Learning from data to model the Earth system and predict climate impacts on the biosphere

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INPUTBern Research Meeting, 23. Nov. 2022

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CLIMATE CHANGE RESEARCH

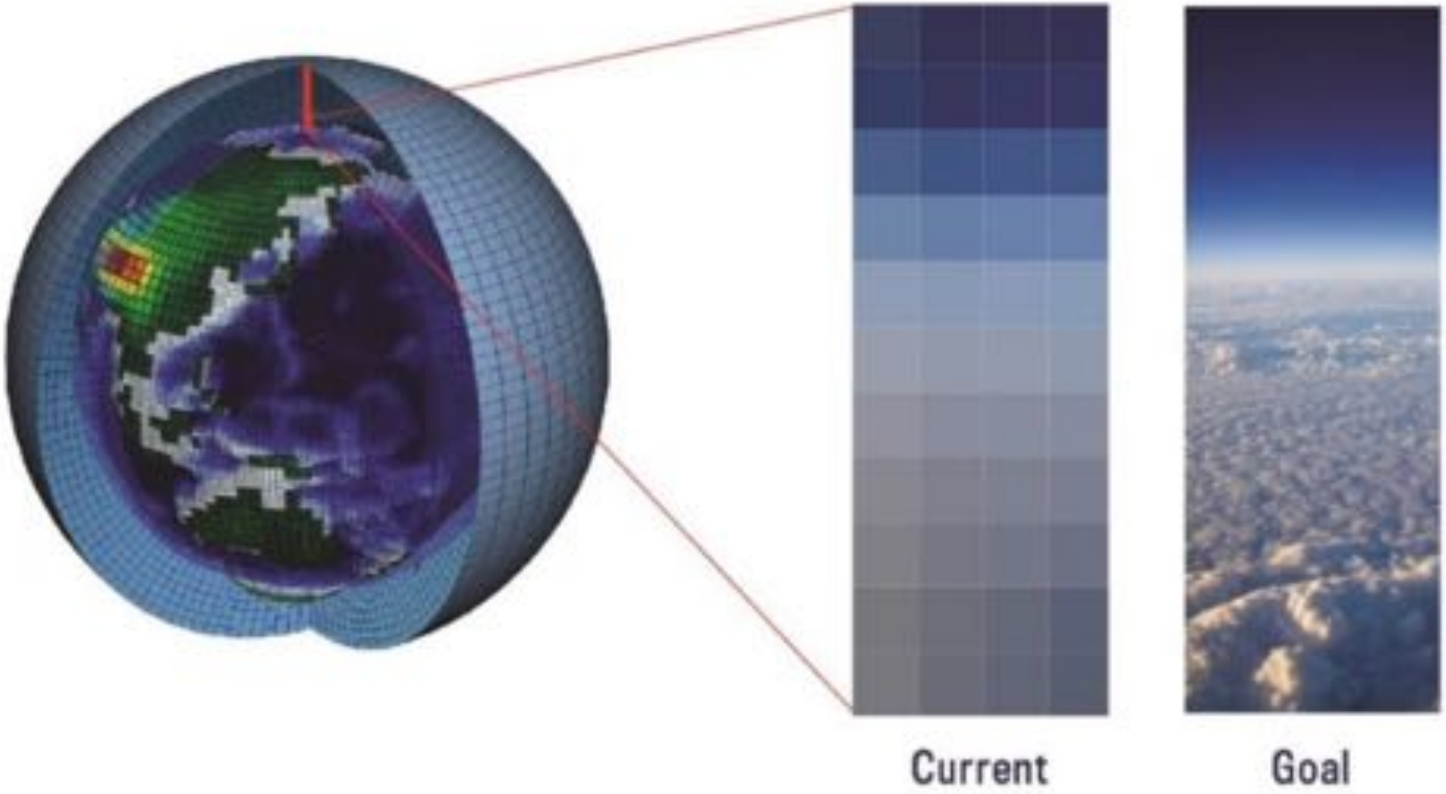
https://pixy.org/372871/

Earth System Model
- Description of physics and mechanisms
- Systems dynamics
- Multiple state variables
- Feedbacks

Data
- Data assimilation
- “Nudging” the state of the system towards observations

- Numerical weather prediction models

https://pixy.org/372871/


Current
Goal

Data revolution in Earth and Environmental Sciences

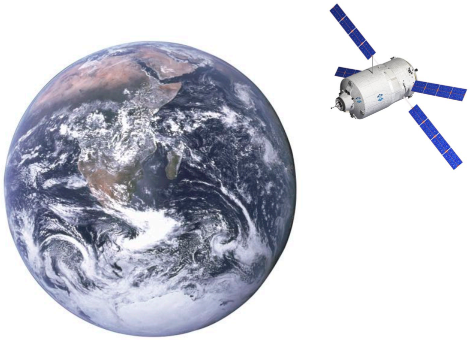


Image Markus Staudinger,

Kattge et al., 2019

Remote sensing

Example: NASA missions

- 12 TB / day (in 2017)

Continuous monitoring

Example: FLUXNET

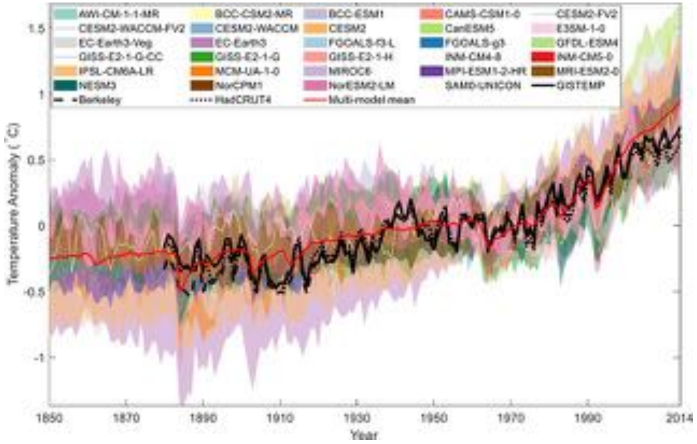
- 166 sites with open access data
- <25 years

Data compilations

Example: TRY plant traits database

- 12 mio. records
- 280’000 species
- 21’000 sites

Data revolution in Earth and Environmental Sciences



Climate model outputs

Example: CMIP6

- 30 PB

Data + Machine Learning = ✔

Promise

- Learn more than possible with traditional data assimilation methods

Challenge

- How to extract interpretable information and knowledge from data?
- How to keep track with increasing data availability?

Systems modelling paradigm *vs* data-driven

Theory *vs* data

Attempt at classification of ML in Earth system modelling

A: Making sense of information

B: (Black box) prediction

C: Hybrid modelling

This talk

1. Some success stories

    A: Making sense of information

    B: (Black box) prediction

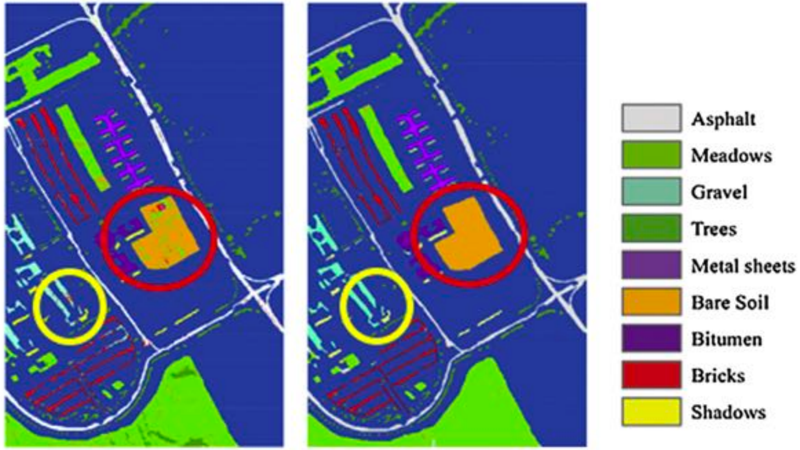
    C: Hybrid modelling

2. Our research in Geocomputation and Earth Observation

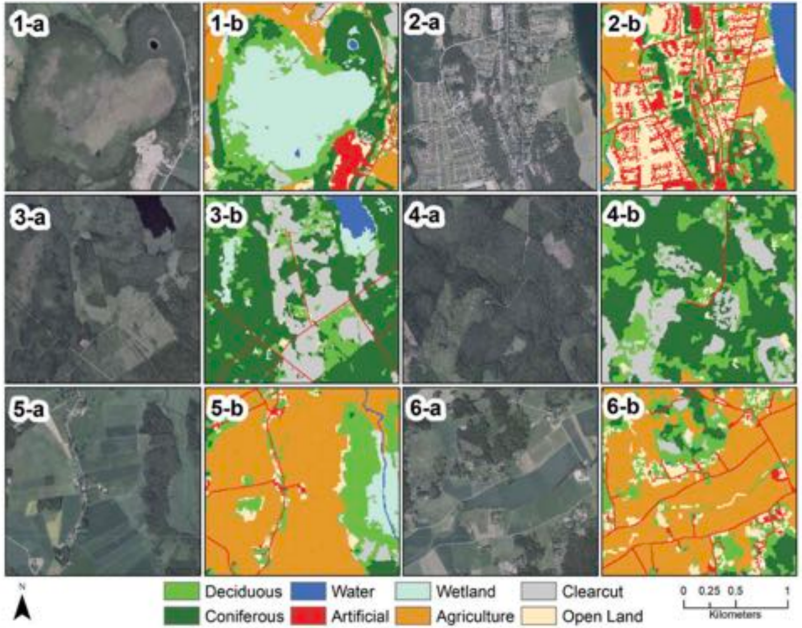
3. Outlook

A: Making sense of information

- **Land cover classification**
  - **Pixel-wise:** Y = *f*(**x**)
  - **Accounting for spatial dependencies**



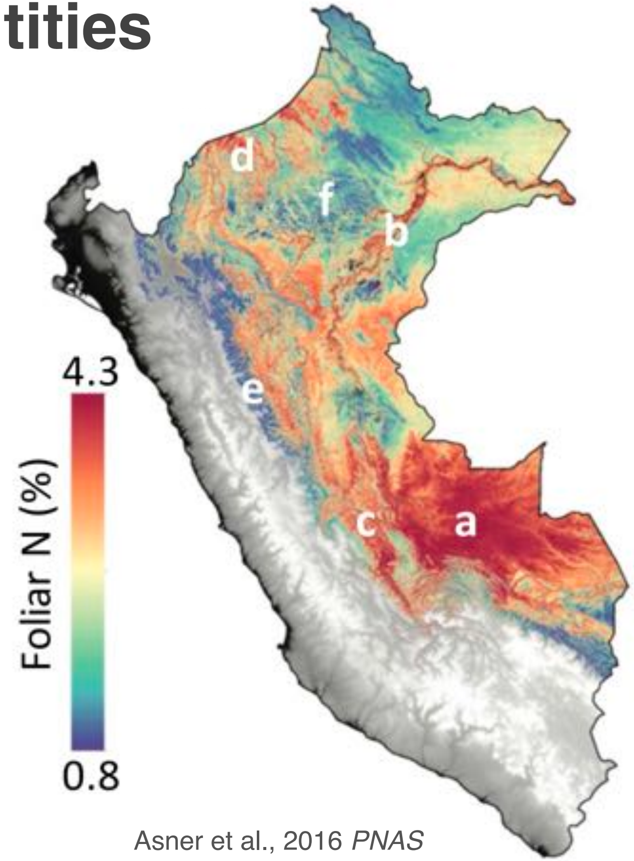
Zhao & Du, 2016



Abdulhakim et al., 2020 *GIScience*

A: Making sense of information

- **Regression of biogeophysical quantities**
  - **Pixel-wise:** Y = $f(\mathbf{x})$

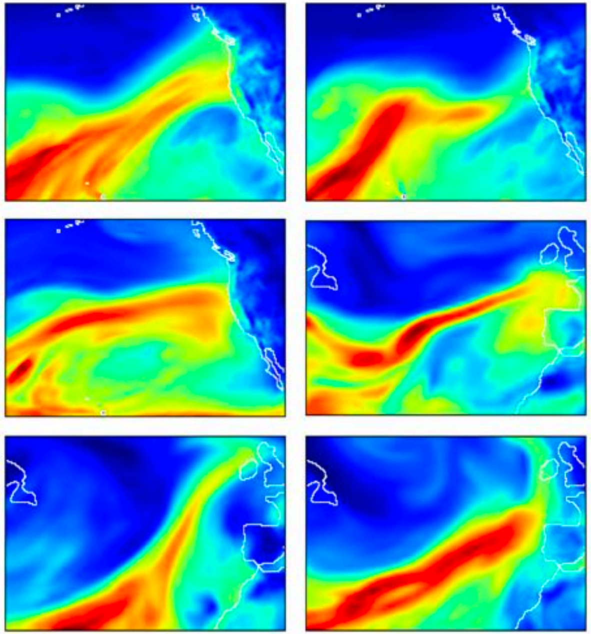


Asner et al., 2016 *PNAS*

A: Making sense of information

- **Detecting and classifying (extreme) weather patterns**
  - **Accounting for spatial dependencies**

Total column water vapour

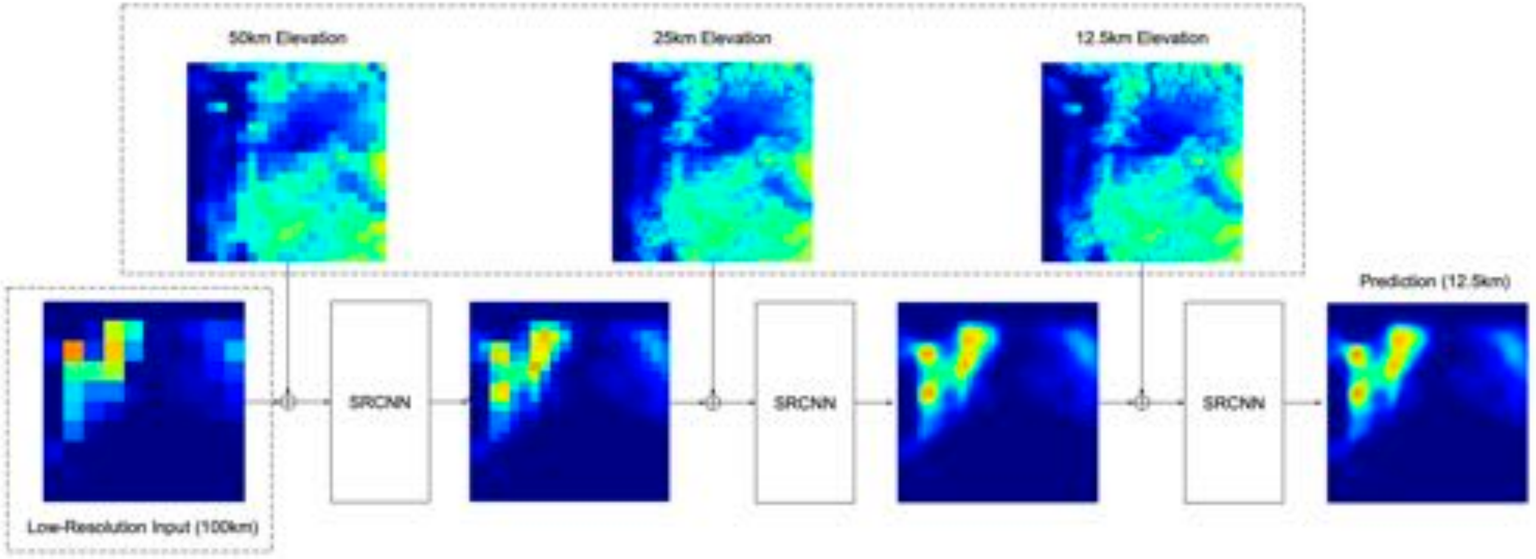


- **Anomaly detection**

Liu et al., 2016 *arXiv*

A: Making sense of information

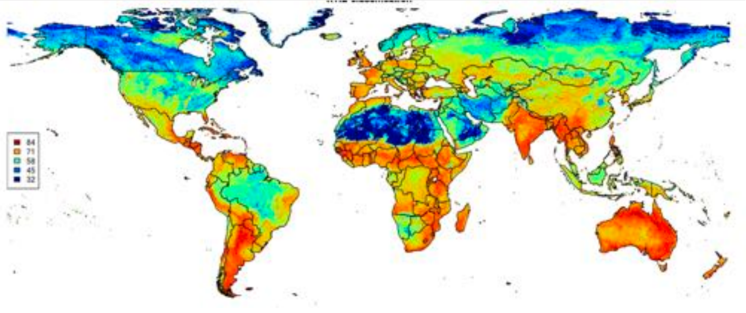
- **Downscaling, gap-filling, making data analysis-ready**



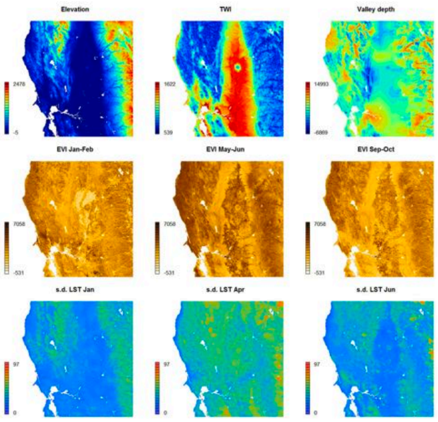
Vandal et al., 2018

A: Making sense of information

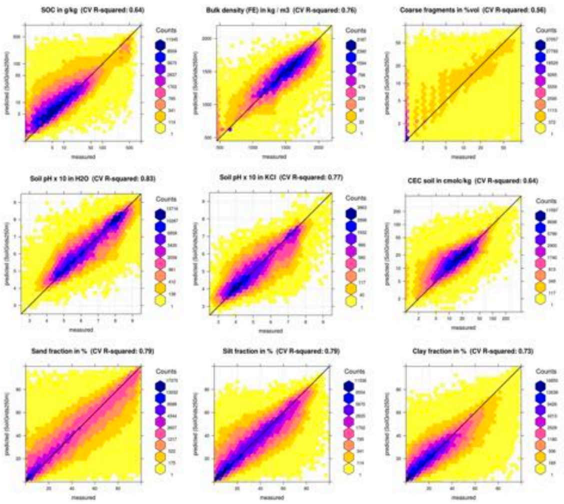
- **Spatial upscaling**
  - **Digital soil mapping**
  - **Pixel-wise:** Y = *f*(**x**)




Training data:
150,000 soil profiles



Environmental covariates
with global coverage

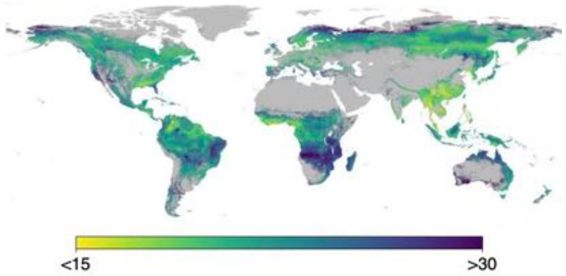

Out-of-sample prediction
and globally upscaled
product

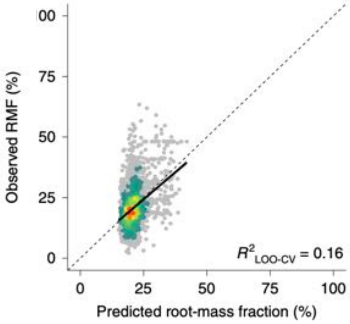
Hengl et al., 2017

A: Making sense of information

- **Spatial upscaling everything**

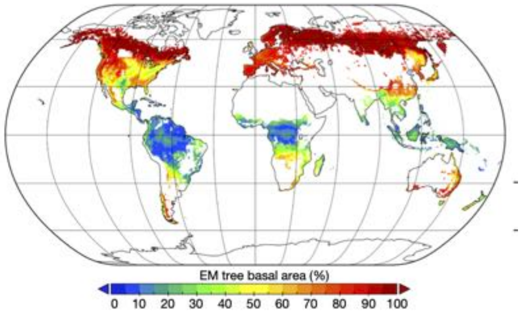
Root mass fraction (%)

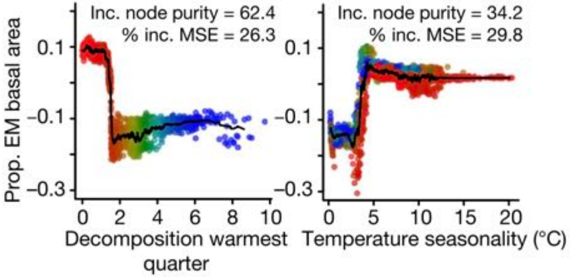




Ma et al., 2020 *Nature Eco. Evo.*

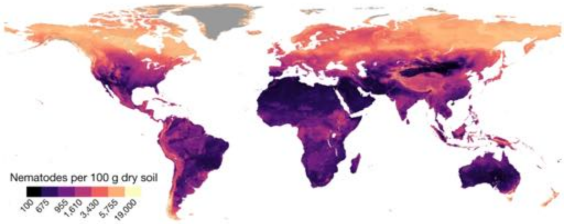
Fraction of trees associated with ectomycorrhizal fungi (%)



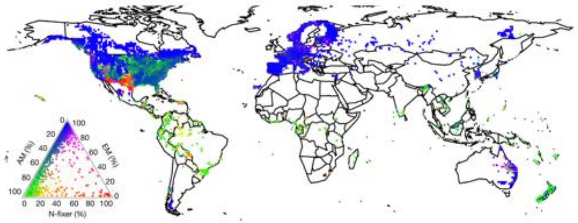


Steidinger et al., 2019 *Nature*

Soil nematode abundance



Van der Hoogen et al., 2019 *Nature*



A: Making sense of information

State estimation

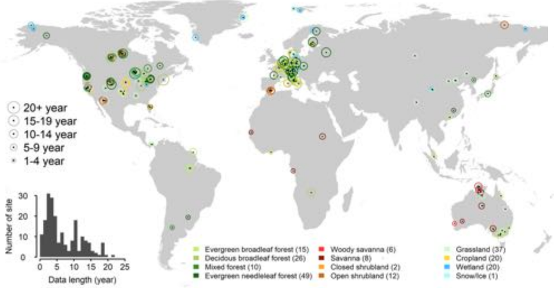
B: (Black box) prediction

Dynamics prediction

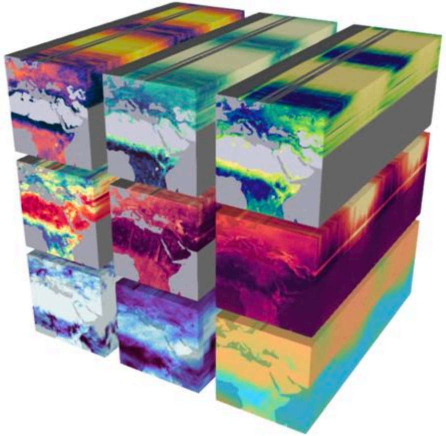
B: Prediction

- **Temporal-spatial upscaling**
  - **Pixel-wise** $Y_t = f(\mathbf{x}_t)$

Image Markus Staudinger,

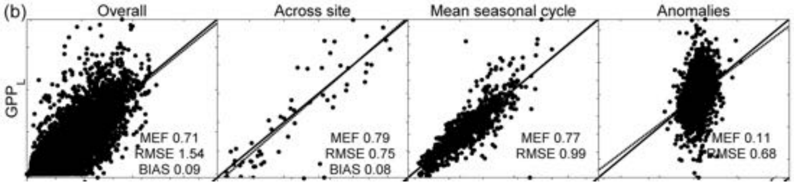


Pastorello et al., 2020 *Sci. Dat.*



Mahecha et al., 2020 *ESD*

Jung et al., 2020 *BG*



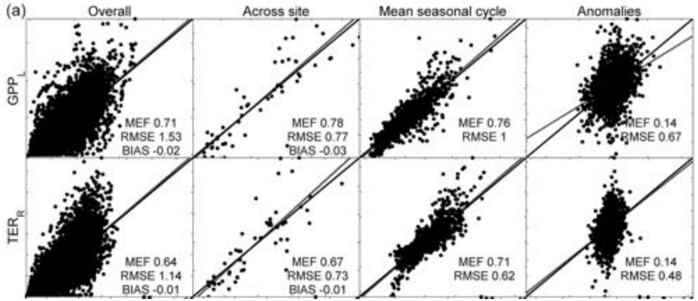
Tramontana et al., 2016

B: Prediction

- **Adding physics into the black box**

NEE = TER - GPP

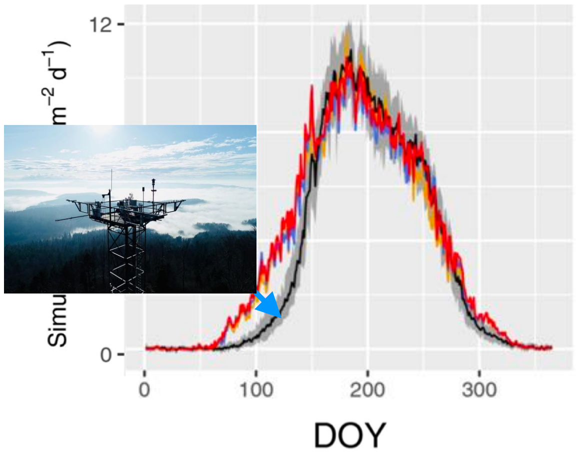
But: TER and GPP are predicted independently

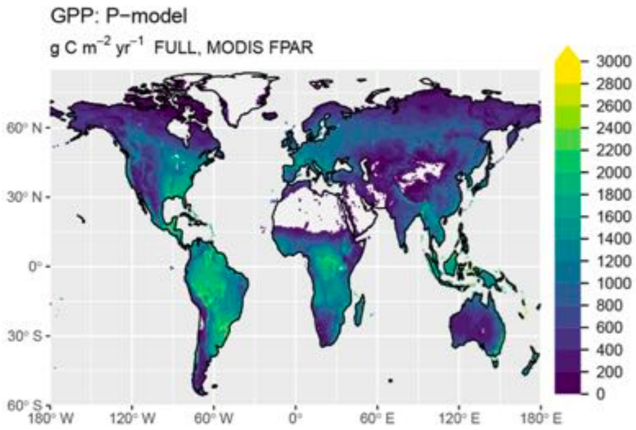


Tramontana et al., 2016

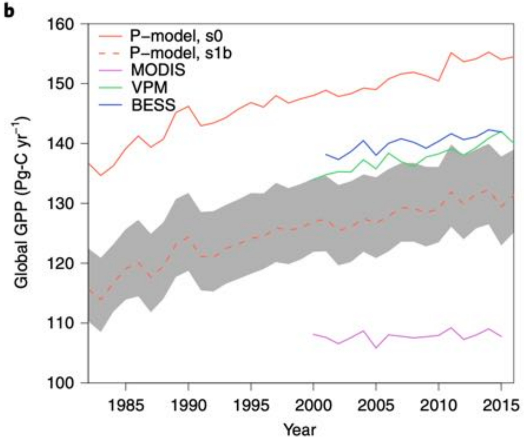
- Penalise “unphysical” predictions in the cost function
- Account for conservation laws in the network

- **ML for error correction**
  - E.g., numerical weather prediction to remove known biases
  - Combines advantages of theoretical understanding and data





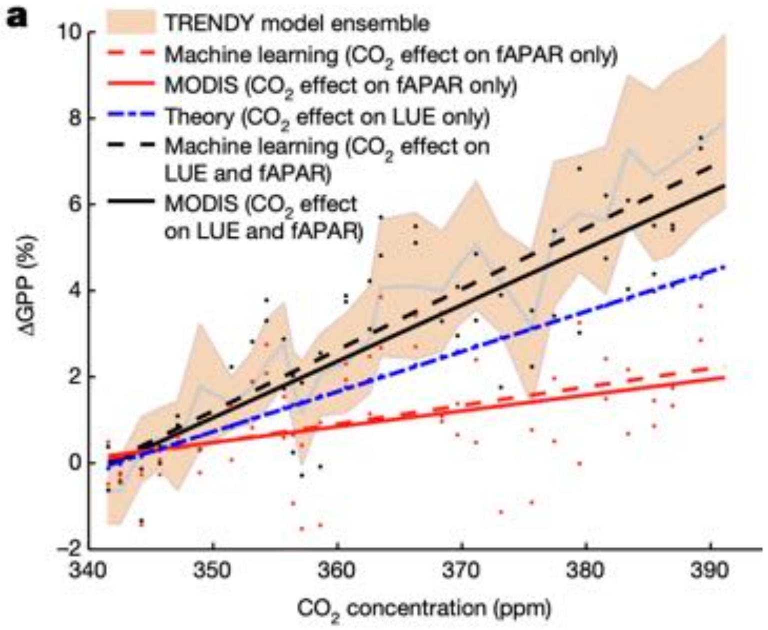
Stocker et al., 2020 *GMD*



Stocker et al., 2019 *Nature Geosci.*

B: Prediction

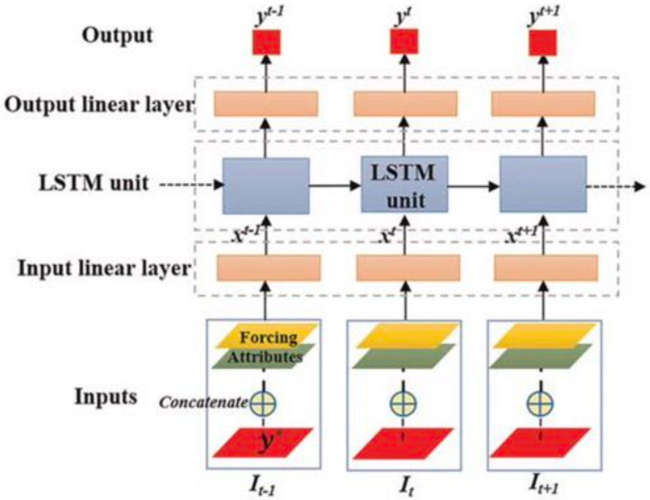
- **Adding theory to ML**

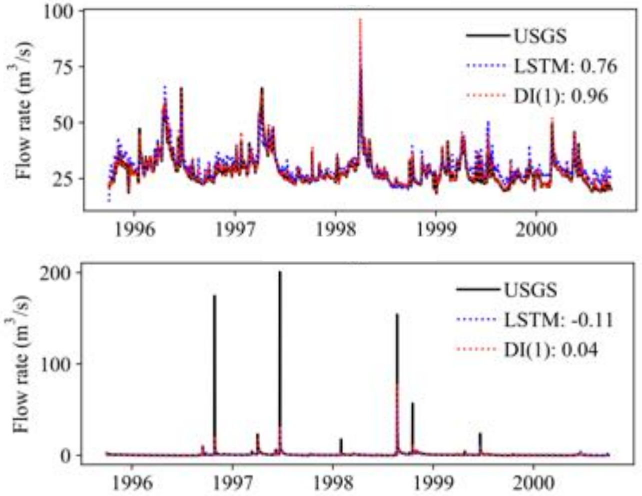


Keenan et al., *in prep.*

B: Prediction

- **Streamflow modelling**
  - **Catchment scale** $Y_t = f(\mathbf{x}_t, \mathbf{x}_{t-1}, \ldots$
    $\mathbf{x}_N$

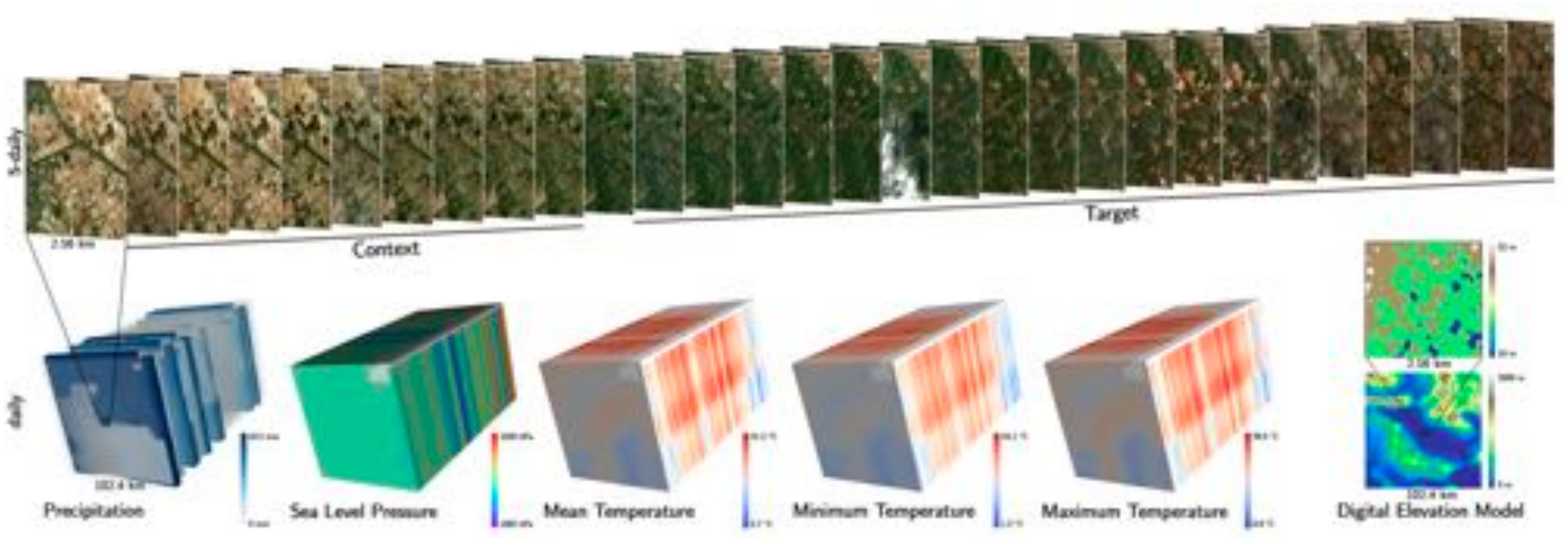




Feng et al., 2020 *WRR*

B: Prediction

- **Learning spatial-temporal dependencies**



EarthNet2021 Challenge
Requena-Mesa et al., 2021 *arXiv*

Attempt at classification of ML in Earth system modelling

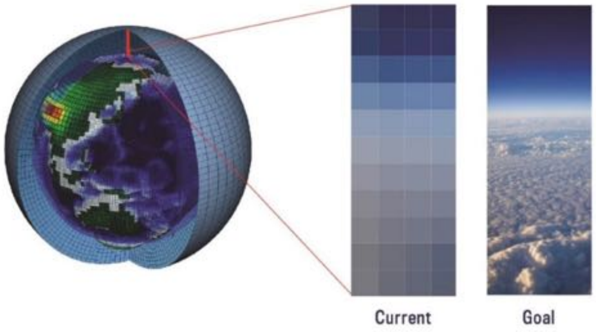
A: Making sense of information

B: (Black box) prediction

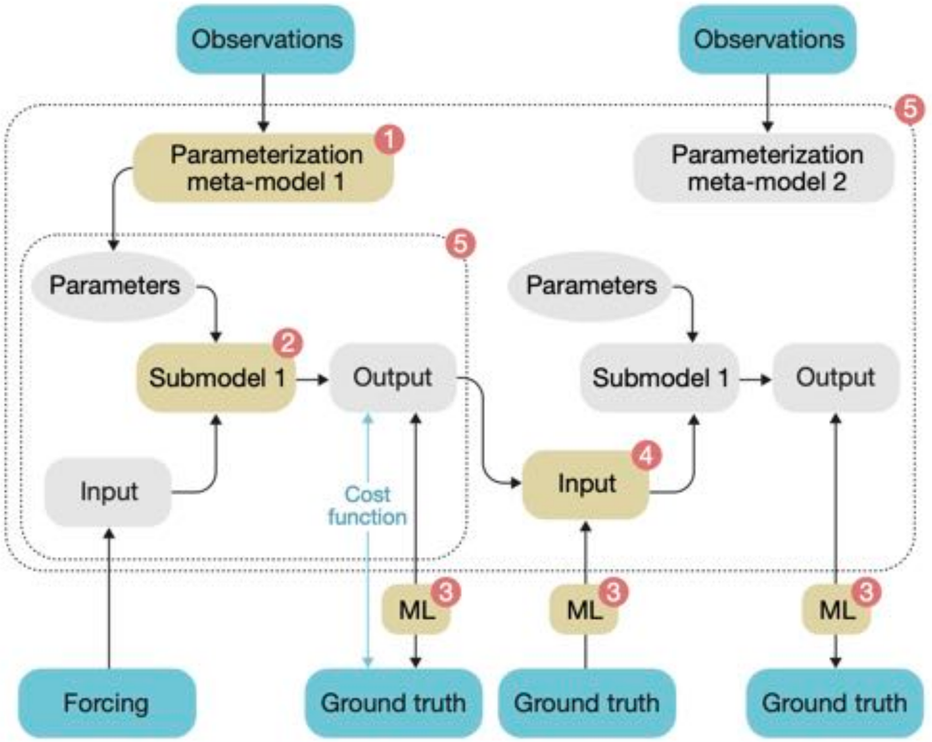
C: Hybrid modelling

C: Hybrid modelling

- ML informed by costly high-resolution model



C: Hybrid modelling



1. ML to learn the parameters of a physical model
2. ML for parametrisation of expensive process representations
3. Error interpretation (and correction)
4. Avoiding error propagation between submodules
5. Emulating the full model

Reichstein et al., 2019 *Nature*

This talk

1. Some success stories

2. **Our research in Geocomputation and Earth Observation**

3. Outlook

The drivers of ecosystem CO_2 exchange and gross primary production

Temperature

Radiation

Vapour pressure deficit

Soil moisture

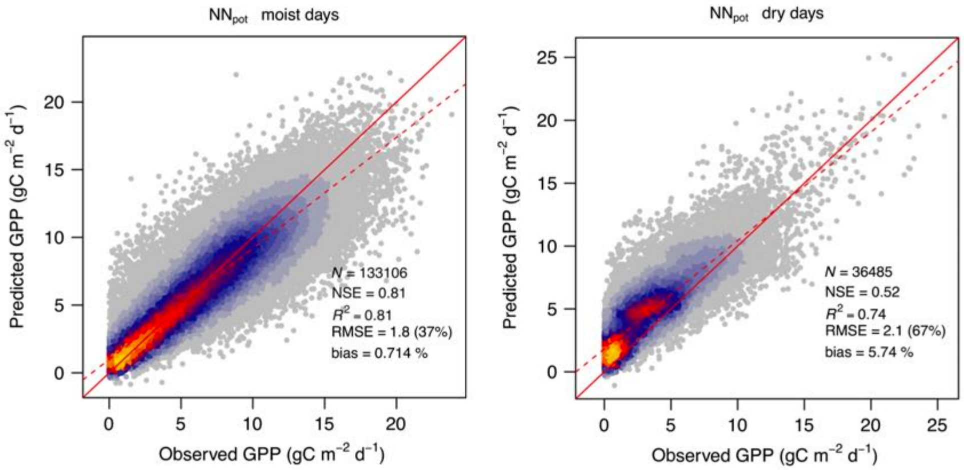
Net CO_2 exchange

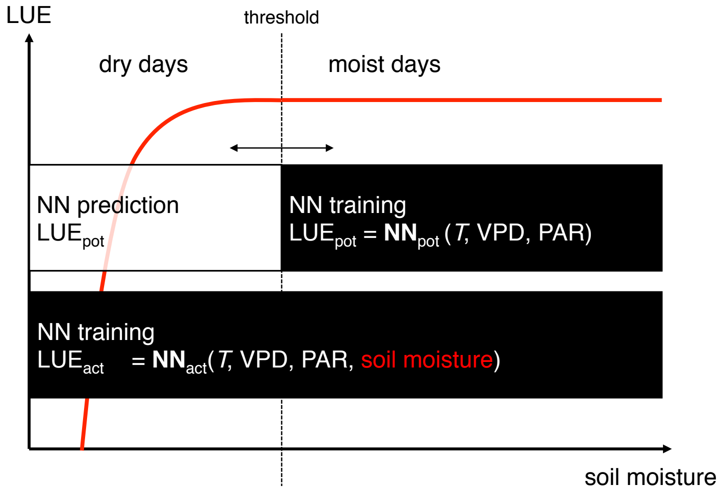
GPP

Theory-informed NN modelling

$$\text{GPP} = \text{PAR} \times \text{fAPAR} \times \text{LUE}$$

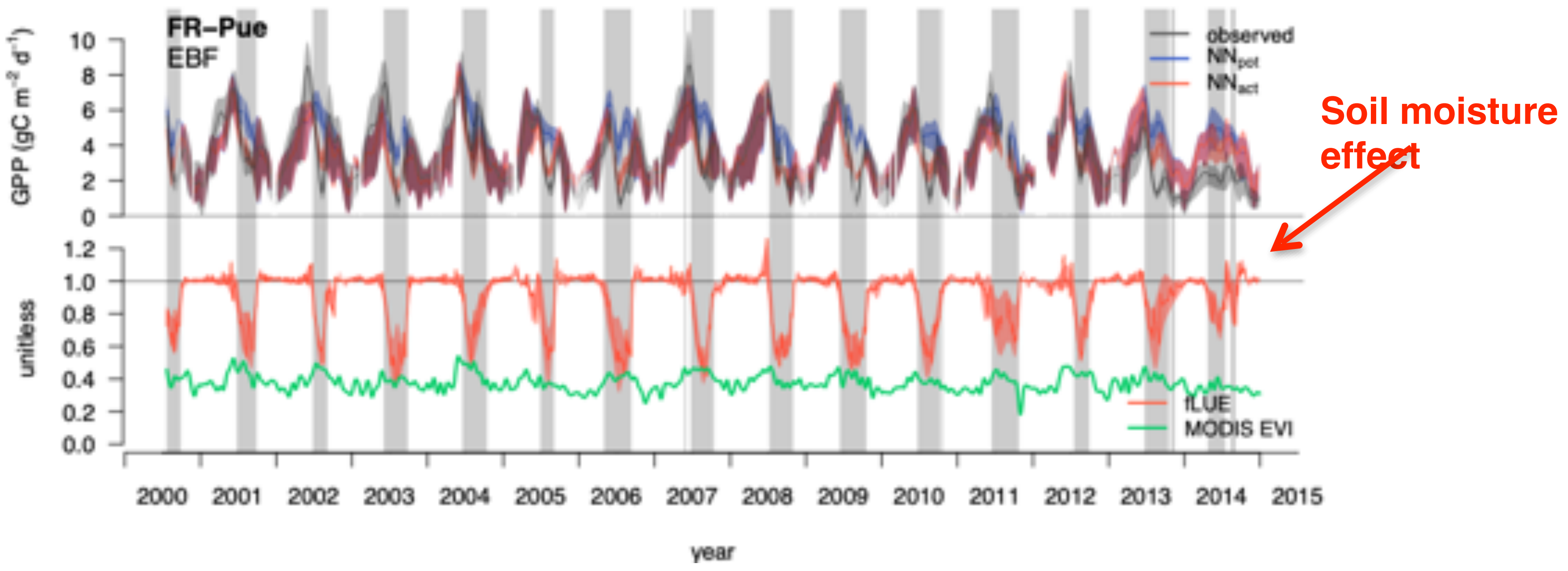
$$\text{fLUE} = \text{LUE}_{\text{act}} / \text{LUE}_{\text{pot}}$$





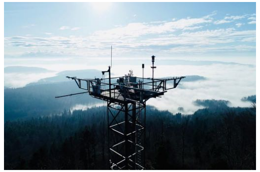
Stocker et al., 2018 *New Phytologist*

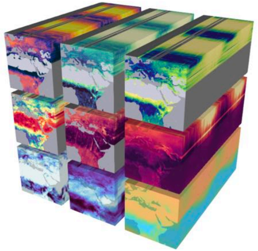
The soil moisture effect, separated



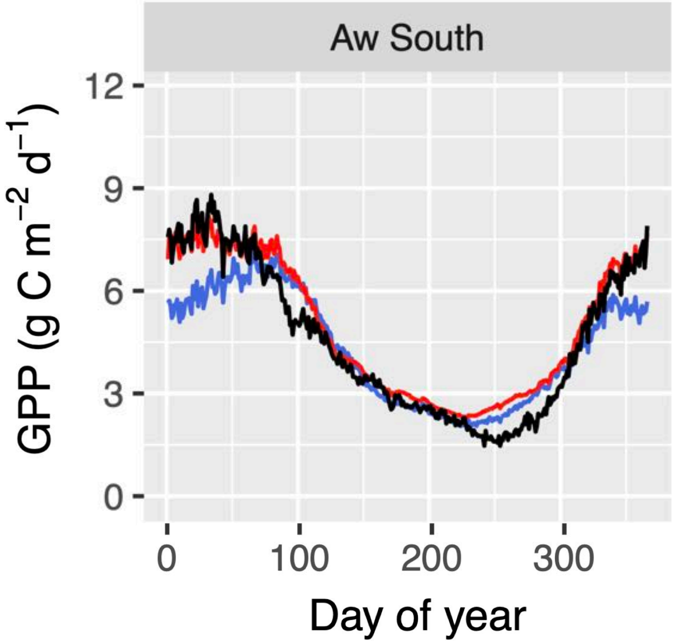
Stocker et al., 2018 *New Phytologist*

LSTM for GPP modelling



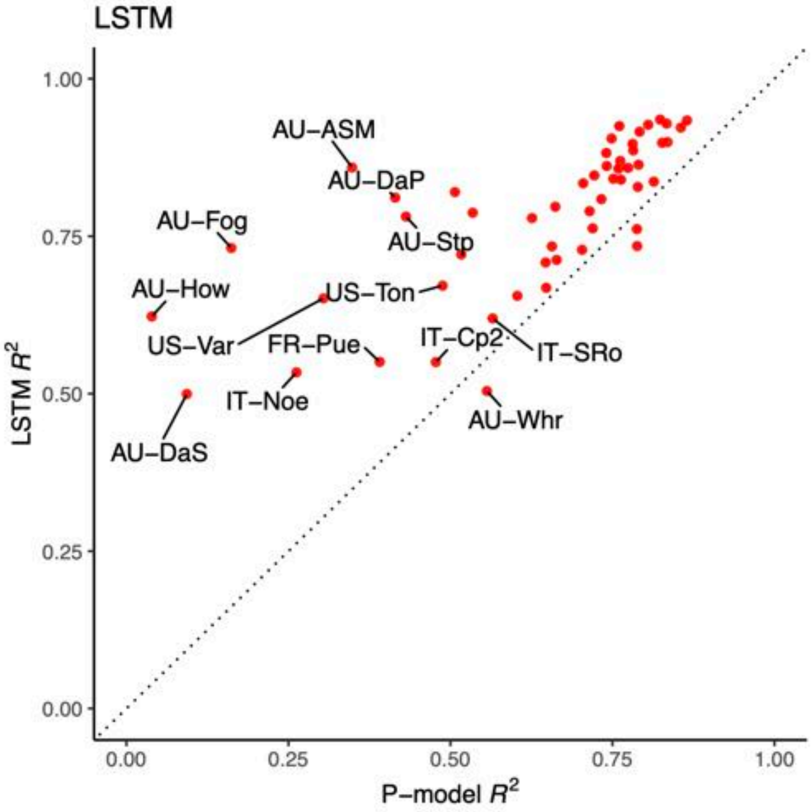


- **Point-scale** $Y_t = f(\mathbf{x}_t, \mathbf{x}_{t-1}, \ldots \mathbf{x}_N)$
- Considering the multivariate temporal context
- Avoiding iid assumption
- Avoiding hand crafted features (e.g, to capture memory effect of precipitation - soil moisture - water stress)



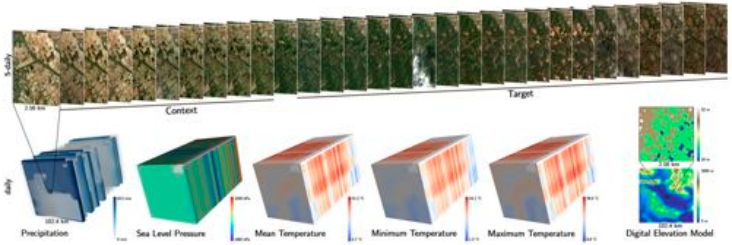
Stocker et al., *in prep.*

LSTM for GPP modelling

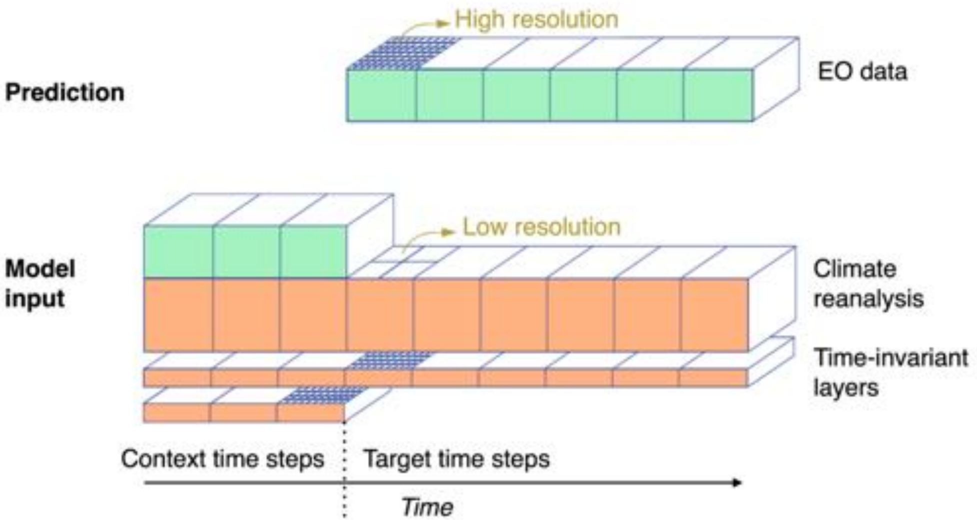


Stocker et al., *in prep.*

Data-driven drought impact prediction



- Considering spatial and temporal context (ConvLSTM)
- Implicit downscaling from coarse climate to local impacts



Stocker, *unpublished*

Data-driven drought impact prediction

Kladny et al., 2022 *bioRxiv*

This talk

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2. Our research in Geocomputation and Earth Observation
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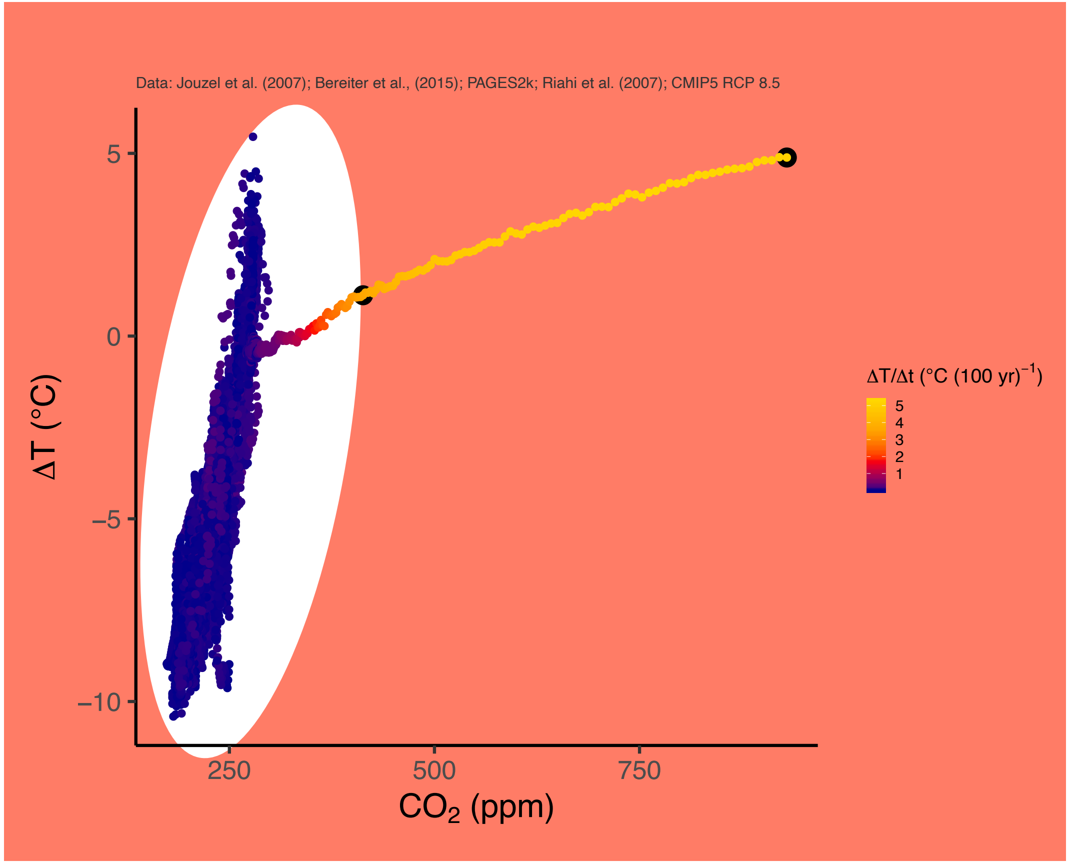
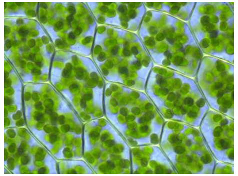
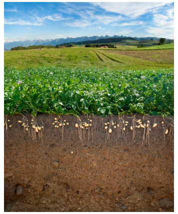
Moving outside the domain of past observations

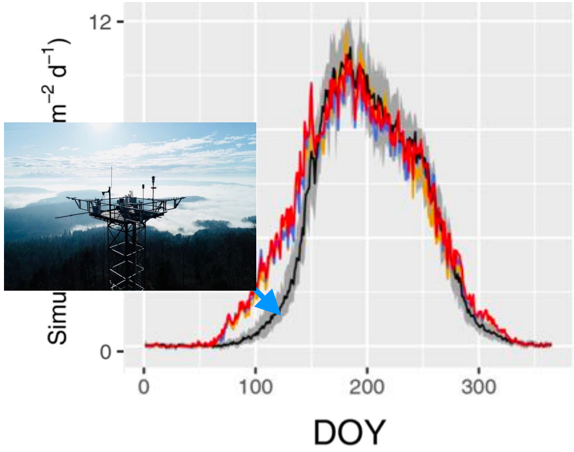


Stocker, *unpublished*

The CO_2 fertilisation cascade



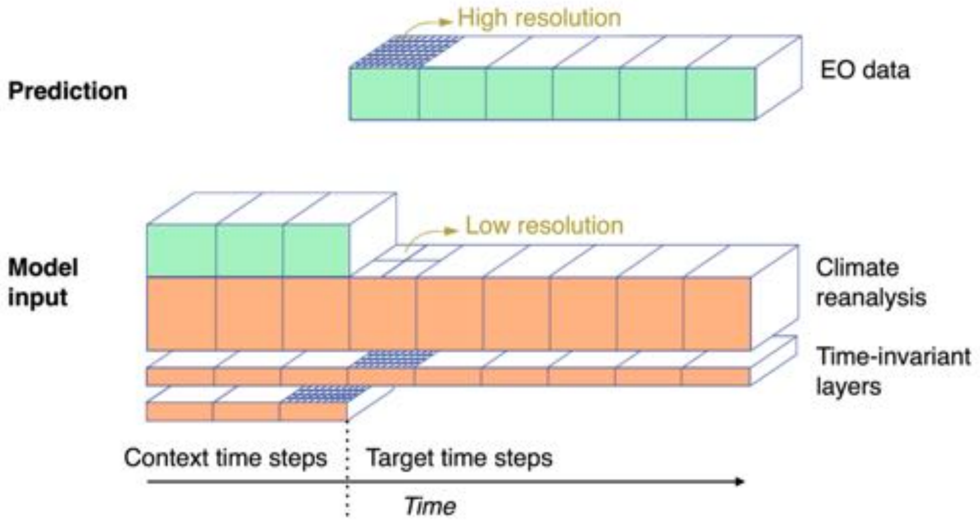




Earth observation-informed near-term forecasting

Promising applications

- Crop and grass yield forecasting
- Wildfire forecasting



Stocker, *unpublished*

“Conclusion”

- Many applications of ML that are complementary and supporting Earth system modelling.
- Interesting: Combining ML with theory and physical laws.
- Interesting: Hybrid modelling where ML can become useful as a part, but not to replace ESM.

GECO Group

GECO

Geocomputation and Earth Observation

https://github.com/computationales

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