Flood Intensity Mapping Based on the SAR images Using Deep Learning in Rice

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Abstract

The frequency of floods during the monsoon in South Asia has been increased over the years that raising the risk of loss and damage to rice crops. The staple food for majority of people in the world, resulted in production uncertainty. Timely and accurate loss and damage estimation is critical for effective compensation, relief distribution, crop insurance policy development, and ensure the food security in the country or in region. To quantify crop losses, the data on flood intensity is required, which eventually measures the extent of damage caused by floods in rice crops. Synthetic Aperture Radar (SAR)-based flood mapping methods have been validated and well accepted, but challenges remain in accurately mapping flood intensity. We uses a U-Net deep learning model with ResNet 34 backone for automatically mapping flood intensity using SAR and optical images, along with topographic information. The deep learning approach requires a large amounts of training dataset. We prepared them considering the different flood events in an ex-post flood case of the Ganga River basin in Nepal, India and Bangladesh from 2019 to 2024. The flood extension and intensity were labelled using the visual interaction in the Sentinel 1 SAR, Sentinel 2 and PlanetScope dataset where available. The duration of standing water and vegetation condition were major indicator to confirm the damage level manually. The digitized flood intensity level were refined with the field visit and validated with the stakeholder discussion. The extent of crop damage is affected by flood duration (i.e., how long standing water remains in the field) and the speed of the water current. Therefore, we used these dataset to fit the model. The U-Net model was trained with more than 20,000, 64 × 64 patches across three countries, covering different agro-ecological zones and topographic conditions in South Asia. The model was able to precisely map the flood intensity in different ecological zones and topography. The comparative analysis between the ground truth data with the model generated damage intensity showed high agreement: 94% over all accuracy and iou is 0.906 with validation loss is 0.03 demonstrates the capacity of the model. The study demonstrated, for the first time, the potential of using automated method that combined deep learning algorithm and remote sensing data for flood intensity mapping in the rice crop.

Keywords: Flood, Rice Crop, South Asia, Deep Learning.

Background

Natural disasters, such as floods, storms, droughts, and earthquakes, cause significant loss globally. Among these disasters, floods are one of the most widespread and result in substantial losses. The frequency and intensity of floods have increased due to climate change in recent years. According to the Food and Agriculture Organization of the United Nations, more than 93 thousand hectares of cropland and 1.6 million tons of crops are damaged by flooding annually (2003–2013), accounting for more than half of the aggregate crops damaged by natural hazards and disasters (FAO, 2015). South Asian countries, in particular, incur higher losses due to inadequate preparedness and the lack of timely information dissemination about possible extreme weather conditions, specifically during monsoon (Caballero-Anthony et al., 2024).

Mapping flood loss in rice crops increasingly relies on multi-sensor remote sensing data, combining optical and SAR imagery to overcome cloud cover and capture flood dynamics. Machine learning and time-series vegetation indices enhance damage detection and yield loss estimation. While remote sensing offers powerful tools for flood loss mapping in rice, significant gaps remain in accounting for environmental variability, ensuring data quality and validation, and developing scalable, rapid assessment methods (Mishra et al 2024; Rahman, 2021; Lateef et al 2025)

Most studies focus on traditional remote sensing indices (e.g., NDVI, DVDI) combined with machine learning classifiers or statistical models to estimate flood damage and loss intensity in rice crops. These frameworks developed typically using optical (Sentinel-2) and SAR (Sentinel-1) data fusion, time-series analysis, and vegetation indices to assess crop status before and after flooding, estimating loss based on spectral changes and inundation duration.

Machine learning techniques (e.g., random forests, SVM) have been applied to improve flood damage classification and recovery assessment, validated with participatory mapping data. The focus remains on classical ML and index-based approaches.

There is a clear gap to develop and apply deep learning architectures (e.g., CNNs, LSTMs, attention models) to improve accuracy and automate flood loss intensity estimation in rice crop. Therefore, this study focuses to develop a deep learning-based framework for quantitative flood loss intensity mapping in rice crops using multi-source remote sensing data.

Method

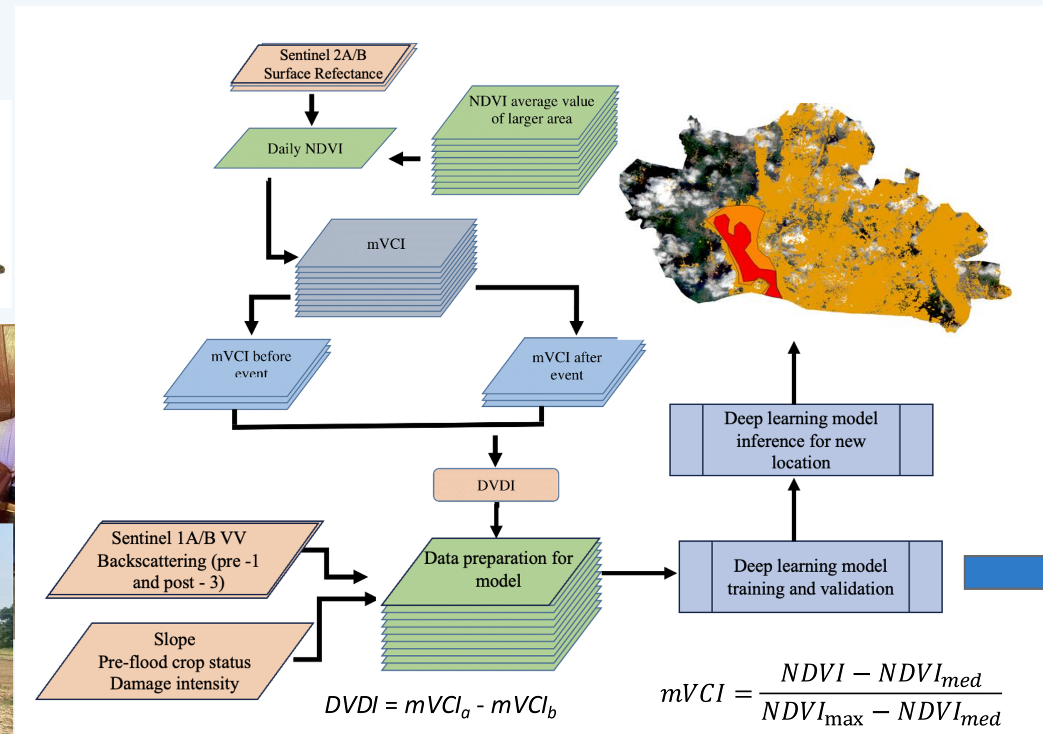
Data Collection

- **Satellite Data**
  - Sentinel-1 SAR for flood extent and inundation mapping (cloud-penetrating).
  - Sentinel-2 multispectral optical imagery for vegetation condition monitoring.
  - High-resolution PlanetScope imagery for detailed damage assessment interactively.
- **Ground Truth Collection**
  - Field surveys and participatory mapping for flood damage severity.
  - Crop stage vs loss
  - Inundation duration vs. loss
  - Slope vs. loss
  - Overall crop yield statistics with flood and without flood

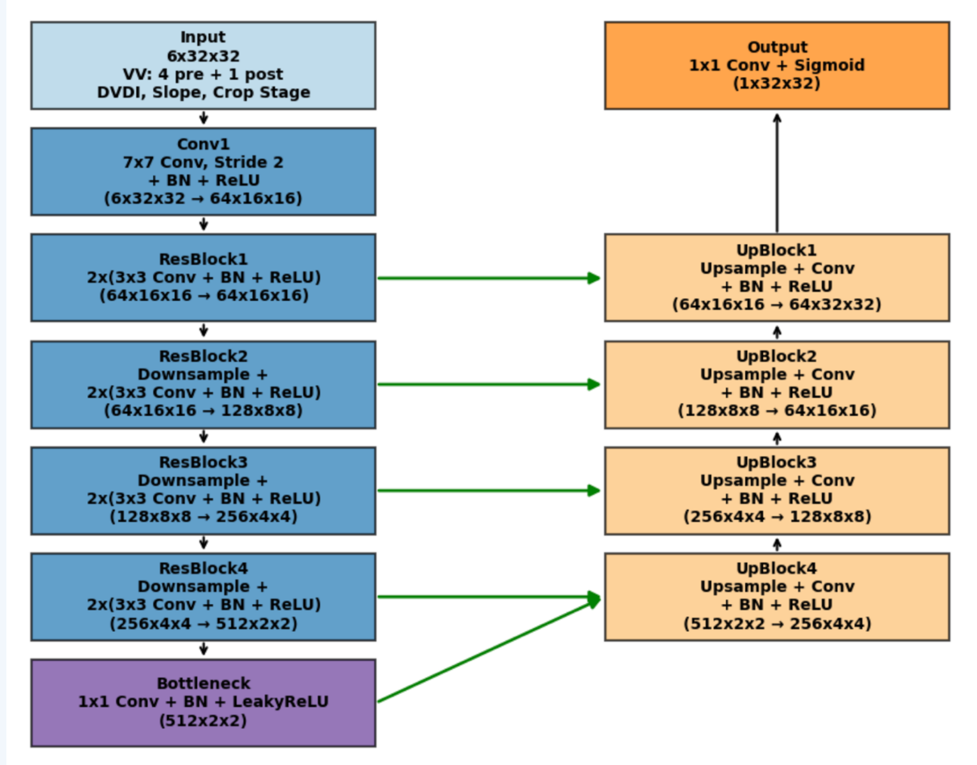
Data Preprocessing

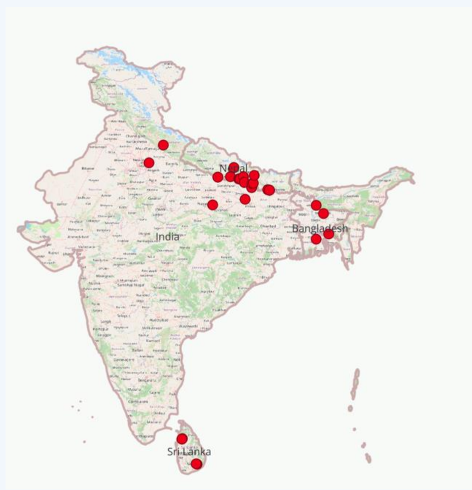
- Co-registration and normalization of multi-temporal images (pre-flood, during flood, post-flood).
- Labeling of damage intensity classes based on ground truth (e.g., no damage, mild, moderate, severe loss).
- Input dataset: DVDI - pre-flood vs post-flood, three post flood
- SAR images: pre-flood, during-flood (nearest day after flood) – three post flood, post-flood align with optical, crop status, slope

Field visit: Farmer consultation at the local government office, site inspection, and field waypoint

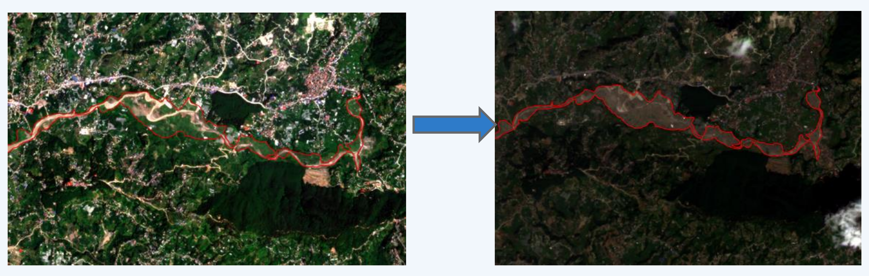


Workflow for data preparation, and model development





Study Sites: Red dots indicate the locations of flood events analyzed between 2019 and 2024.



Before and after flood event in Manohara river, Nepal.

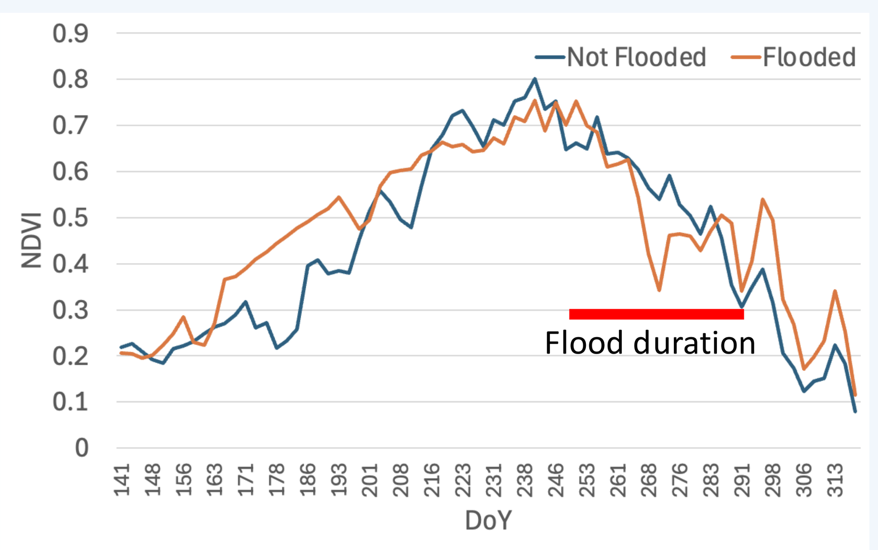
Temporal Information Fusion
Incorporate temporal attention mechanisms to enhance the understanding of dynamic flood progression and damage patterns.

Ablation Studies
Systematically assess the contribution of key architectural components (e.g., attention modules, multi-sensor inputs) by removing them individually.

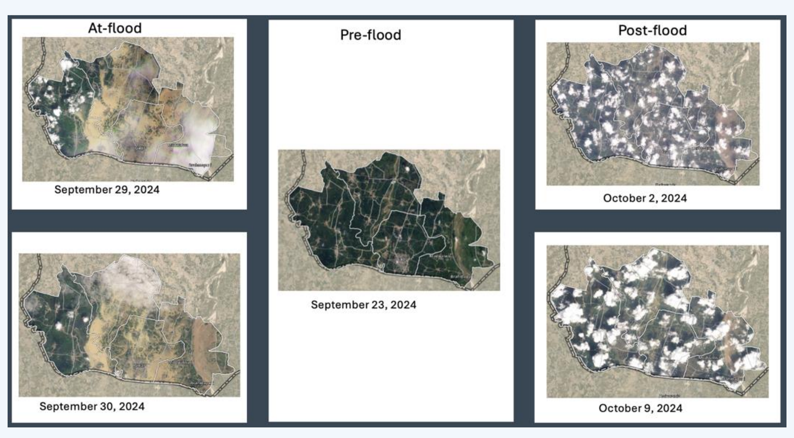
Scalability and Generalizability Assessment
Test the model on datasets from diverse regions or countries to evaluate ability to generalize across geographies and varying conditions.

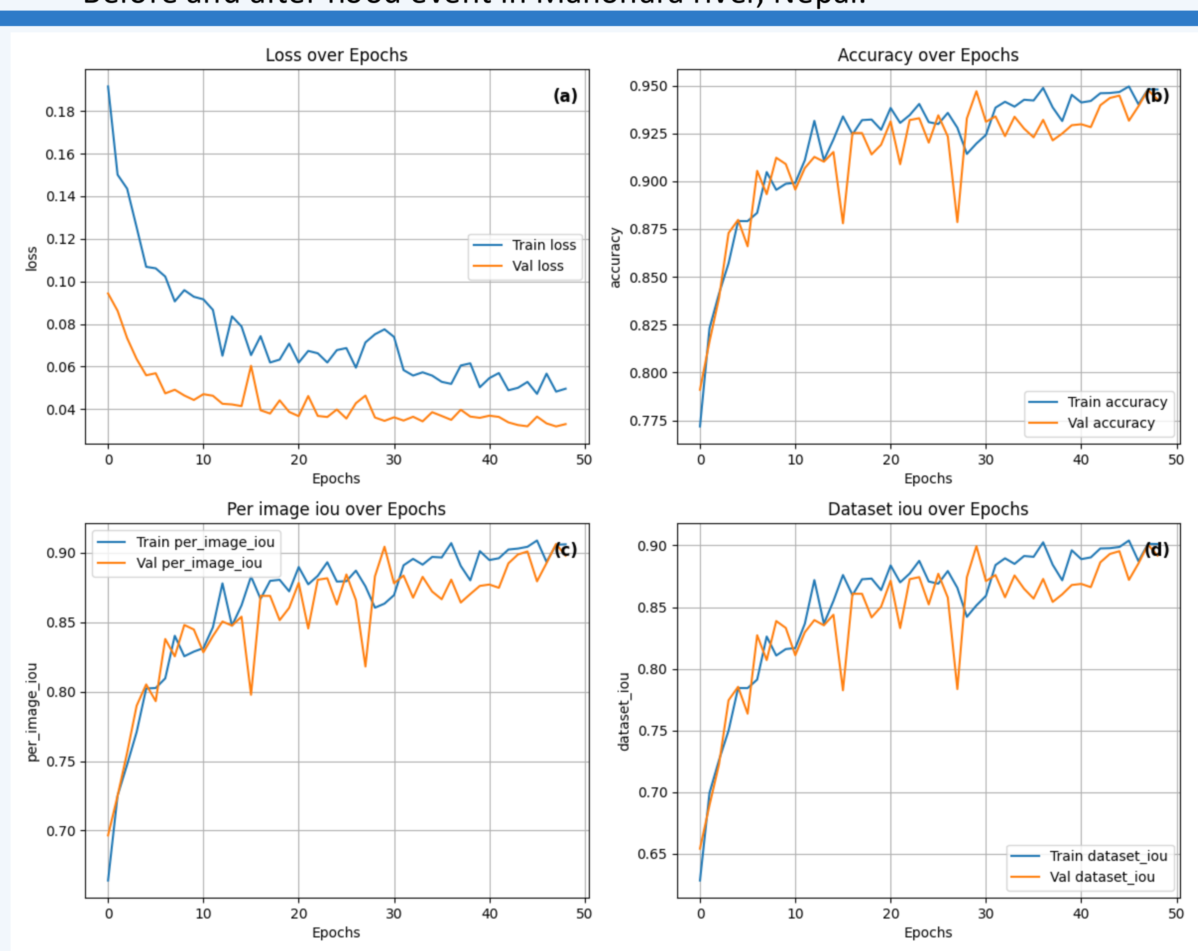
Model Explainability
Integrate Grad-CAM to visualize and interpret the model's decision-making process.

Results

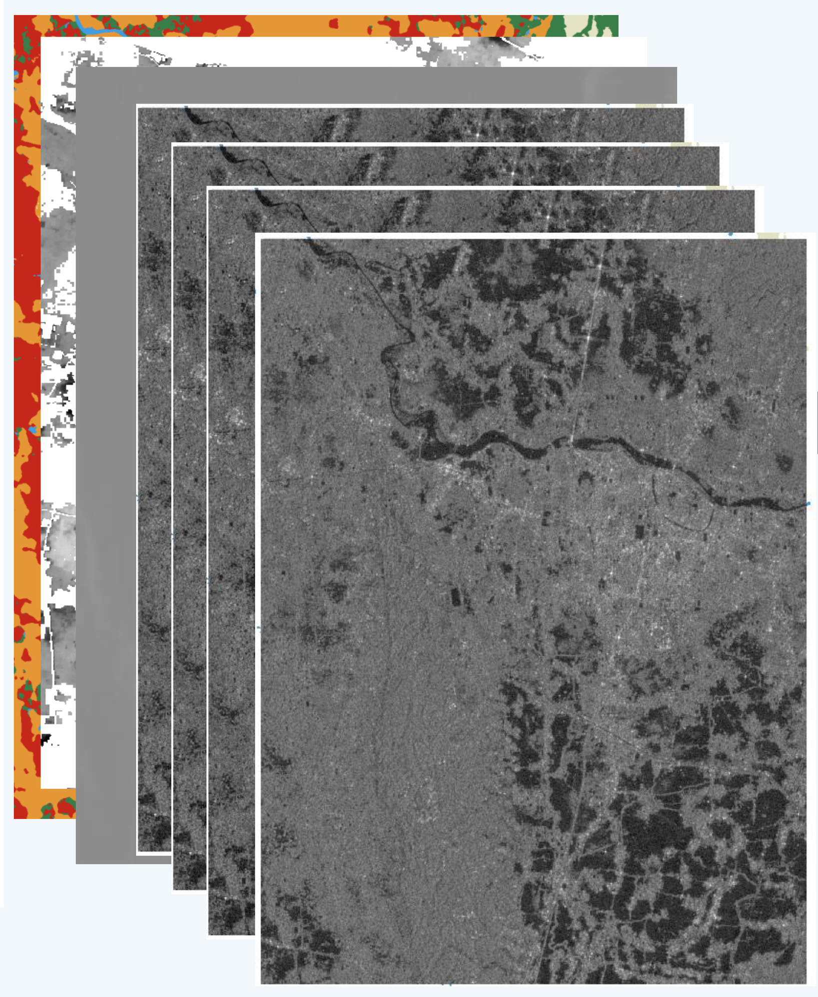


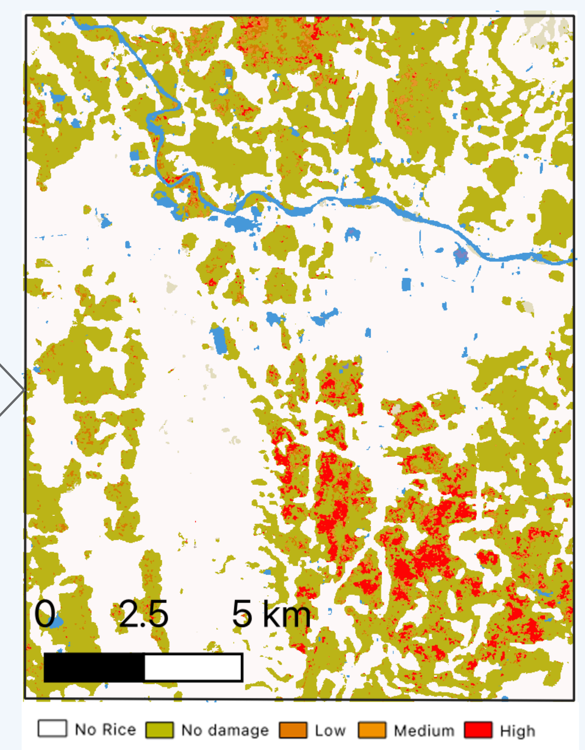
Aggregated time-series NDVI for both flooded and non-flooded areas.





Training is improving
Loss steadily decreases, accuracy rises from 0.77 → ~0.95 and IoU (both per-image and dataset) also improves significantly.
No overfitting
There's no clear increase in val_loss or decrease in val_iou after training loss continues dropping,
Generalization
val_loss decreases from 0.09 → ~0.03, and **val_accuracy** and **IoU** improve
Best epos: 49





Sample outcome of the model in Bangladesh flood in August – September 2024

- Persistent standing water causes severe damage to crops, particularly when it occurs during or after the flowering stage.
- Damage at flowering stage or later is difficult to recover from.
- By flowering stage, farmers have typically made significant investments in inputs such as seeds, fertilizers, and labor.
- As a result, the level of economic loss is high.

Conclusion and Discussion

Crop damage caused by flooding is strongly influenced by
- Terrain slope — steeper areas may drain faster, while flatter regions retain water longer
- Duration of standing water — prolonged inundation increases the risk of crop failure

Accurate flood damage assessment can be achieved through the integration of
- Synthetic Aperture Radar (SAR) imagery — useful for detecting water presence under cloud cover
- Pre- and post-flood optical imagery — helps in identifying visible vegetation changes
- Topographic slope data — provides critical context for water accumulation and flow

Modeling approach
- A UNet model with a ResNet34 backbone offers a robust framework for learning and predicting spatial patterns of damage intensity from the combined datasets

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