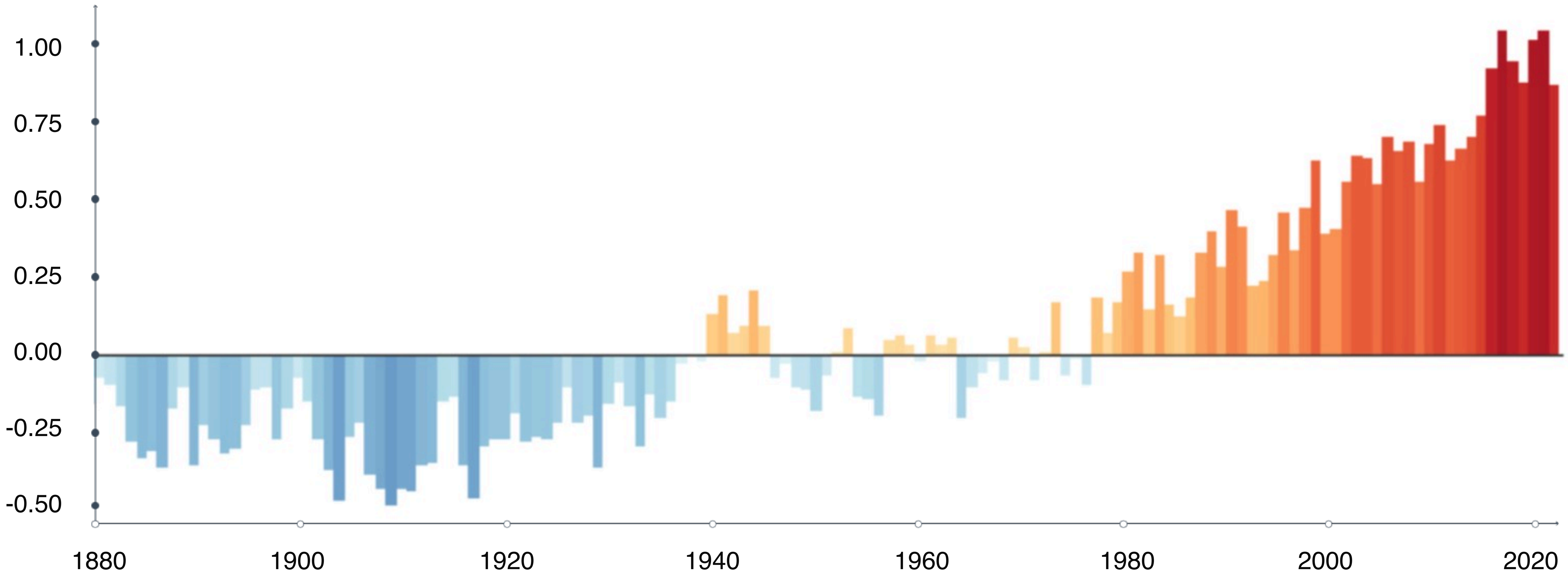
CliMA
CLIMATE MODELING ALLIANCE

Earth System Modeling 2.0: Toward Accurate and Actionable Climate Predictions with Quantified Uncertainties

Tapio Schneider and the CliMA Team

Earth has already warmed 1.2°C since 1850s

Global Temperature Anomaly (°C compared to the 1951-1980 average)



earthobservatory.nasa.gov

Limiting global warming to 2°C would require drastic global emission cuts

To limit warming to 1.5°C

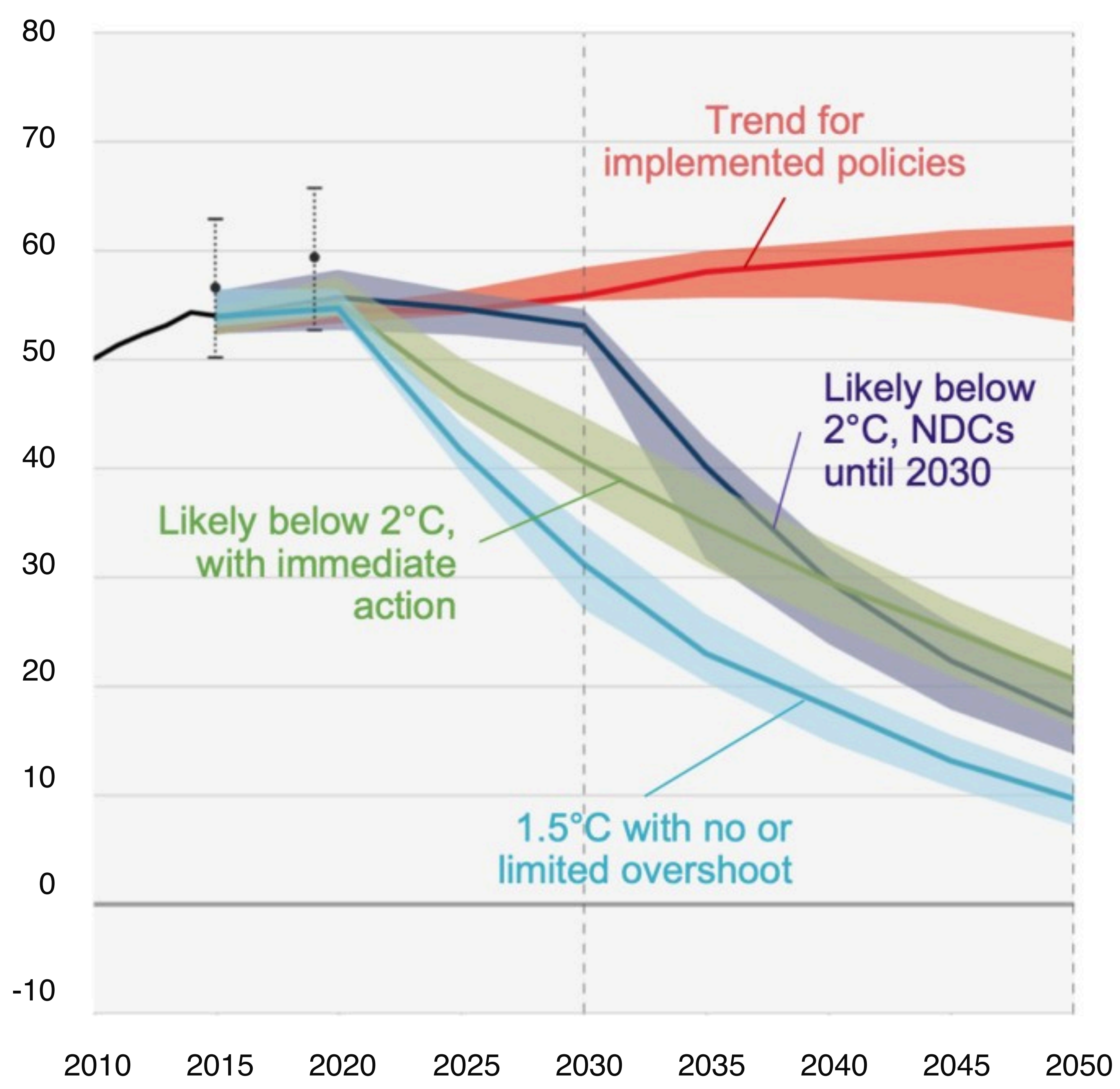
Global GHG emissions **peak before 2025**, reduced by **43% by 2030**

Methane reduced by **34% by 2030**

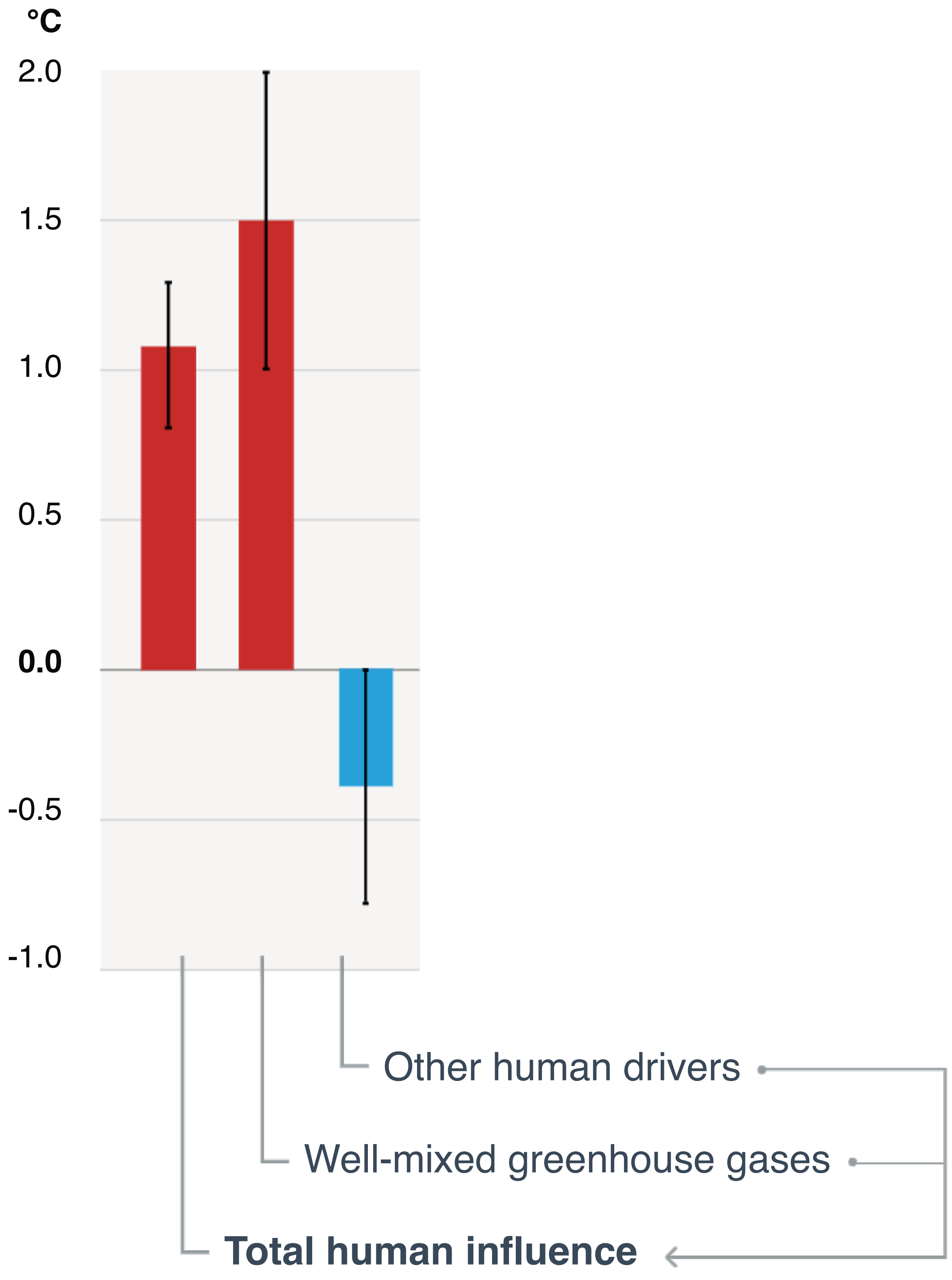
To limit warming to around 2°C

Global GHG emissions **peak before 2025**, reduced by **27% by 2030**

Global GHG Emissions (Gt CO_2-eq. yr^{-1})



IPCC AR 6, Working Group III



A by-product of emission cuts will be more warming because of reduced air pollution

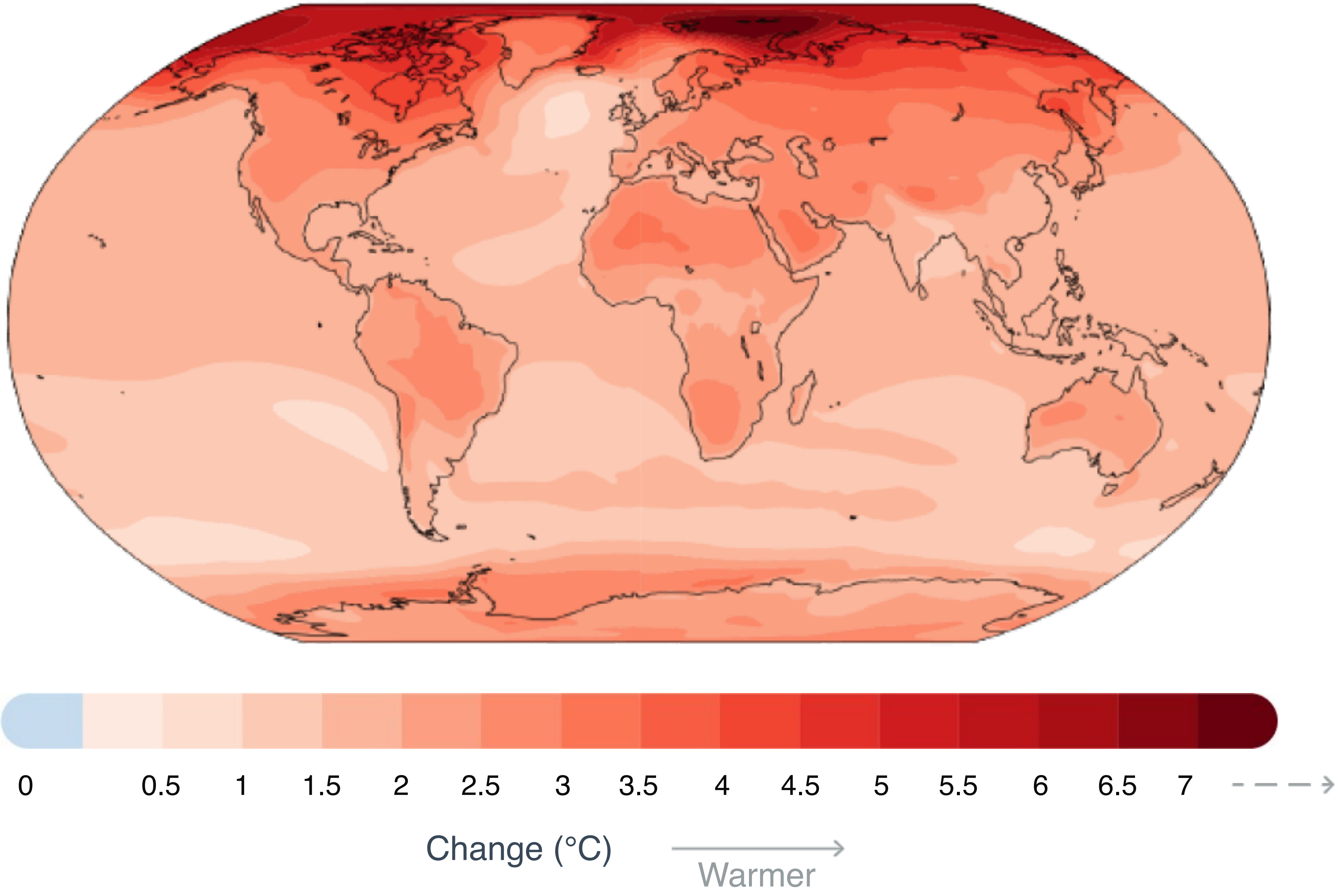
Human contribution to warming 2010-19 relative 1850-1900

- GHG responsible for all warming that occurred
- But some GHG warming is masked by air pollution (primarily, sulphur dioxide)

IPCC AR 6, Working Group I, SPM

In the best-case scenario, we will need to learn to live with about 2°C global warming

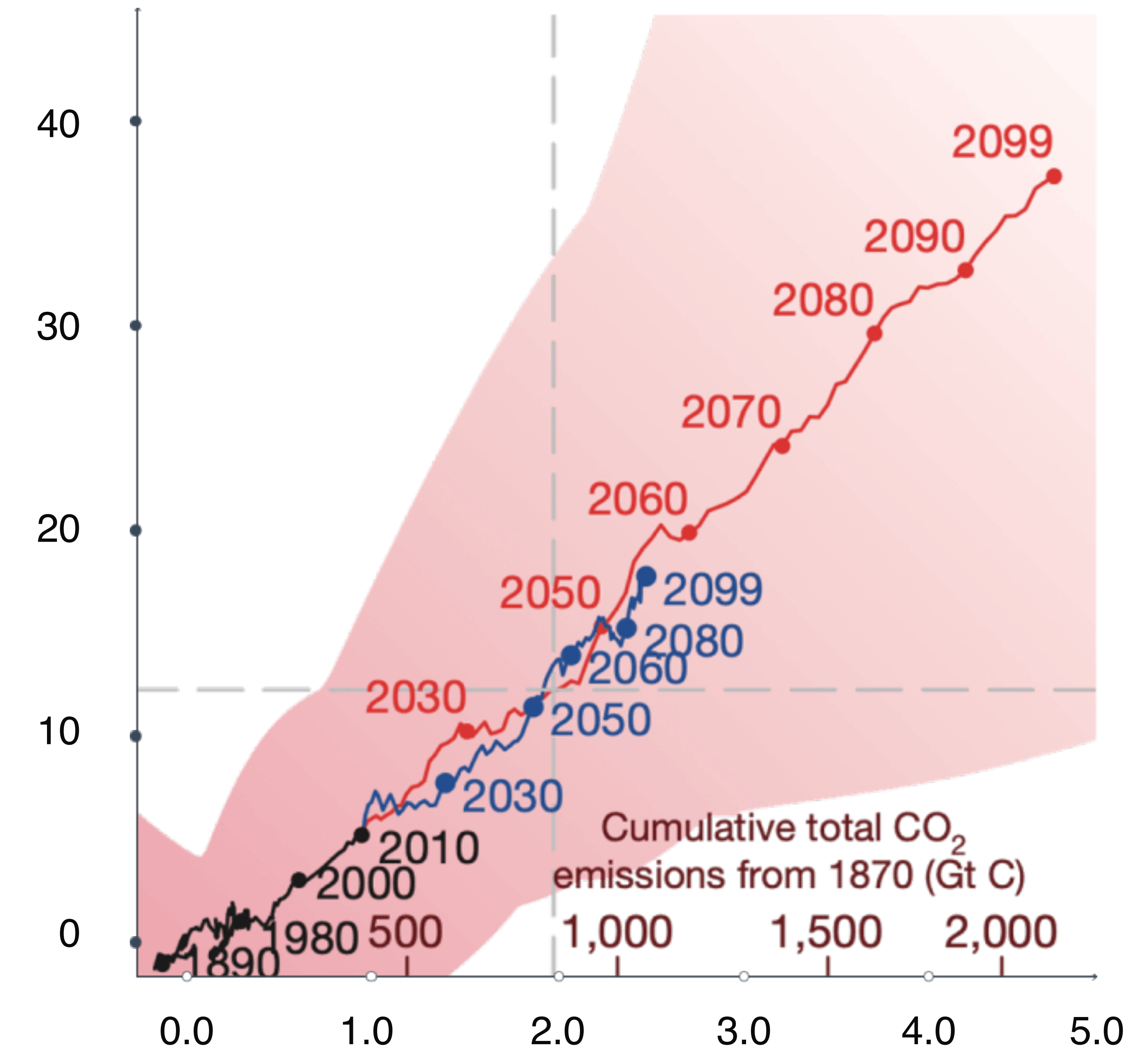
Simulated temperature change at 2°C global warming



IPCC AR 6, Working Group I, SPM

Because almost all climate impacts scale with global warming, mitigation remains critical

Percentage Change in Heavy Rainfall Intensity in Southern Asia



Global Warming (°C) Relative to 1861-1880

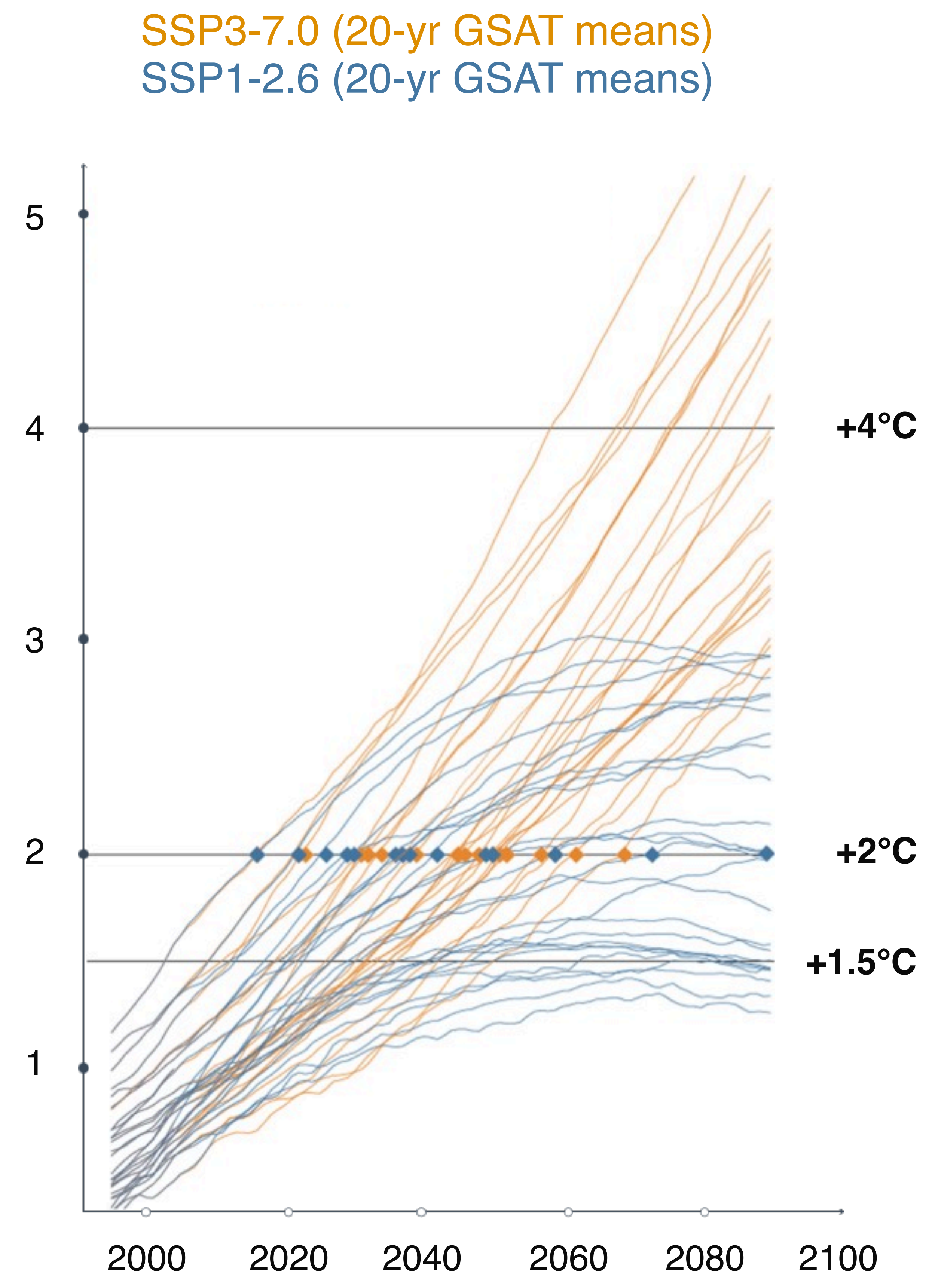
Seneviratne et al., *Nature*, 2016

But some climate impacts are already manifest, so adaptation is unavoidable

→ Recent warming tripled risk of Hurricane Harvey's rainfall in Texas

Emanuel, 2017; Risser and Wehner, 2017; van Oldenborgh et al., 2017

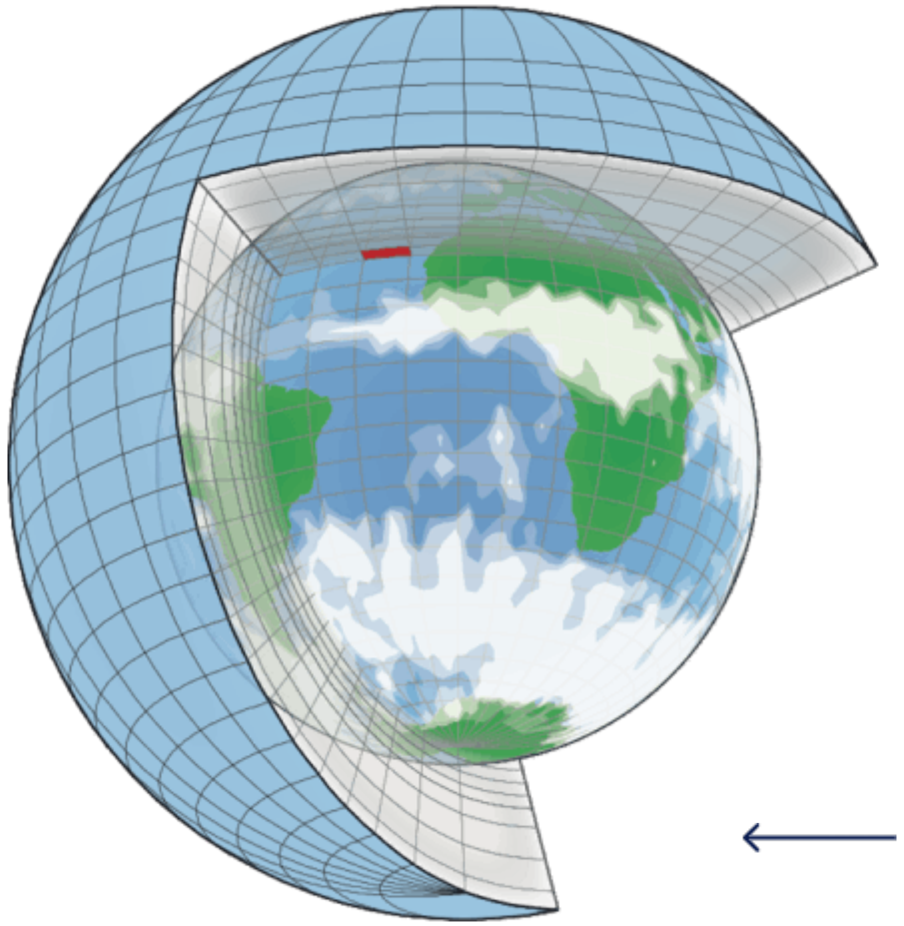
But the value chain from data to usable climate information has gaps in 2 places, impeding effective climate adaptation



Global warming under high (SSP3-7.0) and low (SSP1-2.6) emission scenarios in current (CMIP6) climate models

IPCC AR 6, Working Group I

Clouds dominate uncertainties in climate projections; they depend on small-scale motions

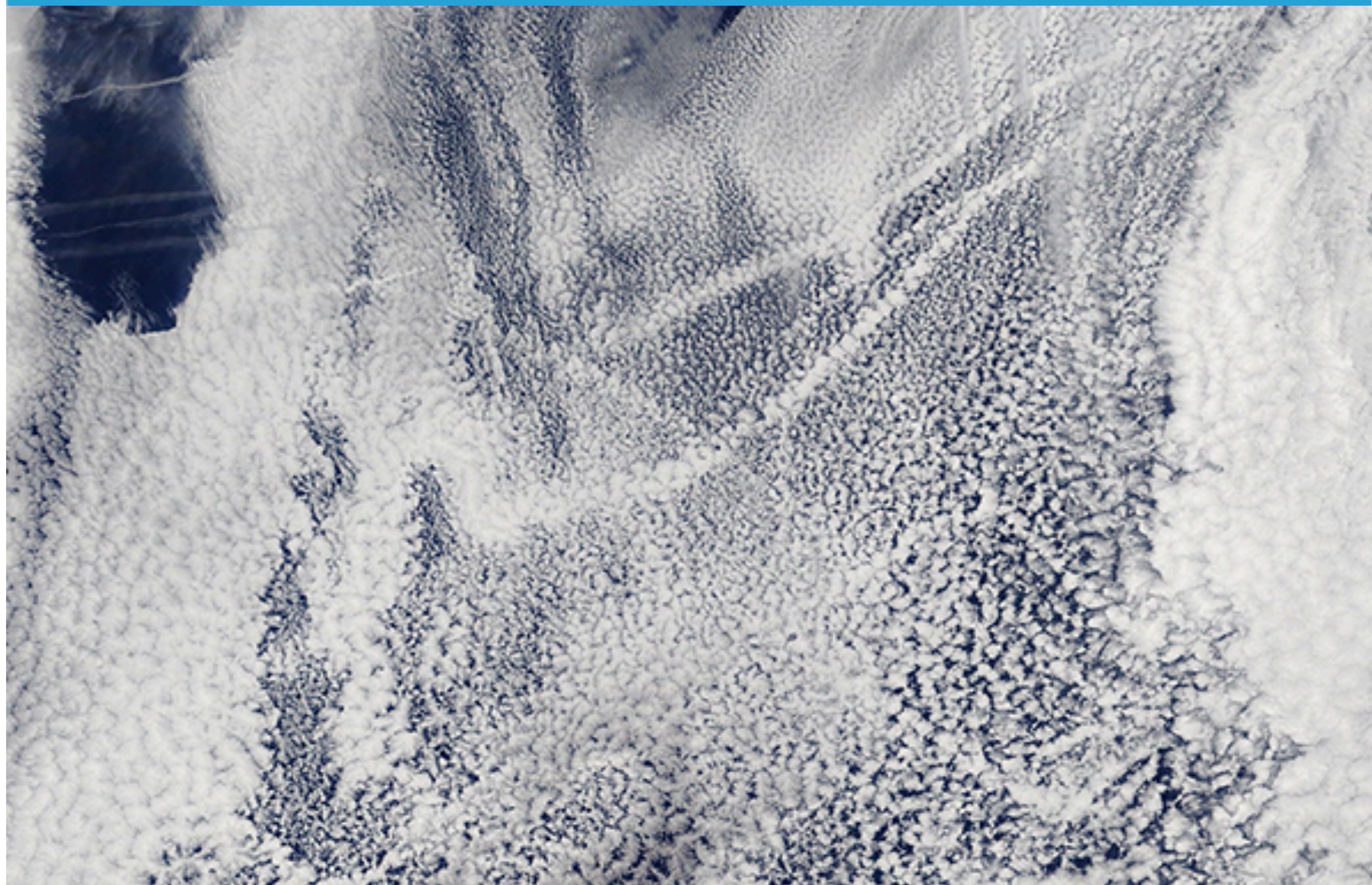


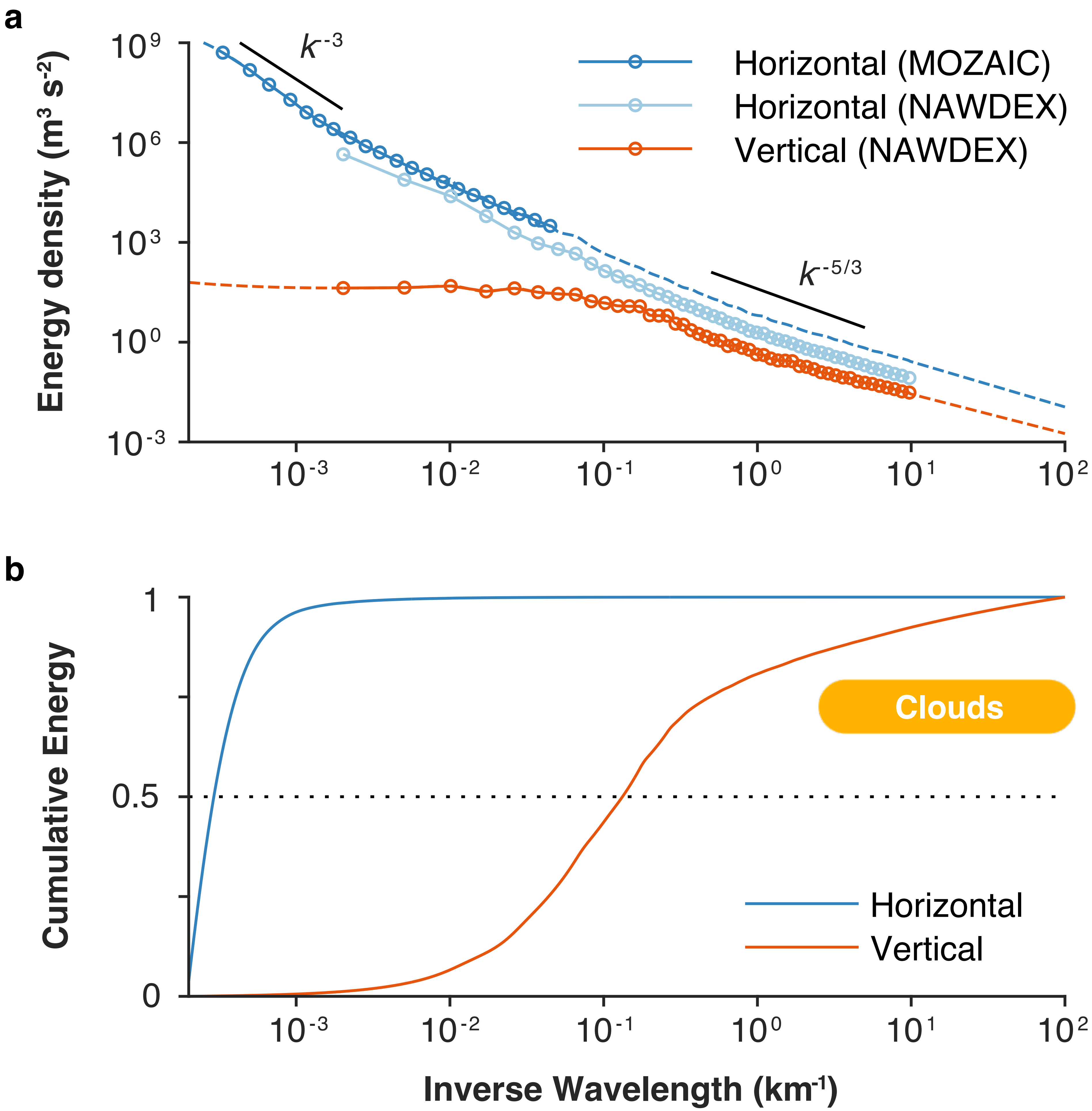
Cloud scales: ~10-100 m

Global model: ~10-50 km resolution

Subgrid-scale processes (e.g., clouds and turbulence) are represented in ad-hoc fashion (not data-driven)

NASA MODIS



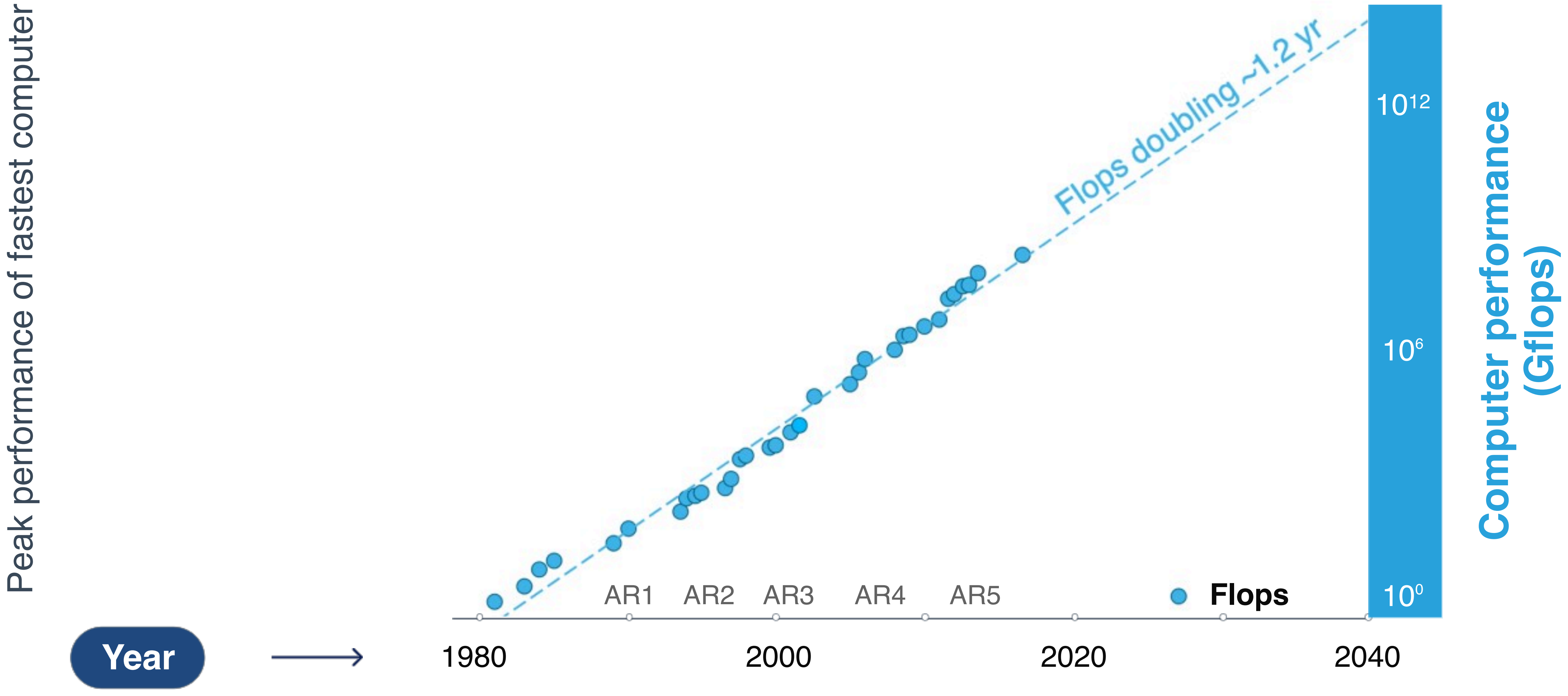


Spectra of atmospheric turbulence (aircraft measurements)

Challenge: compute scales like $(\Delta x)^{-3}$

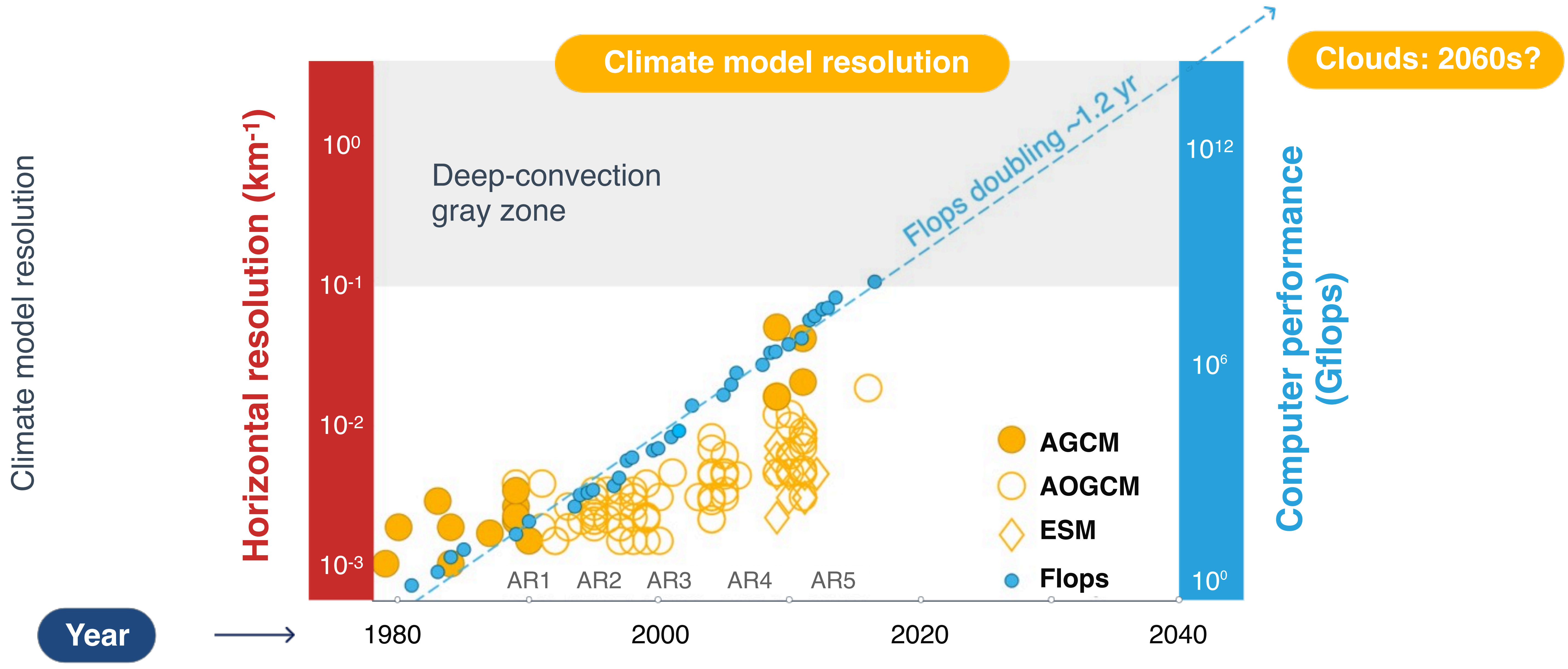
Schneider et al. *ACP* 2023

While computer performance has been increasing exponentially, …



Schneider et al. Nature Climate Change, 2017

We would need 100 billion times currently available compute to resolve low clouds globally



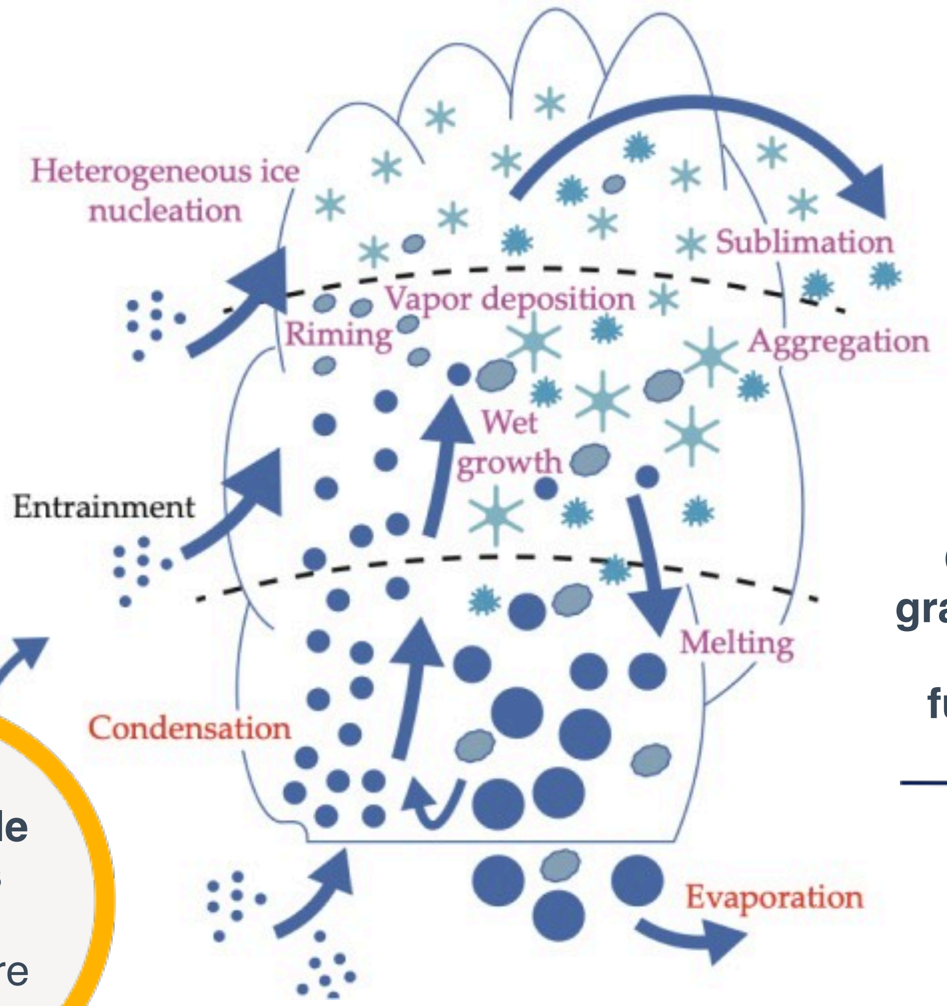
Schneider et al. Nature Climate Change, 2017

Below turbulent scales lie yet smaller scales; core challenge is bridging scales from small to large

Droplet-scale physics

Cloud-scale physics

What a climate model provides



Coarse-graining and closure functions

What it needs to predict

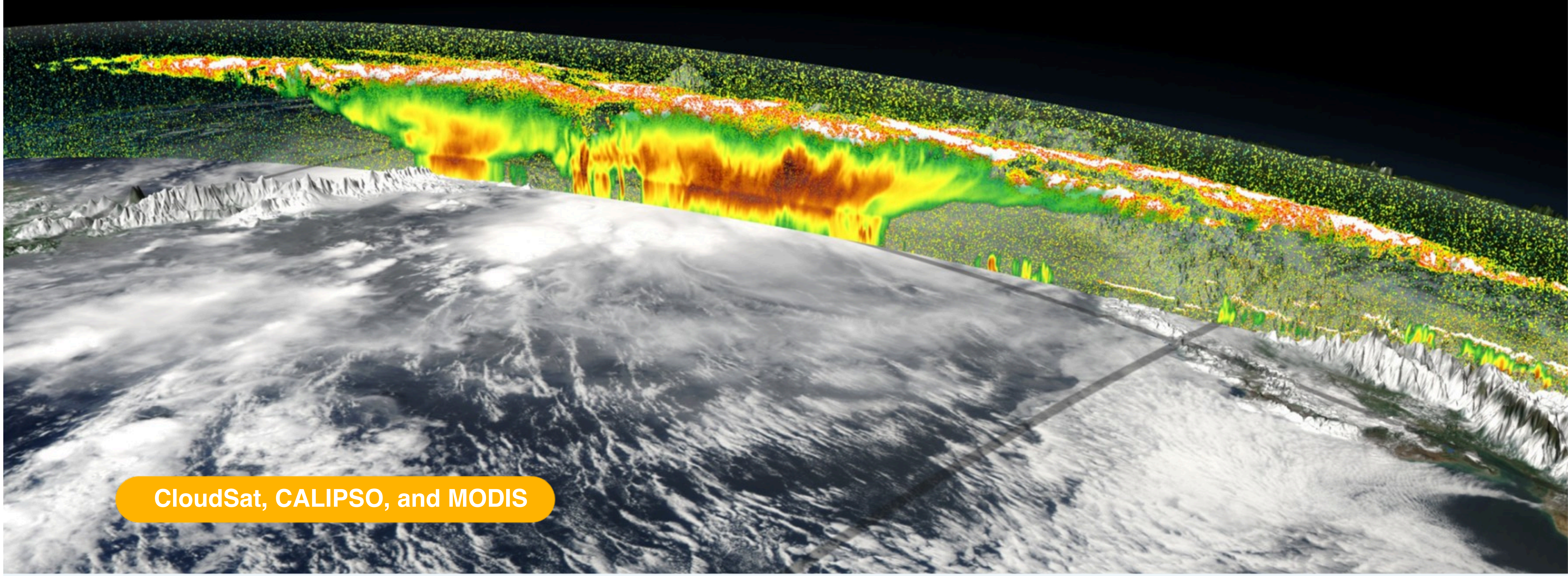
Large-scale variables
Humidity
Temperature

Cloud Effects
Cloud albedo
Cloud cover
Precipitation

Scales cannot be bridged by brute force computing

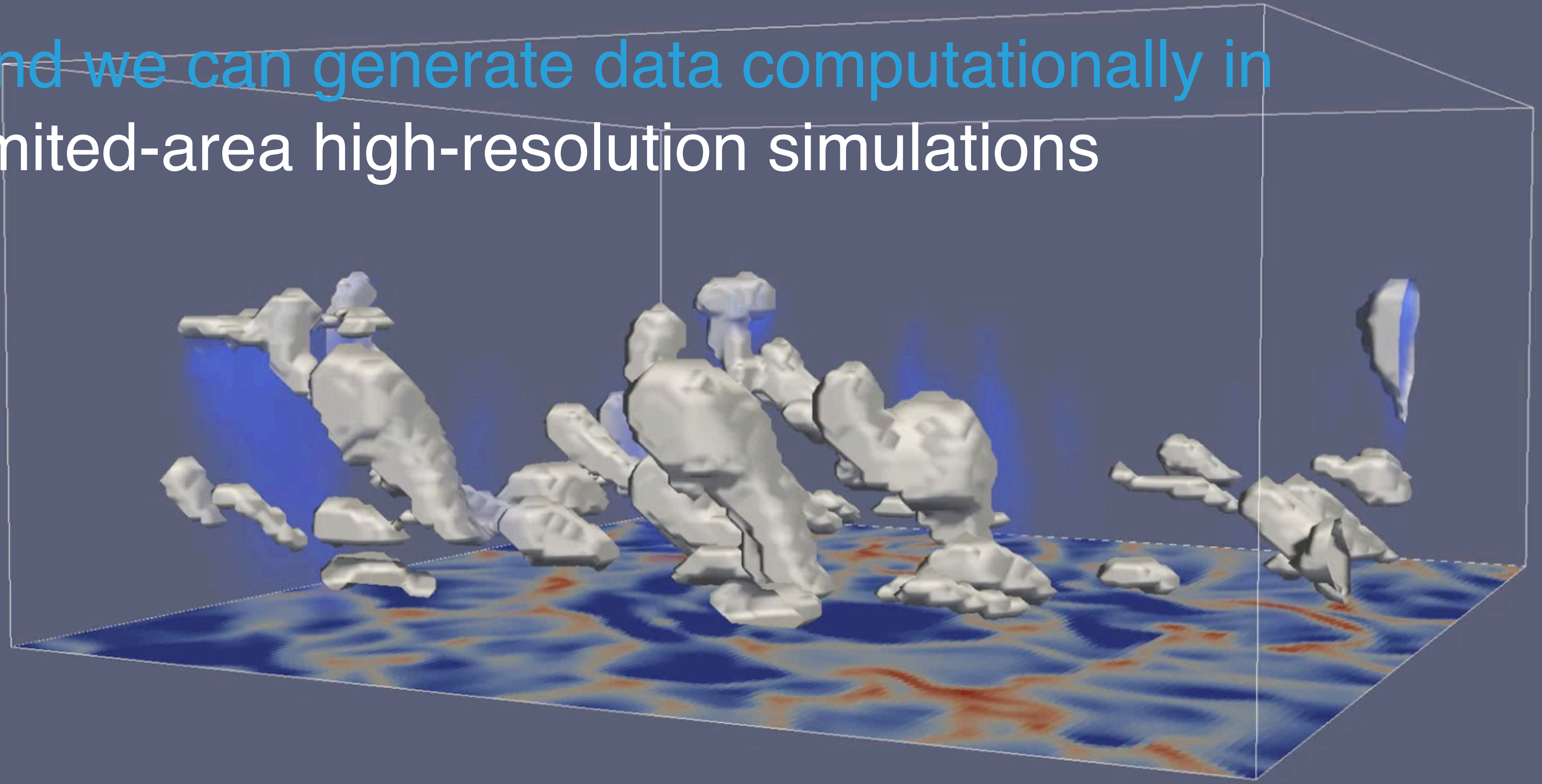
Schneider, Jeevanjee, Socolow, Accelerating Progress in Climate Science, *Physics Today* 6/2021; Morrison et al., *JAMES*, 2020

We live in the golden age of Earth observations



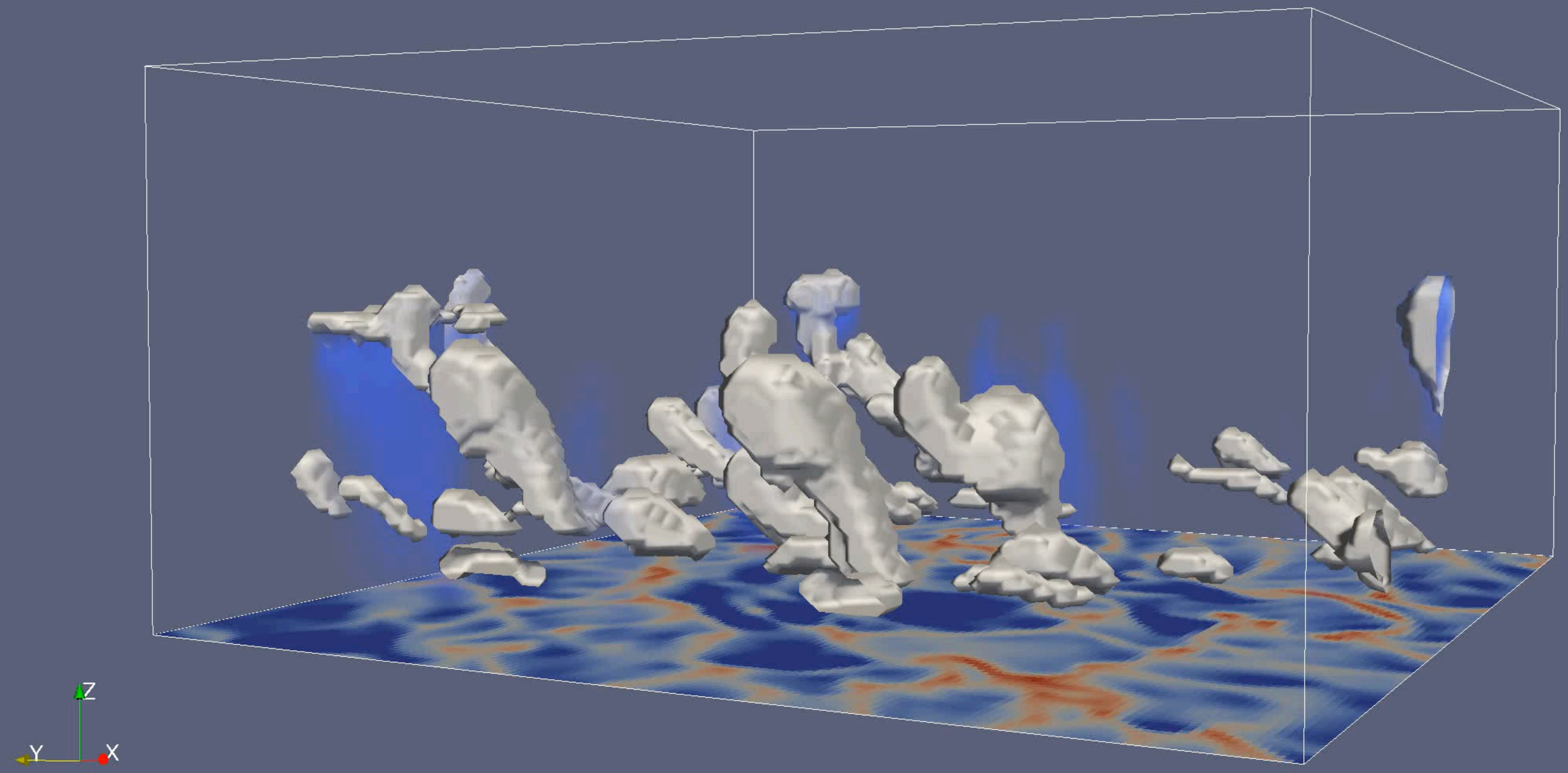
NASA/Goddard Space Flight Center Scientific Visualization Studio

And we can generate data computationally in limited-area high-resolution simulations



Simulation of tropical cumulus with O(10 m) resolution (blue: rain)

Simulation with PyCLES (Kyle Pressel et al. 2015)


Z
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The Climate Modeling Alliance was founded in 2018 to capitalize on the opportunities at the intersection of computing and data

CliMA's comprises about 60 scientists, applied mathematicians, and engineers

Caltech

Jet Propulsion Laboratory
California Institute of Technology

Data-informed Earth system models must meet three critical requirements

1.

Generalizability out of sample:

To predict a climate without an observed analogue

2.

Interpretability:

To trust models that cannot immediately be verified with climate-change data

3.

Uncertainty quantification (UQ):

To estimate risks for climate change adaptation

The 3 requirements can be met by combining the best of reductionist science with data-driven approaches

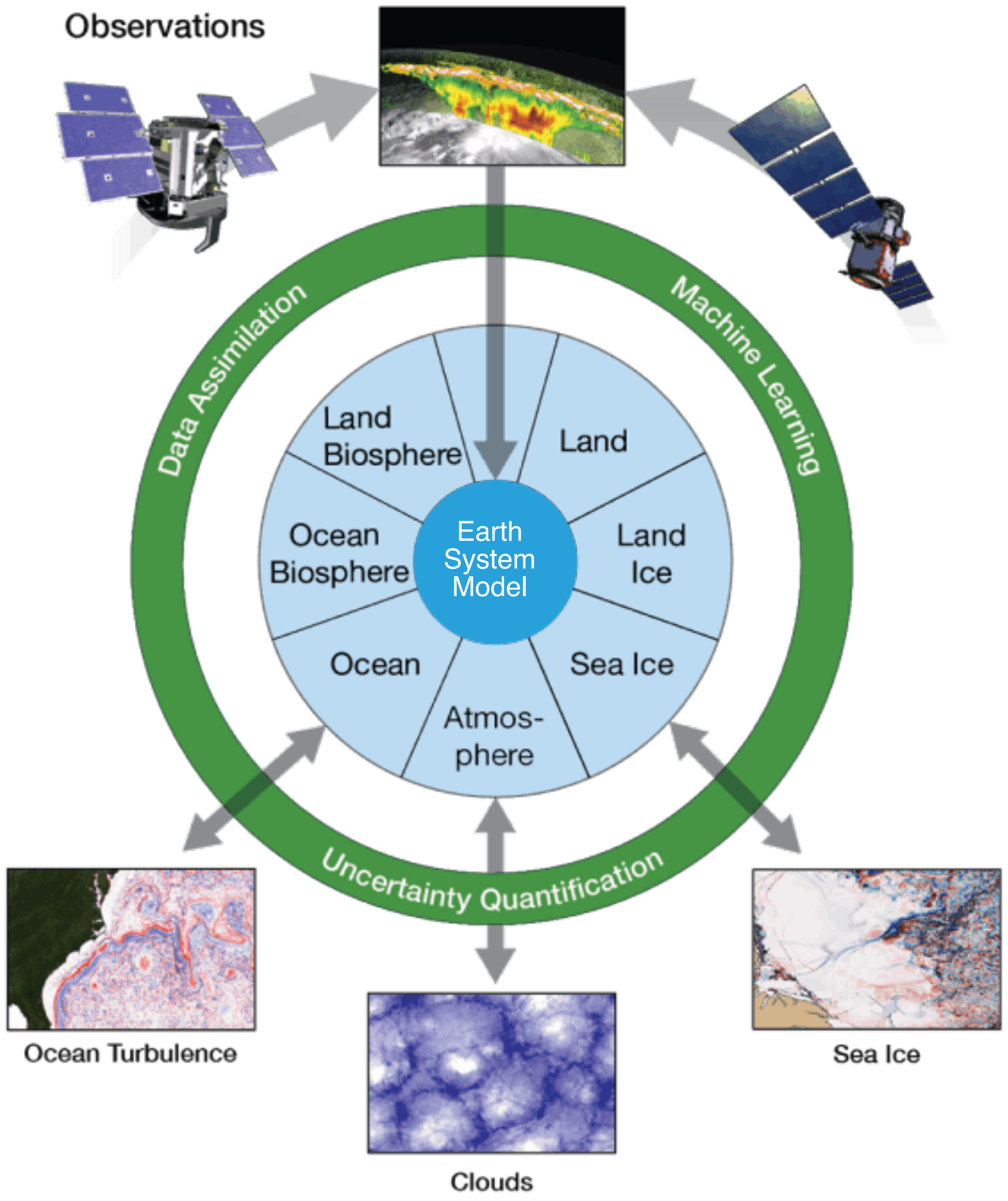
Combine both, traditional reductionist science with AI where reductionism reaches its limits

Deep learning's success rests on overparameterization:

- Leads to expressive models and data-hungry methods
- Makes generalizability, interpretability, and UQ challenging

Reductionist science's success rests on parametric sparsity:

- Generalizable and interpretable (e.g., Newton's Law of Universal Gravitation)
- Reaches limits in complex systems such as the Earth system



Targeted High-Resolution Simulations

CliMA is making an end run around the factor 10^{11} problem through a physics/AI hybrid approach

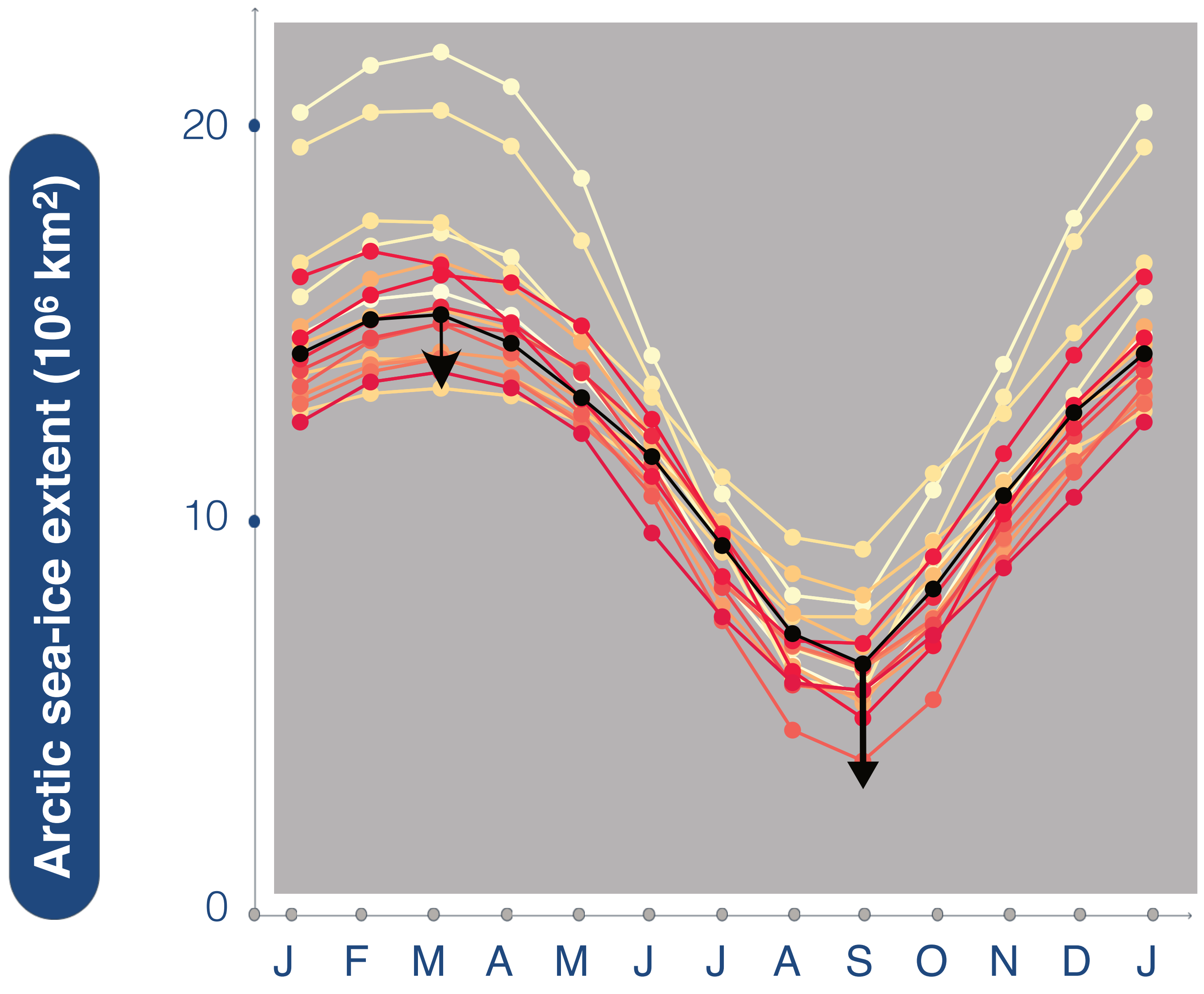
More accurate climate predictions with quantified uncertainties by

- **Advancing theory** to promote parametric sparsity
- **Harnessing diverse data** for calibration and UQ
- **Leveraging computing power** (e.g., GPUs) to enable distributed local high-resolution simulations

To be able to harness diverse data, we learn from time-averaged climate statistics

- Statistics are **what matters for climate**
- Their spatial smoothness **mitigates observation/simulation resolution mismatch**
- **Climate-relevant statistics** can include, e.g., emergent constraints and precipitation extremes
- Treats machine learning as **inverse problem**, rather than supervised learning
- Guarantees **stable models**
- But loss function evaluation (accumulation of averages) is **extremely expensive**

For example, current models simulate seasonal cycle poorly, yet it is informative about climate change response



- Observations in black
- Magnitude of expected global warming response by 2050 indicated by arrows
- Models colored from yellow to red in order of increasing equilibrium climate sensitivity
- Model biases correlate with ECS

Schneider, Jeevanjee, Socolow, Physics Today 6/2021; data processing by Dave Bonan

Treat learning about parameters θ from data as inverse problem, and speed up Bayesian learning 1000x through ML emulators

For a map $G : \Theta \to Y$ (climate model) from a space of parameters Θ to climate statistics Y, we want to learn about distribution of the parameters θ

Calibrate

$$y = \mathcal{G}(\theta) + \eta$$

Sample parameter space efficiently (Kalman algorithms)

$\longrightarrow$

Emulate

$$\mathcal{G}^{(m)}(\theta) \approx \mathcal{G}(\theta)$$

Train emulator on calibration data (GP, NN, RFM, ...)

$\longrightarrow$

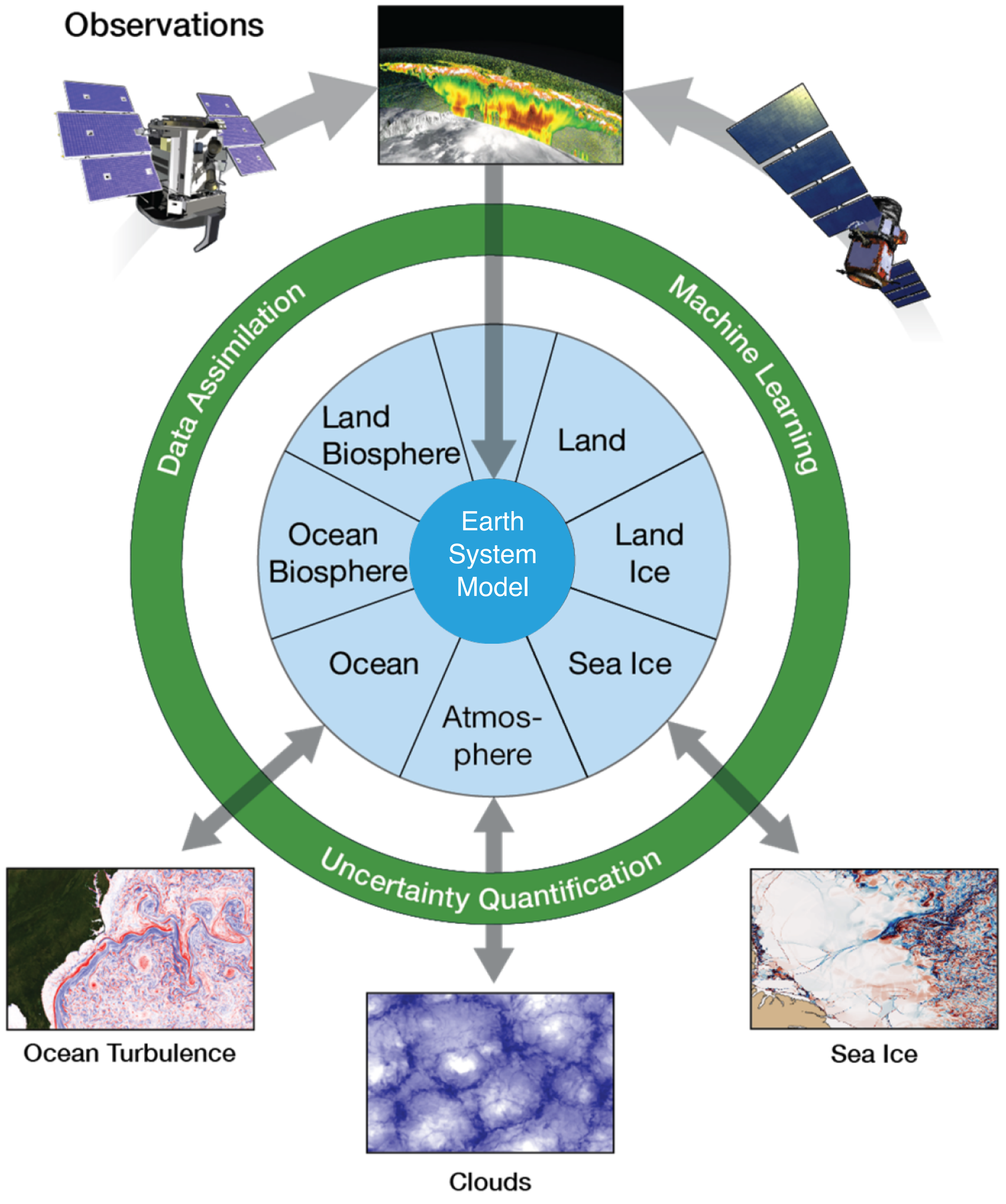
Sample

$$y = \mathcal{G}^{(m)}(\theta) + \eta(\theta)$$

MCMC sampling from emulator to get posterior density

Cleary et al., JCP, 2021; Dunbar et al., JAMES, 2021, 2002; Howland et al. JAMES 2022

At CliMA, we are working on a new Earth system model in which all components jointly learn from data



Targeted High-Resolution Simulations

HOW DOES THAT ACTUALLY WORK?

An example from modeling clouds

Goals for atmosphere model development

1.

Advance physics of parameterizations

Unified parameterizations from controlled approximations for SGS dynamics and microphysics

2.

Use data extensively

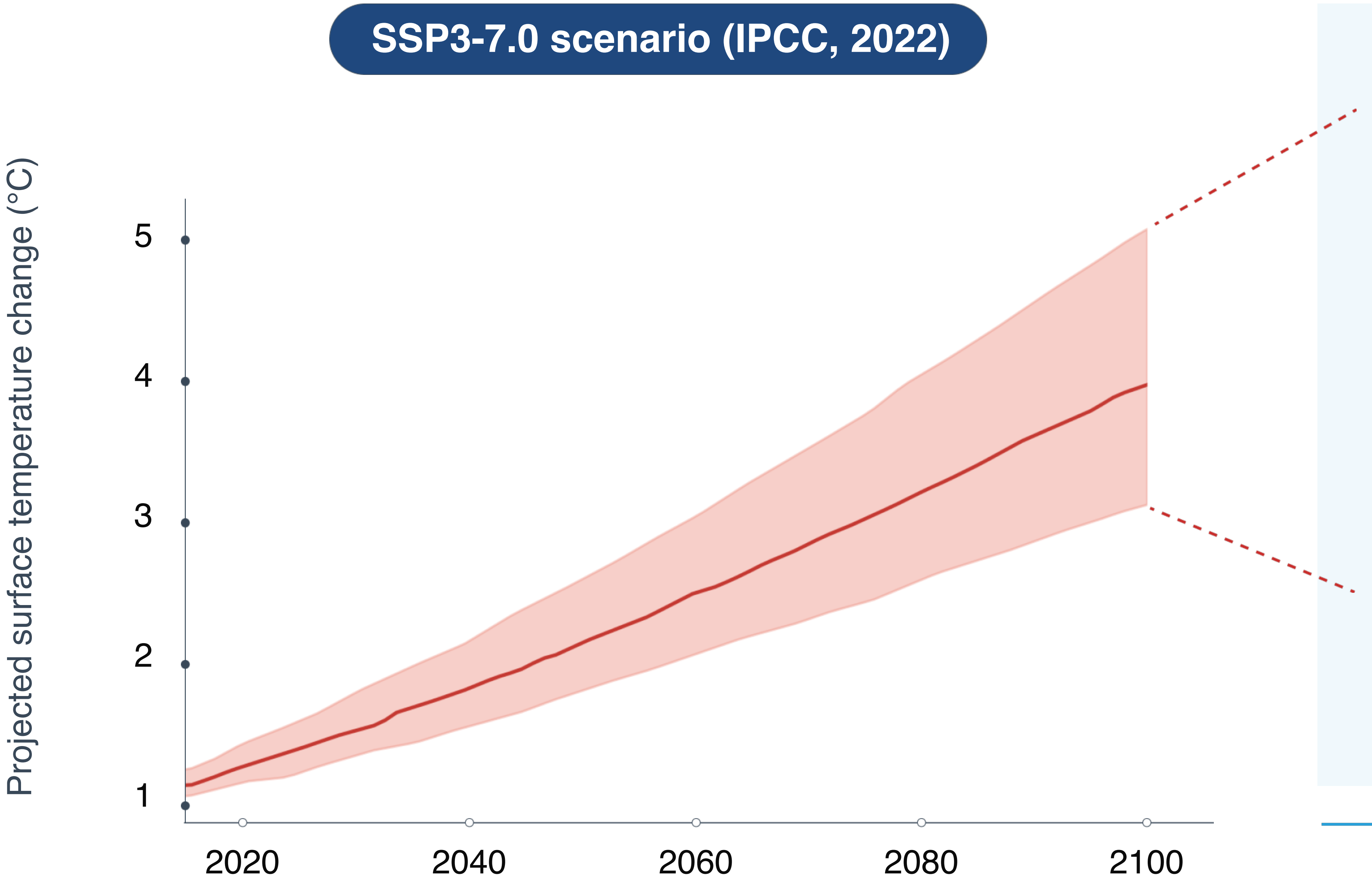
Build automated pipelines for calibration/ UQ of parameterizations with simulated and observed data

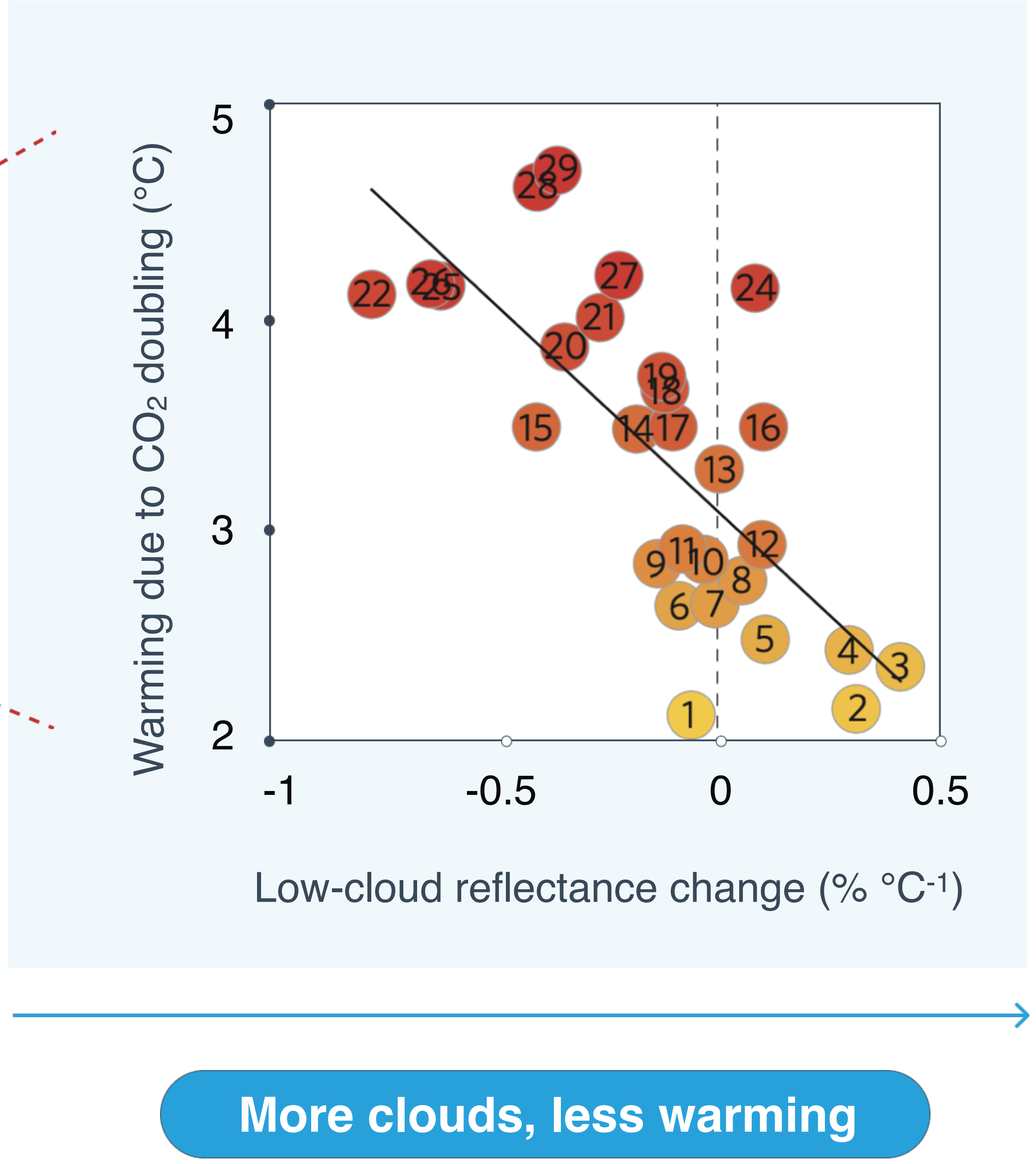
3.

Set new standards in software quality

Make software performance-portable and easy to use for research

Projection uncertainty primarily due to low clouds

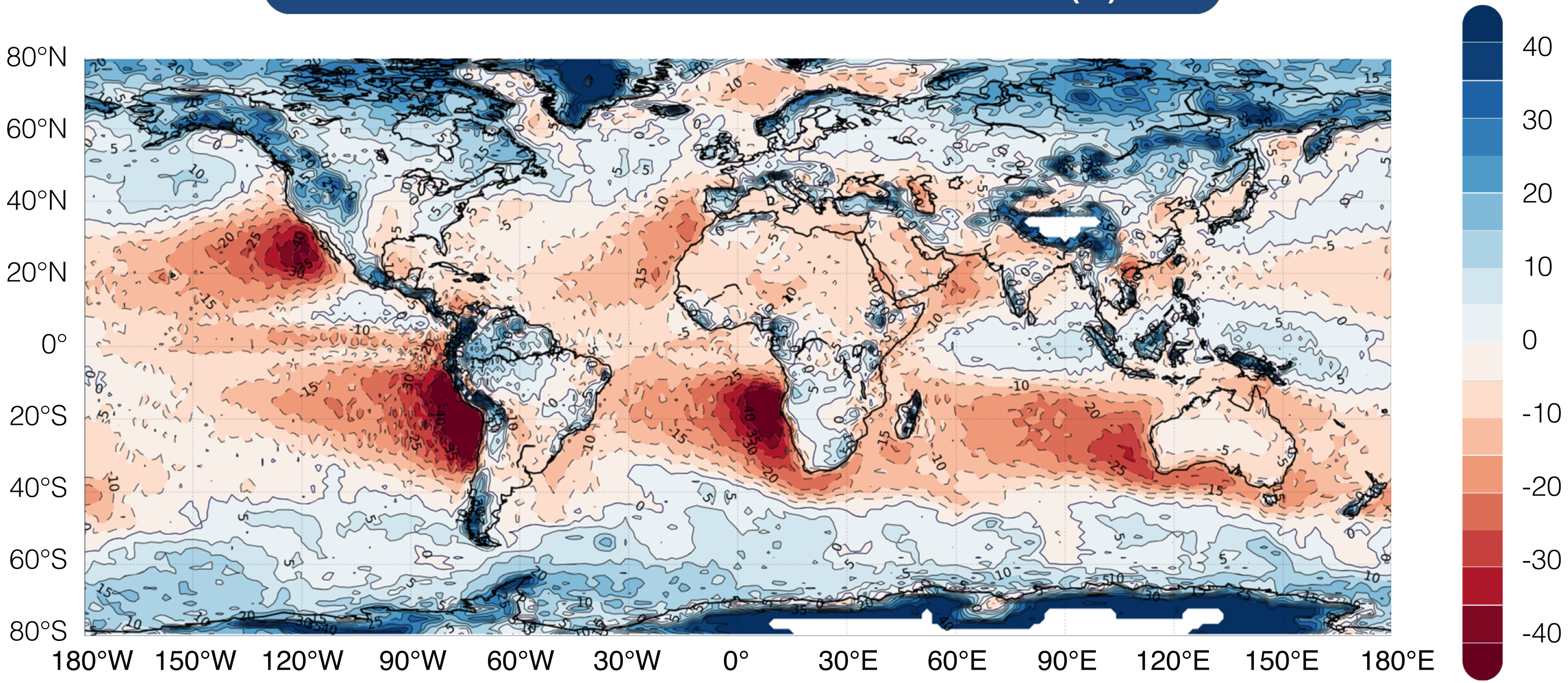




Schneider et al., Nat. Clim. Change (2017)

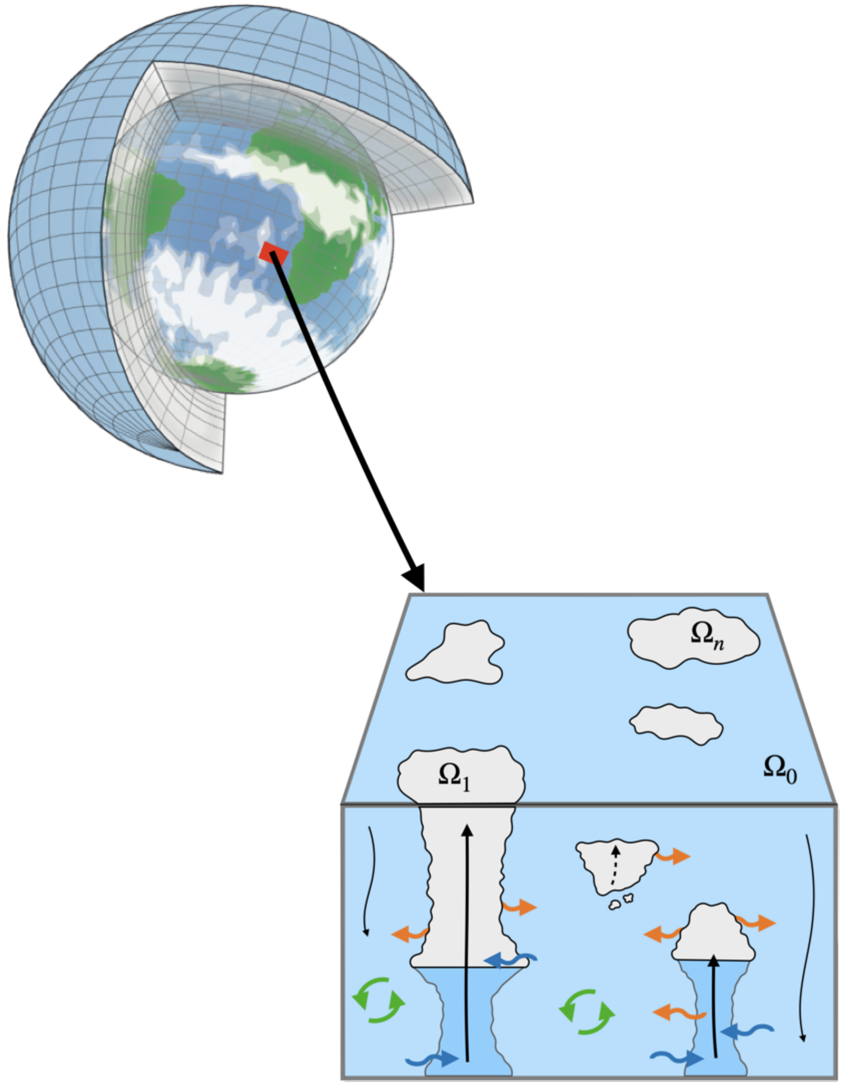
Current models cannot represent low clouds accurately

CNRM-CM6 low-cloud bias relative to GOCCP (%)



Brient et al., JAMES, 2019

Unified physics-based model of clouds



Continuity

$$\frac{\partial(\rho a_i)}{\partial t} + \frac{\partial(\rho a_i \overline{w}_i)}{\partial z} + \nabla_h \cdot (\rho a_i \langle \mathbf{u}_h \rangle) = \boxed{\underbrace{\rho a_i \overline{w}_i \left(\sum_j \epsilon_{ij} - \delta_i \right)}_{\text{Mass entrainment/detrainment}}}$$

Closure functions

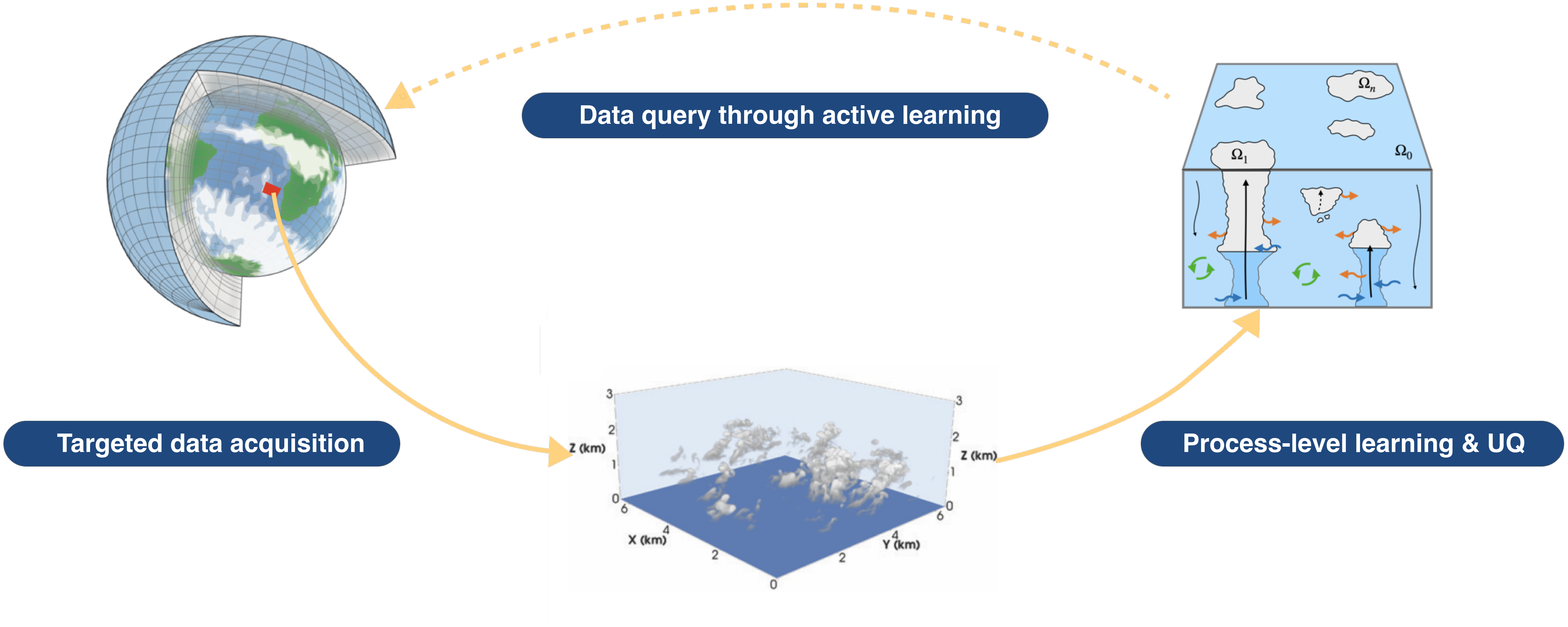
Tracers

$$\frac{\partial(\rho a_i \overline{\phi}_i)}{\partial t} + \frac{\partial(\rho a_i \overline{w}_i \overline{\phi}_i)}{\partial z} + \nabla_h \cdot (\rho a_i \langle \mathbf{u}_h \rangle \overline{\phi}_i) = \boxed{\underbrace{-\frac{\partial(\rho a_i \overline{w_i' \phi_i'})}{\partial z}}_{\text{Turbulent transport}}} + \boxed{\underbrace{\rho a_i \overline{w}_i \left(\sum_j \epsilon_{ij} \overline{\phi}_j - \delta_i \overline{\phi}_i \right)}_{\text{Entrainment/detrainment}}} + \underbrace{\rho a_i \overline{S}_{\phi,i}}_{\text{Sources/sinks}}$$

Tan et al., JAMES (2018), Cohen et al. JAMES (2020), Lopez-Gomez et al., JAMES (2020)

Conservation laws where simplified unknowns are consistently encoded

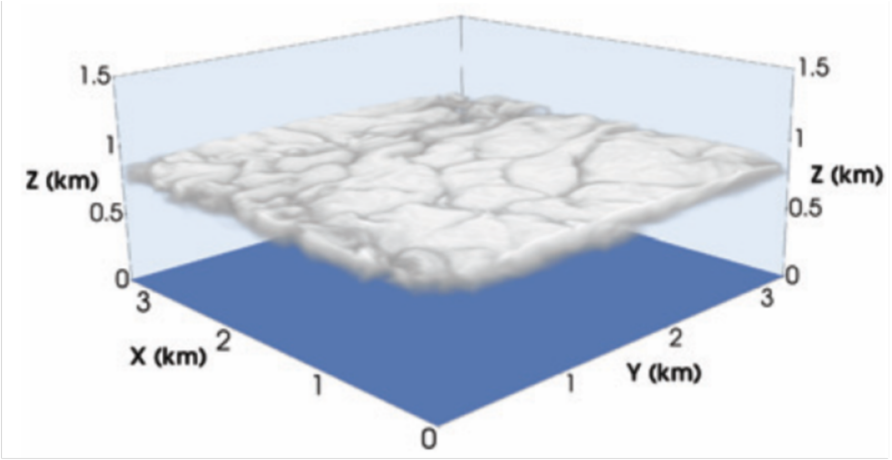
Learning from climate-relevant data



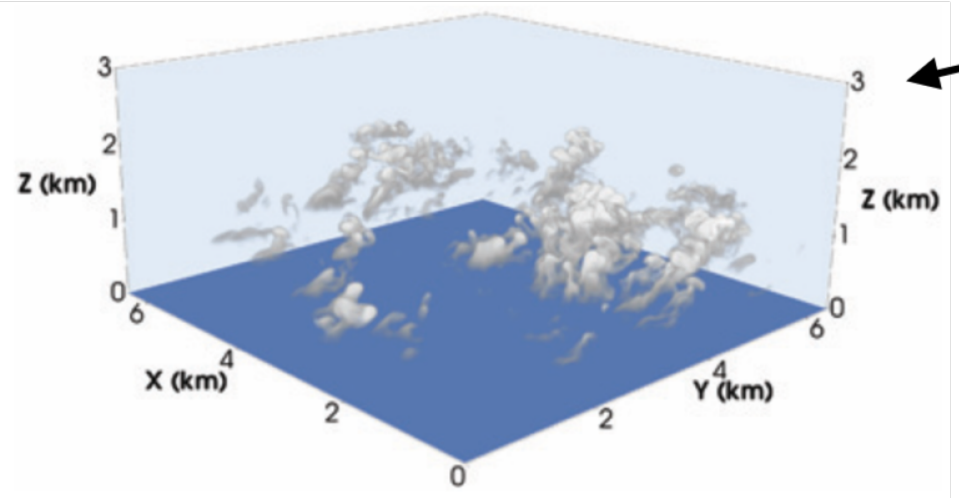
Schneider et al., JAMES (2017); Lopez-Gomez et al., JAMES (2022); Dunbar et al. JAMES (2022)

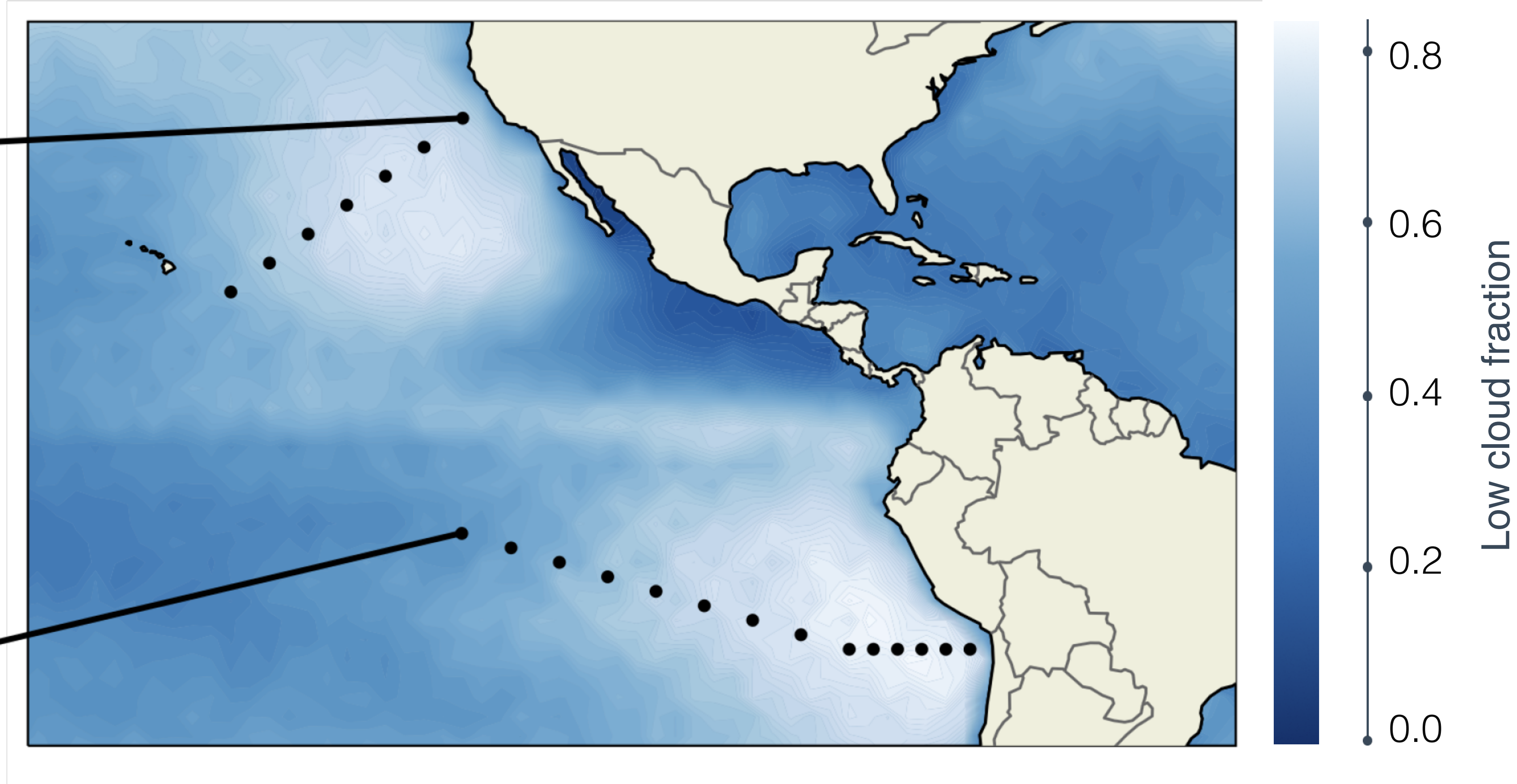
Large library of simulated data (>500 LES)

Stratocumulus



Shallow cumulus





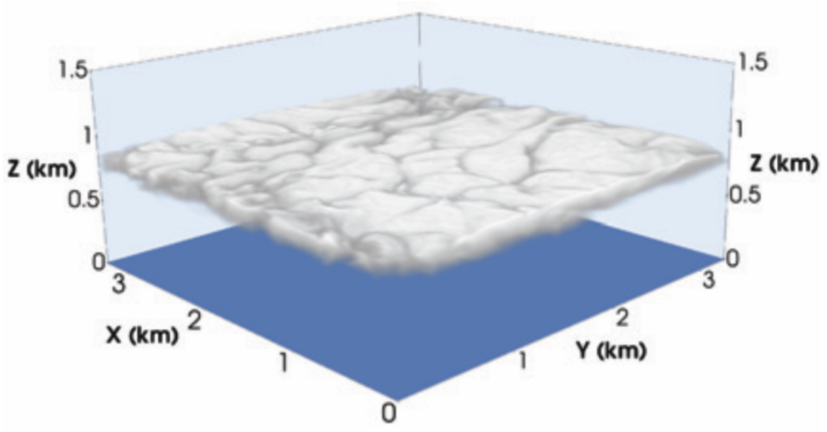
Synthetic data generation in different seasons and climates

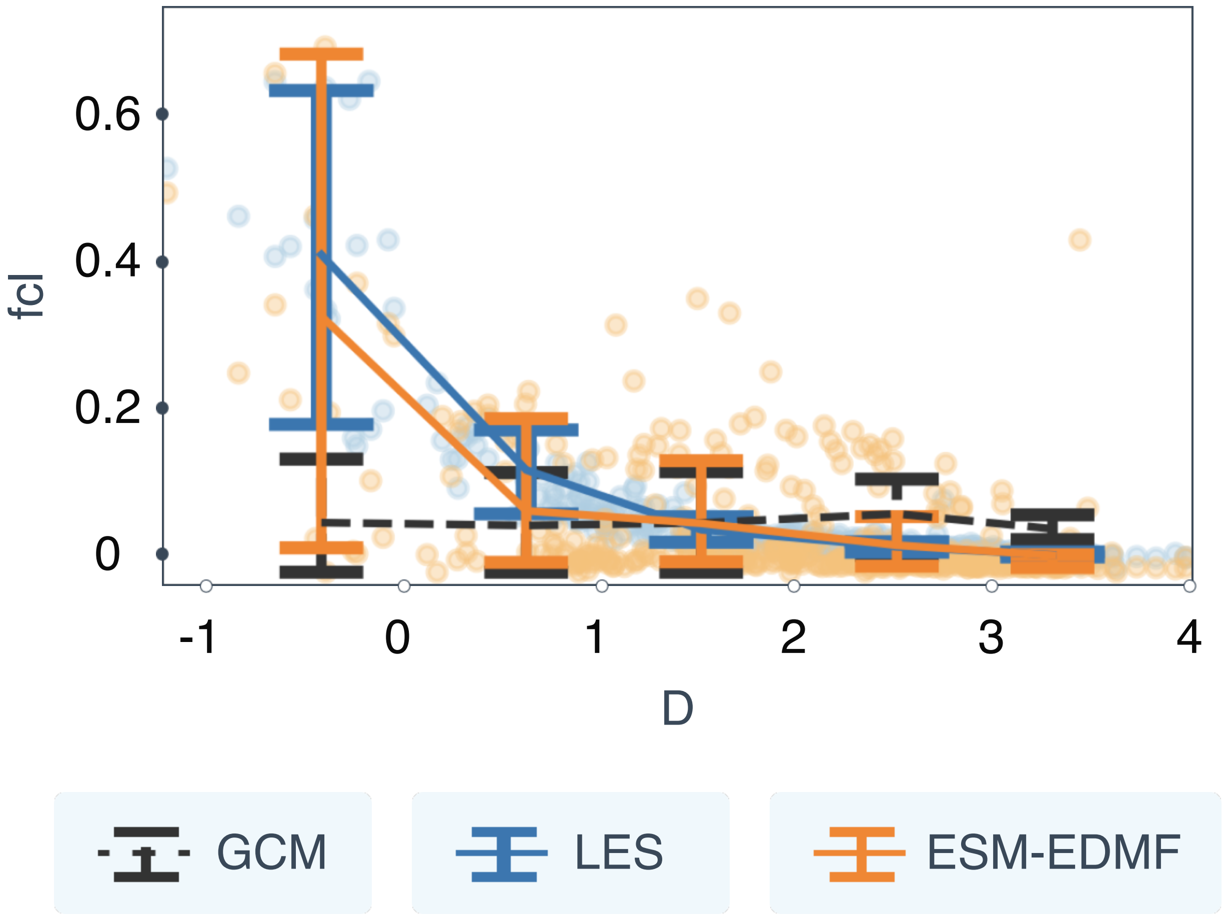
Shen et al., JAMES (2022)

Accurate representation of low clouds

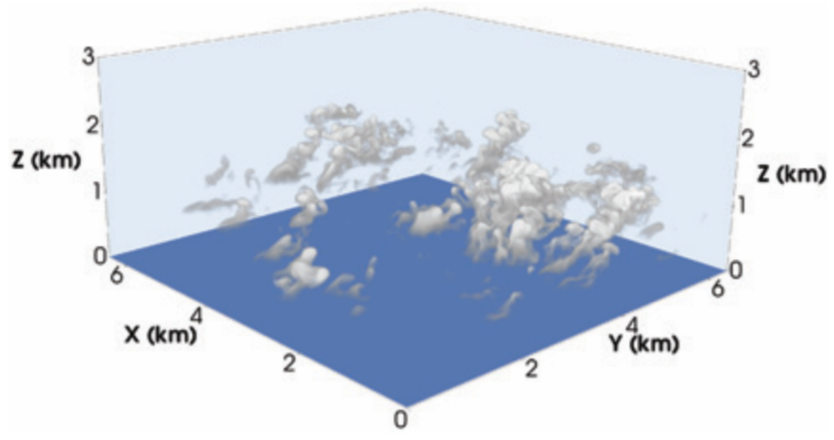
Transition

Stratocumulus





Shallow cumulus

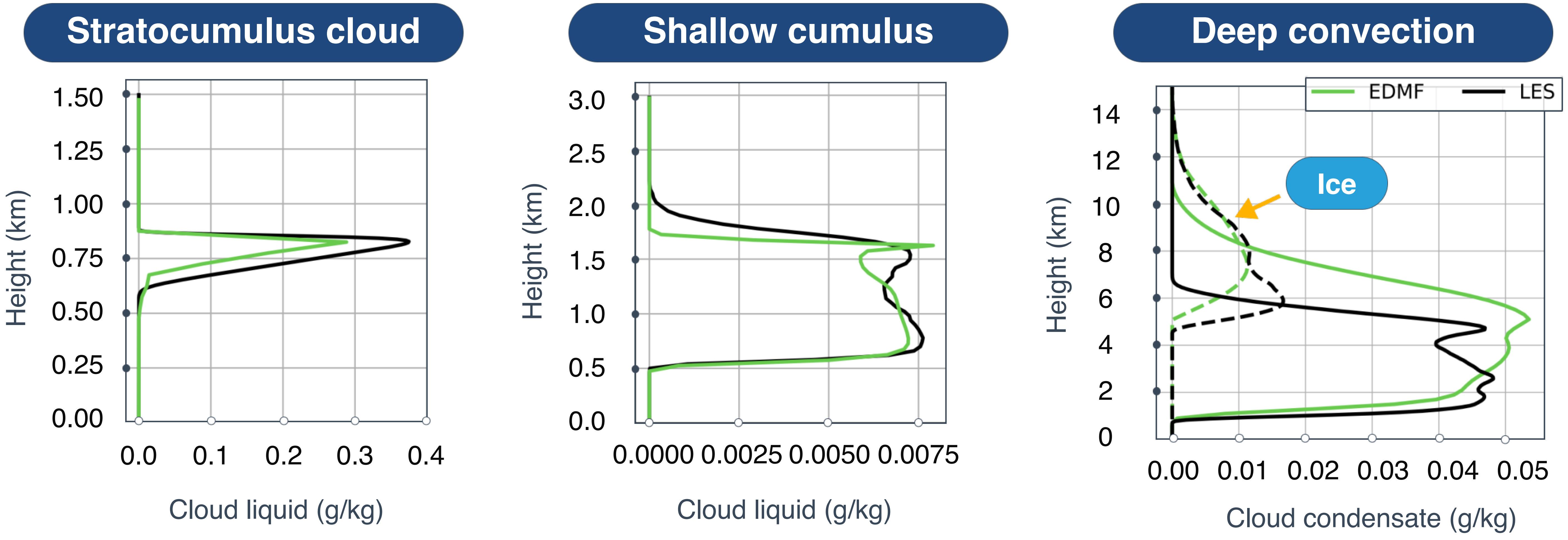


Current climate models

Lopez-Gomez et al., in prep.; Singer and Schneider (submitted)

Unified turbulence and convection scheme

- **EDMF:** A unified scheme that captures all of Earth's cloud regimes



- **Ongoing:** First global climate simulations with unified model

Accomplishments

- Developed a unified physics-based model of turbulence, convection and clouds.
- Produced an extensive dataset of cloud regimes and a machine learning framework to learn from it.
- Our model reduces biases in crucial cloud regimes by a factor of ~3 with respect to current models (offline).

Ongoing work

- Increase data coverage (with Google) and calibrate with Earth observations, to train and validate model from the equator to the poles.
- Testing in global atmosphere model and performance engineering ongoing

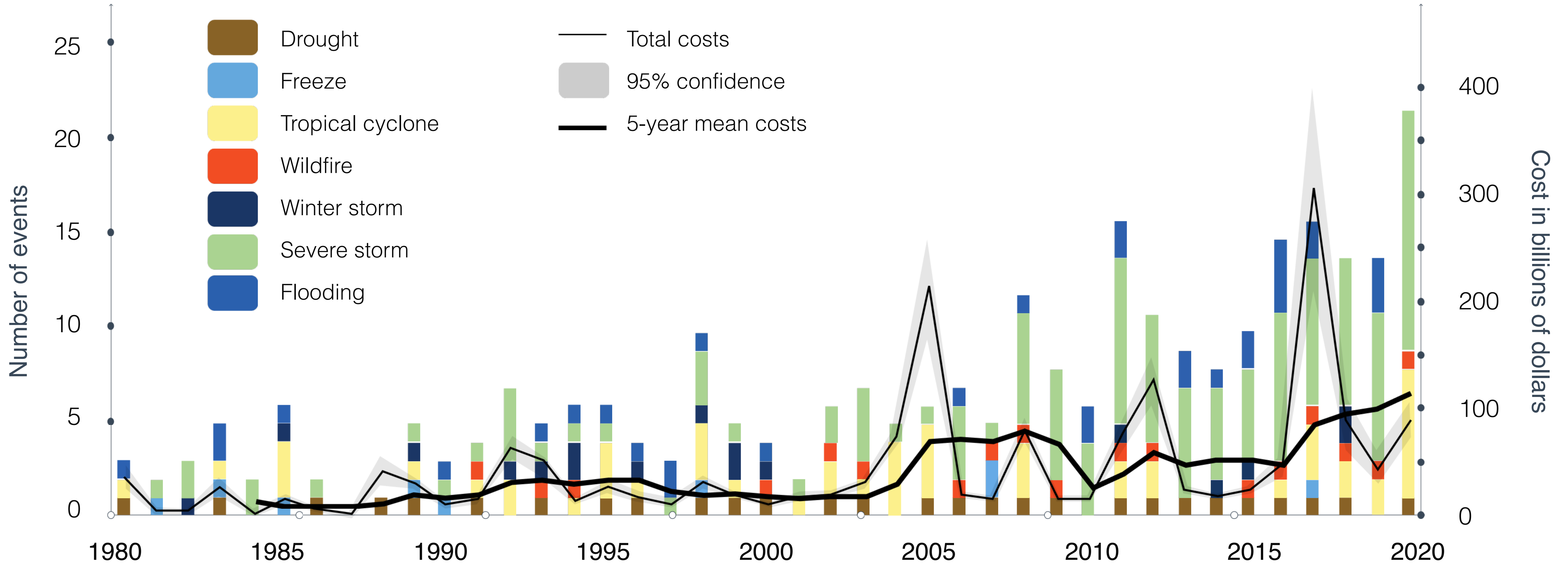
NEXT STEP:

Learn from cloud observations once reduced-order model is integrated in global climate model

So far, this was about integrating the first part of the value chain. Large opportunities lie at the user-facing end too.

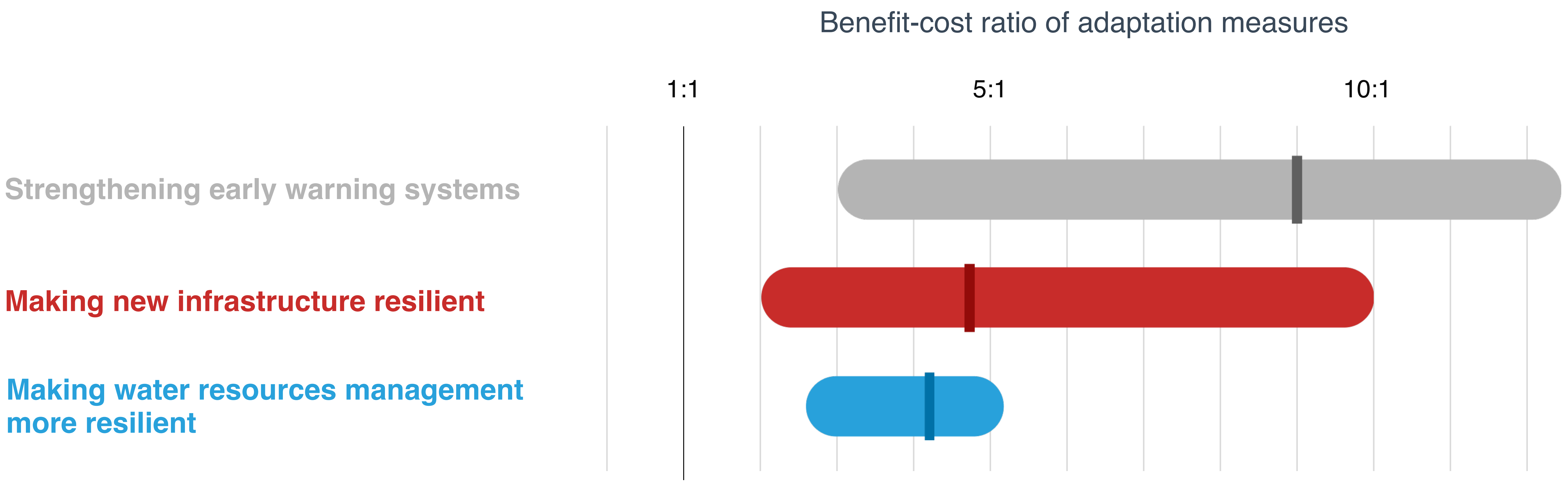
Damages from climate-related disasters are already increasing (~$150B annually in the U.S. alone)

Billion-dollar disasters and costs (1980-2020)



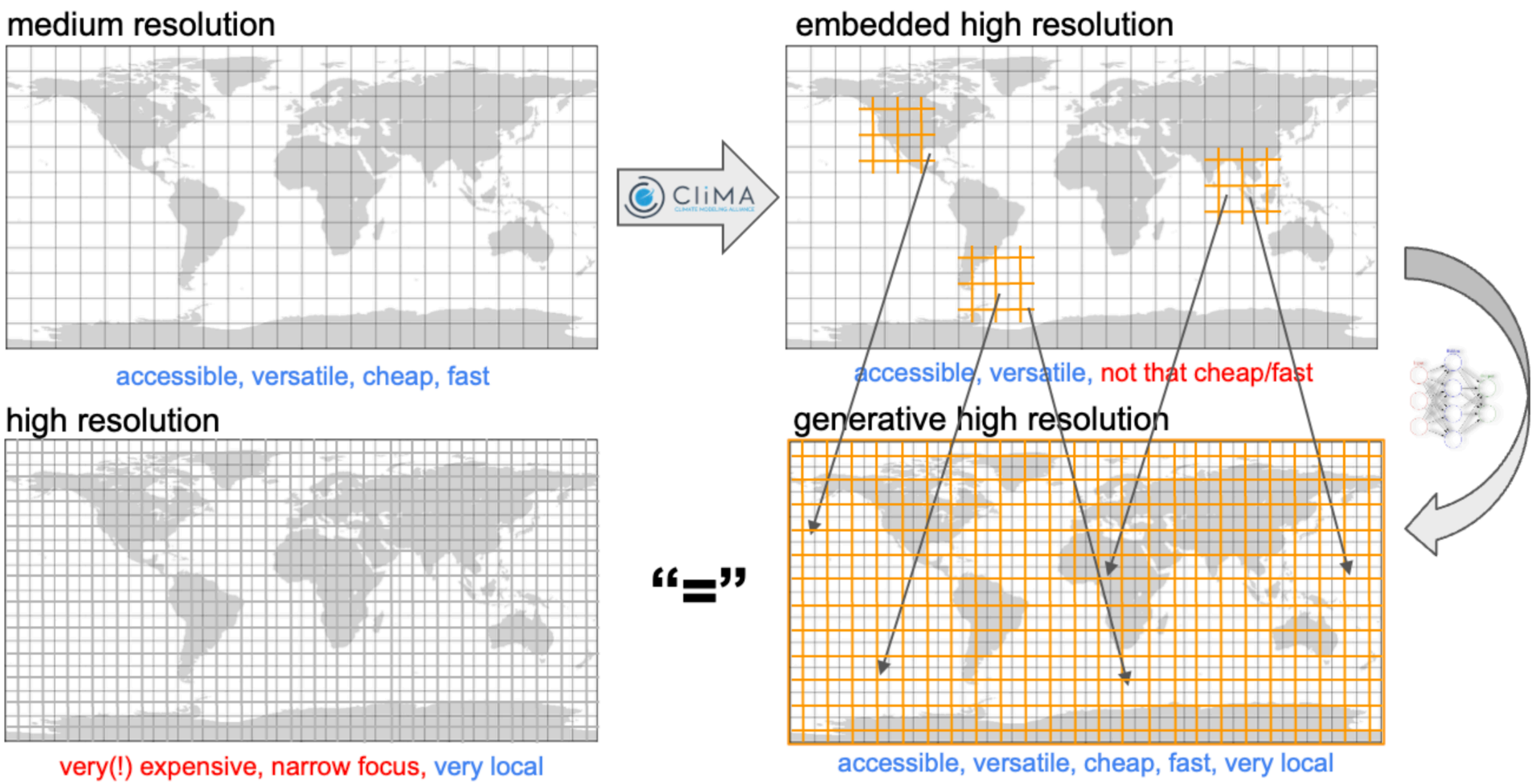
NOAA Climate.gov. Data: NCEI

Adapting to what is coming has a large benefit-cost ratio



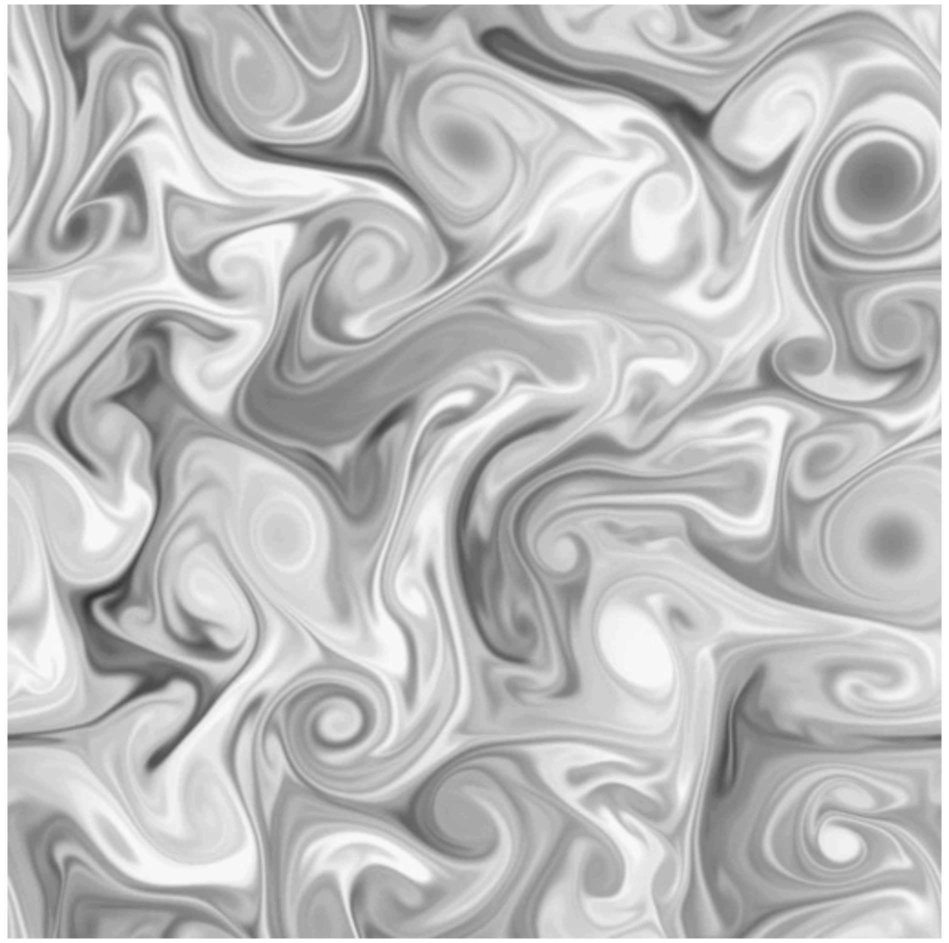
Global Commission on Adaptation, Adapt Now: A Global Call for Leadership on Climate Resilience, 2019

Adaptation requires risks of rare events on kilometer-scales (or better)

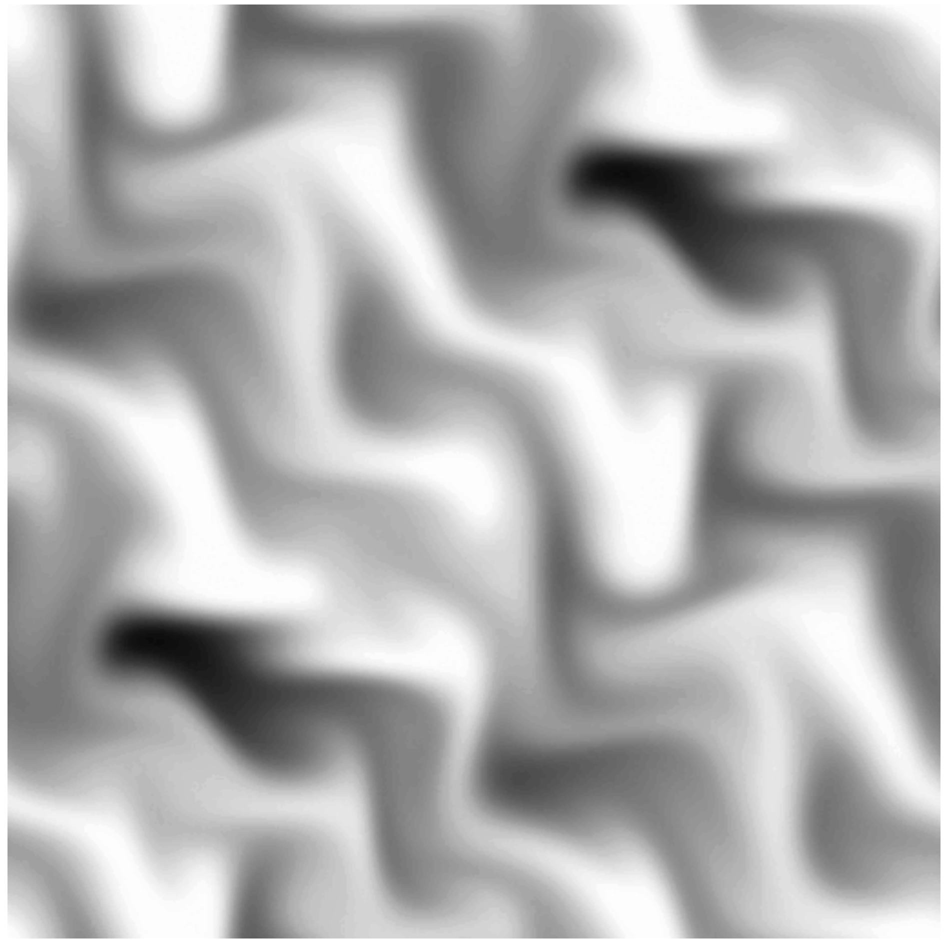


Generative models for downscaling from coarse to fine resolution (with focus on rare-event statistics)

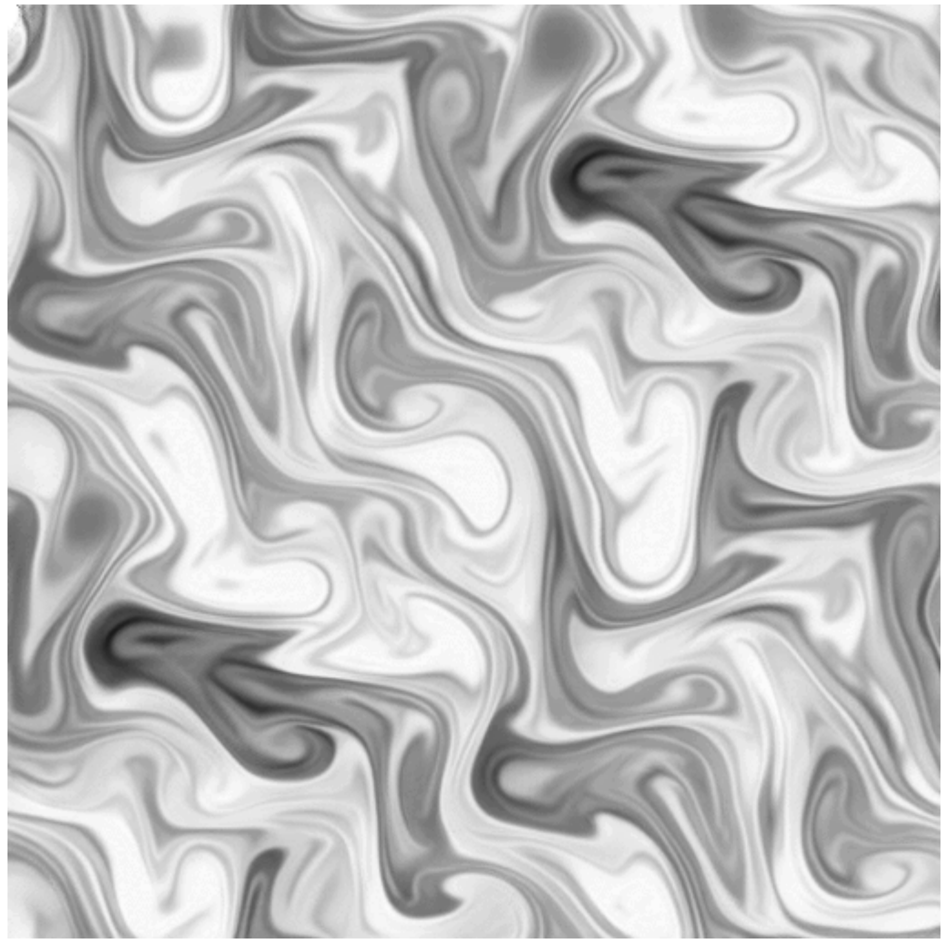
High-resolution for training

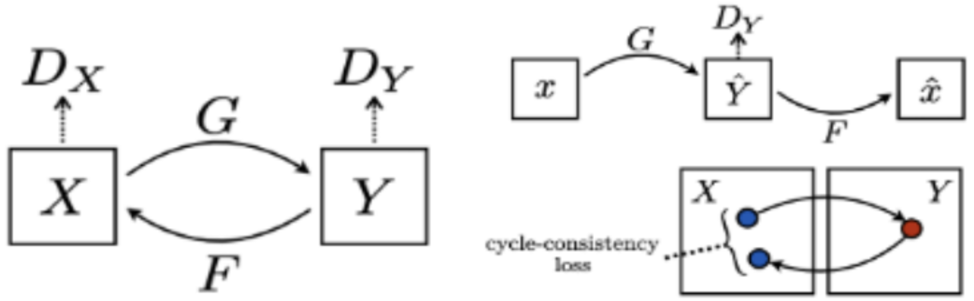


Standard low resolution



AI generated high resolution

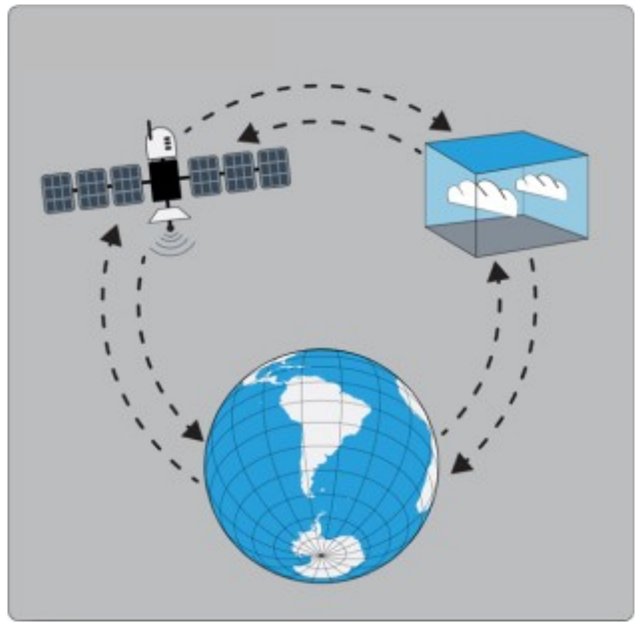




512 times faster than direct high-resolution simulation

Toby Bischoff, Katherine Deck, Andrew Stuart

CliMA's goal: accelerate climate science and become a hub for actionable climate information



Fine-grained climate projections on demand:

- Down to kilometer-scale spatial resolution
- Extreme scenarios (e.g., heat waves, droughts) with associated probabilities

- Anchor ecosystem of apps for detailed predictions of flood risks, risks of extreme heat, crop yields, and other impacts
- Provide actionable information to facilitate resiliency throughout public and private sectors

Conclusions

Many scientific and commercial opportunities for AI & computing (combined judiciously)!

- **Reducing and quantifying uncertainties** in climate models is urgent but within reach
- To reduce and quantify uncertainties, **combine process-informed models with ML approaches harnessing climate statistics**
- Treat ML as **inverse problem**, to be able to harness diverse, noisy, and multifidelity data
- **Sparsely parameterized, physics-based subgrid-scale models** can capture turbulence and cloud regimes that have vexed climate models for decades
- **Calibrate-emulate-sample** forms the core of the data assimilation/machine learning layer and achieves up to 1,000x speed-up relative to traditional Bayesian learning methods

CliMA
CLIMATE MODELING ALLIANCE

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DEPARTMENT OF DEFENSE · UNITED STATES OF AMERICA

NSF

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