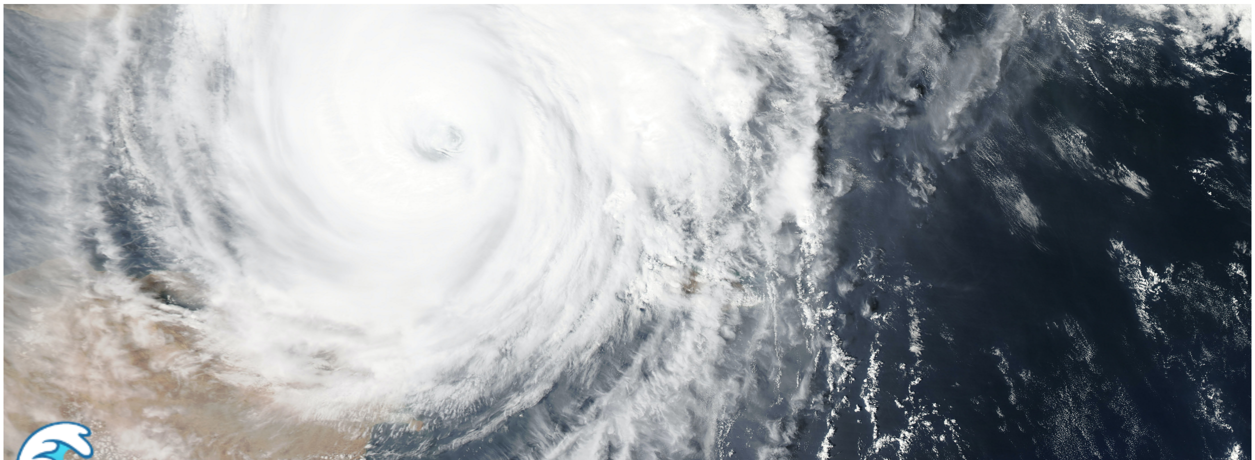

A Case Study in Exeter, UK - Assessing Surface Water Flood Risks in Urban Areas Using Machine Learning

Assessing Surface Water Flood Risks in Urban Areas Using Machine Learning

Urban flooding is a devastating natural hazard for cities around the world. Flood risk mapping is a key tool in flood management. However, it is computationally expensive to produce flood risk maps using hydrodynamic models. To this end, this paper investigates

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This article explores using machine learning algorithms to assess the risk of surface water flooding in urban areas, which can cause significant damage to property and residents. Producing flood risk maps using traditional methods like hydrodynamic models is expensive, so this study looks at using machine learning models instead, including naïve Bayes, perceptron, artificial neural networks (ANNs), and convolutional neural networks (CNNs).

The models takes **(a) elevation; (b) slope; (c) soil type; (d) substrate; (e) land cover; (f) NDVI; (g) land use; (h) imperviousness; (i) distance to river; (j) distance to road** as input. VIF was used to select features. The study tests several machine learning algorithms and finds that **convolutional and artificial neural networks** perform best.

Data Pipeline

Data Pipeline Step	Description
Data Collection	Obtain geo-environmental data of Exeter, including elevation, slope, soil type, substrate, land cover, NDVI, land use, imperviousness, distance to river, and distance to road
Preprocessing	Use QGIS to project all maps into an EPSG:27700 projected coordinate system for the United Kingdom, convert vector maps into raster maps, extract the clip of maps by mask layer based on the boundary of Exeter from an administrative division map of England, resample and set the resolution as 1 m, and convert data to numerical data from raster images with a grid size of 10 m using Rasterio tool
Feature Selection	Use multicollinearity diagnosis test to prevent inputting similar features into the models and save training time and computation power. All features with VIF less than 10 are applied to train NB, perceptron, ANN, and CNN models
Data Balancing	Use oversampling and undersampling methods to balance the data, as the distribution of flood risks is extremely imbalanced. Non-flood areas account for about 98%, 95%, and 90% for 30-year, 100-year, and 1000-year flood events. Level 4 risk areas only account for 0.01% and 0.06% for 30-year and 100-year flood events, respectively
Model Selection and Assessment	Apply NB, perceptron, ANN, and CNN models to assess the flood risk of 30-year, 100-year, and 1000-year flood events. Evaluate model performance using appropriate metrics

Result

The performance of models on the 30-year flood event is better than the 100-year and 1000-year flood events.

The paper also discusses the evaluation metrics such as accuracy, F-beta score, and receiver operating characteristic (ROC) curve, as well as the oversampling and undersampling techniques used to address the issue of data imbalance.

The case study shows that the proposed method effectively identifies flood-prone areas in Exeter.

Table 3. Accuracy of models for the assessment of 30-year, 100-year, and 1000-year flood events in
Exeter.

Model	30-Year Flood Event	100-Year Flood Event	1000-Year Flood Event
Naïve Bayes	77.36%	77.39%	69.61%
Perceptron	72.10%	69.96%	78.27%
ANNs	93.61%	94.44%	81.34%
CNNs	92.59%	92.92%	83.34%

Table 4. F-beta score of models for the assessment of 30-year, 100-year, and 1000-year flood events in Exeter (β = 0.5).

Model	30-Year Flood Event	100-Year Flood Event	1000-Year Flood Event
Naïve Bayes	92.41%	89.91%	80.92%
Perceptron	90.89%	87.66%	81.41%
ANNs	96.53%	93.51%	83.98%
CNNs	95.71%	92.49%	84.11%

What do we mean by accuracy:

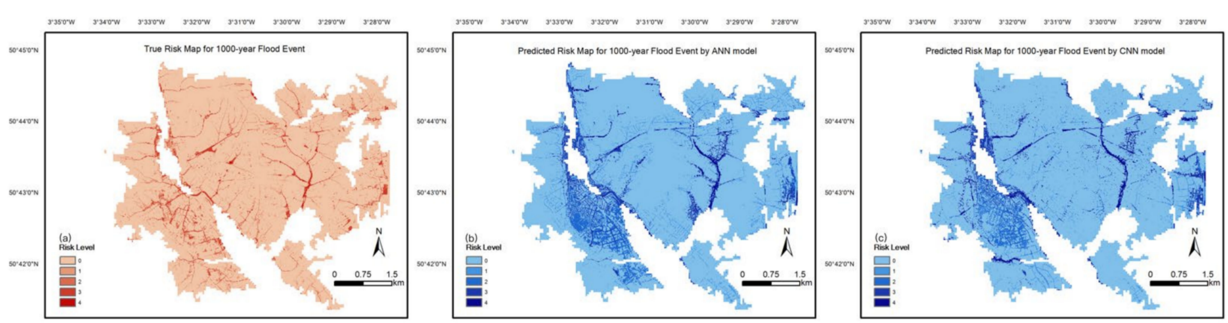

Figure 5. 1000-year flood event: (**a**) ground-truth risk map; (**b**) predicted risk map by ANNs; (**c**) predicted risk map by CNNs.