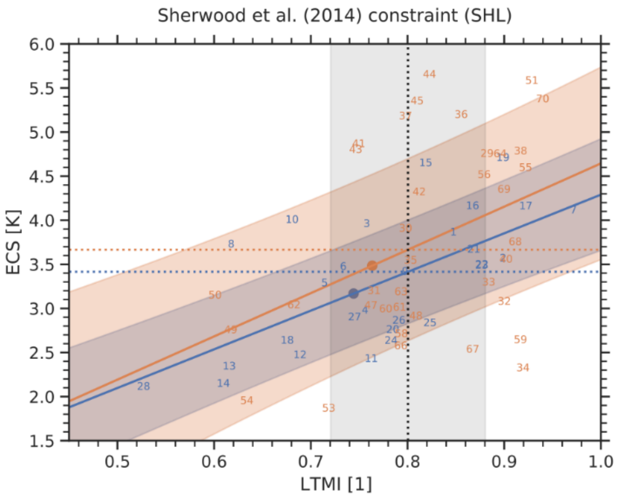
Constraining Uncertainties in Effective Climate Sensitivity and Future Gross Primary Production

Manuel Schlund[1] and Veronika Eyring[1,2]

[1]Deutsches Zentrum für Luft- und Raumfahrt (DLR), Institut für Physik der Atmosphäre, Oberpfaffenhofen, Germany

[2]University of Bremen, Institute of Environmental Physics (IUP), Bremen, Germany



Acknowledgements

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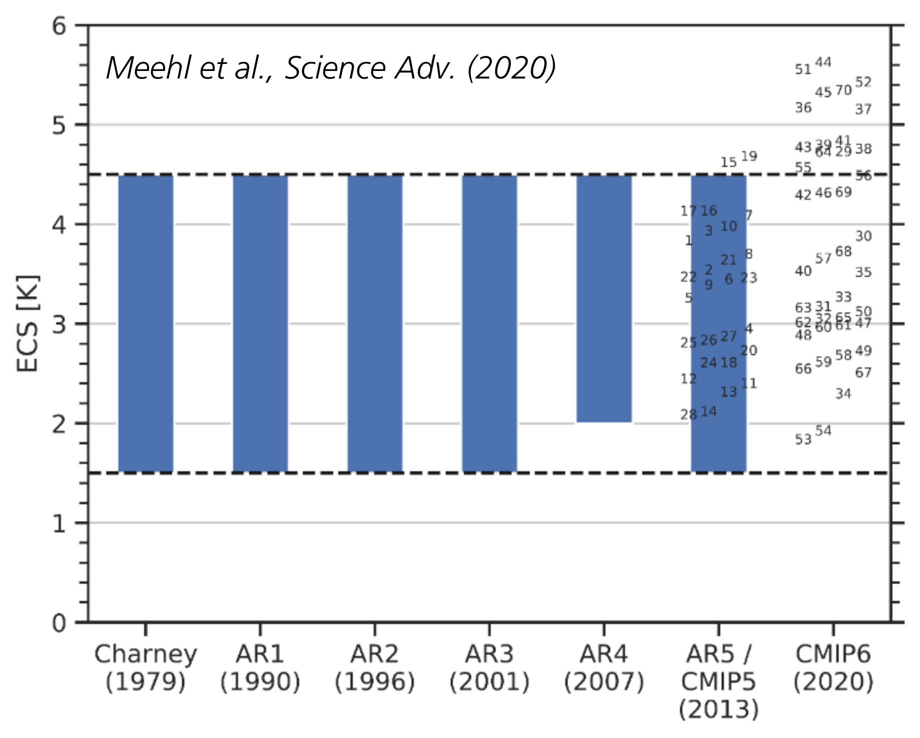
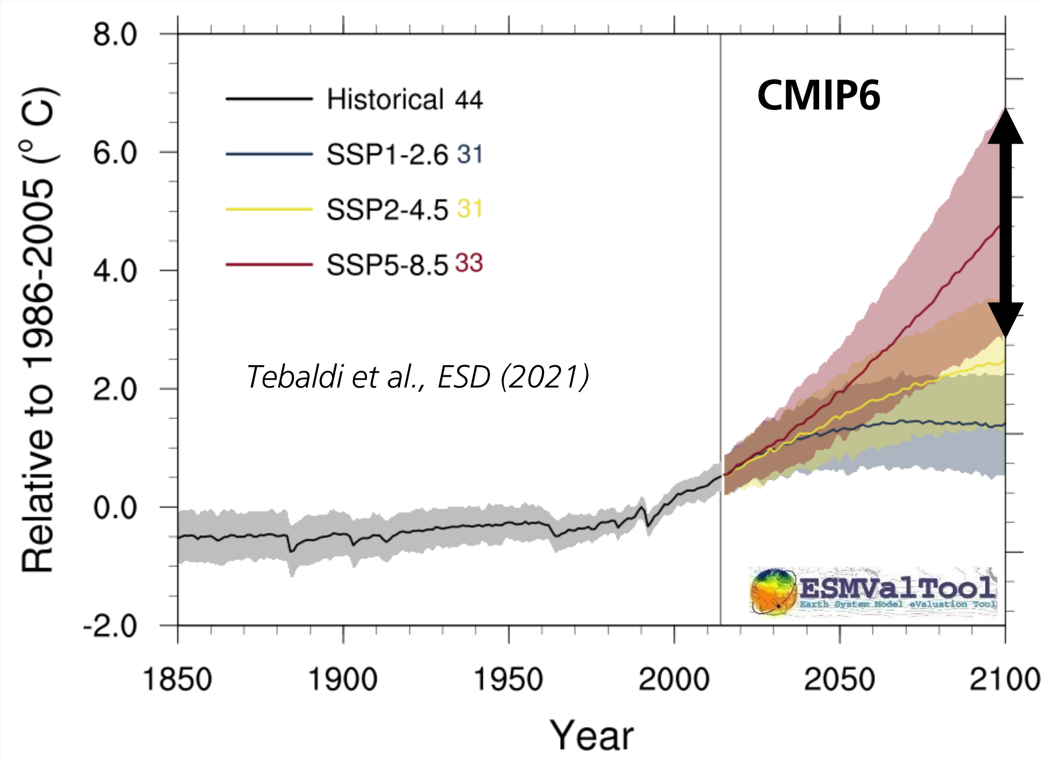
Large Uncertainties in Climate Projections Remain

Effective Climate Sensitivity

Global mean temperature change for doubling of atmospheric CO_2



Global warming projections



Overview

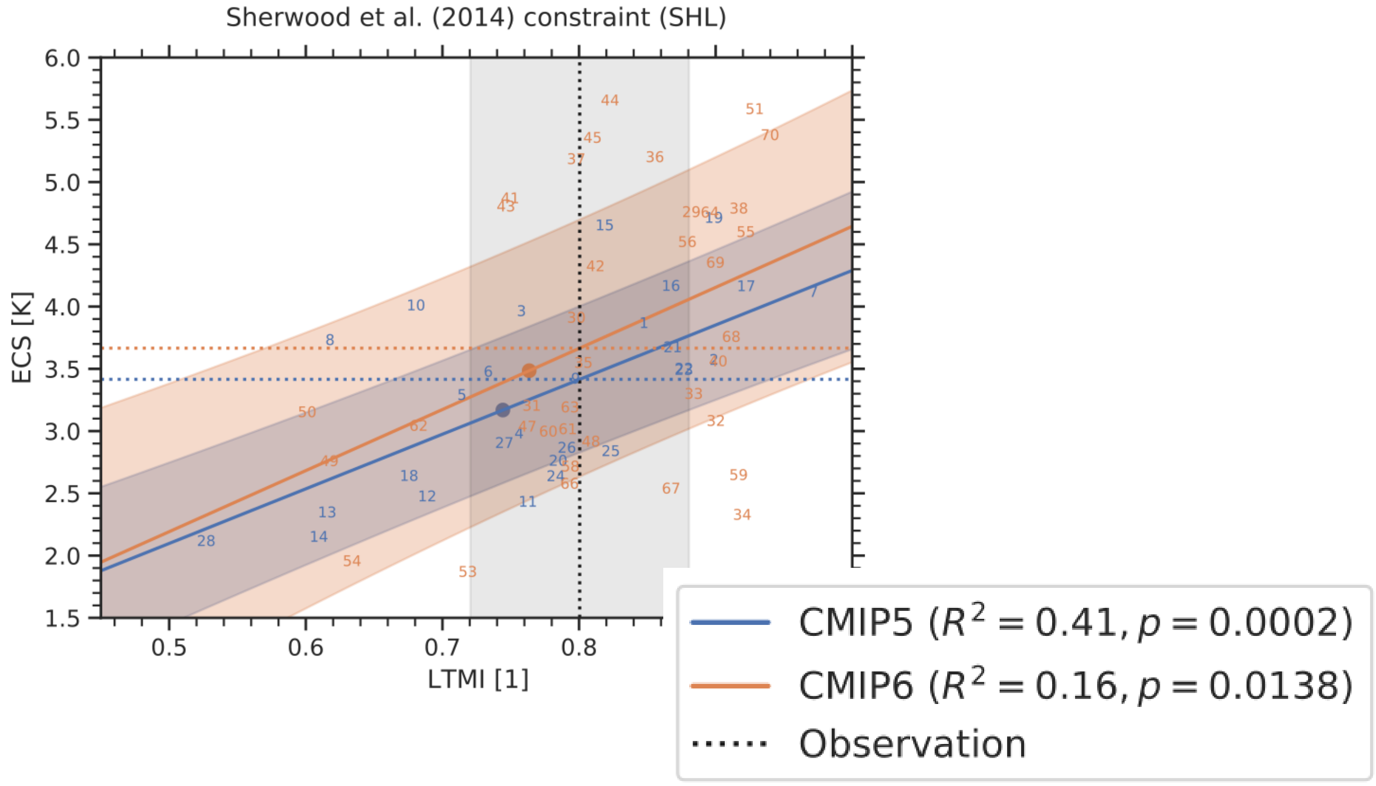
1. Emergent constraints on Effective Climate Sensitivity in CMIP5: do they hold for CMIP6? (*Schlund et al., ESD, 2020*)

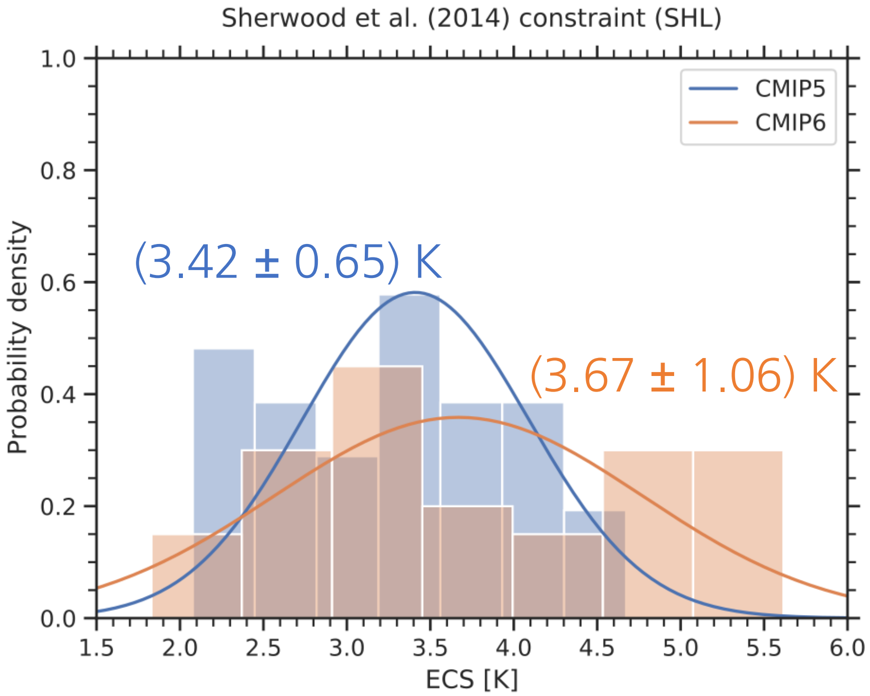
2. Constraining uncertainty in projected gross primary production with machine learning (*Schlund et al., JGR: Biogeosci., 2020*)

1. Emergent constraints on Effective Climate Sensitivity in CMIP5: do they hold for CMIP6?

Example – Sherwood et al. (2014)

X-axis: Lower tropospheric mixing index (LTMI)





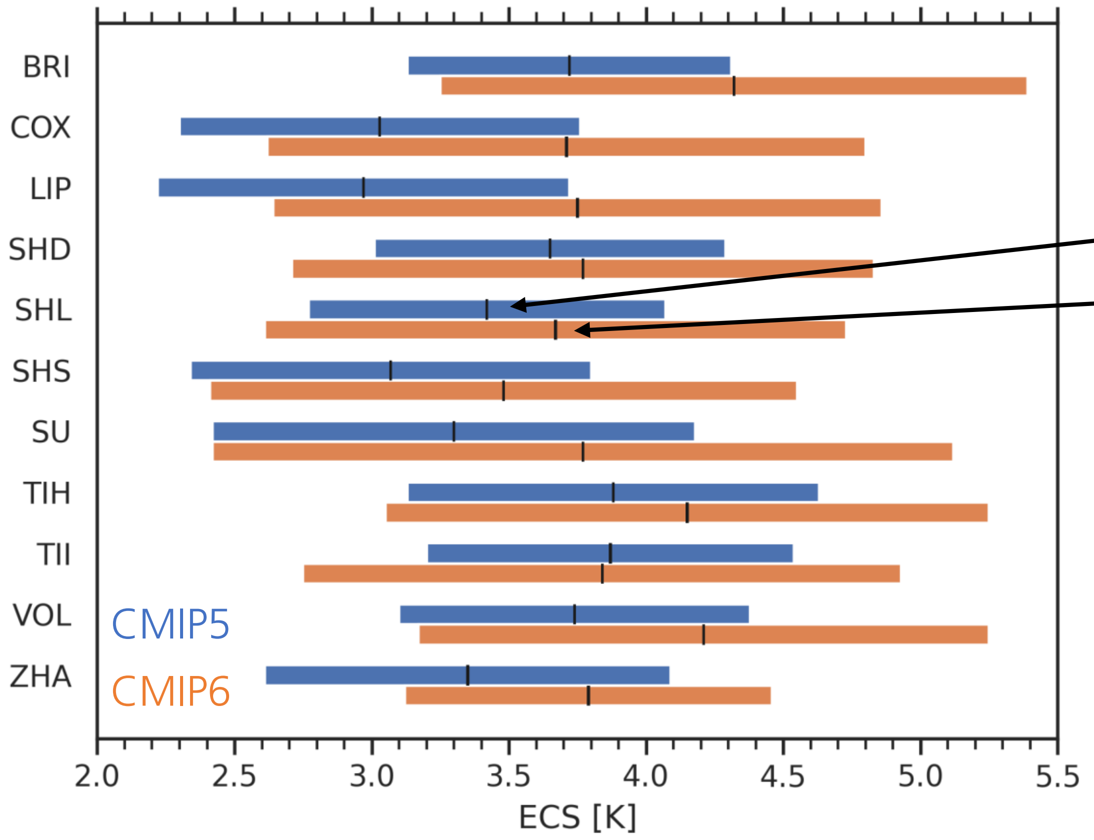
Schlund et al., ESD (2020)

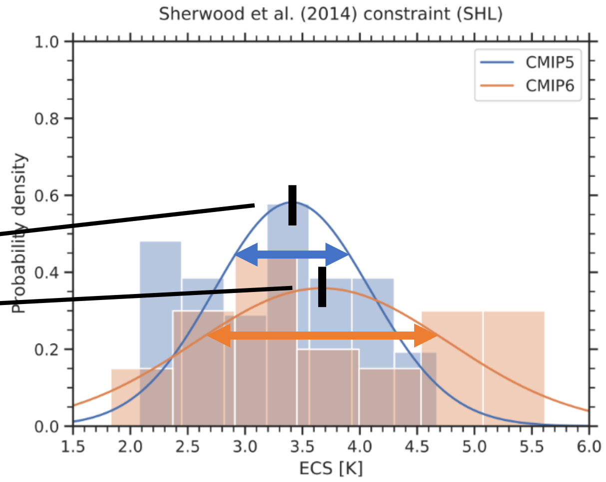
Evaluation of 11 Emergent Constraints on ECS

Name	Reference	Description
BRI	Brient & Schneider (2016)	Response of tropical low-level cloud albedo to changes in SST
COX	Cox et al. (2018)	Temperature variability metric
LIP	Lipat et al. (2017)	Extent of the Southern hemisphere Hadley cell
SHD	Sherwood et al. (2014)	Large-scale lower-tropospheric mixing (D index)
SHS	Sherwood et al. (2014)	Small-scale lower-tropospheric mixing (S index)
SHL	Sherwood et al. (2014)	Lower tropospheric mixing index (LTMI) = D + S
SU	Su et al. (2014)	Error in vertical profile of relative humidity
TII	Tian (2015)	Tropical mid-tropospheric humidity asymmetry index
TIH	Tian (2015)	Southern ITCZ index
VOL	Volodin (2008)	Difference in tropical and mid-latitude cloud fraction
ZHA	Zhai et al. (2015)	Response of marine boundary layer cloud fraction to SST changes

Schlund et al., ESD (2020)

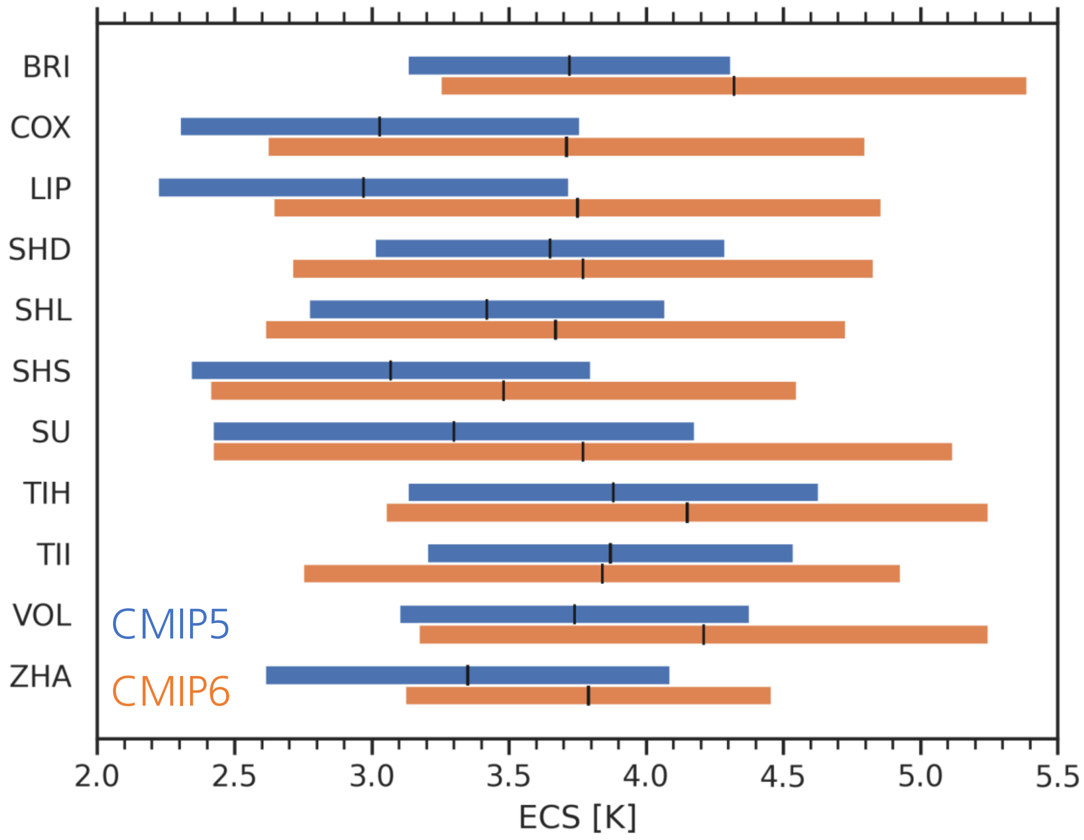
Summary: Evaluation of 11 emergent constraints on ECS





Schlund et al., ESD (2020)

Summary: Evaluation of 11 emergent constraints on ECS



- For all but one constraint (TII), the best estimate ECS is higher in CMIP6
- For all but one constraint (ZHA), the constrained ECS range is wider in CMIP6
- For all but one constraint (ZHA), the coefficient of determination (R^2) is higher in CMIP5

Schlund et al., ESD (2020)

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Conclusions from this study

- **Higher best estimates/ranges of constrained ECS** in CMIP6: Likely related to higher multi-model mean/spread of ECS in CMIP6
- Possible reason for **reduced skill of emergent constraints when applied to CMIP6**: Basic assumption for single-process emergent constraints is that a **single observable process dominates uncertainty** in ECS which might not hold

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Emergent constraints on equilibrium climate sensitivity in CMIP5: do they hold for CMIP6?

Manuel Schlund[1], **Axel Lauer**[1], **Pierre Gentine**[2,3], **Steven C. Sherwood**[4], **and Veronika Eyring**[1,5]

[1]Deutsches Zentrum für Luft- und Raumfahrt (DLR), Institut für Physik der Atmosphäre, Oberpfaffenhofen, Germany
[2]Department of Earth and Environmental Engineering, Columbia University, New York, NY 10027, USA
[3]Earth Institute and Data Science Institute, Columbia University, New York, NY 10027, USA
[4]Climate Change Research Centre and ARC Centre of Excellence for Climate System Science, University of New South Wales, Sydney 2052, Australia
[5]Institute of Environmental Physics (IUP), University of Bremen, Bremen, Germany

Correspondence: Manuel Schlund (manuel.schlund@dlr.de)

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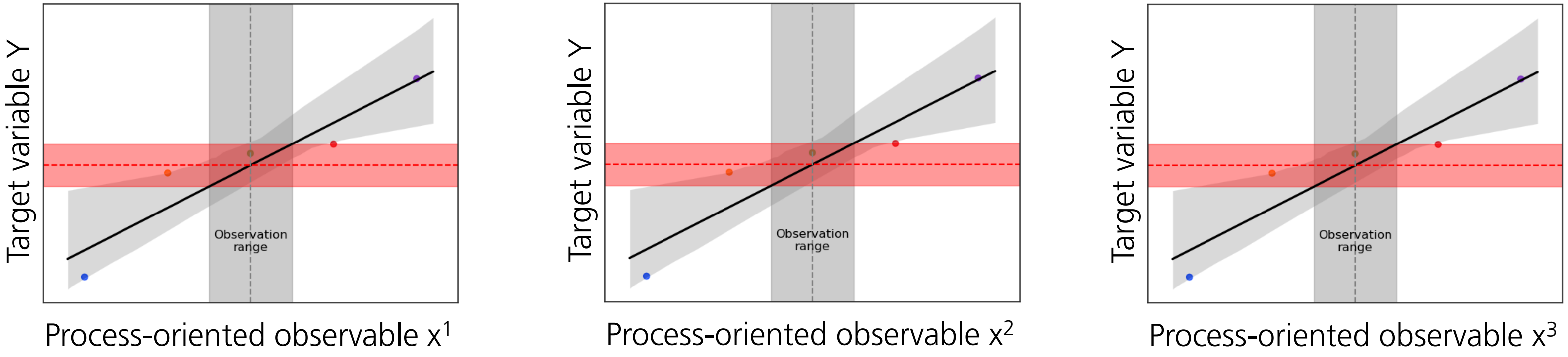
Abstract. An important metric for temperature projections is the equilibrium climate sensitivity (ECS), which is defined as the global mean surface air temperature change caused by a doubling of the atmospheric CO_2 concentration. The range for ECS assessed by the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment

Schlund, M., A. Lauer, P. Gentine, S. Sherwood and V. Eyring, ESD (2020)

2. Constraining uncertainty in projected gross primary production with machine learning

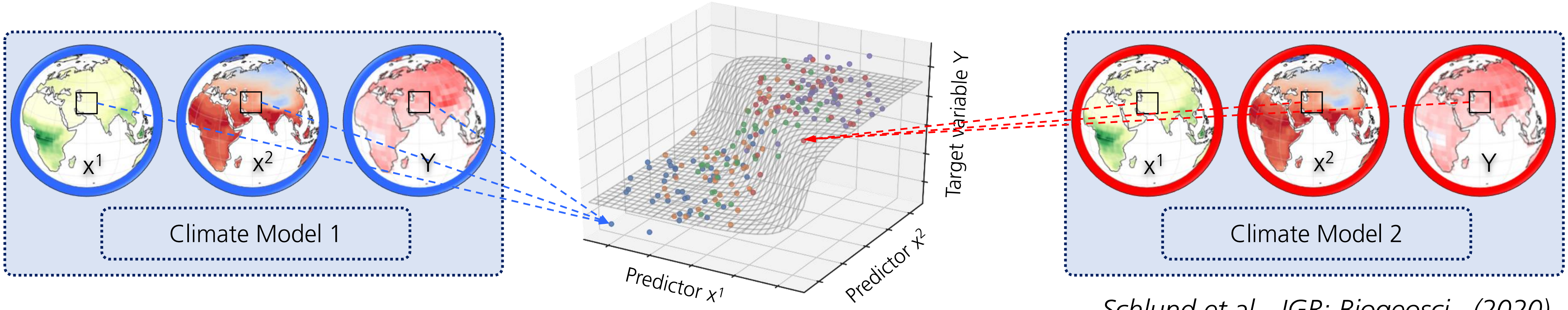
Machine Learning-based weighting - Concept

Use **multiple** process-oriented diagnostics to **constrain multi-model projection of Y** using observations



Multivariate linear regression

Use **supervised** Machine Learning to learn **non-linear** relationships from **gridded** data



Schlund et al., JGR: Biogeosci,. (2020)

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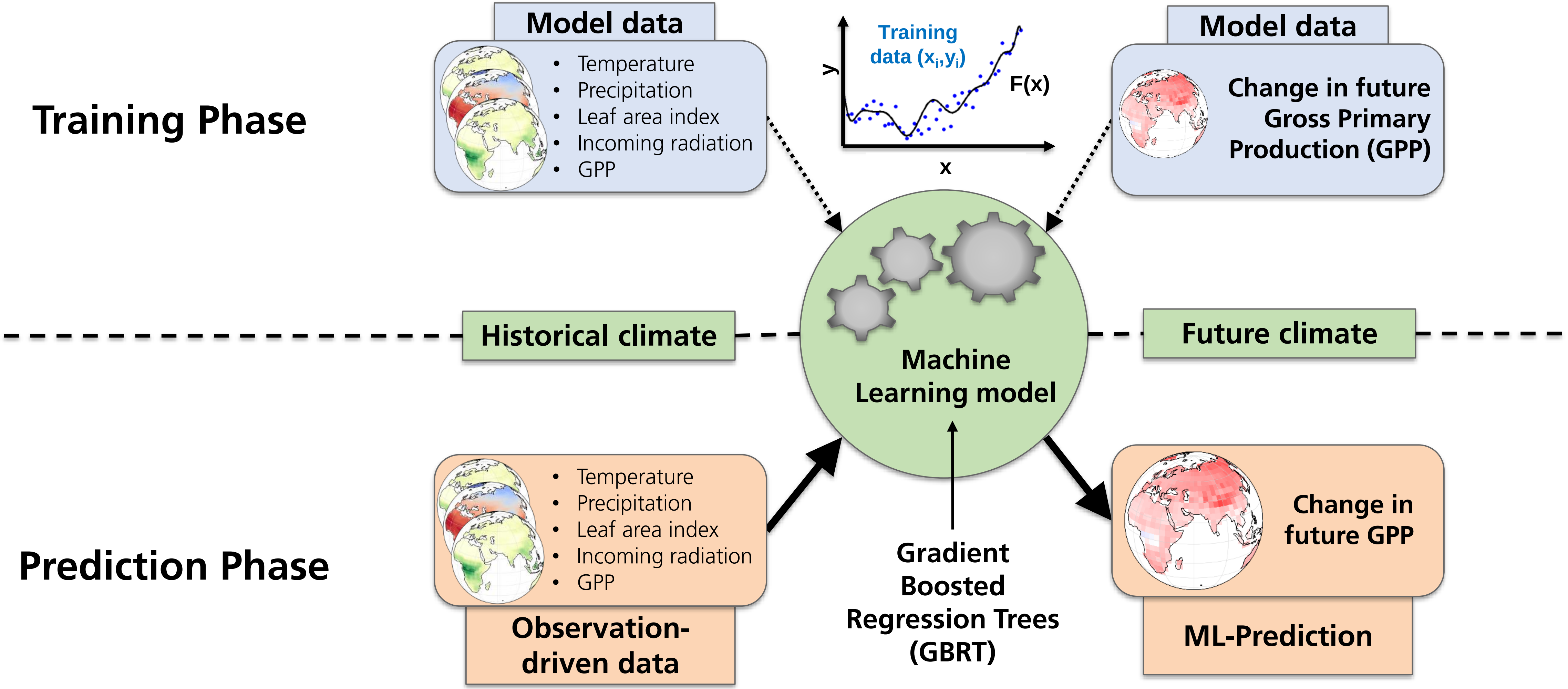
Constraining Future GPP with ML



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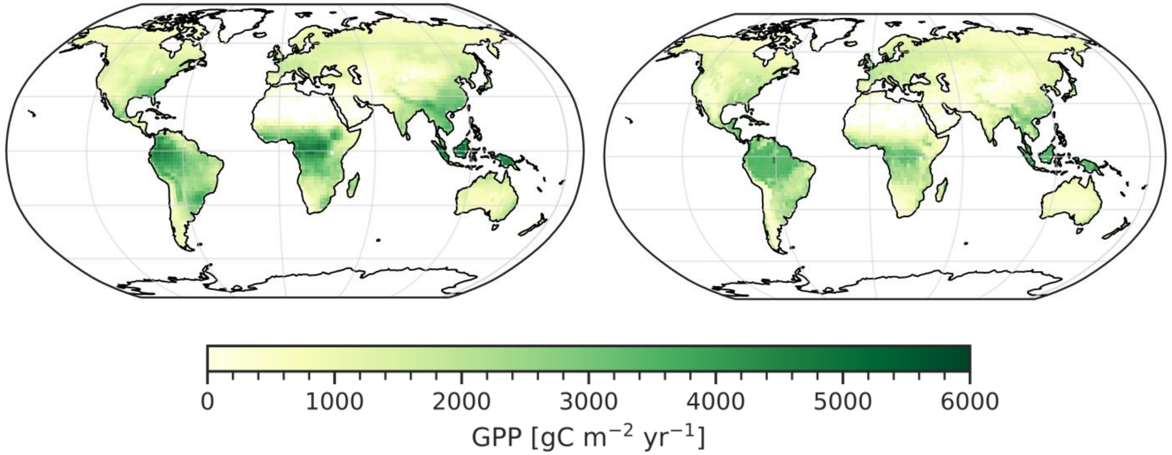
Constraining Future GPP with ML

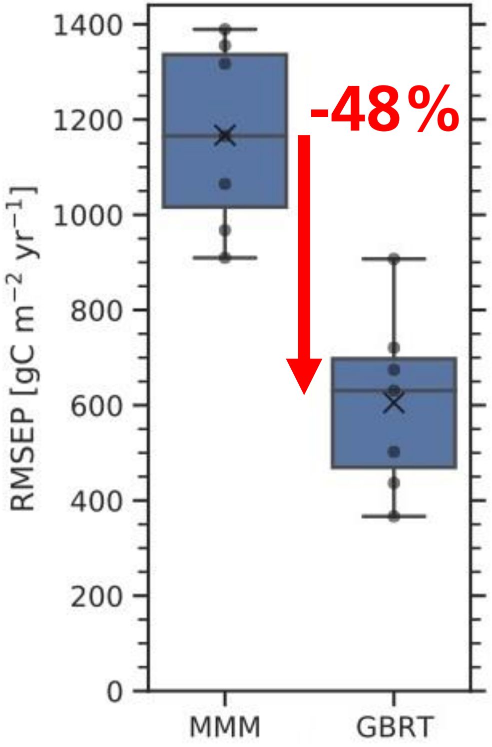
Future GPP in RCP 8.5 scenario (2091-2100)

Unweighted CMIP5 mean | **ML-constrained projection**



156 - 247 GtC yr^{1} | **171 ± 12 GtC yr^{1}**

Root mean square error between prediction and ground-truth (RMSEP)



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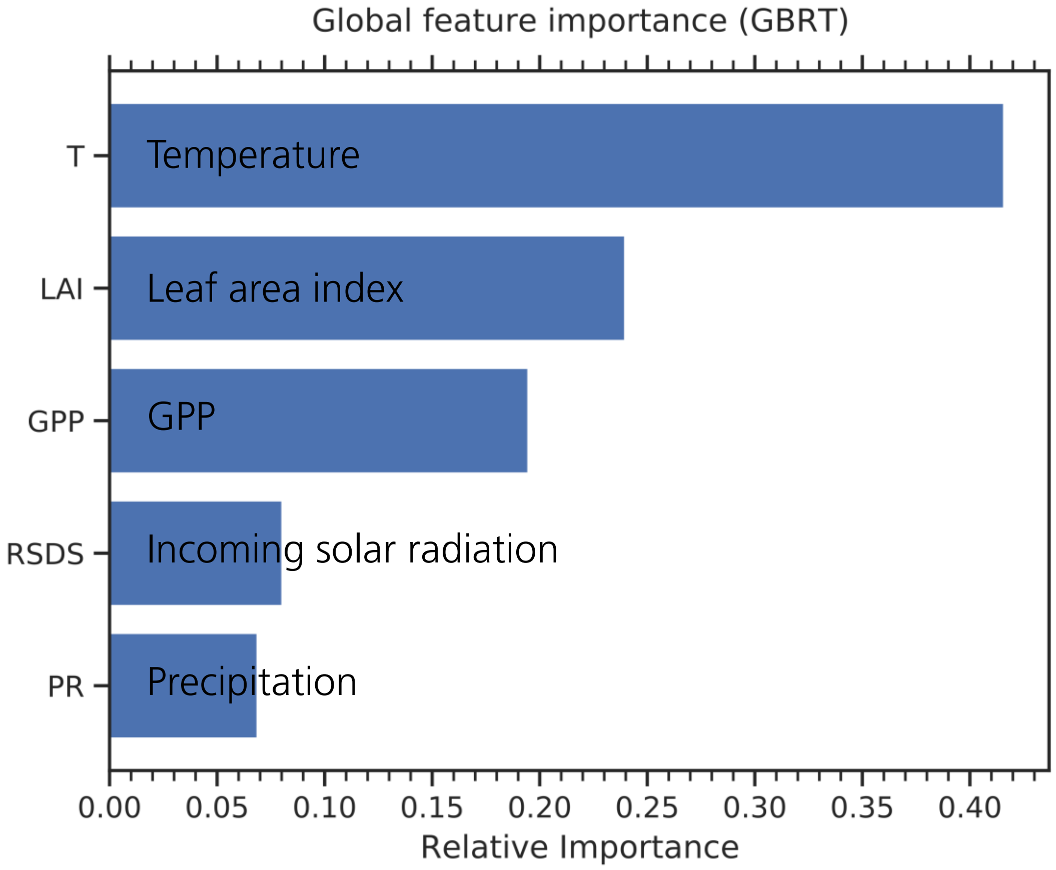
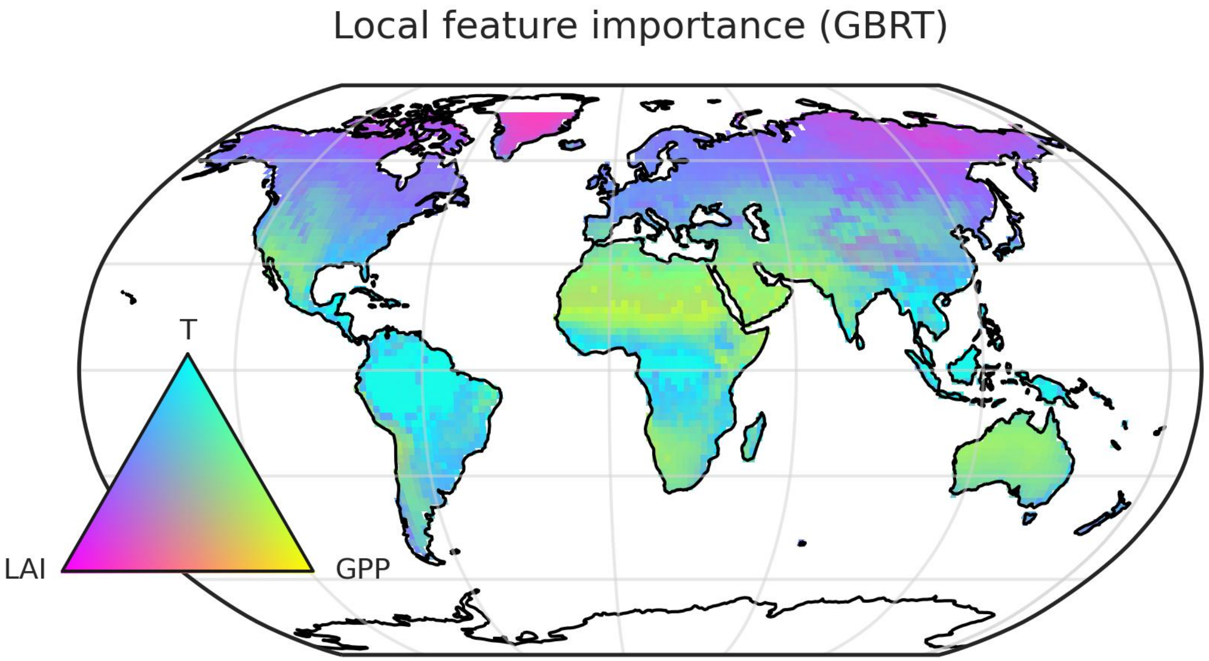
Constraining Future GPP with ML

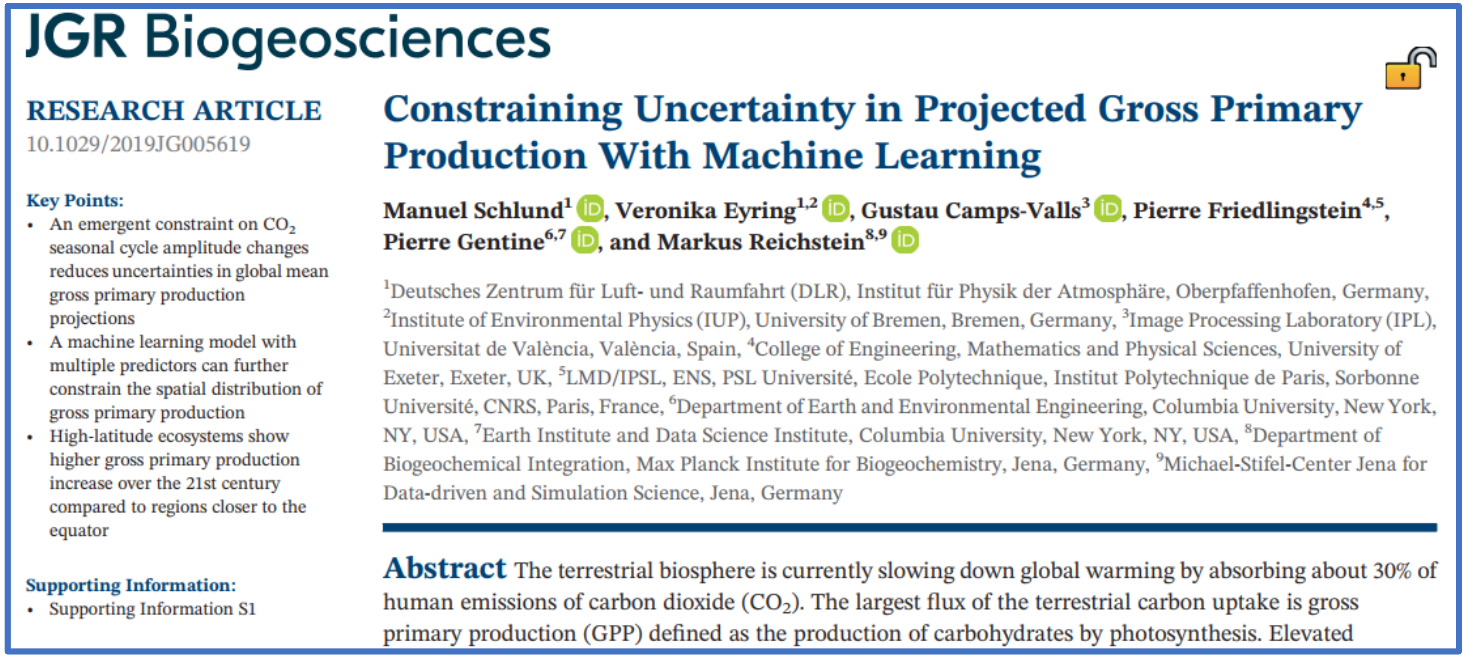




Schlund et al., JGR: Biogeosci., (2020)

Conclusions from this study

- **Machine Learning-based approaches** can reduce uncertainties in gridded climate projections using multiple predictors
- Evaluation of **feature importance** allows us to explore process-oriented physical relations



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Key Points:
- An emergent constraint on CO_2 seasonal cycle amplitude changes reduces uncertainties in global mean gross primary production projections
- A machine learning model with multiple predictors can further constrain the spatial distribution of gross primary production
- High-latitude ecosystems show higher gross primary production increase over the 21st century compared to regions closer to the equator

Supporting Information:
- Supporting Information S1

Constraining Uncertainty in Projected Gross Primary Production With Machine Learning

Manuel Schlund[1], Veronika Eyring[1,2], Gustau Camps-Valls[3], Pierre Friedlingstein[4,5], Pierre Gentine[6,7], and Markus Reichstein[8,9]

[1]Deutsches Zentrum für Luft- und Raumfahrt (DLR), Institut für Physik der Atmosphäre, Oberpfaffenhofen, Germany, [2]Institute of Environmental Physics (IUP), University of Bremen, Bremen, Germany, [3]Image Processing Laboratory (IPL), Universitat de València, València, Spain, [4]College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, UK, [5]LMD/IPSL, ENS, PSL Université, Ecole Polytechnique, Institut Polytechnique de Paris, Sorbonne Université, CNRS, Paris, France, [6]Department of Earth and Environmental Engineering, Columbia University, New York, NY, USA, [7]Earth Institute and Data Science Institute, Columbia University, New York, NY, USA, [8]Department of Biogeochemical Integration, Max Planck Institute for Biogeochemistry, Jena, Germany, [9]Michael-Stifel-Center Jena for Data-driven and Simulation Science, Jena, Germany

Abstract The terrestrial biosphere is currently slowing down global warming by absorbing about 30% of human emissions of carbon dioxide (CO_2). The largest flux of the terrestrial carbon uptake is gross primary production (GPP) defined as the production of carbohydrates by photosynthesis. Elevated

Schlund, M., V. Eyring, G. Camps-Valls, P. Friedlingstein, P. Gentine, and M. Reichstein, JGR: Biogeosci., (2020)

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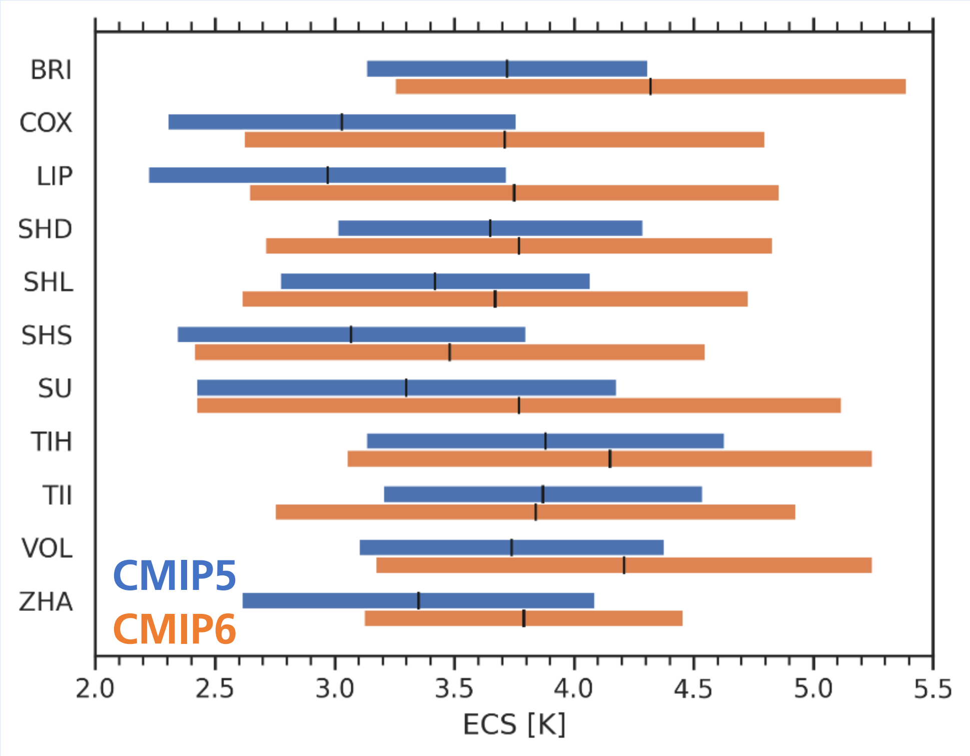
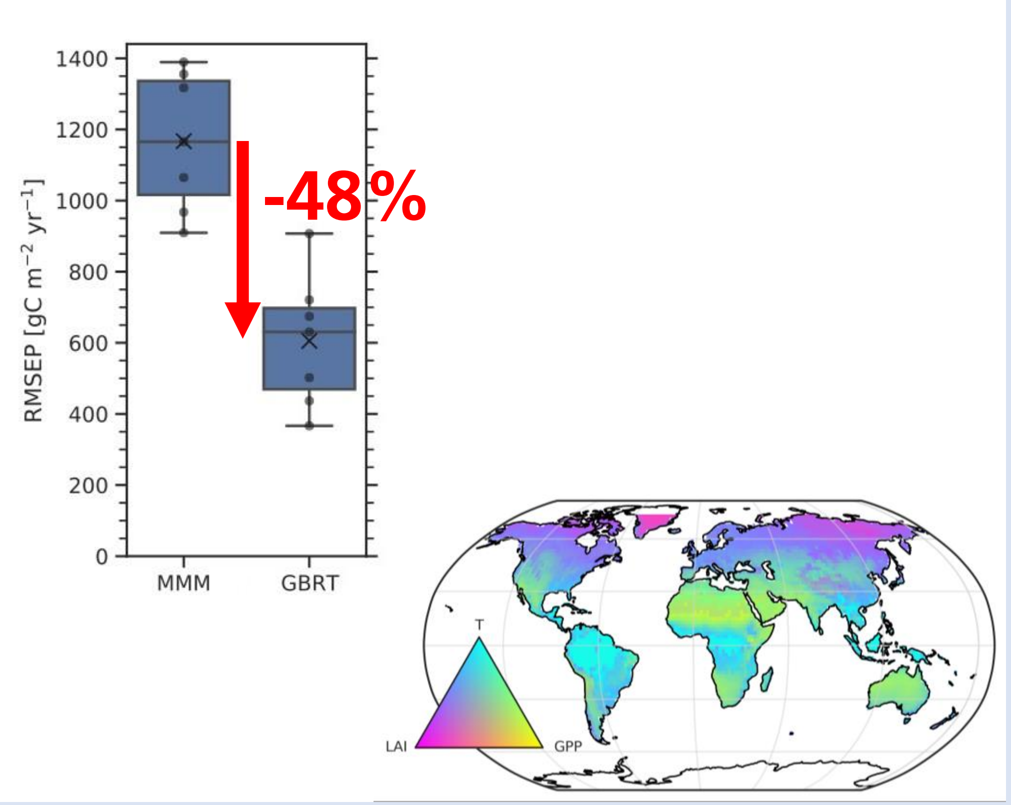
Summary

Emergent constraints on ECS show reduced skill and increased best estimates of ECS in CMIP6



Machine learning techniques are promising methods to improve ESM Analysis



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