



OBIA Classification of Riverine Vegetation in a Small Open Channel Using RGB Drone Imagery

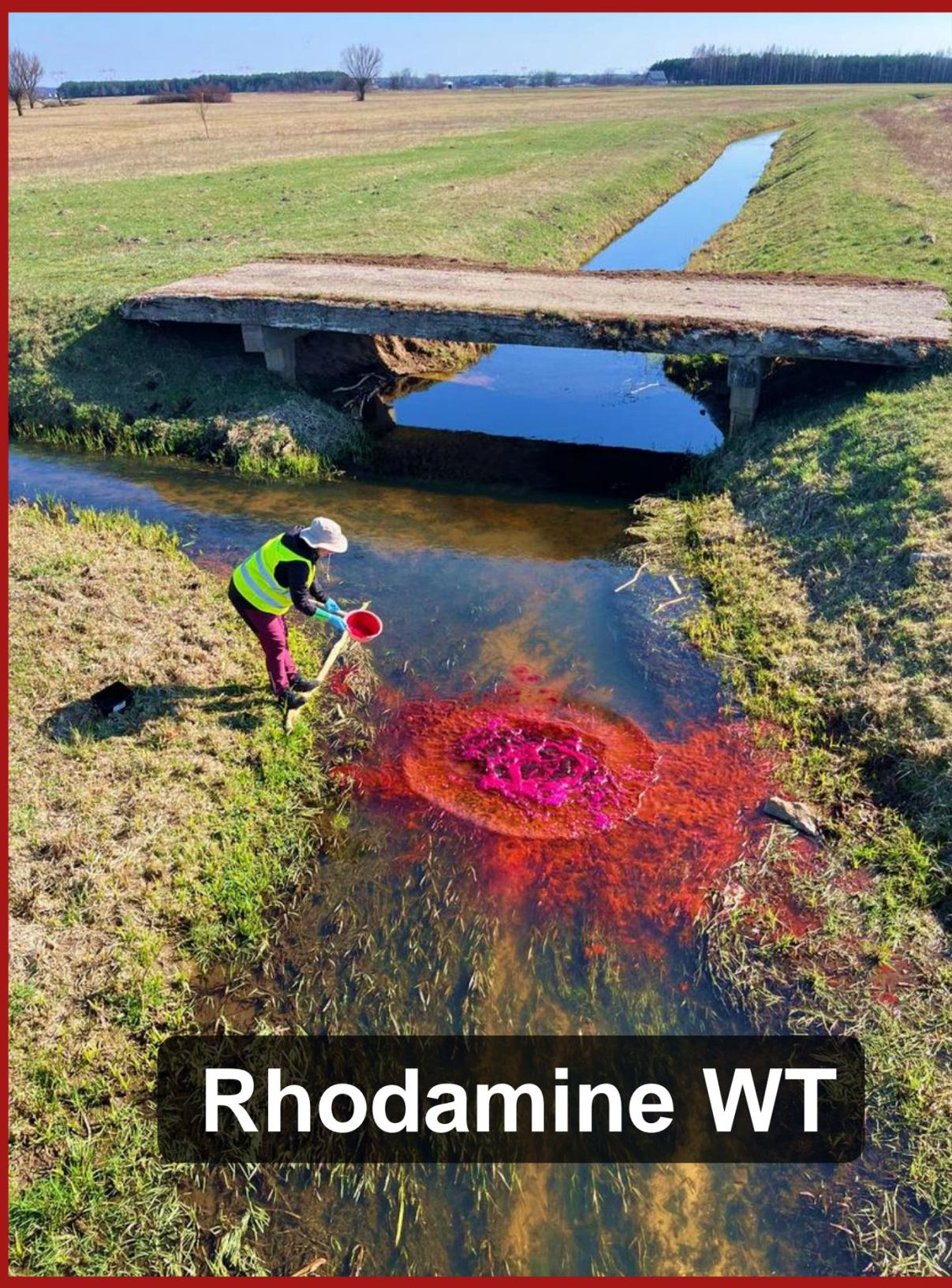
Adrian **BRÓŹ**¹, Monika **KALINOWSKA**¹, Emilia **KARAMUZ**¹,

¹Institute of Geophysics Polish Academy of Science, Warsaw, Poland

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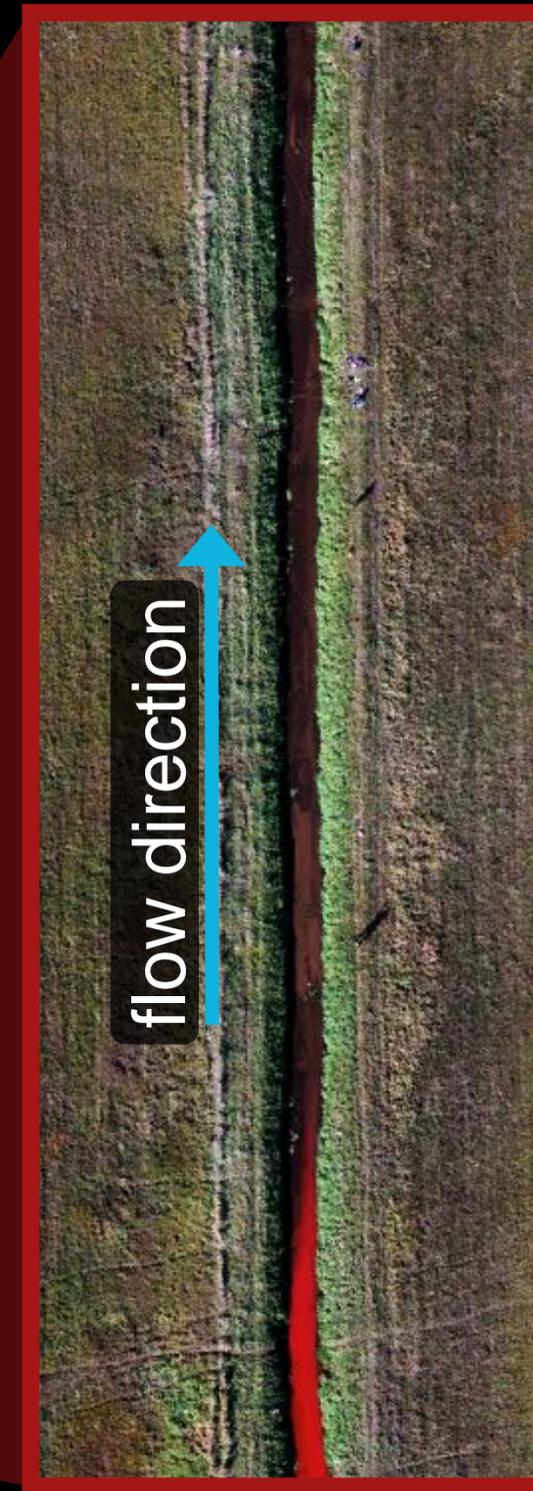
Tracer experiments





Author: Kmusser

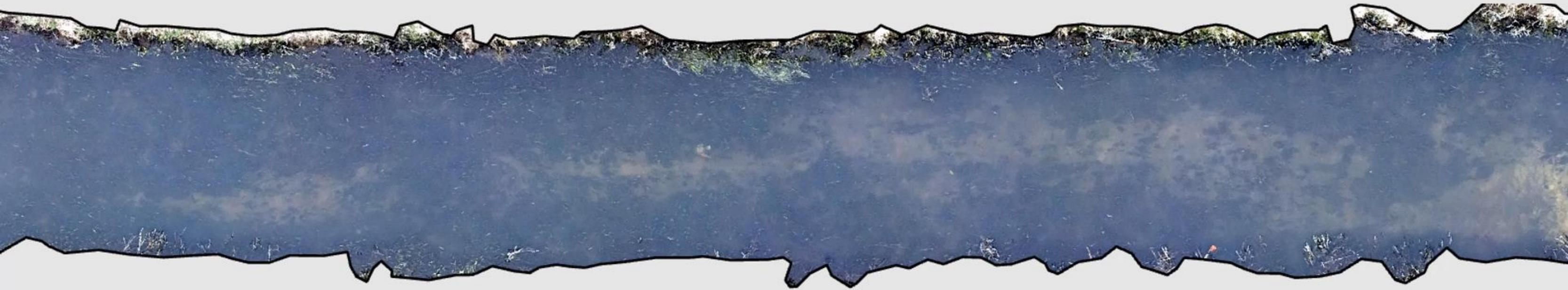
Source: https://en.wikipedia.org/wiki/Vistula#/media/File:Vistula_river_map.png





flow direction



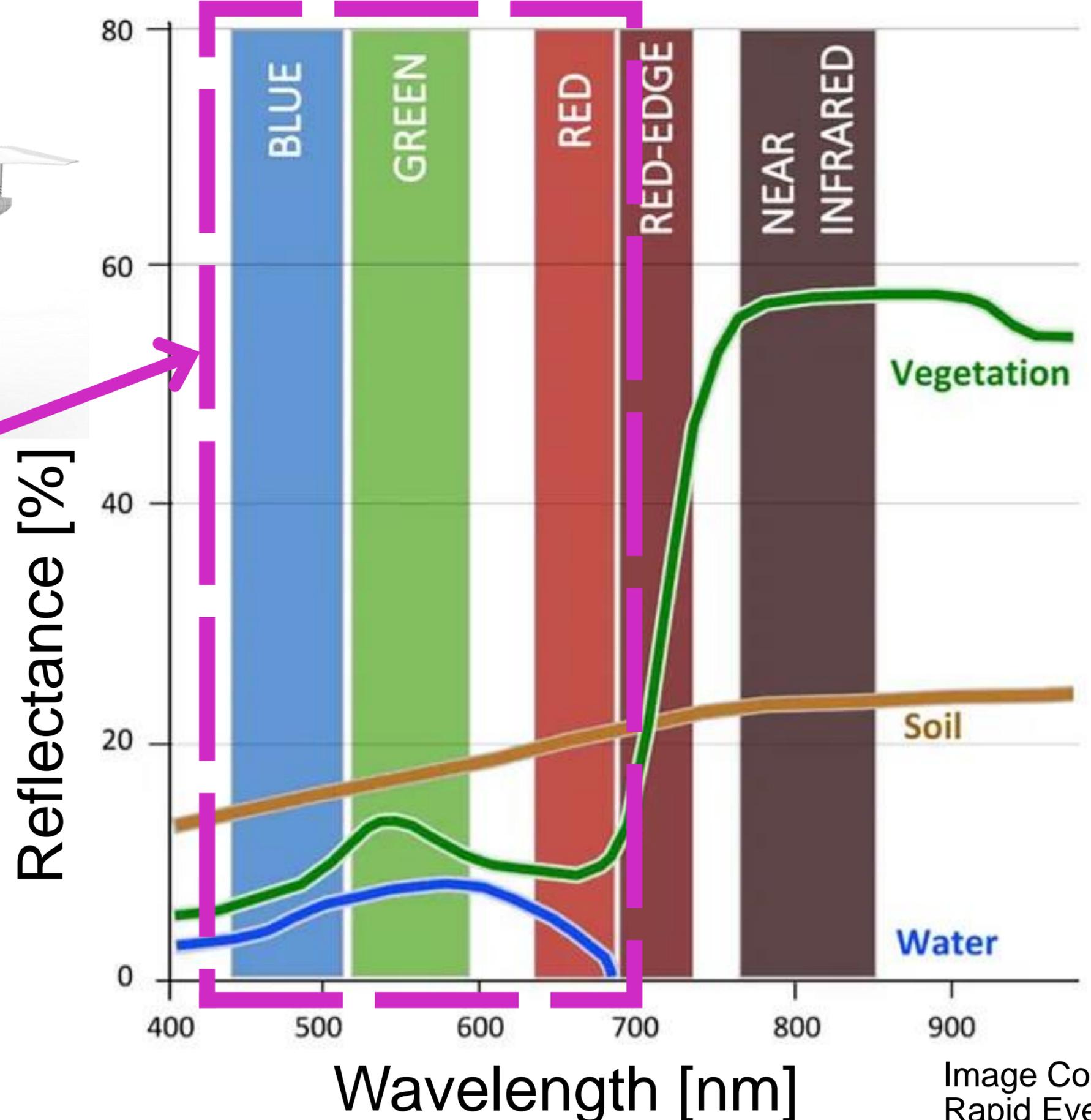


7th March 2025

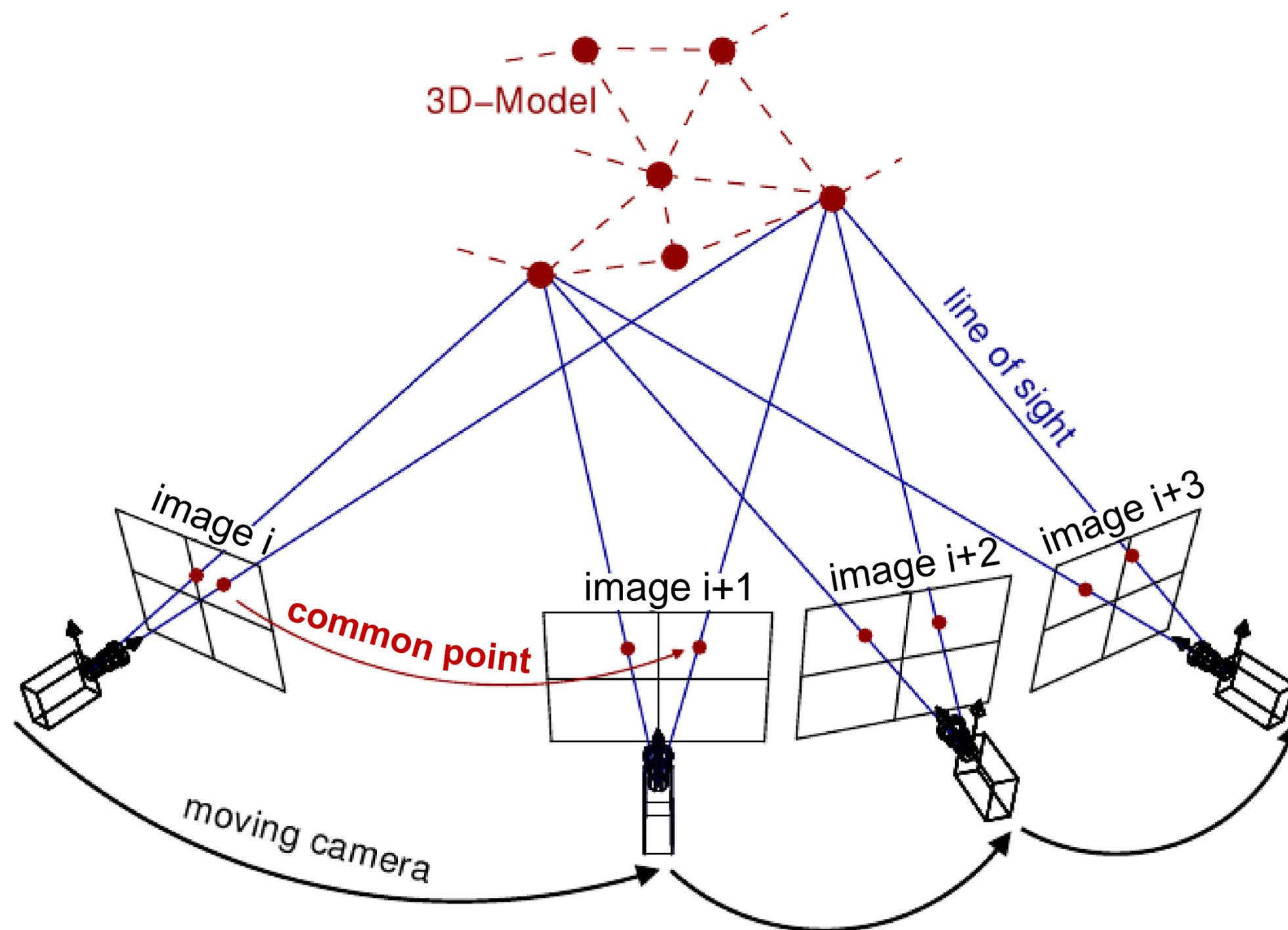
DJI Phantom 4



Methods



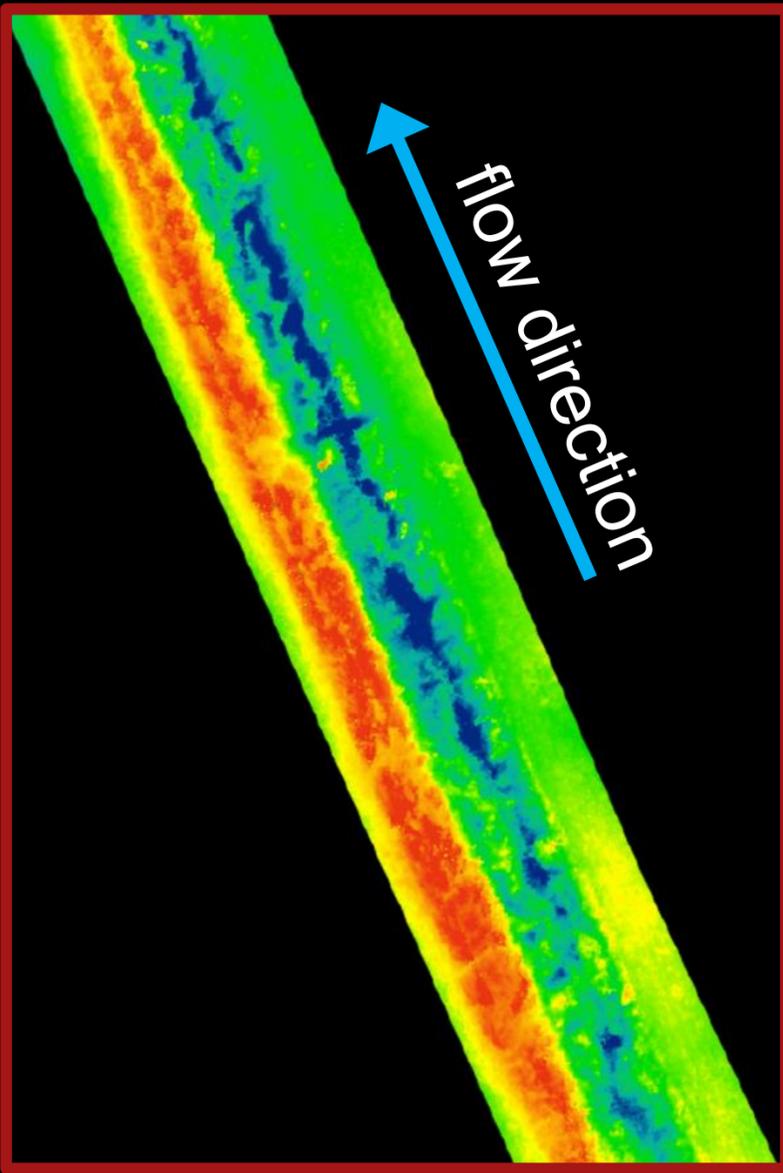
Structure from Motion



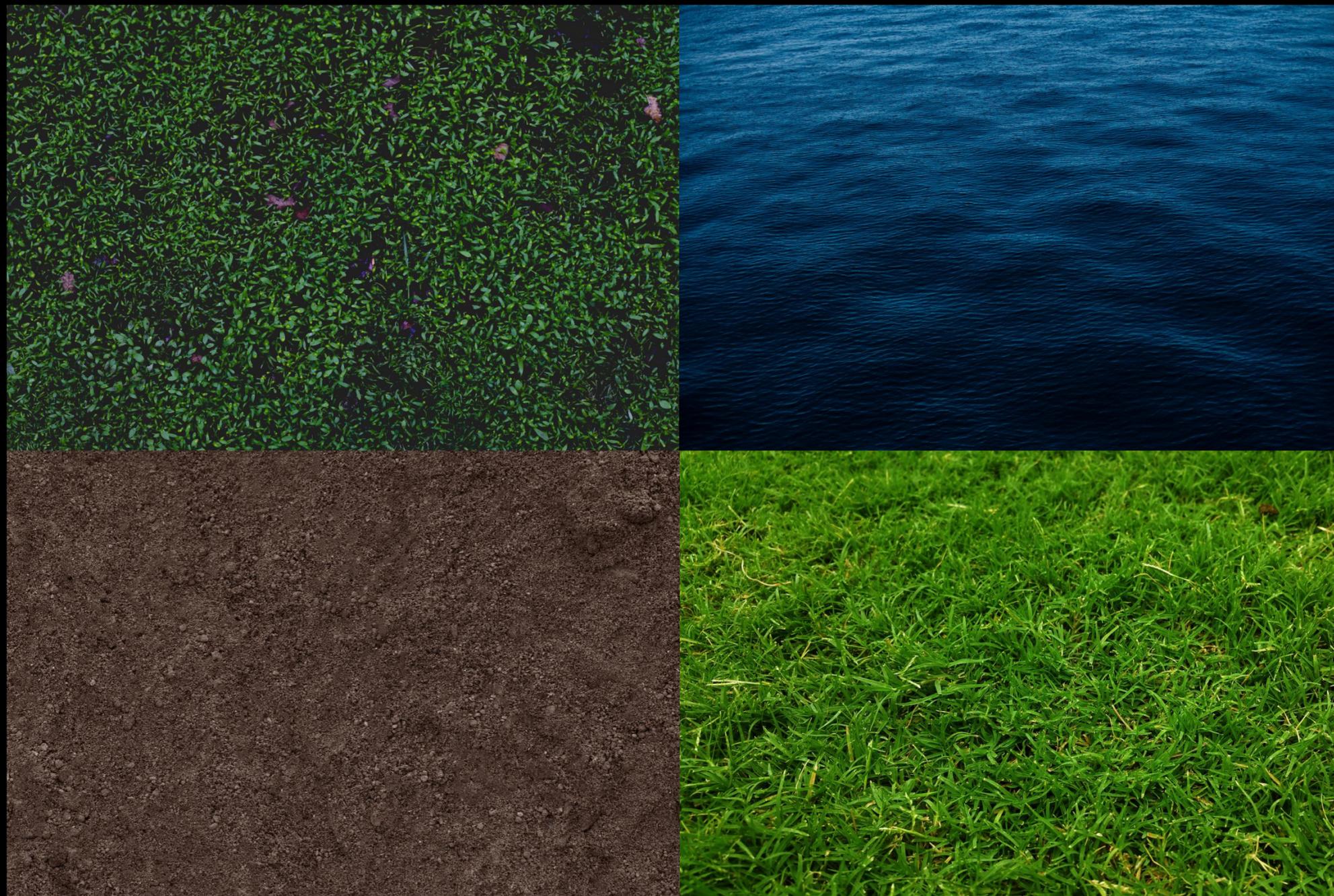


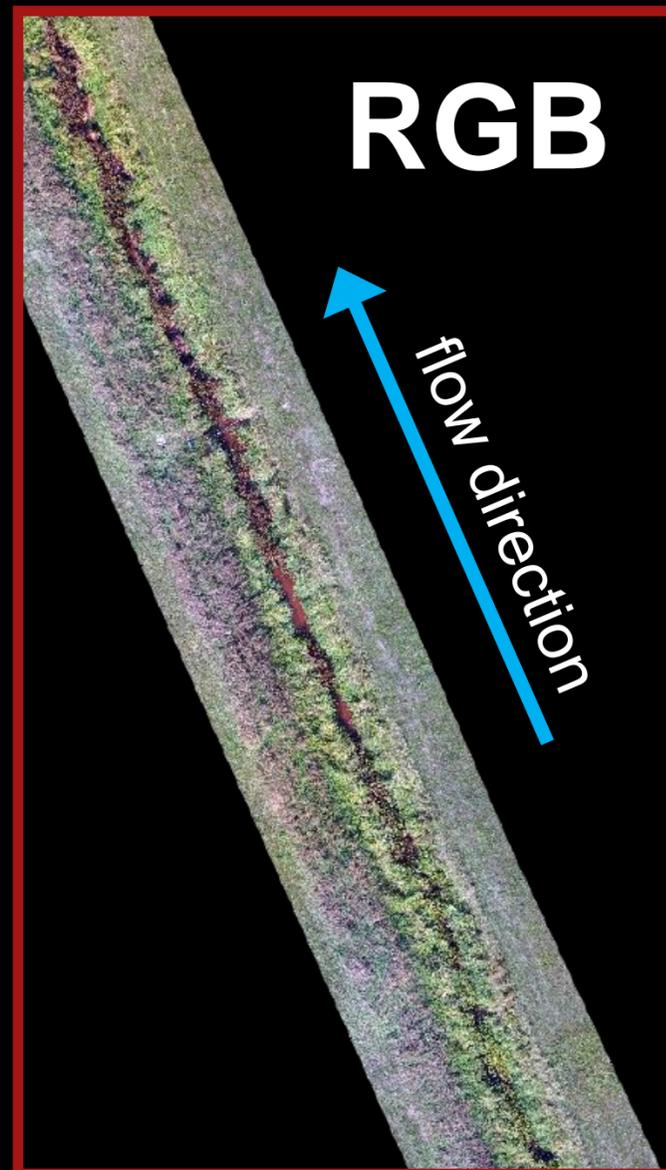
DEM

Orthomosaic

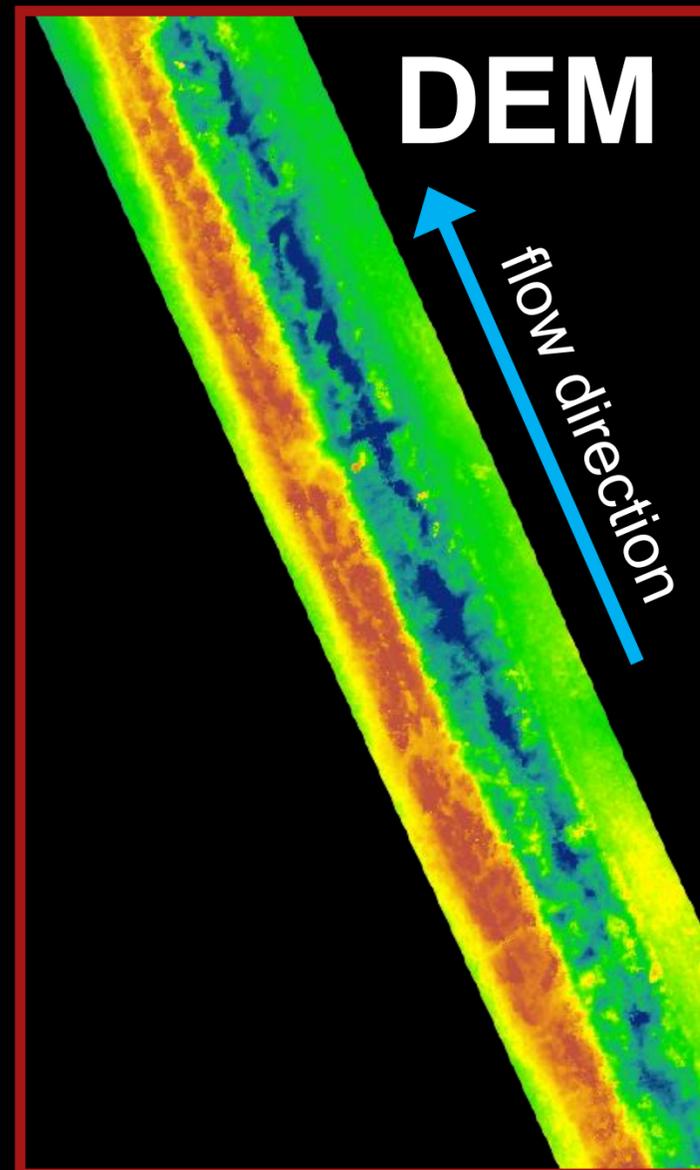


Haralick Texture Analysis



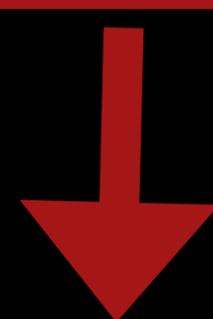
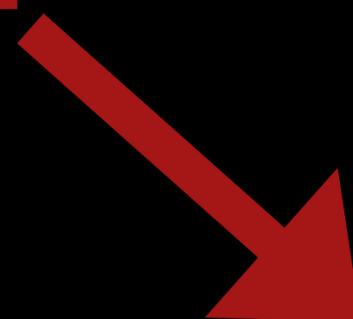


+

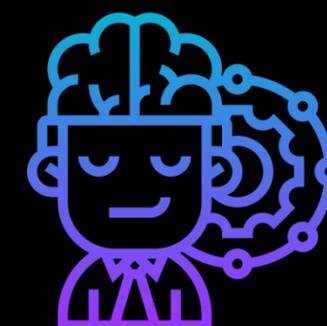


+

**Haralick
Texture
Statistics**



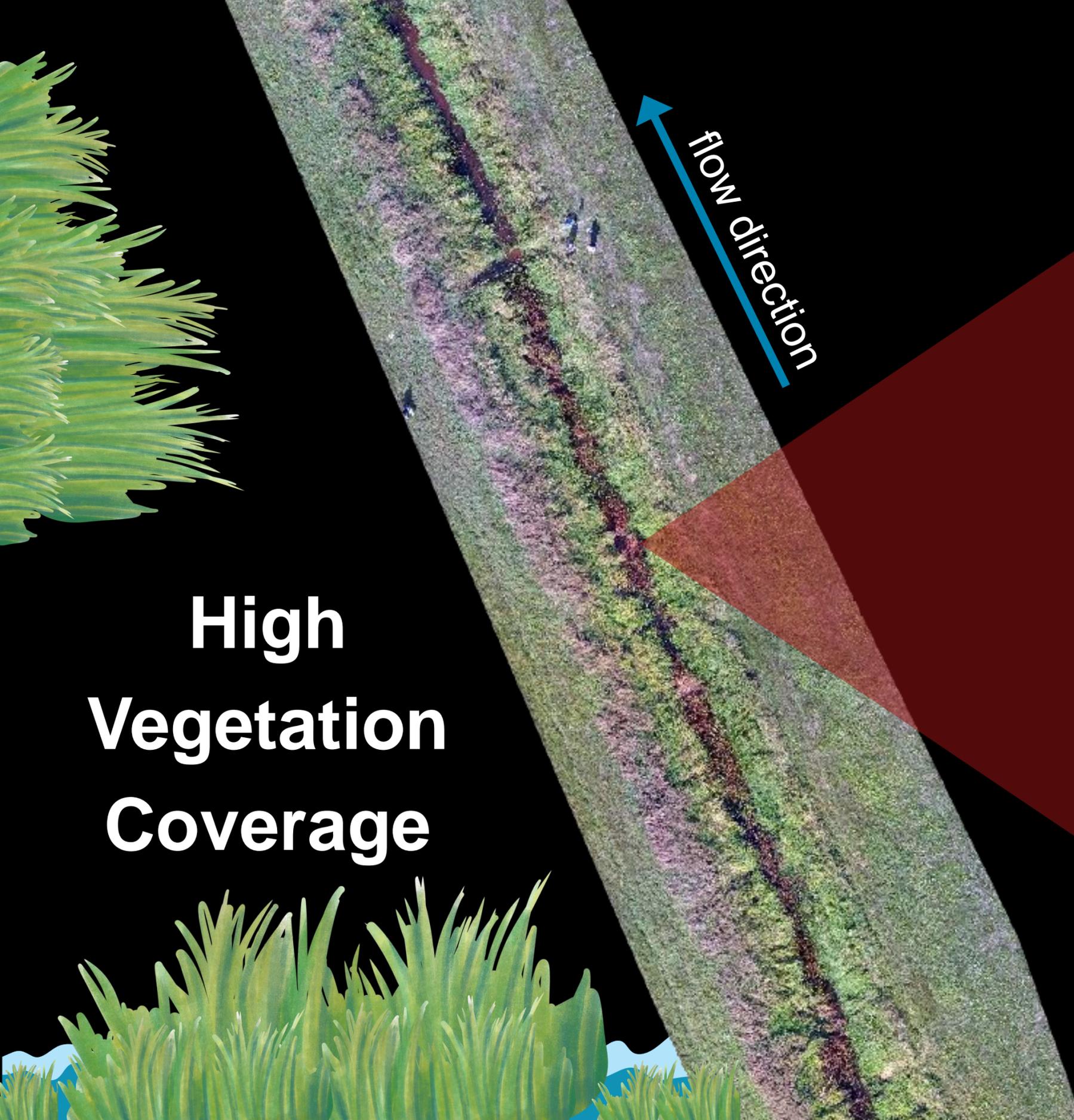
Machine Learning Algorithms





**High
Vegetation
Coverage**

**Low
Vegetation
Coverage**



**High
Vegetation
Coverage**





flow direction

**Low
Vegetation
Coverage**

Support Vector Machine (RGB+DEM)

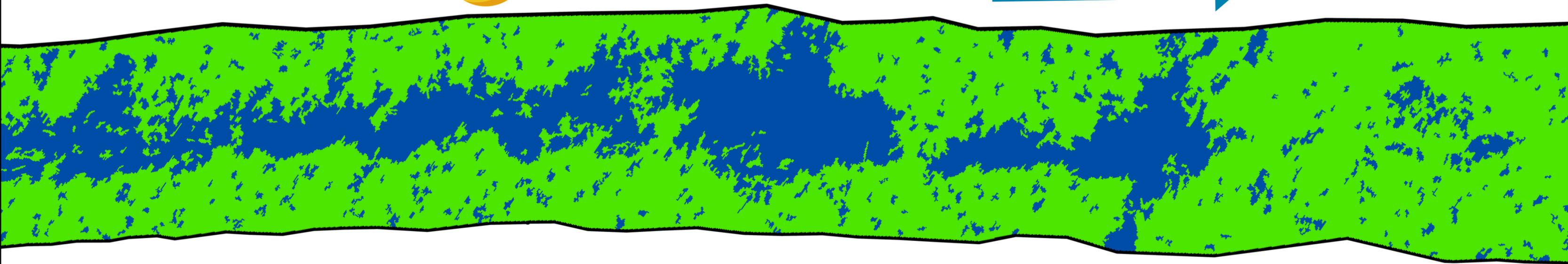
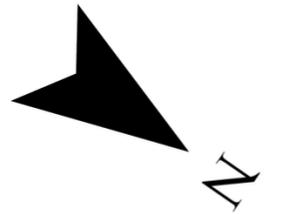
Vegetation Coverage: 80.7%

Accuracy: 90.8%

Cohen's Kappa: 69.9%



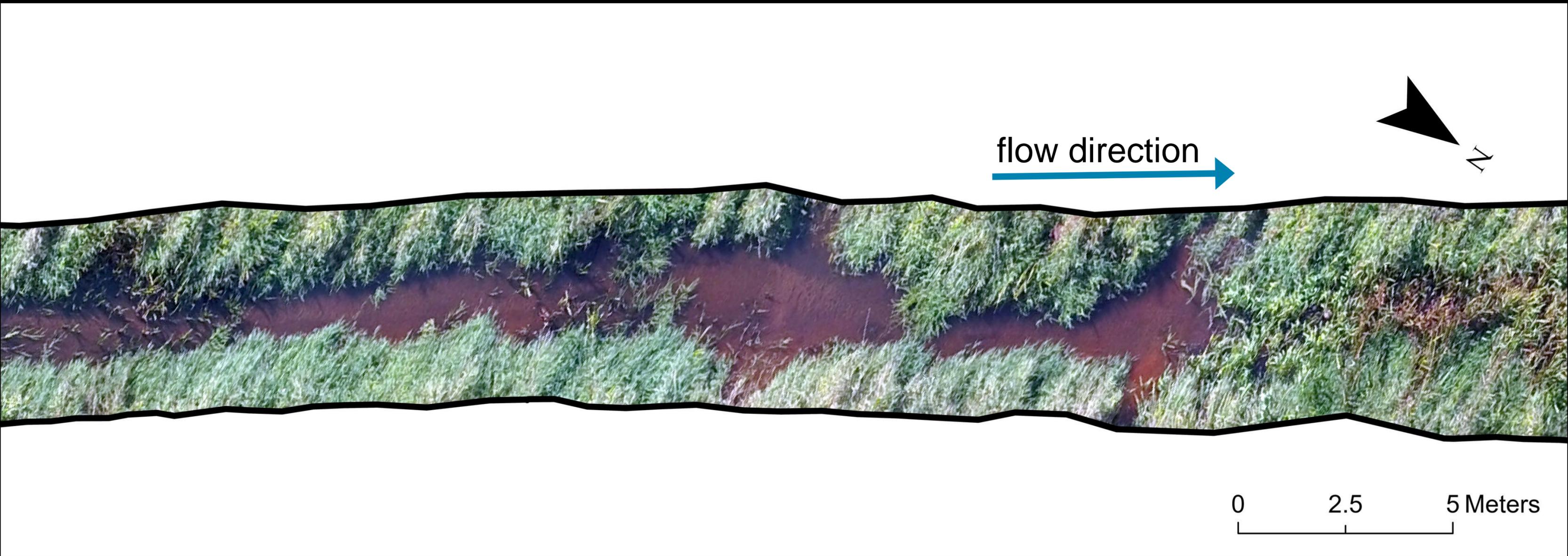
flow direction 



 – **Vegetation**  – **Water**

0 2.5 5 Meters





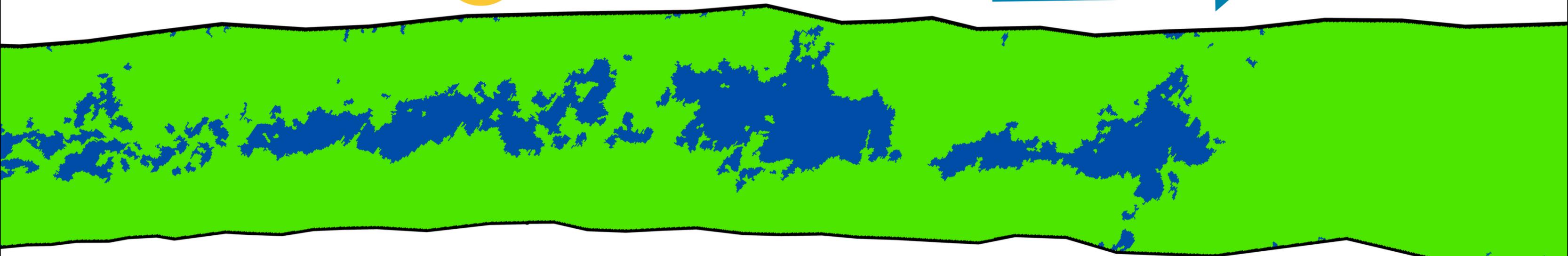
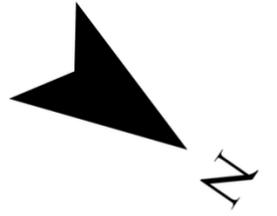
Maximum Likelihood (RGB+DEM+Haralick)

Vegetation Coverage: 96.7%

Accuracy: 86.7%

Cohen's Kappa: 27.4% 😞

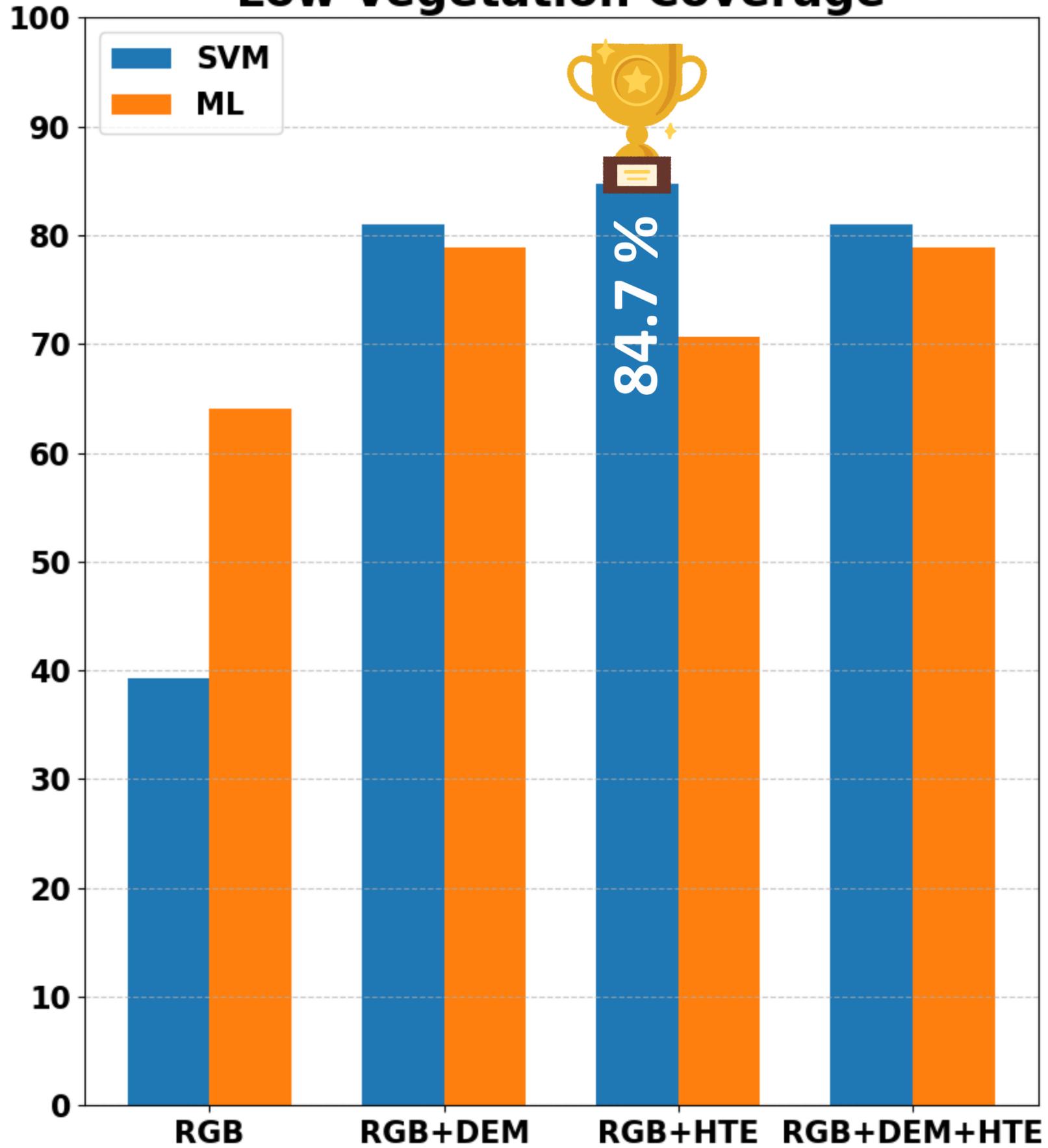
flow direction 



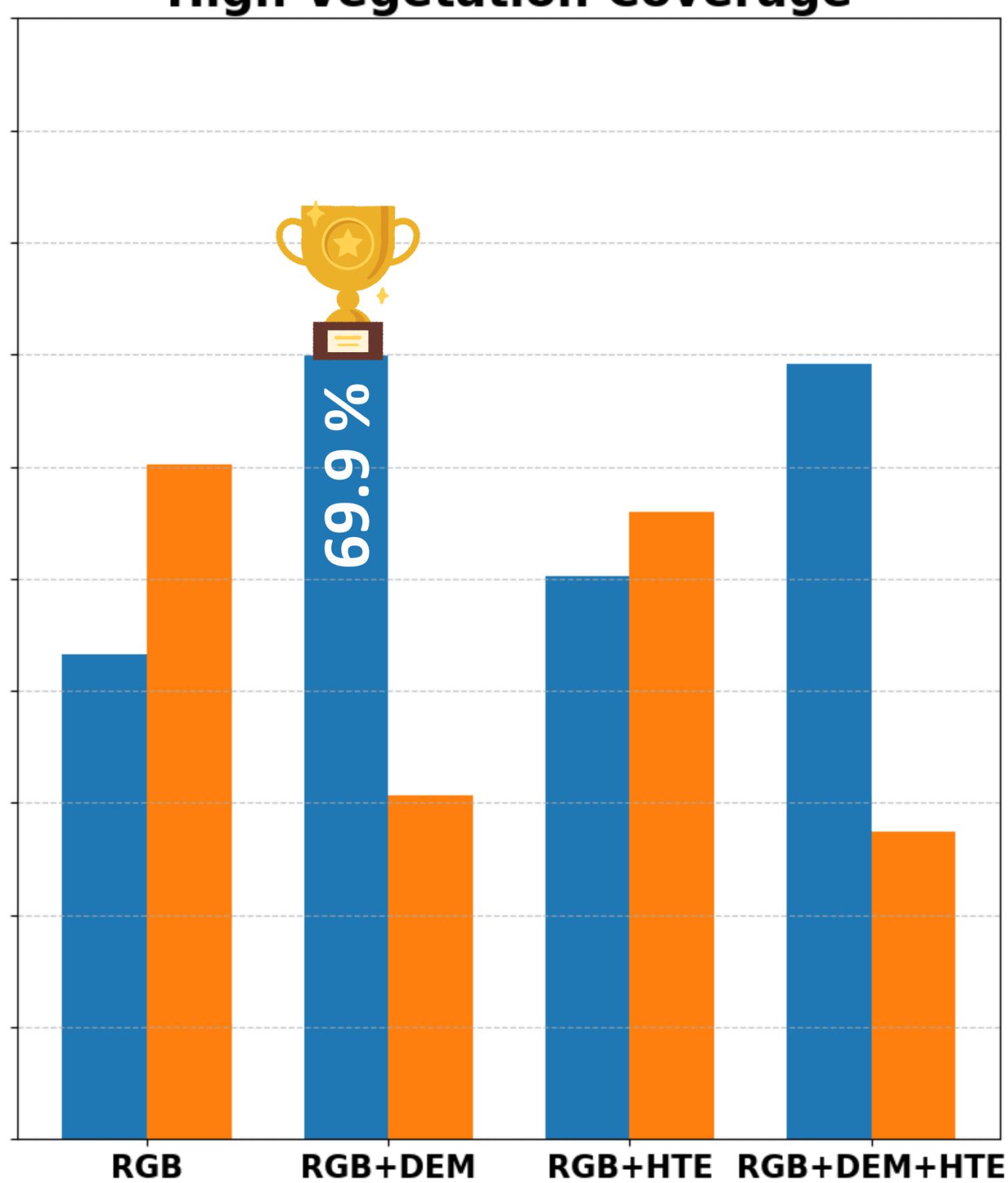
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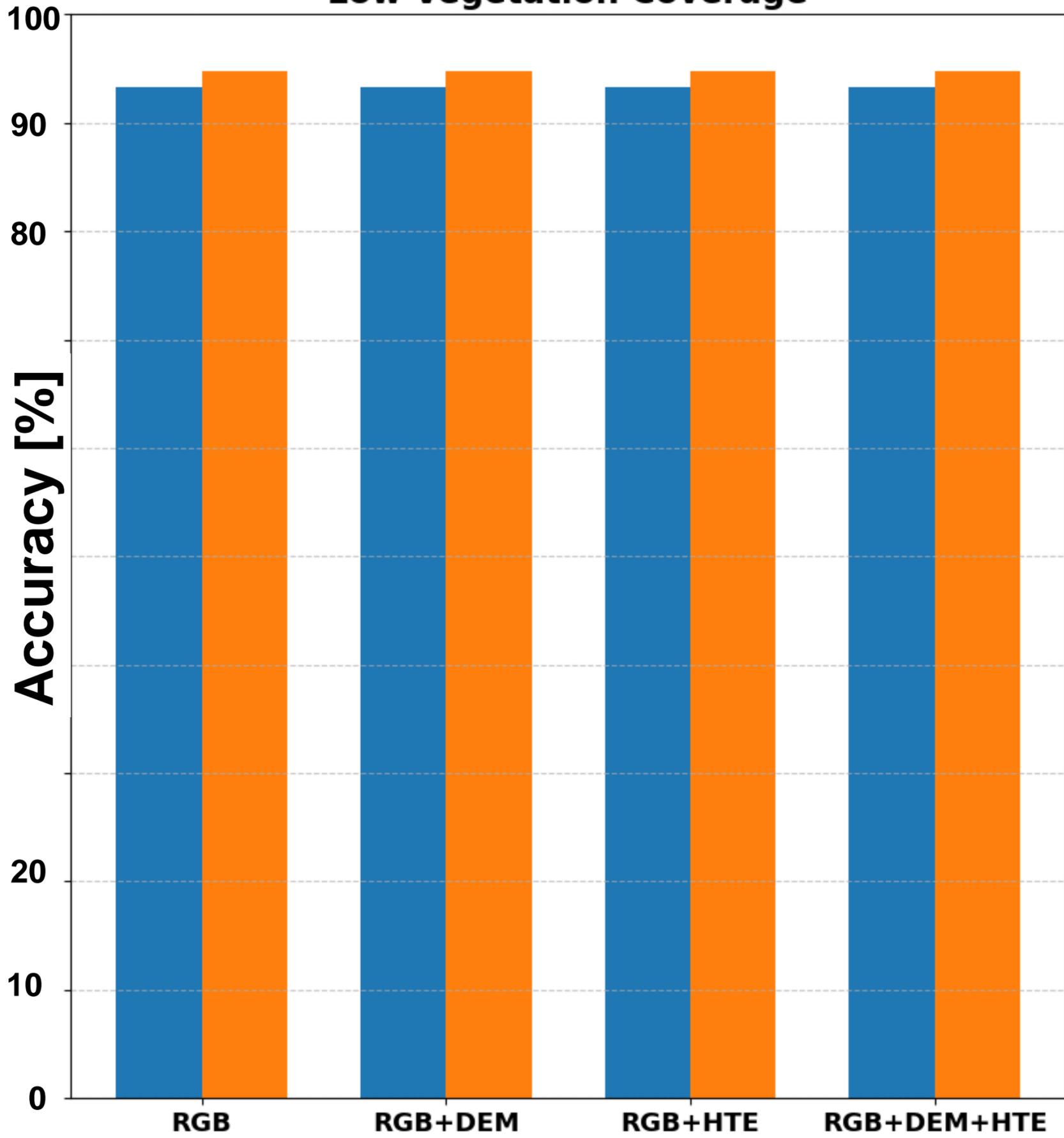
Low Vegetation Coverage



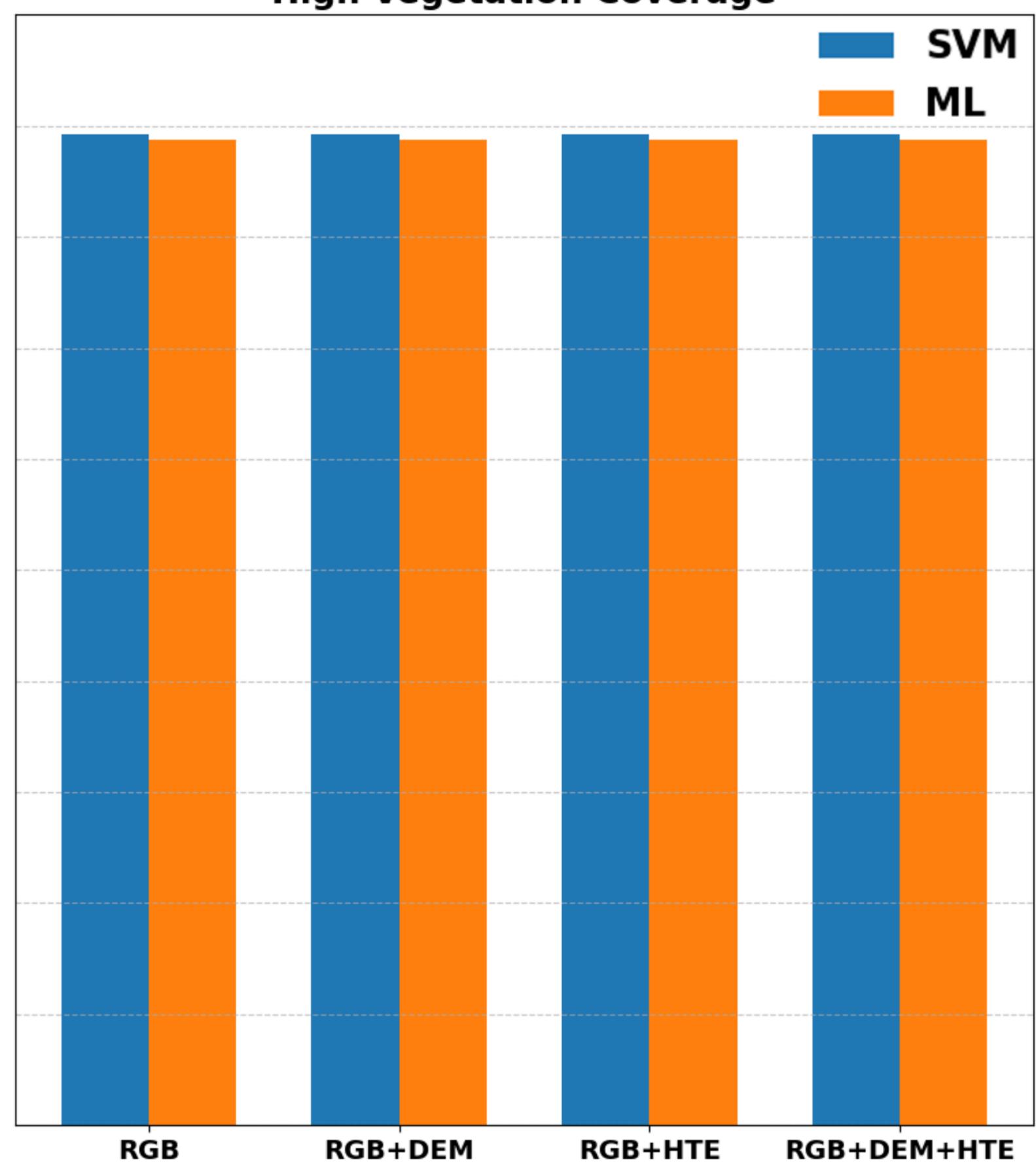
High Vegetation Coverage



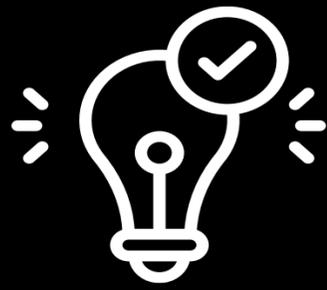
Low Vegetation Coverage



High Vegetation Coverage



Conclusions

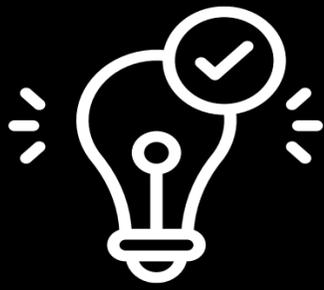


- **Very good results for low V_c**



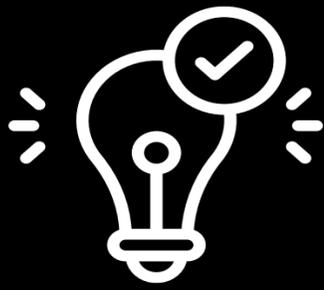
Conclusions

- **Very good** results for **low V_C**
- **Good** results for **high V_C**



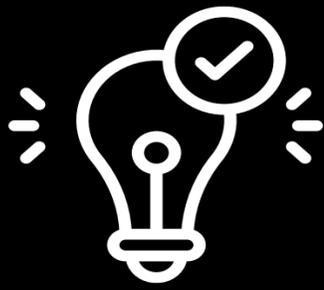
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- **Good results for high V_c**
- **Adding DEM or HTE to RGB enhances performance**



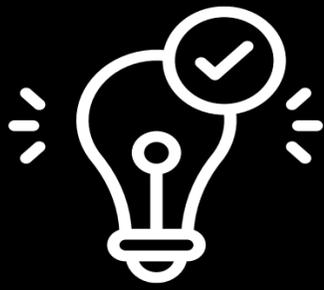
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- **SVM** performed **better** than **ML**



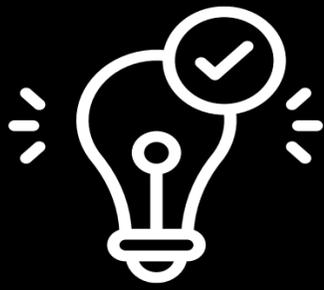
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- **RGB drone images** provide sufficiently good results



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NATIONAL SCIENCE CENTRE
POLAND



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Polish Academy of Sciences

Cohen's kappa

$$\frac{TP + TN}{Total}$$

Observed agreement

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

Expected agreement if
random judgment

$$P_e = (P_{\text{true},1} \cdot P_{\text{pred},1}) + (P_{\text{true},2} \cdot P_{\text{pred},2})$$

Value of κ	Strength of Agreement
< 0.20	Poor
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Good
> 0.80	Very Good

Henry et al. (2016)

Kappa corrects accuracy for chance agreement,
especially useful with imbalanced classes

Situation: 900 pixels of vegetation and 100 pixels of water



model ignores water and
predicts only vegetation



Accuracy = $900 / 1000 = 90\%$ 🧠

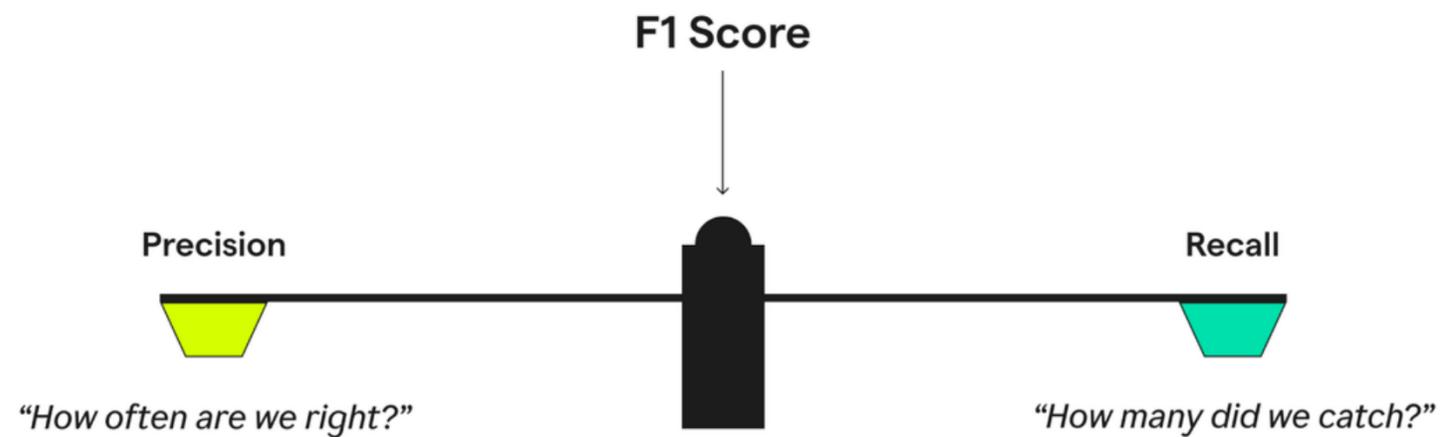
F1 score for water = 0 ✖

Kappa value \approx low ✖

F1 Score vs Cohen's Kappa

focuses on a single class

measures overall agreement between the classification and ground truth, while correcting for chance agreement

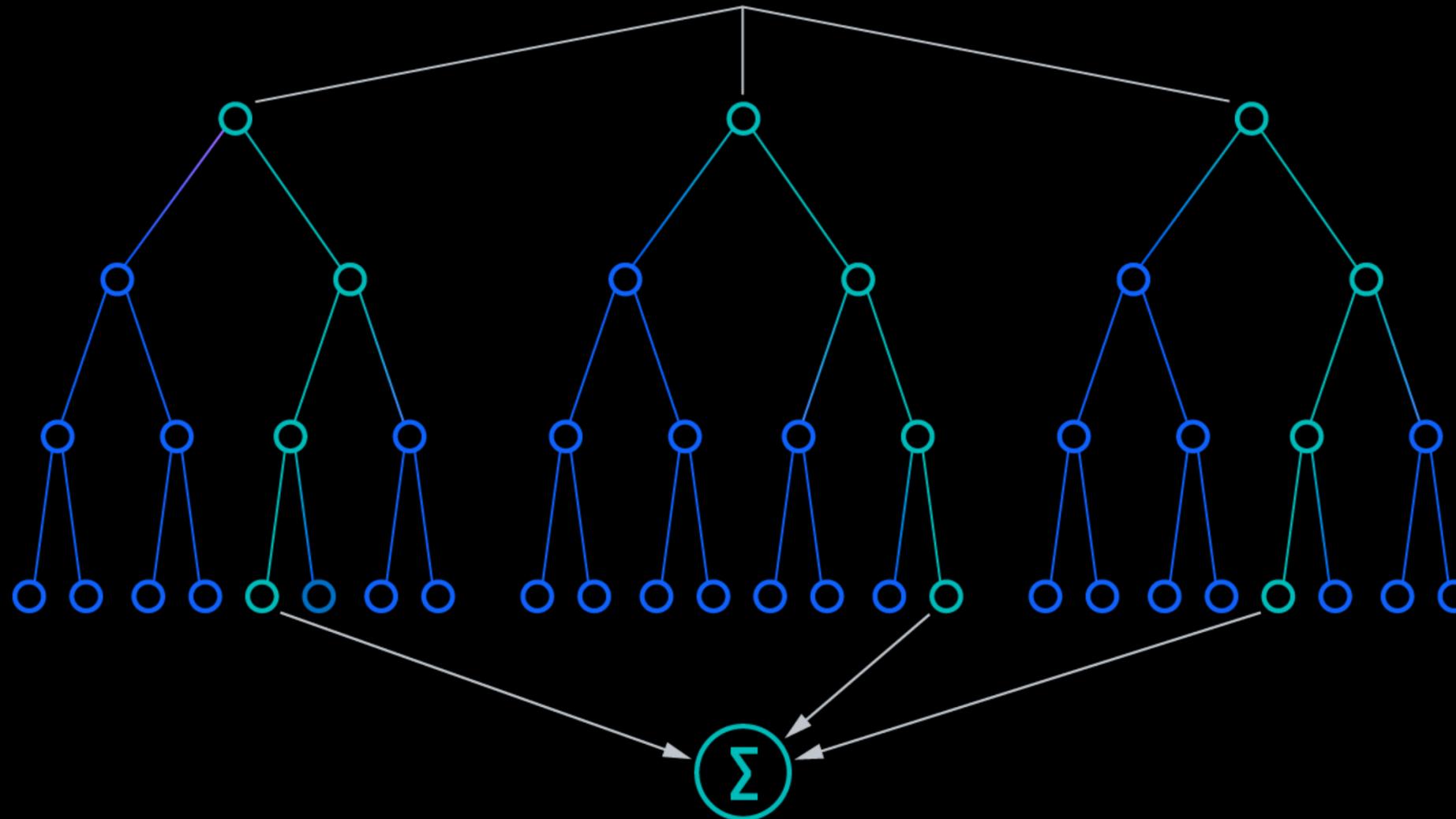


$$\mathcal{K} = \frac{p_0 - p_e}{1 - p_e},$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

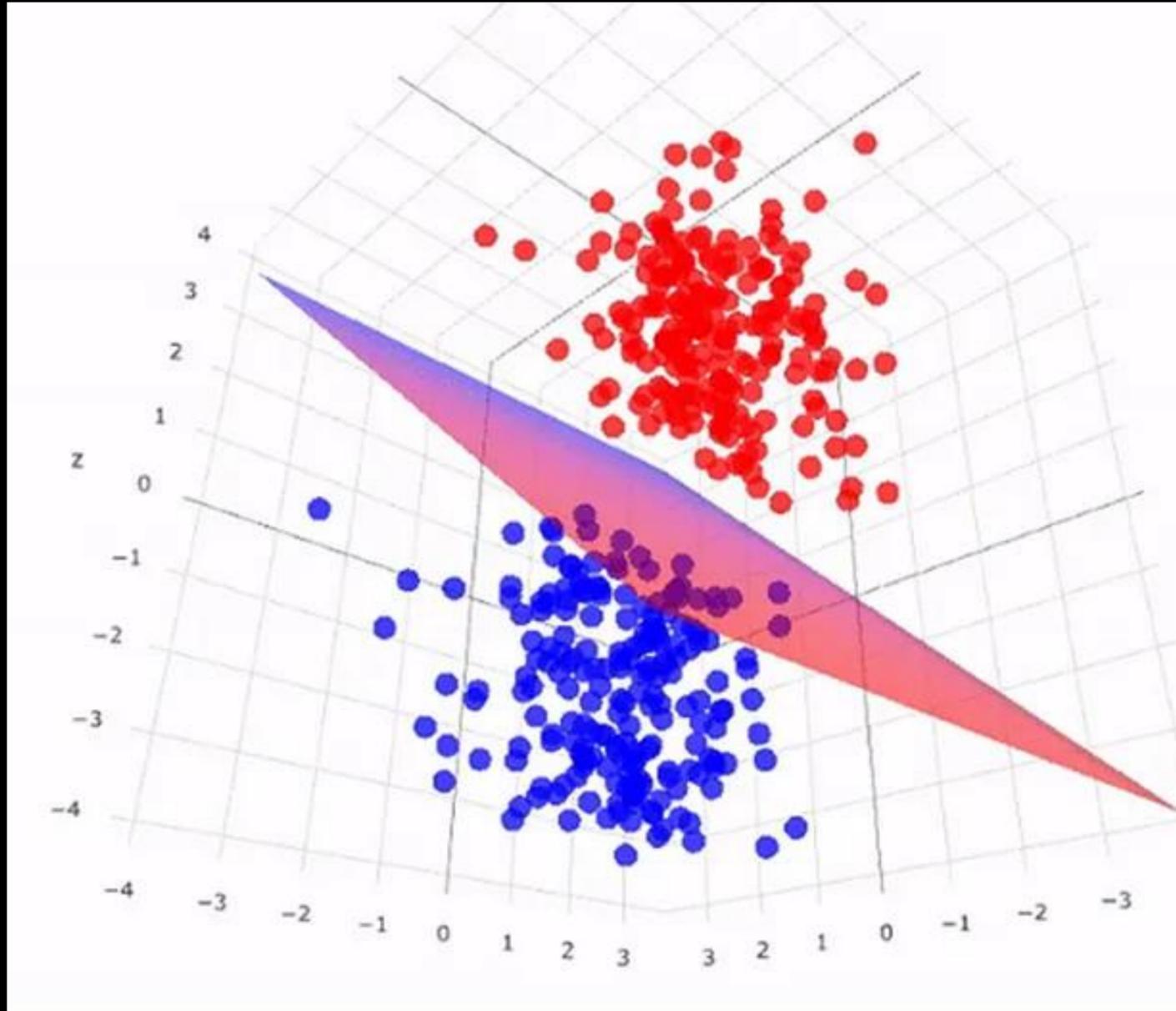
Random Forest

1. Constructing a flowchart of questions and answers leading to a decision
2. The wisdom of the (random and diverse) crowd

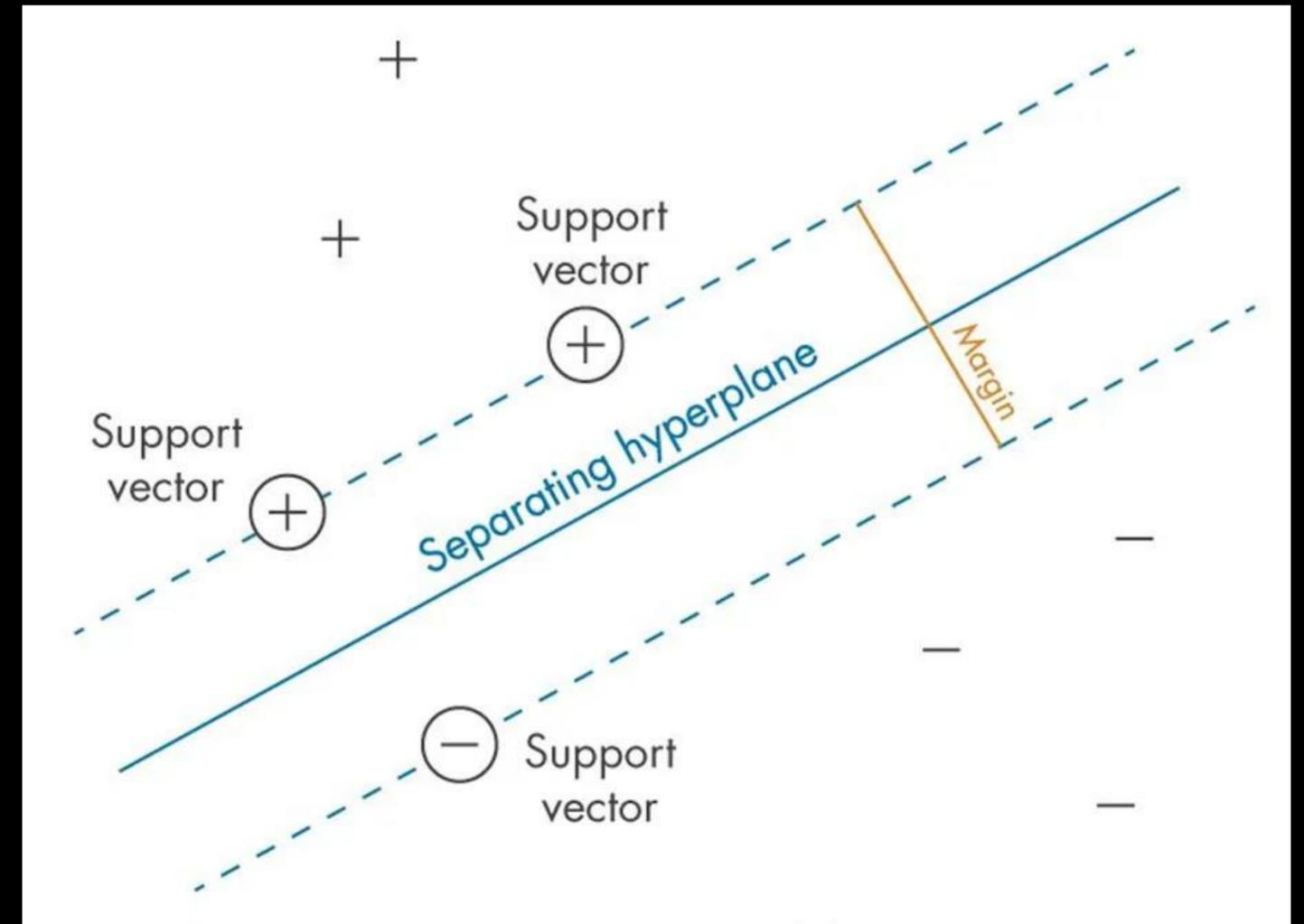


Huang, Boming (2024)

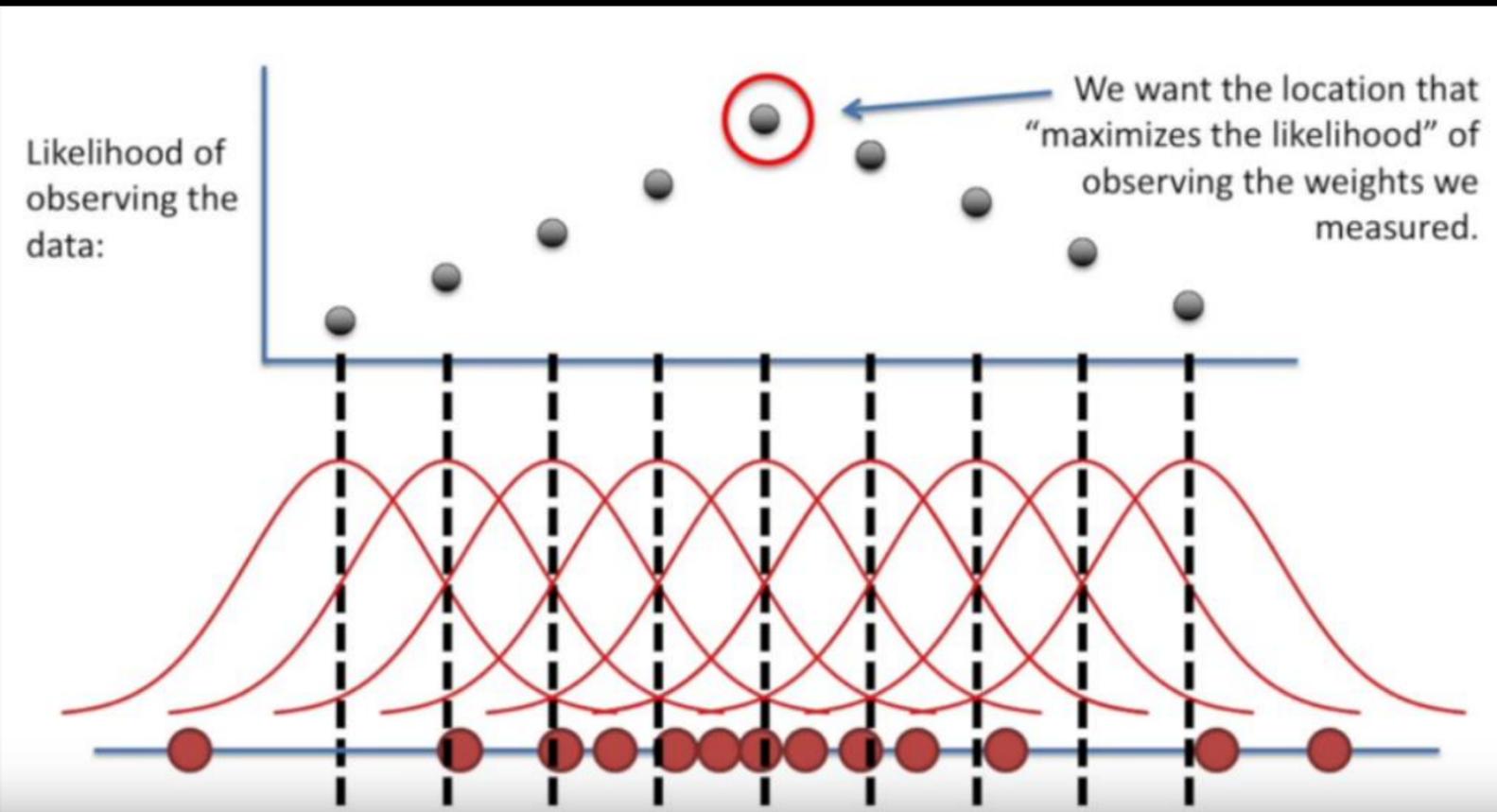
Support Vector Machines



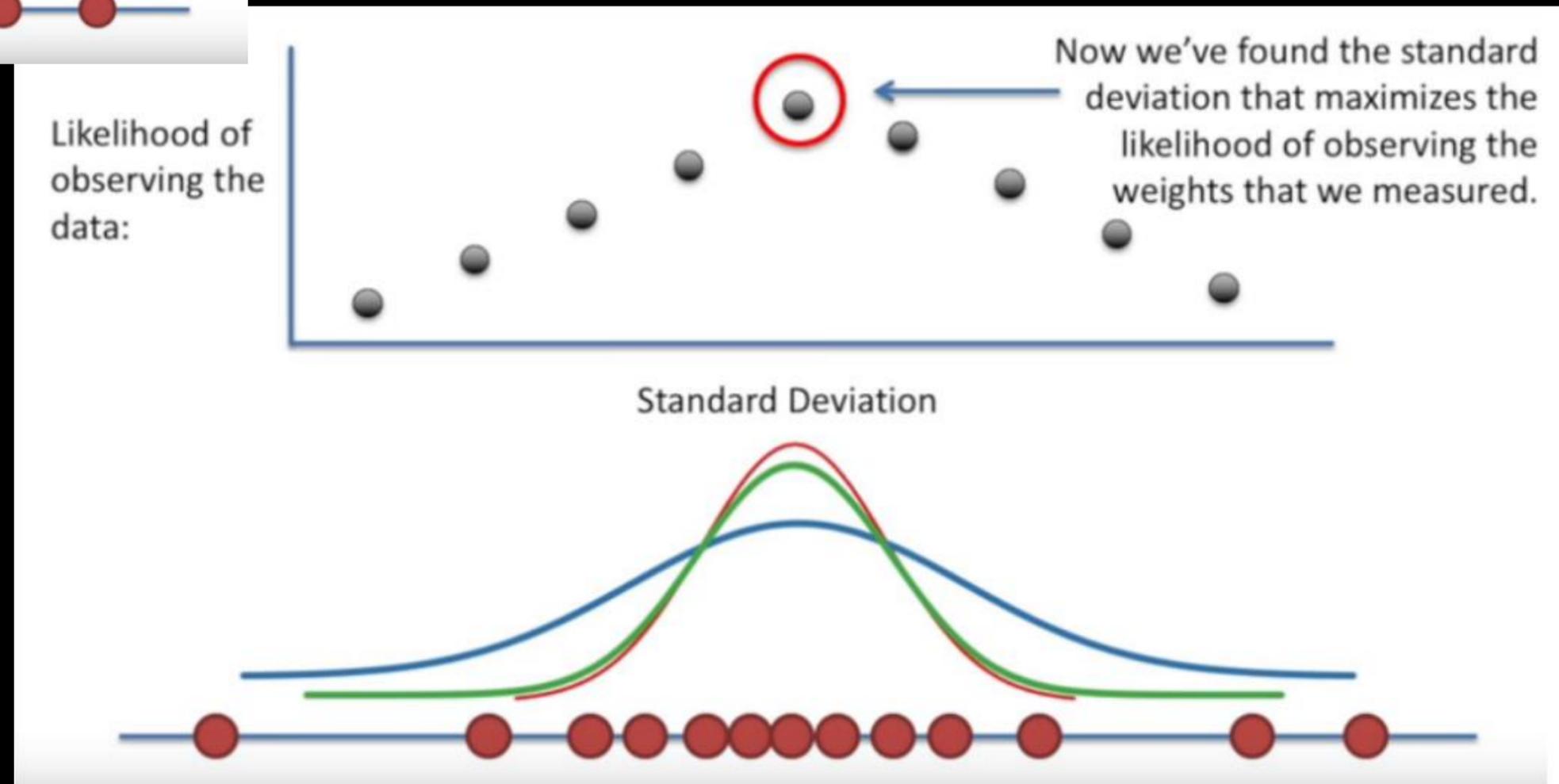
margin = degree of confidence



GOAL : find the hyperplane that maximizes the margin



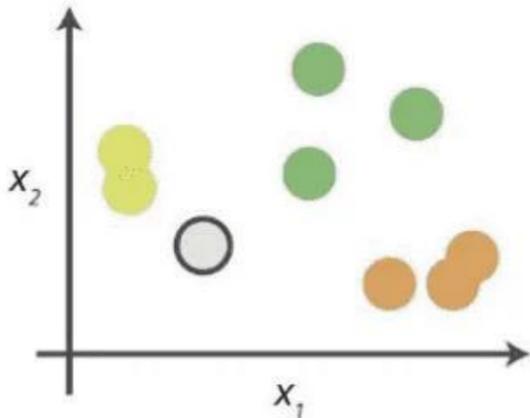
Maximum Likelihood



Likelihood = $L(\theta/\text{events})$

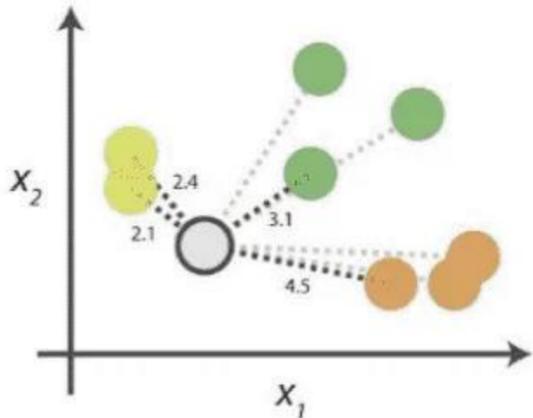
K-Nearest Neighbor

0. Look at the data



Say you want to classify the grey point into a class. Here, there are three potential classes - lime green, green and orange.

1. Calculate distances



Start by calculating the distances between the grey point and all other points.

2. Find neighbours

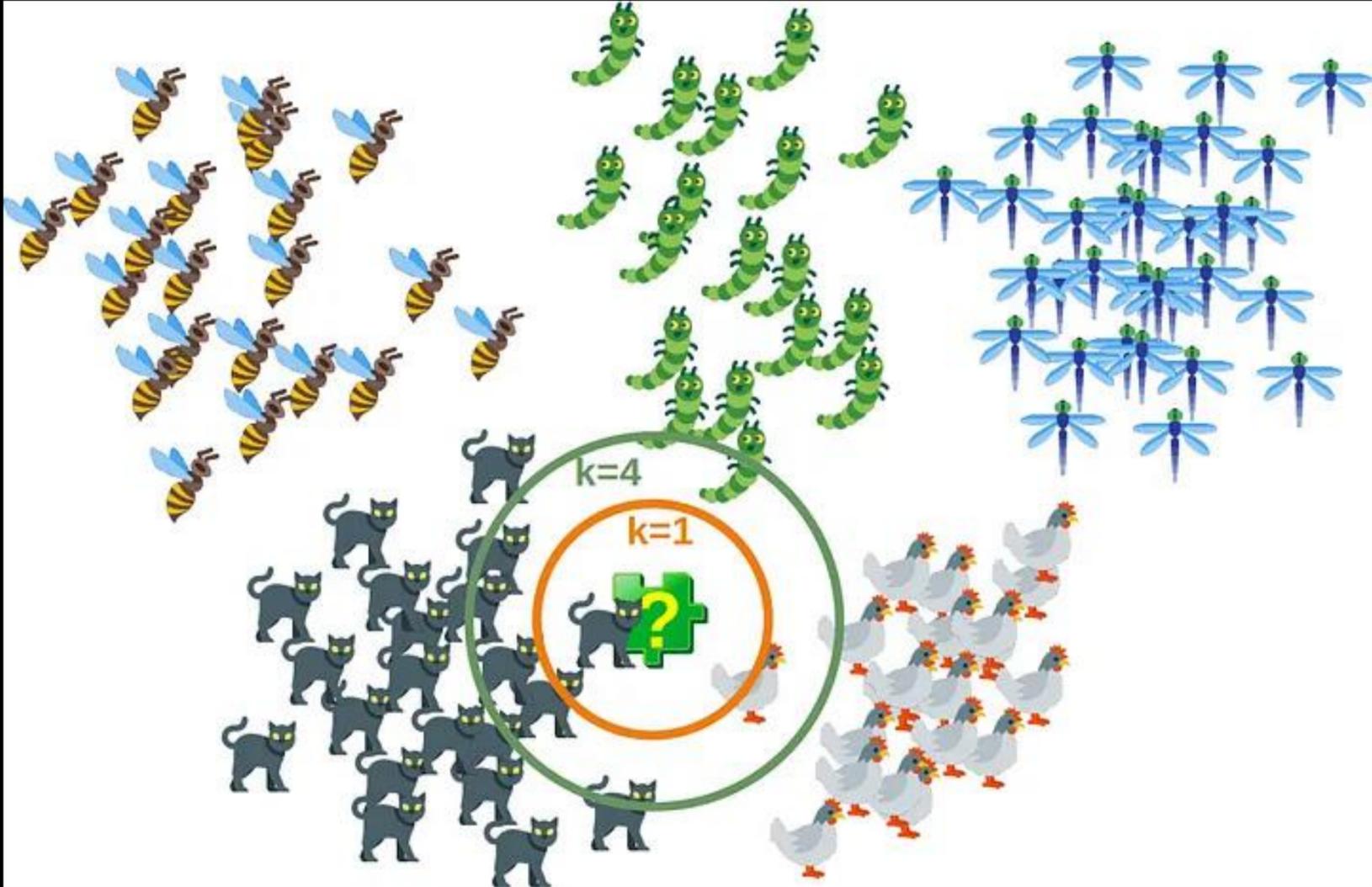
Point		Distance	
○	●	2.1	→ 1st NN
○	●	2.4	→ 2nd NN
○	●	3.1	→ 3rd NN
○	●	4.5	→ 4th NN

Next, find the nearest neighbours by ranking points by increasing distance. The nearest neighbours (NNs) of the grey point are the ones closest in dataspace.

3. Vote on labels

Class	# of votes	
●	2	→ Class ● wins the vote!
●	1	→ Point ○ is therefore predicted to be of class ●.
●	1	

Vote on the predicted class labels based on the classes of the k nearest neighbours. Here, the labels were predicted based on the k=3 nearest neighbours.



Gray-Level Co-occurrence Matrix

