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

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

[1] MISU, Stockholm University, Stockholm, Sweden

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

Introduction

Objectives

- Develop artificial neural network (ANN) for determination of cloud types from low-resolution satellite and GCM data.
- Use the global network of surface observations and CERES as a training set.
- Apply the ANN on the abrupt-4xCO2 CMIP6 experiment to identify changes in cloud type occurrence in response to global near-surface air temperature change.
- Link the results to model cloud feedback and equilibrium climate sensitivity.

Classical cloud types (reduced to 4 categories) | Source: International Cloud Atlas (WMO)

Cumuliform (example: cumulus)

Stratiform (example: stratocumulus)

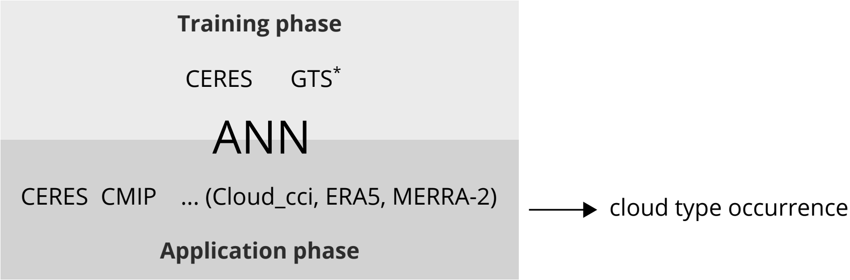
Middle (example: altostratus)

High (example: cirrus)

Methods

Datasets and tools

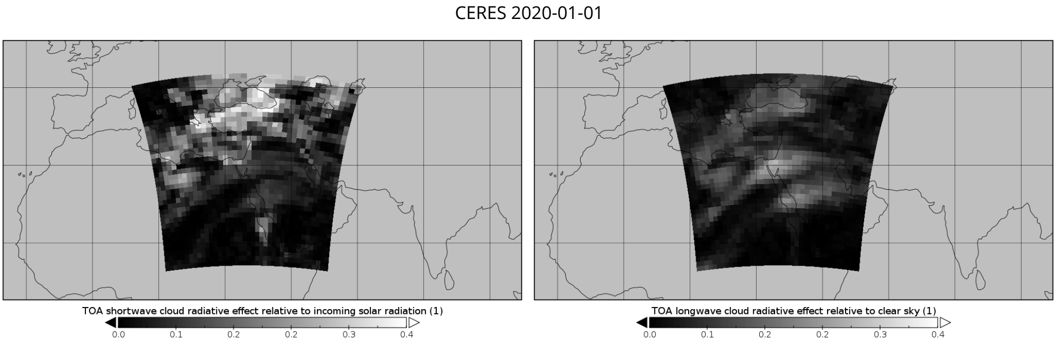
- Training data: CERES, historical surface (land, marine) observations.
- Data: CMIP5, CMIP6, (Cloud_cci, ERA5, MERRA-2).
- Tools: TensorFlow.



*Global Telecommunication System

Satellite/model datasets

- Daily TOA shortwave and longwave radiation.
- 4000 × 4000 km samples, 20 per day, centred at random geographical points.
- Resolution about 1–3 degrees.

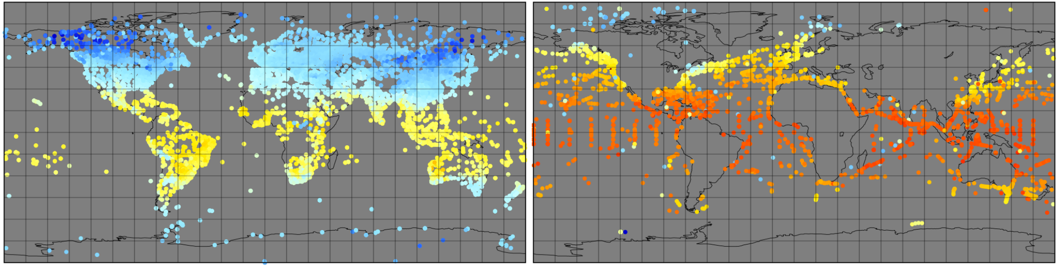


IDD/GTS

- Unidata Internet Data Distribution (IDD) / Global Telecommunication System (GTS).
- Historical synoptic observations.
- Classical human-identified cloud classes: Cu, St, Sc, Ac, As, Ci, ...
- Cloud classes grouped into four classes: cumuliform (Cu, Cb), stratiform (St, Sc), middle (As, Ac), high (Ci, Cs, Cc).

Distribution of GTS stations

Land stations   "Buoy" stations



TensorFlow

- Deep convolutional neural network.
- Input: (1) samples of daily TOA SW and LW radiation in 4000 $\times$ 4000 km squares, (2) cloud type occurrence calculated from stations within the square.
- Output: vector of four numbers in the interval [0, 1] – occurrence of each cloud type. Cloud types are non-exclusive – multiple types can be identified in a single observation.
- Loss function: root mean square error (RMSE) of the cloud type occurrence.

```
Sequential()
Conv2D(32, (3, 3), activation='relu', padding='same'))
AveragePooling2D((2, 2)))
Dropout(0.1))
Conv2D(32, (3, 3), activation='relu', padding='same'))
AveragePooling2D((2, 2)))
Dropout(0.1))
Conv2D(64, (3, 3), activation='relu', padding='same'))
AveragePooling2D((2, 2)))
Dropout(0.1))
Conv2D(64, (3, 3), activation='relu', padding='same'))
AveragePooling2D((2, 2)))
Dropout(0.1))
Conv2D(64, (3, 3), activation='relu', padding='same'))
AveragePooling2D((2, 2)))
Flatten())
Dropout(0.1))
Dense(64, activation='relu'))
Dropout(0.1))
Dense(64, activation='relu'))
Dropout(0.1))
Dense(nclasses, activation='sigmoid'))
```

Training

TensorFlow results

- Separate validation set.
- Comparison with an uninformative predictor: predicted cloud type occurrence always equal to the long-term average.
- RMSE reduced to about 50–60% of the uninformative predictor.

Validation results (%)

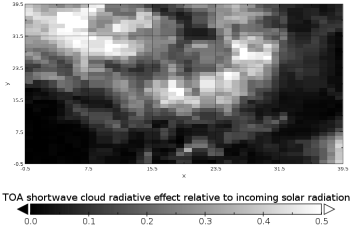
By type:	Hi	Mi	Cu	St
RMSE predicted	8	7	7	5
RMSE const. model	14	12	14	11

Total:	
RMSE predicted	7
RMSE const. model	13

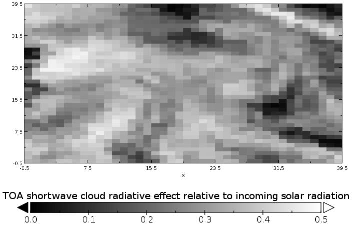
Samples

What samples are most typical in the cumuliform, stratiform, middle and high cloud class?

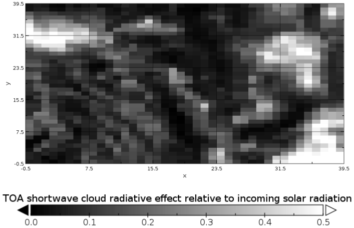
Cumuliform



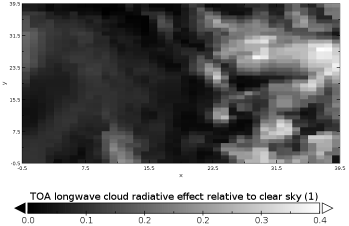
Stratiform



Middle



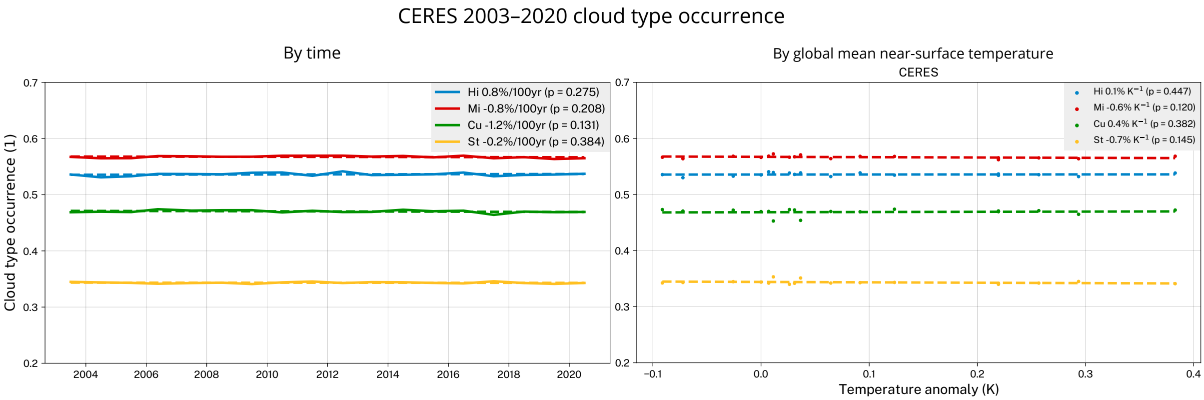
High



Results

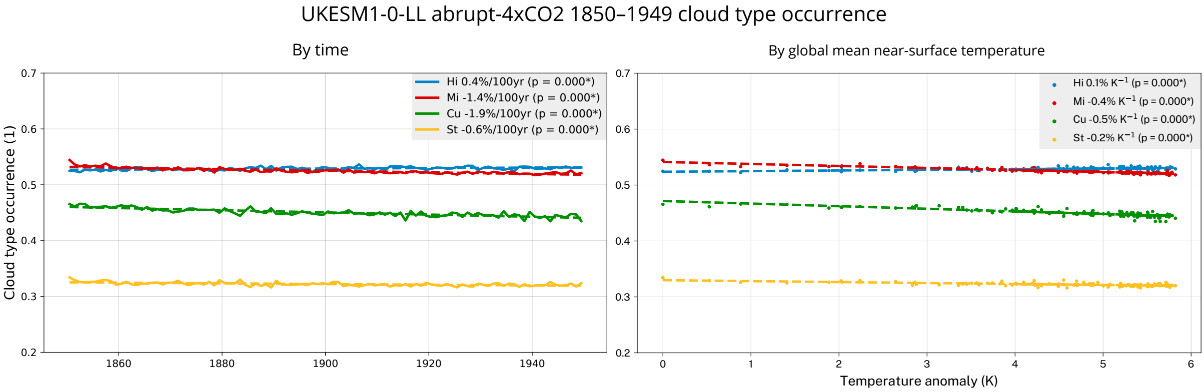
CERES

- CERES 2003–2020.

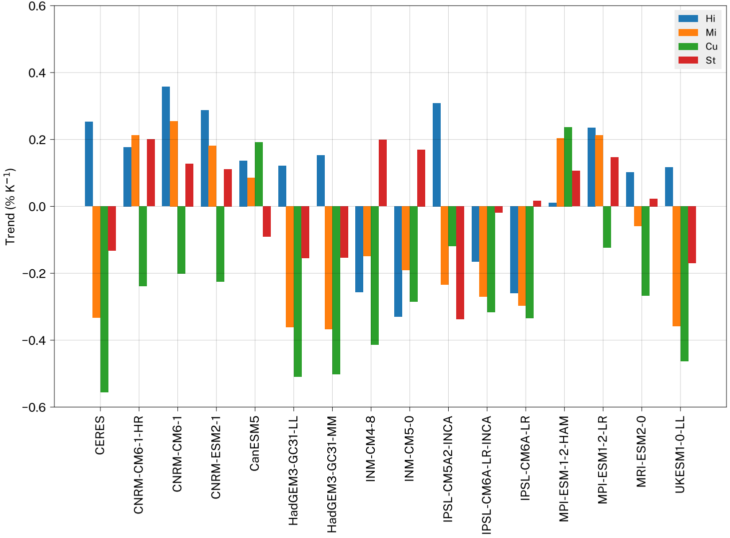


CMIP

- CMIP6 (and CMIP5) abrupt-4xCO2 experiment.
- UKESM1-0-LL as an example:



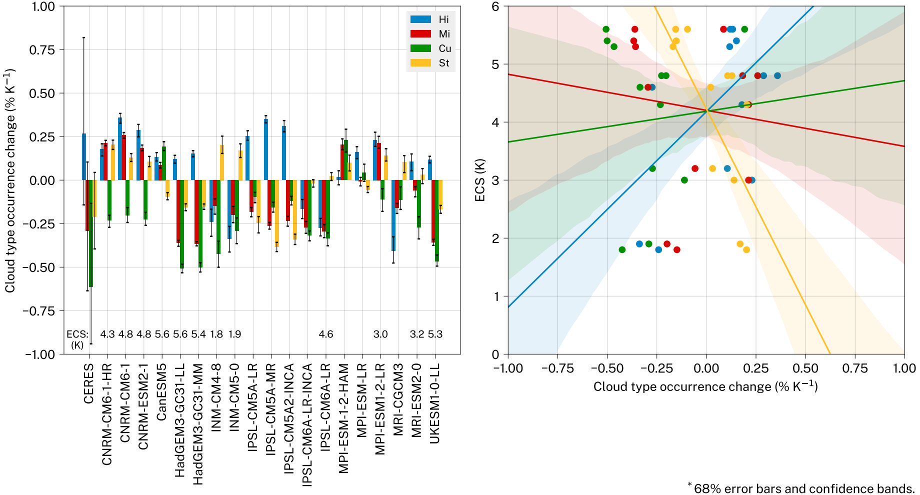
CERES and CMIP results



CMIP relative to CERES, ECS

- Can we use the results as an emergent constraint for ECS or cloud feedback?

Cloud type occurrence change with global near-surface air temperature
CERES 2003–2020 and CMIP6 abrupt-4xCO2 1850–1949 *



* 68% error bars and confidence bands.

Conclusions

Conclusions

- We trained an ANN to identify cloud types on CERES satellite observations and historical surface observations. It can explain about 40–50% of the variance.
- CMIP models show diverse significant trends in cloud types, CERES is unfortunately not significant.
- Input resolution has little impact on the results.
- Stratiform and high cloud classes are strongly related to the model ECS.
- Future research: Cloud_cci long-term series (1980–present), reanalyses (ERA5, MERRA-2).
- Can we explain ECS or cloud feedbacks in terms of changes in the classical cloud types?