Correction of the COSMO-Ru fields in the troposphere using the convolutional neural network

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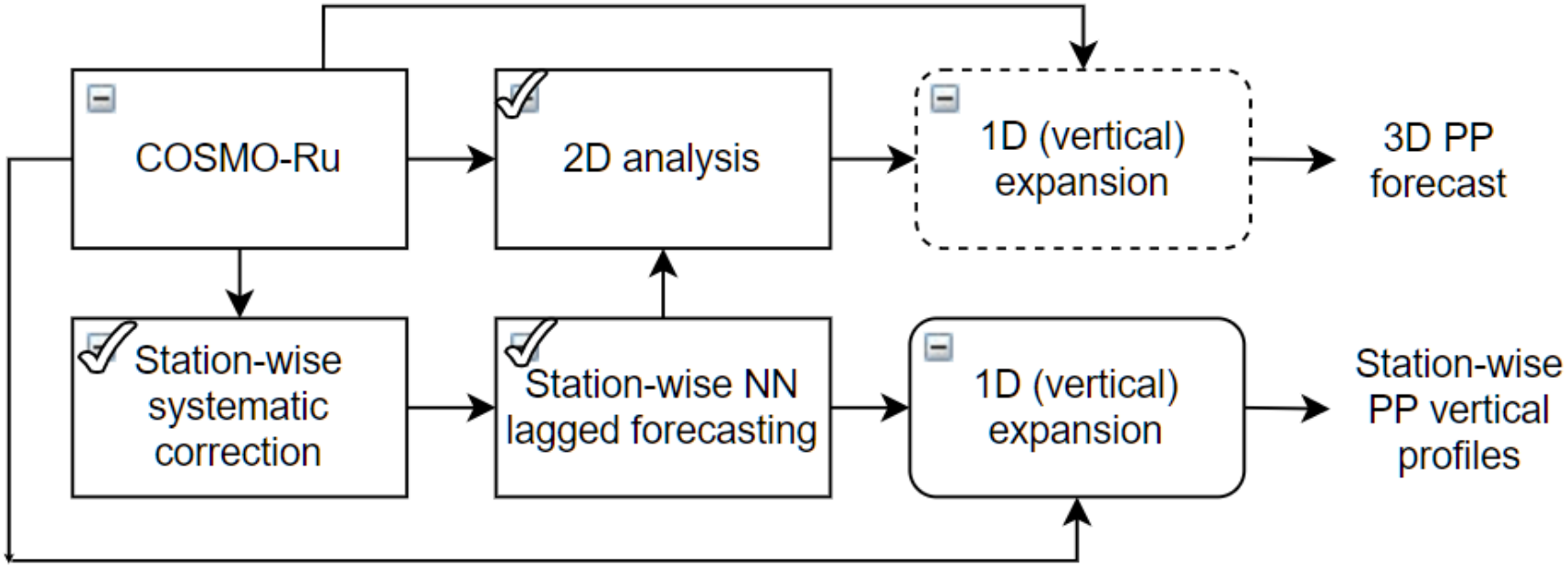
COSMO-Ru refinement post-processing (PP) at RHM



Now we develop the method for expansion the station-wise near-surface correction to the vertical column.

This method allow us to pass from 2D PP fields to 3D PP fields.

The near-surface correction expand to the vertical column

The dataset contains ~640 000 pairs of the COSMO-Ru6-ENA 0-72h forecast and high-resolution radiosonde BUFR profile.

Corrected fields: temperature *T*, water vapor *Qv*, pressure *p.*

ML model: e.g. for temperature *T* :

$$T_{corr}(z) = T_{\mathrm{cosmo}}(z) + f(z)[T_{corr}(2m) - T_{\mathrm{cosmo}}(2m) + b(z) - b(2m)],$$

where $f(z) \in [0,1]$ and *b(z)* is the 1D (vertical column) convolutional neural network outputs; $T_{corr}(2m)$ is corrected forecast, calculated with take into account the last SYNOP data.

Predictors

A) the COSMO-Ru6-ENA vertical profiles (40 layers: 0, 10m, 30m, …)

$$z, T, \Theta(\text{potential temperature}), P, Q(\text{specific humidity});$$

B) the near-surface predictors

$$z(0), T_{\text{cosmo}}(2m), \Theta_{\text{cosmo}}(2m), Q_{\text{cosmo}}(2m), PMSL_{\text{cosmo}},$$

$$T_{corr}(2m), \Theta_{corr}(2m), Q_{corr}(2m), PMSL_{\text{corr}};$$

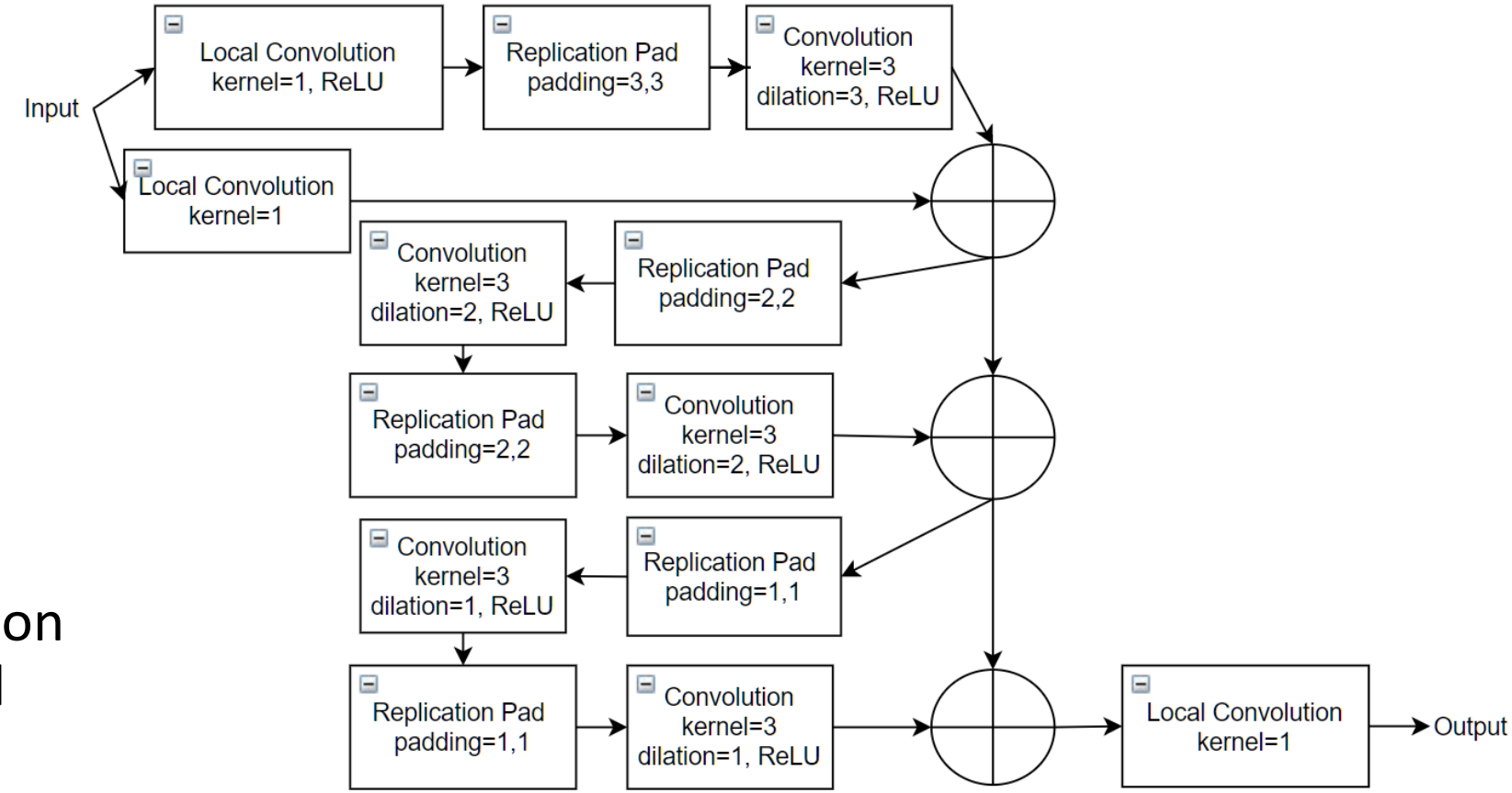
C) the additional predictors

$$\alpha_{Sun}(\text{the height of the Sun}), \sin(2\pi t / 1year), \cos(2\pi t / 1year),$$

$$\tau(\text{lead time}).$$

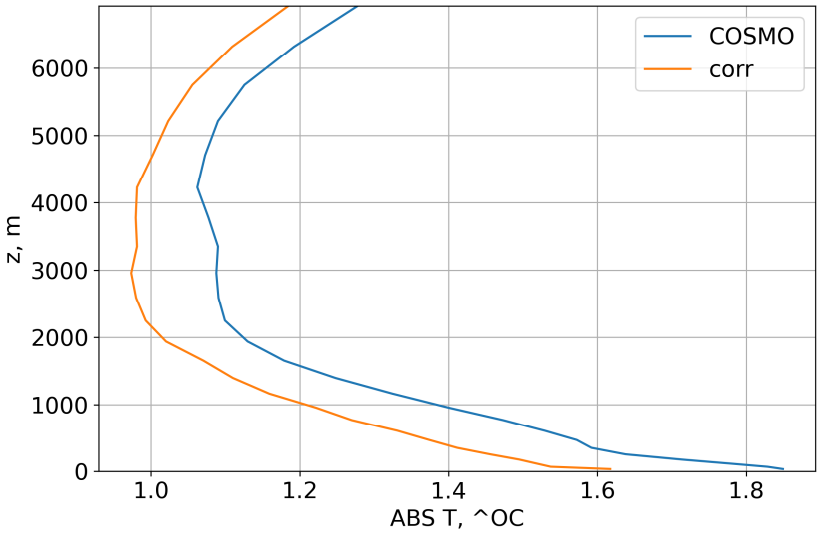
The neural network architecture

- Residual connections
- Local (level-dependend) convolutions on the input and the output

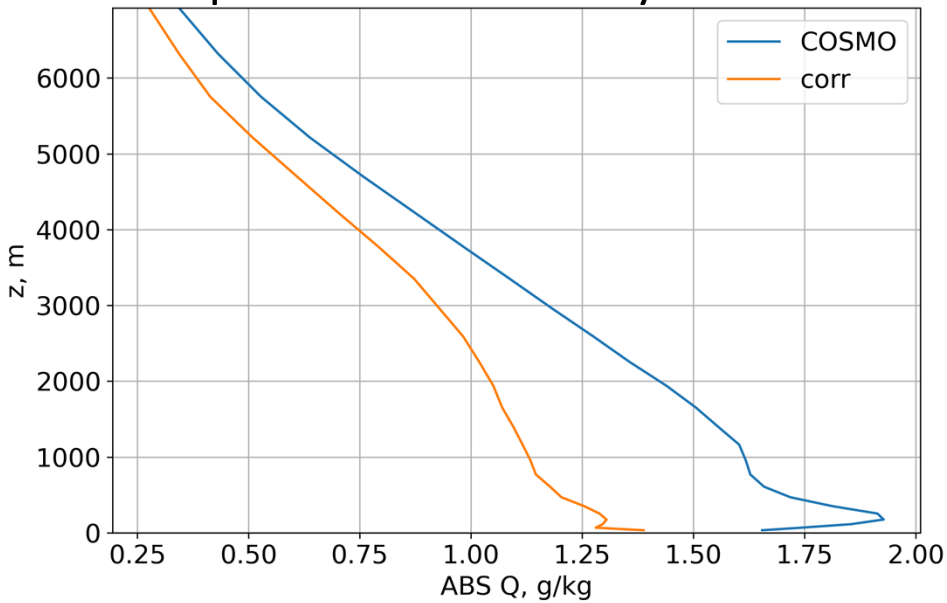


The MAE of 36 h forecasts

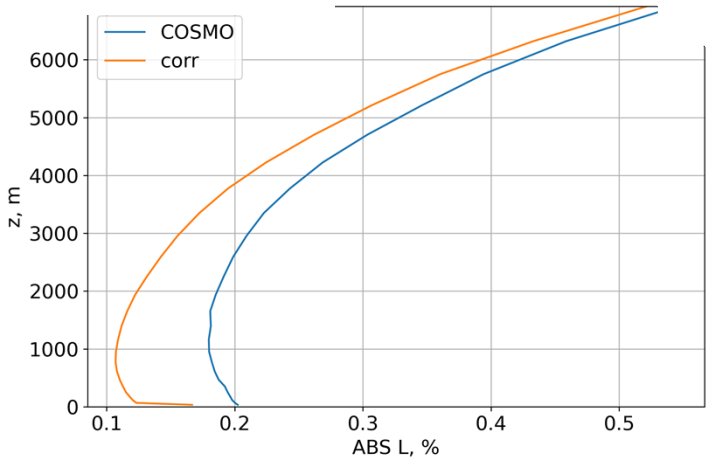
Temperature



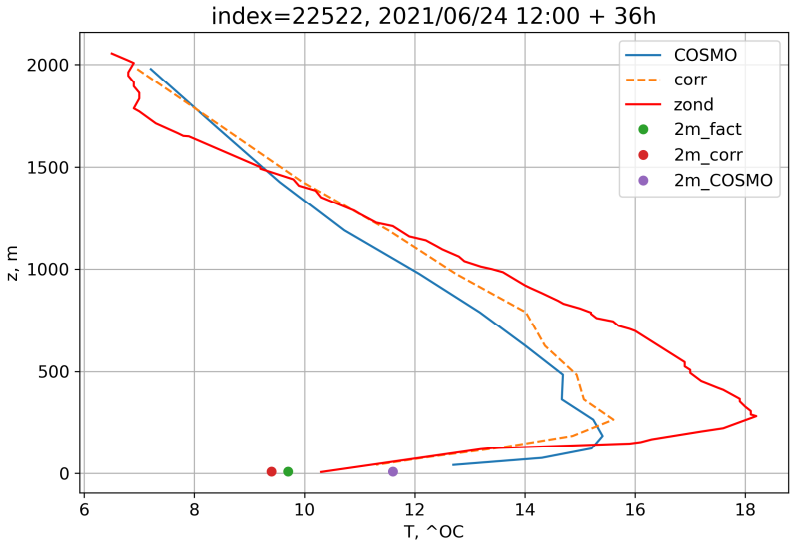
Specific himidity

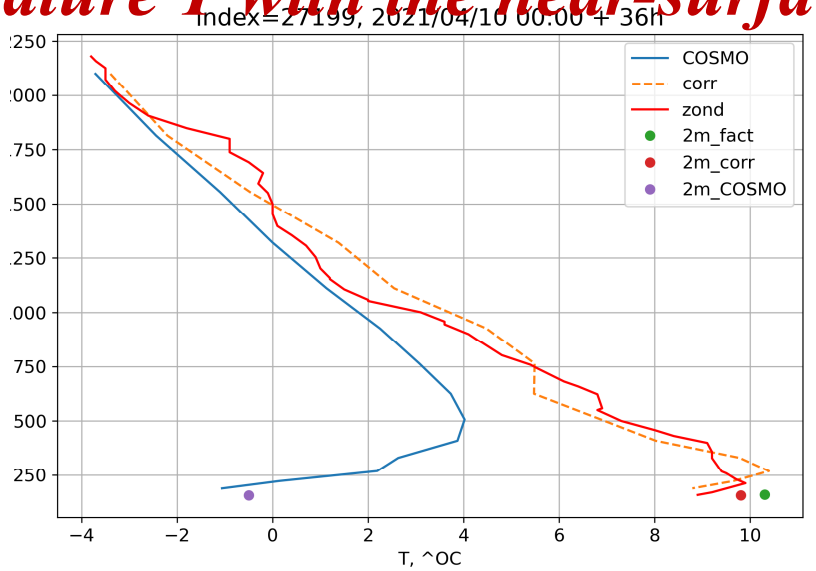


log p

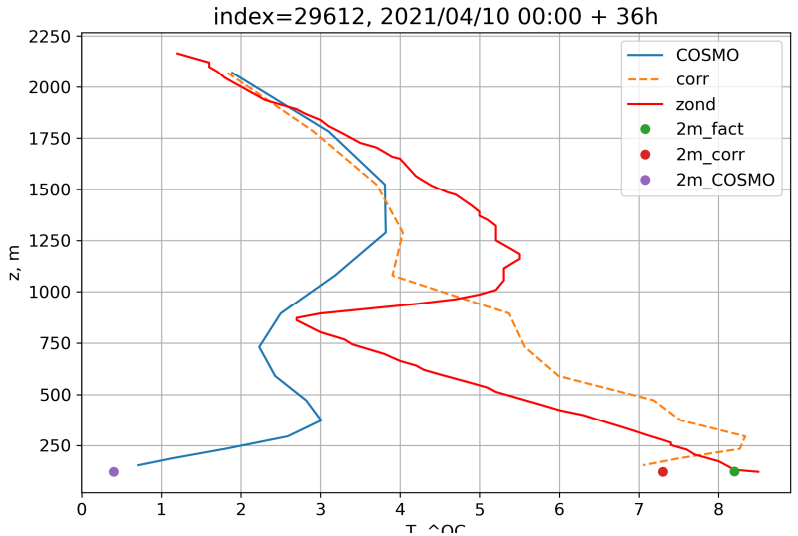


Profiles of the temperature T with the near-surface inversion

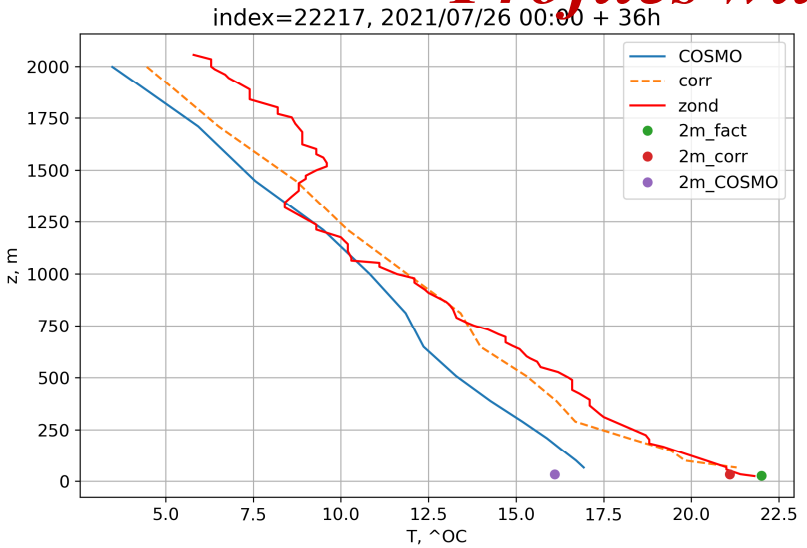


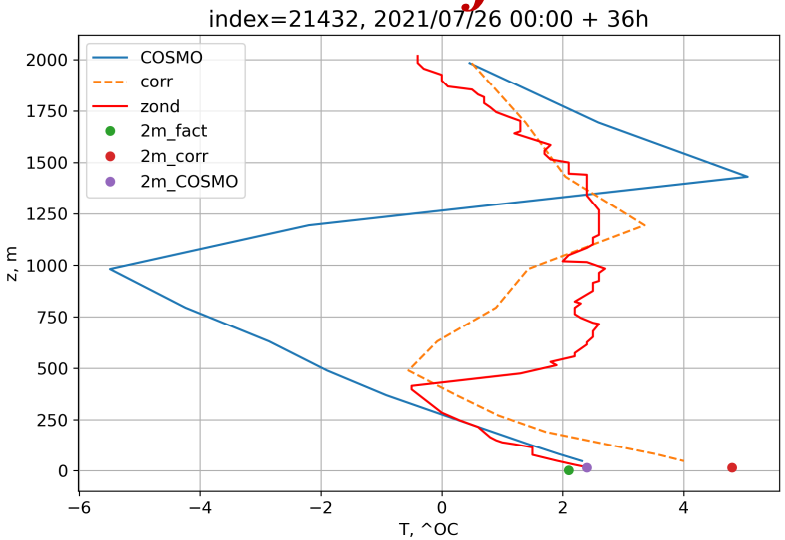


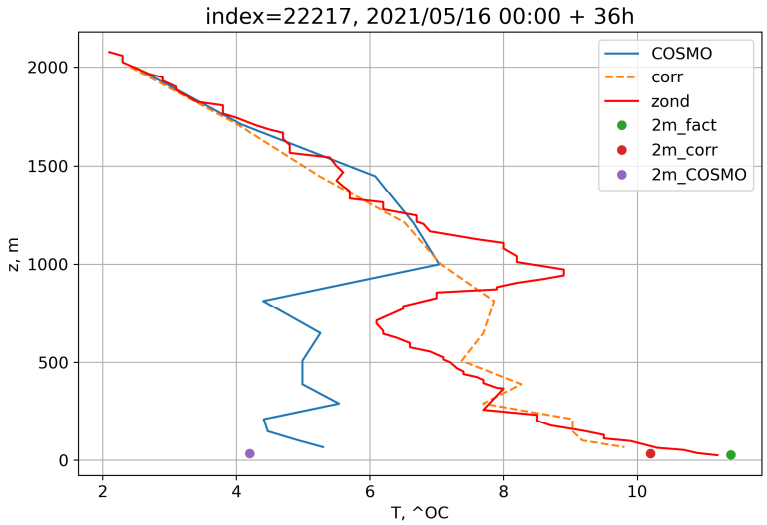
The corrections can be expanded to near-surface inversion layer only.

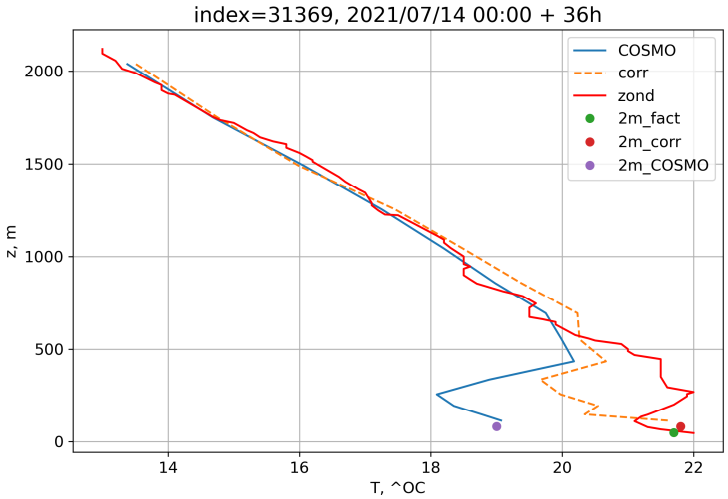


Profiles without the near-surface inversion









The hydrostatic regularizer

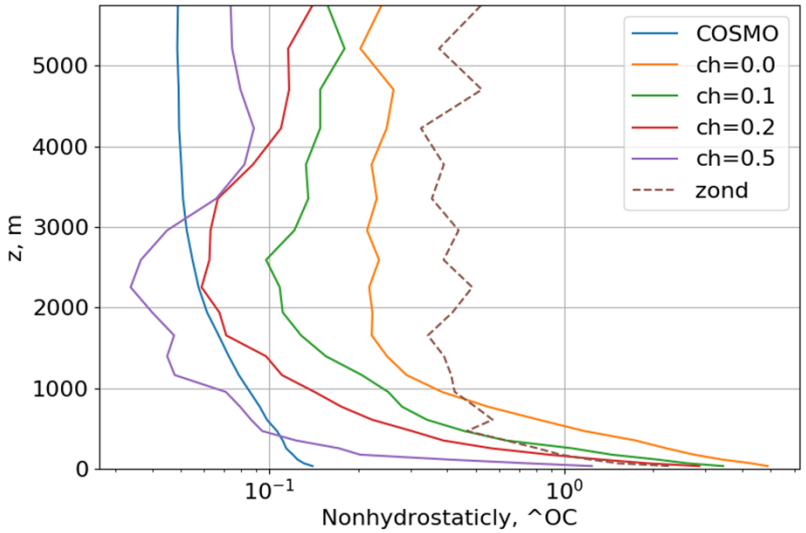
- We estimate the non-hydrostaticity of the corrected profiles by formula

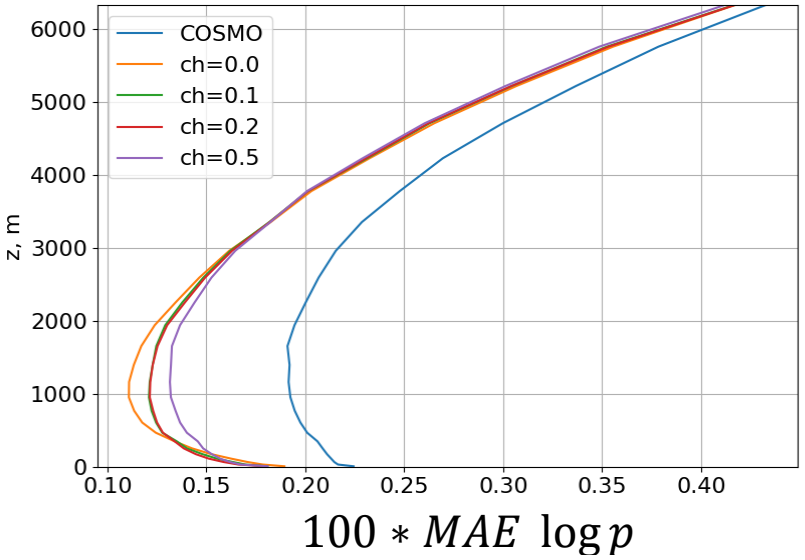
$$e_{hydro}(z_{i+1/2}) = e\left(\frac{1}{2}\left(T_{E,corr}(z_i) + T_{E,corr}(z_{i+1})\right), -\frac{g}{R}\frac{z_{i+1} - z_i}{\log\frac{p_{corr}(z_{i+1})}{p_{corr}(z_i)}}\right)$$

and add it into the loss functional as the additional regularization :

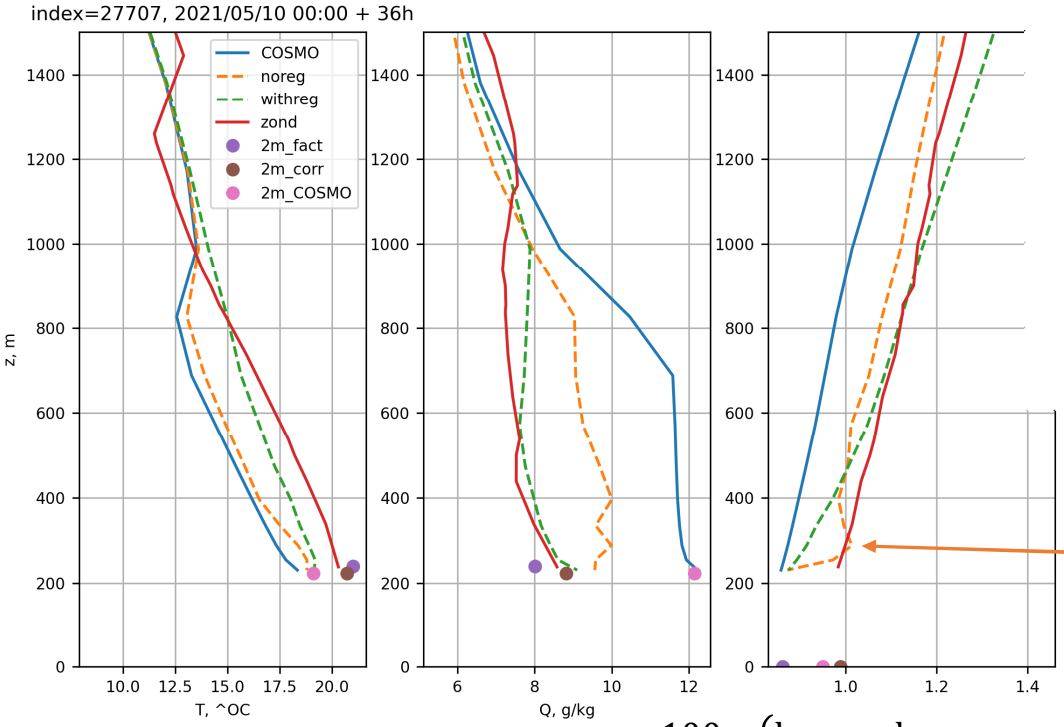
$$L = \int \left[e(T_{zond}, T_{corr}) + e(Q_{zond}, Q_{corr}) + 1000e(\log p_{zond}, \log p_{corr}) + \boldsymbol{c_h e_{hydro}}\right] p_{\mathrm{cosmo}}(z)dz \to min.$$

- **The hydrostaticity conflicts with the best accuracy of the post-processed pressure profile in the lower 3000 m layer**

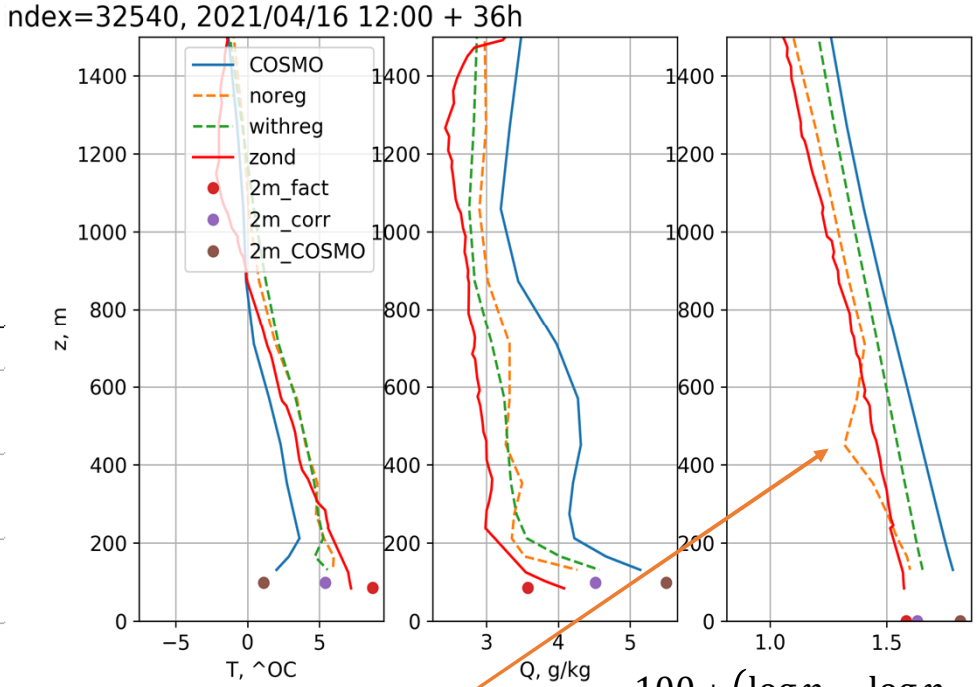




The regularization reduces the artefacts



$100 * (\log p - \log p_{\text{standart atm.}})$



$100 * (\log p - \log p_{\text{standart atm.}})$

The correction **without regularization** produces the non-physical oscillations, but it is more accurate than the correction **with regularization**

Discussions

1) The near-surface correction can be expanded to the thin (boundary?) layer.

2) The correction in middle and upper troposphere take into account the synoptic situation.

- On the boundary between this two layers the hydrostatic conflicts with best accurary of the PP profile.

Conclusions

- The PP increase the non-hydrostaticity
- The residual of ODE (hydrostatic equation) is used as a regularizer for convolutional neural network

To do

- Estimation the non-hydrostaticity using the 4-order scheme instead the 2-order scheme
- Apply to wind profiles
- Calculation the 3D post-processed fields

Thank you for attention!