climate change initiative

→ CLIMATE MODELLING USER GROUP

WP5.1 Machine learning to advance climate model evaluation and process understanding

Lisa Bock[1], Axel Lauer[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

cmug cci

CCI Colocation & CMUG Integration meetings 2024
16 - 18 October 2024

DLR

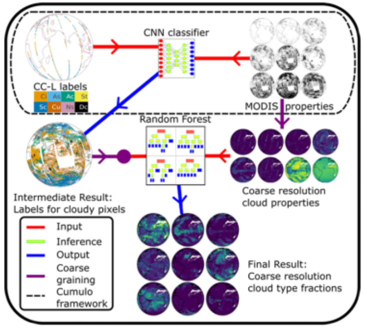
WP5.1.1 Enhancing observational products for climate model evaluation with machine learning

Input variable
Cloud water path
Cloud top phase
Effective particle radius
Cloud optical thickness
Cloud top pressure
Effective emissivity
Surface temperature

ESACCI-Cloud (complete record)

- ESA Cloud_cci L3U-AVHRR-PM v3.0
- Coarse-grained
- Grid box averages of physical variables

Trained Random Forest



Kaps et al., 2023, IEEE Transactions on Geoscience and Remote Sensing

Cloud Class Climatology dataset (CCClim, 1982-2016)

https://doi.org/10.5281/zenodo.8369201

- 8 WMO-like cloud types with a long coverage period (35 years) and high spatial resolution (1° x1°) as daily samples
- consistent seasonal variations, sensible regional distributions and little drift over the complete period
- all cloud types can be associated with relevant physical quantities

Kaps et al., 2024: Characterizing clouds with the CCClim dataset, a machine learning cloud class climatology, Earth Syst. Sci. Data

Machine-Learned Cloud Classes From Satellite Data

1. Step:

- pixel-wise classifier based on the Invertible Residual Network framework
- trained on the CUMULO dataset (year 2008) created by Zantedeschi et al. (2019)
- CUMULO contains physical variables obtained from the MODIS Cloud Product MYD06 dataset
- target labels are WMO-like cloud-type labels from CloudSat's 2B-CLDCLASS-LIDAR (CC-L) dataset

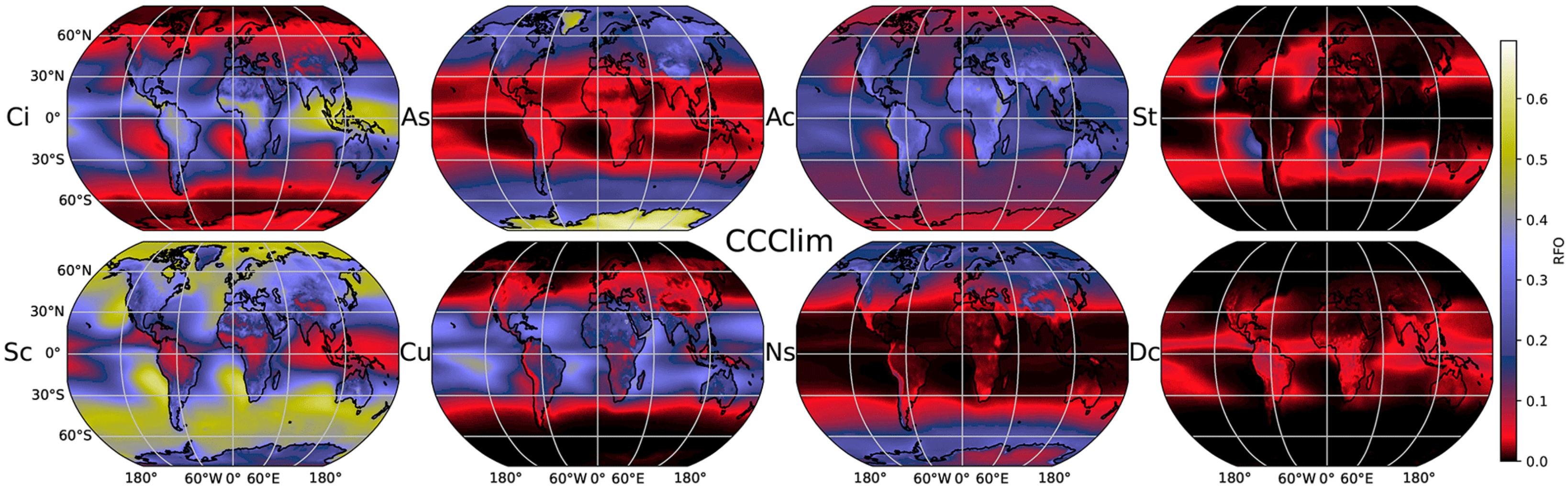
2. Step:

- application of a Random Forest (RF), which is used as a regression model to predict the relative frequency of occurrence (RFO) of each of the nine classes
- regression model trained on coarse-grained output from the first stage

CCClim

Kaps et al., 2024: Characterizing clouds with the CCClim dataset, a machine learning cloud class climatology, Earth Syst. Sci. Data

Average geographical distribution of the relative frequencies of occurrence (RFOs)



→ Can be used for the evaluation of climate models

Lisa Bock, Axel Lauer and Veronika Eyring

WP5.1.1
Enhancing observational products for climate model evaluation with machine learning

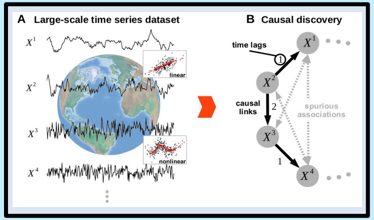
→ Paper published
Kaps et al., ESSD, 2024

- → Developing ML-based approach to derive cloud classes from coarse-scale datasets
- → Application of NN: timeseries of labelled ESA CCI Cloud data
- → Evaluation of climate models

WP5.1.2
Causal model evaluation for cloud regimes and land cover types

CCI Cloud +

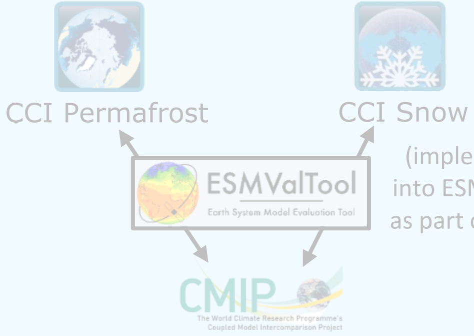
CCI Land cover, Land surface temperature, Sea surface temperature, Water vapour, Soil moisture



Causal inference (Runge et al., 2019)

- → Investigate the causal connections among the cloud properties and their controlling factors (in ESA CCI data)
- → Evaluation of global climate models

WP5.1.3
Evaluation of CMIP6 models with the ESMValTool

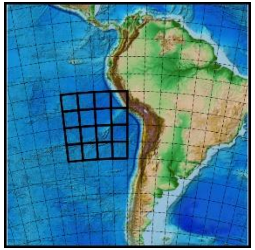


(implemented into ESMValTool as part of Task 4)

- → Evaluation of CMIP6 models
- → Investigate use of uncertainty information

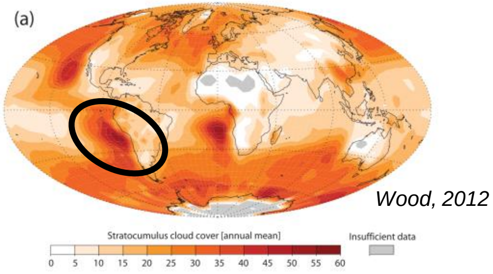
WP5.1.2 Causal model evaluation for cloud regimes and land cover types

Quantifying the causal effect of cloud controlling factors on marine stratocumulus clouds



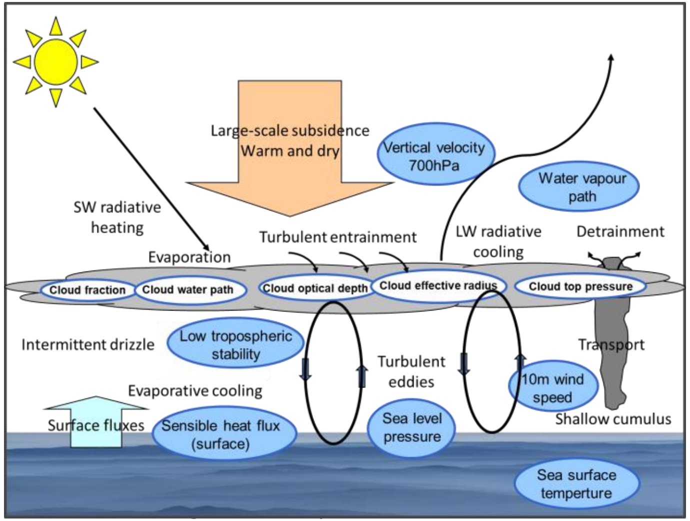
Region (South East Pacific):
75° - 95° W, 10° - 30° S
5 years daily data (2003 – 2007)

5° × 5° spatial resolution:
at this grid scale clouds are in equilibrium with their large-scale environmental controls (Klein et al., 1995)



Wood, 2012

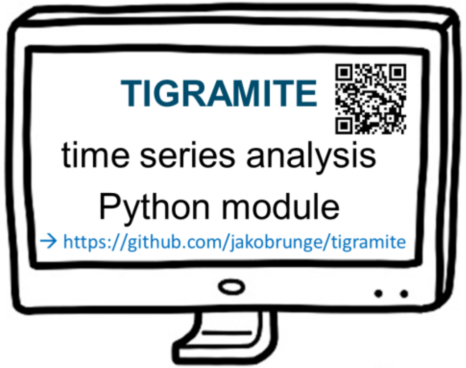
Geostationary Operational Environmental Satellites (GOES)



Data

	Variable	Dataset
Cloud Properties	Total Cloud Fraction (clt), Total Cloud Water Path (clwvi), Cloud Optical Depth (cod), Cloud Effective Radius (reff), Cloud Top Height (ctp)	ESACCI-Cloud (v3.0, L3U, AVHRR-PM, NOAA-16, daily instantaneous data) (Stengel et al., 2020)
Cloud-controlling factors	Sea Surface Temperature (tos)	ESACCI-SST (v3.0, Level 4 Analysis Product, daily) (Good et al., 2024)
	Water Vapour Path (prw)	ESACCI-Watervapour (CM SAF/CCI TCWV-global (COMBI), v3.1, daily mean data) (Schröder et al., 2023)
	Vertical Velocity at 700hPa (wap700), Lower Tropospheric Stability (LTS), Sea Surface Pressure (psl), Sensible Heat Flux at Surface (hfss), 10m Horizontal Wind Speed (sfcWind)	ERA5 (daily average from hourly data) (C3S, 2017)

Method: Causal inference



PCMCI (*Runge et al., 2019*)

→ identifies causal relationships and quantifies their strengths from time series data

→ unsupervised machine learning

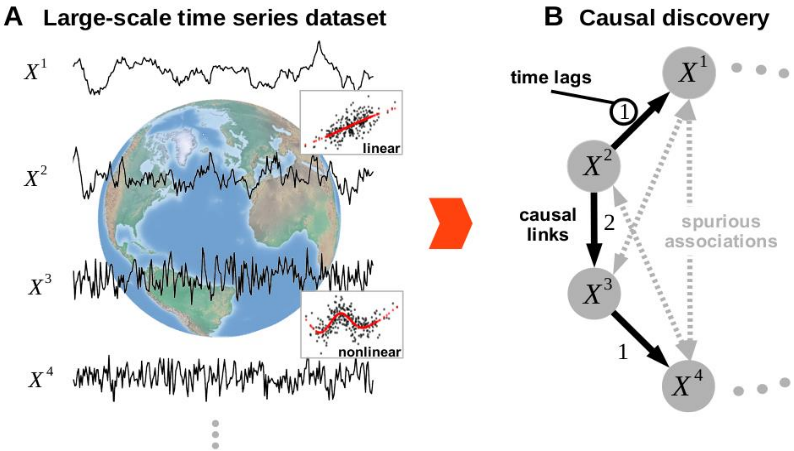
→ approach goes beyond correlation-based measures by systematically excluding common driver effects and indirect links

LPCMCI based on **Fast Causal Inference (FCI)** Algorithm: constraint-based causal discovery with conditional independence tests equal to Peter Clark (PC)-Algorithm but in the presence of unobserved variables (possibility of latent confounders)

Gerhardus and Runge, 2020

CausalEffects class: allows to estimate (conditional) causal effects and mediation based on assuming a causal graph.

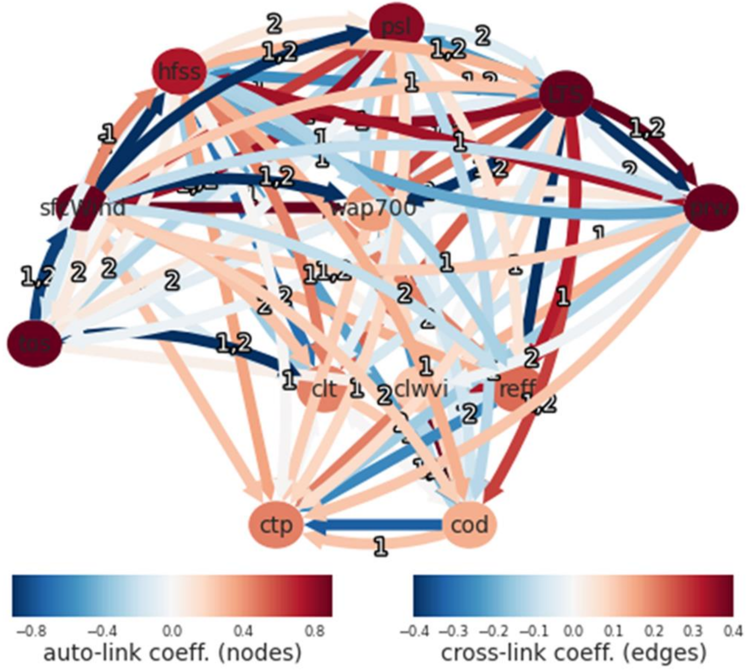
Runge et al., 2015



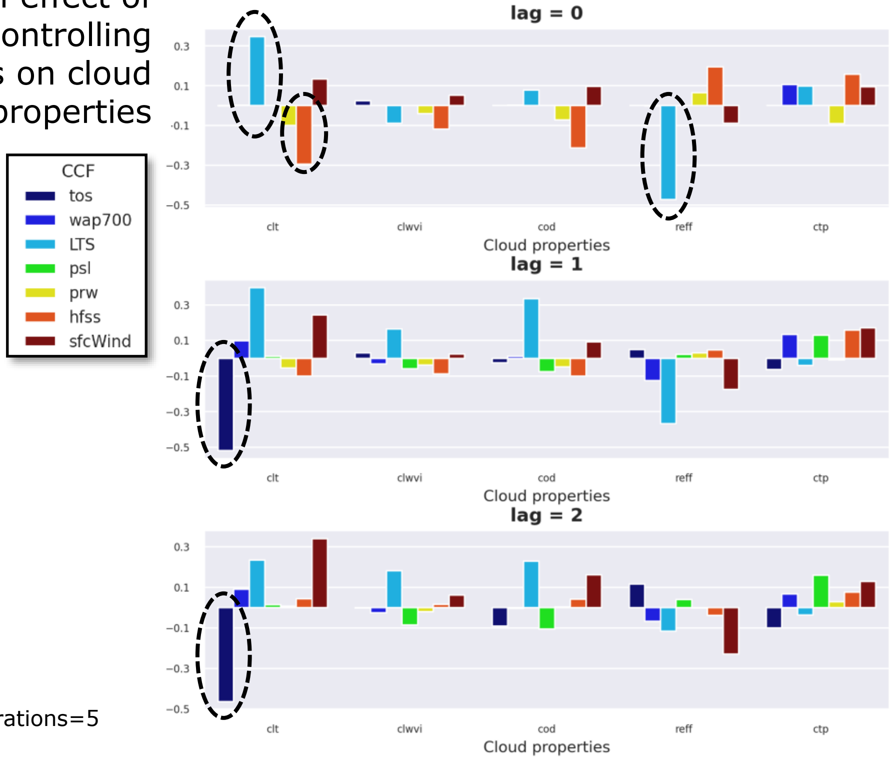
Runge et al., 2019

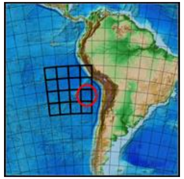
First results

Causal network



Total causal effect of cloud controlling factors on cloud properties



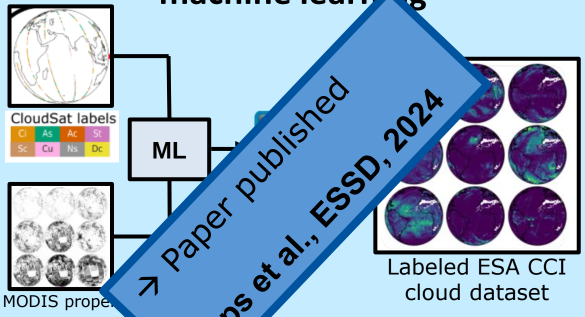


LPCMCI
max. time lag = 2
pc_alpha=0.01
tau_max = 2
n_preliminary_iterations=5

WP5.1 **Machine learning to advance climate model evaluation and process understanding**

Lisa Bock, Axel Lauer and Veronika Eyring

WP5.1.1
Enhancing observational products for climate model evaluation with machine learning



→ Paper published
Kaps et al., ESSD, 2024

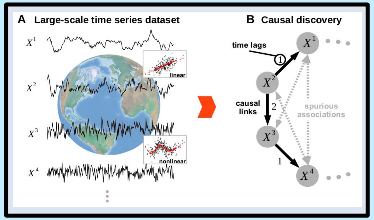
→ Developing ML-based approach to derive cloud classes from coarse-scale datasets

→ Application of NN: timeseries of labelled ESA CCI Cloud data

→ Evaluation of climate models

WP5.1.2
Causal model evaluation for cloud regimes and land cover types

CCI Cloud + CCI Land cover, Land surface temperature, Sea surface temperature, Water vapour, Soil moisture

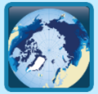


Causal inference (Runge et al., 2019)

→ Investigate the causal connections among the cloud properties and their controlling factors (in ESA CCI data)

→ Evaluation of global climate models

WP5.1.3
Evaluation of CMIP6 models with the ESMValTool



CCI Permafrost

Snow

(implemented into ESMValTool as part of Task 4)

→ Part of optional WPs

CMIP6 models

→ Evaluation of CMIP6 models

→ Investigate use of uncertainty information