Data Assimilation of Lightning in WRF 4-D VAR Using Observation Operators and 1-D. 4-D VAR

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Outline

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GOES - R Lightning Mapper (GLM)

- Optical detector to sense
- Intracloud (IC) lightning
- Cloud to ground (CG) lightning
- The GLM will detect both IC and CG, but will not distinguish between them
- 90% detection rate
- To be launched during $\approx$ 2015

Previous lightning data assimilation efforts

- Newtonian Nudging (Fita et al 2009, Pessi and Businger 2009 - empirical relationship between lightning and convective rainfall, Papadopulos et al. 2009; MM5, ECMWF; Mansell et al 2007 - flash data used as a proxy for the presence or absence of deep convection).
- EnKF (Hakim et al. 2008) - Lightning data used as a proxy for convective rainfall.
- Hybrid Variational ensemble data assimilation using NOAA WRF - NMM model (Zupanski, 2010).

Present lightning data assimilation effort

- Our research will use 4-D VAR data assimilation technique to assimilate lightning into numerical models (WRF) using proxies such as temperature lapse rate, rainfall rate or other physical storm parameters
- National Lightning Detection Network (NLDN), Lightning Mapping Array (total lightning detection), Vaisala GLD360 system and the World Wide Lightning Location Network (WWLLN)
- Assimilation of lightning data into tropical cyclone models, mid-latitude cyclones, severe storms over the U.S.
- NLDN only gives data over the U.S, Canada and a few hundred km offshore.

Present lightning data assimilation effort

- The new Vaisala GLD360 system and the World Wide Lightning Location Network (WWLLN) give world-wide coverage, but their detection efficiencies are much worse than the NLDN. NLDN and these two networks only give CG data (and the strongest of the IC flashes if close enough to a sensor). Therefore, we will have to adjust the NLDN data to give total lightning.
- If we use GLD360 or WWLLN away from the U.S. we will first have to adjust to give the proper number of CG flashes and then adjust them to give total lightning.

Present lightning data assimilation effort

- For WRF to assimilate lightning our choice depends on the horizontal resolution of the WRF.
- If we choose a mesh which is cloud resolving, we can calculate flash rates based on ice fluxes. These are the approaches described by Barthe, C., Deierling, W., Barth, M.C.,2010.
- We want to exploit (as in Barthe et al, 2010) the strong linear correlation between the updraft volume with vertical velocity $\mathrm{w} > 5\mathrm{m\ s}^{-1}$ and the total lightning flash rate as well as between maximum vertical velocity and the total flash rate.

Present lightning data assimilation effort

- $f = 6.75 * 10^{-11} w_s - 13.9 (\mathrm{linear\ correlation})$, with w_s - updraft volume (m^3) above the -5^o Celsius isotherm with vertical velocity $> 5\mathrm{m\ s}^{-1}$ and f being the flash rate.

- $f = 5 * 10^{-6} * w_{max}^k$, with w_{max} - the maximum vertical velocity

Present lightning data assimilation effort

- So we will link the maximum verical velocity with w_{max} to the lightning flash rate and then translate it in temperature lapse rate using CAPE(Convective available potential energy)

$$w_{max} = \sqrt{2 * CAPE},$$

according with parcel theory, so we have to adjust for entrainment.

$$\mathrm{CAPE} = \int_{z_g}^{z_n} g \frac{T_{\mathrm{parcel}} - T_{\mathrm{env}}}{T_{\mathrm{env}}} dz,$$

with T_{parcel} the virtual temperature of the specific air parcel, T_{env} the environment temperature, z_f and z_n the heights of free convection and that of equilibrium (neutral buoyancy)

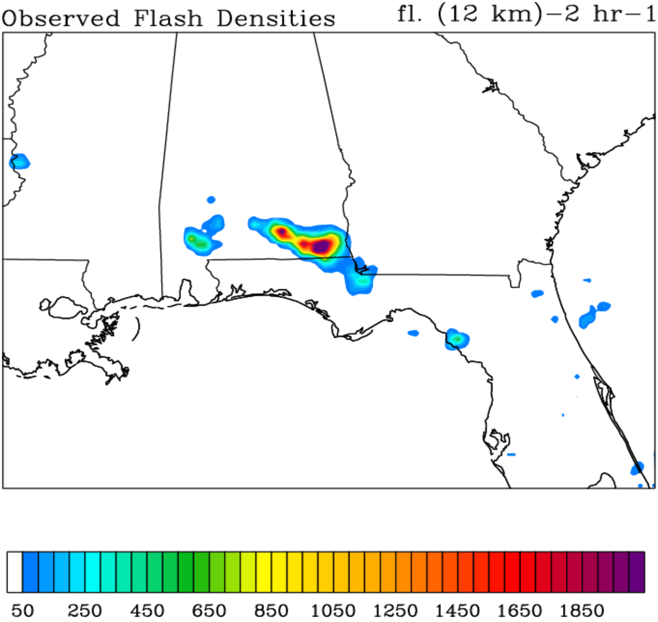
Present lightning data assimilation effort

- In the sequel we describe a short experiment in which we determined correlation coefficients between flash rate coming from NLDN (06/30/2004 - 24 hours) and w_s(updraft volume) and w_{max}(maximum vertical velocity) obtained from WRF model.
- The NLDN flash rate observations are given on a 12 km spacing grid situated in the South-East part of the U.S.
- The chosen WRF domain has a resolution of 3 km and is positioned inside the NLDN domain.

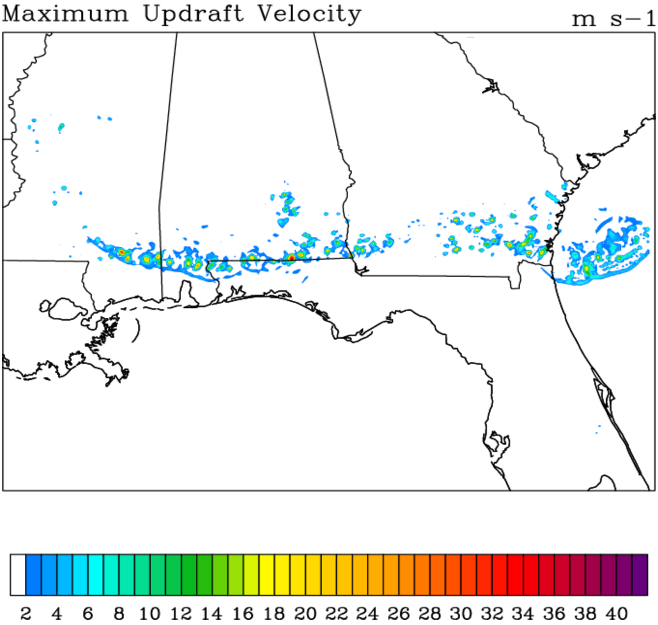
Present lightning data assimilation effort

- We interpolate the observations to the WRF domain grid points using the inverse distance weighting method and the Haversine formula for calculating the distance between points.
- We obtained very poor correlation coefficients between data in contrast with the results obtained by Barthe et al, 2010.
- This differences may be explained by model errors.

Present lightning data assimilation effort



Present lightning data assimilation effort



1D + 4D -VAR approach

- 1-D+4-D VAR technique of Mahfouf (2002, 2003), Mahfouf et al. (2005), Bauer et al. (2006a, 2006 b)
- Once we established the proxy to a model state variable (temperature) we start considering a 1-D VAR problem.

Let X be a vector representing atmospheric state

$$X = (t, P_s, q)$$

and F_{0i} a set of observations with errors σ_{0i}.

Let $F_i(x)$ be an observation operator generating the needed flash rate.

1D + 4D -VAR approach

The optimum profile X minimizes a cost function of the form:

$$J(X) = \frac{1}{2}(X - X_b)^T \mathbf{B}^{-1}(X - X_b) +$$

$$+\frac{1}{2}\sum_{i=1}^{n}\left(\frac{F_i(X) - F_{oi}}{\sigma_{oi}}\right)^T \mathbf{R}^{-1}\left(\frac{F_i(X) - F_{oi}}{\sigma_{oi}}\right),$$

$$\nabla J(X) = \mathbf{B}^{-1}(X - X_b) + \sum_{i=1}^{n}\mathbf{F_i^T}\mathbf{R}^{-1}\left[\frac{F_i(X) - F_{oi}}{\sigma_{oi}^2}\right],$$

1D + 4D VAR approach

- $\mathbf{B}$ background-error covariance matrix
- X_b background state obtained usually from previous short forecast.
- $\mathbf{R}$ observation-error covariance matrix
- $\mathbf{F_i^T}$ is the adjoint of the Observation Operators

1D + 4D VAR approach

- Use 1-D VAR to adjust the temperature profile which modifies the CAPE.
- Consider the 1-D VAR temperature profile as new observations and assimilate them in 4-D VAR (or incremental 4-D VAR).
- This approach minimizes problem that nonlinearities in the most convective scheme can introduce discontinuities in the cost function between inner and outer loops of the considered incremental 4-D VAR.

Non-smooth observation operators using non-smooth large-scale optimization

- A new approach is to allow discontinuities in the observation operator (or the cost function) by using non-smooth nondifferentiable large - scale minimization algorithm (Haarala 2008) LMBM (limited memory bundle method).
- Consider cost of nonsmooth optimization vs the linearization or regularization of the cost functional.(Lopez 2009 ECMWF)

Non-smooth observation operators using non-smooth large-scale optimization

- The issue of data assimilation with discontinuous observation operators is relevant to many outstanding data assimilation problems.
- For example, the data assimilation of "all-sky" satellite radiance observations, which may or may not be acted by clouds, has a discontinuous observation operator with respect to cloud microphysical variables (M. Janiskova, J. F. Mahfouf, J. J. Morcrette, and F. Chevallier,R. M. Errico, P. Bauer, and J. F. Mahfouf.)

Non-smooth observation operators using non-smooth large-scale optimization

- As in Baurer et al (2006a, 2006b), we mention that observation operators like in our case may require more input variables than there are contained in the control vector X.
- Since the operator is applied within incremental variational assimilation systems it is fundamental to ask how linearly the observation operator behaves.
- The linearity tests are based on comparing the output of the tangent-linear model with those from finite-difference calculations using the forward model.

Non-smooth observation operators using non-smooth large-scale optimization

- One may look at the ratio

$$F = \frac{H(x + \lambda\delta x) - H(x)}{\lambda H(\delta x)}$$

  where δx represents the initial perturbation of the control vector and λ a scaling factor ranging from 10^{-10} to 10^{-1}.
- In the linear case, scaling of the output of the tangent-linear model should produce the same result as the scaling of the input to the forward model.
- The δx should be realistic because, theoretically, δx could be chosen too small so that even rather nonlinear models show a nearly linear performance.