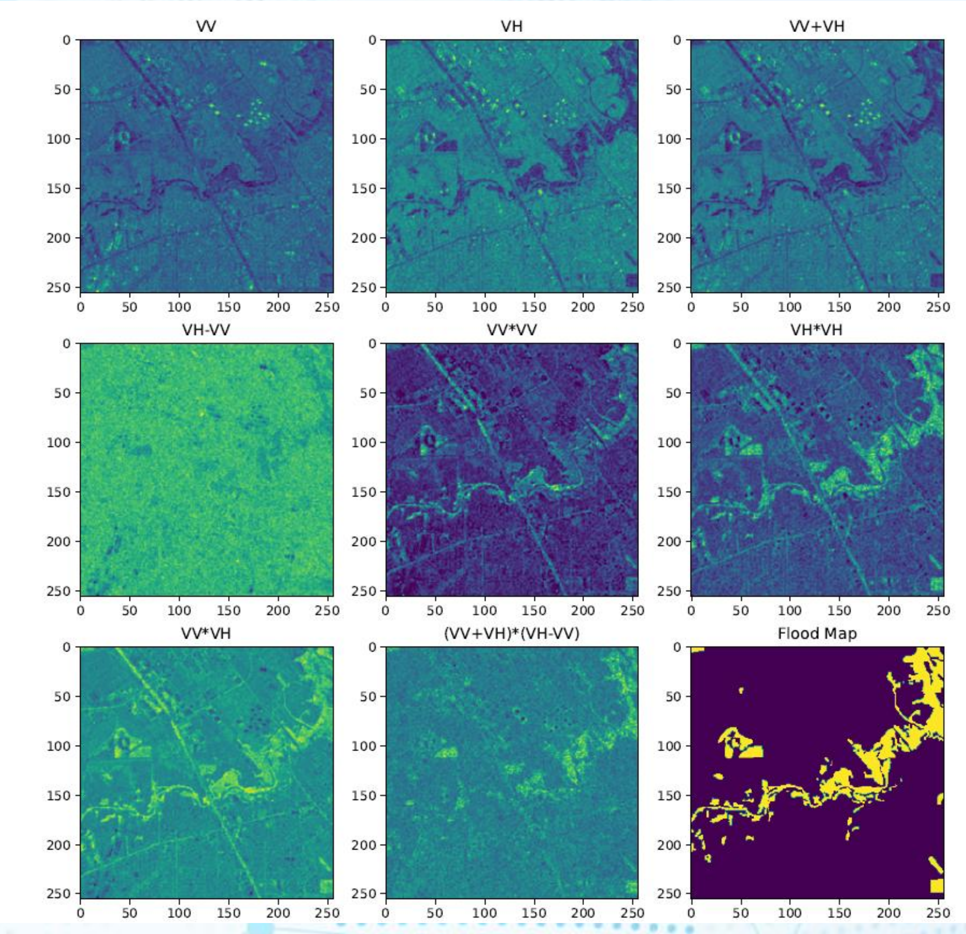
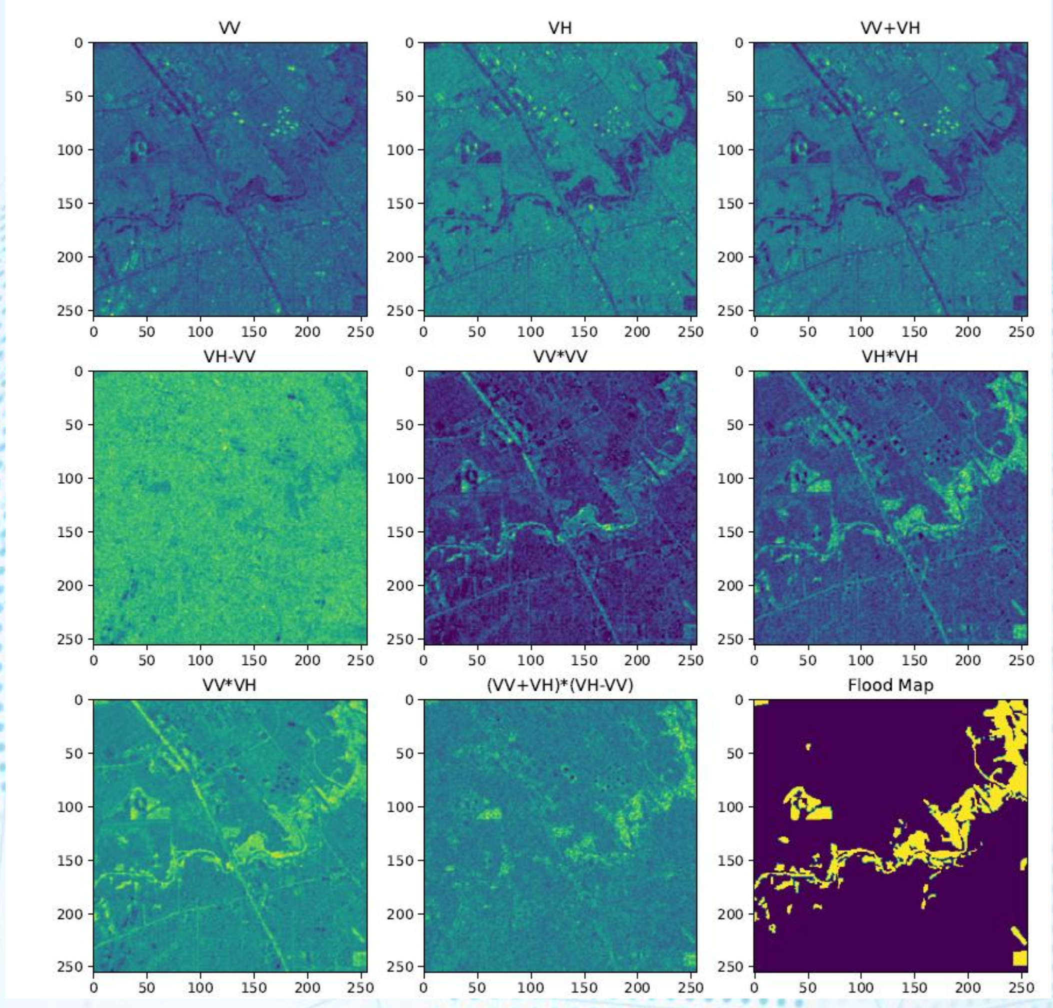
Flood Mapping using Dual Polarization Sentinel-1 Synthetic Aperture Radar (SAR) Data



Motivation and Challenges:

- Floods are among the most frequent and destructive natural disasters.
- Climate change, urbanization, and population growth increase risks.
- Accurate and timely flood maps are crucial for emergency response and mitigation.
- Synthetic Aperture Radar (SAR) from Sentinel-1 is widely used due to all-weather, day/night capability.
- **Challenges**: Speckle noise and complex backscatter patterns in SAR make segmentation task challenging.



Why Dual Polarization Sentinel-1 SAR Data?

1. All-Weather, Day and Night Capability

- SAR uses **microwave signals**, not visible light.
- Works under **cloud cover, heavy rain, and at night** → crucial during floods when optical satellites fail.

2. Water Detection Advantage

- **Smooth water surfaces** reflect radar signals away from the satellite → appear as **dark areas.**
- **Land/urban/vegetation** scatter signals back → appear **bright.**
- Creates strong **land–water contrast** for flood detection.

3. High Spatial and Temporal Coverage

- Sentinel-1 revisits every **6-12 days** globally.
- Wide swath (~250 km) allows **large-scale flood mapping.**

Why Dual Polarization Sentinel-1 SAR Data?

4. Independence from Sunlight & Atmosphere
- Unlike optical imagery, SAR penetrates **clouds, haze, and smoke.**
- Ensures **reliable monitoring** during disaster conditions.

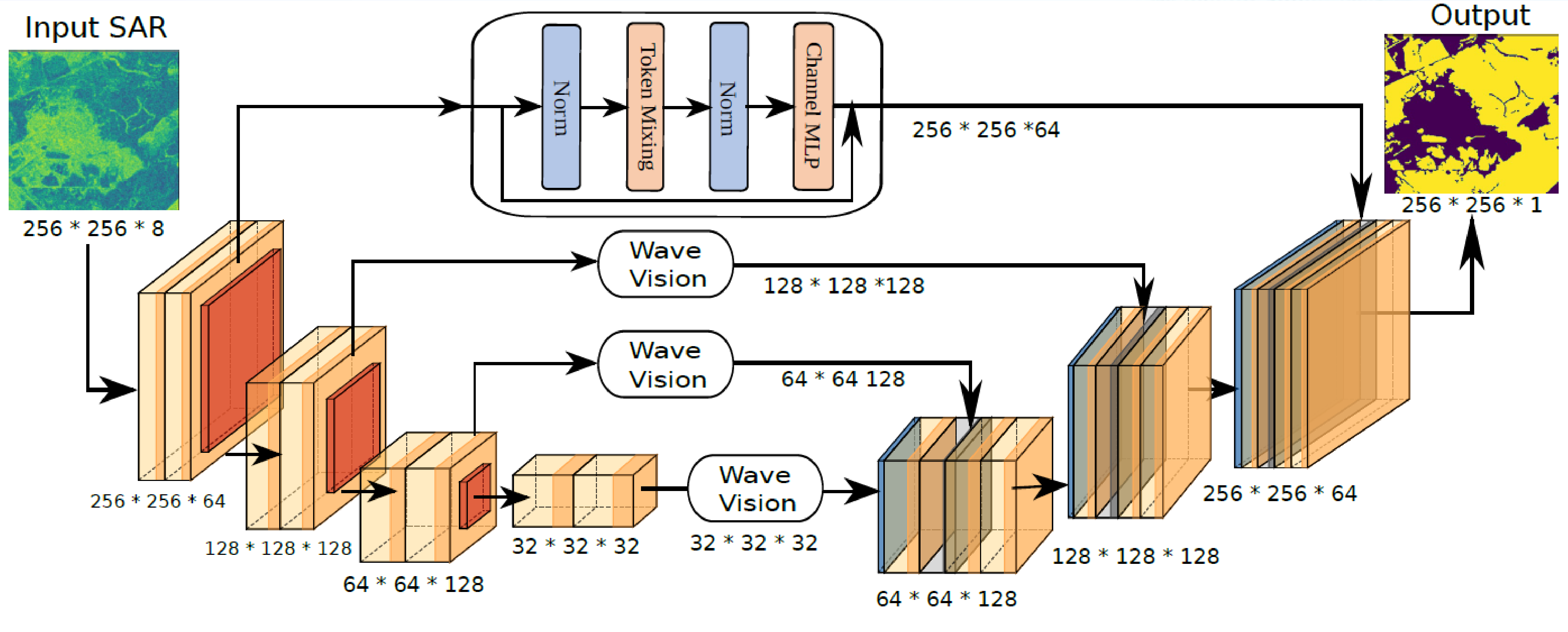
5. Compatibility with Advanced Models
- Dual polarization (VV, VH) enhances classification.
- Combined with **deep learning**, SAR supports accurate flood segmentation despite speckle noise.

Limitations of Traditional Approaches

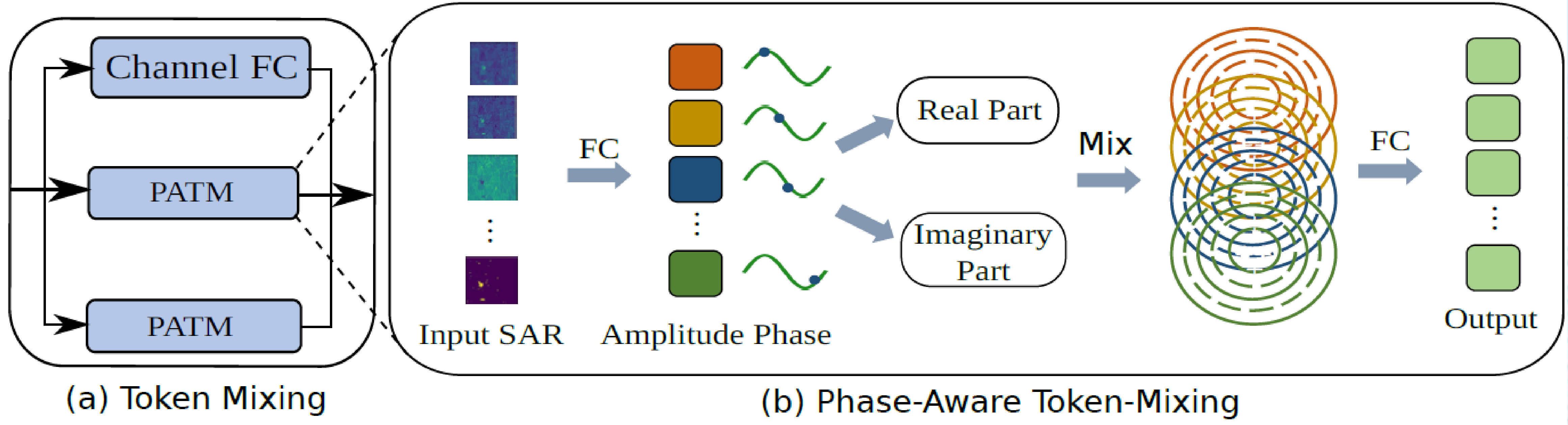
- **Thresholding / region growing / Random Forest** require manual feature engineering.
- Struggle in **urban/vegetated areas** with complex backscatter.
- Ignore spatial context → rely only on **pixel-level values**.

Strength of Deep Learning

- Learns **hierarchical spatial-spectral features** directly from SAR data.
- Captures both **local textures** (via CNNs) and **global context** (via Vision Transformers).
- Handles **speckle noise** and complex patterns better than rule-based or shallow models



Residual wave vision U-Net


Channel FC
PATM
PATM
(a) Token Mixing
Input SAR
FC
Amplitude Phase
Real Part
Imaginary Part
Mix
FC
Output
(b) Phase-Aware Token-Mixing

Residual wave vision U-Net

The adopted Phase Aware Token Mixing (**PATM)** is a lightweight token- and channel-mixing module as an **alternative** to conventional self-attentions by dividing features into **height, width, and channel** branches.

The PATM applies **phase-aware modulation (cosine/sine)** to the **token-mixing branches for directional sensitivity** (performing spatial mixing) and a **channel-mixing module** (performing channel mixing). **SAR backscatter is naturally a complex signal**.

$$t \cong |t| \cdot (\cos\theta + i \sin\theta)$$

$|t|$ amplitude = SAR feature intensity (VV, VH, or derived features)
θ learnable phase term → gives positional/directional modulation
Concatenating cos/sin parts = representing the complex feature in real form

Residual wave vision U-Net

PATM uses cos θ and sin θ to model features as complex numbers (**real** + **imaginary**). **Amplitude** comes from SAR intensity, **phase** from modulation. This allows wave-like, direction-aware token mixing directly aligned with the physics of SAR signals.

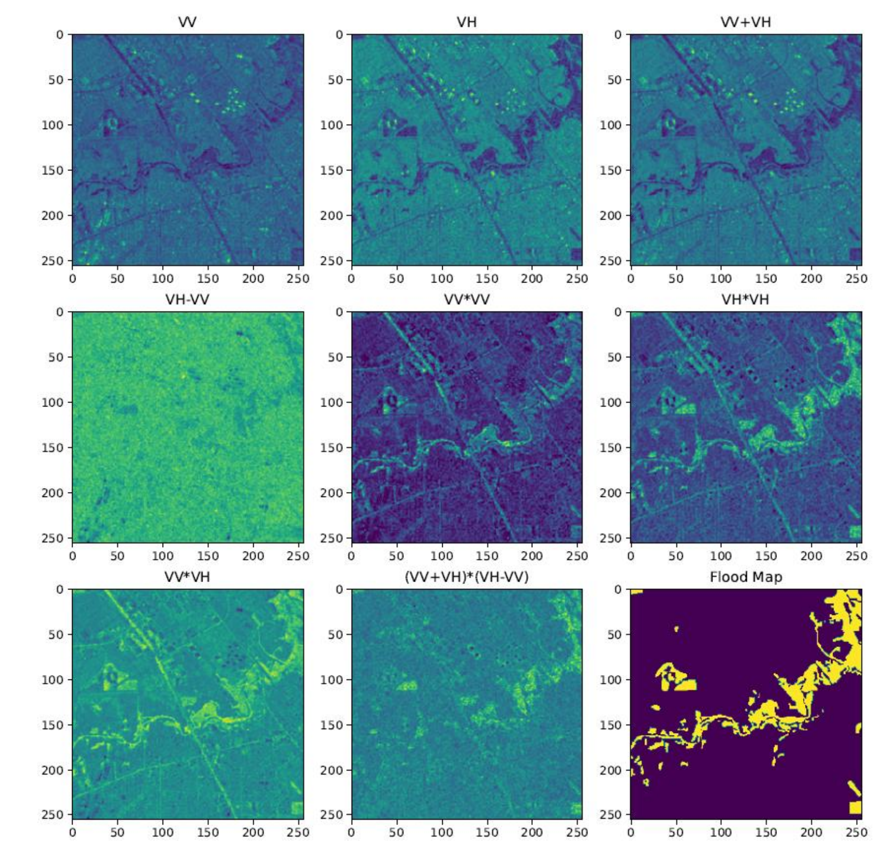
In the **token-mixing branches**, the **SAR backscatter intensity** acts as **amplitude** (VV, VH, and derived polarimetric features), while **phase-aware modulation** (**cosine/sine of learnable θ**) provides the phase component **capturing positional/directional variation in the SAR signals**, enabling directional sensitivity and more accurate spatial mixing of flood patterns.

The **Wave-Vision block** can be regarded as a **mixture-of-experts module** consisting of **two phase-aware token-mixing branches** (height and width), one **channel-mixing branch based** on **Vision MLPs**, and an **additional channel-mixing component implemented** with **standard MLPs**.

Experimental Setup

Data: 542 Sentinel-1 SAR "chips" (**dual polarization VV, VH**) from multiple global flood events (e.g., United States, Paraguay, India, and Slovakia).

- Derived polarization features (VV+VH, VH-VV, VV*VH, etc.).
- Input size: **256×256×8**.
- Evaluation metrics: Accuracy, Precision, Recall, F1-score, Dice, AUC



The developed **WVResU-Net** outperformed all baseline models, including Swin U-Net, U-Net+++, Attention U-Net, R2U-Net, ResU-Net, TransU-Net, and TransU-Net++ (ours, was tested for deforestation mapping).

- **Overall Accuracy**: 96.2%
- **Precision**: 92.97%
- **Recall**: 69.67%
- **F1-score**: 82.03%
- **Dice coefficient**: 0.7345
- **AUC**: 0.845

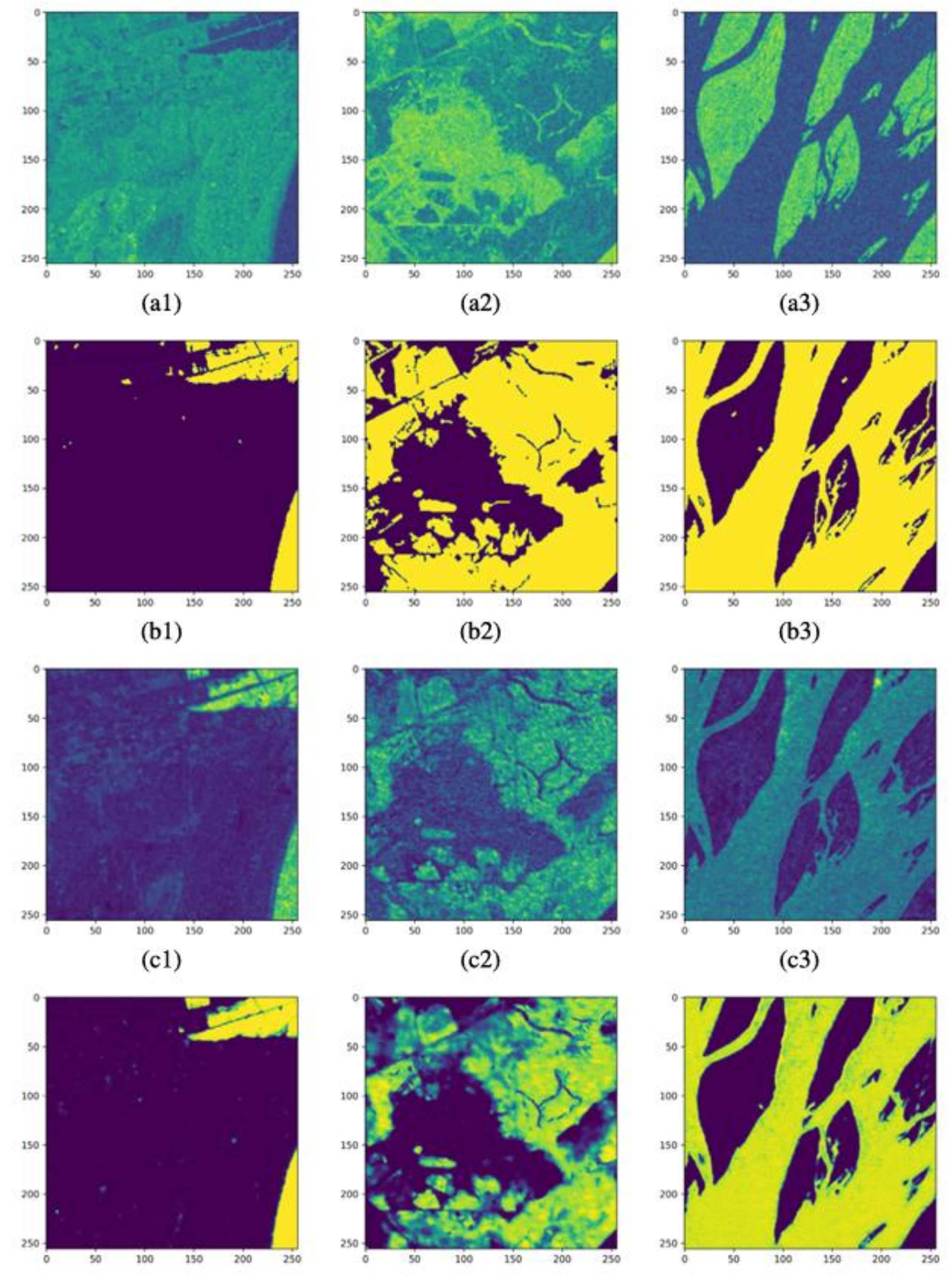
Visualization and Insights

Segmentation maps showed:

- **WVResU-Net** **best distinguishes flooded vs. non-flooded areas** compared to other models.

- **Lower over/under-estimation of floods** compared to other models.

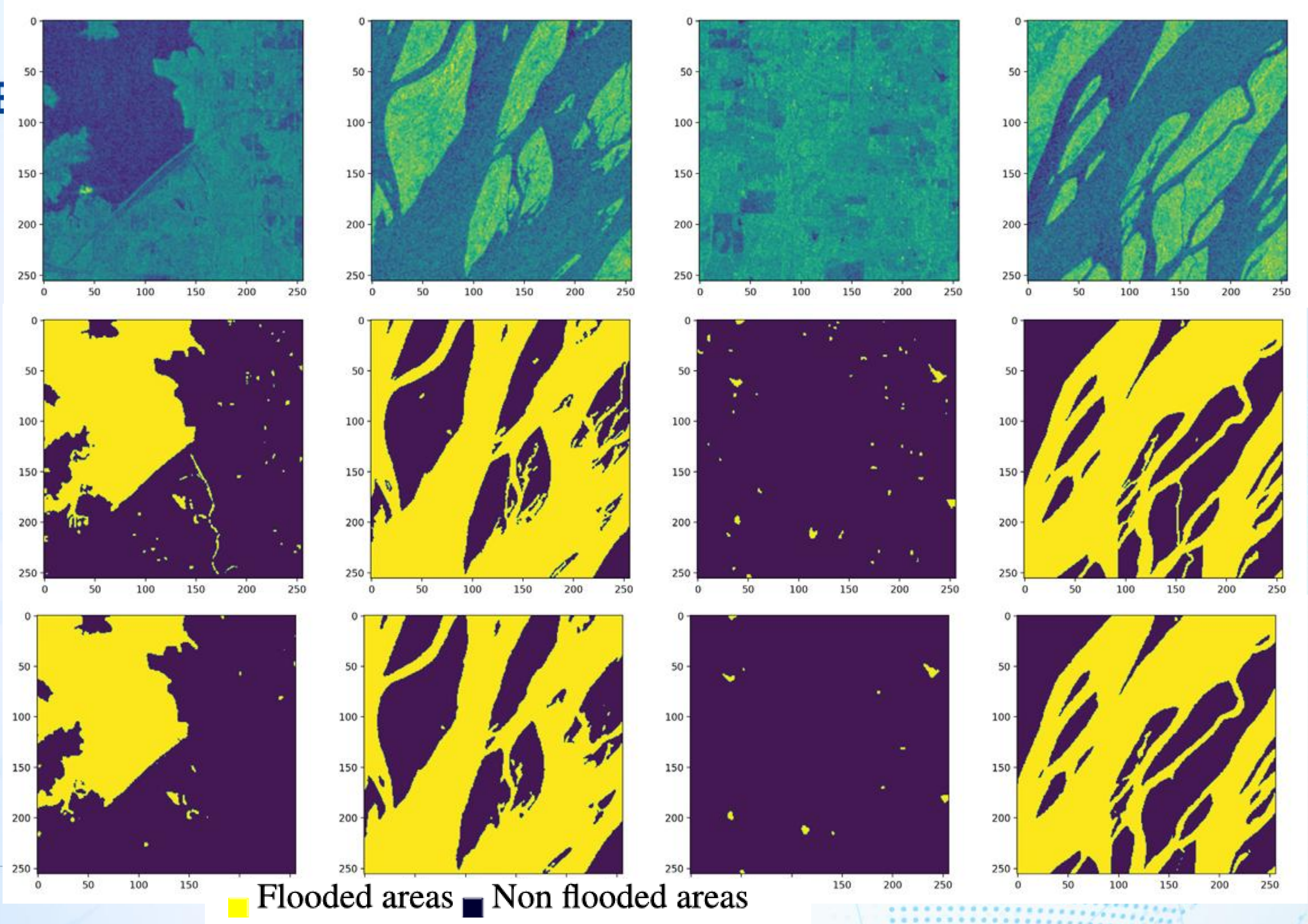
- Feature maps reveal **effective focus on flooded regions**.



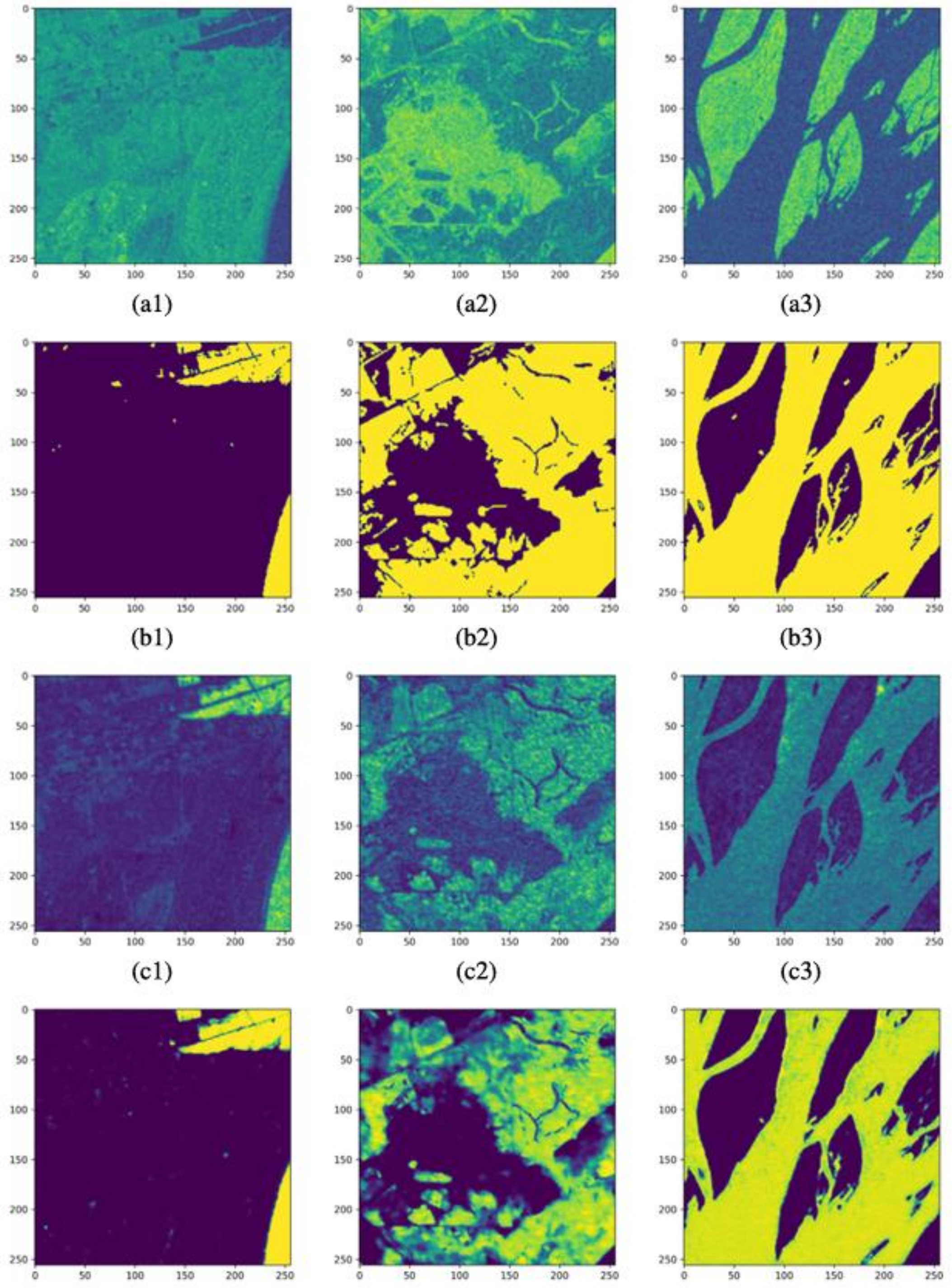
Sentinel-1 polarization data of VV

Flood masks

Results of the developed WVResU-Net



Feature maps derived from the developed segmentation algorithm of the **WVResU-Net** for three randomly selected areas (a1-a3) **SAR polarization data of *VV***, (b1-b3) **flood masks**, (c1-c3) derived feature map from **last vision network** and (d1-d3) **last convolutional layer**, respectively.



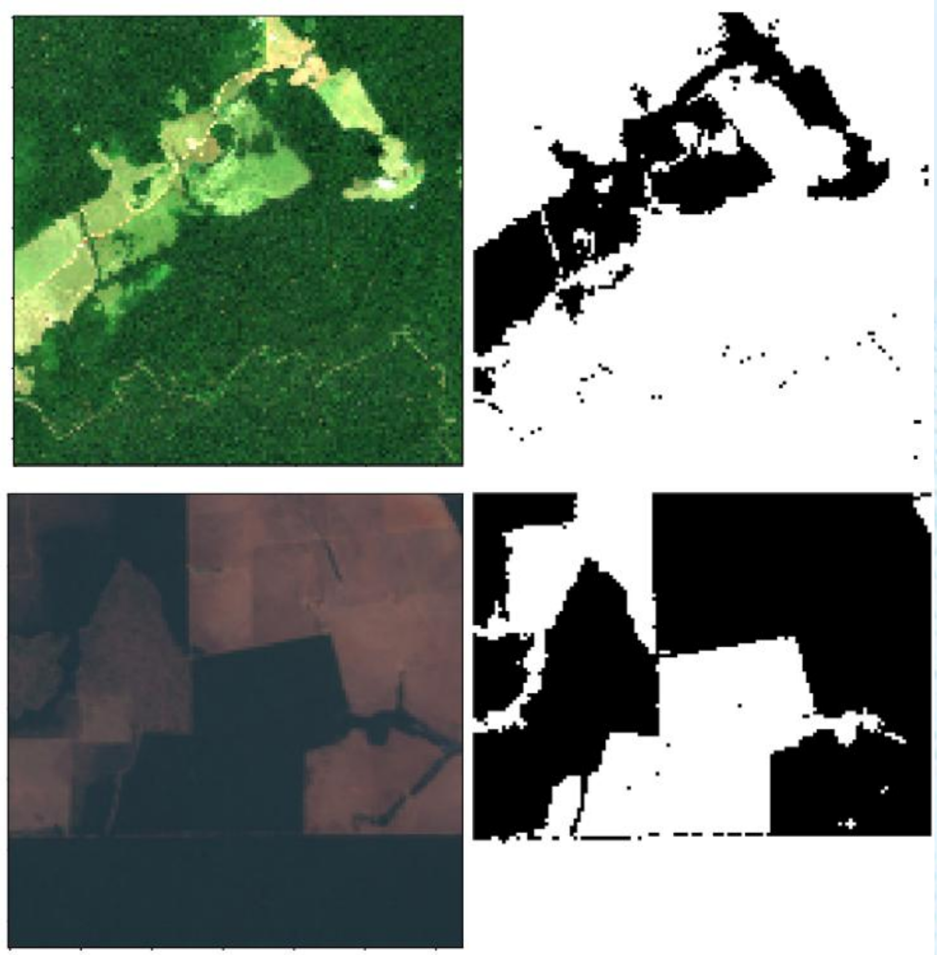
Conclusion

- **WVResU-Net** is a **robust, accurate, and efficient flood mapping architecture**.
- Integrates **wave-based Vision MLPs + residual learning**.
- **Adaptively learn** **flood patterns** from dual-pol SAR data.
- **Significantly outperforms** CNN and ViT architectures on Sentinel-1 SAR data.
- Demonstrated **strong generalization** on global Sentinel-1 flood events with limited labeled data.
- **Push beyond** CNNs and ViTs by **combining their strengths**.

Paper: https://www.sciencedirect.com/science/article/pii/S1569843224000165

Codes: https://github.com/aj1365/RWVUNet/tree/main

Deforestation Mapping using Sentinel-2 Satellite Imagery



Motivation and Challenges:

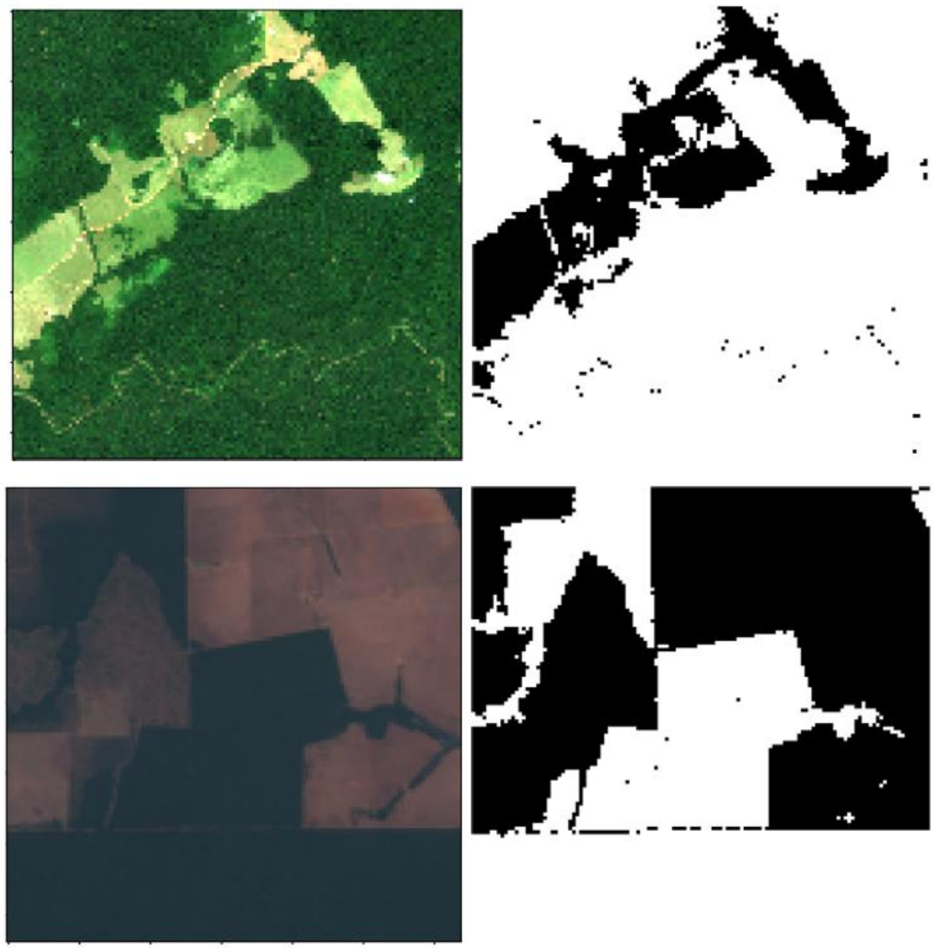
Deforestation is a major driver of climate change - especially in tropical biomes like the **Amazon Rainforest** and **Atlantic Forest**.

Monitoring forest loss is critical for biodiversity conservation, carbon capture, and climate stabilization.

Remote sensing with Sentinel-2 imagery provides high-resolution, multi-spectral data ideal for **large-scale forest monitoring**.

Deep learning models (CNNs, U-Net, Transformers) have advanced forest mapping but face challenges:

- CNNs struggle with **long-range dependencies**.
- Vision Transformers (ViTs) need **large datasets** and **high compute power.**



Why Sentinel-2 Data?

1. High Spatial Resolution

- 10-20 m resolution captures detailed patterns of deforestation and small-scale clearings.

2. Rich Spectral Information

- 13 spectral bands (visible, NIR, SWIR) allow monitoring of **vegetation health**, **canopy structure**, and **soil-water contrasts**.

- The **NIR band** is particularly useful for forest monitoring and biomass estimation.

3. High Temporal Frequency

- 5-day revisit time ensures frequent monitoring - essential for tracking rapid forest changes.

Why Sentinel-2 Data?

4. Free and Open Access

- Global coverage → scalable monitoring for large regions like the **Amazon** and **Atlantic** Forests.

5. Proven Success in Deforestation Monitoring

- Widely used in **forest loss detection**, vegetation indices (**NDVI**, **EVI**), and environmental monitoring.
- Provides the reliability and consistency needed for **training deep learning models**.

TransU-Net++

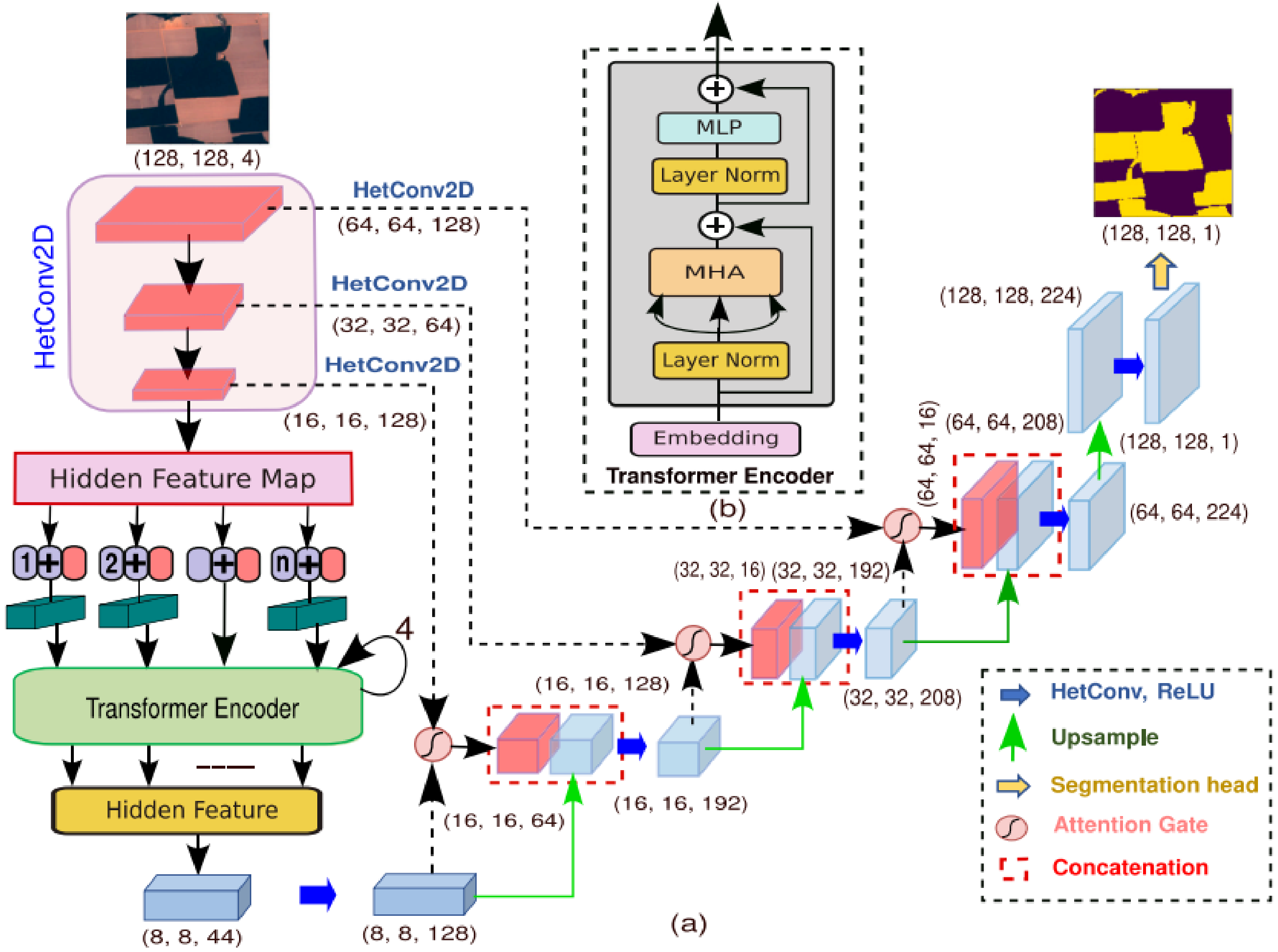


Fig. 1. Graphical representation of the proposed architecture (a) TransU-Net++ and (b) Transformer encoder.

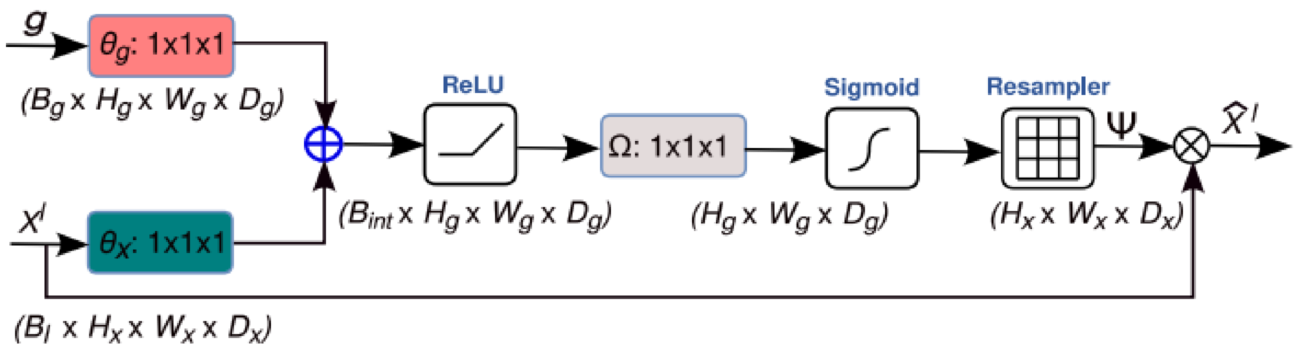


Fig. 3. Schematic representation of attention gates (AG).

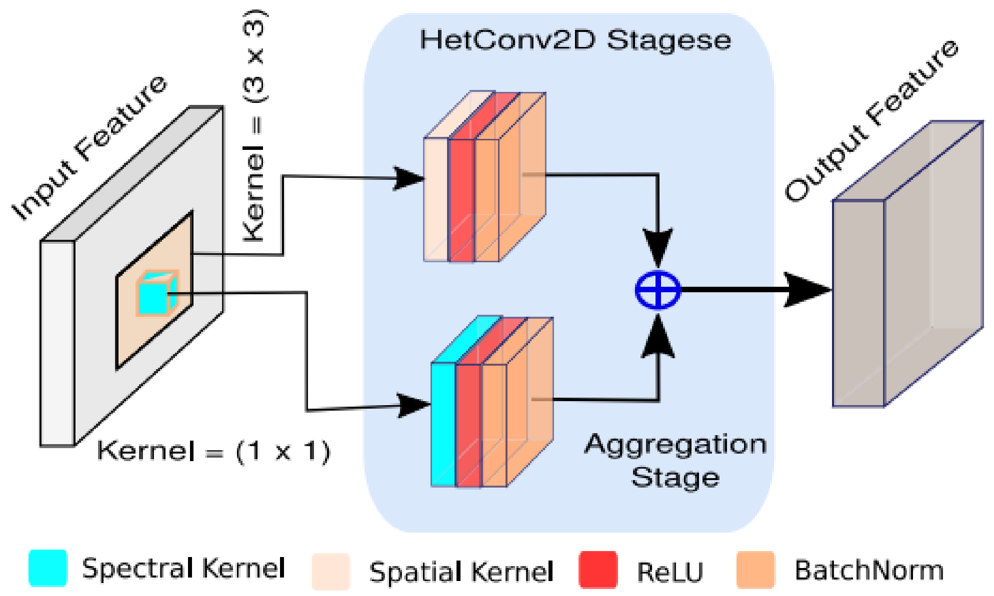


Fig. 4. Step of the heterogeneous kernel convolution, which combines both the features.

TransU-Net++:

An enhanced segmentation architecture that integrates:

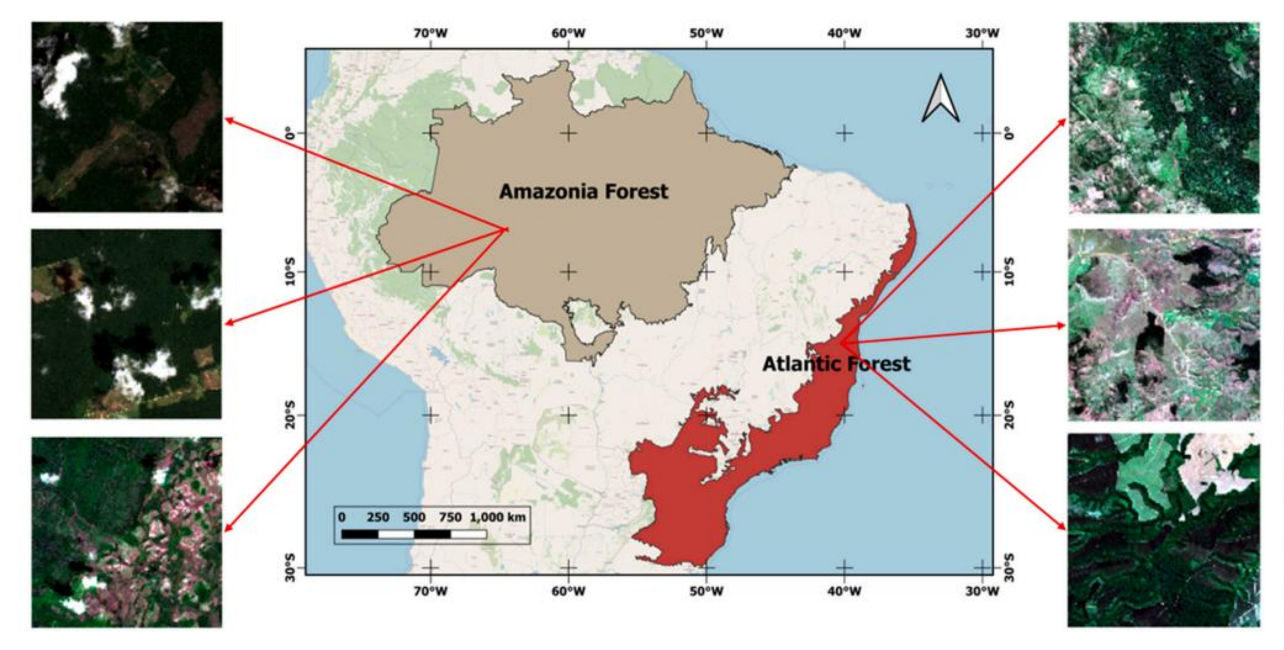
- **Heterogeneous Kernel Convolution (HetConv):** combines point-wise and depth-wise convs for efficient multi-scale feature extraction.
- **U-Net backbone**: encoder–decoder structure with skip connections.
- **Attention Gates (AGs)**: **highlighting relevant spatial regions**, reducing false positives.
- **Vision Transformers (ViTs)**: capturing long-range dependencies and global contextual information.

Key Contributions:

- Introduced **TransU-Net++**, combining **HetConv**, **AGs**, and **ViTs** for **deforestation mapping**.

- Demonstrated **significant improvements** over state-of-the-art models (e.g., U-Net, U-Net+++, Attention U-Net, Swin U-Net, ResU-Net).

- Showed **excellent generalization** across forest biomes (Amazon → Atlantic).



Experimental Setup

Data: Sentinel-2 satellite imagery via SentinelHub.
Regions: **Amazon Rainforest** and **Atlantic Forest**.
Datasets:
- **Amazon** (3-band RGB)
- **Amazon** (4-band RGB + NIR)
- **Atlantic Forest** (4-band RGB + NIR)
- Evaluation metrics: OA, F1-score, Precision, Recall, AUC

Amazon 3-band dataset:

- *TransU-Net++*: OA = **91.96%**, F1 = **91.48%**
- Outperformed TransU-Net by ~3–6% in accuracy, F1, and precision.

Amazon 4-band dataset:

- *TransU-Net++*: OA = **97.2%**, F1 = **97.18%**
- Improved baseline TransU-Net by ~3–7%.

Atlantic 4-band dataset:

- *TransU-Net++*: OA = **93.97%**, Recall = **93.96%**
- Enhanced TransU-Net by ~4–16%.

Spatial transferability (Amazon → Atlantic test):

- *TransU-Net++* maintains higher generalization with OA = **88.21%**, **best** among tested models.

AUC (all datasets): TransU-Net++ consistently achieved the **highest values** (e.g., 0.972 for 4-band Amazon).

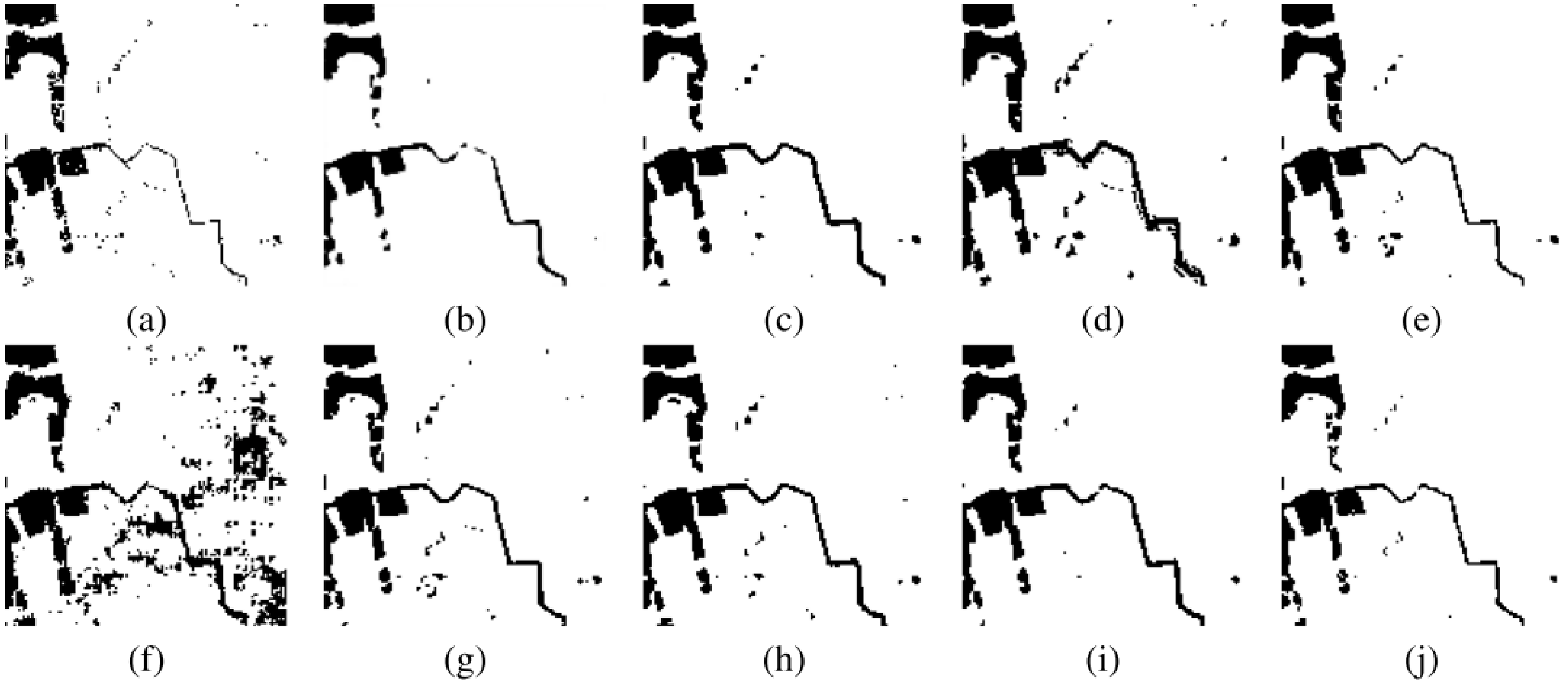


Fig. 5. Segmentation maps over 3-band Amazon Forest dataset obtained using (a) Ground Truth, (b) U-Net, (c) Attention U-Net, (d) R2U-Net, (e) ResU-Net (f) Swin U-Net, (g) U-Net+++, (h) Attention U-Net-2, (i) TransU-Net, and (j) TransU-Net++, respectively.

Conclusion

- **TransU-Net++** is a powerful, efficient architecture for **deforestation mapping** using **Sentinel-2** data.
- **Outperforms** both CNN-based and Transformer-based segmentation models.
- Provides excellent **spatial transferability**, making it suitable for large-scale, real-world forest monitoring.
- The developed architecture has **potential applications** beyond deforestation, e.g., **Flood mapping**.

Paper: https://www.sciencedirect.com/science/article/pii/S1569843223001541

Code: https://github.com/aj1365/TransUNetplus2