

Data Assimilation of Lightning in WRF 4-D VAR using observation operators

H. Fuelberg and I. M. Navon

February 24, 2011

Florida State University, Tallahassee, Florida

hfuelberg@fsu.edu, inavon@fsu.edu

- 1 GOES - R Lightning Mapper (GLM)
- 2 Previous lightning data assimilation efforts
- 3 Problems with using (assimilating) lightning observations using proxies
- 4 1D + 4D -VAR approach
- 5 Experimental non-smooth observation operators (using non-smooth large-scale optimization)
- 6 Assessment and Validation against other assimilation methods
- 7 Consider image data assimilation in future research

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

- EnKF (Hakim et al. 2008) - Lightning data used as a proxy for convective rainfall.
- Improvement to predicted intensity + location of extratropical cyclones.
- Newtonian Nudging (Pessi and Businger 2009, Papadopoulos et al. 2009).
- Hybrid Variational ensemble data assimilation using NOAA WRF - NMM model (Zupanski, 2010).

Present lightning data assimilation effort

- Present research will utilize a form of 4-D VAR to assimilate lightning into numerical models (Total lightning data) using proxy rainfall rate (or other physical storm parameters if using cloud resolving WRF version).
- Use the National Lightning Detection Network (NLDN) to assimilate lightning data into tropical cyclone models, mid-latitude cyclones (e.g., over the North Pacific) as well as severe storm cases 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. All three schemes 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.

Various WRF scenarios

- For WRF to assimilate lightning our choice depends on the horizontal resolution of the WRF.
- If the mesh resolution is about 10 km—then we can calculate flash rate from WRF generated cloud tops. using the approach based on Futyan and Del Genio (GRL, 2007).
- If the mesh 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
- Once we get WRF-derived flash rates, we can assimilate the observed flash rates (NLDN, GLD360, or WWLLN) to get an improved lightning field. Then, we use the proxy of rain rate (or something else).
- NCAR has developed a simple-physics adjoint of the WRF

Data Assimilation of Lightning Data

- 1-D+4-D VAR technique of Mahfouf (2002, 2003), Mahfouf et al. (2005)

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 providing equivalent data for variable X .

Data Assimilation of Lightning Data

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

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

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

Data Assimilation of Lightning Data

where \mathbf{F}^T is the transpose of the Jacobian matrix

$$\left[\frac{\partial F}{\partial x_j} \right],$$

and it can be obtained either explicitly from calculation based on small perturbations or using the adjoint.

Here the observation operator is identified with the physical parametrization.

1D + 4D VAR approach

- Use 1-D VAR to adjust rainfall rate from moist physics (mass flux convection scheme and large scale condensation).
- Consider the 1-D VAR Total Column Water Vapor (TCWV) retrievals as new observations and assimilate them in 4-D VAR (or incremental 4-D VAR).
- This approach minimizes problem that nonlinearities of the most convective scheme can introduce discontinuities of cost function between inner and outer loops of the considered incremental 4-D VAR.

1D + 4D VAR approach

- 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.
- Consider cost of nonsmooth optimization vs the linearization or regularization of the cost functional.(Lopez 2009 ECMWF)

Non-smooth observation operators

- 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.)

Nonsmooth observation operators

The observation operator is given by

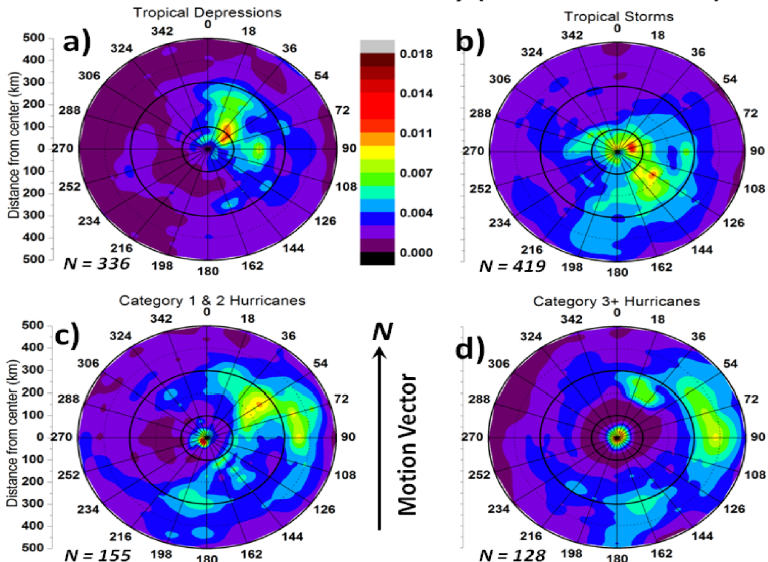
$$\mathcal{H}(x_i) = \begin{cases} \mathcal{H}_1(u_i) & 1 \leq i \leq MN \\ \mathcal{H}_2(v_{i-MN}) & MN + 1 \leq i \leq 2MN \\ \mathcal{H}_3(\phi_{i-2MN}) & 2MN + 1 \leq i \leq 3MN \end{cases} \quad (11)$$

$$\mathcal{H}_1(u_i) = \begin{cases} u_i^3/u_{min}^2 & u_i < u_{min} \\ u_i^2/u_{max} & u_i \geq u_{max} \\ u_i & \text{else} \end{cases} \quad (12)$$

$$\mathcal{H}_2(v_i) = v_i \quad (13)$$

$$\mathcal{H}_3(\phi_i) = \begin{cases} \phi_i & \phi_i < H_{max} \\ \phi_i^2/H_{max} & \phi_i \geq H_{max} \end{cases} \quad (14)$$

Storm-relative Flash Density (flashes $\text{km}^{-2} \text{6 h}^{-1}$)



Explanations of the Picture

- It is based on 45 tropical cyclones over the Atlantic Basin between 2004 through 2008. Only CG lightning is detected.

We examine 6 hourly intervals

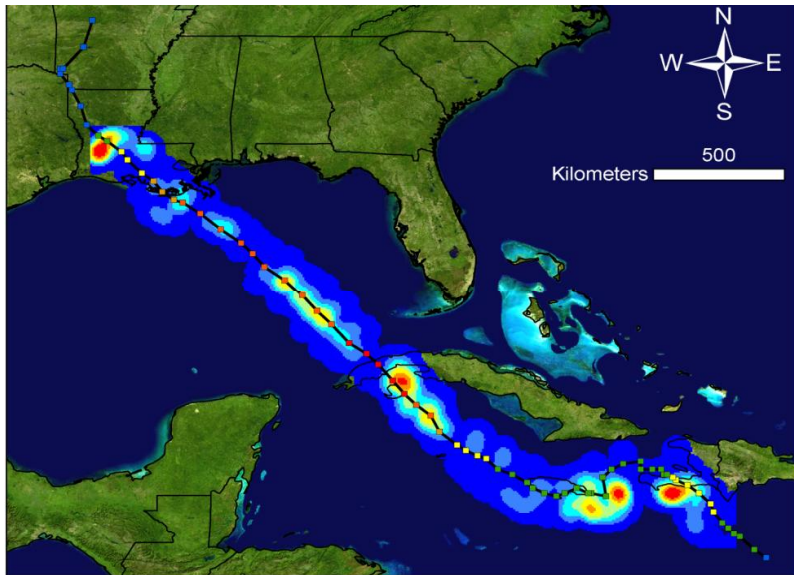
- a) 336 6h positions of tropical depressions
- b) 419 6h positions of tropical storms
- c) 155 6h positions of Category 1-2 hurricanes
- d) 128 6 h positions of Category 3,4,5 hurricanes

Explanations of the Picture

- The lightning was plotted with respect to storm motion—extending from the eye out to a radius of 500 km. The inner core lightning is best defined for Cat 3+ storms. Most lightning for all categories is located in the right front and right rear quadrants. And, the stronger the storm, the more organized the lightning patterns are.

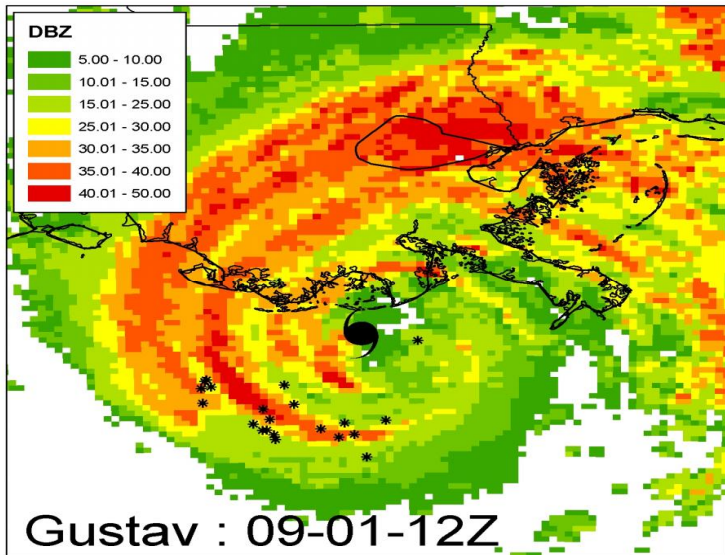
Flash Density Within 100 km of Gustav (2008)

Vaisala Long Range Data Little lightning at landfall



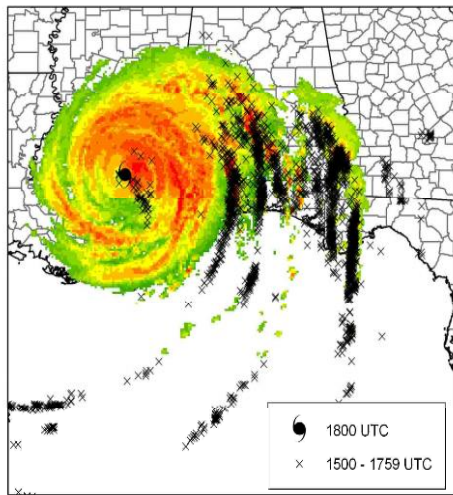
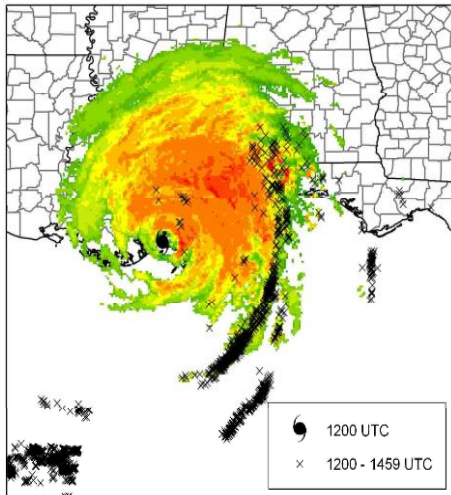
Flash Density Within 100 km of Gustav (2008)

Close up at landfall Only scattered lightning * over Gulf



CG Lightning in Katrina

Mostly in rainbands, but some inner core



Pictures Explanations

- It is a time series for Gustav (2008).
- It also includes a close up at landfall when there is very little lightning. The third slide is for Katrina at landfall. Contrary to Gustav, there is much lightning at landfall, but most is in the rainbands—some is quite distant from the eye.

Assimilation of Images

- Lagrangian information: the movement of fronts and vortices give information on the dynamics of the fluid. Presently this information is scarcely used in meteorology by following small cumulus clouds and using them as Lagrangian tracers, but the selection of these clouds must be done by hand and the altitude of the selected clouds must be known, done by using the temperature of the top of the cloud.
- Basic Technique: a) from images deduce pseudo-observation as the velocity of the flow, then assimilate these data as pseudo observations using a regular variational data assimilation scheme.

Assimilation of Images

- b) Consider "objects" in the images (fronts, vortices) then compare with the same objects created by the model and inject them into a scheme of assimilation which takes them into account.

Third Approach: direct assimilation of images

Images are considered as observations of the state variables:

Observation operators

- Classical (“physical”) observation operator:
 $H_{P \rightarrow P}$: maps the space of state variables onto the space of observed state variables \mathcal{O}_P
- “Image” observation operator:
 $H_{P \rightarrow I}$: maps the space of state variables onto the space of images \mathcal{O}_I
Constructs an image from model outputs (synthetic image)

Extended cost function

$$J = \frac{1}{2} \int_0^T \|H_{P \rightarrow P}[X] - X_P^{obs}\|_{\mathcal{O}_P}^2 dt + \frac{1}{2} \int_0^T \|H_{P \rightarrow I}[X] - I^{obs}\|_{\mathcal{O}_I}^2 dt$$