Global seasonal pre-training dataset (SSL4Eco) and self-supervised model (SeCo-Eco) for ecological applications

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CVPR EarthVision 2025, Accepted

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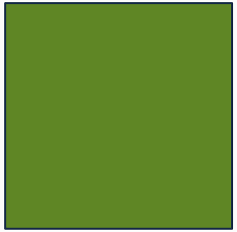
Remote sensing for ecological applications

Tasks

- land cover classification
- species distribution modelling

Remote sensing for ecological applications

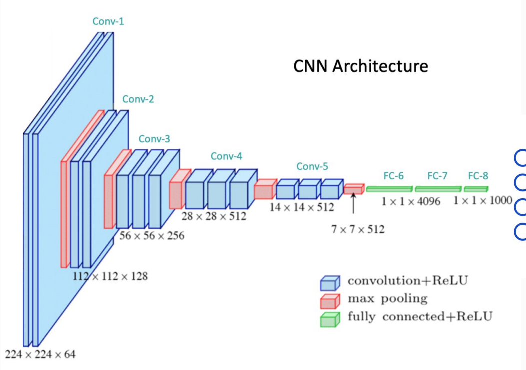
300 m

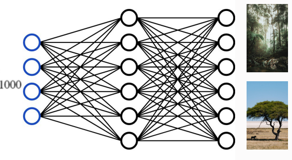


Low resolution

300 m

High resolution





Objective

01

Design Sentinel-2 pre-training dataset global and seasonal

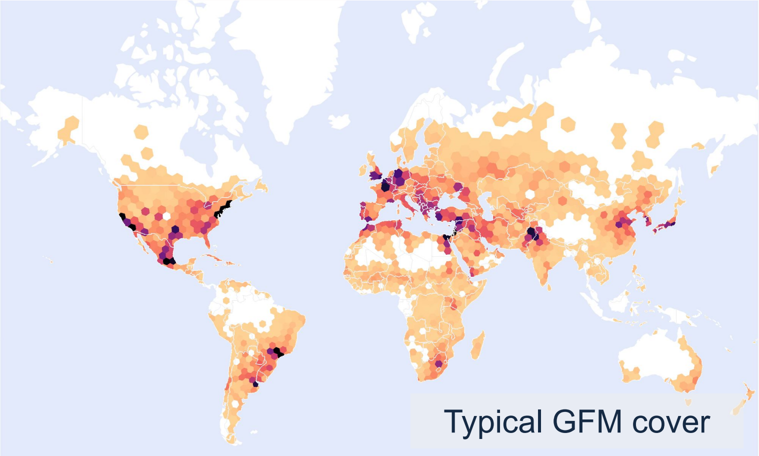
02

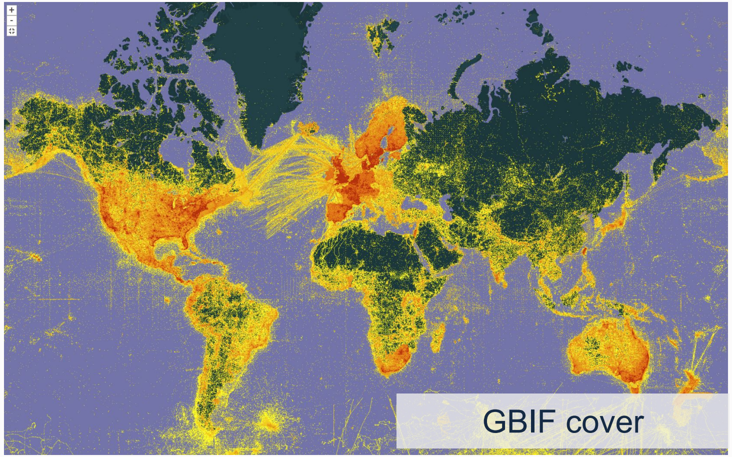
Train Geospatial Foundation Model (GFM)

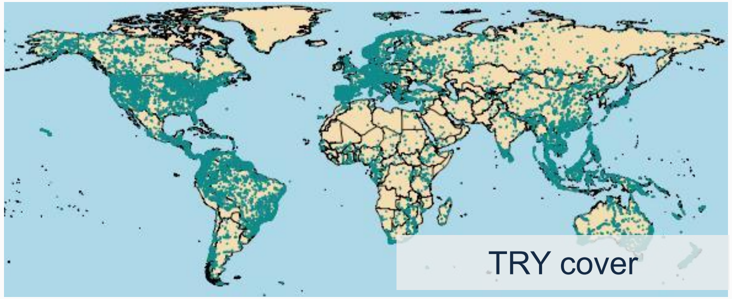
03

Test on ecologically relevant benchmarks

Geographical distribution





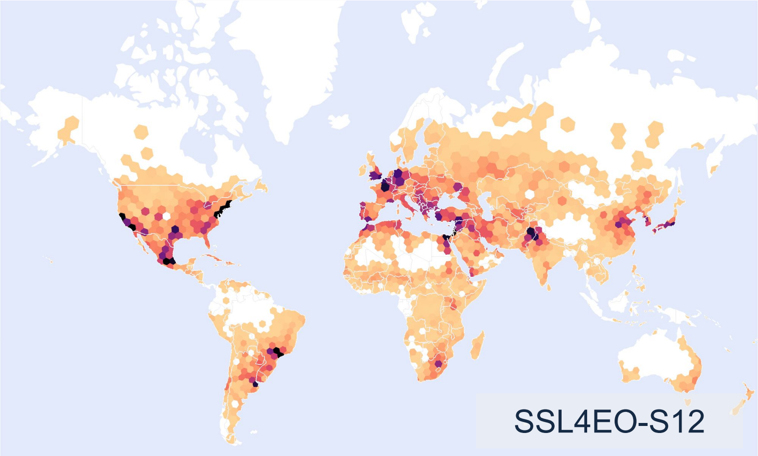


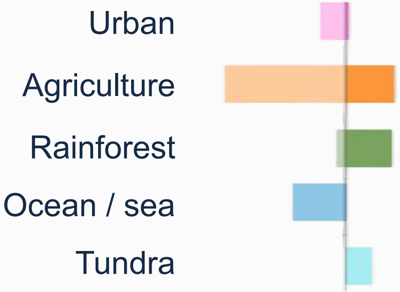
Sampling bias

- centred on cities
- missing entire ecosystems

Plekhanova et al., *CVPR EarthVision*, 2025. Accepted

Geographical distribution of pre-training dataset





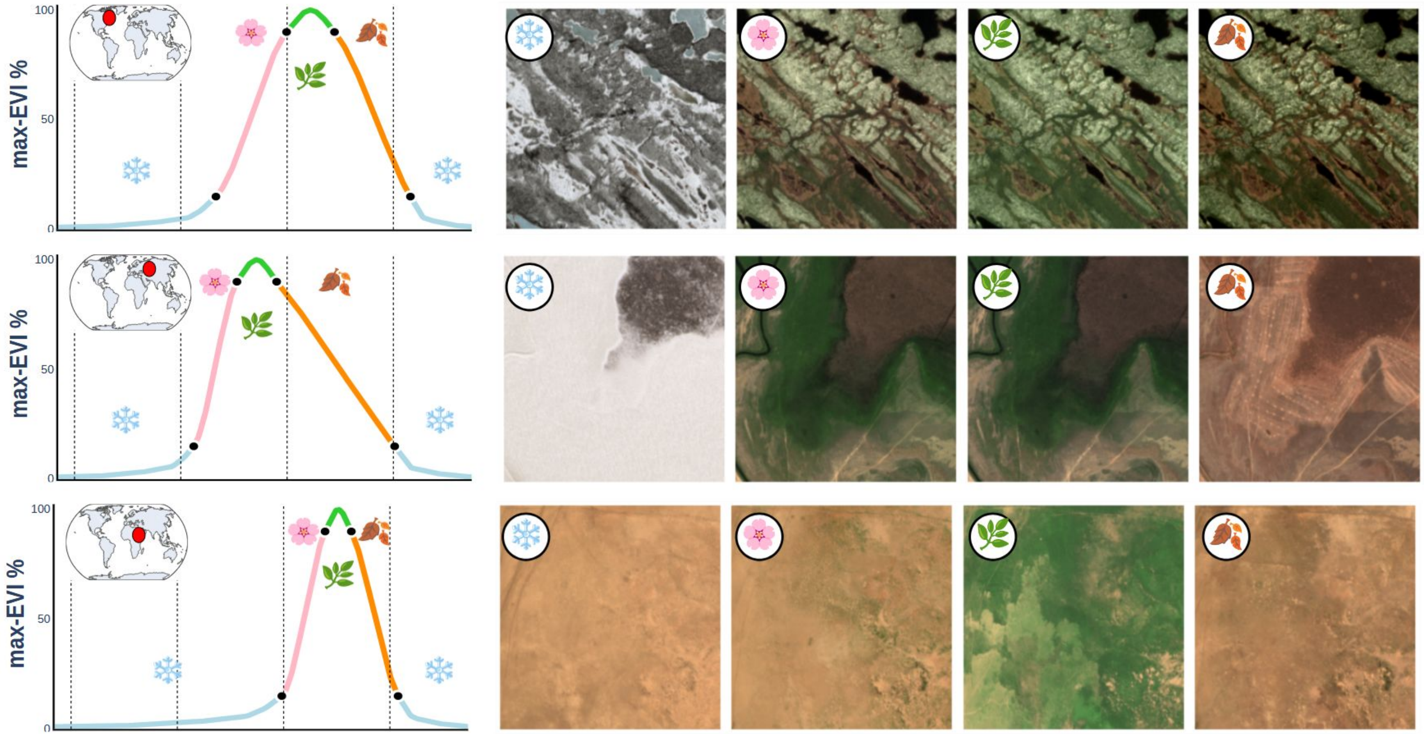
Plekhanova et al., *CVPR EarthVision*, 2025. Accepted

Seasonality

How to pick seasons?

- at random
- calendar date
- **phenology curve**

Seasonality

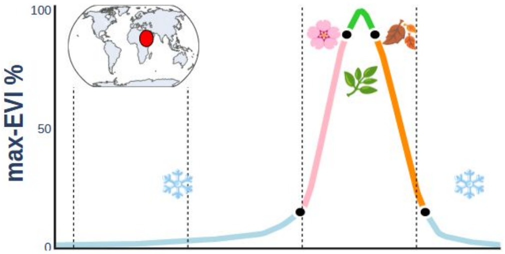


(a) EVI-based seasons (b) Seasonal images

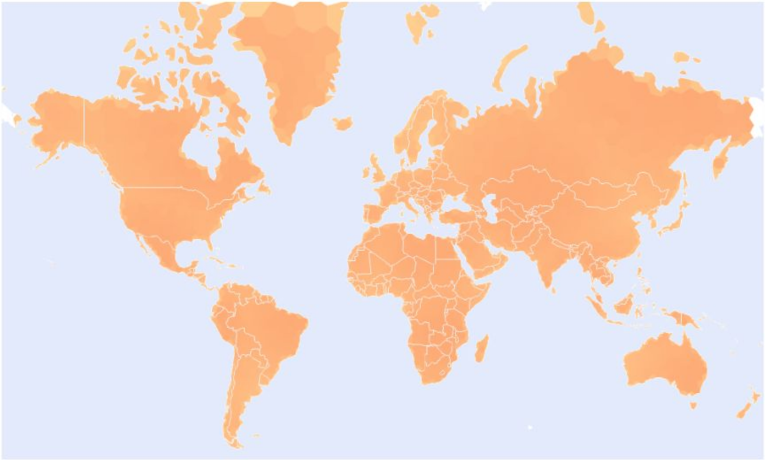
Pre-training dataset

SSL4Eco

250K, Sentinel-2, 2.56 × 2.56 km



(a) EVI-based seasons



(b) Spatial distribution of SSL4Eco

SeCo-Eco – GFM model

Momentum Contrast (MoCo) He et al., *CVPR* 2020

+

What Should Not Be Contrastive in Contrastive Learning

Xiao et al., *ICLR* 2021

↓

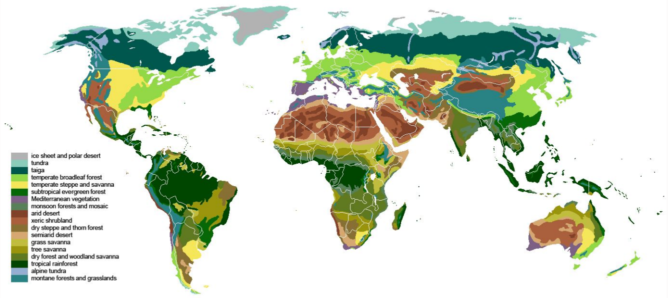
Seasonal Contrast (SeCo) Mañas et al., *ICCV* 2021

learns to capture seasons instead of being invariant to seasons

SeCo-Eco - ResNet50 trained on SSL4Eco with Seasonal Contrast technique

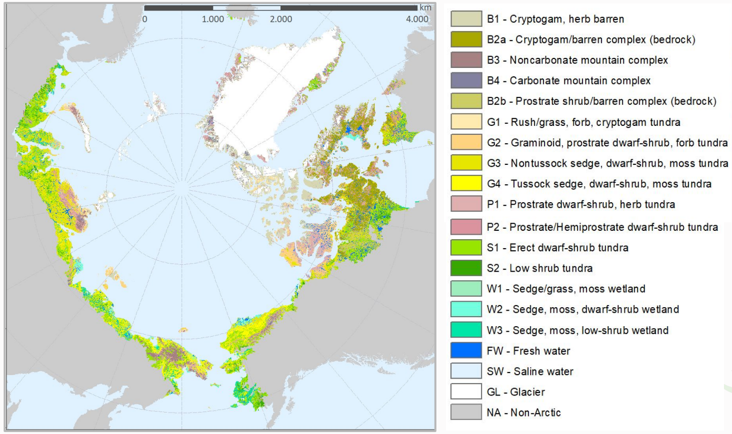
New benchmarks

Biomes — global biomes



Olson et al., *BioScience*, 2001

CAVM — Arctic vegetation types



Raynolds et al., *Remote Sens. Environ.*, 2019

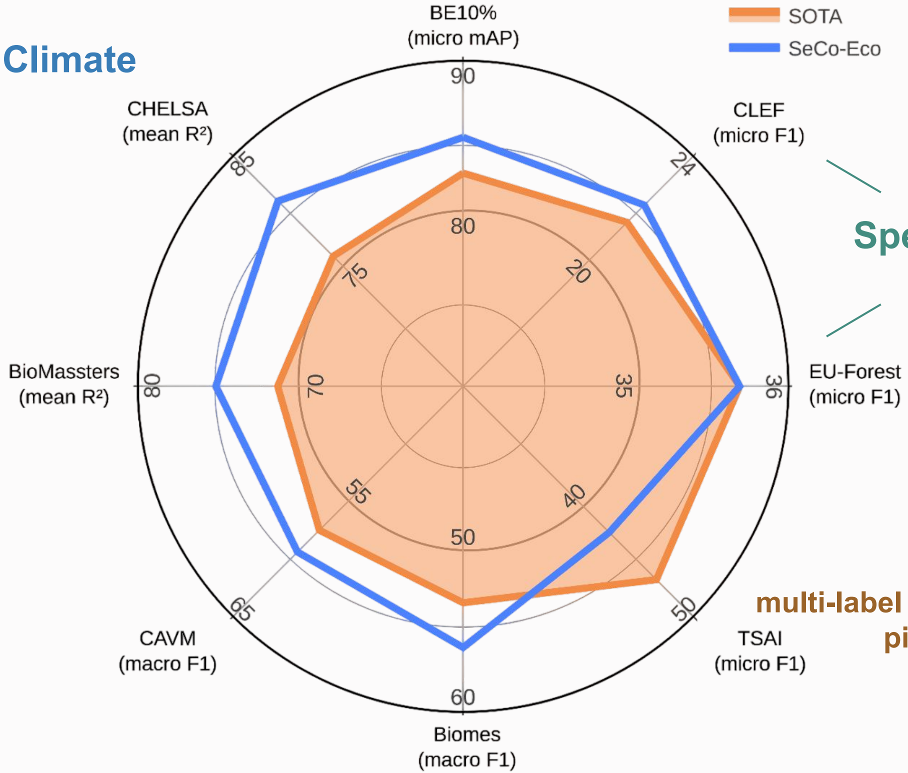
Results

Model	Biomes (macro F1) ↑		CAVM (macro F1) ↑	
	LP	10-NN	LP	20-NN
SeCo [58]	41.5 ± 0.5	36.9 ± 1.0	54.4 ± 0.7	52.1 ± 0.7
SatMAE [16]	51.3 ± 1.1	47.7 ± 0.7	56.3 ± 1.4	55.8 ± 0.7
Satlas [5]	48.3 ± 1.6	47.6 ± 0.9	53.8 ± 2.0	53.2 ± 0.5
Croma [31]	47.1 ± 1.4	42.2 ± 0.6	53.6 ± 1.2	51.6 ± 0.8
SSL4EO [89]	$\underline{53.3} \pm 1.0$	$\underline{49.7} \pm 0.5$	$\underline{57.5} \pm 9.6$	$\underline{56.9} \pm 0.6$
DOFA [93]	49.7 ± 1.3	42.9 ± 0.5	56.4 ± 1.6	53.5 ± 0.6
SeCo-Eco (ours)	$\mathbf{56.1} \pm 0.7$	$\mathbf{51.1} \pm 0.9$	$\mathbf{59.4} \pm 1.0$	$\mathbf{59.5} \pm 0.8$

Table 4. Linear probing and K-Nearest Neighbor comparison of state of the art models with our SeCo-Eco pretrained on our SSL4Eco on classification of two land cover datasets: global biomes and Arctic vegetation types [73]. **Best**, <u>second best</u>.

Plekhanova et al., *CVPR EarthVision*, 2025. Accepted

Results



Climate

Biomass distribution

Species distribution modelling

multi-label classification on 6x6 pixel patches

Takeaways

Recommendation for future GFM design

- geographical sampling
- EVI-based seasonality

Practical outcomes

- SSL4Eco pre-training dataset
- SeCo-Eco model for ecological tasks
- ecological benchmarks
- easy to combine with other data modalities

CVPR

EARTH VISION

EARTHVISION 2025

June 11/12th, Nashville, TN, USA

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