



# 1 Enhanced Land Subsidence Interpolation through a Hybrid

## 2 Deep Convolutional Neural Network and InSAR Time Series

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11Abstract- Land subsidence, the gradual or sudden sinking of the land, is a global issue threatens infrastructure and 12 the environment. This paper introduced a hybrid method based on deep convolutional neural networks (CNN) and 13 persistent scattered interferometric synthetic aperture radar (PSInSAR) to estimate land subsidence in areas where 14 PSInSAR cannot provide reliable measurements. This approach involves training a deep CNN with subsidence driving 15 forces and PSInSAR data to learn patterns and estimate subsidence values. Our evaluation of the model shows its efficiency in overcoming the discontinuities observed in the PSInSAR results, producing a continuous subsidence 16 17 surface. The deep CNN was evaluated on training, validation, and testing data, resulting in mean squared errors of 5 18 mm, 9 mm, and 11 mm, respectively. In contrast, the kriging interpolation method showed a mean square error of 37.19 mm in the experimental data set. subsidence prediction using the deep CNN method showed a 70% improvement 19 20 compared to the Kriging interpolation method.

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22 Index Terms- Convolutional Neural Network (CNN); Prediction of subsidence; PSInSAR; driving forces; Kriging

23 interpolation.





#### 24 **1. Introduction**

25 The gradual decrease in the height of the earth's surface, which is accompanied by slight horizontal displacements, is 26 called subsidence. Due to the gradual nature of land subsidence, this phenomenon is also called "silent earthquake". 27 Its harmful effects appear over a long period of time and carry significant risks. However, land subsidence is a global 28 threat to urban areas around the world (Sun et al., 2023). This issue is an important global concern and is not limited 29 to one region. Iran is facing an increasing challenge especially in this field. Human activities, such as mining and 30 excessive underground water extraction, contribute to this problem. To address it, effective groundwater management 31 to prevent unauthorized water extraction would help. However, land subsidence is not only caused by human actions, 32 natural factors also play an important role. These include water table fluctuations, soil characteristics, depth of the bed rock, terrain features like elevation and aspect, vegetation cover, and prevailing climate. All these factors together 33 34 create a complex landscape of land subsidence occurrences.

35 Precise leveling and GNSS observations offer high precision in measuring subsidence. Still, they are limited in their 36 ability to investigate subsidence over a wide area due to their reliance on measuring sparse stations. These methods 37 require multiple measurements at different locations, making it difficult to monitor subsidence over large areas (Fialko 38 et al., 2005; Hu et al., 2012). On the other hand, Interferometric Synthetic Aperture Radar (InSAR), has emerged as a 39 high spatial resolution and cost-effective technique for monitoring subsidence on a large scale (Chang et al., 2010; 40 Tamburini et al., 2010; Tomás et al., 2011; Rucci et al., 2012; Amighpey & Arabi, 2016; Biswas et al., 2018; Gonnuru 41 & Kumar, 2018; Khorrami et al., 2019). InSAR uses radar waves to carefully monitor changes in the Earth's crust 42 surface over time. Methods that analyse radar images over time, known as time series analysis, make them very 43 effective for monitoring subsidence, which usually occurs gradually over time. Persistent Scatterer Interferometric 44 Synthetic Aperture Radar (PSInSAR) is particularly valuable for monitoring urban land subsidence. This is because 45 there are many high-density Persistent Scatterer (PS) points, mainly associated with buildings and man-made structures. This abundance significantly improves the quality of the data within interferograms (Gao et al., 2019). 46 47 Although these advantages are significant, dealing with the sparse and uneven distribution of PSs in both spatial and 48 temporal dimensions is a significant computational challenge. The PSInSAR approach generates discontinuous results, 49 as it calculates subsidence exclusively at PS points. Consequently, it becomes imperative to employ intelligent 50 interpolation instead of mathematical or stochastic methods, between these data points to fill out these gaps (Naghibi 51 et al., 2022).





52 Subsidence is a complex physical phenomenon influenced by a multitude of factors, such as changes in groundwater 53 levels, soil type, bedrock depth, slope, elevation, Aspect, etc. To obtain the subsidence in the whole area, interpolation 54 methods between PSs and artificial intelligence methods (which are trained with features affecting subsidence) can be 55 used. Interpolation methods between PSs and artificial intelligence methods (trained with features affecting 56 subsidence) can be used to obtain subsidence in the entire area. Classical interpolation methods (e.g. Kriging, IDW, 57 RBF (Mehrabi & Voosoghi, 2018), RMLS (Mehrabi & Voosoghi, 2015)) do not consider the physics of the issue, 58 making their results less reliable. So, it is very important to apply methods that take into account the real characteristics 59 of the phenomenon, especially when monitoring the subsidence. Recently, machine learning methods specifically deep 60 convolutional neural network (CNN) shows encouraging results in various applications. In the larger context of land 61 subsidence prediction models, we find two main categories: Physical Process Models: These models simulate 62 subsidence by incorporating factors like geotechnical mechanics, soil properties, and water dynamics. They are 63 frequently used in large-scale projects but require a substantial amount of prior knowledge and data (Nie et al., 2015); 64 Mathematical or Statistical Models: These models predict subsidence based on historical elevation data and past trends 65 (Zhu et al., 2010).

66 Several studies have investigated various forecasting models, methodologies, and influencing factors to improve our 67 understanding of this field. Neural networks have emerged as powerful prediction tools, so neural networks have been 68 used in the field of subsidence prediction using its driving forces. (Zhu et al., 2010; Azarakhsh et al., 2022; Ku & Liu, 69 2023). Lee et al. (2023) employed data from an urban area in Korea to develop a machine learning-based model for 70 predicting land subsidence risk. Their methodology incorporated historical land subsidence data along with attribute 71 information pertaining to underground utility lines in the specified region. The research team utilized machine learning 72 algorithms such as Random Forest (RF), eXtreme Gradient Boosting (XGBoost), and Light Gradient Boosting 73 Machine (LightGBM) for the analysis and prediction of land subsidence risks (Lee et al., 2023). Sadeghi et al. (2023) 74 combined full consistency decision-making (FUCOM) and GIS methodologies to assess Iran's vulnerability to land 75 subsidence. Their approach resulted in the development of a hierarchical FUCOM-GIS framework, which highlighted 76 critical factors such as water stress, groundwater depletion, soil type, geological time scale, and rainfall amount as the 77 main drivers of land subsidence. Researchers commonly validate their results by comparing them with InSAR 78 analyses, identifying areas exhibiting notable subsidence. Furthermore, the research assessed the risks to power 79 transmission lines and substations, revealing structural issues such as pier sinking, electric insulator deviation, and 80 cracking(Sadeghi et al., 2023). In another study focused on Dechen County, China, Wang et al. (2023) employed





81 Backpropagation Neural Network (BPNN) and RF algorithms, in conjunction with various monitoring data sources, 82 GIS, and SBAS technology, to predict trends in land subsidence. Their findings underscored Sugianto town as the most severely affected area, with an annual average subsidence rate of -40.71 mm per year. The study highlighted that 83 84 changes in both deep and shallow groundwater levels were the primary drivers of land subsidence in this region. 85 Notably, the BPNN model demonstrated higher prediction accuracy compared to the RF model, especially when 86 considering changes in groundwater levels (Wang et al., 2023). Furthermore, Zhuo et al. (2020) demonstrated that the 87 integration of the GM (1,3) model with neural networks and ground-related variables shows great potential for 88 achieving highly accurate subsidence predictions. The proposed approach has the capability to replace traditional precise leveling methods in long-term subsidence forecasting, offering valuable 89 90 insights for urban disaster prevention (Zhou et al., 2020). 91 Deng et al. (2017) conducted research on the integration of PSInSAR with Grey system theory for monitoring and 92 predicting land subsidence, as demonstrated in the Beijing plain (Deng et al., 2017). Precision mapping of complete 93 subsidence basins faces challenges, especially when dealing with image pairs with limited temporal separation. Rapid 94 deformations and vegetative changes in such scenarios introduce complexity. Strategies, such as combining 95 differential interferometric synthetic aperture radar (DInSAR) with the probability integral model (PIM), have been 96 introduced to effectively delineate subsidence basins resulting from mining activities (Fan et al., 2015).

97 The remarkable effectiveness of the RF model in mapping the susceptibility of land subsidence deserves attention. 98 This approach demonstrates exceptional capabilities in identifying key factors that contribute to subsidence 99 occurrences, such as the proximity to faults, elevation, slope angle, land use patterns, and water table levels. These 90 factors play a crucial role in influencing the likelihood of subsidence events (Mohammady et al., 2019). In addition, 91 the integration of fuzzy logic techniques and neural networks has been used to predict subsidence (Ghorbanzadeh et 92 al., 2020).

- In this study we used a CNN model trained over the area where subsidence is available through PSInSAR. Then this model is used over other areas where subsidence cannot be obtained from PSInSAR processing. The proposed method
- 105 follows three main steps: Calculation of subsidence in PSs by PSInSAR method, calculation of subsidence driving
- To solve the main steps. Calculation of subsidence in 155 by 15 month include, calculation of subsidence arving
- 106 factors, and training CNN.





#### 107 2. Methodology

#### 108 2.1 PSInSAR

- 109 PSInSAR is a remote sensing technique that utilizes SAR images to monitor surface deformation over time. It relies 110 on identifying PSs, which are stable points on the Earth's surface reflecting radar signals consistently. PSInSAR combines multiple interferograms created by comparing SAR images of the same area taken at different times. By 111 112 analysing phase differences between radar signals in these interferograms, it detects changes in the Earth's surface 113 over time. PSInSAR has significant advantages over DInSAR, as it effectively eliminates topographic errors, 114 atmospheric noise, and addresses temporal and spatial correlation issues between radar images (Ferretti et al., 2001; 115 Wasowski & Bovenga, 2014; Gonnuru & Kumar, 2018). PSInSAR, a form of differential interferometry, involves 116 analysing a collection of at least 15 SAR images captured at different times, all covering the same area (Crosetto et 117 al., 2016). PSInSAR finds diverse applications, including monitoring subsidence in urban areas (Ferretti et al., 2000; Luo et al., 2013) and tracking natural hazards such as landslides, earthquakes, and volcanic 118 119 activity (Peltier et al., 2010). However, one drawback of PSInSAR is the lack of continuity between PSs, as they 120 depend on the land use of the area. These PSs are more abundant in areas with buildings, dams, oil wells, pipelines, 121 electric fences, roads, rocks, and bridges (Din et al., 2015), but they are relatively scarce in vegetated areas. 122 Consequently, PSInSAR performs best in urban areas and regions with rocky terrain (Oštir & Komac, 2007). 123 In this article, the amplitude dispersion index is used to select the persistent scatterer points, Eq. (1). The usual 124 threshold of the amplitude dispersion index is limited between 0.2 and 0.4 (Conway, 2016). 125 (1)  $D_A = \sigma_A / \mu_A$ where  $\mu_A$ ,  $\sigma_A$  are standard deviation and mean values of the radiometrically corrected amplitude of pixels. In PSInSAR 126 127 the amplitude data from SAR images is carefully examined to identify specific PSs while excluding those affected by 128 space-time decoherence and atmospheric delay (Li et al., 2004).
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#### 130 **2.2. Deep Convolutional neural network (CNN)**

131 CNN is a type of deep learning algorithm widely employed for various image-related tasks like image recognition, 132 classification, and regression. CNNs can automatically learn and extract essential features from raw image. They 133 accomplish this by processing images through multiple layers of filters, known as "convolutions," which progressively 134 extract more abstract features. These filters are trained using backpropagation, a technique that adjusts filter weights





- based on the difference between predicted and actual outputs. In addition to convolutional layers, CNN typically
- 136 includes pooling layers to down sample the convolutional output and fully connected layers to use the extracted
- 137 features for image classification. CNN has gained popularity, particularly after the success of AlexNet in the ImageNet
- 138 challenge in 2012 and has since become the dominant approach for image recognition tasks.

139 CNN is used in various fields, including medical imagery (Lee et al., 2017), classification (LeCun & Bengio, 1995), 140 segmentation (Nair & Hinton, 2010; Van Do et al., 2024), image reconstruction (Christ et al., 2016; Lakhani & 141 Sundaram, 2017; Elboushaki et al., 2020), and natural language processing (Kim et al., 2018). While CNN are often 142 associated with categorical tasks, they are also highly effective in regression tasks, where the goal is to predict 143 continuous output variables instead of discrete labels. In CNN regression, the network typically has a single output 144 neuron in the final layer that generates a continuous value instead of a probability distribution for classification. It is 145 important to note that CNN requires a lot of input data, especially for image processing. As the network's depth 146 increases, so does its complexity, resulting in a larger number of weight parameters, which can sometimes create 147 challenges during training (Liu et al., 2018). CNN introduced the concept of local connections between layers with 148 typical components including convolution, activation and pooling layers (Chen et al., 2018). The convolutional layer 149 learns image features from small sections of input data through mathematical operations involving the input image 150 matrix and a filter or kernel. The activation layer introduces nonlinearity into the network, commonly using the 151 Rectified Linear Unit (ReLU) function.

152 CNN regression is a valuable approach for predicting continuous output variables and has found applications in 153 various fields including geology and civil engineering. CNN regression can also be used to predict subsidence. By 154 training a CNN model with input-output pairs, where inputs are subsidence driving forces and outputs represent 155 subsidence values, researchers can predict subsidence at single-pixel levels and provide valuable insights.

To predict land subsidence, we trained a CNN regression model with the architecture shown in **Error! Reference** source not found.. The CNN has 31 layers, including three  $1 \times 1$  convolutional layers, three  $3 \times 3$  convolutional layers followed by three  $2 \times 2$  max-pooling layers, Batch Normalization layers, drop out layers with a rate of 0.1, and two fully-connected layers with 1024 Rectified Linear Unit (ReLU) activation neurons, two fully-connected layers with 512 ReLU activation neurons, and a fully-connected layer with 256 ReLU activation neurons. The input dimensions are  $30 \times 30 \times 9$ , where  $30 \times 30$  patches separated from the neighborhood of each scattered point and 9 features are used as network input.







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#### 164 Figure 1: Illustration of CNN Architecture

165 We used the mean square error function as the cost function, a batch size of 128, a learning rate of 0.0001, and trained

166 the network for 150 epochs. To divide the data, we allocated 15% to the test data, 15% to the validation data, and 70%

167 to the training data. However, we noticed high-cost function fluctuations for the training and validation data, so we

168 increased the training data to 80%, and allocated 10% each to the test and validation data. This helped to reduce the

- 169 fluctuations (Table 1).
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- 171

#### 172 Table 1. Key parameters of the CNN

parameters	value
Activation function of hidden layer, input layer	ReLu
Activation function of output layer	Linear
Input shape	30×30×9
Loss function	MSE
Batch size	128
Epoch	150
Train-validation-test	80% -10% -10% Of total data

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#### 174 **2.3. Driving forces of subsidence**

175 Previous research in this field has identified several factors that impact land subsidence. These factors include changes

176 in the water table, soil type, depth of the rock bed, elevation, slope, aspect, rainfall patterns, vegetation cover, flow

177 index, topography index, distance from rivers, distance from faults, lithology (Yang et al., 2014; Fan et al., 2015;





- 178 Conway, 2016; Abdollahi et al., 2019; Andaryani et al., 2019; Mohammady et al., 2019; Zang et al., 2019;
- 179 Ghorbanzadeh et al., 2020; Shi et al., 2020; Zhou et al., 2020; Zhao et al., 2021; Wang et al., 2023).
- 180 The Topographic Wetness Index (TWI) is a mathematical formula that quantifies the effect of local topography on the
- 181 flow of surface water. It is a physically based index that can be used to determine flow direction and accumulation
- 182 and has many practical applications in fields such as hydrology, agriculture, and geology. In rainfall runoff modeling,
- 183 TWI can be used to predict the amount and timing of runoff in a specific area, while in soil moisture modeling it can
- 184 be used to predict the spatial distribution of soil moisture. Overall, the TWI is a useful tool for understanding and
- 185 predicting the movement of water across the landscape (Qin et al., 2011). Also, TWI identifies areas that can be
- affected by flooding from rainfall events (Ballerine, 2017). TWI equation is as follows (Moore et al., 1991):
- 187 TWI =  $\ln(\alpha/\tan\beta)$

(2)

188 Where  $\alpha$  the upslope contributing area and  $\beta$  is slope. TWI is calculated utilizing a Digital Elevation Model (DEM) 189 of the study areas. The flow power index (SPI) measures the power of water flow in depositing and causing soil 190 erosion. As a result, this index can be an important input for subsidence prediction models. The equation used to 191 calculate SPI is as follows (Pradhan et al., 2014):

192 SPI =  $\alpha * \tan \beta$ 

(3)

193 Here,  $\alpha$  flow accumulation, and  $\beta$  represents the slope. Land subsidence results from a combination of factors, 194 including both topographic and altitude-related features, such as rainfall and lithology. Research has demonstrated 195 that areas at lower altitudes tend to experience more subsidence. Additionally, the slope and aspect of an area can 196 influence drainage patterns, erosion, and sediment production, all contributing to subsidence. The amount of 197 vegetation, as measured by the Normalized Difference Vegetation Index (NDVI), also plays a significant role. Less 198 vegetation often indicates a higher risk of subsidence. The distance from a river and distance from faults are other 199 crucial subsidence driving forces. Groundwater depletion is a primary contributor to subsidence, emphasizing the 200 importance of preventing unauthorized withdrawals and effectively managing water resources. It's essential to 201 recognize that examining one factor alone is not enough to predict subsidence. A linear relationship between 202 groundwater level changes and subsidence may exist in certain regions, but this linear relationship does not exist in 203 all regions. Each region has unique characteristics such as soil type, fault lines and slope, etc. Subsidence is a complex 204 phenomenon that requires a comprehensive investigation that takes into account all relevant factors. Therefore,





- thorough analysis is necessary to obtain a comprehensive understanding of subsidence in a particular area (Azarm et
- 206 al., 2023).
- 207 3. Study Area and Datasets
- 208 **3.1. Study area**

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209 The studied area is in Isfahan province and includes the cities of Isfahan, Mahyar, Khomeinishahr and Falavarjan. 210 This region has a rich history of human habitation, diverse cultural heritage and a wide range of economic activities. 211 Covering approximately 7000 square kilometers, this area displays various uses, including urban, agricultural and 212 industrial areas. Its climate is semi-arid, characterized by hot summers and cold winters. The primary sources of water 213 in this area are the Zayandeh-Rud River and several underground aquifers that provide various uses such as agriculture, 214 drinking water, and industrial needs (Neysiani et al., 2022) (Fig. 2). To effectively monitor and predict land subsidence 215 in this study area, we used advanced techniques such as radar interferometry and convolutional neural networks 216 (CNN). Our goal was to provide an accurate and reliable estimate of land subsidence in the study area by integrating 217 these techniques and considering complex subsidence driving forces.



Figure 2: Geographic overview of the study area. (© Google Earth)





#### 226 3.2. Datasets

- 227 This study uses radar images obtained from the Sentinel-1A satellite to analyse subsidence trends in the study area
- 228 over a six-year period, 2014 to 2020. The PSInSAR technique was applied to the data using the Sarproz software. The
- 229 30 meters SRTM DEM of
- the study area, with a spatial resolution of 30 meters, was used to calculate the SPI, TWI, slope, and aspect using the
- 231 ArcMap software. The obtained data provided insights into the subsidence driving forces (Fig. 3).



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236 Figure 3: Subsidence driving forces - (a) Altitude, (b) Slope, (c) SPI, (d) TWI (e) Aspect





The Landsat 8 satellite launched by NASA provided optical images that were used in this study to extract the NDVI and land use information in the study area for the year 2020. Average annual changes of NDVI between 2014 and 2020 were calculated with Envi software. The relationship between subsidence and groundwater level changes should be investigated over a long period of time. Therefore, in this research, using the piezometric wells of the region, the water table map was calculated for the period of 2014 to 2018In areas where the density of exploitation wells is higher due to the extraction of underground water resources, the probability of subsidence is higher in those areas, so the distance from exploitation wells was calculated as one of the driving forces (Fig. 4).





247 Figure 4: Driving forces of subsidence- (a) NDVI (b) Distance of Wells (c) Land use, (d) Water table map in 2018 to 2020

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- 252 4. Result
- 253 4.1. Results of CNN
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- 255 CNN was trained using the calculated driving forces and subsidence at the PSs and the performance of the network
- 256 by analysing the graphs of the cost function (mean squared error) for the training and validation data, as shown in
- 257 Figure 5, the MSE values of this model for the training, validation and test data are 5, 9 and 11 mm, respectively.



259 Figure 5: Cost function of training and validation data

#### 260 4.2. Comparison between CNN and Kriging

We employed two distinct methods to create continuous subsidence surface: interpolation and CNN. To establish a continuous subsidence surface within the study area, we utilized Kriging interpolation. This method only performs interpolation between the PSs and calculates the subsidence of all the pixels in the study area and does not consider the subsidence driving forces. In contrast, a CNN was trained using subsidence driving forces and used to predict subsidence, producing a continuous subsidence surface with higher reliability. CNN can effectively handle irregularly distributed data points, making them suitable for scenarios where PSs may not be evenly distributed across the study area. Kriging relies on the spatial distribution of data points, and irregular distributions can impact its accuracy.





- 268 To assess the accuracy of these methods in predicting subsidence, we calculated MSE for both the methods, MSE of
- 269 CNN, Kriging is 11 and 37.19 mm, respectively. By comparing these outcomes, we can evaluate the effectiveness of
- 270 both interpolation and CNN in predicting land subsidence.

#### 271 4.3 Subsidence of Study area

- 272 In our analysis of land subsidence in the Isfahan region, we processed a total of 73 Sentinel-A images using the
- 273 PSInSAR method. Through this process, we identified PSs by applying a range amplitude dispersion index threshold
- of 0.2 and a temporal correlation threshold of 0.8. The maximum velocity for these PSs was observed in the northeast
- of the study area, specifically near Shahid Beheshti Airport in Isfahan, measuring at -67 mm per year. This significant
- rate resulted in a cumulative displacement of approximately -33 cm in the period from 2014 to 2020 (Fig. 6).



278 Figure 6: Cumulative displacement of PSs in 2014 to 2020

- 279 A velocity map was created using Kriging interpolation between PSs. The results showed that the highest velocity,
- approximately 67 mm per year, was observed in the northeast of the study area (Fig. 7).







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282 Figure 7: Velocity map using Kriging

283 In this research, in order to obtain a continuous subsidence surface of a specific area, two methods, Kriging and CNN,

284 Kriging method is based on mathematics and interpolation between cumulative displacement of PSs. The maximum

amount of cumulative displacement obtained by the Kriging method in the studied area is approximately 36 cm (Fig.





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288 Figure 8: Cumulative displacement using Kriging in 2014 to 2020

The CNN method was trained with the cumulative displacement of PSs and the subsidence driving forces in these points, and finally the subsidence of the entire area was predicted with this model. The maximum amount of cumulative displacement obtained by the CNN method in the studied area is approximately 33 cm (Fig. 9).







293 Figure 9: Cumulative displacement using CNN in 2014 to 2020

294 Shahid Beheshti Airport in Isfahan is currently facing a concerning situation with the estimated velocity reaching more 295 than 45 mm each year. This rate has resulted in a significant cumulative displacement of 41 cm in the region from 2014 to 2020. In addition, the map produced by CNN shows that the maximum cumulative displacement in this area 296 297 has reached 42 cm. Our study also revealed noteworthy findings for Mahyar and Nasr Abad Jarqouye. In these areas, 298 the velocity is approximately 5 cm per year, resulting in a maximum cumulative displacement of approximately 33 299 cm between 2014 and 2020. The maximum cumulative displacement using kriging interpolation showed 300 approximately 35 cm. However, the maximum cumulative displacement using CNN showed approximately 32 cm 301 (Fig. 10).

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310 Figure 10: Cumulative Displacement of Shahid Beheshti Airport and Mahyar and Nasr Abad Jarqouye in 2014 to 2020: 311 (a), (b) Continuous surface of cumulative displacement using Kriging interpolation between PSs (c), (d) Continuous surface 312 of cumulative displacement (e), (f) Cumulative displacement of PSs

313 In the Naqsh-Jahan area, the maximum cumulative displacement estimated through the kriging and CNN methods

314 between 2014 and 2020 was approximately 6 cm and 12 cm, respectively. Meanwhile at the Si-o-Se Pol area, the

- maximum cumulative displacement estimated through the kriging and CNN methods between 2014 and 2020 was 315
- approximately 6 cm and 19 cm, respectively (Fig. 11). 316







Figure 11: Cumulative Displacement of Naqsh-Jahan and Si-o-Se Pol area, 2014 to 2020: (a), (b) Continuous surface of
 cumulative displacement using Kriging interpolation between PSs (c), (d) Continuous surface of cumulative displacement
 resulting from CNN (e), (f) Cumulative displacement of PSs

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The city of Khomeini Shahr is facing a concerning situation where the velocity has been estimated to be more than 45 mm per year. Unfortunately, this has resulted in displacement in residential areas, with the maximum cumulative displacement of PSs reaching 30 cm from 2014 to 2020. According to the map generated using CNN, the maximum cumulative displacement is currently at 31 cm. It has been estimated that the velocity in Falavarjan city is more than 23 mm per year, which is concerning. As a result, there has been a maximum cumulative displacement of 16 cm in the area from 2014 to 2020. According to the CNN-generated map, the maximum cumulative displacement in Falavarjan is 23 cm (Fig. 12**Error! Reference source not found.**).







Figure 12: Cumulative Displacement of Khomeini Shahr and Falavarjan, 2014 to 2020: (a), (b) Continuous surface of
 cumulative displacement using Kriging interpolation between PSs (c), (d) Continuous surface of cumulative displacement
 resulting from CNN (e), (f) Cumulative displacement of PSs

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#### 338 Data Availability

The SAR Sentinel-1A dataset used in this study is freely available for access on the web at
 <a href="https://dataspace.copernicus.eu">https://dataspace.copernicus.eu</a>





#### 341 5. Conclusion

- 342 The PSInSAR method has proven to be a dependable technique for investigating gradual land deformation, particularly 343 subsidence. However, it yields discrete results limited to PSs only, making it less suitable for areas with vegetation. 344 In such scenarios, Kriging interpolation between PSs is commonly used to create a continuous subsidence surface. Nevertheless, this approach has its limitations due to the complex nature of subsidence influenced by various factors. 345 346 In our study, we tackled this challenge by generating a continuous subsidence surface for the entire study area using 347 a CNN. We factored in the driving forces of subsidence in this process. We evaluated the accuracy of both Kriging 348 interpolation and CNN methods by calculating the mean square error on the test data. The results revealed that the 349 study area experienced more than 38 cm of subsidence between 2014 and 2020. Notably, the velocity was estimated 350 to be over 45 mm per year at Shahid Beheshti airport, exceeding 54 mm per year in the Mahyar Plain, and around 6 351 mm per year in Naqsh-Jahan and Sio-Se-Pol Bridges. The mean square error values for the training, validation, and test data using the CNN were determined to be 5 mm, 9 mm, and 11 mm, respectively. These results indicated a 352 353 significant improvement of 70% in the prediction of subsidence with intelligent interpolation CNN compared to the 354 kriging interpolation method. This CNN-based method offers a robust and accurate interpolation approach, even when 355 dealing with sparse and irregularly distributed data. 356 Code and data availability 357 The code to the CNN model in accordance with this paper are accessible through the Zenodo archive with the 358
- 359 following link: <u>https://zenodo.org/records/10956394</u> (Azarm,2024)

#### 360 Author contribution

- 361 Azarm contributed to the writing of the manuscript and conducted the analytic calculations and numerical simulations
- 362 with the support and supervision of Mehrabi and Nadi. All authors actively participated in discussing the results,
- 363 providing comments on the manuscript, and revising the final version.

#### 364 Competing interests

365 The contact author has declared that none of the authors has any competing interests.





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