# Extraction of Waterways from Remote Sensing Imagery using Deep Learning based Semantic Segmentation

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Network Systems and Advanced Computing
Computing for Global Challenges

## Background

### Remote Sensing and Agriculture

- Data regarding farms, fields, and irrigation systems is hard to collect
- Gathering information from satellite images instead of surveys results in less time spent obtaining data

### Waterway Extraction

- Creating a map of how water flows throughout a region can greatly help with optimal distribution of water
- These maps can be used to identify each farm's water access point, where they draw water from

### Impact

- Unauthorized water abstraction can be quite problematic
- Difficult to monitor and regulate water usage, usually rely on self reporting[1]
- In times of drought, there is not enough water for all the farms, and farmers may illegally take water so that their crops do not die
- Satellite surveillance of waterways can help address this

## Data

### Study Area

- The area of interest for this project is Central Washington State
- Despite being a desert, this region is the most productive agricultural region in Washington, and one of the top producers of apples in the world[2]
- The region's agricultural success is reliant on its well-designed and extensive irrigation systems (canals, reservoirs, etc.)

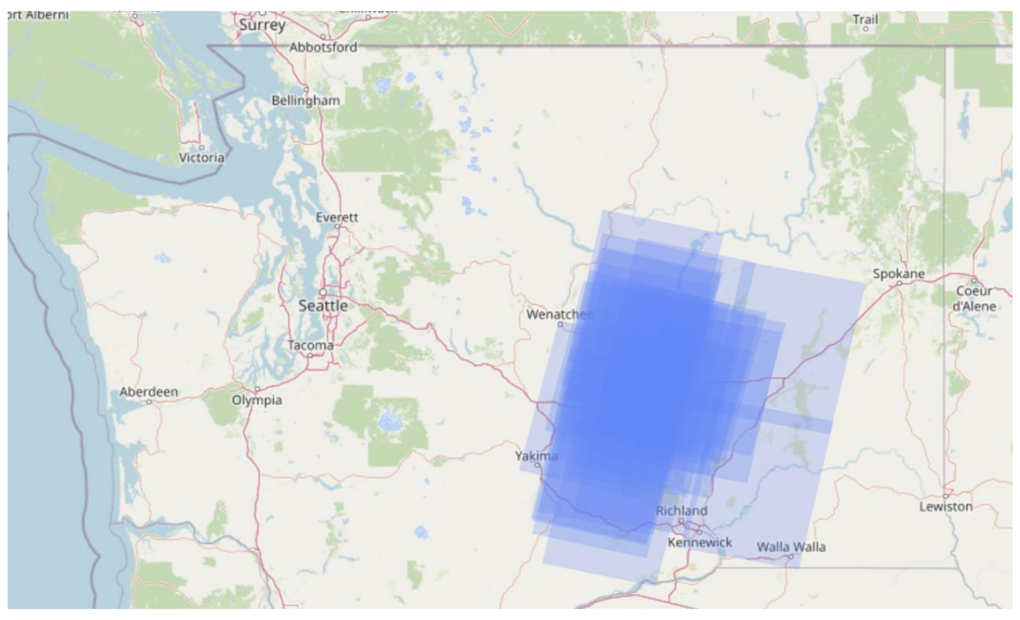

*Figure 1. Satellite Image Coverage*

### RapidEye Satellite Imagery

- Constellation of 5 satellites launched in 2009 and remained active for 10 years until 2019
- Collected 5 bands of data (Blue, Green, Red, Red-Edge, Near-Infrared)[3]
- Utilized 29 satellite images from over 10 years, covering over 124,000 square kilometers total
- Georeferenced using Rational Polynomial Coefficients (RPC)

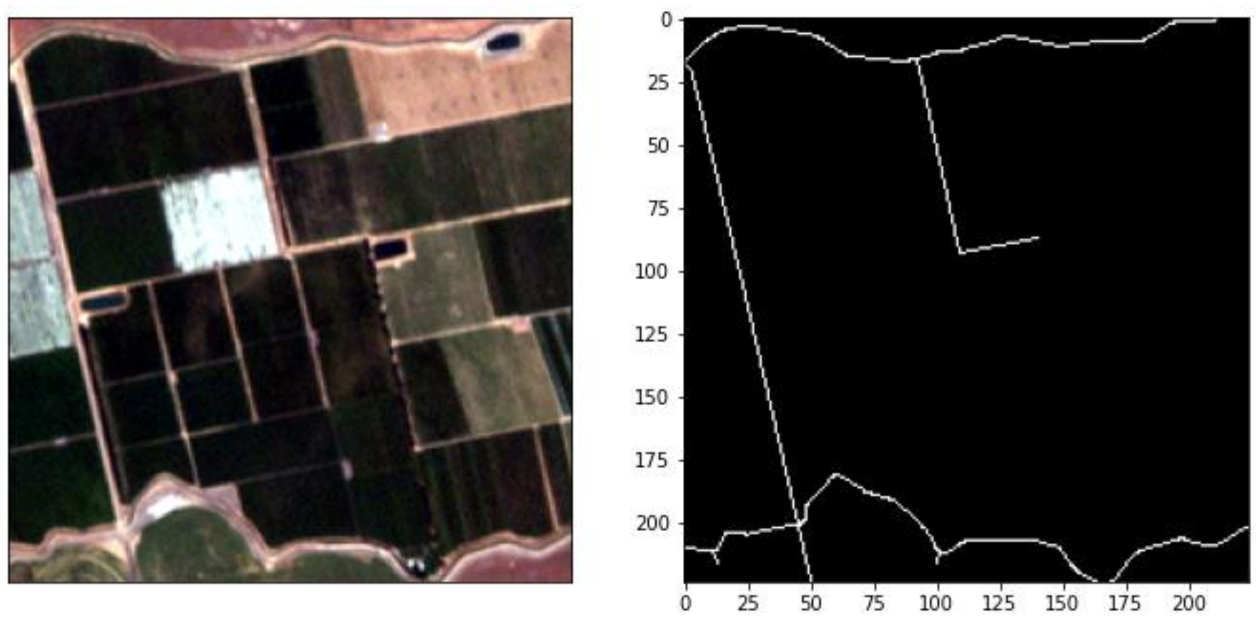

*Figure 2. Ground Truth Example*

### WSU Waterway Data

- Coordinate data shared with us by collaborators at WSU
- Created ground truth images by georeferencing and drawing the waterways on a blank image

## Model

### Data Preprocessing

- Satellite images and Ground Truth images are split into 224 x 224 sized patches
- Each band is then scaled from 0 to 1
- Input shape: (224, 224, 5); Output shape: (224, 224, 1)

### ResUNet Model

- ResUNet is a state-of-the-art segmentation model that has been shown to perform well in road extraction (a similar task)
- Based on the UNet architecture, a well-established Encoder-Decoder based segmentation model
    - Encoder-Decoder allows for a learned transformation from input to output mask[4]
- Convolutional layers are the primary layer, with Batch Normalization and ReLU activation layers between
- In ResUNet, skip connections, or "identity mappings," are added to each block in the UNet architecture[5]
    - Directly connects input and output of a block
    - Passes information along without degradation
    - Results in similar/improved performance while greatly reducing training time

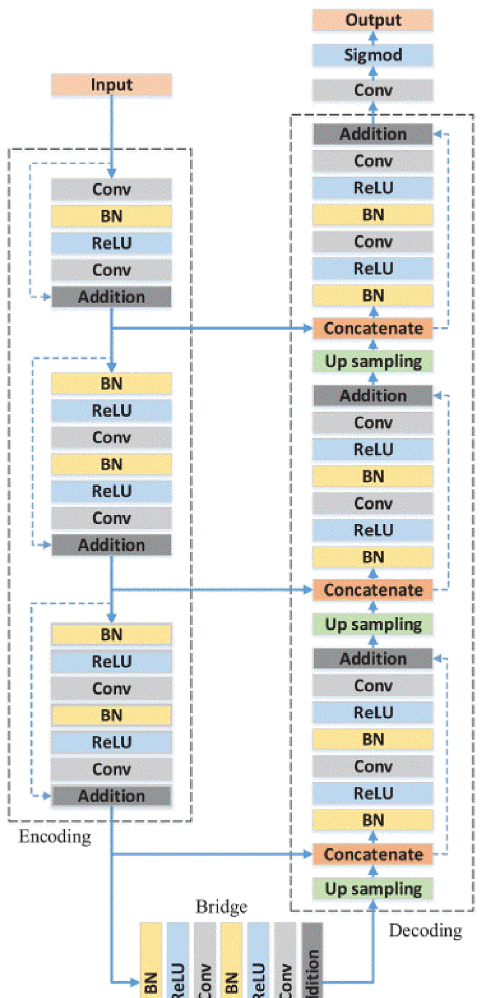


*Figure 3. ResUNet Architecture*

## Training

### Loss Functions

- Binary Cross Entropy (BCE) Loss
- Dice Coefficient Loss
    - 1 – Dice Similarity Coefficient (DSC)

### Metrics

- Precision, Recall, F1-Score

$$DSC = \frac{2\,|X \cap Y|}{|X| + |Y|}$$

*Figure 4. Dice Similarity Coefficient Equation*

### Training

- 150 epochs
- Loss stopped improving after about 50 epochs, but F1 continued to improve until about 150 epochs

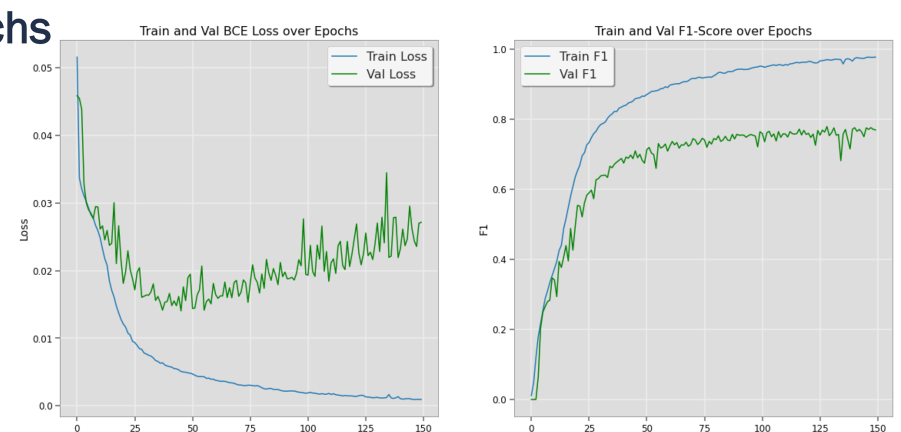


*Figure 5. Training and Validation Metrics over Epochs*

## Results

### Final Validation Data Metrics

- BCE Loss: 0.0271
- Recall: 0.7217
- DSC: 0.754
- F1-Score: 0.7691
- Precision: 0.8172

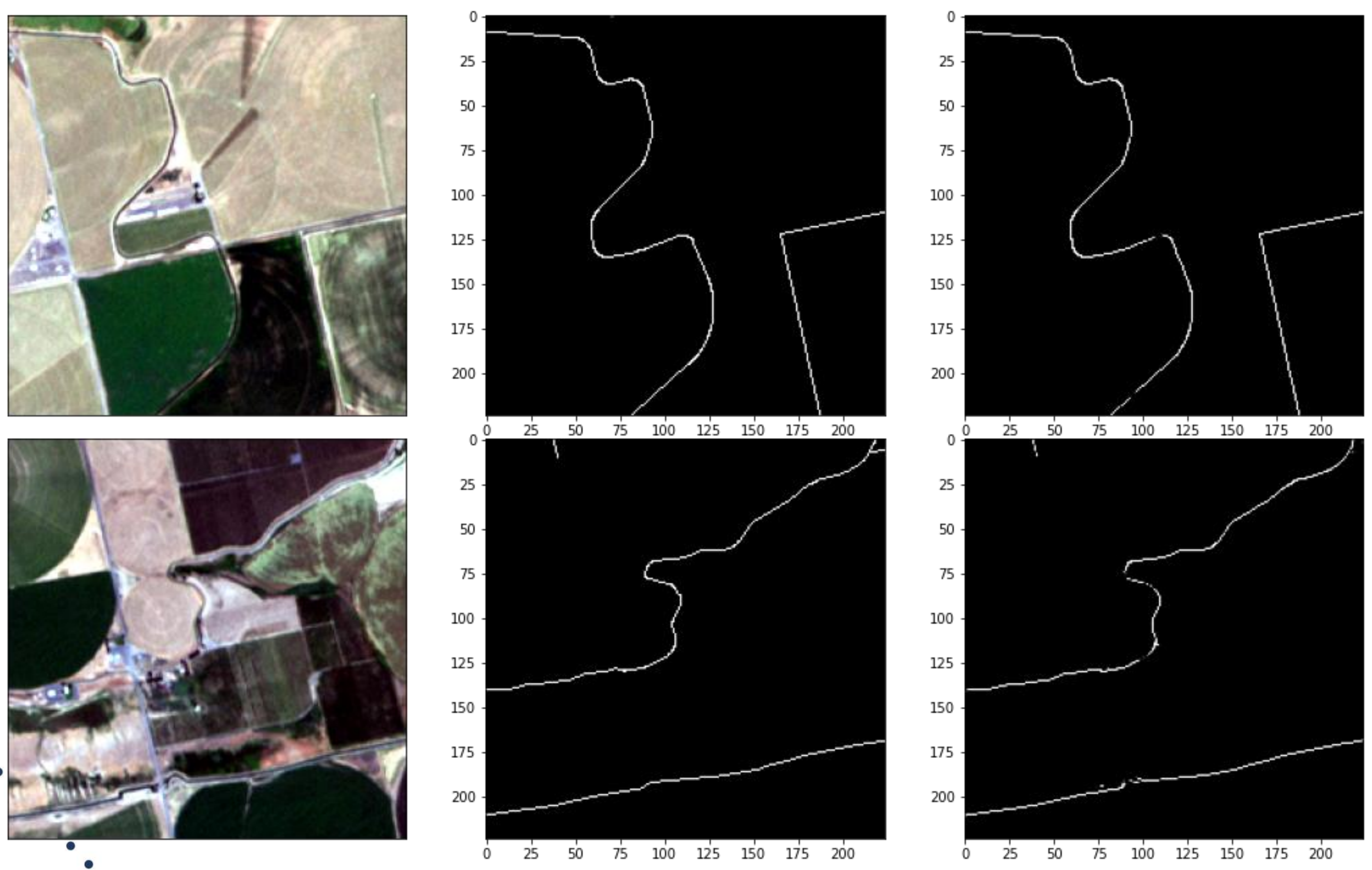

*Figure 6. 1st column shows the input image, 2nd column shows the ground truth, and 3rd column shows model prediction*

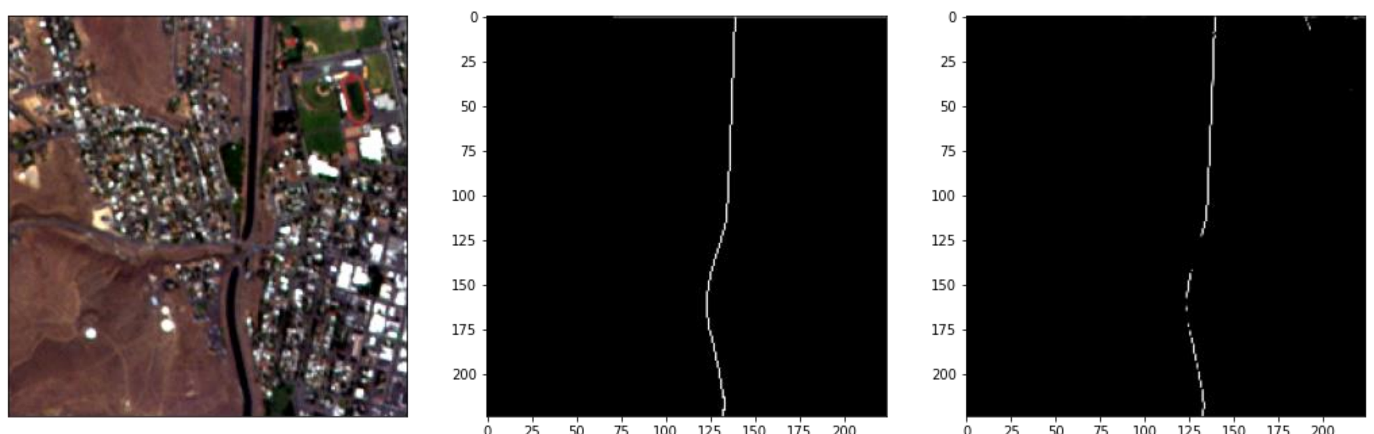

*Figure 7. Obstructed view can hinder model predictions and cause discontinuities*

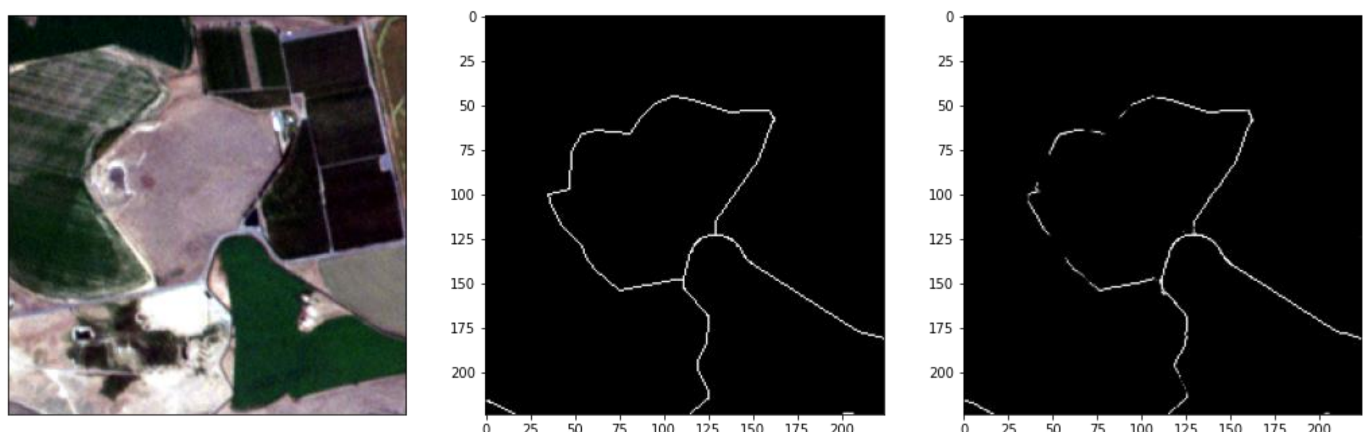

*Figure 8. Model uncertainty can also cause discontinuities*

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