

TEMPORAL AND SPATIAL SUBSIDENCE MONITORING AND PREDICTION OF RECLAMATION AIRPORTS BASED ON TIME-SERIES INSAR MEASUREMENTS

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ABSTRACT

Recently, land subsidence in urban land reclamation areas has become increasingly prominent, which has brought severe challenges to the safety operation and maintenance of airports in reclamation areas. InSAR technology can accurately monitor surface deformation due to its advantages of long-term, large coverage, and continuous monitoring. Machine learning techniques have demonstrated great capabilities in geospatial data analysis. In addition, they have advantages in spatiotemporal series prediction, thanks to their powerful nonlinear modeling capabilities and automatic feature learning ability. In this study, time-series InSAR technology was firstly applied to extract and analyze the surface deformation of Dalian Jinzhou Bay International Airport (DJBIA) and Shanghai Pudong International Airport (SPIA). Based on the surface deformation data, the stacked long short-term memory network (Stacked LSTM) and sequence-to-sequence long short-term memory network (Seq2Seq LSTM) were used to predict the future deformation of the two airports, supporting the operation and maintenance of airports in the reclamation area.

STUDY AREA AND DATA

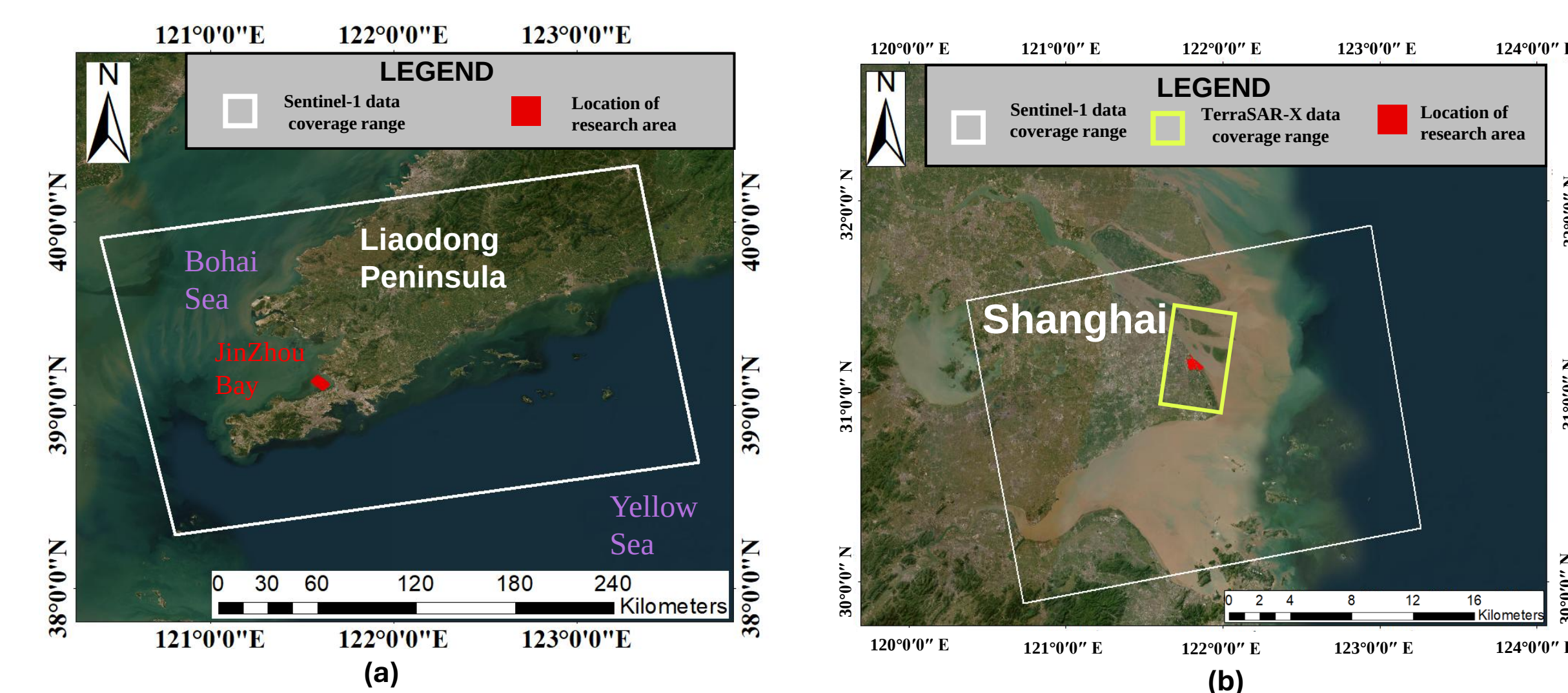


Figure 1 Study area: (a) Dalian Jinzhou Bay International Airport, (b) Shanghai Pudong International Airport.

Table 1 Dataset parameter table

Study area	DJBIA	SPIA
Time frame	20170318~20230627	20130427~20161024 20161229~20250104
Data source	C-band Sentinel-1A	X-band TerraSAR C-band Sentinel-1A
Number of images	180	39 237

METHODS

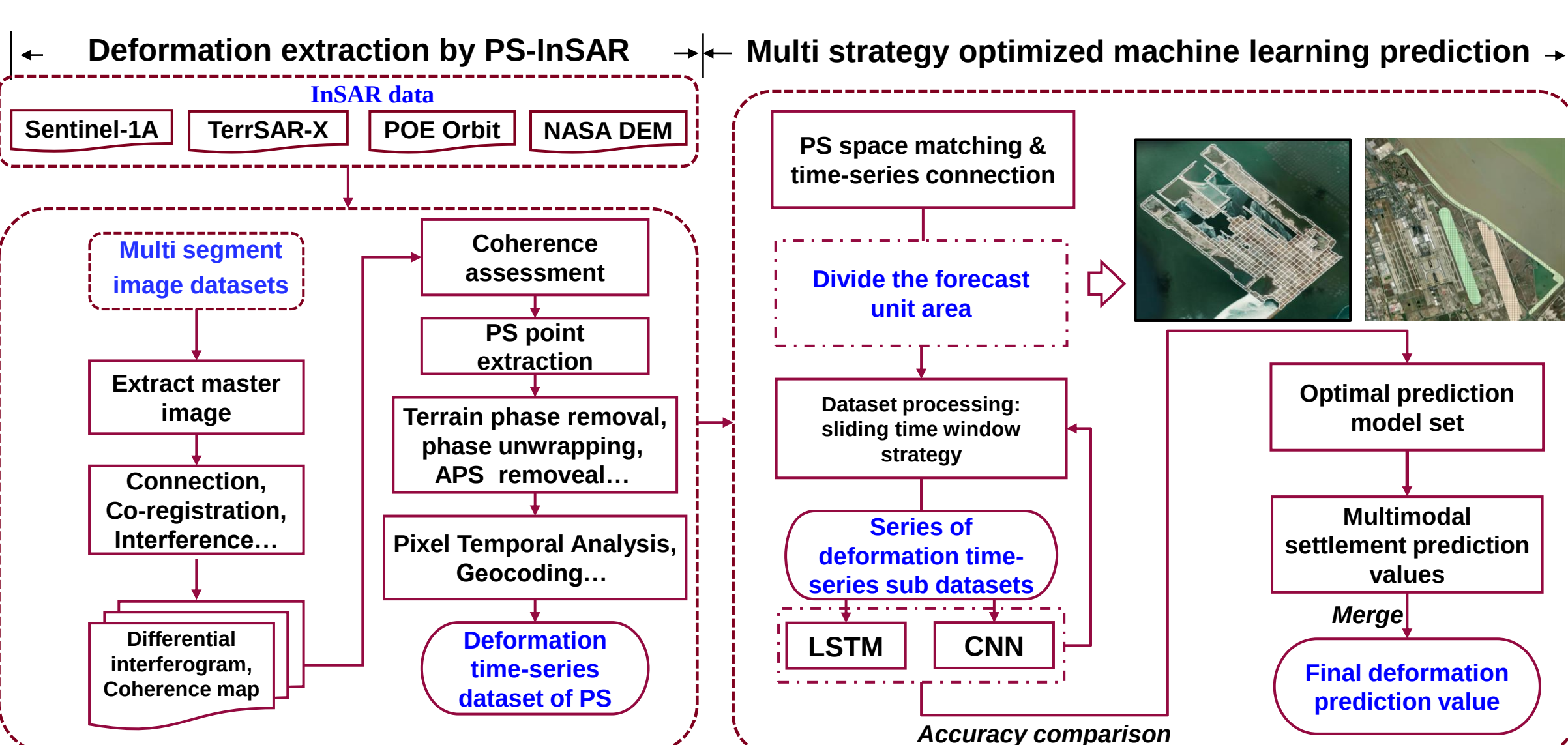


Figure 2 Overall technical flowchart

CONCLUSIONS

- Comparing the settlement results of the two airports reveals that the degree of subsidence is closely related to the reclamation time; the closer the reclamation time, the more significant the subsidence.
- For DJBIA, the results of deformation prediction show that LSTM has higher accuracy and predictive ability than CNN when processing sedimentation time series data. For SPIA, the results indicate that Seq2Seq LSTM has higher predictive ability than LSTM.

ACKNOWLEDGEMENT

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MAJOR REFERENCE

Bao X, Zhang R, et al. Ground Deformation Pattern Analysis and Evolution Prediction of Shanghai Pudong International Airport Based on PSI Long Time Series Observations[J]. Remote Sens, 2022, 14, 610.

RESULTS

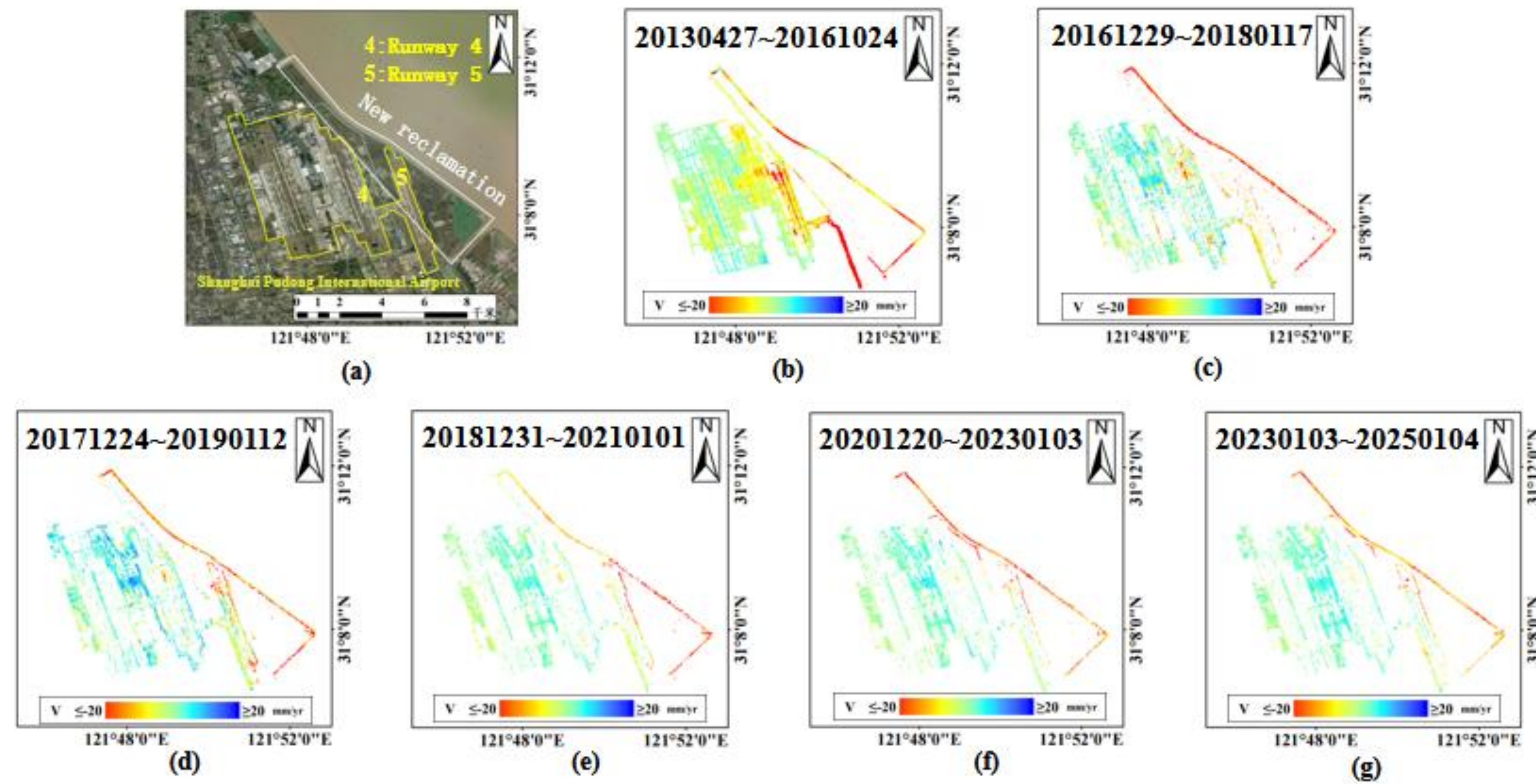


Figure 3 SPIA study area and annual sedimentation rate

The subsidence of SPIA is large in the east and small in the west, and the eastern part is close to the sea and the reclamation time is relatively close. Three significant areas were identified: Runway 4, Runway 5, and the outer embankment of the reclamation area. The proportion of PS points in the range of -10 mm/year to -50 mm/year within Runway 4 has changed to 0 since 2021, while the same index in the outer embankment area is close to 83% in 2024. The subsidence risk in Runway 5 and the outer embankment areas remains high and requires ongoing monitoring.

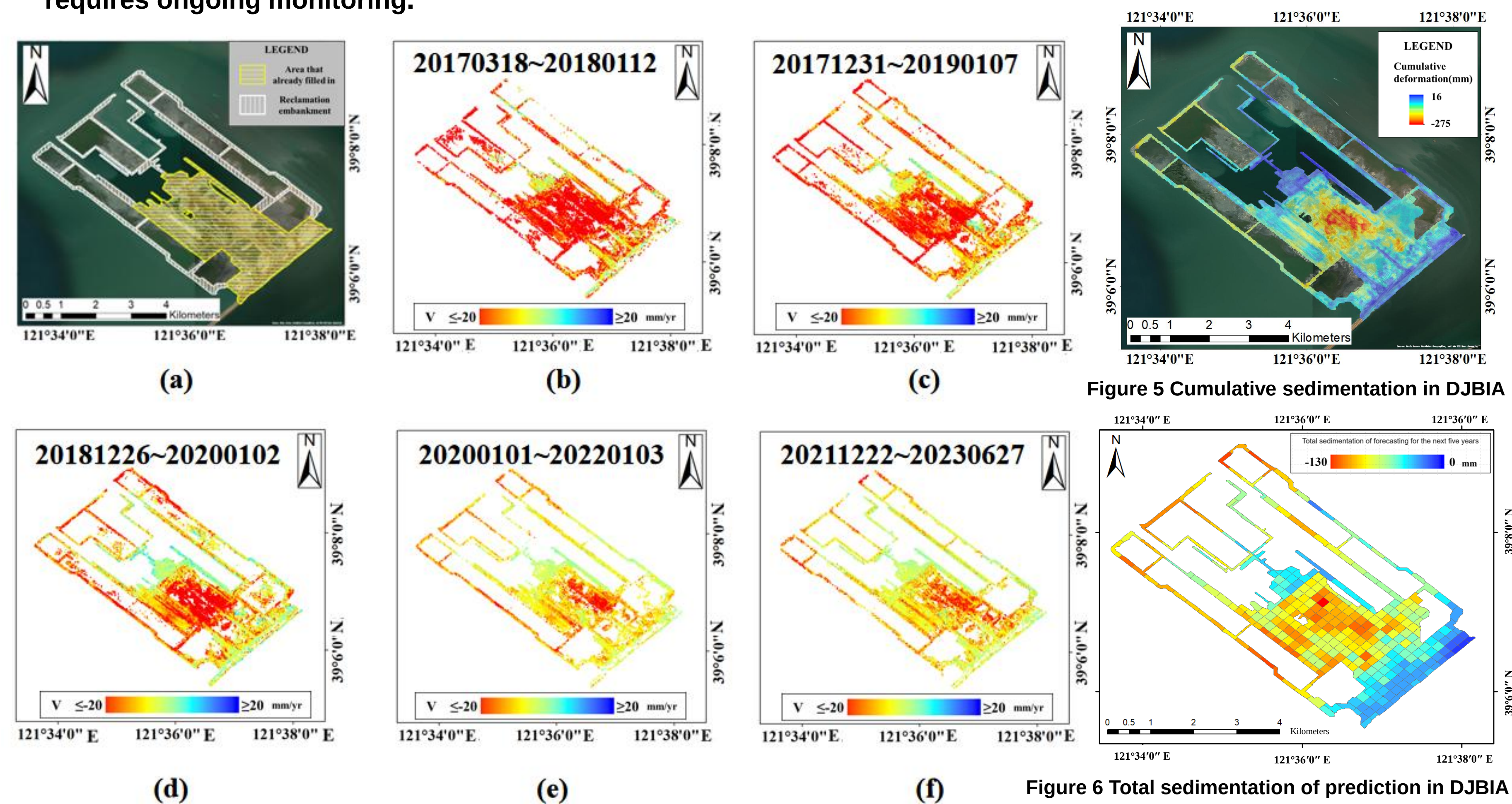


Figure 4 DJBIA study area and annual sedimentation rate

The most serious subsidence area in DJBIA is located in the center of the reclamation area, and the soil layer is relatively new. As shown in Fig.5, the large-scale filling area shows significant settlement, mainly concentrated in its central region, where cumulative subsidence exceeds 200 mm. In contrast, the maximum uplift in the study area is only about 16 mm. Temporally, settlement across the area is gradually slowing down.

DISCUSSION

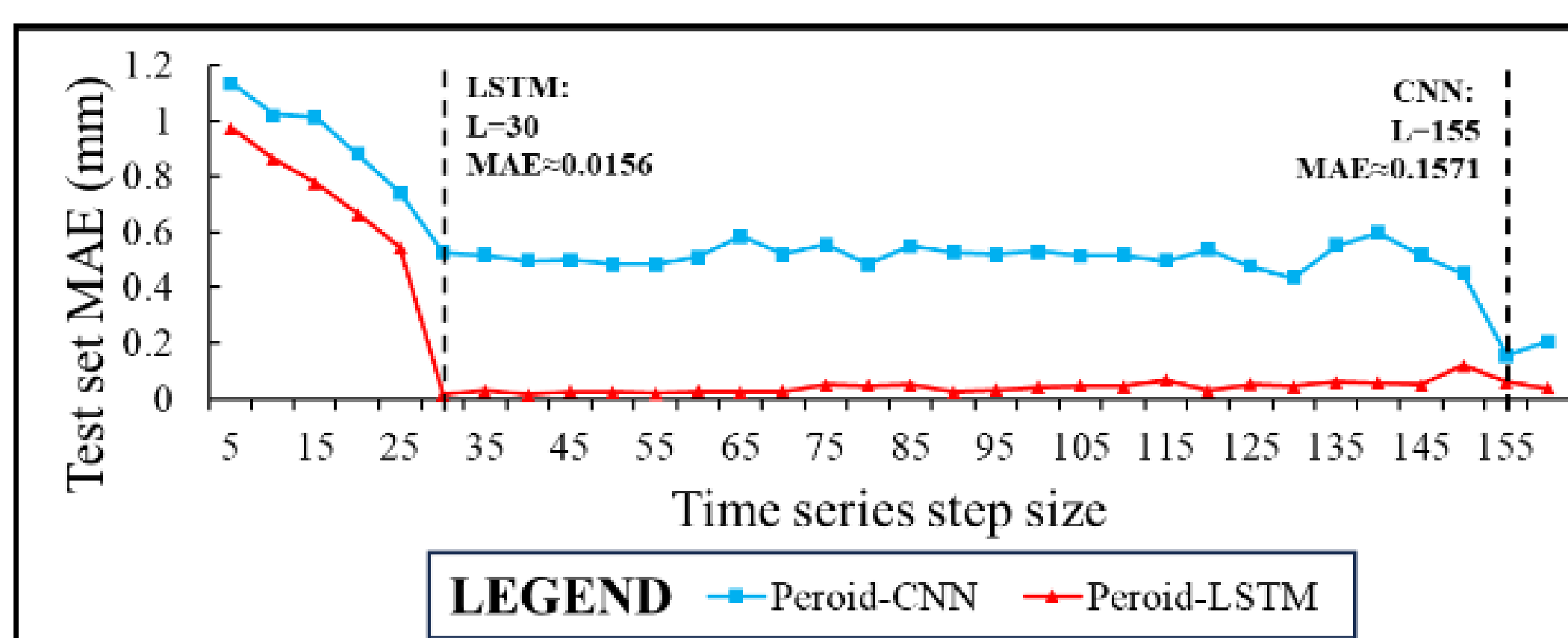


Figure 7 Average absolute error of LSTM and CNN model training sets under different sample time series step sizes

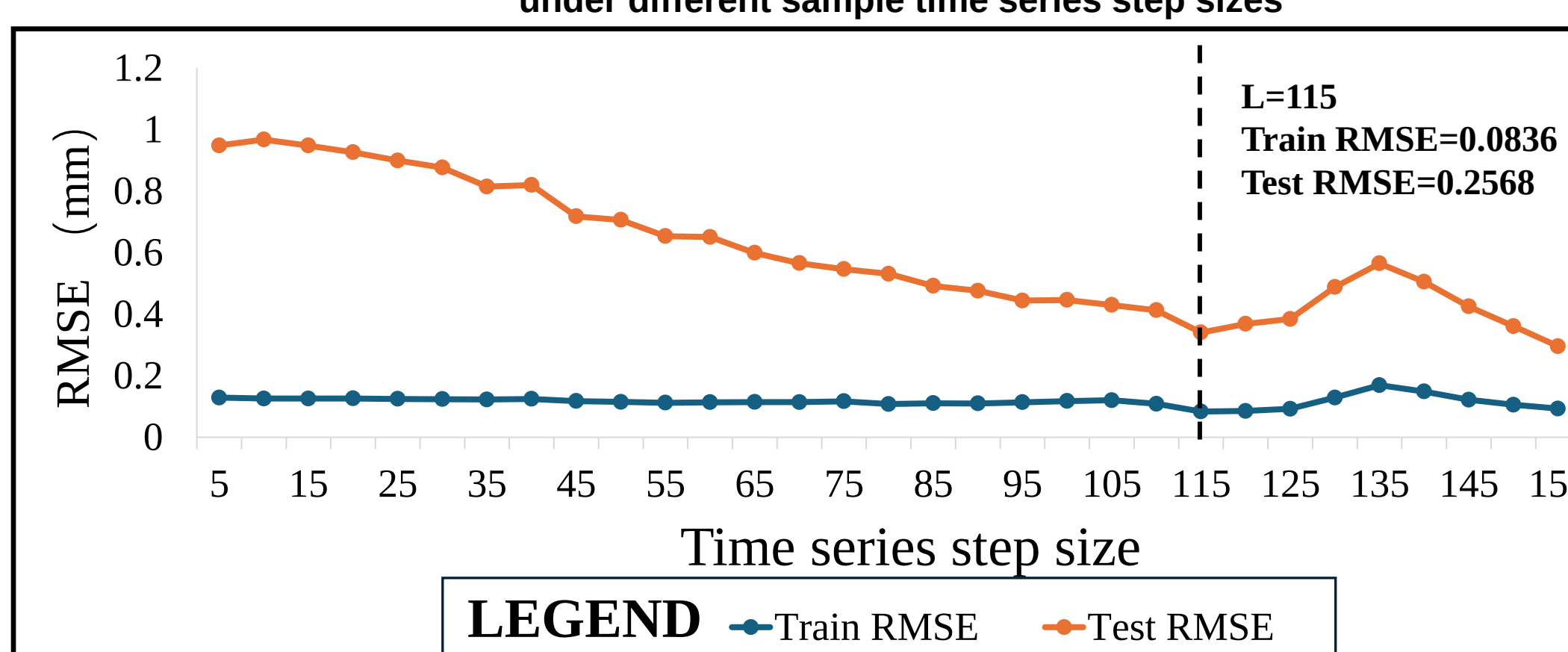


Figure 8 RMSE of Seq2Seq LSTM training and testing sets under different sample time series step lengths

As shown in Fig.7, the optimal step size of LSTM is 30 and the MAE of the test set is about 0.0156, while the optimal step size of CNN is 150 and the MAE is 0.1571 mm. The results show that the stacked LSTM model performs better than CNN.

As shown in Fig. 8, the optimal step size of the Seq2Seq LSTM is 30, and the test RMSE is 0.2568 mm. According to the LSTM model predictions made by Bao X et al. in 2022, the minimum test RMSE was 4.25 mm. In the same research area, SPIA, the model used in this article has a test RMSE of less than 4.25 mm.