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On the impact of the diabatic component in the Forecast Sensitivity Observation Impact diagnostics

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Abstract

Over the years, a comprehensive set of the linearized physical parametrization schemes has been developed at ECMWF. These linearized schemes, operationally used in data assimilation, parametrize both the dry physical processes (vertical diffusion, gravity wave drag, shortwave and longwave radiation) and the moist processes (convection, large-scale condensation and clouds) consistently with the physical parametrization of the nonlinear model (though some simplifications are applied).

In this work, the representation of the moist physical processes in the adjoint assimilation model is compared with the representation of humidity in the energy norm used to compute the forecast sensitivity to observations in the short-range forecasts. Forecast Sensitivity Observation Impact using the adjoint model with only dry processes (dry adjoint) but moist energy norm in the sensitivity gradient calculation is examined in contrast with the observation impact obtained when moist processes (moist adjoint) and dry energy norm are used. The performed study indicates that the use of the humidity term in the norm produces unrealistic humidity and temperature sensitivity gradients, which largely affect the observation forecast impact results.

1 Introduction

Nowadays sophisticated data assimilation schemes are used for exploiting information from irregularly distributed observations in order to provide initial conditions for a numerical weather prediction (NWP) model. One of them is the four-dimensional variational (4D-Var) data assimilation, which is the operational system at the European Centre for Medium-Range Weather Forecast (ECMWF) since November 1997 (Rabier *et al.* 2000). 4D-Var minimizes the distance between the model trajectory and the observations over a given time interval, using the adjoint equations of the model to compute the gradient of the cost function with respect to the model state at the beginning of the assimilation period. The mismatch between model solution and observations can remain large if the adiabatic adjoint model would only be used in the minimization. In addition, many satellite observations, such as radiances, rainfall and cloud measurements, cannot be directly assimilated with such overly simple adjoint model. Therefore representation of physical processes in the assimilating models is crucial. Initially, adjoint models used only very simple parametrization schemes, such as Buizza (1994), which aimed at removing very strong increments produced by the adiabatic adjoint models. Gradually, more complex, but still incomplete schemes were developed by Zou *et al.* (1993), Zupanski and Mesinger (1995), Janisková *et al.* (1999), Mahfouf (1999), Laroche *et al.* (2002), Mahfouf (2005). More comprehensive schemes, which can describe the whole set of physical processes and interactions between them, almost as in the non-linear model, with just a few simplifications and/or regularizations compared to the reference non-linear model, were implemented more recently (e.g. Janisková *et al.* 2002, Tompkins and Janisková 2004, Lopez and Moreau 2005, Janisková and Lopez 2013).

Using sophisticated data assimilation schemes, such as 4D-Var, also requires effective performance monitoring of such a complex system. A traditional tool for estimating data impact in a forecasting system is provided by Observing System Experiments (OSEs). These are usually performed by removing subsets of observations from the assimilating system and the resulting forecasts are compared against a control experiment that includes all observations (e.g. Bouttier and Kelly 2001, English *et al.* 2004, Kelly and Thépaut 2007, Bauer *et al.* 2014). Recently, new diagnostics in data assimilation and numerical weather prediction provides an assessment of each observation contribution to the analysis. For example, techniques have been derived to indicate which level of influence is given to observations and which one to the background during the assimilation procedure (Purser and Huang 1993, Cardinali *et al.* 2004, Chapnik *et al.* 2004, Cardinali 2015), thus allowing some tuning of the weights assigned in the assimilation system. To measure the observation contribution to the forecast quality, the adjoint methodology can also be used where the observation impact is evaluated with respect to a scalar function representing the short-range forecast error, see for example Baker and Daley (2000), Cardinali and Buizza (2004), Langland and Baker (2004), Xu *et al.* (2006), Zhu and Gelaro (2008), Cardinali (2009, 2015) or Lorenc and Marriot (2014).

An advantage of the adjoint-based observation sensitivity compared to OSE is that it measures the impact of observations when the entire observation dataset is present in the assimilation system. It provides the response of a single forecast metric to all perturbations of the observing system. However, this technique is influenced by simplified adjoint model used to carry the forecast error information backwards and therefore limited by the validity of the tangent-linear assumptions in a different way from OSE. Generally, experiments performed with adjoint technique for estimating the forecast sensitivity to observations, use a different level of complexity for simplified adjoint model. Some of them contain only a basic description of physical processes, mainly dry processes (Zhu and Gelaro 2008, Gelaro and Zhu 2009), while others use a comprehensive set of physical parametrizations describing both moist and dry processes (Cardinali 2009, 2015). Another factor which can have a significant impact in adjoint-based method is the selection of the total energy (TE) norm used for the sensitivity gradient computations. Dry energy norm is used by Cardinali (2009, 2015), Daescu and Todling (2010), Zhu and Gelaro (2008), Gelaro and Zhu (2009), while Langland and Baker (2004), Lorenc and Marriot (2014) apply the moist TE norm for their gradient computations. Which norm is the most appropriate for these computations is a matter of permanent discussion.

At ECMWF, over the years an extensive set of linearized physical parametrizations (Janisková and Lopez 2013) has been developed for the global data assimilation system and sensitivity studies. It comprises dry parametrization schemes (radiation, vertical diffusion, orographic gravity wave drag and non-orographic gravity wave activity) and moist parametrizations (moist convection, large-scale condensation/precipitation). The current linearized physics package is therefore quite sophisticated and is believed to be the most comprehensive one currently used in operational global data assimilation. As mentioned above, the dry TE norm is used in the adjoint-based observation sensitivity studies at ECMWF (Cardinali 2009, 2015). Being in position of having a comprehensive description of physical processes in the adjoint model, different experiments have been performed to compare observation impacts obtained by using different sets of the physical processes in the adjoint assimilation model and different representation of energy norms. In this paper, the Forecast Sensitivity Observation Impact (FSOI) using the adjoint model with only dry processes (dry adjoint) but moist energy norm in the sensitivity gradient calculation is examined in contrast with FSOI obtained with moist processes (moist adjoint) and dry energy norm. This type of study provides information on the use of moist processes in the adjoint models and some information on the role of the moist component in the TE norm. In section 2, the methodology of adjoint-based observation sensitivity and its relation with the energy norm and the simplified adjoint model is described. Details of the experimental framework and the results are provided in section 3. Finally, conclusions are given in section 4.

2 Forecast sensitivity impact

2.1 Method

The aim of 4D-Var assimilation is to find the optimal initial atmospheric state (the analysis, $\mathbf{x}^a$) for numerical weather forecast. Information on short-range model forecast (background,$\mathbf{x}^b$) and observations, $\mathbf{y}$ (over a given time interval), are combined accordingly to their weights. Once the cost (objective) function, J, measuring the weighted misfit between the model trajectory and the observations has been defined, the gradient of the cost function with respect to the model state at the beginning of assimilation period can be computed using the adjoint equations of the model. The analysis $\mathbf{x}^a$ can be obtained by providing this gradient to an iterative minimization algorithm (Courtier *et al.* 1998). The analyses weights are obtained by the Kalman gain matrix $\mathbf{K}$.

The forecast sensitivity equation with respect to the observations in the context of variational data assimilation has been derived by Baker and Daley (2000). The sensitivity of the objective function, J_E, with respect to the observations can be written using a simple derivative chain as:

$$\frac{\partial J_E}{\partial \mathbf{y}} = \frac{\partial J_E}{\partial \mathbf{x}^{a,b}} \frac{\partial \mathbf{x}^a}{\partial \mathbf{y}} \tag{1}$$

where $\partial J_E / \partial \mathbf{x}^{a,b}$ is the mean sensitivity of the forecast error with respect to the analysis and the background (second order gradients, see for example Errico 2007). As explained for instance by Cardinali *et al.* (2004) or Cardinali (2009), $\partial \mathbf{x}^a / \partial \mathbf{y}$ is the sensitivity of the analysis system with respect to observations, that is $\mathbf{K}^T$.

Once the forecast sensitivity is computed, FSOI, i.e. the variation δJ_E of the forecast error due to the assimilated observations can be found by applying the adjoint property for a linear operator as:

$$\begin{aligned} \delta J_E &= \left\langle \frac{\partial J_E}{\partial \mathbf{x}^{a,b}}, \delta \mathbf{x}^a \right\rangle = \left\langle \frac{\partial J_E}{\partial \mathbf{x}^{a,b}}, \mathbf{K}(\mathbf{y} - H[\mathbf{x}^b]) \right\rangle = \left\langle \mathbf{K}^T \frac{\partial J_E}{\partial \mathbf{x}^{a,b}}, \mathbf{y} - H[\mathbf{x}^b] \right\rangle = \left\langle \mathbf{K}^T \frac{\partial J_E}{\partial \mathbf{x}^{a,b}}, \delta \mathbf{y} \right\rangle \\ &= \left\langle \frac{\partial J_E}{\partial \mathbf{y}}, \delta \mathbf{y} \right\rangle \end{aligned} \tag{2}$$

where $\delta \mathbf{x}^a = \mathbf{x}^a - \mathbf{x}^b$ are the analysis increments, $\delta \mathbf{y} = \mathbf{y} - H[\mathbf{x}^b]$ is the innovation vector, H is the nonlinear observation operator (moving the background value to the observation location) and $\mathbf{K}$ and $\mathbf{K}^T$ are the gain matrix and its adjoint, respectively. According to Eq. 2, FSOI is then a function of the sensitivity gradient $\partial J_E / \partial \mathbf{x}^{a,b}$, the adjoint of the gain matrix, $\mathbf{K}^T$, and the innovation vector, i.e.

$$\delta J_E = f\left(\frac{\partial J_E}{\partial \mathbf{x}^{a,b}}, \mathbf{K}^T, \mathbf{y} - H[\mathbf{x}^b] \right) \tag{3}$$

For instance, at ECMWF, δJ_E is computed for a 12-hour window. The second order sensitivity gradient $\partial J_E / \partial \mathbf{x}^{a,b}$ is valid at the starting time of the 4D-Var window, typically 09 and 21 UTC (Cardinali 2009). The variation of the forecast error due to a specific measurement can be summed up over time and space in different subsets to compute the total contribution of the different components of the observing system towards reduction of the forecast error.

The role of the energy norm objective function and the simplified adjoint model in FSOI computation will be assessed in this study. The description of the energy norm is provided in the following subsection.

2.2 Energy norm

As explained in section 1 (Introduction), the total energy (TE) norm in sensitivity studies is used either in the dry form (Cardinali 2009, Daescu and Todling 2010) or with the moist contribution (Langland and Baker 2004). The only difference between the dry and moist norms in these studies is in the additional term which explicitly measures specific humidity q. The TE norm in the moist form can be expressed in a continuous formulation as follows:

$$J_E = \frac{1}{2}\int_0^1\int_\Sigma\left(\nabla\triangle^{-1}\xi_{\mathbf{x}}\cdot\nabla\triangle^{-1}\xi_{\mathbf{x}}+\nabla\triangle^{-1}D_{\mathbf{x}}\cdot\nabla\triangle^{-1}D_{\mathbf{x}}+\frac{c_p}{T_r}T_{\mathbf{x}}T_{\mathbf{x}}+w_q\frac{L_c^2}{c_pT_r}q_{\mathbf{x}}q_{\mathbf{x}}\right)\mathrm{d}\Sigma\left(\frac{\partial p}{\partial\eta}\right)\mathrm{d}\eta + \frac{1}{2}\int_\Sigma R_dT_rP_r\ln\pi_{\mathbf{x}}\cdot\ln\pi_{\mathbf{x}}\mathrm{d}\Sigma \tag{4}$$

where c_p is the specific heat of dry air at constant pressure, R_d is the dry constant of dry air, L_c is the latent heat of condensation, T_r is the reference temperature and P_r is the reference pressure (e.g. T_r = 350 K and P_r = 1000 hPa at ECMWF). The TE norm (Eq. 4) has contributions from vorticity $\xi_{\mathbf{x}}$, divergence $D_{\mathbf{x}}$, temperature $T_{\mathbf{x}}$, specific humidity $q_{\mathbf{x}}$ with certain weight w_q and logarithm of surface pressure $\ln\pi_{\mathbf{x}}$ of the model state $\mathbf{x}$. In the case of the dry TE norm, the term with specific humidity is missing, i.e. $w_q = 0$.

Questions were raised on what is more appropriate - to use dry or moist energy norm. A lot of studies using the moist norm refer to the paper of Ehrendorfer *et al.* (1999) about singular-vector perturbation growth in a primitive equation model with moist physics. They made experiments with both dry and moist norm based on the fact that a strict theoretical basis for the humidity component does not exist. Unlike for dry TE norm and dry model, it is not evident that the moist TE norm will be conserved if other physical processes than condensation occur.

Using the moist TE norm requires a definition of the weight w_q. Several studies (such as Buizza *et al.* 1996, Mahfouf *et al.* 1996, Ehrendorfer *et al.* 1999, Barkmeijer *et al.* 2001) used the moist TE norm with $w_q = 1$ based on condensation physics and with the aim to ensure significant contribution to the norm in the singular vector computation by all components of the state vector both at initial and final time. Barkmeijer *et al.* (2001) also experimented with q weight derived from background-error statistics and Ehrendorfer *et al.* (1999) made some investigations by applying $w_q = 0.1$ or $w_q = 10$. The different weights would lead to different contributions of moisture and therefore qualitatively different results. Because of that, for instance, Ehrendorfer *et al.* (1999) concluded that further studies are required in order to understand how to specify the appropriate weight and the role of moist physics for a proper accounting for moist processes in the growth of perturbations (e.g. fast growing components of the analysis error).

2.3 Simplified adjoint model

In the adjoint-based technique, a simplified adjoint model is usually used to carry the forecast error information backwards. This model should have a certain level of reality, i.e. to be comprehensive enough to ensure that the observations are given a dynamically realistic, as well as statistically likely response in the analysis. However, it is important to achieve some trade-off between reality and linearity of the model since any adjoint-based technique is restricted by the tangent-linear (TL) assumption and its validity. Therefore one must be very careful with the non-linear nature of physical processes, especially in the presence of thresholds, which can affect the range of validity of the TL approximation.

The better the tangent-linear approximation, the more realistic and useful the sensitivity patterns. Results obtained through the adjoint integration when using a too simplified adjoint model with large inaccuracies or adjoint models without a proper treatment of nonlinearities and discontinuities can be incorrect. Most of the adjoint sensitivity experiments (e.g. Baker and Daley 2000, Langland and Baker 2004, Xu *et al.* 2006, Zhu and Gelaro 2008) are performed with simplified adjoint models that only describe dry processes with different levels of complexity. Adjoint models accounting for both dry and moist processes were only used by Cardinali (2009, 2015) and to some extent by Lorenc and Marriot (2014).

At ECMWF, the current set of physical parametrizations used in the linearized model describes both dry and moist processes: vertical diffusion, subgrid-scale orographic effects, radiation (shortwave and longwave), non-orographic gravity wave activity (not yet used in this study), clouds with large-scale condensation and convection as described by Janisková and Lopez (2013). Therefore, in the context of operational global data assimilation, this linearized physics package is quite sophisticated and comprehensive.

Validation studies of the ECMWF linearized model clearly demonstrate the impact and the importance of including physical processes for the validity of the tangent-linear approximation. For this validation, the accuracy of the linearization is studied with respect to pairs of non-linear simulations. The difference between two non-linear integrations (one starting from a background field and the other one starting from analysis) of the full nonlinear model is used as the standard reference to which the TL integrations from the analysis increments are compared. For a quantitative evaluation of the impact of linearized schemes, their relative importance is determined by using mean absolute errors between tangent-linear and non-linear integrations. The absolute mean error of the TL model without physics is usually taken as a reference for the comparisons. Errors and improvements relative to the reference can then be computed. Validity tests of the TL approximations are usually performed over the time period and at the resolution at which adjoint models will be applied in practice: resolution and time length of 4D-Var inner-loop integration (e.g. 12 hours, T255[1] and 91 vertical levels at ECMWF) or longer time periods for singular vectors and sensitivity applications (e.g. 24 hours at ECMWF).

Examples of results from the TL approximation assessment using the ECMWF linearized physics are shown in Fig. 1. The impact of the different physical processes on the TL evolution of temperature increments is presented in Fig. 1 as zonal mean cross-sections of the error difference (in terms of fit to the nonlinear model with full physics) between the TL model including different parametrization schemes and the adiabatic TL model. Negative values are associated with an improvement of the model using the parametrization schemes with respect to the adiabatic TL model, since they correspond to a reduction of the errors. The improvement is observed over most of the atmosphere, and is maximum in the lower troposphere for two sets of parametrization schemes, one describing dry processes only (vertical diffusion, gravity wave drag and radiation; Fig. 1a) and the other one with moist processes also included (clouds with large-scale condensation and convection; Fig. 1b). Results also clearly show that taking into account moist processes lead to additional significant improvement which is, however, not only coming from these schemes, but also from cloud-radiation interactions. The global relative improvement of the TL approximation for temperature coming from including physical parametrization schemes into the linearized model compared to the purely adiabatic TL model is $\sim$12% for dry parametrization schemes alone and close to 18% when combined with the moist schemes (Janisková and Lopez 2013). For specific humidity, the relative improvement becomes even larger when including moist processes (improvement of $\sim$20%) on top of the dry ones (improvement of $\sim$10%). Thus the TL model with all physical processes included performs remarkably better than its dry version. The representation of moist processes in the adjoint model not only provides a better description of the time evolution of the model state during the assimilation procedure and sensitivity calculations, but also allows the assimilation of observations sensitive to precipitation or clouds.

3 Experiments

Several experiments with the ECMWF assimilation system have been performed in order to study the impact of using different representations of the objective function and different representations of physical processes in the adjoint model in the FSOI computation. Which norm is the most appropriate for

[1]T255 corresponding approximately to 80 km

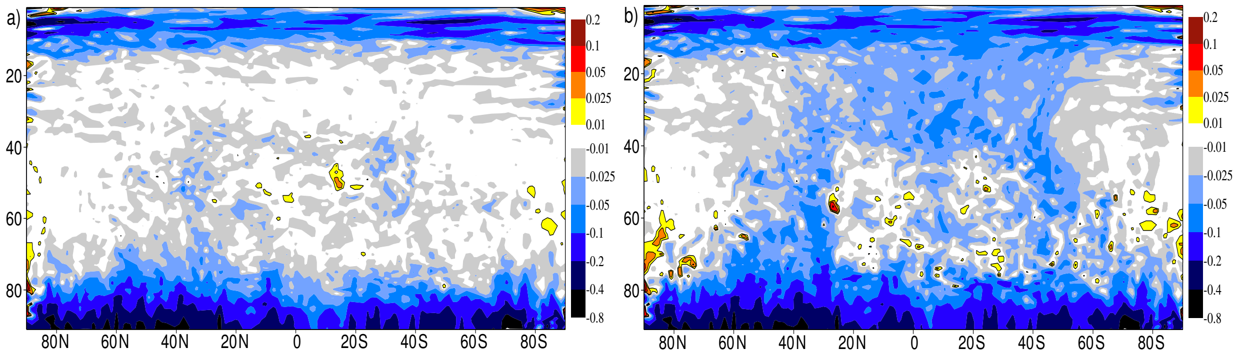

Figure 1: Zonal mean impact of the different ECMWF linearized parametrization schemes on the evaluation of temperature increments. Results are presented as the error differences (in terms of fit to the non-linear model with full physics) between the TL model with physical parametrization schemes (including (a) dry processes alone - vertical diffusion, gravity wave drag and radiation or (b) in combination with moist processes - convection and cloud with large-scale condensation) and the purely adiabatic TL model.

this type of computations is a matter of permanent discussion in the scientific community dealing with sensitivity studies. Thanks to the comprehensive description of physical processes in the adjoint model of ECMWF (Janisková and Lopez 2013), experiments with different combinations of norm definition and moist physics directly included in adjoint model could be performed.

3.1 Experimental setup

The experiments have been run for the period of 25 August to 10 September 2010 using the ECMWF 4D-Var system at that time operational resolution, i.e. 91 levels in vertical (L91) combined with the horizontal resolution of T1279[2] for the standard forecast model run and a much lower resolution of T159/T255 [3] for the minimization in assimilation computation. Although moist processes in the adjoint model allows the assimilation of observations related to clouds and precipitation, these observations have not been assimilated in order to unify observation usage among all performed experiments.

Adjoint sensitivity computations have then been performed at the resolution T255L91. Sensitivity calculations have been done using:

1) dry parametrization schemes alone: vertical diffusion, gravity wave drag and radiation;
2) moist parametrization schemes: convection and cloud with large-scale condensation in combination with dry processes.

These two adjoint model versions have been combined with either the dry or the moist TE norm as described by Eq. 4. In the case of the moist norm, different weights for the moisture contribution (w_q), such as 1 (results not presented), 0.5 or 0.1, have been used. Most results presented here have been obtained with $w_q = 0.5$.

The results from experiments using the following combinations of adjoint model versions and norm specifications will be shown:

- **dryAD_dryN**: dry processes in adjoint (AD) model and dry TE norm;
- **dryAD_moistN_0.5**: dry processes and moist TE norm with the weight for moist contribution equal to 0.5;
- **moistAD_dryN**: moist processes in combination with the dry ones in AD model and dry TE norm;

[2] T1279 corresponding approximately to 16 km

[3] T159/T255 corresponding approximately to 130 km/80 km, respectively

- **moistAD_moistN_0.5**: moist and dry processes in AD model combined with the moist norm using $w_q = 0.5$;
- **moistAD_moistN_0.1**: moist and dry processes in AD model combined with the moist norm using $w_q = 0.1$.

3.2 Sensitivity gradient

Several results from the combination of either dry or moist adjoint model with either dry or moist energy norm in the sensitivity gradient calculations are presented here.

Figures 2, 4, 5, 7 display the global horizontal distribution of the second order sensitivity gradient (SG) for the situation on 28 August 2010 at 21:00 UTC only. Similar sensitivity structures have been observed for all the other days (not shown). Zonal mean and vertical profiles of sensitivity gradient averaged over the whole test period (i.e. 25 August 2010 - 10 September 2010) are shown in Fig. 6 and Fig. 8 - 9, respectively.

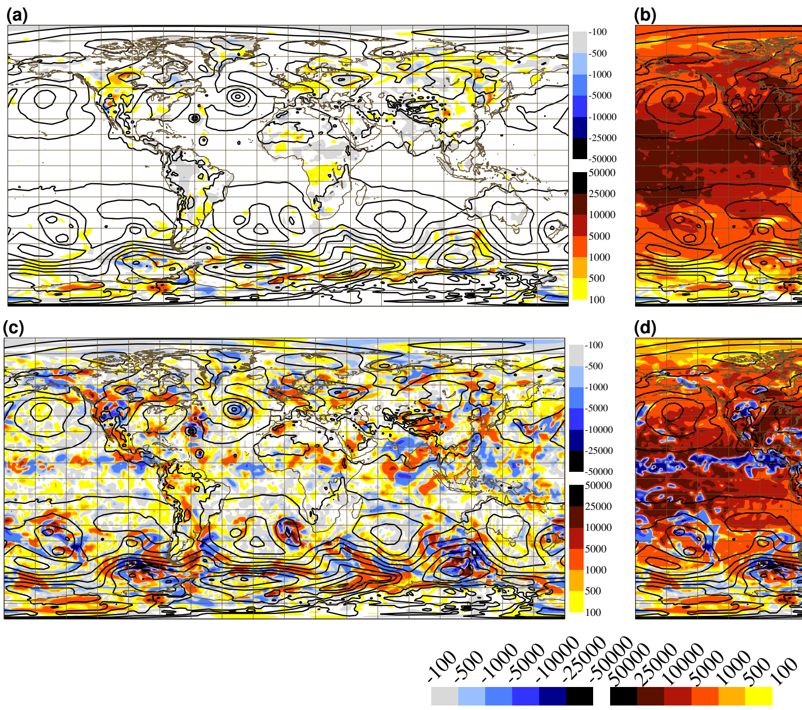

Figure 2: Specific humidity sensitivity gradient (J kg^{-1}/(g kg^{-1})) at the lowest model level for the situation on 28 August 2010 at 21:00 UTC. The results are presented for experiments with dry parametrization schemes (i.e. vertical diffusion, gravity wave drag and radiation) included in the adjoint model using (a) dry or (b) moist norm, and for experiments with moist processes also added using (c) dry or (d) moist norm. Sensitivities are shown with colour shading. Black isolines represent mean-sea-level pressure (hPa).

Figure 2 displays the specific humidity sensitivity gradient at the lowest model level for four different combinations of the physical processes in adjoint model and TE norms: **dryAD_dryN** (Fig. 2a), **dryAD_moistN_0.5** (Fig. 2b), **moistAD_dryN** (Fig. 2c) and **moistAD_moistN_0.5** (Fig. 2d). When using dry physical processes and dry TE norm, the sensitivity to specific humidity is quite small and mainly localized in areas of intense dynamical activity. Adding moist processes in the adjoint model (Fig. 2c) brings additional structures in the sensitivity, especially in areas of condensation and convective development. When using the moist norm in combination with the dry adjoint (Fig. 2b), no new structures appear, and on the contrary, a lot of structures are masked by large-scale positive sensitivities. Using all processes and moist norms (Fig. 2d) leads to overall enhanced sensitivities, with a clear prevalence of positive values over the globe. However, there are no additional sensitivity patterns when compared with **moistAD_dryN** (Fig. 2c).

The described behaviour of the forecast sensitivity with respect to specific humidity is more obvious from the zoom over the tropical cyclone in the Atlantic Ocean (Fig. 3). Missing moist physical processes clearly lead to underdetermined structures around the cyclone. Using the moist TE norm does not enhance the humidity structure (Fig. 3b). When moist processes are added in the adjoint model (Fig. 3c), a lot of sensitivity structures related to condensation and convection in the area of cyclone development are observed, as expected. When adding the moist norm, the humidity sensitivity pattern around the tropical cyclone remains very similar, but it is somehow embedded in a constant and larger humidity sensitivity background. This comparison indicates that only when moist processes are represented in the adjoint model the sensitivity gradients realistically depict the expected physical structure pattern, for example around tropical cyclones, whilst the dry adjoint model is not sufficient to correctly describe it. Moreover, adding the moisture term in the TE norm, either in combination of the dry or the moist adjoint model, provides a larger but somehow physically meaningless humidity pattern spread everywhere.

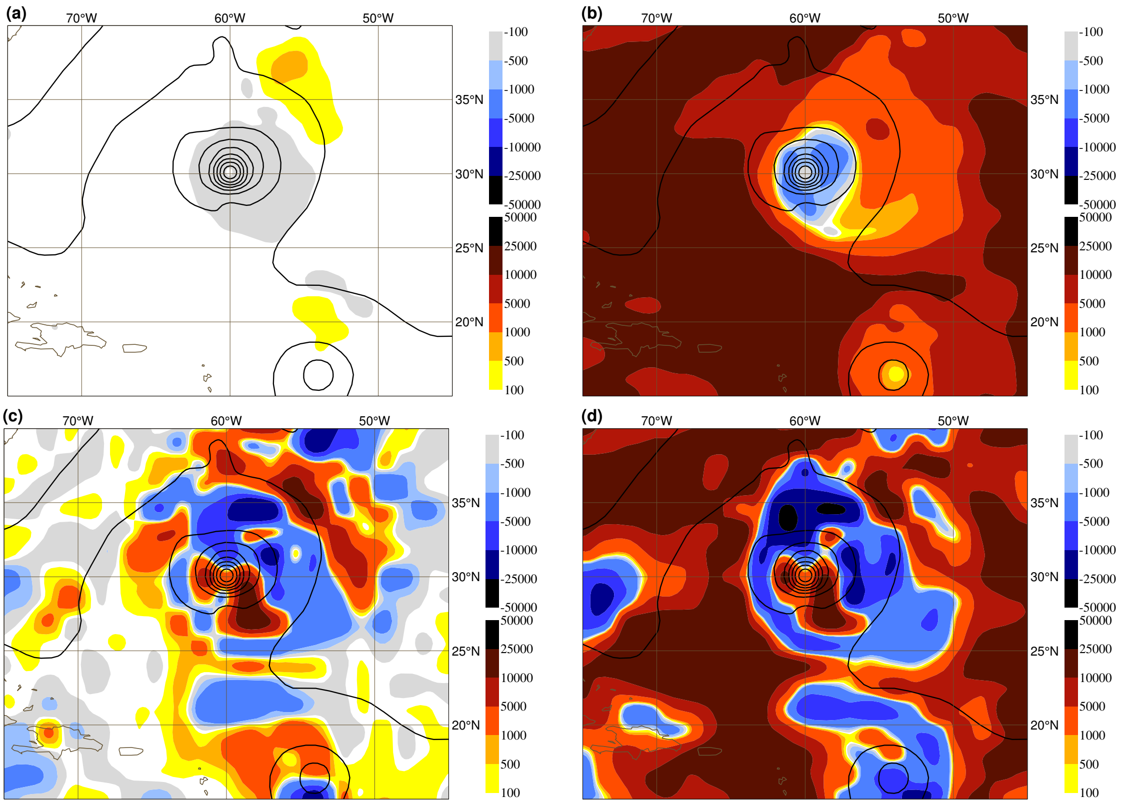

Figure 3: Same as Fig. 2, but for the areas around tropical cyclones over the Atlantic ocean.

The temperature sensitivity gradient displayed in Fig. 4 suggests that the impact of moist processes used in the adjoint model on the sensitivity structures is less dramatic (Fig. 4c) than for humidity. In fact, larger sensitivity patterns already appear in the SG with the dry adjoint model and the dry TE norm (Fig. 4a). On top of the enhanced patterns around tropical cyclones, few additional ones associated to convective and condensation activities emerge. In general, in **moistAD_dryN**, both the specific humidity and the temperature structures are quite consistent. Using the moist norm has a similar impact on temperature as observed for specific humidity (i.e. positive sensitivities prevailing), though a lot of structures, which already appeared when using the dry TE norm, are preserved in contrast with the specific humidity sensitivity gradient (Fig. 4b). In the areas with larger specific humidity when the moist TE norm is used, the sensitivities are enhanced significantly more in the case of moist adjoint model (Fig. 4d).

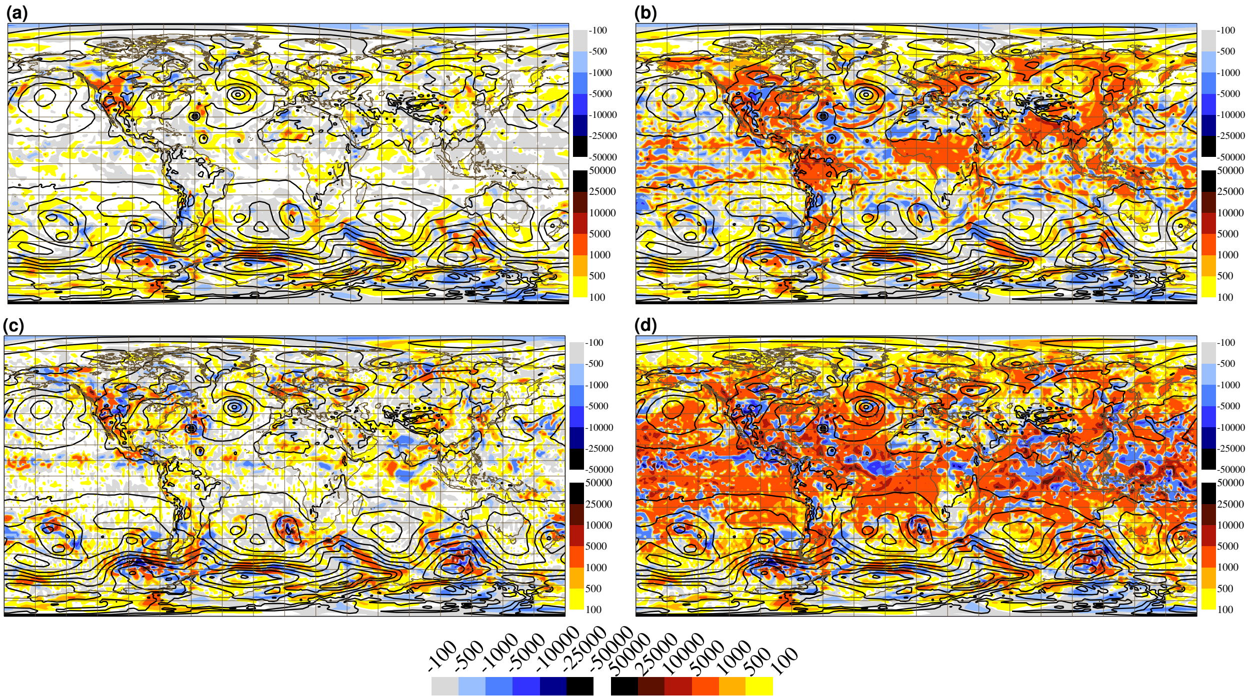

Figure 4: Same as Fig. 2, but for temperature sensitivity gradient (J kg^{-1}/K) at the lowest model level.

In the case of sensitivity to surface pressure, when using moist TE norms (Fig. 5b, d), significantly enhanced sensitivities are found in the tropics, especially around the whole Inter Tropical Convergence Zone (ITCZ). As indicated by the isobars (black lines), the surface pressure there is not changing significantly and therefore one would assume a small overall forecast error sensitivities with some slightly more pronounced variations in convective regions (as seen in Fig. 5c for **moistAD_dryN**). However, when using the moist norm, wherever the humidity is large the sensitivity to surface pressure is large as well.

Overall, sensitivities with respect to different variables suggest two main pattern differences between the experiments. When the moist physics is used in the adjoint model, new structures emerge on top of those which already appeared when the dry adjoint model is used. Using the moist norm rather than the dry one leads to globally larger sensitivity patterns, but inconsistent with the physical processes observed.

Many of the results described for the horizontal structures are confirmed when assessing zonal means (Fig. 6) and vertical profiles (Fig. 8, 9) of the set averaged over the whole test period.

The zonal mean SG with respect to specific humidity confirms that the sensitivity is very small and located in the mid-low troposphere when using only dry adjoint model and dry norm (Fig. 6a). Including moist processes in the adjoint model leads to the appearance of much more structures in the boundary layer (Fig. 6e) and also to substantial changes in the sensitive regions of Fig. 6a. When the moist norm is used, the zonal mean of sensitivity reminds more of the structure of the humidity background error (as will be illustrated later on the vertical profiles of sensitivity), just modulated by the amount of

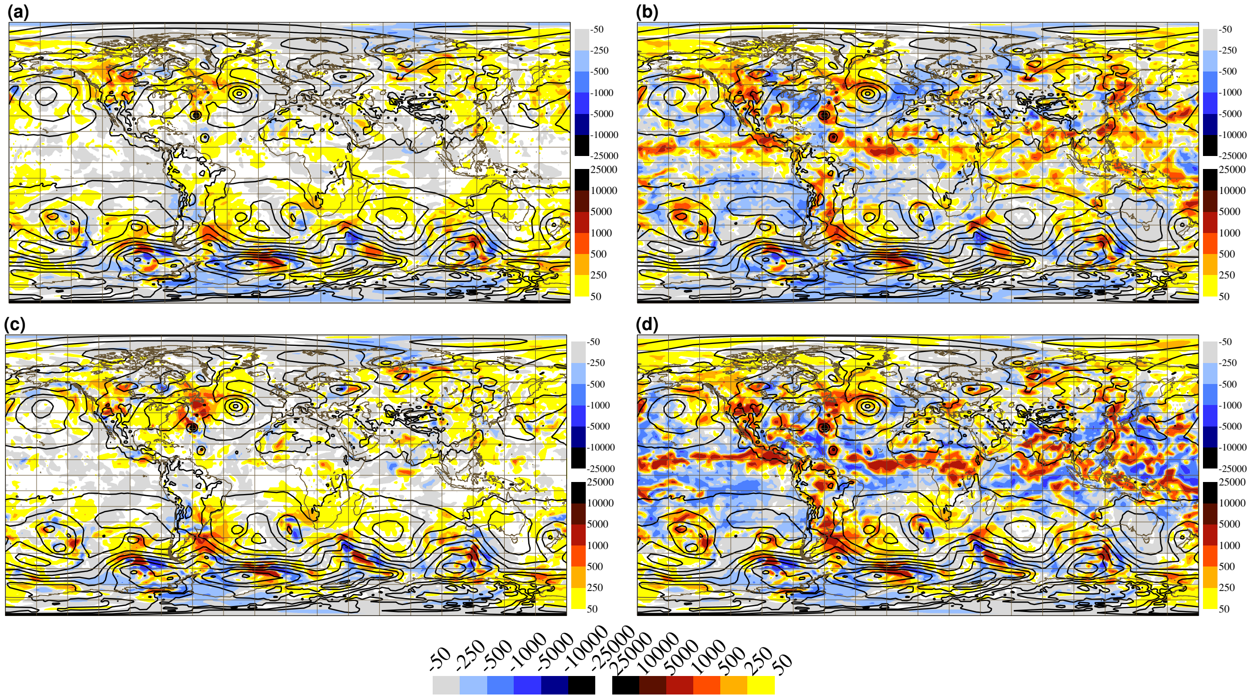

Figure 5: Same as Fig. 2, but for the logarithm of surface pressure, p_s, sensitivity gradient (J kg^{-1}/Pa.)

the available moisture, i.e. decreasing from tropics towards the poles and from the low to the middle troposphere (Fig. 6c). The moist TE norm also leads to extensive, mainly positive temperature SGs in the zonal mean (Fig. 6b,d,f). This feature is more pronounced when the moist TE norm is combined with the moist adjoint model (not shown).

Generally, experiments with the moist TE norm indicate that the weight $w_q = 0.5$ of the moisture term is too big. When the experiments were performed with $w_q = 1$ (not shown here) as often used in different studies, the described predominance of positive sensitivities is even more striking. Decreasing the weight for moisture term will lead to generally lower sensitivities. This is illustrated in Fig. 7, which compares specific humidity (Fig. 7a, c) and temperature (Fig. 7b, d) sensitivity gradient using $w_q = 0.5$ (Fig. 7a, b) and $w_q = 0.1$ (Fig. 7c, d). By reducing the weight not only sensitivities are reduced, but also some negative sensitivities emerge.

For a quantitative comparison of the different experiments performed in this study, vertical profiles of mean SGs with respect to specific humidity, q, and temperature, T, averaged over the whole period together with their standard deviations are presented in Fig. 8 and 9, respectively. In principle, one would expect that SG averaged over a long period of time and over the whole globe should be unbiased, i.e. positive sensitivities should not prevail over negative ones or vice versa. For specific humidity (Fig. 8) using the dry TE norm, combined with either dry or moist processes in the adjoint model, leads to very small mean sensitivity values (Fig. 8a). The standard deviations (Fig. 8b) are also quite small (values are even smaller when using only dry processes given the generally very small sensitivities to specific humidity). On the contrary, when the moist TE norm is used, SGs are significantly positively biased and the standard deviations are also large. Definitely, the standard deviation shape is similar to the typical standard deviation of the ECMWF background errors for specific humidity (see Fig. 8c). Decreasing the weighting factor for moisture contribution in the moist TE norm from 0.5 to 0.1 leads to smaller bias and standard deviation (Fig. 8a, b dotted line). However, even when the moisture contribution in

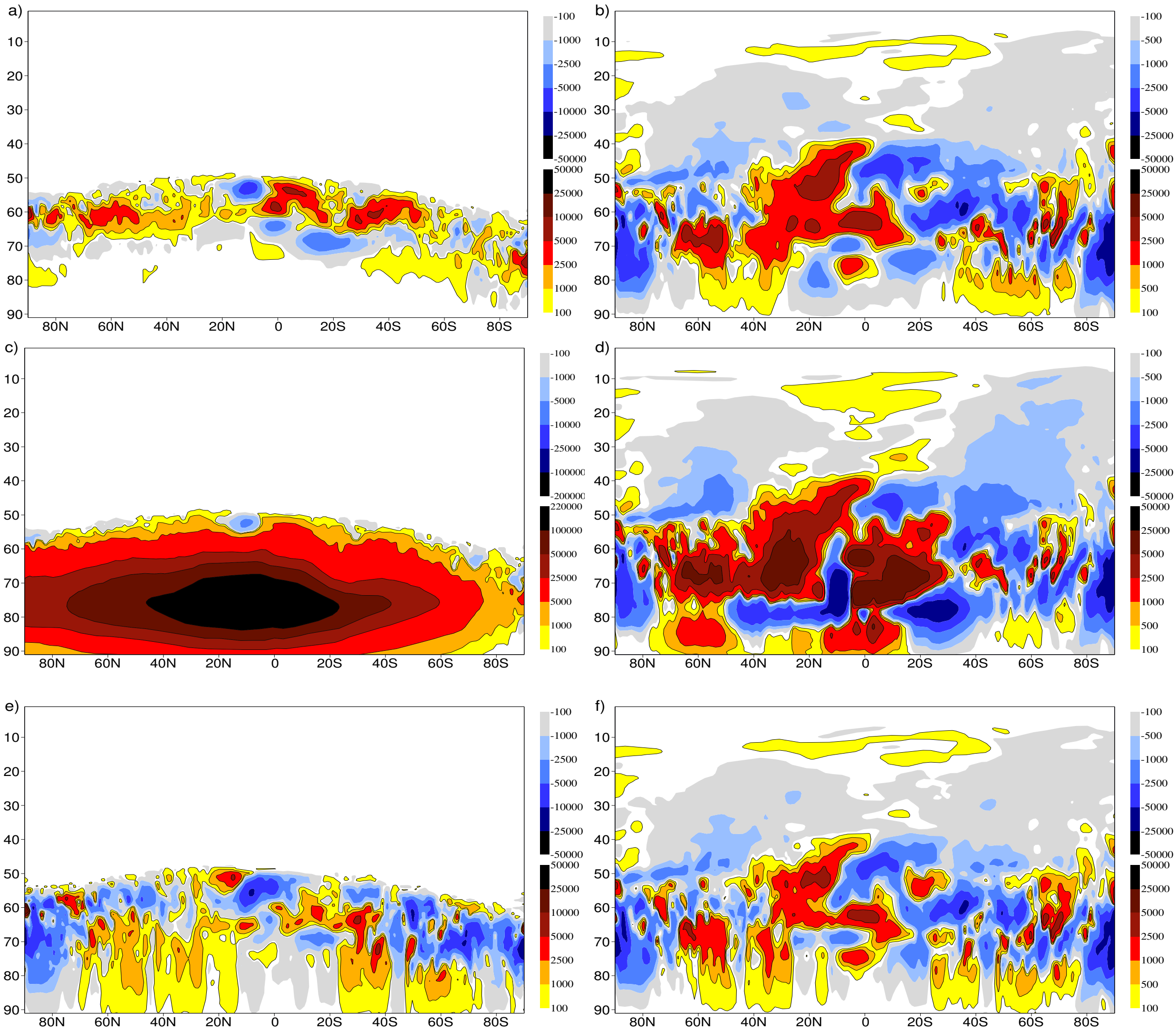

Figure 6: Zonal mean of (a,c,e) specific humidity sensitivity gradient (J kg^{-1}/(g kg^{-1})) and (b,d,f) temperature sensitivity gradient (J kg^{-1}/K) for the whole test period (25 August 2010 - 10 September 2010). The results are presented for experiments with dry parametrization schemes (i.e. vertical diffusion, gravity wave drag and radiation) included in the adjoint model using (a,b) dry or (c,d) moist norm, and (e,f) for experiments with moist processes also added and using dry norm. Sensitivities are shown with colour shading.

the TE norm is significantly decreased, the sensitivity with respect to specific humidity remains biased. Similarly for the sensitivity to temperature (Fig. 9), mean values and standard deviations are close to zero when using the dry TE norm. The least biased SGs are determined by the moist adjoint and the dry TE norm. Interestingly when the moist TE norm is combined with the moist adjoint, the mean SGs with respect to temperature are the most biased. To demonstrate that sensitivities are indeed biased when the moist TE norm is used, an experiment has been done in which the mean humidity contribution was extracted from specific humidity SG (not shown). Doing that, the overrepresentation of the positive structures disappear, though a small positive bias remains.

In conclusions, results indicate that the inclusion of moist processes through the adjoint model compared to accounting for the moisture through the energy norm leads to substantial differences in the intensity

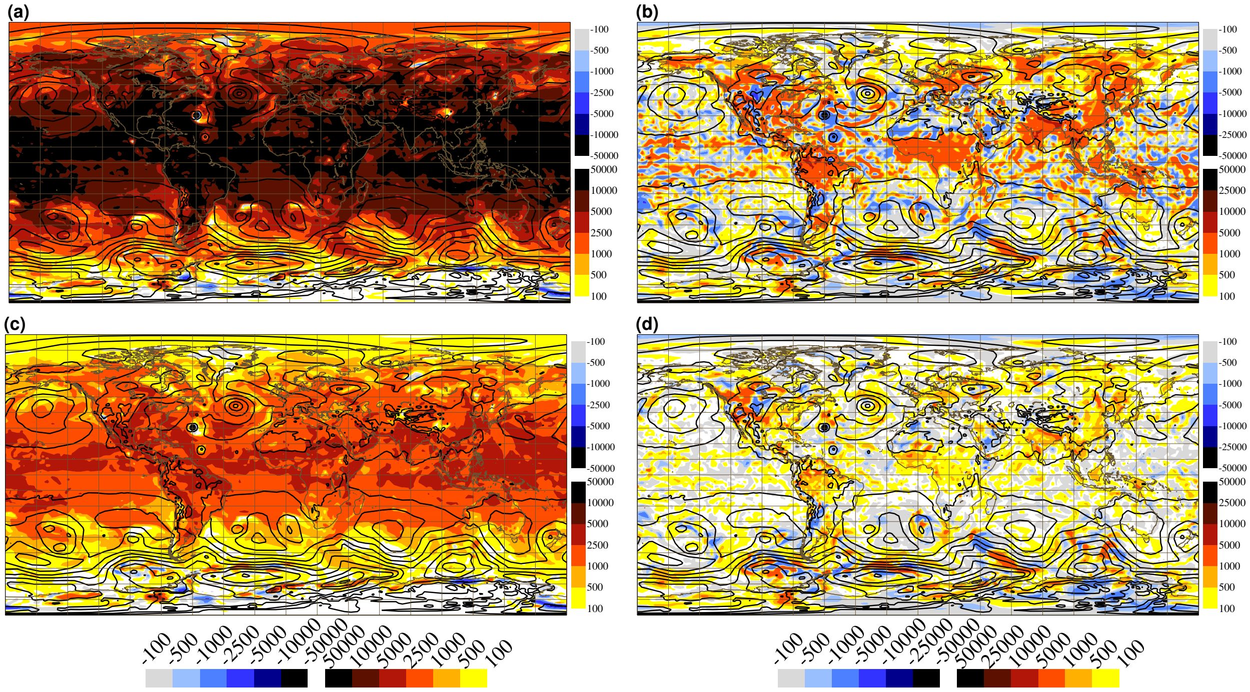

Figure 7: (a,c) specific humidity (J kg^{-1}/(g kg^{-1})) and (b,d) temperature (J kg^{-1}/K) sensitivity gradients at the lowest model level for the situation on 28 August 2010 at 21:00 UTC. The results are presented for experiments with dry adjoint model and using moist norm with weighting factor of (a,b) 0.5 or (c,d) 0.1. Black isolines represent mean-sea-level pressure (hPa).

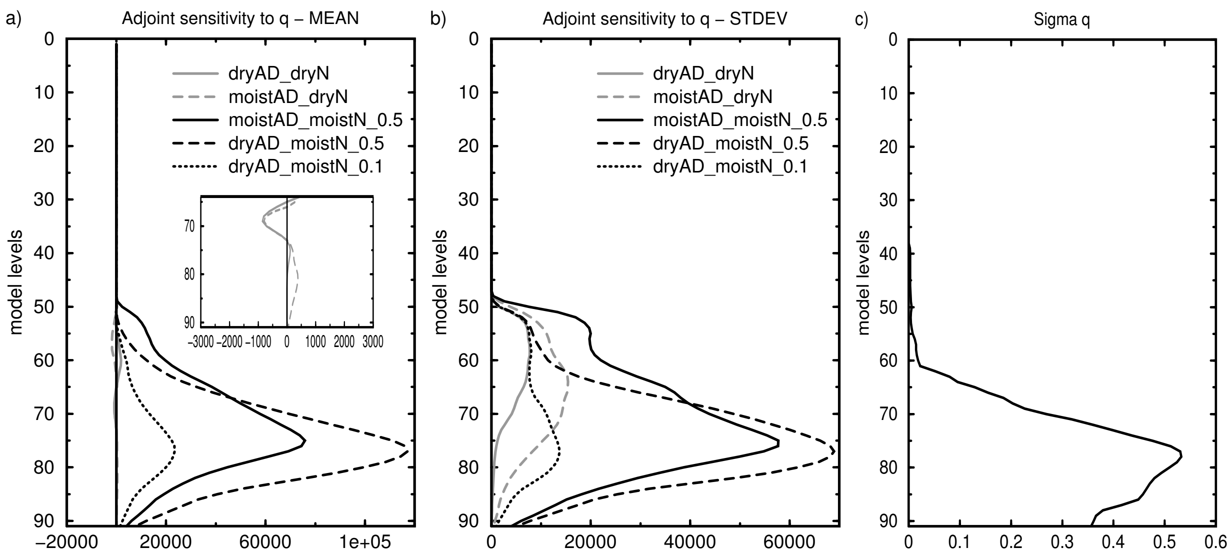

Figure 8: Vertical profile of (a) mean specific humidity SG (J kg^{-1}/(g kg^{-1})) and (b) its standard deviation obtained by averaging over the whole test period (25 August 2010 - 10 September 2010). The results are presented for experiments with dry parametrization schemes (i.e. vertical diffusion, gravity wave drag and radiation) included in the adjoint model using dry (grey solid line) or moist norm (grey dashed line), and for experiments with moist processes also added using dry (black solid line) or moist norm with weighting factor of 0.5 (black dashed line) and 0.1 (black dotted line). Panel (c) displays vertical profile of typical values of the standard deviation of the ECMWF background errors for specific humidity (in g kg^{-1}).

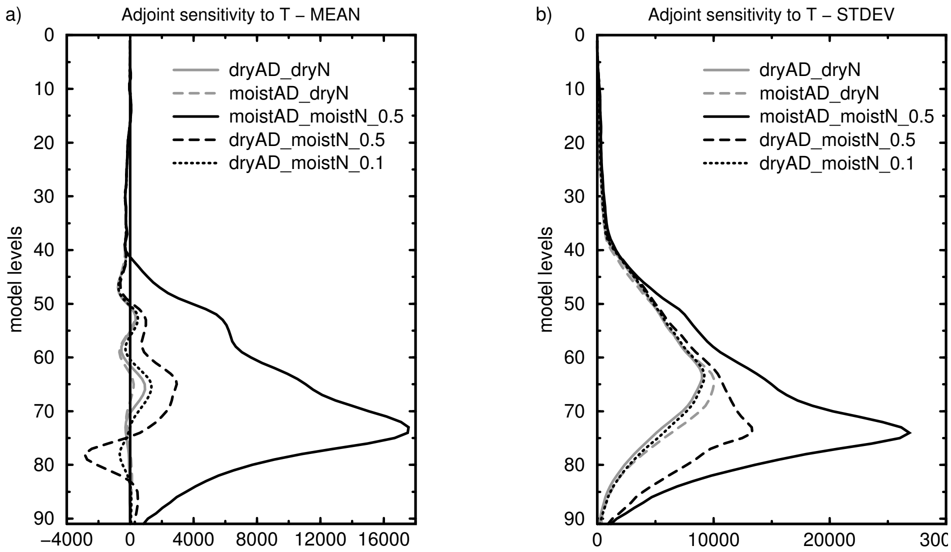

Figure 9: Same as. Fig. 8, but for temperature SG (J kg^{-1}/K) and over the whole test period.

and the structure of the perturbations. The largest differences are obviously observed for the SGs with respect to specific humidity. While including moisture information in the adjoint model generate new structures on top of the already generated by the dry adjoint model, the usage of the moist TE norm usually globally enhances the sensitivity. Decreasing (respectively increasing) the weight of moist contribution in the norm (i.e the weighting factor w_q in Eq. 4) will also decrease (respectively increase) the intensity of the sensitivity. Thus the different weights lead to qualitatively different results.

The impact on the FSOI diagnostics coming from different representation of physical processes in the adjoint model and different norms (dry or moist) used in SG will be illustrated in the following subsection.

3.3 FSOI

In this section, Forecast sensitivity Observation Impacts, FSOIs, computed using different sensitivity gradient configurations are compared. To obtain statistically significant results, the observation impacts have been averaged over 31 cases. Positive (negative) values mean forecast error increase (decrease) due to the assimilation of the observations. In this section, FSOI is shown in percentage, therefore positive values indicate forecast improvement. The observation types analysed are summarized in Table 1. Figure 10 compares FSOI computed with dry and moist adjoint model when the dry norm is used. FSOI differences are in general very small (less than 1%) and for the majority of the observation types they are within the FSOI error calculation as shown by the error bars. These small differences reflect the small SG differences between **dryAD_dryN** and **moistAD_dryN** experiments (Fig. 2a and Fig. 4a versus Fig. 2c and Fig. 4c). The results as shown in Fig. 10 have been validated (by different FSOI developers and for different cases) by comparison with OSE observation impact diagnostics and an agreement within 10% error was found (see for instance Gelaro and Zhu 2009). Completely different results are obtained when a moist norm is used to compensate for the lack of moist processes in the model adjoint. Figure 11 shows the observation impact computed by using either the dry adjoint model and the moist norm or the moist adjoint model and the dry norm. GEO-Rad, AIRS, HIRS and GPS-RO show a ~5% larger impact in **dryAD_moistN_0.5** than in **moistAD_dryN** whilst SCAT and SYNOP exhibit a detrimental impact of -2% and -1%, respectively. The differences between two configurations are actually -5% for

SCAT and -7% for SYNOP. On the contrary, MHS and TEMP have ∼2% and ∼5% smaller impact, respectively. The observation impact differences are due to the large mismatch between the forecast error sensitivity pattern with respect to both the humidity and temperature fields in the two experiments compared (Fig. 2c and 4c versus Fig. 2b and 4b).

Table 1: Observation types assimilated in the experiments. Number of observations per assimilated cycle is $\sim 10^7$.

Data name	Data kind	Information
OZONE (O3)	Backscattered solar UV radiation, retrievals	Ozone, stratosphere
GEO-Rad	US/Japanese/EUMETSAT geostationary satellite infrared sounder radiances	Moisture, mid/upper troposphere
AMSU-B	Microwave sounder radiances	Moisture, troposphere
MHS	Microwave sounder radiances	Moisture, troposphere
MERIS	Differential reflected solar radiation, retrievals	Total column water vapour
GPS-RO	GPS radio occultation bending angles	Temperature, surface pressure
IASI	Infrared sounder radiances	Temperature, moisture, ozone
AIRS	Infrared sounder radiances	Temperature, moisture, ozone
AMSU-A	Microwave sounder radiances	Temperature
HIRS	Infrared sounder radiances	Temperature, moisture, ozone
SCAT	Microwave scatterometer backscatter coefficients	Surface wind
AMV-WV	Atmospheric Motion Vectors, retrievals from Water Vapour	Wind, troposphere
AMV-VIS	Atmospheric Motion Vectors, retrievals from Visible	Wind, troposphere
AMV-IR	Atmospheric Motion Vectors, retrievals from Infrared	Wind, troposphere
PROFILER	American, European and Japanese Wind profiles	Wind, troposphere
DROP	Dropsondes from aircrafts	Wind, temperature, moisture, pressure, troposphere
TEMP	Radiosondes from land and ships	Wind, temperature, moisture, pressure, troposphere
DRIBU	Drifting and Stationary buoys	Surface pressure, temperature, moisture, wind
Aircraft	Aircraft measurements	Wind, temperature, troposphere
SYNOP	Surface Observations at land stations and on ships	Surface pressure, temperature, moisture, wind

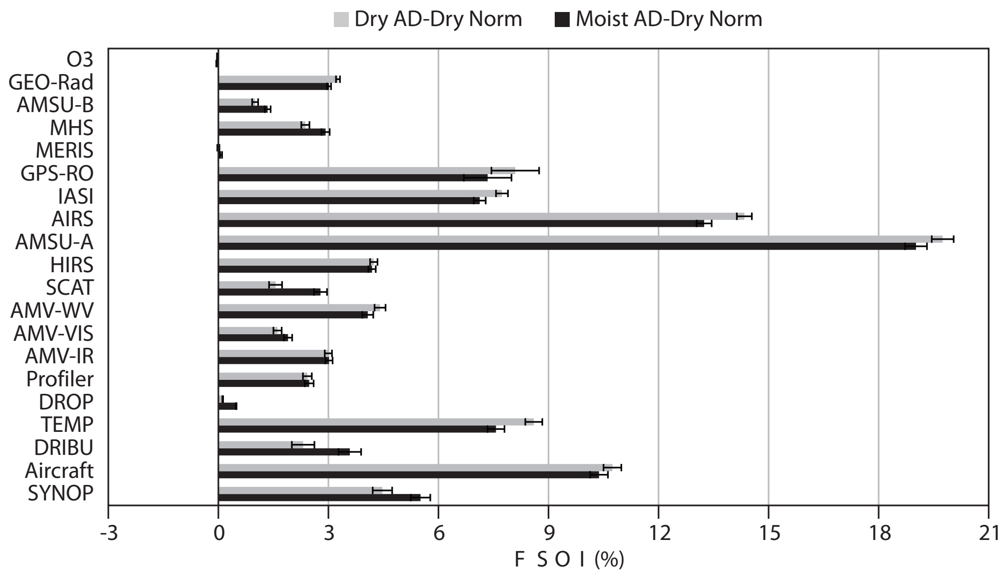

Figure 10: Comparison of FSOI computed with the dry and the moist adjoint models (grey and black bars, respectively) using the dry norm. Results were averaged over 31 cases.

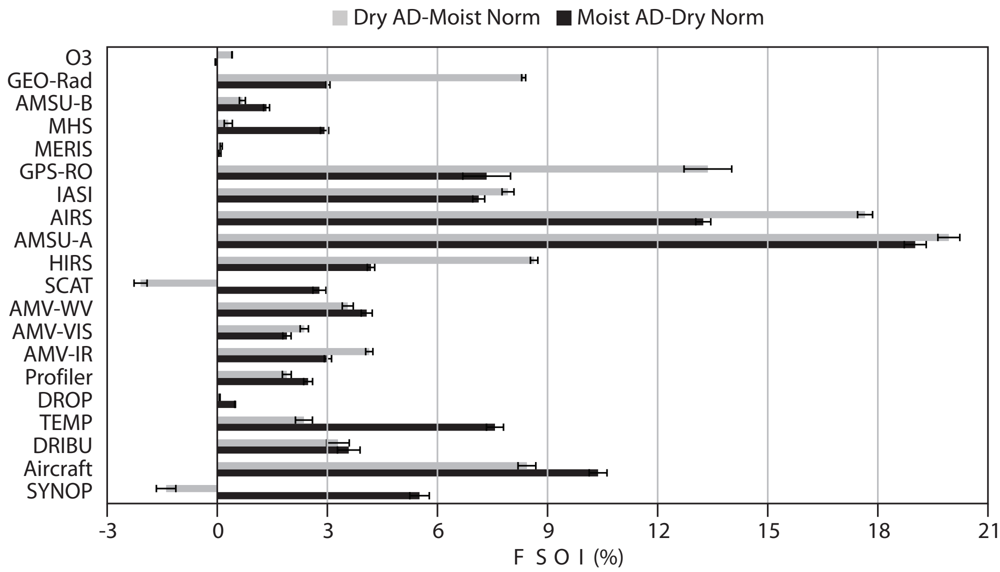

Figure 11: Same as Fig. 10, but using either the dry adjoint model and the moist norm (grey bars) or the moist adjoint model and the dry norm (black bars).

Finally, the impact of using two different humidity weight factors, $w_q = 0.5$ and $w_q = 0.1$ in the forecast error energy norm is illustrated in Fig. 12. With $w_q = 0.1$, the negative impact of SCAT and SYNOP is replaced by a small positive one, which is still 2% smaller than in **moistAD_dryN** (Fig. 11). Despite the larger impact reduction (∼3%) when $w_q = 0.1$ is used instead of $w_q = 0.5$, GEO-Rad, GPS-RO, AIRS and HIRS still show at least 2% more forecast impact than in **moistAD_dryN**. In conclusion, by decreasing the weight factors the negative impact of some observations vanishes and more consistency with the moist adjoint and dry norm experiment is found. However, the factor cannot be exactly determined but can only be experimentally tuned and the moist norm mainly introduces large-scale positive values in the sensitivity gradients on which FSOI strongly depends.

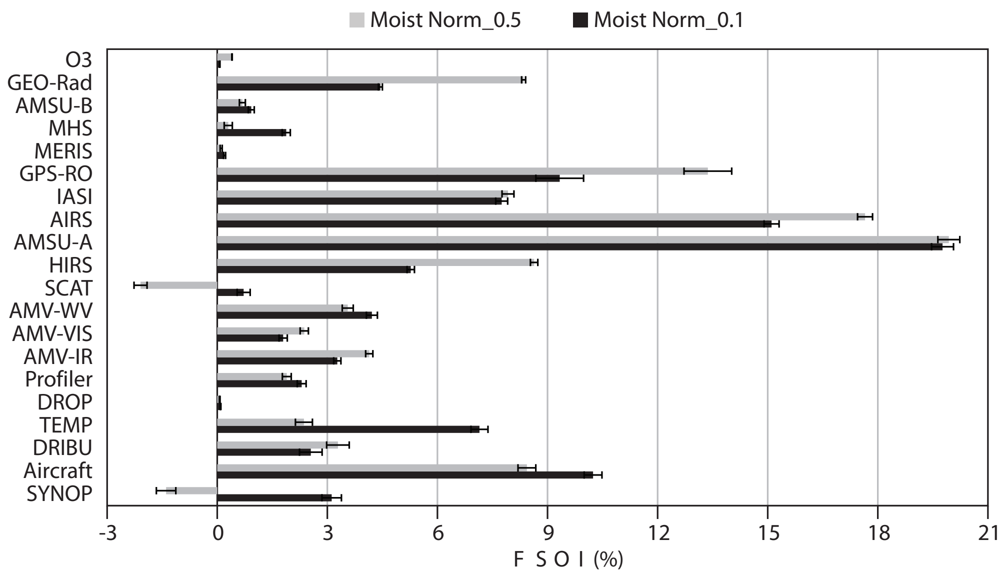

Figure 12: Same as Fig. 11, but using the dry adjoint model and the moist norm with humidity weight factors w_q = 0.5 (grey bars) or w_q = 0.1 (black bars).

4 Conclusions

Forecast sensitivity observation impact experiments have been performed by using either dry or moist total energy norm combined with either dry or moist (i.e. combining dry and moist physical processes) adjoint model to evaluate the relevance of the humidity term in the norm.

It has been clearly shown that the use of the humidity term in the norm produces unrealistic humidity and temperature sensitivity gradients, which largely affect the observation forecast impact results. When the moist norm is combined with either dry or moist adjoint model the computed sensitivity gradient shows large scale positive sensitivity patterns, which are more representative of biases of the model than realistic forecast error sensitivity with respect to the initial and background conditions.

The forecast sensitivity observation impact tends to be very different when the moist norm is used as a quite larger impact is found for few observation types that measure atmospheric humidity (together with temperature), like the infrared sounder radiances. Unexpectedly, both surface observations and surface winds retrieved from satellite over the ocean show degradation. These differences are due to the unrealistic sensitivity patterns mainly with respect to humidity which are generated by the norm. In fact, with the moist norm the humidity forecast error sensitivity patterns are artificially inflated, instead of showing the true effect of moist processes.

An appropriate tuning of the humidity weight factor in the norm is necessary to reduce the large unphysical patterns. Nevertheless, decreasing the humidity contribution up to 90% still does not solve the problem. It is believed that the extra term in the norm is only an unnecessary artefact and that the humidity contribution in the norm is implicitly expressed through the temperature component, which varies to properly account for condensation and evaporation processes.

A full comprehensive description of the moist physical processes in the adjoint of the linearized model is necessary to properly propagate backward in time and space the humidity component of the forecast error. For systems that miss the representation of such processes the use of the dry adjoint model is recommended together with the dry norm; this combination provides, in percentage, a similar observation contribution to forecast error reduction. Moreover, to account for moist processes in the absence of moist physical parametrization in the adjoint model, the possibility of using hydrometeors in the energy norm could be explored in the future. This could provide more localized sensitivity gradients related to physical processes.

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References

Baker N.L. and Daley R., 2000: Observation and background adjoint sensitivity in the adaptive observation targeting problem. *Q. J. R. Meteorol. Soc.*, **126**, 1431–1454

Barkmeijer J., Buizza R., Palmer T.N., Puri K. and Mahfouf J.-F., 2001: Tropical singular vectors computed with linearized diabatic physics. *Q. J. R. Meteorol. Soc.*, **201**, 685–708

Bauer P., Radnoti G., Healey S. and Cardinali C., 2014: GNSS Radio Occultation observing system experiments. *Mon. Weather Rev.*, **142**, 555–572

Bouttier F. and Kelly G., 2001: Observing-system experiments in the ECMWF 4D-Var data assimilation system. *Q. J. R. Meteorol. Soc.*, **127**, 1469–1488

Buizza R., 1994: Impact of simple vertical diffusion and of the optimisation time on optimal unstable structures. ECMWF Technical Memorandum **192**, ECMWF, Reading, UK, 25 pp

Buizza R., Palmer T.N., Barkmeijer J., Gelaro R. and Mahfouf J.-F., 1996: Singular vectors, norms and large-scale condensation. In Proceedings of Conference on numerical weather prediction, Norfolk, Virginia, American Meteorological Society, 50–52

Cardinali C. and Buizza R., 2004: Observation sensitivity to the analysis and the forecast: A case study during ATreC targeting campaign. In Proceedings of the First THORPEX International Science Symposium, 6-10 December 2004, Montreal, Canadan WMO TD 1237 WWRP/THORPEX N. 6

Cardinali C., Pezzulli S. and Andersson E., 2004: Influence-matrix diagnostic of a data assimilation system. *Q. J. R. Meteorol. Soc.*, **130**, 2767–2786

Cardinali C., 2009: Monitoring the observation impact on the short-range forecast. *Q. J. R. Meteorol. Soc.*, **135**, 239–250

Cardinali C., 2015: Advanced Data Assimilation for Geosciences. École de Physique des Houches, Les Houches 2012. Chapters 5 and 6. Oxford University Press.

Chapnik B., Desroziers G., Rabier F. and Talagrand O., 2004: Properties and first applications of an error-statistics tuning method in variational assimilation. *Q. J. R. Meteorol. Soc.*, **132**, 543–565

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

Daescu D.N. and Todling R., 2010: Adjoint sensitivity of the model forecast to data assimilation system error covariance parameters. *Q. J. R. Meteorol. Soc.*, **136**, 2000–2012

Ehrendorfer M., Errico R.M. and Raeder D., 1999: Singular-vector perturbation growth in a primitive equation model with moist physics. *J. Atmos.Sci.*, **56**, 1627–1648

English S., Saunders R., Candy B., Forsythe M. and Collard A., 2004: Met. Office satellite data OSEs. In Proceedings of Third WMO workshop on the impact of various observing systems on numerical weather prediction, Alpbach, Austria, WMO/TD-1228 Geneva, 146–156

Errico R. M., 2007: Interpretation of an adjoint-derived observational impact measure. *Tellus*, **59A**, 273-276

Gelaro R. and Zhu Y., 2009: Examination of observation impacts derived from observing system experiments (OSEs) and adjoint models. *Tellus*, **61A**, 179–193

Janisková M., Thépaut J.–N. and Geleyn J.–F., 1999: Simplified and regular physical parameterizations for incremental four-dimensional variational assimilation. *Mon. Weather Rev.*, **127**, 26–45

Janisková M., Mahfouf J.-F., Morcrette J.-J. and Chevallier F., 2002: Linearized radiation and cloud schemes in the ECMWF model: Development and evaluation. *Q. J. R. Meteorol. Soc.*, **128**, 1505–1527

Janisková M. and Lopez P., 2013: Linearized physics for data assimilation at ECMWF. In: S.K. Park and L. Xu (eds.), Data assimilation for Atmospheric, Oceanic and Hydrological Applications (Vol. II), DOI 10.1007/978-3-642-35088-7_1, Springer-Verlag Berlin Heidelberg, 251–286

Kelly G. and Thépaut J.-N., 2007: Evaluation of the impact of the space component of the Global Observation System through Observing System Experiments. ECMWF Newsletter **113**, Autumn, 16–

28

Langland R. and Baker N.L., 2004: Estimation of observation impact using the NRL atmospheric variational data assimilation adjoint system. *Tellus*, **56A**, 189–201

Laroche, S., Tanguay, M. and Delage, Y., 2002: Linearization of a simplified planetary boundary layer parametrization. *Mon. Weather Rev.*, **130**, 2074–2087

Lopez P. and Moreau E., 2005: A convection scheme for data assimilation: Description and initial tests. *Q. J. R. Meteorol. Soc.*, **131**, 409–436

Lorenc A.C. and Marriot R.T., 2014: Forecast sensitivity to observations in the Met Office Global numerical weather prediction system. *Q. J. R. Meteorol. Soc.*, **140**, 209–224, doi.10.1002/qj.2122

Mahfouf J.-F., Buizza R. and Errico R.M., 1996: Strategy for including physical processes in the ECMWF variational data assimilation system. In Proceedings of ECMWF Workshop on non-linear aspects of data assimilation, 9-11 September 1996, Reading, U.K., 595–632

Mahfouf J.-F., 1999: Influence of physical processes on the tangent-linear approximation. *Tellus*, **51**, 147–166

Mahfouf J.-F., 2005: Linearization of a simple moist convection for large-scale NWP models. *Mon. Weather Rev.*, **133**, 1655–1670

Purser R.J. and Huang H.-L., 1993: Estimating effective data density in a satellite retrieval or an objective analysis. *J. Appl. Meteteorol. Soc.*, **32**, 1092–1107

Rabier F., Järvinen, H., Klinker E., Mahfouf J.-F.,Simmons A. 2000. The ECMWF operational implementation of four-dimensional variational assimilation. Part I: Experimental results with simplified physics. *Q. J. R. Meteorol. Soc.*, **126**, 1143–1170

Tompkins A.M. and Janisková M., 2004: A cloud scheme for data assimilation: Description and initial tests. *Q. J. R. Meteorol. Soc.*, **130**, 2495–2517

Xu L., Langland R., Baker N. and Rosmond T., 2006: Development and testing of the adjoint of NAVDAS-AR. In Proceedings of Seventh international workshop om adjoint applications in dynamic meteorology, 8-13 October 2006, Obergurgl, Austria

Zupanski, D. and Mesinger, F., 1995: Four-dimensional variational assimilation of precipitation data. *Mon. Weather Rev.*, **123**, 1112–1127

Zhu Y. and Gelaro R., 2008: Observation sensitivity calculations using the adjoint of the Gridpoint Statistical Interpolation (GSI) analysis system. *Mon. Weather Rev.*, **136**, 335–351

Zou, X., Navon, I.M. and Sela, J.G., 1993: Variational data assimilation with moist threshold processes using the NMC spectral model. *Tellus*, **45A**, 370–387