

Effect of observation error variance adjustment on numerical weather prediction using forecast sensitivity to error covariance parameters

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ABSTRACT

In this study, the forecast sensitivity to error covariance parameters was calculated using the forecast sensitivity to observations (FSO) and was employed to adjust the observation error variance in the Korea Meteorological Administration (KMA) Unified Model (UM) four-dimensional variational (4DVAR) system. The error covariance adjustment parameters were estimated by applying a multiple linear regression method to the forecast error reduction (FER) and forecast sensitivity to error covariance parameters in July and August 2012. The adjustment parameters were applied for numerical weather prediction (NWP) in August 2012 using the KMA UM 4DVAR system to validate the adjusted observation error variance in the operational NWP. The results indicated that most observation error variances should be decreased to reduce the forecast error. By decreasing the observation error variance of Advanced Television and Infrared Observational Satellite Operational Vertical Sounder (ATOVS) data by 72.14% for the NWP of August 2012, the residual within the assimilation window (O-A) decreased by 10.62% and that in the 24–29 h forecast range (O-F) decreased by 5.4%; therefore, the analysis and forecast results verified with radiosonde, surface, and satellite observations showed more similar values to all those observations. The upper atmospheric O-F was reduced by approximately 2–3.5% verified by Advanced Microwave Sounding Unit-A, and 21.7% verified by Infrared Atmospheric Sounding Interferometer (IASI) and Atmospheric Infrared Sounder (AIRS) sensors. Therefore, the adjustment of ATOVS observation error variance using the forecast sensitivity to error covariance parameters was effective for reducing the forecast error in the KMA UM 4DVAR system.

Keywords: forecast sensitivity to error covariance parameters, forecast sensitivity to observations, observation error variance, four-dimensional variational data assimilation, forecast error

1. Introduction

In recent decades, data assimilation (DA) has been developed for complex systems, such as the variational DA, to assimilate the surface and atmospheric observations. A cost function of the variational DA is composed of mainly four variables: the background, observations, background error covariance (**B**), and observation error covariance (**R**). The analysis provides an estimate of the atmospheric state with minimal discrepancy from the background and observations.

Nowadays, a variety of observations, including millions of satellite data, are assimilated with a numerical model in

the DA system. The contribution of each observation to forecasts (i.e. observation impact) can be quantitatively estimated within a very short computation time using the adjoint-based forecast sensitivity to observation (FSO) method (Baker and Daley, 2000). The observation impact using the FSO has been used semi-operationally to determine observation types, locations, and variables that are beneficial or detrimental to forecasts (Langland and Baker, 2004; Cardinali, 2009; Gelaro and Zhu, 2009; Gelaro et al., 2010; Joo et al., 2013; Jung et al., 2013; Kim et al., 2013; Kim and Kim, 2013; Kim and Kim, 2014; Lorenc and Marriott, 2014; Kim et al., 2017; Kim and Kim, 2017).

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The performance of numerical weather prediction (NWP) is also associated with error covariances in DA. The forecast sensitivity to the error covariance parameters indicates whether the error covariances should be inflated or deflated to obtain more precise forecasts (Daescu and Todling, 2010; Daescu and Langland, 2013; Jung et al., 2013; Kim et al., 2014). Daescu and Todling (2010) and Jung et al. (2013) demonstrated that inflated $\mathbf{B}$ and deflated $\mathbf{R}$ s are helpful to reduce forecast errors in the DA system they used, which implies that the $\mathbf{R}$ s are too large and need to be decreased to improve forecasts by the guidance obtained from the adjoint-based forecast sensitivity. Weston et al. (2014) and Bormann et al. (2016) showed that the satellite observation error variances are too large and need to be decreased by considering inter-channel error correlations to improve forecasts. In addition, recent studies (e.g. Bormann and Bauer, 2010; Bormann et al., 2010; Weston et al., 2014; Bormann et al., 2016; Waller et al., 2016a, 2016b; Cordoba et al., 2017) showed that the error covariances of the Advanced Microwave Sounding Unit-A (AMSU-A), the Infrared Atmospheric Sounding Interferometer (IASI), and the Atmospheric Infrared Sounder (AIRS) calculated based on diagnostic analyses are smaller than those error covariances currently used in most operational centres. Therefore, the $\mathbf{R}$ s used in most operational centres can be modified appropriately to obtain better forecasts. Lupu et al. (2015) suggested approximately 60% deflation of the observation error variances for 33 IASI channels using the diagnosed observation-error standard deviation (Desroziers et al., 2005) with the guidance obtained from the adjoint-based forecast sensitivity in the recent version of European Centre for Medium-Range Weather Forecasts (ECMWF) four-dimensional variational (4DVAR) system. However, Lupu et al. (2015) do not provide the information of the specific inflation and deflation of $\mathbf{R}$ s using the forecast sensitivity to observation error covariance parameters. Thus, the specific magnitude of inflation and deflation of the specific $\mathbf{R}$ s has never been suggested, using the forecast sensitivity to observation error covariance parameters.

As a way to improve the operational NWP, this study provides a method for adjusting the error covariances using the forecast sensitivity to error covariance parameters and investigates the effect of observation error variance adjustment on operational NWP. In the Korea Meteorological Administration (KMA), various satellite data and other observations are assimilated in DA to form the initial conditions (i.e. analysis) of an operational forecast. Kim et al. (2013) diagnosed the characteristics of the FSO for high-impact weather cases in summer and winter over

the Korean peninsula. Kim and Kim (2014) showed that the uncertainty (i.e. sampling error) associated with the observation impact statistics should consider lagged correlations between observation impact (i.e. total observation impact) data because the observation impact data at different times are correlated. The Unified Model (UM) 4DVAR system at the KMA (hereafter the KMA UM 4DVAR system) is used to investigate the effect of observation error variance adjustment on operational NWP. The adjusted observation error variance parameters were calculated based on a multiple linear regression method for NWP in July and August 2012. Then, the adjusted observation error variance was applied to the operational KMA UM 4DVAR system for NWP in August 2012 to verify the performance of the adjusted observation error variance for one-month period. Sections 2–4 provide the methodology, results, and conclusions, respectively.

2. Methodology

2.1. Forecast error reduction, observation impact, and FSO

In the KMA UM 4DVAR system, the 27-hour forecast error (e) with respect to the true state $\mathbf{x}_t$ which is measured by the total energy norm (Lorenc and Marriott, 2014) is expressed as

$$e = (\mathbf{x}^f - \mathbf{x}_t)^T \mathbf{C} (\mathbf{x}^f - \mathbf{x}_t) \\ = \frac{1}{M_{\text{domain}}} \int \int \int \frac{1}{2} \left[\rho u'^2 + \rho v'^2 + \frac{\rho g^2}{\theta^2 N^2} \theta'^2 + \frac{1}{\rho c^2} p'^2 + \varepsilon \frac{\rho L^2}{C_p} q'^2 \right] \\ r^2 \cos \phi d\lambda d\phi dr, \quad (1)$$

where $\mathbf{x}^f$ is the 27-h forecast; M_{domain} is the mass of the atmosphere in the model domain; N^2 is the square of the buoyancy frequency; r^2 is the square of the earth radius; g , θ , c , ρ , L , C_p , and ε are the gravity, potential temperature, speed of sound, air density, specific latent heat of condensation, specific heat capacity, and weighting factor on the moisture term, respectively; u' , v' , θ' , p' , and q' denote the forecast errors that correspond to the zonal wind, meridional wind, potential temperature, pressure, and specific humidity, respectively; ϕ , λ , and r denote the latitude, longitude, and earth radius, respectively; and $\mathbf{C}$ is a diagonal matrix that denotes the dry total energy norm with $\varepsilon = 0$. The non-zero diagonal components in $\mathbf{C}$ correspond to all grid points from the surface to 150 hPa. Because $\mathbf{x}_t$ is unknown, the analysis $\mathbf{x}_a$ of the KMA UM 4DVAR system was substituted for $\mathbf{x}_t$. The KMA UM 4DVAR has a 6-h assimilation window ($T-3$, $T+3$) starting from 03, 09, 15, and 21 UTC. The 3-h forecast from $T-3$ is used as the analysis at $T+0$. The adjoint

model to calculate the observation impact is integrated back to $T-3$, thus the 27-h forecast error is used instead of 24-h forecast error in this study.

The nonlinear forecast error reduction (FER; δe) is defined as the difference between the error of the forecast integrated from the analysis ($\mathbf{x}_a^f$) and the error of the forecast integrated from the background ($\mathbf{x}_b^f$) (Jung et al., 2013; Kim and Kim, 2014):

$$\begin{aligned} \delta e &= (\mathbf{x}_a^f - \mathbf{x}_t)^T \mathbf{C} (\mathbf{x}_a^f - \mathbf{x}_t) - (\mathbf{x}_b^f - \mathbf{x}_t)^T \mathbf{C} (\mathbf{x}_b^f - \mathbf{x}_t) \\ &= (\mathbf{x}_a^f - \mathbf{x}_b^f)^T \mathbf{C} [(\mathbf{x}_a^f - \mathbf{x}_t) + (\mathbf{x}_b^f - \mathbf{x}_t)]. \end{aligned} \quad (2)$$

The $\mathbf{x}_a$ is determined from the optimal linear analysis equation as

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}(\mathbf{y} - \mathbf{H}\mathbf{x}_b) = \mathbf{x}_b + \mathbf{K}\mathbf{d}, \quad (3)$$

where $\mathbf{x}_b$ is background, $\mathbf{K} = (\mathbf{B}^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{R}^{-1}$ denotes the Kalman gain where $\mathbf{H}$ is the linear observation operator, $\mathbf{y}$ is observation, and $\mathbf{d}$ represents the innovation vector. By applying the linearised model (the perturbation forecast (PF) model ($\mathbf{M}$) in the KMA UM 4DVAR system) to Equation (3) and using the relationships $\mathbf{x}_a^f \approx \mathbf{M}\mathbf{x}_a$ and $\mathbf{x}_b^f \approx \mathbf{M}\mathbf{x}_b$, δe is approximated in the observation space as

$$\delta e \approx \mathbf{d}^T \mathbf{K}^T \mathbf{M}^T \mathbf{C} [(\mathbf{x}_a^f - \mathbf{x}_t) + (\mathbf{x}_b^f - \mathbf{x}_t)], \quad (4)$$

where $\mathbf{M}^T$ is the adjoint of the PF (APF) model. The approximated FER (δe) in the observation space is called the observation impact.

Then FSO, the gradient of δe with respect to $\mathbf{y}$, is represented as

$$\frac{\delta e}{\delta \mathbf{y}} \approx \mathbf{K}^T \mathbf{M}^T \mathbf{C} [(\mathbf{x}_a^f - \mathbf{x}_t) + (\mathbf{x}_b^f - \mathbf{x}_t)]. \quad (5)$$

The observation impact corresponding to the i th observation type is expressed using FSO as

$$\delta e_i \approx \delta \mathbf{y}_i \left(\frac{\delta e}{\delta \mathbf{y}} \right)_i. \quad (6)$$

In the KMA UM, the APF model $\mathbf{M}^T$ is linearised along an average trajectory between two forecast trajectories initialised at the analysis and the background (Lorenc and Marriott, 2014), and the adjoint of the Kalman gain is designed as an iterative linear system which is an algorithm for estimating the minimum of a cost function, similar to the algorithm by Cardinali (2009). Lorenc and Marriott (2014) showed that the linear and nonlinear perturbation growths based on an average trajectory between two forecast trajectories initialised at the analysis and the background are closer compared to those based on either analysis or background forecast trajectory. Furthermore, Lorenc and Marriott (2014)

demonstrated that correlations between nonlinear FERs for various runs are higher for the FERs based on the average trajectory than that based on either analysis or background forecast trajectory. Lorenc and Marriott (2014) mentioned that these results are caused by the fact that the PF model of the 4DVAR system of the United Kingdom Met Office (UKMO) and the KMA does not use the Taylor expansion that assumes infinitesimal perturbation, but uses the linearised function of the analysis increment due to the batch of observations that allows finite perturbations.

2.2. Forecast sensitivity to error covariance parameters and error covariance impact

In a DA system, the analysis is obtained by combining background and observations considering the associated error covariances $\mathbf{B}$ and $\mathbf{R}$. $\mathbf{B}$ and $\mathbf{R}$ can be adjusted using parametric variables (i.e. proper weighting) in parametric space (Desroziers et al., 2009):

$$\mathbf{B}(s^b) = s^b \mathbf{B}, \quad (7a)$$

$$\mathbf{R}(s_i^o) = s_i^o \mathbf{R}_i, \quad i = 1, 2, \dots, P, \quad (7b)$$

where i , P , s^b , and s_i^o are the observation subset, the total number of observation subset, the background error covariance parameter, and the observation error covariance parameter, respectively; s^b and s_i^o should be positive for all i .

Daescu and Todling (2010) derived the forecast sensitivity to error covariance parameters in parametric space. The forecast sensitivity to error covariance parameters has been globally calculated in the Naval Research Laboratory (NRL) atmospheric variational DA system (Daescu and Langland, 2013) and regionally calculated in the Advanced Research version of the Weather Research and Forecasting (WRF)-ARW system (Jung et al., 2013; Kim et al., 2017).

Following Daescu and Todling (2010) and Daescu and Langland (2013), the forecast sensitivity to error covariance parameters is represented as:

$$\frac{\delta e}{\delta s^b} = \sum_{i=1}^P (\mathbf{y}_i - h_i(\mathbf{x}_a)) \frac{\delta e}{\delta \mathbf{y}_i}, \quad (8a)$$

$$\frac{\delta e}{\delta s_i^o} = (h_i(\mathbf{x}_a) - \mathbf{y}_i)^T \frac{\delta e}{\delta \mathbf{y}_i}, \quad i = 1, 2, \dots, P, \quad (8b)$$

where $\frac{\delta e}{\delta s^b}$ is the forecast sensitivity to background error covariance parameter (s^b -sensitivity), $\frac{\delta e}{\delta s_i^o}$ is the forecast sensitivity to observation error covariance parameter (s_i^o -sensitivity), and h is the nonlinear observation operator. The intrinsic property between s^b -sensitivity and s_i^o -sensitivity is $\sum_{i=1}^P \frac{\delta e}{\delta s_i^o} + \frac{\delta e}{\delta s^b} = 0$. The approximated FER in the parametric space (i.e. error covariance impact) is expressed as

$$\delta e \approx \delta e^b + \sum_{i=1}^P \delta e_i^o = \left\langle \left(\frac{\partial e}{\partial s^b}, \frac{\partial e}{\partial s_i^o} \right), (\delta s^b, \delta s_i^o) \right\rangle, \quad (9)$$

where δs^b and δs_i^o are the adjustment parameters of the **B** and **Rs**, respectively.

Different from Daescu and Todling (2010) and Daescu and Langland (2013) in which the δe and forecast sensitivity to error covariance parameters (i.e. Equation (8a) and (8b)) are calculated based on an analysis trajectory, those in this study are calculated based on an average trajectory between two forecast trajectories initialised at the analysis and the background, as in Equation (4). Although the forecast sensitivity to error covariance parameters is more directly associated with the analysis trajectory, the average trajectory between two forecast trajectories initialised at the analysis and the background is assumed to be a substitute for the analysis trajectory in this study. The average trajectory is used to reduce the computational cost and storage space for data backup in the operational KMA UM 4DVAR system. By using the FSO calculated routinely in the operational KMA UM 4DVAR system, additional adjoint integrations to evaluate the FSO based on the analysis trajectory are not necessary. Because the methodology suggested in this study aims at application to the operational KMA NWP system, the computational cost and storage space for adjoint integration are important issues. In addition, the difference between the analysis trajectory and the average trajectory may not be large for short-term forecasts in the UKMO and KMA UM 4DVAR system as shown in Lorenc and Marriott (2014).

2.3. Error covariance adjustment parameters

Using matrix representation, the error covariance impact in Equation (9) can be expressed as

$$\begin{pmatrix} \delta e_1 \\ \delta e_2 \\ \vdots \\ \delta e_m \end{pmatrix} = \begin{pmatrix} \frac{\partial e}{\partial s^{b(1)}} & \frac{\partial e}{\partial s_1^{o(1)}} & \cdots & \frac{\partial e}{\partial s_{n-1}^{o(1)}} \\ \frac{\partial e}{\partial s^{b(2)}} & \frac{\partial e}{\partial s_1^{o(2)}} & \cdots & \frac{\partial e}{\partial s_{n-1}^{o(2)}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e}{\partial s^{b(m)}} & \frac{\partial e}{\partial s_1^{o(m)}} & \cdots & \frac{\partial e}{\partial s_{n-1}^{o(m)}} \end{pmatrix} \begin{pmatrix} \delta s^b \\ \delta s_1^o \\ \vdots \\ \delta s_{n-1}^o \end{pmatrix}, \quad (10)$$

where m denotes the number of realisations of Equation (9) from specific analyses and n denotes the total number of error covariance adjustment parameters (i.e. δs^b and δs_i^o). Note that n is the sum of 1 and the total number of observation subset P in Equation (8b).

If the first matrix on the right-hand side of Equation (10) has a full rank or is over-determined, then the error covariance adjustment parameters (i.e. the vector on the right-hand side of Equation (10)) can be calculated using

multiple linear regression. The estimated error covariance adjustment parameters are used to calculate the error covariance parameters as:

$$s^b = 1 + \delta s^b, \quad (11a)$$

$$s_i^o = 1 + \delta s_i^o, \quad i = 1, 2, \dots, P, \quad (11b)$$

Then, Equation (11a) and (11b), along with Equation (7a) and (7b), are used to obtain **B** and **R**.

However, δs^b and δs_i^o cannot be uniquely determined by Equation (10) because the first matrix on the right-hand side of Equation (10) is rank deficit by the relationship $\sum_{i=1}^P \frac{\delta e}{\delta s_i^o} + \frac{\delta e}{\delta s^b} = 0$. To calculate δs_i^o in Equation (10), an appropriate value needs to be assigned to δs^b , which converts the first matrix on the right-hand side of Equation (10) to full rank. After assigning the pre-determined δs^b , Equation (10) becomes

$$\begin{pmatrix} \delta e_1 - \frac{\partial e}{\partial s^{b(1)}} \delta s^b \\ \delta e_2 - \frac{\partial e}{\partial s^{b(2)}} \delta s^b \\ \vdots \\ \delta e_m - \frac{\partial e}{\partial s^{b(m)}} \delta s^b \end{pmatrix} = \begin{pmatrix} \frac{\partial e}{\partial s_1^{o(1)}} & \cdots & \frac{\partial e}{\partial s_{n-1}^{o(1)}} \\ \frac{\partial e}{\partial s_1^{o(2)}} & \cdots & \frac{\partial e}{\partial s_{n-1}^{o(2)}} \\ \vdots & \ddots & \vdots \\ \frac{\partial e}{\partial s_1^{o(m)}} & \cdots & \frac{\partial e}{\partial s_{n-1}^{o(m)}} \end{pmatrix} \begin{pmatrix} \delta s_1^o \\ \vdots \\ \delta s_{n-1}^o \end{pmatrix}. \quad (12)$$

Because the first matrix on the right-hand side of Equation (12) has full rank, the observation error covariance adjustment parameters δs_i^o (i.e. the vector on the right-hand side of Equation (12)) can be calculated using multiple linear regression.

2.4. Experimental framework

The KMA UM version 7.7 with 4DVAR DA system version 27.2 (Courtier et al., 1994; Clayton, 2004) was used for this study. The model domain covers 769×1024 horizontal grid points with a resolution of approximately 25 km; 70 vertical eta-height hybrid layers exist from the surface to 80 km. The eta-height hybrid layers follow terrain near the surface but evolve to constant height surfaces as the layers go up. To make the minimisation more affordable, the KMA UM 4DVAR system uses a simplification operator, which truncates the forecast trajectory to a reduced resolution and dynamically balances the truncated trajectories (Lorenc and Payne, 2007). The model domain of the 4DVAR DA system covers 217×288 horizontal grid points with a resolution of approximately 80 km.

The physical parameterisations used in the KMA UM include Edwards–Slingo radiation (Edwards and Slingo, 1996), mixed-phase precipitation (Wilson and Ballard, 1999), the UKMO surface exchange scheme (Essery

Table 1. Abbreviations for various observation types.

Abbreviation		Description
ATOVS	AMSU-A	Advanced microwave sounding unit-A (Tb)
	AMSU-B	Advanced microwave sounding unit-B (Tb)
Geo_AMV	HIRS	High-resolution infrared radiation sounder (Tb)
	GOES	Geostationary operational environmental satellite (u, v)
	MFG	Meteosat first generation (Meteosat-7) by European organisation for the exploitation of meteorological satellites (u, v)
	MSG	Meteosat second generation (Meteosat-9) by European organisation for the exploitation of meteorological satellites (u, v)
	MTSAT	Multi-functional transport satellite (u, v)
	KMA COMS	Communication, ocean and meteorological satellite by Korea meteorological administration (u, v)
IASI		Infrared atmospheric sounding interferometer (Tb)
AIRS		Atmospheric infrared sounder (Tb)
SSMIS		Special sensor microwave imager/sounder (Tb)
ASCAT		Advanced scatterometer (u, v)
GPSRO		Global positioning system radio occultation (bending angle)
SONDE	TEMP	Upper-air observations from a radiosonde (u, v, t, p, q)
	PILOT	Upper-air wind profile from a Pilot Balloon or Radiosonde (u, v)
	PRFL	Wind profiler (u, v)
AIRCRAFT		Upper-air wind and temperature from aircraft (u, v, t)
SURFACE	SYNOP	Land surface synoptic weather observations (u, v, t, p, q)
	METAR	Surface weather observations and reports (u, v, t, p, q)
	SHIP	Sea surface weather observation by ship (u, v, t, p, q)
	BUOY	Sea surface weather observation by buoy (u, v, t, p, q)
	TCBOGUS	Tropical cyclone bogus observations generated by national meteorological centres (u, v, p)

et al., 2001), the non-local boundary layer (Lock et al., 2000), the new gravity wave drag scheme (Webster et al., 2003), and the mass flux convection scheme (Kershaw and Gregory, 1997; Gregory et al., 1997). The same physical parameterisations are employed in the PF and APF models of the DA system, with the exception that a fixed boundary layer scheme is used instead of the non-local boundary layer scheme and that the simplified moisture physics is used instead of the mixed-phase precipitation and mass flux convection schemes. That is, the DA system uses simple physics parameterisations instead of complex physics parameterisations in the KMA UM to achieve numerical stability. The FSO tool is version 27.2 developed by the UKMO (Lorenc and Marriott, 2014). The assimilated observations include all operational observations from the KMA (Table 1).

The error covariance parameters were estimated for July and August 2012. Then, the adjusted observation error variance using the error covariance parameters was applied to the operational KMA UM 4DVAR system for August 2012 to verify the suitability of the adjusted observation error variance for operational forecasts. The analyses and forecasts using the current operational observation error variances and the analyses and

forecasts with the adjusted observation error variances were compared to verify the effect of the newly adjusted observation error variances. The experiment using the operational (adjusted) observation error variances is called the CTL (ADJ_COV) experiment. For both ADJ_COV and CTL experiments, the operational **B** matrix of the KMA UM 4DVAR system was used and not inflated.

As in most operational DA system, the **B** and **R** of the KMA UM 4DVAR system are error variances with only block diagonal and diagonal elements, respectively. Therefore, the background and observation error covariances are the background and observation error variances in this study.

3. Results

3.1. Characteristics of forecast sensitivity to error covariance parameters

Figure 1 shows the time-averaged forecast sensitivity to error covariance parameters and standard deviation in August 2012. The error bar in Fig. 1 was calculated based on the first-order auto regression, as discussed in Kim and Kim (2014). On the vertical axis, the **B** matrix indicates s^b -sensitivity and others correspond to s_i^o -sensitivity for each

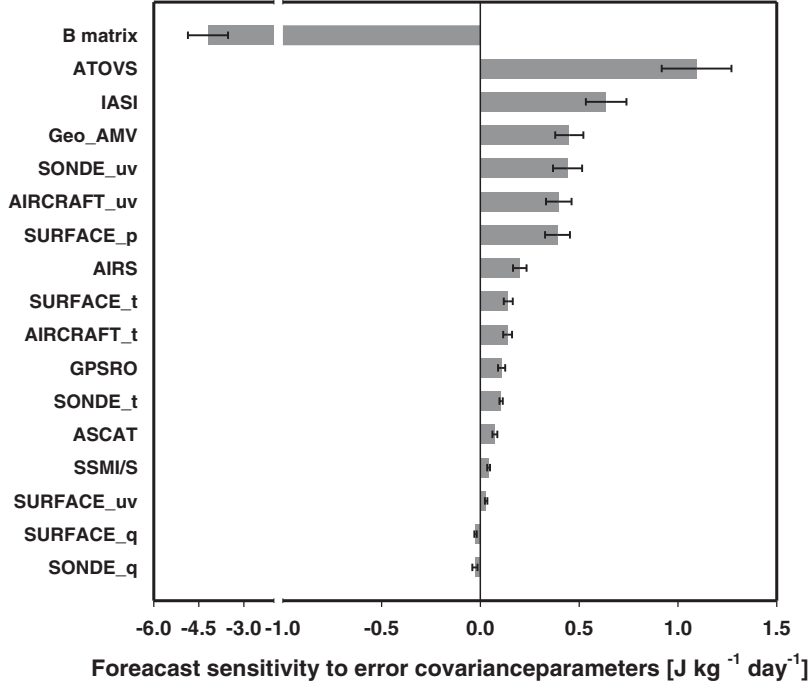


Fig. 1. The average forecast sensitivity to the background error covariance parameter (grey bar, $\text{J kg}^{-1} \text{d}^{-1}$), the average forecast sensitivity to the observation covariance parameters (grey bar, $\text{J kg}^{-1} \text{d}^{-1}$), and the associated 99% confidence interval (black line) in August 2012.

type of observation. The s^b -sensitivity is a linear combination of all FSOs (Equation (8a)) and can be projected onto the observation space (Daescu and Todling, 2010; Daescu and Langland, 2013; Jung et al., 2013). The s^b -sensitivity is negative, which implies that δs^b should be positive and **B** be inflated to have negative δe (i.e. reduction of the forecast error), as indicated in Equation (9). All average s_i^o -sensitivity values are positive except for the sensitivity associated with SONDE_q and SURFACE_q, which implies that all **Rs** except for SONDE_q and SURFACE_q need to be deflated to reduce the forecast error. The s_i^o -sensitivity of ATOVS is largest, followed by that of IASI, Geo_AMV, SONDE winds (SONDE_uv), and aircraft winds (AIRCRAFT_uv). A large s_i^o -sensitivity indicates that the variation in δe may be large when the associated error covariance is adjusted. The s_i^o -sensitivities associated with SONDE and surface-specific humidity (i.e. SONDE_q and SURFACE_q) are relatively small, which may be attributable to the dry energy norm used to calculate δe .

3.2. Determining error covariance adjustment parameters

The δs^b needs to be determined to solve δs_i^o in Equation (12). As shown in Fig. 1, the negative s^b -sensitivity implies that **B** should be inflated to reduce the forecast error, similar to the results of Daescu and Todling (2010)

and Jung et al. (2013). To inflate **B**, δs^b should be positive from Equation (7a) and (11a). The magnitude of inflation may depend on the DA system. Then the question is how much inflation is appropriate in the KMA UM 4DVAR system. The **B** of the hybrid ensemble/4DVAR DA system of the KMA is a linear combination of the statistical error covariance and the ensemble-based error covariance. Clayton et al. (2013) showed that a combination of 100% weighted statistical **B** and 30% weighted ensemble-based **B** resulted in the better analysis in a hybrid ensemble/4DVAR DA system at the UKMO which is a similar system with that in the KMA. Although theoretically, the sum of statistical and ensemble-based **B** needs to be 100%, operational performance of the UM was improved by adding 30% weighted ensemble-based **B** to the 100% weighted statistical **B**. Therefore, the 30% inflation of the statistical **B** may be appropriate in the KMA UM 4DVAR system to lead better forecasts. The validity of specifying δs^b as 0.3 is discussed in detail at the end of this subsection.

Once δs^b was pre-determined as 0.3, δs_i^o in Equation (12) were calculated using multiple linear regression of Chatterjee and Hadi (1986). The s^b -sensitivity, s_i^o -sensitivity, and error covariance impact δe are in the parametric space and should be known to calculate δs_i^o . Because the error covariance impact cannot be diagnosed without δs^b and δs_i^o , the observation impact in Equation (4) was

Table 2. The error covariance adjustment parameters corresponding to the background error covariance (**B**) and the observation error variances of ATOVS, AIRS, IASI, Geo_AMV, ASCAT, SSMI/S, GPSRO, aircraft temperature (AIRCRAFT_t), aircraft wind (AIRCRAFT_uv), SONDE temperature (SONDE_t), SONDE wind (SONDE_uv), SONDE specific humidity (SONDE_q), surface temperature (SURFACE_t), surface wind (SURFACE_uv), surface pressure (SURFACE_p), and surface specific humidity (SURFACE_q) for July and August 2012. Rejection occurs when the specific forecast sensitivity to the error covariance data is greater than three times of standard deviation from the time-averaged values.

B	ATOVS	AIRS	IASI	Geo_AMV
0.3000	−0.7214	−0.6886	−0.7491	−0.8101
ASCAT	SSMI/S	GPSRO	AIRCRAFT_t	AIRCRAFT_uv
−0.5100	−0.1541	−0.5031	−0.3452	−0.7304
SONDE_t	SONDE_uv	SONDE_q	SURFACE_t	SURFACE_uv
−0.7250	−0.7453	0.1893	−0.6731	−0.3971
SURFACE_p	SURFACE_q		Rejection rate	
−0.5610	0.1343		17/244 (6.9%)	

used as a substitute for the error covariance impact. The similarity between the observation impact and error covariance impact is discussed in detail in the following Section 3.4. The s^b -sensitivity (Equation (8a)), s_i^o -sensitivity (Equation (8b)), and observation impact (Equation (4)) for July and August 2012 were used to solve Equation (12) in a preconditioned conjugate gradient algorithm of the multiple linear regression method. The s^b -sensitivity and s_i^o -sensitivity greater than three times of standard deviation from the time-averaged values were considered outliers and not included in solving Equation (12). By solving Equation (12) by the aforementioned method, δs_i^o that correspond to δs^b are obtained.

Table 2 shows δs_i^o obtained by solving Equation (12) based on data for July and August 2012. Because δs_i^o are independent variables of the multiple linear regression equation, as shown in Wilks (2006), they can be used to adjust the error covariance of August 2012. Because the s_i^o -sensitivity of ATOVS was largest (Fig. 1), the reduction of the **R** of ATOVS used in the KMA UM 4DVAR system by 72.14% (Table 2) may have large reduction of forecast error. The **R** of ATOVS for July and August, which was diagnosed by one analysis-forecast iteration using the method suggested by Desroziers et al. (2005), indicates that the current **R** of ATOVS should be deflated by 62.2%, which supports that the 72.14% reduction in the ATOVS **R** may be appropriate. ATOVS observations include AMSU-A, AMSU-B, and HIRS (Table 1); the **R**s of AMSU-A, AMSU-B, and HIRS used in the KMA UM 4DVAR system are shown in Table 3. In addition, Lupu et al. (2015) suggested the average 60% deflation of the **R** for 33 IASI channels assimilated in the ECMWF 4DVAR system. The **R**s of AMSU-A and IASI used in the KMA UM 4DVAR system are similar to those in the UKMO 4DVAR system, but are 25–50% greater than those of the ECMWF 4DVAR system. Considering the overinflation of the **R**s of AMSU-A and IASI in the KMA UM 4DVAR system, the 72.14% reduction seems

appropriate for the ATOVS **R**. The overinflation of observation error variances in most operational centres is associated with the compensation for the incorrect assumption of uncorrelated observation errors.

To check the validity of 30% inflation of the statistical **B**, dependence of δs_i^o on the choice of δs^b was investigated. The δs^b was varied to 0.1, 0.3, 0.5, and the corresponding δs_i^o was calculated. The δs_i^o of ATOVS corresponding to 0.1, 0.3, 0.5 δs^b are −0.8714, −0.7214, and −0.4714, respectively. As δs^b increases, the absolute value of δs_i^o for most observation types decrease approaching 0, which results in additional reduction in forecast error (not shown). Figure 2 shows the δs_i^o of each observation type corresponding to 0.1, 0.3, 0.5, 0.7, and 0.9 δs^b . When δs^b is 0.1, δs_i^o of Geo_AMV, AIRCRAFT_uv, SONDE_q, SURFACE_t are less than −1. When δs^b is 0.9, δs_i^o of SSMIS is above 1. When δs^b is 0.3, 0.5, 0.7, δs_i^o of all observation types show physically meaningful values between −1 and 1. Because the s_i^o -sensitivity of SURFACE_q and SONDE_q are negative (Fig. 1), the δs_i^o of SURFACE_q and SONDE_q need to be positive. Only 0.3 δs^b provides positive δs_i^o for SURFACE_q and SONDE_q, which is consistent with the sensitivities shown in Fig. 1. Therefore, 0.3 δs^b is the most appropriate choice among the several values tested.

3.3. Time series of FER

Figure 3a shows the time series of the nonlinear FER, the approximated FER in the observation space (i.e. observation impact), and the approximated FER in the parametric space (i.e. error covariance impact) for July and August 2012. The time series shows generally negative values because the forecast error integrated from the analysis is smaller than the forecast error integrated from the background due to the DA effect (Langland and Baker, 2004; Gelaro et al., 2007; Jung et al., 2013; Lorenc and Marriott, 2014). Because the approximated FERs

Table 3. The observation error variances (K) of AMSU-A, AMUS-B, and HIRS, used operationally in the KMA UM 4DVAR system and those deflated. Channels 1, 2, 3, and 15 of AMSU-A, channels 1 and 2 of AMSU-B, and channels 1, 2, 3, 8, 9, 10, 13, 14, 16, 17, 18, 19, and 20 of HIRS are not used for the DA.

Channel number	Sensor					
	AMSU-A	AMSU-B	HIRS	Deflated AMSU-A	Deflated AMSU-B	Deflated HIRS
1	4.0	8.0	2.0	1.11	2.22	0.55
2	4.0	5.0	0.8	1.11	1.39	0.22
3	2.0	4.0	0.8	0.55	1.11	0.22
4	1.265	4.0	0.5	0.35	1.11	0.13
5	0.25	4.0	0.5	0.07	1.11	0.13
6	0.25	—	0.8	0.07	—	0.22
7	0.25	—	1.2	0.07	—	0.33
8	0.25	—	6.0	0.07	—	1.67
9	0.4	—	6.0	0.11	—	1.67
10	0.4	—	6.0	0.11	—	1.67
11	0.5	—	5.0	0.13	—	1.39
12	0.95	—	5.0	0.26	—	1.39
13	1.225	—	1.2	0.34	—	0.33
14	4.0	—	1.2	1.11	—	0.33
15	3.0	—	0.5	0.83	—	0.13
16	—	—	0.5	—	—	0.13
17	—	—	0.5	—	—	0.13
18	—	—	0.5	—	—	0.13
19	—	—	0.5	—	—	0.13
20	—	—	0.5	—	—	0.13

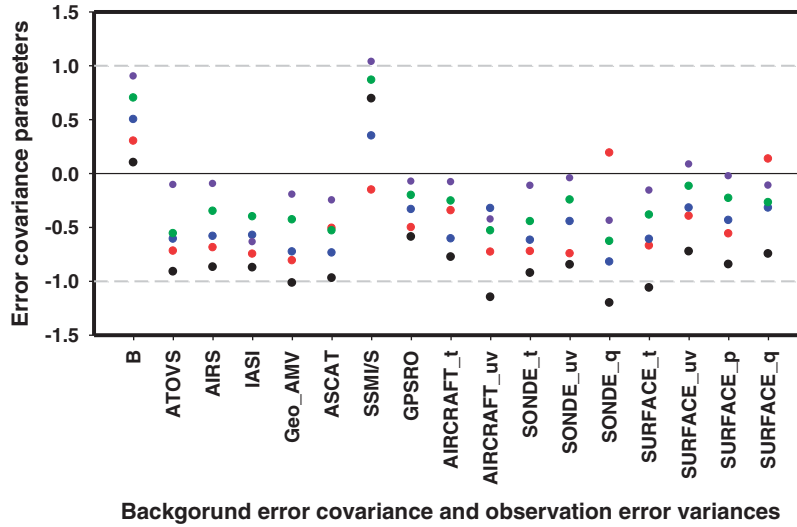


Fig. 2. The δs_i^o for various observation types and variables for July and August 2012, corresponding to 10% (black circle), 30% (red circle), 50% (blue circle), 70% (green circle), and 90% (purple circle) inflation of δs_i^o .

that correspond to 06, 12, 18 UTC 6, 00 UTC 7, 12 UTC 21, 12 UTC 22, 06 UTC 30 July 2012, 06, 12, 18 UTC 6, 00 UTC 7, and 12 UTC 17 August 2012 were zero or positive due to numerical instability, the approximated FERs for those times were not used for determining δs_i^o . The numerical instability is originated from problems in

the computational stability of the adjoint model's time-integration scheme and temporal resolution of the adjoint model, which may be associated with the static instability of the linearisation trajectory, small grid length near the poles, and steep orography as mentioned in Joo et al. (2012).

The error covariance impact in July and August 2012 was estimated using the δs_i^b and δs_i^o in Table 2. The correlation coefficient between the error covariance impact and the observation impact of July and August 2012 is 0.98 (Fig. 3a), which is quite reasonable because the observation impact is used as a substitute for the error covariance impact to calculate the δs_i^o . Once the 16 δs_i^o of July and August 2012 listed in Table 2 were calculated, the δs_i^o were applied to calculate the error covariance impact of August 2012 by the inner product with s^b -sensitivity and s_i^o -sensitivity of August 2012, and $0.3 \delta s^b$. The resulting error covariance impact is similar to the observation impact of August 2012 (Fig. 3b). Therefore, the number of predictors used in the multiple linear regression is appropriate for statistically estimating the error covariance impact of August 2012, as indicated by Wilks (2006). In an additional experiment, the error covariance impact calculated by the error covariance adjustment parameters in July 2012 and the forecast sensitivity to error covariance parameters in August 2012 were similar to the observation impact in August 2012, which implies that the number of predictors was appropriate for statistically forecasting the error covariance impact in August 2012 (not shown) although some of the error covariance adjustment parameters in July 2012 are not physically meaningful due to small number of data during one month period for the multiple linear regression.

3.4. Cycling experiment and verification

To verify the impact of the adjusted observation error variance using δs_i^o , the adjusted observation error variance was applied to the operational KMA UM 4DVAR system for NWP in August 2012. Because the s_i^o -sensitivity of ATOVS is largest (Fig. 1), the ATOVS $\mathbf{R}$ was adjusted by applying the δs_i^o in Table 2 to Equation (11b). Then, 24-h forecasts were generated from the updated analyses ($\mathbf{x}(\hat{\sigma})_a$) using the deflated ATOVS $\mathbf{R}$ in the cycling DA system for August 2012 (ADJ_COV). These forecasts were compared with the operational (i.e. control) forecasts generated from the analyses ($\mathbf{x}(\sigma)_a$) using the operational ATOVS $\mathbf{R}$ in the cycling DA system (CTL) for the same period. For both ADJ_COV and CTL experiments, the operational $\mathbf{B}$ matrix of the KMA UM 4DVAR system was used and not inflated. Thus, the difference between ADJ_COV and CTL is caused by the reduced $\mathbf{R}$ of ATOVS. The green shading in Fig. 3b represents the additional error covariance impact by applying the δs_i^o of ATOVS in ADJ_COV compared to CTL, which suggests that additional approximated FER is expected when using a new analysis generated by the adjusted $\mathbf{R}$ of ATOVS for forecasts. The approximated

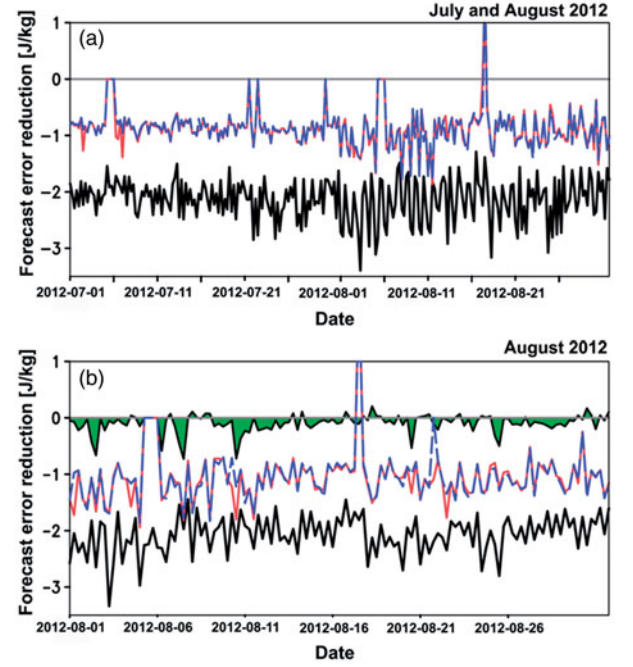


Fig. 3. Time series of the nonlinear FER (black solid line, J kg^{-1}), the approximated FER in the observation space (observation impact; red solid line, J kg^{-1}), the approximated FER in the parametric space (error covariance impact; blue dashed line, J kg^{-1}) in (a) July and August 2012 and (b) the nonlinear FER (black solid line, J kg^{-1}), the observation impact (red solid line, J kg^{-1}) in August 2012, the error covariance impact (blue dashed line, J kg^{-1}) by the s^b -sensitivity and s_i^o -sensitivity of August 2012 and the error covariance adjustment parameters in Table 2. The green shading with black solid line (J kg^{-1}) in (b) denotes the difference between error covariance impact of ADJ_COV and error covariance impact of CTL in August 2012.

FERs corresponding to 06, 12, 18 UTC 5, 00 UTC 6, 12 UTC 17, and 12 UTC 21 August 2012 were zero or positive due to numerical instability (Fig. 3b).

The updated analysis began at 03 UTC 24 July 2012 for spin-up. The residual within the assimilation window (i.e. O-A; the difference between observations and analysis trajectory within the assimilation window) of CTL and ADJ_COV were compared for the corresponding time range (i.e. 0–5 h from T–3 that is 03 UTC in the KMA UM) (Fig. 4). Similarly, the residual in the 24–29 h forecast range (i.e. O-F: the difference between observations and forecast trajectory) of CTL and ADJ_COV were compared (Fig. 4). The O-A (O-F) was verified within a 5-h period because the observation window of the KMA UM 4DVAR is from the T–3 (forecast time) to 5 h after the T–3 (forecast time). The observations used for the verification were quality-controlled over the globe and assimilated in the KMA UM 4DVAR system.

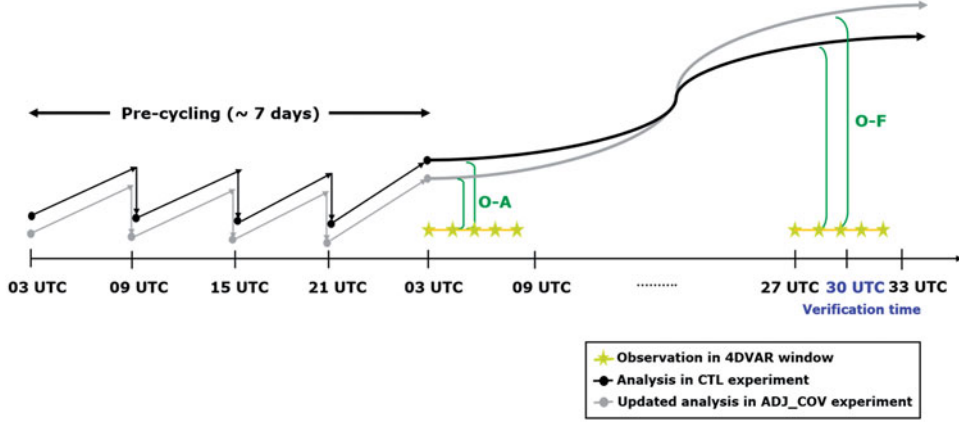


Fig. 4. Schematic of the control experiment (CTL: black line) and the experiment with the adjusted observation error variance (ADJ_COV: grey line).

The ratio between the time-integrated O-A of ADJ_COV and that of CTL in August 2012 was calculated as

$$\text{Ratio}_{O-A} = \frac{\sum_{i=1}^{124} \|y_i - h(x_i(\hat{\sigma})_a)\|_2}{\sum_{i=1}^{124} \|y_i - h(x_i(\sigma)_a)\|_2}, \quad (13)$$

where $\|\cdot\|_2$ denotes the l_2 -norm and 124 (including 6 analysis times that showed the numerical instability in the approximated FER calculation) denotes the number of analysis times of August 2012. A ratio smaller (greater) than 1 implies that the O-A of ADJ_COV is smaller (greater) than that of CTL. That is, a ratio smaller (greater) than 1 implies that the analysis or short-term forecasts (i.e. 0–5 h) from the analysis of ADJ_COV is more (less) similar to the observations compared with the analysis of CTL. Figure 5 shows the ratio in Equation (13) for August 2012, stratified by each observation type and variable. Compared with the CTL analysis, the ADJ_COV analysis was closer to the observations for all data types and variables, but especially ATOVS (AMSU-A, AMSU-B, and HIRS) observations. The time-integrated O-A of ADJ_COV was reduced by 10.62% (3.83% when excluded ATOVS) compared with that of CTL.

The ratio between the time-integrated O-F of ADJ_COV and that of CTL in August 2012 is calculated as

$$\text{Ratio}_{O-F} = \frac{\sum_{j=1}^{124} \|y_j - h(x_j(\hat{\sigma})^{fa})\|_2}{\sum_{j=1}^{124} \|y_j - h(x_j(\sigma)^{fa})\|_2}, \quad (14)$$

where $x(\cdot)^{fa}$ denotes the 24–29 h forecast integrated from the analysis in August 2012. To minimise the interpolation error in the observation operator developed on the grid-based KMA UM, the forecast wind was decomposed into latitudinal and longitudinal wind. Figure 6 shows the

ratio between the time-integrated O-F of ADJ_COV and that of CTL in August 2012, stratified by each observation type and variable. For other observation types and variables, with the exception of PRFL_v, MTSAT_v, MSG_v, and GPSRO, the O-F was reduced in ADJ_COV compared to CTL. By adjusting the $\mathbf{R}$ of ATOVS, the O-F of ADJ_COV is reduced compared with the satellite observations, SONDE observations (TEMP, PRFL, and PILOT), and surface observations (SYNOP, METAR, BUOY, and TCBOGUS). The reduction of the O-F of ADJ_COV is the greatest for TCBOGUS, which implies that the forecast of ADJ_COV is much closer to the synthetic observations near the centres of tropical cyclones than that of CTL. Figure 7 is a time series of the average ratio between the O-F of ADJ_COV and that of CTL for all observation types during August 2012. With the exception of 20 analysis times, the O-F for all other analysis times (84%) was reduced for ADJ_COV. The time-integrated O-F was reduced by 5.4% for ADJ_COV compared with CTL.

Vertical profiles of the root mean square (RMS) of the average O-F of ADJ_COV and CTL verified by SONDE observations are shown in Fig. 8. The O-F of ADJ_COV verified by SONDE observational variables (i.e. zonal wind, meridional wind, temperature, and specific humidity) were smaller than that of CTL. The differences between the O-F of ADJ_COV and CTL increased from the surface towards the mid-troposphere but decreased near the upper troposphere. The small differences in the O-F of ADJ_COV and CTL in the upper troposphere may reflect the small number of reliable SONDE observations in the upper troposphere. Therefore, the O-F of ADJ_COV and CTL should be verified with another reliable observation type in the upper troposphere.

Figure 9 shows the RMS of the average O-F of ADJ_COV and CTL compared with AMSU-A

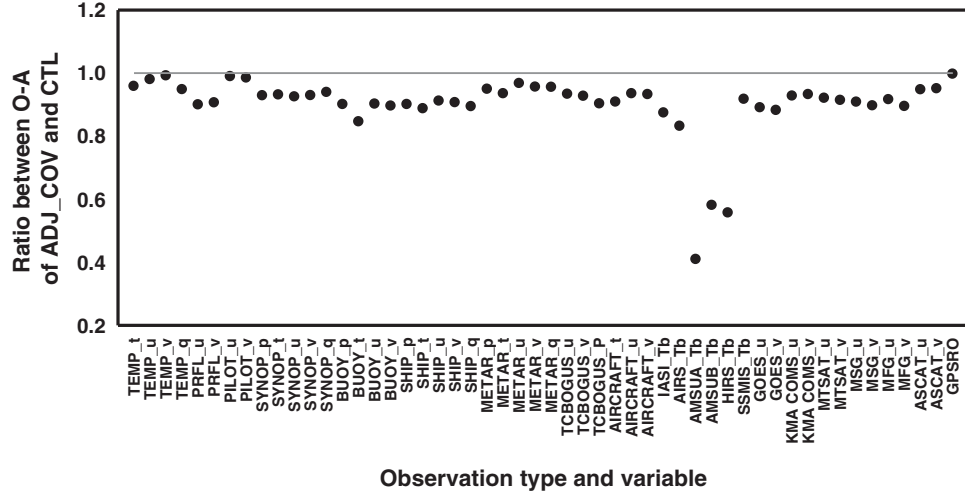


Fig. 5. The ratio between the time-integrated O-A of ADJ_COV and CTL in the observation space for August 2012, stratified by each observation type and variable.

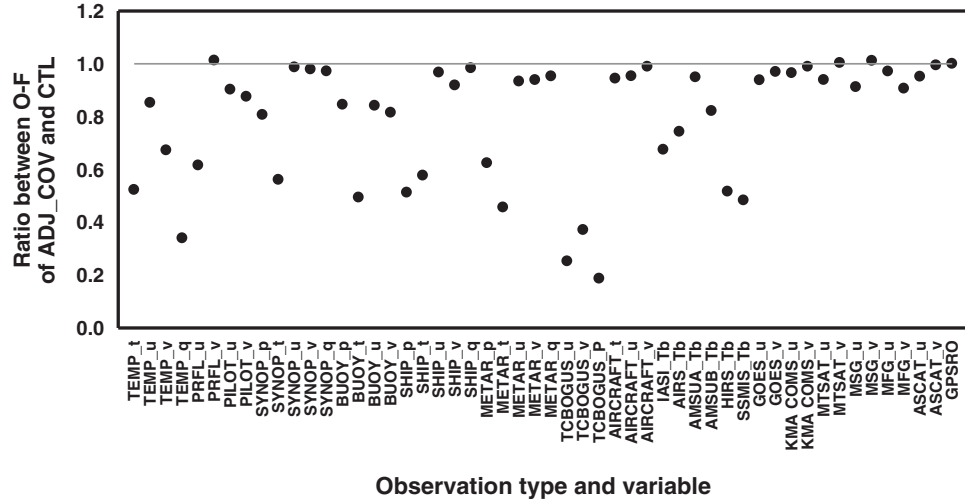


Fig. 6. The ratio between the time-integrated O-F of ADJ_COV and CTL in the observation space for August 2012, stratified by each observation type and variable.

observations for the Meteorological Operational Satellite-A (Metop-A) and the National Oceanic and Atmospheric Administration (NOAA) 19 satellite. The reduction rate for ADJ_COV is calculated as

$$\text{Reduction rate}_{O-F} = \frac{\sum_{j=1}^{124} \|y_j - h(\mathbf{x}_j(\hat{\sigma})^{fa})\|_2 - \sum_{j=1}^{124} \|y_j - h(\mathbf{x}_j(\sigma)^{fa})\|_2}{\sum_{j=1}^{124} \|y_j - h(\mathbf{x}_j(\sigma)^{fa})\|_2} \quad (15)$$

The channel numbers 3, 7 (8), 15 for Metop-A (NOAA 19) were excluded in Fig. 9 because they are not used in the KMA UM. The O-F of ADJ_COV was

smaller than that of CTL for most channels, with the exception of channel 13 of Metop-A AMSU-A. An average of 2.34% (3.53%) of the O-F verified by Metop-A (NOAA 19) AMSU-A was reduced for ADJ_COV compared with CTL (Fig. 9). The O-F for channels 11–14 (with the exception of channel 13 of Metop-A AMSU-A), which are sensitive in the upper troposphere, decreased for both satellites. In addition, the O-F of ADJ_COV verified by the hyperspectral sensor of IASI was reduced compared with that of CTL, showing 21.7% reduction rate for ADJ_COV (Fig. 10). Ozone and window channels of IASI were not used. In addition, the O-F for ADJ_COV in the upper troposphere

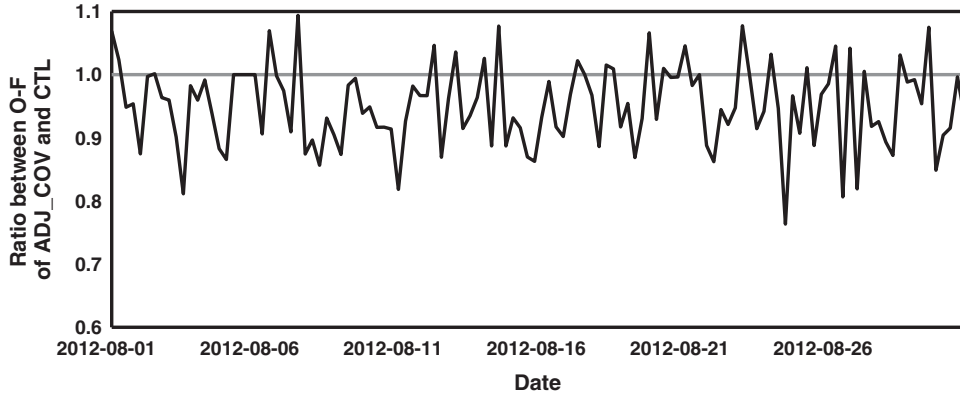


Fig. 7. Time series of the ratio between the average O-Fs of ADJ_COV and CTL in the observation space for August 2012. The O-Fs of ADJ_COV and CTL are averaged for all observation types.

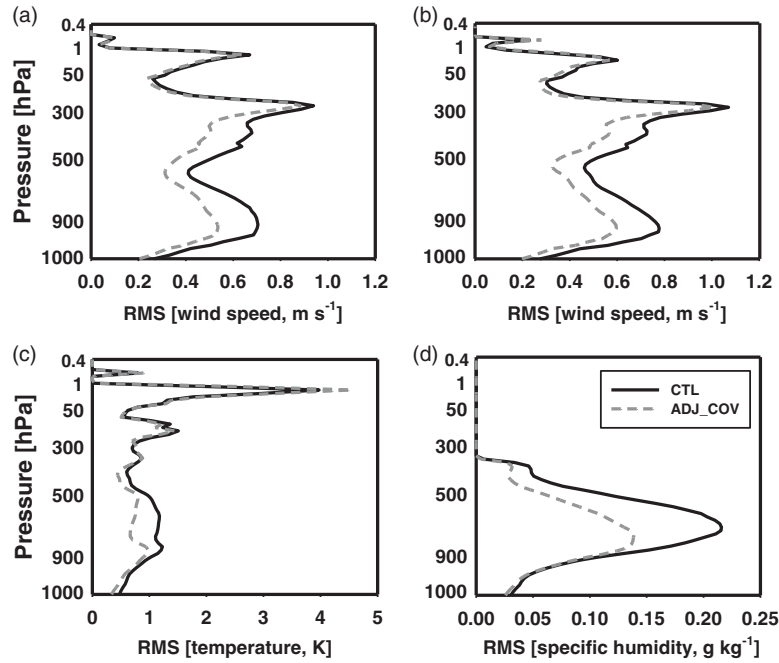


Fig. 8. Vertical profile of the root mean square (RMS) of the average O-F of ADJ_COV (grey dashed) and CTL (black solid) in the observation space. The RMS error is calculated based on global SONDE (TEMP, PILOT, and PRFL) observations in August 2012.

was reduced similarly with IASI when verified by the AIRS sensor (not shown).

4. Summary and discussion

In this study, the error covariance parameters for July and August 2012 were estimated by applying multiple linear regression to the observation impact data and forecast sensitivity to error covariance parameters. Adjusted observation error variances were applied to one-month (August 2012) forecasts using the KMA UM 4DVAR system. In the multiple linear regression analysis, a total of 17 error

covariance parameters were used as predictors, and large enough number of data during two month period is necessary to avoid physically meaningless error covariance adjustment parameters. The error covariance impact calculated by the error covariance adjustment parameters in July and August 2012 and the forecast sensitivity to error covariance parameters in August 2012 were similar to the observation impact in August 2012; therefore, the number of predictors was appropriate for statistically estimating the error covariance impact in August 2012.

The statistics of the forecast sensitivity to error covariance parameters showed that the observation (background)

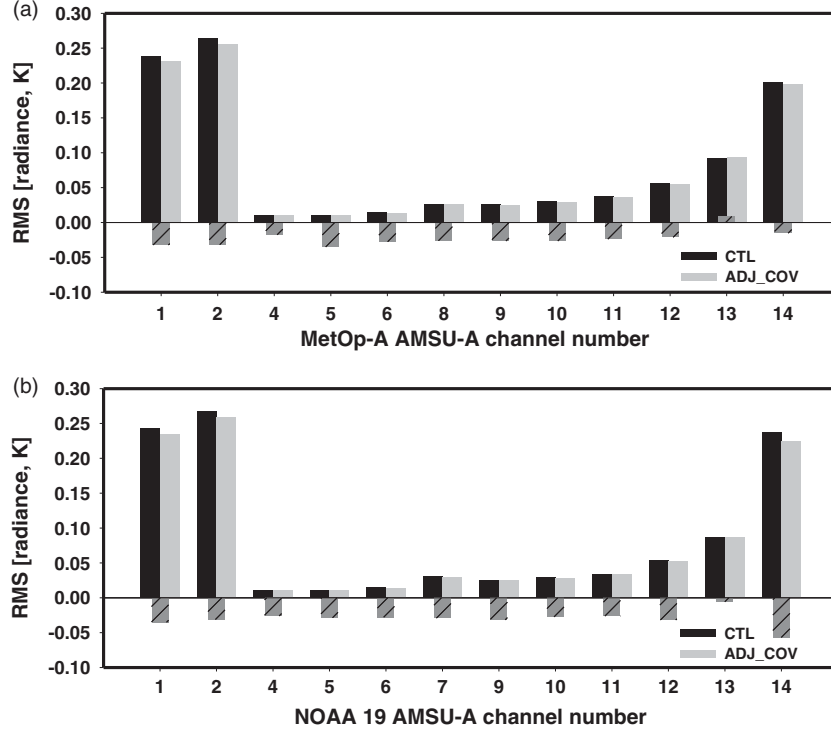


Fig. 9. The RMS of the average O-F of ADJ_COV (grey bar), CTL (black bar), and the reduction rate (dark grey with dashed line) in the observation space. The RMS of the average O-F is calculated based on (a) Metop-A AMSU-A and (b) NOAA19 AMSU-A channels globally in August 2012.

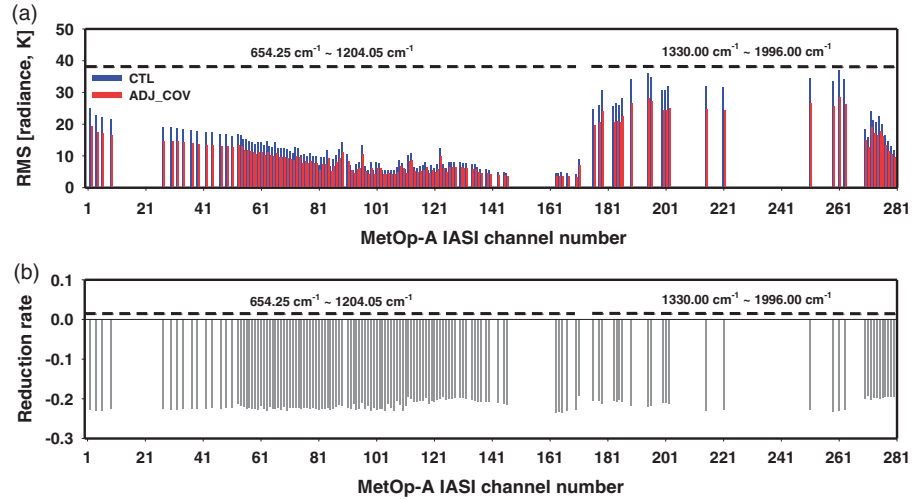


Fig. 10. (a) The RMS of the average O-F of ADJ_COV (red bar) and CTL (blue bar) and (b) reduction rate (dark grey bar) in the observation space. The RMS of the average O-F is calculated based on global MetOp-A IASI channels in August 2012. The wavelength range, which corresponds to the channel number, is represented by a dashed line.

error covariance should be deflated (inflated) to reduce the forecast error. The s_i^o -sensitivity is highest for ATOVS, followed by IASI, Geo_AMV, SONDE wind (SONDE_uv), and aircraft wind (AIRCRAFT_uv). The

high s_i^o -sensitivity indicates that the forecast error reduces greatly when the corresponding observation error covariance is adjusted. Based on sensitivity tests, the **B** was inflated by 30% and the observation error covariance

adjustment parameters were calculated by the multiple linear regression method. Because the s_i^o -sensitivity of ATOVS was highest, the observation error variance of ATOVS was adjusted. The multiple linear regression indicates that the observation error variance of ATOVS should be deflated by 72.14%. The observation error variances of ATOVS calculated by Desroziers' method are roughly similar to that calculated by the multiple linear regression. Compared with Desroziers' method which calculates the adjustment values of observation error variances sequentially using a single analysis-forecast cycle in practice, the method in this study provides the adjustment values of all observation types simultaneously. In addition, the adjustment values of the observation error variances based on the FSO method can be updated easily using the data of two months period up to the analysis time and the process can move forward day by day because the FSO statistics are calculated semi-operationally in the KMA UM 4DVAR system.

The ADJ_COV experiment that uses the adjusted ATOVS error variance was compared with the CTL experiment that employs the current ATOVS error variance used operationally in the KMA UM 4DVAR system. In both experiments, the background error covariance used was the operational one in the KMA UM 4DVAR system. The analysis and forecast of ADJ_COV and CTL were verified by SONDE observations for August 2012. Both residuals within the assimilation window (O-A) and in the 24–29 h forecast range (O-F) decreased for ADJ_COV compared with CTL. This implies that the adjusted ATOVS observation error variance reduced the residuals in both the assimilation window and forecast range. The new analysis of ADJ_COV was most similar to the ATOVS observations. The time-integrated O-A of ADJ_COV was reduced by 10.62% (3.83% when excluded ATOVS) compared with that of CTL for all observation types. Because the ATOVS satellite observations retrieve the vertical profile of temperature and specific humidity in the atmosphere, the adjusted ATOVS observation error variance reduced the O-F verified by the satellite observations as well as those verified by the SONDE and surface observations. The time-integrated O-F of ADJ_COV was reduced by 5.4% compared with that of CTL for all observation types.

The RMS of the average O-F of ADJ_COV was smaller than that of CTL in the vertical when verified by SONDE observations. The difference between the O-F of ADJ_COV and that of CTL increased from the surface towards the mid-troposphere. Because the number of SONDE observations was very small in the upper troposphere, it was difficult to verify the O-F based on the SONDE observations in the upper troposphere. Alternatively, the O-F in the upper troposphere were

verified by AMSU-A channels 11–14 (with the exception of channel 13 of Metop-A AMSU-A), IASI, and AIRS sensors. In the upper troposphere, the O-F of ADJ_COV was also smaller than that of CTL, which implies that the adjusted error variance of ATOVS helps to reduce the O-A and O-F compared with the ATOVS error variance currently used in the KMA UM 4DVAR system.

This study suggests a method for calculating error covariance adjustment parameters and demonstrates that the method can be used to adjust the error covariances in the KMA NWP and DA systems. In future studies, the effect of specific observation error covariance adjustment will be investigated in a hybrid system that uses an error covariance combining both a static and an ensemble-based background error covariance. In addition, application of the error covariance adjustment methodology to NWP in other seasons and adjustment of other observation error variances will be investigated to identify more optimised observation error variances in the KMA UM 4DVAR system. Furthermore, the sensitivity of the adjustment results depending on the use of a moist energy norm instead of a dry energy norm needs to be addressed when adjusting error variances of observation types which are sensitive to humidity (e.g. AMSU-B).

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Disclosure statement

No potential conflict of interest was reported by the authors.

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References

- Baker, N. L. and Daley, R. 2000. Observation and background adjoint sensitivity in the adaptive observation-targeting problem. *Qjr. Meteorol. Soc.* **126**, 1431–1454. doi:10.1002/qj.49712656511.

- Bormann, N. and Bauer, P. 2010. Estimates of spatial and interchannel observation-error characteristics for numerical weather prediction. I: Methods and application to ATOVS data. *Qjr. Meteorol. Soc.* **136**, 1036–1050. doi:10.1002/qj.616.
- Bormann, N., Collard, A. and Bauer, P. 2010. Estimates of spatial and interchannel observation-error characteristics for numerical weather prediction. II: Application to AIRS and IASI data. *Qjr. Meteorol. Soc.* **136**, 1051–1063. doi:10.1002/qj.615.
- Bormann, N., Bonavita, M., Dragani, R., Eresmaa, R., Matricardi, M. and co-authors. 2016. Enhancing the impact of IASI observations through an updated observation-error covariance matrix. *Qjr. Meteorol. Soc.* **142**, 1767–1780. doi:10.1002/qj.2774.
- Cardinali, C. 2009. Monitoring the observation impact on the short-range forecast. *Qjr. Meteorol. Soc.* **135**, 239–250. doi:10.1002/qj.366.
- Chatterjee, S. and Hadi, A. S. 1986. Influential observations, high leverage points, and outliers in linear regression. *Stat. Sci.* **1**, 379–393. doi:10.1214/ss/1177013622.
- Clayton, A. M. 2004. *Var Scientific Documentation 60*. UK Met Office, Exeter, UK, pp. 1–12.
- Clayton, A. M., Lorenc, A. C. and Barker, D. M. 2013. Operational implementation of a hybrid ensemble/4D-Var global data assimilation system at the Met Office. *Qjr. Meteorol. Soc.* **139**, 1445–1461. doi:10.1002/qj.2054.
- Cordoba, M., Dance, S. L., Kelly, G. A., Nichols, N. K. and Waller, J. A. 2017. Diagnosing atmospheric motion vector observation errors for an operational high-resolution data assimilation system. *Qjr. Meteorol. Soc.* **143**, 333–341. doi:10.1002/qj.2925.
- Courtier, P., Thépaut, J.-N. and Hollingsworth, A. 1994. A strategy of operational implementation of 4D-Var using an incremental approach. *Qjr. Meteorol. Soc.* **120**, 1367–1387. doi:10.1002/qj.49712051912.
- Daescu, D. N. and Todling, R. 2010. Adjoint sensitivity of the model forecast to data assimilation system error covariance parameters. *Qjr. Meteorol. Soc.* **136**, 2000–2012. doi:10.1002/qj.693.
- Daescu, D. N. and Langland, R. H. 2013. Error covariance sensitivity and impact estimation with adjoint 4D-Var: theoretical aspects and first applications to NAVDAS-AR. *Qjr. Meteorol. Soc.* **139**, 226–241. doi:10.1002/qj.1943.
- Desroziers, G., Berre, L., Chapnik, B. and Poli, P. 2005. Diagnosis of observation, background and analysis-error statistics in observation space. *Qjr. Meteorol. Soc.* **131**, 3385–3396. doi:10.1256/qj.05.108.
- Desroziers, G., Berre, L., Chabot, V. and Chapnik, B. 2009. A posteriori diagnostics in an ensemble of perturbed analyses. *Mon. Wea. Rev.* **137**, 3420–3436. doi:10.1175/2009MWR2778.1.
- Edwards, J. M. and Slingo, A. 1996. Studies with a flexible new radiation code. I: Choosing a configuration for a large-scale model. *Qjr. Meteorol. Soc.* **122**, 689–719. doi:10.1002/qj.49712253107.
- Essery, R., Best, M. and Cox, P. 2001. *MOSES 2.2 Technical Documentation. Hadley Centre Technical Note 30*. UK Met Office, Exeter, UK, pp. 1–30.
- Gelaro, R., Zhu, Y. and Errico, R. M. 2007. Examination of various-order adjoint-based approximations of observation impact. *Metz.* **16**, 685–692. doi:10.1127/0941-2948/2007/0248.
- Gelaro, R. and Zhu, Y. 2009. Examination of observation impacts derived from observing system experiments (OSEs) and adjoint models. *Tellus A.* **61**, 179–193. doi:10.1111/j.1600-0870.2008.00388.x.
- Gelaro, R., Langland, R. H., Pellerin, S. and Todling, R. 2010. The THORPEX observation impact intercomparison experiment. *Mon. Wea. Rev.* **138**, 4009–4025. doi:10.1175/2010MWR3393.1.
- Gregory, D., Kershaw, R. and Inness, P. M. 1997. Parametrization of momentum transport by convection. II: Tests in single-column and general circulation models. *Qjr. Meteorol. Soc.* **123**, 1153–1183. doi:10.1002/qj.49712354103.
- Joo, S., Lorenc, A. C. and Marriott, R. 2012. Diagnosis of exaggerated impacts on adjoint-based sensitivity studies, *Met Office Technical Report 564*. UK Met Office, Exeter, UK, pp. 1–18.
- Joo, S., Eyre, J. and Marriott, R. 2013. The impact of Metop and other satellite data within the Met Office global NWP system using an adjoint-based sensitivity method. *Mon. Wea. Rev.* **141**, 3331–3342. doi:10.1175/MWR-D-12-00232.1.
- Jung, B. J., Kim, H. M., Auligné, T., Zhang, X., Zhang, X. and co-authors. 2013. Adjoint-derived observation impact using WRF in the western North Pacific. *Mon. Wea. Rev.* **141**, 4080–4097. doi:10.1175/MWR-D-12-00197.1.
- Kershaw, R. and Gregory, D. 1997. Parametrization of momentum transport by convection. I: Theory and cloud modeling results. *Qjr. Meteorol. Soc.* **123**, 1133–1151. doi:10.1002/qj.49712354102.
- Kim, H. M., Kim, S.-M., Joo, S. and Kim, E.-J. 2014. Estimation of satellite observation impact on numerical weather forecast using adjoint-based method. 26 March – 1 April 2014. In: *19th International TOVS Study Conference (ITSC-19)*, Jeju, Republic of Korea.
- Kim, S., Kim, H. M., Kim, E.-J. and Shin, H.-C. 2013. Forecast sensitivity to observations for high-impact weather events in the Korean Peninsula. *Atmosphere*. **23**, 171–186. doi:10.14191/Atmos.2013.23.2.171 (in Korean with English abstract).
- Kim, S.-M. and Kim, H. M. 2013. Observation impact estimation using a Forecast Sensitivity to Observation (FSO) method in the Global and East Asia Regions. 7–12 April 2013. In: *EGU General Assembly 2013*, Vienna, Austria.
- Kim, S.-M. and Kim, H. M. 2014. Sampling error of observation impact statistics. *Tellus A.* **66**, 25435. doi:10.3402/tellusa.v66.25435.
- Kim, S.-M. and Kim, H. M. 2017. Adjoint-based observation impact of Advanced Microwave Sounding Unit-A (AMSU-A) on the short-range forecast in East Asia. *Atmosphere*. **27**, 93–104. doi:10.14191/Atmos.2017.27.1.093 (in Korean with English abstract).
- Kim, M., Kim, H. M., Kim, J., Kim, S.-M., Velden, C. and Hoover, B. 2017. Effect of enhanced satellite-derived atmospheric motion vectors on numerical weather prediction in East Asia using an adjoint-based observation impact method. *Wea. Forecasting*. **32**, 579–594. doi:10.1175/WAF-D-16-0061.1.
- Langland, R. H. and Baker, N. L. 2004. Estimation of observation impact using the NRL atmospheric variational data assimilation adjoint system. *Tellus A.* **56**, 189–201. doi:10.1111/j.1600-0870.2004.00056.x.

- Lorenc, A. C. and Marriott, R. 2014. Forecast sensitivity to observations in the Met Office Global numerical weather prediction system. *Qjr. Meteorol. Soc.* **140**, 209–224. doi:10.1002/qj.2122.
- Lorenc, A. C. and Payne, T. 2007. 4D-Var and the butterfly effect: statistical four-dimensional data assimilation for a wide range of scales. *Qjr. Meteorol. Soc.* **133**, 607–614. doi:10.1002/qj.36.
- Lock, A. R., Brown, A. R., Bush, M. R., Martin, G. M. and Smith, R. N. B. 2000. A new boundary-layer mixing scheme. Part 1: Scheme description and single-column model tests. *Mon. Wea. Rev.* **128**, 3187–3199. doi:10.1175/1520-0493(2000)128<3187:ANBLMS>2.0.CO;2.
- Lupu, C., Cardinali, C. and McNally, A. P. 2015. Adjoint-based forecast sensitivity applied to observation-error variance tuning. *Qjr. Meteorol. Soc.* **141**, 3157–3165. doi:10.1002/qj.2599.
- Waller, J. A., Simonin, D., Dance, S. L., Nichols, N. K. and Ballard, S. P. 2016a. Diagnosing observation error correlations for Doppler radar radial winds in the Met Office UKV model using observation-minus-background and observation-minus-analysis statistics. *Mon. Wea. Rev.* **144**, 3533–3551. doi:10.1175/MWR-D-15-0340.1.
- Waller, J. A., Ballard, S. P., Dance, S. L., Kelly, G. A., and Nichols, N. K. 2016b. Diagnosing horizontal and inter-channel observation error correlation for SEVIRI observations using observation-minus-background and observation-minus-analysis statistics. *Remote Sens.* **8**, 581. doi:10.3390/rs8070581.
- Webster, S. A., Brown, A. R., Cameron, D. R., and Jones, C. P., 2003. Improvements to the representation of orography in the Met Office Unified Model. *Qjr. Meteorol. Soc.* **129**, 1989–2010. doi:10.1256/qj.02.133.
- Weston, P. P., Bell, W. and Eyre, J. R. 2014. Accounting for correlated error in the assimilation of high resolution sounder data. *Qjr. Meteorol. Soc.* **140**, 2420–2429. doi:10.1002/qj.2306.
- Wilks, D. S. 2006. *Statistical Methods in the Atmospheric Sciences*. 2nd ed. Academic Press, Burlington, MA, pp. 627.
- Wilson, D. R. and Ballard, S. P. 1999. A microphysically based precipitation scheme for the UK Meteorological Office unified model. *Qjr. Meteorol. Soc.* **125**, 1607–1636. doi:10.1002/qj.49712555707.