Ensemble-Based Sensitivity Analysis Applied to African Easterly Waves

RYAN D. TORN
National Center for Atmospheric Research,* Boulder, Colorado, and Department of Earth and Atmospheric Sciences,
University at Albany, State University of New York, Albany, New York

(Manuscript received 22 December 2008, in final form 16 July 2009)

ABSTRACT

An ensemble Kalman filter (EnKF) coupled to the Advanced Research version of the Weather Research and Forecasting (WRF) model is used to generate ensemble analyses and forecasts of a strong African easterly wave (AEW) during the African Monsoon Multidisciplinary Analysis field campaign. Ensemble sensitivity analysis is then used to evaluate the impacts of initial condition errors on AEW amplitude and position forecasts at two different initialization times.

WRF forecasts initialized at 0000 UTC 8 September 2006, prior to the amplification of the AEW, are characterized by large variability in evolution as compared to forecasts initialized 48 h later when the AEW is within a denser observation network. Short-lead-time amplitude forecasts are most sensitive to the mid-tropospheric meridional winds, while at longer lead times, midtropospheric \( u \) errors have equal or larger impacts. For AEW longitude forecasts, the largest sensitivities are associated with the \( u \) downstream of the AEW and, to a lesser extent, the meridional winds. Ensemble predictions of how initial condition errors impact the AEW amplitude and position compare qualitatively well with perturbed integrations of the WRF model.

Much of the precipitation associated with the AEW is generated by the Kain–Fritsch cumulus parameterization, thus the initial-condition sensitivities are also computed for ensemble forecasts that employ the Betts–Miller–Janjic and Grell cumulus parameterization schemes, and for a high-resolution nested domain with explicit convection, but with the same initial conditions. While the 12-h AEW amplitude forecast is characterized by consistent initial-condition sensitivity among the different schemes, there is greater variability among methods beyond 24 h. In contrast, the AEW longitude forecast is sensitive to the downstream thermodynamic profile with all cumulus schemes.

1. Introduction

African easterly waves (AEWs) are synoptic-scale waves that propagate westward through sub-Saharan Africa during the Northern Hemisphere summer (Burpee 1972). These waves are important to this region because they provide a significant fraction of seasonal rainfall and are often associated with mesoscale convective systems (e.g., Payne and McGarry 1977; Fink and Reiner 2003). Once over the Atlantic Ocean, AEWs also provide seed disturbances for tropical cyclones (Avila and Pasch 1992).

Much of the work to date has focused on understanding the structure, dynamics, and growth mechanisms of these features. In general, AEWs are characterized by a periodicity of between 2 and 5 days (Burpee 1972) and have amplitudes that are peaked at around 650 hPa (Reed et al. 1977). Composite AEW studies and idealized models indicate that AEWs grow via baroclinic and barotropic conversion processes in the region of the African easterly jet (e.g., Reed et al. 1977; Thornicroft and Hoskins 1994). More recent studies have emphasized the importance of diabatic processes linked to deep convection associated with AEWs (Berry and Thorncroft 2005; Hsieh and Cook 2007).

Numerical weather prediction (NWP) model forecasts of AEWs suffer from a number of problems related to errors in the initial conditions and model formulations. Much of North Africa is characterized by a lack of in situ observations; thus, NWP systems rely on remote sensing data and prior forecasts to generate an analysis in this area.
(e.g., Tompkins et al. 2005). Furthermore, the relationship between diabatic heating, large-scale convection, and AEWs suggests that the formulation of the convective parameterization plays a significant role in the model evolution. Berry et al. (2009, manuscript submitted to Wea. Forecasting) evaluated the skill of AEW forecasts within four different operational NWP systems during 2007. Although each modeling system’s West Africa analysis has nearly identical errors with respect to rawinsonde observations, short-term forecasts of AEWs were characterized by varying degrees of skill. These operational systems use different initial conditions and physics parameterizations; thus, it is difficult to separate the role of initial-condition and model errors.

This paper explores how initial-condition errors affect NWP model forecasts of AEWs using forecast sensitivity analysis. Specifically, this study uses ensemble analysis and forecast data from a cycling ensemble Kalman filter (EnKF) system to compute the sensitivity of forecast metrics related to AEWs to initial conditions via ensemble-based sensitivity analysis (Hakim and Torn 2008). This work focuses on forecasts of an unusually strong AEW during the African Monsoon Multidisciplinary Analyses (AMMA) field campaign (Redelsperger et al. 2006), which provided an unusually rich set of observations over West Africa.

The paper is organized as follows. Section 2 gives details on the data assimilation system and model. An overview of the two forecasts studied is given in section 3. The sensitivity of the AEW forecasts to the initial conditions is presented in section 4, while in section 5 perturbations are added to the initial conditions in the most sensitive regions. In section 6, the role of the cumulus parameterization in the initial-condition sensitivity results is investigated. A concluding summary is given in section 7.

2. Experiment setup

Ensemble analyses of northern Africa are generated every 6 h from 0000 UTC 1 September to 0000 UTC 1 October 2006 by cycling an EnKF system on a 36-km horizontal resolution grid. Figure 1 shows the computational domain for these experiments. The 96-member analysis ensemble is advanced in time using version 2.2.1 of the Advanced Research version of the Weather Research and Forecasting (WRF) model (ARW; Skamarock et al. 2005). This implementation of WRF uses the WRF three-class microphysics scheme (Hong et al. 2004), the Kain–Fritsch (KF) cumulus parameterization (Kain and Fritsch 1990), the Yonsei University (YSU) boundary layer scheme (Hong et al. 2006), and a similarity theory land surface model (Skamarock et al. 2005).

Observations are assimilated every 6 h from surface stations; buoys; ships (altimeter setting); rawinsondes, including data taken during the AMMA field campaign \( (u, v, T, q) \); Aircraft Communications Addressing and Reporting System (ACARS; \( u, v, \) and \( T \)); and cloud motion vectors \( (u, v) \) (Velden et al. 2005) using the Data Assimilation Research Testbed (DART; Anderson et al. 2009), which is an implementation of the ensemble adjustment Kalman filter (Anderson 2001). Both the ACARS and cloud motion vector observations are “superobed” using the procedure described in Torn and Hakim (2008b). A majority of the observations are along the western coast of Africa (Fig. 1); at a typical analysis time, roughly 5000 observations are assimilated. Observation errors are obtained from National Centers for Environmental Prediction (NCEP) statistics.

Approximating covariances via small ensembles tends to produce spurious long-distance covariances and to underestimate the ensemble variance. These problems are partially overcome via covariance localization and covariance inflation. The influence of the observations is limited using the Gaspari and Cohn (1999) localization function [their Eq. (4.10)], where the covariance magnitude reduces to zero 2500 km (700 hPa) in the horizontal (vertical) from the observation location. The horizontal localization scale is obtained from Torn and Hakim (2009a), while the vertical localization scale is determined by repeating the cycling experiments with varying localization values and comparing the resulting 6-h forecasts errors (computed with respect to the rawinsondes). At each analysis time, the deviations from the ensemble mean are inflated using the spatially adaptive inflation scheme of Anderson (2009) without inflation damping and an inflation standard deviation of 0.1; after approximately 5 days, the inflation factor for each state variable reaches an equilibrium value.

Ensemble initial and boundary conditions for this North Africa domain are taken from a comparable parent ensemble data assimilation system cycled over a larger domain. This parent ensemble has 108-km horizontal resolution and extends from the western United States to India and from northern Europe to South Africa; all other model settings are the same as in the Africa domain. The initial and boundary conditions for each parent ensemble member are obtained by adding perturbations from the WRF VAR system (Barker et al. 2004) to the corresponding Global Forecasting System (GFS) analysis valid at the appropriate time (Torn et al. 2006). The parent ensemble assimilates observations every 6 h from 0000 UTC 10 August to 0000 UTC 1 October 2006 using the same observation types, covariance inflation, and covariance localization setup as are used for the North Africa domain. One-way lateral boundary conditions for each North Africa domain ensemble member are obtained by interpolating the corresponding forecasts from a parent
ensemble member onto the North Africa domain boundary points. Moreover, the North Africa ensemble is initialized at 0000 UTC 1 September 2006 by pairing each member with a parent domain analysis member and interpolating onto the North Africa grid.

For analysis times where AEWs exist within the domain, 48-h ensemble forecasts starting from 0000 UTC are generated by integrating all 96 analysis ensemble members forward in time; for brevity, this study focuses on two different initialization times, which are described in the next section. Other initialization times gave qualitatively similar results in terms of forecast performance and initial-condition sensitivity. Lateral boundary conditions for these ensemble forecasts are obtained by interpolating the corresponding time parent ensemble forecast onto the North Africa grid.

3. Overview of wave

Before evaluating how initial-condition errors affect forecasts of AEW at these two initialization times, a short summary of the AEW and forecast performance is presented. This AEW, one of the most vigorous observed during AMMA, is first identified by the Berry et al. (2007) objective tracking algorithm over southern Sudan at 0000 UTC 5 September 2006 (Thornicroft et al. 2007). Beginning 9 September, the 700-hPa curvature vorticity associated with the AEW markedly increases as it moves into western Africa. Once over Burkina Faso, several convective developments are observed in association with this AEW (e.g., Arnault and Roux 2009). At 0000 UTC 14 September (36 h after moving off the African coast), the AEW is classified as Tropical Storm Helene by the National Hurricane Center (Brown 2006).

Forecasts of this AEW at two different points in its life cycle are chosen for investigation, just prior to amplification on 0000 UTC 8 September, and during the mature stage starting 0000 UTC 10 September. Figure 2 shows the WRF EnKF ensemble mean and standard deviation 700-hPa curvature vorticity as a function of forecast hour. At the initial time, the AEW is located over Nigeria and is characterized by the ensemble mean curvature vorticity in excess of $1.5 \times 10^{-5} \, \text{s}^{-1}$ with a standard deviation of $0.7 \times 10^{-5} \, \text{s}^{-1}$, which indicates that each member has varied AEW structures and positions, possibly due to the lack of observations in this region (cf. Fig. 1). During subsequent forecast times, some of the ensemble members have the correct westward propagation and amplification, while others predict a stationary, or even dissipating, system. As a consequence, the 48-h ensemble-mean curvature vorticity forecast does not contain a definitive maximum, while the ensemble standard deviation exceeds $1.0 \times 10^{-5} \, \text{s}^{-1}$ (Fig. 2c). In general, the ensemble-mean precipitation is higher on the southwest side of the maximum in the curvature vorticity standard deviation.

In contrast to above, the 10 September ensemble forecasts show less variability in AEW evolution. At the analysis time, the ensemble-mean curvature vorticity associated with the AEW (located over Burkina Faso near 10°N, 3°W) exceeds $2.5 \times 10^{-5} \, \text{s}^{-1}$, while the standard deviation is less than $0.5 \times 10^{-5} \, \text{s}^{-1}$ (Fig. 2d). By hour 48,
the AEW moves into eastern Senegal and the standard deviation increases to $0.9 \times 10^{-5} \text{ s}^{-1}$ as a result of differences in the AEW position (Fig. 2f). The location of the AEW in the forecast is slightly north and 5° east of the verification position, determined from WRF EnKF ensemble-mean analysis data (Fig. 2g). At both forecast times, the ensemble-mean precipitation is greater than 8 mm (6 h)\(^{-1}\) over a large area on the south and west sides of the AEW. The cumulus parameterization is responsible for greater than 90% of the precipitation; the implications of this are addressed in section 6.

### 4. Forecast sensitivities

The role of the initial-condition errors on these two AEW forecasts is quantified using ensemble analysis.
and forecast data. Here, the sensitivity of a forecast metric $J$ to a state variable $x_i$ is evaluated from an $M$-member ensemble via

$$\frac{\partial J}{\partial x_i} = \frac{\text{cov}(J, x_i)}{\text{var}(x_i)} \sigma_{x_i},$$

where $J$ and $x_i$ are $1 \times M$ ensemble estimates of the forecast metric and the $i$th state variable, respectively; $\sigma_{x_i}$ is the analysis standard deviation of this state variable at the initial time; cov denotes the covariance between the two arguments; and var is the variance (Ancell and Hakim 2007). This equation is the best-fit line to the linear regression between the analysis state variable and forecast metric, which are the independent and dependent variables, respectively. Multiplying the right-hand side by the ensemble standard deviation, which is an approximation of the analysis error, allows for a qualitative comparison between forecast hours and fields since $\partial J/\partial x_i$ has units of the metric. Ensemble sensitivity is estimated from a relatively small ensemble compared to the number of state variables; thus, the regression coefficient is subject to sampling errors, which are addressed by testing for statistical significance in a manner similar to that of Torn and Hakim (2008a). The null hypothesis of no relationship between the metric and analysis state variable is rejected if the absolute value of the regression coefficient is greater than its 95% confidence bounds computed from ensemble data (e.g., Wilks 2005, section 6.2.5).

Initial-condition sensitivity is evaluated for two different metrics either directly or closely related to AEW, the 700-hPa meridional wind kinetic energy in the vicinity of the AEW, and the longitude of the AEW. The meridional wind kinetic energy (MKE), which is used as a proxy for the AEW amplitude, is computed for each ensemble member by averaging the kinetic energy associated with the 700-hPa meridional wind over a box (1600 km $\times$ 1000 km) centered on the AEW. At each forecast hour, the center of the box is found by computing the 700-hPa curvature vorticity for each ensemble member and averaging the latitudes and longitudes of the maxima in all members. Since the metric box is large relative to the AEW, the sensitivity results are almost identical when the MKE is computed for a box centered on each ensemble member’s AEW. AEW longitude is determined for each ensemble member by computing the 700-hPa curvature vorticity using Berry et al.’s (2007) technique, averaging this quantity between 8° and 18°N, and finding the longitude of the maximum value. Initial-condition sensitivities for the 700-hPa curvature vorticity averaged over a box centered on the ensemble-mean AEW were statistically insignificant; thus, this metric is not considered. This metric involves taking the difference between two quantities related to horizontal derivatives, which can be quite noisy and can overwhelm the sensitivity signal.

Given that AEWs have maximum amplitude in the midtroposphere and the role of the diabatic processes in their evolution, the sensitivity of 12- and 48-h MKE forecasts is computed with respect to the analysis of the 700-hPa meridional wind and the equivalent potential temperature ($\theta_e$) averaged between 3000 and 7000 m (i.e., midtroposphere). Although $\theta_e$ is not a WRF state variable, this field allows for a quantitative comparison of the role of thermodynamic errors versus kinematic errors. In general, locations that are sensitive to $\theta_e$ are sensitive to both the temperature and moisture (not shown). Other fields, such as zonal winds, lower-tropospheric fields, horizontal shear (i.e., barotropic term), and vertical shear (i.e., baroclinic term), are characterized by minimal or statistically insignificant sensitivities (not shown).

\subsection{Meridional kinetic energy}

For 8 September, the regions of largest sensitivity for the 12-h MKE forecast are nearly collocated with the AEW (center denoted by an X) over Nigeria (Fig. 3a). Increasing the southerly (northerly) meridional winds on the eastern (western) side of the AEW by one standard deviation is associated with a 2.0 m$^2$ s$^{-2}$ increase in the 12-h meridional kinetic energy, which is equivalent to a 0.5 standard deviation change in this metric. This pattern of sensitivity suggests that short-term forecasts have memory of the initial AEW amplitude. In contrast, the region of maximum sensitivity to midtropospheric $\theta_e$ is on the northern side of the AEW near the Jos Plateau and is comparatively smaller (1.5 m$^2$ s$^{-2}$ per analysis standard deviation) than the meridional wind value (Fig. 3b).

The region of large initial-condition sensitivity is not just limited to the midtroposphere. Figure 4 shows the vertical profile of the sensitivity to the meridional winds and $\theta_e$ for a location within the area of maximum sensitivity (denoted by dots in Figs. 3a and 3b). The initial-condition sensitivity for meridional winds is statistically significant between 2 and 6 km, which roughly coincides with the strongest northerly winds in the column (Fig. 4a). In contrast, the sensitivity for $\theta_e$ is statistically significant from 2 km (just above the boundary layer) to 13 km (near the tropopause), with the largest values (1.5 m$^2$ s$^{-2}$ per analysis standard deviation) generally between 4 and 12 km.

At longer lead times, the sensitivity patterns for the meridional wind and $\theta_e$ contain subtle differences compared to the 12-h MKE forecast. One-standard-deviation errors in the analysis meridional winds near the center and eastern side of the AEW are associated with a 1.8 m$^2$ s$^{-2}$ change in the 48-h MKE, while the sensitivity
on the west side of the AEW is statistically insignificant (Fig. 3c). The region of largest sensitivity for midtropospheric $\theta_e$ (2.0 m$^2$ s$^{-2}$ per analysis standard deviation) is on the northwest side of the initial AEW, slightly west of the main region of sensitivity for the 12-h forecast, but still near the Jos Plateau (Fig. 3d).

The initial-condition sensitivity for 700-hPa meridional winds suggests that the AEW amplitude forecast has memory of the initial AEW amplitude at short lead times, but not necessarily at longer lead times. To quantify this idea, Fig. 5 shows the ensemble correlation between the 700-hPa MKE forecast averaged over a box...
centered on the ensemble-mean AEW position at various lead times to the analysis value. The correlation between the forecast and the initial MKE decreases from 0.7 to 0.4 for 12- and 48-h forecasts, respectively. This result suggests that the initial AEW amplitude has less of an affect at longer lead times, and supports the notion that initial-condition errors in other fields, such as the thermodynamic profile, can have a larger impact on 2-day forecasts.

To quantify the role of kinematic and thermodynamic initial-condition errors in the MKE forecast, multivariate regression is performed every 6 h, where the independent variables are the initial-time MKE and midtropospheric $\theta_e$ averaged over the sensitive region (dashed box in Fig. 3d), and the dependent variable is the forecast MKE at a particular lead time. All variables are normalized by the ensemble standard deviation so the regression coefficients are dimensionless. Figure 6a shows the regression coefficients for these two predictors at various lead times. Over the first 36 h, the initial-time MKE coefficient is greater than the $\theta_e$ coefficient, suggesting that kinematic errors have a larger impact on the MKE forecast. By day 2,
the $\theta_e$ coefficient is larger, indicating that thermodynamic errors have a larger impact than kinematic errors. Even after 48 h, these two predictors explain 40% of the variance in the MKE metric.

Although the AEW is stronger at hour 0, the patterns of the initial-condition sensitivity for 10 September are qualitatively similar to those obtained for 8 September. For 12-h MKE forecasts, errors in the northerly (southerly) winds on the west (east) side of the AEW have a larger impact on the MKE forecast as compared to the meridional winds in other locations (Fig. 3e). Decreasing (increasing) the winds on the west (east) side of the AEW by one standard deviation leads to a 1.5 m$^2$s$^{-2}$ increase in the 12-h MKE forecast within the box, equivalent to a 0.3 standard deviation change in this metric. Similar to 8 September, the MKE is also sensitive to midtropospheric $\theta_e$ at the center and on the western side of the AEW over Burkina Faso (1.8 m$^2$s$^{-2}$ per analysis standard deviation; see Fig. 3f).

Vertical profiles within the most sensitive regions support the idea that errors over a deep column can have a large impact on this metric. For meridional winds, the region of statistically significant sensitivity extends from 2 to 7 km, with the largest sensitivity value (2.0 m$^2$s$^{-2}$ per analysis standard deviation) at 2.5 km, just below the maximum in northerly winds (Fig. 4c). In contrast to the meridional winds, the sensitivity to $\theta_e$ is statistically significant throughout the troposphere (Fig. 4d). Moreover, the largest sensitivity values (1.8 m$^2$s$^{-2}$ per analysis standard deviation) are between 2 and 6 km, which coincides with the $\theta_e$ minimum in the column.

To further understand how the initial-condition errors in $\theta_e$ impact the 10 September forecast, the ensemble member with the largest 12-h MKE (denoted “strong”) is compared to the ensemble member with the smallest forecast MKE (denoted “weak”). For the strong member, the midtropospheric $\theta_e$ is up to 3.5 K higher in the most sensitive region (not shown). Figure 7 shows the vertical profiles of the time-mean cumulus parameterization heating rates and vertical motion averaged over the right half of the box shown in Fig. 3f; this box encloses the region of greatest precipitation. For the strong member, the heating rate and vertical motion in the midtroposphere are, respectively, 40% and 200% greater than in the weak member. The heating profiles in Fig. 7 suggest that the AEW is amplifying through potential vorticity generation via diabatic heating; the strong

![Graph](image-url)
member grows faster due to a larger vertical gradient in diabatic heating (e.g., Hoskins et al. 1985). This result agrees with Hawblitzel et al. (2007), who showed high correlation between convection and subsequent vorticity in ensemble forecasts of mesoscale convective vortices (MCVs) over the central United States. Moreover, the surface-based convective available potential energy (CAPE) is similar in both member’s initial conditions (not shown), which suggests that the higher $u_e$ in the strong member leads to more efficient convection.

At longer lead times, the most sensitive region for the meridional winds generally decreases in area, while the most sensitive region for $u_e$ becomes larger. The 48-h MKE forecast appears to be most sensitive to the meridional winds 400 km to the northwest and 500 km to the east of the center of the initial wave ($2.1 \text{ m}^2 \text{s}^{-2}$ per analysis standard deviation; see Fig. 3g). For $u_e$, the region of largest sensitivity is along the northwest side of the AEW between Burkina Faso and Mali, which is slightly north of the most sensitive region for the 12-h MKE forecast (Fig. 3h). A one standard deviation error in this region leads to a $2.7 \text{ m}^2 \text{s}^{-2}$ change in the 48-h MKE forecast. The larger sensitivity to $\theta_e$ at longer lead times is consistent with Sippel and Zhang (2008), who show that initial-condition errors in CAPE and deep-layer moisture have the largest impacts on an Atlantic TC genesis forecast. In addition, the correlation between the forecast AEW amplitude and the analysis AEW amplitude decreases from 0.4 at hour 12 to 0.1 at hour 48 (Fig. 5); the later value is not statistically significant at the 95% confidence level.

Similar to 8 September, multivariate regression coefficients are computed every 6 h for the 10 September forecast, where the midtropospheric $\theta_e$ is instead averaged over the dashed box in Fig. 3h. For lead times less than a day, the coefficient for the initial MKE is larger than the $\theta_e$ value; beyond this time, the $\theta_e$ coefficient is greater, suggesting that initial-condition errors in the thermodynamic fields have a larger impact (Fig. 6b). These two predictors also explain greater than 40% of the variance in the forecast MKE at all lead times.

b. AEW longitude

The remainder of this section considers how initial-condition errors impact AEW position forecasts at these two initialization times. For this metric positive (negative) sensitivity indicates that increasing the analysis field at that location is associated with eastward (westward) displacement in the AEW.

For 8 September, the AEW longitude forecast is sensitive to the analysis meridional wind in locations similar to what is observed for MKE; however, the same is not true for $u_e$. Specifically, the region of largest sensitivity for meridional winds ($1^\circ$ per analysis standard deviation) is located to the west and east of the AEW center and appears to be related to amplitude changes in the AEW, such that a stronger initial AEW leads to less westward propagation (Fig. 8a). For $u_e$, initial-condition errors on the southern side of the AEW over southern Nigeria have the greatest impact on longitude forecasts (Fig. 8b). Increasing (decreasing) $u_e$ in this region by one standard deviation leads to an AEW that is $1.2^\circ$ to the east (west). Since some of the ensemble member forecasts did not have an AEW beyond 24 h, it is not possible to compute the initial-condition sensitivities at hour 48.

Longitude forecasts for 10 September show consistent sensitivity to the initial conditions at both forecast times. At the 12-h lead time, errors in the meridional wind gradient at the center of the AEW over Burkina Faso (Fig. 8c) have the greatest impacts on position forecasts, with smaller sensitivities on the western and eastern edges of the wave. Decreasing (increasing) the meridional winds at the center of the wave, which is akin to
shifting the AEW to the east or increasing the AEW amplitude, leads to a 0.5° eastward (westward) change in the forecast longitude. For $\theta_e$, the largest sensitivity is along the western side of the AEW along the Burkina Faso–Mali border (0.4° per analysis standard deviation; see Fig. 8d). Similar to the MKE metric, vertical profiles of sensitivity are maximized in the midtroposphere (not shown). Longer lead-time forecasts are characterized by similar areas of large sensitivity; one standard deviation errors in either field are associated with a 0.7° change in AEW position (Figs. 8e and 8f). Although there is strong correspondence in the regions of maximum sensitivity for both AEW longitude and MKE (cf. Figs. 3g and 3h), the absolute value of the correlation between these two metrics at the same lead time is less then 0.15 prior to hour 36; however, by hour 48, the correlation is $-0.44$, which indicates that higher-amplitude waves move faster.

Similar to MKE, multivariate regression coefficients are computed for the 10 September AEW longitude as a function of forecast hour, where the independent variables are the initial MKE, initial AEW longitude, and the initial midtropospheric $u_e$ averaged over the dashed box in Fig. 3h. Figure 9 shows that during short lead times, the AEW longitude is mostly determined by the initial longitude; however, by hour 48, the regression coefficient is largest for the initial $u_e$ and much smaller for the AEW longitude. In contrast, the initial MKE coefficient increases only slightly with time. Overall, this result suggests that similar to MKE, thermodynamic errors are more important for longer lead times and the
5. Perturbed initial conditions

The ensemble-based sensitivity patterns in the previous section indicate that errors in sensitive regions play a significant role in subsequent forecasts of AEW amplitude. This hypothesis is tested here by applying perturbations to the 8 and 10 September initial conditions in the most sensitive regions, integrating the perturbed ensemble forward, and evaluating the impacts on the forecast metric. These experiments also provide a quantitative validation of the sensitivity values shown previously.

Ensemble initial-condition perturbations are generated for each model state variable \( x^a \) using the following procedure. First, a state variable is chosen from within the area where the 48-h MKE forecast is most sensitive to the midtropospheric \( \theta_e \) (denoted \( x_s \); shown as a dot in Figs. 3d and 3h). A perturbation amplitude (\( \alpha \)) is introduced to this location; all other model state variables are adjusted for this perturbation using the ensemble covariances via

\[
x^p_i = x^a_i + \frac{\partial x^a}{\partial x_s} \alpha,
\]

where

\[
\frac{\partial x^a}{\partial x_s} = \frac{\text{cov}(x^a_i, x_s)}{\text{var}(x_s)}.
\]

Here, \( x^p_i \) and \( x_s \) are \( 1 \times M \) ensemble estimates of the \( i \)th control analysis state variable and midtropospheric \( \theta_e \) within the most sensitive region, respectively. This procedure is akin to assimilating a hypothetical \( \theta_e \) observation within the most sensitive region where the observation and model estimate of the observation differ by \( \alpha \), and the observation is assumed to have zero error. The perturbed ensemble is integrated forward 48 h and the forecast MKE is computed and compared to the control ensemble value. This procedure is repeated for various values of \( \alpha \) (±3 standard deviations of \( x_s \)) to determine the valid range of sensitivity values and the range over which the model is linear.

Figures 10a and 10b show the control 700-hPa meridional winds and \( \theta_e \), respectively, and the initial-condition perturbation that is consistent with perturbing the \( \theta_e \) within the most sensitive region by 2 K. The meridional winds and initial-condition perturbation are in phase; this perturbation will increase the AEW winds by 1.5 m s\(^{-1}\). For \( \theta_e \), the largest perturbation is on the western side of the AEW and is maximized at the location of the perturbation. After 48 h, the difference between the control and perturbation forecasts remains maximized near the AEW (Figs. 10c and 10d). The perturbation winds are up to 2.9 m s\(^{-1}\) greater than the control, while the \( \theta_e \) remains 1 K higher on the western side of the AEW, suggesting that the larger \( \theta_e \) remains throughout the forecast. This increase in meridional winds is similar to the upscale error growth described by Zhang et al. (2003). The ensemble-mean 48-h MKE forecast is 2.2 m\(^2\) s\(^{-2}\) larger than the control value, which is in fairly good agreement with the ensemble-based prediction of 2.0 m\(^2\) s\(^{-2}\).

The above process is repeated for various values of \( \alpha \) for both the 8 and 10 September forecasts (Fig. 11). For 8 September, there is generally good agreement between the ensemble prediction and model response for perturbations up to 1 K, while larger-amplitude initial-condition perturbations show an asymmetric response with respect to \( \alpha \). The model response to large negative (positive) perturbations is generally less (greater) than the ensemble prediction and the ensemble variance generally decreases (increases) with larger perturbations. Whereas the negative perturbation results are due to MKE being bounded from below by zero, the positive perturbation results suggest a nonlinear amplification. Perturbations applied to 10 September show better agreement between the ensemble prediction and model response (Fig. 11b), which indicates that the ensemble-derived sensitivity to the downstream \( \theta_e \) is representative of the model behavior.

The above process is repeated for both 8 and 10 September, except that \( x_s \) is a 700-hPa meridional wind
grid point located within the most sensitive region for the 12-h MKE forecast (denoted by dots in Figs. 3a and 3e) and the ensemble is integrated forward 12 h.\(^1\) For 8 September, the results indicate good agreement between the model response and ensemble prediction for perturbations between \(-7\) and \(2\) m s\(^{-1}\) (Fig. 11c). At large \(\alpha\), the model response is less than the ensemble prediction, possibly due to MKE having a lower bound. In contrast, 10 September shows good agreement over all values of \(\alpha\) (Fig. 11d).

Finally, the validity of the initial-condition sensitivities for the 10 September 48-h AEW longitude forecasts is explored by applying perturbations to the midtropospheric \(\theta_e\) and 700-hPa meridional winds in the most sensitive region (denoted by dots in Figs. 8d and 8f). Figure 12 shows that the response of the 48-h AEW longitude forecasts is qualitatively similar to the ensemble prediction of the impacts of \(\theta_e\) and the meridional wind perturbations over much of this range. There is a slight asymmetry whereby positive \(\theta_e\) (meridional wind) perturbations yield position differences that are greater (smaller) than the ensemble prediction.

6. Sensitivity to cumulus parameterization

Given that moist dynamics appear to play an important role in this AEW and that a majority of precipitation is generated by the cumulus parameterization, it is possible that the initial-condition sensitivity to midtropospheric \(\theta_e\) is particular to the Kain–Fritsch scheme. To test this possibility, two sets of 96 member ensemble forecasts are generated from the 10 September analysis ensemble. One set of ensemble forecasts use the Betts–Miller–Janjić (BMJ) cumulus scheme (Janjić 1994), and the second set of forecasts use the Grell–Devenyi cumulus scheme (Grell and Devenyi 2002); all other model settings are kept the same. From each set of ensemble forecasts, the MKE and AEW longitude metrics are calculated and the initial-condition sensitivity is evaluated.

Probability density functions (PDFs) of the MKE and longitude forecasts from these three sets of ensemble forecasts show significant variability arising from using different cumulus parameterizations (Fig. 13). For the 12-h MKE forecast, the PDF for the KF and Grell ensembles peak at \(18\) m\(^2\) s\(^{-2}\) and have a longer positive tail, while the peak in the BMJ ensemble is \(1.5\) standard deviations greater than the other two (Fig. 13a). Moreover, the 12-h accumulated precipitation (averaged over box shown in Fig. 2e) is \(1\) mm higher in the BMJ ensemble.

\(^{1}\) The 12-h forecasts are used here since the ensemble-based sensitivities are generally statistically insignificant beyond this lead time.
The peak in the 12-h AEW longitude PDF is at a similar location for all cumulus schemes, though the Grell (BMJ) is farthest west (east) (Fig. 13b). At 48-h lead time, the peaks in the KF and Grell MKE ensemble PDFs are at 28 m$^2$ s$^{-2}$, compared to 18 m$^2$ s$^{-2}$ for the BMJ ensemble (Fig. 13c). Longitude forecasts show significant variability among the methods, with the Grell (BMJ) peaking at 11.8 W (8.8 W). In addition, the BMJ and KF forecasts have 48-h accumulated precipitation (averaged over the box shown in Fig. 2f) values that are 25% larger than the Grell ensemble; thus, the AEW amplitude is not determined solely by the amount of precipitation. The differences in the forecast metric PDFs show that model formulation errors can also have a large impact on AEW position forecasts, though all three schemes fail to accurately predict the actual MKE and AEW longitude (15 m$^2$ s$^{-2}$ and 16°W, respectively) determined from the verifying-time ensemble-mean analysis.

Figure 14 shows that the 12-h MKE forecast sensitivity is similar for all three cumulus scheme forecasts; however, the same is not necessarily true at hour 48. For 12-h forecasts, the largest sensitivity for the MYJ and Grell MKE forecasts is in western Burkina Faso, west of the AEW, which is similar to the results for the KF.
forecast (cf. Fig. 3g). One-standard-deviation errors in the midtropospheric \( \theta_e \) in this region are associated with a 1.3 (1.8) m\(^2\) s\(^{-2}\) change in the 12-h MKE forecast that employs the BMJ (Grell) scheme (Figs. 14a and 14b). For 48-h forecasts, the BMJ forecast is less sensitive to the \( \theta_e \) on the west side of the AEW as compared to the other forecasts; instead, the region of largest sensitivity to \( \theta_e \) is on the eastern side of the AEW (Fig. 14d). The region of high sensitivity for the Grell ensemble is on the western side of the AEW (Fig. 14e), which is qualitatively similar to the KF results (cf. Fig. 3h). The consistent sensitivity for the KF and Grell schemes suggests that these techniques have a greater memory of the initial-condition errors as compared to BMJ.

In contrast to MKE, the initial-condition sensitivity for AEW longitude demonstrates more consistency among the various cumulus parameterization schemes. The 12-h AEW longitude forecasts are most sensitive to the \( \theta_e \) on the west side of the AEW; increasing \( \theta_e \) by one standard deviation leads to an AEW that is 0.4\(^\circ\) to the west after 12 h (Figs. 15a and 15b); this area is similar to the main region of sensitivity for KF forecasts (cf. Fig. 8e). For 48-h longitude forecasts, the most sensitive region remains along the western side of the AEW. One-standard-deviation errors in this region have the largest (smallest) impacts on the KF (BMJ) longitude forecast.

Finally, the possibility that the initial-condition sensitivity is related to parameterizing cumulus convection is evaluated by generating high-resolution, two-way nested ensemble forecasts initialized from the 10 September analysis ensemble. The two nested domains are shown in Fig. 1 and have 12- and 4-km horizontal grid spacings, respectively. All other model settings are the same as the control ensemble, except that the innermost nest does not employ a cumulus parameterization. For consistency with the previous results, both forecast metrics are computed from the 36-km domain output. For grid points that overlap with the 4-km domain, the 36-km forecast is given by the horizontal average of the 4-km forecast.

Although there are significant formulation differences between the explicit and parameterized forecasts, the MKE forecast PDF from the explicit ensemble is similar to the KF and Grell ensemble (Figs. 13a and 13c). In contrast, the AEW longitude PDF peaks farther west at both 12 and 48 h; thus, the explicit forecast propagates faster than any of the parameterized schemes, though the AEW is still 400 km to the east of the verification position (Figs. 13b and 13d).

Initial-condition sensitivities computed from the explicit convection forecasts show qualitatively similar results to the parameterized convection forecasts. The 12-h MKE and AEW longitude forecasts are sensitive to the \( \theta_e \) on the west side of the AEW; one-standard-deviation errors are associated with 1.8 m\(^2\) s\(^{-2}\) and 0.4\(^\circ\) longitude differences, respectively, which are similar to the cumulus parameterization sensitivity results (Figs. 14c and 15c). At longer lead times, the explicit
forecast initial-condition sensitivities are qualitatively similar to the KF forecast results. Increasing (decreasing) the $u_e$ on the west side of the AEW by one standard deviation is associated with a 2.0 m$^2$s$^{-2}$ increase (decrease) in the 48-h MKE and a 0.78 westward (eastward) displacement in the AEW position, respectively (Figs. 14f and 15f).

7. Summary and conclusions
This manuscript describes the sensitivity of forecasts of a strong AEW to the initial conditions using data drawn from a cycling EnKF system coupled to the WRF model. This EnKF system assimilates conventional in situ observations from surface stations, rawinsondes, ACARS, and cloud motion vectors every 6 h. At two different analysis times representing different points in the AEW’s life cycle, all 96 ensemble members are integrated forward 48 h to provide a sample for initial-condition sensitivity calculations. Whereas the 8 September ensemble forecasts show significant variability among ensemble members, possibly due to the lack of data near the AEW, the 10 September forecasts are characterized by less variability in the AEW evolution.

The sensitivity of the AEW amplitude and position forecasts to the initial conditions is determined via ensemble analysis and forecast data using ensemble-based sensitivity analysis. Short-lead-time forecasts of the meridional wind kinetic energy, which is used as a proxy for AEW amplitude, are most sensitive to the meridional winds within the analysis AEW and to the thermodynamic profile near the AEW, such that a stronger AEW, or higher $u_e$ in the midtroposphere near the AEW, leads to a stronger forecast AEW. In contrast, longer-lead-time forecasts (>24 h) are more sensitive to errors in the downstream $u_e$ field as compared to errors in the meridional wind field. The 8 September forecast, initialized when the AEW is developing, appears to have greater memory of the initial kinematic errors as compared to the 10 September forecast when the wave is mature. Although previous work suggests that AEWs grow by baroclinic and barotropic processes (e.g., Thorncroft and Hoskins 1994), errors in the initial horizontal and vertical shears did not appear to have a large impact on the AEW forecast; initial-condition errors in thermodynamic fields appear to play a greater role in error growth through moist processes.

Diagnostic perturbations in the most sensitive regions are added to the initial conditions to confirm the relationship between initial $\theta_e$ errors and AEW forecasts. For small perturbations to the meridional wind and $\theta_e$, the forecast difference from nonlinear model integrations compare favorably with the ensemble prediction of
how perturbing these fields impacts MKE and AEW longitude forecasts. For large positive $\theta_e$ perturbations, the model response can be greater than the ensemble prediction, which suggests that positive errors lead to nonlinear amplification. The quantitative agreement between the ensemble predictions and actual model differences is similar to the results of Hakim and Torn (2008) and Torn and Hakim (2009b).

Sensitivities are computed for ensemble forecasts that use the same set of initial conditions, but different cumulus parameterizations and a nested ensemble forecast, which uses explicit convection. Whereas the ensemble forecasts using the KF, Grell, and explicit convection schemes showed similar AEW amplitude and position forecasts, the BMJ is more than one standard deviation different. At short lead times, the initial-condition sensitivity for AEW amplitude forecasts is similar regardless of cumulus parameterization scheme. Whereas the 48-h AEW amplitude forecast with the KF scheme and explicit convection show consistent sensitivity to errors in the $\theta_e$ field, BMJ shows less initial-condition sensitivity at longer lead times. In contrast, ensemble position forecasts show consistent regions of sensitivity at all forecast hours and schemes.

These results indicate that moist processes associated with the cumulus parameterization lead to large error growth longer lead times, which result from moist instability errors that ultimately limit the predictability of larger-scale features (e.g., Zhang et al. 2003); other phenomenon driven by diabatic processes have similar sensitivities (e.g., Hawblitzel et al. 2007; Sippel and Zhang 2008). As a consequence, the AEW forecast could benefit from constraining temperature and moisture analysis.

**FIG. 14.** Sensitivity of the 12-h 700-hPa meridional wind kinetic energy forecast averaged over the box for the (a) BMJ, (b) Grell, and (c) explicit forecast ensemble to the analysis of 3000–7000-m $\theta_e$ (shading; units are m$^2$ s$^{-2}$) initialized at 0000 UTC 10 Sep 2006. The contours are the ensemble-mean analysis field (units are K). (d)–(f) As in (a)–(c) but for the 48-h forecast. The gray dashed lines are latitude and longitude every 10°, where the lower-left corner is 0°, 20°W, and the X denotes the initial AEW position.
errors via additional observations, such as from rawinsondes, or from global positioning system (GPS) refractivity profiles (e.g., Anthes et al. 2008), as compared to extra wind data. Tompkins et al. (2005) reached a similar conclusion using the ECMWF four-dimensional variational data assimilation (4DVAR) system.

In addition to showing that errors in the initial thermodynamic fields can impact AEW forecasts, model errors also play an important role. The differences between forecasts with different cumulus schemes are as large as or greater than the span of the ensemble forecasts; thus, refinements to the model, particularly the cumulus scheme, could improve AEW forecasts. Finally, the 8 September results suggest that there could be a subtle interplay between the thermodynamic errors, the Jos Plateau, and the AEW due to the lower barrier to convective initiation over higher terrain. Studies such as Laing et al. (2008) have shown that organized convection over Africa is most frequent over high terrain, which, based on these results, could have a modulating impact on AEWs. The role of topography in the initiation and predictability of AEWs will be explored in future research.

Acknowledgments. A portion of this work was done as a postdoctoral fellowship in the NCAR Advanced Study Program, whose support is greatly appreciated. I would like to thank Jeff Anderson (NCAR), Gareth Berry (University of Albany), Chris Snyder (NCAR), Chris Thorncroft (University of Albany), and Morris Weisman (NCAR) for providing feedback on this work. Nancy Collins and Kevin Raeder provided support on using the WRF-DART system. Two anonymous reviewers provided valuable comments to improve this manuscript. I also acknowledge the high-performance computing support provided by NCAR’s Computational and Information Systems Laboratory, sponsored by the National Science Foundation. This work is partially supported by the College of Arts and Sciences at the University at Albany, State University of New York.
REFERENCES


