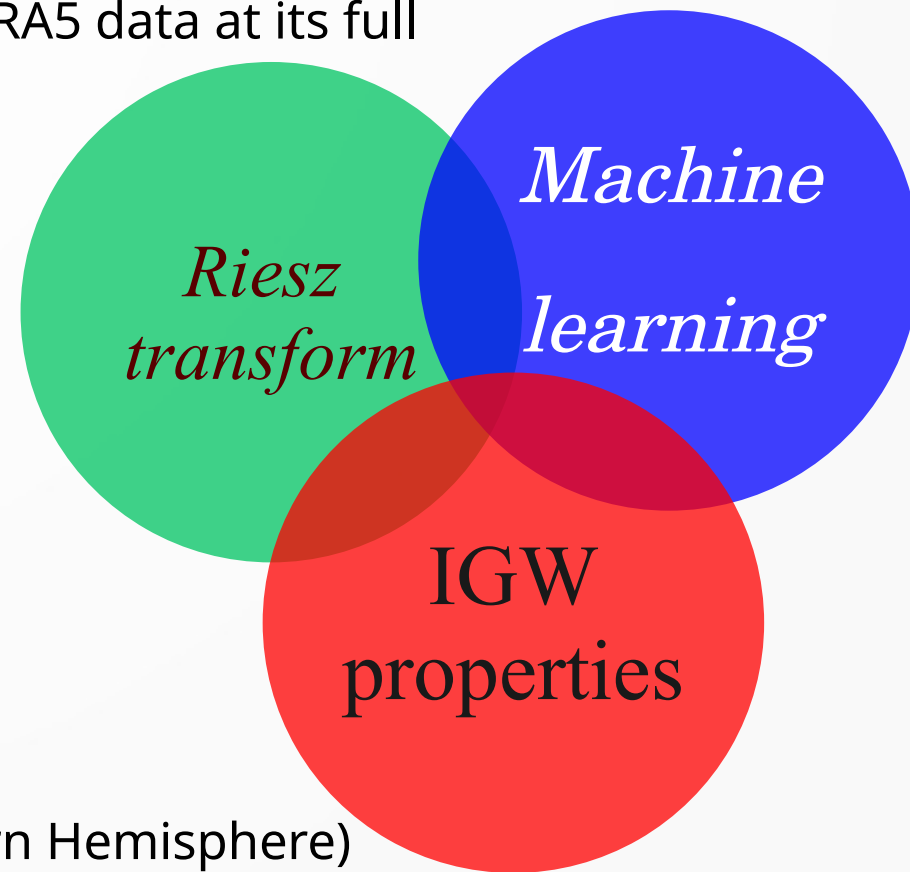


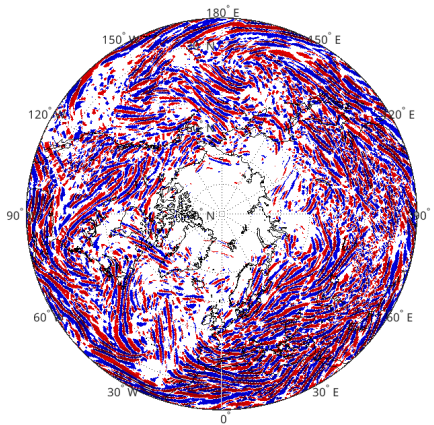
# Main idea: *Estimation of wave characteristics at the launch level*

- 1 . To retrieve the wavenumber using the Riesz Transform from ERA5 data at its full resolution (the generalized form of the Hilbert Transform; Schoon and Zülicke, 2018)
- 2 . To relate the high-res meso-scale wave properties (Mirzaei et al, 2014) to coarse-grained resolvable variables at the launch level (Amiramjadi et al, 2019)
- 3 . Avoiding mountain waves and focusing on non-orographic
- 4 . Time: December 2018 to February 2019 (winter time of Northern Hemisphere)  
Area: Midlatitude of Northern Atlantic and Pacific Oceans

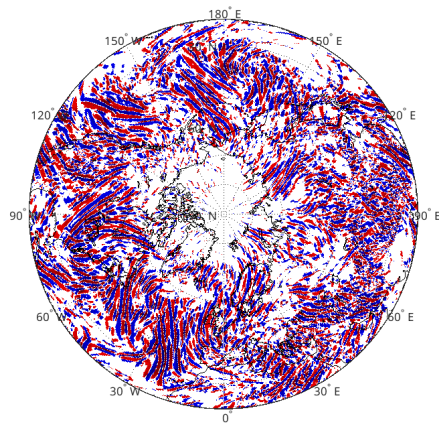


# Application of Riesz Transform: Generalized from of Hilbert Transform in multi-dimensional analysis

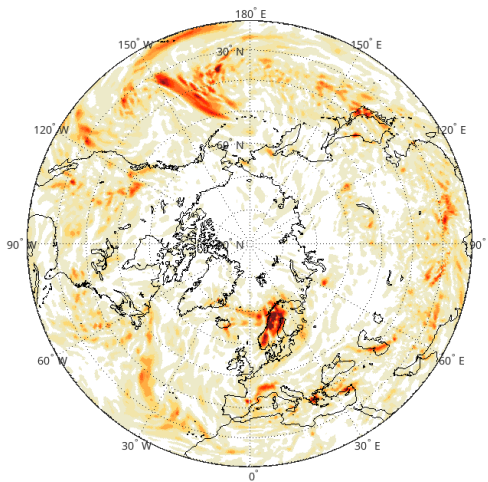
Meridional wavenumber - lev=13.5 km (~150 hPa) - 18Z10JAN2019



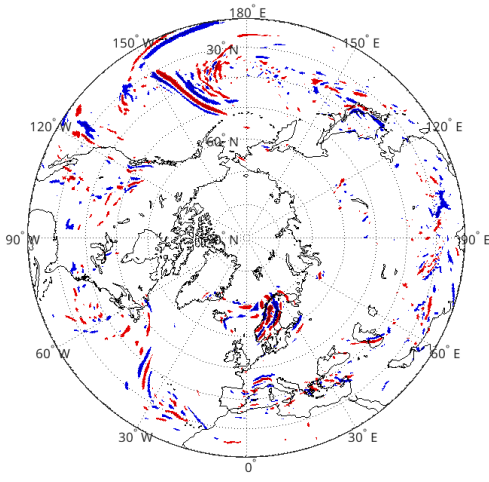
Zonal wavenumber - lev=13.5 km (~150 hPa) - 18Z10JAN2019



Local amplitude - lev=13.5 km (~150 hPa) - 18Z10JAN2019



Horizontal divergence (1/s) - lev=13.5 km (~150 hPa) - 18Z10JAN2019

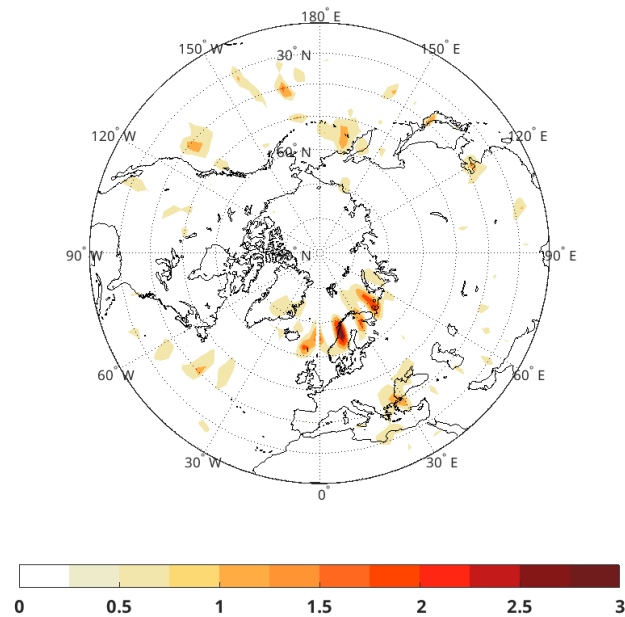


High resolution ERA5:

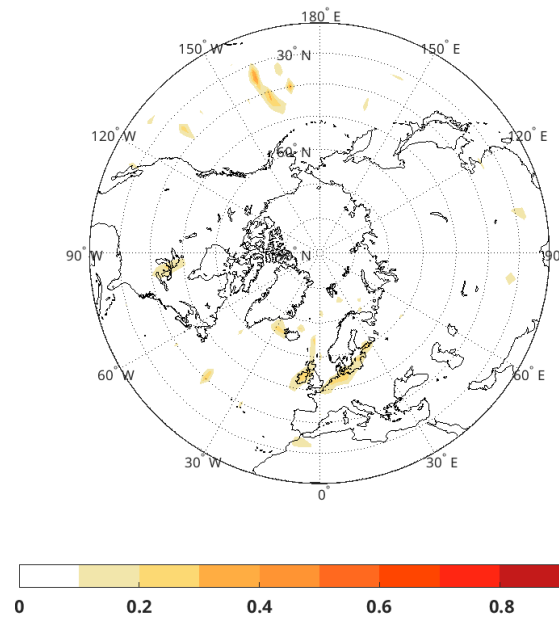
Horizontal resolution:  $0.25^{\circ} \times 0.25^{\circ}$   
Vertical resolution: 500 m

# Diagnostics at the lunch level

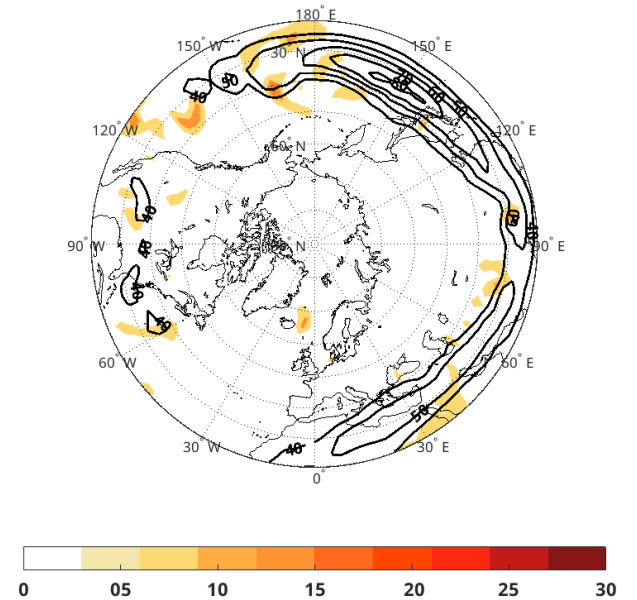
Latent heat released during condensation(K/h)  
lev=13.5 km (~150 hPa) - 18Z10JAN2019



frontogenesis function ( K/(100 km h) )  
lev=13.5 km (~150 hPa) - 18Z10JAN2019



Cross-stream ageostrophic wind speed (shaded, m/s) and  
horizontal wind speed (contours, wind > 40 m/s)  
lev=13.5 km (~150 hPa) - 18Z10JAN2019



*Coarse-grained ERA5: Horizontal resolution:  $2.5^{\circ} \times 2.5^{\circ}$*

# Machine learning: Data preparation and model setup

## Data preparation:

1. To normalize non-normal explanatory variables and target using natural logarithm function

2. To keep the values greater than thresholds:

$$u_a > 1 \text{ ms}^{-1}, \quad F_{\text{front}} > 0.15 \text{ K} (100 \text{ km})^{-1} \text{ h}^{-1}$$
$$q_{\text{conv}} > 0.3 \text{ K h}^{-1}, \quad k_h > 35$$

3. Each set o data must contain at least one diagnostic variable and non-zero target

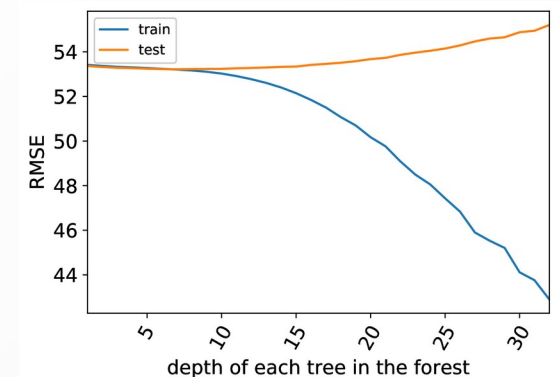
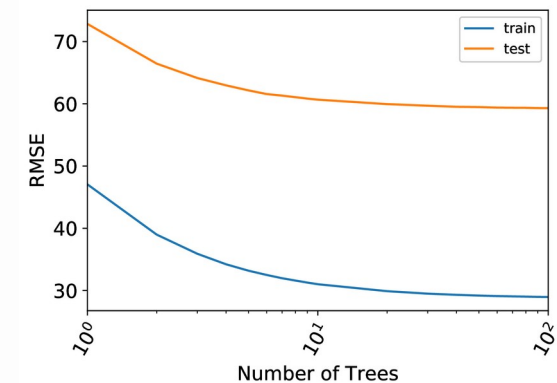
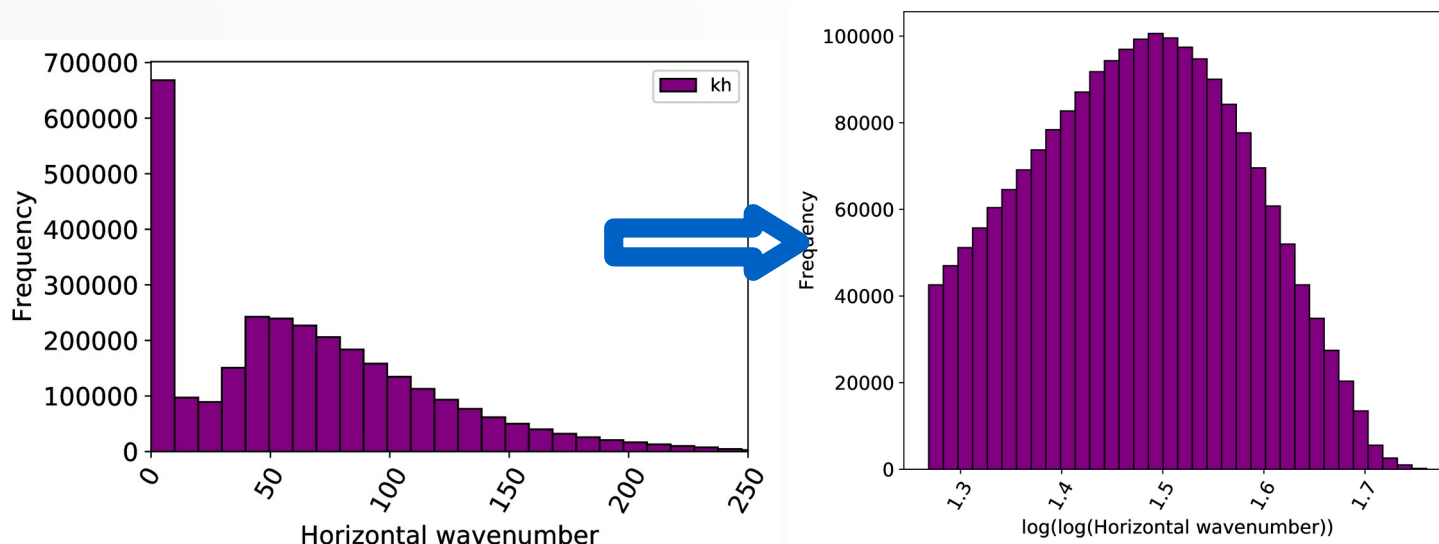
## Model setup:

To optimized the model (Random Forest) performance by setting the tunable parameters to minimized the errors (RMSE):

Number of trees in the forest: 30

Depth of each tree in the forest: 7

Other parameters have been set as their defaults.



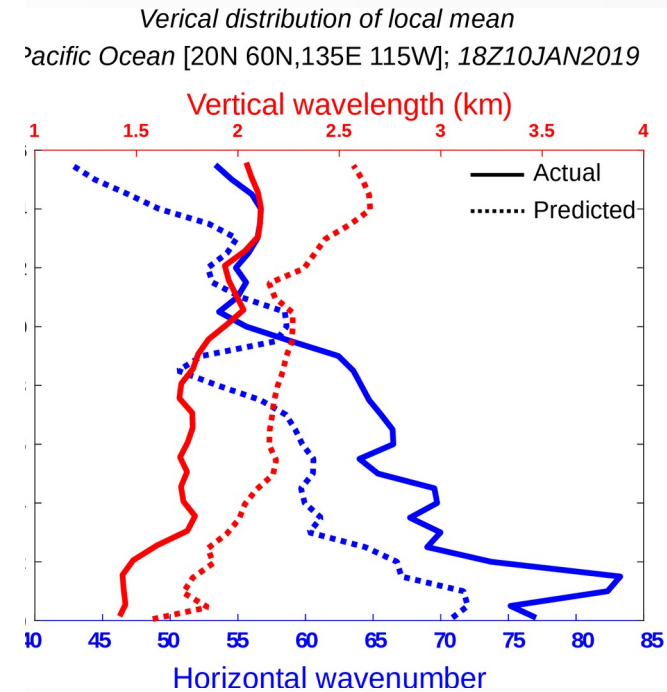
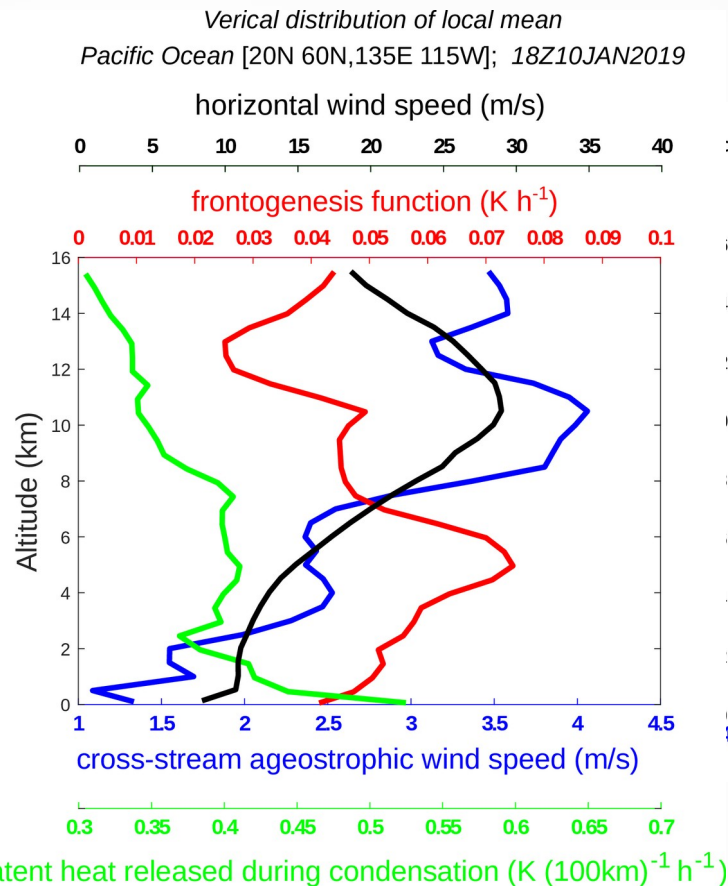
# Result and conclusion

\* Results of the application of Riesz Transform are comparable with the results by Schoon and Zülicke (2018).

\* Correlation coefficient between the actual and the reconstructed wavenumbers is about 0.6 on the average.

\* Geometric mean bias is about 0.86 on the average which means the model somehow underestimates the target.

\* Initial results are positive and promising despite the horizontal and vertical wave propagation given that it reconstructs wave properties at the lunch level.



## References:

- Mirzaei, M., Zülicke, C., Mohebalhojeh, A. R., Ahmadi-Givi, F., & Plougonven, R. (2014). Structure, energy, and parameterization of inertia-gravity waves in dry and moist simulations of a baroclinic wave life cycle. *Journal of the Atmospheric Sciences*, 71(7), 2390-2414.
- Schoon, L., & Zülicke, C. (2018). A novel method for the extraction of local gravity wave parameters from gridded three-dimensional data: description, validation, and application. *Atmos. Chem. Phys.*, 18, 6971–6983.
- Amiramjadi, M., Plougonven, R., Hertzog, A., Mohebalhojeh, A. R., & Mirzaei, M. (2019, January). Using machine learning to estimate Inertia-Gravity Waves properties from a coarse-grained description of the flow. *In Geophysical Research Abstracts (Vol. 21)*.