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ESTIMATION OF OBSERVATION VALUE USING THE NAVDAS ADJOINT SYSTEM

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1. INTRODUCTION

Operational weather forecast centers process and assimilate very large amounts of observation data from satellite and *in-situ* platforms several times each day, in support of numerical weather prediction.

We know, or generally assume, that observations add value to a model analysis and forecast. This is certainly true in the sense that when a large set of observations is assimilated, we believe that the analysis and forecast will be improved, at least in an average statistical sense. However, it is also true that a non-negligible percentage of available observations, when assimilated, actually degrade the analysis and forecast. In fact, this must be expected, because data assimilation is a statistical procedure based on numerous approximations, assumptions, imperfect background fields, and imperfect observations. Even observations from systems that are considered highly accurate, such as radiosondes or dropsondes, may cause forecast error to increase when assimilated. It is thus of substantial interest to examine and understand patterns of observation impact on forecast skill.

The goal of this paper is to describe a new adjoint-based procedure for assessing the value (in terms of forecast impact) of any or all observations used in a data assimilation / forecast system. The procedure can be applied as a diagnostic tool to monitor the assimilation and quality control of any observation type, and can also be used in the design of improved observing networks. It can be applied to any forecast and data assimilation system for which adjoints exists.

2. OBSERVATION VALUE

In this study, observation value is assessed by using adjoint sensitivity gradients and innovations used by NAVDAS to estimate (as described in Sections 3-4, below) the effect of each observation on a measure of short-range forecast error. If this “observation impact” measure is less than zero, a reduction in forecast error is implied, and the observation value can be considered “beneficial.” We do not, however, attempt to directly assess if the observation has improved or degraded the *analysis* from which the forecast is started.

The observation impact (and hence the “value” of the observation) depends both on how the observation is used by the **data assimilation** system to define the initial conditions, and also on local rates of error growth during the **forecast** itself. In the assimilation, the effect of an observation on the initial conditions (the “analysis”) depends on the accuracy of the observation, the number and configuration of other nearby observations, the specified background error, and other features of the assimilation technique. It can be assumed that every numerical weather forecast starts from initial conditions that contain some degree of error.

During the numerical forecast, any errors present in the initial conditions either propagate, decay, or grow, at rates that depend on the instability of the atmosphere; e.g., the potential for error growth. Observations will have the largest impact on forecast error when the observation influences the initial conditions in a dynamically sensitive location. Since error growth during the forecast can be very large, it is not necessary for the observation to make a large change to the *initial conditions* for it to have a large *forecast impact*. Forecast error is also caused by model deficiencies, which is not directly evaluated in this study.

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3. OBSERVATION SENSITIVITY CALCULATION

The forecast model used in this study is the Navy Operational Global Atmospheric Prediction System (NOGAPS, Hogan et al. 1999). It is run with a spectral truncation of T79 (~150 km horizontal resolution), and 18 vertical levels defined in sigma coordinates. The version of NOGAPS used here is an operational forecast system run at reduced resolution, but fully capable of resolving and forecasting synoptic-scale weather features, when provided with accurate initial conditions. The NOGAPS adjoint includes a linearization of the dry dynamics, with simplified physics including vertical diffusion and surface sensible heat and momentum fluxes (Rosmond 1997). The adjoint model uses the same horizontal and vertical grid structure as the nonlinear forecast model, but moist physical processes are not yet included.

Observations are assimilated in a 6-h update cycle with the NRL Atmospheric Variational Data Assimilation System (NAVDAS, Daley and Barker 2001). NAVDAS performs a 3d-variational data assimilation using NOGAPS background fields. All observations available in real-time for operational use are assimilated in this study, including advanced and experimental satellite wind data, surface winds from scatterometers, and all radiosondes, pibals, aircraft flight level observations, and surface data from ship, land, and buoy stations. Moisture is analyzed using a Cressman technique. A comprehensive quality control procedure is used.

The calculation of observation sensitivity is a <u>two-step process</u> that involves the adjoints of NOGAPS and NAVDAS. We seek the gradient ($\partial J/\partial \mathbf{y}$) of a forecast error costfunction (J) with respect to the vector of observations ($\mathbf{y}$).

We first define a forecast error norm:

$$\mathbf{e}_\mathrm{f} = \left\langle \left(\mathbf{x}_\mathrm{f} - \mathbf{x}_\mathrm{a}\right), \mathbf{C}\left(\mathbf{x}_\mathrm{f} - \mathbf{x}_\mathrm{a}\right) \right\rangle \quad , \qquad \textbf{(1)}$$

where $\mathbf{x}$ is the vector of model predictive variables, vorticity, divergence, potential temperature, and surface pressure (humidity is predicted by the model but not used in the error norm calculation). The subscripts, f and a, refer to "forecast" and verifying "analysis", respectively, of the NOGAPS forecast and assimilation. In (1) $\mathbf{C}$ is a matrix of energy weighting coefficients that represents dry total energy (see for example Rabier et al. 1996, or Rosmond 1997). An energy metric is used because it is the most appropriate choice for applications to predictability in the absence of an acceptable estimate of the actual analysis error covariance metric (Palmer et al. 1998). The brackets $\langle \, , \rangle$ represent a Euclidean inner product $\langle \mathbf{x}, \mathbf{y} \rangle = \Sigma \mathbf{x}_i \mathbf{y}_i$. The error norm in (1) has units of J kg^{-1}, and is summed between the lowest near-surface model level and a level near 150 hPa. The forecast verification area (FVA) in which the error is calculated is the global domain.

The costfunction is defined by:

$$J_f = \frac{1}{2} \mathbf{e}_\mathrm{f} \quad , \qquad \textbf{(2)}$$

and the starting condition for the adjoint integration, at forecast verification time, is:

$$\partial J_f \big/ \partial \mathbf{x}_\mathrm{f} = \mathbf{C}\left(\mathbf{x}_\mathrm{f} - \mathbf{x}_\mathrm{a}\right) \quad . \qquad \textbf{(3)}$$

One integration of the <u>forecast model adjoint</u> provides a three-dimensional sensitivity vector for the initial conditions (t=0):

$$\partial J_f \big/ \partial \mathbf{x}_0 = \mathbf{L}^\mathrm{T} \, \partial J_f \big/ \partial \mathbf{x}_\mathrm{f} \quad , \qquad \textbf{(4)}$$

where $\mathbf{L}^\mathrm{T}$ is the operator representing the adjoint of the discretized NOGAPS model. This adjoint sensitivity is obtained in a tangent linear and perfect model framework, and is linearized with respect to a trajectory provided by the nonlinear global forecast model (including moist physics), that is updated every second time step ($2\Delta t$ = 1800 s).

The second and final step in the sensitivity calculations is to operate on the initial condition sensitivity gradient using the <u>adjoint of NAVDAS</u>:

$$\partial J_f / \partial \mathbf{y} = \mathbf{K}^{T} \, \partial J_f / \partial \mathbf{x}_0 \quad , \qquad \textbf{(5)}$$

where $\mathbf{K}^T$ is the operator representing the adjoint[2] of the Kalman gain matrix in the data assimilation procedure (Baker and Daley 2000). The quantity $\partial J_f / \partial \mathbf{y}$ is the sensitivity of the forecast error costfunction with respect to the complete set of observations, $\mathbf{y}$, in observation space. If we consider that the background ($\mathbf{x}_b$) is fixed, then $\partial J_f / \partial \mathbf{y}$ is also the sensitivity to the innovations (observation – background). It should be noted that it is necessary to interpolate the sensitivity gradient $\partial J_f / \partial \mathbf{x}_0$, which is obtained on the forecast model grid in (4), onto the analysis grid before it can be used in (5), and care must be taken in this step to consider special properties of the sensitivity gradient.

4. OBSERVATION IMPACT CALCULATION

We can now adapt the general procedure outlined in Section 3 to address specific questions related to observation impact. For example, what is the impact of observations taken at 00UTC on 72h forecast error[3]? Consider the following analysis and forecast configuration, in Fig. 1:

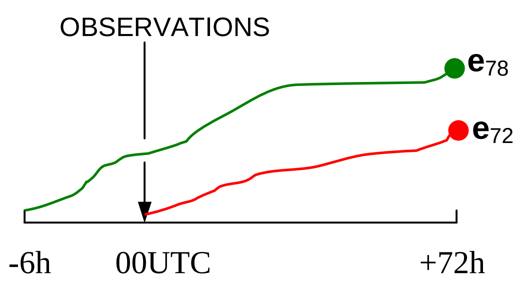

Fig. 1: Observations are assimilated at 00UTC, creating ICs for a new trajectory, which has forecast error $\mathbf{e}_{72}$. The old trajectory starts from 18UTC (-6h), and has forecast error $\mathbf{e}_{78}$. It also provides the background for the analysis at 00UTC.

The difference between the forecast errors ($\mathbf{e}_{72}$ - $\mathbf{e}_{78}$) is due solely to the assimilation of observations at 00UTC. If there are no observations at 00UTC, it is clear that $\mathbf{e}_{72}$ will be equal to $\mathbf{e}_{78}$ since the trajectory starting from 18UTC (-6h) will not be changed when the assimilation has no observations to process.

Using sensitivity gradients from the two forecast trajectories, we can estimate the forecast error difference, $\delta\mathbf{e}_f = \mathbf{e}_{72} - \mathbf{e}_{78}$, using the following equation:

$$\delta\mathbf{e}_{\mathbf{f}} = \left\langle \left(\mathbf{x}_0 - \mathbf{x}_b\right), \left(\frac{\partial J_{72}}{\partial \mathbf{x}_0} + \frac{\partial J_{78}}{\partial \mathbf{x}_b}\right) \right\rangle \quad , \qquad \textbf{(6)}$$

where $\mathbf{x}_0$ is the initial condition of the 72h forecast trajectory and $\mathbf{x}_b$ is the background (6h forecast) used for the analysis at 00UTC.

The observation sensitivity in this case is defined by:

$$\frac{\partial J_{72/78}}{\partial \mathbf{y}} = \mathbf{K}^{\mathbf{T}} \left(\frac{\partial J_{72}}{\partial \mathbf{x}_0} + \frac{\partial J_{78}}{\partial \mathbf{x}_b}\right) \quad . \qquad \textbf{(7)}$$

We may now write an alternative expression for $\delta\mathbf{e}_f$ (derived from (6)) using only quantities in observation space, e.g., the innovations and the observation sensitivity gradient from (7):

$$\delta\mathbf{e}_{\mathbf{f}} = \left\langle \left(\mathbf{y} - \mathbf{H}\mathbf{x}_{\mathrm{b}}\right), \frac{\partial J_{72/78}}{\partial \mathbf{y}} \right\rangle \quad . \qquad \textbf{(8)}$$

In (8), the quantity ($\mathbf{y} - \mathbf{H}\mathbf{x}_b$) is the innovation, and $\mathbf{H}$ is an operator that performs spatial interpolation of the background into observation space. The quantity $\delta\mathbf{e}_f$, as defined in (8) provides the information we require to assess observation impact and value in observation space.

Using (8), the global observation impact can be considered as the sum of contributions made by all individual observations; currently about 250,000 observations are assimilated each day

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[2] The Kalman gain matrix is essentially linear, so the adjoint (transpose) calculation for NAVDAS does not involve approximation of nonlinear terms.
[3] The choice of 72h is arbitrary, and any forecast length may be selected, subject to tangent linear limitations of the forecast model adjoint.

at the 00UTC analysis time in NAVDAS. Eq. (8) is similar in form to the impact function proposed by Dornbecher and Bergot (2001), except that here the costfunction is based on actual forecast error, instead of a function (such as enstrophy) derived from the forecast itself.

5. PRELIMINARY RESULTS

It is convenient to group the observation impact results by instrument type, such as radiosondes, surface data, wind observations from geostationary satellites, or commercial aircraft observations. For example, we might wish to evaluate the summed impact ($\Sigma\delta\mathbf{e}_f$) of all geostationary satellite wind observations using all observations over the global domain. It is possible to also consider any arbitrary subset of observation data, such as only observations below 600 hPa, or only data from within a selected regional area, etc.

Fig. 2 summarizes observation impact results for the 30-day period 29 June – 28 July 2002. Note, first, that the cumulative impact for all observation types is less than zero, which indicates that $\mathbf{e}_{72} < \mathbf{e}_{78}$, due to assimilation of the observations.

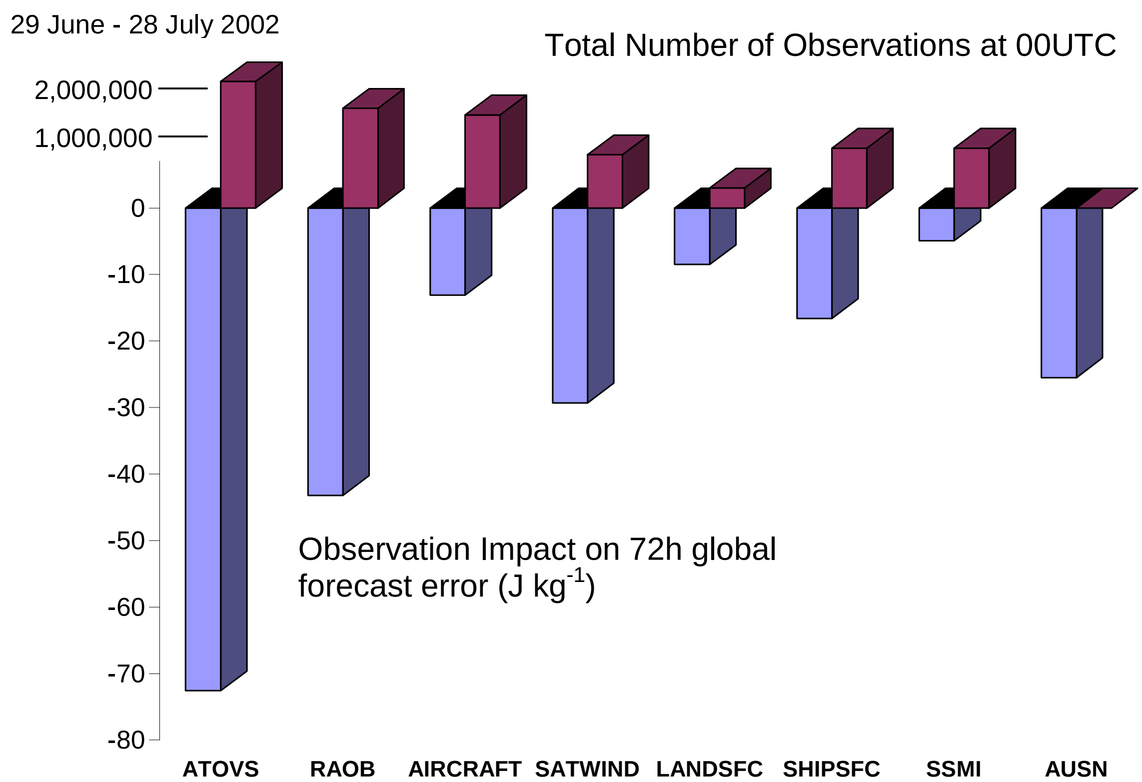
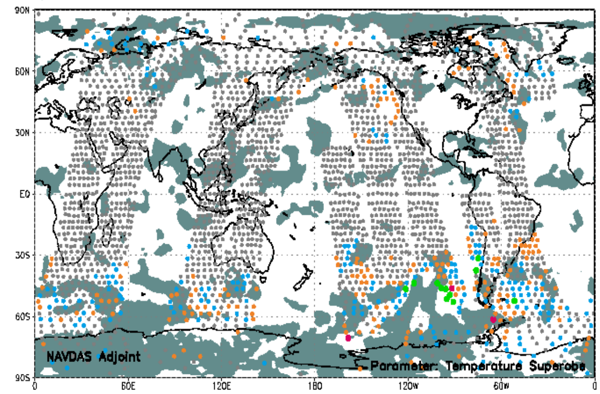


Fig. 2: Cumulative (summed) **observation impact** on 72h global forecast error ($\Sigma\delta\mathbf{e}_f$) and **number of observations** for the 30-day period 29 June - 28 July 2002, including all observations assimilated at 00UTC. Note that every observation data is counted separately; e.g, a sounding from a RAOB contains temperature, wind, and height observations on every significant and mandatory level. A (geostationary) SATWIND contains both u- and v- wind observations. ATOVS are temperature super-obs. LANDSFC are land surface temperature, wind, and height observations. SHIPSFC are ship and buoy surface temperature, wind, and height observations. AIRCRAFT are temperature and wind observations from commercial aircraft. SSMI are near-surface wind speed, and AUSN are Australian synthetic sea-level pressure bogus data.

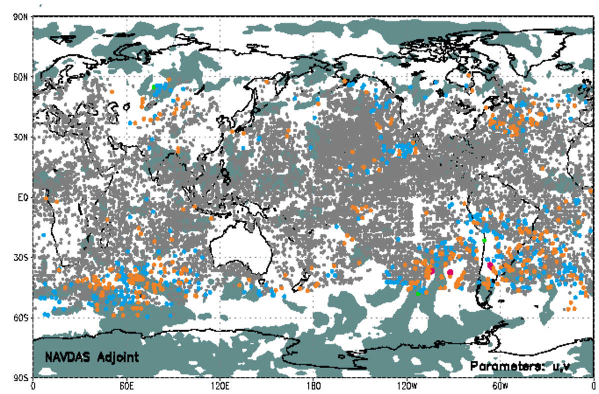
The ATOVS temperature super-obs provide the single largest number of observation data, and also produced the largest reduction in 72h forecast error of any observation type. The next-largest reductions in forecast error are provided by radiosonde and geostationary satellite wind observations, respectively. A surprising result is the significant impact of the Australian synthetic surface pressure observations. While only 4,082 of these data were provided, their impact (-25.5 J kg^{-1}) is nearly equivalent to that provided by satellite wind data (-29.3 J kg^{-1} with 797,830 observations). Lesser (but still beneficial) impacts are associated with aircraft data, land and ship surface observations, and SSMI surface wind observations.

It should be noted that the results summarized in Fig. 2 pertain to June and July, when the largest forecast errors occur in conjunction with baroclinic wave developments in the Southern Hemisphere winter. Errors during July in the Northern Hemisphere are much smaller on average and this seasonal variation should be taken into account when assessing the relative impact of the various observing systems. For example, ATOVS, satellite wind data and AUSN are very important in the Southern Hemisphere, while most radiosonde, aircraft, and land surface data are found in the Northern Hemisphere.

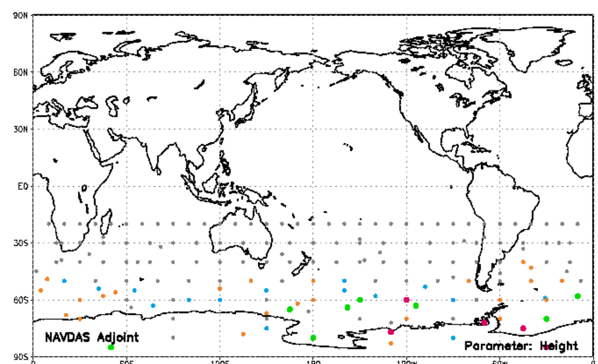
ATOVS TEMPERATURE SUPEROBS



GEOSTATIONARY SAT WINDS



AUSTRALIAN SYNTHETIC SFCP



Key – Impact of observations on 72h error

Error decrease	Error increase
Large	Large
Moderate	Moderate

Small Impact

Fig. 3: Observation impact (color-coded category ranking based on $\delta \mathbf{e}_f$) for the assimilation at 00UTC 6 Sep 2002, with forecast verification at 00UTC 9 Sep 2002 (+72h). Shading in upper two panels indicates diagnosed cloud cover > 60 percent. For ATOVS (upper panel) each dot represents the combined impact of ~30 temperature observations in a profile through the entire depth of the atmosphere.

On any particular day, there is a wide range of observation impact associated with each observation type, and the adjoint-based procedure allows us to quantify the values for every individual observation. For example, in Fig. 3, eight of the AUSN synthetic surface pressure observations have a relatively large beneficial impact on 72h forecast error (green dots in lower panel); e.g., the error is decreased, and four AUSN observations cause a relatively large increase in forecast error (red dots).

In addition, we can determine that the impact from single AUSN surface pressure observations can be as significant as the impact from an entire vertical profile of temperature observations provided by ATOVS (upper panel). However, the number of ATOVS data over the globe is much larger, and so the total impact of ATOVS almost always exceeds that from AUSN.

Based on examination of results like those shown in Fig. 3, over several months, it has been found that the largest observation impacts (positive and negative) tend to occur:

- In the extra-tropical storm tracks of the Southern and Northern hemispheres
- In branches of the sub-tropical jet stream
- In conjunction with tropical cyclones

However, even within these regions, large observation impact is generally quite localized, as suggested by the clusters of color-coded dots in Fig. 3.

Note that the impact calculated for any individual observation depends on the configuration and types of other observations that are assimilated at the same time. Any change, such as adding or removing observations, is likely to increase or decrease the impact of other observations.

It can also be seen in Fig. 3 that a sizeable fraction of observations produce only small impact on 72h forecast error, represented by the grey dots in Fig. 3. These observations are either in regions where forecast error growth is relatively small, or they have received little weight in the analysis, for various reasons. However, the "small impact" observations might improve aspects of the analysis or forecast that are not measured by the error costfunction used here, and so it should not be concluded that the observations have no value in a more general context.

Finally, the results indicate there is a very strong correlation between observation impact and cloud cover. Observation impact (in terms of average magnitude per observation) increases dramatically in locations where cloud cover is greater than 70 percent (Fig. 4). This relationship could exist because cloudy regions are more dynamically sensitive, or because there are relatively fewer observations in cloudy regions and so the available observations receive more weight individually in the assimilation. The result suggests that targeting additional satellite or in-situ observations into cloudy regions may be an effective means to improve forecast skill.

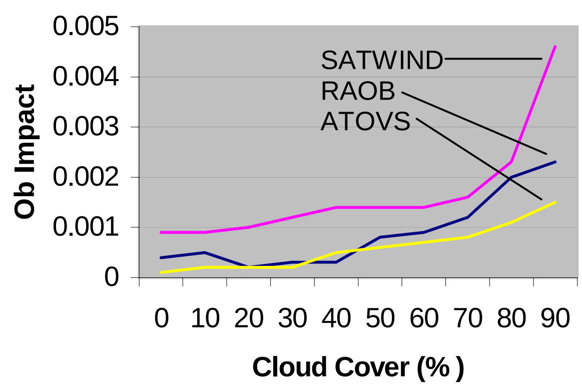


Fig. 4: Observation impact (average magnitude per observation, in J kg^{-1}) as a function of model-diagnosed cloud-cover. The "impact" in this figure includes both improvements and degradations of 72h global forecast error. Based on results from 29 June – 28 July 2002.

6. ACCURACY OF ADJOINT-BASED OBSERVATION IMPACT ESTIMATE

The utility of the results described here depends on the accuracy of the forecast error estimate $\delta\mathbf{e}_f$ provided by (8). We desire that $\delta\mathbf{e}_f$ provide a reasonable estimate of the "true" value of $\mathbf{e}_{72}$ - $\mathbf{e}_{78}$ obtained from the nonlinear model forecasts, although it is not necessary that $\delta\mathbf{e}_f$ be exact in order for the observation impact calculations to provide useful information.

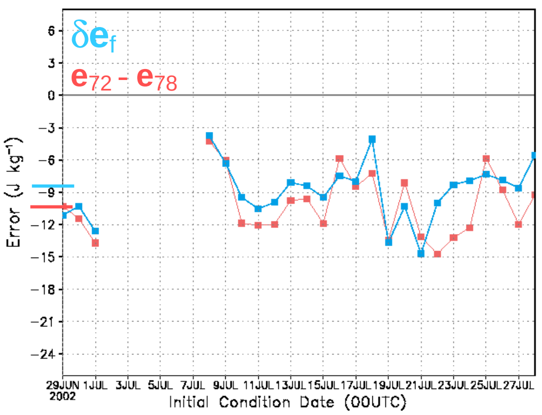


Fig. 5: Adjoint-based estimate of $\delta\mathbf{e}_f$, and actual $\mathbf{e}_{72}$ - $\mathbf{e}_{78}$. Mean values shown by horizontal lines on left axis. Results are shown for 29 June – 28 July 2002 (missing 2-7 July), and include the impact of all observations except humidity.

In Fig. 5, we see that from 29 June to 28 July 2002, the adjoint estimate of $\delta\mathbf{e}_f$ always has the correct sign (< 0), and follows the day- to-day trend of $\mathbf{e}_{72}$ - $\mathbf{e}_{78}$ fairly well through the period, except for 22-24 July. On average, the adjoint-based estimate ($\delta\mathbf{e}_f$) is within about 19 percent of the actual $\mathbf{e}_{72}$ - $\mathbf{e}_{78}$. This level of accuracy is reasonable, since the adjoint model does not account for moist processes, and 72h is a relatively long forecast length for adjoint model applications.

There are three principal reasons why the adjoint estimate of $\delta\mathbf{e}_f$ is not more accurate:

- The NAVDAS adjoint code used in this study is not yet totally consistent with the version of NAVDAS used in the data assimilation procedure (an updated version of the adjoint code is currently under development).

- The calculation of $\partial J_f/\partial \mathbf{x}_0$ (e.g., Eq. 4) using the NOGAPS adjoint is subject to inaccuracy due to tangent linear limitations and the absence of moist processes in the adjoint model. The calculations would be more accurate if the forecast length was reduced to, say, 24h or 48h instead of the 72h forecast length used here.

- Moisture (or humidity) observations are not included in the calculation of observation impact (Eq. 8). This could be one reason why the average error reduction accounted for by $\delta\mathbf{e}_f$ is not as large as the actual $\mathbf{e}_{72}$ - $\mathbf{e}_{78}$. That is, about 80 percent of the total observation impact (on average) is due to temperature, wind and height observations, and the remaining 20 percent would be the impact of humidity observations.

7. DISCUSSION

This paper describes the mathematical framework for observation impact assessment using a new adjoint-based procedure. It requires adjoint versions of the forecast model and the data assimilation code. The computational cost of the sensitivity and observation impact calculations is roughly the same as a single run of the regular forecast model and the data assimilation. Accuracy of the calculations is relatively good, even when applied to forecasts as long as 72h. A significant benefit of the procedure is that observation impact can be estimated and assessed for any individual observation or subset of observation data.

Preliminary results illustrate characteristics and patterns of observation impact on 72h global forecast error. The total (global) observation impact is the sum of a wide range of impact associated with individual observations. Although the total (sum of all observations) impact is beneficial, a substantial fraction of observations increase the forecast error when assimilated. This is a general result that demonstrates the statistical manner in which data assimilation procedures attempt to extract value from observation data.

The impact of individual observations, at any given time and location, depends strongly on the particular assimilation system and forecast model being used. A selected observation used in one assimilation system may have a beneficial impact, but the same observation may not be beneficial when assimilated in another system that uses, for example, different error covariance statistics, a different background, etc.

The observation impact procedure can be used to identify systematic problems that might exist with certain types of observations or for observations in certain locations. For example, a problem with assimilation of ATOVS temperature retrievals in the lower troposphere was corrected in NAVDAS after examining vertical profiles of observation impact over a period of several weeks. Future work will apply the observation impact procedure as a diagnostic tool to monitor the data assimilation process, and in research for the design of improved observing networks in conjunction with the THOR*pex* program (see web site below).

WEB SITE:

Observation sensitivity products produced in near real-time using NAVDAS and NOGAPS can be viewed at:
http://www.nrlmry.navy.mil/shared-bin/adap/adap.cgi

THOR*pex:*

A ten-year international program of research and field work being developed to examine observing system and predictability issues in a global context:
THORpex Presentation

ACRONYMS:

NAVDAS – NRL Atmospheric Variational Data Assimilation System

NOGAPS – Navy Operational Global Atmospheric Prediction System

THOR*pex* – THe Observing System Research and Predictability Experiment

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