Machine learning of cloud types in satellite observations and climate models

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SeRC Annual Meeting 2022
13 May 2022

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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.

Objectives

- Develop convolutional artificial neural network (ANN) for determination of cloud types from low-resolution satellite and climate model data.
- Use the global network of ground observations of cloud genera from WMO stations and satellite observations of shortwave (SW) and longwave (LW) radiation from CERES a training set.
- Determine global distribution of cloud types.
- Identify climate model biases and trends.
- Link the results to climate model cloud feedback and equilibrium climate sensitivity (ECS).

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

Cumuliform (example: cumulus)

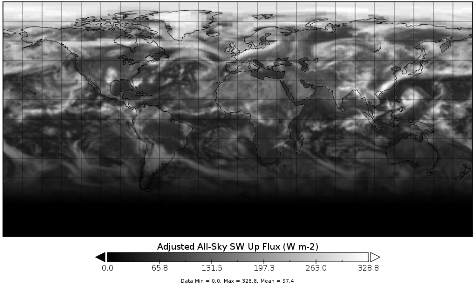
Stratiform (example: stratocumulus)

Middle (example: altostratus)

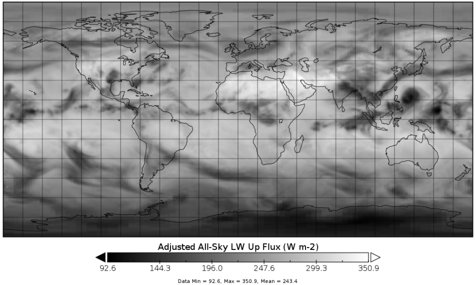
High (example: cirrus)

Input

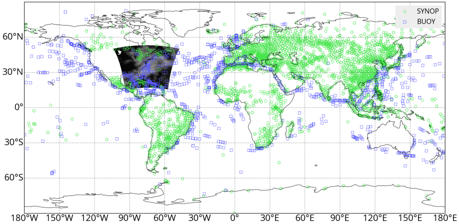
Adjusted All-Sky SW Up Flux



Adjusted All-Sky LW Up Flux



Location of IDD stations: 2010-01-01



Methods

- Deep convolutional ANN based on the U-Net architecture (Ronneberger et al., 2015).

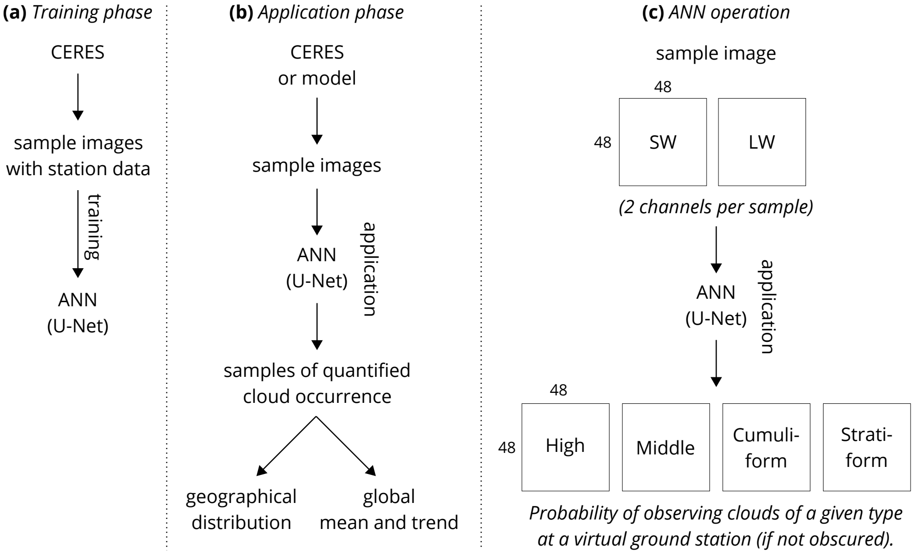
Training phase

- Input: normalised daily mean SW and LW radiation from CERES as 20 samples per day of 4000×4000 km (48×48 pixels) in local geographical projection centred at random locations.
- Reference output: cloud genera observed at WMO stations (IDD dataset) grouped into 4 cloud types, available in a subset of pixels of the samples.
- Loss function: negative of log-likelihood of observing the cloud types at ground stations under per-pixel probability predicted by the ANN.

Application phase

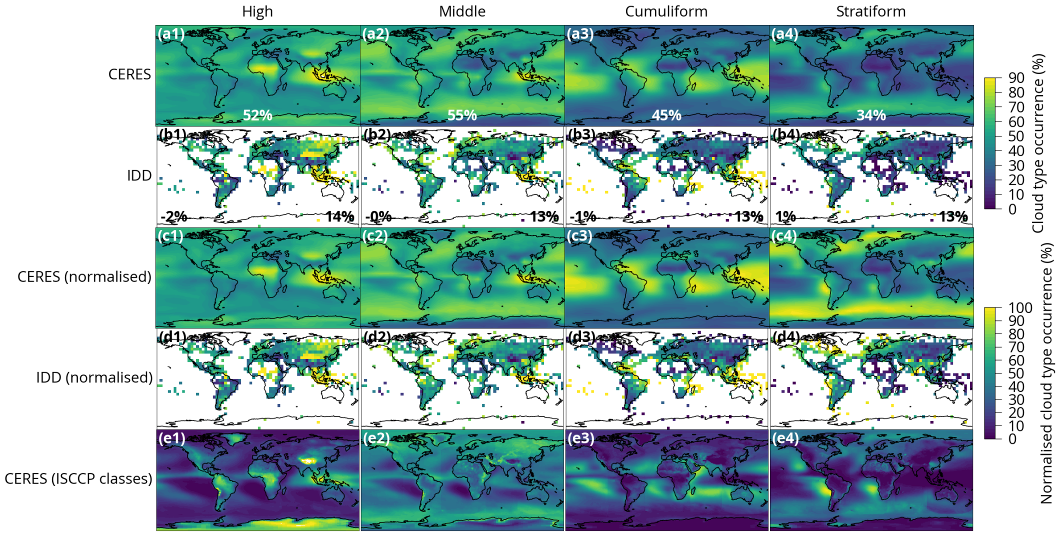
- Input: CERES and equivalent climate model SW and LW radiation data in samples (as above).
- Output: Probability of observing the cloud types for every pixel of the sample.

Outline

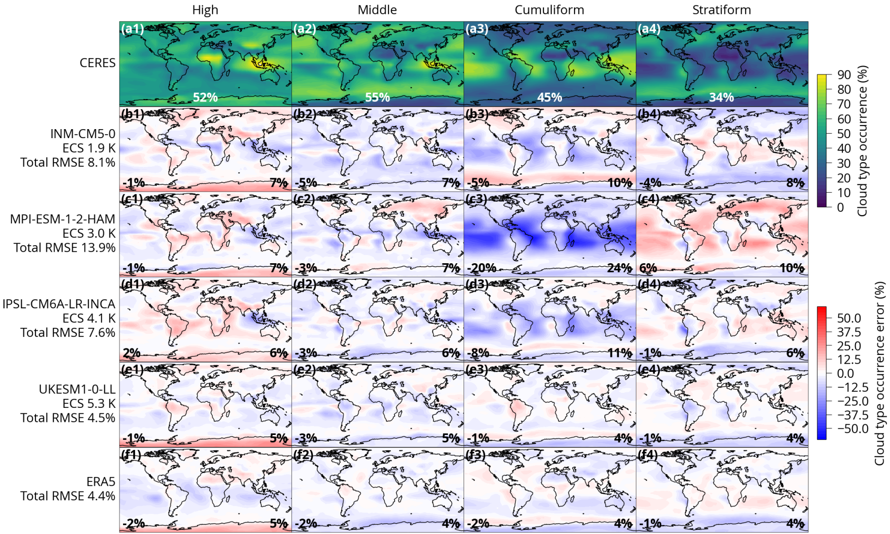


(a) *Training phase*
CERES
sample images
with station data
training
ANN
(U-Net)
(b) *Application phase*
CERES
or model
sample images
ANN
(U-Net)
application
samples of quantified
cloud occurrence
geographical
distribution
global
mean and trend
(c) *ANN operation*
sample image
48
48
SW
LW
(2 channels per sample)
ANN
(U-Net)
application
48
48
High
Middle
Cumuli-
form
Strati-
form
Probability of observing clouds of a given type
at a virtual ground station (if not obscured).

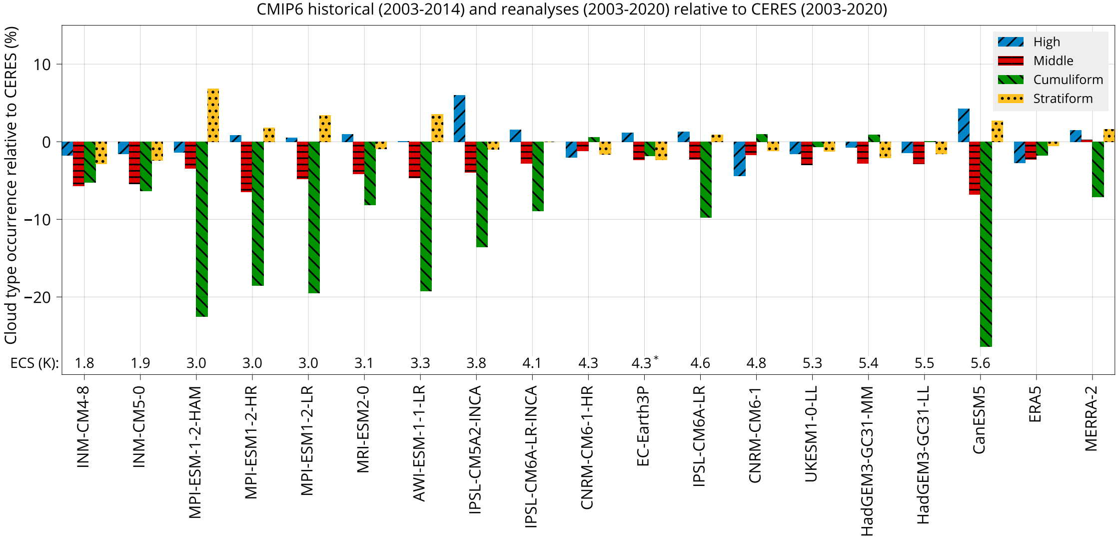
Results: geographical distribution of cloud types in observations



Results: geographical distribution of cloud types in models



Summary



CMIP6 historical (2003-2014) and reanalyses (2003-2020) relative to CERES (2003-2020)
Cloud type occurrence relative to CERES (%)
10
0
−10
−20
High
Middle
Cumuliform
Stratiform
ECS (K):
1.8
1.9
3.0
3.0
3.0
3.1
3.3
3.8
4.1
4.3
4.3*
4.6
4.8
5.3
5.4
5.5
5.6
INM-CM4-8
INM-CM5-0
MPI-ESM-1-2-HAM
MPI-ESM1-2-HR
MPI-ESM1-2-LR
MRI-ESM2-0
AWI-ESM-1-1-LR
IPSL-CM5A2-INCA
IPSL-CM6A-LR-INCA
CNRM-CM6-1-HR
EC-Earth3P
IPSL-CM6A-LR
CNRM-CM6-1
UKESM1-0-LL
HadGEM3-GC31-MM
HadGEM3-GC31-LL
CanESM5
ERA5
MERRA-2

Relation between cloud type occurrence bias and climate sensitivity