以物理模式資料驅動深度學習淹水預測模型之場域驗證

Field verification of a deep learning flood prediction model driven by physical model data

國家高速網路與計算中心

副研究員	專案副管理師
王豪偉	廖于慧
Hau-Wei Wang	Yu-Hui Liao

摘 要

本研究基於 Wang 等人(2022)提出的數據驅動的深度學習方法，在具有觀測資料之宜蘭河壯圍鄉建立模型及驗證。王等人(2022)的成果顯示，在 CNN 柵格洪水預測模型中加入空間資訊是必要的，綜合考慮累積降雨時間序列和座標地形可以得到最佳的洪水預測結果，僅利用降雨預報數據即可實現長期洪水預測。宜蘭河流域位於台灣東北部，該流域的特點包括山地平坦地形、天然河流系統和高洪水潛力地區。洪水往往因颱風入侵和東北季風的影響而變得嚴重，且受地形因素影響而加劇。台灣颱風洪水研究所（TTFRI）與中央氣象局、水利署和宜蘭縣政府在 2012 年至 2016 年間建立高空間密度和高時間分辨率的水文監測（Lu，2012，2013；Liu，2014 ，2015，2016），並提供水文和水資源管理模型校準和模擬。

本研究最初根據 Wang 等人（2022）在台灣桃園縣東門河流域的研究，以 12 小時累積降雨量建立模型。然而，即使 CNN 框架中插入 dropout，訓練 batch size 和訓練資料量也大大增加，也無法改善結果。觀察用於訓練的物理模型數據，洪水通常發生在降雨後約 24 至 30 小時之間。因此，嘗試調整用於訓練的總降雨期，模擬結果得到改善。本模擬結果除了與物理模型比對外，還以 2012 年侵襲台灣的蘇拉颱風事件之觀測雨量作為輸入資料，與實測觀測淹水資料進行比對，以驗證方法的實用性。研究顯示，使用不同累積降雨量訓練的模型，對預測結果有決定性的影響。儘管預測的洪水結果，存在一些不連續性，但整體的趨勢及淹水最大深度的預測有良好的結果。下階段的工作重點是雨量預報資料與淹水模式界接之驗證，並將其應用於防災預測。

關鍵字：捲積神經網路、二維淹水預測、觀測資料、驗證

Abstract

This study is based on the data-driven deep learning method proposed by Wang et al. (2022) to establish a model and verify it in Zhuangwei Township, Yilan watershed, where observation data are available. The results of Wang et al. (2022) show that it is necessary to add spatial information to the CNN grid flood prediction model. Considering time series cumulative rainfall and coordinate terrain can obtain the best flood prediction results. Using only rainfall forecast data can achieve long-term flood predictions. The Yilan River Basin is located in northeastern Taiwan. Characteristics of the basin include mountainous flat terrain, natural river systems, and areas of high flood potential. Floods are often severe due to typhoons and northeast monsoons and are affected by topographic factors. The Taiwan Typhoon Flood Research Institute (TTFRI) worked with the Central Weather Bureau, Water Resources Department, and Yilan County Government from 2012 to 2016 to establish hydrological monitoring with high spatial density and high temporal resolution, which provided hydrology and water resources management model calibration and simulation.

This study was initially based on the analysis of Wang et al. (2022) in the Dongmen River Basin in Taoyuan County, Taiwan, and established a model with 12 hours of accumulated rainfall. However, even if dropout is inserted into the CNN framework, the training batch size and training data greatly increase, and the results cannot be improved. Based on the physical model data used for training, flooding typically occurs approximately 24 to 30 hours after rainfall. Therefore, we tried to adjust the total rainfall period used for training, and the simulation results improved. In addition to comparing the simulation results with the physical model, the simulation results in this paper also use the observed rainfall of the Typhoon Soala event that hit Taiwan in 2012 as the input condition and compare it with the measured flooding data to verify the practicability of the method. The result shows that models trained with different accumulated rainfall have a decisive impact on forecast results. Although there are some discontinuities in the predicted flood outcomes, the overall trends and predictions of maximum inundation depth are good. The next stage of work is to verify inserting rainfall forecast data into our models and use it for disaster prevention predictions.

Keywords: Convolutional Neural Networks, 2D Flood Prediction, field data, verification