Adjoint-Derived Observation Impact Using WRF in the Western North Pacific

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ABSTRACT

An increasing number of observations have contributed to the performance of numerical weather prediction systems. Accordingly, it is important to evaluate the impact of these observations on forecast accuracy. While the observing system experiment (OSE) requires considerable computational resources, the adjoint-derived method can evaluate the impact of all observational components at a lower cost. In this study, the effect of observations on forecasts is evaluated by the adjoint-derived method using the Weather Research and Forecasting Model, its adjoint model, and a corresponding three-dimensional variational data assimilation system in East Asia and the western North Pacific for the 2008 typhoon season. Radiance observations had the greatest total impact on forecasts, but conventional wind observations had the greatest impact per observation. For each observation type, the total impact was greatest for radiosonde and each Advanced Microwave Sounding Unit (AMSU)-A satellite, followed by surface synoptic observation from a land station (SYNOP), Quick Scatterometer (QuikSCAT), atmospheric motion vector (AMV) wind from a geostationary satellite (GEOAMV), and aviation routine weather reports (METARs). The fraction of beneficial observations was approximately 60%–70%, which is higher than that reported in previous studies. For several analyses of Typhoons Sinlaku (200813) and Jangmi (200815), dropsonde soundings taken near the typhoon had similar or greater observation impacts than routine radiosonde soundings. The sensitivity to the error covariance parameter indicates that reducing (increasing) observation (background) error covariance helps to reduce forecast error in the current analysis framework. The observation impact from OSEs is qualitatively similar to that from the adjoint method for major observation types. This study confirms that radiosonde observations provide primary information on the atmospheric state as in situ observations and that satellite radiances are an essential component of atmospheric observation systems.

1. Introduction

In numerical weather prediction (NWP) systems, analysis is conducted using a data assimilation (DA) system that combines observations and the background by considering their respective error statistics. Although the number of observations has rapidly increased, it is not clear that these observations are always beneficial to

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observation type to the improvement of their NWP systems (e.g., Bouittier and Kelly 2001; Kelly et al. 2007; Zapotocny et al. 2008; WMO 2008; Laroche and Sarrazin 2010a,b). However, OSEs require considerable computational resources because the entire DA and forecast system must be run independently of the reference analysis–forecast run to evaluate the impact of each observation.

An alternative method to evaluate the impact of observations on forecasts is the adjoint-derived observation impact method, which is based on the adjoint-based observation sensitivity approach introduced by Baker and Daley (2000) in the context of adaptive observation. The methodology of Baker and Daley (2000) provided the basis for succeeding adjoint-derived observation impact studies. The adjoint-derived observation impact method can simultaneously evaluate the observation impact for all datasets with less computation than OSEs by using the adjoint of the DA system and forecast system. The adjoint of the DA system can be developed by line-by-line adjoint coding (Zhu and Gelaro 2008) or by estimating the analysis error covariance using an iterative minimization algorithm (Tremolet 2008). Higher-order approximations of forecast error measurement and their characteristics in the context of adjoint-derived observation impact calculation have been discussed by Errico (2007), Gelaro et al. (2007), and Tremolet (2007). Other higher-order approximations of forecast error were introduced as a parametric approach by Daescu and Todling (2009). Langland and Baker (2004) analyzed the observation impact of the short-range forecast error in the Naval Research Laboratory (NRL) system. Gelaro et al. (2010) compared the observation impacts from three global operational systems from NRL, Environment Canada (EC), and the Global Modeling and Assimilation Office (GMAO) of the National Aeronautics and Space Administration (NASA).

Two methods of observation impact estimation (i.e., OSEs and the adjoint-derived method) were evaluated and compared by Gelaro and Zhu (2009) for the NASA GMAO system and by Cardinali (2009) for the European Centre for Medium-Range Weather Forecasts (ECMWF) system. These authors found a qualitatively similar observation impact on short-range forecasts using both methods. Observation impact estimation without the adjoint model was also recently suggested and evaluated in the context of ensemble data assimilation (Ancell and Hakim 2007; Torn and Hakim 2008; Liu and Kalnay 2008; Li et al. 2010; Kunii et al. 2012). The impact of observations from special field campaigns was also evaluated for the Fronts and Atlantic Storm-Track Experiment (FASTEX; Doerenbecher and Bergot 2001; Fourrie et al. 2002) and the Atlantic The Observing System Research and Predictability Experiment (THORPEX) Regional Campaign (A-TReC; Langland 2005).

In this study, the impact of observations on forecasts is evaluated using the adjoint-derived method in a limited-area model for the 2008 typhoon season, during which an international field campaign, the THORPEX Pacific Asian Regional Campaign (T-PARC), was performed. This evaluation employs the Advanced Research version of the Weather Research and Forecasting Model (ARW-WRF), its adjoint model (WRFPLUS), and the corresponding three-dimensional variational data assimilation (3DVAR) system, centered in East Asia and the western North Pacific. The adjoint-derived observation impact is compared to that from OSEs for major observation types. Sensitivities to the background and observation error covariance parameter are also evaluated. The adjoint-derived observation impact tool used in this study was developed by Auligné et al. (2011). To the authors’ knowledge, this is the first study to fully assess the adjoint-derived observation impact in the WRF system and the sensitivity to the error covariance parameter within the limited-area model framework. Section 2 introduces the methodology for adjoint-derived observation impact, and section 3 provides the experimental framework. Section 4 provides the observation impact results, and section 5 presents a summary and discussion.

2. Methodology

a. Basic concept

The nonlinear forecast procedure is expressed as

$$\mathbf{x}' = \mathbf{m}(\mathbf{x}^0),$$  

(2.1)

where $\mathbf{x}$ and $\mathbf{x}'$ represent the initial and forecast model states given the nonlinear forecast model $\mathbf{m}$, respectively. In the adjoint sensitivity analysis, the response function or forecast aspect $R$ is expressed as a function of the forecast state: $R = f(\mathbf{x}')$. The first-order variation of $R$ can then be expressed as a product of the forecast (initial) variation and the gradient of $R$ to the forecast (initial) state:

$$\delta R = \left\langle \delta \mathbf{x}', \frac{\partial R}{\partial \mathbf{x}} \right\rangle = \left\langle \delta \mathbf{x}', \frac{\partial \mathbf{m}}{\partial \mathbf{x}} \right\rangle = \left\langle \mathbf{M}\delta \mathbf{x}, \frac{\partial R}{\partial \mathbf{x}} \right\rangle,$$

(2.2)

for the forecast variation $\delta \mathbf{x}' = \mathbf{M}\delta \mathbf{x}$ with tangent linear model $\mathbf{M}$ and initial variation $\delta \mathbf{x}$.

Using the adjointness relationship, the sensitivity to the initial state can be calculated as follows:

$\left\langle \mathbf{A} \mathbf{x}, \mathbf{y} \right\rangle = \left\langle \mathbf{x}, \mathbf{A}^T \mathbf{y} \right\rangle$ for vector $\mathbf{x}$, $\mathbf{y}$, and matrix $\mathbf{A}$.
\[ \frac{\partial R}{\partial \mathbf{x}^0} = \mathbf{M}^T \frac{\partial R}{\partial \mathbf{x}_a^T}, \]  

(2.3)

where \( \mathbf{M}^T \) represents the adjoint model.

There have been many previous studies using adjoint-derived forecast sensitivity analysis for idealized cyclogenesis (Rabier et al. 1992; Langland et al. 1995; Kim and Beare 2011), real cyclogenesis (Errico and Vukicevic 1992; Rabier et al. 1996; Klinker et al. 1998; Zou et al. 1998; Langland et al. 2002; Kleist and Morgan 2005; Ancell and Mass 2006, 2008; Jung and Kim 2009), tropical cyclones (Kim and Jung 2006; Wu et al. 2007; Chu et al. 2011), and Asian dust transport events (Kim et al. 2008; Kim and Kay 2010). A detailed introduction to adjoint theory and applications can be found in Errico (1997).

In NWP, the analysis is determined by a DA system that combines the background state with their corresponding error statistics \( \mathbf{B} \) and \( \mathbf{R} \). With the Kalman gain matrix \( \mathbf{K} = (\mathbf{B}^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{R}^{-1} \) and linear observation operator \( \mathbf{H} \), the optimal linear analysis can be expressed as follows:

\[ \mathbf{x}_a = \mathbf{x}_b + \mathbf{K}(\mathbf{y}^0 - \mathbf{Hx}_b) = (1 - \mathbf{K})\mathbf{x}_b + \mathbf{K}\mathbf{y}^0 \].  

(2.4)

Hereafter, the analysis \( \mathbf{x}_a \) replaces the initial condition \( \mathbf{x}^0 \). The variation of \( \mathbf{R} \) in (2.2) can be expressed using (2.4) and the adjointness relationship as

\[ \delta \mathbf{R} = \left< \delta \mathbf{x}_a^T, \frac{\partial \mathbf{R}}{\partial \mathbf{x}_a} \right> = \left< \mathbf{Kd}, \frac{\partial \mathbf{R}}{\partial \mathbf{x}_a} \right> = \left< \mathbf{d}, \mathbf{K}^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}_a} \right> = \left< \mathbf{d}, \frac{\partial \mathbf{R}}{\partial \mathbf{y}^0} \right>, \]

(2.5)

where \( \mathbf{d} = \mathbf{y}^0 - \mathbf{Hx}_b \) represents the innovation vector. From (2.3) and the two terms on the right-hand side in (2.5), the observation sensitivity of \( \mathbf{R} \) can be calculated as in Baker and Daley (2000):

\[ \frac{\partial \mathbf{R}}{\partial \mathbf{y}^0} = \mathbf{K}^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}_a} = \mathbf{K}^T \mathbf{M}^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}_a^T}. \]

(2.6)

b. Practical approach

The forecast error is measured with respect to the true state \( \mathbf{x}_t \) as

\[ e = (\mathbf{x}' - \mathbf{x}_t)^T \mathbf{C}(\mathbf{x}' - \mathbf{x}_t) \]

(2.7a)

\[ = \sum_{s, t, \varphi} \frac{1}{\mathbf{C}_{s,t}^2} \left[ \beta^2 + \varphi^2 + \left( \frac{\beta}{N \theta} \right)^2 \varphi^2 + \left( \frac{1}{\mathbf{C}_{t}^2} \right)^2 \varphi^2 \right], \]

(2.7b)

where \( \mathbf{C} \) is a diagonal matrix that has the weighting coefficients of the forecast error components. Usually, the dry total energy norm is used for \( \mathbf{C} \) (Rabier et al. 1996; Palmer et al. 1998; Zou et al. 1997). The coefficients \( N, \theta, \varphi, \) and \( c_i \) are reference values of the Brunt–Väisälä frequency, potential temperature, density, and the speed of sound, respectively. In practice, the true state is not known, and this lack of knowledge is a major problem in providing an objective assessment of the observation impact on forecast error reduction. Usually, the analysis from one’s own NWP system is used as a proxy of the true state.

For NWP at a given time, there are two state estimations (i.e., \( \mathbf{x}_b \) and \( \mathbf{x}_a \)). At the given analysis time, there exist observations and a background \( \mathbf{x}_b \), which is usually a short-term forecast from the analysis in the previous cycle. The analysis \( \mathbf{x}_a \) at the given time is obtained using the DA procedure as described in (2.4). We can then define the forecast errors \( e_a \) and \( e_b \) that initiate from \( \mathbf{x}_b \) and \( \mathbf{x}_a \), respectively:

\[ e_a = (\mathbf{x}'_a - \mathbf{x}_t)^T \mathbf{C}(\mathbf{x}'_a - \mathbf{x}_t), \]

(2.8a)

\[ e_b = (\mathbf{x}'_b - \mathbf{x}_t)^T \mathbf{C}(\mathbf{x}'_b - \mathbf{x}_t), \]

(2.8b)

where \( \mathbf{x}'_a \) and \( \mathbf{x}'_b \) are the forecast states initialized from \( \mathbf{x}_b \) and \( \mathbf{x}_a \), respectively. To evaluate the impact of observations on the reduction in forecast error, we can define the response function \( \Delta e \) as the difference between \( e_a \) and \( e_b \):

\[ \Delta e = e_a - e_b. \]

(2.9)

Combined with (2.5), (2.6), (2.7), and (2.8), the approximation of (2.9) can be introduced as

\[ \delta e = \mathbf{d}^T \mathbf{K}^T [\mathbf{M}_b^T \mathbf{C}(\mathbf{x}'_b - \mathbf{x}_t) + \mathbf{M}_d^T \mathbf{C}(\mathbf{x}'_b - \mathbf{x}_t)]. \]

(2.10)

where \( \mathbf{M}_a = \frac{\partial \mathbf{x}'}{\partial \mathbf{x}_a} = \frac{\partial \mathbf{m}(\mathbf{x}_a)}{\partial \mathbf{x}_a} \) and \( \mathbf{M}_b = \frac{\partial \mathbf{x}'}{\partial \mathbf{x}_b} = \frac{\partial \mathbf{m}(\mathbf{x}_b)}{\partial \mathbf{x}_b} \) are the resolvent matrices of the tangent linear model for given trajectories. A variant of (2.10) is employed in the following sections to estimate the observation impact on the forecast error. The variant of (2.10) is expressed as \( \delta e' \) in Gelaro et al. (2007):

\[ \delta e = \mathbf{d}^T \mathbf{K}^T [\mathbf{M}_b^T \mathbf{C}(\mathbf{x}'_b - \mathbf{x}_t) + \mathbf{M}_d^T \mathbf{C}(\mathbf{x}'_b - \mathbf{x}_t)]. \]

(2.11)

The Kalman gain matrix (Courtier 1997) can also be defined as

\[ \mathbf{K} = \mathbf{A}^T \mathbf{R}^{-1}. \]

(2.12)

where \( \mathbf{A} \) represents the matrix of analysis error covariance and corresponds (at convergence) to the inverse of the Hessian matrix of the cost function \( J \) (Lorenc 1986; Kalnay 2003):
The domain has 41 vertical levels with the spacing that includes East Asia and the western North
titude and 125°E longitude, with a 45-km horizontal grid spacing that includes East Asia and the northern


\[ J(x) = \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b) + \frac{1}{2}(y - y_0)^T R^{-1}(y - y_0), \]  

(2.13)

where \( y = H(x) \) is a model equivalent of observation with the observation operator \( H \). The transpose of the Kalman gain matrix is then

\[ K^T = R^{-1} H A. \]

(2.14)

Eigenpairs of the Hessian (and hence those of \( A \)) can be obtained using the Lanczos method in the minimization procedure (Golub and Van Loan 1996; Tremolet 2008; Auligné et al. 2011).

3. Experimental framework

a. Modeling system

The numerical experiments in this study use the ARW-WRF system (Skamarock et al. 2008). The model domain comprises 141 (zonal direction) by 131 (meridional direction) horizontal grid points centered at 25°N latitude and 125°E longitude, with a 45-km horizontal grid spacing that includes East Asia and the western North Pacific.\(^2\) The domain has 41 vertical levels with the model top at 50 hPa. The subgrid-scale parameterizations used in this study include the new Kain–Fritsch scheme (Kain 2004) for cumulus parameterization, the WRF single-moment 6-class scheme (Hong and Lim 2006) for microphysics parameterization, the Dudhia scheme (Dudhia 1989) for shortwave radiation parameterization, the Rapid Radiative Transfer Model (RRTM) scheme (Mlawer et al. 1997) for longwave radiation parameterization, the Yonsei University (YSU) scheme (Hong et al. 2006) for planetary boundary layer parameterization, and the Noah land surface model (Chen and Dudhia 2001) for land surface parameterization.

The adjoint version of WRF is needed to calculate the adjoint-derived observation impact. This study uses the WRFPLUS system (Xiao et al. 2008; Huang et al. 2009; Zhang and Huang 2011), which includes the adjoint and tangent linear version of WRF.

Because the WRF system is based on a limited-area model, the lateral boundary condition (LBC) is essential. This study uses the Final Analysis (FNL) data of the National Centers for Environmental Prediction (NCEP) at 1° × 1° horizontal resolution to provide the LBC and initial condition in the analysis–forecast cycles.

b. Analysis system

The 3DVAR (Barker et al. 2004; Barker et al. 2012) DA system within the WRFDA system is used as an analysis system.\(^3\) In WRFDA, the analysis procedure is performed using the incremental formulation (Courtier et al. 1994) with the definition of analysis increment \( \delta x = x - x^k \) and control variable transform (CVT; Bannister 2008a,b; Michel and Auligné 2010), and the cost function \( J \) in (2.13) is minimized using the Lanczos algorithm (Golub and Van Loan 1996; Auligné et al. 2011). The background error statistics (BES) for the 3DVAR DA system are calculated using the National Meteorological Center (NMC, now known as NCEP) method (Parrish and Derber 1992). This study uses 47-day statistics of the difference between the 12- and 24-h forecasts from 15 August to 30 September 2008 to estimate the BES for a given domain using the gen_be utilities within the WRFDA system.

c. Observations

Table 1 provides acronyms of the observation types, and Table 2 summarizes the observations used in this study with their assimilated observational variables. The observation data are from prepared Binary Universal Form for the Representation of Meteorological Data (PREPBUFR) format files, which are assimilated to the operational NCEP Global Data Assimilation System (GDAS) and archived in the National Center for Atmospheric Research (NCAR) Research Data Archive (RDA). The raw data are already processed in PREPBUFR format as done at NCEP, and additional processing is performed in the WRFDA system, including data thinning, bias correction, and other quality control procedures. Conventional observations and satellite wind observations [i.e., atmospheric motion vector (AMV) wind from a geostationary satellite (GEOAMV) and Quick Scatterometer (QuikSCAT)] are thinned at 20-km resolution, and the satellite radiance observations are thinned at 90-km resolution.

d. Reference experiment

The reference state (REFER) is produced by assimilating all observations introduced in section 3c into the

\(^2\) The domain is centered in the typhoon region rather than near the Korean Peninsula because the experiments were conducted for the 2008 typhoon season, when the international field campaign T-PARC was conducted.

\(^3\) The WRFDA system includes four-dimensional variational data analysis (4DVAR; Huang et al. 2009) and hybrid systems (Wang et al. 2008), as well as the 3DVAR system. Because of the complex characteristics of the adjoint-derived observation impact estimation, we adopted 3DVAR as an analysis system. It does not consider the time variation of state. First guess at appropriate time (FGAT) was not used in this study.
TABLE 1. Acronyms used for the various observation types studied.

<table>
<thead>
<tr>
<th>Acronyms</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SYNOP</td>
<td>Surface synoptic observation from a land station</td>
</tr>
<tr>
<td>SHIP</td>
<td>Surface synoptic observation from a ship</td>
</tr>
<tr>
<td>BUOY</td>
<td>Surface synoptic observation from a buoy</td>
</tr>
<tr>
<td>METAR</td>
<td>Aviation routine weather report from an automatic weather station (AWS)</td>
</tr>
<tr>
<td>SOUND</td>
<td>Upper-level observations from a radiosonde</td>
</tr>
<tr>
<td>PILOT</td>
<td>Upper-air wind profile from a pilot balloon or radiosonde</td>
</tr>
<tr>
<td>PROFL</td>
<td>Upper-air wind profile from profiler</td>
</tr>
<tr>
<td>AIREP</td>
<td>Upper-air wind and temperature from aircraft</td>
</tr>
<tr>
<td>GPSPW</td>
<td>Global positioning system precipitable water vapor</td>
</tr>
<tr>
<td>QuikSCAT</td>
<td>Sea surface winds from QuikSCAT</td>
</tr>
<tr>
<td>GEOAMV</td>
<td>Atmospheric motion vector (AMV) wind from a geostationary satellite</td>
</tr>
<tr>
<td>AMSU-A</td>
<td>Advance Microwave Sounding Unit-A</td>
</tr>
</tbody>
</table>

WRF 3DVAR DA system from 15 August to 2 October 2008. The earliest integration starts at 0000 UTC 15 August 2008 with the NCEP FNL data as an initial condition. The reference analyses are subsequently constructed with a 6-h assimilation cycle. The radiance observations are directly assimilated in the 3DVAR DA system with the Community Radiative Transfer Model (CRTM; Han et al. 2006) as a forward operator. To handle systematic biases in the radiance observations, the variational bias correction scheme (VarBC; Derber and Wu 1998; Dee 2005; Auligné et al. 2007) is used.

e. Experimental design

The adjoint-derived observation impact is evaluated from 0000 UTC 16 August to 1800 UTC 1 October 2008 using the WRF, WRFPLUS, and WRFDA systems. The response function for the adjoint model integration is the difference in the forecast errors shown in (2.9). The error reduction of 6-h forecasts is chosen partly because the data assimilation window of most operational centers is 6 h and partly because of limited computational resources. An additional experiment with 24-h forecasts was performed to demonstrate the validity of the results with 6-h forecasts. To define the forecast errors in (2.8), the reference analysis that assimilated all observation types in the WRFDA system (section 3d) is considered a true state. The dry total energy norm is used to define the forecast error norm in (2.7). The forecast error is calculated for the entire domain.

4. Results

a. Validity of the linear estimation

Figure 1a compares the forecast error reduction in (2.9) with its linear estimation in (2.11). Overall, \( \Delta e \) and its estimation are negative, implying that the forecast error starting from \( x_d \) is smaller than that starting from \( x_0 \). This result also implies that the assimilation of observations in the DA system reduces the forecast error. The linear estimation \( \Delta e \) agrees well with the forecast error reduction in respect to its time variability and magnitude. From 1800 UTC 20 to 1800 UTC 21 August 2008, the forecast error reduction was smaller than for nearby analysis times because the Advanced Microwave Sounding Unit (AMSU)-A data were missing. Because of the variation in the observation amount, the forecast error reduction and its estimate vary significantly for each analysis time (i.e., 0000, 1200 UTC vs 0600, 1800 UTC). Figure 1b shows the forecast error reduction at 0000 UTC for each day. The linear estimate \( \Delta e \) slightly underestimates \( \Delta e \). This underestimation may be due to 1) neglected moist physics in adjoint integration, 2) the validity of the tangent linear assumption, and/or 3) the validity of the approximated formulation of forecast error reduction. Compared to the other period, a greater difference is observed between \( \Delta e \) and \( \Delta e \) for the period of Typhoon Sinlaku (from 8 to 21 September 2001), which may be due to the rapid intensification and concentric eyewall of Typhoon Sinlaku that were accompanied by strongly nonlinear processes (Liu and Li 2010; Wu et al. 2012).

b. Sensitivity to observation

1) Observation impact estimation

In this section, the observation impact is aggregated with some subset (i.e., variable, type, or channel) for each analysis time; then, the time-averaged statistic is
evaluated. Figure 2 shows the observation impact according to the observation variables (i.e., $u$, $v$, $T$, $P_s$, $q$, and $T_b$). The satellite wind observations (wind_s) are distinguished from the conventional wind observations (wind_c). Because the dry total energy norm is used for the forecast error definition, the observation impact has the unit of joules per kilogram (i.e., $J\ kg^{-1}$). The greatest total observation impact is from the radiance observations (Fig. 2a). This impact is one order of magnitude greater than the impacts of the other variables. For conventional observations, the total observation impact of the momentum variables is greater than those of the mass and moisture variables, which is consistent with the recent result reported in (World Meteorological Organization) WMO (2012). The satellite wind observations have a much smaller total impact than the conventional wind observations. The magnitude of the total observation impact is closely related to the number of observations (Fig. 2b). The radiance observation has the greatest observation number, which contributes to the greatest total observation impact of the radiance observation. For conventional observations, the observation number for wind variables is greater than the observation numbers for temperature, surface pressure, and humidity variables (Fig. 2b). To evaluate the normalized observation impact, the observation impact per observation number is calculated (Fig. 2c). The conventional wind observations have the greatest normalized impact. The pressure ($P_s$) observation,
which has the least total impact, has the second greatest normalized impact.

In an idealized study, Bengtsson (1980) found that surface pressure observations contain useful information about the amplitudes and phases of vertically tilted baroclinic modes throughout the troposphere. Compo et al. (2006) and Whitaker et al. (2009) also found that surface pressure observations provide more information on large-scale tropospheric circulation than do surface temperature or wind observations. Through geostrophy, the surface pressure information yields a reasonable approximation of the barotropic part of the flow, which accounts for a substantial part of the total flow (Compo et al. 2011). The normalized impact of radiance observations is comparable to that of temperature. The moisture observations have the smallest normalized impact.

Figure 2d shows the fraction of beneficial observations that reduce the 6-h forecast error for each observational variable. This statistic is averaged for all analysis times. Only two-thirds of the observations contribute to the reduction in the 6-h forecast error, a proportion that is significantly greater than that found in previous studies [50%–54% in Gelaro et al. (2010) and slightly greater than 50% in Kunii et al. (2012)]. This difference may be because the true state is taken from an analysis made at every 6 h in a cycling experiment; hence, the true state is partly correlated to the forecast based on the assimilation at the initial time.

Figure 3 shows the observation impact due to the observation types, which are nine types of conventional observations (SOUND, SYNOP, PILOT, AIREP, GPSPW, METAR, SHIPS, PROFIL, and BUOY; see Table 1 for explanations of the terms) and three types of satellite observations (QuikSCAT, GEOAMV, and AMSU-A radiance observations) obtained from four different satellites: National Oceanic and Atmospheric Administration (NOAA)-15, -16, and -17, and the Meteorological Operational satellite MetOp-A. In the time-averaged total observation impact for each observation type, the SOUND observations have the greatest impact. The radiance observations of each satellite also have a large total observation impact. The sum of the AMSU-A impacts from the four satellites is much greater than the impact of SOUND, which demonstrates that satellite observation is an indispensable observing system component in the NWP system. The SYNOP and
two satellite wind observations (i.e., QuikSCAT and GEOAMV) followed the SOUND and AMSU-A in importance. The smaller impact of GEOAMV, when used together with many satellite radiance data (i.e., AMSU-A), is consistent with recent studies in WMO (2012). By normalizing with the observation number (Fig. 3b), the impact of radiance observations from four satellites and SOUND observation is greatly reduced and becomes comparable to that of other observation types (Fig. 3c). The greatest observation impact per observation number is obtained from the GPSPW, which observes the total precipitable water from the surface global positioning system (GPS). Note that GPSPW has a great impact on 6-h forecast error reduction even though the forecast error is defined without the moisture term, and moisture is assimilated with a univariate formulation in the WRFDA system. In contrast to the results obtained for the total observation impact, the satellite wind observations (i.e., GEOAMV and QuikSCAT) have a relatively small observation impact per observation number. When examining the fraction of beneficial observations (Fig. 3d), it is observed that 60%–70% of the observations are beneficial, similar to the result shown in Fig. 2d.

Figure 4 shows the observation impact for each channel of the AMSU-A radiance observations. The time-averaged total observation impact is greatest for most channels of the MetOp-A and NOAA-18 satellites. Both the total and normalized observation impacts are greatest for channel 9, which is sensitive to the upper troposphere (Figs. 4a and 4c). Whereas the larger beneficial fraction is indicated by channel 9, the smaller fraction is indicated by channel 5, which is related to mid-to lower-tropospheric temperatures (Fig. 4d), and is not consistent with the results of Gelaro et al. (2010), which indicated that channels 5–7 had the greatest impact. This discrepancy may be due to the different configuration of the modeling system used. The modeling...
system in this study has a relatively low model top (50 hPa), which makes the forecast error largest in the upper troposphere (not shown). In addition, the error norm used in this study does not consider the weighting for vertical level thickness; thus, the forecast in the upper level where the density is low may be overemphasized. Proper norm definition is one of the problems encountered when the adjoint-derived observation impact methodology is used.

Figure 5 presents scatterplots of the innovation and corresponding observation impact at 0000 UTC 11 September 2008. Overall, the scatterplots display bow-shaped features, which indicate that greater innovation corresponds to greater observation impact. However, a small observation impact can occur despite a large innovation because the given observation may have low observation sensitivity. The observations near the x axis represent those characteristics. As discussed in sections 4b(2) and 4b(3), not all observations beneficially contribute to forecast error reduction. At a given analysis time, a larger beneficial fraction is shown for AMSU-A channels 7 and 9 from MetOp-A (70% and 72%, respectively) than for GEOAMV u and v (53% and 60%, respectively). Channel 9 shows higher observation sensitivity than channel 7, as shown in Fig. 4c.

To verify the validity of the observation impact discussed above for forecast errors longer than 6 h, the observation impact on the 24-h forecast error reduction was also evaluated for a 2-week period from 0000 UTC 1 to 1800 UTC 14 September 2008. The results of the 24-h forecast error reduction are generally consistent with that of the 6-h forecast error reduction except for the beneficial fraction (not shown). The major rankings of the observation variables and major observation types are unchanged. The relative impact of the surface pressure observation is increased for the 24-h forecast error reduction. Except for the surface pressure observation, the beneficial fraction of the other observation variables is reduced by approximately 6% (from 66%–72% to 60%–66%). This implies that the verifying analysis is partly correlated with the assimilated observations. Although the impact of LBC for the longer forecast time is one of the main interests of a limited-area model (e.g., Errico et al. 1993; Gustafsson et al. 1998), the impact of LBC on the results may be small for the longer forecast
period examined here because the general features of the observation impacts for both the 6- and 24-h forecast error reductions are very similar. The impact of LBC on the forecast sensitivity to observations within a limited-area model deserves further study with greater detail.

2) OBSERVATION IMPACT DISTRIBUTION

This section presents the vertical and horizontal distributions of the observation impact for SOUND and GEOAMV. Figure 6 shows the vertical distribution of the observation impact evaluated in this study. The observation impact is categorized for eight vertical intervals: surface (1000)–850, 850–700, 700–500, 500–400, 400–300, 300–200, 200–100, and 100–model top (50) hPa. For SOUND, although the total observation impact has two peaks at 100–200 and 500–700 hPa (Fig. 6a), the observation impact per observation number is greatest in the upper troposphere (Fig. 6c). Compared to the results obtained for SOUND, the vertical distribution obtained for GEOAMV exhibits more vertical variations. The total observation impact for GEOAMV is greatest at 200–300 hPa (Fig. 6d) and is one order of magnitude greater than those of other levels. Although the total observation impact is small at the lower levels, the observation impact per observation number is greatest at 500–700 hPa and below 850 hPa because GEOAMV provides wind retrievals in the oceanic area where the observation network is sparse.

Figure 7 shows the observation impact per observation number for SOUND during targeted dropsonde observations for Typhoons Sinlaku (200813) and Jangmi (200815). Most soundings benefit the 6-h forecast error reduction. The impact of the dropsonde soundings near the typhoon is similar to or greater than that of the radiosonde soundings. However, the dropsonde observations near the typhoon core region degrade the 6-h forecast (Fig. 7c). This negative impact of dropsonde observations near the core regions has been reported in Aberson (2008) and Weissmann et al. (2011) and is mainly due to the lack of representation of the inner-core structure in model fields and the DA procedure.

3) OBSERVATION IMPACT FOR TARGETED REGIONS

This section presents the observation impacts for targeted regions. Figure 8a shows the analyzed track and the best track from the Regional Specialized Meteorological Center (RSMC) Tokyo for Typhoon Sinlaku (200813). In general, the REFER analysis simulates the major movement of the typhoon track well. However, it cannot simulate the track during the periods of initial

FIG. 5. Scatterplots of innovation and observation impact for (a) zonal and (b) meridional wind observations of GEOAMV; and channels (c) 7 and (d) 9 of AMSU-A from METOP-A satellite at 0000 UTC 11 Sep 2008.
development and rapid development. This may be due to 1) the coarse resolution in the current configuration of the numerical modeling system, 2) the use of static background error statistics for analysis of the typhoon, and/or 3) the limited in situ observations near the storms. While the observation impact on the 6-h forecast error reduction was calculated for the entire domain in the previous sections, it is calculated here for a limited area that is defined horizontally over most of the typhoon tracks and vertically from the surface to 300 hPa for the period from 8 to 21 September 2008 (Fig. 8a).

Figure 8b presents the time-averaged total observation impact. The satellite wind observations provide less information than the conventional wind observations, similar to the findings presented in Fig. 2a. Comparing Fig. 8b with Fig. 3a, the impact of radiance observation is reduced because the targeted region has less chance of collocating the passage of a polar-orbited satellite than does the entire region (Fig. 8c). Relative to the radiance observation, the impacts of SOUND and SYNOP are increased. By defining the forecast error in the targeted (limited) area near the typhoon, the observation impact related to the typhoon forecast can be emphasized. Compared to Fig. 7c, whereas the impacts of dropsonde and radiosonde observations near the coastline are emphasized in terms of the typhoon forecast, the impacts of radiosonde over the north of Japan are greatly reduced (Fig. 8d).

c. Sensitivity to the error covariance parameter

As in (2.4), the analysis state is determined by a mixture of the background state and innovation, weighted by the background error covariance and the observation error covariance that are also input to the DA system. Although the error covariance should be appropriately prescribed for an optimal solution, it is difficult to estimate the error covariance. Recently, Daescu and Todling (2010) proposed a way to calculate the sensitivity to the error covariance parameters based on Le Dimet et al. (1997) and Daescu (2008). In these studies of error covariance tuning, the parametric representation is considered as $B(s^\phi) = s^\phi B$ and $R_i(s^\phi) = s^\phi R_i$, where the
subscript \(i\) represents a certain subset of observations. The sensitivities to the error covariance parameter are then

\[
\frac{\partial e(x_u)}{\partial s^b} = [y - h(x_u)]^T \frac{\partial e(x_u)}{\partial y},
\]

(4.1a)

and

\[
\frac{\partial e(x_i)}{\partial s_i} = [h_i(x_u) - y_i]^T \frac{\partial e(x_u)}{\partial y_i},
\]

(4.1b)

which are determined by the product of the residual and the sensitivity to the observation. These sensitivities are evaluated in the DA configuration that corresponds to the nominal parameter value \(s = [s^b, s_1^b, s^r_1, s^r_2, \ldots, s^r_I] = 1\) (Daescu and Todling 2010).

Figure 9a shows the sensitivity to \(s^b\) for each cycle. A negative value denotes that increasing background error covariance helps to reduce forecast error. Figures 9b and 9c show the time-averaged sensitivity to \(s^r_i\) for the observation variable and observation type, respectively. These figures also demonstrate (in the current prescribed configuration) that the background error covariance is overconfident, that the observation error covariance is underconfident, and that reducing observation error covariance helps to reduce forecast error. However, the amount of increase (or decrease) in the error variance cannot be determined, and the sensitivity information provides directional guidance. Daescu and Langland (2013) attempted the combined use of the posterior estimation of error variance and sensitivity information and diagnosed an additional 3.5%–12% of observation impact from the tuning of the AMSU-A observation error variance. Further studies on the use of this information to optimize a DA system are necessary.

d. Observing system experiments

This section compares the impact of observations evaluated using typical OSEs with that evaluated using the adjoint-derived method. The REFER that assimilates all observation types (section 3d) is used as a control experiment. Each OSE is then conducted by performing new analysis–forecast cycles for a given period (i.e., from 15 August to 2 October 2008). In the new analysis procedure, the specific observation type to be evaluated is removed from the observation set in data-denial experiments (Arnold and Dey 1986). Through
a series of OSEs, the impact of five major observation types (i.e., AMSU-A, SOUND, SYNOP, GEOAMV, and QuikSCAT) is evaluated. The corresponding OSEs are referred to as EXP_AMSU-A, EXP_SOUND, EXP_SYNOP, EXP_GEOAMV, and EXP_QuikSCAT, respectively. The configurations of the analysis and forecast system are the same as those described in section 3.

Figure 10 shows the time-averaged forecast error norms for each OSE using (2.7) for 6- to 24-h forecast times. The forecast fields are verified with respect to reference analysis fields. For all forecast times, the forecast error is greatest for EXP_AMSU-A. The second greatest impact is shown for EXP_SOUND. This is consistent with the result obtained from the adjoint-derived observation impact.\(^4\) In addition, a comparable impact is shown for SYNOP and QuikSCAT in both the adjoint-derived experiment and the OSE. However, although the impact of GEOAMV is similar to that of SYNOP and QuikSCAT in the OSE, the impact of GEOAMV is smaller than that of SYNOP and QuikSCAT in the adjoint-derived experiment. Gelaro and Zhu (2009) and Cardinali (2009) also reported qualitative similarity between the adjoint method and the OSE for the major observation types, but dissimilarity for the minor observation types. During the evaluation of the observation impact on the forecast, the adjoint-derived method and OSEs have different characteristics. The adjoint-derived method can provide the observation impact for an individual observation component (and for each analysis cycle) using the adjoint of the data assimilation system in the context of all present observations. Conversely, the observation impact from OSEs is cumulative from the analysis and forecast cycles during some period. During such a period, the removal of a specific observing system changes the quality of the DA system in each OSE. This fundamental difference

\(^4\) Note that the sum of the observation impacts of four satellites for AMSU-A is greater than that of SOUND in Fig. 3b.
may affect the comparison of the observation impact of the two methods.

5. Summary and discussion

In NWP systems, an analysis is determined by a data assimilation (DA) system that combines observations and a background that usually consists of short-term forecast fields, together with their error statistics. Although the available number of observations has increased rapidly, it is not clear that these observations always benefit forecast performance. Thus, it is necessary to monitor and evaluate how the observations are used in DA and forecast systems. In this study, the impact of observation was evaluated using two methods: the adjoint-derived method and traditional OSEs. In the adjoint-derived method, the adjoint of the forecast system and the adjoint of the analysis system were used to simultaneously estimate the observation impact for all observations. The adjoint-derived method also requires fewer computational resources than OSEs and can monitor the observation impact in an operational framework.

In the adjoint-derived observation impact method, the radiance observation has the greatest total impact, partly due to its high number of observations. Normalized by observation number, the impact is greatest for conventional wind observations. The greater impact of conventional wind observations compared with mass observations is consistent with recent studies reported in WMO (2012). Surface pressure observations (the second largest normalized impact) have been reported.
to contain a greater amount of useful information about large-scale circulation than that provided by surface wind or temperature observations (Compo et al. 2006; Whitaker et al. 2009). When aggregated with each observation type, the total impact is greatest for SOUND and each satellite, followed by SYNOP, QuikSCAT, GEOAMV, and METAR. The normalized impacts for QuikSCAT and GEOAMV are smaller than for other observation types. The fraction of beneficial observations is approximately 66%–72%, which is significantly greater than that reported in previous observation impact studies [50%–54% in Gelaro et al. (2010) and slightly greater than 50% in Kunii et al. (2012)]. This difference may occur because the true state in this study was taken from an analysis conducted every 6 h during a cycling experiment; thus, the true state is partly correlated with the forecast integrated from the analysis at the initial time.

An additional experiment with 24-h forecast error reduction showed that the observation impact decreases to 60%–66%, a value that is also higher than that obtained in the previous studies. The fraction of non-beneficial observations (30%–40%) found here may be inevitable for the data assimilation and forecast system used in this study. Although the error statistics were perfectly specified, only 60%–65% of the observations have a beneficial impact on the analysis field in a simple idealized assimilation system when the background field and observations are of comparable accuracy (Ehrendorfer 2007). This indicates that further investigations regarding the statistical nature of the data assimilation procedure are needed.

For radiance observations, channel 9, which is sensitive to the upper troposphere, had a greater impact than channel 5, which is sensitive to the middle to lower troposphere. These results are inconsistent with the results of Gelaro et al. (2010), which state that the impacts of channels 5–7 are the greatest. This difference is mainly due to the different configurations of the modeling systems used in each study and the different definitions of the forecast error norm used.

For vertical distribution, whereas the total impact for GEOAMV was greatest in the layer between 200 and 300 hPa, the normalized impact was greatest in the middle to lower troposphere. For SOUND, both the total and normalized impacts were greatest in the upper troposphere. For several analysis times of Typhoons Sinlaku (200813) and Jangmi (200815), the observation impact of the dropsonde soundings near the typhoon is similar to or greater than that of the radiosonde soundings. When the adjoint-derived observation impact was evaluated for the targeted area near Typhoon Sinlaku, the impact of the radiance observations was reduced, whereas the impact of the surface pressure observations was increased.

Based on work by Daescu and Todling (2010), the sensitivity to the error covariance parameter was also evaluated. In the current framework of the analysis system, the background error covariance is overconfident, the observation error covariance is underconfident, and reducing observation error covariance helps to reduce forecast error.

The adjoint-derived observation impact was compared to the observation impact deduced from OSEs that were performed as data-denial experiments for the major observation types. Consistent with the adjoint-derived impact results, the greatest impact of AMSU-A and SOUND was found with OSEs. Overall, a qualitatively similar impact was demonstrated for the major observation types between the adjoint method and OSEs, and a dissimilar impact was shown for minor observation types; these findings are similar to those obtained in previous research using operational global models (Cardinali 2009; Gelaro and Zhu 2009). The disagreement in the observation impact for minor observation types may be due to the different characteristics of the methods used to evaluate the observation impact. The variation of forecast error reduction from the assimilated observations used in this study is somewhat greater than that in previous studies using a global modeling system, as shown in Gelaro et al. (2010). This difference may occur because the distribution of the observation systems (mainly polar-orbiting satellites) is largely variable for a given limited domain.

This study confirms that SOUND provides primary information on the atmospheric state as an in situ observation and that satellite radiance observations are an essential component among the atmospheric observation

![Figure 10](http://journals.ametsoc.org/mwr/article-pdf/141/11/4080/4297551/mwr-d-12-00197_1.pdf)
systems as a remote sensing measurement. This study also confirms that the adjoint-derived method can be used to evaluate the observation impact in a limited area analysis and forecast system that is focused on East Asia and the western North Pacific, whereas OSEs are not feasible in an operational sense. Furthermore, the adjoint-derived sensitivity can be used to evaluate the background and observation error covariance, which play important roles in NWP systems. The adjoint-derived method and OSEs can provide comprehensive information on the effects of the observation systems on the overall forecast ability of the NWP systems, especially when abundant satellite observations are available.

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