SPATIOTEMPORAL DEEP LEARNING FRAMEWORK FOR MULTI-SOURCE FLOOD INUNDATION MAPPING USING SAR AND OPTICAL DATA

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Introduction:

Floods are among the most frequent and devastating natural disasters, causing significant loss of life, property damage, and long-term socio-economic disruption across the world. Their impact is especially severe in densely populated and low-lying regions, where even short-duration flooding can affect millions of people. With the increasing influence of climate change, the frequency and intensity of extreme rainfall events have risen, making flood monitoring and management more critical than ever.

Traditional flood monitoring systems rely heavily on ground-based observations and manual reporting, which are often limited in coverage, delayed, or unavailable in remote areas. This creates a need for more reliable and scalable solutions that can provide timely and accurate flood information.

Remote sensing has emerged as a powerful alternative, enabling large-scale observation of the Earth's surface using satellite imagery. Synthetic Aperture Radar (SAR) satellites, such as Sentinel-1, are particularly useful as they can capture images regardless of weather conditions or time of day. Optical satellites like Sentinel-2 complement this by providing spectral information that helps distinguish water bodies and vegetation.

However, single-source or single-date imagery is often insufficient to capture the dynamic nature of floods, which evolve over time due to rainfall, terrain, and drainage conditions. To address this, recent advancements in deep learning have enabled the development of models that can learn complex spatial and temporal patterns from multi-source data.

By integrating satellite imagery with terrain information (DEM) and meteorological data (rainfall, soil moisture), modern approaches aim to generate more accurate and consistent flood extent maps. These systems not only improve disaster response and emergency planning but also support long-term climate resilience and sustainable urban development.

Overall, the combination of remote sensing and artificial intelligence provides a promising direction for building efficient, scalable, and data-driven flood monitoring systems.

Objectives:

1. To develop a deep learning-based framework for accurate flood inundation mapping using multi-source satellite data.
2. To integrate spatial features from SAR, optical imagery, and DEM for improved flood detection.
3. To incorporate temporal information such as rainfall and soil moisture to study flood dynamics.
4. To design and compare different model architectures for effective spatio-temporal learning.
5. To evaluate model performance using metrics like IoU, F1-score, precision, and recall.
6. To analyze the impact of data resolution and feature fusion on model performance.
7. To ensure the model generalizes well across different geographic regions.
8. To build a reliable system that can support disaster management and flood monitoring applications.

Methodology

Overview of Proposed Approach

The proposed system performs flood segmentation by integrating spatial and temporal information using a dual-branch deep learning architecture. Each 512×512 satellite image chip is processed through two parallel branches—spatial and temporal—whose outputs are fused to generate a final flood probability map.

Input Data Representation

The model uses two types of inputs:

- **Spatial Tensor (14 channels):** Includes Sentinel-1 SAR (VV, VH),

Sentinel-2 optical bands (B2, B3, B4, B8, B11, B12), DEM-derived features (elevation, slope, TWI, HAND), and spectral indices (NDWI, NDVI).
- **Temporal Tensor (15×2 channels):** Consists of 15-day sequences of rainfall (CHIRPS) and soil moisture (ERA5), capturing pre-flood environmental conditions.

This combination ensures comprehensive representation of terrain, vegetation, and meteorological trends.

Spatial Feature Extraction (U-Net Branch)

The spatial branch utilizes a U-Net architecture with encoder-decoder structure and skip connections. It extracts hierarchical spatial features while preserving fine boundary details essential for accurate flood segmentation.

Temporal Feature Modeling (ConvLSTM Branch)

The temporal branch employs a ConvLSTM network to process sequential meteorological data. It captures spatio-temporal dependencies and outputs a hidden state representing the cumulative effect of rainfall and soil moisture over time.

Feature Fusion Strategy

A late fusion approach is applied at the bottleneck layer. The spatial and temporal feature maps are concatenated and passed through a 1×1 convolution layer to align dimensions. This ensures effective integration of both feature types without disrupting individual learning processes.

Segmentation and Output Generation

The fused features are decoded using the U-Net decoder to produce a pixel-wise flood probability map. This map is then thresholded to obtain a binary segmentation output indicating flooded and non-flooded regions.

Loss Function and Optimization

A hybrid loss function combining Dice Loss and Binary Cross-Entropy (BCE) is used to address class imbalance and improve segmentation accuracy. Invalid pixels are masked during training to ensure reliable learning.

Training and Evaluation

The model is trained on the Sen1Floods11 dataset with data augmentation techniques such as flipping and rotation to enhance generalization. Performance is evaluated using metrics including IoU, F1-score, precision, recall, and specificity.

Comparative Analysis

To validate the contribution of temporal features, a baseline model using only the spatial branch is also implemented. The performance comparison highlights the effectiveness of incorporating temporal dynamics in improving flood detection accuracy.

Result and Conclusion:

1. The experimental evaluation demonstrates that the spatial-only U-Net model establishes a strong and competitive baseline, achieving an IoU of 0.7360, primarily due to effective multi-source data fusion (SAR, optical, and DEM features).
2. Among the proposed variants, the Terrain-Conditioned Temporal MLP performs best with a marginal improvement (IoU = 0.7367), while the ConvLSTM-based model slightly underperforms despite increased architectural complexity.
3. A critical observation is the extremely small performance variation across all models (ΔIoU ≈ 0.0027), indicating that the inclusion of temporal meteorological data contributes minimally to segmentation accuracy.
4. This limitation arises due to a spatial resolution mismatch, where coarse-resolution meteorological inputs (CHIRPS and ERA5), when resampled, become nearly uniform across each image chip. As a result, temporal models fail to extract meaningful spatial variations.
5. The study identifies a “resolution ceiling”, where increasing model complexity (e.g., ConvLSTM with attention) does not translate into performance gains. Instead, modeling meteorological data as chip-level contextual information proves to be a more effective strategy.
6. In cross-region evaluation on the Assam 2023 dataset, both models exhibit a significant IoU drop (~50%), highlighting the impact of domain shift rather than inherent model limitations.
7. Despite this, the terrain-conditioned approach maintains a slight performance advantage, demonstrating improved generalization by incorporating physically meaningful terrain-based conditioning.
8. Overall, the findings emphasize that data compatibility and resolution alignment are more crucial than increasing model complexity when integrating temporal information.
9. The study concludes that future work should focus on higher-resolution meteorological data and improved context-aware fusion mechanisms to enhance flood mapping performance.

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Future Scope:

1. The proposed flood mapping system can be further enhanced by incorporating **higher-resolution meteorological datasets**, which can overcome the identified resolution mismatch and improve the effectiveness of temporal modeling. Future work can also explore **real-time data integration** using live satellite feeds and weather APIs to enable near real-time flood monitoring and early warning systems.
2. Advanced architectures such as **Vision Transformers, hybrid CNN-Transformer models, or geospatial foundation models** can be investigated to improve feature representation and scalability across diverse regions. Additionally, integrating **multi-temporal SAR imagery (pre- and post-flood sequences)** at native resolution may provide richer temporal signals compared

to coarse meteorological inputs.

3. To address domain shift, **domain adaptation and transfer learning techniques** can be applied to improve generalization across unseen geographies like Assam. Incorporating **self-supervised or semi-supervised learning** can also help utilize large amounts of unlabeled satellite data.
4. The system can be extended to include **flood forecasting (prediction before occurrence)** by combining hydrological models with deep learning approaches. Integration with **GIS platforms and cloud-based deployment (AWS/GCP)** can make the system scalable and accessible for government agencies and disaster management authorities.
5. Further improvements can include **uncertainty estimation and explainable AI (XAI)** to increase trust and interpretability in critical decision-making scenarios.
6. Finally, the framework can be generalized to detect and monitor other natural disasters such as **landslides, droughts, and wildfires**, making it a versatile tool for environmental monitoring and climate resilience.