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LAND SUBSIDENCE PREDICTION THROUGH MODELING OF TEMPORAL ATTRIBUTE PREDICTION OF KNOWLEDGE GRAPH

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ABSTRACT:

Land subsidence is a geological disaster. It will lead to the decline of land elevation, resulting in the potential safety hazards of urban facilities. Thus, the prediction of land subsidence displacement is significant. Among the existing prediction methods, the methods based on the time-series prediction model only analyze the settlement series data without considering the settlement mechanism, so they are easy to apply. However, they less consider the influence of other factors on land subsidence. Besides, they independently input displacement time-series data from different monitoring points without considering their relationship. To solve these problems, we take the monitoring point as the entity and take the DEM, soil type, building height, and land subsidence displacement sequence at the corresponding position of the monitoring point as the attributes to construct the knowledge graph. And then, we propose a framework Graph-TAP for modeling temporal attribute prediction of the knowledge graph's entity. This framework learns the representation of events with the specific entity at first. Then it captures the temporal dependency between historical events using GRU. Finally, it predicts the entity's displacement attribute. We randomly selected 61 subsidence monitoring points in Shenzhen, China. We used the land subsidence displacement InSAR time-series data (12-day time interval) and other attribute data from June 22, 2015, to April 5, 2016, for model training, validation, and testing. The experimental results show that our method is better than the time-series prediction based on the LSTM model and the DARNET(a knowledge graph temporal attribute prediction framework).

1. INTRODUCTION

Land subsidence refers to the phenomenon that the ground sinks relative to the surrounding terrain or sea level under the influence of natural factors or human activities (Xu et al., 2016). It is generally manifested as regional subsidence and local subsidence. Crustal movement, sea-level rise, and other natural factors will cause regional subsidence; the construction of a large number of high-rise buildings, the exploitation of groundwater, and the excavation of underground tunnels will cause local settlement of urban land (Xue et al., 2005). Land subsidence is a slow and continuous geological disaster. It is not easy to detect in the early stage of the disaster. However, after the local surface settlement accumulates to a certain extent, it will lead to a series of secondary disasters, such as building tilt deformation, urban traffic road damage, and seawater backflow (Xue et al., 2005, Hu et al., 2019). Therefore, the accurate prediction of land subsidence can provide the basis for the early warning of secondary disasters caused by land subsidence, which has essential research significance.

The existing land subsidence prediction methods are mainly divided into two categories: the prediction method based on physical mechanism, and the other is the prediction method based on the time series prediction model. The first method is to build a numerical simulation model according to the hydrogeological and settlement mechanisms to establish the corresponding mathematical control equation by studying the internal development trend of settlement. And then solve the equation according to the model's initial conditions and boundary parameters to predict land settlement displacement. The classical models include subway settlement model (Yang et al., 2013) and groundwater coupling model (Phi and Strokova, 2015, Li et al., 2019). Although this kind of method considers the mechanism of land subsidence, it needs to obtain the hydrological, lithologic, and other parameters required for modeling through field measurement and experiment. Hence, its application is complex, and its generalization is poor. The second kind of method can be divided into methods based on mathematical statistics and methods based on deep learning. The methods based on mathematical statistics include gray model (Xu et al., 2014, Deng et al., 2017, Zhou et al., 2020) , BP neural network (Li et al., 2009), extreme learning machine and support vector machine (Abdollahi et al., 2019, Mohammady et al., 2019). These methods do not pay attention to the settlement mechanism but only explore and fit historical settlement displacement data's internal law and development trend. Although the implementation is relatively simple, the prediction accuracy is not high due to the single data and easy overfitting of the model. The method based on deep learning is mainly based on LSTM network (Chen et al., 2021, Kumar et al., 2021, Liu et al., 2021). Compared with previous methods, these methods improve the prediction accuracy to a certain extent by better simulating the nonlinear effects between land subsidence displacement and various influencing factors. However, in the model training, the improvement in accuracy is limited without considering the relationship between different monitoring point data.

To solve this problem, we construct the knowledge graph using land subsidence displacement monitoring data and subsidence influencing factor data and using the knowledge graph to improve the accuracy of displacement prediction. The land subsidence time-series data is obtained by Interferometric Synthetic Aperture Radar (InSAR) technique. We take the displacement monitoring point as the entity. Then, we take the longitude and latitude, DEM, soil type, building height, settlement displace-

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ment, and monitoring timestamp of the corresponding position of the displacement monitoring point as the entity's attributes to construct the knowledge graph. Subsequently, we calculate the spatial distance between monitoring points according to longitude and latitude and then establish the spatial adjacency relation between monitoring nodes with a spatial distance of less than 100m. Next, we propose a framework for temporal attribute prediction of the knowledge graph, namely Graph-TAP. We divide this framework into three steps: (1) learning the representation of events in the knowledge graph; (2) learning the temporal dependency between historical events in the knowledge graph; (3) predicting the displacement attribute at the next time.

Using the land subsidence monitoring data and land subsidence influencing factor data of the location of the impervious surface in Shenzhen, we construct a knowledge graph with 395149 entities and 22619704 spatial adjacency relations. Then we extract 27370 event tuples for training and validation. The ratio of the training set to validation set is 9:1, the number of entities is 61, the monitoring time is from June 22, 2015, to March 24, 2016 (the time interval is 12 days). The testing set contains 1190 events with the same entities on April 5, 2016. Moreover, the maximum length of the historical event sequence is 10. Finally, we compare our proposed Graph-TAP method with the time-series prediction method based on LSTM and another knowledge graph temporal attribute prediction method, DARNET. The experimental results on the testing set show that our method outperforms these methods.

The paper is organized as follows. Section 2 briefly reviews the land subsidence displacement prediction methods and the knowledge graph temporal attribute prediction method. In Section 3, we give the formal definition of the problem studied in this paper. Section 4 provides an overview of our proposed method. Section 5 introduces the experimental datasets, evaluation metrics, experimental results and analysis, and Section 6 summarizes our work and draws conclusions.

2. RELATED WORK

2.1 Land subsidence displacement prediction

Land subsidence prediction methods can be divided into physical mechanism-based, mathematical statistics-based, and deep learning-based methods.

The method based on physical mechanisms first establishes a physical model or numerical simulation model according to hydrogeology and settlement mechanism, then determines the relevant physical parameters through field measurement, and finally predicts the future land settlement. These methods are mainly aimed at the land subsidence caused by groundwater development (Phi and Strokova, 2015, Li et al., 2019) and subway project (Yang et al., 2013). Although this kind of method considers the mechanism of land subsidence, it is difficult to obtain accurate physical parameters, which leads to its complex application and poor generalization.

The settlement displacement is predicted based on mathematical statistics by mining the internal law in the historical displacement monitoring data. These methods' model structures are relatively simple, there is no need to obtain physical parameters, and the implementations are also relatively simple. The classic method among these methods is the (Xu et al., 2014) based on the gray model. In order to further improve the accuracy of the model, in (Deng et al., 2017), the authors adapt to the conventional GM (1,1) model by using the sliding mechanism and integrating the K-means clustering method into the Markov chain state interval division to predict the land subsidence in Beijing from 2015 to 2016. In (Zhou et al., 2020), the authors combine terrain factor and neural network to correct the error of the Gray Prediction GM(1,3) model.

Compared with the method based on mathematical statistics, the method based on deep learning can better learn the nonlinearity and randomness in data. Among the land subsidence prediction models based on deep learning, the models based on LSTM and its variants are most widely used (Chen et al., 2021, Kumar et al., 2021, Liu et al., 2021). In (Liu et al., 2021), considering the spatial heterogeneity of land subsidence, the authors first cluster the land subsidence data and then train the prediction model based on LSTM for each subclass. The experimental results show that this method can improve the accuracy of displacement prediction. However, these aforementioned methods are only for historical settlement data, without considering other settlement influencing factors. In (Ding et al., 2021), the authors quantitatively analyze the relationship between land subsidence and influencing factors by using geographic detectors. In (Li et al., 2021), the authors use geospatial weighting to analyze the spatial correlation between land subsidence and groundwater level change. The obtained spatial correlation is combined with LSTM to predict the subsidence of Beijing. The experimental results show that considering the spatial correlation between land subsidence and groundwater level change can significantly improve the accuracy of the displacement prediction model.

2.2 Knowledge graph temporal attribute prediction

In order to further improve the accuracy of land subsidence prediction, we need to consider both the spatial relationship between land subsidence data and the relationship between land subsidence data and data of other subsidence influencing factors. Therefore, we consider introducing knowledge graph technology. We first use the knowledge graph to represent these relations and then predict the temporal attributes of the knowledge graph. In (Zhang et al., 2020), the authors regard entities, attributes, and attribute values as attribute triples and then use a deep convolution neural network to learn the representation of entities. Similarly, in (Tay et al., 2017), attributes are represented by a neural network and then predicted. However, these are all for non-temporal knowledge graphs. A method for predicting temporal attributes based on dynamic knowledge graphs is proposed in (Garg et al., 2020), namely DARNET. Since the relation of the knowledge graph in (Garg et al., 2020) changes with time, the authors propose the prediction process of joint modeling the relations and the attributes to improve the accuracy of attributes prediction.

3. PROBLEM FORMULATION

We first construct a land subsidence knowledge graph based on land subsidence displacement time-series data of multiple monitoring points obtained by InSAR technology. The knowledge graph G at time τ can be represented by multiple hexagons $(h, r, t, a_h, a_t, \tau)$, and a hexagon is called an event E. The h and t in the hexagon refer to the head entity and the tail entity, both of which represent the monitoring points of land subsidence; r is the relationship between the head entity and the tail entity, which in the graph we constructed refers to the spatial distance between the monitoring points represented by the head

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and tail entities is less than 100 meters; τ represents the observation timestamp; a_h and a_t refer to the set of attributes of the head entity and the tail entity.

The land subsidence displacement prediction problem is converted into the prediction problem of the land subsidence displacement attribute in the knowledge graph. The solution to this problem is to learn a set of functions $\{F(.)\}$ that predict the events corresponding to future timestamps from the events corresponding to historical timestamps, thus predicting the unknown land subsidence displacement attributes of the events, i.e.:

$$(E_{h,1}, E_{h,2}, \ldots, E_{h,\tau}) \xrightarrow{\{F(.)\}} (E_{h,\tau+1}) \tag{1}$$

where $E_{h,\tau}$ represents events with the head entity h at time τ. An event of $E_{h,\tau}$ is composed of (h, r, t) and (a_h, a_t). a_h and a_t include the longitude and latitude of the location of the monitoring point, DEM, soil type, building height, and the displacement of land settlement at time τ. In this paper, the longitude and latitude coordinates, soil type, and building height are not temporal and known, and the spatial relation between nodes is not changed with time and known. The displacement of land subsidence is the temporal attribute we want to predict.

4. METHODOLOGY

4.1 Land subsidence knowledge graph construction

As mentioned before, various factors can influence the change of land subsidence displacement. In order to improve the accuracy of land subsidence displacement prediction, we set the monitoring points of land subsidence as nodes and the influencing factors of land subsidence as attributes of nodes to construct a graph. Following are the representative influence factors we choose as nodes' attributes:

- DEM: DEM is a visual and mathematical representation of the height values, related to the mean level, which can reflect surface characteristics, such as slope (Tafreshi et al., 2020, Galeana-Pérez et al., 2021).
- Soil type: Different types of soil have different softness. Engineering construction on soft soil is easier to cause land subsidence (Nameghi et al., 2013).
- Building height: The construction of buildings, especially high-rise buildings, will increase the ground load and accelerate the land subsidence (Cui et al., 2010).

Considering that the land subsidence monitoring point's land subsidence displacement will also be influenced by the land subsidence displacement of the monitoring points in the neighboring areas, we establish the relationship between monitoring nodes based on spatial distance. In this paper, we use a two-way edge to indicate that two monitoring nodes possess a spatial adjacency relation, and the attribute of the edge is the spatial distance between two nodes, which is less than 100 meters. The structure of the knowledge graph at time τ is shown in Figure 1.

We store nodes and node attributes in the graph database Neo4j [1]. Then, according to nodes' longitude and latitude attributes, the Neo4j Spatial plug-in is used to build the spatial index between nodes. After building the spatial index, it is more convenient to calculate the distance between nodes and establish the spatial adjacency relationship between nodes.

[1] https://neo4j.com/

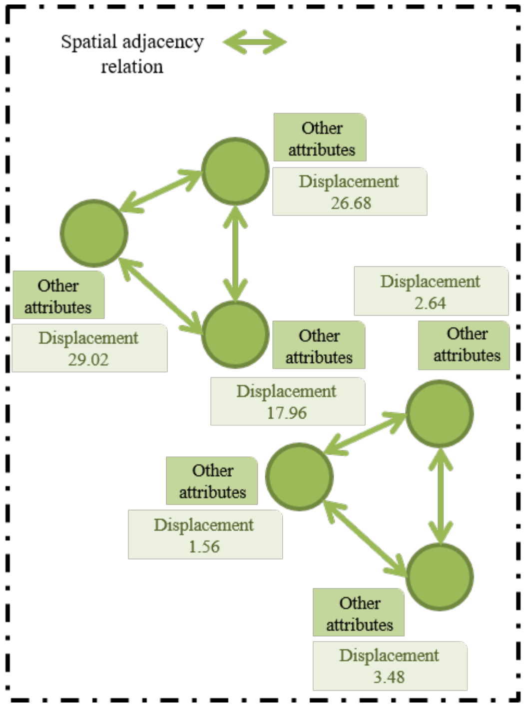

Figure 1. The structure of a knowledge graph at time τ. **Other attributes** include DEM, soil type, and building height attributes. **The number in displacement** represents the value of the displacement attribute.

4.2 Temporal attribute prediction

We propose a framework for learning a set of functions to predict nodes' land subsidence displacement attributes in the next timestamp through the input historical events. We named this framework as **Graph-TAP**, i.e., a **G**raph-based framework for **T**emporal **A**ttribute **P**rediction.

The Graph-TAP framework includes three steps: first, learning the representation of events in the graph, then learning the temporal dependency between historical events, and finally predicting the displacement attributes of nodes in the event corresponding to the next timestamp. The whole process is shown in Fig 2.

Representation of events in the knowledge graph Firstly, we use randomly initialized $e_h \in \mathbb{R}^d$, $e_t \in \mathbb{R}^d$ represents the head entity h and tail entity t in the event at time τ. However, these embeddings have nothing to do with land subsidence influence factor attributes. Then, we need to concatenate the attributes' embeddings. The head entity's attributes in each event can be divided into two components: static attributes $a_{h,S} \in \mathbb{R}^{k1}$ that do not change with time and dynamic attributes $a^{\tau}_{h,D} \in \mathbb{R}^{k2}$ that change with time, $k1$ and $k2$ are the number of the attributes. After linear transformation, we can obtain the static attribute embedding $e_{a_{h,S}} = a_{h,S} \cdot W_1$ and dynamic attribute embedding $e_{a^{\tau}_{h,D}} = a^{\tau}_{h,D} \cdot W_2$, of which $W_1 \in \mathbb{R}^{k1\times d}$, $W_2 \in \mathbb{R}^{k2\times d}$ are learnable parameter matrices. At next, $(e_h; e_{a_{h,S}}; e_{a^{\tau}_{h,D}})$ is the embedding representation of the head entity h at time τ, of which ';' represents concatenation operator. The tail entity's attributes are embedded in the same way.

Then we aggregate the information of neighborhood entities using the mean method. The neighbor entities of the head entity h

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Table 1. An event's contents

Head entity	Spatial adjacent relation	Tail entity	Static attributes of the head entity			Static attributes of the tail entity			Dynamic attribute of the head entity	Dynamic attribute of the tail entity	Timestamp
			DEM	Soil type	Building height	DEM	Soil type	Building height	Subsidence displacement	Subsidence displacement	

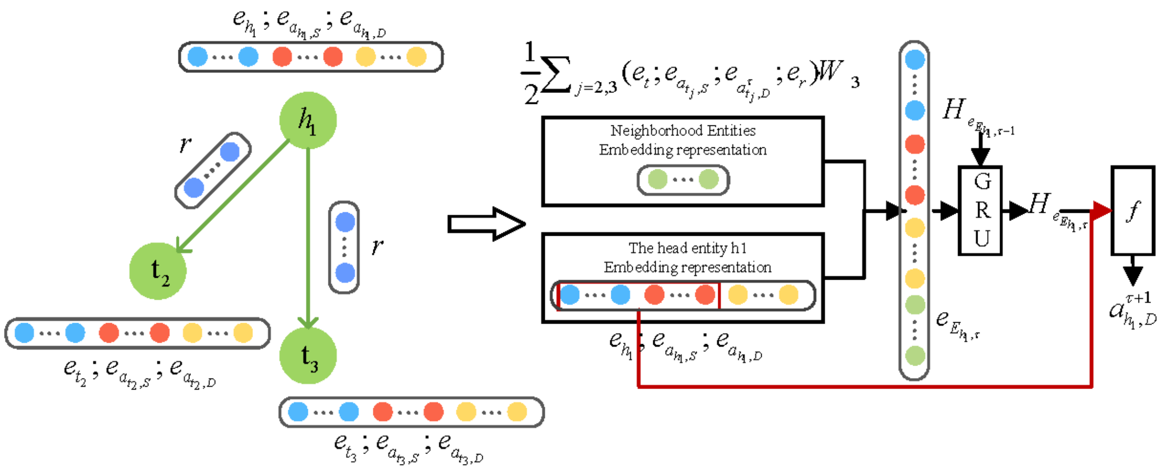

Figure 2. The whole process of the Graph-TAP framework

refer to all tail entities connected to the head entity through the spatial adjacency relation r. Therefore, the embedding of all events with the head entity h at time τ, i.e., $e_{E_{h,\tau}}$ is represented as:

$$e_{E_{h,\tau}} = \left(e_h; e_{a_{h,S}}; e_{a^{\tau}_{h,D}}; \frac{1}{|E_{h,\tau}|}\sum (e_t; e_{a_{t,S}}; e_{a^{\tau}_{h,D}}; e_r)\cdot W_3\right) \tag{2}$$

where $e_r \in \mathbb{R}^d$ indicates the embedding of relation, $a_{t,S}$ and $a^{\tau}_{t,D}$ are the attributes of the tail entity and ';' represents concatenation operator. Through linear transformation, we obtain an embedding representation of the neighbor entity t, i.e., $(e_t; e_{a_{t,S}}; e_{a^{\tau}_{h,D}}; e_r)W_3$, where $W_3 \in \mathbb{R}^{4d\times d}$ is a learnable parameter matric. Then we sum the embeddings of all neighbor entities and take the average, i.e., $\frac{1}{|E_{h,\tau}|}\sum(e_t; e_{a_{t,S}}; e_{a^{\tau}_{h,D}}; e_r)W_3$, where $|E_{h,\tau}|$ is the cardinality of set $E_{h,\tau}$.

Temporal dependency between historical events Previously, we obtained the representation of all events at time τ. Next, we use the Gated Recurrent Unit (GRU) (Sutskever et al., 2014) to learn the temporal dependency between historical events. $[e_{E_{h,1}}, e_{E_{h,2}}, \ldots, e_{E_{h,\tau-1}}]$ represents the embedding sequence of historical events with the head entity h.

$$H_{e_{E_{h,\tau}}} = \mathrm{GRU}(e_{E_{h,\tau}}, H_{e_{E_{h,\tau-1}}}) \tag{3}$$

Displacement attribute prediction The displacement attribute value for the head entity h is a function of the historical events' embedding and static embeddings for the h. Therefore, the land subsidence displacement attribute value can be predicted as follows:

$$a^{\tau+1}_{h,D} = f(H_{e_{E_{h,\tau}}}, e_h, e_{a_{h,S}}) \tag{4}$$

where f is a single-layered feed-forward network.

Parameter learning We use the Adam with decoupled weight decay (AdamW) algorithm (Loshchilov and Hutter, 2019) to optimize the parameters in the Graph-TAP framework. We use the mean square error (MSE) of the real value and predicted value of the dynamic displacement attribute of the head and tail entity as the loss function. The loss function is calculated as follows:

$$\begin{aligned} Loss &= Loss\_att(h) + Loss\_att(t) \\ &= \frac{1}{n}\sum_{1}^{n}(a^{\tau+1}_{h,D} - a^{\widehat{\tau+1}}_{h,D})^2 + \frac{1}{n}\sum_{1}^{n}(a^{\tau+1}_{t,D} - a^{\widehat{\tau+1}}_{t,D})^2 \end{aligned} \tag{5}$$

where $a^{\hat{\tau}}_{h,D}$ and $a^{\hat{\tau}}_{t,D}$ are the predicted attributes, $a^{\hat{\tau}}_{h,D}$ and $a^{\hat{\tau}}_{t,D}$ are the ground truth attributes at time $\tau+1$.

Table 2. The information of datasets

Dataset name	Type	Spatial resolution
Displacement time-series data	Point vector data	-
DEM	Grid data	30 meters
Soil type	Grid data	1 kilometer
Building height	Point vector data	-

5. EXPERIMENTS

5.1 Datasets

This paper takes the land subsidence displacement monitoring points on the impervious surface of Shenzhen, China, as the research object and uses the DEM, soil type data, building height data, and land subsidence displacement time series data to predict the land subsidence displacement of the monitoring points at the next time. The land subsidence displacement data we used is time series data based on multi-stage Sentinel-1 data and InSAR technology. The data contains a total of 395149 subsidence monitoring points. Each monitoring point contains longitude and latitude coordinates and 130 pieces of subsidence displacement monitoring data from June 22, 2015, to December 10, 2019 (the time interval is 12 days). On April 19, 2018, the ground elevation was taken as the datum plane for settlement displacement. Each displacement value of the subsidence monitoring point represents the elevation difference between the ground elevation on the monitoring day and the datum plane, and the unit is millimeter (mm), that is, the subsidence displacement of the monitoring point at that day. We use the above data to construct a knowledge graph, i.e., a multi-attribute relational graph of land subsidence.

Then, we extracted 27370 events with timestamps from June 22, 2015, to March 24, 2016, from this graph. These events contain a total of 61 entities. Moreover, we divided these events into a training set and a valid set according to the ratio of 9:1. Finally, we extracted 1190 events on April 5, 2016, with the same entities as the test set. The contents of each event are shown in Table 1.

5.2 Hyperparameters setting

In this paper, we use the AdamW algorithm to optimize the parameters of the Graph-TAP. The learning rate is 0.001, the batch size is 50, the max historical sequence length is 10, the epoch num is 50, the dimensions of the embeddings are 200, and the dropout is 0.5.

5.3 Evaluation Metrics

The aim is to predict the land subsidence displacement of each monitoring node at the next time step. Therefore, MSE loss is used in training. The lower MSE indicates better performance. In addition, We choose the root mean square error(RMSE) as the evaluation index of the model on the testing set. The RMSE is computed as follow:

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(a-\hat{a})^2} \tag{6}$$

where a is the predicted displacement, $\hat{a}$ is the ground truth displacement and n is the number of the land subsidence monitoring points.

5.4 Results

In Figure 3, we show a part of the knowledge graph we built, in which the green circle represents entities, i.e., monitoring points, and the green line represents spatial adjacency relationships.

We extract the fact training graph tap from the constructed knowledge map. The loss curves of the training set and the test set during the training process are shown in the figure. It can be seen from Figure 4 that the loss curve of the test set of the training set decreases rapidly at first and then tends to be flat, which shows that Graph-TAP can converge quickly in the training process.

In this paper, we also test the performance of our proposed Graph-TAP method on the testing set and compares it with the time-series prediction method based on the LSTM model and the DARNET (Garg et al., 2020). The DARNET is also a framework for temporal attribute prediction on the knowledge graph. The experiment uses the root mean square error of the predicted value and the real value to evaluate the model's accuracy. The experimental results are shown in Table 3.

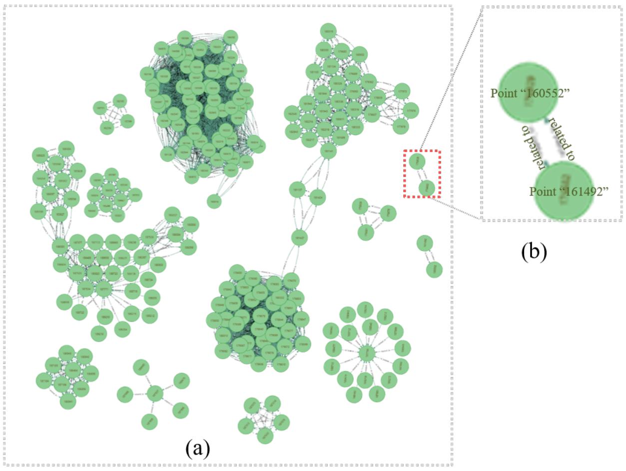

Figure 3. A partial display of the graph we constructed. (a) shows multiple nodes of the knowledge graph, and (b) is the zoom in version of the red part of (a).

Table 3. RMSE results of different methods on test sets

Method	RMSE (mm)
LSTM	13.311
DARNET	3.250
Graph-TAP	2.466

At first, we can find that the prediction accuracy of using a knowledge graph to construct the relationship between monitoring points is higher than the method based on the LSTM model without considering the spatial relationship of points.

Then we found that the prediction accuracy of our proposed method is higher than that of the DARNET. We think this is because the static attribute information, i.e., the influencing factors of land subsidence, is not considered in the DARNET.

6. CONCLUSIONS

The existing land subsidence displacement prediction methods can not consider the nonlinear relationship between multiple land subsidence influencing factors and land subsidence monitoring data and the spatial relationship between monitoring points simultaneously. Therefore, we first use InSAR land subsidence displacement time-series data, DEM grid data, soil

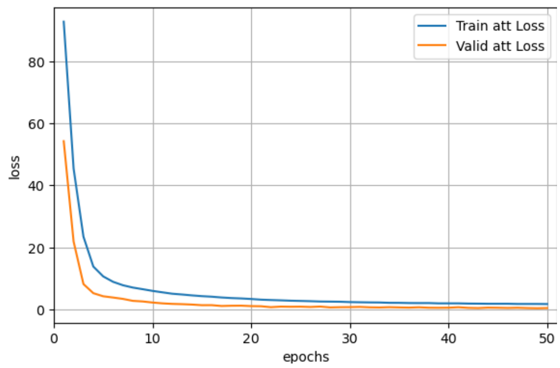

Figure 4. The loss of Graph-TAP

type grid data, and building height vector data jointly construct the knowledge graph (the entity of the graph is the displacement monitoring point, the attribute is the longitude and latitude, DEM, soil type, building height, settlement displacement and monitoring time of the corresponding position of the monitoring point, and the relation is the spatial adjacency relationship between the monitoring points). Then we propose a Graph-TAP framework for dynamic attribute prediction of the knowledge graph. Graph-TAP consists of three steps: event representation learning, historical event time dependency learning, and displacement attribute prediction. Then, we extracted 27370 events with timestamps from June 22, 2015, to March 24, 2016, from the relational graph. These events contain a total of 61 entities. We divide these events into training set and verification set according to the ratio of 9:1. Finally, we extracted 1190 events with a timestamp of April 5, 2016. The entities in these events are the same as the test set. The experimental results on the test set show that this method is better than the method based on the LSTM model and the DARNET method.

In future work, we will continue to consider other influencing factors, such as rainfall, groundwater level, etc. In addition, we will also consider other relationships other than spatial adjacency.

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