Disaster Risk Reduction Capacity Assessment with TOPSIS and Machine Learning and Analysis of Regional Disaster Characteristics of Shanghai

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Abstract

Coastal regions have dense populations, buildings, and infrastructures, and are vulnerable to natural disasters. Frequent natural disasters will cause huge economic losses and human casualties. Shanghai is a coastal megacity located in the low-elevation coastal zones of the Yangtze River Delta. The city is frequently affected by typhoons and storm surges. Besides, The geological foundation of the city consists of soft alluvial deposits, including clay, silt, and sand. Due to its geological conditions, Shanghai is vulnerable to ground subsidence, flooding, and other geohazards.

In order to prevent, resist, and reduce the impact of disasters, this study assesses the regional disaster reduction risk (DRR) capacity of a district of Shanghai with a Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) and established a machine learning aided evaluation models. We also retrieved long-term and recent ground deformation of the coastal areas of Shanghai with Small Baseline Subset (SBAS) technology and multi-sensor Synthetic Aperture Radar image time series. We also simulate the possible flood inundation extent under different scenarios based on the LISFLOOD-FP simulation model in coastal regions. For towns with weak DRR capacity, we analyze the sensitivity of evaluation indicators to explore key indicators that affect the improvement of DRR capacity. Finally, we proposed optimal strategies that could improve DRR capacity based on the assessment results of DRR capacity and regional disaster characteristics.

Keywords: DRR capacity; TOPSIS; Machine Learning; Shanghai; regional disaster characteristics

1. Introduction

As the economic center of China, Shanghai is a mega-city with a permanent population of more than 24 million. There are various kinds of buildings and major infrastructures. As a coastal city, it is vulnerable to typhoons, rainstorms, waterlogging, storm surges, and red tide. In addition, Shanghai is located at the mouth of the Yangtze River, formed by alluvial sediment. As a result, geological disasters such as land subsidence are also prone to occur with rapid economic development and frequent land reclamation activities. Therefore, it is of great significance to carry out an assessment of natural disaster mitigation capability, and then to improve natural disaster mitigation capability. Based on this, the government can make disaster-prevention strategies to minimize casualties and property damage when disaster strikes. Some scholars have also researched the assessment of natural disaster risk reduction capacity. The index system of natural disaster risk reduction capacity in this work is shown in Table 1.

Table1. The index system of natural disaster risk reduction capacity

First-level indicators	Second-level indicators
Capacity of disaster management	Capacity of team management
	Capacity of assessment of disaster risk
	Capacity of financial investment
Capacity of disaster preparation	Capacity of materials reserves
	Capacity of medical aid
Capacity of self-rescue and transfer	Capacity to help each other
	Capacity of public safety
	Capacity of transfer and resettlement

2. Method

TOPSIS is a common intra-group comprehensive evaluation method, which can make full use of the information of the original data, and its results can accurately reflect the gap between the evaluation schemes. This method has no strict limit on data distribution and sample content and is easy to calculate. The basic calculation process is as follows: Suppose there are n evaluation objects, and each object has m indicators

1. Construct the normalized initial matrix.
2. Determine the best solution and the worst solution.
3. Calculate the distance between each evaluation object and the best and worst scheme.
4. Calculate and sort the closeness degree between each evaluation object and the optimal scheme.

Bagging, also known as bootstrap aggregation, is the ensemble learning method that is commonly used to reduce variance within a noisy dataset. In bagging, a random sample of data in a training set is selected with replacement, meaning that the individual data points can be chosen more than once.

After several data samples are generated, these weak models are then trained independently, and depending on the type of task—regression or classification, for example, the average or majority of those predictions yield a more accurate estimate.

bagging algorithm has three basic steps:

1. Bootstrapping
2. Parallel training
3. Aggregation

Random forest is a commonly used machine learning algorithm trademarked by Leo Breiman and Adele Cutler, which combines the output of multiple decision trees to reach a single result. Its ease of use and flexibility have fueled its adoption, as it handles both classification and regression problems.

Random forest algorithms have three main hyperparameters, which need to be set before training. These include node size, the number of trees, and the number of features sampled. From there, the random forest classifier can be used to solve regression or classification problems.

Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, i.e., models that make very few assumptions about the data, which are typically simple decision trees. When a decision tree is the weak learner, the resulting algorithm is called a gradient-boosted trees; it usually outperforms random forest. A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

Small Baseline Subset Algorithm (SBAS) is one of the well-known MT-InSAR algorithms to retrieve ground deformation time series with high accuracy. In this study, the SBAS algorithm is applied for the generation of the line-of-sight (LOS)-projected ground deformation time series and deformation velocity in Shanghai. To mitigate the decorrelation effects that corrupt the interferograms, in SBAS processing interferometric pairs characterized by short temporal and spatial baselines, are selected for retrieving ground deformation time series. The interferograms with short baselines are arranged in a few subsets and combined with the singular value decomposition (SVD) method. The residual topographic and atmospheric phases are estimated and filtered out from the phases of interferograms. The differential interferograms with deformation phases are unwrapped by applying the minimum cost flow algorithm. The residual topographic artifacts are recovered and compensated. Atmospheric phase artifacts are also extracted and filtered out. The SBAS-derived products, i.e., the mean deformation velocity maps and the relevant displacement time series, are geocoded to a common spatial grid.

3. Results

(a)

	TOPSIS	Bagging	Random Forest	GBDT
Baoshan District	medium	medium	medium	medium
Chongming District	medium	medium	medium	medium
Fengxian District	weak	weak	weak	weak
Hongkou District	weak	weak	weak	medium
Huangpu District	strong	strong	strong	strong
Jiading District	weak	medium	medium	medium
Jinshan District	medium	medium	medium	medium
Jinan District	medium	medium	medium	medium
Minhang District	weak	medium	medium	medium
Pudong New District	medium	medium	medium	medium
Putuo District	weak	weak	weak	medium
Qingpu District	strong	strongest	strongest	strong
Songjiang District	strongest	strongest	strongest	strong
Xvhui District	strong	strongest	strongest	strong
Yangpu District	weak	weak	weak	weak
Changning District	medium	medium	medium	medium

(b)

	TOPSIS	Bagging	Random Forest	GBDT
Baoshan District	strong	strong	strong	strong
Chongming District	strongest	strongest	strongest	strongest
Fengxian District	strongest	strongest	strongest	strongest
Hongkou District	weakest	weak	weak	weak
Huangpu District	weak	weak	weak	weak
Jiading District	medium	strong	strong	strong
Jinshan District	strong	strongest	strongest	strongest
Jinan District	medium	strong	strong	strong
Minhang District	medium	medium	medium	medium
Pudong New District	medium	medium	medium	medium
Putuo District	medium	medium	medium	medium
Qingpu District	medium	strong	strong	strong
Songjiang District	medium	medium	medium	strong
Xvhui District	medium	medium	medium	medium
Yangpu District	weak	weak	weak	weak
Changning District	weak	weak	weak	weak

Figure 1. Hierarchy diagram of disaster risk reduction capacity in Shanghai. (a) represents the DRR capacity of the town (street) and (b) represents the DRR capacity of the community (village).

The DRR capacity assessment data will constantly change with the use and input of human, material, and financial resources. Therefore, machine learning was introduced into the assessmentof DRR capacity of all streets and towns based on the simulation data in Shanghai. It is found that the results evaluated by Bagging and Random Forest are mostly consistent with the results evaluated by TOPSIS and the inconsistent results float between adjacent grades.

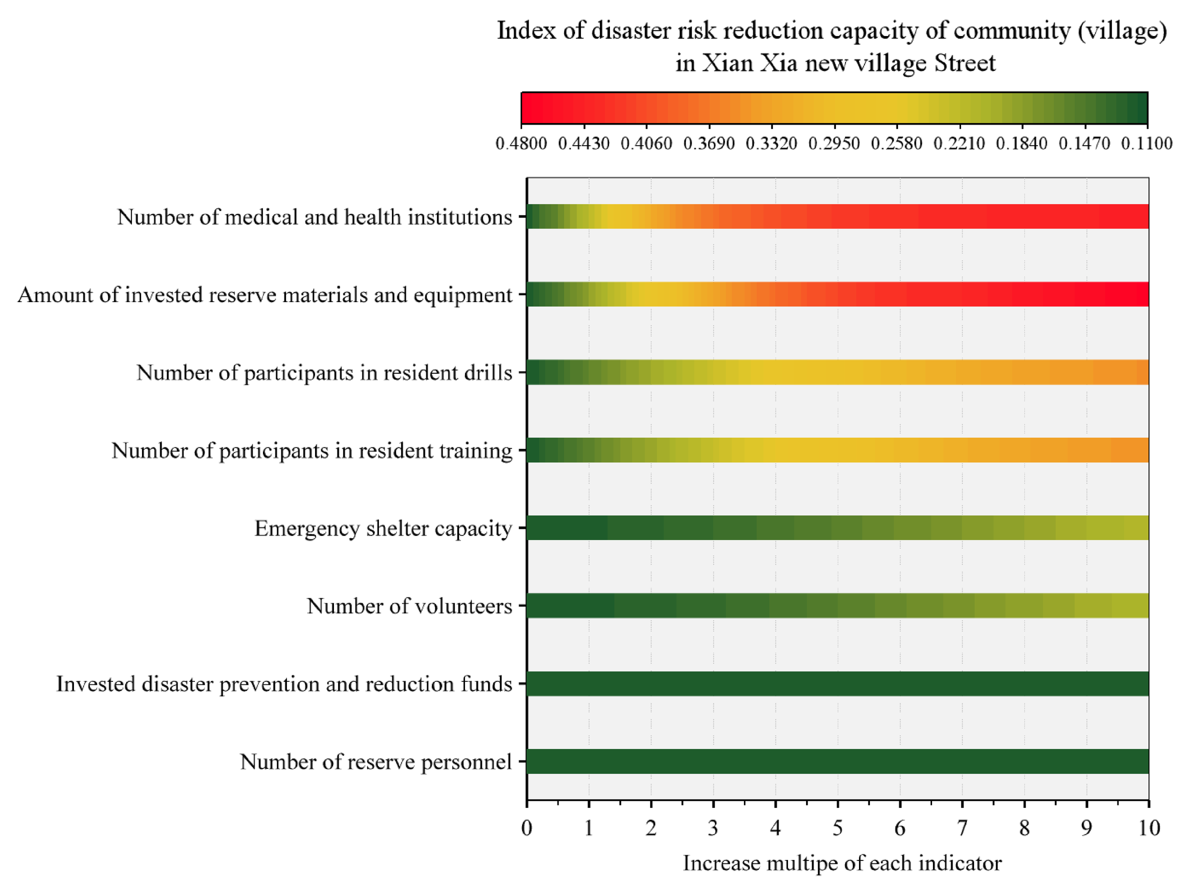

Figure2. Variation diagram of the index of disaster risk reduction capacity of the community (village) in Xian Xia new village Street

Based on the assessment results of DRR capacity, we focused on the streets where DRR capacity of the town (street) and community (village) are weak. Using a simple variable method, sensitivity analysis is made on the indicators participating in the assessment to explore the key indicators influencing DRR capacity.

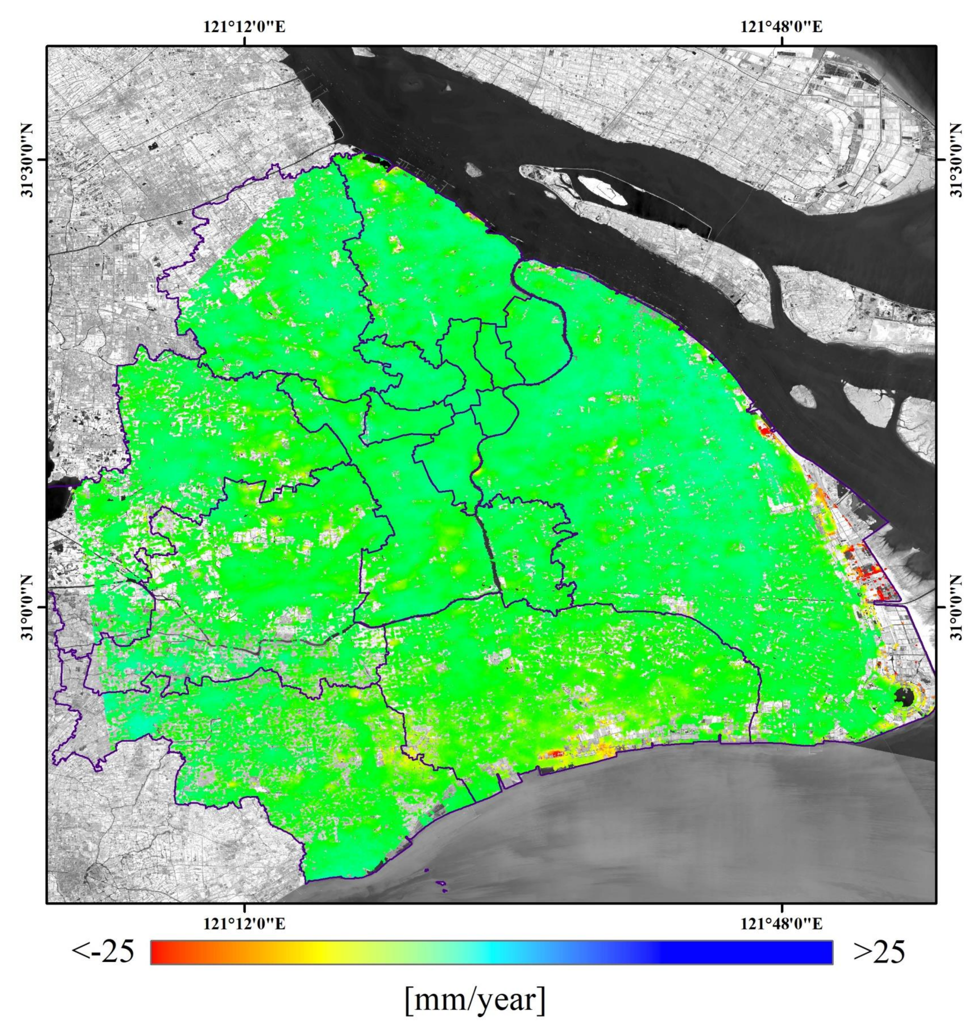

Figure2. Map of vertical annual average ground deformation velocity in Shanghai.

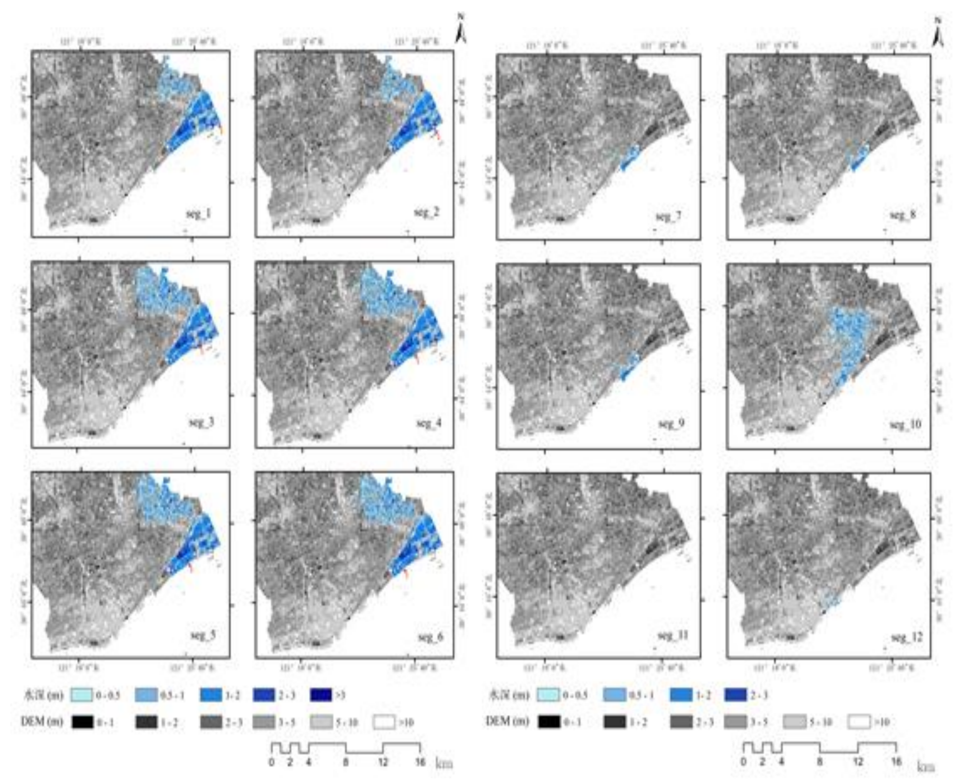

Figure3. Simulated inundation scenarios subject to different seawall-failure coastal flood scenarios (1 km/seg) when the water level is the maximum tide level in Jinshan District

4. Conclusion

In this study, considering the characteristics of regional disasters in Shanghai, strategies to improve DRR capacity are proposed for areas with weak DRR capacity, possible flooding, and land subsidence, providing disaster risk information and scientific decision-making basis for improving comprehensive regional DRR capacity.

5. Reference

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