Machine learning-based parameterizations for ICON and evaluation with satellite data

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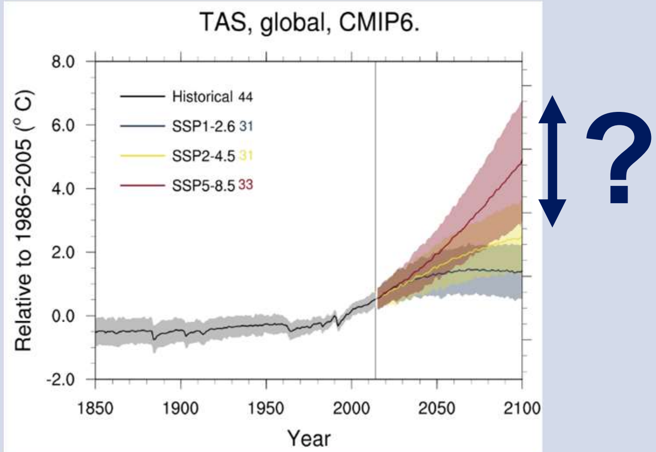
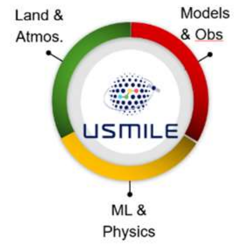


Living Planet Symposium
27 May 2022

Outline

I. ERC Synergy Grant USMILE "Understanding and Modelling the Earth System with Machine Learning"

– Problem: subgrid scale parameterizations



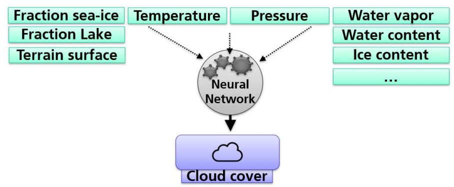
II. ML-based cloud classes from satellite data

– Towards process-based model evaluation

III. ML-based Atmospheric Parameterizations for ICON-A

– Building a machine learning based parameterization

– ML-based cloud cover parametrization for ICON-A

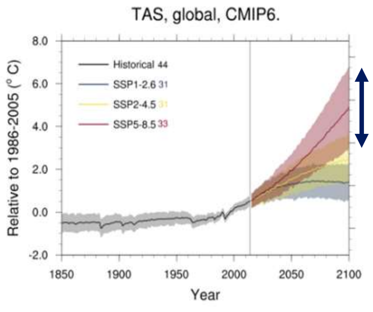


IV. Summary and Outlook

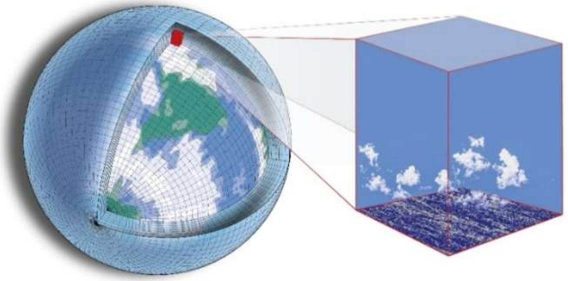
ICON: ICOsahedral Non-hydrostatic model (MPI-M, Giorgetta et al. 2018)

I. Problem: subgrid scale parameterizations

Problem …



Tebaldi et al., ESD (2021)



~50-150 km

… our approach

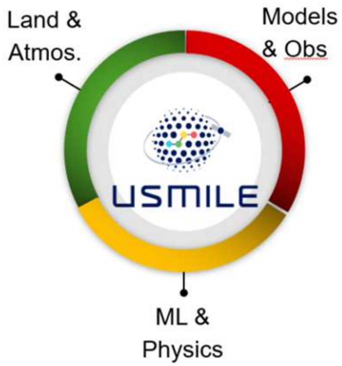
1. Massive data from Earth observation

2. High-resolution cloud resolving models

3. Progress in machine learning

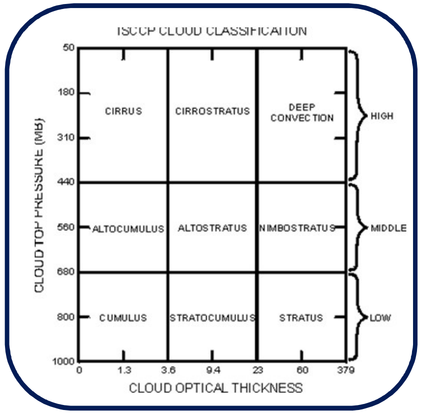
Coupled hybrid model

(ICON-ML-ESM)



II. ML-based cloud classes from satellite data (I): classification

Motivation



Data driven ML

Leverage labelled satellite products

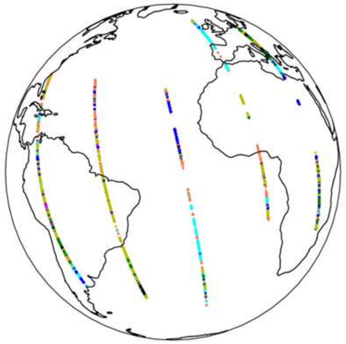
Cloud classification method
- consistent
- no simple thresholds (e.g. *cod, ptop*)
- more objective
- apply to model output

Cloud classes for **process based** model evaluation.

Improved assessment of **model realism.**

Method

CloudSat (*CLDCLASS-LIDAR*)



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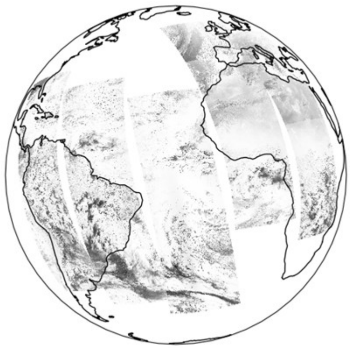
MODIS *(Cloud Product)*



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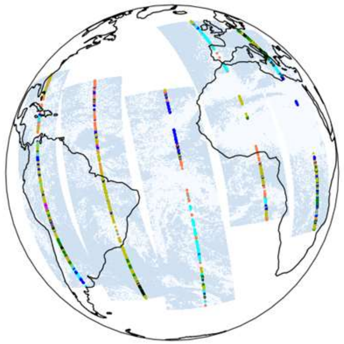
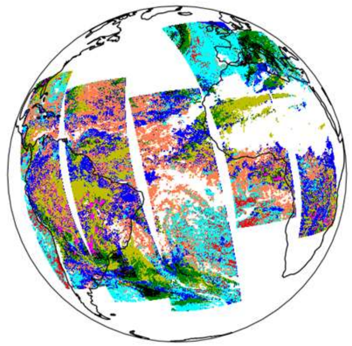
CUMULO (Zantedeschi et al., 2020)



CNN

Fully labelled 1km² data



Mean accuracy (R^2): 0.89

Kaps et al., in review

II. ML-based cloud classes from satellite data (II): coarse scale

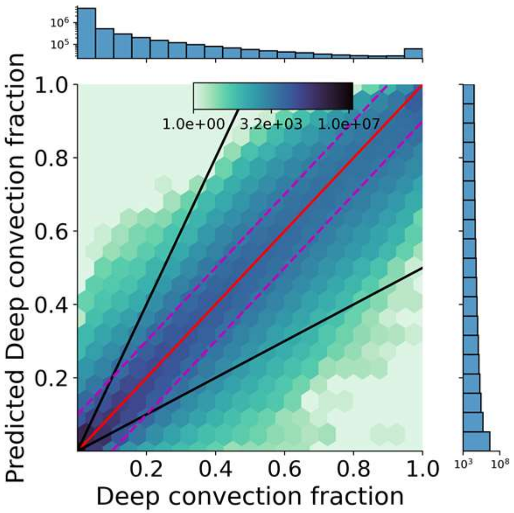
Translate labelled data (1 km^2) to coarse climate models resolution (~100 km^2)

Input variables as **grid box averages**

Cloud classes at **grid box fractions**

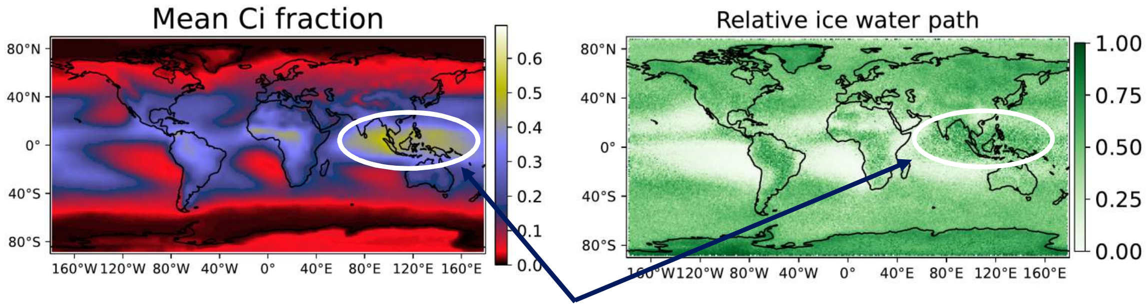
Random Forest (RF)

Multivariate regression: $\mathbb{R}^8 \rightarrow \mathbb{R}^9$



RF test-split predictions
Accuracy (R^2): 0.85

RF applied to ESA Cloud_cci



Cirrus (Ci) in the tropics, particularly over the Maritime Continent => <u>physically meaningful cloud classification</u>

Kaps et al., in review

III. Building a ML-based parameterization: cloud cover

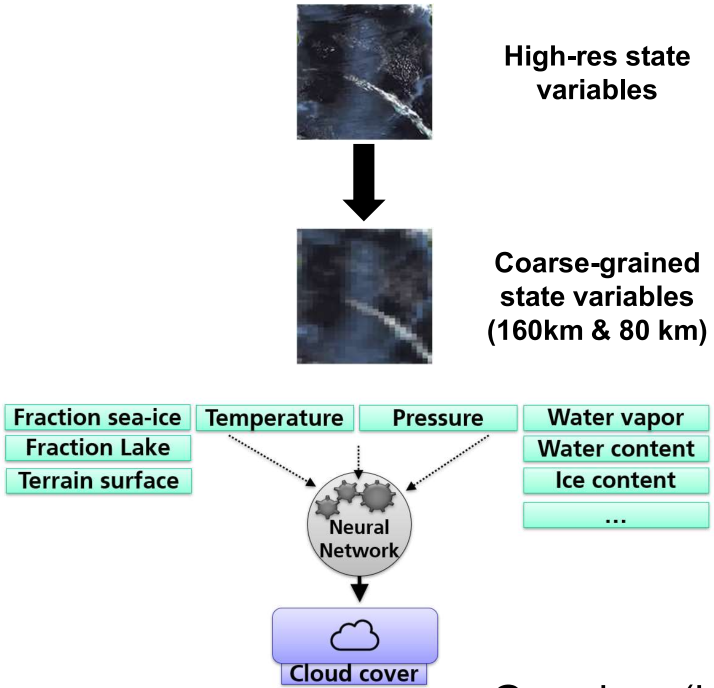
Training data from ICON CRM simulations

<u>Regional NARVAL simulations</u>

- 2.5 km resolution
- 66 layers up to 21 km
- 12/2013 and 08/2016

<u>Global QUBICC hindcast simulations</u>

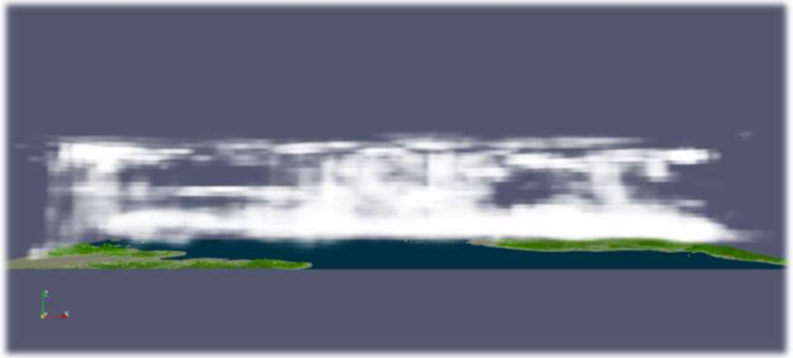
- 5 km resolution
- 87 layers up to 21 km
- 11/2004, 04/2005, 11/2005



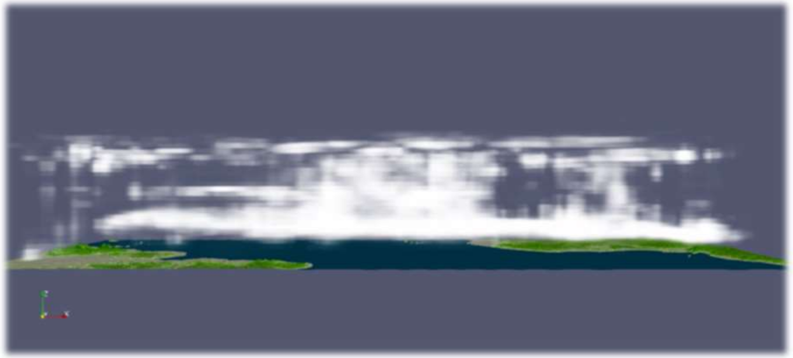
Grundner (incl. Iglesias-Suarez) et al., in review

III: ML-based cloud cover for ICON-A: visual inspection

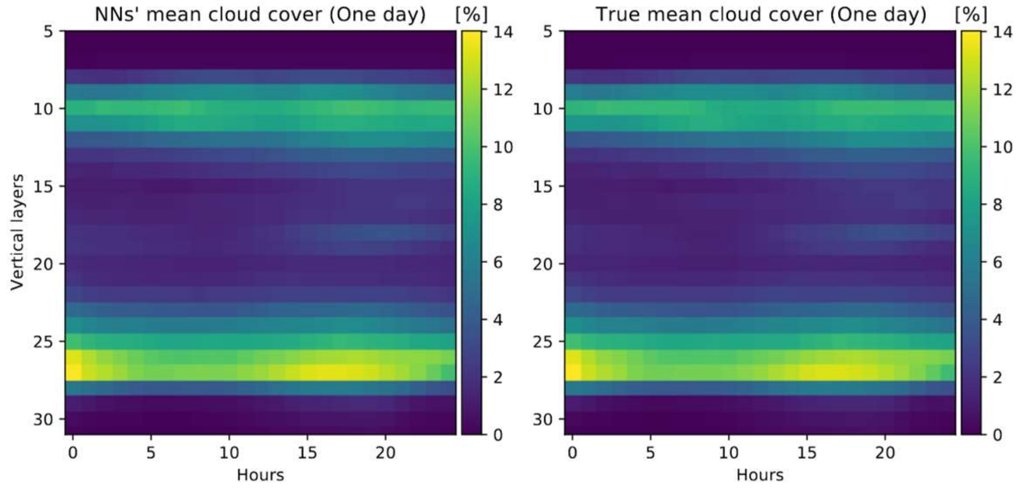
ML prediction



Reference (Coarse-grained)

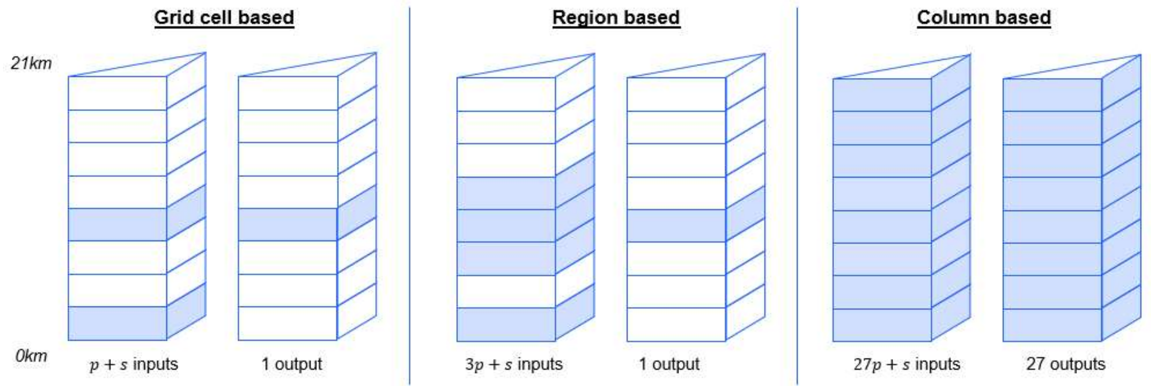


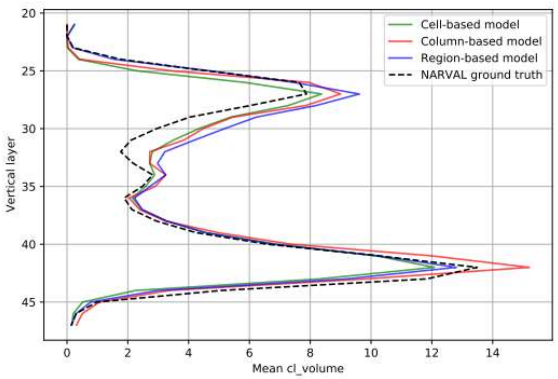
Mean Cloud Cover on 1st December, 2013
(averaged predictions on the left)



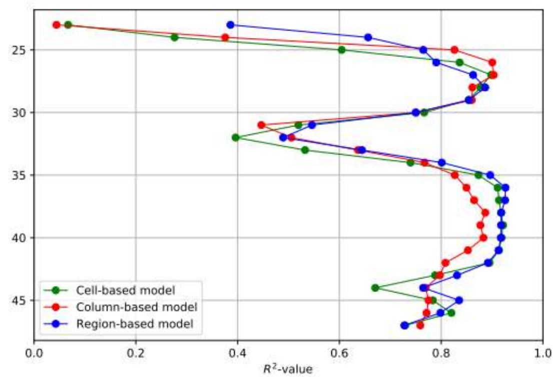
Grundner (incl. Iglesias-Suarez) et al., in review

III: ML-based cloud cover for ICON-A: accuracy & generalization





Average cloud cover profile



R^2-values

- The NNs can accurately learn subgrid cloud cover from coarse-grained CRM simulations
- **Globally trained NNs** (QUBICC) can reproduce subgrid cloud cover of the CRM simulation over the NARVAL region
- While an **increase of reproduction skill** with model complexity is visible, the skill is similar in generalizability tests across data derived from both global and regional CRM simulations.

Grundner (incl. Iglesias-Suarez) et al., in review

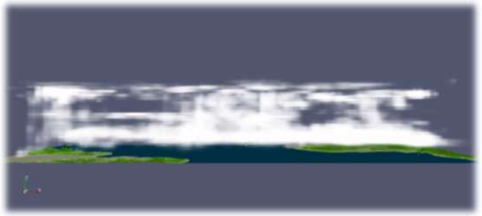
IV: Summary and Outlook

ML CLOUD CLASSES (from satellite data) FOR MODEL EVALUATION:

- Good results on high-resolution data (mean R^2 ~0.89)
- and on coarser climate models resolution (mean R^2 ~0.85);
- Physically meaningful predictions.

ML FOR ATMOSPHERIC SUBGRID PHYSICAL PROCESSES:

- Potential to be as performant as high-resolution simulations
- Demonstrates the potential of deep learning to derive accurate cloud cover parameterizations from CRMs for coarse-scale Earth system models



FUTURE OF CLIMATE MODELING:

ML-based hybrid Earth System Models with improved subgrid scale physical processes

- Novel ML-based parameterisations incorporated into Earth system models
- Key goal: a *hybrid* modelling approach that maintains physical consistency and realistically extrapolates to unseen climate regimes while reducing climate projection uncertainties.