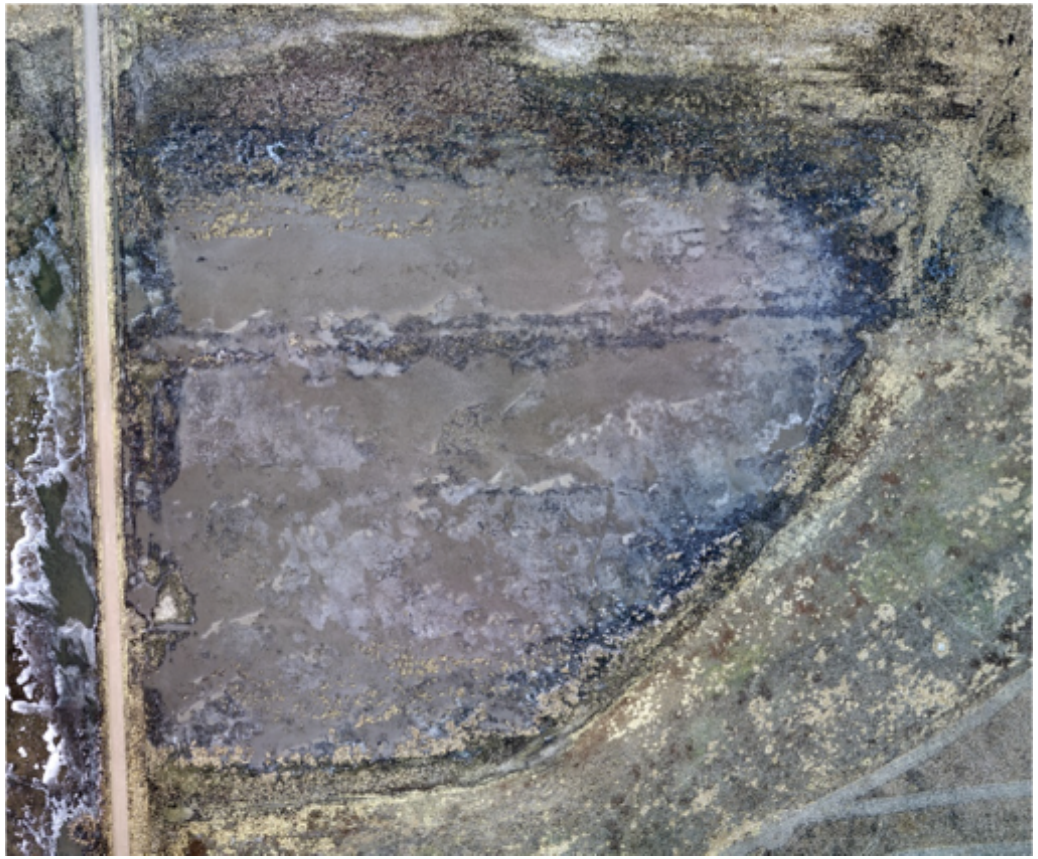
Final Project

UAV Imagery based **Wetland Land Cover Classification**



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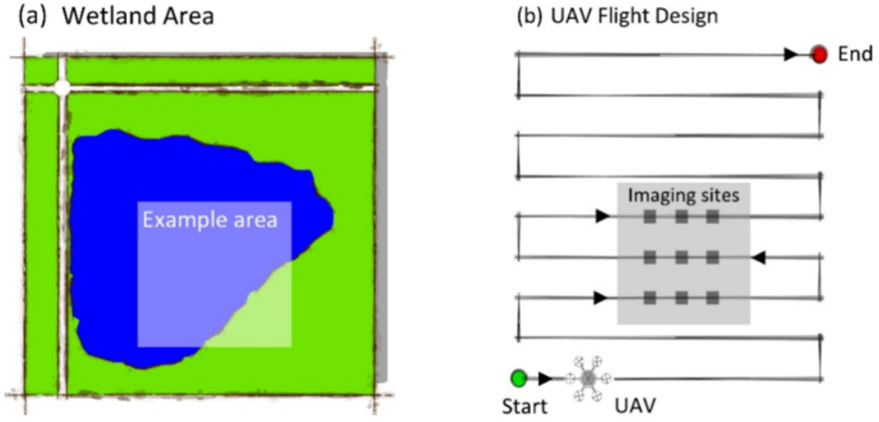
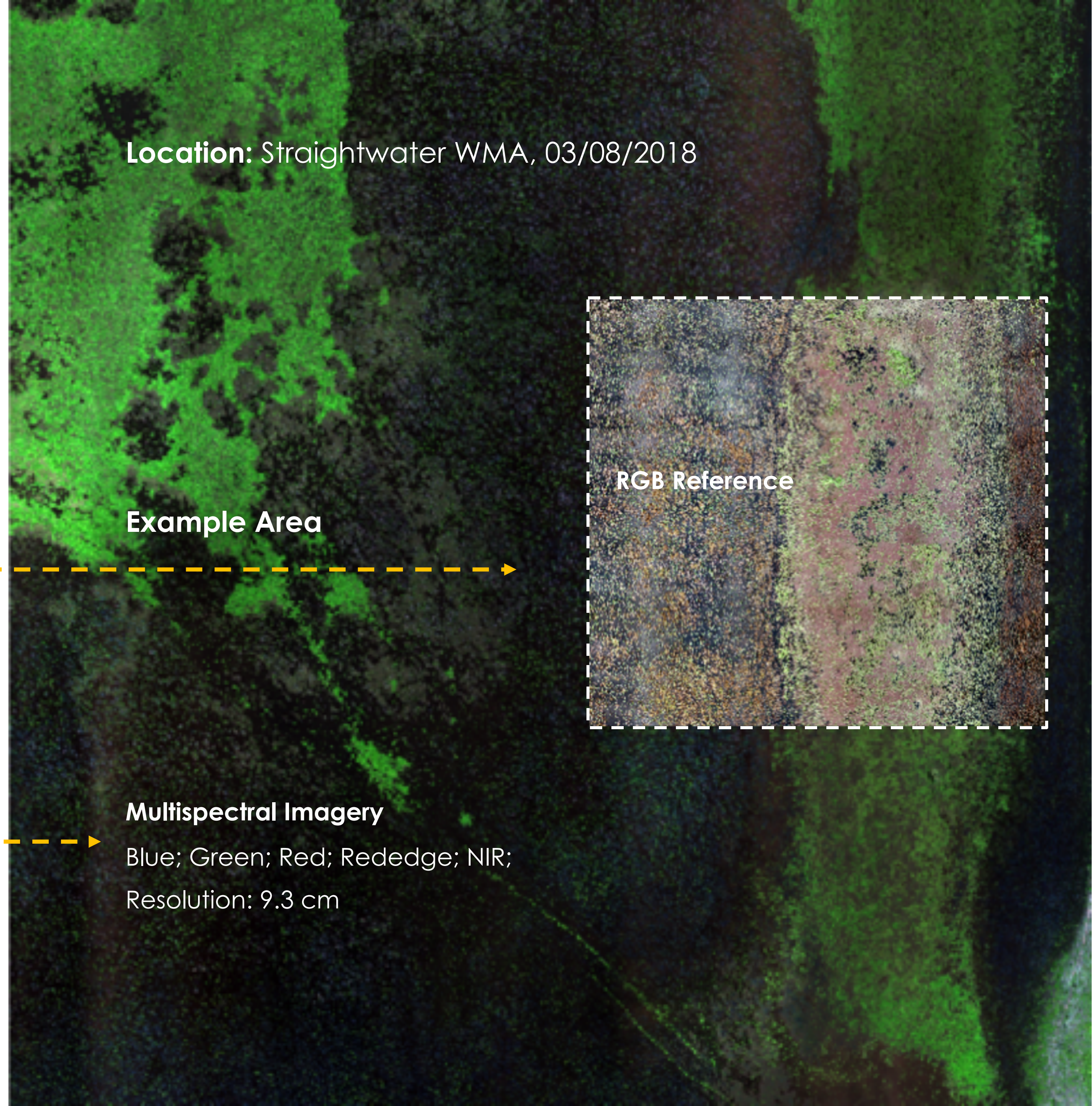
April 22, 2021

Data & Goals



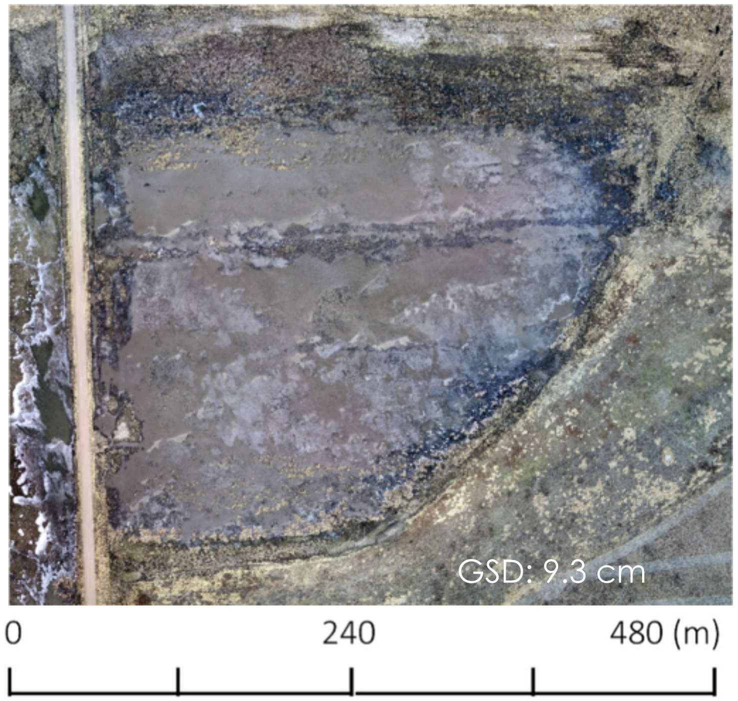
Goal: Develop machine learning method to automatically **delineate wetland area** based on UAV **multispectral data.**



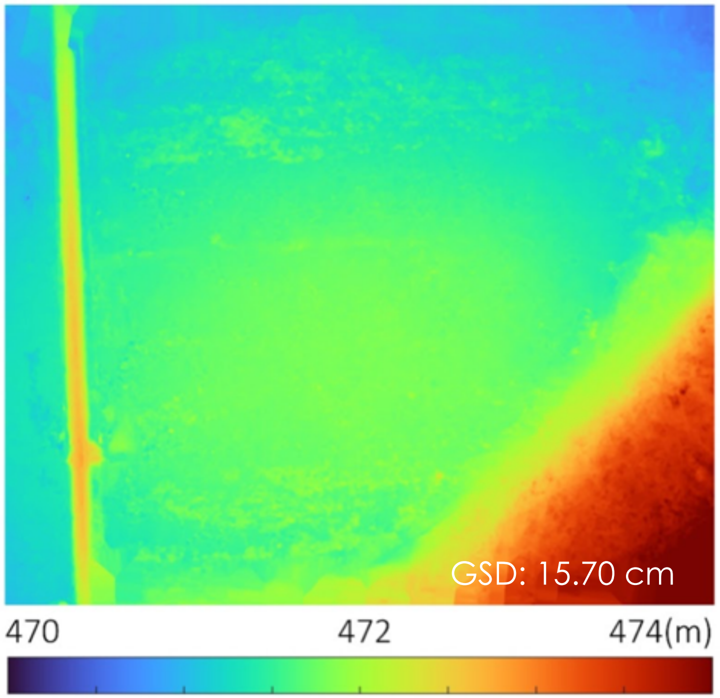
Data

Multispectral Imagery: 6 bands = Blue, Green, Red, Rededge, NIR + **DSM (5123x8045x6)**

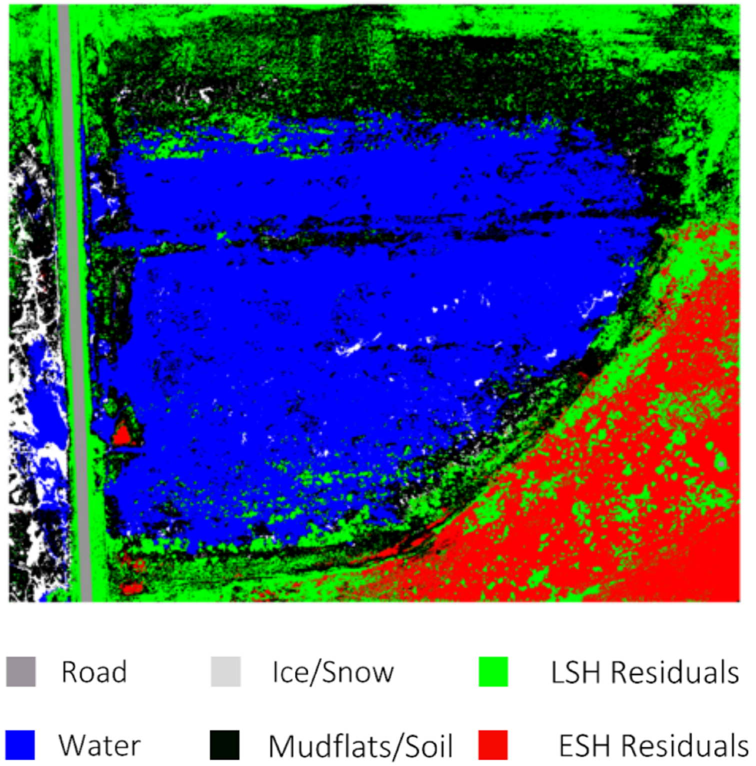
RGB



Elevation



Ground Truth



Data and Features

Multispectral Imagery: 6 bands = Blue, Green, Red, Rededge, NIR + **DSM (5123x8045x6)**

Feature 1: Multi-spectral Reflectance - Red (numeric 0-1)

Feature 2: Multi-spectral Reflectance - Blue (numeric 0-1)

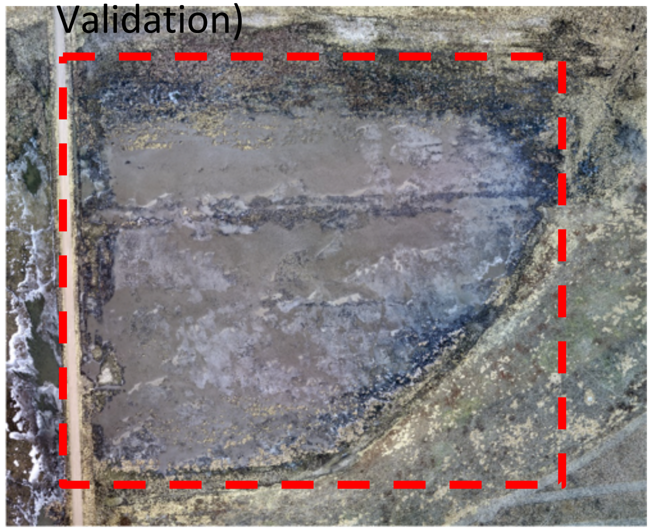
Feature 3: Multi-spectral Reflectance - Green (numeric 0-1)

Feature 4: Multi-spectral Reflectance - NIR (numeric 0-1)

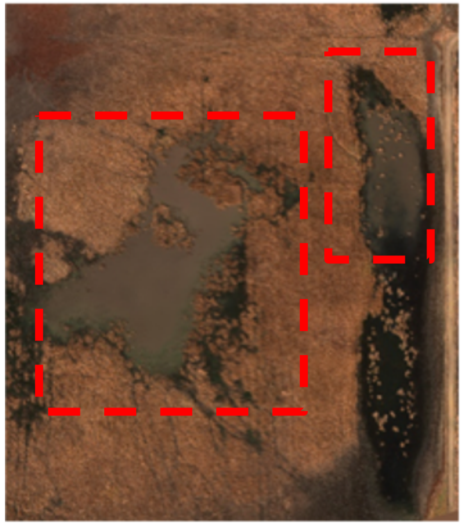
Feature 5: Multi-spectral Reflectance - Red Edge (numeric 0-1)

~~**Feature 6:** Elevation information - DSM (numeric by meter)~~

Dataset 1 (Train & Validation)



Dataset 2 (for test)



Water ponding area

Dataset 1: 3559 / 50 million (03/08/2018)

Dataset 2: 10117830 / 50 million (03/01/2018)

Workflow

Classification Problem

- Water
- LSH residual
- Soil
- Ice
- ESH residual
- Vegetation cluster

Segmentation

- K-mean
- CNN-segmentation
- Ensemble

Preprocessing

- Feature Normalizing
- Feature selection

Multispectral Data

- Blue
- Green
- Red
- Red-edge
- NIR
- DSM

Metric: Accuracy & IoU

$$Y = W * X$$

Objective 1: Data preprocessing

Objective 2: K-means clustering

Objective 3: Using a single classifier and ensemble method to classify the image

Objective 4: Using a CNN-based semantic segmentation to conduct semantic segmentation over an image

Metrics

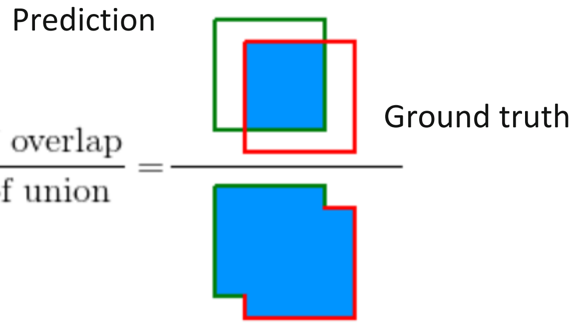
Metrics

- **Accuracy**: Accuracy is the ratio of correct predictions to the total number of predictions.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

- **Intersection over Union (IoU):** IoU is a metric that measures how similar our predicted boundary is to the ground truth boundary.

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

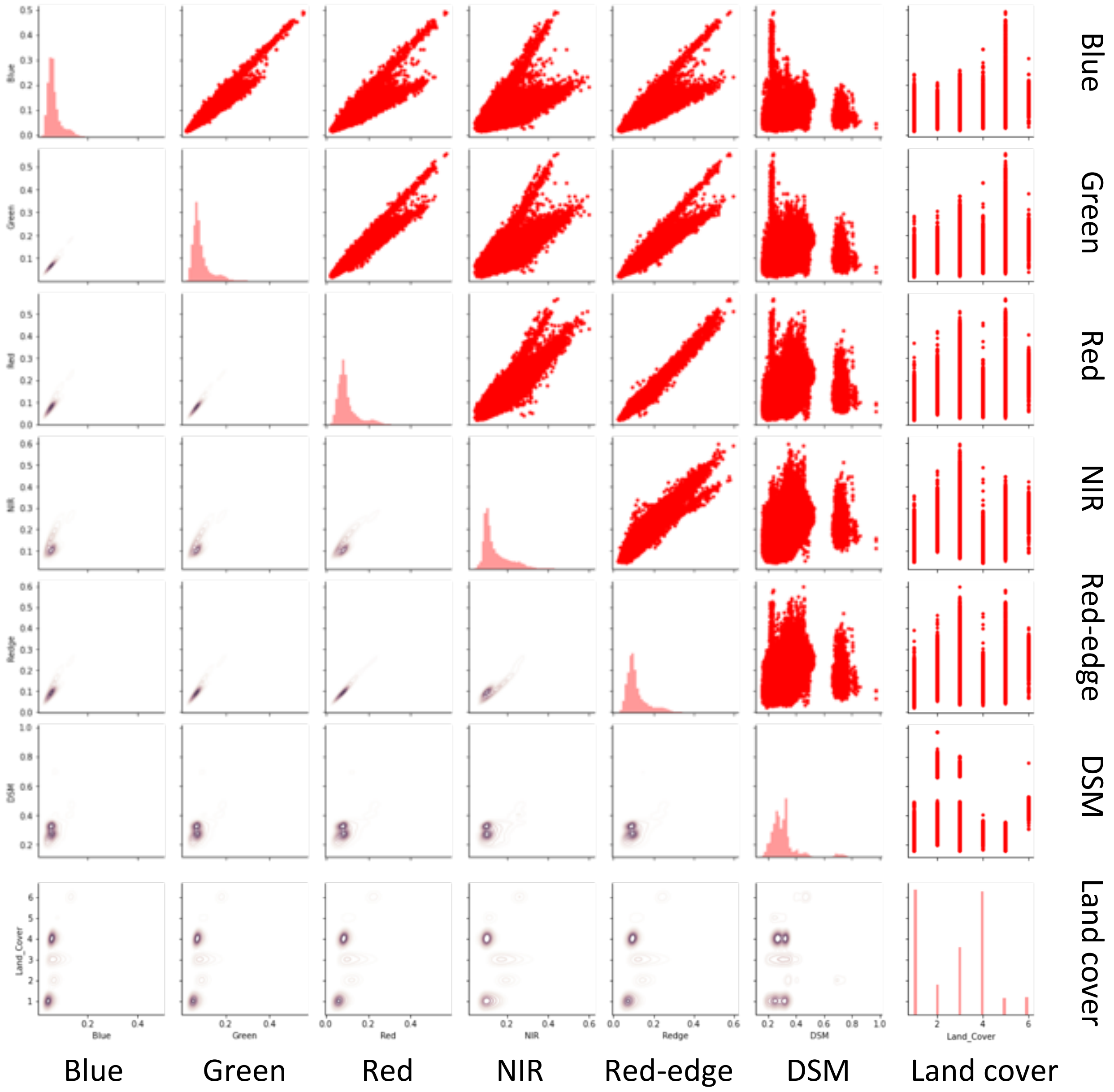


Sources: https://supervise.ly/explore/plugins/mean-average-precision-m-ap-75277/overview

Preprocessing

Image Conversion

- Six Identical resolution images loaded into memory and converted to **single numerical** value
- Entries with six features and X vs Y coordinates
- Each feature **Z score normalized** with a normal distribution
- PCA Considered but not deemed necessary

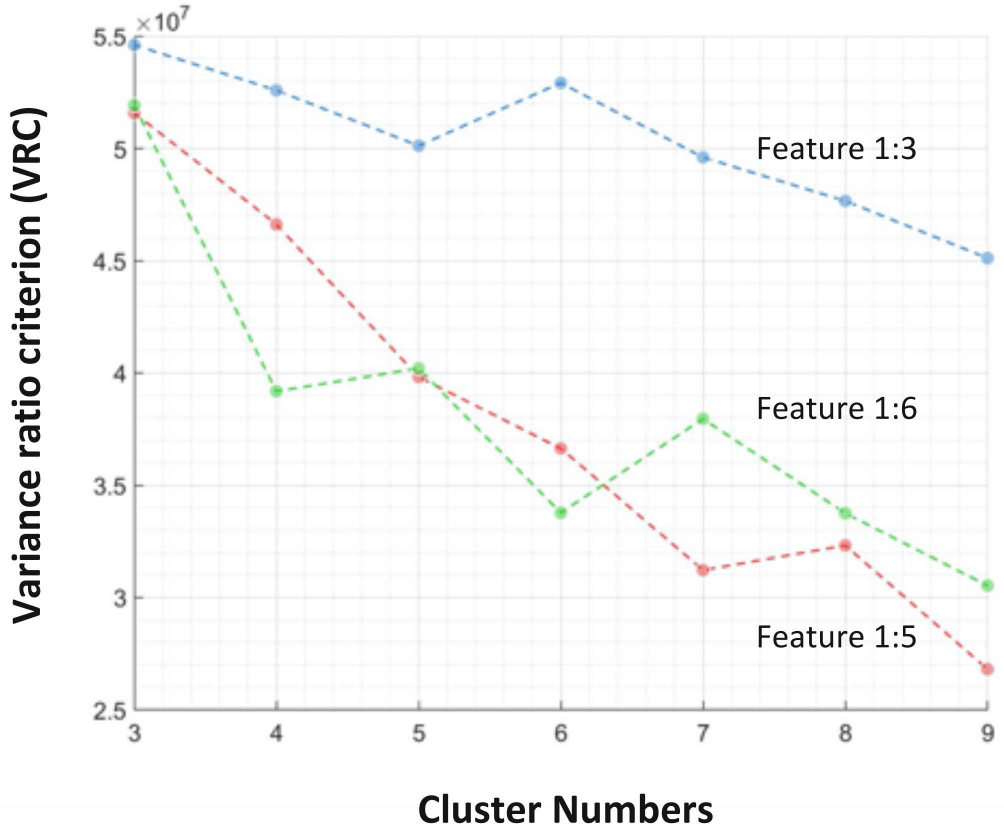


K-means

VRC ratio

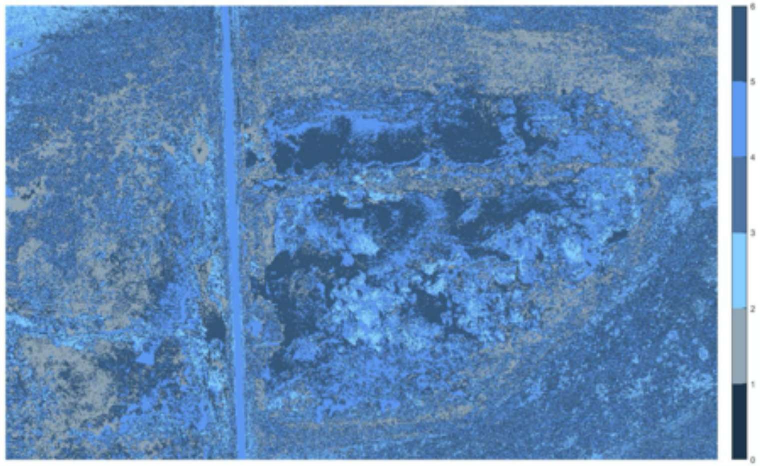
- Ratio of between-cluster variance to within-cluster variance
- Higher ratios indicate better clustering operation
- Elbow point indicate optimal clustering

Clustering with **5-7 clusters** show good VRC performance, so we choose 6 to conduct our clustering operation later.

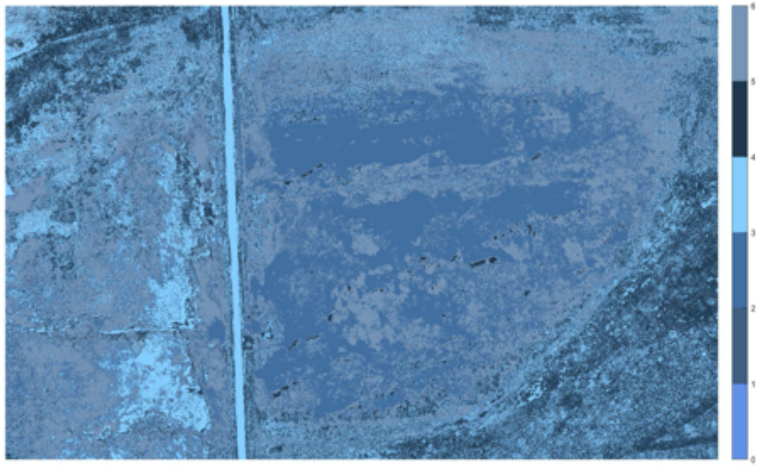


K-means

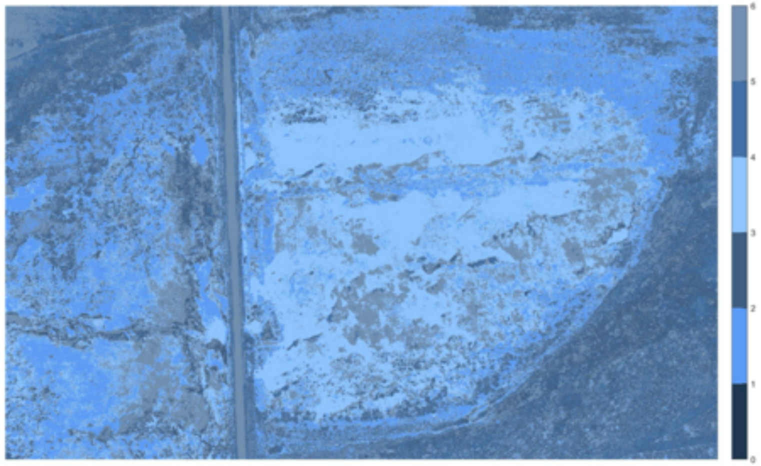
Feature 1:3



Feature 1:5



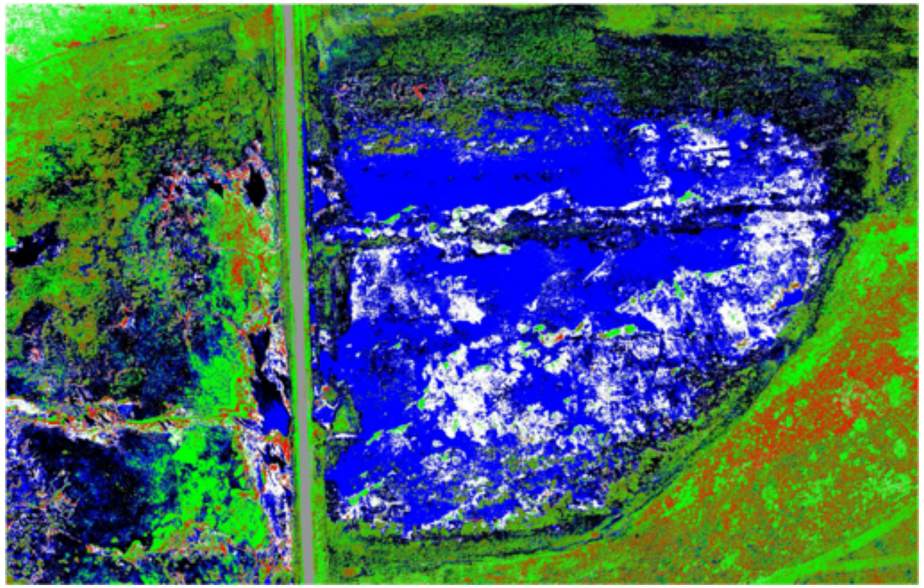
Feature 1:6



- Visually, adding NIR and red-edge band (Feature 1:5) and elevation (Feature 1:5) enhance the clustering cohesion.
- But it is hard to connect the unsupervised cluster to the really groundtruth directly.
- We select the **result of feature 1:6** for later accuracy test as it return the best clustering performance visually.

K-means

Results from Feature 1:6 with 6 clusters



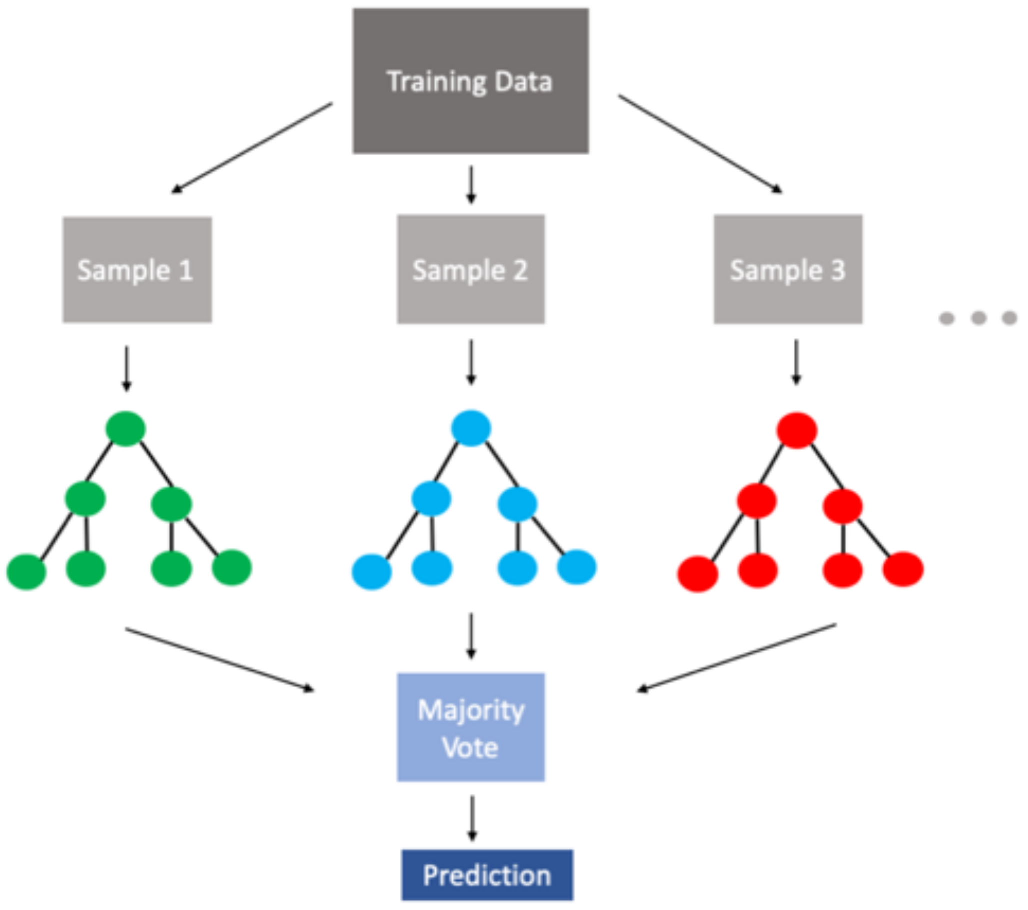
Category		Band 1:6	
Class	**Label**	**Accuracy**	**IoU**
Soil	1	61.2%	57.3%
ESH Residual	2	46.8%	35.7%
LSH Residual	3	77.8%	47.7%
Water	4	**70.9%**	60.8%
Ice	5	25.7%	0.04%
Road	6	**91.1%**	80.0%
Global	-	65.9%	60.0%

- We select the k-mean results from feature 1:6 and manually assign the closest label to each cluster.
- Accuracy of each class was measured.

Ensemble Method: Bagging Classifier

Decision Tree Bagging Classifier

- Comparison of single decision tree with bagging classifier.
- Bagging: sampling with replacement and training on multiple decision trees.
- Prediction made based on majority vote.
- Trained on 20% of the total data set (random pixels).
- Implemented in Scikit Learn [1].



Ensemble Method: Bagging Classifier for Site 1

Results

Category		Band 1:3		Band 1:5		Band 1:6	
Class	**Label**	**DT Accuracy**	**Bag Accuracy**	**DT Accuracy**	**Bag Accuracy**	**DT Accuracy**	**Bag Accuracy**
Soil	1	80.4%	84.0%	86.0%	89.2%	88.2%	90.1%
ESH Residual	2	48.6%	38.3%	55.9%	52.1%	88.2%	91.2%
LSH Residual	3	67.4%	66.1%	72.2%	71.3%	84.2%	83.0%
Water	4	82.1%	84.8%	93.2%	94.0%	94.5%	94.8%
Ice	5	77.0%	79.3%	79.8%	80.3%	82.8%	82.0%
Road	6	80.0%	79.8%	91.6%	92.1%	95.7%	95.2%
Global	-	74.7%	75.4%	81.7%	82.5%	89.0%	90.0%

	Band 1:3		Band 1:5		Band 1:6	
	DT	**Bag**	**DT**	**Bag**	**DT**	**Bag**
Training Runtime (seconds)	185.5	171.25	264.58	258.19	304.94	312.16

- Full band feature set resulted in best performance overall.
- Bagging classifier results in marginal increase in performance in each case (≈ 1%).
- ESH Residual highly sensitive to inclusion of DSM (band 6).
- Water *not* sensitive to DSM; high accuracy from bands 1:5.

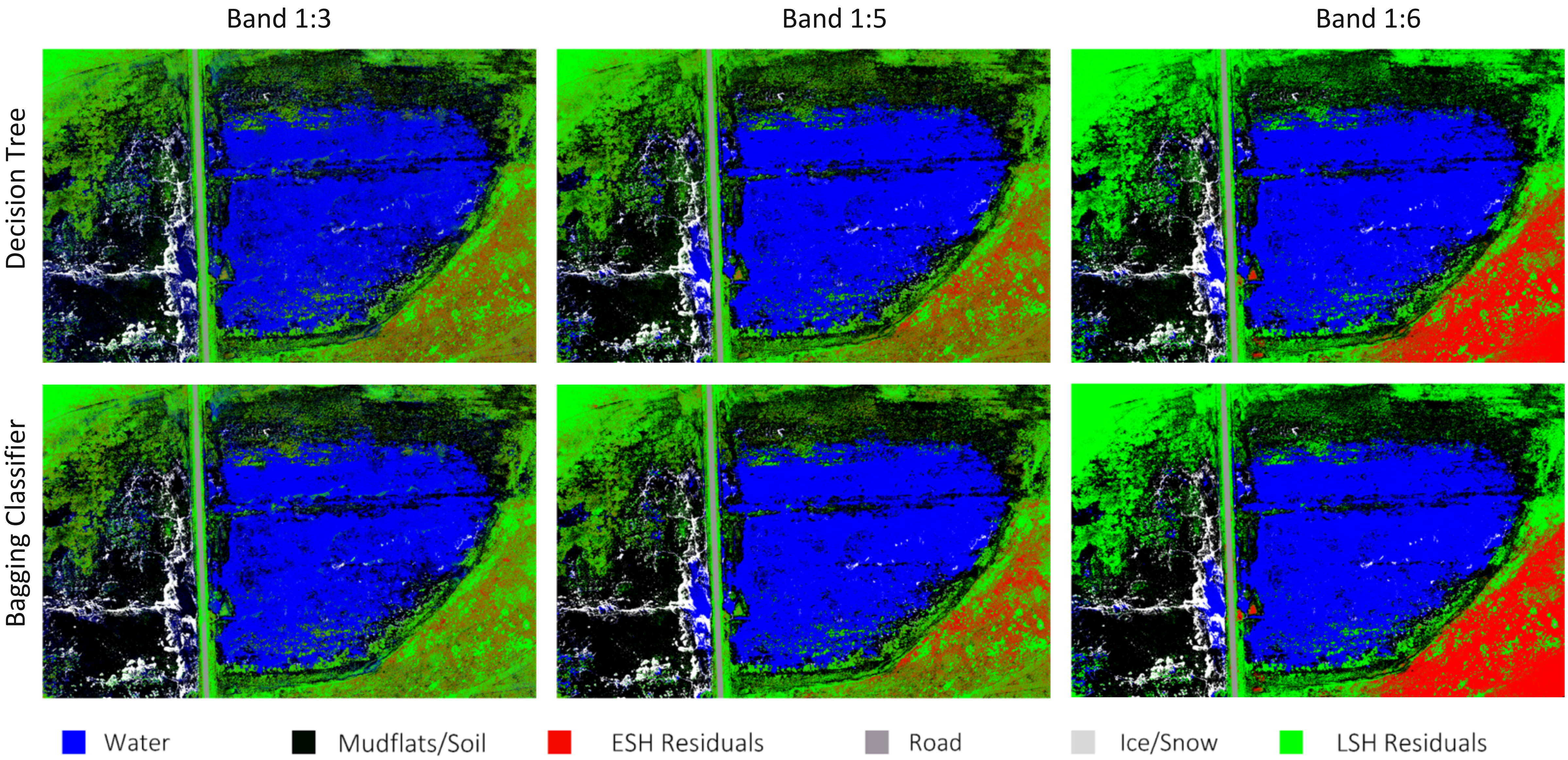
Ensemble Method: Bagging Classifier

Results

Confusion Matrix							
Class	**Label**	**Soil**	**ESH Residual**	**LSH Residual**	**Water**	**Ice**	**Road**
Soil	1	12,982,044	35,024	748,042	421,658	84,459	14
ESH Residual	2	49,048	3,599,014	297,269	102	1,187	1,353
LSH Residual	3	1,116,981	452,944	8,043,637	40,391	33,527	12,842
Water	4	493,806	74	43,283	10,917,645	54,993	24
Ice	5	118,370	335	37,923	76,052	1,066,777	33
Road	6	14	3,988	19,142	232	63	462,245

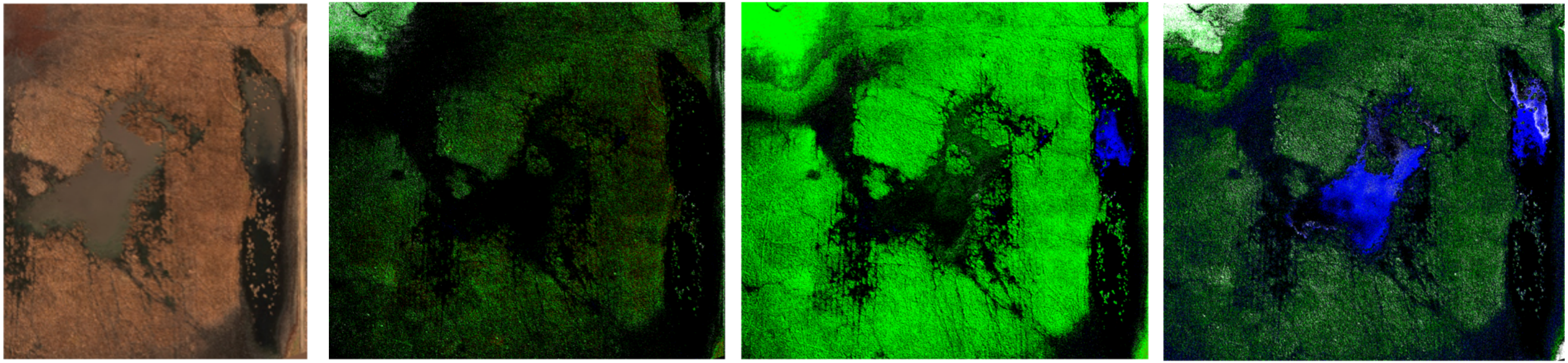
- LSH Residual, Water, and Ice were most often misclassified as Soil.
- Soil, ESH Residual, and Road were most often misclassified as LSH Residual.
- Road had lowest rate of misclassification and also lowest representation in the data set.

Ensemble Method: Bagging Classifier for Site 1



Ensemble Method: Bagging Classifier for Test

RGB Reference | Band 1:3 | Band 1:5 | Band 1:6



Water | Mudflats/Soil | ESH Residuals | Road | Ice/Snow | LSH Residuals

- RGB bands are insufficient alone to provide classification of varying land covers.
- Adding DSM improves the classification, especially with respect to water.

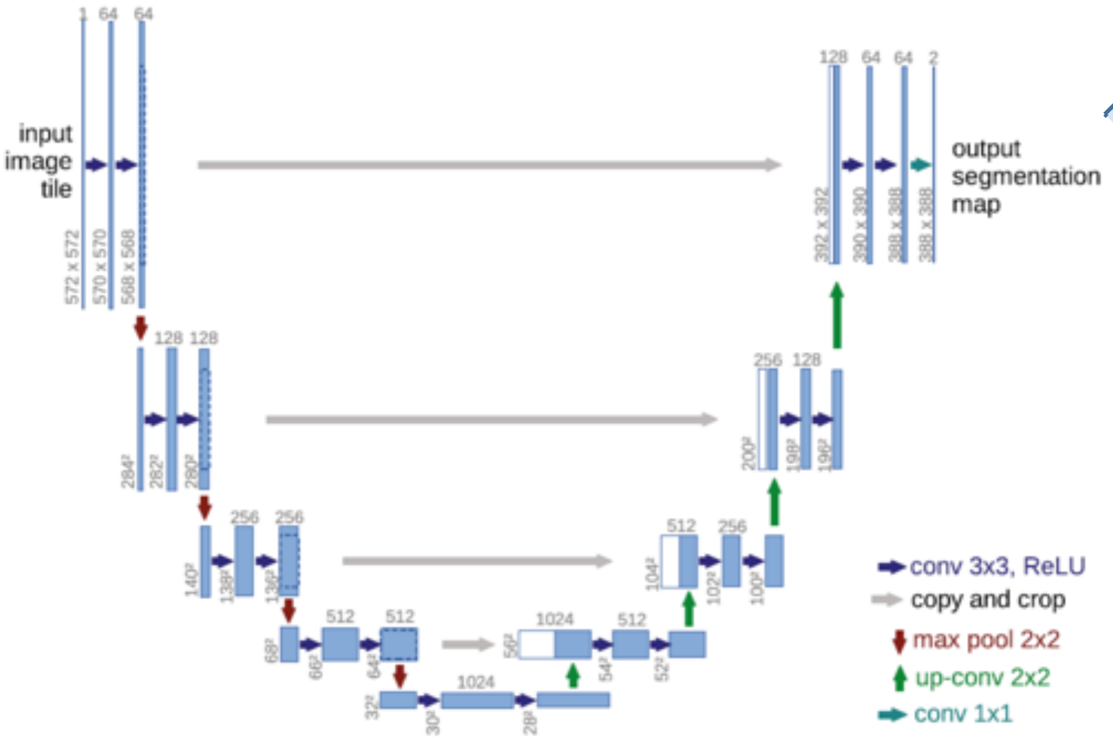
Semantic Segmentation: U-net Architecture

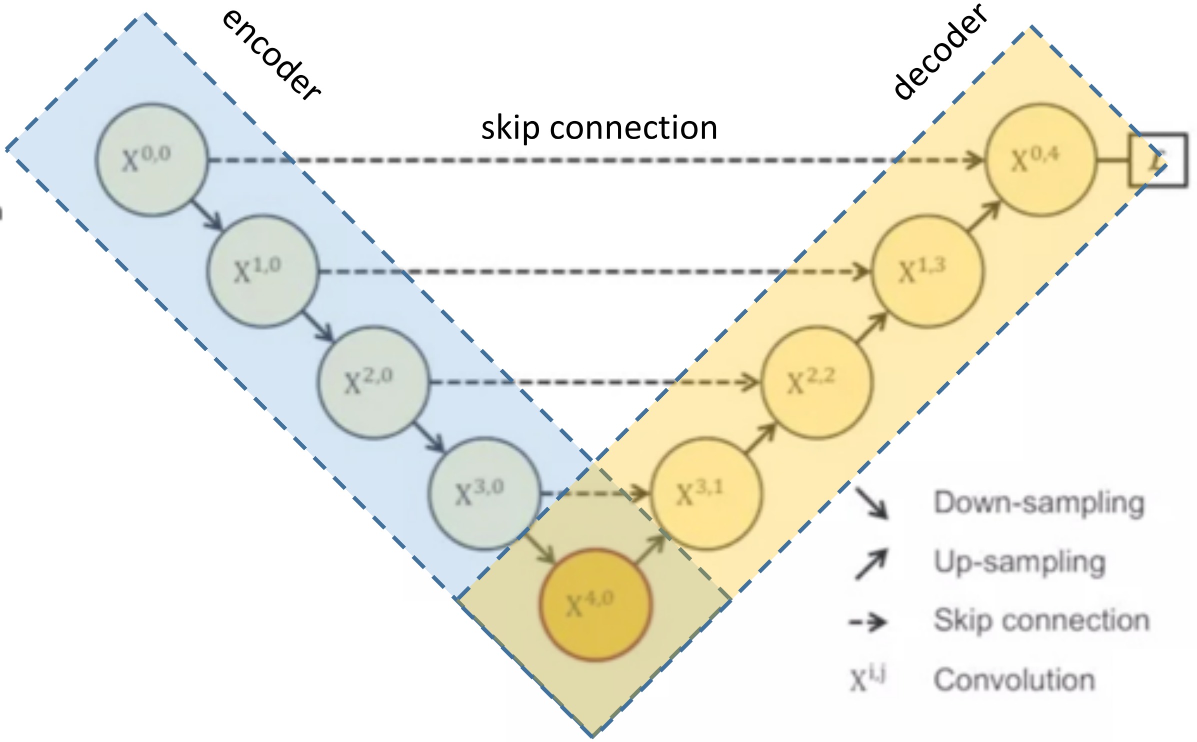
Key characteristics

- Encoder-decoder CNN architecture
- Skip connection
- Multi-scale spatial features

Input & output

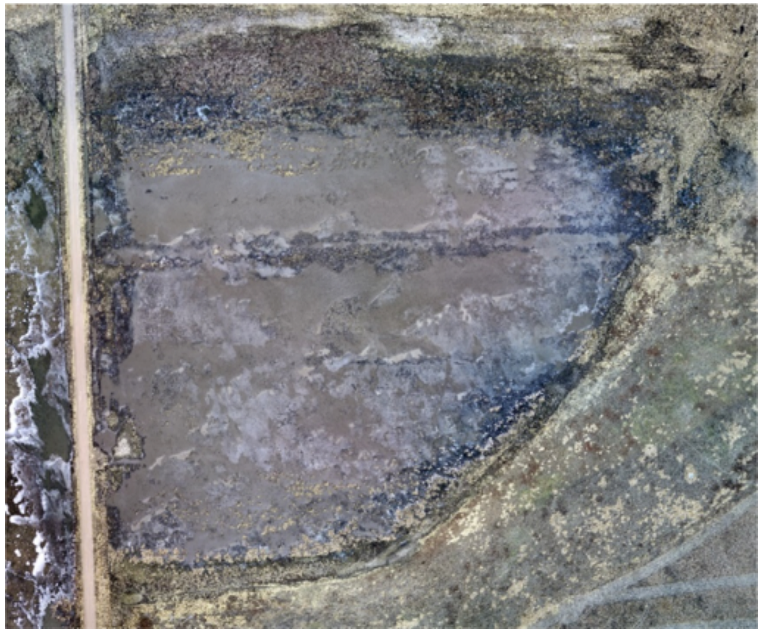
- Given image with shape of (m,n,c)
- Produce label with shape of (m,n,1)
- Cross entropy loss



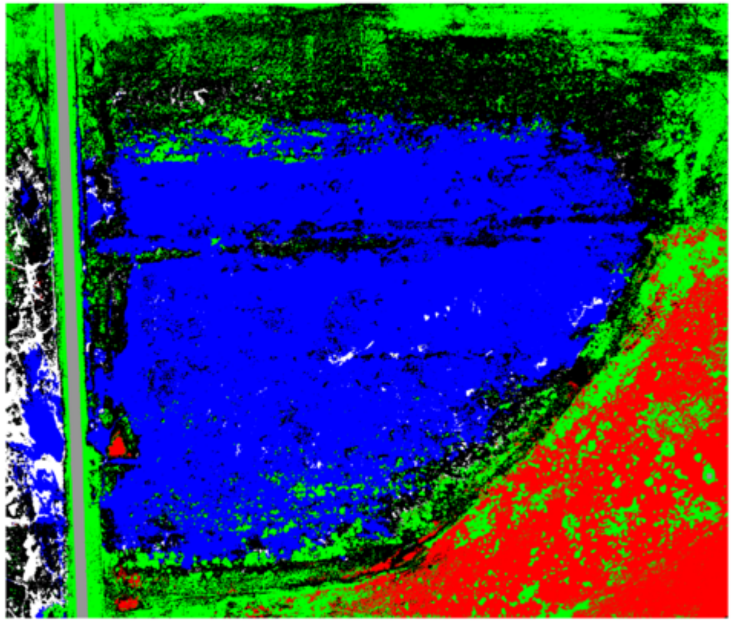


Semantic Segmentation: U-net Training

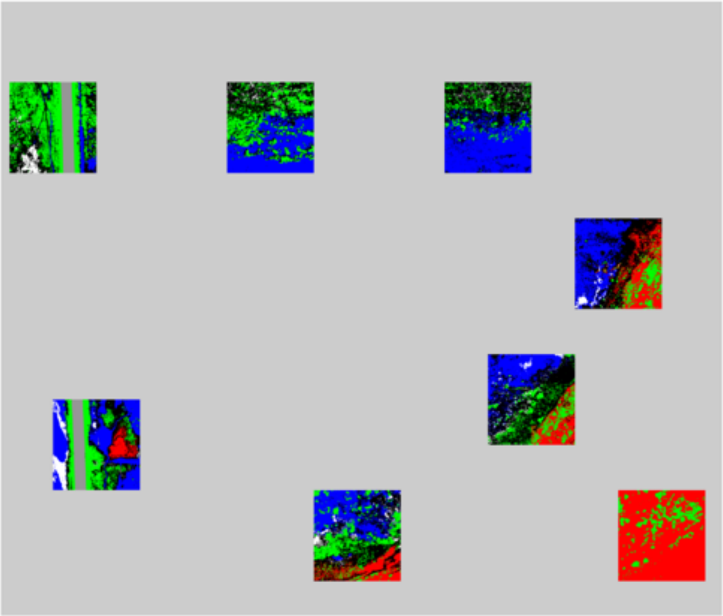
RGB reference



Ground truth



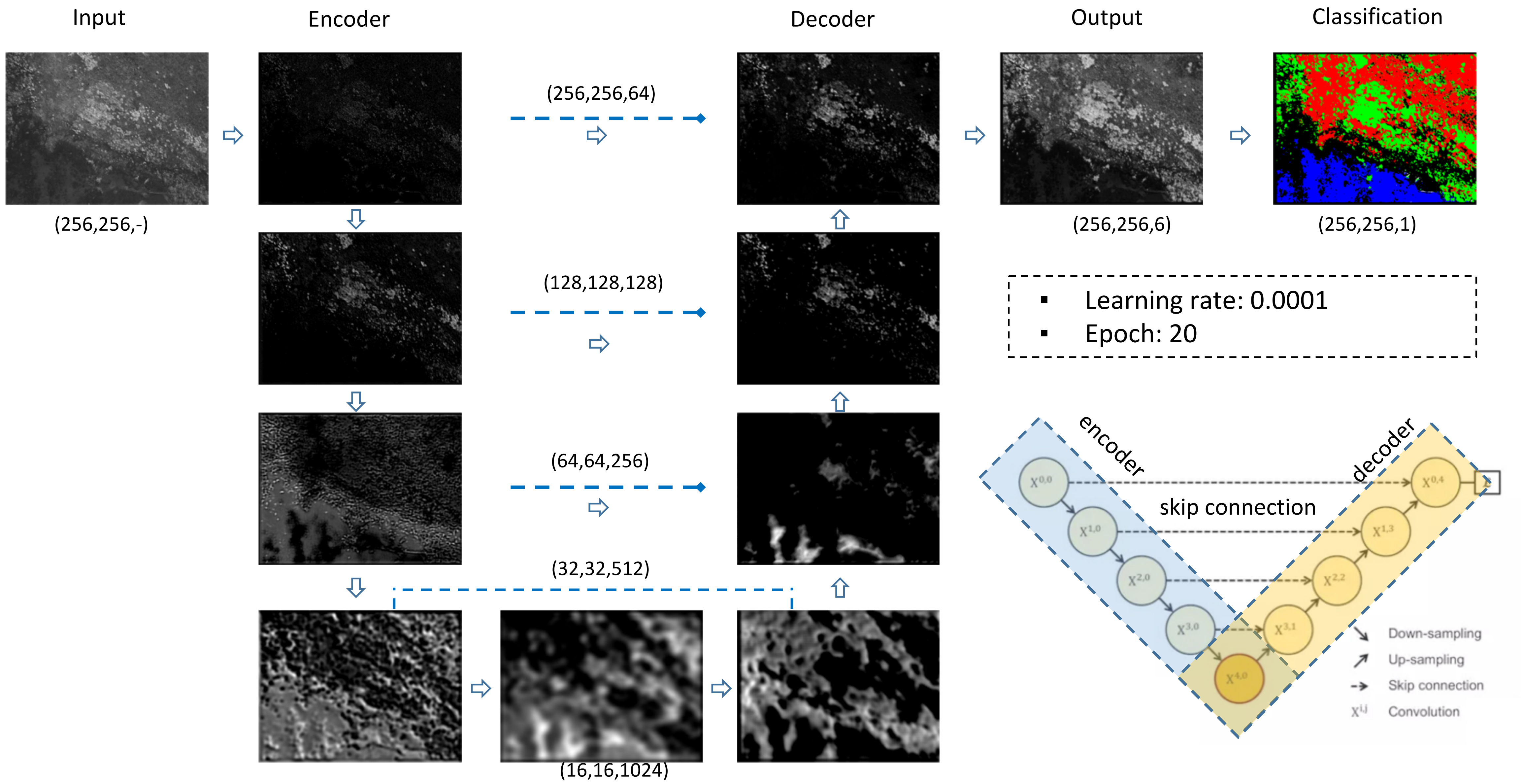
Sample region



Water | Mudflats/Soil | ESH Residuals | Road | Ice/Snow | LSH Residuals

- Sample region: 8
- Training sample shape: 256x256x6
- Training sample number: 1600
- Data augmentation: reflection, translation and rotation

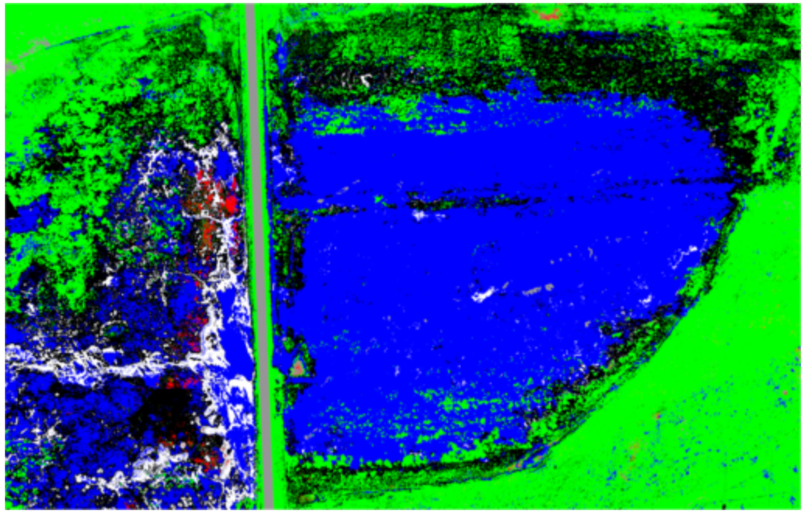
Semantic Segmentation: U-net Feature Flow



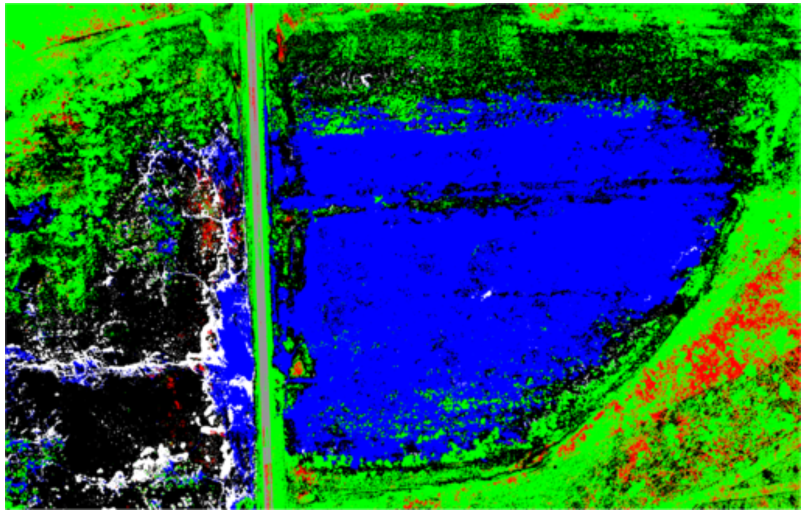
- Learning rate: 0.0001
- Epoch: 20

Semantic Segmentation Results for Site 1: U-Net

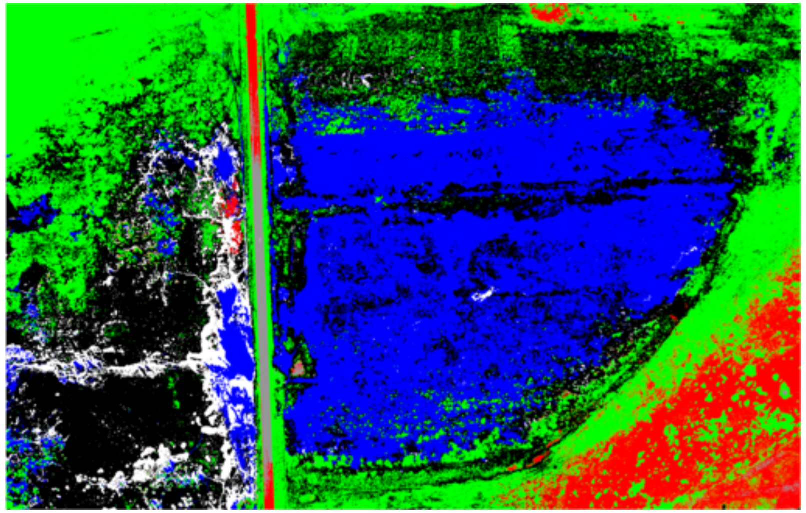
Feature 1:3



Feature 1:5



Feature 1:6



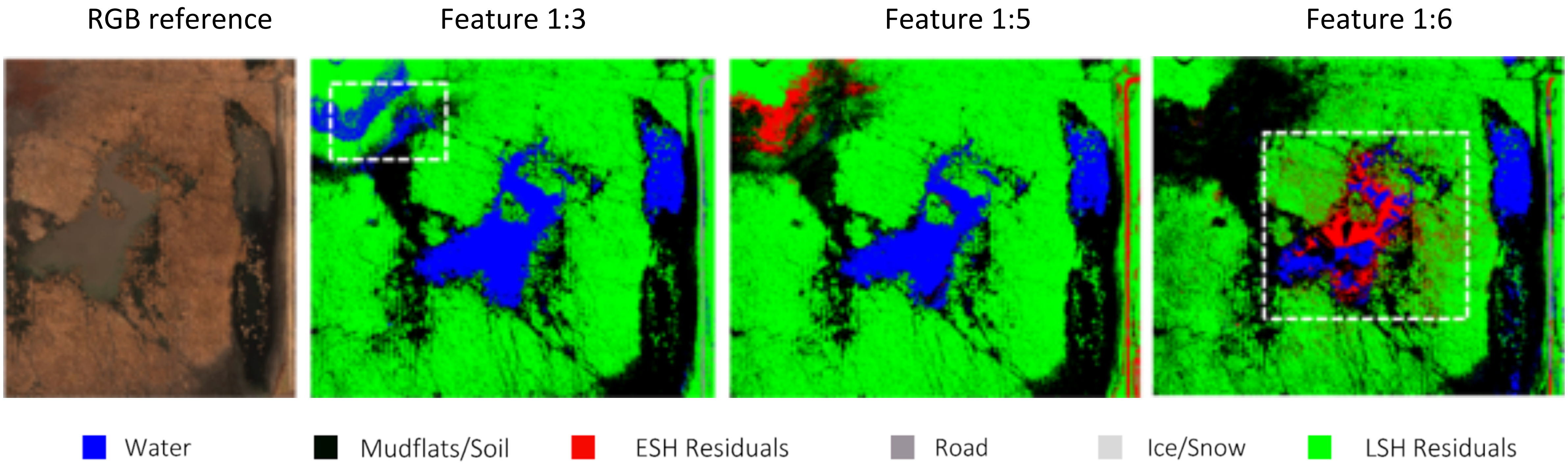
Water | Mudflats/Soil | ESH Residuals | Road | Ice/Snow | LSH Residuals

Semantic Segmentation Results for Site 1

Category		Band 1:3		Band 1:5		Band 1:6	
Class	**Label**	**Accuracy**	**IoU**	**Accuracy**	**IoU**	**Accuracy**	**IoU**
Soil	1	73.1%	67.8%	**95.0%**	75.0%	61.2%	59.5%
ESH Residual	2	0.4%	0.4%	55.4%	47.1%	**71.2%**	69.3%
LSH Residual	3	89.0%	51.8%	69.5%	56.6%	**93.3%**	70.5%
Water	4	**99.1%**	83.9%	95.4%	93.4%	**99.5%**	80.6%
Ice	5	74.2%	69.4%	**89.0%**	65.6%	60.0%	59.3%
Road	6	**98.1%**	86.9%	51.0%	50.7%	**96.5%**	95.0%
Global	-	72.3%	60.0%	86.2%	67.3%	83.7%	80.3%

- Generally, full band return significantly higher performance than three bands.
- Adding DSM band enhance the boundary matchness of the segmented land cover.

Semantic Segmentation Results for Site 2



- Adding NIR and rededge band enhance the classification performance.
- Adding DSM band decrease the performance of the land cover classification.
- CNN-semantic segmentation have better generalization than division tree.

Conclusion

Key points

- This study used multispectral UAV wetland image data to conduct a **pixel level semantic segmentation task**.
- **K-means clustering** returned weaker performance in terms of both accuracy and efficiency (labor investment required)
- **Ensemble Decision Tree** performed well with 90% overall accuracy and relatively fast training runtime (< 6 minutes in all cases) but have potential overfitting issue.
- Results showed **CNN semantic segmentation** effectively learn the spatial patterns and generalize well on different datasets.
- The study proved the potential of using **data mining/machine learning method** to automate the land cover classification task, enhancing the **efficiency and accuracy**, assisting future wetland delineation and management.

Pros & Cons

- ***Kmean*** *is efficient but additional human inspection have to be engaged*
- ***CNN-based semantic segmentation training is*** *time consuming, computing intensive during training (10h with 2 RTX 2060 GPU)*
- ***Ensemble decision tree*** *offer cost-effective approach for the delineation task*

Future perspective

- *Improving the model robustness by collecting data from a* ***wider range of experiments***
- *Utilized* ***PCA*** *or other advanced* ***feature selection*** *approaches to preprocessing the data for potential efficiency and accuracy gain*

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[2] C. L. Zweig, M. A. Burgess, H. F. Percival, and W. M. Kitchens, "Use of unmanned aircraft systems to delineate fine-scale wetland vegetation communities," *Wetlands*, vol. 35, no. 2, pp. 303–309, 2015

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[6] T. Liu and A. Abd-Elrahman, "Multi-view object-based classification of wetland land covers using unmanned aircraft system images," Remote Sens. Environ., vol. 216, no. June, pp. 122–138, 2018.

[7] T. Liu and A. Abd-Elrahman, "An object-based image analysis method for enhancing classification of land covers using fully convolutional networks and multi-view images of small Unmanned Aerial System," Remote Sens., vol. 10, no. 3, 2018.

[8] T. Liu, A. Abd-Elrahman, A. Zare, B. A. Dewitt, L. Flory, and S. E. Smith, "A fully learnable context-driven object-based model for mapping land cover using multi-view data from unmanned aircraft systems," Remote Sens. Environ., vol. 216, no. July, pp. 328–344, 2018.

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Thanks!