URBAN SUBSIDENCE MONITORING IN MEXICO CITY USING SBAS AND PS-INSAR: ANALYSING GROUND DEFORMATION WITH SENTINEL-1 SAR DATA

by

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Abstract

Urban subsidence, largely driven by extensive groundwater extraction, presents significant challenges to infrastructure and urban planning, particularly in rapidly urbanizing regions like Mexico City. This study utilizes Sentinel-1 synthetic aperture radar (SAR) data in conjunction with advanced interferometric techniques—Small Baseline Subset (SBAS) and Persistent Scatterers (PS)—to monitor and analyze subsidence patterns across Mexico City from 2019 to 2024. By integrating these methods, the study provides a detailed understanding of both broad subsidence trends and localized deformations, revealing critical insights into infrastructure vulnerabilities. The analysis identifies specific areas, particularly in Venustiano Carranza and Iztapalapa, where subsidence poses significant risks to buildings and infrastructure, underscoring the importance of targeted mitigation efforts. The study also highlights the potential for future research to incorporate additional data sources, such as high-resolution optical imagery and ground-based GPS measurements, as well as advanced deep learning techniques, to further refine subsidence monitoring and enhance urban planning strategies.

Keywords:

Urban subsidence, Sentinel-1 SAR, SBAS, Persistent Scatterers, Mexico City, ground deformation, infrastructure risk, remote sensing, interferometric techniques, groundwater extraction.

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CHAPTER ONE: INTRODUCTION

1.1. Introduction

Urban subsidence, a phenomenon primarily caused by extensive underground water extraction, poses significant risks to infrastructures and urban planning. Mexico City, one of the largest metropolitan areas globally, has been experiencing continuous subsidence from 2019 to 2024. This subsidence has serious implications for infrastructure stability, urban planning, and environmental management, affecting buildings, roads, and other critical infrastructure. This paper aims to analyze and understand the subsidence patterns in Mexico City using Sentinel-1 synthetic aperture radar (SAR) data. By leveraging advanced interferometric techniques, specifically the Small Baseline Subset (SBAS) and Persistent Scatterers (PS) methods, this study seeks to provide detailed insights, into the spatial and temporal dynamics of subsidence in the region.

1.2. Research Context

The study focuses on Mexico City, which is highly susceptible to subsidence due to factors such as groundwater extraction, natural sediment compaction, and other anthropogenic activities. The city's vulnerability to subsidence makes it an ideal case study for developing and testing improved monitoring and management strategies. The use of Sentinel-1 SAR data offers a cost-effective and comprehensive approach to monitor ground deformation over large areas, providing valuable data for urban planning and risk mitigation efforts.

1.3. Research Questions

The primary objective of this research is to analyze and understand the subsidence patterns in Mexico City using Sentinel-1 SAR data. The research addresses the following questions:

1. How do the SBAS and PS methods compare in their effectiveness for monitoring and quantifying urban subsidence in Mexico City?
2. How can the SBAS and PS methods be used to accurately identify specific buildings and infrastructures that are at the greatest risk due to ongoing subsidence?

By answering these questions, this study aims to provide valuable insights into how subsidence can be managed and mitigated, contributing to more informed urban planning decisions and risk management strategies.

1.4. Area of Interest

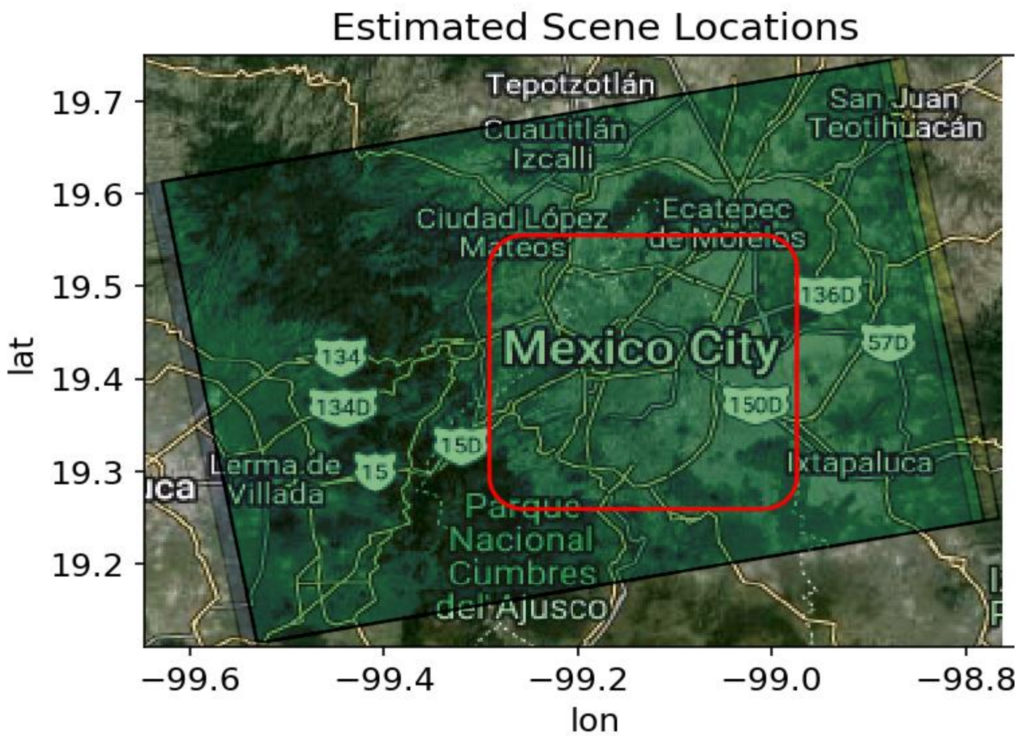

Figure 1: The map displays Mexico City (red box) as the area of interest and the SAR imagery sub-swath (green area) covering the region.

Mexico City, located in the Valley of Mexico, is one of the most populous cities in the world, with nearly 22 million people in its metropolitan area. Sitting at an altitude of nearly 7,350 feet above sea level atop ancient lake beds, the city is highly prone to subsidence. The soft, water-saturated clay soils compress when water is extracted, leading to significant ground deformation.

The rapid urbanization of Mexico City has driven extensive groundwater extraction to meet the water demands of its growing population. This extraction has significantly worsened subsidence, with some areas experiencing ground sinking at rates of up to 20 inches per year, impacting buildings, roads, and other infrastructure.

The study area spans a variety of urban and suburban regions, providing a comprehensive view of how subsidence affects different parts of the city. In the historic center, centuries-old structures like the Metropolitan Cathedral visibly lean due to uneven sinking. Residential and commercial areas face issues like cracked walls and uneven floors, while critical infrastructure such as airport runways and metro lines require frequent and costly repairs.

1.4.1 Point of Interest

The point of interest (POI) for this study is located near the Metropolitan Cathedral in Mexico City, one of Latin America's oldest and largest cathedrals. Construction of the cathedral began over 500 years ago, and it has been experiencing continuous subsidence since then. This issue remains a present-day concern, with visitors frequently reporting feeling the slope within the cathedral. One visitor remarked, "I do feel the slope now," while walking from a side camber to the main entry hall (Sims, 2024). The cathedral's leaning structure is a visible testament to the subsidence issues that plague Mexico City, primarily caused by the excessive groundwater extraction.

1.5. Summary

Urban subsidence in Mexico City is a significant challenge for infrastructure stability and urban planning. The research focuses on leveraging Sentinel-1 SAR data and advanced interferometric techniques to analyze and understand subsidence patterns. The study aims to provide detailed insights into the spatial and temporal dynamics of subsidence, identify at-risk infrastructure, and evaluate the effectiveness of SBAS and PS methods in subsidence monitoring and risk mitigation. The following sections will elaborate further into the methodology, data analysis, results, and implications of this research.

CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction

Land subsidence, a significant and often irreversible deformation of the Earth's surface, poses a critical challenge to the urban and suburban environments worldwide. This phenomenon, which is often accelerated by rapid urban developments and overreliance of groundwater extraction, necessitates advanced monitoring techniques to prevent and mitigate its adverse side effects on infrastructure and human settlements.

The impacts of land subsidence are substantial and complex. In Jakarta, land subsidence has caused extensive damage to infrastructure, increased the frequency of flooding, and complicated the city's drainage system, thereby reducing the quality of life within the city (Abiden et al., 2011). These impacts complicate urban planning and emphasize the need for precise and effective monitoring solutions to ensure sustainable urban living.

Interferometric Synthetic Aperture Radar (InSAR) is critical for precise and accurate monitoring of land subsidence. It provides critical data for urban planners and engineers, aiding in the management of urban growth and environmental sustainability (Abidin et al., 2011). InSAR's high-resolution capabilities makes it an invaluable and effective tool for detecting and analyzing the land surface changes over time.

Deep learning, a branch of machine learning, makes use of artificial neural networks to extract high-level features from data. This will be utilized through the use of Convolutional Neural

Networks (CNNs), a subset of deep-learning, which are neural networks specifically designed to handle image classification and object-recognition tasks, which would aid in the monitoring process by offering accurate urban environment classification (Diakogiannis et al., 2020). This process is essential for enhancing the precision of urban monitoring applications.

The integration of InSAR with deep learning technologies has brought forth significant advancements in the field of subsidence monitoring. Utilizing the U-Net architecture, a proven model in the realm of semantic segmentation aides in this integration. U-Net is renowned for its efficient analysis of spatial hierarchies in images, which is pivotal for more detailed and accurate delineation of the urban land deformation. This model simplifies the segmentation process by focussing on relevant features without the need for extensive preprocessing, thereby improving the accuracy of subsidence detection and analysis (Ronneberger, Fischer, & Brox, 2015). Leveraging U-Net in conjunction with InSAR data offers urban planners a powerful tool capable of interpreting complex urban dynamics, essential for proactive planning and effective disaster management.

2.2. Understanding Urban Subsidence

Urban subsidence remains a persistent issue in densely populated cities worldwide, significantly influenced by the overexploitation of groundwater resources. This phenomenon is exemplified in Mexico City, where over-extraction of groundwater since the early 20th century led the city into severe geological and infrastructural challenges. According to Ortega-Guerrero et al., (1999), the extensive pumping activities, especially within the urban core during the 1930's, resulted in the depressurization and consolidation of aquitards, resulting in pronounced land subsidence in various locations within the downtown areas.

This problem is not only confined to Mexico City but is also a common challenge amongst other major cities such as Bangkok, Houston, Osaka, Tokyo, Jakarta, where similar patterns of groundwater extraction has led to substantial land subsidence. For instance, the rapid population growth in Bangkok between 1958 to 1983 has resulted in a greater demand for groundwater, resulting in subsidence that often exceeded 1 meter, thereby exacerbating risks of flooding due to the city's lower elevation (Holzer & Johnson, 1985). Similarly, Houston and Jakarta have seen significant economic and infrastructural damages as a result of subsidence, increasing their vulnerability to floods and storm surges. In Jakarta, subsidence rates vary from 1-15 cm per year, with some locations experiencing rates up to 25-28 cm per year, leading to severe structural damages and expanded flooding zones (Abidin et al., 2011).

2.3. InSAR Technology in Urban Subsidence Monitoring

Interferometric Synthetic Aperture Radar (InSAR) is a pivotal technology that is crucial in the realm of subsidence monitoring, capitalizing on the advanced capabilities of SAR systems that emit and capture electromagnetic waves, thereby producing high-resolution spatial imagery onto the Earth's surface. The crux of InSAR lies in its ability to precisely measure the phase of return signals from consecutive satellite acquisitions which are termed the master and slave acquisitions, allowing for the detections of quick minute ground displacements with high accuracy (Osmanoğlu et al., 2016).

The applications of InSAR in urban settings are profoundly enhanced by its high temporal resolution and sensitivity to various subsurface conditions, including topography, ground motion, and atmospheric variations. This sensitivity is particularly advantageous in densely populated urban areas where the precise monitoring of land subsidence is crucial for infrastructure safety and urban planning. Moreover, InSAR's ability to conduct time-series analyses provides an essential tool for continued monitoring and evaluation of surface displacement, which is critical for assessing the risk and progression of subsidence over time (Osmanoğlu et al., 2016).

In terms of practical advantages, InSAR stands out for its cost-effectiveness and extensive area coverage compared to traditional ground-based monitoring methods. This makes it a viable option for accessing and assessing remote or hazardous areas without the logistical and financial burdens typically associated with ground surveys. The technology's high resolution and accuracy are paramount for applications like monitoring urban subsidence, where the detection of subtle ground movements can prevent substantial economic losses and enhance disaster preparedness (Kim et al., 2019).

Persistent Scatterer InSAR (PS-InSAR) and Small Baseline Subset (SBAS) are two specialized techniques under the InSAR methodology tailored for urban applications. PS-InSAR utilizes persistent scatterers within the urban fabric, which are abundant due to the constructed environment, thereby providing continuous, reliable data for subsidence analysis. This method achieves remarkable precision in DEM generation and surface motion measurement, making it particularly effective for urban settings (Osmanoğlu et al., 2016). Conversely, SBAS offers flexibility and adaptability in processing, capable of handling deformation analysis with adjustable baseline parameters and sophisticated atmospheric filtering, which are essential for maintaining data integrity in complex urban landscapes (Osmanoğlu et al., 2016).

Case Study: Monitoring of Mexico City's Metro System

A compelling illustration of InSAR's application in urban subsidence monitoring is the study conducted by Solano-Rojas et al. (2024), which assessed the geohazard of land subsidence on Mexico City's Metro system. Using a combination of C- and X-band satellite SAR data, the study identified critical areas where differential subsidence had caused significant infrastructural damage, including track deformations, structural collapses, and slope changes. These findings emphasize the direct impact of subsidence on urban infrastructure, leading to reduced operational performance, service interruptions, and increased risk of accidents. The ability of InSAR to provide detailed, time-sensitive data across large urban areas was crucial in pinpointing high-risk zones and informing subsequent repair and monitoring strategies.

2.4. Deep Learning and Semantic Segmentation in Remote Sensing

Deep learning has revolutionized the field of remote sensing by introducing state-of-the-art techniques for semantic segmentation, where the goal is to accurately segment an image based on the semantic information, enabling the prediction of the semantic category of each pixel within a given label set (Mo et al., 2022). This technique is pivotal in remote sensing applications, as it enables for detailed, pixel-level analysis of vast and complex datasets that traditional methods cannot efficiently process.

Semantic segmentation's utility in remote sensing is emphasized by its ability to enhance the accuracy and efficiency of environmental monitoring, urban planning, and disaster management. The advent of convolutional neural networks (CNNs) marked a significant departure from earlier methods like random forests and conditional random fields, offering drastic improvements in processing speed and predictive accuracy. Notably, the introduction of the Fully Convolutional Network (FCN) by Long et al. represented a paradigm shift, achieving a 20% performance enhancement on benchmark datasets such as Pascal VOC 2012 by enabling end-to-end training of segmentation models (Mo et al., 2022).

Further innovations in semantic segmentation have been driven by models like U-Net, initially proposed by Ronneberger, Fischer, & Brox, (2015) for biomedical imaging. U-Net's architecture uniquely combines a context path to learn contextual information and a spatial path to preserve spatial detail, making it exceptionally effective for high-resolution image segmentation tasks in remote sensing (Mo et al., 2022).

The application of these advanced deep learning frameworks are exemplified through various case studies, demonstrating their utility in addressing urban and environmental issues. In one instance, the M-UNet model, a modified version of the U-Net framework, has been particularly tailored for high-precision segmentation of satellite imagery. This model, as specified by Soni et al. 2020, relies on Fully Convolutional Network (FCN)-based architecture to enhance the resolution of the outputted images through upsampling operations (which is the operation to increase the spatial resolution while maintaining the same two-dimensional (2D) format. This allows for better propagation of information to higher resolution layers, thus creating a symmetric expansion in the network that mirrors the contraction part. The result is a symmetric U-structure that significantly improves the precision of segmentation results, even with limiting training data, which is particularly beneficial in applications involving detailed mapping of urban landscapes or environmental monitoring.

These advancements in deep learning exemplify the transformative potential in remote sensing, particularly through the application of semantic segmentation to managing complex urban and environmental challenges more effectively. These advancements not only enhance the ability to monitor and analyze urban changes but can also play a crucial role in disaster management and mitigation, urban planning and conservational efforts.

2.5. Integration of InSAR and Deep Learning

The integration of Interferometric Synthetic Aperture Radar (InSAR) with deep learning techniques is revolutionizing the field of remote sensing by enhancing the accuracy and efficiency of data analysis. Recent studies have explored various methodologies, demonstrating significant advancements in both theoretical frameworks and practical applications.

Agrawal et al. (2022), use Long Short-Term Memory (LSTM) networks with InSAR data to effectively handle the temporal variations inherent in SAR interferograms. This integration has proven particularly effective in regions like Central and East Java, Indonesia, reducing mean absolute percentage errors in displacement predictions to around 2%. Such advancements emphasize the capability of deep learning models to enhance the precision of geospatial analyses in seismically active regions (Agrawal et al., 2022).

Deep learning, especially LSTM architectures, offers new avenues for analyzing time-series data from InSAR, enabling more accurate predictions of crustal deformations. This approach not only enhances the accuracy but also improves the handling of large data volumes, which are typical in areas prone to seismic activities (Agrawal et al., 2022).

The Fully Complex-Valued Fully Convolutional Multi-Feature Fusion Network (FC2MFN) introduced by Sikdar et al. (2022), addresses the challenges of building segmentation in SAR images. By leveraging complex-valued convolutional and multi-feature fusion approaches, this methodology significantly enhances segmentation performance, providing superior results compared to other advanced networks. This novel approach is pivotal for urban area analysis, utilizing the intricate data properties of InSAR such as phase information and scattering characteristics, optimizing the utilization of these data traits in deep learning frameworks (Sikdar et al., 2022).

Another notable study by Rouet-Leduc et al. (2021) describes an autonomous system that extracts millimeter-scale deformation signals from noisy InSAR time series without prior knowledge of fault locations or behaviors. Their convolutional autoencoder architecture is specifically tailored for InSAR data, allowing for effective noise differentiation and signal clarity. This innovation significantly improves the reliability of interpreting subtle ground deformations obscured by atmospheric noise. Applied to the North Anatolian Fault and the Coso geothermal field, their model demonstrated robustness across different geophysical contexts, successfully identifying and quantifying slow-slip events and geothermal-induced deformations with minimal user intervention. This approach has not only enhanced the detection sensitivity down to 2 mm but has also revealed larger extents of slow earthquakes than previously recognized (Rouet-Leduc et al., 2021).

2.6. Decision to Focus on OpenStreetMap Data for Building Analysis

While deep learning presents a valuable opportunity for future subsidence monitoring, the current study opted to focus on a more practical approach: using OpenStreetMap building polygons for Mexico City. This dataset contains crucial information on building footprints and types, which can be spatially intersected with ground deformation maps derived from InSAR analysis.

This approach allows for the identification of buildings at risk of subsidence or uplift and provides actionable insights for urban planners and engineers without the need for complex neural network models. Given the study's time constraints, this method proved to be more feasible for assessing the subsidence impacts on infrastructure in Mexico City (OpenStreetMap contributors, 2024).

2.7. Implications for Mexico City

Mexico City's unique geology significantly impacts its subsidence monitoring and urban planning strategies. Built on an ancient lakebed, the city is particularly susceptible to subsidence due to the soft, water-laden sediments beneath it. This geological characteristic exacerbates the challenges faced in urban planning and infrastructure stability.

The extensive extraction of groundwater has historically led to significant land subsidence in Mexico City. This process, detailed in studies like Holzer & Johnson (1985), involves the compaction of fine-grained sediments that form a major part of the aquifer systems beneath the city. Over-consolidation of these sediments results in largely irreversible subsidence, complicating the urban infrastructure's stability and longevity.

Moreover, the integration of InSAR and Landsat data, as explored by Poreh et al. (2021), highlights how accelerated subsidence rates correlate highly with urban density, demonstrating the gravity of subsidence impacts in densely populated areas. Their findings suggest that “the fastest subsidence zones in Mexico City occur in areas with high and moderate building distribution density,” illustrating the direct relationship between urban development and increased subsidence risk.

In this context, the use of OpenStreetMap building data, which provides essential details on building footprints and types, allows for more precise analysis of how different structures are affected by subsidence. This approach enables urban planners to focus on specific buildings and areas most at risk.

Policies and urban planning must adapt to the ongoing challenge of subsidence. The incorporation of remote sensing data, such as that from the InSAR and CGPS methods described by Poreh et al. (2021), offers critical insights into the spatial distribution and intensity of subsidence, which can inform better urban planning decisions. These technologies, alongside building-level data, allow for precise monitoring of subsidence, facilitating timely interventions to mitigate risk.

Enhanced subsidence data, combined with detailed building information, could lead to significant improvements in urban planning and risk management. For instance, areas identified with rapid subsidence rates could be prioritized for intervention, potentially involving restrictions on groundwater extraction or the reinforcement of existing structures to withstand subsidence impacts.

CHAPTER THREE: DATA AND METHODS

3.1. Introduction

This section outlines the data and methodologies employed to analyze ground deformation in Mexico City using advanced interferometric techniques. The analysis primarily utilizes Sentinel-1 synthetic aperture radar (SAR) imagery, which is well-suited for detecting and monitoring surface deformations over time. The preprocessing steps necessary to ensure data accuracy are detailed, followed by a comprehensive explanation of the methods used—namely, the Small Baseline Subset (SBAS) technique and Persistent Scatter Interferometry (PS-InSAR).

In addition to Sentinel-1 SAR data, this study incorporates the OpenStreetMap buildings dataset for Mexico City, which contains polygons of buildings along with their types. This dataset is critical for analyzing how different building types are affected by ground deformation across the city (OpenStreetMap contributors, 2024).

A key tool utilized in this analysis is PyGMTSAR, a Python-based implementation and wrapper for the GMTSAR package. PyGMTSAR integrates the powerful geodetic processing capabilities of GMTSAR with the flexibility of Python, allowing for more interactive and automated workflows in InSAR analysis. GMTSAR, developed by the Scripps Institution of Oceanography, is widely recognized for its ability to process radar data into displacement maps, providing insights into surface changes due to various geophysical processes (Sandwell et al., 2011). PyGMTSAR extends these capabilities, enabling efficient and detailed analysis of SAR data within Python environments, which is crucial for the subsequent application of SBAS and PS-InSAR methods. These methodologies and tools are crucial in detecting and analyzing subtle surface deformations across Mexico City, contributing to valuable insights into the city's subsidence patterns and their impact on infrastructure (Pechnikov, 2024).

3.2. Data

3.2.1. Data Collection

For this study, Sentinel-1 synthetic aperture radar (SAR) imagery was obtained using the ASF (Alaska Satellite Facility) Python library, which archives SAR data from the Sentinel-1 mission since its launch (ASF, 2024). This library allows for efficient querying, filtering, and downloading of SAR imagery directly from the ASF's archive. The first step involves defining the area of interest (AOI) to focus on the specific location under observation. In this study, the AOI encompasses the entire Mexico City over the past 5 years. Additionally, a specific point of interest within the city is identified to analyze subsidence or uplift using various machine learning models and methods.

To complement the SAR data, the OpenStreetMap buildings dataset for Mexico City is employed. This dataset contains building polygons and building type classifications, which are vital for assessing how ground deformation affects various types of infrastructure in the city (OpenStreetMap contributors, 2024).

Given that the temporal resolution for Sentinel-1A is 12 days, a total of 156 Sentinel-1A images were used, spanning the five-year period. To maintain consistency in the quality of imagery, only ascending images were collected for this study. The S1 (Sentinel-1) Python library is also utilized to obtain orbit and DEM (Digital Elevation Model) files, ensuring the accuracy and precision of the images used during the preprocessing stage.

3.3. Data Preprocessing

To ensure the integrity and accuracy of the interferometric analysis, a series of preprocessing steps were undertaken. The flowchart in Figure 2 outlines the entire preprocessing workflow, from initial data acquisition to the preparation of interferograms for deformation analysis.

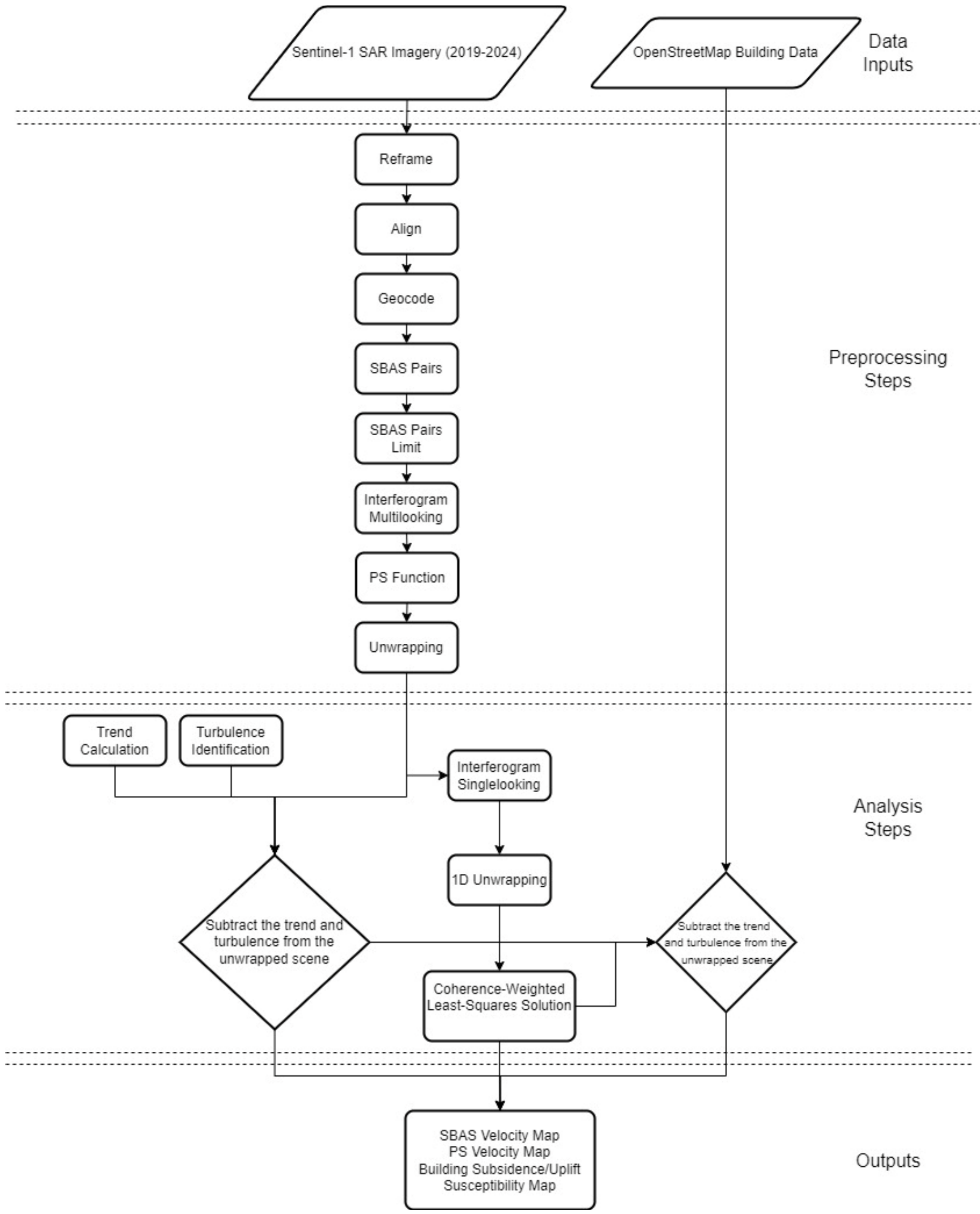

Figure 2: InSAR Methodology Workflow

3.3.1. Reframing of Scenes

The first step in the preprocessing workflow, as observed in Figure 2, involves reframing the SAR scenes around the Area of Interest (AOI). This process includes cropping out unused bursts, which are small sections of the subswath, to focus exclusively on the AOI. This approach optimizes computational efficiency and resource usage, ensuring that the analysis is concentrated on the relevant geographical area.

```
# Reframe scenes around the AOI
reframed_scenes = sbas.compute_reframe(AOI)
```

3.3.2. Geometric Alignment and Coregistration

Subsequent to reframing, the 'compute_align' function is employed to geometrically align and coregister the SAR scenes. Coregistration is a critical step that ensures all scenes are accurately aligned to a common reference frame, maintaining the precision required for consistent interferometric measurements.

```
# Align and coregister scenes
aligned_scenes = sbas.compute_align(reframed_scenes)
```

3.3.3. Geocoding of Scenes

The geocoding process transforms the radar coordinates into geographical coordinates, specifically latitude and longitude. This transformation is crucial for making the data more intuitive and applicable for visualization and further analysis.

```
# Geocode scenes
geocoded_scenes = sbas.compute_geocode(aligned_scenes)
```

3.3.4. Creation of Baseline Pairs

For interferogram generation, images from different acquisition times must be paired. The 'sbas_pairs' function is used to create these baseline pairs, with specific temporal and spatial baseline parameters set to ensure the optimal pairing of images for interferometric analysis.

In this study, the SBAS pairs are formed by pairing each SAR image with others based on two key criteria: temporal and spatial baseline distances. These parameters are chosen to optimize coherence and minimize atmospheric effects:

- max_temp_baseline=50: This parameter ensures that only SAR image pairs taken within 50 days of each other are used. Limiting the temporal difference between images helps maintain high coherence, reducing the likelihood of changes on the ground that could negatively impact the analysis.
- max_spatial_baseline=150: This setting restricts the spatial difference between the satellite positions to less than 150 meters. By keeping the spatial baseline small, this ensures that geometric distortions becomes minimized, resulting in more accurate interferometric analysis and better quality displacement measurements.

These constraints ensure that the image pairs used in interferometric analysis maintain high coherence and minimize the introduction of noise and errors caused by temporal and spatial changes, ultimately providing more reliable and accurate ground deformation measurements.

```
# Create baseline pairs
baseline_pairs = sbas.sbas_pairs(geocoded_scenes,
max_temp_baseline=50, max_spatial_baseline=150)
```

3.3.5. Compute Persistent Scatterers

Using the 'compute_ps' function in the PyGMTSAR library, this function is responsible for providing Persistent Scatterers (PS) analysis within the Small Baseline Subset (SBAS) framework. It achieves this by analyzing the temporal stability of scatterers and using amplitude dispersion index (ADI) or coherence measures to identify persistent scatterers. The identification of persistent scatterers is crucial as it enhances the robustness and accuracy of the subsequent interferometric analysis. Persistent scatterers, typically man-made structures like buildings and bridges, maintain high coherence over time, providing reliable points for detailed displacement measurements (Pechnikov, 2024)

```
# Use the selected dates for the pixels stability analysis
Ps = sbas.compute_ps()
```

3.3.6. Multilooking for Noise Reduction

The next preprocessing step involves applying multilooking to the interferograms. This process reduces speckle noise and enhances both the quality and resolution of the interferograms by averaging the noise over multiple sub-images, which is essential for accurate subsequent analysis.

```
# Apply multilooking
Multilooked_interferograms =
sbas.compute_interferogram_multilook(baseline_pairs,
psfunction=True)
```

3.3.7. Unwrapping for Phase Continuity

The final step in the preprocessing workflow involves unwrapping the interferograms' phase values. Interferometric phase measurements produce wrapped phases constrained within the range of $-\pi$ to π due to the radar signal processing. The unwrapping process removes these 2π ambiguities, resulting in a continuous phase distribution. This unwrapped phase provides a clearer view of surface deformation over time, which is essential for qualitative and quantitative analysis.

To achieve this, we apply the SNAPHU algorithm (Statistical-Cost Network-Flow Algorithm for Phase Unwrapping) using the 'sbas.unwrap_snaphu(intf_sbas, corr_sbas)' function. This algorithm works by minimizing a cost function that balances the smoothness of the unwrapped phase with the need to preserve significant phase discontinuities that reflect actual surface deformation (Chen & Zebker, 2000). By incorporating the correlation plot (corr_sbas), the algorithm distinguishes between noise and real phase changes, enhancing the accuracy of the unwrapping process.

```
# Unwrap the interferograms using the correlation mapping
intf_sbas = intf_sbas.sel(pair=baseline_pairs_best.pair.values)
corr_sbas = corr_sbas.sel(pair=baseline_pairs_best.pair.values)
unwrap_sbas = sbas.unwrap_snaphu(intf_sbas, corr_sbas)
```

The result is a continuous phase map, crucial for further analysis in both SBAS and PS (Persistent Scatterers) techniques, as it allows us to assess ground deformation with high precision. This phase map retains the true signal of ground displacement while minimizing the impact of noise and atmospheric disturbances, leading to a coherent and interpretable distribution that accurately reflects the Earth's surface deformation. In SBAS, the unwrapped phase is essential for identifying broad deformation trends, while in PS analysis, it provides high-precision measurements at stable, reflective points over time.

This comprehensive preprocessing workflow produces high-quality, accurately geocoded interferograms and unwrapped phase maps. These outputs serve as a robust foundation for both SBAS and PS analysis, enabling precise detection of ground deformation patterns, including subsidence and uplift, across Mexico City throughout the study period. This combined approach allows for a thorough understanding of both large-scale surface movements and localized, high-precision displacement measurements.

3.4. Methods

3.4.1. Method 1: Small Baseline Subset (SBAS)

In SBAS analysis, the primary objective is to extract the true ground deformation signal from the interferometric data. This process involves two critical steps to ensure the accuracy and reliability of the deformation measurements.

3.4.1.1. Trend Calculation and Subtraction.

In this step, a linear model is fitted to the unwrapped phase time series to capture the long-term deformation signal over the 5-year observational period. This trend represents the cumulative deformation, such as subsidence or uplift, driven by ongoing processes like tectonic activity or urban development. By applying a linear regression model to the unwrapped phase values, the overall linear deformation trend is identified. This trend is extracted from the data by using the ‘sbas.regression()’ function, which applies the regression to the unwrapped phase values (unwrap_sbas.phase) against a set of variables that include topographic data (topo), spatial coordinates (yy, xx), and the radar incidence angle (inc). These variables are critical for accurately modeling surface deformation. The correlation data (corr_sbas) is also used in the regression to weight the calculation, ensuring areas with higher reliability contribute more to the model.

To avoid overfitting, especially in smaller areas, a decimation process is applied using the ‘sbas.decimator()’ function, which reduces the data resolution. This decimation ensures that only a limited set of variables is used in the regression, preventing the model from becoming overly complex. Once the linear trend is fitted, the function ‘sbas.sync_cube()’ is used to synchronize the calculated trend with the data cube, aligning it with other datasets for further analysis.
After the long-term trend is calculated and synchronized, it is subtracted from the unwrapped phase data, isolating the short-term and residual phase variations. These residuals include non-linear deformation components, such as seasonal fluctuations and specific events like underground water extraction or other anomalies in surface deformation. By removing the long-term trend, the analysis focuses on the dynamic, short-term deformation signals that are crucial for understanding localized phenomena and changes in surface deformation patterns. This step is essential for identifying deformation behaviors that may not be evident in the overall trend, providing deeper insights into specific events.

```
# use limited set of fitting variables to avoid overfitting in
```

```
# small areas
decimator = sbas.decimator(resolution=15, grid=(1,1))
topo = decimator(sbas.get_topo())
# get topography data
inc = decimator(sbas.incidence_angle())
# get incidence angle yy,
xx = xr.broadcast(topo.y, topo.x)
# create broadcasted grids of coordinates
trend_sbas = sbas.regression(unwrap_sbas.phase, [topo, topo*yy,
topo*xx, topo*yy*xx, yy, xx, inc], corr_sbas)
# perform regression
# synchronize the calculated trend trend_sbas =
sbas.sync_cube(trend_sbas, 'trend_sbas')
```

This code illustrates the decimation process to prevent overfitting, followed by the use of the 'sbas.regression()' function to compute the trend and 'sbas.sync_cube()' to align the trend data with the rest of the dataset. The subtraction of this trend then allows for a focused analysis of the residual, non-linear deformations that may reveal specific ground movements or anomalies.

3.4.1.2. Turbo Identification and Mitigation

The final step in the SBAS analysis is Turbo Identification and Mitigation. "Turbo" refers to the residual phase variations that remain after the long-term trend has been removed from the unwrapped phase data. These residuals are primarily influenced by atmospheric turbulence and other short-term atmospheric effects. Once the long-term trend is subtracted, the remaining phase variations, known as turbo, are identified and analyzed to determine the extent of atmospheric noise present in the data. This is crucial because these variations can obscure the true deformation signals, leading to inaccuracies if left unaddressed.

To mitigate the impact of these atmospheric disturbances, various techniques, such as filtering and correction algorithms, are applied. The `sbas.polyfit()` function is employed to model and reduce the turbo effect by fitting a polynomial to the residual phase variations. This process effectively smooths out the noise, making the final deformation measurements more accurate and less influenced by atmospheric disturbances.

In the provided code:

```
turbo_sbas = sbas.polyfit(unwrap_sbas.phase - trend_sbas,
corr_sbas)
turbo_sbas
```

The `sbas.polyfit()` function is used to fit a polynomial to the residual phase data (obtained by subtracting the long-term trend, `trend_sbas`, from the unwrapped phase data, `unwrap_sbas.phase`). The correlation data (`corr_sbas`) is also used in this fitting process to ensure that areas with higher reliability are weighted more heavily. The result, stored in `turbo_sbas`, represents the mitigated phase variations, where the influence of atmospheric turbulence has been reduced.

This step is vital for enhancing the clarity and accuracy of the final deformation measurements by minimizing the impact of atmospheric noise, ensuring that the detected deformation patterns reflect actual ground movements rather than artifacts caused by atmospheric conditions.

This results in a SBAS imagery that is more refined and is an accurate representation of ground deformation. This imagery highlights the true deformation patterns by effectively removing the long-term linear deformation trend and minimizing atmospheric noise. The final SBAS imagery clearly delineates areas of subsidence, uplift, and other deformation phenomena with high precision. This improved clarity allows for better interpretation and analysis of the deformation patterns, enabling more accurate monitoring and assessment of ground movements over time. In the case of Mexico City, the refined imagery can provide crucial insights into subsidence caused by underground water extraction, helping to inform mitigation strategies and urban planning efforts.

3.4.2. Method 2: Persistent Scatterer Interferometry (PS-InSAR)

In the Persistent Scatterer Interferometry (PS-InSAR) analysis, the primary objective is to identify and extract persistent scatterers within the radar images. Persistent scatterers are points on the ground that consistently reflect radar signals back to the satellite, maintaining high coherence over time. These typically include man-made structures such as buildings, bridges, and other infrastructure.

The analysis begins with the creation of interferograms using singlelooking, which involves averaging the radar signal in one direction to improve the signal-to-noise ratio while maintaining spatial resolution in the other direction. This process is crucial for identifying stable scatterers in urban environments where high coherence is expected.

```
sbas.compute_interferogram_singlelook(baseline_pairs_best,
'intf_slook', wavelength=30, weight=sbas.psfunction(),
phase=trend_sbas+turbo_sbas)
```

Next, the interferometric phase data undergoes 1D phase unwrapping, which is different from the 2D unwrapping performed earlier during preprocessing. The initial unwrapping is applied in two dimensions (2D) across the entire scene, whereas 1D unwrapping is specifically focused on unwrapping along the temporal dimension for each identified persistent scatterer. This step improves the accuracy of displacement measurements at these points by minimizing errors associated with phase ambiguities along this single dimension.

```
1dUnwrap = sbas.unwrap1d(intf_ps, corr_ps)
```

Finally, the Least-Squares (lstsq) function is used to compute the best-fit solution for the unwrapped phase data, weighted by the correlation values. This step provides precise surface displacement measurements at the identified persistent scatterer points, which are then visualized in displacement maps.

```
lstsq = sbas.lstsq(1dUnwrap, corr_ps)
```

These displacement maps, generated through PS-InSAR, provide detailed and accurate measurements of ground deformation over time, highlighting stable scatterer locations with high temporal coherence. This allows for the identification of subtle and significant surface movements in areas with reliable scatterers.

3.4.3. Spatial Intersection with Building Data

After completing both the SBAS and PS-InSAR analyses, the final step involves spatially intersecting the velocity maps generated by each method with the OpenStreetMap building data for Mexico City. This step is performed using ArcGIS Pro to integrate ground displacement results with the city's building footprint data. The building dataset, which includes polygons and building types, is overlaid onto the velocity maps to determine how subsidence or uplift affects different structures across the city.

By intersecting the velocity maps with the building data, we can generate a detailed map that highlights the buildings in Mexico City that experience varying levels of subsidence or uplift. This spatial analysis allows us to assess which areas and specific buildings are more prone to ground deformation, providing critical insights for urban planning and infrastructure management. Buildings that are experiencing higher levels of subsidence or uplift are identified as being at greater risk, enabling city officials and planners to prioritize areas that may require reinforcement or mitigation efforts.

3.5. Summary

This section has provided an in-depth explanation of the data and methods utilized to monitor and analyze ground deformation in Mexico City. Sentinel-1 SAR imagery, chosen for its availability and compatibility with the employed Python libraries, served as the primary data source. Additionally, the OpenStreetMap buildings dataset was incorporated to assess how different types of infrastructure are affected by subsidence and uplift across the city.

The preprocessing steps—including reframing, coregistration, geocoding, and noise reduction—were essential for preparing the data for interferometric analysis. Two key preprocessing steps, phase unwrapping and the identification of Persistent Scatterers (PS), were also performed. The unwrapping of the interferometric phase was critical to convert the radar signal's wrapped phase values into a continuous phase distribution for accurate deformation analysis. The identification of Persistent Scatterers ensured reliable points for further analysis, enhancing the accuracy of both SBAS and PS methods.

The Small Baseline Subset (SBAS) method focused on detecting broad deformation patterns by calculating and subtracting long-term trends and mitigating atmospheric noise. The Persistent Scatterer Interferometry (PS-InSAR) method concentrated on identifying stable scatterer points to provide high-precision displacement measurements.

Following the SBAS and PS-InSAR analyses, the final stage involved spatially intersecting the velocity maps from both methods with the building data in ArcGIS Pro. This process generated a map identifying which buildings in Mexico City are experiencing subsidence or uplift, highlighting those at greater risk. This integration of geospatial and infrastructure data offers valuable insights into structures most vulnerable to ground deformation, supporting urban planning and risk mitigation efforts.

CHAPTER FOUR: RESULTS

4.1. Introduction

This chapter presents the results of ground deformation analysis using the SBAS and PS methods. Ground displacement maps, comparisons between the methods, and their impact on buildings in Mexico City are analyzed.

4.2. Ground Displacement Maps

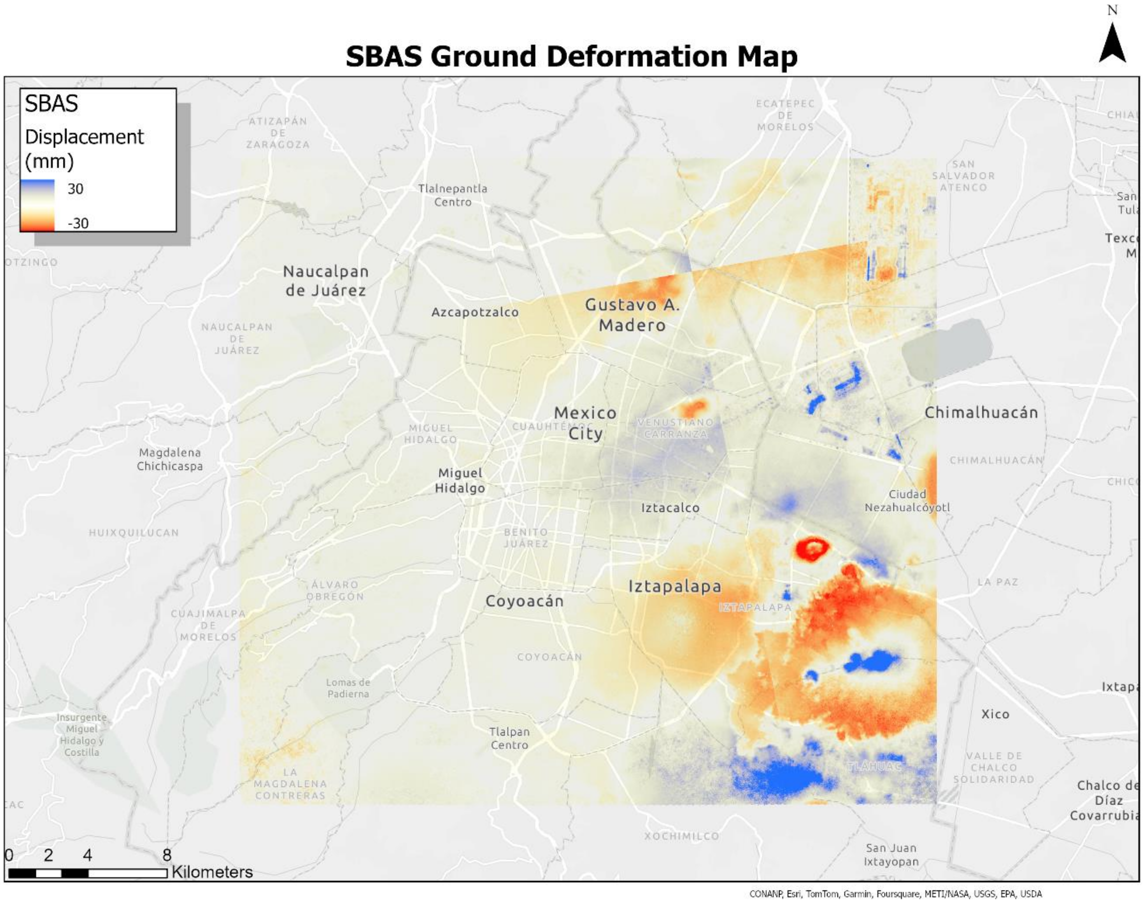

Figure 3: SBAS Ground Displacement Map (mm)

The SBAS ground displacement map (Figure 3) provides a broad view of subsidence and uplift patterns across Mexico City, particularly in the southeast and central regions. SBAS captures large-scale deformation trends over the 5-year period from 2019 to 2024. This map highlights the influence of underground water extraction, especially in densely populated urban areas. The result indicates that subsidence rates are more pronounced in areas with extensive infrastructure, confirming the need for long-term monitoring.

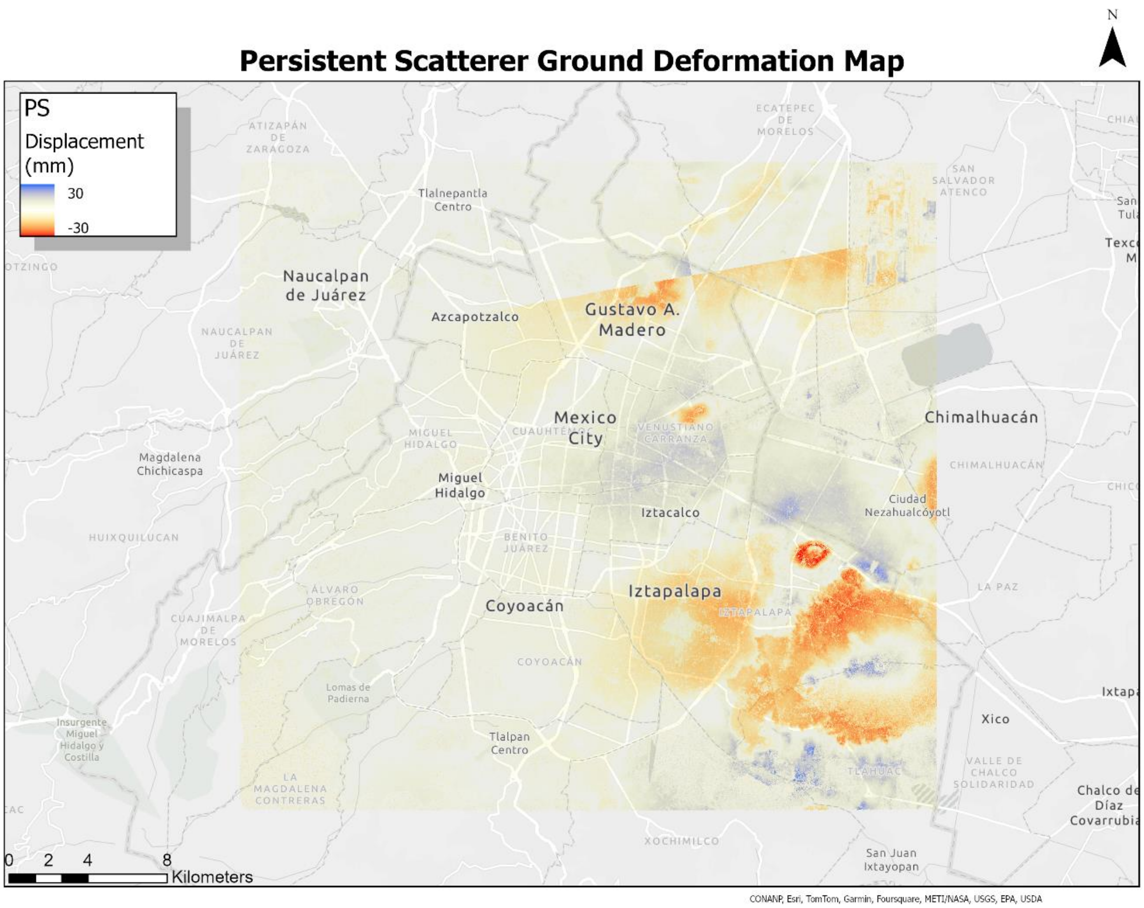

Figure 4: PS Ground Displacement Map (mm)

In Figure 4, the PS ground displacement map offers a more localized perspective, capturing detailed variations in displacement across the city. The PS method is particularly effective in detecting subtle ground deformations in urban areas due to its ability to focus on stable structures such as buildings and bridges. The precision provided by the PS method helps identify areas that SBAS might overlook, ensuring a detailed analysis of subsidence at specific locations.

4.3. Comparisons of SBAS and PS Methods

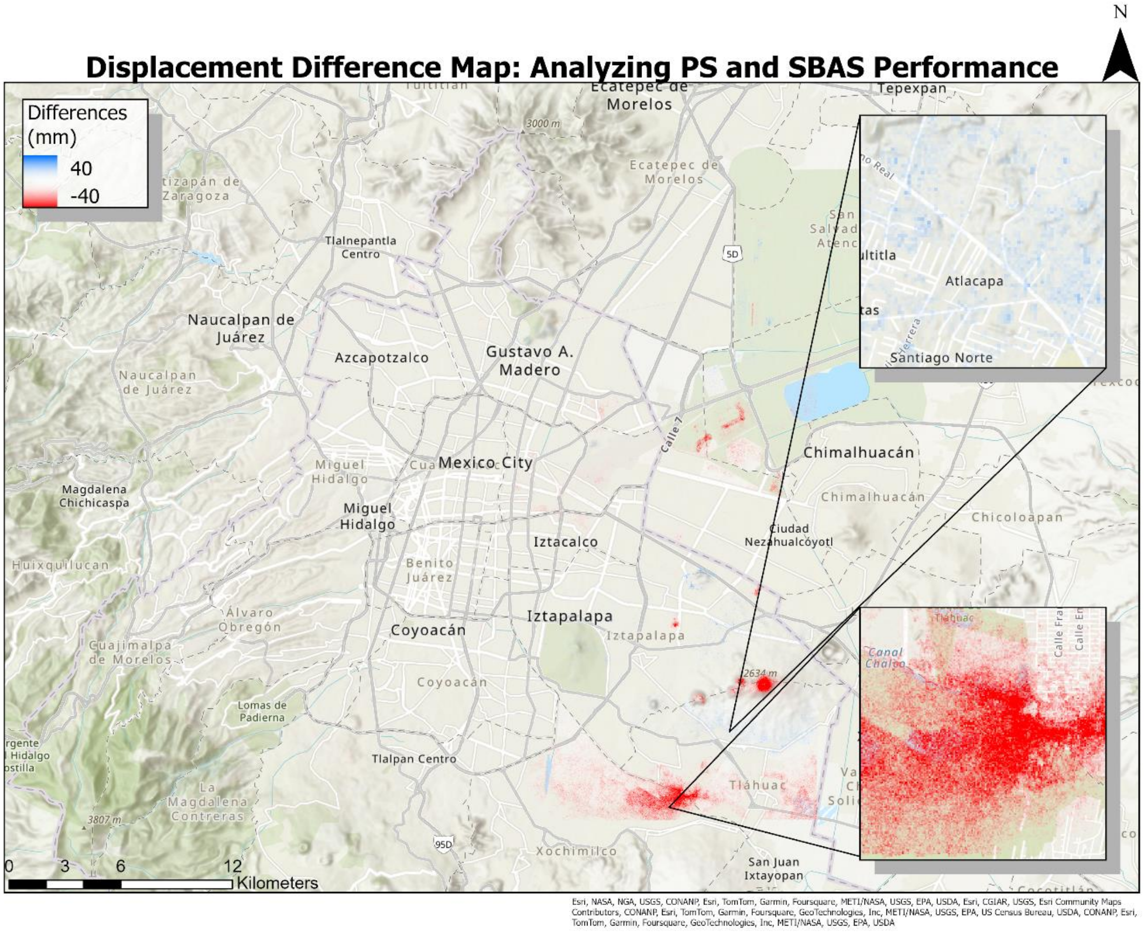

Figure 5: Map Displaying the Difference between the PS and SBAS method velocities

Figure 5 presents the velocity difference between the SBAS and PS methods. Positive values represent areas where SBAS detected more displacement, while negative values show where PS identified greater movement. The results highlight how SBAS captures distributed displacements across larger areas, particularly in vegetated regions, while PS excels at detecting precise, localized displacements in urban zones. These complimentary strengths provide a fuller picture of ground deformation patterns across the city.

4.4. Distribution and Impact on Buildings

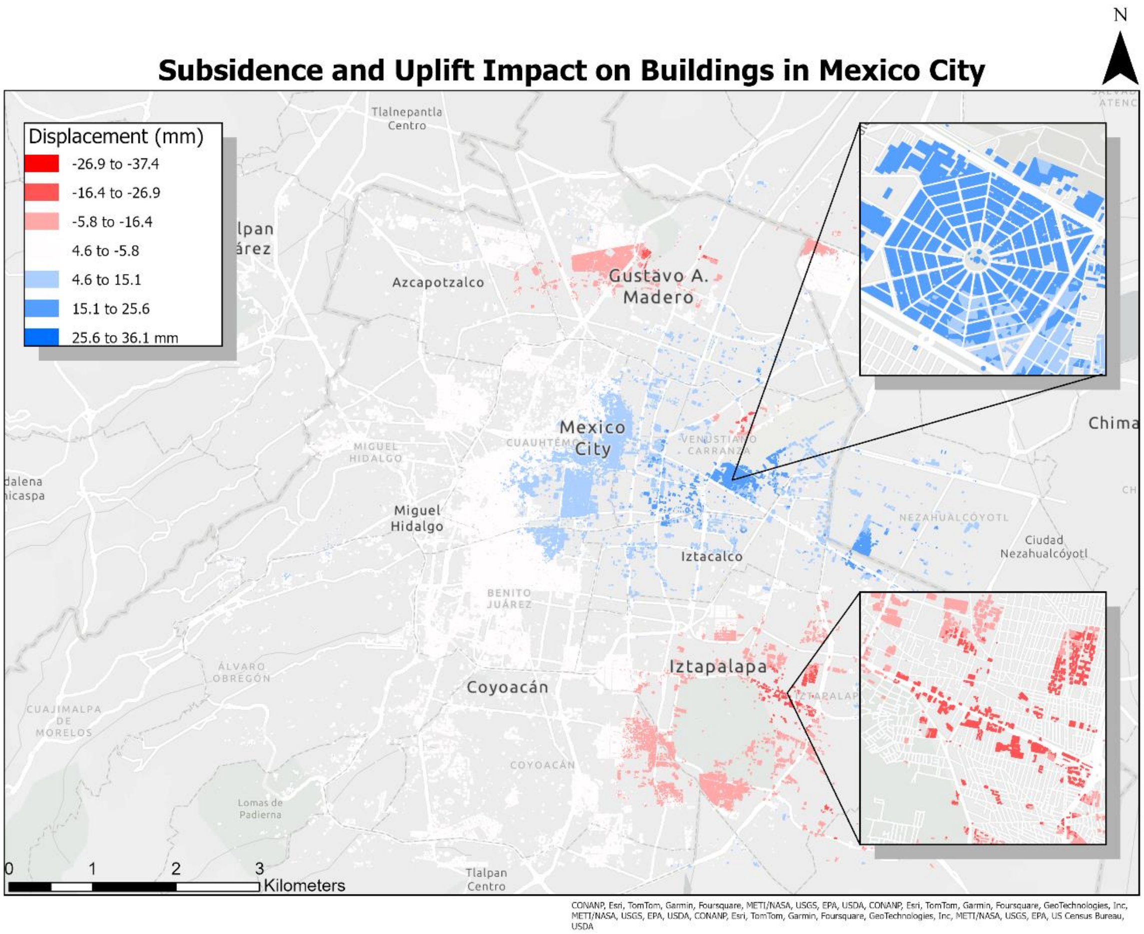

Figure 6: Map displaying buildings facing subsidence/uplifting to varying degrees

Figure 6 visualizes the buildings in Mexico City affected by varying levels of subsidence and uplift, identified by intersecting the displacement velocity maps with the OpenStreetMap building dataset. This map is critical for determining which structures are at risk of damage due to ground movement. Areas with severe subsidence coincide with regions of heavy groundwater extraction, impacting buildings and infrastructure.

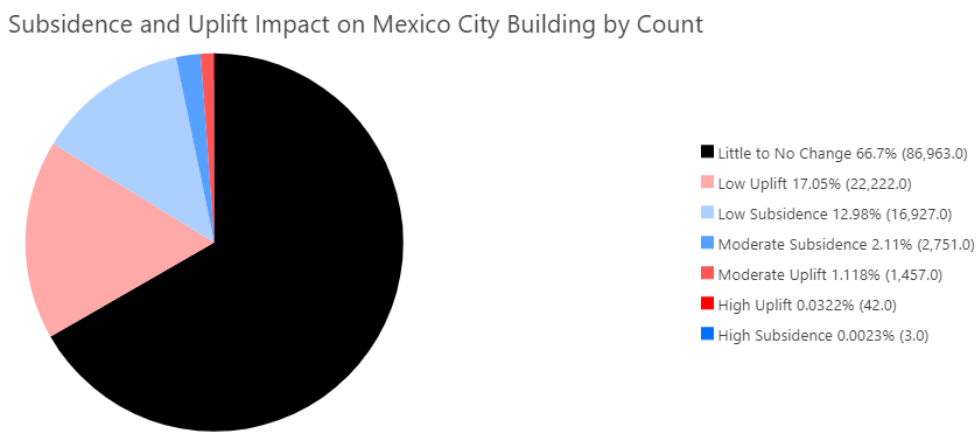

Figure 7: Pie-graph Indicating the Effects of Subsidence / Uplifting

Figure 7 presents a pie chart showing the distribution of buildings affected by varying degrees of subsidence and uplift across Mexico City. The chart reveals that 33.3% of the buildings in the dataset experienced some form of ground deformation, with the majority falling into the low subsidence or uplift categories. Low subsidence impacts 12.98% of buildings, while low uplift affects 17.05%, highlighting the prevalence of minor ground movements. More severe cases, such as moderate subsidence (2.11%), moderate uplift (1.118%), high uplift (0.0322%), and high subsidence (0.0023%), are relatively rare but indicate critical areas where the structural integrity of buildings might be at higher risk. These findings stress the need for ongoing monitoring and targeted interventions to safeguard the city's infrastructure against potential damage.

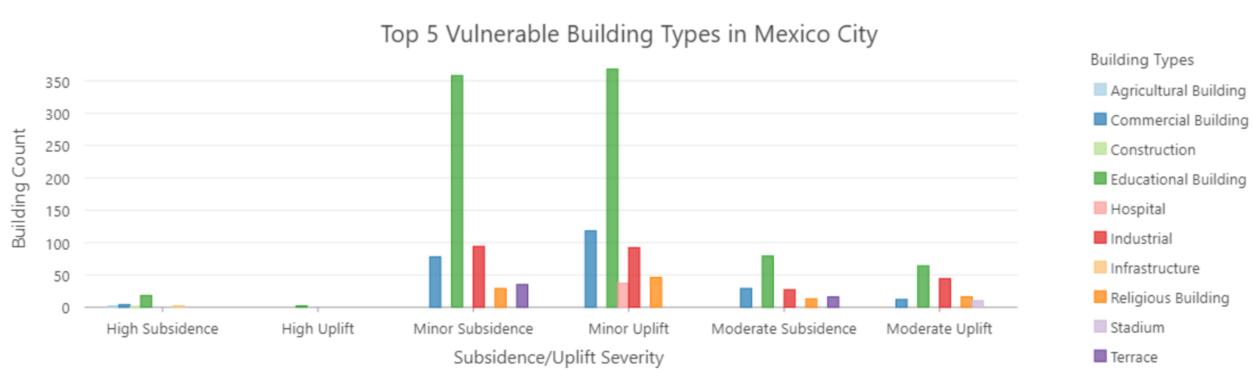

Figure 8: Bar-graph Illustrating the Top 5 Building Types Prone to Subsidence / Uplifting

Figure 8 highlights the types of buildings most affected by ground deformation in Mexico City, particularly focusing on subsidence and uplift. The bar chart identifies the top 5 building types impacted, with commercial buildings, educational buildings, and industrial infrastructure being the most vulnerable. Commercial buildings are predominantly affected by minor and moderate subsidence, likely due to their location in densely populated urban areas with heavy traffic and surrounding infrastructure. Educational buildings appear in both minor and moderate subsidence categories, emphasizing the need for close monitoring of public infrastructure to ensure safety. Industrial buildings, due to their large surface areas and structural loads, are also particularly susceptible to ground deformation. This detailed breakdown emphasizes the need for targeted interventions to protect critical infrastructure from subsidence and uplift in Mexico City.

4.5. Time Series and Displacement Analysis at Point of Interest (POI)

Figure 9Figure 10 illustrate the displacement observed at the point of interest (POI) within Mexico City over the study period from 2019 to 2024, using the SBAS and PS methods, respectively. The y-axis represents displacement in millimeters (mm), while the x-axis spans the timeline from 2019 to 2024. These figures provide a comprehensive view of the ground deformation, highlighting both the overall trend and the residuals from the least squares (LSQ) model.

The LSQ Mean Displacement line represents the mean displacement calculated using the least squares method, serving as a baseline for assessing the overall subsidence at the POI. The LSQ Trend Line, depicted in blue, shows the linear trend derived from the least squares fitting of the displacement data. The slope ($\beta 1$) represents the rate of subsidence per year, while the intercept (β0) indicates the initial displacement value at the start of the study period. These parameters are crucial for understanding the long-term deformation pattern at the POI.

Additionally, the STL Components offer further insights:

- The STL Trend captures the underlying long-term deformation trend after accounting for seasonal effects.
- The STL Seasonal Component identifies periodic changes in displacement potentially linked to environmental factors.
- The STL Residuals highlight short-term deviations from the overall trend, which might indicate localized events or noise in the data.

The Root Mean Square Error (RMSE) values for both methods provide a measure of the model's accuracy, with lower values suggesting higher precision in the model's fit to the observed data.

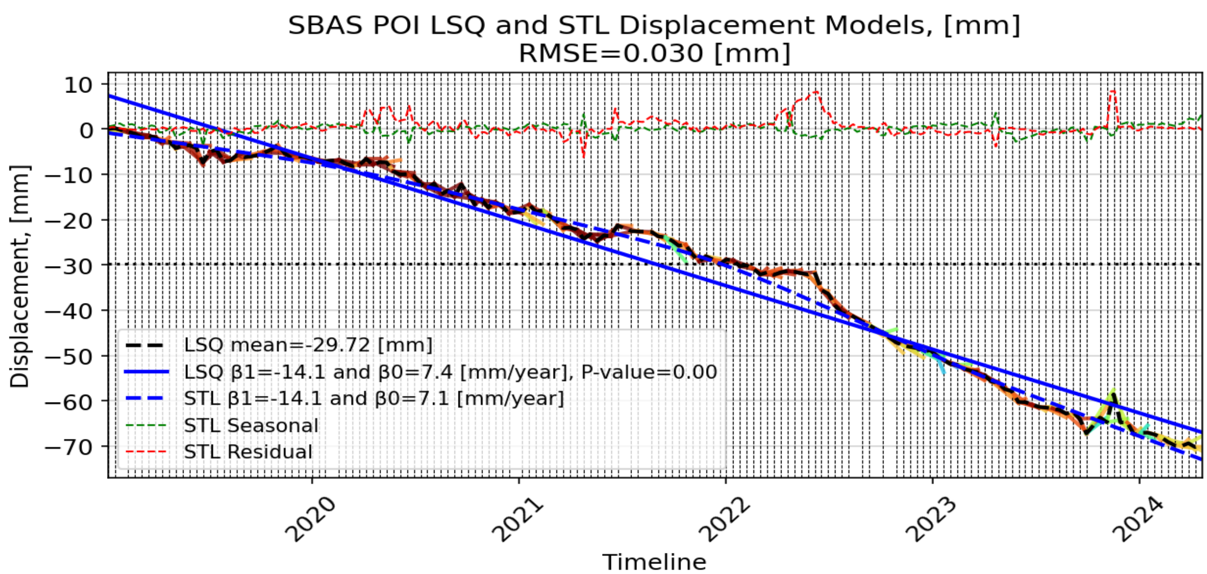

Figure 9:Displacement Time Series at Point of Interest in Mexico City Using SBAS Method

Figure 9 illustrates the displacement time series at the point of interest (POI) in Mexico City using the SBAS method, revealing a significant subsidence trend. The LSQ Mean Displacement is calculated at -29.72 mm over the 5-year study period. The LSQ Trend Line, with a slope of -14.1 mm/year and an intercept of 7.4 mm, indicates a steady rate of subsidence, statistically significant with a P-value of < 0.05, aligning with the hypothesis of extensive groundwater extraction in the area. Seasonal variations are captured by the STL Seasonal Component, likely due to fluctuations in groundwater levels, while STL Residuals reveal short-term deviations, potentially tied to localized events or noise in the data.

The STL Trend closely mirrors the LSQ trend, with a slope of -14.11 mm/year and an intercept of 7.1 mm, reinforcing the robustness of the subsidence analysis. With a Root Mean Square Error (RMSE) of 0.030 mm, the model demonstrates high accuracy, making it a reliable indicator of long-term deformation patterns in the area. The agreement between the LSQ and STL trends confirms the consistency of the findings, emphasizing a clear and steady subsidence trend at the POI, largely driven by environmental factors and groundwater extraction.

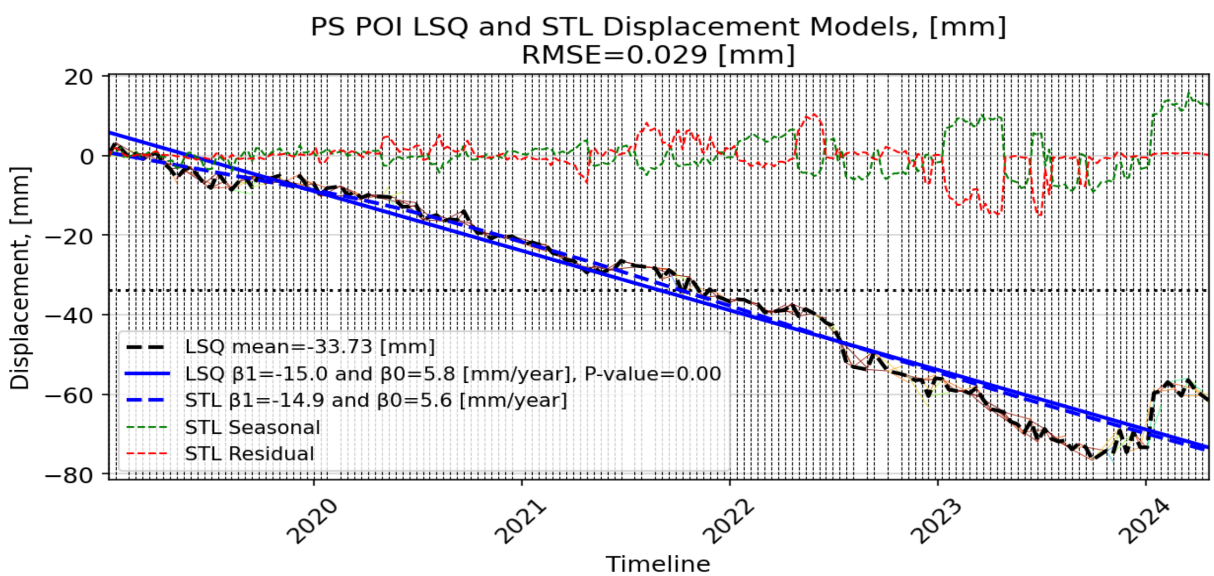

Figure 10:Displacement Time Series at Point of Interest in Mexico City Using PS Method

Figure 10 presents the displacement time series at the POI using the PS method, revealing a slightly steeper slope compared to SBAS. The LSQ Mean Displacement is calculated at -33.73 mm over the 5-year period, indicating significant subsidence. The LSQ Trend Line, with a slope of -15.0 mm/year and an intercept of -5.8 mm, suggests a marginally higher rate of subsidence than SBAS. Both the trend and intercept are statistically significant, with a P-value of < 0.05.

The STL Trend closely aligns with the LSQ trend, with a slope of -14.9 mm/year and an intercept of -5.7 mm, confirming the consistency of the subsidence pattern. The STL Seasonal Component reveals periodic fluctuations that may be linked to environmental factors such as seasonal water extraction, while the STL Residuals highlight short-term deviations that could be attributed to localized events or noise in the data. The RMSE value of 0.029 mm indicates a high level of accuracy in the PS method's displacement measurements.

Overall, the findings from the PS method align closely with those from SBAS, capturing a consistent subsidence trend at the POI. While the PS method indicates a slightly higher subsidence rate, both methods effectively capture the long-term deformation pattern, with seasonal variations and residuals providing additional insights into environmental influences on subsidence.

4.6. Comparison of SBAS and PS Methods

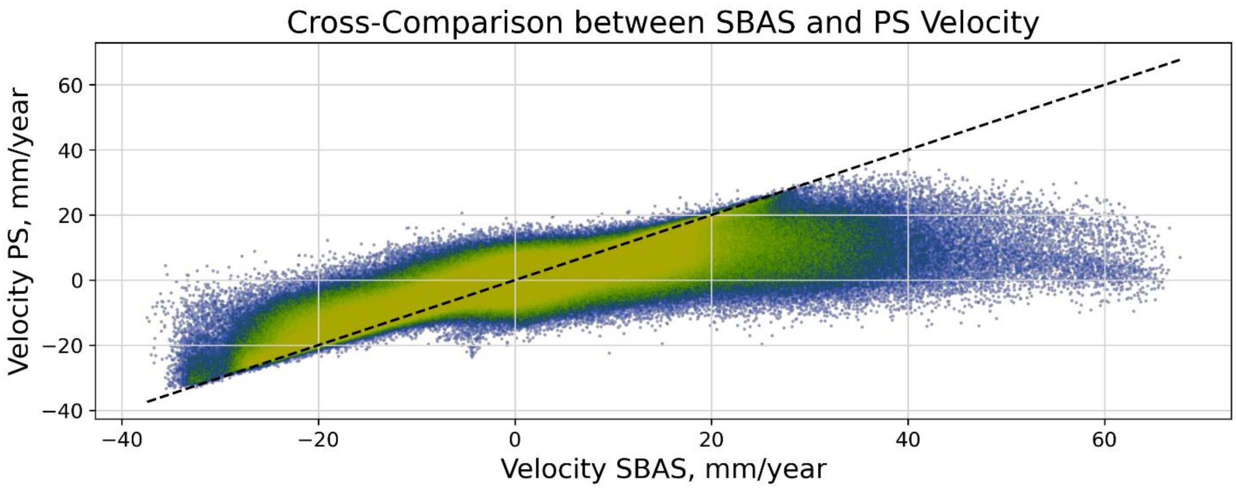

Figure 11: Cross-Comparison of Displacement Velocity between the SBAS and PS Method

Figure 11 presents a scatterplot comparing the displacement velocities derived from SBAS and PS. The clustering of data points along the diagonal line indicates a strong linear relationship between the two methods, suggesting they consistently capture the velocity of ground deformation across the study area. Both SBAS and PS velocities range from -40 mm/year to 60 mm/year, further emphasizing their alignment.

However, it is important to note that the PS method tends to show slightly lower velocities in areas of higher displacement compared to SBAS. This deviation, particularly at higher velocity values, highlights a critical difference in the sensitivity of the two methods. While SBAS detects broader, distributed displacements, PS shows greater sensitivity to localized deformations, making it more responsive to smaller, stable points but with slightly lower velocities in areas of significant ground movement.

4.6.1. Distribution of Affected Buildings

Both SBAS and PS methods show similar rates of subsidence at the POI, with SBAS indicating a mean displacement of -29.72 mm and PS showing -33.65 mm. The PS method demonstrates slightly higher accuracy, as indicated by a lower RMSE (0.029 mm) compared to SBAS (0.030 mm). This improved precision can be attributed to the PS method's reliance on stable scatterers in urban settings, where reflective surfaces allow for more accurate displacement measurements.

Importance of 1D Unwrapping and Single-Looking in PS:

- **1D Phase Unwrapping**: PS processing involves 1D unwrapping along the temporal axis for each persistent scatterer. This approach minimizes errors that could arise from more complex 2D unwrapping, particularly in areas with significant topographic variation or atmospheric noise.
- **Single-Looking**: The single-looking technique maximizes the coherence of persistent scatterers by selecting a single radar look. This process reduces noise and maintains high spatial resolution, further contributing to the PS method's accuracy.

4.7. Residual Analysis and Method Discrepancies

The residual analysis reveals distinct differences between the SBAS and PS methods. The SBAS method generally benefits from its ability to average across a larger number of scatterers, resulting in more stable and distributed residuals. In contrast, the PS method exhibits larger and more noticeable residuals. This can be attributed to the fact that the PS method relies on a smaller, highly stable subset of points. As a result, any errors or noise affecting these points have a greater impact on the residuals, leading to larger deviations. This characteristic of the PS method highlights its sensitivity to even minor changes at these stable points. The SBAS method, by incorporating a broader range of scatterers that include points with varying stability, produces residuals that are more evenly distributed but leads to a slightly higher overall RMSE.

4.8. Displacement Discrepancies Between Urban and Vegetated Zones

Figure 3Figure 4 present ground displacement maps derived from the SBAS and PS methods. While both maps show nearly similar subsidence patterns, key differences emerge between urban and vegetated areas. SBAS tends to capture distributed displacements over wider areas, making it more effective for broad-scale urban analysis. In contrast, PS-InSAR is more precise at detecting localized movements, particularly in stable, reflective surfaces like buildings, bridges, and other man-made structures in urban areas.

Figure 5 highlights areas where each method detects greater movement by subtracting the PS raster from the SBAS raster. Positive values indicate areas where SBAS captures greater displacement, particularly in urban regions. In vegetated areas, negative values show that PS detects more displacement due to its sensitivity to scatterers. This distinction arises because PS identifies persistent scatterers—points that consistently reflect radar signals—but these are rarer in dynamic, vegetated environments where surfaces like tree canopies and grasslands exhibit more variability. SBAS, being designed for broader surface types, often captures more diffuse ground movement in these areas, which PS may miss due to its focus on fewer, more stable scatterers.

Thus, SBAS excels at monitoring widespread urban deformation, while PS proves more sensitive to localized, dynamic movements in both urban and vegetated zones.

4.9. Conclusion of Results

In summary, both SBAS and PS methods offer valuable insights into subsidence and uplift across Mexico City. SBAS provides comprehensive coverage, making it ideal for broader surface types, while PS excels in urban areas where stable structures allow for precise measurements. The integration of these methods with building data offers critical insights for urban planners and policymakers, helping identify at-risk infrastructure and informing mitigation strategies.

CHAPTER FIVE: DISCUSSION AND CONCLUSION

5.1. Revisiting the Research Questions

This study aimed to analyze and understand the subsidence patterns in Mexico City using Sentinel-1 synthetic aperture radar (SAR) data, focusing on the following research questions:

1) How effectively can integrating SBAS and PS methods monitor and quantify urban subsidence in Mexico City?
2) Which specific buildings and infrastructure are at the greatest risk due to ongoing subsidence, and how can these be accurately identified?
3) What are the implications of detected subsidence rates for urban planning and risk mitigation in Mexico City?

5.2. Discussion

The findings of this study indicate that both SBAS and PS methods are effective in monitoring and quantifying the urban subsidence in Mexico City. These findings are consistent with previous research by Osmanoğlu et al. (2016) which highlighted the effectiveness of PS-InSAR in urban settings due to its reliance on persistent scatterers within the urban fabric, offering continuous and reliable data for subsidence analysis. Similarly, SBAS has been recognized for its flexibility in processing and adaptability in complex urban landscapes, as also noted by Osmanoğlu et al. (2016). The integration of subsidence reveals significant deformation patterns that align with existing literature on the subject.

In addition to identifying broad subsidence trends, the integration of SBAS and PS methods demonstrated that when used in conjunction, these techniques can overcome individual limitations. For example, while SBAS was critical in identifying macro-level subsidence trends across wide areas, the PS method was indispensable in ensuring that minute, localized subsidence events were not overlooked. This combination allows for a nuanced understanding of subsidence, making the dual-method approach particularly advantageous for continuous monitoring in complex urban environments like Mexico City.

The study has incorporated a more detailed examination of specific buildings and infrastructure at risk, as illustrated in Figure 6. This figure shows a detailed map of Mexico City highlighting areas experiencing significant subsidence (in red) and uplift (in blue). By mapping these changes, the study identifies critical zones where infrastructure is particularly vulnerable. This approach mirrors the findings of studies like Abidin et al. (2011), which documented the impacts of subsidence on infrastructure in Jakarta, leading to severe structural damages and expanded flooding zones. Similarly, in Mexico City, our analysis identified critical zones where infrastructure is particularly vulnerable. For instance, areas like Venustiano Carranza and Iztapalapa exhibit substantial subsidence, putting numerous buildings and essential infrastructure at risk. These findings emphasize the need for targeted mitigation efforts, as recommended by similar studies on urban subsidence in other global cities.

For instance, in the Venustiano Carranza district, several residential buildings that are home to a large population have been identified as being at significant risk. The PS method highlighted subsidence rates exceeding 20 mm/year in these areas, which could compromise structural integrity if unaddressed. Similarly, key transportation infrastructure, such as the central thoroughfares in Iztapalapa, exhibited notable subsidence, potentially leading to road deformation and increased maintenance costs. These findings emphasize the necessity of prioritizing mitigation efforts in these critical areas to prevent future infrastructures failures.

The displacement analysis revealed a consistent subsidence trend with a mean annual subsidence rate of 14.1 mm/year. Seasonal variations and residuals highlighted short-term deviations and specific events contributing to the deformation. The detailed subsidence maps and displacement data can inform infrastructure management and support the development of strategies to mitigate the impacts of subsidence.

The integration of SBAS and PS methods demonstrates enhanced reliability for policymakers and urban planners. Moreover, the identification of specific at-risk buildings and infrastructure, as highlighted in figure 6, allows for a more targeted approach to subsidence mitigation, ensuring that resources are effectively allocated to areas with the highest need. This comprehensive approach emphasizes the value of integrating advanced remote sensing techniques with detailed ground-based observations to improve urban resilience in subsidence-prone regions.

5.3. Strengths of the Study

5.3.1. Comprehensive Dataset

One of the major strengths of this study is its reliance on a comprehensive and robust dataset of over 156 Sentinel-1 SAR scenes spanning a five-year period. This provides a rich temporal resolution, allowing the study to capture both long-term subsidence trends and seasonal variations in ground deformation, which many other studies lack. This extensive temporal coverage strengthens the reliability and depth of the analysis, enabling the detection of both gradual subsidence and short-term deviations with high accuracy. Additionally, the consistent use of high-quality Sentinel-1 SAR data ensures that the study maintains a uniform resolution throughout the research, contributing to precision and consistency in the findings. The fact that this data spans over 300 gigabytes also demonstrates the scale and depth of the study, allowing for the comprehensive modeling of subsidence patterns, a major contribution to urban planning research.

5.3.2. Advanced Interferometric Techniques

The study leverages two advanced interferometric techniques—Small Baseline Subset (SBAS) and Persistent Scatterer Interferometry (PS-InSAR)—which combine the strengths of broad coverage and high precision. The SBAS method, known for reducing the effects of temporal decorrelation and atmospheric noise, was particularly effective in detecting widespread subsidence across Mexico City. In contrast, the PS method offered a more fine-grained analysis, identifying stable points in the urban landscape and providing highly accurate localized deformation measurements.

By combining both methods, this study achieves a level of precision and scope rarely seen in subsidence analysis. The integration of SBAS and PS provides a unique advantage in capturing large-scale patterns and localized details simultaneously, offering a comprehensive view of subsidence in the city that allows urban planners to assess both macro-level trends and the risks posed to specific infrastructures. This integration of methods stands out as a significant methodological advancement in the field, enhancing the reliability and actionability of the results for urban planning and risk mitigation.

5.3.3. Effective Data Preprocessing

A further strength of this study lies in the meticulous data preprocessing steps that were employed, including reframing, coregistration, geocoding, and multilooking. These steps ensured that the SAR imagery was highly accurate and geocoded correctly, which is crucial for ensuring the quality of the final interferometric results. The attention to detail in the preprocessing stage—such as the use of multilooking to reduce speckle noise—greatly enhanced the clarity of the data, resulting in precise interferograms that formed the foundation of the study's high-quality analysis. These efforts in preprocessing demonstrate the level of care and rigor applied to ensure the data's integrity, which in turn strengthens the overall conclusions of the study.

5.3.4. Detailed and Nuanced Analysis

Another key strength of this study is the comprehensive analysis of the subsidence data, which includes displacement trend calculations, seasonal variation assessments, and residual analysis. By combining long-term subsidence trends with detailed analysis of short-term fluctuations, the study offers a nuanced understanding of subsidence dynamics in Mexico City. This is further bolstered by the analysis of specific areas and infrastructures at risk, providing valuable insights into the implications of subsidence on urban infrastructure.

The detailed analysis not only uncovers significant subsidence trends—with an annual rate of 14.1 mm/year—but also highlights the seasonal and short-term deviations, offering urban planners and policymakers a full picture of how subsidence is likely to evolve. This level of detailed analysis is a major strength of the study, positioning it as a comprehensive guide for urban planning and risk mitigation strategies.

5.3.5. Actionable Insights for Urban Planning

This study doesn't just present an analysis—it provides actionable insights for urban planning and infrastructure risk management. By identifying specific buildings and infrastructures at risk due to ongoing subsidence, such as the Venustiano Carranza district and central thoroughfares in Iztapalapa, the study enables targeted mitigation efforts. The detailed mapping of subsidence zones and infrastructure vulnerabilities offers practical, data-driven solutions for policymakers and urban planners to address and mitigate risks, ensuring the safety and resilience of Mexico City’s urban landscape. This real-world applicability is one of the study’s standout strengths.

5.3.6. Pioneering Workflow for Broader Application

The workflow established in this study, combining advanced SAR interferometry and detailed infrastructure mapping, provides a pioneering methodology that can be applied to other cities facing similar challenges. Its scalability and adaptability to other urban areas make it a significant contribution to the global discourse on urban subsidence, offering cities around the world a blueprint for monitoring, analyzing, and mitigating subsidence risks.

5.4. Limitations and Future Research

While the study has successfully mapped and analyzed subsidence patterns across Mexico City, further refinement and additional data sources could provide even more accurate and actionable insights. Incorporating high-resolution optical imagery and ground-based measurements could enhance the robustness of the analysis. Addressing the observed limitations, such as the four-way artifact anomaly discussed further into detail in the limitations section, will also be crucial for future research. By continually improving data integration and processing techniques, future studies can achieve a more detailed and nuanced understanding of subsidence dynamics, ultimately contributing to more effective urban planning and risk mitigation strategies.

One significant limitation of this study is the exclusion of detailed data on all buildings and infrastructure across Mexico City. The primary dataset used for this analysis was derived from OpenStreetMap (OSM) buildings for Mexico City, which, while valuable, has limitations in terms of completeness and specificity. The OSM dataset lacks comprehensive coverage of all buildings within the city and provides limited details beyond building type and geographical location. This constraint presented challenges in achieving a more precise and accurate assessment of the specific structures at risk of subsidence or uplift. The dataset's limitations mean that certain areas and buildings might not have been fully accounted for, potentially impacting the specificity of the risk assessments and the effectiveness of subsequent mitigation strategies.

Recent developments in AI-driven global building datasets, such as the Open Buildings dataset by Google, offer a promising alternative. The Open Buildings dataset provides building footprints derived from high-resolution satellite imagery, covering a large portion of the Global South, including Latin America and the Caribbean, which encompasses Mexico City. This dataset includes over 1.8 billion building detections across an inference area of 58 million square kilometers. Each building in the dataset is represented by a polygon describing its footprint, along with a confidence score indicating the reliability of the detection. While the dataset currently lacks detailed information such as building type or address, its scale and the accuracy provided by the confidence scores make it a significant improvement over existing datasets like OSM.

If a comprehensive dataset like Open Buildings becomes available for Mexico City, it could significantly enhance the findings of this type of analysis. The increased coverage and higher confidence in building detection would allow for a more detailed and accurate assessment of infrastructure at risk. This would enable more targeted and effective mitigation efforts, improving the reliability of urban planning and disaster management strategies. Additionally, the ability to integrate high-resolution building data with subsidence and uplift analysis would provide a more nuanced understanding of how ground deformation impacts various types of structures across the city.

One notable limitation observed in this study is the presence of a processing artifact in the form of a four-way mark that appeared in the SBAS velocity map of Mexico City. This anomaly, situated at the intersection of different map sections, suggests potential inconsistencies during the data processing stages There are several plausible explanations for this phenomenon. Firstly, the seam line anomaly can arise where different SAR image frames or subswaths are stitched together, potentially due to variations in data calibration, orbit correction, or atmospheric conditions across these frames. Mismatched temporal baselines and processing parameters can also contribute to such discontinuities, highlighting the need for standardized procedures throughout the dataset. Additionally, atmospheric disturbances, which vary between acquisition times, may introduce inconsistencies that manifest as visible anomalies. Coregistration errors, where inaccuracies in aligning SAR images occur, can further exacerbate this issue. Another potential source of the anomaly is errors in the multilooking or decimation processes, where data resolution is reduced, potentially creating visible discrepancies. Finally, inaccuracies in removing the topographic phase, especially in areas with significant elevation changes, could lead to such anomalies. To mitigate these issues, future work should focus on ensuring uniform processing steps, applying robust atmospheric and topographic corrections, and conducting detailed visual inspections to identify and address the stage at which the anomaly occurs.

One significant limitation of this study is the exclusive reliance on Sentinel-1 SAR data. While Sentinel-1 provides valuable high-resolution imagery for monitoring ground deformation, the inclusion of additional SAR data sources could substantially enhance the robustness and comprehensiveness of the analysis. The RADARSAT Constellation Mission (RCM) and other SAR platforms, such as TerraSAR-X and COSMO-SkyMed, offer different imaging capabilities that could complement Sentinel-1 data, particularly in capturing complex urban environments. However, the software utilized in this study was compatible only with Sentinel-1 data, limiting the scope to a single data source and potentially missing out on the benefits that other SAR platforms could provide.

Incorporating high-resolution optical imagery alongside SAR data could further enhance the analysis by providing detailed visual context, helping to identify and verify surface changes and deformations with greater precision. Studies like Kim et al. (2019) have demonstrated that integrating optical data with InSAR can improve the accuracy of subsidence monitoring, especially in urban areas with complex infrastructure.

Ground-based measurements, such as GPS and leveling data, could also play a crucial role in validating and refining satellite-derived measurements. These ground validation techniques offer accurate, localized information on subsidence rates and ground movements, which is essential for confirming the reliability of satellite data. The inclusion of Continuous GPS (CGPS) stations and traditional leveling surveys could serve as critical validation points, ensuring that the InSAR data accurately reflects actual ground deformation, as highlighted in studies like those by Poreh et al. (2021) and Osmanoğlu et al. (2016).

By leveraging a multi-source data approach, future studies could achieve a more detailed and nuanced analysis of subsidence, offering richer insights and more effective solutions for urban planning and risk mitigation. Expanding the data sources beyond Sentinel-1—and ensuring software compatibility with various SAR platforms—is essential for developing a more comprehensive and accurate assessment of subsidence in Mexico City.

Another notable limitation of this study is the potential influence of atmospheric noise on the accuracy of deformation measurements. This challenge has been well-documented in the literature, with studies like Rouet-Leduc et al. (2021) developing convolutional autoencoder architectures tailored for InSAR data to effectively differentiate noise from signal. Incorporating similar advanced atmospheric noise reduction techniques, as suggested by these studies, could enhance the reliability of our measurements. Furthermore, integrating high-resolution optical imagery and ground-based GPS data, as recommended by Kim et al. (2019), could offer a multi-dimensional view of subsidence impacts, improving the robustness of the analysis and contributing to more effective urban planning and infrastructure management.

A limitation of this study is the absence of deep learning and semantic segmentation techniques, which were initially considered but ultimately not implemented due to time constraints. However, recent advancements in these areas suggest that their integration with InSAR data could enhance the accuracy of subsidence detection. For instance, Agrawal et al. (2022) demonstrated the potential of Long Short-Term Memory (LSTM) networks in handling temporal variations in InSAR data, while Sikdar et al. (2022) explored the use of Fully Complex-Valued Fully Convolutional Multi-Feature Fusion Networks (FC2MFN) to improve segmentation performance.

Future research could incorporate deep learning and semantic segmentation techniques to further refine subsidence analysis. By leveraging Convolutional Neural Networks (CNNs) for semantic segmentation and LSTM networks for time-series analysis, it would be possible to achieve a more nuanced understanding of subsidence dynamics, capturing both large-scale and localized deformations with greater precision. This integration could improve the accuracy of subsidence detection and the identification of at-risk infrastructure, providing urban planners with more reliable tools for risk mitigation and infrastructure management.

5.5. Conclusion

This study analyzed the subsidence patterns in Mexico City using Sentinel-1 SAR data and advanced interferometric techniques. The integration of SBAS and PS methods provided a comprehensive understanding of ground deformation, capturing both large-scale subsidence patterns and localized deformations with high precision. The findings highlight significant subsidence trends in Mexico City, with important implications for urban planning and risk mitigation. Detailed subsidence maps and displacement data offer valuable insights for infrastructure management, thus supporting the development of effective strategies to mitigate the impacts of subsidence.

Key Findings:

- Monitoring and Quantifying Subsidence: The integration of SBAS and PS methods effectively monitored and quantified urban subsidence in Mexico City. The combined approach allowed for the detection of both widespread subsidence patterns and localized deformations with high precision.
- Buildings and Infrastructure at Risk: The study identified specific areas, particularly in Venustiano Carranza and Iztapalapa, where buildings and infrastructure are at significant risk due to ongoing subsidence. These areas were accurately identified by analyzing the detailed displacement maps, enabling targeted intervention efforts.
- Implications for Urban Planning and Risk Mitigation: The detected subsidence rates emphasize the necessity for proactive urban planning and risk mitigation strategies.

Future research should address the limitations identified in this study by exploring additional data sources and advanced techniques. Integrating high-resolution optical imagery and ground-based GPS data with existing interferometric methods could offer a more comprehensive and multi-dimensional view of subsidence impacts. Furthermore, incorporating deep learning techniques, such as convolutional neural networks (CNNs), may enhance the accuracy of subsidence detection and classification, particularly in densely populated urban areas where traditional methods might miss small-scale deformations. These advancements will contribute to more effective urban planning and infrastructure management in Mexico City and other subsidence-prone areas.

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