

Flexible Multimodal Foundation Learning for Heterogeneous Earth Observation and Environmental Monitoring

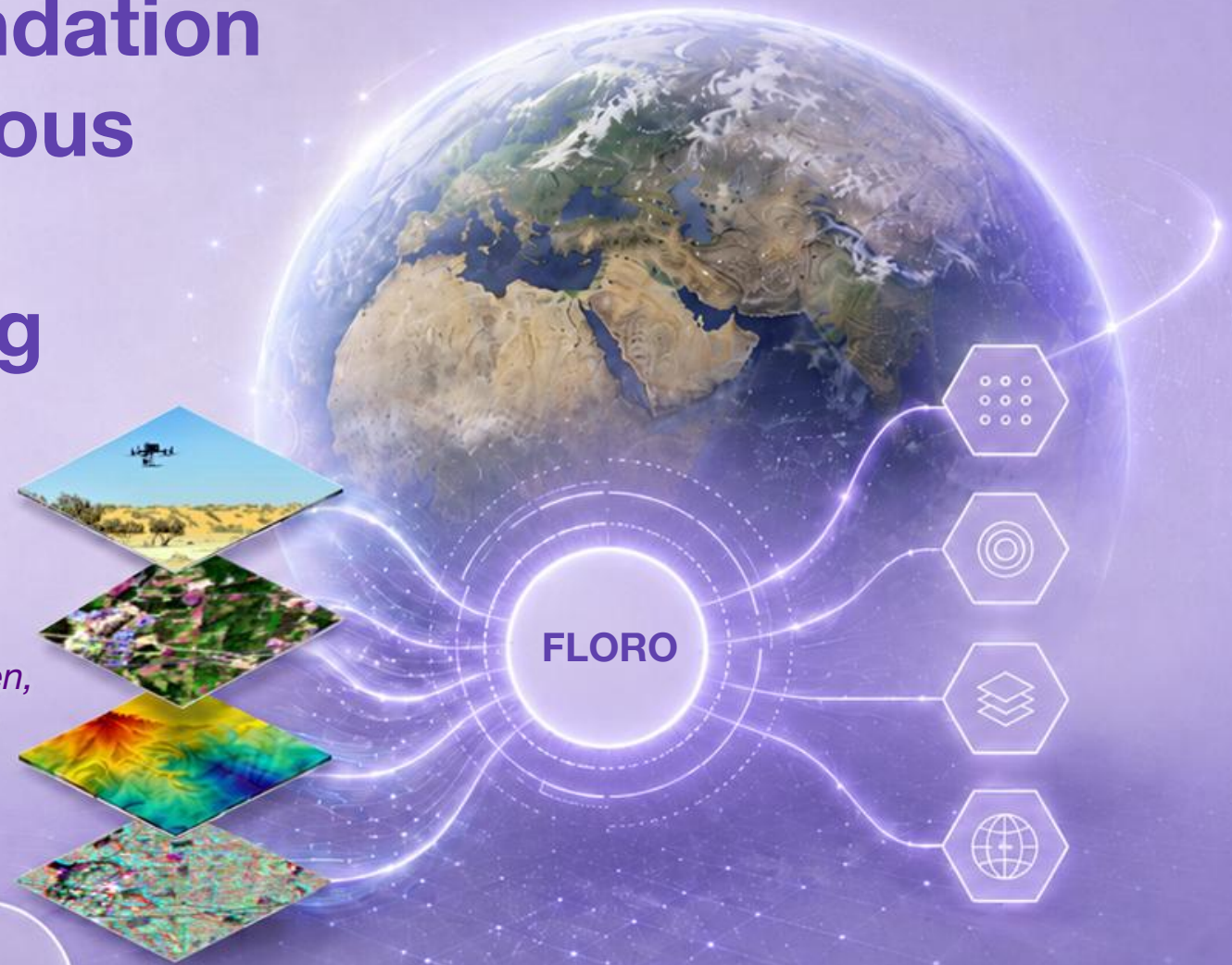
Understanding Earth across sensors and scales

Jorge L. Rodríguez, Victor Angulo Morales, Areej Alwahas, Mariana Elías Lara, Fida Mohammad Thoker, Kasper Johansen, Bernard Ghanem, Fernando T. Maestre, Matthew F. McCabe



Jorge L. Rodríguez

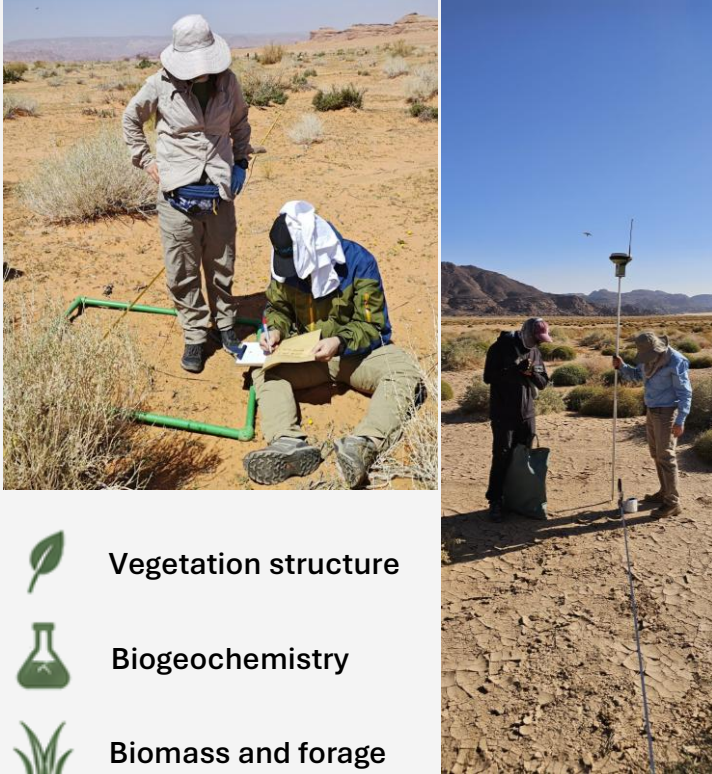
*King Abdullah University of Science and
Technology | Presenting author*



From local measurements to regional ecological inference

Field ecology

Ground measurements of ecosystems and biodiversity



Vegetation structure



Biogeochemistry



Biomass and forage

UAV data acquisition

High resolution observations at local scale



RGB



Multispectral

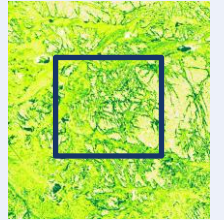


LiDAR

Scaling to satellites

From local to regional and national coverage

High-resolution satellites (SkySat)



Medium-resolution satellites (Sentinel-1/2)



Large-area coverage



Frequent revisits



Multi-source and complimentary

Our research integrates **field measurements**, **UAV data acquisition**, and **satellite data** across scales to better understand and monitor ecosystems at regional to global scales.

Multisensor, multimodal, multiresolution ecological data



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Common workflows do not share a fixed set of spectral bands or modalities.



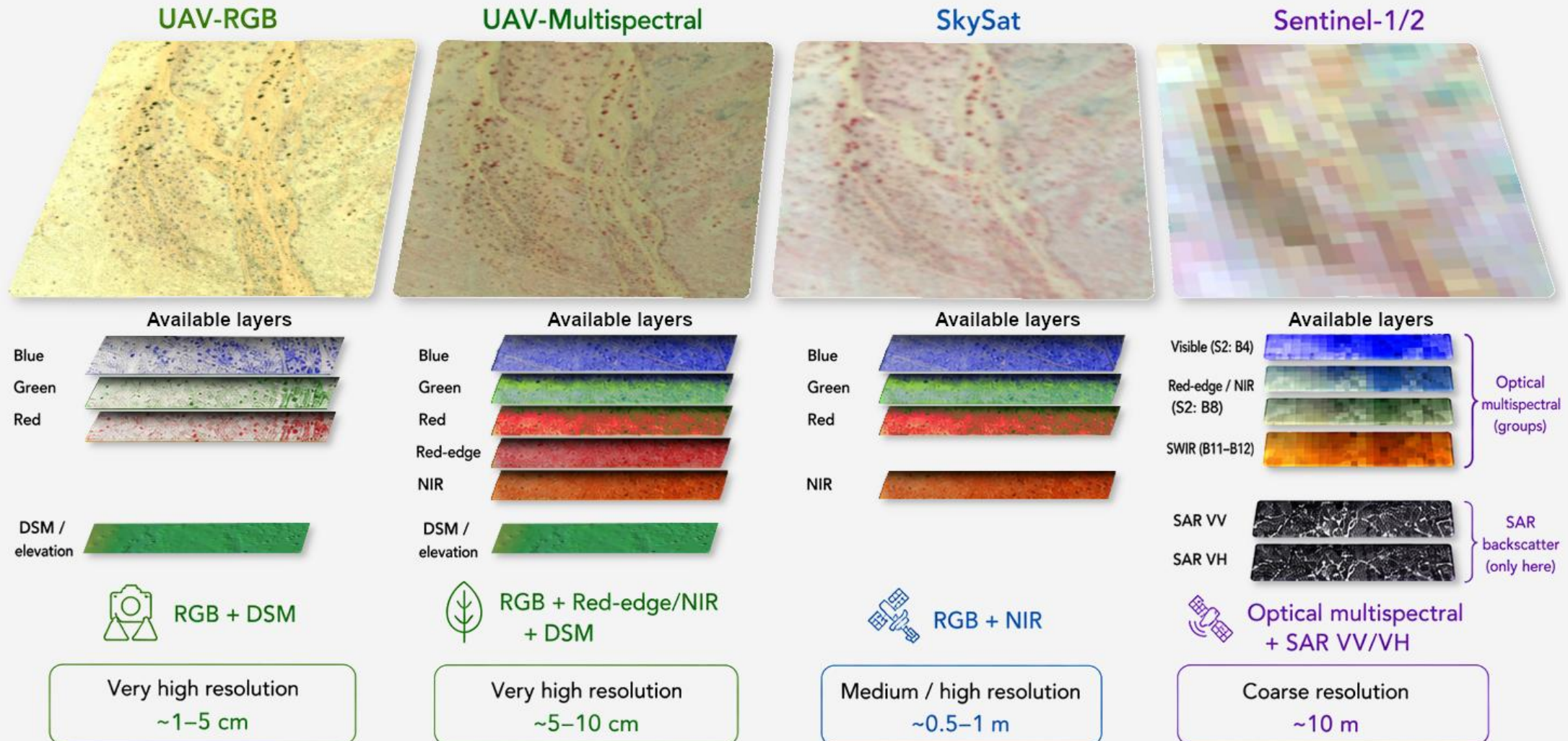
Multisensor
Different platforms,
different strengths.



Multimodal
Optical, elevation,
and SAR — not
always together.



Multiresolution
Spatial resolution
varies by orders
of magnitude.



Ecological remote sensing requires models that can work across incomplete, sensor-specific inputs.

FLORO: A Multimodal Geospatial Foundation Model for Ecological Remote Sensing Across Sensors and Scales



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1 Multimodal inputs

Diverse sensors and resolutions

UAV-RGB
(cm-dm)

UAV-Multispectral
(cm-dm)

High-Resolution
Satellite
(m)

Sentinel-2 Optical
(10–20 m)

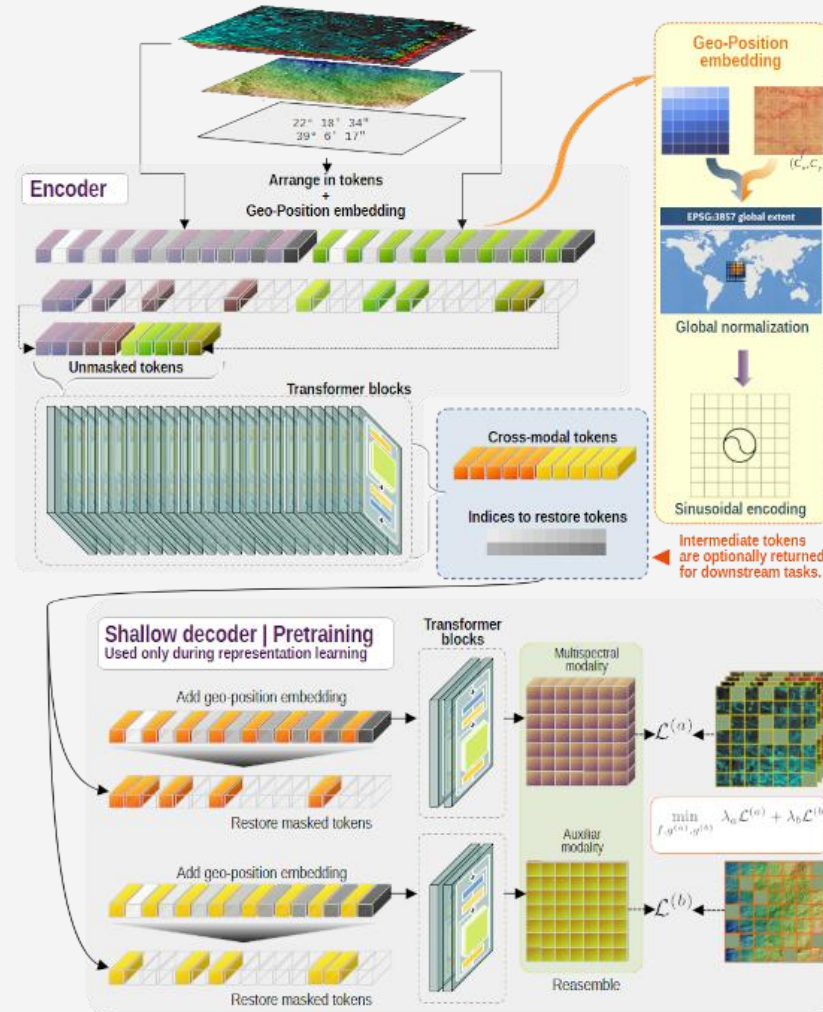
Sentinel-1 SAR
(10 m)

Elevation / Terrain
(DEM, DSM)

Global coverage
across ecosystems

2 FLORO Representation Learning (Pretraining)

Learn once, transfer everywhere



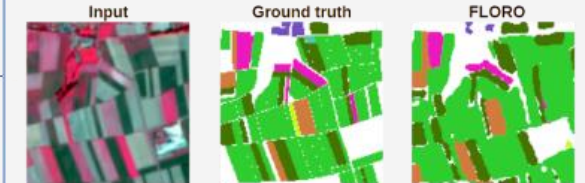
3 Transfer Learning / Downstream Tasks

Frozen encoder, many applications

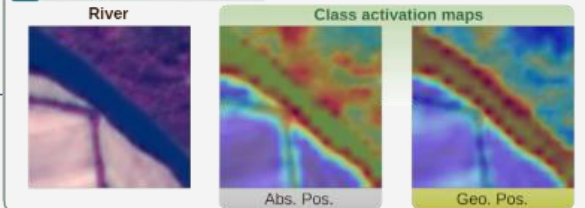
Frozen Encoder

Transferable ecological representations

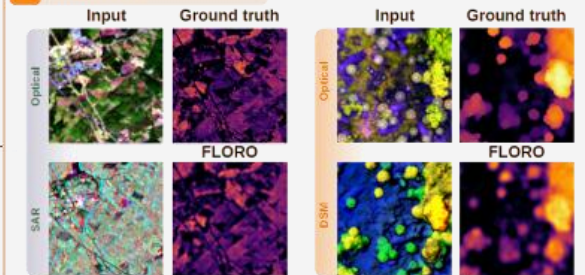
1 Semantic segmentation



2 Scene classification



3 Regression



Ecological remote sensing requires models that can work across incomplete, sensor-specific inputs.

Sensor availability (data are heterogeneous)

UAV-RGB UAV-MS HR Sat. S1 / S2

Optical

Blue	☒	☒	☒	☒
Green	☒	☒	☒	☒
Red	☒	☒	☒	☒
Red edge	☐	☒	☐	☒
Near infrared	☐	☒	☒	☒
Near infrared (B8A)	☐	☐	☐	☒
SWIR 1	☐	☐	☐	☒
SWIR 2	☐	☐	☐	☒

Modalities

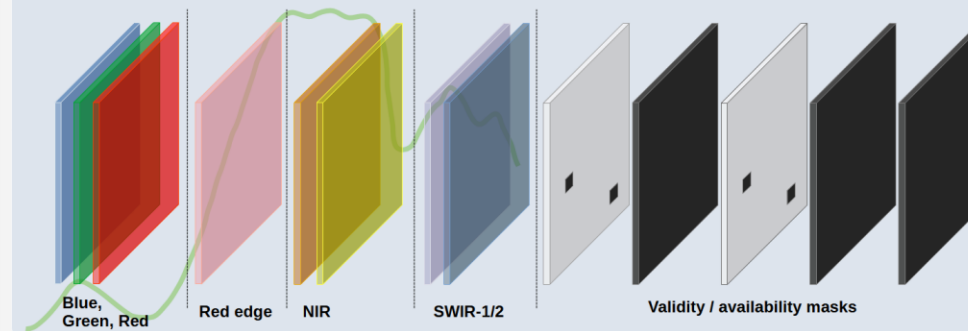
Elevation	☒	☒	☒	☒
VV	☐	☐	☐	☒
VH	☐	☐	☐	☒

☒ Available ☐ Not available

Input representation (FLORO inputs)

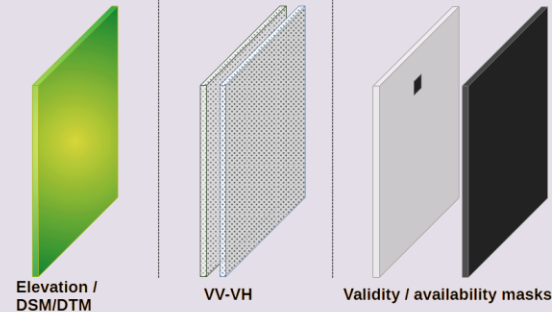
a) Optical inputs

13 input channels



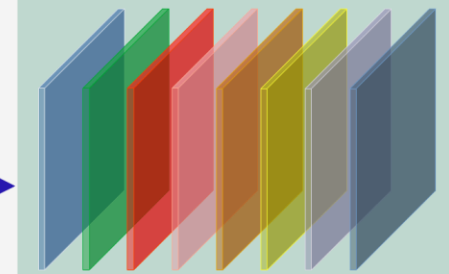
b) Auxiliary inputs

5 input channels

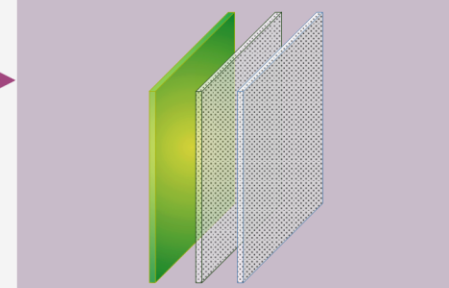


Representation learning (reconstruction targets)

8 output bands



3 output bands



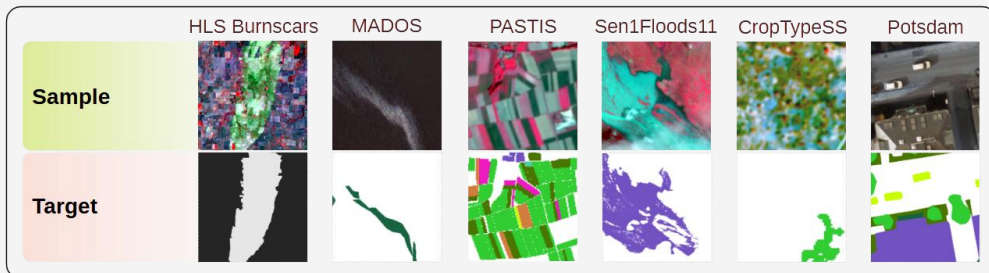
Validity / availability masks indicate which bands are present for a sample. They modulate contributions by modality and band group, but do not remove valid pixels within an available group.

During pretraining FLORO learns representations from incomplete, sensor-specific optical, elevation and SAR data.

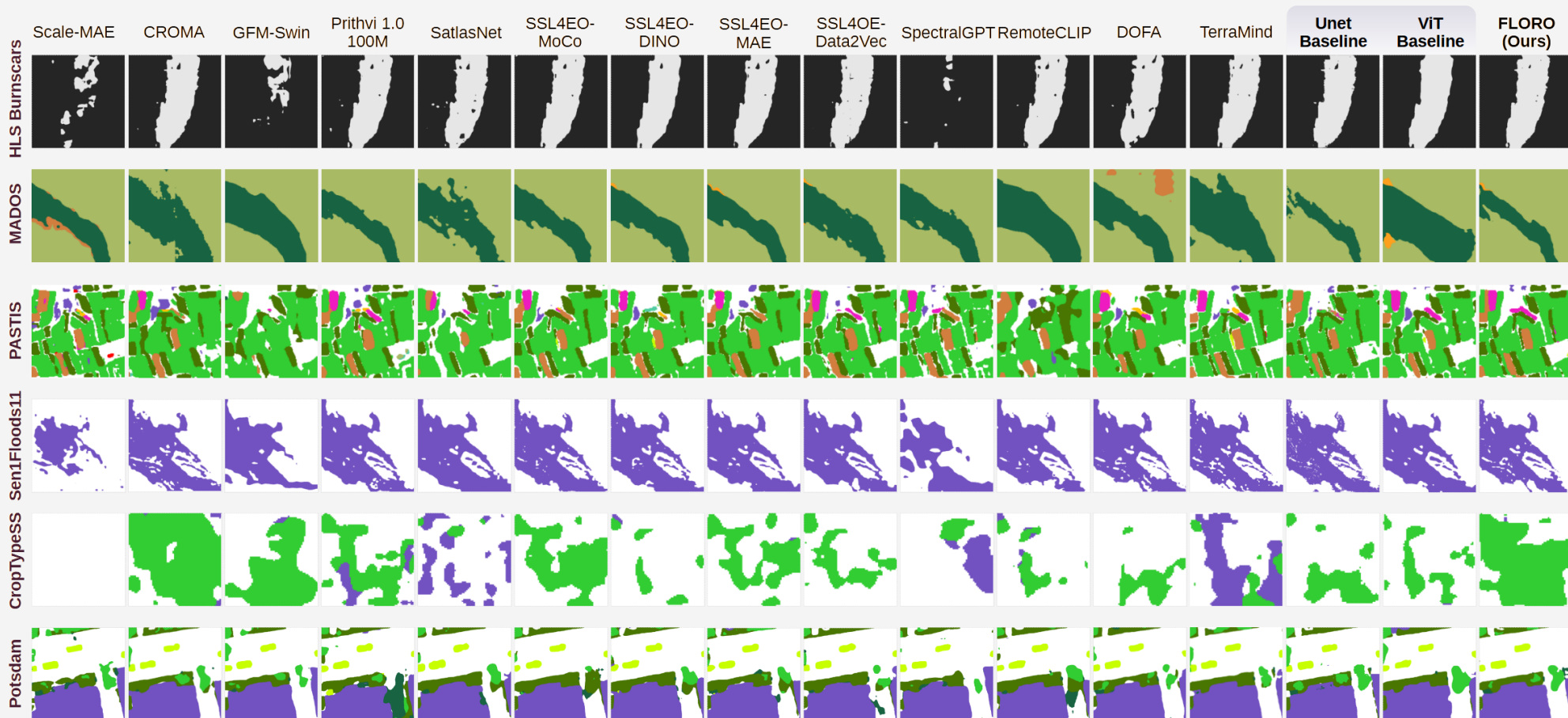
Segmentation transfer across diverse benchmarks



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FLORO provides competitive and consistent segmentation transfer across heterogeneous sensors, spatial resolutions, and land-cover types.



FLORO

Avg. rank: 4.0

Competitive transfer across **six** segmentation benchmarks



Multiple sensors



Different spatial resolutions



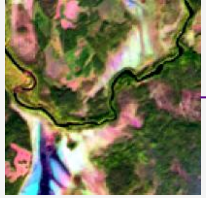
Diverse land-cover types

Regression transfer on BioMassters

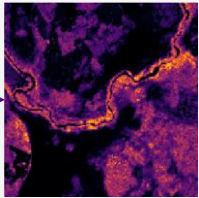
Biomass estimation from optical and SAR data

Benchmark inputs

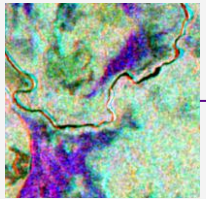
Optical



Ground
truth
biomass



SAR



Paired optical-SAR
inputs

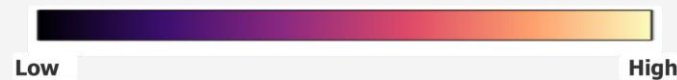
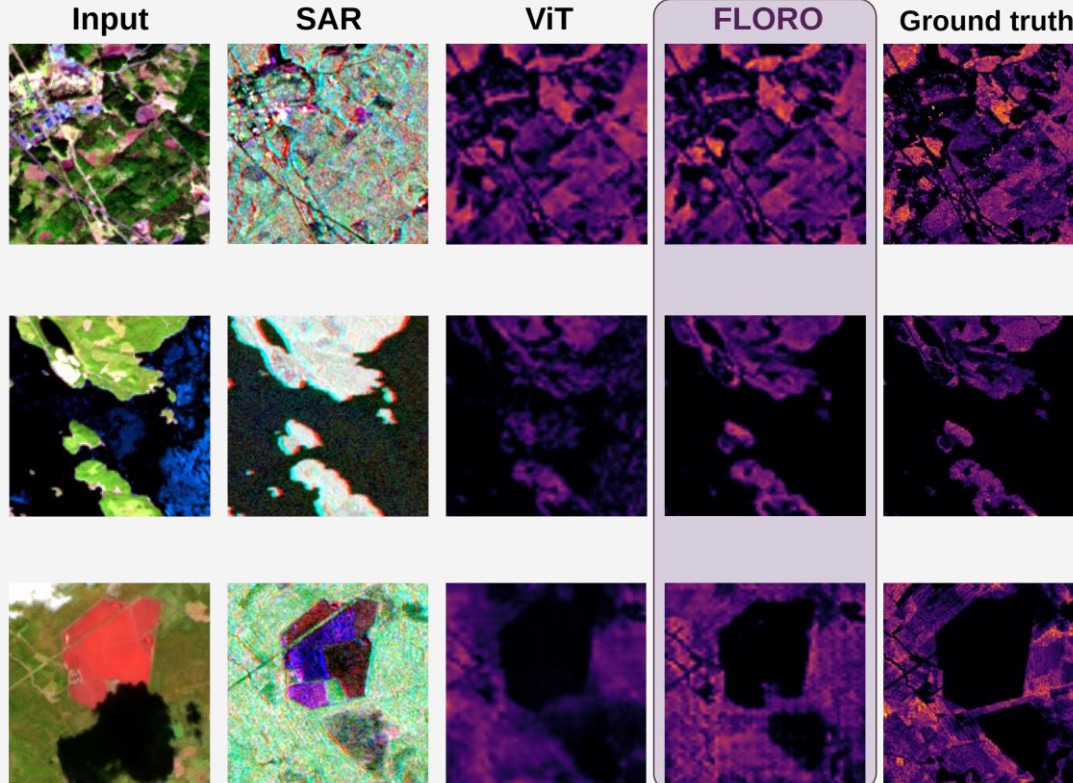


Pixel-wise height
estimation

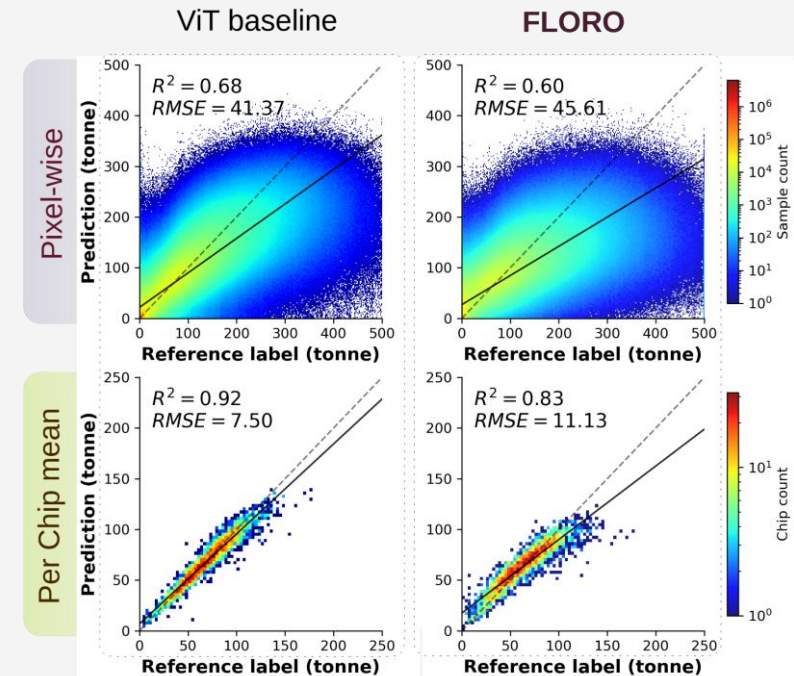


Evaluation at pixel-
wise and chip-level
scales

Some qualitative examples



Quantitative summary



Strong chip-level agreement



Competitive pixel-wise estimation



Benefits from multimodal pretraining

FLORO provides competitive biomass regression transfer, capturing meaningful spatial patterns from optical and SAR inputs.

Regression transfer on Espeletia

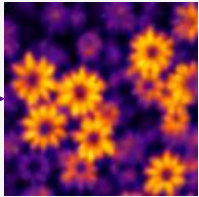
Canopy height estimation from optical and elevation data

Benchmark inputs

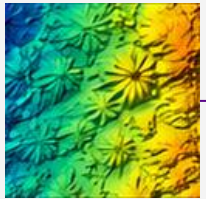
Optical



Ground
truth CHM



DSM



Paired optical-DSM
inputs

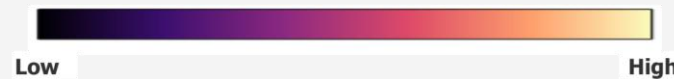
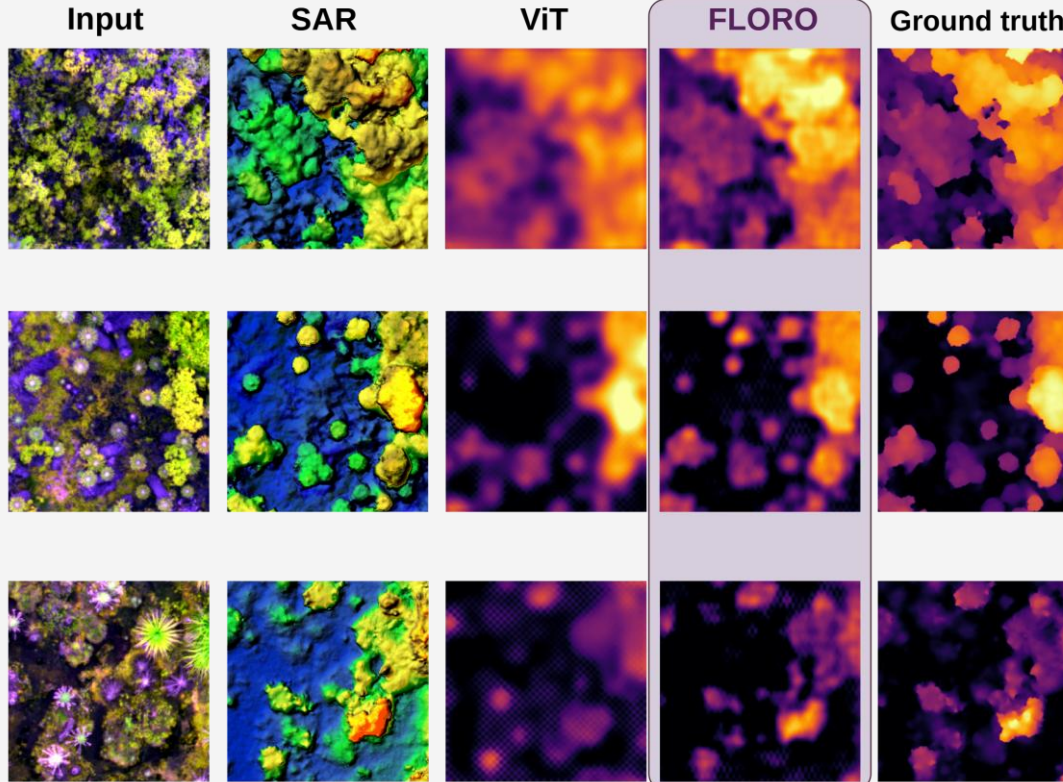


Pixel-wise height
estimation

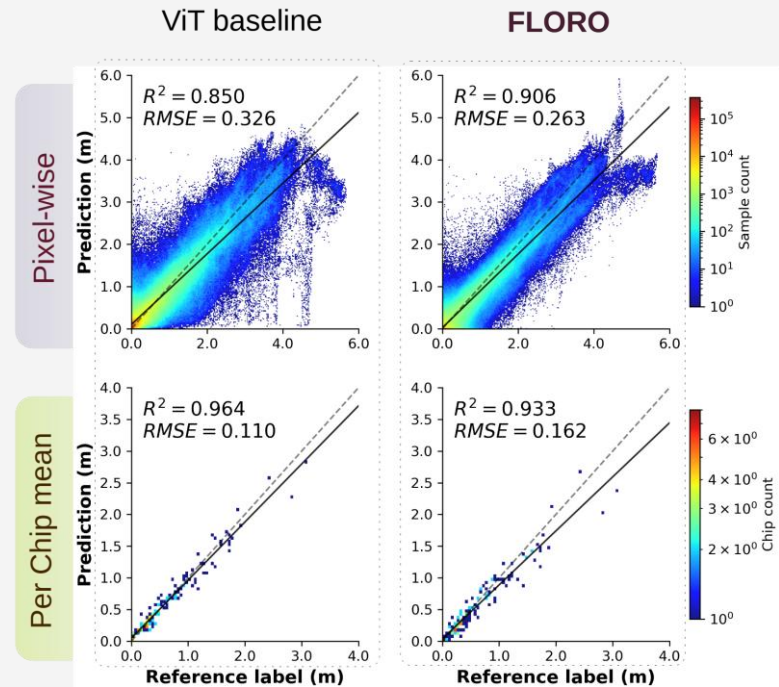


Evaluation at pixel-
wise and chip-level
scales

Some qualitative examples



Quantitative summary



Stronger pixel-wise estimation



Competitive chip-level agreement



Benefits from multimodal pretraining

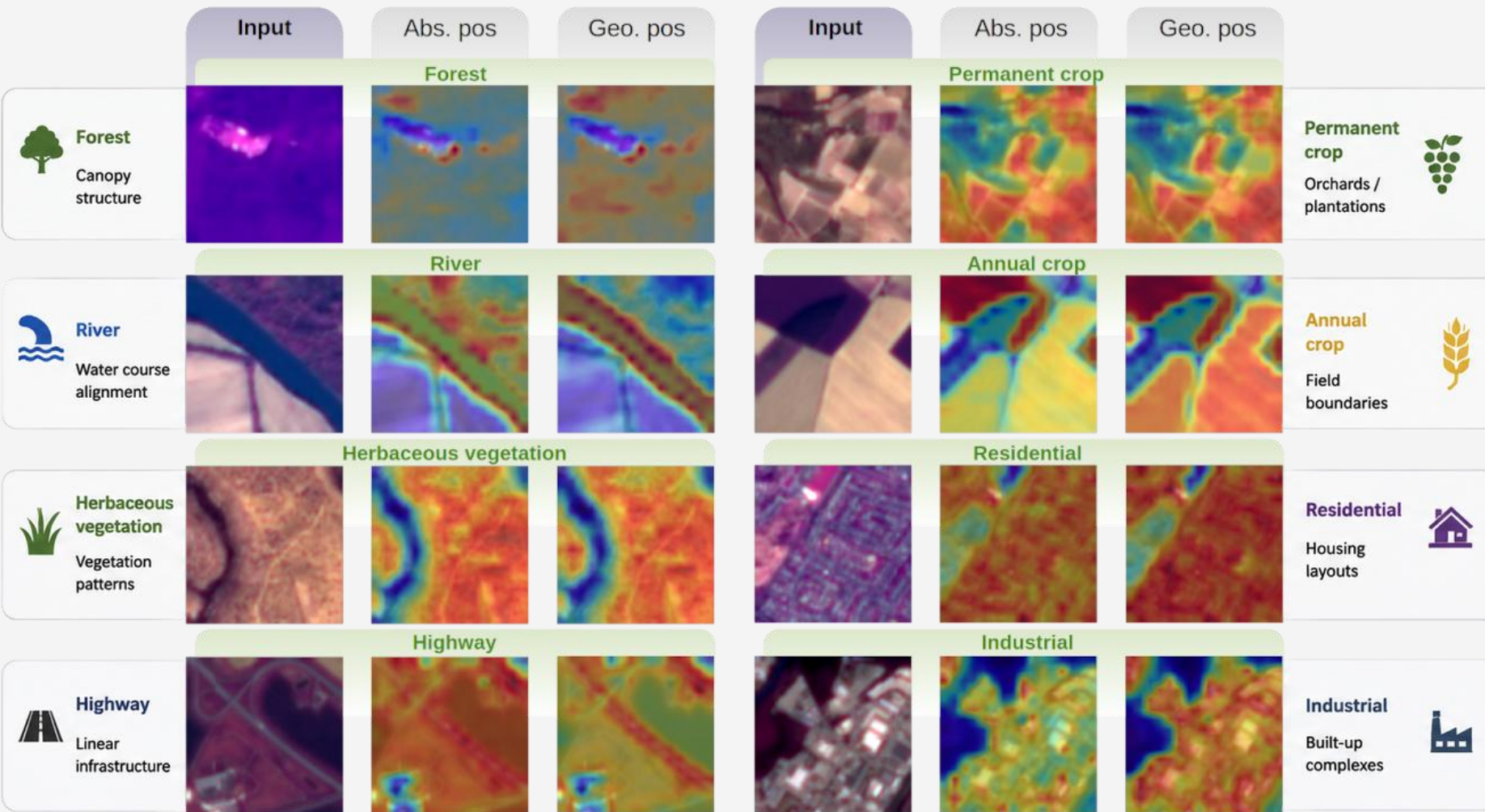
FLORO provides strong transfer for canopy-height estimation, capturing meaningful spatial structure from optical and DSM inputs.

Geo-position embeddings matter for CAMs

Location helps the model focus on the right places



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Key takeaways



Better localization

Geo-pos embeddings produce CAMs that focus on the correct objects and boundaries.



Stronger generalization

Helps the model transfer across locations, sensors, and spatial layouts.



Spatial awareness is key

Absolute position alone is insufficient; geographic context provides the missing signal.

Low activation



High activation

Geo-position embeddings **improve the spatial focus and interpretability** of CAMs across land cover types.

Diverse pretraining, not just massive pretraining

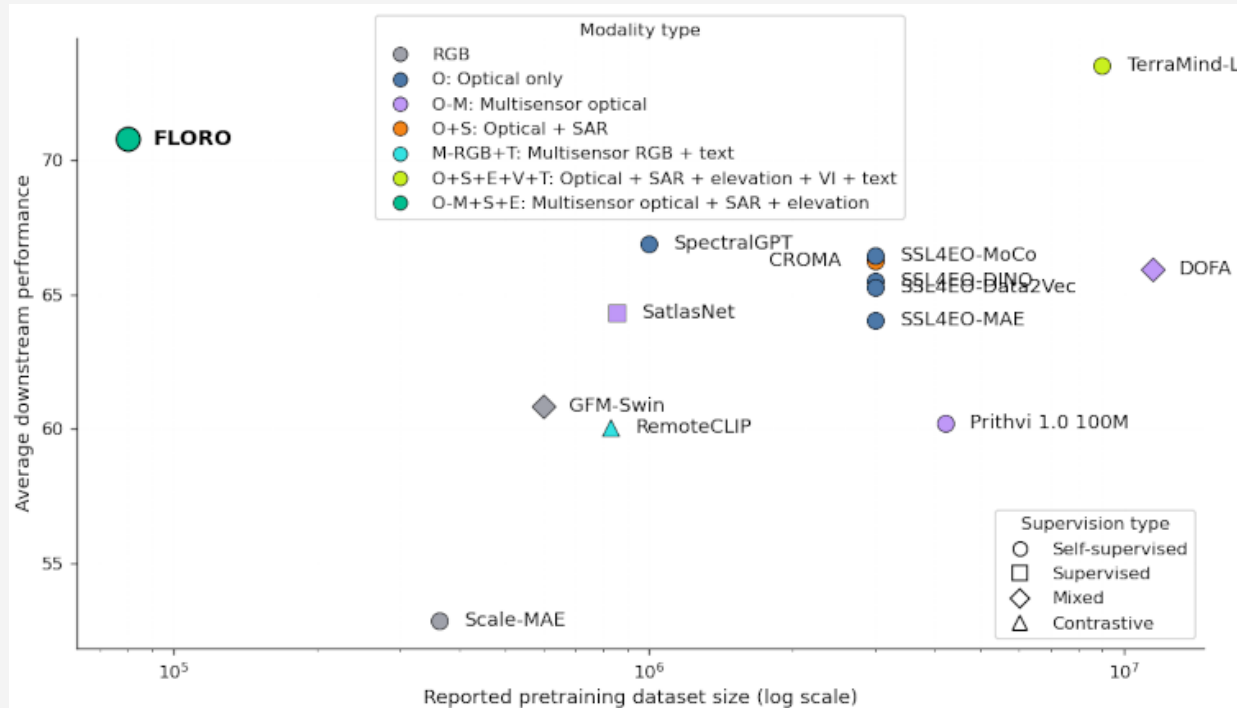
FLORO achieves competitive transfer with ~112.5x fewer pretraining images than TerraMind-L



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Cross-benchmark performance versus pretraining dataset size

FLORO delivers strong average downstream performance while using the smallest pretraining dataset



Visualizing scale comparison

FLORO was pretrained on substantially fewer images than similarly sized models

TerraMind-L
9,000,000 images



900 stacks
10,000 images per stack



Each small stack represents
10,000 images
0.1 mm paper thickness

FLORO
80,000 images



8 stacks
10,000 images per stack

~112.5x
larger
pretraining set



Competitive transfer

Top-tier average performance
across 11 diverse benchmarks



Scale efficiency

~112.5x fewer images
than TerraMind-L



Sensor & task diversity

Optical, SAR, elevation, and
multiple ecological tasks



Practical for ecology

Enables foundation models when
massive homogeneous corpora
are not available

Takeaway: Carefully curated, diverse multimodal pretraining can deliver strong generalization without massive scale

Thanks!

Pre-print available:

FLORO: A Multimodal Geospatial Foundation Model for Ecological Remote Sensing Across Sensors and Scales

<https://doi.org/10.48550/arXiv.2605.28174>

jorge.rodriguezgalvis@kaust.edu.sa