Project: **1233**

Project title: **DataWave**

Principal investigator: **Claudia Stephan**

Report period: **2021-11-01 to 2022-10-31**

Overall goal

The main goal of DataWave, an international project for gravity wave research, is to develop a machine learning based parameterization of gravity waves for global models, among others for ICON. To train neural networks, one needs large amounts of training data capturing the relevant physical phenomenon, in our case gravity waves. This training data is obtained from high-resolution model output.

Achievements of the last year

<u>ICON R2B10 simulations for machine learning applications</u>

We are running ICON NWP R2B10 to generate training data. To cover all seasons, we simulate a week per month in the year 2017. We have run ten out of twelve weeks so far (four of them on Mistral). Successfully completed are January, March, April, June, July, August, September, October, and November. Not finished yet are February and December due to technical problems on Levante. For the machine learning applications, we output 3d instantaneous values of temperature, pressure, and all three wind components in addition to several 2d fields. For the gravity wave diagnostics, we additionally output averaged momentum fluxes uv, uw, and vw where we separate positive from negative values, i.e., we save the mean of uv > 0 as uv+, all uv < 0 as uv-, and analogously for uw and vw. This allows us to extract not only information about the mean fluxes but also about their variability and the magnitude of fluxes since positive and negative values don't cancel out. For all variables we use 3 hourly output timesteps. Each one-week simulation includes 8 days, i.e. one extra day is discarded for spin-up. The runs are initialized with IFS-9km data and use prescribed sea surface temperature and sea ice forcing.

The data are currently used by at least 4 groups: My MPI-M group, Stanford university, NY University and the University of Frankfurt. My postdoc Laura Koehler, who is funded by DataWave, is currently finishing a publication that compares our simulations with observations (see below). Our partners are training various neural networks based on our data. There are at least two more international groups who expressed interest in the simulations (LMD in France, and Charles University of Prague). It is therefore necessary to have all of the data on disk.

<u>Postprocessing considerations</u>

To extract gravity waves, we perform a Helmholtz decomposition. In the DataWave project, several models are included. To adapt machine learning schemes to ICON, we have to prepare the ICON output accordingly or adapt the neural networks to the ICON native grid. We are in the process of optimizing this procedure and comparing the two alternatives, i.e., remapping the output to a Gaussian grid, transforming it to spectral space, applying a low pass filter or a Helmholtz decomposition and transforming back to position space versus using coarse graining on the native ICON grid. In a next step we will run first tests using our ICON output for machine learning applications.

<u>Comparing with other models and observations</u>

To assess the capability of different high-resolution models (DYAMOND) of resolving gravity waves in a realistic way, the DataWave project aims to compare models to superpressure balloon data from the project Loon [1]. Loon provides balloon data from 2014 to 2019, where the superpressure balloons were drifting at heights of 16 to 21 km. The balloon segment lengths range between hours and months where they fly approximately on surfaces of constant density. In between, the balloons were manoeuvred in height. For one selected week of good balloon coverage we wrote 3d output of temperature, pressure, and the wind components with 15 min timesteps. The precipitation output timestep is 5 minutes. This simulation was still performed on Mistral.

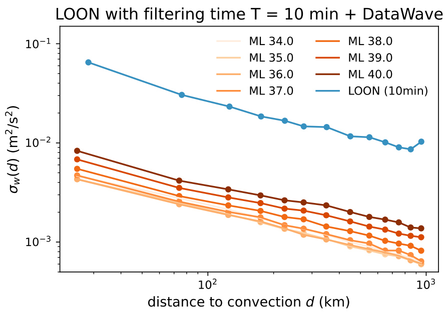

Figure 1 Variance of w as function of distance to closest convection for ICON NWP-2.5km at different model levels (orange) and Loon (blue).

In the comparison we have especially focused on the vertical wind component w. The variance as a function of distance to the closest convection serves as a measure for gravity waves. Figure 1 presents ICON R2B10 at different model levels in the height range of the Loon data. We notice that ICON shows smaller variances of w compared to the observations. We suppose that this is due to the averaging effect of models running on relatively coarse grids in contrast to the balloons, which measure more or less points in space and time.

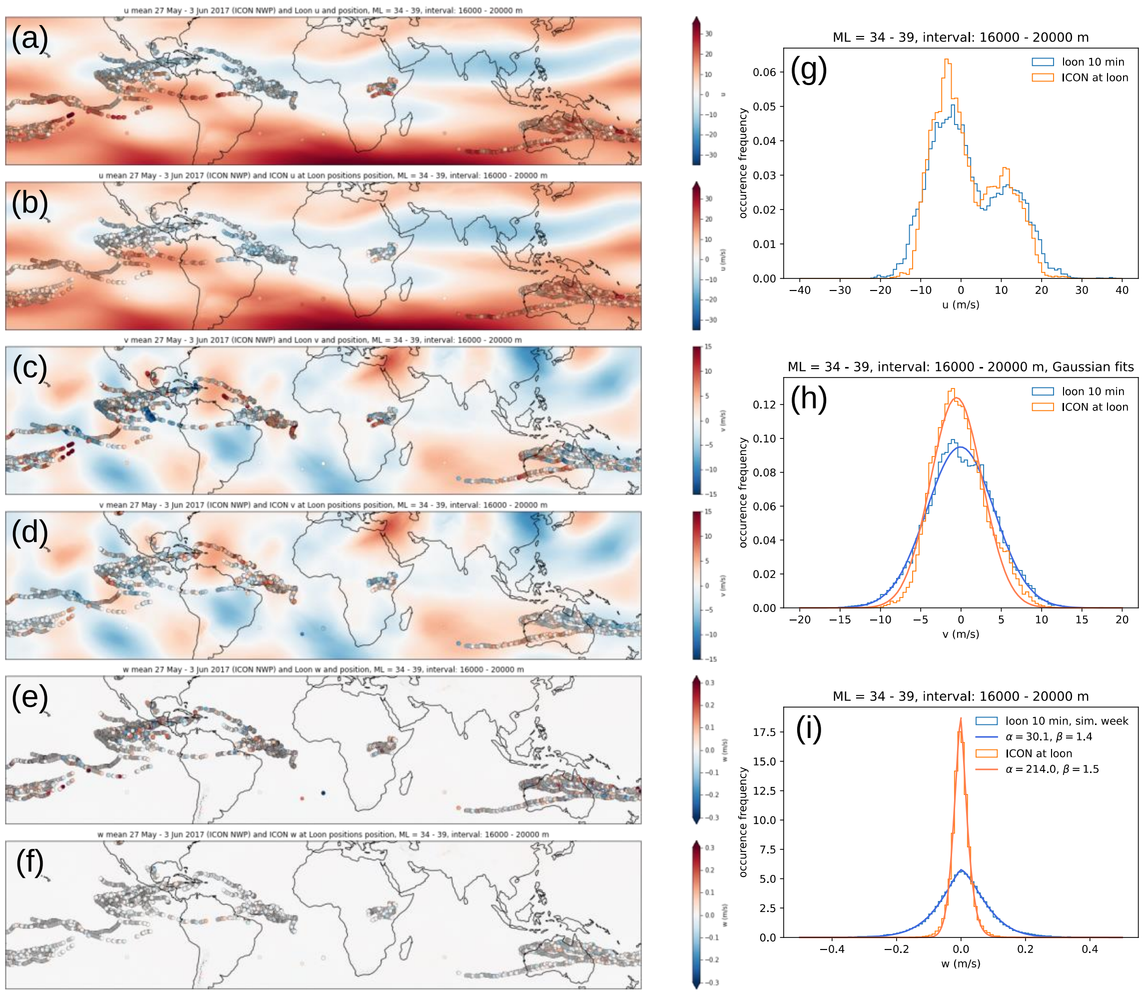

Figure 2 Wind components u, v, w. (a) - (f): Background represents the ICON mean flow, points indicate the Loon positions, colour shading (a) u, (c) v, (e) w of Loon points, and (b) u, (d) v, (f) w of ICON closest to Loon points. (g) - (i): corresponding wind distributions.

This effect becomes obvious when comparing the distributions of the wind components. To have comparable samples, we determine the points in space and time in the ICON output which are closest to the Loon measurement points in the simulated week. We avoid interpolation to ensure that we capture the maximum simulated amplitudes of gravity waves. Figure 2 presents the analysis of the three wind components. The background in (a) and (b) is the same: it shows the mean of u over the simulated week. The points represent the positions of the balloons. The colour filling denotes u (a) measured by Loon and (b) simulated by ICON, respectively. (g) compares the distributions at the Loon positions. The distribution of u is dominated by the background flow and thus the agreement between Loon and ICON is very good. Subfigures (c), (d), (h) and (e), (f), (i) are the analogous plots for the wind components v and w, respectively. We notice, that v follows approximately a normal distribution shown by the solid fitting curves in panel (h). For v Loon tends to larger values than the model. This effect is even more pronounced for the vertical velocity which follows approximately a stretched exponential distribution, i.e., $p(|w|)=c \exp(-\alpha|w|^{\beta})$ as indicated by the solid lines in panel (i).

The R2B10 run with 15 minute output enables such a pointwise comparison and lets us examine the reasons for different quantitative behaviour. In a next step, we will calculate offline trajectories for virtual balloons in ICON which allows a comparison of trajectories.

Review of the plan proposed last year

We mostly followed our proposed plan. We have not completed all of the planned simulations at this point. This is mostly due to delays caused by the well-known instabilities of Levante. Nevertheless, we are currently using nearly all of our allocated disk space, tape space, and have nearly used up all of our allocated compute time.

[1] Project Loon, https://x.company/projects/loon, doi.org/10.5281/zenodo.3755988