Climate modelling
&
ML for Climate Science

Lecturer: Dr Kasia Tokarska

In this lecture you will learn about:

1. What is a climate model?

- Major earth system components
- Feedbacks in the climate system

2. What climate models tell us about future climate change?

- Expected outcomes in different scenarios
- Negative emissions
- Regional aspects of climate change

Discussion & Coffee Break

3. How Machine Learning can be useful for climate data science?

- Overview of ML applications for climate modelling
- Hybrid modelling & Physically informed modelling

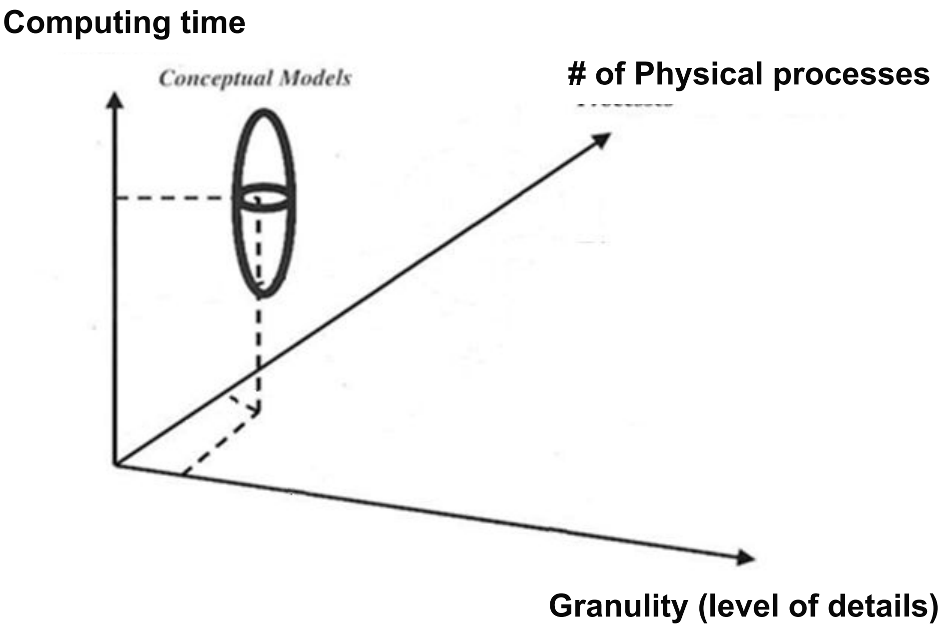
Discussion

4. Tutorial introduction

Climate models

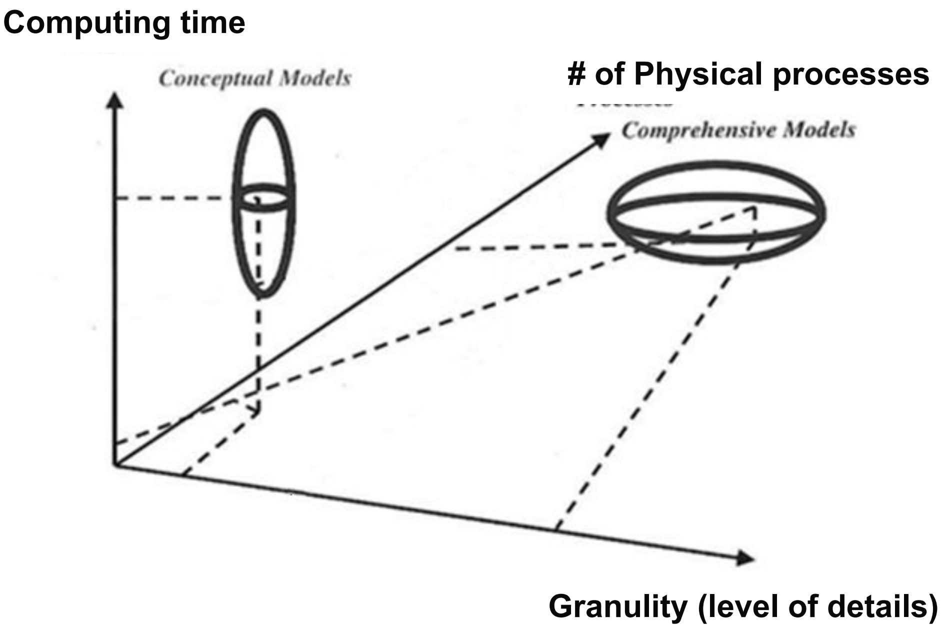
Source: Gavin Schmidt – The emergent patterns of climate change
https://www.ted.com/talks/gavin_schmidt_the_emergent_patterns_of_climate_change?language=en

Climate models



Adapted from Claussen et al. (2000)

Climate models



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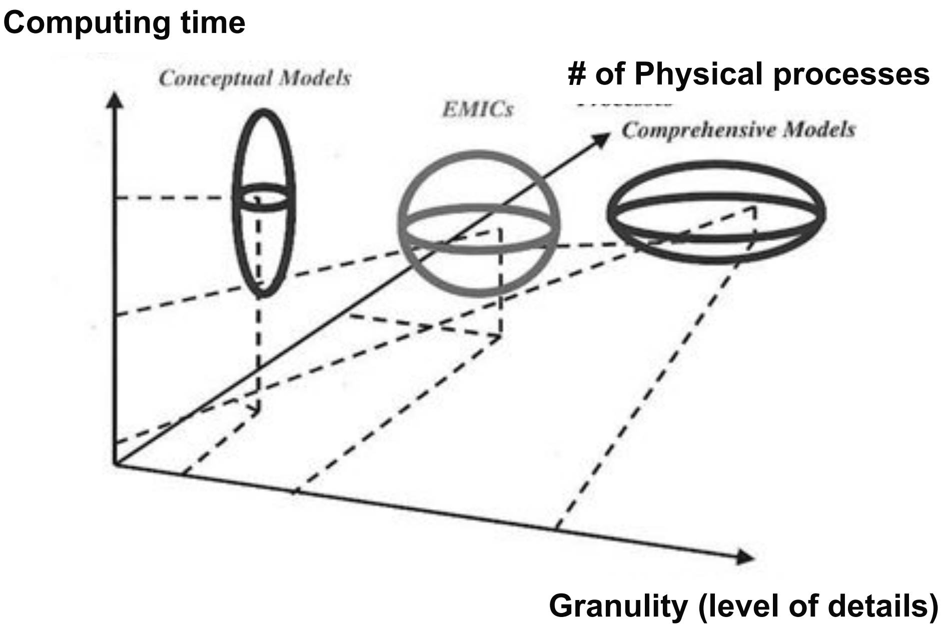
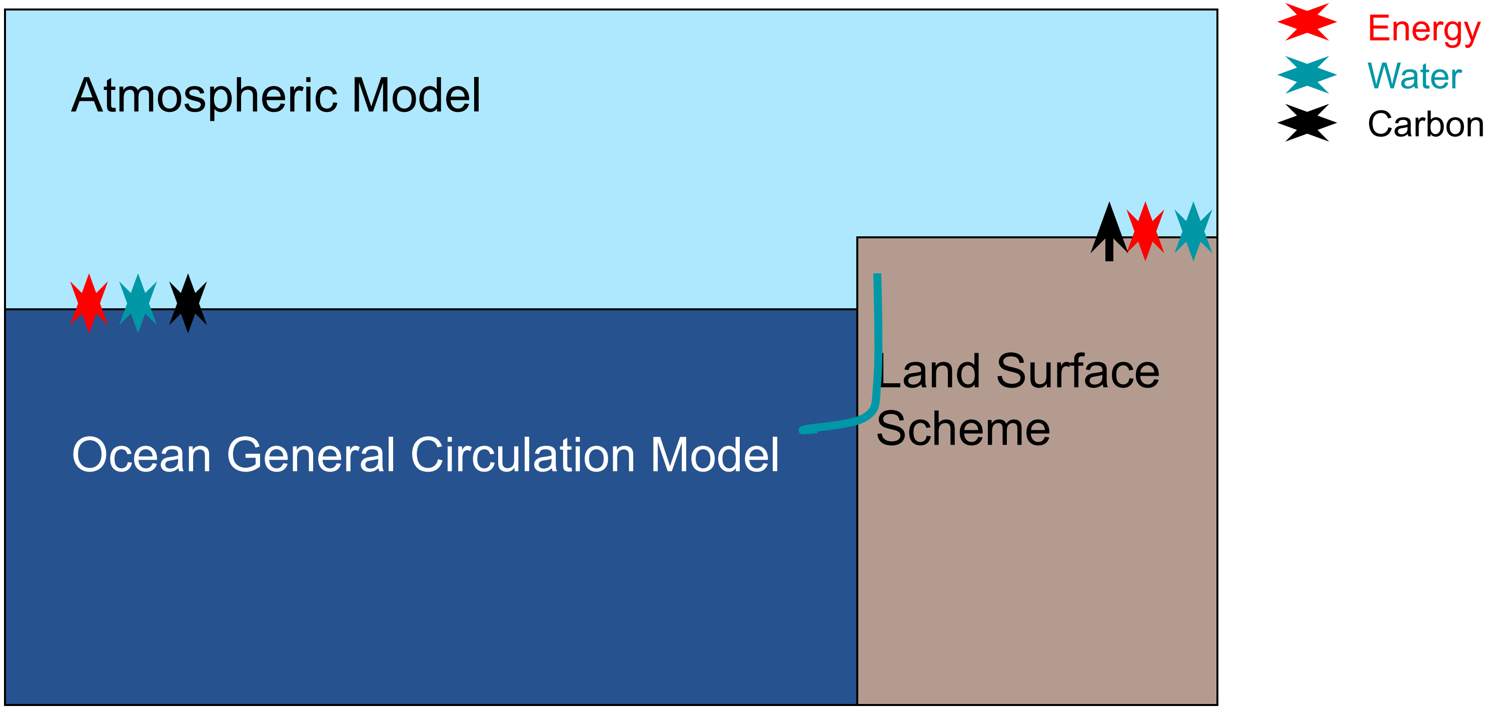
Climate models



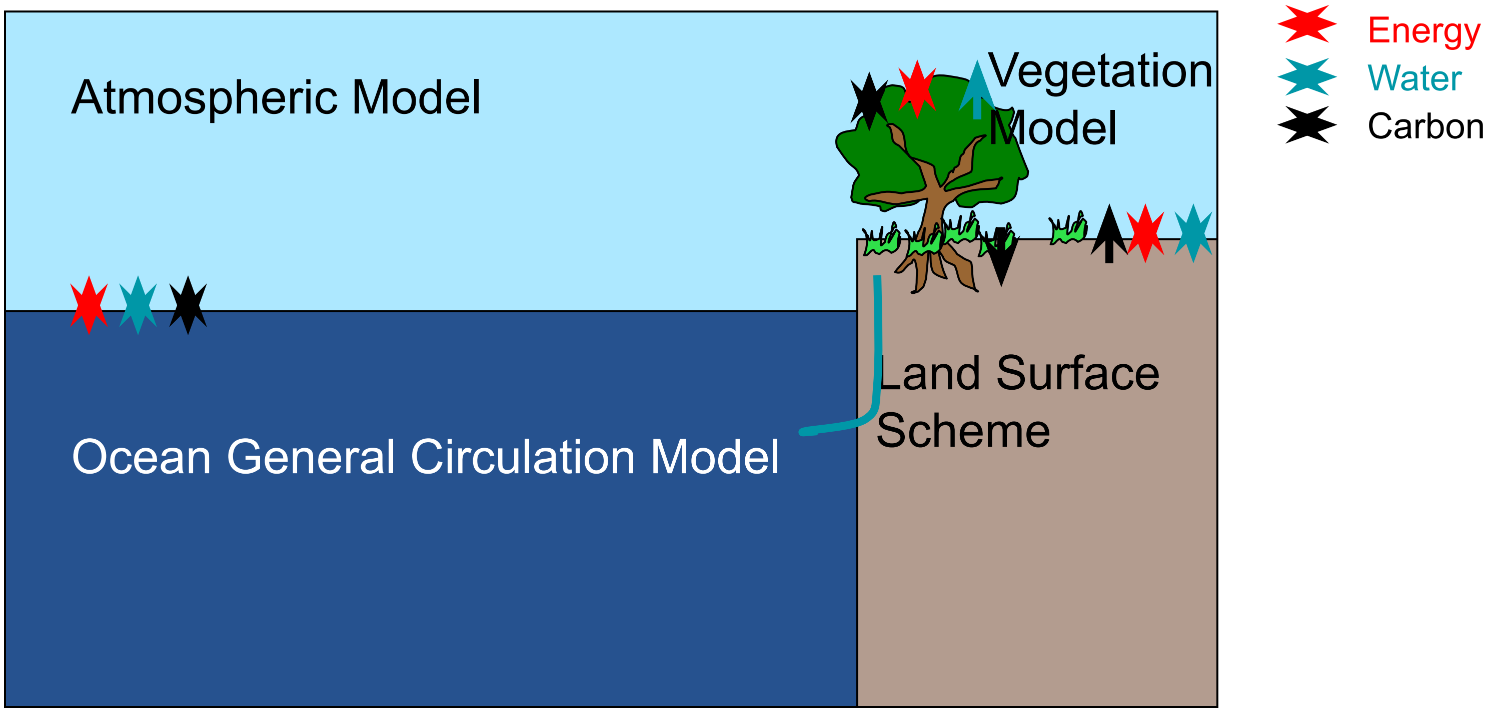
Adapted from Claussen et al. (2000)

Earth system model of intermediate complexity (UVic ESM)



Courtesy K. Meissner

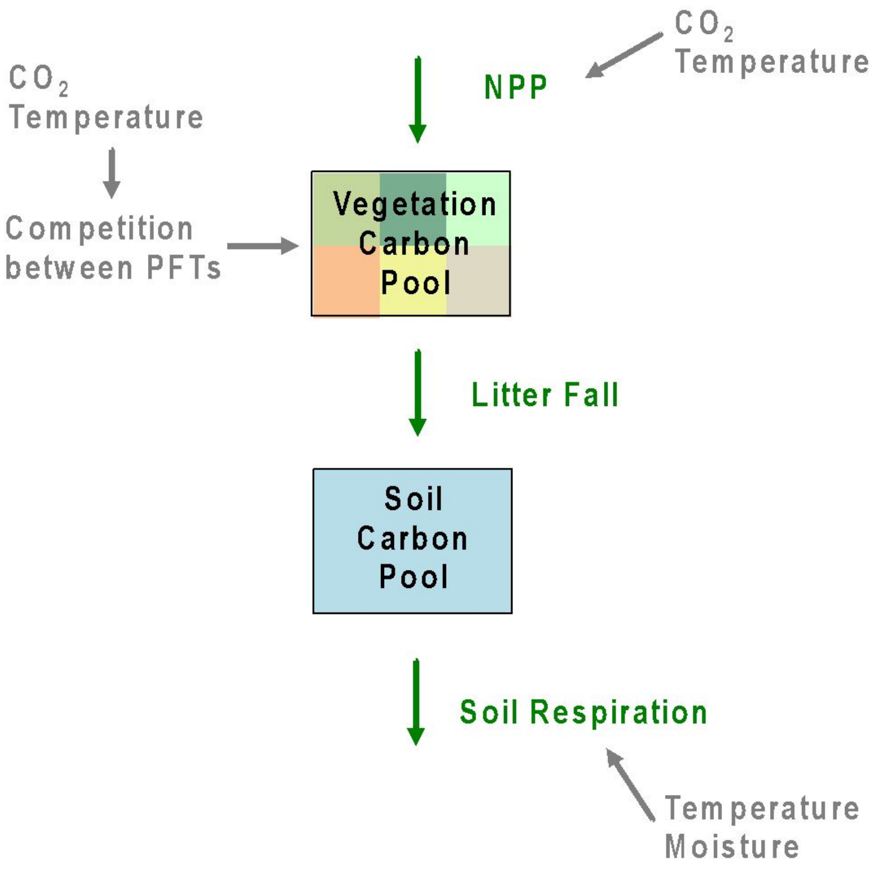
Earth system model of intermediate complexity (UVic ESM)



Courtesy K. Meissner

Terrestial carbon sinks

- CO_2 and temperature driven
- Various plant types



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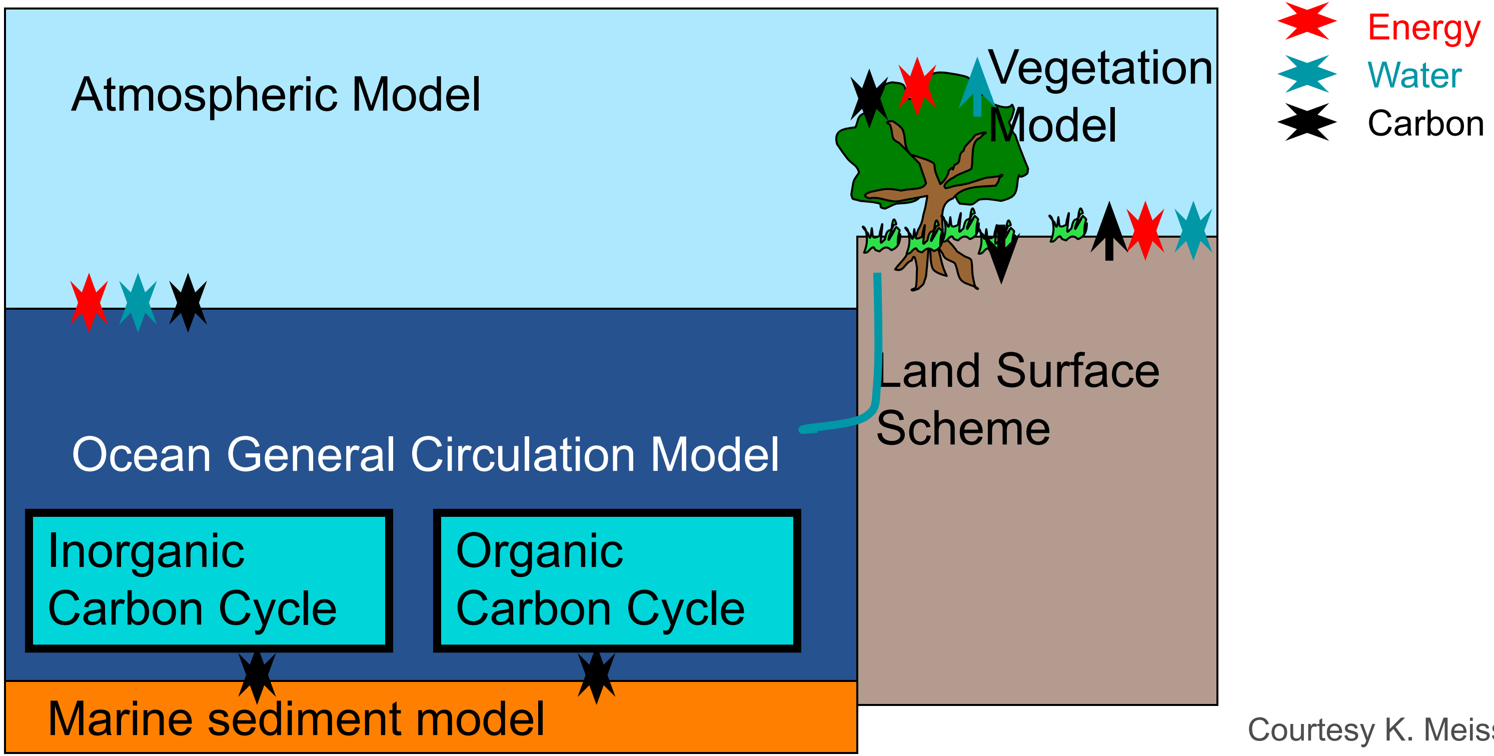

Courtesy K. Meissner

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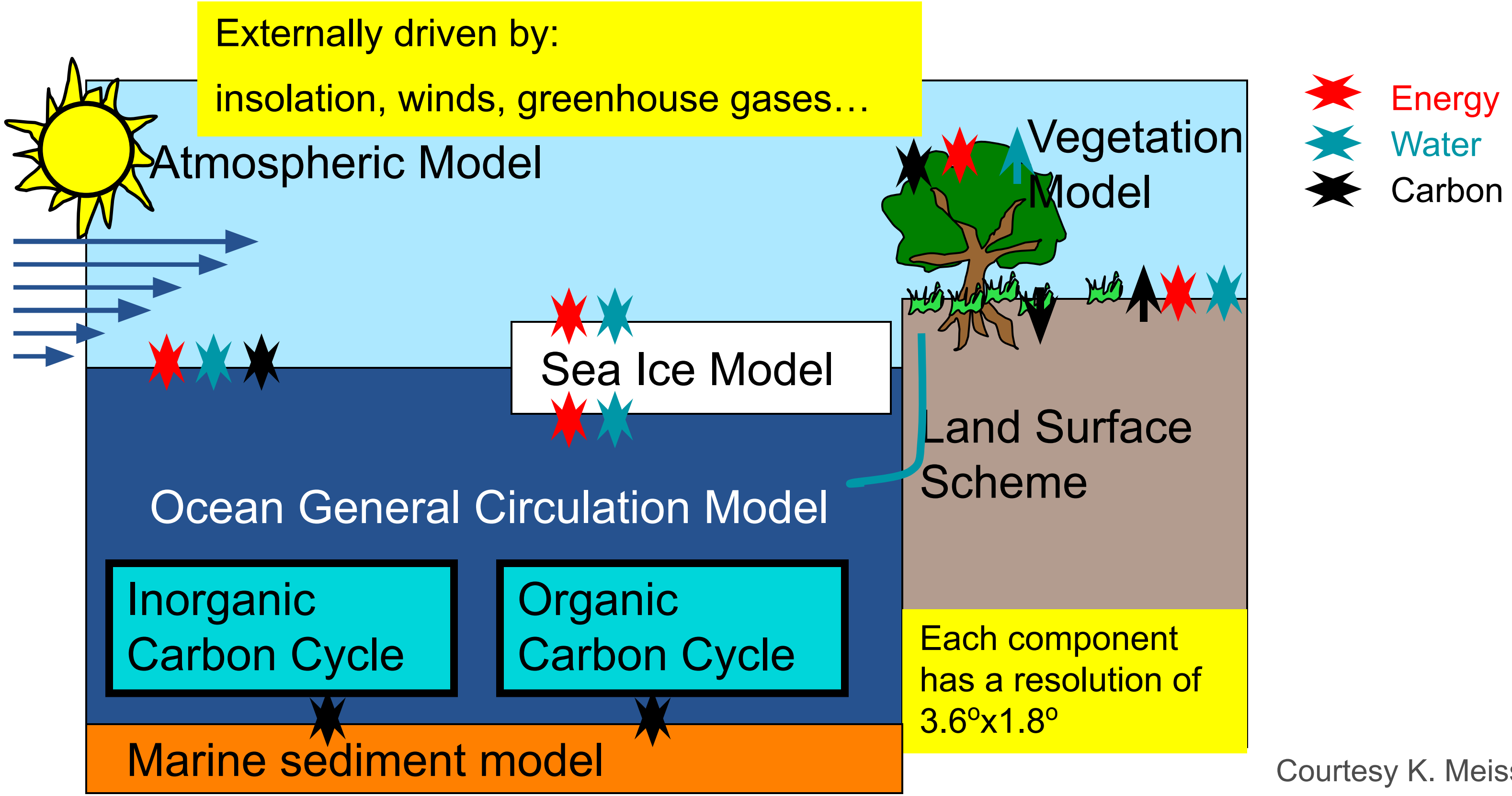
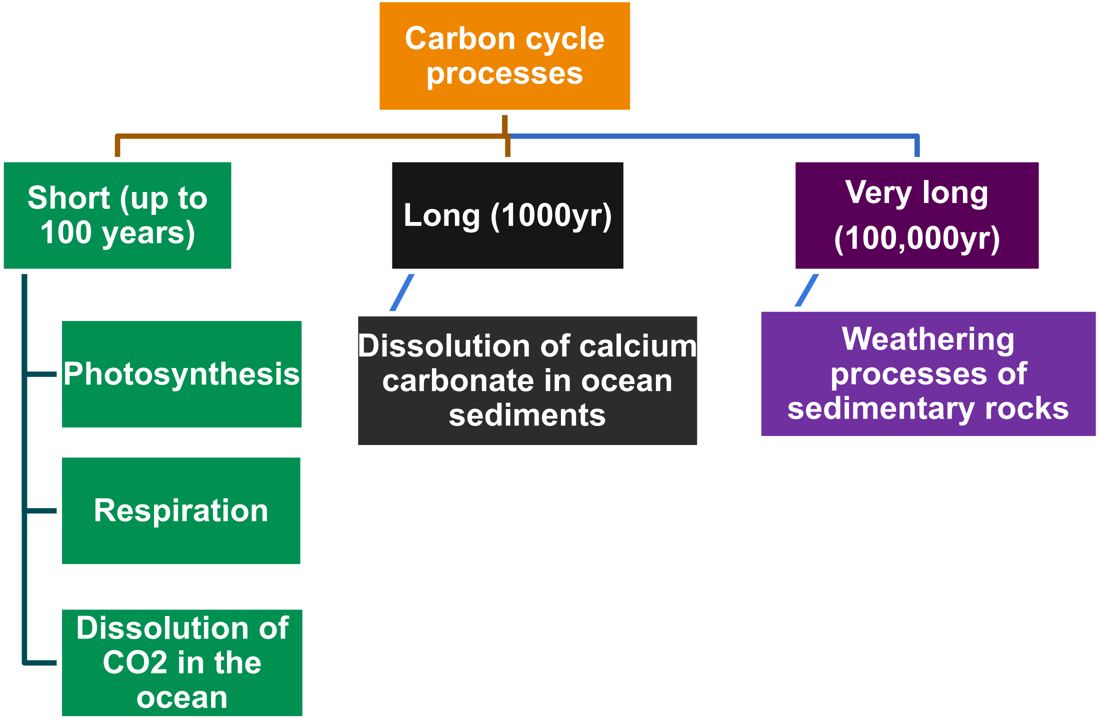
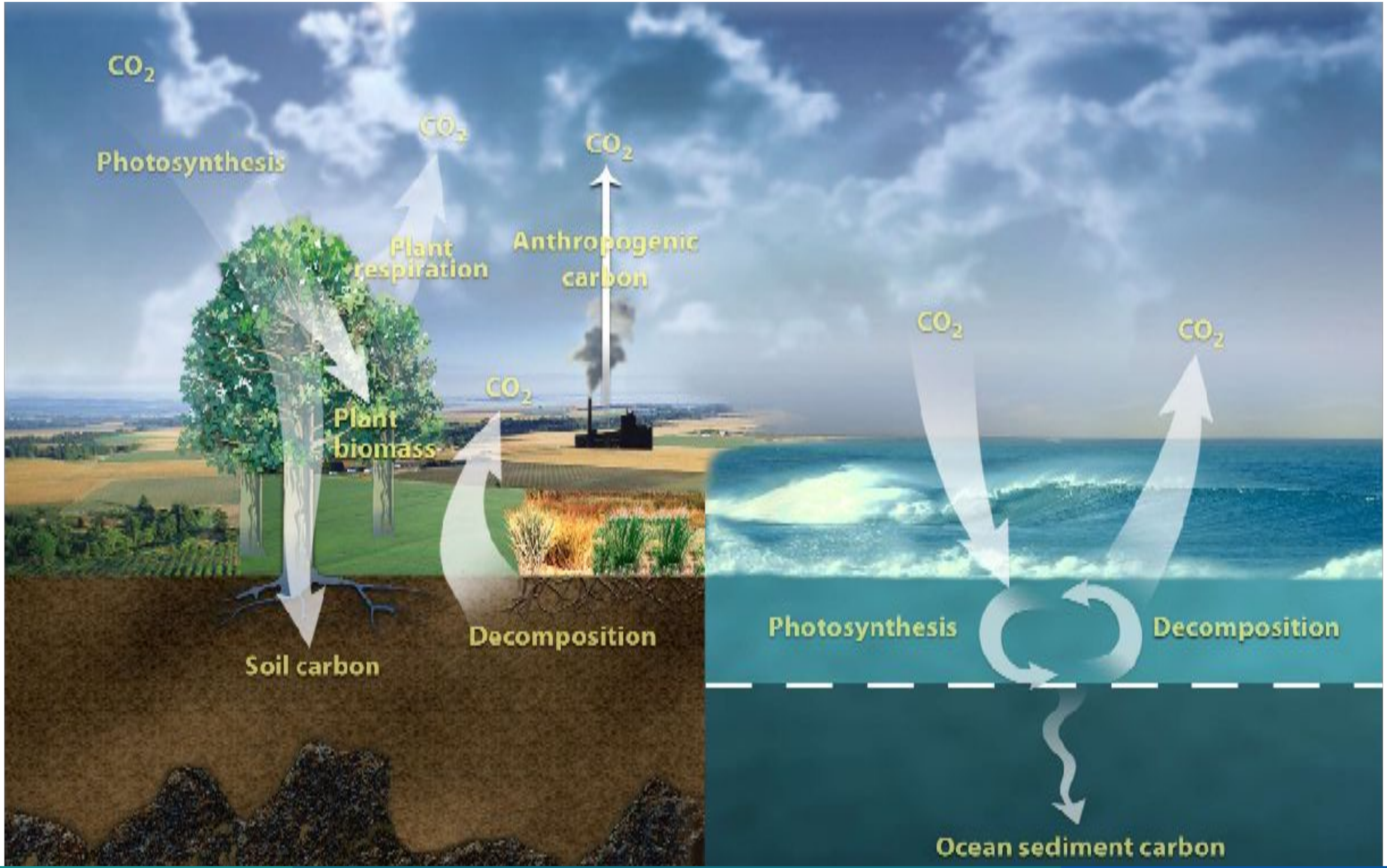


Courtesy K. Meissner

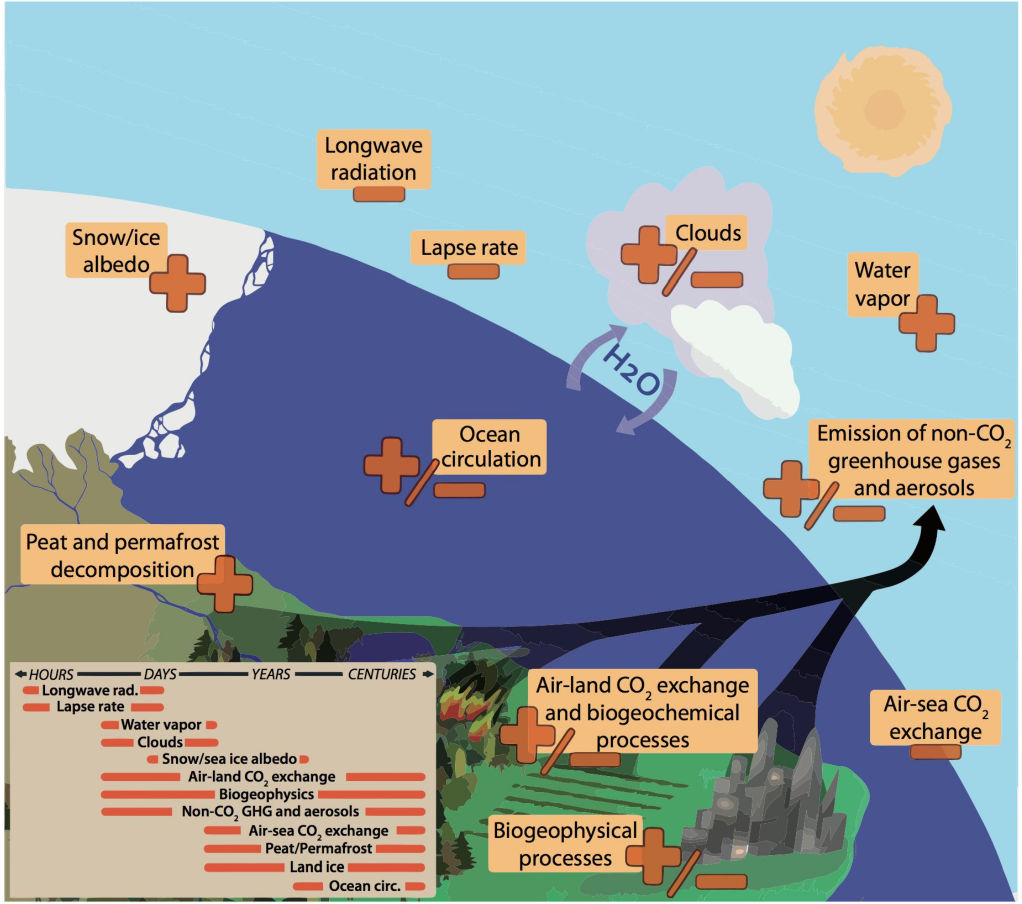
Natural carbon sinks act on different time scales



Feedbacks in the climate system

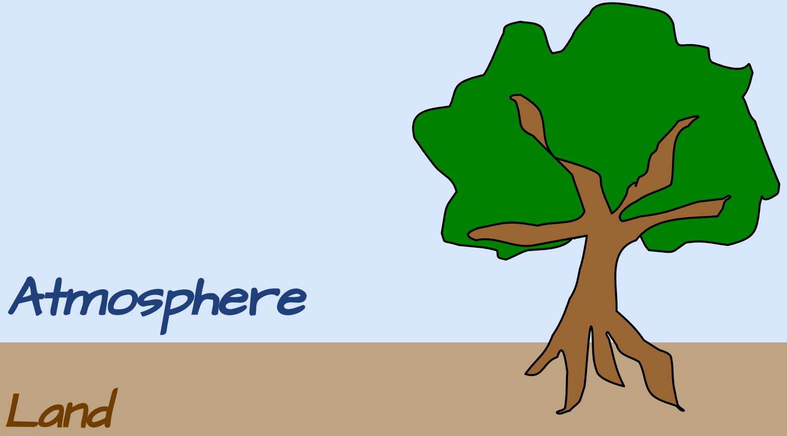


Feedbacks in the climate system

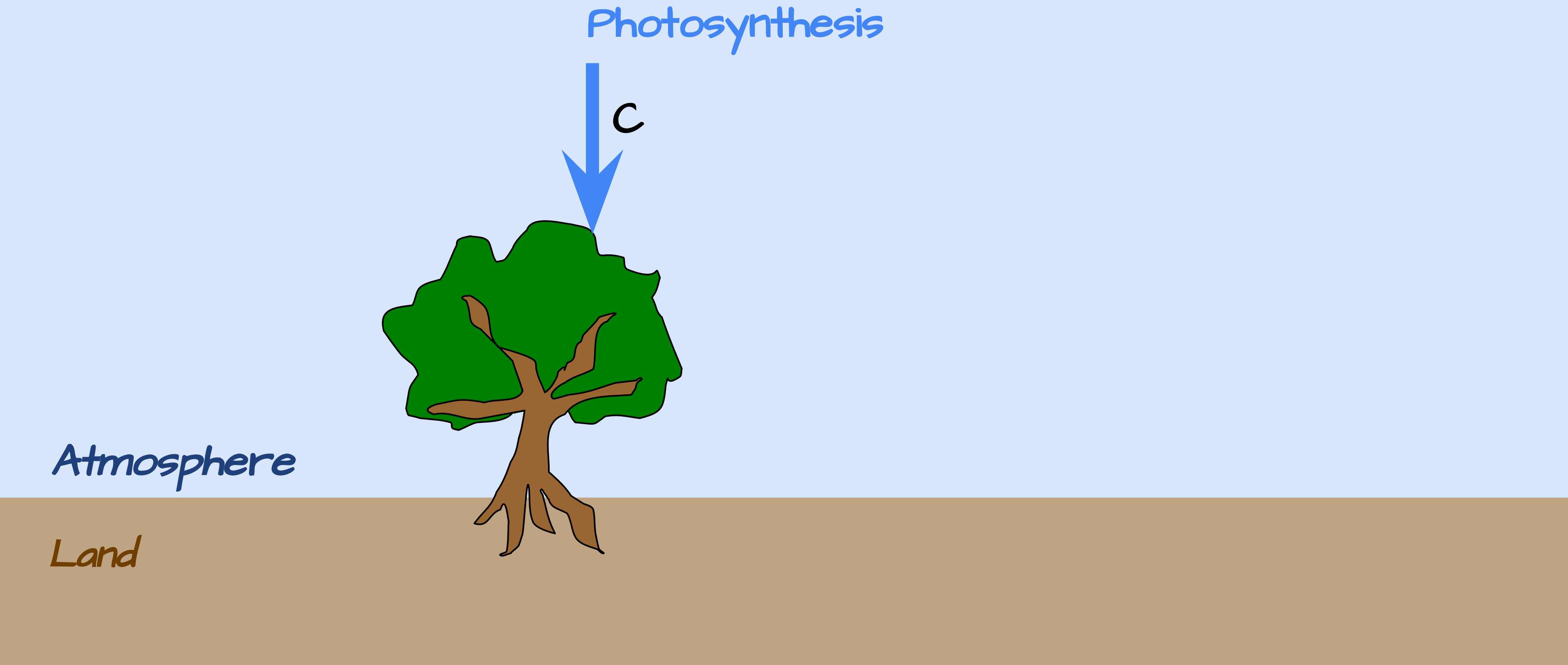


IPCC AR5 Fig 1.2

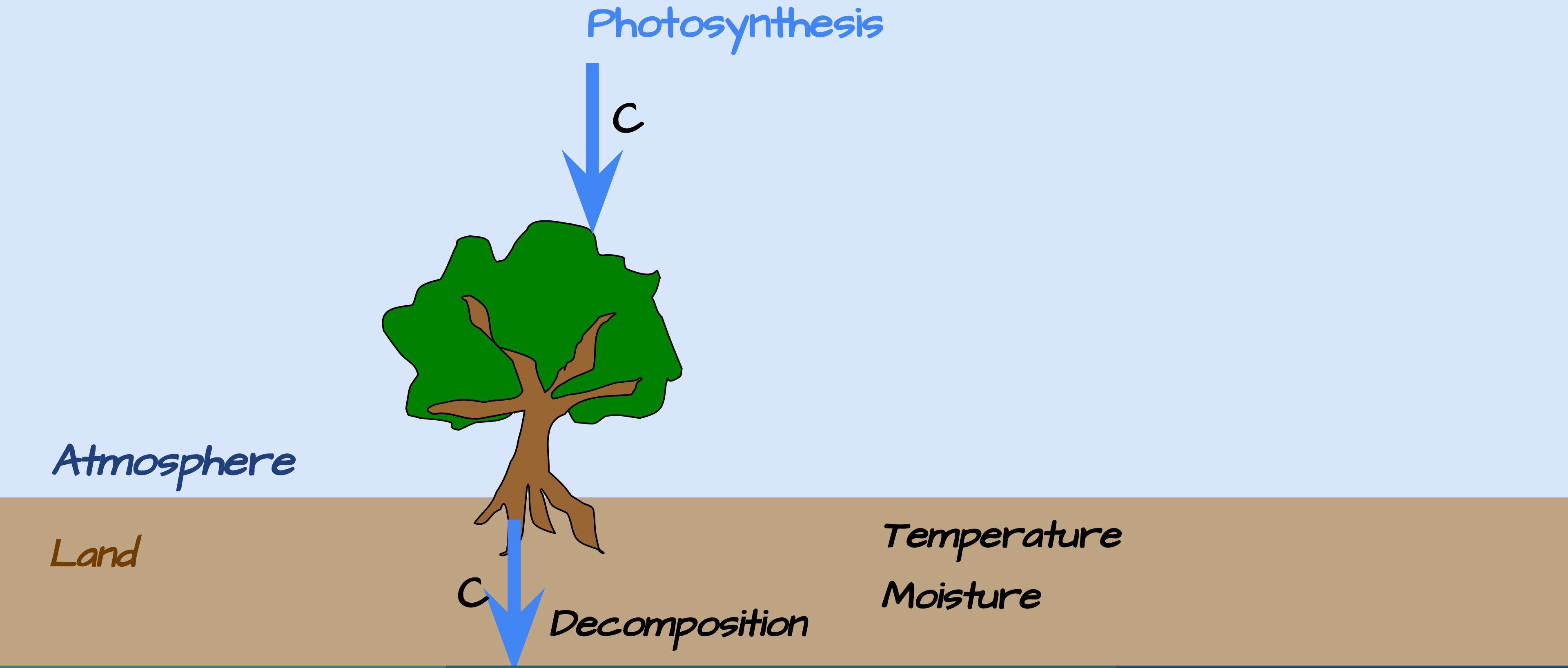
Carbon cycle feedbacks



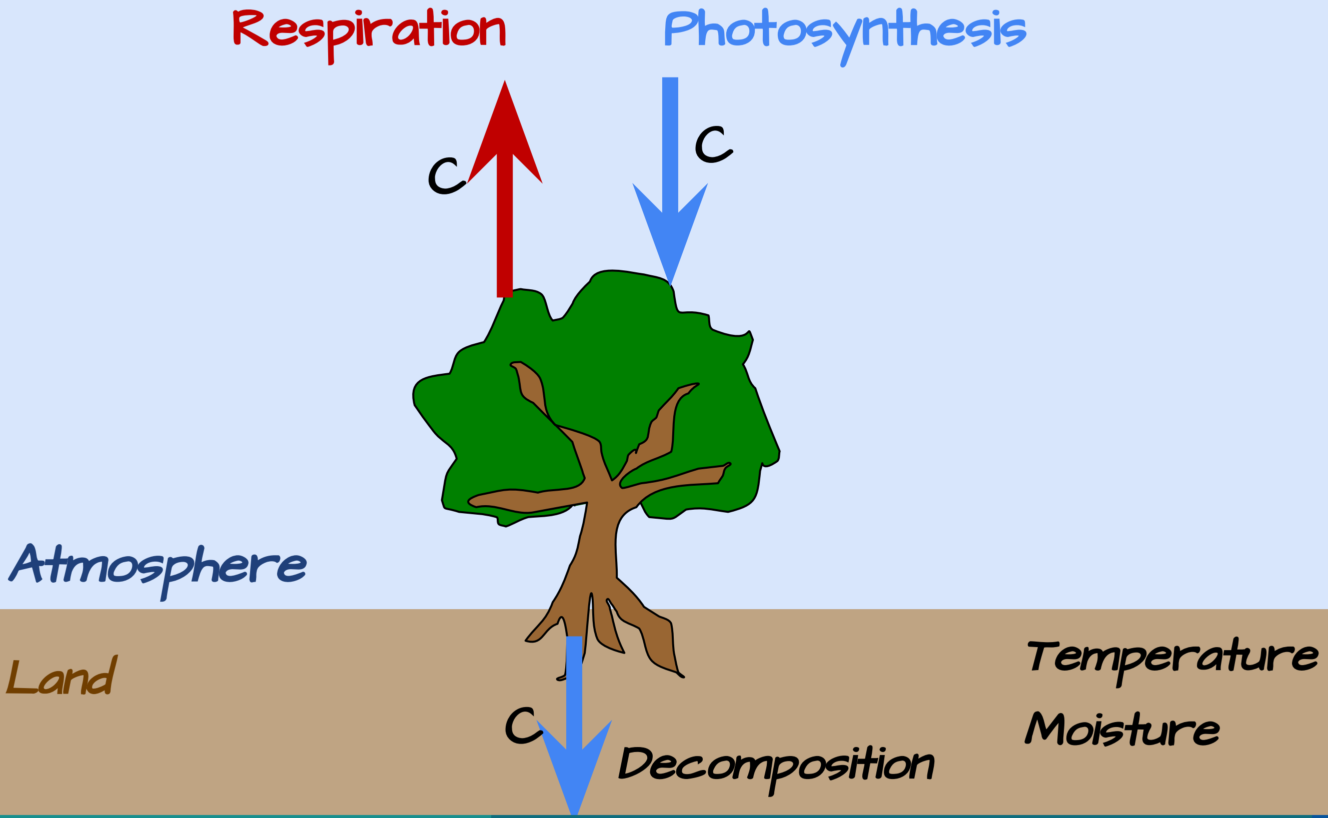
Carbon cycle feedbacks



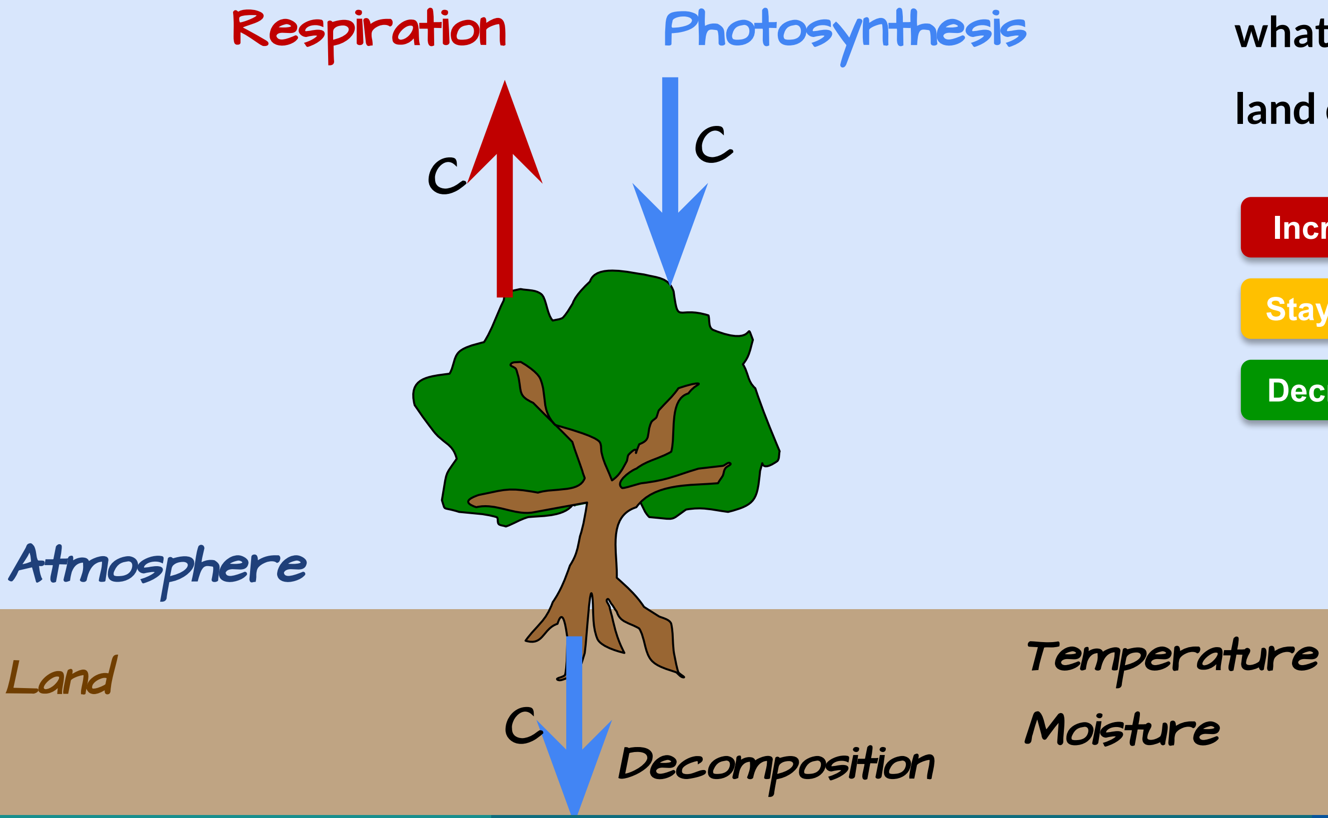
Carbon cycle feedbacks



Carbon cycle feedbacks



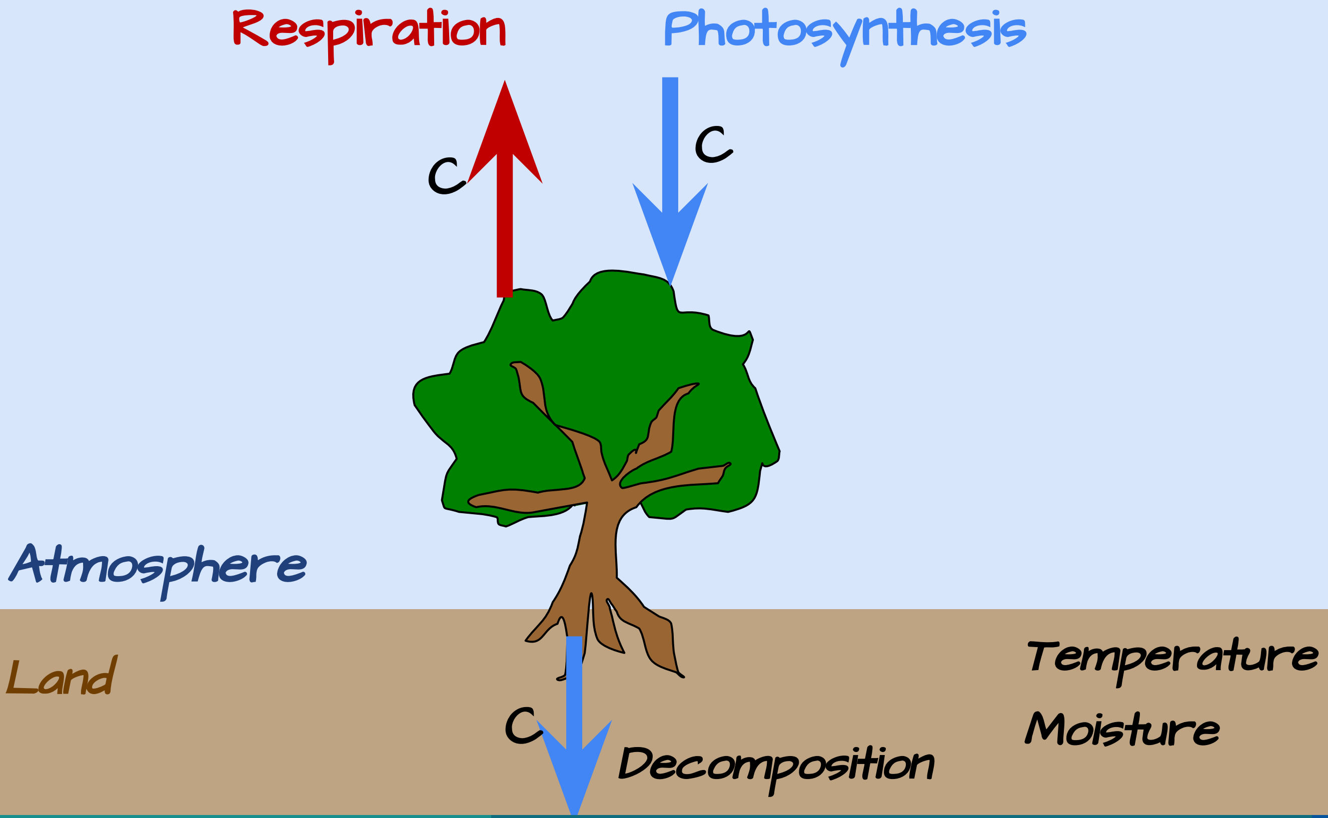
Carbon cycle feedbacks



If CO_2 emissions increase in the atmosphere, what will happen to the net land carbon uptake?

- Increase
- Stay the same
- Decrease

Carbon cycle feedbacks



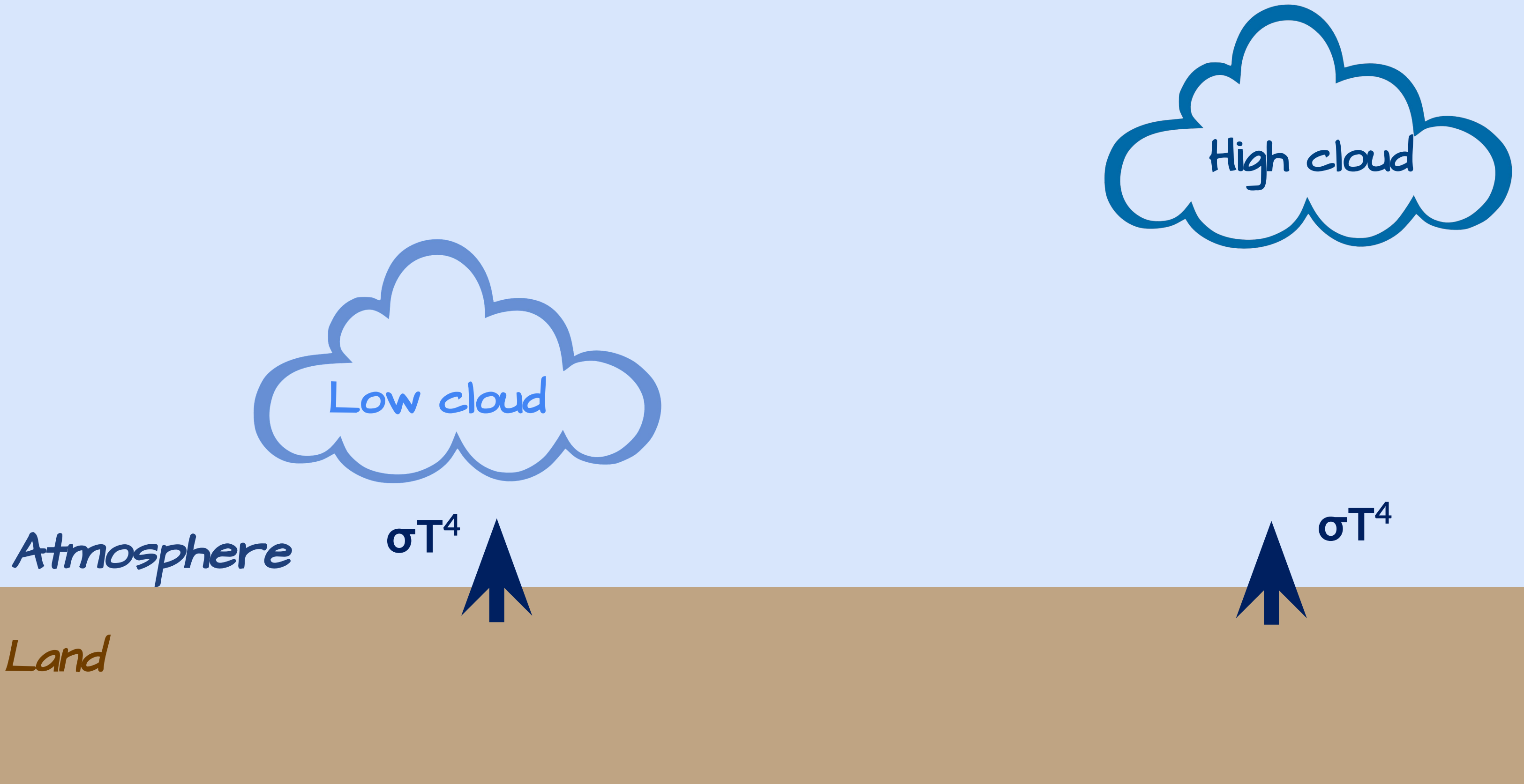
Net effect:

Temperature

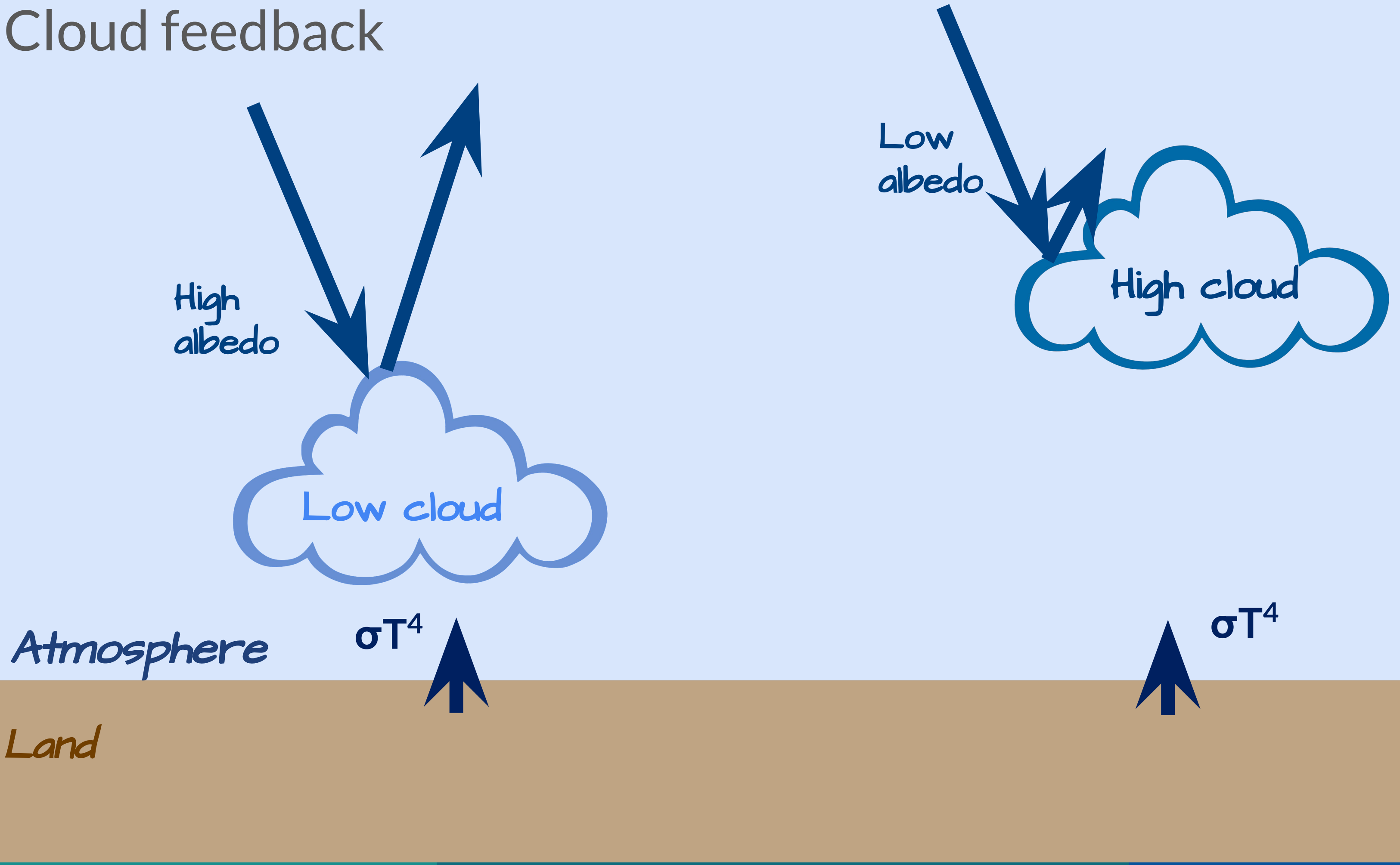
CO_2 concentration

Cloud feedback

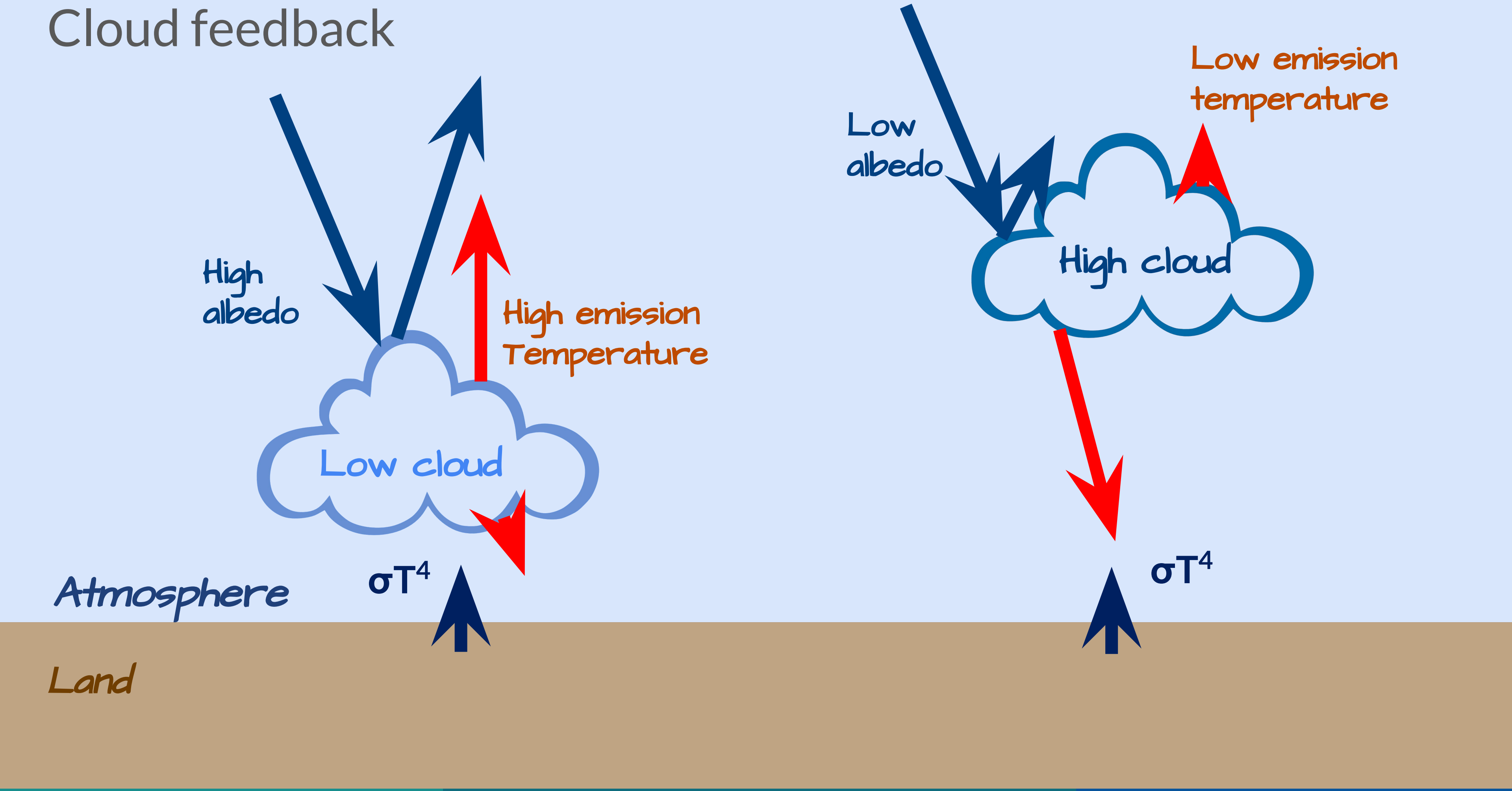
Cloud feedback



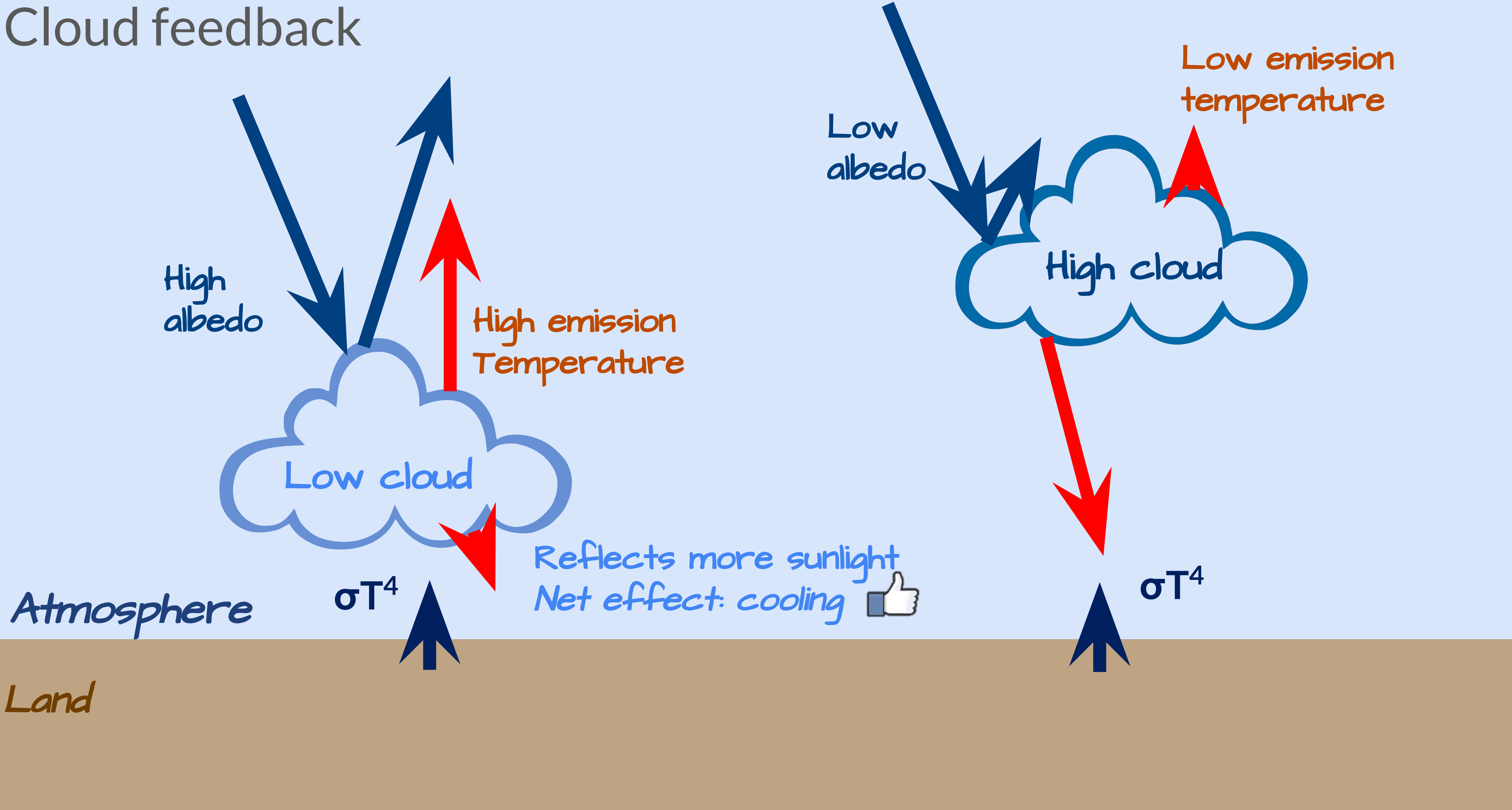
Cloud feedback



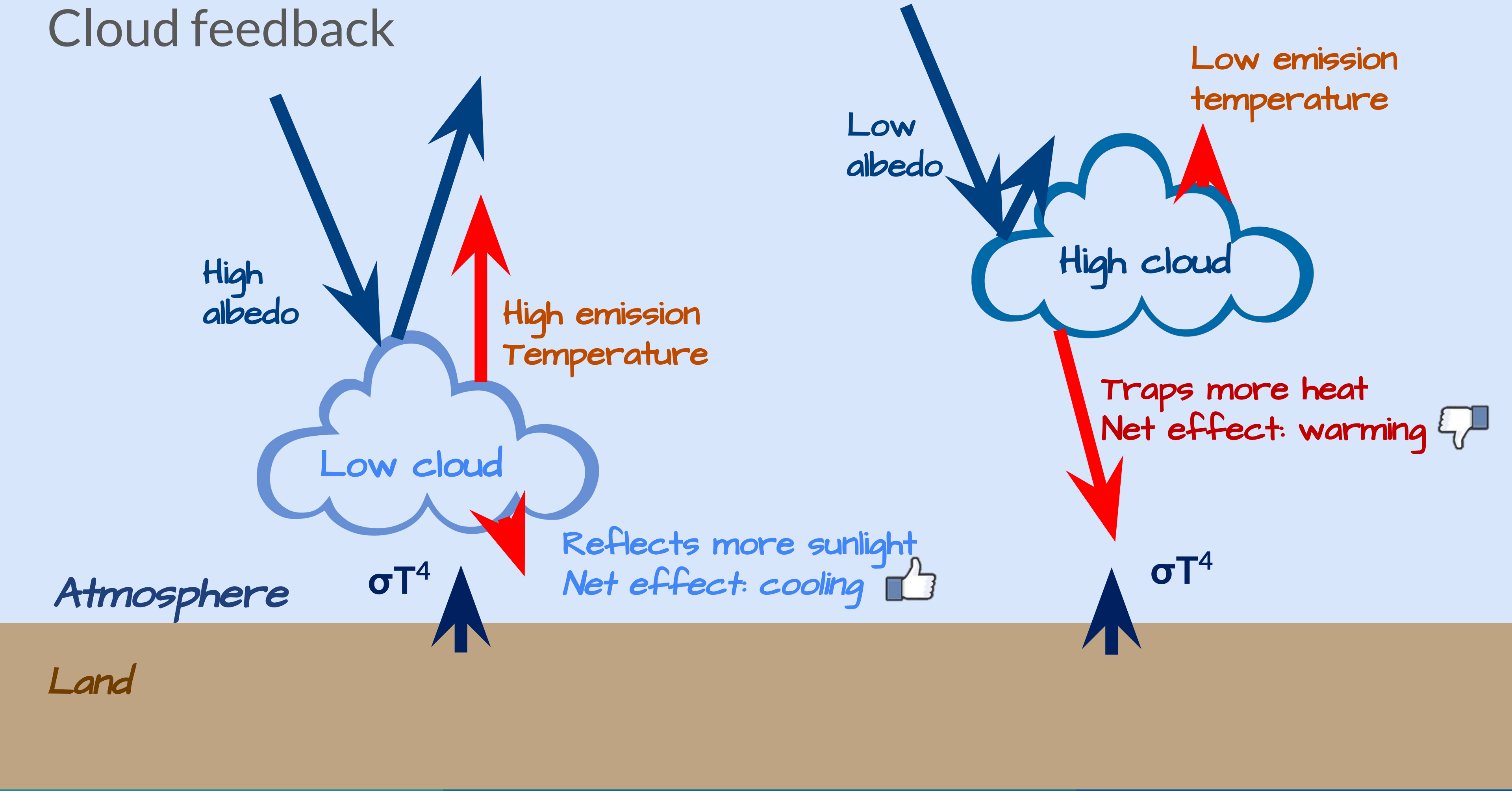
Cloud feedback



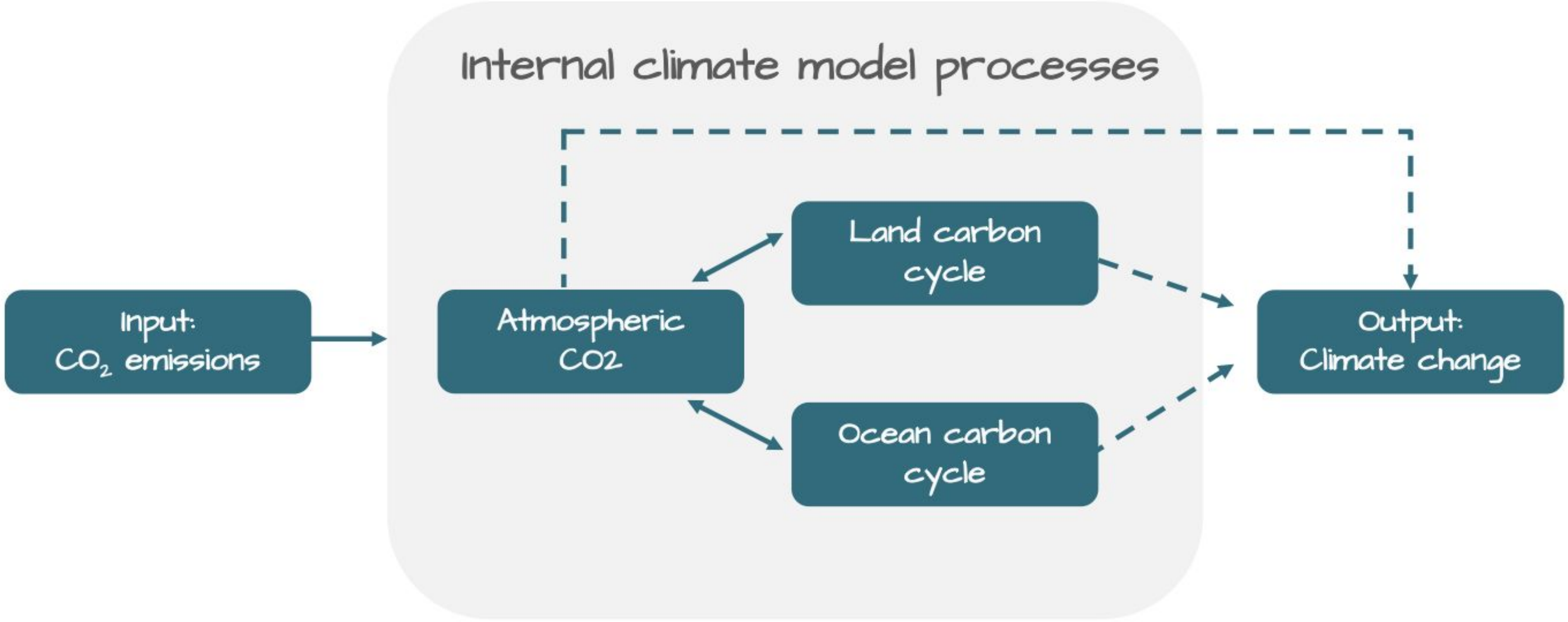
Cloud feedback



Cloud feedback

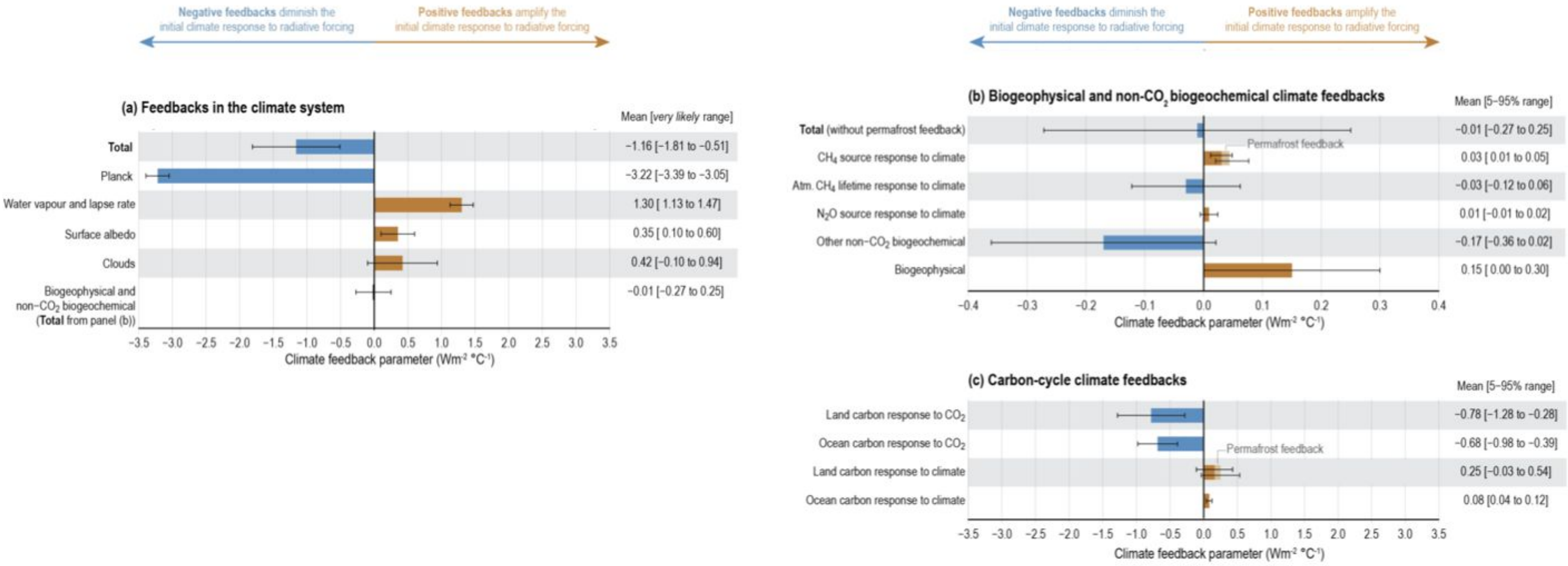


Feedbacks



Based on IPCC AR5 Box 6.4 Figure 1

Uncertainties in climate and carbon feedbacks



IPCC AR6, Figure TS.17

What’s next?

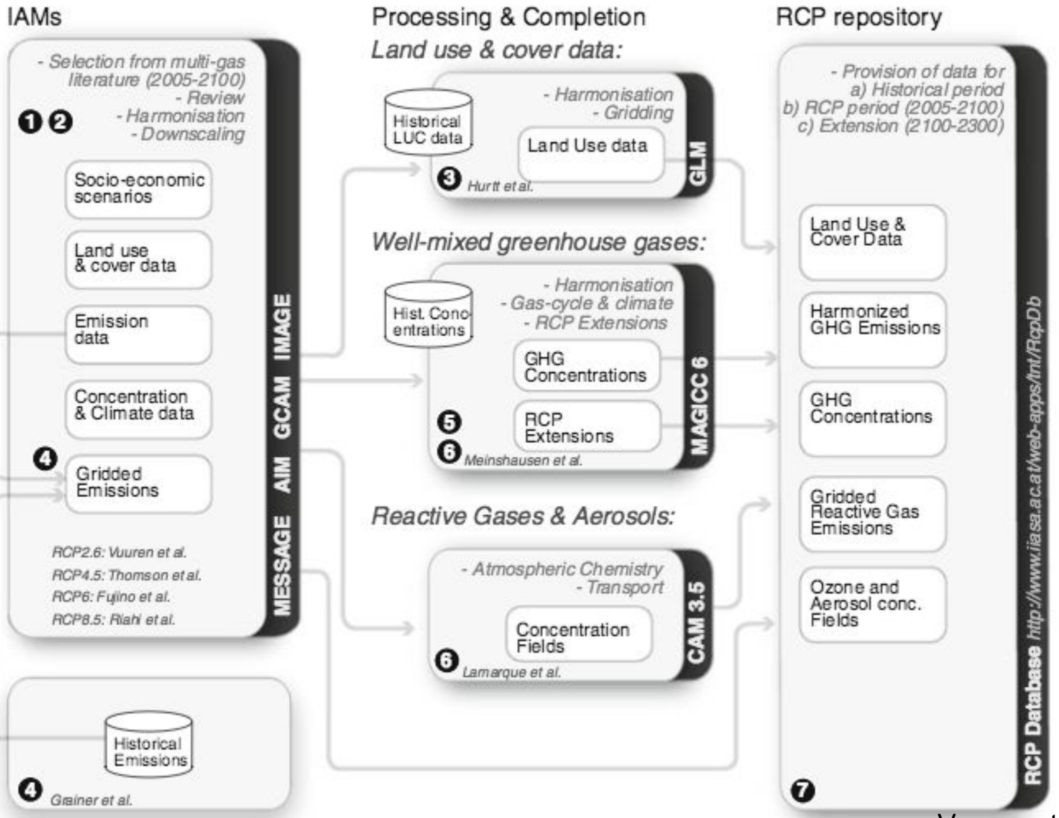

carbon dioxide level (parts per million)
500
480
460
440
420
400
380
360
340
320
300
280
260
240
220
200
180
160
For 650,000 years, atmospheric carbon dioxide had never been above this line
current level
1950 level
400,000
350,000
300,000
250,000
200,000
150,000
100,000
50,000
0
years before today (0 = 1950)
Source: http://climate.nasa.gov/evidence/

Future climate scenarios

- Representative Concentration Pathways (RCPs and SSPs)

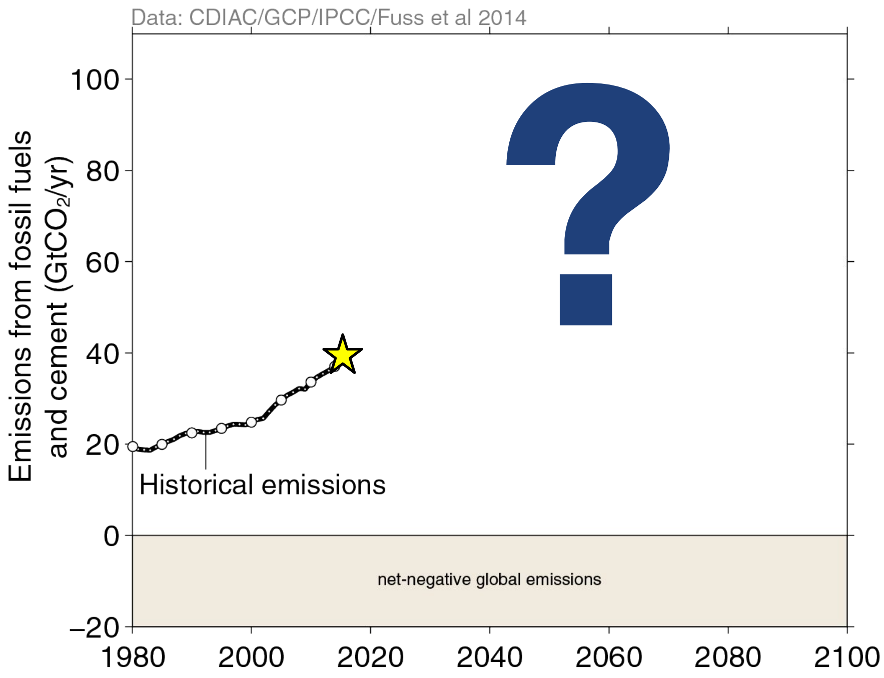
- Result from different combinations of:
    - economic
    - technological
    - demographic
    - policy and institutional projections

Climate Scenario design



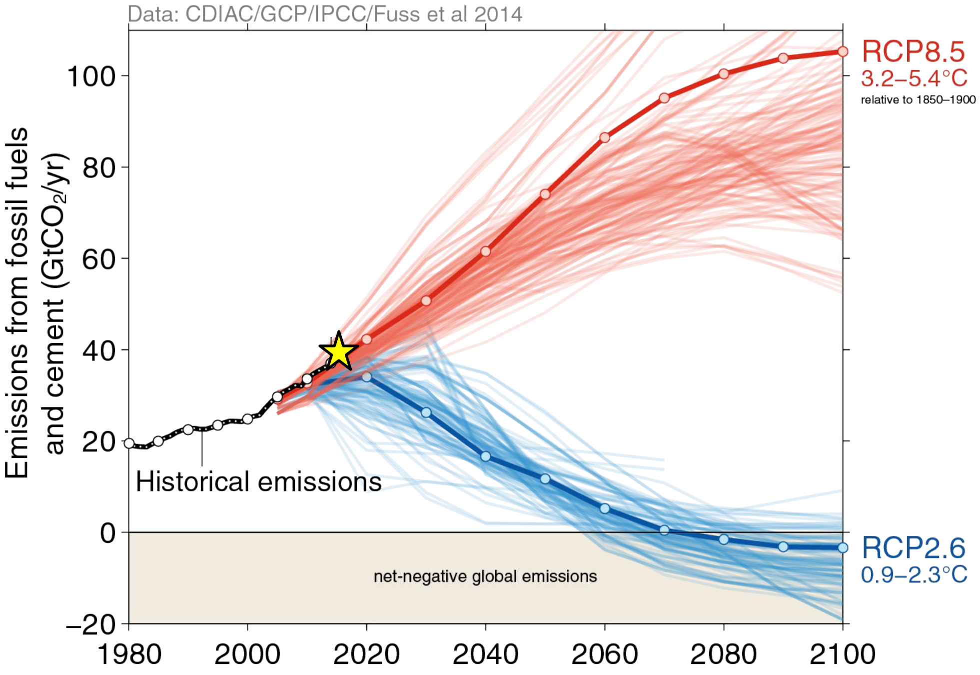
vanVuuren et al 2011

Future climate scenarios



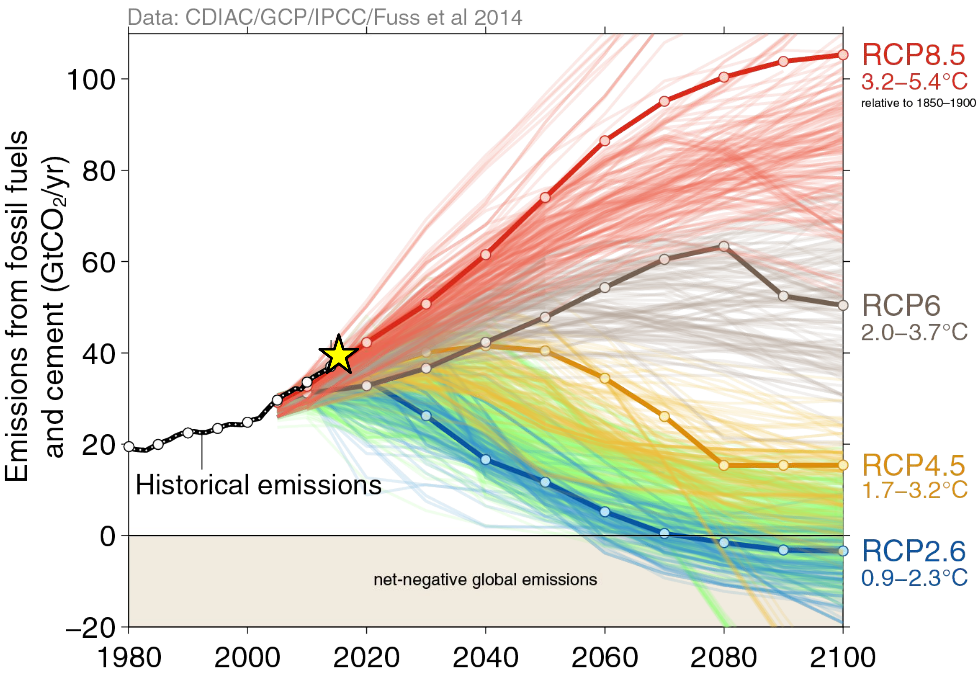
Source: Glen Peters

Future climate scenarios



Source: Glen Peters

Future climate scenarios

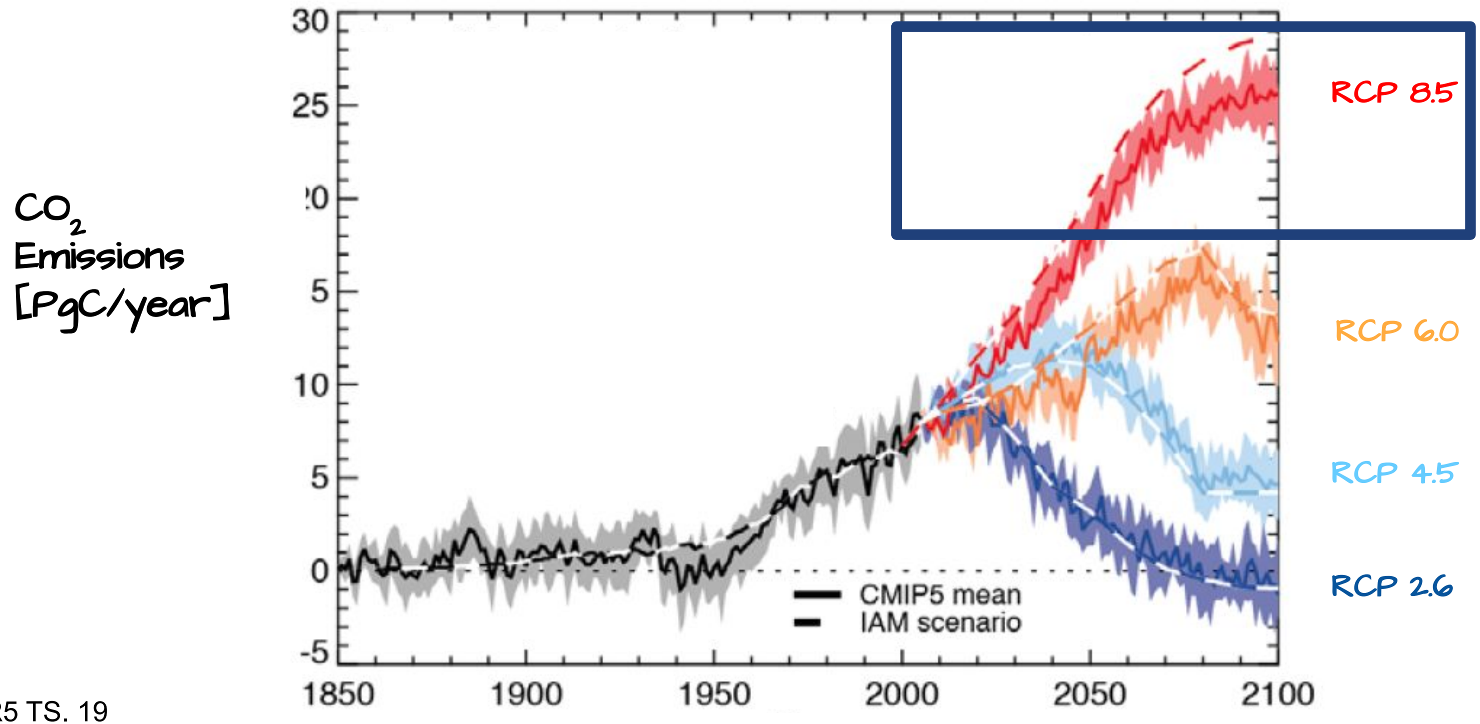


Source: Glen Peters

Uncertainty

- **What humans will do in the future?**
- **How well climate models represent the climate system?**
    - Internal climate variability?
    - Climate system feedbacks?

Fossil fuel emissions



IPCC 2013 AR5 TS. 19

High emission scenario

What will happen to surface air temperature?

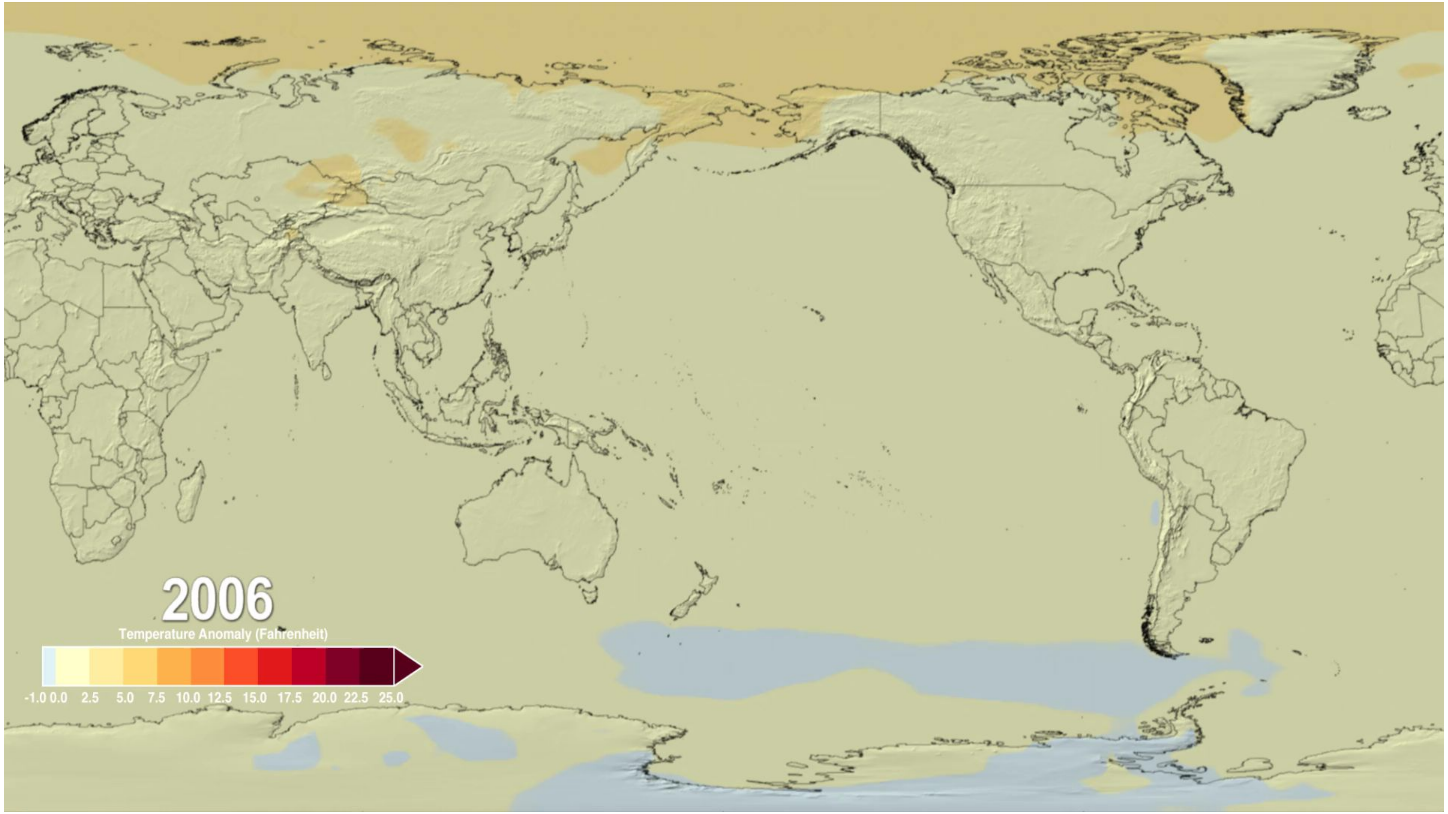
Increase

Stay the same

Decrease

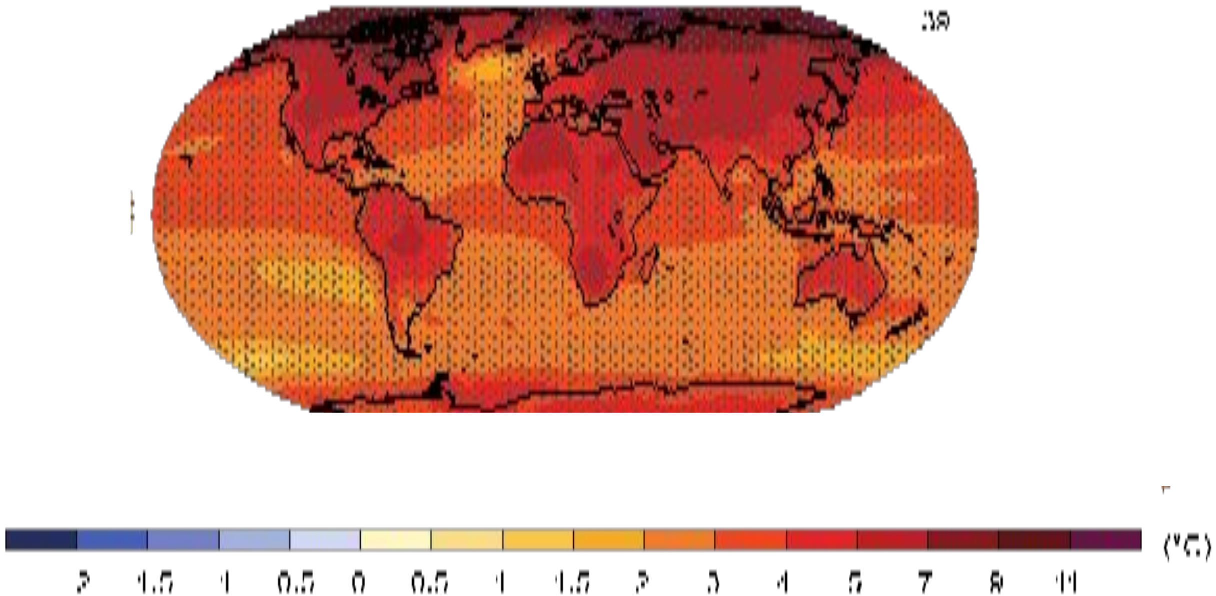
Which regions will be affected the most?

High emission scenario



Source: https://svs.gsfc.nasa.gov/

Temperature change

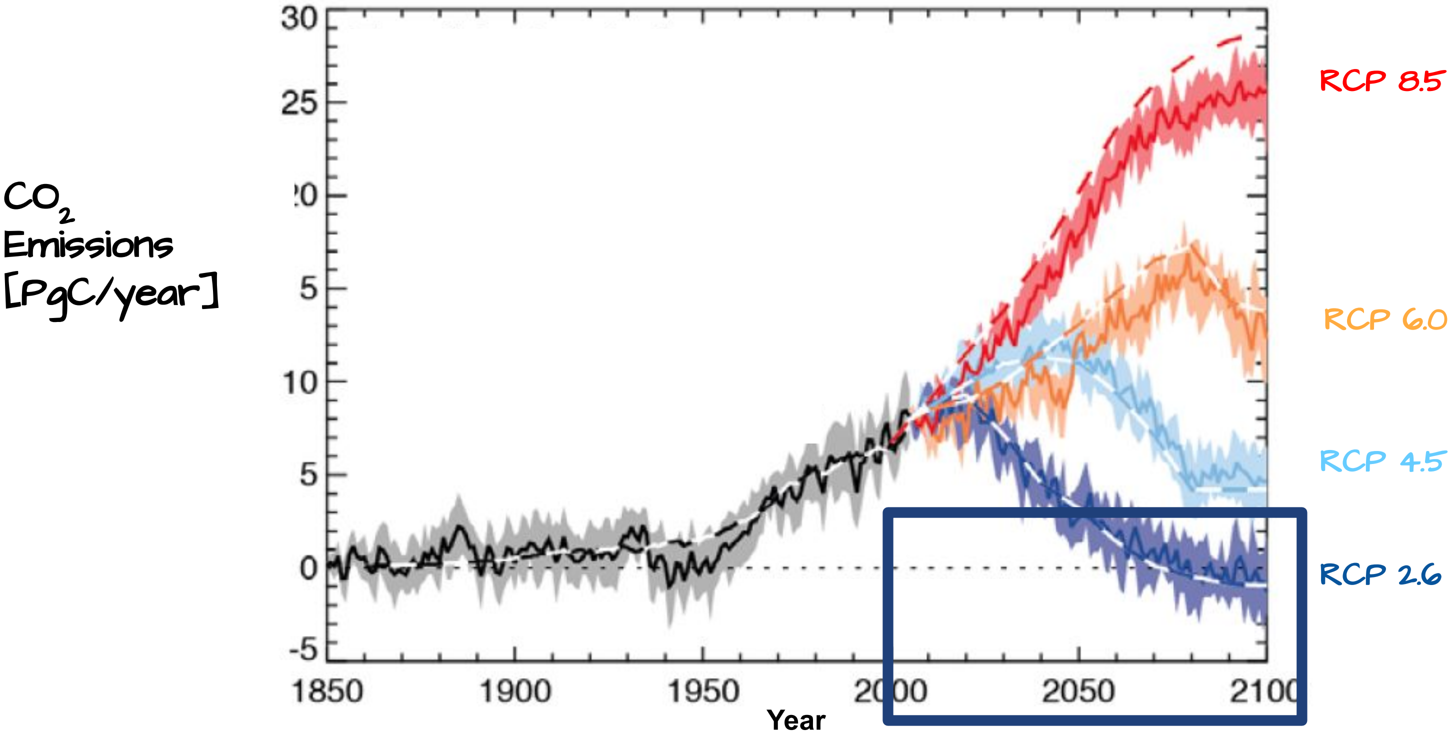


Change in average surface temperature (1986-2005 to 2081-2100)

IPCC 2013, AR5 Summary for Policy Makers SPM.8

Ambitious mitigation scenario

IPCC 2013 AR5 TS. 19



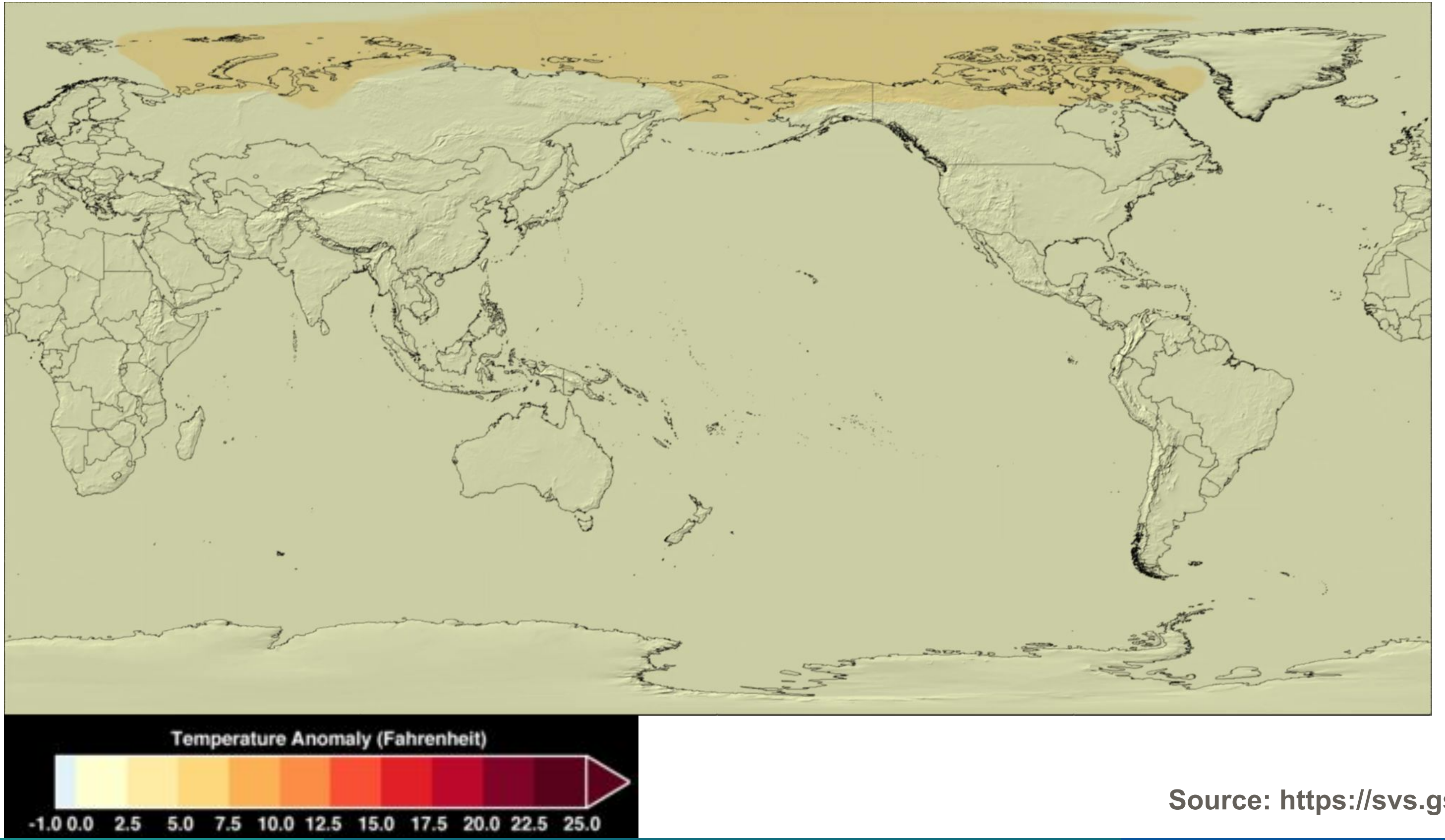
Ambitious mitigation scenario

What will happen to surface air temperature?

Increase | **Stay the same** | **Decrease**

Which regions will be affected the most?

Ambitious mitigation scenario

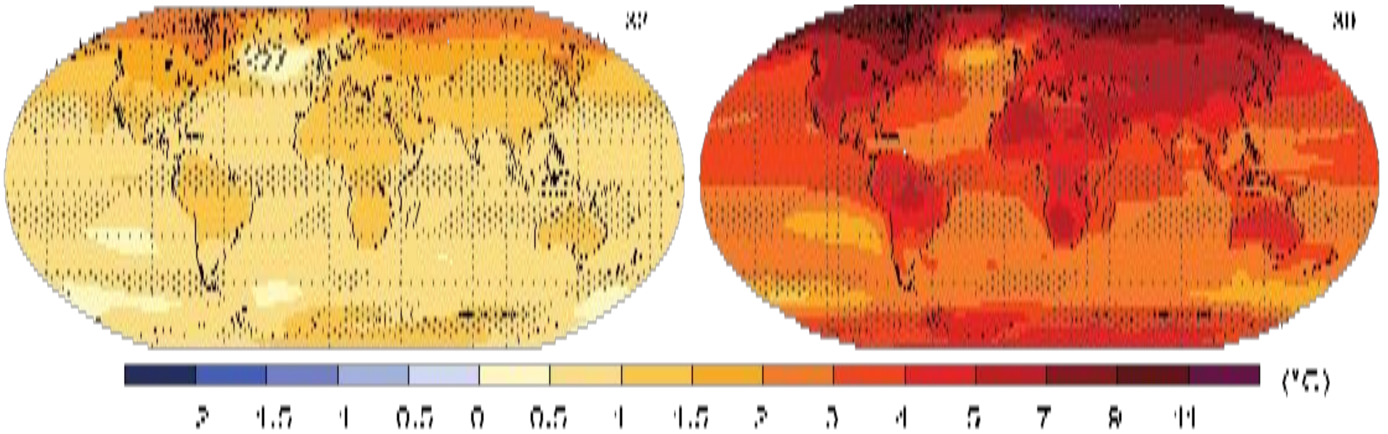


Source: https://svs.gsfc.nasa.gov/

Temperature response

RCP 2.6

RCP 8.5



IPCC 2013, AR5 Summary for Policy Makers SPM.8

Change in average surface temperature (1986-2005 to 2081-2100)

Ambitious mitigation scenario

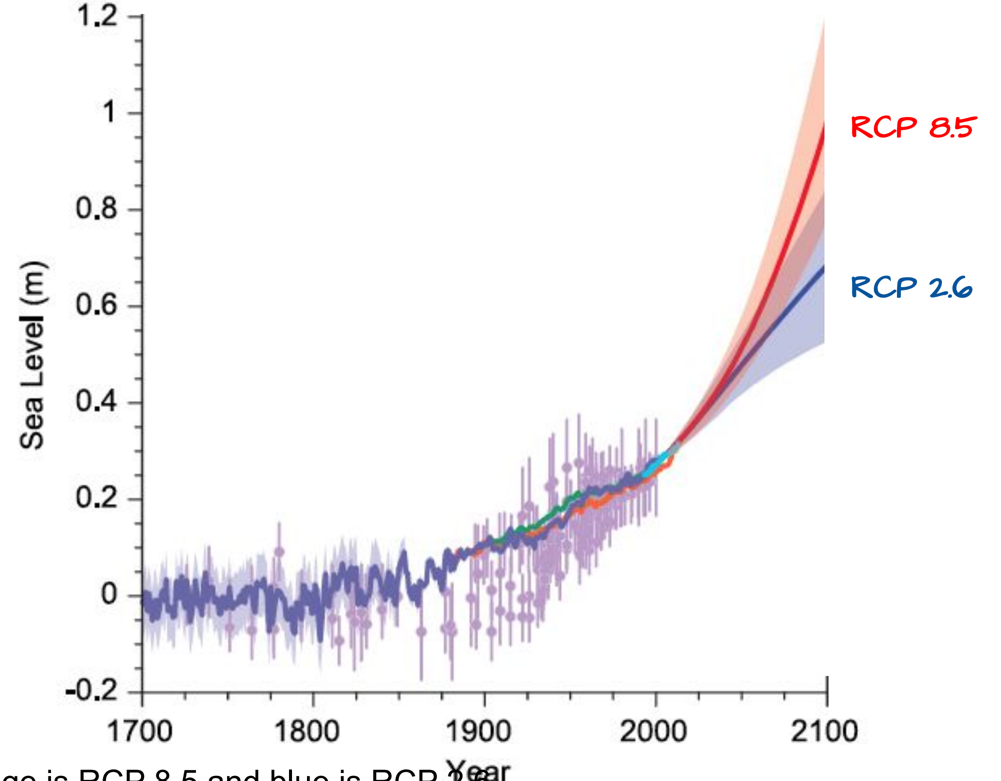
What will happen to global mean sea level?

Increase

Stay the same

Decrease

Sea level rise



IPCC AR5 Figure 13.27. Red range is RCP 8.5 and blue is RCP 2.6

Can we trust climate models

No

Maybe

Yes

A trillion dollar party

Analogy Source: Knutti R. *Climatic Change* 2010

Can we trust climate models

- We calibrate climate models against the historical record
- However, ‘instrumental’ record only goes back 100 years and there is incomplete data (missing coverage)
- Compare a range of different models and look at the variation in the outputs
- If a climate model over-estimates or under-estimates historical (observed) conditions is it likely to carry on that bias into the future

Despite these limitations, climate models have been **remarkably accurate** in predicting climate change in response to greenhouse gas emissions

Can we trust climate models

Nobel Prize for Physics winners Syukuro Manabe, Klaus Hasselmann, and Giorgio Parisi
ILLUSTRATION BY NIKLAS ELMEHED, NOBEL PRIZE OUTREACH

ENVIRONMENT | PLANET POSSIBLE

How climate models got so accurate they earned a Nobel Prize

Climate predictions were treated with heavy skepticism just 30 years ago, but they've become our main window into how global warming works.

https://www.nationalgeographic.com/environment/article/how-climate-models-got-so-accurate-they-earned-a-nobel-prize#:~:t Modelers%20agree%2C%20and%20note%20that,predictions%20of%20global%20temperature%20increases.

How much time is left until 1.5 °C?

5-10 years

15-20 years

20-30 years

https://climateclock.net/?buttons=1&audio=0

The climate clock

https://climateclock.net/?buttons=1&audio=0

Zero emissions

What if we stop emissions today?

Temperature? Sea level?

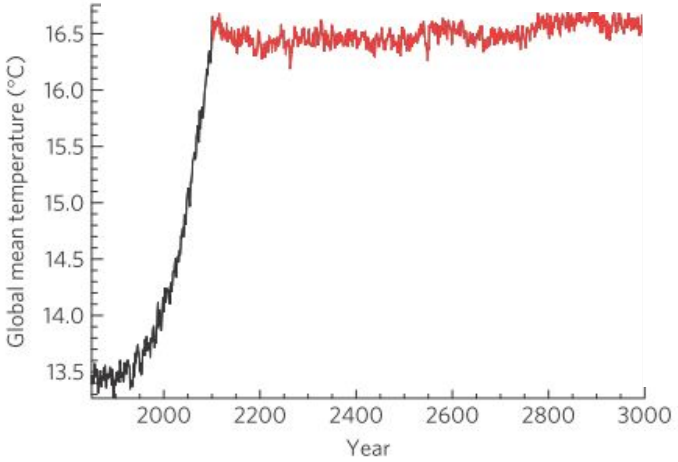
Increase

Stay the same

Decrease

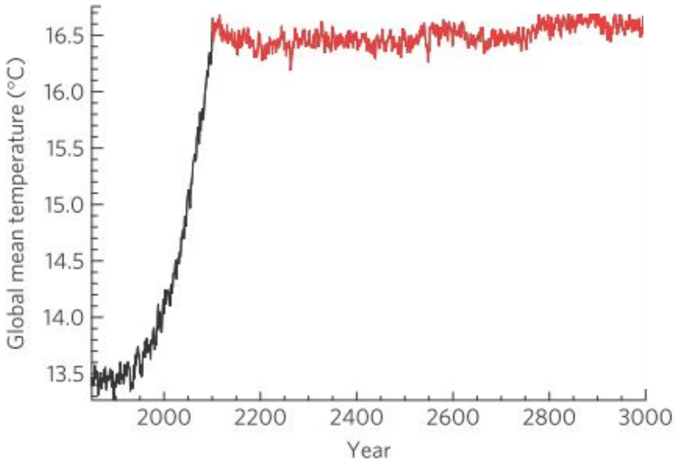
Zero emissions

Global mean temperature

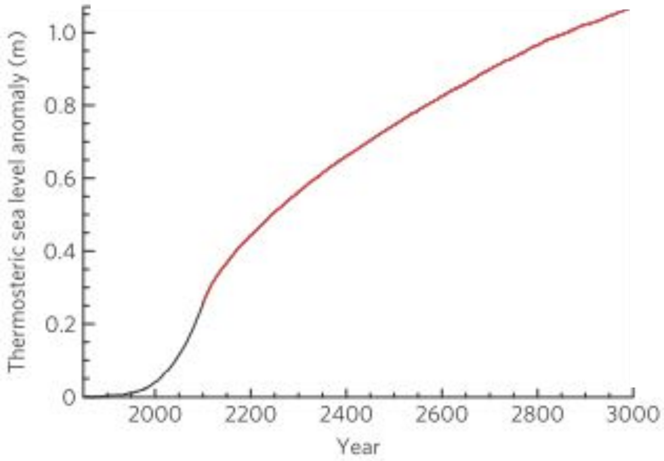


Zero emissions

Global mean temperature

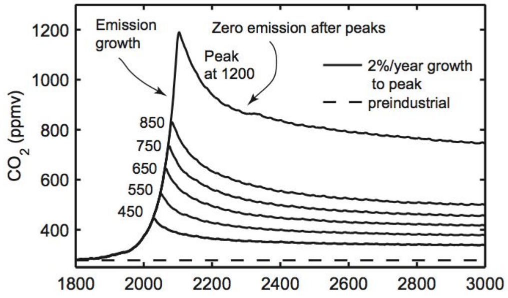


Thermosteric sea level



Irreversibility of climate change

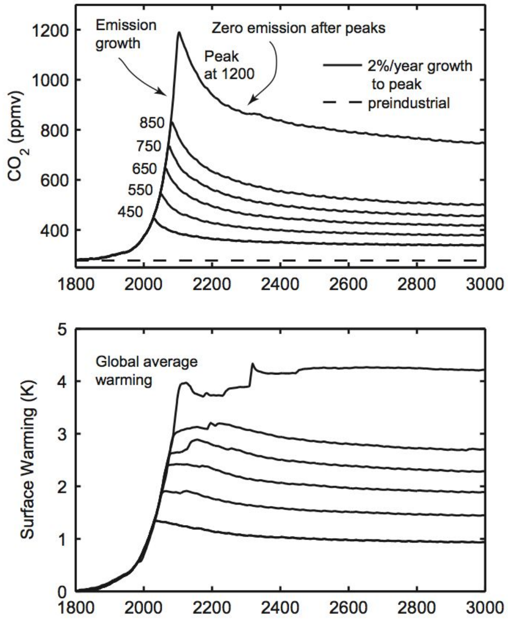
- Emissions are stopped



Solomon et al 2009

Irreversibility of climate change

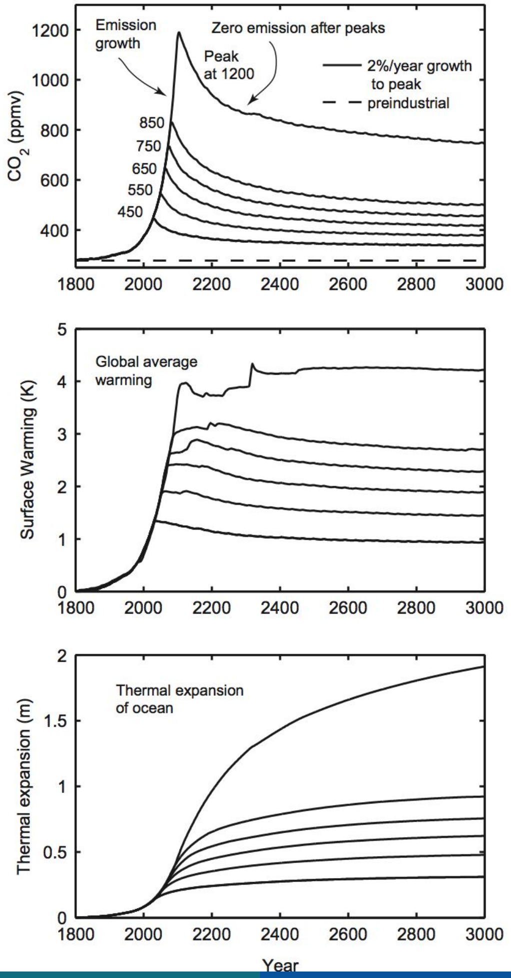
- Emissions are stopped
- Decrease in radiative forcing is compensated by slower ocean heat uptake



Solomon et al 2009

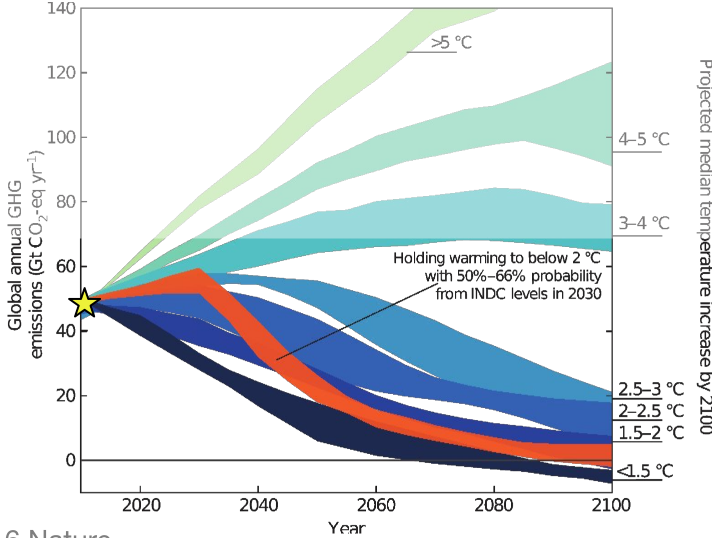
Irreversibility of climate change

- Emissions are stopped
- Decrease in radiative forcing is compensated by slower ocean heat uptake
- Atmospheric temperatures do not decline for another 1000 years

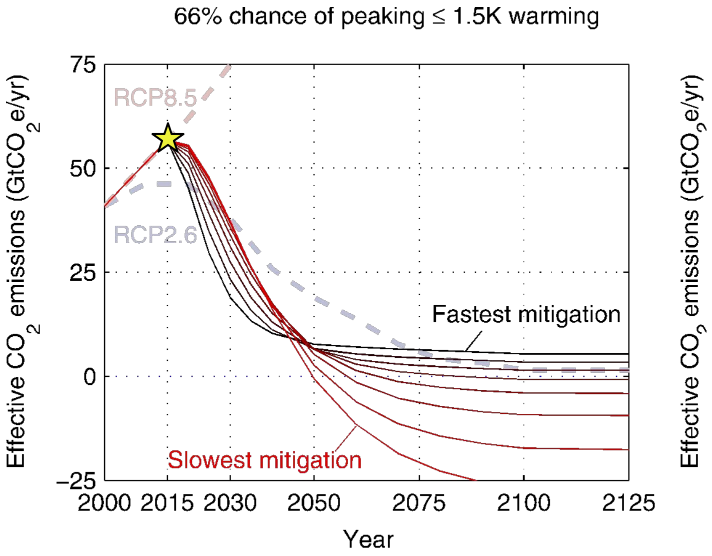


Solomon et al 2009

What would it take to get to 1.5°C



Rogelj et al., 2016 Nature



Sanderson et al., 2016 GRL

These pathways heavily rely on rapid emission reductions and negative emissions in the next few decades

Negative emissions

Direct Air Capture

Ocean Fertilization

Afforestation or Reforestation

Enhanced weathering

Biochar

BECCs

MCC Policy Brief, 2016

Negative emissions

Caveats:

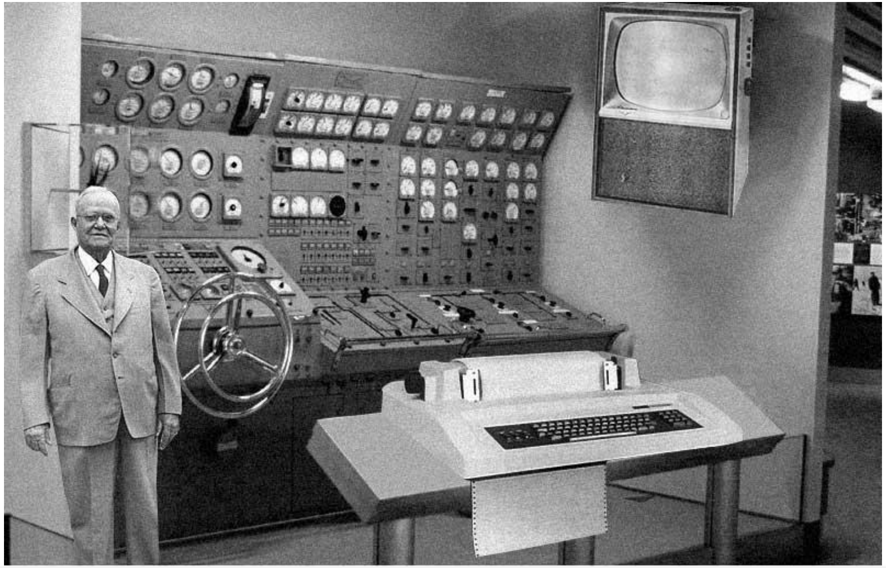
- Large scale deployment?
- Geological storage?
- Bio-energy +CCS = BECCS
- High cost
- Moral risk of postponing climate action indefinitely

  (far away future vs. immediate action is needed)

The power of human potential

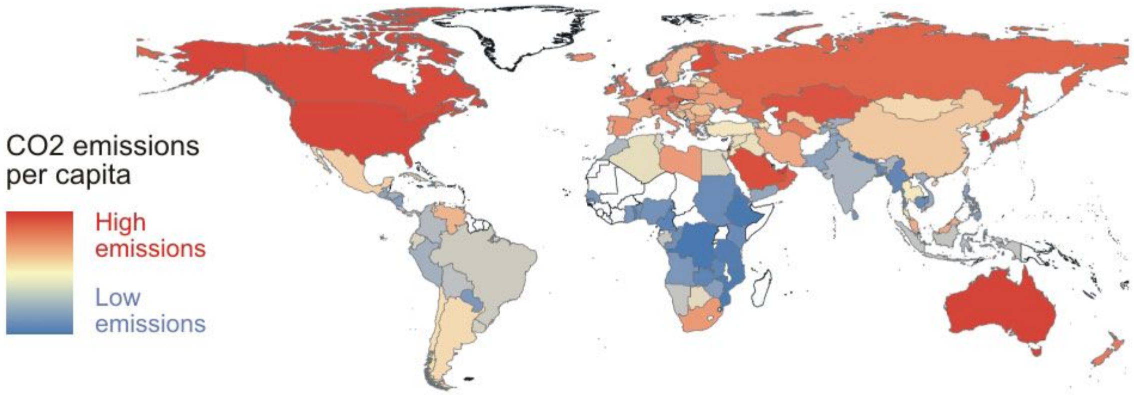
1954

Source: 1954 Popular Mechanics



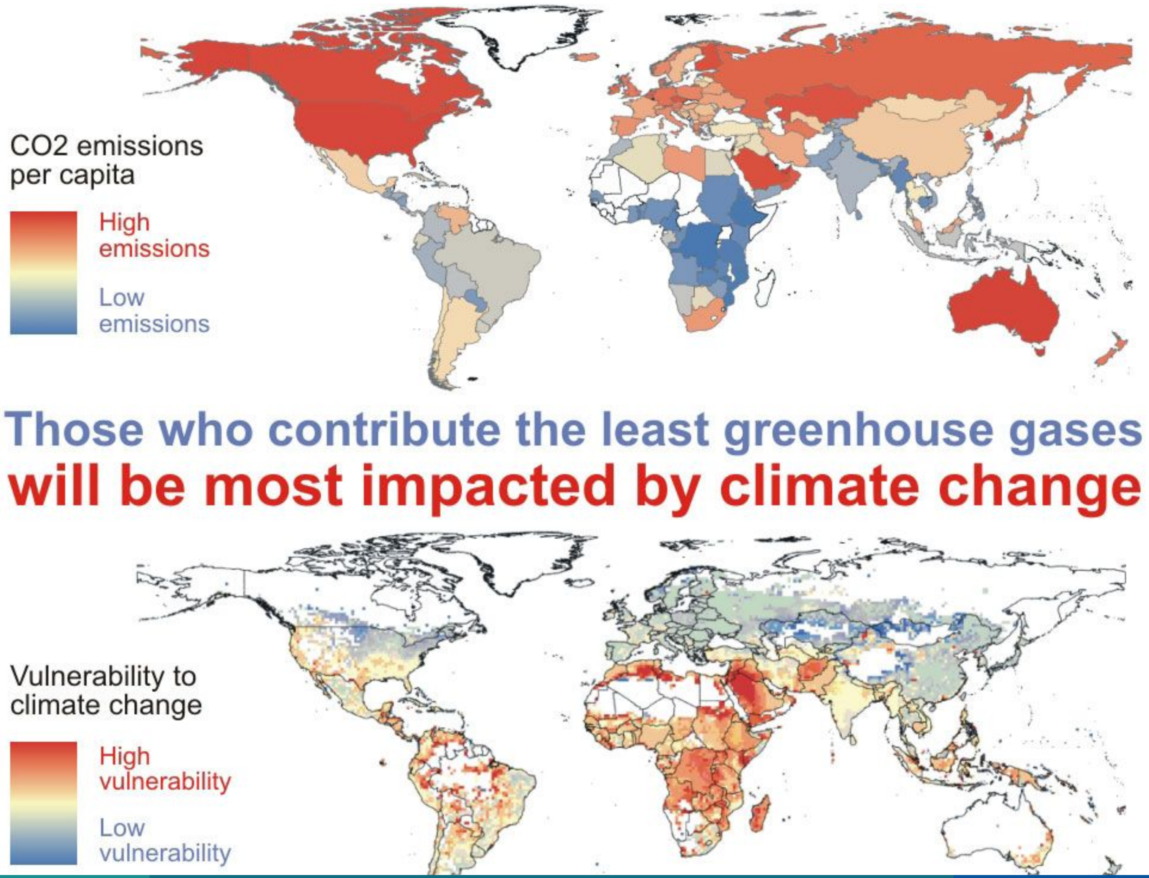
‘Scientists from the RAND Corporation have created this model to illustrate how a “home computer” could look like in year 2004. However much of the needed technology will not be feasible for the average home. Also, the scientists readily admit that the computer will require not yet invented technology to actually work,
but 50 years from now scientific progress is expected to solve these problems.
With teletype interface and Fortran language, the computer will be easy to use’.

Why is it important?



Those who contribute the least greenhouse gases

Why is it important?



Samson et al 2011

Discussion and coffee break

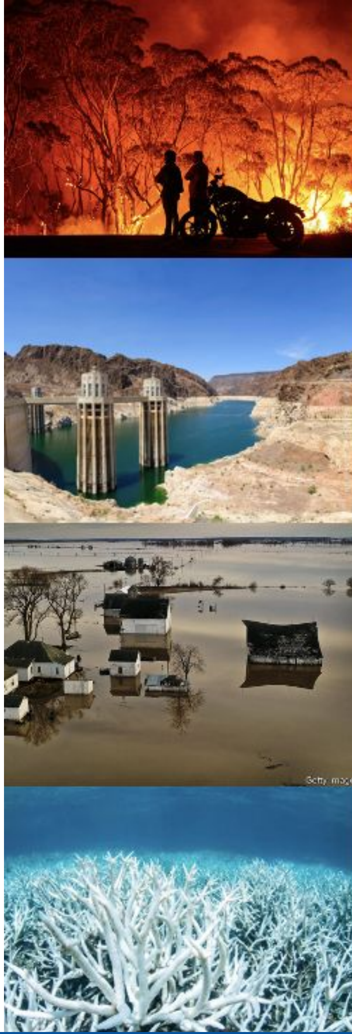
(followed by ML applications)

Machine learning applications to climate science

Machine learning (ML):
*the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyse and draw **inferences from patterns in data**.*

Strengths
- Doing simple tasks quickly and automatically
- Finding patterns in big datasets
- Optimizing complex systems

Weaknesses
- Sensitive to bad or biased data
- Poor at generalizing if data changes
- Finds correlation, not causation



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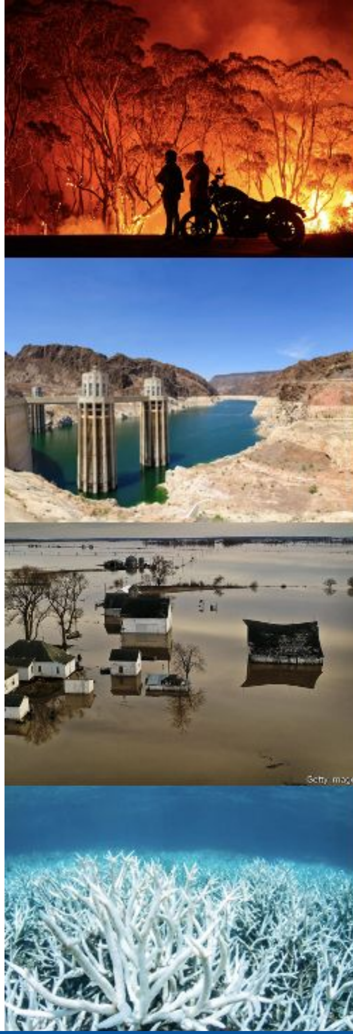
Climate change impacts:
Increasing severity and frequency of:

- Storms, droughts, fires, flooding, extreme heat, etc.
- Uneven impacts
- Feedbacks (e.g., permafrost thaw)

Need **net-zero greenhouse gas emissions**

- Need for a robust carbon accounting **verification** systems (top-down and bottom-up) to ensure true net-zero
- Need for **monitoring** (deforestation, nature-based solutions and land management)



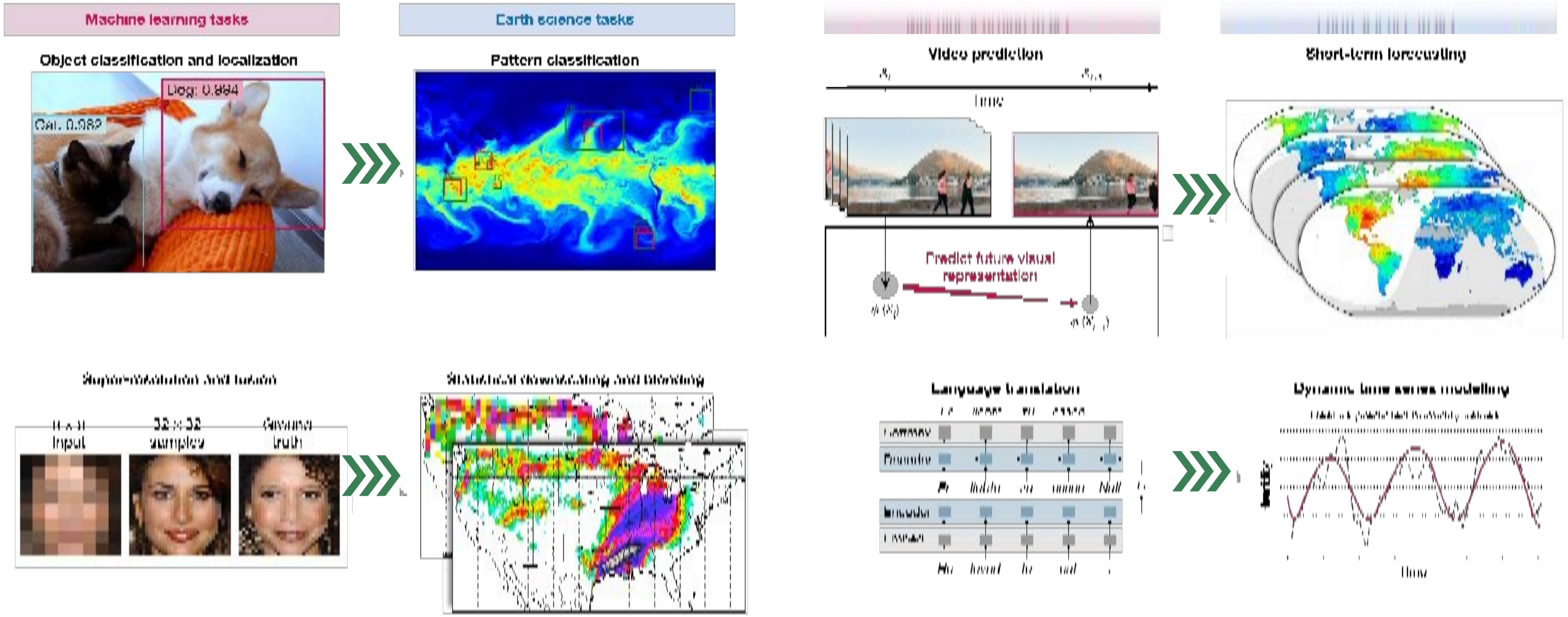
Machine learning applications

PERSPECTIVE

https://doi.org/10.1038/s41586-019-0912-1

Deep learning and process understanding for data-driven Earth system science

Markus Reichstein, Gustau Camps-Valls, Bjorn Stevens, Martin Jung, Joachim Denzler, Nuno Carvalhais & Prabhat



Forecasting on near-term and sub-seasonal time-scales

Need: Accurate near-term forecasting

ML: Predictions from past and present-day data based on multiple predictors (inputs)

Examples

- "Nowcasting" of precipitation
- El Nino forecasting
- Madden-Julian Oscillation predictions
- Forecasting agricultural yield

Active research

- Extreme event forecasting

nature

Article | Open Access | Published: 29 September 2021

Skilful precipitation nowcasting using deep generative models of radar

Suman Ravuri, Karel Lenc, Matthew Willson, Dmitry Kangin, Remi Lam, Piotr Mirowski, Megan Et al.

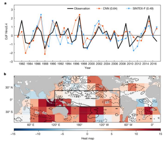
Letter | Published: 18 September 2019

Deep learning for multi-year ENSO forecasts

Yoo-Geun Ham, Jeong-Hwan Kim & Jing-Jia Luo

Nature **573**, 568–572 (2019) | Cite this article

37k Accesses | **259** Citations | **275** Altmetric | Metrics



JAMES Journal of Advances in Modeling Earth Systems

Research Article | Open Access

Using Simple, Explainable Neural Networks to Predict the Madden-Julian Oscillation

Zane K. Martin, Elizabeth A. Barnes, Eric Maloney

First published: 01 May 2022 | https://doi.org/10.1029/2021MS002774 | Citations: 1

ELSEVIER

Crops yield prediction based on machine learning models: Case of West African countries

Lontsi Saadio Cedric [a], Wilfried Yves Hamilton Adoni [b], Rubby Aworka [a], Jérémie T
Franck Kalala Mutombo [a, e], Moez Krichen [f, g], Charles Lebon Mberi Kimpolo [a]

CLIMATE Ai

Down-scaling to finer resolution

Need: High resolution output from climate models

ML: Approximating the output of GCMs to finer resolutions, including dynamical downscaling

Achieving higher resolution of historical data

Examples

- Downscaling of precipitation and temperature
- Down-scaling over mountain ranges and challenging topography regions
- Downscaling of low-resolution historical data to higher resolution

JAMES Journal of Advances in Modeling Earth Systems

Research Article | Open Access

Correcting a 200-km resolution climate model in multiple climates by machine learning from 25-km resolution simulations

Spencer K. Clark, Noah D. Brenowitz, Brian Henn, Anna Kwa, Jeremy McGibbon, W. Andre Perkins, Oliver Watt-Meyer, Christopher S. Bretherton, Lucas M. Harris

First published: 02 September 2022 | https://doi.org/10.1029/2022MS003219

Geosci. Model Dev., 14, 4977–4999, 2021
https://doi.org/10.5194/gmd-14-4977-2021
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Geoscientific Model Development
Open Access
EGU

Latent Linear Adjustment Autoencoder v1.0: a novel method for estimating and emulating dynamic precipitation at high resolution

Christina Heinze-Deml[1], Sebastian Sippel[1,2], Angeline G. Pendergrass[3,4,2], Flavio Lehner[3,4,2], and Nicolai Meinshausen[1]

[1]Seminar for Statistics, ETH Zurich, Zurich, Switzerland
[2]Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland
[3]Department of Earth and Atmospheric Sciences, Cornell University, Ithaca, NY, USA
[4]Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, CO, USA

Correspondence: Christina Heinze-Deml (heinzedeml@stat.math.ethz.ch)

Received: 14 August 2020 – Discussion started: 28 October 2020
Revised: 27 May 2021 – Accepted: 7 July 2021 – Published: 12 August 2021

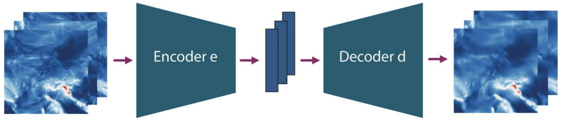
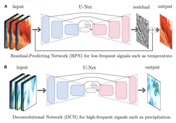


Figure 1. Illustration of a standard autoencoder model: the spatial fields Y are fed to the encoder e which maps them to the latent space variables L (illustrated in blue). These are in turn fed to the decoder d which computes a reconstruction of the input, $\hat{Y}$.

Spatio-Temporal Downscaling of Climate Data Using Convolutional and Error-Predicting Neural Networks



Agon Serifi[1]*, Tobias Günther[2] and Nikolina Ban[3]

[1] Department of Computer Science, ETH Zurich, Zurich, Switzerland, [2] Department of Computer Science,

Accelerating simulations

Need: Fast-resolving physical models

ML: Approximating some components of climate models

Examples

- Cloud emulators (substituting cloud physics in GCMs)
- Vegetation emulators

JAMES | Journal of Advances in Modeling Earth Systems

Research Article | Open Access

Machine Learning Emulation of 3D Cloud Radiative Effects

David Meyer, Robin J. Hogan, Peter D. Dueben, Shannon L. Mason

First published: 18 January 2022 | https://doi.org/10.1029/2021MS002550 | Citations: 2

Physics-Guided Machine Learning for Prediction of Cloud Properties in Satellite-Derived Solar Data

Publisher: IEEE | Cite This | PDF

Grant Buster ; Mike Bannister ; Aron Habte ; Dylan Hettinger ; Galen Maclaurin ; Michael Rossol ; Manajit Sengupt... All Authors

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Research Article | Open Access

A Hybrid Approach to Atmospheric Modeling That Combines Machine Learning With a Physics-Based Numerical Model

Troy Arcomano, Istvan Szunyogh, Alexander Wikner, Jaideep Pathak, Brian R. Hunt, Edward Ott

First published: 16 February 2022 | https://doi.org/10.1029/2021MS002712

Geophysical Research Letters

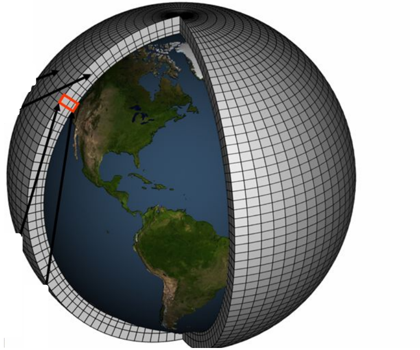
Research Letter | Free Access

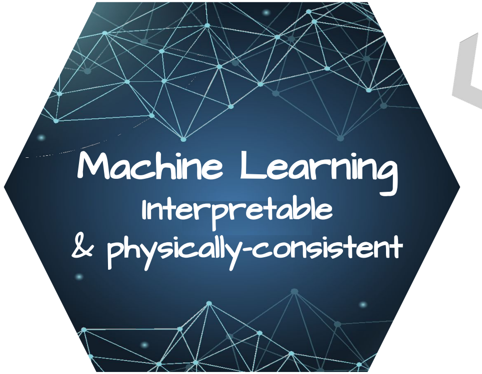
Prognostic Validation of a Neural Network Unified Physics Parameterization

N. D. Brenowitz, C. S. Bretherton

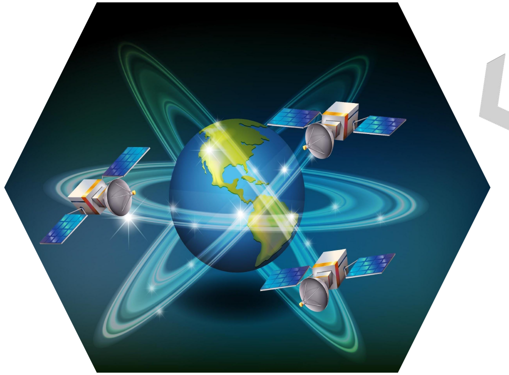
Physics-informed ML

Physics-based climate models



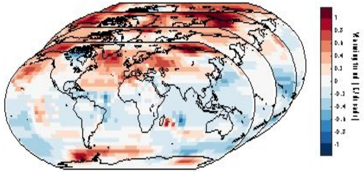


Observational products



e.g., Temperature data,
Carbon observations

Climate physics



$$\rho\left[\frac{\partial u}{\partial t}+\frac{\partial u}{\partial x}u+\frac{\partial u}{\partial y}v+\frac{\partial u}{\partial z}w\right]=-\frac{\partial p}{\partial x}+\mu\left(\frac{\partial^2 u}{\partial x^2}+\frac{\partial^2 u}{\partial y^2}+\frac{\partial^2 u}{\partial z^2}\right)+\rho g_x$$

$$\rho\left[\frac{\partial v}{\partial t}+\frac{\partial v}{\partial x}u+\frac{\partial v}{\partial y}v+\frac{\partial v}{\partial z}w\right]=-\frac{\partial p}{\partial y}+\mu\left(\frac{\partial^2 v}{\partial x^2}+\frac{\partial^2 v}{\partial y^2}+\frac{\partial^2 v}{\partial z^2}\right)+\rho g_y$$

$$\rho\left[\frac{\partial w}{\partial t}+\frac{\partial w}{\partial x}u+\frac{\partial w}{\partial y}v+\frac{\partial w}{\partial z}w\right]=-\frac{\partial p}{\partial z}+\mu\left(\frac{\partial^2 w}{\partial x^2}+\frac{\partial^2 w}{\partial y^2}+\frac{\partial^2 w}{\partial z^2}\right)+\rho g_z$$

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Hybrid modelling and physical constraints

Need: ML predictions that are robust on longer time-scales and physically consistent

ML: Physically-informed neural networks (PINN) or physical constraints hard-coded into ML architectures

Examples

- Hybrid atmospheric models (incl. atmospheric variability)
- Cloud emulators (substituting cloud physics in GCMs)
- Wildfire modelling

Review articles

Physics-informed machine learning: case studies for weather and climate modelling

K. Kashinath, M. Mustafa, A. Albert, J-L. Wu, C. Jiang, S. Esmaeilzadeh, K. Azizzadenesheli, R. Wang, A. Chattopadhyay, A. Singh, A. Manepalli, D. Chirila, R. Yu, R. Walters, B. White, H. Xiao, H. A. Tchelepi, P. Marcus, ... See all authors

Published: 15 February 2021 | https://doi.org/10.1098/rsta.2020.0093

JAMES | Journal of Advances in Modeling Earth Systems

Research Article | Open Access

A Hybrid Approach to Atmospheric Modeling That Combines Machine Learning With a Physics-Based Numerical Model

Troy Arcomano, Istvan Szunyogh, Alexander Wikner, Jaideep Pathak, Brian R. Hunt, Edward Ott

First published: 16 February 2022 | https://doi.org/10.1029/2021MS002712

nature communications

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Article | Open Access | Published: 22 March 2022

Machine learning–based observation-constrained projections reveal elevated global socioeconomic risks from wildfire

Yan Yu, Jiafu Mao, Stan D. Wullschleger, Anping Chen, Xiaoying Shi, Yaoping Wang, Forrest M. Hoffman, Yulong Zhang & Eric Pierce

Three-fold objectives in ML projects for observational constraints

Prediction and Uncertainty Quantification

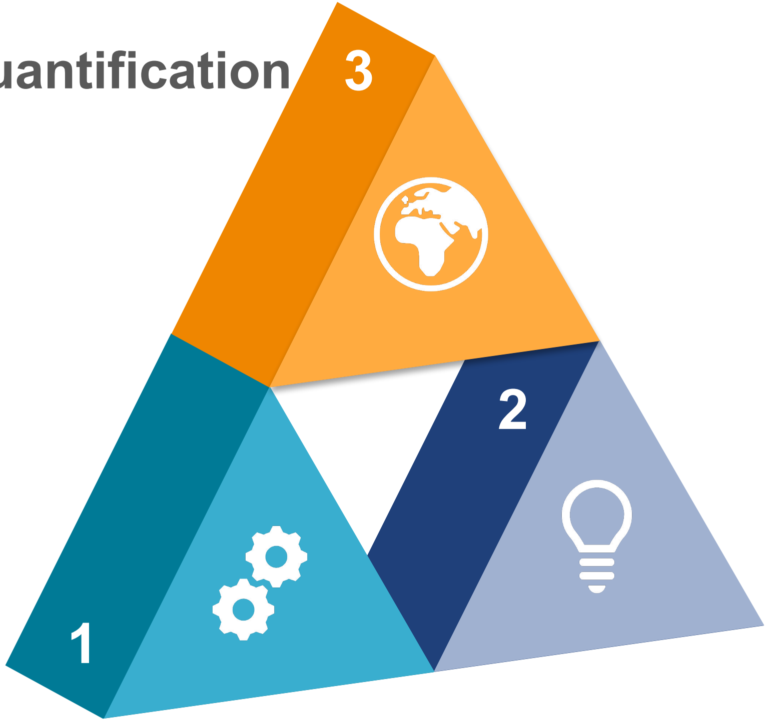
- Quantification of uncertainty
- Predictions on real-world data
- **Estimates of future warming, and other variables (e.g., remaining carbon budgets)**

Interpretability

- Feature importance (key inputs)
- Key regions for making robust predictions
- Conceptual understanding

Model development

- Data-driven models development
- Inclusion of physical constraints
- Evaluation & Benchmarking



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ML is one piece of the puzzle

ML is a powerful tool, **not a silver bullet**

Not relevant to every problem

Where ML is relevant, **collaboration** is key:

- Targeting meaningful problems
- Avoiding oversimplification or overcomplication
- Recognizing potential risks
- Guiding deployment

nature machine intelligence

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nature > nature machine intelligence > perspectives > article

Perspective | Published: 17 August 2021

Towards neural Earth system modelling by integrating artificial intelligence in Earth system science

Christopher Irrgang, Niklas Boers, Maike Sonnewald, Elizabeth A. Barnes, Christopher Kadow, Joanna Staneva & Jan Saynisch-Wagner

Nature Machine Intelligence **3**, 667–674 (2021) | Cite this article

2744 Accesses | **18** Citations | **45** Altmetric | Metrics

PHILOSOPHICAL TRANSACTIONS A

royalsocietypublishing.org/journal/rsta

Introduction

Check for updates

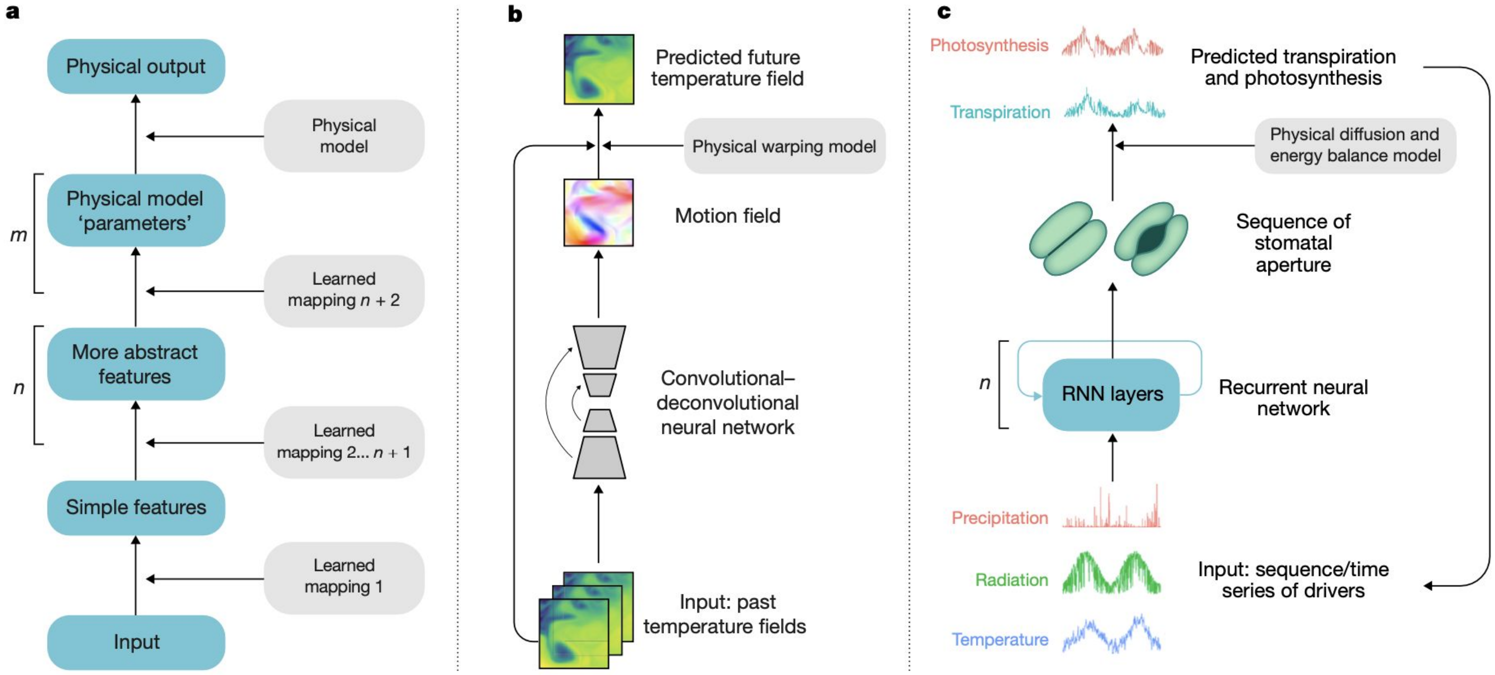
Cite this article: Chantry M, Christensen H, Dueben P, Palmer T. 2021 Opportunities and challenges for machine learning in weather and climate modelling: hard, medium and soft AI. *Phil. Trans. R. Soc. A* **379**: 20200083. https://doi.org/10.1098/rsta.2020.0083

Opportunities and challenges for machine learning in weather and climate modelling: hard, medium and soft AI

Matthew Chantry[1], Hannah Christensen[1], Peter Dueben[2] and Tim Palmer[1]

[1]Atmospheric, Oceanic and Planetary Physics, University of Oxford, Oxford, UK
[2]European Centre for Medium Range Weather Forecasts, Reading, UK

Physics-informed ML and hybrid modelling



Earth systems model output as a test bed

Reichstein et al. 2019, Nature

Can we use ML to predict climate change in 2050?

No

Maybe

Yes

Summary of ML applications to climate science

Non-exhaustive

- **Short term forecasting** (< 20 years) of near-term weather and climate changes & oscillating events & **climate variability** (e.g., ENSO oscillation, PDO) **Tutorial**
- **Subseasonal forecasting** *promising area
- **Extreme event forecasting** *promising area
- **Down-scaling climate model output to finer resolution** (e.g., temperature, precipitation)
- **Detection and attribution** (attributing observed changes to climate change)
- **Causality** (understanding drivers of observed changes)
- **Hybrid modelling** – ML used in Climate models development (e.g., cloud emulators, vegetation emulators)
- And many more areas of application… (references to some interesting papers are provided by the end of this deck)

ML applications to climate science

Non-exhaustive

- Deep learning and process understanding for data-driven Earth system science - https://www.nature.com/articles/s41586-019-0912-1
- Towards neural Earth system modelling by integrating artificial intelligence in Earth system science - https://www.nature.com/articles/s42256-021-00374-3
- Revealing the Impact of Global Heating on North Atlantic Circulation Using Transparent Machine Learning - https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2021MS002496
- Bridging observations, theory and numerical simulation of the ocean using machine learning - https://iopscience.iop.org/article/10.1088/1748-9326/ac0eb0
- Viewing Forced Climate Patterns Through an AI Lens https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019GL084944

Climate data landscape

- Where do I find climate data?
  - ESGF; Pangeo, Large Ensemble Simulations (look for CMIP5 and CMIP6 data)
  - ECMWF data (for historical data and near-term predictions)
  - CORDEX (for downscaled climate models)
- Remote sensing data (e.g., ESA-phi lab)
- NASA climate datasets
- NCAR Climate Data Guide
- ClimateBench (for training ML models)

Additional resources

Non-exhaustive

- Carbon Brief- how do climate models work: https://www.carbonbrief.org/qa-how-do-climate-models-work/
- Applied Machine Learning Tutorial for Earth Scientists https://github.com/eabarnes1010/ml_tutorial_csu
- Analyse CMIP6 data from the cloud servers

https://cmip6moap.github.io/resources/loading-data-xarray/

- Pangeo: http://gallery.pangeo.io/repos/pangeo-gallery/cmip6/
- Plot CMIP data using xarray https://nordicesmhub.github.io/Norway_Sweden_training/pangeo/CMIP6_example.html
- https://cmip6moap.github.io/resources/loading-data-xarray/

Applications -Tutorial

- Introduction to Tutorial on Forecasting of El Niño/ Southern Oscillation

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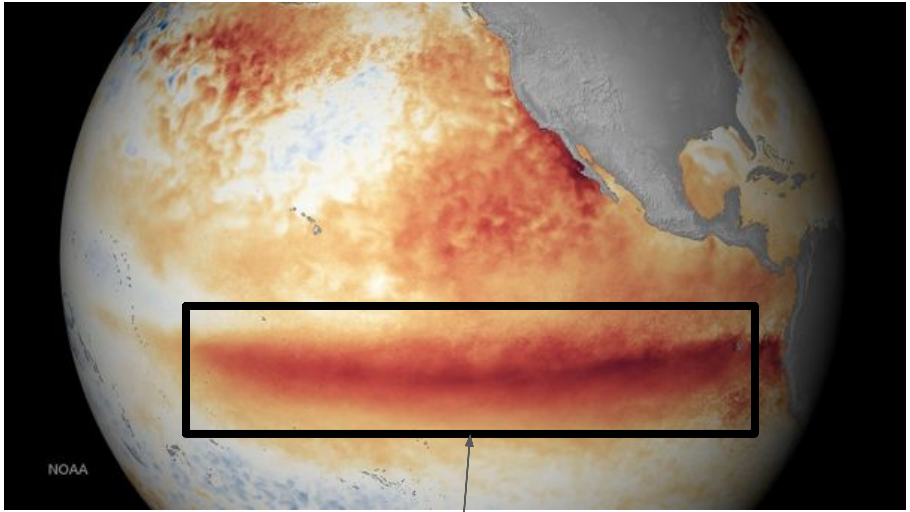
ML for forecasting of El Niño/ Southern Oscillation

- **Cycle of warm and cold temperatures** in the equatorial Pacific Ocean
- Dominant pattern that influences **seasonal temperature**
- Broad implications for climate-sensitive sectors, such as energy and agriculture



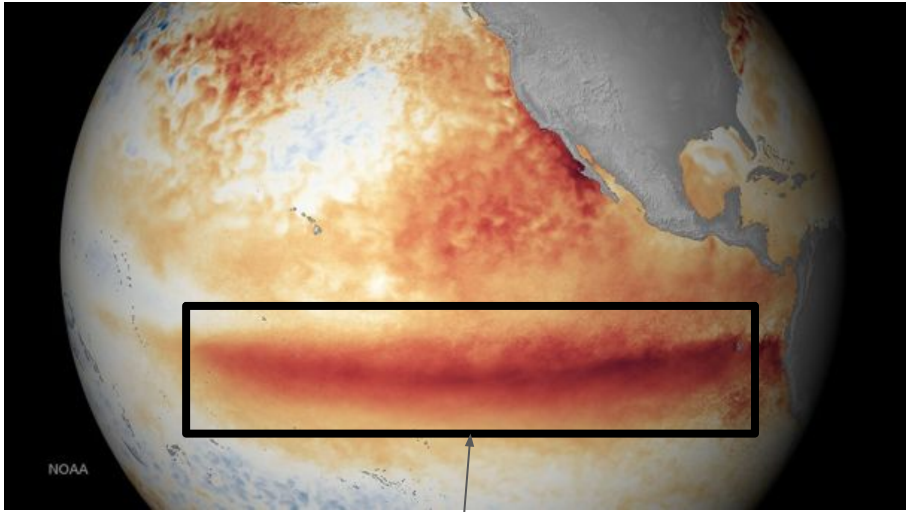
Source: National Oceanic and Atmospheric Administration

Equatorial Pacific Ocean with abnormally warm temperature: El Niño event

© Ankur Mahesh

ML for forecasting of El Niño/ Southern Oscillation

- **Cycle of warm and cold temperatures** in the equatorial Pacific Ocean
- Dominant pattern that influences **seasonal temperature**
- Broad implications for climate-sensitive sectors, such as energy and agriculture
- **How is El Niño measured?** *Niño3.4 Index* Rolling 3-month average of sea surface temperatures in the equatorial Pacific



Source: National Oceanic and Atmospheric Administration

Equatorial Pacific Ocean with abnormally warm temperature: El Niño event

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ML for forecasting of El Niño/ Southern Oscillation

What is the current state of the art?

- Most ENSO forecasts are issued by weather centers, who run physics-based models

Why use neural networks?

- Potential for more accurate forecasts?
- Lighter computational cost *during inference*

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ML for forecasting of El Niño/ Southern Oscillation

What is the current state of the art?

- Most ENSO forecasts are issued by weather centers, who run physics-based models

Why use neural networks?

- Potential for more accurate forecasts?
- Lighter computational cost *during inference*

Challenge: limited historical observations to use as training data for a neural network

Solution: train on simulated climate data from Atmosphere-Ocean General Circulation Models (AOGCMs)

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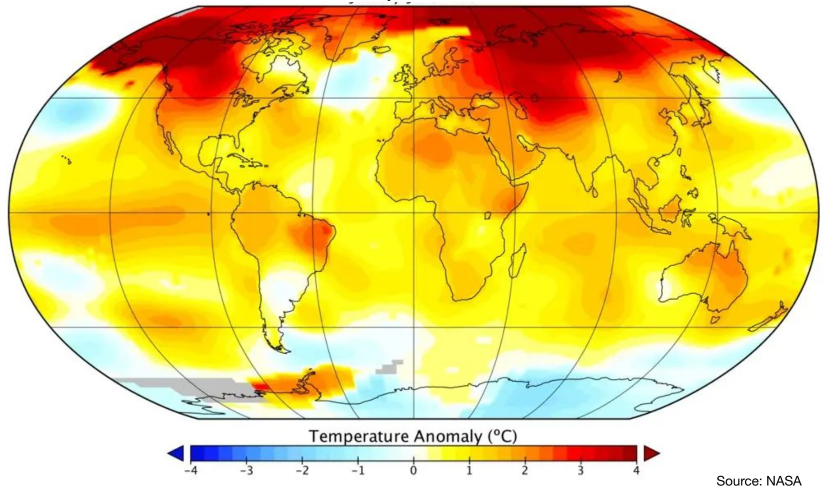
ML for forecasting of El Niño/ Southern Oscillation

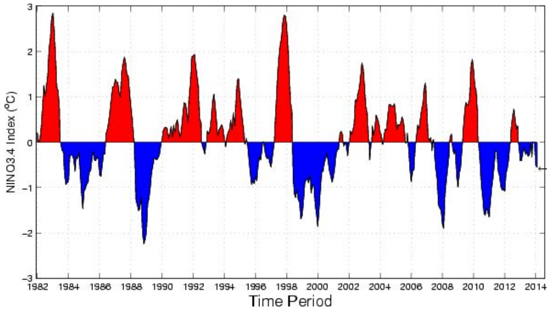
- **Data:** How does an increase in data affect the performance of machine learning?
- **Validation:** how can we ensure that we validate the model rigorously?
- **Ensembling:** What combination of models and training schemes creates the best forecasts?
- **Lead time:** How far ahead can machine learning make skillful predictions?
- **Extendability:** Can we use our neural network architecture to forecast *temperatures on land*?

Predictor Data: surface temperature



Source: NASA

Target Data:



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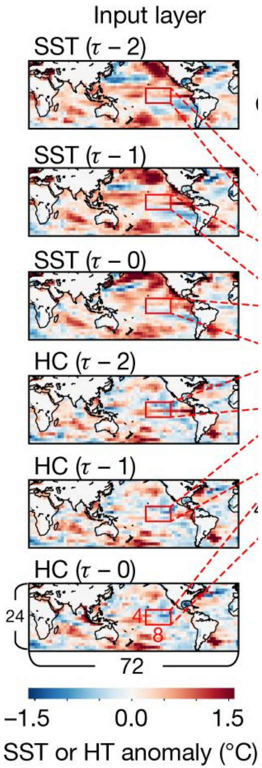
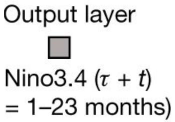
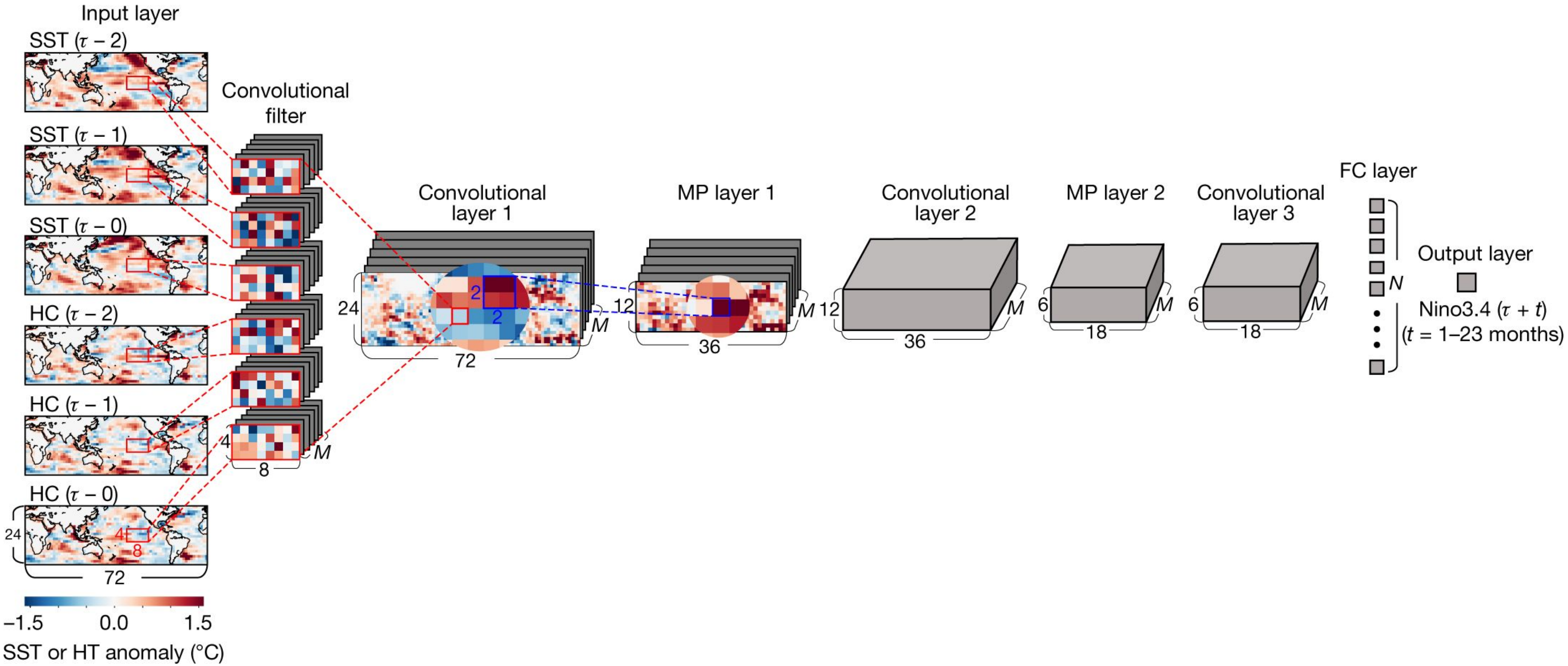
Model architectures





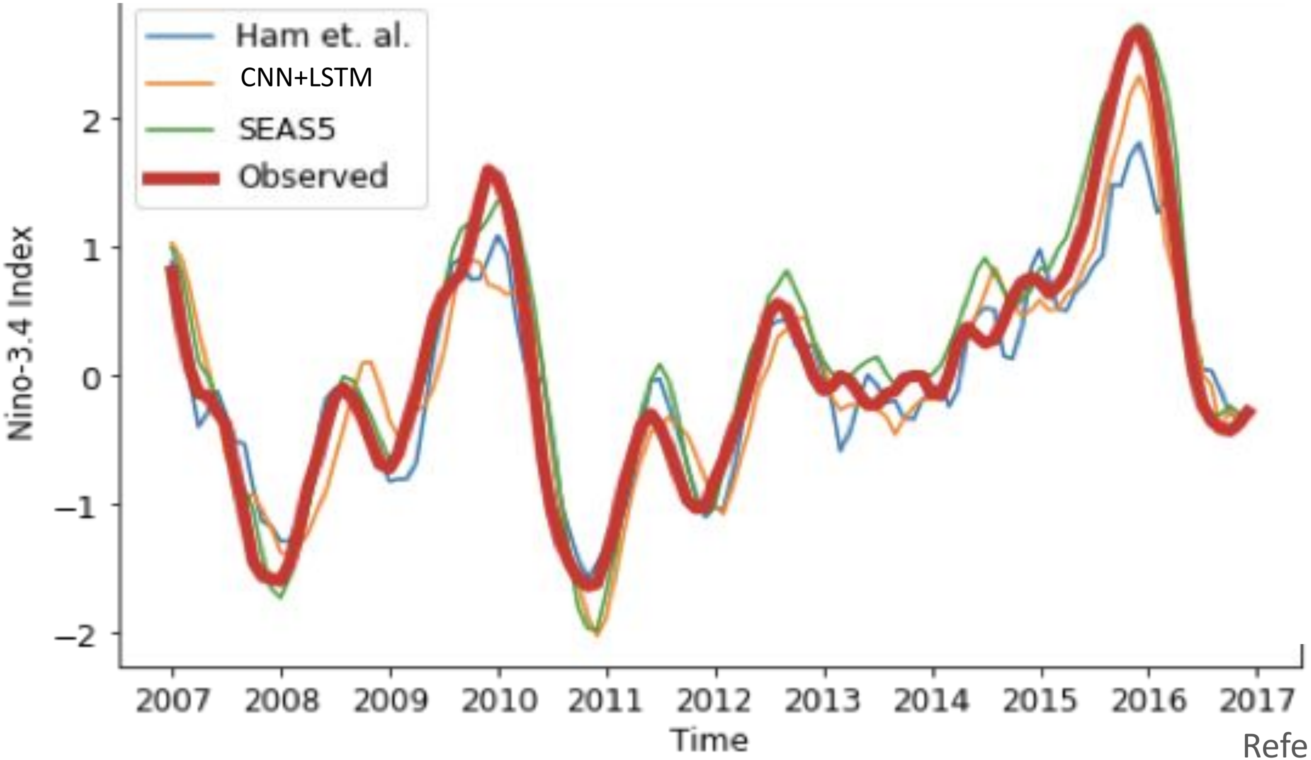
Source Image: Ham et al. 2019. *Deep learning for multi-year ENSO forecasts. Nature.*

Model architectures



Source Image: Ham et al. 2019. *Deep learning for multi-year ENSO forecasts. Nature.*

ML for forecasting of El Niño/ Southern Oscillation



Reference: Ham et al.

SEAS5: seasonal forecasting model from the European Center for Medium-range Weather Forecasts
CNN+LSTM: a deep learning architecture designed to learn from spatial and time series data

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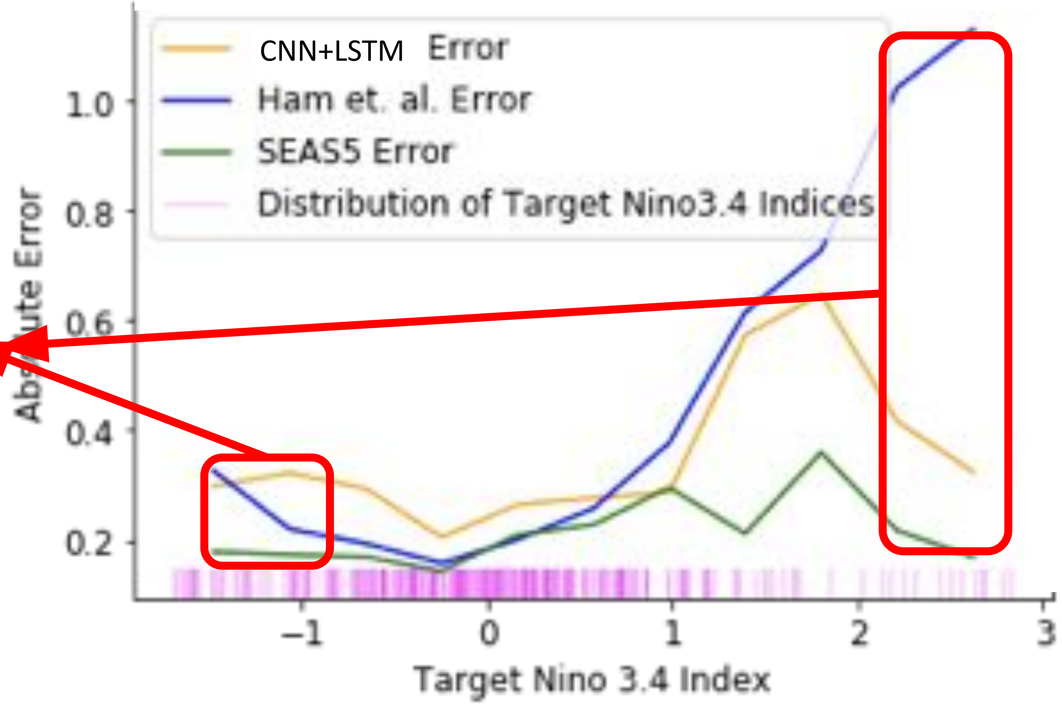
ML for forecasting of El Niño/ Southern Oscillation

- Why work on this problem?

- Deep learning's performance at extreme values of the Niño3.4 index still has room for improvement!



SEAS5: seasonal forecasting model from the European Center for Medium-range Weather Forecasts
CNN+LSTM: a deep learning architecture designed to learn from spatial and time series dataΩz

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Let’s get started with the tutorial!

Tutorial Lead: Ankur Mahesh