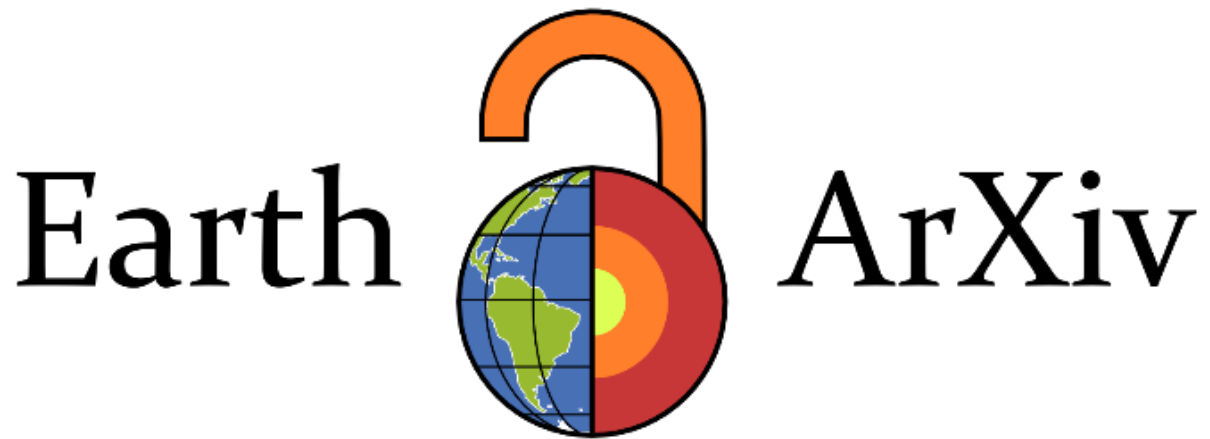




Peer review status:

This is a non-peer-reviewed preprint submitted to EarthArXiv.

Nitya D. Dhagat

University of California, San Diego, California, USA

ORCID: <https://orcid.org/0009-0005-2916-4599>

Evaluating Cross-Country Generalization of Deep Learning-Based Flood Mapping Using Sentinel-1 SAR and Sentinel-2 Imagery

Nitya D. Dhagat
Nadiad, Gujarat, India
nityaddhagat@gmail.com

Abstract—Benchmark performance in flood mapping does not reliably predict how a model will behave in a new country. This paper tests that directly. Using the Sen1Floods11 dataset, we evaluate twelve model configurations—two architectures (Vanilla U-Net and ResNet34-encoder U-Net) across three sensing modalities (Sentinel-1 SAR, Sentinel-2 augmented with NDWI and MNDWI spectral indices, and multimodal Fusion)—under a standard random train-test split and a geographically disjoint country-level split where test countries are held out entirely from training. The gap between these two conditions is large and consistent. The worst case is Vanilla U-Net with Sentinel-2: IoU drops from 0.727 under random splitting to 0.464 under country splitting, a 36.2% relative loss. SAR degrades least. ResNet34+Fusion is the strongest country-level configuration, reaching IoU 0.555 and average precision 0.850. NDWI and MNDWI provide the clearest class separation of all input features (mean flood-to-background difference of 2.21 and 2.27 standard deviations respectively), and their inclusion improves country-level IoU consistently across architectures. Somalia is harder than Paraguay in every configuration, with SAR-only models showing a $2.4\times$ country ratio that narrows to $1.3\times$ for ResNet34+Fusion. The key finding: the evaluation protocol matters as much as the model design.

Index Terms—flood mapping, Sentinel-1, Sentinel-2, SAR, U-Net, ResNet34, domain generalization, cross-country evaluation, Sen1Floods11, NDWI, MNDWI, semantic segmentation

I. INTRODUCTION

Every few months a new paper reports high IoU scores on Sen1Floods11 and frames it as progress toward operational flood mapping. The numbers are real, but the evaluation protocol has a structural problem: random train-test splits often place samples from the same flood event, same country, and similar land cover on both sides of the split. A model tested this way has likely seen nearly identical scenes during training. It has not been tested on a country it has never seen.

This matters because operational flood response works in the opposite direction. A model trained on floods in India, Ghana, and the United States needs to delineate flooding in Paraguay or Somalia on day one of a new disaster, with no in-country calibration. Geographic variability between those regions—different vegetation, terrain, acquisition geometry, and SAR backscatter—can break models that looked strong on random-split benchmarks [1].

Sentinel-1 SAR and Sentinel-2 optical imagery are the two most common satellite sources for flood mapping. SAR works through cloud cover, which matters during storms. Sentinel-2

provides richer spectral information but is unavailable when clouds are present [2], [3]. Combining them is a natural idea, but whether the combination helps across geographically unseen regions is an open question. So is whether pretrained encoders like ResNet34 [4] generalize better than lightweight U-Nets trained from scratch, and whether water-sensitive spectral indices (NDWI [5], MNDWI [6]) change generalization beyond in-distribution accuracy.

This paper runs those experiments directly. We reorganize Sen1Floods11 [7] into a country-disjoint split with Paraguay and Somalia held out for testing, and evaluate all twelve configurations on both the standard random split and the country split. Contributions:

- 1) A geographically disjoint country-level evaluation protocol for Sen1Floods11 with no spatial leakage between train and test countries.
- 2) A complete quantitative comparison of all twelve architecture-modality combinations under both protocols, quantifying how much random-split evaluation overestimates real-world performance.
- 3) Feature distribution analysis confirming that NDWI and MNDWI provide stronger flood-versus-background separation than any raw spectral band, with per-pixel mean differences of 2.21 and 2.27 respectively.
- 4) Per-image IoU distributions with 95% bootstrap confidence intervals, precision-recall curves, and confusion matrices across both test countries.

II. RELATED WORK

A. Deep Learning for Flood Mapping

Flood mapping before deep learning mostly meant thresholds: if a pixel's backscatter or NDWI falls below a cutoff, call it water [8]. This works when scenes are clean and parameters are tuned per region. It breaks at scale. Fully convolutional networks [9] changed that by producing pixel-wise predictions end to end. U-Net [10] became the standard architecture for satellite segmentation because skip connections preserve spatial resolution through the decoder, which matters for thin flood boundaries along rivers and roads.

Sen1Floods11 [7] gave the field a common dataset. Since its release, most work has focused on architectural improvements: attention modules, residual connections, transformer encoders, lightweight models [11]–[13]. Pretrained backbones

like ResNet [4] show consistent gains in remote sensing segmentation by importing general visual features from ImageNet. Whether these gains persist when the model is applied to a country it has never seen has received less attention.

B. SAR and Spectral Water Indices

SAR backscatter from open water is consistently low because smooth water reflects radar energy away from the sensor—a physically reliable signal that generalizes across geographic regions without local calibration [2]. The complication is that dry riverbeds, sand, and smooth roads also produce low backscatter, and radar return varies with incidence angle, soil moisture, and vegetation canopy in ways that differ substantially between regions [14].

NDWI [5] encodes water detection in the Green-NIR ratio, positive for water and negative for most vegetation and soil. MNDWI [6] replaces NIR with SWIR, suppressing bright built-up areas that confuse NDWI. Konapala et al. [11] found that SWIR bands B11 and B12 are among the most useful Sentinel-2 channels for flood mapping; Bai et al. [12] used them in a SAR-optical fusion architecture for distinguishing permanent from temporary floodwater. We extend this by computing NDWI and MNDWI directly as input features and verifying their discriminative value empirically in Section V.

C. Geographic Generalization

Domain shift in remote sensing is well documented. Tuia et al. [1] showed that a model trained on one region encounters different class statistics, spectral distributions, and spatial patterns elsewhere, and performance degrades. For flood mapping this is especially sharp because training data typically come from a small number of flood events, and test deployment happens in the next emergency, wherever it occurs.

Geographically disjoint evaluation has been recommended for remote sensing benchmarks [15], but most flood mapping papers still use random splits or the official Sen1Floods11 partitions designed for consistency rather than geographic separation. This paper builds on that protocol direction and applies it specifically to flood mapping, with full quantitative comparison against random-split results.

III. DATASET AND EVALUATION PROTOCOL

A. Sen1Floods11

Sen1Floods11 [7] contains co-registered Sentinel-1 SAR and Sentinel-2 multispectral imagery with hand-labeled flood masks across 11 flood events spanning six continents. Sentinel-1 provides dual-polarization C-band SAR (VV and VH). Sentinel-2 provides 13 bands, all resampled to 10 m resolution. All chips are 512×512 pixels.

B. Country-Level Split

We reorganize the dataset by country rather than by random index. Training: USA, India, Ghana, Sri Lanka, Spain, Mekong, Pakistan (320 chips). Validation: Bolivia, Nigeria (33 chips). Test: Paraguay, Somalia (93 chips). Paraguay and Somalia represent distinct environmental contexts—tropical riverine lowlands and arid semi-desert respectively—that differ mean-

TABLE I
COUNTRY-LEVEL DATASET STATISTICS.

Split	Chips	Countries	Flood %
Train	320	USA, India, Ghana, Sri Lanka, Spain, Mekong, Pakistan	10.5%
Validation	33	Bolivia, Nigeria	20.3%
Test	93	Paraguay, Somalia	7.9%

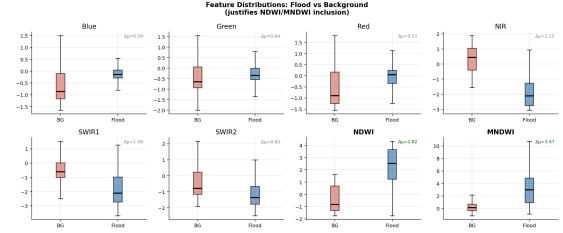


Fig. 1. Feature distributions (flood vs. background) across all eight S2 input channels from 20 training chips. $\Delta\mu$ = absolute mean difference in standard deviations. NDWI and MNDWI (bold) show the strongest class separation.

ingfully from all training countries. Table I shows the resulting statistics.

C. Preprocessing and Feature Engineering

Sentinel-1 VV and VH channels are each z-score normalized per chip: subtract the chip mean, divide by the chip standard deviation plus 10^{-6} . This removes absolute backscatter differences between acquisition geometries and regions while preserving relative within-chip contrast. Without this step, models trained on Indian flood scenes fail to transfer to Somalia because absolute backscatter values shift by several dB across regions even for identical land cover.

Sentinel-2 data are divided by 10000 to convert to approximate surface reflectance, then z-score normalized per band per chip. The eight-channel S2 tensor comprises:

- Blue (B2), Green (B3), Red (B4), NIR (B8): standard spectral bands.
- SWIR1 (B11), SWIR2 (B12): shortwave infrared, sensitive to soil moisture and water content [11], [12].
- NDWI = $(\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR} + \epsilon)$ [5]: positive for water.
- MNDWI = $(\text{Green} - \text{SWIR1}) / (\text{Green} + \text{SWIR1} + \epsilon)$ [6]: suppresses built-up false positives.

Fig. 1 shows per-feature distributions across 20 randomly sampled training chips. NDWI and MNDWI have mean class separations of 2.21 and 2.27 standard deviations between flood and background pixels—the largest of any feature. NIR and SWIR1 also separate well (2.32 and 2.07). Raw Blue, Green, and Red bands separate much less cleanly. For Fusion experiments, the two SAR channels are concatenated with the eight S2 channels to form a 10-channel input.

IV. METHODOLOGY

A. Architectures

Two architectures are evaluated. The first is a standard U-Net [10] trained from scratch: four encoder levels with double-convolution blocks (3×3 conv, BatchNorm, ReLU, repeated twice per level), max-pooling for downsampling, transposed

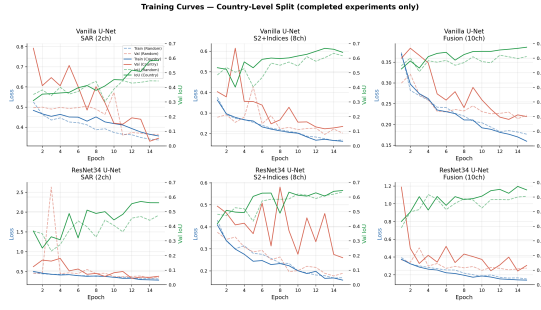


Fig. 2. Training loss and validation IoU across 15 epochs for all twelve configurations. Solid: country split. Dashed: random split. Blue/red: train/val loss (left axis). Green: val IoU (right axis).

convolutions for upsampling, and skip connections at each level. Encoder widths are 64, 128, 256, bottleneck 512. Total parameters: 7.7M. This is the lightweight baseline with no pretraining.

The second is a ResNet34-encoder U-Net [4] implemented via segmentation-models-pytorch, initialized with ImageNet pretrained weights. Encoder: ResNet34 residual blocks. Decoder channels: (256, 128, 64, 32, 16). Total parameters: 24.4M. For inputs beyond three channels, the first convolutional layer is adapted: the first three channels reuse pretrained weights; additional channels use Kaiming uniform initialization. All three modalities—SAR (2ch), S2 (8ch), Fusion (10ch)—therefore receive partial ImageNet weight transfer. Both architectures use identical loss functions, optimizers, and training schedules.

B. Training Details

Loss: Weighted cross-entropy with class weights [1.0, 5.0] for background and flood; ignore-label pixels (value -1) excluded. **Optimizer:** Adam [16], $\text{lr} = 10^{-3}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$. **Schedule:** cosine annealing over 15 epochs. **Batch size:** 4. The checkpoint with the highest validation IoU is used for test evaluation. No data augmentation was applied so that differences between configurations reflect the input data, not augmentation policy.

C. Evaluation

Primary metric: $\text{IoU} = \text{TP} / (\text{TP} + \text{FP} + \text{FN})$, computed over valid pixels only. Secondary metrics: Dice, Precision, Recall, Accuracy. Average Precision (AP) is computed from precision-recall curves at 300 000 randomly subsampled pixels. Country-level IoU statistics use 1 000-iteration bootstrap resampling for 95% confidence intervals.

V. RESULTS

A. Full Results

Table II shows all twelve configurations under both protocols. Random-split IoU exceeds country-split IoU in every row, across both architectures and all modalities, by margins ranging from 6.7 to 26.3 IoU points.

B. How Much Does the Evaluation Protocol Matter?

The gap is large enough to change the interpretation of every configuration. Vanilla U-Net with S2 looks like the best model under random split (IoU 0.727). Under country split it falls to second-worst of the six country-split configurations (IoU

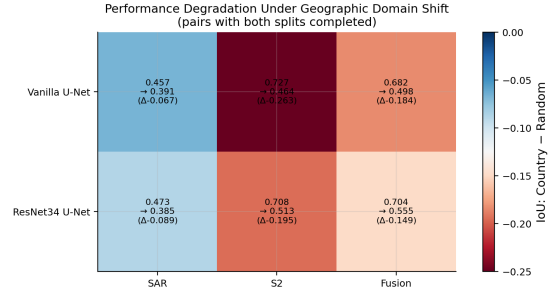


Fig. 3. Performance degradation under geographic domain shift. Each cell shows: random-split IoU → country-split IoU (Δ). Darker red = larger drop. SAR degrades least; S2 degrades most.

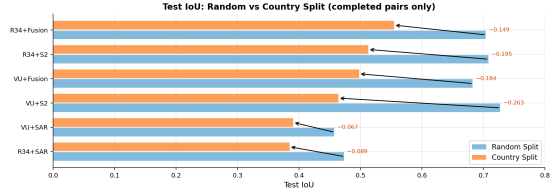


Fig. 4. Test IoU under random split (blue) vs. country split (orange) for all six architecture-modality pairs, sorted by country-split IoU. Arrows show degradation direction and magnitude.

0.464). ResNet34+Fusion, second under random split (IoU 0.704), is the best under country split (IoU 0.555). The ranking of configurations is not stable across protocols.

Fig. 3 shows the degradation for each pair. SAR has the smallest drop: Vanilla U-Net SAR loses 0.067 IoU points (14.7% relative), ResNet34 SAR loses 0.089 (18.8%). S2 degrades most: Vanilla U-Net S2 loses 0.263 (36.2%), ResNet34 S2 loses 0.195 (27.5%). Fusion sits in between. This ordering is consistent across both architectures, suggesting it reflects the modality, not the model.

The physical explanation is direct. Water has near-constant low SAR backscatter regardless of country. Spectral reflectance of water is also stable, but the non-water classes—vegetation, soil, urban surfaces—vary enormously across climates. A model that learned to distinguish water from Ghanaian savanna and Indian rice paddies has not seen Somali scrubland or Paraguayan tropical forest. NDWI and MNDWI reduce this variability by focusing on ratios that stay high for water regardless of region, which is why Fusion consistently outperforms raw S2.

C. Does Pretraining Help?

ResNet34 outperforms Vanilla U-Net on the country split for S2 and Fusion inputs (+0.049 IoU for S2, +0.057 IoU for Fusion), but not for SAR (ResNet34: 0.385 vs. Vanilla: 0.391, a difference well within noise). ImageNet features encode texture and color priors from natural photographs, which partially transfer to multispectral satellite imagery because both share RGB-like channels and spatially coherent boundaries. SAR backscatter shares neither—it has different statistical properties, coherence speckle, and no meaningful color. Pretraining brings no structural advantage for SAR inputs.

The precision-recall curves (Fig. 5) reinforce this. ResNet34+Fusion reaches $\text{AP} = 0.850$ versus $\text{AP} = 0.777$ for Vanilla+Fusion, a 7.3-point gap reflecting better probability

TABLE II

COMPLETE RESULTS ACROSS ALL TWELVE EXPERIMENTAL CONFIGURATIONS. BOLD = BEST VALUE PER METRIC UNDER THE COUNTRY-LEVEL SPLIT.

Split	Architecture	Modality	Val IoU	IoU	Dice	Prec.	Recall	Acc.
Random	Vanilla U-Net	SAR	0.4465	0.4573	0.6276	0.5321	0.7647	0.9200
	Vanilla U-Net	S2	0.6332	0.7272	0.8420	0.8031	0.8850	0.9707
	Vanilla U-Net	Fusion	0.6206	0.6824	0.8112	0.7670	0.8609	0.9647
	ResNet34 U-Net	SAR	0.4759	0.4732	0.6424	0.5513	0.7697	0.9245
	ResNet34 U-Net	S2	0.6348	0.7081	0.8291	0.7640	0.9062	0.9671
	ResNet34 U-Net	Fusion	0.6174	0.7037	0.8261	0.8250	0.8271	0.9693
Country (Ours)	Vanilla U-Net	SAR	0.5865	0.3906	0.5618	0.4665	0.7061	0.9127
	Vanilla U-Net	S2	0.6674	0.4643	0.6341	0.4984	0.8715	0.9203
	Vanilla U-Net	Fusion	0.6752	0.4979	0.6648	0.5446	0.8531	0.9318
	ResNet34 U-Net	SAR	0.5699	0.3846	0.5556	0.4661	0.6875	0.9128
	ResNet34 U-Net	S2	0.6447	0.5128	0.6779	0.5335	0.9295	0.9300
	ResNet34 U-Net	Fusion	0.6729	0.5547	0.7136	0.6016	0.8769	0.9442

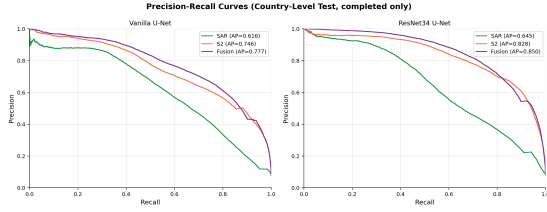


Fig. 5. Precision-recall curves for Vanilla U-Net (left) and ResNet34 U-Net (right) on the country-level test partition. AP = area under the curve. ResNet34+Fusion reaches AP 0.850.

TABLE III

COUNTRY-LEVEL TEST METRICS BY MODALITY, AVERAGED ACROSS ARCHITECTURES. BOLD = BEST PER COLUMN.

Modality	IoU	Dice	Prec.	Recall	Acc.
SAR (2ch)	0.387	0.559	0.466	0.697	0.913
S2+Indices (8ch)	0.489	0.656	0.516	0.901	0.925
Fusion (10ch)	0.526	0.689	0.573	0.865	0.938

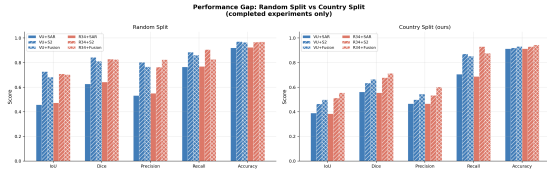


Fig. 6. Metric comparison under random split (left) and country split (right) for all six configurations. Note the consistent score reduction and shift in relative ranking under the country split.

calibration across the full decision threshold range.

D. Modality Comparison

Table III averages across both architectures to isolate the modality effect. SAR gives the highest precision (0.466): when it predicts flood, it is correct more often. The confusion matrices (Fig. 7) confirm fewer false positives on background pixels for SAR models. S2 gets the highest recall (0.901) but misclassifies a large share of background (precision 0.516). Fusion achieves the highest IoU (0.526) by sitting between the two extremes: SAR suppresses spectral false positives; S2 adds recall that SAR misses alone.

E. Country Breakdown: Paraguay vs. Somalia

Table IV reports per-chip IoU by country with bootstrap confidence intervals.

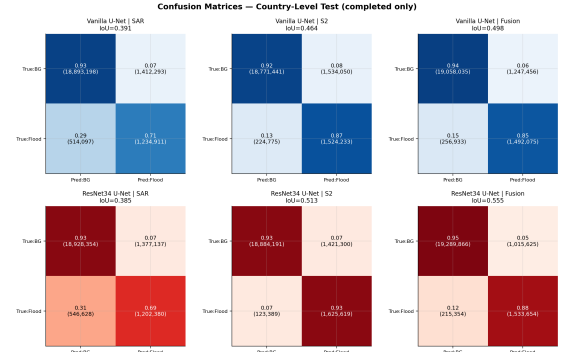


Fig. 7. Normalized confusion matrices for all six configurations on the country-level test partition. Top row (blue): Vanilla U-Net. Bottom row (red): ResNet34 U-Net. Numbers show normalized rates with absolute pixel counts in parentheses.

Paraguay is easier than Somalia across every configuration. The gap is widest for SAR: Vanilla U-Net SAR gives mean IoU 0.325 in Paraguay and 0.134 in Somalia, a $2.4\times$ ratio. Fusion narrows this: ResNet34+Fusion gives 0.393 vs. 0.298 ($1.3\times$). Multimodal fusion reduces country-to-country variance more than any other variable tested.

Somalia's difficulty has a physical basis. It has arid terrain where soil moisture fluctuations and smooth surfaces produce SAR backscatter similar to water. Wet soil in semi-arid regions can also overlap with shallow floodwater in Sentinel-2 spectral space. Somalia also has only 26 test chips, so a handful of challenging scenes have an outsized effect on the mean.

The per-image boxplots (Fig. 9) show this: both countries have low medians with long right tails. Two specific chips—Paraguay_12870 and Paraguay_198534—appear as the worst predictions (IoU = 0.000) across every configuration. The ground truth label is nearly blank, but the imagery contains signatures that resemble water. This is most likely a labeling artefact rather than model failure.

F. Qualitative Analysis

Fig. 8 puts all three modalities side by side on three test scenes—one from Somalia and two from Paraguay—using the Vanilla U-Net. The top row (Somalia_61368) has a blank ground truth label, yet every model predicts flood. The SAR VV image and the Sentinel-2 RGB both contain signatures that look like

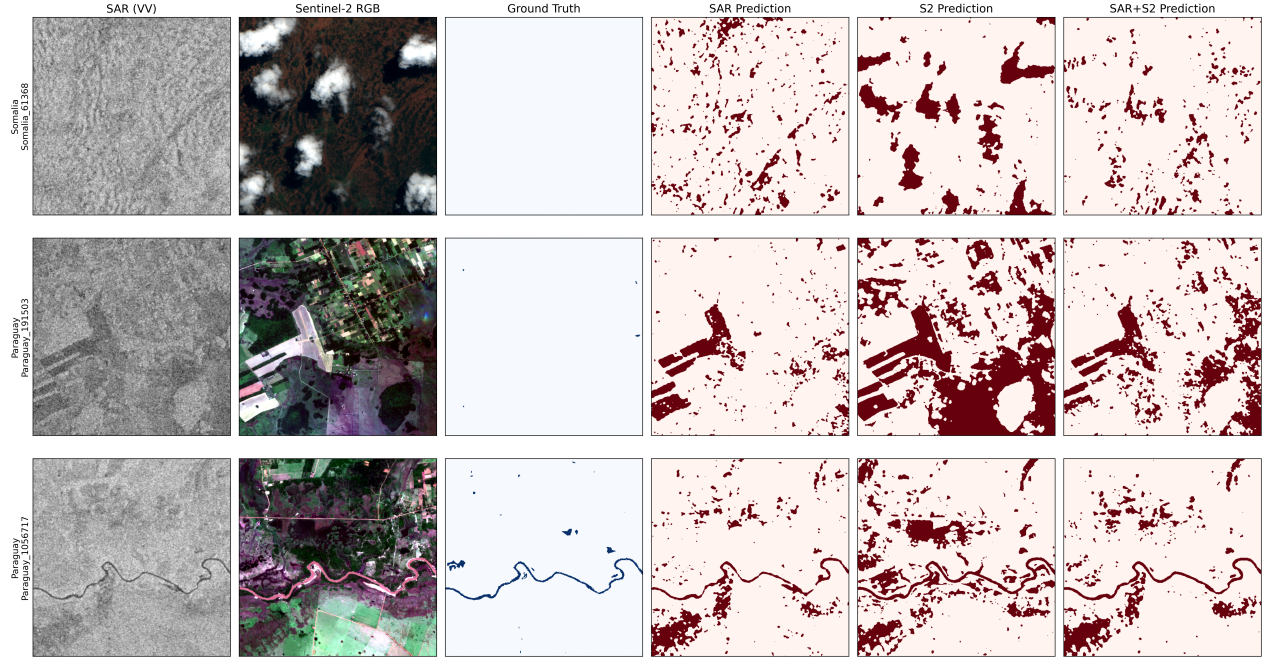


Fig. 8. Modality comparison on three representative test scenes (Vanilla U-Net). Columns: SAR VV, Sentinel-2 RGB, ground truth (blue = flood), SAR prediction, S2 prediction, SAR+S2 Fusion prediction (dark red = flood). Top: Somalia_61368—blank ground truth, false positive predictions across all modalities (labelling artefact). Middle: Paraguay_191503—near-blank label, all models over-predict. Bottom: Paraguay_1056717—partial river channel where Fusion delineates the boundary most cleanly.

TABLE IV
PER-COUNTRY IOU WITH 95% BOOTSTRAP CI (1 000 ITERATIONS).
BOLD = BEST MEAN IOU PER COUNTRY.

Arch.	Mod.	Ctry	N	Mean	95% CI	Median
VU	SAR	Paraguay	67	0.325	[0.255, 0.399]	0.295
		Somalia	26	0.134	[0.071, 0.205]	0.051
	S2	Paraguay	67	0.352	[0.278, 0.425]	0.303
		Somalia	26	0.288	[0.177, 0.418]	0.235
	Fusion	Paraguay	67	0.349	[0.276, 0.419]	0.318
		Somalia	26	0.297	[0.186, 0.414]	0.267
R34	SAR	Paraguay	67	0.342	[0.270, 0.415]	0.362
		Somalia	26	0.147	[0.079, 0.229]	0.065
	S2	Paraguay	67	0.366	[0.291, 0.440]	0.324
		Somalia	26	0.296	[0.178, 0.423]	0.245
	Fusion	Paraguay	67	0.393	[0.324, 0.464]	0.354
		Somalia	26	0.298	[0.187, 0.412]	0.302

water; the hand label simply contains no flood pixels. This is the labelling artefact discussed in the country breakdown, not a model error. The middle row (Paraguay_191503) is a similar case: the ground truth is nearly empty while both SAR and spectral cues push the models toward positive predictions. The bottom row (Paraguay_1056717) shows a partial river channel in the ground truth. Here the Fusion prediction traces the channel more cleanly than SAR or S2 alone—the S2 model over-segments into surrounding fields, while the SAR model under-detects the thinner tributaries.

Figs. 10–13 show the best and worst predictions for each architecture-modality combination. In the best cases (Paraguay_790830, Paraguay_896458, Paraguay_989230, IoU up to 0.950), all models trace major river corridors with precise boundaries. ResNet34+Fusion produces the cleanest delineation,

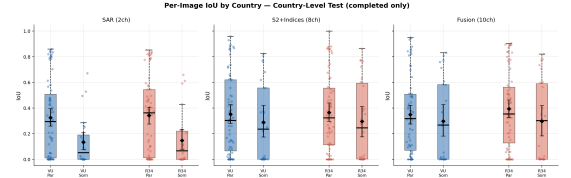


Fig. 9. Per-image IoU distributions by country for all six configurations. Jittered points show individual chip scores. Diamonds show mean with 95% bootstrap confidence intervals.

consistent with its highest precision. Three failure patterns recur: cloud shadow in the S2 RGB triggers false positives in S2 and Fusion models; bright agricultural fields with high soil moisture produce ambiguous SAR returns; urban areas with double-bounce scattering mask the low-backscatter water signal.

VI. DISCUSSION

The central result is straightforward: the protocol you use to evaluate a flood mapping model changes its apparent ranking, and the change is large enough to matter for deployment decisions. Vanilla U-Net with Sentinel-2 is the best model under random split. It is not the best model under country split. Picking the wrong evaluation protocol means deploying the wrong model.

The reason random splits inflate performance is geographic autocorrelation. Chips from the same flood event in the same country share land cover, acquisition geometry, and backscatter statistics. A model trained on 70% of Bolivia can predict the other 30% with much less adaptation than it needs for Paraguay. This is not a design flaw in prior papers—random splits were

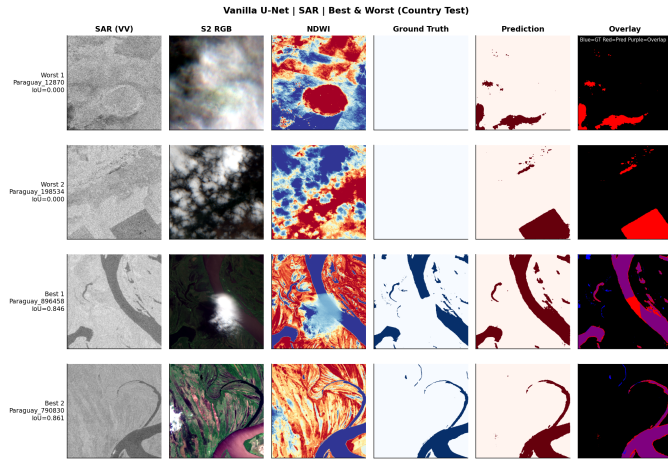


Fig. 10. Vanilla U-Net, SAR: worst 2 and best 2 predictions. Columns: SAR VV, S2 RGB, NDWI, ground truth (blue = flood), prediction (dark red), overlay (blue = GT only, red = pred only, purple = overlap).

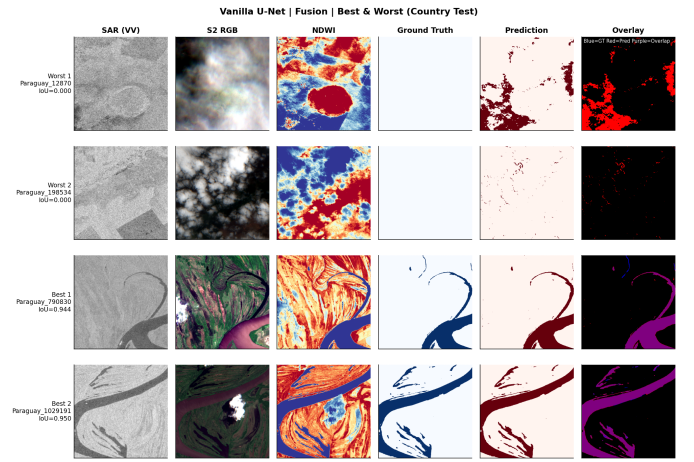


Fig. 11. Vanilla U-Net, Fusion: worst 2 and best 2 predictions. Best cases reach IoU 0.944 and 0.950 on Paraguay river scenes.

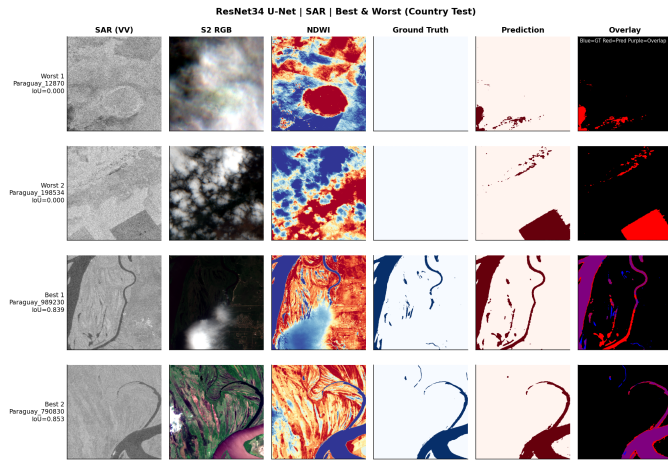


Fig. 12. ResNet34 U-Net, SAR: worst 2 and best 2 predictions.

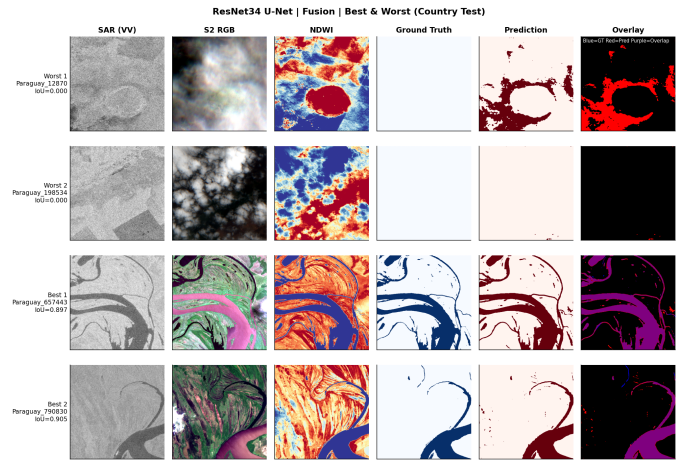


Fig. 13. ResNet34 U-Net, Fusion: worst 2 and best 2 predictions. Best cases show precise river boundary delineation at IoU 0.897 and 0.905.

a reasonable starting point—but they have led to benchmarks where method rankings are unstable under realistic deployment conditions.

The finding that SAR generalizes better than Sentinel-2 reflects physics, not model design. Water has near-constant low radar backscatter regardless of region. Optical reflectance of water is stable too, but surrounding land cover varies enormously between tropical forest, savanna, and semi-desert. NDWI and MNDWI reduce this variability by encoding ratios that stay high for water regardless of region.

The fact that ResNet34 pretraining helps for S2 and Fusion but not SAR points to a clear follow-on experiment: SAR-specific pretraining on large Sentinel-1 archives. Self-supervised methods such as masked autoencoding on unlabeled Sentinel-1 data could give the SAR encoder the same head start that ImageNet gives the S2 encoder.

Three limitations deserve acknowledgment. First, two test countries is a thin sample. Paraguay and Somalia cover a useful

environmental range, but conclusions about Mediterranean or central Asian environments would require those regions in the test set. Second, no data augmentation was applied, deliberately excluded to isolate modality and protocol effects, but production systems would benefit from it. Third, early-fusion concatenation is the simplest possible SAR-Sentinel-2 combination. Dual-stream encoders [13], cross-attention fusion, or modality-specific normalization layers may extract more.

VII. CONCLUSION

The standard practice of evaluating flood mapping models on random train-test splits produces IoU numbers that do not generalize. Across twelve configurations, the difference between random-split and country-split IoU ranges from 0.067 to 0.263 points, and the ranking of configurations changes substantially between the two protocols.

SAR generalizes better across countries than optical imagery, with the smallest absolute degradation under geographic transfer. Adding Sentinel-2 with NDWI and MNDWI improves over

raw S2 and reduces the IoU gap between Paraguay and Somalia. ResNet34 pretraining helps for optical and multimodal inputs but provides no consistent advantage for SAR-only configurations. ResNet34+Fusion is the strongest country-level configuration, reaching IoU 0.555 and AP 0.850. Somalia is harder than Paraguay in every experiment, with SAR-only models showing a $2.4\times$ country ratio that narrows to $1.3\times$ for ResNet34+Fusion.

The practical recommendation is to evaluate flood mapping models on geographically disjoint splits before reporting results. The protocol introduced here—train on seven countries, validate on two, test on two held-out countries with distinct environments—is a concrete way to do that with Sen1Floods11.

The most direct next experiment is SAR-specific pretraining: a ResNet34 encoder pretrained on large unlabeled Sentinel-1 archives before fine-tuning on Sen1Floods11 could provide for SAR the same generalization benefit that ImageNet provides for optical inputs.

REFERENCES

- [1] D. Tuia, C. Persello, and L. Bruzzone, "Domain adaptation for the classification of remote sensing data: An overview of recent advances," *IEEE geoscience and remote sensing magazine*, vol. 4, no. 2, pp. 41–57, 2016.
- [2] D. Amitrano, G. Di Martino, A. Iodice, D. Riccio, and G. Ruello, "Unsupervised rapid flood mapping using sentinel-1 grd sar images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 56, no. 6, pp. 3290–3299, 2018.
- [3] M. Wieland and S. Martinis, "A modular processing chain for automated flood monitoring from multi-spectral satellite data," *Remote Sensing*, vol. 11, no. 19, p. 2330, 2019.
- [4] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.
- [5] S. K. McFeeters, "The use of the normalized difference water index (ndwi) in the delineation of open water features," *International journal of remote sensing*, vol. 17, no. 7, pp. 1425–1432, 1996.
- [6] H. Xu, "Modification of normalised difference water index (ndwi) to enhance open water features in remotely sensed imagery," *International journal of remote sensing*, vol. 27, no. 14, pp. 3025–3033, 2006.
- [7] D. Bonafilia, B. Tellman, T. Anderson, and E. Issenberg, "Sen1floods11: A georeferenced dataset to train and test deep learning flood algorithms for sentinel-1," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops*, 2020, pp. 210–211.
- [8] L. Landuyt, A. Van Wesemael, G. J.-P. Schumann, R. Hostache, N. E. Verhoest, and F. M. Van Coillie, "Flood mapping based on synthetic aperture radar: An assessment of established approaches," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, no. 2, pp. 722–739, 2018.
- [9] J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 3431–3440.
- [10] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *International Conference on Medical image computing and computer-assisted intervention*. Springer, 2015, pp. 234–241.
- [11] G. Konapala, S. V. Kumar, and S. Khalique Ahmad, "Exploring sentinel-1 and sentinel-2 diversity for flood inundation mapping using deep learning," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 180, pp. 163–173, 2021. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0924271621002227>
- [12] Y. Bai, W. Wu, Z. Yang, J. Yu, B. Zhao, X. Liu, H. Yang, E. Mas, and S. Koshimura, "Enhancement of detecting permanent water and temporary water in flood disasters by fusing sentinel-1 and sentinel-2 imagery using deep learning algorithms: Demonstration of sen1floods11 benchmark datasets," *Remote Sensing*, vol. 13, no. 11, p. 2220, 2021.
- [13] R. Yadav, A. Nascetti, and Y. Ban, "Attentive dual stream siamese u-net for flood detection on multi-temporal sentinel-1 data," in *IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium*. IEEE, 2022, pp. 5222–5225.
- [14] X. X. Zhu, S. Montazeri, M. Ali, Y. Hua, Y. Wang, L. Mou, Y. Shi, F. Xu, and R. Bamler, "Deep learning meets sar: Concepts, models, pitfalls, and perspectives," *IEEE Geoscience and Remote Sensing Magazine*, vol. 9, no. 4, pp. 143–172, 2021.
- [15] G. I. Drakonakis, G. Tsagkatakis, K. Fotiadou, and P. Tsakalides, "Ombrianet—supervised flood mapping via convolutional neural networks using multitemporal sentinel-1 and sentinel-2 data fusion," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 2341–2356, 2022.
- [16] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014, available: <https://arxiv.org/abs/1412.6980>.