Exploring the capability of Noah-MP LSM in predicting fractional flooded area using U-Net architecture

COLLEGE OF SCIENCE
Hydrology & Atmospheric Sciences

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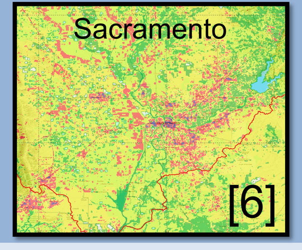
1. Introduction and Motivation

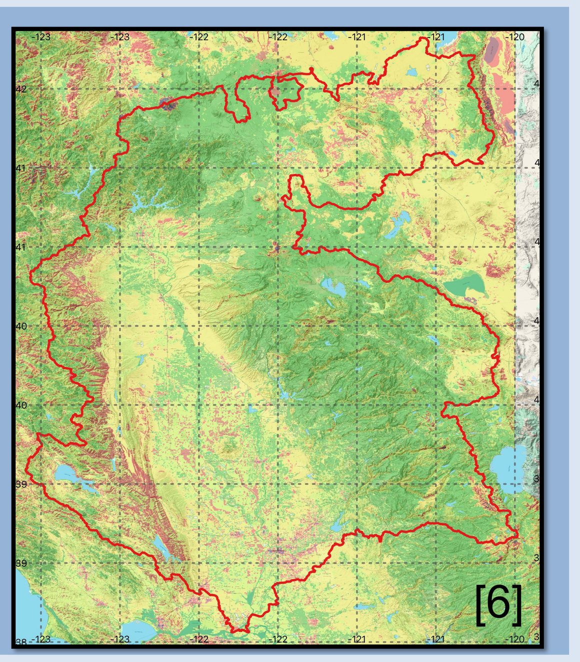
- Flooding is one of the costliest natural hazards [1, 7]


- Flood inundation mapping (FIM) can be achieved using satellite imagery and modeling techniques [2]
- Spatial and temporal limitations of satellite imagery create significant FIM challenges [3]
- Combining continuous output for several hydrologic variables from the Noah-MP land surface model (LSM) with machine learning (ML) can be used to supplement FIM efforts
- Studies show that an approach using a U-Net Deep Learning framework is effective at identifying surface water extent

2. Study Area

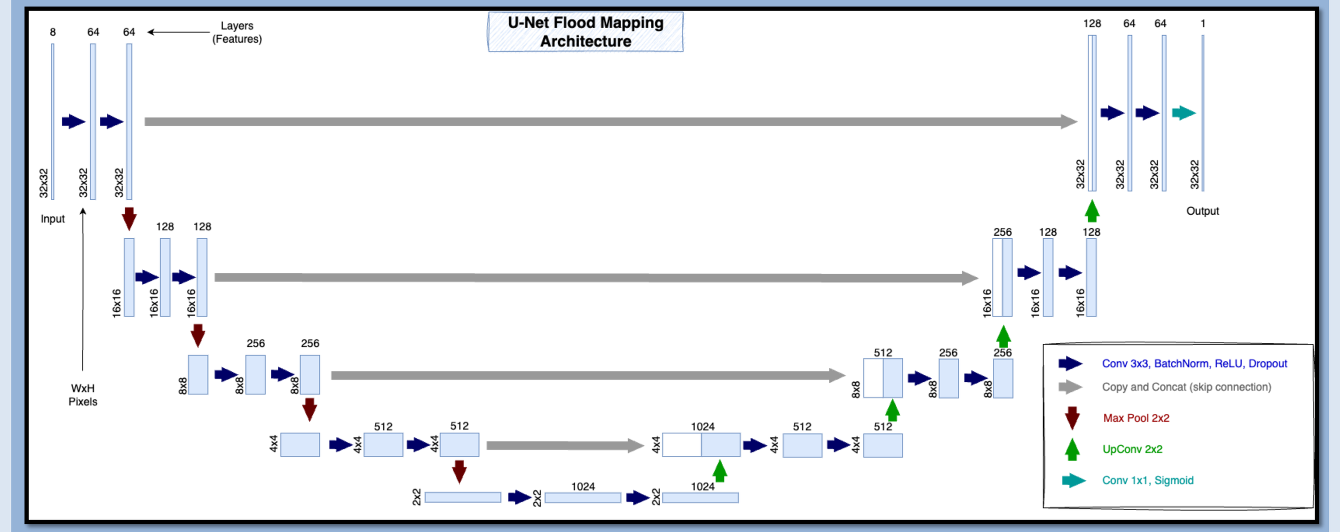
- Sacramento Valley Watershed
  - 16,740,330 acres
  - 67,746 sq. km
- NOAA Flash Flood Potential Index
  - Low
  - Moderate
  - High
  - Very High





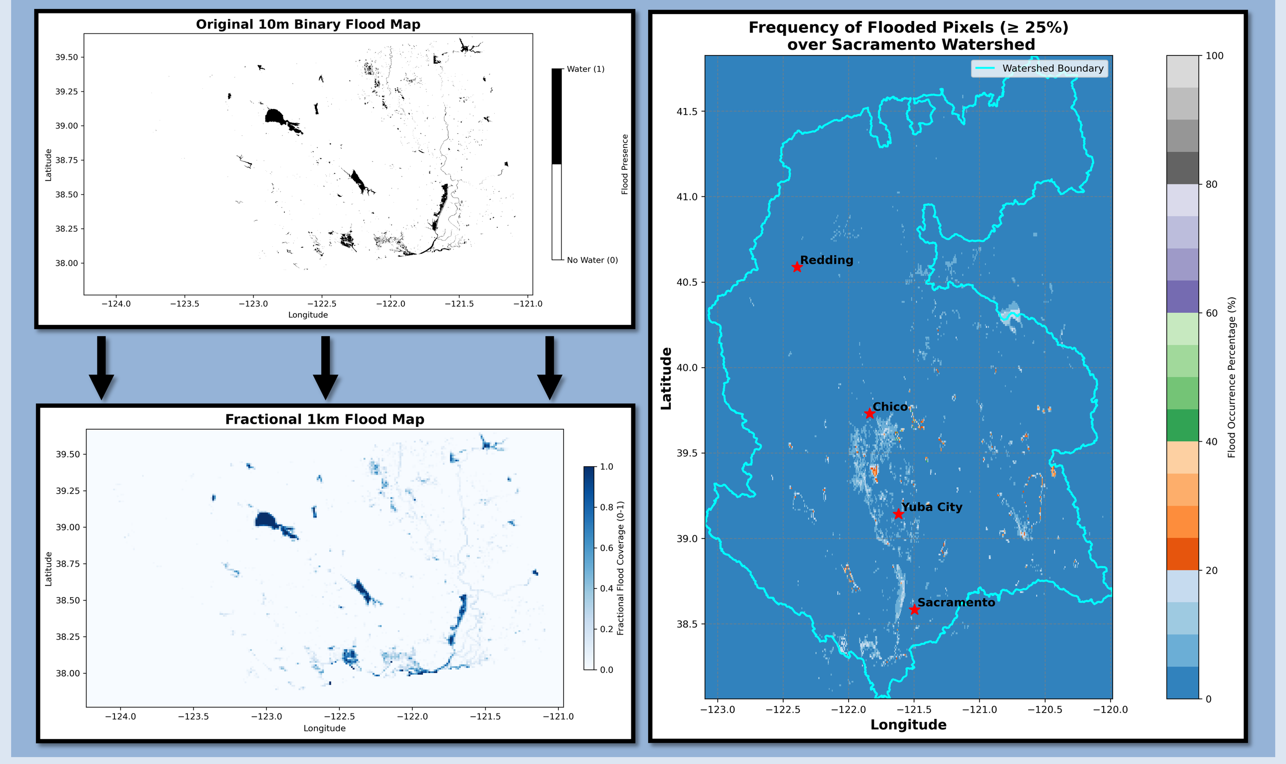
3. Methodology

- Target flood maps from Radar Produced Inundation Diary (RAPID) [4]
- Noah-MP dynamic prediction and terrain features as inputs
- Reproject and scale all data to 1km spatial resolution
- Process all data into smaller tiles of 32x32 pixels, normalize based on the distribution of each chosen variable for input
- U-Net architecture [5]
  - Modify and train to predict fractional water values
  - Batch Normalization
  - ReLU Activation, Final Layer: Sigmoid
  - Dropout: 15% of neurons deactivated during training
- Input: 8 channels (32x32) → Output: 1 channel (32x32)



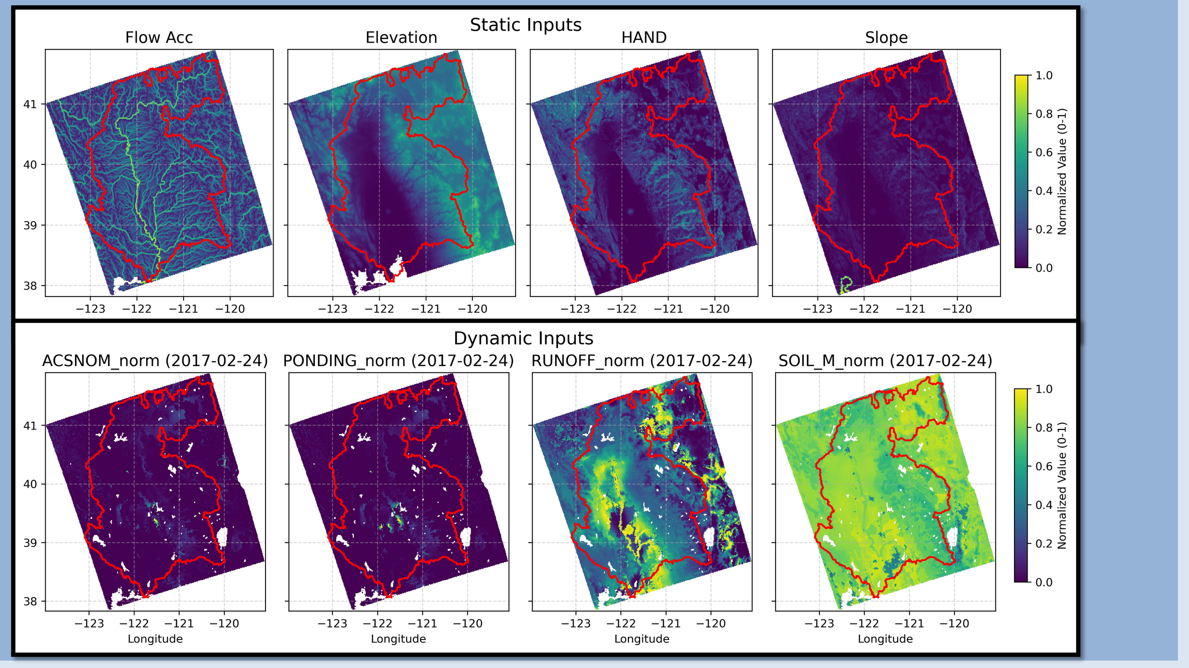
4. Target Flood Maps

- RAPID Near Real Time Flood Inundation Archive [4]
  - Maps created from Sentinel-1 imagery
- 10m flood maps rescaled to fractional 1km maps
- 31 flood events from 2017-2019 over the study area



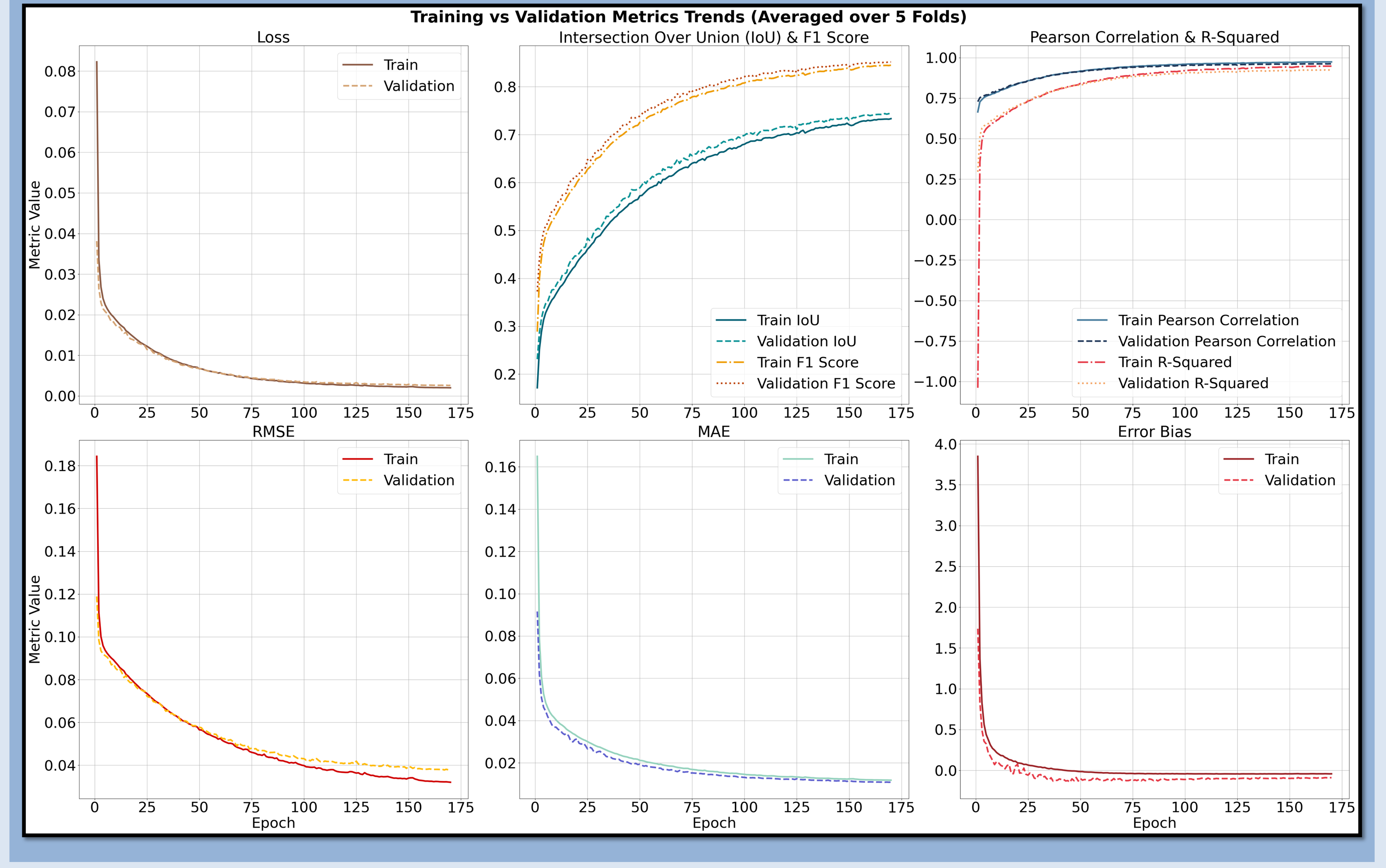
5. Inputs and Dataset

- Static: elevation, slope, Height Above Nearest Drainage (HAND), HydroSHEDS flow accumulation
- Dynamic: LSM output for soil moisture, surface-subsurface runoff, ponding, and snowmelt, aggregated daily
- Processing Strategy: 75% overlap, ignore "dry" pixels
- 4,780 samples, each with 8 inputs and 1 target flood map



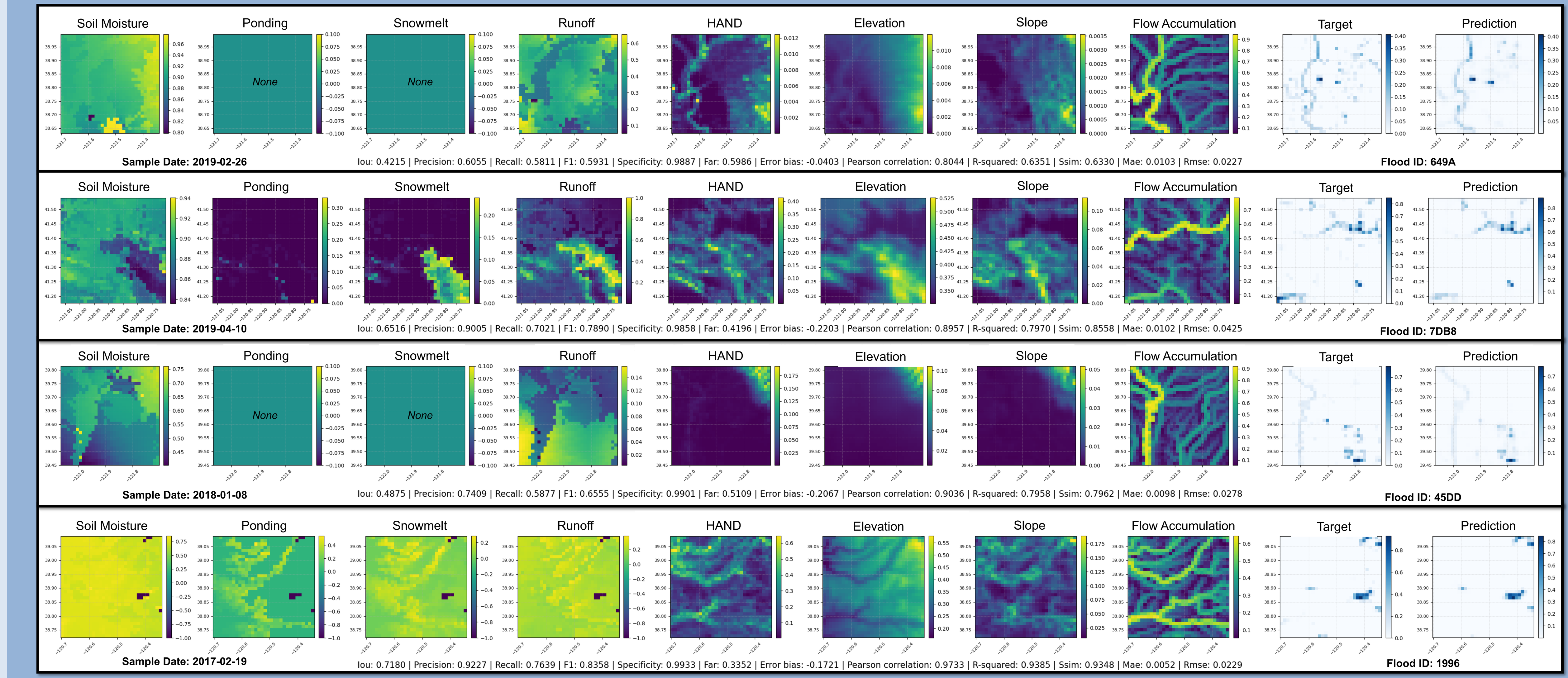
6. Model Training and Validation

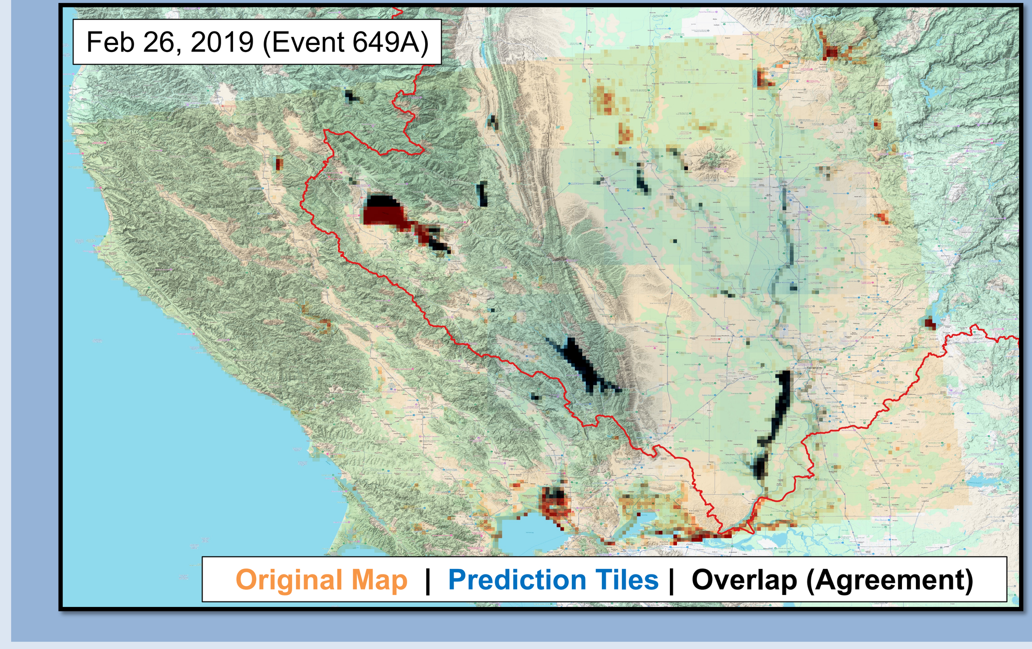
- K-Fold Cross-Validation with 5 folds (80/20 split); batch size 32
- Set a max of 250 epochs with early stopping sensitive to RMSE
- LR Scheduler: reduce by 0.5 from after 10 stagnant epochs
- Custom Weighted Huber Loss Function
- Training Time: 3 h, 1 m, 16 s using one Tesla P100 GPU

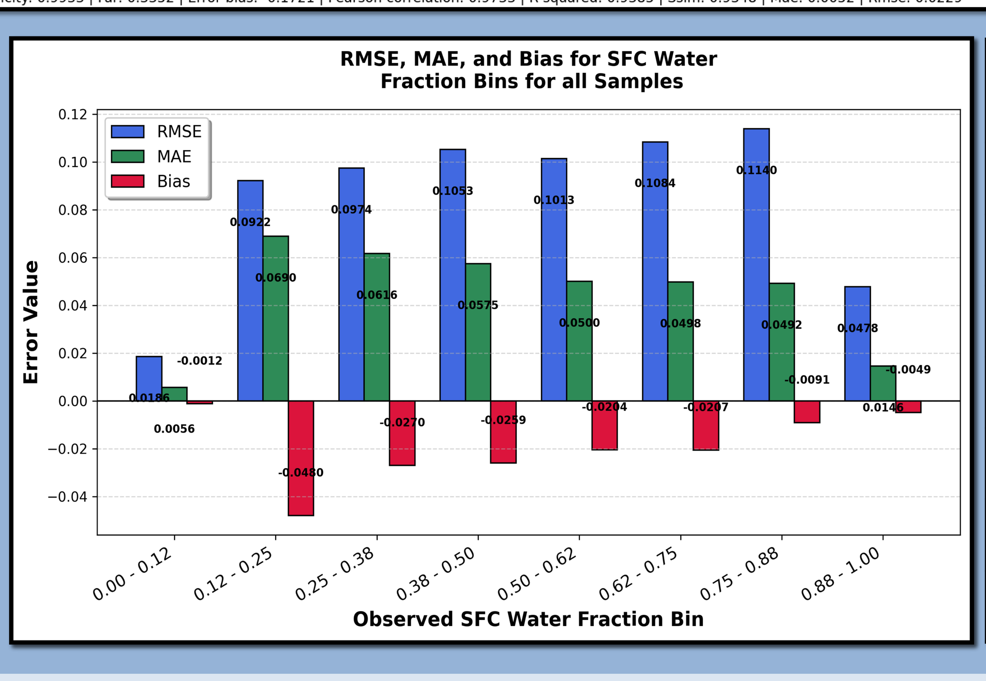


7. Test Results and Predictions

- Test Set = 15% of samples (717) held out from cross-validation



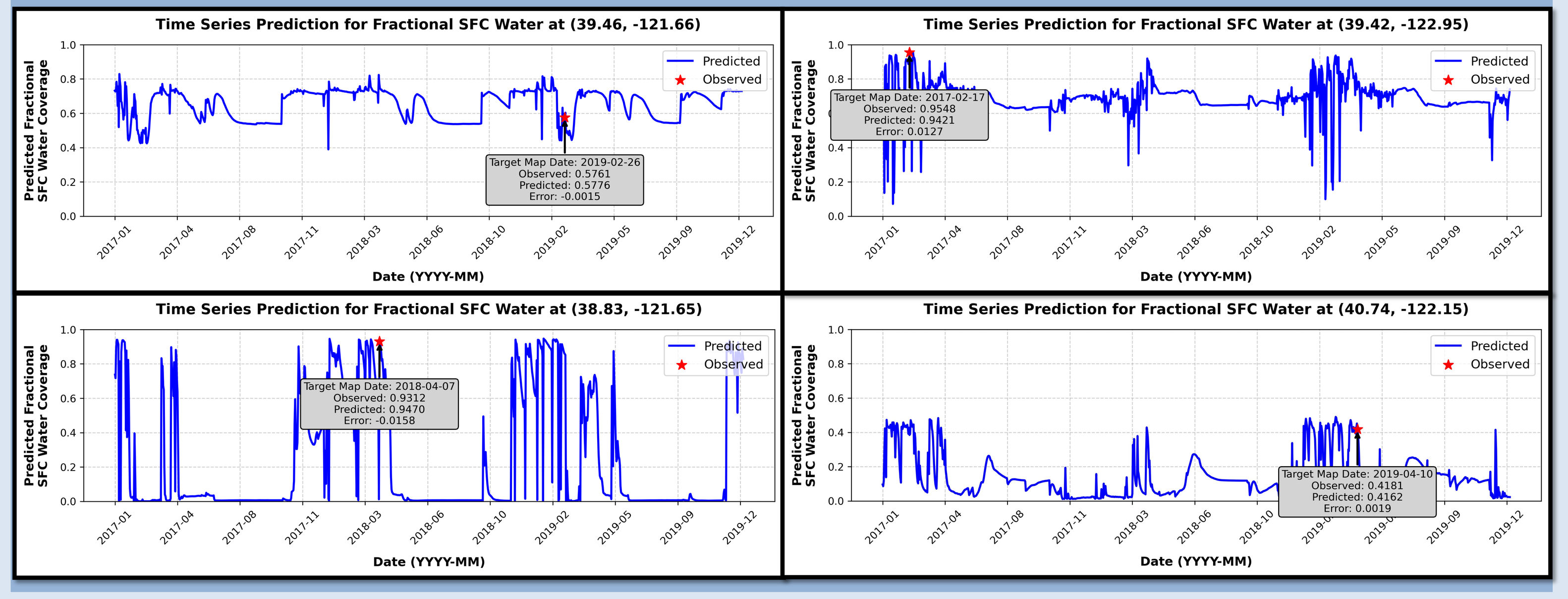




Metrics	Avg Value		
	Train	Val	Test
Intersection over Union	0.731	0.742	0.741
F1 Score	0.844	0.851	0.850
Error Bias	-0.042	-0.092	-0.094
MAE	0.012	0.011	0.011
RMSE	0.032	0.039	0.037
Pearson Correlation	0.973	0.961	0.962
R-Squared	0.947	0.921	0.926

8. Conclusion & Future Work

- Noah-MP can be effective at making reasonable predictions of potential surface flood water using U-Net model architecture
- The proposed method enables continuous flood monitoring and prediction with accuracies comparable to airborne synthetic aperture radar observations
- Multi-year training data improves predictions by capturing diverse flood characteristics
- Train the model on additional watersheds with available target maps to improve generalization and robustness



References

- [1] Jonkman and Vrijling, "Loss of Life Due to Floods." (2008)
- [2] Bentivoglio et al., "Deep Learning Methods for Flood Mapping." (2021)
- [3] Frame et al., "Rapid Inundation Mapping Using the US National Water Model, Satellite Observations, and a Convolutional Neural Network." (2024)
- [4] Yang et al., "A High-Resolution Flood Inundation Archive (2016–the Present) from Sentinel-1 SAR Imagery over CONUS." (2019)
- [5] Ronneberger, Fischer, and Brox, "U-Net." (2015)
- [6] https://www.arcgis.com/home/item.html?id=05a88ca5b34c47c6b9487ac923ba57ba
- [7] https://sacoes.saccounty.gov/Documents/2017%20Annual%20Report.FINAL.pdf