Using deep learning cloud classification in cloud feedback and climate sensitivity determination

Peter Kuma[1]*, Frida Bender[1]

[1]Stockholm University, Sweden

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

FORCeS Annual Meeting 2021
27 October 2021

Stockholm University

FORCeS

Constrained aerosol forcing for improved climate projections

https://forces-project.eu

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 821205.

Abstract

We develop a deep convolutional neural network for determination of cloud types in low-resolution daily mean top-of-atmosphere shortwave and longwave radiation images, corresponding to the classical cloud types recorded by human observers in the Global Telecommunication System. We train this network on the CERES top of atmosphere radiation dataset, and apply this network on the CMIP6 abrupt-4xCO2 model output to determine long-term change in cloud type occurrence in these models with increasing CO2 concentration. We contrast these results with corresponding cloud type change in historical satellite measurements. The proposed neural network approach is broadly applicable for model, reanalysis and satellite imagery evaluation because it does not require high resolution and corresponds to the cloud types commonly recorded at weather stations worldwide.

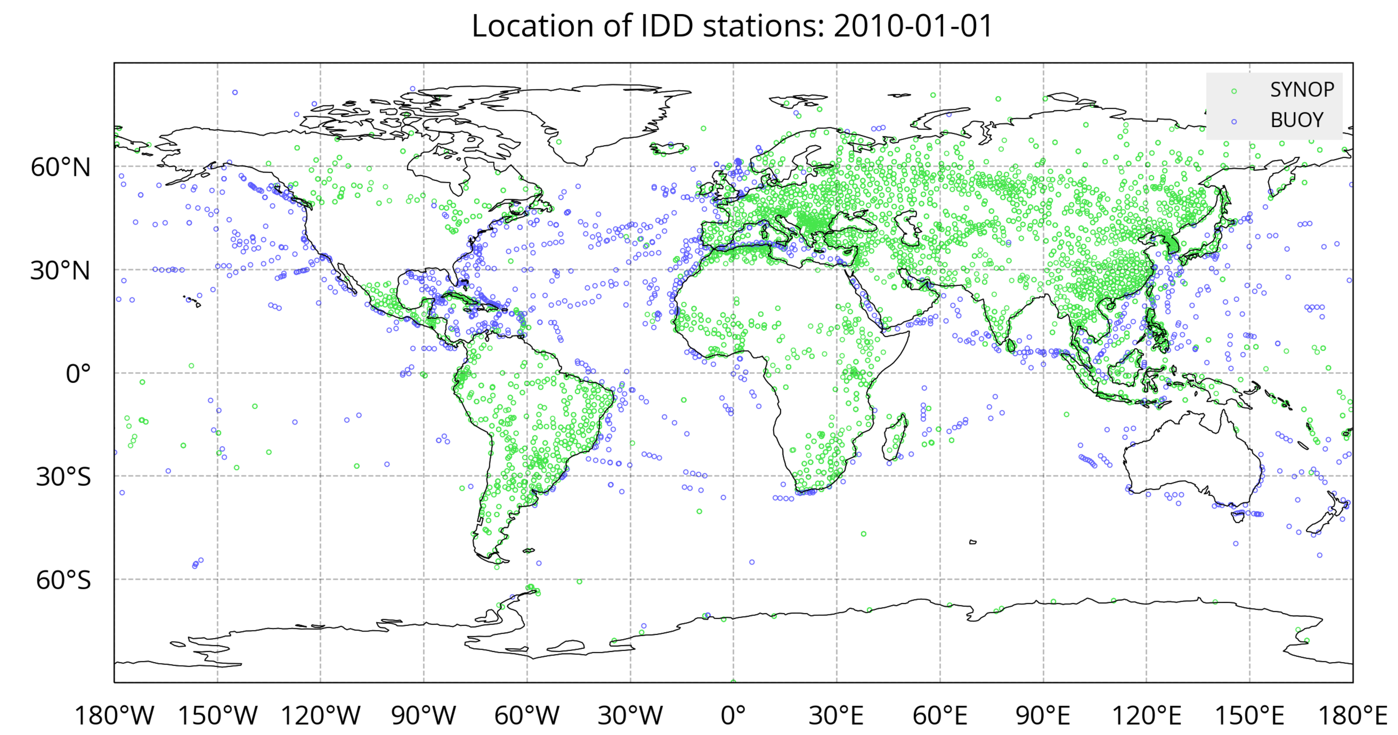

Figure 1: A map showing location of Internet Data Distribution (IDD) station reports containing cloud information on a single day.

Key points

- ‣ We developed an artificial neural network (ANN) to identify the occurrence of cloud types in satellite and model data.
- ‣ The types correspond to WMO cloud genera, grouped into 4 groups: high (Hi), middle (Mi), cumuliform (Cu) and stratiform (St).
- ‣ The training was based on WMO ground station reports and CERES.
- ‣ We find large differences between CMIP6 models in their cloud type occurrence relative to CERES.
- ‣ The root mean square error (RMSE) of a model correlates strongly with the model equilibrium climate sensitivity (ECS).
- ‣ Models with smaller error have greater ECS, transient climate response (TCR) and cloud feedback.

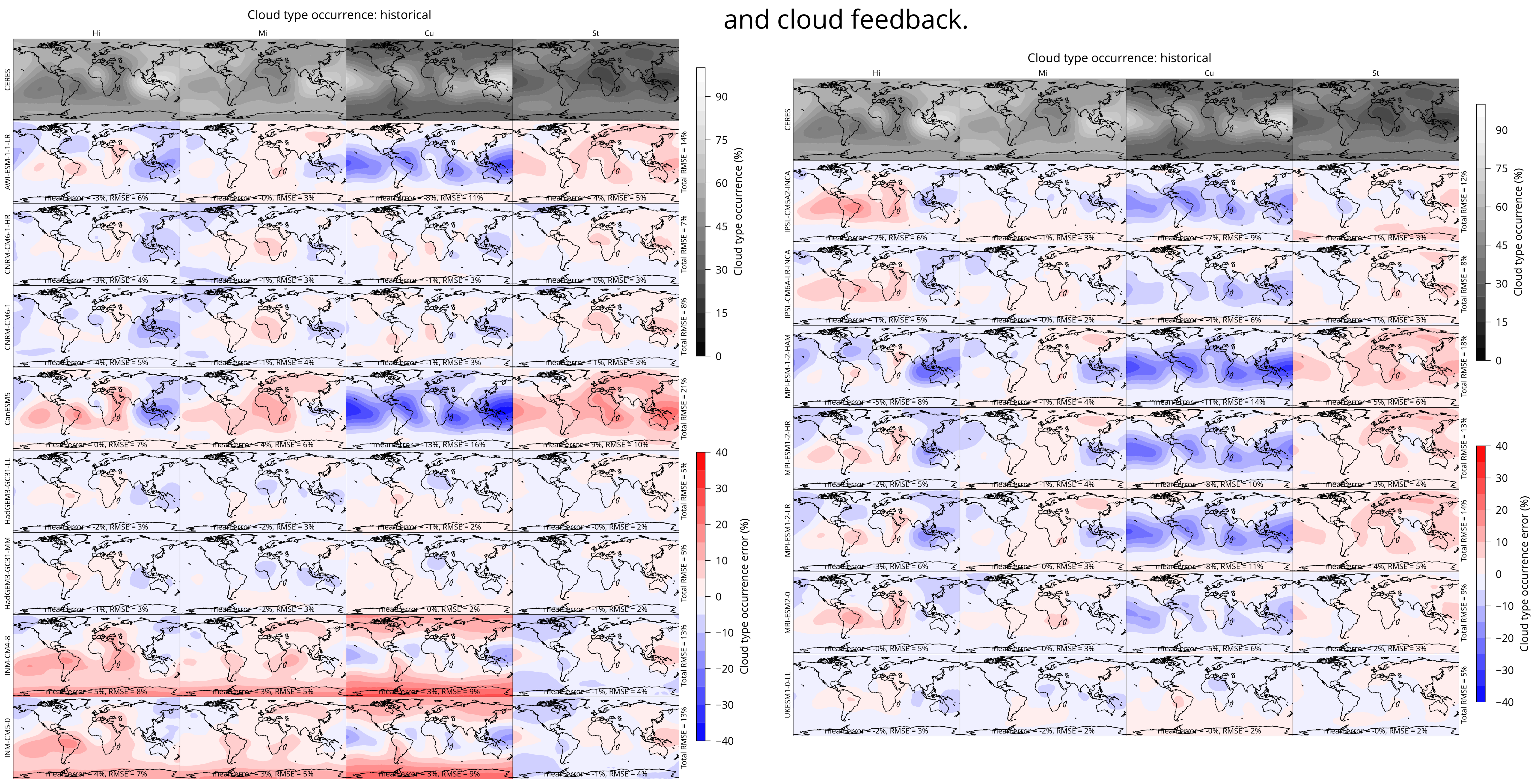

Figure 2: Geographical distribution of cloud type occurrence derived by applying the ANN on observed CERES satellite data in years 2003–2020 and on models output of the historical experiment of CMIP6 in years 2003–2014 relative to CERES. Shown is also the mean error and the root mean square error (RMSE) relative to CERES.

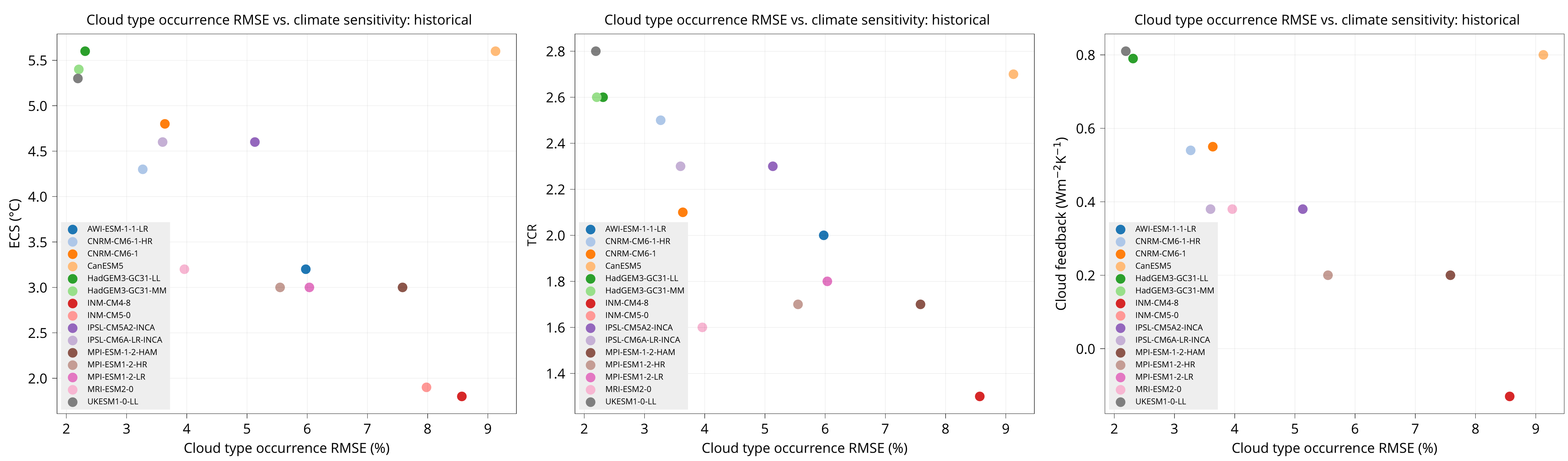

Figure 3: Dependence of model ECS, TCR and cloud feedback on the total cloud type occurrence root mean square error (RMSE) as shown in Figure 2.