Hybrid method for rapid flood scenario assessment

Why speed matters, what was built and how it may be useful

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Stormwater 2026
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About awa ENVIRONMENTAL

Modelling

Planning

Engineering

Excellence Heart Innovation

SHAPING STORMWATER | BUILDING RESILIENCE

DIGITAL ENVIRONMENTS

CATCHMENT DYNAMICS

Understanding how water moves, behaves and shapes catchments

DIGITAL SOLUTIONS

Automation and digital tools that strengthen catchment understanding

Today’s agenda

Why speed matters

1 Context

2 Motivation

What was built

3 Catchment

4 Method

What it proves

5 Results

Where it helps

6 Contribution

7 Next steps

PART 1

The Context

Obvious Context

- The most frequent hazard in New Zealand
- Highest cost for insurers
- Urban development is in floodplains
- The climate is changing
- Growing exposure of homes, infrastructure and communities

West Coast Floods July 2021

Cyclone Gabrielle February 23

Project Context

ESNZ led 5-year research programme:
Mā te haumaru ō ngā puna wai ō Rākaihautū ka ora mō ake tonu Increasing flood resilience across Aotearoa

Objective: develop a system to map flood hazard consistently across the whole country

Research aims:

1. National flood mapping → **PhD in Water Resources Management**
2. Flood risk to the built environment
3. Societal vulnerability to cascading events
4. Reducing flood risk and adapting to change

Earth Sciences New Zealand

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Read published paper here!

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Auckland Floods January 23

Canterbury Floods May 2021

PART 2

The Motivation

Motivation: the modelling bottleneck

2D hydrodynamic models provides reliable flood information

But they are **computationally expensive**

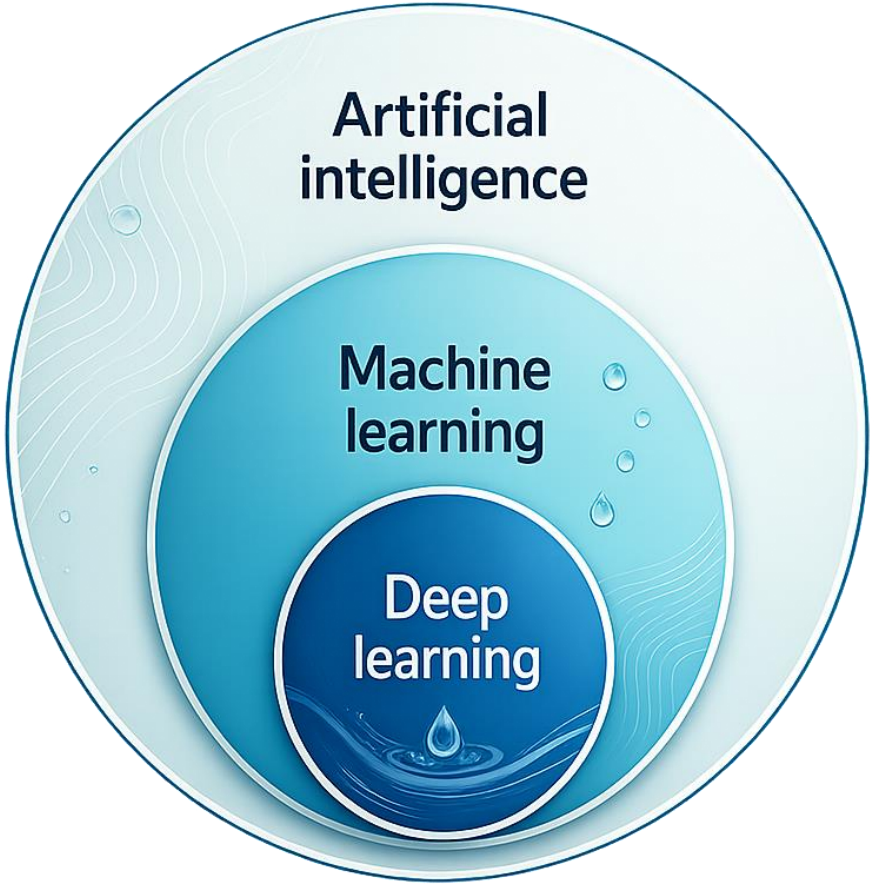
This make application to **ensemble scenario analysis** and **operational flood prediction** difficult

Solution: machine learning

Hybrid modelling:

combine different approaches to leverage the strengths of each

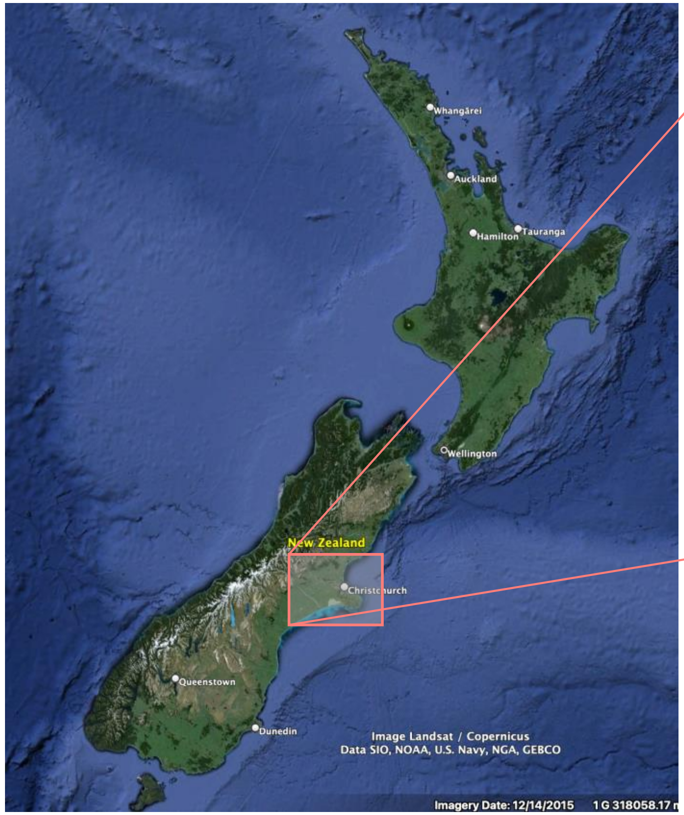
Hybrid hydrodynamic - machine learning method

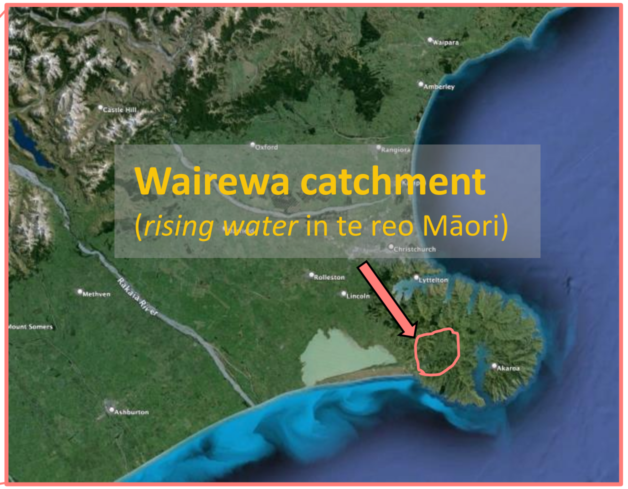


PART 3

The Study Catchment

Study catchment: Wairewa





85 km2
Catchment Size

13
13 major flooding since 2010

Funnel
Shape of catchment

PART 4

The Method

Hybrid modelling method

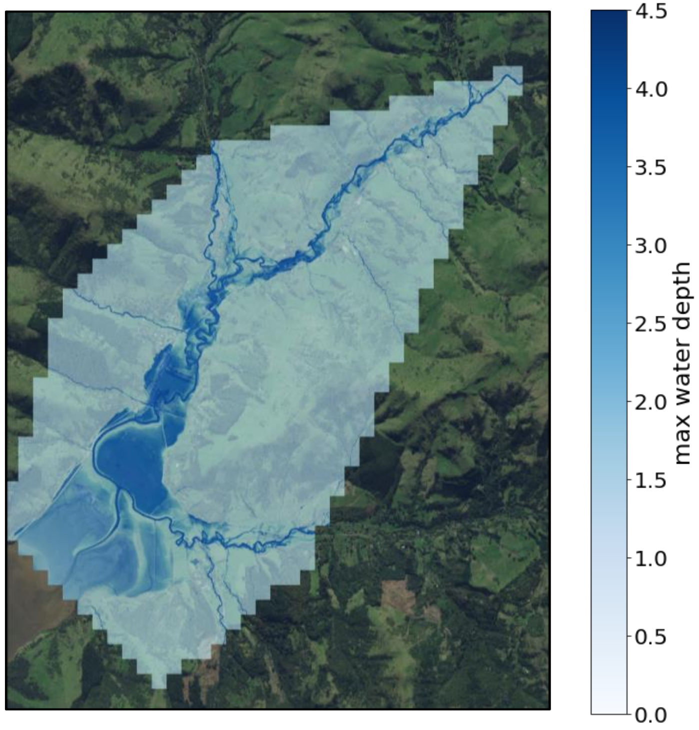
Objective: Build a hybrid model to make rapid flood predictions

Rainfall

Geographic characteristics

Hybrid model
(hydrodynamic +
machine learning)

Inundation map
maximum flood depth and flood extent



What the hybrid model learns from

Rainfall and geographic characteristics → (Hybrid model) → Inundation map (flood extent and maximum flood depth)

Predictor variables

- **Storm variables**: Total rainfall, peak intensity, storm peakiness factor

- **Geographic variables**: slope, elevation, aspect, roughness, total wetness index, distance to river

Target variables

- **Inundation map:**
- Flood/non-flood (threshold=0.1 m)
- Maximum inundation depth (m)

→ **Does the location flood?** → Classification model

→ **How much does the location flood?** → Regression model

Data → Train Machine Learning model

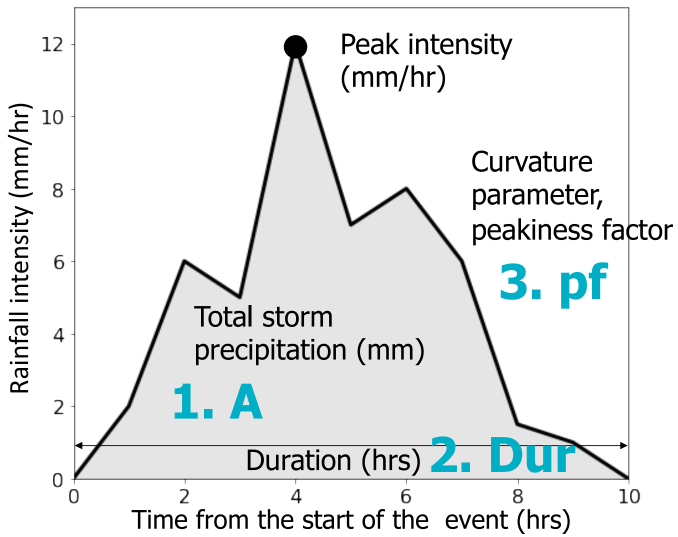
What the hybrid model learns from

Predictor variables

Storms

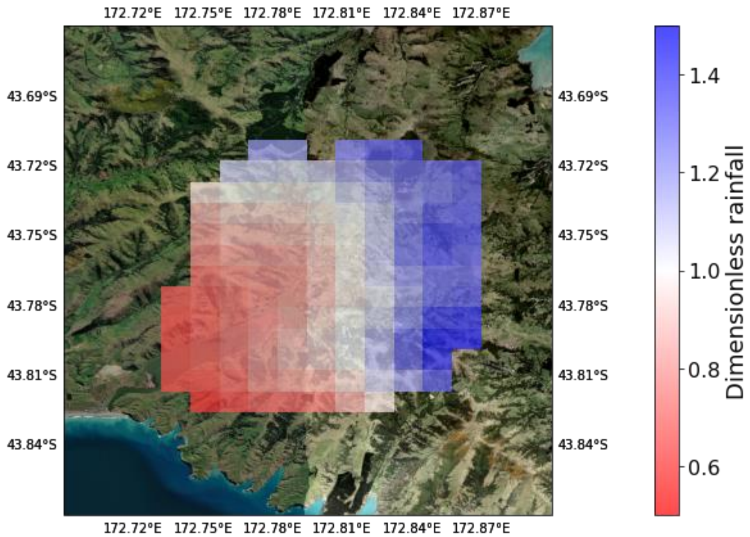
- Atmospheric conditions
- WRF rainfall dataset (validated against the rain gauge network)
- Monte Carlo approach

Temporal characteristics



Spatial characteristics

4. PC1, 5. PC2 and 6. PC3



Geographic variables: slope, elevation, aspect, roughness, total wetness index, distance to river

What the hybrid model learns from

Rainfall and geographic characteristics → Hybrid model → Inundation map (flood extent and maximum flood depth)

Predictor variables

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Does the location flood? → Classification model

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What the hybrid model learns from

Target variables

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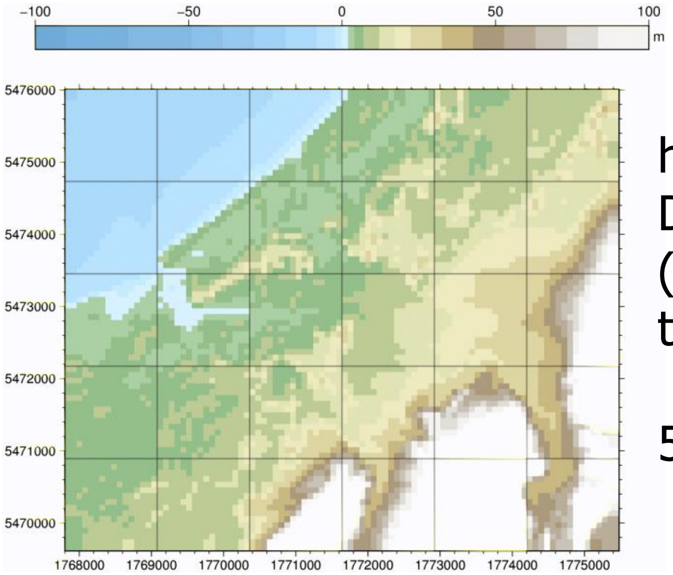
BG-Flood

Fast, open-source, inundation model



hydrologically conditioned DEM from Geofabrics (open-source, automatic tool)

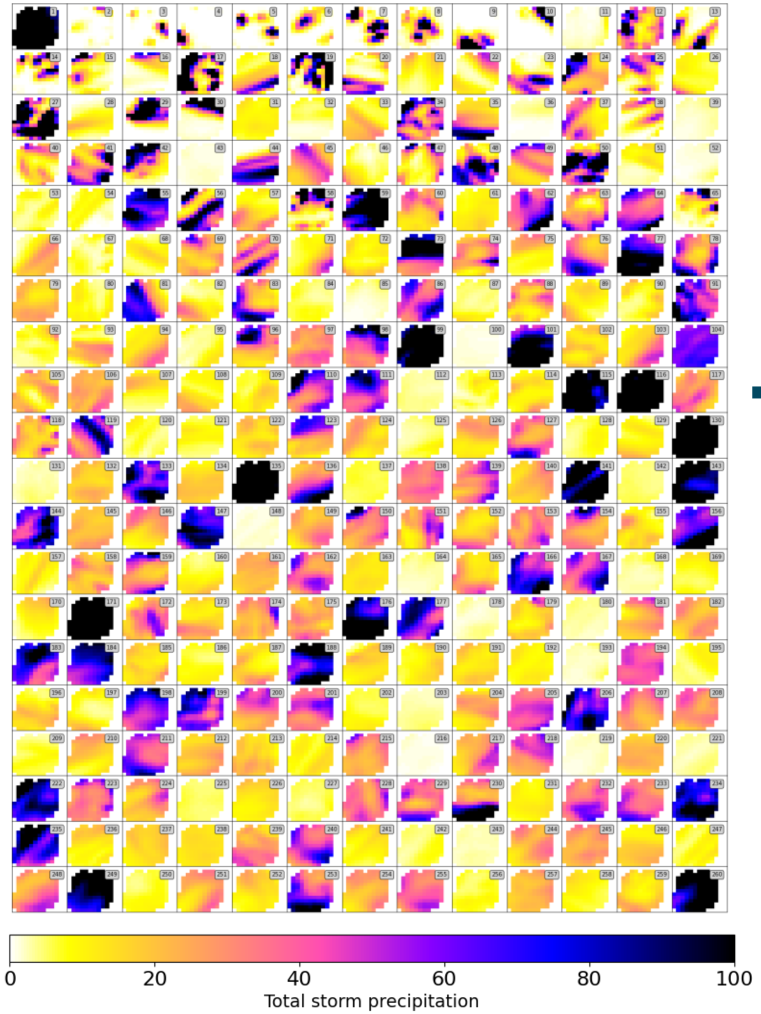
50 m resolution model

Pearson, Rose et al., Geofabrics 1.0.0: An Open-Source Python Package for Automatic Hydrological Conditioning of Digital Elevation Models for Flood Modelling. [*https://github.com/rosepearson/GeoFabrics*](https://github.com/rosepearson/GeoFabrics)

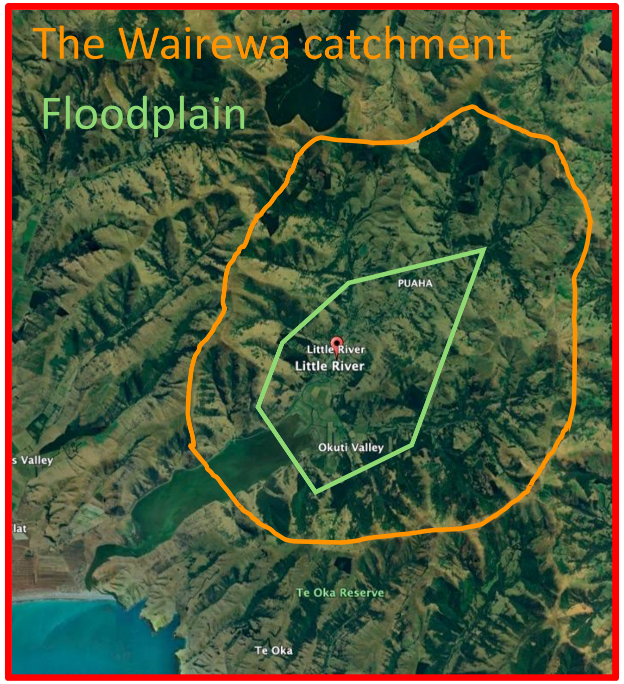
Bosserelle, C.; Lane, E.; Harang, A. BG-Flood: A GPU adaptive, open-source, general inundation hazard model. In Proceedings of the Australasian Coasts & Ports 2021 Conference, Christchurch, New Zealand, 11–13 April 2022. [*https://github.com/CyprienBosserelle/BG_Flood*](https://github.com/CyprienBosserelle/BG_Flood)

What the hybrid model learns from

Storms



BG-Flood



Inundation maps

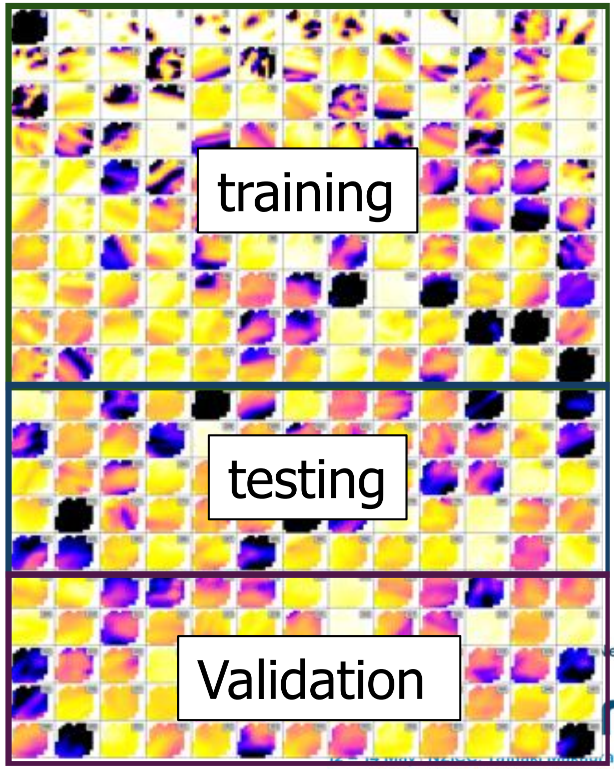
Chosing the machine learning algorithm

Data: predictor and target variables

Choose machine learning algorithm

Develop the machine learning model

- Random Forest
- XGBoost
- SVM
- RBFNs



Optimisation and validation

- Accuracy
- Speed
- Training set size
- Predictor variables

PART 5

The Results

Results: Validation

Classification model
(flooded/non-flooded)

Recall	Precision	F1 Score
0.88	0.90	0.89

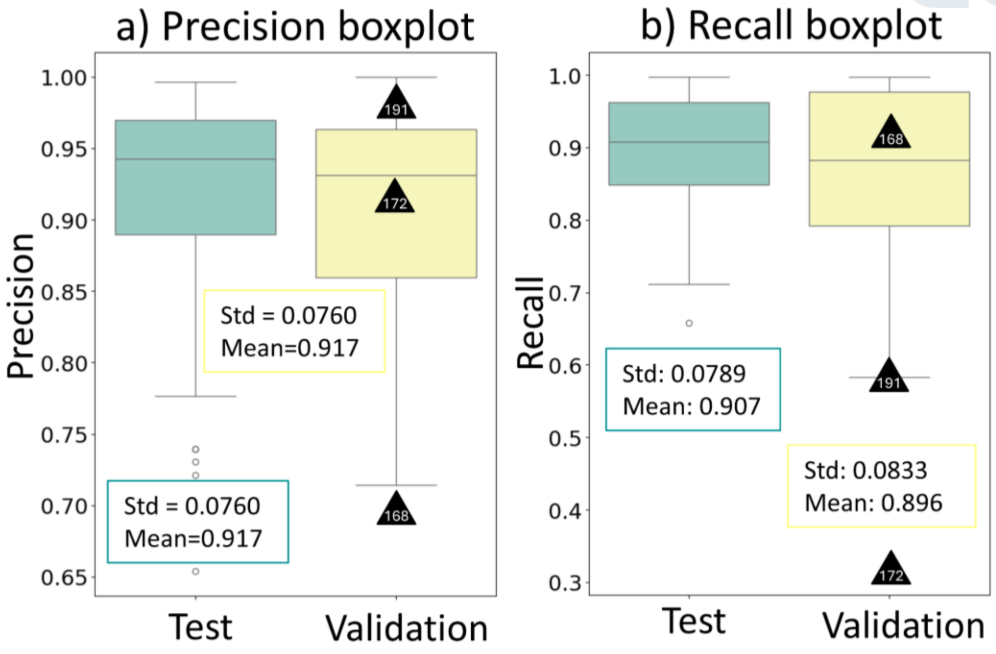
Regression model
(max inundation depth)

RMSE	NSE
0.061 m	0.87

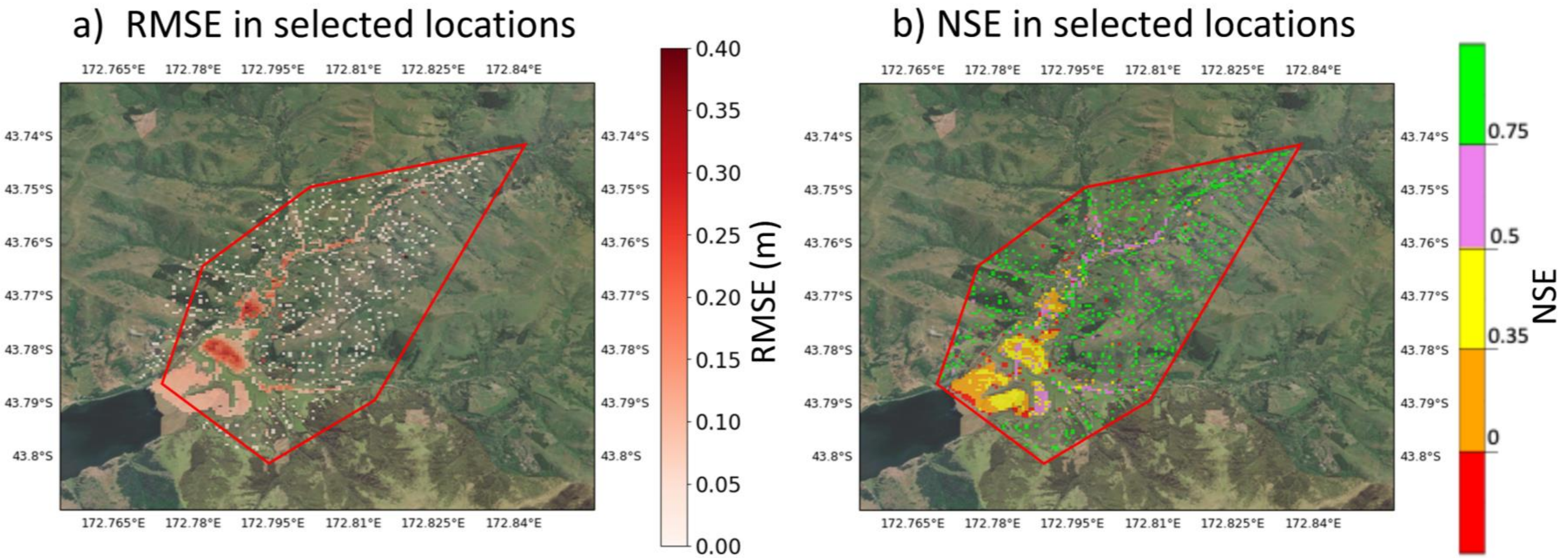
Models' performance varies with:

- Location
- Storm

Flood/non-flood prediction



Maximum inundation depth prediction

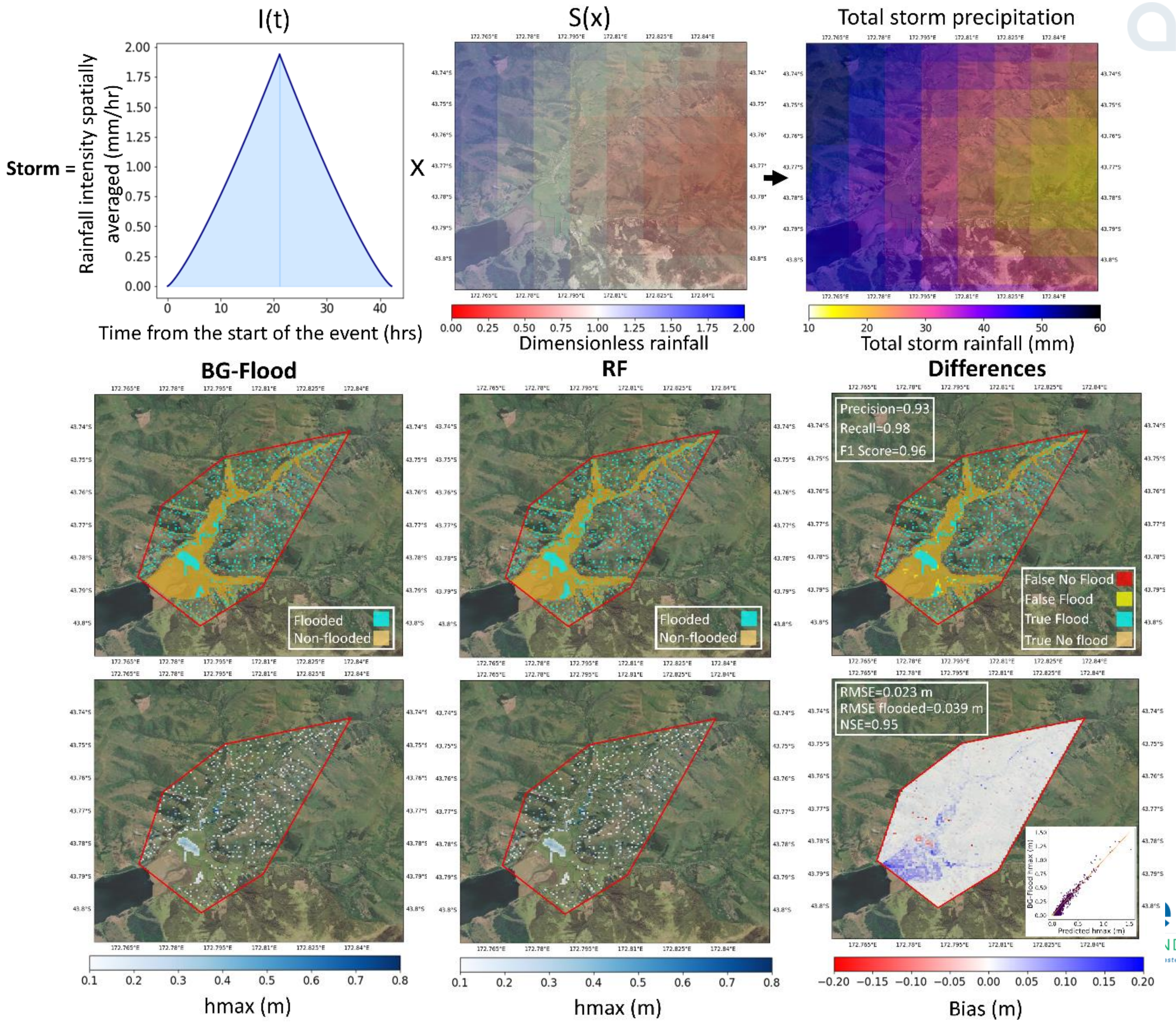


Results

Speed changes the workflow:

<1 second

versus hours



PART 6

The Contribution

Contribution: what this enables

Physically informed

Grounded in robust and reliable reference data methods

Data driven

Machine learning provides rapid flood predictions

Scenario prioritisation

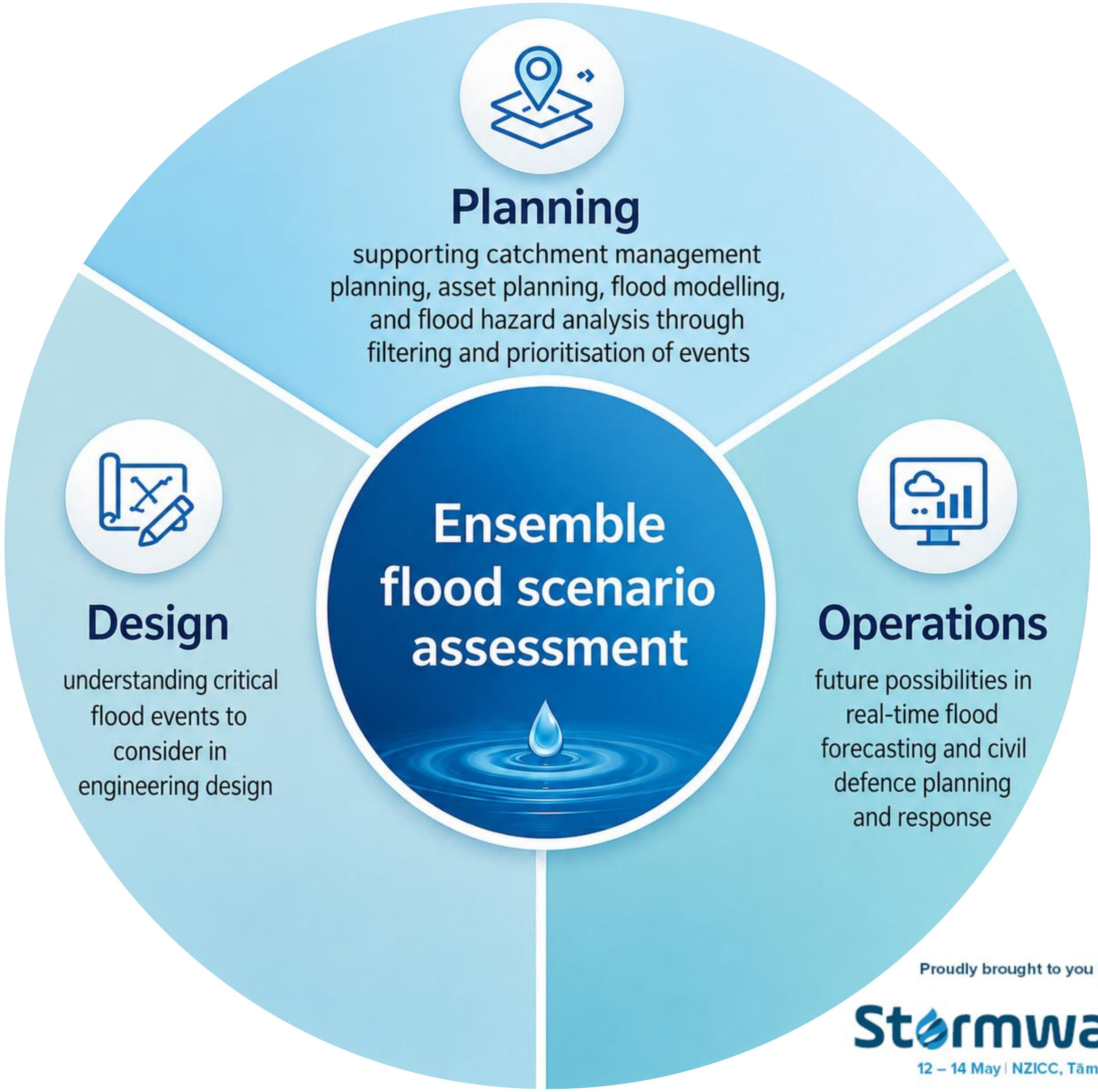
Simulation of multiple scenarios and identification of the critical ones

Key Takeaway

This is not AI hype, or a replacement of physics based numerical models. It is a fast screening approach for more computationally efficient workflows.

Contribution: what this enables

Contribution: what this enables



PART 6

Next steps

What comes next

Methodology transferability

- Local catalogue of storms (spatial rainfall dataset)
- Inundation maps (physics based model)
- Inundation drivers (parametrisation)
- Catchment size
- Spatial resolution
- Initial time and computing effort

Rainfall forecast system

- Test with rainfall forecast data

High resolution hybrid model

Read published paper here!

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Thank you!
Questions? Patai?

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