EnviLink

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Modeling Vegetation Indicators in Urban Areas using Sentinel-2 and High Resolution Reference Data based on Neural Networks

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Structure

1. Introduction

2. High Resolution Reference Data

3. Sentinel-2 Modelling

4. Outlook & Next Steps

Introduction

Introduction

Urban Green Eye

<u>Project Partners:</u> **Luftbild Umwelt Planung GmbH**, Potsdam
City Leipzig, Amt für Stadtgrün und Gewässer
TU Berlin, Institut für Ökologie

<u>Duration:</u> 01/2022 to 12/2025

<u>Cities involved:</u> Gütersloh, Hamburg, Stuttgart, Potsdam, Duisburg, Augsburg, Würzburg, Essen, …

<u>Funded:</u> Bundesministerium für Digitales und Verkehr (BMDV)

Introduction

Urban Green Eye

Germany wide indicators for cities to monitor climate adaptaion management

Thermal Load

- Landsurface Temperature
- Albedo
- Shading

Thermal Relief

- **Green Volume**
- Tree Cover Density
- Tree Vitality
- Soil cooling Potential

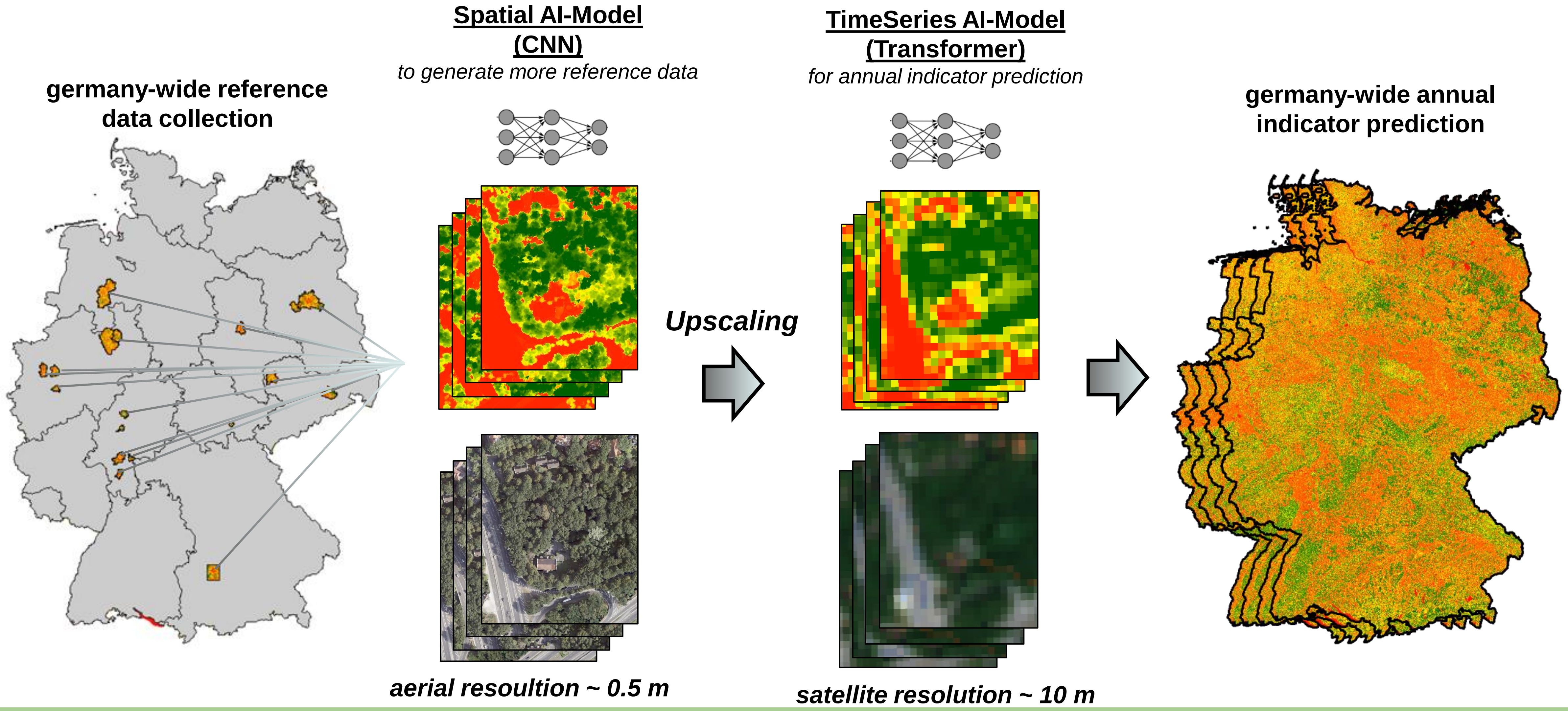
Hydrological Relief

- Sealed Areas

What data should we use to model the green volume?

	Sentinel-2	Aerial Image (+ Height)
		
Temporal Resolution	**~ 3-5 days**	~ 2-3 years
Spatial Resolution	up to 10 m	**up to 0.2 m**
OpenData & Nationwide Coverage	**Yes**	Partially

Introduction



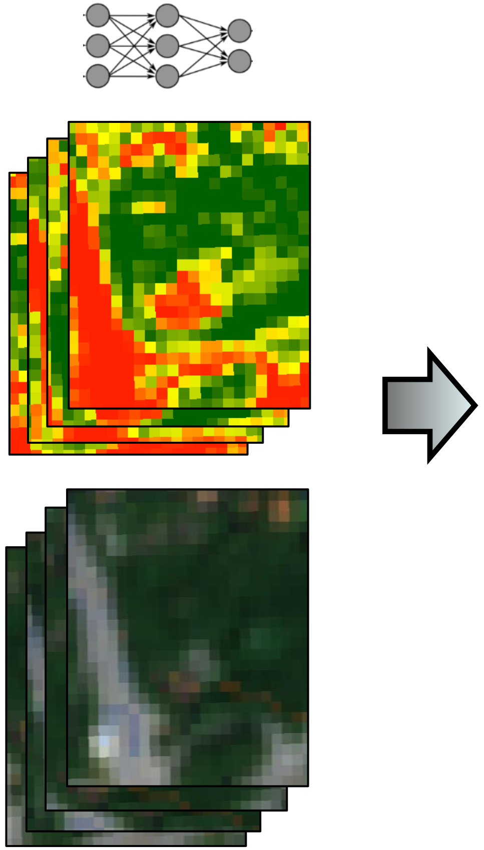
Introduction

How does the model perform on:

- Independent areas?
- Independent years?

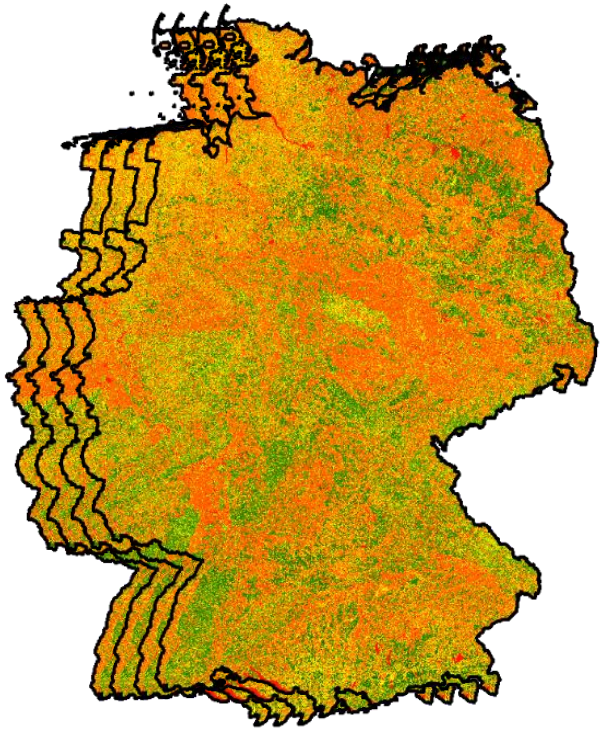
<u>TimeSeries AI-Model (Transformer)</u>

for annual indicator prediction



satellite resolution ~ 10 m

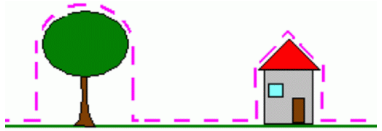
germany-wide annual indicator prediction



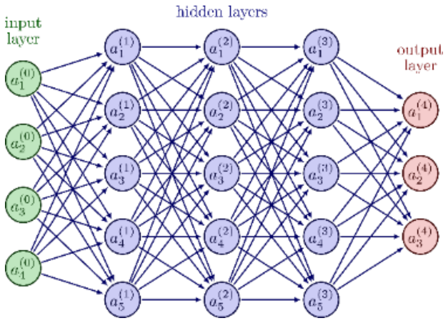
High Resolution Reference Data

High Resolution Reference Data

RGB(I) Orthofoto



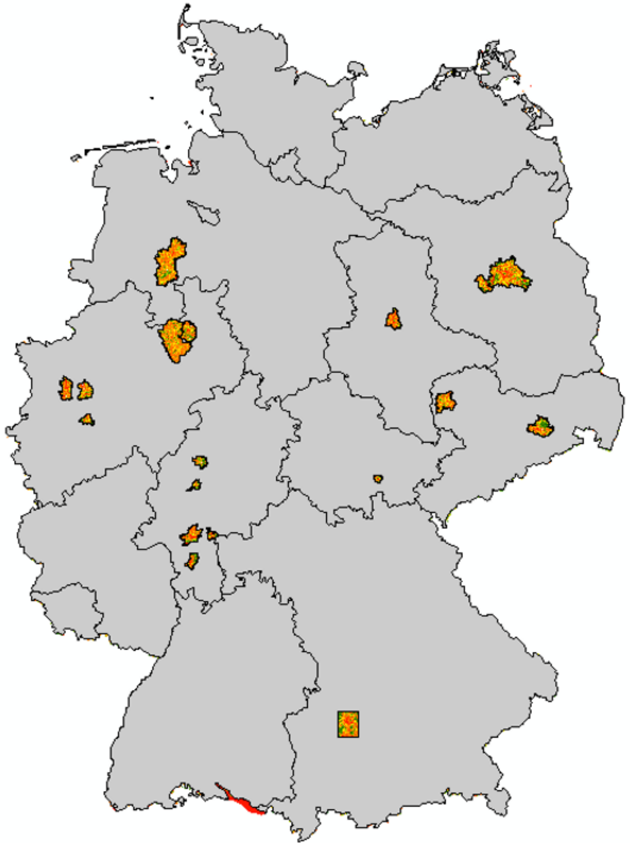
Normalized Digital Surface Model



Vegetation Height Map

High Resolution Reference Data

Reference Areas



Year	City
2018	Duisburg
	Essen
	Leipzig
	Saalfeld
	Solingen
2019	Bielefeld
	Magdeburg
2020	Berlin
	Dresden
	Giessen
	Guetersloh
	Marburg
	Vechta
2021	Darmstadt
	Frankfurt
	Hanau
2022	Augsburg
	Duisburg
	Essen
	Potsdam

Rule based Vegetation Height

UNet based Vegetation Height

UNet Reference Data

High Resolution Reference Data

Reference Areas

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	Potsdam

Rule based Vegetation Height
UNet based Vegetation Height
UNet Reference Data

1000 visually interpreted points per city for:

- No Vegetation
- Grassland (0.5 m)
- Agriculture (1 m)
- Vegetation

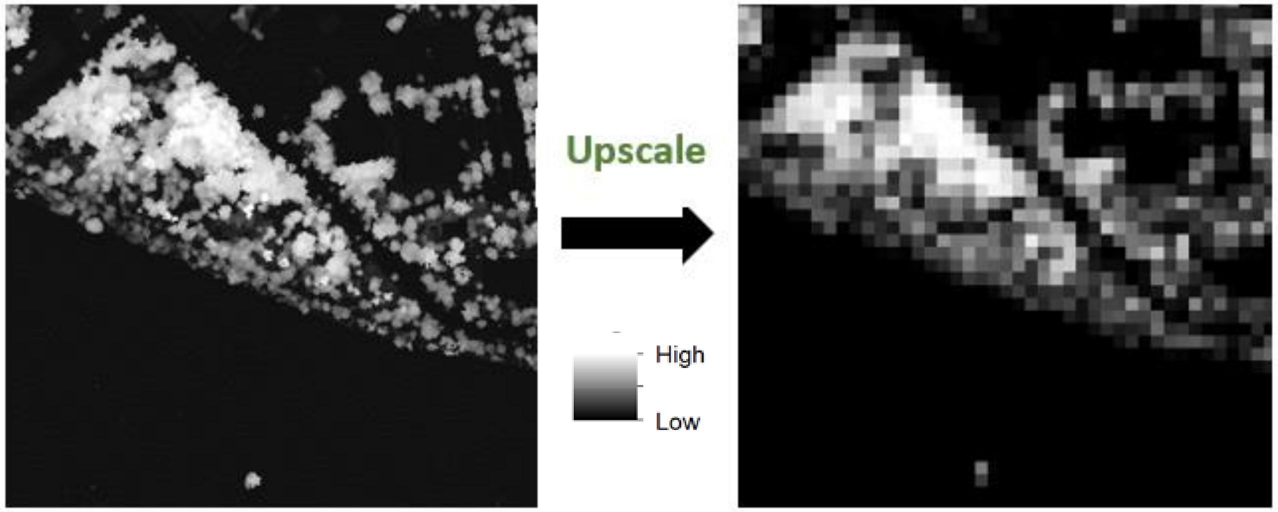
Year	No Vegetation		Grassland		Agriculture		Vegetation	
	Median	Std	Median	Std	Median	Std	RMSE	R^2
2018	0.00	1.11	0.50	1.29	1.00	0.29	1.18	0.98
2019	0.00	0.48	0.50	1.00	1.00	0.10	0.87	0.99
2020	0.01	1.20	0.50	0.78	0.82	0.36	0.96	0.99
2021	0.01	1.56	0.55	1.25	0.81	0.36	0.36	1.00
2022	0.01	0.37	0.50	0.83	0.90	0.48	1.09	0.98

High Resolution Reference Data

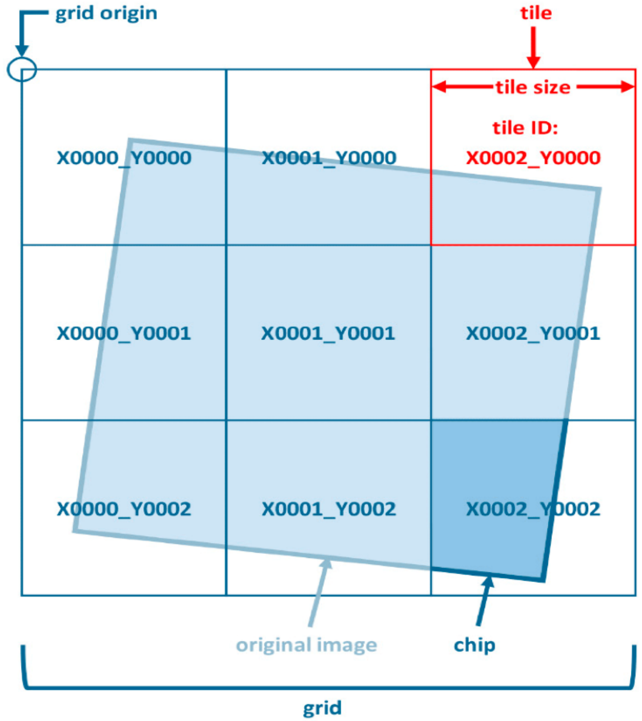
Upscaling High Resolution Reference to Sentinel-2 FORCE Extend

Vegetation Height (0.5 m)

Green Volume (10 m)



FORCE
Framework for Operational Radiometric Correction for Environmental Monitoring



Frantz, David (2019): FORCE—Landsat + Sentinel-2 Analysis Ready Data and Beyond, https://doi.org/10.3390/rs11091124

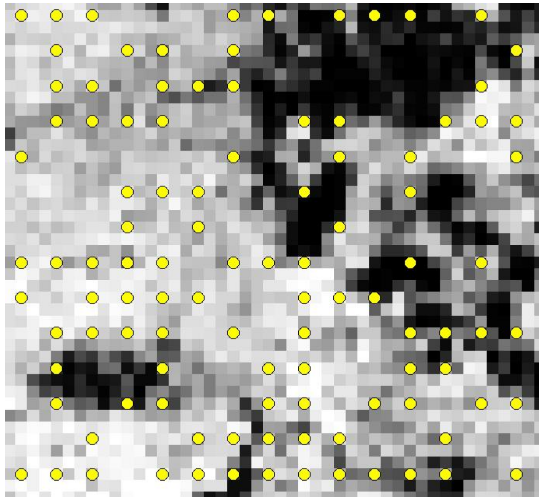
Sentinel-2 Modelling

Sentinel-2 Modelling

1. **Stratified** sample points to learn from equally distributed response variables
2. Sampled reference data with **30 m distance** to minimize spatial autocorrelation
3. **Temporally equalized** sample points to minimize temporal autocorrelation

Year	City	Reference	Equalized Reference	
2018	Duisburg	94.685	41.475	185.562
	Essen	88.885	41.475	
	Leipzig	118.793	41.475	
	Saalfeld	21.344	21.344	
	Solingen	39.792	39.792	
2019	Bielefeld	113.912	113.912	185.562
	Magdeburg	71.650	71.650	
2020	Berlin	395.104	30.727	185.562
	Dresden	138.801	30.727	
	Giessen	31.926	31.926	
	Guetersloh	321.601	30.727	
	Marburg	54.595	30.727	
	Vechta	291.567	30.727	
2021	Darmstadt	54.256	54.256	185.562
	Frankfurt	108.833	97.338	
	Hanau	33.968	33.968	
2022	Augsburg	242.502	46.391	185.562
	Duisburg	94.685	41.475	
	Essen	93.488	46.391	
	Potsdam	82.552	46.391	
Absolut		2.497.167	927.810	

Berlin (Upscaled GV)



Berlin (DOP)

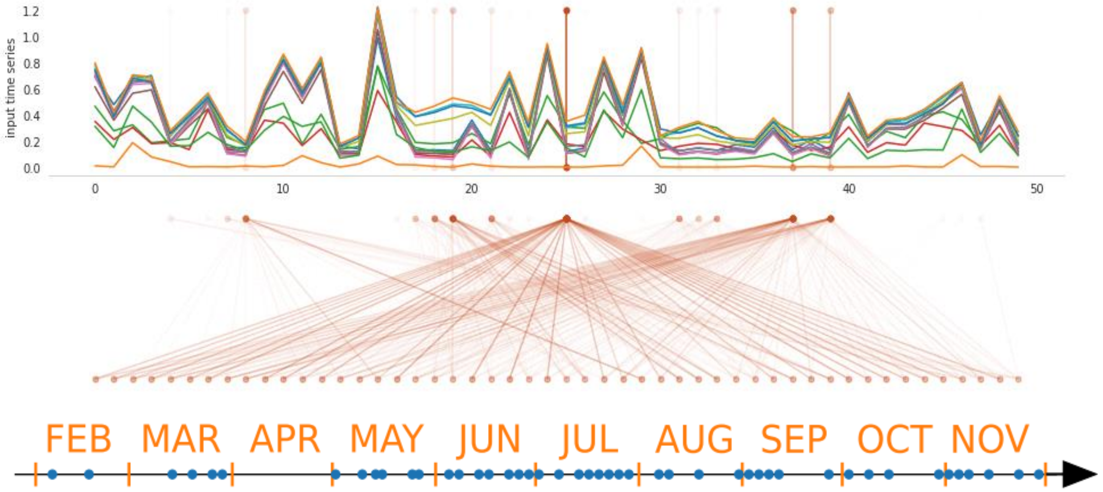
Equalized Reference

Reference

Sentinel-2 Modelling

Model & Features:

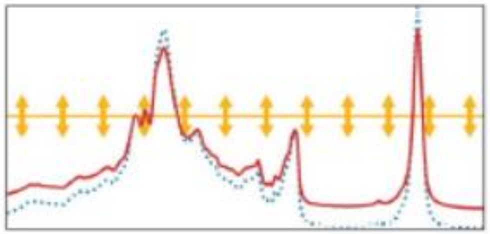
- **3 Years Time Series**
  10 Sentinel-2 Bands, QAI masked
- **Transformer Encoder Architecture**
  Irregular TimeSeries Classification
- **Hyperparameter Tuning**
  Model Parameters (Batch Size, Attention Head, …)

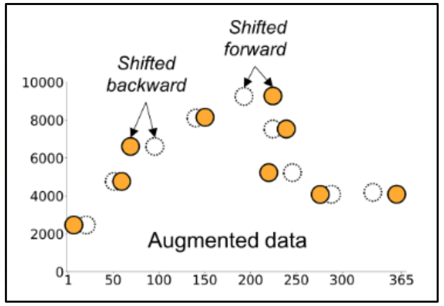


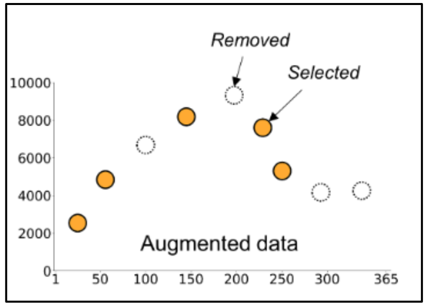
Regularizations:

- **Positional Encoding[1]**
  Periodically (1-12 Month) & Continous (1-1095 Days)
- **Time Series Augmentation[2,3]**
  Day Shifting & Annual Scaling & Zero Out

Scaling







[1]Tseng, G., Cartuyvels, R., Zvonkov, I., Purohit, M., Rolnick, D., & Kerner, H. (2023). Lightweight, pre-trained transformers for remote sensing timeseries. *arXiv preprint arXiv:2304.14065*.
[2]Pham, V. D., Tetteh, G., Thiel, F., Erasmi, S., Schwieder, M., Frantz, D., & van der Linden, S. (2024). Temporally transferable crop mapping with temporal encoding and deep learning augmentations. *International Journal of Applied Earth Observation and Geoinformation*, *129*, 103867.
[3]Iwana, B. K., & Uchida, S. (2021). An empirical survey of data augmentation for time series classification with neural networks. Plos one, 16(7), e0254841.

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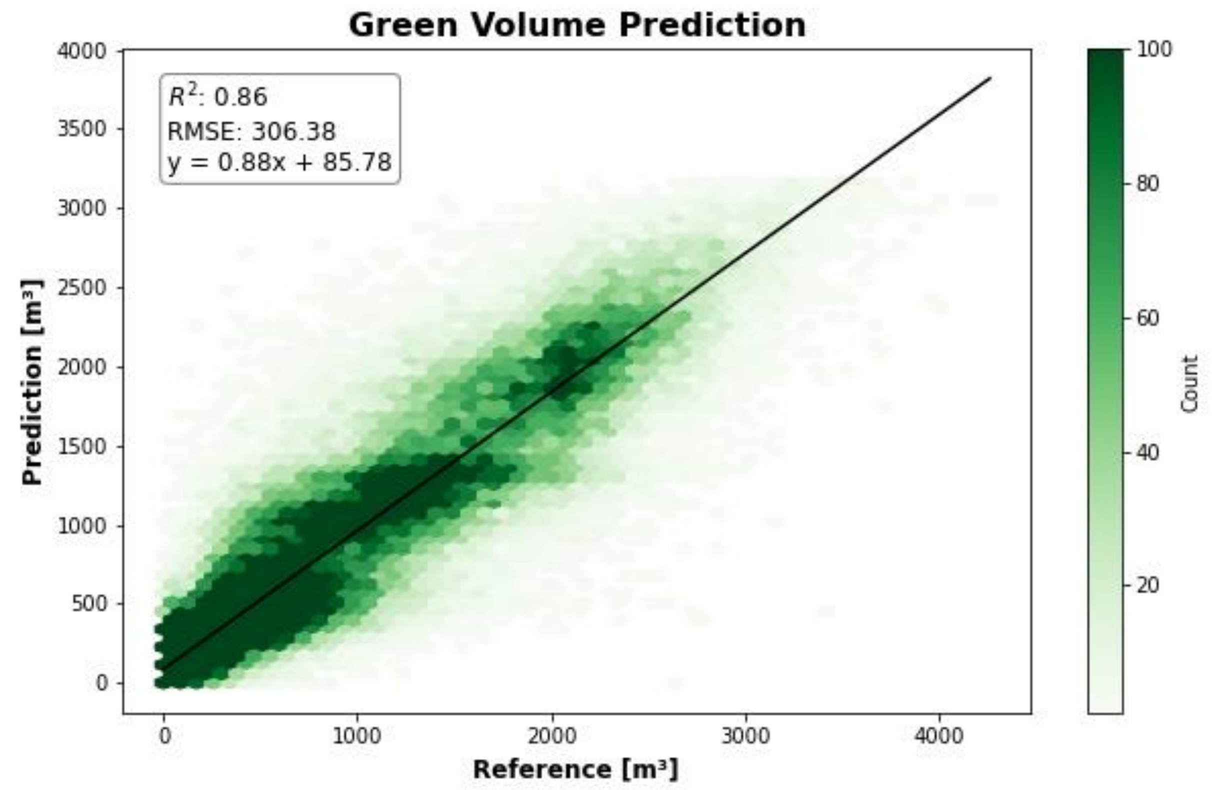

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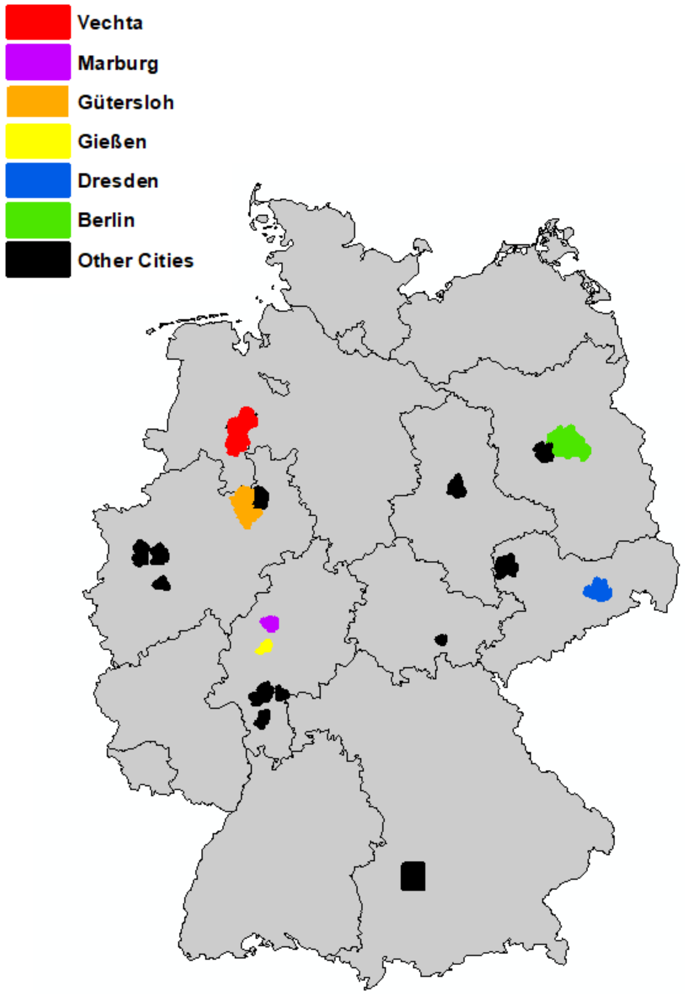

How does the model perform on spatial independent areas?

- Keep temporal bias at a minimum (comparing within 2020)
- Hold back predicting city & train with all other cities

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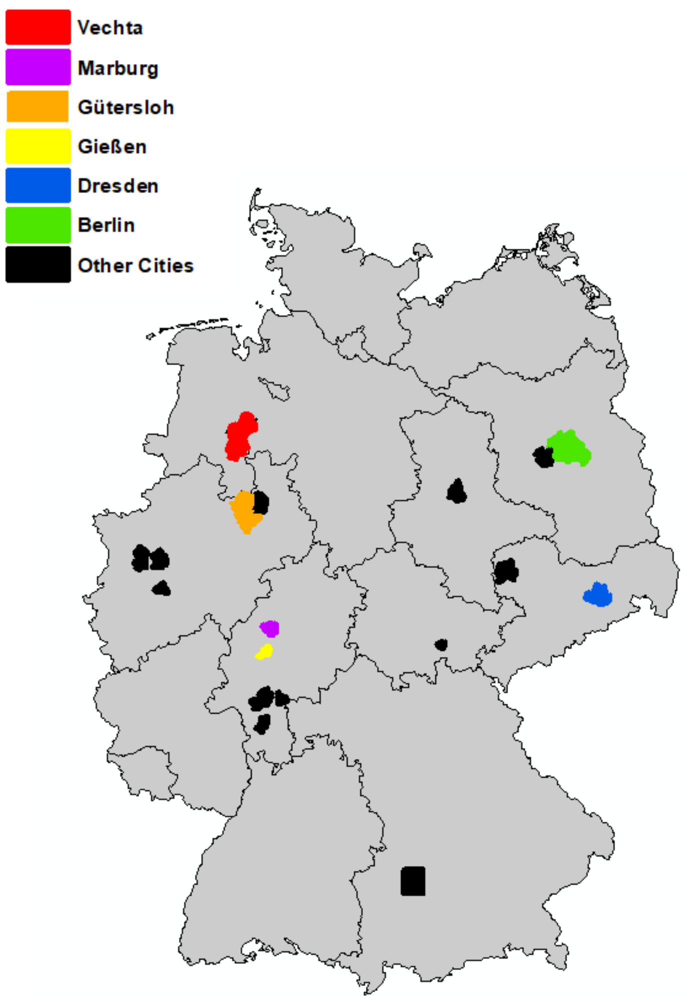
Training

Predicting

Sentinel-2 Modelling



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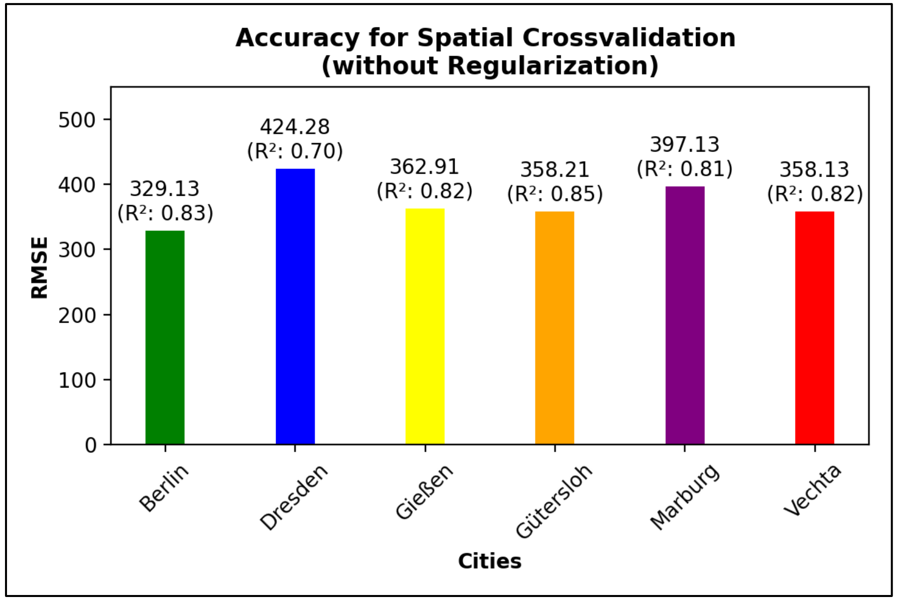

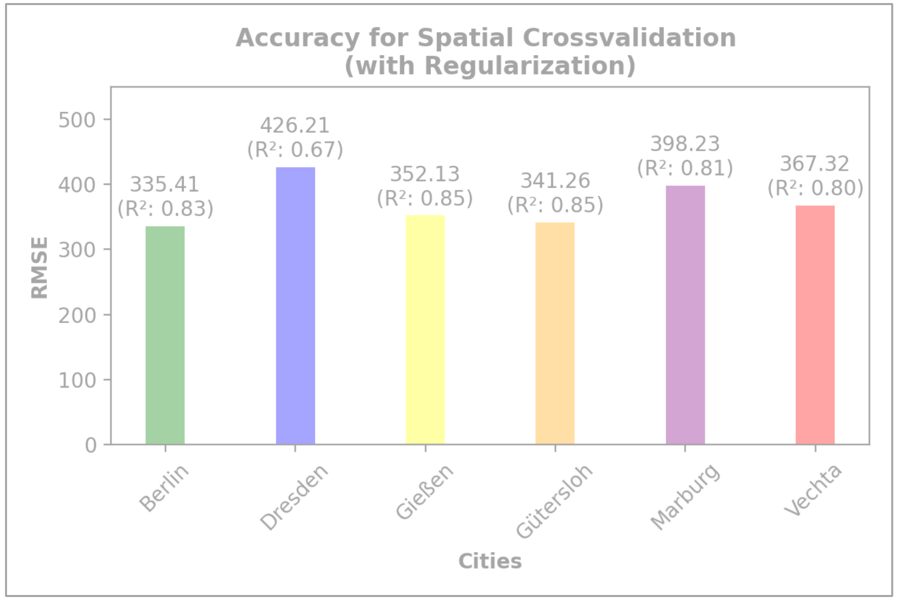

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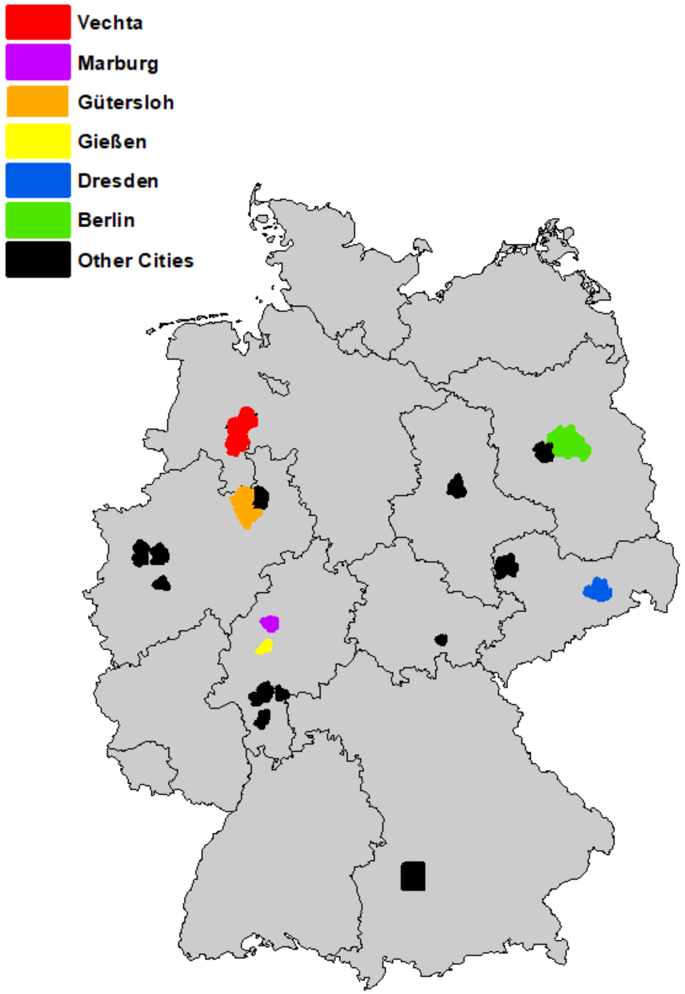

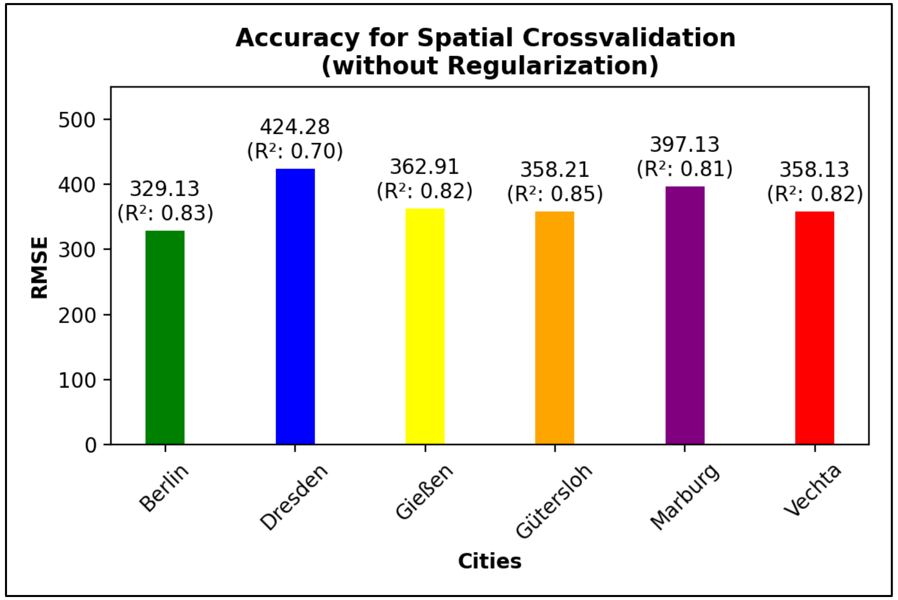

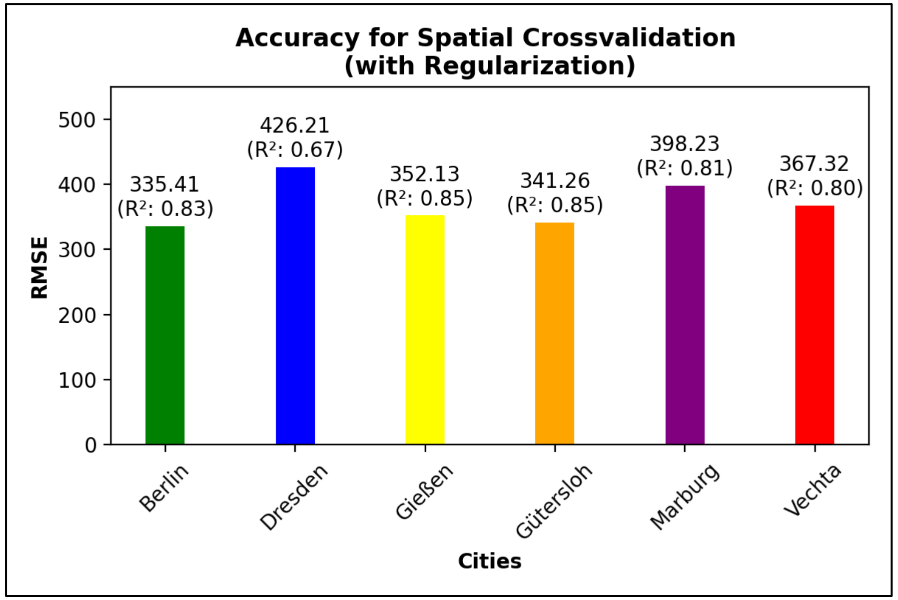

Sentinel-2 Modelling

How does the model perform on independent years?

- Fixed spatial domain
- 100 invariant points in leipzig per class
- Hold back predicting year & train with all other years

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	Potsdam
Absolut	

LUFTBILD UMWELT PLANUNG

Sentinel-2 Modelling

Without Regularization

With Regularization

How does the model perform on independent years?

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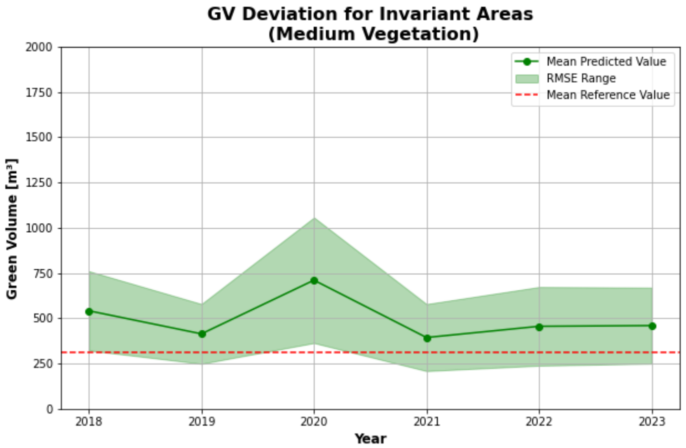

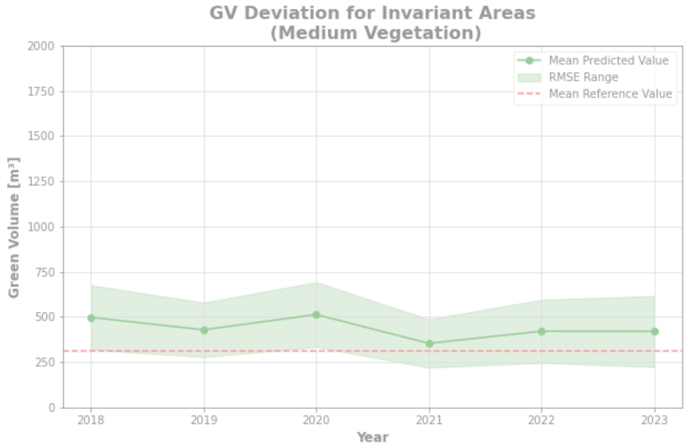

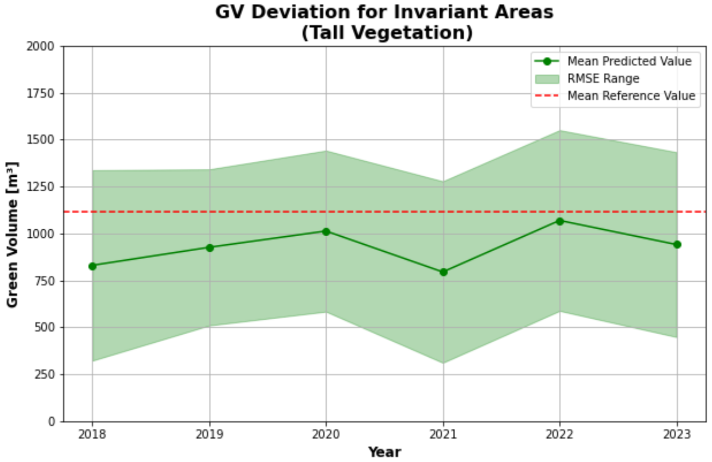

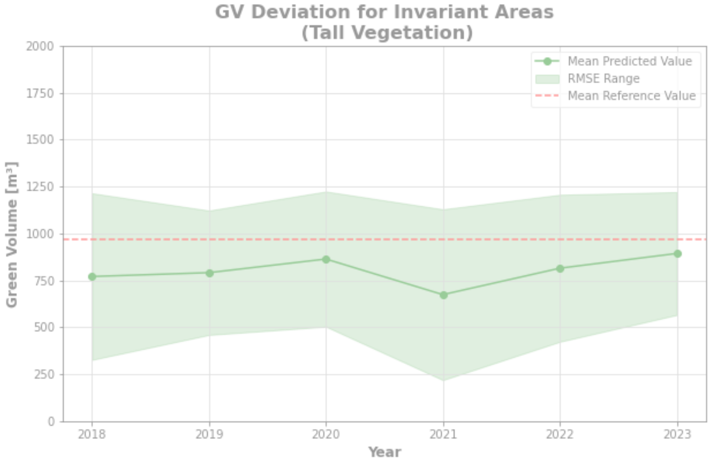

Sentinel-2 Modelling

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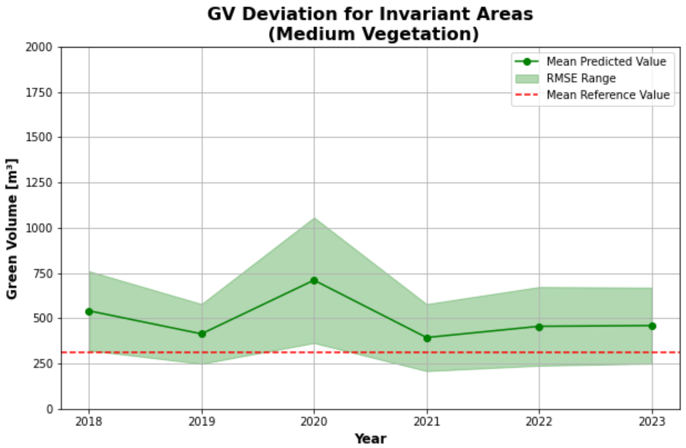
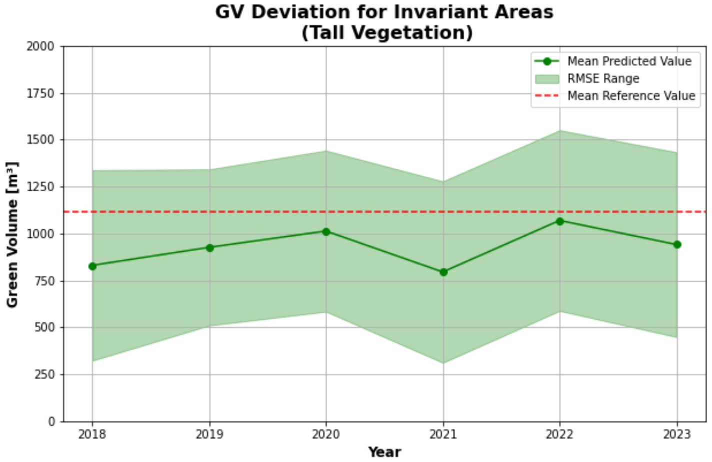
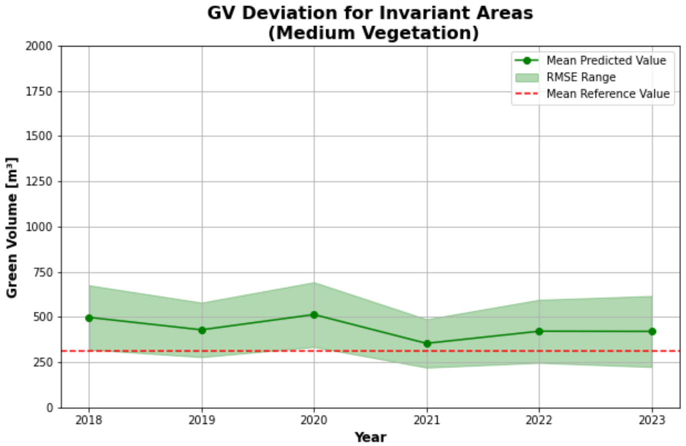
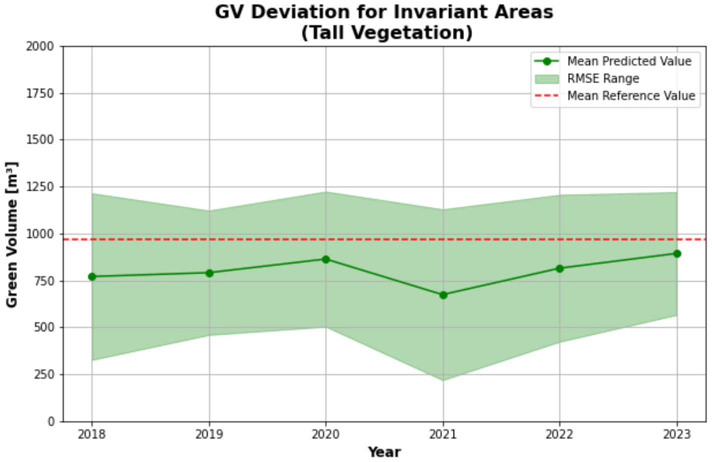
Without Regularization





With Regularization





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RMSE with Regularization (and Change in RMSE)

Year	Street	Building	Grassland	Cropland	Medium Vegetation	Tall Vegetation
2018	20.37 (-11.61)	19.79 (-7.26)	34.46 (-43.44)	51.12 (-9.39)	177.66 (-41.14)	443.59 (-63.47)
2019	31.62 (+12.79)	14.53 (+1.29)	40.65 (-0.38)	35.35 (+1.70)	150.63 (-14.37)	331.15 (-84.50)
2020	15.15 (-34.76)	11.06 (-14.60)	27.84 (-21.82)	42.63 (+5.70)	179.05 (-167.45)	359.87 (-68.88)
2021	17.99 (-19.23)	17.83 (-17.73)	23.40 (+1.24)	36.16 (+4.71)	133.65 (-51.18)	454.76 (-28.37)
2022	3.63 (-10.33)	14.97 (-5.93)	43.30 (+1.44)	86.54 (+2.36)	174.23 (-42.93)	391.26(-89.80)
2023	22.67 (+20.34)	24.96 (+20.92)	36.24 (-11.22)	51.20 (-47.08)	196.21 (-13.75)	327.18 (-164.85)

Outlook & Next Steps

Outlook & Next Steps

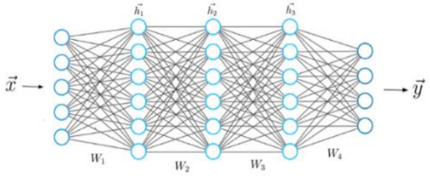
Improvements

- **Satellite Image Foundation Models**
  - Privthi[1]
  - Presto[2]

- **Coordinate encoding for better spatial generalization[2]**

- **Thermal postional encoding for better generalization[3]**

Foundation Modell

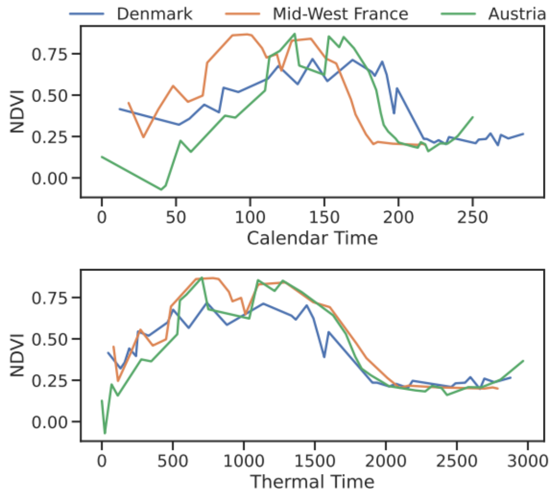


Fine Tuning

Adjustment

Data, Prompts, Reinforcement Learning, …

Thermal Postional Encoding



[1]Jakubik, J., Roy, S., Phillips, C. E., Fraccaro, P., Godwin, D., Zadrozny, B., ... & Ramachandran, R. (2023). Foundation models for generalist geospatial artificial intelligence. *arXiv preprint arXiv:2310.18660*.

[2]Tseng, G., Cartuyvels, R., Zvonkov, I., Purohit, M., Rolnick, D., & Kerner, H. (2023). Lightweight, pre-trained transformers for remote sensing timeseries. *arXiv preprint arXiv:2304.14065*.

[3]Nyborg, J., Pelletier, C., & Assent, I. (2022). Generalized classification of satellite image time series with thermal positional encoding. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 1392-1402).

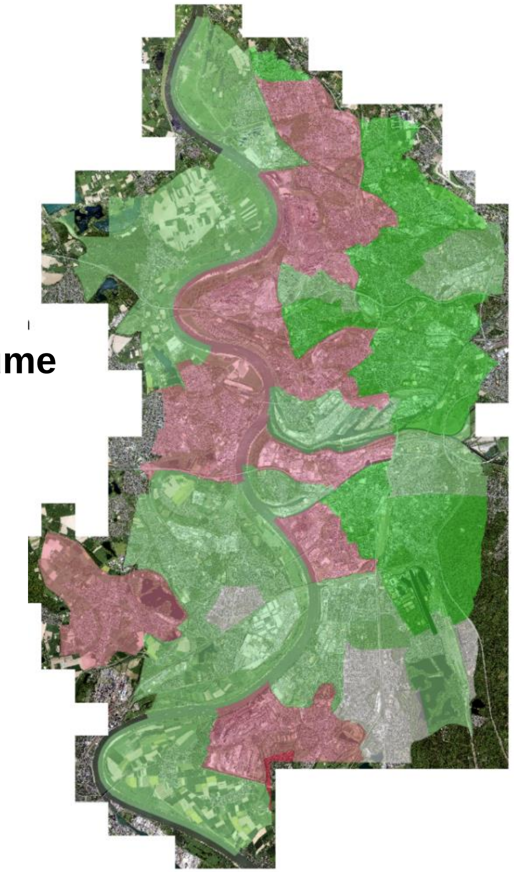
Outlook & Next Steps

Further Analysis

- **Analysis for tree cover density**
- **How does pixel heterogenity influence the model?**
- **Accuracy for aggregated results**
- **Combining indicators and socio-demographic data**

Change in Green Volume (2018 to 2022)

- -5 % bis -1,25 %
- -1,25 % bis -0,1%
- - 0,1% bis 0,1%
- 0,1% bis 1,25%
- 1,25% bis 5%



Thank You!

We fully support Open Science

Data:
- Coming Soon -

Code:
https://github.com/LUP-LuftbildUmweltPlanung/UNet
https://github.com/LUP-LuftbildUmweltPlanung/SITS_classification

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