

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

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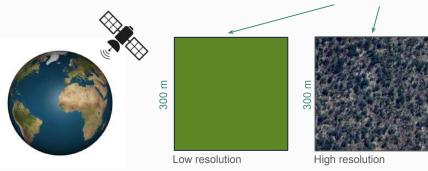
² University of Zurich, Switzerland



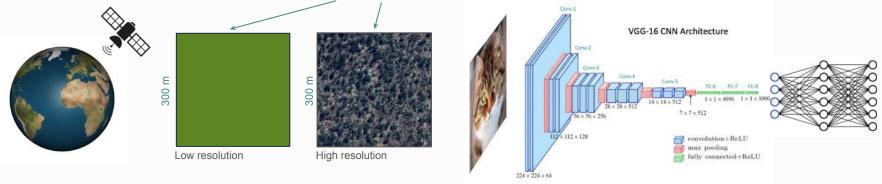
Tasks

- land cover classification
- species distribution modelling

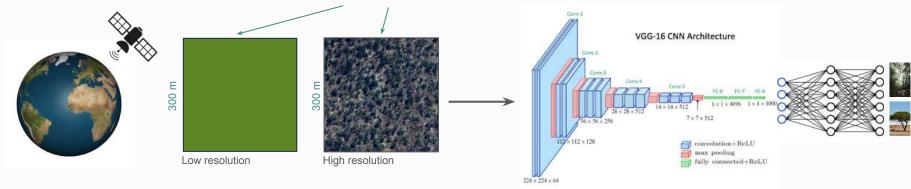














01

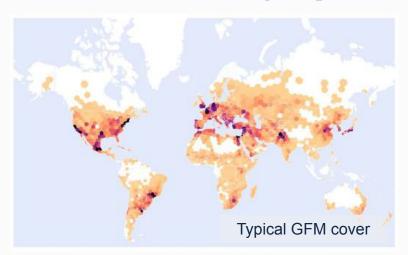
02

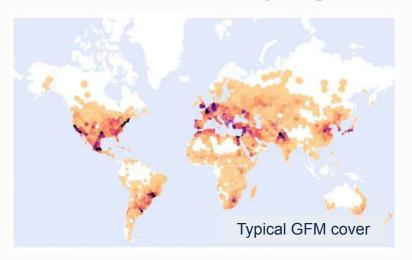
03

Design Sentinel-2 pre-training dataset global and seasonal

Train Geospatial Foundation Model (GFM)

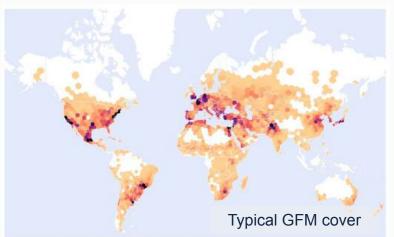
Test on ecologically relevant benchmarks

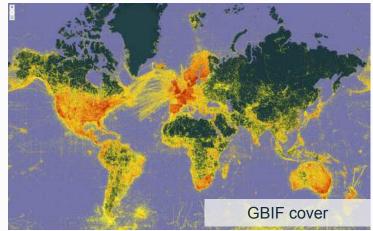




Sampling bias

- centred on cities
- missing entire ecosystems

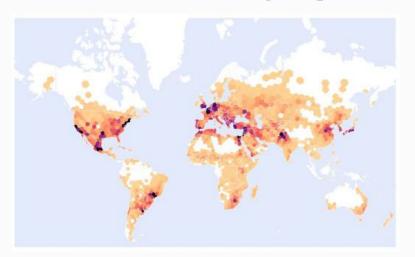




Sampling bias

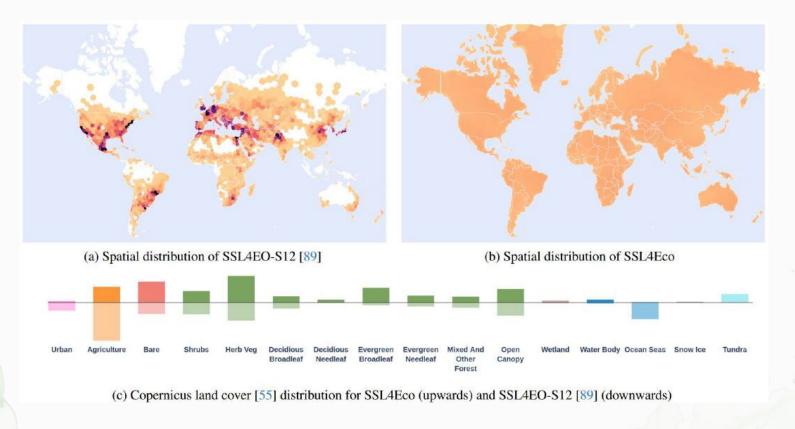
- centred on cities
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Geographical distribution of pretraining dataset



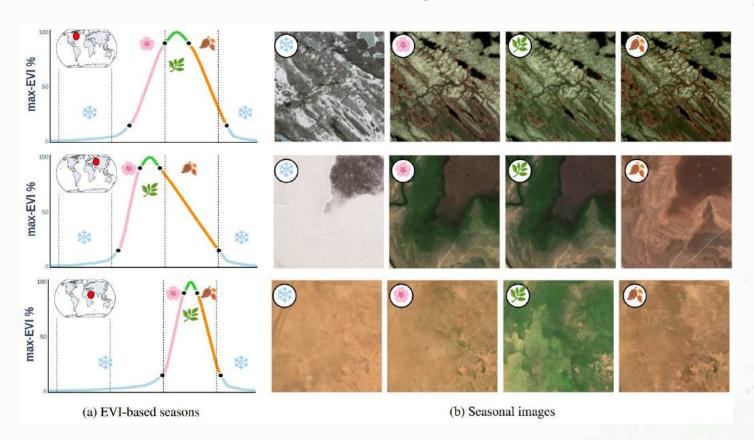
Seasonality

How to pick seasons?

- at random
- calendar date
- phenology curve

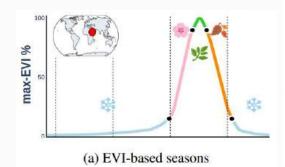


Seasonality



Pre-training dataset

SSL4Eco









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

GFM model

Momentum Contrast (MoCo)

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He et al., *CVPR* 2020

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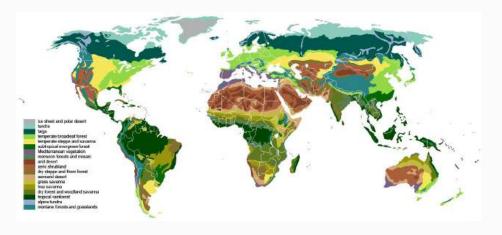
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New benchmarks

Biomes

Image classification into one of 15 global biomes based on Olson et al.



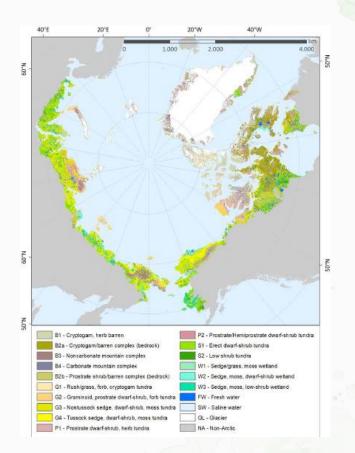


New benchmarks

CAVM

Classification of an image into one of Arctic vegetation types based on CAVM.





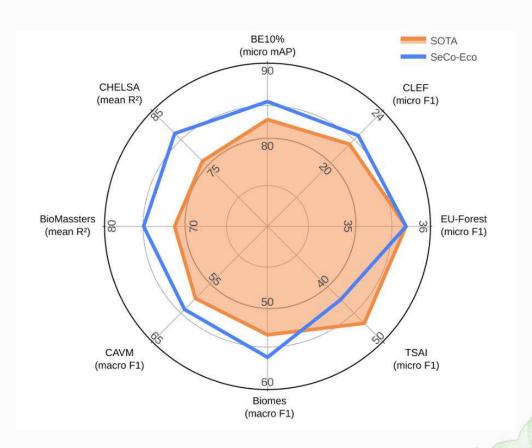


Results

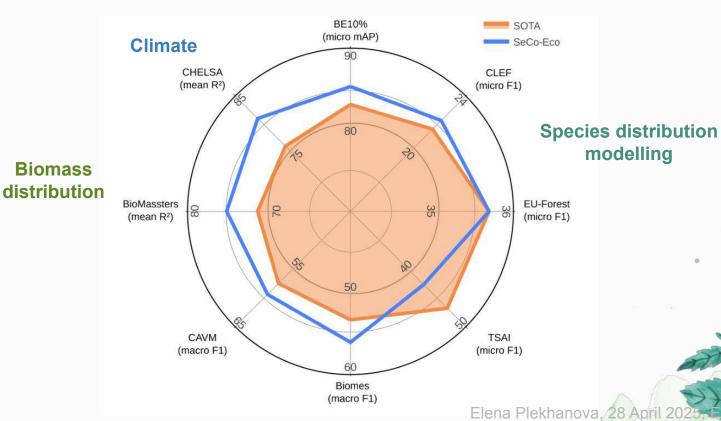
Model	Biomes (macro F1) [↑]		CAVM (macro F1)	
	LP	10-NN	LP	20-NN
SeCo [58]	41.5 ± 0.5	36.9 ± 1.0	54.4 ± 0.7	52.1 ± 0.7
SatMAE [16]	51.3 ± 1.1	47.7 ± 0.7	56.3 ± 1.4	55.8 ± 0.7
Satlas [5]	48.3 ± 1.6	47.6 ± 0.9	53.8 ± 2.0	53.2 ± 0.5
Croma [31]	47.1 ± 1.4	42.2 ± 0.6	53.6 ± 1.2	51.6 ± 0.8
SSL4EO [89]	53.3 ± 1.0	49.7 ± 0.5	57.5 ± 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)	56.1 ± 0.7	51.1 ± 0.9	59.4 ± 1.0	59.5 ± 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**, second best.

Results



Results



Takeaways

Recommendation for future GFM design

- geographical sampling
- EVI-based seasonality

Practical outcomes

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

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Recommendation for future GFM design

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github.com/PlekhanovaElena/ssl4eco