Spatiotemporal analysis and forecasting of ground deformation in Kolkata using PS-InSAR

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Abstract

In Kolkata, potential land subsidence occurred primarily due to excessive groundwater extraction, which has been one of the major environmental crises, along with rapid urbanization and soft soil characteristics. This study investigates Kolkata's land surface deformation patterns from 2017 to 2023 using Persistent Scatterer Interferometric Synthetic Aperture Radar (PS-InSAR) technology. The study comprehensively analyzes deformation scenarios from 2017 to 2022; additionally, a detailed examination of the 2023 deformation scenario reveals continued trends and localized changes in subsidence patterns. The result shows that the mean ground velocity between 2017 and 2022 varies between -2.8 and -5.5 mm/year, and the area under the subsidence zone shows an increasing trend. Predictive models for 2024 and 2025 are developed based on historical data, providing forecasts of future subsidence trends. The prediction indicates that in 2024, the area under the high deformation class will be relatively higher compared with 2025. Spatial association analyses explore correlations between subsidence patterns of different years in Kolkata. The findings of this study may facilitate the assessment of the possible effects of ground-level movement on resource management, safety, and economics in this densely populated city.

1. Introduction

Kolkata is one of the most densely populated and rapidly urbanizing cities in eastern India (Basu et al., 2025; Mandal et al., 2019). Despite its historical significance and economic vitality, the city is facing multiple problems, including unplanned urban growth, environmental degradation, and infrastructure stress (Bose and Halder, 2024; Gupta et al., 2024; Haque and Singh, 2017; Maity et al., 2022; Shastri et al., 2023). Ground subsidence due to excessive groundwater extraction adds to these challenges, posing serious risks to buildings and public safety. A D-InSAR (Differential Interferometric Synthetic Aperture Radar) based study detected slow land subsidence in Kolkata City between 1992 and 1998, primarily due to groundwater over-drafting under confined conditions. The subsidence, observed at a rate of 5 to 6.5 mm/year, was most prominent near Machhua Bazar, Calcutta University, and Raja Bazar Science College (Chatterjee et al., 2006). A subsequent PSInSAR (Persistent Scatterer Interferometric Synthetic Aperture Radar) based study using 20 ALOS PALSAR images from 2007 to 2011 estimated ground deformation rates ranging from -16 to +16 mm/year across Kolkata. The analysis identified over 568,000 persistent scatterer points and demonstrated a strong correlation between deformation patterns and groundwater level fluctuations (Biswas et al., 2019). Further, a multi-sensor InSAR study from 2003 to 2021 revealed significant land subsidence in Kolkata, primarily driven by groundwater over-extraction, with rates up to −12 mm/yr. The spatial shift of subsidence zones and reduced deformation in some areas suggest improved groundwater recharge, but high-risk zones remain vulnerable to seismic hazards due to high PGA values (Shastri et al., 2023). These findings highlight the urgent need for integrated groundwater management and continuous geodetic monitoring to mitigate the long-term deformation risks in Kolkata.

Remote sensing, combined with advanced mathematical tools like machine learning (ML) and deep learning (DL), plays a crucial role in accurately assessing various disasters such as floods, rainfall, landslides, subsidence, pollution, and earthquakes by enabling real-time, large-scale monitoring (Ali et al., 2022; Chaurasia et al., 2025; Chowdhury and Bhardwaj, 2025; Chowdhury and Dwarakish, 2022; Jefriza et al., 2020; Soudagar and Thakur, 2025; Srivastava et al., 2026, 2025; Thakur et al., 2026a, 2026b; Tiwari et al., 2026; Verma and Jana, n.d.; Wang et al., 2022; Yan et al., 2020). Other important applications include material characterization and testing, structural health monitoring, agricultural and crop assessment, and urban growth and land-use change analysis (Ahmed et al., 2026, 2025; Stead et al., 2019; Verma and Vijay, 2024). Specifically, microwave remote sensing techniques like InSAR are vital for detecting ground deformation with high precision, even under cloud cover or in low-light conditions. A study in New Delhi NCR using multi-sensor PS-InSAR data (2007–2018) revealed significant land subsidence, with deformation rates up to ±20 cm/year. The findings strongly correlate with groundwater depletion, highlighting the effectiveness of SAR-based monitoring over conventional methods (Malik et al., 2022). Another study in East Jharia Coalfield used Sentinel-1 SAR data (2021–2023) and subsidence metrics to map high-risk zones, revealing critical deformation in mining and built-up areas. The integration of subsidence, gradient, and curvature highlighted 41.15% of the area as vulnerable, emphasizing the need for targeted mitigation (Thakur et al., 2025). Moreover, a study in the Himalayan region used time-series DInSAR analysis with 118 Sentinel-1A images to estimate unknown landslide dates based on deformation patterns. The method showed high accuracy, with 87% precision and validation through Planet imagery, highlighting its effectiveness in remote landslide detection (Niraj et al., 2023). These collectively demonstrate the transformative potential of remote sensing and

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advanced analytical techniques in enhancing disaster preparedness, early warning systems, and sustainable land management.

Previous research on Kolkata's ground deformation often overlooked the detailed spatial-temporal evaluation of ground deformation in Kolkata, especially in terms of year-to-year variations and localized deformation patterns. Most studies provided either a broad overview or a limited time-frame analysis, failing to capture the dynamic nature of subsidence and uplift across different urban zones. In this study, we conducted a comprehensive assessment of ground deformation in Kolkata from 2018 to 2025 using InSAR-derived velocity data, reclassification of deformation classes, and spatial association techniques. The analysis reveals a dominant trend of subsidence throughout the years, with significant variations in mean, median, and mode velocities, highlighting localized ground instability. Notably, the highest negative velocities and standard deviations point to critical subsidence in densely developed areas like Metiabruz and Bijoygarh. The reclassification analysis shows a consistent dominance of stable ground, yet moderate and severe subsidence areas have increased during key years, likely due to urban expansion and groundwater depletion. Furthermore, the Spearman rank correlation coefficient illustrates strong spatial correlations between consecutive years, confirming persistent deformation patterns. The comparative study of subsiding and uplifting zones highlights a steady decline in uplift and an expansion of subsiding areas. These findings offer vital insights for urban planning, groundwater management, and disaster mitigation strategies in a rapidly developing city like Kolkata.

2. Methodology

2.1. Study Area

Kolkata, referred to as Kolkata City, was developed on the eastern and western banks of the River Hooghly, situated within the Ganges Delta, the largest delta formed by the Ganga–Brahmaputra Rivers. Approximately 7.5 km thick, Palaeocene covers the crystalline basement to Holocene sediments, which comprise the lower portion of the Bengal Delta and encompass Kolkata City. The city exhibits a flat fluvial-deltaic morphology with an average elevation of around 6 meters above mean sea level (Shastri et al., 2023). Clay and a silty clay layer 20-60 m thick cover the upper part of Kolkata's sedimentary sequence. The groundwater in Kolkata City exists beneath the clay layer in a confined condition (Sahu and Sikdar, 2011). The monsoonal precipitation from June to September is the primary source of groundwater replenishment in Kolkata. Fig 1 illustrates the persistent scatterer point density map of Kolkata, demonstrating the concentration of persistent scatterer points in the city, with each point representing a stable feature on the Earth's surface that consistently reflects radar signals over time, facilitating accurate measurement of ground deformation (Crosetto et al., 2016). The total area of Kolkata city considered in this study is about 196 sq.km.

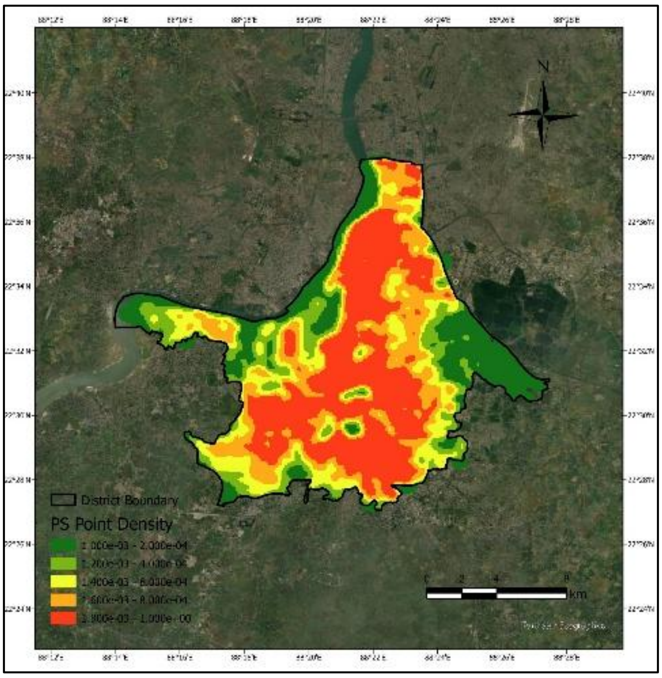

Fig 1: Persistent scatterer points density map of Kolkata

2.2. Workflow

For analyzing Kolkata's deformation, 122 Sentinel-1 SLC images were processed, generating 121 interferometric pairs in Interferometric Wide (IW) swath mode (250 km swath, 5×20 m resolution). The PS-InSAR (Persistent Scatterer Interferometric Synthetic Aperture Radar) technique was applied in SARPROZ software, starting with image co-registration, reference point selection, and interferogram generation (Fig 2). Study uses a small temporal baseline connection to generate interferograms from pairs of SAR (Synthetic Aperture Radar) images. The method ensures a minimal temporal baseline between them by creating each interferogram from consecutive pairs of images. This approach effectively reduces temporal decorrelation, which can degrade the quality of the interferometric data. As a result, it maintains high coherence between the image pairs, enabling more accurate measurement and analysis of surface deformations and other changes over time (Fig 3). Atmospheric Phase Screen (APS) corrections and Goldstein filtering were applied to reduce noise and enhance coherence. Phase unwrapping was performed to resolve ambiguities, followed by topographic phase removal using SRTM DEM. Persistent Scatterer (PS) points were identified using the Amplitude Stability Index (ASI) and coherence thresholds. LOS velocities were extracted by analyzing the displacement phase component at each Persistent Scatterer (PS) point after correcting for topography and atmospheric noise. A time series of deformation was generated and fitted to calculate the rate of ground movement over time.

The displacement data, representing ground movement, is recorded at multiple time points for various spatial locations (latitude and longitude). Cumulative displacement is computed for each spatial point by summing the displacement measurements over time. Equation (1) gives the cumulative displacement for a point at time t.

$$Cumulative\ Displacement_i(t) = \sum_{j=1}^{t} Displacement_i\,(j) \quad (1)$$

Here, $\mathrm{Cumulative\ Displacement}_i(t)$ indicates the cumulative displacement for the i[th] spatial point at time t and $\mathrm{Displacement}_i$ (j) represents the displacement value for the i[th] point at time j.

Since the target dates (January 1[st] of each year) may not exactly match the dates in the dataset, spline interpolation in Equation (2) is used to estimate the cumulative displacement for these dates. The interpolation is conducted using a cubic spline function, which minimizes the overall error by ensuring that the second derivative of the interpolated curve is continuous at the data points.

$$S(t) = \sum_{i=1}^{n} a_i(t - x_i)^3 + b_i(t - x_i)^2 + c_i(t - x_i) + d_i \quad (2)$$

Here, $S(t)$ indicates the interpolated value at the target time t, x_i are the known points (data in this case), a_i, b_i, c_i, d_i are the coefficients determined by solving a system of equations to ensure the curve is smooth and passes through all the known data points. After this the cumulative displacement values at the specified target dates are calculated to know the year-wise velocity. Inverse Distance Weighting (IDW) is a method to interpolate scattered data points to a grid by assigning weights to the known data points based on their distance from the interpolation location. After performing the interpolation, the results are masked based on the geographical boundary. The statistical calculations involve determining the mean, median, mode, and standard deviation of the valid velocity values from the interpolated grid, considering only the points within the district boundary. The velocity values are then classified into five categories. Finally, the number of points within each class is counted, and the area covered by each category is displayed based on these counts.

Further, the Spearman correlation between the classified maps of two different years (for example, 2018 and 2019) is used to assess the spatial association between the reclassified velocity values over time. In the Spearman Correlation Calculation step, the Spearman rank correlation coefficient (ρ) is computed between the classified maps of two different years to assess how well the classifications agree over time as in Equation (3). This step evaluates the monotonic relationship between two variables, specifically the classification of velocity values in two years.

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \quad (3)$$

Here, ρ is the Spearman rank correlation coefficient, d_i indicates the rank difference for each pair of observations, and n is the number of paired observations. Moreover, the truth table represents the classification agreement between the two years. The velocity data is classified into subsidence (negative values) and uplift (positive values). Separate statistical calculations are performed for each group, offering insights into the behavior of land deformation in terms of both subsidence and uplift.

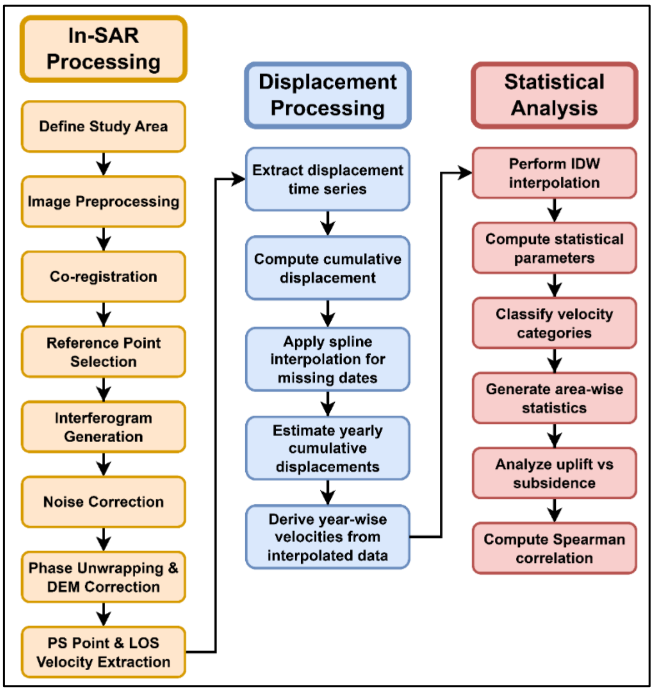

Fig 2. Methodological Workflow of InSAR-Based Land Deformation Analysis

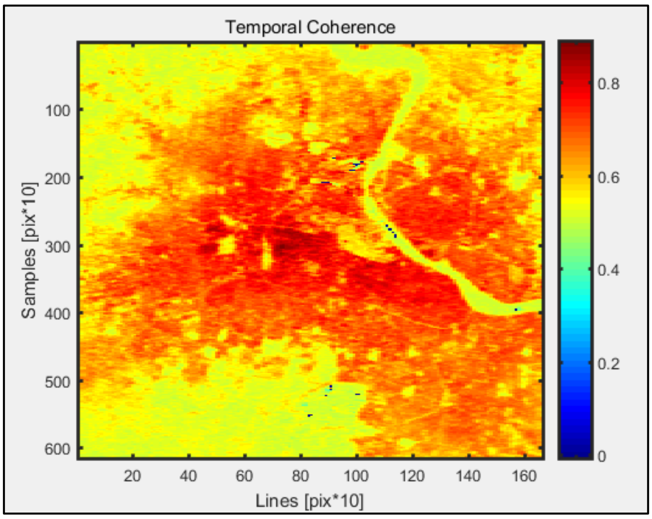

Fig 3: Temporal Coherence map in In-SAR coordinate

3. Results and Discussion

3.1. Statistical Analysis

The result shows a generally negative mean velocity, indicating subsiding ground movement across the years, fluctuating between -0.14 mm/year in 2021 and -5.53 mm/year in 2022 (Table 1). The mode velocity, which represents the most frequent value, is notably negative, with extreme values like -137.54 mm/year in 2018 and -171.84 mm/year in 2021. The median velocity is also negative, reflecting the skewed nature of the data toward the subsiding ground. The standard deviation, ranging from 40.91 mm/year in 2025 to 65.36 mm/year in 2021, indicates considerable variability in ground velocity over the years. This suggests significant fluctuations in the ground's motion, with occasional periods of intense subsidence.

Table 1: Various Statistical Parameters of Ground Velocity Measurements from 2018 to 2025.

Year	Velocity Statistical Parameters (mm/year)			
	Mean	Median	Mode	Std Dev
2018	-2.8395	-3.2490	-137.5418	43.2710
2019	-0.5027	-1.3397	-141.526	50.2239
2020	-3.9849	-4.6633	-168.6578	59.6158
2021	-0.1374	-0.6230	-171.8394	65.3595
2022	-5.5292	-5.2713	-170.0063	57.6306
2023	-2.8828	-2.4075	-171.1234	56.4982
2024	-2.8014	-2.1219	-147.5827	47.1985
2025	-5.0243	-4.4717	-160.5914	40.9105

The probable reasons for ground subsidence in Kolkata could be attributed to several factors. Urbanization and rapid construction activities in the city have led to groundwater extraction, causing the land to sink. Additionally, Kolkata's proximity to the Hooghly River and its underlying soft soil composition may amplify the effects of subsidence. The mode of negative velocities, especially in years like 2018 and 2021, could also be linked to localized construction-related ground disturbances or changes in river morphology affecting the foundation stability. Furthermore, industrial activities, including soil compaction from heavy machinery and the impact of drainage systems, particularly in flood-prone areas, may contribute to the ground's fluctuating velocities, as seen in the significant standard deviation values.

3.2. Reclassification

The distribution of land area (sq. Km) in Kolkata across various ground deformation classes is presented in Table 2. In terms of percentage of the total area, the majority of the land consistently falls under the neutral or stable ground movement class (-40 to 40 mm/year), which remains the dominant category throughout the period. This suggests that most of the region has experienced minimal ground movement. The percentage of area under moderate subsidence (-120 to -40 mm/year) fluctuates, peaking in 2020 and 2021, indicating a higher occurrence of land sinking, possibly due to urban activities and groundwater depletion.

Table 2: Measure of Area (sq.km.) under different Deformation Class from 2018-2022

	Area (sq.km.)				
Year	<-120 mm/year	-120 to -40 mm/year	-40 to 40 mm/year	40 to 120 mm/year	>120 mm/year
2018	0.09	40.63	122.17	33.05	0.38
2019	0.85	43.66	108.20	42.47	1.14
2020	4.74	51.47	93.19	43.33	3.60
2021	5.87	49.96	83.81	50.62	6.06
2022	3.84	52.61	95.18	42.29	2.41
2023	2.70	50.43	96.31	44.51	2.37
2024	0.71	43.37	114.45	37.12	0.66
2025	0.28	40.72	128.70	26.37	0.24

The area under severe subsidence (< -120 mm/year) represents a very small fraction of the total area, with the highest percentage in 2021 (Fig 4). Conversely, the area showing uplift (40 to 120 mm/year and >120 mm/year) remains a minor portion of the total area throughout the years, suggesting limited upward ground movement. By 2025, while the percentage of land experiencing moderate subsidence decreased slightly, the neutral class continued to dominate. The percentage changes from year to year reflect variations in ground deformation that could be influenced by factors such as construction, industrial activities, and natural environmental changes in Kolkata.

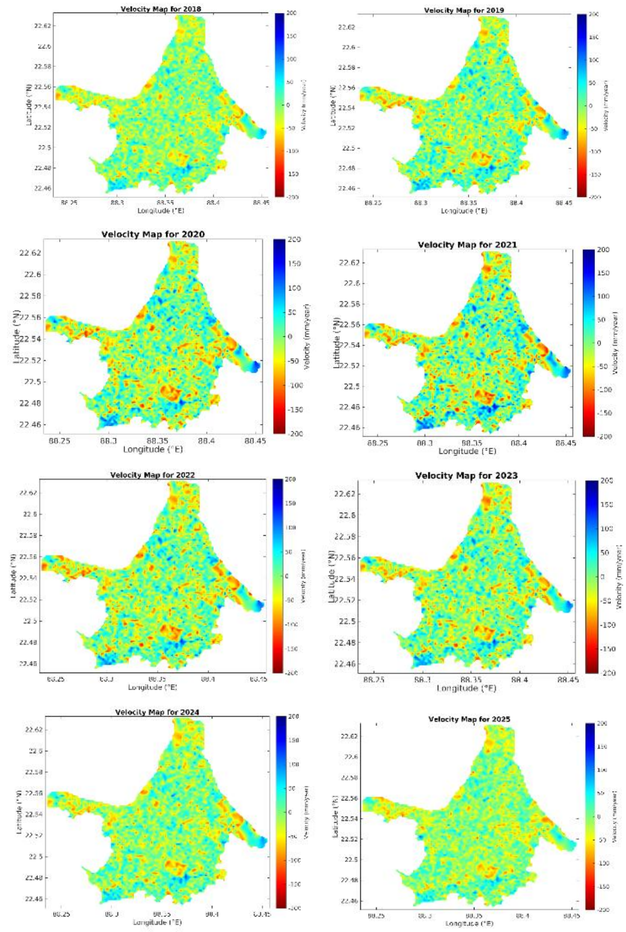

Fig 4: Deformation Class map from 2018-2025.

3.3. Correspondence Analysis

Table 3 shows the correlation values between consecutive years, represented by the Spearman rank correlation coefficient . The values, ranging from 0 to 1, indicate the strength of spatial correlation between ground velocities from one year to the next. Higher values closer to 1 suggest a strong spatial association, meaning the spatial patterns of deformation are more consistent between the years, while lower values suggest weaker or more fluctuating spatial relationships.

The table shows a generally strong spatial correlation between the consecutive years, especially from 2019 to 2024, with GMSA values mostly above 0.8, peaking at 0.90 between 2022 and 2023. This suggests that the spatial patterns of ground deformation in Kolkata have remained relatively consistent over these years. The GMSA values in 2018 show a moderate association with subsequent years, with a peak of 0.85 between 2024 and 2025. However, the spatial correlation tends to decrease slightly in the later years (2024-2025), reflecting a potential divergence in ground motion patterns or external factors influencing ground deformation trends in those years. The overall trend suggests stable but gradually evolving ground movement patterns in Kolkata over the studied period.

Table 3: Spearman rank correlation coefficient Between Consecutive Years from 2018 to 2025

Year	2019	2020	2021	2022	2023	2024	2025
2018	0.81	0.81	0.81	0.83	0.84	0.85	0.76
2019		0.83	0.84	0.85	0.84	0.83	0.73
2020			0.87	0.88	0.87	0.83	0.74
2021				0.89	0.89	0.84	0.74
2022					0.90	0.86	0.75
2023						0.86	0.75
2024							0.75

3.4. Analysis of subsiding and uplifting area

Table 4 provides detailed statistics of ground deformation for two classes, i.e., subsiding and uplifting. The table shows the area, mean, median, mode velocity, and standard deviation for each class across the years. For the subsiding class, which represents areas with negative ground velocities, the mean velocity shows an increasing trend over the years, from -36.04 mm/year in 2018 to -35.04 mm/year in 2025, suggesting that subsidence is a prominent issue in Kolkata. The areas affected by subsidence also fluctuated, with a general trend toward an increase in the area experiencing negative velocities, particularly in regions such as Metiabruz, Bijoygarh, and South Sinthee.

Table 4: Area and Velocity Statistics for Subsiding and Uplifting Classes from 2018 to 2025. S denote subsiding and U denote Uplifting.

Year-Class	Area (km^2)	Statistical Parameters (mm/year)			
		Mean	Median	Mode	Std.dev
2018-S	103.61	-36.04	-32.34	-137.54	25.57
2018-U	92.71	34.26	29.35	0.01	25.00
2019-S	100.15	-40.48	-34.88	-141.53	29.07
2019-U	96.17	41.12	36.43	0.06	29.53
2020-S	103.75	-49.81	-43.72	-168.66	35.08
2020-U	92.57	47.37	40.69	0.02	34.15
2021-S	98.96	-53.07	-47.15	-171.84	37.51
2021-U	97.36	53.67	46.91	0.00	37.94
2022-S	105.26	-49.10	-43.34	-170.01	34.47
2022-U	91.06	44.84	39.22	0.01	32.47
2023-S	101.05	-47.68	-41.97	-171.12	32.96
2023-U	95.27	44.63	39.59	0.01	32.23
2024-S	101.43	-39.91	-34.85	-147.58	28.12
2024-U	94.89	36.86	32.77	0.02	26.80
2025-S	106.92	-35.04	-31.14	-160.59	25.28
2025-U	89.40	30.87	25.99	0.04	23.35

In contrast, the uplifting class, representing areas with positive ground velocities, shows a decreasing trend in mean velocity over the years, from 34.26 mm/year in 2018 to 30.87 mm/year in 2025. This suggests that while some areas of Kolkata experience uplift (notably in regions such as Thakurpukur Bazar and Bansdroni), the extent of uplift has been gradually reducing. The standard deviation for subsiding and uplifting classes remains high, indicating considerable variability in ground movement within these regions. Overall, the data highlights that while subsidence is becoming more widespread and intense in Kolkata, uplifting areas are comparatively more stable but show a gradual decline in movement over time.

4. Conclusion

This study provides a comprehensive spatio-temporal analysis of ground deformation in Kolkata from 2018 to 2025 using statistical and geospatial techniques. The results reveal a dominant trend of subsidence across the city, with negative mean velocities observed throughout the study period, peaking at –5.53 mm/year in 2022. The presence of extreme mode values and high standard deviations suggests localized areas of intense ground movement. Factors such as rapid urbanization, excessive groundwater extraction, soft alluvial soil composition, and proximity to the Hooghly River are likely contributors to the observed deformation patterns. Reclassification analysis further confirms that the majority of the area remains in the stable class, but moderate and severe subsidence areas peaked during 2020–2022, indicating the increasing impact of anthropogenic and environmental stressors.

The correspondence analysis using Spearman rank correlation coefficient demonstrates strong spatial consistency of ground deformation over consecutive years, with highest correlations observed between 2022 and 2023. The detailed breakdown of subsiding and uplifting areas shows that subsidence is becoming more widespread and pronounced, particularly in regions such as Metiabruz, Bijoygarh, and South Sinthee. On the other hand, uplifting areas, though present, are declining in both intensity and spatial extent. This study underscores the need for urgent urban planning, groundwater regulation, and infrastructure risk assessment in Kolkata to mitigate potential hazards associated with continued ground subsidence.

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