Leveraging Remote Sensing Datasets and Deep Learning Algorithms for Flood Probability and Risk Assessment in Port St. Johns, South Africa

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Introduction

- Flood risk is determined by estimating the extent of loss, number of lives lost, property damage, and disruption to economic activity (Shen,2018; Maranzoni et al., 2024).

- In 2010, 56.1% of all disasters recorded by the Centre for the Epidemiology of Disasters (CRED) were flood-related, affecting nearly 189 million people, and global floods increased by 145.1% compared to the annual averages between 2000 and 2009 (CRED, 2022).

- In January 2022, 14 people were killed in Mdantsane, South Africa, while in April 2022, 435 people died in KwaZulu Natal and Eastern Cape provinces, affecting Durban and surrounding areas, and an estimated R10 billion worth of infrastructure was damaged (Reuters, 2022).

- Most developing countries, including South Africa, are not adequately prepared for emergency events to improve disaster risk reduction.

Aim and Objectives

- **Aim**

This study aim to utilize geospatial data and a Convolutional Neural Network (CNN) for Flood Probability and Risk Assessment in Port St Johns, South Africa.

- **Specific objective**
  - To assess the integration of multisource flood influencing factors with deep learning-based approach.
  - To develop a flood probability and risk model for Port St. Johns using the fully connected CNN.

Problem statement

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- Over the past decade, Port St. Johns has experienced a significant increase in precipitation, causing surface runoff, potential flooding, infrastructure damage, and environmental degradation (Rebelo et al., 2015; Nhamo et al., 2021).

- Recurrent flooding in the region is a result of climate change and variability, and inadequate ground observation data (Zengeni et al., 2016; Dalu et al., 2018).

- Thus, necessitating comprehensive geospatial intelligent approach for long-term flood risk prediction to minimise the impact of flood disasters in the area.

Significance of the study

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- Artificial Intelligence-based methods and geospatial data are increasingly being used to understand flood dynamics and risks (Chen et al., 2022; Maranzoni et al., 2024), but their integration is still underutilized in flood risk assessment studies.

- The Fully Connected Convolutional Neural Network (CNN) approach, applied in Port St. Johns, South Africa, has proven to be a highly effective algorithm for flood predictive modelling in flood-prone areas (Chen et al., 2022; Lemenkova, 2024).

- The model uses thirteen layers for feature extraction, training, and validation, including HAND, floods, TWI, MNDWI, TRI, DWI, curvature, aspect, slope, FAC, FDR, land cover, and precipitation for the analysis

Research Gaps

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- Limited use of geospatial intelligence approach in flood risk assessment.
- Lack of an integrated multisource geospatial and AI based approach at a local level.
- Inadequate innovative intervention strategies to mitigate flood disasters.

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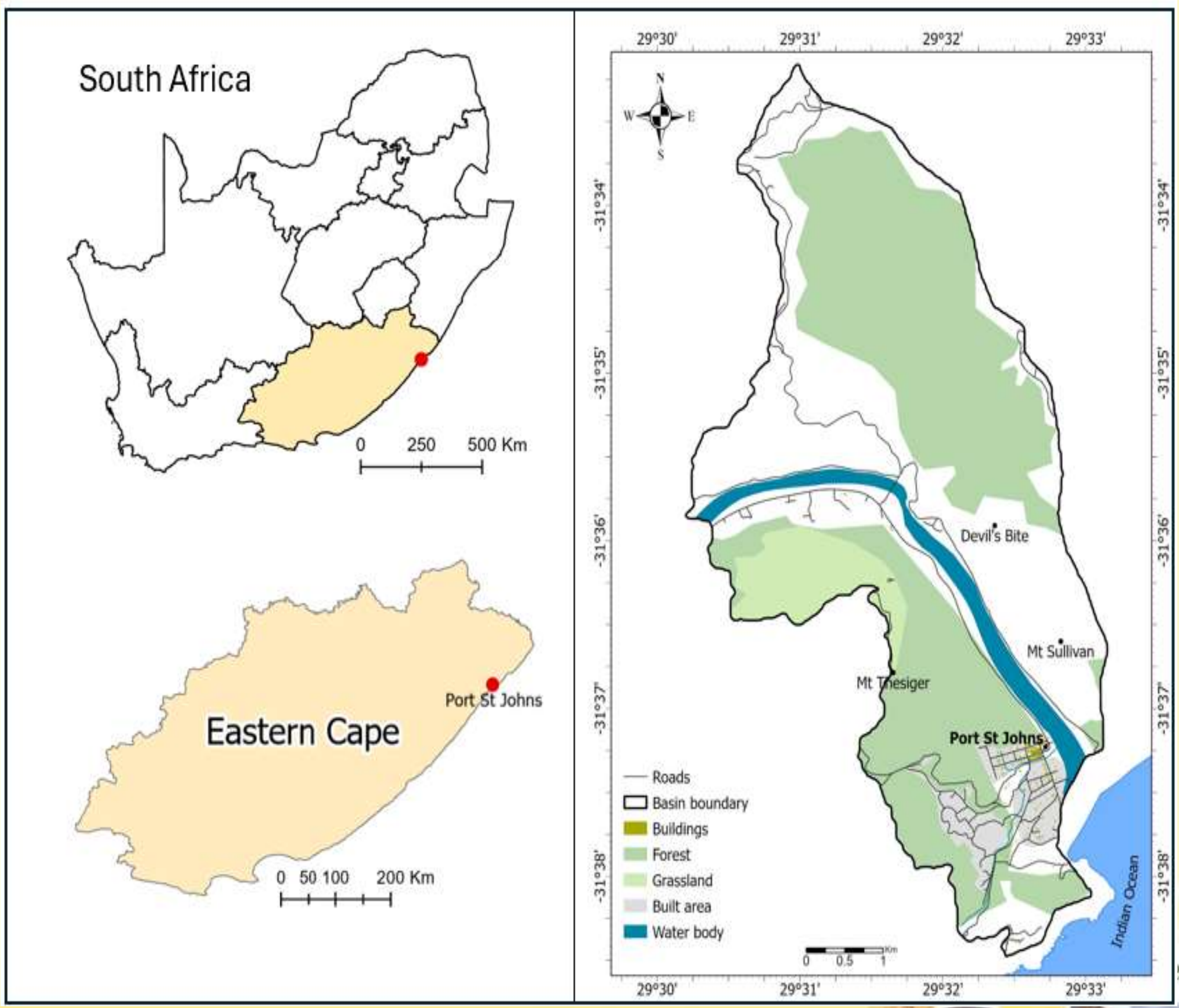
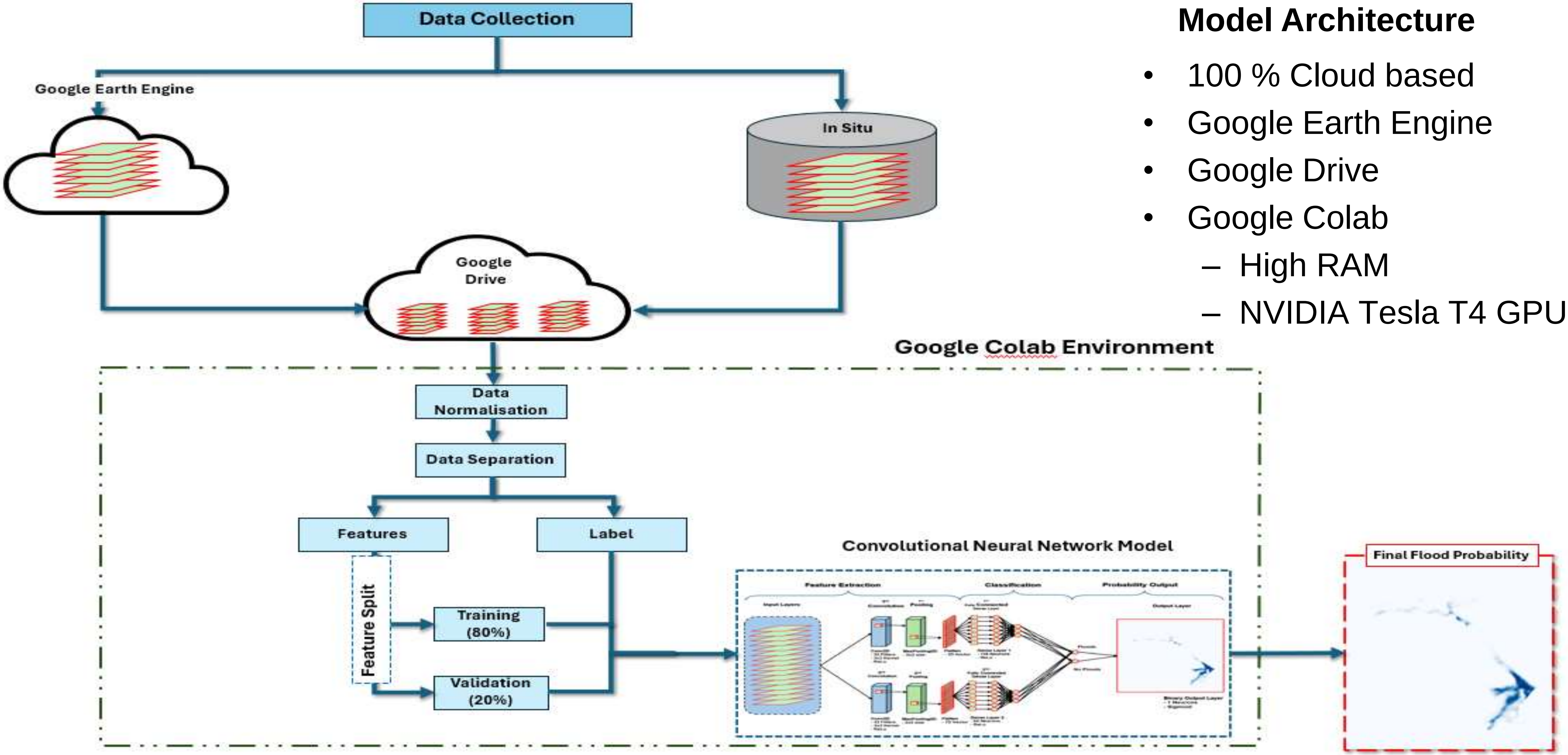
Study Area



- **Port St Johns**
- Coastal town at the Umzimvubu mouth.
- Population of 179 325 (STATSSA, 2023)
  - 37% < 15 years
  - 54% between 15 – 64 years
  - 6% > 65 years
- Housing structure
  - 33% is informal
  - 66% is formal
- Climate
  - Humid sub-tropical climate
  - Rains during the summer season

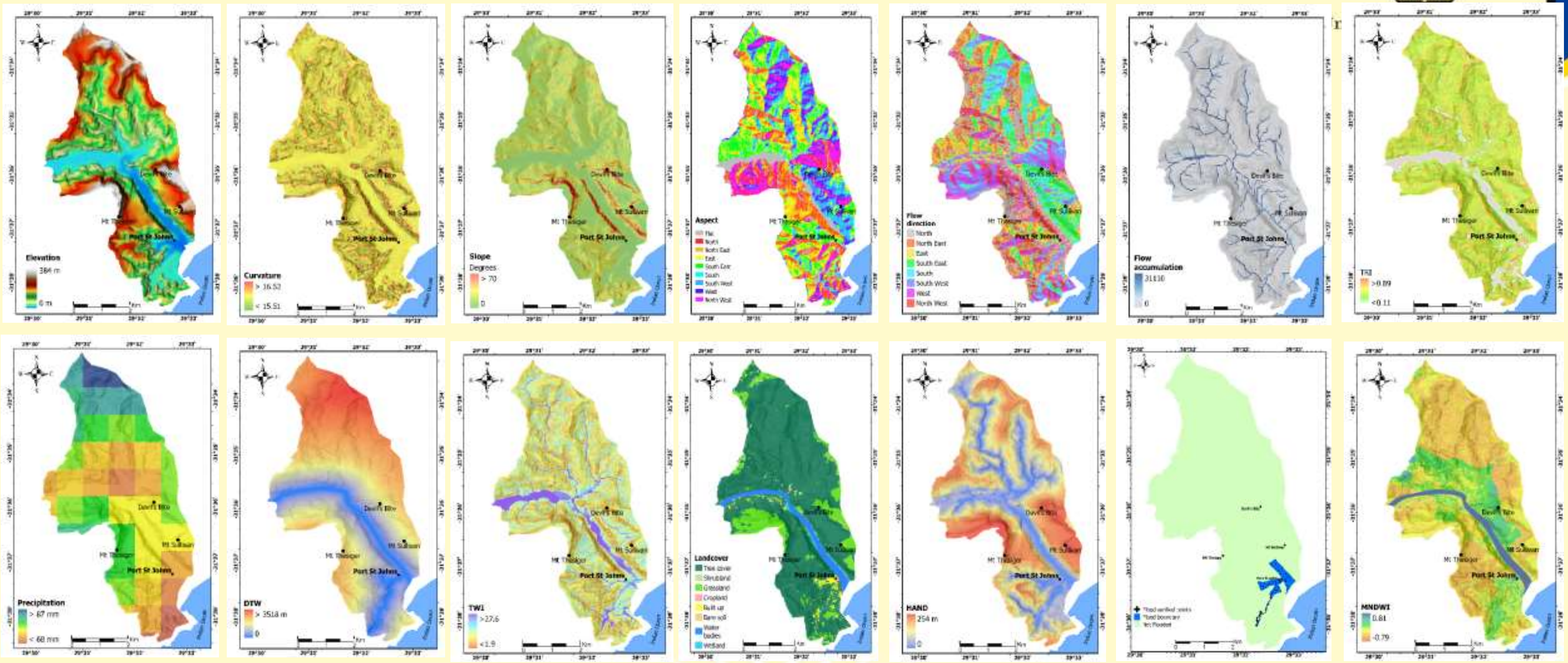
Methodology



Model Architecture

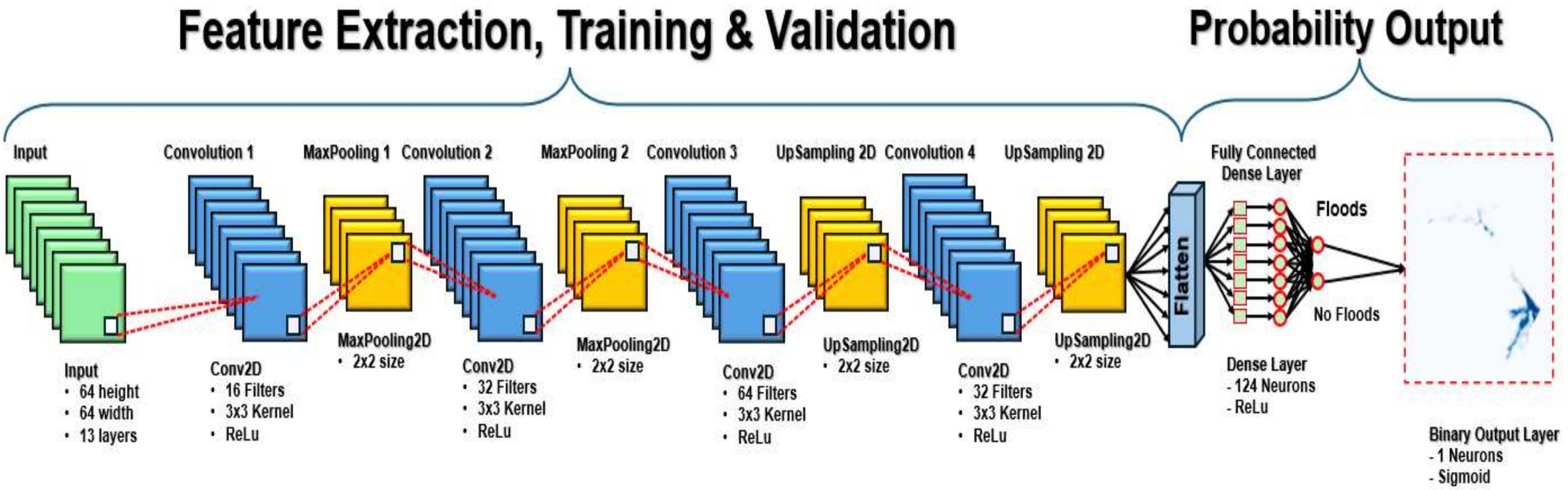
- 100 % Cloud based
- Google Earth Engine
- Google Drive
- Google Colab
  - High RAM
  - NVIDIA Tesla T4 GPU

Methodology cont..

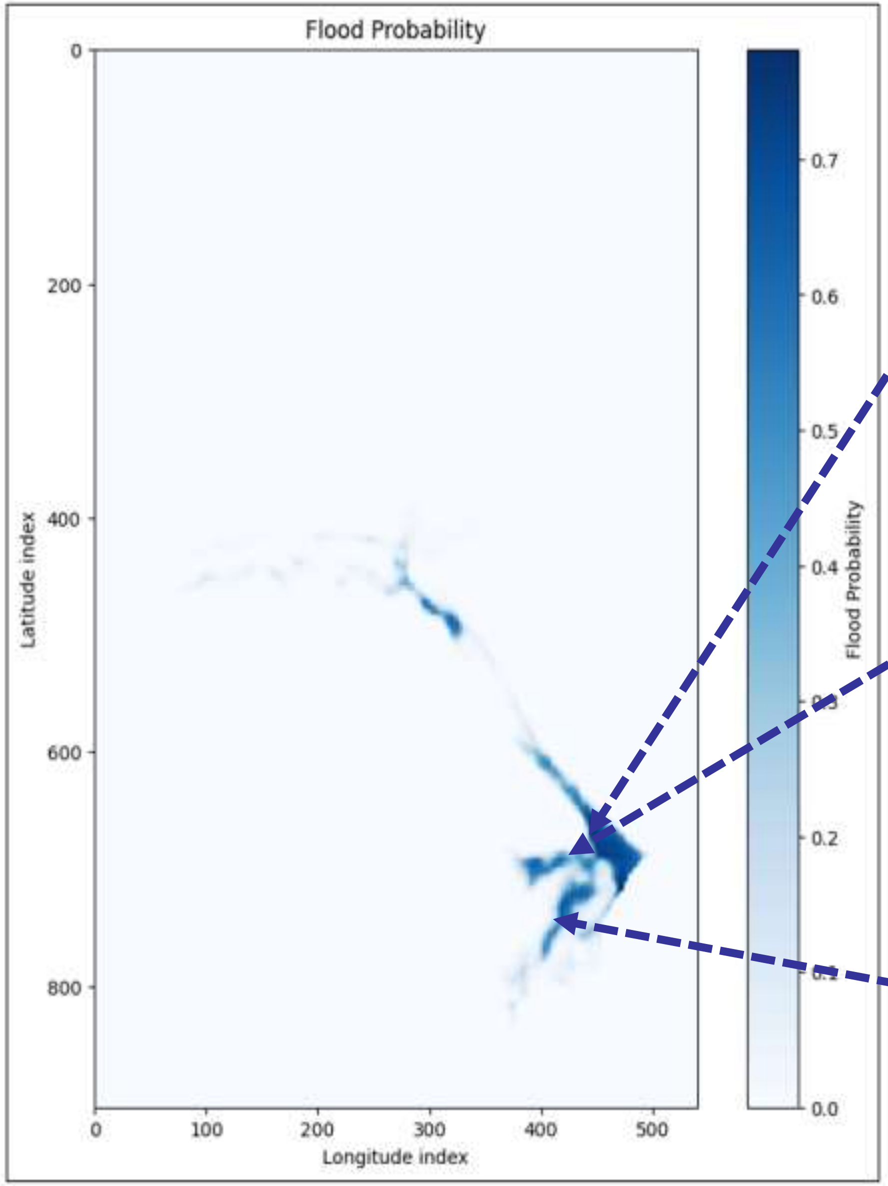


Flood influencing factors

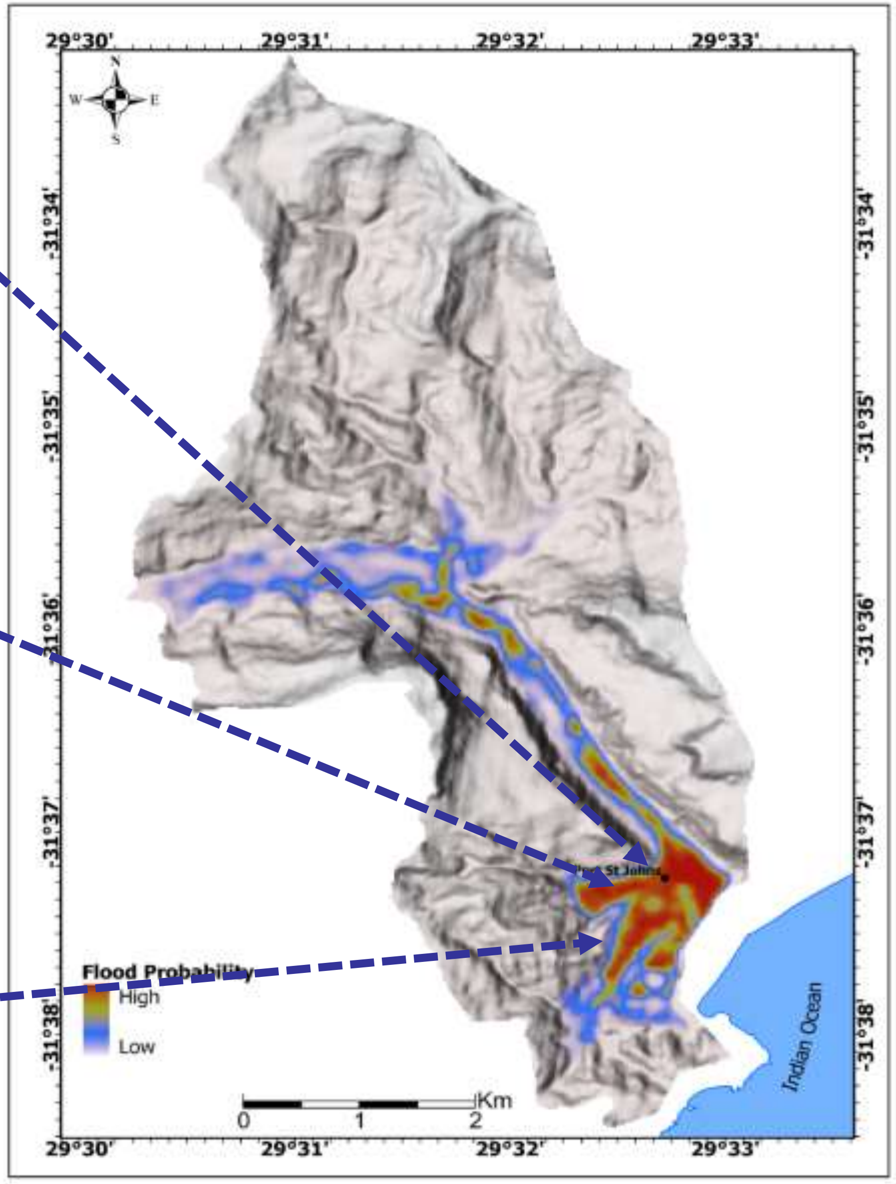
Methodology cont..



Results



Flood Probability
Latitude index
Longitude index
0
200
400
600
800
0
100
200
300
400
500
Flood Probability
0.7
0.6
0.5
0.4
0.2
0.0



29°30'
29°31'
29°32'
29°33'
-31°34'
-31°35'
-31°36'
-31°37'
-31°38'
N
W
E
S
Flood Probability
High
Low
Km
0
1
2
Indian Ocean

Results

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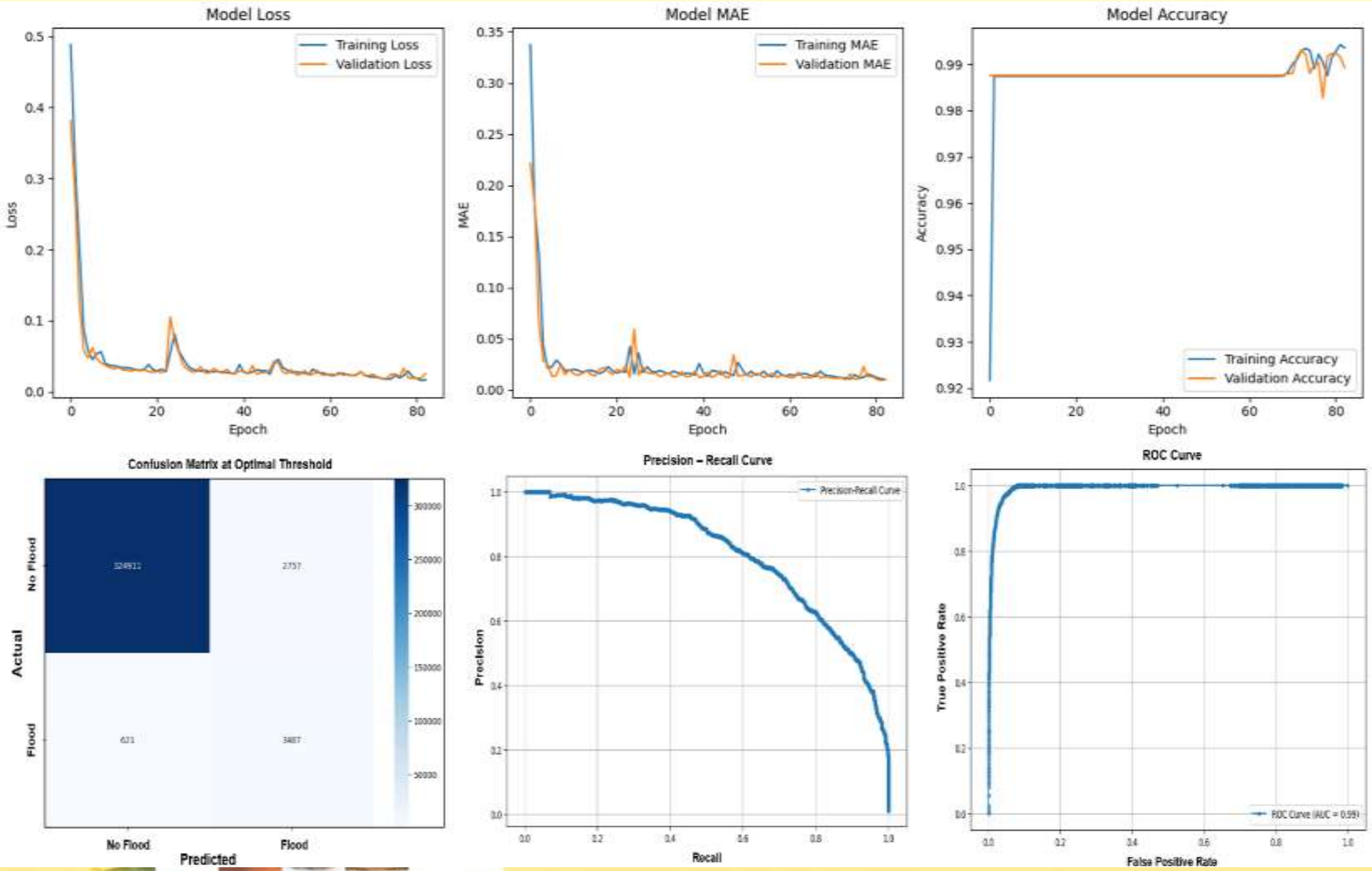
Model calibration and Validation

Metrics	Training	Validation
Loss	0.0167	0.0251
MAE	0.0105	0.0100
Accuracy	0.9936	0.9876
	Score	
Precision	63.2%	
Recall	63.5%	
F1 Score	63.3%	
ROC AUC	99.2%	



Discussion

- The CNN model prediction is consistent with flood-affected areas, especially in low-lying areas such as the PSJ central town and KwaGreen informal settlements.
- The model demonstrated that it was able to self correct to maintain accuracy when showing signs of overfitting (Early stop function).
- However, it also had false positives for both floods and non-flooded areas (More factors needs to be included)
- The incorporation of soil types as a potentially influential factor in the fully connected CNN model may improve the robustness of the results.

Conclusion and Recommendations

- The study successfully developed a deep learning CNN model using multisource variables to identify flood risk zones in Port St. Johns.
- The CNN flood risk prediction model was successfully tested in the cloud environment, achieving an accuracy rate of 98%.
- The flood probability map revealed that low-lying areas are highly susceptible to floods, consistent with previous flooding events at Port St Johns.
- The findings of the study can be applied to larger catchments areas, supporting disaster management agencies, and local communities in early warning to prevent potential damage to assets and other infrastructure.
- This study serves as baseline to provide information for policies formulation, development of pre and post event strategies as well as decision-making.

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Thank you