Dr. Ólafur Rögnvaldsson
Dr. Gláuber Camponogara
Dr. João Hackerott

Data Assimilation for Weather Forecast Systems

Technical Report for RANNÍS project nr. 1910034-0611

August 2020

BELGINGUR
Experts in high resolution weather forecasting

Belgingur - Grensásvegur 9 - IS-108 Reykjavík - Iceland

www.belgingur.eu

Introduction

Since the last century, the global meteorological observation net has been significantly improved while it has also been widely expanded. Within this context, sophisticated Data Assimilation (DA) algorithms have been developed in order to incorporate these large and improved datasets into atmospheric models and, as consequence, improve the numerical weather predictions.

During the past few decades, many DA techniques have been developed by the scientific community and one of them has received a lot of attention: The Four-Dimensional Variational (4D-Var). As mentioned by Huang et al. (2009), this technique incorporates observations at the time they are measured, which tends to reduce the weather forecast bias, especially when assimilating higher frequency observations. 4D-Var is also capable of improving simulations of fast-developing meteorological systems since its background error covariance matrix is flow-dependent. Furthermore, this technique can use the numerical weather model as a constraint to strengthen the analysis dynamic balance and propagate the observations into the model during the simulation.

The 4D-Var technique has been successfully implemented in WRF (Weather Research and Forecasting) model (Huang et al., 2009) and many studies have shown significant improvements in the numerical weather prediction by assimilating different types of data. Xu et al. (2013) obtained improvements on the forecast skill with respect to the Typhoon Megi trajectory by assimilating IASI (Infrared Atmospheric Sounding Interferometer) radiances. Wind speed and direction data measured on surface and estimated via satellite-derived Atmospheric Motion Vectors (AMV) were successfully assimilated via 4D-Var by Huang et al. (2013) and Gao (2015), who observed a significant reduction of the wind speed bias in the simulations. Recently, Wu et al. (2020) assimilated AHI (Advanced Himawari Imager) radiances, in the water vapor channel, for every 10 min and the variables temperature, moisture and wind fields were highly improved, resulting on better precipitation forecast.

Belgingur has developed its own weather forecasting system based on the WRF model, called Weather On Demand (WOD). In order to improve this system a coupling system has been developed for integrating WRFDA (WRF Data Assimilation system) with the WOD system. We choose WRFDA because this software is the most suitable to our system since we already run WRF model operationally.

In this report we present the current development status of our DA framework. Section 1 describes in detail the DA framework structure. The experiment settings used to test the DA framework are shown in Section 2. Then, in Section 3, the preliminary results with respect to the experiment are reported. Finally, Section 4 brings the next steps that we intend to work on in the next months, while making the data assimilation process an integrated part of our operational weather forecast system.

1. Data assimilation framework

We have developed a coupling system in order to combine WRFDA with the WOD system. The main steps executed by the DA framework is shown in Figure 1.1 and discussed in detail as follows:

1. Data from the Global Forecast System (GFS) is downloaded to initialize the WRF model and feed its lateral boundary. Moreover, surface in-situ observations, remotely sensed/derived observations and satellite radiances data are also downloaded for the data assimilation process.
2. The WRF Pre-processing System (WPS) begins by running *ungrib.exe* and *metgrid.exe* programs. In this step GFS's meteorological fields are horizontally interpolated to the model grid.
3. The *real.exe* program is executed for vertically interpolating the meteorological fields to WRF grid levels, generating the initial and boundary condition files *wrfinput* and *wrfbdy.*
4. A cold run starts in order to give time for WRF adjusting to the initial conditions (spin up time). As a result, the *wrfout* file is generated.
5. The program *da_update_bc.exe* updates the lower boundary conditions from *wrfout* with the *wrfinput* file generated at step 3. This is necessary since WRF does not update lower boundary conditions during integration, such as vegetation fraction and snow cover.
6. The DA cycle begins by running WRFDA with the *wrfout* file as a first guess to compute the analysis (*wrfvar_output*).
7. Lateral boundary condition of *wrfbdy* are updated via *da_update_bc.exe* to be consistent with the *wrfvar_output* file.
8. WRF is run forward with the updated *wrfbdy* and *wrfvar_output* (equivalent to *wrfinput*) as input files.
9. The steps 5, 6, 7, and 8 are repeated until the algorithm complete the data assimilation window, which involves either one or more DA cycles.
10. Finally, after the DA window is completed, a weather forecast is produced by running WRF with the final analysis field, generated by the WRFDA system.

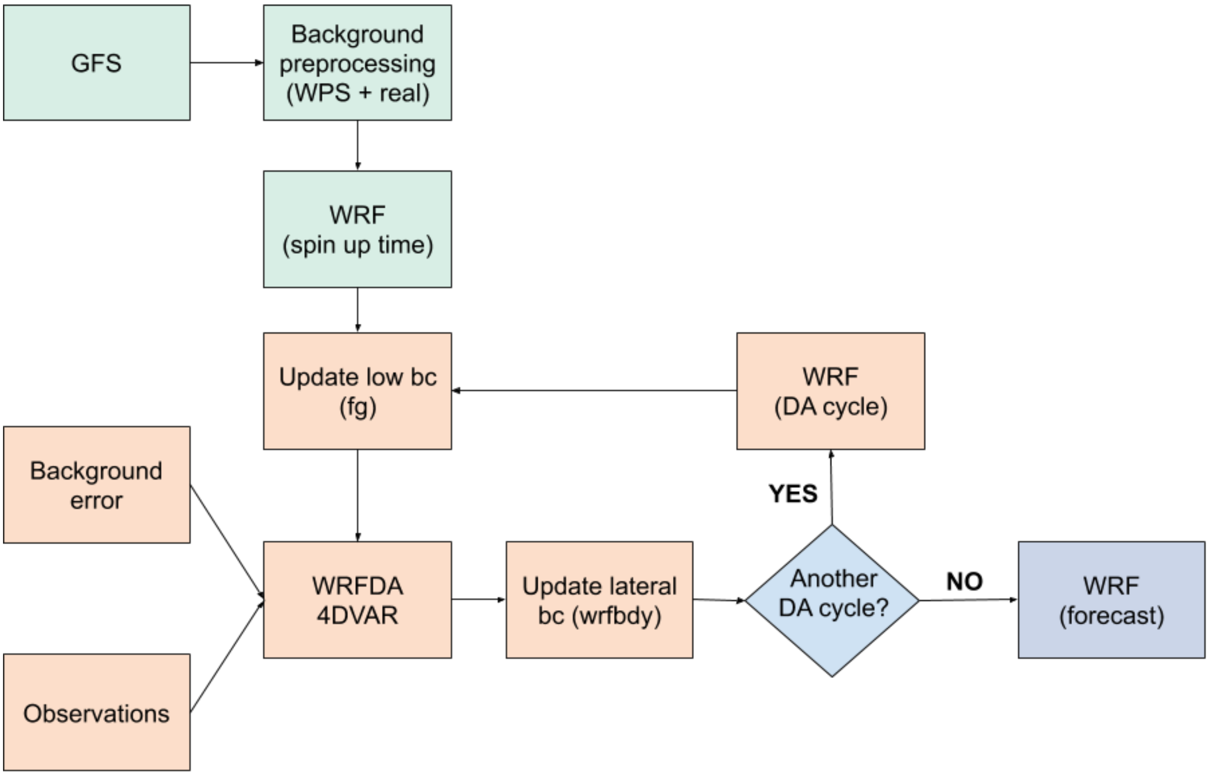

Figure 1.1: Flow diagram for the data assimilation framework.

Below follows the set of scripts that runs all the steps previously described along a brief explanation with respect to their functions:

- *get_gfs.sh* downloads GFS data from ftp.ncep.noaa.gov;
- *get_bufr_obs.sh* downloads observations data from ftp.ncep.noaa.gov;
- *run_wps.sh* runs WPS;
- *run_real.sh* runs *real.exe*;
- *run_wrf.sh* runs WRF model;
- *run_wrfda-4dvar.sh* runs WRFDA with 4D-Var technique and updates low and lateral boundary conditions;
- *make_figs.py* creates figures from WRFDA results to allow us deeply understanding how WRFDA changes the first guess;
- *run_all.sh* runs all scripts mentioned above following the flow diagram shown in Figure 1.1.

The current version of the DA framework is not capable of generating a background error covariance matrix from our weather forecasts. Thus, our system uses NCEP background error covariance already available in the WRFDA package. It is worth mentioning that this feature will be implemented soon.

2. Experiment design

We designed a simple experiment to test if our DA framework is actually working properly, that is, reducing the background error. Figure 1.2 shows the grid domain used in the experiment, with 45 x 45 grid points and 20 km of horizontal spacing, covering an area of 810 km^2. The simulation starts at 00:00 UTC in 23 June 2020 and has 6 hours of cold run (WRF spin up time), 18 hours of data assimilation window with 4 DA cycles, and 72 hours of weather forecast (not showing in this report). Thus, the assimilation starts at 06:00 UTC on Jun 23 and ends at 00:00 UTC on June 24.

We assimilated SYNOP, SOUND, METAR, SHIPS and observations as well as radiance measurements of AMSU (Advanced Microwave Sounding Unit)-A instrument from NOAA-18, MetOp-1 and MetOp-2 satellites.

Currently, this DA framework is not prepared to compute the background error covariance matrix with respect to our weather forecasts. For this reason, we are assuming the same NCEP background error covariance for the WOD system, which is already available in the WRFDA package.

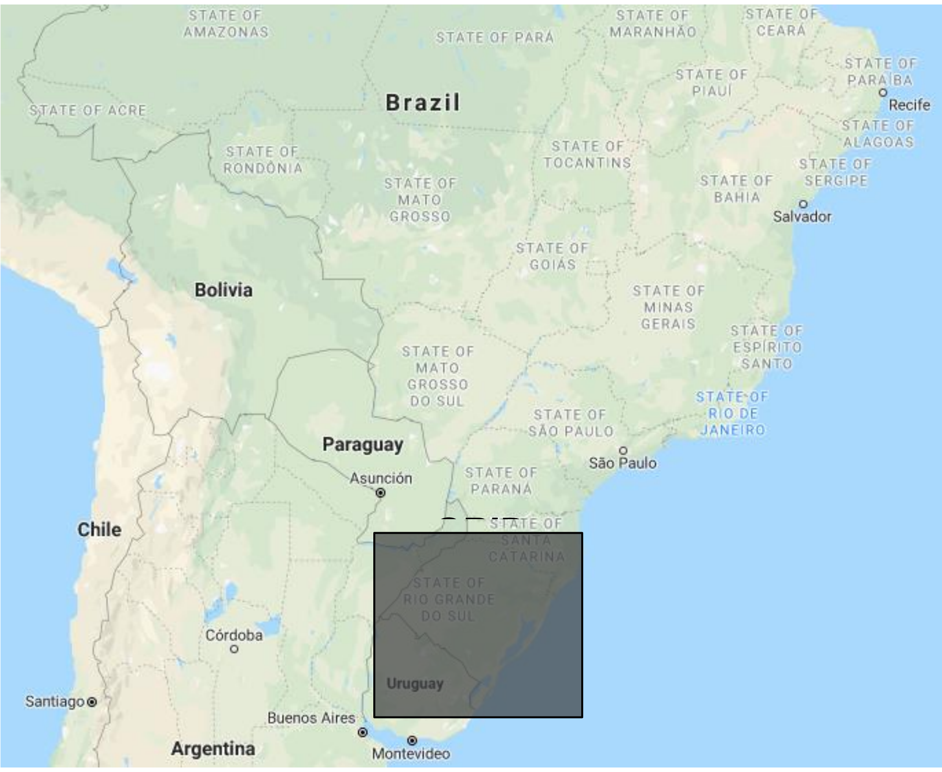

Figure 1.2: Grid domain used in the experiment (grey box).

3. Preliminary results

Figure 3.1 compares the root mean square errors (RMSE) of analysis (*oma*) and first guess (*omb*) simulations in terms pressure (*p*), water vapor mixing ratio (*q*), temperature (*t*), zonal wind (*u*) and meridional wind (*v*) from SYNOP observations for each DA cycle. Except for temperature in the two first cycle, WRFDA was able to reduce the analysis error of all variables compared with the first guess. In general, larger differences between analysis and first guess can be seen in the *u* and *v* RMSE.

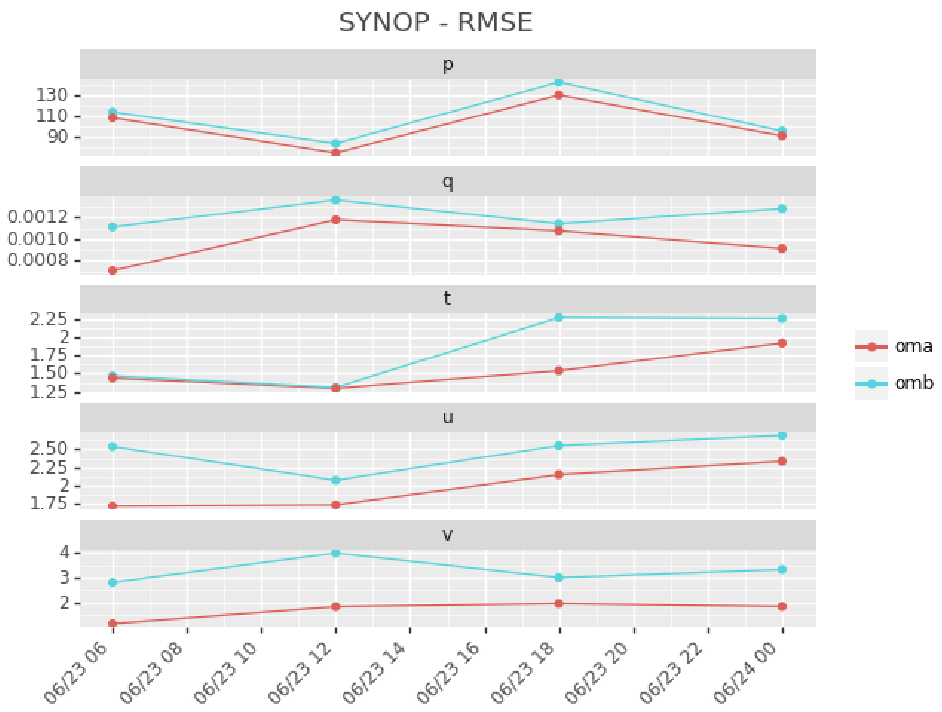

Figure 3.1: RMSE of analysis (*oma*) and first guess (*omb*) simulations in terms pressure (*p*), water vapor mixing ratio (*q*), temperature (*t*), zonal wind (*u*) and meridional wind (*v*) from SYNOP observations throughout the DA cycles.

Figure 3.2 is built similar to Figure 3.1, but for radiances of AMSU-A instrument from NOAA-18 satellite for channels 5, 6 and 8. Comparing the analysis with first guess RMSE, relevant differences between them become apparent, especially for channels 6 and 8. *oma* presents a smaller error than *omb,* and the error of both simulations decreases as DA framework goes to the final cycle. This result suggests that, by correcting the analysis during the first DA cycle, WRFDA is reducing the error of the first guess in the final DA cycle.

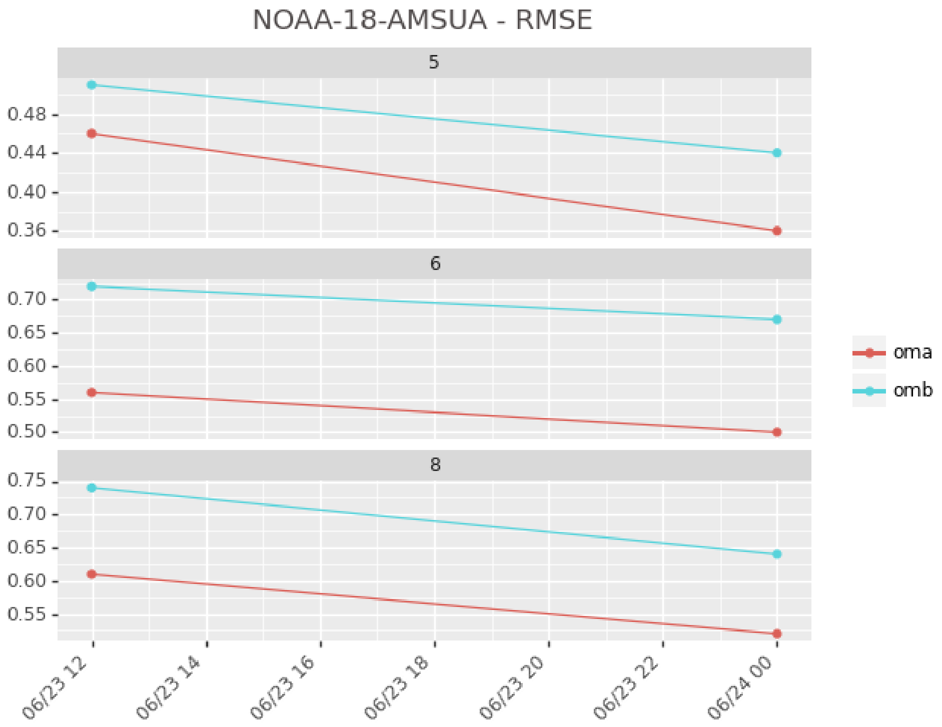

Figure 3.2: RMSE of analysis (oma) and first guess (omb) simulations in terms of radiance of AMSU-A sensor from NOAA-18. The top, middle and bottom panels refer to channels 5, 6 and 8, respectively, for two DA cycles (12:00 UTC Jun 23 and 00:00 UTC Jun 24).

Horizontal mean of *p*, *q*, *t*, *u* and *v* vertical profiles in terms of analysis increment (analysis minus first guess) are presented in Figure 3.3. Since we are using the NCEP generalized background covariance error matrix (as previously mentioned), WRFDA did not updated the pressure state variable, thereby, mean vertical profile of *p* is zero. We can see that the algorithm adjusts temperature and wind in all model vertical levels and water vapour mixing ratio from the surface until level 22. These results suggest that we provided enough information for WRFDA to change the entire atmosphere of the simulation, not only the lower levels.

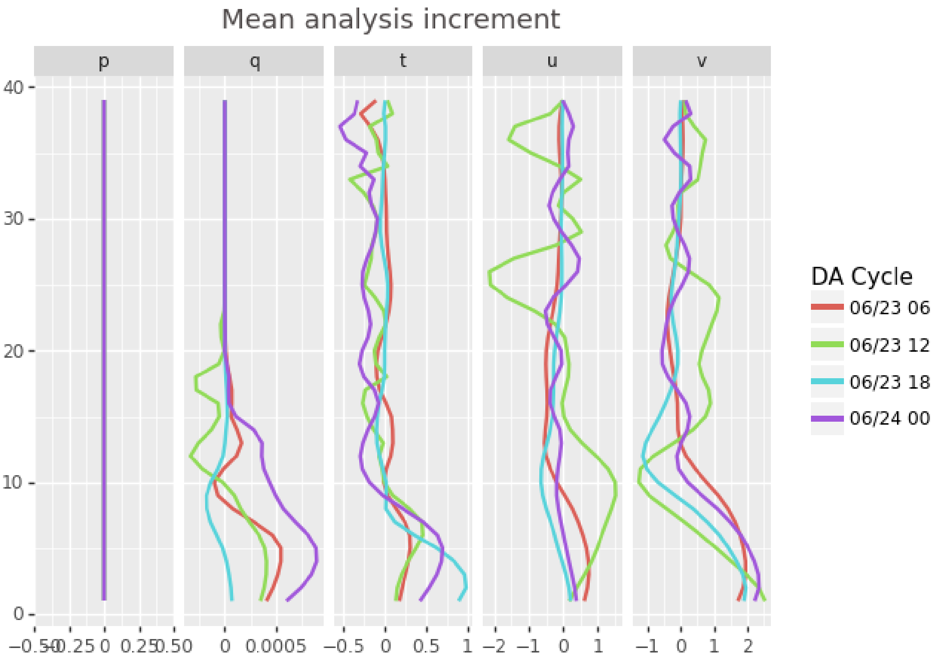

Figure 3.3: Horizontal mean of *p*, *q*, *t*, *u* and *v* vertical profiles in terms of analysis increment. The colours represent the data assimilation cycles as shown in the figure legend.

Analysis increment for the last DA cycle (00:00 UTC on June 24) is shown in Figure 3.4 for temperature at the first level (surface), water vapor mixing ratio at levels 0 and 10 (about 2 km height) as well as wind speed and direction at level 10. Stronger wind speed is verified over South Brazil and Argentina where the low-level jet is observed. Also, it is possible to note a relevant increase of moisture near the low-level jet at level 10 and over the surface with the greater values slightly displaced eastward. An increase about 1.6 ºC of temperature can be seen over Northeast of Argentina and by 1.2 ºC on southern Brazil. These spatial patterns of the analysis increment show that WRFDA can modify important features of the simulations and, therefore, has the potential to improve our weather forecasts. In addition, changes in the low-level jet, which is an important source of heat and moisture for mesoscale convective complex, might significantly modify the precipitation field over the region.

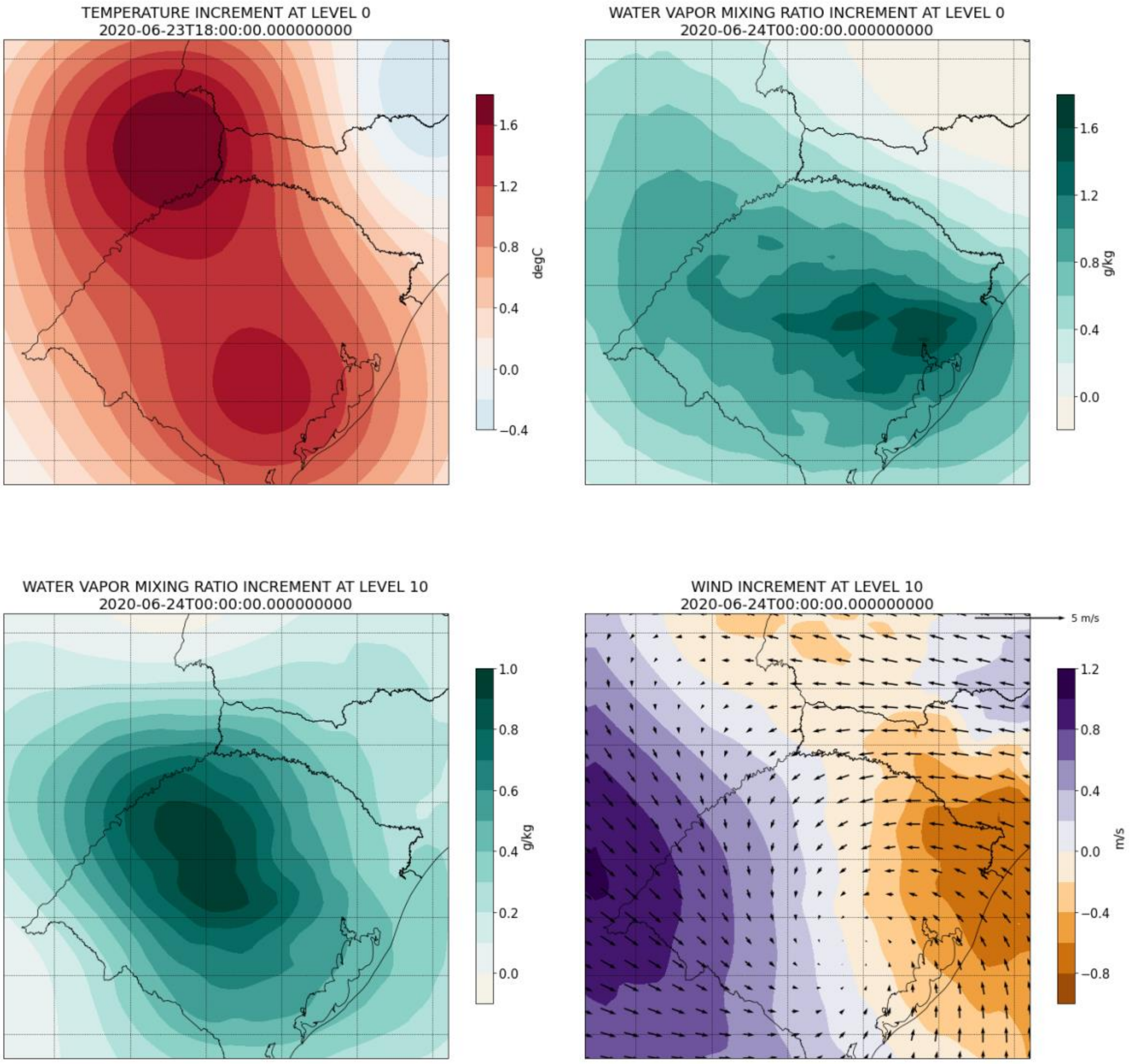

Figure 3.4: Analysis increment for the last DA cycle (00:00 UTC on June 24) of temperature at level 0 (surface), water vapour mixing ratio at levels 0 and 10 (at about 2 km height) as well as wind speed and direction at level 10.

4. Future steps

Despite the good results presented in Section 3, there are still some tasks to do before this coupling system becomes operational:

- Finish the post-processing script;
- Run experiments on operational grids;
- Include weather station data from our database in DA;
- Compute a background covariance error matrix based on our own weather forecasts via GEN_BE. It will provide properly weights to the cost function;
- Integrate the DA framework module with the WOD system.

5. References

Gao, F., Huang, X.-Y., Jacobs, N., A., and Wang, H., 2015: Assimilation of wind speed and direction observations: results from real observation experiments. Tellus A: Dynamic Meteorology and Oceanography, 67:1, 27132, doi: 10.3402/tellusa.v67.27132.

Huang, X.-Y., Gao, F., Jacobs, N., A., and Wang, H., 2013: Assimilation of wind speed and direction observations: a new formulation and results from idealised experiments, Tellus A: Dynamic Meteorology and Oceanography, 65:1, 19936, doi: 10.3402/tellusa.v65i0.19936

Xu, D., Liu, Z., Huang, X.-Y., Min, J., and Wang H., 2013: Impact of assimilating IASI radiance observations on forecasts of two tropical cyclones. Meteorology and Atmospheric Physics, 122, 1–18, doi: 10.1007/s00703-013-0276-2.

Huang, X., and Coauthors, 2009: Four-Dimensional Variational Data Assimilation for WRF: Formulation and Preliminary Results. Monthly Weather Review, 137, 299–314, doi: https://doi.org/10.1175/2008MWR2577.1.

Wu, Y., Liu, Z., and Li, D., 2020: Improving forecasts of a record-breaking rainstorm in Guangzhou by assimilating every 10-min AHI radiances with WRF 4DVAR. Atmospheric Research, 239, doi: https://doi.org/10.1016/j.renene.2019.09.011.