Climate Analytics Lab

SCRIPPS INSTITUTION OF OCEANOGRAPHY

UC San Diego

HALICIOĞLU DATA SCIENCE INSTITUTE

Machine Learning for Climate

Duncan Watson-Parris, SIO/HDSI

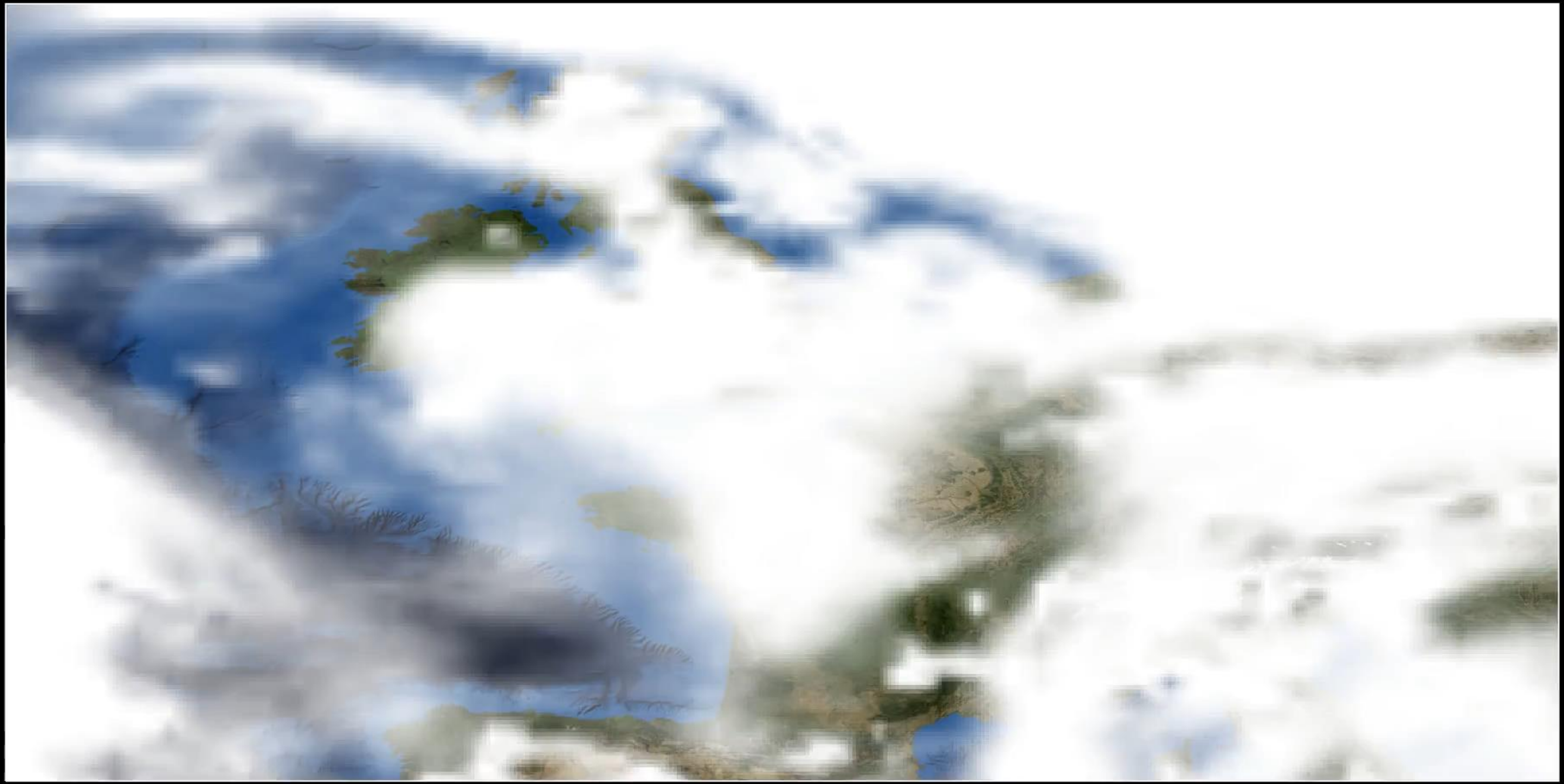
DSC 106: 6th May 2026

Overview

- Introduction to machine learning and aerosol forcing
- Three example approaches:
  1. Emulating climate models for improved calibration
  2. Deep-learning for measuring aerosol-cloud perturbations
  3. Exploring future climates with physical climate emulators
- Summary and my journey here

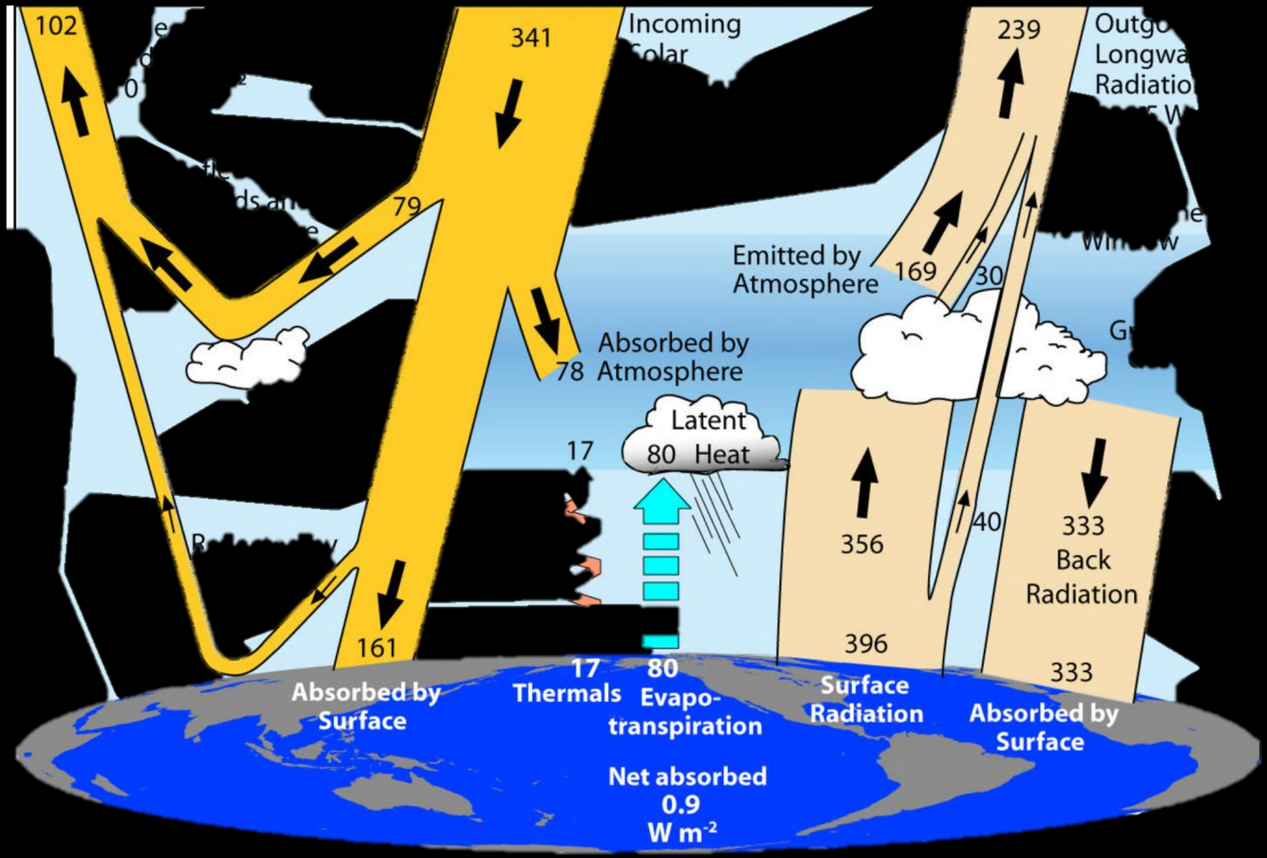
ML for Weather and Climate are worlds apart

Date: 01-01-1982, averaged over 3 hours



c.f. Watson-Parris 2021

The Global Energy Balance



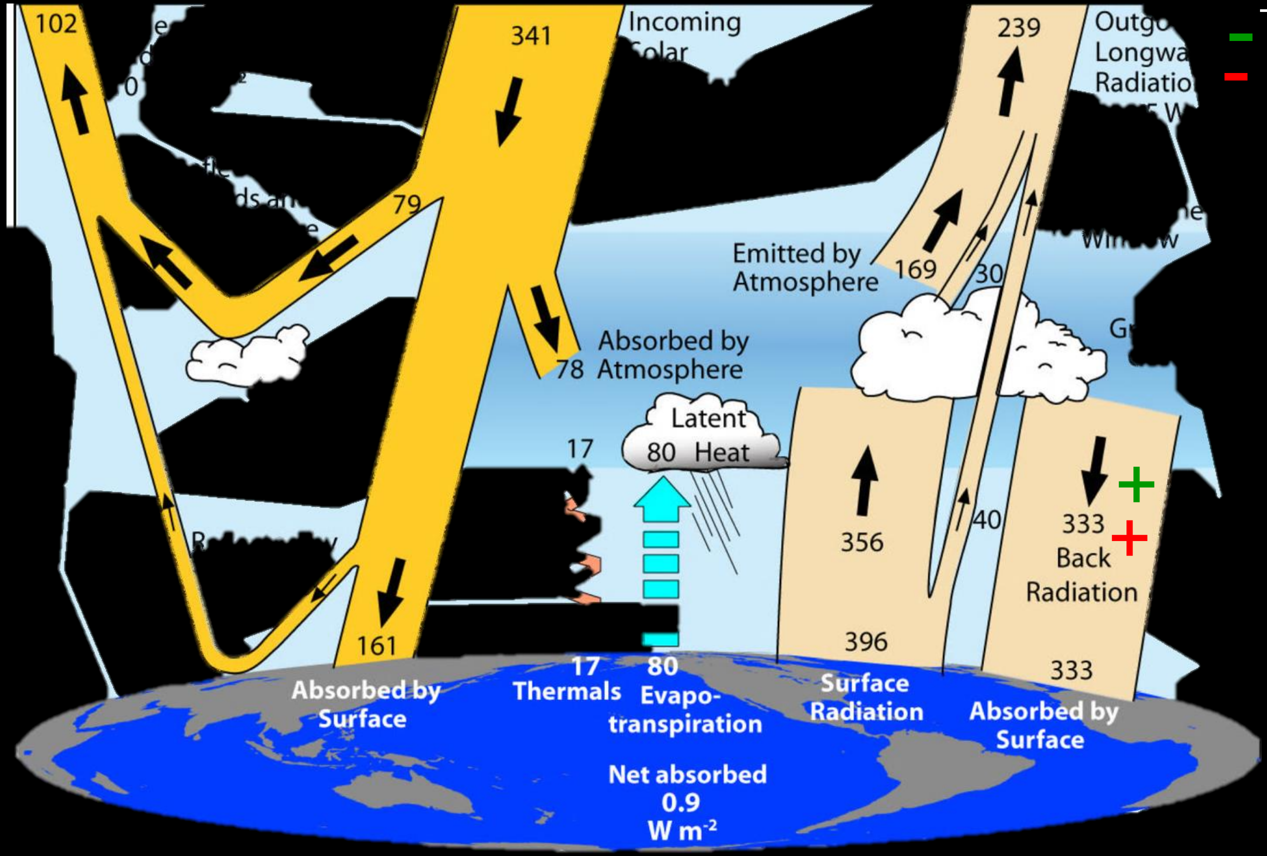
(Trenberth, 2009)

The Global Energy Balance

Natural Greenhouse Effect

Anthropogenic Greenhouse Effect

positive "radiative forcing"
⇒ warming



CH_4 H_2O

N_2O

CO_2

(Trenberth, 2009)

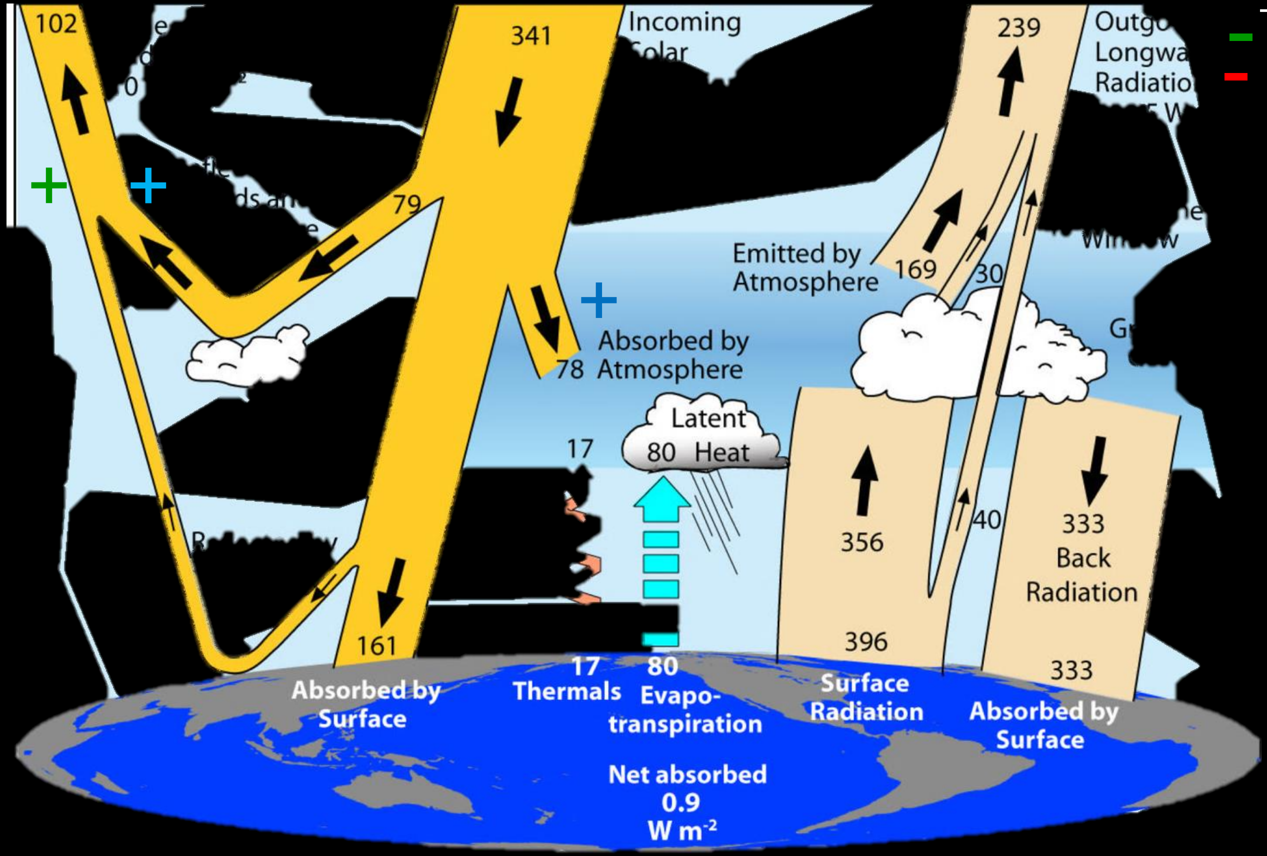
The Global Energy Balance

Natural Aerosol Effect

Anthropogenic Aerosol Effect

negative "radiative forcing"
⇒ cooling

SO_4

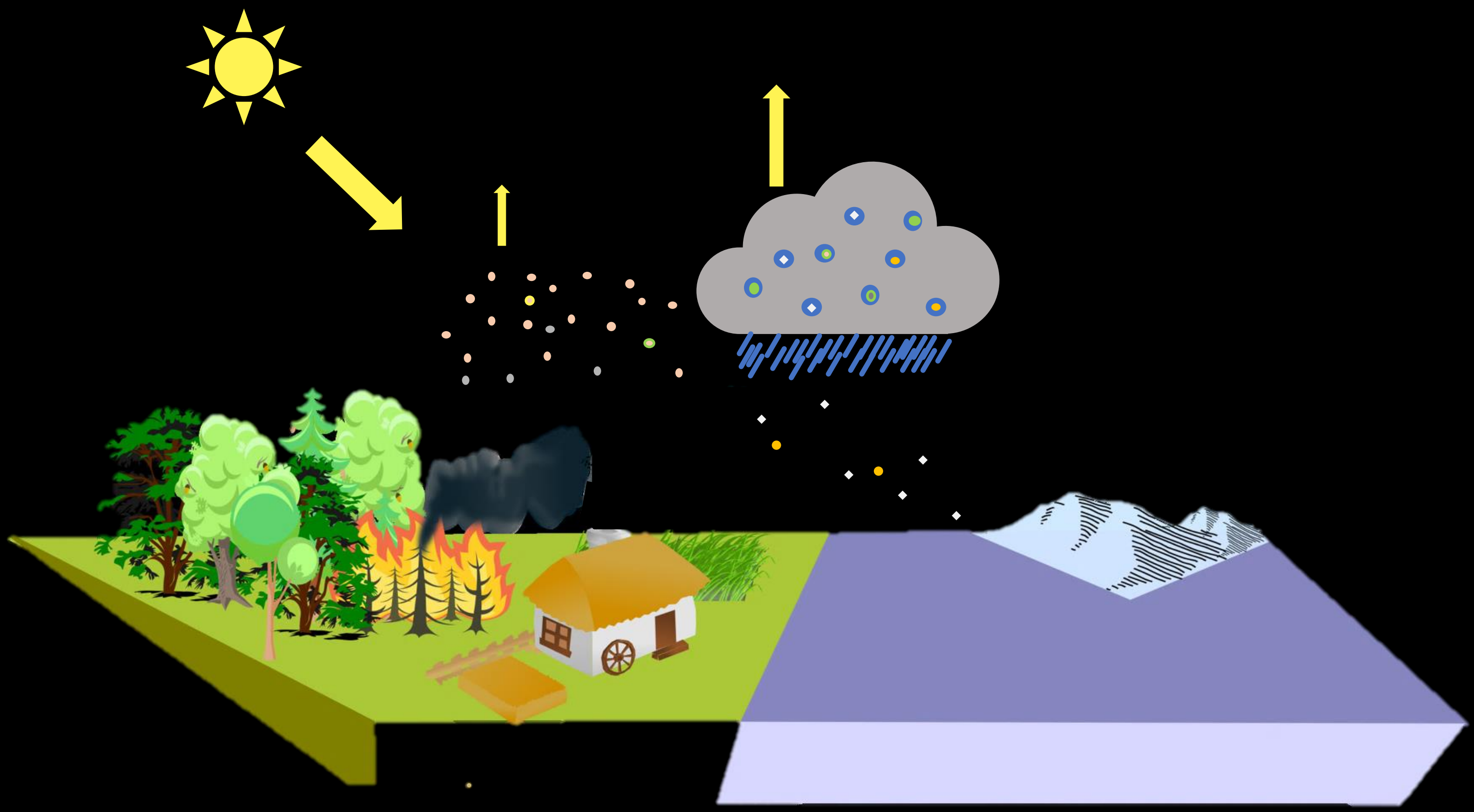


SO_4

Black Carbon

(Trenberth, 2009)

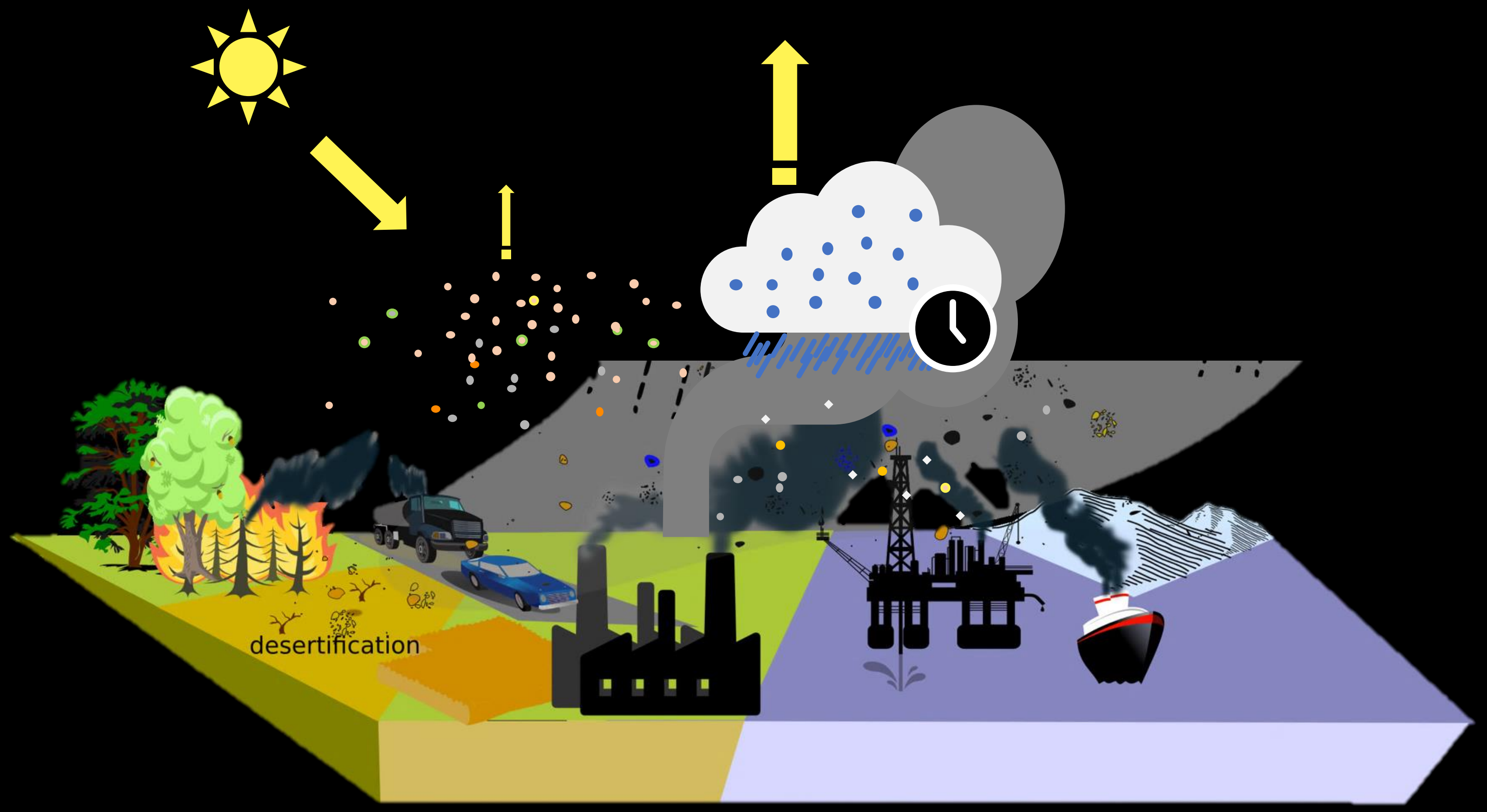
Natural aerosol



Pre-industrial

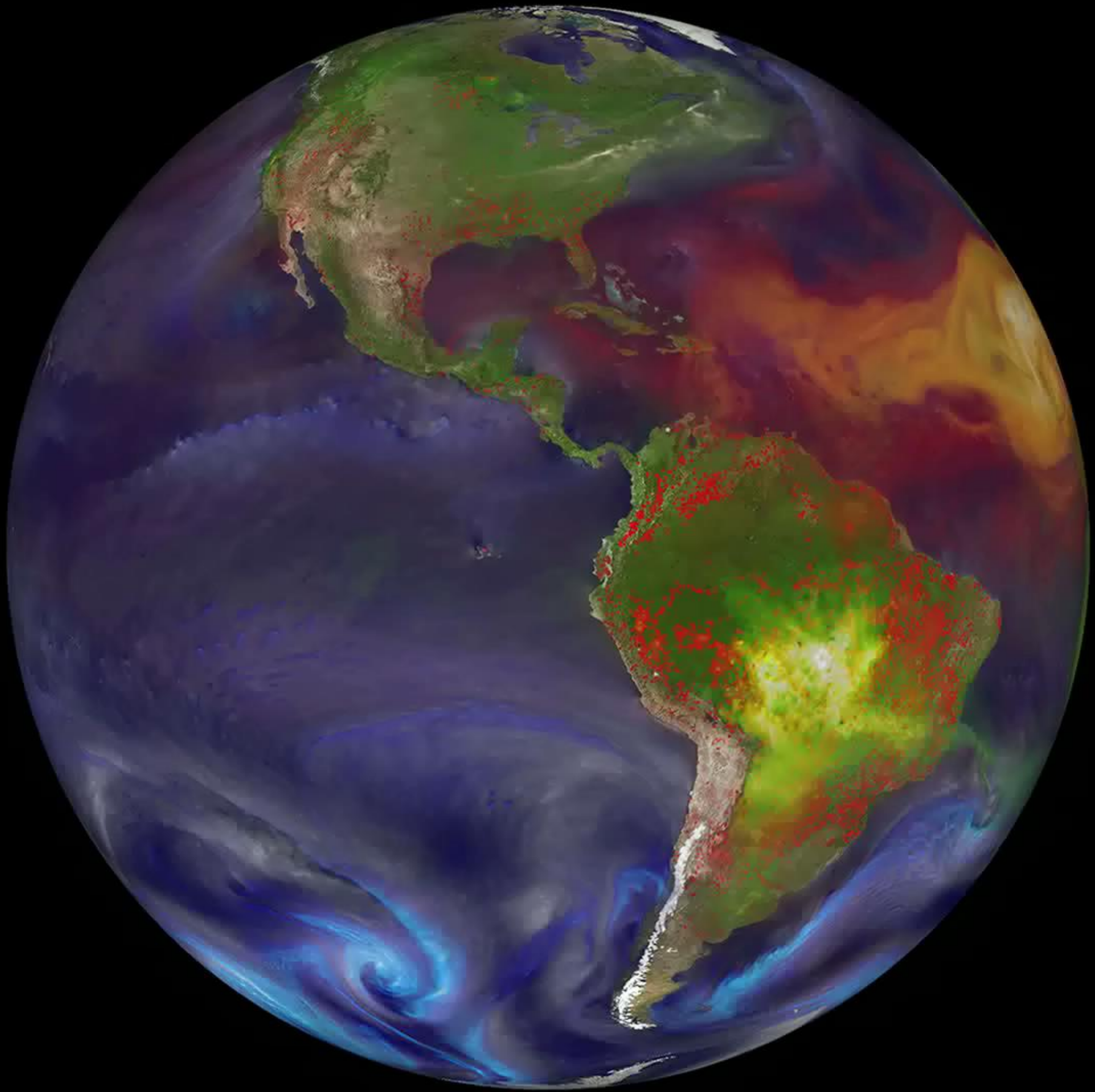
After Bellouin et al. *Rev. Geophysics* (2019)

Aerosol Forcing

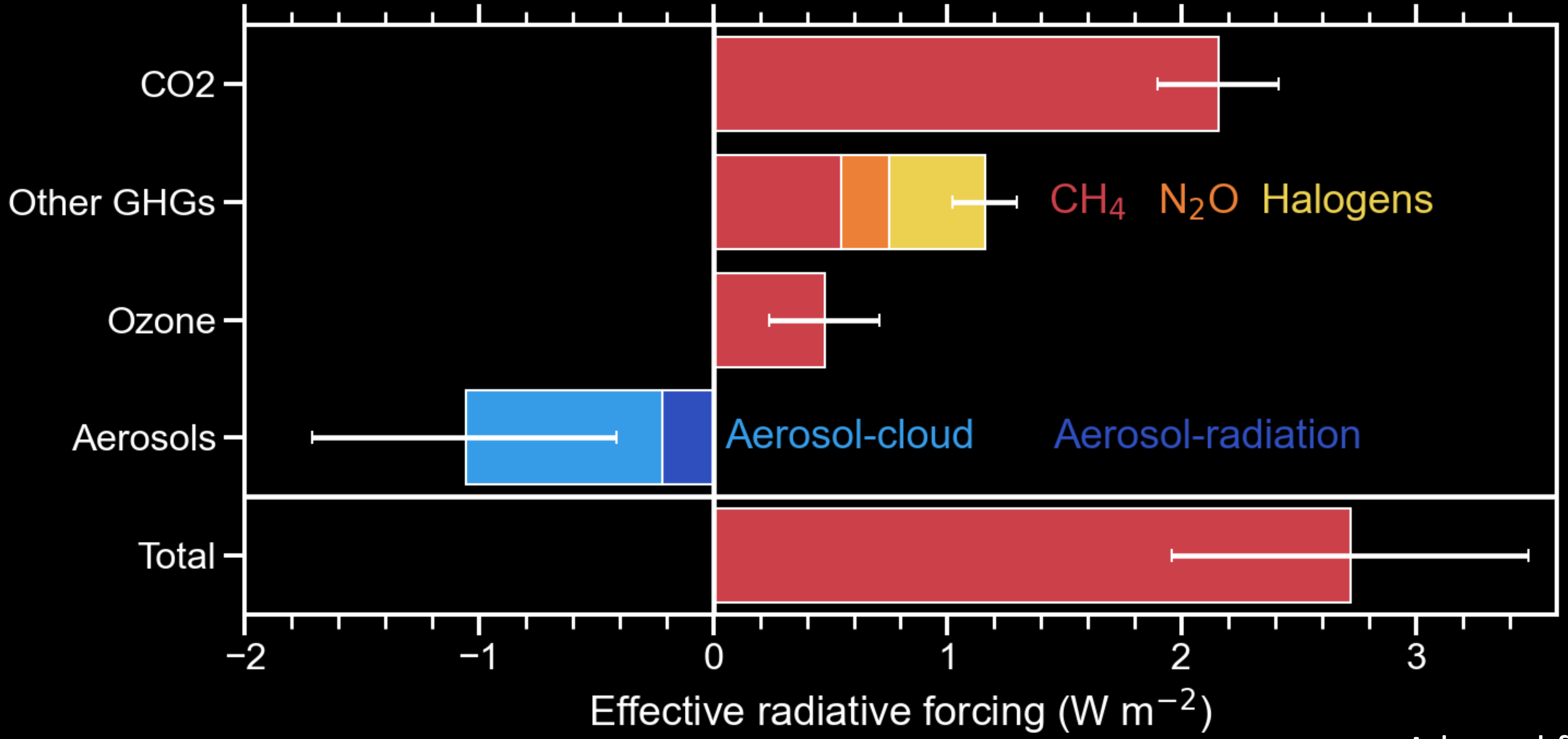


Present day

After Bellouin et al. *Rev. Geophysics* (2019)

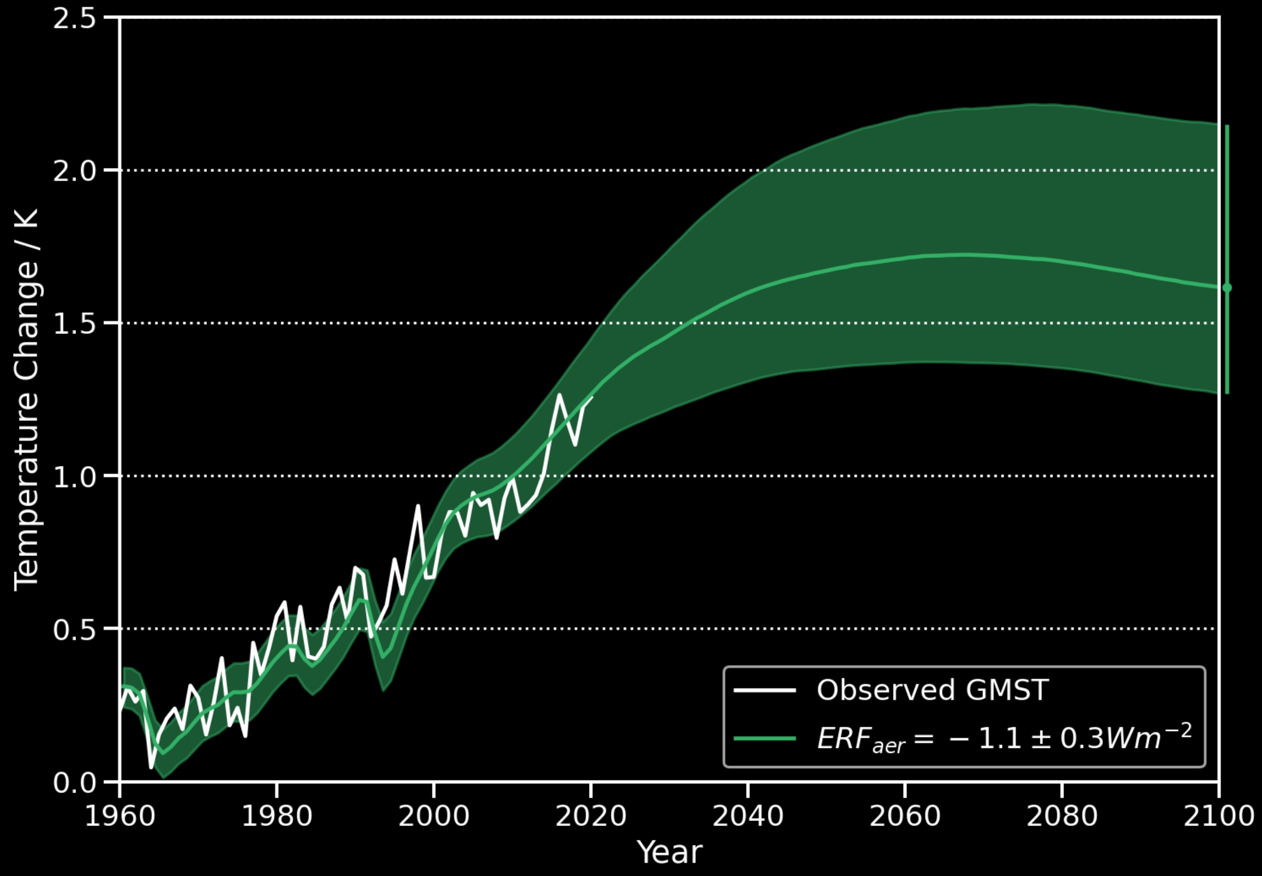


Anthropogenic Forcing Uncertainty



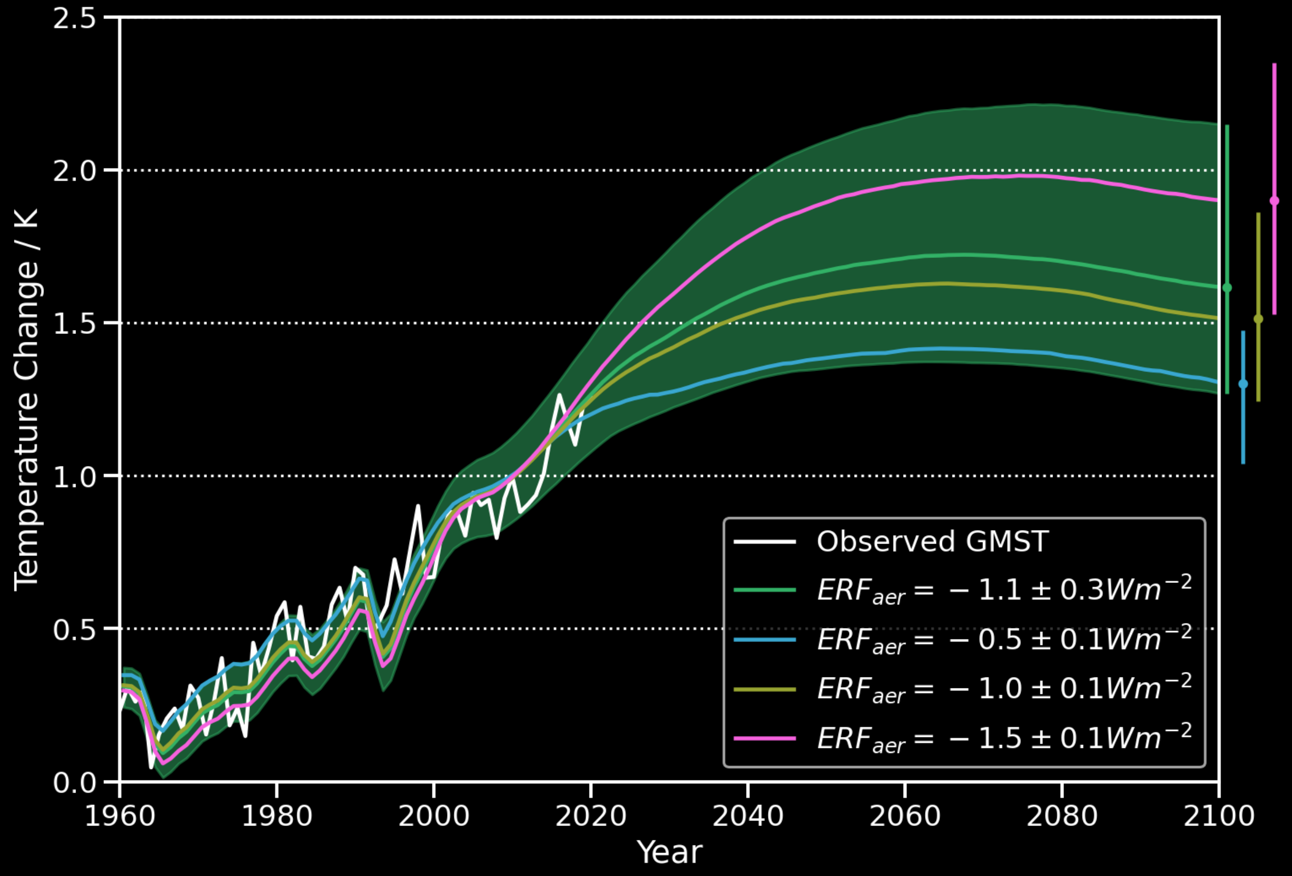
Adapted from IPCC AR6

Uncertain Aerosol Forcing - Uncertain Climate Projections



Watson-Parris & Smith *Nature Clim. Change* (2022)

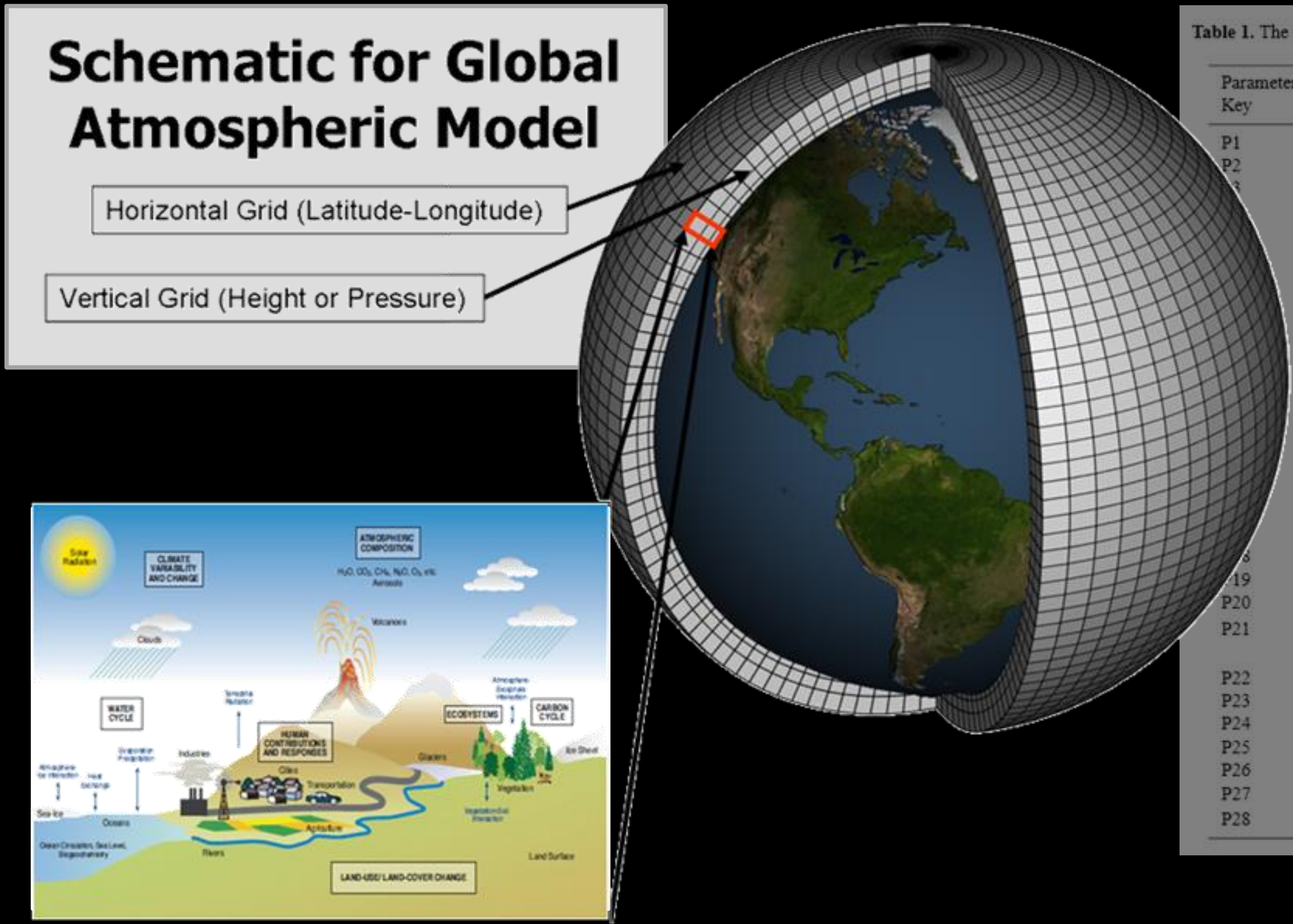
Uncertain Aerosol Forcing - Uncertain Climate Projections



Watson-Parris & Smith *Nature Clim. Change* (2022)

1. Climate model emulation for calibration

Climate models



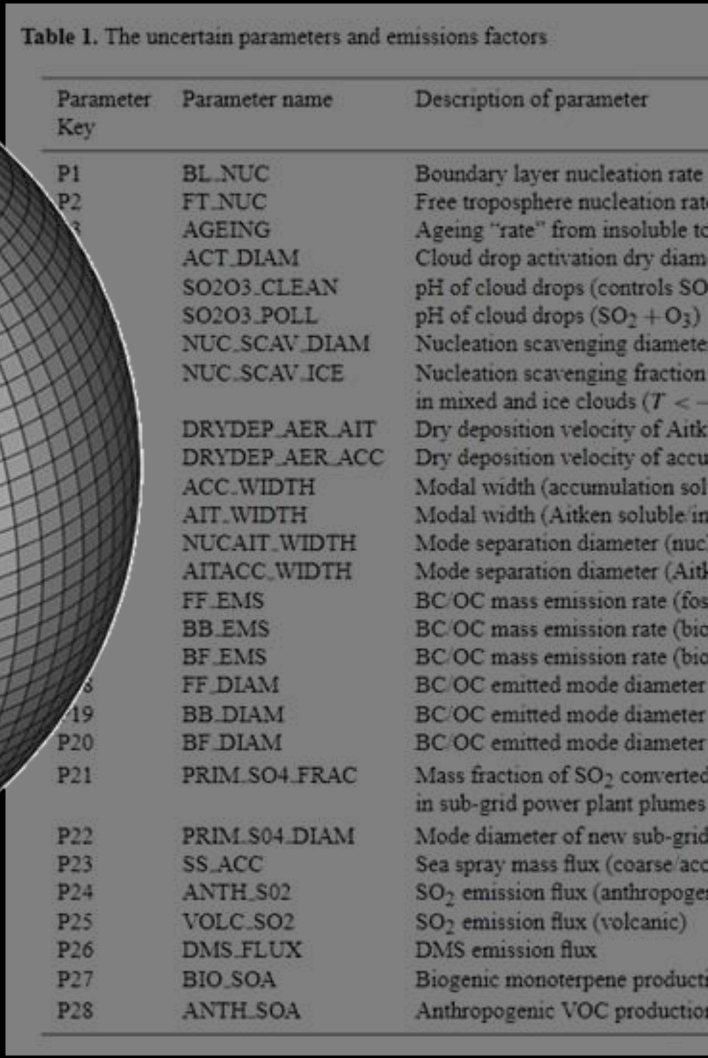


Table 1. The uncertain parameters and emissions factors

Parameter Key	Parameter name	Description of parameter
P1	BL_NUC	Boundary layer nucleation rate
P2	FT_NUC	Free troposphere nucleation rat
3	AGEING	Ageing "rate" from insoluble to
	ACT_DIAM	Cloud drop activation dry diam
	SO2O3_CLEAN	pH of cloud drops (controls SO
	SO2O3_POLL	pH of cloud drops ($SO_2 + O_3$)
	NUC_SCAV_DIAM	Nucleation scavenging diamete
	NUC_SCAV_ICE	Nucleation scavenging fraction in mixed and ice clouds (T < –
	DRYDEP_AER_AIT	Dry deposition velocity of Aitk
	DRYDEP_AER_ACC	Dry deposition velocity of accu
	ACC_WIDTH	Modal width (accumulation sol
	AIT_WIDTH	Modal width (Aitken soluble/in
	NUCAIT_WIDTH	Mode separation diameter (nuc
	AITACC_WIDTH	Mode separation diameter (Aitk
	FF_EMS	BC/OC mass emission rate (fos
	BB_EMS	BC/OC mass emission rate (bio
	BF_EMS	BC/OC mass emission rate (bio
8	FF_DIAM	BC/OC emitted mode diameter
19	BB_DIAM	BC/OC emitted mode diameter
P20	BF_DIAM	BC/OC emitted mode diameter
P21	PRIM_SO4_FRAC	Mass fraction of SO_2 converted in sub-grid power plant plumes
P22	PRIM_S04_DIAM	Mode diameter of new sub-grid
P23	SS_ACC	Sea spray mass flux (coarse/acc
P24	ANTH_S02	SO_2 emission flux (anthropoge
P25	VOLC_SO2	SO_2 emission flux (volcanic)
P26	DMS_FLUX	DMS emission flux
P27	BIO_SOA	Biogenic monoterpene producti
P28	ANTH_SOA	Anthropogenic VOC productior

Exploring parametric uncertainty

- A climate model is a function $\mathcal{F}$ of input forcers X and parameters θ and generates outputs Y: $\mathcal{F}(X, \theta) = Y$.
- Given a set of observations of Y, denoted Y^0, we would like to calculate the inverse: $\mathcal{F}^{-1}(Y^0) = \theta$.
- Or, more precisely, we would like to know the posterior probability distribution of the input parameters:

$$p(\theta | Y^0) = \frac{p(Y^0 | \theta) p(\theta)}{p(Y^0)}$$

Likelihood-free inference

- We cannot compute the full likelihood but can approximate it using Approximate Bayesian computation (ABC; or rejection sampling):
    1. Draw θ from $p(\theta)$
    2. Calculate $\mathcal{F}(\theta)$ to determine Y
    3. Accept θ if $\rho(Y^0, Y) \leq \epsilon$
- As $\epsilon \rightarrow \infty$, we get observations from the prior, $p(\theta)$
- As $\epsilon \rightarrow 0$, we generate observations from $p(\theta|Y^0)$
- In practice we need many, many samples and so a surrogate model, or emulator, is used: $\mathcal{E}(\theta) \sim \mathcal{F}(\theta)$

Implausibility

- In practice, we need to define the distance, $\rho(Y^0, Y)$
- We use the concept of an implausibility metric:

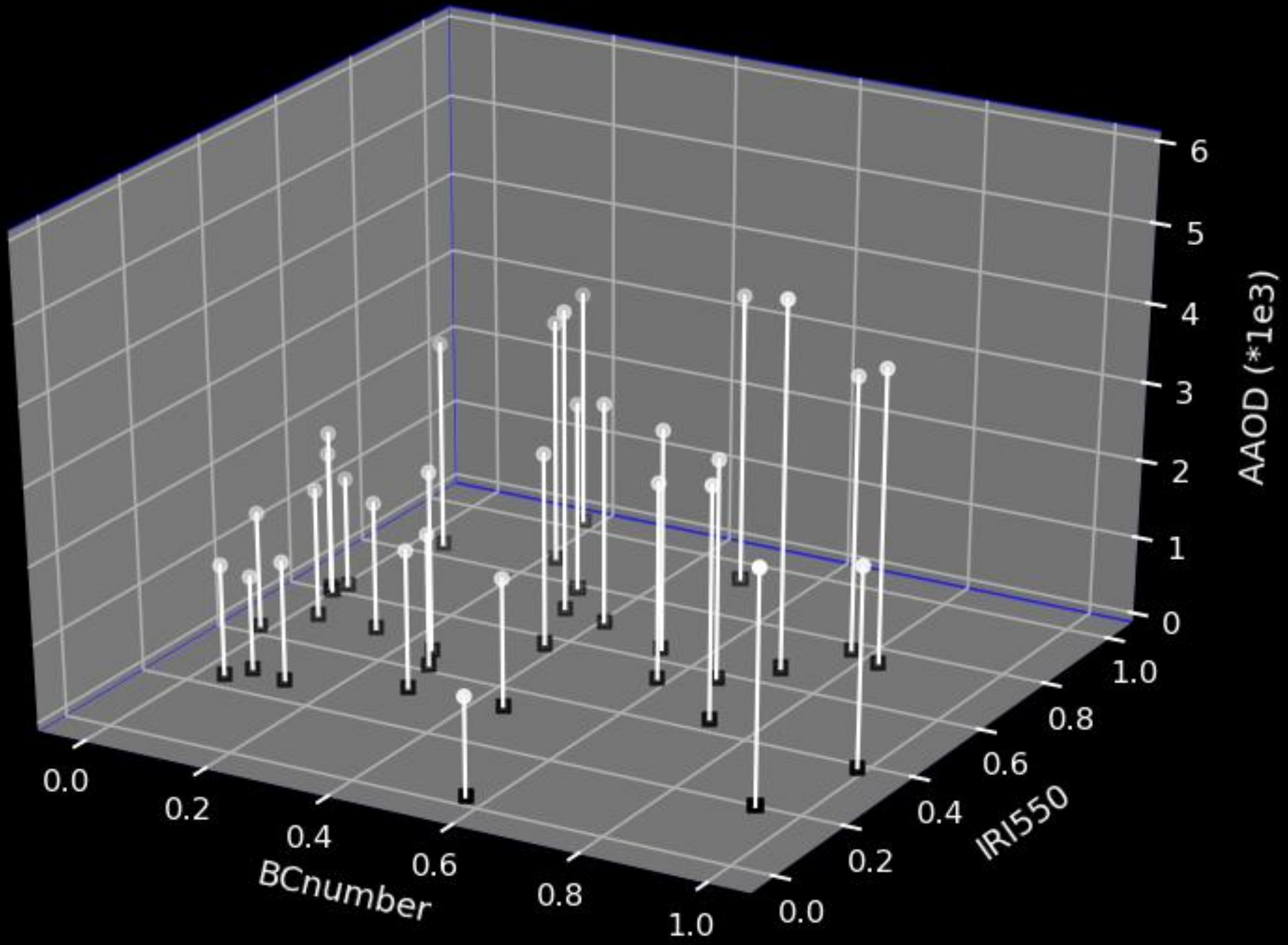
$$I(\theta) = \frac{|Y^0 - E[\eta(\boldsymbol{\theta})]\,|}{\sqrt{[Var(\phi(\boldsymbol{\theta})) + Var(\epsilon) + Var(\delta)]}}$$

Observation
Model output
[Prediction from emulator]
Emulator prediction uncertainty
Observational uncertainty
Structural uncertainty

- Assuming this distribution is unimodal, we can then use the 3σ to rule out parameter combinations at 95% confidence

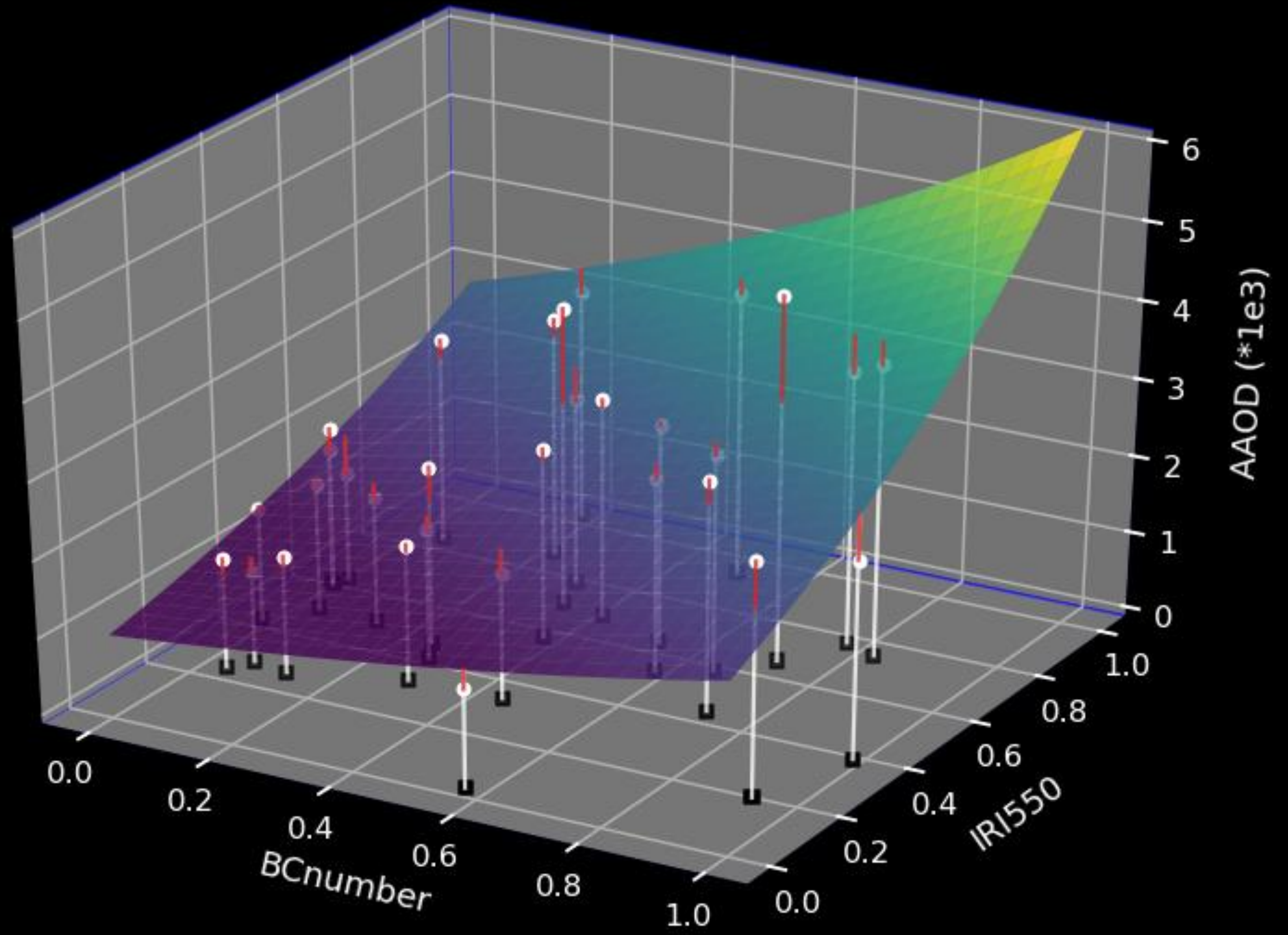
Vernon et al. *2010*

Emulation



AAOD (*1e3)
0
1
2
3
4
5
6
BCnumber
0.0
0.2
0.4
0.6
0.8
1.0
IRI550
0.0
0.2
0.4
0.6
0.8
1.0

Emulation



AAOD (*1e3)
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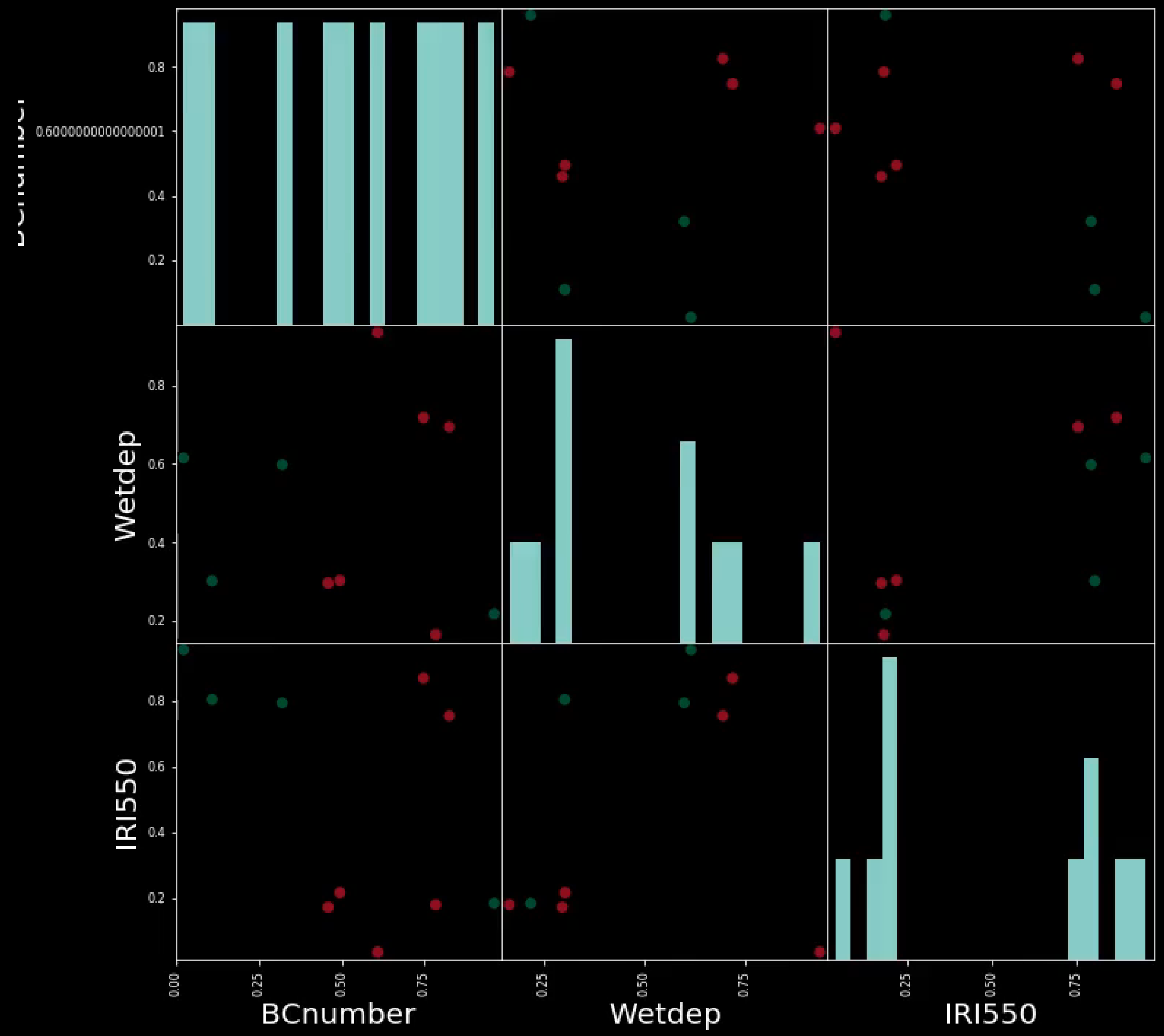
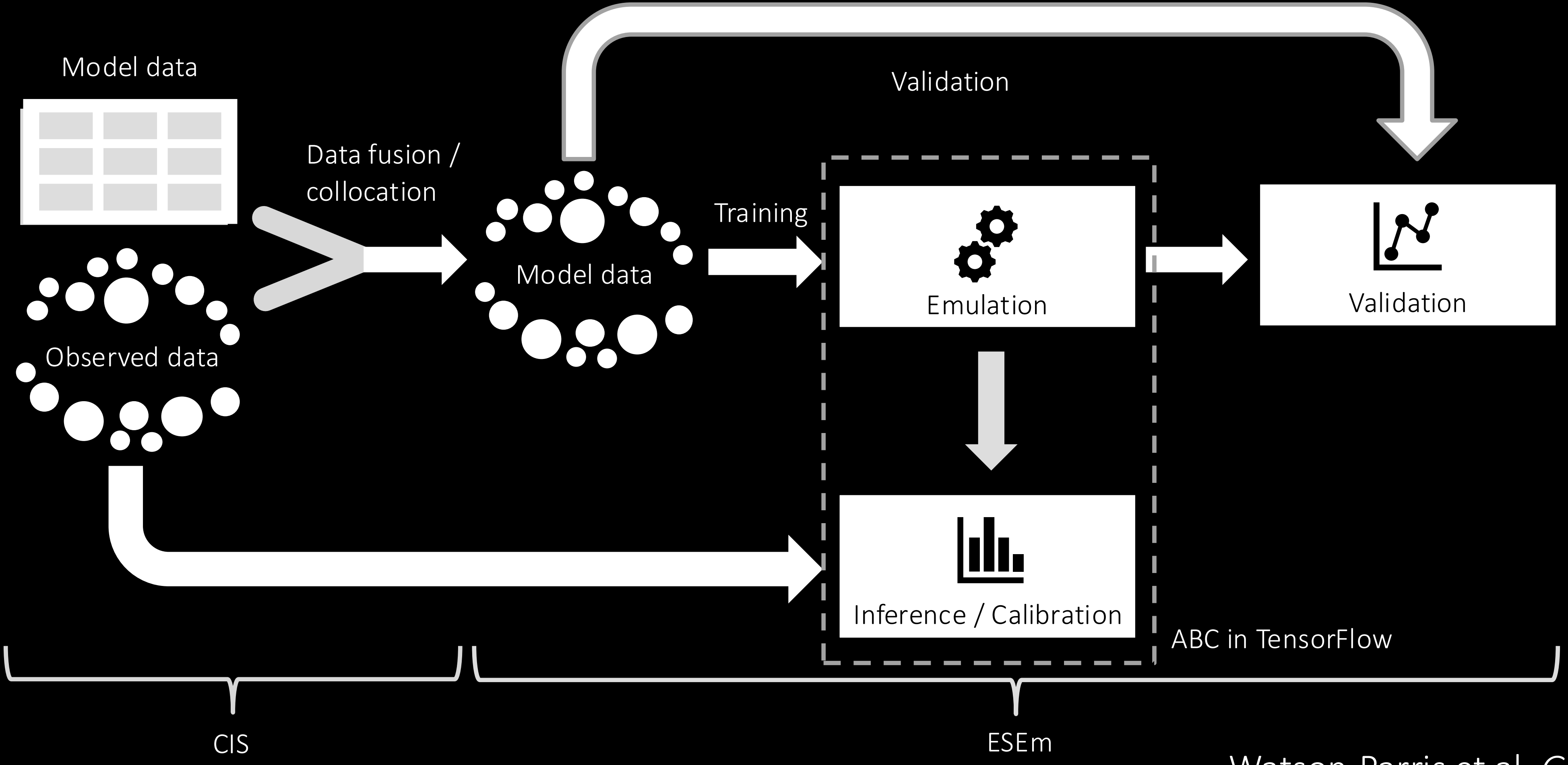
0.2
0.4
0.6
0.8
1.0
IRI550
0.0
0.2
0.4
0.6
0.8
1.0

Sampling



0.8
0.6000000000000001
0.4
0.2
Wetdep
0.8
0.6
0.4
0.2
IRI550
0.8
0.6
0.4
0.2
0.00
0.25
0.50
0.75
BCnumber
0.25
0.50
0.75
Wetdep
0.25
0.50
0.75
IRI550

Earth System Emulator (ESEm)



Watson-Parris et al. *GMD 2016*

Watson-Parris et al. *GMD 2021*

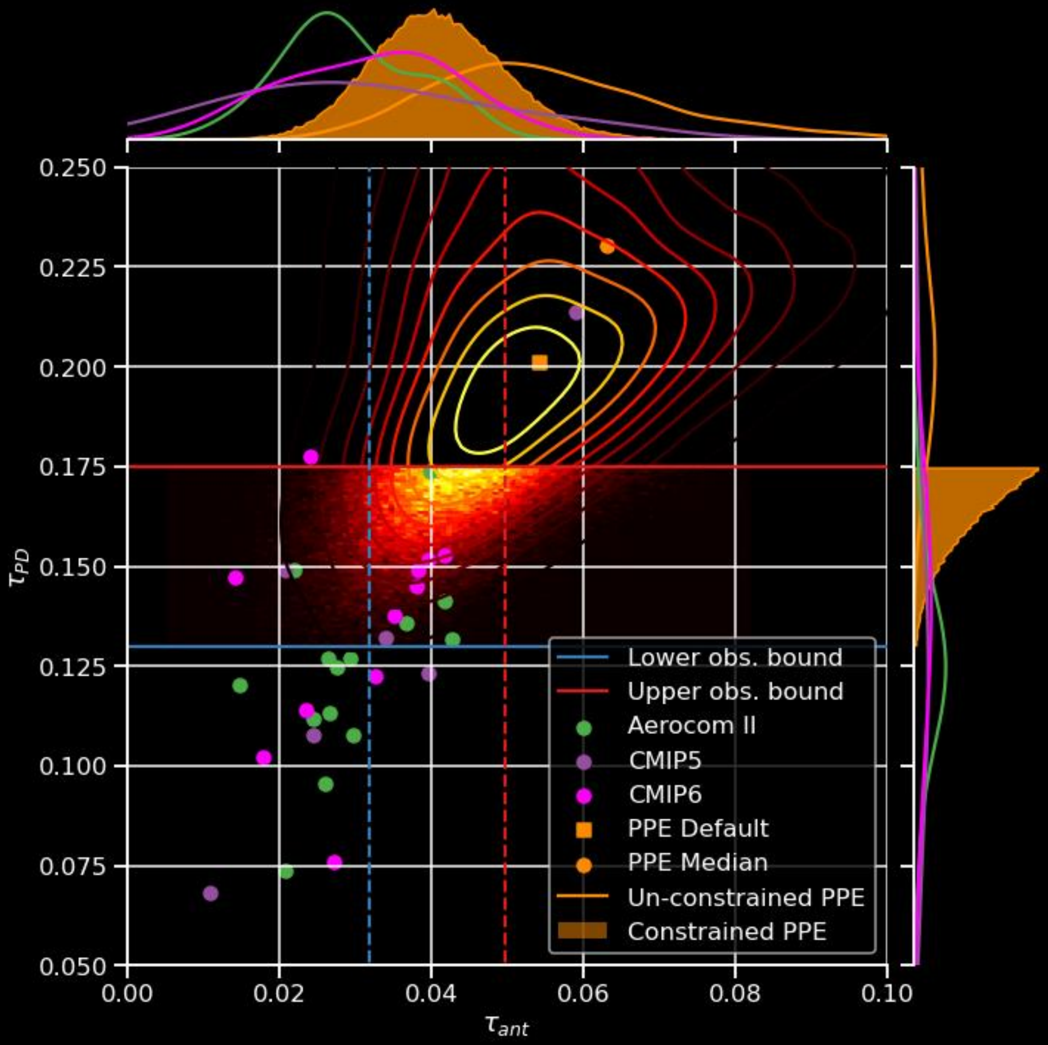
Parametric uncertainty

Table 1. The uncertain parameters and emissions factors

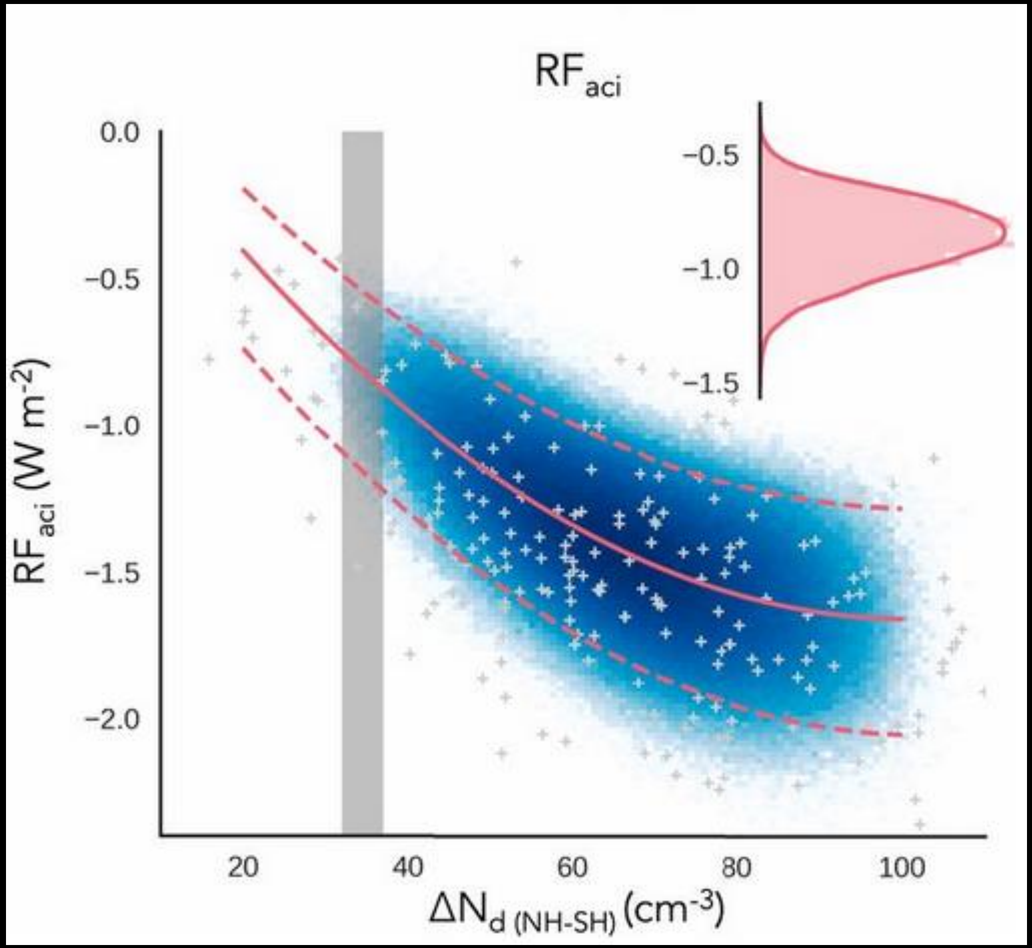
Parameter Key	Parameter name	Description of parameter	Uncertainty range	Effect
P1	BL_NUC	Boundary layer nucleation rate coeff (A)	$3.2e^{-7}$–$2e^{-4}$ s^{-1}	Absolute
P2	FT_NUC	Free troposphere nucleation rate	0.01–10	Scaled
P3	AGEING	Ageing "rate" from insoluble to soluble	0.3–5 monolayer	Absolute
P4	ACT_DIAM	Cloud drop activation dry diameter	50–100 nm	Absolute
P5	SO2O3_CLEAN	pH of cloud drops (controls $SO_2 + O_3$)	pH 4–6.5	Absolute
P6	SO2O3_POLL	pH of cloud drops ($SO_2 + O_3$)	pH 3.5–5	Absolute
P7	NUC_SCAV_DIAM	Nucleation scavenging diameter offset dry diameter	0–50 nm	Absolute
P8	NUC_SCAV_ICE	Nucleation scavenging fraction (accumulation mode) in mixed and ice clouds ($T < -15\,^{\circ}C$)	0–1	Scaled
P9	DRYDEP_AER_AIT	Dry deposition velocity of Aitken mode aerosol	0.5–2	Scaled
P10	DRYDEP_AER_ACC	Dry deposition velocity of accumulation mode aerosol	0.1–10	Scaled
P11	ACC_WIDTH	Modal width (accumulation soluble/insoluble)	1.2–1.8	Absolute
P12	AIT_WIDTH	Modal width (Aitken soluble/insoluble)	1.2–1.8	Absolute
P13	NUCAIT_WIDTH	Mode separation diameter (nucleation/Aitken)	9–18 nm	Absolute
P14	AITACC_WIDTH	Mode separation diameter (Aitken/accumulation)	0.9–2 × ACT_DIAM	Scaled
P15	FF_EMS	BC/OC mass emission rate (fossil fuel)	0.5–2	Scaled
P16	BB_EMS	BC/OC mass emission rate (biomass burning)	0.25–4	Scaled
P17	BF_EMS	BC/OC mass emission rate (biofuel)	0.25–4	Scaled
P18	FF_DIAM	BC/OC emitted mode diameter (fossil fuel)	30–80 nm	Absolute
P19	BB_DIAM	BC/OC emitted mode diameter (biomass burning)	50–200 nm	Absolute
P20	BF_DIAM	BC/OC emitted mode diameter (biofuel)	50–200 nm	Absolute
P21	PRIM_SO4_FRAC	Mass fraction of SO_2 converted to new SO_4^{2-} particles in sub-grid power plant plumes	0–1 %	Absolute
P22	PRIM_S04_DIAM	Mode diameter of new sub-grid SO_4^{2-} particles	20–100 nm	Absolute
P23	SS_ACC	Sea spray mass flux (coarse/accumulation)	0.2–5	Scaled
P24	ANTH_S02	SO_2 emission flux (anthropogenic)	0.6–1.5	Scaled
P25	VOLC_SO2	SO_2 emission flux (volcanic)	0.5–2	Scaled
P26	DMS_FLUX	DMS emission flux	0.5–2	Scaled
P27	BIO_SOA	Biogenic monoterpene production of SOA	5–360 $Tg\,a^{-1}$	Absolute
P28	ANTH_SOA	Anthropogenic VOC production of SOA	2–112 $Tg\,a^{-1}$	Absolute

Lee et al. *2013.*

Constraining parametric uncertainty



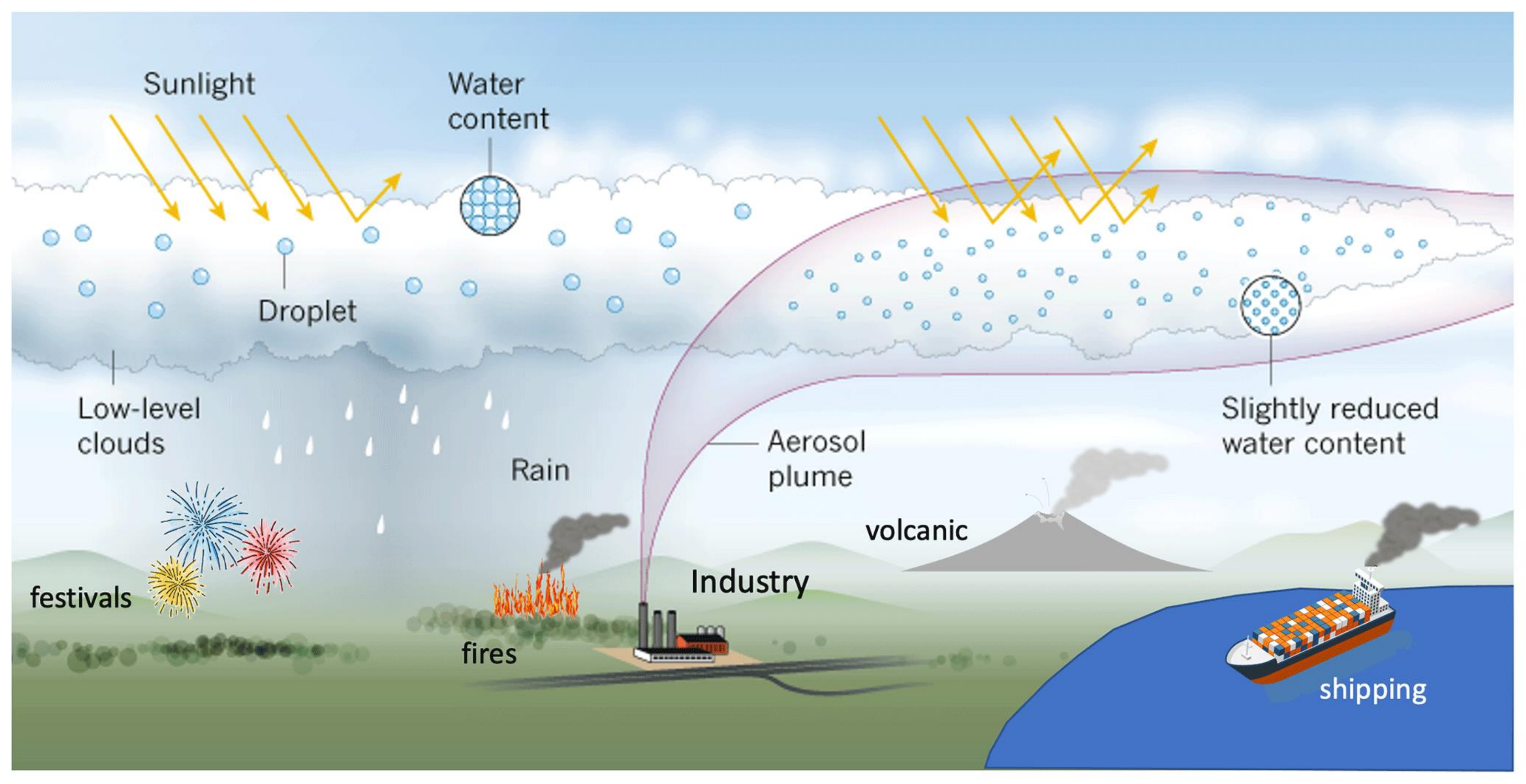
Watson-Parris et al. *GRL* 2020



McCoy et al. 2020

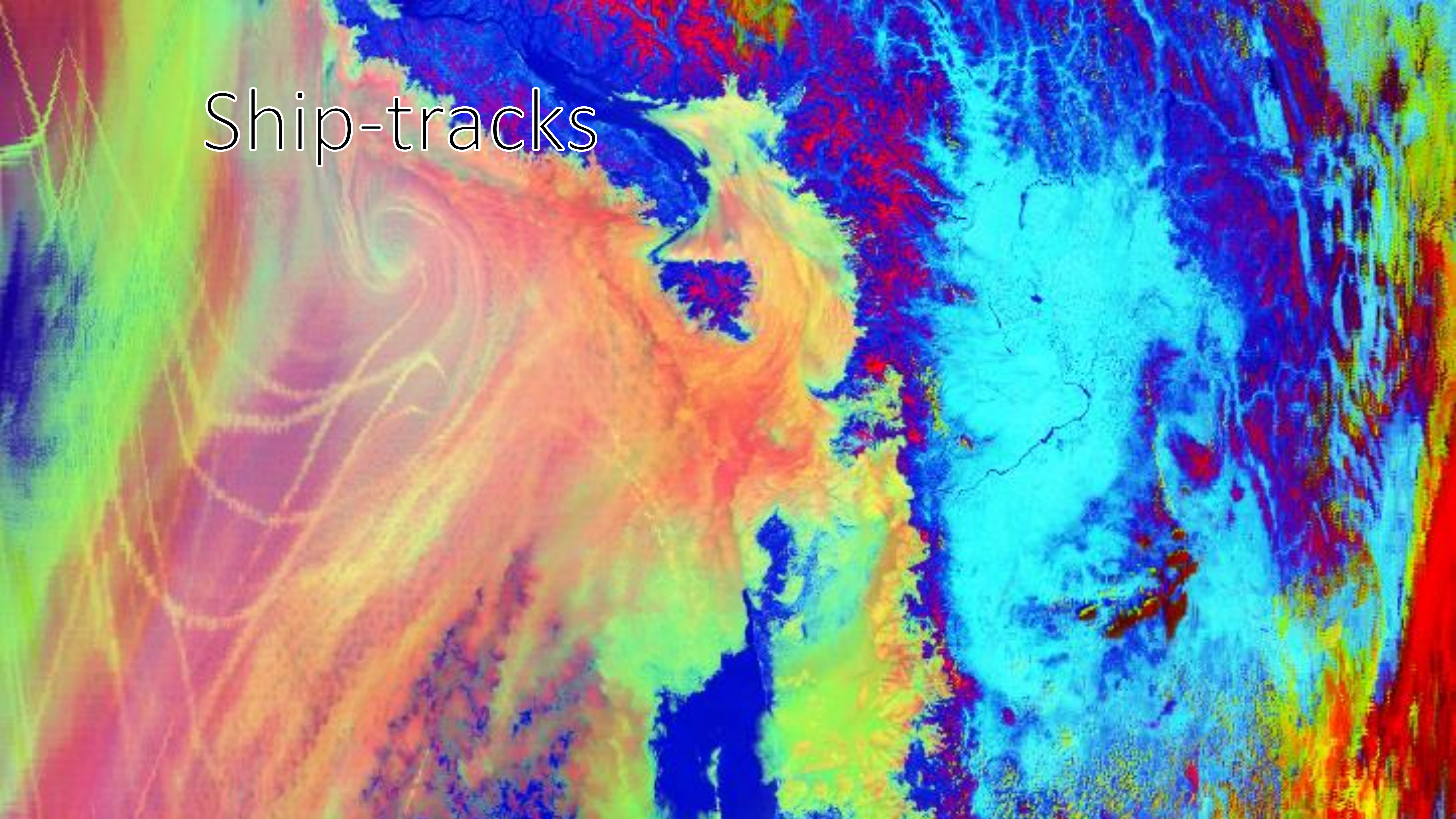
2. Measuring aerosol-cloud perturbations

Opportunistic Experiments



Christensen et al. *ACP 2022*

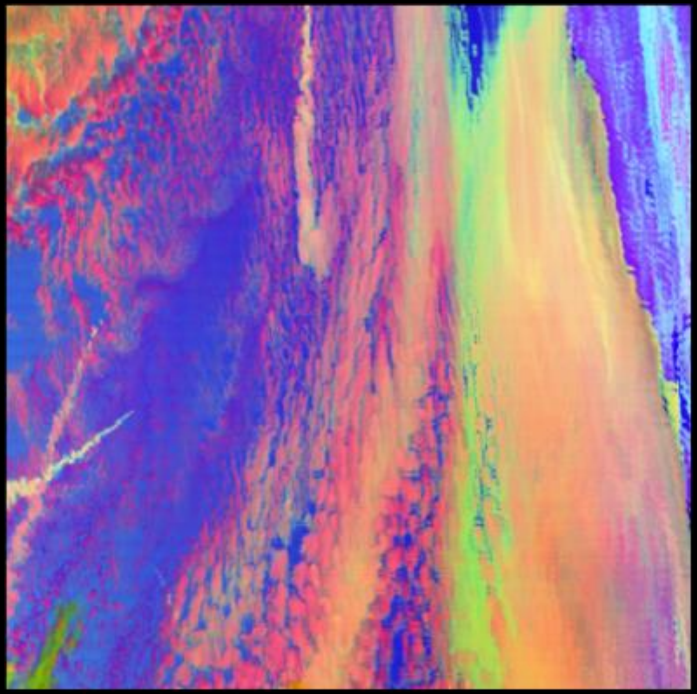
Ship-tracks



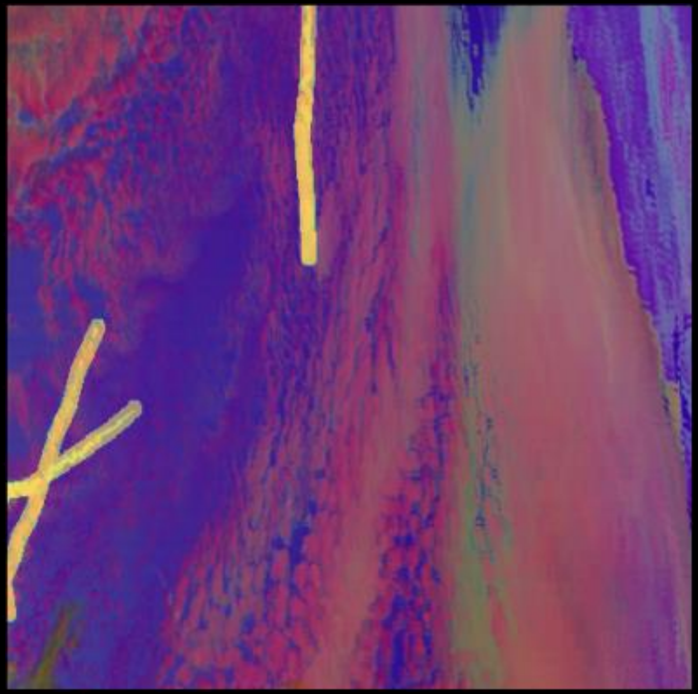
Ship-track detection

We use a ‘micro-physics’ RGB composite include visible, near-IR and IR channels and target rasterized masks

Composite input



Hand-logged tracks

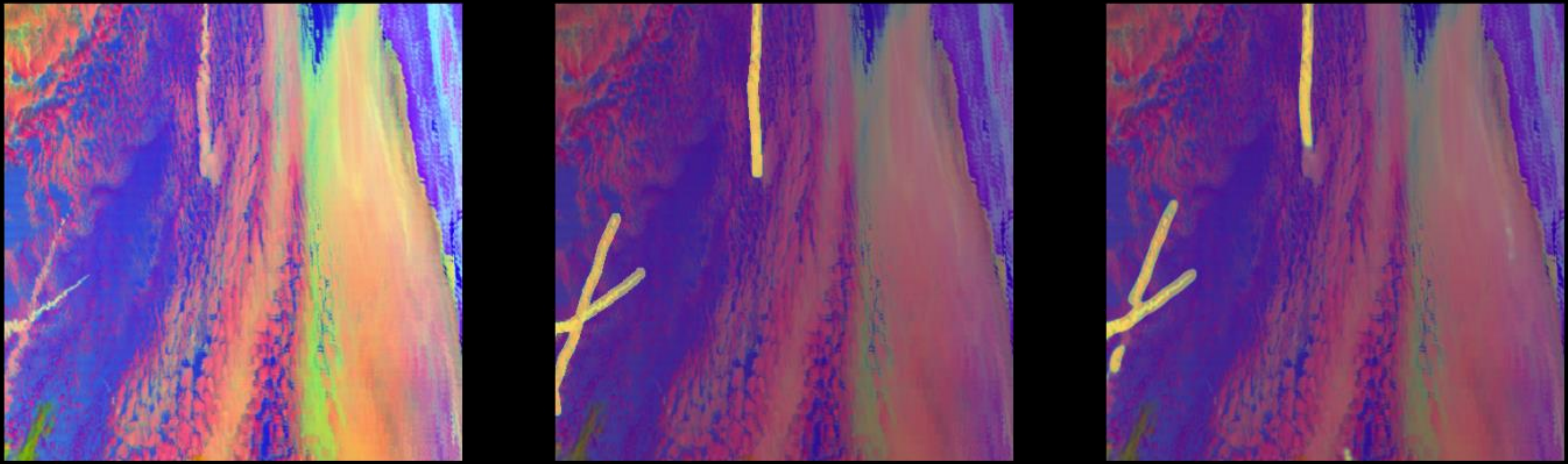


Watson-Parris et al. *PNAS* (2022)

Ship-track detection

We have developed multiple models that perform well against the held-back test data

Composite input	Hand-logged tracks	Detected tracks



Watson-Parris et al. *PNAS* (2022)

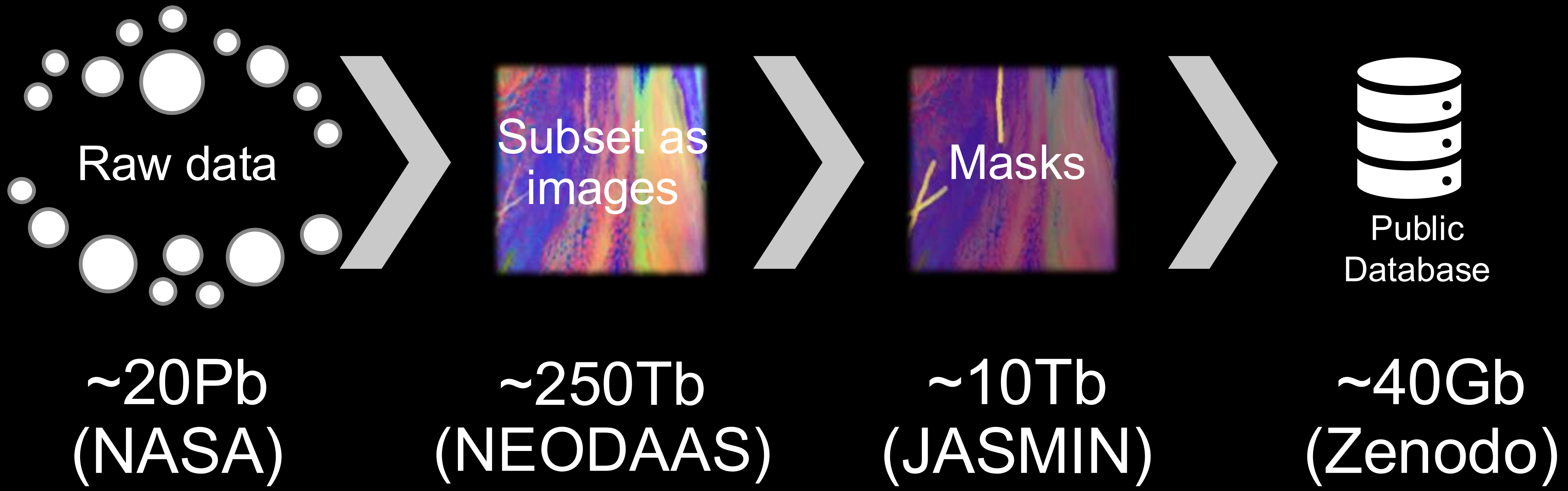
Ship-track detection

Using Bayesian Optimisation we found the resnet-152 model with the Jacard loss function to be optimal.

Composite input | Hand-logged tracks | Detected tracks

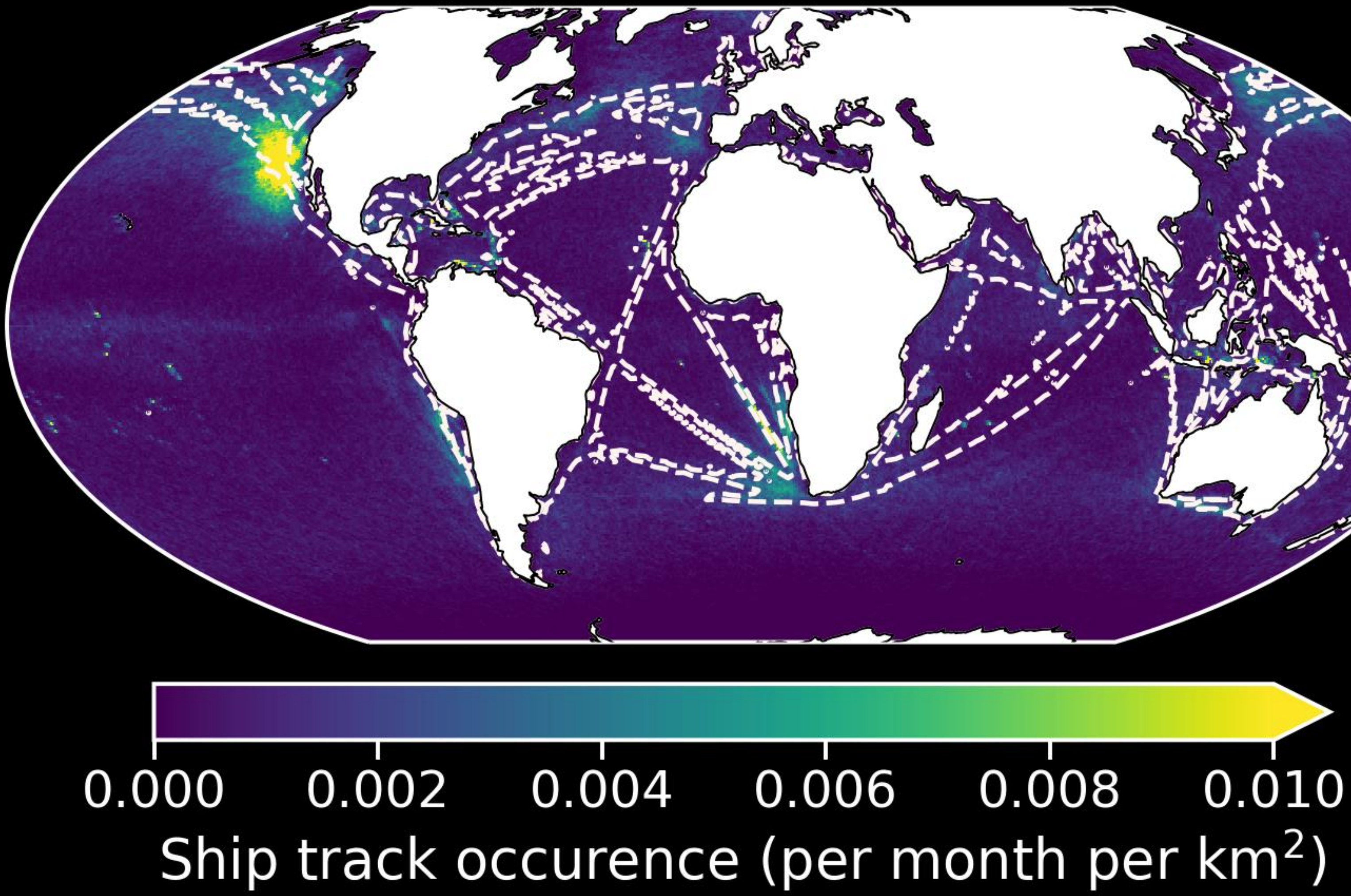
Watson-Parris et al. *PNAS* (2022)

Inference



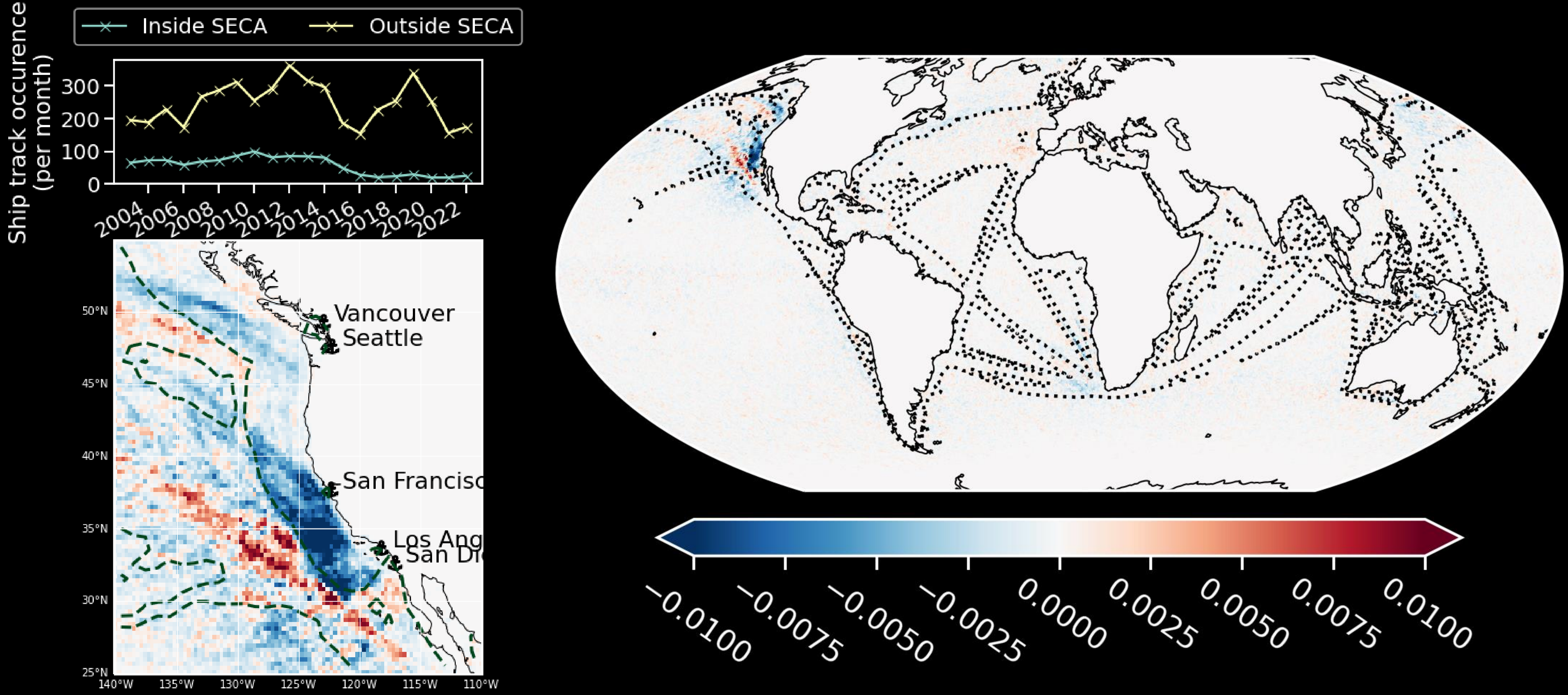
Watson-Parris et al. *PNAS* (2022)

Ship-track density (2003-2021)

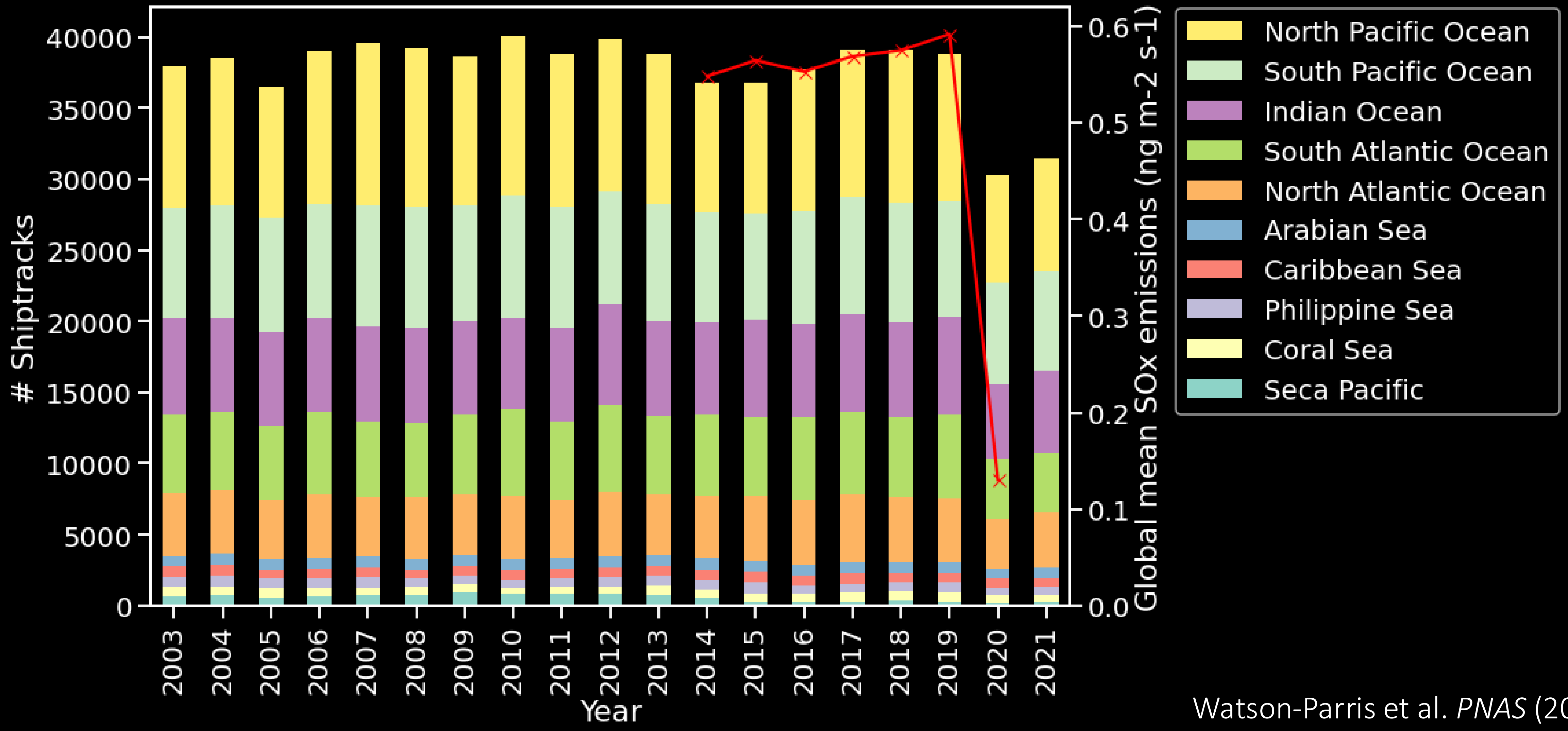


Watson-Parris et al. *PNAS* (2022)

Change in ship-track density: SECA



Ship-track counts (2003-2021)



Watson-Parris et al. *PNAS* (2022)

Measuring the causes of cloud transitions

Tim Pearce
ML Researcher

Sorawit Saengkyongam
ML Researcher

Will Jones
Clouds Researcher

Lucas Kruitwagen
Climate Researcher

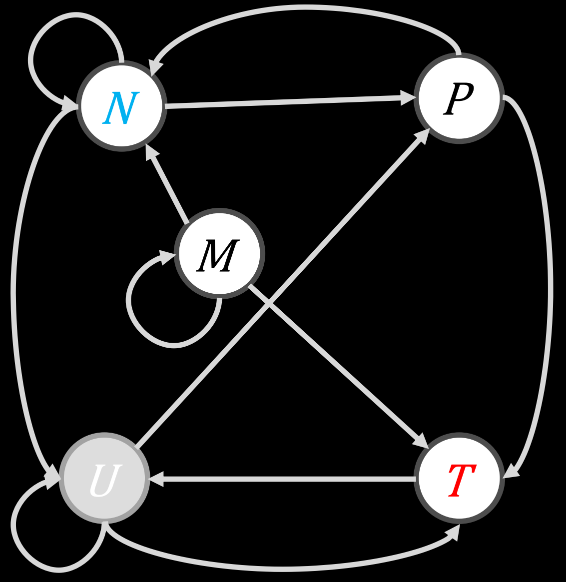
Matt Kusner
ML Lead

Matt Christensen
Domain Lead

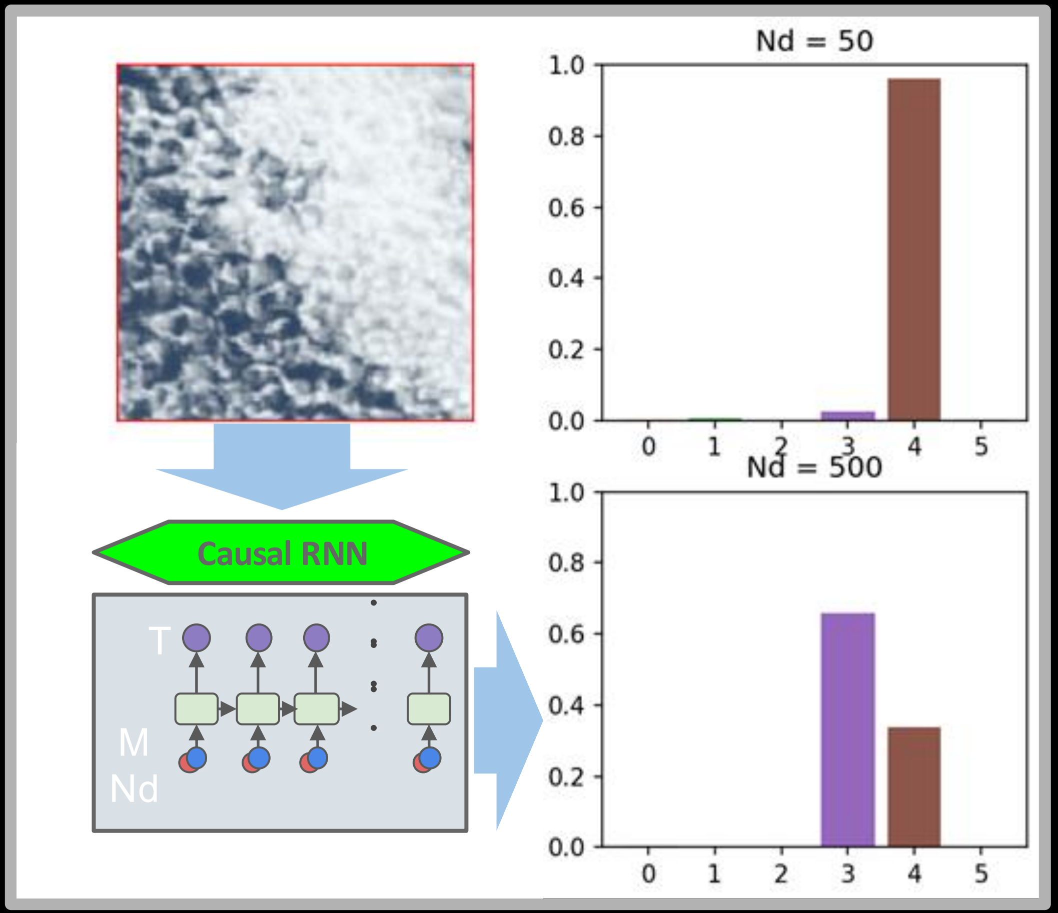
Duncan Watson-Parris
Super Mentor

Measuring the causes of cloud transitions

- Nd
- P(recipitation)
- U(nobserved) cloud properties
- T(ype)
- M(eteorology)



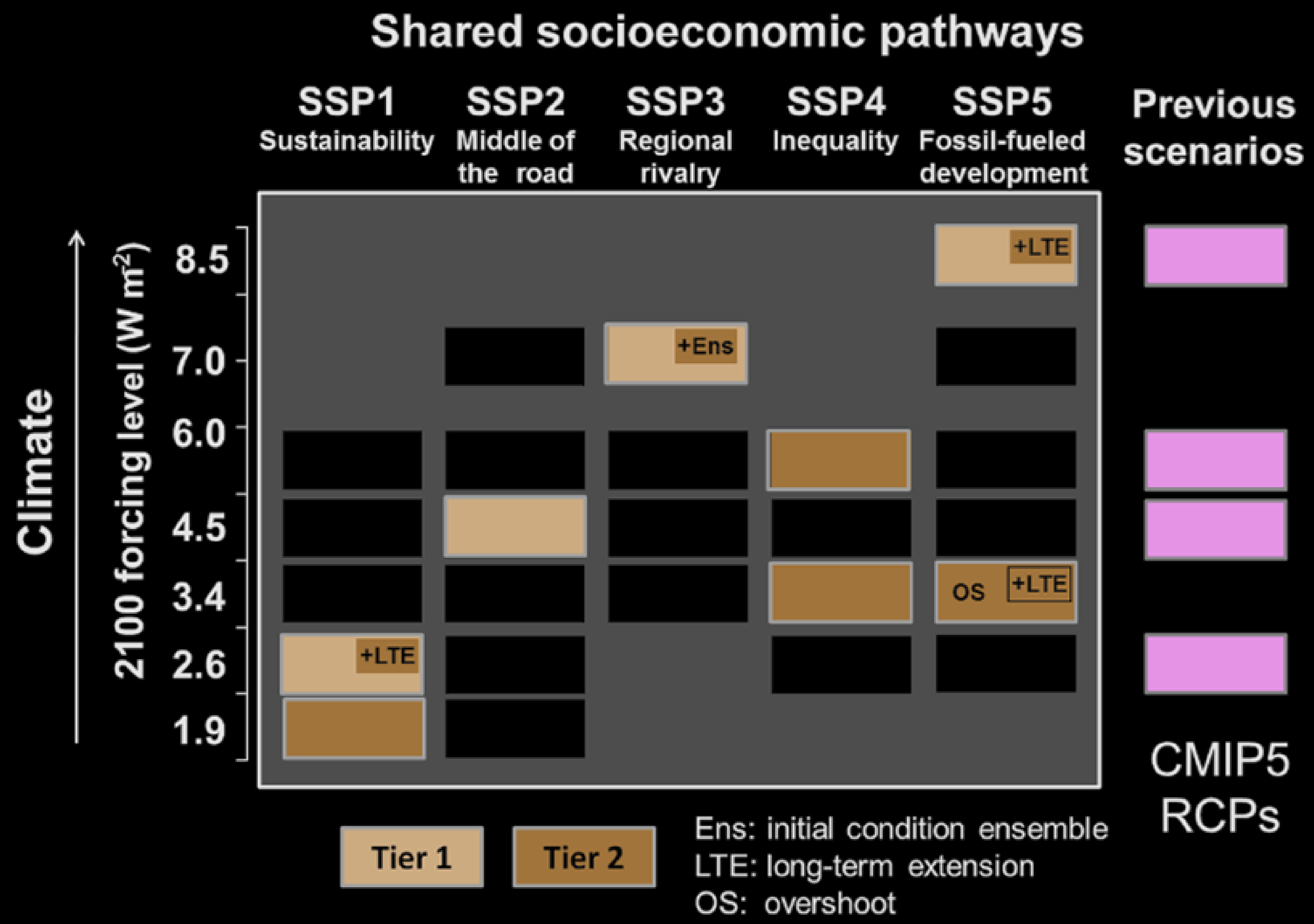
$$P(T_t|do(N_{t'}),M_t) = \sum_{M_{t'}N_{t'-1}P_{t'-1}} P(T_t|N_{t'},M_t,M_{t'}N_{t'-1}P_{t'-1})P(M_{t'}N_{t'-1}P_{t'-1})$$



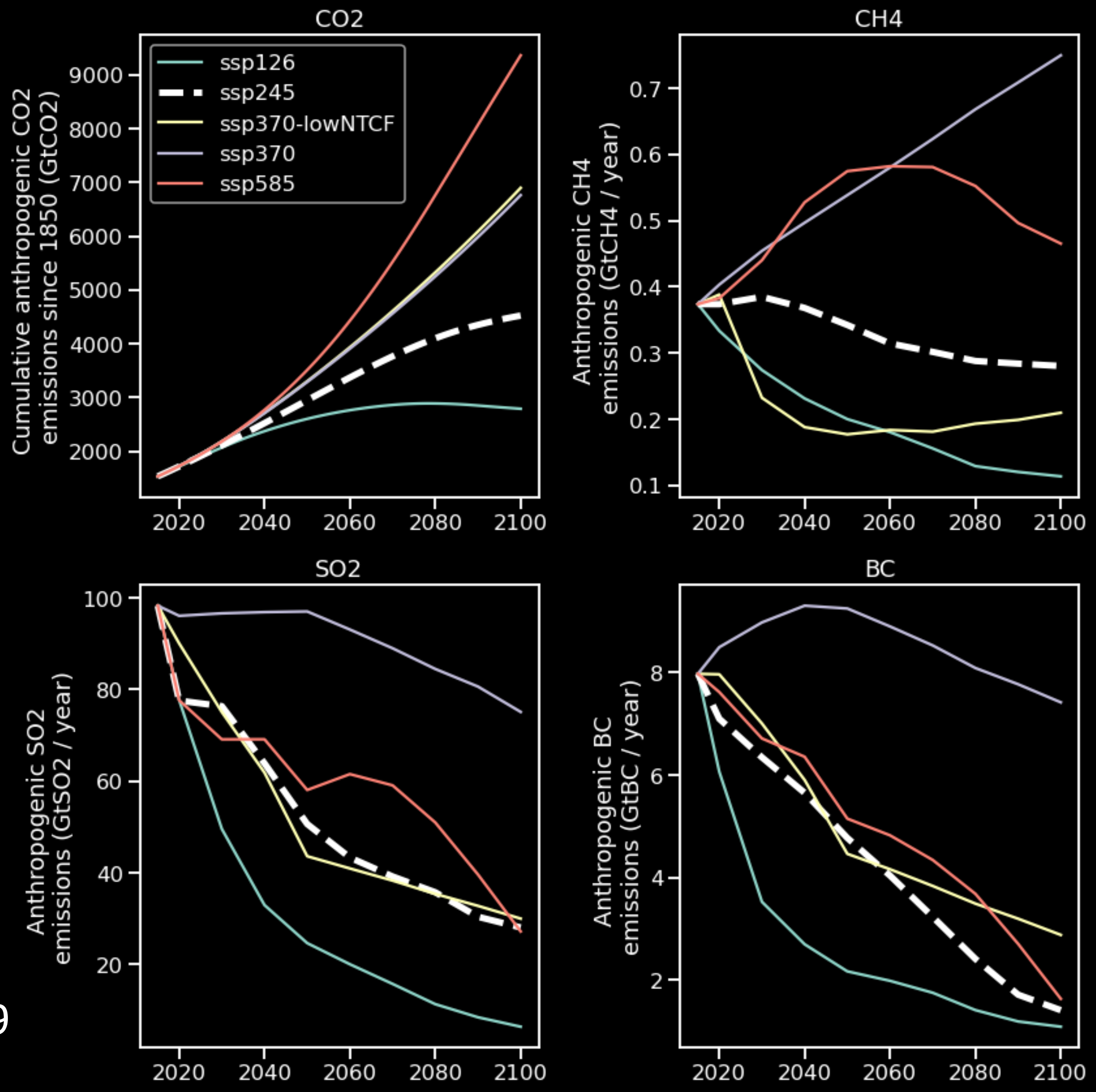
Watson-Parris et al. *in prep.*

Exploring different climates with emulators

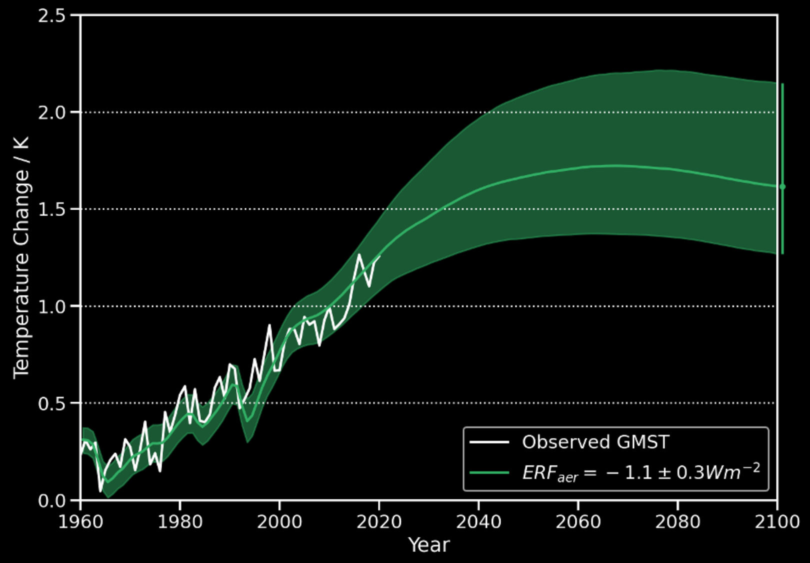
Climate projections: ScenarioMIP



Exploring different scenarios: (Simple) Emulators

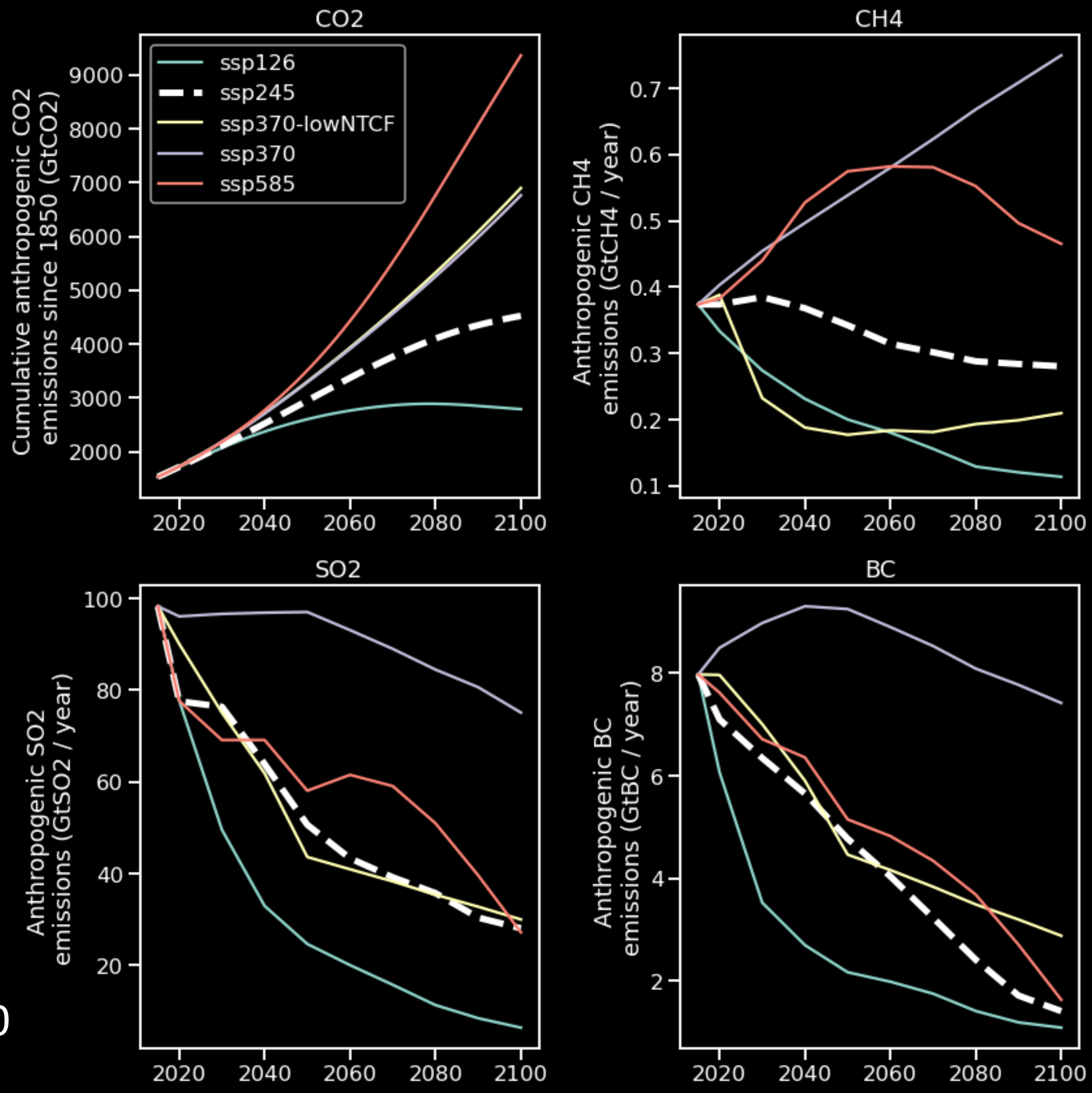


Emulate $|\mathcal{F}(X, \theta)|$

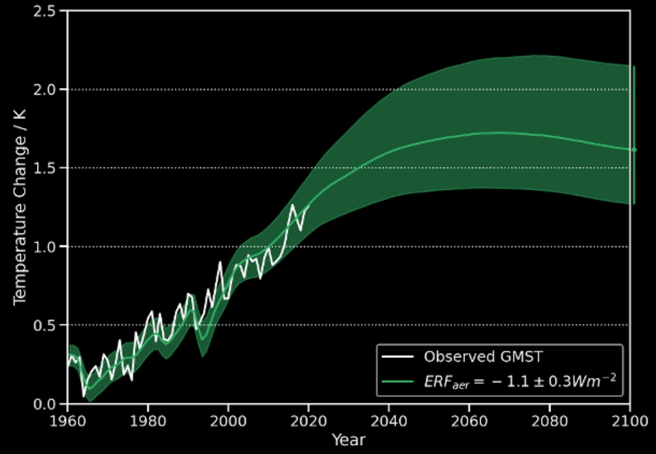


E.g., FAIR, MAGGIC, WASP etc.

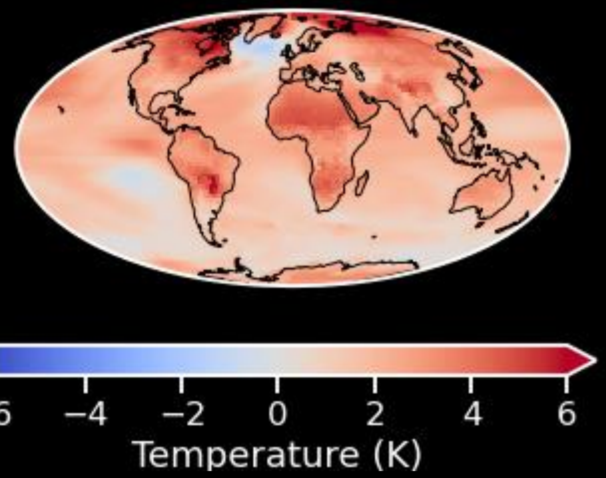
Exploring different scenarios: Pattern Scaling



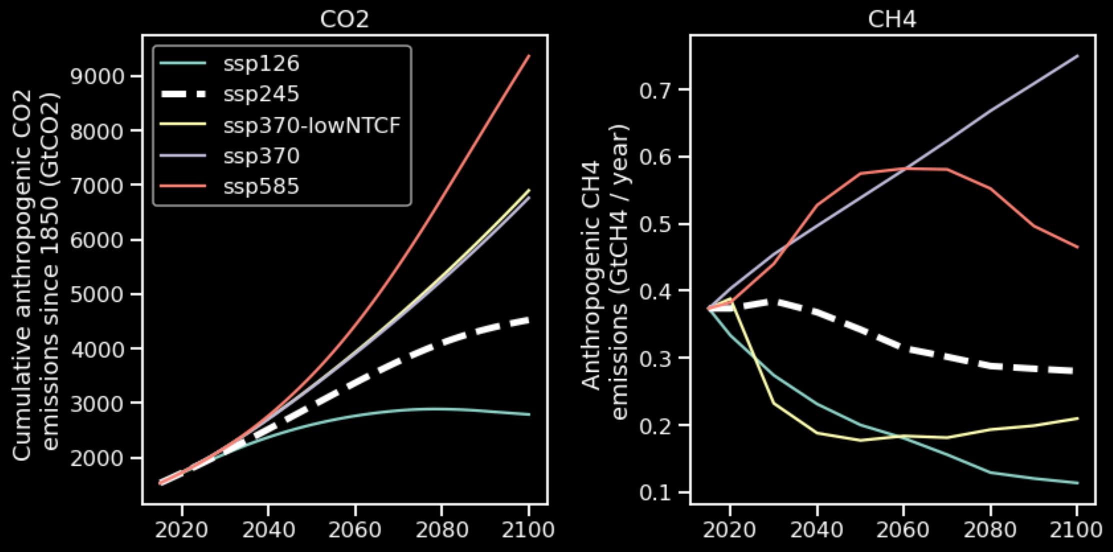
Emulate $|\mathcal{F}(X, \theta)|$



E.g., MESMER

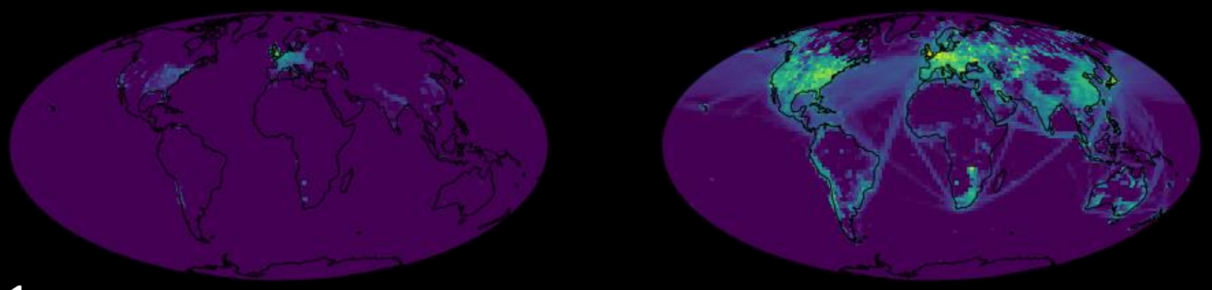


Exploring different scenarios: ClimateBench

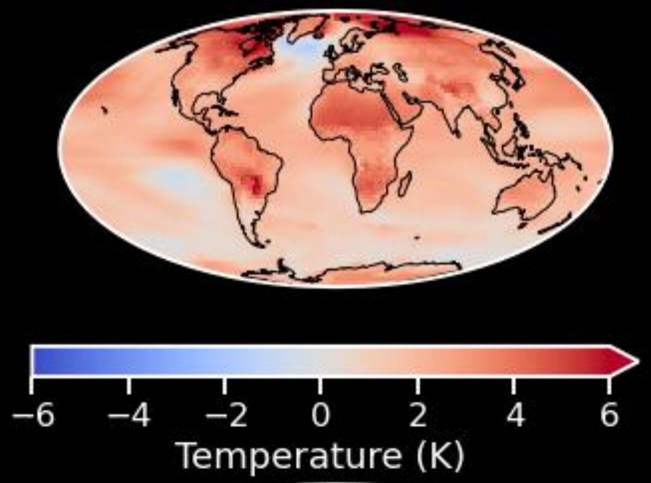


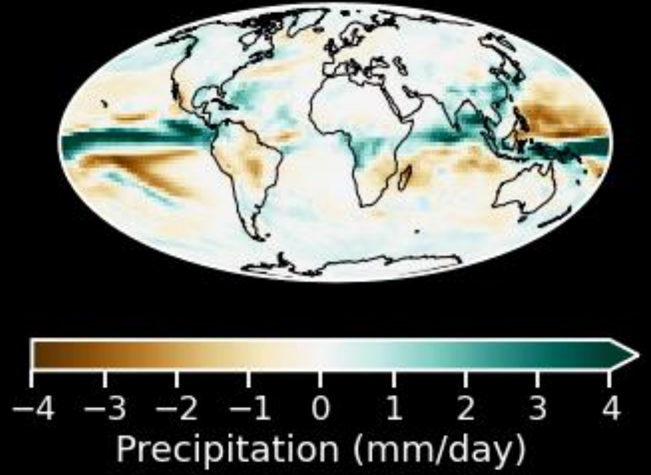
Spatially resolved emissions of SO_2 and BC

1850 2020



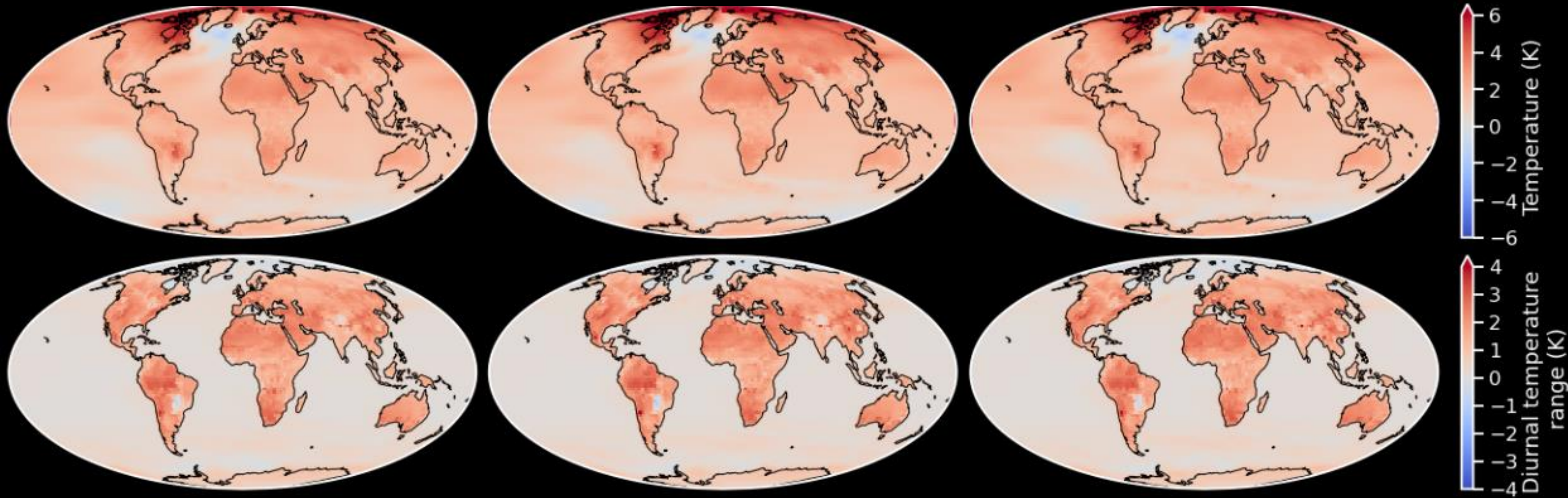
Emulate $\mathcal{F}(X, \theta)$





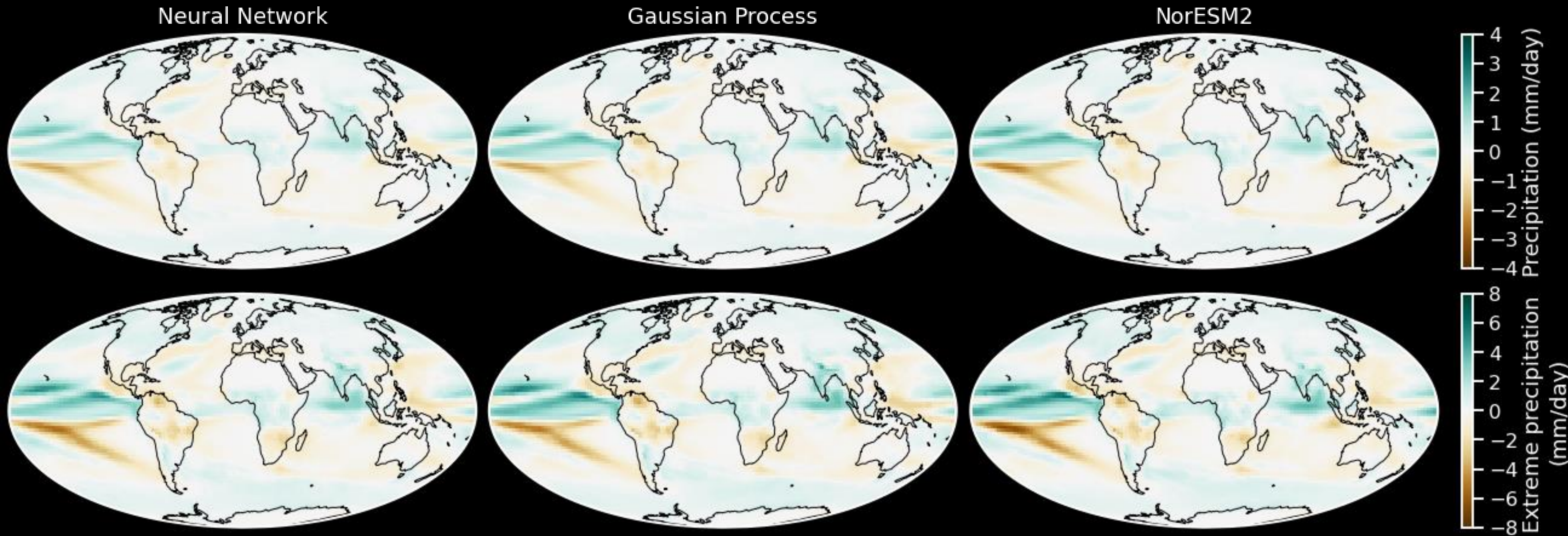
Watson-Parris et al. *JAMES* (2022)

Baseline Models



Watson-Parris et al. *JAMES* (2022)

Baseline Models



Watson-Parris et al. *JAMES* (2022)

Summary

- Machine learning can be harnessed to accelerate climate science
- Such techniques are used to create Earth system model emulators for parameter estimation and constraining uncertainty
- We have also used it for detecting ship-tracks and detecting and quantify the changes aerosol are causing on different clouds
- ClimateBench has enabled new emulators for the fast and accurate exploration of different future climates
- Ultimately these approaches will allow better informed policy.

ClassBuzz

MM3Z

Spare slides

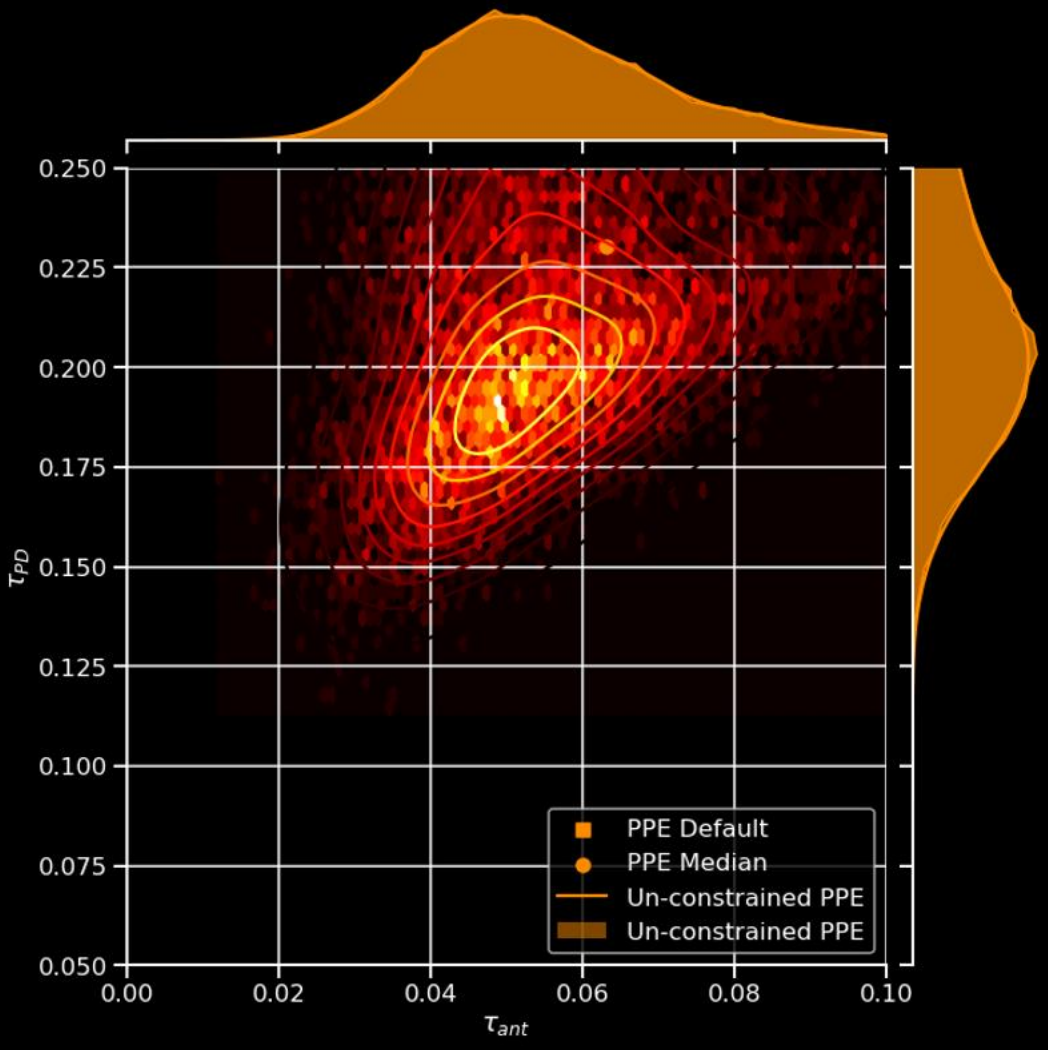
Box model of the climate

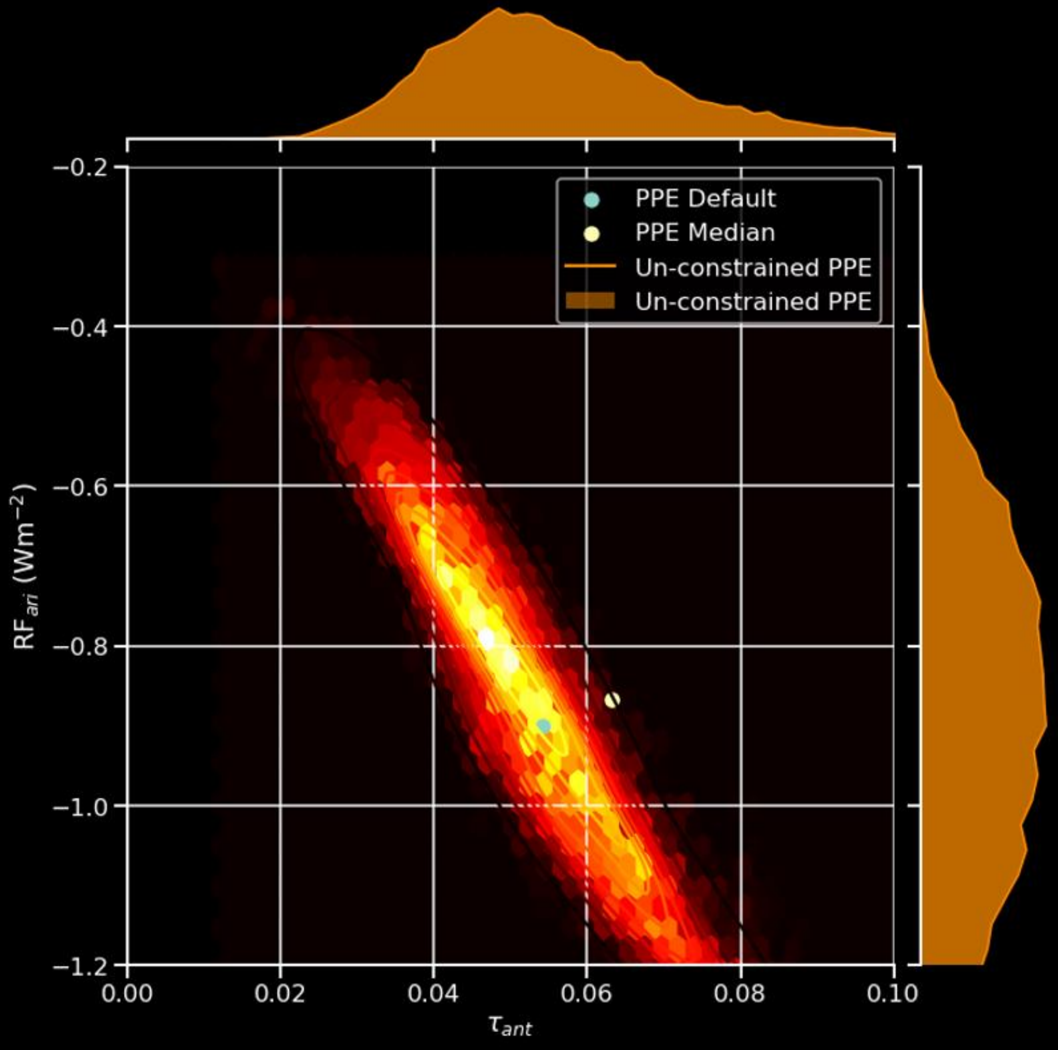
The simplest model we can write of the climate system:

$$C\frac{dT}{dt} = F_{ext} - \lambda T$$

- T is the global average surface temperature change.
- C is the "effective heat capacity".
- F_{ext} is imbalance between incoming and outgoing energy.
- λ is a constant "sensitivity parameter".

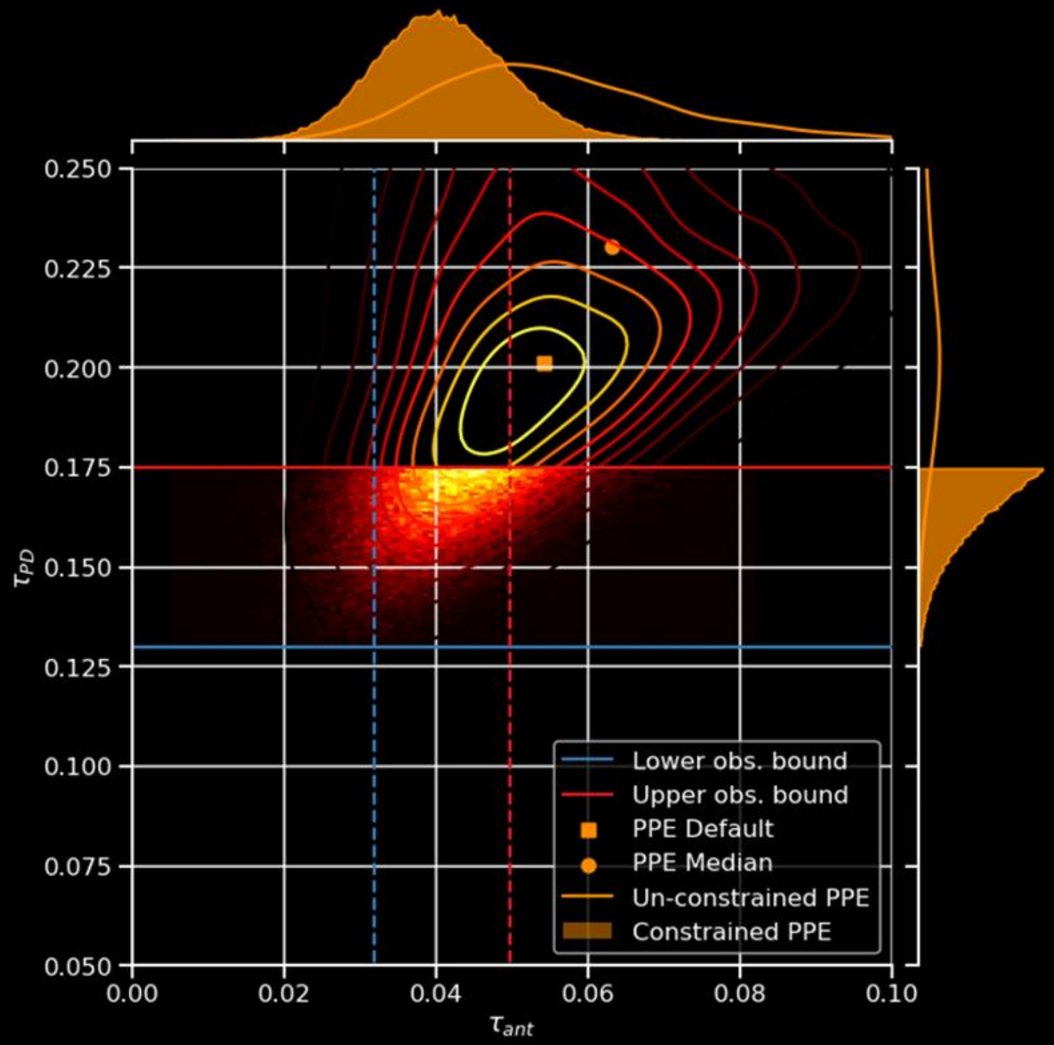
Constraining parametric uncertainty

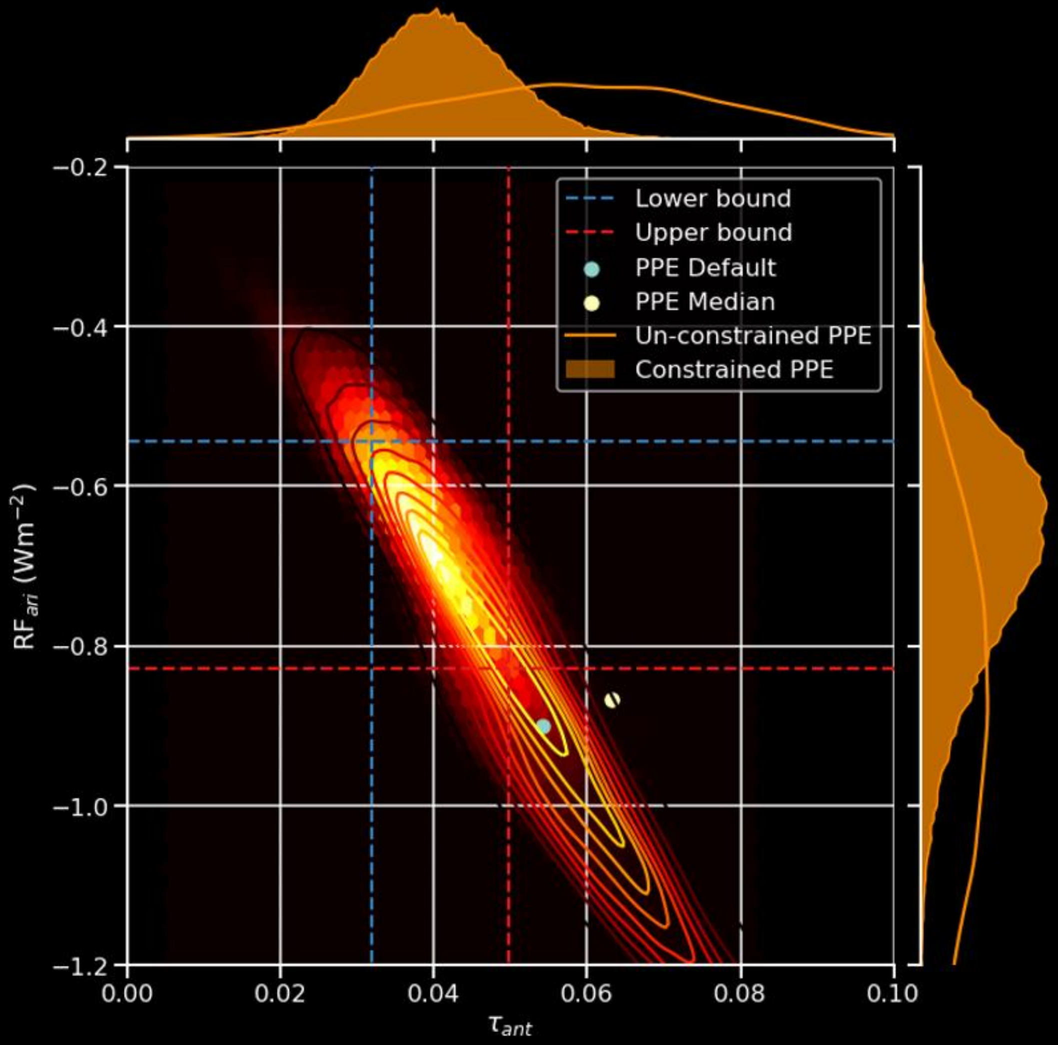




Watson-Parris et al. *GRL* 2020

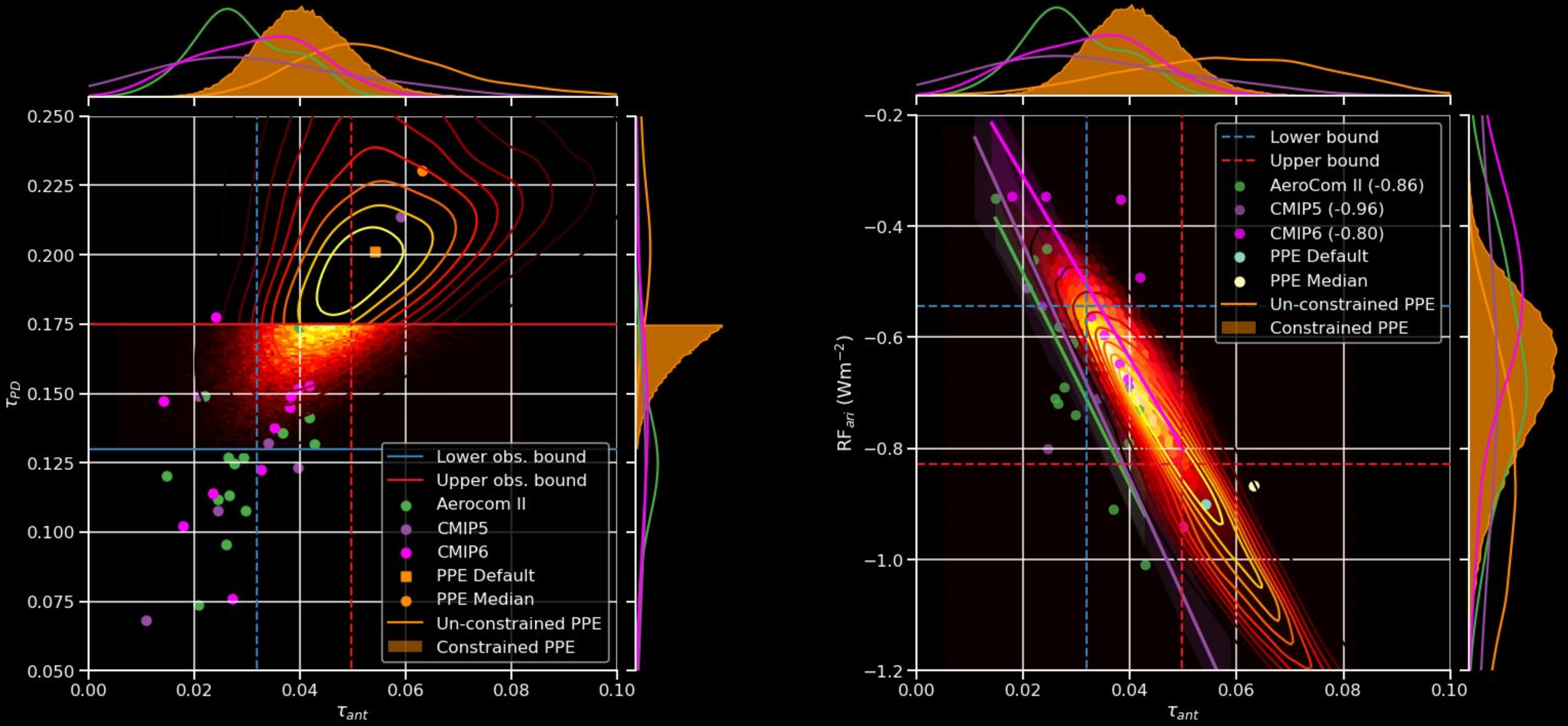
Constraining parametric uncertainty





Watson-Parris et al. *GRL* 2020

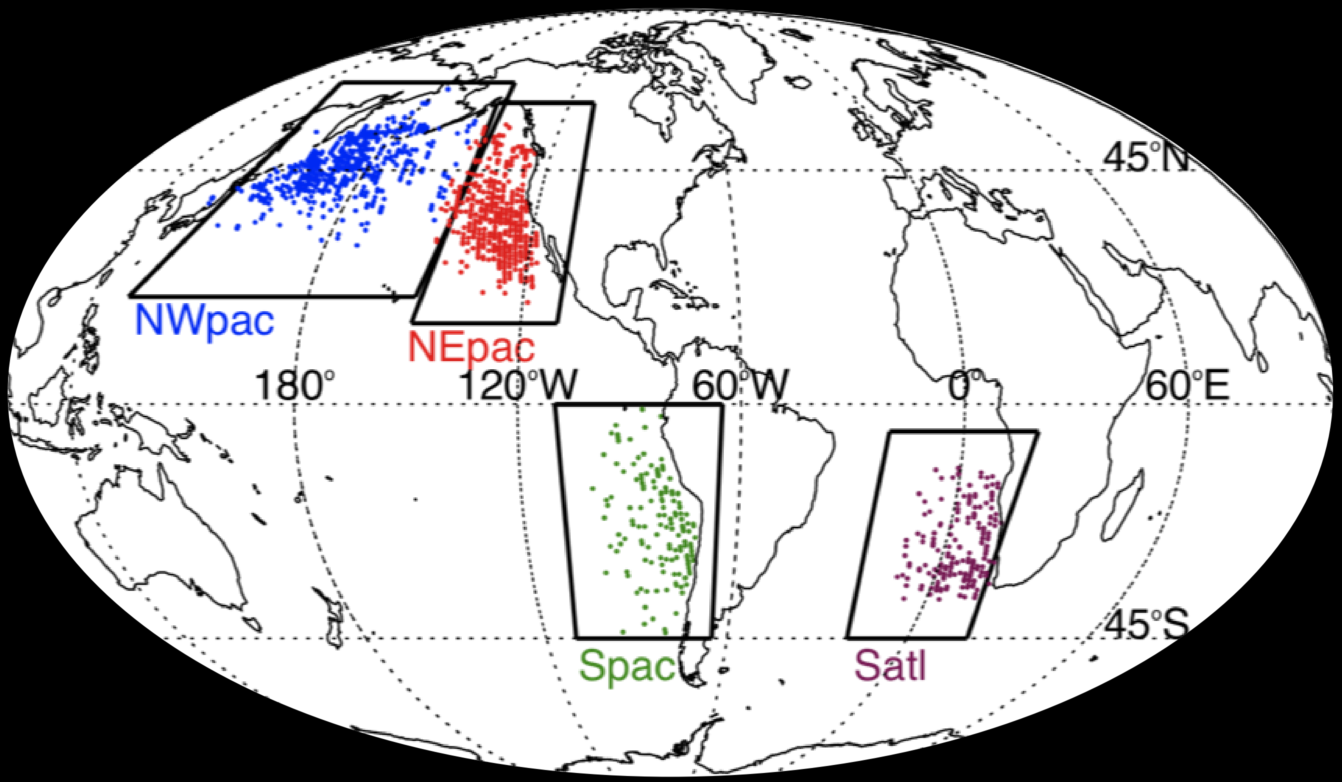
Constraining parametric uncertainty

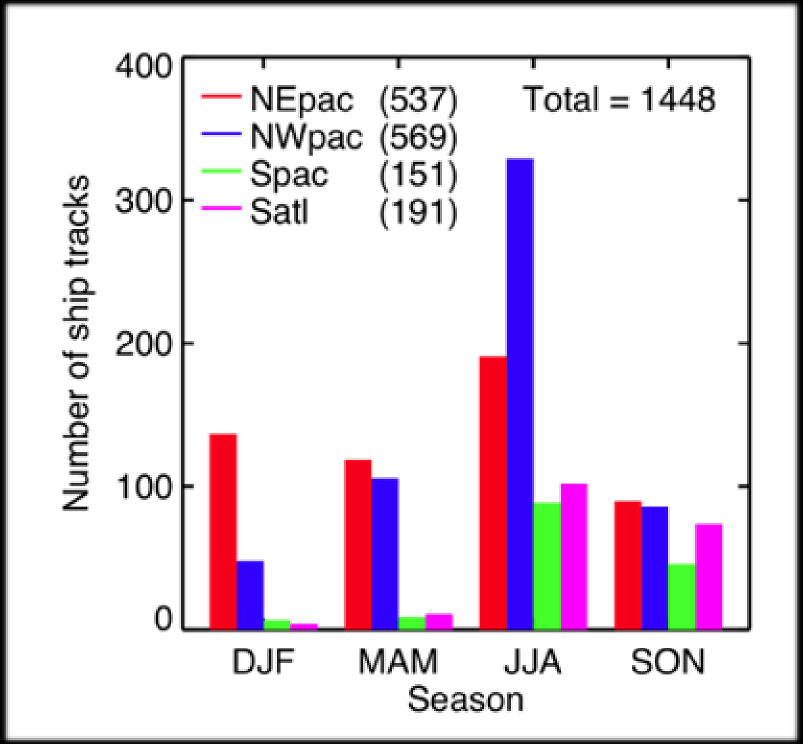


Watson-Parris et al. *GRL* 2020

Shiptrack spares

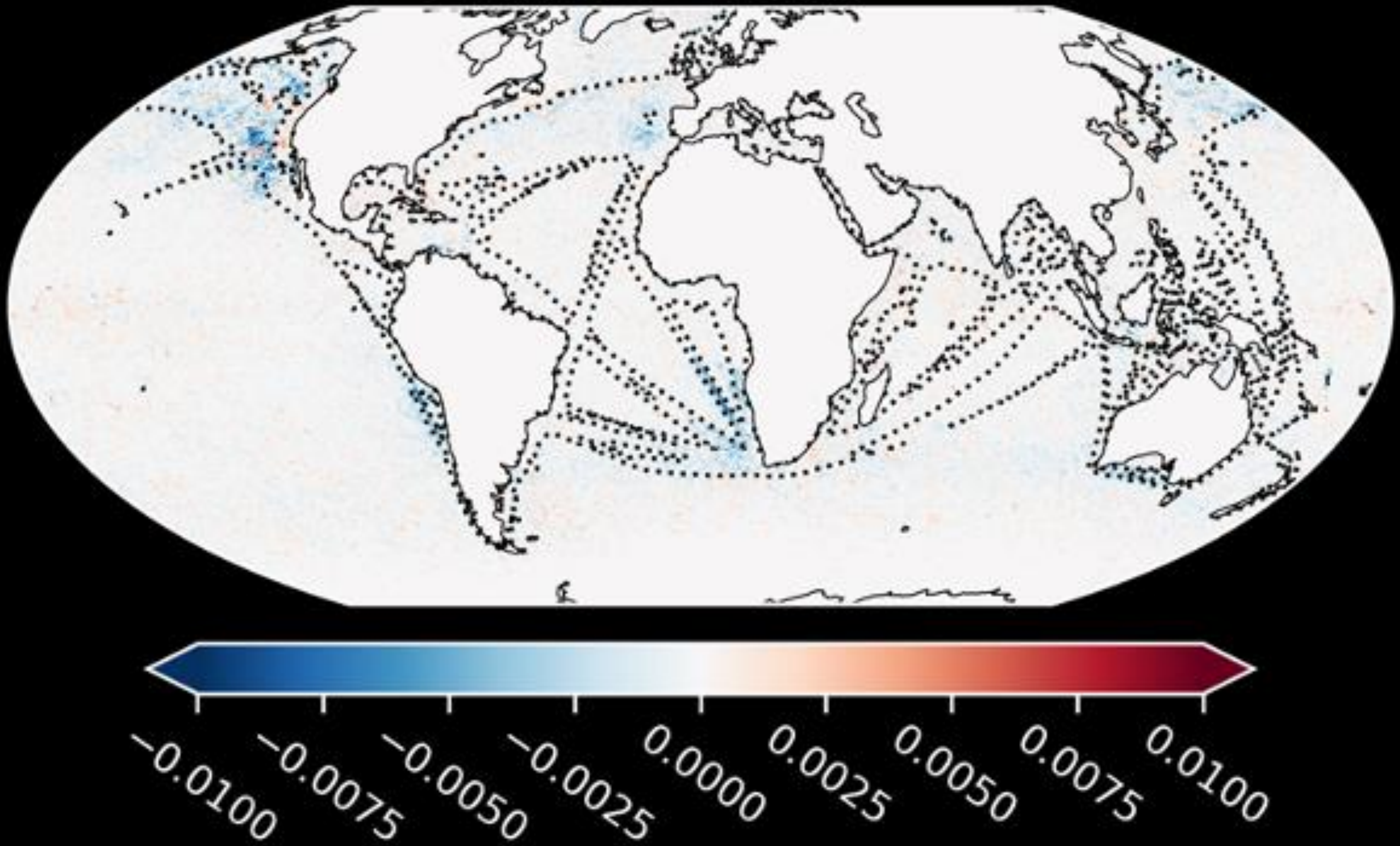
Training data

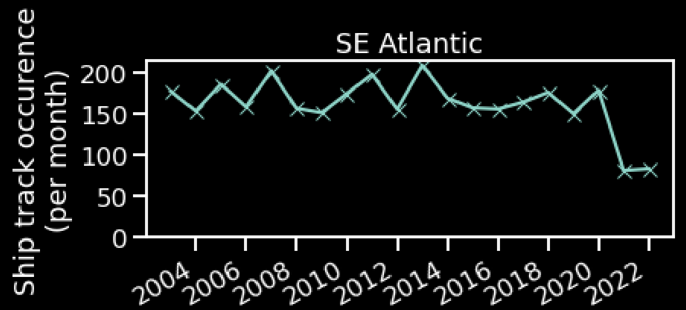


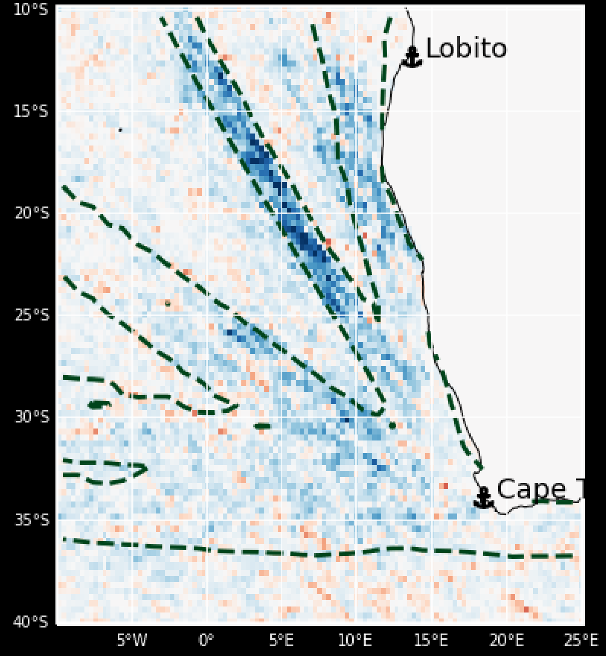


4,000 ship tracks from Segrin et al. (2007), off the coast of California (MODIS)
1,000 volcano tracks from Toll et al. (2017), South Sandwich and Kuril Islands
***Total:* 5,500 hand-logged tracks**

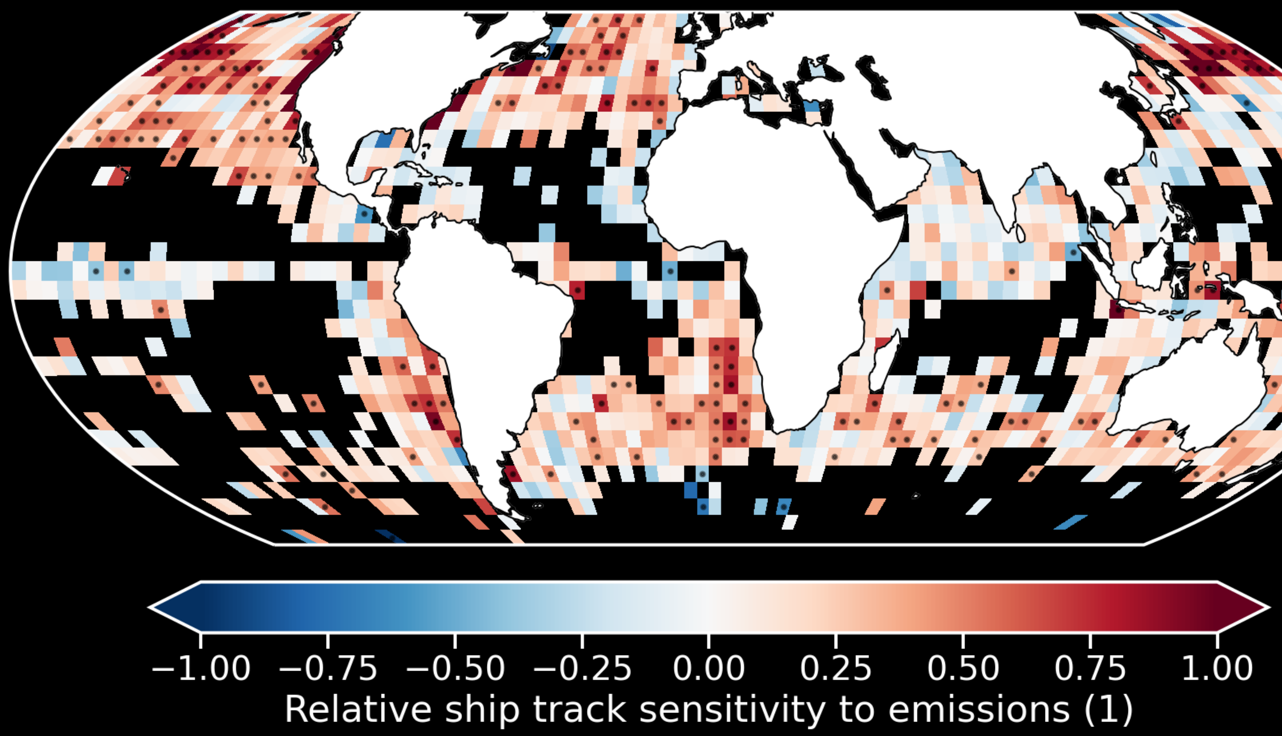
Change in ship-track density: IMO

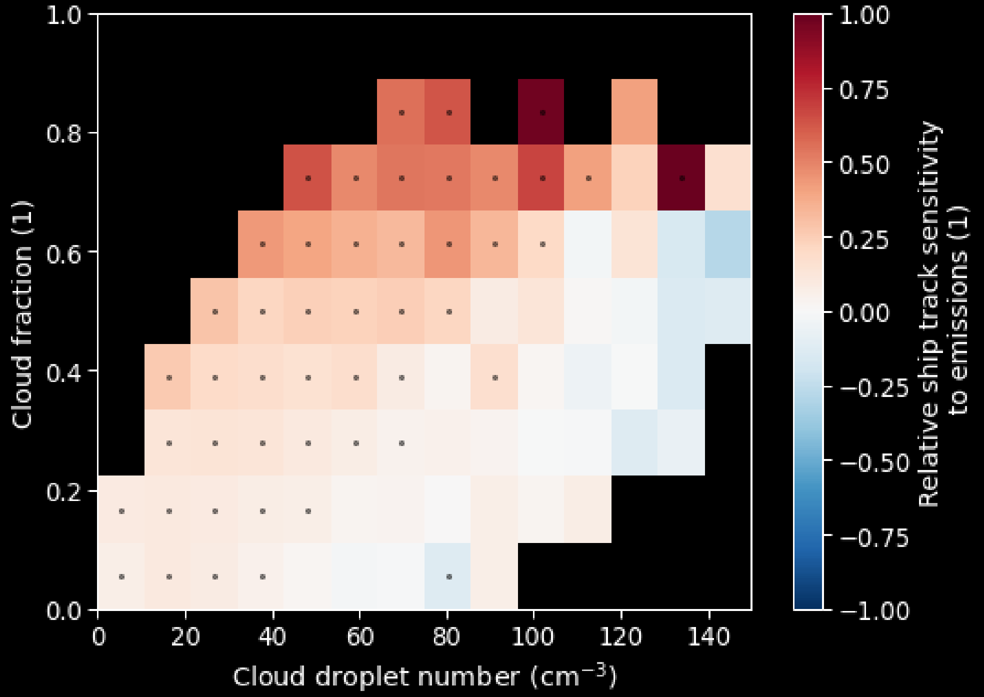






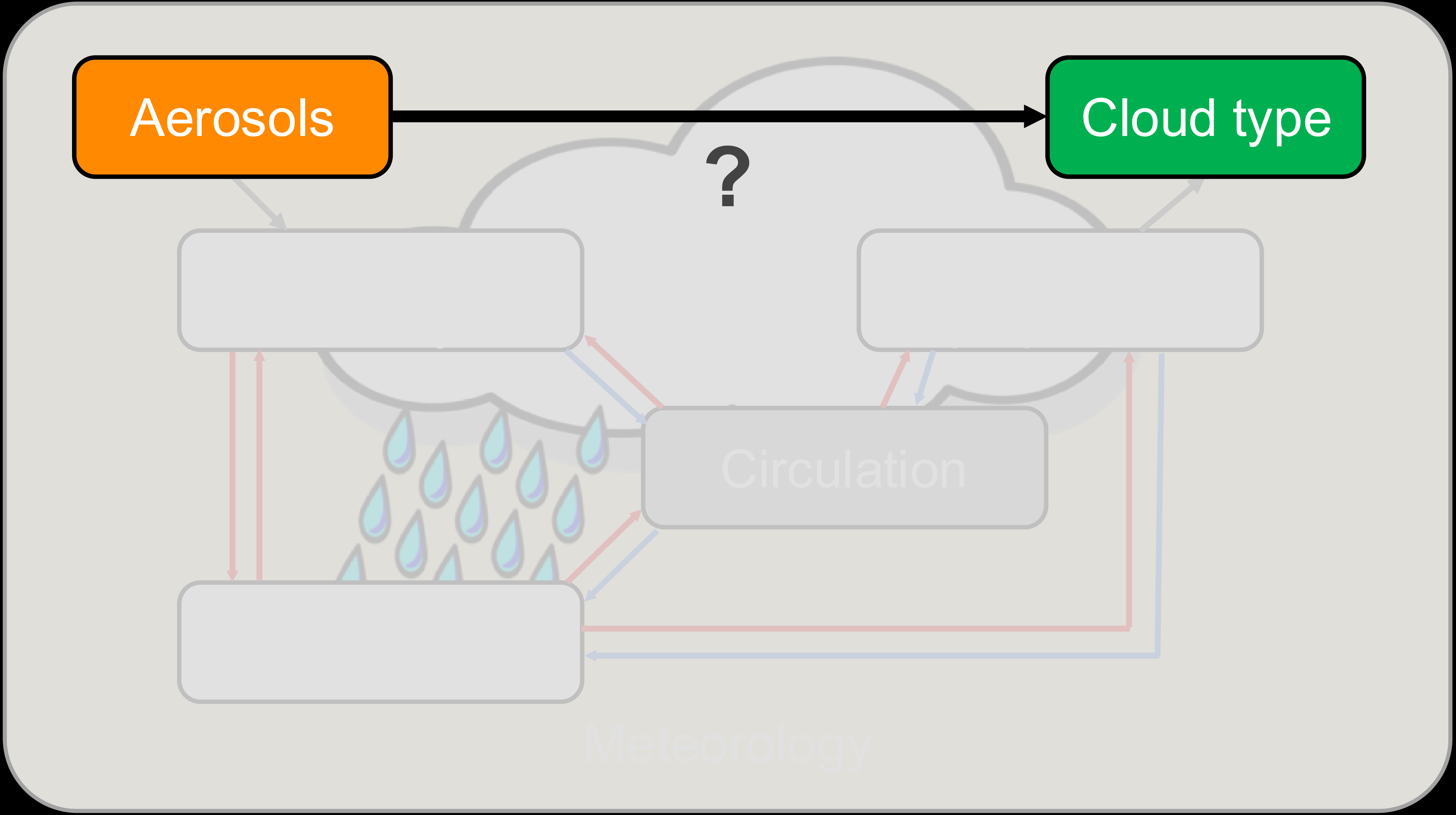
Ship-track sensitivity to emissions



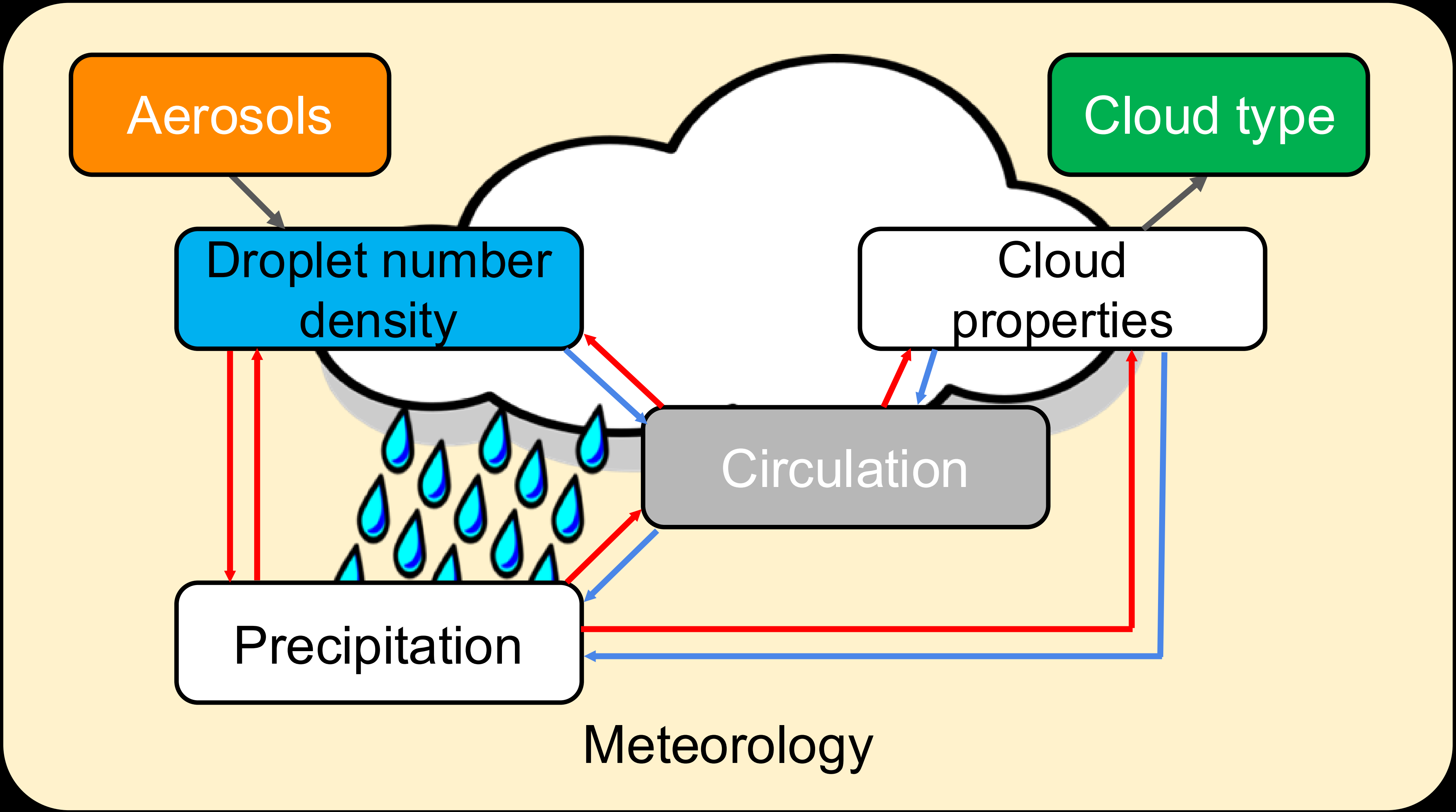


Causal spares

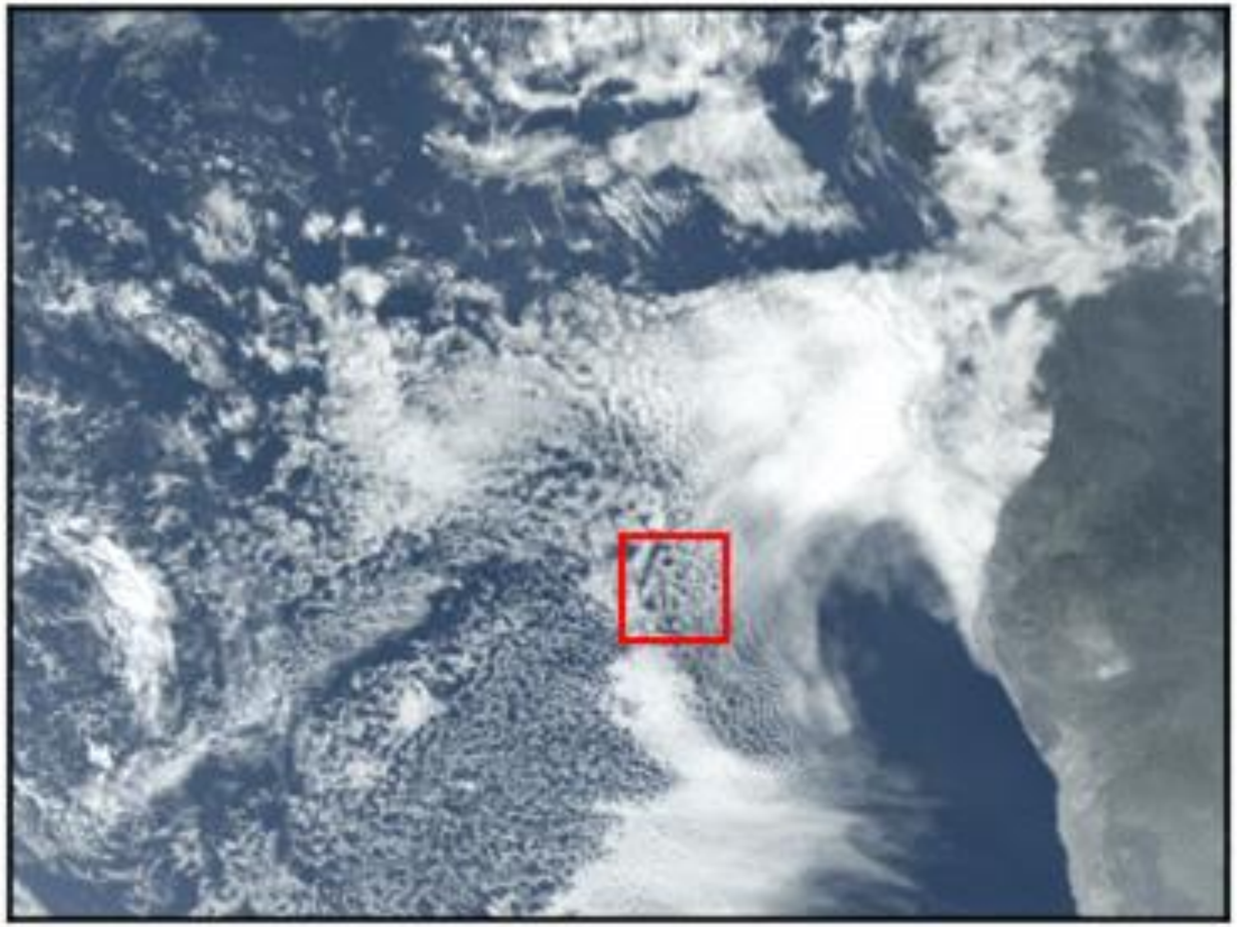
Causal Effect of Aerosol on Cloud Type



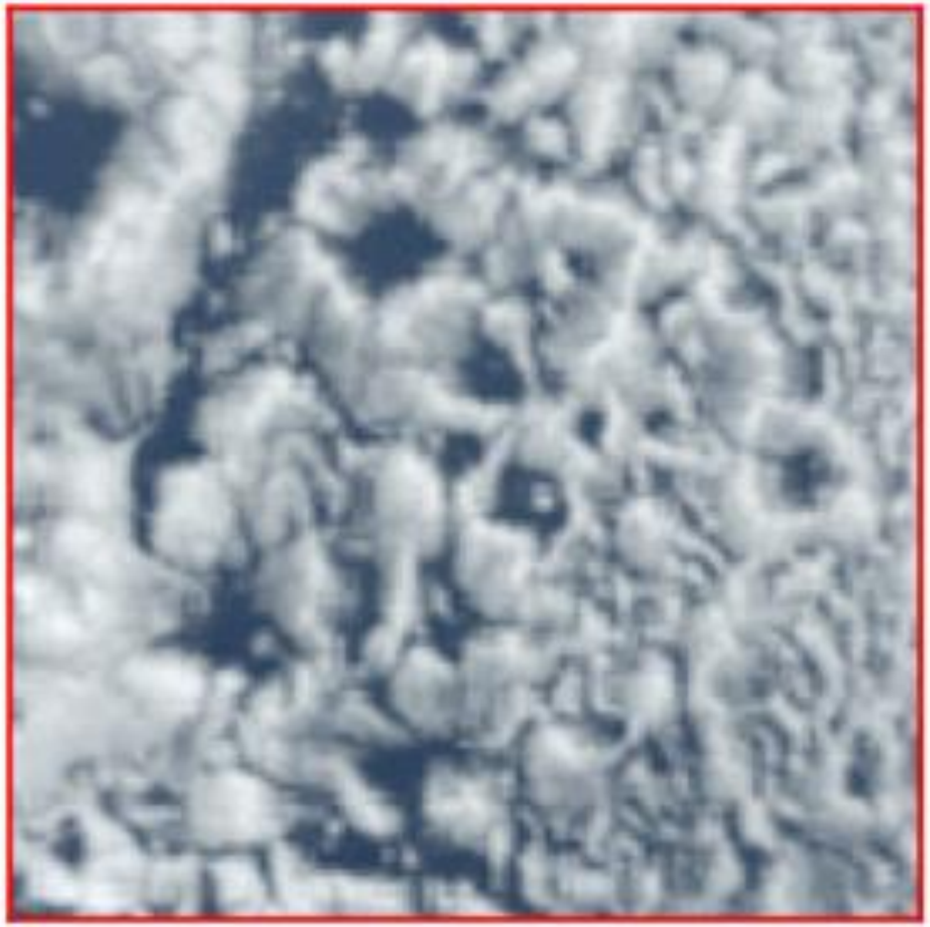
Causal Effect of Aerosol on Cloud Type



Lagrangian Reference Data

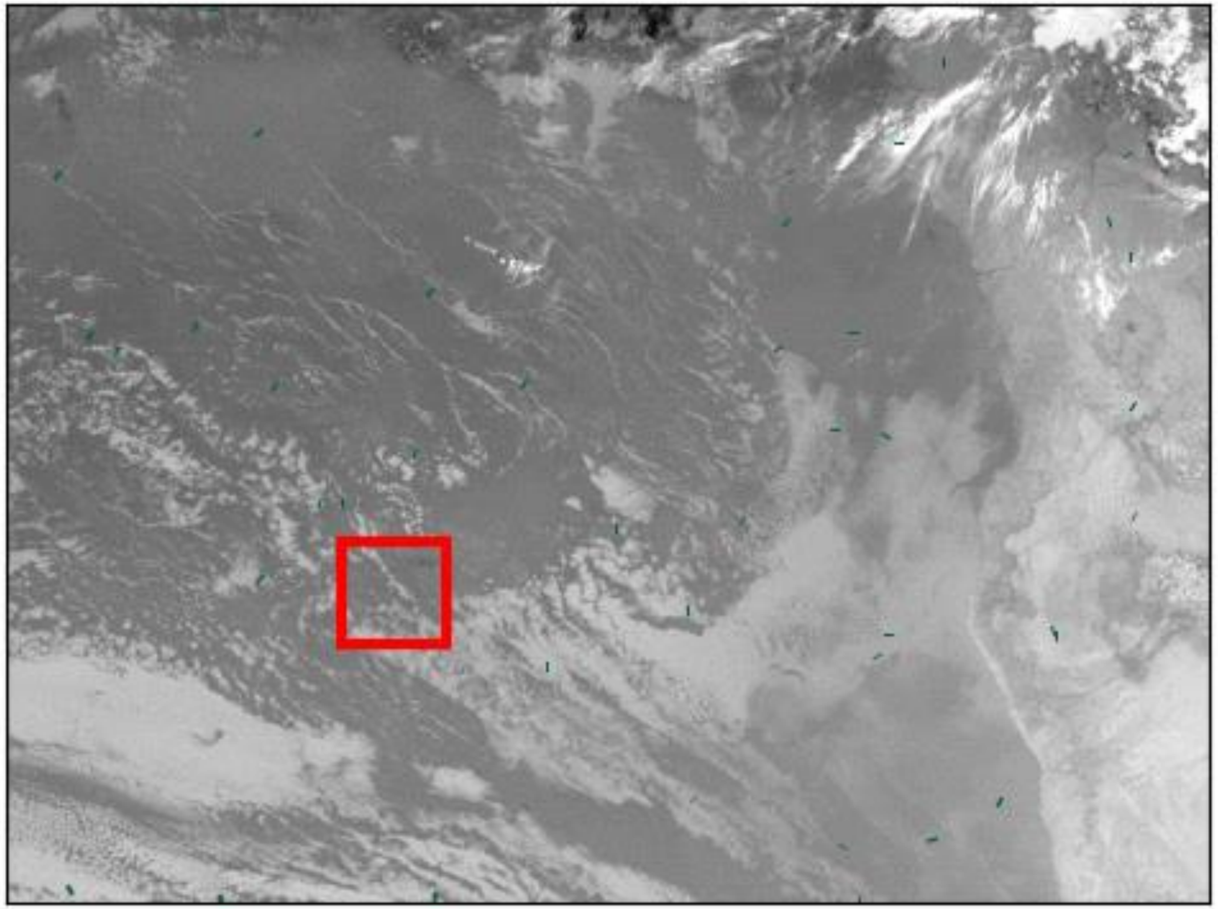


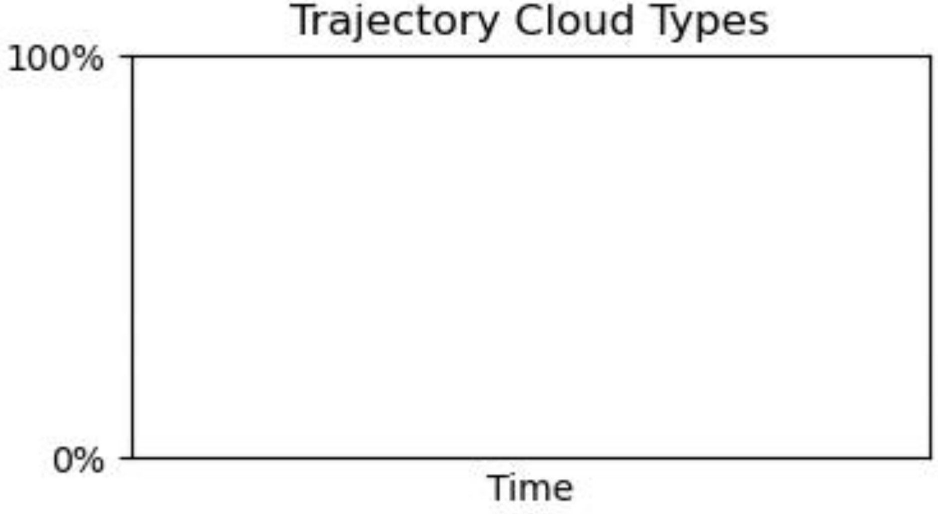
4500km



400km

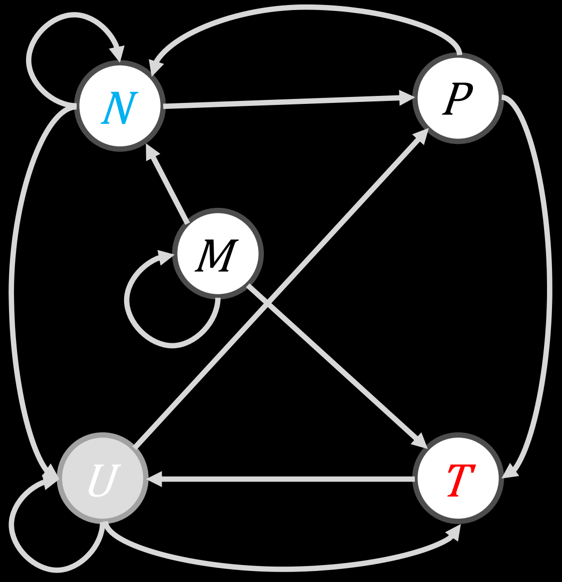
Cloud Types Along Trajectories



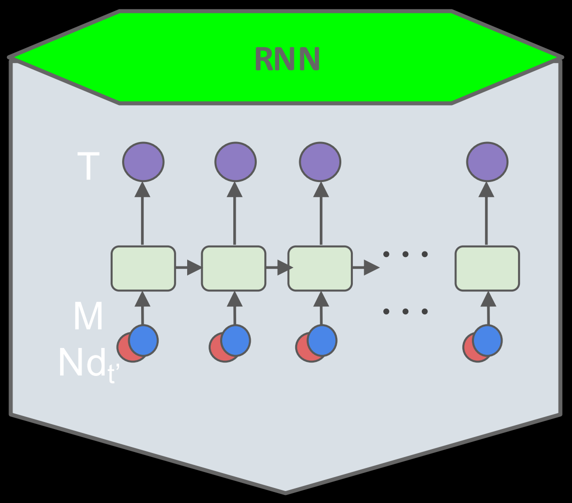


Causal Effect of Droplet Number on Cloud Type

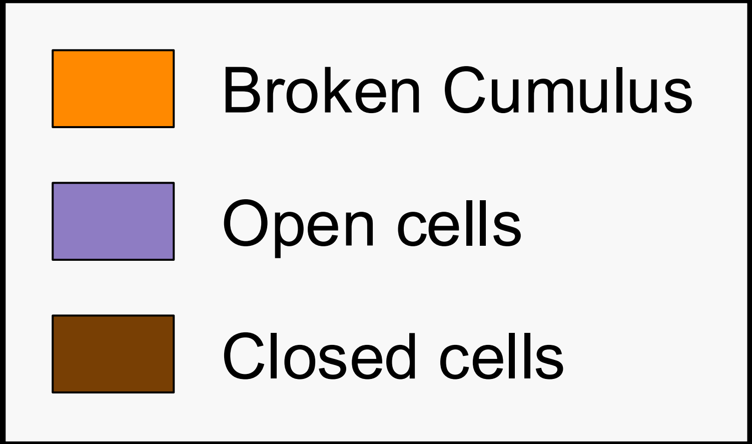
- Nd
- P(recipitation)
- U(nobserved) cloud properties
- T(ype)
- M(eteorology)

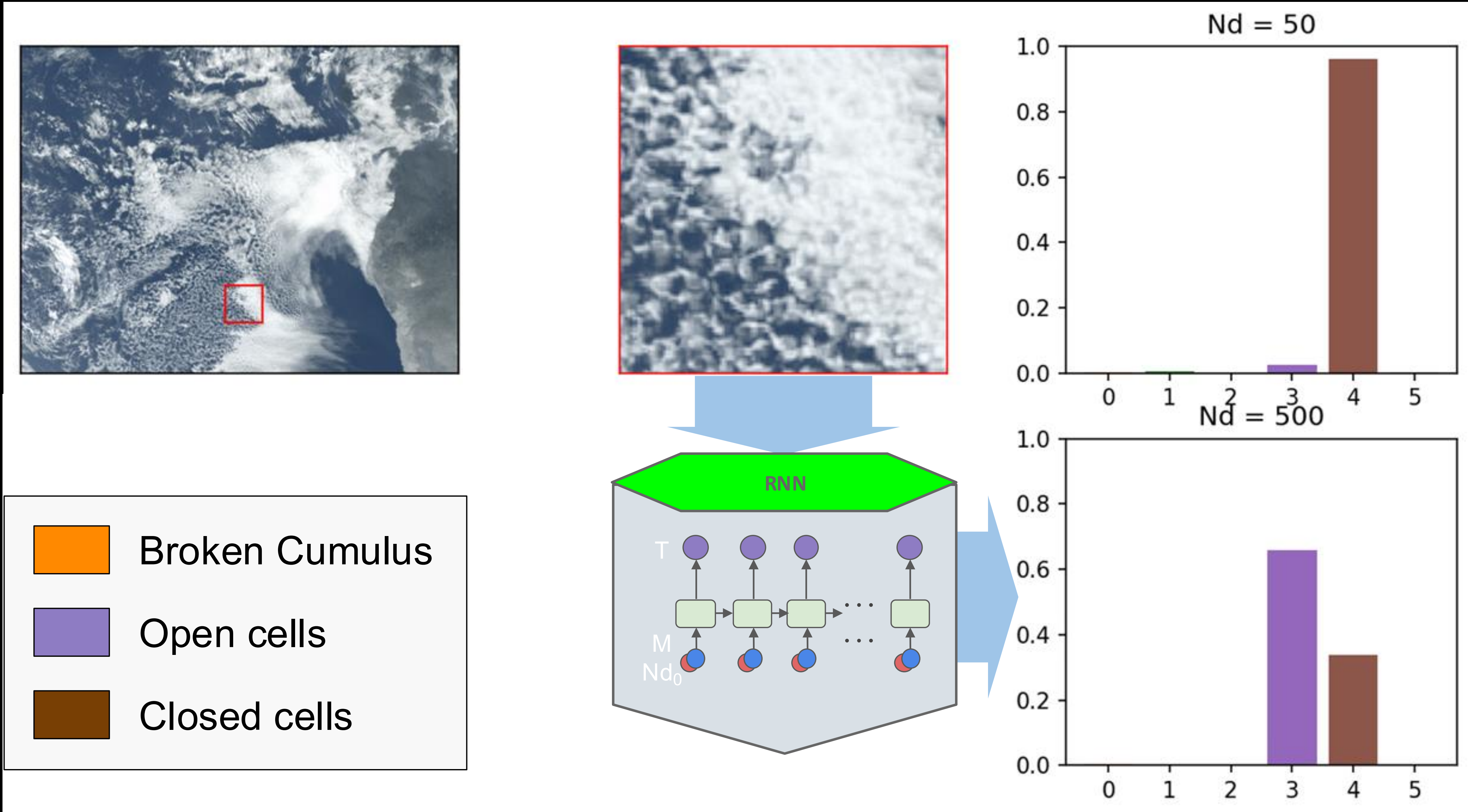


$$P(T_t | do(N_{t'}), M_t) = \sum_{M_{t'} N_{t'-1} P_{t'-1}} \underbrace{P(T_t | N_{t'}, M_t, M_{t'} N_{t'-1} P_{t'-1}) P(M_{t'} N_{t'-1} P_{t'-1})}$$



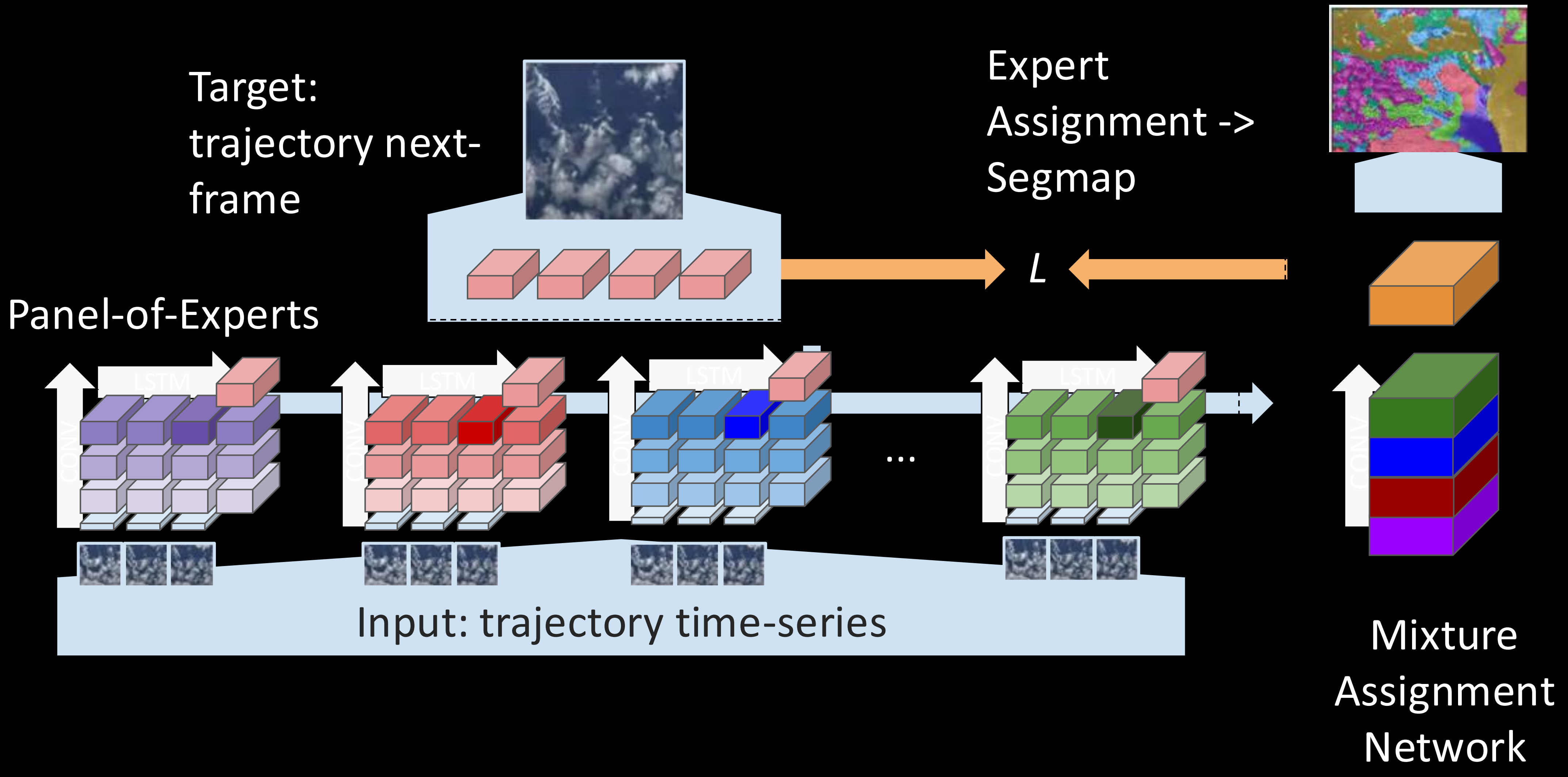
What if we increased the aerosols?





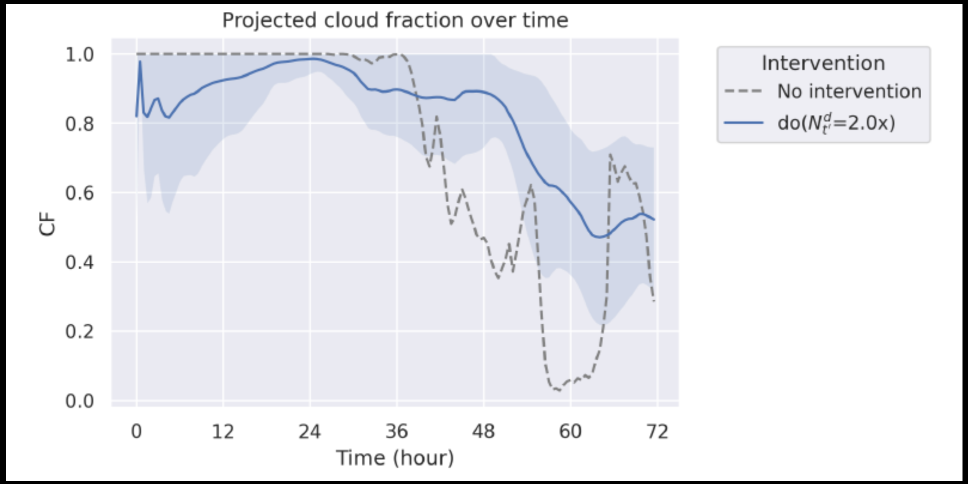
Broken Cumulus
Open cells
Closed cells
RNN
T
M
Nd_0
Nd = 50
Nd = 500
1.0
0.8
0.6
0.4
0.2
0.0
0
1
2
3
4
5

Self-supervised Learning of Cloud Types
Mixture-of-Experts

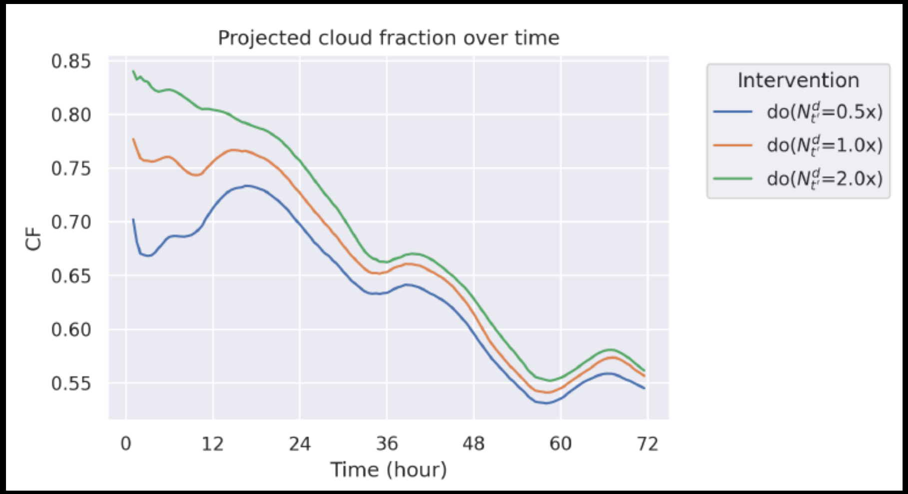


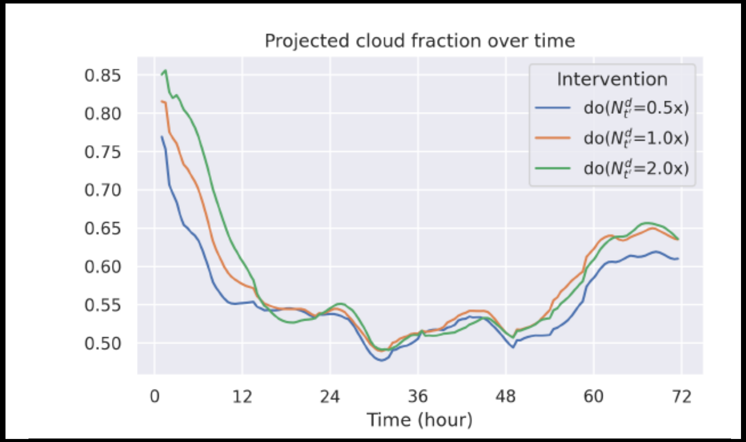
Causal Effect of Aerosol on Cloud Fraction

a) Example trajectory

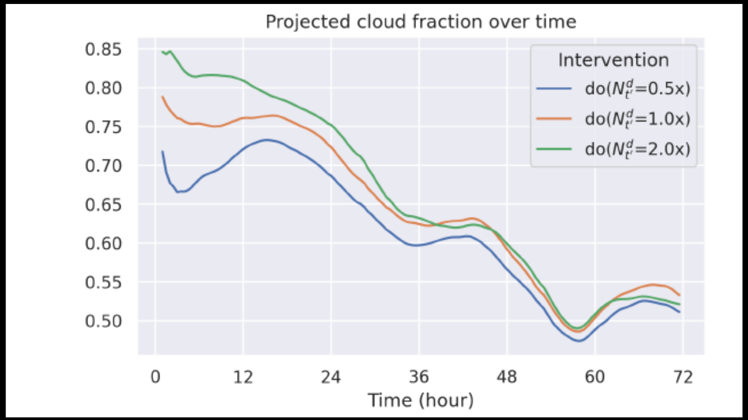


b) Mean trajectory

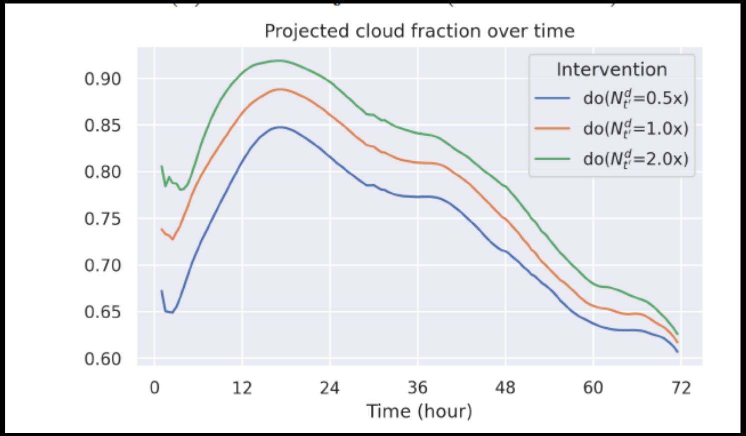




c) Unstable trajectories (16.5 +/- 1.5K)



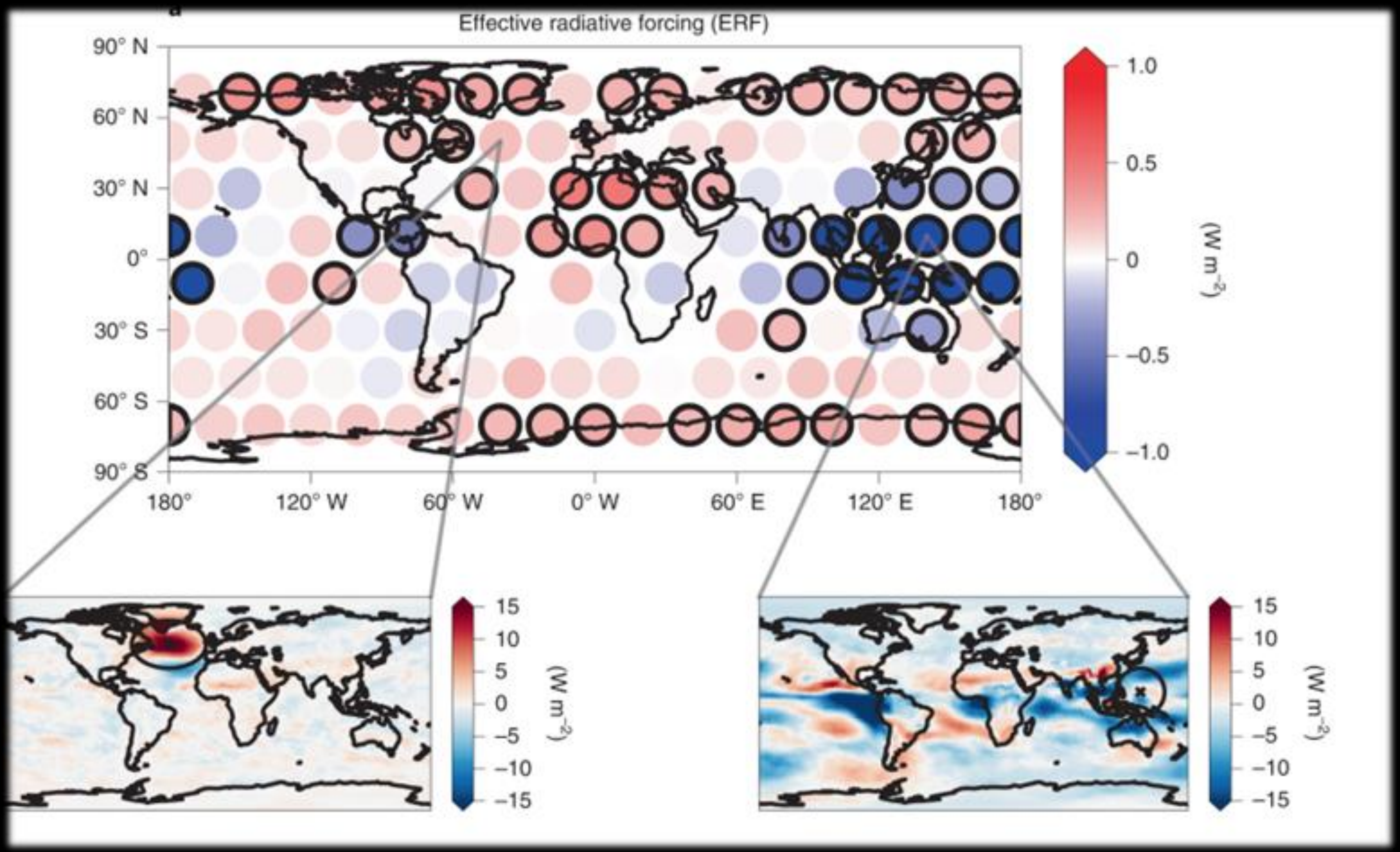
d) Stable trajectories (22.5 +/- 1.5K)



e) Very Stable trajectories (28.5 +/- 1.5K)

ClimateBench spares

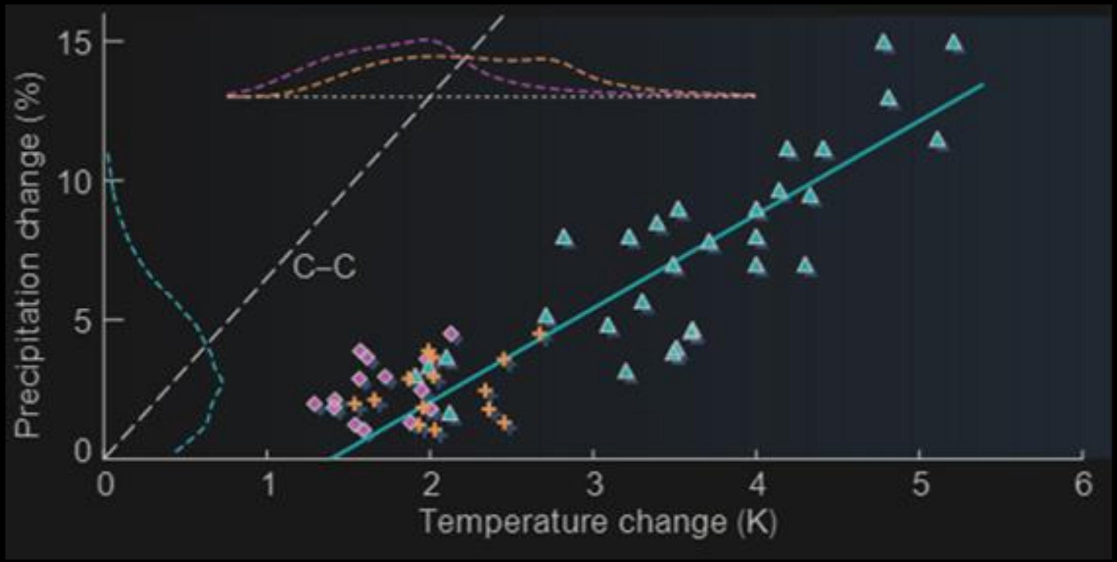
Dependence of forcing on spatial distribution



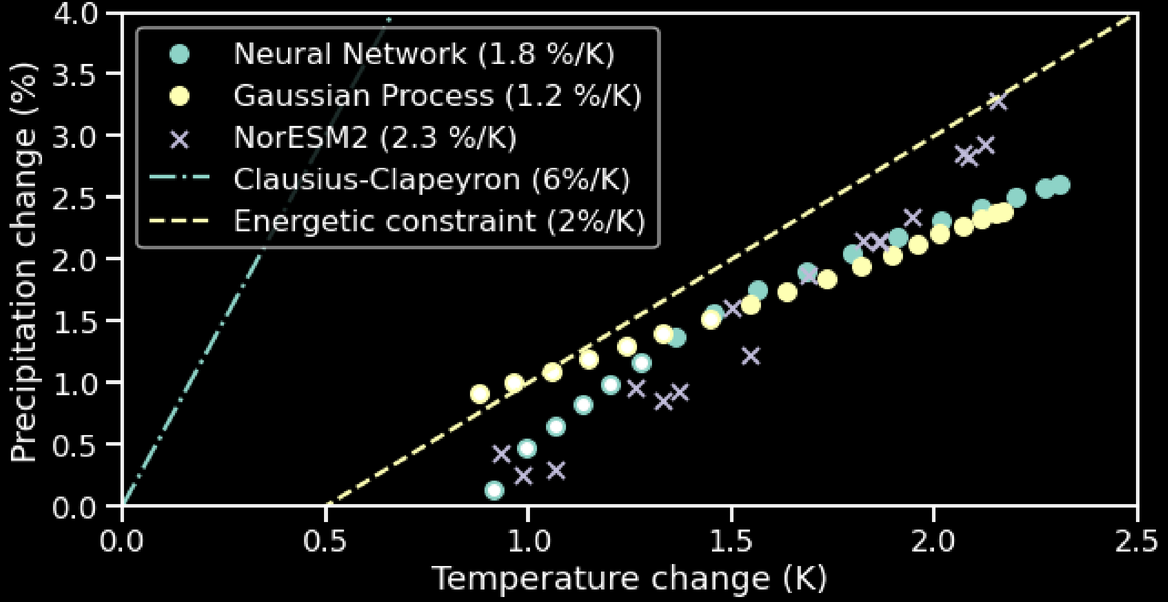
Williams et al. *Nat. Clim. Change* (2022)

Global energy conservation

$$L\Delta P \cong \Delta R$$



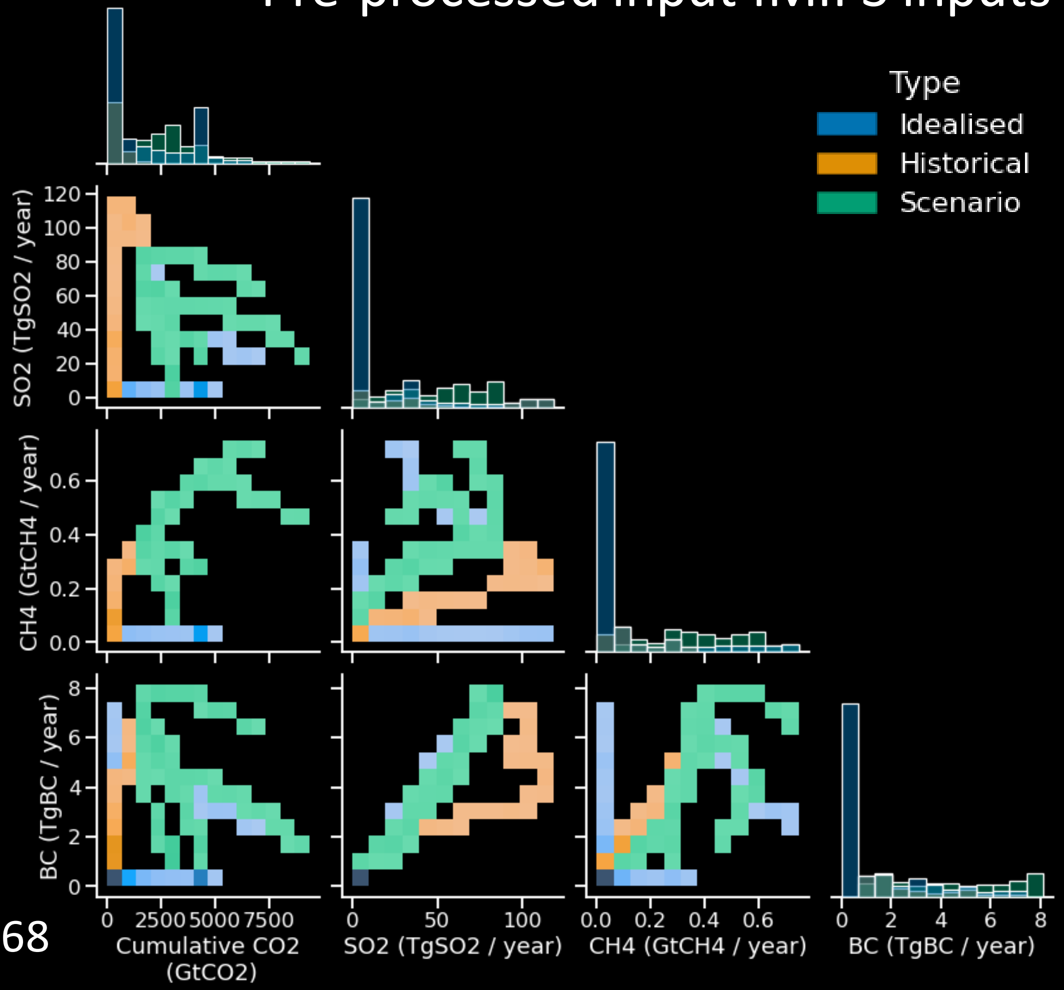
Allen & Ingram 2002



Watson-Parris et al. *JAMES* (2022)

ClimateBench training dataset

Pre-processed input4MIPS inputs and NorESM2 outputs for multiple experiments



- Selection of future socio-economic pathways designed to span range of likely future scenarios
- Two idealised simulations modelling the effect of abrupt and gradual increases in CO2
- Core historical experiment plus two detection and attribution simulations of the historical period with either aerosol or GHG held constant
- Together they do a good job of spanning the input space – although aerosol species are correlated

Seland et al. 2020

My Data Science Journey

Theoretical Physics BSc (2007)

Theoretical Physics PhD (2011)

Software Consultant (2016)

PostDoc (2021)

Faculty (...)