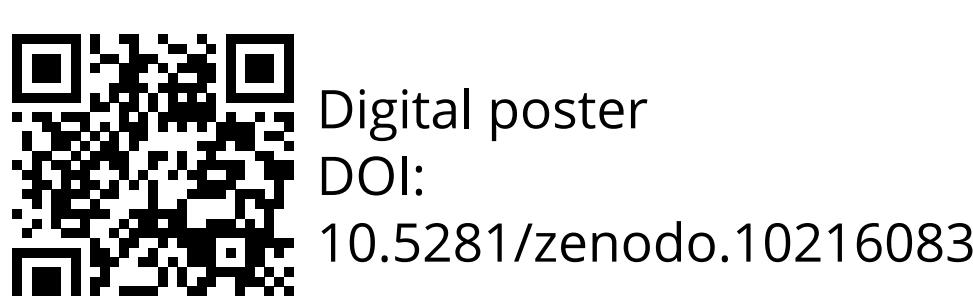


Using ship observations to assess Southern Ocean clouds in a storm-resolving general circulation model ICON



Digital poster

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Abstract

Substantial biases in Southern Ocean boundary layer clouds exist in climate models. Is this also true for storm-resolving global models at 5 km resolution which explicitly resolve convection without parametrisation? We evaluate clouds in the ICON model compared to ceilometer observations on RV *Polarstern* voyages and compare concurrent radiosonde observations.

Aims

- Process ceilometer, lidar, radiosonde and automatic weather station (AWS) data from RV *Polarstern* voyages in the Southern Ocean.
- Use a (offline) ground-base lidar simulator to generate co-located virtual lidar profiles from ICON and compare them with the observations.
- Use radiosonde profiles and AWS to link biases in boundary layer clouds to the driving processes.

Methods

Voyages

- We analysed 24 voyages of RV *Polarstern* in the Southern Ocean south of 40°S between years 2010 and 2021: ANT-XXIX/2–9, ANT-XXVII/2–3, ANT-XXVIII/2–4, PS89, PS96–97, PS103–104, PS111–112, PS117–118, PS123–124.
- We only included data south of 40°S
- A total of 1156 days of observations were included.
- Ceilometer Vaisala CL51 operating at 910 nm was used on the voyages.
- Radiosondes were launched at synoptic times during the voyages.
- Surface meteorological quantities were measured continuously.

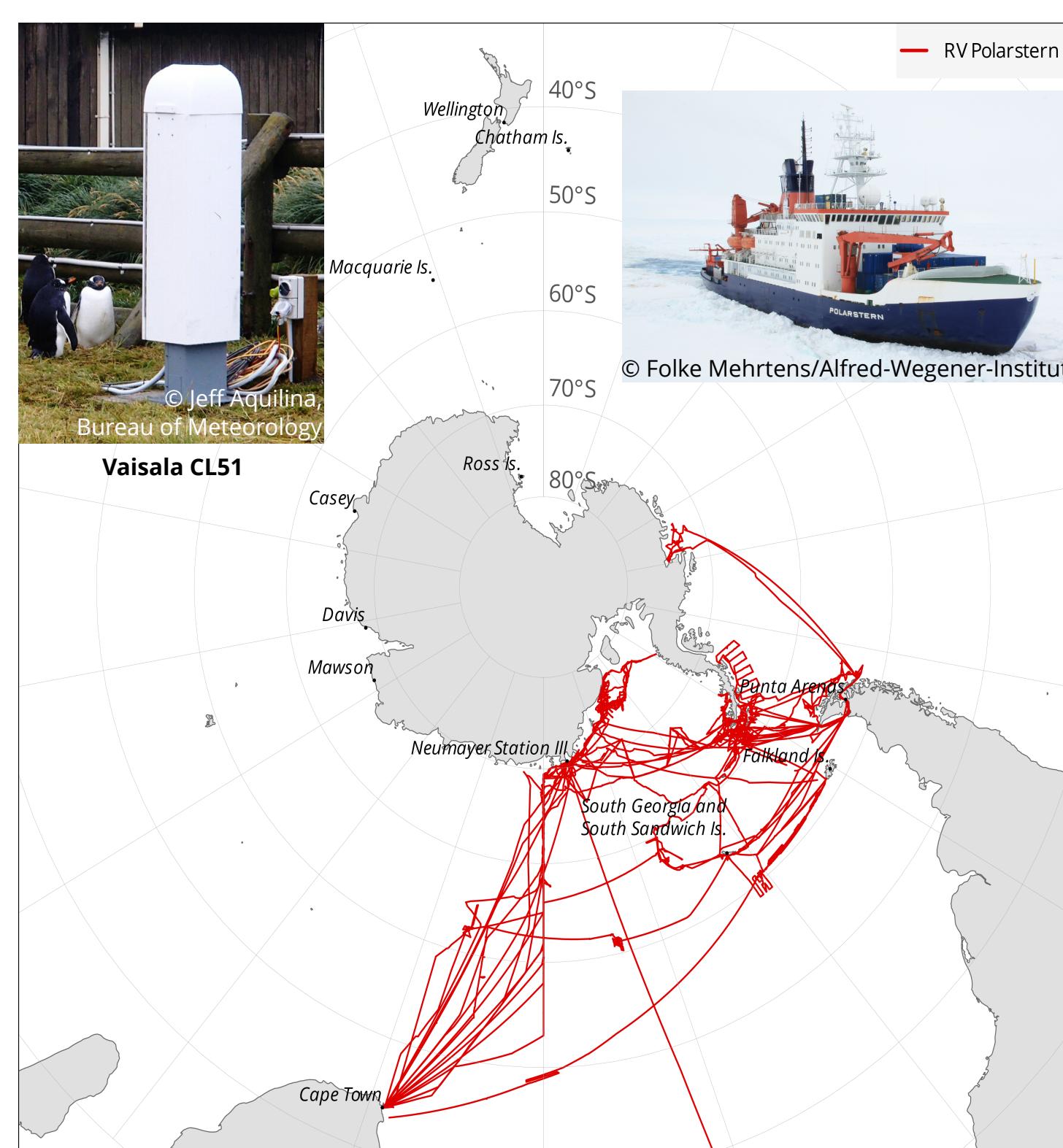


Figure | Tracks of the 24 RV *Polarstern* voyages between Africa, South America and Antarctica in years 2010 to 2021, a photo of the ship, and a photo of the Vaisala CL51 ceilometer.

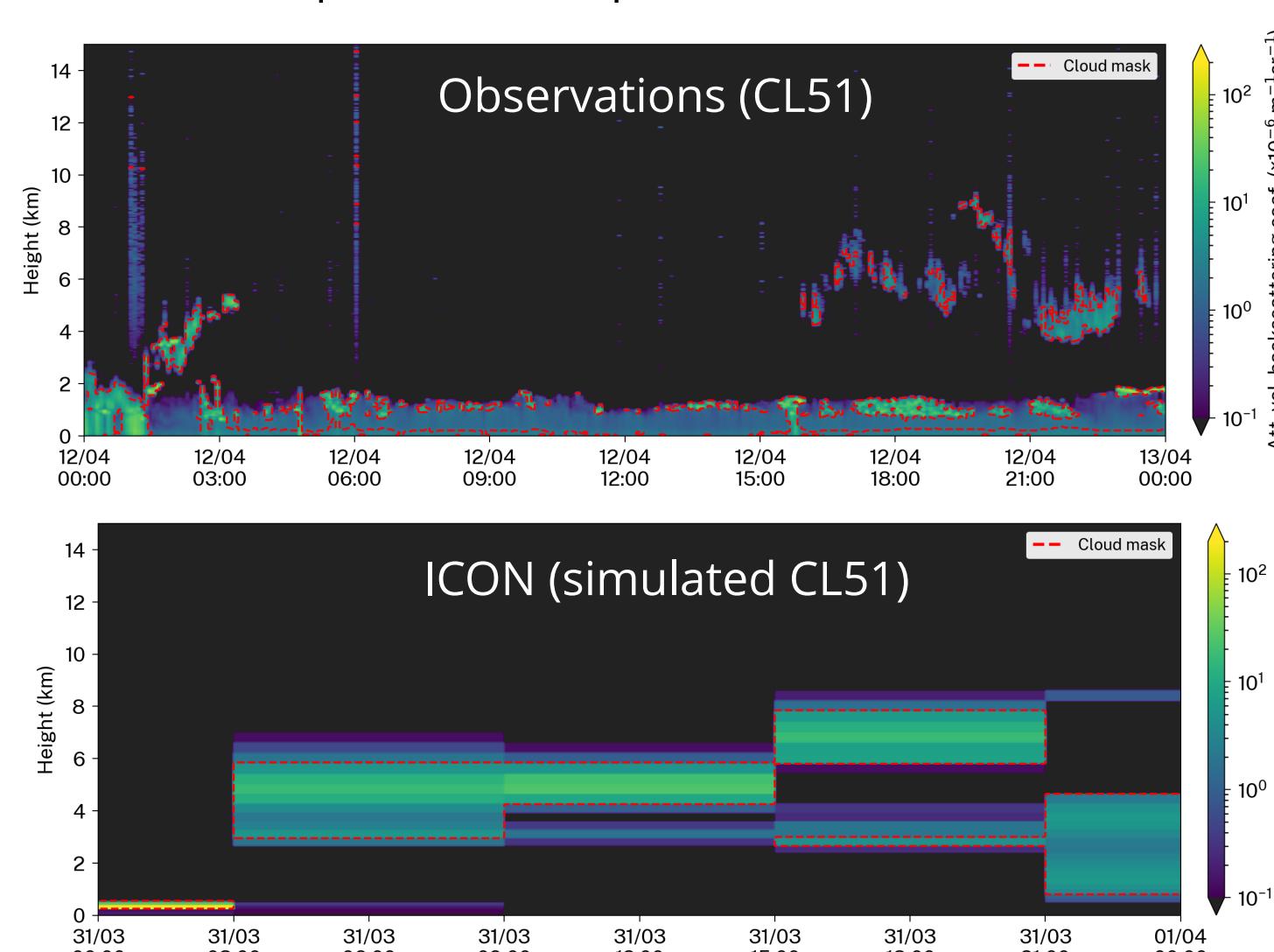
ICON

- We used 'Cycle 3' storm-resolving version of the Icosahedral Nonhydrostatic (ICON) Weather and Climate Model in development by the NextGEMS project.
- The horizontal resolution is about 5 km.
- 1 year coupled simulation in 2021.
- Unlike current GCMs, it does not parametrise mass flux, but resolves convection explicitly.
- Turbulence is parametrised.
- Grid box cloud fraction is always either 0 or 100%.
- The model is free running. Therefore, when comparing to observations, we take the same geographical location and time relative to the start of the year.



Lidar simulator

- We used the ground-based lidar simulator Automatic Lidar and Ceilometer Framework (ALCF) to compare the model with observations.
- ALCF is based on the instrument simulator COSP.
- ALCF calculates simulated lidar backscatter from offline model fields of cloud liquid and mixing ratio, cloud fraction, temperature and pressure.

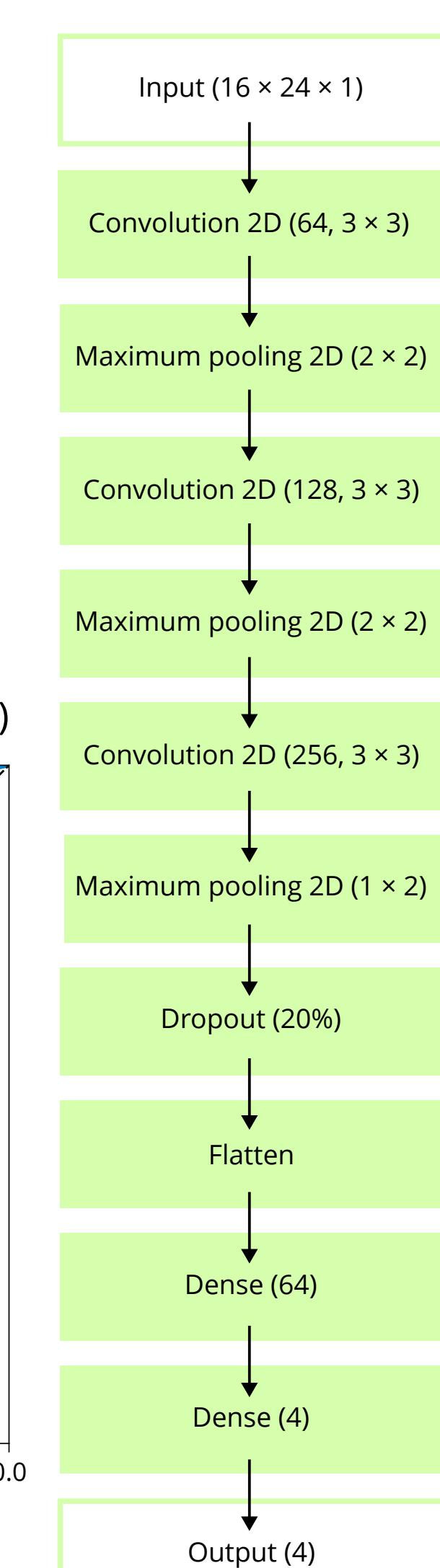


Conclusions

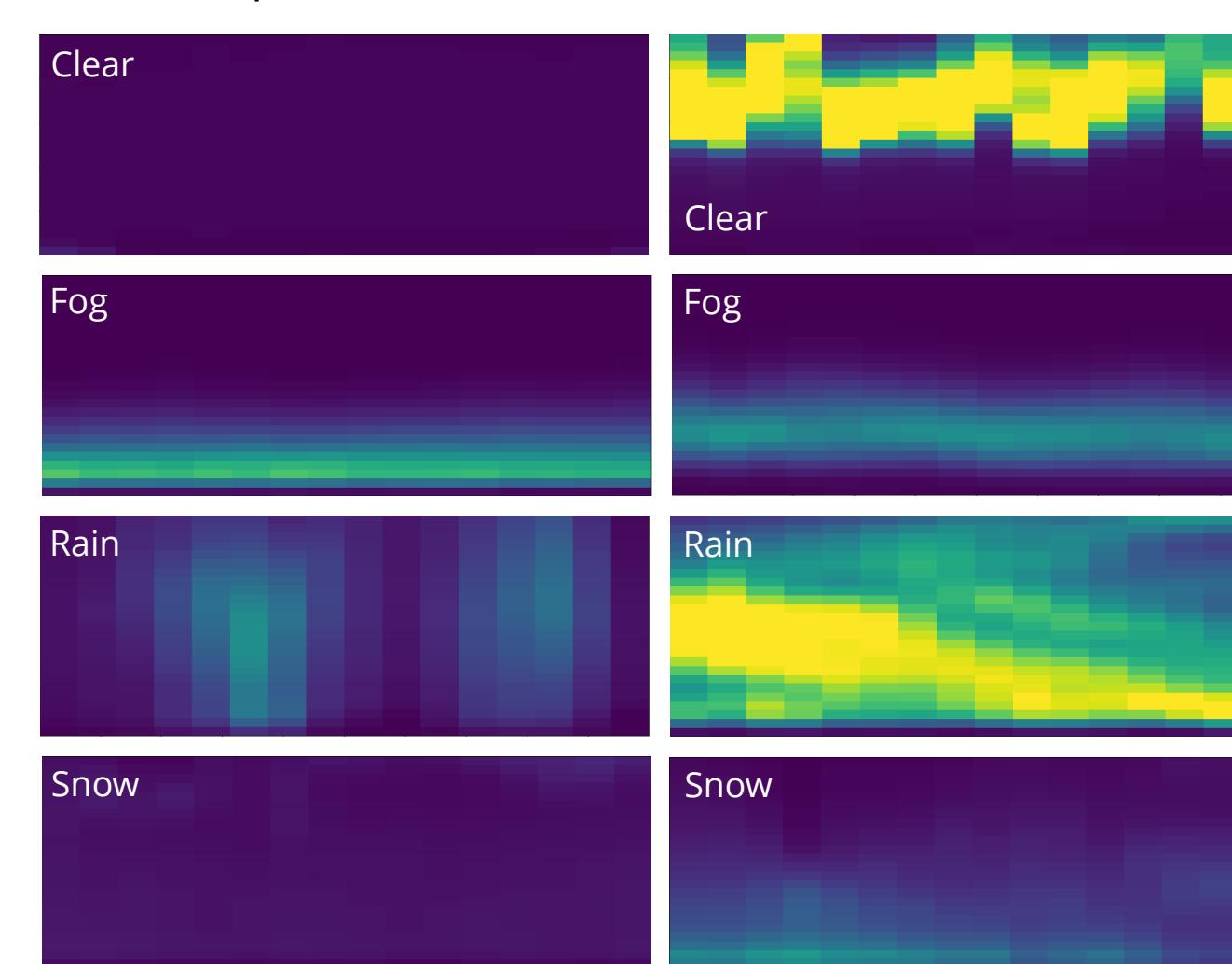
- The model underestimates the total cloud fraction by about 10%.
- The model overestimates cloud occurrence near the surface (0–1 km), but underestimates cloud occurrence above 1 km.
- The peak of cloud occurrence is at the surface in observations, indicating frequent fog, but in the model the peak is higher (about 250 m).
- Comparison of radiosonde profiles indicates that this is due to the lifting condensation level peaking higher in the model (about 200 m) than in the observations (at the surface).
- The model does not reproduce the entire natural variability of the atmospheric thermodynamic profile.
- The causes for the overestimated and underestimated cloud occurrence remain to be investigated.
- We hypothesise that the surface mixed layer is shallower in the model than in observations, causing the cloud cover to peak at lower height.

Filtering out precipitation using machine learning

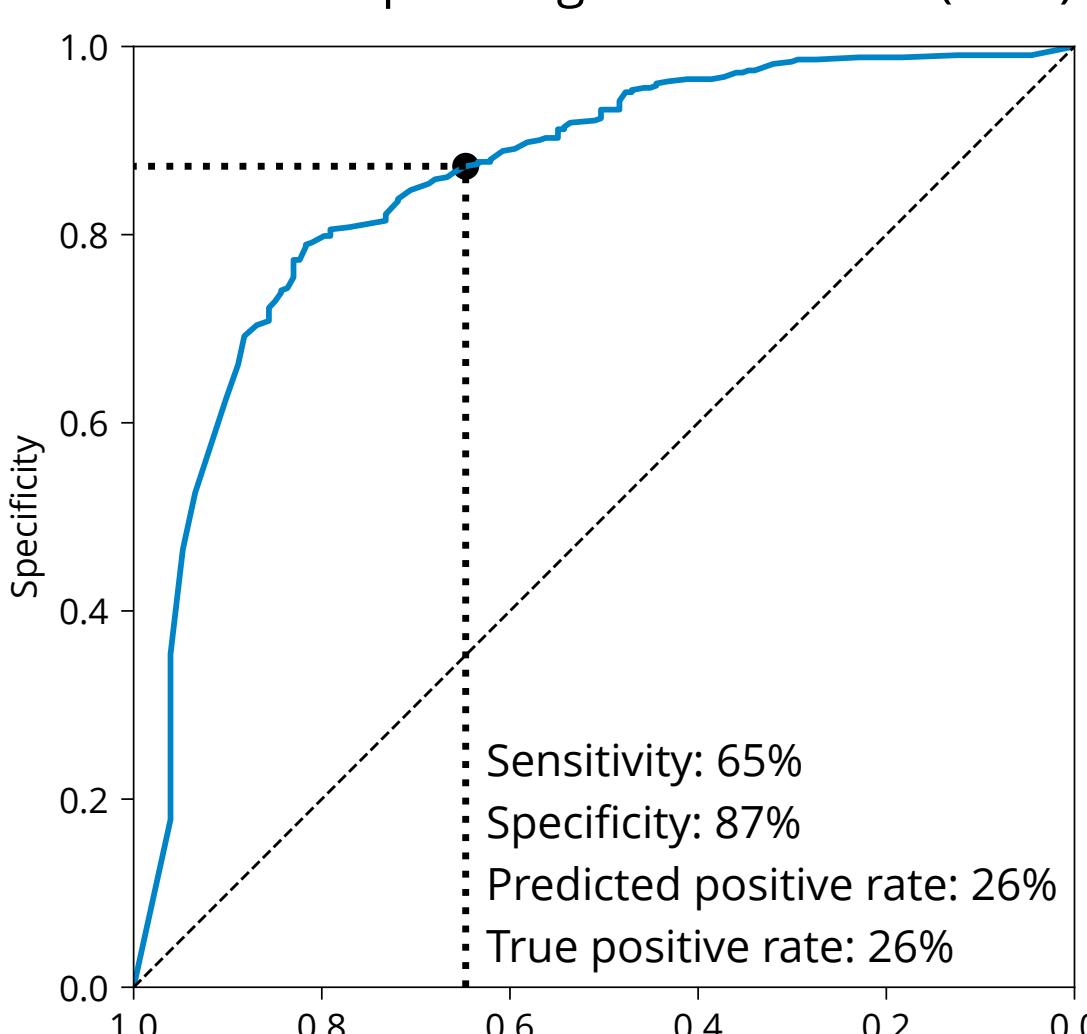
- We need to filter out profiles with precipitation because it cannot be easily distinguished from clouds in observations, and cannot be compared with the model, which does not provide precipitation mixing ratios.
- Instruments such as a rain gauge are not reliable on ships.
- We train a convolutional artificial neural network (ANN) to recognise short time intervals (10 min) of near-surface backscatter (0–250 m) as having precipitation or fog.
- Human-performed observations at synoptic times are used as a training reference for clear, fog, rain and snow conditions near the surface.
- The ANN achieves 65% sensitivity and 87% specificity when the true positive rate (26%) is made to match observations.



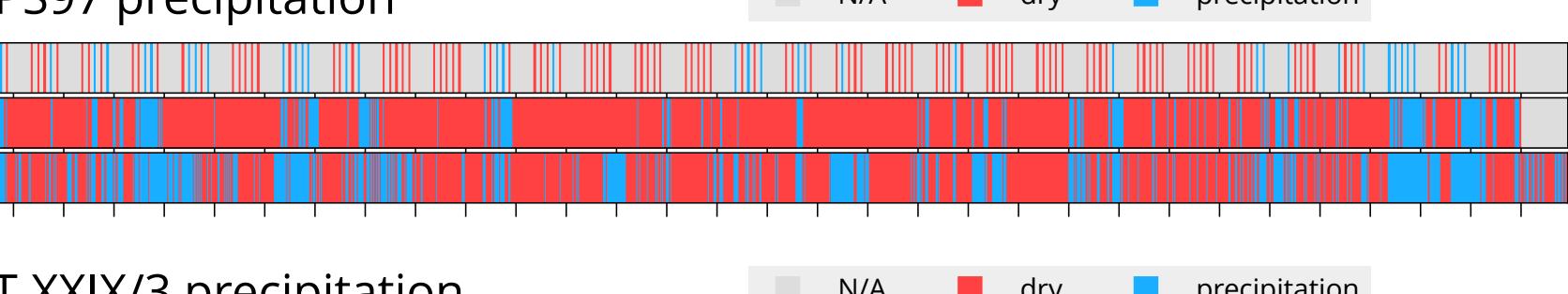
Samples of CL51 backscatter (10 min, 0–250 m)



Receiver operating characteristic (ROC)



PS97 precipitation



Human AWS

Lidar ANN

N/A dry precipitation

Human AWS

Lidar ANN

N/A dry precipitation

Human AWS

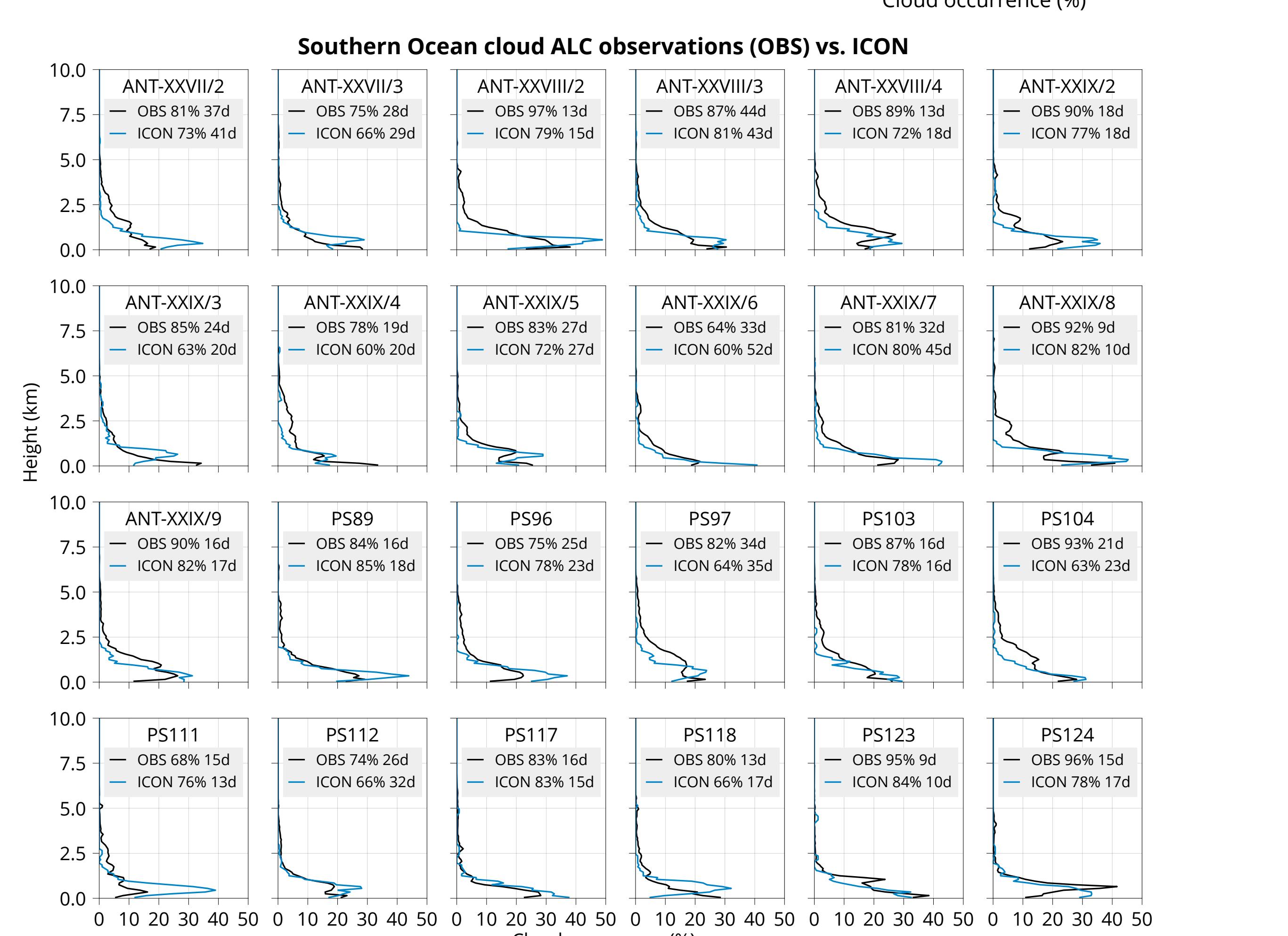
Lidar ANN

N/A dry precipitation

Results

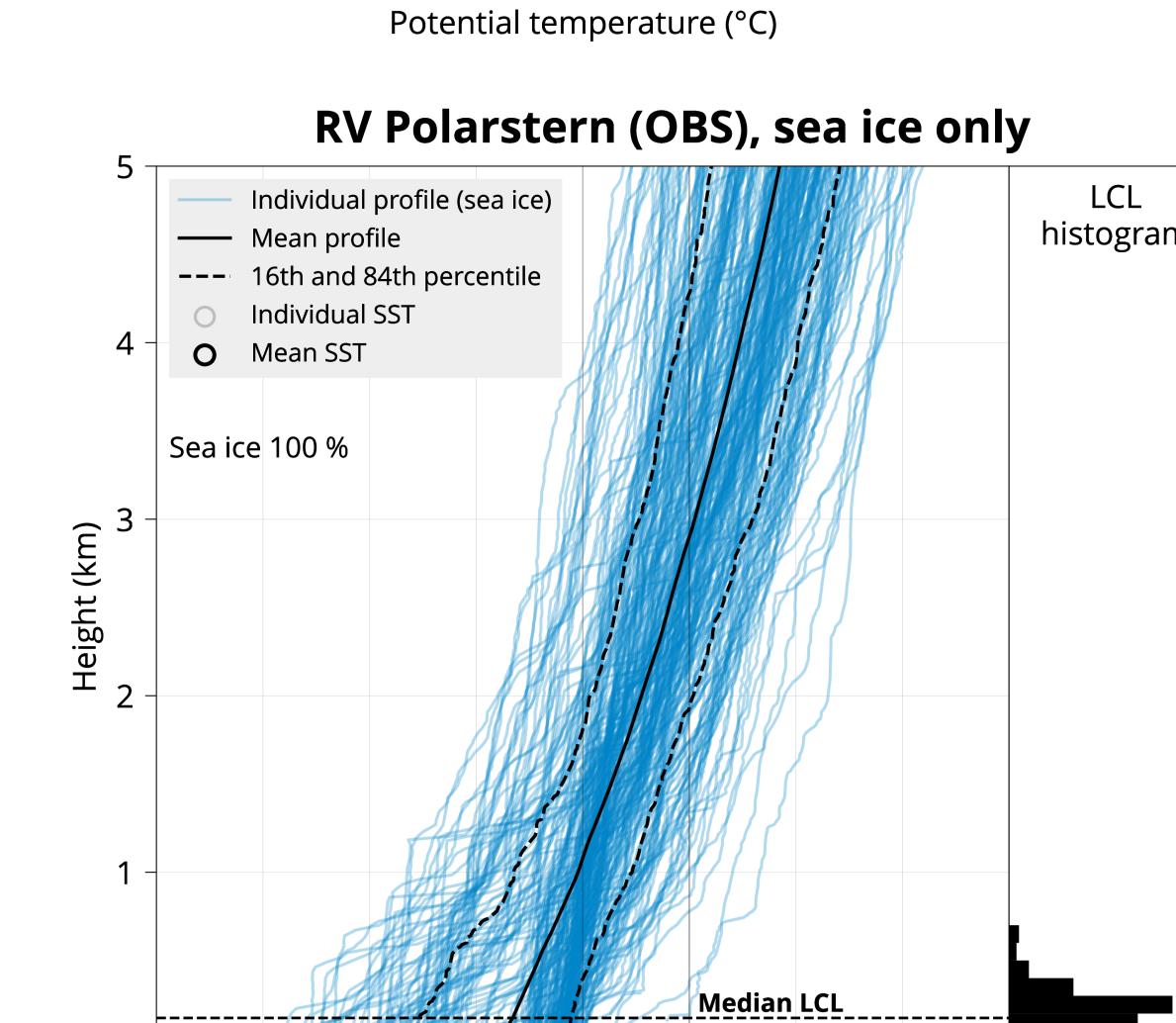
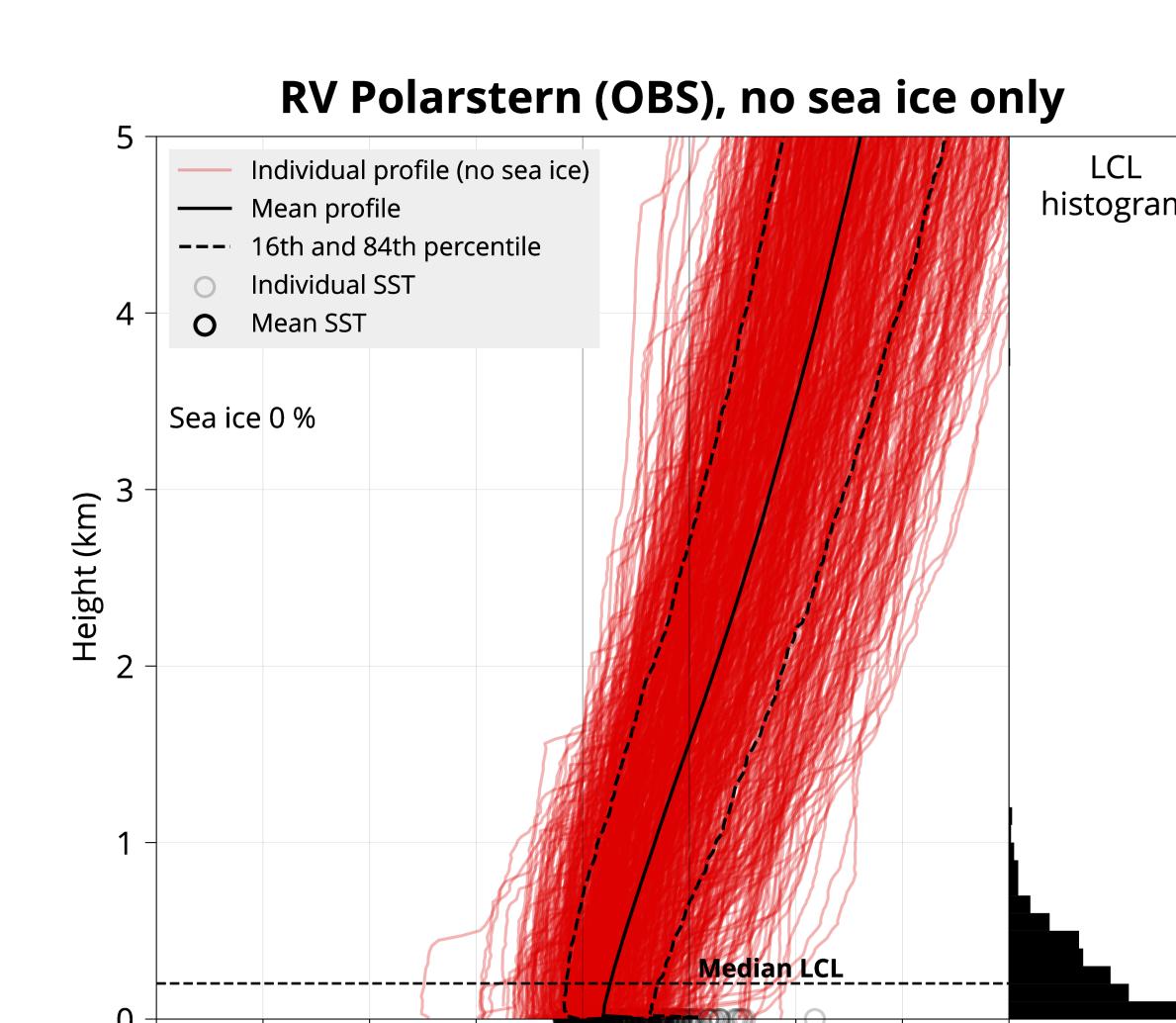
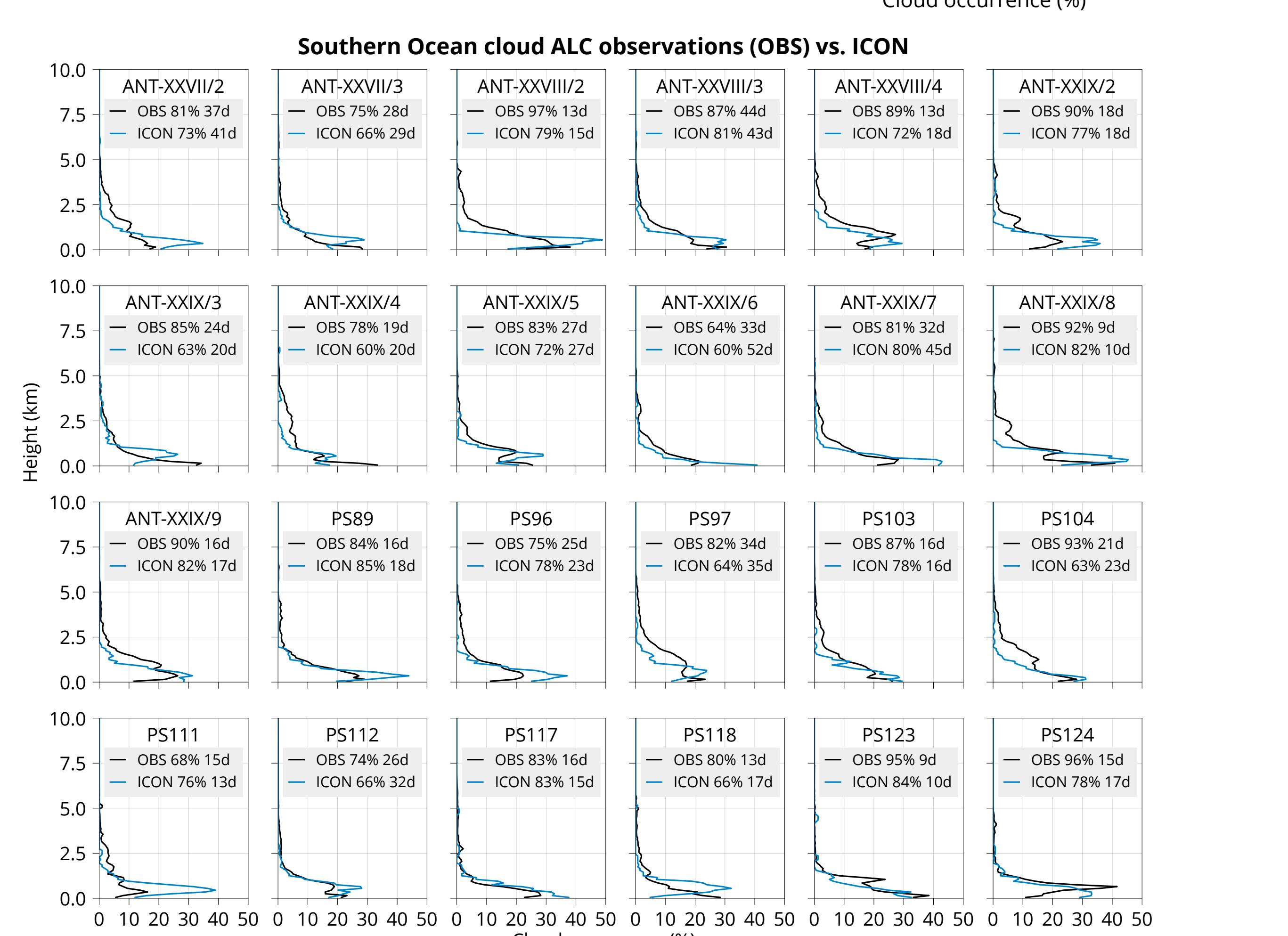
Cloud occurrence

- We calculated cloud occurrence by height for each voyage and then calculated an aggregate of all profiles (mean and the 16th and 84th percentiles).
- Notable biases in ICON are:
 - Overestimation of cloud occurrence between 0 and 1 km.
 - Overestimation of the cloud occurrence peak height, which is almost at the ground level in observations and at about 0.5 km in ICON.
 - Underestimation of cloud occurrence above 1 km.
 - Underestimation of the total cloud fraction in ICON by about 10%.
- Limitations:
 - The model is free running. Thus, the profiles cannot be expected to represent the same weather conditions.
 - Only profiles with the same sea ice conditions (present or not present) are included. However, large-scale sea ice conditions might differ.



Radiosonde profiles

- We compared about 2000 radiosonde profiles from the 24 voyages between the observations and the model.
- Profiles in the model are taken at the same geographical location and time relative to the start of the year.
- Only profiles for which the sea ice conditions (sea ice present or absent) are the same in the observations and the model are included.



RV Polarstern (OBS), sea ice only

Individual profile (sea ice)

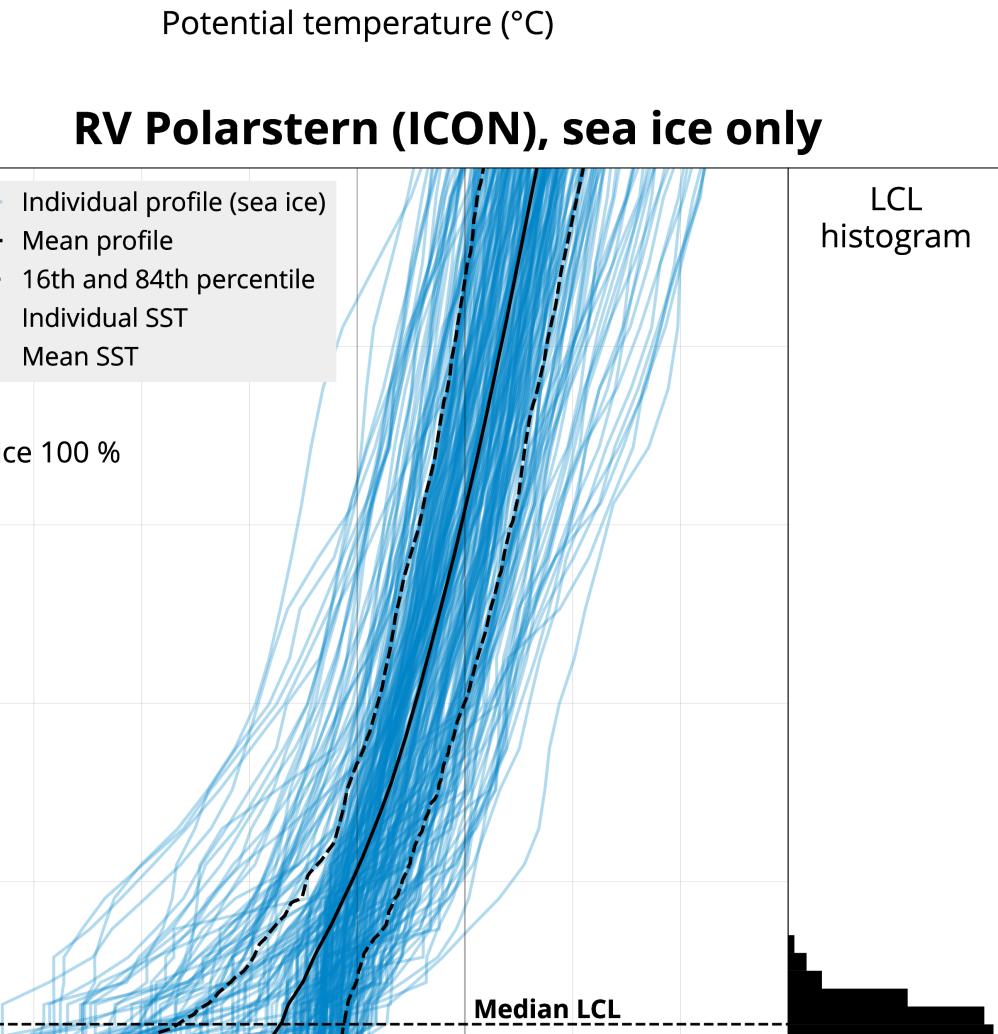
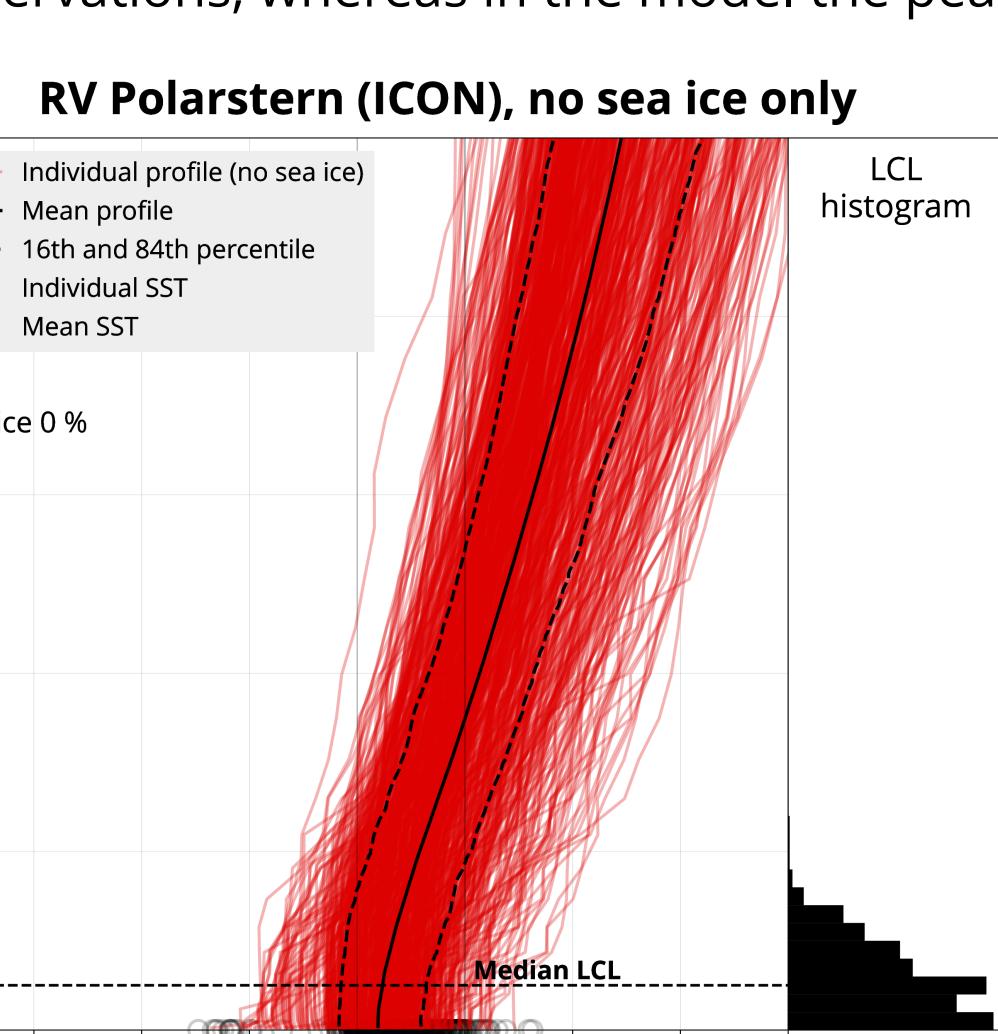
Mean profile

16th and 84th percentile

Individual SST

Mean SST

Median LCL



RV Polarstern (ICON), sea ice only

Individual profile (sea ice)

Mean profile

16th and 84th percentile

Individual SST

Mean SST

Median LCL

Acknowledgements

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