CNN-based Hydrological Connectivity Modeling

NSF-sponsored Online Workshop on DL-GPU

Dr. Ruopu Li

Associate Professor in Geography and Environmental Resources

Southern Illinois University

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GeoFEW

Geoinformatics for Food, Energy, and Water

A research lab dedicated to innovative geographic solutions to food, energy, and water issues

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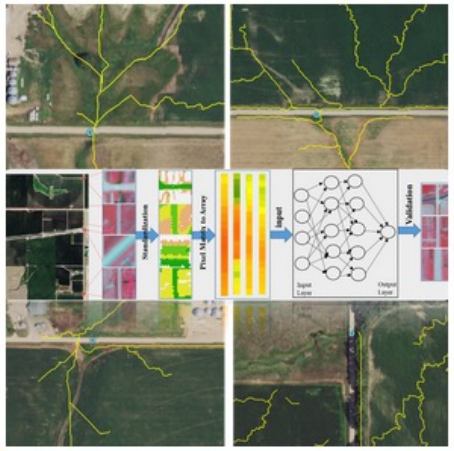
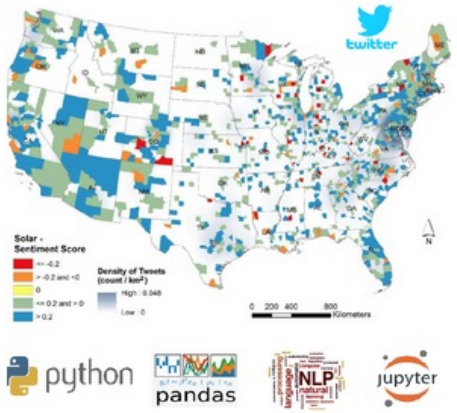
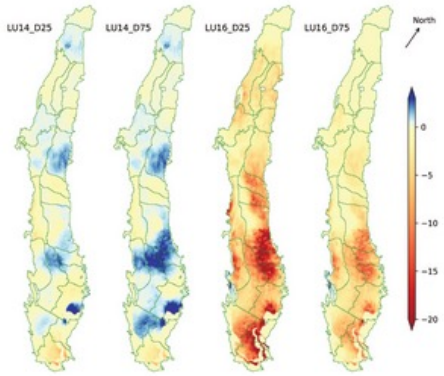
News about our recent large NSF grant!

Our recent paper on GeoAI was just published in *GIScience & Remote Sensing*!

Selected Work





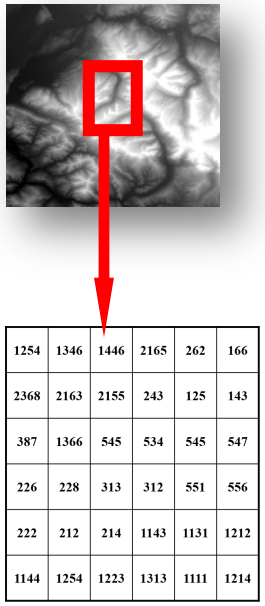


Lecture Outline

- Overview
- Learning Objectives
- Part I – CNN-based drainage crossing classification and detection
  - CNN-based classification
  - Faster R-CNN for object detection
- Part II – U-Net model for drainage flowline detection
  - Data processing & Cost path analysis
  - U-Net for flowline mapping
- Discussion
- Summary

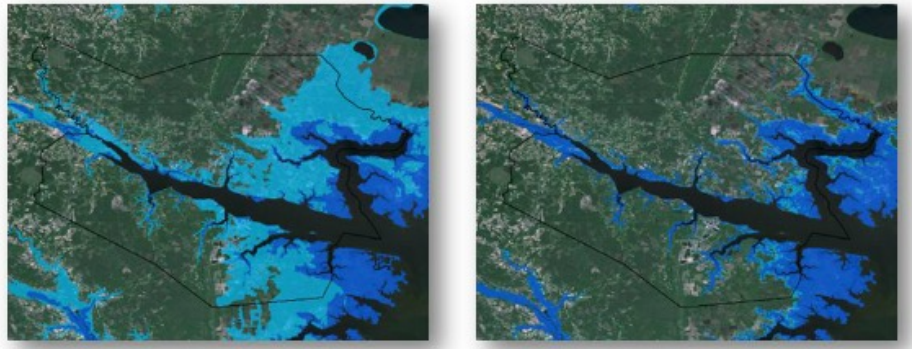
Overview

- Hydrologic connectivity is critical for environmental management issues.
  - Overland nutrient transport, fish passage, runoff routing, …
- Digital Elevation Models (DEMs) are commonly used to delineate the network of hydrologic features.
  - Conventional DEMs
    - With relatively coarse spatial resolutions
    - Unsuitable for capturing small terrain variations in a flat topography
  - High-resolution DEMs (HRDEMs)
    - Derived from Light Detection and Ranging (LiDAR) points cloud
    - With high spatial resolutions and vertical accuracy
    - Provide highly accurate representation of terrain and hydrological attributes



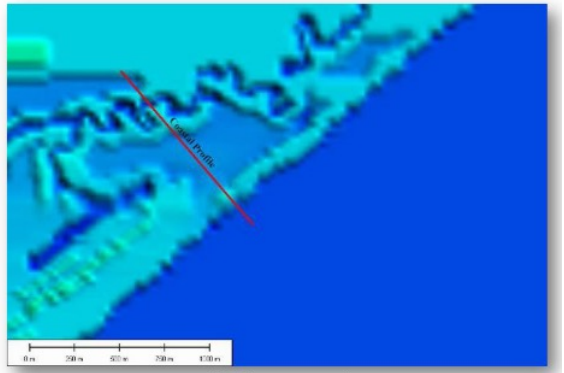
Overview

- High-resolution Digital Elevation Models (HRDEMs)
  - High spatial resolution (1-3 ft)
  - Good vertical accuracy
  - LiDAR (most popular and cost effective)
    - US Geological Survey expected to have the national coverage this year.

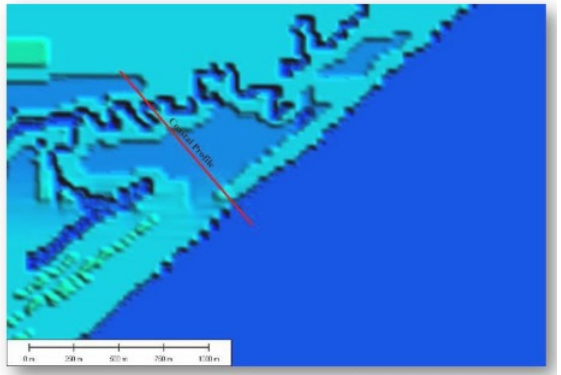


Low-accuracy NED | High-accuracy lidar data

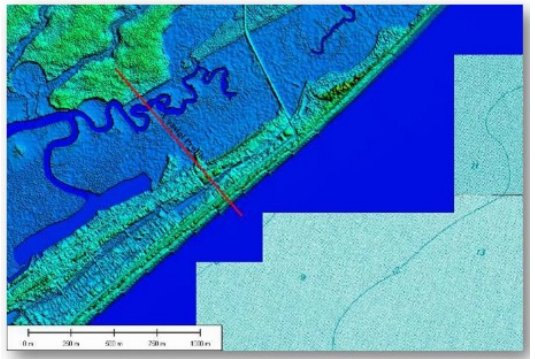
Darker blue tint: Inundated land if sea level rises ≤1-meter
Lighter blue tint: Area of uncertain inundation if sea level rises ≤1-meter



NED 1 arc-second



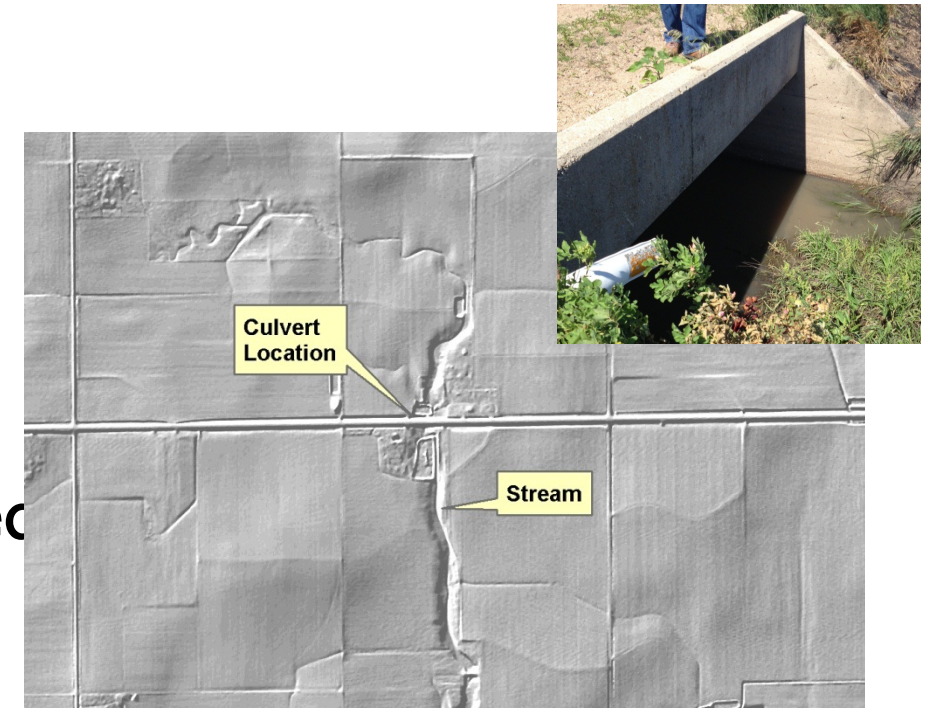
NED 1/3 arc-second



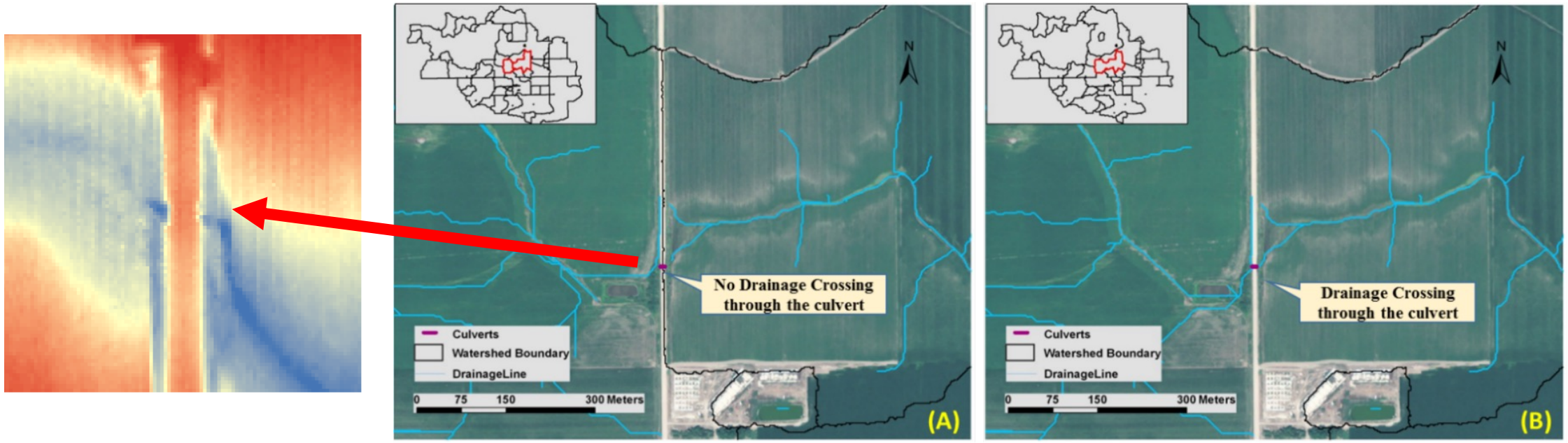
Lidar

Overview

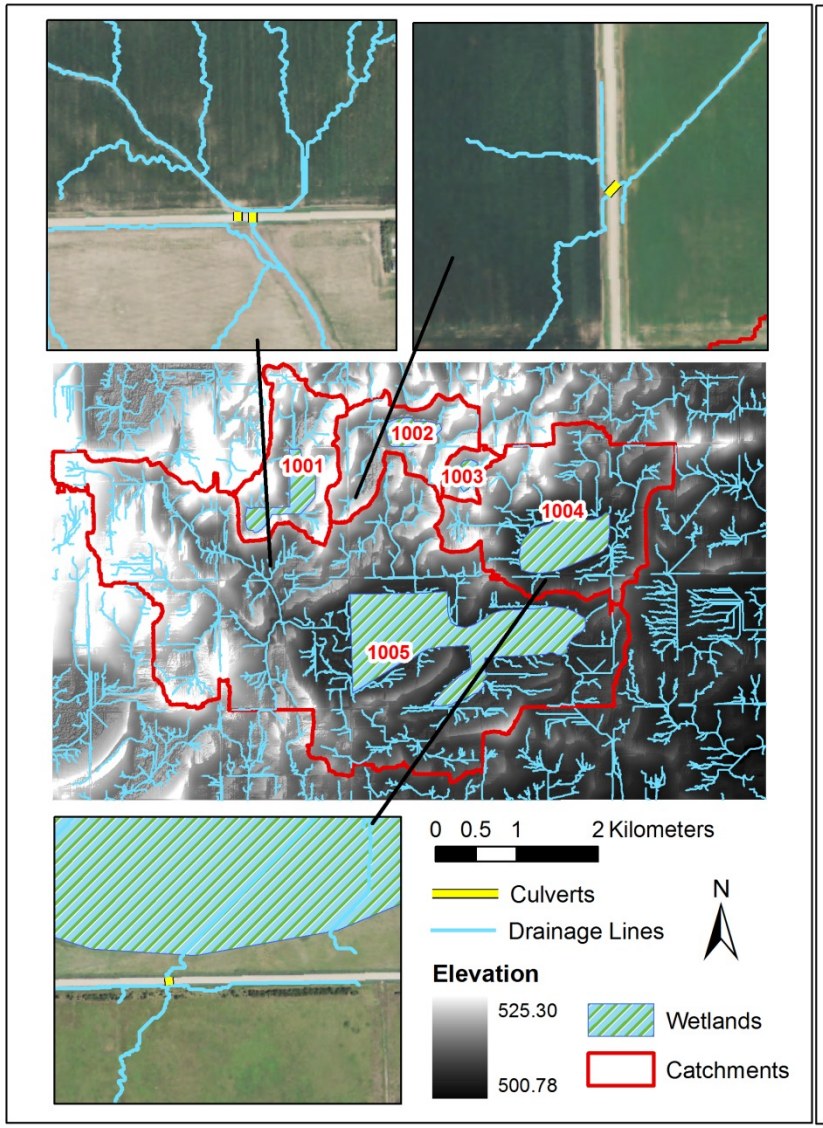
- Limitations of HRDEMs
  - "Digital dams" caused by roads
    - The virtual flow obstructions associated with artificial embankments (e.g., bridges and roads).
    - HRDEM-derived underpass flow routing is unavailable or has variable quality.
  - Increased land roughness associated with widespread depressions
    - Spurious depressions and minor topographic variations
    - Results in fragmented patterns of derived flowlines



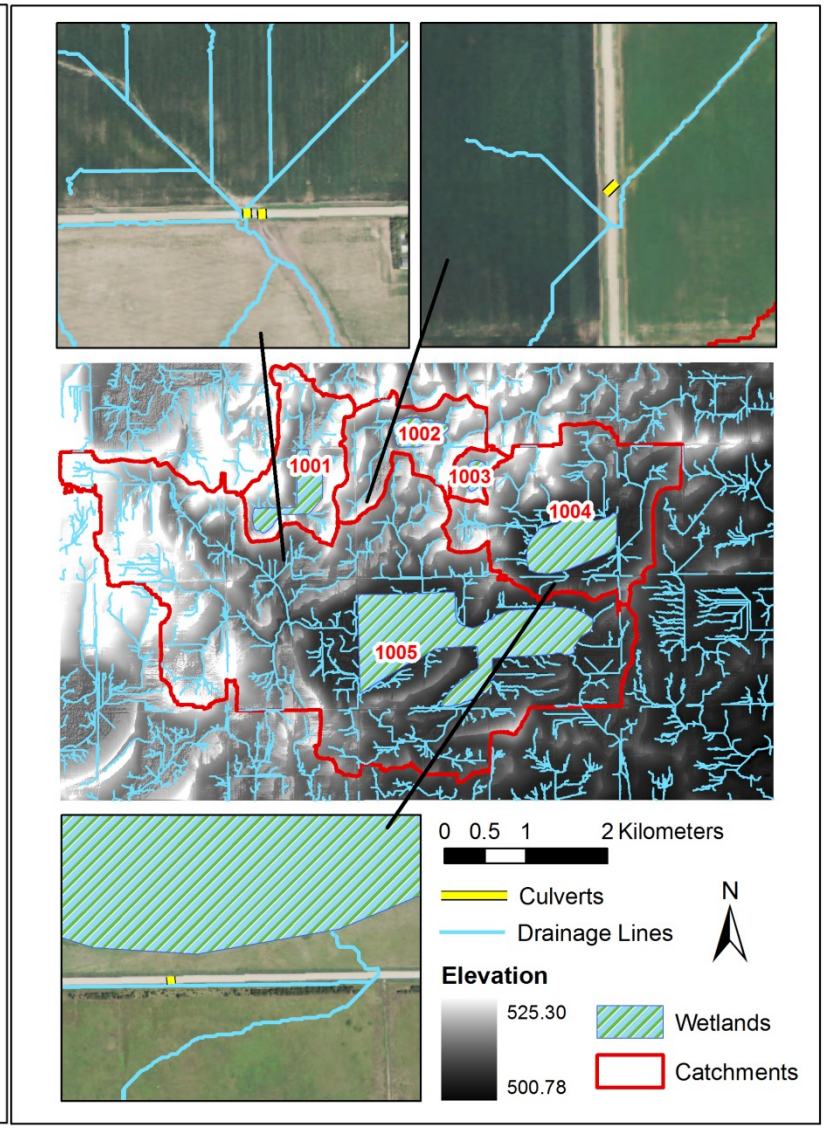
Overview



Li, R., Z. Tang and X. Li. 2013. Drainage Structure Dataset and its Effects on LiDAR-derived Surface Flow Modeling. *ISPRS International Journal of Geo-Information* 2(4), 1136-1152.



After burning culverts



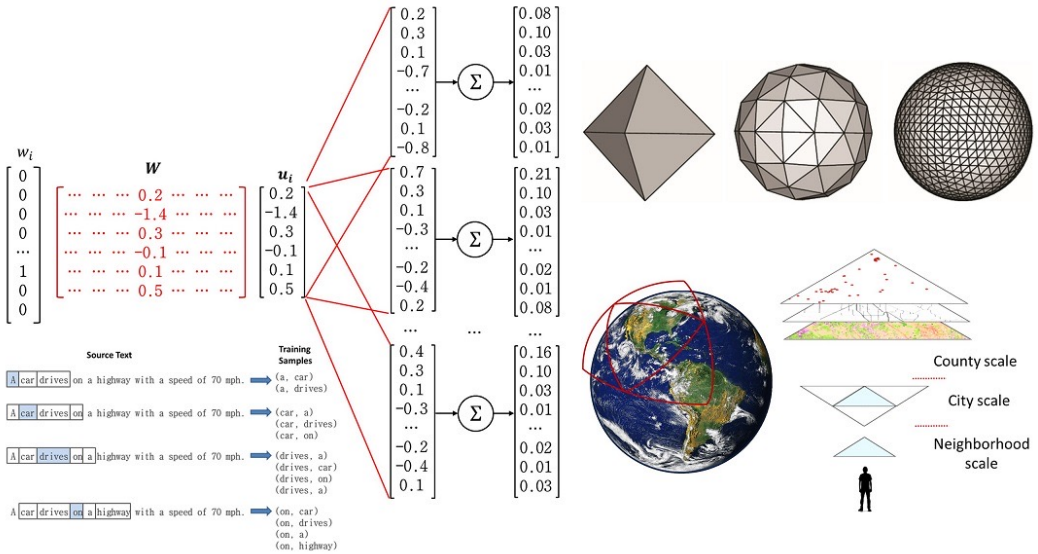
Before burning culverts

Overview

- Incorporating locations of culverts/bridges into HRDEMs has been proved to improve the accuracy of modeled drainage network.
  - Traditional manual on-screen digitization
  - Geospatial Artificial Intelligence (GeoAI)
    - Converge methods in spatial science, AI, data mining, and high-performance computing
    - Show excellent performance in fast and accurate detections of terrain features by achieving near-automated processing
- To overcome computational intensity caused by high data volume of HRDEMs, cyberinfrastructure is indispensable.
- It is essential to develop high-quality drainage crossing datasets and new modeling methods to improve the accuracy of HRDEMs-derived hydrologic connectivity and the performance of geocomputation.

Overview - GeoAI

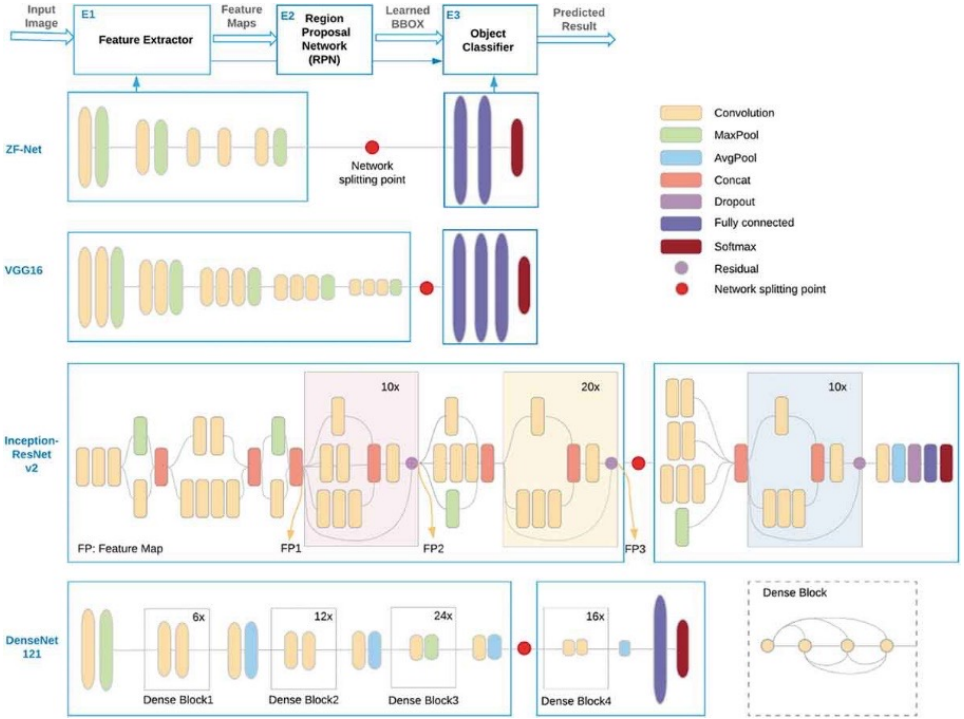
- AI in Geoscience
  - An emerging discipline that combines innovations in geospatial science, artificial intelligence methods in machine learning (e.g., deep learning), and high-performance computing to extract knowledge from spatial big data.

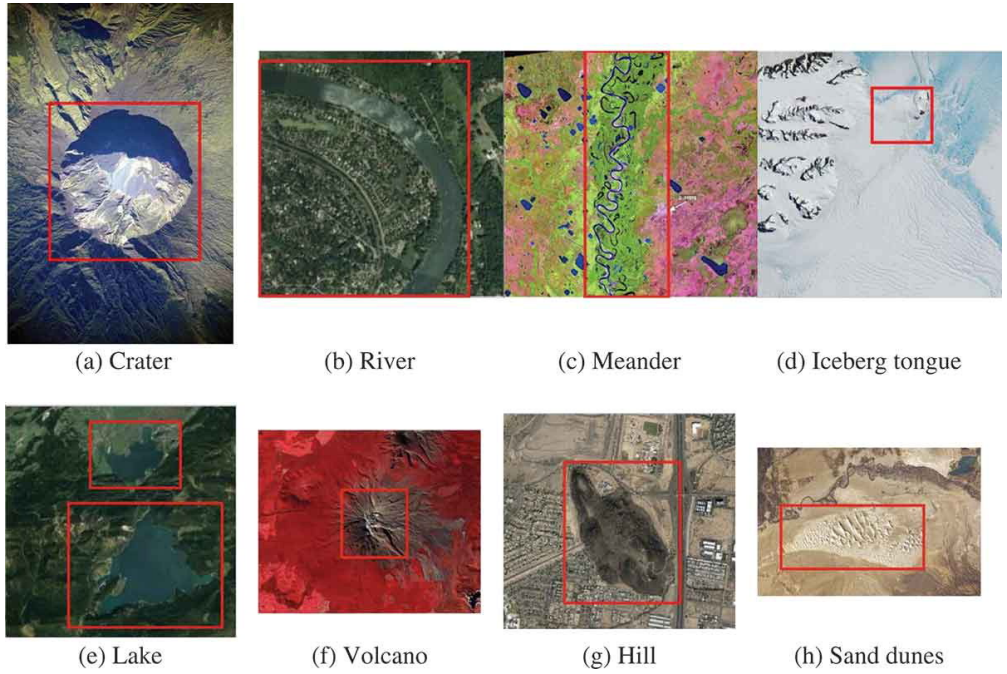


Source: https://geoai.geog.buffalo.edu/

Overview - GeoAI

- Example: Li and Hsu (2020) Automated terrain feature identification from remote sensing imagery





Overview - Workflow

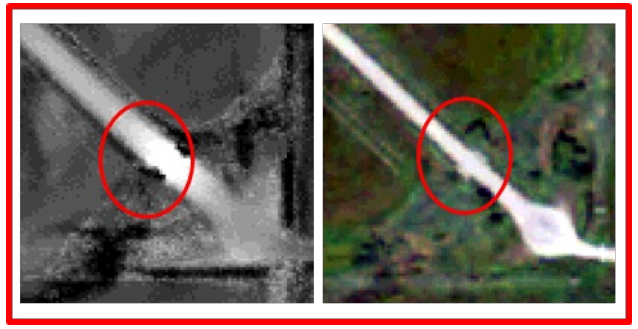


Image with drainage crossing

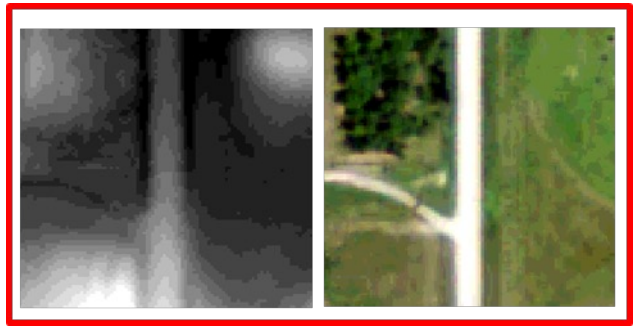
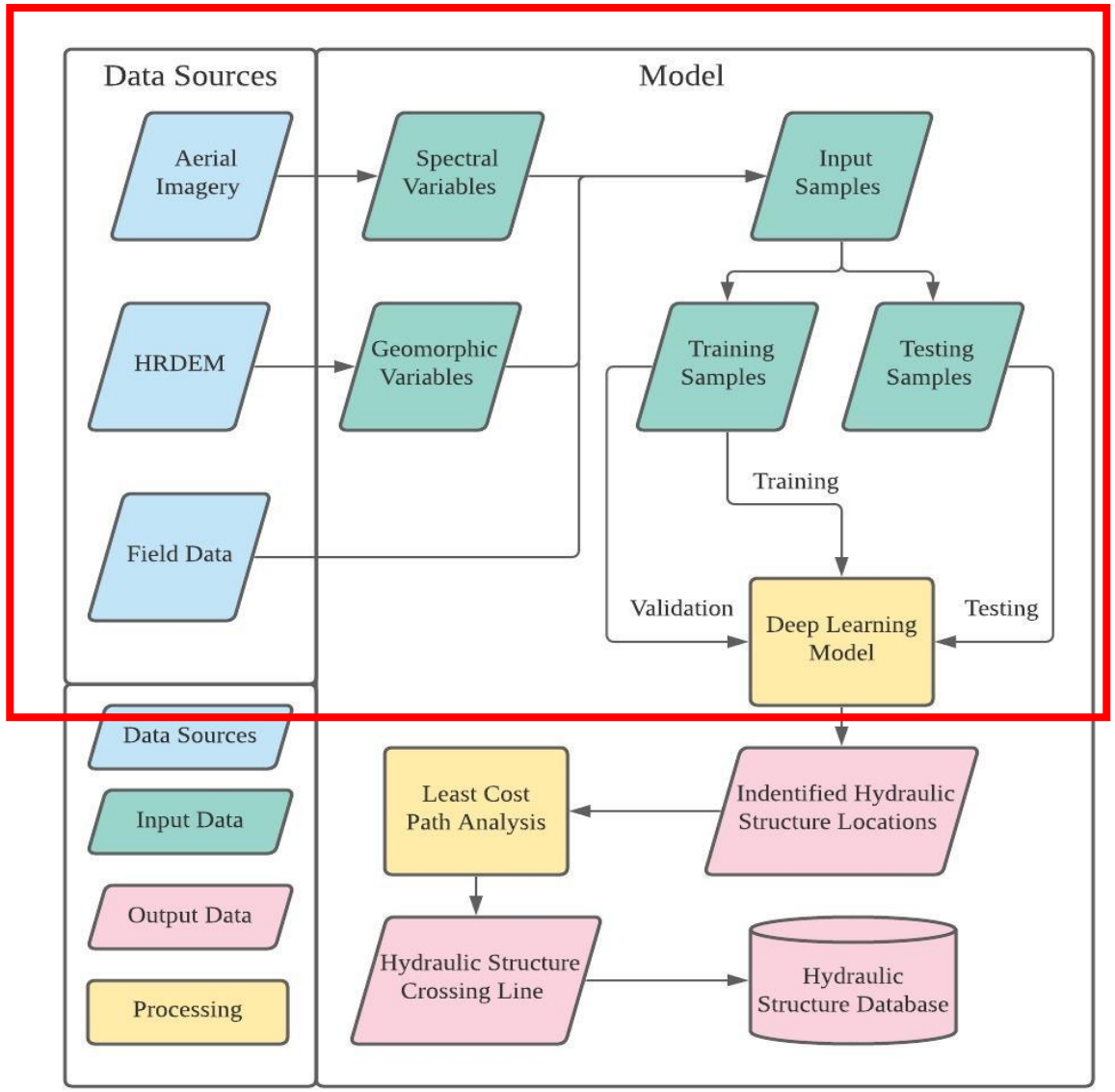


Image without drainage crossing



Learning Objectives

- Goal - To develop a GeoAI-Hydro modeling system to improve the delineation of hydrologic connectivity using HRDEMs in agricultural landscapes.

Objective 1	Objective 2	Objective 3
• Determine if and how GeoAI can be used to identify artificial flow barriers that disconnect the simulated flowlines.	• Develop a method for improving the quality of HRDEM-derived hydrologic connectivity network.	• Develop an integrated modeling system implementable on GPU computing infrastructure to speed up the geo-computation.

Learning Objectives

- Goal - To develop a GeoAI-Hydro modeling system to improve the delineation of hydrologic connectivity using HRDEMs in agricultural landscapes.
- Code Demonstration
  - CNN-based Image Classification
  - Faster RCNN-based Object Detection
  - Cost-path analysis and HRDEM modification
  - U-Net drainage line mapping

Part I

- CNN-based Drainage Crossing Classification and Detection

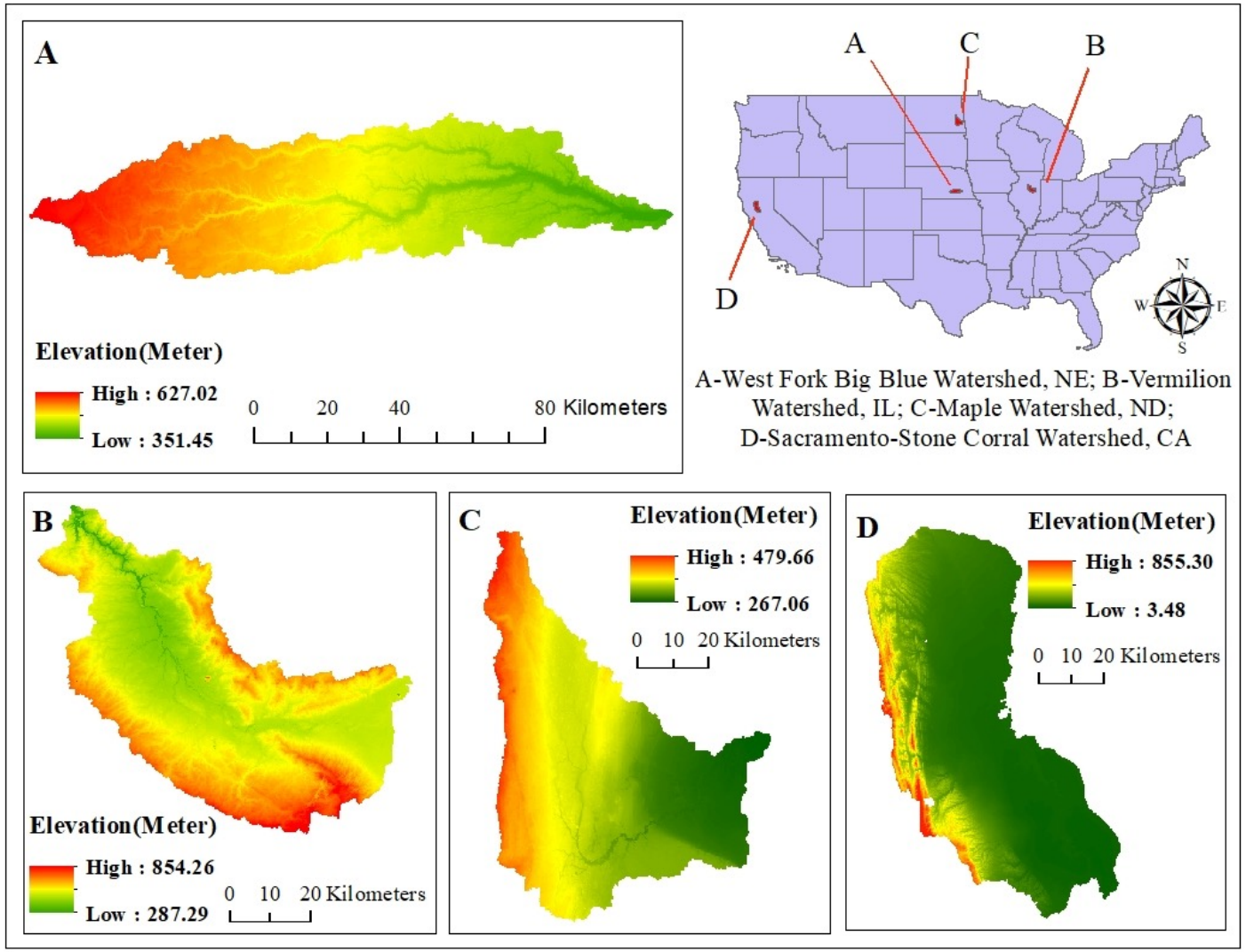
Part I – Purpose

- The ***purpose*** of this section is to develop a deep learning (DL) model for classifying the images and detecting the locations of drainage crossings and evaluate the transferability of the model in different geographic areas.
  - Drainage crossings were focused on those locations where natural streams or artificial canals pass roads through underpass structures, such as bridges or culverts.
  - The gained knowledge can be used to guide the application of DL models for improving hydrologic connection in broader geographic areas.

Wu, D., R. Li, C. Talbert, M. Edidem, B. Rekabdar, G. Wang. 2023. Classification of Drainage Crossings on High-resolution Digital Elevation Models: A Deep Learning Approach. *GIScience & Remote Sensing*. 60:1

Part I – Study Area

- Four agricultural watersheds from Nebraska, Illinois, North Dakota, and California
  - Dominated by intensive agriculture
  - Relatively level topography
  - Dense road networks



Part I – Study Area

- Dataset Specification

Data	Locations	Sources	Horizontal Resolution	Vertical Accuracy RMSE
HRDEM	West Fork Big Blue Watershed, Nebraska	NE Department of Natural Resource	1.0m	0.185m
	Vermilion River Watershed, Illinois	IL Geospatial Data Clearinghouse	0.30m	1.19ft (~0.36m)
	Maple River Watershed, North Dakota	North Dakota GIS Hub Data Portal	2.0ft (~0.61m)	0.15m
	Sacramento-Stone Corral Watershed, California	USGS	1.0m	0.196m
Aerial Orthophotos	Four watersheds	USGS National Agriculture Imagery Program (NAIP)	1.0m	

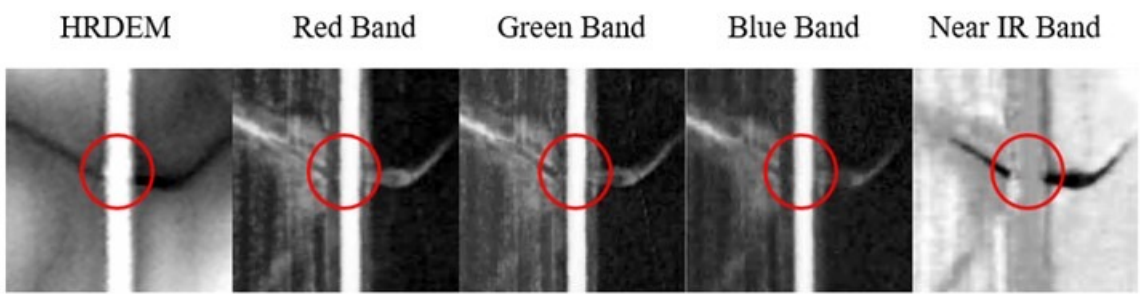
Part I – Image classification

- Input Features
  - Unique topographic and spectral signatures at drainage crossing locations are commonly used as indicators to guide manual digitization of these structures on HRDEMs and aerial orthophotos
    - Microtopographic patterns
    - Soil erosion near drainage crossing locations

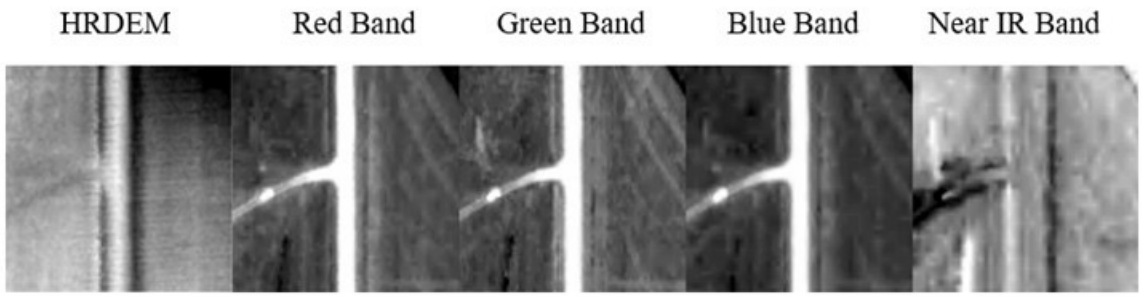
Input features	Applied methods	References
HRDEM (1 band) HRDEM, NAIP Orthophotos (R, G, B, NIR) (5 bands)	To remove image dependency on lighting geometry and illumination color, the data were normalized to a scale of (0,1). $X_{scaler} = \frac{X - X_{min}}{X_{max} - X_{min}}$ $X_{scaled} = X_{scaler} * (max - min) + min$ $max = 1, min = 0$	(Finlayson, Schiele, and Crowley 1998; Patro and Sahu 2015; Saranya and Manikandan 2013).
HRDEM, NDVI (2 bands)	$NDVI = \frac{NIR - Red}{NIR + Red}$	(Brown 2015).
HRDEM, NDWI (2 bands)	$NDWI = \frac{GREEN - NIR}{GREEN + NIR}$	(McFeeters 1996).

Part I – Image classification

- Datasets Preprocessing
  - All HRDEMs from four study areas are resampled to 1-meter resolution and manually digitized drainage crossing locations.
  - Five-band images with drainage crossing in the identical size (100x100 px) clipped as True samples.
  - Equal amounts of False samples without a drainage crossing along the roads are randomly generated.



(a)



(b)

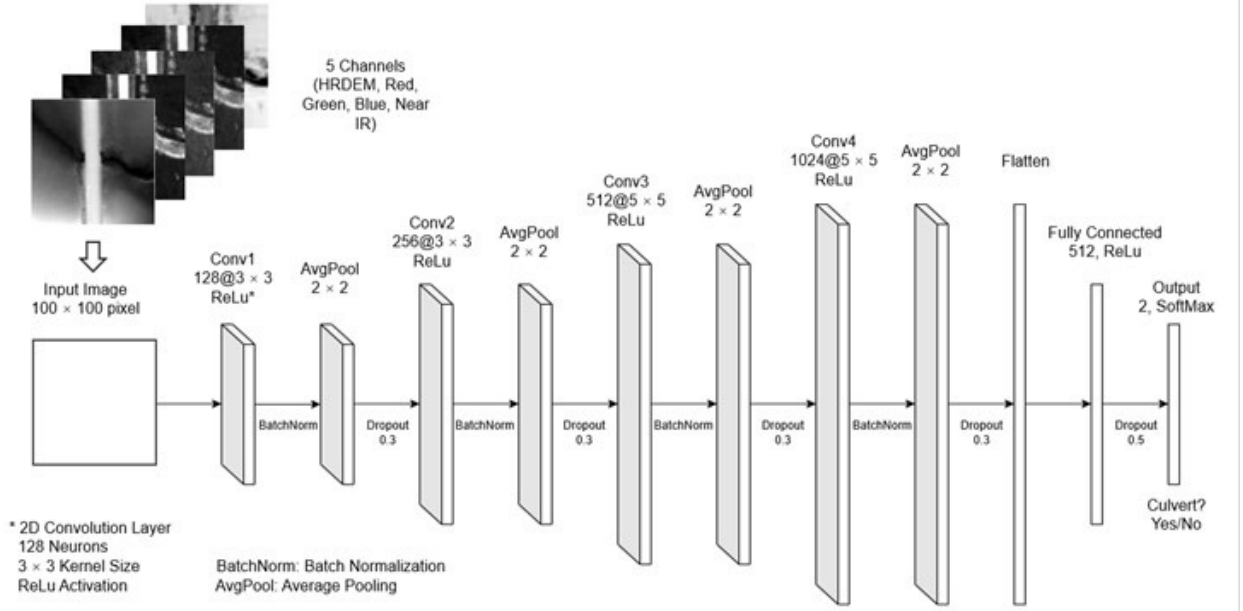
Part I – Image classification

- Training Samples

Locations	True Sample (Label 1, with culvert)	False Sample (Label 0, without culvert)	Total
Nebraska	2022	2022	4044
Illinois	1011	1011	2022
North Dakota	613	613	1226
California	2388	2388	4776

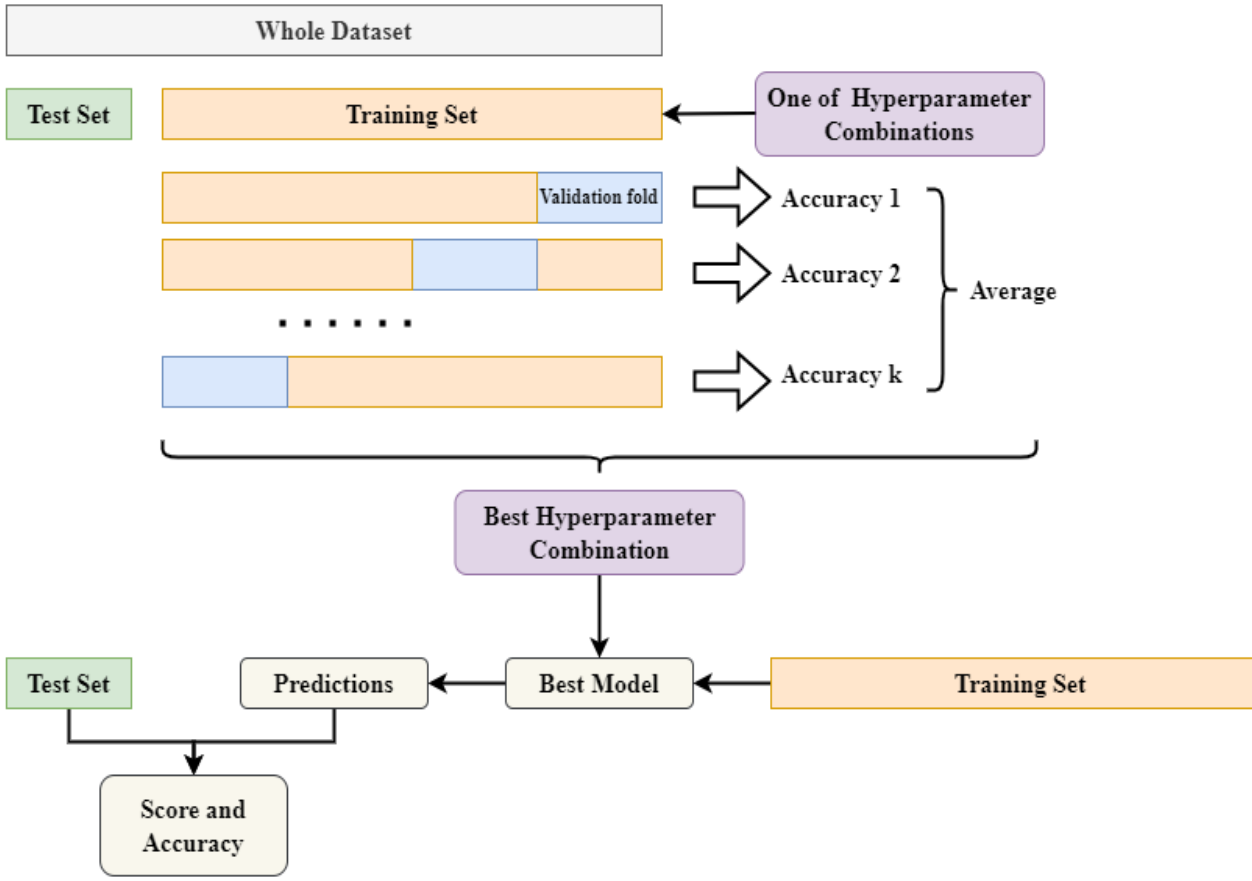
Part I – Image classification

- Model Selection
  - CNN deep learning model
    - Excellent flexibility and effectiveness in complex data intensive tasks.
    - A convolution unit of CNN: includes convolution, activation, and pooling layers.
  - Architecture of the CNN model
    - 4 convolution layers
    - 1 flatten layer
    - 2 fully connected layers



Part I – Image classification

- CNN model development
  - Data was divided into training, validation, and test sets.
  - K-fold cross-validation was used to avoid the randomness from estimates produced by imbalanced data and overfitting.
  - Adam optimizer was utilized.
  - Different batch sizes are examined, and the results will be compared to find the optimum.



Part I – Image classification

- Model Evaluation
  - Using the data samples from the Nebraska watershed to trained the best-fit CNN model.
    - Sparse categorical cross entropy method was used to calculate the loss of model.

$$Loss = -\sum_{i=1}^{n} y_i \log(p_i)$$

    - A binary confusion matrix was applied to represent accuracy.

		Predicted class	
		P	N
Actual Class	P	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

$$Acc = \frac{TP+TN}{TP+FP+TN+FN}$$

    - A multicollinearity analysis was conducted to estimate the contribution of each input features to the classification outcome and the relationships among them
      - Tolerance (TOL)

$$TOL_i = 1 - R_i^2$$

      - Variance inflation factor (VIF)

$$VIF_i = \frac{1}{TOL_i}$$

VIF > 10 or TOL < 0.1 is regarded as a threshold for a multicollinearity problem.

Part I – Image classification

- Results of k-fold cross validation (k = 4)
  - The total sample size is 4044 (50% False, 50% True)
    - Train samples are 2426 (60%), validate sample are 809 (20%), and test samples are 809 (20%).
  - The model is with optimizer Adam, learning rate 0.001, and Epoch 100.

		Training		Validation	
Feature inputs	Batch size	Loss	Accuracy	Loss	Accuracy
HRDEM	8	0.0159	0.9968	0.3745	0.9607
	16	0.0117	0.9970	0.3826	0.9638
	32	0.0094	0.9975	0.2998	0.9601
HRDEM+NAIP Aerial Orthophoto	8	0.0193	0.9965	0.2806	0.9713
	16	0.0208	0.9965	0.2545	0.9607
	32	0.0053	0.9988	0.3312	0.9592
HRDEM+NDVI	8	0.0108	0.9981	0.3372	0.9710
	16	0.0121	0.9965	0.2997	0.9682
	32	0.0084	0.9974	0.3141	0.9608
HRDEM+NDWI	8	0.0087	0.9972	0.3884	0.9737
	16	0.0219	0.9955	0.1546	0.9743
	32	0.0098	0.9973	0.2024	0.9734

Part I – Image classification

- Classification results of best-fit CNN models with different combinations of input features
  - The total sample size is 4044 (50% False, 50% True)
    - Train samples are 2,426 (60%), validate sample are 809 (20%), and test samples are 809 (20%).
    - The model with input HRDEM and batch size 16 has the best testing accuracy (93.33%).

		Training		Testing	
Feature inputs	Batch size	Loss	Accuracy	Loss	Accuracy
HRDEM	16	0.0065	0.9969	0.7398	0.9333
HRDEM +NAIP Aerial Orthophotos	8	0.0062	0.9981	1.0977	0.9246
HRDEM +NDVI	8	0.0269	0.9947	0.8423	0.9197
HRDEM +NDWI	16	0.0187	0.9966	0.7979	0.9271

Part I – Image classification

- Among all combinations of input features, HRDEM appears to be a dominant feature to accurately classify images with drainage crossings being present.
- The results suggest that most CNN models can properly perform the classification tasks.
- The CNN model with HRDEMs as the sole feature allows the best model-fit while maintaining relatively a lower computation cost.
- The addition of aerial imagery and derived spectral indices show little improvement on the model accuracy.

		Training		Testing	
Feature inputs	Batch size	Loss	Accuracy	Loss	Accuracy
HRDEM	16	0.0065	0.9969	0.7398	0.9333
HRDEM +NAIP Aerial Orthophotos	8	0.0062	0.9981	1.0977	0.9246
HRDEM +NDVI	8	0.0269	0.9947	0.8423	0.9197
HRDEM +NDWI	16	0.0187	0.9966	0.7979	0.9271

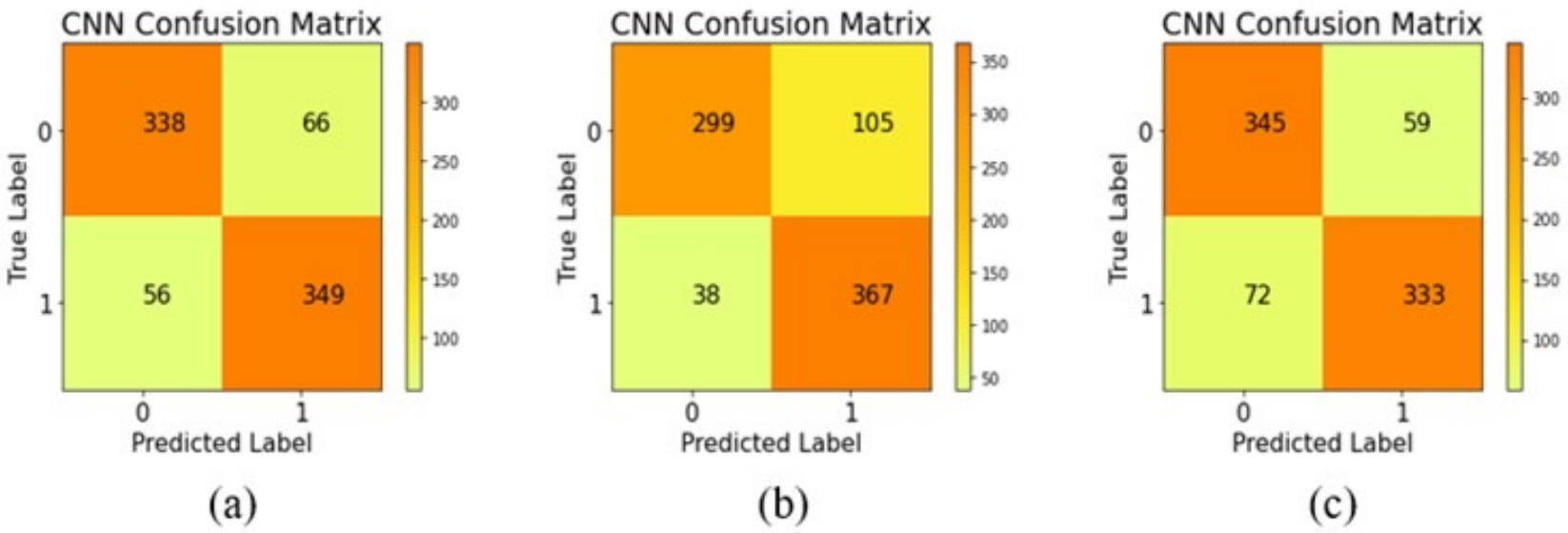
Part I – Image classification

- The contributions of aerial orthophoto bands to model accuracy
  - We trained CNN models with four aerial orthophoto bands, NDVI, and NDWI (with a batch size of16).
  - NAIP aerial orthophotos and their derived spectral indices can be used as features to classify drainage crossing locations albeit with relatively lower accuracies.

	Training		Validation		Testing	
Feature inputs	Loss	Accuracy	Loss	Accuracy	Loss	Accuracy
NAIP Aerial Orthophotos	0.0242	0.9922	0.9638	0.8591	1.0914	0.8492
NDVI	0.0353	0.9885	1.1865	0.8022	1.1080	0.8232
NDWI	0.0548	0.9802	0.6269	0.8665	0.8215	0.8381

Part I – Image classification

- Both HRDEMs and aerial orthophotos appear to contribute similarly to the classification of images with and w/o drainage crossings.



The inputs feature for model (a) is NAIP orthophotos, (b) is NDVI, (c) is NDWI.

Part I – Image classification

- Model Transferability
  - The best-fit CNN model (Input: HRDEM; Learning rate: 0.001; Epoch: 100; Batch size: 16) is used to test its transferability of classifying drainage crossing locations in the other three watersheds.

- Classification results in other watersheds

Location	Testing loss	Testing accuracy
Vermilion River Watershed, Illinois	0.7995	0.8734
Maple River Watershed, North Dakota	1.1490	0.8320
Sacramento-Stone Corral Watershed, California	2.3472	0.7067

Part I – Image classification

- Features affecting model accuracies
  - To better understand whether HRDEMs and digital numbers (DNs) of aerial photos exhibit interdependencies in terms of image classification, a multicollinearity test has been conducted.
    - TOL values are all larger than 0.1 and VIF values are far less than 10.
    - No serious multicollinearity existed between HRDEMs and aerial photo-derived features

		Collinearity statistics	
Model input	Features	TOL	VIF
HRDEM+NAIP	HRDEM	0.994	1.006
	NAIP-R	0.802	1.248
	NAIR-G	0.787	1.271
	NAIP-B	0.816	1.226
	NAIP-NIR	1.000	1.000
HRDEM+NDVI	HRDEM	1.000	1.000
	NDVI	1.000	1.000
HRDEM+NDWI	HRDEM	1.000	1.000
	NDWI	1.000	1.000

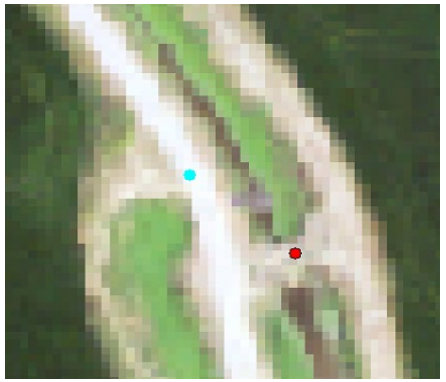
Part I – Image classification

- Baseline Model Comparison
  - To assume the classification ability of CNN model, we compare it with Support Vector Machine (SVM).
    - SVM is a supervised learning model that analyze data for classification and regression analysis.
    - A SVM with linear kernel was applied to West Fork Big Blue Watershed in Nebraska. The train-test dataset split was 0.8 to 0.2.
    - Based on the results, SVM is not able to identify the samples without flow barriers. CNN model shows its potential comparing with this traditional technique.

Class	Precision	Recall	F1-score
False Sample	0.00	0.00	0.00
True Sample	0.50	1.00	0.67
Overall Accuracy		0.5006	

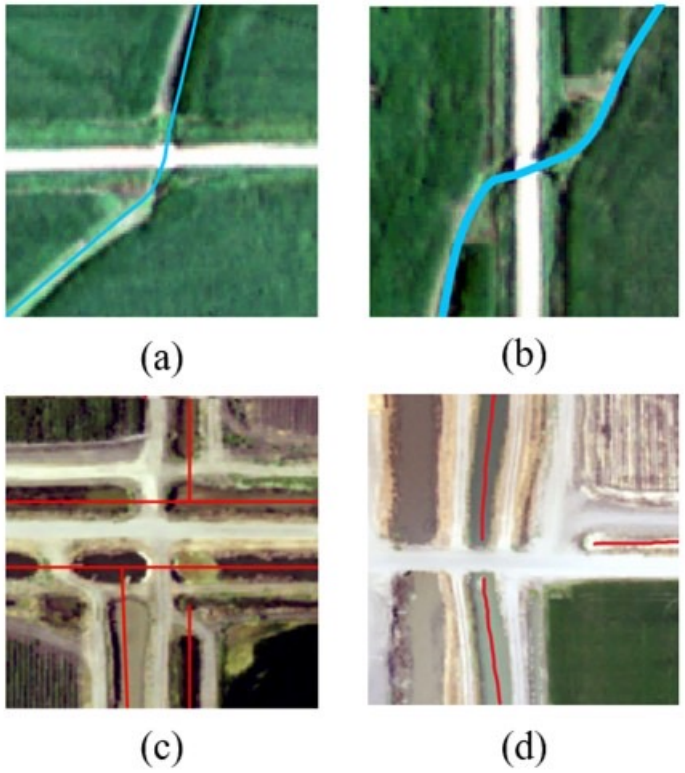
Part I – Image classification

- Observations from Experiments
  - The best-performing model developed in the Nebraska watershed with HRDEM as the sole input (0.001 learning rate and 16 batch size). The prediction show good accuracy (~93%).
  - The transferability results confirmed the model's good performance in the new watersheds.
    - Collecting flow barriers training data from broader geographic contexts can increase data variability, and thus improve the transferability of our model.
  - No serious multicollinearity existed between HRDEMs and aerial photo-derived features.
  - Data quality of the NAIP aerial photos is a concern.



Part I – Image classification

- Discussion
  - CNN model developed in Nebraska has better performance in North Dakota and Illinois watershed than it is in California watershed.
    - Most hydrologic features crossing the roads in NE, IL, and ND watersheds: natural streams.
    - Unlike the situation in other three watersheds, artificial canals and road ditches existing widely, resulting in more complex crossing patterns in the CA watershed.



The blue lines in (a) and (b) are natural streams in the Nebraska watershed, whereas red lines in (c) and (d) are canal ditches in the California watershed.

Part I – Image classification

- Summary
  - (1) Compared with baseline machine learning techniques like SVM, CNN-based deep learning model is a promising tool to accurately classify drainage crossings from our image samples.
  - (2) Among all models for the study area in Nebraska, the one with a batch size of 16, a learning rate of 0.01, an epoch of 100, and the HRDEM as the sole input feature exhibits the best performance (~93% accuracy).
  - (3) The best-fit CNN model shows its transferability in different geographic regions, although the classification accuracy appears to link to their hydrography similarity.
  - (4) The addition of aerial orthophotos and their derived spectral indices was found to be insignificant to or even worsen the best-fit model's performance, which may be explained by the interference of vegetation and data quality issues.

Part I – Image classification

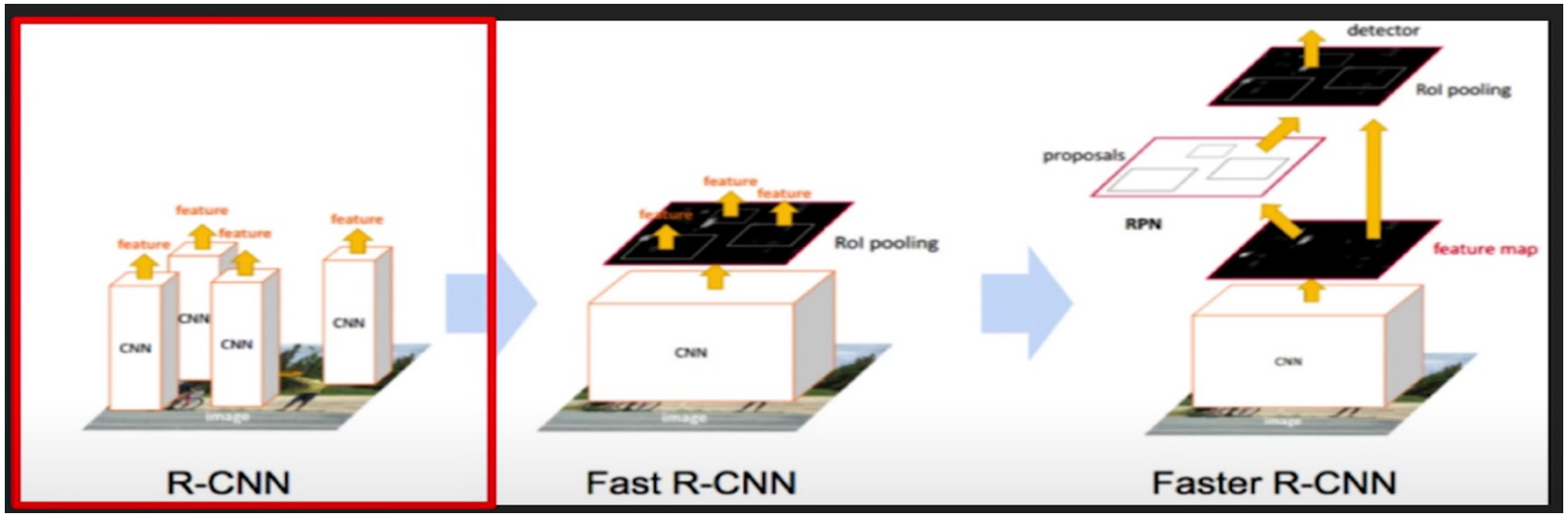
- Now, coding time…

Part I – Image object detection

- **This section introduces the use of the Faster RCNN for drainage structures detection.**
  - The CNN has been found to produce better results in classification, but directly combining CNN with the sliding window strategy has difficulties in precise localized objects.
  - Region-based CNN (R-CNN) and the Fast R-CNN algorithm have been proposed to improve object detection performance.

Part I – Image object detection

Difference between the R-CNN networks



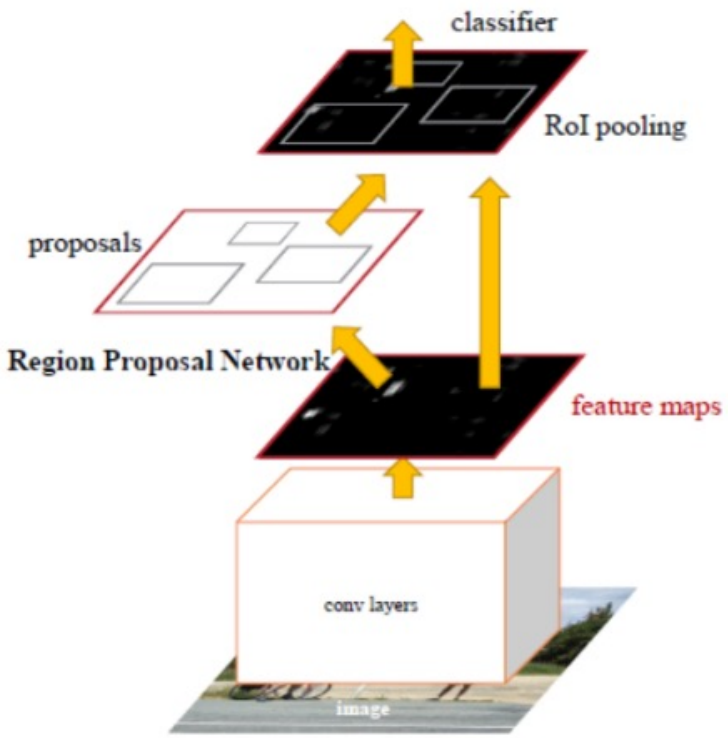
- Selective search to make proposals
- Slow classifying ~ 2000
- Takes 47 sec. per image

- Conv. applied only once on an image
- Proposals are cropped in the feature level
- Faster than R-CNN
- Bottleneck in the proposal stage

- Does not use selective search
- Region Proposal Network (RPN) used to make proposal
- Anchor boxes of different sizes

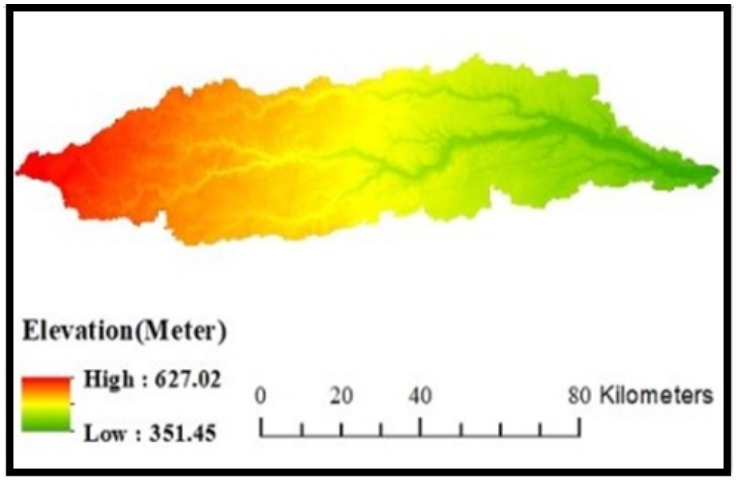
Part I – Image object detection

- **Deep learning**: Faster R-CNN
  - Convolution layers
    - Use a set of convolution layers from CNN to generate features maps for desired object.
  - Region Proposal Networks (RPNs)
    - A small convolutional network predicting the bounding box of desired objects.
    - Make region proposal computations nearly cost-free.
  - Region of Interest (RoI) Pooling
    - Use bounding box proposals from the RPN to pool features from the feature map, generating proposal feature maps.
  - Classification
    - Proposal feature maps are fed into classifier.
    - Make the coordinates of the object bounding box more precise.



Part I – Image object detection

- Study Area
  - West Fork Big Blue Watershed Nebraska
    - Dominated by intensive agriculture
    - Relatively level topography
    - Dense road networks



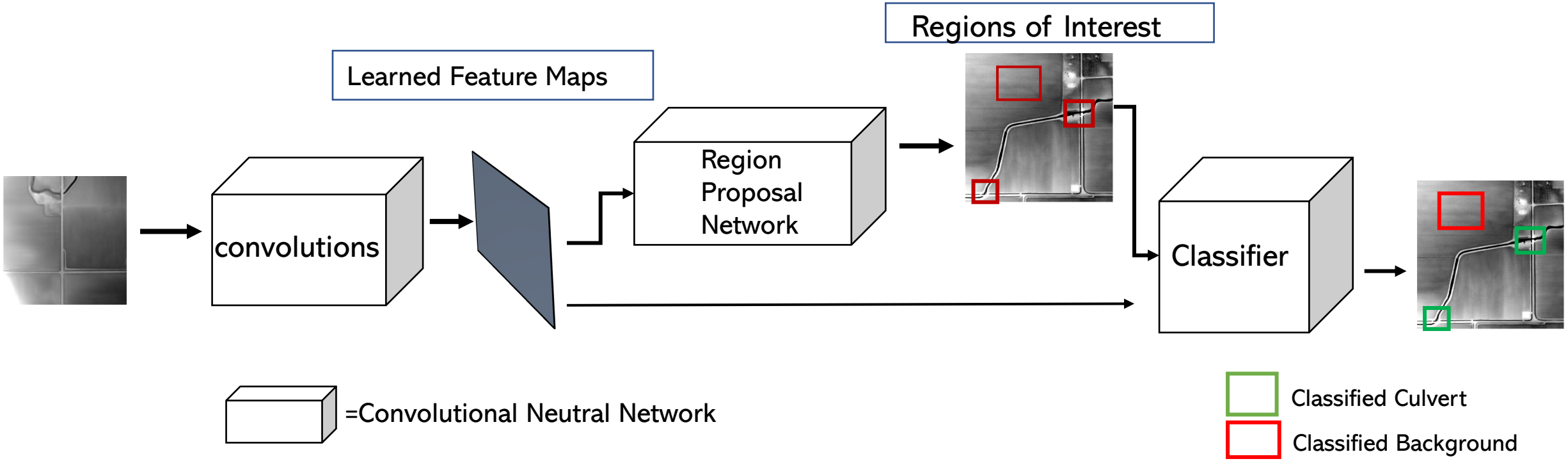
Data	Location	Source	Spatial Resolution	Vertical Accuracy RMSE	Number of Samples
DEM	West Fork Big Blue watershed, Nebraska	Nebraska Department of Natural Resource	1.0m	0.185m	2022

Part I – Faster R-CNN object detection

- Data Preprocessing
  - Manually digitized drainage crossing locations.
  - Culvert centroids are converted from the georeferencing system to image-based local referencing system
  - Generated training samples of 800x800
  - Compressed images from 32-bit floating point to 8-bit
  - Feature normalization between 0 and 255
  - Culverts centroids are used to create ground truth labels with 100x100 bounding box dimensions.
  - Bounding box information for each image is stored as VOC XML.

Part I – Faster R-CNN object detection

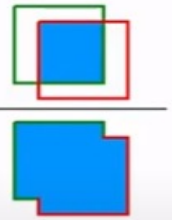
- **Model**
  - Pre-trained Resnet-50 is used as the backend convolutional neural network for this model.



Part I – Faster R-CNN object detection

- **Model Evaluation**
  - IOU: Intersection over union is used to account for the accuracy of the predicted bounding boxes which have been mapped to each label.
  - Extra: Accounts for the rate at which a given model provides too many bounding boxes.
  - Miss: accounts for the rate at which a given model provides too little bounding boxes.
  - Accuracy: the percent of culverts correctly identified out of the total present - a percentage of ground truth labels which have been assigned a culvert prediction.

$$IOU = \frac{\text{area of overlap}}{\text{area of union}} =$$



$$Extra = \frac{\text{Extra predicted labels}}{\text{Total True Labels}}$$

$$Miss = \frac{\text{Unpredicted Labels}}{\text{Total True Labels}}$$

Part I – Faster R-CNN object detection

Results

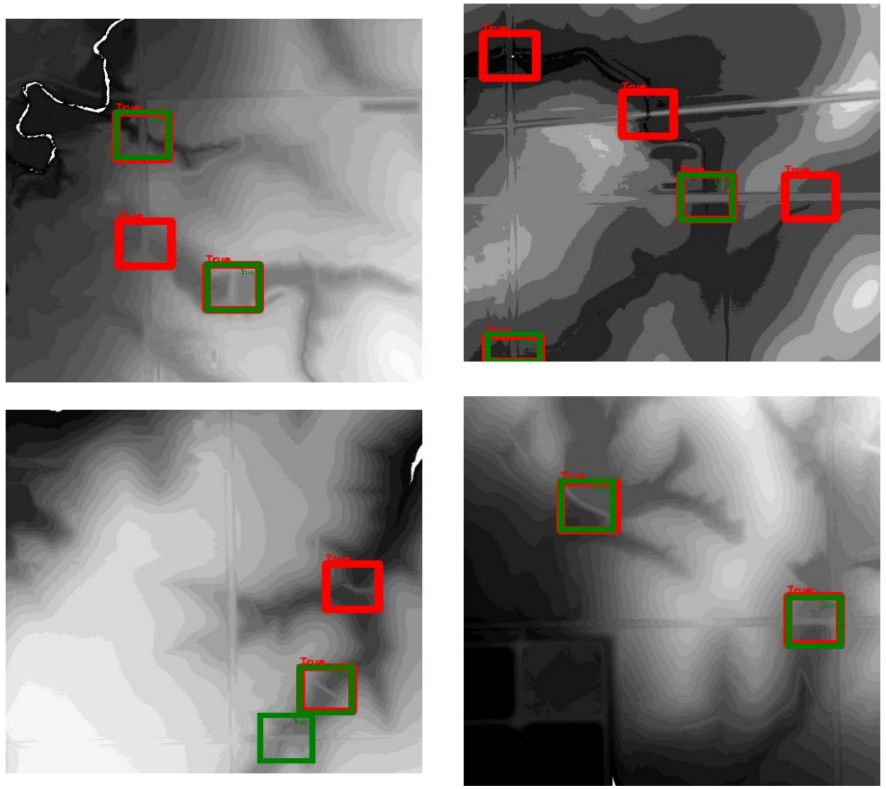
- The model used the SGD optimizer with learning rate of 0.001 and a decay factor of 0.005 and momentum of 0.9
- Confidence threshold of 0.7, to filter out low confidence detection.

Accuracy	IOU	Miss	Extra
0.882	0.668	0.11	0.24

- Accuracy: The accuracy of which the model correctly identifies all drainage crossings (Accuracy).
- IOU: Intersection Over Union of predicted bounding boxes.
- Extra: Rate of predicting extra labels and bounding boxes.
- Miss: Rate the model misses the presence of a culvert

Part I – Faster R-CNN object detection

- Discussion
  - The model shows a high rate of overlap between the true and predicted bounding boxes, indicating its capability to accurately identify culverts in images.
  - The model excelled in providing precise bounding boxes for the remaining images, even those that were initially missed or unlabeled in the dataset.
  - The model developed in Nebraska was able to detect culverts on other locations.



The green boxes represent the ground truth bounding boxes. The red boxes represent the predicted bounding boxes generated by the Faster R-CNN model

Part I – Faster R-CNN object detection

- Limitations
  - Conversion of DEM from 32-bit to 8-bit results in loss of elevation precision and finer terrain details.
  - Thus, less accurate terrain representation and reduced performance.
- Future Work
  - Testing deep learning models (e.g., SPP-Net)

Part I – Faster R-CNN object detection

- Now, coding time…

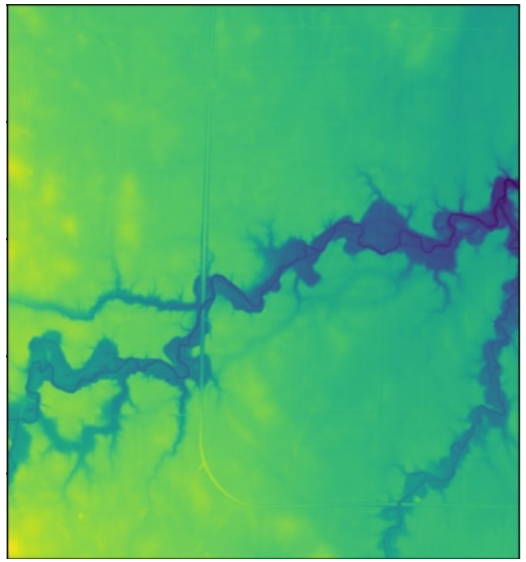
Part II

- U-Net Deep Learning Model for Drainage Flowline Detection

Part II – Data preprocessing

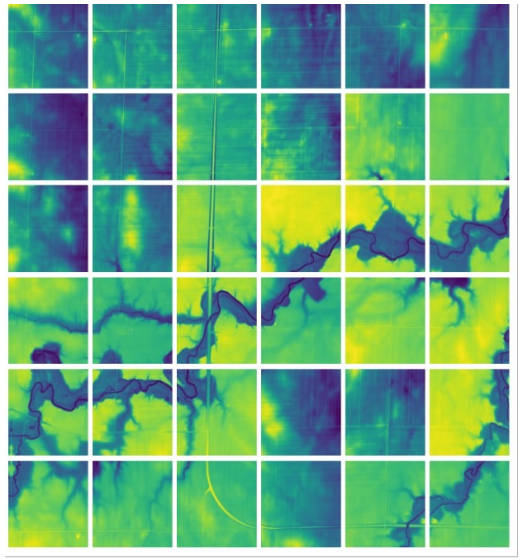
- Get bounding boxes coordinates:
  - The bounding boxes generated from the Faster-RCNN culvert detection need coordinate conversion.
  - The geographic coordinates are used to clip the large image to get exact locations of drainage crossings.

Original Image



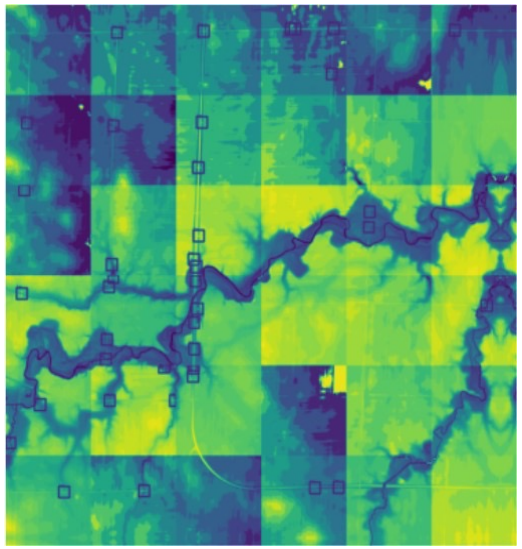
Shape: (4800, 4800)

Patchified Image

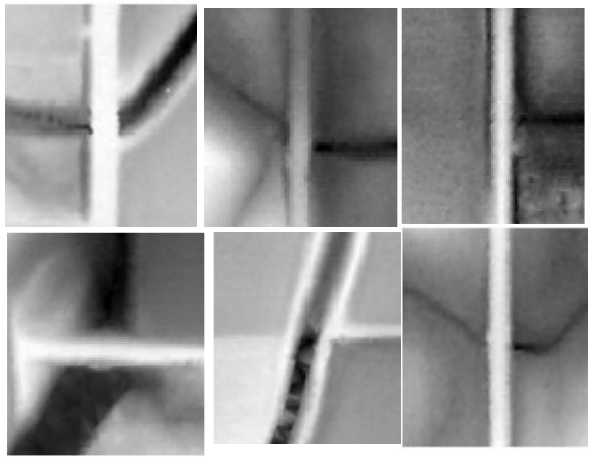


Shape: (6, 6, 800,800)

Reconstructed Image



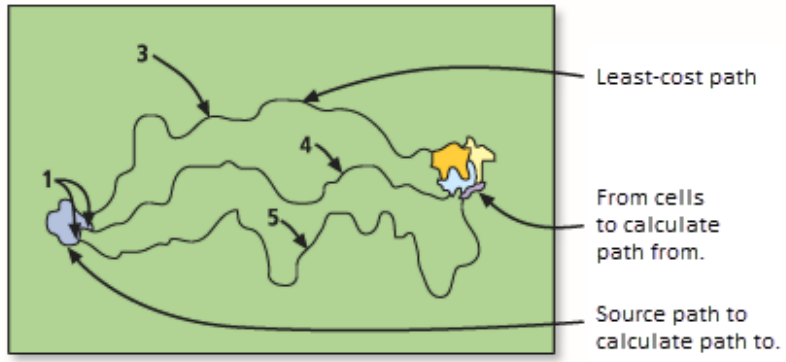
Shape: 4800x4800



Clipped Culvert locations

Part II – Data preprocessing

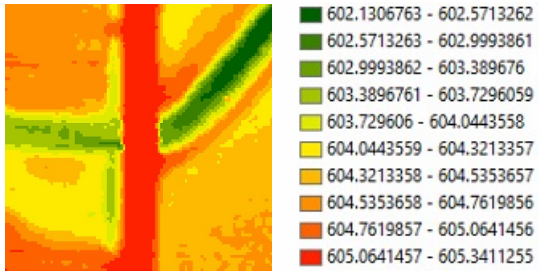
- **Least Cost Path Analysis**
  - Find most cost-effective route between a source and destination.
  - Extend identified culvert location to a drainage crossing line.

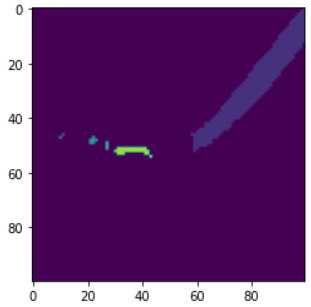


Part II – Data preprocessing

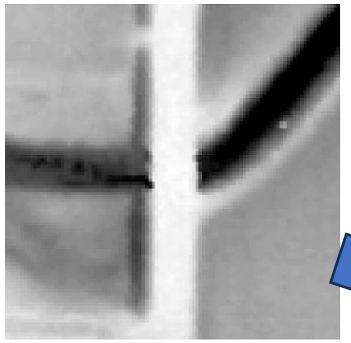
- To generate the least cost path, two endpoints and cost should be determined.
  - The elevation ‘jump’ caused by the road/bridge usually separates the depression into two groups.
  - Since the water flow direction is modeled from each cell to its steepest downslope neighbor, slope was selected as cost.
- Endpoints Selection
  - Generate depressions by the difference between filled DEM and original DEM.
  - Use Nature break (=10) to reclassify the elevation in samples. Two classes with top minimum elevation are selected for consideration.
    - Regions with top 2 largest areas are selected as mask to narrow down the potential depression group
  - Pick up one depression from each region, using its central point as one of endpoint. Different rules could be examined.
    - The paired depressions with nearest distance
    - Average depth of each depression

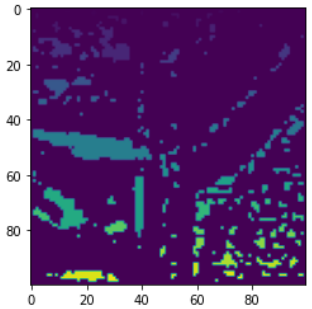
Part II – Data preprocessing



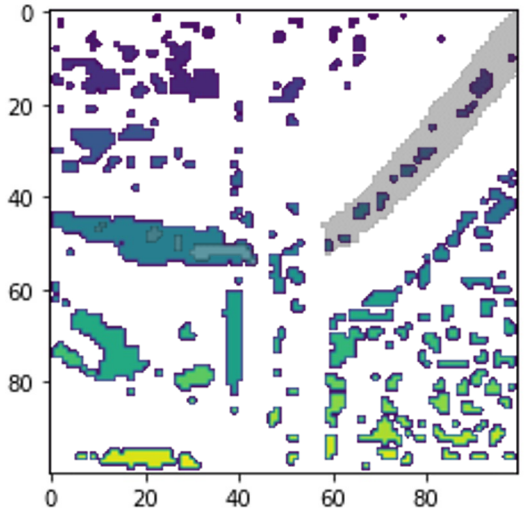


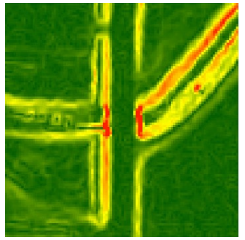
Nature Break

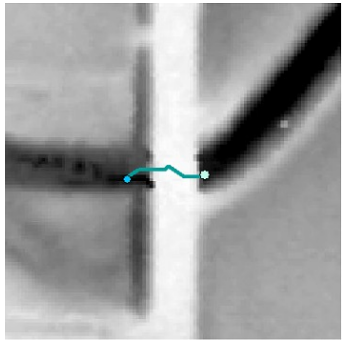




(Filled DEM – Original DEM)







Cost: Slope

Part II – Data preprocessing

- The least cost path raster is converted to a shapefile.
- 5m buffer is created along the least cost path line.
- The minimum elevation within the buffered area is estimated and the entire buffered area is set to that minimum elevation.
- The calculated values are replaced in the large DEM.

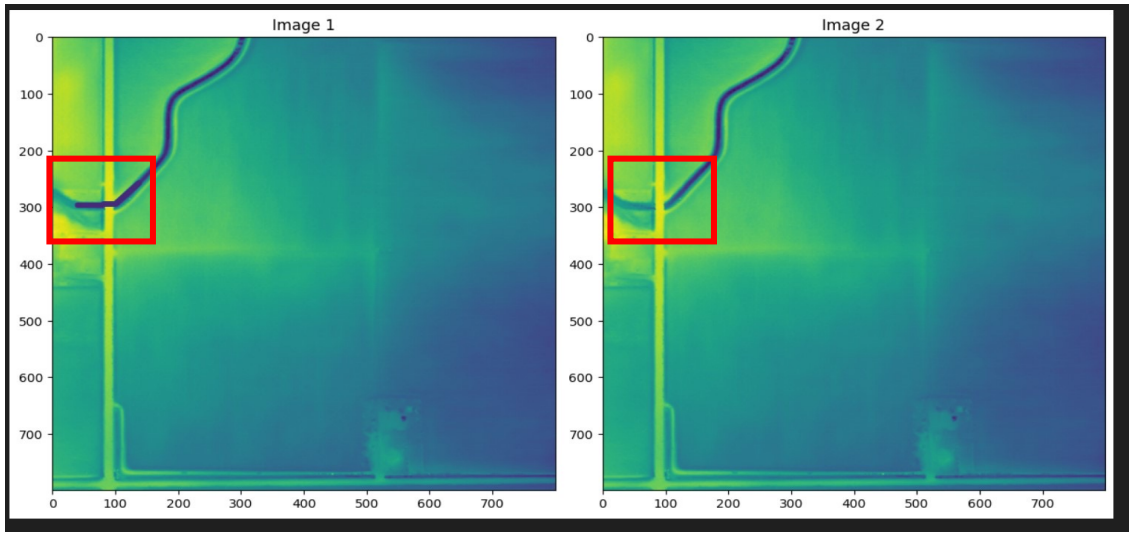


Image 1 = New DEM, Image 2 = Original DEM

Part II – Data preprocessing

- Now, coding time…

Part II – U-Net for flowline mapping

- Introduction
  - The U-net model is a state-of-the-art Fully Convolutional Network (FCN) that achieves high accuracy for solving image segmentation problems.
  - A special type of FCN for image segmentation.
  - FCNs replace the last fully connected layer with transposed convolutional layers for upsampling.
  - Built using locally connected layers (convolution, pooling, and upsampling), reducing parameters and computation.

Part II – U-Net for flowline mapping

Model Components:

- Convolutional Layer: Extracts important features from images using kernel filters.
- Pooling Layer:Downsampling to reduce resolution and preserve strong feature signals.
- ReLU Layer: Activation function truncating unimportant features.
- Transposed Convolutional Layer: Projects dense features to precise locations in the interpolation.

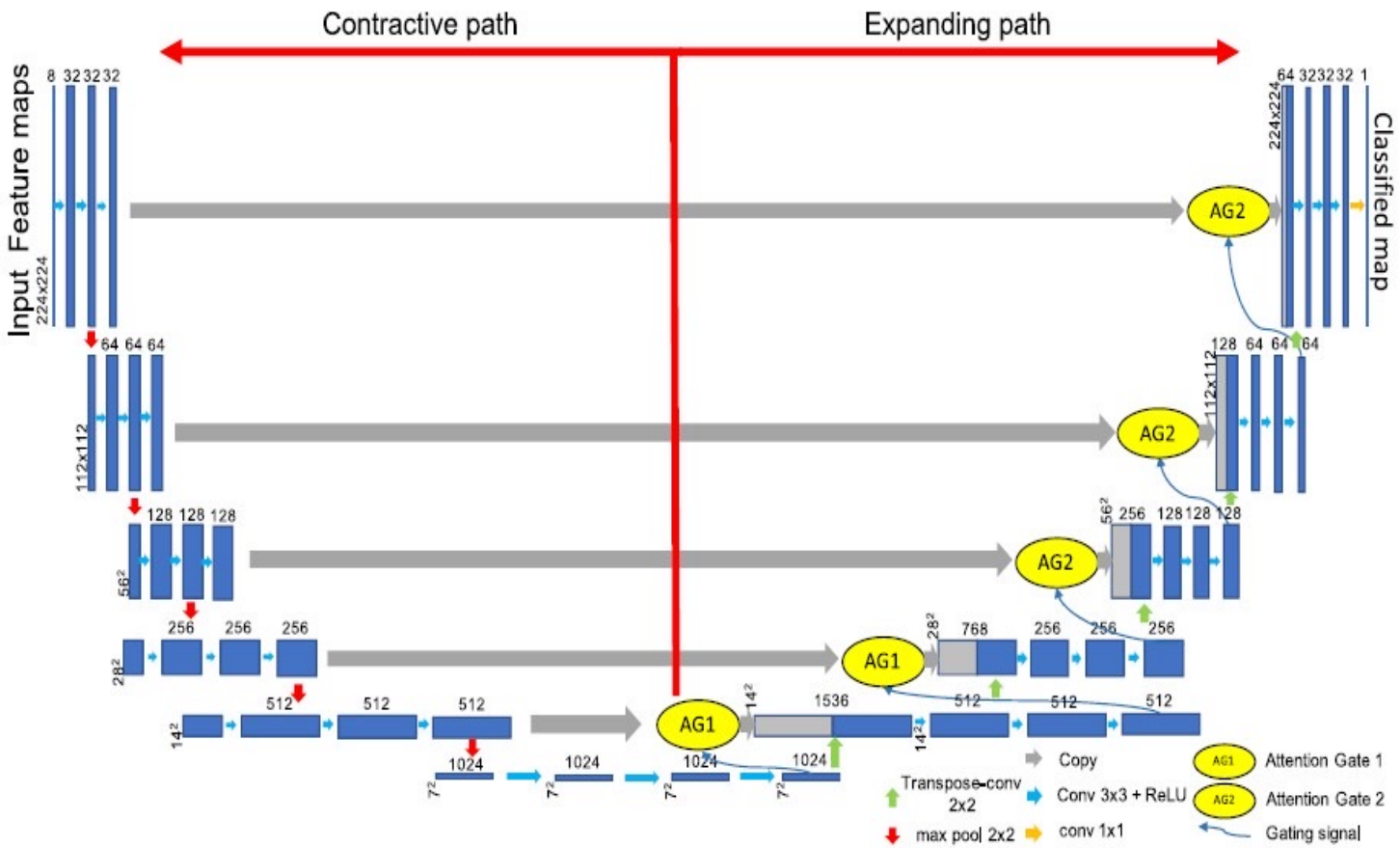
Model Architecture:

Six triple convolutional layers in the contractive path, five in the expanding path.

- Five pooling layers for downsampling.
- Five transposed convolutional layers for feature upsampling.
- Attention Gates used to filter propagated features through skip connections.
- Utilizes "Adam" optimizer for back-propagation.

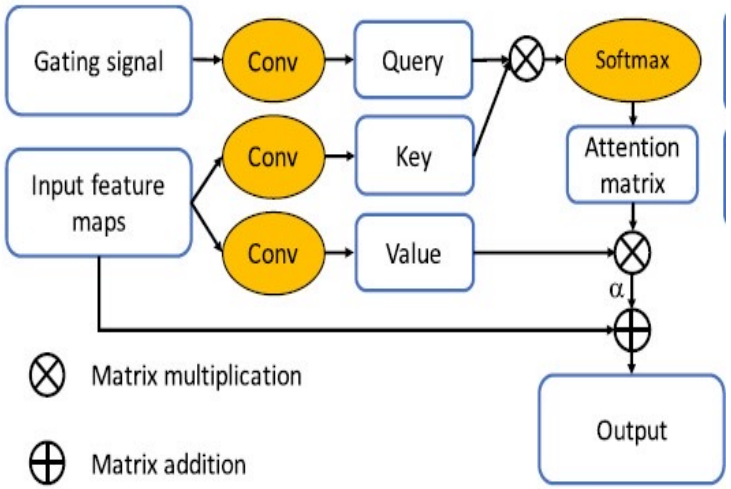
Part II – U-Net for flowline mapping

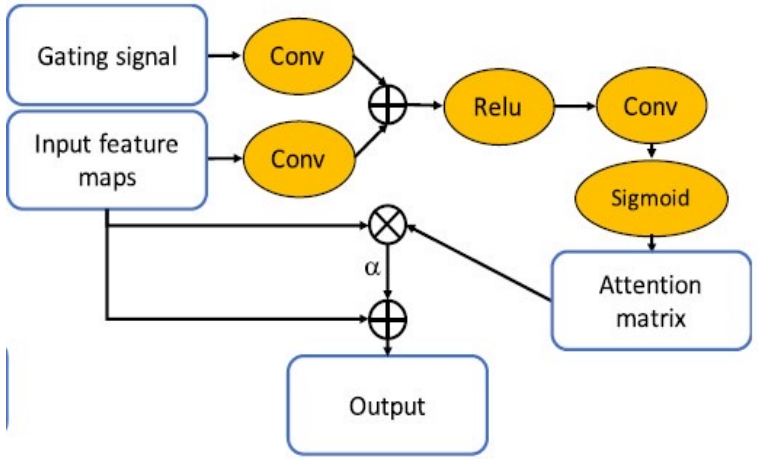
- U-Net Attention Module Model



The Architecture of the attention U-net model

Attention Gate 1





Attention Gate 2

Part II – U-Net for flowline mapping

- Input Data
  - **Data format:** tiff (feature maps), and Numpy array (organized data)
  - **Mask.npy:** The mask of research area. 1 indicates research area, 0 for outside area.
  - **Reference.npy:** numpy array format of reference data. 1 indicates streamlines, and 0 for non-streamlines
  - **Total.npy:** total prediction data of all feature maps
  - **TIFF:** All of the feature maps are DEM derived:
    - **1) DEM(digital elevation model):** 1-m HRDEMs
    - **(2) Curvature map:** geometric curvature determined from the DEM. Geometric curvature is determined using GeoNet software (Sangireddy, et al., 2016).
    - **(3) TPI1:** a topographic position index (TPI) derived from the DEM using a 3 x 3 window.
    - **(4) TPI2:** a TPI derived from the DEM using a 21 x 21 window.
    - **(5) Geomorphon openness:** zenith angle openness derived from the DEM using a 10-cell radius with 32 directions (Doneus, 2013).

Part II – U-Net for flowline mapping

Layer Name	Source	Description
Non-linear filtered DTM	USGS */GeoNet	IfSAR derived 5-m elevation model filtered using a non-linear diffusion filter for noise removal and enhancement of edges.
IfSAR DSM (resampled)	USGS */open-source	Elevation model representing the highest elevation on the surface, including vegetation and buildings
IfSAR DTM (resampled)	USGS */open-source	Elevation model representing the land surface
IfSAR ORI (resampled)	USGS */open-source	Orthorectified radar backscatter intensity image
Curvature	GRASS	The normalized sum of surface curvature in the x and y directions, generated from the filtered DTM
Geomorphon (10 cell radius)	GRASS	Identifies terrain landforms such as ridge, valley, and slope by analysis of elevation distribution within a 10-cell radius. Values are landform class ID's
2-D shallow-water channel depth model	GRASS	A storm water drainage model that considers the amount and duration of rain, surface friction, and surface water volume resulting in a water depth raster
Topographic wetness index	GRASS	Natural log of contributing upslope area of a cell over the local slope
Negative openness (5 cell radius)	RVT **	The mean of the angle between nadir and the horizon in 32 directions surrounding a cell
Positive openness (5 cell radius)	RVT **	The mean of the angle between zenith and the horizon in 32 directions surrounding a cell
Sky view factor	RVT **	The amount of incoming "light" from a diffuse hemisphere centered on a cell. As more of the hemisphere visible from the cell, lower the surrounding horizon, the higher the value
Sky illumination	RVT **	A hillshade generated assuming a diffuse illumination
Topographic position index (3×3 kernel)	open source	Difference between a cell elevation value and the average elevation of cells in a 3×3 window surrounding it
Topographic position index (11×11 kernel)	open source	Difference between a cell elevation value and the average elevation of cells in a 11×11 window surrounding it

Stanislawski et al. 2021

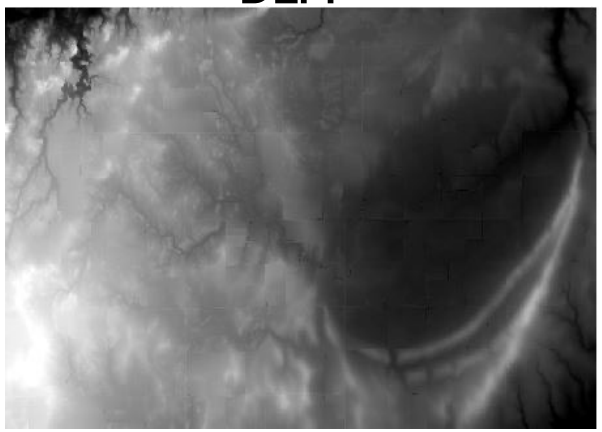
Raster Dataset	Minimum	Maximum	Mean	Standard Deviation	Range
Digital elevation model (meters)	194.11	256.19	229.07	12.96	62.07
Geometric curvature	−97.25	97.93	0.01	3.05	195.18
Topographic position index (3×3 window)	−8.59	5.58	6.38	0.18	14.167
Topographic position index (21×21 window)	−13.62	13.29	0	0.93	26.91
Openness (R10, D32) degrees	21.52	118.8	83.41	7.35	97.28
Return intensity	0	55185.39	29047.18	10624.11	55185.39
Return point density 1 ft above ground (points per m^2)	0	0.94	0.02	0.04	0.94
Return point density 3 ft above ground (points per m^2)	0	2.89	0.12	0.23	2.89

Xu et al. 2021

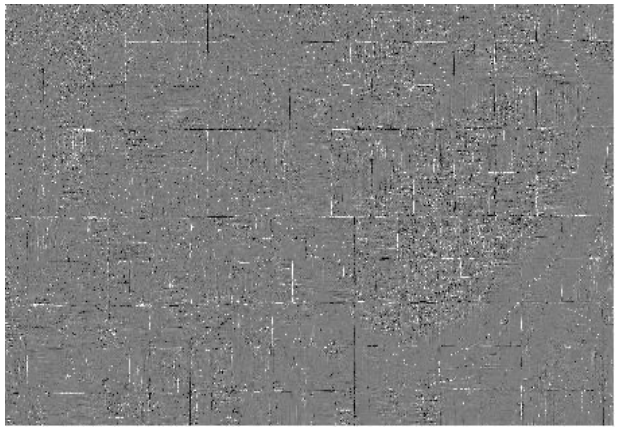
Part II – U-Net for flowline mapping

- Feature layers

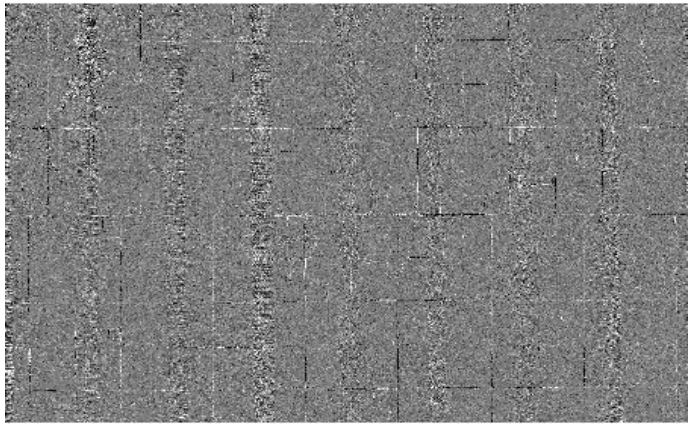
DEM



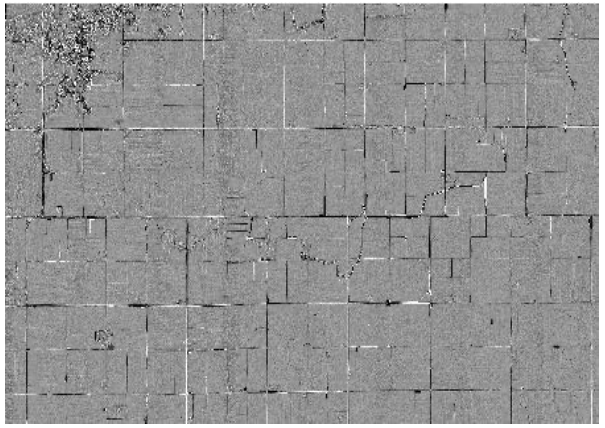
TPI 2 (21x21)



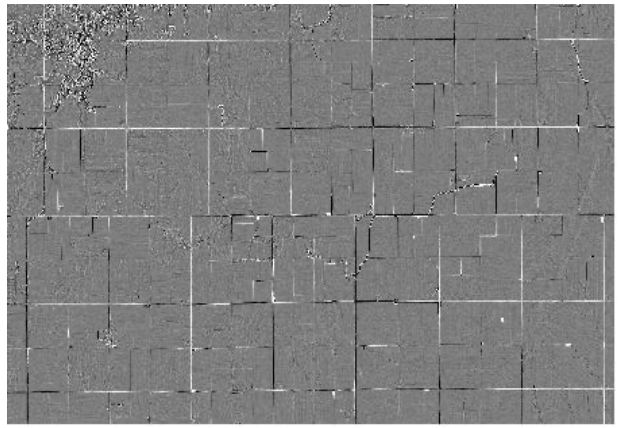
TPI 1(3x3)



Positive Openness



Curvature



Label(Reference Layer)

Part II – U-Net for flowline mapping

- Data Preprocessing
  - Normalization of feature maps between 0 and 255
  - Random site selection for patch generation and data augmentation.
  - Data augmentation include:
    - Randomly rotating each training patch by 30–150 and 210–330◦
    - Rescaling each sample by 0.5–0.8 and 1.5–2.0
    - Shearing each sample by random ranges from −30 to 30
    - Mirroring each sample horizontally to create six augmented samples for each training sample.

Part II – U-Net for flowline mapping

- Evaluation Metrics
  - Precision: A metric on how well the model avoids false positives. It is the ratio of true positive (TP) predictions to the total number of positive predictions made by the model.
  - Recall: (also known as Sensitivity or True Positive Rate): A metric that measures the ability of a model to capture all the positive instances in the dataset.
  - F1 Score: A harmonic mean of precision and recall. It is used to balance the trade-off between precision and recall. The F1 score provides a single value that represents the model's performance, taking into account both false positives and false negatives. It ranges from 0 to 1, where 1 indicates perfect precision and recall.

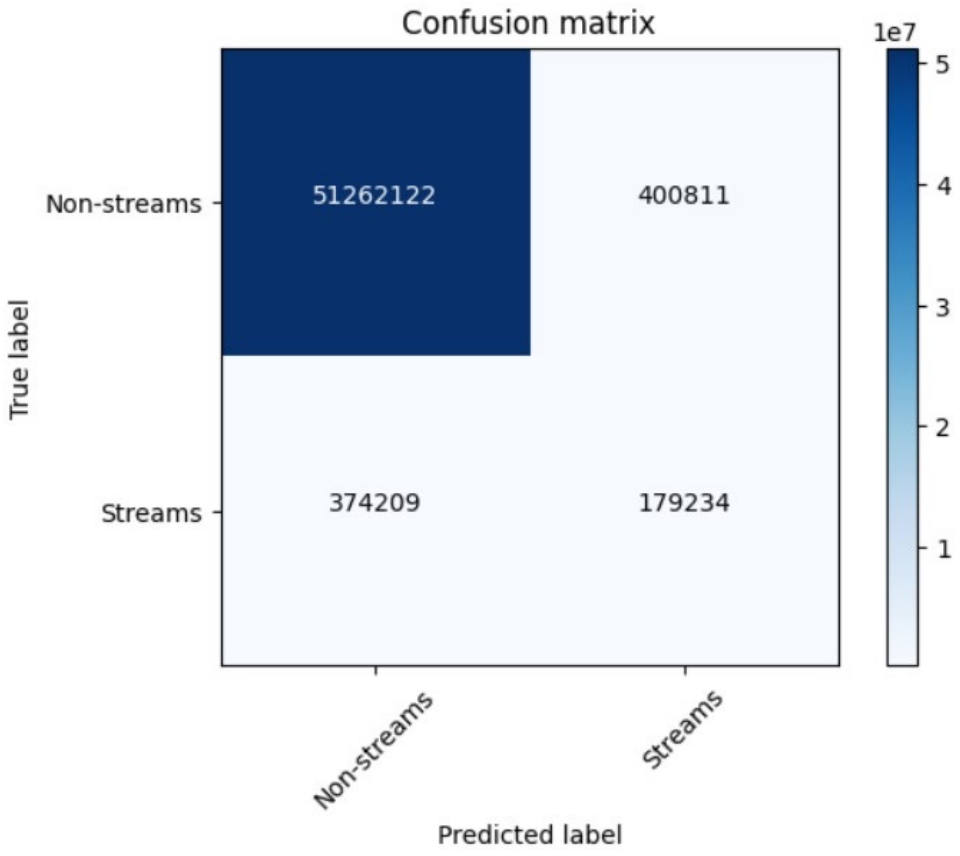
$$Precision = \frac{TP}{TP + FP}$$

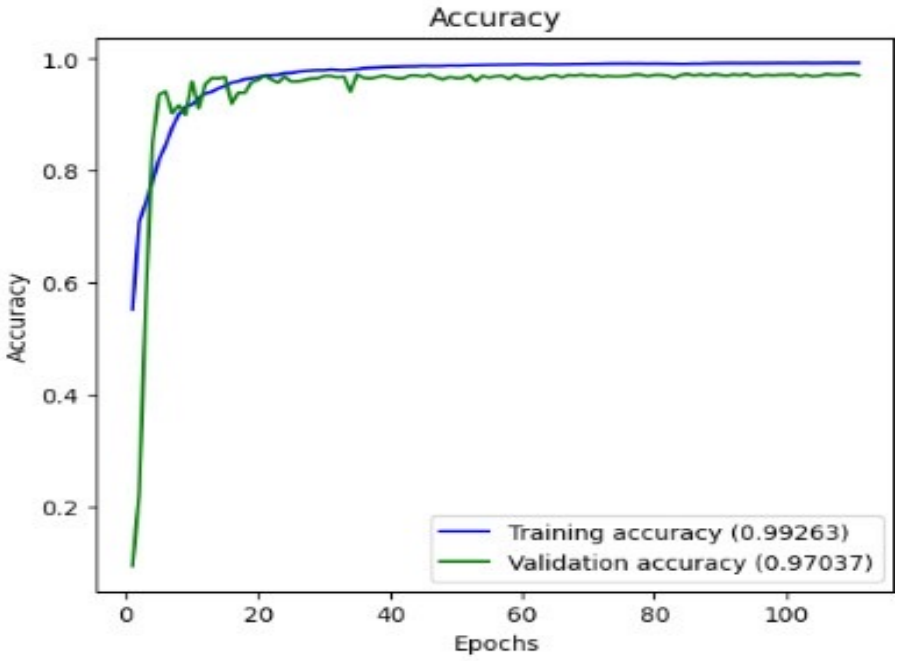
$$Recall = \frac{TP}{TP + FN}$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Part II – U-Net for flowline mapping

- Results & Discussion



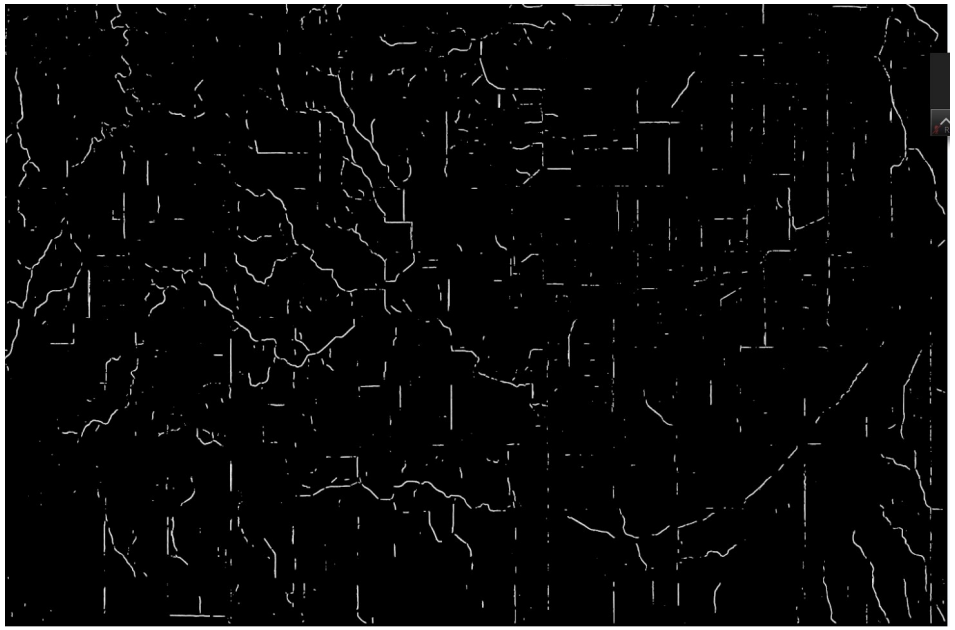


F1 score of stream: 0.31625
F1 score of nonstream: 0.99249
Precision of stream: 0.30900
Precision of nonstream: 0.99275
Recall of stream: 0.32385
Recall of nonstream: 0.99224

Part II – U-Net for flowline mapping

- Results & Discussion

Predicted Flowlines



Manually Developed Ground Truth Flowlines

- The difficulty in developing reliable ground truth drainage channels at local scales
- Stream and nonstream cells are hard to distinguish for some shallow stream channels and road ditches

Part II – U-Net for flowline mapping

- Now, coding time…

Discussion & Conclusion

- Q & A
  - More combinations of features for improve accuracies
  - Mapping based on the TauDEM for flow accumulation
  - Please share your experience with deep learning model use

- Deep learning models are robust tools for addressing hydrological connectivity mapping using HRDEMs.
- The GPU infrastructure is critical to advance intensive GeoAI computation tasks.

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Thank you

- Contact

Ruopu Li
Associate Professor – Geography and Environmental Resources

SCHOOL OF EARTH SYSTEMS AND SUSTAINABILITY
SOUTHERN ILLINOIS UNIVERSITY
1000 FANER DRIVE
CARBONDALE, ILLINOIS 62901

Ruopu.Li@siu.edu
https://www.geofew.org
P: 618-453-6038