Modelling Group
WATER NEW ZEALAND

Modelling Symposium

Advancing methods of rapid flood scenario assessment using hybrid approaches of hydrodynamic modelling and machine learning

Presented by
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UC UNIVERSITY OF CANTERBURY Te Whare Wānanga o Waitaha CHRISTCHURCH NEW ZEALAND

NIWA Taihoro Nukurangi

Waterways Centre for Freshwater Management

GRI GEOSPATIAL RESEARCH INSTITUTE Toi Hangarau

Geomatics and Ocean Engineering Group UNIVERSIDAD DE CANTABRIA

PhD supervisors: Emily Lane, Matthew Wilson, Marwan Katurji and Fernando Méndez

water NEW ZEALAND
The New Zealand Water & Wastes Association Waiora Aotearoa

Motivation

- Most frequent hazard
- Cost $
- Urban development in floodplains
- Climate change

Mā te haumaru ō ngā puna wai ō Rākaihautū ka ora mō ake tonu: Increasing flood resilience across Aotearoa

1. National flood mapping
2. Flood risk to the built environment
3. Societal vulnerability to cascading events
4. Reducing flood risk and adapting to change

PhD supervisors: Emily Lane, Matthew Wilson, Marwan Katurji and Fernando Méndez

Wairewa visit (July 2022)


Dr Benita Wakefield and me (July 2022)

PhD research project motivat

Computer power and memory limits:

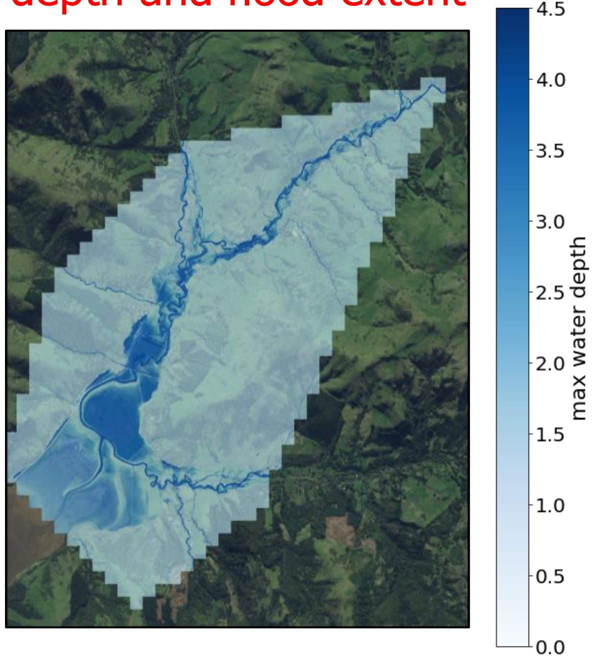
- Number of scenarios
- Level of detail and complexity of the model
- Catchment size

PhD research project outline

Objective: build a model to make rapid predictions of potential flooding events from an ensemble of previously assessed events

Inundation drivers → Heavy rainfall

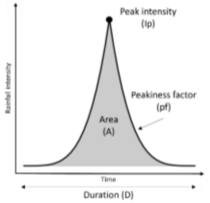
→ Hybrid model → Rapid flood hazard mapping: maximum flood depth and flood extent

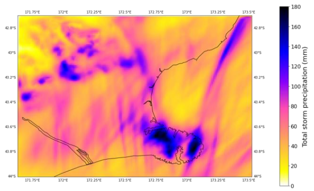


Hybrid model outline

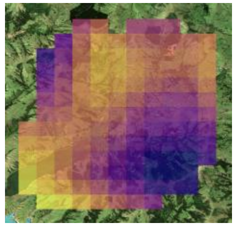
Heavy rainfall

Temporal and spatial characteristics





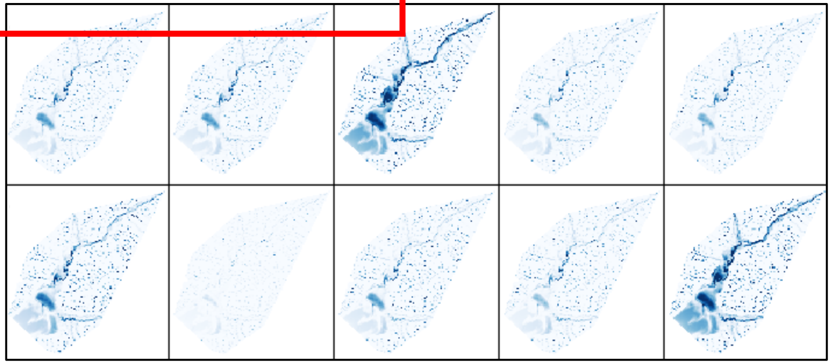
Synthetic storms



2D Hydrodynamic modelling

BG-Flood

Inundation maps



Split the storms + inundation maps

Training dataset

Testing dataset

Machine learning model

Trained and tuned machine learning model

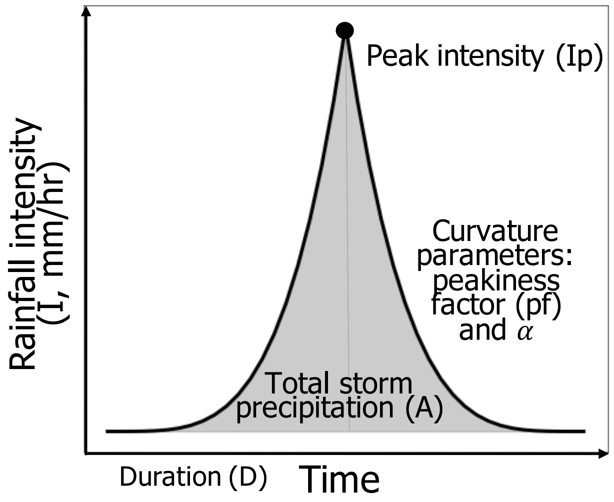
Inundation maps

Synthetic storms: concept

$$I\,(x_i, t) = \bar{I}\,(t) \cdot S(x_i)$$

Temporal dimension $\bar{I}\,(t)$

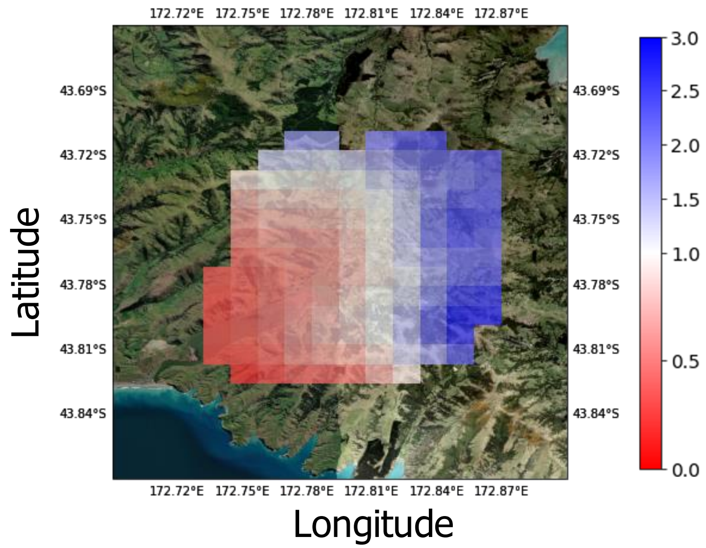
Synthetic hyetograph: mean rainfall intensity



$$I(t) = \begin{cases} \dfrac{h^* \cdot t^{\alpha}}{D/2}, & t \leq \dfrac{D}{2} \\ \dfrac{h^* \cdot (D - t)^{\alpha}}{D/2}, & t \geq \dfrac{D}{2} \end{cases}$$

Spatial dimension $S(x_i)$

Rainfall spatial distribution pattern: dimensionless rainfall

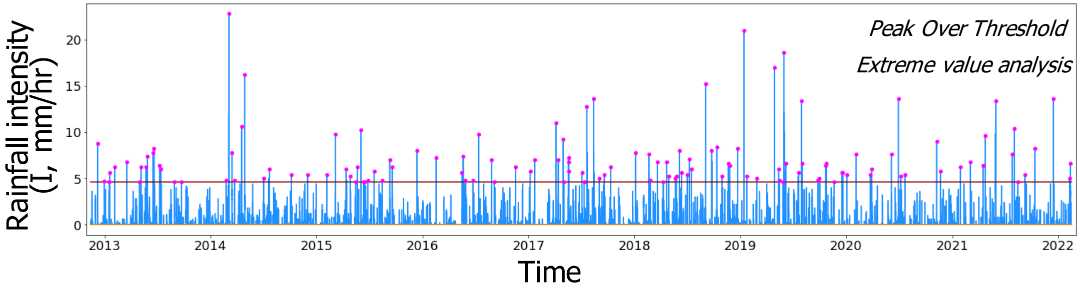


$$\bar{I} = \sum_{i=0}^{N} \frac{I\,(x_i)}{N+1}$$

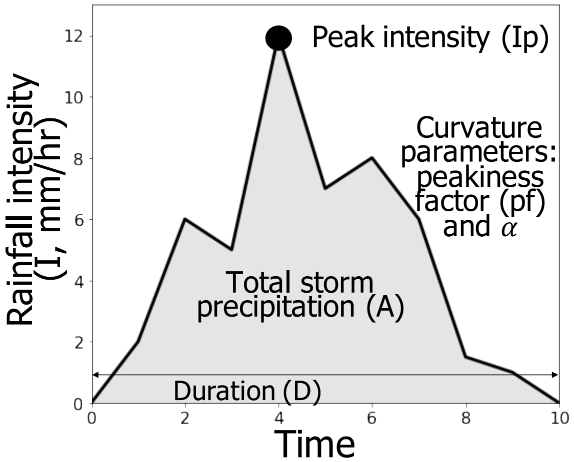
$$S\,(x_i) = \frac{I\,(x_i)}{\bar{I}}$$

Synthetic storms: rainfall databases

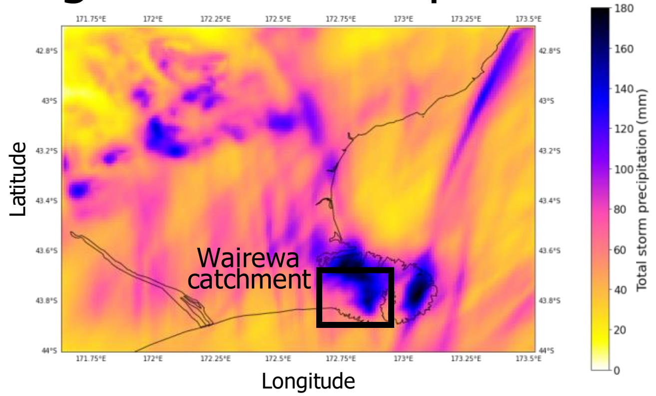
Rain gauge



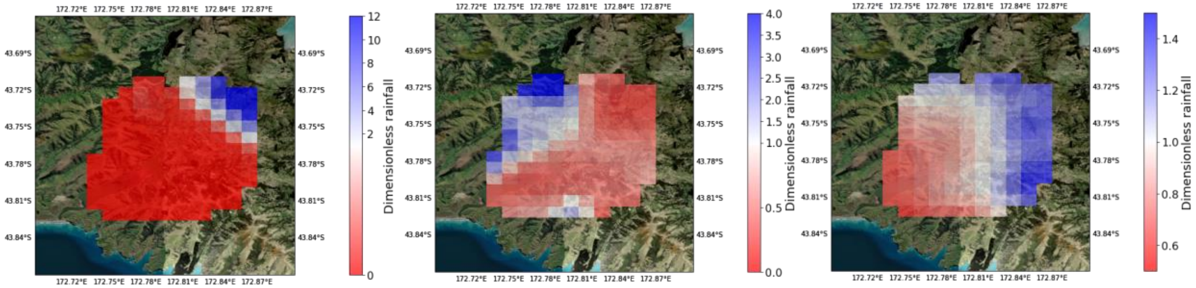
Temporal characteristics



Weather Research and Forecasting Model (WRF) gridded rainfall product



Spatial characteristics



$$\bar{I} = \sum_{i=0}^{N} \frac{I\,(x_i)}{N+1}$$

$$S\,(x_i) = \frac{I\,(x_i)}{\bar{I}}$$

Synthetic storms: generation

$$I\,(x_i, t) = \bar{I}\,(t) \cdot S(x_i)$$

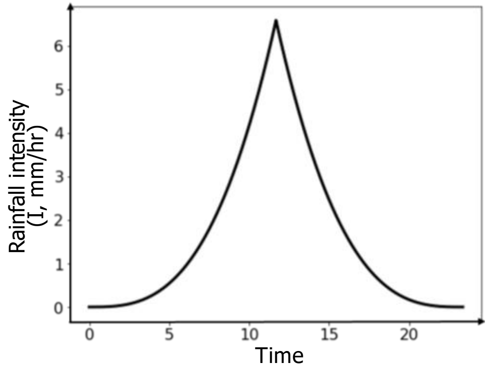
Temporal dimension $\bar{I}\,(t)$

Synthetic hyetograph: mean rainfall intensity

D = 24 hrs

Ip = 6.5 mm/hr

α = 0.3



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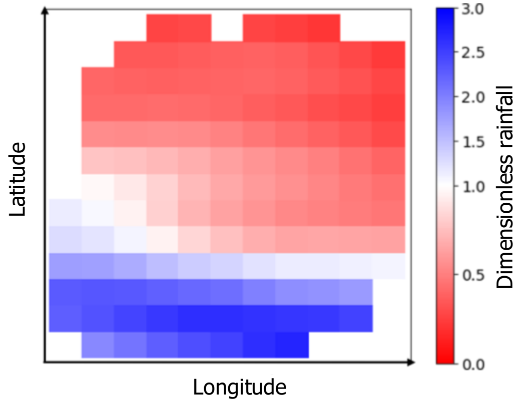
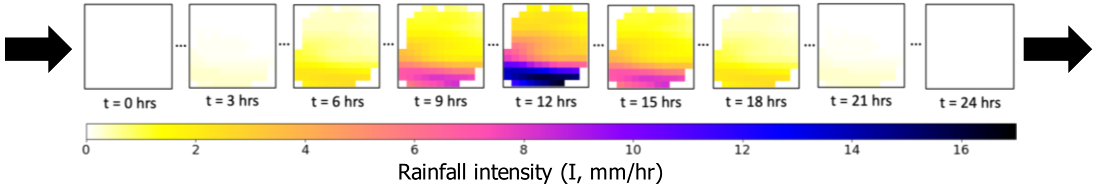
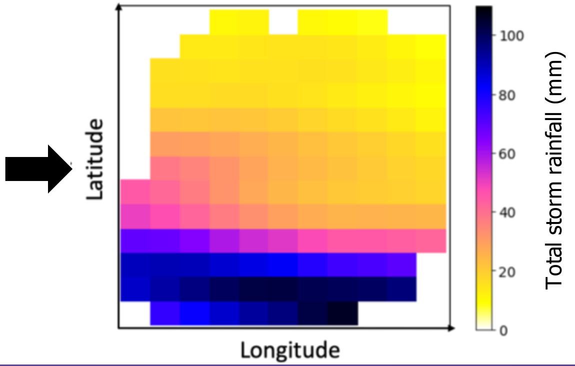
Spatial dimension $S(x_i)$

Rainfall spatial distribution pattern



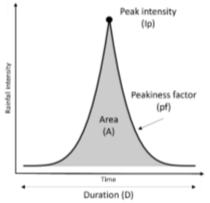


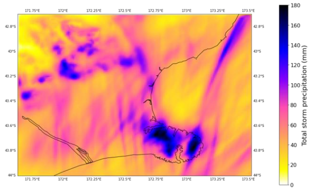


Hybrid model outline

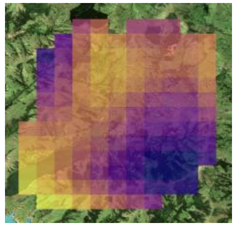
Heavy rainfall

Temporal and spatial characteristics





Synthetic storms



2D Hydrodynamic modelling

BG-Flood

Inundation maps

Split the storms + inundation maps

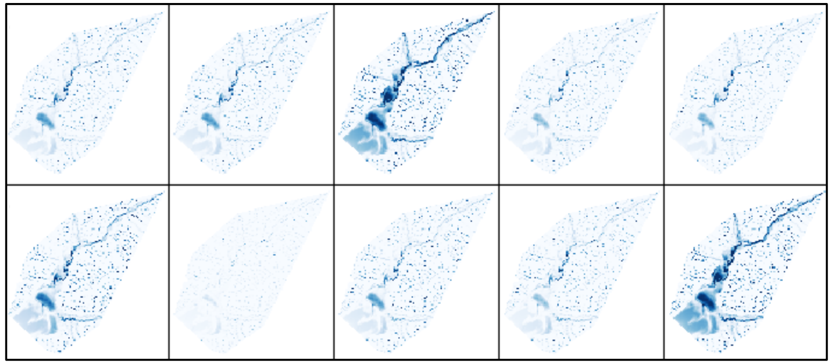
Training dataset

Testing dataset

Machine learning model

Trained and tuned machine learning model

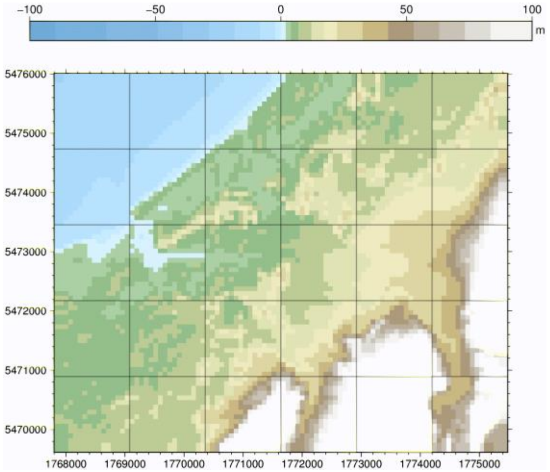
Inundation maps



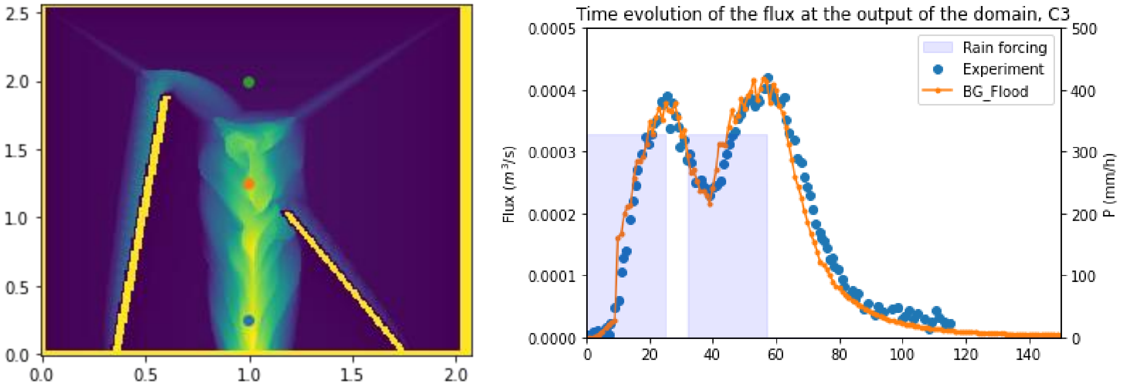
Hydrodynamic modelling: BG-Flood

<u>Fast, easy to use, free, open-source inundation model</u>

- Compound flooding: fluvial, pluvial, storm surge, tsunami
- Shock-capturing Shallow Water Equation
- GPU + No interface + BUQ grid
- Square adaptable grid



CEA2008 benchmark test: Uniform rain on grid



https://github.com/CyprienBosserelle/BG_Flood

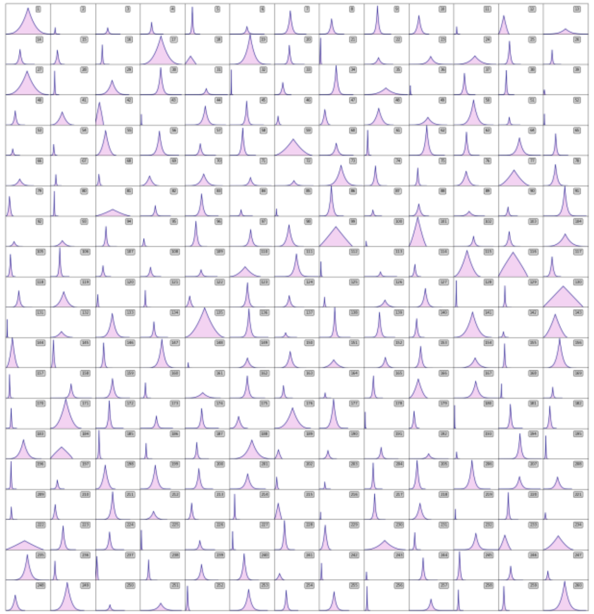
Bosserelle, C.; Lane, E.; Harang, A. BG-Flood: A GPU adaptive, open-source, general inundation hazard model. In Proceedings of the Australasian Coasts & Ports 2021 Conference, Christchurch, New Zealand, 11–13 April 2022.

Hydrodynamic modelling: Storms

$$I\,(x_i, t) = \bar{I}\,(t) \cdot S(x_i)$$

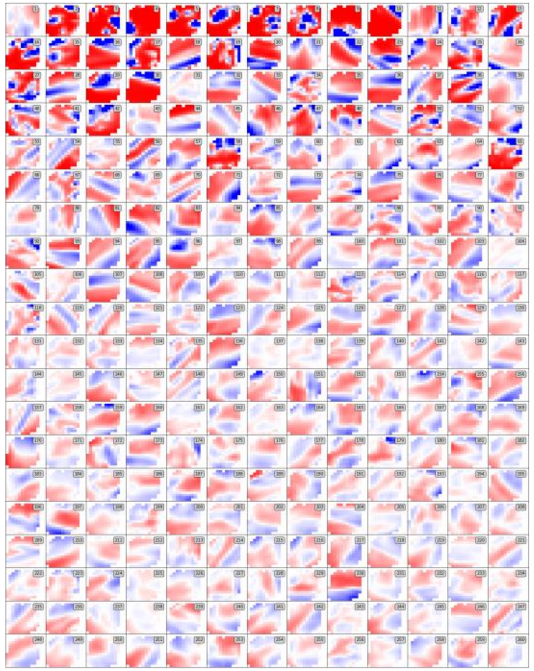
Temporal dimension $\bar{I}\,(t)$

Synthetic hyetograph:
mean rainfall intensity

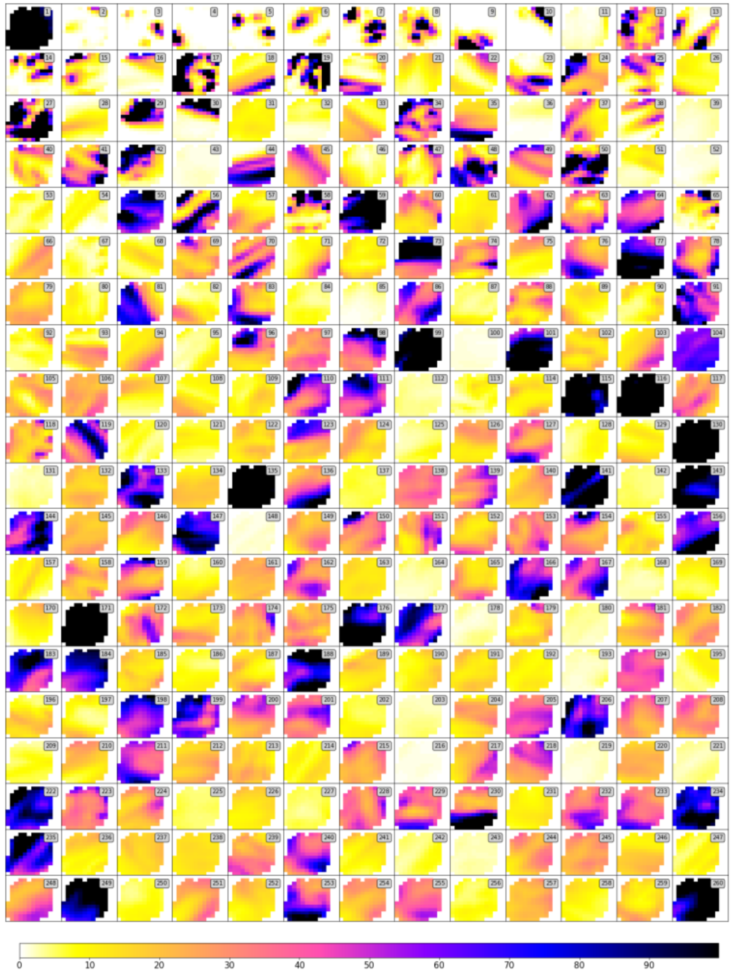


Spatial dimension $S(x_i)$

Rainfall spatial distribution pattern



Total storm precipitation



Hydrodynamic modelling: BG-Flood set up

Creation of a hydrologically conditioned DEM (Digital Elevation Model)

- Extraction of LiDAR data
- Add sea iso-contours
- Open waterways
- Estimate the River Bathymetry
- Add estuary fan (for big rivers)
- Using OSM (Open Street Map) to include drains, culvert, streams

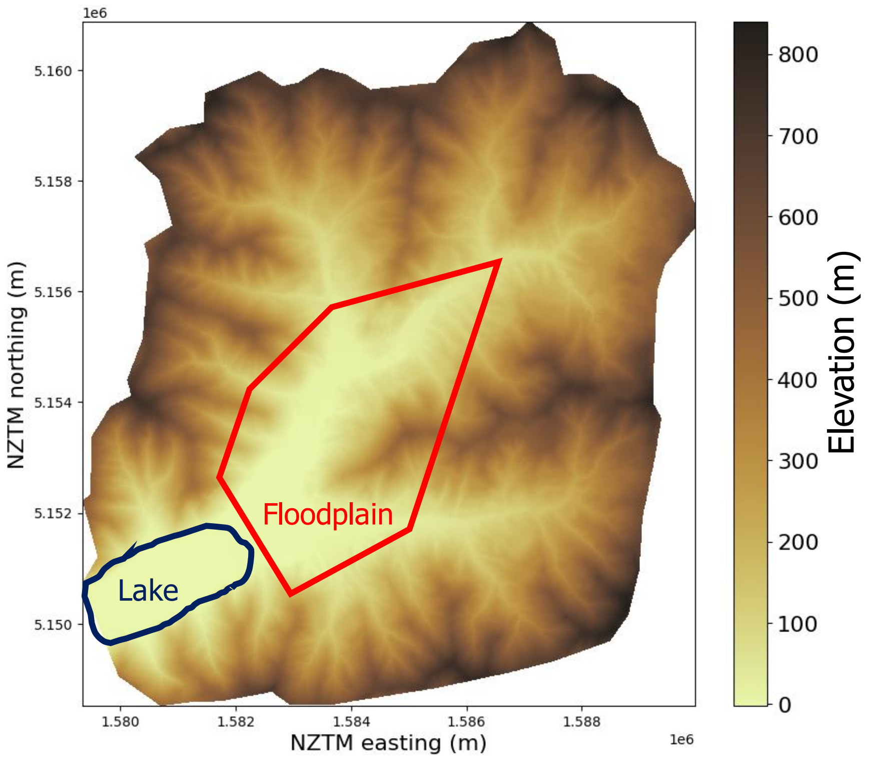
Creation of the roughness map

- Based on LiDAR data distribution

Open-source, automatic

GitHub: *https://github.com/rosepearson/GeoFabrics*

Paper: Pearson, Rose et al., Geofabrics 1.0.0: An Open-Source Python Package for Automatic Hydrological Conditioning of Digital Elevation Models for Flood Modelling. Available at SSRN: http://

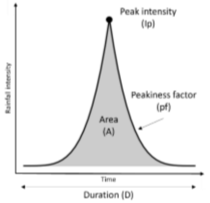


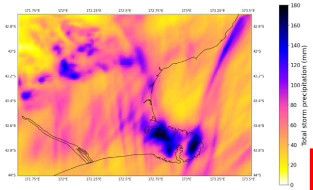
- Total Adaptive mesh: 50 m
- Lake input

Hybrid model outline

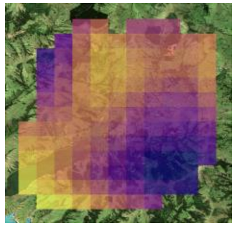
Heavy rainfall

Temporal and spatial characteristics





Synthetic storms



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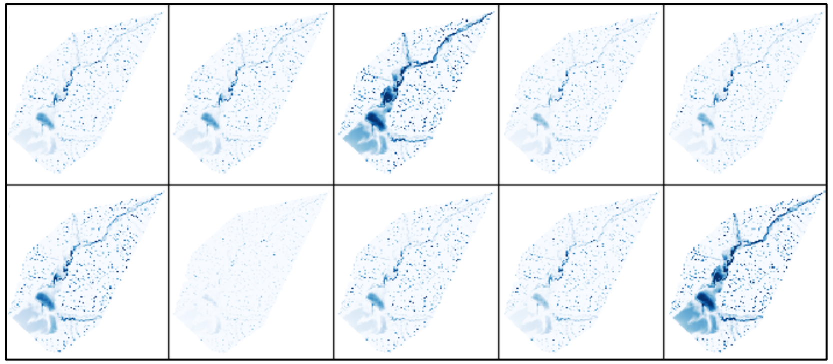
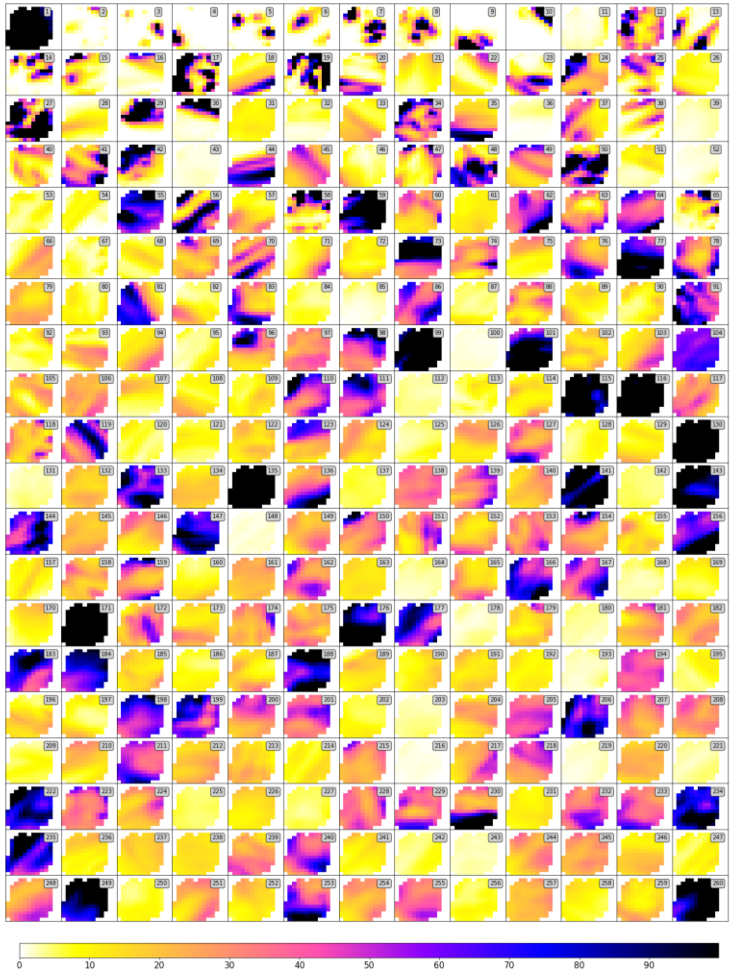


Machine learning model: split the dataset

- Maximum dissimilarity algorithm
- 1/3 testing dataset
- 2/3 training dataset



Machine learning model: outline

- Storm variables: Total storm rainfall (R), storm peak intensity (Ip), storm duration (D), storm peakiness factor
- Geographic variables: slope, elevation, aspect, total wetness index, distance to river

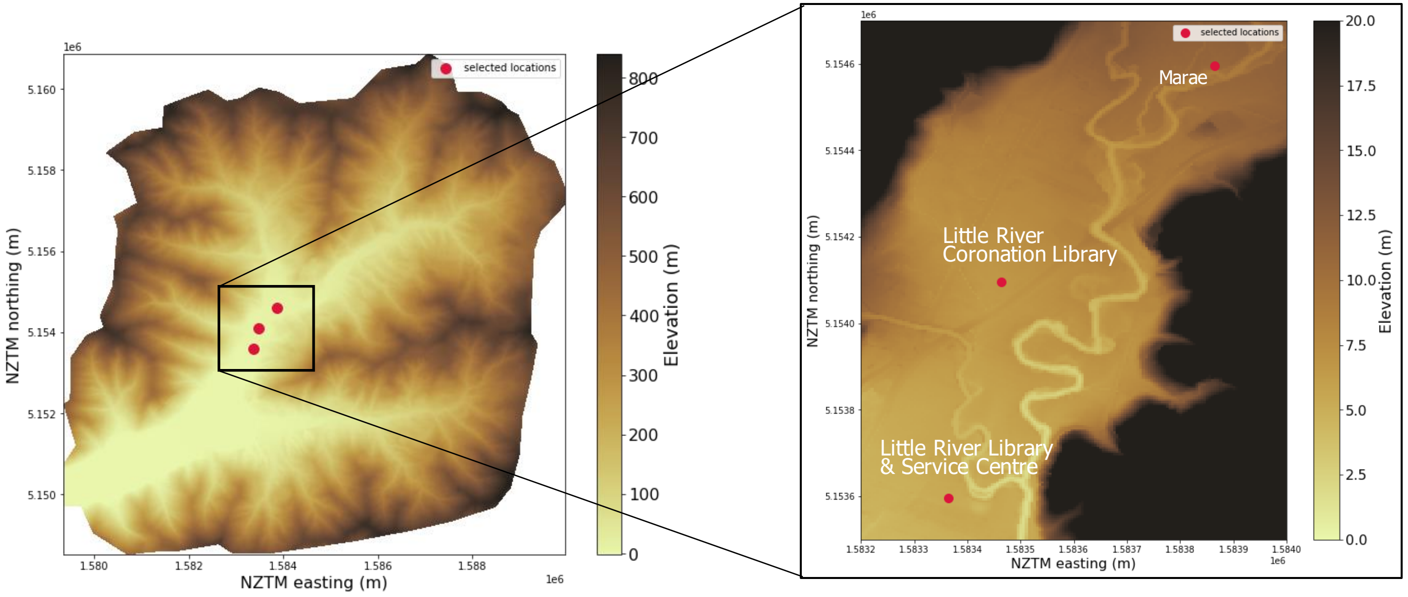
Does the location flood? (threshold 0.1 m)

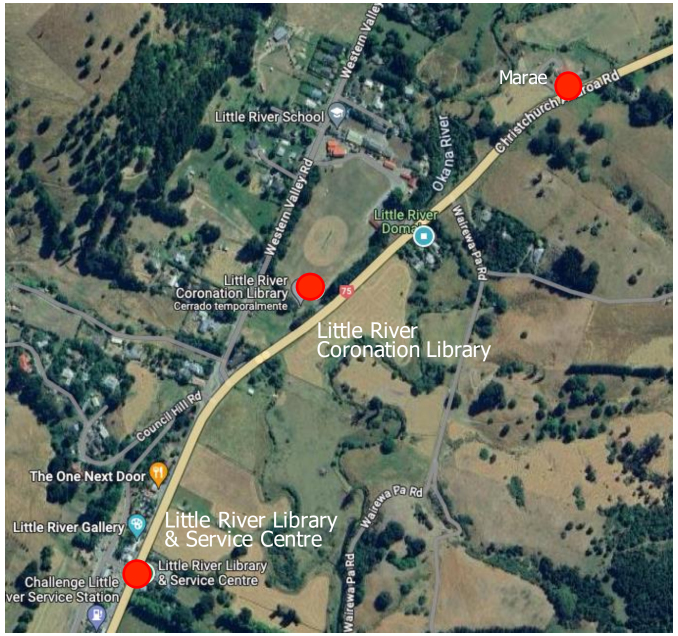
How much is the maximum flood depth?

Predictor variables → Classification model → Regression model

Which machine learning method would work best?

Machine learning model: point experiments





- Random Forest
- XGBoost
- SVM
- RBFNs

	Little River Coronation Library	Marae	Little River Library & Service Centre
Class balance	Floods 43% of the time	Floods 53% of the time	Floods 33% of the time

Machine learning model: inundation maps results

Does the location flood?
(classification model)

MARAE

MODEL	RF	XG-Boost	RBFs	SVM
Accuracy	Precision=0.857 Recall=0.964 F1=0.908	Precision=0.959 Recall=0.922 F1=0.940	Precision=1.0 Recall=0.131 F1=0.232	Precision=0.947 Recall=0.900 F1=0.9230
Speed	Fast	Fast	Medium	Slow
Training set size	52 %	60 %	47 %	35 %
Predictor variables	R, Ip, D	R	R	R, Ip

LIBRARY

MODEL	RF	XG-Boost	RBFs	SVM
Accuracy	Precision=0.929 Recall=1.00 F1=0.963	Precision=0.892 Recall=1.00 F1=0.943	Precision=0.942 Recall=0.983 F1=0.262	Precision=0.957 Recall=0.978 F1=0.968
Speed	Fast	Fast	Medium	Slow
Training set size	35 %	35 %	42 %	54 %
Predictor variables	R	R, Ip, D, pf	R, Ip, D	R, Ip, D, pf

CORONATION LIBRARY

MODEL	RF	XG-Boost	RBFs	SVM
Accuracy	Precision=0.904 Recall=0.970 F1=0.935	Precision=0.937 Recall=0.892 F1=0.914	Precision=0.870 Recall=0.905 F1=0.864	Precision=0.877 Recall=0.934 F1=0.904
Speed	Fast	Fast	Medium	Slow
Training set size	45 %	53 %	47 %	57 %
Predictor variables	R, Ip, D	R, Ip, D	R	R, D, Ip

Machine learning model: inundation maps results

How much the location floods (regression model)?

MARAE

MODEL	RF	XG-Boost	RBFs	SVM
Accuracy	RMSE=0.114 m NSE=0.847	RMSE=0.138 m NSE=0.772	RMSE=0.205 m NSE=0.510	RMSE=0.126 m NSE=0.813
Speed	Fast	Fast	Medium	Slow
Training set size	64 %	57 %	66 %	64 %
Predictor variables	R, Ip, D	R, Ip, D	R, Ip, D	R, Ip, D, pf

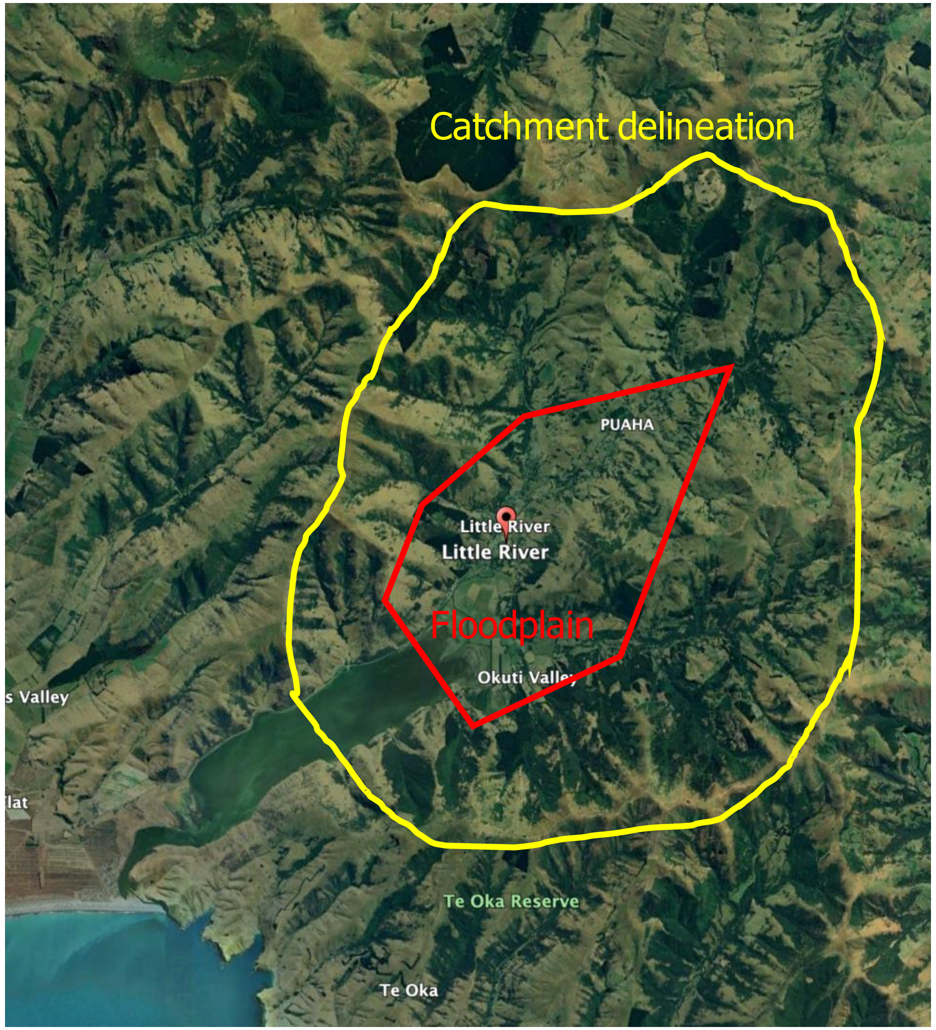
LIBRARY

MODEL	RF	XG-Boost	RBFs	SVM
Accuracy	RMSE=0.0945 m NSE=0.858	RMSE=0.121 m NSE=0.800	RMSE=0.161 m NSE=0.592	RMSE=0.107 m NSE=0.818
Speed	Fast	Fast	Medium	Slow
Training set size	64 %	55 %	66 %	64 %
Predictor variables	R, Ip, D	R, Ip, D, pf	R, Ip, D, pf	R, Ip, D, pf

CORONATION LIBRARY

MODEL	RF	XG-Boost	RBFs	SVM
Accuracy	RMSE=0.0945 m NSE=0.845	RMSE=0.114 m NSE=0.772	RMSE=0.198 m NSE=0.310	RMSE=0.124 m NSE=0.728
Speed	Fast	Fast	Medium	Slow
Training set size	66 %	66 %	66 %	66 %
Predictor variables	R, Ip, D	R, Ip, D	R, Ip, D, pf	R, Ip, D

Machine learning model: inundation maps



Machine learning model: inundation maps

	Classification model	Regression model
Accuracy	Precision = 0.882 Recall = 0.896 F1 = 0.889	RMSE = 0.0557 m NSE = 0.823
Speed	Fast	Fast
Training set size	47 %	47 %
Predictor variables	Storm and geographical variables	Storm and geographical variables

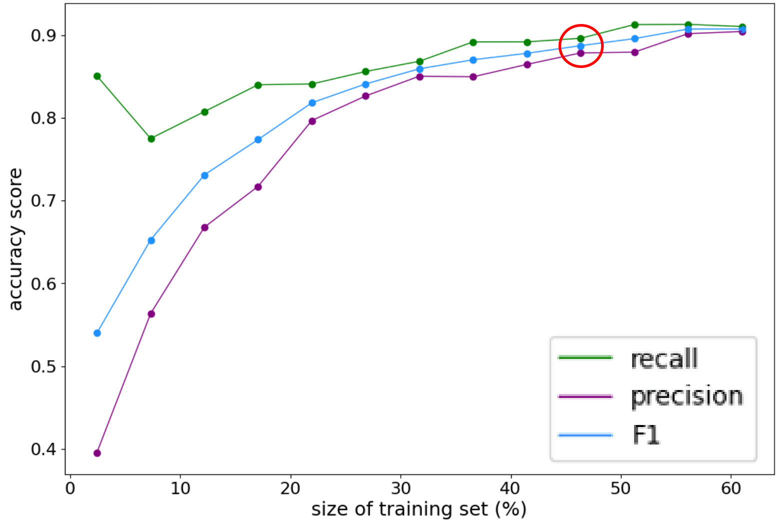
$$Precision = \frac{True\ predicted\ flood}{Total\ predicted\ flood}$$

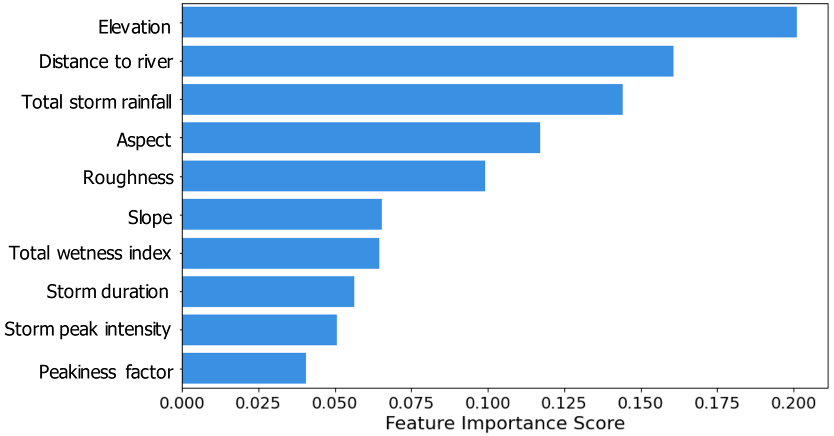
$$Recall = \frac{True\ predicted\ flood}{Total\ actual\ flood}$$

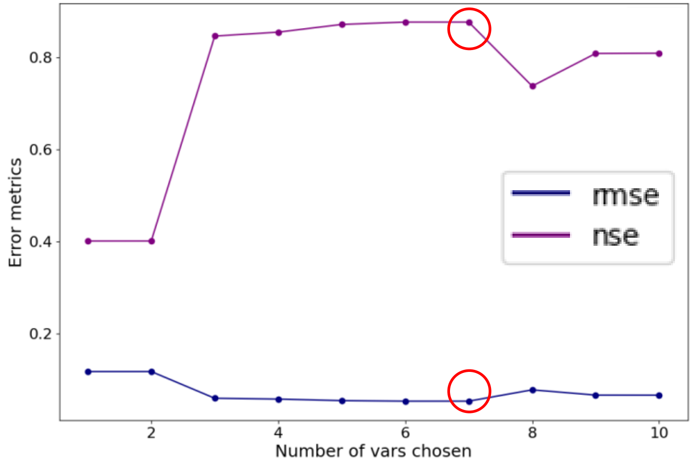
$$F1 = 2\,x\,\frac{Precision\ x\ Recall}{Precision +\ Recall}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(O_i - P_i)^2}{N}}$$

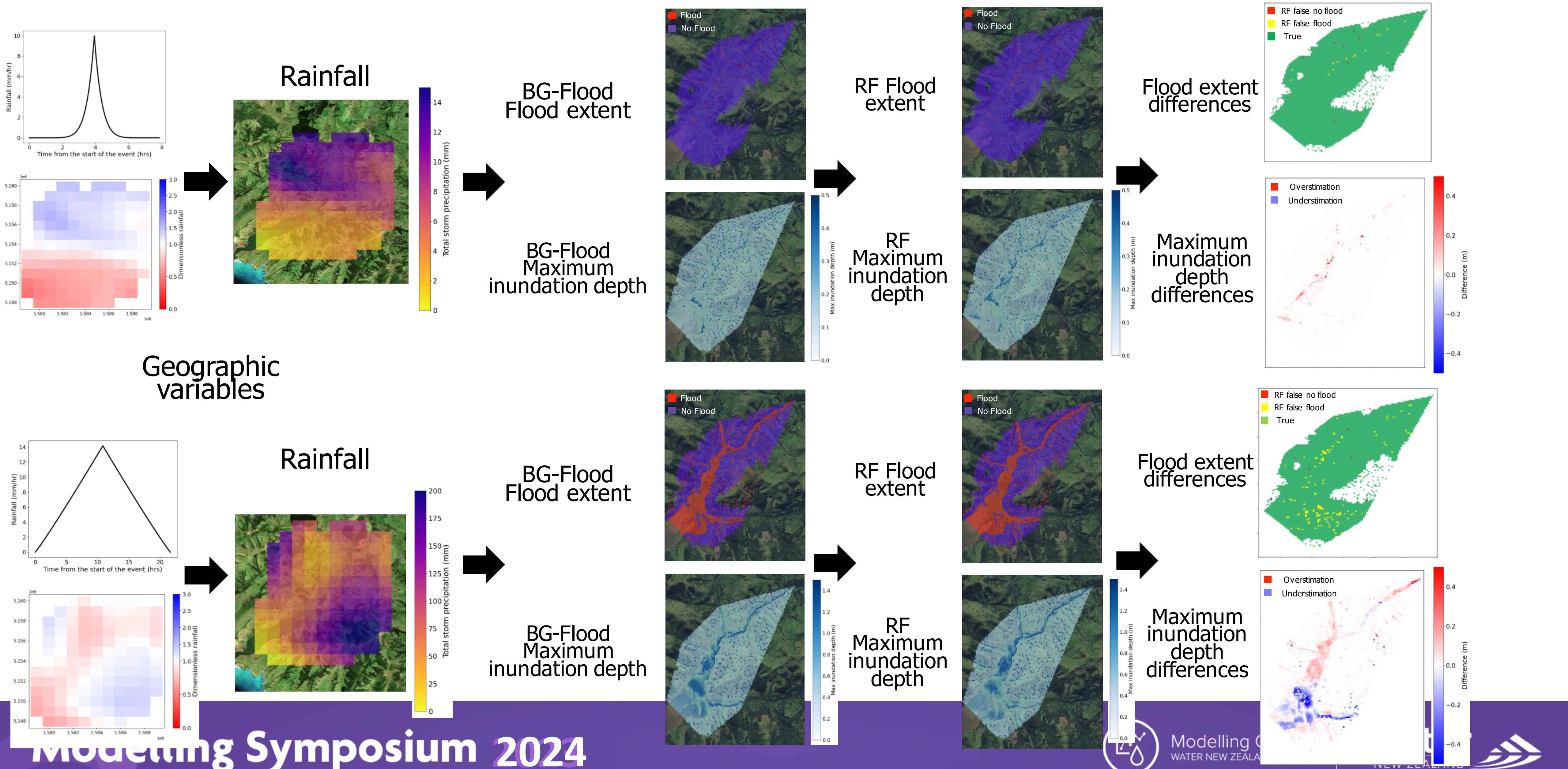
$$\text{NSE} = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2}$$







Machine learning model: inundation maps



Machine learning model: inundation maps

Summary

- Fast, efficient, accurate tool for flood scenario assessment

Next steps

- Create model based on 5 meters resolution maps
- Think about other possible machine learning algorithms that can work better
- Extend the methodology to other locations

Modelling Group
WATER NEW ZEALAND

Modelling Symposium

Thank you!
Questions? Patai?

water
NEW ZEALAND
The New Zealand Water & Wastes Association Waiora Aotearoa