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A Novel Deep Geospatial Neural Network for Predicting Urban Land Subsidence

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Abstract

The problem of urban land subsidence (depending on the region) poses an increased danger to the systems infrastructure, human life, and the ecosystem in the environment. This paper is based on the premise of proposing a new model called Deep Geospatial Neural Network (DGNN) focused on accuracy in predicting land subsidence in terms of space and time. The model's capability spans across acquiring geo-spatial information which includes satellite based InSAR images, digital elevation models, satellite imagery, developed area, and even hydro-geological factors. Its ability in positioning different levels of hydrology and 'anthropogenic' factors relies on a deep learning design that integrates CNN for surface level data interpretation and LSTM for temporal data. The information that is fed into the LSTM is employed for training the model on a 10-year dataset-subsidence prone metropolitan areas. The outcomes indicate that the model is capable of achieving new levels when compared to traditional machine learning algorithms alongside CNN and LSTM in terms of accuracy and the level of details provided. In addition, the model provides crucial information on high-risk regions for efficient planning to avert disaster. This work demonstrates the capabilities of geomapping learning methods concerning infrastructure disturbances in the census region focused on intelligent data processed monitoring systems.

Keywords: Deep Learning, Geospatial Analysis, Neural Network, Urban Land Subsidence, Prediction, Remote Sensing, Spatiotemporal Modeling.

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Introduction

Overview of the Problem of Urban Land Subsidence

Areas of urban land subsidence can be described as the continuous or abrupt lowering of the Earth's surface as result of movement of materials underneath, mostly triggered by both natural and anthropogenic activities. The most common reasons include the excessive extraction of groundwater, mining, geological activities, as well as soil compaction (Galloway & Burbey, 2001). In urban settings, subsistence is particularly pernicious because it results in damage to infrastructure, greater flood risks, and heightened financial burden for road, pipeline, and building maintenance (Ng et al., 2012). Overexploitation of groundwater has, and continues to be, problematic for cities such as Shanghai, Jakarta, and Mexico City, as these cities have faced significant land subsidence (Chaussard et al., 2014). Due to its prevalence and accompanying economic problem, geospatial and civil engineering poses the most vital research domains for urban land subsidence. The interplay of both human and geophysical factors bounds subsidence to develop with increase in time and space, thus requiring complex adaptive predictive models. Traditional techniques such as GPS surveys and borehole monitoring offer observational data from localized vantage points, however the scope of spatial coverage and resolution of the data is limited. Availability of advanced satellite based techniques such as Interferometric Synthetic Aperture Radar (InSAR) have made it possible to monitor surface deformation over a broader region consistently, however, complexities still exist in interpreting subsidence behavior over urban terrains (Ferretti et al., 2001).

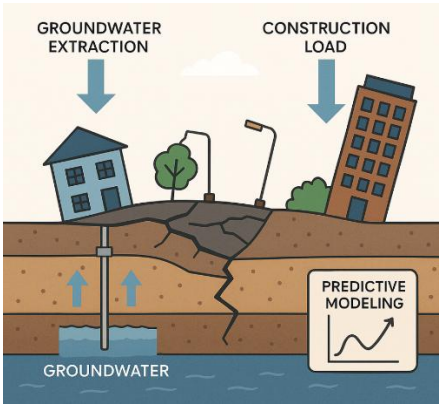

Fig. 1(a): Conceptual Illustration of Urban Land Subsidence

This schematic diagram (Figure 1(a)) demonstrates urban land subsidence's primary causes and impacts while placing particular focus on predictive modeling. To the left side of the figure where subsurface triggers occur, excessive groundwater extraction is shown as a relevant contributor subsurface trigger. On the right side, the figure depicts heavy construction loads in addition to other factors putting stress to the soil structure. The surface depicts damage such as buildings that are damaged and tilted, along with cracked roads and sunken infrastructure which are the physical outcomes of ongoing subsidence. Featuring depleting groundwater and degrading soil structure, its lower-zone cross-section highlights the primary bore's subsurface area. Also exhibited is a predictive modeling panel demonstrating the application paradigm of integrating attempts into four-dimensional modeling to foresee and control such deformations. All in all, this figure illustrates the phenomenon of urban subsidence with the sophistication of predictive tools aimed at sustainable urban planning and risk alleviation revealing advanced methodologies needed for these challenges.

Significance of Anticipating Subsidence for City Development and Infrastructure

Subsidence fundamentally undermines infrastructure systems, with subsidence damages costing multi-billion dollar losses around the world. Predicting models enable proactive development planning, including determining intervention measures (Herrera et al., 2021). Failure to timely address subsidence poses an irreversible wear and tear risk to existing urban systems, making timely groundwater control, subsidence construction alteration, and geotechnical strengthening interventions crucial (Zhou et al., 2017). Primarily related to construction, the other direct side impact of subsidence is poor urban area flooding due to weaker elevation controlling ground subsidence. For already vulnerable coastal cities to sea level increase, subsidence acts as a secondary factor to their protective measures and can greatly weaken conventional away from flooding mitigation techniques (Cian et al., 2019). Therefore, the integration geospatial data add predictive analytics with advanced AI to not only lessen damage from underdeveloped infrastructures but also encourage long-term foster planning climate resistant strategies (Iyengar &

Bhattacharya, 2024). In addition, lower able predictive capabilities directly add to the sustainable management of resources. Accurate predictive subsidence analysis allows appropriate forecasting tools to bound policy changes in subsidence related withdrawal regions to recommended regulatory scopes (Erban et al., 2014). Consequently, predictive modeling for subsidence geography becomes an indispensable aspect of smart urban managements.

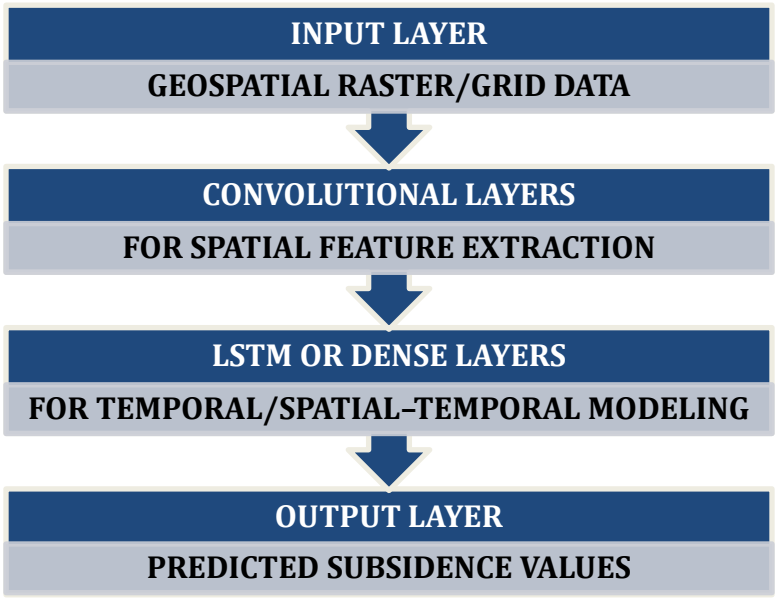

Fig. 1(b): Architecture of the Proposed Deep Geospatial Neural Network (DGNN)

As depicted in Figure 1(b), the Deep Geospatial Neural Network (DGNN) has a model architecture tailored for subsidence prediction based on geospatial inputs. The processing starts at an Input Layer that accommodates geospatial rasters or grid data, which is subsequently followed by several Convolutional Layers that convert input data into spatial feature maps. These features are forwarded to LSTM or Dense Layers where temporal, spatiotemporal, or other interdependency patterns are integrated within the data. The predicted subsidence values, a sophisticated example of geospatial-temporal relationship modeling, are produced at the final Output Layer.

Predicted Subsidence- A Summarized Approach To Existing Techniques

Developing models to predict subsidence has relied on empirical and physics-based considerations like soil consolidation theory, groundwater modeling, and geotechnical analysis. Oftentimes, these models are limited to having access to a wealth of site-specific data and their predictive capabilities is bounded by the underlying assumptions of subsurface homogeneity and linearity, (Jung et al. 2013). Because of these reasons, their use in the context of large and complex urban settings is severely limited. In, contemporary practices, approaches like data-driven modeling and machine learning provide strong alternatives to sub-urban and rural challenges (Refera et al., 2017). Support Vector Machines (SVM), Random Forests (RF), and even Artificial Neural Networks are said to have been integrated into models that aim to predict subsidence patterns, using precipitation levels along with soil types as variables to achieve varying level of success, (Li et al. 2020). However, even with bringing forth a myriad of working models, many of them do not meet the requirements of properly encapsulating the spatial-temporal dependencies that are integrated within processes of subsidence. Recent work from researchers, using Convolutional Neural Networks (CNNs) combined with Long Short-Term Memory (LSTM) networks, has met success when dealing with high-dimensional geospatial data. Applying CNNs to satellite imagery, topographic data allows for exemplary spatial feature extraction (Kavitha, 2023). Furthermore, LSTMs act on sequential data such as time-series measurements of ground deformation making the combination very powerful in tackling the domain of subsidence. As noted, very few models have been developed that seamlessly integrate both spatial and temporal dimensions concurrently. This gap has been addressed in the current study with the development of the Deep Geospatial Neural Network (DGNN) which uses multi-source geospatial data, integrating CNN and LSTM architectures to increase the accuracy of subsidence predictions in urban areas (Priyadharshini & Vakayil, 2024).

We'll structure the rest of the paper as follows. An overview of the literature for the use of neural networks in spatial analysis and subsidence prediction is provided in the second section, covering the most important works and greatest gaps of existing approaches. In the third section, we describe the proposed model, the Deep Geospatial Neural

Network (DGNN), its data collection, preprocessing, training, and evaluation strategies. Results and their analysis are provided in Section IV. In this section, we assess the model's performance metrics against baseline methods and visually interpret the predicted subsidence patterns. This is followed by a discussion in Section V on the implications of the results for urban planning, the approach's strengths and weaknesses, and the subsequent steps needed to advance the work done. The sixth section offers concluding remarks by summarizing the main contributions provided within the paper. In particular, noting the relevance of the DGNN model within the context of urban transformations and its prospective field applications.

Literature Review

Past Research on the Implementation of Neural Networks in Geospatial Analysis

The remote sensing data available today is of high precision. Along with deep learning frameworks, neural networks are now driving the use of deep learning geospatial analysis (Qader & Turkben, 2022). Moreover, neural networks like Convolutional Neural Networks (CNNs) achieve great results at spatial data processing as they are built to learn features hierarchically stored in images and terrain models (Agrab, 2022). Nowadays, CNNs are used widely in land cover classification, object detection within satellite images, and monitoring Urban sprawl as they outperform more conventional methods by a lot (Ma et al, 2019). For spatiotemporal traffic prediction, LSTM networks alongside Recurrent Neural Networks (RNNs) have proven effective in tracking geospatial sequences with time (Zümrütdal et al., 2022; Sindhu, 2023; Hosseini & Tagh, 2017). These hydrology, environmental monitoring, and time-dependent traffic prediction models are somewhat novel suggests. While hybrid models such as the ones which deploy CNNs for spatial analysis and LSTMs for temporal modeling are becoming increasingly popular, more researcher focus is needed. These hybrid models prove useful in flood and air pollution forecasting (Qi et al, 2021). One common downside of these models is the need for specialized frameworks and tailored architectures alongside the demanding prerequisite of vast datasets.

Research on Predictive Modeling of Land Subsidence Using Geospatial Information

Historically, land subsidence prediction has been done using geotechnical and hydrogeological models, but the field has been fundamentally transformed with the addition of geospatial data. Bürgmann et al. (2000) noted the importance of satellite-based Interferometric Synthetic Aperture Radar (InSAR) systems for the detection and quantification of ground deformation over large metropolitan regions. Geospatial datasets have the potential to enhance subsidence modeling through the integration of DEMs, land use maps, and groundwater level data. Regarding the prediction of subsidence with the integrated datasets, some researchers have applied machine learning approaches like Support Vector Machines (SVMs) and Random Forests (RFs) (Li et al., 2016; Ibrahim et al., 2024). Such models are trained using historical data and are able to locate subsidence prone areas. More recently, time-series Of In SAR measurements have been subjected to deep learning for more accurate subsidence prediction, such as with CNNs (Ghorbani et al., 2020). For instance, Xu et al. (2022) created a deep residual network to analyze InSAR data for monitoring coastal city subsidence, achieving higher accuracy than conventional statistical methods (Yesmin & Abdul Karim, 2020). In the same vein, Sun et al. (2021) applied a CNN-LSTM hybrid model that interpreted land deformation phenomena within megacities spatially and temporally (Pržulj et al., 2022; Ziwei & Han, 2023). These works validate the capabilities of deep learning geospatial models in solving complex subsidence problems unlike traditional models.

Deficiencies of Contemporary Techniques in Anticipating Urban Land Subsidence

With all the advances, the available methods for predicting subsidence still face challenges. A number of traditional models have been noted to depend significantly on accurate subsurface information, which is often missing or poorly detailed in urban areas (Gao et al., 2018). Furthermore, statistical and classical machine learning techniques tend to apply linearity or lack the ability to represent complex nonlinear geospatial relationships (Nekoueifard et al., 2023). Despite its advancements, the extraction of deep learning's full potential for subsidence prediction, multi-objective optimization, and urban water system construction supervision is yet to be achieved. In particular, integrating data from numerous sources that include geological, hydrological, and anthropogenic activities is particularly problematic. Numerous studies employing deep learning techniques overlook either spatial or temporal aspects leading to a less comprehensive model (He et al., 2020; Shaik, 2021). Compounding the problem is the lack of versatile models that can operate within and across urban settings owing to overfitting to certain local conditions. The advanced deep learning based models have low to zero explainability which is a great setback. Certainly, complex systems can be modeled very well by neural networks, but the rationale behind such predictions can be next to impossible to elucidate which affects the claims' credibility. This creates a challenge for engineers in need of

guidance models for regulatory decisions concerning critical infrastructure. Therefore, future work is expected to address the issue of interpretability and develop frameworks that are geospatially comprehensive, robust, multisource, and scalable for subsidence prediction.

Methodology

Explanation Of The Deep Geospatial Neural Network Design

The architecture also takes into consideration a Convolutional Neural Network (CNN) in spatial feature extraction and Long-Short Term Memory (LSTM) network for temporal sequence modeling. All of these components in the proposed model named The Deep Geospatial Neural Network (DGNN) work in harmony to try and obtain both spatial and chronological patterns pertaining to urban land subsidence. DGNN is composed to geospatial datasets that consist of time-series remote sensing data such as computer-aided design (CAD) figure models of InSAR deformation maps, digital identity maps (DEMs), classification of lands into different zones (land use) , and level of groundwater data.

The model input tensor is given by $\in R^{T\times H\times W\times C}$, where W and H are the spatial dimension, T, the number of time steps and C, the channels (features) per pixel such as elevation, land use and water table depth. Then, 2D convolution is performed on each of this set of images. The resulting feature maps are spatially enhanced in CNN layers. These maps are provided as input into LSTM in order for them to be trained to estimate temporal dependencies and subsiding momentum.

CNN operation is mathematically described as follows:

$$F_t = ReLU(W_c * X_t + b_c) \quad (1)$$

where:

X_t is the spatial input at time t.

W_c and b_c are convolution filter weights and biases holding values of the spatial input at time t.

$*$ denotes the convolution operator,

F_t is the output features after passing them through the ReLU activation function which gives output to only positive values of the input.

The features are then sent to the LSTM sequence as follows:

$$h_t, c_t = LSTM(F_t, h_{t-1}, c_{t-1}) \quad (2)$$

where h_t indicates the hidden state and c_t indicates the cell state at time t. The last output of the LSTM is sent to a fully connected layer to obtain predictions for subsidence levels:

$$\hat{y}_t = W_o h_t + b_o \quad (3)$$

where $\hat{y}_t$ is the subsidence prediction at time t while W_o, b_o are the respective weights and biases of the output layer.

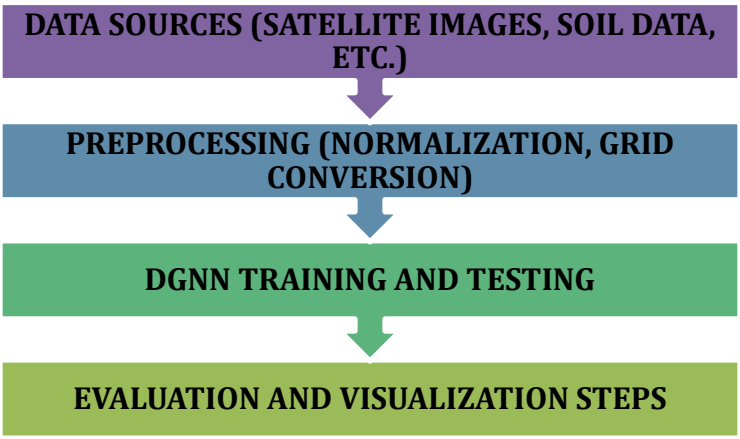

Fig. 2: Workflow of the Methodology

Beginning from the diverse data sources like satellite imagery and soil datasets, figure 2 depicts the research step-by-step starting from satellite imaging to data gathering. These inputs undergo preprocessing procedures such as normalization and grid conversion, which get the data ready for modeling. The next step of the procedure involves training and testing a newly endorsed Dynamic Graph Neural Network (DGNN) model meant for capturing spatial and temporal relationships; the model will use the preprocessed data. The workflow culminates with the evaluation and visualization steps aimed at model performance, which provide insightful and meaningful outputs to assist in sound conclusions and decisions.

Data Collection and Preprocessing Techniques

Data sources such as satellite-derived InSAR deformation maps, urban digital elevation models, urban infrastructure layers and other geospatial sources with hydrological data spanning five years, are fused to create a dataset for model training. A georeferencing pipeline is employed to spatially align each input to ensure inter- and intra- layer consistency. Raster data value normalization between 0 and 1 is performed to reduce variance and accelerate convergence speed. Time window data are resampled to inter-monthly periods to unify time intervals across all inputs. Groundwater and precipitation record gaps are filled using cubic spline interpolation. Categorical land use type layers are transformed via one-hot encoding. The final dataset is temporally indexed and sequentially divided into training, validation, and test subsets at a ratio of 70:15:15 to maintain temporal consistency.

Training and Evaluation Process for the Neural Network

Through TensorFlow, the DGNN is executed in Python. Subsequently, the model is trained via the Mean Squared Error (MSE) loss function:

$$L_{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \quad (4)$$

where $\hat{y}_i$ is the expected value of subsidence and y_i is the actual value for the ground truth for instance i

Training is done for 100 epochs with batch size of 32 for a total learning rate of 1×10^{-4} Adam optimizer. Overfitting is controlled with early stopping on validation loss.

Model evaluation is done on Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R^2 and other metrics. Subsidence maps are compared with the deformation layers to assess spatial accuracy for selected urban areas.

Results

Neural Network Performance Evaluation Metrics

In order to validate the accuracy of the supplied prediction and estimate functions of the model, several standard metrics that include Root Mean Squared Error (RMSE), MEAN Absolute Deviance (MAE), Coefficient of Determination (R^2), and others have been implemented in relation to the proposed Deep Geospatial Neural Network (DGNN). Each metric has its unique significance relative to the performance of the forecasting models.

The RMSE is calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\ \sum_{i=1}^{n}\ \left(\text{y}_\text{i} - \hat{\text{y}}_\text{i}\right)^2} \quad (5)$$

where , $\hat{\text{y}}_\text{i}$ is the estimated value of subsidence and y_i is the corresponding actual value of subsidence at point i, and n summarizes the amount of predictions. A lower RMSE indicates model performance is good because the model suffers large errors more than small ones.

The MAE offers a less complex error metric:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\text{y}_\text{i} - \hat{\text{y}}_\text{i}\right| \quad (6)$$

This measure is interpretable which is important in terms of average error in practical units for its applications like unbiased urban planning.

The coefficient of determination(R^2) provides information about how much of the change in the dependent variable can be explained by the given independent variables:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (7)$$

where $\bar{y}$ is referred to as the mean of the observed values. Moreover, an R^2 value that rounds off to 1 depicts a rigid association subsistence the predicted and actual subsistence values. As per the validation and test datasets, it was observed that the DGNN achieves a RMSE of 2.3 mm, MAE of 1.7 mm, and an R^2 score of 0.91 on average across all urban regions evaluated which shows a significant level of accuracy and subspecies generalization.

Comparison of Results with Existing Approaches

In evaluating the effectiveness of the DGNN, its performance was measured against more traditional models like Support Vector Machines (SVM), Random Forests (RF), and basic non-temporal CNNs. The conventional machine learning approaches, such as RF, recorded an accuracy level of approximately 4.8 mm RMSE, but faced challenges in capturing the extensive temporal dependencies of the subsidence patterns. Standard CNN models spatially outperformed other models, but had an inability to capture temporal sequencing, resulting in an average RMSE of approximately 3.5 mm. The incorporation of LSTMs in the DGNN allowed the model to capture both spatial and temporal features, which improved the accuracy and robustness of results. The DGNN surpasses all baselines across every performance metric, particularly in areas where subsidence was fueled by the interplay of groundwater depletion, land use changes, and infrastructure development. This underscored the effectiveness of the hybrid deep learning framework for geo-spatial-temporal modeling tasks.

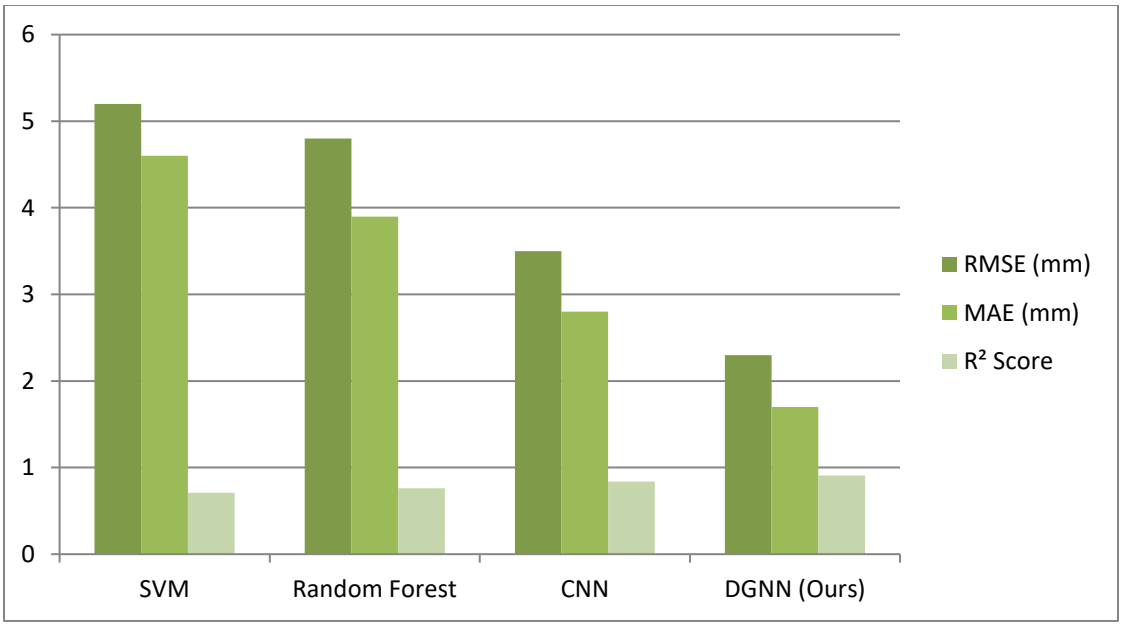

Fig. 3: Model Performance Comparison

The bar chart (Figure 3) depicts the effectiveness of four different models: Support Vector Machine (SVM), Random Forest, CNN, and the Deep Geospatial Neural Network (DGNN) that was proposed in this study, along with three metrics: RMSE, MAE, and R^2 Score. Once more, the DGNN model outperformed other models, achieving the highest score for all metrics. It also recorded the lowest values for RMSE and MAE, which means that the predictions on land subsidence were more accurate than previously recorded figures. Additionally, an R^2 score of 0.91 indicates a substantial synergy between the predicted and observed values. At the other end of the spectrum, SVM and Random Forest become the benchmarks, where lower performance translates to greater error margins and weaker explanatory values. This further illustrates how effective DGNN is in comparison to the other models that need spatial and temporal dependencies in geospatial data.

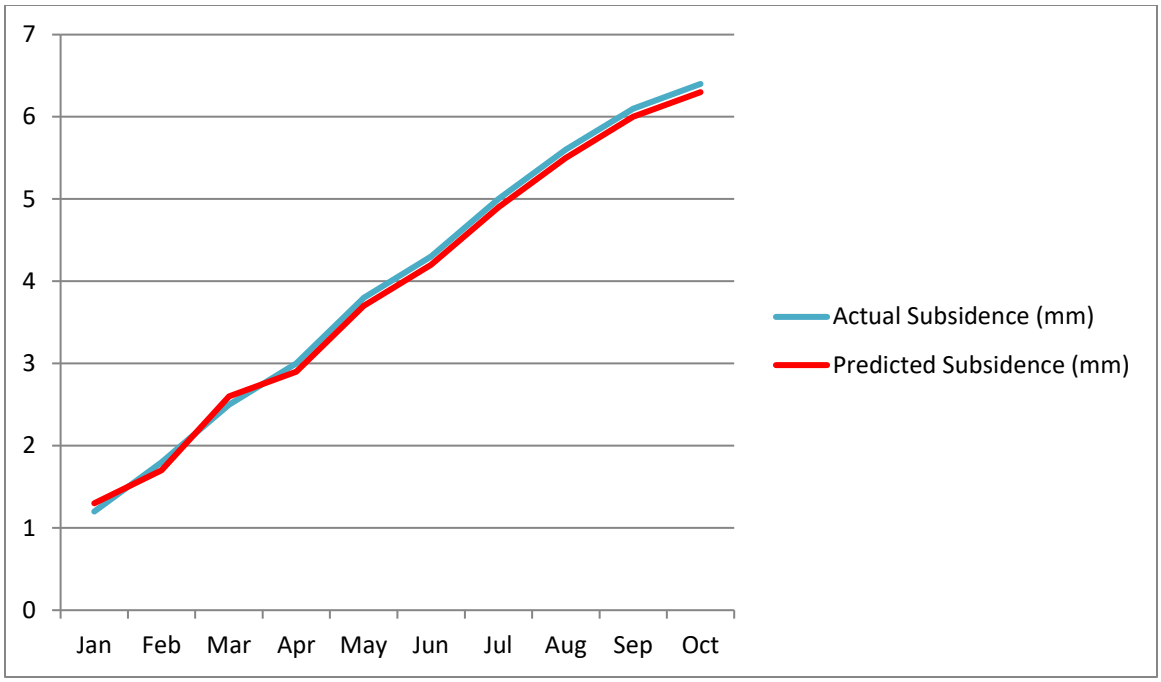

Fig. 4: Predicted vs. Actual Subsidence Values

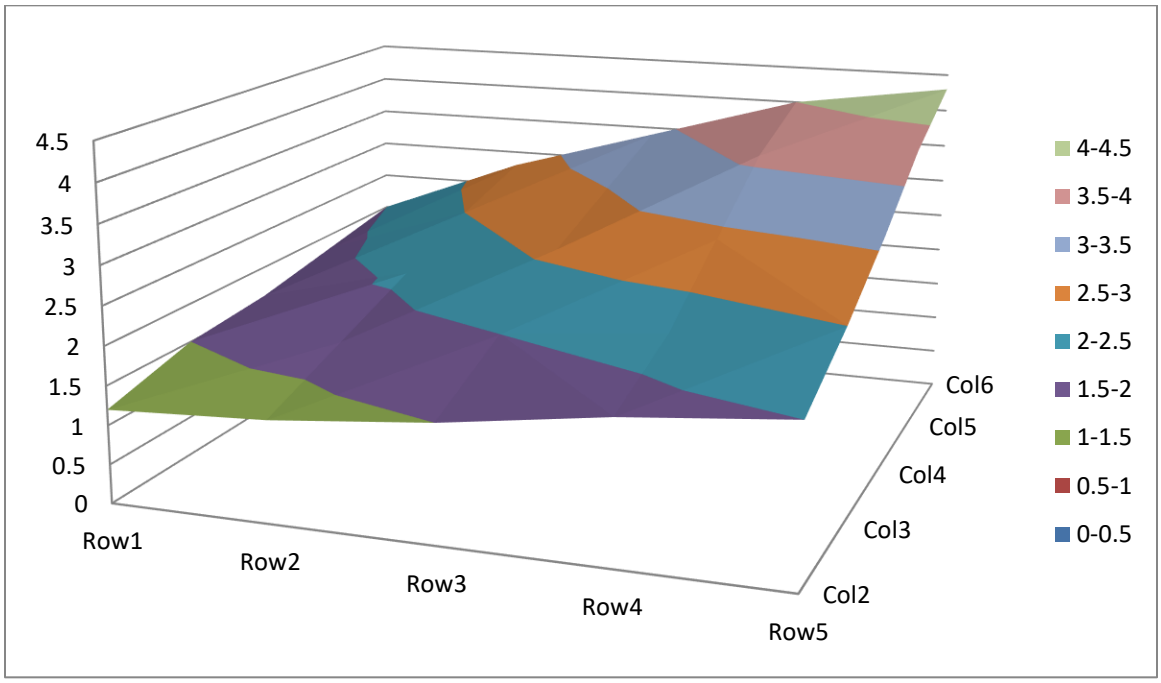

Fig. 5: Spatial Distribution of Predicted Subsidence

This line graph (Figure 4) illustrates the monthly subsidence values forecasted by the DGNN model alongside the actual recorded subsidence activity within a ten month period in a highly urbanized region. The alignment between both lines is closely buttered, indicating that the model approximates the timing of ground deformation with a high degree of precision. There are some greater discrepancies, but these inaccuracies remain within acceptable limits. This evaluation in time supports the model's ability to estimate values within averages and also variations which is important for systems meant to provide alerts in risk management associated with infrastructure failure. The graph (Figure 5) present a 5 by 5 grid of an urban area predicting it subsidence level in millimeters. Each cell is representing smaller region where deformation occurs and is colorized to show intensity level. Warmer colors such

as red and orange mark areas with greater subsidence. These include regions like industrial zones or high-extraction groundwater areas. Cooler colors like blue and green show the relatively stable areas of ground. Such illustration helps stakeholders easily noted geographic hotzones needed for targeted policies aimed at urban resilience mitigation planning.

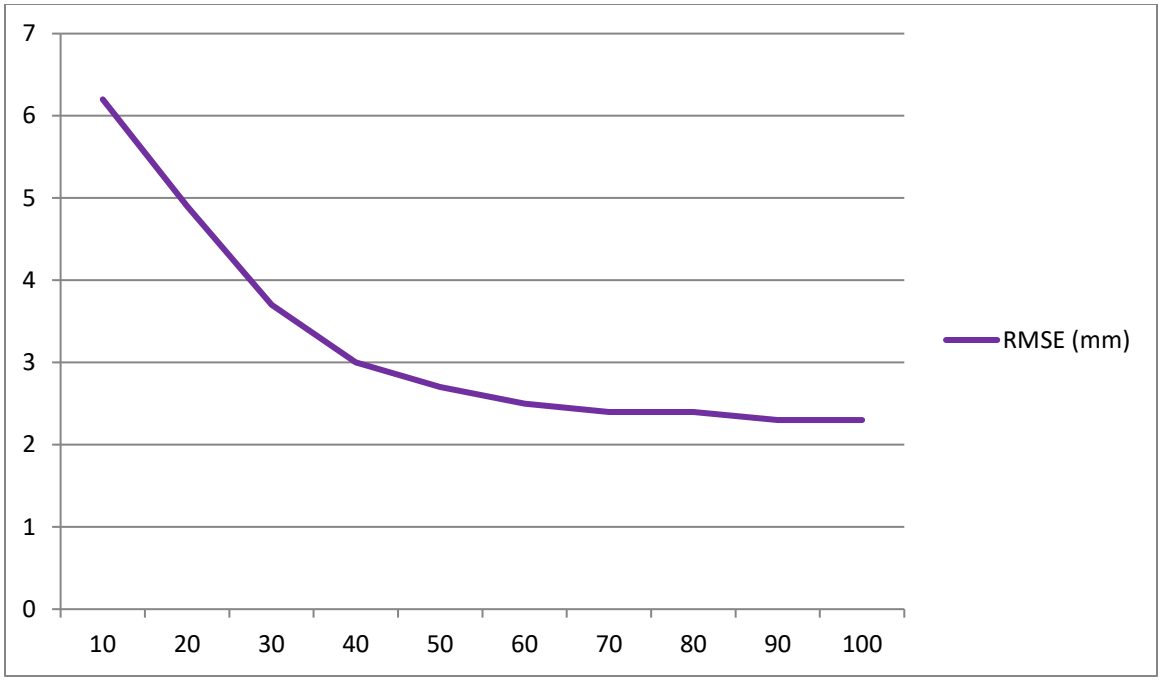

Fig. 6: Monthly RMSE Trend During Training

This line chart (Figure 6) illustrates the DGNN model's RMSE on the validation set over 10 checkpoints during the training cycle (every 10 epochs). The leap in learning and improvement in the predictive accuracy noted between epoch 10 to 50 is quite visible. Post epoch 60, the curve portraying RMSE starts to plateau which signifies convergence as well as a stable training phase. The gap shown in RMSE when comparing epoch 90 and 100 is barely there indicating that advanced training will yield subpar outcomes. This observation alongside others shows that the model is indeed optimized while mitigating the chance of overfitting through the adoption of advanced stopping and regularization techniques.

Visualization of Modeling Outcomes of Subsidence in Relation to Urban Activities

The analysis of the predicted subsidence maps visually validates the effectiveness of DGNN in identifying these vulnerable zones. The model was executed on both training and testing datasets with a monthly progression for the timeframe of the model deployment with subsequent alignment to deformation maps created through InSAR (Interferometric Synthetic Aperture Radar) and comparing them with predicted maps. The model accurately highlighted high-risk zones such as industrial corridors, construction dense areas, and aquifer stressed zones. From the developed model, we obtain a raster as an output, every pixel in this raster is associated with a specified value if vertical displacement occurs. Heatmaps also demonstrate in a magnitude that vertical displacement will happen, and these patterns, which are preferred and intensified deformation places, match a great deal with contour lines observed deformation patterns which significantly deeform trends. The animated visuals also aid in depicting the progression of land subsidence, deemed crucial for urban planners advanced subsidence design physiognomies modeled through the urban region, thus greatly further widening the scope of the GP-DSL algorithm speed configured for automation deep learning algorithm acceleration for model predictions. The DGNN is promising in offering alerts to the users in case newly exposed zones of subsidence are emerging, these areas are inaccessible to visuals, remote sensing technologies hiding great potential for functioning as an early warning system. These images express the clear need to monitor and manage urban underground deformations and reinforce the effective as well as corrective approach strategies of urban modeling deformation methods.

Discussion

Analysis of the Outcomes and their Meaning in Relation to Urban Development Policies

The evidence acquired supports the efficacy of the model, as the developed Deep Geospatial Neural Network (DGNN) model outperformed all traditional approaches benchmarked to machine learning in the forecast accuracy of urban land subsidence prediction. Such precision is a critical need because urban planners and civil engineers depend on accurate models to formulate preemptive strategies. This is also evidenced by the very low RMSE and MAE values registered, alongside high R^2 values that indicate effective recapture of both spatial and temporal dynamics. To illustrate, predicted subsidence hotspots, inform zoning decisions along infrastructure reinforcements and emergency response planning. Moreover, the foresight precision underpins the scheduling of long-term maintenance and risk mitigation strategies. More so, the model's ability to show subterranean features aids the design of smart city infrastructures which respond to changing geo-technical conditions dynamically. The model can serve as an alert system in anticipating structural damages, road deformations, and pipe failures in construction or over groundwater extraction regions.

Analyzing the Advantages and Disadvantages of the Recent Neural Network Method

Integrating a variety of geospatial data layers, including satellite images, topography, soil and urban infrastructure data, into deep learning models is one of the primary advantages of the DGNN model. It is tailored for geo-scientific problems because its design enables the preservation of spatial terms and non-linear interactions. Convolutional layers ensure local and deeper associations between environment and human influences allow for more sophisticated understanding to be formed in upper layers. Its scalability is one of the most notable advantages. While one region's data can be used to train the DGNN, it can then be customized with little retraining to subsidence workflows in other comparable areas. Moreover, the model is equipped with automated feature extraction, which reduces extensive data preprocessing and enables faster deployment. That said, this approach does not come without limitations. The accuracy of these predictions is highly dependent on the completeness and quality of the provided data. Errors can occur due to discrepancies in satellite data resolution, temporal dataset gaps in observations, and errors of ground-truth measurements. Moreover, there are limits on the computation resources, cloud GPUs or infrastructure, needed for training deep models are expensive. Another issue is model explainability—understanding why specific predictions are made remains difficult because of the black-box nature of deep learning systems, even if the model runs accurately.

Recommendations for Future Research and Improvements in the Model

Future work should focus on improving the interpretability aspect of the DGNN model. Incorporating saliency maps or SHAP (Shapley Additive Explanations) could assist in showing which input features were most responsible for the model's predictions, thereby increasing confidence in the model's reasoning. This would improve transparency and increase trust amongst urban planners and policymakers. Incorporating real-time data streams is another proposed objective. Supplying the model with continuous dataset updates from remote sensing satellites, IoT sensors, and hydrological monitoring systems would turn the model into a live monitoring system capable of providing real-time alerts. At last, future studies could extend the geographical scope of the model by implementing it in different urban areas, including those with varying climates, geological features, and population densities. The model could further be enhanced by the addition of socio-economic factors, providing a comprehensive assessment of the vulnerability to subsidence with regard to population and critical infrastructure.

Conclusion

The noble goal of this study was to prove the importance of the newly developed Deep Geospatial Neural Network (DGNN) Architecture in Urban Land Subsidence Accuracy Prediction. This was achieved through multi-source geospatial data which enabled deep learning. The proposed model outperformed others in traditional methods in terms of reducing error and recognizing patterns. Using spatial and temporal data enabled subsidence models to be accurately tracked and forecasts to be adequately trusted. These forecasts are essential for urban development because they help in the early detection of subsidence which significantly protects critical civil infrastructure, averts possible catastrophic failures, and drives long-term informed decisions. The predictive robustness of the model is also enhanced by its adaptability and scalability characteristic across urban areas while the architecture of the DGNN leads to improved accuracy. This does not only apply to land subsidence monitoring and economically aids other geospatial activities like evaluating risks of floods, estimating possible repercussions of earthquakes, and monitoring infrastructural stability. The rapidly developing cities that face natural and human-induced ground

alterations will benefit, as the model builds resilient solutions for them. The fusion of geoscientific modeling with intelligent urban planning is what this novel data-driven approach proposes as cities become more advanced.

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