Revista Brasileira de Meteorologia, **v. 36, n. 1,** 87−96, 2021 rbmet.org.br
DOI: http://dx.doi.org/10.1590/0102-77863610001

Article

Data Assimilation Using WRFDA Over the Terminal Area of Rio de Janeiro

Vinícius Albuquerque de Almeida[1], Gutemberg Borges França[1],
Haroldo Fraga de Campos Velho[2], Nelson Francisco Favilla Ebecken[3]

[1]*Laboratório de Meteorologia Aplicada, Universidade Federal do Rio de Janeiro, Rio de Janeiro, RJ, Brasil.*
[2]*Laboratório de Computação e Matemática Aplicada, Instituto Nacional de Pesquisas Espaciais, São José dos Campos, SP, Brasil.*
[3]*Instituto Alberto Luiz Coimbra de Pós-Graduação e Pesquisa de Engenharia, RJ, Brasil.*

Received: 27 July 2020 - Accepted: 18 October 2020

Abstract

The impact of the data assimilation process of air temperature and relative humidity from surface meteorological stations and sounding at airports in the terminal area of Rio de Janeiro is evaluated using the *Weather Research and Forecast Data Assimilation* system. Synthetic data of temperature, relative humidity and wind are generated in the locations of airport sensors by applying a white-noise perturbation in the forecast data. Results show a positive overall impact of the assimilation process with the removal of part of the noise in the observation data but keeping the effect of local conditions in the later timesteps of the simulation. In addition, with the assimilation process there is a global reduction of the error between the analysis data and the observation data. In the future, a neural network will be trained to emulate the data assimilation process to speed-up the assimilation process in the WRF model.

Keywords data assimilation, 3d Var, surface data, profile data.

Assimilação de Dados Utilizando o WRFDA na Área Terminal do Rio de Janeiro

Resumo

O impacto do processo de assimilação de dados de temperatura do ar e umidade relativa de estações meteorológicas de superfície e sondagem em aeroportos na área terminal do Rio de Janeiro é avaliado usando o sistema *Weather Research and Forecast Data Assimilation*. Dados sintéticos de temperatura, umidade relativa e vento, são gerados nas localidades dos sensores dos aeroportos a partir da aplicação de uma perturbação gaussiana nos dados de previsão. Resultados mostram um resultado positivo do processo de assimilação com remoção de parte do ruído nos dados de observação, mas mantendo o efeito das condições locais nos instantes posteriores da simulação. Além disso, com o processo de assimilação há uma redução global no domínio do erro entre os dados da análise e os dados de observação. No futuro, uma rede neural será treinada para emular o processo de assimilação de dados para acelerar o processo de assimilação no modelo WRF.

Palavras-chave: assimilação de dados, 3d Var, dados de superfície, sondagem.

1. Introduction

Numerical weather forecasting is considered an initial-value problem where the present state of the atmosphere is used as input to a numerical model for simulating or forecasting its evolution on space and time. The problem of the initial condition determination for a forecast model is essential and complex, and has become a science in itself (Daley, 1991). Several methods have been developed since the 1950s to tackle this problem. Lorenc (1986), Daley (1991), Talagrand (1997), Zupanski and

---

Autor de correspondência: Vinícius A. Almeida, vinicius@lma.ufrj.br.

Kalnay (1999), Kalnay (2002), Barker *et al.* (2004), Barker *et al.* (2012), Lorenc and Jardak (2018), among others provide a broader review on data analysis and assimilation techniques.

In meteorology, there is a wide variety of data sources to be assimilated to accurately estimate the state of the atmosphere, which includes conventional and non-conventional data. Conventional data include surface meteorological stations, balloon soundings, aircraft and ship observations. On the other hand, data retrieved from satellites (e.g. radiance), wind profilers (e.g. SODAR, LIDAR), and radar are usually known as non-conventional. Conventional data are commonly assimilated in global models, but very often the local conditions they represent are smoothed due: low-resolution models, data quality control that let some data sources out of the global model run1 due to missing data or errors, delay in data transmission to the global operational centers, many data sources are not part of the Global Telecommunication System (GTS), such as local wind profilers (SODAR, LiDAR) and RADAR. interpolation methods and quality control routines. Also, not all observations are part of the global observation network and thus are not processed by data assimilation routines of global models. Therefore, to accurately determine the state of the atmosphere it is mandatory not to rely only on the global model's analysis, but also, to assimilate all the available local data.

The present article is part of a sequence of studies related to nowcasting that have been executed by the Applied Meteorological Laboratory at the Federal University of Rio de Janeiro, following Almeida (2009), Silva *et al.* (2016), França, Almeida, and Rossete (2016), França *et al.* (2018), Paulucci *et al.* (2019), and Almeida *et al.* (2020a, 2020b). All these studies encompass researches based on artificial intelligence and methods of limited-area numerical weather forecasts. This work relates to the latter, exploring the sensibility of the Weather Research and Forecasting (WRF) regional model for surface and upper-air data assimilation in the metropolitan area of Rio de Janeiro.

2. Material and Methods

The study area in the present work is the metropolitan area of Rio de Janeiro and its surroundings (Fig. 1) located approximately at latitude 22°55’44.3” S and longitude 43°24’21.1” W. The most import airports in the region are highlighted in Fig. 1 by their International Civil Aviation Organization (ICAO) codes: Santos Dumont Airport (SBRJ), Galeão International Airport (SBGL), Santa Cruz Air Force Base (SBSC), Jacarepaguá Airport and Afonsos Air Force Base (SBAF).

Each airport is responsible for local hourly routine and special reports surface observations of several meteorological parameters as surface wind (direction and speed), visibility, significant weather, cloud cover, air and dewpoint temperature, and station pressure. Besides, the SBGL airport has an upper-air (or sounding) station that produces regularly atmospheric soundings twice a day, the atmospheric profile of pressure, air and dewpoint temperature, relative humidity, and wind (direction and speed), from the surface up to more than 25 km.

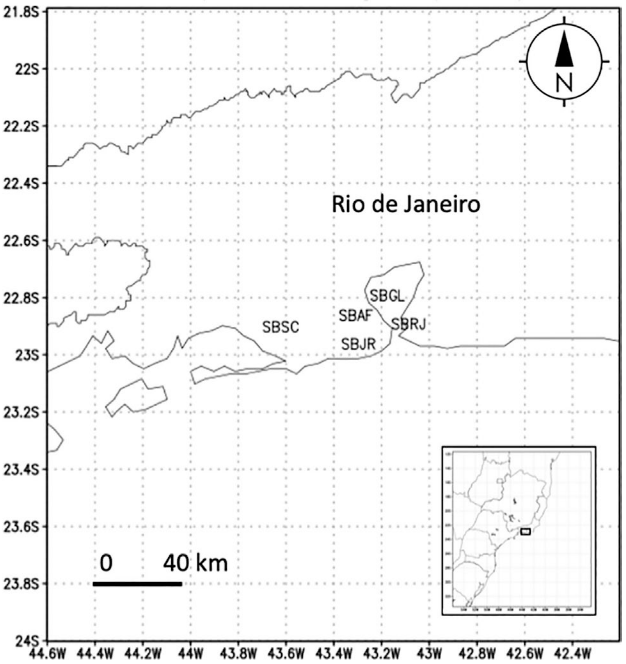


Figure 1 - Domain and computational grid. The labels SBSC, SBAF, SBJR, SBRJ and SBGL are the locations of the airports in the metropolitan area of Rio de Janeiro.

The numerical experiments performed using the NCEP FNL (Final) Operational Global Analysis data for initial and boundary conditions. The FNL data are available on 1-degree grids prepared operationally every 6 h. This product is from the Global Data Assimilation System (GDAS), which continuously collects observational data from the Global Telecommunications System (GTS), and other sources.

2.1. WRF model

The WRF Model is a mesoscale numerical weather prediction system designed for both atmospheric research and operational forecasting applications. It features two dynamical cores, a data assimilation system, and a software architecture supporting parallel computation and system extensibility. The effort to develop WRF began in the latter 1990s and was a collaborative partnership of the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (represented by the National Centers for Environmental Prediction (NCEP) and the Earth System Research Laboratory), the U.S. Air Force, the Naval Research Laboratory, the University of Oklahoma, and the Federal Aviation Administration (FAA). Please refer to the WRF Users Guide and the Technical Note document available at WRF website for completeness of the description of WRF (Skamarock *et al.*, 2019).

The WRF model solves a set of equations that control the state and evolution of the atmosphere, including: (i) conservation of momentum; (ii) thermodynamic energy conservation; (iii) mass conservation; (iv) geopotential relation; and (v) the equation of state. Also, several physical processes are parameterized (e.g. short and longwave radiation transfer, surface modeling, turbulence, cumulus convection, cloud microphysics and precipitation), because these ones are too small, too brief, too complex, too poorly understood, or too computationally costly to be explicitly represented.

In our numerical experiments, the WRF model is integrated into a 2-km grid with 35 levels in vertical, generating hourly outputs from the surface and pressure-level variables. Regarding the parametrizations the following options were chosen: Microphysics - WRF Single-moment 3 (Hong *et al.*, 2004), Cumulus - Grell-Freitas Ensemble Scheme (Grell and Freitas, 2014), Radiation - Dudhia Shortwave Scheme (Dudhia, 1989)/ RRTM Longwave Scheme (Mlawer *et al.*, 1997) , Planetary Boundary Layer - Yonsei University Scheme (YSU) (Hong, 2006) and Land-Surface model - Unified Noah Land Surface Model (Tewari *et al.*, 2004).

2.2. Data assimilation method: 3D-Var

The 3D-Var approach was used as implemented in the Data Assimilation component of the WRF framework. The basic ideas of variational data assimilation and specifically the WRF Data Assimilation (WRFDA) system is deeply discussed in Barker *et al.* (2004) and Barker *et al.* (2012).

Among various data assimilation methods, the variational approaches have been widely used in meteorology, specifically the method 3D-Var. In the 3D-Var approach, a cost function (Eq. (1)) is defined which is proportional to the square of the distance between the analysis ($\vec{x}^{a}$) and both the background ($\vec{x}^{b}$) and the observations ($\vec{y}^{O}$) (Sasaki, 1970; Kalnay, 2012). The analysis field is computed by the direct minimization of such function. Important to notice that the error matrices for both the background *(B)* and observation R are considered in the minimization process. The operator H mapped the gridded analysis to the observation space for comparison against the observation matrix $\vec{y}^{O}$. The analysis $\vec{x}^{a}$ is computed by minimizing the cost function (J) expressed below:

$$J = \frac{1}{2}\left\{ \left[\vec{y}^{O} - H(\vec{x})\right]^{T} R^{-1}\left[\vec{y}^{O} - H\left(\vec{x}\right)\right] + \left(\vec{x} - \vec{x}^{b}\right)^{T} B^{-1}\left(\vec{x} - \vec{x}^{b}\right)\right\} \tag{1}$$

where R is the covariance matrix of the observation errors, and B is the covariance of the background errors matrix. The latter matrix is computed as a vector product from the difference of two WRF executions for a certain initial condition (Barker *et al.*, 2004). Here, the B matrix was computed by the NMC method (Parrish and Derber, 1992) and the R matrix entries are the same from a table of observation errors for each major observation type, as used in the US Air Force Weather Agency applications (Barker *et al.*, 2012).

The 3D-Var approach is described in the details in Barker *et al.* (2004), and also in chapter 6 of the WRF User's Guide.

2.3. Description of Experiments

Experiments with 6h-cycle for 7 days with data assimilation are performed using the WRFDA in 2014 and 2015 starting on February 1st with 168 h for time-integration (seven days). February is a very important month in Southern Hemisphere summer. This month is characterized by a peak of atmospheric discharges in Rio de Janeiro (Paulucci *et al.*, 2019) and the development of intense convective events. Lastly, after the end-of-the-year holidays, February has a peak of movements in airports, becoming the period relevant - since our study is a joint research between the Federal University of Rio de Janeiro and the Department of Airspace Control (DECEA), a division of the Brazilian Air Force. The data assimilation is carried out every 6 h for surface variables (air temperature, relative humidity, and wind direction and speed) at the airport locations, and every 12 h for upper-air variables (air temperature, relative humidity, and wind direction and speed) at SBGL location.

The experiment was performed in the following steps:

a. White-noise perturbation is applied to GFS analysis field on Feb, 1st 00 UTC at the airport locations for surface and upper-air data generating synthetic observations;
b. Synthetic observations are placed on the exact coordinates where real sensors are located;
c. New analysis field is generated from synthetic observations and background field using the 3D-Var data assimilation technique;
d. WRF model is integrated for 6-h;
e. Steps (i)-(iii) are repeated until Feb, 8th 00 UTC with surface data assimilation every 6 h and upper-air data assimilation every 12 h;
f. Steps (i)-(iv) are repeated for the same period of 168h for 2014 and 2015.

3. Results and Discussions

This section presents the results of the experiments performed in this work showing the characteristics of data assimilation in the study area.

Before presenting the results, a discussion is necessary regarding the domain definition and the use of a single domain instead of nested domains. An experiment comparing 6-h assimilation cycle was performed considering a nested experiment (with three grids of 32 km, 8 km and 2 km for horizontal resolutions, respectively), and a single-domain experiment (with a 2-km grid). Figure 2 shows the result of a 6-h assimilation cycle for the single-domain (Fig. 2a) and the nested-domain (Fig. 2b) experiments at each airport within the study area. The comparison was performed on the 2-km horizontal resolution grid. Figure 2 shows the effect of the assimilation process is very similar for both experiments, in other words, there is a reduction of the white-noise perturbation for both analysis. Therefore, the mentioned experiments allow us to use a single-domain (computationally cheaper) instead of using nested domains.

Any data assimilation method consists basically in optimally merging observation and forecast fields to generate the best approximation of the true state of a dynamic system. The observations do not represent "the reality" but the closest estimate of the true state superimposed with some noise due to the nature of the sensors. Therefore, a good strategy to evaluate a data assimilation algorithm is to apply some perturbation in the location of the sensors and perform a data assimilation process. If this algorithm is working, the expected result is that the perturbation would be partially removed and the analysis field would be closer to the original field (before the perturbation application), that is, our "true" state of the dynamical system.

Figures 3 to 6 present the results of the assimilation process for air temperature, relative humidity, wind speed and wind speed profile at SBGL. All figures have the following structure: (a) control - 6-h forecast from initial field without assimilation; (b) background - 6-h forecast from initial field with assimilation; (c) analysis - initial field with surface and upper-air assimilation; and (d) the difference from analysis and control field.

Figure 3a shows that on Feb 1st, 2014 06 UTC the process of data assimilation generated an analysis field (Fig. 3c) with greater temperature values in the surround-

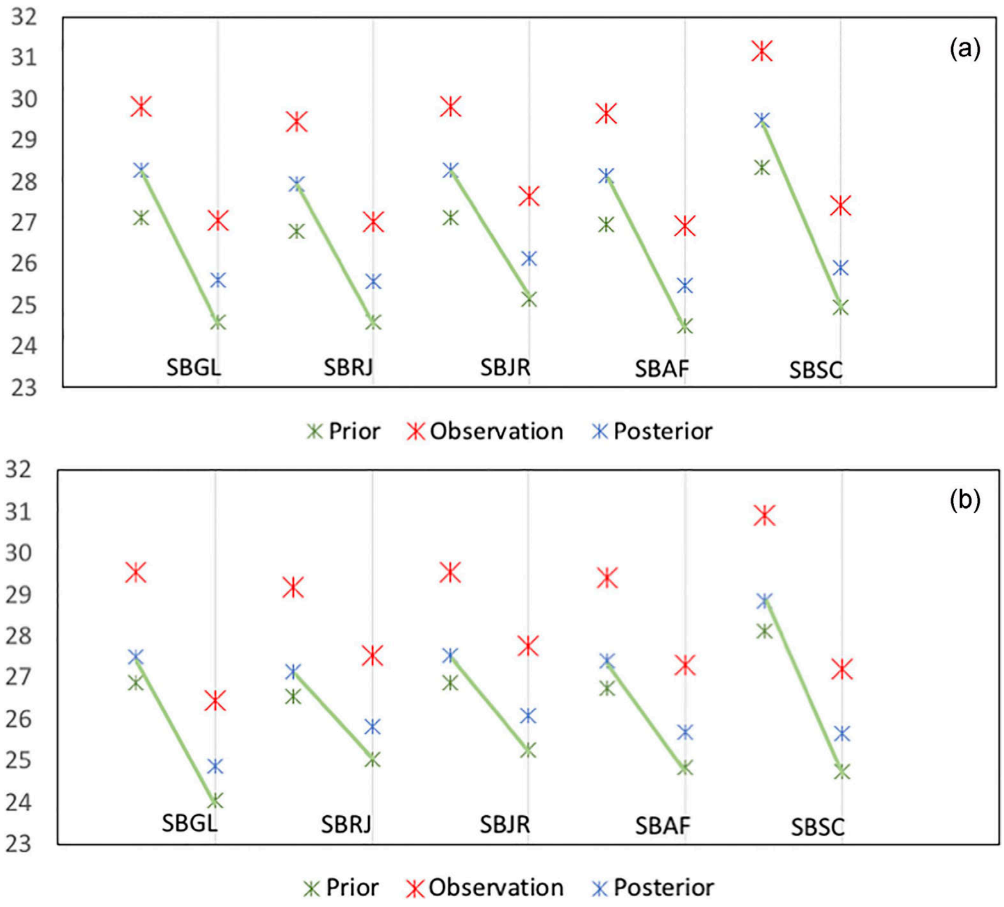
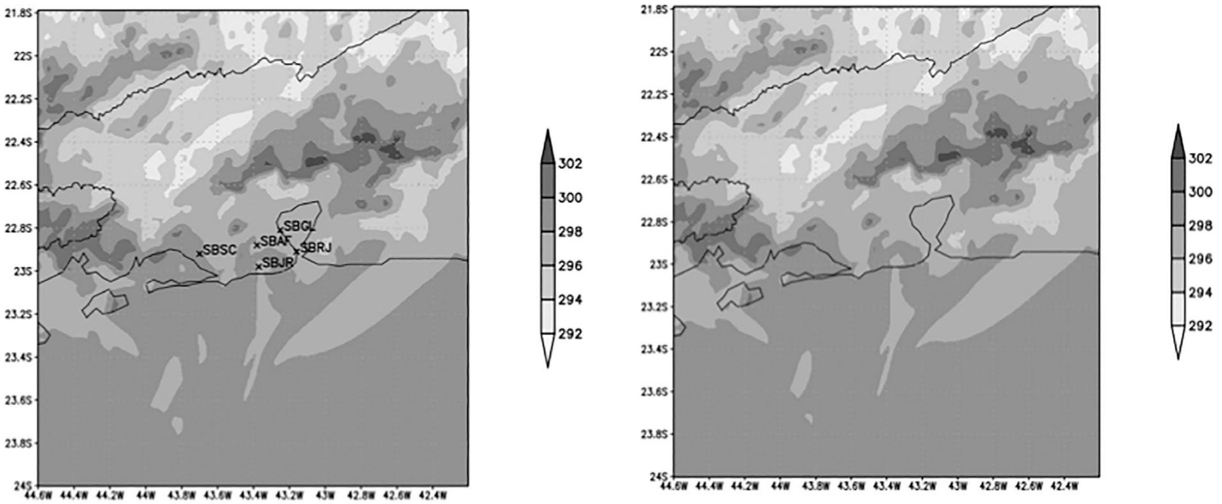
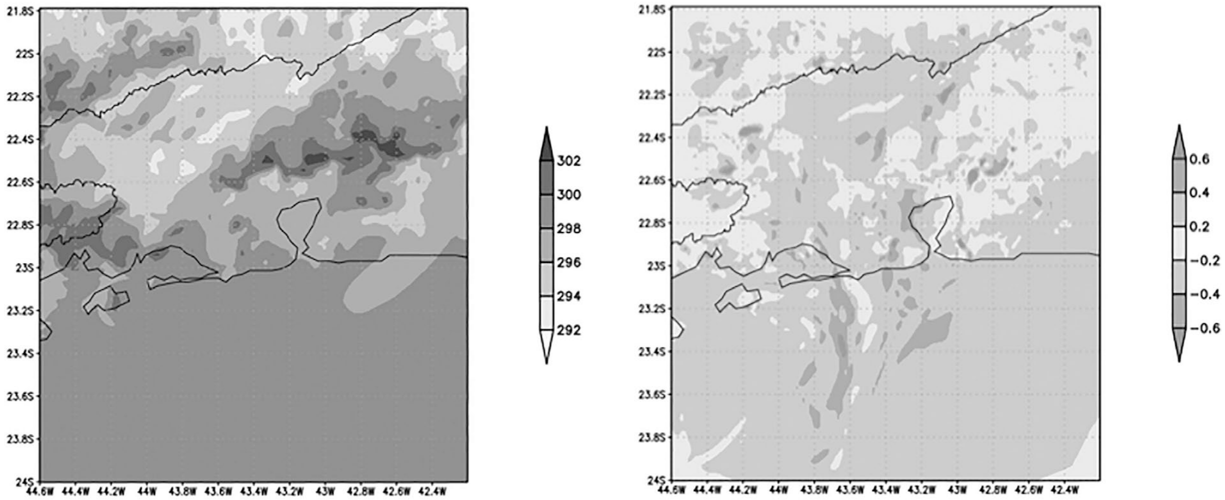


Figure 2 - Experiments for 6-h assimilation cycle at each airport for (a) single domain and (b) nested domain.



Control and observation points (a)

Background (b)



Analysis (c)

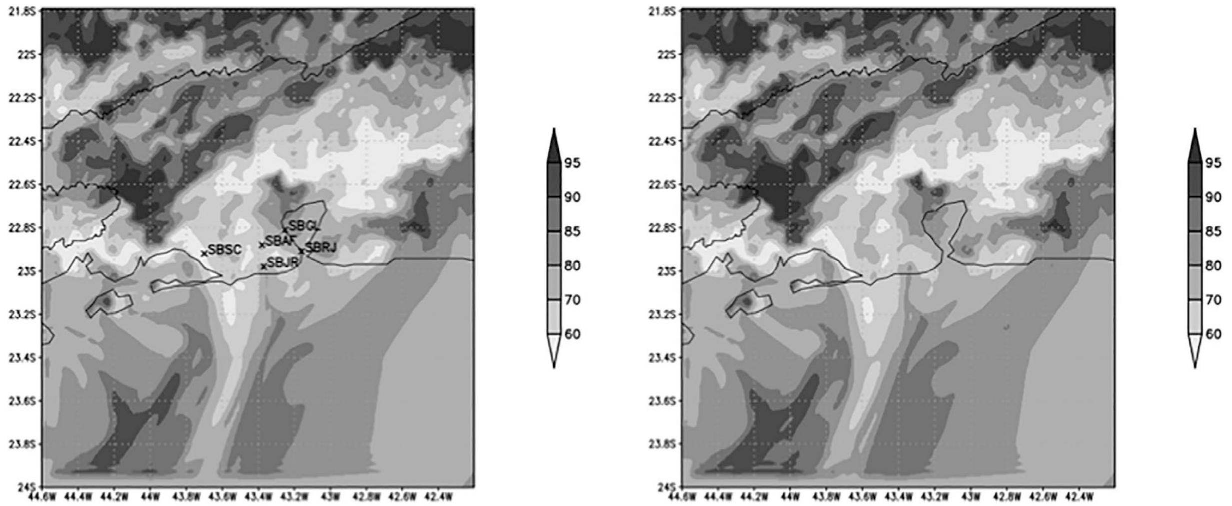
Analysis – Control (d)

Figure 3 - Air temperature field for (a) control and observation points, (b) background, (c) analysis and (d) difference from analysis and control, for Feb 1st, 2014 06 UTC.

ings of the station locations, mainly close to SBAF. Considering that the white-noise perturbation magnitude was a real number between 0 and 3 K the differences between analysis and control field (Fig. 3d) show that the data assimilation process removed 80-90% of the noise, and the resulting magnitude of innovation was not greater than |0.6|.

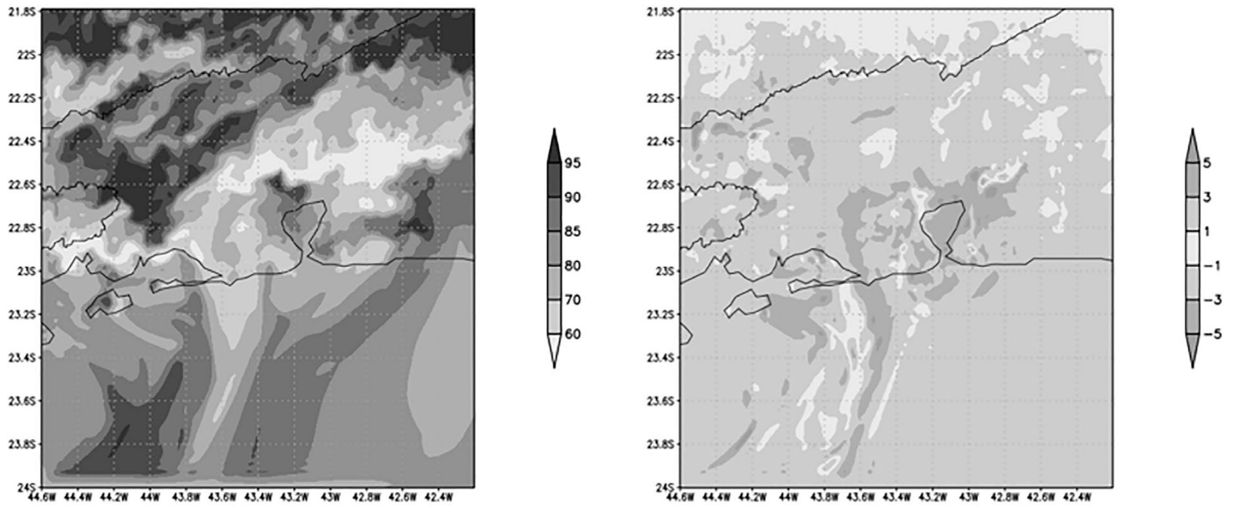
In a similar analysis, Fig. 4 show the impact of data assimilation process to the 2-m relative humidity field. Differently from what was observed for the temperature field in Fig. 3, the resulting innovation matrix generated by the 3D-Var (Fig. 4d) reached greater values, with regions with innovations up to 50% of the initial perturbation.

The wind speed (Fig. 5) shows that the data assimilation process generated an innovation (Fig. 5d) of up to 60% of the white-noise perturbation applied to the control field - which had a magnitude of up to 1 m s^{-1}. The difficulties involved into analyzing a vector field (the wind variable) in comparison to scalar variables (e.g. air temperature and relative humidity) are noteworthy. As shown in Fig. 5d, small perturbations in vector fields seem to cause perturbation in almost the whole domain whereas the innovation in scalar fields (Fig. 3d and 4d) are more restricted to surroundings of stations - where the perturbation was applied. The analysis of wind speed profile (Fig. 6) shows that the difference between analysis and control (Fig. 6d) was close to zero from 850 hPa upward, with small increase in the layer between 800 and 650 hPa. Greater positive impact is observed close to surface, possibly related to the contribution of the surface data assim-



Control and observation points (a)

Background (b)



Analysis (c)

Analysis – Control (d)

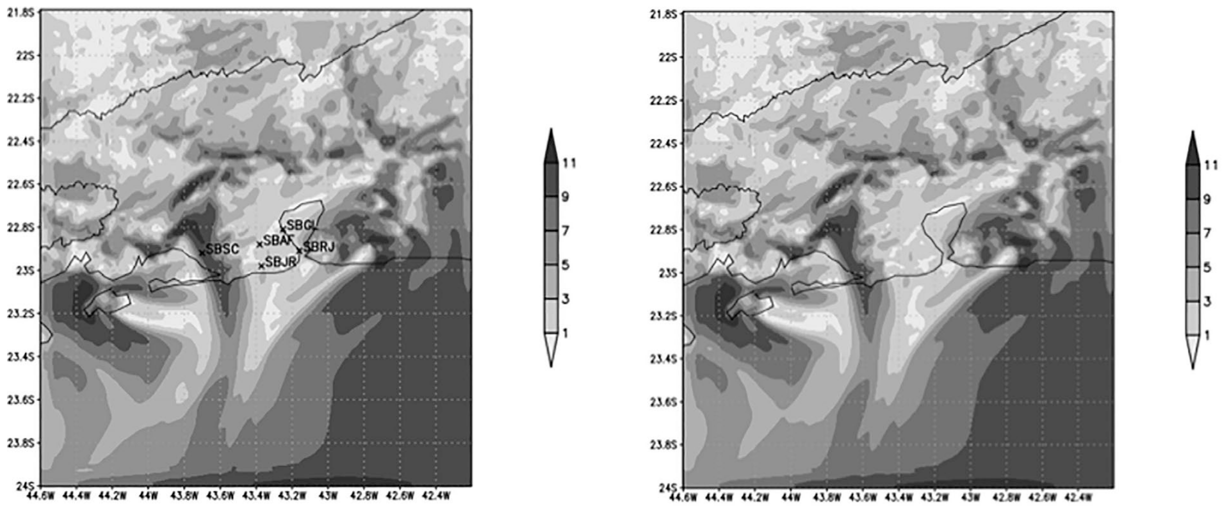
Figure 4 - Relative humidity field for (a) control and observation points , (b) analysis and (c) background and (d) difference from analysis and control field, for Feb 1st, 2014 06 UTC

ilation. Differently from the surface field, the impact in the vertical profile does not exceed 20% of the white noise perturbation. The small effect of the assimilation process might be related to the way that 3D-Var computes the impact of the station data in its surroundings, that is, the process of interpolation from observation grid to the model grid by the H operator (see eq. 1) after the innovation calculation.

In summary, all figures show a similar behavior, with small errors between analysis and control field, as expected, showing that the assimilation process removed most of the white-noise perturbation existent on the observation data.

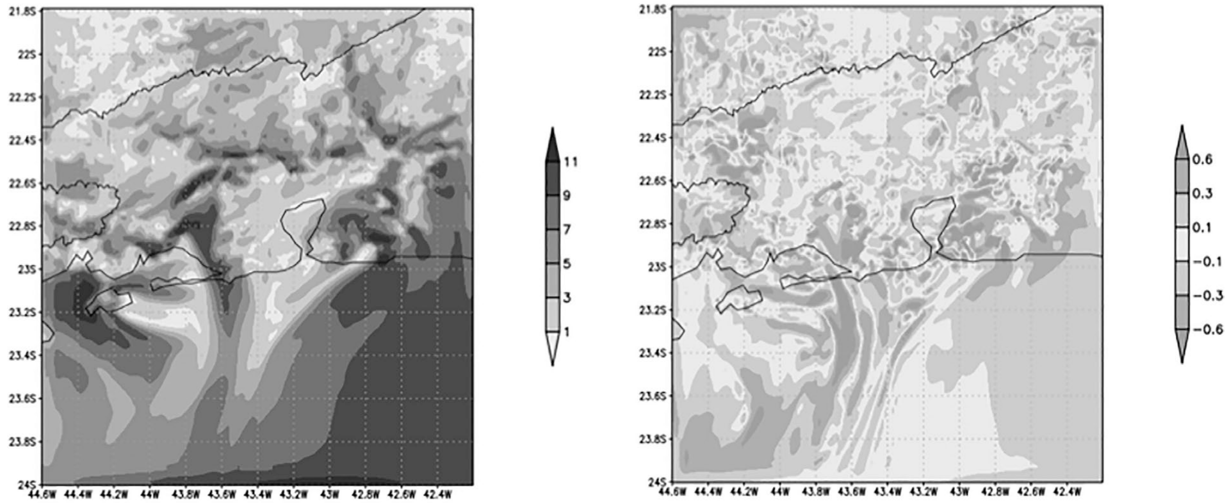
Therefore, the results of data assimilation process using synthetic data (air temperature, relative humidity and wind speed), show that the 3D-Var method in the WRFDA system is able to perform a good estimate of the control field, here representing the "true" state of the dynamic system. The implications of such results are important since it implicitly states that only by using local data in the regional atmospheric model initialization the weather forecasts are to be improved. Currently, many observational data are not used because they are not considered by the global model assimilation system or because they are not part of the global observation system.

Figures 7 presents the result of the background and analysis errors (against synthetic observations) of air temperature assimilation process at SBGL for every 6-h between Feb 1st to 7th, 2014, and Feb 1st to 7th, 2015. As expected, the assimilation process removes most of the



Control and observation points (a)

Background (b)



Analysis (c)

Analysis – Control (d)

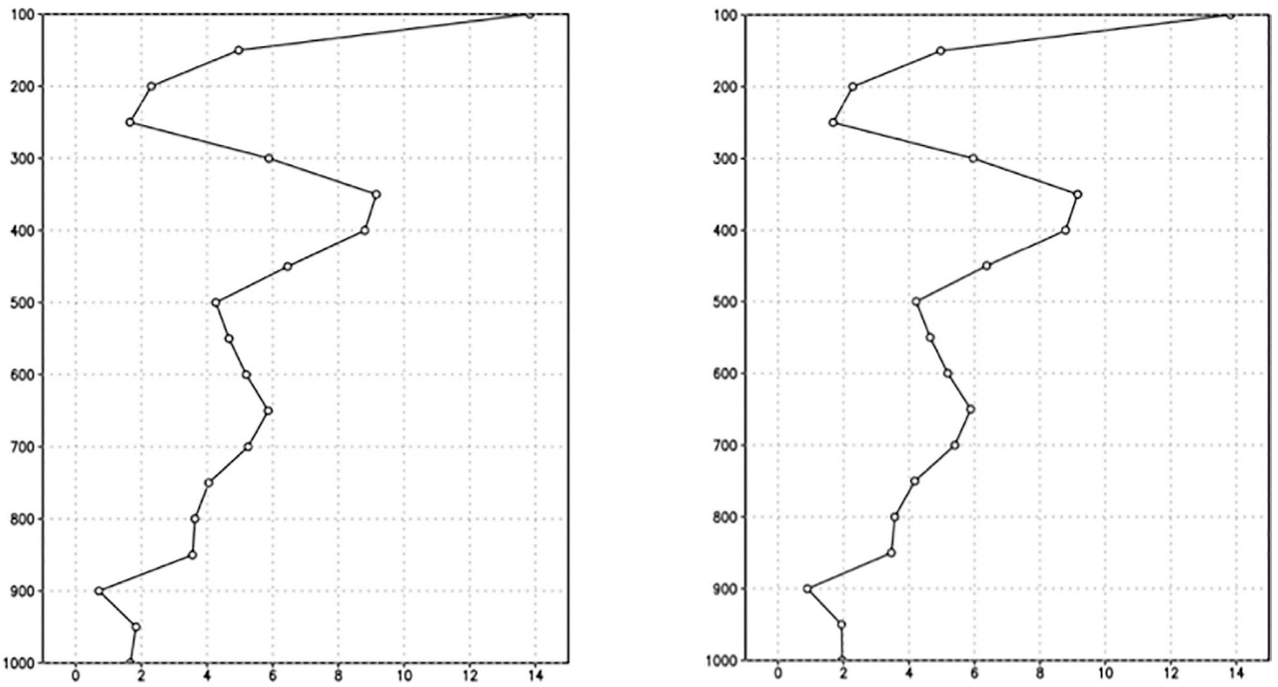
Figure 5 - Wind speed field for (a) control and observation points, (b) analysis and (c) background and (d) difference from analysis and control field, for Feb 1st, 2014 06 UTC.

white-noise perturbation existent on the observation data, represented by lower errors in the data (solid line) compared to the forecast (or background) values (dashed line), as previously discussed in the analysis of Fig. 3.

Table 1 displays the statistics for all grid points and surface variables used on the assimilation process. The overall impact of the assimilation is positive for scalar variables (air temperature and relative humidity) as shown by the smaller values of analysis error compared to the forecast error. As discussed in the analysis of Fig. 5-6 there is a difference in the assimilation for vector fields in comparison to scalar variables. While the standard devia-

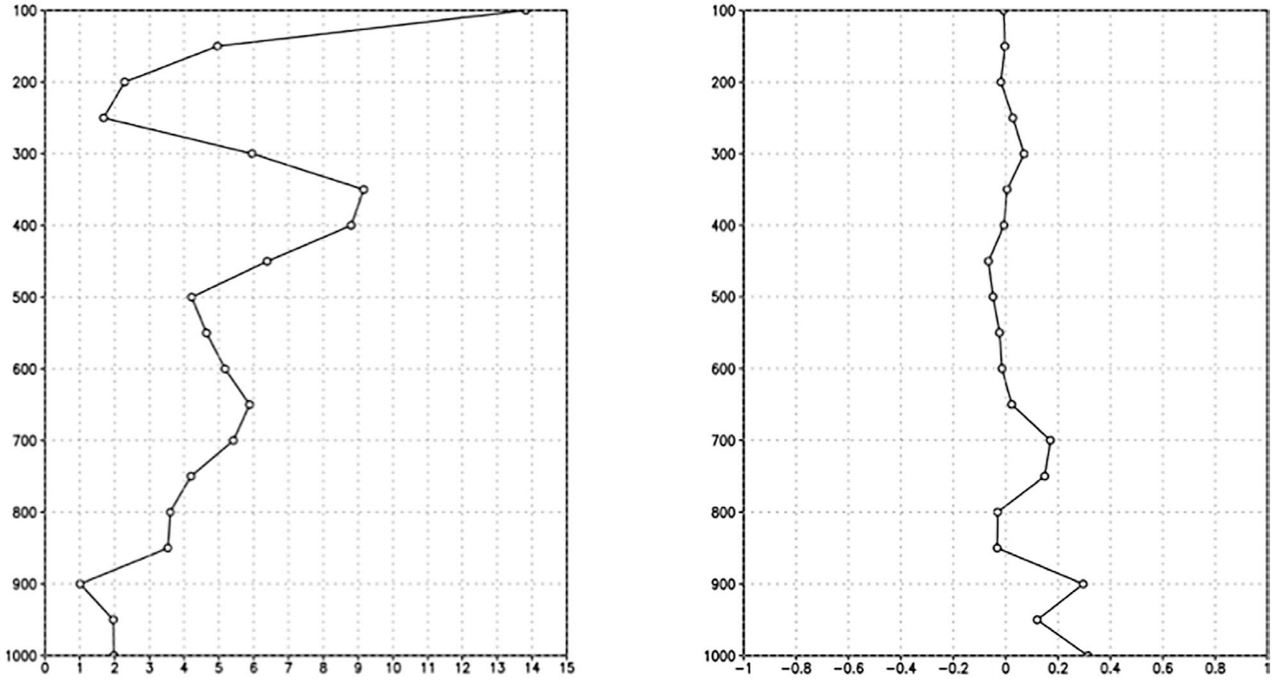
Table 1 - Statistics for all grid points and surface variables in the study domain. In the table, “std” refers to the standard variation and “error” to the difference between the background and analysis field to the synthetic observation.

	Observation		Background			Analysis		
	Mean	Std	Mean	Std	Error	Mean	Std	Error
Air temperature	30.13	3.84	27.48	3.45	9.00%	27.74	3.49	**8.00%**
Relative humidity	69.81	18.71	63.63	17.56	9.00%	65.22	17.46	**7.00%**
Wind speed	4.80	3.37	4.81	3.40	0.21%	4.79	3.38	0.21%



Control (a)

Background (b)



Analysis (c)

Analysis – Control (d)

Figure 6 - Profile field of wind speed for (a) control field, (b) analysis (c) background and (d) difference from analysis and observation field at SBGL, for Feb 1st, 2014 06 UTC.

tions of scalar variables are around 10% and 30% of the mean for air temperature and relative humidity, respectively, the standard deviation for wind speed is of the order of the mean. Although the error is relatively small for wind speed, the innovation in the wind speed is spread for almost the whole domain - see from Fig. 5d, whereas the innovation for scalar variables was closed to the station locations and their surroundings.

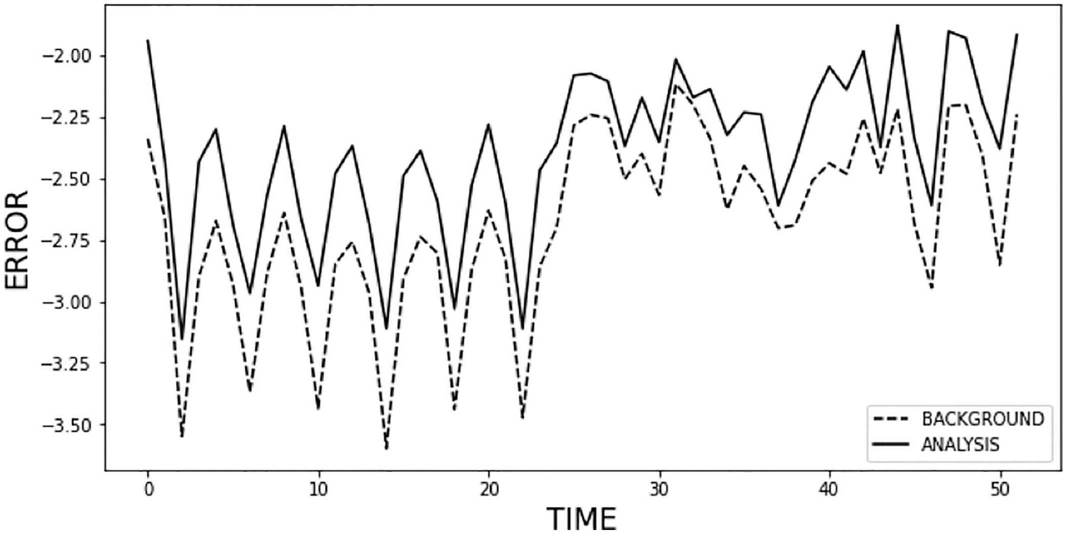


Figure 7 - Error on the air temperature field from synthetic observation to background (dashed line) and analysis (solid line) at SBGL between Feb 1st to 7th, 2014, and from Feb 1st to 7th, 2015.

4. Conclusions

The 3D-Var approach for data assimilation from the WRF framework was evaluated for the surface and upper-air data assimilation of METAR and TEMP at different airports of the metropolitan area of Rio de Janeiro for a 168-h period in February 2014 and 2015.

Results showed that the assimilation routine was able to adjust the background field of the airport temperature, relative humidity, and wind, providing a better estimate of the true state of the atmosphere - closer to the control field. Even though conventional data are commonly assimilated in global models, the local conditions are smoothed. Therefore, meteorological fields can be adjusted for improvements in mesoscale forecasts.

This results are in accordance to the results in the experiments commonly carried out by University Corporation for Atmospheric Research (UCAR) and the National Center for Atmospheric Research (NCAR), where numerical experiments are described for 1D systems and also to the results presented in Almeida *et al.* (2020b). From the cited UCAR-NCAR experiments, they conclude that the data assimilation process reduces the added noise in the prior forecast and makes the posterior field closer to the “actual dynamics”, that is, closer to the true state of the system.

The assimilation method can be effective for the short-range forecast and nowcasting time-window, under 24-h, removing the white-noise perturbation that is present in real observations and also adjusting the meteorological fields to local information.

In the future, the assimilation for real data using neural networks (Cintra and Campos Velho, 2012) will be tested to speed up the assimilation process, allowing for high-frequency assimilation processes (e.g. rapid update cycle) in the operational environment. The neural network approach will be trained to emulate the 3D-Var, as described in the framework described here.

Acknowledgments

This study is funded by the Department of Airspace Control (DECEA) via the Brazilian Organization for Scientific and Technological Development of Airspace Control (CTCEA) (GRANT: 002-2018/COPPETEC_CTCEA). We would like to thank the National Council for Scientific and Technological Development (CNPq, Portuguese) for the research grant for the authors HFCV (CNPq: 312924/2017-8) and GBF (CNPq: 304441/2018-0).

References

ALMEIDA, M.V. **Aplicação de Técnicas de Redes Neurais Artificiais na Previsão de Curtíssimo Prazo da Visibilidade e Teto para o Aeroporto De Guarulhos - SP**. Doctoral Dissertation, COPPE/UFRJ, Federal University of Rio de Janeiro, Brazil, 2009.

ALMEIDA, V.A.; FRANÇA, G.B.; CAMPOS VELHO, H.F. Short-range forecasting system for meteorological convective events in Rio de Janeiro using remote sensing of atmospheric discharges. **International Journal of Remote Sensing**, v. 41, n. 11, p. 4372-4388, 2020a.

ALMEIDA, V.A.; FRANÇA, G.B.; CAMPOS VELHO, H.F. Data Assimilation for Nowcasting in the terminal area of Rio de Janeiro. **Ciência e Natura**, v. 42, e40, 2020b.

BARKER, D.M.; HUANG, W.; GUO, Y.-R.; BOURGEOIS, A.; XIAO, X.N. A Three-Dimensional Variational Data Assimilation System for MM5: Implementation and Initial Results. **Mon. Wea. Rev.**, v. 132, p. 897-914, 2004.

BARKER, D.M.; HUANG, X.-Y.; LIU, Z.; AULIGNE, T.; ZHANG, X.; RUGG, S.; AL KATHERI, A.A.; BOURGEIOS, A.; BRAY, J.; CHEN, Y.; DEMIRTAS, M.; GUO, Y.; HENDERSON, T.; HUANG, W.; LIN, H.-C.; MICHALAKES, J.; RIZVI, S.; ZHANG, X.-Y. The Weather Research and Forecasting (WRF) model's community variational/ensemble data assimilation system: WRFDA. **Bull. Amer. Meteor. Soc.**, v. 93, n. 6, p. 831-843, 2012.

CINTRA, R.S.; CAMPOS VELHO, H.F. Global Data Assimilation Using Artificial Neural Networks In Speedy Model. **Proceedings of the 1st International Symposium on Uncertainty Quantification and Stochastic Modeling**, 2012.

DALEY, R. **Atmospheric Data Analysis**. Cambridge: Cambridge University Press, 466 p., 1991.

DUDHIA, J. Numerical study of convection observed during the Winter Monsoon Experiment using a mesoscale two-dimensional model. **J. Atmos. Sci.**, v. 46, n. 20, p. 3077-3107, 1989.

FRANÇA, G.B.; ALMEIDA, M.V.; ROSSETE, A.C. An automated nowcasting model of significant instability events in the flight terminal area of Rio De Janeiro, Brazil. **Atmospheric Measurement Techniques**, v. 9, n. 8, p. 2335-2344, 2016.

FRANÇA, G.B.; ALMEIDA, M.V.; BONNET, S.M.; ALBUQUERQUE NETO, F.A. Nowcasting model of low wind profile based on neural network using SODAR Data at Guarulhos Airport, Brazil. **International Journal of Remote Sensing**, v. 39, n. 8, p. 2506-2517, 2018.

GRELL, G.A.; FREITAS, S.R. A scale and aerosol aware stochastic convective parameterization for weather and air quality modeling. **Atmos. Chem. Phys.**, v. 14, p. 5233-5250, 2014.

HONG, S.-Y.; DUDHIA, J.; CHEN, S.H. A revised approach to ice microphysical processes for the bulk parameterization of clouds and precipitation. **Mon. Wea. Rev.**, v. 132, p. 103-120, 2004.

HONG, S.-Y.; NOH, Y.; DUDHIA, J. A new vertical diffusion package with an explicit treatment of entrainment processes. **Mon. Wea. Rev.**, v. 134, n. 9, p. 2318-2341, 2006.

KALNAY, E. **Atmospheric Modeling, Data Assimilation and Predictability**. Cambridge: Cambridge University Press, 368 p., 2002.

LORENC, A.C. Analysis methods for numerical weather prediction. **Q.J.R. Meteorol. Soc.**, v. 112, n. 474, p. 1177-1194, 1986.

LORENC, A.C.; JARDAK, M. A comparison of hybrid variational data assimilation methods for global NWP. **Q. J. R. Meteorol. Soc.**, v. 144, n. 717, p. 2748-2760, 2018.

MLAWER, E.J.; TAUBMAN, S.J.; BROWN, P.D.; IACONO, M.J.; CLOUGH, S.A. Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. **J. Geophys. Res.**, v. 102, n. D14, p. 16663-16682, 1997.

PARRISH, D.F.; DERBER, J.C. The National Meteorological Center's spectral statistical interpolation analysis system. **Mon. Wea. Rev.**, v. 120, n. 8, p. 1747-1763, 1992.

PAULUCCI, T.B.; FRANÇA, G.B.; LIBONATI, R.; RAMOS, A.M. Long-term spatial-temporal characterization of cloud-to-ground lightning in the metropolitan region of Rio de Janeiro. **Pure and Applied Geophysics**, v. 176, p. 5161-5175, 2019.

SILVA, W.L.; ALBUQUERQUE NETO, F.A.; FRANÇA, G.B.; MATSCHINSKE, M. Conceptual model for runway change procedure in Guarulhos International Airport based on SODAR data. **The Aeronautical Journal**, v. 120, n. 1227, p. 725-734, 2016.

SKAMAROCK, W.C.; KLEMP, J.B.; DUDHIA, J.; GILL, D.O.; LIU, Z.; BERNER, J.; WANG, W.; POWERS, J.G.; DUDA, M.G.; BARKER, D.M.; HUANG, X.-Y. **A Description of the Advanced Research WRF Version 4. NCAR Tech. Note NCAR/TN-556+STR**. Boulder: UCAR, 145 p., 2019.

TALAGRAND, O. Assimilation of observations, an introduction. **J. Met. Soc.**, v. 75, n. 1B, p. 191-209, 1997.

TEWARI, M.; CHEN, F.; WANG, W.; DUDHIA, J.; LEMONE, M.A.; MITCHELL, K.; EK, M.; GAYNO, G.; WEGIEL, J.; CUENCA, R.H. Implementation and verification of the unified NOAH land surface model in the WRF model. **20th Conference On Weather Analysis And Forecasting/16th Conference On Numerical Weather Prediction**, p. 11-15, 2004.

ZUPANSKI, M.; KALNAY, E. Principles of data assimilation. In: **Global Energy and Water Cycles**, K.A. Browning and R. J. Gurney, (eds). Cambridge: Cambridge University Press, p. 48-54, 1999.

Internet Resources

WRF website http://www2.mmm.ucar.edu/wrf/users/.

WRF User's Guide, http://www2.mmm.ucar.edu/wrf/users/docs/user_guide_V4/WRFUsersGuide.pdf.