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Flood Probability Prediction Based on Machine Learning

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OUTLINE

BACKGROUND

1. Flood Risks in Ghana

1. Annual Floods: Every year from May to July, Ghana faces floods that are risky to people and property [1, 2, 3, 4, 5].

2. Causes of Floods:
   - **Weather:** Heavy rain during the wet season [1, 2, 3].
   - **Geography:** Low land and clayey soil add to flood risks [1, 2, 3].
   - **Human Factors:** Poor drainage and waste disposal make floods worse [1, 2, 3].

2. Modelling Approaches

1. SWE Models:
   - **1D-SWEs**: Good for basic flood simulation, but not for complex scenarios [6].
   - **2D-SWEs**: Better for complex floods but costly and complicated [6, 7].

2. ML Models:
   - **Quick:** Fast predictions and adaptable [6, 8, 9].
   - **Multi-Dimensional:** Considers weather, land, and human factors [6, 8, 9].

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OBJECTIVES

This project aims to develop a **Machine Learning model** capable of predicting the probability of flood occurrence.

The specific objectives of the project include:

- **Objective 1 (Data Collection):** Historical flood data, Rainfall data, and Geospatial information.
- **Objective 2 (Data Processing):** Exploratory data analysis (EDA), Feature extraction.
- **Objective 3 (Model Construction):** Experiments with various machine learning models, Evaluations and performance comparisons, Get the best model.
- **Objective 4 (Model Application):** Flood predictions and evaluate the performance, Generate flood maps for the target regions.

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PROPOSED METHODOLOGY

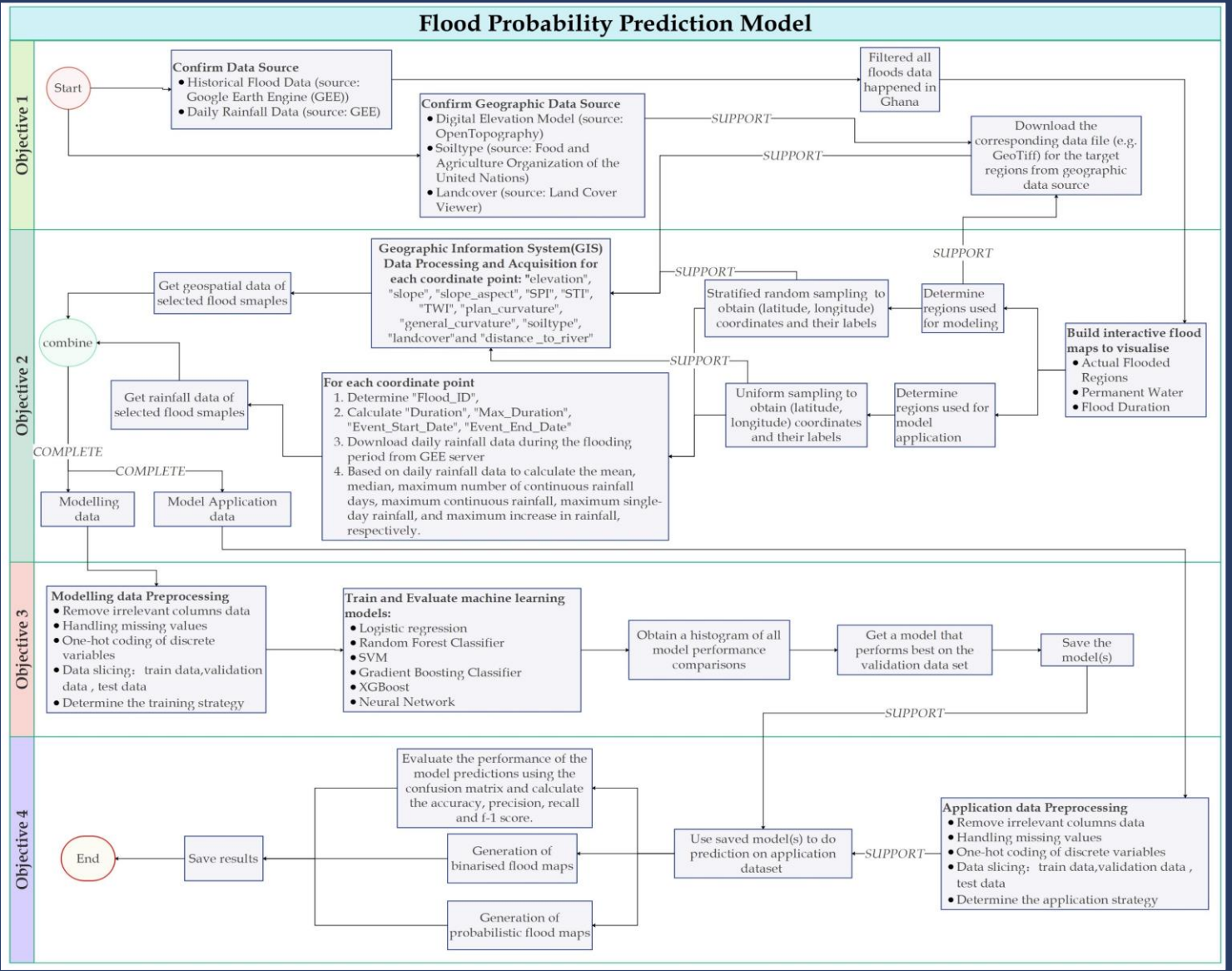

Figure 1: Flow Diagram of the Proposed Methodology.

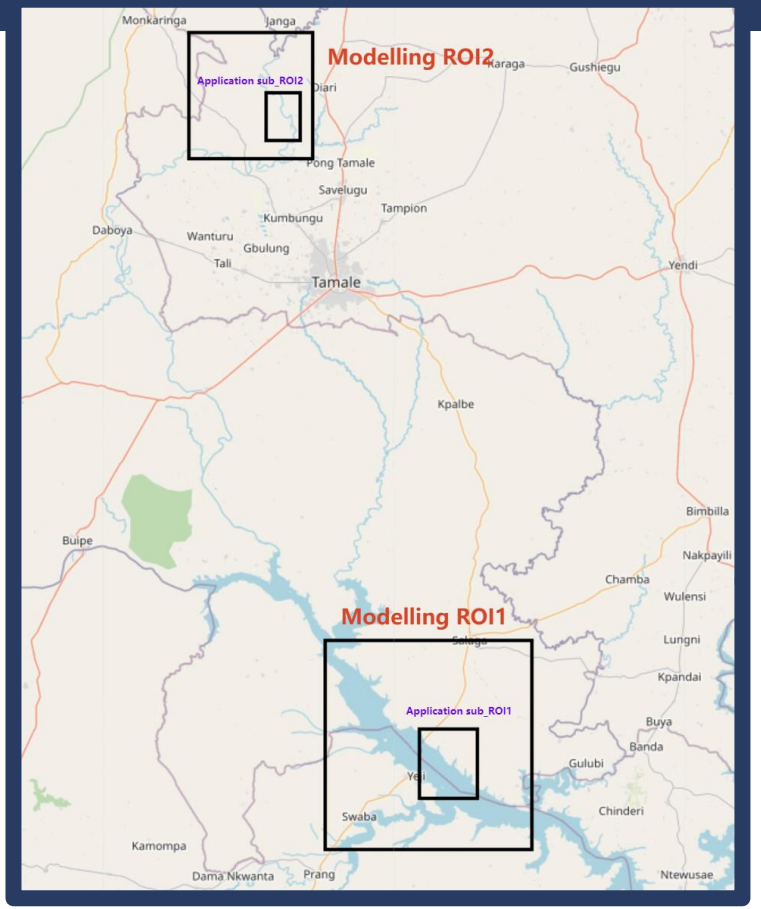

Figure 2: Geographical Representation of Modelling and Application ROI (region of interest)
Areas. Legend: Large Rectangles = Modelling Areas; Small Inner Rectangles = Application Areas.

PROPOSED METHODOLOGY

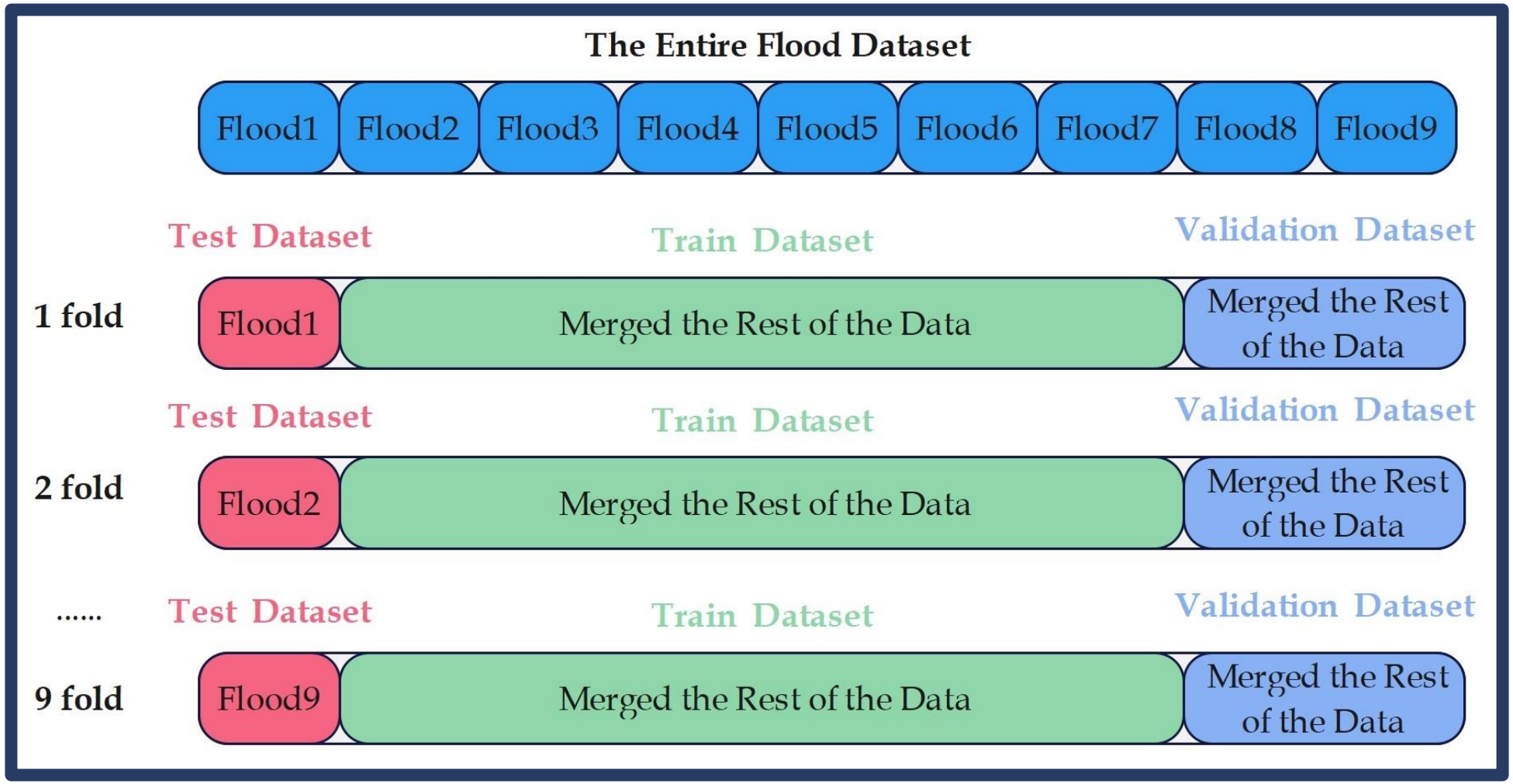

Figure 3: Illustration of Leave-One-Out Cross Validation Strategy. Legend: Test Dataset = Final Model Testing Dataset; Train/Validation Dataset = Model Training and Validation Dataset.

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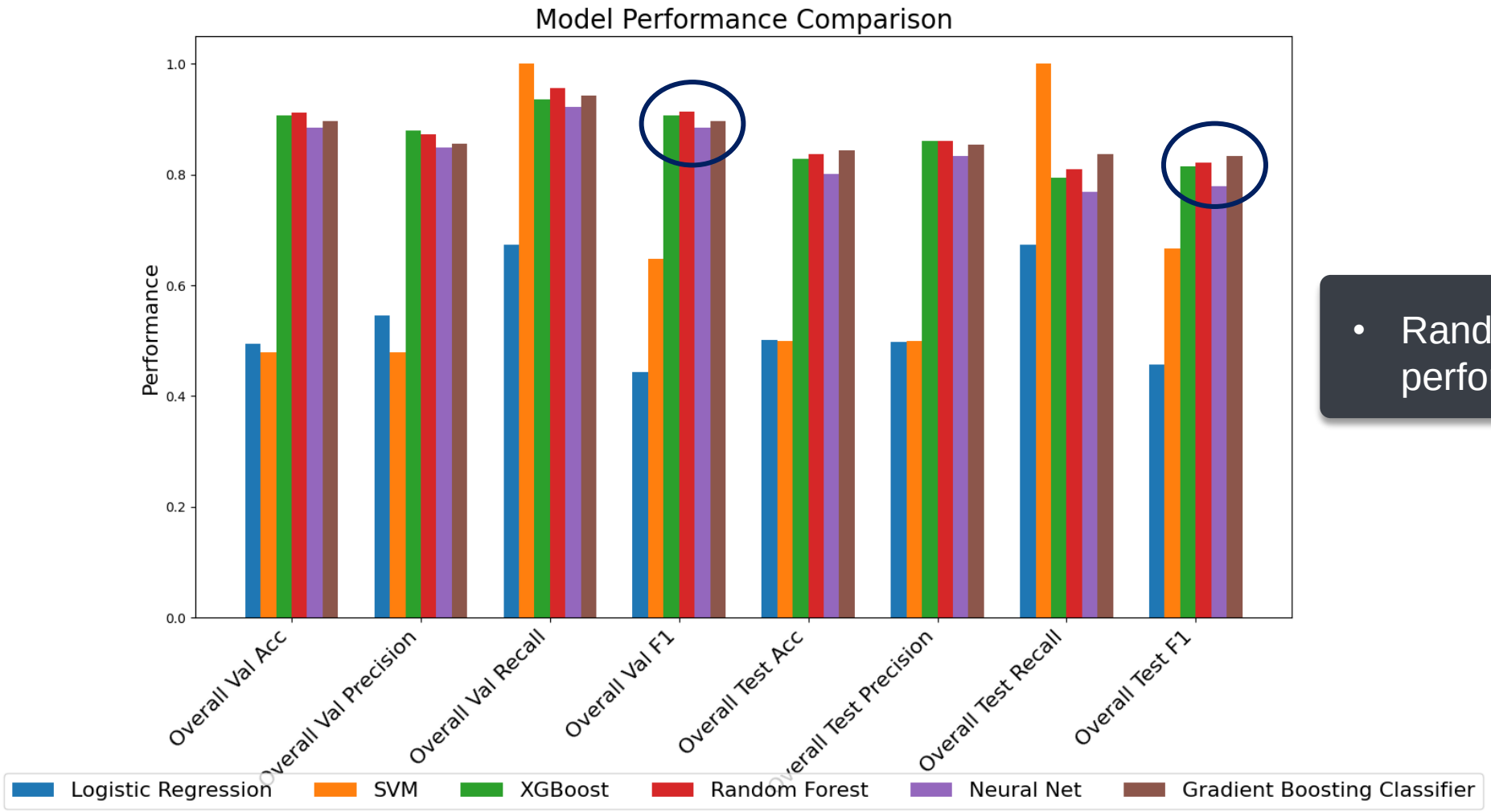
RESULTS



- Random Forest had the best overall performance

Figure 4: Comparative Analysis of Model Prediction Performances.

RESULTS

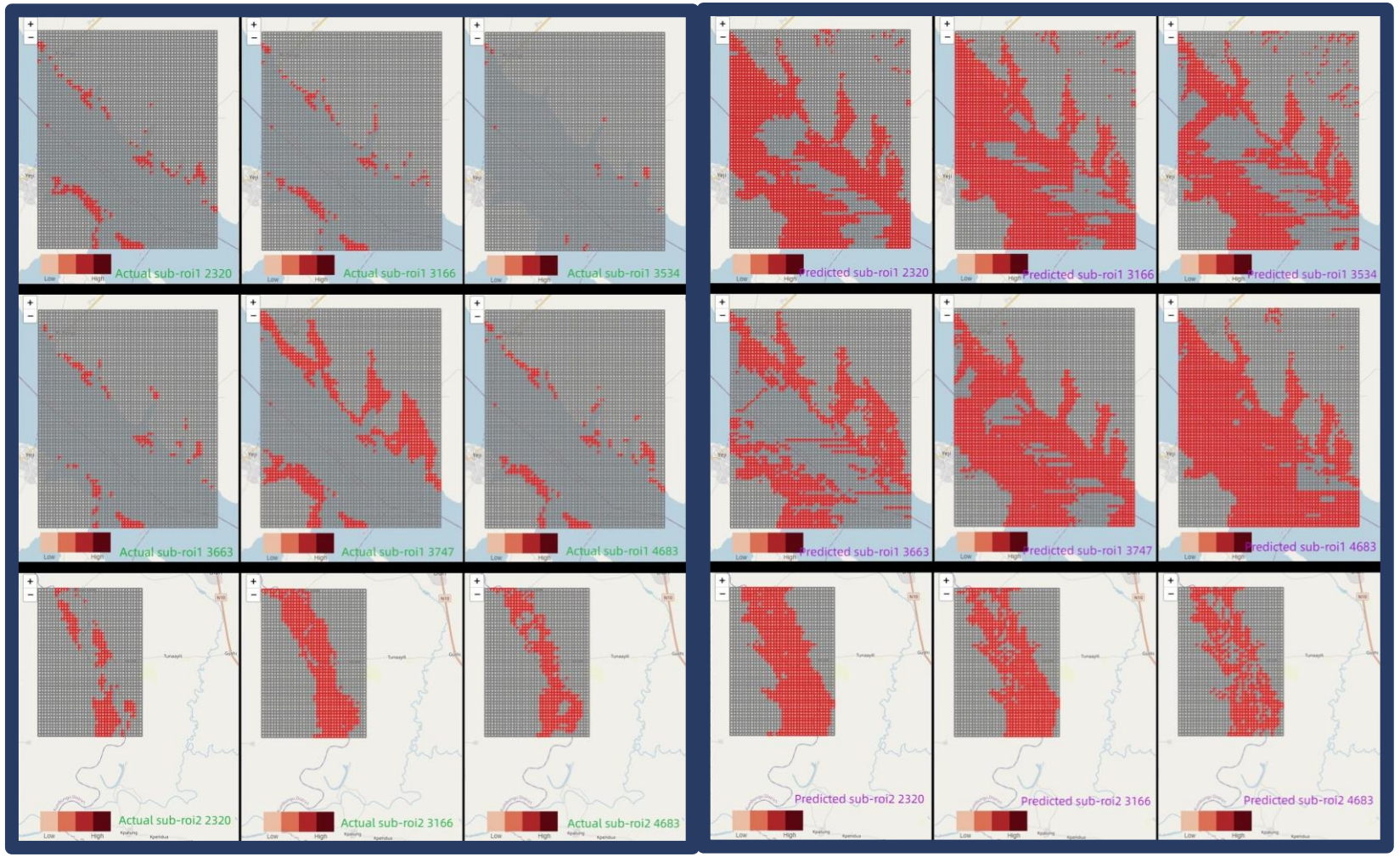


Figure 5: Comparison of Visualised Binary Flood Maps, (left) Actual, (right) Predicted.

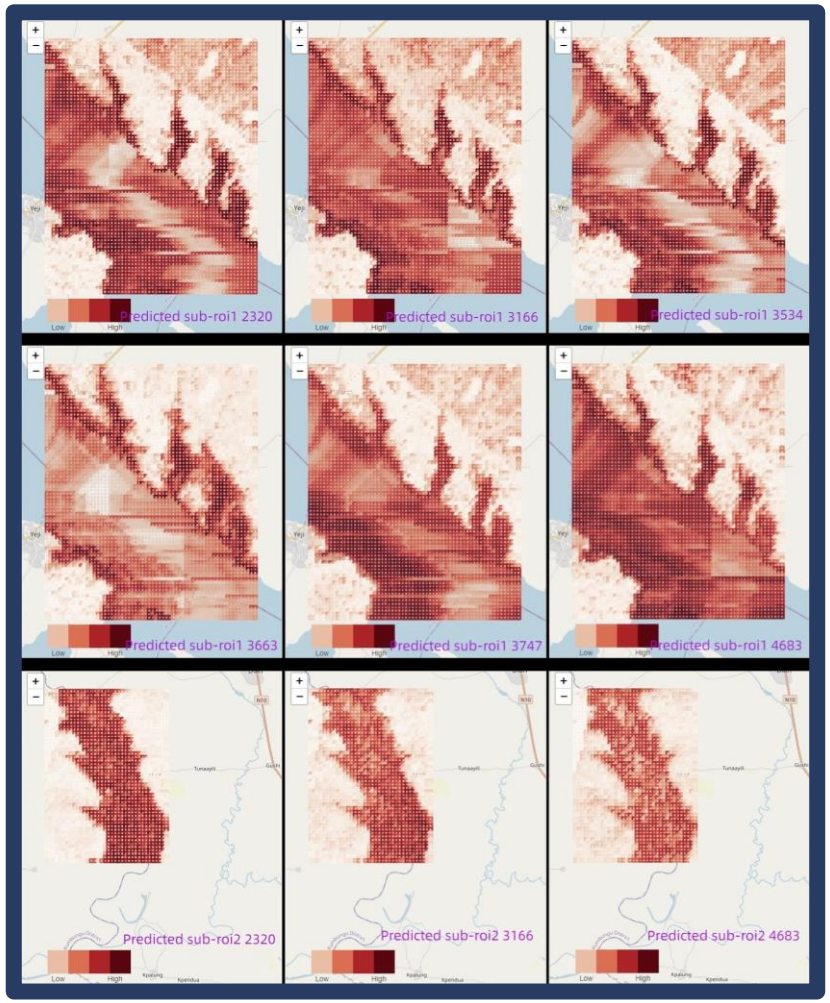


Figure 6: Probabilistic Predicted Flood Maps

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RESULTS

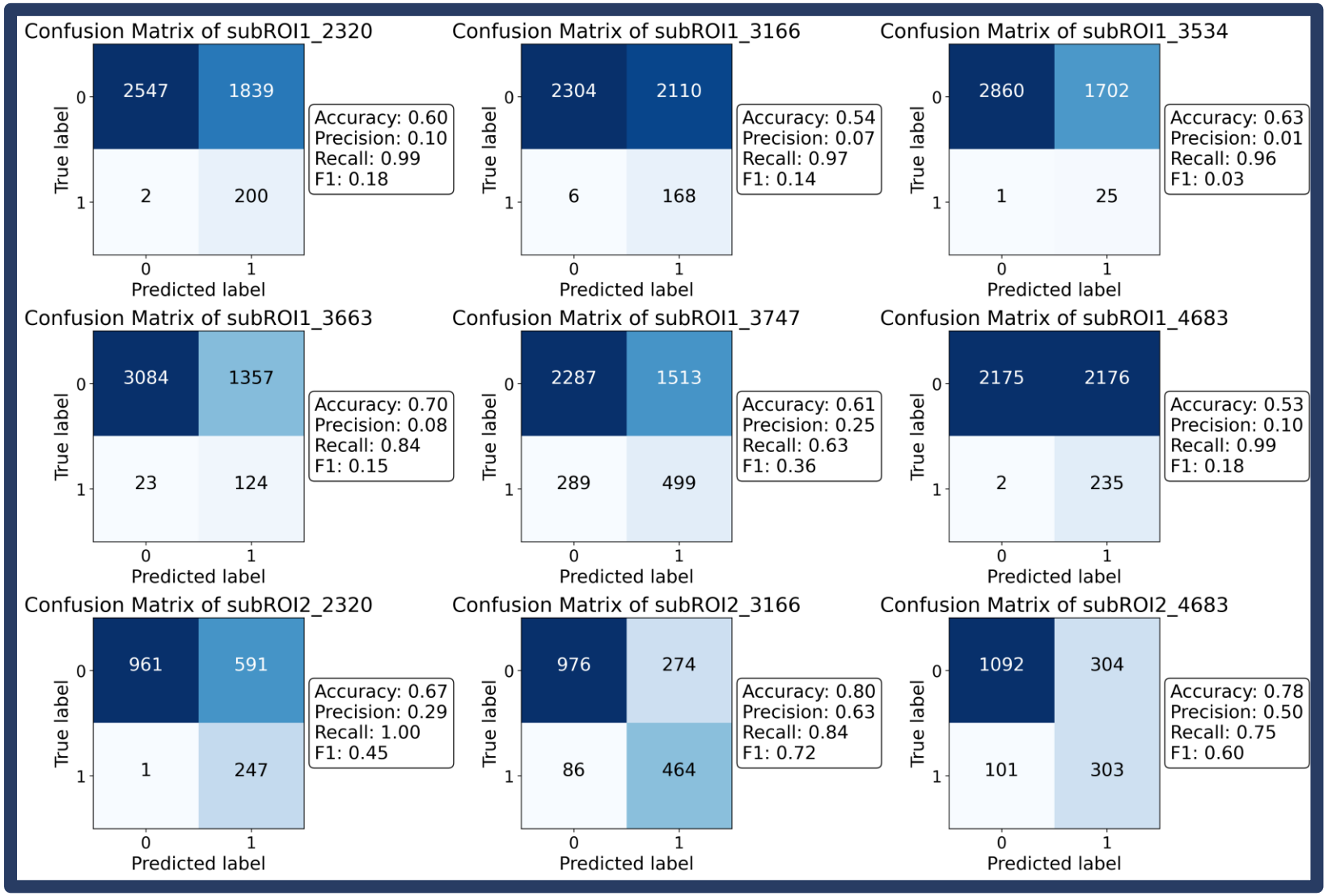

Figure 7: Confusion Matrices for Binary Flood Prediction

It is very clear to see that the model performs exceptionally well on **RECALL** but poorly on **PRECISION**

DISCUSSION

1. Model Strengths & Comparison

- **High Recall:** Better at identifying dangerous flood areas.
- **Data Combo:** Uses both geographical and rain data for more accuracy.
- **Old Models:** Less practical due to focus on single data type.

2. Precision & Resources

- **Low Precision:** Can misallocate resources.
- **Balance:** Need better precision without losing recall.
- **Regional Issues:** Varies in performance across areas.

3. Real-time Limits & Fixes:

- **Old Data:** Cannot predict floods in real-time.
- **Timing:** Needs better timing for upcoming floods.
- **Solution:** Adding rainfall predictions improves but complicates.

4. Scalability & Probability

- **Data acquisition Issues:** very slow (Batch and network)
- **No Truth Map:** Hard to validate probability estimates.

TO SUM UP…

- Objectives Met: All 4 goals achieved using Random Forest as the final model.
- Model Performance: High in recall but needs better precision.
- Study Impact: Helps identify likely flood zones.

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