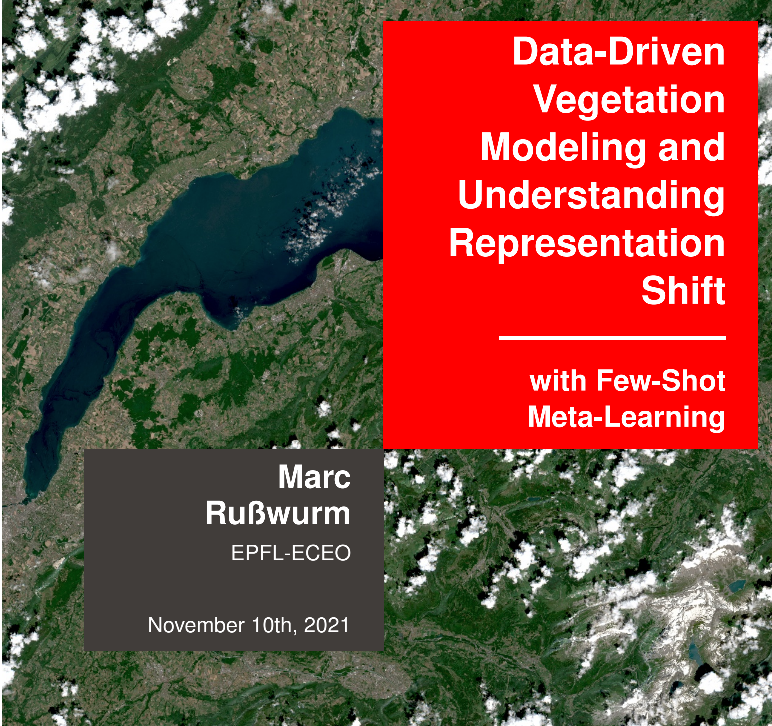
EPFL



Data-Driven Vegetation Modeling and Understanding Representation Shift

with Few-Shot Meta-Learning

Marc Rußwurm
EPFL-ECEO

November 10th, 2021

École polytechnique fédérale de Lausanne

Why do we need Vegetation Modeling?

Zero Hunger — estimating the **crop yield** & predict **food prices**, shortages.

Climate Action — by monitoring **vegetation changes** over time (desertification).

Life on Land — human life depends on **agriculture**, animal life on **biotopes**.

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Crop Type Mapping:

Satellite Time Series Data $\rightarrow$ Crop Type Label (e.g. corn, meadow)

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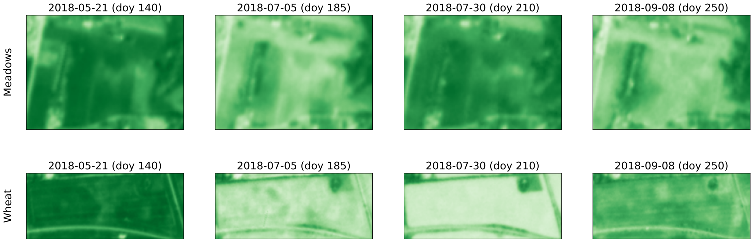
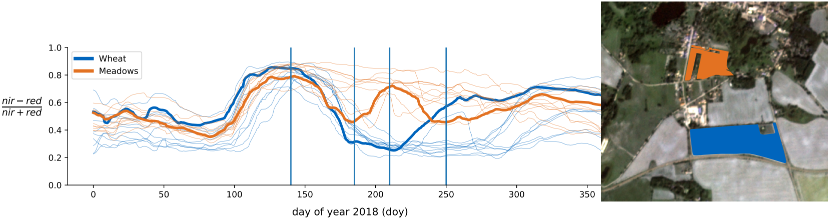
Later: Land Cover Classification

Satellite Image $\rightarrow$ Land Cover Label (e.g. urban, forest)

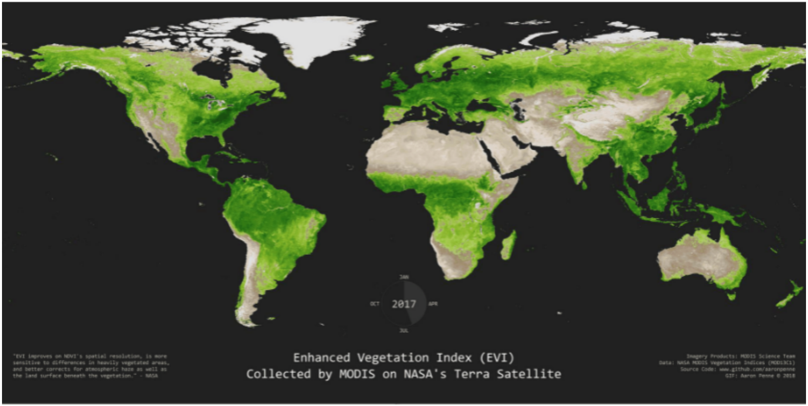
Satellite Time Series → Crop Type





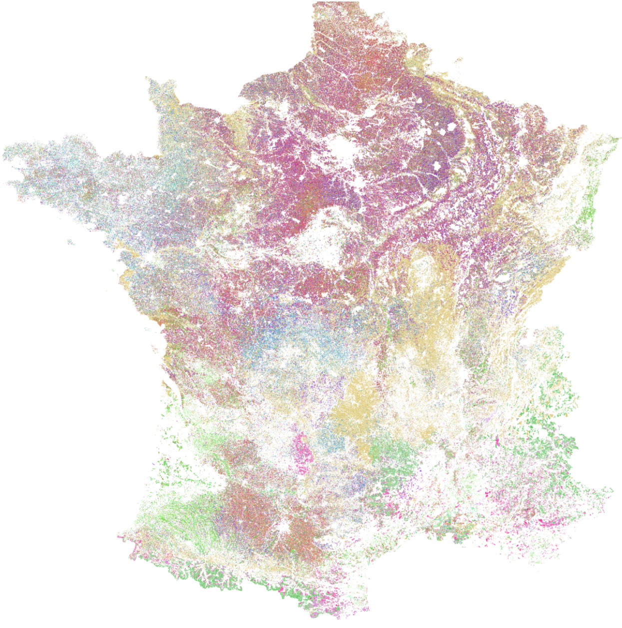
Kondmann, et al., ”DENETHOR: The DynamicEarthNET dataset for Harmonized, inter-Operable, analysis-Ready, daily crop monitoring from space.”. NeurIPS Data Track (2021).

Satellite Time Series Data in Abundance



visualization Aaron Penne Github

Label Data in Abundance



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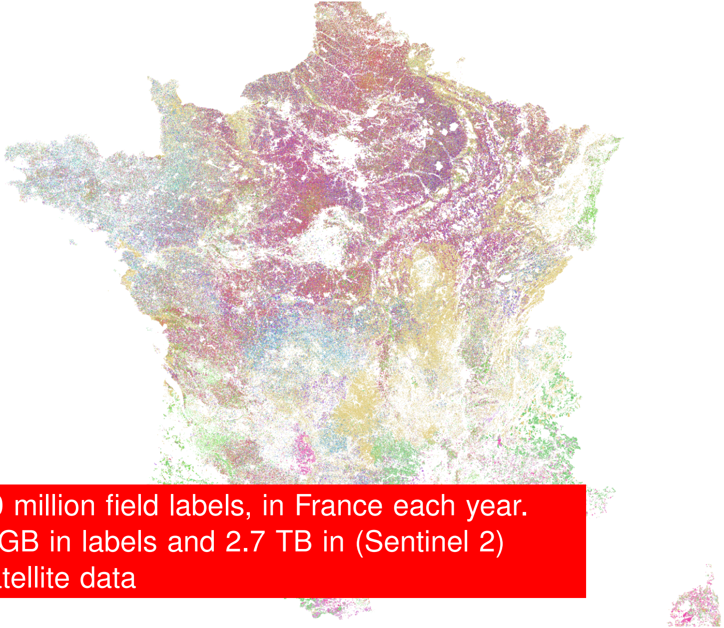

10 million field labels, in France each year.
3 GB in labels and 2.7 TB in (Sentinel 2) satellite data

Problem Solved?

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Plenty of input data!

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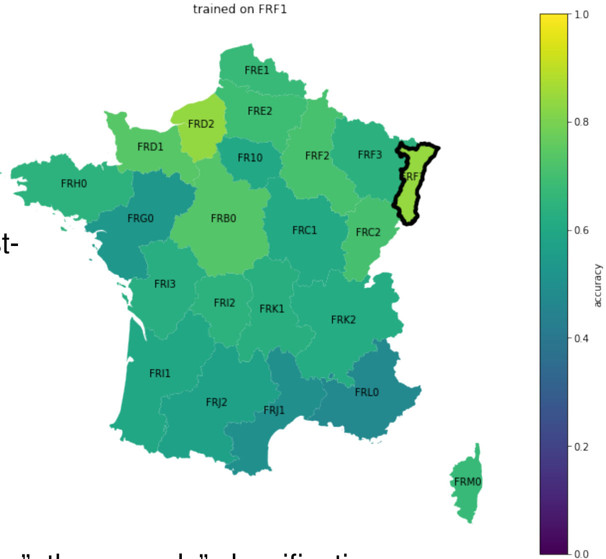
Let’s train a Deep Learning Model!

The ”Data Dilemma”



training and testing on different regions

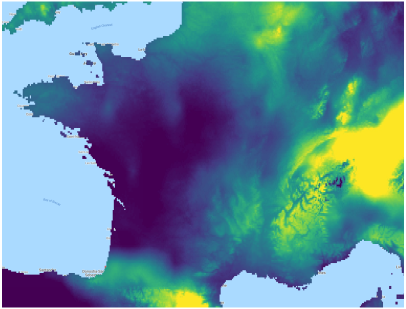
binary ”wheat” vs ”other cereals” classification

crop type time series classification with a simple 1D-CNN and 200 samples per class in each NUTS-2 region

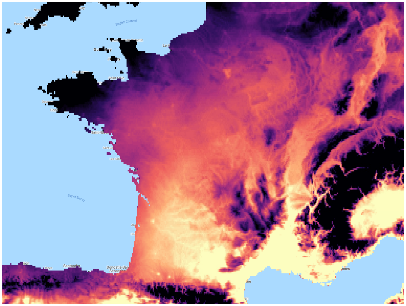
Environmental Conditions

Photosynthesis is a function of the environment.

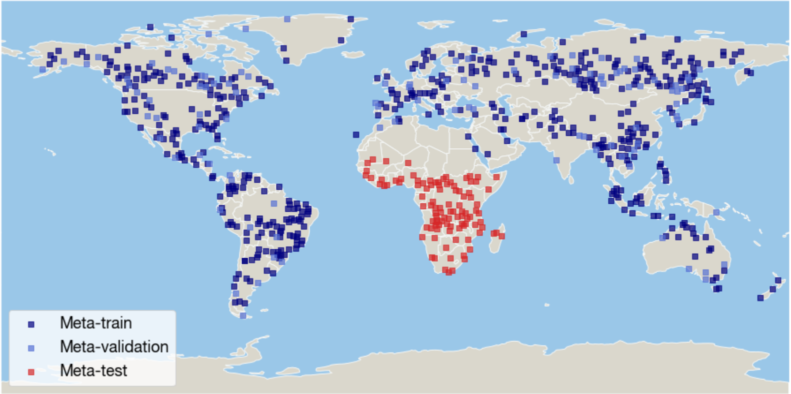
Precipitation 2018-08



Max temp (23-30℃) 2018-08



Apply models on regions of little data



How do we generate data?

Data Generation Model

domain

$$\mathcal{D} = \{\mathcal{X}, P(\mathcal{X})\}$$

Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10), 1345-1359.
Qiang Yang; Yu Zhang, Wenyuan Dai; Sinno Jialin Pan (Editors) (2020). Transfer learning. Cambridge University Press. DOI 9781139061773
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$$\mathbf{X} \sim P(\mathcal{X}) \xrightarrow{\text{predictive function f}} y = f(\mathbf{X})$$

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joint data distribution $P(\mathcal{X} \times \mathcal{Y})$

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Data Generation Model

domain	task
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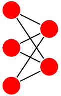
input $\mathbf{X}$ → feature learning f_θ  → label y

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In- and Out-of-Dist. Generalization

The I.I.D assumption is usually enforced via random splitting a single dataset D into training and testing partitions

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$$D \overset{\text{i.i.d}}{\sim} P(\mathcal{X} \times \mathcal{Y})$$

random split

$$D_{\text{train}} \qquad D_{\text{test}}$$

$$f_\theta \xrightarrow{\text{compare with } f(\cdot)} \mathcal{L}_{\text{in}}$$

train model

"in-domain" or "in-distribution" generalization

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$$D \overset{\text{i.i.d}}{\sim} P(\mathcal{X} \times \mathcal{Y})$$

random split

D_{train} $\quad$ D_{test}

Data of another distribution

$$\mathbf{X}, y \sim Q(\mathcal{X} \times \mathcal{Y})$$

$$\mathcal{D}_Q = \{\mathcal{X}, P_Q(\mathcal{X})\}$$
$$\mathcal{T}_Q = \{\mathcal{Y}, f_Q(\cdot)\}$$

$$f_\theta \xrightarrow{\text{compare with } f(\cdot)} \mathcal{L}_{\text{in}} \xrightarrow{\text{compare with } f_Q(\cdot)} \mathcal{L}_{\text{out}}$$

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"in-domain" or "in-distribution" generalization

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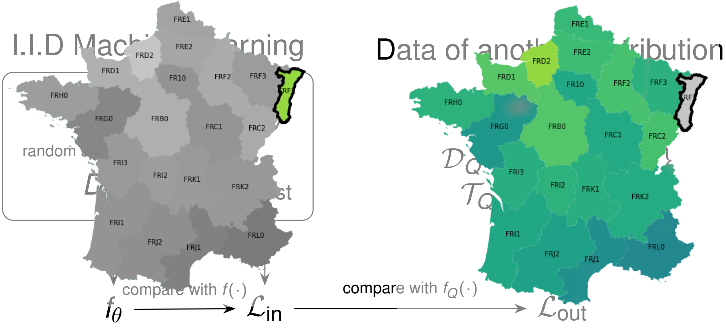

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”in-domain” or ”in-distribution” generalization

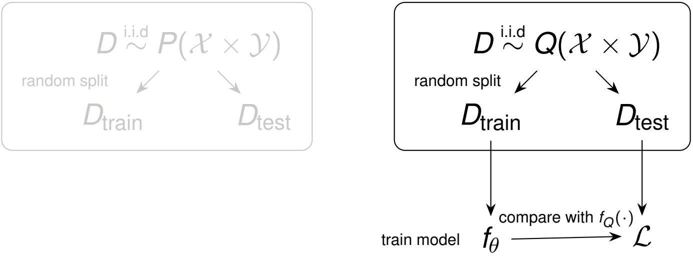
”out-of-domain” or ”out-of-distribution” generalization

Improve on the target Task/Domain

Option 1) Just train on target data (we will call ”random initialization”)

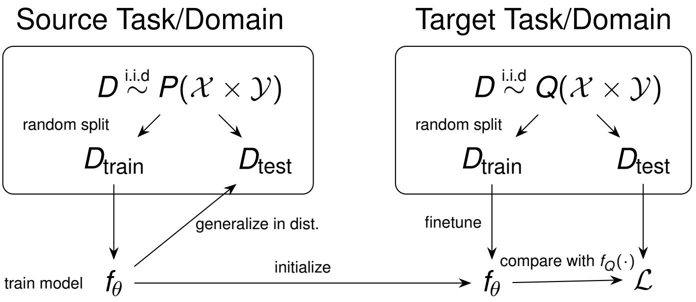
Source Task/Domain

Target Task/Domain



Improve on the target Task/Domain

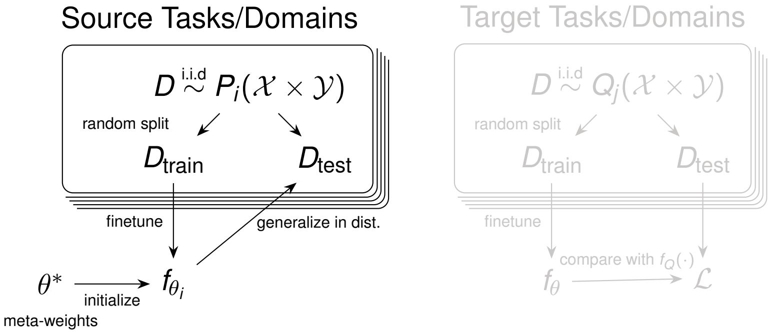
Option 2) "Pretrain" on Source finetune on Target



Improve on the target Task/Domain

Option 3) ML framework that allows not ident. joint dists and in particular Model-Agnostic Meta-Learning

(Finn et al., 2017).



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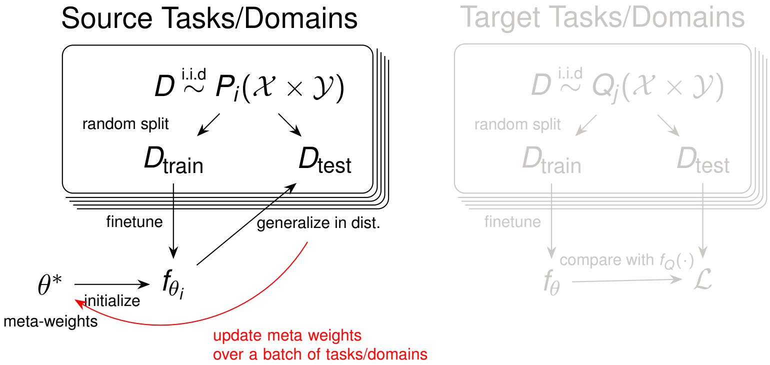

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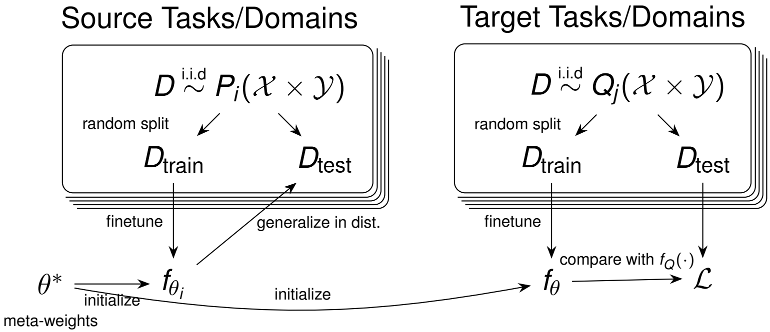

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A Visual Comparison

Algorithm 1: Model-Agnostic Meta-Learning

$p(\mathcal{T})$: distribution over tasks;
α, β step size hyperparameters;
randomly initialize θ;
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Meta-Learned Initialization

f_{P_1}

f_{P_2}

f_{P_3}

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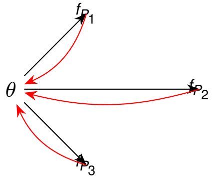

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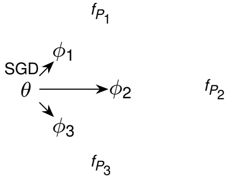

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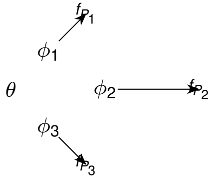

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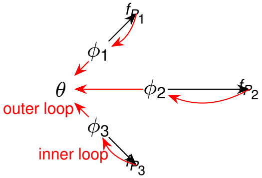

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$\theta \longrightarrow \theta$ f_{P_2}

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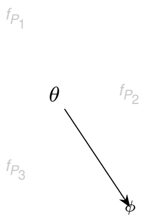

Optimized **to adapt** well to source distributions

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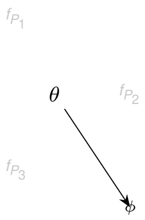
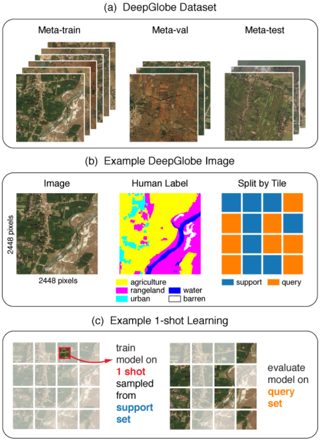


Optimized **to adapt** well to source distributions

while regular **pretraining** is optimized **to perform** well on source distributions.

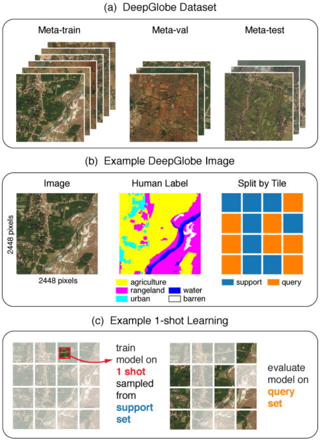
Experiments

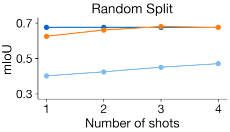
Deepglobe Land Cover Classification



Rußwurm, M., Wang, S., Körner, M., & Lobell, D. (2020). Meta-learning for few-shot land cover classification. In Proceedings of the ieee/cvf conference on computer vision and pattern recognition workshops (pp. 200-201).

Deepglobe Land Cover Classification





random pretrained MAML

Rußwurm, M., Wang, S., Körner, M., & Lobell, D. (2020). Meta-learning for few-shot land cover classification. In Proceedings of the ieee/cvf conference on computer vision and pattern recognition workshops (pp. 200-201).

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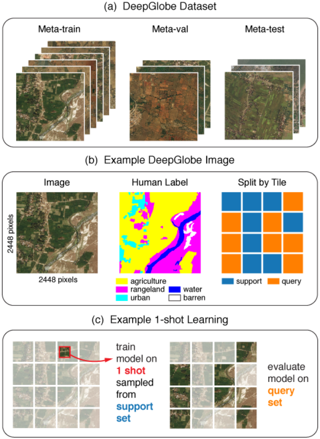

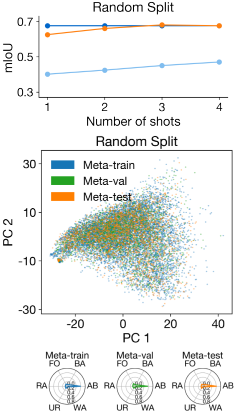

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EPFL

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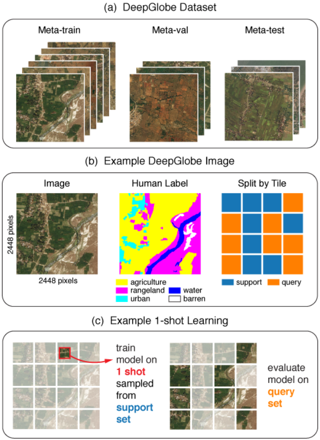

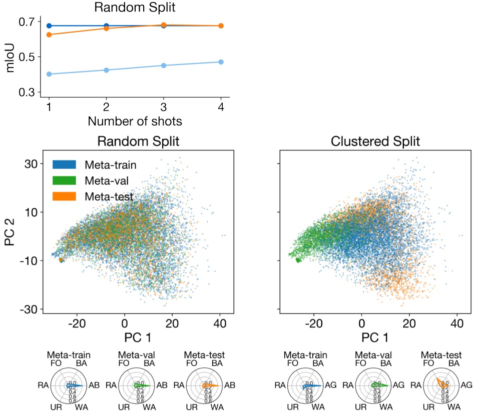

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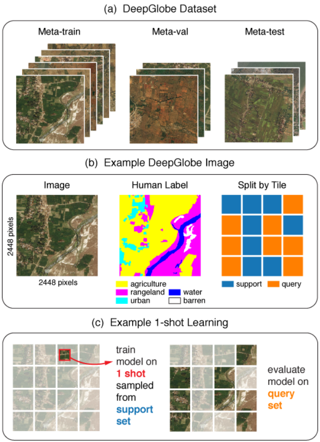

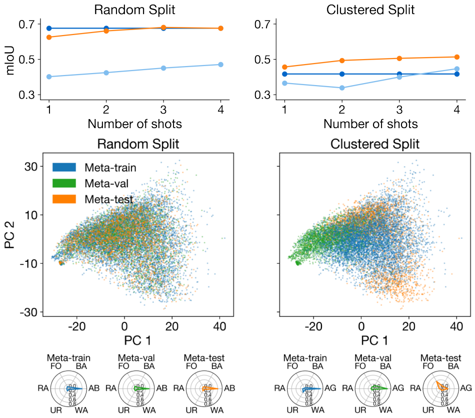

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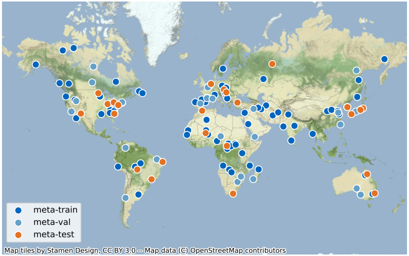
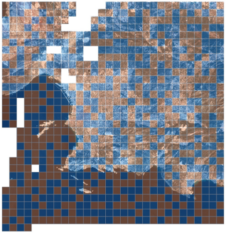
Sen12MS — Land Cover Classification

all Sen12MS regions



one region split in train/test

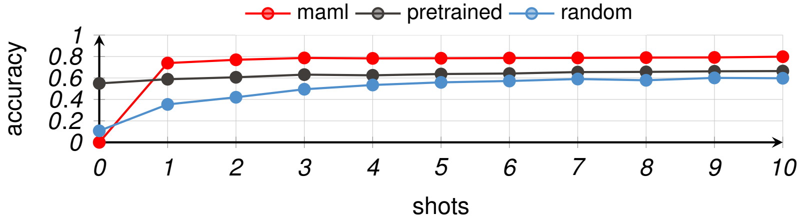


Schmitt, M., Hughes, L. H., Qiu, C., & Zhu, X. X. (2019). SEN12MS–A Curated Dataset of Georeferenced Multi-Spectral Sentinel-1/2 Imagery for Deep Learning and Data Fusion. arXiv preprint arXiv:1906.07789.

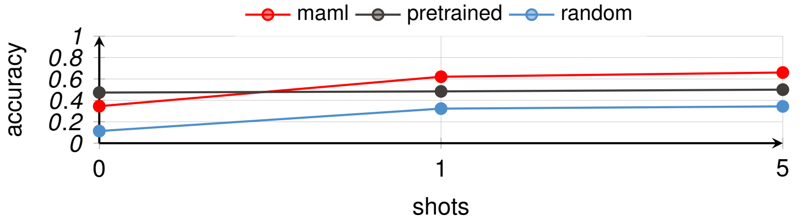
Sen12MS – Few-Shot Performance

Model: 7 stacked CNN layers 64 x 3 x 3 kernels + BN + ReLU + max-pooling

Classification



Segmentation



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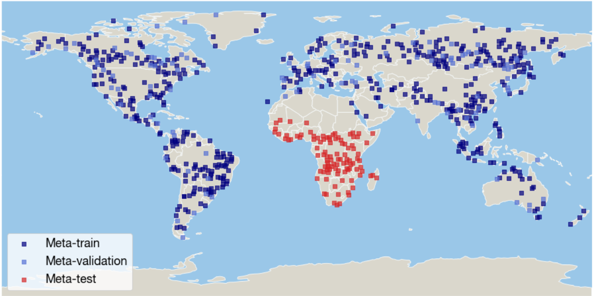
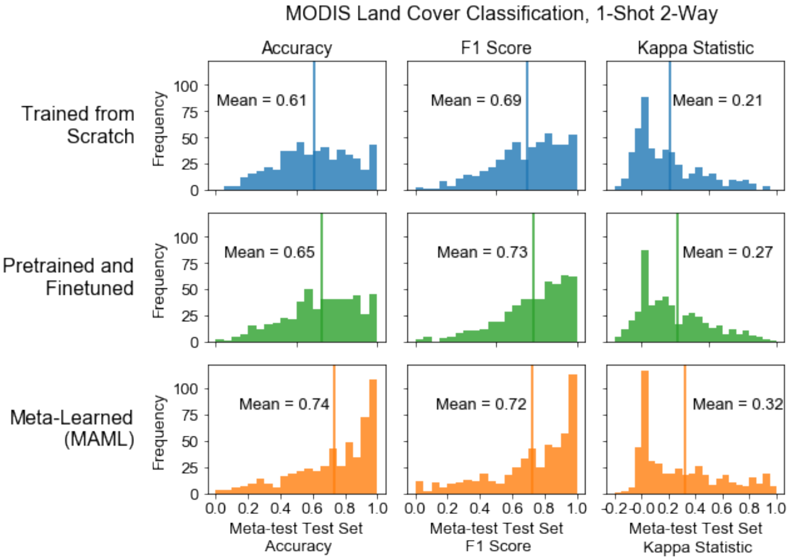
Modis Time Series Classification



1-shot 2-way, 515 meta-test tasks from Africa

Wang, S., Rußwurm, M., Körner, M., & Lobell, D. B. Meta-Learning For Few-Shot Time Series Classification. In IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium (pp. 7041-7044). IEEE.

Challenging Problem: Mixed results



Summary: When to Transfer?

”When to transfer?” of Yang et al., (2020).

- If distributions are too similar, transfer learning is not necessary. (e.g. DeepGlobe, unclustered)
- if distributions are related, transfer learning is effective (e.g. Sen12MS)
- If they are to different, there is no common knowledge to be learned. (e.g. Africa-testset: in Modis Time Series)

Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10), 1345-1359.
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- We may need to decide on the learning-framework on a case by case basis

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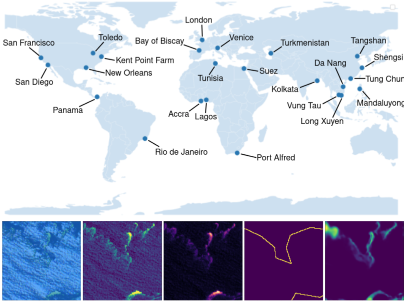
Marine Litter Detection



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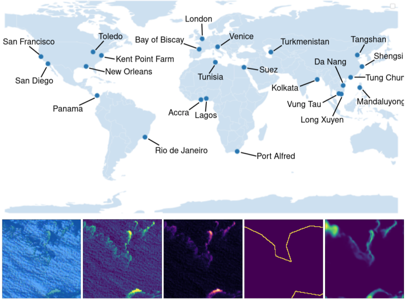

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what features? ➢ what DL models? ➢ what learning algorithms?

Thank you!

Marc Rußwurm @marccoru

marc.russwurm@epfl.ch
EPFL-ECEO epfl.ch/labs/eceo

ISPRS Thematic Session on Time Series ST_STIS

with C. Pelletier, Z. Zhou

Rußwurm, M., Wang, S., Körner, M., & Lobell, D. (2020). Meta-learning for few-shot land cover classification. In Proceedings of the ieee/cvf conference on computer vision and pattern recognition workshops (pp. 200-201).
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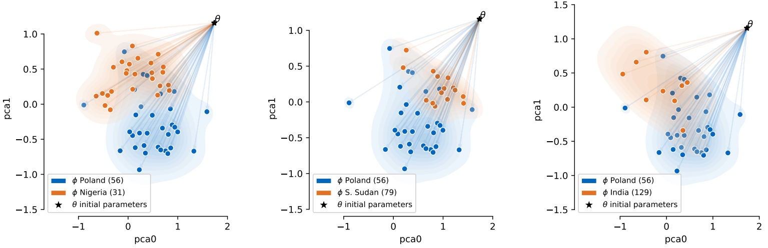
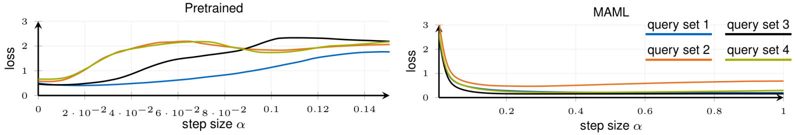
Similar weights after adaptation?

PCA-representations of the neural network weights before (θ) and after adaptation (ϕ).



Traversing the loss landscape from θ to ϕ.



Colors

rouge	montrose	acier	chartreuse
leman	perle	soufre	marron
grosseille	vertedeau	carotte	ardoise
canard	rose	zinzolin	taupe