Machine Learning-Based Approaches to Predict the Autoconversion Rates from Satellite Data

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Methodology

- Generate input-output pairs from atmosphere simulation model
- Train and test data on various machine learning approaches
- Choose the best machine learning (ML) model
- Predict the autoconversion rates directly from satellite data using the best ML model

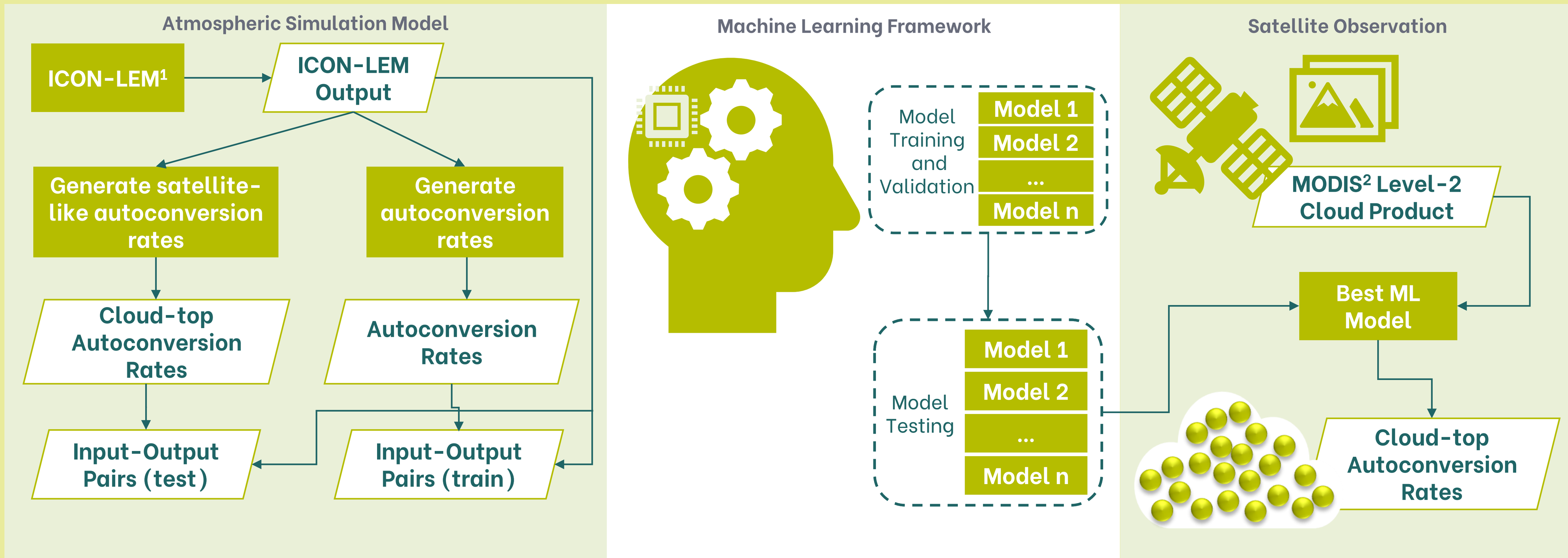


Figure 1: General framework. 1 ICOsahedral Non-hydrostatic Large-Eddy Model; 2 Moderate Resolution Imaging Spectroradiometer.

Results

- The machine learning models produced good outcomes, with Log structural similarity index (SSIM) of the best model exceeding 90%.

Autoconversion on Simulation Models (Cloud-top ICON)

This set of experiments seeks to establish whether one can predict autoconversion rates from simulated satellite data

Table 1: Evaluation of autoconversion prediction results on simulation model - ICON-LEM Germany

ML	SSIM (Log)
LR	88.69%
PR	90.21%
RF	90.31%
DNN	90.32%

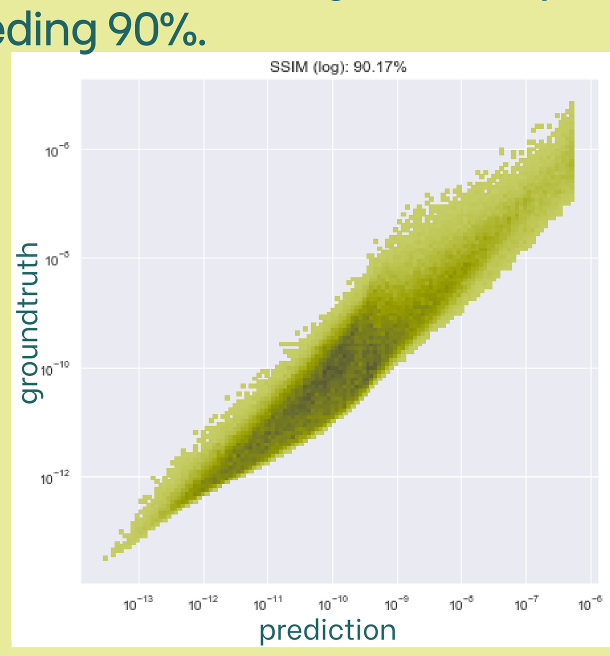


Figure 2: Regression plot of the DNN prediction and groundtruth.

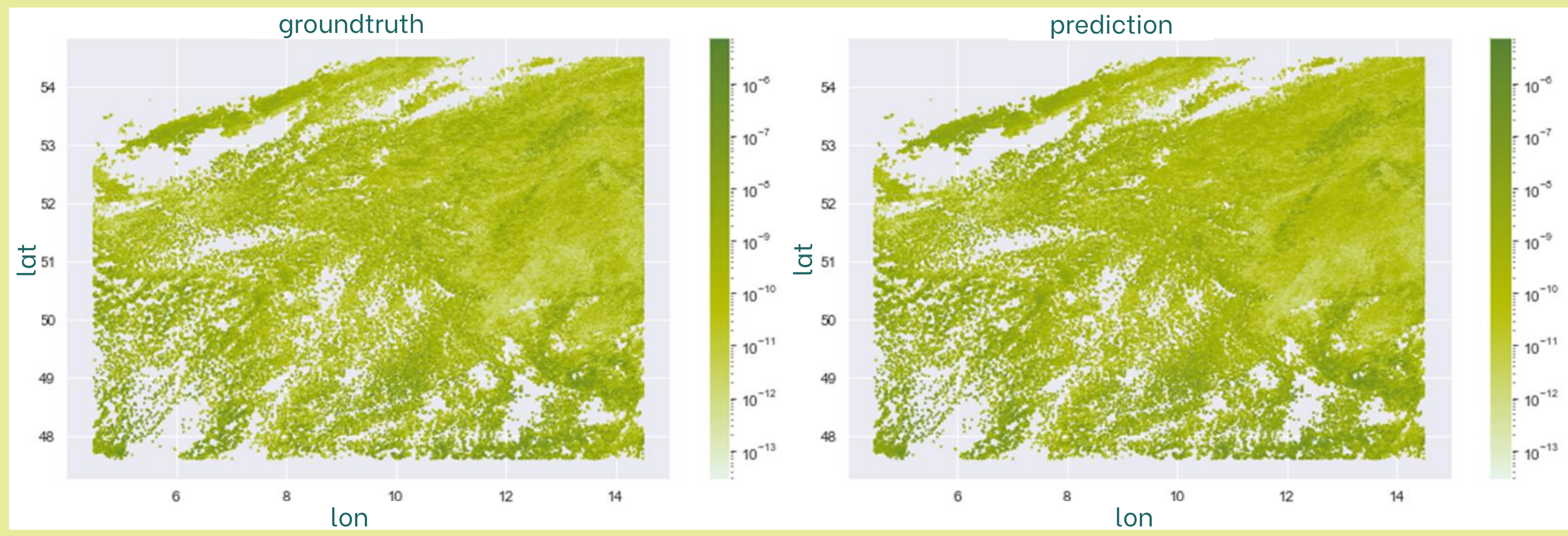


Figure 3: A comparison of the autoconversion rates predicted by DNN with groundtruth over Germany on 2 May 2013 at 1:20 pm.

Autoconversion on Satellite Observation (MODIS)

This set of experiments seeks to establish whether one can predict autoconversion rates from real satellite data

Table 2: Statistical properties of the autoconversion rates of satellite simulator (COSP) and satellite prediction (MODIS) over Germany on 2 May 2013 at 1:20 pm.

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
Aut ICON (kg m^{-3} s^{-1})	1.25e-08	8.75e-08	2.86e-11	2.12e-10	1.73e-09
Aut MODIS (kg m^{-3} s^{-1})	1.31e-08	4.19e-08	6.28e-11	2.20e-10	1.70e-09

- The autoconversion rates of satellite data (MODIS) predictions demonstrate statistical agreement with the autoconversion rates of satellite-like data (cloud-top ICON).

Background

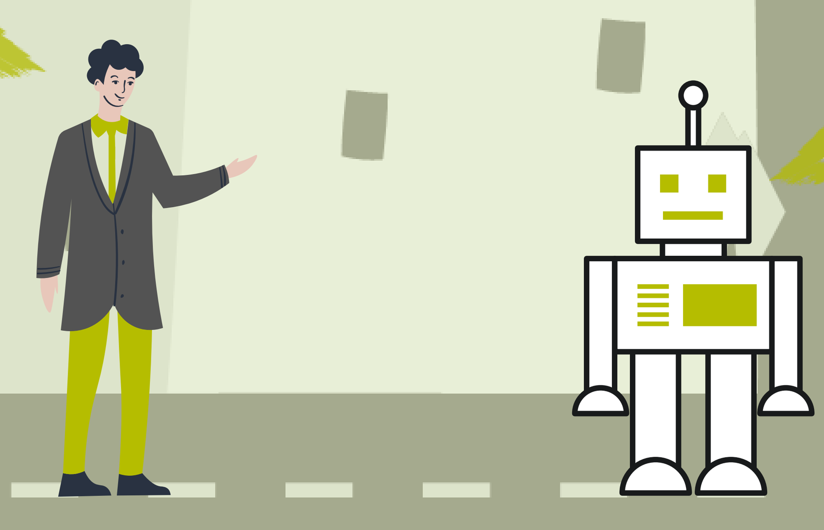
10: Ohh, I forgot to explain. It's the term used to describe the rate of **collision and coalescence of cloud droplets responsible for raindrop formation**.

8: Sadly, this model is **bloody expensive** [2] thus **impractical for global coverage and a longer period of time**. If only I could leverage a plethora of satellite observations which provide long-term global spatial coverage.

6: Yes, we have high-resolution model simulations such as ICON-LEM.

4: One way of reducing those uncertainties is by unravelling one of the key processes of precipitation formation for liquid clouds, namely the autoconversion rate, which in turn is key to better understanding cloud responses to anthropogenic aerosols.

2: Hey! I keep thinking about the **largest source of uncertainty in future climate projections** [1]. Pollution particles (aerosols) have most likely offset some of the greenhouse warming to date, particularly through their interaction with clouds. However, despite decades of intensive research, significant uncertainties in the magnitude of this cooling still persist.



9: Ahha, that's easy! Have you forgotten that **I am a machine learning**? I'll show you some magic! Btw, what is the **autoconversion rate**?

7: Then, problem solved right?

5: I thought you have some kind of atmosphere simulation model to solve this problem, no?

3: Is there any way to reduce those uncertainties?

1: Hey scientist, why do you look so gloomy today?

Conclusions

- Machine learning could help unravel the key process of precipitation -- autoconversion rates -- directly from satellite data (*this has not been attempted by other studies*)

References:

[1] IPCC. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen,. Cambridge Univ. Press, (In Press):3949, 2021.

[2] M. Costa-Surós, O. Sourdeval, C. Acquistapace, H. Baars, C. Carbajal Henken, C. Genz, J. Hesemann, C. Jimenez, M. König, J. Kretzschmar, N. Madenach, C. I. Meyer, R. Schrödner, P. Seifert, F. Senf, M. Brueck, G. Cioni, J. F. Engels, K. Fieg, K. Gorges, R. Heinze, P. K. Siligam, U. Burkhardt, S. Crewell, C. Hoose, A. Seifert, I. Tegen, and J. Quaas. Detection and attribution of aerosol–cloud interactions in large-domain large-eddy simulations with the icosahedral non-hydrostatic model. Atmospheric Chemistry and Physics, 20(9):5657–5678, 2020.

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