An Algorithm to Nowcast Lightning Initiation and Cessation in Real-time

An Data Mining Model

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The Big Picture

Focus is on creating a 30-minute nowcast field

- Cloud-to-ground lightning from NLDN
- Use radar, RUC, satellite products to train neural network
  - CONUS 1-km resolution WDSS-II products
  - NOT pixel-by-pixel ...
- Run NN in real-time and advect results

Evaluate against a steady-state prediction with motion correction.

Motivation

Difficult:

- tied to problems of determining convective initiation.
- location subject to knowledge of how lightning travels within storm.

Important:

- Potent weather-related hazard
- Spatial and temporal resolution desired in warnings
- Short-term warning has a potential to become valuable NWS product

Goal

At a particular location, we seek to estimate the **probability** that there will be **a C-G lightning strike** at that position in the next 30 minutes.
Not intensity of lightning; simply its occurence

State of the field

- Rules of thumb
- Use model forecasts to lightning potential [Keller, 2004] – not at nowcasting time scale
- Use NN to forecast lightning at 22-km resolution – not at nowcasting spatial scale [Burrows et al., 2005]

Data Mining

One advantage of cloud-to-ground lightning is that it is a hazard that is observed in real-time. Easy to train a data mining approach ...

If a system can be trained on input spatial grids of reflectivity and VIL at t_{-30min} to predict the cloud-to-ground lightning activity that is observed at t_0, it should be possible to use that system on the set of input spatial grids at t_0 to predict the lightning activity at t_{30min}.

Pixel-to-pixel

Straight input-output mapping to train NN works at a 22 *km* resolution [Burrows et al., 2005].
At 1 *km* resolution, this approach will not work.

- Storms move. VIL at x_i, y_i, t_{-30min} was an indicator of lightning activity not at x_i, y_i, t_0 but at $x_i + u_i\delta t, y_i + v_i\delta t, t_0$ where u_i, v_i is the motion of the storm at x_i, y_i.
- Target lightning field t_0 needs to be advected backwards before training the engine using inputs and outputs at x_i, y_i.
- Reflectivity at -10^oC leading indicator but not neccessarily at the location of the overshooting top.
- Lightning activity often in anvil region (where refl is low)

Lightning Density

Lightning flashes within 3km of grid center in the past 15 minutes

The t_{30min} lightning density grid was advected backward 30 minutes and used as one of the inputs to the attribute extraction algorithm.

Input Predictors

Following [Hondl and Eilts, 1994, Watson et al., 1995]:

1. Reflectivity isotherm values at 0^oC, -10^oC and -20^oC.
2. Vertical Integrated Liquid (VIL), estimated from multiple radars [Greene and Clark, 1972, Kitzmiller et al., 1995].
3. Layer averages of reflectivity between -20^oC and 0^oC.
4. Maximum VIL and Reflectivity of the storm over its life cycle
5. Increase over time of VIL and Reflectivity isotherms
6. Size and aspect ratio of the storm
7. Speed at which the storm is moving
8. Current lighting density

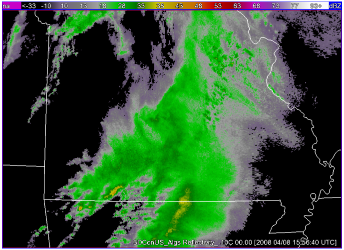
Other fields (CAPE, LclHeight, Satellite IR, etc. also used, but not very useful)

Technique

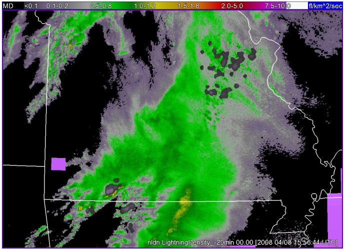
1. identify storms from remotely sensed images
2. estimate the motion of these storms
3. use the spatial extent of the storms and their movement to extract geometric, spatial and temporal properties of the storms
4. In training, use observed lightning density from 30 minutes later advected backwards by 30 minutes as the ”target” or ideal lightning density. Accumulate all such training ”patterns” and train a neural network to carry out the prediction
5. In real-time, provide the geometric, spatial and temporal properties of the storms to the neural network to generate a predicted lighting density. Advect this predicted lighting density field forward by 30 minutes to create nowcast

Does reverse advection work?

But will this work?



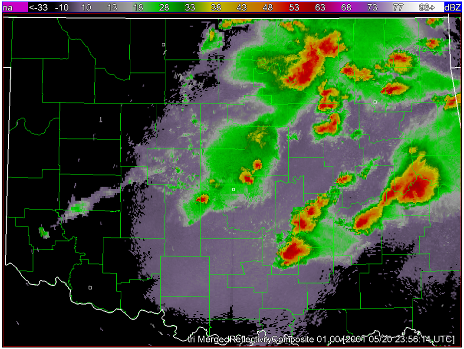
Ref at -10^oC



LightningDensity$_{-30min}$ overlaid

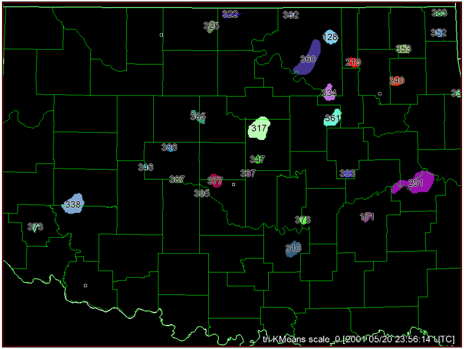
Data from April 8, 2008 over Missouri

Identifying Storms



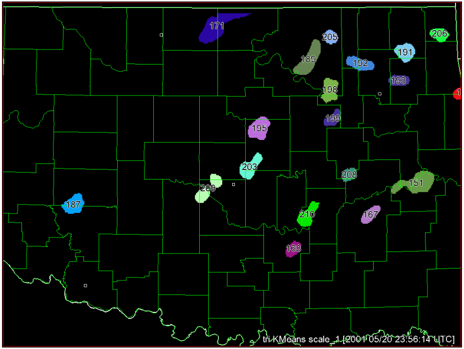
Z

Identifying Storms



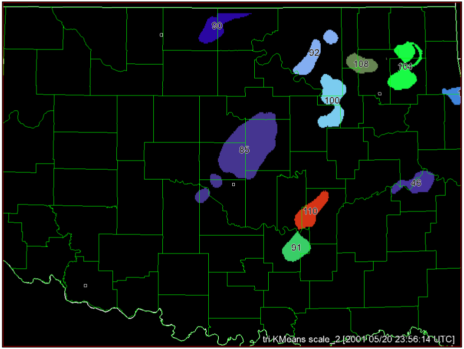
$20km^2$

Identifying Storms



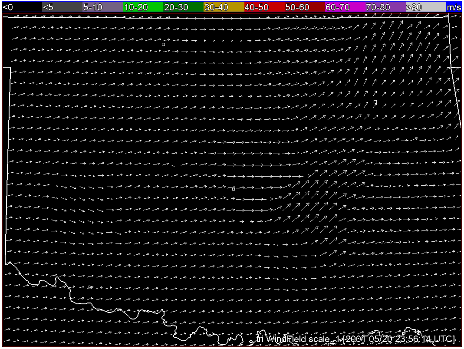
$160 km^2$

Identifying Storms



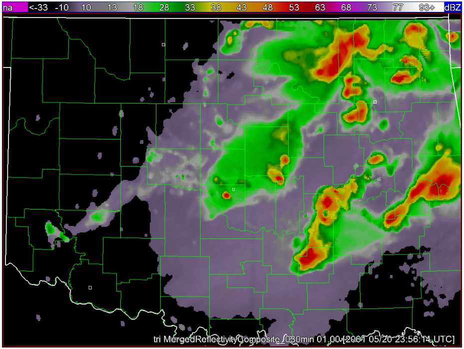
$480 km^2$

Identifying Storms



Motion vector

Identifying Storms



30-minute nowcast

Spatial attributes

Multi-radar spatial grids of VIL and reflectivity isotherms are created using the techniques described by [Lakshmanan et al., 2006].
Given a spatial grid of VIL, the maximum VIL within the j^{th} cluster could be expressed as:

$$VIL_{cluster_j} = max_i(VIL_{x_i,y_i} | x_i, y_i \epsilon cluster_j) \tag{1}$$

Increase/decrease in VIL

A potential indicator for lightning initiation/decay is the rate of increase or decrease of VIL.

$$\begin{aligned}\delta_{VIL,cluster_j} = \quad & max_i(VIL_{t_0,x_i,y_i}|x_i, y_i \epsilon\ cluster_j, t_0) - \\ & max_i(VIL_{t_{-1},x_i-u_i*(t_0-t_{-1},y_i-v_i*(t_0-t_{-1})}| \\ & \qquad x_i, y_i \epsilon\ cluster_j, t_0))\end{aligned} \tag{2}$$

Relies only on the clustering of the current field, and not on the clustering of the previous frame.

Training Attributes

Attribute	Source (Cluster/Grid)	Unit
Speed	Motion	m/s
Size	Geometric	km^2
Orientation	Geometric	deg
Aspect Ratio	Geometric	None
MaxRef	Reflectivity Composite	dBZ
Ref-10^oC	Reflectivity -10^oC	dBZ
Ref-10^oCincr	Reflectivity -10^oC	dBZ
LayerAverageRef	Reflectivity -20^oC 0^oC	dBZ
VIL	VIL	kg/m^2
VILincr	VIL	kg/m^2
MaxVIL	VIL	kg/m^2
LightningDensity	LightningDensity at t_0	$fl/km^2/s$
IdealLightningDensity	LightningDensity at t_{30} (reverse advected)	$fl/km^2/s$

Training Dataset

The neural network was trained using spatial (1*km* resolution every 5 minutes) grids over the continental United States on six days between April and September, 2008: April 10, May 14, June 13, July 1, August 20 and Sep. 11 These days were selected because they had relatively widespread lightning activity and because we did not experience hardware or software problems when collecting the data on these days.

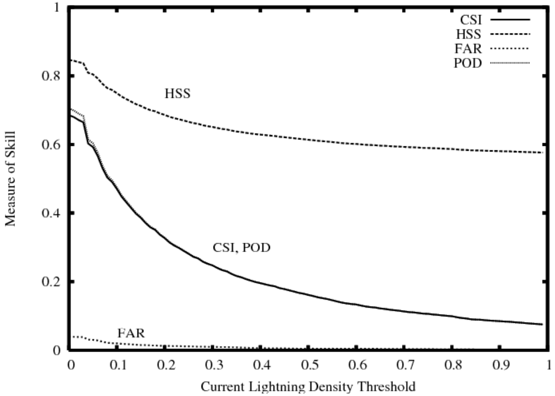
The resulting patterns were randomly divided into 3 sets of 50%, 25% and 25% which were used for training, validation and testing respectively.

The neural network

A neural network with one hidden layer consisting of 8 nodes was trained on the training set using ridge regression, with the validation set utilized for early stopping.

Algorithm Performance

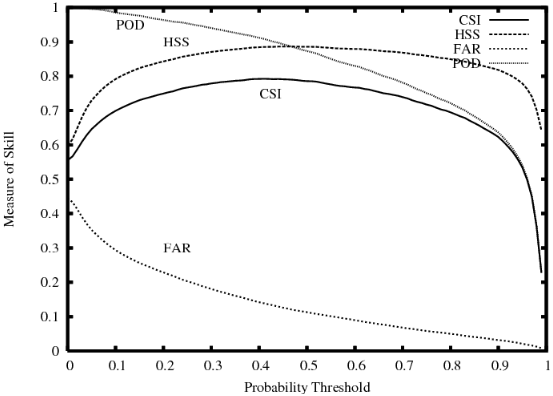
On independent test set:



Steady-state Forecast Skill

Algorithm Performance

On independent test set:



Lightning Prediction Skill

Algorithm Performance: Numbers

NN predicting 30-minutes ahead

- Best threshold = 0.41
- HSS=0.89
- POD=0.91; FAR=0.14; CSI=0.79

Advecting current lightning density by 30 minutes

- Best threshold = 0
- HSS=0.85
- POD=0.71; FAR=0.04; CSI=0.69

Difference in skill on the order of 0.10 in CSI
Can be explained by the ability to predict initiation of lightning (on the order of 0.2 in probability of detection).

Summary

In real-time, the neural network can be employed to predict the lightning activity associated with a storm. This probability can be distributed within the extent of the storm and then advected forward in time to yield the probability of cloud-to-ground lightning at a particular point 30 minutes in the future.

Acknowledgements

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The attribute-extraction algorithm described in this paper has been implemented within the Warning Decision Support System Integrated Information (WDSSII; [Lakshmanan et al., 2007]) as the w2segmotionll process. It is available for download at www.wdssii.org.

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