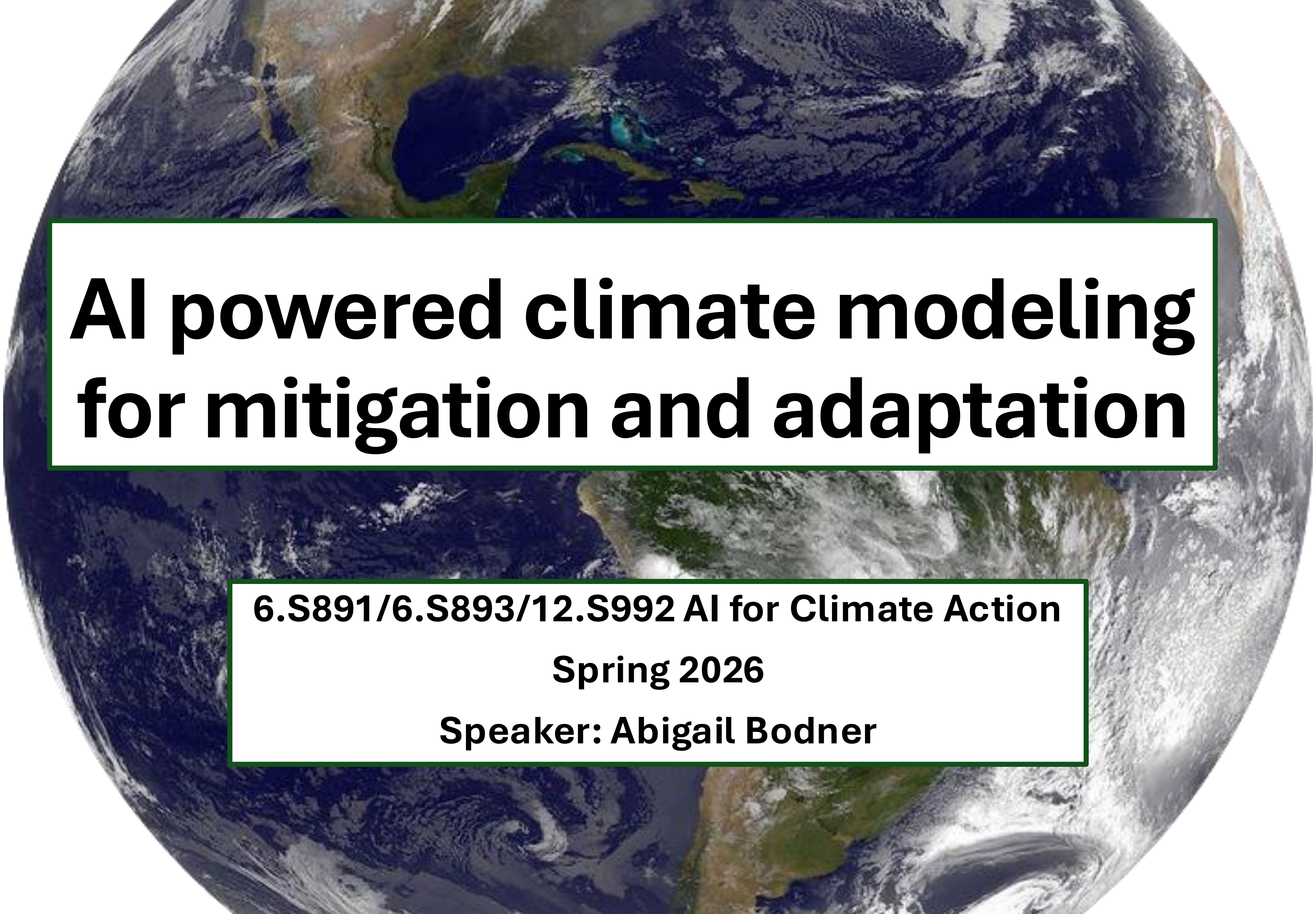


AI powered climate modeling for mitigation and adaptation

6.S891/6.S893/12.S992 AI for Climate Action

Spring 2026

Speaker: Abigail Bodner

Variations in Earth’s Climate System

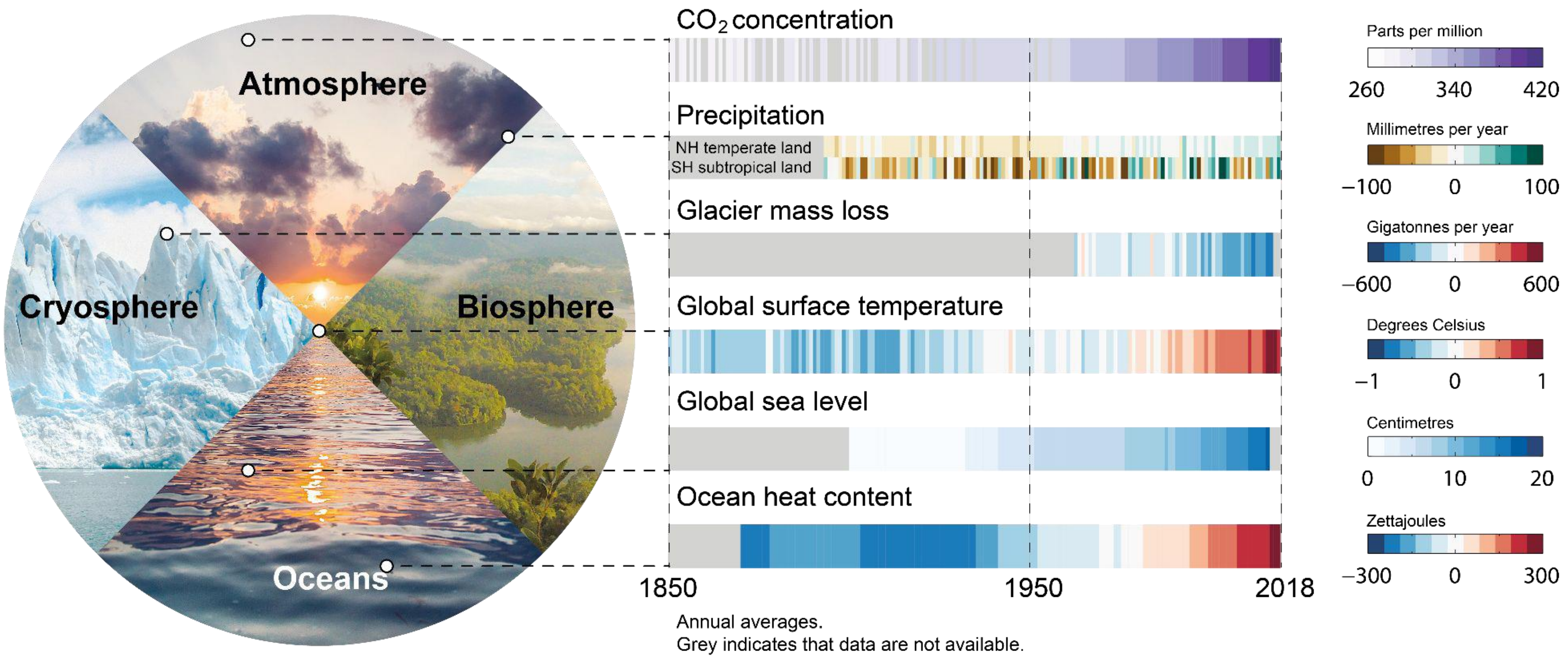
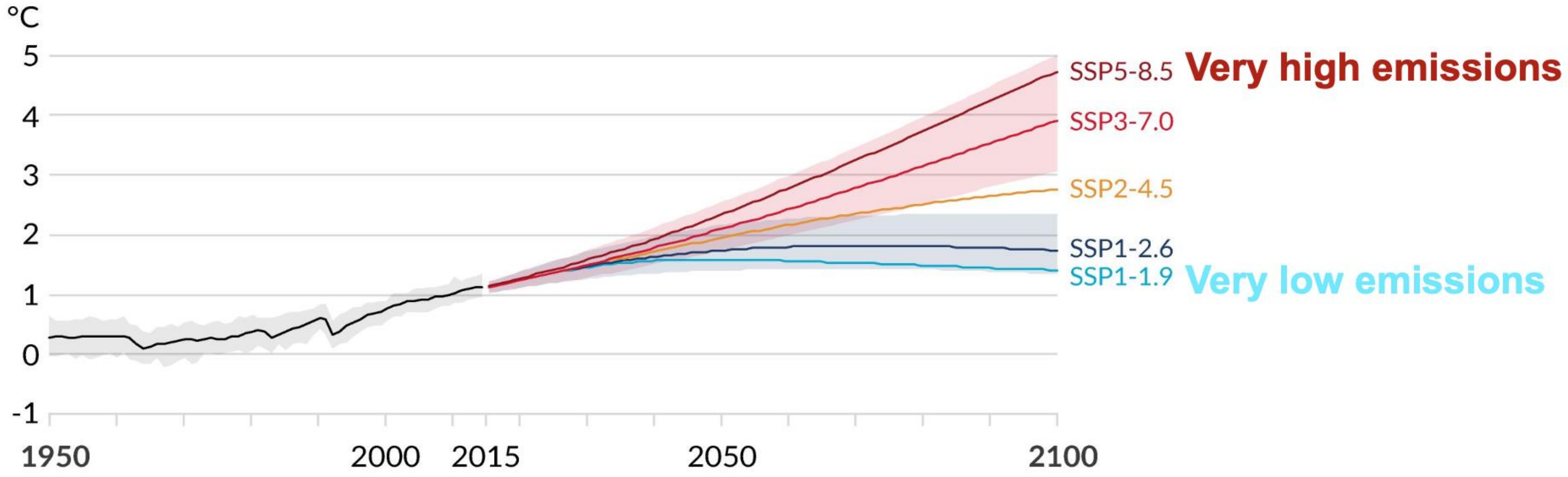


Figure 1.4 | Changes are occurring throughout the climate system. Left: Main realms of the climate system: atmosphere, biosphere, cryosphere and ocean. Right: Six key indicators of ongoing changes since 1850, or the start of the observational or assessed record, through 2018. Each stripe indicates the global (except for precipitation which shows two latitude band means), annual mean anomaly for a single year, relative to a multi-year baseline (except for CO2 concentration and glacier mass loss, which are absolute values). Grey indicates that data are not available. Datasets and baselines used are: (i) CO2: Antarctic ice cores (Lüthi et al., 2008; Bereiter et al., 2015) and direct air measurements (Tans and Keeling, 2020) (see Figure 1.5 for details); (ii) precipitation: Global Precipitation Climatology Centre (GPCC) V8 (updated from Beckeret al., 2013), baseline 1961–1990 using land areas only with latitude bands 33°N–66°N and 15°S–30°S; (iii) glacier mass loss: Zemp et al. (2019); (iv) global surface air temperature (GMST): HadCRUT5 (Morice et al., 2021), baseline 1961–1990; (v) sea level change: (Dangendorf et al., 2019), baseline 1900–1929; (vi) ocean heat content (model–observation hybrid): Zanna et al. (2019), baseline 1961–1990. Further details on data sources and processing are available in the chapter data table (Table 1.SM.1).

Figure 1.4 in IPCC, 2021: Chapter 1. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Chen, D. et al.)

Human activities affect all the major climate system components, with some responding over decades and others over centuries

a) Global surface temperature change relative to 1850-1900



AR6 WG1 Figure SPM.8a

Figure SPM.8 | Selected indicators of global climate change under the five illustrative scenarios used in this Report
The projections for each of the five scenarios are shown in colour. Shades represent uncertainty ranges – more detail is provided for each panel below. The black curves represent the historical simulations (panels a, b, c) or the observations (panel d). Historical values are included in all graphs to provide context for the projected future changes.

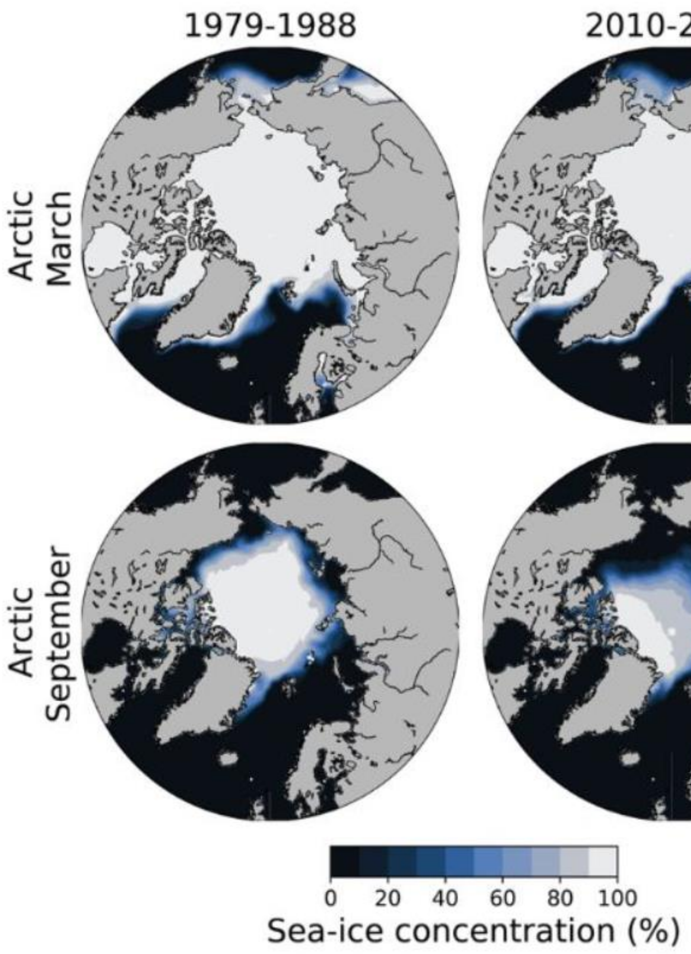
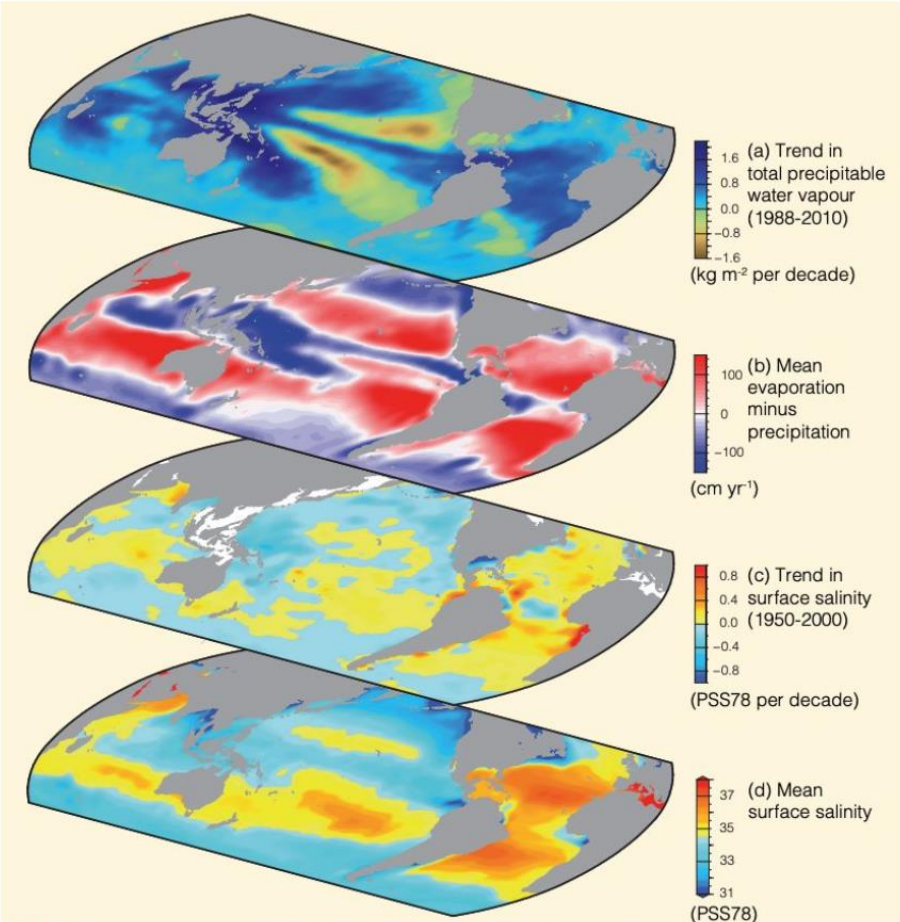


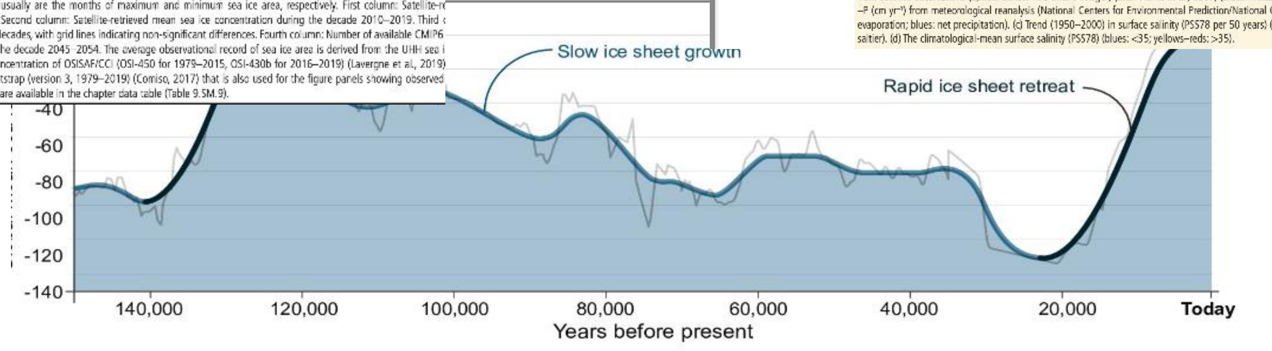
Figure 9.13 | Arctic sea ice historical records and Coupled Model Intercomparison Project Phase 6 (CMIP6) projections. (Left) Absolute ano monthly-mean Arctic sea ice area during the period 1979 to 2019 relative to the average monthly-mean Arctic sea ice area during the period 1979 to 2008. **(Right)** concentration in the Arctic for March and September, which usually are the months of maximum and minimum sea ice area, respectively. First column: Satellite-re mean sea ice concentration during the decade 1979–1988. Second column: Satellite-retrieved mean sea ice concentration during the decade 2010–2019. Third c Absolute change in sea ice concentration between these two decades, with grid lines indicating non-significant differences. Fourth column: Number of available CMIP6 that simulate a mean sea ice concentration above 15 % for the decade 2045–2054. The average observational record of sea ice area is derived from the UHH sea i product (Doerr et al., 2021), based on the average sea ice concentration of OSISAF/CCI (OSI-450 for 1979–2015, OSI-430b for 2016–2019) (Lavergne et al., 2019) Team (version 1, 1979–2019) (Cavalieri et al., 1996) and Bootstrap (version 3, 1979–2019) (Comiso, 2017) that is also used for the figure panels showing observed concentration. Further details on data sources and processing are available in the chapter data table (Table 9.SM.9).

AR6 WG1 Figure 9.13
1st and 2nd column of right panels



FAQ 3.2, Figure 1 | Changes in sea surface salinity are related to the atmospheric patterns of evaporation minus precipitation (E – P) and trends in total precipitable water: (a) Linear trend (1988–2010) in total precipitable water (water vapor integrated from the Earth's surface up through the entire atmosphere) (kg m-2 per decade) from satellite observations (Special Sensor Microwave Imager) (after Wentz et al., 2007) (blues: wetter; yellows: drier). (b) The 1979–2005 climatological mean net E –P (cm yr-1) from meteorological reanalysis (National Centers for Environmental Prediction/National Center for Atmospheric Research; Kalnay et al., 1996) (reds: net evaporation; blues: net precipitation). (c) Trend (1950–2000) in surface salinity (PSS78 per 50 years) (after Durack and Wijffels, 2010) (blues freshening; yellows-reds saltier). (d) The climatological-mean surface salinity (PSS78) (blues: <35; yellows–reds: >35).

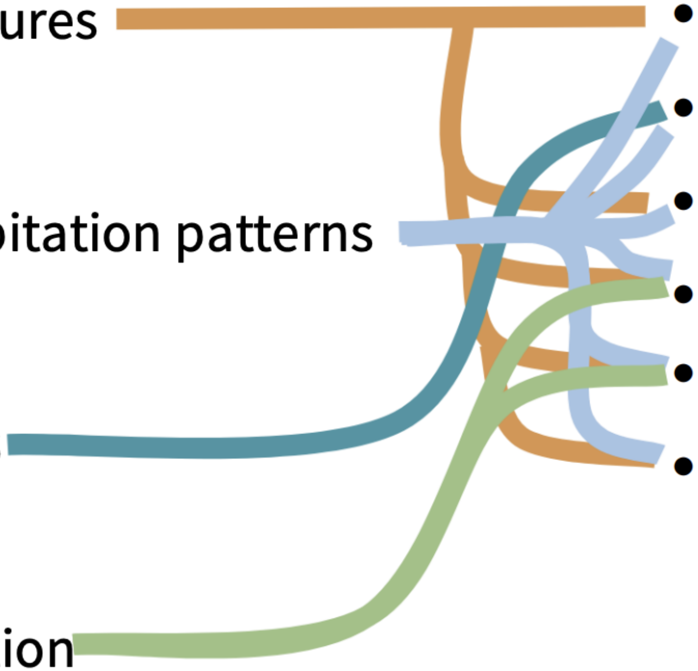
AR5 WG1 FAQ3



Climate impacts and downstream effects

Climate impacts

- Rising temperatures
- Changing precipitation patterns
- Rising sea levels
- Ocean acidification



Downstream effects

- Droughts and heatwaves
- More intense storms & flooding
- More frequent wildfires
- Loss of ecosystem services
- Biodiversity loss
- Spread of disease vectors & pests

Figure adapted from Kris Sankaran

Climate change adaptation

Adaptation: Responding to the effects of a changing climate

1. Measuring and predicting risks
   - **Risk**: Impact x probability

2. Strengthening adaptive capacity
   - **Robustness:** Withstanding a range of outcomes with no/minimal impact
   - **Resilience:** Recovering quickly after impact

Human & ecological systems

Connections with UN SDGs

Figure source (bottom): United Nations

Climate change mitigation

Mitigation: Reducing or preventing GHG emissions

Sectors

Energy supply
Transportation
Buildings
Industry
Agriculture
Forestry
Other land use
CO_2 removal

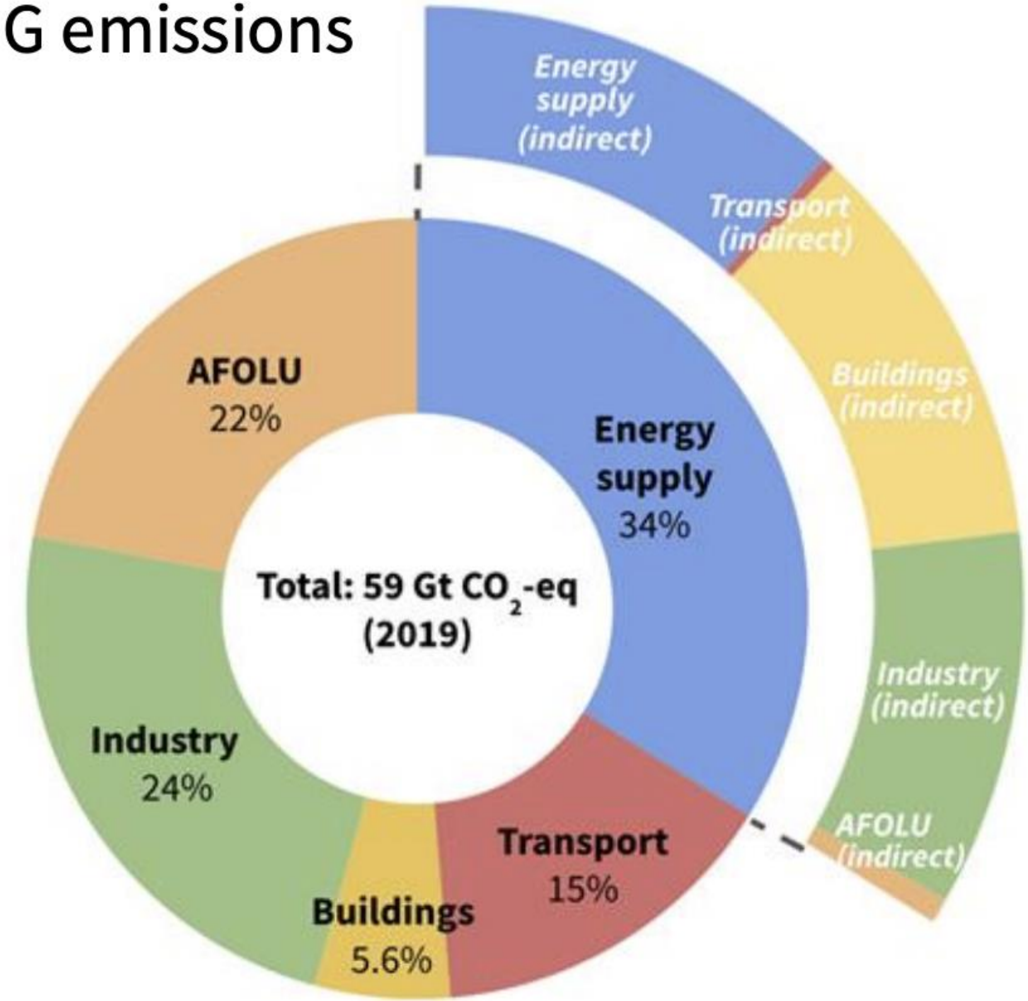


Figure data based on IPCC AR6 WG3 Report (2022). Percentages shown do not add to exactly 100% due to rounding to two significant figures.

Climate change mitigation

Mitigation: Reducing or preventing GHG emissions

Sectors	
Energy supply Transportation Buildings Industry	**Energy-related emissions**
Agriculture Forestry Other land use	**Land use (AFOLU) emissions**
CO_2 removal	**“Negative emissions”**

Outline

- What are the gaps between climate models and adaptation /mitigation strategies?

- How can AI help?

- Show me some examples!

The power of local action, ctd.

ICLEI
Local Governments for Sustainability

2500+
Cities towns & regions

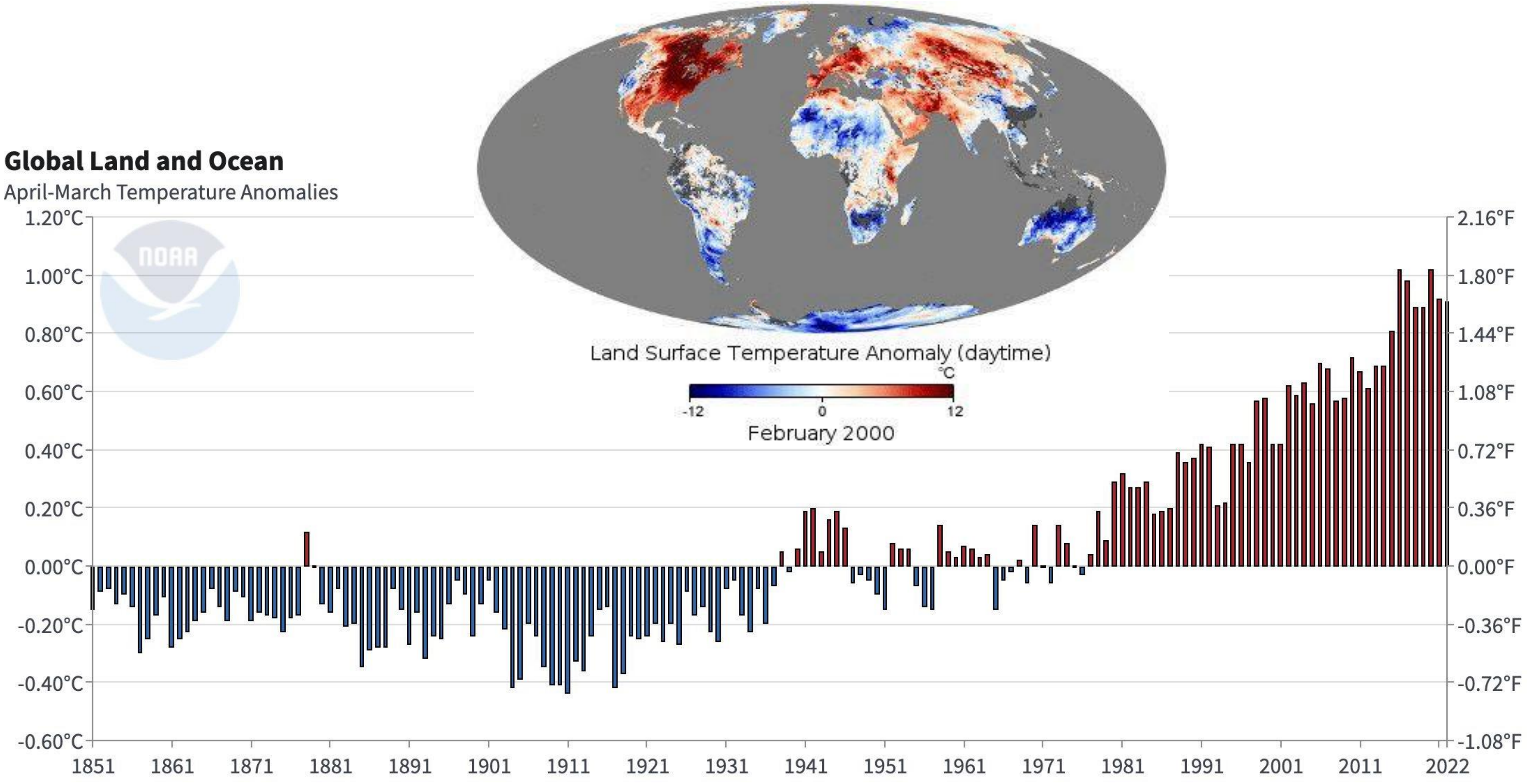
25+
% Global urban population

125+
Countries worldwide

20+
% Global population

Source: https://iclei.org/our_network/

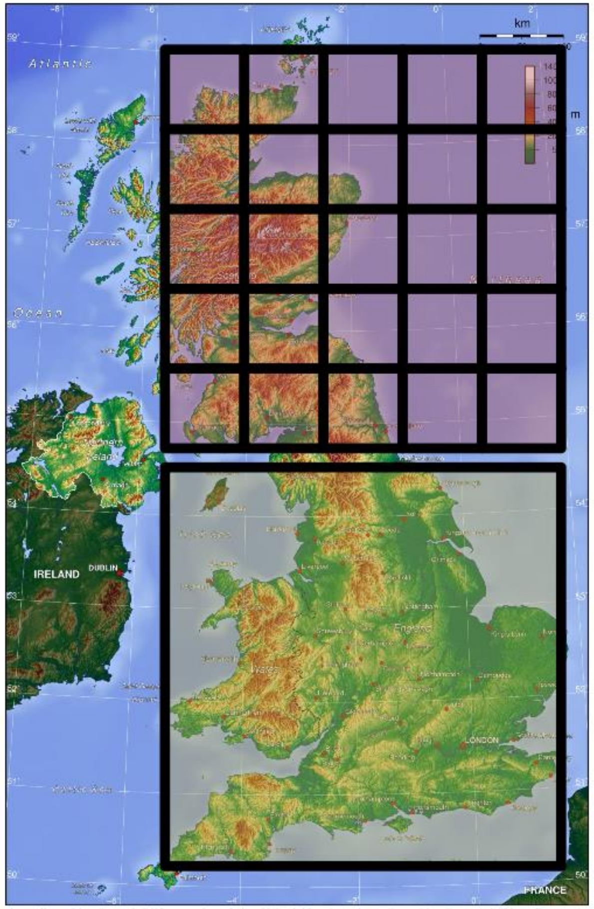
Anomaly for Climate Monitoring



Observed global average surface temperature anomaly are one of the key indicators for monitoring climate change.

Credit: NOAA

What's smaller than 100km?



New Models
(~100km)

Old Models
(~500km)

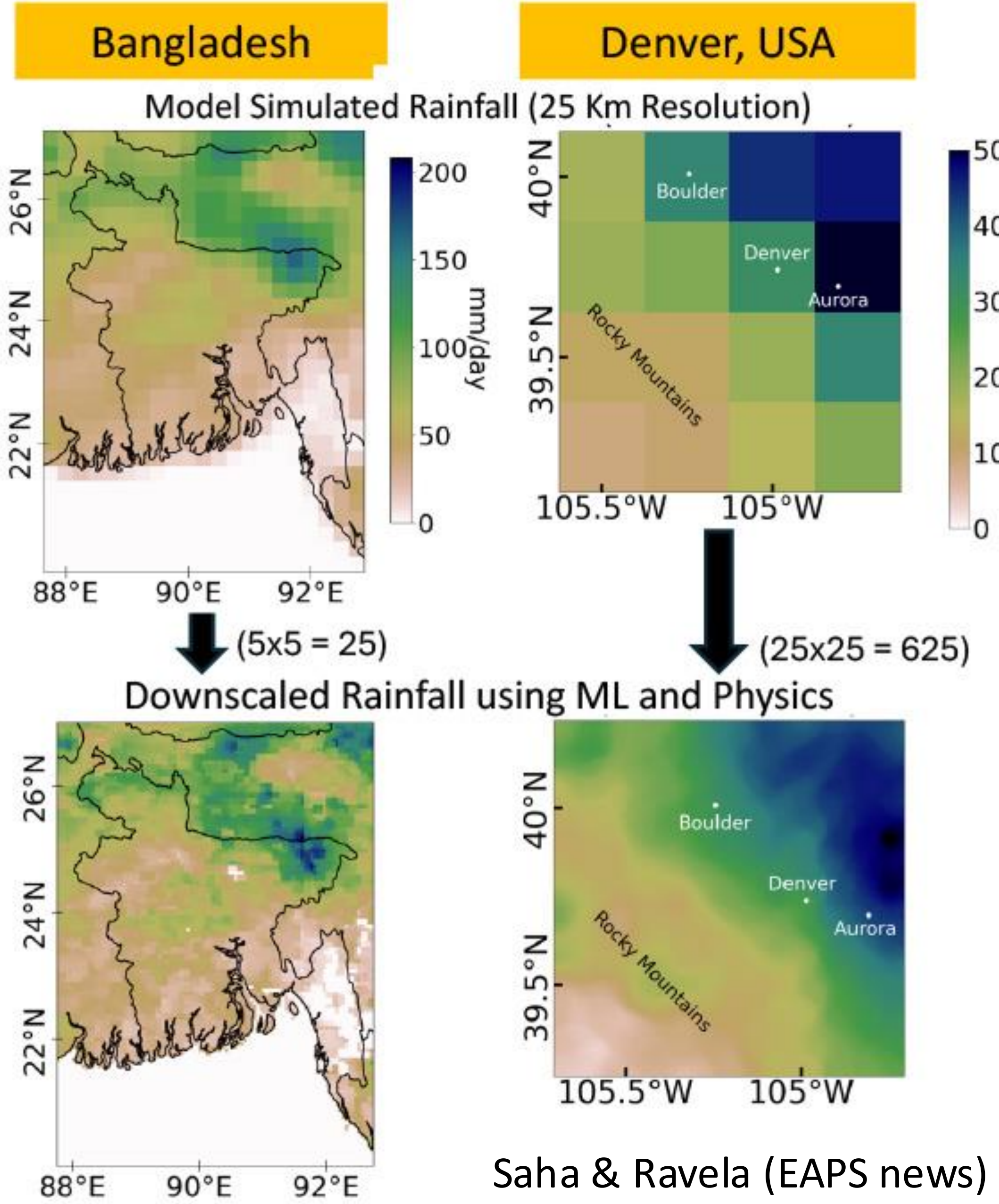
Clouds (atmosphere) & surface conditions (land)

https://en.wikipedia.org/wiki/Geography_of_the_United_Kingdom ; https://en.wikipedia.org/wiki/New_Forest ; https://en.wikipedia.org/wiki/Iceberg ; https://en.wikipedia.org/wiki/Phytoplankton

What do we need?

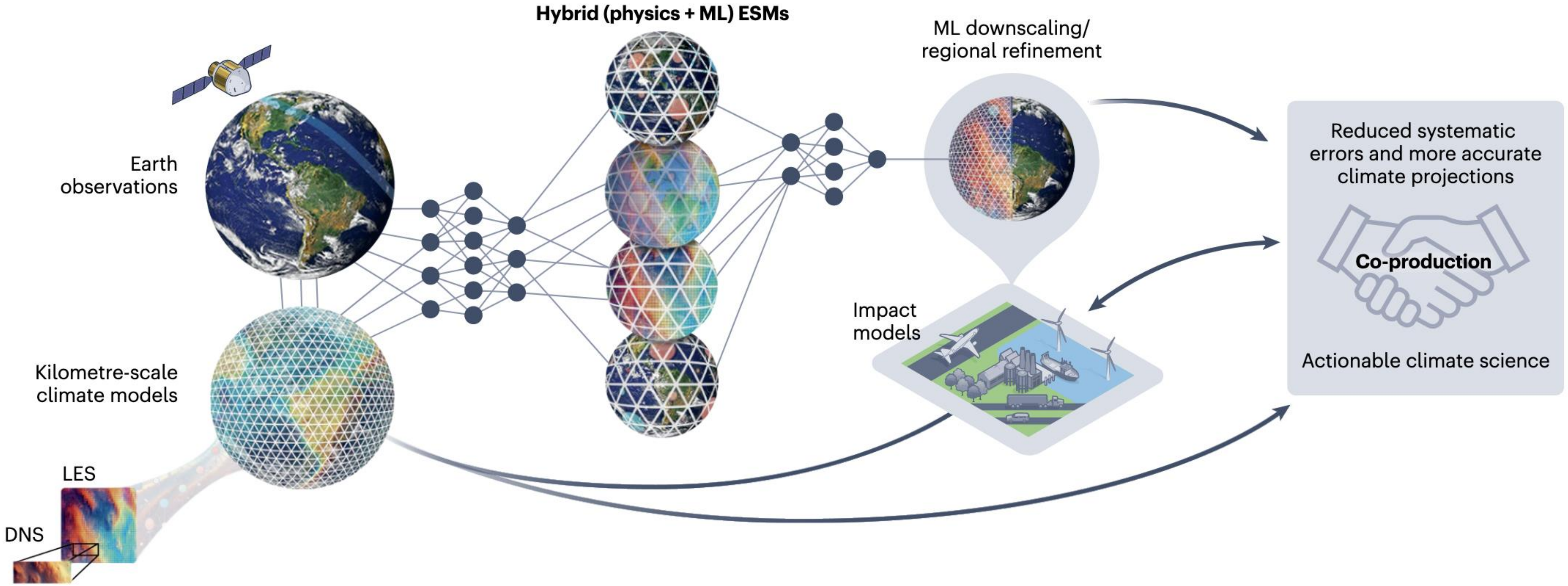
What do we need?

- High resolution data to assess local impacts
- Account for complexity and feedbacks with larger-scale climate
- Short term AND long-term predictions



Saha & Ravela (EAPS news)

AI-empowered next-generation multiscale climate modelling for mitigation and adaptation



Eyring et al. (2024)

AI-empowered next-generation multiscale climate modelling for mitigation and adaptation

Coupled Model Intercomparison Project (CMIP)

- **CMIP6 included over 23 Model Intercomparison Projects (MIP) and more than 70 different models**
- **As well as MIPs, there is a set of experiments characterising the models (Diagnostic, Evaluation and Characterization of Klima - DECK)**
- **To extend CMIP projections beyond 2100 and (in some cases) to the full range of scenarios, the model responses are sometimes emulated**

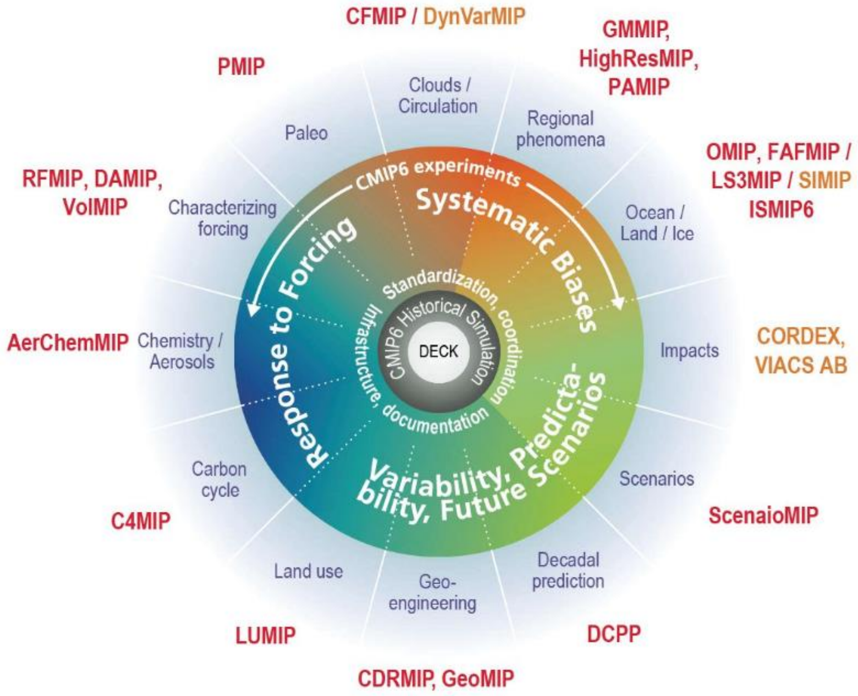
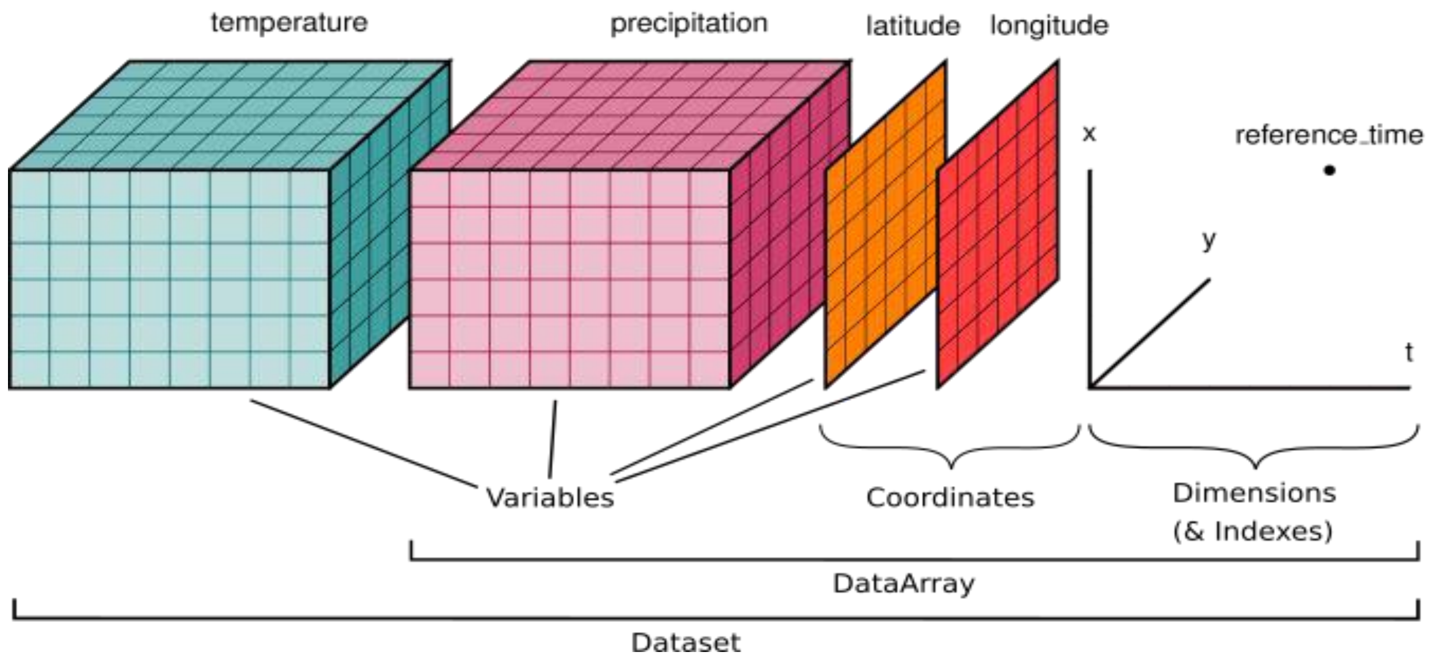


Figure 1.22 | Structure of CMIP6, the 6th phase of the Coupled Model Intercomparison Project. The centre shows the common DECK (Diagnostic, Evaluation and Characterization of Klima) and historical experiments that all participating models must perform. The outer circles show the topics covered by the endorsed (red) and other MIPs (orange). See Table 1.3 for explanation of the MIP acronyms. Figure is adapted from Eyring et al. (2016).

IPCC AR6 WG1 Figure 1.22

New computing opportunities

- CPUs vs parallelized hardware and languages that can take advantage of differentiable computing and AI methods
- Climate models on GPUs can also harness AI integration



- Assessing changes in global climate systems and their forcings, involves large, global datasets with multiple dimensions and variables

Example: Climate Modeling Alliance (Clima)

Eos

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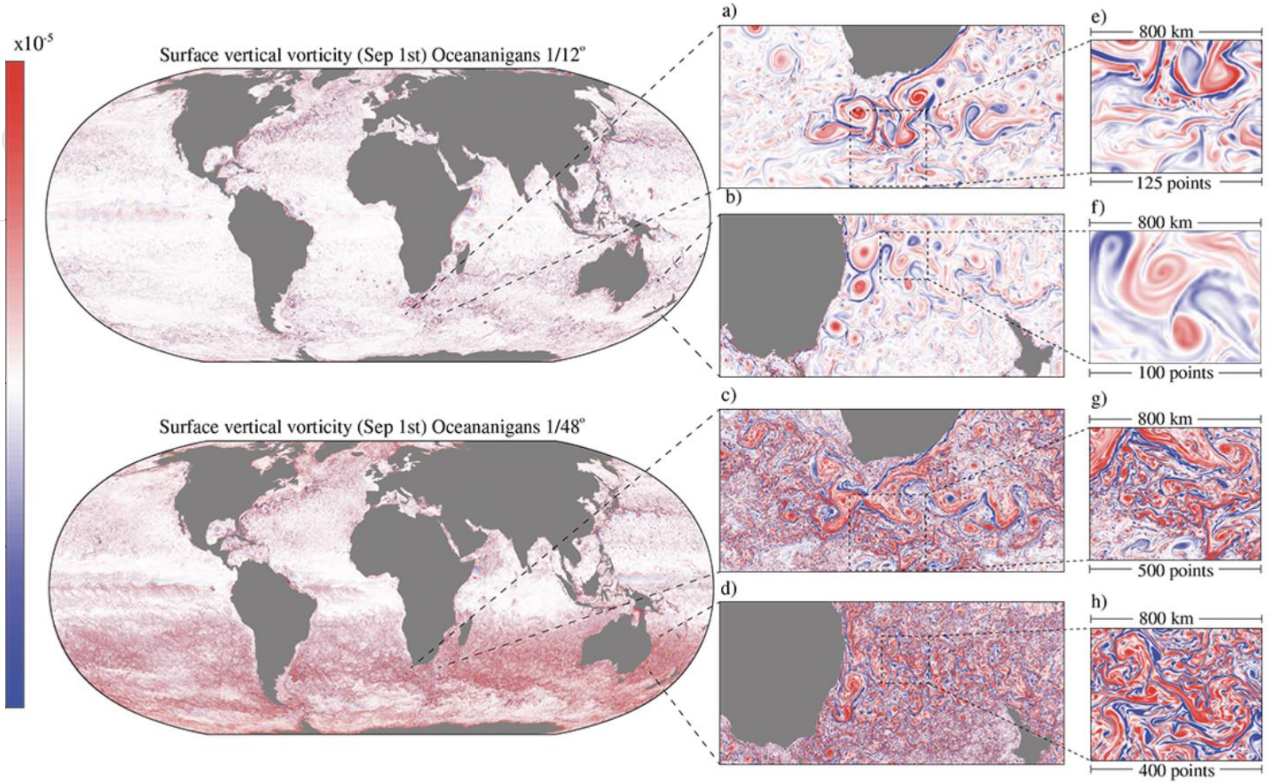
A Leap Toward Next-Generation Ocean Models

GPU-optimized ocean modeling achieves decade-long simulations in a day, enabling mesoscale-resolving climate simulations that open new opportunities for long-term planning in a changing climate.

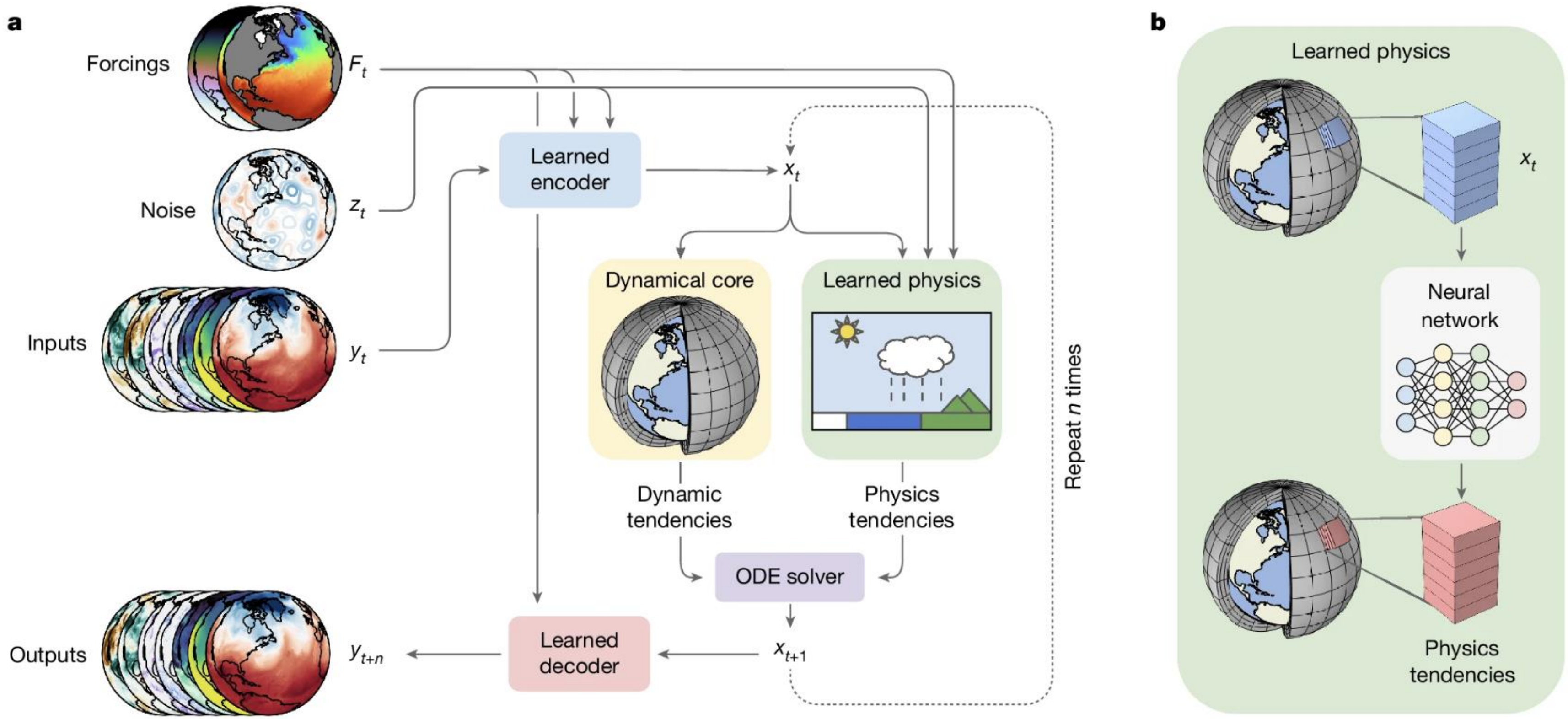
By **Florian Lemarié** and **Stephen M. Griffies** 1 May 2025



- Written in Julia, optimized for GPUs
- Speeds up computations
- Unprecedented high resolutions at a fraction of the speed

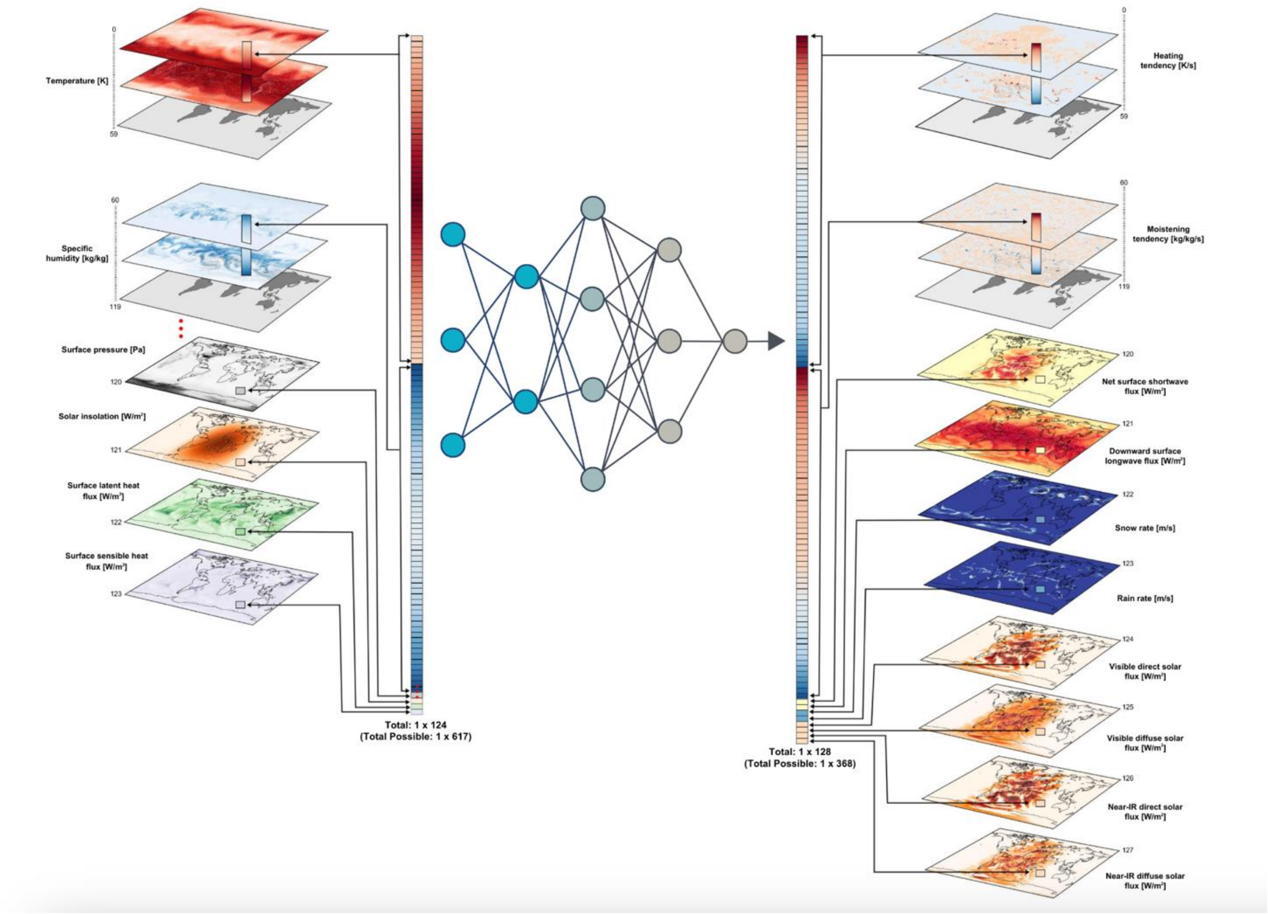
Example: Neural GCM (Google)

- Written in python/JAX
- Enables AI to be easily integrated to improve predictive skill



Example: ClimSim (LEAP)

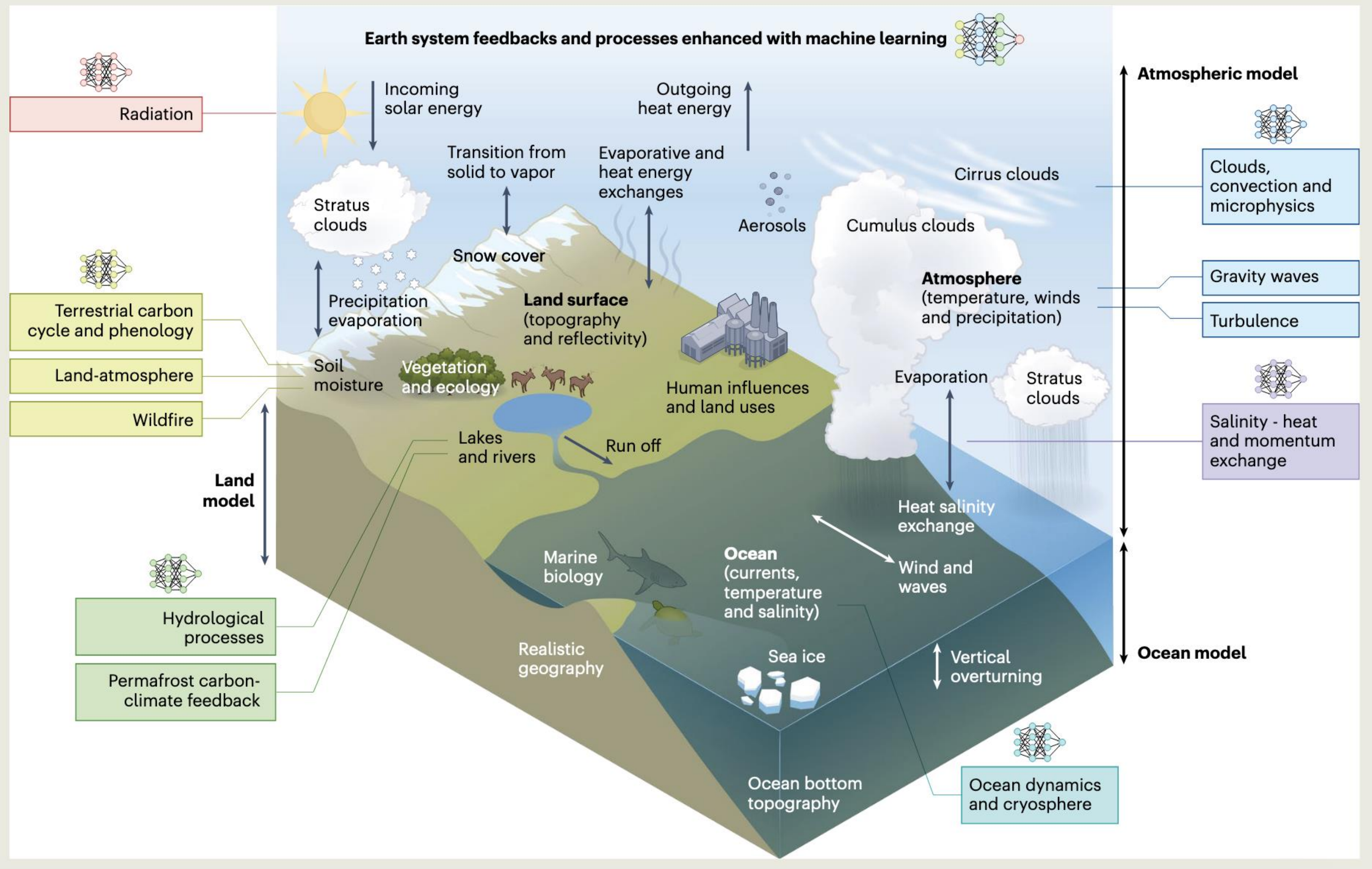
- Preprocessed climate variables for training AI methods
- Creating benchmarks for AI hybrid modeling



Physics aware ML

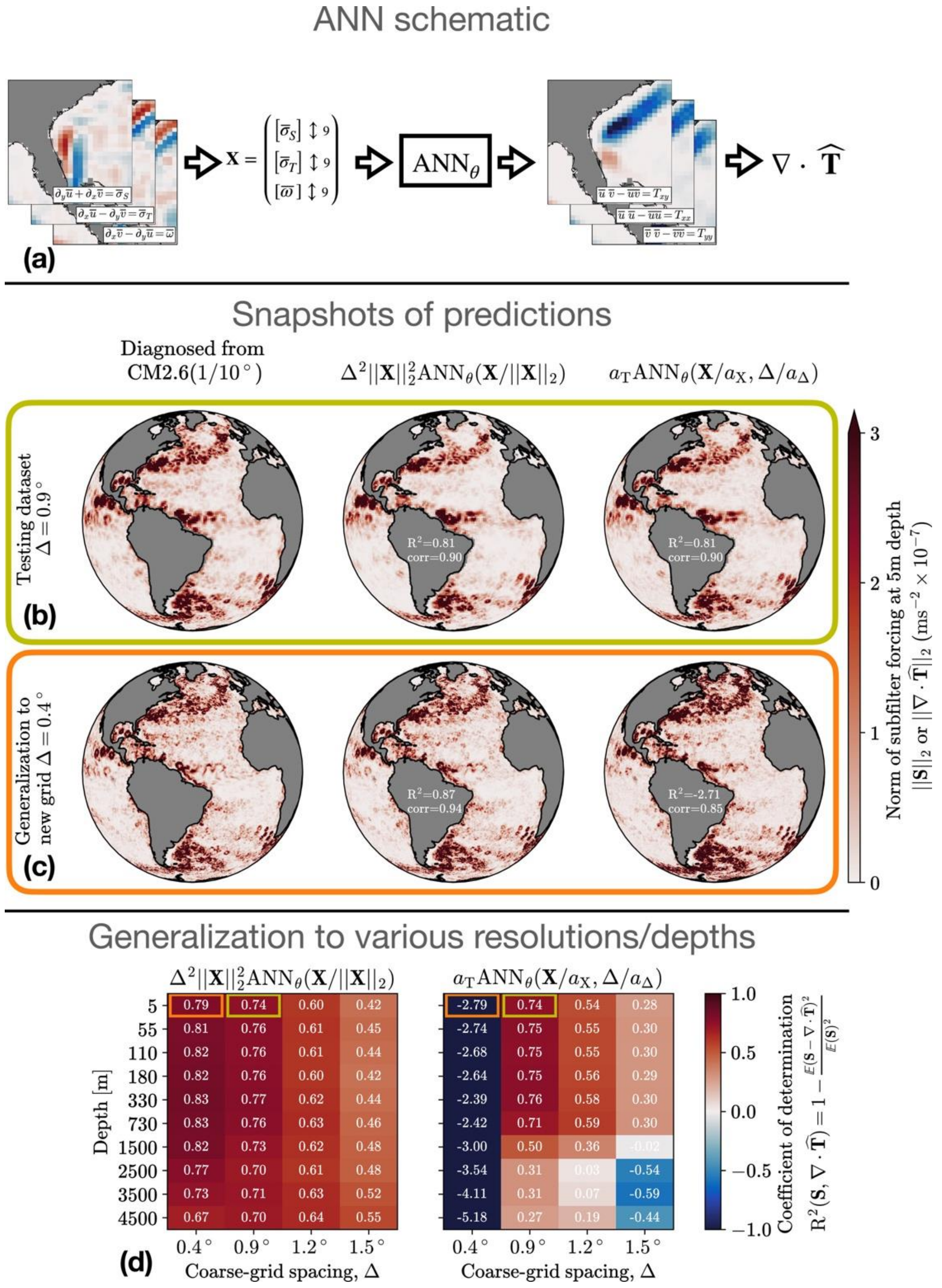
- Uncertainties in small-scale (unresolved) physics contribute to uncertainties in long-term projections (i.e clouds, ocean turbulence, etc.)

- Correct small-scale biases using ML



Physics aware ML (M2Lines)

- Learn the sub-grid physics using ML
- Integrate back into large-scale climate models
- Reduce biases that stem from grid processes

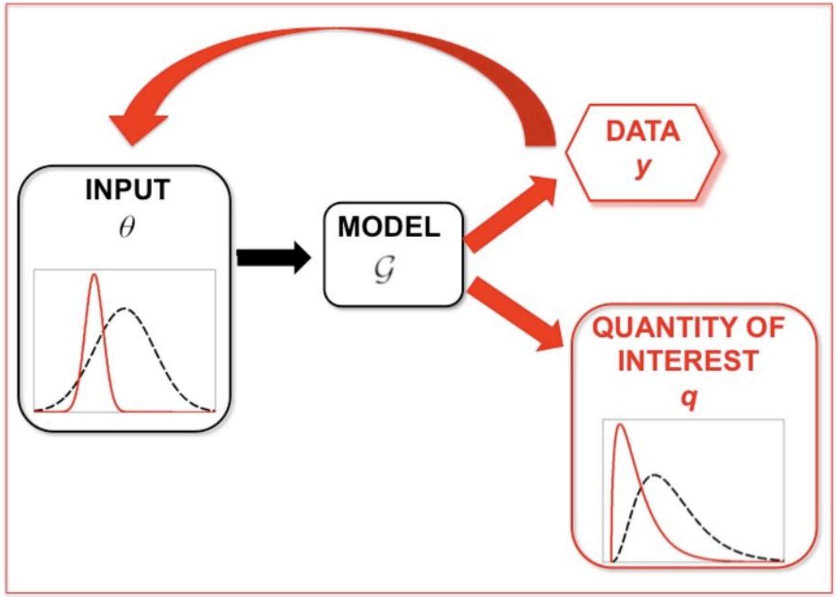


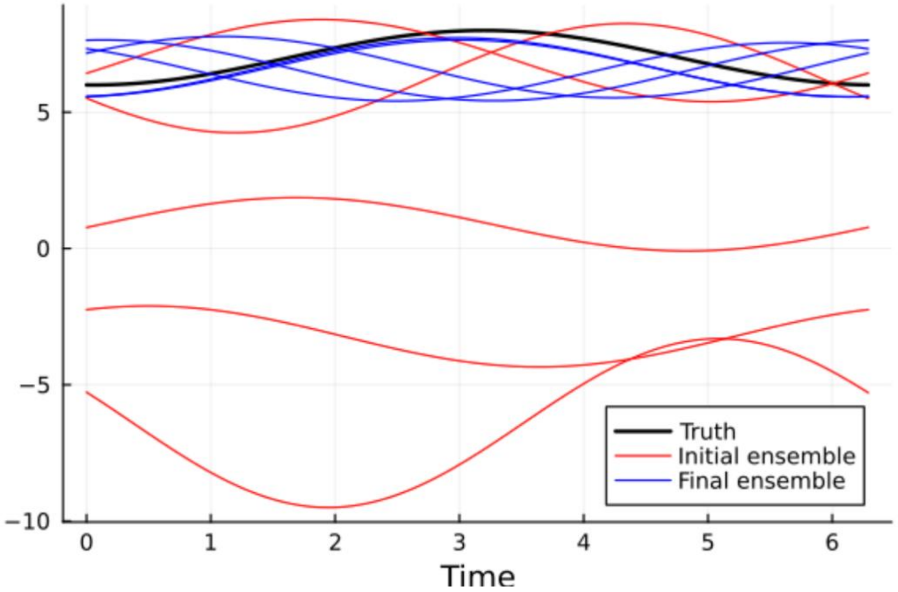
Physics aware ML (Clima)

- Calibrate model parameters based on high-fidelity data

- Reduce systematic bias in climate models

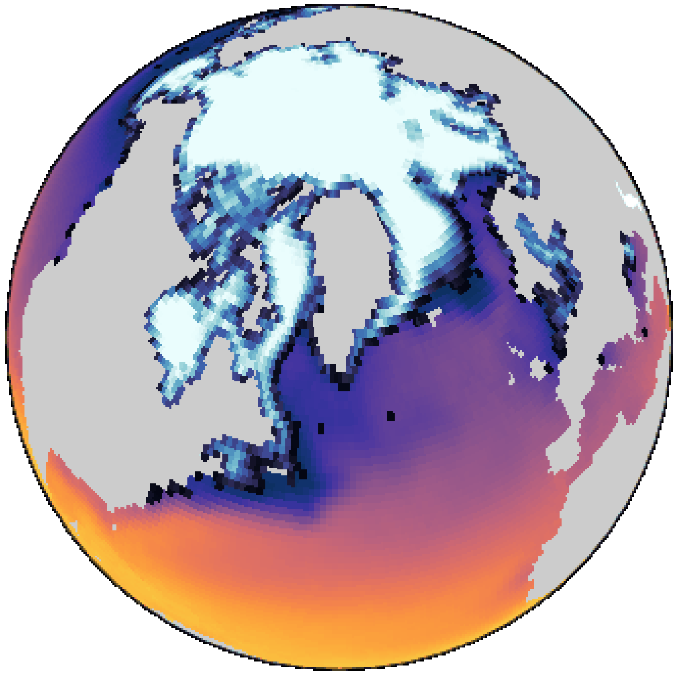
- Quantify parametric uncertainty





Example: SamudrACE (M2Lines & AI2)

- Coupling of climate-relevant physics
- 3D AI ocean-atmosphere-sea-ice climate emulator
- Enabling long-term projections at a fraction of the cost

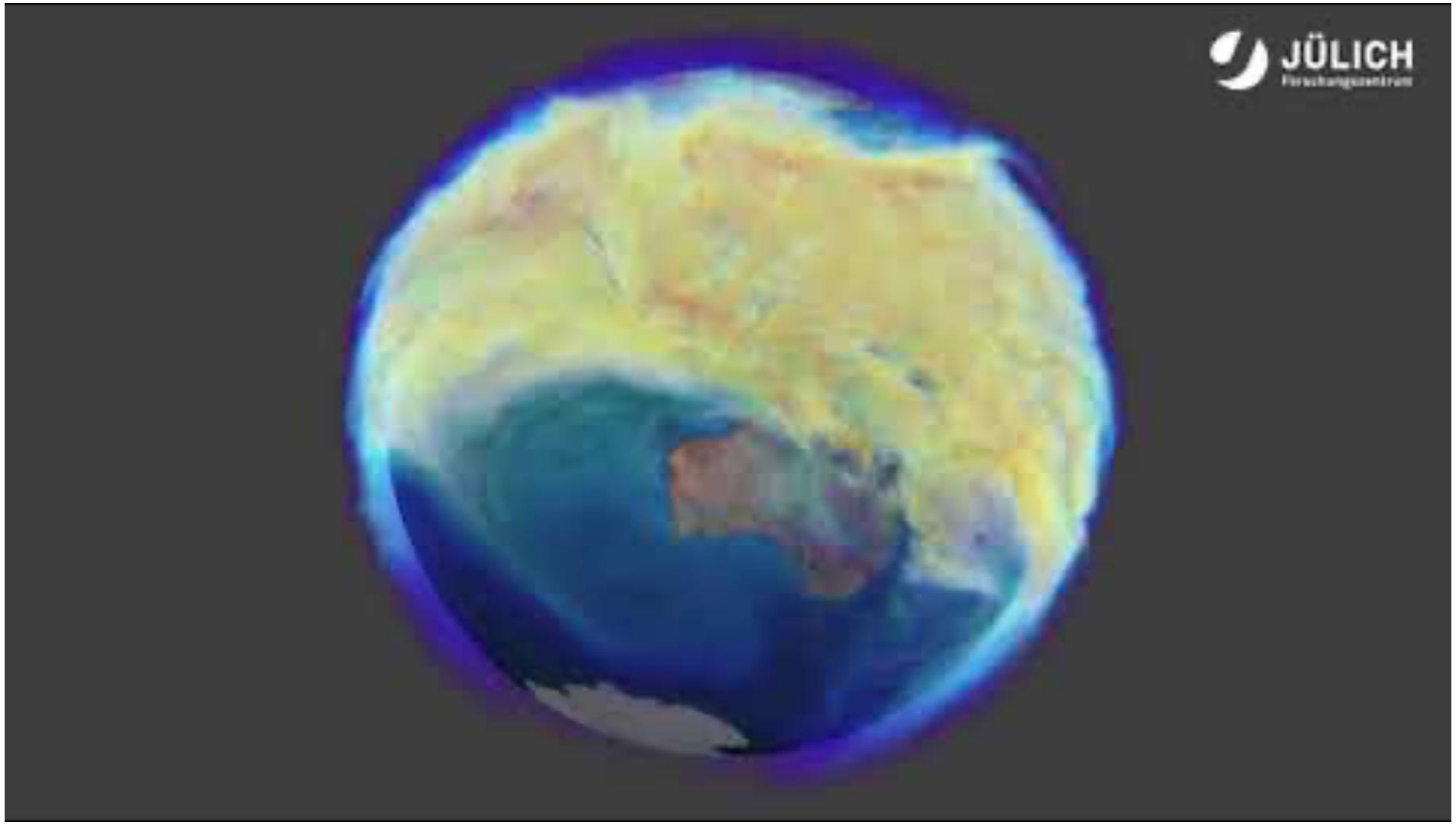


Why it is important to integrate observations?

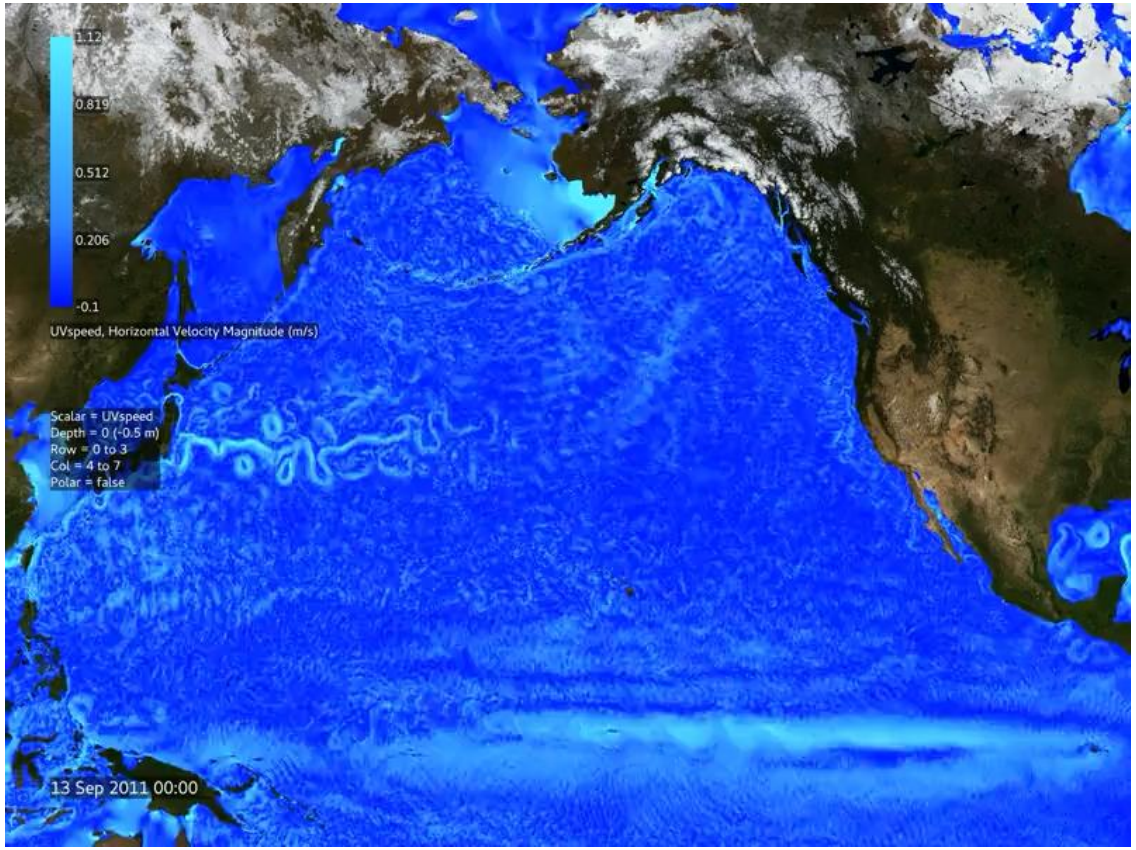
Why it is important to integrate observations?

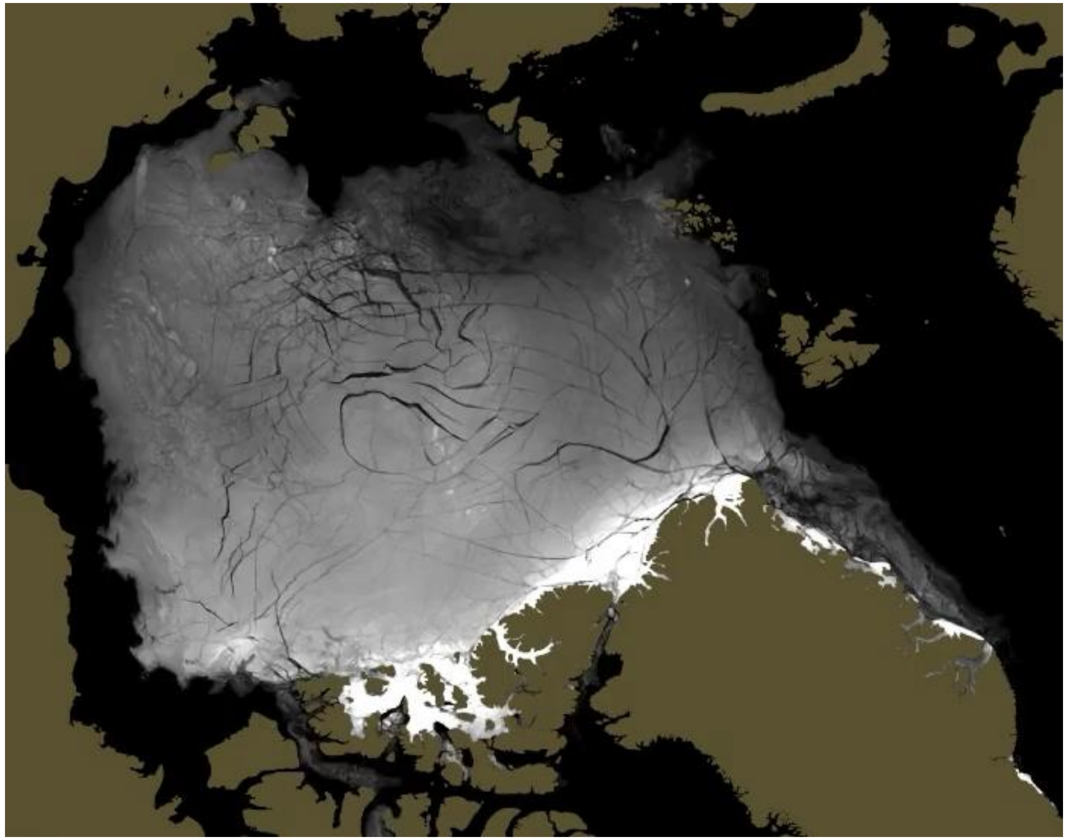
- Stays physically consistent and respond to earth’s energy imbalance
- Serves as benchmarks with policy-relevant criteria, close interaction with “people on the ground”
- Integrated with models, provides “state estimates” given a set of observed variables.

Example: atmospheric reanalysis (ERA)

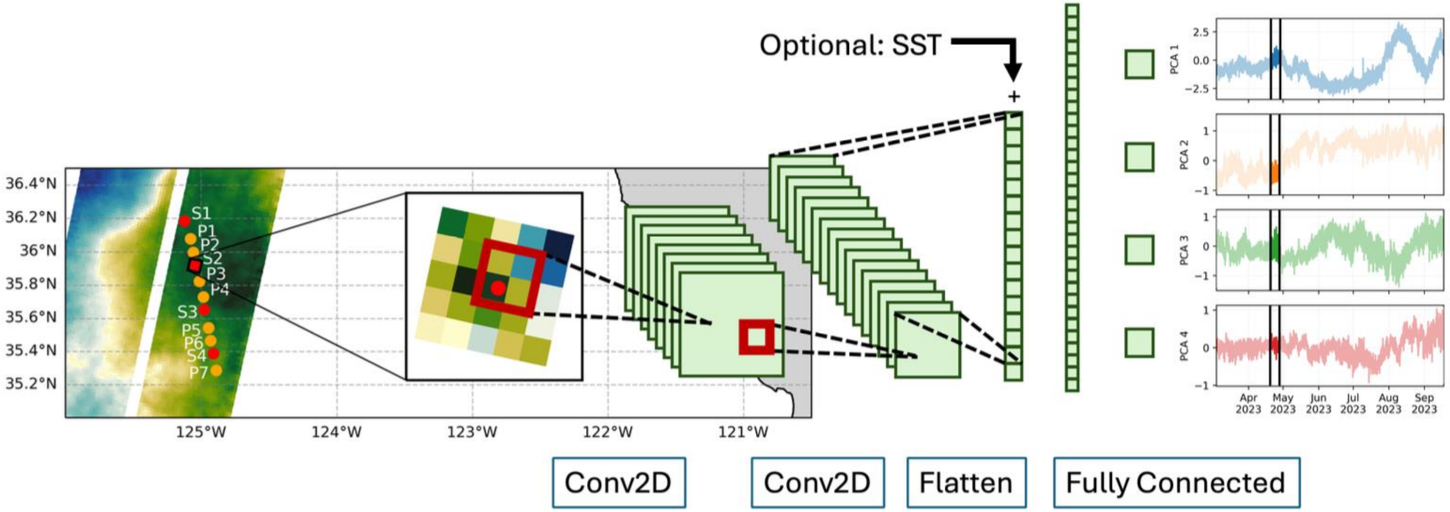


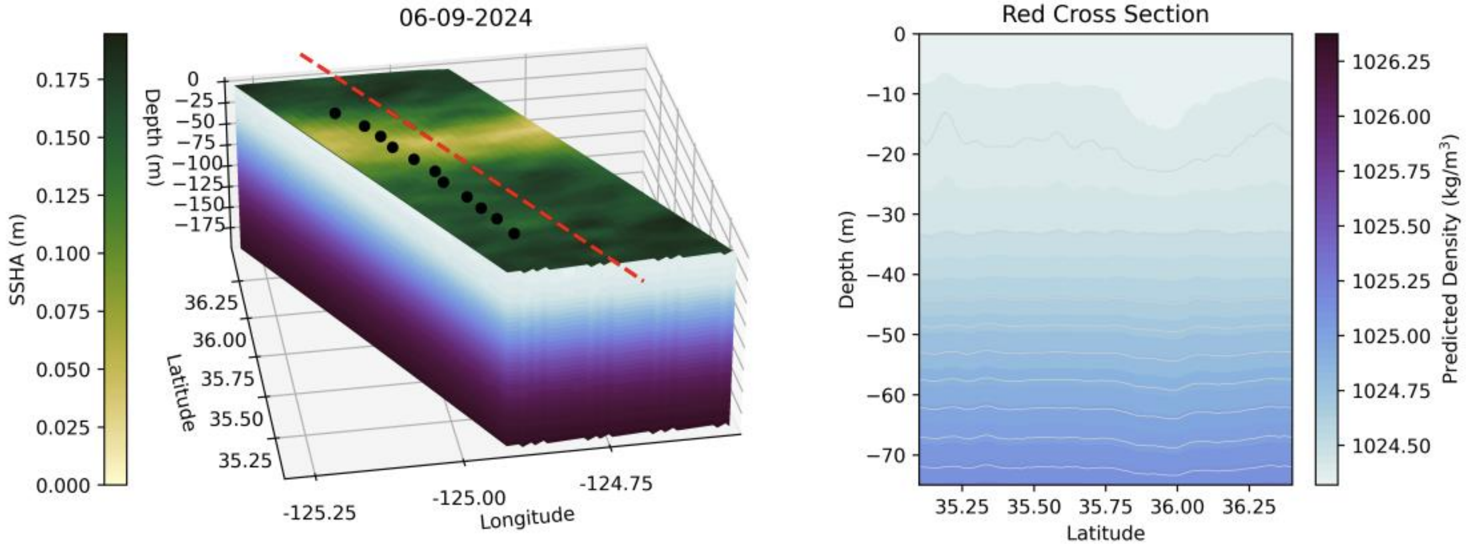
Example: Ocean state estimate (ECCO)





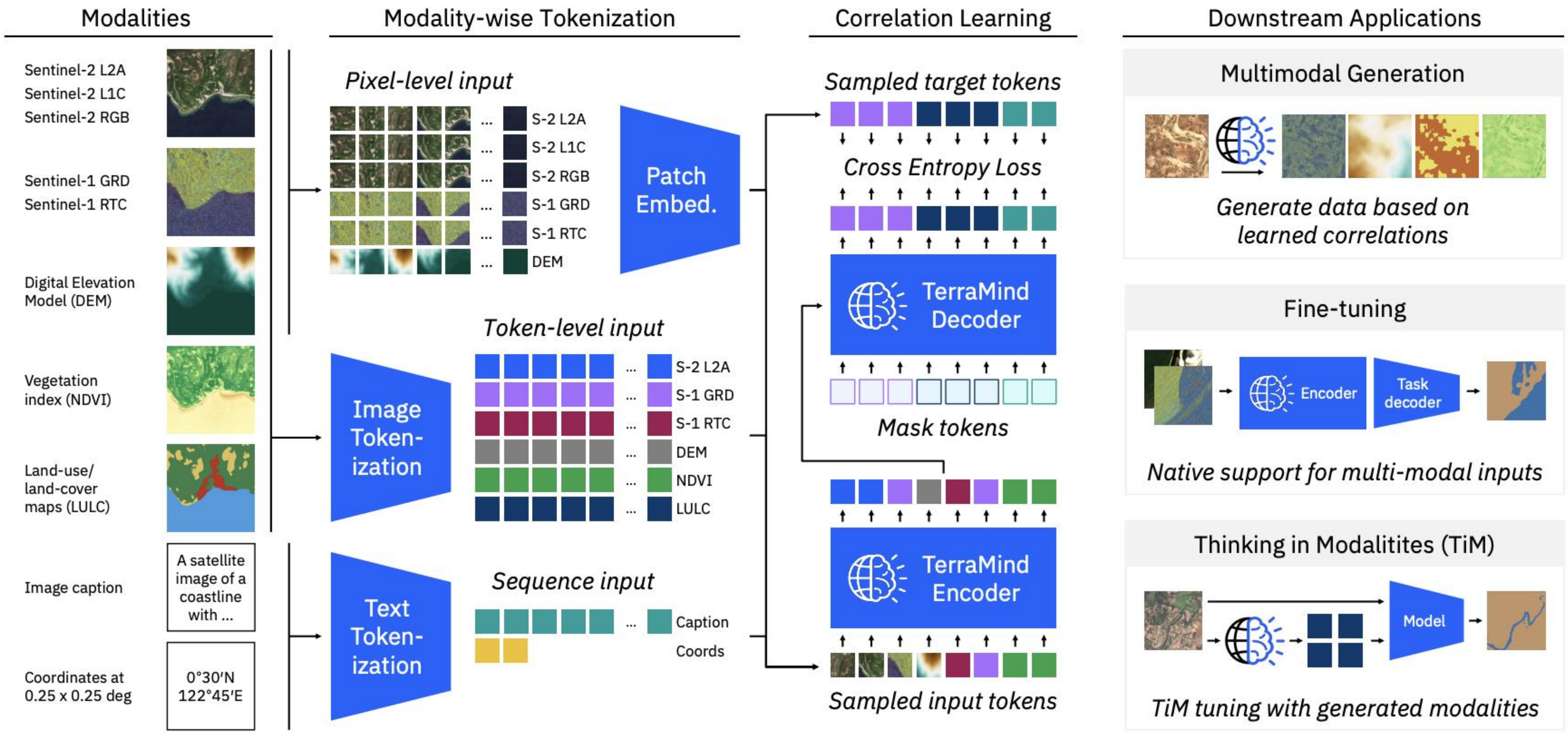
Example: Inference of undersampled variables





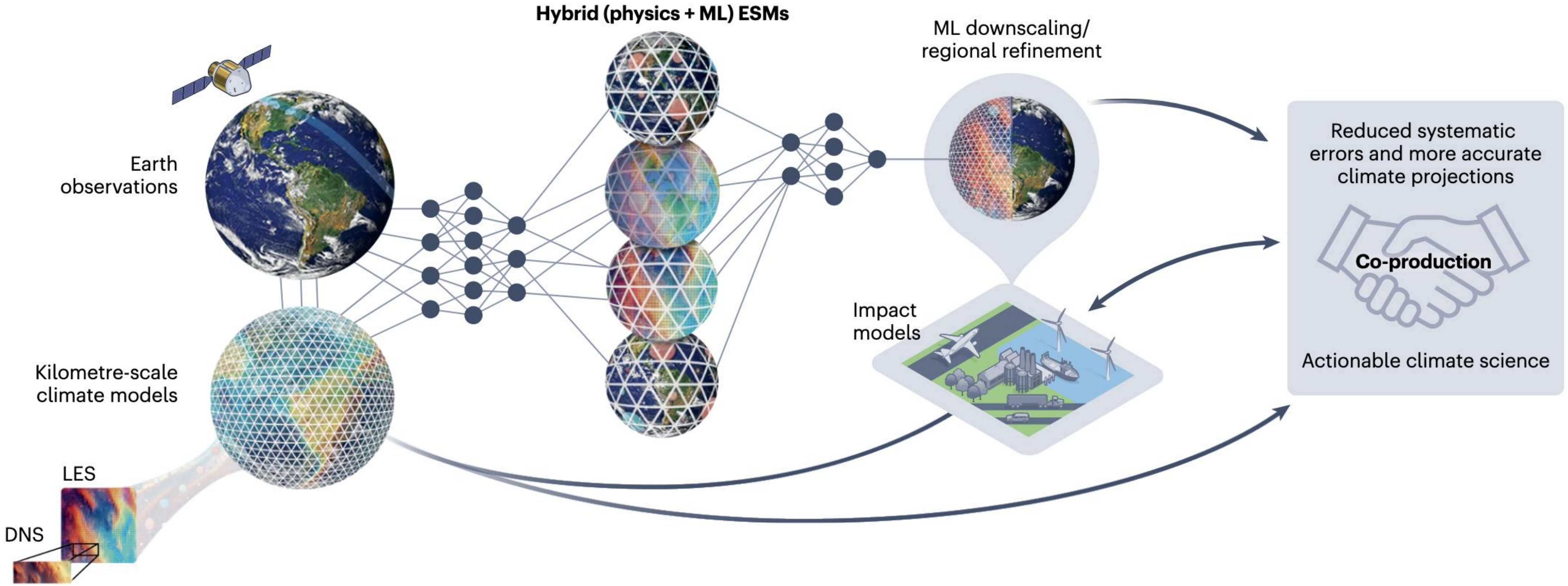
Campenois et al. (under review)

Example: Multi-modality



Jakubik et al. (2025)

AI-empowered next-generation multiscale climate modelling for mitigation and adaptation



Eyring et al. (2024)

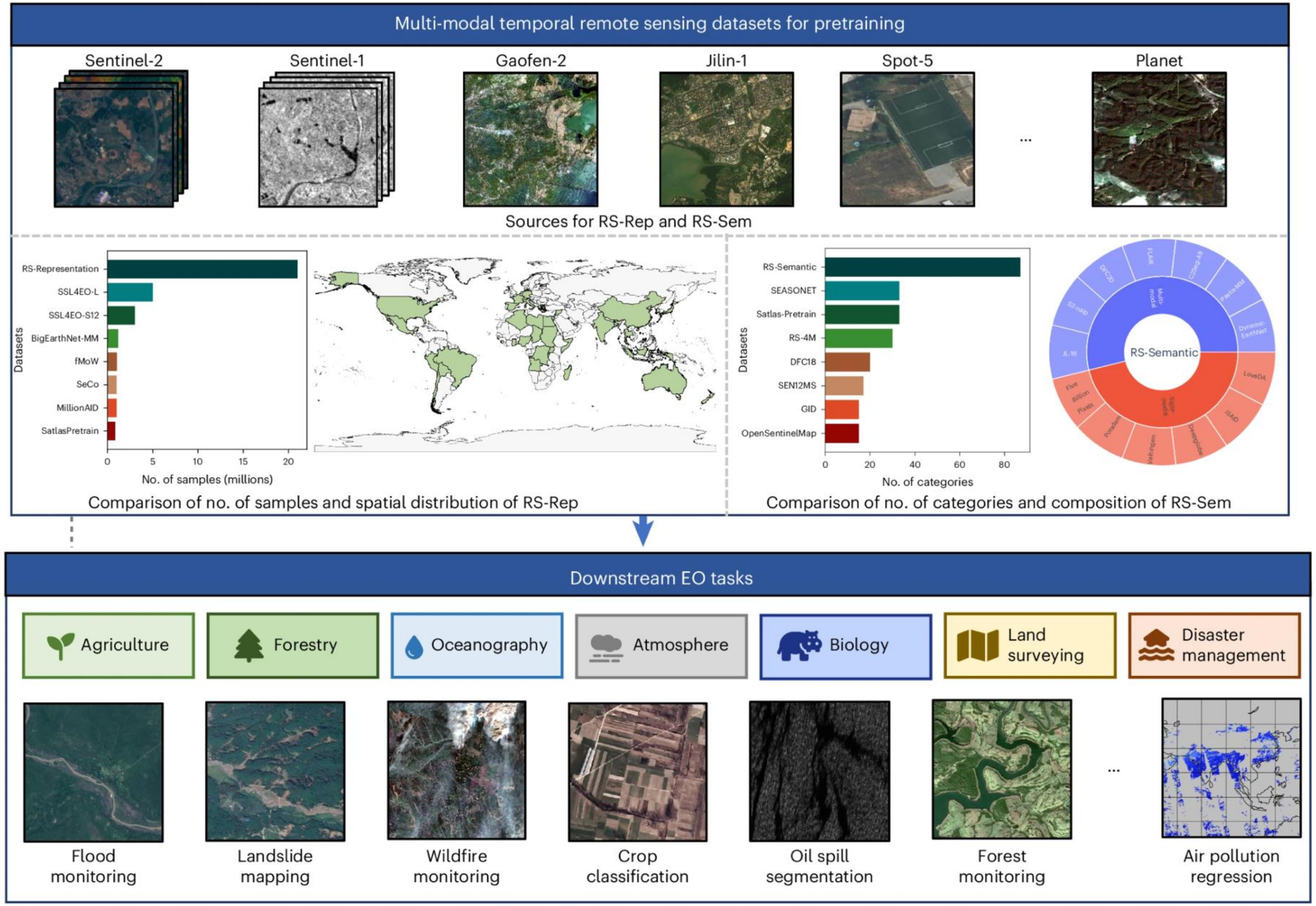
Connection to stakeholders

Connection to stakeholders

Information needs to be

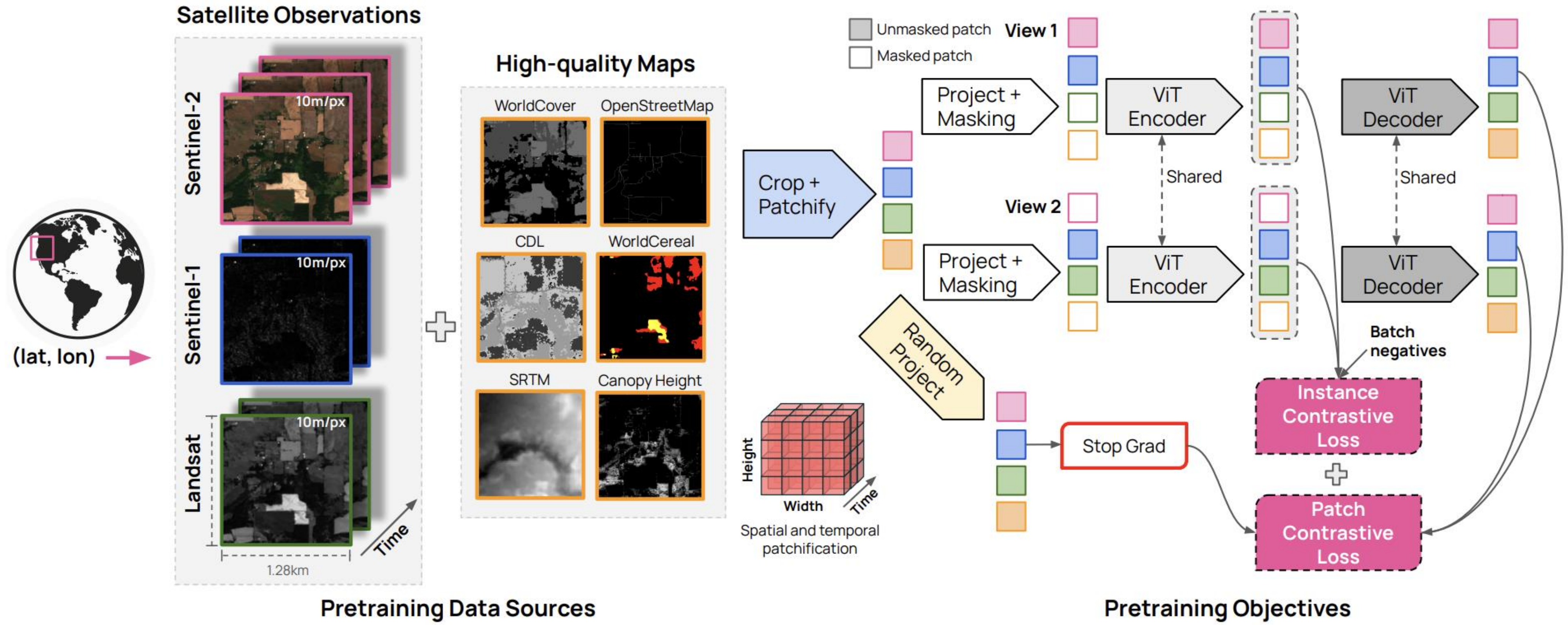
1) Relevant
2) Accessible

Example: foundation model for Earth observation (SkySense++)



Wu et al. (2025)

Example: foundation model for Earth observation (OlmoEarth)



https://olmoearth.allenai.org/viewer

Herzog et al (2025)

Campus activities worth engaging with:

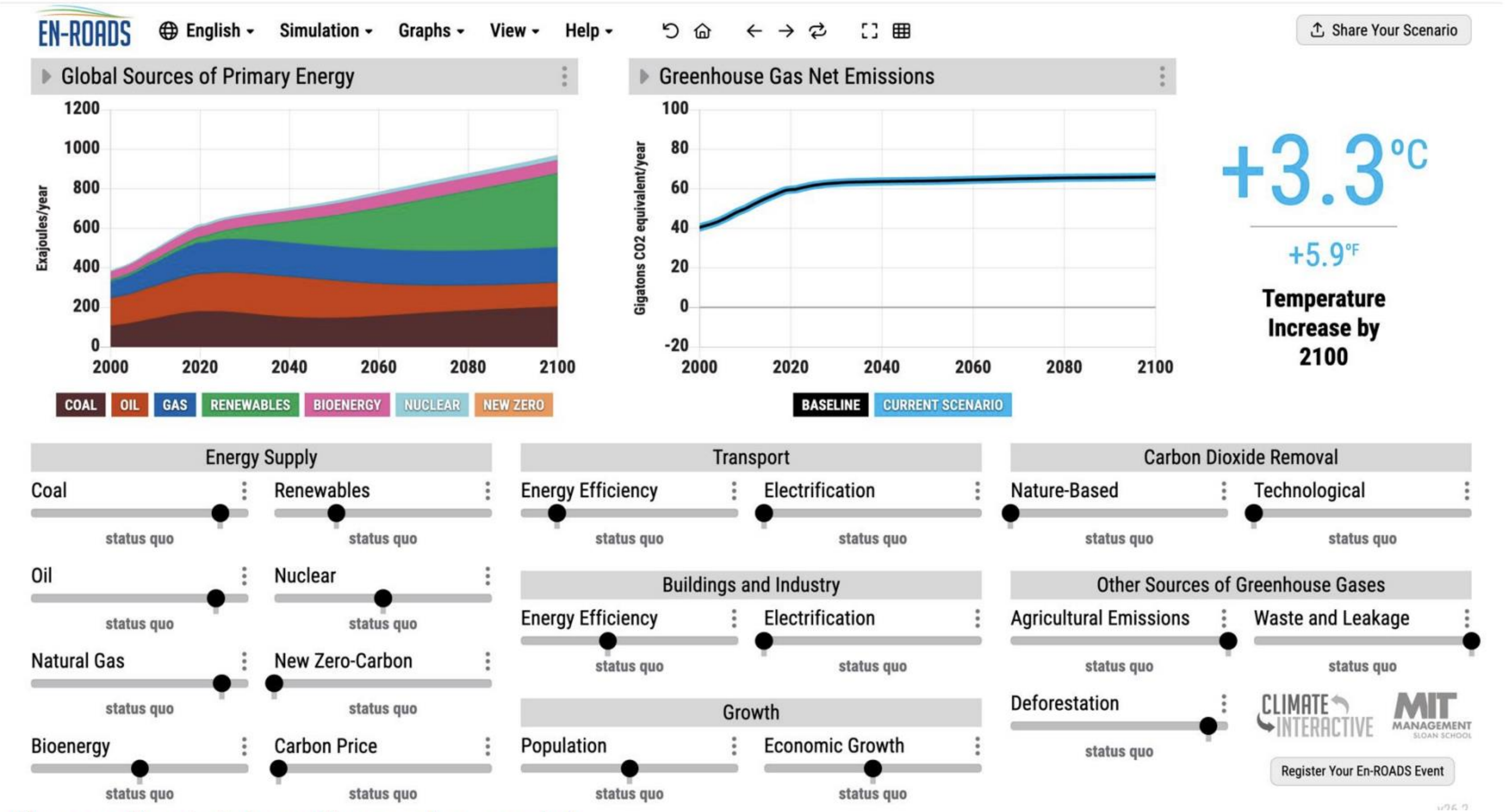
- MIT Climate Project
- CS3 Center for Sustainability Science and Strategy (CS3)

- Climate Interactive: MIT Sloane
  - C-ROADS: https://www.climateinteractive.org/c-roads/
  - En-ROADS

Summary

- AI is becoming a powerful tool, helping to close the gap between climate data, models, and local stakeholders.
- Stakeholders need access to reliable, fine-grained data for planning ahead and adaptation /mitigation efforts
- Foundation models are especially useful in combining multimodal data streams for diverse downstream tasks

En-ROADS: Test out the impacts of different strategies!



https://www.climateinteractive.org/en-roads/