Variational data assimilation of lightning with WRFDA system using nonlinear observation operators

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- Fundamental research in numerical methods and develop novel algorithms for the adaptive solution of ordinary and partial differential equations, linear algebra, optimization, data assimilation, methods to model systems with uncertainty, reduced order modelling, etc.
- Modeling of atmospheric pollution for better environmental policies, design of optimal trajectories for the future generation of satellites at Jet Propulsion Laboratory, assimilation of real data streams into atmospheric models for improved forecasts of extreme events like hurricanes, etc.
- Data Assimilation: Strong and Weak Constraint 4D-Var, Hybrid Ensembles
- A-posteriori error estimates for inverse problems and reduced order inverse problems.
Outline

Introduction

Present lightning data assimilation effort

Results

Conclusions
Our work addresses the impact of assimilating data from the Earth Networks Total Lightning Network (ENTLN) during two cases of severe weather: a supercell occurring predominantly in Mississippi and Alabama on 27 April 2011, and a squall line that initiated in Kentucky and Tennessee and later spread to coastal South Carolina and Georgia on 15 June 2011.

Data from the ENTLN at 9km resolution serve as a substitute for those from the upcoming launch of the GOES Lightning Mapper (GLM).

Weather Research and Forecast (WRF) model and variational data assimilation techniques at 9 km spatial resolution - 3D-VAR, 1D+nDVAR (n=3,4); a highly non-linear observation operator based on convective available potential energy (CAPE) as proxy.
Previous lightning data assimilation efforts

- Alexander et al. (1999) used data derived from spaceborne and lightning-derived rainfall measurements to improve simulated latent heating rates.


- EnKF (Hakim et al. 2008) - Lightning data used as a proxy for convective rainfall. Hybrid Variational ensemble data assimilation using WRF - NMM model (Zupanski, 2010).

- Fierro et al. 2013 recently implemented an explicit lightning physical package within WRF using a bulk lightning model (BLM) based on charging of hydrometeors, polarization of cloud water and exchange of charge during collisional mass transfer.
Present lightning data assimilation effort

\[ H(X) = 5 \cdot 10^{-7} \cdot (0.677 \cdot \sqrt{2 \cdot CAPE} - 17.286)^{4.55} \]

- Price and Rind (1992) and Barthe et al. (2010)
- The input \( X \) consists of one dimensional vertical arrays of pressure, temperature, water vapor mixing ratio, and geopotential height.
- Parcel theory: If a parcel near the surface becomes warmer than its environment, it becomes buoyant and is more likely to reach its level of free convection (LFC), form a cloud, and possibly produce lightning.
- Approach: the VA schemes adjust the vertical temperature profile at each grid point where innovation vectors are positive.
- If the model simulated lightning via CAPE is greater than observed non-zero flash rate, we rejected the observation.
The incremental approach is designed to find the analysis increment $\delta x = X - X^b_0$ that minimizes

$$J(\delta x) = \frac{1}{2} \delta x^T B^{-1} \delta x + \frac{1}{2} \sum_{k=1}^{N} (d_k - H_k M_k \delta x)^T R_k^{-1} (d_k - H_k M_k \delta x)$$

$R_k$ is the observation error covariance matrix, $B$ contains the background error covariance matrix, $d_k = Y_k^0 - H_k M_k X^b_0$ are the innovation vectors.

$M_k(X_0) = M_{0 \rightarrow k}(X_0)$; $M_k$ and $H_k$ denote the tangent linear versions of the forecast model and observation operator.
Methodology for lightning assimilation

- The direct assimilation of lightning is restricted by tangent linear assumption.
- The algorithm performs better where there is at least a small amount of CAPE in the model background (otherwise the lightning sensitivities are close to zero).
- We estimated $\mathbf{B}$ using ensemble statistics and vertical and horizontal error covariances are represented by empirical orthogonal functions and a recursive filter.
- The lightning observations were assumed to be uncorrelated. The observation error covariance matrix is diagonal.
1D+nDVAR (n=3,4)

▶ (1D-VAR): the raw lightning measurements are used to produce increments of temperature that are added to the model background to generate column temperature retrievals;(nD-VAR): these temperature pseudo observations are assimilated as conventional observations into the variational WRFDA systems.

▶ The NMC method (Parrish and Derber (1992)) - B for temperature profiles. We used 12 h and 24 h forecasts valid at the same time from a one month dataset generated by the WRF model.

▶ Quasi-Newton limited memory conjugate gradient, was employed to generate the 1D-VAR analysis.

▶ Advantages: additional quality control tests, better handle the less linear inversion problem, present 'smooth' pseudo observations to nD-VAR.
NWP model

- Non-hydrostatic WRF model V3.3 with ARW core.
- Outer domain with 27 km horizontal grid spacing and a 9 km horizontal grid spacing covering a two way nested inner domain of approximately \(1413 \text{ km} \times 1170 \text{ km}\) for both storm events. 60 vertical levels were selected to cover the troposphere. The grid size of the 9km model domain is \(157 \times 130 \times 60\).
- For initial and boundary conditions the NCEP Global Forecasts System (GFS) 1 degree resolution final analyses were used.
- Kain-Fritsch cumulus parameterization, Yonsei planetary boundary layer scheme, rapid radiative transfer model (RRTM), Dudhia scheme and a single moment, 6 class, cloud microphysics scheme.

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Results

- All of the simulations included 6 h of model spin up between 1200 UTC and 1800 UTC, after which lightning assimilation began with an assimilation window varying between 2 to 6 h. The simulations then were run an additional 3 – 7 h without assimilation, ending at 0300 UTC of the next day.

- Two control variable settings: 1. unbalanced temperature (configuration I - C1); 2. unbalanced temperature, stream function, unbalanced velocity potential, unbalanced surface pressure, and pseudo relative humidity (configuration II - C2).

- 3D-VAR and 1D+3D-VAR schemes: a cycling procedure was adopted to assimilate the lightning observations between 1800 UTC and 0000 UTC.

- The first guesses were obtained by integrating the previous 3D-VAR analysis 1 h in time using the WRF model.

- 1D+4D-VAR scheme: we used a 2 h assimilation window between 1800-2000 UTC.
Figure: Average vertical increments of temperature (K) for the successful 1DVAR retrievals at 1800 UTC on 27 April (left) and 15 June (right).
Results

Figure: Innovation vectors (flashes $(9\text{km})^{-2}\text{min}^{-1}$) before (left) and corresponding increments of CAPE (right; $J\text{kg}^{-1}$) following 3DVAR lightning assimilation at 1800 UTC 15 June.
Results

Figure: Skew-T diagrams (left, no lightning; right, after 3DVAR assimilation of lightning) at 1800 UTC 15 June at the location of greatest change in CAPE observed in central Florida with air temperature (°C, black line), dew point temperature (°C, blue line), and horizontal wind (kt, barbs along right axis).
Figure: Simulated radar reflectivity (dBZ) at 2010 UTC 15 June
**Figure:** 1 h precipitation (mm) ending at 2000 UTC 27 April from the control run, various assimilation procedures, and stage IV precipitation.
Results

Figure: 1 h precipitation (mm) ending at 2000 UTC 15 June from the control run, various assimilation procedures, and stage IV precipitation.
Results

Figure: RMSE of precipitation (mm) for both study days compared with stage IV observations. Assimilation was not performed after 2000 UTC for the 1D+4D-VAR simulation, and not after 0000 UTC for the 3D-VAR and 1D+3D-VAR approaches.
Conclusions

- 3D-VAR and 1D+nD-VAR (n=3,4), have been developed to assimilate lightning data into WRF.
- Hourly precipitation patterns, its statistics, and radar reflectivity were improved by assimilating the lightning observations.
- The 1D+4D-VAR approach performed best, improving the precipitation areas and totals by 25% and 27.5% compared to the control run on the two days that were studied during the assimilation window.
- RMSE of the 1D+4D-VAR simulations were the smallest during a subsequent 7 h forecast period on 15 June. However, on 27 April the 1D+4D-VAR forecasts outside the assimilation window were not improved.
Conclusions

▶ We tested two control variable configurations.
▶ The number of observations assimilated by the proposed methods can be increased by including observations that have negative innovation vectors.
▶ A nudging scheme that would artificially increase background CAPE to an amount that allows the observation operator to sustain the lightning data assimilation would increase the number of 1D-Var successful retrievals.
▶ Results of the 1D+4D-VAR lightning assimilation and short term forecasts indicate improvements in precipitation scores and show promise for operational implementation.