On the benefit of explainable machine learning for the agricultural and environmental sciences

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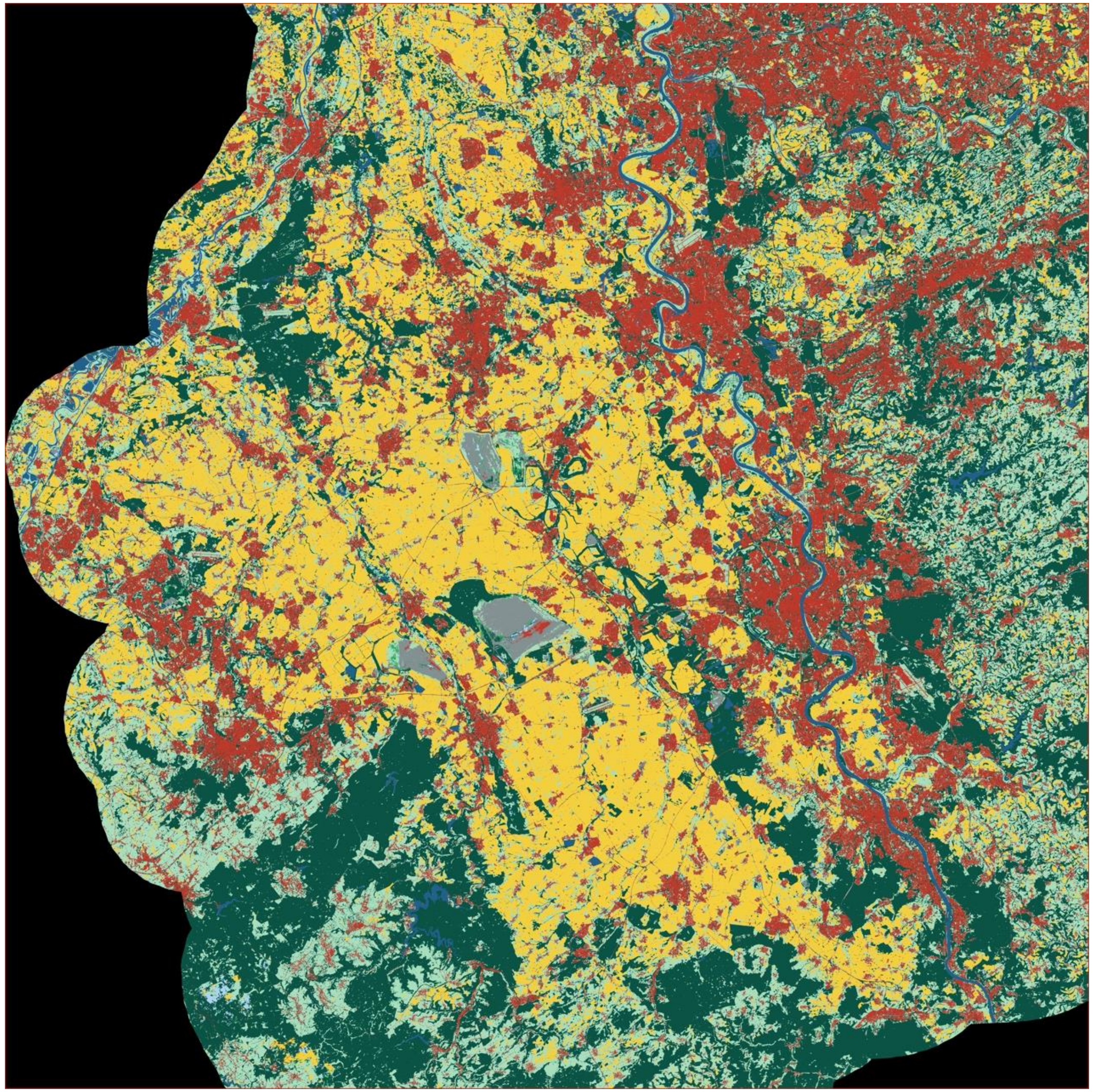
What is on the field?
What is the yield in this area?
What will this plant look like tomorrow?

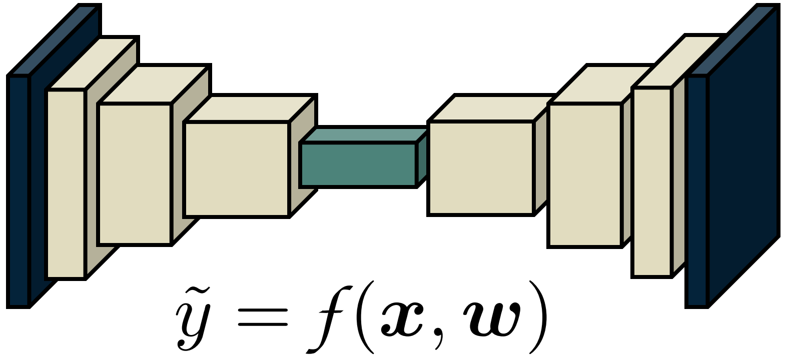
Landcover classification



Leonhardt, J., Gall, J., & Roscher, R. (2024). Large-Scale Land Cover Classification from Satellite Imagery and Sparse In-Situ Labels. *Machine Learning for Remote Sensing Workshop at International Conference on Learning Representations.*


Why does my algorithm perform poorly here?
How did my algorithm come to a specific result?
What is on the field?
What is the yield in this area?
What will this plant look like tomorrow?
Why does the plant look like this?

Core elements



Transparency

Access to different ingredients

Interpretability

Presentation of properties of a machine learning model in understandable terms to a human

Explainability

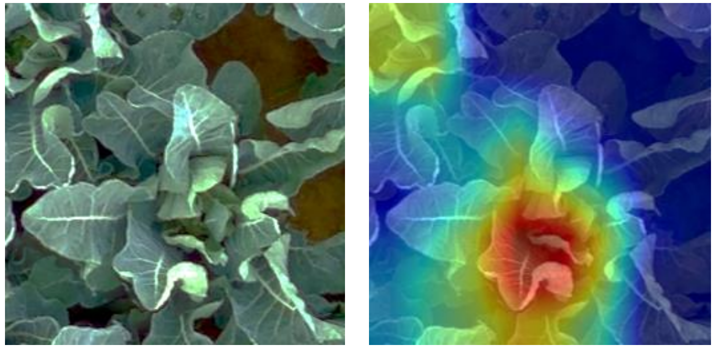
Combination of interpretable entities with domain knowledge (and analysis goal)

➢ Explanation depends on the use case

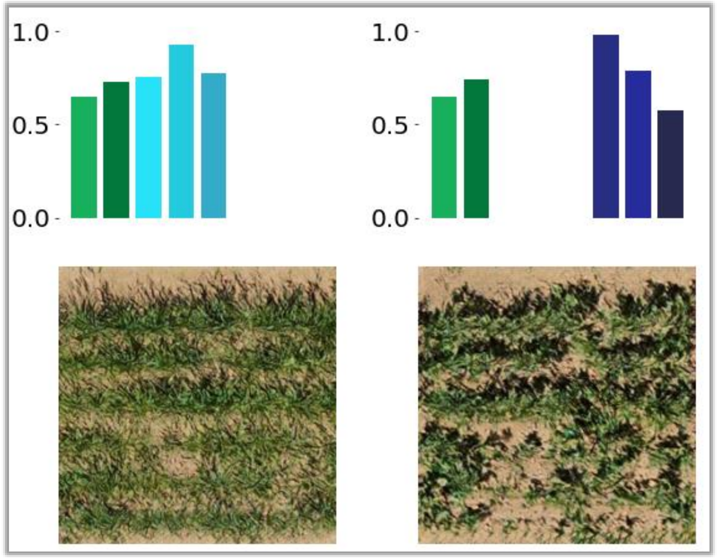
Roscher, R., Bohn, B., Duarte, M. F., & Garcke, J. (2020). Explainable machine learning for scientific insights and discoveries. *IEEE Access*, *8*, 42200-42216.

Reasons to seek explanations

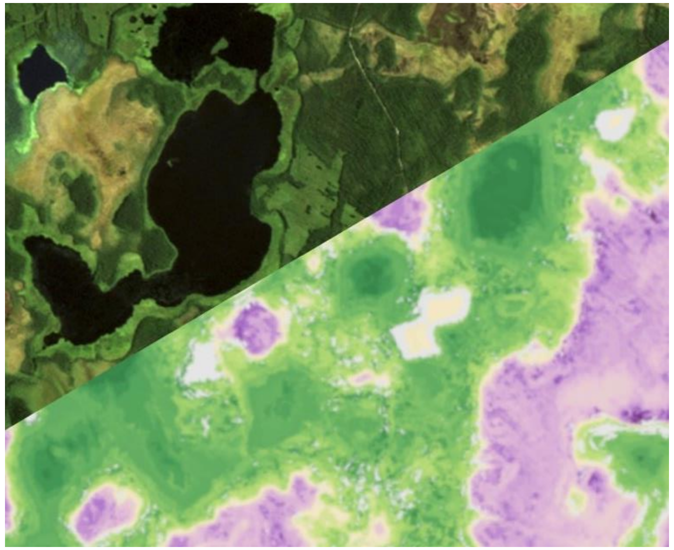
Justify decisions and improve models



Enhance control



Discover knowledge



Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE Access*, *6*, 52138-52160.

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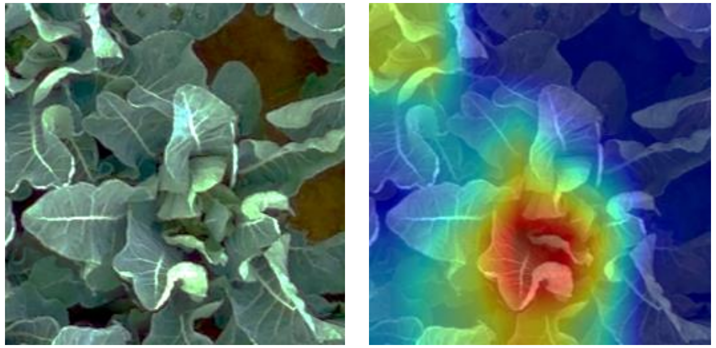
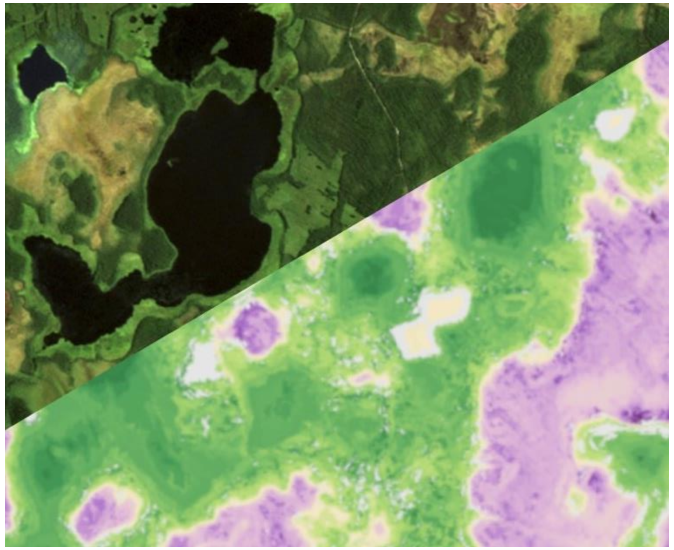


Enhance control

Discover knowledge



Data-centric machine learning

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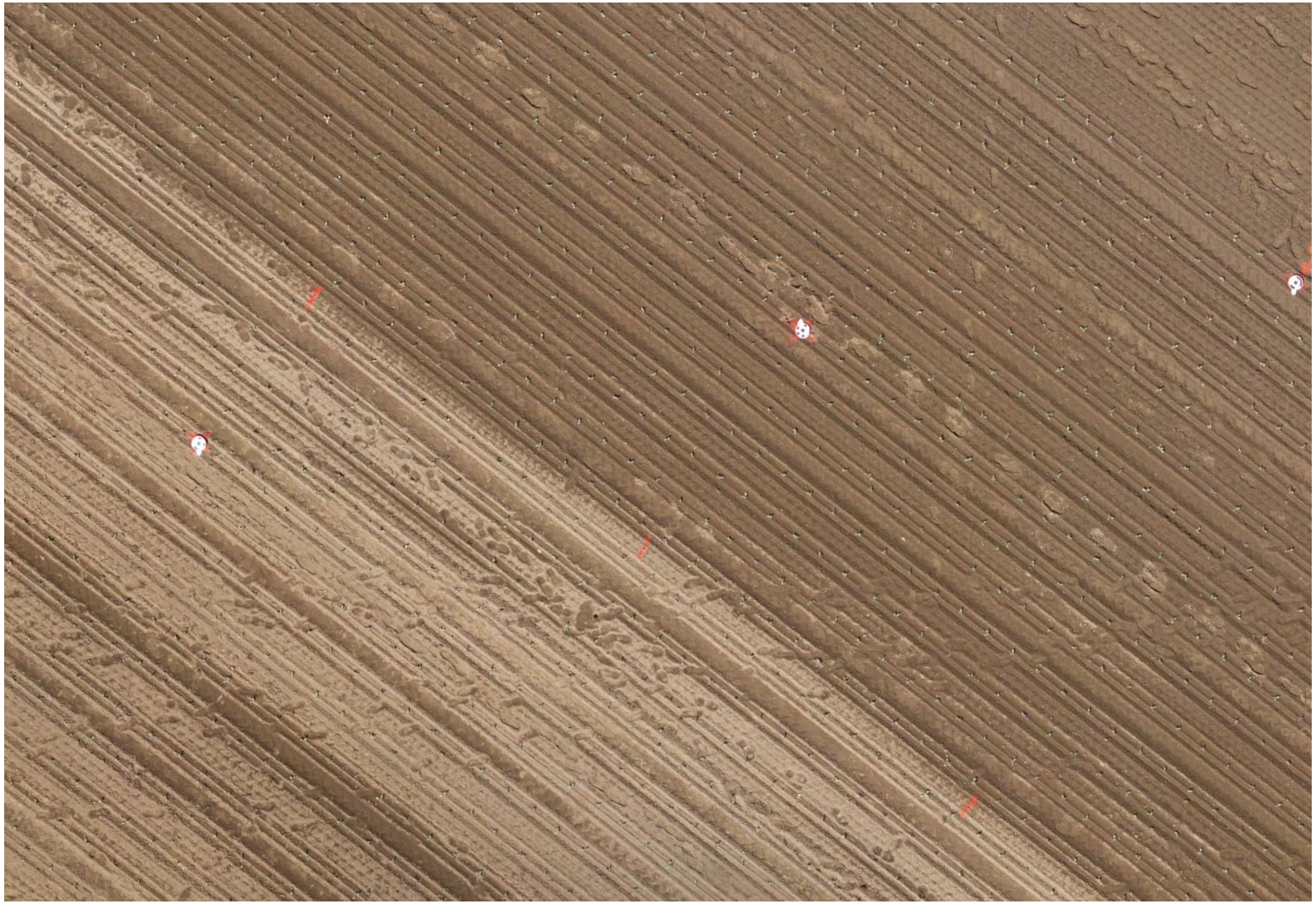
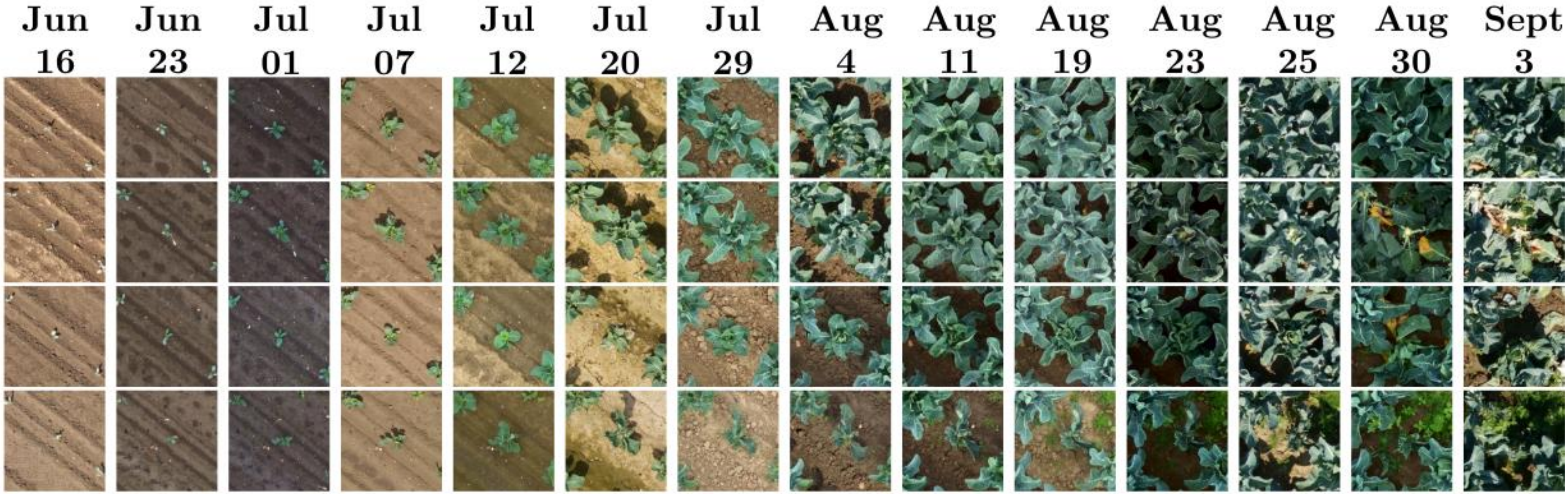
Optimization of cauliflower cultivation



Manually harvested based on spot checks

Irregular development



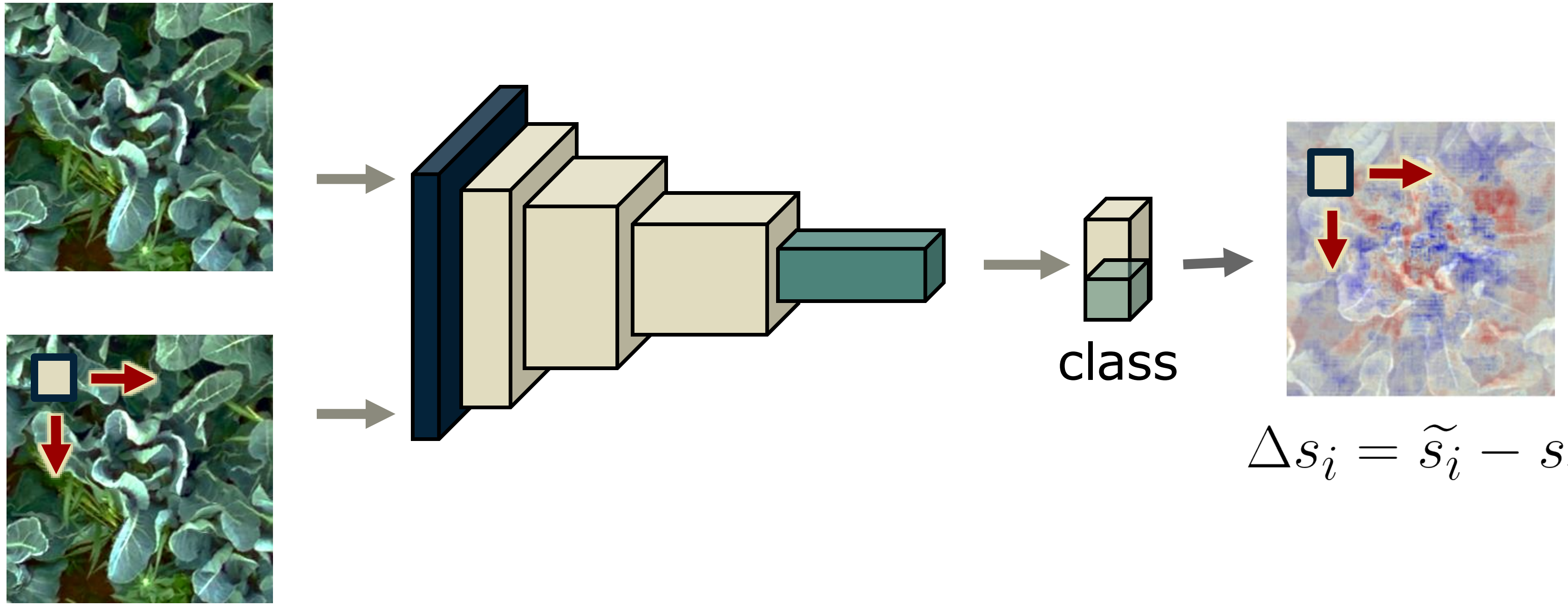
ready for harvesting?

		Predictions	
		Not Ready	**Ready**
References	**Not Ready**	45	31
	Ready	9	60

Is the decision based on the right reasons?

Occlusion sensitivity maps

- Evaluate the **sensitivity** of the trained model to **occlusions**
- **Difference** between the original score and the score after applying occlusion

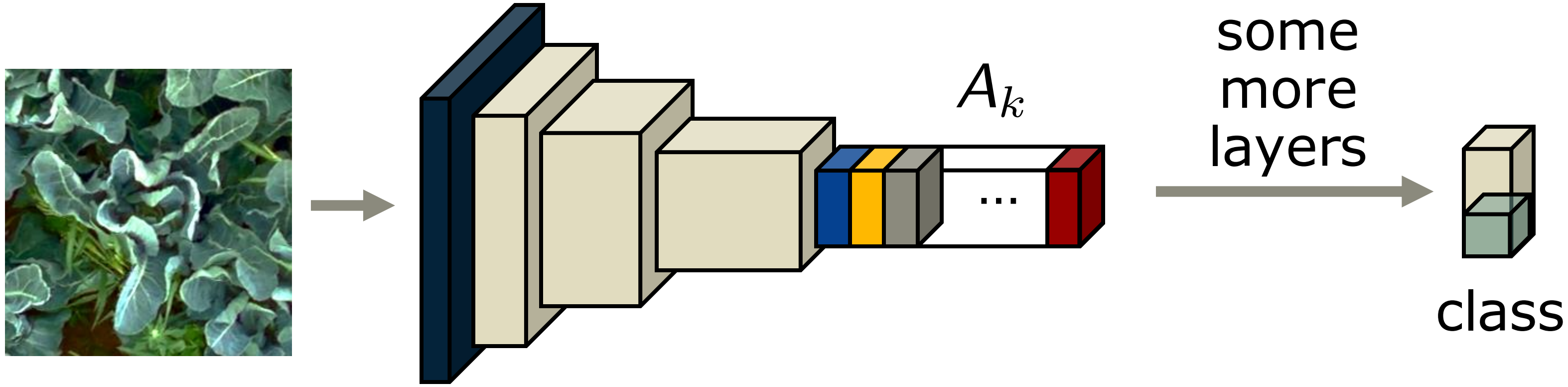


$$\Delta s_i = \widetilde{s}_i - s_i$$

Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *European conference on computer vision* (pp. 818-833)

Gradient-weighted class activation maps (Grad-CAM)

Uses the **gradient** of the learned network to indicate from which part of an image a given convolutional layer takes information



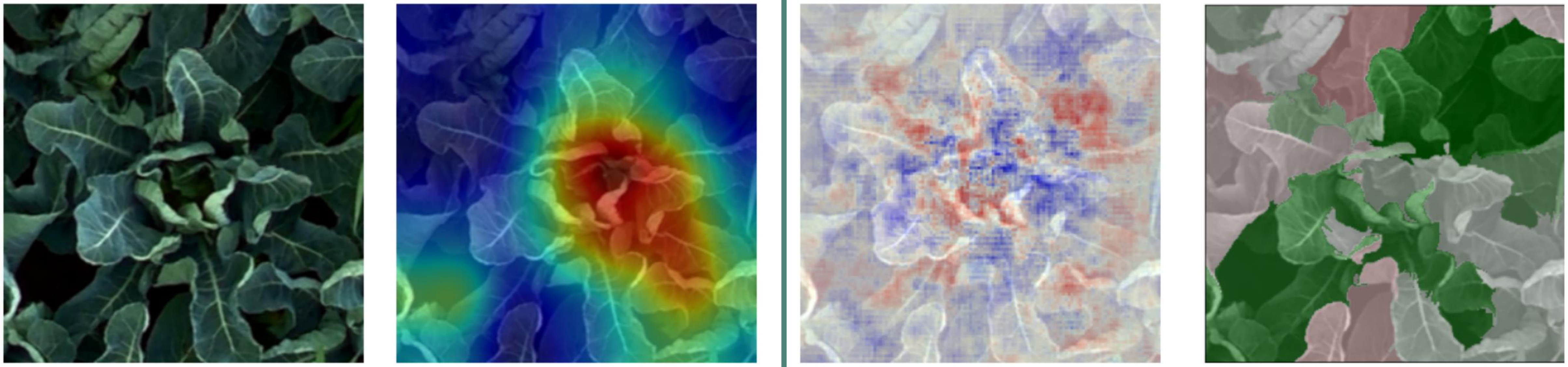
$$\mathrm{ReLU}\left(\sum_k \left(\frac{1}{Z}\sum_i \sum_j \frac{\partial y_c}{\partial A_{ij}}\right) A_k\right)$$

class-specific gradient of the score for class c (before softmax) w.r.t. feature maps of a convolutional layer

activation maps

Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2019). Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. *International Journal of Computer Vision*, *128*(2), 336-359.

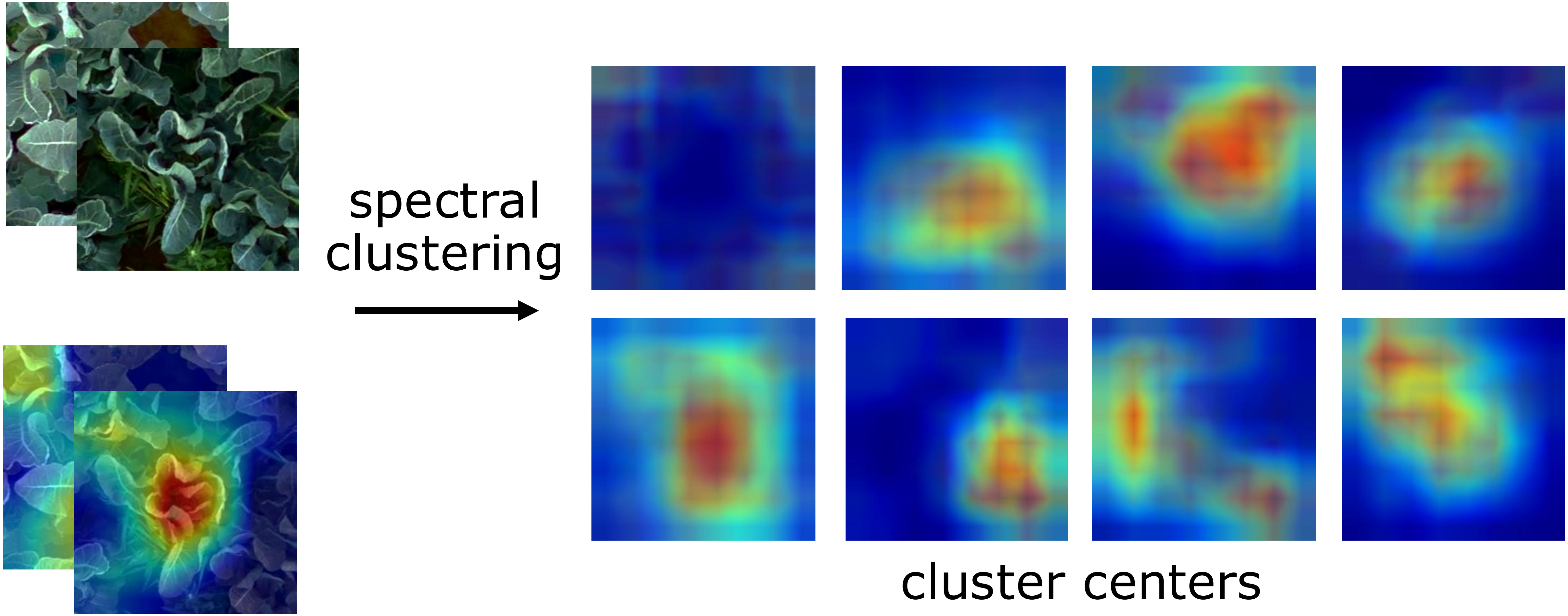
Attribution/saliency maps



RGB GradCAM OSM LIME

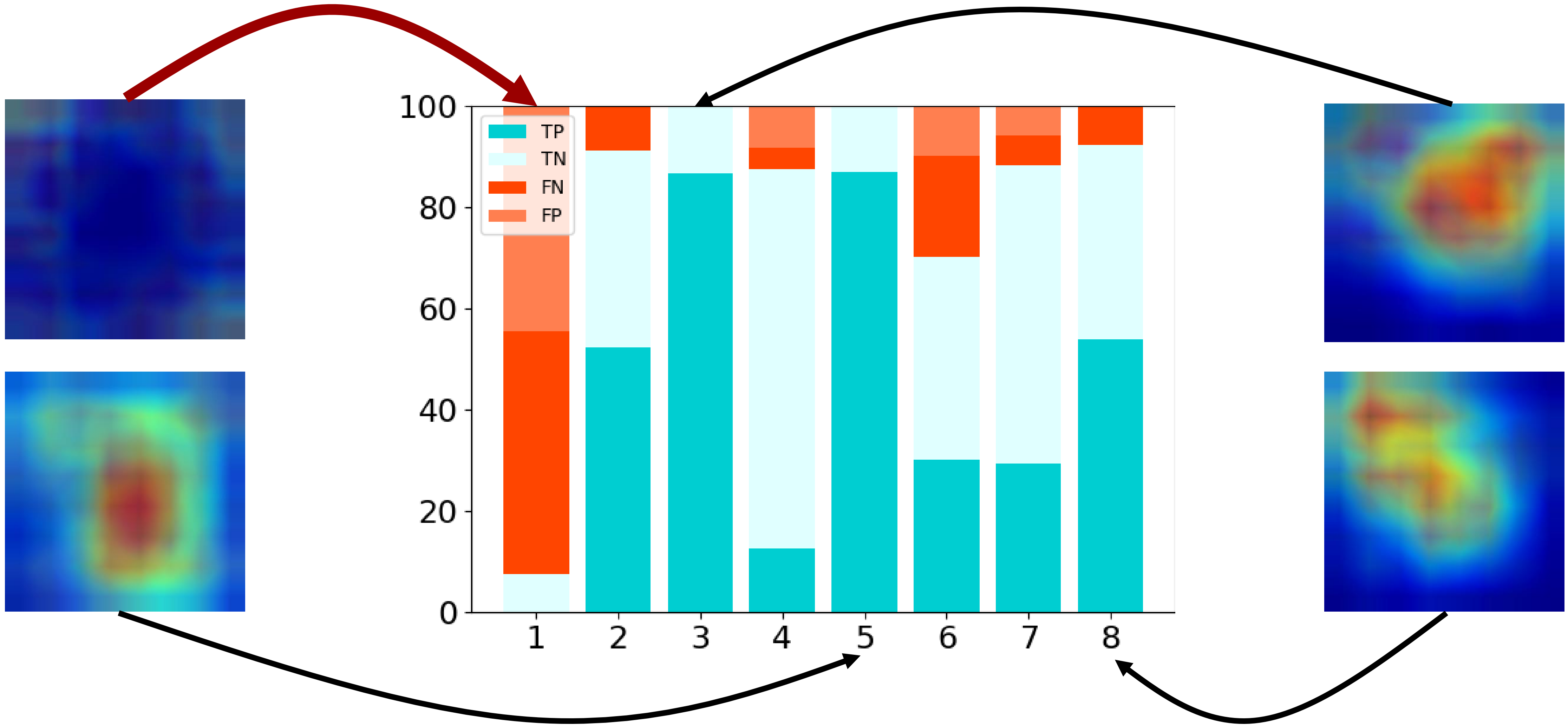
- Spectral clustering

Saliency maps for justification

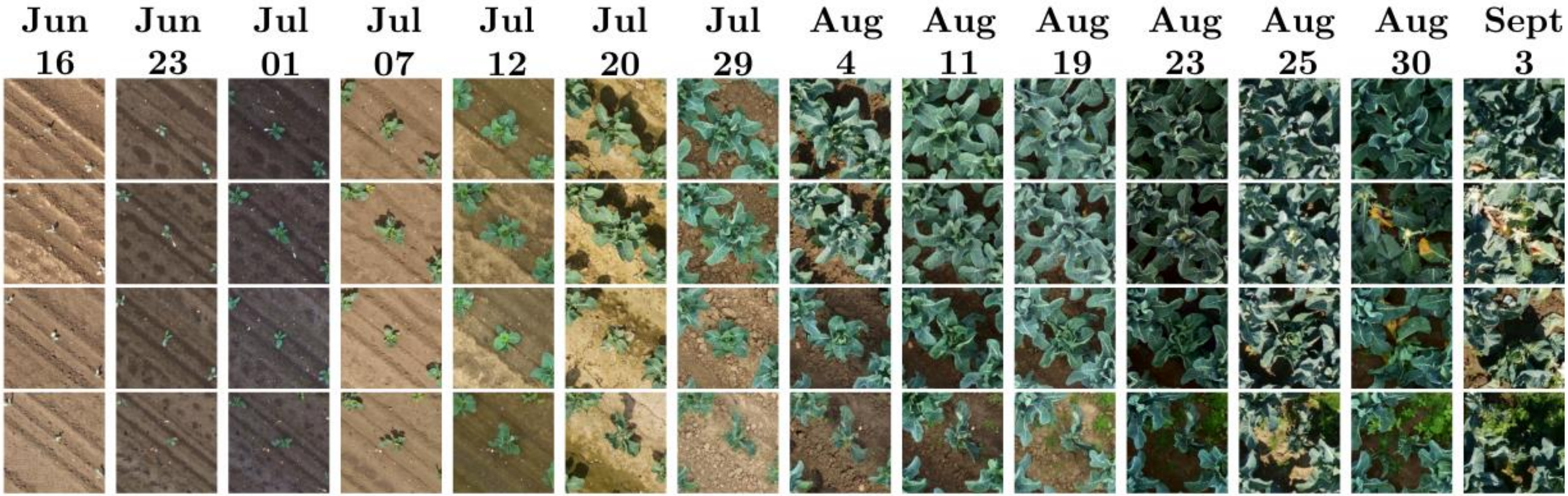


Nearly all heatmaps in cluster 1 are associated with wrong classifications

- Spurios correlation



Time-series analysis

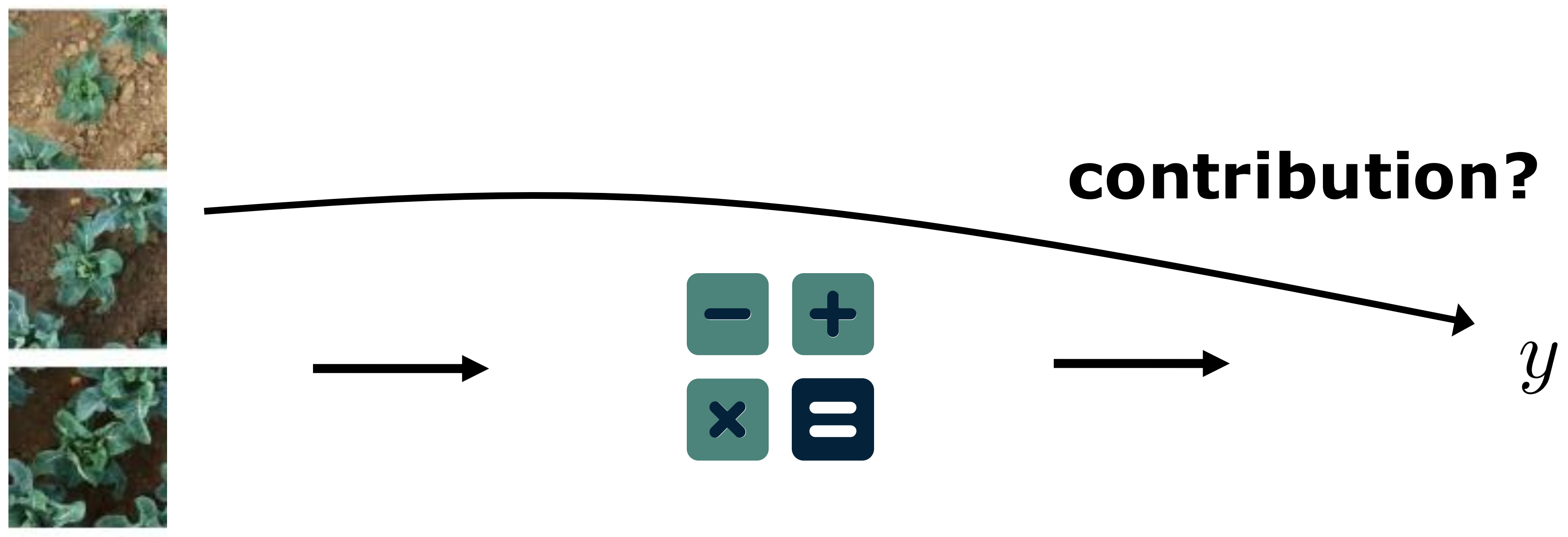


Question: Which time-points (UAV overflights) are important?

➢ Shapley values

Kierdorf, J., Stomberg, T.T., Drees, L., Rascher, U., Roscher, R. (2024). Investigating the Contribution of Image Time Series Observations to Cauliflower Harvest-Readiness Prediction, submitted.

Concept originates from game theory



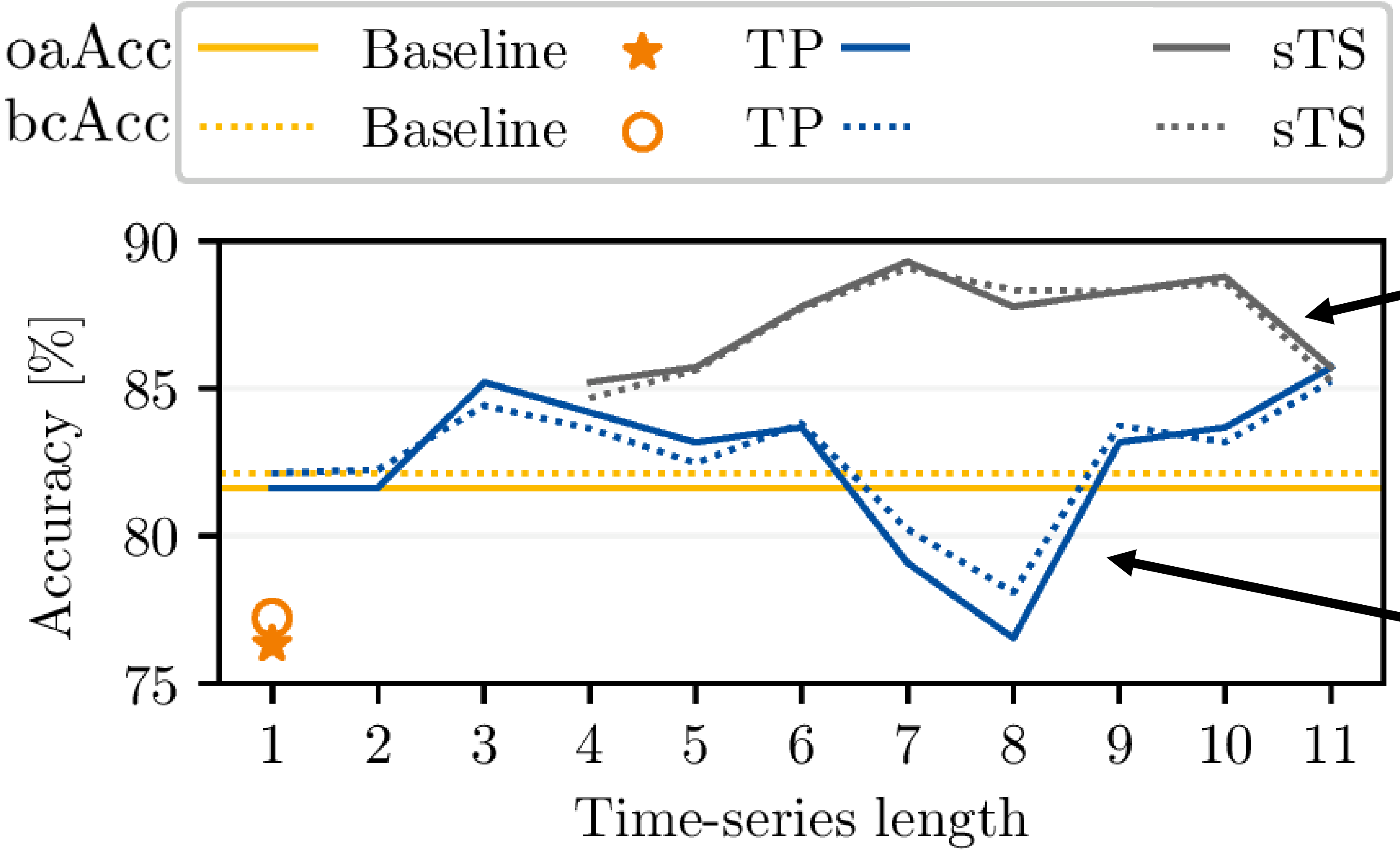
features/set of images (players in coalition)

prediction task for a single instance (game)

output (overall payout)

➢ Assignment of a payout to each player based on the contribution with mean prediction being the reference

Time series analysis



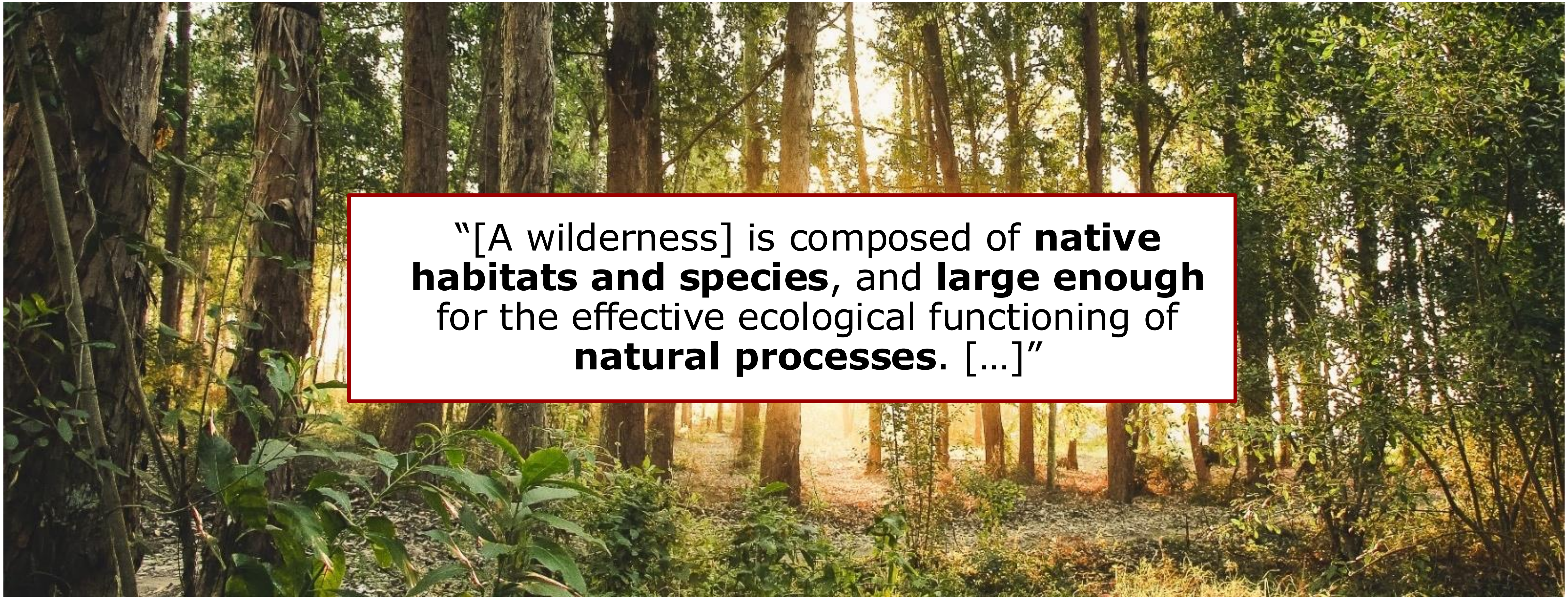
Added time points based on contribution

Single time points

Added time points based on date

Kierdorf, J., Stomberg, T.T., Drees, L., Rascher, U., Roscher, R. (2024). Investigating the Contribution of Image Time Series Observations to Cauliflower Harvest-Readiness Prediction, submitted.

Discover wilderness characteristics



No existing definition that can be used for machine learning

➢ **Discover characteristics** of wilderness to deepen our understanding about the land cover class so that it is useful for mapping

Study site

Fennoscandia (Norway, Sweden, Finland)

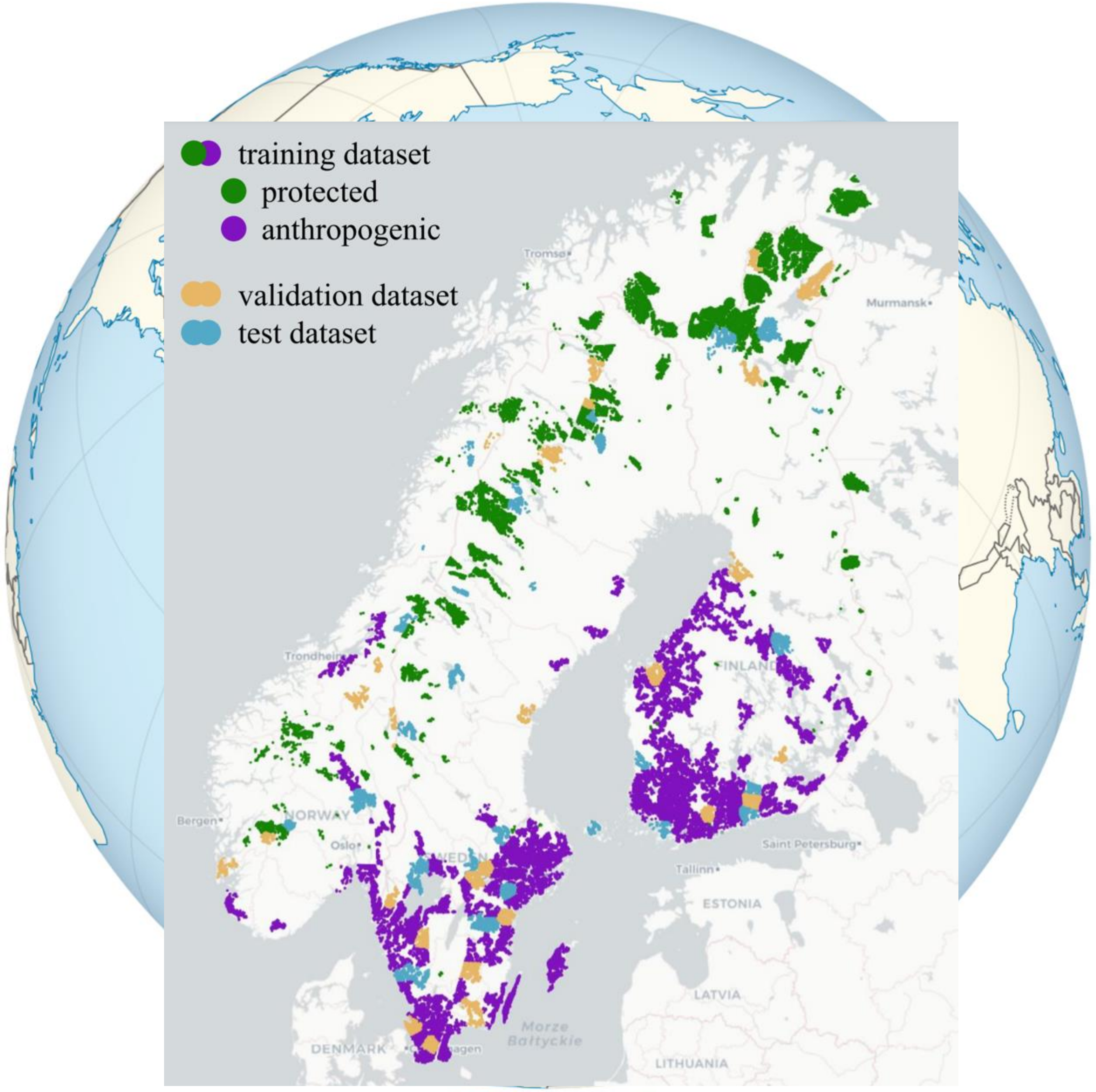
Study site

World Database on Protected Areas (WDPA)

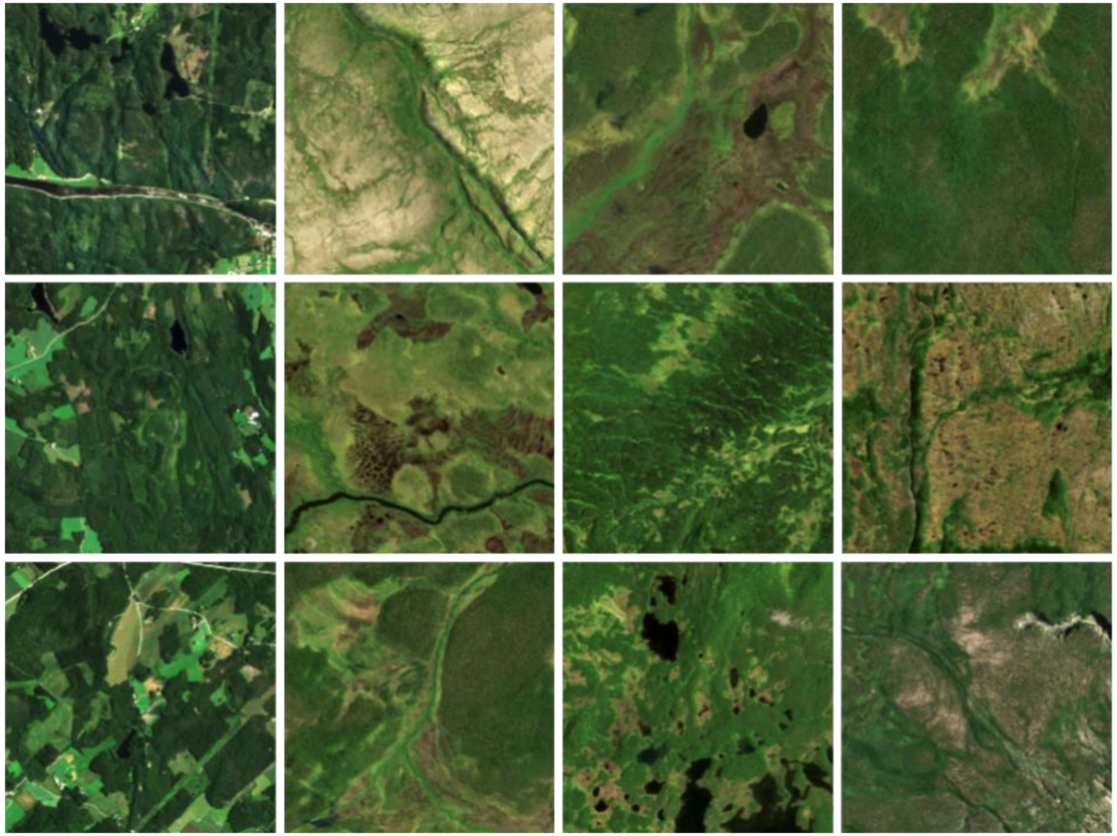
vs.

Anthropogenic Areas

(artificial and agricultural surfaces)

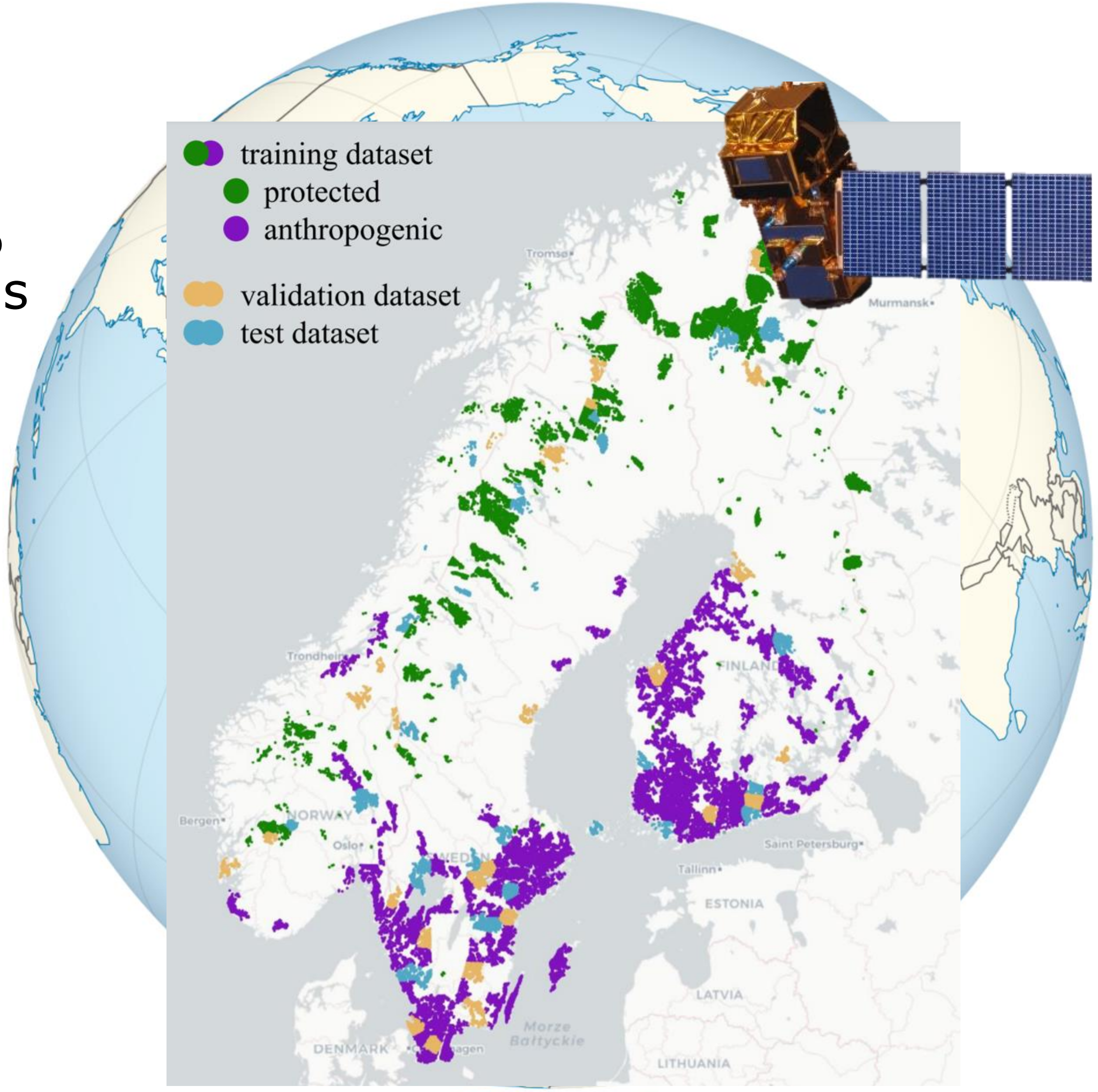


Sentinel-2 data



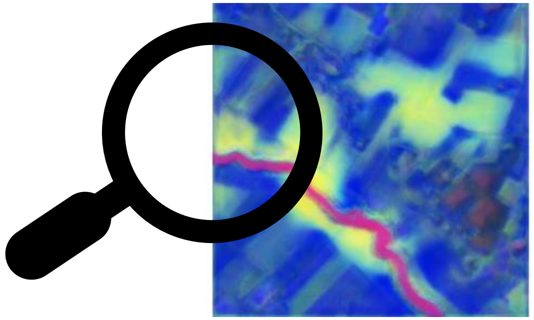
256 pixels

anthropogenic protected

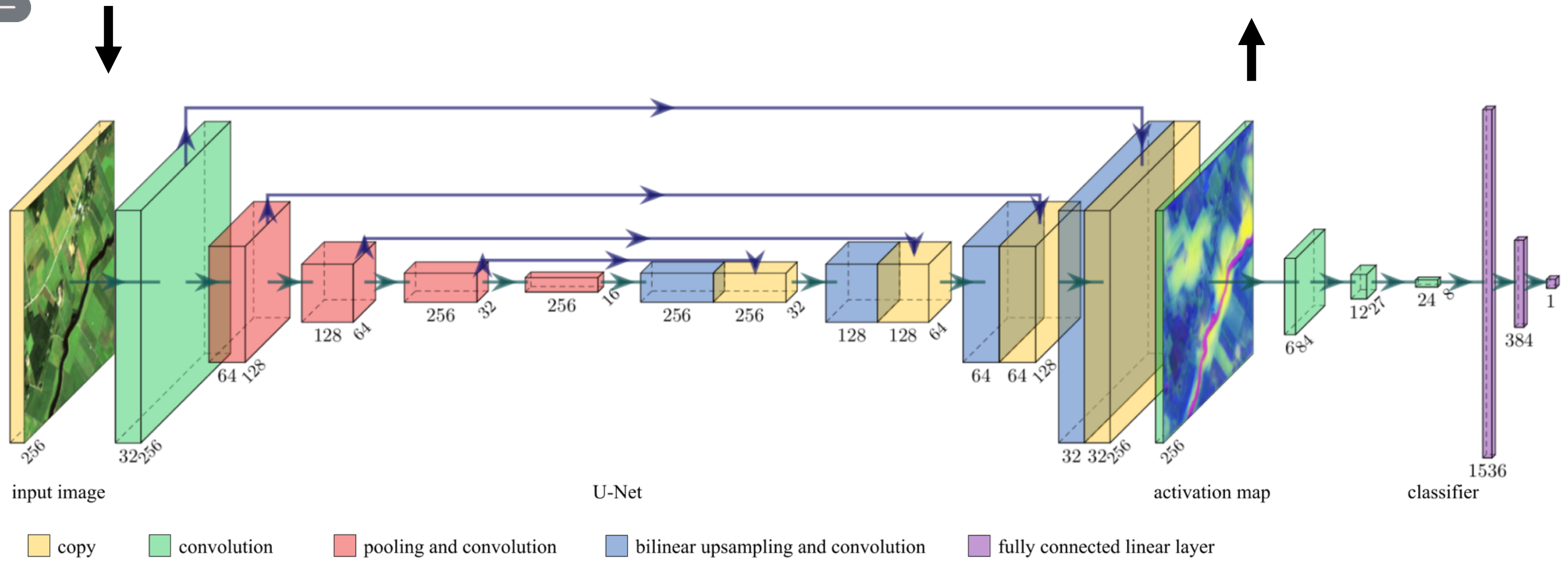


Conceptual framework (jUngle-Net)

multispectral Sentinel-2 images (mixed with CutMix)



D-dimensional activation maps



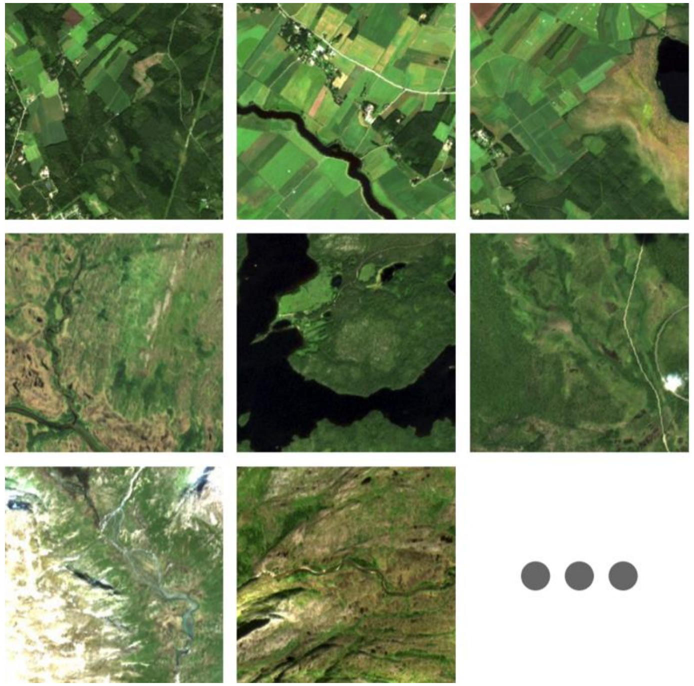
wilderness fraction

Stomberg, T., Weber, I., Schmitt, M., & Roscher, R. (2021). jUngle-Net: Using explainable machine learning to gain new insights into the appearance of wilderness in satellite imagery. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *3*, 317-324.

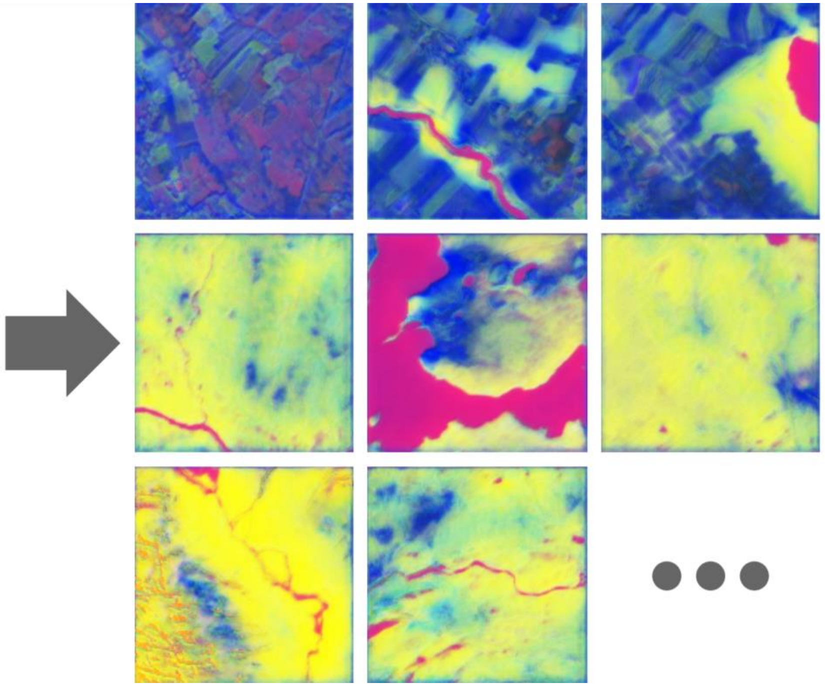
Stomberg, T. T., Leonhardt, J., Weber, I., & Roscher, R. (2023). Recognizing protected and anthropogenic patterns in landscapes using interpretable machine learning and satellite imagery. *Frontiers in Artificial Intelligence*, *6*.

Activation space

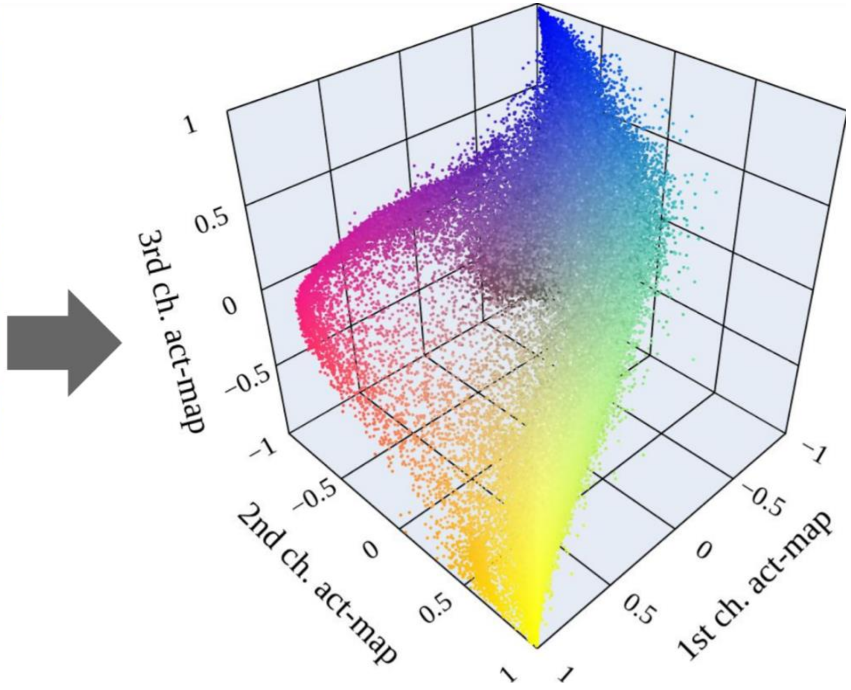
19.123 training samples



activation maps (3 channels)

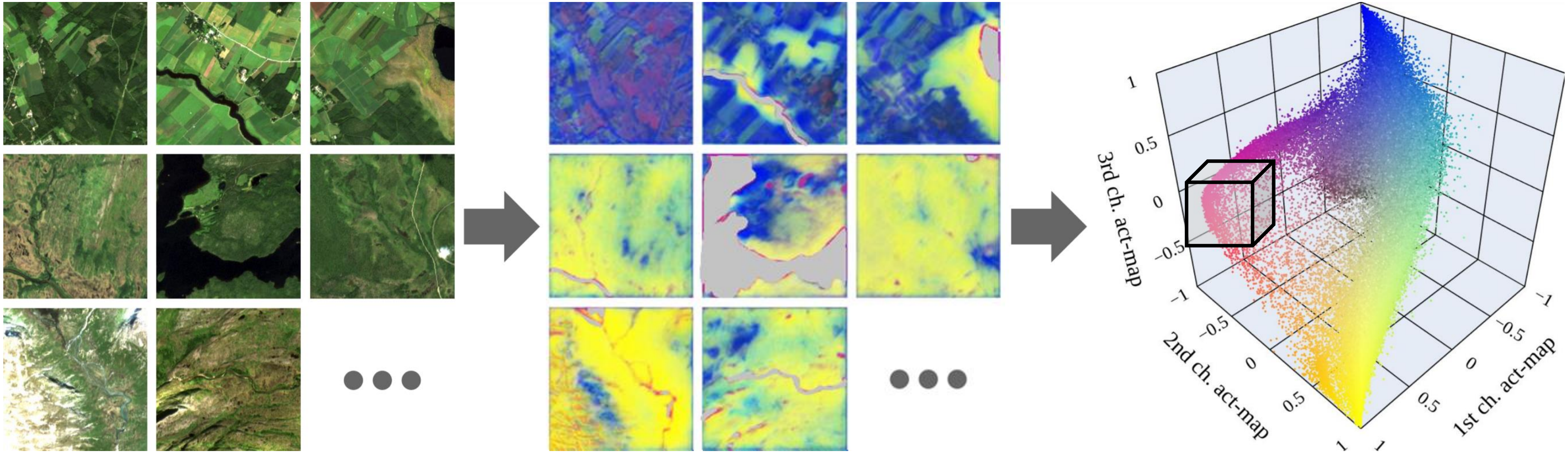


activation space

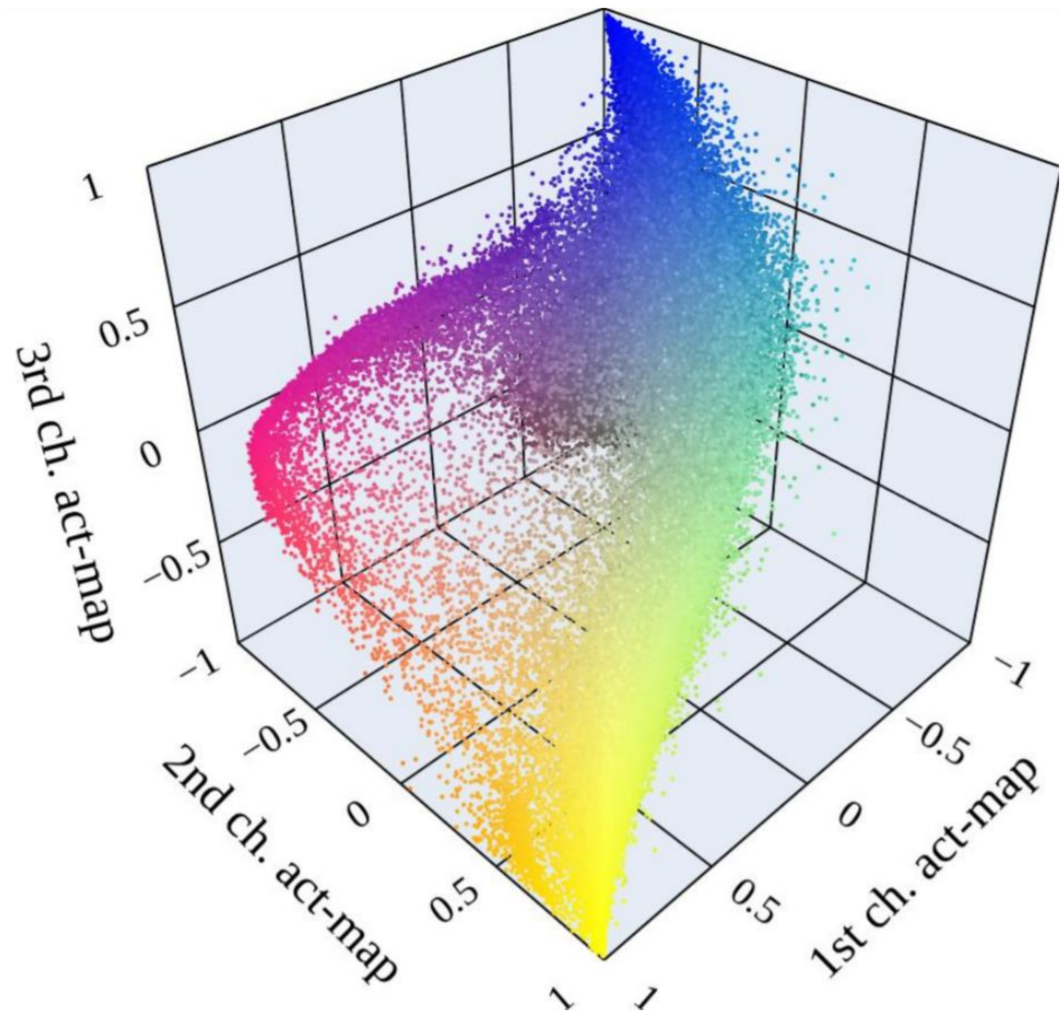


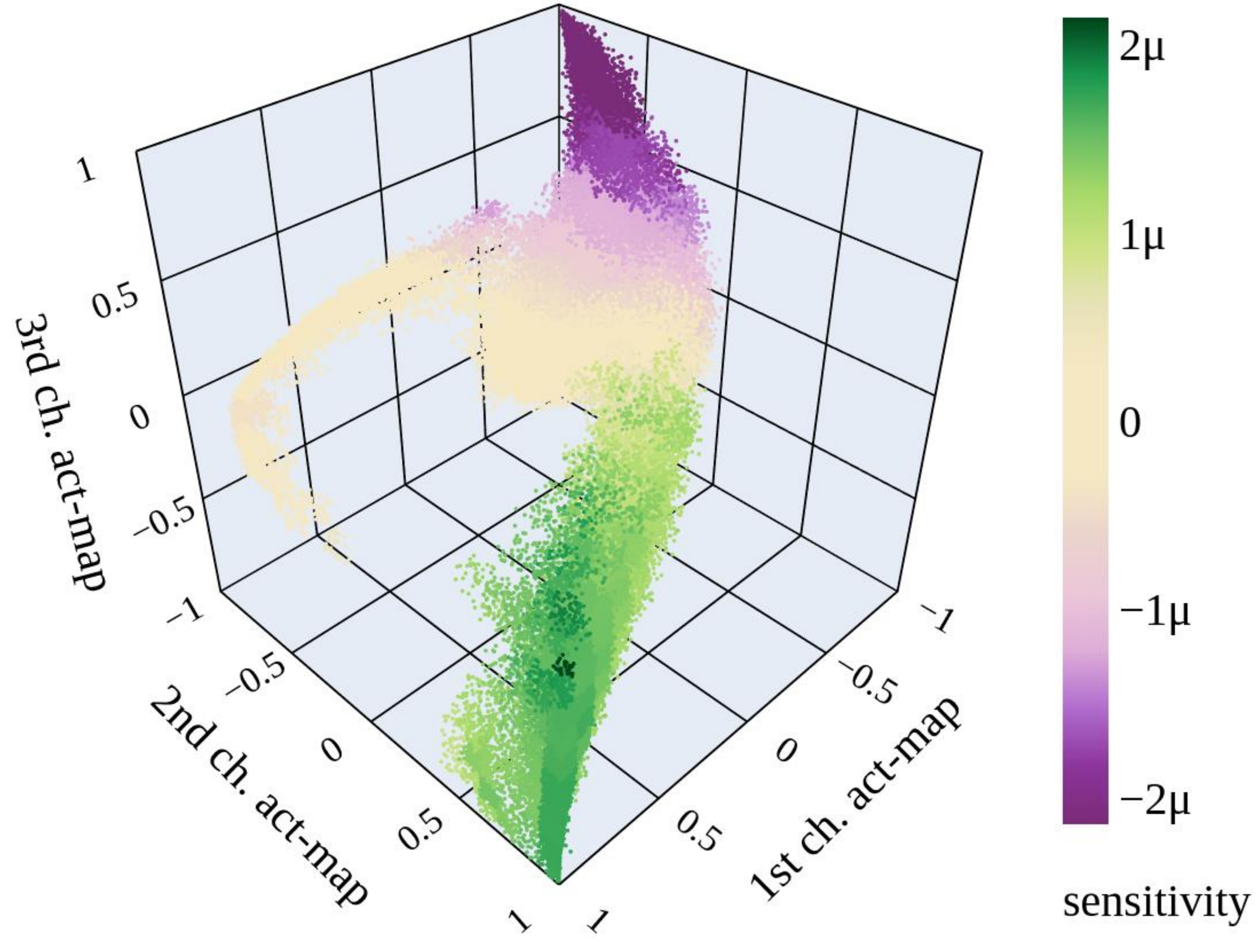
Activation space occlusion sensitivity

19.123 training samples | activation maps (3 channels) | activation space

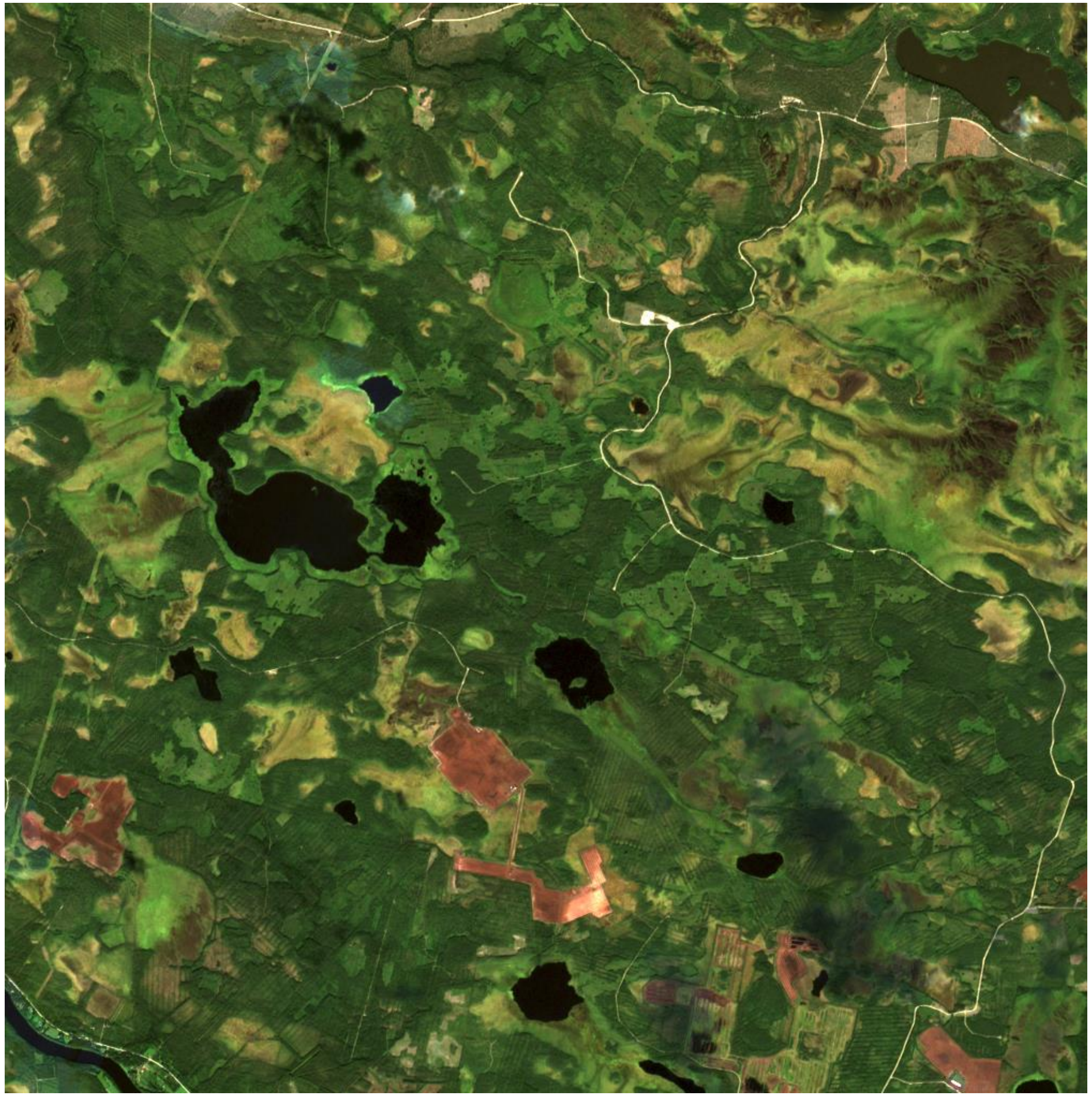


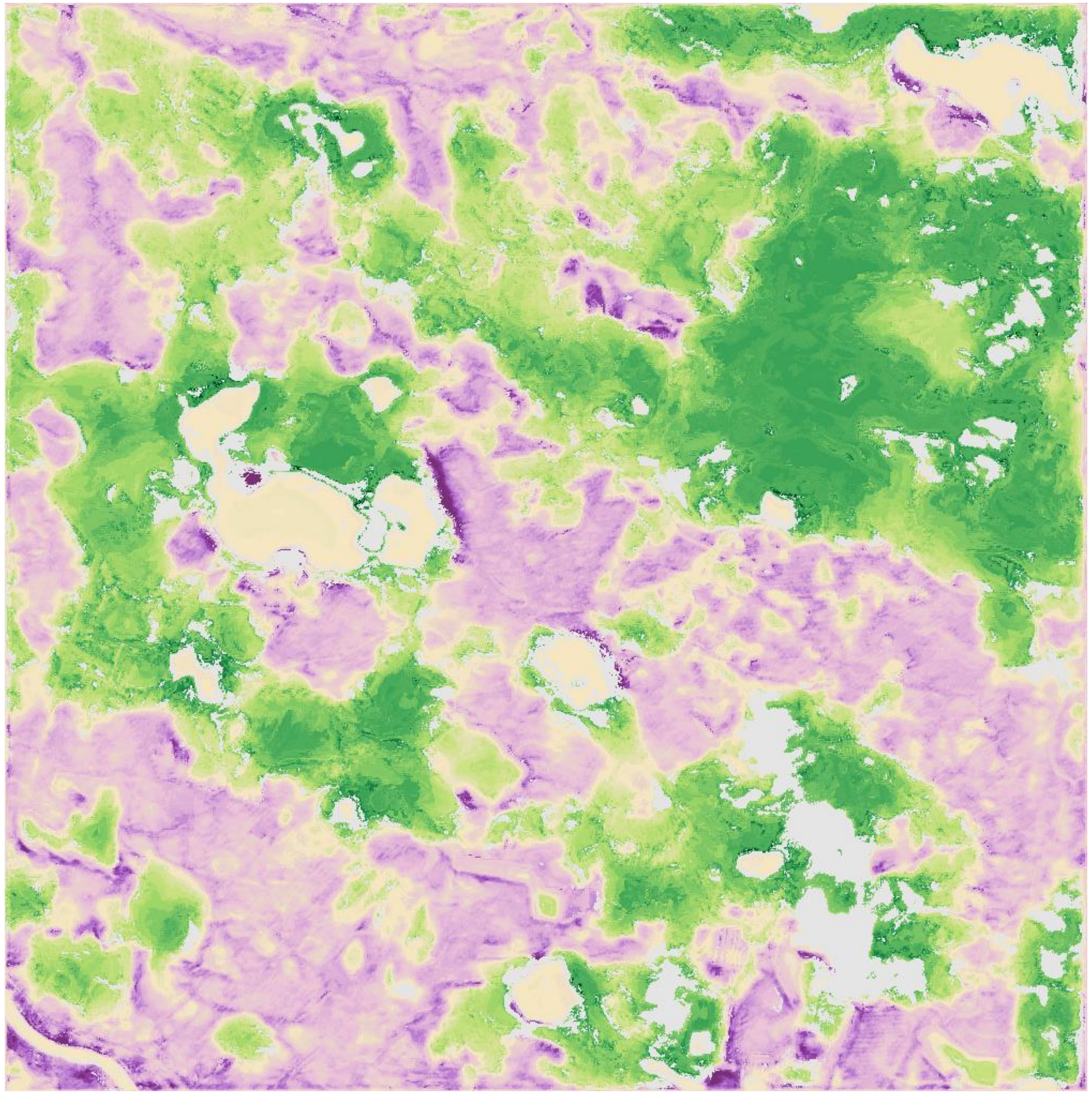
Activation space occlusion sensitivity (ASOS)



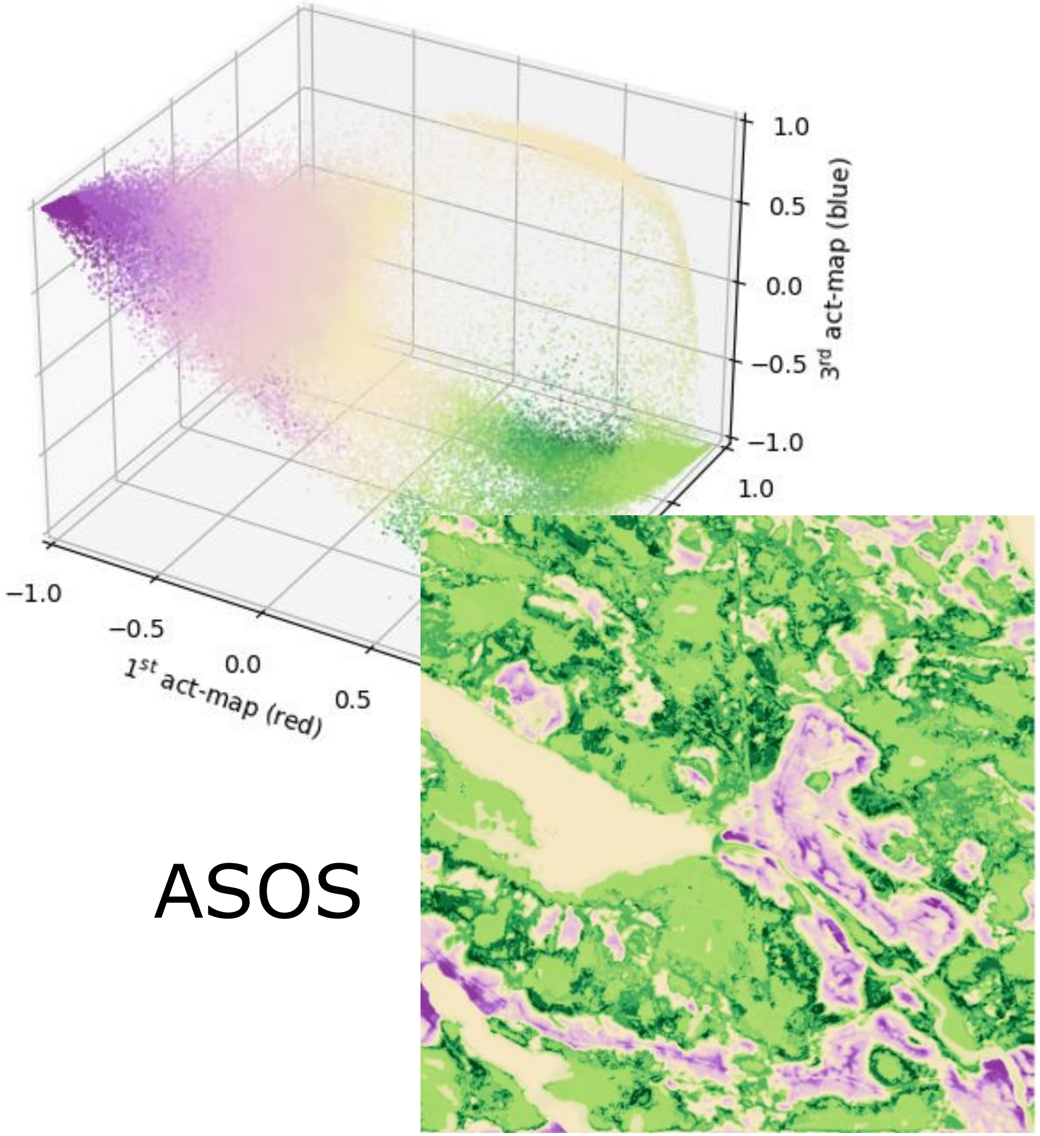


Results: North Ostrobothnia, Finland

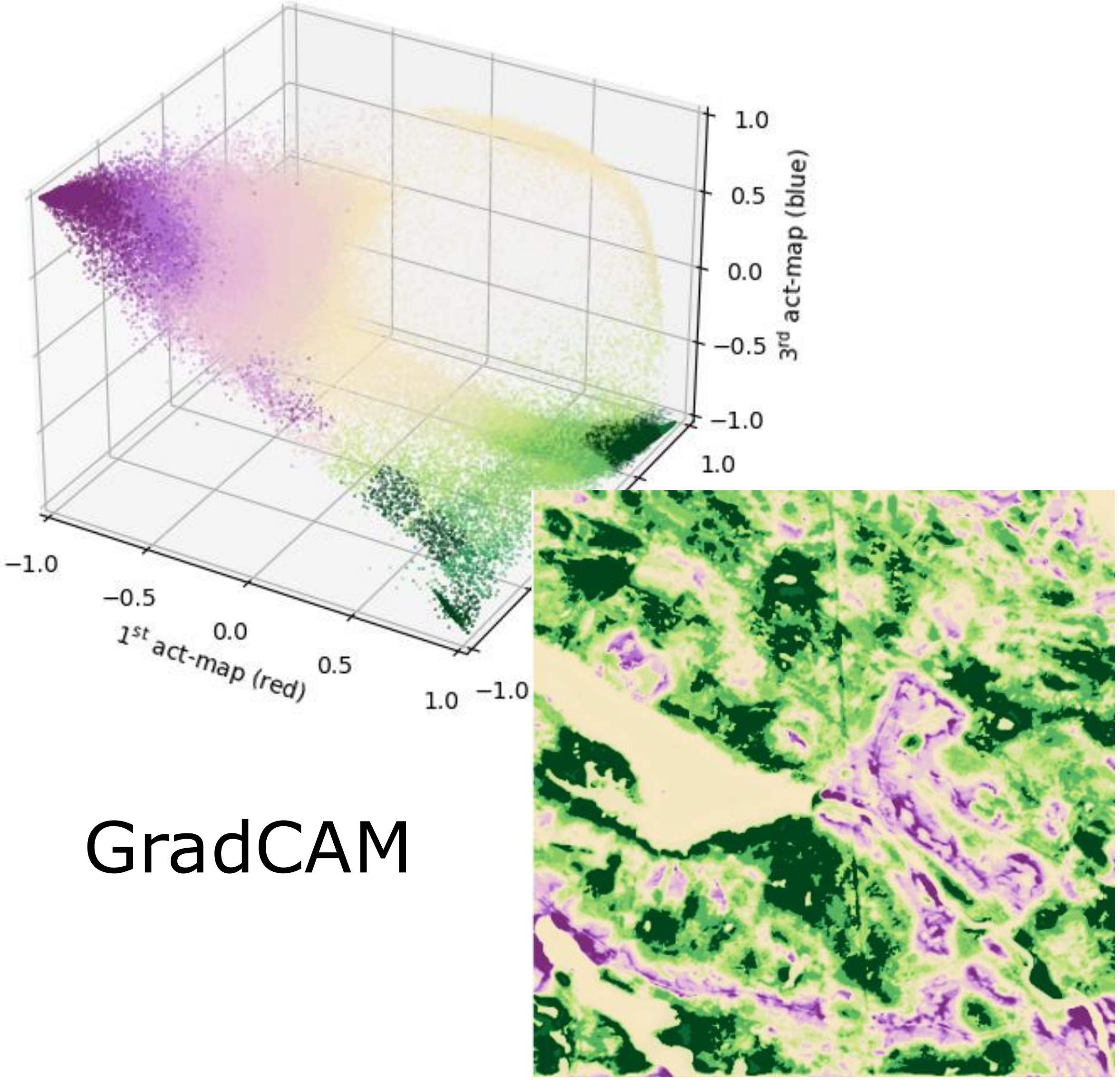




Activation space with attributions

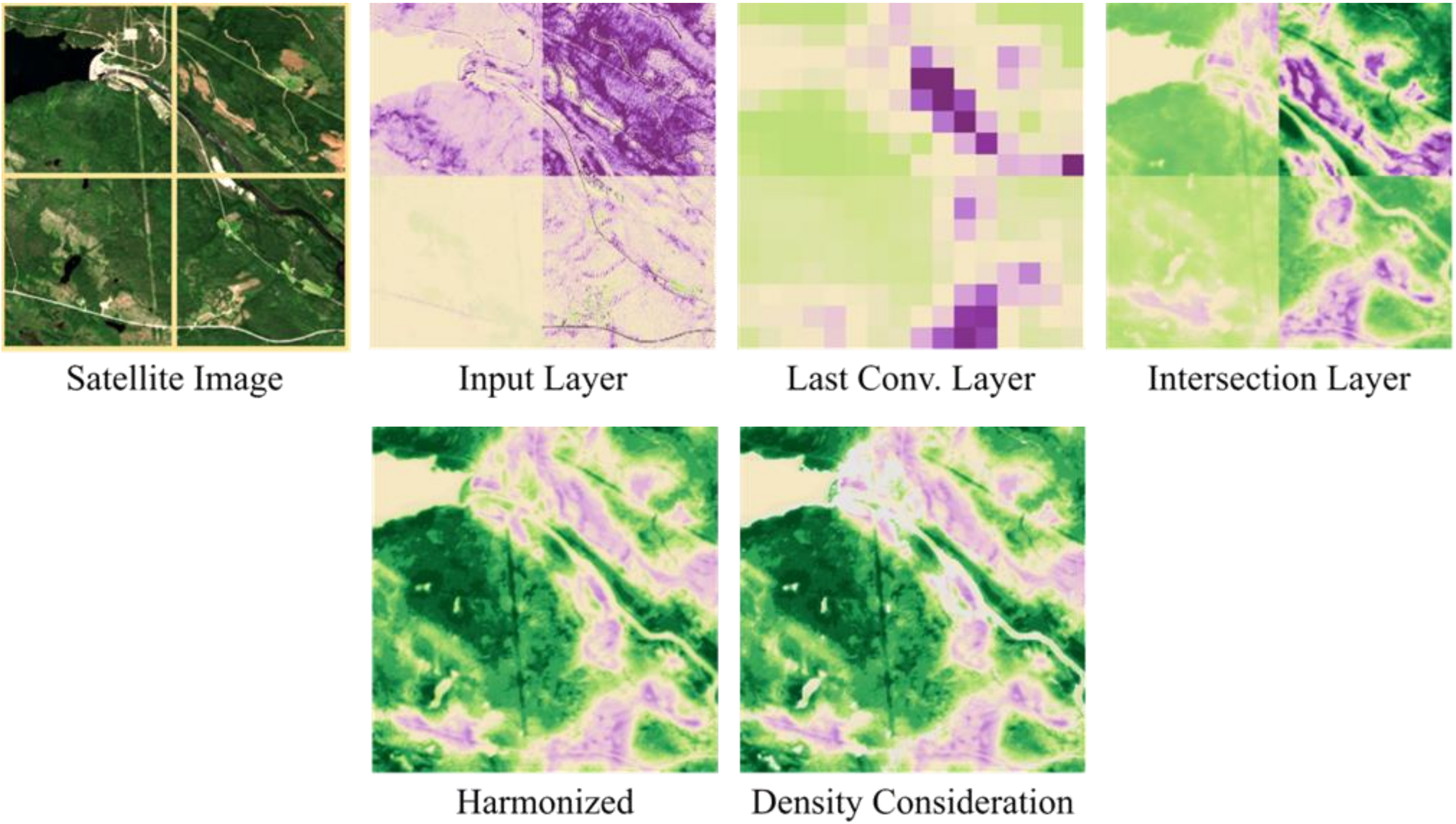


ASOS

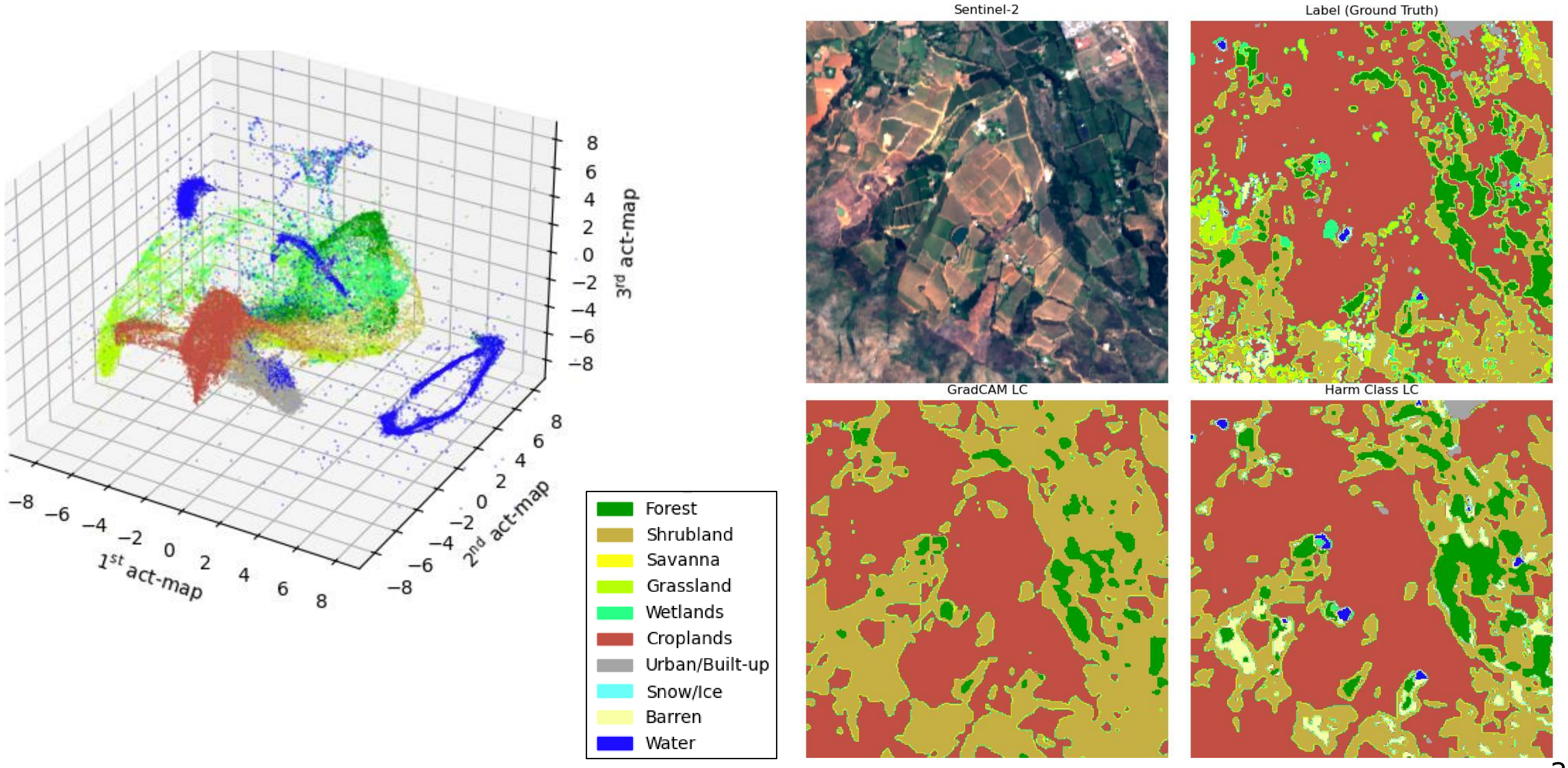


GradCAM

Harmonization and density consideration



Weakly supervised learning (DFC dataset)



Data-centric machine learning

Model-centric learning

Optimization of the model parameters and hyperparameters, such as the model design, as well as the learning objective as a loss function

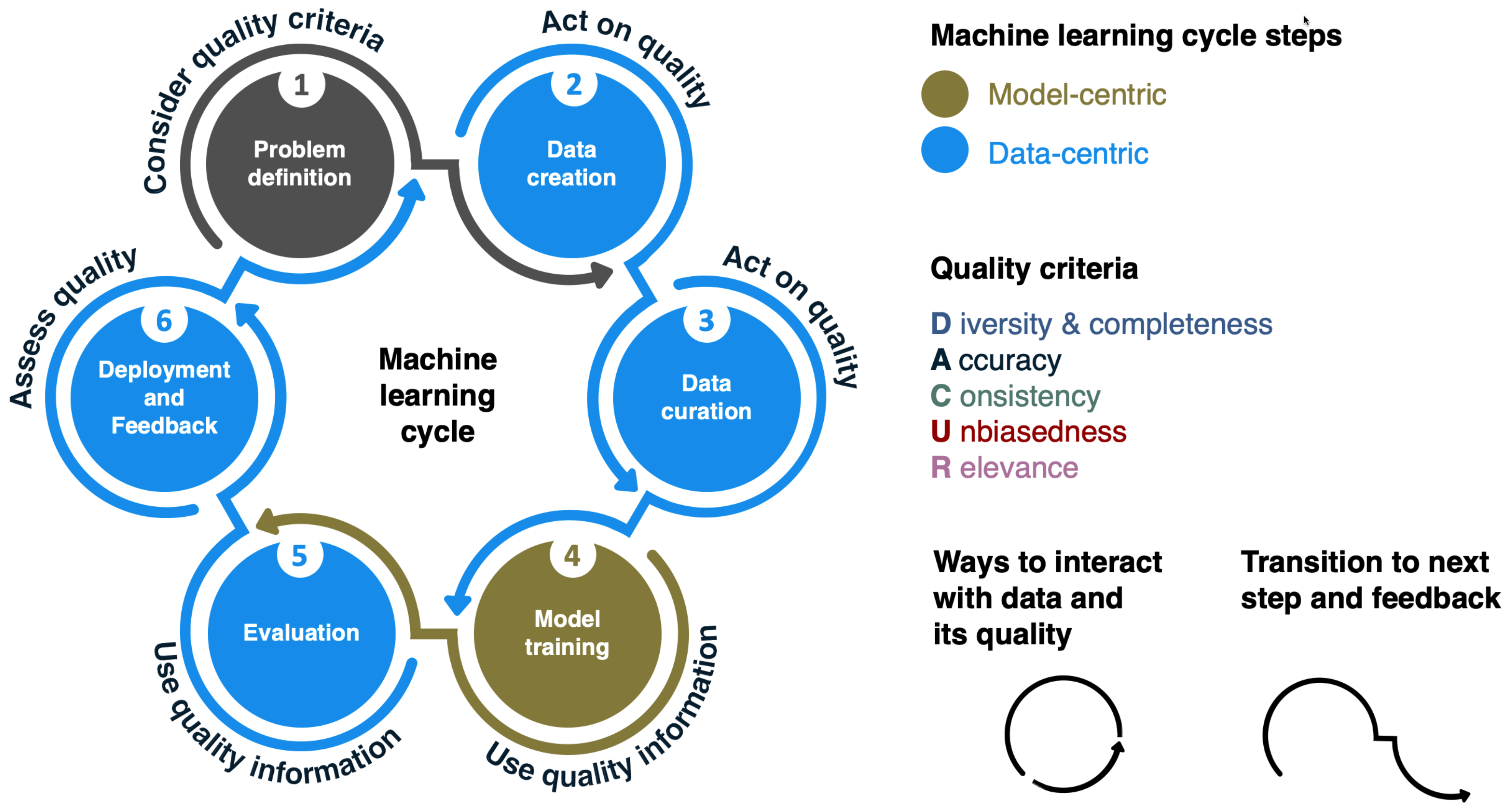
Data-centric learning

Systematic, automated, and algorithmic determination, as well as the utilization of a rich and high-quality dataset, including a rigorous evaluation process to ensure that the model performs optimally on the dataset for the intended task

Roscher, R., Rußwurm, M., Gevaert, C., Kampffmeyer, M., dos Santos, J.A., Vakalopoulou, M., Hänsch, R., Hansen, S., Nogueira, K., Prexl, J. and Tuia, D., (2024). Better, Not Just More: Data-Centric Machine Learning for Earth Observation. IEEE Geoscience and Remote Sensing Magazine, accepted.

Roscher, R., Roth, L., Stachniss, C., & Walter, A. (2023). Data-Centric Digital Agriculture: A Perspective. *arXiv preprint arXiv:2312.03437*.

Data-centric machine learning



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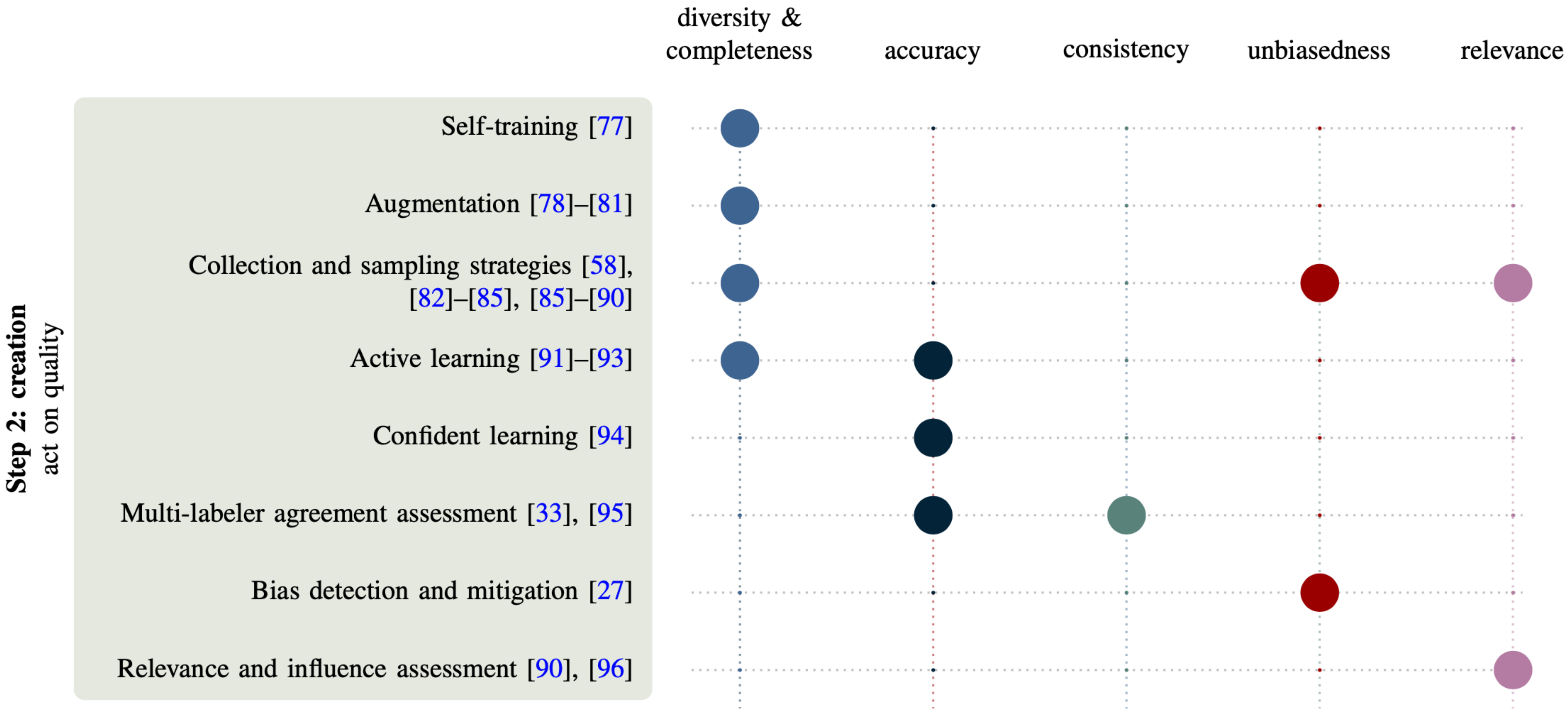

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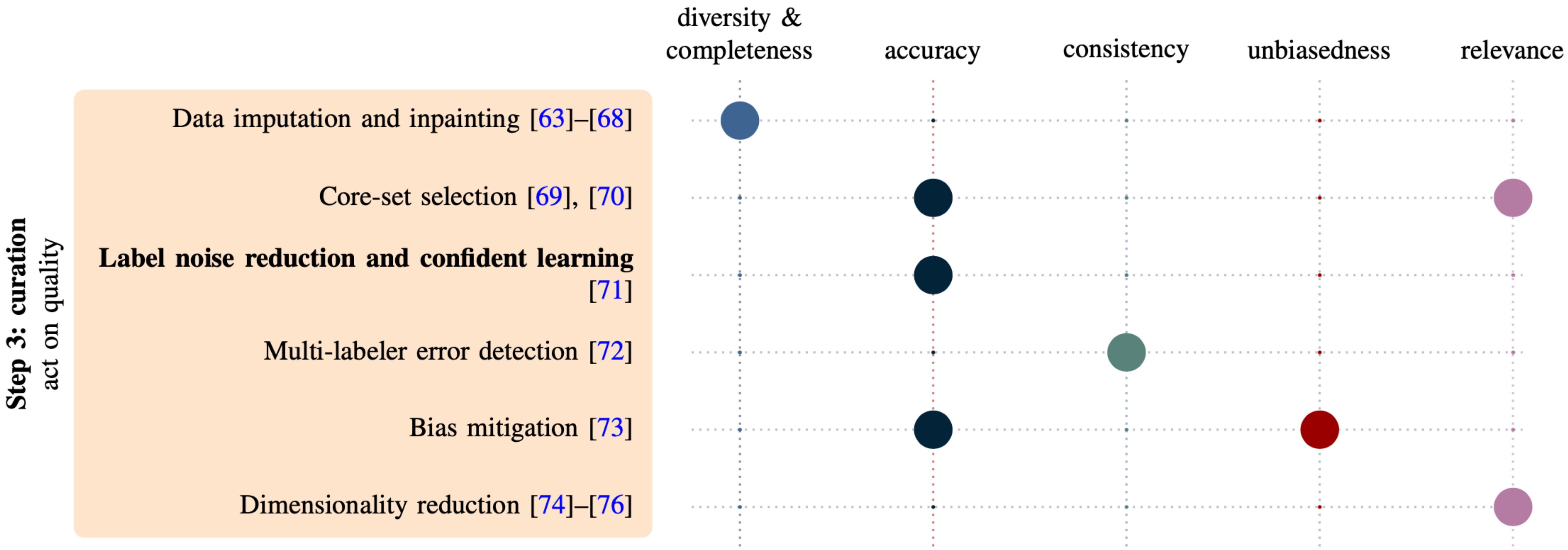

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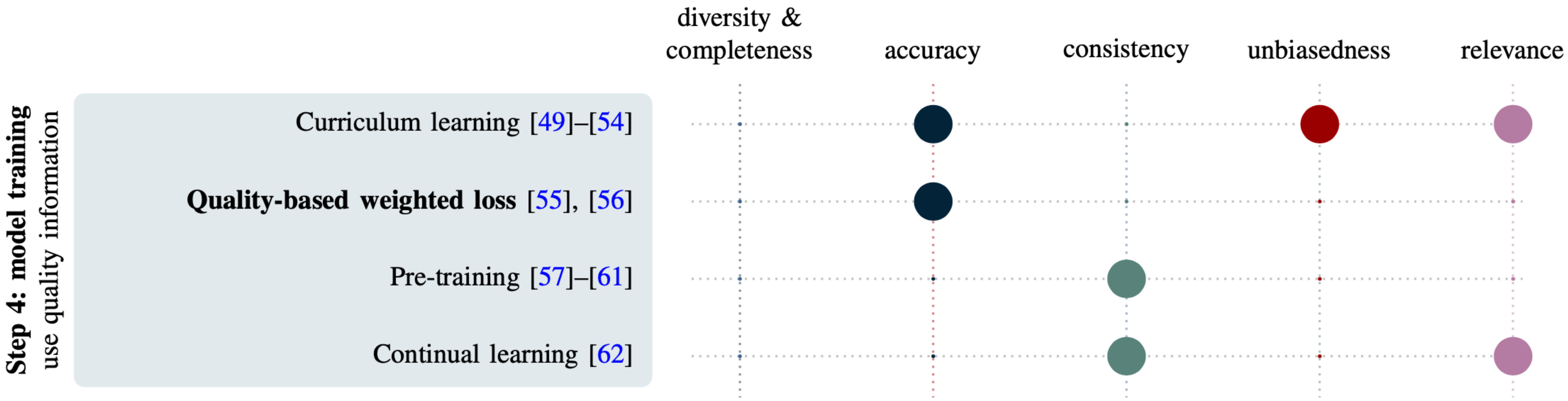

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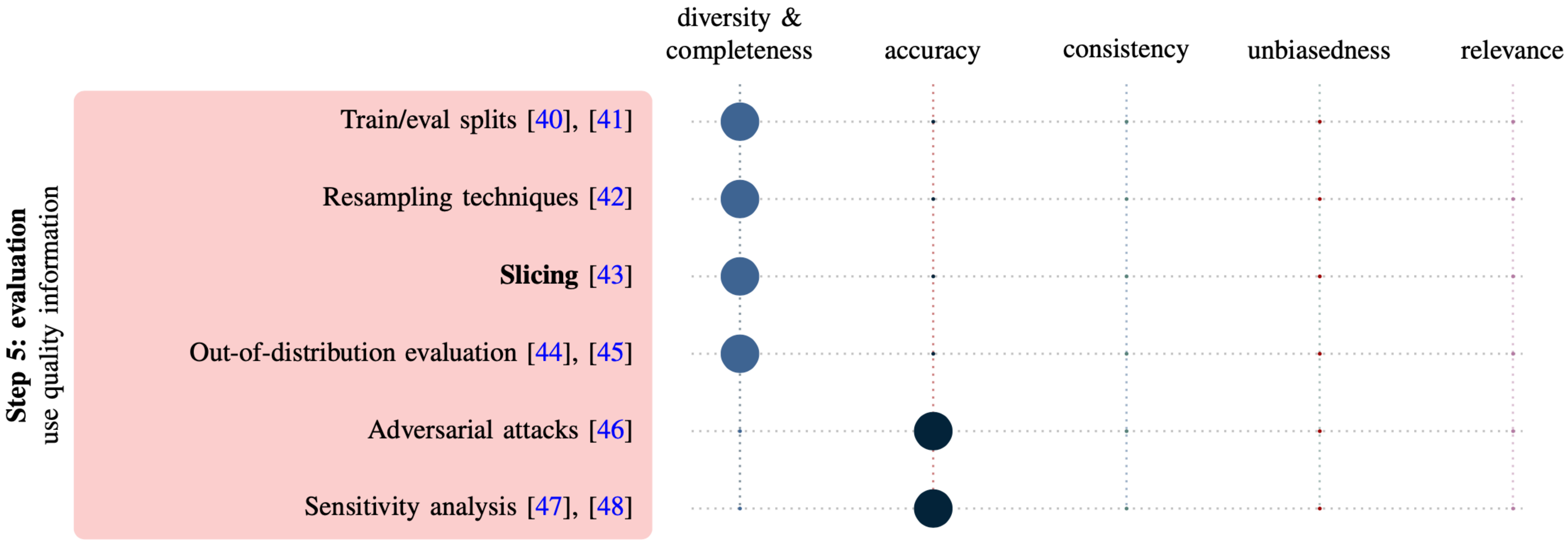

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Thank you for your attention.

More about my research on my website
http://rs.ipb.uni-bonn.de
or my YouTube channel

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OPTIKO

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Europäischer Landwirtschaftsfonds für die Entwicklung des ländlichen Raums:
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