Exploring the Potential Application of MetOp/GOME2 Ozone Data to Weather Analysis

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Abstract

In this study, a methodology of constructing and incorporating potential-vorticity (PV) data into initial conditions of a limited-area model is proposed. This methodology is based on the linear correlation between vertical (100hPa-500hPa) mean PV (MPV) and MetOp/GOME2 total ozone (O_3) data. On one hand, a linear regression model is implemented to generate MPV from O_3 data. On the other hand, a 3D-variational method is designed to assimilate MPV pseudo-observations as a first step toward investigating their dynamical impact.
Keywords: Remote Sensing, Ozone, Meteorology, Data assimilation, Numerical Weather Prediction.

1 Introduction

Synoptic weather systems have long been recognized as sources of total ozone variability, and many studies have explored the relationship between ozone (O_3) and meteorological variables, particularly the Potential Vorticity (PV) [1].
In line with [2], the present study makes use of the statistical correlation between vertical (100 hPa-500 hPa) mean PV (MPV) and MetOp/GOME2 O_3 data to generate MPV pseudo-observations. Furthermore, using a 3D-Var approach, the MPV data are assimilated within the Moroccan version of the ALADIN limited-area model (Aire Limitée Adaptation Dynamique).
This article reports on the technical implementation of the assimilation of MPV data. Section 2 describes GOME2 O_3 and MPV data. Section 3 presents the statistical correlation between GOME2 O_3 and MPV data. Section 4 describes MPV data assimilation. Section 5 summarizes the results and discusses their implication.

2 MetOp/GOME O_3 and ALADIN MPV data

In this section, a brief overview of MetOp/GOME2 O_3 and ALADIN MPV data is given.
Launched in October 2006, MetOp delivers continuous datasets supporting operational meteorology, global weather forecasting and climate monitoring [3]. On board MetOp, Global Ozone Monitoring Experiment 2 (GOME-2) obtains the total ozone with a high spatial and temporal resolution from the backscattered solar ultraviolet–visible radiance emerging at the top of the atmosphere [4].
The PV computation utilizes ALADIN (resolution 10 km and 60 levels) dynamical fields based on the following formulation [5]

$$PV = -g\xi_a \frac{\partial \theta}{\partial p} - g\frac{fp}{R}(\frac{p_0}{p})^{\frac{R}{C_p}}[(\frac{\partial U}{\partial p})^2 + (\frac{\partial V}{\partial p})^2] \quad (1)$$

Where ξ_a is the vertical component of the absolute vorticity, U and V the horizontal wind components, θ the potential temperature, R gas constant, C_p specific heat at constant pressure, p the pressure, p_0 a reference pressure, g the gravity and f Coriolis parameter.

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IJCSI International Journal of Computer Science Issues, Vol. 10, Issue 2, No 3, March 2013
ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org

The MPV is estimated using the following expression

$$MPV = \frac{1}{P_1 - P_2} \int_{P_1}^{P_2} PV.\delta p \qquad (2)$$

With $P_1 = 500\ hPa$ and $P_2 = 100\ hPa$

3 Correlation between MPV and O_3

As in [2], this study aims at establishing a linear regression model that links O_3 and MPV as described by the following expression

$$MPV = \alpha * O_3 + \beta \qquad (3)$$

where α and β are constants to be determined from the statistics of GOME2 O_3 and ALADIN MPV data. By using data covering the period from the 21^{st} of January 2010 to the 21^{st} of January 2011, the correlation between O_3 and MPV, as shown in Fig.1, is found to be dependent on latitudes and on months. Latitudes over 30° give a correlation coefficient that varies between 0.6748 and 0.8696 with a mean value of 0.7675.

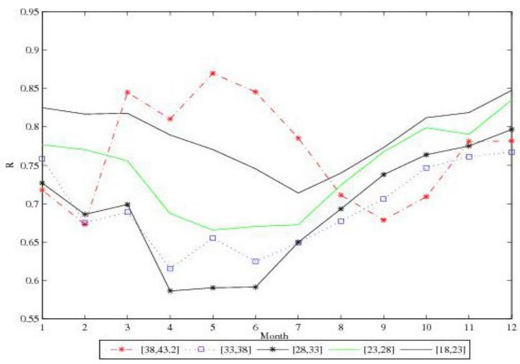

Fig. 1: MPV-O_3 correlation coefficient per month and per latitude over 2010.

Figure 2 shows daily MPV-O_3 correlation coefficients over November 2010. Over the latter period, GOME2 O_3 are found to be correlated to MPV with a correlation coefficient varying between 0.43 and 0.94, and a mean value of 0.7653.

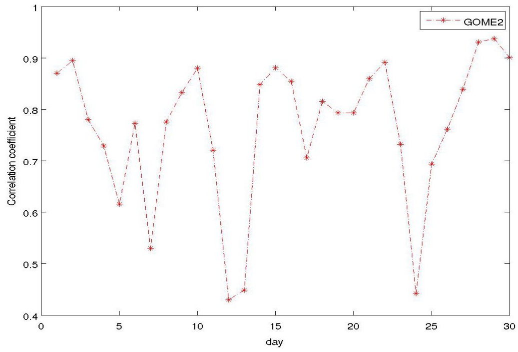

Fig. 2: Correlation coefficient per day over November 2010.

Data covering November 2010 gives a correlation coefficient of 0.8054 and a linear regression as follows

$$MPV = 0.3712\ 10^{-2} * O_3 - 0.8448 \qquad (4)$$

where O_3 and MPV are given in Dobson Unit (DU) and PVU ($1\ PVU = 10^{-6}\ m^2\ K\ kg^{-1}\ s^{-1}$), respectively. Hereafter, MPV pseudo-observations are generated from GOME2 O_3 data using Eq.4.

4 MPV data assimilation

4.1 Technical implementation

The dynamical impact of MPV data depends very much on how the information contained in the data is extracted and incorporated into the initial condition. For the latter purpose, data assimilation is a convenient statistical framework to estimate the initial state of the atmosphere given imperfect short-range forecasts (first-guess) and observations with limited precision. The aim is to produce an analysis for which the error from the reality (unknown) is lower than that of the first-guess and the observations. The assimilation system used in this study is based on a 3D-Variational scheme (3D-Var) [6]. The notation in this paper will follow [7] as closely as possible.

The 3D-Var scheme minimizes the following function $J(\delta x)$

$$J(\delta x) = J_b(\delta x) + J_o(\delta x) \qquad (5)$$

where the increment vector δx is the difference between the model state x and the first-guess state x^b. The $J_b(\delta x)$ term in Eq.5 refers to the first-guess cost function

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$$J_b(\delta x) = \delta x^T \mathbf{B}^{-1} \delta x \tag{6}$$

and the $J_o(\delta x)$ term refers to the observation cost function

$$J_o(\delta x) = (\mathbf{d} - \mathbf{H}(\delta x))^T \mathbf{R}^{-1} (\mathbf{d} - \mathbf{H}(\delta x)) \tag{7}$$

where $\mathbf{d}=\mathbf{y}^\circ-\mathscr{H}(\mathrm{x}_b)$ is the departure between the observation vector y° and its model equivalent in observation space $\mathscr{H}(\mathrm{x}_b)$. The operator $\mathscr{H}$ is a generalized interpolator (including model estimation of MPV) from the model grid to the observation location and $\mathbf{H}$ represents its tangent-linear. In Eq.6 and Eq.7 $\mathbf{B}$ and $\mathbf{R}$ represent the first-guess and observation error covariance matrices, respectively. In order to assimilate MPV observations, the following changes in the operational version of the ALADIN/3D-Var system have been applied. The PV at each level of the ALADIN model is computed using Eq.1. The expression of MPV at a level n is estimated through the following expression

$$MPV_n = \frac{1}{(P_1 - P_2)} \Delta P_n PV_n + MPV_{n-1} \tag{8}$$

where

- MPV_n: vertical mean PV from the level 1 to the level n
- MPV_{n-1}: vertical mean PV from the level 1 to the level $n-1$
- PV_n: PV at level n
- ΔP_n: pressure difference between the level n and the level $n-1$

The tangent-linear is estimated through the following expression

$$\delta MPV_n = \frac{1}{(P_1 - P_2)} \Delta P_n \delta PV_n + \frac{1}{(P_1 - P_2)} PV_n \delta \Delta P_n + \delta MPV_{n-1} \tag{9}$$

And then, it is algebrically defined by the following matrix

$$\begin{bmatrix} \delta PV_n \\ \delta \Delta P_n \\ \delta MPV_{n-1} \\ \delta MPV_n \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ \frac{\Delta P_n}{(P_1-P_2)} & \frac{PV_n}{(P_1-P_2)} & 1 & 0 \end{bmatrix} \begin{bmatrix} \delta PV_n \\ \delta \Delta P_n \\ \delta MPV_{n-1} \\ \delta MPV_n \end{bmatrix} \tag{10}$$

Defined as the transpose of the tangent-linear operator, the adjoint is algebraically presented by the following matrix

$$\begin{bmatrix} \delta PV_n^{\mathbf{AD}} \\ \delta \Delta P_n^{\mathbf{AD}} \\ \delta MPV_{n-1}^{\mathbf{AD}} \\ \delta MPV_n^{\mathbf{AD}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \frac{\Delta P_n}{(P_1-P_2)} \\ 0 & 1 & 0 & \frac{PV_n}{(P_1-P_2)} \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta PV_n \\ \delta \Delta P_n \\ \delta MPV_{n-1} \\ \delta MPV_n \end{bmatrix} \tag{11}$$

where superscript AD denotes the adjoint.
The adjoint operator can be written more explicitly as

$$\delta PV_n{}^{\mathbf{AD}} = \delta PV_n + \frac{1}{(P_1 - P_2)} \Delta P_n \delta MPV_n \tag{12}$$

$$\delta \Delta P_n^{\mathbf{AD}} = \delta \Delta P_n + \frac{1}{(P_1 - P_2)} PV_n \delta MPV_n \tag{13}$$

$$\delta MPV_{n-1}^{\mathbf{AD}} = \delta MPV_{n-1} + \delta MPV_n \tag{14}$$

$$\delta MPV_n^{\mathbf{AD}} = 0 \tag{15}$$

4.2 Results

MPV pseudo-observations are constructed from MetOp/GOME2 O_3 observations of the 29^{th} November 2010 between 09h UTC and 15h UTC (as shown in Fig.3) using Eq.4. The first-guess is a 6-hour forecast from the 29^{th} November 2010 at 06 UTC.

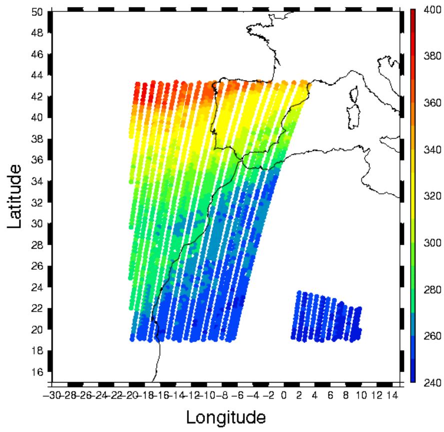

Fig. 3: MetOp/GOME2 total Ozone in DU observed on the 29^{th} November 2010 between 09h UTC and 15h UTC.

Figure 4 shows OMA and OMF, which refer to Observation minus Analysis and Observation minus

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First-guess for MPV, respectively. The assimilation system gives consistent OMA and OMF departures: the MPV analysis is closer to the observation than the first-guess.

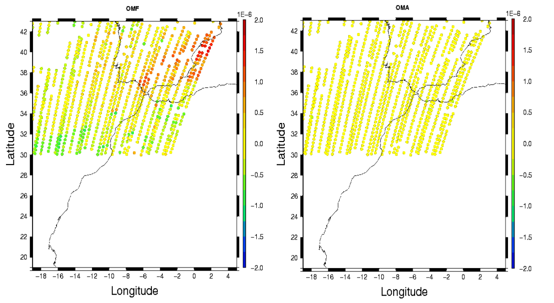

Fig. 4: Difference between Observation and Guess (on the left) and between Observation and Analysis (on the right).

5 Conclusion

In this study, a method was proposed for constructing and incorporating MPV data into the initial conditions of a limited area model. The MPV data are inferred from MetOp/GOME2 O_3 data using a simple linear regression model between O_3 and MPV. The produced MPV pseudo-observations were successfully assimilated using a 3D-Var approach within the Moroccan version of the ALADIN limited-area model. In the designed MPV assimilation experiment, the operator that computes MPV was developed together with its associated tangent-linear and adjoint. The OMA and OMF departures showed that when MPV data are assimilated, the departures are reduced and the analysis agrees better with the MPV data in comparison to the first-guess. It must be noticed that OMA and OMF diagnostics only show that the system is behaving properly. Therefore, further information on system performance can be obtained by comparison against independent data. In ongoing work, the impact of MPV assimilation on the initial conditions of wind and temperature is under examination.

References

[1] Semane, N., Teitelbaum, H. and Basdevant, C. (2002), A very deep ozone minihole in the Northern Hemisphere stratosphere at mid-latitudes during the winter of 2000. Tellus A, 54: 382–389.

[2] Jang, Kun-Il, X. Zou, M. S. F. V. De Pondeca, M. Shapiro, C. Davis, A. Krueger, (2003), Incorporating TOMS Ozone Measurements into the Prediction of the Washington, D.C., Winter Storm during 24–25 January 2000. J. Appl. Meteor., 42, 797–812.

[3] Edwards, P. G., Berruti, B., Blythe, P., Callies, J., Carlier, S., Fransen, C., et al. (2006), The MetOp satellite-Weather information from polar orbit. ESA Bulletin, 127, 8−17.

[4] Munro, R., Eisenger, M., Anderson, C., Callies, J., Carpaccioli, E., Lang, R., et al. (2006), GOME-2 on MetOp. Proc. The 2006 EUMETSAT Meteorological Satellite Conference, Helsinki, Finland, EUMETSAT (pp. 48).92-9110-076-5.

[5] Guerin, R., Desroziers, G. and Arbogast, P. (2006), 4D-Var analysis of potential vorticity pseudo-observations. Q.J.R. Meteorol. Soc., 132: 1283–1298.

[6] Courtier, P., Andersson, E., Heckley, W., Vasiljevic, D., Hamrud, M., Hollingsworth, A., Rabier, F., Fisher, M. and Pailleux, J. (1998), The ECMWF implementation of three-dimensional variational assimilation (3D-Var). I: Formulation. Q.J.R. Meteorol. Soc., 124: 1783–1807.

[7] Ide, K., Courtier, P., Ghil, M., and Lorenc, A. C.: Unified notation for data assimilation: operational, sequential and variational, J. Met. Soc. Japan, 75, 181–189, 1997.

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