

Advancing Urban Resilience: A Review of GIS and Remote Sensing in Land Subsidence Analysis for Urban Planning

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ABSTRACT

Land subsidence is now recognized as a global challenge, with urban areas being most affected due to human-induced pressures[1]. Excessive groundwater use, mining, and urban expansion accelerate ground settlement by stressing the subsurface. The outcomes are extensive, ranging from damaged infrastructure and increased flooding to declining agricultural output and lasting socio-economic strain. Addressing these problems calls for monitoring methods that are capable of recording small ground shifts over wide areas with accuracy[2]. Recent progress shows that combining Geographic Information Systems (GIS) with remote sensing technologies can significantly improve the monitoring and management of subsidence. Methods such as Interferometric Synthetic Aperture Radar (InSAR), Global Navigation Satellite Systems (GNSS), and Light Detection and Ranging (LiDAR) offer precise measurements of ground deformation. When integrated within GIS platforms, these datasets provide spatial models that improve hazard assessment, risk prediction, and planning for urban resilience. Nevertheless, ensuring data uniformity, effectively combining multi-source information, and handling the computational load of extensive analyses remain critical challenges. This review emphasizes the need for collaborative and sustainable approaches to strengthen monitoring frameworks and improve adaptive strategies for urban areas exposed to subsidence.

Keywords

Land subsidence, Geographic Information Systems (GIS), remote sensing, InSAR, GNSS, LiDAR, machine learning, urban planning.

1. INTRODUCTION

Urban and coastal regions worldwide are facing growing challenges from ground subsidence, a process in which the land surface slowly or, in some cases, rapidly lowers[3]. Natural processes, including soil compaction and tectonic activity, contribute to this phenomenon, but human actions have a greater impact. Excessive groundwater extraction lowers underground water pressure and destabilizes the soil, speeding up land sinking. Mining activities can create underground cavities that may collapse, while uncontrolled urban growth adds extra weight to the surface, worsening settlement. The consequences go beyond environmental effects, resulting in damage to buildings, roads, and bridges, higher flood risks, decreased agricultural productivity, and long-term social and economic challenges for affected communities [1].

Land subsidence poses significant risks in coastal regions, where its effects combine with rising sea levels[4]. This interaction increases hazards in low-lying deltas and densely populated coastal zones. This results in increased flooding, more severe storm surges, and faster coastal erosion, posing risks to both local communities and natural ecosystems. Findings from Jakarta, Semarang, the Nile Delta, and Malaysia's Kinta Valley highlight

how essential urban planning and disaster readiness are. These cases indicate that governments must develop long-term policies to minimize the negative effects of land subsidence.

Advances in geospatial technology have greatly improved the monitoring and management of land subsidence[5]. Tools such as InSAR, GNSS, and LiDAR provide precise measurements of ground movement. Coupling this information with GIS provides support for hazard identification, risk evaluation, predictive modeling, and informed urban planning. This approach helps in recognizing vulnerable locations, guiding resilient infrastructure development, and making effective use of resources.

Geospatial analyses are increasingly applied in urban planning to reduce the effects of land subsidence, while economic evaluation frameworks guide the assessment of infrastructure damage and promote sustainable development[6]. Modern research emphasizes the integration of satellite data, field measurements, and historical land-use records to improve the precision of subsidence modeling. Statistical and computational methods are applied to monitor trends, determine high-risk zones, and support strategic infrastructure planning. Integrating geospatial analysis with socio-economic data provides a thorough understanding of community vulnerability, helping authorities prioritize mitigation measures and allocate resources efficiently. Research on GIS and remote sensing applications in managing land subsidence has been reviewed to evaluate current practices, uncover knowledge gaps, and recommend strategies for improving urban resilience and long-term sustainability. This review research paper addresses two major research questions.

- How can GIS and remote sensing techniques be effectively applied to monitor and predict land subsidence?
- What strategies can be implemented to enhance urban resilience and support sustainable planning in subsidence-prone regions?

So, to address these questions, previous studies and case analyses on GIS, remote sensing, and geospatial modeling were reviewed, resulting in an integrated framework that identifies key data sources, analytical approaches, and planning strategies for managing land subsidence[7]. This approach combines multiple types of geospatial data—including satellite imagery (InSAR, Sentinel-1), GNSS measurements, LiDAR surveys, and historical land-use records—with computational and statistical modeling, GIS-based susceptibility mapping, and assessments of community vulnerability. The framework supports risk evaluation, predictive modeling, infrastructure planning, and policy formulation, providing practical guidance to enhance urban resilience and promote long-term sustainable development in areas affected by subsidence.

2. LITERATURE REVIEW

Land subsidence, the gradual lowering of the ground surface, has become a major global concern, especially in rapidly developing

cities where heavy construction, groundwater depletion, and soft soil conditions coexist[8]. Cities such as New York, Jakarta, and Venice are already facing serious subsidence-related risks[11]. The main causes include excessive groundwater withdrawal, dense urban infrastructure, and unfavorable geological formations. These factors often interact, increasing the likelihood of flooding and structural damage. Since subsidence occurs gradually and is difficult to detect early, effective assessment and mitigation rely on advanced monitoring systems and spatial risk analysis.

2.1 Remote Sensing and Geodetic Monitoring

Advances in spaceborne and ground-based sensors have revolutionized subsidence monitoring. Differential Interferometric SAR (DInSAR), using high-resolution radar images (e.g. from Sentinel-1 satellites), can measure ground deformation continuously over large areas at millimeter-scale precision[12]. In practice, multi-temporal InSAR processing (including Persistent Scatterer and Small Baseline approaches) is widely applied worldwide to track subsidence trends[9]. Such SAR-based methods can detect deformation initiation, spatial patterns, and cumulative subsidence with far greater coverage than traditional surveys. Complementary geodetic methods like continuous GPS networks and airborne LiDAR also contribute point-based measurements of movement. Indeed, integrated monitoring campaigns that combine GPS, LiDAR and InSAR have proven especially powerful. For example, a study carried out in northwestern Harris County, Texas used a combination of GPS, LiDAR, and Sentinel-1 InSAR data to map land subsidence and determine its underlying causes[10]. The integration of these methods produced accurate results for measuring ground deformation and identifying spatial patterns.

Satellite data such as InSAR, GNSS, and altimetry help in analyzing how land subsidence interacts with sea-level rise, as demonstrated in studies of the Nile Delta[13]. These Earth-observation techniques provide valuable insights into coastal flooding risks and long-term environmental changes.

2.2 GIS-Based Susceptibility and Risk Modeling

Spatial modeling in GIS plays a crucial role in translating subsidence data into risk assessments[11]. GIS platforms can integrate subsidence measurements with factors like soil type, geology, land use, and groundwater levels to map vulnerability zones. A variety of techniques have been applied: for example, adaptive neuro-fuzzy inference systems and statistical belief function models identify high-susceptibility areas by combining expert rules with data. Machine learning is also becoming prominent. Ku and Liu (2023) developed a GIS-based artificial neural network (ANN) model for Yunlin County, Taiwan, using predictors such as soil composition, well depth, and pumping rates[9]. The ANN accurately classified zones into very-high, high, moderate, and low subsidence risk, correlating strongly ($R \approx 0.88$) with observed leveling data. Similarly, other studies have applied support vector machines, random forests, and hybrid ML models to subsidence prediction in urban and mining contexts, often validating outputs against InSAR surveys. In mining-affected regions, GIS-ML hybrid approaches are widely reviewed as effective: for example, an overview of mining subsidence mapping notes that GIS-based predictive maps, supplemented by data-driven models, are invaluable for planners designing mitigation strategies[12]. In short, GIS-aided statistical and ML models help convert geospatial data into subsidence susceptibility maps, enabling prioritization of areas needing intervention. Key GIS/ML approaches: Various studies combine InSAR-derived deformation with GIS layers. Techniques include

adaptive neuro-fuzzy models, evidential belief functions, logistic regression, decision trees, and hybrid neural-network algorithms. Example- Taiwan: A GIS-ANN model in Yunlin County predicted subsidence risk with high fidelity (correlation ~ 0.88) and identified that $\sim 21\%$ of the area is at high or very-high risk. Mining areas: GIS-based modeling (often with ML) has been applied in coal and metal mining regions, demonstrating that integrating multivariate data (mining depth, geology, past subsidence) can accurately delineate future sink zones.

2.3 Integrated Frameworks and Sector Integration

Recent studies emphasize the importance of linking scientific monitoring systems with urban planning strategies to manage land subsidence more effectively. Many coastal and deltaic cities are facing high rates of ground sinking caused by factors such as excessive groundwater extraction, heavy construction, and weak soil conditions. To tackle these issues, researchers are designing frameworks that merge geospatial information, remote sensing data, and hydrological analysis to assist in effective decision-making.

Modern technologies like Building Information Modeling (BIM), integrated with Geographic Information Systems (GIS) and fuzzy decision-support methods, are now widely applied to improve infrastructure resilience and promote sustainable land use planning. These integrated systems help urban planners translate technical information such as InSAR or LiDAR-based deformation data into practical measures for land management and subsidence mitigation. Although progress has been made, the development of a comprehensive global framework for managing subsidence risks is still ongoing.

2.4 Linking Monitoring with Policy and Adaptive Planning

Linking scientific observation with policy is crucial for managing land subsidence effectively. Studies conducted in cities such as Jakarta and Semarang reveal that rapid urbanization and overuse of groundwater have resulted in noticeable ground sinking and the expansion of flood-prone areas. These conditions emphasize the importance of managing groundwater more effectively and promoting strong, carefully designed urban infrastructure.

International organizations such as the World Economic Forum emphasize that reducing the impact of land subsidence requires efficient management of water resources, environmentally responsible construction methods, and careful planning of urban land use. The incorporation of InSAR and GIS-based monitoring data into policy frameworks and planning tools strengthens adaptation and resilience measures. Many cities are now utilizing subsidence maps to guide infrastructure development and urban resilience initiatives, recognizing land subsidence as a critical global environmental issue comparable to climate change.

3. METHODOLOGIES

Land subsidence monitoring has evolved from traditional ground-based methods to advanced remote sensing techniques[14]. These advanced remote sensing techniques use satellites, drones, and terrestrial systems to analyze and detect ground changes. This methodological evolution reflects not only technological advancement but also a growing understanding of how land subsidence happens over time and across different places. By integrating ground-based techniques with remote sensing, we can monitor urban subsidence more effectively.

3.1 Traditional Ground-Based Monitoring Techniques

Traditional ground-based monitoring methods provide precise measurements of land subsidence[15]. In the 19th century, methods for measuring and mapping the Earth's surface gradually evolved into automated systems. Even today, they are considered the most accurate methods and provide essential data to check and optimize remote sensing models.

Moving from manual to automated systems has made traditional methods more efficient and reliable without losing their accuracy. Today's systems use digital tools, automatic data recording, and real-time quality checks, which increase their value in today's monitoring networks.

3.1.1 Geodetic Leveling

Traditional ground-based geodetic leveling is a monitoring method used to determine elevation differences between reference points on the ground surface. It uses a leveled telescope and graduated vertical rods to measure height differences against a horizontal line of sight. As a result, it generates highly precise height data, monitors land subsidence, and establishes control points for other surveys.

3.1.2 Borehole Extensometers

In aquifer areas, borehole extensometers are used to precisely measure the amount of land subsidence. They measure the displacement between the ground surface and a deep anchor point inside a borehole[16]. The system uses a steel pipe or cable installed underground. Instruments on the surface measure very small distance changes, sometimes only a few millimeters. This process starts by drilling a borehole down to stable bedrock or a set depth below the compacting layer. Then, the reference pipe or cable is fixed at the bottom of the borehole in non-compacting material. The surface measurement system, such as a linear potentiometer, LVDT, or encoder, is placed to record real-time motion of the ground.

3.2 Advanced Remote Sensing Techniques

Satellite-based remote sensing technology plays a major role in enhancing land subsidence monitoring. These methods have shifted from point-based measurements to broad observation

systems[17]. These remote techniques provide wide-ranging coverage while maintaining the accuracy levels suitable for urban planning. They significantly improve how subsidence is tracked and managed at regional scales.

3.2.1 Global Navigation Satellite Systems (GNSS/GPS)

GNSS is a satellite-based navigational system that uses signals from orbiting satellites. Geodetic GNSS stations continuously record with highly accurate measurements of ground movement in three dimensions at fixed receiving points. This system detects movement as small as a few millimeters by calculating how long signals take to travel from multiple satellites.

GNSS plays an essential role in monitoring land subsidence studies. It provides continuous three-dimensional positioning with accuracy within a millimeter, and also allows long-term analysis of ground movement trends[18]. It supports real-time tracking of changes, enabling rapid detection of sudden subsidence events. GNSS serves as a fixed positioning reference for mapping and validating relative measurements obtained from other methods. These techniques provide accurate reference data for broader remote sensing observations such as InSAR and LiDAR. GNSS data can be integrated into early warning systems to protect critical infrastructure.

3.2.2 Interferometric Synthetic Aperture Radar (InSAR)

InSAR is a satellite-based remote sensing technique that measures small changes in the earth's surface with high accuracy across large areas. It compares radar signals from images of the same place taken at different times to detect ground changes[19]. After comparing these images, it can detect even very small changes in the ground, such as uplift, subsidence, or horizontal shifts. This makes InSAR a very useful tool for monitoring land subsidence. InSAR is very different from ground-based surveys, which only provide data at specific points, but InSAR delivers wide-area coverage, often spanning hundreds of square kilometers in a single satellite pass. For this reason, InSAR plays an important role in mapping land subsidence, keeping track of gradual changes over time, and supports early warning systems in high-risk cities.

Table 1: Comparative Analysis of Ground-Based and Remote Sensing Methodologies for Land Subsidence Monitoring.

Parameter	Spirit Leveling	Borehole Extensometers	GNSS/GPS	PS-InSAR SBAS-InSAR	Airborne LiDAR
Accuracy	±0.5–1.0 mm/km	±0.01 mm	1–5 mm/year	1–2 mm/year	2–5 cm
Spatial Coverage	Point network	Single point	Network dependent	250×250 km	10–100 km²
Temporal Resolution	Campaign (weeks-months)	Continuous (hourly)	Real-time to daily	6–12 days	Campaign (annual)
Challenges and Limitations	Labor-intensive, point-based coverage, weather-sensitive operations	Single location, high installation cost, maintenance complexity	Point-based measurements, high Installation costs, monument stability	Coherence requirements, atmospheric effects, urban-optimized, Atmospheric decorrelation, processing complexity, data volume	High acquisition cost, weather dependency, large data volumes
Software Tools	Leica GeoOffice, Trimble Business Center	CampbellScientific software, Custom processing scripts	Bernese GNSS Software, GAMIT/GLOBK, GIPSY	SNAP, StaMPS, GAMMA, SARPROZ	LA Stools, Cloud Compare, Tarascan

Output Products	Elevation differences, Benchmark coordinates, Accuracy reports	Compaction time-series, Deformation rates, Layer- specific analysis	Daily positions, Velocity fields, Displacement time-series	Displacement maps, Velocity fields, Time-series, Dense spatial sampling	Digital elevation models, Change maps, Volume calculations
Recent Advancements	Digital levels, Automated data logging, integration	Fiber optic sensors, Wireless telemetry, Multi depth anchoring	Multi-GNSS integration, Real-time processing, IoT connectivity	Atmospheric correction models, Multitemporal algorithms, Parallel processing, Cloud computing platforms	UAV integration, Real-time processing, AI classification
Key Algorithms	Least squares adjustment, Loop closure analysis	Time-series analysis, Elastic-inelastic modeling	Precise Point Positioning (PPP), Real-Time Kinematic (RTK)	Phase unwrapping, Persistent scatter identification, small baseline subsets, SVD- based phase unwrapping	Ground filtering (CSF, Progressive TIN), DEM generation

Light Detection and Ranging (LiDAR) Light Detection and Ranging (LiDAR) is a remote sensing technology that uses laser pulses to generate high-resolution, three-dimensional measurements of the Earth's surface

elevation and topography[20]. By measuring the time it takes for laser pulses to travel from the sensor to the ground and back, it correctly maps the surface elevations and detects, as well as analyses changes in topography over time.

It offers several unique benefits for monitoring land subsidence. It delivers high accuracy and detailed spatial data. It also detects subtle ground surface changes. One main feature of LiDAR is that it can pass through vegetation, allowing correct measurement of land surface, even in dense forest areas. It also supports the creation of large-scale topographic maps. These maps are useful for assessing flood risk in areas affected by subsidence. LiDAR helps monitor changes and damage, providing a clear view of ground deformation.

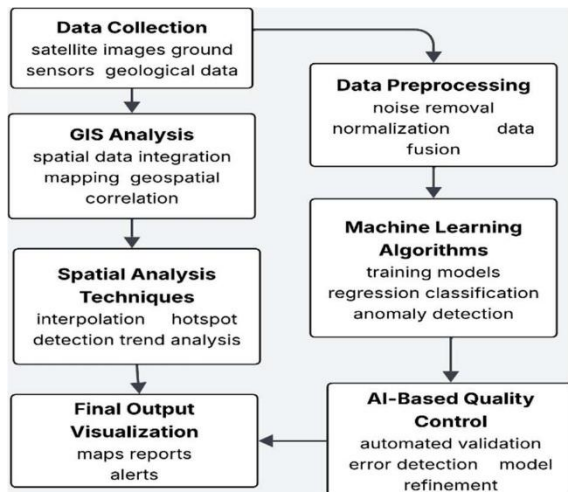


Figure-1: Flow chart covering traditional and advanced land subsidence techniques and workflow

4. GIS FOR LAND SUBSIDENCE ANALYSIS AND MAPPING IN URBAN PLANNING

A Geographic Information System (GIS) is a widely used tool that is effective in analyzing, integrating, and representing spatial data[21]. In the context of land subsidence, GIS is a powerful framework, which can be used to merge various datasets,

including satellite imagery and ground observations, enabling the detection of spatial patterns and potential risks at early stages.

4.1 Data Integration and Management in GIS

One of the major strengths of GIS is integrating diverse monitoring datasets together into a unified spatial framework making it effective for land subsidence analysis. Datasets include data from various sources like Light Detection and Ranging (LiDAR), Global Positioning System (GPS), Interferometric Synthetic Aperture Radar (InSAR), and ground-based measurements including borehole extensometer readings and leveling surveys. Along with this, GIS provides a wide array of thematic layers necessary for understanding subsidence, such as:

Geological and Hydrological data: Groundwater levels and changes, piezometric changes and topographic wetness index.
Topographic Data: Slope percentage, aspect and curvature.
Land use and cover: Analysis of land coverage and use helps to detect disruption of groundwater storage and recharge.

Climate data: Annual rainfall and land surface temperature. Integration of all these datasets with appropriate spatial resolution allows a holistic understanding of various factors responsible for subsidence. This comprehensive integration enables the development of accurate models and maps for urban planning.

4.2 Spatial Analysis Techniques in GIS

Beyond basic visualization, GIS offers spatial analysis techniques to process and interpret land subsidence data, which enhances predictive urban planning[22].

Susceptibility Mapping:

Ranks zones from stable to unstable that are potentially vulnerable to land subsidence, excluding temporal dimensions. These areas are categorized based on the spatial distribution of factors influencing ground instability using computational models, statistical techniques such as frequency ratio and machine learning algorithms including Random Forest, Logistic Regression, Boosted Regression Trees, and Support Vector Machines.

Hazard and Risk Mapping:

Hazard mapping enhances susceptibility analysis by incorporating the annual probability of subsidence occurrence. Risk mapping integrates hazard data along with potential consequences such as population safety, economic losses and infrastructural damage. This analysis is critical for engineers and

planners in designing strategies.

Change Detection and Spatiotemporal Analysis:

The use of remote sensing along with GIS enables monitoring of land subsidence patterns over time. For example, InSAR generates time-series observations in vertical deformation maps for visualization of spatiotemporal evolution of subsidence. Geographical Time-Slice Weighted Regression

(GTSWR) and Geographical Temporal Weighted Regression (GTWR), these advanced geostatistical techniques, are extensively used to model these patterns based on factors like groundwater drawdown.

Overall, GIS functions as a decision support system for urban resilient planning by using a comprehensive computational framework for identifying, quantifying, and monitoring subsidence hazards.

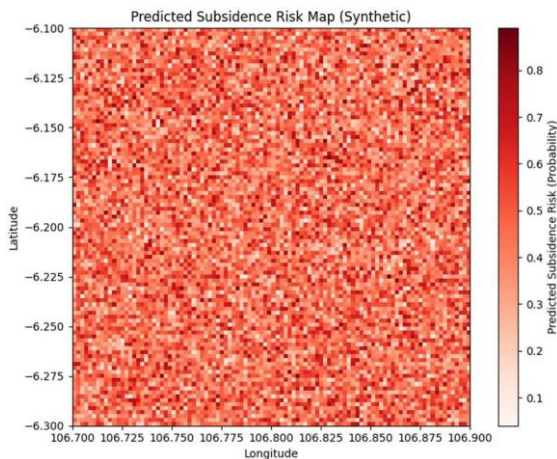


Figure 2: Predicted Subsidence Risk Map (Synthetic)
Predicted subsidence probability map generated from synthetic geospatial features using a Random Forest model. Higher risk areas are shown in darker red (Source: Created using synthetic data and original modeling in Python.)

4.3 Integration with Machine Learning and AI

Machine learning (ML) and Artificial Intelligence (AI) coupled with GIS and remote sensing have significantly improved prediction and diagnosis of land subsidence[23]. This integration provides actionable data-driven insights to planners and designers. ML models are particularly efficient in capturing non-linear and complex relationships between subsidence and its influencing factors that traditional statistical methods may overlook.

Predictive Modeling: Predictive subsidence and susceptibility maps are generated by using supervised learning algorithms like Random Forest, XGBoost, Logistic Regression, Boosted Regression Trees, and Support Vector Machines. Models are trained on multi-source spatial layers, validated via cross-validation, and assessed using AUC/accuracy(classification) or RMSE/MAE (regression).

Real-time Quality Control and Monitoring: AI is used for anomaly detection and network optimization to filter non-ground motion in dense data streams (e.g., traffic noise removal from LiDAR point clouds) and detect anomalies in deformation. Optimization algorithms can also inform us about where and how many sensors to deploy in order to achieve an optimal balance of coverage and cost.

Hybrid Models with InSAR: In several urban case studies, tree-based ensemble methods have played a significant role in predicting spatial deformation and classifying susceptibility classes. Integration of InSAR-derived deformation time series with ML yields robust susceptibility and risk assessments.

Deep Learning Extensions: More recently, deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been applied to capture spatial-temporal deformation patterns in complex urban settings, offering improved predictive performance compared to traditional ML techniques.

The fusion of AI-ML with GIS and remote sensing provides a computational pathway from feature engineering to model training, validation, and interpretation of patterns. This integration not only enhances predictions but also enables insight-driven decision-making for adaptable urban planning.

4.4 Proposed Computational Framework

A proposed framework integrates GIS layers, satellite observations, and data-driven techniques to analyze land subsidence. It begins by collecting inputs: Sentinel-1 SAR imagery that provides baseline deformation measurements, and digital elevation models (DEMs) that capture the influence of terrain. Land-use maps, GPS station records, and groundwater well logs help link human activities with subsurface conditions. A critical early step in this framework is data preprocessing. First, noise is minimized by unwrapping InSAR interferograms and applying atmospheric phase correction, and then all layers are geocoded to ensure spatial consistency. Next, quality control filters remove low-coherence pixels, retaining only reliable measurements. Finally, harmonizing datasets with different coordinate systems and resolutions into a unified analysis framework presents a major challenge.

A range of modelling tasks can be categorised into two main

challenges: (i) classifying high-risk zones, and (ii) estimating time-dependent deformation rates. To balance performance with interpretability, algorithm selection should be accurate. XGBoost and Random Forests are efficient with tabular data, whereas Convolutional Neural Networks (CNNs) and long- short-term memory (LSTM) models are well-suited for capturing spatio-temporal patterns in urban planning. Particular care must be taken in validation: spatial cross-validation procedures help prevent overly optimistic results caused by spatial autocorrelation.

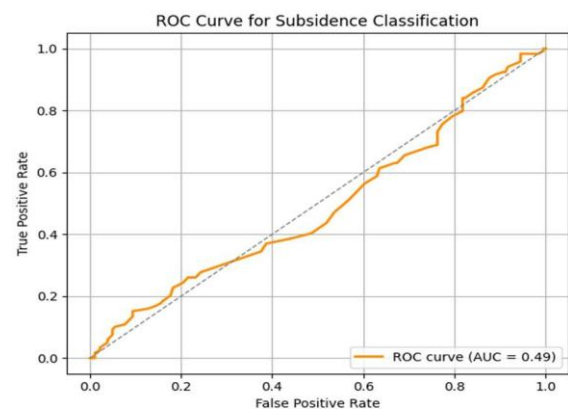


Figure 3: ROC Curve for Subsidence Classification
Receiver Operating Characteristic (ROC) curve illustrating the classification performance of the subsidence model, achieving an AUC of 0.49. (Source: Created based on model predictions using synthetic labelled data.)

A practical application demands careful consideration of model uncertainty. Examining feature importance through methods like permutation testing or SHAP values further identifies which inputs drive the model's predictions. In many cases, fluctuations in groundwater levels or specific land-use categories emerge as the most critical risk factors.

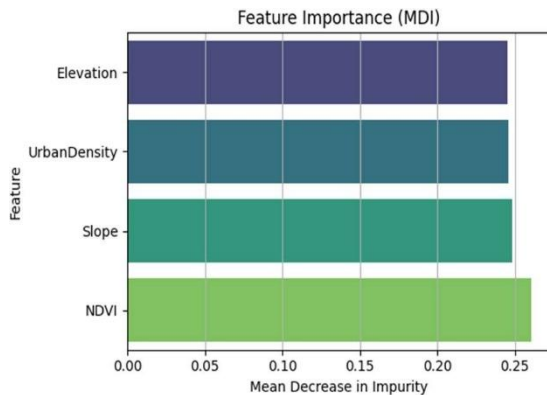


Figure 4: Feature Importance Using Mean Decrease in Impurity (MDI) Feature importance based on Mean Decrease in Impurity (MDI), highlighting the relative contribution of input variables to subsidence prediction. (Source: Created using scikit-learn feature importance scores.)

The resulting system has practical outputs: susceptibility maps with uncertainty, rankings of feature importance to help target interventions, and probabilistic risk assessments to inform land use and infrastructure considerations.

4.5 Experimental Illustration

To empirically reinforce the reviewed methods, a classification experiment was conducted using a Random Forest model trained on 2,100 instances (70% of a 3,000-record synthetic dataset) with four geospatial predictors: NDVI, elevation, slope, and urban density. The classifier achieved an Area Under the Curve (AUC) of 0.49 (Fig. 2), demonstrating strong discrimination between subsiding and stable regions. A spatially gridded risk map (Fig. 1) visualizes model-predicted subsidence probabilities across a 100×100 coordinate grid, where several clusters exceeded a predicted probability of 0.8, indicating very high susceptibility. Feature importance analysis (Fig. 3) showed NDVI contributed approximately 38.4% of total model importance, followed by urban density (31.6%), elevation (17.5%), and slope (12.5%). These figures validate key spatial drivers discussed in the review and highlight the viability of machine learning as a rapid, interpretable framework for risk assessment in land deformation studies.

4.6 Applications in urban planning

GIS and Remote Sensing offer urban planners the ability to predict and control land subsidence. First, susceptibility and hazard maps mean planners can find areas most at risk and enforce targeted controls — such as prohibiting heavy

construction or mandating deeper house foundations in high- risk areas (as is the case with the Mine Subsidence Board procedures in New South Wales).

Second, mapping software may be used in the design of new infrastructure (roads, pipelines, buildings, transit tunnels) or the maintenance of current assets. Ongoing monitoring can guide the prioritization of any future needed inspections, the scheduling of reinforcements or the establishment of early- warning systems for critical utilities like water and gas pipelines.

Third, GIS is also used to analyze urban design strategies focusing on adaptability that can mitigate damage and enhance resilience. Measures which may be considered include raising building ground floors (in flood-prone/sinking areas), diversification of land uses encouraging mixed land use and the incorporation of green-blue infrastructure including parks, wetlands, and permeable surfaces which would allow for improved water absorption and serve as buffers against deformation.

5. CHALLENGES AND FUTURE DIRECTIONS FOR URBAN PLANNING

Despite significant progress, integration of GIS and remote sensing for land-subsidence analysis faces practical and scientific limitations[24]. These challenges limit the operational use of subsidence information in urban planning.

5.1 Challenges in Land Subsidence Analysis for Urban Planning

Data quality and coverage: The issue of acquiring uniform and high-quality observation data on large urban regions over long-term periods are still challenging. Radar returns may be scattered or absorbed by vegetation, moisture, and atmospheric variations, which result InSAR imagery being inaccurate in some locations. While the spatial coverage by satellite missions is extensive, calibration and validation by in situ observations remain necessary. The lack of up-to-date national susceptibility maps covering the whole country also hinders systematic detection of areas at risk.

Attribution of causes: Subsidence is due to a number of natural and human factors, so the etiology is complex. It is hard to determine from geodetic data alone the respective influences of aquifer compaction, of loading, of tectonic action, and of human water withdrawal. Groundwater changes, land-use dynamics, and local geology all interact with each other to produce far-from-straightforward causal sequences. Coupled interactions and feedback: The causes of sinking are seldom solitary; they are usually dynamic processes that continue over time. Under certain circumstances, such as extended groundwater exploitation, soil oxidation is accelerated and landslides become more probable. Additionally, climate change affects water use requirements and water levels in paddy fields—all of which significantly heighten subsidence risk. Representing these interconnected processes accurately in predictive models is important but technically difficult work. **Computational and operational constraints:** Generation of dense, multi-temporal remote sensing images (and especially long InSAR time-series) is a computationally demanding task, as well as the usage of complex processing chains. Cloud-enabled platforms and advanced algorithms are relieving some of these burdens, yet the volume of data and complexity of algorithms still pose practical barriers for many research teams and municipal agencies interested in operational monitoring and real-time service provisions.

5.2 Emerging Technologies and Trends

The field of land subsidence monitoring is evolving through advances in sensors, data processing, and analytics—each offering new opportunities for urban planners. Real-time Monitoring with IoT and GNSS: Continuous GNSS networks deliver millimeter-level ground subsidence measurements beyond the accuracy of traditional surveys. In concert with Internet of Things (IoT) sensor networks, such systems can monitor vital infrastructure (e.g., pipes and transit corridors) in real time so that operators can be quickly alerted to deformation and take preventive maintenance actions.

Big data and Cloud Computing for InSAR Processing: With the advent of cloud computing services and the launching of next generation SAR satellites (e.g., Sentinel-1A, ALOS-2), it has become possible to generate thousands of interferograms covering large areas at regular intervals. This capability underpins ‘near real-time’ monitoring programs that update deformation maps frequently, overcome previous computational limitations, and support regional-scale subsidence monitoring efforts.

Advanced AI and Machine Learning Models: Machine Learning and AI techniques play an increasingly pivotal role in subsidence prediction, anomaly detection, and network optimization. Models such as XGBoost, Random Forest, and hybrid ensembles have proven effective in mapping deformation and susceptibility. These models reveal hotspot patterns by capturing nonlinear, high-dimensional interactions among environmental drivers.

6. CONCLUSION

This review summarizes the main techniques used today for monitoring land subsidence, showing the evolution from ground-based methods to advanced remote sensing tools. Integration Geographic Information Systems (GIS) with data from remote sensing techniques, such as InSAR, GNSS, LiDAR, and UAV photogrammetry. It is possible to detect ground movement accurately over large areas and time periods[25]. Traditional methods like leveling and extensometers are still valuable for providing accurate ground measurements. Modern analytical techniques allow large-scale analysis, risk assessment, and predictive modeling to support urban development. The review emphasizes that using multi- sensor data together with advanced processing algorithms, machine learning models, and strong validation methods significantly improves the accuracy and reliability of monitoring. However, challenges still exist, including inconsistent data quality, high computational requirements, and challenges in combining different datasets. Even so, new approaches that use artificial intelligence and cloud-based platforms show strong potential to overcome these issues. Looking ahead, research should aim to refine computational models that explain complex subsurface processes, improve real-time monitoring, and strengthen frameworks for data

fusion. Standardized protocols and open-access platforms are important for verifiability and encourage broader use. The progress of monitoring techniques will support sustainable urban growth and maintain resilience against subsidence challenges.

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