CECMWF



Machine Learning for Earth Observation and Beyond

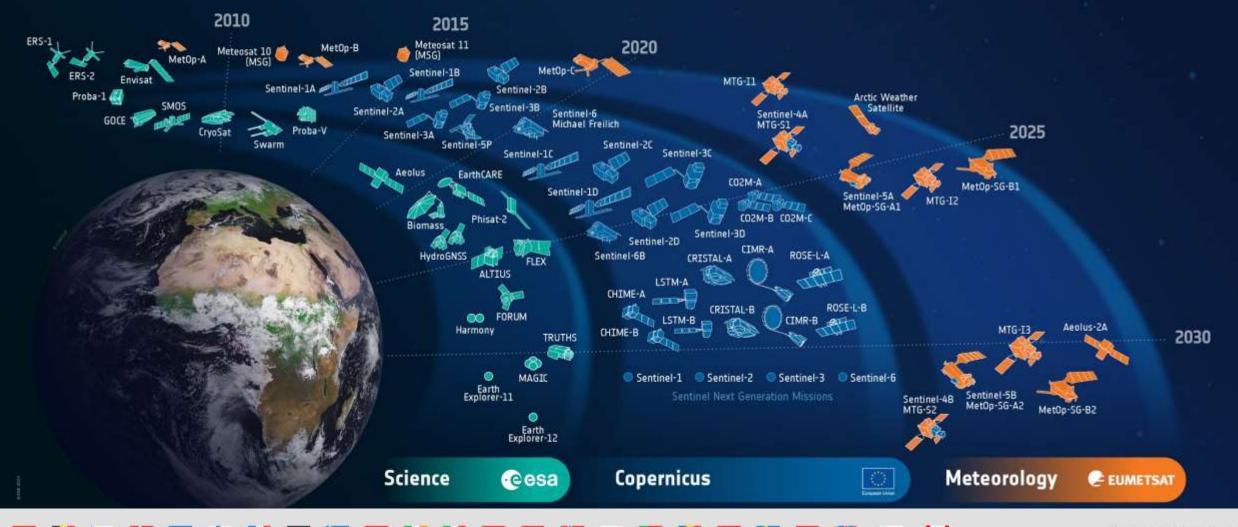
Xiaoxiang Zhu

Technical University of Munich, Germany





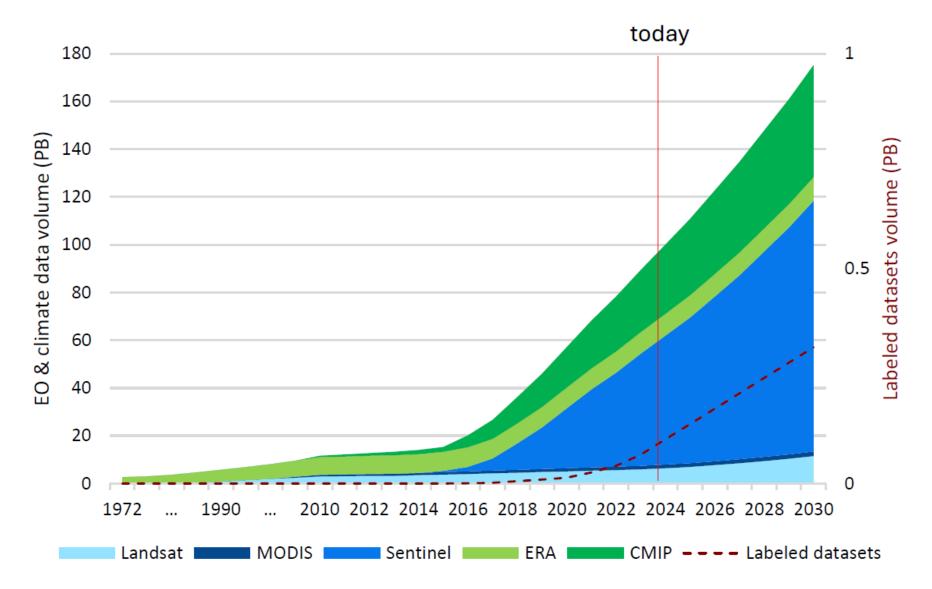
ESA-DEVELOPED EARTH OBSERVATION MISSIONS



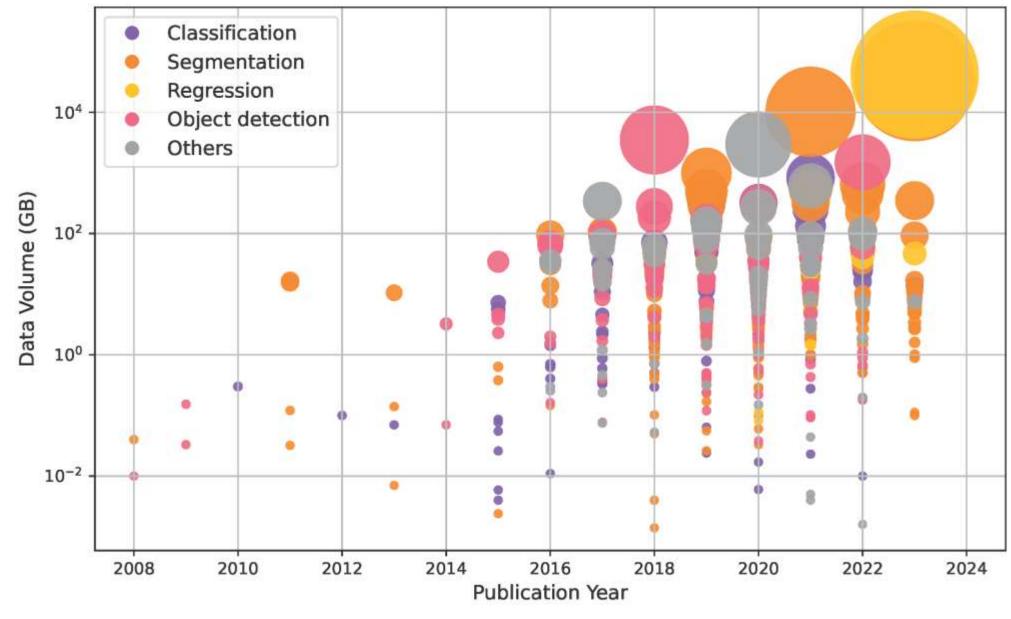
Euro Euro

European Space Agency

The Open Big Earth Data



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Zhu et al., On the Foundations of Earth and Climate Foundation Models, under review.

ESA-ECMWF WORKSHOP 2024 - Machine Learning for Earth System Observation and Prediction

ALC: NO



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ALC: NO



Al and Data Science in Earth Observation



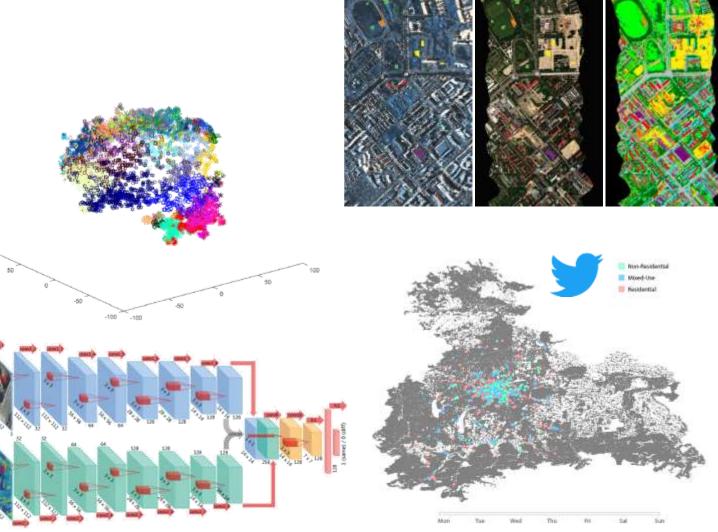
Date Fusion

Information Mining

Machine Learning/Deep Learning

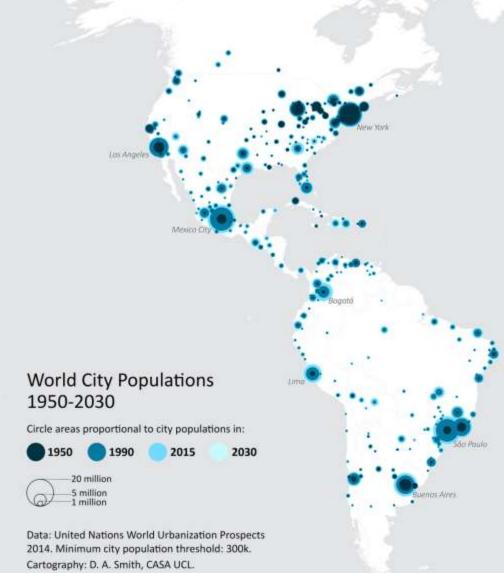
Big Data Management and HPC

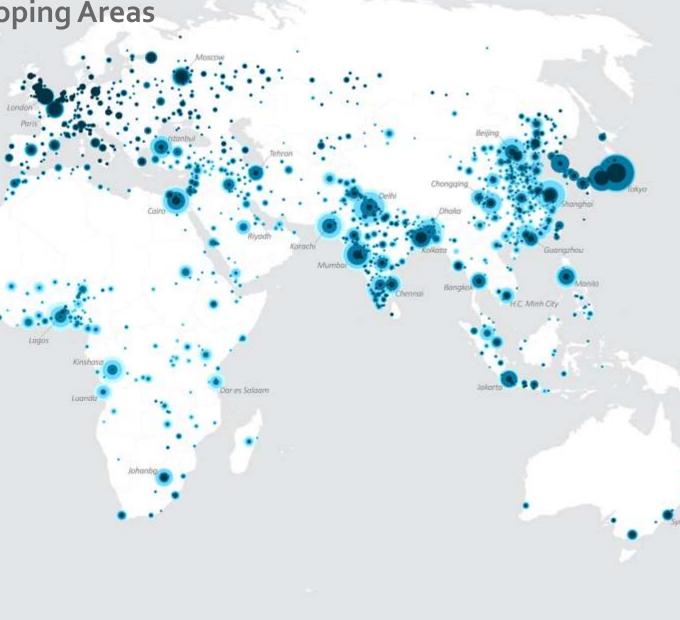




What can ML4Earth offer? A few motivating examples of tackling societal grand challenges

Urban Growth Happens Mostly in Developing Areas





Open Data for Urban Research?

> 4.1 Billion buildings in the world (UN, 2019)

604 Million building footprints in OSM < 15%



Only 3% buildings in OSM have height information < 0.5 %



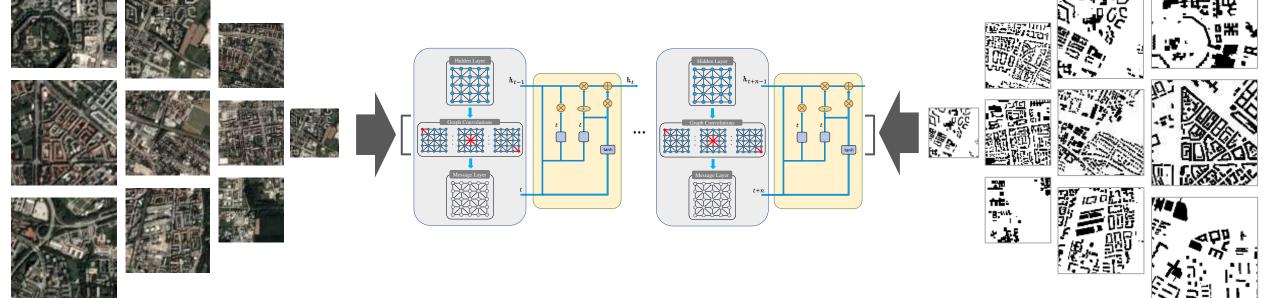
Status: April 16, 2024

Building Footprint Extraction from *NewSpace*-Satellite Images

planet



satellite image and GIS building footprint pairs from 74 cities





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A: Data acquisition

Urban detection
Image querying

B: Analysis-ready data

Radiometric calibration
Mosaicing

C: Machine learning pipeline

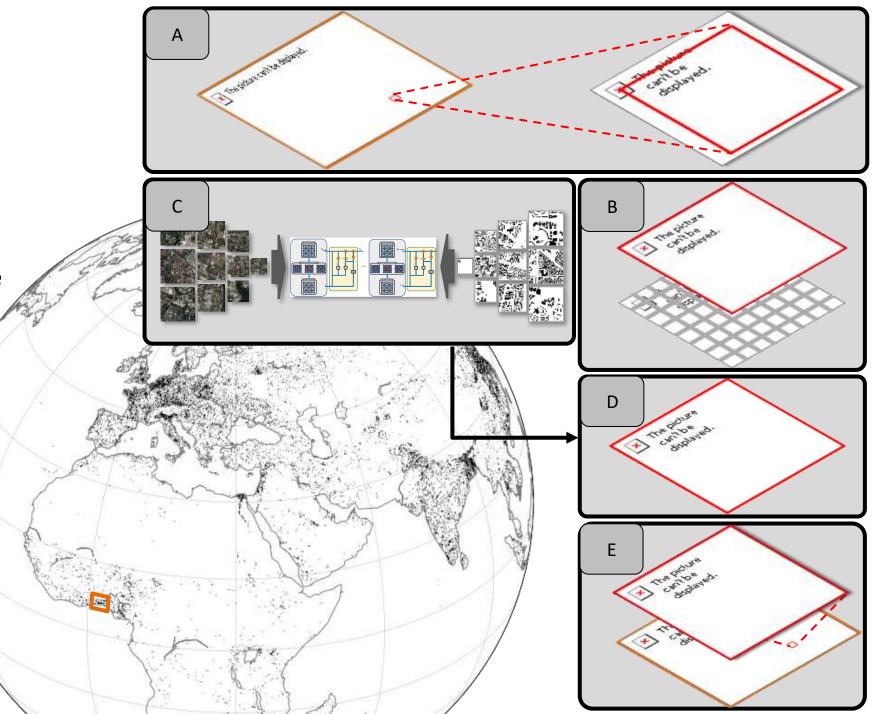
5. Training data preparation
6. Machine learning methods
7. Model training

D: Inferencing

8. Parallel processing
9. Model averaging

E: Post-processing

10. Editing/ Filtering



Data Overview

Sensor: Planet Doves # of images: 779072 # of 0.2 degree tiles: 45065





Global Buildings

Red: Google Green: Global OpenBuildingMap(ours) Blue: OpenStreetMap

Two examples

 \bigstar

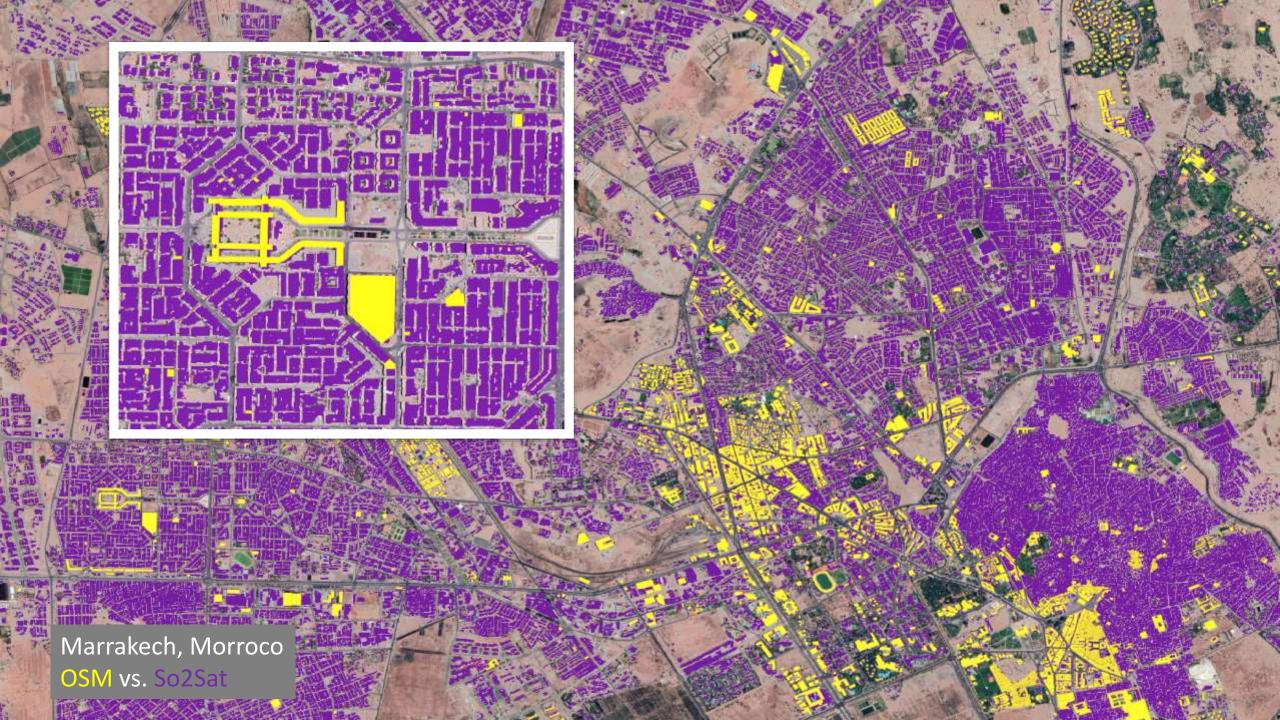
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- Marrakech, Morocco
- Cairo, Egypt







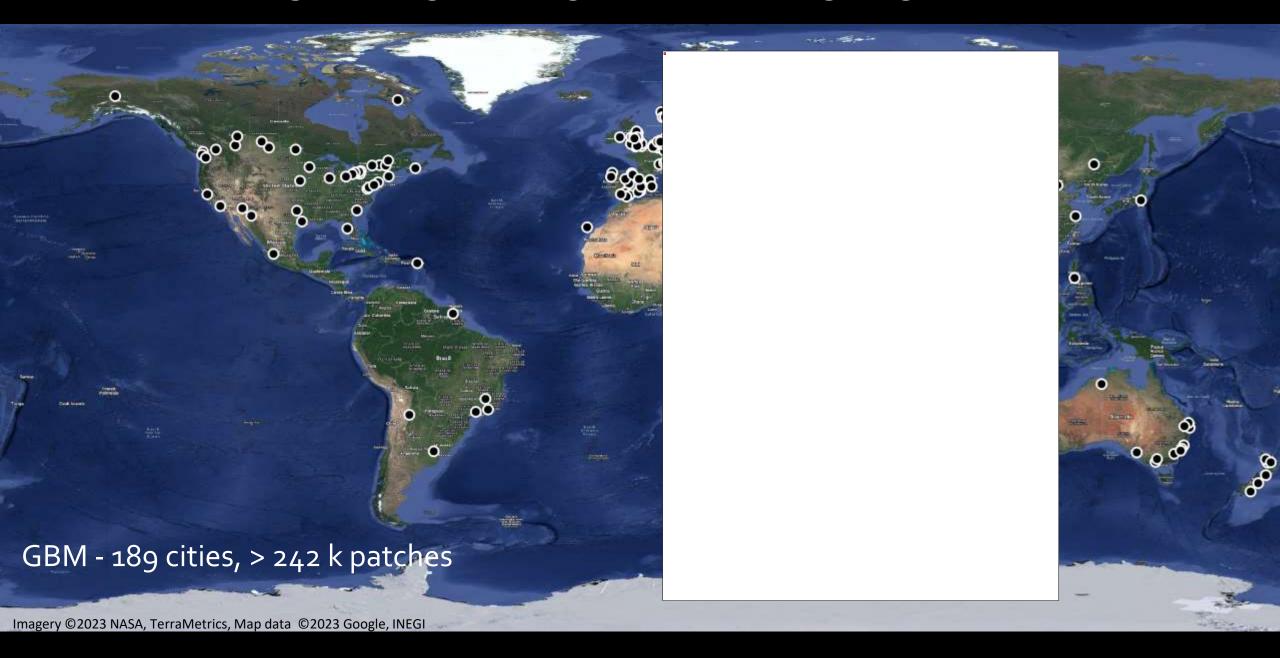


10 [GWh/year]

Solar Potential Analysis of Global Buildings

If we place solar panel on the roof of all buildings, it is possible to supply 1.1 to 3.3 times of the global energy consumption of 2020! Zhu et al., under review

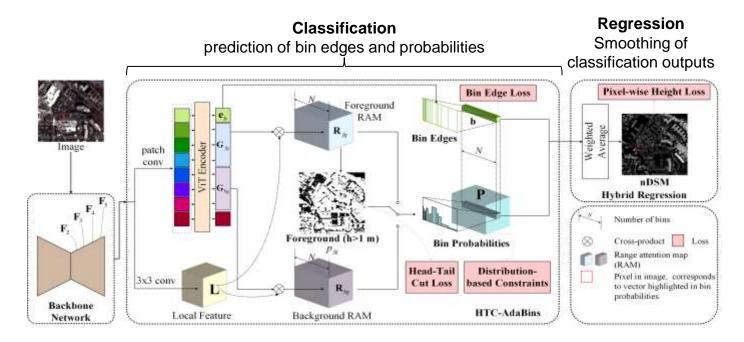
Global 3D Building Modeling from Single Remote Sensing Images



HTC-DC Net: Monocular Height Estimation from Single Remote Sensing Images

– Ill-posed problem

- Use of ViTs for enforcement of global consistency
- Classification-regression paradigm
- Distribution-based method
- Long-tailed distribution of the height values
 - Head-Tail Cut (HTC) for distinct treatment of background and foreground
- Unconstraint distributions lead to large errors
 - Distribution-based constraints (DC) as regularization



Test Building Height Accuracy of 3.8m on 21 cities across the globe Global inference will be finished by the mid of May!



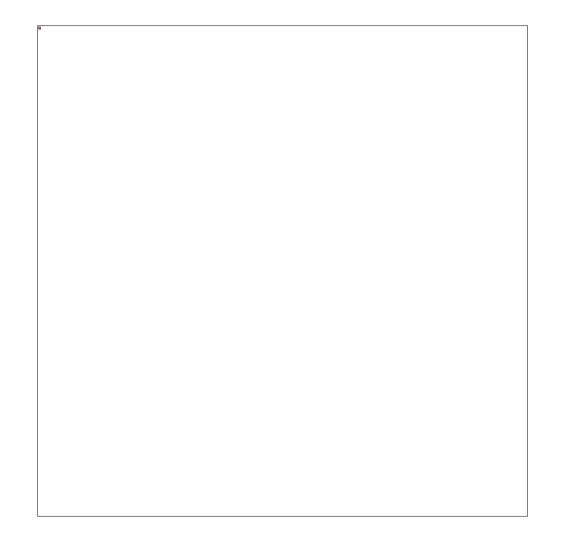
Monitoring the Antarctic Coastline

Sentinel 1 GRD @ 40m

Jun 2017 – Dec 2018

Dense Annotations: Land / Water

~ 510,000 km² Training ~ 220,000 km² Validation



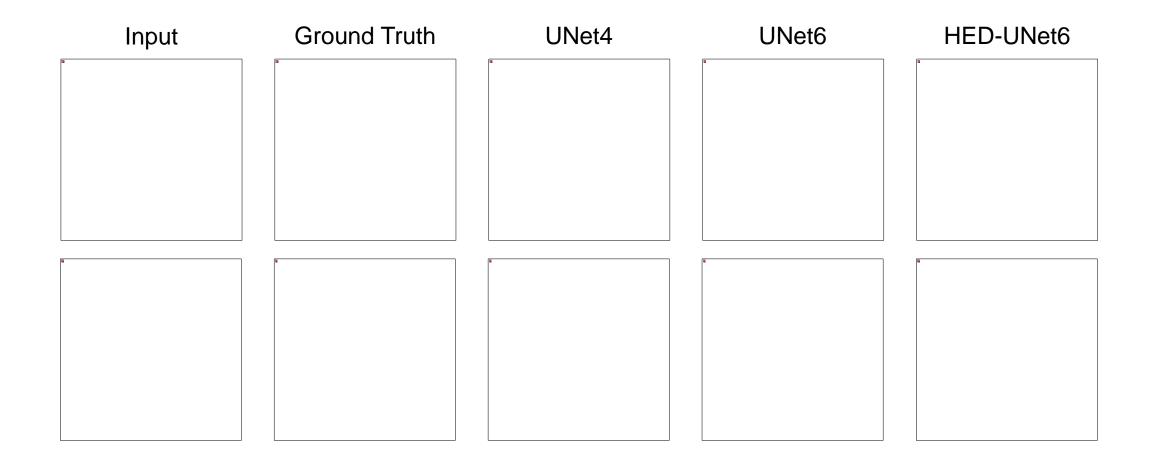


HED-UNet: Combined Segmentation and Edge Detection for Monitoring the Antarctic Coastline

- coastline detection as a dual inference task.
- predictions at multiple resolutions
- a hierarchical attention mechanism



Results – Qualitative





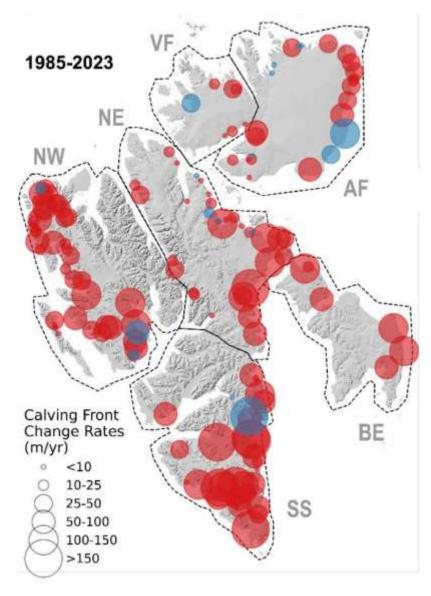
A High-Resolution Calving Front Data Product for Marine-Terminating Glaciers in Svalbard

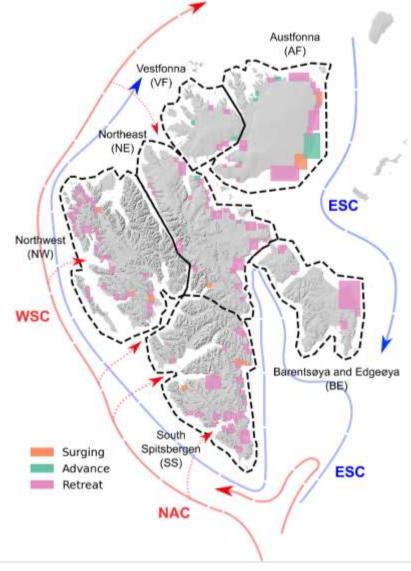
Features:

- 149 marine-terminating glaciers in Svalbard
- 124919 glacier calving front positions during the period of 1985-2023



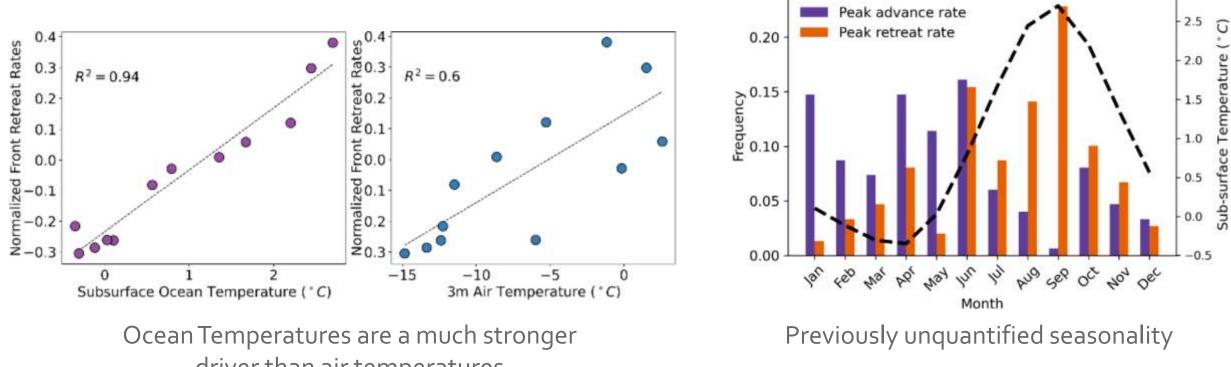






Li et al., ESSD 2024

Correlating with Environmental Factors



driver than air temperatures

Li et al., in review

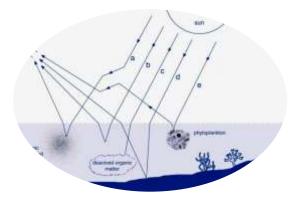
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ALC: NO

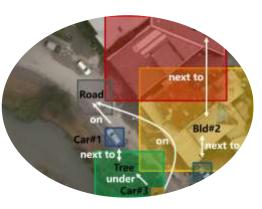


What are the open challenges in ML4Earth?

Open Issues in AI4EO



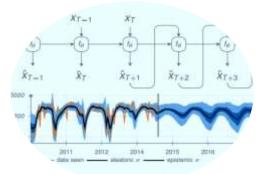
Re-implant physics, Bayes and domain expertise



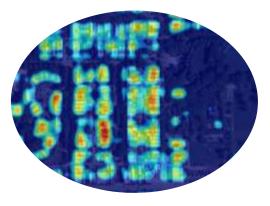
Reasoning



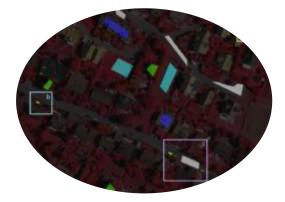
Transferability



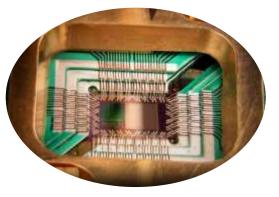
Uncertainty



Explainability



Green Al



Quantum Machine Learning

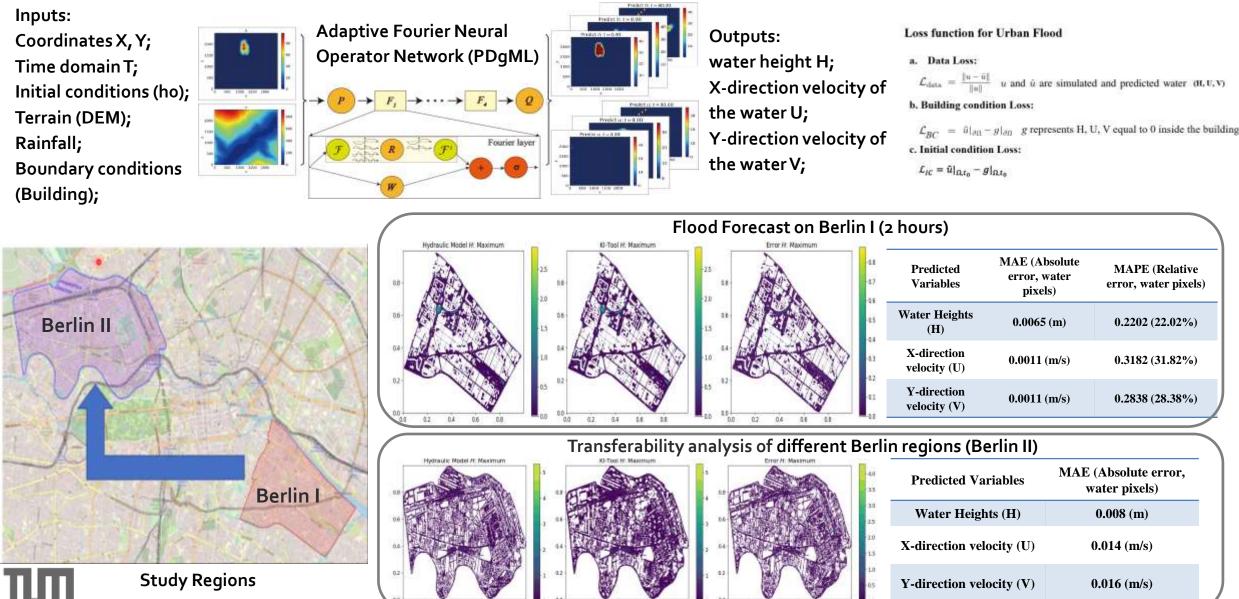
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Ethics

Image Sources: D-Wave Systems, Inc., wikimedia common <u>Trent Kuhn</u>, Creative Commons

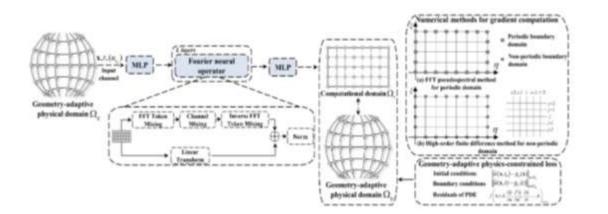


Physical Data-guided Machine Learning (PDgML) for Urban Flood Modeling and Forecast

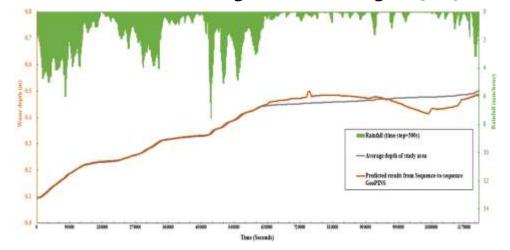


Physics-informed Machine Learning (PiML) for Large-scale Flood Modeling and Forecast

Geometry-adaptive physics-informed neural solver (PiML)



Flood depth validation over a 14-day period (flood simulation from August 18th to August 30th, 2022)



PiML-based flood forecast achieves an average MAPE of 14.93% for 14day flood depth predictions. (Pakistan flood prediction in 2022)

ESA-ECMWF WORKSHOP 2024 - Machine Learning for Earth System Observation and Prediction

ALC: NO





Process-based <u>Hydro</u>logy in <u>P</u>hysics-aware <u>Machine Learning</u> (HydroPML)







MODEL ZOO

More than 100 methods of different physics-aware machine learning



BENCHMARKS

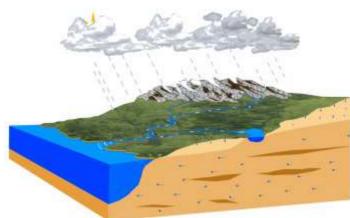
Benchmarking results for different hydrology applications using standard datasets

DATASETS

Standard and large-scale datasets for process-based hydrology, such as floods, landslides and other dynamic process datasets

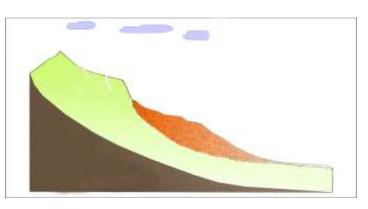
CASE STUDY

Different application case studies and PaML-based method recommendations

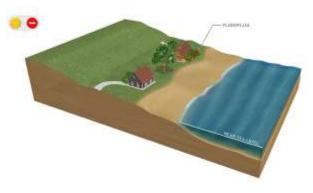


Rainfall-runoff Modeling and Forecast

Rainfall-Induced Landslide Modeling and Forecast



Flood Modeling and Forecast

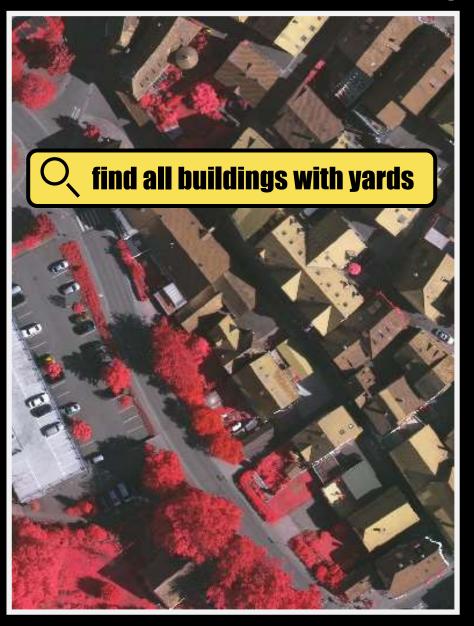


Rainfall-runoff-inundation Modeling and Forecast

Parameterization and Calibration	PaML-based Rainfall- Ranoff Forecasts	PaML-based Bydrodynamik Modeling	Alerts
Regional Astributions	Gauged River Rainfall-runoff Modeling	PDgML	Flood Maps
Forcing data (e.g. precipitation)	Modeling S Unganged River at Rainfall-maniff U Modeling Urban Hainfall	PIML PeML	Real-fine Forecasts
Observations and Meaverements	Critan Reinfall-	· Fall.	Hink Maps
	Macroscopic Time Scale (Yearly/ Menthly/ Dolly)	Microscopic Time Scale (Second: Hourty: Doily)	

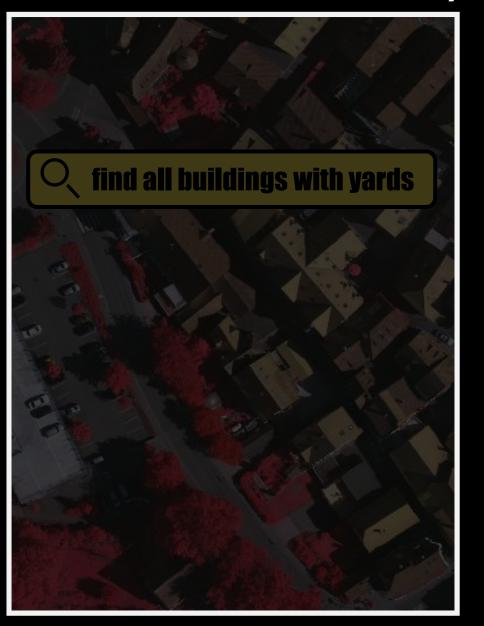
Xu et al., 2024

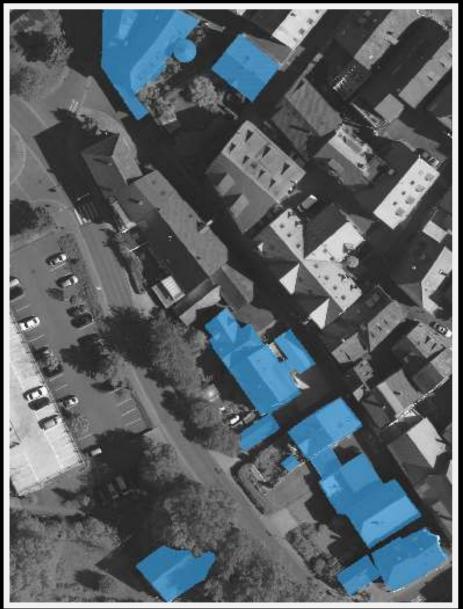
Human-centered AI analytics of EO data



Yuan et al., TGRS, 2024

Human-centered AI analytics of EO data





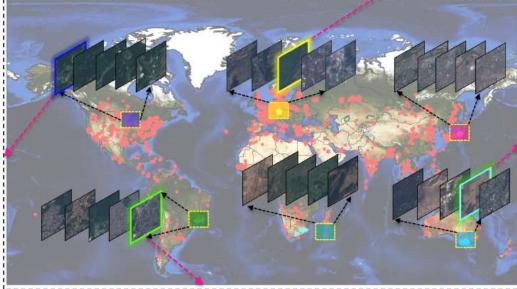
Yuan et al., TGRS, 2024

ChatEarthNet: A Global-Scale Image-Text Dataset Empowering Vision-Language **Geo-Foundation Models**



In this image, the developed areas manifest as a branching network. perhaps indicative of transportation routes or urban sprawl, interspersed throughout a substantial presence of trees. Small, isolated pockets of water are scattered, none large enough to form substantial watercourses or lakes. Sparse instances of crop cultivation are noted, with minor patches breaking the dominance of the other vegetation, Grasslands are widely distributed, with substantial coverage, suggesting a landscape that balances natural tree coverage with human development and open grassy areas. The overall theme presents a mixed use of land, where nature and development coexist, but with a clear predominance of tree cover and grassy fields.

In this image, grass areas predominate, especially in the middle and top left, with substantial coverage observed throughout the image. Water bodies are less extensive but have intricately meandering shapes, mainly concentrated towards the middle and top right regions. Developed areas have a more concentrated footprint in the bottom right region with geometrically shaped patches throughout. Tree coverage is significant but mostly towards the top and bottom left sections, and small crop areas are scattered sparsely, with low presence and no distinct shapes or significant coverage. This image is characterized by the dominance of grass areas and a ChatGPT-4V notable presence of developed areas, particularly in the bottom right quadrant.





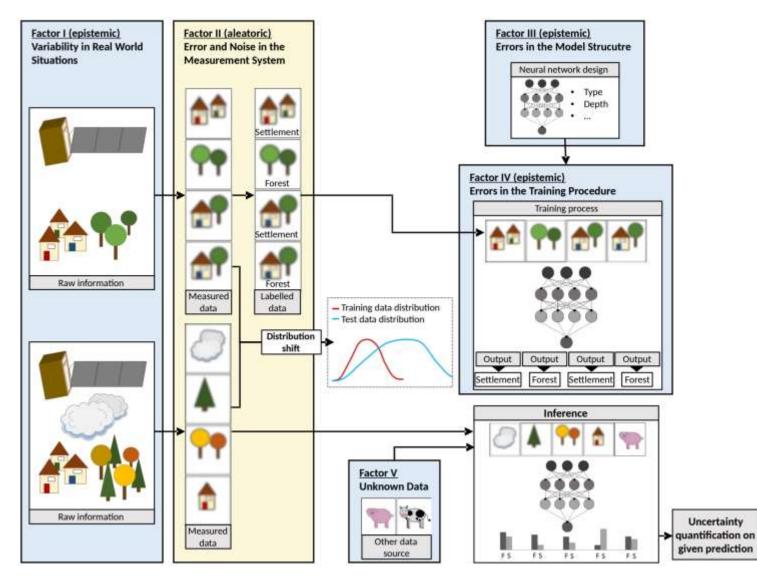
The image exhibits varied land cover types across different spatial locations. The dominant land cover type is developed area, which occupies an extra large fraction of the overall area. In the top left portion, the land cover primarily comprises developed area, followed by a small quantity of tree, and extra small quantity of grass. Moving to the top right, the developed area is still the most prevalent, with an extra large part, accompanied by an extra small part of water and an extra small part of tree. In the bottom left, the area is mainly covered by developed area, followed by a small portion of tree and an extra small quantity of grass. The bottom right section is also dominated by developed area, with a small quantity of tree and an extra small quantity of water. In the middle, the land cover consists of an extra large quantity of ChatGPT-3.5 developed area, an extra small amount of tree, and an extra small portion of water. Overall, the image depicts a landscape dominated by developed areas, with variations in the presence of trees, grass, and water in different spatial locations.

ChatGPT-3.5

The image primarily consists of crop fields, which are most dominant across all sections. In the top left, there is a significant expanse of crop fields, with a small area of grass and developed land. Moving to the top right, crop fields continue to dominate, followed by a smaller developed area and grassy patches. In the bottom left, the landscape is mostly covered by crop fields, followed by a few trees and a small amount of grass. The bottom right also exhibits a large area of crop fields, accompanied by a small developed area and a small portion of grass. In the middle section, crop fields are again the main feature, with a small number of trees and a tiny developed area. Overall, the image depicts a landscape predominantly characterized by crop cultivation, with minor presence of developed areas, trees, and grass.



Uncertainty Quantification



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Gawlikowski et al, 2023

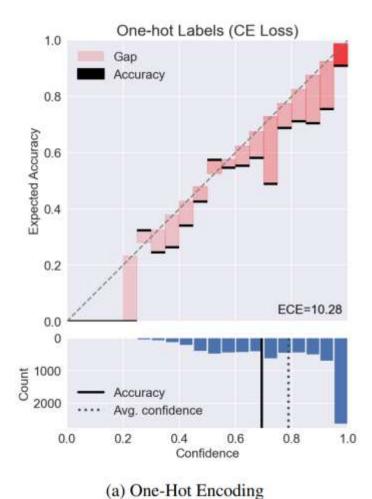
How Certain are the Uncertainty Estimates?

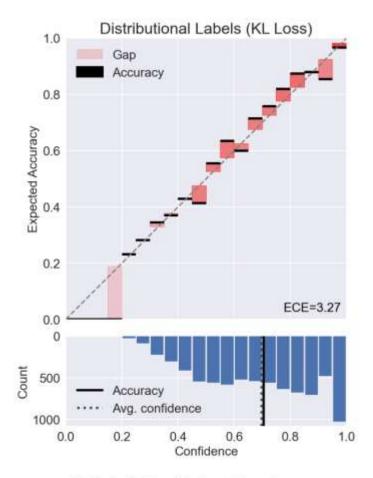


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Wang et al., GRSM, under review

Can Human Uncertainty Improve Model Performance in Earth Observation?





(b) Label Distribution Encoding

Koller et al, 2023

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Ethics in AI4EO



This article has been adoppted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Earth Observation and Artificial Intelligence

Understanding emerging ethical issues and opportunities

MRINALINI KOCHUPILLAI^O, MATTHIAS KAHL, MICHAEL SCHMITT^O, HANNES TAUBENBÖCK, AND XIAO XIANG ZHU^O

thics is a central and growing concern in all applications Eutilizing artificial intelligence (AI). Earth observation (EO) and remote sensing (RS) research relies heavily on both big data and AI or machine learning (ML). While this reliance is not new, with increasing image resolutions and the growing number of EO/RS use cases that have a direct impact on governance, policy, and the lives of people, ethical issues are taking center stage. In this article, we provide scientists engaged with Al for EO (AI4EO) research. 1) a practically useful overview of the key ethical issues emerging in this field, with concrete examples from within EO/RS to explain these issues, and 2) a first road map (flowchart) that scientists can use to identify ethical issues in their ongoing research. With this, we aim to sensitize scientists to these issues and create a bridge to facilitate constructive and regular communication among scientists engaged in AI4EO research, on the one hand, and ethics research, on the other hand. The article also provides detailed illustrations from four AI4EO research fields to explain how scientists can redesign research questions to more effectively grab ethical opportunities to address real-world problems

Digital Object Identifier 10:1009/66/365.2002.5208007 Date of carriest vendors: 17 November 2002

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that are otherwise akin to ethical dilemmas with no winwin solution in sight. The article concludes by providing recommendations to institutions that want to support ethically mindful AMEO research and provides suggestions for future research in this field.

INTRODUCTION

Big data lies at the heart of many EO and RS research and development activities. In fact, applications and algorithms emerging from RS and EO research rely heavily on big data collected via satellitea, unmanned aerial vehicles, drones, and other state-of-the-art devices. At the same time. RS and EO research is rapidly transforming in the era of A1 and ML. A1 and M1, permit the petabytes of data collected by satellites and other EO/RS devices to be systematically organized and used to train models that can predict a large diversity of events, objecta, and circumstances, even in the absence or lack of so-called pround truth.

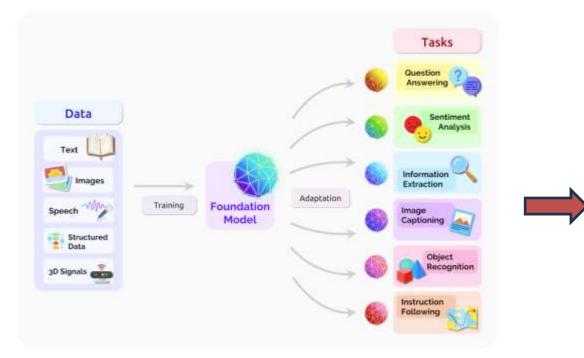
The close relationship between (big) data and AI is reflected in the German Data Ethics Commission's understanding of "artificial intelligence" as "a collective term for technologies and their applications which process potentially very large and beterogeneous data sets using complex methods modeled on human intelligence to arrive at a result which

Hey, how about Foundation Models?

What is a foundation model (FM)?

A model that:

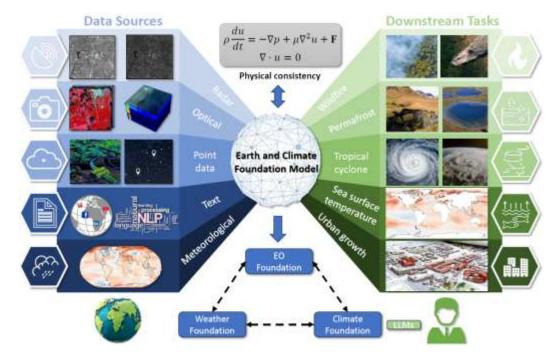
- is trained on broad data (generally using self-supervision), and
- can be adapted to a wide range of downstream tasks.



Bommasani, Rishi, et al. "On the opportunities and risks of foundation models." *arXiv* (2021).

Link to paper:

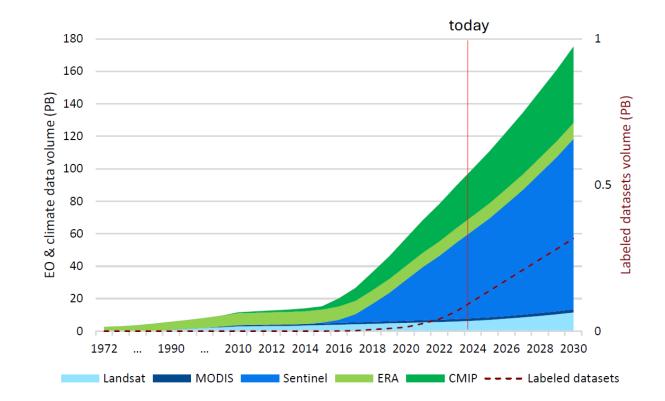






The potential of Earth and climate FMs

- Unlocking the value of big EO and climate data
- Enhancing label efficiency
- Reducing carbon footprints
- Bridging EO and climate science
- Improving Earth system modeling



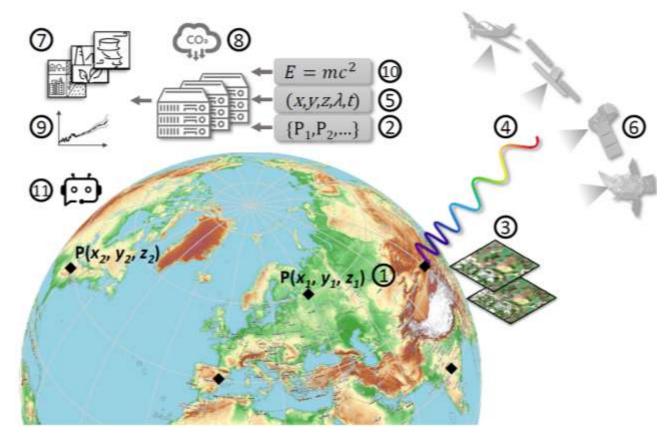
The ideal Earth and climate FM

Must have features:

- 1. Geolocation embedding
- 2. Balanced geographical representations
- 3. Scale awareness
- 4. Wavelength embedding
- 5. The time variable
- 6. Multisensory
- 7. Task-agnostic
- 8. Carbon minimized

Highly desirable features:

9. Uncertainty quantification10. Physical consistency11. Al assistants



Zhu et al., On the Foundations of Earth and Climate Foundation Models, under review.

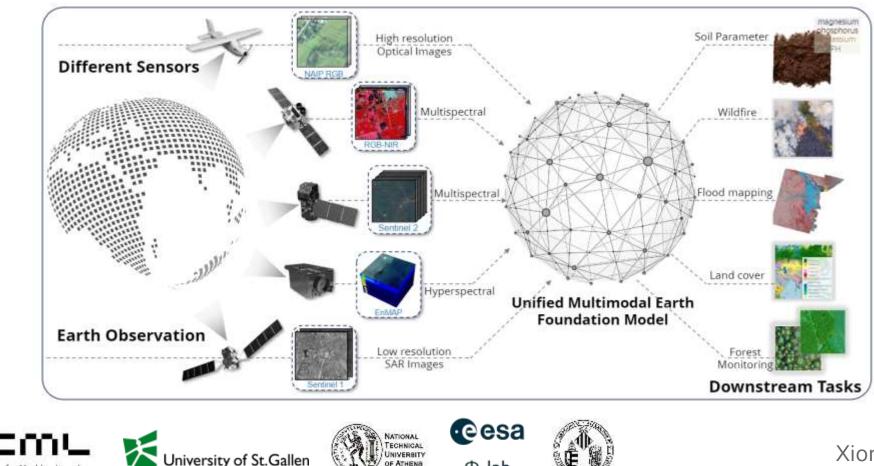


DOFA: Neural Plasticity-Inspired Foundation Model for Observing the Earth Crossing Modalities

- Integrate various data modalities into a single framework adaptively

funich Center for Machine Learning

- Excel across 12 distinct Earth observation tasks, including sensors never seen during pretraining



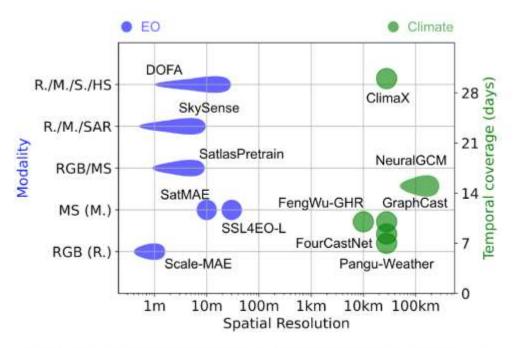
Φ-lab

Xiong et al., 2024

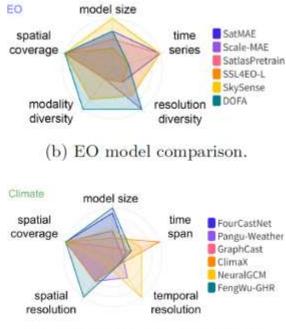
SOTA FMs and gaps

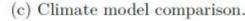
- Most models focus on only one or two of "must-have" features

– Big potential but gaps exist in connecting EO and climate FMs



(a) Comparison between EO and climate spatial resolutions.



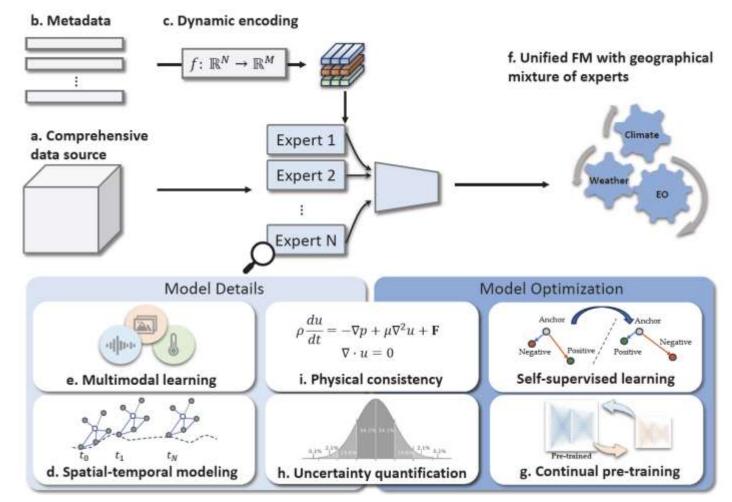


edding Geolocation Embedding **Balanced Distribution** Consistency Language Alignment Carbon-minimized variable Wavelength Embe Awarene Cask-agnostic Multisensor Uncertainty Time Physical Scale The ġ FMs 100 10Ú tini. SatMAE⁴⁶ Scale-MAE⁴⁵ × SatlasPretrain³⁶ SSL4EO-L35 SkySense⁴¹ DOFA⁵² FourCastNet 57 Pangu-Weather 67 GraphCast⁶⁸ ClimaX⁶³ NeuralGCM⁶⁹ FengWu-GHR⁵⁹



The way forward

- a) Comprehensive data source
- b) Metadata integration
- c) Dynamic encoder
- d) Spatial-temporal modeling
- e) Multimodal learning
- f) Geographical mixture of experts
- g) Continual pre-training
- h) Uncertainty quantification
- i) Physical consistency



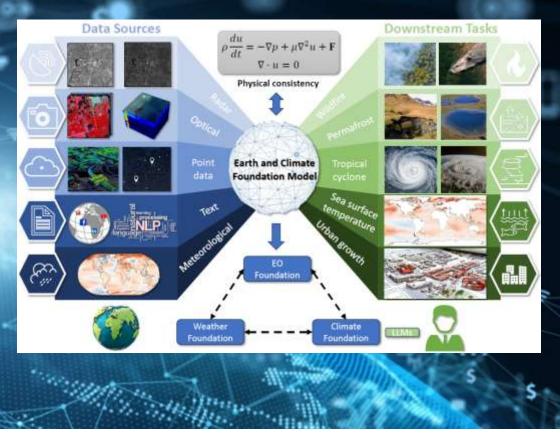
What comes after the Foundation Models?





ML4Earth Foundation Model Workshop

Where: Kolpinghaus in Munich When: September 18, 2024



Contact: ai4eo@tum.de

In collaboration with



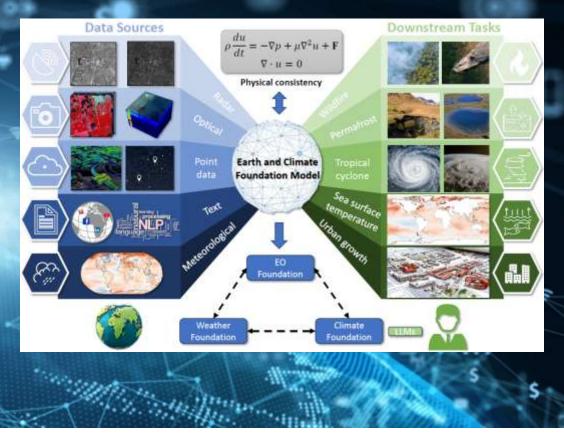






ML4Earth Foundation Model Hackathon

Where: Technical University of Munich When: September 19 - 23, 2024



Contact: ai4eo@tum.de

In collaboration with









AI4EO Symposium 2024

Where?

TUM Campus Ottobrunn Lise-Meitner-Straße 9, 85521 Ottobrunn

When? July 15-16, 2024



A Few Statements

 Big Earth data and AI₄EO offer invaluable geo-information helping tackling societal grand challenges

-Towards large scale and actionable geoinformation retrieval and prediction, fundemental methodological challengues must be addressed, such as uncertainty, physical-consistency, explainability, transferrability etc.

–Earth and climate foundation models have enormous potential, but we are just scratching the surface …

