Forecast Sensitivity Observation Impact in the 4DVAR and Hybrid-4DVAR Data Assimilation Systems

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ABSTRACT

In this study, the observation impacts on 24-h forecast error reduction (FER), based on the adjoint method in the four-dimensional variational (4DVAR) data assimilation (DA) and hybrid-4DVAR DA systems coupled with the Unified Model, were evaluated from 0000 UTC 5 August to 1800 UTC 26 August 2014. The nonlinear FER in hybrid-4DVAR was 12.2% greater than that in 4DVAR due to the use of flow-dependent background error covariance (BEC), which was a weighted combination of the static BEC and the ensemble BEC based on ensemble forecasts. In hybrid-4DVAR, the observation impacts (i.e., the approximated nonlinear FER) for most observation types increase compared to those in 4DVAR. The increased observation impact from using hybrid-4DVAR instead of 4DVAR changes depending on the analysis time and regions. To calculate the ensemble BEC in hybrid-4DVAR, analyses at 0600 and 1800 UTC (0000 and 1200 UTC) used 3-h (9-h) ensemble forecasts. Greater observation impact was obtained when 3-h ensemble forecasts were used for the ensemble BEC at 0600 and 1800 UTC, than with 9-h ensemble forecasts at 0000 and 1200 UTC. Different from other observations, the atmospheric motion vectors (AMVs) deduced from geostationary satellite are more frequently observed in the same area. When the ensemble forecasts with longer integration times were used for the ensemble BEC in hybrid-4DVAR, the observation impact of the AMVs decreased the most in East Asia. This implies that the observation impact of AMVs in East Asia shows the highest sensitivity to the integration time of the ensemble members used for deducing the flow-dependent BEC in hybrid-4DVAR.

1. Introduction

Data assimilation (DA) aims at estimating the atmospheric state as accurately as possible using observations and the background state (i.e., a short-term forecast) at the analysis time. The estimated atmospheric state is called the analysis state. There are many DA methods: optimal interpolation (OI), three- or four-dimensional variational data assimilation (3DVAR or 4DVAR, respectively; Courtier et al. 1994), and ensemble Kalman filter (EnKF; Evensen 1994). 4DVAR and EnKF are

mainly used in operational numerical weather prediction (NWP) centers. Local ensemble transform Kalman filter (LETKF; Hunt et al. 2007) is one of variations of EnKF.

Variational (Var) DA has a cost function comprising the background error and the observation error, which needs to be minimized to obtain the atmospheric state with minimum error. The weightings for the background and observations are the background error covariance (BEC) and observation error covariance, respectively. The BEC used in the Var DA is usually calculated statistically from averaged differences between background states and true states for a certain period (Barker et al. 2004). Since the true atmospheric states are not known, the differences between forecasts with longer lead time and those with shorter lead time (e.g., 48- and 24-h forecasts) for a period can be used to calculate the BEC. This method is called the National Meteorological Centre (NMC) method (Parrish and Derber 1992; Derber and Bouttier 1999; Ingleby 2001). The BEC estimated by the NMC method is a matrix with

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approximate dimensions of $10^8 \times 10^8$, which is not feasible to invert. To obtain the inversion numerically, the BEC is usually modeled as a block diagonalized matrix by horizontal, vertical, and variable conversion (Bannister 2008a,b). The BEC by the NMC method has limitations because it is static and cannot capture the flow variations in time and space.

In contrast, the EnKF calculates the BEC from the perturbations of the ensemble forecasts. The BEC in the EnKF includes the errors of the day (Corazza et al. 2003), and changes depending on flow variations. Although the BEC in the EnKF can include the effect of flow variations, the BEC can be skewed if there is a filter divergence due to small ensembles (Houtekamer and Zhang 2016). To overcome the limitation of static BEC used for the Var DA and the possible skew of the flow-dependent BEC due to small ensembles in the EnKF, the BEC that combines the static BEC and flow-dependent BEC was proposed. Wang et al. (2008) developed the hybrid-3DVAR system by combining the 3DVAR and EnKF (i.e., the static BEC and flow-dependent BEC), and showed that the hybrid-3DVAR provides better predictability than the 3DVAR system does. Since 2014, the Korea Meteorological Administration (KMA) has used the hybrid-4DVAR system developed by the U.K. Met Office (Clayton et al. 2013) as the operational DA system. The hybrid-4DVAR system couples the 4DVAR and the global component of the Met Office Global and Regional Ensemble Prediction System (MOGREPS-G; Bowler et al. 2008). The hybrid-4DVAR DA system uses the BEC that combines the static BEC for the 4DVAR DA system with the flow-dependent BEC (i.e., ensemble BEC) from the MOGREPS-G. Except for the BEC, the other parts of the hybrid-4DVAR DA system are the same as in the 4DVAR DA system. Clayton et al. (2013) showed that the hybrid-4DVAR DA system shows better predictability than the 4DVAR DA system.

The observation impact by the DA on the forecast performance has been studied to quantitatively evaluate the contribution of an individual observation to a forecast. The observation impact can be calculated using the forecast sensitivity to observations (FSO; Baker and Daley 2000). Since the observation impact for hundreds of thousands of observations can be calculated quickly using the FSO method in a semioperational way, the impact of satellite observations in certain types or channels for the forecast improvement can be determined very effectively using the FSO method (Kim 2016; Kim and Kim 2017). The observation impact and FSO are calculated differently depending on the type of DA systems: adjoint-based FSO impact (FSOI) estimation methods have been used for the Var DA

system (Tremolet 2007, 2008; Cardinali 2009; Gelaro and Zhu 2009; Lorenc and Marriott 2014; Jung et al. 2013; Kim and Kim 2014, 2016; Kim et al. 2013; Kim 2016; Kim and Kim 2017), whereas FSOI methods based on ensemble forecasts have been used for the LETKF (Liu and Kalnay 2008; Li et al. 2010; Kunii et al. 2012) and EnKF (Kim et al. 2014; J. Kim et al. 2017) systems. For some DA systems in which the observation impact was estimated, the observation impact of the Advanced Microwave Sounding Unit-A (AMSU-A) radiance observations was the largest for forecasts over the globe (Cardinali 2009; Gelaro and Zhu 2009; Lorenc and Marriott 2014). More recently, the observation impact of the Infrared Atmospheric Sounding Interferometer (IASI) becomes the largest for forecasts over the globe (Cotton and Morgan 2016). Regionally, the ranking of the observation impact changes depending on the regional situation (Kim et al. 2013; Jung et al. 2013; M. Kim et al. 2017).

There have been many studies of using the adjoint-based FSO method in the 4DVAR system of the KMA Unified Model (UM); 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 data because the observation impact data at different times are correlated. Kim and Kim (2017) also evaluated FSOI of the AMSU-A on the short-range forecast in East Asia. S.-M. Kim and H. M. Kim (2018) showed that the forecast sensitivity to error covariance parameters could be calculated using the FSO and employed them to adjust the observation error variance in the 4DVAR system, which reduced the forecast error in the KMA UM 4DVAR system.

In contrast, the adjoint-based observation impact for the hybrid-4DVAR DA system has not been fully investigated. The adjoint-based FSO method used in the 4DVAR DA system can be applied to the hybrid-4DVAR DA system in the KMA because every part in the 4DVAR is the same in the hybrid-4DVAR, except the BEC. The effect of using the combined BEC (i.e., combination of static BEC and flow-dependent BEC) on the adjoint-based observation impact has also never been investigated. Thus, the effects of assimilating observations in the 4DVAR DA system and hybrid-4DVAR DA system (i.e., the effects of using the static BEC and combined BEC) on the observation impact estimation are investigated and compared. Sections 2, 3, and 4 provide the methodology, results, and summary and discussion, respectively.

2. Methodology

a. Model

In this study, the global UM, version 7.9, and hybrid-4DVAR DA system, version 29.2 (Courtier et al. 1994; Clayton et al. 2013), in the KMA were used. The 4DVAR was implemented by choosing the static BEC instead of the combined BEC in the hybrid-4DVAR DA system, version 29.2. The model domain consisted of 1024 horizontal grid points latitudinally and 769 horizontal grid points longitudinally. The model resolution was horizontally $25\text{ km} \times 25\text{ km}$ in the midlatitudes, with vertically 70 eta–height hybrid layers from the surface to 80 km above it.

To reduce the computational cost in minimization process, the DA system uses the simplification operator that decreases the model resolution for the forecast path of the UM but keeps the dynamic balance of the forecast path (Lorenc and Payne 2007). The model domain of the DA system consisted of 288 horizontal grid points latitudinally and 217 horizontal grid points longitudinally, with horizontal resolution of 80 km.

The physical parameterizations of the KMA UM were Edwards–Slingo radiation (Edwards and Slingo 1996), mixed-phase precipitation (Wilson and Ballard 1999), Met Office surface exchange scheme (Essery et al. 2001), nonlocal boundary layer (Lock et al. 2000), new gravity wave drag (GWD) scheme (Webster et al. 2003), and mass flux convection scheme (Kershaw and Gregory 1997; Gregory et al. 1997).

The same physical parameterizations were used in the perturbation forecast (PF) model and its adjoint integration in the DA system, except for the nonlocal boundary layer scheme and the mixed-phase precipitation and mass-flux convection schemes. The fixed boundary layer scheme was used instead of the nonlocal boundary layer to consider the turbulence effect. The simplified moisture effect was used instead of the mixed-phase precipitation and mass-flux convection schemes. For computational stability, aforementioned simplified physical parameterizations were used for the DA system. The FSO was calculated based on the FSO algorithm, version 29.2, developed in the Met Office, discussed in detail in Lorenc and Marriott (2014).

b. Observation

Table 1 shows the observations and observed variables assimilated in the KMA UM DA system. All observations were collected via the global telecommunication system (GTS) and used operationally in the KMA UM DA system. Satellite observations go through a preprocessing process in the observation processing system (OPS), which includes bias correction, cloud detection, channel selection, and quality control using 1D-Var (Hilton et al.

TABLE 1. Abbreviations for the various observation types.

Abbreviation	Description
AMSU-A	Advanced Microwave Sounding Unit-A (radiance)
MHS	Microwave Humidity Sounder (radiance)
HIRS	High Resolution Infrared Radiation Sounder (radiance)
IASI	Infrared Atmospheric Sounding Interferometer (radiance)
AIRS	Atmospheric Infrared Sounder (radiance)
SSMIS	Special Sensor Microwave Imager/Sounder (radiance)
COMS CSR	Communication, Ocean, and Meteorological Satellite by Korea Meteorological Administration (radiance)
GOES	Geostationary Operational Environmental Satellite (wind)
MFG	Meteosat First Generation (<i>Meteosat-7</i>) by European Organization for the Exploitation of Meteorological Satellites (wind)
MSG	Meteosat Second Generation (<i>Meteosat-9</i>) by European Organization for the Exploitation of Meteorological Satellites (wind)
COMS AMV	Communication, Ocean, and Meteorological Satellite by Korea Meteorological Administration (wind)
MTSAT	Multifunctional Transport Satellite (wind)
ASCAT	Advanced Scatterometer (wind)
GPSRO	Global positioning system radio occultation (bending angle)
TEMP	Upper-air observations from a radiosonde (wind, temperature, specific humidity)
PILOT	Upper-air wind profile from a pilot balloon (wind)
PRFL	Wind profiler (wind)
Dropsonde	Upper-air observations from aircraft (wind, temperature, specific humidity)
AIRCRAFT	Upper-air wind and temperature from aircraft (wind, temperature)
SYNOP	Land surface synoptic weather observations (wind, temperature, surface pressure, specific humidity)
METAR	Surface weather observations and reports (wind, temperature, surface pressure, specific humidity)
SHIP	Sea surface weather observation by ship (wind, temperature, surface pressure, specific humidity)
BUOY	Sea surface weather observation by buoy (wind, temperature, surface pressure, specific humidity)
TCBOGUS	Tropical cyclone bogus observations generated by national meteorological centers (wind, pressure)

2009), after which additional quality control is done in the DA system. Conventional observations and satellite wind data (AMV data from geostationary satellites and advanced scatterometer) are thinned by 200-km resolution, and satellite radiance data are thinned by 120-km resolution. Some channels of satellite radiance data are blacklisted by the recommendation of the World Meteorological Organization (WMO; e.g., *NOAA-15* AMSU-A channels 4, 6, and 11–14; *NOAA-19* AMSU-A channel 8; *MetOp-A* AMSU-A channel 7); thus, these were not assimilated in the DA system.

c. *Background error covariance used in the data assimilation system*

The hybrid-4DVAR and 4DVAR DA systems of the KMA UM are the same except for the BEC, and the analyses from both hybrid-4DVAR and 4DVAR were obtained from the 4DVAR minimization algorithm (Lorenc and Payne 2007). Thus, the difference between the BECs in the hybrid-4DVAR and 4DVAR DA systems is explained in detail.

The static BEC averaged over some period ($\mathbf{B}_c$) is used in 4DVAR, where $\mathbf{B}_c$ is modeled to $\mathbf{P}_c$ using the conversion matrix $\mathbf{U}$, control variable $\mathbf{V}$, tangent linear model (i.e., PF model) $\mathbf{M}$ of the nonlinear model, and adjoint of $\mathbf{M}$ ($\mathbf{M}^T$) (Lorenc et al. 2000; Ingleby 2001) as

$$\mathbf{P} = \mathbf{P}_c = \mathbf{M}\mathbf{B}_c\mathbf{M}^T = \mathbf{M}\mathbf{U}\mathbf{U}^T\mathbf{M}^T. \quad (1)$$

In the hybrid-4DVAR DA system, the operational 4DVAR DA system and MOGREPS-G (used for the operational EPS of the KMA) are coupled (Clayton et al. 2013). Since the MOGREPS-G has 24 members (23 ensemble members and 1 control member) and uses them to calculate the ensemble BEC, the ensemble mean may not represent the maximum likelihood of the probability density function. To accommodate this issue, the 4DVAR analysis produced at 0000 and 1200 UTC is used as the control member, replacing the ensemble mean in the MOGREPS-G (Clayton et al. 2013; Kay et al. 2013; Kay and Kim 2014). At 0000 and 1200 UTC, the 23 ensemble members are produced and integrated for 9 h. From the integrated ensemble members, the normalized ensemble perturbation matrix $\mathbf{X} = [\mathbf{x}'_1, \dots, \mathbf{x}'_N]$ is calculated, where $\mathbf{x}'_k = (\mathbf{x}_k - \bar{\mathbf{x}})/\sqrt{N-1}$, $\mathbf{x}_k$ is the ensemble member, $\bar{\mathbf{x}}$ is the ensemble mean, and N is the number of ensemble members. The localized ensemble BEC is calculated as $\mathbf{D} \circ \mathbf{X}\mathbf{X}^T$, where $\circ$ is the Schur operator that multiplies each component of two matrices, and $\mathbf{D}$ is the correlation matrix used to localize the ensemble BEC and to reduce the sampling error as in Hamill et al. (2001). The BEC used in the hybrid-4DVAR combines $\mathbf{B}_c$ and $\mathbf{D} \circ \mathbf{X}\mathbf{X}^T$ from the MOGREPS-G, and is modeled to $\mathbf{P}_h$ as (Clayton et al. 2013; Lorenc et al. 2015)

$$\mathbf{P} = \mathbf{P}_h = \mathbf{M}(\beta_c^2 \mathbf{B}_c + \beta_e^2 \mathbf{D} \circ \mathbf{X}\mathbf{X}^T)\mathbf{M}^T, \quad (2)$$

where β_c^2 and β_e^2 are scaling factors for the static BEC and ensemble BEC, respectively. The two BECs (i.e., $\mathbf{B}_c$ and $\mathbf{D} \circ \mathbf{X}\mathbf{X}^T$) are assumed to be independent, thus linear combination of two BECs is used to get $\mathbf{P}_h$. In the hybrid-4DVAR system, 1.0 is assigned for β_c^2 and 0.3 is assigned for β_e^2 from the surface to 16 km, then β_e^2 decreases exponentially from 16 to 21 km, and above 21 km β_e^2 is zero. The $\mathbf{P}_h$ includes the error of the day

$\mathbf{M}(\beta_e^2 \mathbf{D} \circ \mathbf{X}\mathbf{X}^T)\mathbf{M}^T$ and thus is inflated with respect to the static BEC. Clayton et al. (2013) showed that the operational performance of the UM was improved by combining the 30% weighted ensemble BEC to the 100% weighted static BEC in the hybrid-4DVAR system in the Met Office. In addition, S.-M. Kim and H. M. Kim (2018) showed that the 30% inflation of the static BEC leads the most appropriate adjustment parameters for the observation error variance when using the forecast sensitivity to error covariance parameters method in the KMA 4DVAR system.

At 2100, 0300, 0900, and 1500 UTC, $\mathbf{P}_h$ is calculated and used in the 4DVAR minimization algorithm to produce the analysis increments. The added quantities of analysis increments to background states are integrated for 3 h to make the 4DVAR analyses of 0000, 0600, 1200, and 1800 UTC. Since the 4DVAR analyses produced at 0000 and 1200 UTC are used as the control member of MOGREPS-G, the MOGREPS-G ensemble members $\mathbf{x}_k$ used to calculate $\mathbf{P}_h$ for the 4DVAR minimization algorithm are integrated with different lengths at each analysis time (Fig. 1 in Clayton et al. 2013). For the analyses at 0600 and 1800 UTC, $\mathbf{P}_h$ is produced using the MOGREPS-G ensemble forecasts integrated for 3 h (hereafter T+3 MOGREPS-G) from 0300 and 1500 UTC, which coincides with the starting time of the 4DVAR analysis window. In contrast, for the analyses at 0000 and 1200 UTC, $\mathbf{P}_h$ is produced using the MOGREPS-G ensemble forecasts integrated for 9 h (hereafter T+9 MOGREPS-G) from 1500 and 0300 UTC, which also coincides with the starting time of the 4DVAR analysis window. Thus, the ensemble BEC used at each analysis time is calculated based on different ensemble integration times in the hybrid-4DVAR DA system.

d. *Observation impact estimation*

The error of the forecast $\mathbf{x}^f$ with respect to the true state $\mathbf{x}_t$, measured by the moisture total energy norm, is defined as (Lorenc and Marriott 2014)

$$\begin{aligned} e &= (\mathbf{x}^f - \mathbf{x}_t)^T \mathbf{C} (\mathbf{x}^f - \mathbf{x}_t) \\ &= \frac{1}{M_{\text{domain}}} \iint \int_0^1 \left(\rho u^2 + \rho v^2 + \frac{\rho g^2}{\theta^2 N^2} \theta^2 \right. \\ &\quad \left. + \frac{1}{\rho c^2} p^2 + \varepsilon \frac{\rho L^2}{C_p} q^2 \right) r^2 \cos \phi \, d\lambda \, d\phi \, dr, \end{aligned} \quad (3)$$

where $\mathbf{C}$ is a diagonal matrix that denotes the moisture total energy norm, M_{domain} is the mass of the atmosphere in the model domain, and N^2 is the square of the Brunt–Väisälä frequency. Here, ρ is the air density, g and c are

the gravitational acceleration and speed of sound, respectively, and r^2 is the square of Earth's radius. The terms ϕ and λ are the latitude and longitude, respectively, and u' , v' , θ' , p' , and q' represent the forecast errors of the zonal wind, meridional wind, potential temperature, pressure, and specific humidity, respectively. Finally, ε is the factor used to control the forecast error of the specific humidity (Kim and Jung 2009). The diagonal components of $\mathbf{C}$ are calculated for all the grid points from the surface to 150 hPa, so as not to consider the numerical noise accumulated at the model top (Gelaro et al. 2010; Lorenc and Marriott 2014). The term ε is set to 1 to fully consider the moisture effect, and the analysis $\mathbf{x}_a$ of the KMA UM DA system is used as $\mathbf{x}_t$ because $\mathbf{x}_t$ is unknown.

The nonlinear forecast error reduction (FER) is defined as the difference between the forecast errors with and without data assimilation. The difference between the total moisture error of the forecast integrated from the analysis, $(\mathbf{x}_a^f - \mathbf{x}_t)^T \mathbf{C}(\mathbf{x}_a^f - \mathbf{x}_t)$, and that integrated from the background, $(\mathbf{x}_b^f - \mathbf{x}_t)^T \mathbf{C}(\mathbf{x}_b^f - \mathbf{x}_t)$, is expressed as (Jung et al. 2013; Kim and Kim 2014)

$$\begin{aligned} \delta e &= (\mathbf{x}_a^f - \mathbf{x}_t)^T \mathbf{C}(\mathbf{x}_a^f - \mathbf{x}_t) - (\mathbf{x}_b^f - \mathbf{x}_t)^T \mathbf{C}(\mathbf{x}_b^f - \mathbf{x}_t) \\ &= (\mathbf{x}_a^f - \mathbf{x}_b^f)^T \mathbf{C}[(\mathbf{x}_a^f - \mathbf{x}_t) + (\mathbf{x}_b^f - \mathbf{x}_t)]. \end{aligned} \quad (4)$$

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

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}(\mathbf{y} - \mathbf{H}\mathbf{x}_b) = \mathbf{x}_b + \mathbf{K}\mathbf{d}, \quad (5)$$

where $\mathbf{x}_b$ is the background, $\mathbf{K} = \mathbf{P}\mathbf{H}^T(\mathbf{H}\mathbf{P}\mathbf{H}^T + \mathbf{R})^{-1}$ denotes the Kalman gain where $\mathbf{H}$ is the linear observation operator, $\mathbf{y}$ is the observation, and $\mathbf{R}$ is the observation error covariance. Here, $\mathbf{P} = \mathbf{P}_c$ in the 4DVAR, $\mathbf{P} = \mathbf{P}_h$ in the hybrid-4DVAR, and $\mathbf{d}$ represents the observation increment. By applying the linearized model (the PF model $\mathbf{M}$) to Eq. (5) 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

$$\delta e \approx \mathbf{d}^T \mathbf{K}^T \mathbf{M}^T \mathbf{C}[(\mathbf{x}_a^f - \mathbf{x}_t) + (\mathbf{x}_b^f - \mathbf{x}_t)]. \quad (6)$$

The approximated FER δe in the observation space is called the ‘‘observation impact,’’ and can be calculated independently for each observation assimilated.

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

$$\frac{\delta e}{\delta \mathbf{y}} \approx \mathbf{K}^T \mathbf{M}^T \mathbf{C}[(\mathbf{x}_a^f - \mathbf{x}_t) + (\mathbf{x}_b^f - \mathbf{x}_t)]. \quad (7)$$

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

$$\delta e_i \approx \delta \mathbf{y}_i \left(\frac{\delta e}{\delta \mathbf{y}} \right)_i. \quad (8)$$

The adjoint of the PF model ($\mathbf{M}^T$) used in observation impact estimation is linearized along the forecast trajectory of the nonlinear model, which can be $\mathbf{x}_a^f$, $\mathbf{x}_b^f$, and the average between $\mathbf{x}_a^f$ and $\mathbf{x}_b^f$. In the KMA UM DA system, the average forecast trajectory between $\mathbf{x}_a^f$ and $\mathbf{x}_b^f$ [as in Eq. (6)] is used to calculate the observation impact, which approximates the nonlinear FER most closely (Lorenc and Marriott 2014). Since the analyses of the hybrid-4DVAR and 4DVAR of the KMA UM are 3-h forecasts, the adjoint of the PF model is integrated three hours backward from the analysis times (i.e., 0000, 0600, 1200, and 1800 UTC) for the observation impact estimation in Eqs. (7) and (8).

The $\mathbf{x}_t$ used in the hybrid-4DVAR and that in the 4DVAR are from different systems; thus, values are different. This is because the nonlinear FER and observation impact do not measure which system is superior based on the same reference state (i.e., $\mathbf{x}_t$), but show how observations affect the forecast errors in each experiment's own cycle in each system. If the same reference state is used for experiments in the hybrid-4DVAR and 4DVAR, then the nonlinear FER can be affected by observations as well as differences between the hybrid-4DVAR and 4DVAR.

3. Results

a. Performance of forecast and analysis in the hybrid-4DVAR and 4DVAR

Clayton et al. (2013) showed that 24–120-h forecast errors of the hybrid-4DVAR are approximately 1% less than those of 4DVAR using various reference states (e.g., analysis of their own system, ERA-Interim, and observations). The hybrid-4DVAR and 4DVAR systems are used operationally in KMA, and as mentioned in section 2, the only difference between the hybrid-4DVAR and 4DVAR systems is the BEC.

Using the radiosonde (TEMP) observations as the reference, the 6-h forecast errors (i.e., bias) and analysis errors of the hybrid-4DVAR and 4DVAR are compared. The analysis error was calculated using the method in Desroziers et al. (2005). Compared to when $\mathbf{P}_c$ is used as the BEC (i.e., 4DVAR), when $\mathbf{P}_h$ is used as the BEC (i.e., hybrid-4DVAR), the 6-h forecast errors for the zonal wind, meridional wind, temperature, and specific humidity are reduced by 9.86%, 10.68%, 5.32%, and 5.84%, respectively, and the analysis errors for the same variables are reduced by 2.03%, 1.89%, 2.20%, and 0.12%, respectively (Table 2). This implies that the analyses and short-range forecasts produced by the

TABLE 2. Average of the 6-h forecast errors (bias) and the analysis errors corresponding to TEMP using the Desroziers et al. (2005) method in the hybrid-4DVAR and 4DVAR system from 0000 UTC 5 Aug to 1800 UTC 26 Aug 2014. The reduction rates of bias and analysis error in the hybrid-4DVAR system compared to those of 4DVAR system is also shown. U , V , T , and SH represent zonal wind, meridional wind, temperature, and specific humidity, respectively.

		U (m s^{-1})	V (m s^{-1})	T (K)	SH (g kg^{-1})
Hybrid-4DVAR	Bias	0.08	0.05	0.20	9.29
	Analysis error	1.09	1.07	1.00	30.86
4DVAR	Bias	0.09	0.06	0.21	9.86
	Analysis error	1.12	1.09	1.02	30.90
Reduction rate (%)	Bias	−9.86	−10.68	−5.32	−5.84
	Analysis error	−2.03	−1.89	−2.20	−0.12

hybrid-4DVAR are closer to the radiosonde observations than are those produced by 4DVAR.

b. Forecast error reduction

The observation impacts of the 24-h FER were calculated from 0000 UTC 5 August to 1800 UTC 26 August 2014 using both hybrid-4DVAR and 4DVAR. To obtain numerically stable results, the DA was implemented with a spinup period of two weeks before the experimental period.

1) NONLINEAR FORECAST ERROR REDUCTION

Figure 1 shows the time series of the nonlinear FER [Eq. (4)] from both hybrid-4DVAR and 4DVAR. Independent of the type of BEC ($\mathbf{P}_c$ or $\mathbf{P}_h$), the nonlinear FERs fluctuate over a 6-h period depending on the number of observations assimilated, similar to the results of previous studies (e.g., Jung et al. 2013; Lorenc and Marriott 2014; Kim and Kim 2014; Kim 2016). Two nonlinear FER data evaluated using the Student's t test were significantly different at the 99% significance level, which shows that the nonlinear FER changes much depending on the type of BEC. The daily average nonlinear FER in hybrid-4DVAR is $-12.42 \text{ J kg}^{-1} \text{ day}^{-1}$, whereas that in 4DVAR is $-11.07 \text{ J kg}^{-1} \text{ day}^{-1}$, which indicates that the nonlinear FER increases by 12.2% on average when using $\mathbf{P}_h$ instead of $\mathbf{P}_c$.

2) OBSERVATION IMPACT

The accuracy of the observation impacts [i.e., the approximated FER (δe) in the observation space using Eq. (8)] estimated from hybrid-4DVAR and 4DVAR may be different because the BECs are different in the two systems. To check their accuracy, the time series of the observation impacts estimated from the two systems were compared with the time series of nonlinear FER, and the correlation between the observation impact and the nonlinear FER was 0.94 (0.95) in hybrid-4DVAR (4DVAR). This indicates that the accuracies of the observation impacts estimated from hybrid-4DVAR and

4DVAR are very similar, and that the observation impacts from the two systems can be compared without much concern about their accuracy.

Similar to the previous observation impact studies using the FSO method (e.g., Cardinali 2009; Gelaro and Zhu 2009; Gelaro et al. 2010; Jung et al. 2013; Kim 2016), the observation impact was largest in AMSU-A followed by IASI, TEMP, AIRCRAFT, and SYNOP at the 95% significance level, in hybrid-4DVAR and 4DVAR (Fig. 2a). The rate of beneficial observations that decreased the forecast error when assimilated was mostly above or close to 50%, except for the TCBOGUS observations (Fig. 2b). Thus, approximately half of the observations contributed to decrease the forecast error. The degradation of forecasts by the other half may be associated with observation error, analysis error, growing mode background error (Lorenc and Marriott 2014), and sampling error (Kim and Kim 2014). Figure 2c shows the additional observation impact when using hybrid-4DVAR compared to 4DVAR (hereafter additional observation impact; the difference between the observation impacts from hybrid-4DVAR and 4DVAR). In hybrid-4DVAR, the observation impacts for all observation types increase except for dropsonde, PILOT, and wind profiler (PRFL), compared to those in 4DVAR (Fig. 2c). Comparing the observation impacts for satellite observations that observe vertical profiles of the atmosphere, the observation impacts for surface observations increase less in hybrid-4DVAR (Fig. 2c). This seems to be associated with the smaller “errors of the day” at the bottom of the model by high-frequency filtering (Clayton et al. 2013) for the BEC ($\mathbf{P}_h$) in the hybrid-4DVAR. The increase of the beneficial observations in hybrid-4DVAR (Fig. 2d) is associated with the smaller analysis error in hybrid-4DVAR compared to 4DVAR, as shown in Table 2. The rate of beneficial observations increased most in the TCBOGUS observations for Typhoon Genevieve (2014; Fig. 2d), although this result may not be statistically significant due to the small number (i.e., 28) of TCBOGUS observations.

FIG. 1. Time series of the nonlinear forecast error reduction (J kg^{-1}) calculated in the hybrid-4DVAR (black line) and 4DVAR (gray line) systems, together with the additional error reduction (bars) due to the use of hybrid-4DVAR from 0000 UTC 5 Aug to 1800 UTC 26 Aug 2014.

c. Effect of integration length of ensemble forecast on the additional observation impact

As the model integration time increases in the MOGREPS-G, the probability of producing ensemble members that diverge from the truth increases due to the increase of the background error. The ensemble members that are far different from the truth estimate “the error of the day” quite differently from the truth by diverging the localized ensemble BEC ($\mathbf{D} \cdot \mathbf{X}\mathbf{X}^T$). This misestimation of “the error of the day” prevents observations from enhancing forecast performance, which may lead to small observation impacts.

In hybrid-4DVAR, $\mathbf{P}_h$ at 0000 and 1200 UTC is produced from T+9 MOGREPS-G ensemble members, whereas $\mathbf{P}_h$ at 0600 and 1800 UTC is produced from T+3 MOGREPS-G ensemble members. Because of this, Clayton et al. (2013) expected that $\mathbf{P}_h$ at 0000 and 1200 UTC has less forecast improvement than $\mathbf{P}_h$ at 0600 and 1800 UTC. However, Clayton et al. (2013) found that the model integration length used to produce ensemble members and ensemble BEC does not much affect the forecast performance over the globe, except for tropical regions.

The hybrid-4DVAR shows increased additional observation impacts compared to the 4DVAR in section 3b(2), and those effects are associated with the use of the ensemble BEC that brings flow dependency as well as inflation to the static BEC. Since the integration time of the ensemble forecasts used to construct the ensemble BEC may affect the observation impact, variation of the observation impacts depending on the integration length of ensemble forecasts in calculating the $\mathbf{P}_h$ was investigated.

1) TOTAL ADDITIONAL OBSERVATION IMPACT

In hybrid-4DVAR, $\mathbf{D} \cdot \mathbf{X}\mathbf{X}^T$ in Eq. (2) at 0600 and 1800 UTC (0000 and 1200 UTC) are calculated using

T+3 (T+9) MOGREPS-G members. To investigate how the additional observation impact varies depending on the use of the $\mathbf{P}_h$ calculated by T+3 or T+9 MOGREPS-G members in hybrid-4DVAR, the additional observation impacts were evaluated both at 0600 and 1800 UTC and at 0000 and 1200 UTC. The additional observation impact is $-0.55 \text{ J kg}^{-1} \text{ day}^{-1}$ at 0600 and 1800 UTC, whereas it is $-0.45 \text{ J kg}^{-1} \text{ day}^{-1}$ at 0000 and 1200 UTC (Table 3), which implies that the additional observation impact based on the BEC calculated from T+3 MOGREPS-G members is 22% greater than that calculated from T+9 MOGREPS-G members. Thus, the additional observation impact in hybrid-4DVAR compared to 4DVAR is greater when the ensemble BEC in hybrid-4DVAR is based on the shorter integration of ensemble members, which is associated with the misestimation of “the error of the day” by the diverged ensemble forecasts from the truth as the integration becomes longer. Therefore, the effect of the ensemble BEC on the total observation impact is greater when shorter integration times are used to generate the ensemble forecasts for the BEC at 0600 and 1800 UTC, compared to when longer ensemble integration are used for the BEC at 0000 and 1200 UTC.

2) ADDITIONAL OBSERVATION IMPACT FOR OBSERVATION TYPES AND AMVs

Figure 3 shows the additional observation impact depending on the integration length of MOGREPS-G members, stratified by the observation type (e.g., surface observation, ground-based sounding observation, satellite wind observation, and satellite sounding observation). The additional observation impact is largest in satellite sounding-type observations (e.g., AMSU-A, IASI, AIRS) followed by satellite wind (e.g., AMVs, ASCAT), surface observation, and ground-based sounding observations.

FIG. 2. Time-averaged statistics (mean and 95% confidence interval) stratified by each observation type for (a) total observation impact, (b) the fraction of beneficial observation, (c) the difference of observation impact, and (d) the difference of fraction of beneficial observation between the hybrid-4DVAR and 4DVAR DA systems from 0000 UTC 5 Aug to 1800 UTC 26 Aug 2014.

For all the observation types, except the ground-based sounding observations, the additional observation impact is greater when using T+3 MOGREPS-G members than T+9 MOGREPS-G members, similar to the total additional observation impact discussed in section 3c(1). Because most ground-based sounding observations are assimilated at 0000 and 1200 UTC, the additional observation impact based on different forecast times (e.g., T+3 and T+9 MOGREPS-G members) cannot be evaluated fairly using the ground-based sounding observations. In contrast, the satellite observations are nearly equal at all times; therefore, the additional observation

impact depending on the ensemble BEC based on different forecast times can be evaluated at all times. Among the satellite observations, the sound observations of polar-orbiting satellites have the limitation of varied observation regions depending on the time, which leads to the existence of additional observation impact for specific regions at specific times.

Different from the ground-based sounding observations and sound observations of polar-orbiting satellites with limitations for evaluating additional observation impact in space and time, the AMVs deduced from visible and infrared sensor of geostationary satellites are

TABLE 3. Total observation impact ($\text{J kg}^{-1} \text{day}^{-1}$) for all the observation types assimilated in the hybrid-4DVAR and 4DVAR systems. The 0600 and 1800 UTC hybrid analyses use the 3-h forecast (T+3) data from MOGREPS-G, and the 0000 and 1200 UTC hybrid analyses use the 9-h forecast (T+9) data from MOGREPS-G.

	Hybrid-4DVAR	4DVAR	Additional impact
0600 and 1800 UTC analyses (use T+3 forecast member from MOGREPS-G)	−4.42	−3.87	−0.55
0000 and 1200 UTC analyses (use T+9 forecast member from MOGREPS-G)	−5.95	−5.50	−0.45

more frequently observed in the same area (Salonen and Bormann 2011; D.-H. Kim and H. M. Kim 2018), although the AMVs have relatively large observation error. Thus, using the AMVs from geostationary satellites, the additional observation impact depending on the ensemble BEC calculated by T+3 and T+9 MOGREPS-G members can be evaluated for fixed regions at all times, which elucidates the effect of the ensemble integration times on the additional observation impact more clearly.

The total additional observation impact of AMVs using the ensemble BEC based on T+3 and T+9 MOGREPS-G members are -0.14 and $-0.10 \text{ J kg}^{-1} \text{day}^{-1}$, respectively (Fig. 3). The impact of assimilating AMVs increases by 40% when T+3 MOGREPS-G members

are used for the ensemble BEC rather than T+9 MOGREPS-G members in hybrid-4DVAR, which reaffirms that the small divergence of the ensemble BEC from the truth by the shorter integration of ensemble members causes the increased additional impact at 0600 and 1800 UTC compared to that at 0000 and 1200 UTC, as discussed for total observations in section 3c(1). The increasing rate (40%) of additional observation impact for AMVs at 0600 and 1800 UTC compared to that at 0000 and 1200 UTC is much higher than that for total observations [22% in section 3c(1)], which may be caused by the difference in total observation numbers at 0600 and 1800 UTC compared to those at 0000 and 1200 UTC. The greater number of total observations at 0000 and 1200 UTC than at 0600 and 1800 UTC seems to complement the effect of the diverged ensemble forecasts from the truth for the longer integration times at 0000 and 1200 UTC, which lead to relatively smaller differences between the additional observation impact at 0600 and 1800 UTC and that at 0000 and 1200 UTC. In contrast, based on the similar number of AMV data at 0600 and 1800 UTC compared to at 0000 and 1200 UTC, only divergence of the ensemble BEC from the truth affects the additional observation impact, thus the difference between the additional observation impact at 0600 and 1800 UTC and that at 0000 and 1200 UTC is much greater than that for total observations. The mean additional observation impact of AMVs per observation is $-2.13 \times 10^{-6} \text{ J kg}^{-1} \text{day}^{-1}$ at 0600 and 1800 UTC

FIG. 3. Time-averaged statistics (mean) stratified by each observation type for additional observation impact, corresponding to analyses at (a) 0600 and 1800 UTC and (b) 0000 and 1200 UTC.

and $-1.55 \times 10^{-6} \text{ J kg}^{-1} \text{ day}^{-1}$ at 0000 and 1200 UTC, showing 37% increasing rate at 0600 and 1800 UTC.

3) REGIONAL DISTRIBUTION OF ADDITIONAL OBSERVATION IMPACT FOR AMVs

Figure 4 shows the horizontal distribution of the additional observation impact of the AMVs from geostationary satellites (e.g., *GOES-13/15*, *Meteosat-7*, *Meteosat-10*, MTSAT, *COMS*) depending on the ensemble BEC from T+3 and T+9 MOREPS-G members. The additional observation impact of AMVs based on the ensemble BEC from T+3 MOGREPS-G shows large values in North Africa, East Asia, East Pacific, South Atlantic, and the Antarctic Ocean near 180° (Fig. 4a). Except for East Asia, the additional observation impact of the AMVs based on the ensemble BEC from T+9 MOGREPS-G also shows large values in the same regions when the T+3 members are used (Fig. 4b). The AMVs in East Asia are from *Meteosat-7*, MTSAT, and *COMS*, and the variation in the additional observation impact of AMVs using T+3 and T+9 MOREPS-G members is mainly due to the AMV data from MTSAT (not shown). This implies that the additional observation impact of AMVs over East Asia when using hybrid-4DVAR (compared to 4DVAR) is sensitive to the length of ensemble integration used for constructing the ensemble BEC. Especially the AMVs from MTSAT are the most sensitive to the length of ensemble integration in calculating the ensemble BEC in the hybrid-4DVAR system.

4. Summary and discussion

In this study, the observation impacts for 24-h forecast error reduction calculated in the 4DVAR and hybrid-4DVAR DA systems were evaluated and compared for the period from 0000 UTC 5 August to 1800 UTC 26 August 2014. After the static BEC of 4DVAR was updated by the hybrid BEC (i.e., combination of the static BEC and ensemble BEC) of hybrid-4DVAR, the daily averaged nonlinear forecast error reduction increased by 12.2% on average for all observations except for dropsonde, PILOT, and PRFL. The increased additional observation impact (i.e., approximated forecast error reduction) was largest for AMSU-A, followed by IASI, GOES, MSG, ASCAT, AIRS, MHS, SYNOP, BUOY, AIRCRAFT, TEMP, MFG, MTSAT, GPSRO, METAR, HIRS, *COMS* CSR, SHIP, TCBOGUS, *COMS* AMV, PILOT, dropsonde, and PRFL.

The analyses and short-range forecasts produced by the hybrid-4DVAR are closer to the radiosonde observations than those produced by 4DVAR, which implies better analyses and forecasts in the hybrid-4DVAR than

FIG. 4. Vertically integrated additional observation impact ($10^{-5} \text{ J kg}^{-1} \text{ day}^{-1}$) to the AMV on *GOES-13* and *-15* (black line), *Meteosat-7* (orange line), *Meteosat-10* (aqua line), MTSAT (purple line), and *COMS* (pink line) assimilated in the analyses at (a) 0600 and 1800 UTC and (b) 0000 and 1200 UTC.

4DVAR. The nonlinear forecast error reduction and observation impact are also greater in the hybrid-4DVAR than 4DVAR. In contrast, *M. Kim et al. (2017)* showed that the total observation impact is smaller as the analysis–forecast system is improved by assimilating the enhanced AMVs, using the Weather Research and Forecasting (WRF) Model and its adjoint. The differences between the results in this study and *M. Kim et al. (2017)* may be due to the different experimental framework used in two studies. *M. Kim et al. (2017)* used WRF and 3DVAR with explicitly different set of observations, whereas UM and different DA systems (i.e., hybrid-4DVAR and 4DVAR) with almost similar set of observations were used in this study. Therefore, further studies are necessary to clarify the relationship between the forecast improvement and observation impact.

The additional observation impact from using hybrid-4DVAR instead of 4DVAR changes depending on the analysis time and regions. The ensemble BEC in hybrid-4DVAR uses MOGREPS-G ensemble members of which the integration times are different at different analysis times. The total observation impact at analysis

times using the BEC with T+3 integration ensemble members was greater by $0.10 \text{ J kg}^{-1} \text{ day}^{-1}$ compared to that using T+9 integration ensemble members.

Different from other observation types that are distributed relatively sporadically in space and time, the AMVs observe the same area all the time, and are thus useful to investigate the regional distribution of the observation impact. The observation impact of the AMVs at the analysis time when using the BEC with T+3 ensemble members was $-0.04 \text{ J kg}^{-1} \text{ day}^{-1}$ greater than that when using the T+9 ensemble members. This implies that the additional observation impact by the hybrid-4DVAR increases when using the BEC based on ensemble members that are relatively shortly integrated because the flow-dependent BEC is better estimated by the shorter-integrated ensemble members. The additional observation impact classified by the observation types shows that the surface observations, satellite winds, and satellite sounder observations show greater observation impact when using T+3 MOGREPS-G members than using T+9 members. The exceptions are the surface sounder observations, which seem to be associated with smaller “errors of the day” at the bottom of the model caused by high-frequency filtering (Clayton et al. 2013) for the BEC $\mathbf{P}_h$ in hybrid-4DVAR.

The horizontal distribution of the additional observation impact was evaluated using the AMVs of geostationary satellites (e.g., *GOES-13/15*, *Meteosat-7*, *Meteosat-10*, *MTSAT*, and *COMS*) that frequently observe the same regions. The additional observation impact shows high values in North Africa, East Asia, East Pacific, South Atlantic, and the Antarctic Ocean near 180° , when using T+3 ensemble members. When using T+9 ensemble members, all the regions above except East Asia show high values. The largest impact of AMVs in East Asia is caused by MTSAT. Thus, the observation impact of AMVs in East Asia is sensitive to the integration time of the MOGREPS-G members. AMVs derived from MTSAT, in particular, show the greatest sensitivity to the integration time of ensemble members. When assimilating the AMVs from several geostationary satellites together in East Asia in the hybrid-4DVAR and 4DVAR, the evaluation of the observation impact depending on the BEC would be very helpful in designing the optimal set of observations assimilated.

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REFERENCES

- Baker, N. L., and R. Daley, 2000: Observation and background adjoint sensitivity in the adaptive observation-targeting problem. *Quart. J. Roy. Meteor. Soc.*, **126**, 1431–1454, <https://doi.org/10.1002/qj.49712656511>.
- Bannister, R. N., 2008a: A review of forecast error covariance statistics in atmospheric variational data assimilation. I: Characteristic and measurements of forecast error covariances. *Quart. J. Roy. Meteor. Soc.*, **134**, 1951–1970, <https://doi.org/10.1002/qj.339>.
- , 2008b: A review of forecast error covariance statistics in atmospheric variational data assimilation. II: Modeling the forecast error covariance statistics. *Quart. J. Roy. Meteor. Soc.*, **134**, 1971–1996, <https://doi.org/10.1002/qj.340>.
- Barker, D. M., W. Huang, Y.-R. Guo, A. J. Bourgeois, and Q. N. Xiao, 2004: A three-dimensional variational data assimilation system for MM5: Implementation and initial results. *Mon. Wea. Rev.*, **132**, 897–914, [https://doi.org/10.1175/1520-0493\(2004\)132<0897:ATVDAS>2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132<0897:ATVDAS>2.0.CO;2).
- Bowler, N. E., A. Arribas, K. R. Mylne, K. B. Robertson, and S. E. Beare, 2008: The MOGREPS short-range ensemble prediction system. *Quart. J. Roy. Meteor. Soc.*, **134**, 703–722, <https://doi.org/10.1002/qj.234>.
- Cardinali, C., 2009: Monitoring the observation impact on the short-range forecast. *Quart. J. Roy. Meteor. Soc.*, **135**, 239–250, <https://doi.org/10.1002/qj.366>.
- Clayton, A. M., A. C. Lorenc, and D. M. Barker, 2013: Operational implementation of a hybrid ensemble/4D-Var global data assimilation system at the Met Office. *Quart. J. Roy. Meteor. Soc.*, **139**, 1445–1461, <https://doi.org/10.1002/qj.2054>.
- Corazza, M., and Coauthors, 2003: Use of the breeding technique to estimate the structure of the analysis “errors of the day.” *Nonlinear Processes Geophys.*, **10**, 233–243, <https://doi.org/10.5194/npg-10-233-2003>.
- Cotton, J., and L. Morgan, 2016: FSOI results at the Met Office. *Data Assimilation and Observing Systems Working Group Meeting*, Exeter, United Kingdom, WMO.
- Courtier, P., J.-N. Thepaut, and A. Hollingsworth, 1994: A strategy for operational implementation of 4D-Var, using an incremental approach. *Quart. J. Roy. Meteor. Soc.*, **120**, 1367–1387, <https://doi.org/10.1002/qj.49712051912>.
- Derber, J., and F. Bouttier, 1999: A reformation of the background error covariance in the ECMWF global data assimilation system. *Tellus*, **51A**, 195–221, <https://doi.org/10.3402/tellusa.v51i2.12316>.
- Desroziers, G., L. Berre, B. Chapnik, and P. Poli, 2005: Diagnosis of observation, background and analysis-error statistics in observation space. *Quart. J. Roy. Meteor. Soc.*, **131**, 3385–3396, <https://doi.org/10.1256/qj.05.108>.
- Edwards, J. M., and A. Slingo, 1996: Studies with a flexible new radiation code. 1: Choosing a configuration for a large-scale model. *Quart. J. Roy. Meteor. Soc.*, **122**, 689–719, <https://doi.org/10.1002/qj.49712253107>.
- Essery, R., M. Best, and P. Cox, 2001: MOSES 2.2 technical documentation. Hadley Centre Tech. Note 30, 31 pp.
- Evensen, G., 1994: Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte-Carlo methods to forecast error statistics. *J. Geophys. Res.*, **99**, 10 143–10 162, <https://doi.org/10.1029/94JC00572>.

- Gelaro, R., and Y. Zhu, 2009: Examination of observation impacts derived from observing system experiments (OSEs) and adjoint models. *Tellus*, **61A**, 179–193, <https://doi.org/10.1111/j.1600-0870.2008.00388.x>.
- , R. H. Langland, S. Pellerin, and R. Todling, 2010: The THORPEX Observation Impact Intercomparison Experiment. *Mon. Wea. Rev.*, **138**, 4009–4025, <https://doi.org/10.1175/2010MWR3393.1>.
- Gregory, D., R. Kershaw, and P. M. Inness, 1997: Parametrization of momentum transport by convection 2: Test in single-column and general circulation models. *Quart. J. Roy. Meteor. Soc.*, **123**, 1153–1184, <https://doi.org/10.1002/qj.49712354103>.
- Hamill, T. M., J. S. Whitaker, and C. Snyder, 2001: Distance dependent filtering of background error covariance estimates in an ensemble Kalman filter. *Mon. Wea. Rev.*, **129**, 2776–2790, [https://doi.org/10.1175/1520-0493\(2001\)129<2776:DDFOBE>2.0.CO;2](https://doi.org/10.1175/1520-0493(2001)129<2776:DDFOBE>2.0.CO;2).
- Hilton, F., N. C. Atkinson, S. J. English, and J. R. Eyre, 2009: Assimilation of IASI at the Met Office and assessment of its impact through observing system experiments. *Quart. J. Roy. Meteor. Soc.*, **135**, 495–505, <https://doi.org/10.1002/qj.379>.
- Houtekamer, P. L., and F. Zhang, 2016: Review of the ensemble Kalman filter for atmospheric data assimilation. *Mon. Wea. Rev.*, **144**, 4489–4532, <https://doi.org/10.1175/MWR-D-15-0440.1>.
- Hunt, B. R., E. J. Kostelich, and I. Szunyogh, 2007: Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter. *Physica D*, **230**, 112–126, <https://doi.org/10.1016/j.physd.2006.11.008>.
- Ingleby, N. B., 2001: The statistical structure of forecast errors and its representation in the Met Office global 3D variational data assimilation scheme. *Quart. J. Roy. Meteor. Soc.*, **75**, 181–189, <https://doi.org/10.1002/qj.49712757112>.
- Jung, B.-J., H. M. Kim, T. Auligne, X. Zhang, and X.-Y. Huang, 2013: Adjoint-derived observation impact using WRF in the western North Pacific. *Mon. Wea. Rev.*, **141**, 4080–4097, <https://doi.org/10.1175/MWR-D-12-00197.1>.
- Kay, J. K., and H. M. Kim, 2014: Characteristics of initial perturbations in the ensemble prediction system of the Korea Meteorological Administration. *Wea. Forecasting*, **29**, 563–581, <https://doi.org/10.1175/WAF-D-13-00097.1>.
- , Y.-Y. Park, and J. Son, 2013: Effect of doubling the ensemble size on the performance of ensemble prediction in the warm season using MOGREPS implemented at the KMA. *Adv. Atmos. Sci.*, **30**, 1287–1302, <https://doi.org/10.1007/s00376-012-2083-y>.
- Kershaw, R., and D. Gregory, 1997: Parametrization of momentum transport by convection 1: Theory and cloud modeling results. *Quart. J. Roy. Meteor. Soc.*, **123**, 1133–1151, <https://doi.org/10.1002/qj.49712354102>.
- Kim, D.-H., and H. M. Kim, 2018: Effect of assimilating Himawari-8 atmospheric motion vectors on forecast errors over East Asia. *J. Atmos. Oceanic Technol.*, **35**, 1737–1752, <https://doi.org/10.1175/JTECH-D-17-0093.1>.
- Kim, H. M., and B.-J. Jung, 2009: Influence of moist physics and norms on singular vector for a tropical cyclone. *Mon. Wea. Rev.*, **137**, 525–543, <https://doi.org/10.1175/2008MWR2739.1>.
- Kim, J., H. M. Kim, and C.-H. Cho, 2014: Influence of CO₂ observations on the optimized CO₂ flux in an ensemble Kalman filter. *Atmos. Chem. Phys.*, **14**, 13 515–13 530, <https://doi.org/10.5194/acp-14-13515-2014>.
- , and Coauthors, 2017: Impact of Siberian observations on the optimization of surface CO₂ flux. *Atmos. Chem. Phys.*, **17**, 2881–2899, <https://doi.org/10.5194/acp-17-2881-2017>.
- Kim, M., H. M. Kim, J. Kim, S.-M. Kim, C. Velden, and B. Hoover, 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, <https://doi.org/10.1175/WAF-D-16-0061.1>.
- Kim, S., H. M. Kim, E.-J. Kim, and H.-C. Shin, 2013: Forecast sensitivity to observations for high-impact weather events in the Korean Peninsula (in Korean with English abstract). *Atmosphere*, **23**, 171–186, <https://doi.org/10.14191/Atmos.2013.23.2.171>.
- Kim, S.-M., 2016: Forecast sensitivity to observations in the KMA UM and the effect of observations on numerical weather prediction. Ph.D. thesis, Yonsei University, 183 pp.
- , and H. M. Kim, 2014: Sampling error of observation impact statistics. *Tellus*, **66A**, 25435, <https://doi.org/10.3402/tellusa.v66.25435>.
- , and —, 2017: Adjoint-based observation impact of Advanced Microwave Sounding Unit-A (AMSU-A) on the short-range forecasts in East Asia (in Korean with English abstract). *Atmosphere*, **27**, 93–104, <https://doi.org/10.14191/Atmos.2017.27.1.093>.
- , and —, 2018: Effect of observation error variance adjustment on numerical weather prediction using forecast sensitivity to error covariance parameters. *Tellus*, **70A**, 1–16, <https://doi.org/10.1080/16000870.2018.1492839>.
- Kunii, M., T. Miyoshi, and E. Kalnay, 2012: Estimating impact of real observations in regional numerical weather prediction using an ensemble Kalman filter. *Mon. Wea. Rev.*, **140**, 1975–1987, <https://doi.org/10.1175/MWR-D-11-00205.1>.
- Li, H., J. Liu, and E. Kalnay, 2010: Letter to the editor correction of ‘Estimating observation impact without adjoint model in an ensemble Kalman filter.’ *Quart. J. Roy. Meteor. Soc.*, **136**, 1652–1654, <https://doi.org/10.1002/qj.658>.
- Liu, J., and E. Kalnay, 2008: Estimating observation impact without adjoint model in an ensemble Kalman filter. *Quart. J. Roy. Meteor. Soc.*, **134**, 1327–1335, <https://doi.org/10.1002/qj.280>.
- Lock, A. R., A. R. Brown, M. R. Bush, G. M. Martin, and R. N. B. Smith, 2000: A new boundary layer mixing scheme. Part I: Scheme description and single-column model tests. *Mon. Wea. Rev.*, **128**, 3187–3199, [https://doi.org/10.1175/1520-0493\(2000\)128<3187:ANBLMS>2.0.CO;2](https://doi.org/10.1175/1520-0493(2000)128<3187:ANBLMS>2.0.CO;2).
- Lorenc, A. C., and T. Payne, 2007: 4D-Var and the butterfly effect: Statistical four-dimensional data assimilation for a wide range of scales. *Quart. J. Roy. Meteor. Soc.*, **133**, 607–614, <https://doi.org/10.1002/qj.36>.
- , and R. Marriott, 2014: Forecast sensitivity to observations in the Met Office global numerical weather prediction system. *Quart. J. Roy. Meteor. Soc.*, **140**, 209–224, <https://doi.org/10.1002/qj.2122>.
- , and Coauthors, 2000: The Met. Office global three-dimensional variational data assimilation scheme. *Quart. J. Roy. Meteor. Soc.*, **126**, 2991–3102, <https://doi.org/10.1002/qj.49712657002>.
- , N. E. Bowler, A. M. Clayton, S. R. Pring, and D. Fairbairn, 2015: Comparison of hybrid-4DVar and hybrid-4DVar data assimilation methods for global NWP. *Mon. Wea. Rev.*, **143**, 212–229, <https://doi.org/10.1175/MWR-D-14-00195.1>.
- Parrish, D. F., and J. C. Derber, 1992: The National Meteorological Center’s spectral statistical-interpolation analysis system. *Mon. Wea. Rev.*, **120**, 1747–1763, [https://doi.org/10.1175/1520-0493\(1992\)120<1747:TSMC>2.0.CO;2](https://doi.org/10.1175/1520-0493(1992)120<1747:TSMC>2.0.CO;2).
- Salonen, K., and N. Bormann, 2011: Accounting for the characteristics of AMV observations errors in data assimilation. EUMETSAT Tech. Note, 7 pp.

- Tremolet, Y., 2007: First-order and higher-order approximations of observation impact.765. *Meteor. Z.*, **16**, 693–694, <https://doi.org/10.1127/0941-2948/2007/0258>.
- , 2008: Computation of observation sensitivity and observation impact in incremental variational data assimilation. *Tellus*, **60A**, 964–978, <https://doi.org/10.1111/j.1600-0870.2008.00349.x>.
- Wang, X., D. M. Barker, C. Snyder, and T. M. Hamill, 2008: A hybrid ETKF-3DVAR data assimilation scheme for the WRF Model. Part I: Observing system simulation experiment. *Mon. Wea. Rev.*, **136**, 5116–5131, <https://doi.org/10.1175/2008MWR2444.1>.
- Webster, S., A. R. Brown, D. R. Cameron, and C. P. Jones, 2003: Improvements to the representation of orography in the Met Office Unified Model. *Quart. J. Roy. Meteor. Soc.*, **129**, 1989–2010, <https://doi.org/10.1256/qj.02.133>.
- Wilson, D. R., and S. P. Ballard, 1999: A microphysically based precipitation scheme for the UK Meteorological Office Unified Model. *Quart. J. Roy. Meteor. Soc.*, **125**, 1607–1636, <https://doi.org/10.1002/qj.49712555707>.