An aerial photograph showing a wide, dry riverbed with a winding stream of water. The surrounding landscape is arid and brown, with some sparse vegetation and buildings visible in the distance.

## **Drought-climate feedbacks: Model uncertainties and potential for surprises**

*(... and some other reflections on confronting models with obs)*

**Sonia I. Seneviratne**, Laibao Liu, Dominik Schumacher, Svenja Seeber, Francesco Giardina, Lukas Gudmundsson, Martin Hirschi, Mathias Hauser, Felix Jäger, Ryan S. Padron, Jonas Schwaab and Kathrin Wehrli  
**ETH Zurich, Switzerland**

**Workshop on confronting Earth System Model trends with observations: The Good, the Bad, and the Ugly**

US CLIVAR, NCAR, March 15, 2024

## Confronting ESMs with observations:

- Observational uncertainties
- Separating sources of biases (forcing; thermodynamic vs dynamic biases)

## Drought-climate feedbacks

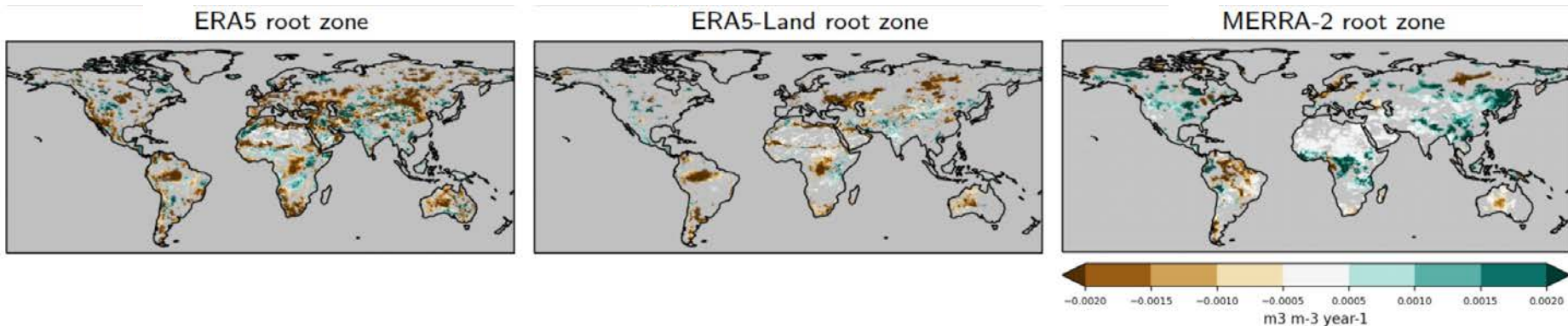
- Relevant processes
- Drought trends in ESMs vs observations
- Potential biases in global drought-carbon feedbacks

## Some open questions

- Drought relevance for record-shattering heatwaves
- 2023 Record temperatures

## Conclusions

## Drought trends (dry-season soil moisture), 2000-2020

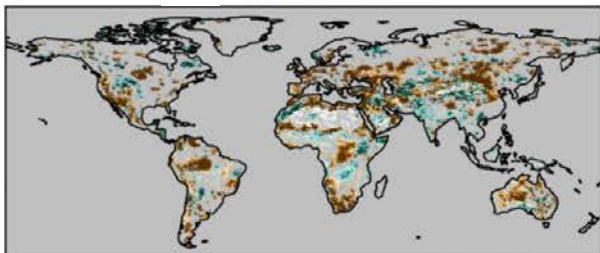


There are also large uncertainties in observational products!

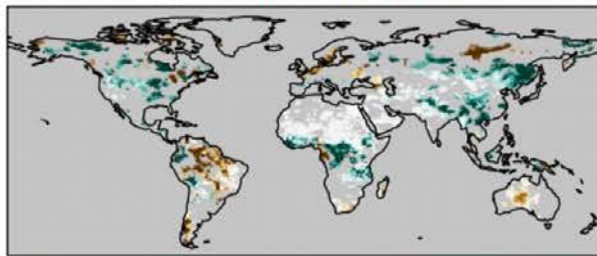
*(Hirschi et al, submitted to HESS)*

## Drought trends (dry-season soil moisture), 2000-2020

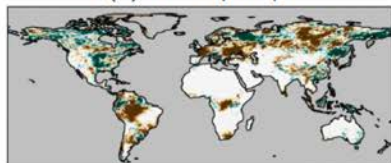
ERA5 root zone



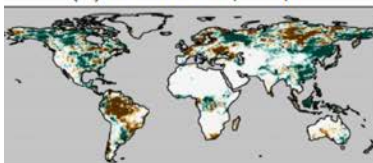
MERRA-2 root zone



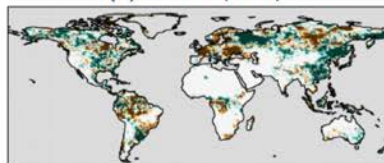
(a) ERA5 precip.



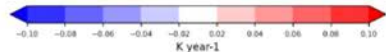
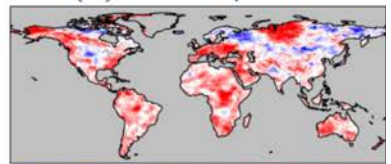
(b) MERRA-2 precip.



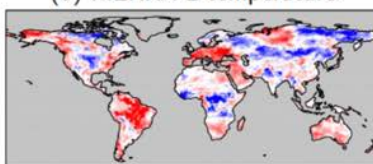
(c) GPCP precip.



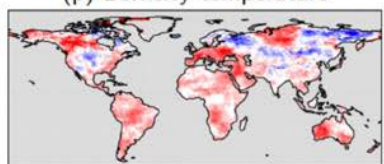
(m) ERA5 temperature



(o) MERRA-2 temperature



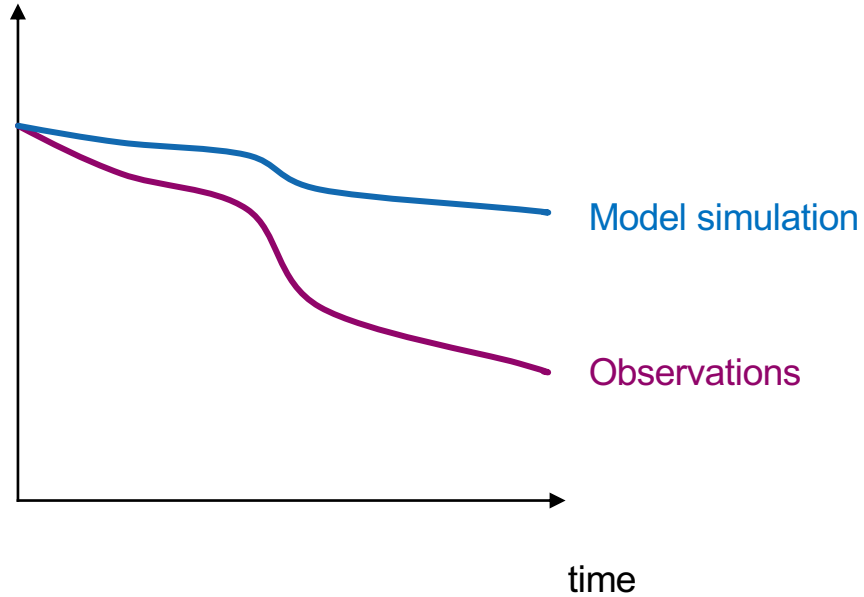
(p) Berkeley temperature



Comparison with ground observations suggest some biases in MERRA-2 product

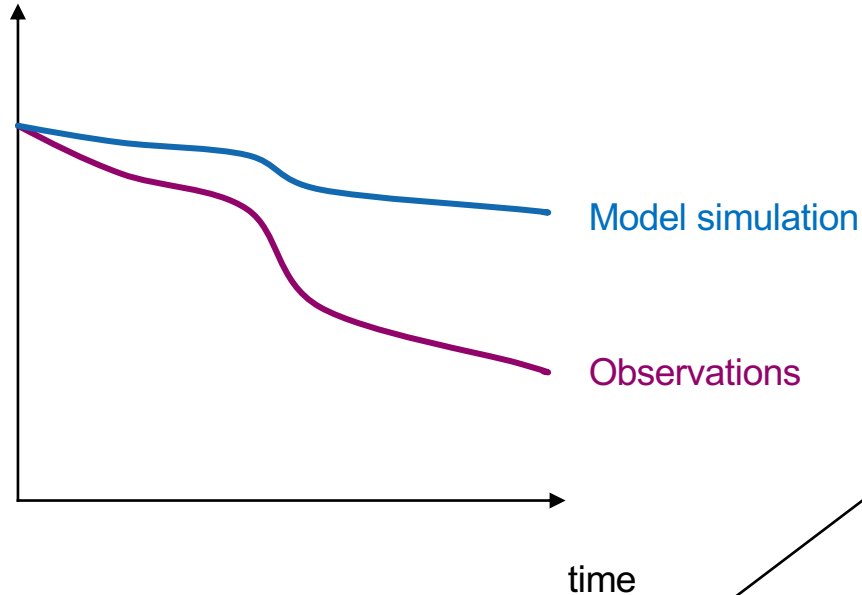
(NB: 2-m temperatures are not assimilated in MERRA-2!)

soil moisture



Is the ESM consistent with observations?

soil moisture

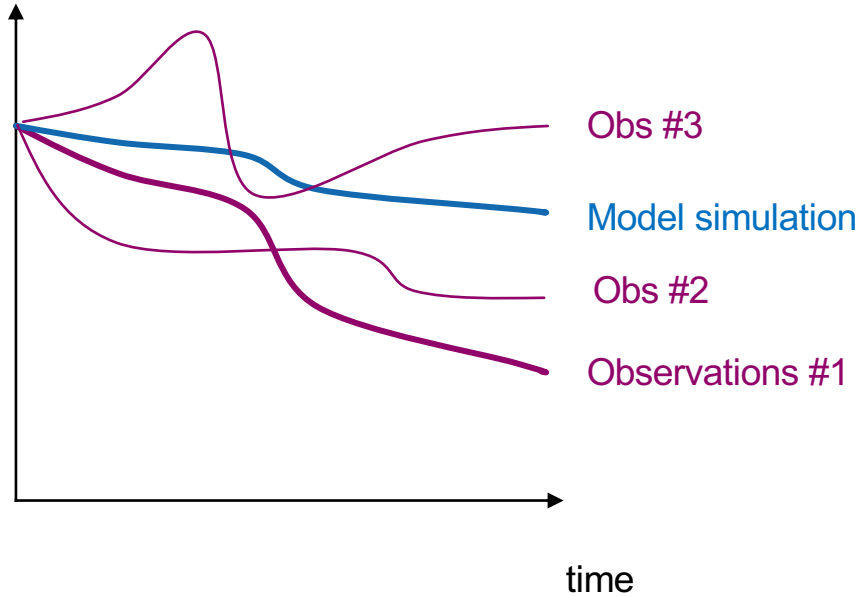


Is the ESM consistent with observations?

- 1) Consider observational spread
- 2) Consider model spread (several realizations)
- 3) Process-based evaluation of single components (e.g. dynamics vs thermodynamics, land vs atm vs ocean, extremes vs mean, forcing)

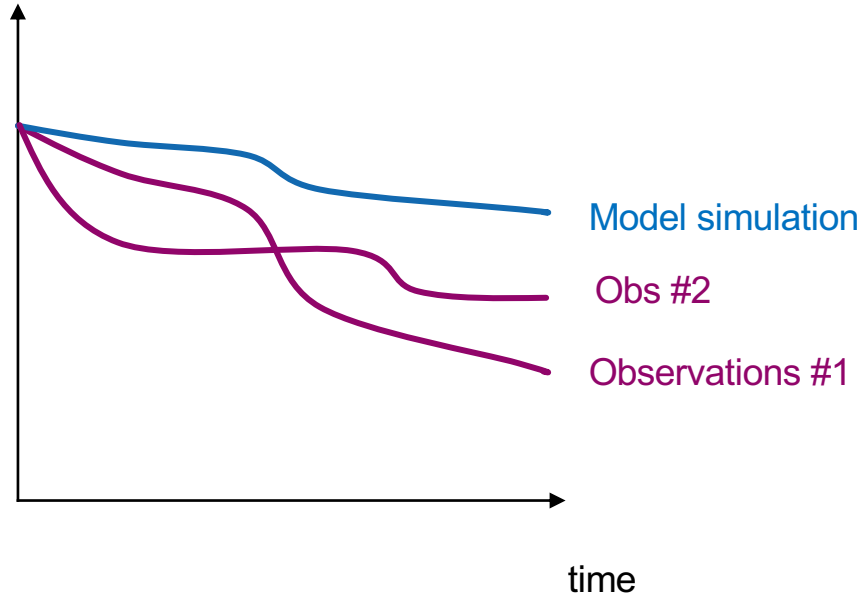
3-step evaluation

soil moisture



1) Need to consider  
**observational spread ...**

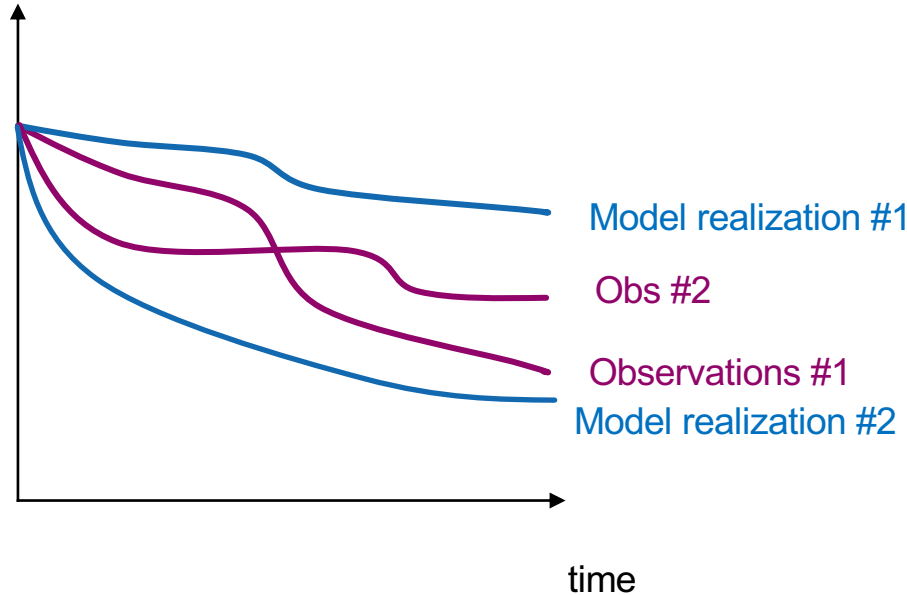
soil moisture



1) Need to consider **observational spread** and possibly exclude some observational products with biases



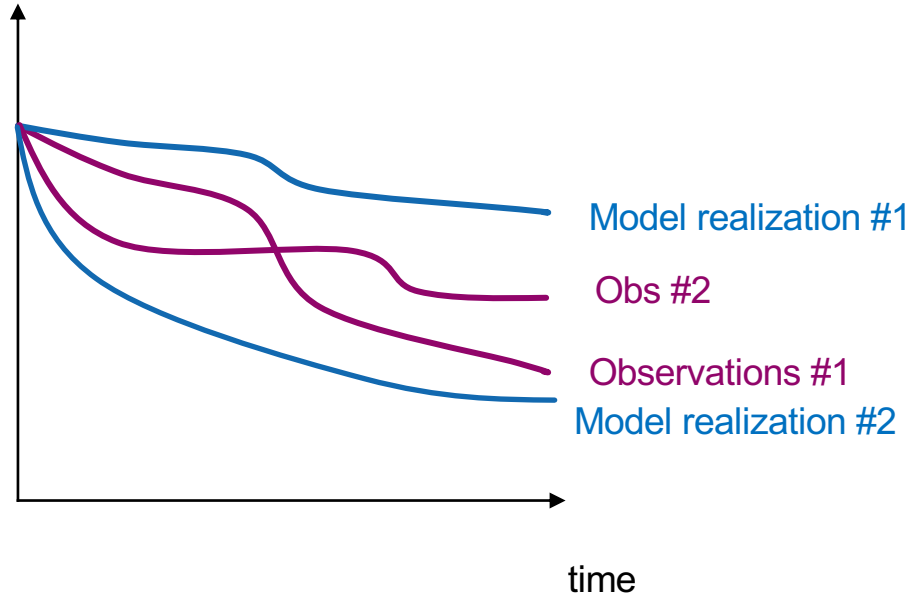
soil moisture



1) Need to consider **observational spread** and possibly exclude some observational products with biases

2) Consider **multiple realisations from climate model** (not only single runs)  
(Deser et al. 2012, *Nature Climate Change*)

soil moisture

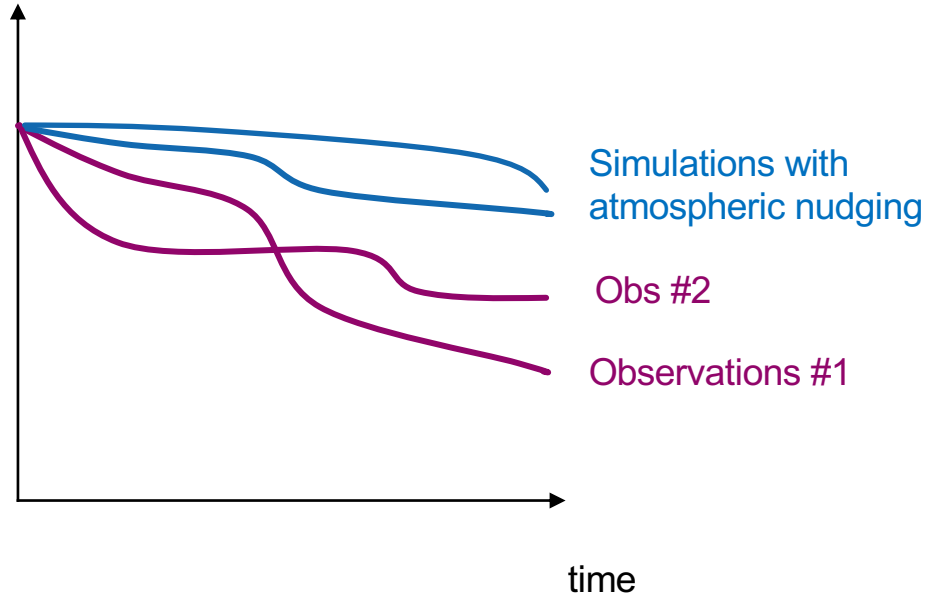


1) Need to consider **observational spread** and possibly exclude some observational products with biases

2) Consider **multiple realisations from climate model** (not only single runs)  
(Deser et al. 2012, *Nature Climate Change*)

NB: The source for some of the model spread can be isolated and constrained (atmospheric dynamics)

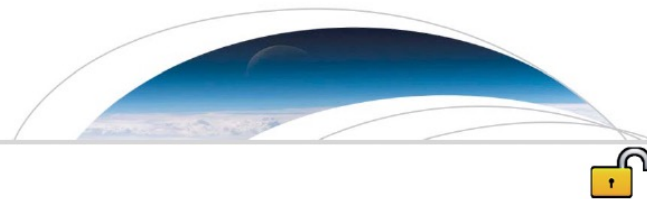
soil moisture



1) Need to consider **observational spread** and possibly exclude some observational products with biases

2) Consider **multiple realisations from climate model** (not only single runs)  
(Deser et al. 2012, *Nature Climate Change*)

3) **Process-based evaluation of single ESM components** (some with obs constraints, others not)  
(e.g. Wehrli et al. 2018, *GRL*)



## Geophysical Research Letters

### RESEARCH LETTER

10.1029/2018GL079220

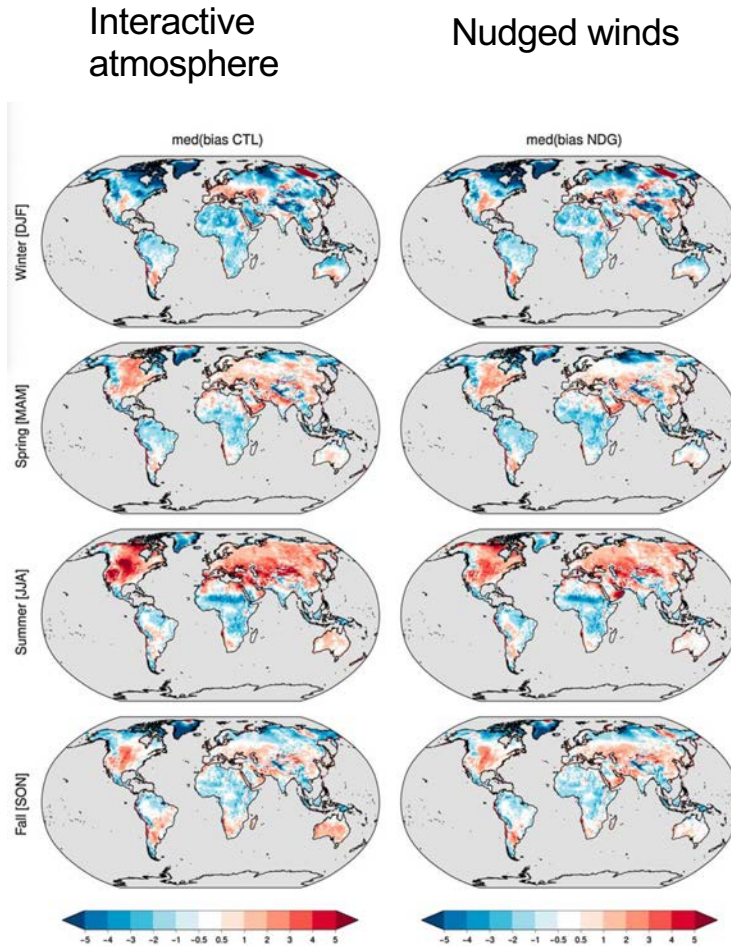
#### Key Points:

- Thermodynamical versus dynamical sources of biases can be identified using atmospheric nudging of horizontal winds in a climate model
- Atmospheric nudging improves simulated temperature and precipitation in CESM; however,

## Assessing the Dynamic Versus Thermodynamic Origin of Climate Model Biases

**Kathrin Wehrli<sup>1</sup>** , **Benoit P. Guillod<sup>1,2</sup>** , **Mathias Hauser<sup>1</sup>** , **Matthieu Leclair<sup>1</sup>**, and **Sonia I. Seneviratne<sup>1</sup>** 

<sup>1</sup>Institute for Atmospheric and Climate Science, Department of Environmental Systems Science, ETH Zurich, Zurich, Switzerland, <sup>2</sup>Institute for Environmental Decisions, Department of Environmental Systems Science, ETH Zurich, Zurich, Switzerland



CESM 1.2

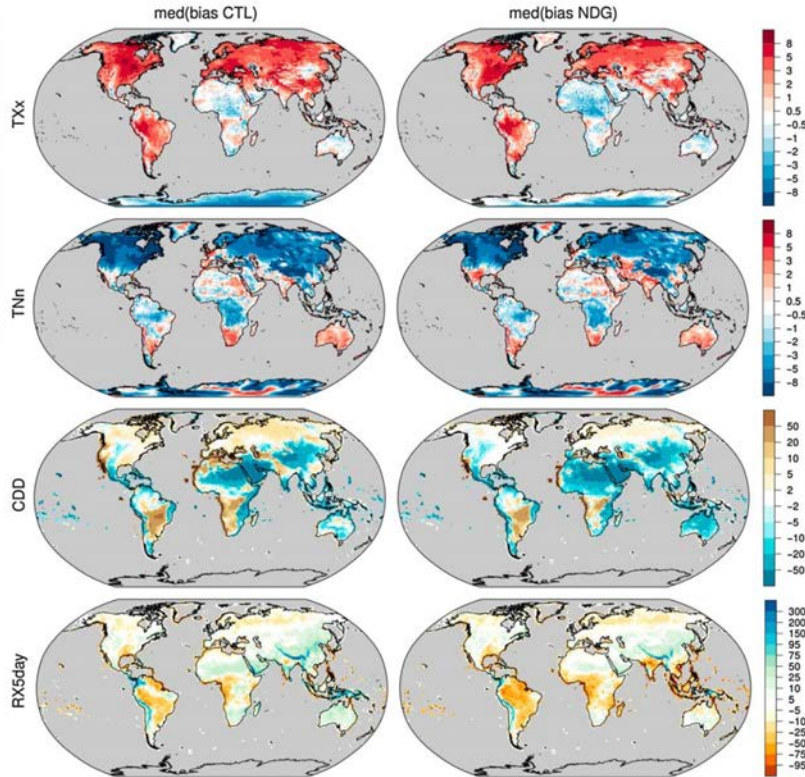
(comparison to CRU TS, 1982-2021; mean bias)

A large fraction of the biases remain, i.e. are of thermodynamic origin!

(Wehrli et al. 2018, GRL)

Interactive  
atmosphere

Nudged winds



CESM 1.2

(comparison to ERA-interim (Txx, Tnn) and MERRA-2 (CDD, Rx5dday), 1982-2021; mean bias)

A large fraction of the biases remain, i.e. are of thermodynamic origin!

EXTREMEX simulations: 2009-2015/2016; CESM, EC-EARTH, MIROC

Several set-ups, either with prescribed atmospheric winds, SST or soil moisture (contribution to climate extremes)

NB: New simulations with CESM2.1.2 and ERA5 atmospheric winds are currently on-going (D. Schumacher, ETH Zurich)

Earth Syst. Dynam., 13, 1167–1196, 2022

<https://doi.org/10.5194/esd-13-1167-2022>

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Earth System  
Dynamics

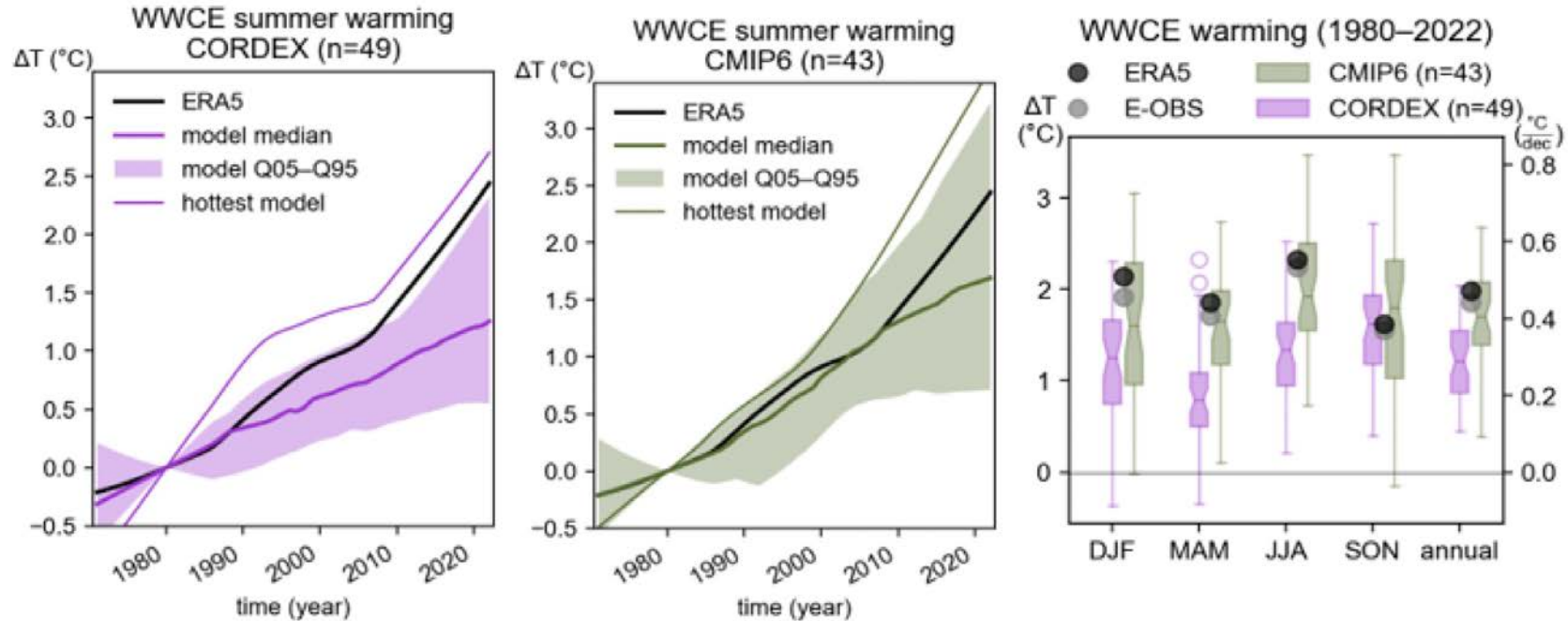


## The ExtremeX global climate model experiment: investigating thermodynamic and dynamic processes contributing to weather and climate extremes

Kathrin Wehrli<sup>1</sup>, Fei Luo<sup>2,3</sup>, Mathias Hauser<sup>1</sup>, Hideo Shiogama<sup>4</sup>, Daisuke Tokuda<sup>5</sup>, Hyungjun Kim<sup>5,6,7</sup>,  
Dim Coumou<sup>2,3</sup>, Wilhelm May<sup>8</sup>, Philippe Le Sager<sup>3</sup>, Frank Selten<sup>3</sup>, Olivia Martius<sup>9,10,11</sup>,  
Robert Vautard<sup>12</sup>, and Sonia I. Seneviratne<sup>1</sup>

(Wehrli et al. 2022, ESD)

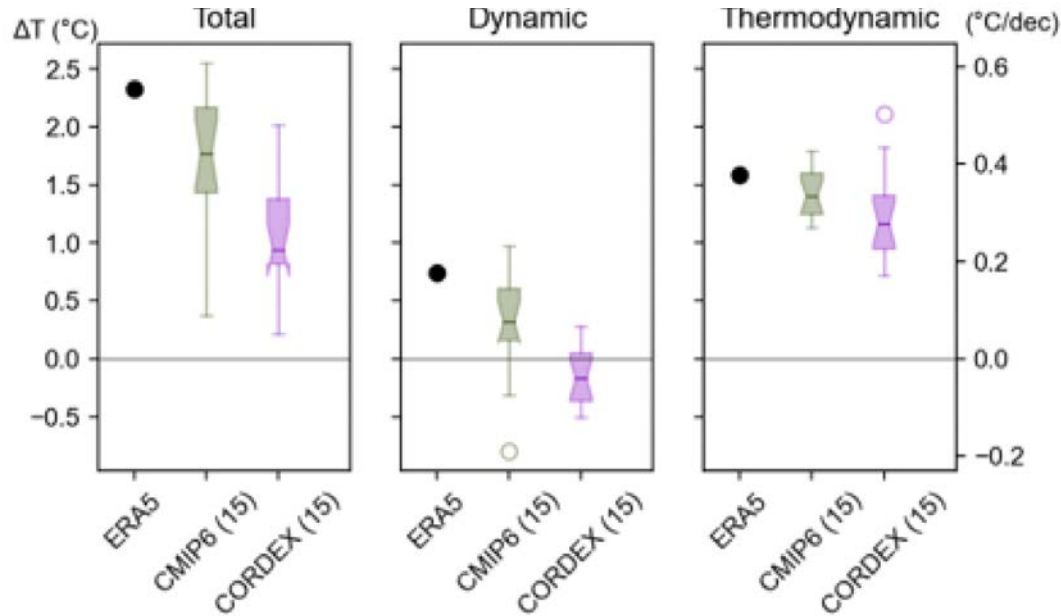
## Temperature trends in Western West-Central Europe



(Schumacher et al., submitted; Preprint:  
<https://www.researchsquare.com/article/rs-3314992/v1>)

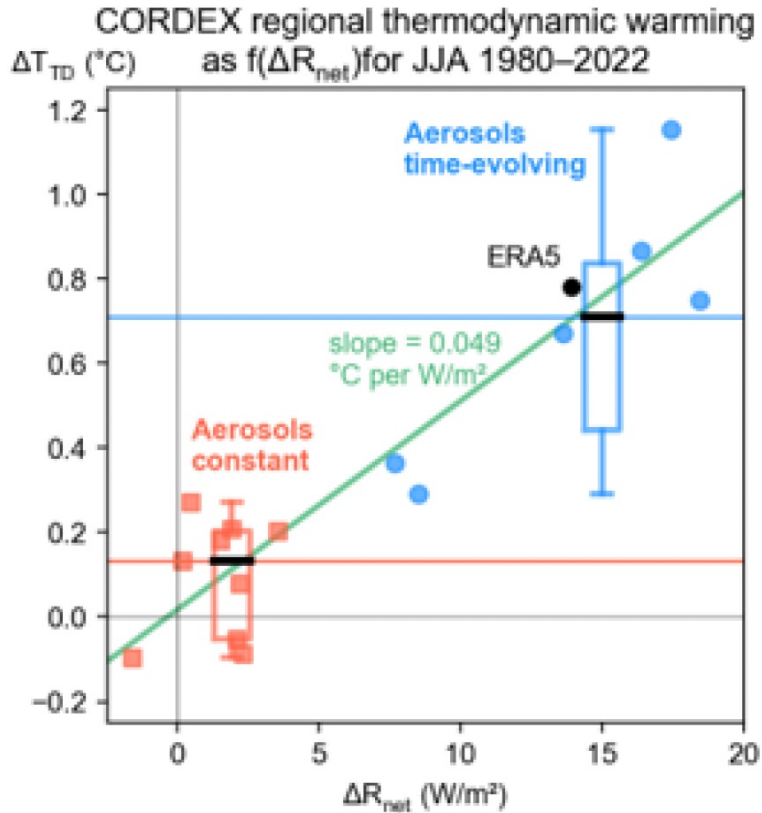


## Temperature trends in Western West-Central Europe



Most of the observed warming is of thermodynamic origin (with some contribution of dynamic origin)

(Schumacher et al., submitted; Preprint:  
<https://www.researchsquare.com/article/rs-3314992/v1>)



Constant aerosols in most of the CORDEX simulations: lead to substantial bias in temperature and radiation simulations! (important also for other regions!)

(Schumacher et al., submitted; Preprint:  
<https://www.researchsquare.com/article/rs-3314992/v1>)

## Confronting ESMs with observations:

- Observational uncertainties
- Separating sources of biases (forcing; thermodynamic vs dynamic biases)

## Drought-climate feedbacks

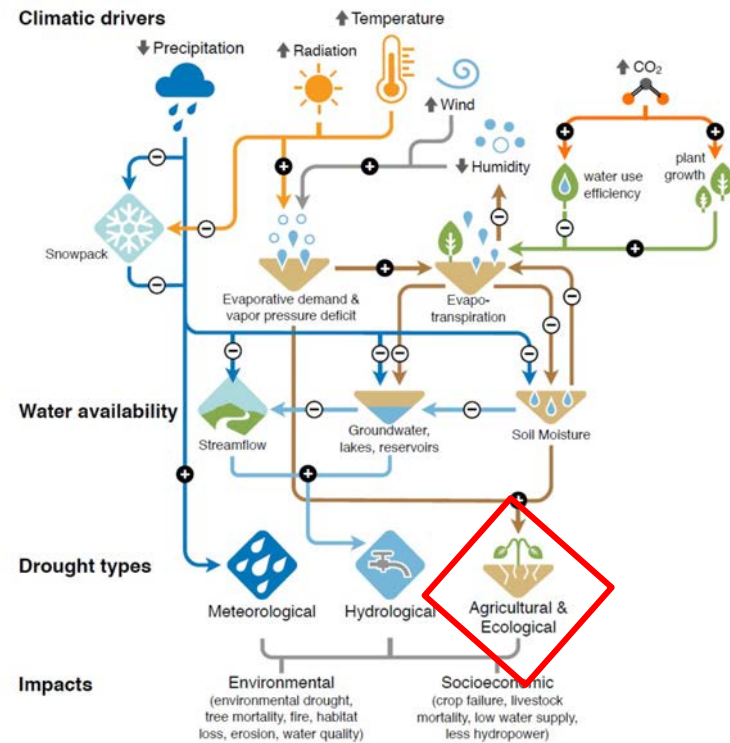
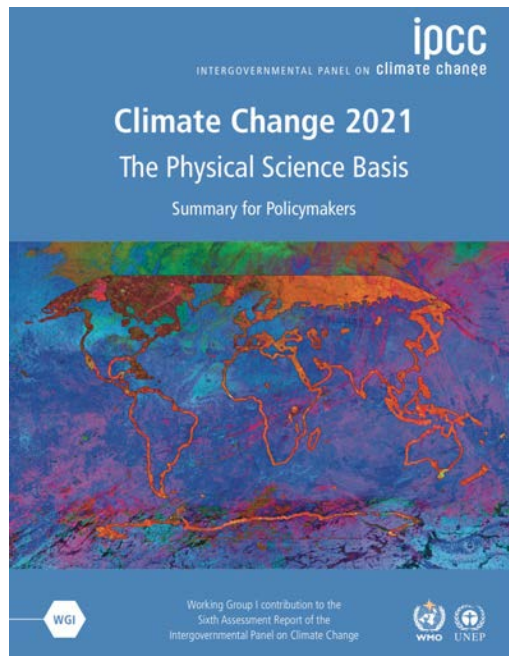
- Relevant processes
- Drought trends in ESMs vs observations
- Potential biases in global drought-carbon feedbacks

## Some open questions

- Drought relevance for record-shattering heatwaves
- 2023 Record temperatures

## Conclusions

The IPCC AR6 distinguishes 3 drought types



(IPCC AR6, Chapter 8; Douville et al. 2021)

Regional changes in agricultural and ecological drought since 1950s (soil moisture, water-balance estimates, measures combining precipitation & atmospheric evaporative demand)

c) Synthesis of assessment of observed change in **agricultural and ecological drought** and confidence in human contribution to the observed changes in the world's regions

Type of observed change  
in agricultural and ecological drought

● Increase (12)

● Decrease (1)

▨ Low agreement in the type of change (28)

○ Limited data and/or literature (4)

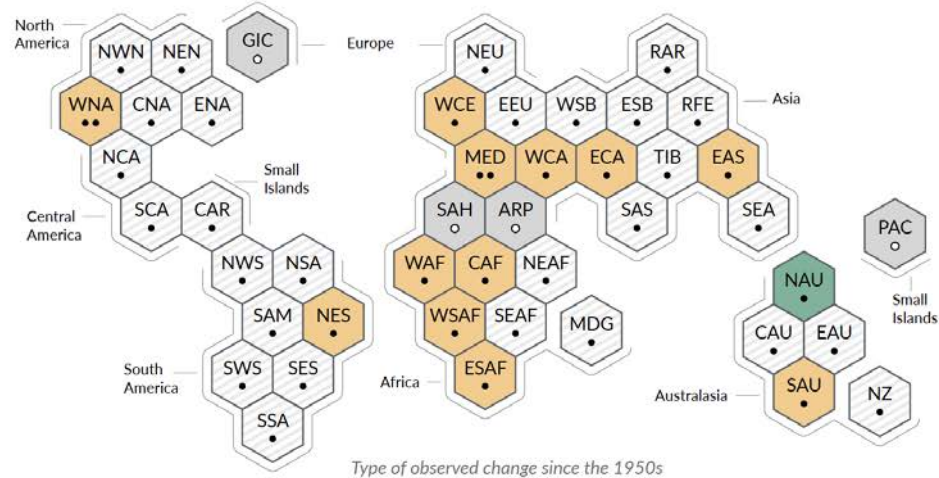
Confidence in human contribution  
to the observed change

●●● High

●● Medium

● Low due to limited agreement

○ Low due to limited evidence



Dominant signal shows drying  
Strong attributable signals in some regions (MED, WNA)

“Human-induced climate change has contributed to increases in agricultural and ecological droughts in some regions **due to increased land evapotranspiration** (*medium confidence*)”

c) Synthesis of assessment of observed change in **agricultural and ecological drought** and confidence in human contribution to the observed changes in the world's regions

Type of observed change in agricultural and ecological drought

● Increase (12)

● Decrease (1)

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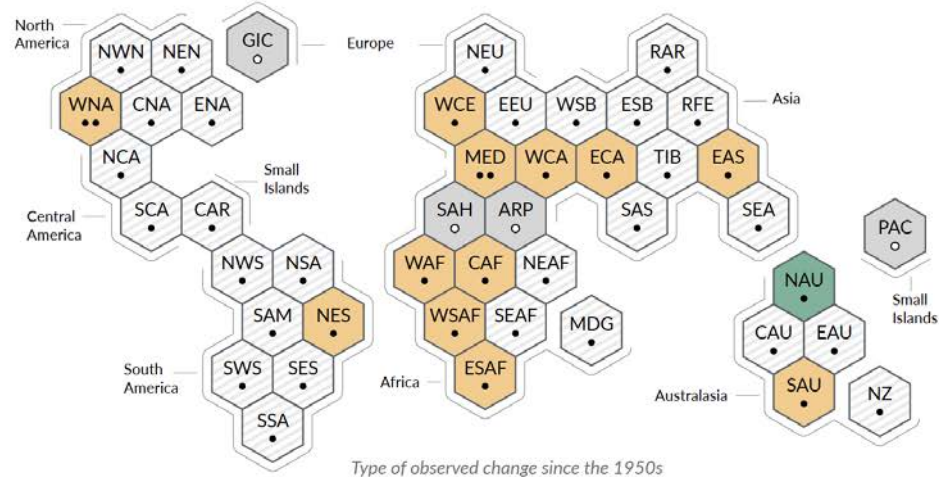
Confidence in human contribution to the observed change

●● High

●● Medium

● Low due to limited agreement

○ Low due to limited evidence



Dominant signal shows drying  
Strong attributable signals in some regions (MED, WNA)

Region and Drought Types		Observed Trends	Detection and Attribution: Event Attribution	Projections		
				+1.5°C	+2°C	+4°C
Greenland/Iceland (GIC) continued	AGR ECOL	<i>Low confidence: Limited evidence, given limited number of studies and limited data</i> (Walsh et al., 2020)	<i>Low confidence: Limited evidence because of lack of studies</i>	<i>Low confidence: Limited evidence because of lack of studies</i> (Walsh et al., 2020) and <i>inconsistent changes in soil moisture in CMIP6</i> (11.5M)	<i>Low confidence: Limited evidence because of lack of studies</i> (Walsh et al., 2020) and <i>inconsistent changes in soil moisture in CMIP6</i> (11.5M)	<i>Low confidence: Limited evidence because of lack of studies</i> (Walsh et al., 2020) and <i>inconsistent changes in soil moisture in CMIP6</i> (11.5M)
	HYDR	<i>Low confidence: Limited evidence given limited number of studies and limited data</i> (Walsh et al., 2020)	<i>Low confidence: Limited evidence because of lack of studies</i>	<i>Low confidence: Limited evidence because of lack of studies</i>	<i>Low confidence: Limited evidence because of lack of studies</i>	<i>Low confidence: Limited evidence because of lack of studies</i>
Mediterranean (MED) <sup>10</sup>	MET	<i>Low confidence: Mixed signals. Observed land precipitation trends show pronounced variability within the region, with magnitude and sign of trends in the path century depending on time period</i> (Donat et al., 2014a; Stageg et al., 2018a; Zitis, 2018). There is <i>low confidence</i> in an increase of drought frequency and severity based on SPI (Spinoni et al., 2015; Gudmundsson and Seneviratne, 2016; MedECC, 2020; Peña-Angulo et al., 2020a; Driouech et al., 2021; Vicente-Serrano et al., 2021)	<i>Low confidence: Mixed signals. There are mixed signals within the region and low confidence in human influence on meteorological drought over MED</i> (Kelley et al., 2015; Gudmundsson and Seneviratne, 2016; Knutson and Zeng, 2018; Wilcox et al., 2018)	<i>Medium confidence: Increase. With medium confidence</i> CMIP5 and CMIP6 show a decline in winter and summer total precipitation and increase in number of CDD (percentage precipitation change per degree of local warming is with <i>high confidence</i> larger in June–July–August (JJA) than December–January–February (DJF) (Interactive Atlas, Cardell et al., 2020; Li et al., 2021, 11.5M). Also weak increase in meteorological drought based on SPI (Touma et al., 2015; L. Xu et al., 2019)	<i>Medium confidence: Increase. With medium confidence</i> CMIP5 and CMIP6 show a decline in winter and summer total precipitation and increase in number of CDD (percentage precipitation change per degree of local warming is with <i>high confidence</i> larger in JJA than DJF) (Interactive Atlas, Cardell et al., 2020; Li et al., 2021, 11.5M). Also weak increase in meteorological drought based on SPI (Touma et al., 2015; L. Xu et al., 2019)	<i>High confidence: Increase. With high confidence</i> CMIP5 and CMIP6 (and EURO-CORDEX) show a decline in winter and summer total precipitation and increase in number of CDD. Drought intensity and frequency increase with <i>high confidence</i> , particularly in the southern Mediterranean (11.5M; Interactive Atlas; Samuels et al., 2018; Cardell et al., 2020; Cook et al., 2020; Driouech et al., 2020; Spinoni et al., 2020; Coppola et al., 2021a; Li et al., 2021)
	AGR ECOL	<i>Medium confidence: Increase.</i>  Increases in probability and intensity of agricultural and ecological droughts based on soil moisture and water-balance deficits, but weaker signals in some studies (Greve et al., 2014; Hanel et al., 2018; García-Herrera et al., 2019; Moravec et al., 2019; Padrón et al., 2020; Markonis et al., 2021).	<i>Medium confidence: of attribution of increasing trend in ecological and agricultural drought, based on soil moisture and water-balance metrics</i> (Mariotti et al., 2015; García-Herrera et al., 2019; Marvel et al., 2019; Padrón et al., 2020) García-Herrera et al. (2019); Attribution of the 2016–2017 drought in southwestern Europe to climate change based on NCEP trends in soil moisture for weather analogues to 2016–2017 event	<i>Medium confidence: Drought increase for pre-industrial and recent past baselines</i>  <i>Recent past baseline:</i> Decreasing soil water availability during drought events compared to 1971–2000, even when accounting for adaptation to mean conditions (Samaniego et al., 2018)  Increasing drought duration and frequency compared to 1971–2000 (L. Xu et al., 2019)	<i>High confidence: Drought increase for pre-industrial and recent past baselines</i>  <i>Recent past baseline:</i> Decreasing soil water availability during drought events compared to 1971–2000, even when accounting for adaptation to mean conditions; about twice larger signal compared to response at +1.5°C (Samaniego et al., 2018)	<i>Very likely: Drought increase for pre-industrial and recent past baselines</i>  <i>Recent past baseline:</i> Based on projections at +3°C. Large decreasing soil water availability during drought events compared to 1971–2000, even when accounting for adaptation to mean conditions; more than three times larger signal compared to response at +1.5°C (Samaniego et al., 2018)

# 11

## Weather and Climate Extreme Events in a Changing Climate

**Coordinating Lead Authors:**  
 Sonia I. Seneviratne (Switzerland), Xuebin Zhang (Canada)

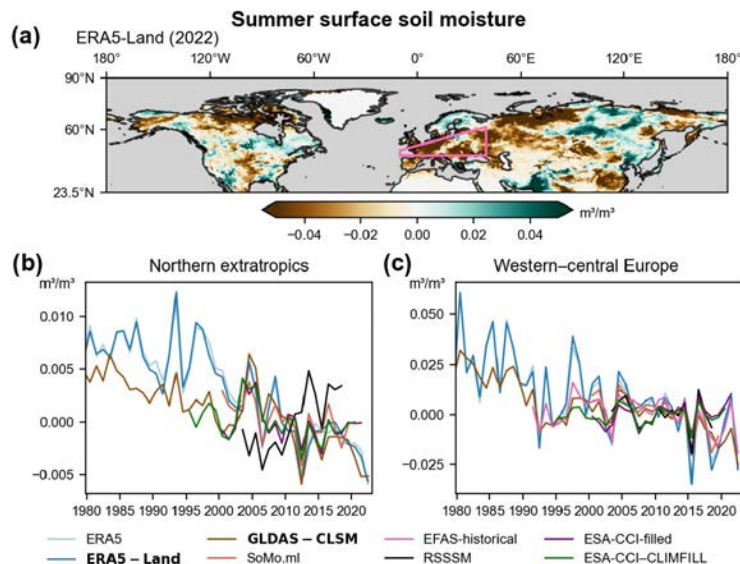
**Lead Authors:**  
 Muhammad Adnan (Pakistan), Wafae Badi (Morocco), Claudine Dereczynski (Brazil), Alejandro Di Luca (Australia/Canada/Argentina), Subimal Ghosh (India), Iskhaq Iskandar (Indonesia), James Kossin (United States of America), Sophie Lewis (Australia), Friederike Otto (United Kingdom/Germany), Izidine Pinto (South Africa/Mozambique), Masaki Satoh (Japan), Sergio M. Vicente-Serrano (Spain), Michael Wehner (United States of America), Botao Zhou (China)

“Large tables” in Chapter 11, pages 1613-1705

(Seneviratne, Zhang, et al. 2021)

## Detecting the human fingerprint in the summer 2022 western–central European soil drought

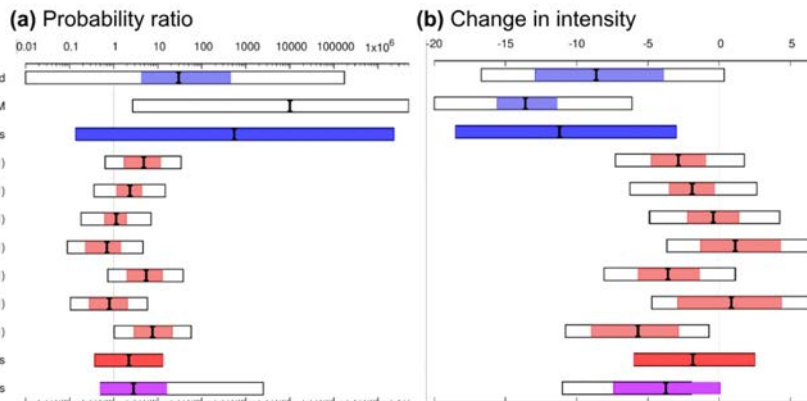
Dominik L. Schumacher<sup>1</sup>, Mariam Zachariah<sup>2</sup>, Friederike Otto<sup>2</sup>, Clair Barnes<sup>2</sup>, Sjoukje Philip<sup>3</sup>, Sarah Kew<sup>3</sup>, Maja Vahlberg<sup>4</sup>, Roop Singh<sup>4</sup>, Dorothy Heinrich<sup>4</sup>, Julie Arrighi<sup>4,5,6</sup>, Maarten van Aalst<sup>4,6,7</sup>, Mathias Hauser<sup>1</sup>, Martin Hirschi<sup>1</sup>, Verena Bessenbacher<sup>1,18</sup>, Lukas Gudmundsson<sup>1</sup>, Hiroko K. Beaudoin<sup>8,9</sup>, Matthew Rodell<sup>8</sup>, Sihan Li<sup>10</sup>, Wenchang Yang<sup>11</sup>, Gabriel A. Vecchi<sup>11,12</sup>, Luke J. Harrington<sup>13</sup>, Flavio Lehner<sup>14,15,17</sup>, Gianpaolo Balsamo<sup>16</sup>, and Sonia I. Seneviratne<sup>1</sup>






## Detecting the human fingerprint in the summer 2022 western–central European soil drought

Dominik L. Schumacher<sup>1</sup>, Mariam Zachariah<sup>2</sup>, Friederike Otto<sup>2</sup>, Clair Barnes<sup>2</sup>, Sjoukje Philip<sup>3</sup>, Sarah Kew<sup>3</sup>, Maja Vahlberg<sup>4</sup>, Roop Singh<sup>4</sup>, Dorothy Heinrich<sup>4</sup>, Julie Arrighi<sup>4,5,6</sup>, Maarten van Aalst<sup>4,6,7</sup>, Mathias Hauser<sup>1</sup>, Martin Hirschi<sup>1</sup>, Verena Bessenbacher<sup>1,18</sup>, Lukas Gudmundsson<sup>1</sup>, Hiroko K. Beaudoin<sup>8,9</sup>, Matthew Rodell<sup>8</sup>, Sihan Li<sup>10</sup>, Wenchang Yang<sup>11</sup>, Gabriel A. Vecchi<sup>11,12</sup>, Luke J. Harrington<sup>13</sup>, Flavio Lehner<sup>14,15,17</sup>, Gianpaolo Balsamo<sup>16</sup>, and Sonia I. Seneviratne<sup>1</sup>




**Figure 6.** Synthesis for WCE root zone soil moisture. Synthesized (a) probability ratios and (b) intensity changes (%) when comparing the return period and magnitudes of the 2022 summer root zone soil moisture for the WCE region in the current climate and a 1.2 °C cooler climate. Note that while the employed observation-based products are restricted to 1950–2022, for models we make use of the additional available data for the statistical analysis (1850–2022).

NB: ESMs appear to underestimate the observed drying signal!



**Observed humidity trends in dry regions contradict climate models**  
Isla Simpson<sup>1</sup>, Karen McKinnon<sup>2</sup>, Daniel Kennedy<sup>1,3</sup>, David Lawrence<sup>1</sup>, Flavio Lehner<sup>4</sup>, Richard Seager<sup>4</sup>  
<sup>1</sup>National Center for Atmospheric Research, <sup>2</sup>University of California Los Angeles, <sup>3</sup>University of California Santa Barbara, <sup>4</sup>Cornell University, <sup>5</sup>Lamont-Doherty Earth Observatory



### BACKGROUND

Why should we care about near surface atmospheric humidity?  
(1) Humidity is an important quantity in relation to wildfire!  
(2) Humidity can provide an indicator of how processes of relevance to the hydroclimate such as evapotranspiration or moisture transports have been evolving.

What do we expect humidity to do?  
We expect atmospheric water vapor to rise under warming because a warmer atmosphere can hold more moisture. Whether it will rise at the rate expected from Clausius Clapeyron scaling (~7%/K), maintaining a fixed relative humidity, will depend on whether there is enough water available to satisfy the increased atmospheric demand. Over land, climate models do show slight reductions in relative humidity out to 2100, but they still suggest that water vapor should increase in general<sup>1</sup>. Prior studies have suggested that water vapor has not risen as much in models as observations<sup>3,4,5</sup>.

Here we compare historical near surface (2m) humidity trends in Earth System Models, with those in Observations and demonstrate a major discrepancy that is closely linked to climatological aridity.

### DATASETS

Observation-based humidity and vapor pressure

- ERA5<sup>6</sup>, ISD stations<sup>7</sup>, HadISDH homogenized station data<sup>8</sup>

Observation-based precipitation

- GPCC<sup>9</sup>, GPCP<sup>10</sup>, CRUTS<sup>11</sup>

Observation-based near surface air temperature

- ERA5<sup>6</sup> and BEST<sup>12</sup>

Aridity Index

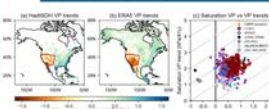
- PIPET from the TerraClim<sup>13</sup> dataset

Model simulations

- CMIP6 historical 1980 to 2014 and SSP5-8.5 to 2020
- CMIP6 AMIP simulations to 1980 to 2014
- LENS2: CESM2 large ensemble<sup>14</sup> (100-members)
- GOGAZ: CESM2 GOGA/AMIP simulations, 1980 - 2020 (10-mems)

We consider trends in annual means from 1980 to 2020 unless stated otherwise.

### A CASE STUDY: THE US SOUTHWEST



Since 1980 vapor pressure (VP) has declined over the US Southwest. HadISDH and ERA5 agree (Fig 1a,b).

Saturation VP has risen, and the observations lie within the model distribution (Fig 1c).

The decline in VP lies totally outside of the model distribution, even when prescribing observed SSTs (Fig 1c).

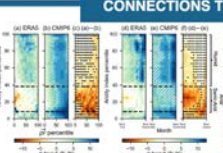
While models suggest VP should have increased, the real world has seen a rather steady decline (Fig 2a).

As a result, relative humidity has declined more than in models (Fig 2b).

Vertical profiles of specific humidity (q) trends suggest that the discrepancy is largest near the surface but exists throughout the lower troposphere (Fig 2c).

The discrepancy (in percent of the seasonally varying climatology) is fairly uniform throughout the year (Fig 2d).

### CONNECTIONS TO ARIDITY



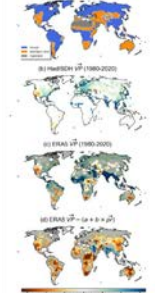
Binning land regions according to climatological aridity and ordering based on precipitation trends, we can see that the discrepancy occurs primarily in arid/semi-arid regions and occurs regardless of precipitation trends (Fig 5a-c).

Ordering the months of the year according to climatological aridity, we can see the discrepancy also happens in humid regions, but only during the most and months of the year (Fig 5d-f).

There are close links between where the discrepancy occurs and climatological aridity, both spatially and seasonally.

### GLOBAL TRENDS

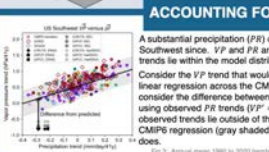
Observed VP trends lie outside of the CMIP6 distribution in a number of regions (Fig 4c). The discrepancy is even more widespread when accounting for PR trends (Fig 4d). ERA5 shows relatively negative trends compared to CMIP6, mostly in arid/semi-arid regions.



### ACCOUNTING FOR PRECIPITATION

A substantial precipitation (PR) decline has occurred over the US Southwest since. VP and PR are correlated. While the observed PR trends lie within the model distribution the VP trend does not (Fig 3).

Consider the VP trend that would be predicted based on PR using the linear regression across the CMIP6 models  $VP^* = a + b \cdot PR$ . We can consider the difference between the observed VP trend  $VP^*$  predicted using observed PR trends ( $VP^* = VP - VP^*$ ) and assess whether observed trends lie outside of the  $\pm 2\sigma$  range of the residuals of the CMIP6 regression (gray shaded range in Fig 3). In the Southwest it does.

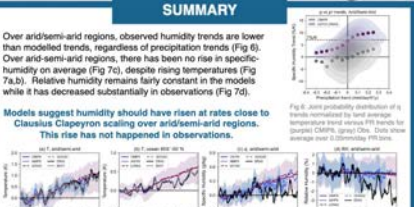


### SUMMARY

Over arid/semi-arid regions, observed humidity trends are lower than modelled trends, regardless of precipitation trends (Fig 6).

Over arid/semi-arid regions, there has been no rise in specific-humidity on average (Fig 7c), despite rising temperatures (Fig 7a,b). Relative humidity remains fairly constant in the models while it has decreased substantially in observations (Fig 7d).

Models suggest humidity should have risen at rates close to Clausius Clapeyron scaling over arid/semi-arid regions. This rise has not happened in observations.



### REFERENCES AND ACKNOWLEDGEMENTS

**ACKNOWLEDGEMENTS**

1 O'Gorman and Williams (2016), DOI: 10.1029/2015JD023113  
2 O'Gorman and Muller (2016), DOI: 10.1086/1748-9326/2015202527  
3 Dorris et al. (2017), DOI: 10.5194/esd-8-719-2017  
4 Douville and Paoliello (2017), DOI: 10.1002/2017JD027063  
5 Jones and Richards (2017), DOI: 10.3390/atmos81210157  
6 Douville and Willett (2020), DOI: 10.1029/2019JD031853  
7 Harshbarger et al. (2020), DOI: 10.1002/qj.3803  
8 Smith et al. (2011), DOI: 10.1175/2010AM015011

**REFERENCES**

1 Willett et al. (2016), DOI: 10.5194/gwp-10-1983-2014  
2 Schwanen et al. (2018), DOI: 10.5058/GEMOBSORT  
3 Aulic et al. (2017), DOI: 10.3390/atmos8040138  
4 Harries et al. (2014), DOI: 10.1002/qj.3111  
5 Rutledge and Harshbarger (2020), DOI: 10.5194/esd-12-3469-2020  
6 Douville and Willett (2020), DOI: 10.1029/2019JD031853  
7 Harshbarger et al. (2020), DOI: 10.1002/qj.3803  
8 Smith et al. (2011), DOI: 10.1175/2010AM015011

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Is the ESM-obs discrepancy in atmospheric drying in West-Central Europe part of a global feature?

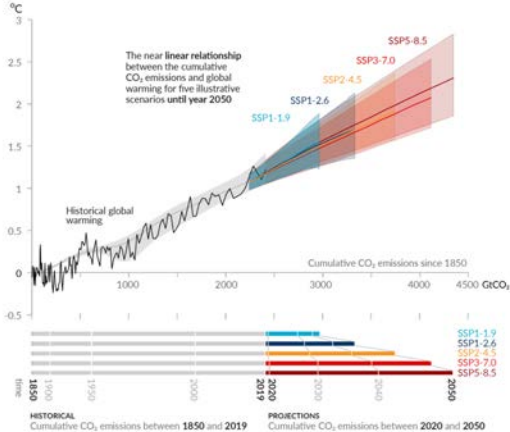
(See poster of Isla Simpson “Observed humidity trends in dry regions contradict climate models)

(see also: Douville and Piazzota 2017, GRL)

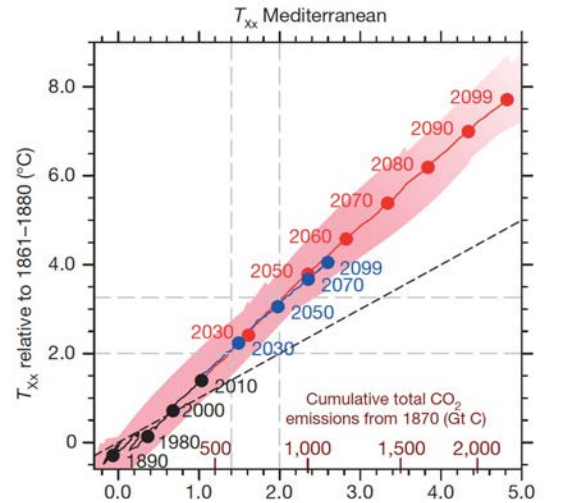
- Yes, possibly
- There are uncertainties in climate models, and these increase when we move further away from known climate conditions
- **Models behave very linearly** and this is so far consistent with observations, but **what is the potential for tipping points?**
- Literature (*IPCC AR6, Armstrong MacKay et al. 2022, Science*) shows increasing risks of hitting tipping points with increasing global warming, with higher risks above 1.5°C-2°C

## Every tonne of CO<sub>2</sub> emissions adds to global warming

Global surface temperature increase since 1850-1900 (°C) as a function of cumulative CO<sub>2</sub> emissions (GtCO<sub>2</sub>)



(IPCC AR6 WG1)



Global mean temperature anomaly relative to 1861-1880 (°C)

(Seneviratne et al. 2016, Nature)

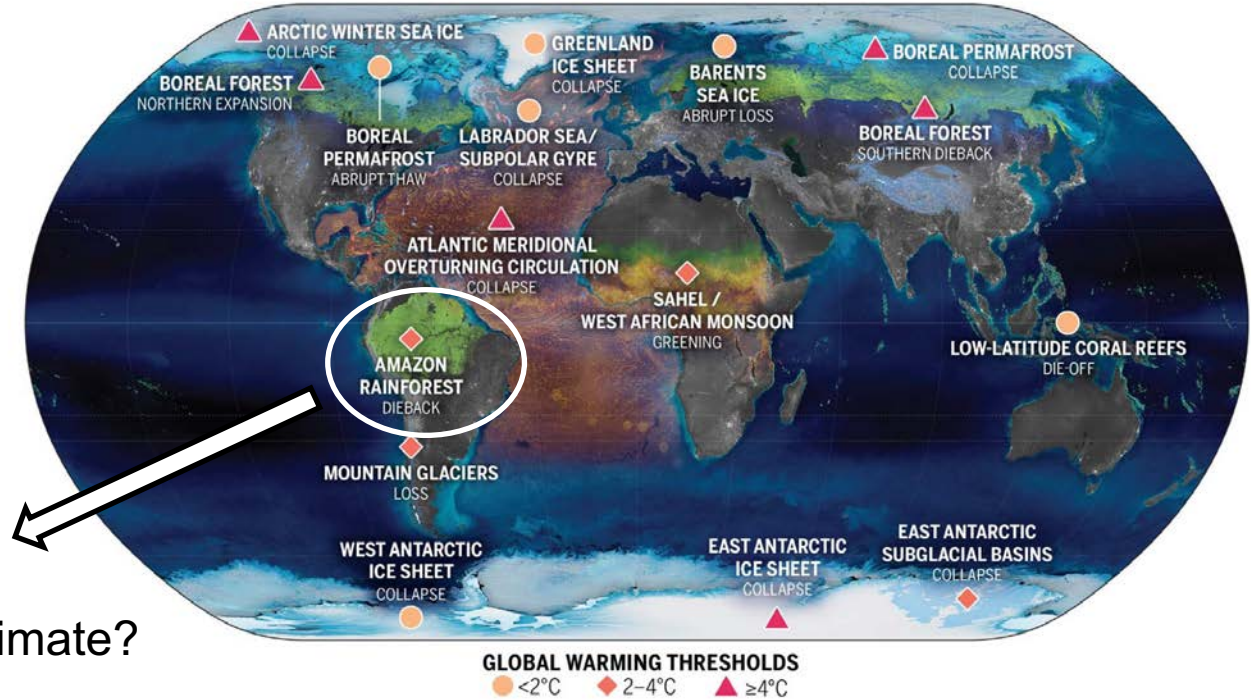
# Could climate change turn worse than we expected?

## RESEARCH ARTICLE SUMMARY

### CLIMATE CHANGE

Exceeding 1.5°C global warming could trigger multiple climate tipping points

David I. Armstrong McKay\*, Arie Staal, Jesse F. Abrams, Ricarda Winkelmann, Boris Sakschewski, Sina Loriani, Ingo Fetzer, Sarah E. Cornell, Johan Rockström, Timothy M. Lenton\*



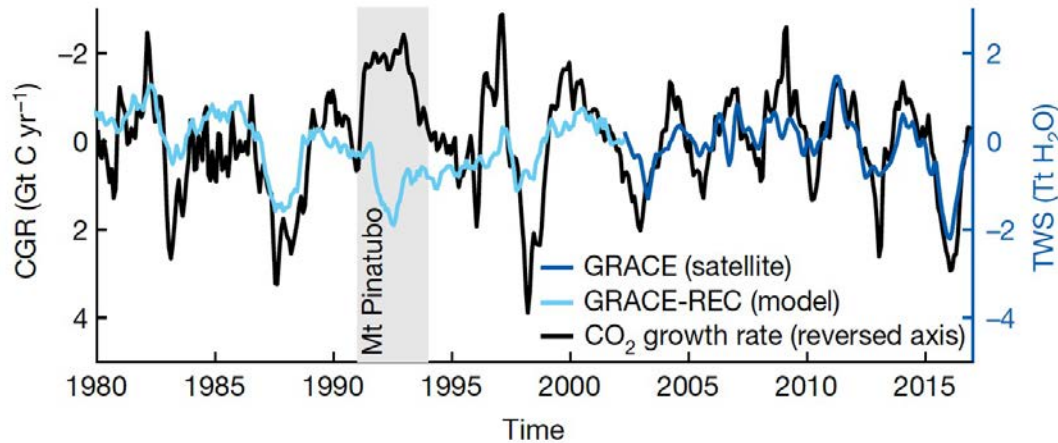
Maybe too optimistic estimate?

(Armstrong McKay et al. 2022, Science)

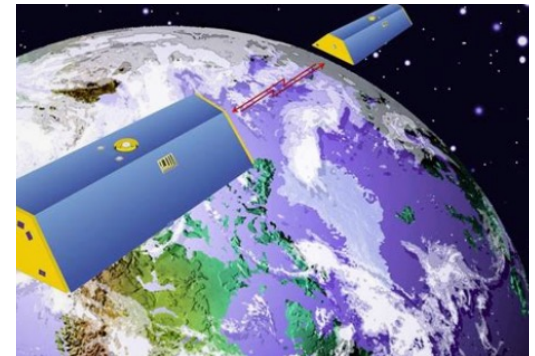
## Effects of soil moisture/droughts on **global** carbon cycle

Comparing anomalies in global observations of:

- CO<sub>2</sub> growth rate from atmospheric observations
- Terrestrial water storage from GRACE satellites



(Humphrey et al. 2018, Nature)



Observation-based data reveal a strengthening of correlation between yearly anomalies of land water availability and CO<sub>2</sub> growth rate: **Not captured in models**

Article

## Increasingly negative tropical water–interannual CO<sub>2</sub> growth rate coupling

<https://doi.org/10.1038/s41586-023-06056-x>

Received: 5 January 2022

Accepted: 5 April 2023

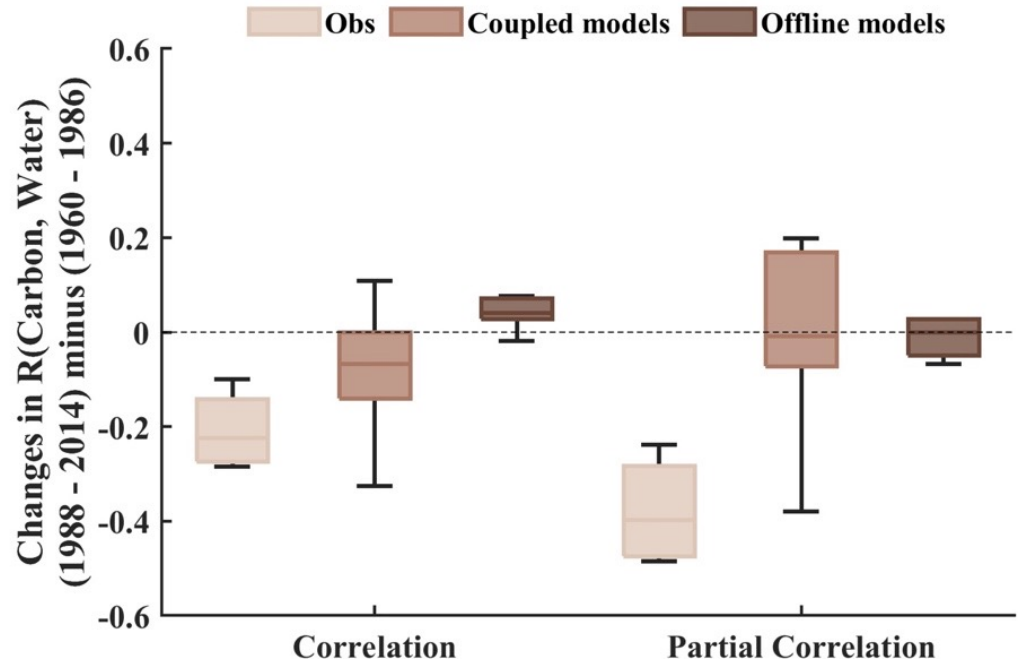
Published online: 31 May 2023

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Laihao Liu<sup>1</sup>, Philippe Ciais<sup>1</sup>, Mengxi Wu<sup>2</sup>, Ryan S. Padrón<sup>1</sup>, Pierre Friedlingstein<sup>1</sup>, Jonas Schwaab<sup>1</sup>, Lukas Gudmundsson<sup>1</sup> & Sonia I. Seneviratne<sup>1</sup>

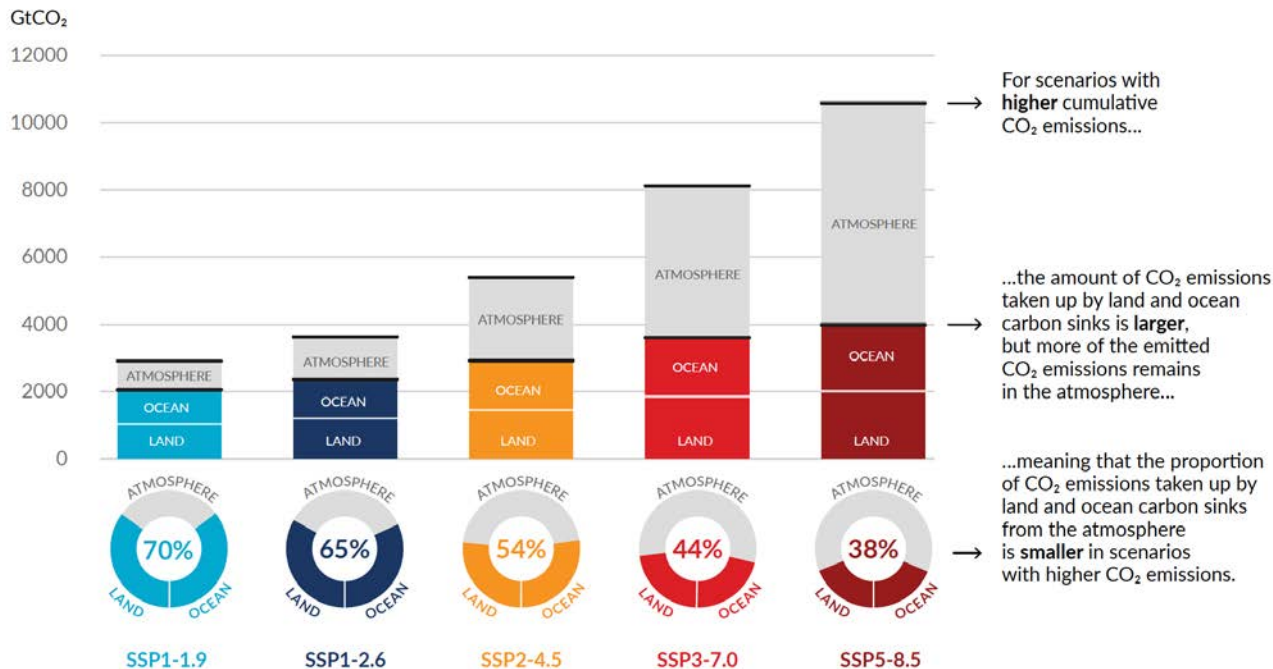
Terrestrial ecosystems have taken up about 32% of the total anthropogenic CO<sub>2</sub> emissions in the past six decades<sup>1</sup>. Large uncertainties in terrestrial carbon–climate feedbacks, however, make it difficult to predict how the land carbon sink will respond to future climate change<sup>2</sup>. Interannual variations in the atmospheric CO<sub>2</sub> growth rate (CGR) are dominated by land–atmosphere carbon fluxes in the tropics, providing an opportunity to explore land carbon–climate interactions<sup>3–5</sup>. It is thought that variations in CGR are largely controlled by temperature<sup>6–10</sup> but there is also evidence for a tight coupling between water availability and CGR<sup>11</sup>. Here, we use a record of global atmospheric CO<sub>2</sub>, terrestrial water storage and precipitation data to investigate changes in the interannual relationship between tropical land climate conditions and CGR under a changing climate. We find that the interannual relationship between tropical water availability and CGR became increasingly negative during 1989–2018 compared to 1960–1989. This could be related to spatiotemporal changes in tropical water availability anomalies driven by shifts in El Niño/Southern Oscillation teleconnections, including declining spatial compensatory water effects<sup>5</sup>. We also demonstrate that most state-of-the-art coupled Earth System and Land Surface models do not reproduce the intensifying water–carbon coupling. Our results indicate that tropical water availability is increasingly controlling the interannual variability of the terrestrial carbon cycle and modulating tropical terrestrial carbon–climate feedbacks.



(Liu et al. 2023, Nature; see also Humphrey et al. 2018, Nature)

# Could climate change turn worse than we expected?

Total cumulative CO<sub>2</sub> emissions **taken up by land and oceans** (colours) and **remaining in the atmosphere** (grey) under the five illustrative scenarios from 1850 to 2100



Could the land carbon sink become even less effective with increasing global warming?

## Land-based carbon dioxide removal vs extremes

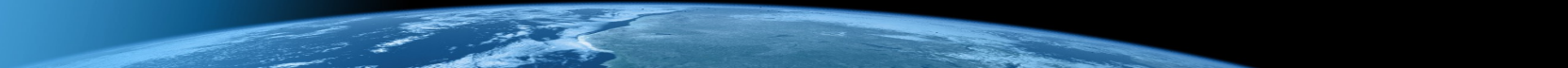


- Afforestation
- Bioenergy with carbon capture and storage

- How about extremes? (generally not included in integrated assessments models deriving emissions scenarios); could be too optimistic  
(see poster of Felix Jaeger; fire biases in ESMs: see Sanderson and Fisher, 2020)







## Confronting ESMs with observations:

- Observational uncertainties
- Separating sources of biases (forcing; thermodynamic vs dynamic biases)

## Drought-climate feedbacks

- Relevant processes
- Drought trends in ESMs vs observations
- Potential biases in global drought-carbon feedbacks

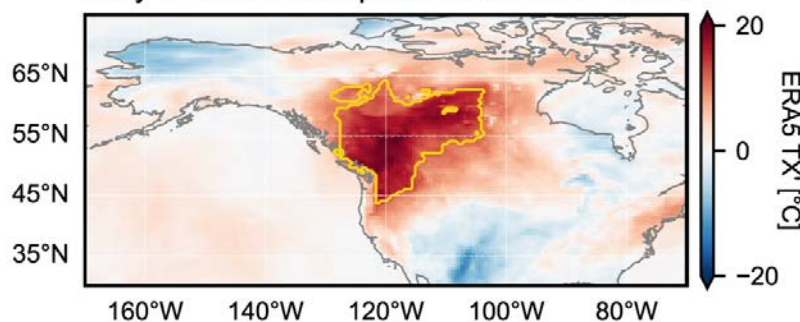
## Some open questions

- Drought relevance for record-shattering heatwaves
- 2023 Record temperatures

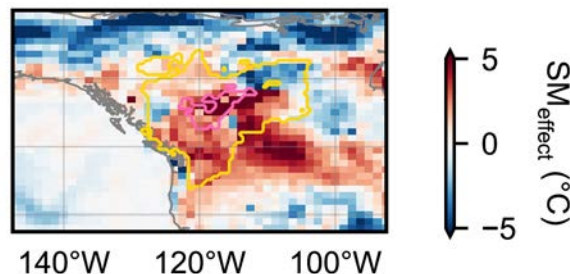
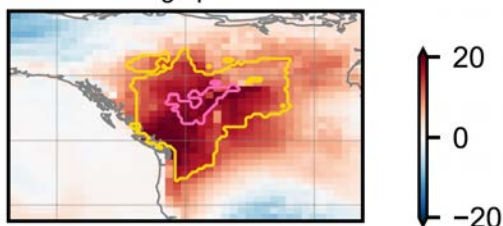
## Conclusions



Daily maximum temperature on 2021-06-30

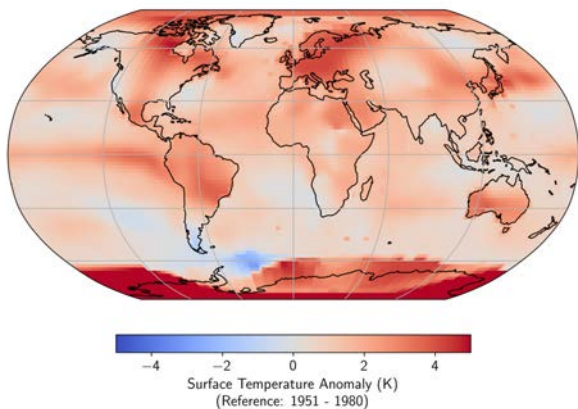


CESM<sub>nudge</sub>  $p < \sim 400$  hPa



What does it imply for climate projections of heat extremes, in particular record-shattering heatwaves, if drought trends are underestimated in ESMs?

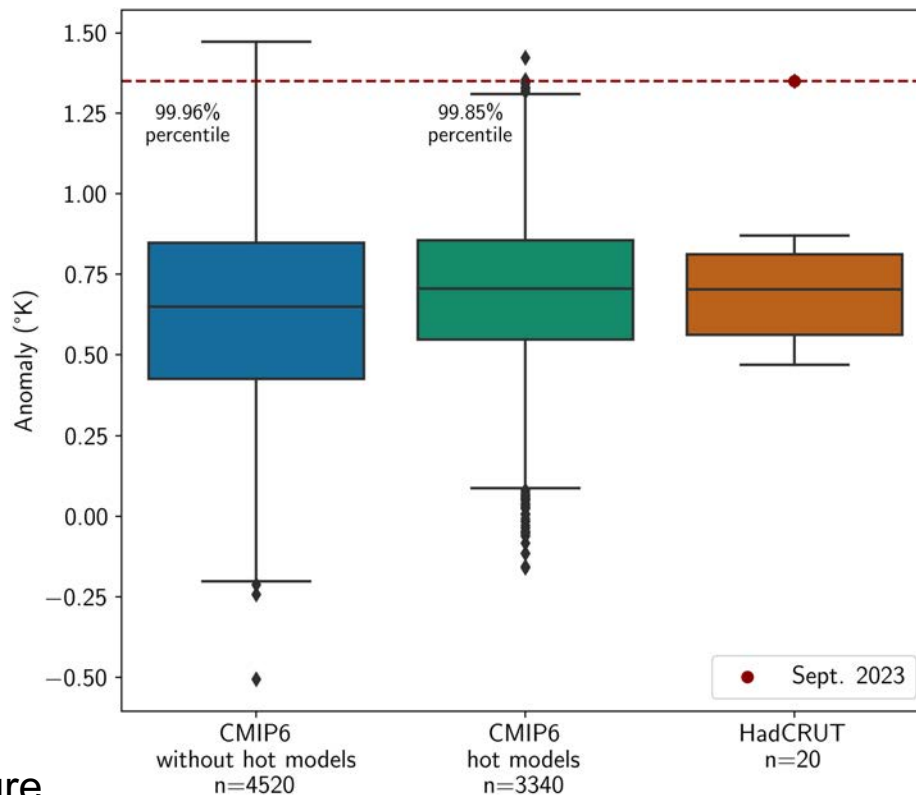
Soil moisture anomalies contributed up to 5°C to the heatwave!



Data source:  
GISTEMP v4

Clear anomaly in observations, very low probability in available ESMs, often 0% probability.

NB: “Hot models” do not capture the anomaly better & soil moisture-temperature feedbacks may have played a role



- **Confronting ESMs with observations requires consideration of several dimensions:**
  - Observational uncertainty
  - Internal climate variability in ESMs
  - Isolating sources of biases (e.g. thermodynamics vs dynamics, atmosphere vs land vs ocean, forcing):
    - Factorial experiments replacing some elements with observations or assessing potential spread can help identify the root causes for biases
- **Some biases in representation of droughts-climate feedbacks in ESMs:**
  - Implications for attribution and projections (also for heatwaves and global carbon cycle, including potential tipping points)
  - Need to better understand possible underlying causes (in particular land-atmosphere interactions)
  - Are the latest 2023-2024 observations consistent with ESMs?