Clouds in climate models and atmospheric observations

Peter Kuma[1,2,*]

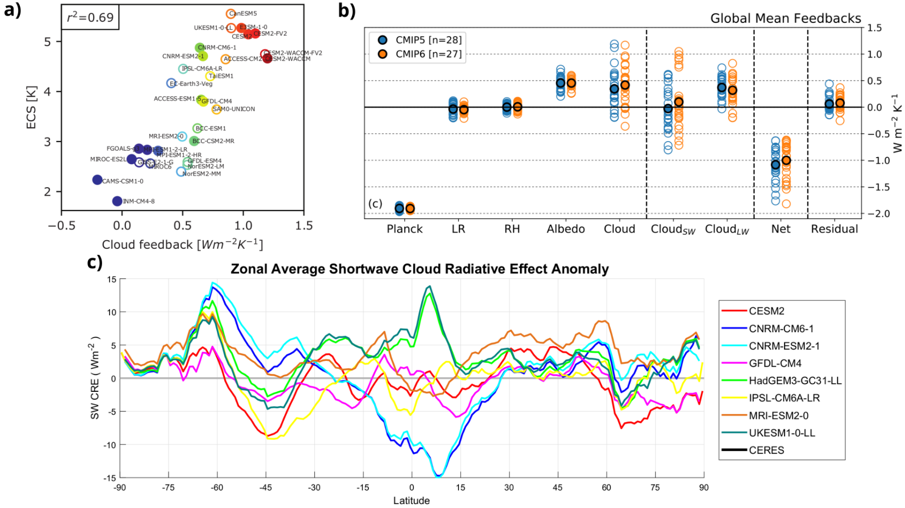
[1]Stockholm University, Stockholm, Sweden
[2]Before: University of Canterbury, Christchurch, Aotearoa/New Zealand

14 December 2021

Co-authors: Adrian J. McDonald, Olaf Morgenstern, Simon P. Alexander, John J. Cassano, Sally Garrett, Jamie Halla, Sean Hartery, Mike J. Harvey, Simon Parsons, Graeme Plank, Vidya Varma, Jonny Williams, Richard Querel, Israel Silber, Connor J. Flynn, Guang Zeng, Stefanie Kremser, Alexia Saint-Macary, John McGregor, Alex Schuddeboom, Marc von Hobe, Sinikka T. Lennartz, Alex Geddes, Maija Peltola, Karine Sellegri, Cliff S. Law, Andrew Marriner, Thomas C. J. Hill, Paul J. DeMott, Carson C. Hume, Geoffrey Graham and Frida Bender

[*]peter.kuma@misu.su.se, https://peterkuma.net/science

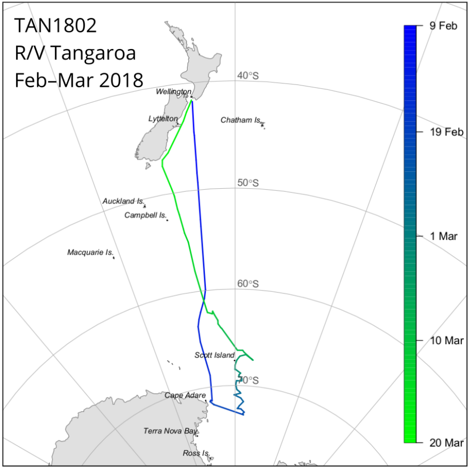
Introduction

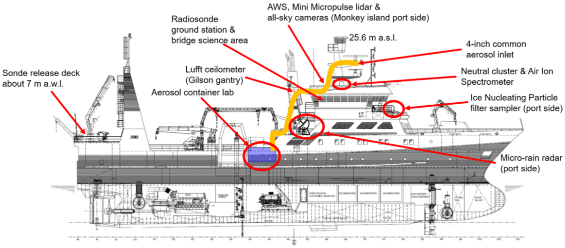


a, Adopted from Wang et al. (2021), Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. **b,** Adopted from Zelinka et al. (2020), Causes of Higher Climate Sensitivity in CMIP6 Models. **c,** Adopted from Schuddeboom and McDonald (2021), The Southern Ocean Radiative Bias, Cloud Compensating Errors, and Equilibrium Climate Sensitivity in CMIP6 Models.

Ship-based measurements of clouds

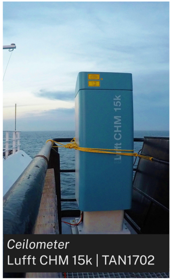
Kremser et al. (2021), Southern Ocean Cloud and Aerosol data: a compilation of measurements from the 2018 Southern Ocean Ross Sea Marine Ecosystems and Environment voyage (Earth System Science Data)





Ship-based measurements of clouds: Instruments

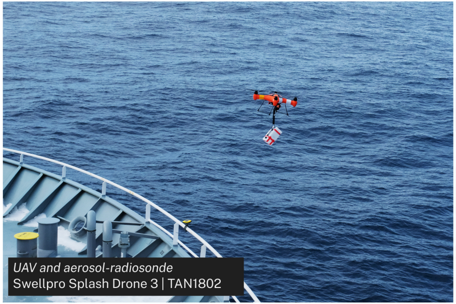
Ceilometer
Vaisala CL51 | Macquarie Is.



Ceilometer
Lufft CHM 15k | TAN1702

Micro rain radar
Meter MRR-2 | TAN1802

Helikite | TAN1802



UAV and aerosol-radiosonde
Swellpro Splash Drone 3 | TAN1802

Radiosonde release
iMet-1 ABx | TAN1802

Ship-based measurements of clouds: Mandatory penguin

Photos by Glen Walker (2018).

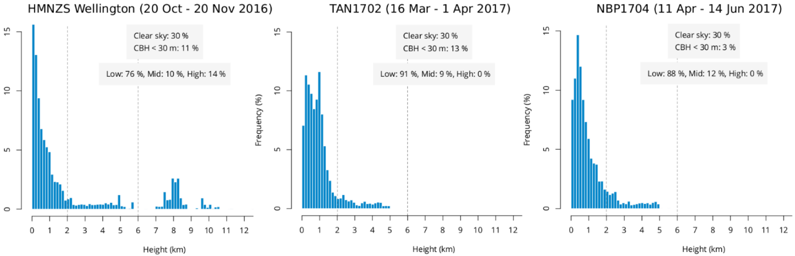
Ship-based measurements of clouds: Night radiosonde launch on R/V Tangaroa

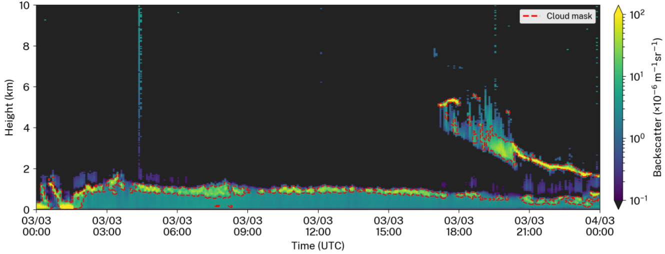
video

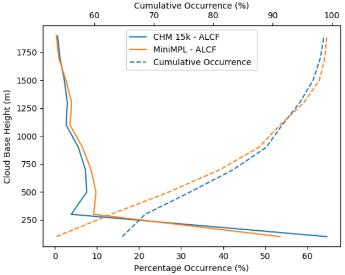
Ship-based measurements of clouds: UAV flight on R/V Tangaroa

video

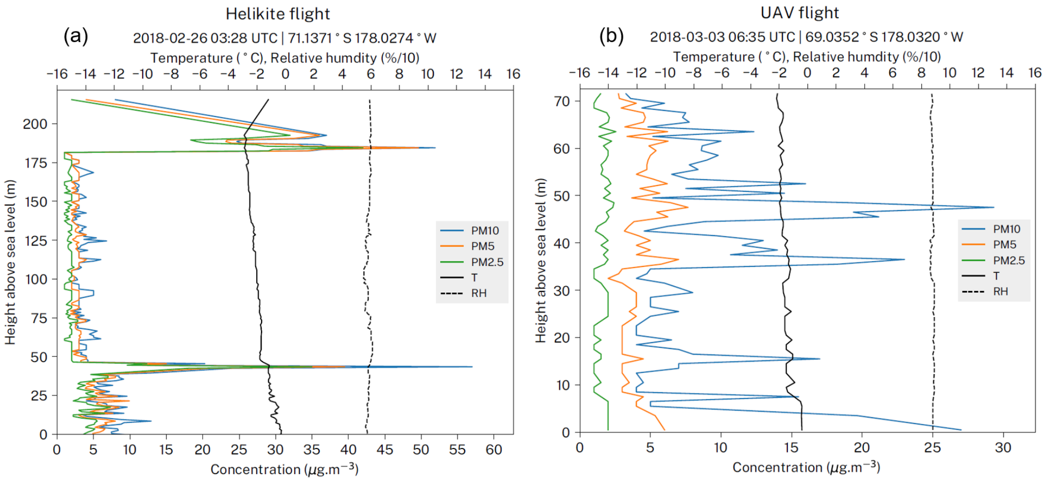
Ship-based measurements of clouds: Clouds in the Southern Ocean





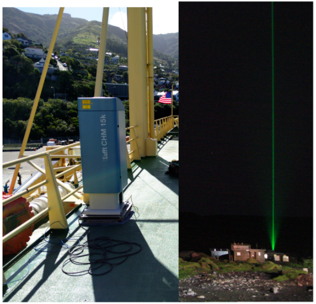


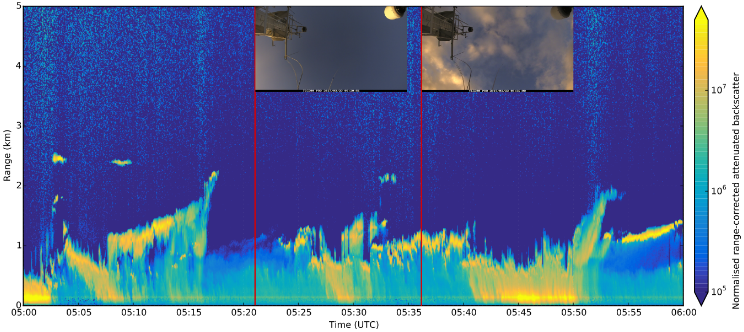
Ship-based measurements of clouds: Aerosol sampling with a UAV and helikite



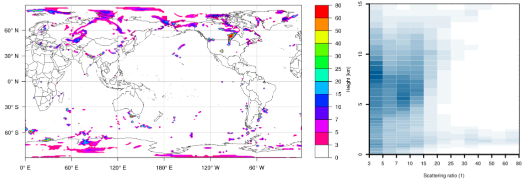
Ground-based lidar simulator: ALCF (alcf-lidar.github.io)

Kuma et al. (2021), Ground-based lidar processing and simulator framework for comparing models and observations (ALCF 1.0) (Geoscientific Model Development)

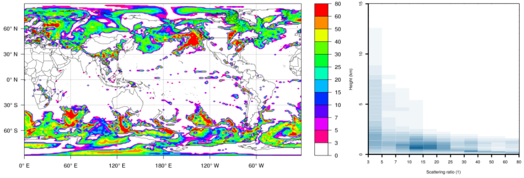




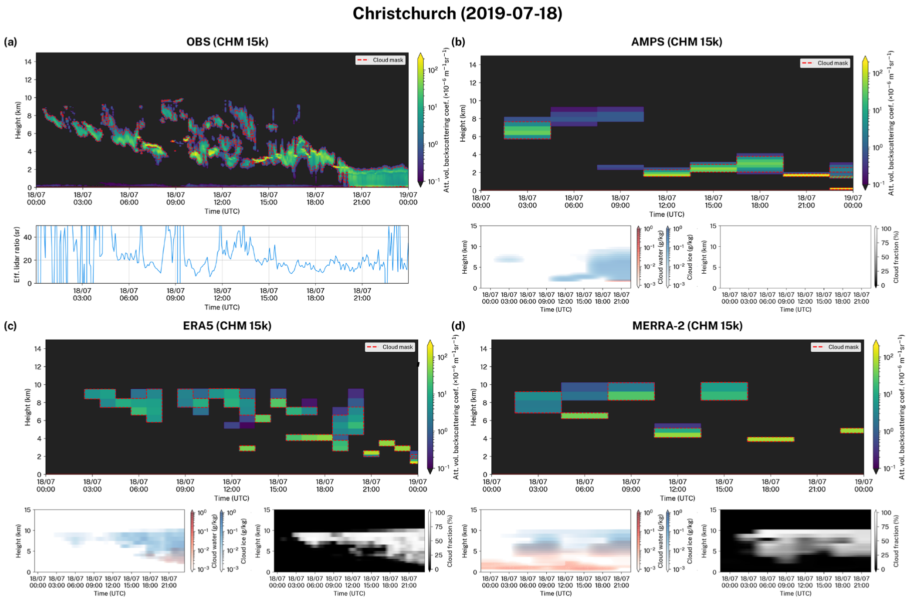
Simulated spaceborne lidar, 532 nm wavelength



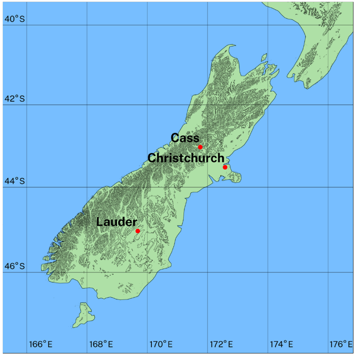
Simulated ground-based lidar (ceilometer), 532 nm wavelength

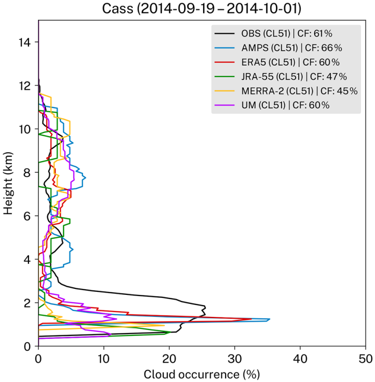


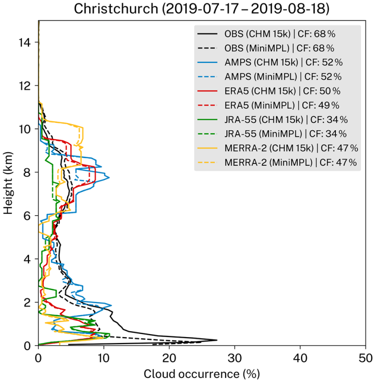
Ground-based lidar simulator: Comparing models with observations



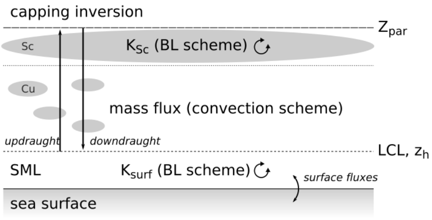
Ground-based lidar simulator: Comparing models with observations

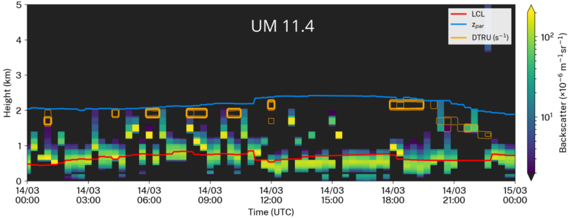


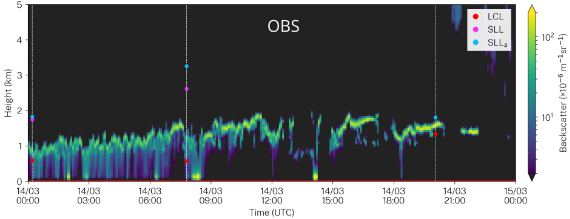


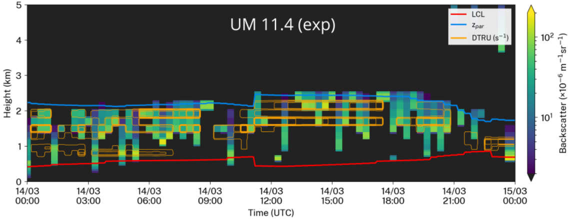


Ground-based lidar simulator: Southern Ocean clouds in the Unified Model (UM)



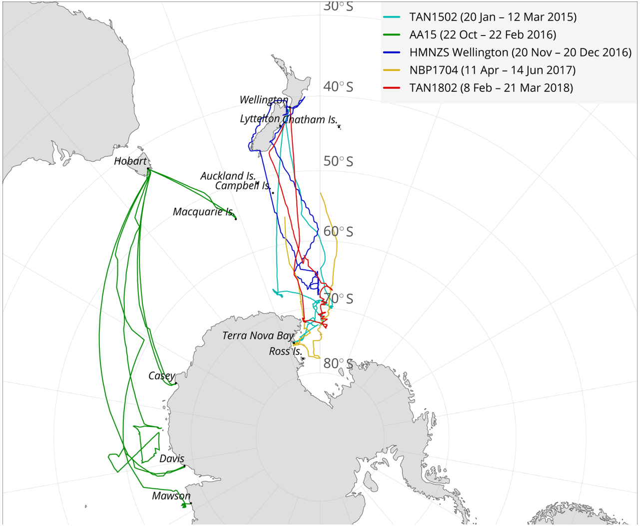




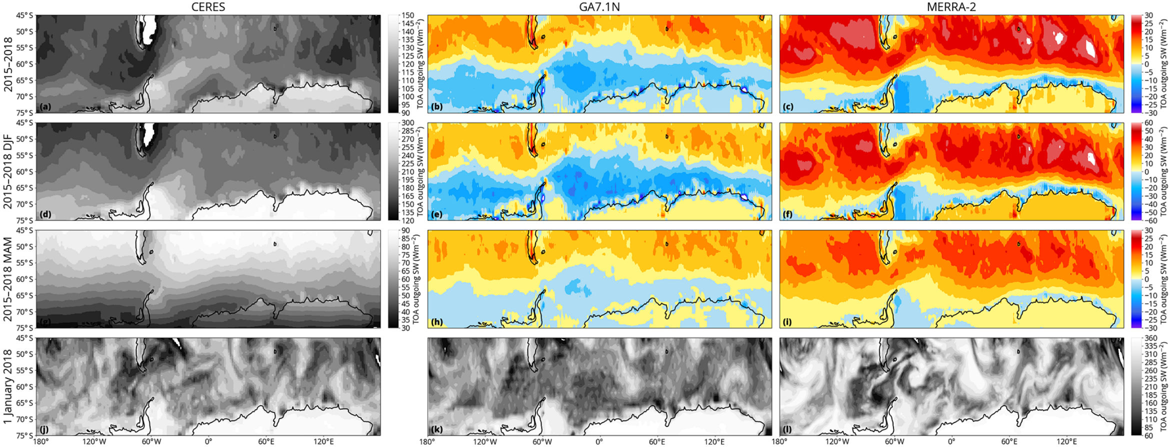


Southern Ocean clouds

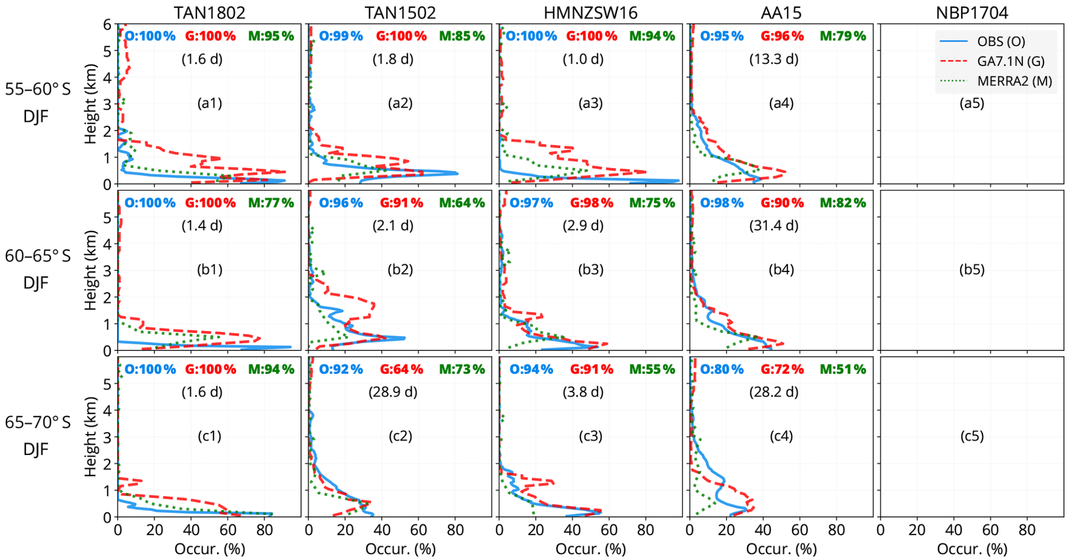
Kuma et al. (2020), Evaluation of Southern Ocean cloud in the HadGEM3 general circulation model and MERRA-2 reanalysis using ship-based observations (Atmospheric Chemistry and Physics)



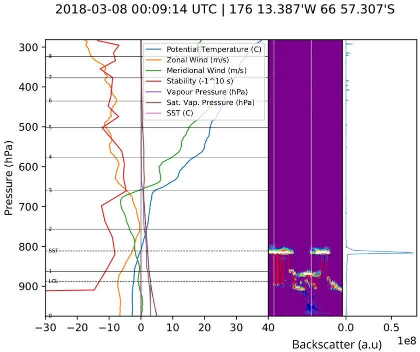
Southern Ocean clouds: Model radiation biases

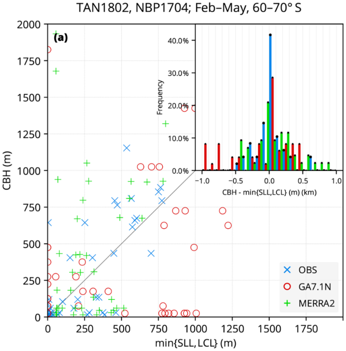


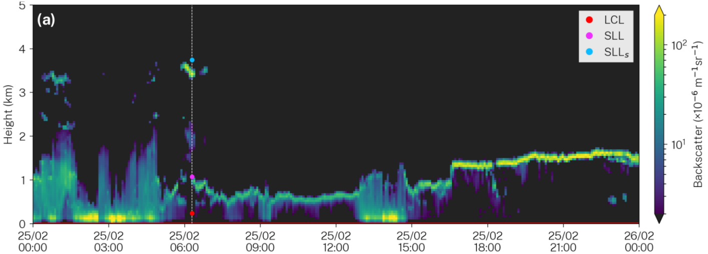
Southern Ocean clouds: Models cloud biases



Southern Ocean clouds: Models cloud biases

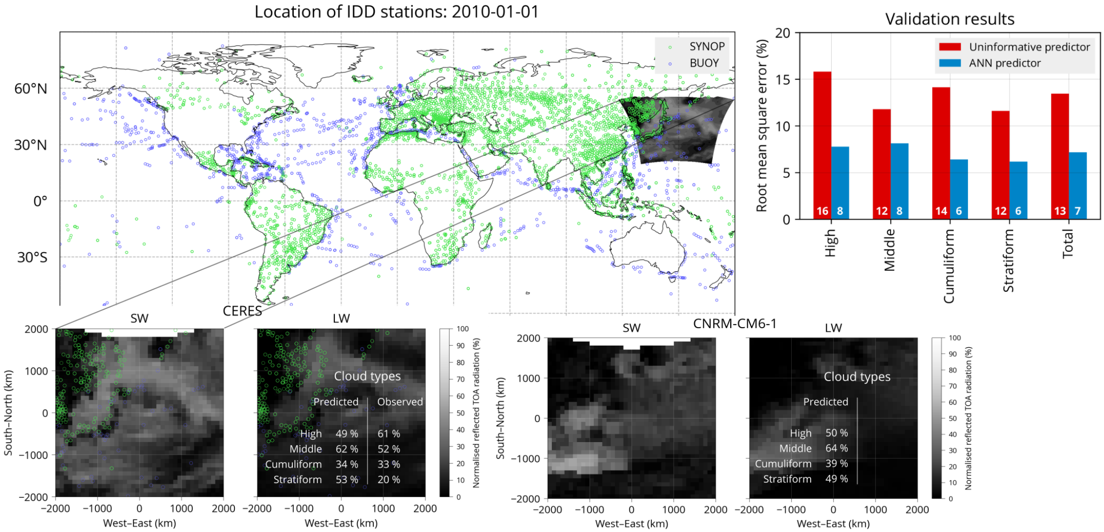




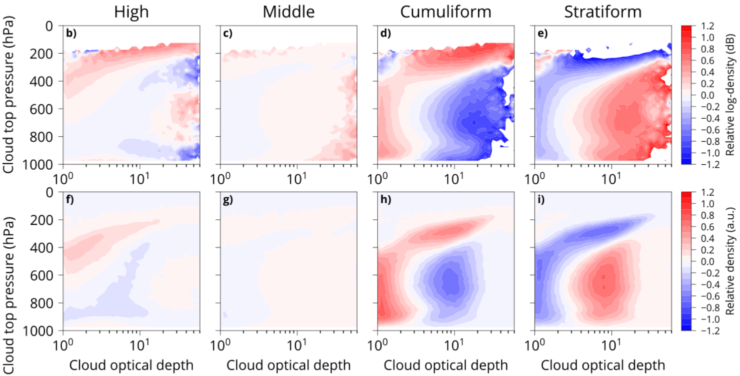


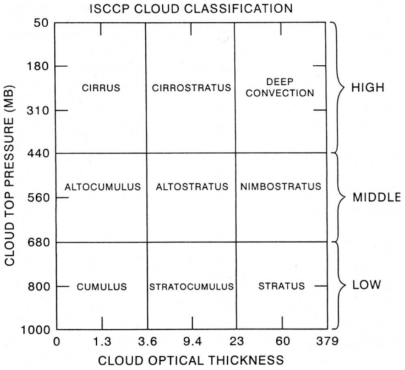
Machine learning of clouds

Kuma and Bender, Machine learning of cloud types shows lower present-day bias in climate models is associated with higher climate sensitivity (manuscript in preparation)



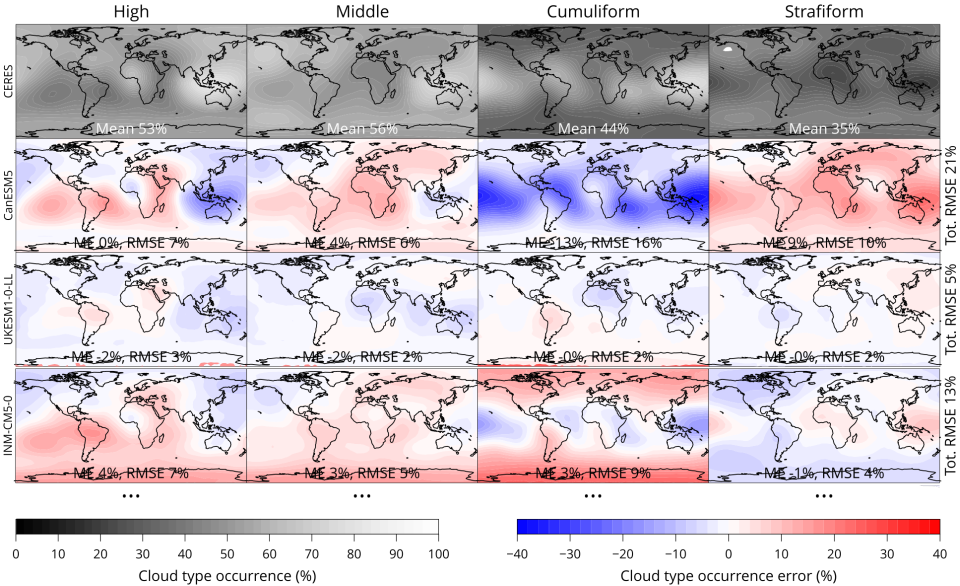
Machine learning of clouds: Optical depth vs. cloud top pressure





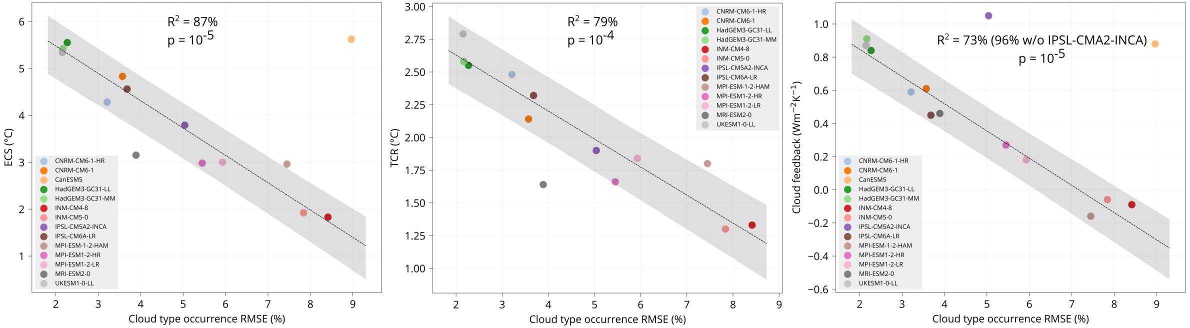
Adopted from Rossow and Shiffer (1999), Advances in understanding clouds from ISCCP.

Machine learning of clouds: Geographical results

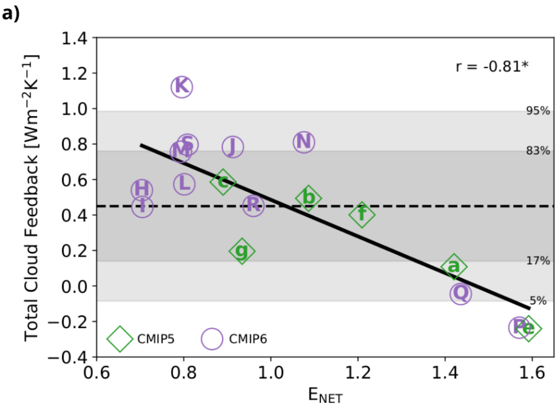


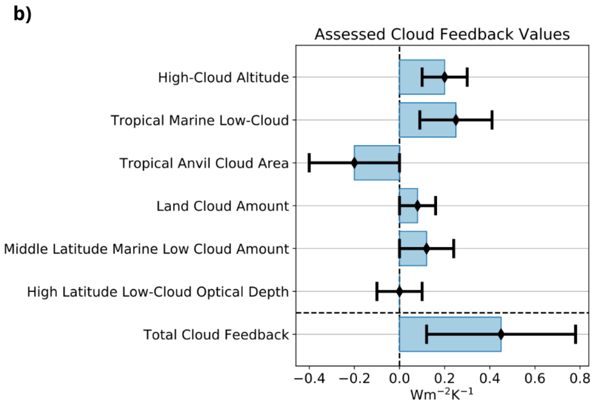
Machine learning of clouds: Present-day cloud RMSE vs. climate sensitivity

- We see a strong linear relationship between model cloud RMSE and its climate sensitivity and cloud feedback.



Machine learning of clouds: What do other papers say?





a, Adopted from Zelinka et al. (2021), Evaluating climate models' cloud feedbacks against expert judgement (submitted).

b, Adopted from Sherwood et al. (2020), An assessment of Earth's climate sensitivity using multiple lines of evidence.

Conclusions

- Future cloud errors are the main reason for climate sensitivity biases in climate models. Present-day cloud biases are still a problem in CMIP6, especially the Southern Ocean.
- We measured clouds and aerosol on the TAN1802 and TAN1702 Southern Ocean voyages with a ceilometer and a lidar, radiosondes, UAV and a helikite.
- Southern ocean clouds are dominated by low clouds, which are poorly observed from space. They are driven by boundary layer processes (shallow convection).
- Ground-based lidar simulator is a useful tool for comparing models and observations, available now at https://alcf-lidar.github.io (open source).
- The HadGEM (aka UKESM aka UM aka GA) models and especially MERRA-2 underestimate the amount of low clouds.
- Artificial neural networks can be used for determining clouds types in satellite observations and climate models. Model present-day cloud type error is strongly linked to the cloud feedback and climate sensitivity.
- Open question: Are models with better present-day representation of clouds better at simulating future clouds? If so, then high climate sensitivity is plausible.