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Regional Disaster Loss Prediction Under Tropical Cyclone Hazard to Support Real-time Risk Forecasting: A Data-driven Approach

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ABSTRACT: Rapid prediction of high-probability disaster hotspots during a tropical cyclone is crucial to facilitate proactive mitigation measures. In this study, a data-driven model based on a convolutional neural network (CNN) is developed for Zhejiang Province, China, to provide rapid and fine-resolution regional prediction of tropical cyclone induced losses. The model considers both hazard intensity measures and environmental characteristics as explanatory predictors, and outputs county-level disaster losses. In addition, through a unique design of an intermediate layer in the CNN architecture, the model can also produce grid-level loss predictions with 1km resolution. Such a gridded outcome (1 km^2) can further inform disaster hotspots across the entire region of Zhejiang Province (approximately 105,000 km^2). The CNN model is trained and calibrated using loss records of 9 severe historical tropical cyclones that impacted Zhejiang during the period of 2012 to 2019. The proposed model, with promising accuracy and resolution, shows evident advantages in time efficiency and computational cost for regional loss predictions compared to physics-based simulations.

1. INTRODUCTION

Tropical Cyclone (TC) is a major hazard threatening China's coastal areas, characterized by high occurrence frequency, intrinsic complexity of disaster mechanism, broad range of impacts, as well as significant uncertainties. A reliable quantification of potential losses and a rapid prediction of disaster hotspots during a TC event can effectively inform proactive disaster response and mitigation actions. Conventional physics-based models targeting to assess TC impacts (e.g., Vickery et al., 2006; Li et al., 2012; Park et al., 2013; Zhu et al., 2013; Blanton et al., 2018) are challenged by computational cost, time pressure, and data integrity when applied to large regions, hindering their application to regional risk forecast under evolving TCs. With great improved data acquisition technologies and mechanisms in disaster-related research and practice, data-driven models are becoming a promising alternative for regional-scale loss predictions.

Many existing studies have focused on developing data-driven approaches for total loss prediction using event-wise gross impact data from field studies or reported statistics of historical events (Chen et al., 2011; Chiang et al., 2012; Pilkington & Mahmoud, 2016, 2017; Chen et al., 2018; Yuan et al., 2019; Kim et al., 2019). These models typically take a scalar of parameters critical to a TC event as input information (e.g., maximum wind speed upon landfall, maximum total accumulated precipitation, etc.) and output a total loss for an entire region without spatial outcome. Only a few models have been developed to achieve impact assessment of multiple areas within a sizable region, taking into account the regional-scale characteristics of the hazard-formative environment underlying the disaster mechanisms of these areas (Lou et al., 2012; Cai et al., 2020). These models usually include spatial vectors featuring vulnerability and environmental exposure of the region, and predict losses for multiple municipal administrative areas (e.g., cities or counties) within a sizable region (e.g., a province or a state). Nevertheless, such predictions, although have somewhat reflected the spatial distribution of losses across multiple administrative divisions within a larger region, have not achieved enough fine-resolution to the extent of locating disaster hotspots, let alone facilitating effective and prompt decision support.

Taking advantage of the increasingly refinement of data collection mechanisms over the past years in China, the principal objective of this study is to propose a spatial model for rapid regional TC disaster loss assessment with high-resolution results by constructing a convolutional neural network (CNN), which takes both hazard and environmental (exposure and vulnerability) factors into consideration. The proposed model is experimented on Zhejiang China, a province covering an area of more than 105,000 km^2 and embracing complex topographies, dense population, and a centralized structure of decision-making hierarchy. Zhejiang has 11 prefecture-level cities and 90 counties (county-level cities and districts). Figure 1 shows the geographic location, elevation and boundaries of the 90 counties in Zhejiang.

2. METHODOLOGY

An end-to-end CNN model is constructed to achieve the following: (1) regress post-disaster losses from pre-defined hazard influencing factors in a computationally efficient manner; and (2) interpolate/downscale loss observations from their original administrative level to 1km-grid level to obtain spatial estimation with much finer resolution. The CNN model is selected due to its extraordinary capability to deal with image data and high-dimensional nonlinear problems.

2.1 Datasets

The preliminary work, prior to the model training, involves a process of feature selection, data collection and pre-processing. A sequence of explanatory factors is selected as model input based on a comprehensive review of existing regional loss assessment models and on the accessibility of the data itself. The explanatory factors can be categorized into two groups: hazard-formative environment factors that include elevation, slope, aspect, land use, river density, population density; and hazard intensity factors that include three meteorological features, namely, maximum wind speed, maximum rain intensity and accumulated rain. As for the output variables, disaster damage and loss metrics that are commonly investigated can be chosen, such as number of damaged or collapsed houses, affected population and direct economic loss. In the case

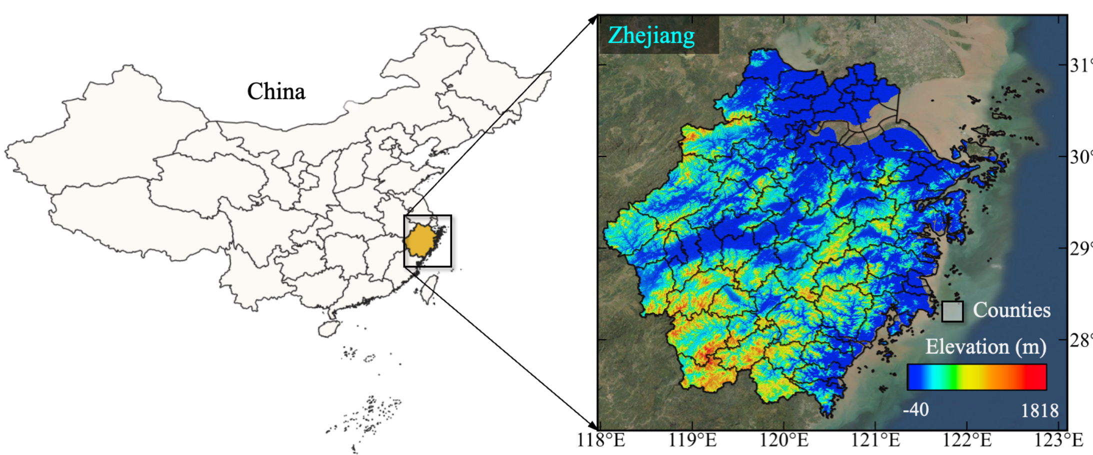

Figure 1. Topography and counties of Zhejiang

study introduced herein we choose affected population (AP) as the model output.

To collect data, we have particularly collaborated with relevant governmental agencies in Zhejiang, and have obtained records of 9 historical TC events severely impacted Zhejiang occurred during 2012 to 2019, with detailed information listed in Table 1. Note that only the total AP for each of the 9 events is listed, while the AP for each of the affected counties are also available and are actually used to train the model.

For the explanatory predictors, information sources of datasets relating to hazard intensity, hazard-formative environment, and TC disaster loss are provided in the following:

Hazard intensity data: the raw data of the hazard intensity factors are hourly wind and rain observations collected at national and local meteorological stations in Zhejiang for the 9 historical events investigated. These point observations at heterogeneously distributed stations are further spatially interpolated to obtain a grid field with 1km resolution using the kernel regression estimation. Subsequently, the three pre-selected key features (i.e., maximum wind speed, maximum rain intensity and accumulated rain) are extracted from the interpolated hourly wind and rain data for each 1km-grid. An example of the gridded hazard intensity maps for the Typhoon Lekima (2019) are plotted in Figure 2.

Hazard-formative environment data: Four types of land use data are considered, i.e., impervious area, green land, water area, and wetland. The area ratios in terms of 1km grid are calculated through spatially aggregating land use data at 10-meter resolution, which is downloaded from ROM-GLC (Finer Resolution Observation and Monitoring of Global Land, http://data.ess.tsinghua.edu.cn/fromglc10_2017v01.html). Additionally, topographic factors (including elevation, slope, aspect) and river density are also collected and processed into 1km-grid data. Gridded population densities at 1km resolution of different years are downloaded from the Open Spatial Demographic Data and Research (WorldPop datasets, Tatem, 2017) and adjusted by the county-level datasets from the statistical yearbooks in Zhejiang Province.

Loss data: TC disaster loss in terms of AP is collected in the form of county-level records with standard format and quality check, which is obtained from the Zhejiang Emergency Management Department.

Table 1. Information of the 9 TC events

TC ID	*TC Name*	*No. of Affected Counties*	*Total Affected Population (million)*
1211	*Haikui*	*90*	*6.579*
1307	*Soulik*	*27*	*0.626*
1312	*Trami*	*28*	*1.465*
1323	*Fitow*	*83*	*11.38*
1410	*Matmo*	*13*	*0.630*
1509	*Chan-hom*	*93*	*2.101*
1513	*Soudelor*	*31*	*3.522*
1808	*Maria*	*17*	*0.616*
1909	*Lekima*	*76*	*7.631*

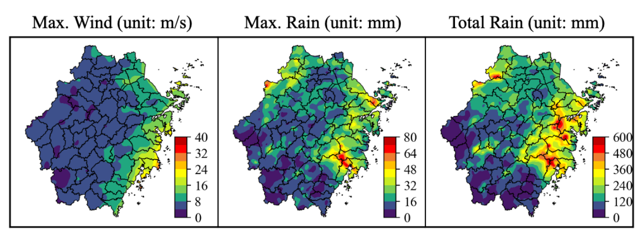

Figure 2. The gridded hazard intensity map

2.2 The CNN architecture

The CNN model is one specific type of neural networks with multiple convolutional layers, and is most commonly used for image processing and classification. This model is appealing here in part because of its exceptional strength in extracting key features from grid-like data. To serve the purpose of our problem, we particularly design a CNN model with an autoencoder architecture to map our spatial data (multichannel images by concatenating all 1km-grid data of the pre-selected explanatory factors) to output variables (i.e., TC induced loss), as shown in Figure 3.

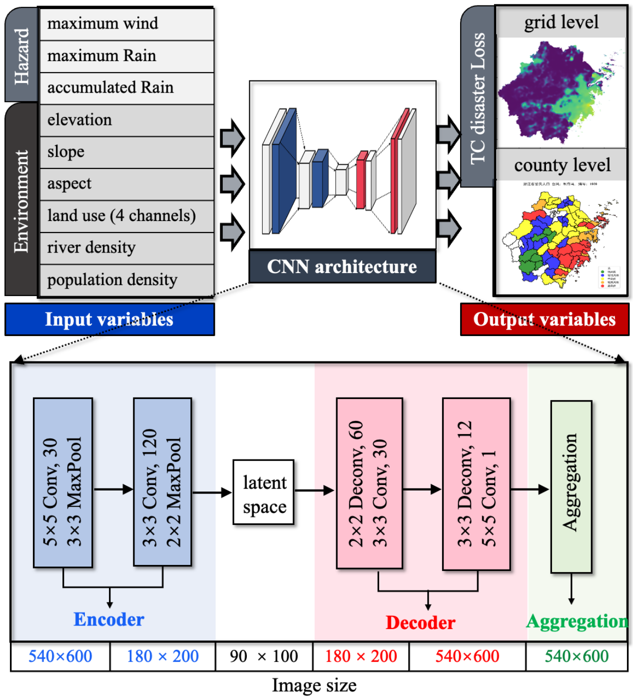

Figure 3. Structure of the CNN model

Specifically, there are three modules in the proposed CNN model (see Figure 3): firstly, an encoder that compresses the high-dimensional input into a latent low-dimensional space, which contains two components with each consisting of a convolutional layer and a pooling layer; secondly, a decoder that reconstructs the compressed data into its original size, which contains two components with each consisting of a deconvolutional layer and a convolutional layer; lastly, an aggregation layer that maps the gird-level output into county-level output, which is the genuine output of this supervised learning. Detailed information on the kernel size and depth of each layer is labeled on each component of the network architecture in Figure 3. Moreover, the image size of each component is also labeled at the bottom of Figure 3. Note that the output of the decoder is set as the gridded affected population ratio (APR, i.e., the ratio of AP to population density), which has restricted the range of the output as [0, 1]. To improve fitting strength, rectified linear unit (ReLU) activations are added to all the intermediate layers except that the sigmoid function is added to the last layer of the decoder. As for the aggregation layer, the gridded APR is multiplied by the gridded population density and further spatially aggregated over the county areas to obtain the county-level output.

2.3 Model performance and validation

The 9 historical TC events introduced in Section 2.1 constitute the complete datasets, resulting in a sample size of 657 (with each corresponding to a county-level loss). Further, the samples are randomly divided into training and test data with a ratio of 9:1. The mean squared error (MSE) in terms of the county-level losses is adopted to evaluate model performance, i.e.,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \qquad (1)$$

in which the y_i is the observed value while the $\tilde{y}_i$ is the predicted results; n is the sample size.

Figure 4(a) displays the regression plot associated with the training and test datasets, with the predicted value of AP in the *x* axis and the ground truth data in the *y* axis. The Pearson correlation between the observed and predicted values is 0.907 and 0.885 for training and test data, respectively. Their R-squared values are 83.32% and 55.77%, respectively. These results indicate that the overall model performance is well given the limited data we currently have. Figure 4(b) displays the error plot associated the training and test datasets, with ground truth of AP in the *x* axis and relative error in the *y* axis. It's obviously observed that generally a larger ground truth value achieves a smaller relative error. This is partially attributed to the loss function we have defined for the CNN model, in which all samples are assigned with uniform weights and by nature inclines to minimize errors for those counties with large outcome. Note that the performance of our model is heavily influenced by the data volume and quality. Currently only 9 historical TC events are used in this model development, we believe there is great potential to improve model accuracy as long as the data volume increases.

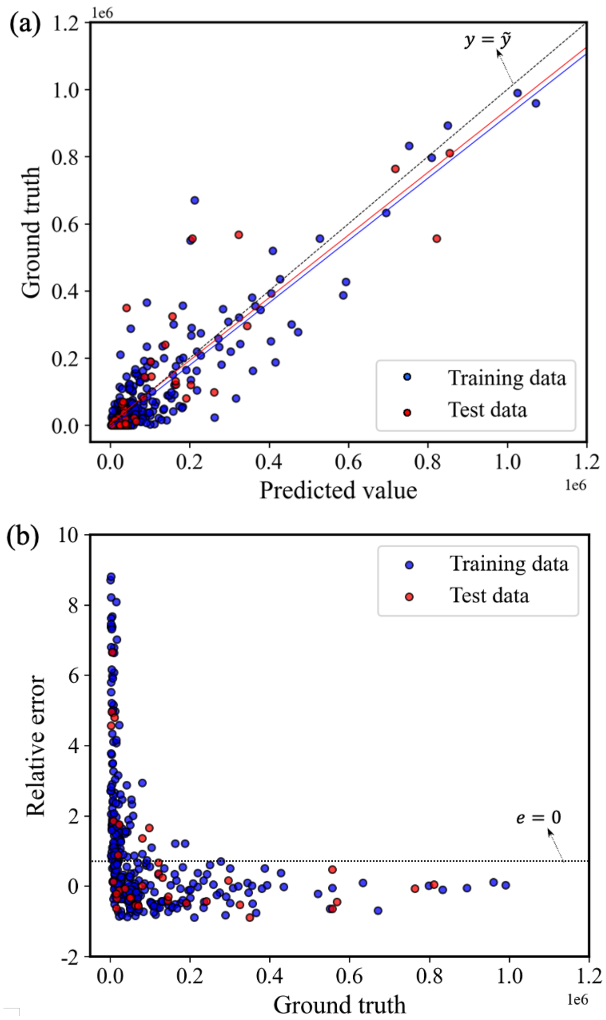

Figure 4. Visualization of the model performance with: (a) regression plot and (b) error plot

3. DISCUSSIONS

A notable focus of this study is to project the spatial distribution of potential losses and locate disaster hotspots under a TC hazard, thereby examining the spatial outcome is of great importance. Taking Typhoon Lekima (2019) as an example, Figure 5 shows the comparison between spatial distribution of the predicted outcome and ground truth data at the county level. It can be seen that the areas with high value of AP are well predicted, as clustered in the southeast and northeast of the province. Comparatively, the areas with low values of AP are less accurate, as consistent with the discussion of results in Figure 4(b). This tendency of accuracy towards high impact is acceptable for decision makers whose primary focus is locating disaster-stricken areas across the province domain. The province-level AP for predicted value and ground truth are 7.63 million and 7.52 million, respectively, indicating that our model can produce reliable results at province level.

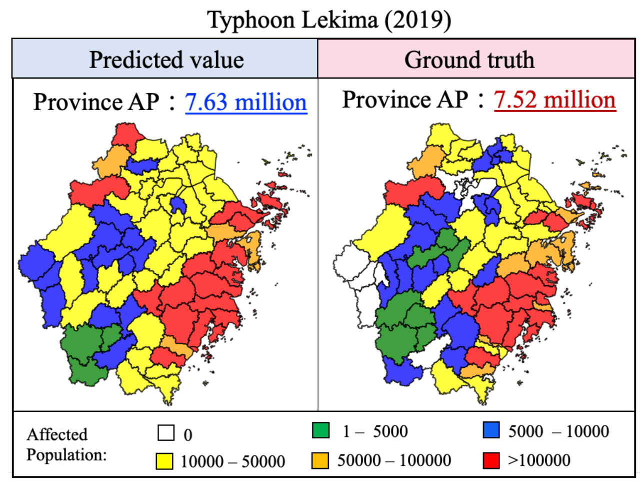

Figure 5. County-level spatial distribution of the predicted value and ground truth for the Typhoon Lekima (2019)

Going one step further, the CNN model is expected to produce spatial estimation of TC loss with 1km resolution owing to the intermediate layer in the CNN structure. Figure 6 presents the spatial prediction of the APR under Typhoon Lekima at 1km resolution. It's clearly visualized that the resolution of this spatial outcome is far more delicate than the county-level results (i.e., the results in Figure 5). Moreover, one can easily capture and track disaster hotspots from these spatial outputs, which can undoubtedly provide much more risk information to decision makers than those other simulations without spatial outcomes.

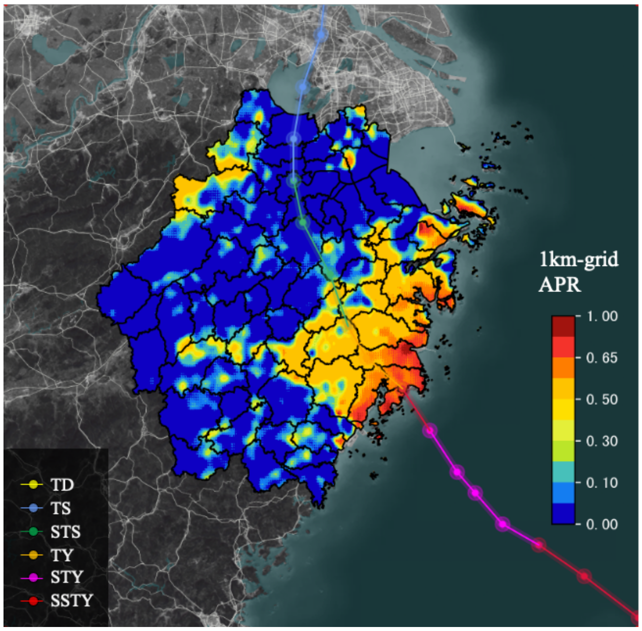

Figure 6. Typhoon track and spatial results of the predicted disaster loss in terms of 1km-grid APR under Typhoon Lekima (2019).

4. CONCLUSIONS

In this paper, we have proposed an end-to-end CNN model to predict regional TC disaster loss for Zhejiang Province, China. This model takes as input several crucial explanatory factors such as meteorological, vulnerability and exposure variables, and outputs both county-level and 1km-grid disaster loss (more specifically, affected population) for the whole province. To the authors' best knowledge, a TC disaster loss prediction model based on CNN which produces fine-resolution gridded outcome has not been tested so far. The model developed is computationally efficient and has maintained promising accuracy.

The model is expected to assimilate real-time meteorological data provided by the current advanced weather forecast service in order to dynamically communicate risk throughout the evolution of TCs.

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