



Evaluation of Computer Vision Based Flood Mapping Using High Resolution Satellite Imagery

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Flood Modeling with Traditional Remote Sensing

- There is an uptick in floods in US both in frequency and spatial extent [1-3]
- Rapid, accurate, and automated modeling of flood affected areas crucial in disaster response
- Spatial and temporal resolution of satellite imagery are critical factors which determine effectiveness of flood prediction
- Traditional remote sensing methods for flood modeling are well established
→ data processing can be slow, require in-depth domain knowledge, depend on sensor type

Rapid flood modeling with traditional remote sensing methods can be challenging

Machine Learning Based Flood Mapping

- Can substitute traditional modeling methods
- Relies on pixel based detection of flood and non-flood regions
- When combined with high resolution satellite imagery can be trained to accurately predict flood extent
- Do not rely on additional data, fewer processing steps, faster
- Can be automated, fast, and accurate
- Commonly used supervised ML methods: RF, SVM, MLC, CNN etc.

ML-based techniques can provide faster, simplified, accurate flood prediction

Previous Work

- Assessed computer vision-based flood prediction with HiRes Planet imagery
 - ML model trained on single representative flood case
 - Demonstrated reasonable accuracy in predicting flood extent
- Limitations
 - Model trained on a single flood event
 - Rigorous assessment of results required

Objectives

- Evaluation of an updated ML model with spatially and temporally varying training data samples
- Validate model based on multiple independent flood events
- Present accuracy assessment results (ML and traditional RS)
- Demonstrate advantages of computer vision-based workflow as an alternative to traditional remote sensing techniques for flood mapping.

Analysis Workflow



- Seven global flood events
- Methods to identify flood extent
- Generate flood extent masks
- Generate training dataset
- Train the model
- Tune model parameters
- Run the model on test datasets
- Compare predicted region with traditional flood mask
- Calculate Intersection over Union (IoU)

Use Case: Global Flood Events

United States



Europe



Australia



- We consider ten flood events
 - global, spatio-temporally diverse
 - between 2017 - 2023
- Multispectral satellite imagery from Planet Labs at 3m spatial resolution

Input Data

Pre-processing

Model Training

Flood Prediction

Use Case: Global Flood Events

Location	Before Event Date	After Event Date	Event Type	Area (km ²)
Colusa, California	November 16, 2016	February 11, 2017	Training	326.8
Gilroy, California	December 23, 2022	January 18, 2023	Training	27.3
Houston, Texas	May 24, 2017	August 31, 2017	Training	243.8
Kingscliff, Australia	February 9, 2022	March 1, 2022	Training	130.3
Manville, New Jersey	August 25, 2021	September 2, 2021	Training	171.3
Richford, Vermont	October 21, 2019	November 2, 2019	Training	8.5
Windsor, Australia	March 3, 2021	March 23, 2021	Training	120.2
Palamas, Greece	August 11, 2023	September 8, 2023	Testing	49.1
Roermond, Netherlands (AOI 1)	June 14, 2021	July 17, 2017	Testing	25.6
Roermond, Netherlands (AOI 2)	June 14, 2021	July 17, 2017	Testing	TBD

Input Data

Pre-processing

Model Training

Flood Prediction

Imagery Data

True color image Manville, NJ before and after Ida

- PlanetScope PSScene GeoTIFF Imagery
 - Orthorectified
 - 3 m spatial resolution, near-daily coverage
 - 4 band multispectral (R, G, B, NIR)
 - Radiometrically and geometrically calibrated
 - 16 bit scaled radiance
- Microsoft Building Footprints



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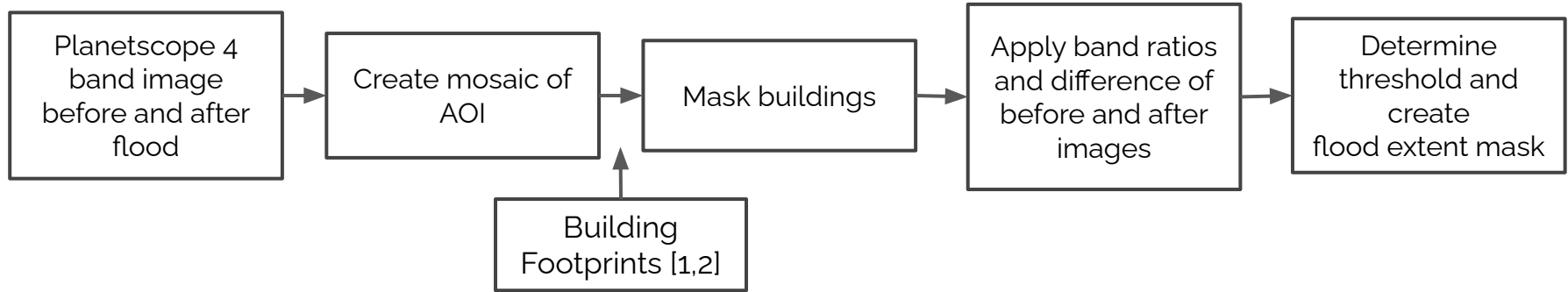
Input Data

Pre-processing

Model Training

Flood Prediction

Data Preprocessing Workflow



[1] <https://www.microsoft.com/en-us/maps/building-footprints>

[2] Not available for Europe yet

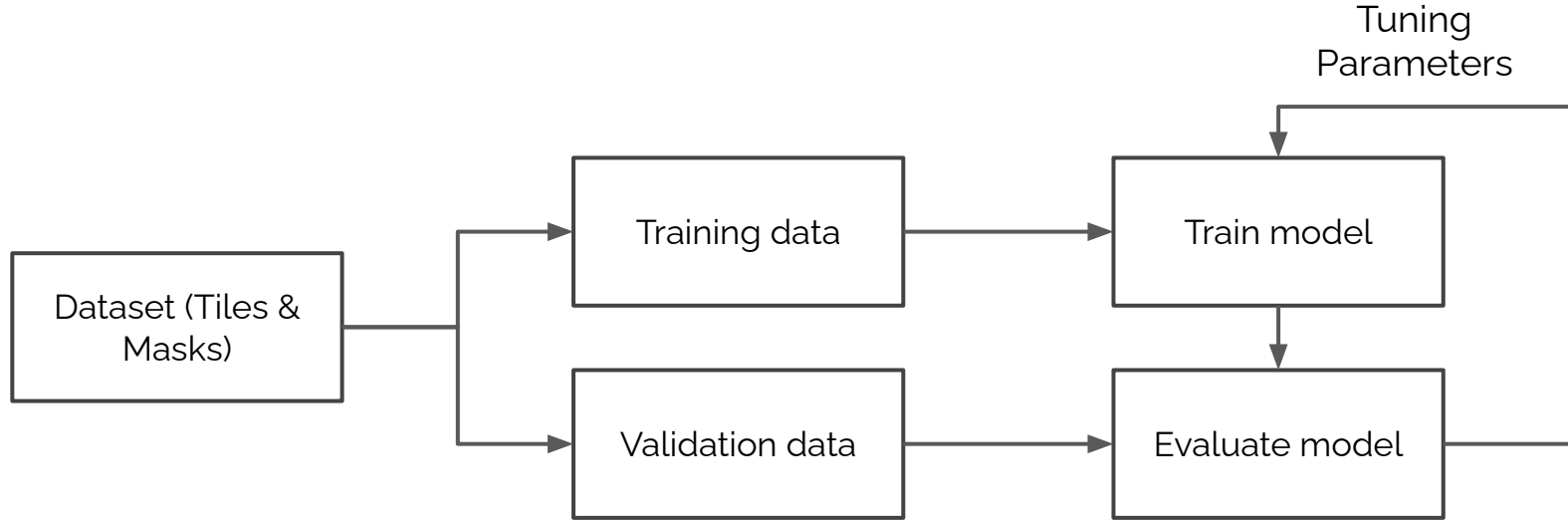
Input Data

Pre-processing

Model Training

Flood Prediction

ML Model Training



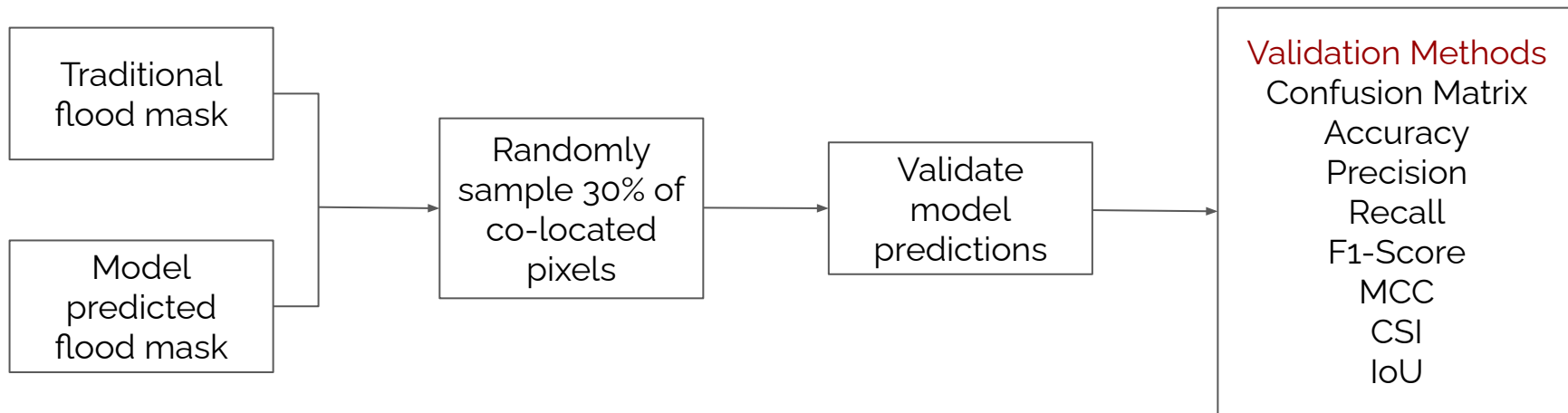
Input Data

Pre-processing

Model Training

Flood Prediction

Accuracy Assessment



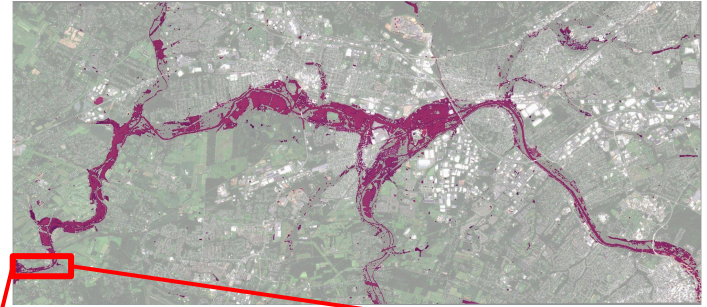
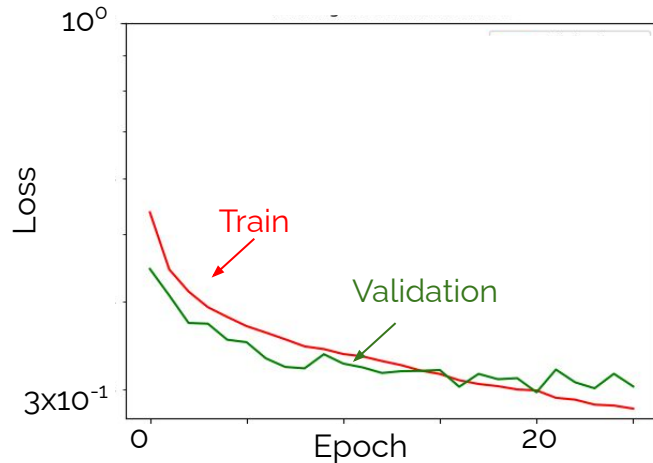
MCC = Matthew's Correlation Coefficient

CSI = Critical Skill Index

IoU = Intersection over Union

Model Training

- Create flood mask using traditional remote sensing techniques
- Generate subsamples of input tiles and mask
- Augment base subsamples that contain flood
- Train model
 - CNN based deep learning model (U-Net)
 - Apple M1 Mac, 32 GB RAM, ~2.5 hours



Base images



Flood region

Flood mask



128

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Input Data

Pre-processing

Model Training

Flood Prediction

Results: Predicted Flood Masks

Tipton

Flood RGB composite



Unet mask



Reference mask



Greece AOI 1



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Input Data

Pre-processing

Model Training

Flood Prediction

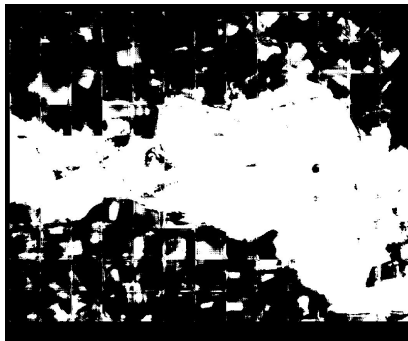
Results: Predicted Flood Masks

Flood RGB composite

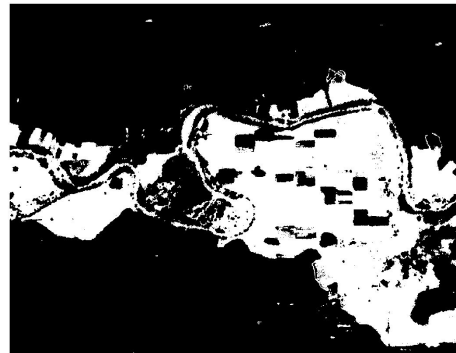


Greece AOI 2

Unet mask



Reference mask



Roermond AOI 1



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Input Data

Pre-processing

Model Training

Flood Prediction

Results: Accuracy Assessment

	Traditional Remote Sensing				
Test case	Accuracy	MCC	CSI	User Accuracy	Producer Accuracy
Tipton	0.87	0.74	0.71	0.73	0.96
Greece AOI 1	0.86	0.67	0.56	0.95	0.58
Greece AOI 2	0.78	0.62	0.56	1	0.56
Roermond AOI 1	0.85	0.65	0.62	0.79	0.74

ML				
precision	recall	f1-score	IoU	support
0.97	0.67	0.8	0.66	1642314
0.59	0.96	0.73	0.57	582810
0.6	1	0.75	0.59	654604
0.76	0.81	0.79	0.64	771103

Input Data

Pre-processing

Model Training

Flood Prediction

Summary and Conclusions

Motivation and Objectives

- Flood modeling using tradition remote sensing → challenging
- High resolution satellite imagery → accurate flood prediction
- Assess computer vision-based flood prediction with HiRes Planet imagery

Computer Vision Based Flood Mapping

- Reasonable accuracy in predicting flood extent
- Highly scalable

Limitations

- Sensitivity to radiometric issues
- False positives near agricultural fields

Thank you.

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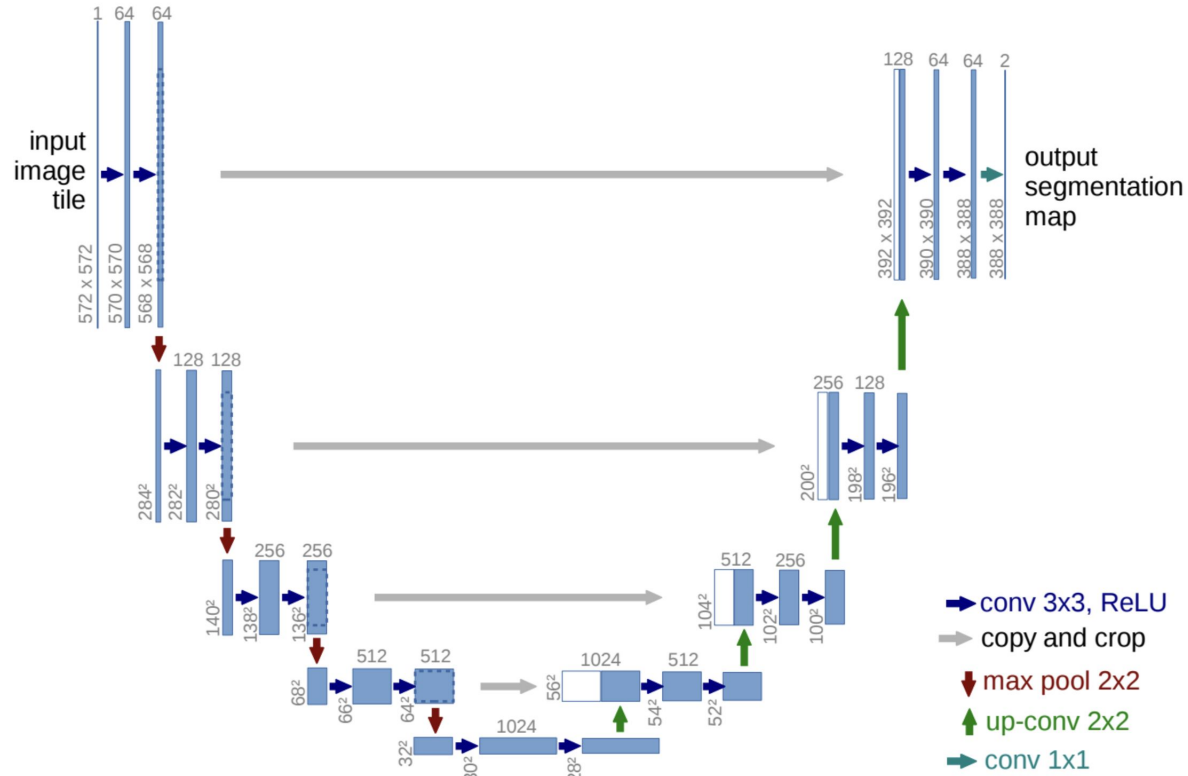
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Backup slides

Unet



Generating Flood Extent Masks



Before Event True Color

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- Flood extent overlaid on true color base image
- Flood extent determined using traditional remote sensing techniques

Input Data

Pre-processing

Model Training

Flood Prediction

Generating Flood Extent Masks



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Input Data

Pre-processing

Model Training

Flood Prediction

Kingscliff, AU

Before

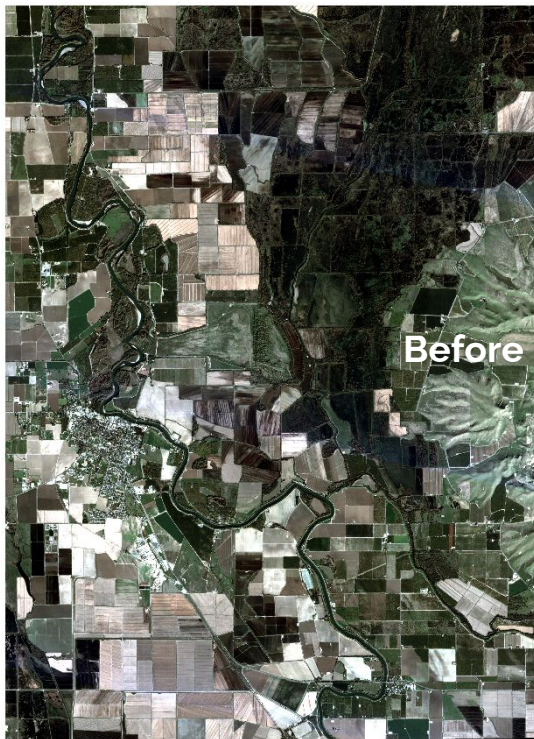


After



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Colusa, CA



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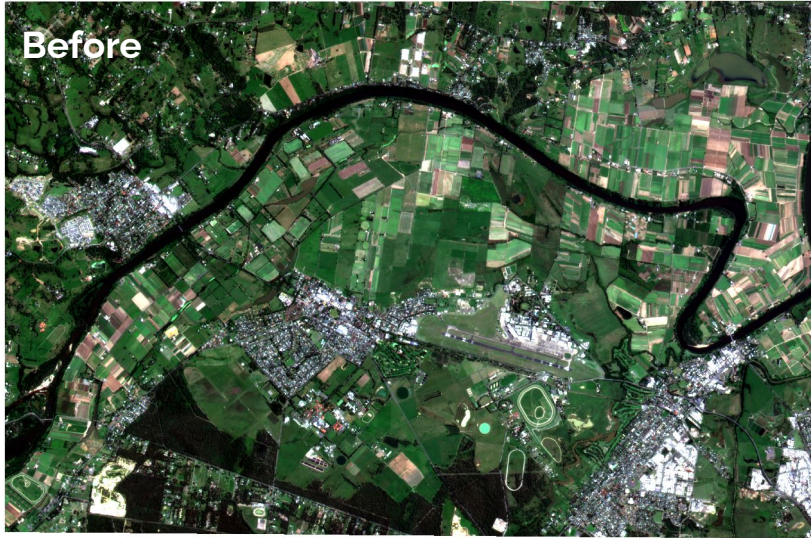
Gilroy, CA



Vermont



Windsor, AU



Houston, TX

