Transfer Learning with Convolutional Neural Networks for Hydrological Streamline Delineation

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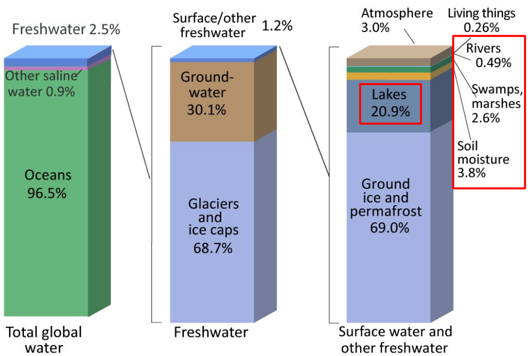
AAG 2023

March 24, 2023

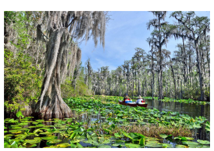
Background

Where is Earth's Water?

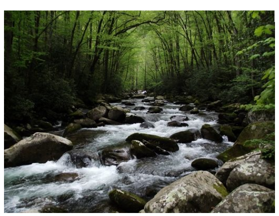


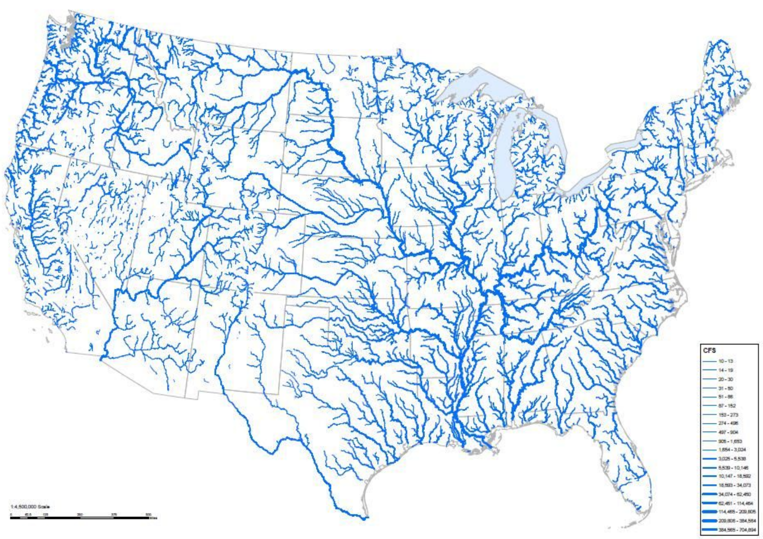
Source: Igor Shiklomanov's chapter "World fresh water resources" in Peter H. Gleick (editor), 1993, Water in Crisis: A Guide to the World's Fresh Water Resources. (Numbers are rounded).


rivers


swamps

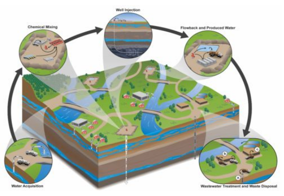

lakes


creeks



National Hydrography Dataset


Manage riverine and coastal navigation and safety


Assess water availability and water rights


Agriculture suitability

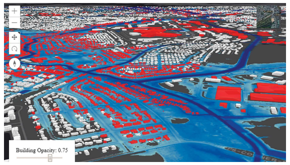
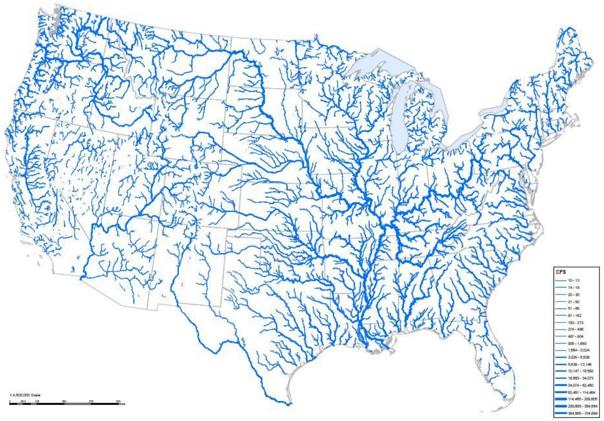

Model and map flood risk

Image courtesy of Google

Traditional Methods

Flow accumulation techniques are often used to derive stream networks from Digital Elevation Models (DEMs)

- National Hydrography Dataset



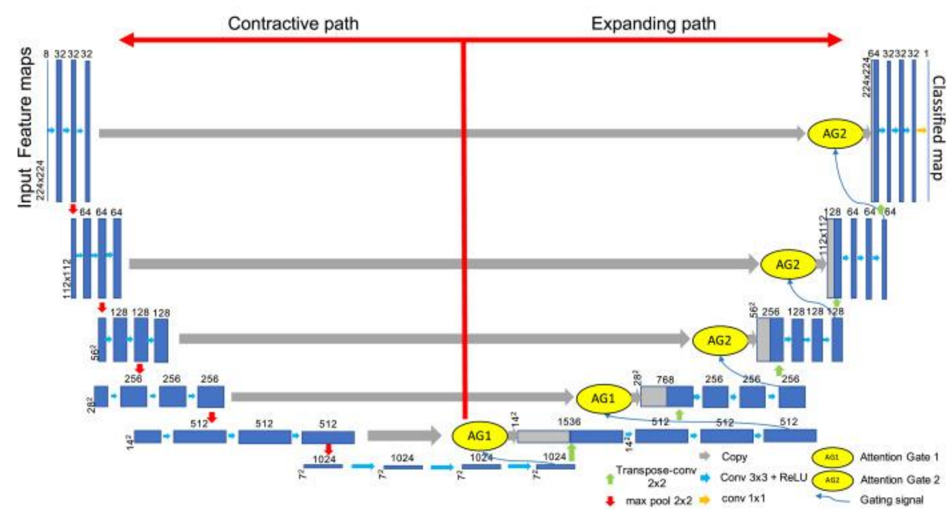
Problems

- Flow accumulation methods require appropriate thresholds to extract an accurate density of drainage lines
- Elevation-derived drainage lines must be validated or edited using high-resolution image data or field data
- At intersections between roads (or bridges) and valleys, flow accumulation could be obstructed by the higher elevation of roads, producing inaccurate extraction of drainage lines

Image courtesy of USGS

Attention U-net Model

In our recent study (Xu et al. (2021)), an attention U-net model is proposed for streamline network delineation. It is a CNN model trained on topological features derived from LiDAR data. This new method has achieved higher precision than traditional methods.



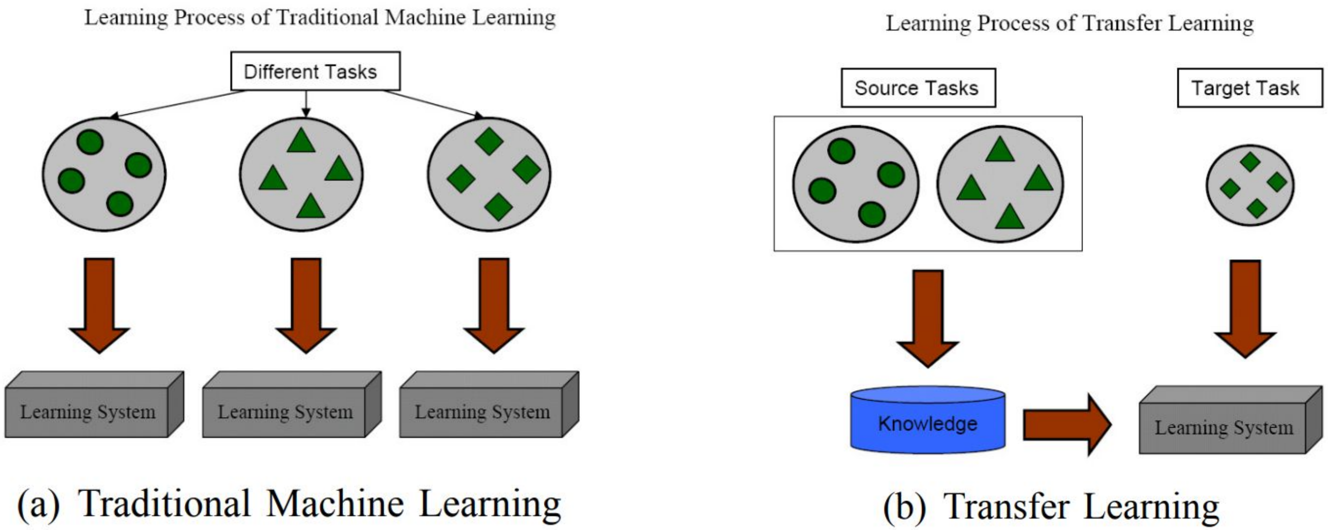
Xu, Z., Wang, S., Stanislawski, L. V., Jiang, Z., Jaroenchai, N., Sainju, A. M., Shavers, E., Usery, E. L., Chen, L., Li, Z., and Su, B. (2021) “An Attention U-Net Model for Detection of Fine-scale Hydrologic Streamlines”. *Environmental Modelling and Software*, https://doi.org/10.1016/j.envsoft.2021.104992

Remaining problems

- The model performance is lower when it is used to detect streamlines in other areas
- To achieve desirable performance, the entire model needs to be retrained with samples extracted from a targeted area

Image courtesy of Xu, Z.. et al., 2021

Why Transfer Learning?



- With **traditional machine learning**, each task has separated datasets and a training process. No knowledge is retained between models.
- With **transfer learning**, knowledge from a previous model (e.g., features, weights, etc.) can be transferred to a new model that could require less training data and a shorter training process.

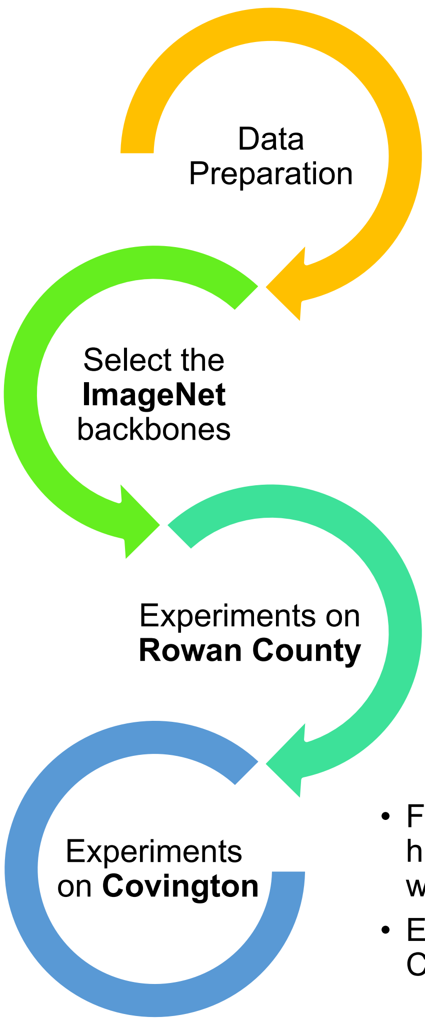
Image courtesy of Pan, S. J., & Yang, Q. 2009

Research Objectives

We examine the application of transfer learning in convolutional neural networks to:

1. Test whether general purpose convolutional neural networks can achieve better streamline delineation than the recently proposed U-net model
2. Compare the transferability between the models trained on a specific task and the models trained on a large general image dataset (ImageNet)
3. Scale up the streamline delineation models to the national level (ongoing experiment)

Scientific Workflow



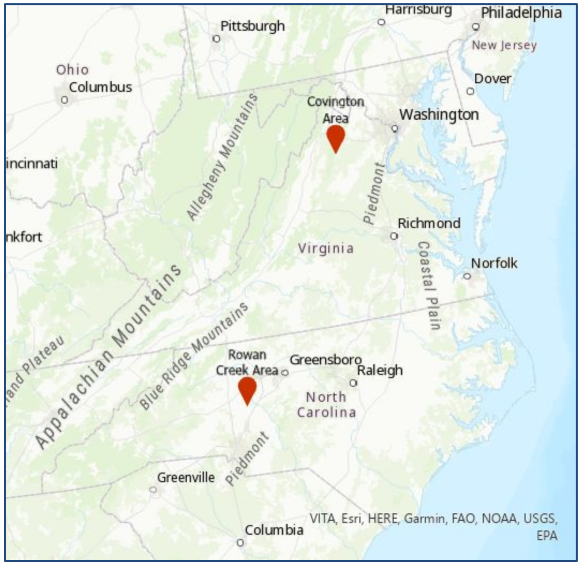
- Download the Rowan County samples published by Xu et al. (2021)
- Generate samples from the Covington river area

- DenseNet
- ResNet
- VGG
- Inception

- Train the attention U-net model
- Fine-tune selected models pre-trained on ImageNet with Rowan County samples
- Evaluate the models’ performance with Rowan County test set

- Fine-tune the three ImageNet models with the highest F1-score and the attention U-net model with the Covington samples
- Evaluate the models’ performance with the Covington test set

Differences between study areas



Study Area:
Covington River, VA

Study Area:
Rowan Creek, NC

When we examine the two study areas, which are over 250 miles apart, we found that there are several differences that may lower the performance of the attention U-net model.

Rowan Creek, NC

- Area of ~18.11km^2
- Virtually flat with about 222 meters elevation variation
- Land cover dominated by forest, wetlands, and agricultural land

Covington River, VA

- Area of ~108km^2
- High elevation variation ranging from 125 to 1,040 meters
- Land cover dominated by forest and agricultural land

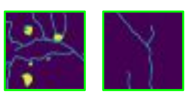
Data Preparation

Training and validation data

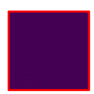
- 200 samples are randomly selected from the **upper half** of the study area. Then, the samples are augmented to create 1400 samples dataset.

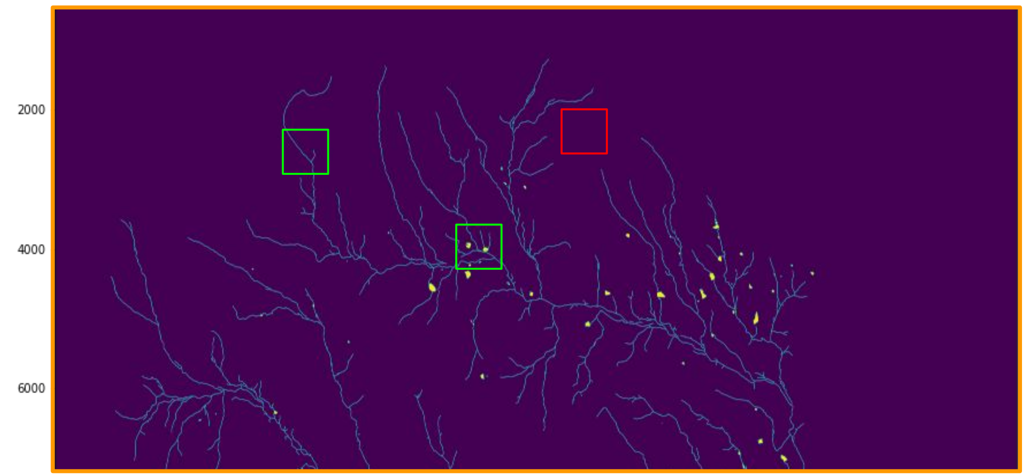
*patch size = 224 pixels *224 pixels

Streamline Patches



Non-streamline Patches



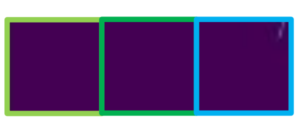


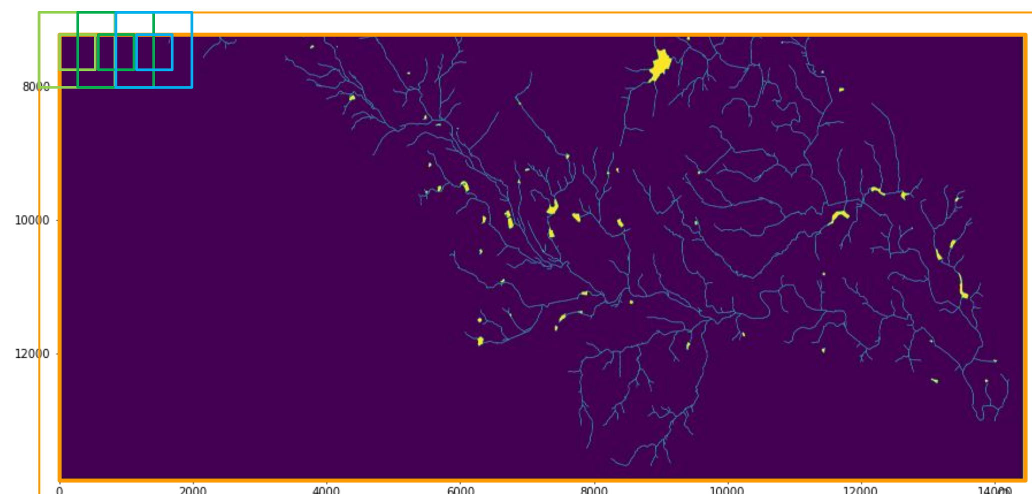
Testing data

- Testing samples are generated from the entire lower half of the study area
- To eliminate the edge effect, samples are generated using a moving window strategy with 30-pixel padding.

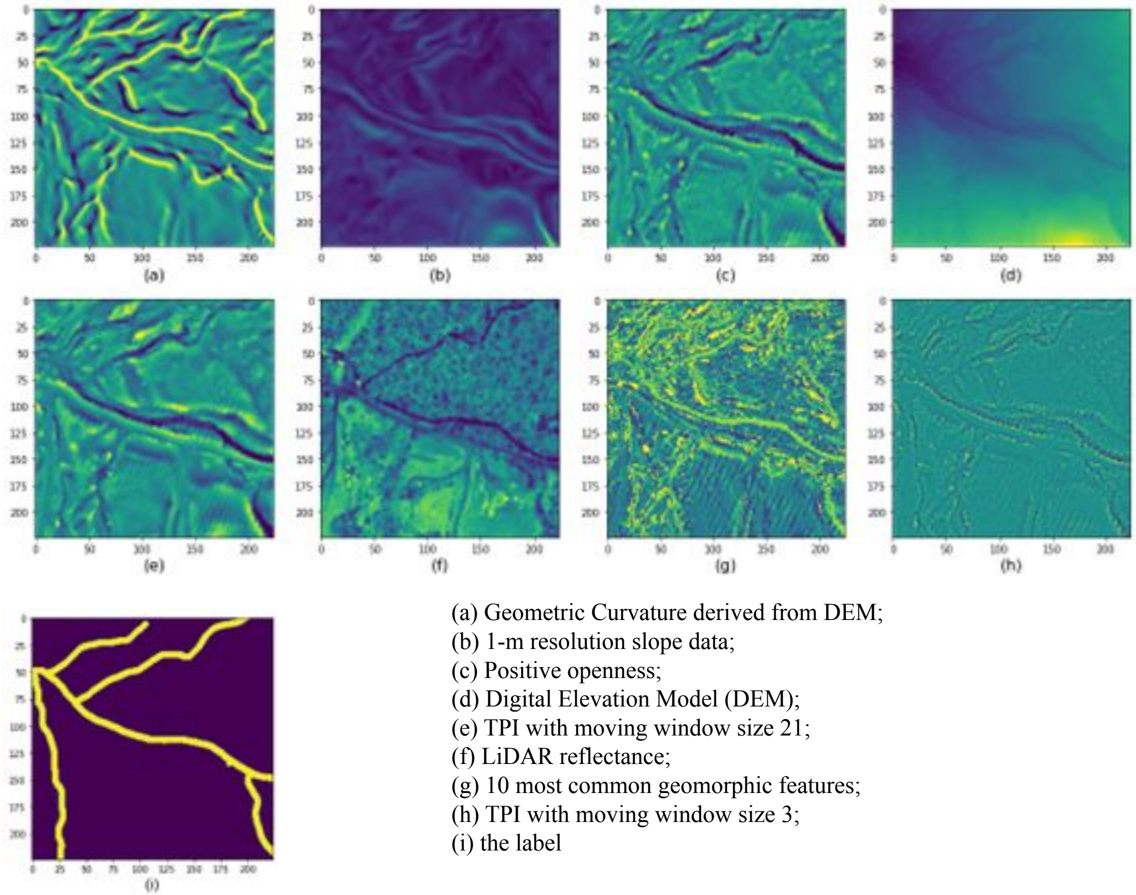
*patch size = 224 pixel *224 pixel

Testing patches





Example of Input Data



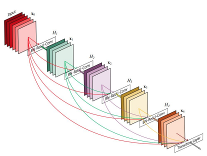
(a) Geometric Curvature derived from DEM;
(b) 1-m resolution slope data;
(c) Positive openness;
(d) Digital Elevation Model (DEM);
(e) TPI with moving window size 21;
(f) LiDAR reflectance;
(g) 10 most common geomorphic features;
(h) TPI with moving window size 3;
(i) the label

Experiments in Rowan County

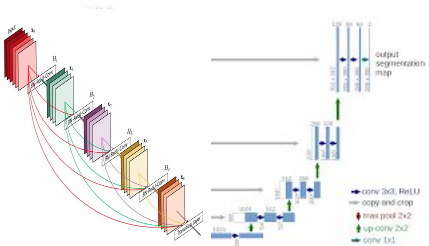
Other U-net models
(ImageNet)

Pretrained

CNN

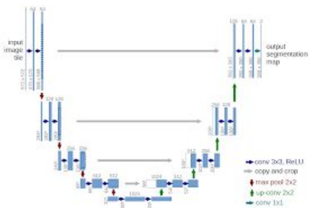


ImageNet dataset



Study Area:
Rowan Creek, NC

Attention U-net model



Study Area:
Rowan Creek, NC

Experiments in Rowan County (cont.)

Network Base Models	F1-Score for Stream Class		#Parameters
	Initialized ImageNet	randomly initialized	
DenseNet169	**85.11%**	**81.80%**	**19,545,964**
ResNet50	**83.77%**	**78.00%**	**32,587,253**
DenseNet121	**83.73%**	**81.85%**	**12,171,116**
DenseNet 201	82.95%	80.37%	26,404,716
ResNet 34	82.51%	76.68%	24,482,293
ResNet 101	81.78%	75.85%	51,631,605
ResNet 152	81.65%	78.40%	67,321,333
Attention-Unet (Xu et al., 2021)	**-**	**81.28%**	**53,508,217**
VGG16	80.98%	74.23%	23,778,412
InceptionResNet V2	80.76%	73.79%	62,087,692
Inceptionv3	80.42%	75.45%	29,959,244
VGG19	78.96%	74.79%	29,088,108

All models **pre-trained on ImageNet** are fine-tuned with the same hyperparameters as follows:
max epoch = 500
learning_rate = 0.001 (classifier) and 0.00001 (fine-tuning)
batch size = 16

The **attention U-net model** is trained from scratch with the following hyperparameters:
max epoch = 500
learning_rate = 0.0000359 (as reported by Xu et al. 2021)
batch size = 16

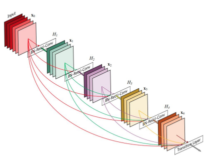
Early stopping and model checkpoint callbacks were used during training to monitor validation loss, stop training when validation loss did not decrease after a specified number of epochs, and to save the model with the highest validation accuracy.

Experiment in Covington

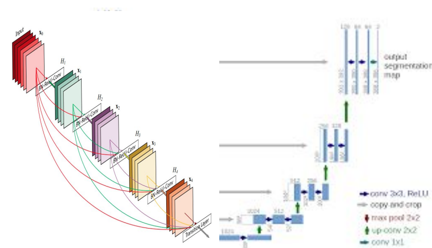
Other U-net models
(ImageNet)

Pretrained

CNN

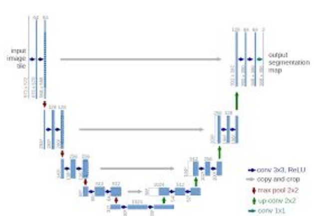


ImageNet dataset



Study Area:
Covington
River, VA

Attention U-net model



Study Area:
Covington
River, VA

Experiment in Covington (cont.)

First, we apply the model trained on Rowan County directly to Covington, the performance drastically drops.

Models	F1-score in Covington	F1-score in Rowan Creek
ResNet50	29.30%	83.77%
Attention-Unet	27.43%	81.28%
DenseNet121	24.60%	83.73%
DenseNet169	**10.00%**	**85.11%**

All models are fine-tuned with the same hyperparameters as follows:

max epoch = 500
learning_rate = 0.001 (classifier) and 0.00001 (fine-tuning)
batch size = 16

Early stopping and model checkpoint callbacks were used during training to monitor validation loss, stop training when validation loss did not decrease after a specified number of epochs, and to save the model with the highest validation accuracy.

Experiment in Covington (cont.)

Secondly, when we train the selected models with Covington, the performance decrease 20% on average compared to the performance in Rowan County.

Models	F1-score in Covington	F1-score in Rowan Creek	#Parameters
DenseNet121	66.43%	85.11%	12,171,116
DenseNet169	66.40%	83.77%	19,545,964
ResNet50	64.39%	83.73%	32,587,253
Attention-Unet	64.25%	81.28%	53,508,217

All models are fine-tuned with the same hyperparameters as follows:

max epoch = 500
learning_rate = 0.001 (classifier) and 0.00001 (fine-tuning)
batch size = 16

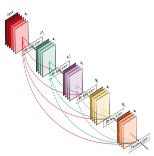
Early stopping and model checkpoint callbacks were used during training to monitor validation loss, stop training when validation loss did not decrease after a specified number of epochs, and to save the model with the highest validation accuracy.

Transfer from Rowan Creek to Covington

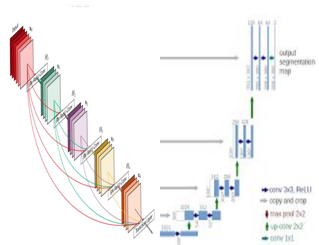
Other U-net models
(ImageNet)

Pretrained

CNN



ImageNet dataset

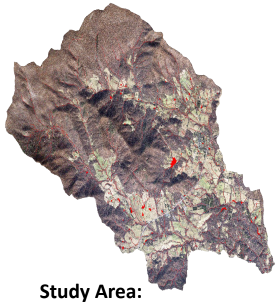


Study Area:
Rowan Creek, NC

Study Area:
Covington
River, VA

Attention U-net model

Study Area:
Rowan Creek, NC



Study Area:
Covington
River, VA

Transfer from Rowan Creek to Covington (Cont.)

Secondly, when we train the selected models with Covington, the performance decrease 20% on average compared to the performance in Rowan County.

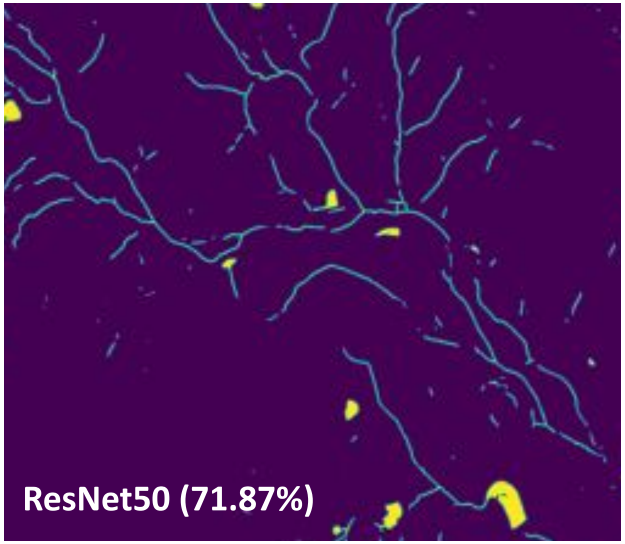
Models	F1-score	
	Rowan Creek Fine-tuned to Covington	Only Covington
ResNet50	**71.87%**	64.39%
DenseNet169	71.04%	66.40%
Attention-Unet	70.41%	**64.25%**
DenseNet121	69.77%	66.43%

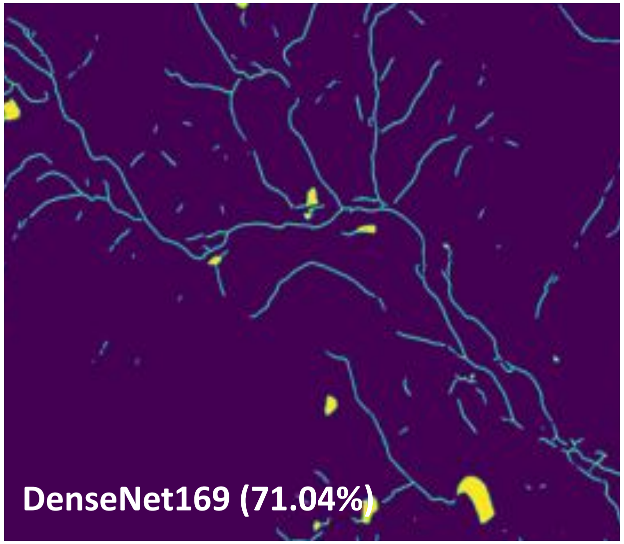
All models are fine-tuned with the same hyperparameters as follows:

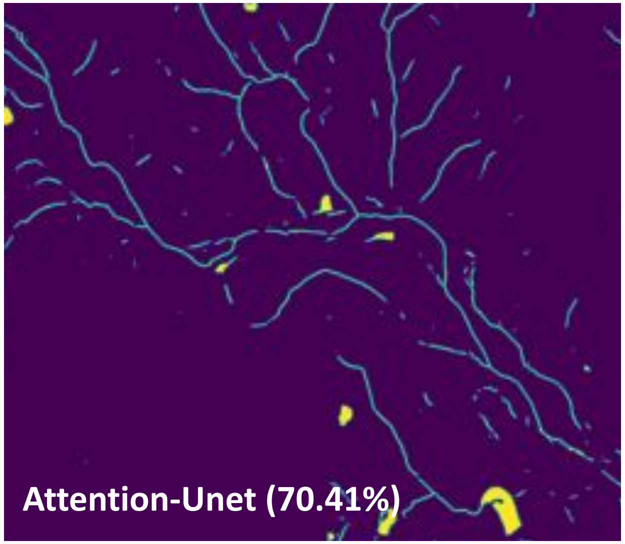
max epoch = 500
learning_rate = 0.001 (classifier) and 0.00001 (fine-tuning)
batch size = 16

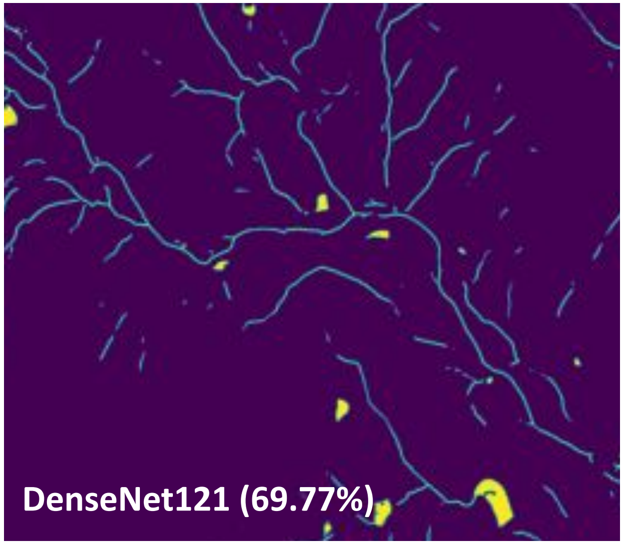
Early stopping and model checkpoint callbacks were used during training to monitor validation loss, stop training when validation loss did not decrease after a specified number of epochs, and to save the model with the highest validation accuracy.

Covington Prediction Results









Conclusions

1. The results from the Rowan County show significantly higher performance can be achieved with transfer learning.
   a. DenseNet169 can achieve 85.11% of F1-score which is about 6% higher than the attention U-net model.
2. The results from the Covington area show transfer learning can significantly improve the models' performance as high as 7.48% in ResNet50.
   a. The top 3 ImageNet models perform as good as the attention U-net model in Covington area when they are fine-tuned from the Rowan County to the Covington area.
3. The results from the Covington area show the scalability benefit of transfer learning.
   a. The models pre-trained on ImageNet are significantly smaller, the DensNet169 has 2.73 times and ResNet50 has 1.6 time less parameters than the attention U-net model, which could help scale up the models more efficiently.

Future Work

1. Experiments on new areas are needed to further test the transferability of the models and to scale up the models to the national level.
2. We are looking into other techniques of transfer learning such as domain adaptation to address geospatial differences such as resolution and variation of elevation.

Acknowledgements

- National Science Foundation
  - 2112356
  - 2118329
- Collaborators
  - Zhe Jiang, University of Florida
  - Ethan Shavers, USGS
  - Lawrence V. Stanislawski, USGS
  - E. Lynn Usery, USGS

Thanks！

- **Comments / Questions?**
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