https://doi.org/10.18485/resylab.2024.6.ch13

Evaluating the Effectiveness of Deep Learning Algorithms and InSAR Data in Early Warning Systems for Landslide Risk Mitigation

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Abstract Landslides are a significant natural hazard that can cause severe damage to infrastructure and impact local communities' safety and prosperity. Accurate and reliable prediction of deformation caused by landslides is crucial to implementing effective disaster management strategies that can mitigate the risk of landslides and their impact on communities and provide an accurate early warning system. This study proposes a comprehensive approach to cumulative deformation induced by landslide prediction in the Caiazzo hamlet (southern Italy), a critical area that has experienced significant landslides that have impacted settlements and infrastructure. The study uses a CNN-LSTM algorithm with Spatio-Temporal dependency to predict cumulative deformation caused by landslides, employing geological, geomorphological, and geospatial data as predisposing factors. These factors include elevation, slope, aspect, Topographic Wetness Index (TWI), Stream Power Index (SPI), geology, flow direction, curvature, Normalized Difference Vegetation Index (NDVI), and land use. The Permanent Scatterer Interferometry (PSI) technique was applied on 132 and 143 SENTINEL1-A ascending and descending tracks, respectively, to obtain cumulative deformation data as labels, providing an extensive data set that allowed for accurate and reliable prediction of landslide deformation. The proposed CNN-LSTM algorithm integrates convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to learn the spatio-temporal dependencies between landslides' predisposing factors and their cumulative deformation. This approach allows the algorithm to capture the complex relationships between the predisposing factors and the occurrence of landslides, resulting in accurate and reliable understanding of landslide kinematics and providing early warning system accurately. The close match between predicted and observed cumulative deformation indicates that the CCN-LSTM model effectively captures the complex relationships between the various factors contributing to cumulative deformation prediction. Our finding illustrates more than 70% of predicted deformation with less than 2 mm error and 90% with less than 5 mm error after prediction. Overall, the proposed algorithm's superior performance in predicting cumulative deformation caused by landslides highlights the potential of deep learning algorithms to enhance landslide prediction and disaster management strategies.

Keywords Landslide prediction, CNN-LSTM algorithm, Spatio-Temporal dependency, Deep learning, Early Warning System, PSI technique

Introduction

The Landslides are one of the most pervasive natural hazards globally, posing a significant threat to human lives, infrastructure, and ecosystems (Di Martire et al., 2015). These geological phenomena, characterized by the downward and outward movement of slope-forming materials, are triggered by various factors that can significantly vary across different geographical locations. These triggers include intense precipitation, seismic activities, volcanic eruptions, anthropogenic actions such as deforestation, urban development, and alterations in land use (Calò et al., 2009). The complexity and interplay of these triggers necessitate a sophisticated approach to understanding, predicting, and managing landslide risks (Bravo-López et al., 2022).

Focusing on the Caiazzo hamlet in southern Italy, this area exemplifies a region highly susceptible to the devastating effects of landslides (Sammartini et al., 2019). The lithological setting, characterized by weak geological materials coupled with the region's geotechnical properties, such as soil composition and water content, significantly contributes to slope instability. This instability is further exacerbated by human activities and climatic factors, leading to morphodynamic events that have historically impacted the local communities and infrastructure. The landslides in Caiazzo, encompassing both active and dormant phases, manifest predominantly as rotational and translational slides and Earth flows (Carannante et al., 2010).

The advent of remote sensing technologies, particularly Multi-temporal Interferometric Synthetic Aperture Radar (MT-InSAR), has revolutionized the monitoring and analysis of landslides. Among the techniques derived from MT-InSAR, the Permanent Scatterer Interferometry (PSI) technique stands out for its precision in detecting and measuring ground displacement over time (Hooper, 2008). SENTINEL1-A satellite imagery equipped with Synthetic Aperture Radar (SAR) is particularly advantageous in landslide studies. SAR's ability to penetrate cloud cover and its independence from daylight conditions make it an invaluable resource for continuously monitoring Earth's surface changes, including the subtle displacement preceding or indicating landslide activity (Potin et al., 2016).

Predicting the cumulative deformation caused by landslides is crucial for the timely implementation of disaster management and mitigation measures Khalili et al., 2023a). This prediction is inherently challenging due to the need for integrating diverse and complex datasets, encompassing spatial data on predisposing factors and temporal data on landslide cumulative deformation. Machine Learning Algorithm (MLA) has been applied in various ways to predict landslides accurately and rapidly (Gan et al., 2019). It includes Decision Trees, Random Forests (Hong et al., 2016), and Support Vector Machines (Liu et al., 2021), which are extensively used to detect landslides. However, most time-series prediction applications prefer Deep Learning Algorithms (DLAs) over traditional statistical models. Yet, they cannot describe the behaviour of multivariate time series. DLAs can analyze datasets with multiple dimensions by integrating numerous processing layers, extracting learning features, and nonlinear dependencies (Khalili et al., 2023b; Li et al., 2020). Recent advances in the field have shown that DLAs can be used as a model for predicting deformation (Hajimoradlou et al., 2020).

The introduction of Convolutional Neural Networks (CCN) and Long Short-Term Memory (LSTM) networks marks a significant advancement in the field of landslide prediction (Greff et al., 2017; Zarándy et al., 2015). CCNs are adept at processing spatial data, including geospatial data (predisposing factor), to identify patterns and features indicative of landslide susceptibility. On the other hand, LSTMs excel in analyzing time-series data, making them ideal for modeling the temporal progression of landslide cumulative deformations based on historical and real-time data.

Our study proposes a novel approach that synergizes the spatial data processing capabilities of CCN with the temporal data (cumulative deformation) modeling strengths of LSTM. This integrated CCN-LSTM model is designed to harness the full potential of both neural network architectures, thereby providing a more accurate and reliable prediction of landslide-induced cumulative deformations in the Caiazzo hamlet. By doing so, this research addresses the existing challenges in accurately predicting landslides and contributes to the development of more effective early warning systems and disaster management strategies.

Case Study

Caiazzo is a municipality of Campania region (Italy) located in the Caserta province, in the northern part of the regional territory, at 200 m a.s.l. According to the CARG Project (Geological Cartography of Italy), the area is mainly characterized by coarse sandstones, conglomerates, and microconglomerates, which belongs to Caiazzo Sandstones Unit. Such formation is also composed by marly-silty intercalations and chaotic deposits alternate with extra-basial elements (olistostroms) consisting of limestone and marly limestone referable to scaly clays. These rocks alternate with eluvial and colluvial deposits (Holocene-Current), which are silty-sandy deposits of a pyroclastic nature with calcareous clasts and silty-clayey deposits with arenaceous or calcareous-marly clasts. In the northern sector of the urban center Pietraroja Formation (Tortonian) of Matese-Taburno-Camposauro Unit outcrops, it consists of stratified clayey-silty marls and subordinate fine sandstones. While, in the southern sector Casalnuovo-Casoria Unit outcrops, including levels of laminated cinerites passing through a level of pumices in a cineritic matrix (Pleistocene Sup. - Holocene).

From a geomorphological and structural point of view, Caiazzo area is characterized by a landscape with reliefs with medium-low slopes (less than 20°), consisting of arenaceous-marly-clay lithostratigraphic units, and areas at lower altitudes characterized by Quaternary eluvial-colluvial deposits. The arenaceous hilly reliefs are in stratigraphic (Scarsella, 1971) and tectonic (Pescatore et al., 1971) relationship with the underlying formations. These lithologies have low resistance to erosion, so although some tectonic structures (normal faults NE-SW) are present, they do not have significant structural morphologies. The slopes are concave-convex, and they are characterized by linear erosion valleys and landslide bodies of various typologies and sizes (Carannante et al., 2010).

The lithological and geotechnical characteristics of the investigated area contribute to the instability of the hilly slopes. They are affected by gravitational phenomena, marked by different morphodynamic events. Specifically, they involve the terrigenous units of Caiazzo and consist of active and quiescent landslides (Carannante et al., 2010), mainly rotational and translational slides and earth flows. The landslides involving arenaceous slopes are in total 140, they include 99 rotational/translational slides, 20 mass creep, 17 soil creep, 3 falls and 1 undefined landslide (Fig. 1). Many of them have a complex style and consist of slide evolving to flows, that overtake 1000 m. As could be seen, this area is characterized by a large number of mass movements which affect urban center and rural zones, therefore, they represent a danger for structures and infrastructures, in particular in the eastern sector of the town.

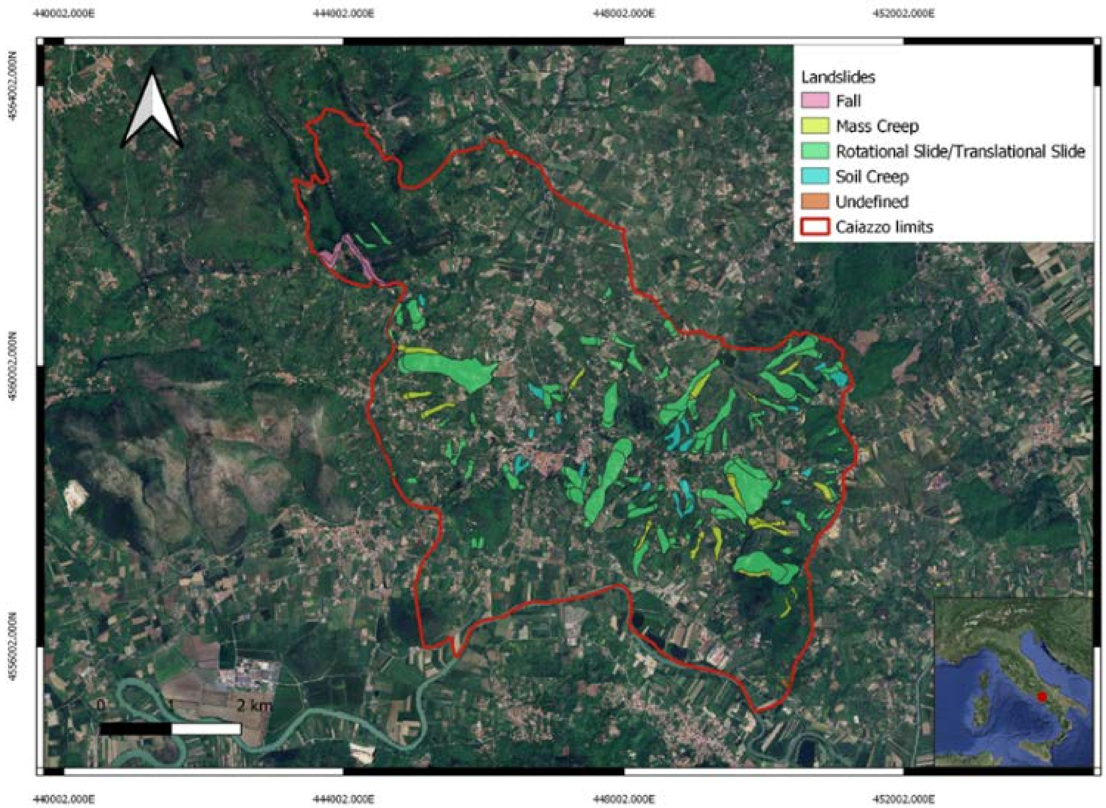

Figure 1 Landslides inventory map of Caiazzo municipality.

Material

SAR Data Acquisition

Synthetic Aperture Radar (SAR) data have emerged as indispensable tools in natural disaster analysis, particularly landslide detection and monitoring. SAR's unique advantages, including its all-weather, day-and-night operation capabilities and its sensitivity to ground movement, make it ideal for observing and analyzing Earth's surface changes over time. This study utilizes SAR data from the SENTINEL1-A satellite, part of the Copernicus program managed by the European Space Agency (ESA), which provides comprehensive coverage and detailed images essential for monitoring landslide-prone areas (Potin et al., 2016).

The SAR data for the Caiazzo hamlet were acquired from the SENTINEL1-A satellite, focusing on ascending and descending tracks to capture comprehensive deformation patterns across different times and viewpoints. A total of 132 ascending and 143 descending tracks from 14/01/2017 to 25/11/2021 and from 16/01/2017 to 27/11/2021, respectively, were analyzed to ensure a robust dataset for accurate cumulative deformation analysis as temporal data for training and predicting by LSTM algorithms.

Predisposing Factors

In the context of landslide prediction, predisposing factors are critical elements that contribute to the likelihood of landslide occurrence. These factors, derived from geological, geomorphological, and geospatial data, provide a foundation for understanding the conditions under which landslides are most likely to occur. This study incorporates a comprehensive set of predisposing factors, including elevation, slope, aspect Topographic Wetness Index (TWI), Stream Power Index (SPI), geology, flow direction, curvature, Normalized Difference Vegetation Index (NDVI), and land use. Each factor plays a vital role in the landslide prediction model, contributing to accurately assessing landslide susceptibility.

The study makes use of primary geological, geospatial, and geomorphological data, including:

i) To understand the geological background, A geological map of the Caiazzo hamlet with a scale of 1:50,000.

ii) A Digital Elevation Map (DEM) of the case study with a 20-meter pixel resolution, primarily utilized to investigate the topographic and geomorphological features of the Caiazzo hamlet, such as elevation, slope, flow direction, aspect, curvature, Topographic Wetness Index (TWI), and Stream Power Index (SPI).

iii) Landsat7 ETM+ took remote sensing images with a 30-meter resolution for bands 1 to 7 to discuss the climatic and environmental characteristics of the Caiazzo hamlet. This data is used to acquire the normalized differential vegetation index (NDVI) and land use type.

Methods

Permanent Scatterer Interferometry (PSI) technique

Permanent Multi-temporal Interferometric Synthetic Aperture Radar (MT-InSAR) is a sophisticated technique that analyzes phase differences in SAR images over time to detect ground deformations. This approach offers unparalleled precision in measuring surface movements, which is essential for monitoring geological hazards. MT-InSAR's capability to capture data under any weather conditions and its broad area coverage make it an invaluable dataset for understanding and predicting natural disasters, including landslides and earth subsidence (Ferretti et al., 2001; Hanssen and Ferretti, 2002).

Permanent Scatterer Interferometry (PSI) is a specialized subset of MT-InSAR that focuses on the identification and monitoring of stable reflection points or permanent scatterers over time. This method enhances the accuracy of deformation measurements in urban or rocky terrains, where two-pass InSAR might face challenges due to coherence loss. PSI's ability to provide long-term deformation trends with millimeter-level accuracy is critical for assessing structural stability and ground movements, offering vital data for infrastructure planning and risk assessment (Hooper, 2008).

A Digital Elevation Model (DEM) with a cell resolution of 20m × 20m and a multi-looking factor of 1 × 1 in range and azimuth is used for this technique in this study. The SUBSIDENCE software developed at Universitat Politecnica de Catalunya implemented the Coherent Pixels Technique and was used to apply the PSI method (Blanco-Sànchez et al., 2008). The software processed the co-registered images and selected all possible interferogram pairs (including 456 for ascending track and 428 for descending) with spatial baselines lower than 100 meters. It used a Temporal Phase Coherence threshold of 0.7. Finally, the deformation rate map along the line of sight (LoS) and time series of cumulative deformation was calculated.

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) represent a class of deep neural networks highly effective at processing data with a grid-like topology. A fundamental concept in CNNs is their ability to learn spatial hierarchies of features automatically and adaptively from input data. This is achieved through convolutional, pooling, and fully connected layers (Zarándy et al., 2015).

Our paper explores using CNNs to identify and learn spatial patterns from predisposing factors related to landslide occurrences. By treating each predisposing factor as a separate channel (similar to the RGB channels in color images), we can feed a multi-dimensional array into the CNN, where each layer is designed to detect patterns and features indicative of potential landslide hazards automatically. Through convolutional and pooling layers, the CNN condenses this spatial information into a high-level feature vector that encapsulates the critical spatial dependencies among these predisposing factors. This vector serves as a compact yet rich representation of the input data, which is then used by the LSTM network to predict landslide cumulative deformations by considering the temporal evolution of these spatial features. This approach allows us to leverage the strengths of CNNs in processing visual data and in any domain where understanding spatial relationships is critical to making accurate predictions.

For the CNN component of our study, we calibrate and tune an array of hyperparameters to ensure optimal extraction and learning of spatial patterns from the predisposing factors associated with landslides. These hyperparameters, set before the training phase, play a pivotal role in defining the architecture and learning dynamics of the CNN. Key hyperparameters for our CNN include the number of convolutional layers (12 layers), the number of filters (initial layer = 64 and deeper layer = 256) in each convolutional layer, and the size of these filters (3x3). We chose ReLU as an activation functions enabling it to learn complex patterns. Pooling layer configurations, specifically the selection of max pooling and their respective kernel sizes (2x2), dictate the Downsampling strategy, affecting the model's sensitivity to feature localization. The dropout rate (0.3) is another crucial hyperparameter that prevents overfitting by randomly omitting a subset of features during training. Lastly, the learning rate and optimization algorithm (Adam) are fine-tuned to balance the speed and stability of the learning process.

Long Short-Term Memory (LSTM)

LSTM networks are a special kind of Recurrent Neural Network (RNN) architecture designed to overcome the limitations of traditional RNNs in capturing long-term dependencies. LSTMs are particularly adept at remembering information for extended periods, thanks to their unique structure, which includes memory cells and multiple gates (input, output, and forget gates). These components work together to regulate the flow of information, allowing the network to retain or discard data based on its relevance to the task at hand. This capability makes LSTMs highly effective for various sequence prediction problems (Greff et al., 2017; Khalili et al., 2023b).

In our paper, we leverage LSTM's prowess in handling time-series data to model the temporal aspect of landslide deformation, explicitly focusing on cumulative deformation data obtained from ascending and descending tracks. The cumulative deformation data, characterized by its sequential nature over time, serves as an ideal input for the LSTM network, allowing it to learn the temporal patterns and dependencies inherent in the deformation process. By training separate LSTM models on datasets from ascending and descending tracks, we aim to capture the nuances and variances in deformation patterns that might be specific to the direction of satellite observation. This dual approach enables a more comprehensive understanding of landslide dynamics, potentially improving prediction accuracy by integrating insights from both perspectives. Each LSTM model is trained on a sequence of past deformation measurements to predict future deformation, utilizing the LSTM's capacity to learn from long-term sequences to anticipate changes in landslide behaviour over time in ascending and descending separately.

In our research, optimizing and fine-tuning hyperparameters for the LSTM component are critical to accurately modeling the temporal dynamics of cumulative landslide deformation. Key hyperparameters for the LSTM include the number of hidden layers and the number of units (or neurons) in each layer, which dictate the model's capacity to learn from the data. Typically, we experiment with one to three hidden layers containing 50 to 200 units, balancing model complexity with computational efficiency. The learning rate, another crucial hyperparameter, is carefully selected to ensure convergence without overshooting, with initial values set at 0.001. The optimizer's choice, Adam, is made to effectively minimize the loss function, considering their ability to adapt learning rates based on the history of gradients. Dropout rates are applied within the LSTM layers, 0.3, to prevent overfitting by randomly omitting a subset of the features during training. The sequence length, or the number of times steps the LSTM looks back on, is six time steps of cumulative deformation, ensuring the model captures relevant temporal patterns without noise. Batch size is another parameter adjusted for efficient training, 64, balancing the trade-off between training speed and memory constraints. These LSTM hyperparameters are iteratively refined through validation and cross-validation, aiming to achieve a model that generalizes well to unseen data while accurately capturing the temporal patterns in cumulative deformation and predicting the cumulative deformation in a specific time.

Proposed CNN-LSTM Algorithm

In our study, we propose a novel CNN-LSTM hybrid model that leverages the strengths of CNNs and LSTM networks to accurately predict landslide cumulative deformations by effectively capturing both spatial and temporal dependencies. The CNN component is a powerful feature extractor, processing predisposing factors such as slope, aspect, etc, to identify relevant spatial patterns and interactions. These extracted high-level spatial features are then passed onto the LSTM component, which is adept at modeling time-series data (ascending and descending cumulative deformation). The LSTM uses these features to learn the temporal dynamics of cumulative deformation, considering the sequential nature of the data and its historical progression. This synergistic combination allows our model to understand how spatial configurations evolve, leading to more accurate and insightful predictions of landslide occurrences. By integrating CNN's spatial analysis capabilities with LSTM's temporal dependency modeling, our CNN-LSTM architecture offers a comprehensive approach to landslide prediction, effectively harnessing the complex interplay between the various factors influencing landslide dynamics.

Results and Discussion

Fig 2a represents the cumulative deformations on 25/11/2021 for the ascending track, and Fig 2b represents the last predicted epoch for cumulative deformations on the same date, to help understand how the proposed prediction model (CCN-LSTM) works. The model correctly predicted positive and negative deformation amounts and locations, with a mean absolute error of 0.29. Fig 3a and b also show a good agreement between actual and predicted cumulative deformation on 27/11/2021, with a mean absolute error of 0.34.

Figg. 2 and 3 demonstrate that our model provides an excellent fit to the observed data, indicating its ability to predict cumulative deformation accurately and reliably and, thus, the risk of landslides in the studied area. The close match between the predicted and observed cumulative deformation shows that the CCN-LSTM model effectively captures the complex relationships between the various factors contributing to cumulative deformation prediction, such as geological, geomorphological, and geospatial data types. These figures highlight the potential of the CCN-LSTM model as a valuable tool for predicting cumulative deformation and the risk of landslides, which can inform decision-making and disaster response efforts.

The Bland-Altman plot presented herein is a graphical method to assess the agreement between the cumulative deformation predicted by our model and the observed deformation data. On the y-axis, the differences between the observed and predicted values are plotted against their mean on the x-axis, providing a direct visualization of the prediction error distribution.

The plot is color-coded to represent different ranges of actual cumulative deformation, with distinct colours denoting the intervals as specified: less than -2 mm, between -2 mm to 2 mm, and greater than 2 mm. This colours scheme enables a quick visual correlation between the magnitude of cumulative deformation and the associated prediction error. Horizontal lines are drawn at ±2 mm and ±5 mm to denote the acceptable error thresholds. According to the analysis encapsulated by the plot, a substantial majority of the data points—represented by their spread along the zero line—fall within the ±2 mm error margin, consistent with the assertion that over 70% of the deformation predictions are within this range. Furthermore, when considering the wider ±5 mm margin, the data points enveloped by this criterion rise to 90%, underlining the robustness of the predictive model. The distribution of points across the plot reveals a clustering around the mean difference line, which indicates a high accuracy level in the predictions across the range of cumulative deformation values. Points outside the ±5 mm bounds are few, suggesting that the prediction errors are generally minor, and the model's performance is dependable. Tab 1 presents the proposed algorithms' evaluation metrics for ascending and descending tracks. Two key metrics assess the model's performance: the Root Mean Square Error (RMSE) and the R-squared (R^2) score.

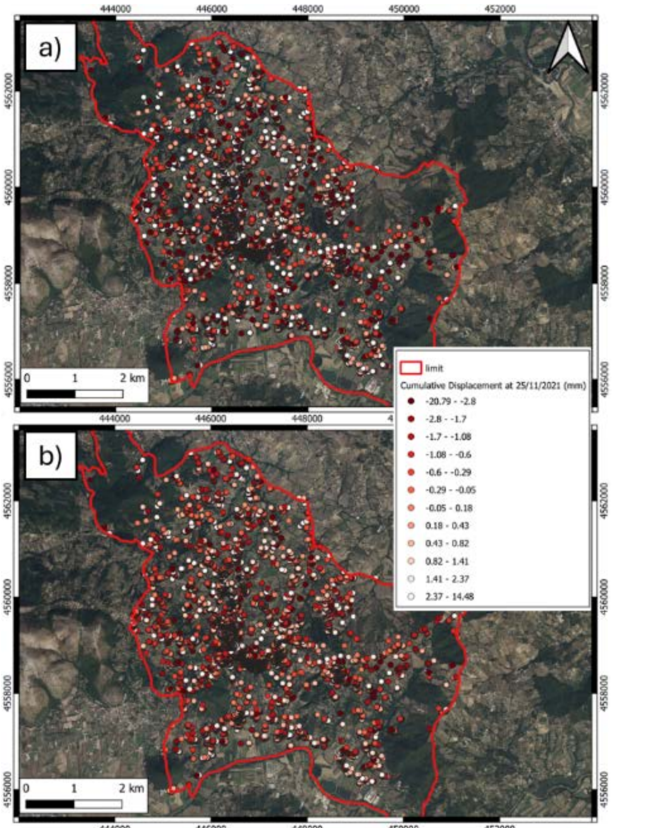

Figure 2 Location and map of deformation by a) PSI technique and b) CCN_LSTM (Unit: MM) in ascending track.

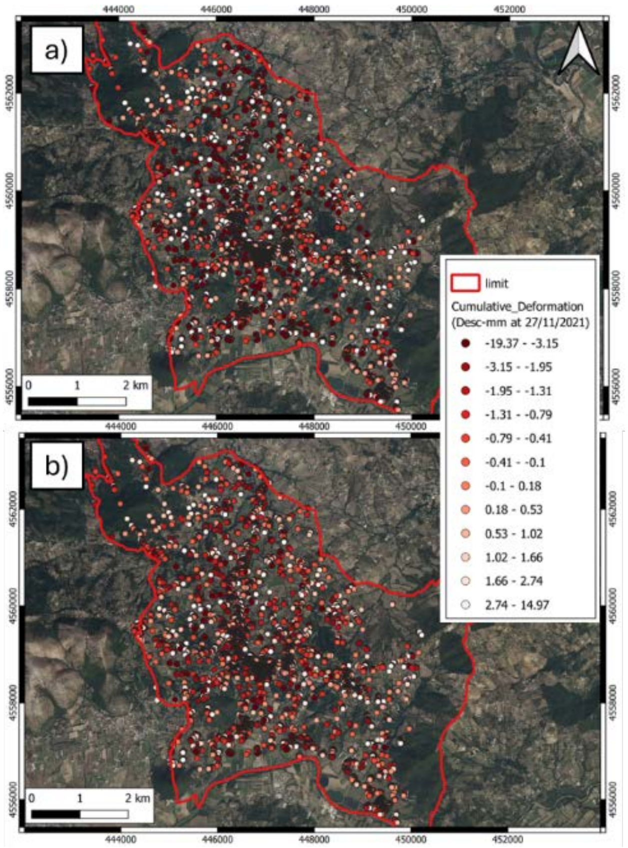

Figure 3 Location and map of deformation by a) PSI technique and b) CCN_LSTM (Unit: MM) in descending track.

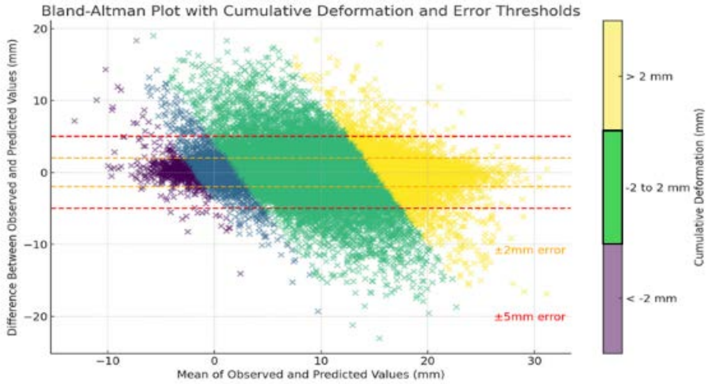

Figure 4 Bland-Altman plot showing prediction accuracy for cumulative deformation, with over 70% of predictions within ±2mm error and 90% within ±5mm error.

RMSE: This metric measures the average magnitude of the errors between the predicted values by the model and the actual values. It's beneficial because it gives more weight to significant errors, making it sensitive to outliers. A lower RMSE value indicates a better fit of the model to the data. According to the table, the CNN-LSTM model applied to the ascending track data has an RMSE of 0.26, suggesting it predicts cumulative deformation with relatively small errors. The descending track data's RMSE is slightly higher at 0.32, indicating more significant average prediction errors.

R^2 Score: Also known as the coefficient of determination, the R^2 score measures the proportion of the variance in the dependent variable that is predictable from the independent variables. It indicates the model's goodness of fit. An R^2 score of 1 indicates perfect prediction, while a score of 0 would mean that the model fails to accurately predict the outcome any better than simply using the mean of the actual values. The CNN-LSTM model achieves an R^2 score of 0.88 for the ascending track, which is relatively high, suggesting that the model accounts for a significant proportion of the variance in the cumulative deformation. For the descending track, the R^2 score is 0.79, which is still substantial but indicates a slightly lesser ability of the model to explain the variance in the data compared to the ascending track.

Table 1 Evaluation metrics for the proposed algorithms.

Model	RMSE	R^2 Score
CNN-LSTM in Ascending Track	0.26	0.88
CNN-LSTM in Descending Track	0.32	0.79

The model demonstrates commendable precision in estimating cumulative deformation, with a notably lower RMSE for the ascending track data. This suggests that the model is slightly more effective in capturing the intricate spatial-temporal dynamics when analyzing data from ascending tracks, potentially due to variations in the satellite's observational geometry or differences in the environmental characteristics captured in each track type.

Conclusion

In conclusion, the comprehensive evaluation of the CNN-LSTM model through quantitative metrics and the Bland-Altman plot analysis has substantiated its ability to accurately predict cumulative deformation from SAR data across ascending and descending tracks. The model exhibited notable precision in its predictions, as evidenced by the low RMSE values and high R^2 scores, particularly for the ascending track data. This level of accuracy is crucial for developing reliable early warning systems for landslides, which can significantly mitigate the risk to infrastructure and communities in vulnerable areas. The Bland-Altman plot further affirmed the model's consistency in prediction accuracy, highlighting its potential applicability in real-world scenarios where precise and reliable predictions are paramount.

Moving forward, it is imperative to address the slight disparity in model performance between ascending and descending tracks, potentially by integrating additional data sources or refining the model architecture better to capture the unique characteristics of each track type. Future research could also explore the integration of more diverse environmental variables and apply advanced Artificial Intelligence algorithms to enhance the model's predictive power. Ultimately, the goal is to refine and adapt the model to serve as a cornerstone in proactively managing landslide risks, contributing to the safety and resilience of affected communities worldwide.

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