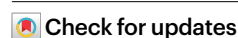


A global view of urban land subsidence and its changing trajectories

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Urban land subsidence is widespread, yet a global assessment using a consistent methodology is lacking, limiting targeted adaptation and mitigation. Here we use satellite interferometric synthetic aperture radar data from 2014 to 2023 to produce high-resolution relative local land subsidence maps for 465 cities worldwide with populations exceeding one million. Subsidence is most severe in Southeast Asia, West–Central Asia and North America, and is evident in historically under-studied regions, including South America, Africa and Russia. These spatial patterns remain broadly consistent after referencing relative local land subsidence to a global vertical land motion product, although the vertical land motion correction adds uncertainty. We further detect marked deceleration across many cities in Southeast and East Asia, while substantial urban areas in these regions continue to show accelerating subsidence. Our global maps and trend estimates provide a consistent basis for identifying hotspots and prioritizing actions to reduce subsidence-related hazards.

Cities worldwide are experiencing varying degrees of land subsidence—the gradual sinking process of urban land surfaces^{1–3}. In the USA, coastal cities including New York, Boston and San Francisco are sinking with a median velocity of approximately -2 to 6 mm yr^{-1} (ref. 4). In China, 16% of the land area of 82 major cities are sinking with a velocity faster than 10 mm yr^{-1} (ref. 5), whereas in Iran, 3.5% of the country's total land area is subsiding⁶. Urban subsidence impairs land stability by damaging buildings, foundations, drainage and sewage systems, while also increasing

flood vulnerability^{7–10}. These consequences directly undermine the United Nations' goal of fostering sustainable cities.

Given the potentially large threat land subsidence poses to urban socio-natural systems, it is imperative to implement effective mitigation and adaptation strategies to minimize its detrimental impacts. Achieving this goal requires a comprehensive understanding of the spatial patterns and evolutionary trends of global urban subsidence. Yet conventional monitoring is based on point-wise measurements

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and cannot be easily scaled to large spatial extents^{3,7,11,12}. Although an increasing number of modeling studies and literature reviews have sought to characterize large-scale subsidence patterns^{3–6,13–19}, they typically lack fine-grained spatial detail.

Recent advances in Interferometric Synthetic Aperture Radar (InSAR) technology, which employs microwave interferometry to measure land displacements with centimeter- to millimeter-level accuracy²⁰, have enabled large-scale monitoring of urban subsidence at high spatial resolution⁷. This approach has successfully revealed the subsidence patterns in regions such as Japan¹³, China⁵, the USA⁴, Iran⁶, India^{21,22} and the world's coastal lands^{4,23–26}, greatly enhancing our understanding of subsidence dynamics. However, previous urban subsidence studies relying on InSAR approach employed inconsistent InSAR processing methodologies, focused on different time periods or predominantly concentrated on a limited number of cities, with 99 coastal cities representing the largest dataset to date²⁴. As a result, a high-resolution analysis of land subsidence for global major cities within a consistent InSAR methodological is still absent; without it, policy efforts to address urban subsidence cannot be effectively targeted.

To fill this gap, we conducted high-resolution (40 m) land subsidence mapping from 2014 to 2023 for major cities worldwide with more than one million population. We obtained self-consistent, high spatial resolution relative local land subsidence (RLLS)²³ velocities with satellite InSAR technique. Currently, large-scale InSAR-derived land subsidence is presented in two approaches (Supplementary Table 1 provides a short review): one adopts InSAR displacements that have been referred to a local ground target during InSAR data processing, and the results can be considered as RLLS; the other aligns InSAR displacements to a given global navigation satellite systems (GNSS) reference frame, depending on which tectonic plate that the area of interest sits on and the alignment leverages InSAR displacements and an existing vertical land motion (VLM) product associated with long-wavelength signals due to glacial isostatic adjustment and regional tectonics²³ (Methods). In this study, we implemented both approaches. More detailed discussions on the purpose and shortage of each approach/product are provided in 'Discussion' and Methods.

We initially focused on 477 large cities that have more than one million population (Methods). Due to the unavailability of SAR imagery, 12 cities were excluded, leaving 465 cities in 107 countries—representing an extensive endeavor for evaluating worldwide urban subsidence under uniform temporal and methodological frameworks (Supplementary Table 2). We fully acknowledged the efforts of previous relevant studies conducted across spatial-temporal scales with varying methods^{4–6,11,13–26}. Thus, we first visually compared our InSAR results with existing ones generated using similar techniques and observation periods to verify that the subsidence patterns were consistent. This provided a qualitative assessment of our results. Next, relying on observations from pairs of GNSS stations, we quantitatively assessed the accuracy of our InSAR results, achieving an averaged uncertainty of 1.88 mm yr⁻¹ (Methods; Supplementary Figs. 1–4 provide more information, including regional variability of the uncertainty). We then examined the spatial pattern of urban subsidence worldwide using different indicators for the severity of subsidence. Additionally, we delved deeper into the temporal acceleration and deceleration trends of land subsidence (Methods), hoping to provide more insights for targeted mitigation and adaptation strategies. With all subsidence maps publicly accessible through our online platform 'GUS' (Global Urban Subsidence)²⁷, our study bridges a critical gap to better understand the present-day urban subsidence conditions in the world, which can help advance United Nation's Sustainable Development Goal of building sustainable cities.

Results

Global pattern of urban subsidence

To comprehensively quantify the severity of urban subsidence, we used three indicators—the median subsidence velocity within a city (V_m), the

5th percentile velocity within a city (V_{5th}) and the proportion of lands with a velocity below -10 mm yr⁻¹ within a city (P_{10}). Here displacement velocity is defined as positive for uplift and negative for subsidence. The three indicators consistently indicated more severe RLLS in Asia than the other continents (Fig. 1a–c). Asian cities' V_m values had a minimum of -33 mm yr⁻¹, much lower than, for example, -6 mm yr⁻¹ in Africa, -3 mm yr⁻¹ in Europe and -17 mm yr⁻¹ in North America (Table 1, top). The median value of V_{5th} (-12 mm yr⁻¹) was also the lowest in Asia, although North America (Mexico) showed the lowest V_{5th} (-217 mm yr⁻¹). Regarding P_{10} , Asia's P_{10} value was also the highest, reaching 71% (Table 1, top). Further, Southeast and West–Central Asia exhibited the most severe sinking, with V_m values as low as -33 and -11 mm yr⁻¹, V_{5th} as low as -151 and -133 mm yr⁻¹ and P_{10} as high as 71% and 52%, respectively (Table 1, top). In alignment with this pattern, we also noted faster subsidence rates in cities from developing countries than those from developed countries (Supplementary Fig. 6).

In addition to the global pattern of urban subsidence revealed by RLLS as presented above, we also examined the pattern using VLM-aligned subsidence maps. We found an altered spatial pattern for V_m but highly similar patterns for V_{5th} and P_{10} (Fig. 1d–f). Importantly, all three indicators continue to identify Asia as the continent experiencing the most severe urban subsidence (Table 1, bottom). At the regional scale, North America (Mexico), Southeast Asia (Indonesia) and West–Central Asia (Iran) remain the most severely affected regions, with the lowest V_{5th} values of -213 , -150 and -114 mm yr⁻¹, respectively (Table 1, bottom).

Our results represent one of the largest efforts to map urban subsidence using a consistent InSAR method. By conducting a literature review using combinations of each city name, 'subsidence' and 'InSAR' as keywords in Google Scholar (Methods and Supplementary Fig. 7; Supplementary Table 3 provides the corresponding literature), we found that no InSAR-based land subsidence studies were identified for 204 cities. Thus, we were able to quantify urban subsidence in some historically under-studied regions, including South America, Africa and Russia. According to the RLLS results, South America exhibits substantial localized subsidence, with the minimum V_{5th} value below -30 mm yr⁻¹ and the maximum P_{10} exceeding 40%. In Africa, V_{5th} highlights notable subsidence hotspots despite the limited attention received in previous studies, with a median value of -6.6 mm yr⁻¹. In Russia, although only five cities were included, the median V_{5th} and P_{10} values were -18.2 mm yr⁻¹ and 15.9%, respectively. Still, such results quantified with V_{5th} and P_{10} remained largely consistent if the VLM-aligned results were considered (Supplementary Fig. 8).

Ranking of the severities of urban subsidence

We also ranked cities based on their severity of RLLS. As expected, the ranking varied slightly depending on the chosen indicator (Supplementary Table 2). Mexico exhibited the lowest V_{5th} (-217 mm yr⁻¹), whereas Medan showed the lowest V_m (-33 mm yr⁻¹) and the highest P_{10} (71%). To overcome this variability, we integrated all three indicators into a final composite severity score which ranges from 0 to 100, with a larger value indicating a more severe subsidence status (Methods), providing a comprehensive ranking that accounts for both spatial extents and rates of sinking lands (Fig. 2a and Supplementary Table 2). Our results showed that the ten most severely subsiding cities worldwide are Medan (V_m : -33 mm yr⁻¹, V_{5th} : -80 mm yr⁻¹, P_{10} : 71%), Bandung (V_m : -22 mm yr⁻¹, V_{5th} : -120 mm yr⁻¹, P_{10} : 60%), Torreon (V_m : -17 mm yr⁻¹, V_{5th} : -80 mm yr⁻¹, P_{10} : 60%), Mexico City (V_m : -8 mm yr⁻¹, V_{5th} : -217 mm yr⁻¹, P_{10} : 47%), Isfahan (V_m : -11 mm yr⁻¹, V_{5th} : -70 mm yr⁻¹, P_{10} : 52%), Tianjin (V_m : -8 mm yr⁻¹, V_{5th} : -65 mm yr⁻¹, P_{10} : 47%), Chittagong (V_m : -10 mm yr⁻¹, V_{5th} : -47 mm yr⁻¹, P_{10} : 50%), Florianopolis (V_m : -8 mm yr⁻¹, V_{5th} : -37 mm yr⁻¹, P_{10} : 46%), Rangoon (V_m : -6 mm yr⁻¹, V_{5th} : -47 mm yr⁻¹, P_{10} : 37%) and Toluca (V_m : -6 mm yr⁻¹, V_{5th} : -46 mm yr⁻¹, P_{10} : 42%) (Table 2, top). It is particularly worth mentioning that six out of the ten most severely sinking cities are in Asia, specifically in Indonesia and Iran, and three are in Mexico (Supplementary Figs. 9 and 10 show representative cities).

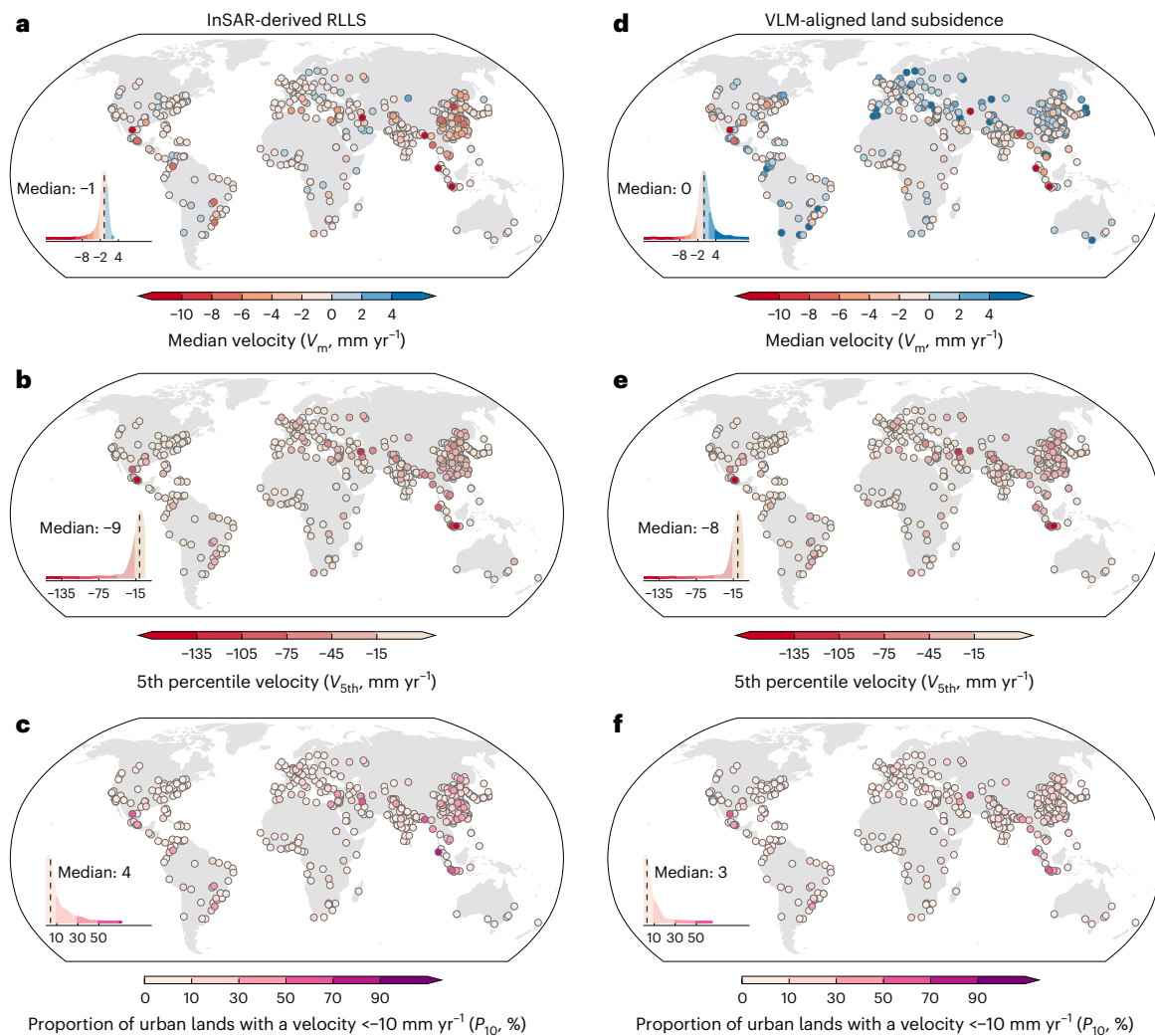


Fig. 1 | Patterns of InSAR-derived RLLS and VLM-aligned land subsidence for 465 global major cities. a–f, Patterns of InSAR-derived RLLS (a–c) and VLM-aligned land subsidence (d–f) (2014–2023) for 465 global major cities. All the 465 cities shown here have a population surpassing one million. VLM-aligned land subsidence was obtained by aligning InSAR-derived RLLS to a global VLM product interpolated from GNSS observations. Severity of urban subsidence is

indicated using three indicators: median velocity of all pixels (each being 40×40 m) within a city (V_m ; a and d), 5th percentile velocity of all pixels within a city (V_{5th} ; b and e) and proportion of subsiding pixels faster than 10 mm yr^{-1} (or $< -10 \text{ mm yr}^{-1}$) within a city (P_{10} ; c and f). Note that land velocity is defined as positive for uplift and negative for subsidence. The insets in the lower-left corner show the histogram of V_m , V_{5th} and P_{10} values of the 465 cities.

We further examined the rankings of subsidence severity using the VLM-aligned subsidence maps and found largely consistent ranking patterns, despite some inevitable changes in the order for certain cities (Fig. 2b and Supplementary Table 2). Notably, among the top ten cities experiencing the most severe subsidence, the majority remain concentrated in Asia and North America, including Bandung and Medan in Indonesia, Mashhad in Iran and Torreón, Mexico City and Toluca in Mexico (Table 2, bottom).

Acceleration and deceleration of RLLS

Thus far, we have focused on assessing the spatial pattern of subsidence rates in major cities globally. A relatively underexplored topic is the temporal acceleration/deceleration trends of land displacements derived from satellite geodesy¹⁶. Despite nine years of time series, it is still valuable to identify urban areas experiencing accelerating/decelerating subsidence, thereby enabling more effective targeting of mitigation measures. We therefore analyzed the temporal evolution of land subsidence across 465 global cities using piecewise regression which identifies the existence of turning point in a time series (Methods). The calculation and analysis of acceleration and deceleration were

conducted based on the time series of RLLS. We opt to identify a single change point primarily because the monitoring period is relatively short. Consequently, the way we used piecewise regression was to detect a turning point that represents the most substantial change in the time series, rather than transient seasonal variations. The acceleration and deceleration of land subsidence were quantified from two perspectives: (1) the proportion of land area exhibiting accelerating or decelerating subsidence and (2) the magnitude of acceleration or deceleration, calculated as the absolute difference in velocities before and after the turning point (Methods).

Our results revealed distinct regional patterns in subsidence dynamics. Africa, Oceania and Russia exhibited a higher proportion of urban lands undergoing accelerating subsidence compared to deceleration, whereas all other regions showed a greater proportion of decelerating subsidence than acceleration (Fig. 3c). This pattern indicates that urban subsidence in global cities generally tends to be alleviating. Among all regions, Europe exhibited the highest proportion of land experiencing both accelerating and decelerating subsidence; however, we noted that the overall subsidence rates in Europe were minor (Fig. 1), and even though a change point was detected in the

Table 1 | Statistics of InSAR-derived RLLS and VLM-aligned land subsidence for 465 global major cities

Continent	Region	Country	V _m (mm yr ⁻¹)			V _{5th} (mm yr ⁻¹)			P ₁₀ (%)		
			Min	Median	Max	Min	Median	Max	Min	Median	Max
InSAR-derived RLLS											
Africa	/	/	-5.6	-0.6	1.6	-32.3	-7.1	-1.9	0.1	2.5	32.1
Asia	/	/	-32.7	-1.1	2.2	-151.4	-11.9	-1.5	0.0	7.0	71.3
/	East Asia	/	-8.3	-1.4	2.2	-64.8	-14.1	-1.5	0.0	10.0	46.5
/	/	China	-8.3	-1.7	2.2	-64.8	-15.6	-3.9	0.2	11.6	46.5
/	South Asia	/	-10.2	-0.8	0.6	-71.4	-9.2	-2.6	0.1	4.0	50.2
/	/	India	-3.7	-0.8	0.0	-23.1	-8.1	-2.6	0.1	3.2	22.5
/	Southeast Asia	/	-32.7	-1.6	-0.1	-151.4	-20.7	-4.6	1.1	19.0	71.3
/	/	Indonesia	-32.7	-1.7	-0.8	-151.4	-24.7	-10.2	5.2	24.8	71.3
/	West-Central Asia	/	-10.6	-0.5	0.8	-133.1	-7.2	-2.3	0.0	2.1	51.6
/	/	Iran	-10.6	-1.7	0.8	-133.1	-55.1	-7.2	2.0	18.0	51.6
Europe	/	/	-2.8	-0.5	1.5	-24.1	-6.8	-1.5	0.0	2.3	21.2
North America	/	/	-17.3	-0.4	0.3	-216.5	-5.3	-1.7	0.0	1.1	60.2
/	/	Mexico	-17.3	-0.7	0.0	-216.5	-20.0	-1.7	0.1	19.2	60.2
/	/	USA	-4.8	-0.4	0.3	-20.3	-4.5	-2.0	0.0	1.0	21.1
Oceania	/	/	-0.6	-0.4	-0.1	-15.2	-8.4	-5.0	1.7	3.6	9.7
South America	/	/	-7.9	-0.7	0.7	-36.9	-7.5	-1.7	0.0	3.1	45.7
/	/	Brazil	-7.9	-1.1	-0.3	-36.9	-11.1	-5.1	1.1	5.9	45.7
/	Russia	/	-4.0	-1.3	0.2	-25.6	-13.9	-4.7	0.6	10.3	28.1
VLM-aligned land subsidence											
Africa	/	/	-3.2	-0.4	4.2	-31.8	-6.6	-0.9	0.1	2.2	26.3
Asia	/	/	-24.4	0.2	16.1	-150.3	-10.2	6.8	0.0	5.2	64.8
/	East Asia	/	-4.0	0.5	8.9	-53.0	-11.6	6.8	0.0	6.6	29.3
/	/	China	-4.0	0.5	5.3	-53.0	-12.9	-3.3	0.2	8.0	29.3
/	South Asia	/	-8.6	-0.3	10.8	-64.8	-9.0	1.6	0.0	4.2	43.9
/	/	India	-5.3	-0.5	2.4	-20.1	-8.9	-1.1	0.0	4.2	15.7
/	Southeast Asia	/	-24.4	-1.4	6.9	-150.3	-18.1	-5.5	1.3	12.0	64.8
/	/	Indonesia	-24.4	-1.4	1.4	-150.3	-24.0	-9.5	4.5	21.6	64.8
/	West-Central Asia	/	-16.5	0.2	16.1	-113.9	-5.9	-1.1	0.0	1.6	61.8
/	/	Iran	-16.5	1.1	16.1	-113.9	-48.2	-5.2	1.1	13.7	61.8
Europe	/	/	-0.9	0.6	11.6	-21.4	-5.6	4.8	0.0	2.2	11.6
North America	/	/	-12.0	-0.7	3.1	-212.8	-5.0	1.0	0.0	1.2	53.2
/	/	Mexico	-12.0	-1.3	2.7	-212.8	-17.9	1.0	0.0	14.4	53.2
/	/	USA	-4.9	-0.8	1.5	-20.4	-5.0	-2.2	0.0	1.2	21.3
Oceania	/	/	-1.9	0.2	5.4	-13.2	-8.1	0.2	0.9	3.5	7.7
South America	/	/	-2.3	0.0	8.0	-31.3	-6.8	1.4	0.0	2.7	34.7
/	/	Brazil	-2.3	-0.2	8.0	-31.3	-9.7	-4.2	1.0	4.7	34.7
/	Russia	/	0.0	1.3	9.3	-19.7	-6.8	-3.9	0.5	2.8	15.3

The VLM-aligned land subsidence was obtained by aligning InSAR-derived RLLS to a global VLM product interpolated from GNSS observations. The table shows the severity of urban subsidence summarized at continental, regional and country levels. The spatial locations of the regions are shown in Supplementary Fig. 5.

InSAR time series, the magnitude of change remained subtle (Fig. 3c; Supplementary Fig. 11 provides examples).

When focusing on accelerating subsidence, Africa, Russia, South Asia and East Asia exhibited the highest proportions of urban land affected by such issue after Europe, accounting for 7.8%, 7.8%, 7.3% and 7.2% of their respective urban areas (Fig. 3c). However, the magnitude of change was small in Africa and Russia despite the high proportion of accelerating subsidence. Regarding decelerating subsidence, apart from Europe, Southeast Asia, East Asia and South Asia exhibited the

highest proportions of decelerating subsidence, amounting to 10.1%, 8.7% and 7.9%, respectively (Fig. 3c). The magnitude of change—whether acceleration or deceleration—was consistently greatest in Southeast Asia and East Asia (Fig. 3c; Supplementary Fig. 11 provides examples).

To get a clearer view, we derived a weighted score (WS) by multiplying the area proportion with the magnitude of acceleration or deceleration. WS was calculated separately for acceleration and deceleration. It has a minimum value of 0, and larger values denote a stronger tendency towards accelerating/decelerating land subsidence (Methods).

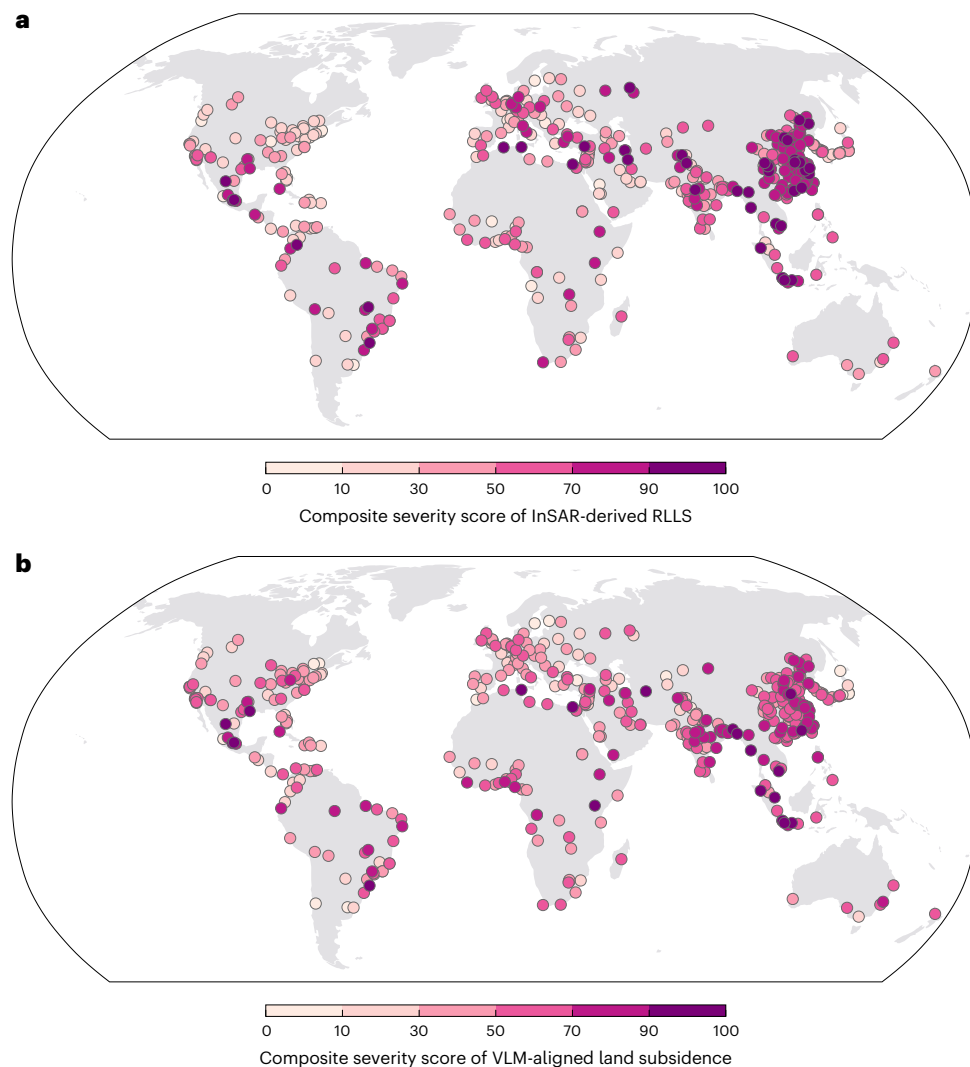


Fig. 2 | Ranking of the severity of InSAR-derived RLLS and VLM-aligned land subsidence for 465 global major cities. a, b. Ranking of the severity of InSAR-derived RLLS (a) and VLM-aligned land subsidence (b) for 465 global major cities. VLM-aligned land subsidence was obtained by aligning InSAR-derived RLLS to a global VLM product interpolated from GNSS observations. The ranking was

based on composite severity score, which was calculated by integrating all three indicators of subsidence severity presented in Fig. 1 (namely, V_m , V_{5th} and P_{10}). The composite severity score ranges from 0 to 100, with a larger value indicating a more severe subsidence status (Methods).

We found that Southeast Asia (WS: 0.7), East Asia (WS: 0.7) and South Asia (WS: 0.5) were the global hotspots for accelerating subsidence (Fig. 3b), whereas Southeast Asia (WS: 1.3) and East Asia (WS: 1.1) led in subsidence deceleration (Fig. 3a). Notably, Southeast Asia and East Asia ranked high in both acceleration and deceleration of subsidence (Fig. 3a,b).

Discussion

Using European Space Agency's Copernicus Sentinel-1 satellite radar images and InSAR methodology, our study quantified urban subsidence rates and trends across 465 cities worldwide, each with a population exceeding one million. We first provided self-consistent RLLS for each city, controlling the biases rising from varying InSAR methods and observation periods. Such citywide relative local land subsidence was obtained through initializing and concluding the selection of the reference point following two runs of time series analysis for each city (Supplementary Table 2 provides the geographic locations of reference and Methods).

Moreover, we aligned the InSAR-derived RLLS results to a global reference frame by using a global VLM product interpolated from GNSS

observations (Supplementary Fig. 12 and Methods). We presented both RLLS and the VLM-aligned results as both have value and can serve different purposes. RLLS captures localized subsidence signals relevant to infrastructure stability and urban risk management^{28–30}, whereas VLM-aligned results, referenced to a global reference frame, are more suitable for plate tectonic studies^{4,23}. However, we would like to emphasize that InSAR-derived RLLS results referenced to a local ground target, in principle, can be transformed into a global reference frame. The most ideal approach is to use observations from stable GNSS stations within the city to constrain the reference frame conversion, as demonstrated in previous studies²⁵. Because such GNSS observations are not available for all the 465 cities, we utilized a global VLM product interpolated from GNSS observations to align the RLLS results to a common global reference frame, thereby obtaining the VLM-aligned results. By doing so, we acknowledge that the VLM-aligned results may introduce additional uncertainties, as the accuracy of the underlying VLM product is inherently dependent on the spatial distribution of GNSS stations. Consequently, in regions with sparse GNSS coverage, such as parts of Asia and Africa, the interpolated VLM field may have reduced accuracy (example of Tianjin in Supplementary Fig. 13).

Table 2 | The ten cities with the most severe InSAR-derived RLLS and VLM-aligned land subsidence as ranked by the composite severity score

Rank	City	Country	Region	V_m (mm yr ⁻¹)	V_{5th} (mm yr ⁻¹)	P_{10} (%)	Composite severity score [0, 100]
InSAR-derived RLLS							
1	Medan	Indonesia	Southeast Asia	-32.7	-80.1	71.3	99.7
2	Bandung	Indonesia	Southeast Asia	-21.9	-119.8	59.7	99.6
3	Torreón	Mexico	North America	-17.3	-79.5	60.2	99.4
4	Mexico City	Mexico	North America	-7.9	-216.5	46.5	99.2
5	Isfahan	Iran	West-Central Asia	-10.6	-70.0	51.6	99.1
6	Tianjin	China	East Asia	-8.3	-64.8	46.5	98.6
7	Chittagong	Bangladesh	South Asia	-10.2	-46.8	50.2	98.5
8	Florianópolis	Brazil	South America	-7.9	-36.9	45.7	97.6
9	Rangoon	Myanmar	Southeast Asia	-6.4	-47.2	36.9	97.5
10	Toluca	Mexico	North America	-6.0	-46.0	42.4	97.3
VLM-aligned land subsidence							
1	Bandung	Indonesia	Southeast Asia	-16.7	-114.5	54.5	99.6
2	Medan	Indonesia	Southeast Asia	-24.4	-71.8	64.8	99.6
3	Mashhad	Iran	West-Central Asia	-16.5	-84.6	61.8	99.5
4	Torreón	Mexico	North America	-12.0	-74.3	53.2	99.2
5	Mexico City	Mexico	North America	-4.2	-212.8	41.1	98.6
6	Toluca	Mexico	North America	-7.3	-47.4	44.7	98.6
7	Chittagong	Bangladesh	South Asia	-5.9	-42.5	43.9	98.3
8	Dhaka	Bangladesh	South Asia	-8.6	-27.9	39.2	97.5
9	Rangoon	Myanmar	Southeast Asia	-3.1	-43.8	32.0	97.1
10	Can Tho	Vietnam	Southeast Asia	-4.8	-23.4	29.9	96.0

VLM-aligned land subsidence was obtained by aligning InSAR-derived RLLS to a global VLM product interpolated from GNSS observations. For the calculation of the composite severity score, please refer to the Methods. The composite severity scores for all 465 cities are provided in Supplementary Table 2.

On the basis of the two complementary InSAR-derived results, this study provides a comprehensive quantification of land subsidence patterns across 465 major cities worldwide. Pronounced subsidence is observed in several regions, particularly in Southeast Asia, West-Central Asia and North America, which is broadly consistent with previous studies^{5,6,15,16,23,24}. An additional literature survey on Google Scholar using combinations of ‘city name’, ‘subsidence’ and ‘InSAR’ as keywords revealed that InSAR-based land subsidence studies were not identified for 204 cities. Thus, we further observed that several historically under-studied regions also experienced subsidence, such as South America, Africa and Russia, suggesting widespread subsidence globally. To characterize subsidence severity, we ranked cities using three complementary indicators. It should be noted that for each city, the indicators are derived from observations within the administrative boundary. Therefore, cities associated with extensive subsidence features extending beyond the city boundary may not rank as highly as expected. This was demonstrated in some cities, for example, Mashhad and Tehran in Iran⁶, where large subsidence bowls extend beyond the administrative boundary, and only the portions falling within it are included in the analysis. All the resulting maps are hosted on ‘GUS’, a newly established, publicly accessible platform²⁷. This innovative tool enables the identification of localized, high-risk subsidence areas, supporting the development of targeted mitigation and adaptation strategies^{5–8,16,31–33}. As such, our study is expected to support the United Nations’ goal of building sustainable cities.

In addition to the spatial pattern of urban subsidence, another notable contribution of our study is the analysis on temporal acceleration/deceleration of subsidence. We found that Southeast Asia and East Asia showed high proportions of both acceleration and deceleration of

subsidence (Fig. 3). These contrasting trends may reflect the region’s rapid economic development, factoring in accelerating subsidence and the implementation of extensive mitigation measures that have effectively curbed or reversed subsidence in certain areas. For example, large-scale interventions such as the world’s largest water diversion project and stringent groundwater regulation policies have been implemented in East Asia^{5,31,34}. One notable case happens in the Beijing–Tianjin–Hebei urban agglomeration in China, where the replenishment of underground aquifers since approximately 2016 has successfully halted land subsidence across several regions of the cities^{5,17} (Supplementary Fig. 11).

Looking ahead, future endeavors could be focused on separating and quantifying the drivers of urban subsidence. Local land subsidence can be linked to a variety of natural and anthropogenic factors³⁵. Natural factors primarily include sediment compaction^{36–38}, whereas anthropogenic factors primarily include urban construction^{39,40} and extraction of natural gas, minerals and especially groundwater^{15,41–44}. Separating and quantifying the multifaceted causes of urban subsidence requires extensive geological and groundwater data along with sophisticated models³⁵. This is becoming increasingly feasible as data availability expands and artificial intelligence advances, enabling the analysis of complex interactions among different mechanisms⁴⁵. Given ongoing urban development and more frequent occurrences of droughts that exacerbate water stress and floods that offer opportunities to store freshwater¹⁴, it is also critical to develop urban planning theory to create the surface and subsurface space for water resource exchanges. It is also valuable to explore the possible impact of subsidence on building integrity and urban population, given increasingly availability of high-resolution building footprint data^{46–50}. Beyond that, continuously

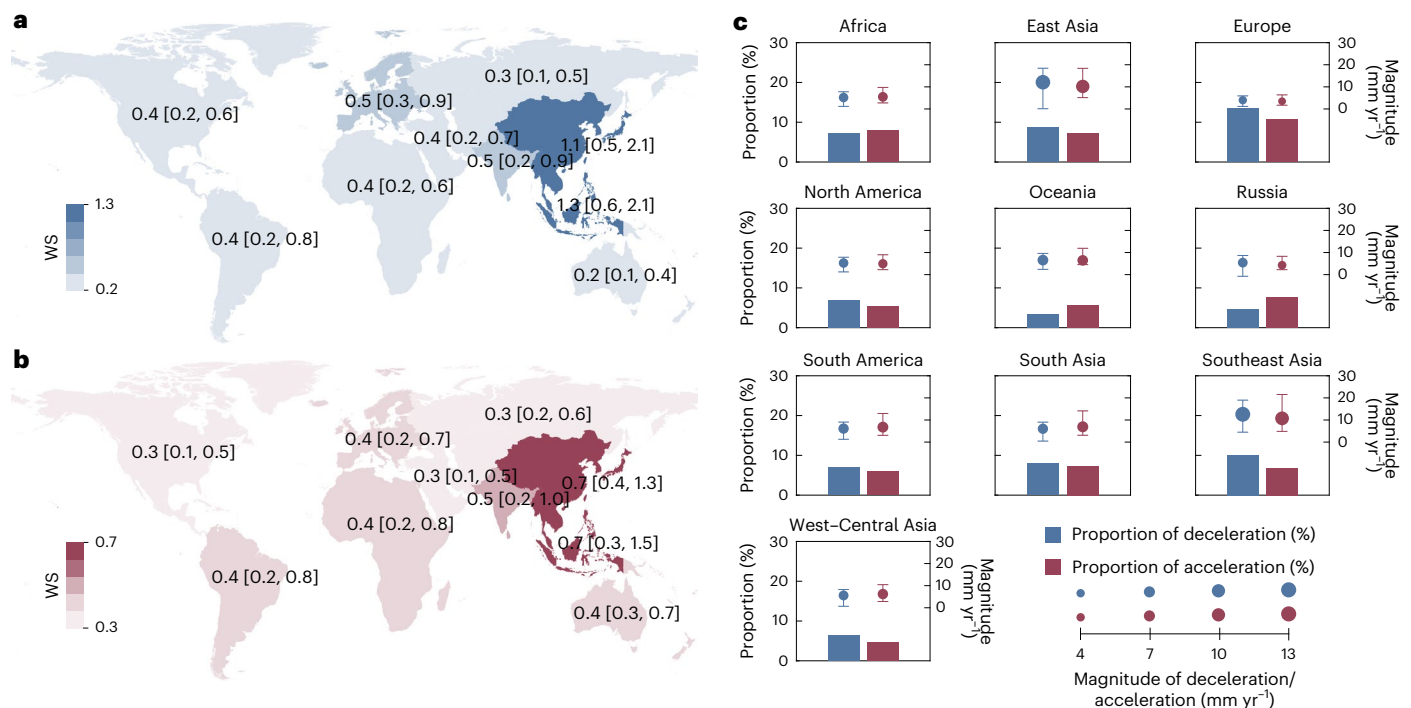


Fig. 3 | Acceleration and deceleration of InSAR-derived RLIS. a, WS for subsidence deceleration by geographical region. **b**, WS for subsidence acceleration by geographical region. The regional-scale WS was calculated as the product of regional area proportion (unit: %) and regional magnitude of acceleration or deceleration (unit: mm yr^{-1}). The area proportion for each region was calculated as proportion of pixels that are undergoing accelerating/decelerating subsidence to the total number of pixels in this region. The magnitude and its uncertainty range at the regional scale were derived from pixel-level magnitudes using the median (number outside the brackets in **a** and **b**) and 25th–75th percentiles (numbers in square brackets in **a** and **b**), respectively. The Methods provides the calculation of pixel-level magnitude of subsidence acceleration/deceleration. WS ranges from 0 upward and increases with the

strength of subsidence acceleration/deceleration. **c**, Regional area proportions and magnitudes of acceleration/deceleration. Bars show the proportion of regional area. Circles above the bars indicate the regional magnitude (median pixel-level magnitude), with error bars representing the 25th–75th percentiles of pixel-level magnitudes. The number of pixels (n) for acceleration and deceleration are 799,698 and 723,361 in Africa, 4,383,900 and 5,355,166 in East Asia, 656,387 and 834,082 in Europe, 735,872 and 937,700 in North America, 221,703 and 131,515 in Oceania, 95,945 and 57,195 in Russia, 524,834 and 600,446 in South America, 743,381 and 800,634 in South Asia, 308,215 and 456,993 in Southeast Asia and 541,720 and 732,155 in West–Central Asia, respectively. The spatial locations of the regions are shown in Supplementary Fig. 5. Supplementary Fig. 11 provides representative cases of subsidence acceleration and deceleration.

monitoring of urban subsidence, not only for major cities but also smaller ones, can help determine whether the acceleration or deceleration observed over the nine-year period will persist or shift¹³. Such long-term efforts could also enable the detection of multiple change points in land motion time series, thus better assisting policymakers in evaluating the effectiveness of interventions, informing targeted mitigation and adaptation strategies and identifying early warning signs of emerging threats.

Methods

Selection of global major cities

This study focused on large cities worldwide with a population exceeding one million. Frolking et al.⁵¹ compiled a list of 477 global cities, which all have a population over one million in the year of 2015, and we followed it in our analysis. Due to limited European Space Agency's Copernicus Sentinel-1 Synthetic Aperture Radar (SAR) images, 12 cities were excluded, resulting in a total of 465 cities from 107 countries. Among them, 128 cities are in developed countries and 337 in developing countries.

Land subsidence has been extensively investigated in the literature using InSAR. We conducted a literature review using combinations of each city name, 'subsidence' and 'InSAR' as keywords in Google Scholar to obtain a preliminary overview of whether InSAR-based land subsidence studies have been reported for each city. The results indicated that land subsidence has been investigated using InSAR for 261 cities, whereas no InSAR-based subsidence studies were identified for the remaining

204 cities (Supplementary Fig. 7; Supplementary Table 3 provides the corresponding literature). It should be noted that this survey is based solely on a literature search and therefore does not represent a comprehensive assessment of all available studies. Large-scale ground motion monitoring platforms such as the European Ground Motion Service, which provide regional-scale products, were not included in this analysis. Despite these limitations, this study represents one of the largest efforts to map urban subsidence using a consistent InSAR methodology.

For cities in China and the USA, the administrative boundaries have been clarified by authorities and can be sourced from the Resource and Environmental Science Data Platform (<https://www.resdc.cn/>) and US Census Bureau (<https://www2.census.gov/geo/tiger/GENZ2023/shp/>), respectively. However, city boundaries for other countries vary across sources, and we referred to Google Maps to select the sources. The global administrative areas (https://gadm.org/download_country.html), the OpenStreetMap Boundaries database (<https://osm-boundaries.com/map/>), the Global Urban Boundaries⁵² and the Common Operational Datasets Subnational Administrative Boundaries database from the Humanitarian Data Exchange (https://data.humdata.org/dataset/?dataseries_name=COD+-+Subnational+Administrative+Boundaries) are four candidate sources. For each city, the one that aligns the most with Google Map's boundaries was selected.

We acknowledge that as our research focused on major cities, the results may not fully capture the dynamics in smaller cities, where urban development patterns, subsurface structures and governance capacities differ substantially.

InSAR-derived RLLS

InSAR has emerged as an essential tool for land subsidence monitoring due to its ability to provide high-precision, millimeter-level surface deformation information over large areas^{14,53–55}. The Small Baseline Subset (SBAS) InSAR constructs a series of interferograms characterized by small spatio-temporal baselines and estimates deformation time series using least squares or singular value decomposition methods^{56,57}. It effectively mitigates the impact of atmospheric delay noise and is well suited for urban land subsidence monitoring^{58–60}. Therefore, we applied the SBAS–InSAR method to evaluate the land subsidence patterns for the 465 cities from June 2014 to June 2023.

For each city, an interferometric network was constructed using all available Sentinel-1 SAR images (June 2014–June 2023) from a single flight direction (ascending or descending) with a maximum temporal baseline of 60 days and a maximum spatial baseline of 200 m. We generated interferograms using the Alaska Satellite Facility (ASF)'s Hybrid Pluggable Processing Pipeline (HyP3) (<https://search.asf.alaska.edu/>). HyP3 cloud computing platform provides two options of range and azimuth look ratios, that is, 10:2 and 20:4. We chose the option of 10:2 to produce differential interferograms at a finer pixel spacing of approximately 40 m. Earth's ellipsoid and topographic phases were simulated based on the imaging geometry and GLO-30 Copernicus digital elevation model (DEM) and were subsequently removed. The Goldstein–Werner Adaptive Phase Filter⁶¹ was employed to reduce phase noise in interferograms, with the adaptive filter parameter of 0.6. Afterwards, the differential interferograms were unwrapped using the Minimum Cost Flow algorithm in GAMMA software applied by the ASF's cloud computing platform. More information about InSAR workflow used in HyP3 is available from ASF's Sentinel-1 InSAR Product Guide (https://hyp3-docs.asf.alaska.edu/guides/insar_product_guide/).

The phase of each pixel in the unwrapped interferogram $\Delta\phi$ can be expressed as:

$$\Delta\phi = \phi(t_1) - \phi(t_2) \approx -\frac{4\pi}{\lambda} [d(t_1) - d(t_2)] + \Delta\phi_{\text{topo}} + \Delta\phi_{\text{atm}} + \Delta\phi_{\text{noise}} \quad (1)$$

where $\phi(t_1)$ and $\phi(t_2)$ denote the phases of the SAR signals acquired at times t_1 and t_2 , respectively, and $d(t_1)$ and $d(t_2)$ denote the cumulative displacement along the radar's line of sight (LOS) at times t_1 and t_2 , respectively. $\Delta\phi_{\text{topo}}$ represents the residual topographic phase resulting from DEM errors, $\Delta\phi_{\text{atm}}$ represents the atmospheric artifacts and $\Delta\phi_{\text{noise}}$ represents noise in SAR signals.

The unwrapped interferograms were used as the input for the Miami InSAR time series software in Python (MintPy)⁶² to generate displacement time series and velocities. Low-coherence pixels were masked out due to a high likelihood of unwrapping errors. Because the acquisition frequency of Sentinel-1 images and the land cover across the globe vary substantially^{63,64}, enlightened by previous attempts^{5,15,62}, we selected different coherence thresholds (from 0.3, 0.35 and 0.4), depending on the decorrelation condition of each city (Supplementary Table 2). Additionally, ERA5 reanalysis meteorological dataset was utilized to correct for atmospheric artifacts⁶⁵, and the residual topographic correction was applied to minimize the impact of DEM errors⁶⁶. After removing these erroneous phases, the phase of the unwrapping interferogram can be written into a matrix form as:

$$\Delta\phi = AV_{\text{LOS}} \quad (2)$$

where A is a design matrix representing the connections in the SBAS network. The LOS deformation velocity V_{LOS} can be obtained via least squares or singular value decomposition method with minimum norm conditions⁶⁷.

InSAR method measures the relative land displacements referring to a specific pixel or area within the extent of the image. Following the guidelines about reference selection addressed in ref. 23, we initially

selected a reference pixel with a coherence greater than 0.85, typically located on man-made structures, ensuring that it showed no phase difference compared to the surrounding pixels in the interferograms. We obtained the preliminary displacement velocities from SBAS–InSAR analysis. Subsequently, we refined our criteria for the reference pixel to match the displacement velocity close to the mode value (most frequent values in all pixels) within the extent of the administrative boundary and repeated the SBAS–InSAR analysis to obtain the final displacement results. The effects of the above processing parameters on the velocity are shown in Supplementary Fig. 14 and Supplementary Table 4.

The LOS deformation velocity V_{LOS} was converted to vertical displacement velocity V using the following equation:

$$V = V_{\text{LOS}} / \cos \theta \quad (3)$$

where θ is the radar's incidence angle and varies pixel by pixel. In this study, land velocity follows the convention that positive values indicate uplift, whereas negative values denote subsidence.

Transforming InSAR-derived RLLS to a global reference frame

To align the RLLS derived by InSAR to a global reference frame, we applied an offset correction²⁵ for each city:

$$\|\mathbf{V} + d_v - \mathbf{VLM}\| = 0 \quad (4)$$

where $\mathbf{V}$ represents the RLLS for all pixels within a given city; $\mathbf{VLM}$ represents the published vertical land motion product⁶⁸ interpolated from GNSS observations in the International GNSS Service 2014 reference frame at a spatial resolution of 0.25°; the parameter d_v is the offset and can be calculated as the difference between the mean of VLM and the median of InSAR RLLS for each city. The offset correction parameter applied for each city can be found in Supplementary Table 2.

The VLM field primarily encapsulates long-wavelength signals, such as glacial isostatic adjustment and regional tectonics, which can span thousands of kilometers. Imposing these broad spatial trends onto our InSAR displacements systematically shifted the results, which may even change the sign of the local signal, for instance, transforming a locally measured subsidence (negative value) into an uplift (positive value) in Yokohama, Japan. Consequently, an alignment to the global frame can obscure localized displacements. Because the long-wavelength signals are relatively uniform on the city scale²³, and the city authorities are primarily concerned with RLLS, we retained the original InSAR-derived RLLS results in our spatial and temporal analysis. We present VLM alignment analysis solely to provide insights for other studies focused on spatially continuous displacement mapping at global or near-global scales. Alternatively, users of our products can calibrate the RLLS dataset within their study area using available GNSS observations^{4,7} or prior knowledge of regional tectonics, glacial isostatic adjustment and reference frame adjustments²³.

Accuracy assessment for InSAR-derived RLLS

The three-dimensional GNSS observations have often been used as the benchmark to assess the accuracy of one-dimensional InSAR line-of-sight measurements. However, InSAR measures the relative displacements with respect to a local pixel within the image, whereas GNSS measures the displacements in a specific reference frame, typically defined by the tectonic plate movements, a direct comparison between the two is not appropriate²³. Here we developed a workflow specialized for accuracy assessment of InSAR measurements to best minimize the ambiguity due to different dimensions of measurements and different reference systems (Supplementary Fig. 1).

GNSS observations in the International Terrestrial Reference Frame 2014 were sourced from the Nevada Geodetic Laboratory (<http://geodesy.unr.edu/NGLStationPages/gpsnetmap/GPSNetMap.html>). We sorted out GNSS observations for InSAR accuracy assessment

based on the four requirements. First, GNSS stations outside the city's administrative boundaries were removed. Second, based on the Environmental Systems Research Institute 2020 Global Land Use Land Cover data⁶⁹ and Google Earth imagery, GNSS stations located outside built-up areas were excluded to ensure that InSAR and GNSS observations represent comparable surface deformation processes^{23,70}. Third, GNSS stations with observations shorter than two years spanning Sentinel-1 image acquisitions or presenting evident anomalies were further removed. Fourth, at least two GNSS stations are available to enable an unambiguous pair-comparison. Consequently, a total of 320 GNSS stations in 83 cities were selected for the accuracy assessment (Supplementary Figs. 2–4).

Although in our global scale analysis, the InSAR-derived displacements were projected to the vertical direction, the assessment of InSAR accuracy can be performed with the least bias by projecting three-dimensional GNSS measurements to the one-dimensional InSAR LOS direction by

$$\text{GNSS}_{\text{LOS}} = -\sin\theta\cos\varphi\text{GNSS}_E + \sin\theta\sin\varphi\text{GNSS}_N + \cos\theta\text{GNSS}_U \quad (5)$$

where GNSS_E , GNSS_N and GNSS_U are the east, north and vertical components of the three-dimensional GNSS measurements, respectively, θ is the incidence angle and φ is the heading angle of the SAR satellite measured from the north with clockwise as positive⁷¹, and both angles correspond to the exact values where the GNSS stations are situated.

To eliminate ambiguity due to reference systems, we adopted pairwise comparison for co-located GNSS stations and InSAR pixels. For each city, the GNSS station with the minimal vertical deformation was selected as the reference station (note that the reference here does not mean the one used to interpret InSAR displacements), and we called the other stations as the counterparts. We computed the relative time series difference between the GNSS reference and its counterparts in the projected LOS direction. Similarly, we obtained the relative difference in InSAR LOS time series between pixels co-located with the GNSS reference and its counterparts. Therefore, any citywide systematic shifts in land displacements, if existent, would be canceled out. We conducted the linear regression of two sets of relative time series differences from GNSS and InSAR LOS results. We considered the absolute difference of their linear coefficients as the uncertainties of InSAR measurements. Overall, the comparison between the relative time series displacements of co-located GNSS stations and InSAR pixels was attempted in the same dimension (direction) and time window and in a self-consistent measuring system.

The uncertainty of InSAR against GNSS varies across regions, with the lowest of 0.3 mm yr⁻¹ observed in Africa and the highest of 2.6 mm yr⁻¹ observed in East Asia (Supplementary Fig. 2). On average, the uncertainty among 83 cities with available data is 1.88 mm yr⁻¹ (Supplementary Figs. 3 and 4). Note that the reported uncertainty mainly reflects InSAR performance where GNSS stations are available; validation in some rapidly subsiding regions is inherently limited by data availability.

Additionally, we calculated the standard deviation of the velocity maps:

$$\text{Vel}_{\text{std}} = \sqrt{\frac{\sum_{i=1}^N (d_i - \hat{d}_i)^2}{(N-2) \sum_{i=1}^N (t_i - \bar{t})^2}} \quad (6)$$

where d_i represents the observed range displacement at epoch i , $\hat{d}_i$ is the predicted linear displacement, N denotes the total number of SAR acquisitions, t_i is the time at epoch i and $\bar{t}$ is the average acquisition times $\bar{t} = \sum_{i=1}^N t_i / N$. Vel_{std} represents the standard deviation of the estimated InSAR velocity at a given pixel relative to a reference pixel, primarily caused by temporal noise^{62,72}.

The velocity standard deviation map for each city is available in our website portal 'GUS'. Supplementary Table 2 contains the median velocity standard deviation for each city. For all 465 cities, the 5th percentile, median and 95th percentile of the median velocity standard deviation are 0.13, 0.30 and 0.71 mm yr⁻¹, respectively.

City rankings based on severity of subsidence

To compare and rank the severity of subsidence of the 465 cities, we account for three independent indicators: the median velocity of all pixels within a city (V_m), the 5th percentile velocity of all pixels within a city (V_{5th}) and the proportion of subsiding pixels faster than 10 mm yr⁻¹ (that is, <-10 mm yr⁻¹) (P_{10}). These three indicators reflect different aspects of the severity of subsidence. V_m represents the overall condition of urban subsidence of a city, V_{5th} focuses on the fastest end of subsidence, and P_{10} reflects the proportion of area undergoing rapid subsidence. Consequently, the rankings of cities based on these three indicators differed slightly (Supplementary Table 2).

To obtain a comprehensive assessment of subsidence severity, we calculated a severity score (S) by integrating the three indicators. Let V_i^j be the value of i th indicator of city j , with i ranging from 1 and 3 and j ranging from 1 and 465,

$$S_i^j = \frac{N_i^j}{N} \quad (7)$$

$$S^j = \frac{1}{3} \sum_{i=1}^3 S_i^j \quad (8)$$

where S^j is the final score of city j , S_i^j is the score of city j according to the i th indicator, N_i^j is the number of cities with the value of i th indicator lower than a given threshold and N is the number of cities (465 in our case). Because V_m and V_{5th} signify severe subsidence (negative values), the absolute values of V_m and V_{5th} were used as the threshold when calculating N_i^j . This composite severity score ranges from 0 to 100, with a larger value indicating a more severe subsidence situation.

Acceleration and deceleration of RLLS

To explore the acceleration/deceleration patterns in subsidence rate, we opt to the piecewise linear regression technique. Here we focused on identifying a single change point primarily because the monitoring period is relatively short, spanning approximately nine years (2014–2023). Within such a timeframe, multiple change points could occur; however, minor ones are likely to reflect short-term or seasonal land motions rather than long-term trends persisting across years. In addition, the alignment of InSAR results to a global GNSS reference frame was performed for land subsidence velocity rather than for land subsidence time series. Accordingly, the calculation and analysis of acceleration and deceleration were conducted based on the time series of RLLS.

Piecewise linear regression has proven to be effective in examining temporal changes, especially the change rate of two periods embedded in a time series^{73–75}. Given the dependent variable y (subsidence time series) and the independent variable t (date), a simple linear model is defined as:

$$y = \beta_0 t + b_0 \quad (9)$$

where β_0 and b denote the trend and intercept of the fitted line for the entire period, respectively. $\beta_0 < 0$ indicates a subsiding trend, and $\beta_0 > 0$ indicates an uplifting trend.

Different from the simple linear regression, piecewise linear regression fits separate linear models on both sides of a change point⁷⁶:

$$y = \begin{cases} \beta_1 t + b_1 & t \leq a \\ \beta_2 t + b_2 & t > a \end{cases} \quad (10)$$

where a denotes the time stamp since when the subsidence rate changes, β_1 and b_1 represent the trend and intercept before the time stamp a , respectively, and β_2 and b_2 represent the trend and intercept after the time stamp a , respectively.

To identify the critical time stamp a , we iteratively selected each time stamp in the time series and fit separate linear models before and after that time. For each candidate time stamp, the total residual sum of squares (RSS) for both the pre- and post-change periods was calculated. The candidate time stamp that minimizes the total RSS was identified as the optimal critical time stamp⁷⁶. Due to potential influence of seasonal ground processes, the critical time stamp was not allowed to be in the first and last two years to better capture multi-annual trends.

The temporal change in subsidence rate (accelerating or decelerating) was then determined by comparing the values of β_0 , β_1 and β_2 . When $\beta_0 < 0$ and $\beta_2 > \beta_1$, the subsidence was considered as decelerating. When $\beta_0 < 0$ and $\beta_2 < \beta_1$, the subsidence was considered as accelerating (Supplementary Fig. 11). A Davies test was used to evaluate the significance of the change⁷⁷. Given K fixed ordered values of breakpoints $\psi_1 < \psi_2 < \dots < \psi_K$ and relevant K values of their Wald statistics $S(\psi_1), S(\psi_2) \dots S(\psi_K)$, the P value can be measured as⁷⁸:

$$P = 2\Phi(-M) + 2V_\psi \exp\left(-\frac{M^2}{2}\right)(8\pi)^{-1/2} \quad (11)$$

where $M = \max(S(\psi_1), S(\psi_2) \dots S(\psi_K))$ indicates the maximum of the statistics, Φ indicates the standard normal distribution function and $V_\psi = \sum_k |S(\psi_k) - S(\psi_{k-1})|$ is the total variation of the statistics. We also demand that the linear trends before and after the critical time stamp should also be evident, and only significant acceleration or deceleration at a P level of 0.05 were presented in Fig. 3. Two aspects of acceleration and deceleration of land subsidence were finally quantified at the regional scale: (1) the area proportion (%) of land exhibiting accelerating or decelerating subsidence. For each region, the area proportion of accelerating/decelerating subsidence was calculated as the ratio of all accelerating/decelerating subsiding pixels in this region to the total pixels in this region. (2) The magnitude of acceleration or deceleration, calculated as the median of pixel-level magnitudes, with pixel-level magnitude defined as the absolute difference in linear coefficients (that is, velocity, in mm per year) before and after the critical time stamp a . To provide an integrated measure of the temporal evolution in subsidence, we further derived a WS for each region by multiplying the regional area proportion by the corresponding magnitude. WS was calculated separately for acceleration and for deceleration. Theoretically, it ranges from 0 upward and increases with the strength of subsidence acceleration or deceleration. In our case, the calculations yield maximum median magnitude values of 10.7 mm yr⁻¹ for acceleration and 12.6 mm yr⁻¹ for deceleration. The uncertainty range for regional magnitude was derived from pixel-level magnitudes using the 25th and 75th percentiles and propagated in the calculation of regional WS. The calculations related with piecewise regression were performed using Matlab R2024b⁷⁹, and the significance level test was performed using the Python package ‘piecewise-regression’⁸⁰.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Sentinel-1 SAR images used by this study are publicly available at <https://search.asf.alaska.edu/>. GNSS and VLM data were sourced from the Nevada Geodetic Laboratory website (<http://geodesy.unr.edu/NGLStationPages/gpsnetmap/GPSNetMap.html>). The land subsidence velocities, InSAR coherence, the standard deviation of velocities and geographic locations of reference points for all 465 cities in this study can be visualized via ‘GUS’ (Global Urban Subsidence) at

<https://ee-pkurelab.projects.earthengine.app/view/gus>. The subsidence map for all cities (RLLS and those aligned to a global VLM product) can be downloaded at <https://doi.org/10.24433/CO.7021098.v2> (ref. 81).

Code availability

All Python/Matlab codes used to produce the figures and to calculate the land subsidence from SAR images are publicly available at <https://doi.org/10.24433/CO.7021098.v3> (ref. 81) and <https://github.com/LandSinking/GlobalUrbanSubsidence>.

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Author contributions

S.T. designed the study. Z.A., Xie Hu, L.W., Y.R., S.W., S.T. and J.F. completed the framework of methodology. Xie Hu, Z.A. and Y.R. aligned the RLLS map to a global VLM. L.W., Z.A., Xie Hu, Xiaomei Hu, H.B., K.J., Y. Lin, Y.H., Y.G., T.J. and Z.P. collected and interpreted SAR images. L.W., Z.A., S.T. and Xie Hu led data analysis. G.W., K.Z., J.X., B.X., X.Z., F.Z., J.Z., S.Z., B.Z., Z.W., H.L., Z.T., H.X. and Y. Liu contributed to the analysis and discussion of the results. S.T., L.W. and Z.A. wrote the first manuscript. Xiaomei Hu developed the website ‘GUS’. All authors edited and approved the manuscript.

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Competing interests

The authors declare no competing interests.

Additional information

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Research sample We focused on 465 large cities that have more than one million population.

Sampling strategy We focused on large cities worldwide with populations exceeding one million. We followed the global city list compiled by Frolking et al., which included 477 cities with populations exceeding one million in 2015. Twelve cities were excluded due to insufficient Sentinel-1 SAR imagery, resulting in 465 cities across 107 countries.

Data collection Sentinel-1 SAR images used by this study are publicly available at <https://search.asf.alaska.edu/>. GNSS and VLM data were sourced from the Nevada Geodetic Laboratory website (<http://geodesy.unr.edu/NGLStationPages/gpsnetmap/GPSNetMap.html>).

Timing and spatial scale Timing scale: 2014–2023, with some cities having different temporal coverage due to the lack of SAR imagery during certain periods. Spatial scale: 465 cities across 107 countries worldwide.

Data exclusions Twelve cities were excluded due to the unavailability of sufficient SAR imagery for analysis.

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