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Enhance pluvial flood risk assessment using spatio-temporal machine learning models

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Extreme weather events (e.g., heavy rainfall) are natural hazards that pose increasing threats to many sectors and across sub-regions worldwide (IPCC, 2014), exposing people and assets to damaging effects. In order to predict pluvial flood risks under different spatio-temporal conditions, three generalized Machine Learning models were developed and applied to the Metropolitan City of Venice: Logistic Regression, Neural Networks and Random Forest. The models considered 60 historical pluvial flood events, occurred in the timeframe 1995-2020. The historical events helped to identify and prioritize sub-areas that are more likely to be affected by pluvial flood risk due to heavy precipitation. In addition, while developing the model, 13 triggering factors have been selected and assessed: aspect, curvature, distance to river, distance to road, distance to sea, elevation, land use, NDVI, permeability, precipitation, slope, soil and texture. A forward features selection method was applied to understand which features better face spatio-temporal overfitting in pluvial flood prediction based on AUC score. Results of the analysis showed that the most accurate models were obtained with the Logistic Regression approach, which was used to provide pluvial flood risk maps for each of the 60 major historical events occurred in the case study area. The model showed high accuracy and most of the occured events in the Metropolitan City of Venice have been properly predicted, demostrating that Machine Learning could substantially improve and speed up disaster risk assessment and mapping helping in overcoming most common bottlenecks of physically-based simulations such as the computational complexity and the need of large datasets of high-resolution information.