Machine-learned cloud classes from satellite data for process oriented climate model evaluation

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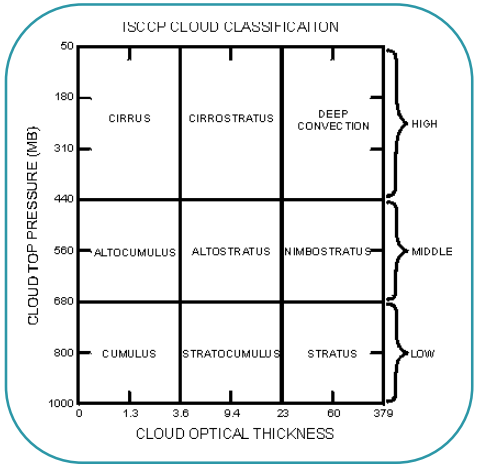
Motivation/Methodology

Aim:

Use cloud classes for **process based** model evaluation

Improve assessment of **model realism**

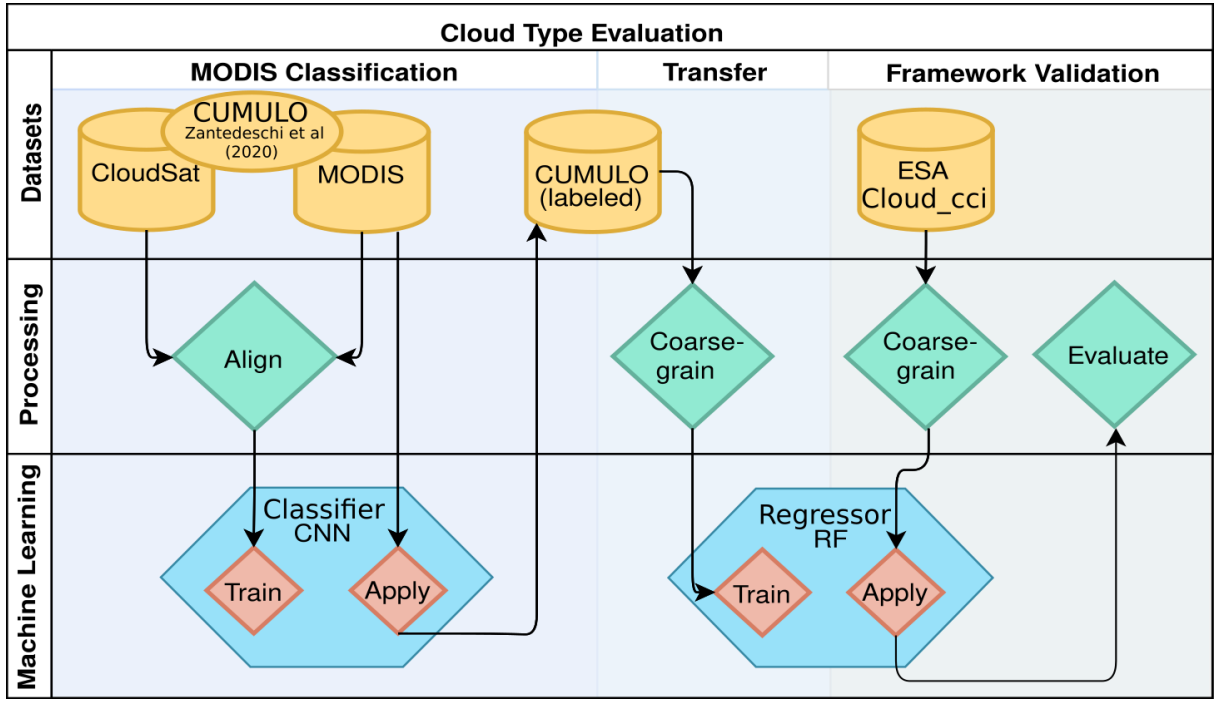


Data driven ML

Leverage labelled satellite products

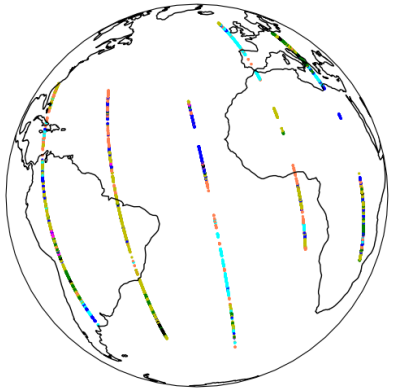
Cloud classification method

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

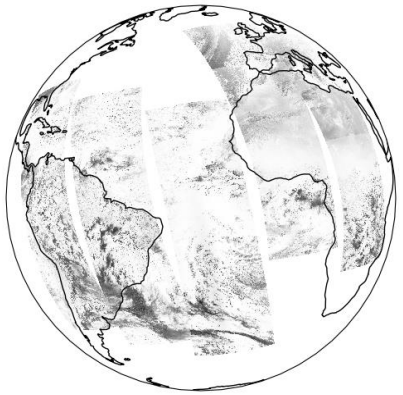


First ML-stage (pixel-wise classification)

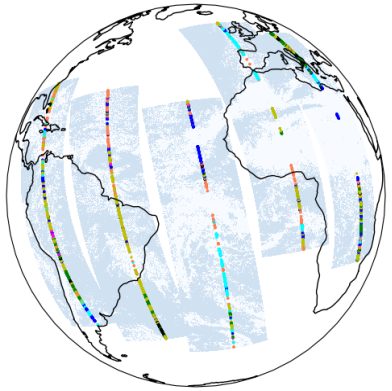
CloudSat (*CLDCLASS-LIDAR*)



MODIS *(Cloud Product)*

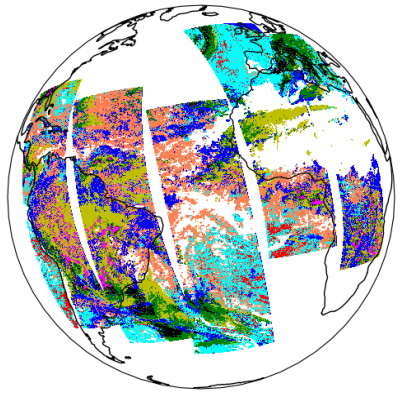


Partly labeled training data
MODIS/Cloudsat collocated



CNN

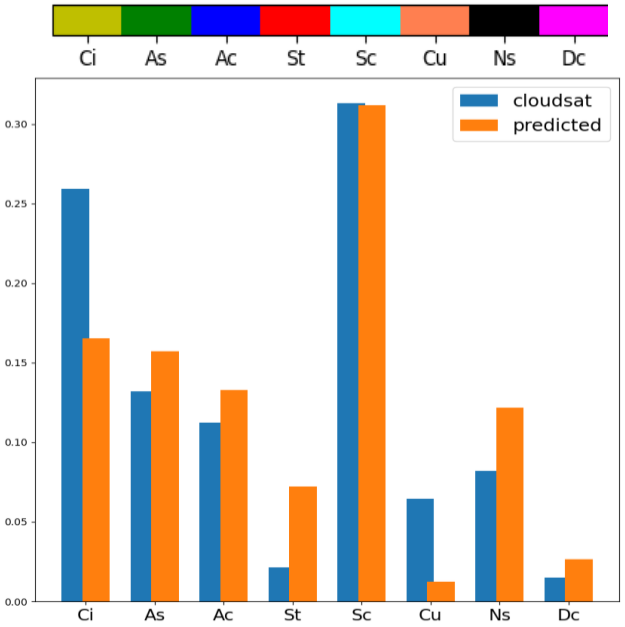
Fully labeled 1km² data
CUMULO(Zantedeschi et al 2020)



Cloud class	WMO name
Ci	Cirrus/ Cirrostratus
As	Altostratus
Ac	Altocumulus
St	Stratus
Sc	Stratocumulus
Cu	Cumulus
Ns	Nimbostratus
Dc	Deep convective

Input feature	Abbv.
Total/liquid/ice water path	cwp/ lwp/ iwp
Effective liquid/ice particle radius	cerl/ ceri
Cloud optical thickness	cod
Cloud top pressure	ptop
Effective emissivity	ceff
Surface temperature	tsurf

- Label each cloudy 1 km² pixel
- Class imbalance well reproduced
  - Mean **accuracy:** 0.89
  - Mean **F1-Score:** 0.47



Second ML stage (regression)

CNN is trained on 1 km² ⇔ climate models output much **coarser**

Translate labelled data to lower resolution: Construct **grid boxes** roughly at model resolution

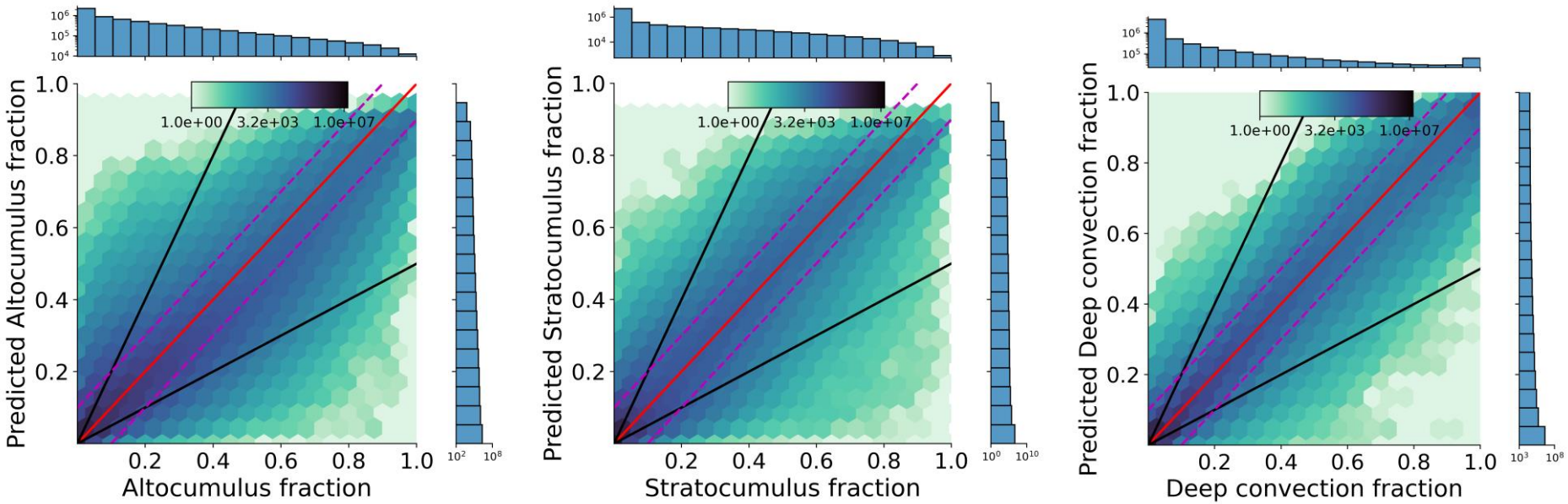
Input variables as **grid box averages**

Cloud classes at **grid box fractions**

Second ML stage: Random Forest
Multivariate regression $\mathbb{R}^8 \rightarrow \mathbb{R}^9$

Test-split predictions for (100x100)km grid boxes

Mean abs. error	Median abs. error
0.027	0.004
Median rel. error	**R2-Score**
52.6%	0.85

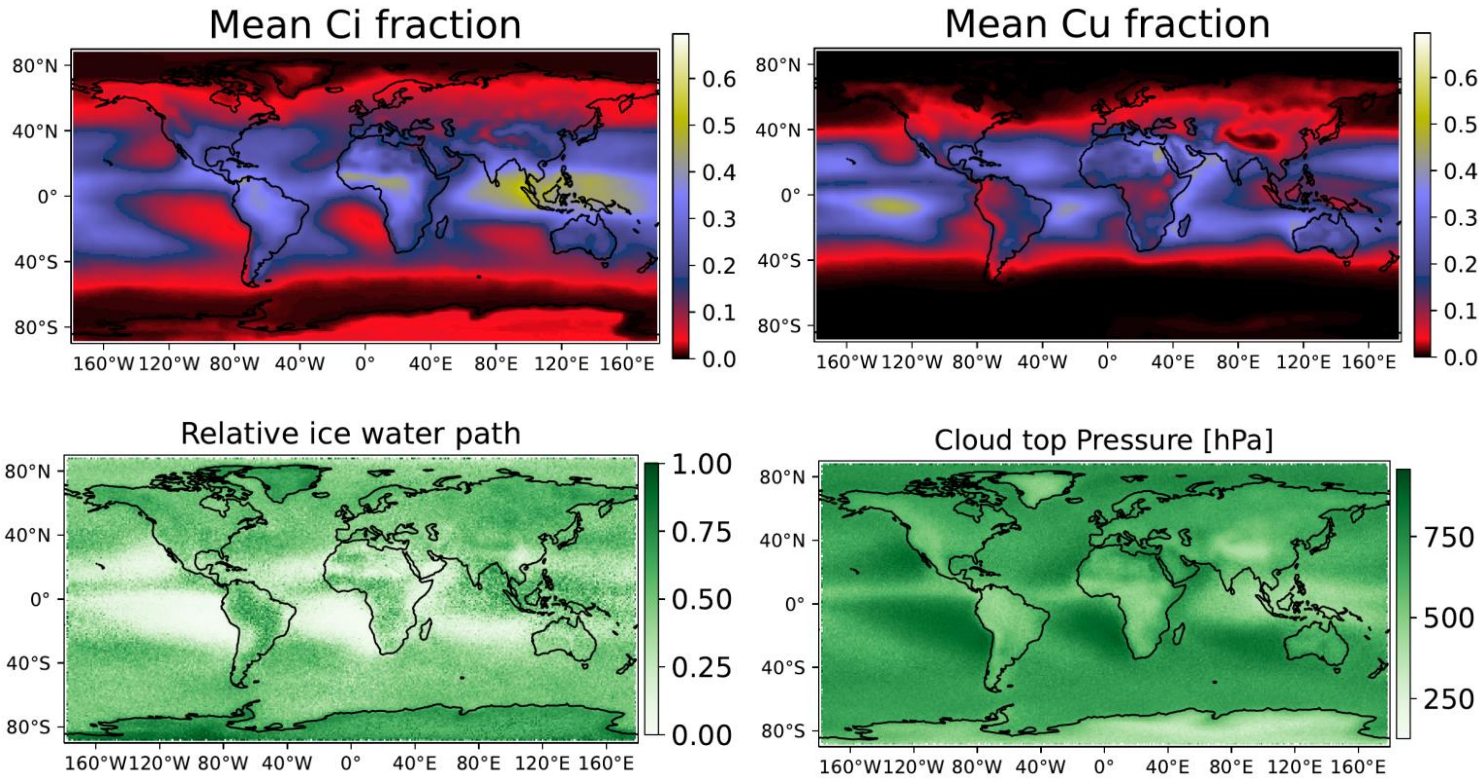


Framework Validation

Apply RF to ESA Cloud_cci

- Independent **observational** data
  - Not influenced by simulation errors
- **Coarse grained** to typical ESM resolution
- Assess physical consistency of framework

RF predictions on ESA Cloud_cci



Conclusion

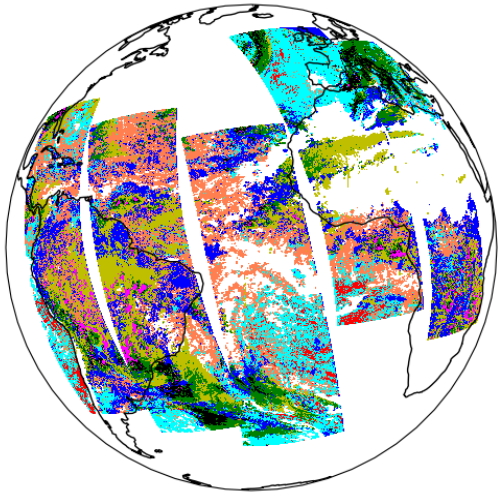
Method for analyzing **coarse** data in terms of **cloud types**:

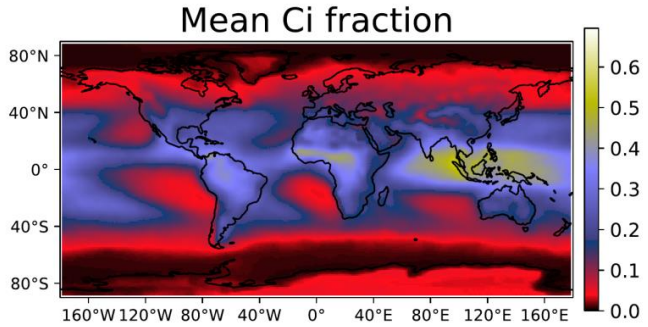
- CloudSat as **objective** basis for classification
- Good results on test data:
  - Mean error 0.027, median error 0.004
- **Physically reasonable** on independent satellite data

→ **Generalization to climate model output is likely**

- Represented directly in terms of cloud types
- Analyse **processes** of cloud formation and evolution
- Compare to predictions on satellite data
- Recommend additonal variables in CMIP7 data request
  - instantaneous
  - e.g. optical thickness, cloud top pressure

High-res classification





Coarse data regression

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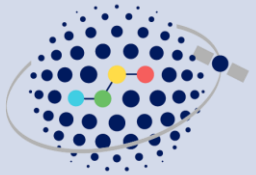

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