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Introducing a fast and scalable method for floodplain inundation modelling

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Abstract: Floodplain inundation supports critical ecological functions in river systems, including habitat provision, connectivity, and nutrient cycling. In the Murray–Darling Basin (MDB), understanding when and where floodplains are inundated is essential for planning, delivering, and evaluating environmental water. Accurate, spatially resolved inundation data helps water managers set priorities, assess ecological outcomes, and adaptively manage water under changing conditions.

While hydrodynamic models are the standard for simulating floodplain inundation, their computational intensity and data demands limit their application across large areas or for routine scenario testing. They are often too slow for real-time operations or basin-scale planning. To address these constraints, the RQ7 floodplain inundation model was developed under the Murray–Darling Water and Environment Research Program (MD–WERP) Research Question 7 (RQ7). The model provides a fast, scalable method for predicting floodplain inundation using satellite observations, river flow data, and machine learning techniques.

RQ7 divides the Basin into modelling windows, each centred on a gauging station and covering surrounding floodplain areas. These windows are designed to capture most flood-prone regions with minimal overlap and are assigned a one-day flow travel time. Satellite-derived flood extent and water depth are used to build a library of floodplain inundation. A machine learning technique relates river conditions to floodplain response, enable the model to estimate daily inundation extent, depth, duration, and water volume at 30-metre spatial resolution.

The model has been tested on seven reaches across the MDB, covering both regulated and unregulated systems with varying geomorphic and hydrologic characteristics. Validation against satellite observations and hydrodynamic model outputs shows that RQ7 produces reasonable estimates of inundation patterns. It tends to underestimate depth and extent near main channels, particularly during high-flow events, but is able to detect flooding from other sources such as overbank or lateral flows—an advantage in complex or poorly gauged floodplain environments.

A key advantage of the RQ7 model is its computational speed. It was developed on the Earth Analytics Science & Innovation Platform, utilising earth observation data through Open Data Cube and parallel computing power provided by Amazon. Once trained, it can generate daily floodplain predictions for large regions within minutes, making it ideal for rapid scenario evaluation, annual water planning, and post-event assessment. Its ability to operate across multiple sites with a consistent method allows for broader integration of inundation metrics into environmental water management.

Rather than replacing detailed hydrodynamic models, RQ7 is intended to complement them. It offers a streamlined option for broad-scale analysis and early-stage planning, while hydrodynamic models remain valuable for local-scale assessments and infrastructure design. Used together, these tools support a more flexible and layered approach to water planning and ecological evaluation.

Ongoing work includes expanding the model to additional MDB regions, refining model inputs and uncertainty handling, and developing graphic user interface (GUI) for wider use. The RQ7 model offers a practical solution for efficiently estimating floodplain inundation across large, complex river systems, helping managers better respond to environmental water needs in a timely and informed manner.

Keywords: *Floodplain inundation, Murray-Darling Basin, climate change, machine learning, environmental water, remote sensing, random forest, MD–WERP*