



University of  
Zurich <sup>UZH</sup>



EcoVision

Department of Mathematical Modeling and Machine Learning (DM<sup>3</sup>L)



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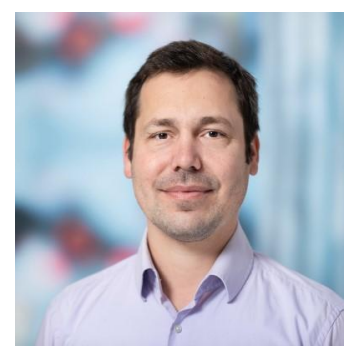
Dr. Damien Robert



Dr. Elena Plekhanova



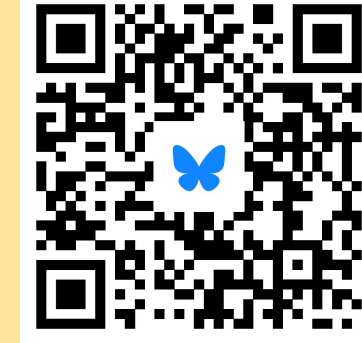
Dr. Lukas Drees



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# Climplicit: Climatic Implicit Embeddings for Global Ecological Tasks

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Project page:



ecovision-uzh.github.io/climPLICIT

## Climatic rasters

- + Essential to ecology
- Storage requirements
- Learn features from scratch

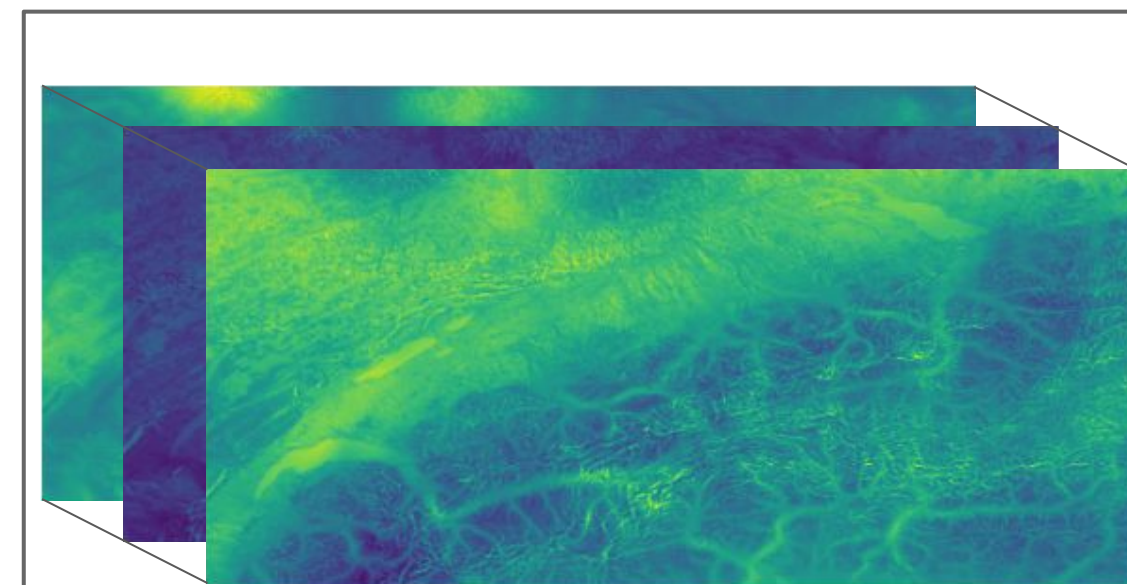
## Neural Networks

- + Feature learning
- Compute requirements
- Technical Know-How

## Motivation

### Climplicit

- + Ready-to-use climatic features
- + Anywhere on
- + Low memory
- + Low compute
- + Little know-how



### Global, dense climatic raster<sup>2</sup>

- 11 climatic variables
- Monthly mean 1981-2010
- 1km resolution at equator

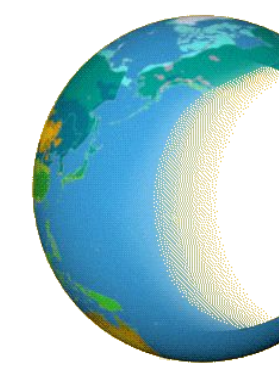
- Climate Moisture Index
- Near-surface relative humidity
- Potential evapotranspiration
- Precipitation amount
- Surface downwelling shortwave flux in air
- Near-surface wind speed
- Mean daily maximum 2m air temperature
- Mean daily air temperature
- Mean daily minimum air temperature
- Total cloud cover
- Vapor pressure deficit

## Pretraining

Coordinate  
& Month

Climplicit  
(ReSIREN)

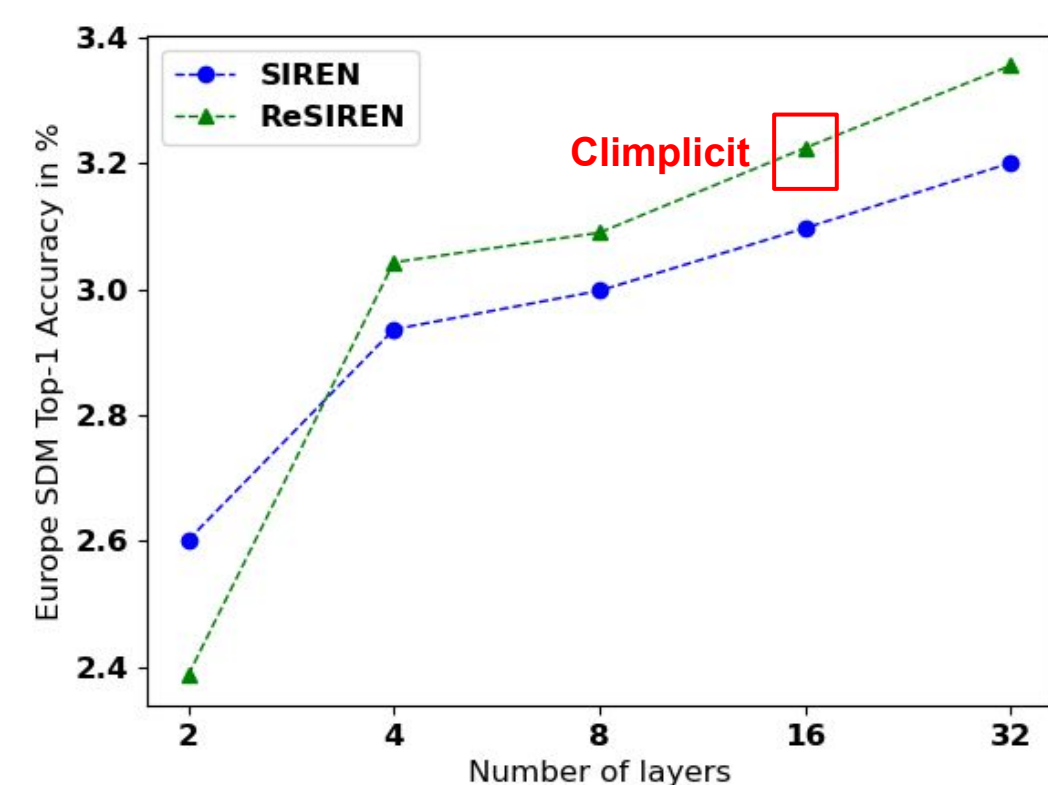
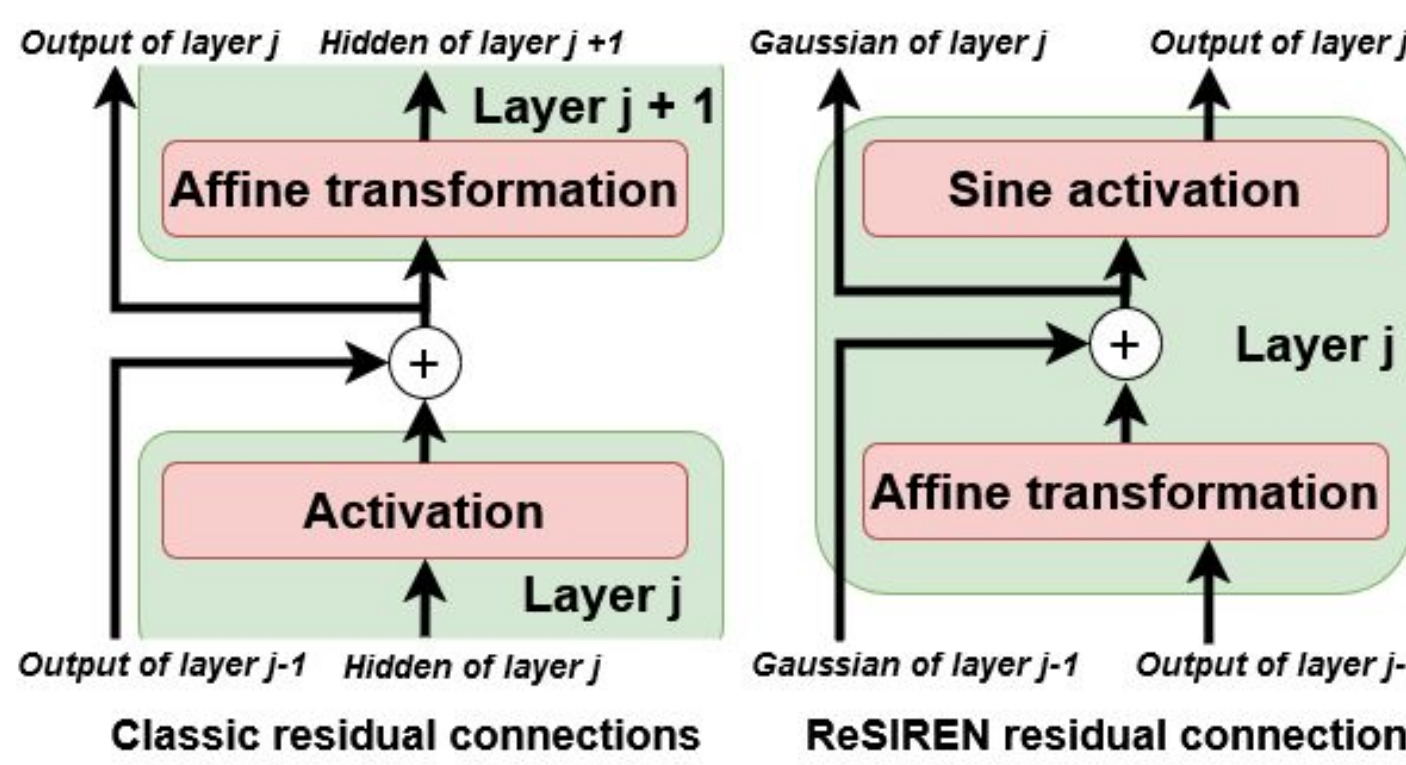
Affine layer



CHELSEA

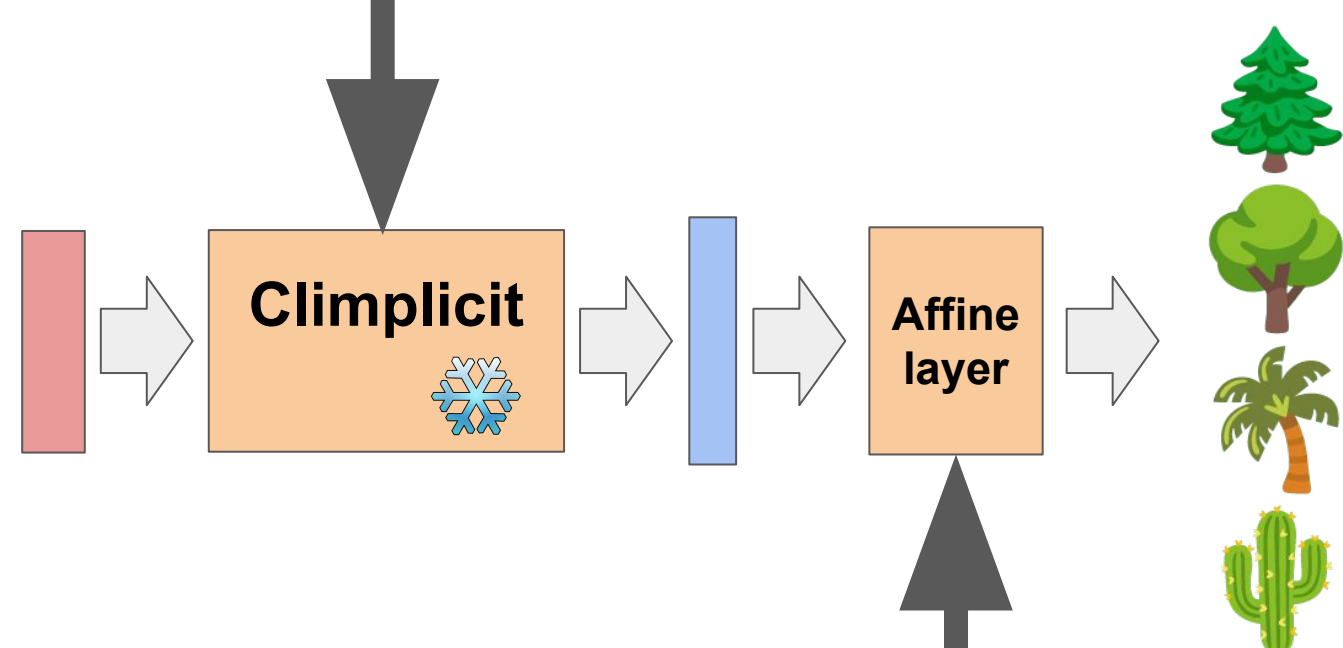
$[\lambda, \phi, \sin(2\pi * m/12), \cos(2\pi * m/12)] \in [-1,1]^4$   
with longitude  $\lambda \in [-1,1]$ , latitude  $\phi \in [-1,1]$  and month  $m \in \{1, \dots, 12\}$

Deep SIREN<sup>1</sup>  
+  
residual  
connections

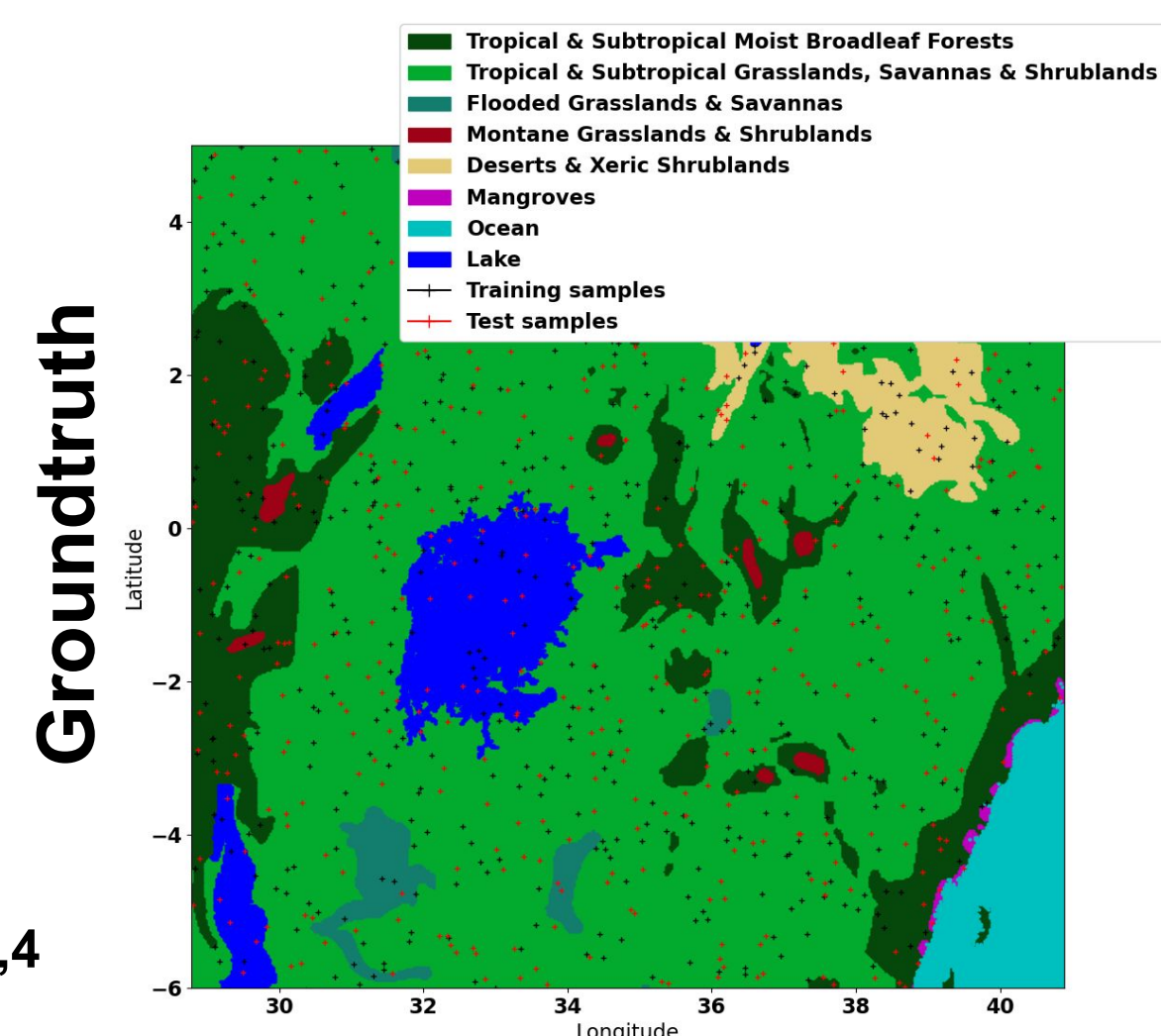
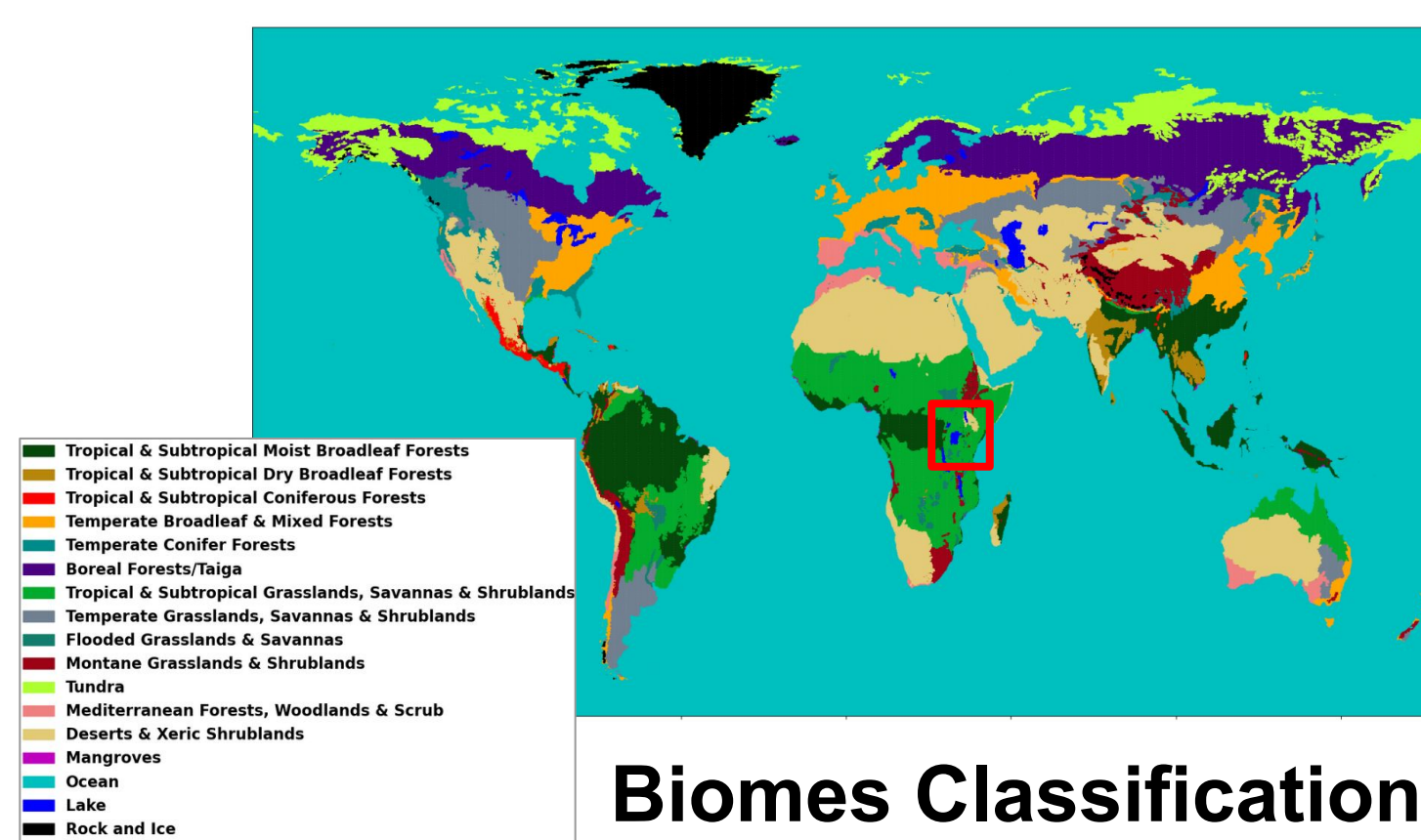


## Application

15MB - x3500 smaller than CHELSA



Single layer probing - GPU optional



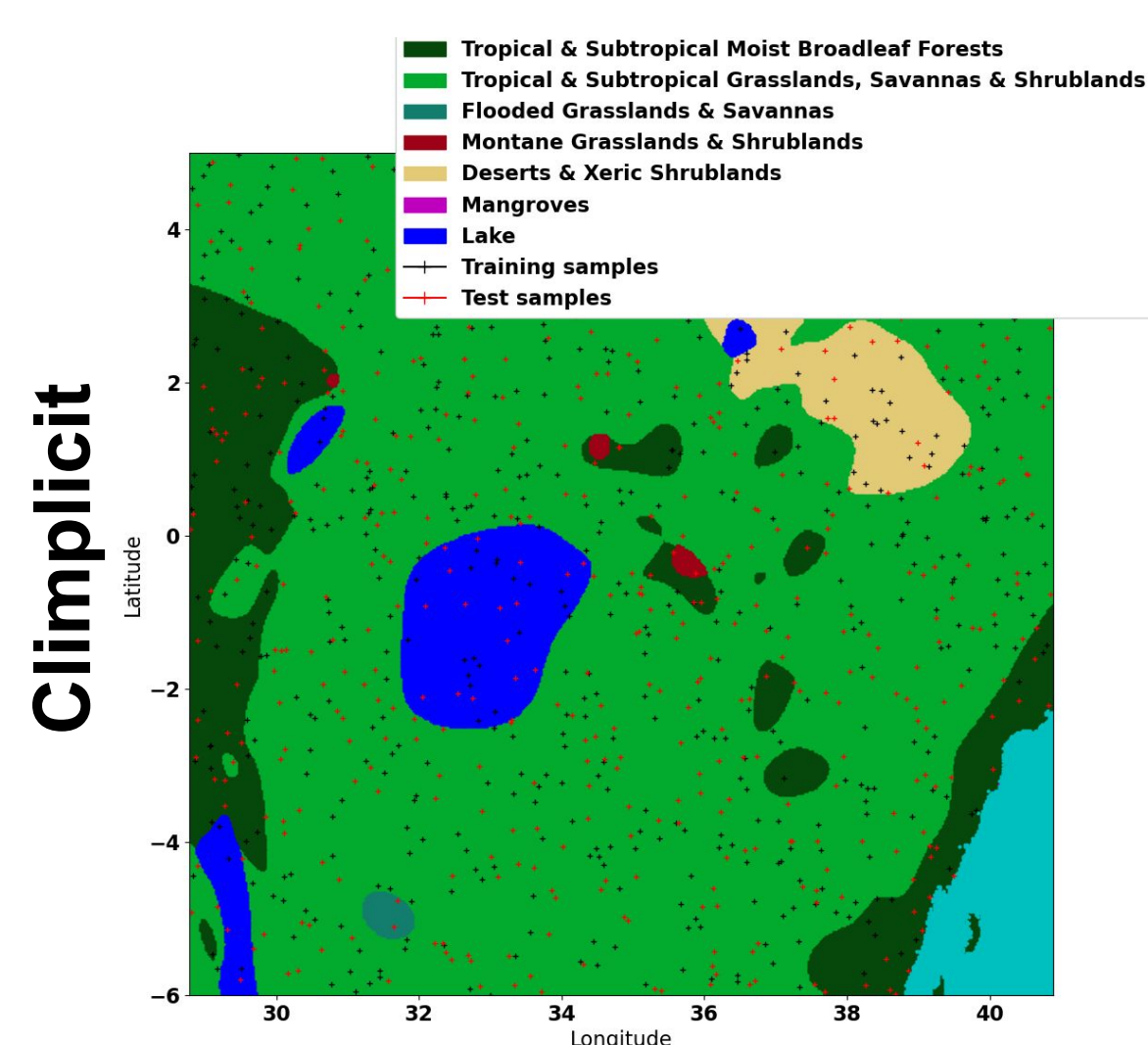
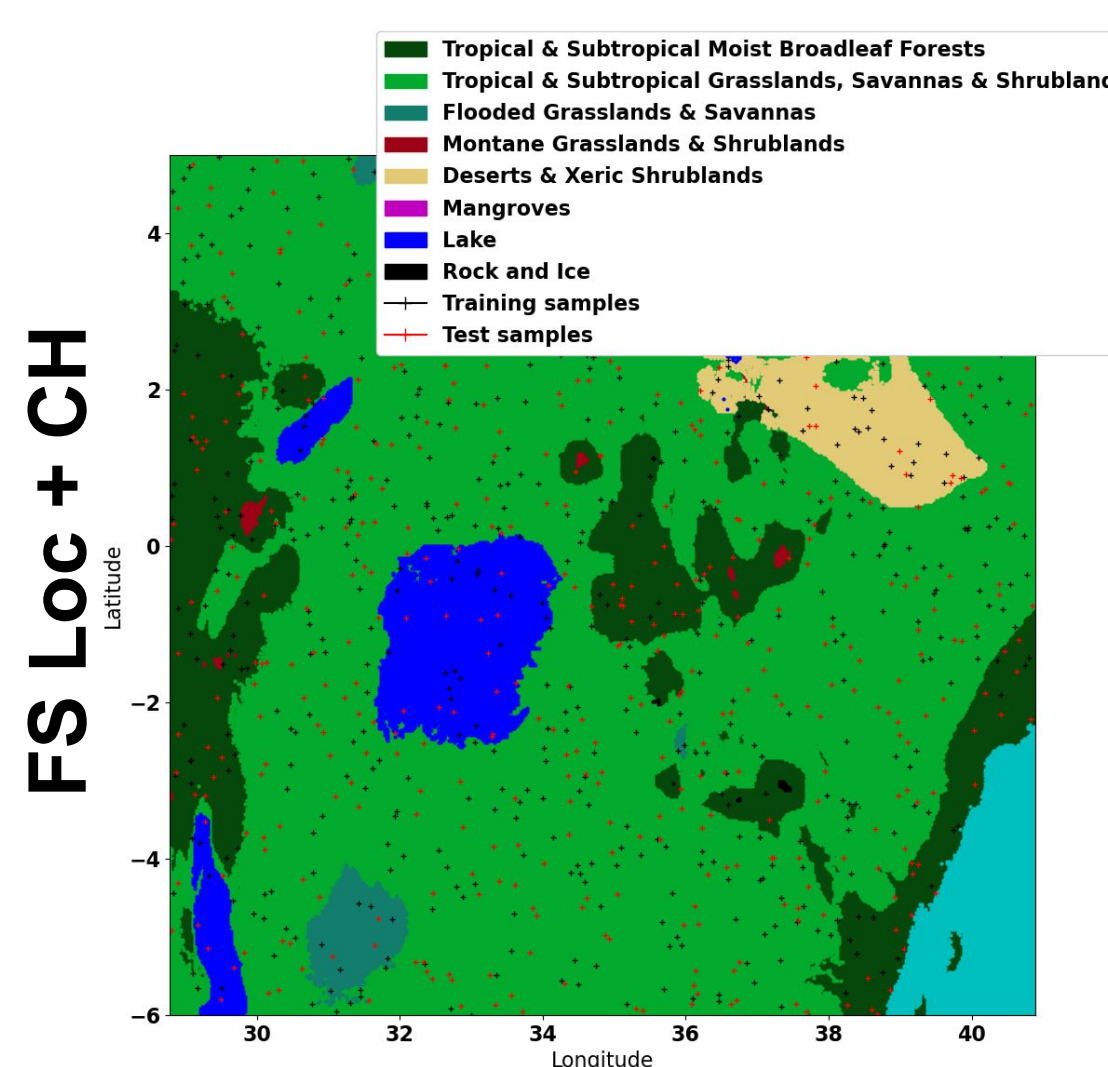
## Results

### Comparison with training “from-scratch” and other pretrained geolocation representations

Model	Biomes (% F1 ↑)	SDM (% Acc ↑)	Plant traits (% R <sup>2</sup> ↑)
FS Loc	73.9 ± 2.4	2.0 ± 0.4	42.2 ± 0.0
FS CH	71.8 ± 1.9	2.5 ± 0.1	60.0 ± 0.3
FS Loc + CH	<b>79.6 ± 1.7</b>	2.5 ± 0.1	<b>64.8 ± 0.4</b>
SATCLIP	68.3 ± 0.4	1.3 ± 0.1	61.6 ± 0.1
TAXABIND	59.3 ± 0.1	3.1 ± 0.0	56.9 ± 0.0
SINR	63.1 ± 0.3	1.7 ± 0.0	63.5 ± 0.1
CSP	58.6 ± 0.4	1.6 ± 0.1	49.7 ± 0.3
GEOCLIP	62.7 ± 0.1	<b>3.5 ± 0.0</b>	57.9 ± 0.1
CLIMPLICIT (Ours)	<b>78.4 ± 0.3</b>	<b>3.2 ± 0.0</b>	<b>70.0 ± 0.1</b>

### Ablation of various model & training choices

Model	Biomes (% F1 ↑)	SDM (% Acc ↑)	Plant traits (% R <sup>2</sup> ↑)
CLIMPLICIT	<b>78.4 ± 0.3</b>	<b>3.2 ± 0.0</b>	<b>70.0 ± 0.1</b>
SIREN	77.5 ± 0.2	3.1 ± 0.0	68.8 ± 0.2
CONCAT MONTHS	75.9 ± 0.3	2.6 ± 0.0	66.0 ± 0.1
MARCH-ONLY	78.2 ± 0.2	2.9 ± 0.0	62.8 ± 0.1
NO H-SIREN	77.9 ± 0.2	<b>3.6 ± 0.0</b>	69.1 ± 0.1
REC-CHELSEA	61.5 ± 0.2	1.5 ± 0.0	55.4 ± 0.1
CH-CLIP	76.5 ± 0.6	2.3 ± 0.1	66.9 ± 0.4
ERA5	63.7 ± 0.5	1.9 ± 0.1	68.6 ± 0.2



## References

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- 2 D. N. Karger, O. Conrad, J. Böhrer, T. Kawohl, H. Kreft, R. W. Soria-Auza, N. E. Zimmermann, H. P. Linder, and M. Kessler. Climatologies at high resolution for the earth's land surface areas. *Scientific data*, 4(1):1–20, 2017.
- 3 D. M. Olson, E. Dinerstein, E. D. Wikramanayake, N. D. Burgess, G. V. Powell, E. C. Underwood, J. A. D'amico, I. Itoua, H. E. Strand, J. C. Morrison, et al. Terrestrial ecoregions of the world: A new map of life on earth: A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. *BioScience*, 51(11):933–938, 2001.
- 4 K. Klemmer, E. Rolf, C. Robinson, L. Mackey, and M. Rufwurm. Satclip: Global, general-purpose location embeddings with satellite imagery. *arXiv preprint arXiv:2311.17179*, 2023.