Guiding Deep Learning with Landscape Metrics for LULC Mapping Applications

Part of project GeoWiKI: Geographisches **Wi**ssen in **K**ünstlicher **I**ntelligenz integrieren
(Integrating Geographical Knowledge into Artificial Intelligence)

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Context & Motivation

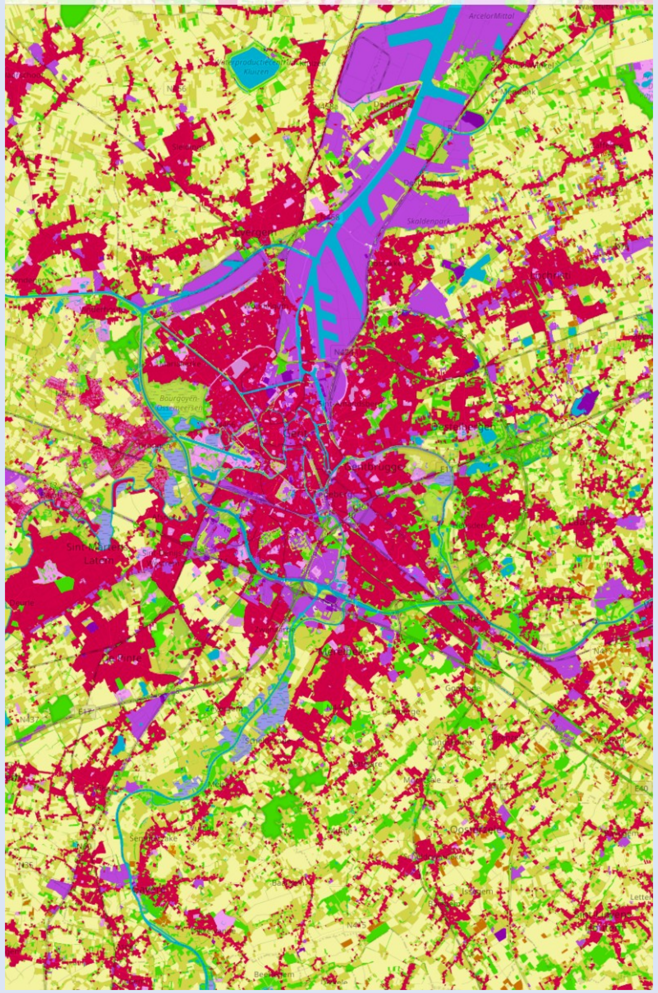
LULC mapping profited strongly from AI

- Image processing of satellite imagery started in 1960s
- Increasing amounts of data required **automation** → AI
- Today: AI-based global datasets

But: limited integration of geographic principles

- High **computational demands**: learn everything from scratch
- Outputs lack **spatial consistency**: transferability often limited
- Affects **generalization** and **interpretability**

S. Zhao et al. 2023; T. Zhao et al. 2024



OSM LULC: https://osmlanduse.org/

We claim:

We always know ***something*** about a region.

Ge et al. 2022

We propose:

→ Use ***expected*** landscape patterns to “guide” models.

Landscape Metrics (LSM)

- Numerical description of landscape patterns
- Pixel-based (raster input)
- Developed for landscape ecology
- Three scales: patch, class, landscape
- “Old” but established research

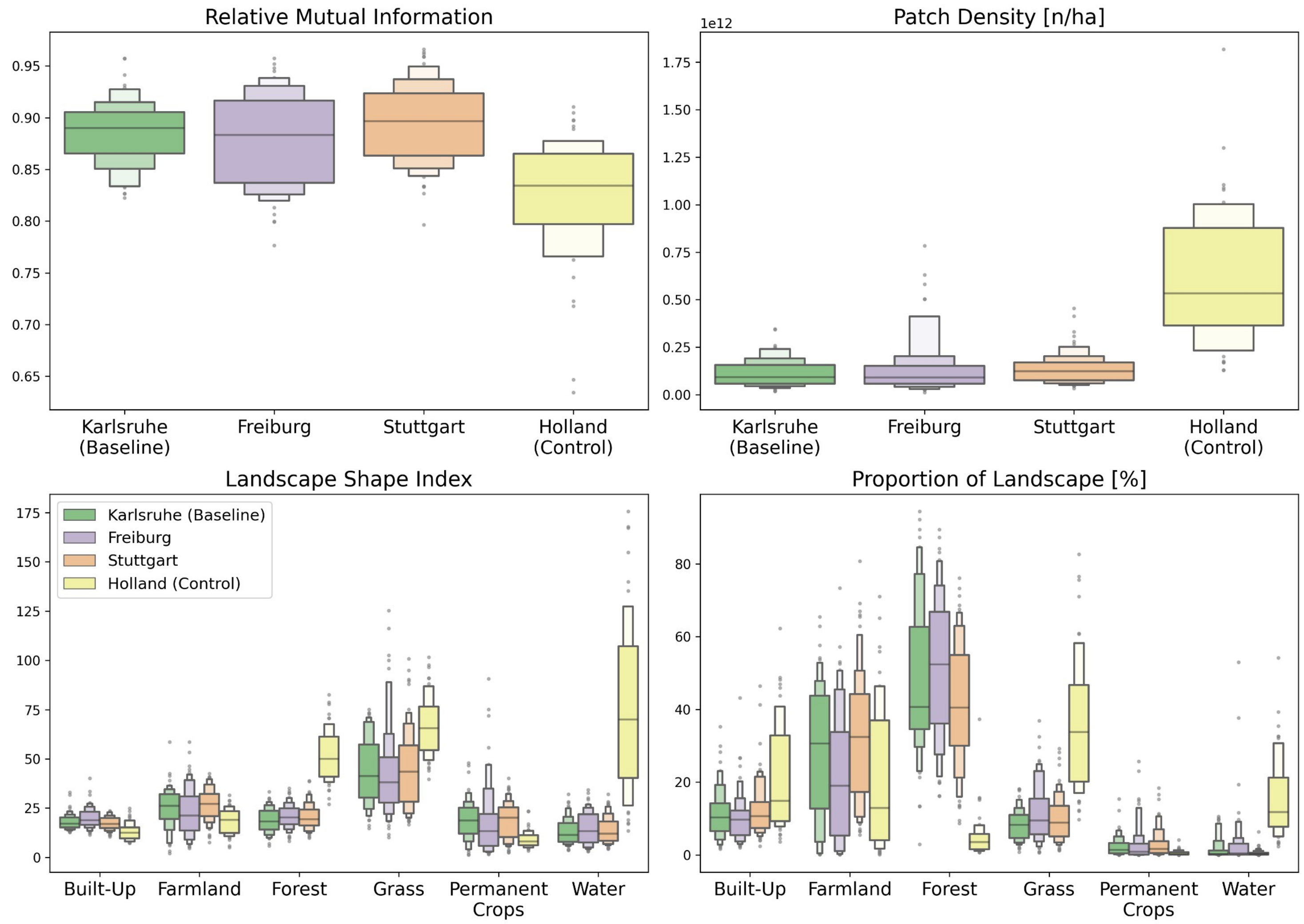
Turner 1989, Wiens et al. (1993), Walz (2004), Walz (2012)

but also more recent works like
Gevaert/Belgiu (2022), Woodman et al. (2025),
Van Duynhoven et al. (2026)

Metrics		Equation	Description	Parameter Explanation
Class level	PLAND	$\left(\sum_{j=1}^{n} a_{ij}/A\right) \times 100$	Porportion of the patch type	a_{ij}—the area of patch ij; A—total landscape area; e_{ik}—total length (m) of edge in landscape between patch types (classes) i and k; g_{ii}—number of adjacent patches of the same landscape type i; p_{ij}—perimeter of patch ij in terms of number of cell surfaces; Z—total number of cells in the landscape.
	LPI	$\left[\max\left(a_{ij}\right)/A\right] \times 100$	Porportion of the largest patch type	
	LSI	$0.25 \sum_{j=1}^{n} e_{ik}/\sqrt{A}$	Shape complexity degree of the patch type	
	AI	$\left[\frac{g_{ii}}{max \to g_{ii}}\right] \times 100$	Aggregation degree of the patch type	
	COHESION	$\left\{1 - \left[\sum_{i=1}^{m}\sum_{k=1}^{m} p_{ij} / \sum_{i=1}^{m}\sum_{k=1}^{m}\left(p_{ij} \times \sqrt{a_{ij}}\right)\right]\right\} \times \left(1 - 1/\sqrt{Z}\right)^{-1} \times 100$	Natural connectivity degree between patches	
Landscape level	SHDI	$-\sum_{i=1}^{n}\left[p_i \times ln(p_i)\right]$	Diversity indicator of all patch types	p_i—proportion of the landscape occupied by patch type (class) i; m—number of patch types (classes) present in the landscape, excluding the landscape border if present; N—number of patches in the landscape of patch type (class) i; A—total landscape area.
	SHEI	$-\sum_{i=1}^{n}\left[p_i \times \ln(p_i)\right]/ln(m)$	Even distribution indicator of all patch types	
	PD	N/A	Number of patches per unit area	
	CONTAG	$\left\{1 + \left[\sum_{i=1}^{m}\sum_{k=1}^{m}\left(p_i \times \frac{g_{ik}}{\sum_{j=1}^{n} g_{ij}}\right) \times ln\left(p_i \times g_{ik}/\sum_{j=1}^{n} g_{ij}\right)\right]/\left[2ln(m)\right]\right\} \times 100$	Aggregation degree of all patch types	

Zhang et al. (2022)

Quantification of Landscape Similarity



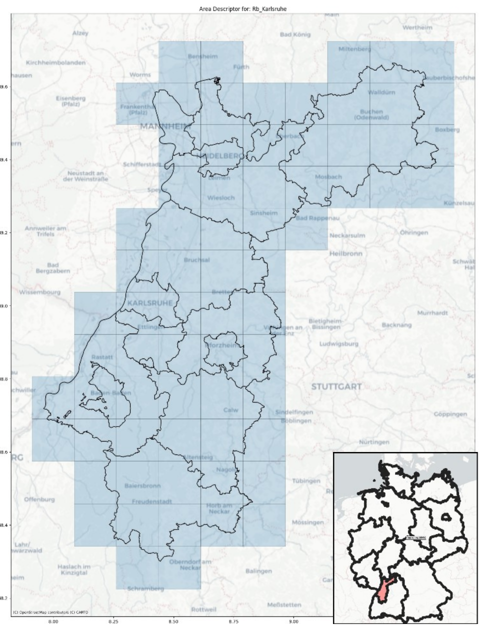
(Dis-)Similarity to the county of Karlsruhe was quantified by averaging difference scores across all LSM

Area of Interest	JS	KL	WS	KS
County of Freiburg	0.1	0.74	9.94e+08	0.21
County of Stuttgart	0.08	1.37	4.29e+08	0.14
Holland (Control)	0.38	5.81	8.92e+09	0.59

Used difference scores:

- *Jensen–Shannon Divergence (JS)*
- *Kullback–Leibler Divergence (KL)*
- *Wasserstein Distance (WS)*
- *Kolmogorov–Smirnov Test (KS)*

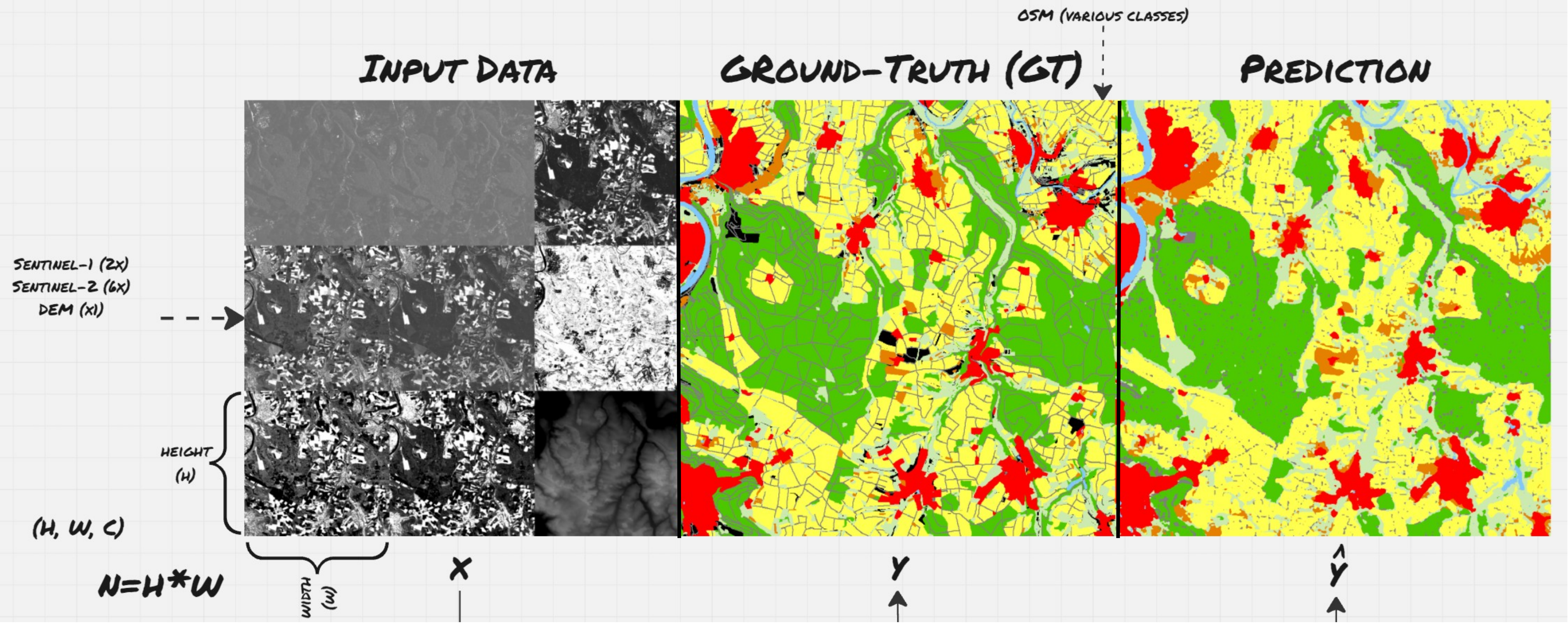
Kolaxidis et al. 2026;
Sertel et al. 2018;
Niesterowicz/Stepinski 2016



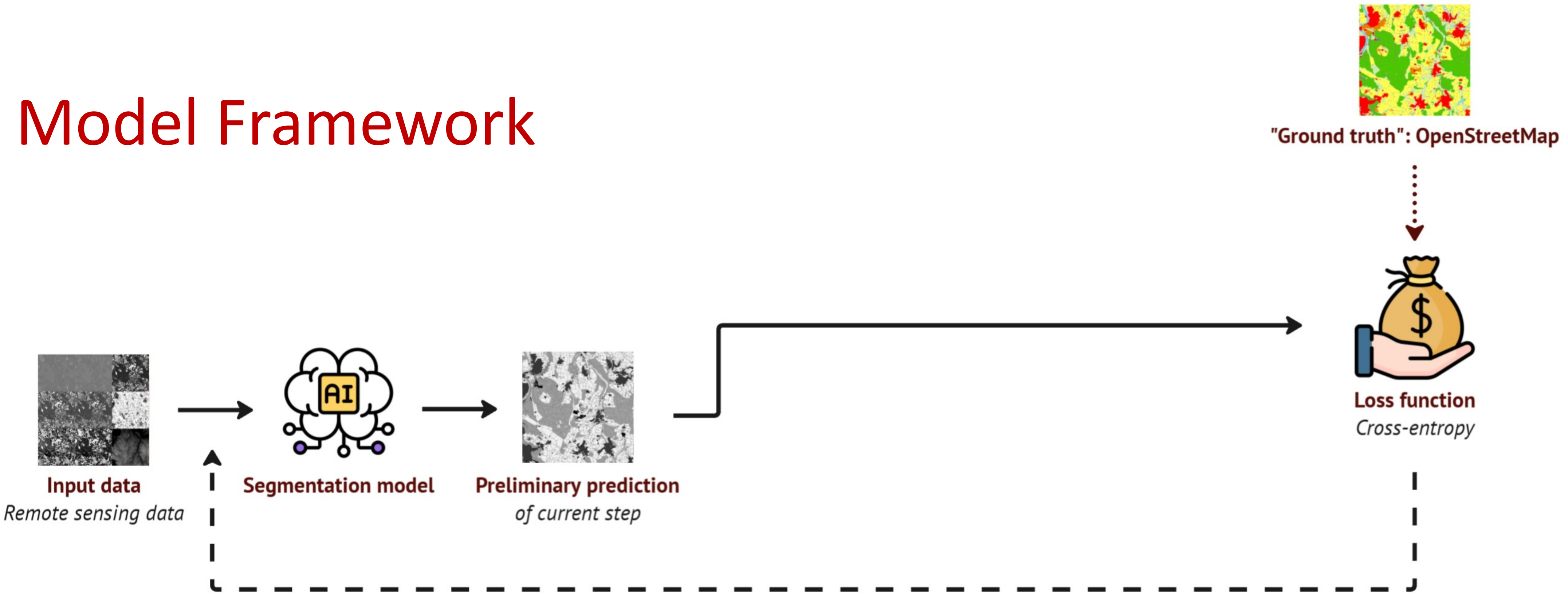
Research Question:

How can we “guide” the model with this information?

Map Landscapes with SegFormer (Xie et al. 2021)

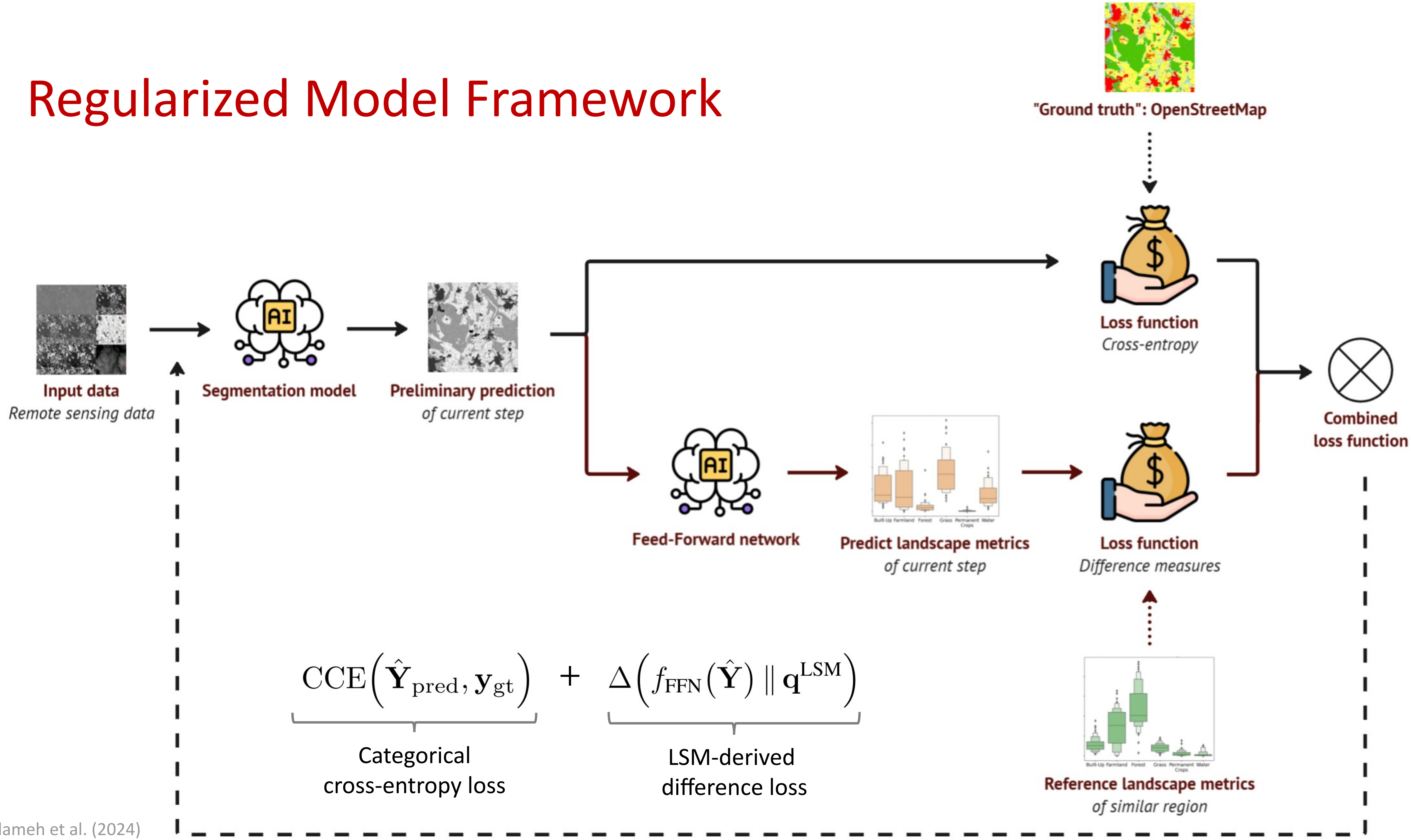


Model Framework



$$\underbrace{\mathrm{CCE}\left(\hat{\mathbf{Y}}_{\mathrm{pred}}, \mathbf{y}_{\mathrm{gt}}\right)}_{\substack{\text{Categorical} \\ \text{cross-entropy loss}}}$$

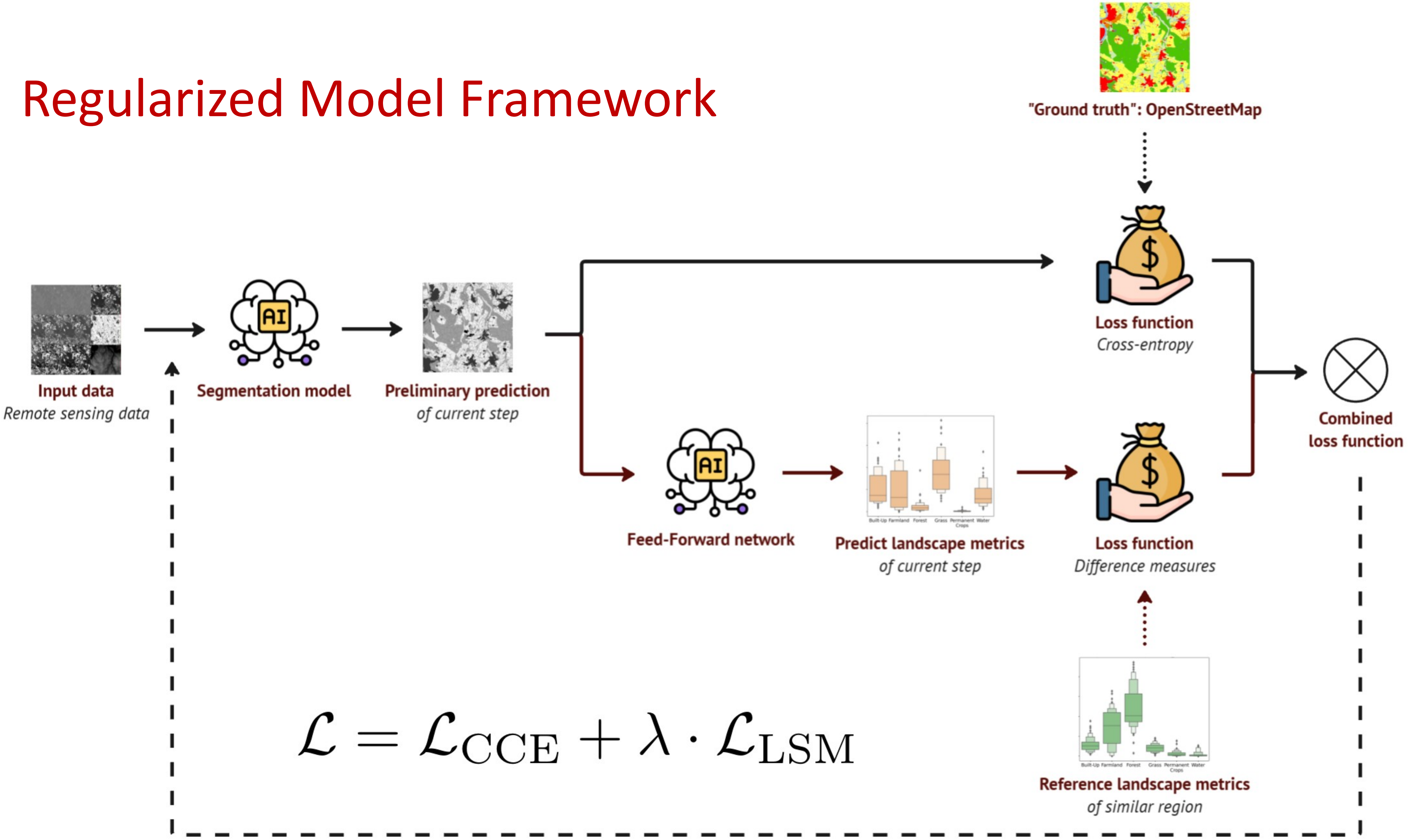
Regularized Model Framework



$$\underbrace{\mathrm{CCE}\left(\hat{\mathbf{Y}}_{\mathrm{pred}}, \mathbf{y}_{\mathrm{gt}}\right)}_{\text{Categorical cross-entropy loss}} + \underbrace{\Delta\left(f_{\mathrm{FFN}}(\hat{\mathbf{Y}}) \,\|\, \mathbf{q}^{\mathrm{LSM}}\right)}_{\text{LSM-derived difference loss}}$$

Dialameh et al. (2024)

Regularized Model Framework



$$\mathcal{L} = \mathcal{L}_{\mathrm{CCE}} + \lambda \cdot \mathcal{L}_{\mathrm{LSM}}$$

Experiments so far

Prior statistical & feature importance analysis

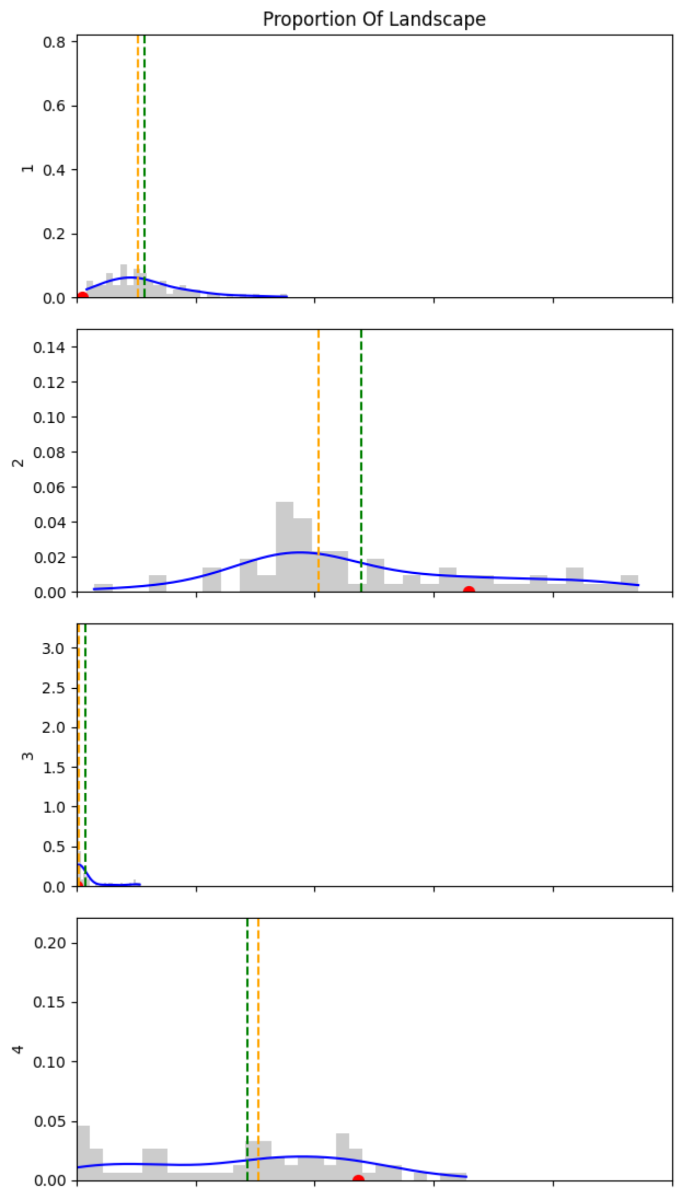
- Selection of 5 **most important landscape metrics**
  (Edge Density, Core Area Index, Landscape Shape Index, Patch Density, Core Area Proportion of Landscape)
- Selection of 3 **AOIs** in south-western Germany and Holland as Control

Generation of reference data

1. Class-wise **average** values with tensor **broadcasting** (MSE)
2. **Random-weighted-sampling** from kernel density estimates (KDE; MSE)
3. Using the KDE with **distributional difference** measures (JS/KL divergence)

Multiple experiments per reference set

- **Weighted regularization** term weighted via λ of 0.1, 0.25, 0.5 and 1.0
- Comparison of experiments to **baseline without regression head**



Initial results

- All experiments **converged**
- Performance **similar or reduced**; differences between LULC classes
- Large **variations** in runtime
- Using **full distributions best** approach

→ Some regularization signals were **beneficial** for training.

→ The framework needs **more optimization.**

So, what does that mean?

We can use knowledge not only as input,
but as contextual data for **guidance and restriction**,
integrated **directly into training process.**

→ **Transfer** information **across regions** already **during training**,
not only during inference.

→ However, more experiments and **optimization** needed.
(alternative reference creation strategies, spatial scale sensitivity of LSM distributions, area up-scaling ...)

Take-Home Messages

There are **other ways to integrate information** into DL models.

Prior **statistical analysis and optimization** still very important.

Look **outside of your domain**, there is a lot to discover and repurpose for your own work.

Always check your coordinate reference system! :)

Thank you all for your attention!

Project GeoWiKI

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