University of Zurich[UZH]

EcoVision

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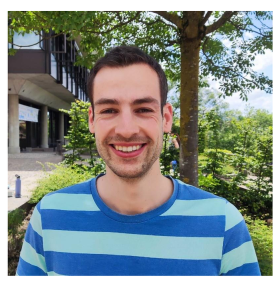
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Climplicit: Climatic Implicit Embeddings for Global Ecological Tasks

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Project page:

ecovision-uzh.github.io/climplicit

Motivation

Climatic rasters

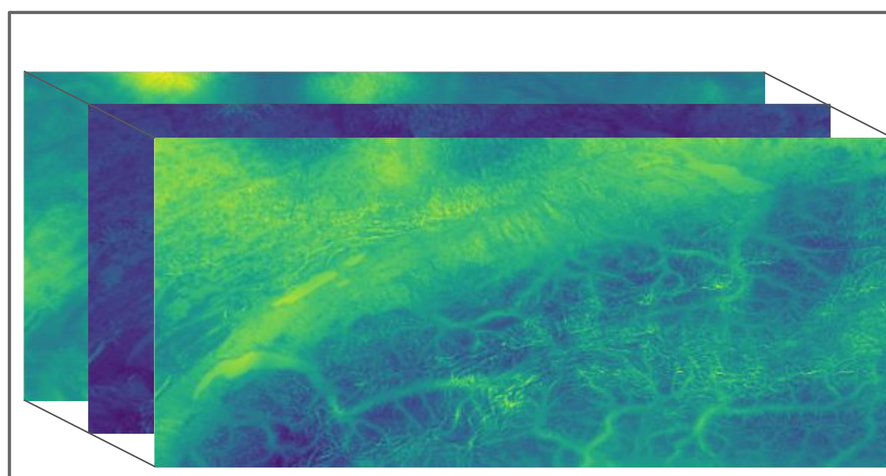
- + Essential to ecology
- - Storage requirements
- - Learn features from scratch

Neural Networks

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

Climplicit

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



Global, dense climatic raster[2]

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

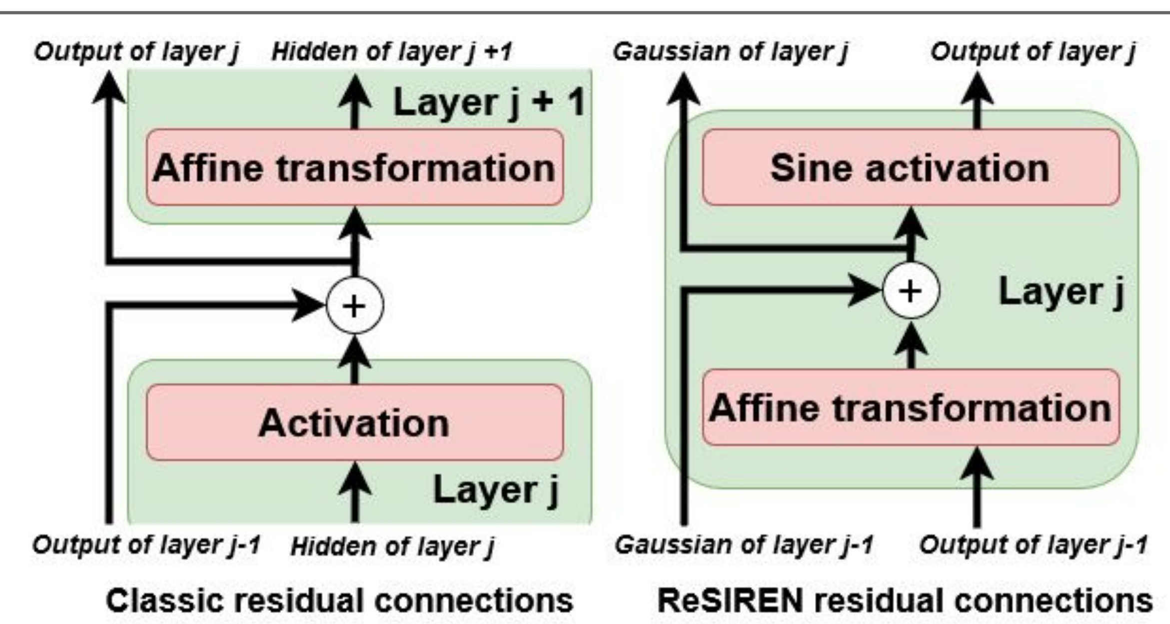
- Climate Moisture Index
- Near-surface relative humidity
- Potential evapotranspiration
- Precipitation amount
- Surface downwelling shortwave flux in air
- Near-surface wind speed
- Mean daily maximum 2m air temperature
- Mean daily air temperature
- Mean daily minimum air temperature
- Total cloud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

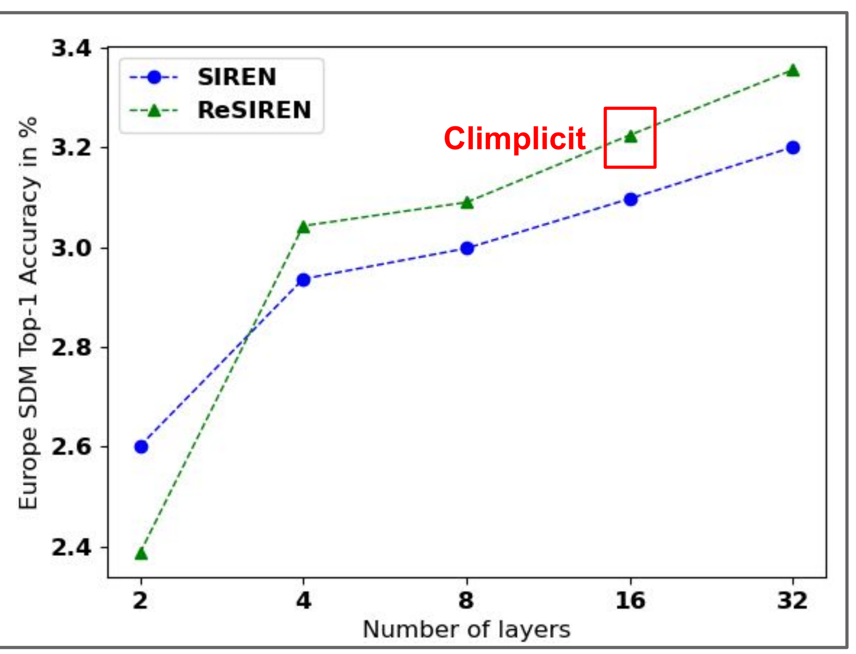
Pretraining

Coordinate & Month → Climplicit (ReSIREN) → Climplicit embedding → Affine layer → CHELSA

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

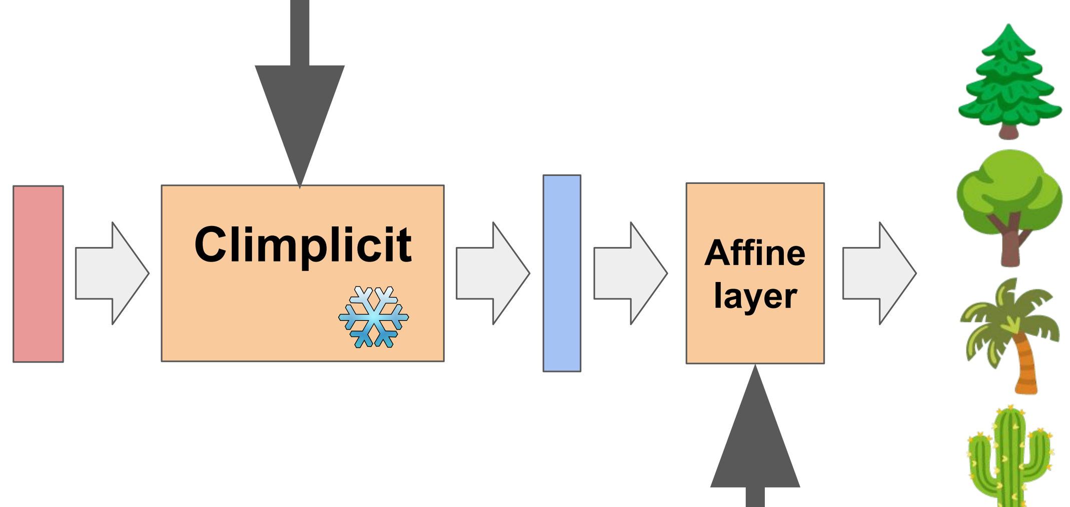
Deep SIREN[1] + residual connections



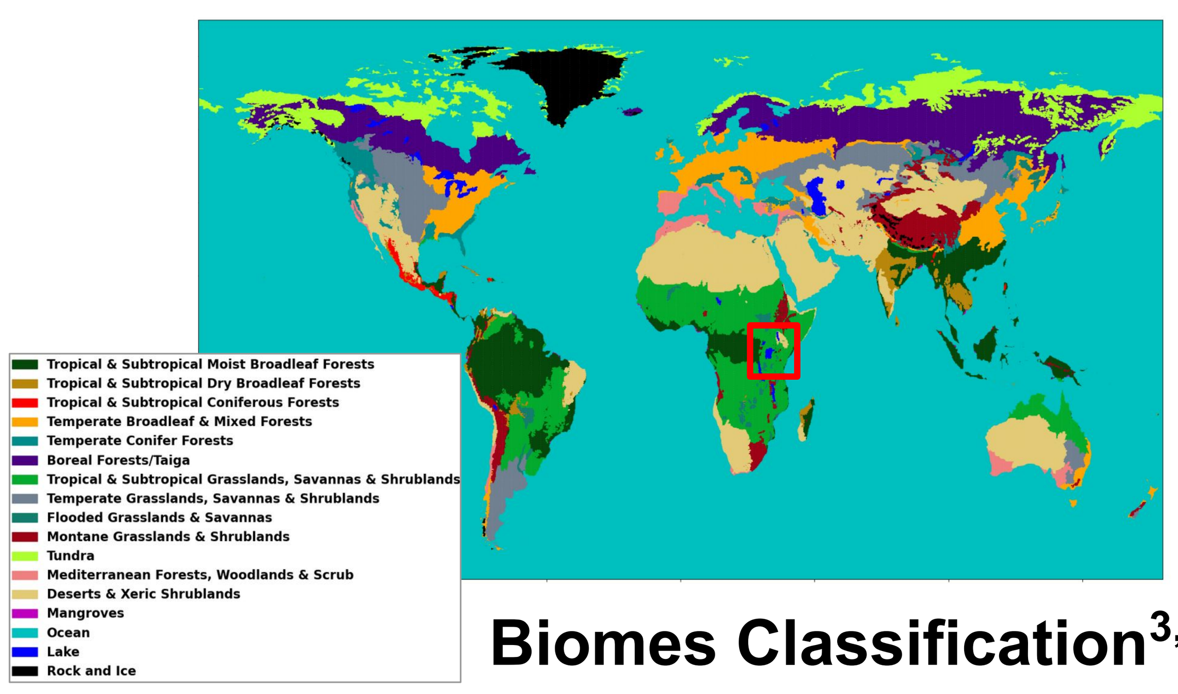


Application

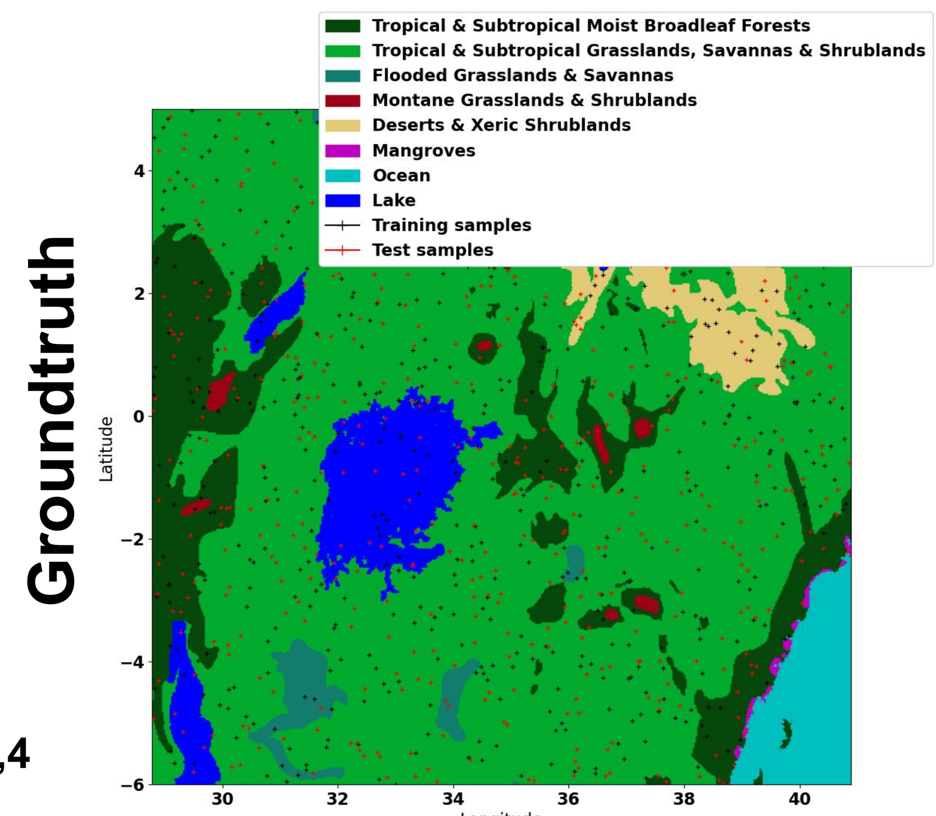
15MB - **x3500 smaller** than CHELSA

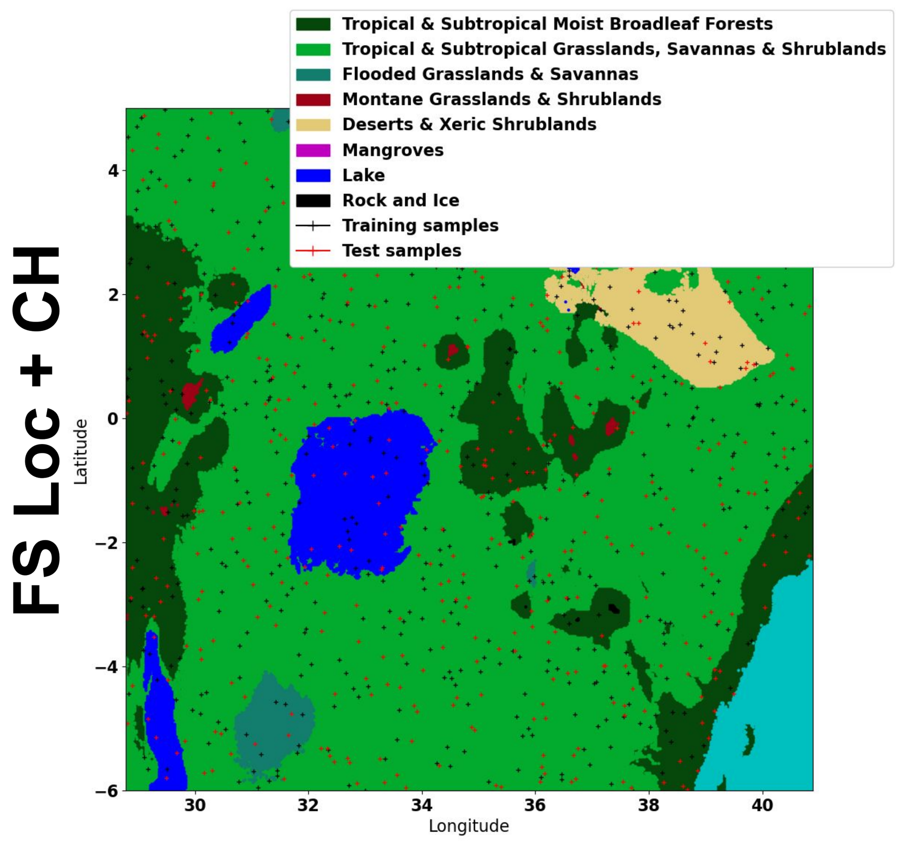


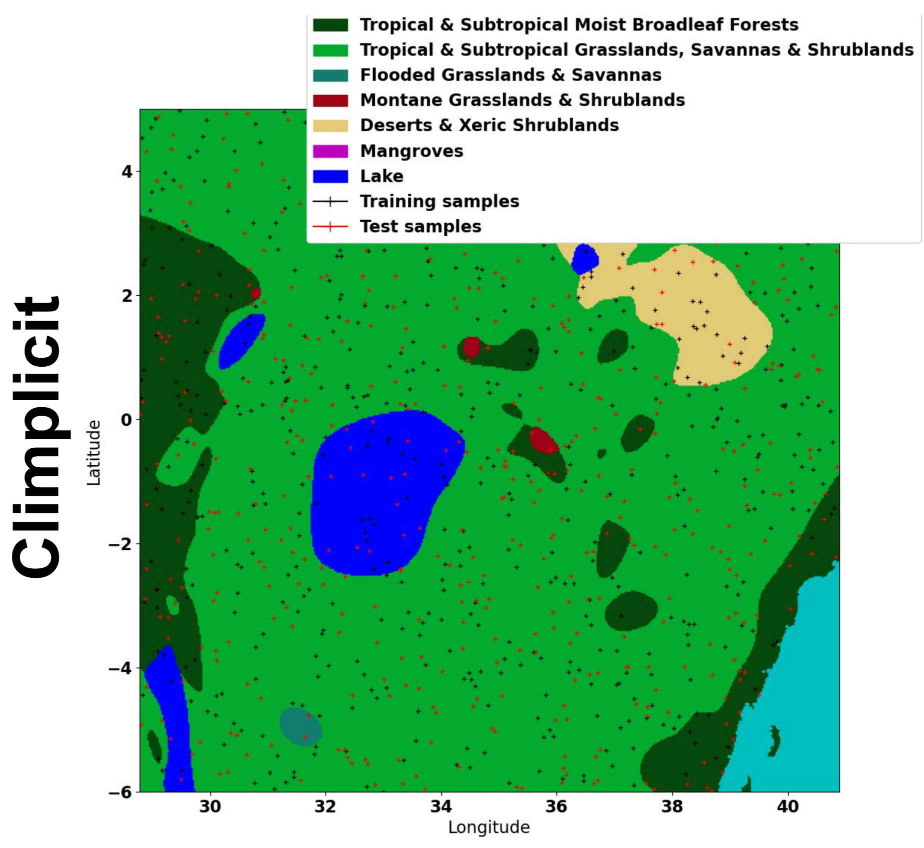
Single layer probing - **GPU optional**



Biomes Classification[3,4]







Results

Comparison with training "from-scratch" and other pretrained geolocation representations

Model	Biomes (% F1 ↑)	SDM (% Acc ↑)	Plant traits (% R^2 ↑)
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	**79.6 ± 1.7**	2.5 ± 0.1	64.8 ± 0.4
SatCLIP[4]	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	**3.5 ± 0.0**	57.9 ± 0.1
Climplicit (Ours)	78.4 ± 0.3	3.2 ± 0.0	**70.0 ± 0.1**

Ablation of various model & training choices

Model	Biomes (% F1 ↑)	SDM (% Acc ↑)	Plant traits (% R^2 ↑)
Climplicit	**78.4 ± 0.3**	3.2 ± 0.0	**70.0 ± 0.1**
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	**3.6 ± 0.0**	69.1 ± 0.1
rec-CHELSA	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. Böhner, 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.

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