ETH zürich

Climate Change AI - Summer School 2024

AI for Climate Science

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Main focus: AI for the Atmosphere (i.e. clouds)

image source: unsplash.com | NASA

Lecture goals
What you will know by the end the lecture

- ❏ Core concepts of climate science
- ❏ Different use cases of AI for climate science
- ❏ Key considerations and challenges
- ❏ How you get started

Peetak Mitra

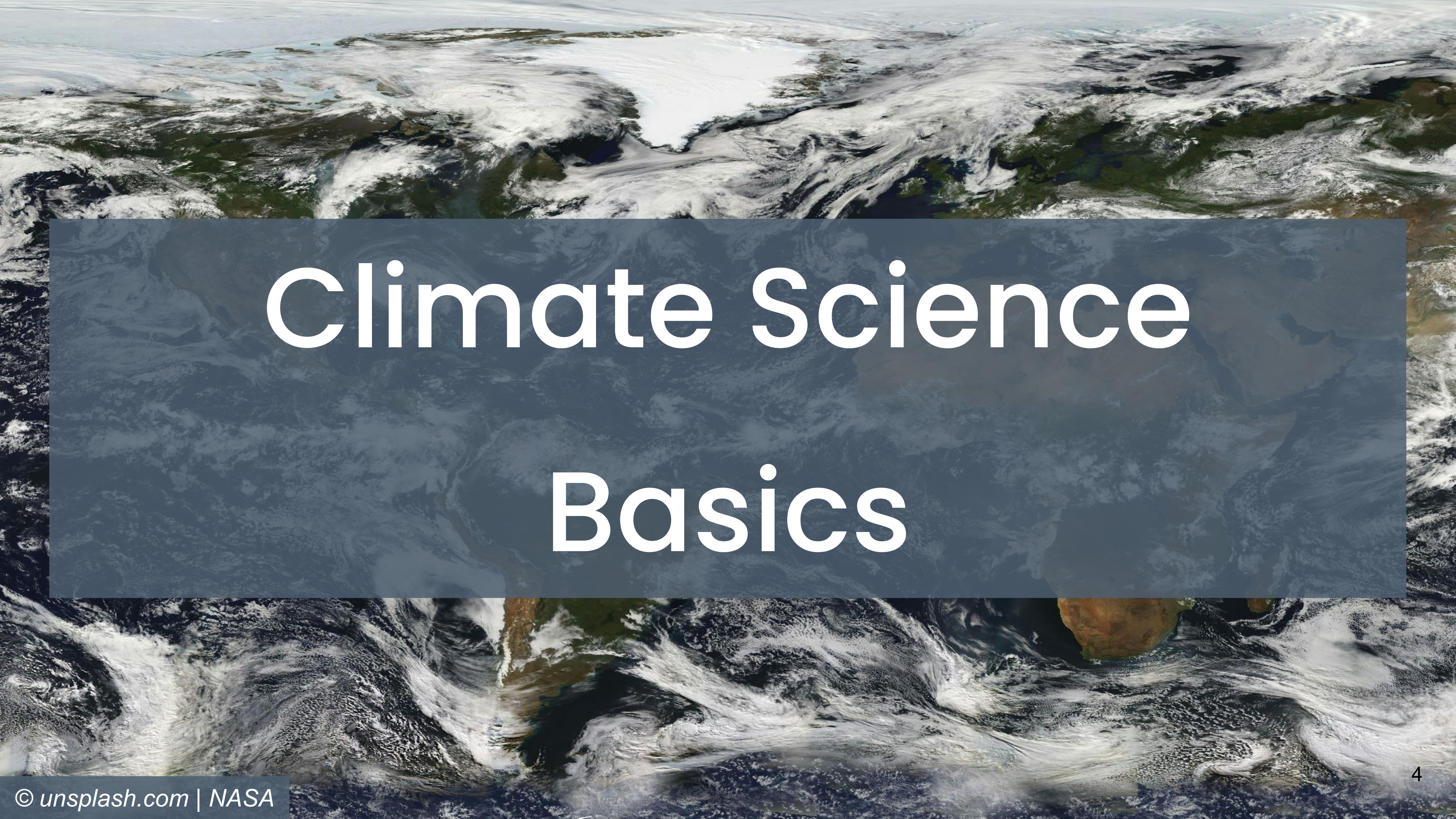
Focus of this lecture : Breadth

Focus of next lecture: Depth (AI for weather and climate models)

Let’s get to know each other :)
What is your background ?

Fill out the poll

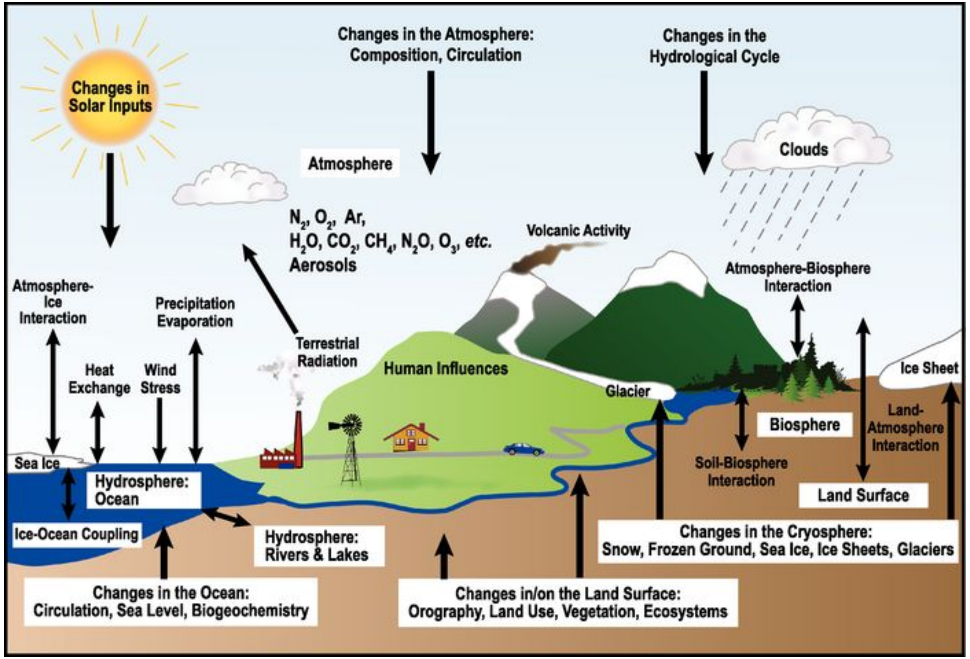
- climate science
- machine learning / AI
- climate science & AI intersection
- different background



Climate Science Basics

© unsplash.com | NASA

Key components and processes of the climate system

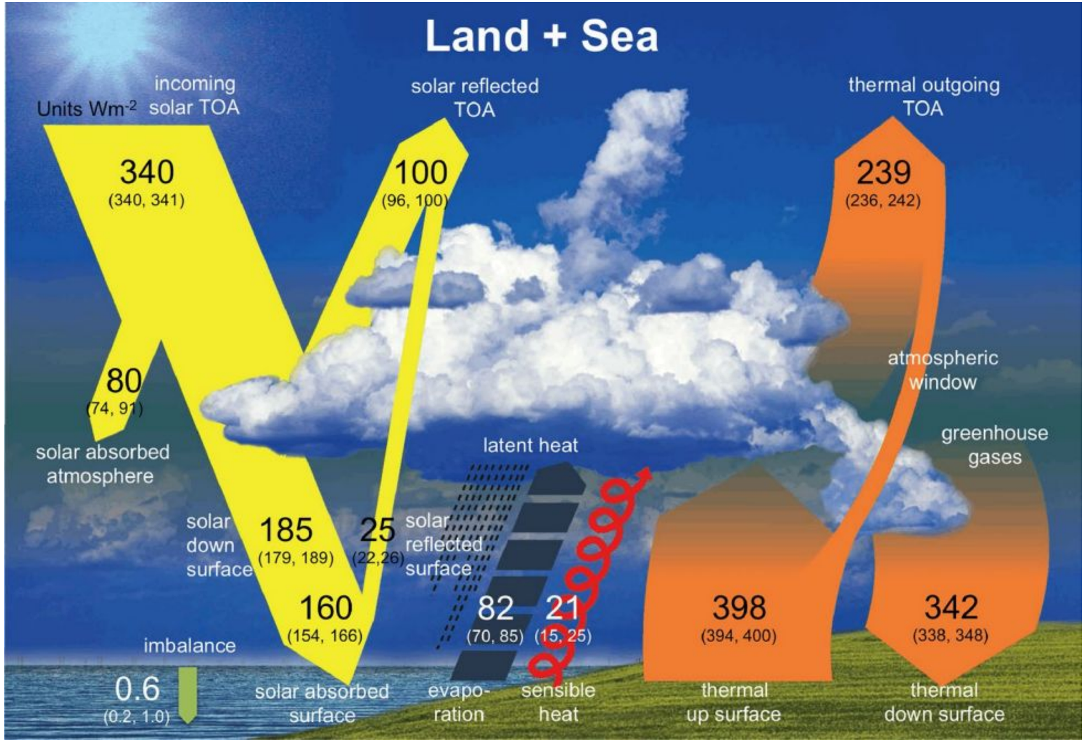


IPCC AR4 FAQ

Key components:

- atmosphere
  (most unstable and rapidly changing)
- hydrosphere
- cryosphere
- land surface

Earth’s Energy budget

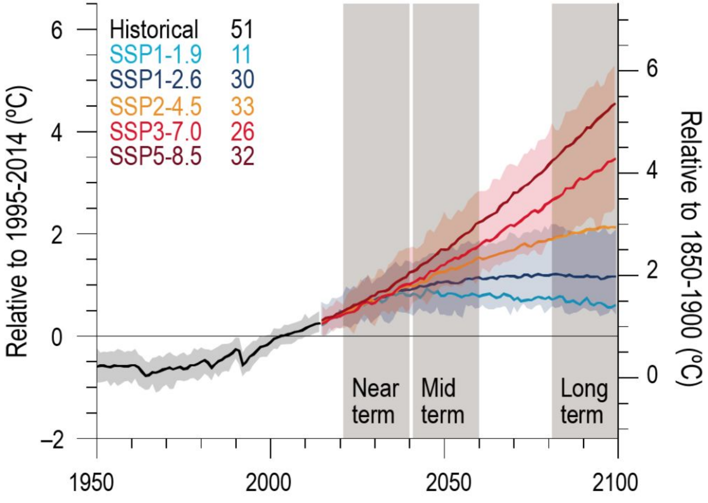


[Wild et al. 2015]

Climate Change

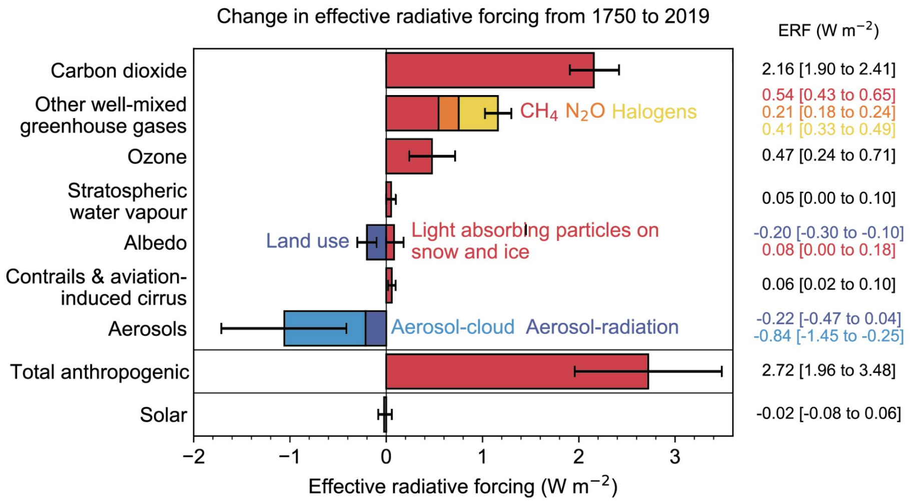
IPCC Summary

Global mean temperature change

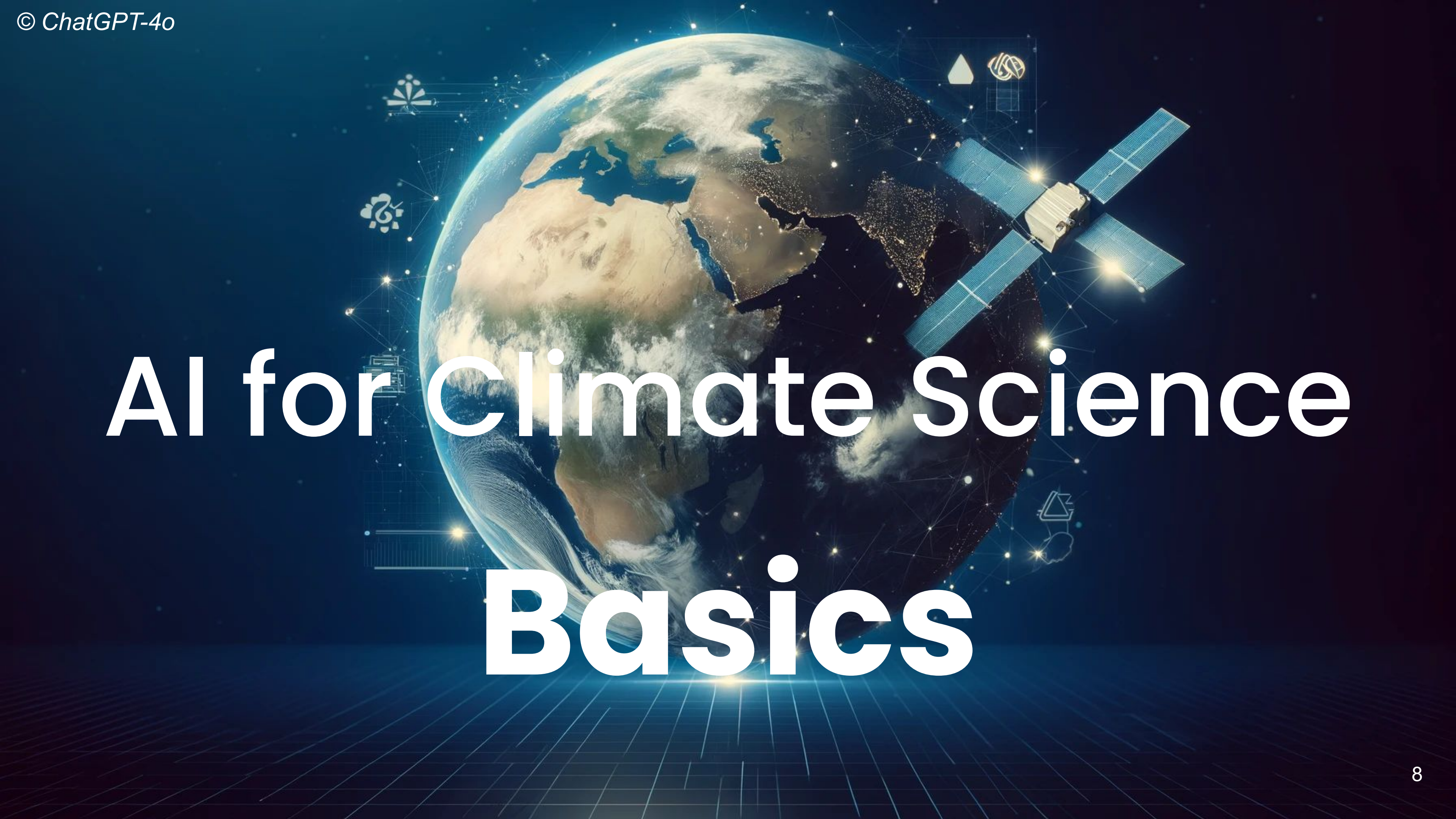


IPCC AR6 WG1 Fig 4.2

Radiative forcing



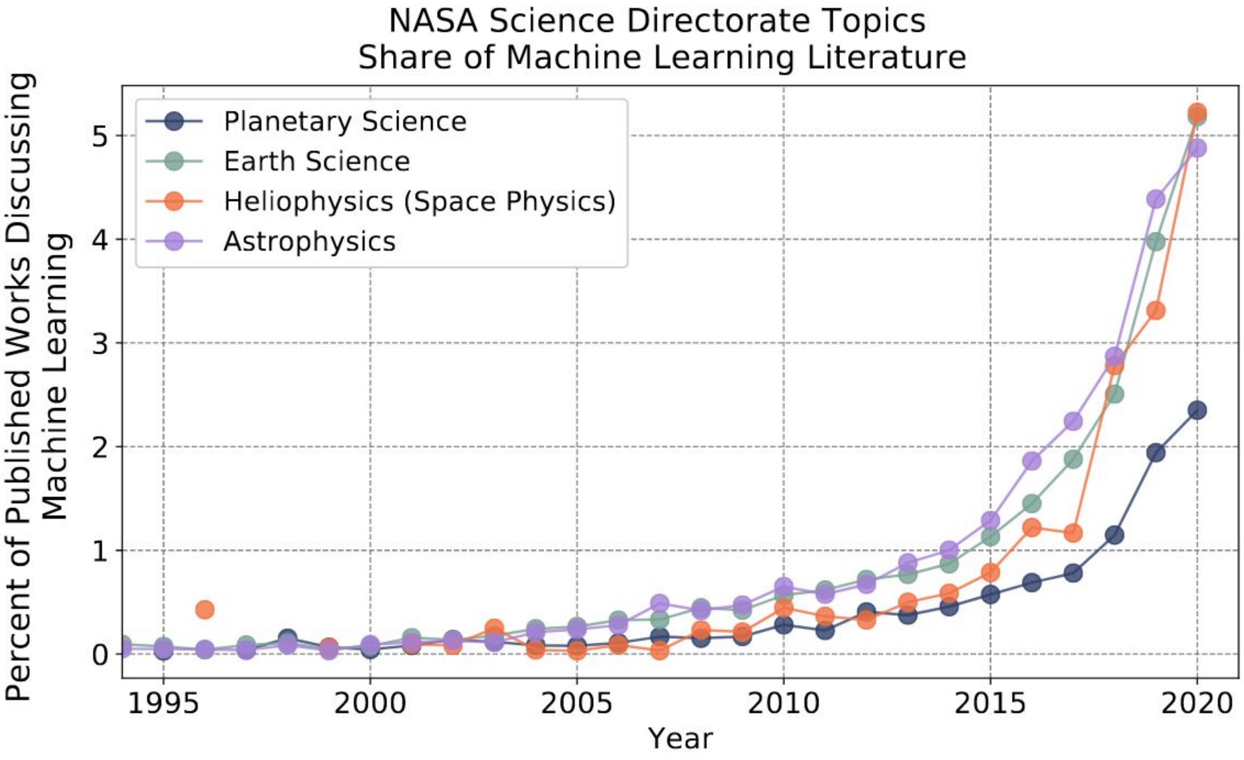
IPCC AR6 WG1 Fig 7.6



AI for Climate Science

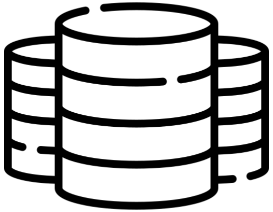
Basics

A rapidly evolving field

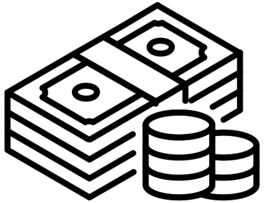


[Azari et al. 2021]

Why use AI for Climate Science ?



Data



cost
savings

Research
questions

Urgency
& impact

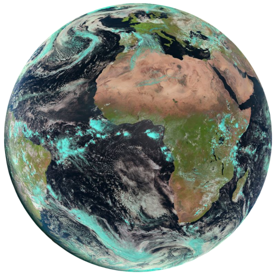
source icons: www.flaticon.com

Why use AI for Climate ?

Data

Petabytes of data available from

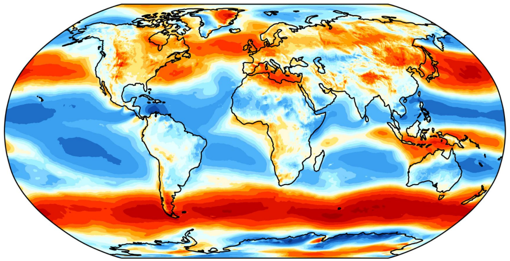
- remote sensing (e.g. satellites)
- climate models
- in-situ observations



Eumetsat: MeteoSat SEVIRI

Data often contain non-linear dependencies

Characteristics of data have analogies to classical ML data (but also key differences!).

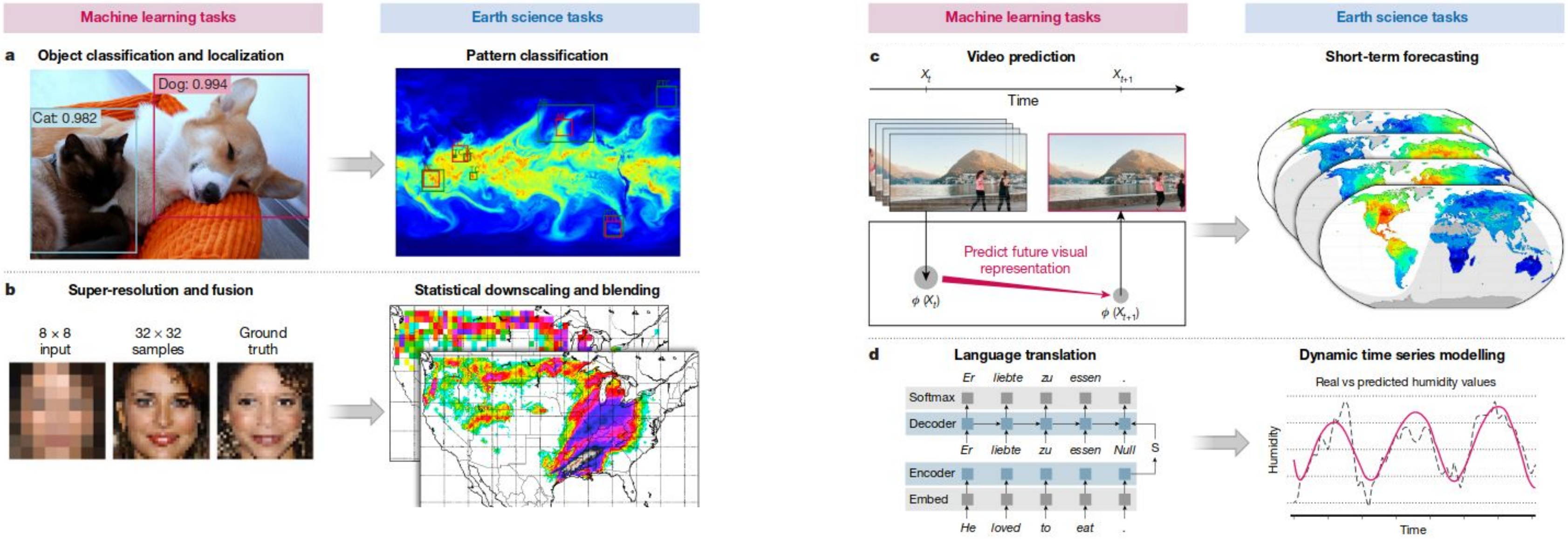


Climate Data Store: ERA5

Why use AI for Climate ?

Research Questions

Analogies to classical ML tasks (predict, classify, detect, etc.)



[Reichstein et al. 2019](#)

Why use AI for Climate ?

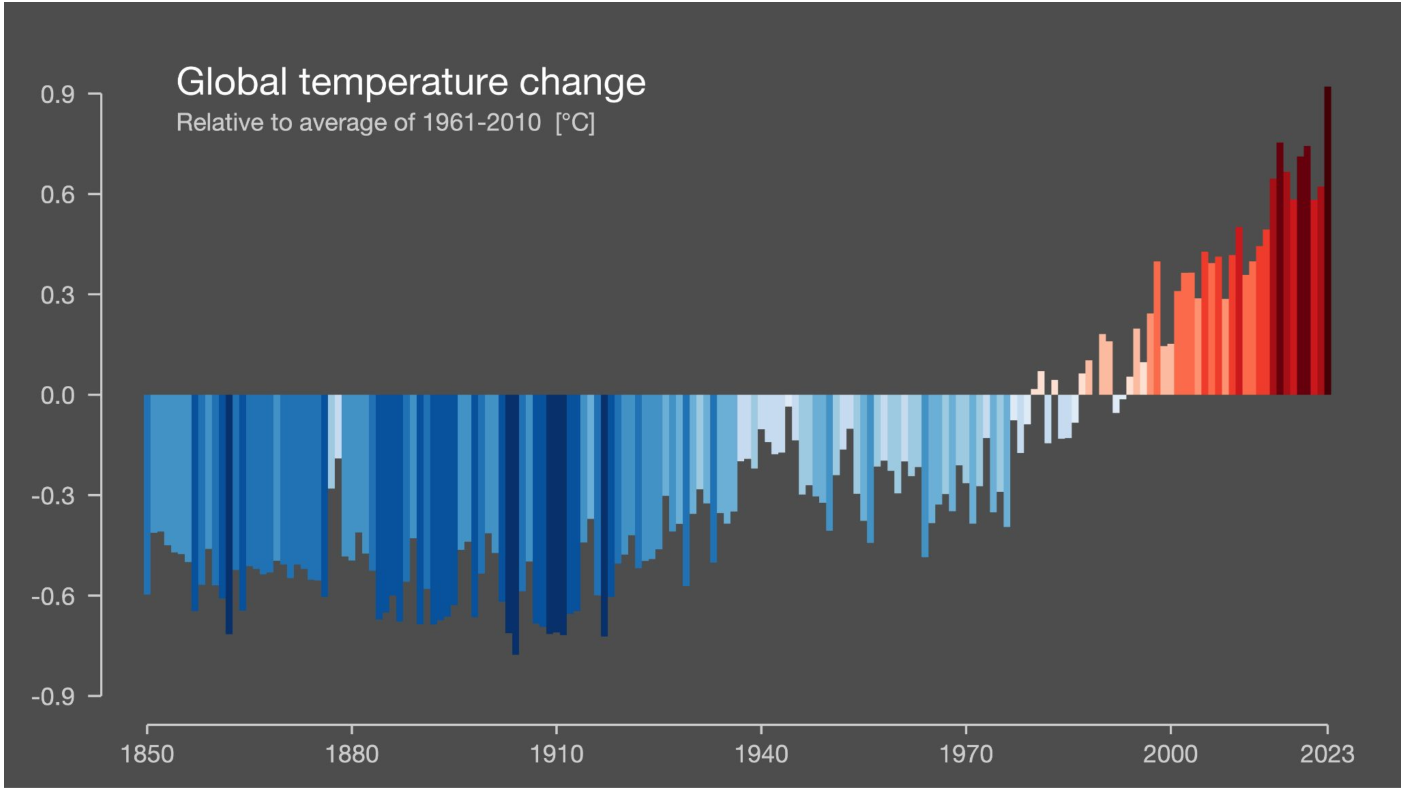
Cost savings

- **Numerical climate models** and other physics based models in climate science are **very costly to run.**
- **ML-based models** can significantly **reduce cost** and time spent on simulation.
- **Cheaper simulations** enable faster projections and larger ensembles, which **can reduce uncertainty.**

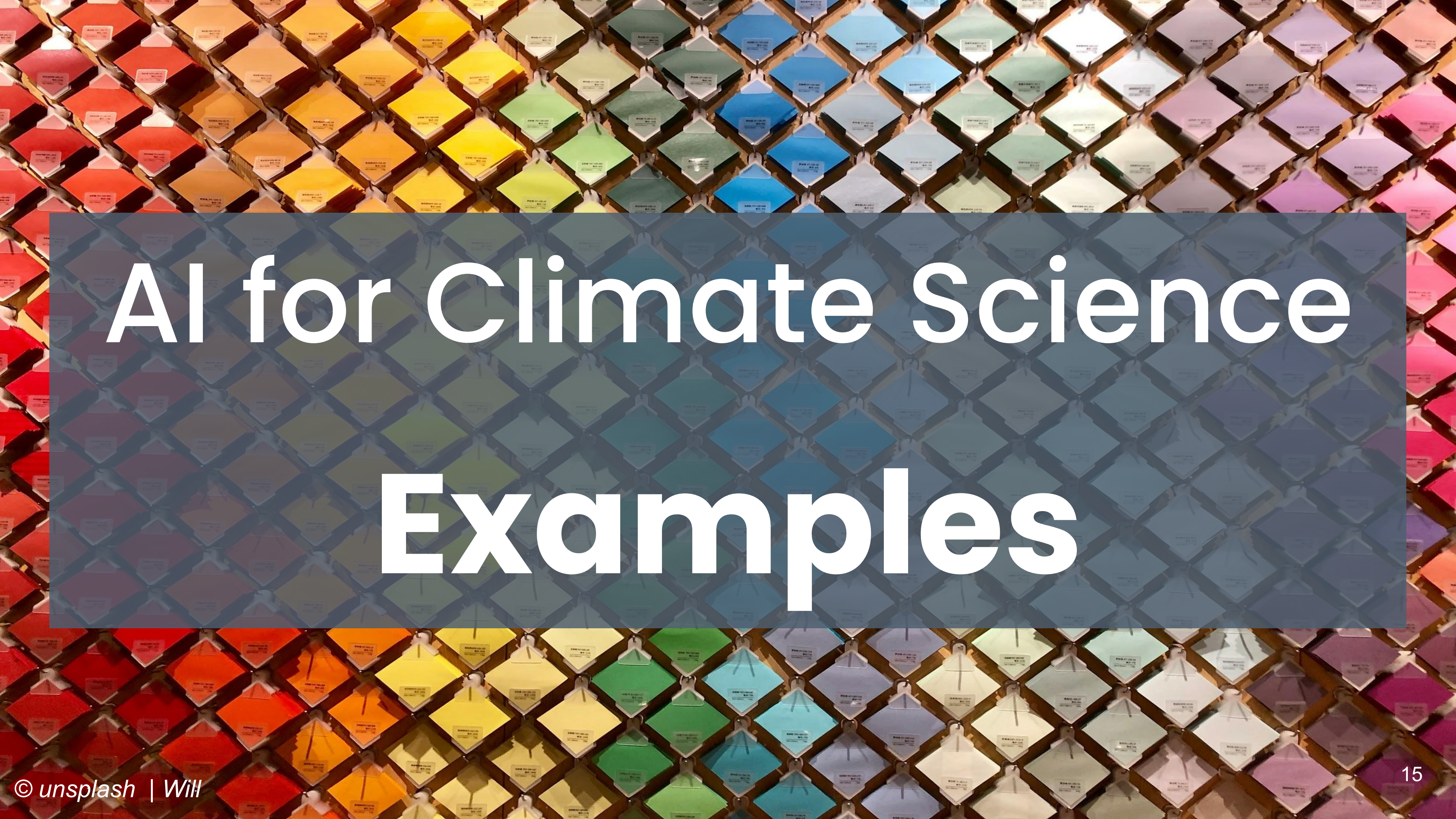
Swiss National Supercomputing Center: Piz Daint

Why use AI for Climate ?

Urgency & Impact



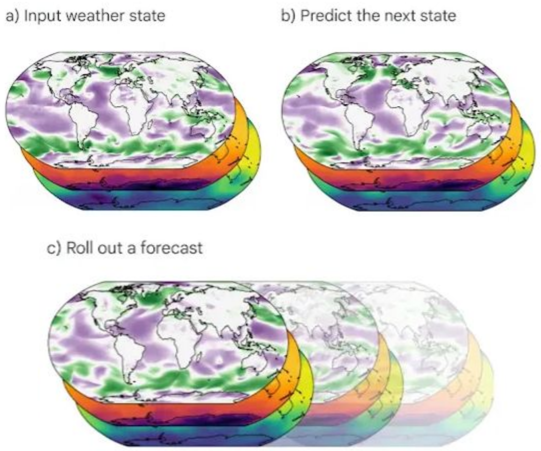
[© showyourstripes | Professor Ed Hawkins (University of Reading)]



AI for Climate Science

Examples

AI for weather and climate models



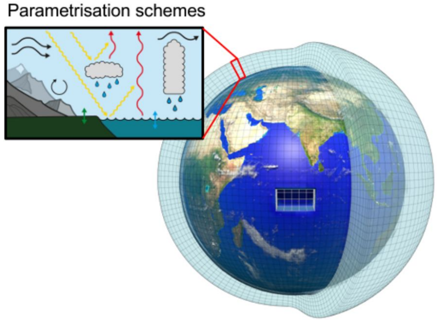
Deepmind blogpost on GraphCast

Fully AI - driven models

- FourCastNet, Pangu-Weather, GraphCast, ...

↳ Outperform traditional NWP models for some variables

↳ Much cheaper simulations



Christensen and Zanna, 2022

AI as emulator for sub-grid processes

↳ Train ML models to learn sub-grid processes from high-res model data

↳ increase speed

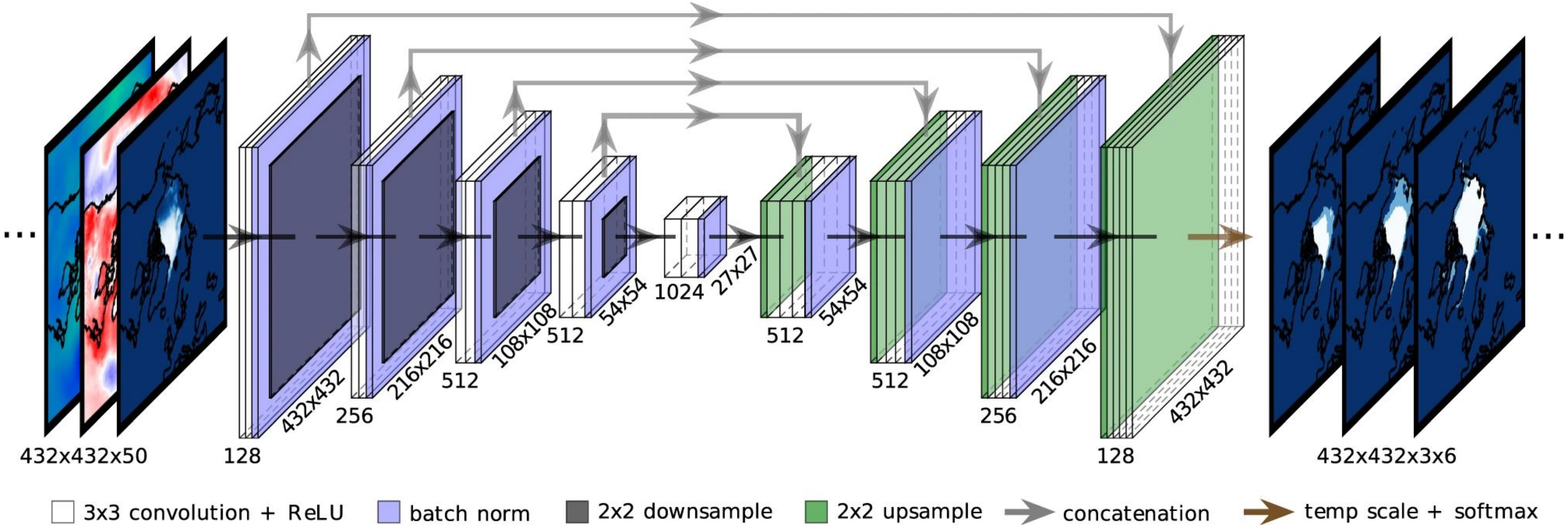
↳ reduce uncertainties and error

Deep dive in the next lecture

AI for ice sheet prediction

IceNet - Andersson et al. 2021

Predict sea ice probability (SIP) from climate variables with an ensemble of U-Nets.

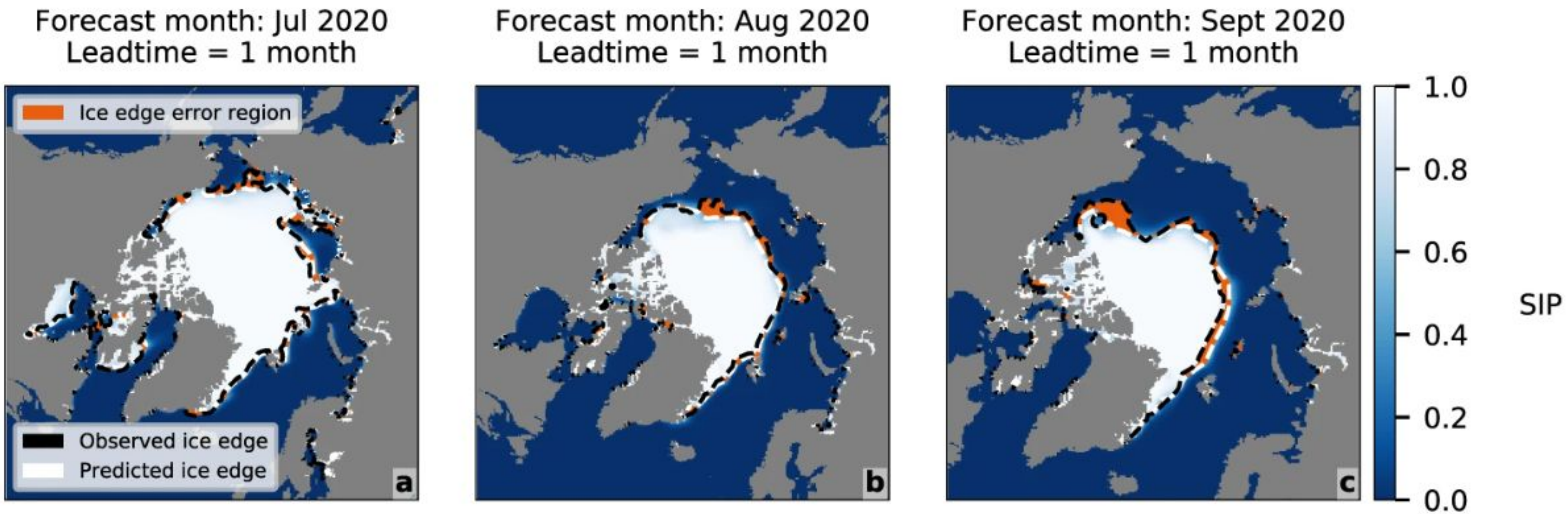


[Andersson et al., 2021](#)

AI for ice sheet prediction

IceNet - Andersson et al. 2021

IceNet's forecasts for July, August, and September 2020 at a 1-month lead time.

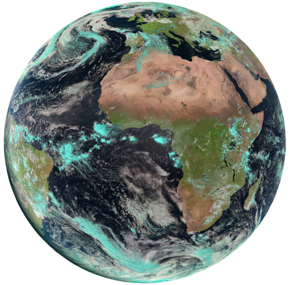


[Andersson et al., 2021]()

AI for sensor fusion: 3D reconstruction of clouds

IceCloudNet - Jeggle et al. 2023, in prep.

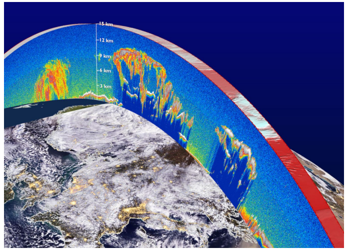
geostationary
passive



Meteosat SEVIRI

+ high spatio-temporal resolution
- only top view

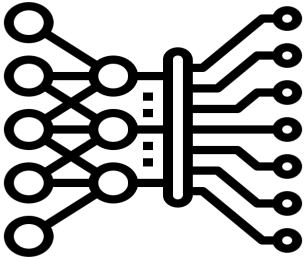
polar-orbiting
active



CALIPSO

+ vertical cloud structure
- sparse availability

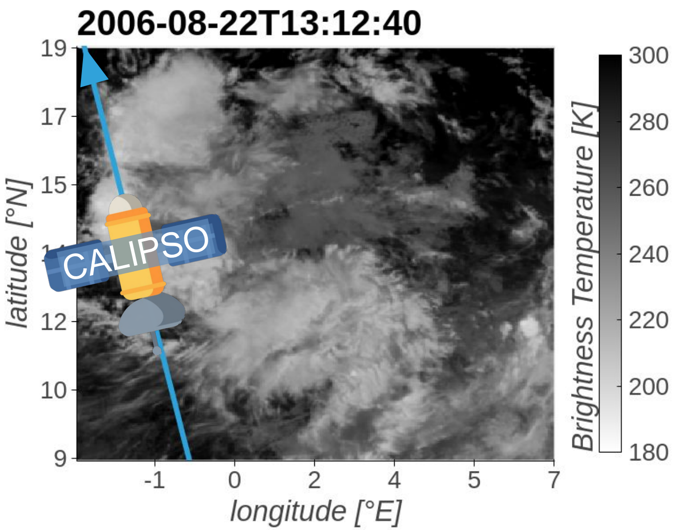
Objective:
Fuse strengths of sensors using AI



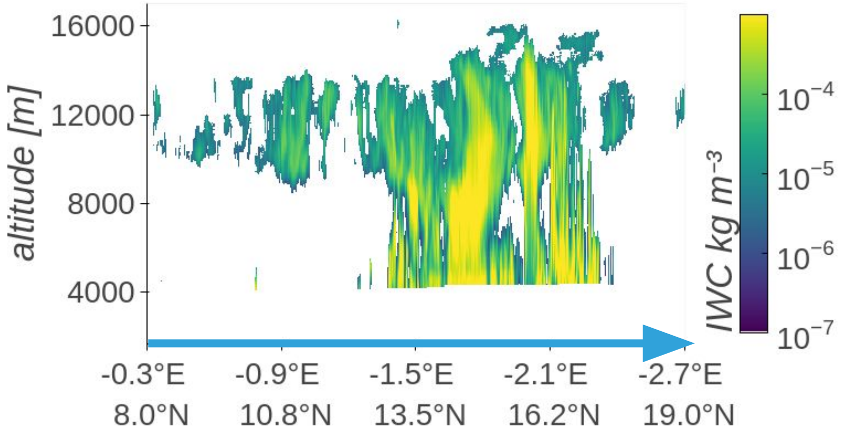
AI for sensor fusion: 3D reconstruction of clouds
IceCloudNet - Jeggle et al. 2023, in prep.

Status quo: availability of vertical cloud informations

Geostationary satellite instrument: SEVIRI
(showing only one Infrared channel)

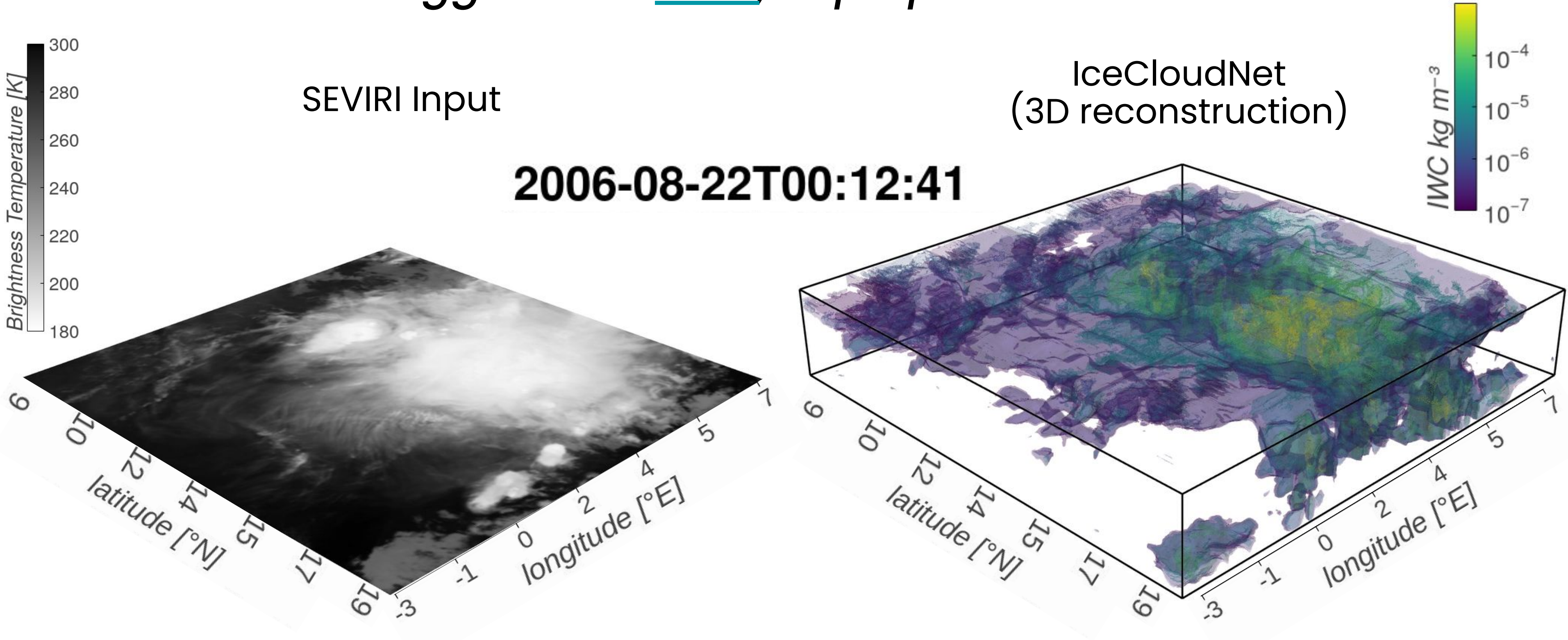


Polar-orbiting active instruments: CALIPSO
(IWC retrieval)



AI for sensor fusion: 3D reconstruction of clouds

IceCloudNet - Jeggle et al. 2023, in prep.

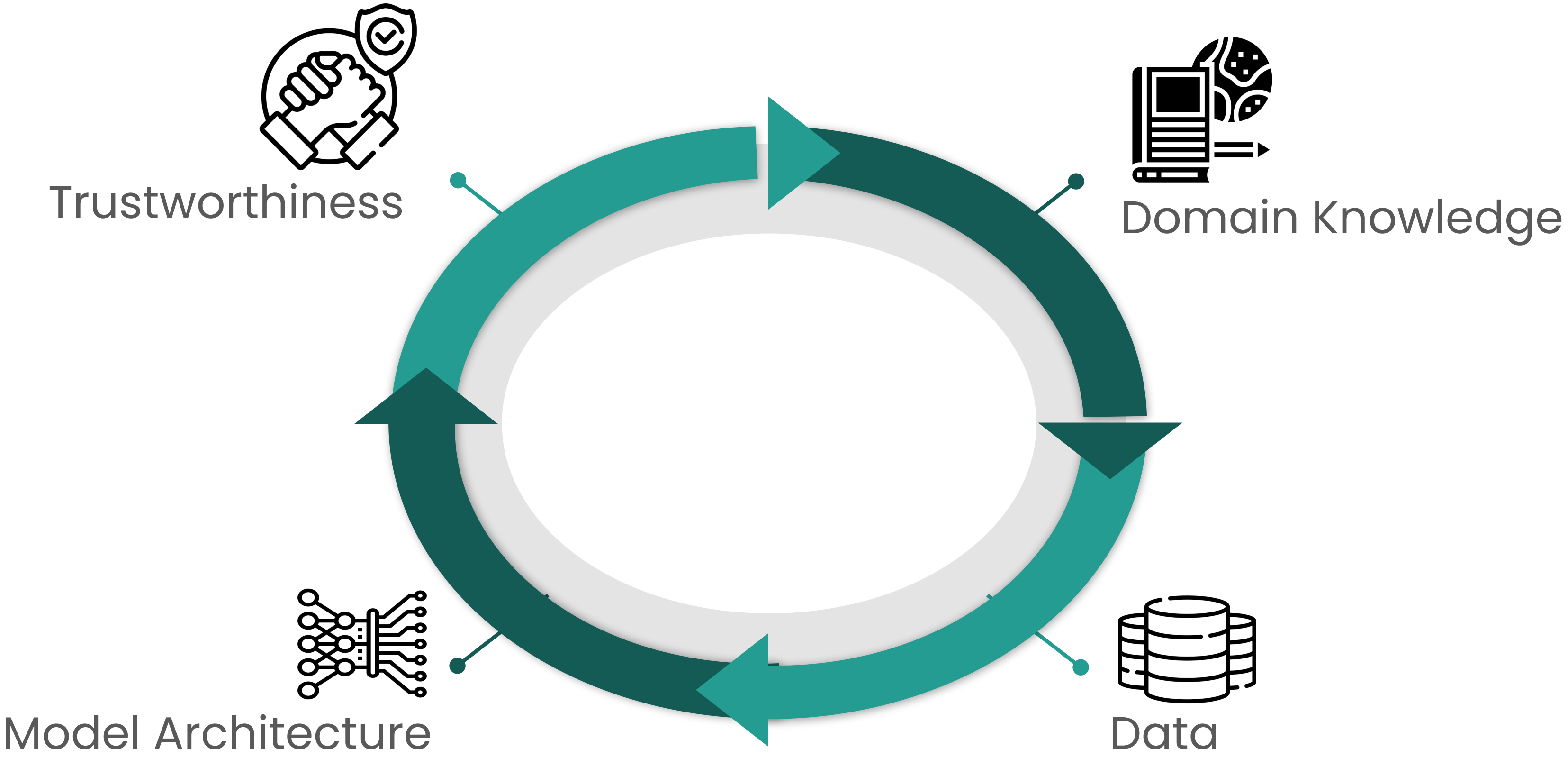


AI helps to Increase availability of vertical cloud information by a factor ~10^6

Considerations & Challenges

source: Pix4free

Key challenges and considerations

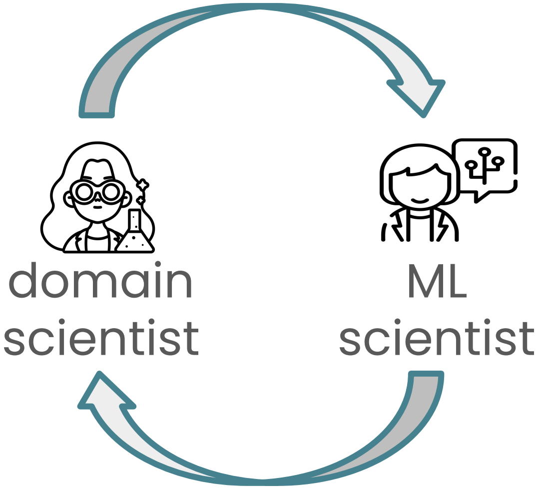


source icons: www.flaticon.com

Key Considerations & Challenges
Domain Knowledge

Domain knowledge is key to …

- … define the scope of a project.
- … inform the choice of datasets and features.
- … inform the choice of model architecture.
  (e.g. trading off model interpretability vs. model skill)
- … interpret results.



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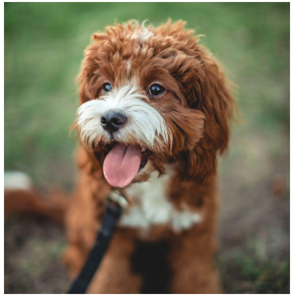
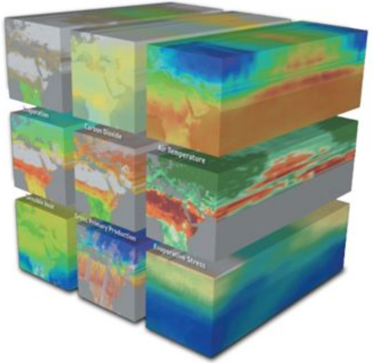
Key Considerations & Challenges
Data I



unsplash.com
Roberto Nickson

≠

NASA worldview



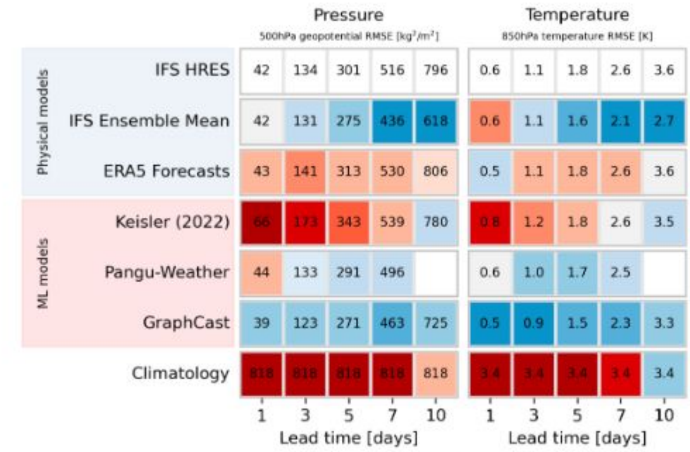
Earth system data cube by ESA

Geospatial data

- # channels > RGB images
- interdependencies on many spatio-temporal scales
- size of images

Key Considerations & Challenges
Data II

- Data is often unlabeled
  - ↳ self supervised learning
- Data is often regionally skewed to Europe/North America
- Benchmark datasets are slowly emerging.
  - ↳ e.g. WeatherBench



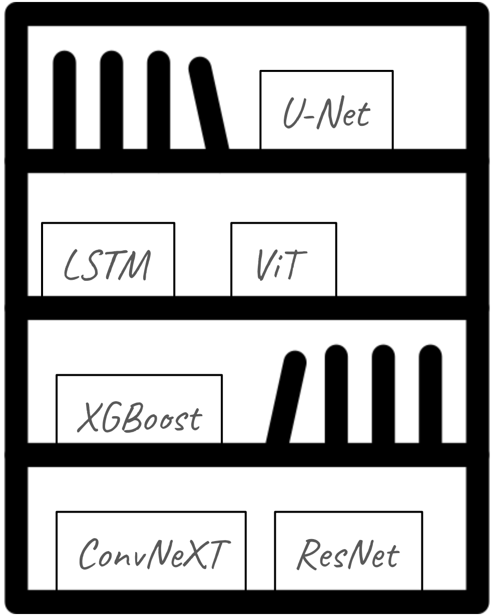
[Rasp et al., 2023](#)
[WeatherBench 2](#)

Key Considerations & Challenges
Model Architecture I

- Data characteristics inform choice of model architecture
    - e.g tabular in situ data vs. spatio-temporal climate model data
- Simple is better than complex

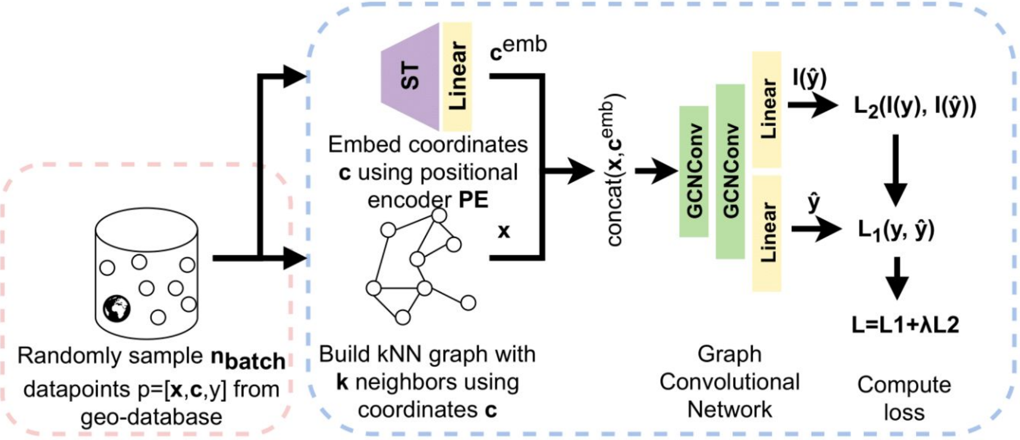
Key Considerations & Challenges
Model Architecture II

From: purely applying ML methods



To: developing application and data specific architectures

example: Positional Encoder Graph Neural Networks for Geographic Data

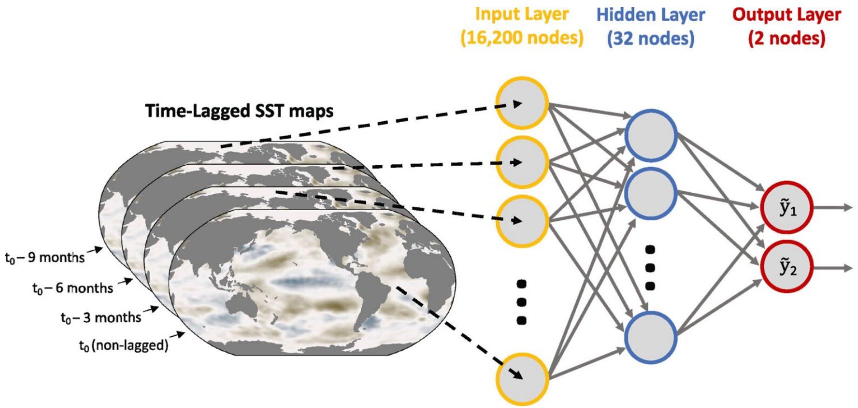


Klemmer et al. (2023)

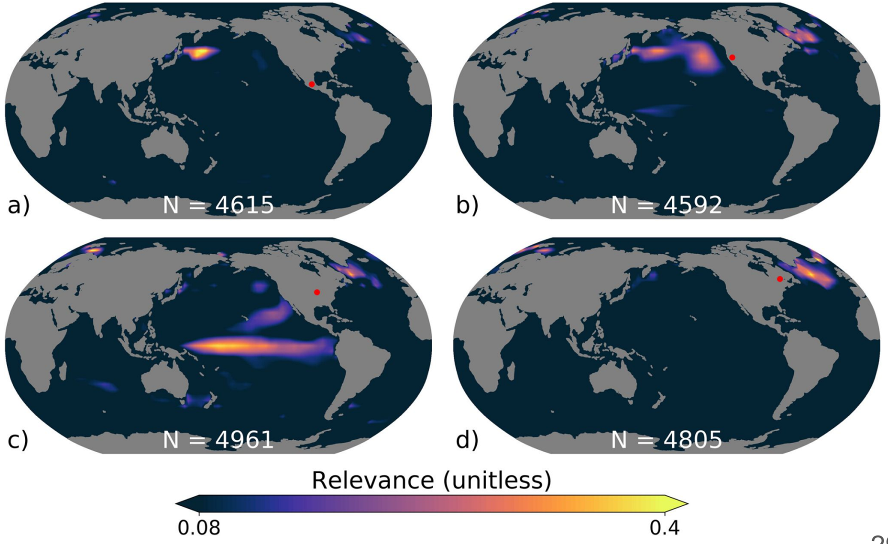
Key Considerations & challenges
Trustworthiness I

ML models are often black boxes ⇨ eXplainable AI (**XAI**)

Predicting land surface temperature anomaly



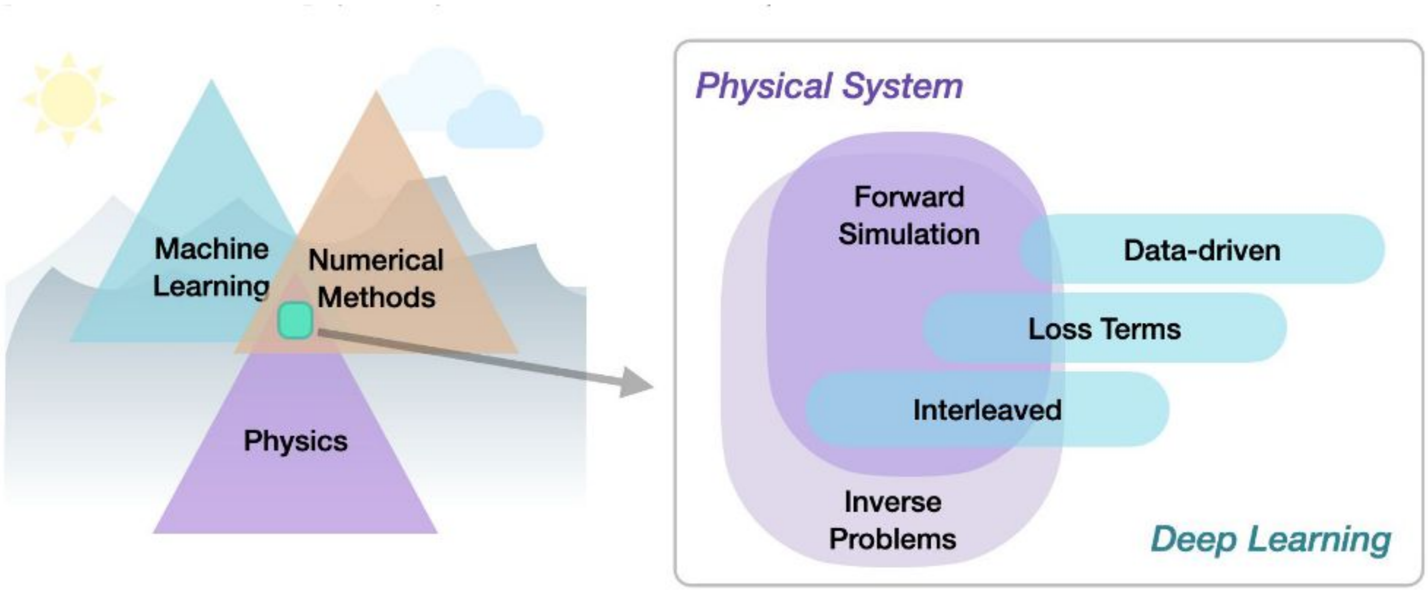
Sources of predictability using XAI



[Toms, Barnes and Hurrell (2021)]

Key Considerations & Challenges Trustworthiness II

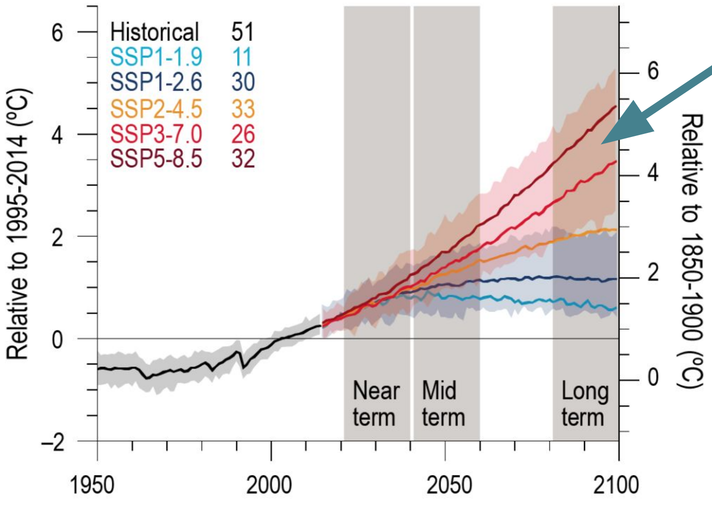
ML models are not necessarily physically consistent ➪ **Physics-Guided ML**



[Thuerey et al., 2021]

Key Considerations & Challenges
Trustworthiness III - Uncertainty quantification

Global mean temperature change



IPCC AR6 WG1 Fig 4.2

Uncertainty quantification is a necessity in climate science

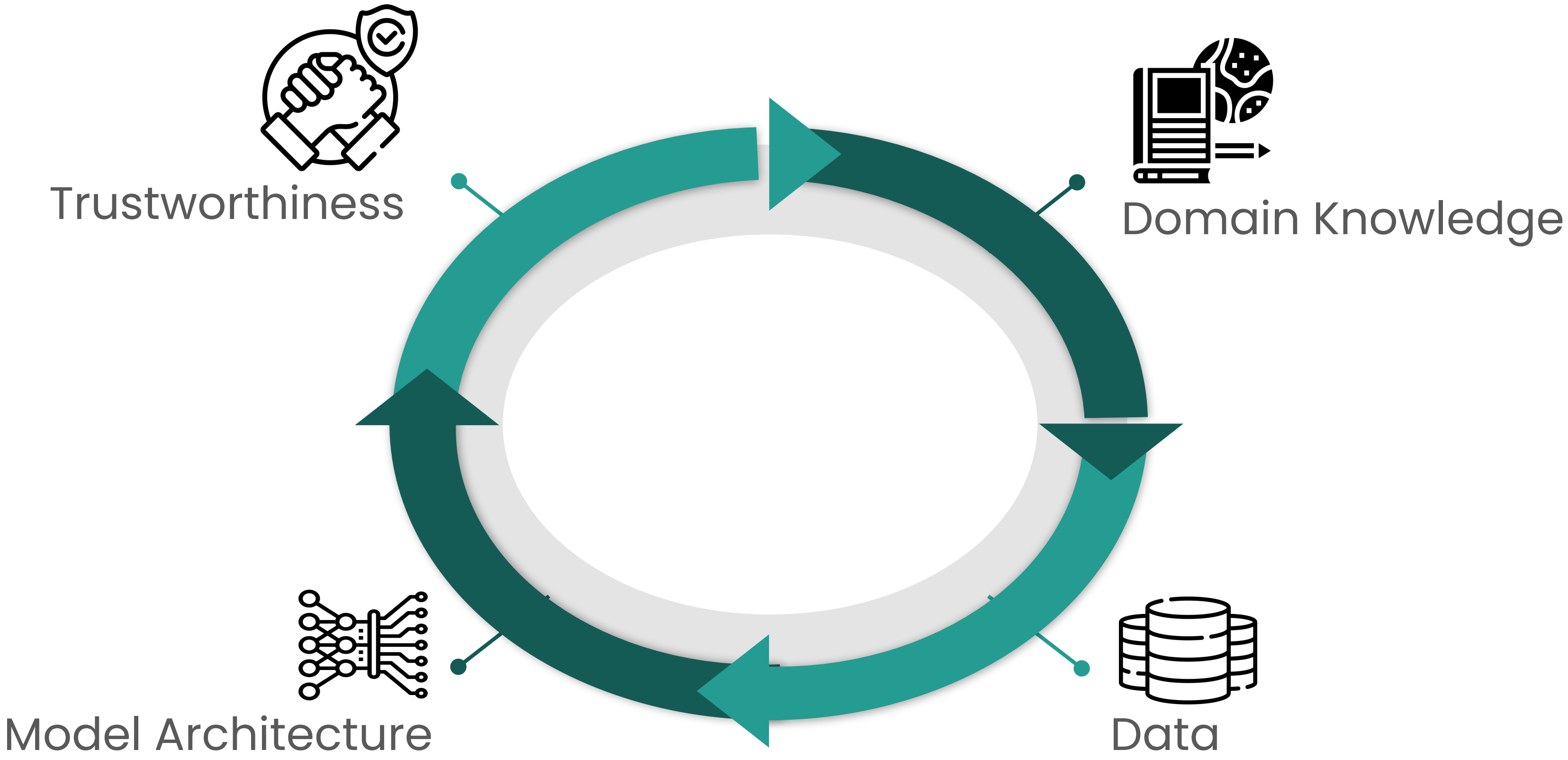
How to do uncertainty quantification:

- Bayesian Methods
  (e.g. Gaussian Processes)
- Probabilistic deep learning
- Ensemble methods

Types of uncertainty:

- epistemic (model)
- aleatoric (data)

Key Considerations & challenges



Key Considerations & challenges

These challenges are all not solved yet!
→ a lot of potential for future research

Model Architecture

Data

Some observations and future developments

- AI/ML can be main workhorse or just a tool for subtask to increase speed/performance.
- from general to sub-disciplines
  (AI for climate to AI for cryosphere/AI for clouds/AI for subseasonal forecasting etc.)
- Increasingly used by domain scientists without ML background
- Climate Scientists are often skeptical towards ML - and they should be!
- Shift towards application specific architectures.
- Foundation models are on the rise.

Pointers (a personally biased selection)

General AI for Climate Science

- Reichstein et al. 2019 (good overview on methods and data)
- ECMWF MOOC ML for weather and climate
- Last year's lecture (focus more on climate science basics)

Conferences and Workshops

- CCAI workshops
- Many sessions at EGU, AGU
- NOAA AI workshop
- Climate Informatics
- the field rapidly evolving !

Data

- Google Earth Engine | Microsoft Planetary Computer | Pangeo (data platforms)
- ESA | NASA | Copernicus | NOAA (check for open-source climate data)
- Rolf et. al 2024 (satellite data considerations for ML)

Challenges / Competitions

- weather4cast @NeurIPS
- ClimSim @Kaggle
- subscribe to CCAI newsletter to be up to date

XAI

- Molnar et al. 2020 (general intro)
- Ebert-Uphoff et al., 2021 (good overview for climate) Mamalakis et al., 2022 (Benchmarking XAI methods)
- Bommer et al., 2024 (Finding the right XAI method)
- Jeggle et al., 2023 (XAI case study)

Physics Guided ML

- Beucler et al. (2020) (case study)
- Beucler et al. (2024) (case study)
- Harder et al. (2023) (case study)

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Thanks for your attention!

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