

Evaluating the potential impact of lightning data assimilation utilizing hybrid variational-ensemble methods

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DA & Model System Set-up Introduction & Goals WRF-NMM, resolution --- 27 and 9km This study demonstrates the utility of assimilating lightning data from the GLM instrument onboard the future GOES-R for severe weather The Maximum Likelihood Ensemble Filter (MLEF) is used as a hybrid variational-ensemble DA system applications Proxy lightning DA into a NWP model with a hybrid variational-ensemble 32-ensembles at 6-hr assimilation interval DA system is investigated Lightning data from the World Wide Lightning Location Network (WWLLN) -- 10km Case Study: April 28-29, 2011 tornado outbreak - Southeastern, United States (Tuscaloosa, Alabama) Control variables: T, Q, U, V, PD, PINT, CWM The goal is to correct the intensity and location of severe thunderstorms 2 experiments with lightning data assimilation (LIGHT) and without data assimilation (NODA) during the analysis and short-time (6-hr) forecast steps Lightning Observation Operator Observation Operator Correction Starts by calculating Assume a multiplicative correction maximum vertical velocity to the lightning observation operator (w_{max}) from WRF-NMM $\rightarrow \alpha h(x),$ where α is the unknown multiplication parameter $\frac{1}{2} + v \cdot \nabla_{\sigma} \Phi + \sigma \frac{\partial}{\partial}$ The cost function will have an adjustable parameter $\alpha > 0$ An empirical relationship w..... = 0 $[\alpha] = \frac{1}{2} \left[\log(\alpha) - \log(\alpha_0) \right]^T W^{-1} W^{-1} \left[\log(\alpha) - \log(\alpha_0) \right]^T W^{-1} W^{-1}$ between lightning flash rate $\frac{1}{2}[\log(y) - \log(\alpha h(x))]^T R_L^{-1}[\log(y) - \log(\alpha h(x))]$ and vertical velocity is used • Where R_{L} = obs. error covariance, α_{0} $f = c\alpha_{opt} w_{max}^{\beta}$ = guess value, W = guess uncertainty Figure 2. PDF Innovations – histograms, before and after correction. Before correction (left), the innovation vector was skewed and positively biased. After correction (right) it was normalized. matrix c=5e⁻⁶, α_{opt} = correction parm., β = 4.5 Search for the optimal parameter α_{opt} > 0 that minimizes the cost function Flow diagram of the $\sum_{k=1}^{N_{\text{obs}}} \log \left(\frac{y}{h(x)} \right)$ MLEF DA system and Obs With a typical guess value of α₀= 1, the (1)solution becomes (1), where $N_{obs} = #$ of r_0 Opt. shown in Figure 1 Figure 1. Flow chart of the MLEF DA system and lightning observation operator 1 +observations, $diag(R_L)=r_0$ and $diag(W)=w_0$ _ _ _ _ _ -_ _ _ _ ESU R Synoptic Representation Rodgers Information Content of Observations The following contour plots, correspond to the LIGHT experiment Use information theory (e.g. entropy) as an objective, pdf-based at April, 28 0000UTC, the touch-down time of the Tuscaloosa, quantification of information (Rodgers 2000; Zupanski et al. 2007); Alabama tornado Change of entropy due to observ H assumes a Ga $\Delta H = d_x = trace \left[I - P_a P_f^{-1} \right]$ $H{X} = -\int p(x)\log(p(x))dx$ $\Delta H = H \{X\} - H \{X \mid Y\}$ The region of strongest winds (Fig. 3a) coincides with the area ethods d, can be computed ex rtly in ensemble su $d_x = \sum \frac{\lambda_1}{1 + \lambda_1^2}$ $P_{i} = P_{i}^{1/2} (I + Z^{T}Z)^{-1} P_{i}^{T/2}$ $Z = R^{-1/2} H P_e^{1/2}$ $Z^T Z = U \Lambda U^T$ where the lightning observations are located (Fig. 7b) (ellipses) By assimilating lightning, the analysis increased making advection Figure 4. (a) background and (b) observed CAPE (LIGHT experiment) and absolute vorticity at 850mb go up (Figure 3b.c) Statistics The wind difference, suggests that stronger vorticity is being RMS errors are calculated from a super-obed advected into the region of high CAPE gradient (dry-line) (Figure 4) domain containing all the lightning observations at 10km resolution CAPE at forecast, exists in the place of observed strong CAPE gradient (Figure 4) From Figure 5a,b, LIGHT achieves a better fit in Figure 6. Rodgers information content during cycles 3, 5 and 7 the assimilation, only partially kept in the forecast Time-dependent covariance P^f shows direct relationship to obs. Improving dynamical balances could positively WWI LN Liebtning Obe MANULAULO impact forecast RMS errors 01.5 MODA

Figure 5. Analysis (a) and (b) observed CAPE (light experiment)

Summary & Future Work

- The assimilation of lightning data adds new information to the system
- Lightning DA impacts winds, advection and absolute vorticity

Figure 3. (a) Background winds at 850mb, (b) wind difference [A-B] and (c) absolute vorticity difference [A-B] (LIGHT)

- Time-dependent forecast error covariance (P_f) follows the observations throughout the assimilation period
- Will include operational observations to constrain the fit in the
- analysis and to test combined GLM and ABI observations from the future GOES-R

Acknowledgements & References

Figure 7. Lightning observations during assimilation cycles 3, 5 and 7

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