MONITORING WATER BODY HEALTH FROM REMOTE SENSING IMAGERY

PURDUE UNIVERSITY | The Data Mine | intelinair

Saumya Verma, Hardit Sandhu, Nitin Nallagatla, Animesh Joshi

INITIAL RESEARCH

- Use remote sensing of satellite imagery to assess the health of a waterbody
- Researched multiple problems relevant to waterbodies including:
  - Droughts
  - Floods
  - Chemicals from fertilizer
- Final research problem: Blue-Green algae

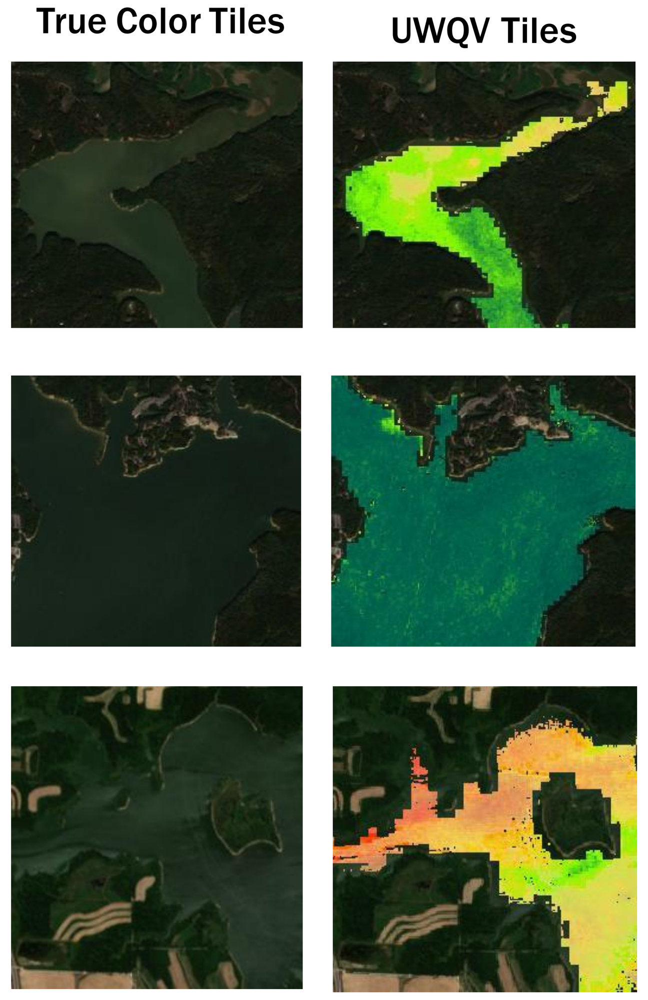
OBJECTIVE

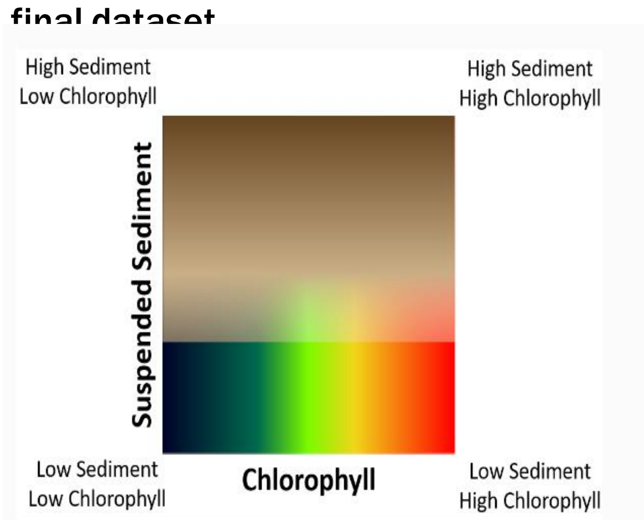
- Goal: Identify healthy vs. unhealthy water bodies based on presence of Blue-Green algae (cyanobacteria)
- Harmful for environment (marine life, human health)
- Caused by run-off from fertilizers
- Relevant in the Midwest region because of the agriculture industry
- Early detection of algae blooms can help with prevention plans

DATASET

- Publicly available data from Sentinel 2
  - Resolution: 10m – 60m
- Data from Intelinair
  - Resolution: 10cm
- True color and Ulysses Water Quality Viewer (UWQV) image pairs
  - UWQV – images filtered by chlorophyll and sediment quantity
  - Weak labels to help identify algae through chlorophyll content
- 32 images
  - 14 lakes in Indiana
  - Data spanned over the past three years and various seasons
- 350+ tiled images (256x256)
- Manually filtered tiles with only land for final dataset

True Color Tiles　UWQV Tiles



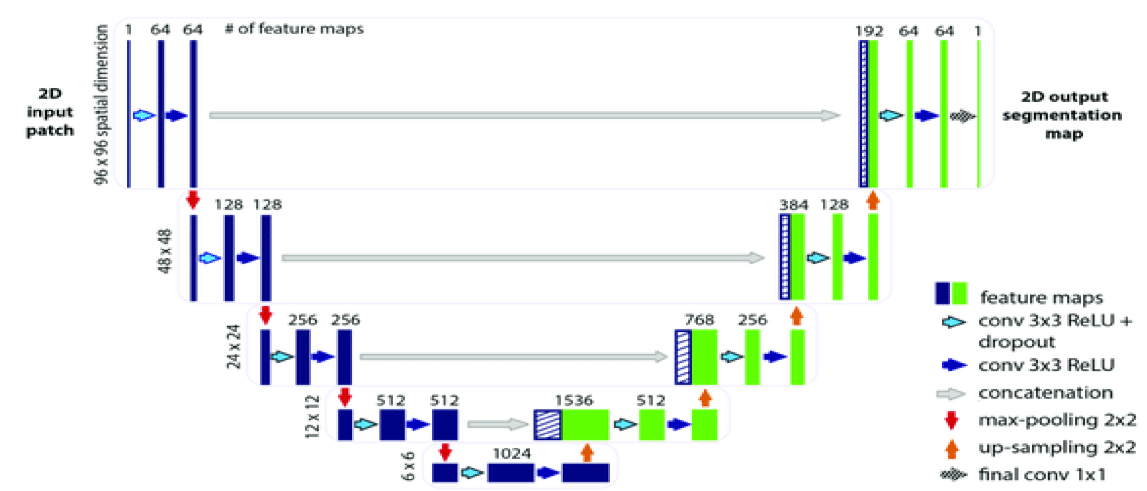


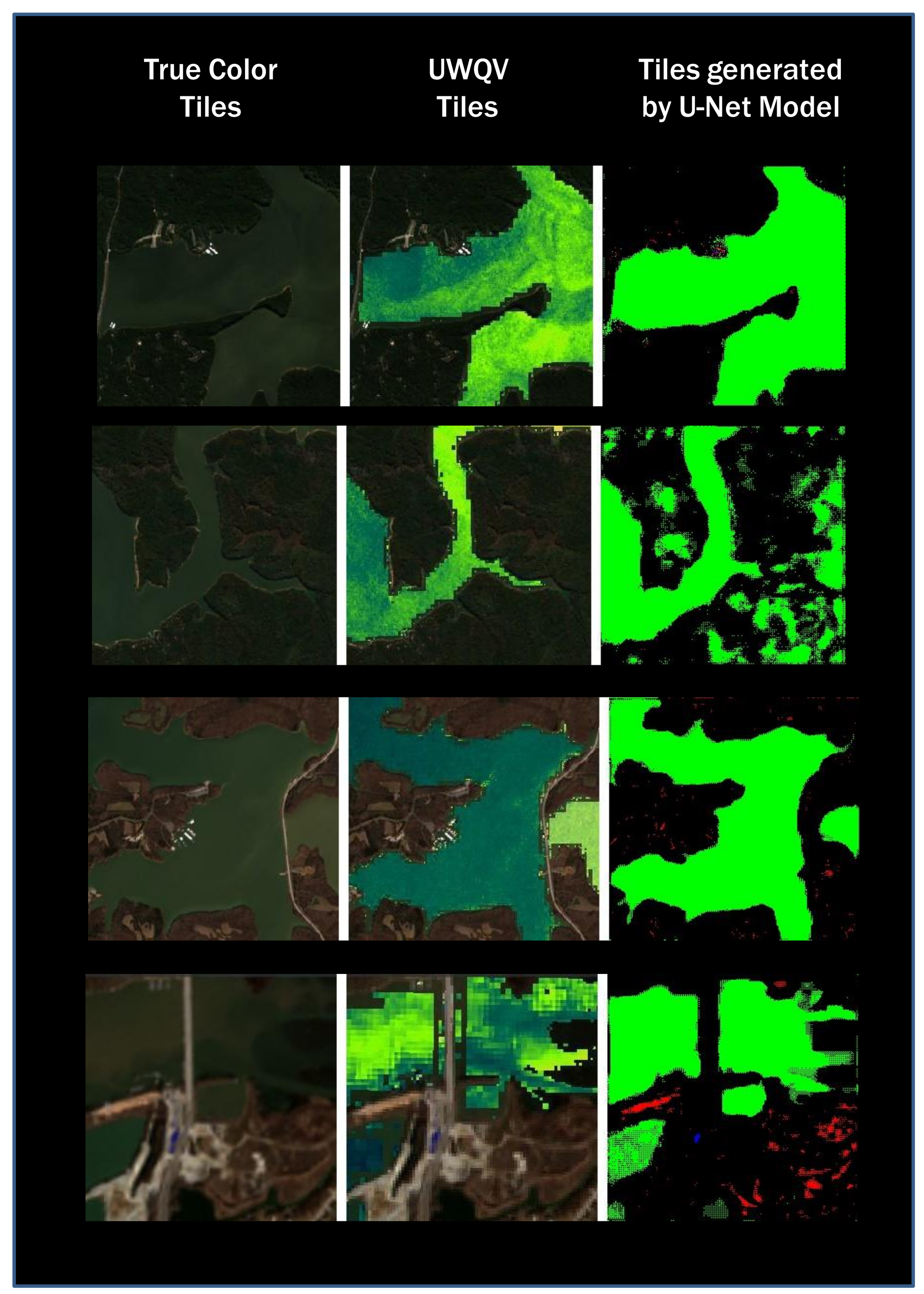
Ulysses Water Quality Viewer Color palette

SEGMENTATION MODEL

•Our team built a U-NET model to generate segmented masks given satellite true color images. These masks were trained to mimic the Ulysses Water Quality filter from the sentinel hub.
•Weakly Supervised Learning: The UWQV provides masks as labels for our U-Net, however these masks are intended to show chlorophyll and sedimentation levels rather than algae.
•The images generated by our model are able to detect water bodies and separate them from their surroundings; however, there are some issues with detecting non-contaminated portions of the water.
•Model uses the Sigmoid Activation function to generate outputs, and the mean squared error loss function to assess predictions.

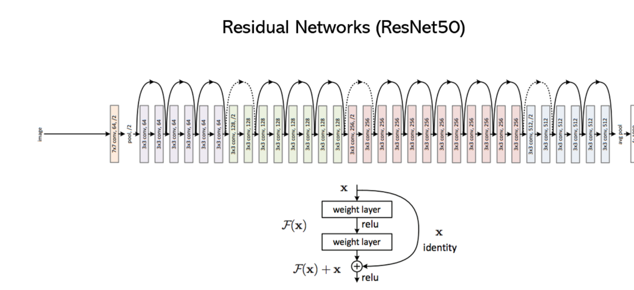
Diagram representing functionality of U-Net Model



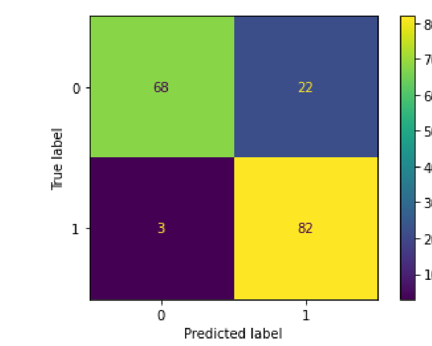


CLASSIFICATION MODEL

•ResNet is a convolutional neural network used to classify images into different categories
•We labeled our satellite true color images by viewing the Ulysses Water Quality masks and determining whether or not the water bodies were contaminated (labels process was not perfect and thus we would describe this model as "weakly supervised")
•The ResNet50 model generates a prediction which is a probability that the water body is infected with algae.
•Achieved 86% accuracy in predicting the health of water bodies. (Specificity = 0.96, Sensitivity = 0.76)



Architecture Diagram of a ResNet Model



Confusion Matrix Plot which shows accuracy of our predictions

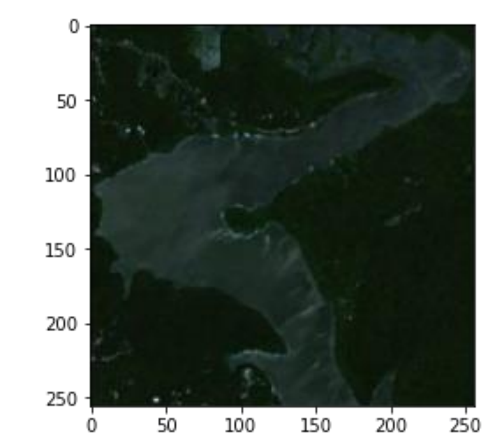


Image that was correctly classified as Infected by the ResNet Model

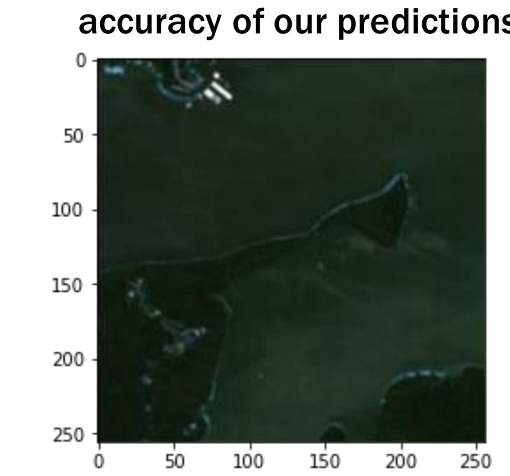


Image that was incorrectly classified as healthy by the ResNet Model

CONCLUSION AND FUTURE GOALS

- Overall, we consider this project to have been a great success. We were able to segment and classify satellite images of water bodies and we were able to produce accurate results and conclusions on the health of those waterbodies

	precision	recall	f1-score	support
0	0.76	0.96	0.84	71
1	0.96	0.79	0.87	104
accuracy			0.86	175
macro avg	0.86	0.87	0.86	175
weighted avg	0.88	0.86	0.86	175

- In the future, we plan to apply these models we have built to the Intelinair data. We plan to generate segmentation masks with our U-Net as well as Infected vs. Healthy predictions from our ResNet. This will be a great test of our models, as the Intelinair data images include the near-infrared channel which is commonly used in agricultural applications of computer vision.

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