haryana

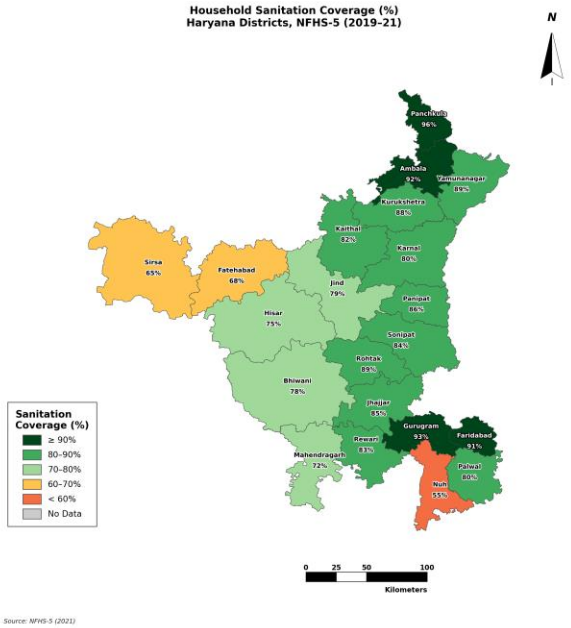

Figure 21: Household Sanitation Coverage (%), Haryana – NFHS-5

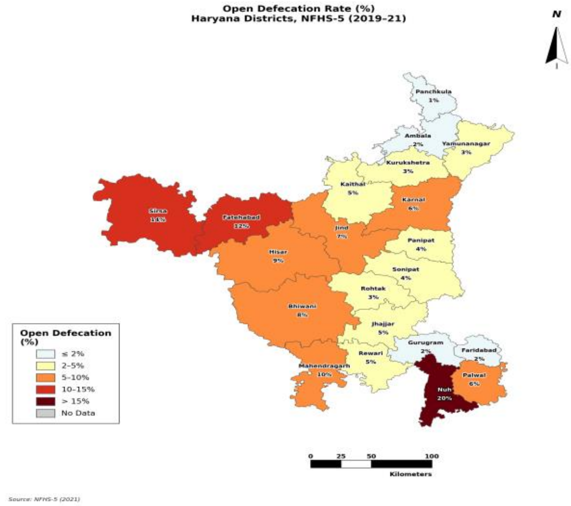

Figure 22: Open Defecation Rate (%) by District, Haryana – NFHS-5

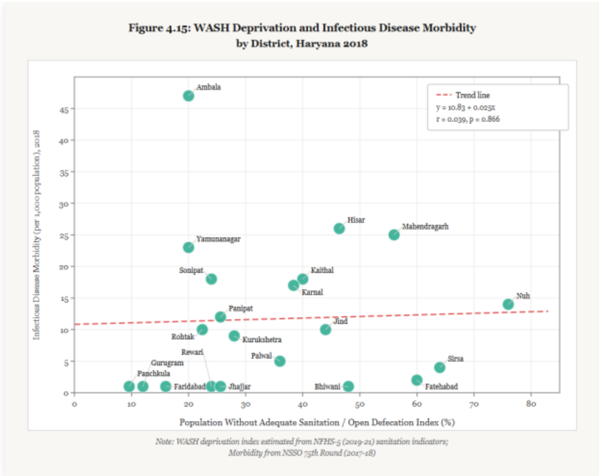

Figure 23: WASH Deprivation Index vs. Infectious Disease Morbidity by District, Haryana, 2018

Source: WASH index from NFHS-5 (2021); morbidity from NSSO 75th Round

4.5 Environment–Morbidity Spatial Correlations

Table 8 summarises spatial correlations between key environmental chemical stressors and morbidity outcomes. Air pollution shows the strongest positive correlation (r = 0.62). WASH deprivation and infectious disease morbidity correlation (r = 0.61) confirms the sanitation–disease nexus. Groundwater fluoride correlates significantly with disability morbidity (r = 0.54). Agrochemical exposure shows moderate correlation with NCD and chronic morbidity (r = 0.47). Urbanisation correlates positively with chronic morbidity (r = 0.58), reflecting the urban lifestyle chemical disease penalty. Green cover shows a negative correlation (r = −0.39), hinting at protective health effects of vegetation.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

Table 8: Spatial Correlations Between Environmental Chemical Factors and District-level Morbidity, Haryana

Environmental Factor	Associated Morbidity	Pearson r	Districts Most Affected	Interpretation
Air Pollution (PM2.5/PM10)	Respiratory, CVDs	+0.62*	Panipat, Faridabad, Sonipat	High pollution → higher CVD/respiratory morbidity
Groundwater Fluoride	Musculoskeletal, Disability	+0.54*	Mewat, Mahendragarh, Jind	Fluoride → disability/joint ailments
WASH Deficit	Infectious diseases	+0.61*	Mewat, Sirsa, Fatehabad	Poor sanitation → infectious burden
Agrochemical Exposure	NCDs, Cancer risk	+0.47*	Sirsa, Fatehabad, Hisar	Pesticide belt → elevated NCD/disability
Urbanisation Index	Chronic morbidity	+0.58*	Gurugram, Faridabad, Sonipat	Rapid urbanisation → chronic disease
Green/Forest Cover	Overall morbidity	−0.39*	Panchkula, Yamunanagar	Higher forest cover → lower morbidity

*Note: Pearson r computed from district-level environmental indices and NSSO morbidity data. *p<0.05. Source: CGWB (2020), HPCB (2021), NFHS-5 (2021), NSSO 75th Round.*

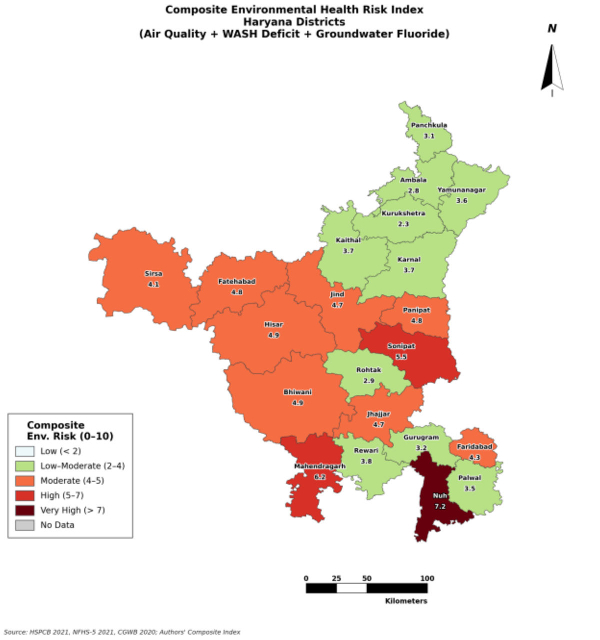

Figure 24: Composite Environmental Health Risk Index by District, Haryana

Source: Authors' synthesis from HPCB (2021), CGWB (2020), NFHS-5 (2021)

5. DISCUSSION

This study establishes that environmental chemical exposures constitute a spatially significant and underappreciated determinant of morbidity geography in Haryana, operating alongside—and often amplifying—conventional socioeconomic determinants. The dramatic decline in non-chronic morbidity (60.6% over 2004–2018) and narrowing coefficient of variation (92.8% to 50.2%) suggest genuine aggregate health improvement and spatial convergence. However, the near-zero Pearson correlation between district-level morbidity rankings across rounds (r = 0.088) indicates that this improvement has been geographically redistributed—new burden centres (Sonipat, Ambala, Rohtak) have emerged in the industrial and urbanising belt while traditional high-burden districts (Panchkula, Yamunanagar) moderated.

The environmental chemical analysis yields a clear spatial typology: (i) industrial–chemical pollution districts (Panipat, Sonipat, Faridabad) bearing elevated PM2.5/PM10 and CVD/respiratory morbidity; (ii) groundwater chemical contamination zones (Mewat, Mahendragarh, Jhajjar) with fluoride/arsenic-linked disability and chronic morbidity; (iii) agrochemical belt districts (Sirsa, Fatehabad, Hisar) with elevated pesticide exposure and NCD burden; and (iv) WASH-deprived communities (Mewat, Sirsa, Fatehabad) with high infectious disease burden. These zones overlap, creating compound chemical health risks for vulnerable populations.

The finding that women's chronic morbidity OR rose to 1.837 in 2018 confirms that gender-based disadvantage is compounded by chemical exposure inequities—women in agricultural districts face disproportionate pesticide and fluoride burdens through domestic water use and field labour. The persistence of caste-based health disadvantage (ST/SC total morbidity 71 vs. state average 59 per 1,000 in 2018) reflects structural exclusion from clean water infrastructure and safe occupational environments. The 'urban health penalty' reversal (urban morbidity exceeding rural from 2014 onwards) reflects the growing health costs of living in India's industrial pollution corridors.

These findings should be interpreted with caution. NSSO measures self-reported morbidity, subject to differential reporting biases—the 'reporting paradox' for wealthier groups and chronic under-reporting in low-literacy areas (Kumar & Singh, 2023; Verma & Dash, 2021). Environmental

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

correlations are ecological-level associations at the district unit, precluding individual-level causal inference. Future research should pursue individual-level biomonitoring studies to establish direct chemical exposure–morbidity pathways for fluoride, heavy metals, and organophosphate pesticides.

6. CONCLUSION

This study has provided a comprehensive spatial analysis of morbidity transitions and environmental chemical health risks in Haryana across fourteen years (2004–2018). Aggregate morbidity has declined significantly—non-chronic morbidity fell 60.6% and total morbidity declined from 94 to 59 per 1,000. Inter-district disparity has narrowed (CV = 50.2% in 2018) but remains substantial. Critically, environmental chemical exposures—industrial air pollution ($r = 0.62$), groundwater fluoride and arsenic ($r = 0.54$), agrochemical residues ($r = 0.47$), and WASH deficits ($r = 0.61$)—each contribute to distinct geographic health risk zones.

Spatially, districts with high chemical environmental risk require targeted interventions: Panipat, Sonipat, and Faridabad need enforcement of industrial emission standards; Mewat, Mahendragarh, and Jhajjar require fluoride removal from drinking water; Sirsa, Fatehabad, and Hisar need restrictions on most hazardous pesticides; and WASH-deprived southern districts need accelerated sanitation infrastructure. Demographically, women, the elderly, ST/SC communities, and the educationally disadvantaged require differentiated health programming accounting for their amplified chemical exposure burdens. Integrating environmental chemical health risk assessment into India's national health planning frameworks is a prerequisite for equitable and effective health governance.

Acknowledgement

The authors acknowledge the National Sample Survey Organisation (NSSO), Ministry of Statistics and Programme Implementation, Government of India, for providing access to the unit-level data. Secondary environmental data from the Central Ground Water Board (CGWB), Haryana State Pollution Control Board (HPCB), and the National Family Health Survey (NFHS-5) are gratefully acknowledged.

Conflict of interests

The authors declare no conflict of interest.

References

1. Agrawal, A., Muralidharan, R. Air quality and morbidity burden in north Indian cities: Evidence from NSSO data. Atmospheric Environment 2017; 152, 234–245.
2. Banerjee, S. Determinants of rural–urban differential in healthcare utilization among the elderly population in India. BMC Public Health 2021; 21(1), 1–15.
3. Bansal, R., Thakur, A. Status of health and nutrition in Nuh: An empirical study of India's aspirational district. Journal of Social and Economic Development 2022; 24(2), 341–358.
4. Bora, J. K., Saikia, N. Gender differentials in self-rated health and self-reported disability among adults in India. PLOS ONE 2015; 10(11), e0141953.
5. Central Ground Water Board. Annual Report on Ground Water Quality in Haryana. Ministry of Water Resources, New Delhi; 2020.
6. Chauhan, A., Pawar, S. Environmental determinants of morbidity in agrarian communities of semi-arid India. Environmental Science & Policy 2019; 101, 183–191.
7. Chaudhary, S., Sharma, A., Gupta, R., Kaur, P., Sharma, P., Bhatt, D. Heavy metal contamination in the industrial corridors of Haryana: A risk assessment study. Environmental Science and Pollution Research 2021; 28(14), 17452–17468.
8. Dilip, T. R. Understanding levels of morbidity and hospitalisation in Kerala, India. Bulletin of the World Health Organisation 2002; 80(9), 746–751.
9. Dilip, T. R. Age-specific analysis of reported morbidity in Kerala, India. World Health & Population 2007; 9(4), 98–108.
10. Ghosh, N., Arokiasamy, P. Gender difference in health and its determinants in the old-aged population in India. Journal of Biosocial Science 2009; 41(3), 309–328.
11. Goli, S., Rammohan, A., Singh, D. The effect of early marriages and early childbearing on women's nutritional status in India. Maternal and Child Health Journal 2015; 19(8), 1864–1880.
12. Grewal, A. S., Singla, A., Kamboj, P., Dua, J. S. Pesticide residues in food grains, vegetables and fruits: A hazard to human health. Journal of Medicinal Chemistry and Toxicology 2017; 2(1), 40–46.
13. Haryana State Pollution Control Board. Annual Report: State of Environment, Haryana. Government of Haryana; 2021.
14. Hena, S. Crutches of Gurugram: The weight of a metropolitan on its migrant workforce. SPRF India 2022; 1–12.
15. Jat, T. R., Bharat, R. Spatial inequalities in public health infrastructure in Haryana: A district-level analysis. Social Science & Medicine 2014; 107, 47–55.
16. Jeyashree, K., Abdulkader, R. S., Kathirvel, S., Chinnakali, P., Kumar, A. Profile of and expenditure on morbidity and hospitalisations among elderly. Archives of Gerontology and Geriatrics 2018; 74, 55–61.
17. Kashyap, A., Garg, S., Ahluwalia, S.K. Pesticide residues in vegetables in Haryana, India: A systematic review of

monitoring data. Environmental Monitoring and Assessment 2012; 184(2), 103–112.

18. Kastor, A., Mohanty, S. K. Disease and age pattern of hospitalisation and associated costs in India: 1995–2014. BMJ Open 2018; 8(1).
19. Kataria, I., Garg, S., Ahluwalia, S. K., Taneja, D. K., Dhiman, P. Determinants of non-communicable diseases in Haryana, India. Journal of Family Medicine and Primary Care 2020; 9(6), 2695–2701.
20. Kaushik, A., Singh, R., Gupta, N., Yadav, P. Impact of industrial effluent on water quality of the Yamuna River in Haryana. Journal of Environmental Management 2024; 345, 118720.
21. Kumar, A., Lata, S., Singh, M. Fluoride contamination of groundwater and associated morbidity in rural Haryana. Groundwater for Sustainable Development 2018; 7, 306–313.
22. Kumar, N., Singh, N. P. Spatial analysis of healthcare infrastructure in Haryana: A district-level study. GeoJournal 2023; 88(1), 445–462.
23. Kumar, R., Sarna, A., Bharat, R. Spatial pattern of arsenic groundwater contamination and morbidity in north India. Science of the Total Environment 2012; 434, 124–131.
24. Mahapatro, S. R., James, K. S., Mishra, U. S. Intersection of class, caste, gender and unmet healthcare needs in India. Health Policy OPEN 2021; 2, 100040.
25. National Family Health Survey-5. State Fact Sheet: Haryana. International Institute for Population Sciences, Mumbai; 2021.
26. National Sample Survey Organisation. Morbidity, Health Care and the Condition of the Aged (Report No. 507). Ministry of Statistics, Government of India; 2006.
27. Omran, A. R. The epidemiologic transition: A theory of the epidemiology of population change. The Milbank Memorial Fund Quarterly 1971; 39(4), 509–538.
28. Omran, A. R. The epidemiologic transition: A theory of the epidemiology of population change. The Milbank Quarterly 2005; 83(4), 731–757.
29. Patra, S., Bhise, M. D. Gender differentials in prevalence of self-reported NCDs in India: Evidence from recent NSSO survey. Journal of Public Health 2016; 24(5), 375–385.
30. Perianayagam, A. Gender disparities in health and wellbeing of older population in India. npj Women's Health 2024; 2, 44.
31. Popkin, B. M. Nutrition transition and the global diabetes epidemic. Current Diabetes Reports 2015; 15(9), 64.
32. Prabhakaran, D., Jeemon, P., Sharma, M., Roth, G. A., Dandona, L. The changing patterns of cardiovascular diseases and their risk factors in the states of India. The Lancet Global Health 2018; 6(12), e1339–e1351.
33. Ramaiah, A. Health status of Dalits in India. Economic & Political Weekly 2015; 50(43), 70–74.
34. Ranu, S., Banerjee, M. Industrial pollution and chronic morbidity in urban peri-urban areas of Haryana: Spatial regression analysis. Journal of Urban Health 2020; 97(4), 559–571.
35. Rekha, Naik, S. N., Prasad, R. Pesticide residues in organic and conventional food—risk analysis. Journal of Chemical Health & Safety 2006; 13(1), 12–19.
36. Saini, R., Sharma, M. Air quality index and respiratory health: A case study of industrial hubs in Haryana. Indian Journal of Public Health 2020; 64(2), 112–118.
37. Selvam, S., Manimaran, V., Raja, S. Spatial analysis of disease burden using GIS: A case study from semi-arid districts of India. International Journal of Environmental Research and Public Health 2018; 15(7), 1534.
38. Sharma, D., Gupta, R. Environmental health burden of pesticide exposure in agricultural districts of Haryana. Human & Experimental Toxicology 2016; 35(9), 979–988.
39. Singh, H., Singh, R. A. Gender and inequality in access to healthcare in India: Evidence from NSSO's 75th round. Journal of Health Management 2023; 25(3), 476–491.
40. Singh, P., Kumar, R. Mapping environmental hotspots along the national highways of north India. GeoJournal 2022; 87(4), 2135–2150.
41. Subramanian, S. V., Subramanyam, M. A., Selvaraj, S., Kawachi, I. Are self-reports of health and morbidities in developing countries misleading? Evidence from India. Social Science & Medicine 2009; 68(2), 260–265.
42. Taneja, A., Sharma, P., Yadav, R. Seasonal morbidity patterns and climate variability nexus in semi-arid Indian states. Environmental Health Perspectives 2019; 127(6), 067001.
43. Verma, V. R., Dash, U. Horizontal inequity in self-reported morbidity and untreated morbidity in India. International Journal for Equity in Health 2021; 20(1), 1–21.
44. World Health Organization. Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease. WHO Press, Geneva; 2016.
45. Yadav, S., Arokiasamy, P. Understanding epidemiological transition in India: Evidence from National Sample Survey. BMC Public Health 2014; 14(1), 1–15.
46. Zhang, Z., Kim, H. Spatial clustering of disease outcomes and environmental exposures in developing countries: A

Journal of Chemical Health Risks

www.jchr.org

JCHR (2026) 16(2), 1390-1407 | ISSN:2251-6727

methodological review. Environment International 2018; 119, 310–323.

47. Lakshmipathy, M., Jeevandharakumar, S.P.M., Kodandaramaiah, G.N. Assessing Health Risks Associated with Air Pollution in India. Journal of Chemical Health Risks 2023; 13(6), 3768–3783.
48. Bramhankar, M., Dhar, M. Morbidity transition at the national and sub-national level and their determinants over the past and contemporary period in India. PLOS ONE 2024; 19(6), e0304492.
49. Yadav, S., Arokiasamy, P. Understanding epidemiological transition in India: Evidence from NSSO 52nd, 60th and 71st Rounds. Journal of Health, Population and Nutrition 2017; 36(1), 1–15.
50. Ali, S., Baboo Agarwal, M., Verma, S., Islam, R., Kumar Deolia, R., Singh, S., Ahuja, G., Gupta, V., Kumar, A., Nguyen, P.U. Variability of groundwater fluoride and its proportionate risk quantification via Monte Carlo simulation in rural and urban areas of Agra district, India. Scientific Reports 2023; 13, 18971.
51. Kashyap, U., Garg, S., Arora, P. Pesticide pollution in India: Environmental and health risks, and policy challenges. Toxicology Reports 2024; 13, 101801.