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Flash flood nowcasting based on deep learning and radar rainfall estimates

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Abstract: Flash floods are among the most destructive natural hazards, posing significant risks to lives, infrastructure, and ecosystems due to their rapid onset and limited lead times for emergency response. Traditional hydrological and hydrodynamic models, while robust for large river systems, often underperform in flash flood contexts because of their high data requirements, computational costs, and limited ability to capture fine-scale variability in rainfall–runoff processes. Recent advances in data-driven modelling, particularly deep learning, provide new opportunities to overcome these limitations by learning complex non-linear relationships directly from observations.

This study presents a novel encoder–decoder Long Short-Term Memory (LSTM) framework for short-term flood forecasting and inundation mapping, leveraging high-frequency radar rainfall and river level observations. Focusing on the flood-prone Hunter Valley, New South Wales, Australia, we test the model across three hydrologically diverse locations: Wollombi Brook, Greta, and Wallis Creek. These sites represent contrasting flood dynamics, from fast-responding catchments to backwater-affected tributaries, thereby offering a comprehensive test bed for operationally relevant flash flood forecasting. The LSTM model was trained on 15-minute radar rainfall inputs from the Bureau of Meteorology's RAINFIELDS system and corresponding water level data from 2022 to 2024, and validated against the major flood event of March 2021. It was capable of forecasting water levels up to 12 hours ahead, conditioned on both antecedent hydrological states and near-real-time radar nowcasts. These forecasts were then combined with high-resolution LiDAR digital elevation models using the Height Above Nearest Drainage (HAND) method to generate spatiotemporal inundation maps, which were evaluated against Sentinel-1 and Sentinel-2 flood products.

Results demonstrate that the LSTM model achieves strong predictive skill across multiple lead times. At short horizons (90 minutes), the model yielded average errors of 0.09 m (RMSE) and 0.06 m (MAE), while at 12 hours, errors increased to 0.45 m (RMSE) and 0.24 m (MAE). Importantly, the model consistently captured the rapid rising limb of flood hydrographs, critical for issuing timely warnings, and maintained reliable skill during flood recession. Flood inundation predictions showed high agreement with satellite benchmarks, achieving over 94% overall accuracy and up to 84.5% critical success index at 12-hour lead time. Notably, model performance remained robust across different catchments, highlighting its transferability within operational settings. Operational capability was further demonstrated through integration with the Bureau's radar-based nowcasting systems, STEPS-ADV (up to 90 minutes) and STEPS-NWP (up to 12 hours). The LSTM framework produced accurate nowcasts when driven by high-skill radar inputs, while performance declined modestly with the increased uncertainty of NWP rainfall at longer horizons. Despite these challenges, antecedent hydrological conditions constrained forecast variability, narrowing ensemble spread and supporting actionable decision-making even under uncertain precipitation inputs.

This research underscores the value of combining deep learning with operational radar rainfall and topographic datasets to deliver rapid, reliable, and spatially explicit flash flood forecasts. By directly producing inundation maps, the framework bridges a critical gap between hydrological prediction and impact-based early warning. Its scalability and computational efficiency make it a promising candidate for operational deployment, complementing existing physically based models while addressing their limitations in flash flood contexts.

Keywords: *Deep leaning, radar rainfall, flood forecasting*