# Physically-based land modelling & ML
# What are the complementarities?

Christoph Rüdiger

ECMWF Land Modelling Team

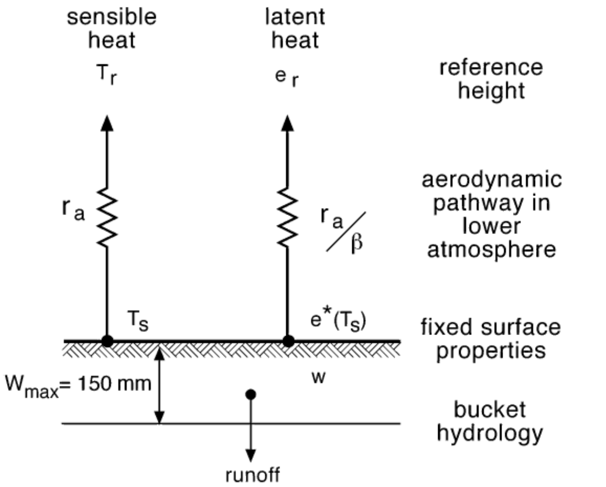
Birgit Sützl, Francesca Covella, Gabriele Arduini, Jasper Denissen, Joe McNorton, Margarita Choulga, Nina Raoult, Souhail Boussetta, Xabier Pedruzo Bagazgoitia, *future hydrologist*

as well as colleagues from ECMWF, in particular in the
Coupled Data Assimilation team
Hydrological Monitoring and Forecasting team
AIFS team

ECMWF

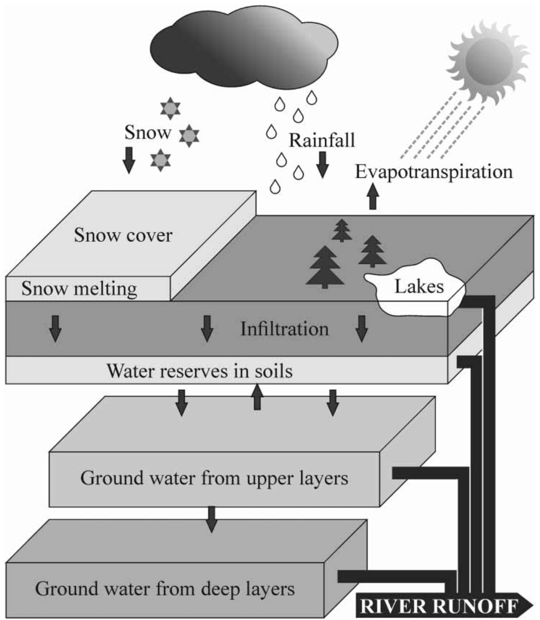
# History of Land Surface Models

- Manabe, 1969 – setting up one of the first fully coupled climate models
  - Simplistic representation of the land (boundary condition):
    - Fixed soil depth and parameters
    - Saturation excess runoff, only
    - Lack of heat conduction into the soil
    - Evaporation limited by water threshold




*from Pitman, 2003 (after Sellers, 1997)*

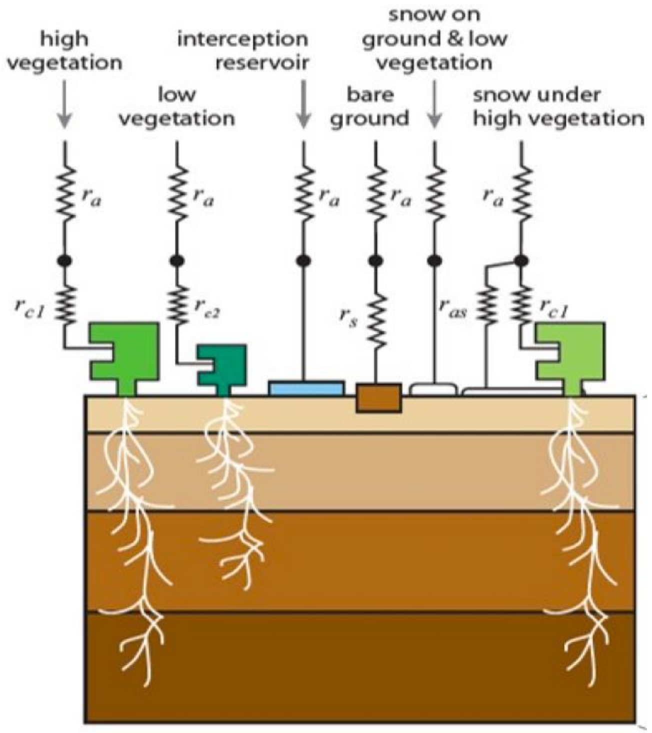
- Lumped models
  - Often catchment-wide single parameter sets, often HRU
    - Calibrated parameter sets, e.g. initial/continuous losses
    - Requires in situ information or transfer of parameters through regionalisation (see also PUB)

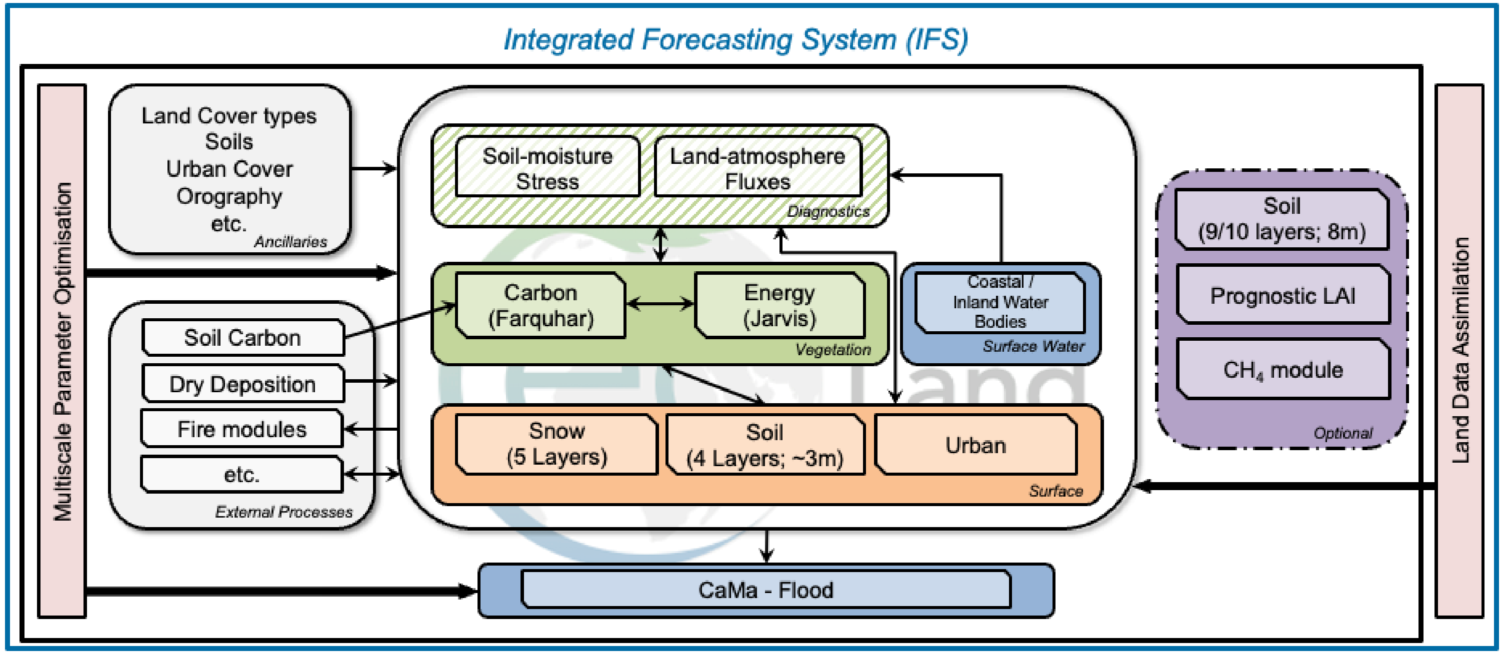



*Akstinas et al., 2019*

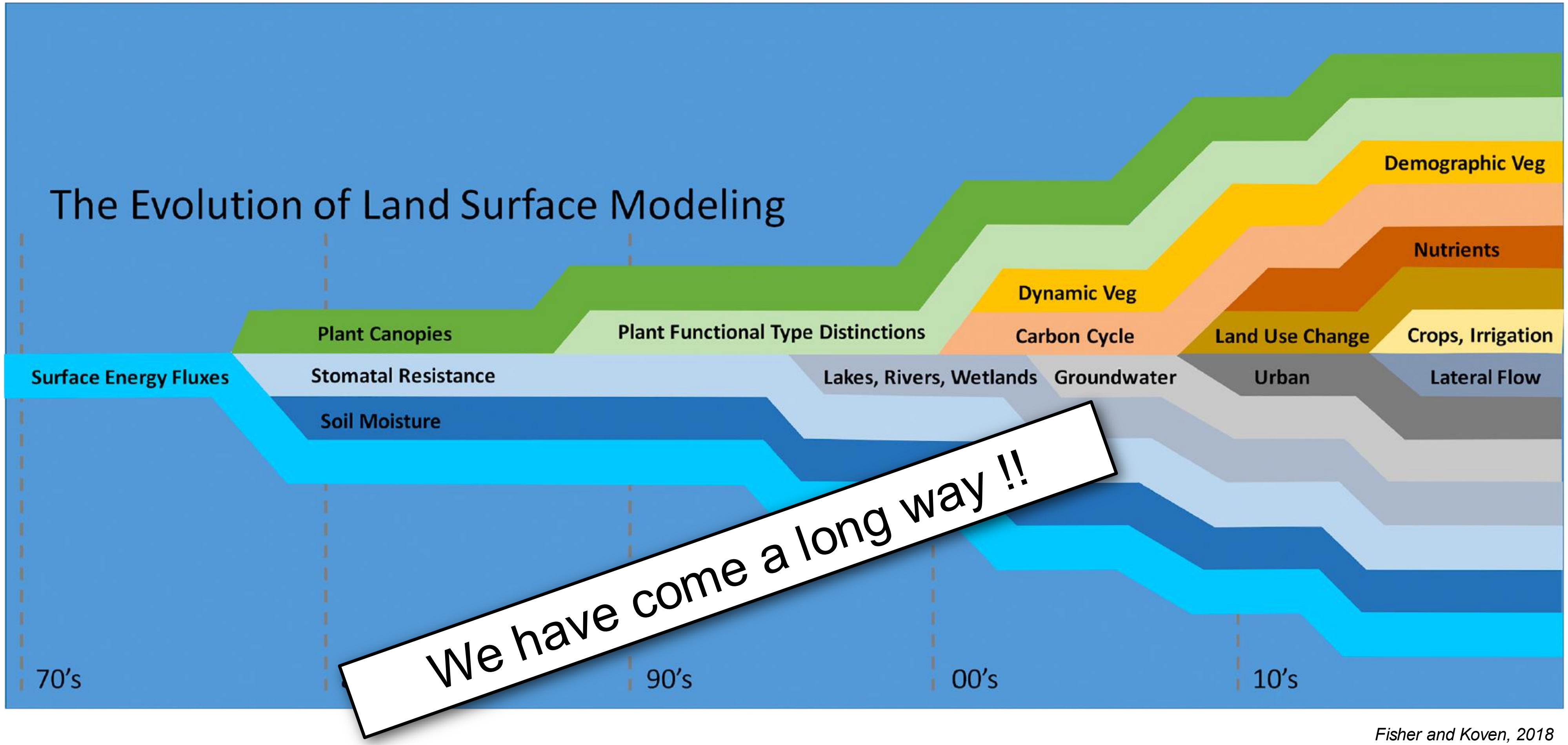
# History of Land Surface Models

- (Semi-)distributed models
  - Usually gridded, global models, increasingly including all land surface processes
    - Limited spatially varying prameters (often based on physical descriptions)
    - Generally tiling of the surface, not the subsurface
    - Mostly single column, some with lateral flows and energy exchange



# Additions to Land Surface Model Over Time

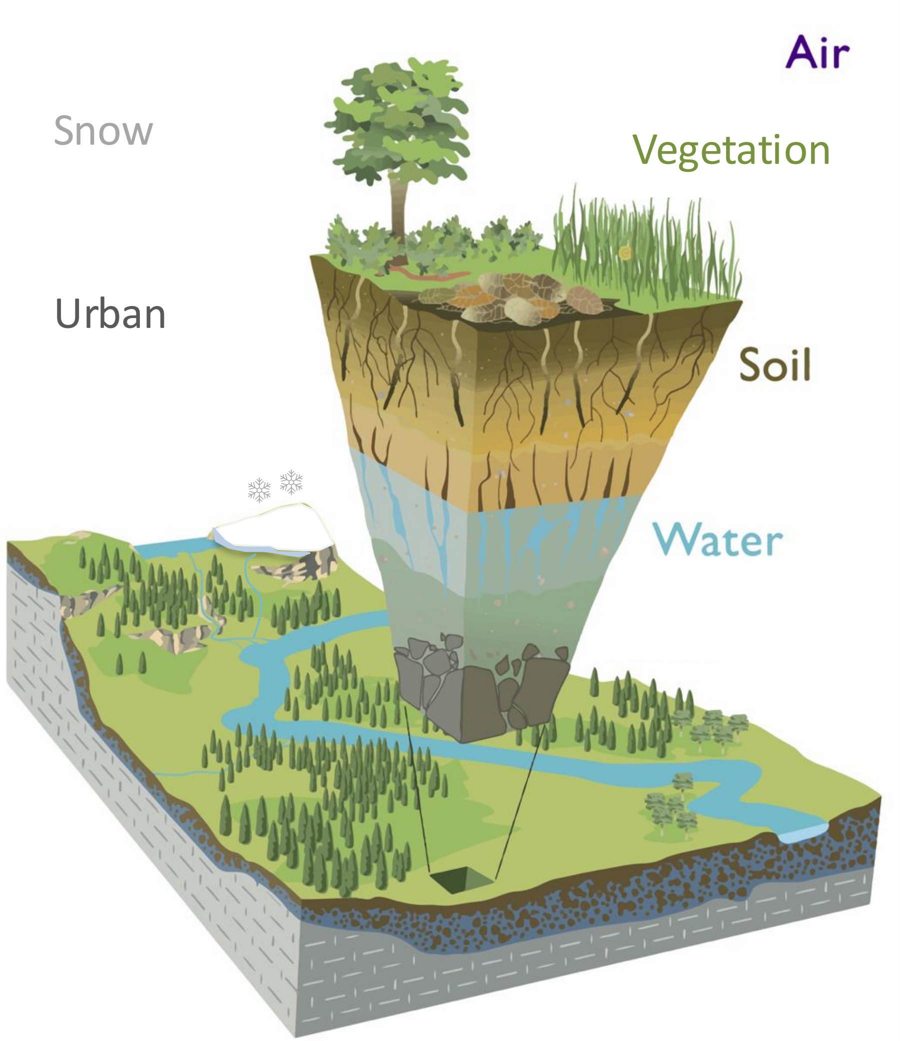



*Fisher and Koven, 2018*

# Processes Under Investigation

- Snow parameterisation/model
- Glaciers and sea-ice
- Sub-grid scale heterogeneity

- Urban processes (hydro, veg)
- Land cover
- Anthropogenic contributions




- Orography
- Coupling

- Updated climatologies
- Land cover and vegetation cover
- Parameterisations and phenology

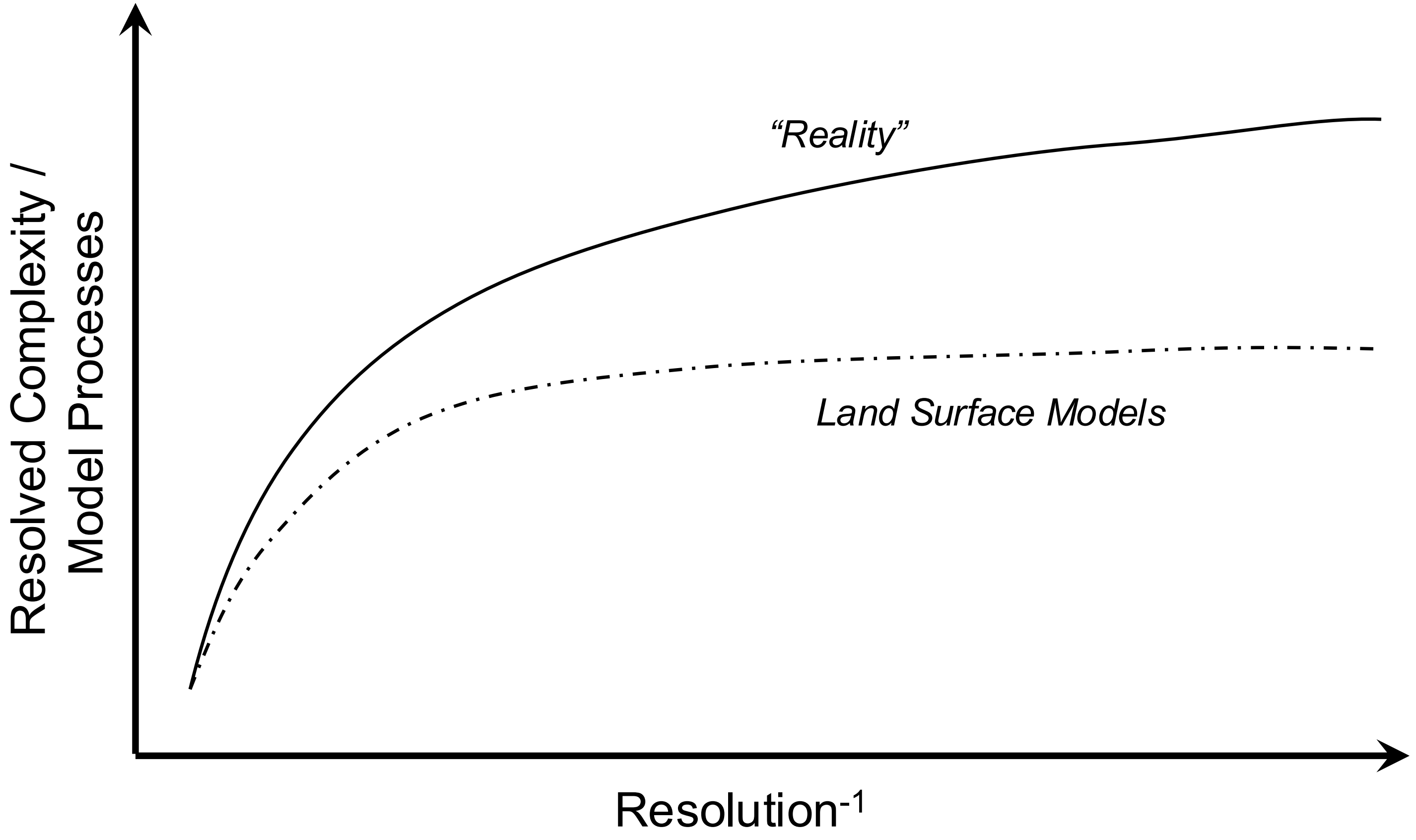
- Additional soil layers
- Soil maps and physics
- Parameterisations

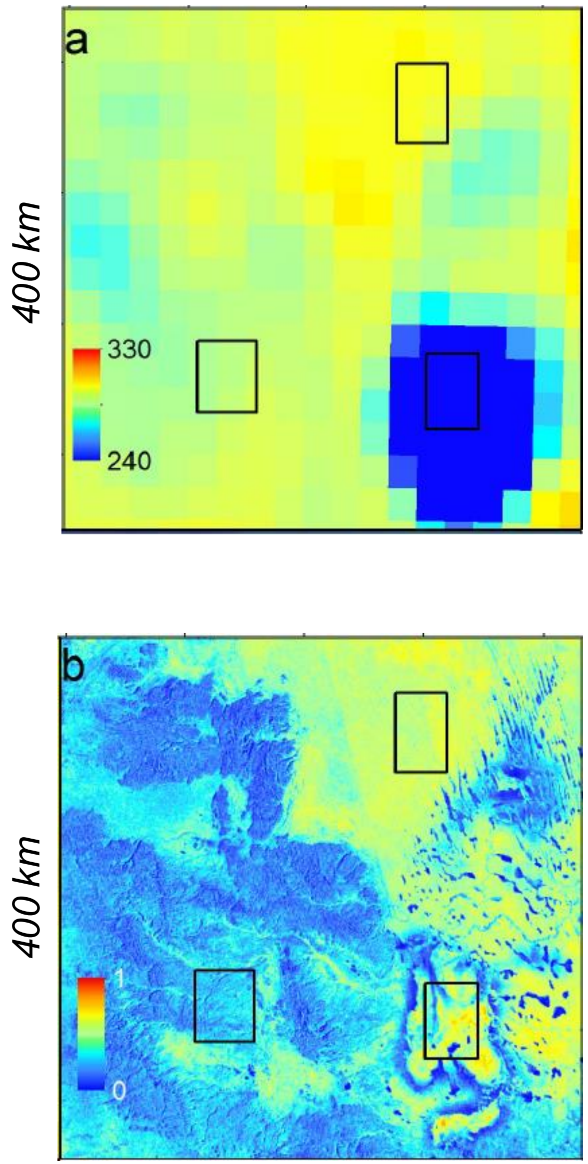
- Runoff generation
- CaMa-Flood
- Irrigation/inundation
- Plant-water availability (soil dynamic range)
- Groundwater table representation

- Dynamic water bodies
- Coupling with ocean (2-ways)
- Lakes

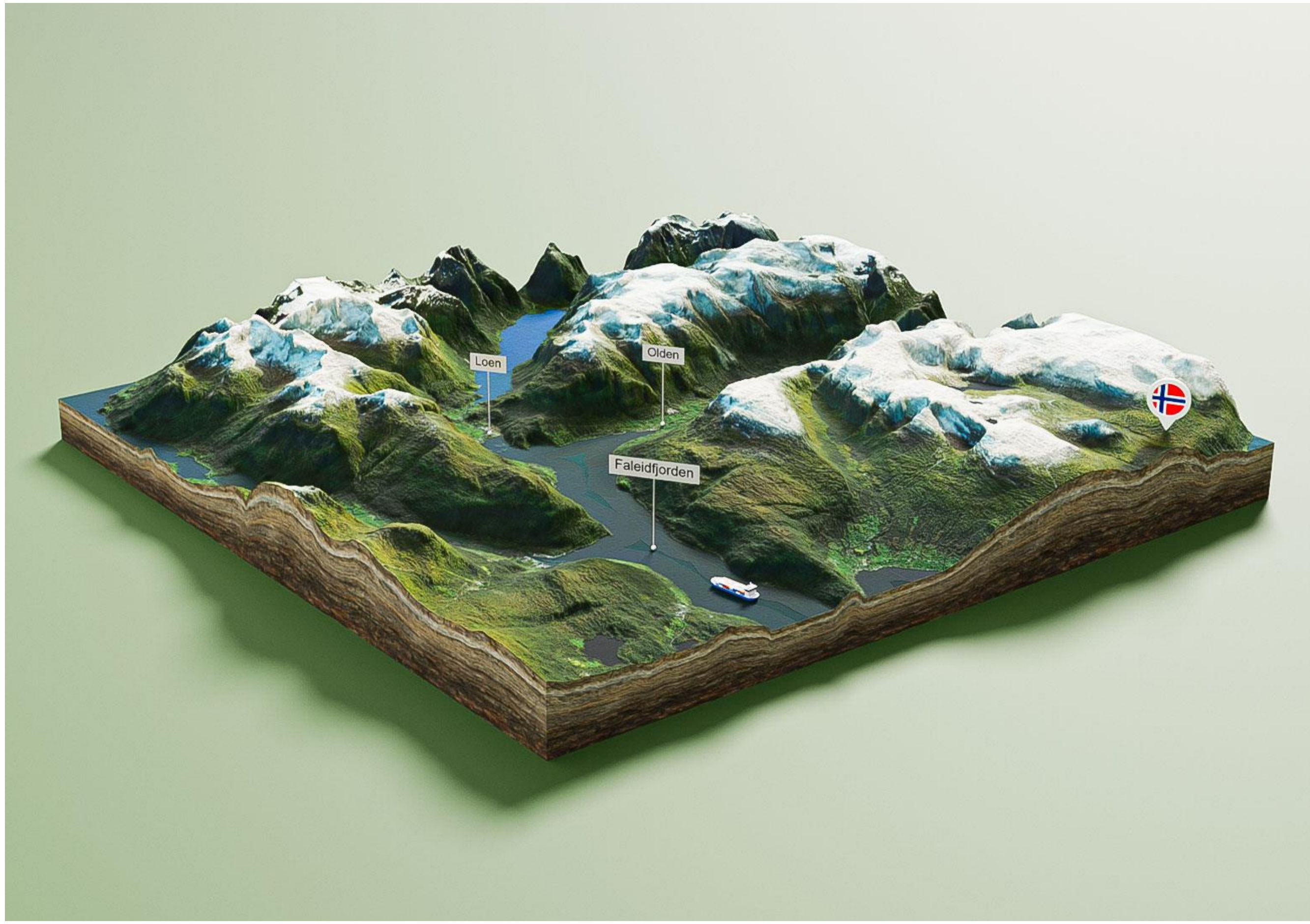
Image from Chorover et al., 2007

# The Land Surface Model Paradigm

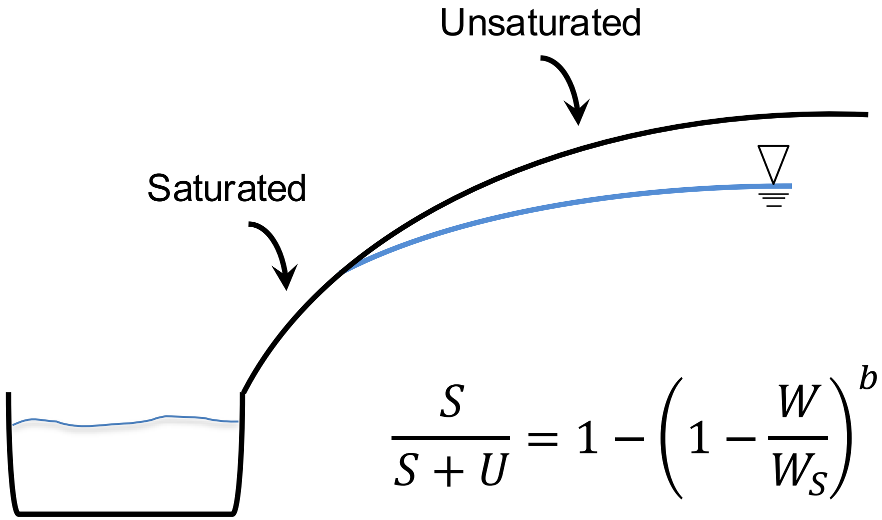


# The Land Surface Model Paradigm




from 3D-Mapper




$$\frac{S}{S+U} = 1 - \left(1 - \frac{W}{W_S}\right)^b$$

# Machine Learning for and with Land Surface Models

**COMBINING PARAMETRIC LAND SURFACE MODELS WITH MACHINE LEARNING**

[1,2,4]*Craig Pelissier*, [3]*Jonathan Frame*, [2,3]*Grey Nearing*

[1]NASA Goddard Space Flight Center, Greenbelt, MD, [2]University of Maryland Baltimore County, Baltimore, MD, [3]University of Alabama, Tuscaloosa, AL, [4]Science Systems Applications Inc., Lanham, MD

nature reviews earth & environment



Perspective | Published: 11 July 2023

**Iterative integration of deep learning in hybrid Earth surface system modelling**

Min Chen, Zhen Qian, Niklas Boers, Anthony J. Jakeman, Albert J. Kettner, Martin Brandt, Mei-Po Kwan, Michael Batty, Wenwen Li, Rui Zhu, Wei Luo, Daniel P. Ames, C. Michael Barton, Susan M. Cuddy, Sujan Koirala, Fan Zhang, Carlo Ratti, Jian Liu, Teng Zhong, Junzhi Liu, Yongning Wen, Songshan Yue, Zhiyi Zhu, Zhixin Zhang, ... Guonian Lü + Show authors

*Nature Reviews Earth & Environment* **4**, 568–581 (2023) | Cite this article



*earth* MDPI

*Review*

**A Review of Machine Learning Applications in Land Surface Modeling**

**Sujan Pal * and Prateek Sharma**

Hydrol. Earth Syst. Sci., 22, 6005–6022, 2018
https://doi.org/10.5194/hess-22-6005-2018


Hydrology and Earth System Sciences | Open Access | EGU

**Rainfall–runoff modelling using Long Short-Term Memory (LSTM) networks**

**Frederik Kratzert[1,*], Daniel Klotz[1], Claire Brenner[1], Karsten Schulz[1], and Mathew Herrnegger[1]**

[1]Institute of Water Management, Hydrology and Hydraulic Engineering, University of Natural Resources and Life Sciences, Vienna, 1190, Austria

* *Invited contribution by Frederik Kratzert, recipient of the EGU Hydrological Sciences Outstanding Student Poster and PICO Award 2016.*

**Article**

**Global prediction of extreme floods in ungauged watersheds**

https://doi.org/10.1038/s41586-024-07145-1

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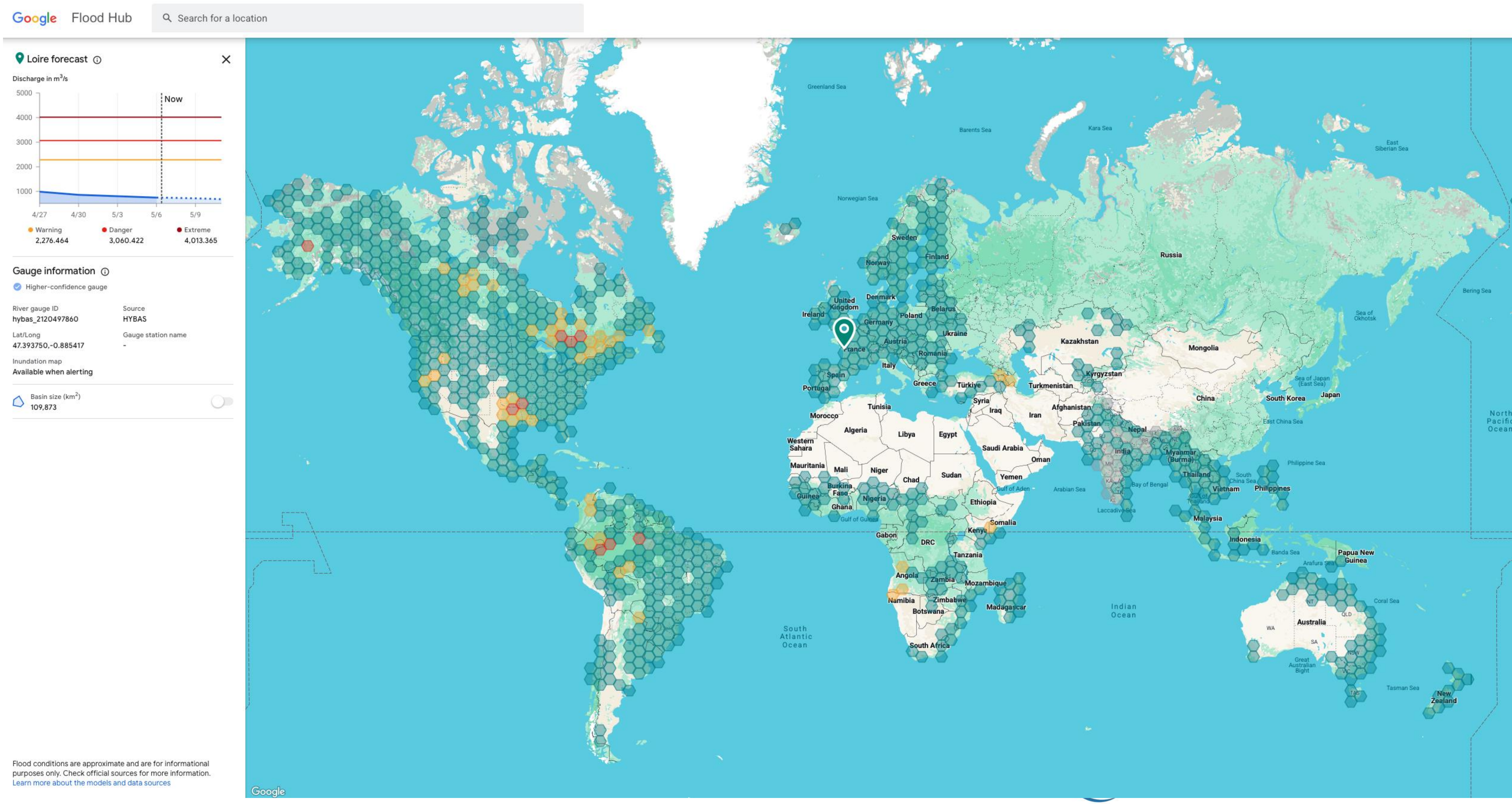
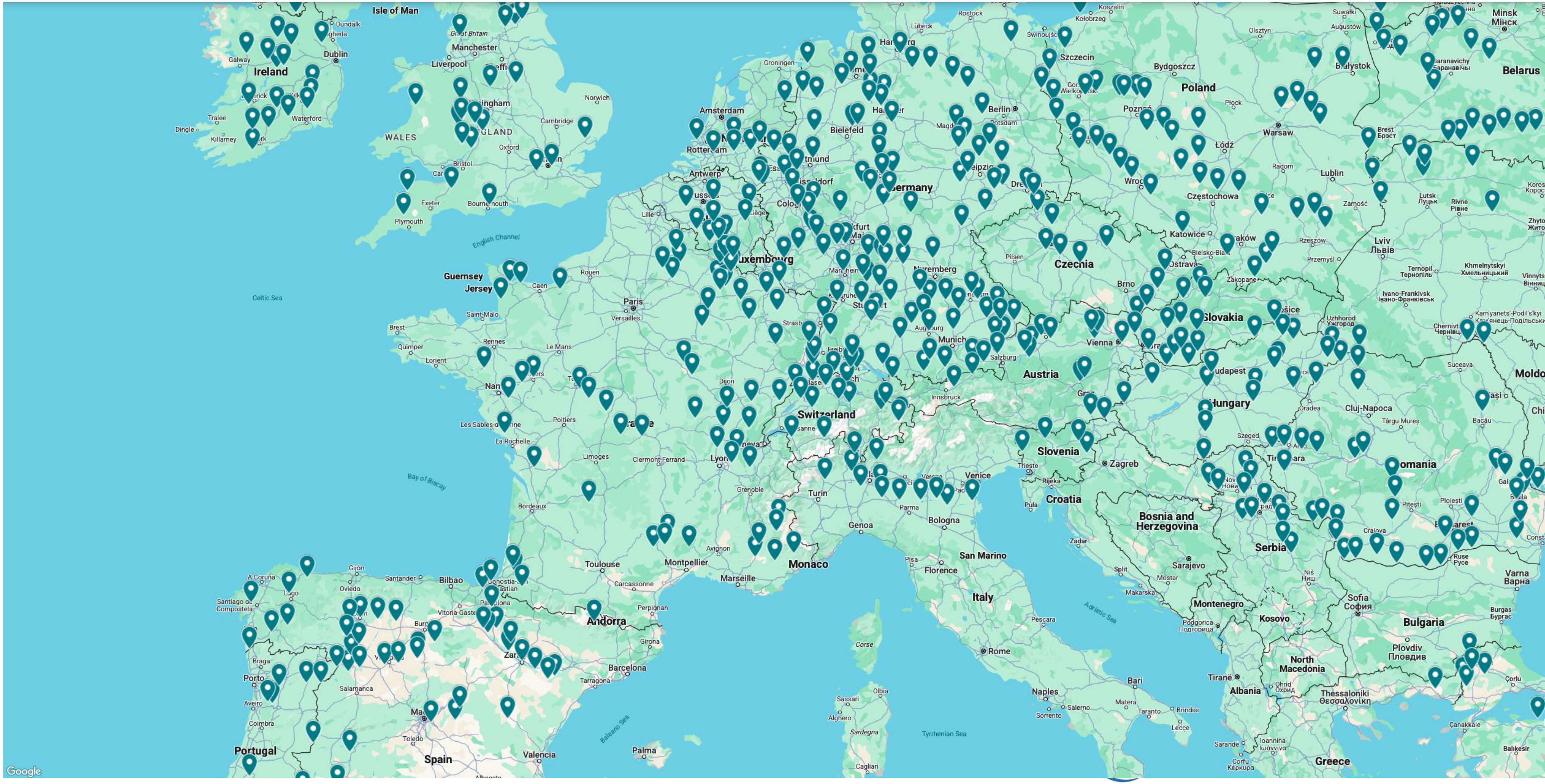
Grey Nearing[1], Deborah Cohen[1], Vusumuzi Dube[1], Martin Gauch[1], Oren Gilon[1], Shaun Harrigan[2], Avinatan Hassidim[1], Daniel Klotz[3], Frederik Kratzert[1], Asher Metzger[1], Sella Nevo[4], Florian Pappenberger[2], Christel Prudhomme[2], Guy Shalev[1], Shlomo Shenzis[1], Tadele Yednkachw Tekalign[1], Dana Weitzner[1] & Yossi Matias[1]



Google Flood Hub
Search for a location
Loire forecast
Discharge in m3/s
5000
4000
3000
2000
1000
Now
4/27
4/30
5/3
5/6
5/9
Warning
2,276.464
Danger
3,060.422
Extreme
4,013.365
Gauge information
Higher-confidence gauge
River gauge ID
hybas_2120497860
Source
HYBAS
Lat/Long
47.393750,-0.885417
Gauge station name
-
Inundation map
Available when alerting
Basin size (km2)
109,873
Flood conditions are approximate and are for informational purposes only. Check official sources for more information.
Learn more about the models and data sources
Greenland Sea
Norwegian Sea
Barents Sea
Kara Sea
East Siberian Sea
Bering Sea
Sea of Okhotsk
Sweden
Norway
Finland
Denmark
United Kingdom
Ireland
Germany
Poland
Belarus
Ukraine
France
Austria
Romania
Italy
Spain
Portugal
Greece
Türkiye
Syria
Iraq
Iran
Russia
Kazakhstan
Mongolia
Kyrgyzstan
Turkmenistan
Afghanistan
Pakistan
Nepal
India
China
South Korea
Japan
Myanmar (Burma)
Thailand
Vietnam
Philippines
Malaysia
Indonesia
Papua New Guinea
Australia
New Zealand
Tunisia
Morocco
Algeria
Libya
Egypt
Western Sahara
Mauritania
Mali
Niger
Chad
Sudan
Saudi Arabia
Oman
Yemen
Ethiopia
Somalia
Kenya
Burkina Faso
Guinea
Nigeria
Ghana
Gabon
DRC
Tanzania
Angola
Zambia
Mozambique
Zimbabwe
Namibia
Botswana
Madagascar
South Africa
Arabian Sea
Bay of Bengal
South China Sea
Philippine Sea
Indian Ocean
South Atlantic Ocean
Coral Sea
Tasman Sea
Google

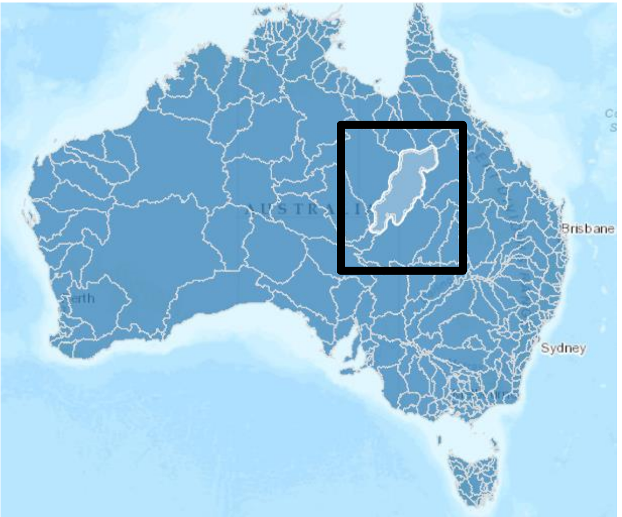
Google Flood Hub

Search for a location

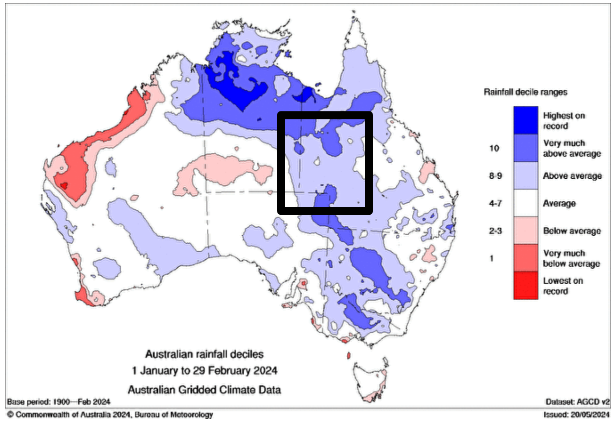


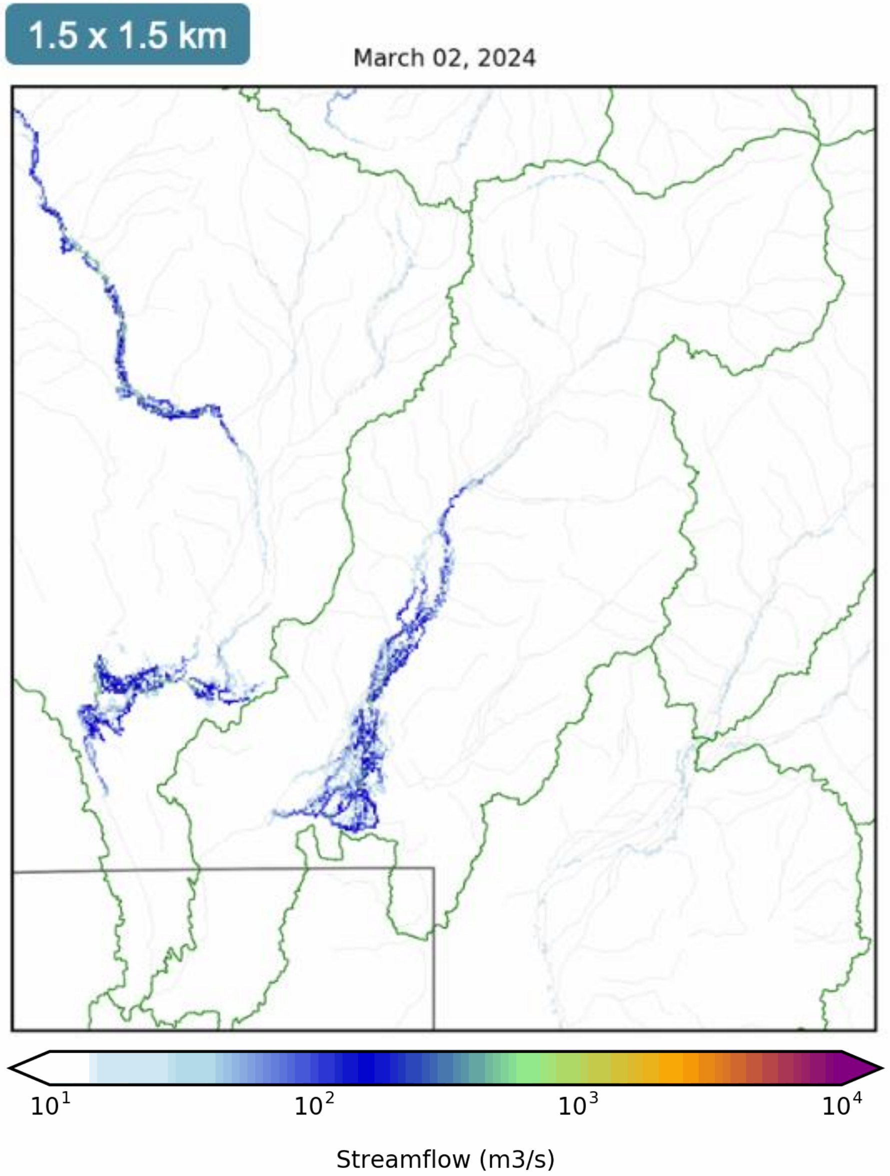
# Spatial Complexity

Diamantina River Catchment




Jan – Feb 2024 rainfall



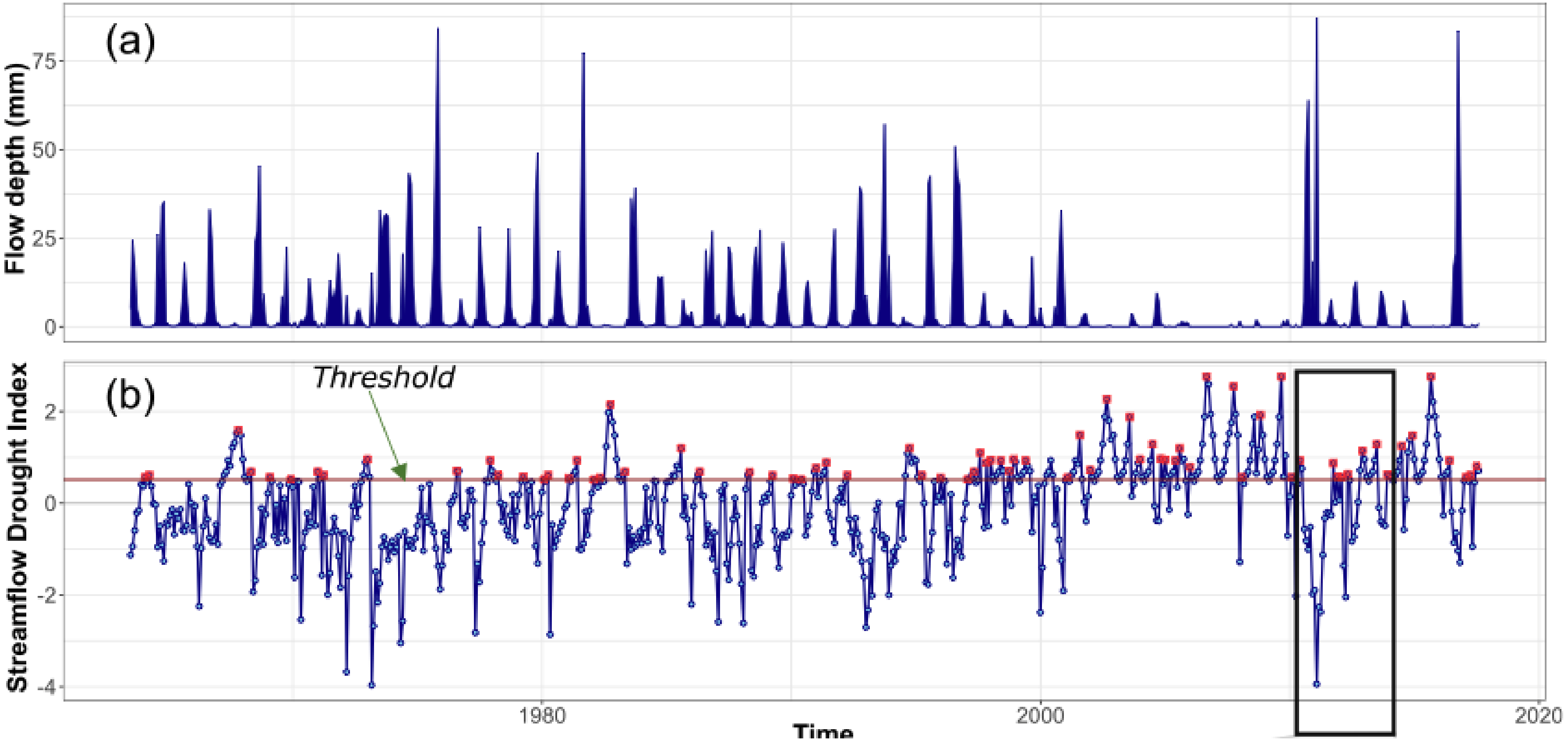






Credit: Fitsum Woldemeskel, BoM

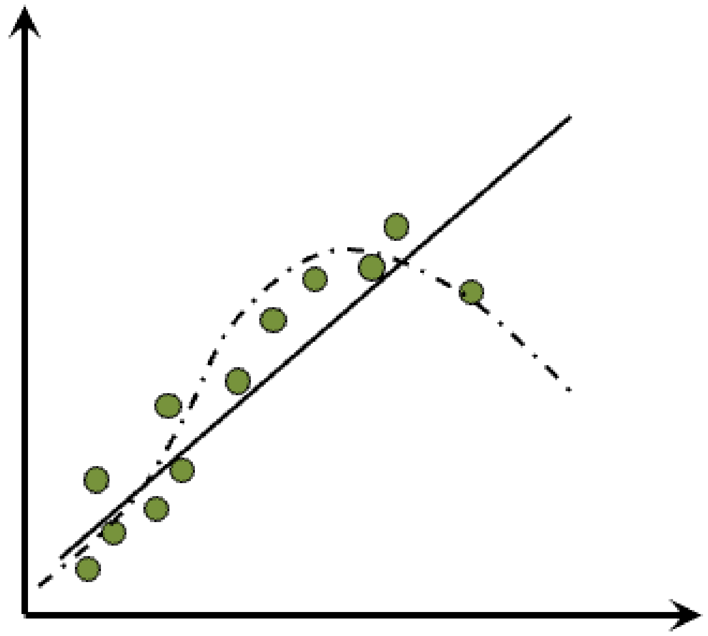
# Stationarity Assumption

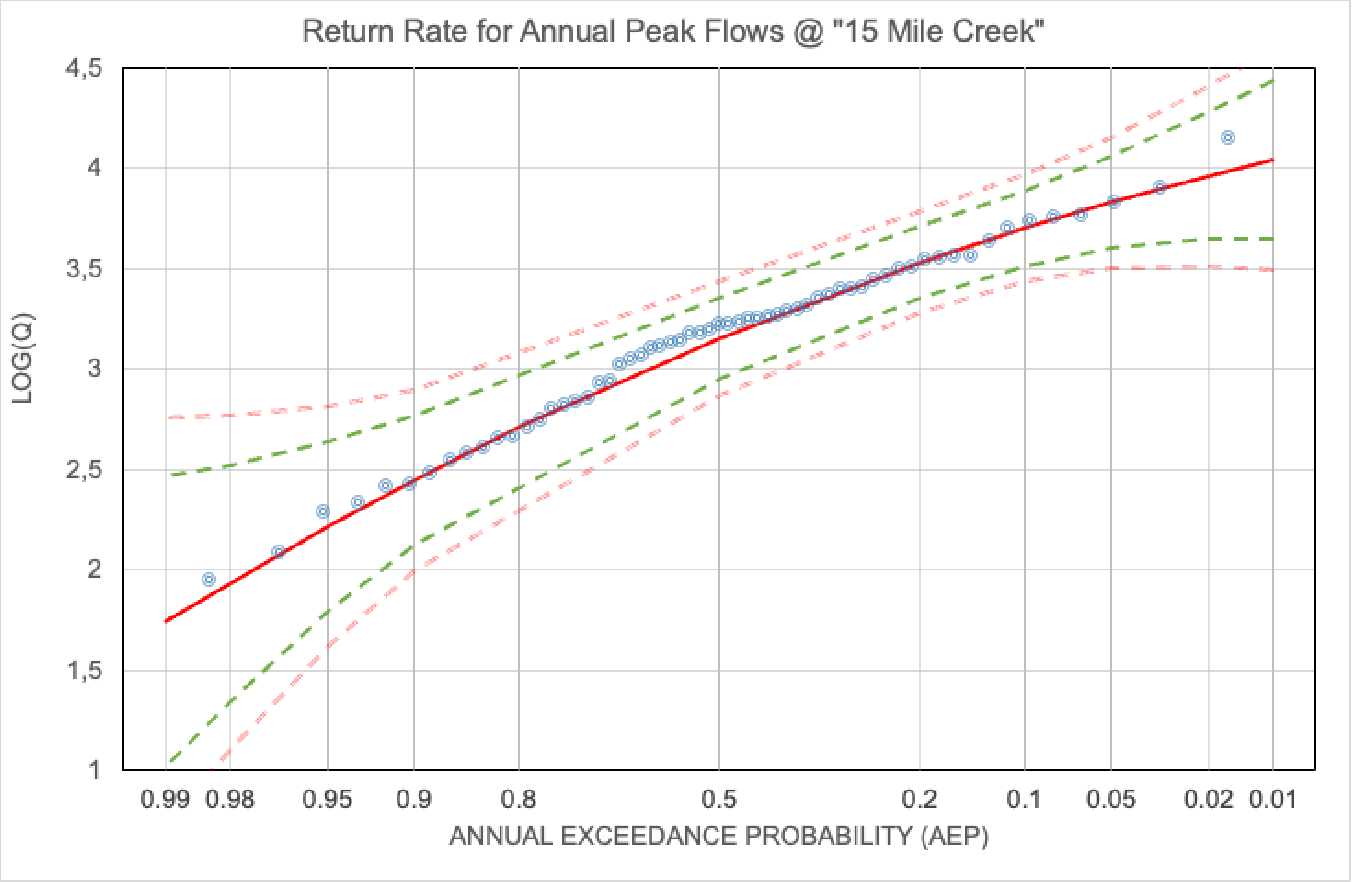
Misquoting Hegel : “History will teach us nothing…”



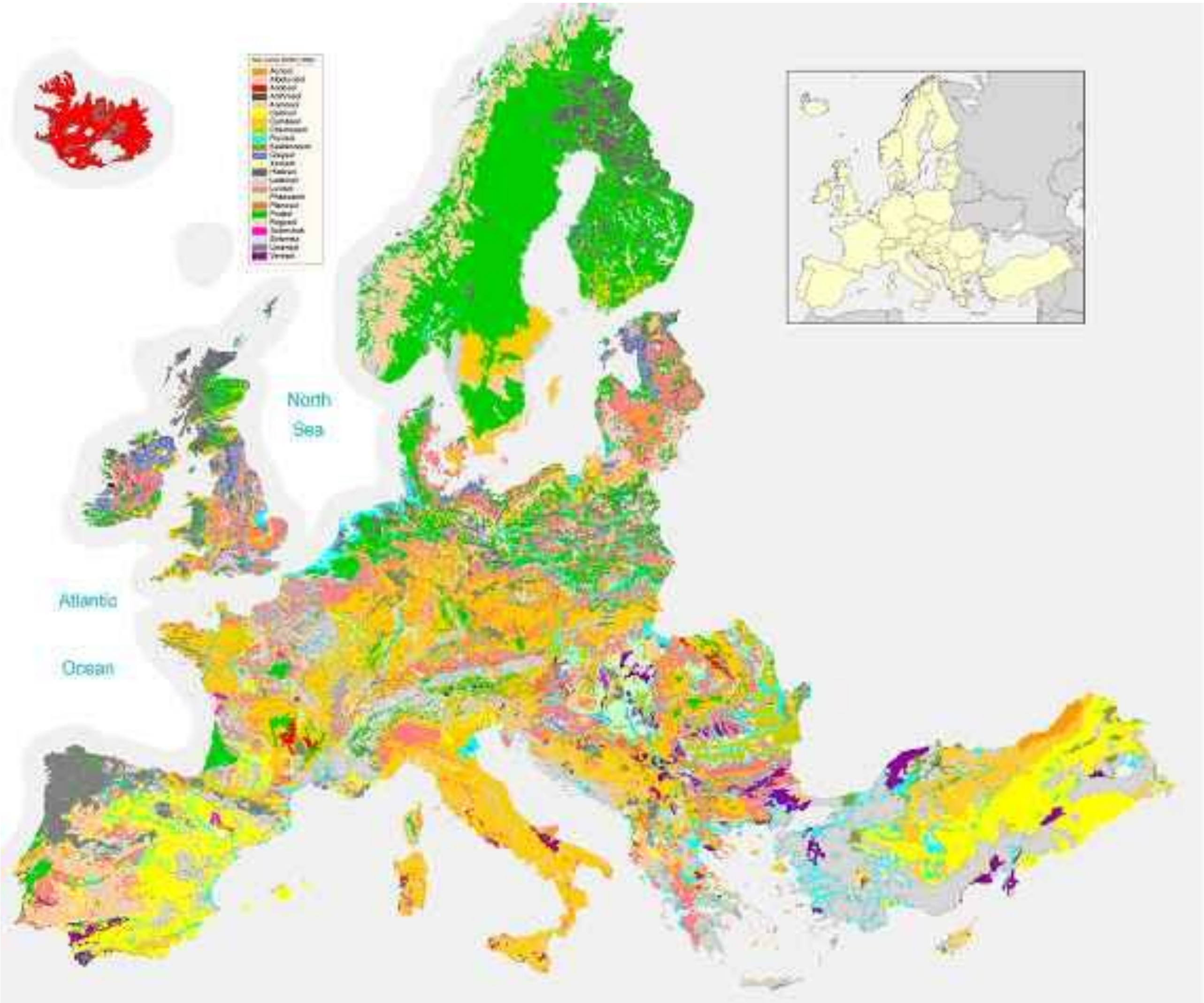

Goswami et al., 2022

# Predicting the Future From the Past

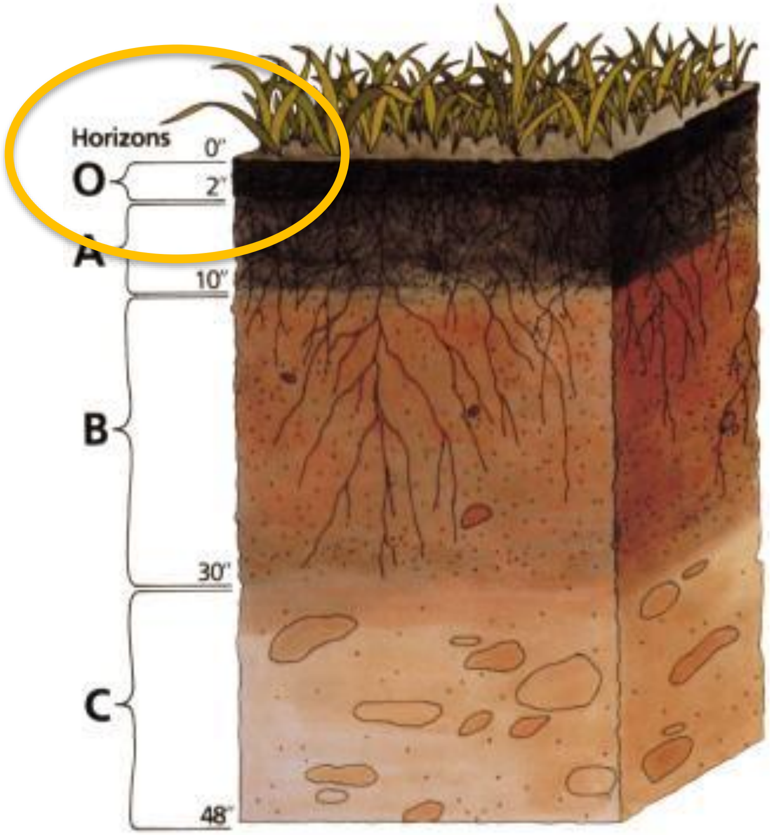




# Limited by Observations




(source: Soil Atlas of Europe)




(source: USDA)

# Are we asking the right questions?

AGU ADVANCING EARTH AND SPACE SCIENCE


Water Resources Research

COMMENTARY
10.1029/2020WR028091

Special Section:
Big Data & Machine Learning in Water Sciences: Recent Progress and Their Use in Advancing Science


## What Role Does Hydrological Science Play in the Age of Machine Learning?


Grey S. Nearing[1], Frederik Kratzert[2], Alden Keefe Sampson[3], Craig S. Pelissier[4], Daniel Klotz[2], Jonathan M. Frame[1], Cristina Prieto[5], and Hoshin V. Gupta[6]

[1]Department of Land Air & Water Resources, University of California Davis, Davis, CA, USA, [2]LIT AI Lab and Institute for Machine Learning, Johannes Kepler University, Linz, Austria, [3]Upstream Tech, Natel Energy Inc., Alameda, CA, USA,



Geophysical Research Letters

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## Challenges in Unifying Physically Based and Machine Learning Simulations Through Differentiable Modeling: A Land Surface Case Study


Shahryar K. Ahmad, Sujay V. Kumar, Clara Draper, Rolf H. Reichle



First published: 24 February 2025 | https://doi.org/10.1029/2024GL112893



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https://doi.org/10.5194/gmd-17-5779-2024




Geoscientific Model Development
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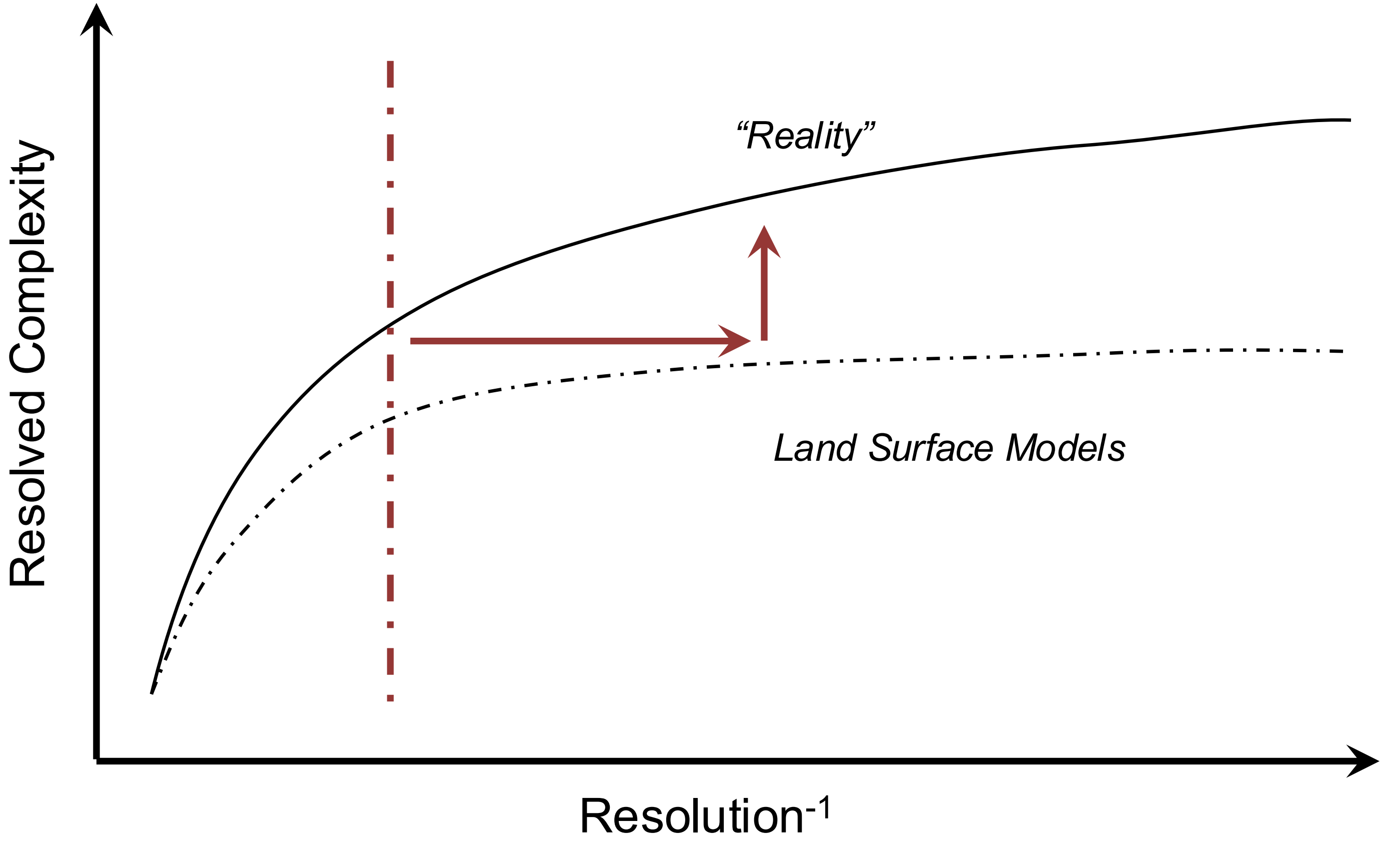
## Exploring the potential of history matching for land surface model calibration

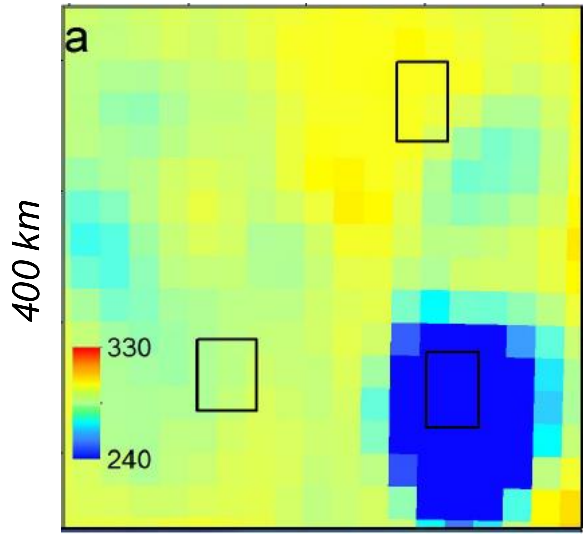

Nina Raoult[1,a], Simon Beylat[2,3], James M. Salter[1], Frédéric Hourdin[4], Vladislav Bastrikov[5], Catherine Ottlé[2], and Philippe Peylin[2]

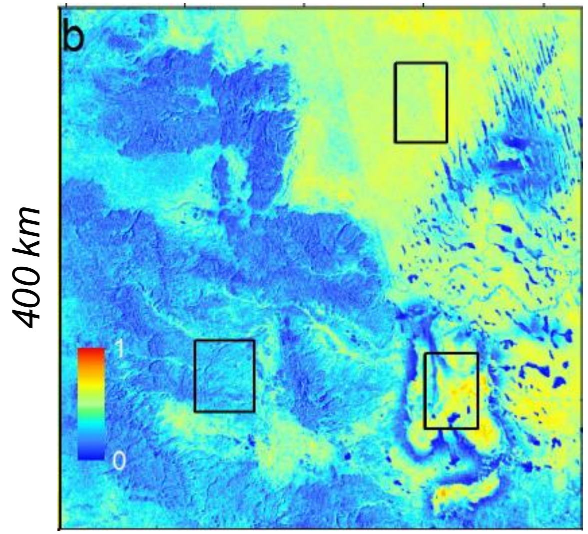
[1]Department of Mathematics and Statistics, Faculty of Environment, Science and Economy, University of Exeter, Laver Building, North Park Road, Exeter, EX4 4QE, UK
[2]Laboratoire des Sciences du Climat et de l'Environnement, LSCE/IPSL, CEA-CNRS-UVSQ, Université Paris-Saclay, 91191 Gif-sur-Yvette, France
[3]School of Geography, Earth and Atmospheric Sciences, University of Melbourne, Parkville, 3010 Victoria, Australia
[4]Laboratoire de Météorologie Dynamique, LMD/IPSL, Sorbonne Université, CNRS, École Polytechnique, ENS, 75005 Paris, France
[5]Science Partners, Paris, France
[a]now at: European Centre for Medium-Range Weather Forecasts, Shinfield Park, Reading, RG2 9AX, UK


Methods for assessment of models

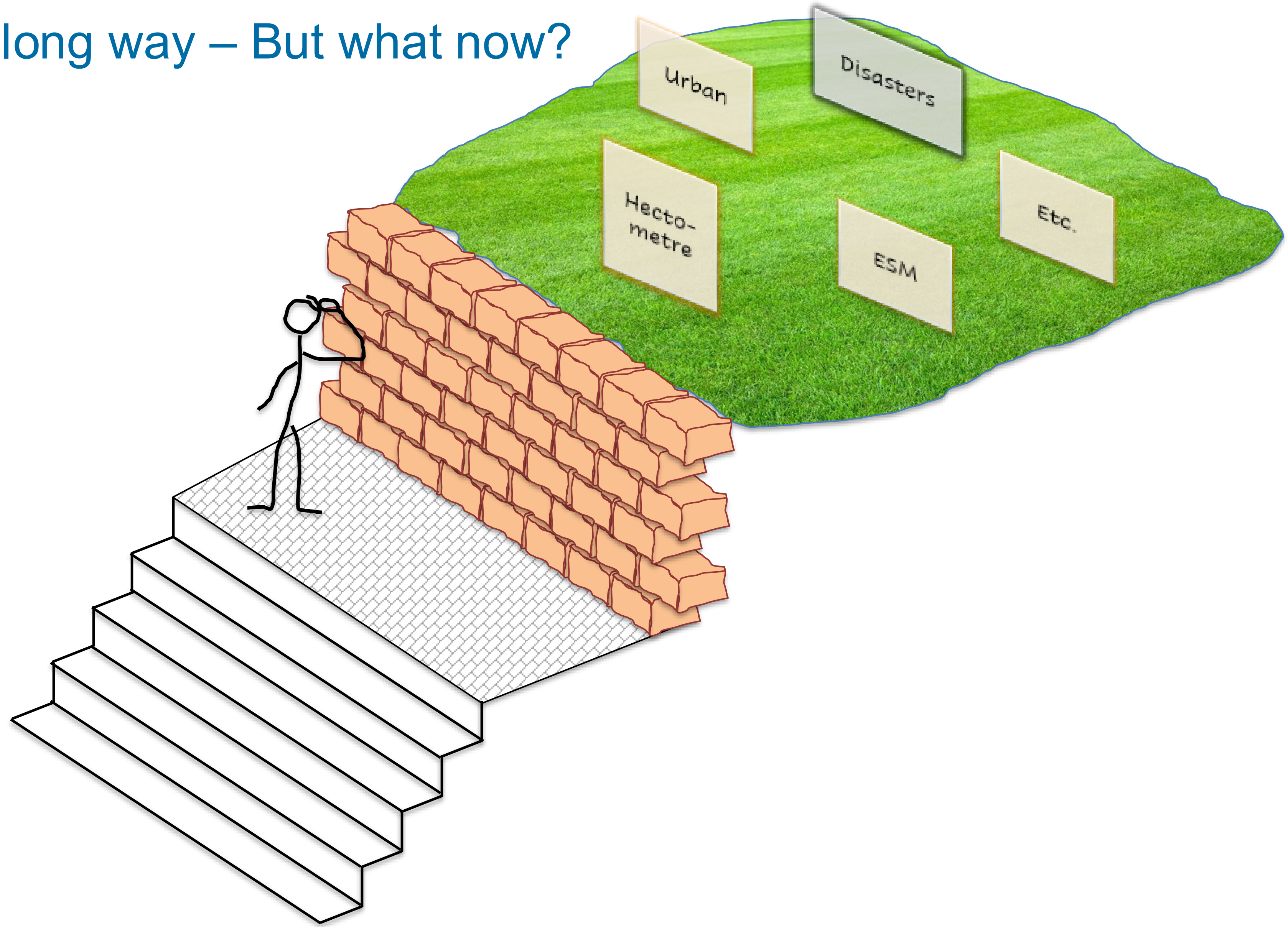
# The Land Surface Model Paradigm



# We have come a long way – But what now?

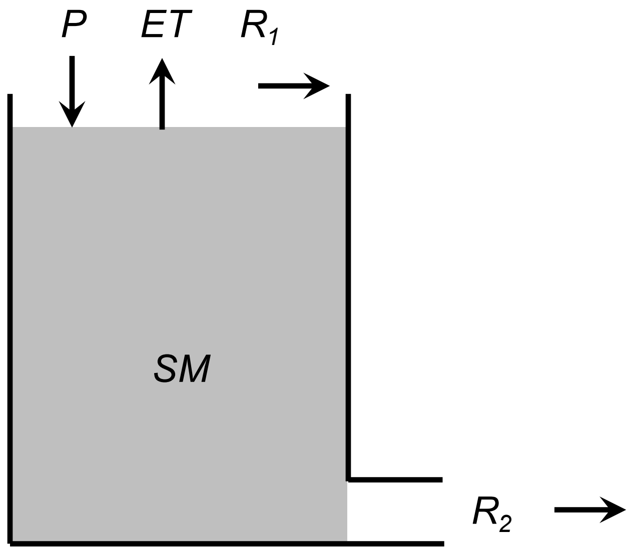


# Rainfall-Runoff Models vs ML – What's the Difference?

$$SM_t = SM_{t-1} \boxed{+ P_t} \boxed{- E_t} \boxed{- R_1} \boxed{- R_2}$$

$$\boxed{P_t - R_1 = (1 - r_t) \times P_t}$$

$$\boxed{-E_t - R_2 = -m_t \times SM_{t-1}}$$



# Rainfall-Runoff Models vs ML – What's the Difference?

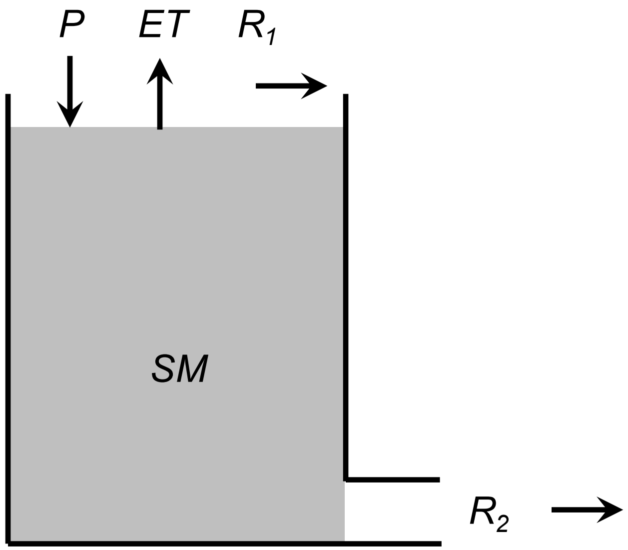
$$SM_t = SM_{t-1} \boxed{+P_t} \boxed{-E_t} \boxed{-R_1} \boxed{-R_2}$$

$$\boxed{P_t - R_1 = (1 - r_t) \times P_t}$$

$$\boxed{-E_t - R_2 = -m_t \times SM_{t-1}}$$

$$SM_t = (1 - m_t) \times SM_{t-1} + (1 - r_t) \times P_t$$

$$SM_t = f_t \times SM_{t-1} + i_t \times P_t$$



# Rainfall-Runoff Models vs ML – What’s the Difference?

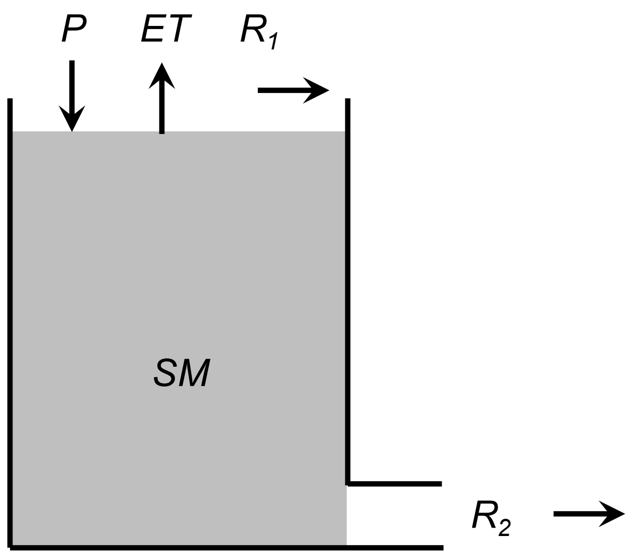
$$SM_t = SM_{t-1} + P_t - E_t - R_1 - R_2$$

$$P_t - R_1 = (1 - r_t) \times P_t$$

$$-E_t - R_2 = -m_t \times SM_{t-1}$$

$$SM_t = (1 - m_t) \times SM_{t-1} + (1 - r_t) \times P_t$$

$$SM_t = f_t \times SM_{t-1} + i_t \times P_t$$

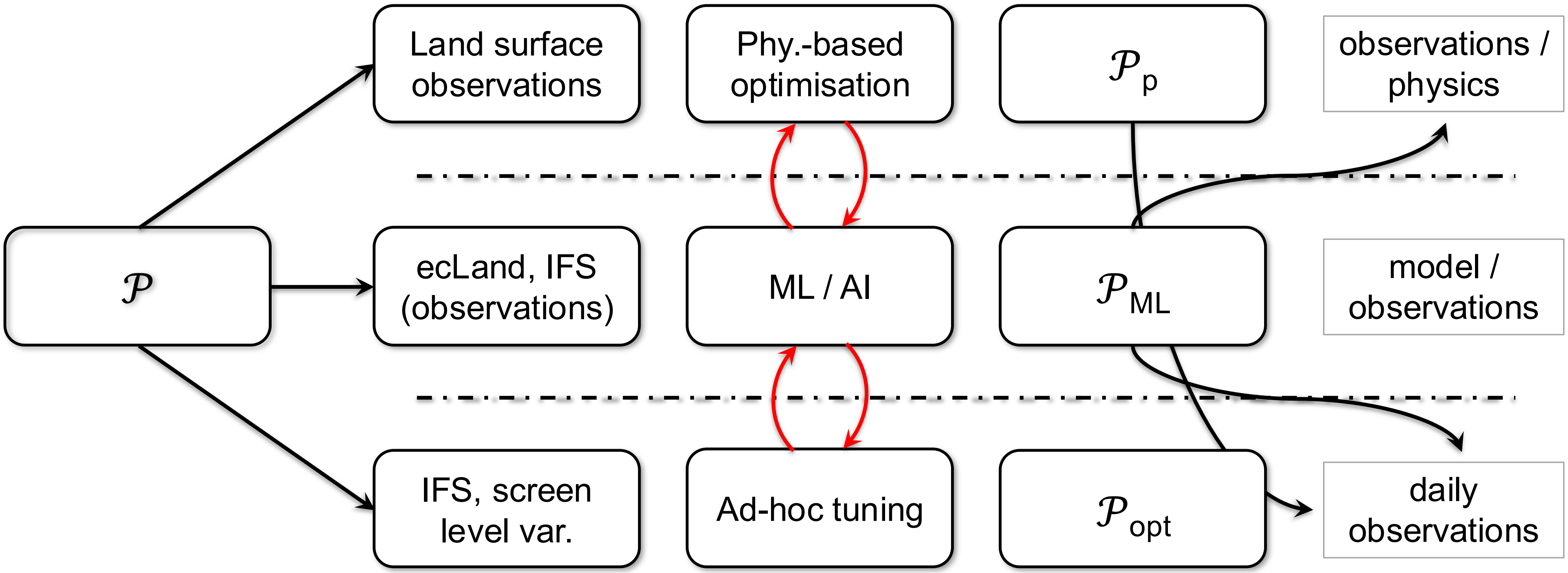



With the results of Eqs. (2)–(4) the cell state $\boldsymbol{c}_t$ is updated by the following equation:

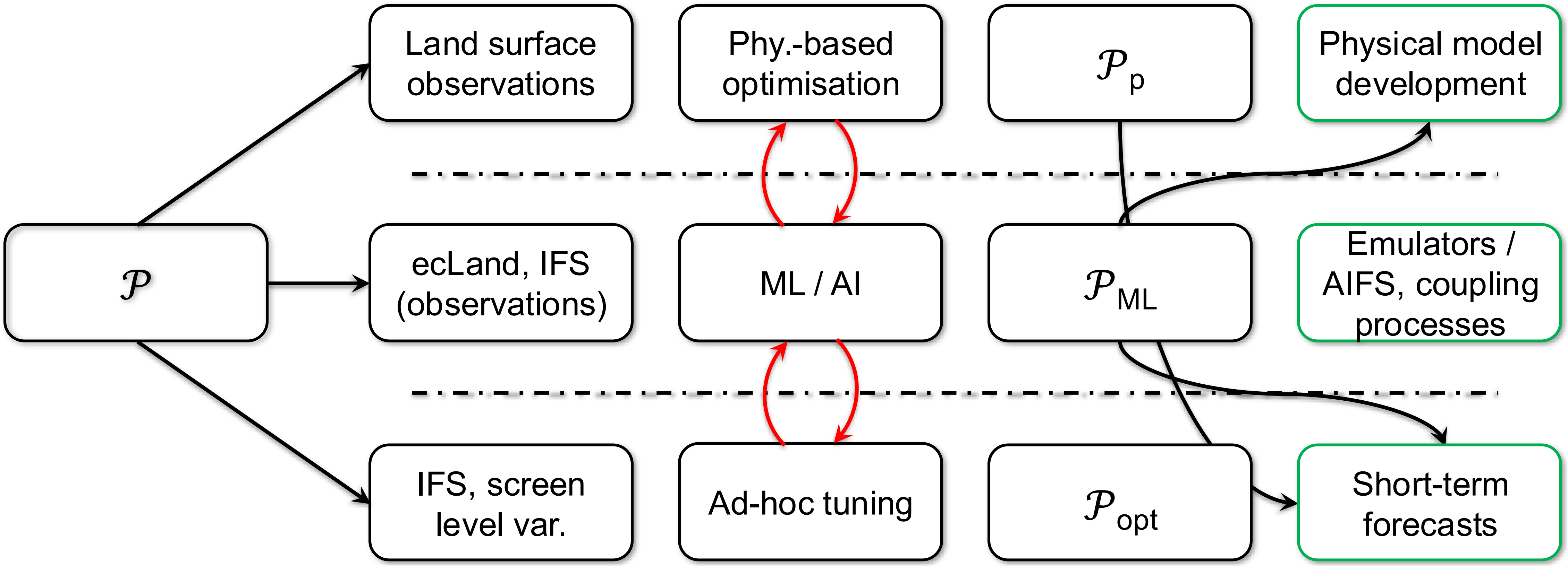
$$\boldsymbol{c}_t = \boldsymbol{f}_t \odot \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \odot \tilde{\boldsymbol{c}}_t, \qquad (5)$$

Kratzert et al., 2017, HESS

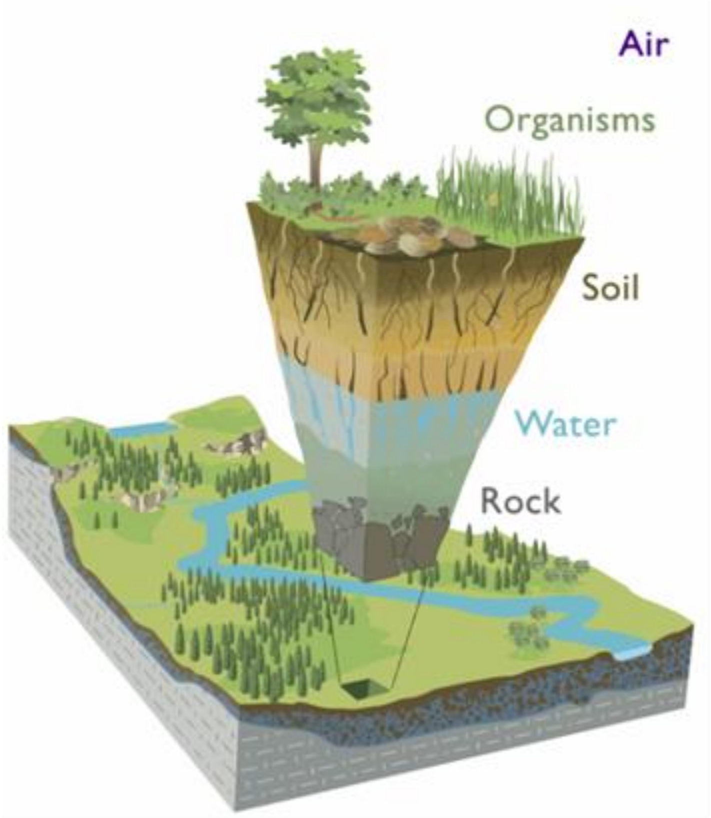
# Bringing together physically- and data-driven parameters



# Bringing together physically- and data-driven parameters



# Moving ecLand to aiLand (slides by Nina Raoult)



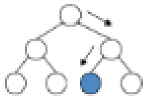

Chorover et al., 2007

**~4 hours** to run 1 year globally (30km) on 16 CPUs

Highly **parameterised**/missing processes

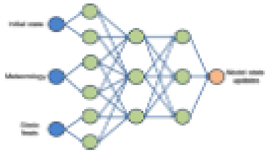
**No communication** between grid cells

# Strengths and Weaknesses of Different ML Approaches



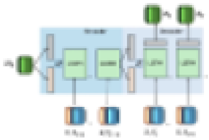
XGBoost

**Pros:** Fast, accurate for structured/tabular data.
**Cons:** Limited for spatiotemporal or complex dependencies.



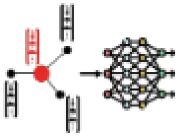
MLP

**Pros:** Simple, light-weight, works well with numerical inputs.
**Cons:** Struggles with spatial/temporal patterns.



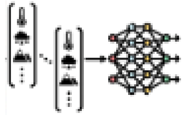
LSTM

**Pros:** Captures temporal dependencies, good for time-series.
**Cons:** Slow training, sensitive to hyperparameters.



Graph NN

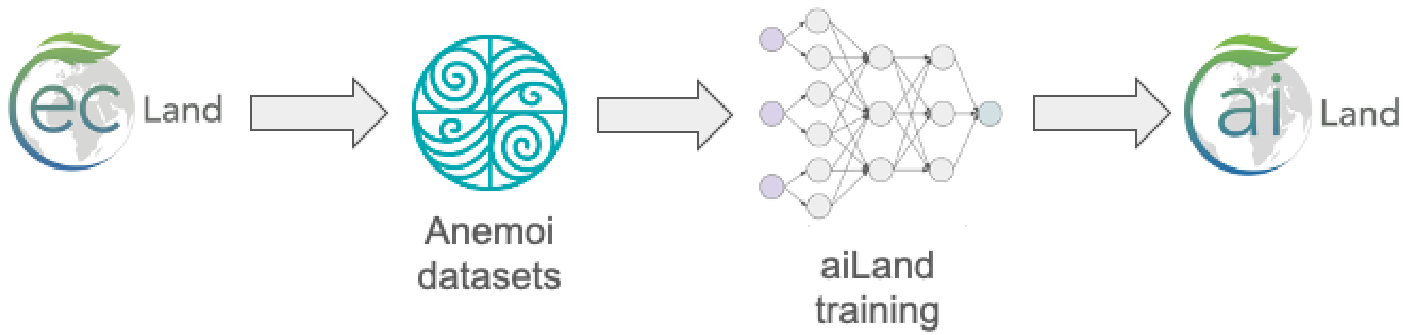
**Pros:** Models spatial relationships effectively.
**Cons:** High computational cost, complex implementation.



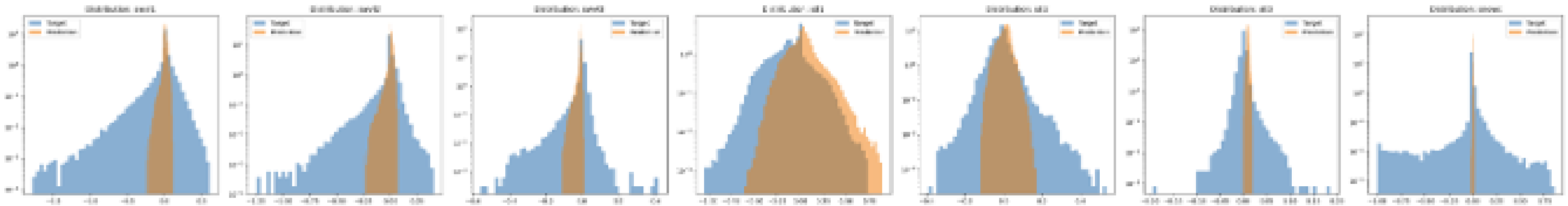
Mamba

**Pros:** Scalable, tailored for large land models.
**Cons:** Niche, limited community support/documentation.

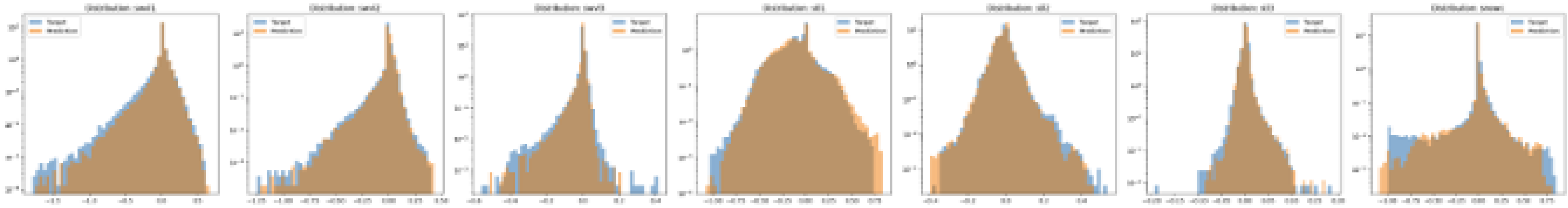
# aiLand Implementation with Anemoi




Epoch 0

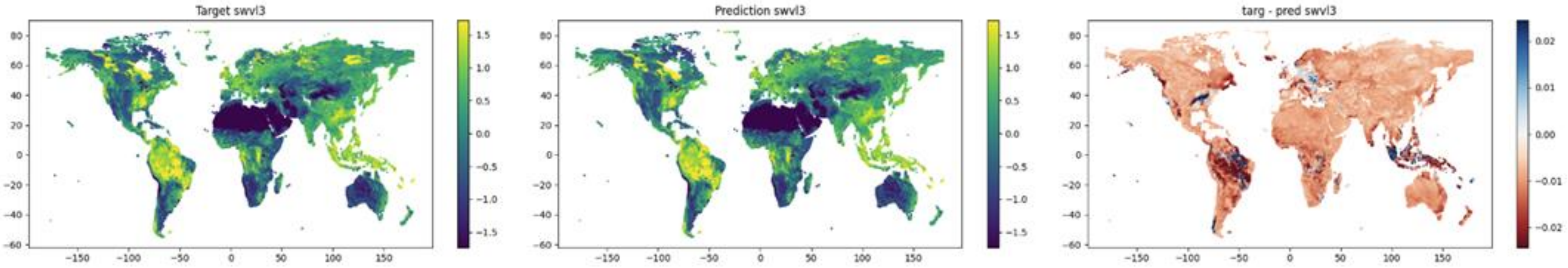


Epoch 80

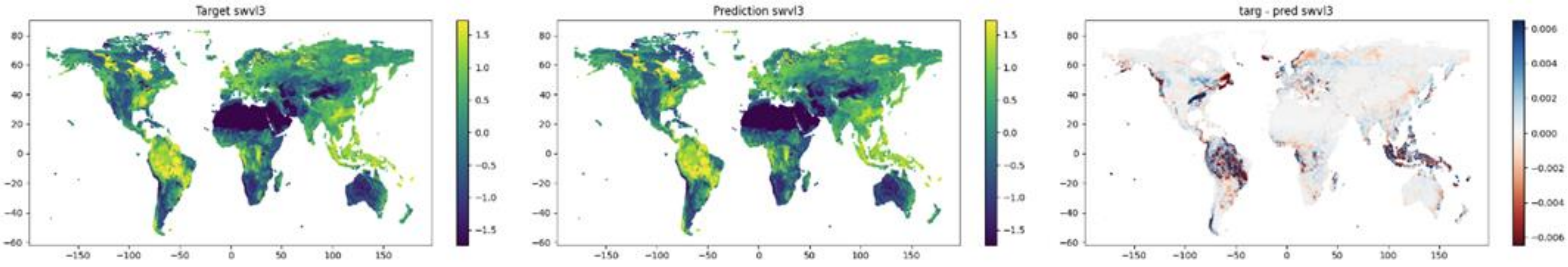


# Learning Root Zone Soil Moisture

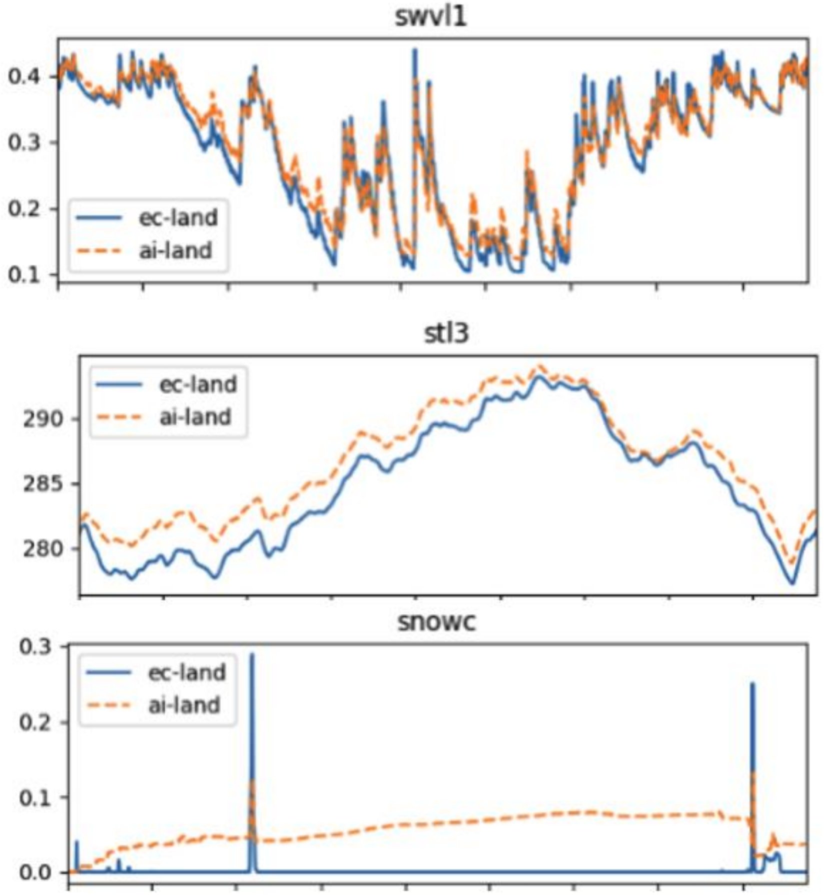
## Epoch 0



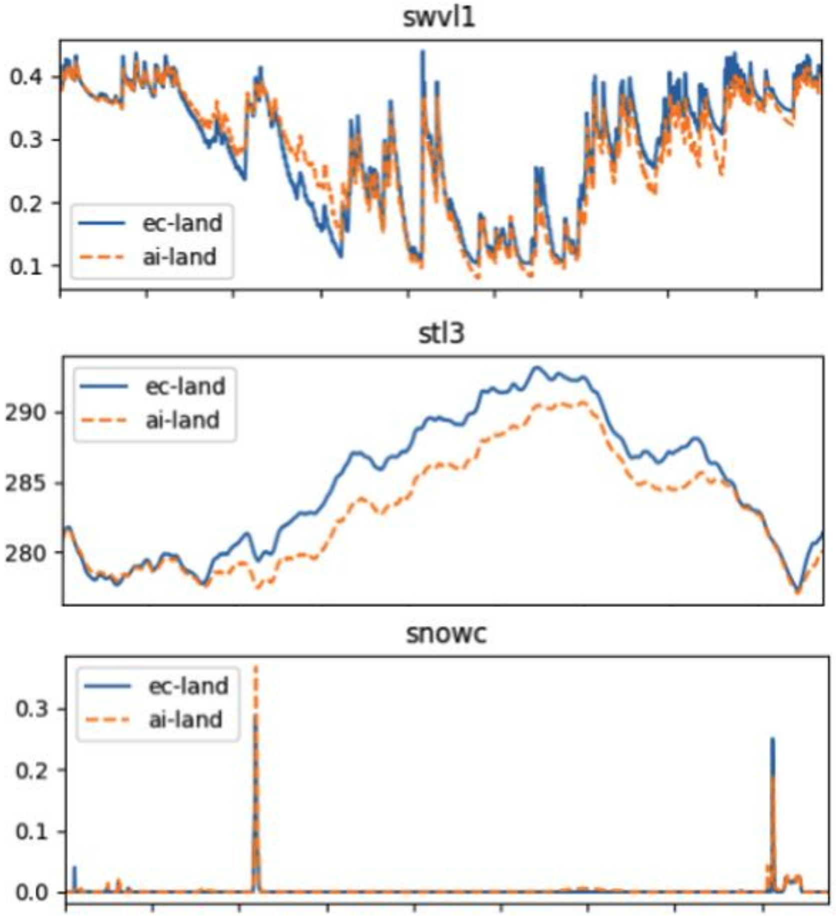

## Epoch 80



# aiLand – Spatial Knowledge Transfer




aiLand trained on **Sahel** region




aiLand trained on **Boreal** region

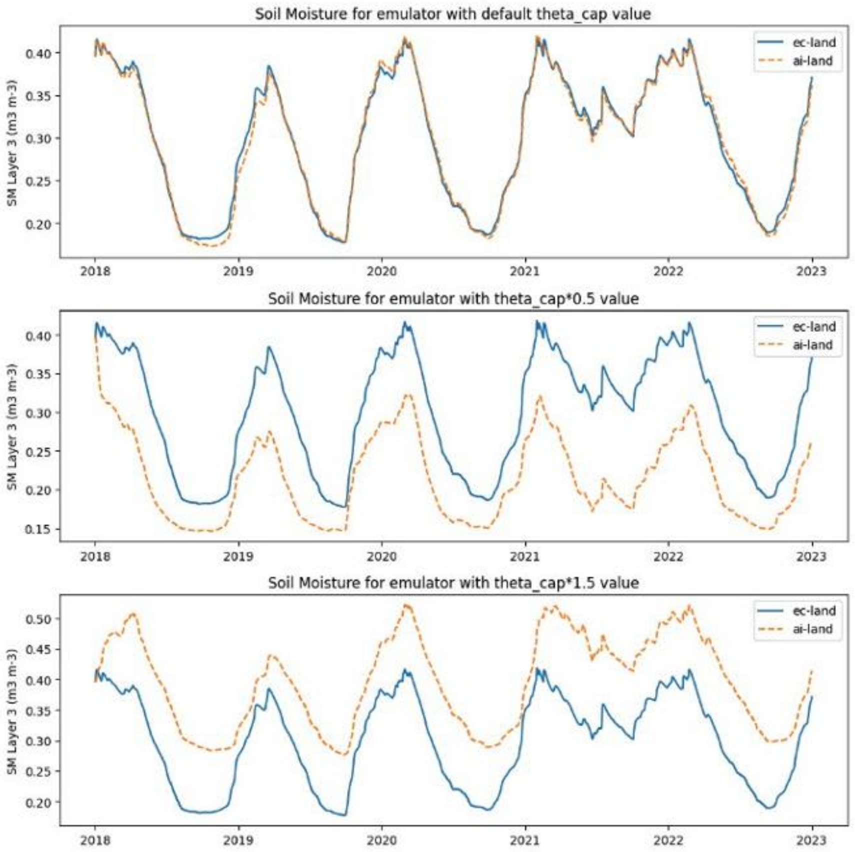
# aiLand – Parameter Perturbations

By fine tuning against **observations**, can we **learn biases** in the model?

With more information on parameter sensitivities, can we use the emulator for **parameter estimation**?

Can we exploit the **differentiability** of aiLand for land model **data assimilation**?

How do we **couple** aiLand with the other **Earth System components** (physical or machine learnt)?



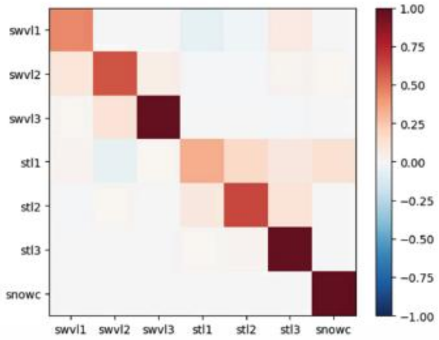
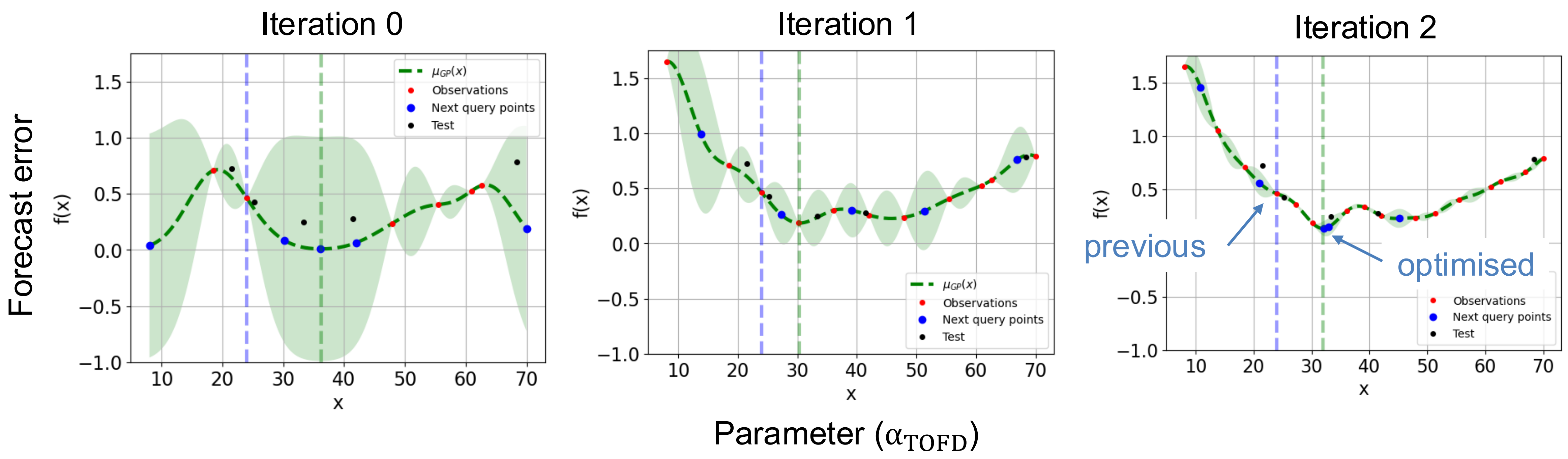




**Fig:** Jacobian

**Credit:** Ewan Pinnington

# Bayesian Multi-Parameter Optimisation (slides by Birgit Sützl)

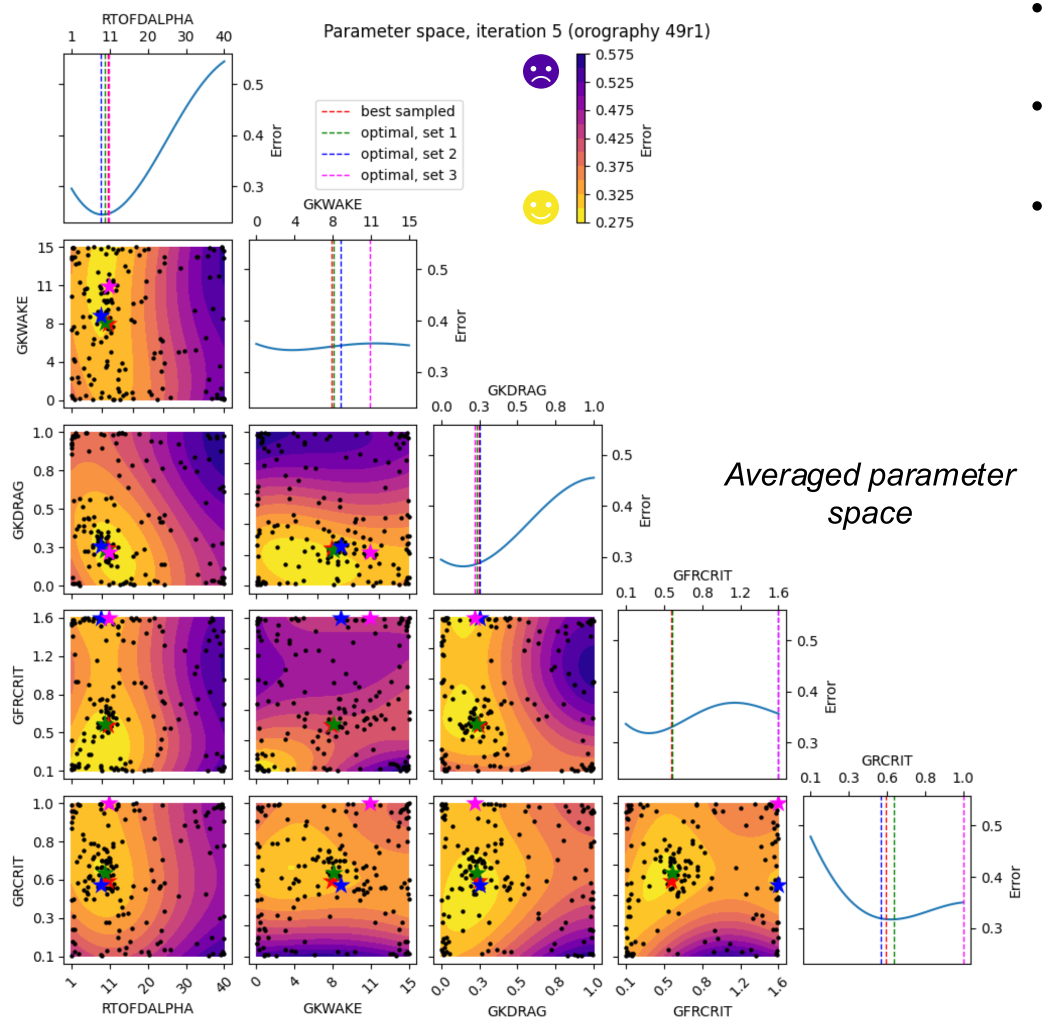



*Bayesian optimisation 1D example*

- Gaussian process emulator estimates forecast error as a function of the parameter space.
- Emulator is trained with simulations sampling the parameter space.

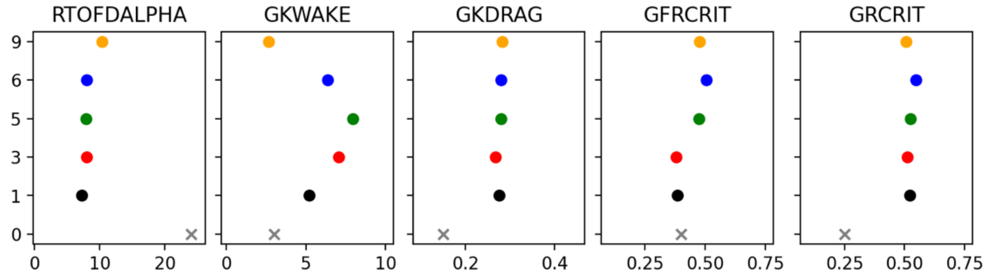
# Parameter Optimisation for Orography

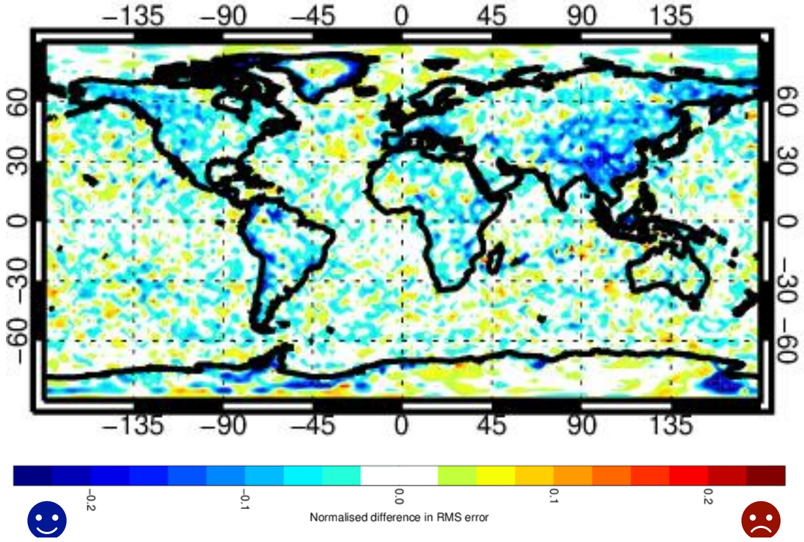
- Multi-parameter optimisation for 5 parameters in the sub-grid orographic parameterisations.
- Using verification scores for different variables as forecast error metric.
- New parameters improve wind, particularly at lower levels.




*Averaged parameter space*

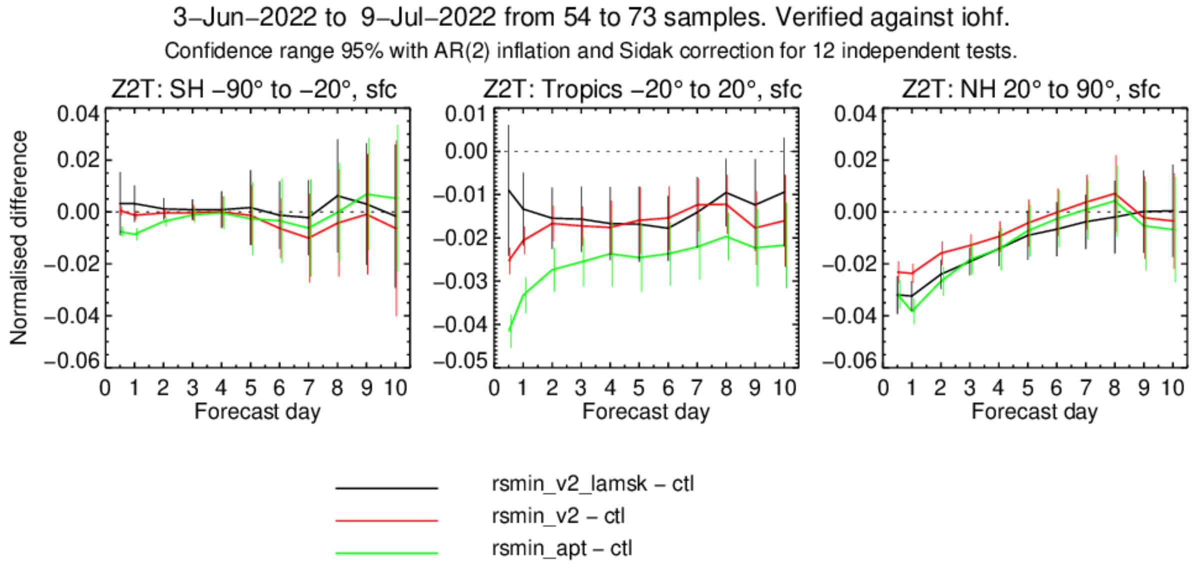
*Parameters partial dependence*

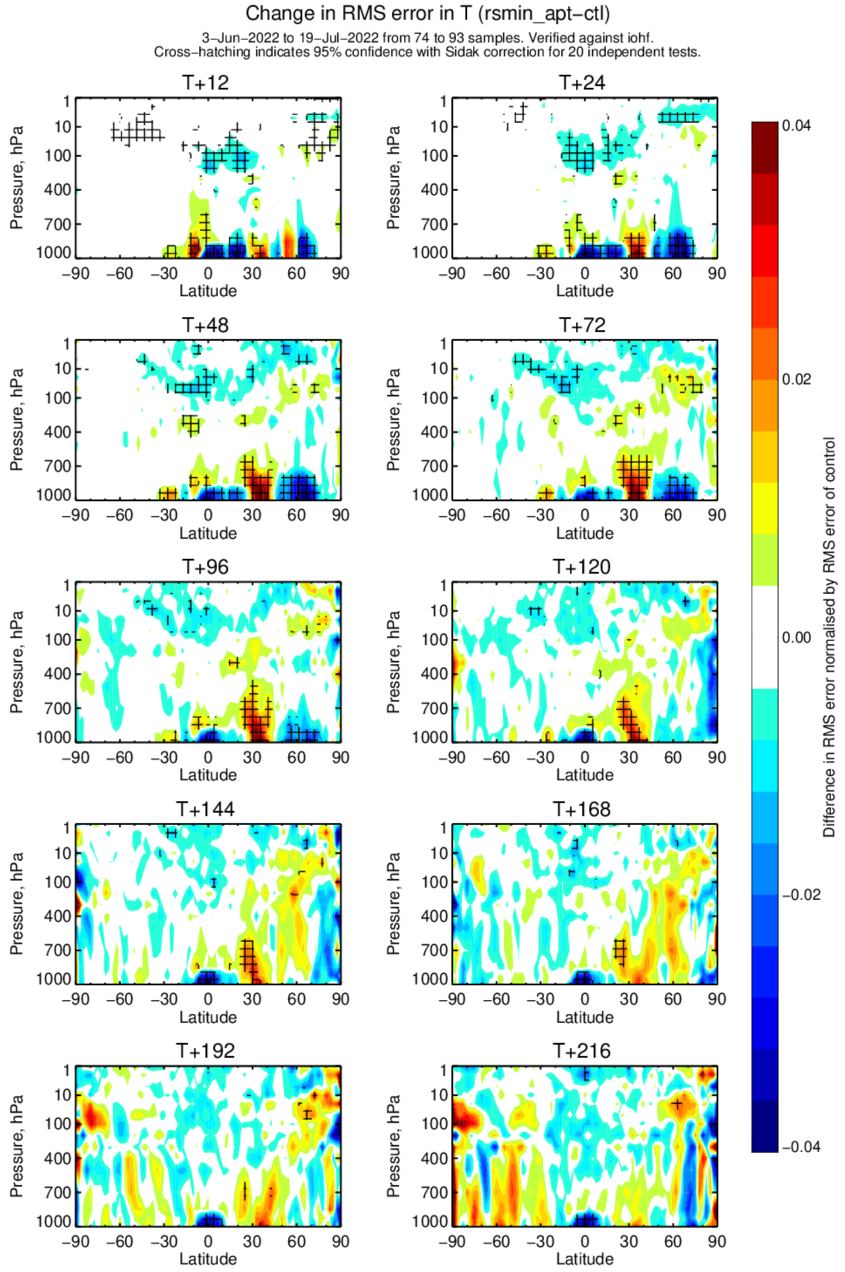


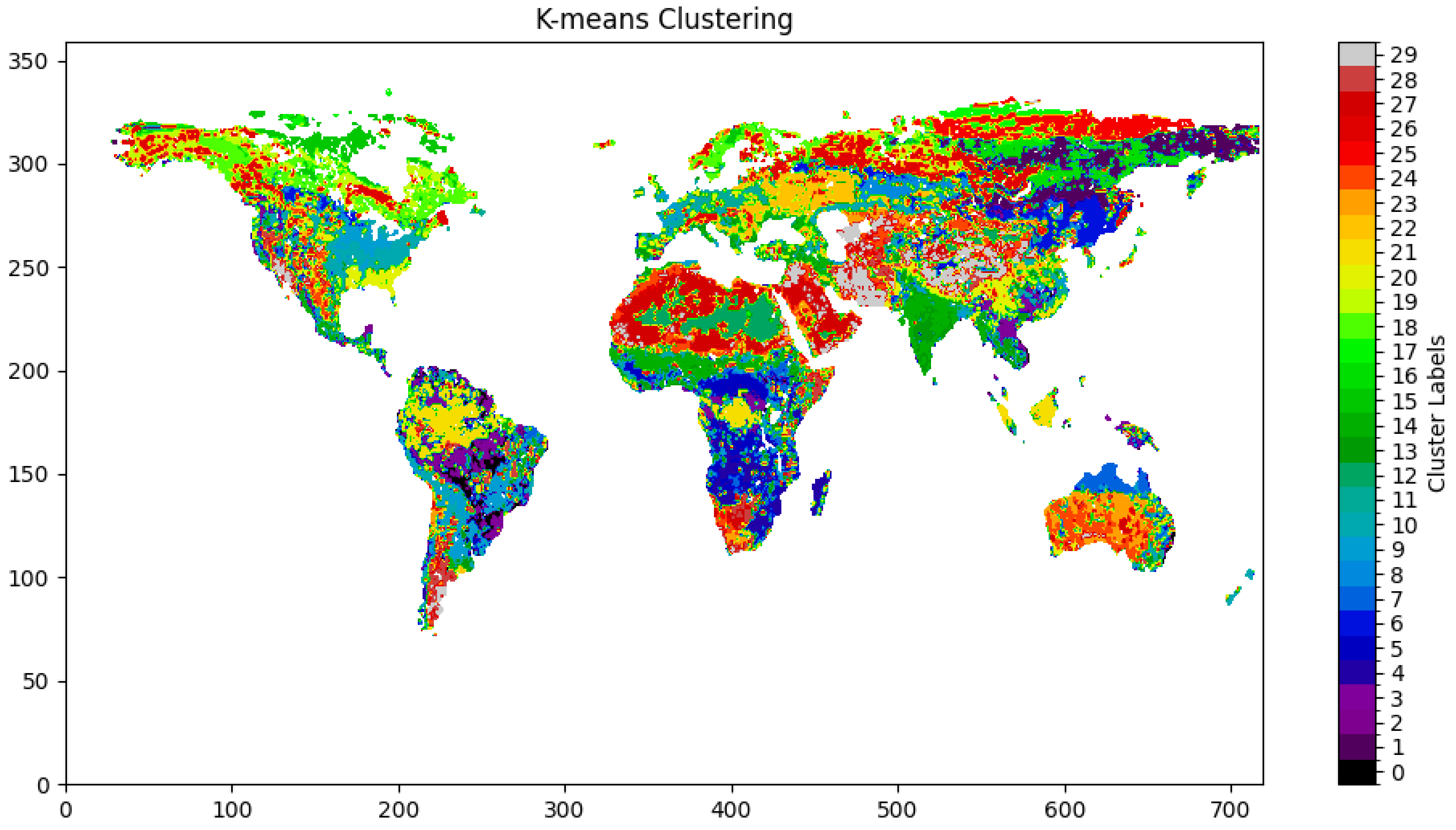

*New vs. old orography: change in RMSE of 10m zonal winds, T+72, 28 km resolution*

# Adaptive Parameter Tuning (slides by Gabriele Arduini)

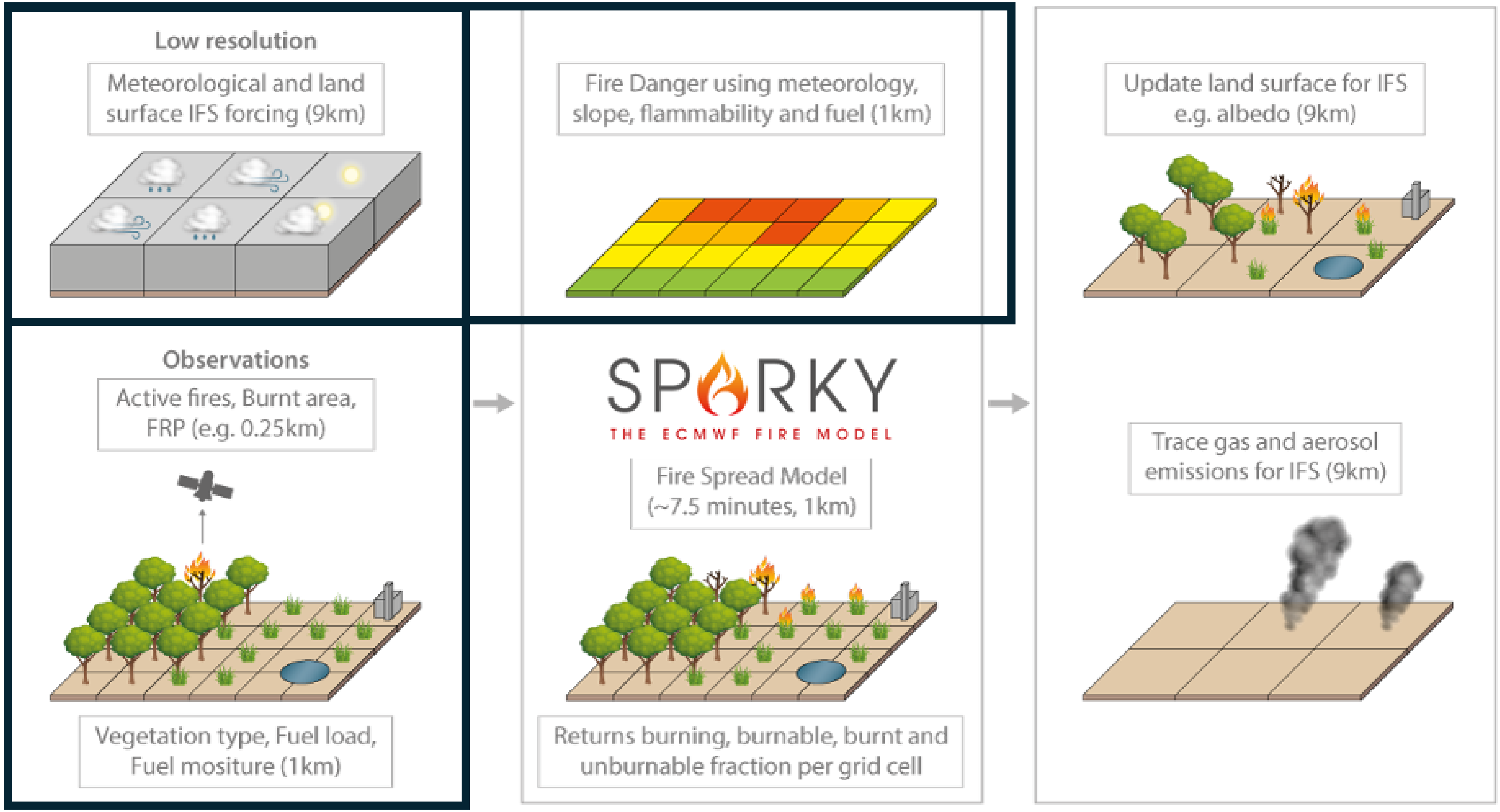


# Spatialisation of Parameters



# Fires with ecLand/IFS (Slides by Joe McNorton)



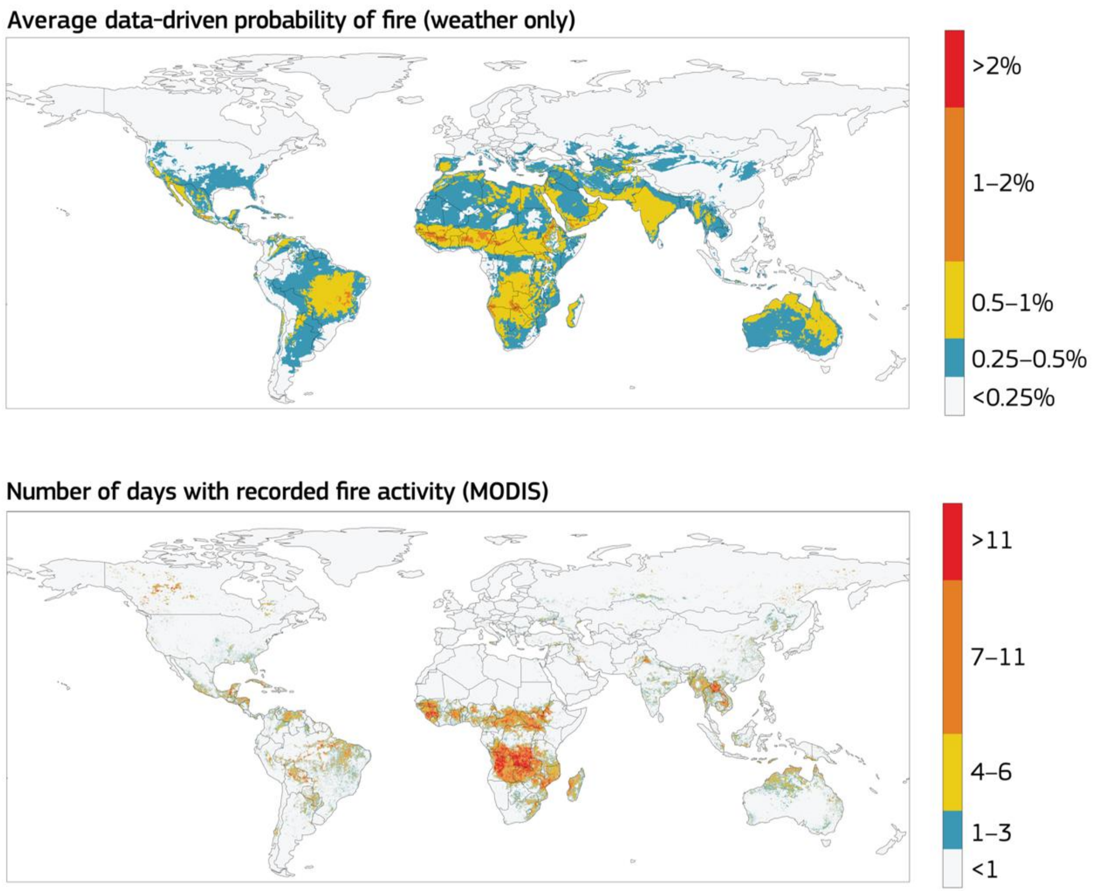
# Fires with ecLand/IFS

***Data-driven forecasts***

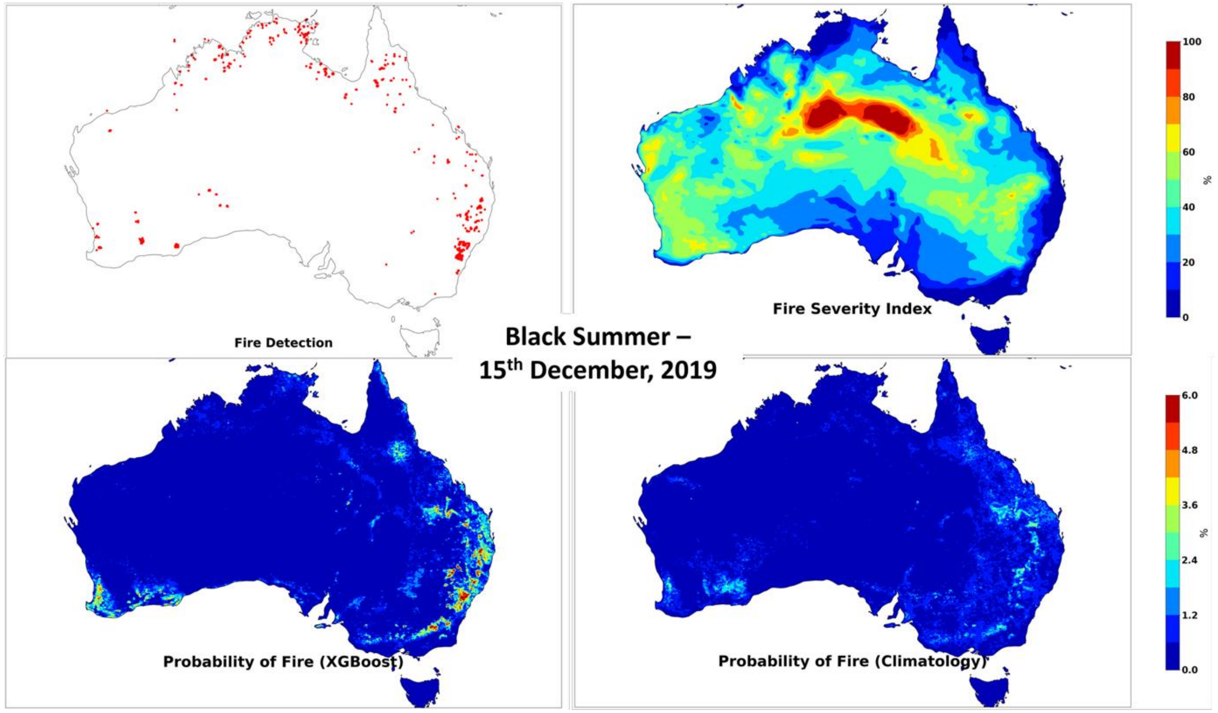
- The global Probability of Fire (PoF) runs operationally in real-time (since 2023).
- PoF combines weather prediction, land surface modelling and satellite data.
- PoF based on Extreme Gradient Boosting (XGBoost), using a probabilistic classifier.
- PoF trained on MODIS/ VIIRS/ GOES/ METEOSAT/ Himawari active fire data.
- The model produces daily 10-day forecasts at both 1 and 9 km horizontal resolution.

| Variable | Category | Frequency | Source | Forecast? |
|---|---|---|---|---|
| Precipitation | Weather | Daily | IFS | Y |
| 2m Temperature | Weather | Daily | IFS | Y |
| 2m Dewpoint Temperature | Weather | Daily | IFS | Y |
| 10m Wind Speed | Weather | Daily | IFS | Y |
| Live Leaf Load | Fuel | Daily | IFS-Sparky | Y |
| Live Wood Load | Fuel | Daily | IFS-Sparky | Y |
| Dead Foliage Load | Fuel | Daily | IFS-Sparky | Y |
| Dead Wood Load | Fuel | Daily | IFS-Sparky | Y |
| Dead Foliage Moisture | Fuel | Daily | IFS-Sparky | Y |
| Dead Wood Moisture | Fuel | Daily | IFS-Sparky | Y |
| Live Fuel Moisture | Fuel | Daily | IFS-Sparky | Y |
| Low Vegetation LAI | Fuel | Monthly | ESA-CCI | N |
| High Vegetation LAI | Fuel | Monthly | ESA-CCI | N |
| High Vegetation Cover | Fuel | Yearly | IFS | N |
| Low Vegetation Cover | Fuel | Yearly | IFS | N |
| Type of High Vegetation | Fuel/Ign | Yearly | IFS | N |
| Type of Low Vegetation | Fuel/Ign | Yearly | IFS | N |
| Urban Cover | Ignition | Static | IFS | N |
| Lightning Intensity | Ignition | Daily | IFS | Y |
| Population Density | Ignition | Static | GPW v4 – SEDAC | N |
| Total Road Length | Ignition | Static | Global Roads Inventory Dataset | N |
| Orography | - | Static | IFS | N |

# Fires with ecLand/IFS

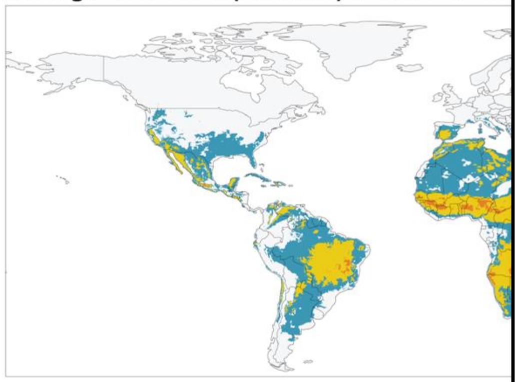



An improved fire prediction compared to current Index and climatology

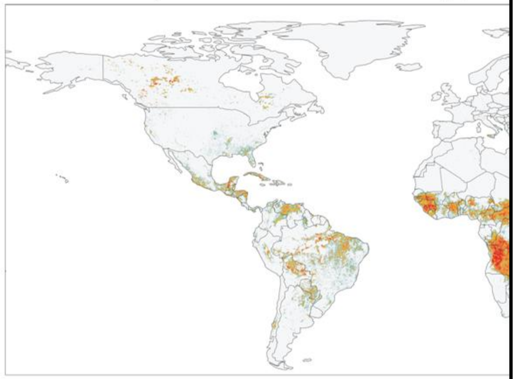


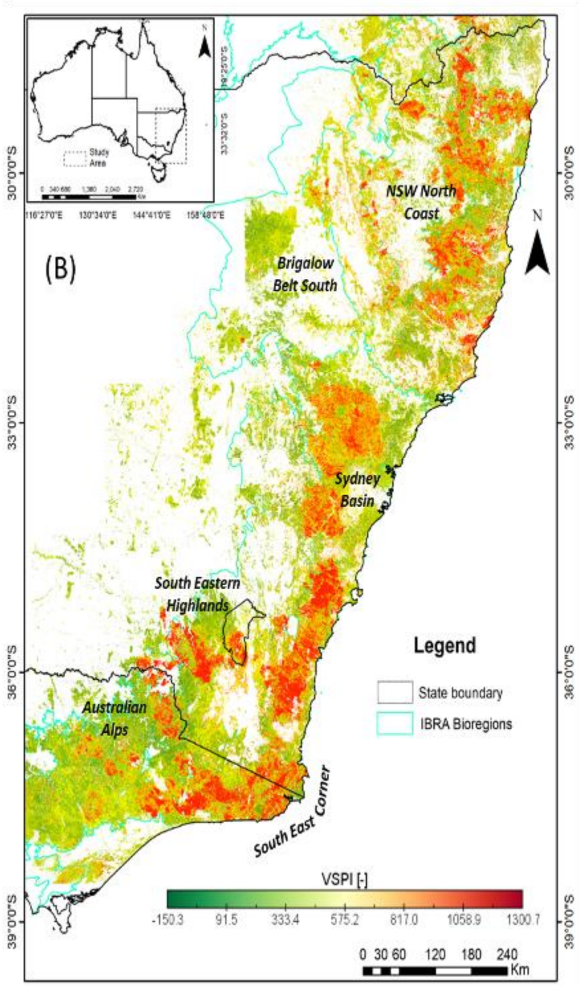
# Fires with ecLand/IFS

Average data-driven probability of fire (weathe

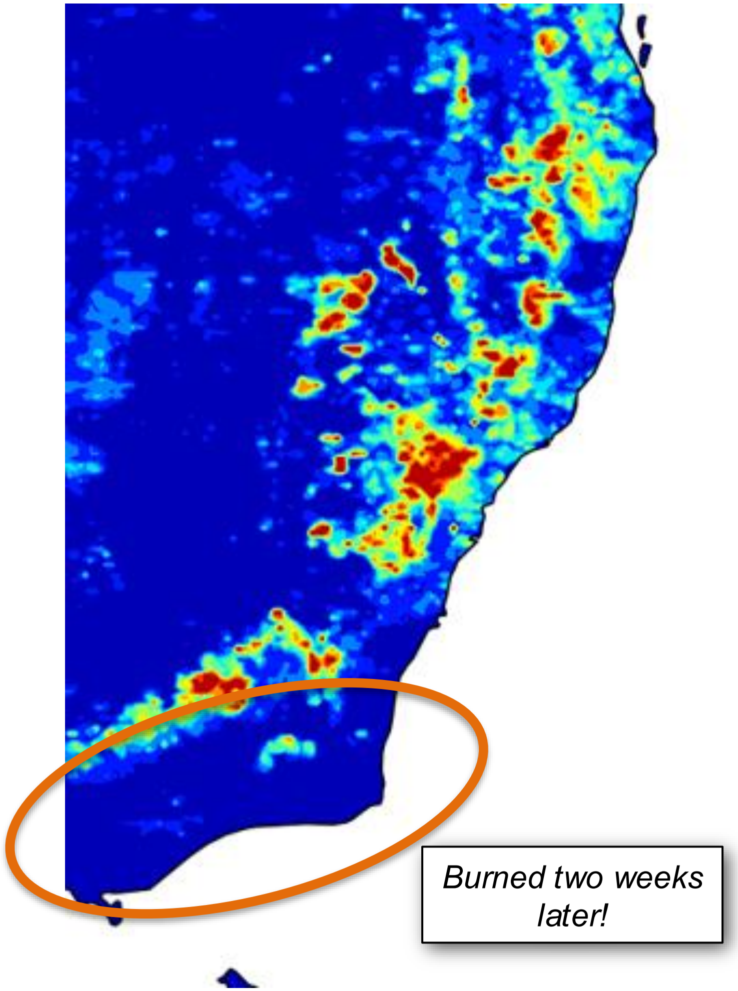


Number of days with recorded fire activity (MOD

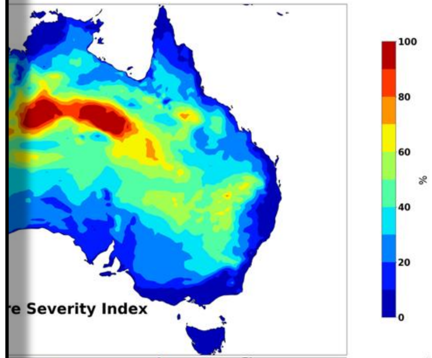


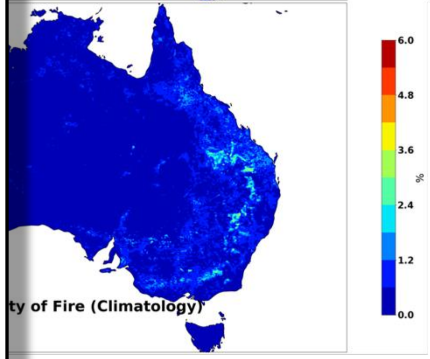



Chhabra et al., 2022

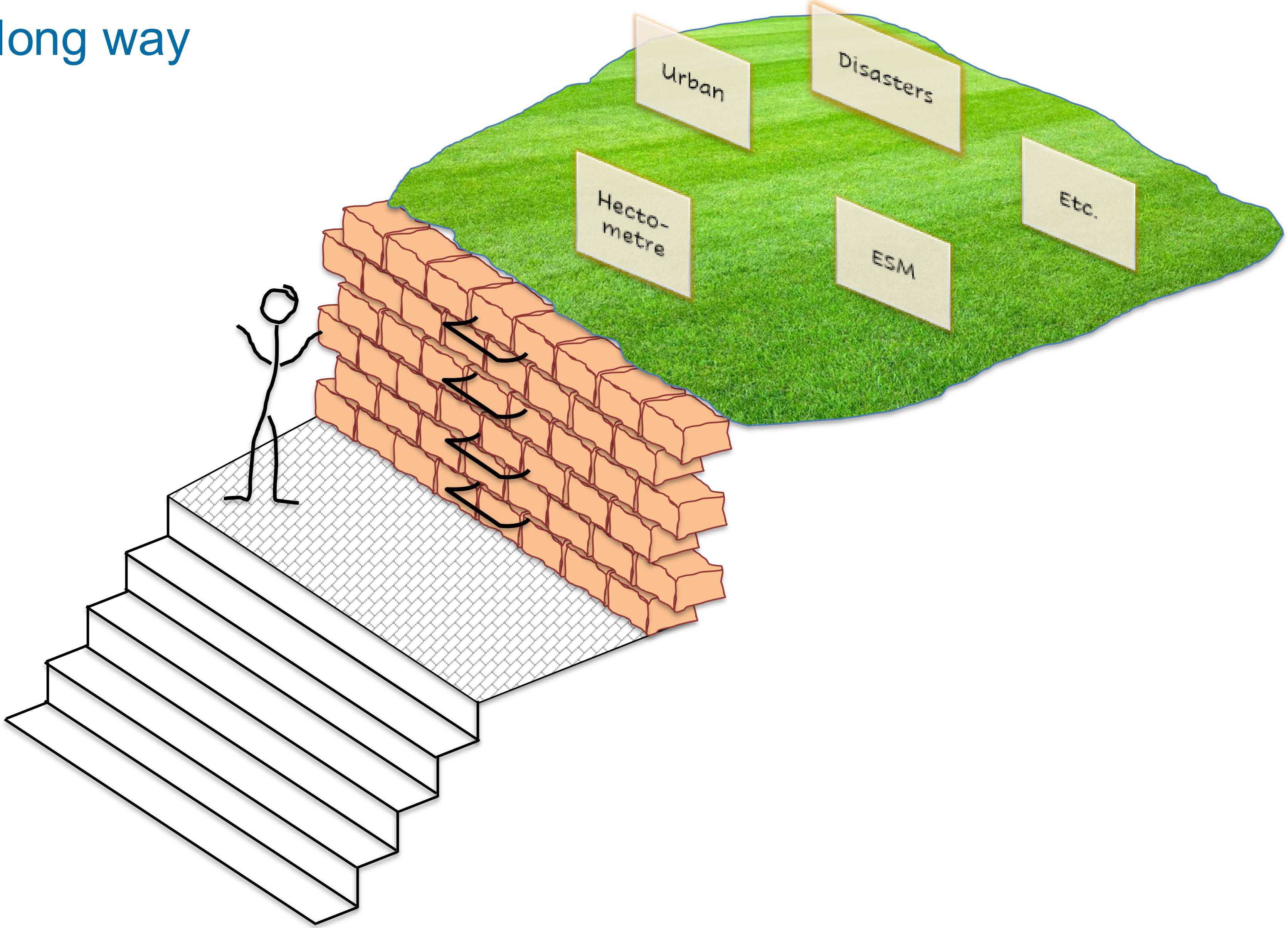



ed to current



# We have come a long way



# Food for Thoughts

Four questions ML can help us with :

The ***known Knowns*** – but how well do we actually know those?

The ***known Unknowns*** – where do we get this information from?

The ***unknown Knowns*** – is there something obvious missing in our models?

The ***unknown Unknowns*** – how do we find out what those are, and if they are relevant?

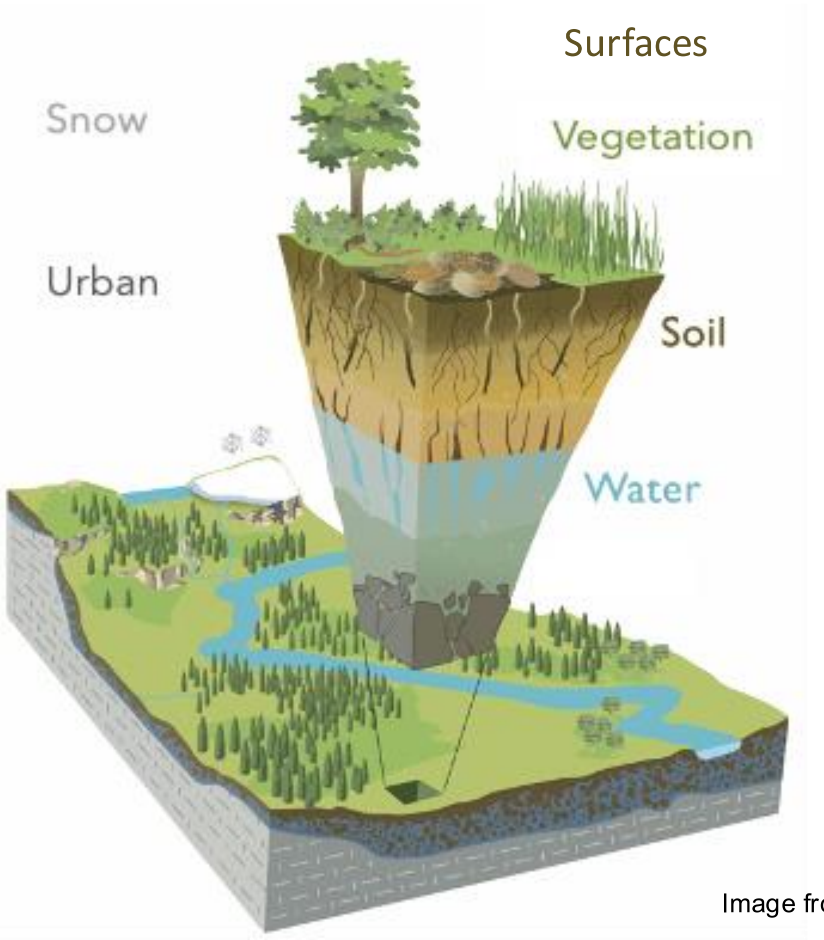



Image from Chorover et al., 2007

# Conclusions

***What now ?***

There may need to be a change to how we “do” land surface modelling

***But how ?***

We need to make more and better use of observations for land surface modelling

The value of ML4LM is not in the computational time, we need to exploit the added value there is in both providing complementary information

There is a need for physical modelling into the future (climate change, non-stationarity) to provide the background states, applications may be ML-driven

***What is the risk ?***

Thin line to walk between physically meaningful and “just” tuned parameters

A lack of spatial, observed data

***Do we have to ?***

Short answer – yes

*Thank you !*