CNN-based Hydrological Connectivity Modeling

CyberTraining Workshop
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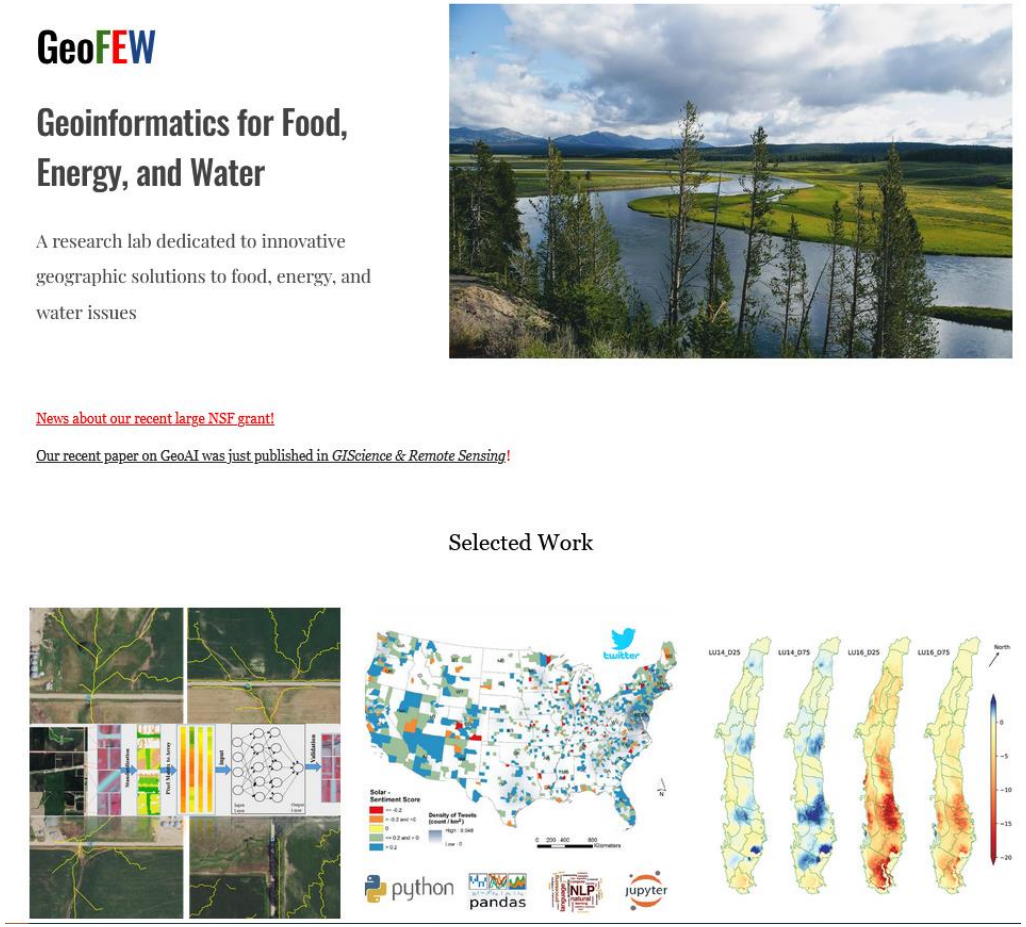
Ruopu Li, Ph.D.
Geography and Environmental Resources Program
School of Earth Systems and Sustainability
Southern Illinois University

About Myself



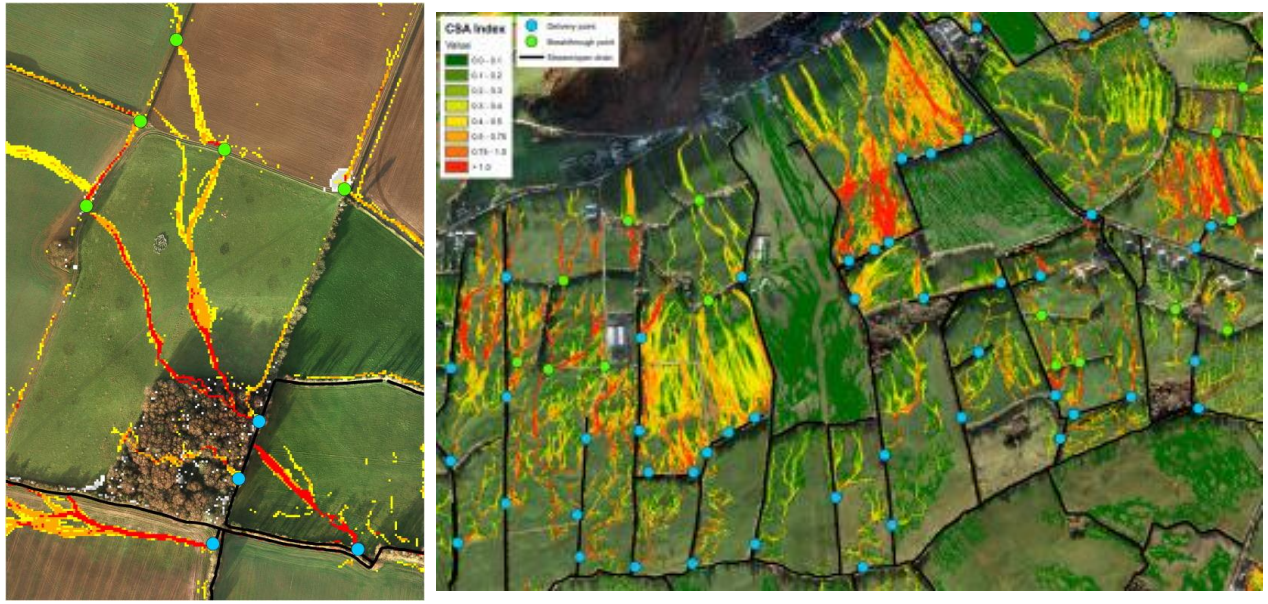
https://www.geofew.org/

Outline

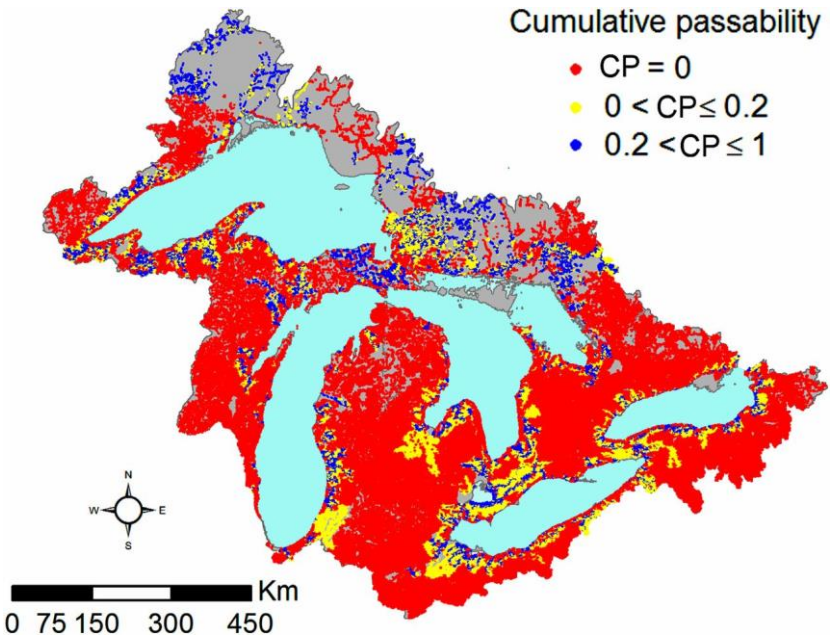
- Background
  - Hydrological connectivity and its applications
- Problem statement and AI solution
  - Why detecting drainage crossings
- CNN-based classification models
  - Baseline model vs advanced models
  - Hands-on exercises
- CNN-based object detection models
  - Faster R-CNN vs YOLOv5
  - Hands-on exercises
- Conclusions
- Workshop project overview

Background

- Hydrologic connectivity is critical for environmental management issues.
  - Overland nutrient transport, fish waterway passage, runoff routing, …



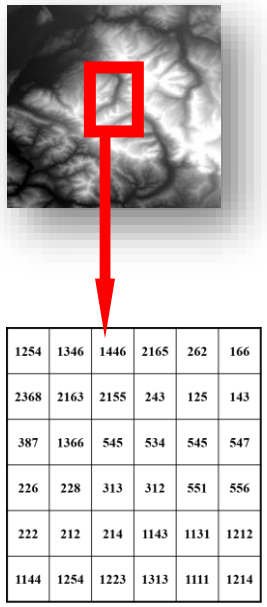
Hydrologically sensitive areas along with interfield delivery points
Thomas et al. 2016a STOTEN, 2016b AGEE



Cumulative passability (CP) of 6,692 dams and 232,068 road crossings (Neeson et al. 2015 PNAS)

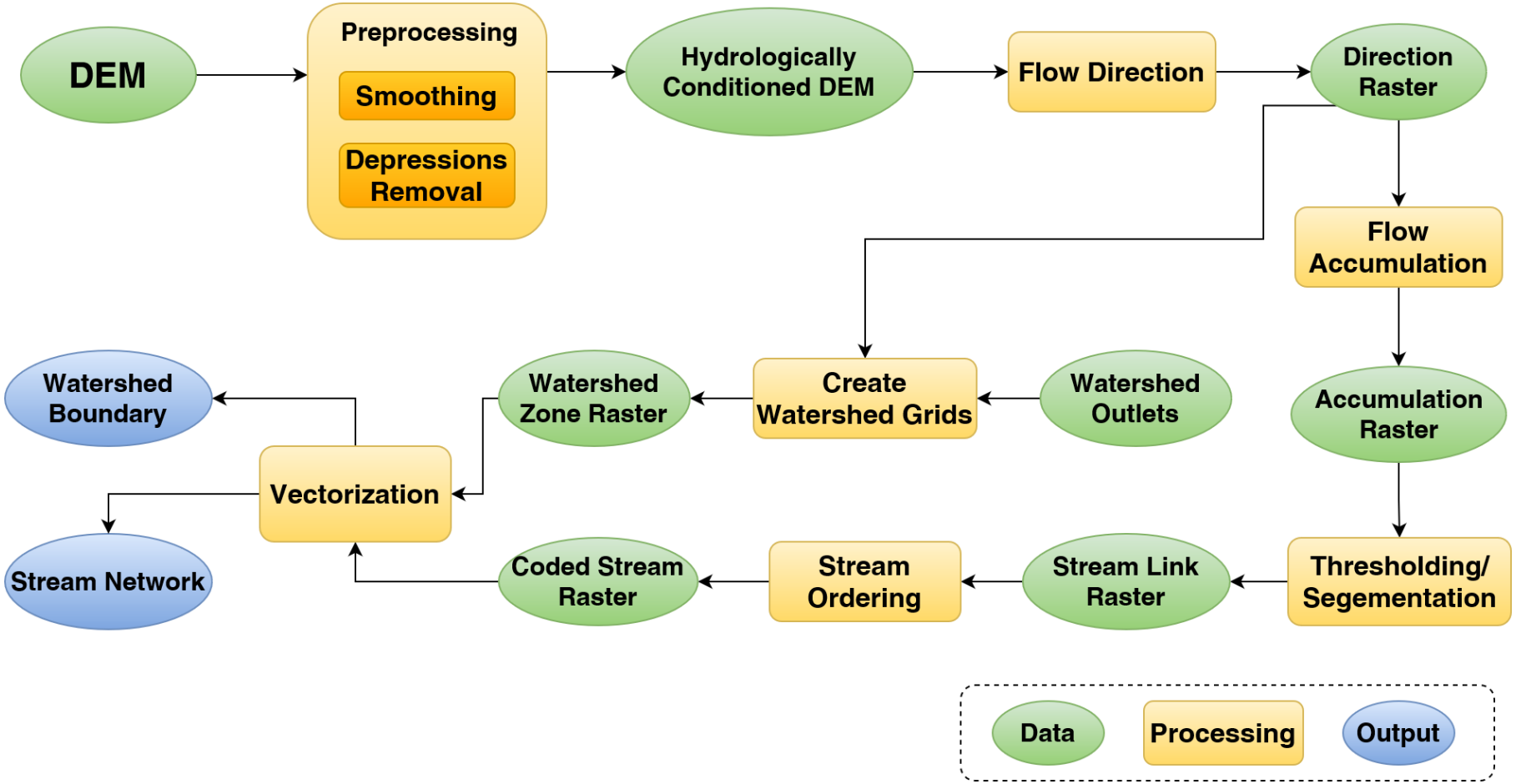
Hydrologic connectivity

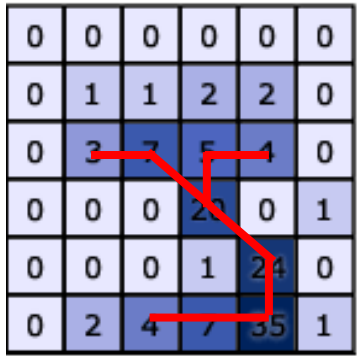
- National Hydrography Dataset (NHD) and its derivative versions
  - Natural and artificial flowlines and water bodies
  - Currently best scale at 1:24,000
- Digital Elevation Models (DEMs) are commonly used to delineate the network of hydrography features.
  - Conventional DEMs
    - With relatively coarse spatial resolutions and inaccurate vertical accuracy
    - 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



Background

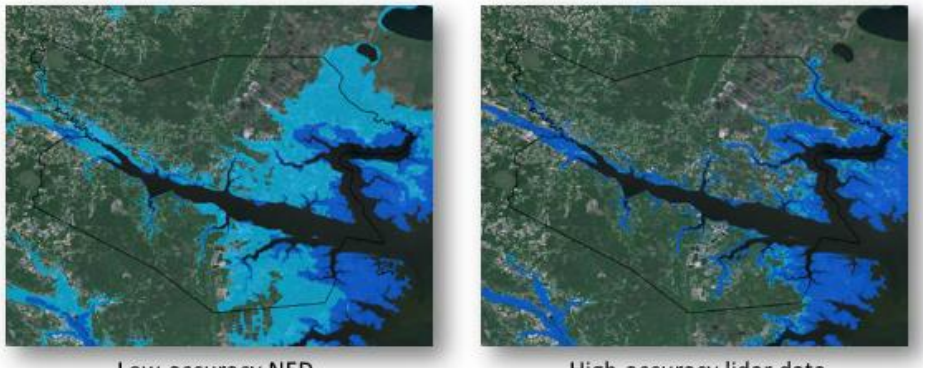
- Terrain-based hydrological analysis





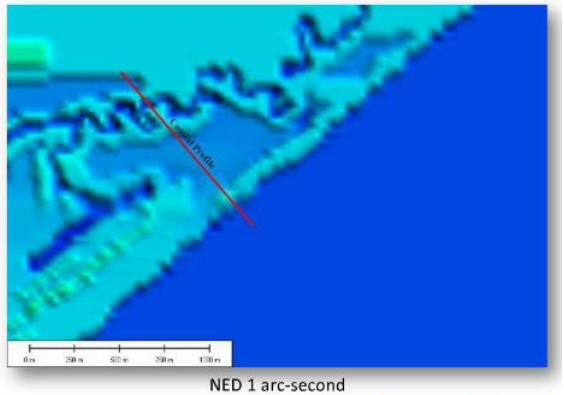
Background

- 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 very soon.

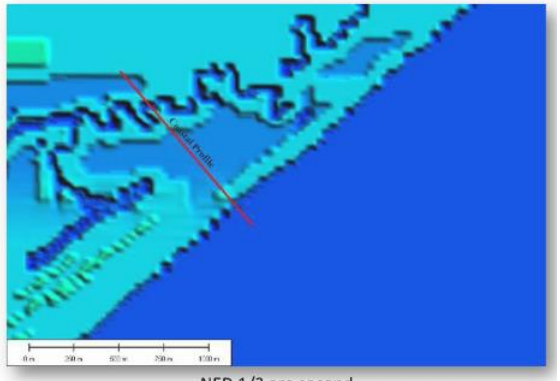


Low-accuracy NED High-accuracy lidar data

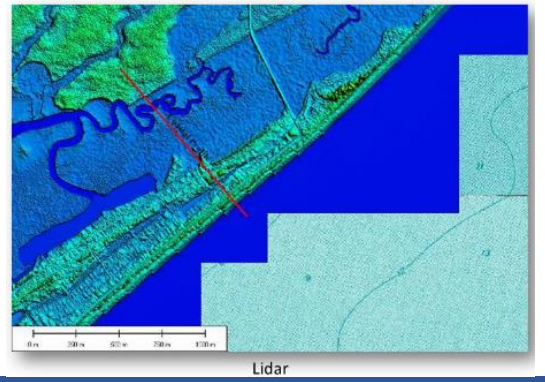
Darker blue tint: Inundated land if sea level rises ≤1-meter
Lighter blue tint: Area of uncertain inundation if sea level rises ≤1-meter



NED 1 arc-second



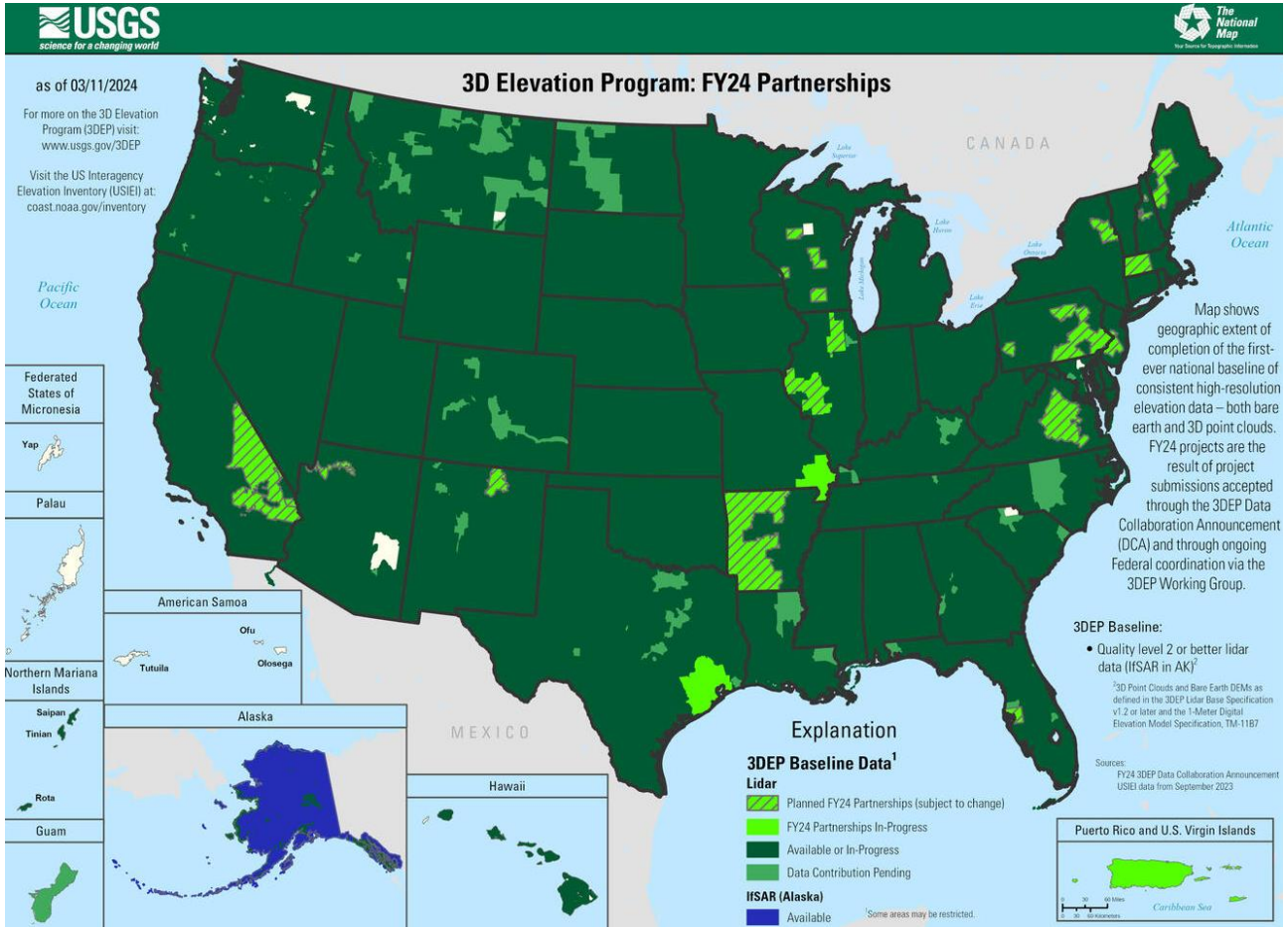
NED 1/3 arc-second



Lidar

3D Elevation Program (3DEP)

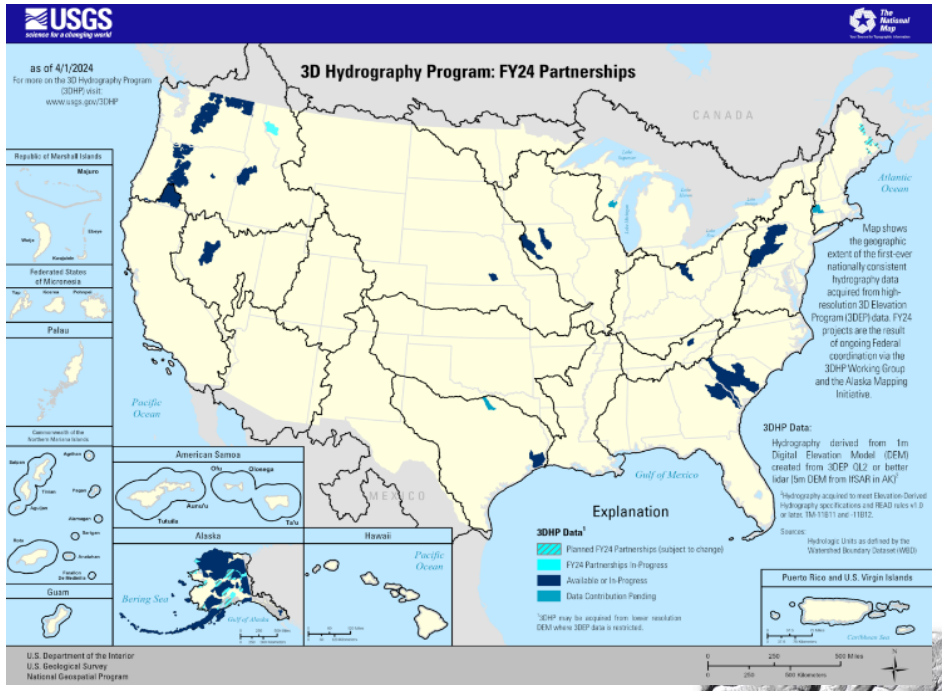
- **Goal:** The 3DEP is to complete nationwide coverage of LiDAR data
- **Data Availability:** All 3DEP products are available free of charge
- **Resolution**:
  - 10, 30, and 60 meters
  - 1-meter LiDAR DEM



https://www.usgs.gov/3d-elevation-program

3D Hydrography Program (3DHP)

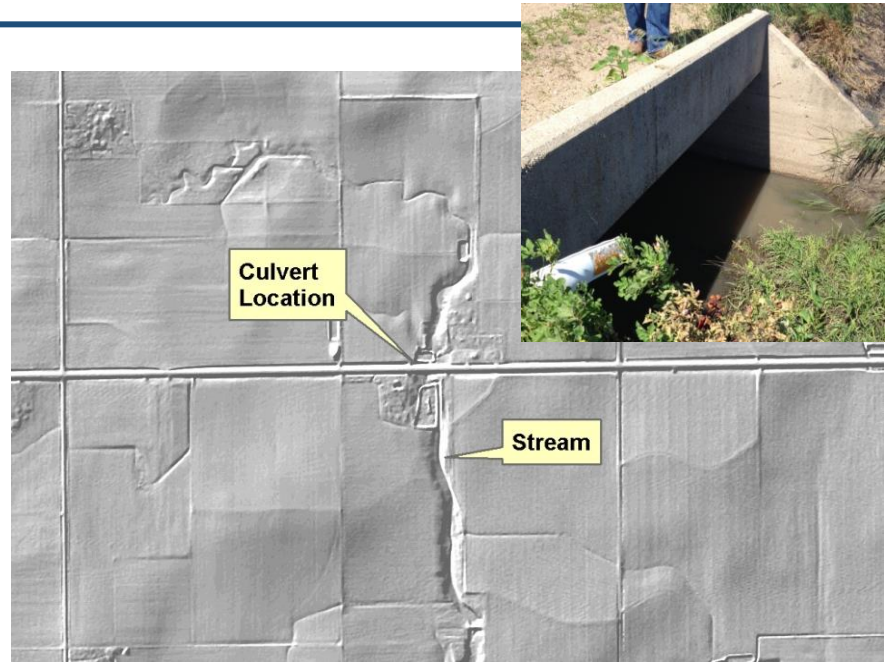
- In 2022, the USGS announced the development of the 3DHP as an eventual replacement for the NHD.
- 3DHP will remap US hydrography, which originated from the USGS 1:24K topographic mapping efforts.
- 3DHP provides surface water data following the elevation-derived hydrography (EDH) guidelines and aligning with LiDAR elevation data.



Problem statement

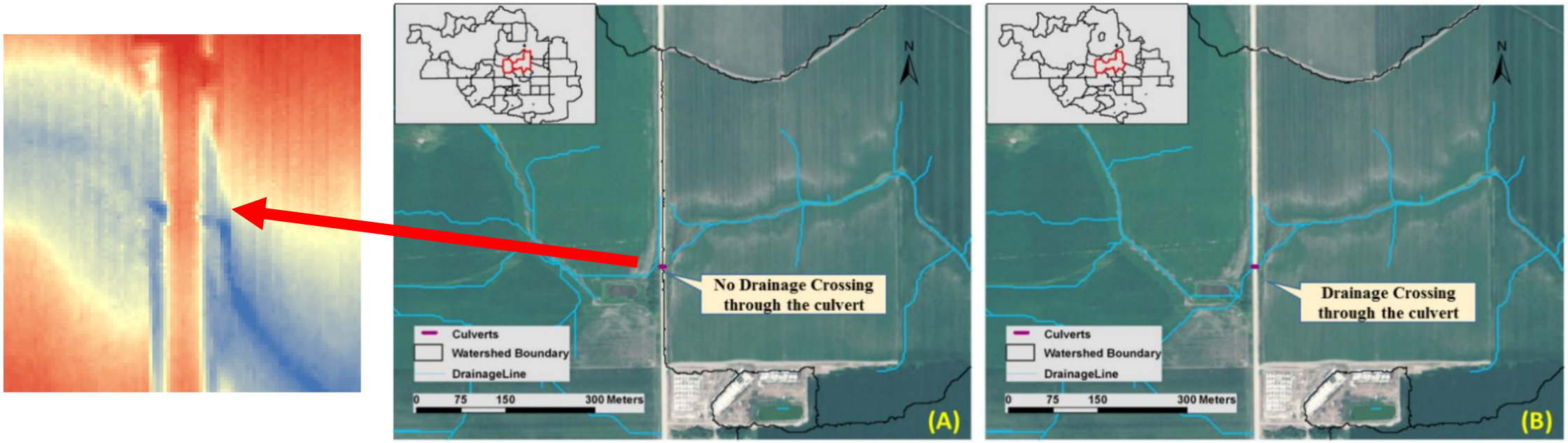
- "Digital dams" caused by artificial structures
  - The virtual flow obstructions associated with artificial embankments (e.g., bridges and roads).
  - HRDEM-derived underpass flow routing is unavailable or has variable quality.
- Land roughness associated with widespread depressions
  - Spurious depressions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

Scale related!



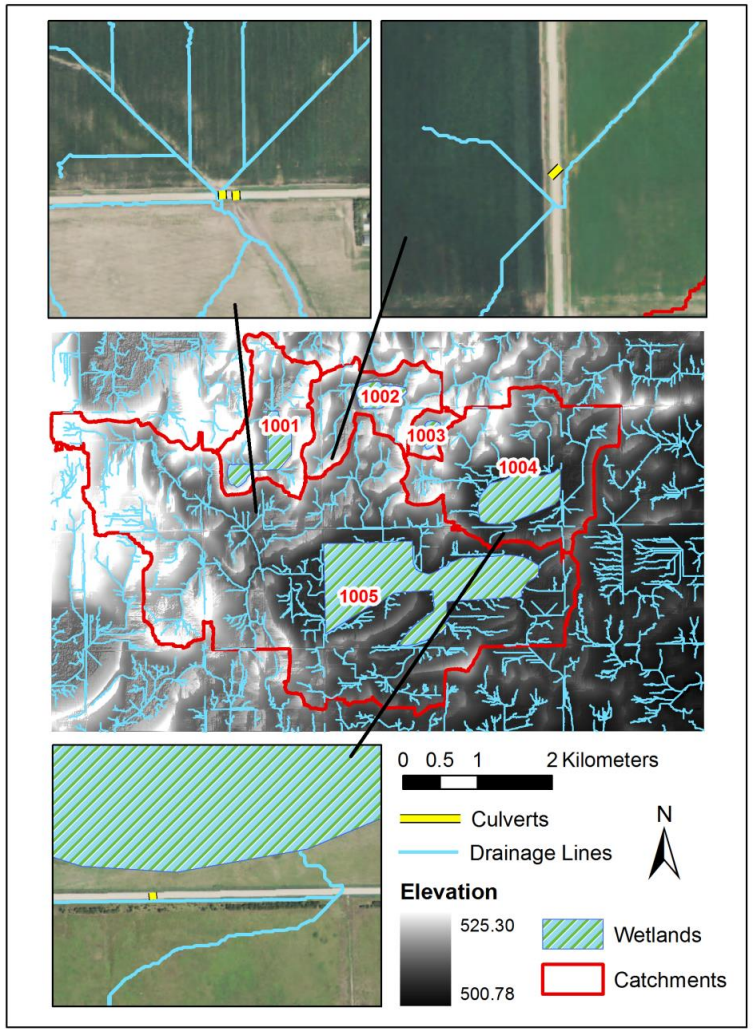
Problem statement

- Most current LiDAR DEMs are not hydrologically corrected.
- Digital dams confuse the flow direction/accumulation algorithms.
- The ground truth datasets for hydro-DEM is needed.

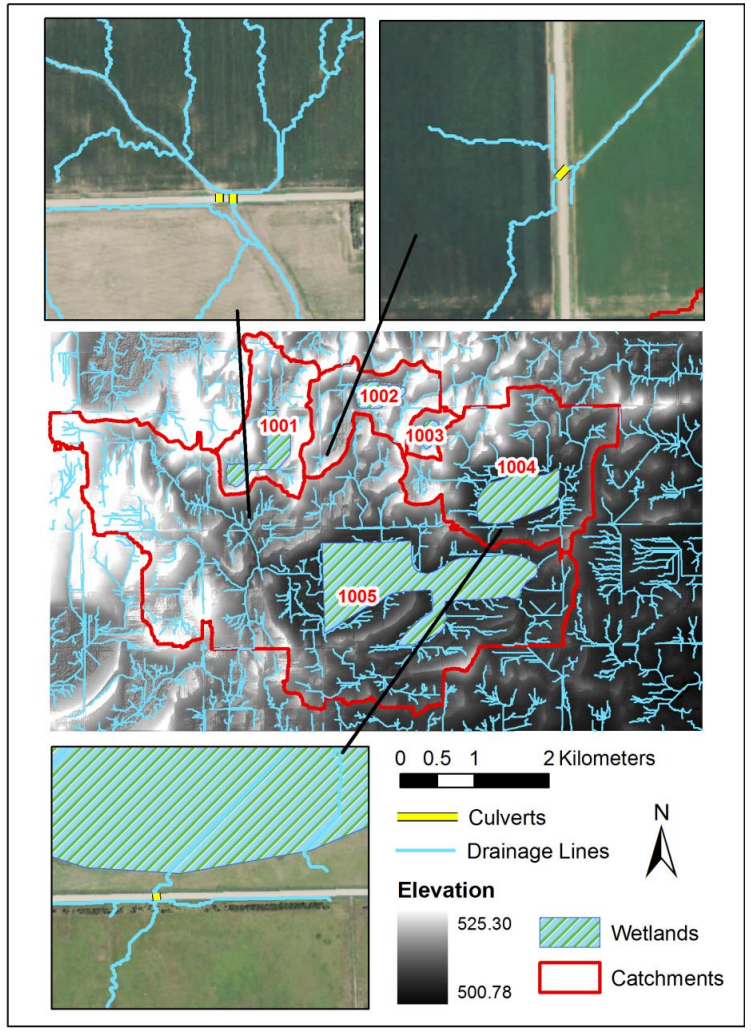


Li et al. 2013. *ISPRS IJGI*.

Problem statement



Before burning culverts



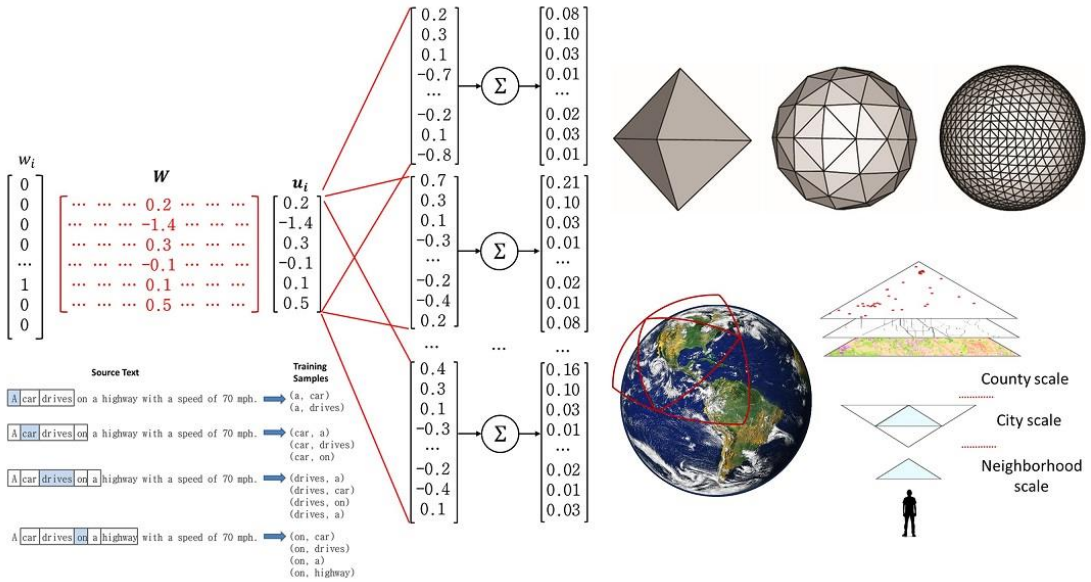
After burning culverts

Research Gaps

- How to effectively identify the locations of culverts/bridges to be integrated into HRDEMs for improved hydrography mapping.
  - Traditional manual on-screen digitization
  - GeoAI for identifying drainage crossing locations
    - Converge geospatial science, AI, data mining, and high-performance computing
    - Scalable performance in fast and accurate detections of terrain features
- Developing high-quality drainage crossing datasets and GeoAI methods based on cyberinfrastructure to improve the characterization of HRDEMs-derived hydrologic connectivity.

Geospatial Artificial Intelligence (GeoAI)

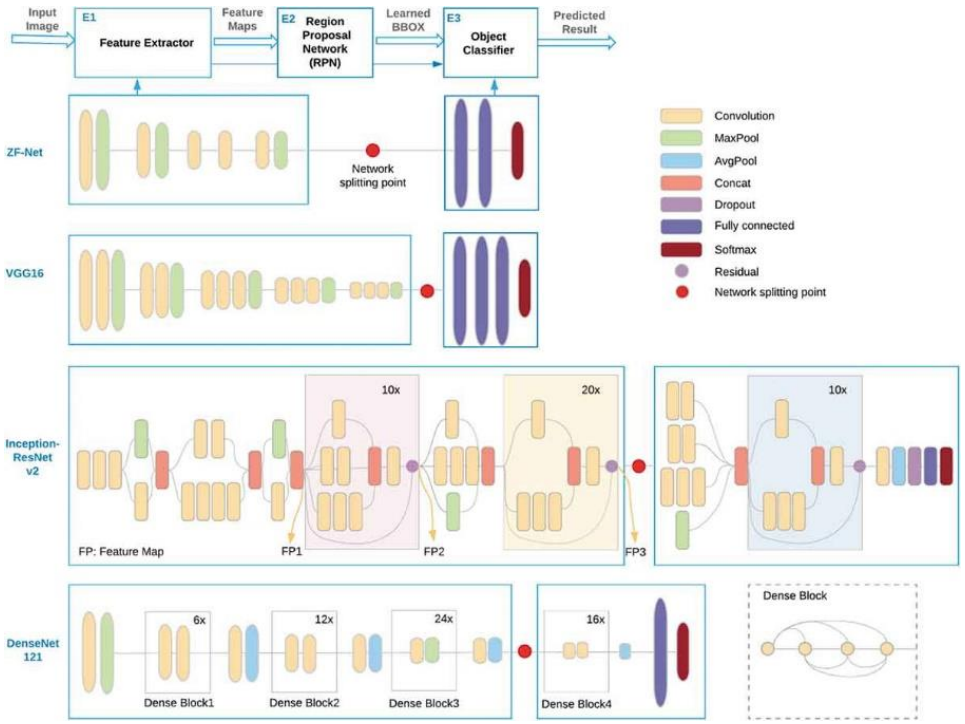
- AI in Geospatial Information Science
  - An emerging discipline that combines innovations in geospatial science, artificial intelligence methods in machine learning (e.g., deep learning), and high-performance computing to extract knowledge from spatial big data.

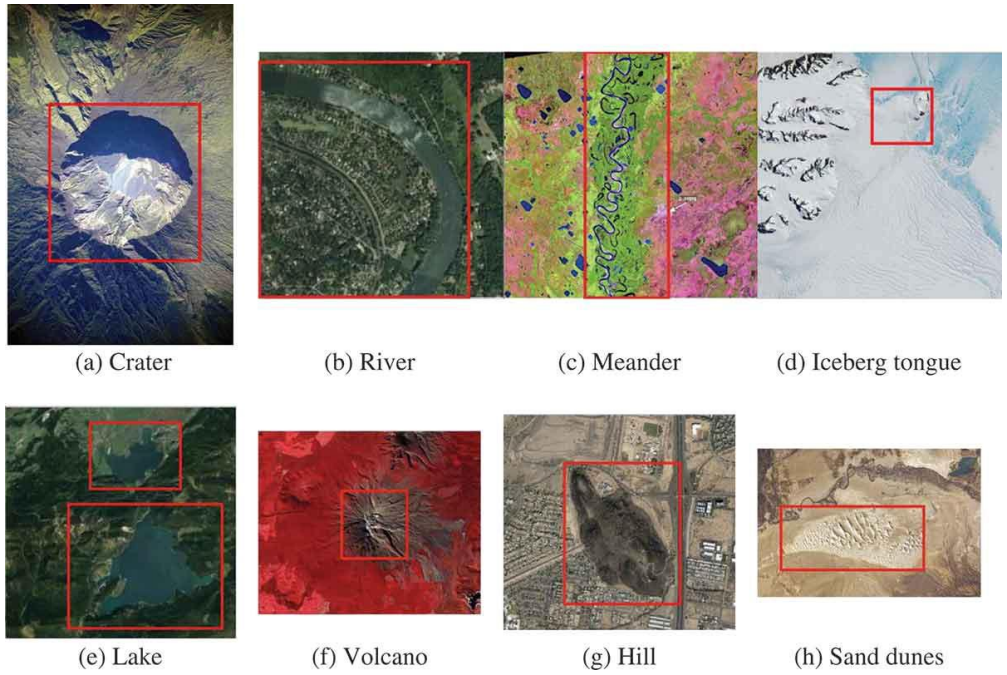


Source: https://geoai.geog.buffalo.edu/

Geospatial Artificial Intelligence

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

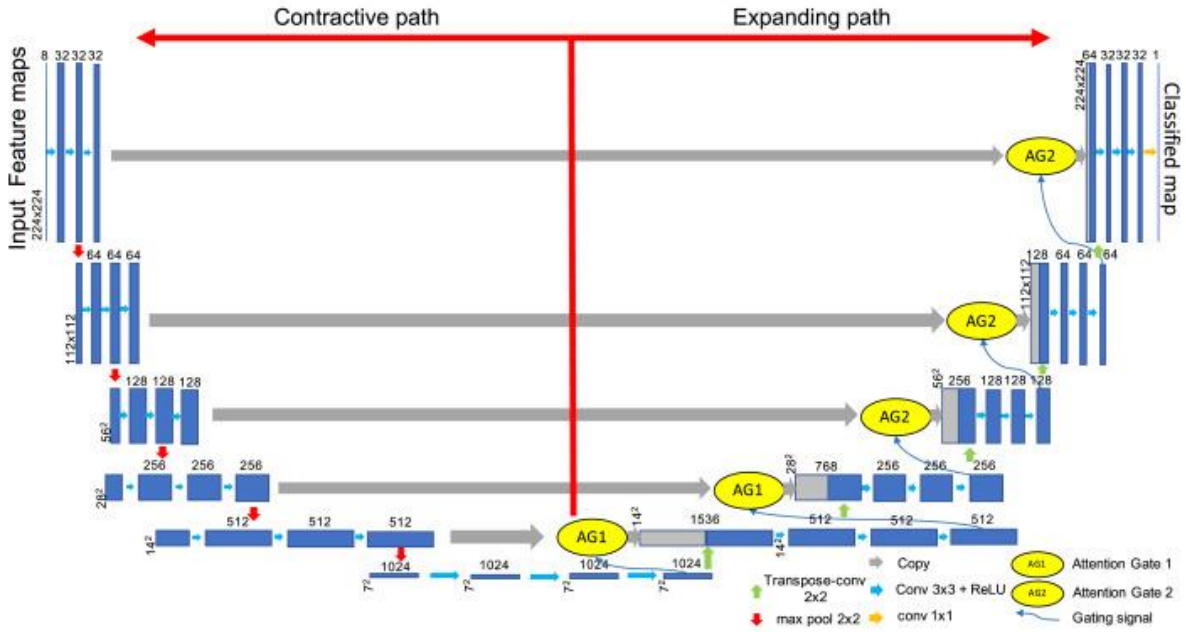




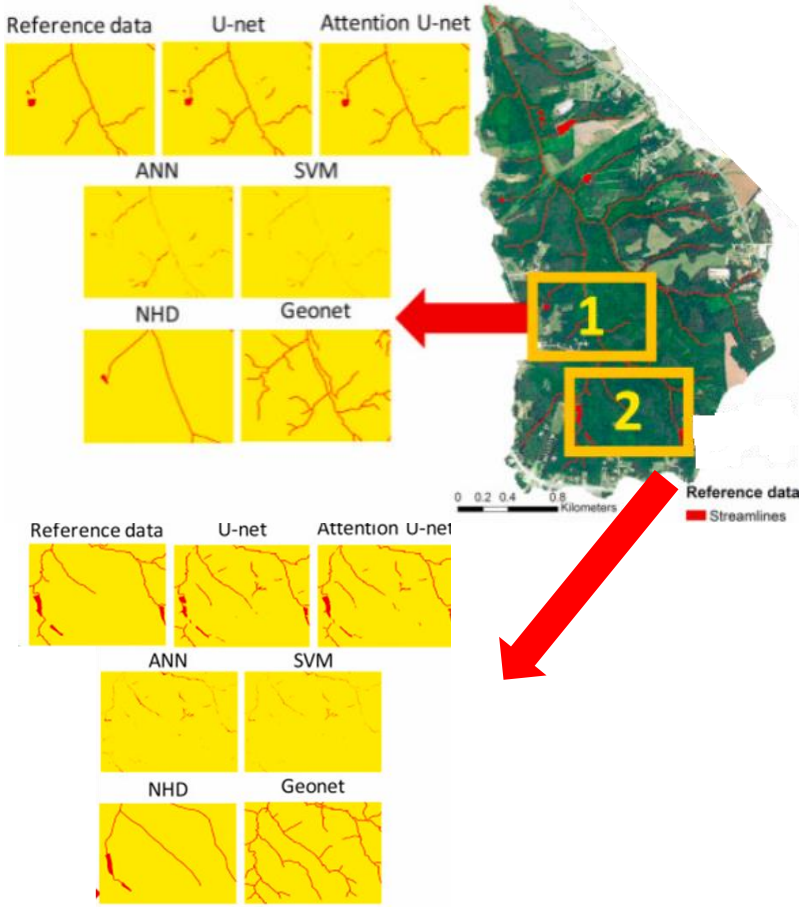
Li and Hsu. 2020 *IJGIS*

Geospatial Artificial Intelligence

- Example: Xu et al (2021) An attention U-Net model for segmenting fine-scale hydrologic streamlines



The architecture of the attention U-net model



Xu et al. 2021 *Environmental Modeling & Software*

Geospatial Artificial Intelligence

- **Our Example**: 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.

Overall Workflow

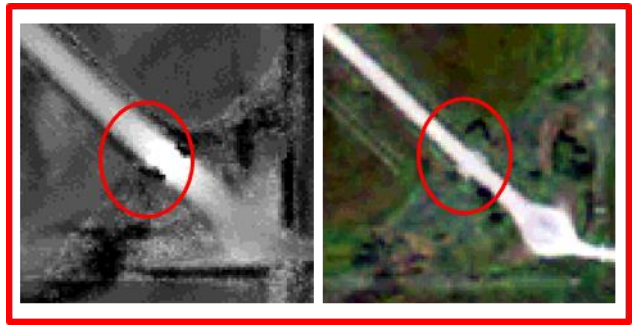


Image with drainage crossing

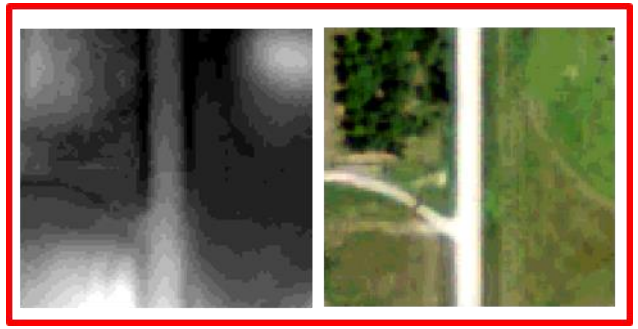
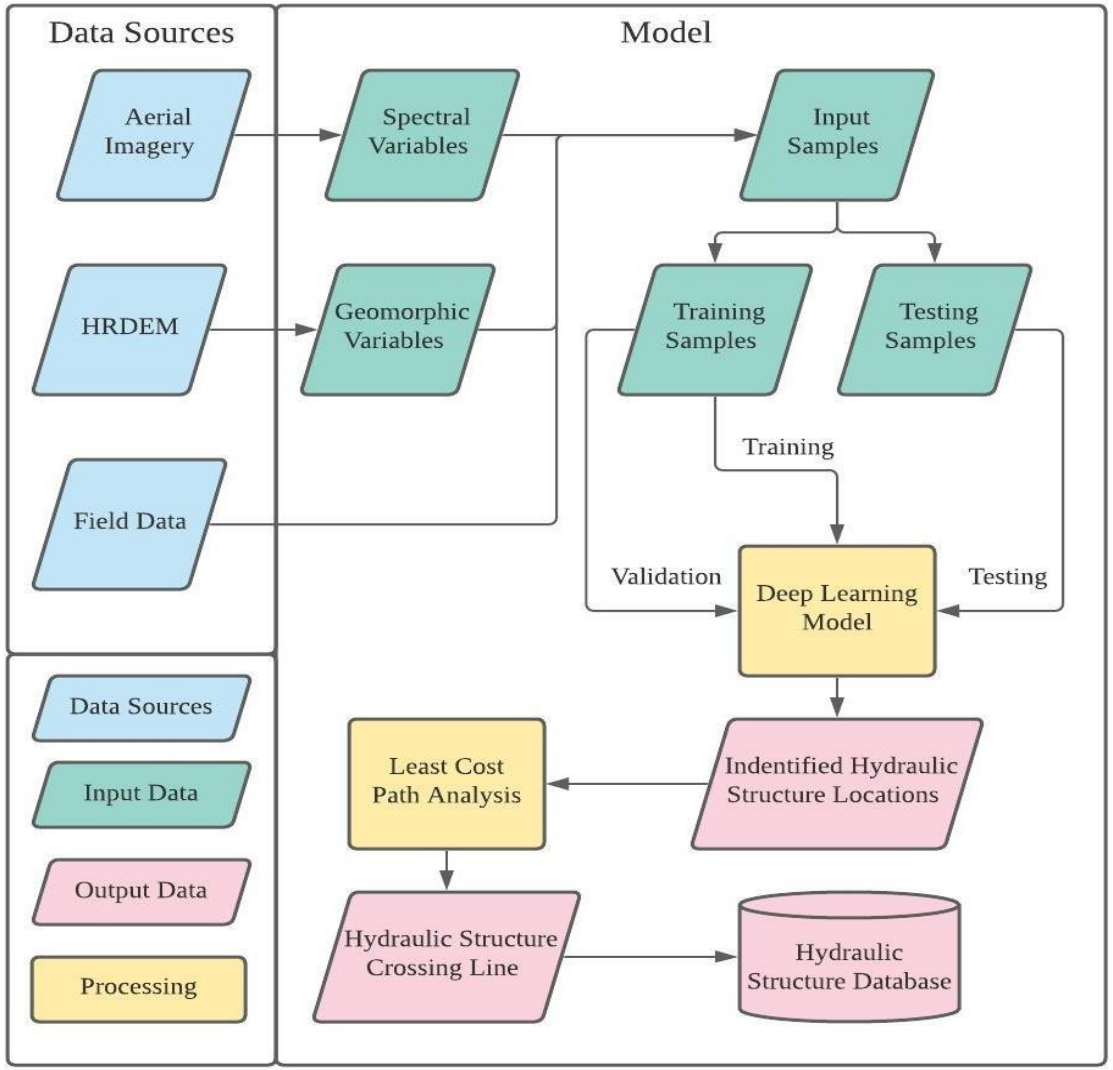
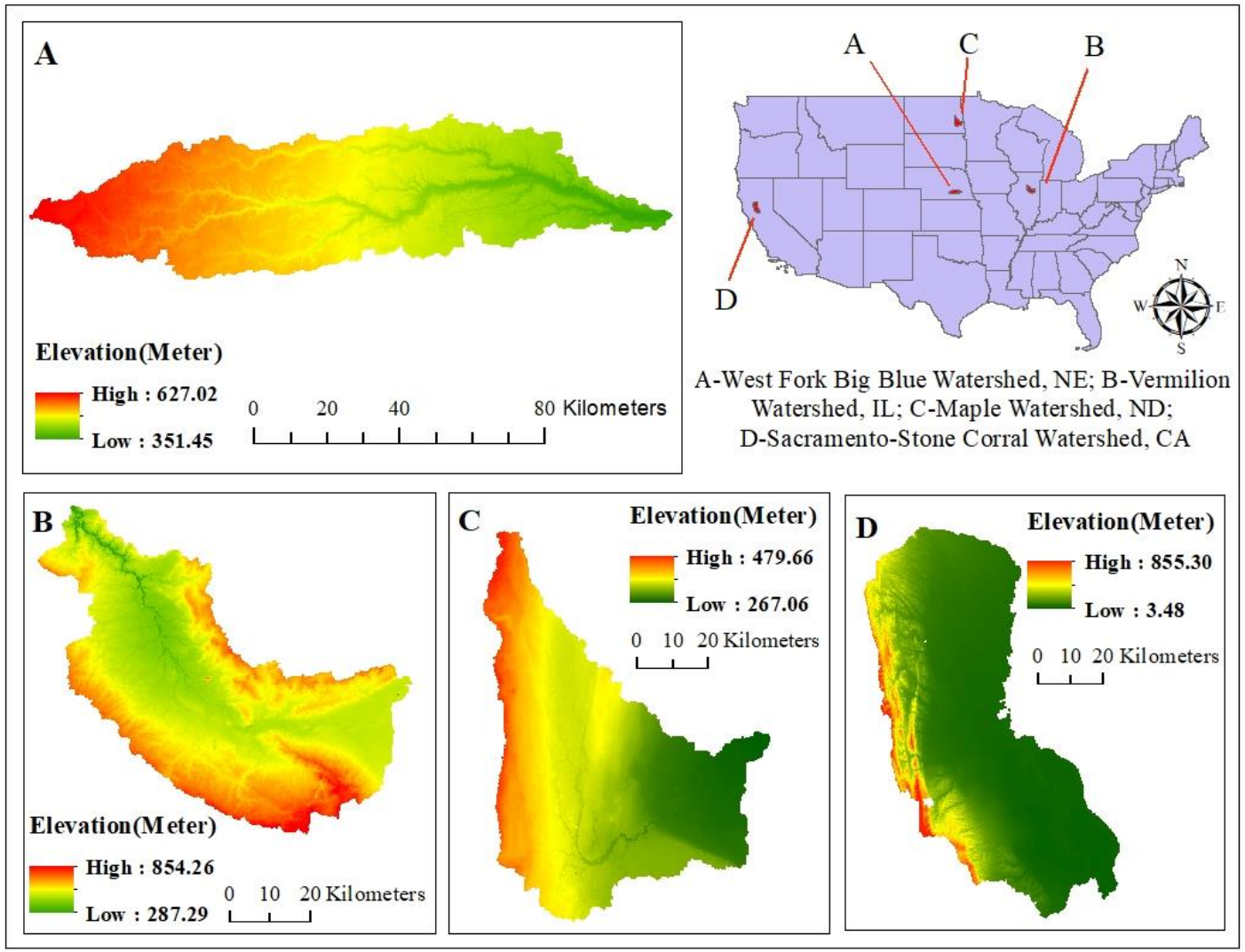


Image without drainage crossing



Study Areas

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



Datasets

- LiDAR DEMs and NAIP aerial imagery
- Manually digitized ground truth (drainage crossing locations)

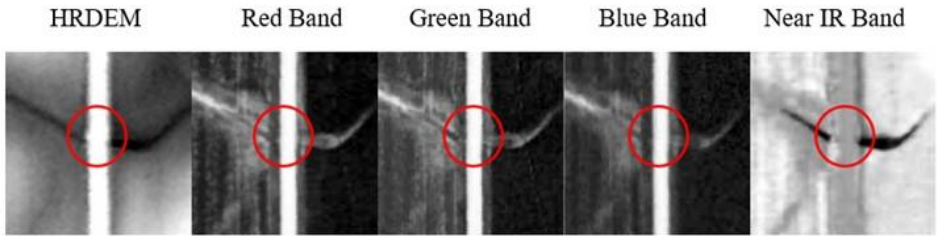
Data	Locations	Sources	Horizontal Resolution	Vertical Accuracy RMSE
HRDEM	West Fork Big Blue Watershed, Nebraska	NE Department of Natural Resource	1.0m	0.185m
	Vermilion River Watershed, Illinois	IL Geospatial Data Clearinghouse	0.30m	1.19ft (~0.36m)
	Maple River Watershed, North Dakota	North Dakota 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	

CNN-based Classification Models

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

CNN-based Classification Models

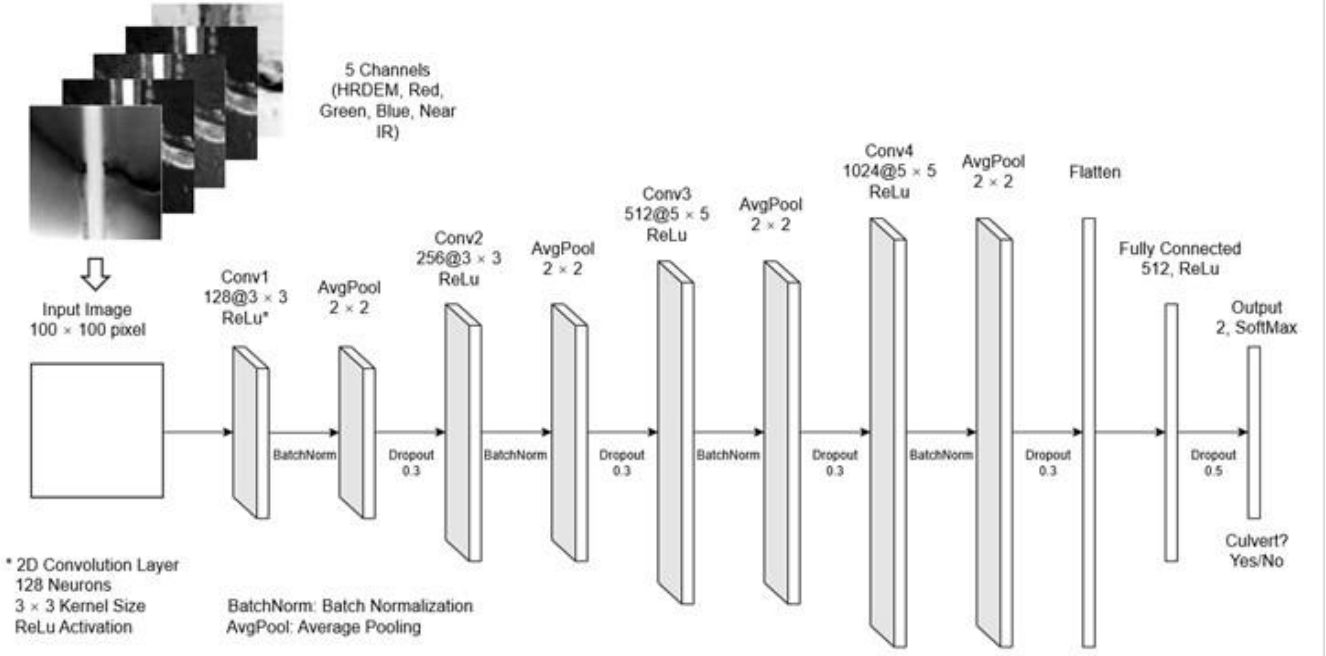
- Input Features
  - Unique topographic and spectral signatures at drainage crossing locations
  - Topographic features
    - Elevation from the HRDEM
    - Positive openness (POS)
    - Topographic Position Index (TPI) with moving window size 3
    - TPI with moving window size 21
    - Topological Curvature
  - Spectral features from aerial photos
    - Red, Green, Blue, and NIR bands
    - NDVI and NDWI



Locations	True Samples	False Samples	Total
Nebraska	2022	2022	4044
Illinois	1011	1011	2022
North Dakota	613	613	1226
California	2388	2388	4776

CNN-based Classification Models

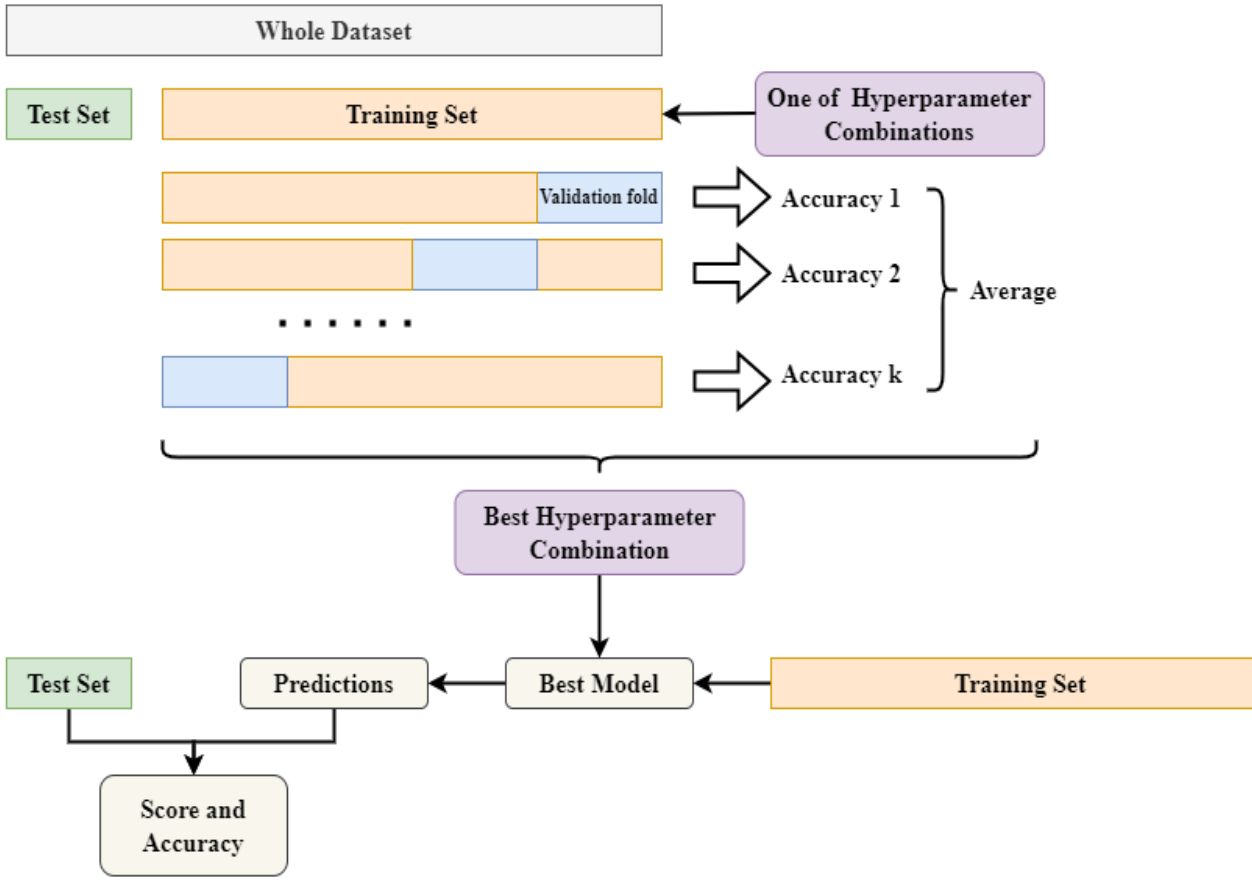
- Convolutional Neural Network (CNN) models
  - Excellent flexibility and effectiveness in complex data intensive tasks.
  - A convolution unit of CNN includes convolution, activation, and pooling layers.
- Baseline CNN model
  - 4 convolution layers
  - 1 flatten layer
  - 2 fully connected layers
- Advanced CNN models
  - ResNet-18
  - EfficientNet



Wu et al. 2023 GIScience & Remote Sensing

CNN-based Classification Models

- 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.



CNN-based Classification Models

- CNN model parameters and outputs
  - 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	Testing
Feature inputs	Batch size	Accuracy	Accuracy
HRDEM	16	0.9969	0.9333
HRDEM +NAIP Aerial Orthophotos	8	0.9981	0.9246
HRDEM +NDVI	8	0.9947	0.9197
HRDEM +NDWI	16	0.9966	0.9271

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

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

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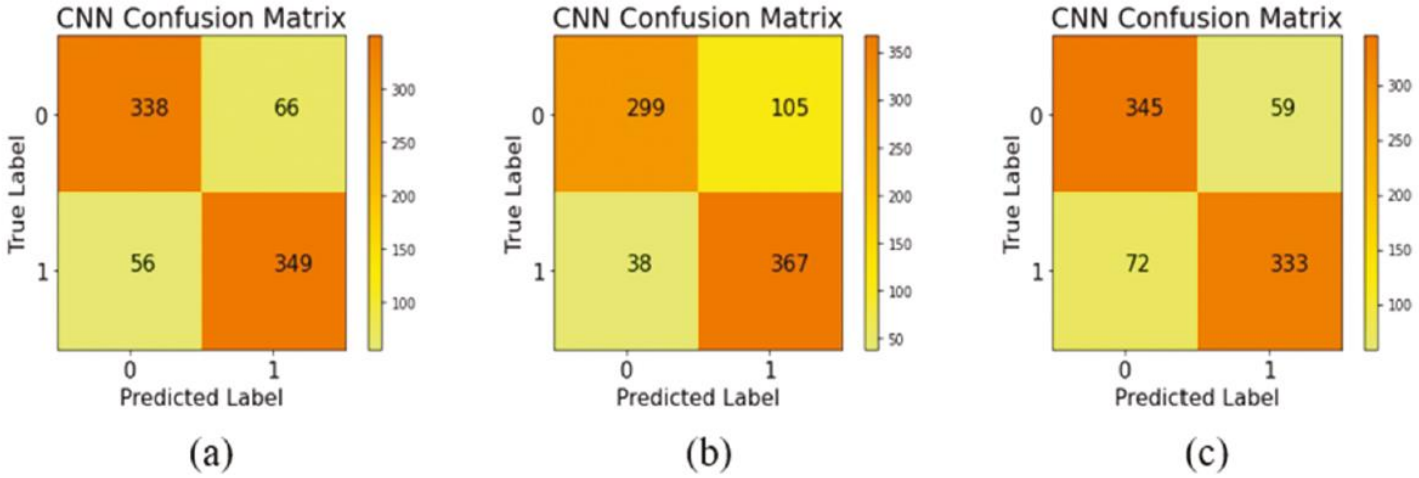
CNN-based Classification Models

- The contributions of aerial orthophoto bands to model accuracy were found negligible or negative.
  - We trained CNN models with aerial orthophoto bands, NDVI, and NDWI (with a batch size of16).
  - NAIP aerial orthophotos and their derived spectral indices show relatively lower accuracies.



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

CNN-based Classification Models

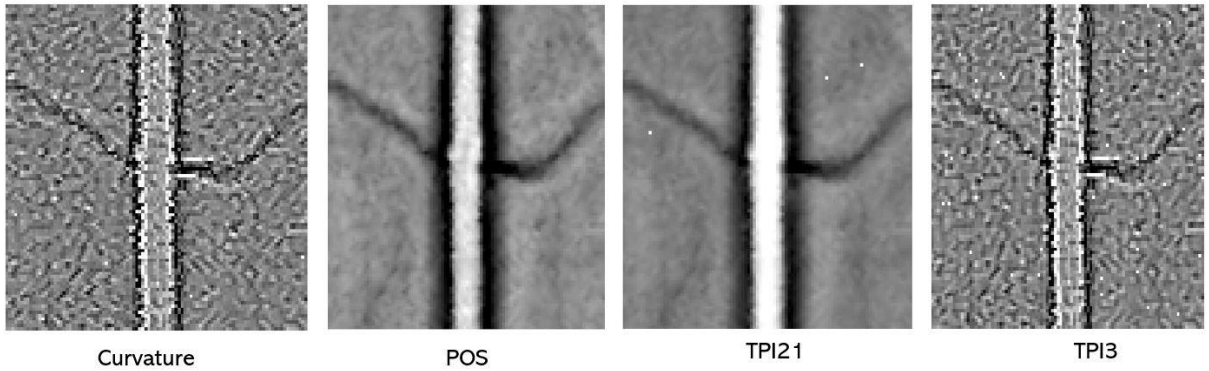
- Model Transferability
  - The best-fit CNN model (Input HRDEM; Learning rate 0.001; Epoch 100; Batch size 16) was used.
  - To test its transferability of classifying drainage crossing locations in the other three watersheds.

- Classification results in other watersheds

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

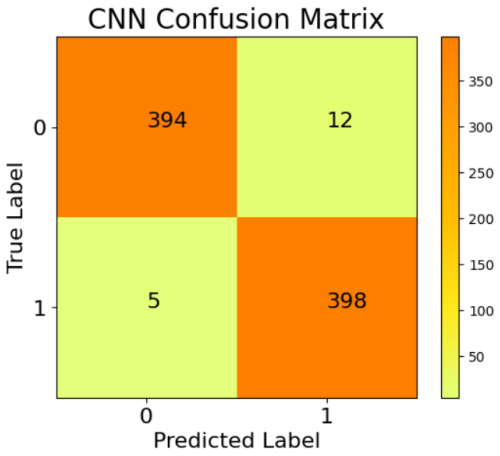
CNN-based Classification Models

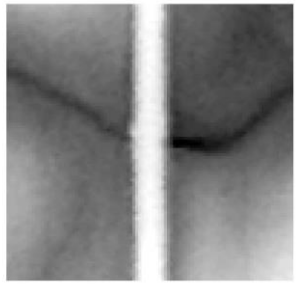
- Advanced CNN models
  - ResNet18 (accuracy 96.13%)
  - EfficientNet (accuracy 97.03%)



Accuracy Metrics from EfficientNet Models with Single Geomorpological Feature

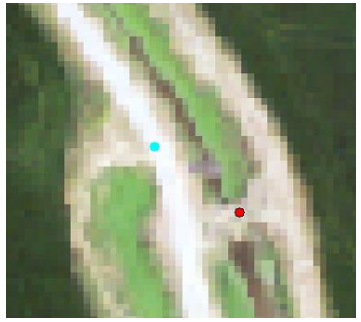
Model	Accuracy	Precision	Recall	F1
HRDEM	0.9679	0.9679	0.9678	0.9679
POS	0.9629	0.9699	0.9556	0.9627
TPI21	0.9703	0.9681	0.9724	0.9701
TPI3	0.9580	0.9581	0.9579	0.9581
Curvature	0.9555	0.9556	0.9554	0.9555

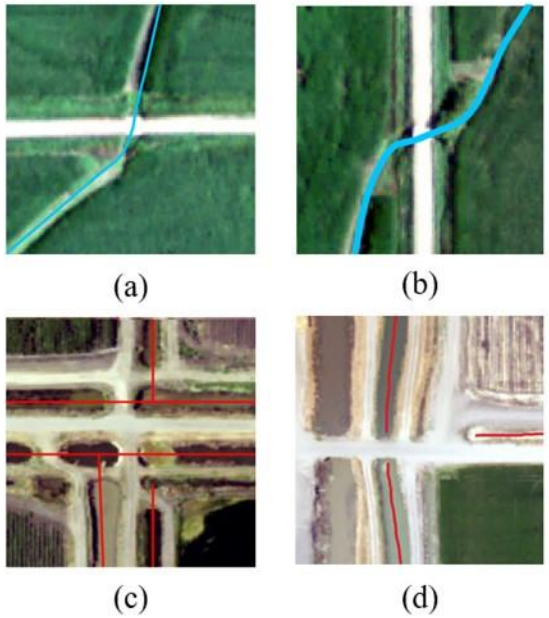




CNN-based Classification Models

- Discussion
  - The HRDEM as the sole feature appears to perform well for image classification.
  - Data quality of the NAIP aerial photos is a concern.
  - Most hydrologic features crossing the roads in NE, IL, and ND watersheds: natural streams.
  - Unlike the other three watersheds, artificial canals and road ditches existing widely in the CA watershed, resulting in more complex crossing patterns.





CNN-based Classification Models

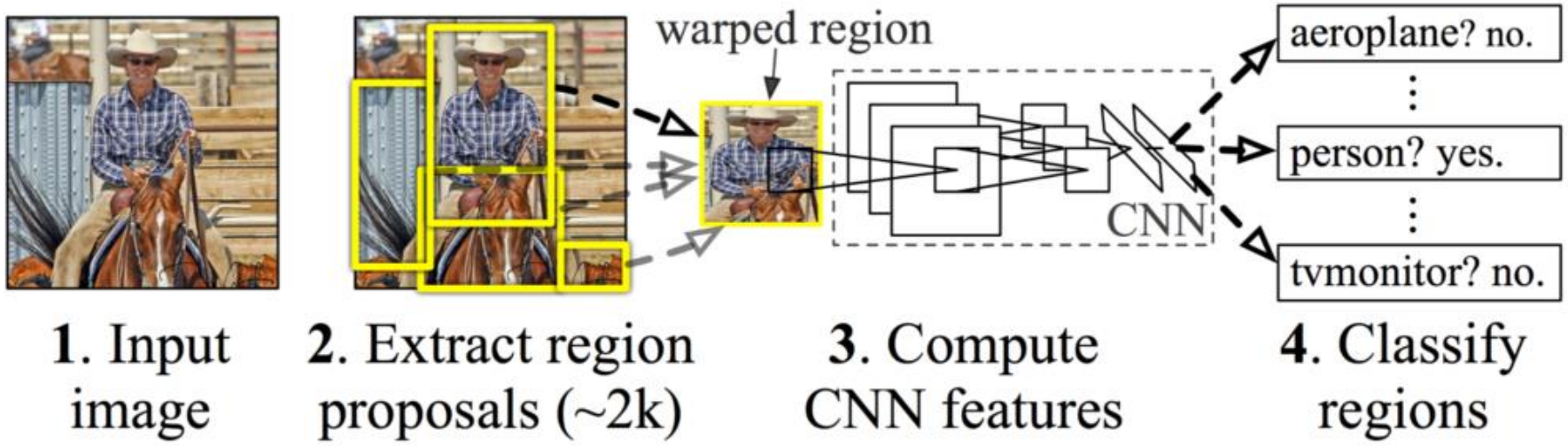
- Summary
  - CNN-based deep learning model is a promising tool to accurately classify drainage crossings from our image samples.
  - The baseline CNN model has a comparable performance to more advanced CNN models such as ResNet18 and EfficientNet model.
  - The best-fit baseline CNN model shows its transferability in different geographic regions, although the classification accuracies are affected by geographic background.
  - The addition of aerial orthophotos and/or spectral indices was found to be insignificant to or even worsen the model's performance

CNN-based Classification Models

- Coding demonstration ….

CNN-based Object Detection

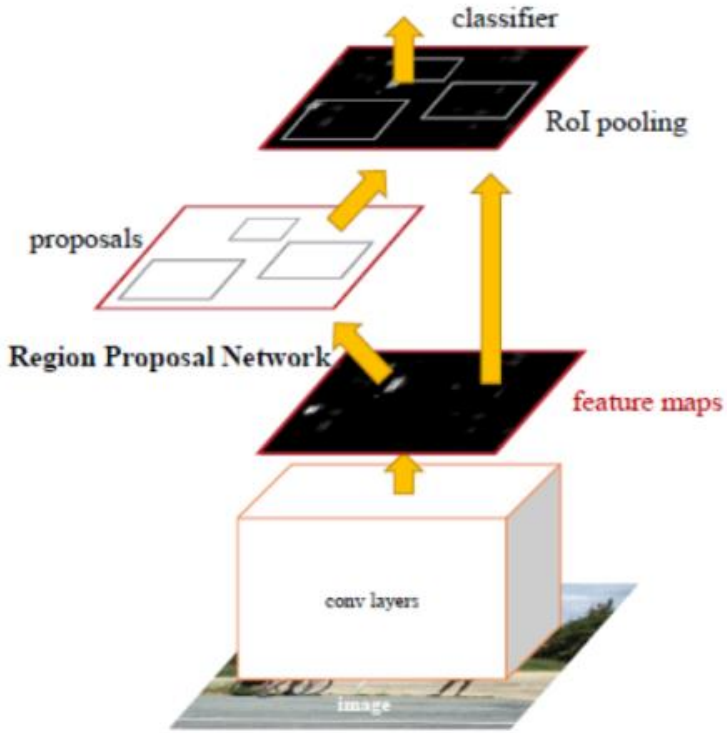
- **The classification task guides object detection**
  - Knowledge learnt from the classification tasks was applied for the detection of stream-road crossings.
  - Object detection is a special classification task.



Source: R-CNN vs Fast R-CNN vs Faster R-CNN - A Comparative Guide (analyticsindiamag.com)

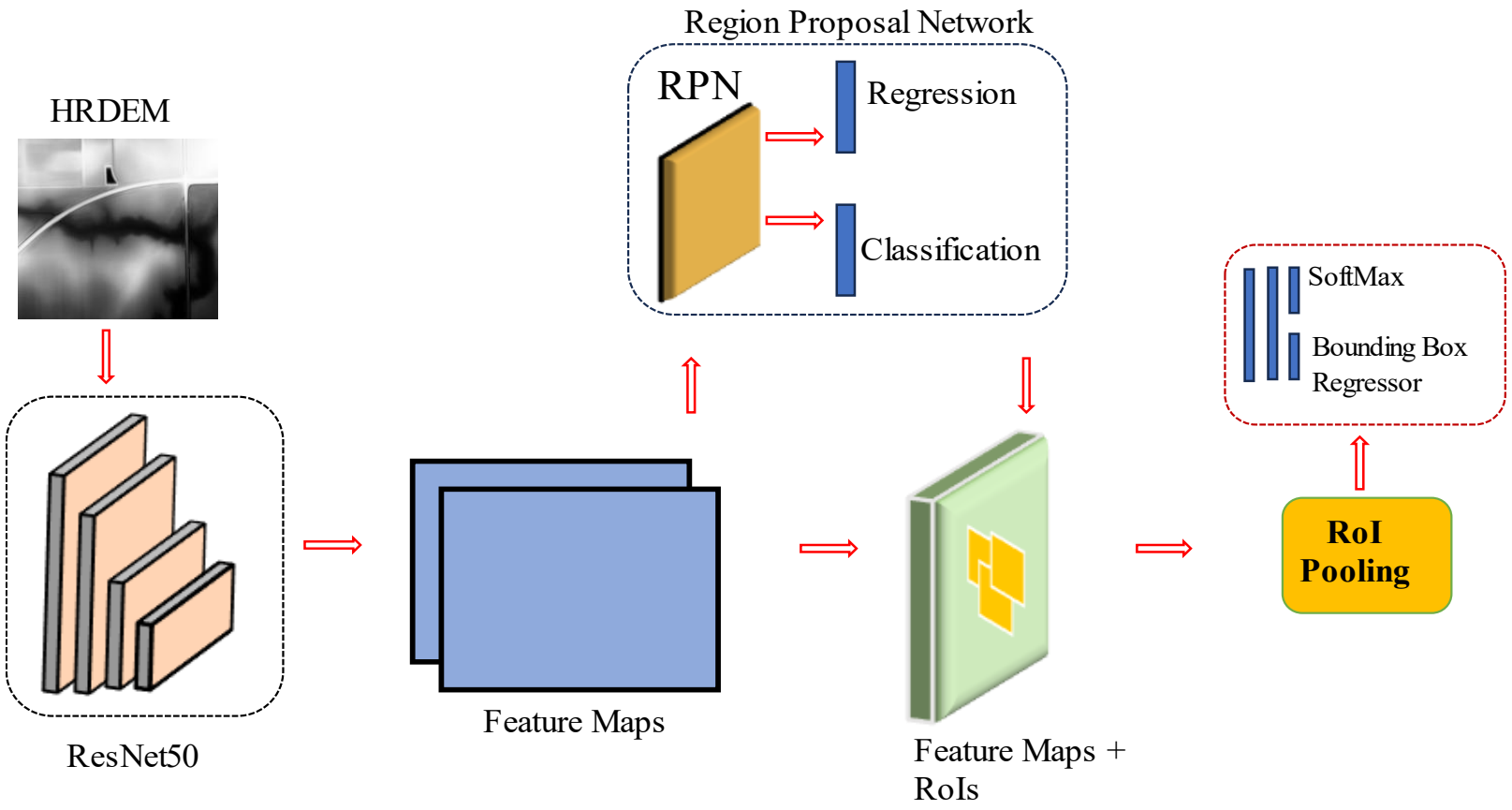
CNN-based Object Detection

- **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.



CNN-based Object Detection

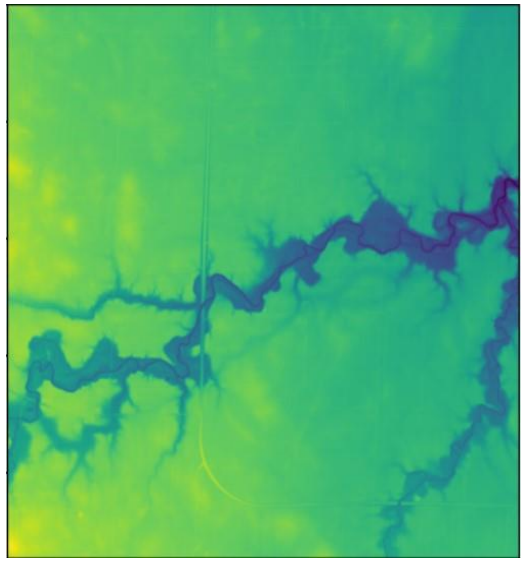
- **Deep learning**: Faster R-CNN



CNN-based Object Detection

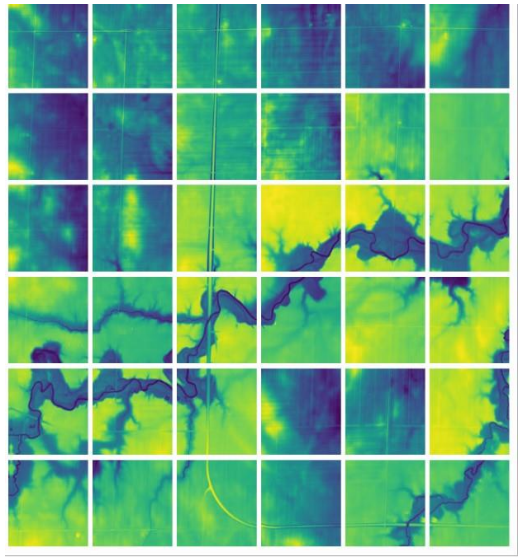
- **Deep learning**: Faster R-CNN
  - Local -> geographic coordinate conversion
  - Subset a big image into smaller patches

Original Image



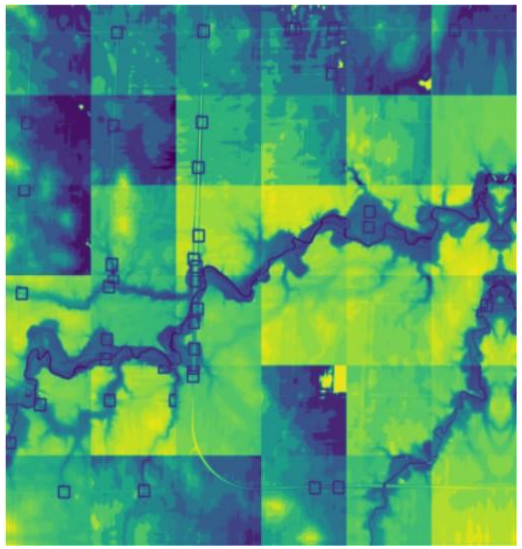
Shape: (4800, 4800)

Patchified Image



Shape: (6, 6, 800,800)

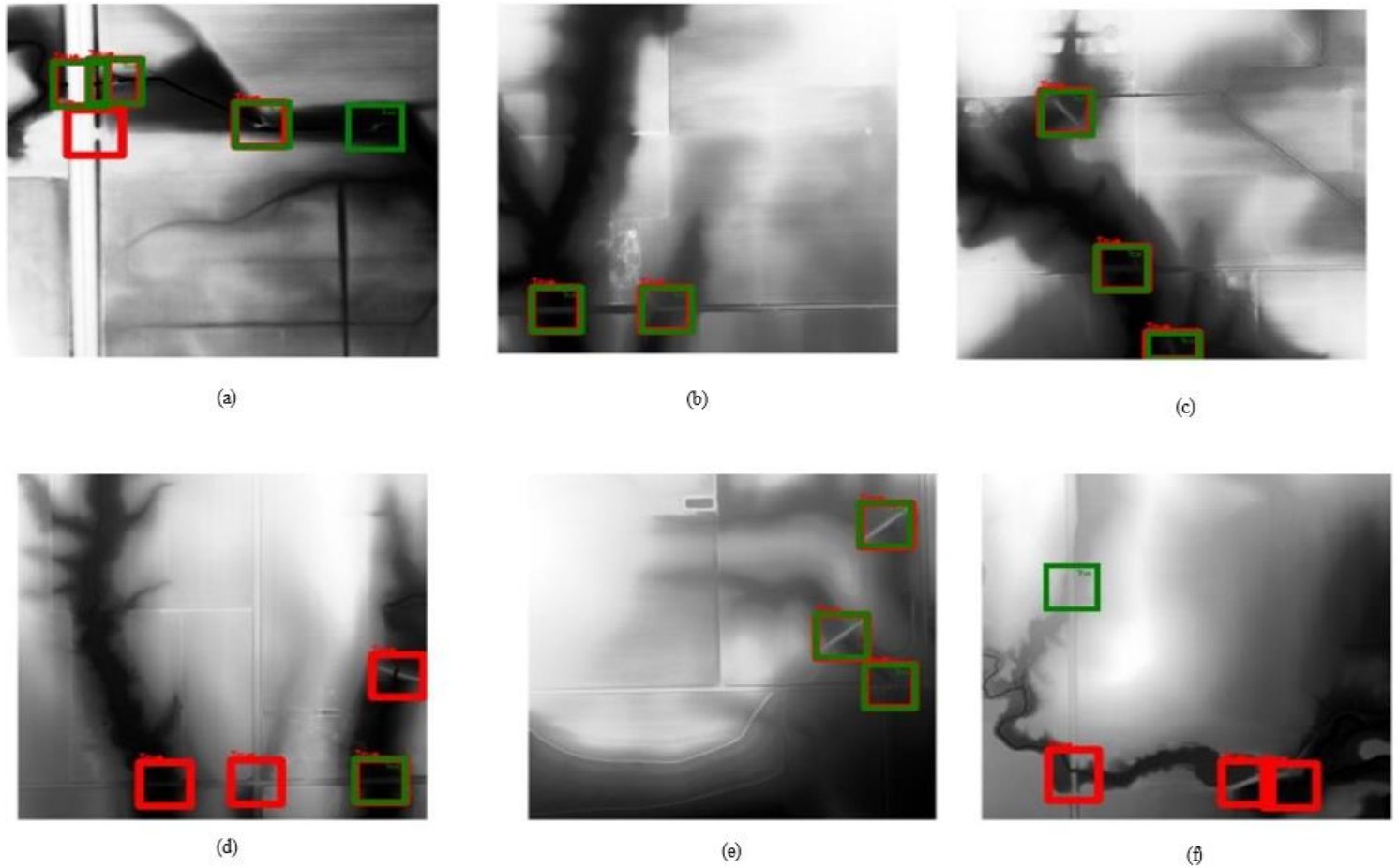
Reconstructed Image



Shape: 4800x4800

CNN-based Object Detection

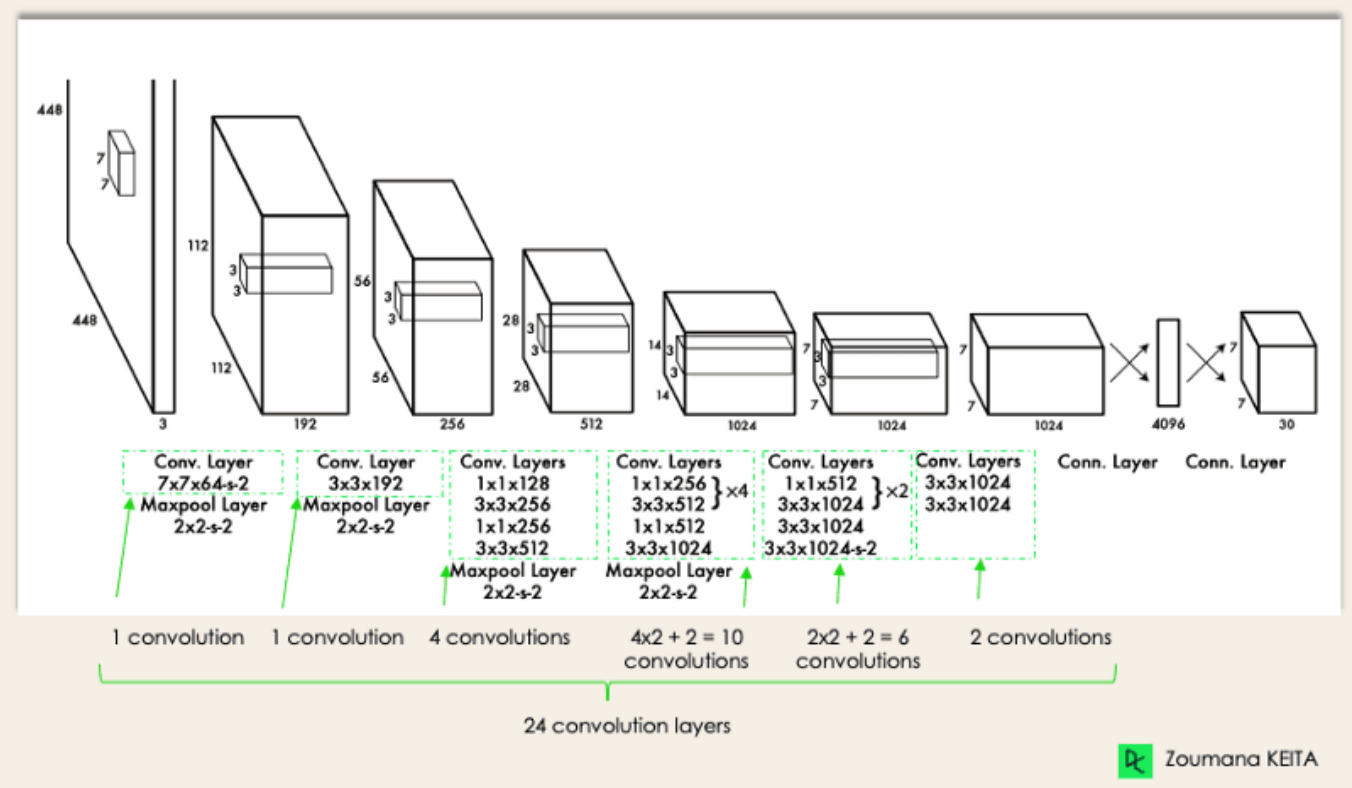
- Faster R-CNN detection examples



Ground truth labels are in green and predictions in red

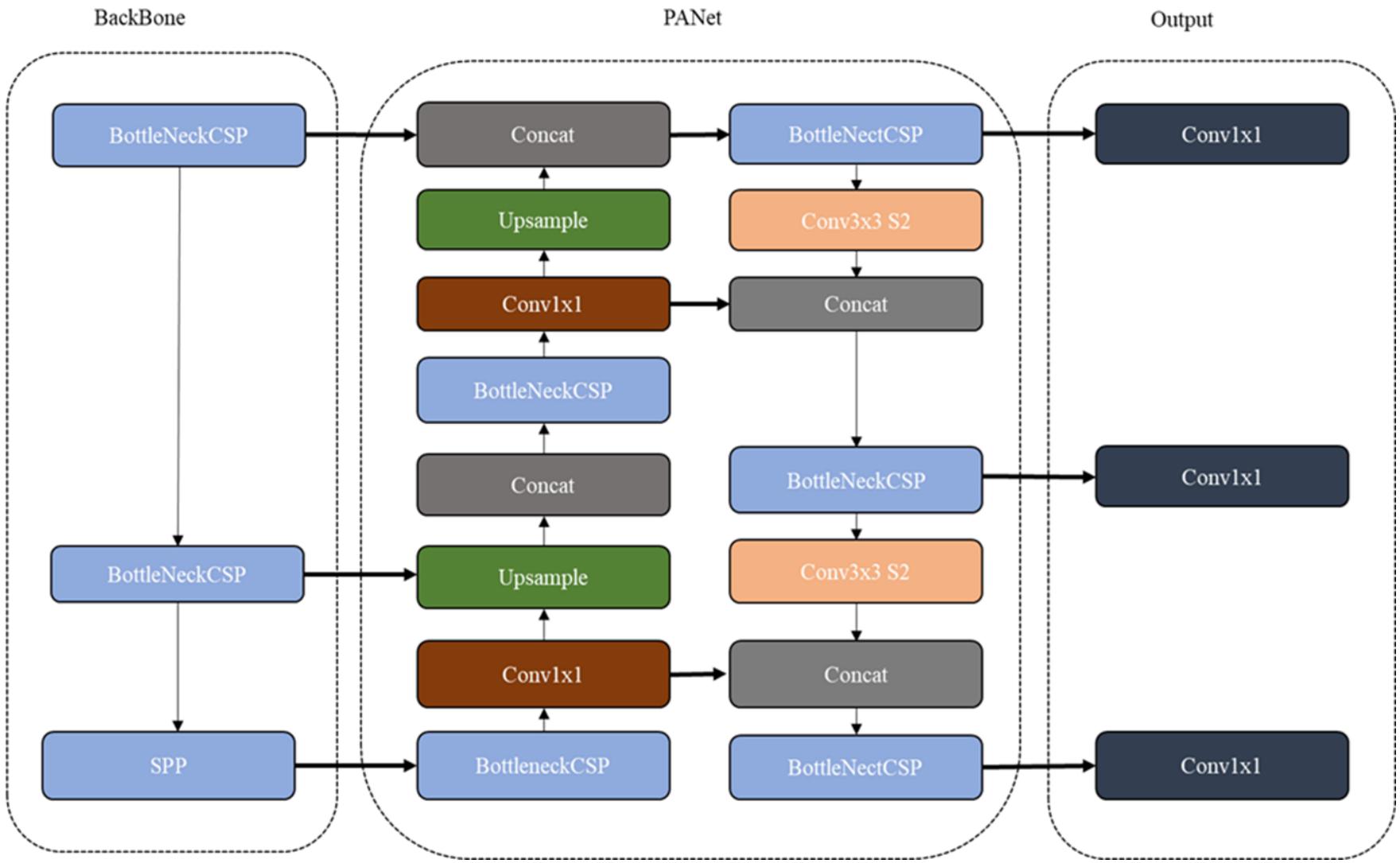
CNN-based Object Detection

- YOLO
  - One-stage object detector architecture treats object recognition as a regression problem.
  - Original architecture has overall 24 convolutional layers, four max-pooling layers, and two fully connected layers.
  - Its popularity is due to its speed, detection accuracy, and good generalization



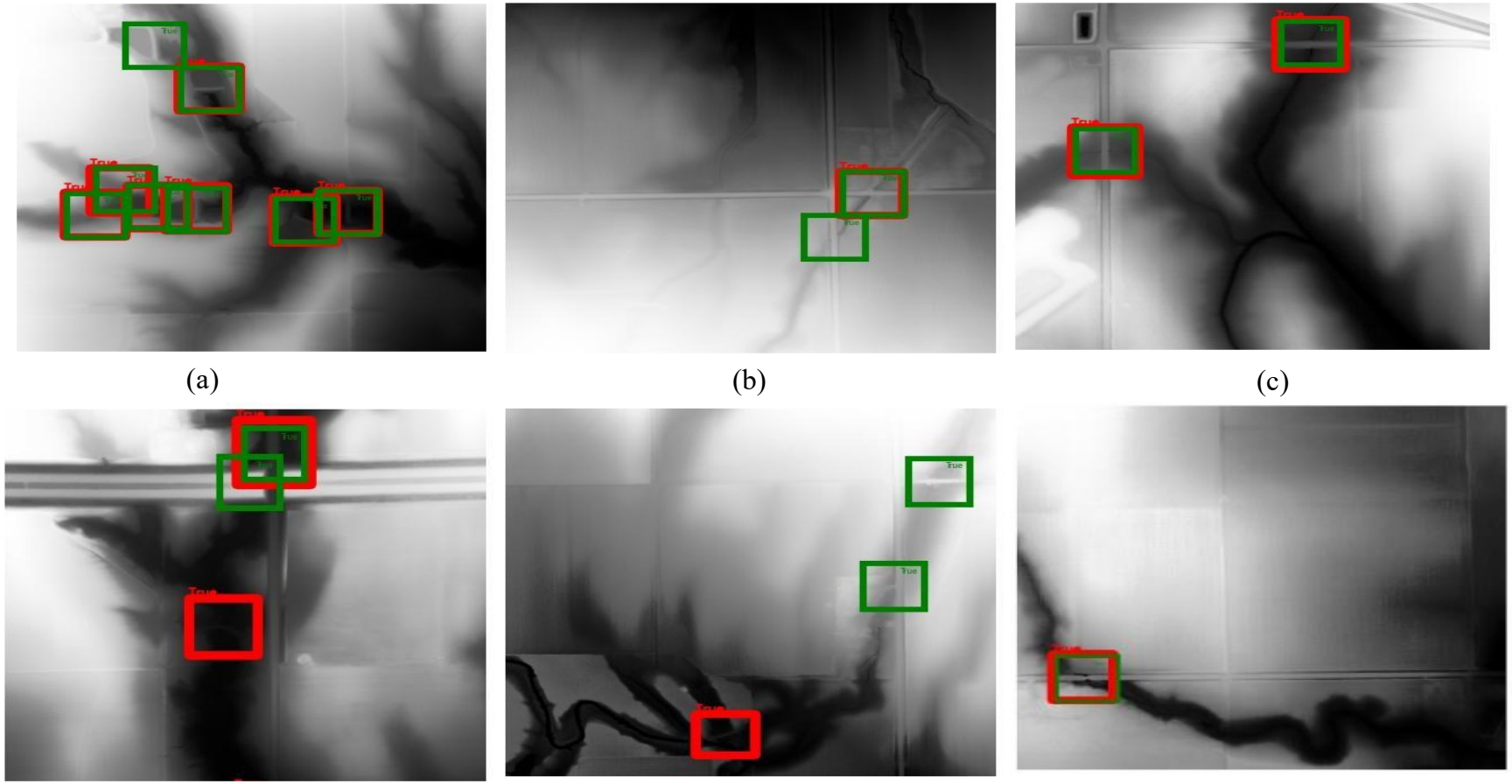
CNN-based Object Detection

- YOLOv5



CNN-based Object Detection

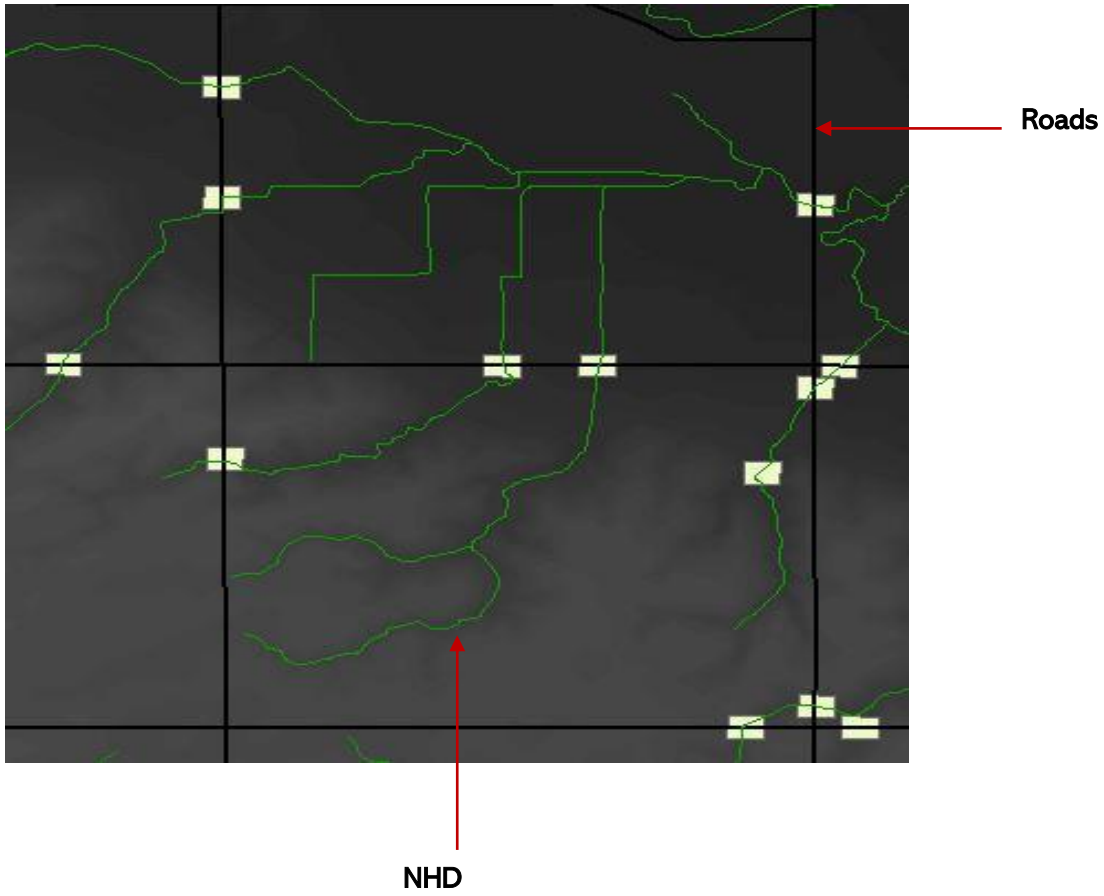
- YOLOv5 detection examples



CNN-based Object Detection

- Baseline method
  - Spatial intersection of NHD flowlines and road layers
  - Benchmarking the performance of GeoAI models

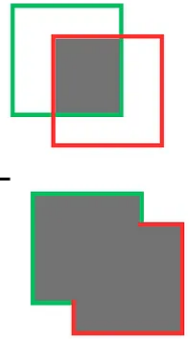
Road – Stream Intersections



CNN-based Object Detection

- Model Performance Metrics
  - IOU: Intersection Over Union to account for the accuracy of the predicted bounding boxes.
  - Precision: the percentage of instances that the model accurately classify as drainage crossings out of all instances it classified as positive.
  - Recall: quantifies the model's ability to identify those true drainage crossing locations regardless of the background case.
  - F1-score: harmonic mean of precision and recall. Highest F1 score means the model has an optimal balance of recall and precision.

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



$$\text{precision} = \frac{TP}{TP + FP}$$

$$\text{recall} = \frac{TP}{TP + FN}$$

$$F_1 = \frac{2 * (\text{precision} * \text{recall})}{(\text{precision} + \text{recall})}$$

CNN-based Object Detection

- Model performance

Model	IOU	Precision	Recall	F1
FRCNN	0.8	0.7	0.89	0.78
YOLOv5	0.7	0.78	0.79	0.78
Baseline	0.68	0.7	0.58	0.68

- Model parameters

Model	Faster R-CNN	YOLOv5
Confidence Threshold	0.8	0.55
Optimizer	SGD	SDG
Optimizer parameters	Batch size = 4 Learning rate = 0.01 Momentum = 0.9 Weight Decay = 0.005	Batch size = 4 Learning rate = 0.01 Momentum = 0.937 Weight Decay = 0.0005

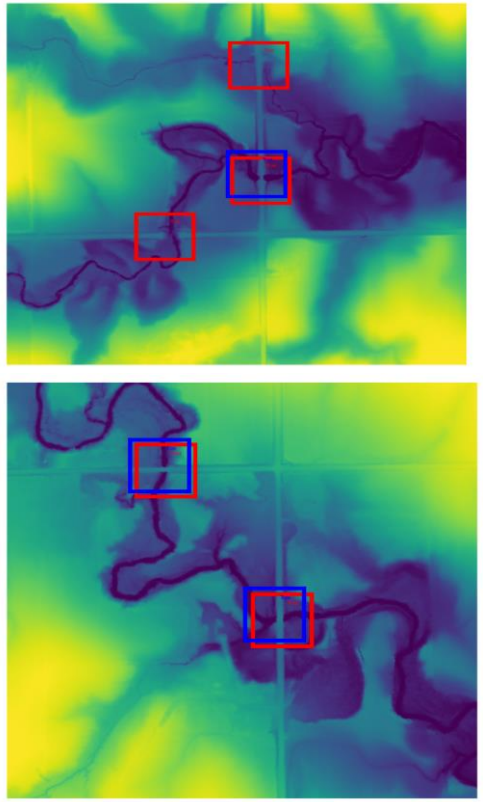
CNN-based Object Detection

- Model transferability
  - Both models developed in the NE watershed exhibit promising transferability.
  - Better transferability metrics for the Illinois watershed than the California watershed.
  - Faster R-CNN exhibits better transferability performance than YOLOvs .
  - California watershed exhibit more intricate drainage crossing patterns compared to the selected watersheds

Watershed	Model	IOU	Precision	Recall	F1
Illinois	FRCNN	**0.75**	0.71	**0.77**	**0.74**
	YOLOv5	0.6	**0.72**	0.62	0.67
North Dakota	FRCNN	**0.71**	0.63	**0.68**	**0.65**
	YOLOv5	0.5	**0.73**	0.48	0.58
California	FRCNN	**0.5**	0.62	**0.75**	**0.68**
	YOLOv5	0.44	**0.67**	0.47	0.55

CNN-based Object Detection

- Summary
  - The developed models exhibit better performance and offer excellent potential for high-precision mapping of drainage crossing locations congruent with 3DHP requirements.
  - The models show good overlaps between true and predicted bounding boxes, indicating they can spatially identify drainage crossings.
  - Faster R-CNN model shows better performance than the YOLOv5 model overall.
  - We expect to train the models using data from broader geographic contexts - CulvNet



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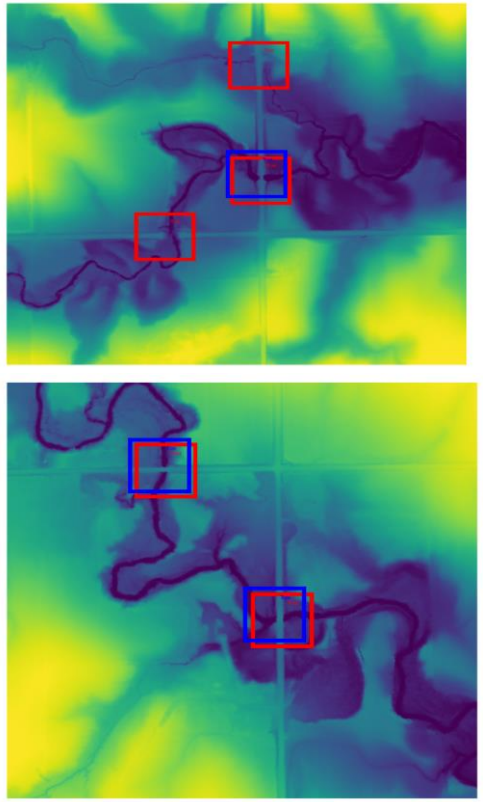
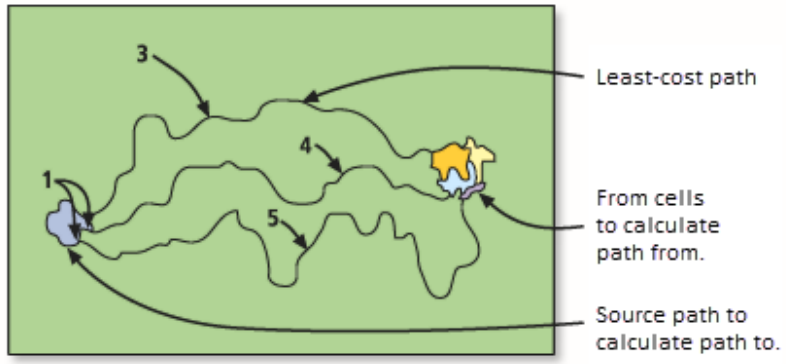
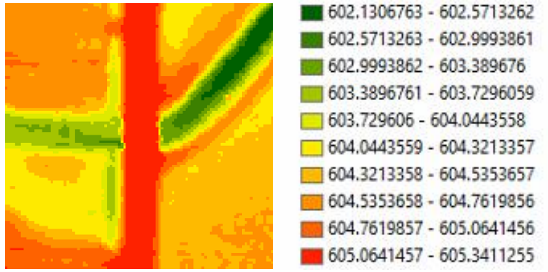


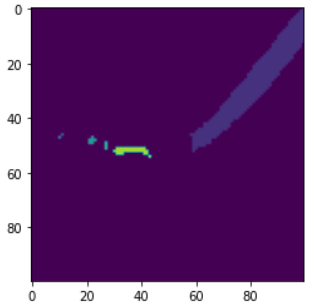
After Object Detection

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

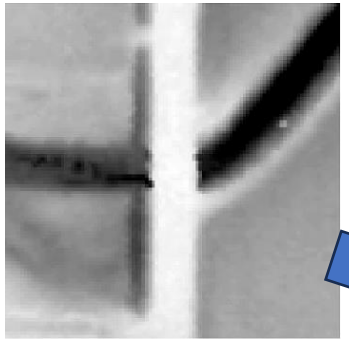


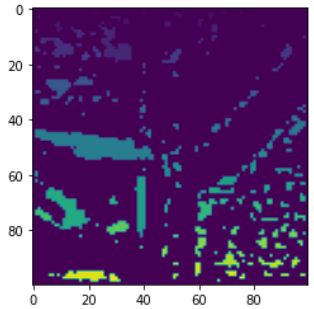
After Object Detection



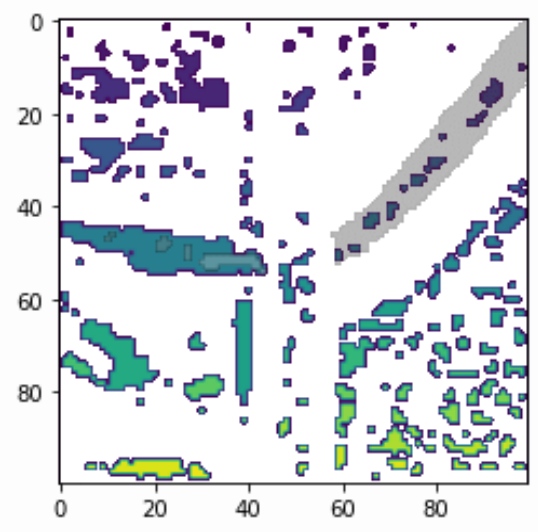


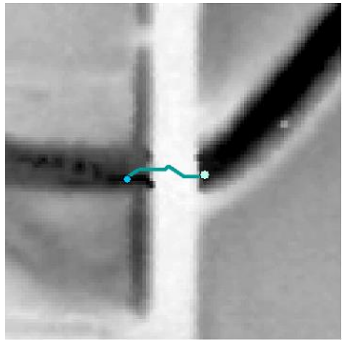
Natural Breaks





(Filled DEM – Original DEM)





Cost: Slope

CNN-based Object Detection Models

- Coding demonstration ….

Future Work

- Tool development
  - Specialized training dataset and model: CulvNet
- Regional and national datasets for drainage crossings
  - GPU Cyberinfrastructure
- GeoAI-based segmentation of drainage features
  - Stream channels not following flow accumulation
- Instance classification of culvert conditions
  - Can we detect if the drainage crossings were blocked or damaged?

Road	Evaluation
Route 143	Severe barrier
Mt. Joy Rd.	no score - missing data
Maplewood Rd.	Severe barrier
River Rd.	No barrier
River Rd.	Severe barrier
Fiske St.	Severe barrier
Deering Drive	Severe barrier

Conclusions

- GeoAI is a promising approach to advance the next-generation hydrological connectivity modeling.
- The high-resolution DEM and its derived features can be used to predict the locations of drainage-road crossings.
- Faster R-CNN outperforms YOLOv5 in terms of model transferability.
- The GPU Cyberinfrastructure is an effective tool for conquering computation challenges.

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- Contributions from students: Michael Edidem, Di Wu, Shayan Jalalipour, Sameerah Talafha, Claire Talbert, Bill Xu.

Thank you!!

Questions?

Ruopu Li, Ph.D.
Southern Illinois University
Ruopu.Li@siu.edu
www.geofew.org
X: @liruopu

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