GSR4B

Biomass Map Super-Resolution with Sentinel-1/2 Guidance

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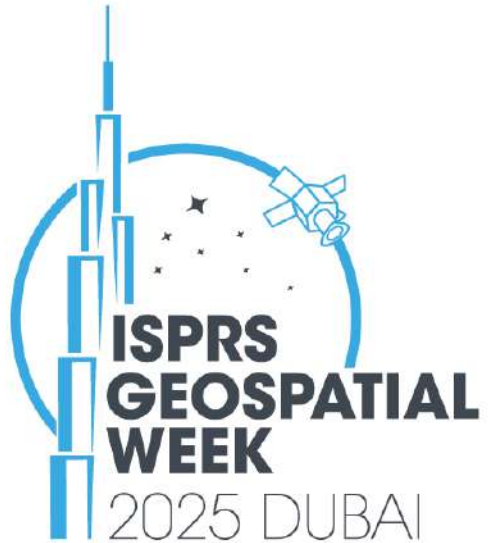
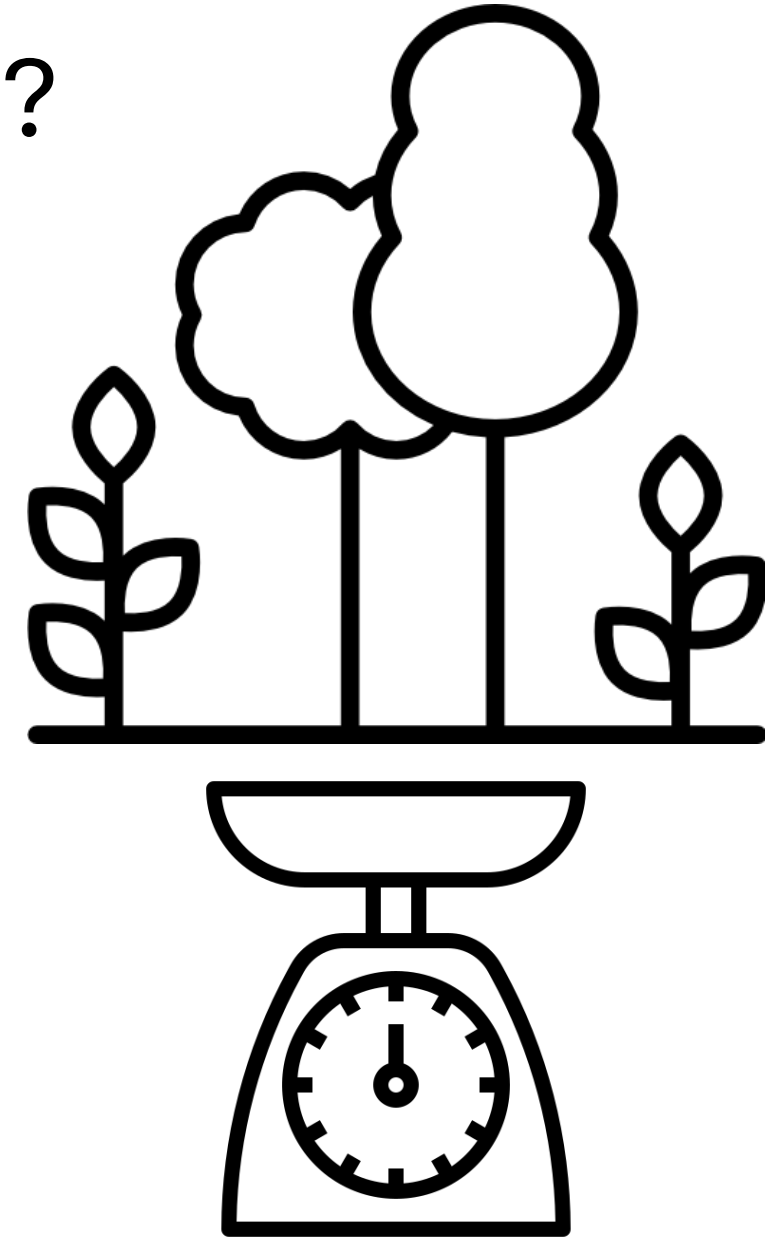


What is Above-Ground Biomass?



Definition of AGB:

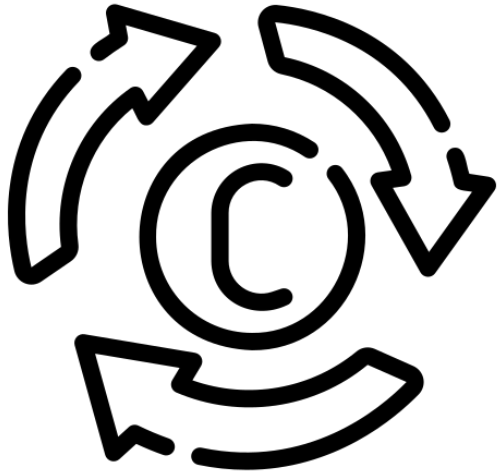
Total carbon amount (in Mg) per area (in ha)

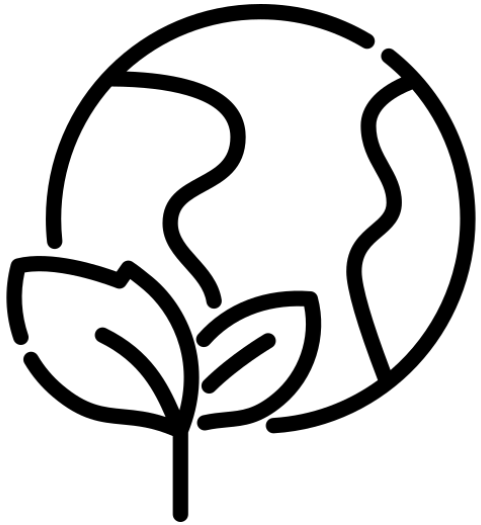
that exists on the ground.

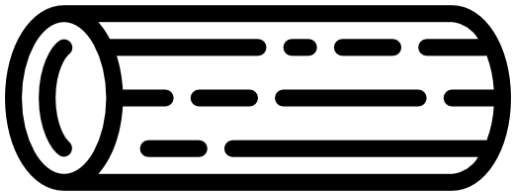
Why do we need biomass?

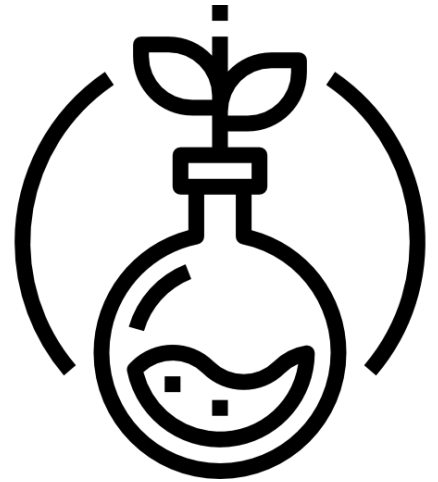
Applications:

- Monitoring Carbon Cycle / Climate Modeling
- Sustainable Supply Chain
- Timber Industry
- Better Understanding Ecology







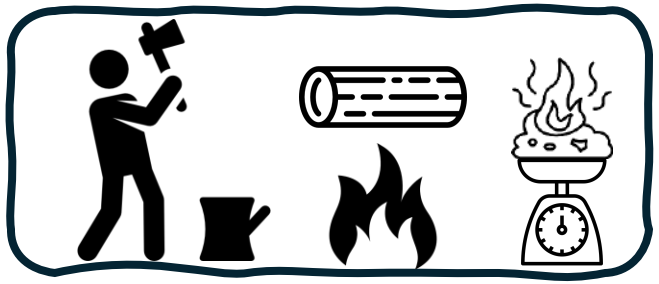


Ideal biomass product:

- Having **high-resolution** & **global** biomass map.

How do we measure/estimate biomass?

In-Situ Methods:

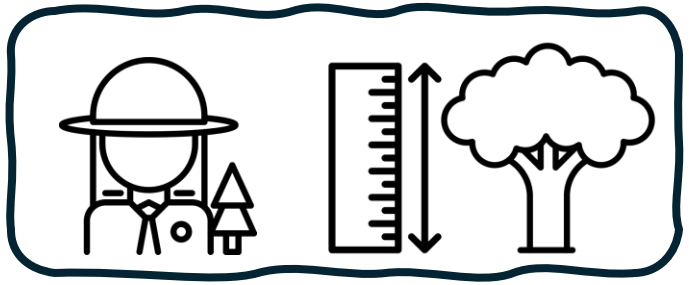


Accuracy:

Cost:

Scalability:

1. Destructive Measurements



Accuracy:

Cost:

Scalability:

2. Using Allometric Equation

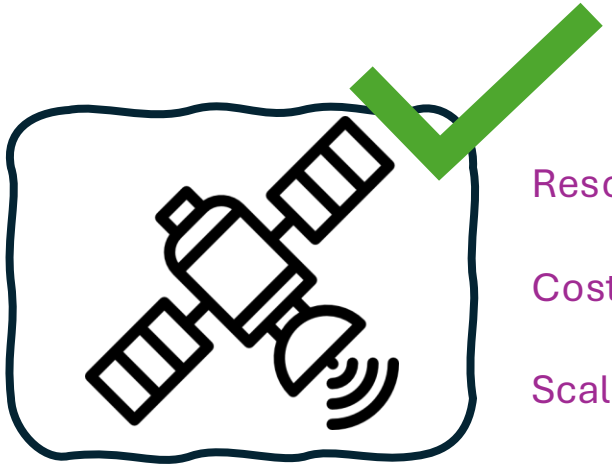
Remote Sensing:

Resolution:

Cost:

Scalability:

3. Airborne Platforms



Resolution:

Cost:

Scalability:

4. Spaceborne Platforms

Our Goal: Mapping Biomass Globally

Potential Data:

1. **ESA Sentinel Mission:**
    - Covering the Whole Globe
    - High Spatial & Temporal Resolution (10-meter, 6 days)
2. **ESA Climate Change Initiative (CCI):**
    - Covering the Whole Globe
    - Lower Spatial & Temporal Resolution (100-meter, yearly)

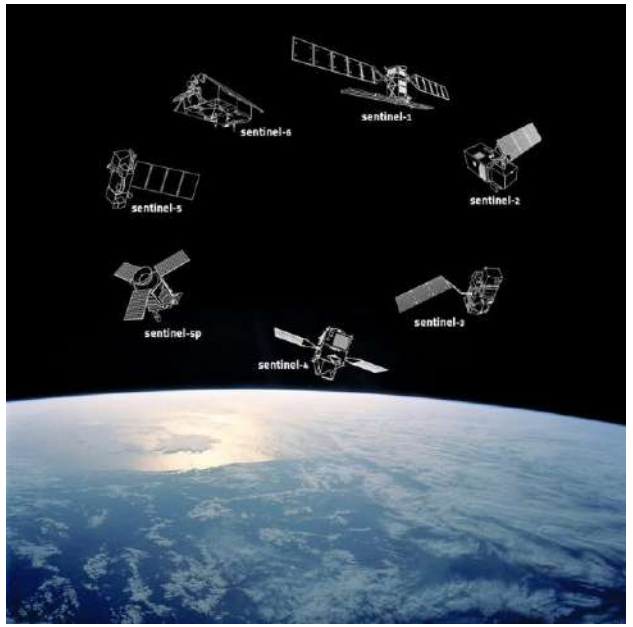


Image Source: ESA Website

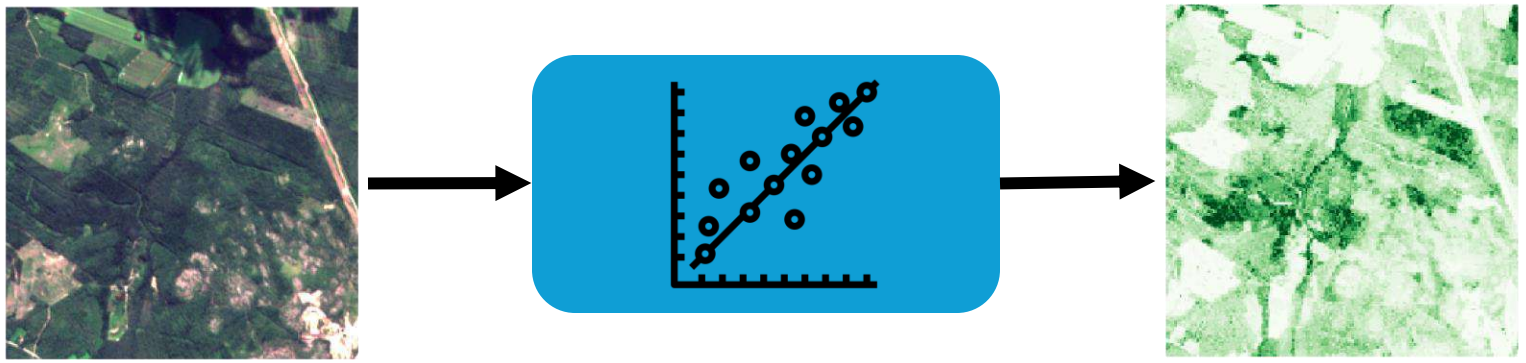
Image Source: ESA Website

Active Field of Research:

- From Sentinel-1/2 to high-resolution biomass estimation

How can we frame the problem?

1. Regression Analysis:



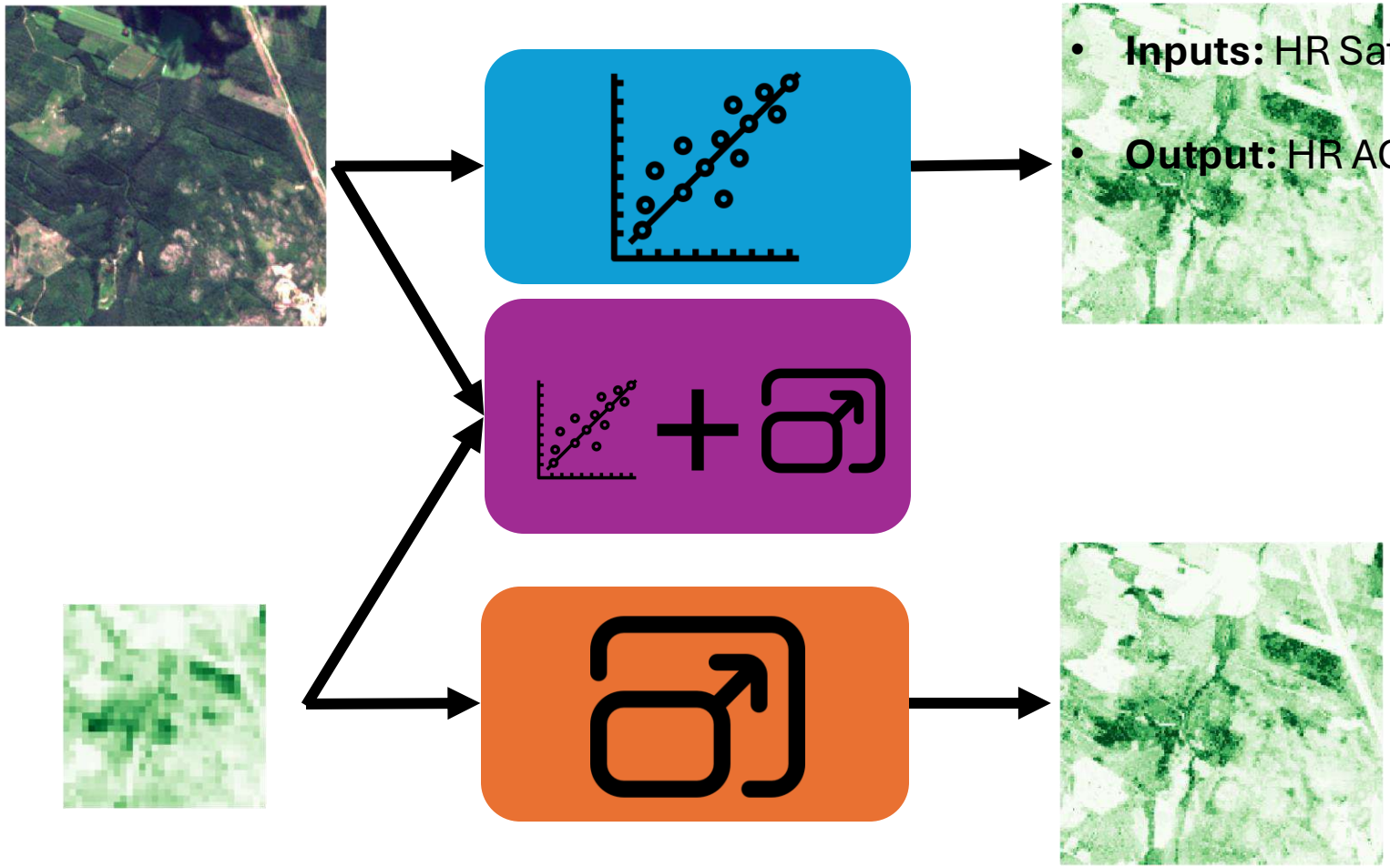
2. Super-Resolution:

Drawbacks:

- Domain Gap
- Lack of High Frequency Info

Combining the Input Information

3. Guided Super-Resolution:

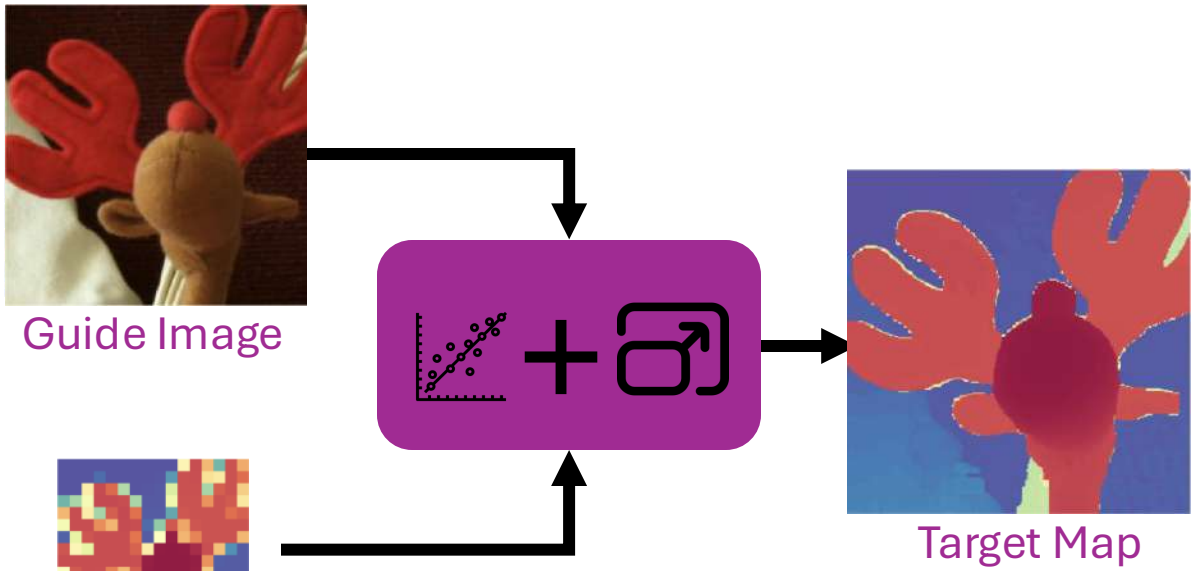


- **Inputs:** HR Satellite Images + LR AGB Maps
- **Output:** HR AGB Maps

Guided Super-Resolution in Literature

Original Setting of GSR:

- **Targeted problem:** Depth Estimation
- **Inputs:** HR RGB Image + LR Depth Map
- **Output:** HR Depth Map



Challenges:

- Texture Copying
- Over-Smoothing

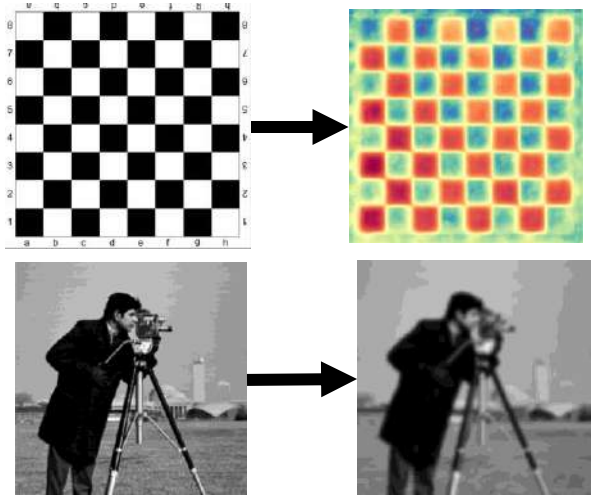
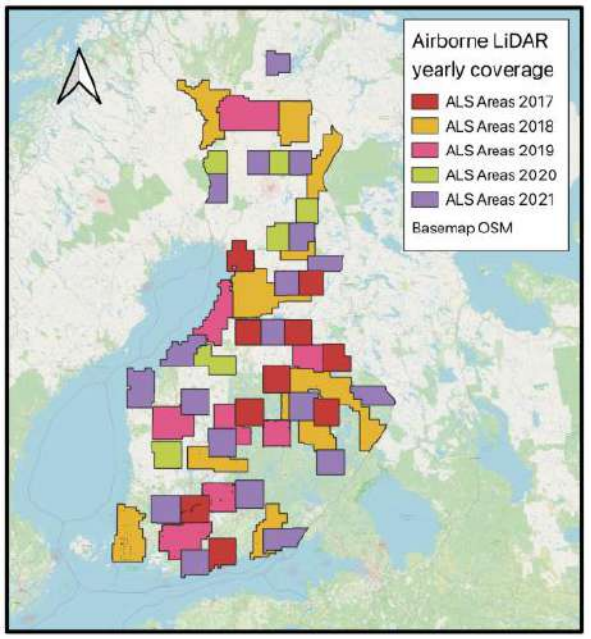


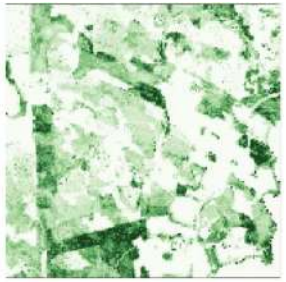
Image Sources: Mathworks, DADA

Dataset Selection: **BioMassters** (NeurIPS 23)

- A recent open-source dataset.
- Study area is Finland. 
- The inputs are **S1 & S2 images** per month.
- Target biomass maps are from **LiDAR imagery**.
- Provides high-resolution biomass maps. (10x10 meter)
- Does not provide geolocation information for each tile.



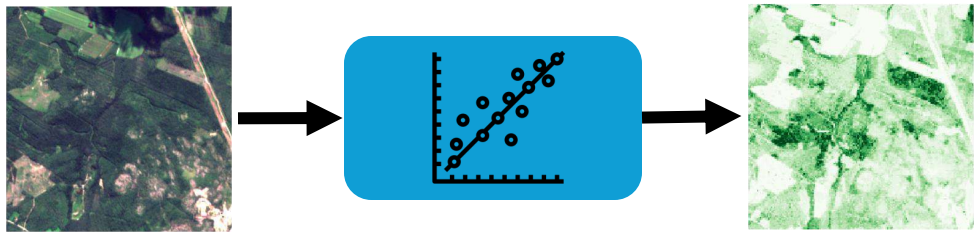
Guide Image



Target Map

Image Source: All the figures from the white paper of BioMassters.

Benchmarks for Biomass

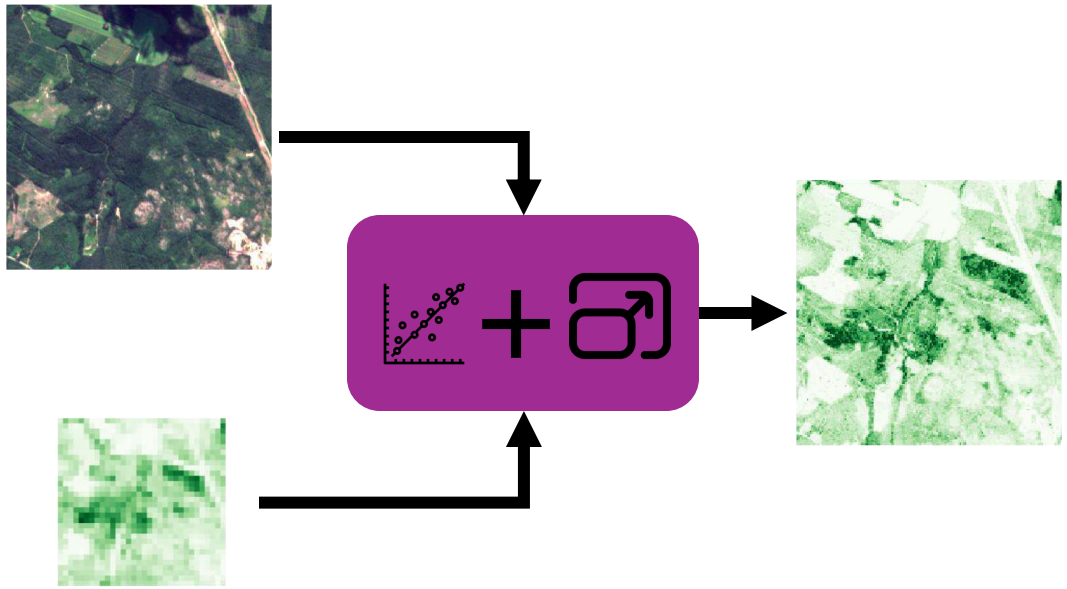


Regression Models:

- UNet
- ResNeXt

Super-Resolution Models:

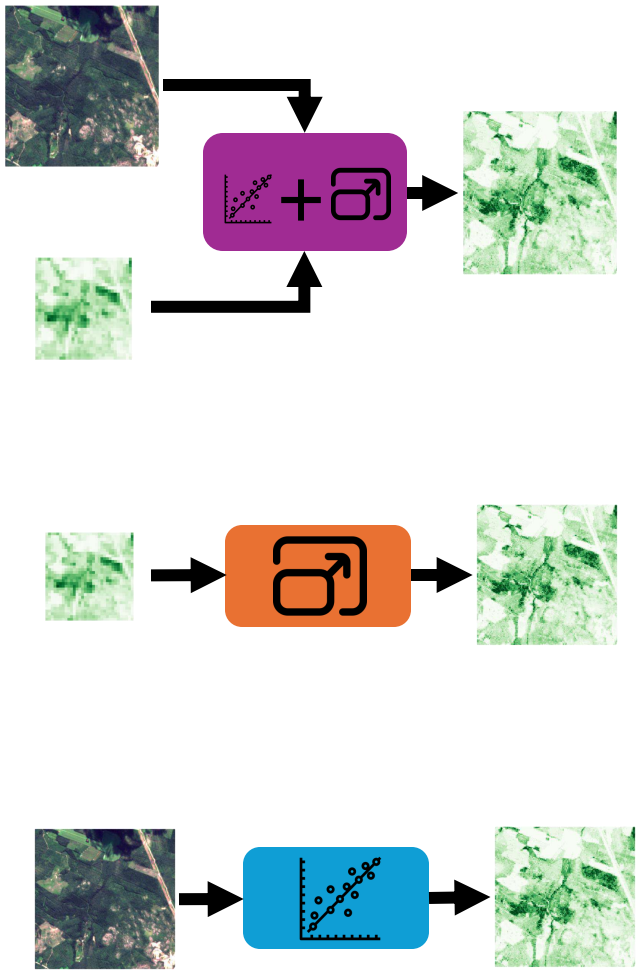
- Standard Interpolation Methods
- Deep-Learning Based Models



Guided Super-Resolution Models:

- Heuristic Models
- Basic Deep-Learning Based Models
- More Complex DL Models

Quantitative Results



	MAE↓ t/px	RMSE↓ t/px	TP↑ Mpix/s

Quantitative Results

What do we expect?

More Advanced Model ⟹ Better Performance

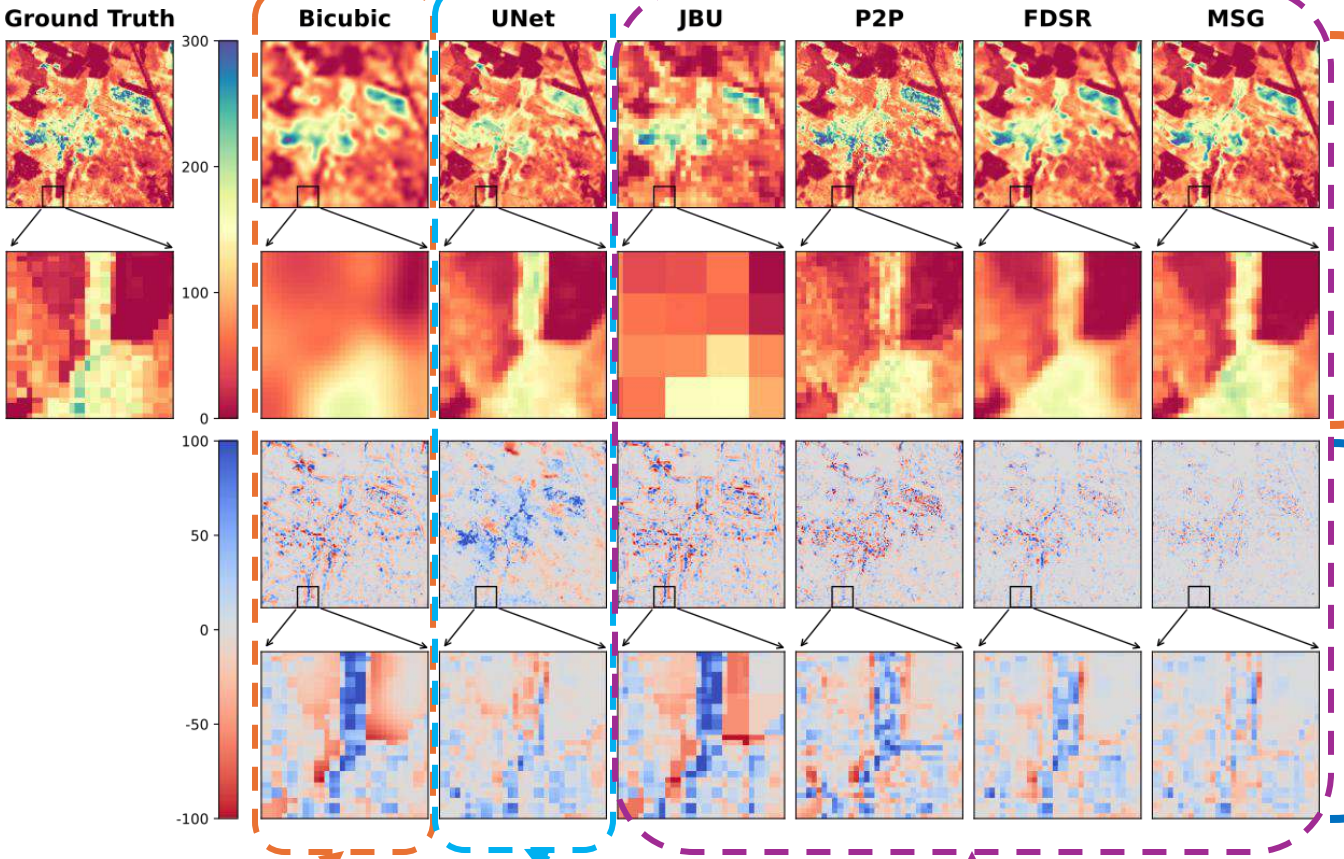
What do we have?

The simplest GSR model is the best performing approach.

Image Source: The Star

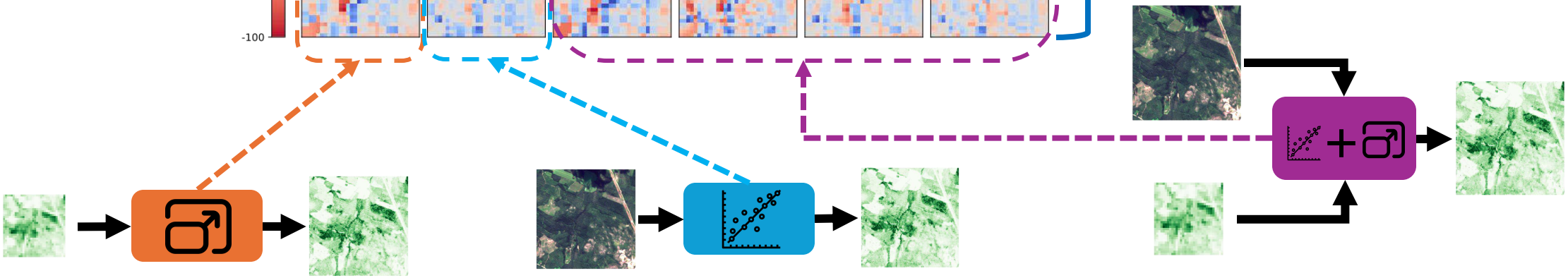
	MAE↓ t/px	RMSE↓ t/px	TP†↑ $Mpix/s$
GSR★			
Basic DL Model	**16.2**	**29.8**	53.2
Complex DL Model	18.4	33.4	240.8
Unsupervised DL Model	26.6	46.3	0.3
Heuristic Model	25.3	42.6	0.9
SR♣			
MSG^{ng}	21.5	37.8	116.8
Nearest	25.3	42.6	**262 K**
Bilinear	25.3	41.1	82 K
Bicubic	24.0	39.5	37 K
BE♠			
U-Net	21.9	37.6	19.0
ResNeXt	22.5	39.0	0.8

Qualitative Analysis

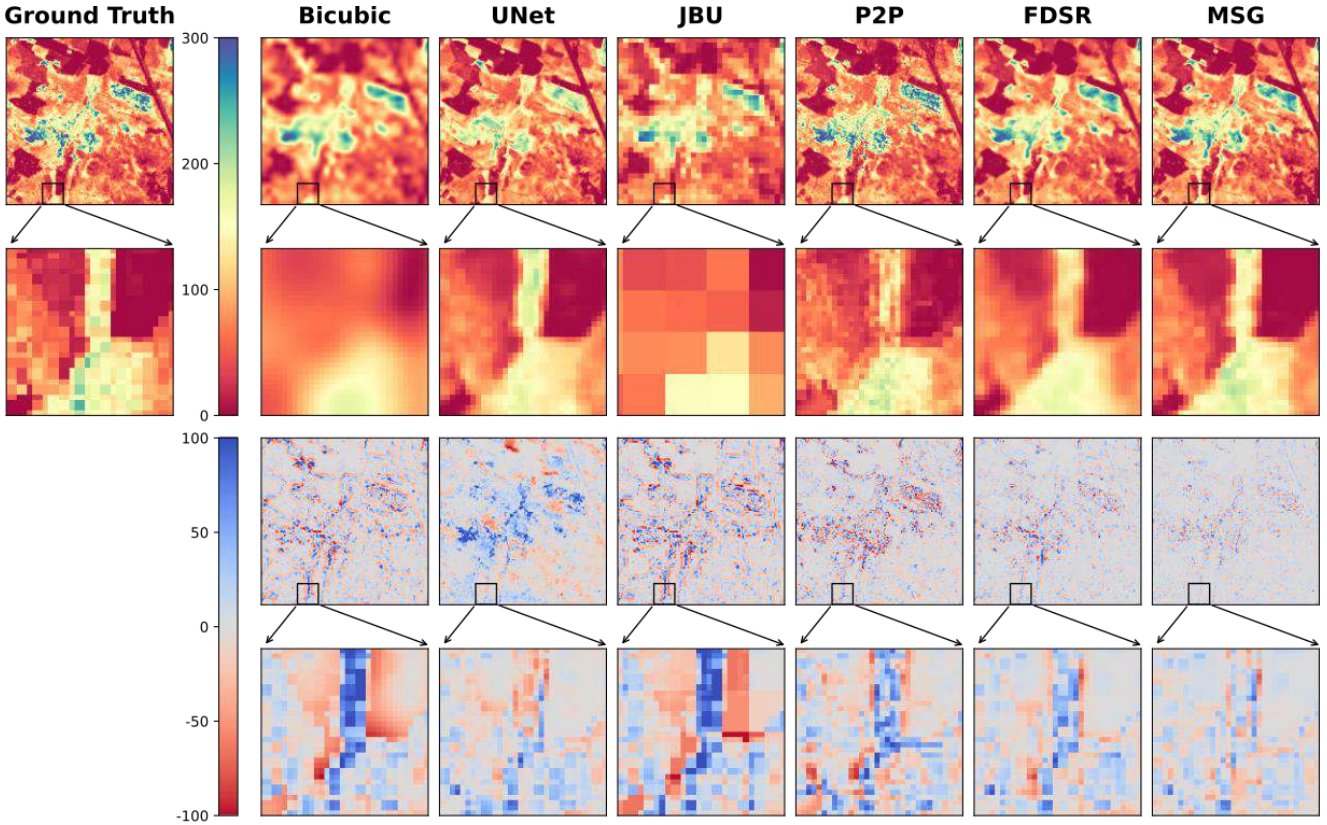


Predictions of the models

Difference Map (Target – Pred)



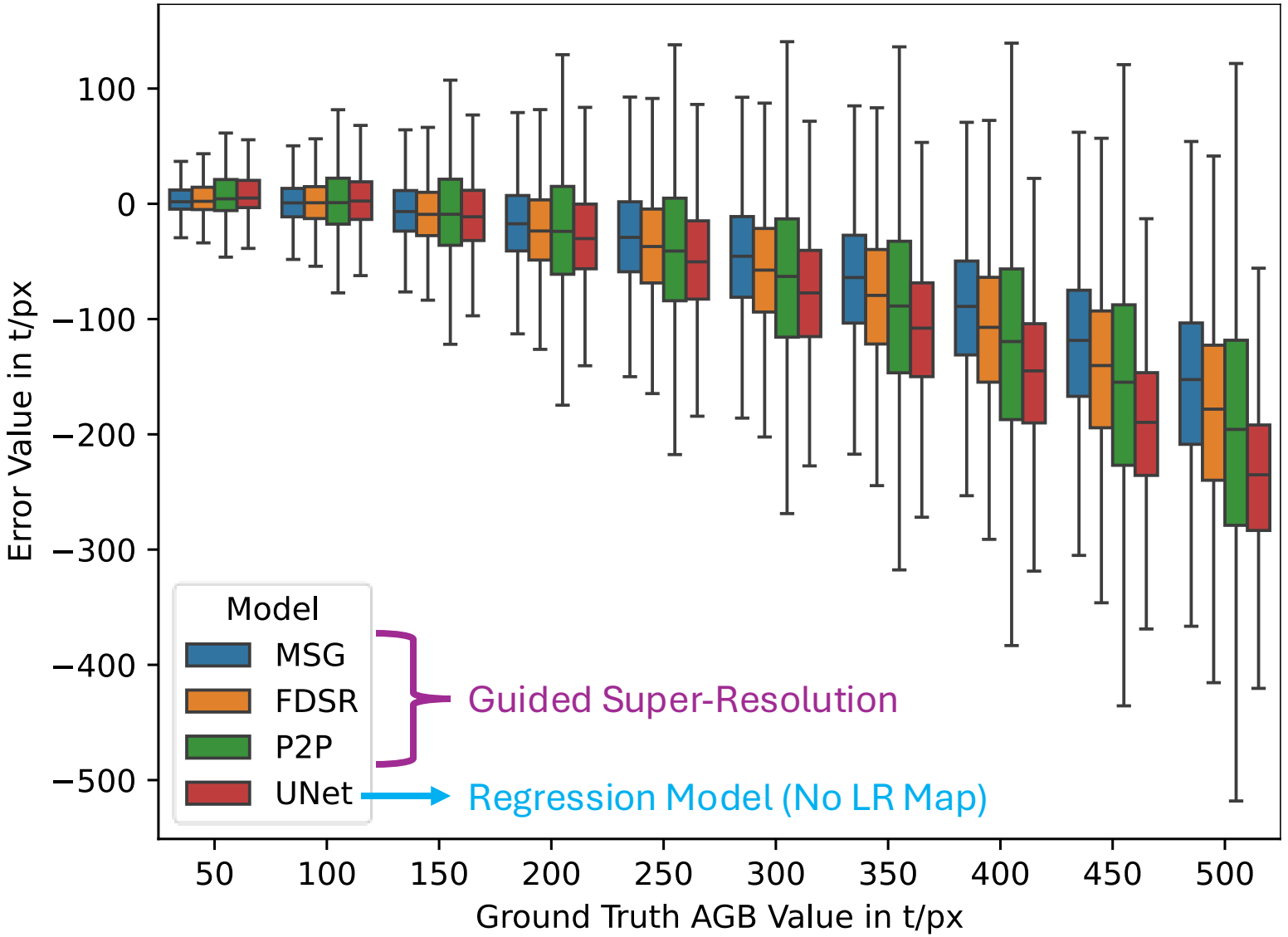
Qualitative Analysis



Comments:

- Bicubic has no high frequency info.
- UNet has no low-resolution values.
- Simple Model (MSG) works better.

MSG is Better on Underestimation Problem



Comparisons:

- UNet vs GSR
- MSG vs Other GSR

Our Findings

- Guided Super-Resolution reaches better performance on the biomass data.

- Texture-copying is indeed beneficial for biomass estimation.

References

For Icons & Images:

- Flaticon, Wikipedia, Reddit

For Models:

- Hui, T.-W., Loy, C. C., Tang, X., 2016. Depth map super-resolution by deep multi-scale guidance. ECCV.
- Kopf, J., Cohen, M. F., Lischinski, D., Uyttendaele, M., 2007. Joint bilateral upsampling. ACM ToG.
- Lutio, R. D., D'aronco, S., Wegner, J. D., Schindler, K., 2019. Guided super-resolution as pixel-to-pixel transformation. ICCV.
- He, L., Zhu, H., Li, F., Bai, H., Cong, R., Zhang, C., Lin, C.,Liu, M., Zhao, Y., 2021. Towards fast and accurate real-world depth super-resolution: Benchmark dataset and baseline. CVPR.
- Garnot, V. S. F., Landrieu, L., 2021. Panoptic segmentation of satellite image time series with convolutional temporal attention networks. ICCV.
- Becker, A., Russo, S., Puliti, S., Lang, N., Schindler, K., Wegner,J. D., 2023. Country-wide retrieval of forest structure from optical and SAR satellite imagery with deep ensembles. ISPRS Journal of Photogrammetry and Remote Sensing.

Take away message:

Guided Super-Resolution

is beneficial for **global-scale biomass estimation**!

Thank you for Listening!