Estimating Convective Precipitation by Using Cloud-to-Ground Lightning Events Over Southern Arizona at High Space and Time Resolutions

by Carlos Manuel Minjarez-Sosa, Chris Castro, Ken Cummins, Phillip Krider and Julio Waissman

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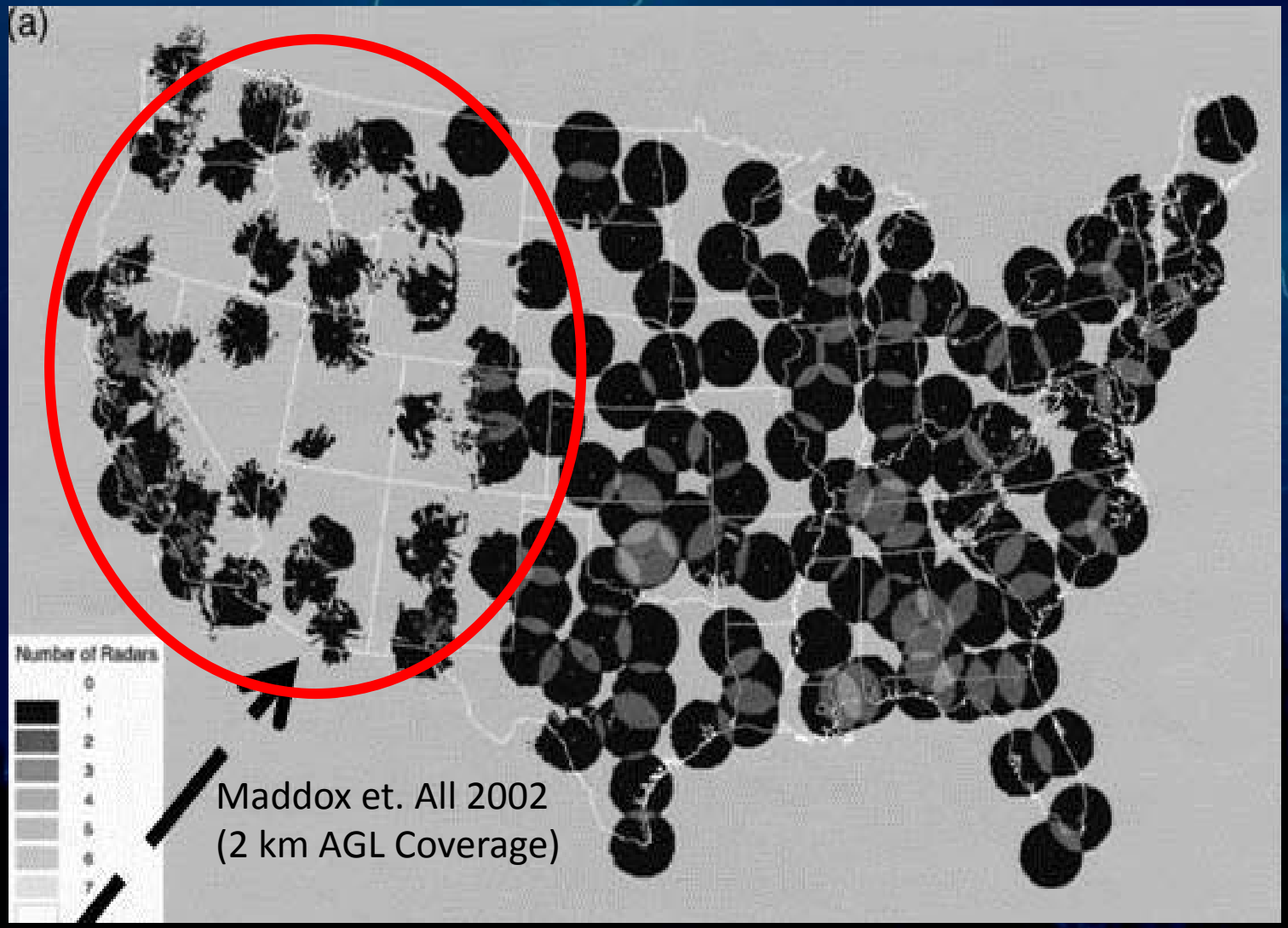
Outline

- Motivation
- General Objectives
- Data
- Lightning-precipitation Relationship (LPR) Exploratory Analysis Results (Minjarez-Sosa et al. 2013, *J. of Hydrometeorology)*
- LPR at Higher Spatio-temporal Resolutions
- Tracking time variation of LPR
- Conclusions and Future Work

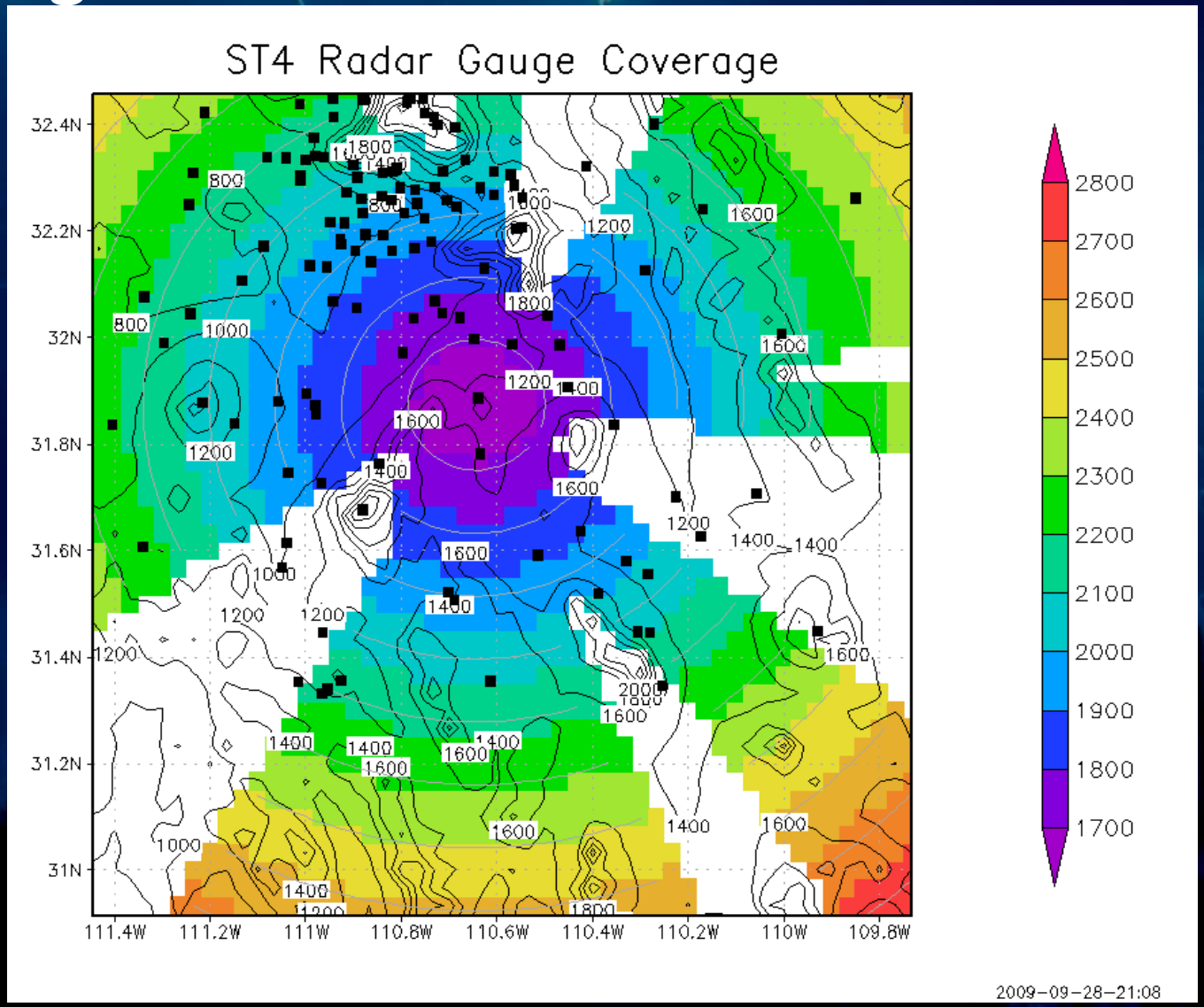
Motivation

The quality of QPE over the SW
is compromised by the poor Radar coverage



Maddox et. All 2002
(2 km AGL Coverage)

Coverage Problem in Tucson



Objectives

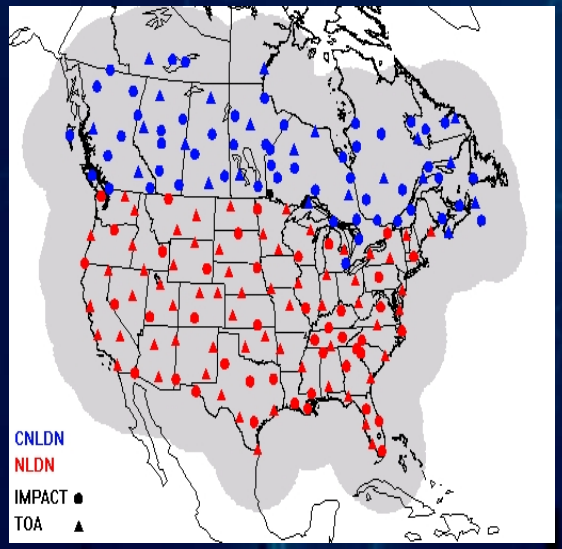
- To evaluate whether lightning can be used as a proxy for convective precipitation in areas of complex terrain by using multisensor gridded precipitation (Minjarez et al., *J. Hydromet, 2013*).

- If so, to "fill in" radar derived QPE data in areas of terrain beam blockage or high radar tilt using a constrained time-varying estimator at high spatio-temporal resolutions.

Data and Spatial Domain

National Lightning Detection Network

National Stage IV QPE Product
Mosaiced from Individual RFC's Multi-sensor Precipitation Analyses (RMPAs)



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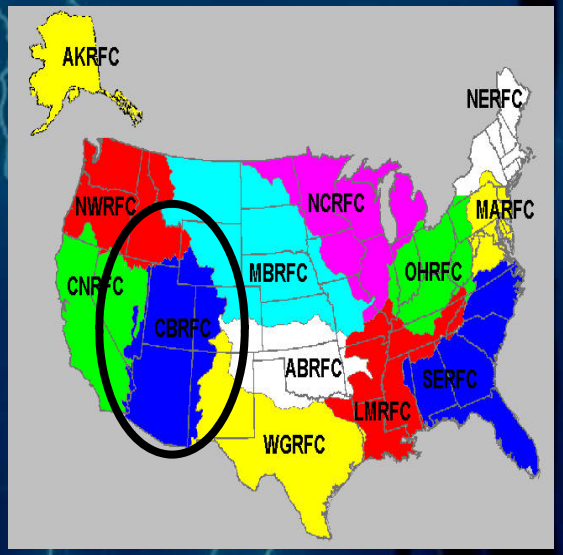

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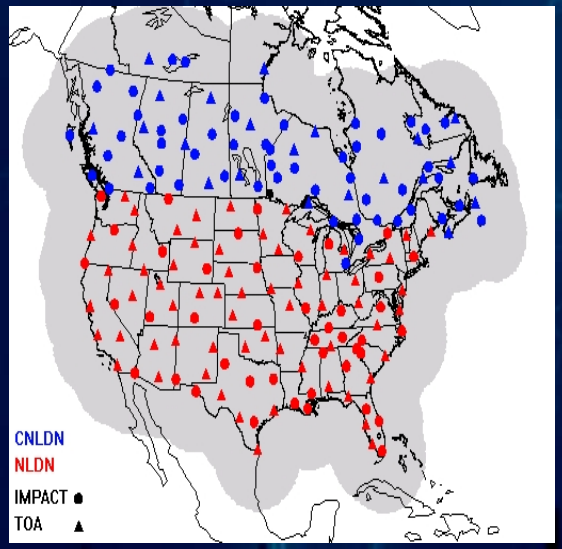
Improved QPE

Stage IV: 4 Km Spatial grid and 1 hr temporal resolution.

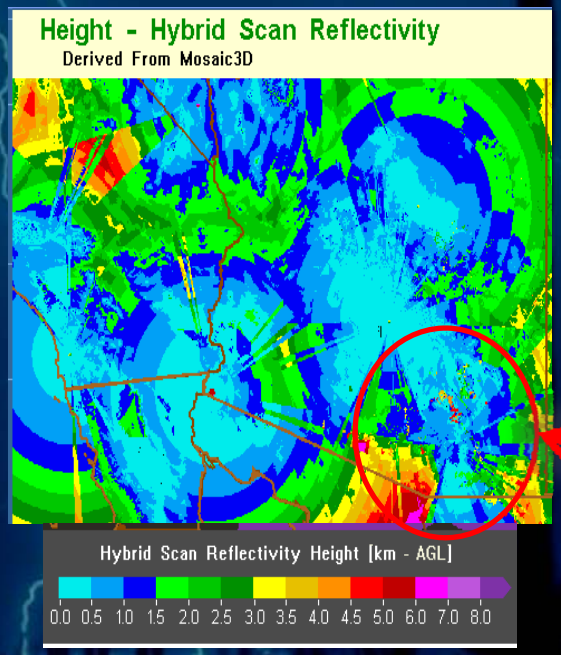
Data and Spatial Domain

National Lightning Detection Network



NATIONAL MOSAIC & MULTI-SENSOR QPE (NMQ)

Advancing the science and science-to-operations of QPE and very short-range QPF

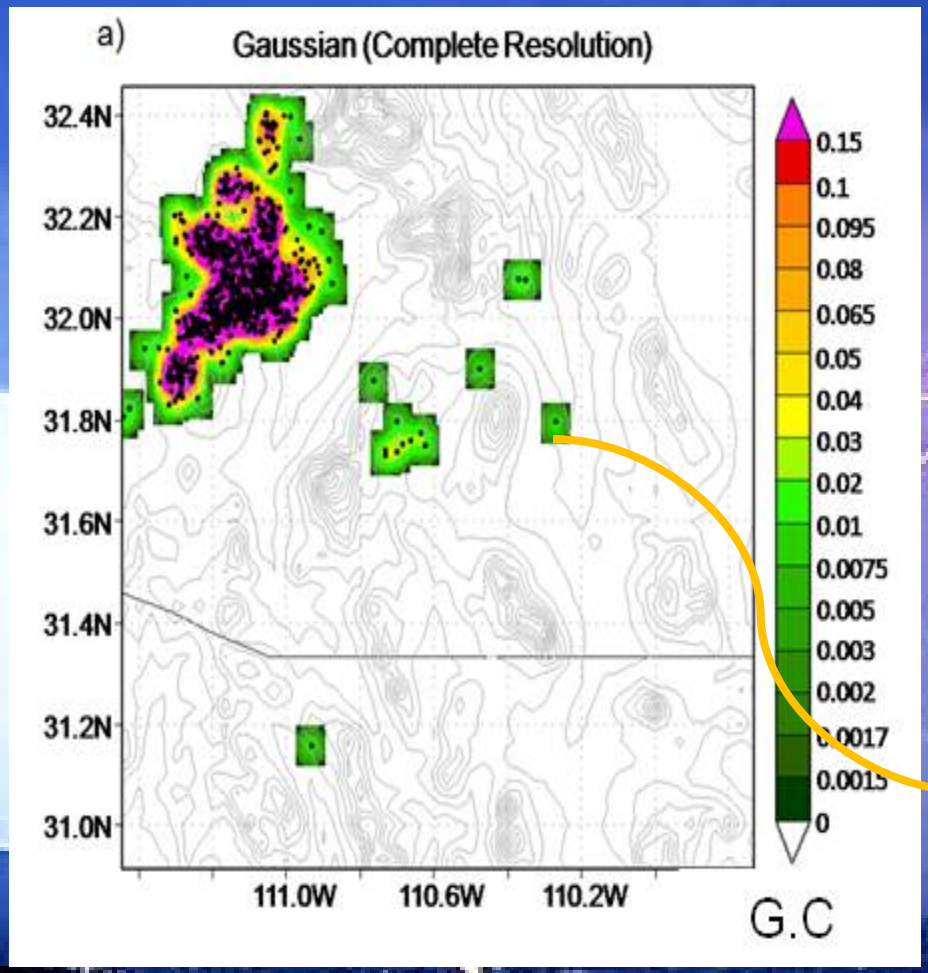


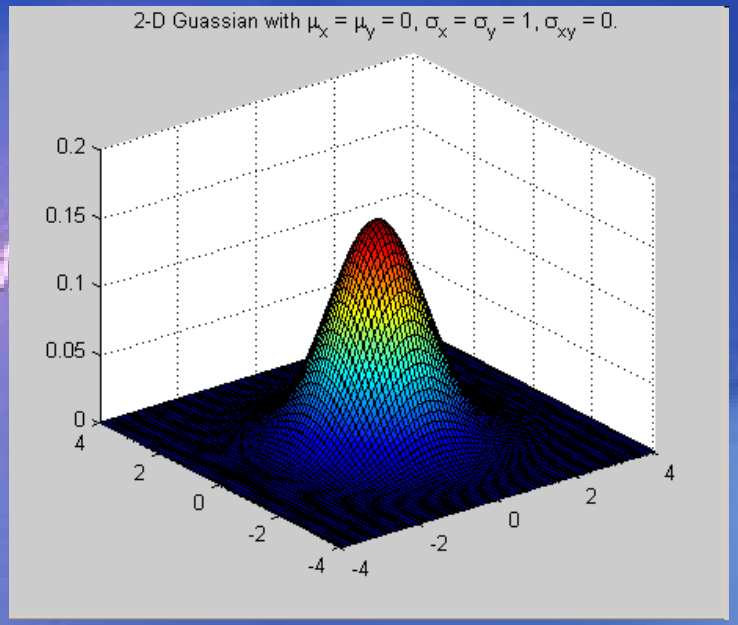
KEMX Radar

Improved QPE

NMQ: 1 Km Spatial grid and 5 minutes temporal resolution.

Lightning Gridding





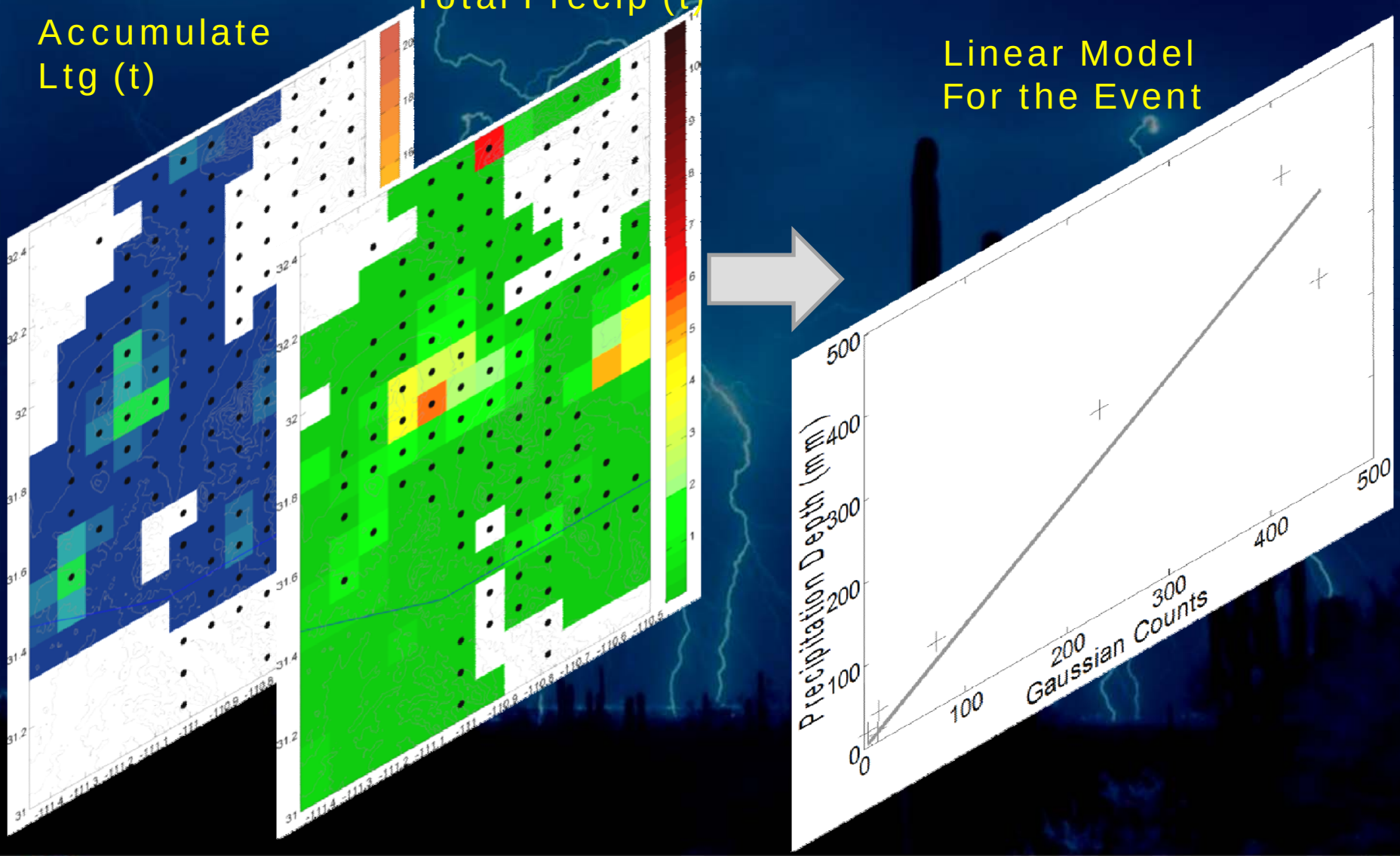
Note how discrete lightning events are spatially extended by a Gaussian convolution

Regional Time-Invariant Model (ST4 data)

Accumulate Ltg (t)

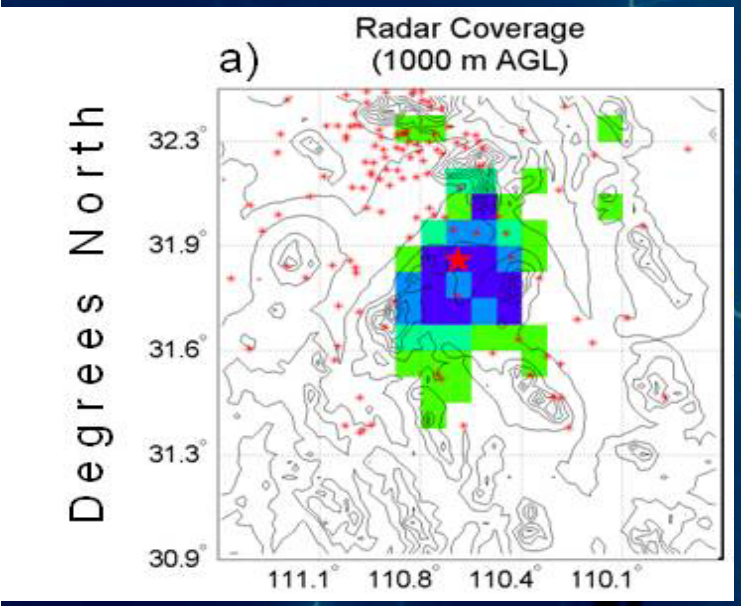
Total Precip (t)

Linear Model For the Event



J. Hydromet. Results (1)

RFC Stage4 QPE is the best operational data we have today, but it is not very good in Southern Arizona



2 count of radar tilts below 1000m AGL

J. Hydromet. Results (1)

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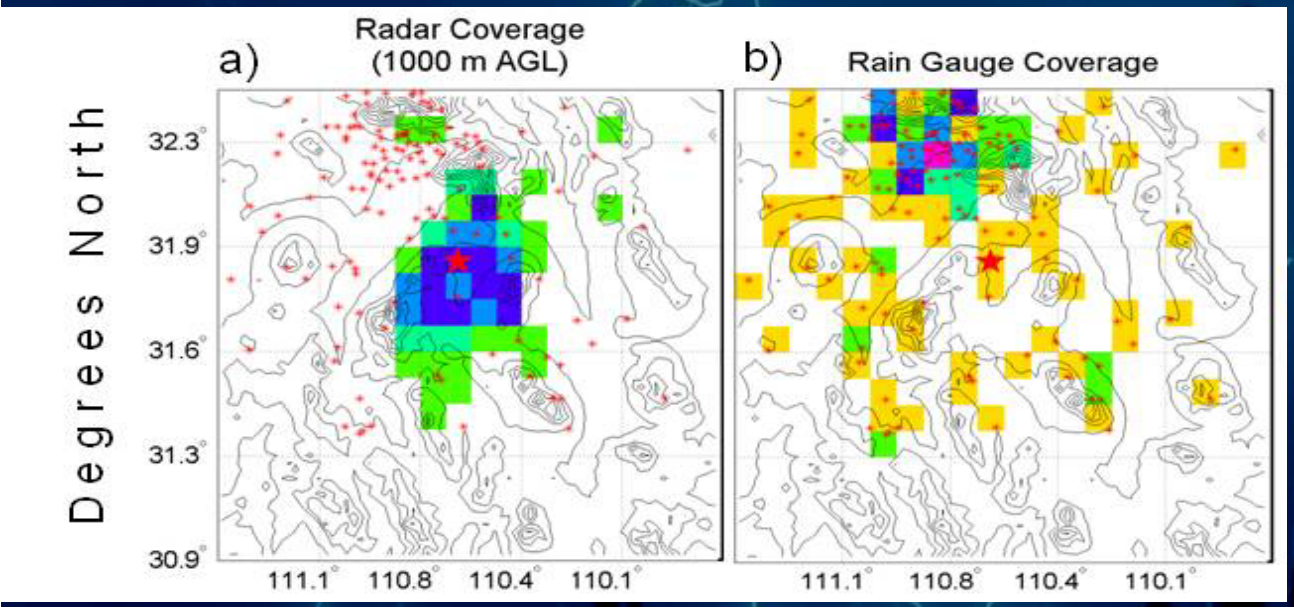

2 count of radar tilts below 1000m AGL

number of rain gauges per grid

J. Hydromet. Results (1)

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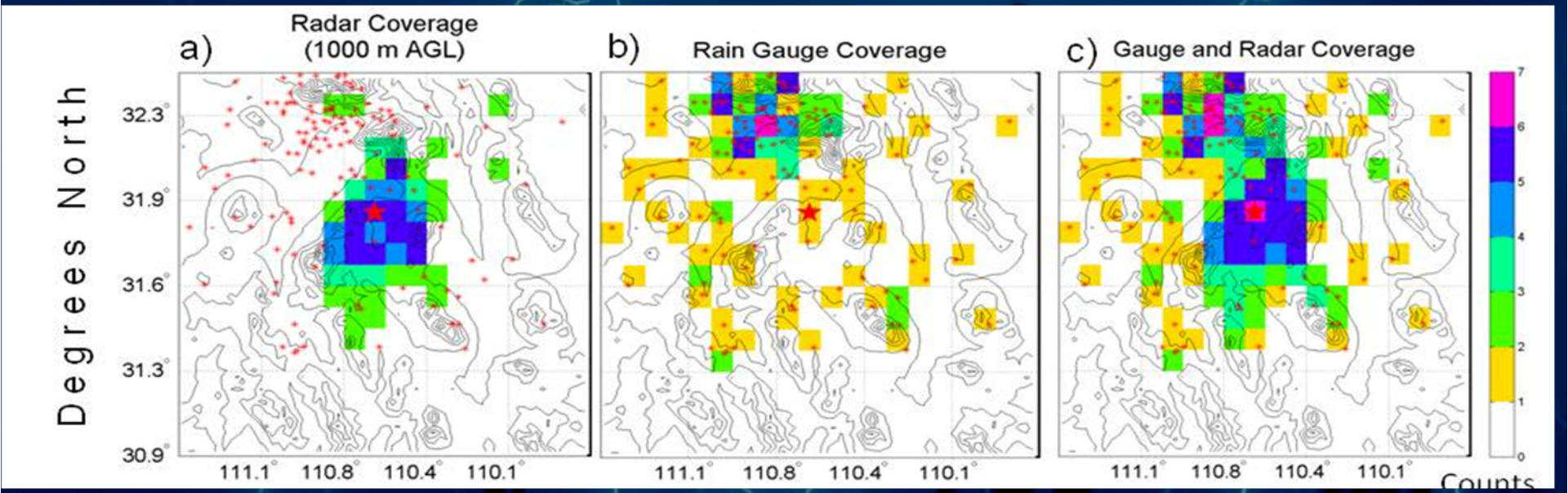
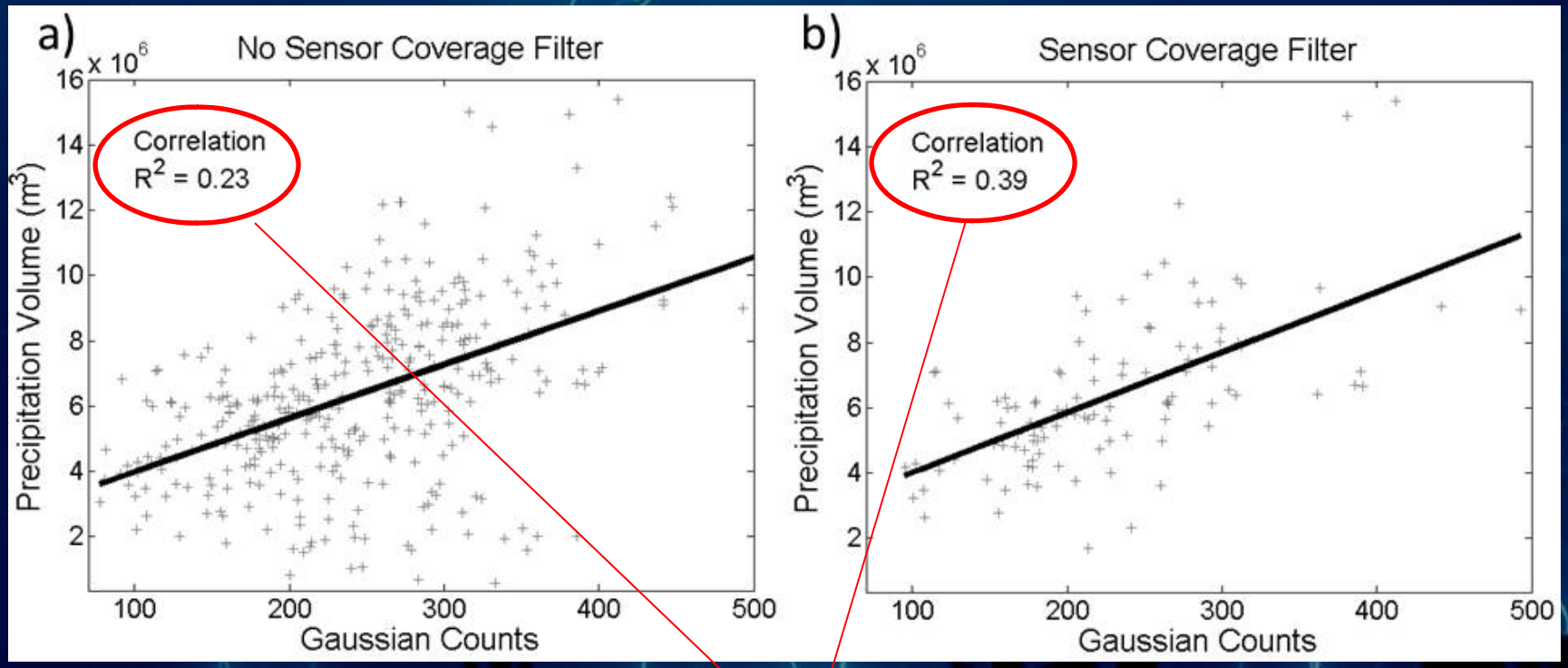


2 count of radar tilts below 1000m AGL

number of rain gauges per grid

union of (a) and (b)

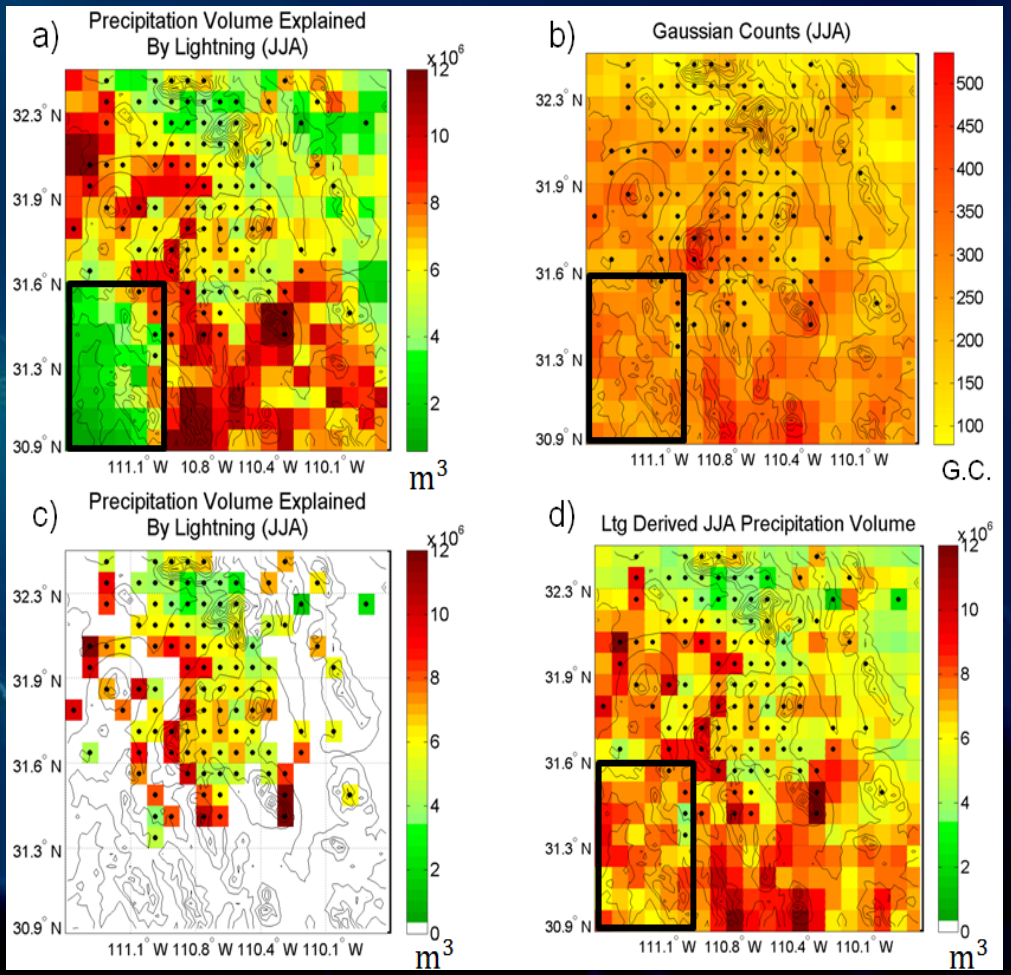
J. Hydromet. Results (2)



Almost twice by just neglecting non covered grids

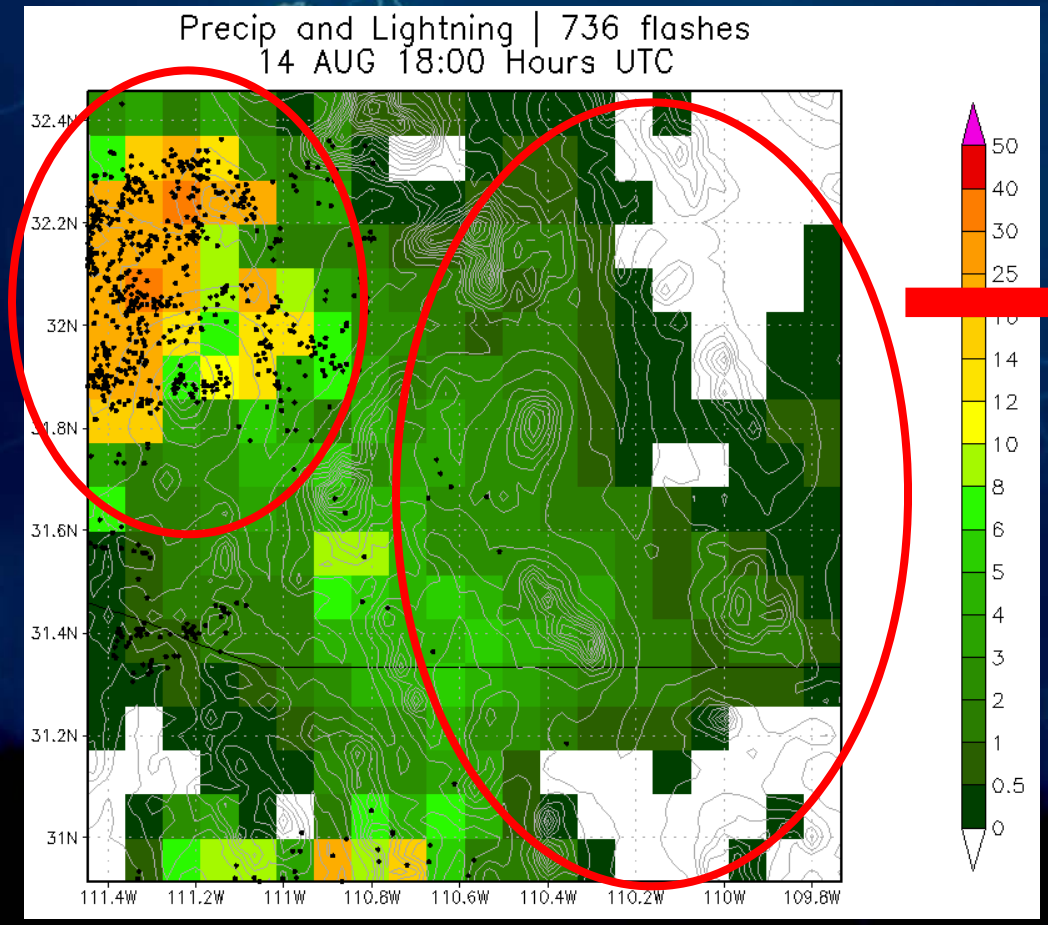
J. Hydromet. Results (3)

- **Procedure for constructing lightning-derived precipitation**
- **Black dots show grid with sensor coverage**
- **Note the black rectangle showing the impact of beam blockage**



Which rain can be estimated with a single parameter model?

PEL Convective precipitation

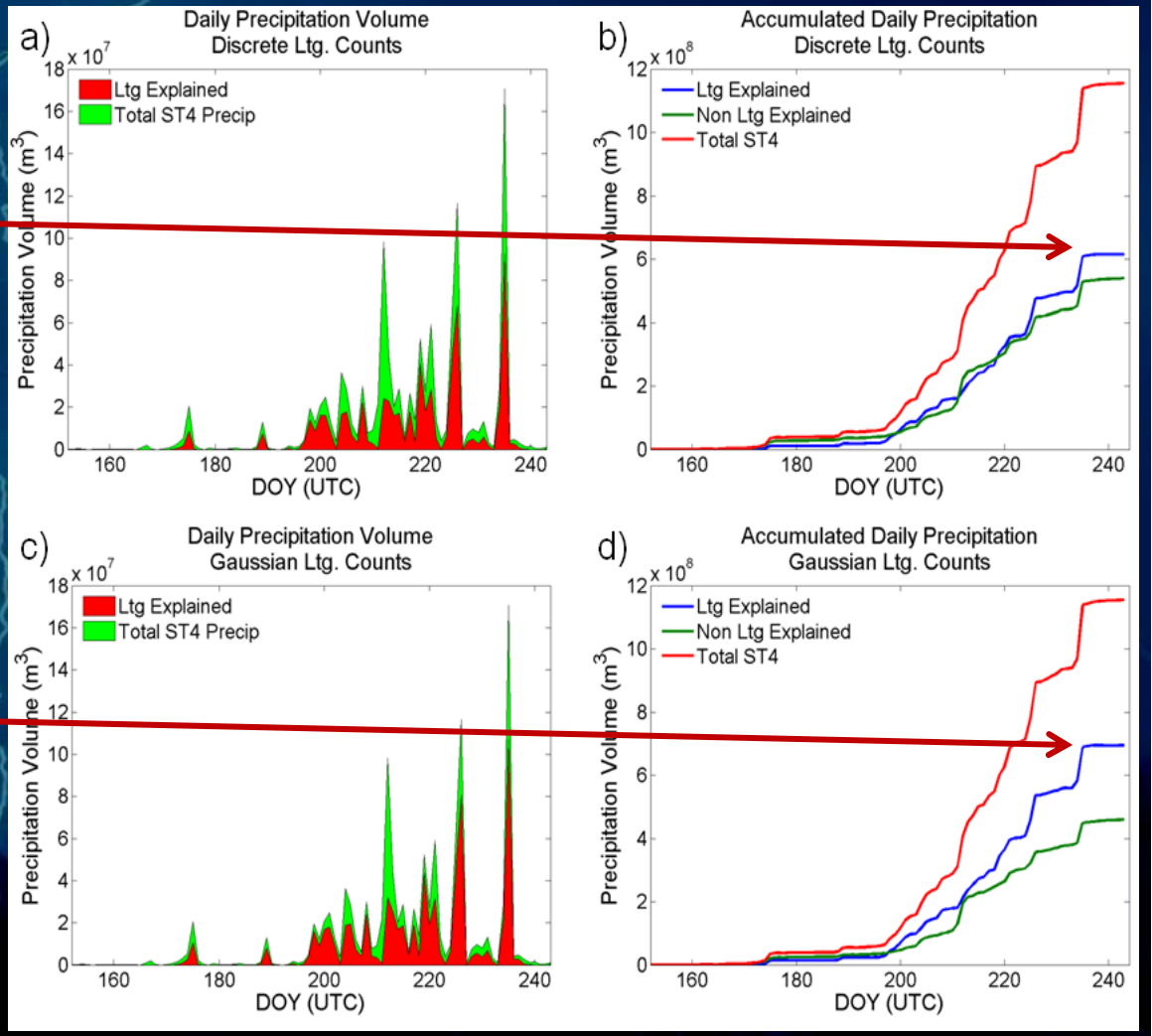


Trailing stratiform precipitation

J. Hydromet. Results (4)

About 50 % of the total precipitation can be explained by discrete lightning

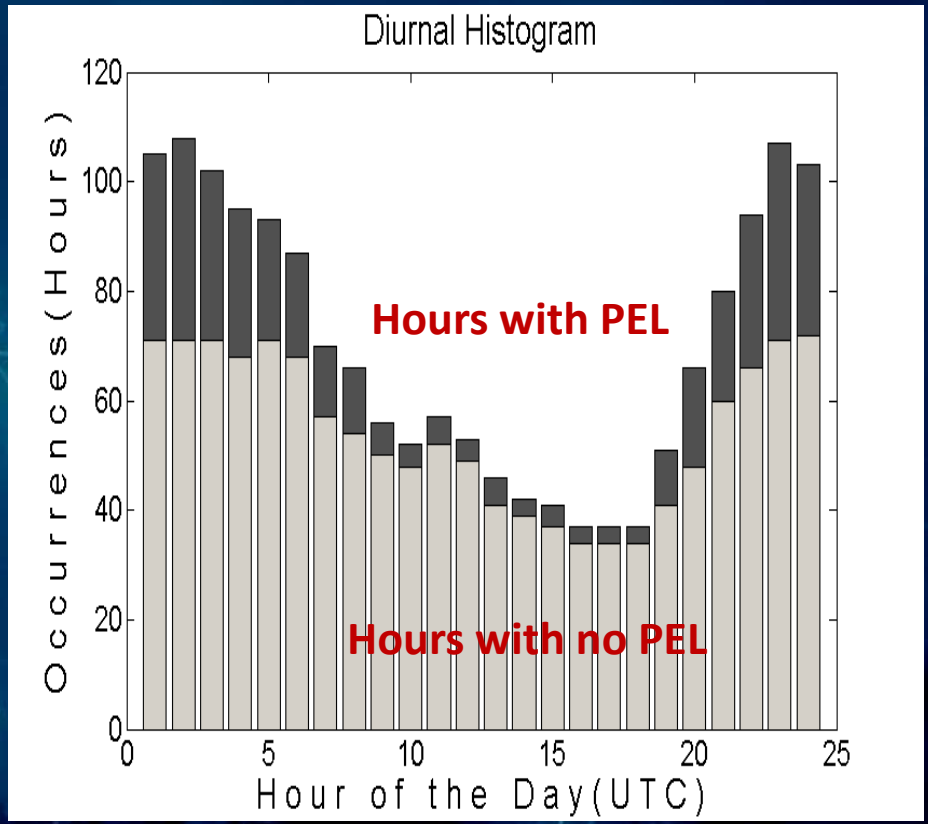
About 60 % of the total precipitation can be explained by Gaussian Counts



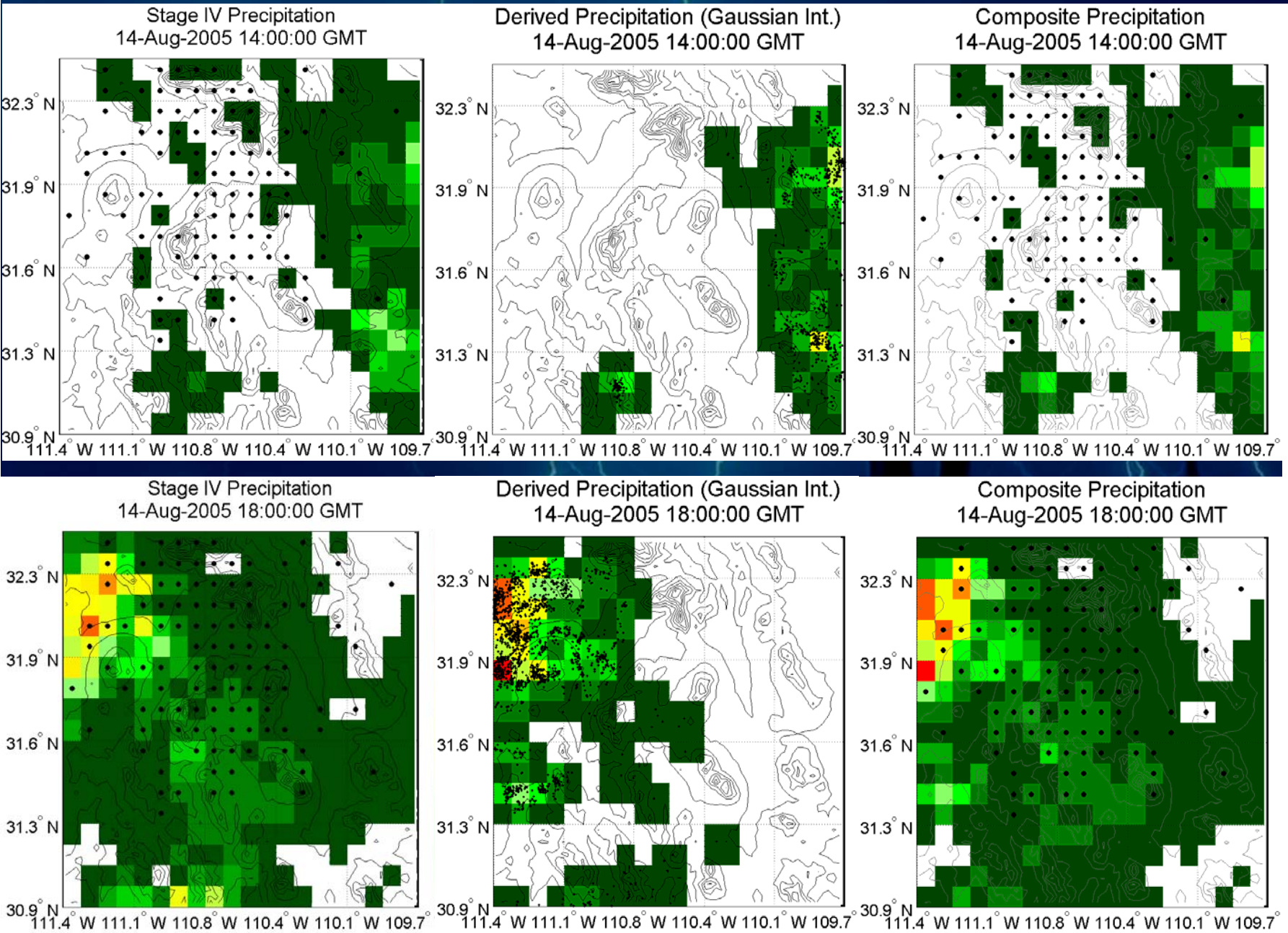
J. Hydromet. Results (5)

In a 24 Hr. time resolution analysis, it is better to consider the diurnal cycle of the convection

We chose the time of less convection as the starting of the "convective" and this improved the LPR correlation about 10 % (from 0.7 to ~0.8)



MCS event August 14 2005 . 1 hr. time resolution



LPR at Higher Spatio-temporal resolutions

- Thus far, precipitation estimation was calculated using 2-parameter least squares.
- The novel Gaussian count allows us to explain more precipitation .
- It was shown that sensor coverage was important to have larger correlations in LPR.
- We were able to estimate precipitation on seasonal, 24-hours and hourly time scales.
- We have not quantified the accuracy of ltg. estimated precip. over non-covered areas

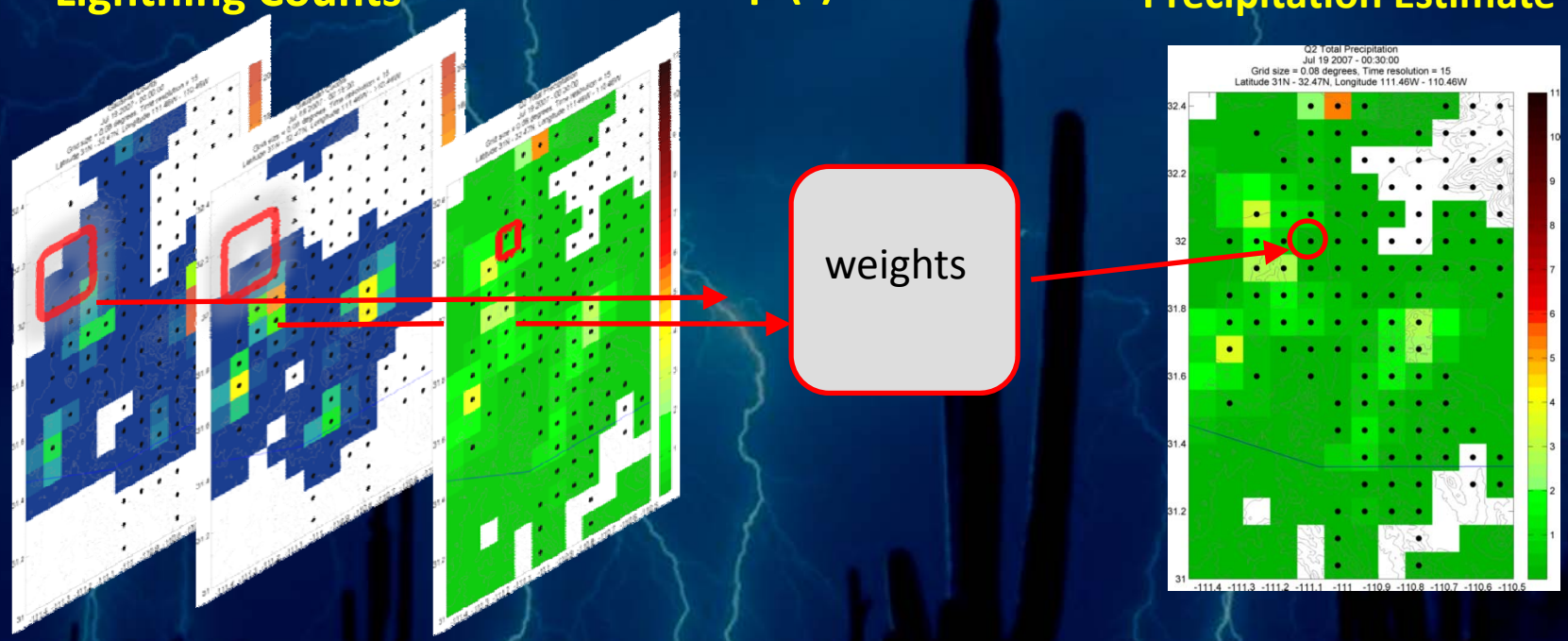
- Can we maintain significant correlation for LPR at higher spatio-temporal resolutions?
- What are the factors that can affect LPR under these conditions?
- Does the LPR vary with time?

Local Gridded Model with either grid point and/or time neighbors (long-term Space-time Invariant (STI))

Lightning Counts

Obs. Precip (t)

Precipitation Estimate

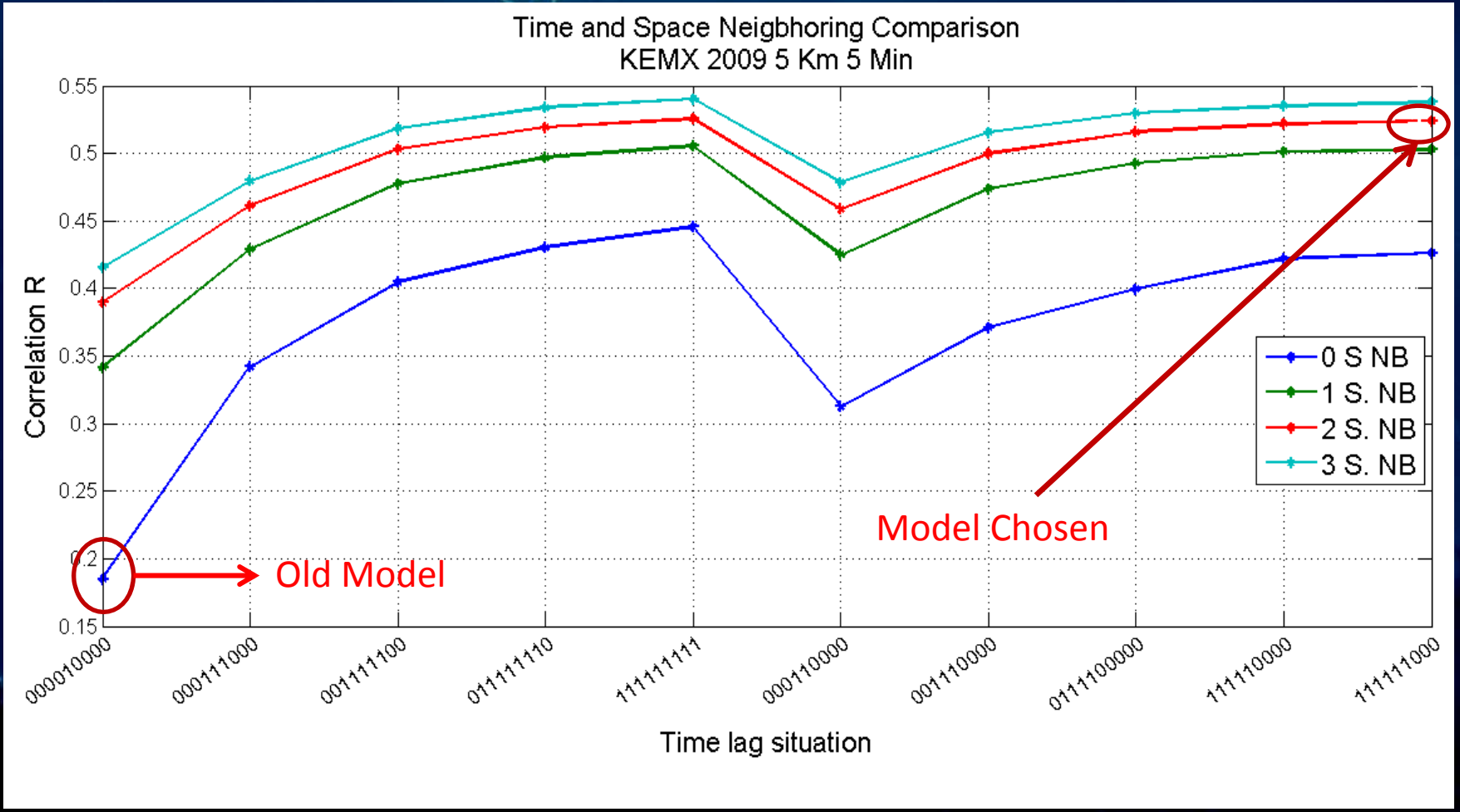


Time Steps: t-1 t

Lag Code: 000110000, Vicinity: 1

Ltg. Derived Precipitation at time t

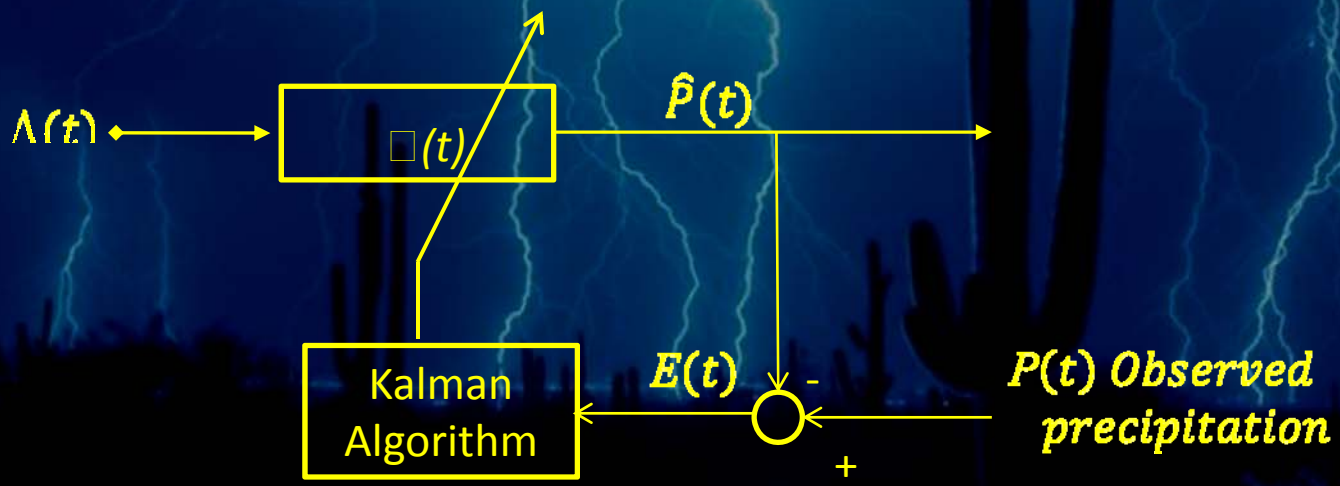
Model Parameters: spatial and temporal resolution and extent



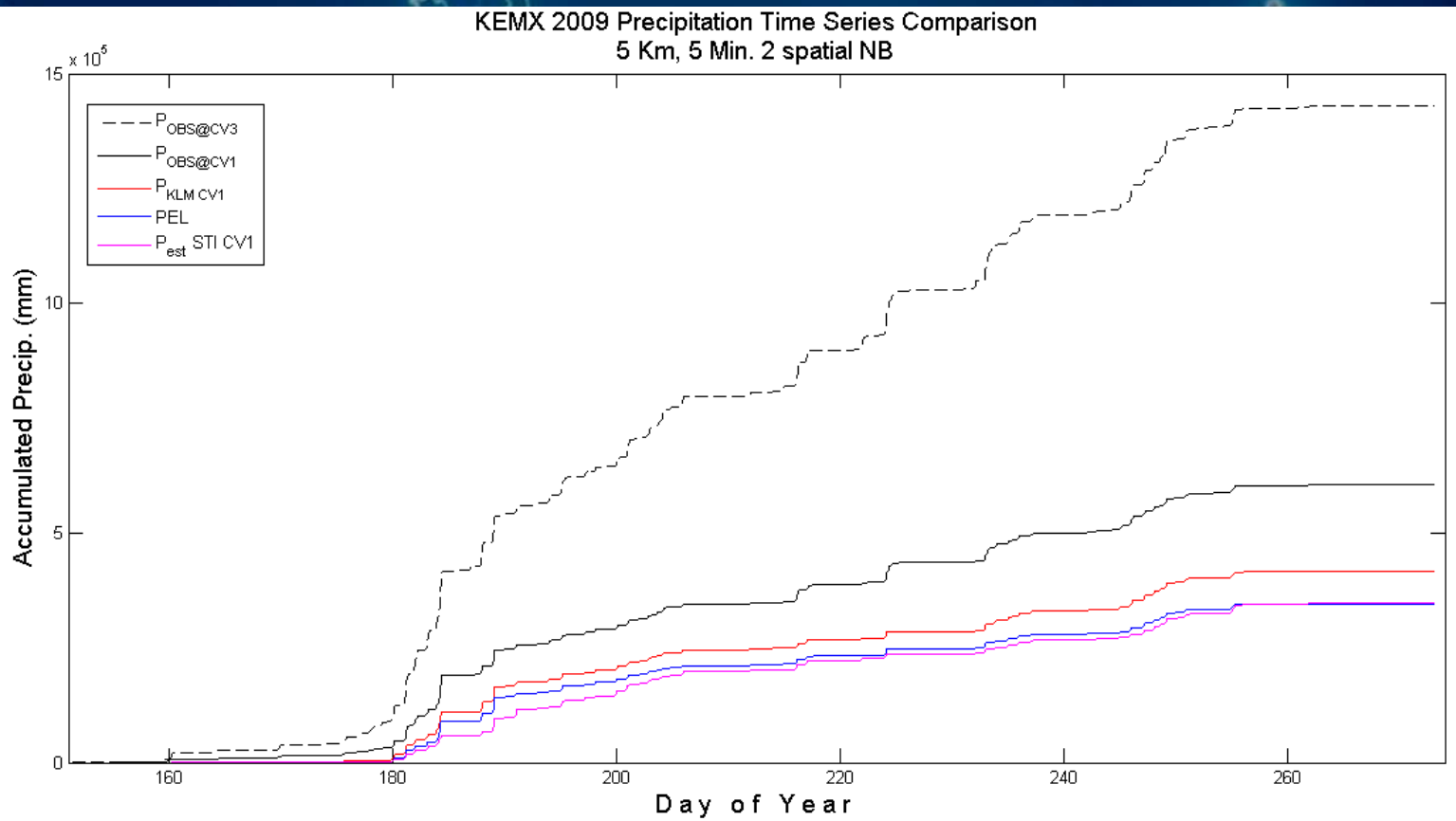
Time variation in the LPR

- Time variations are expected
  - Thunderstorm life cycle (stratiform rain)
  - Impacts of terrain on LPR

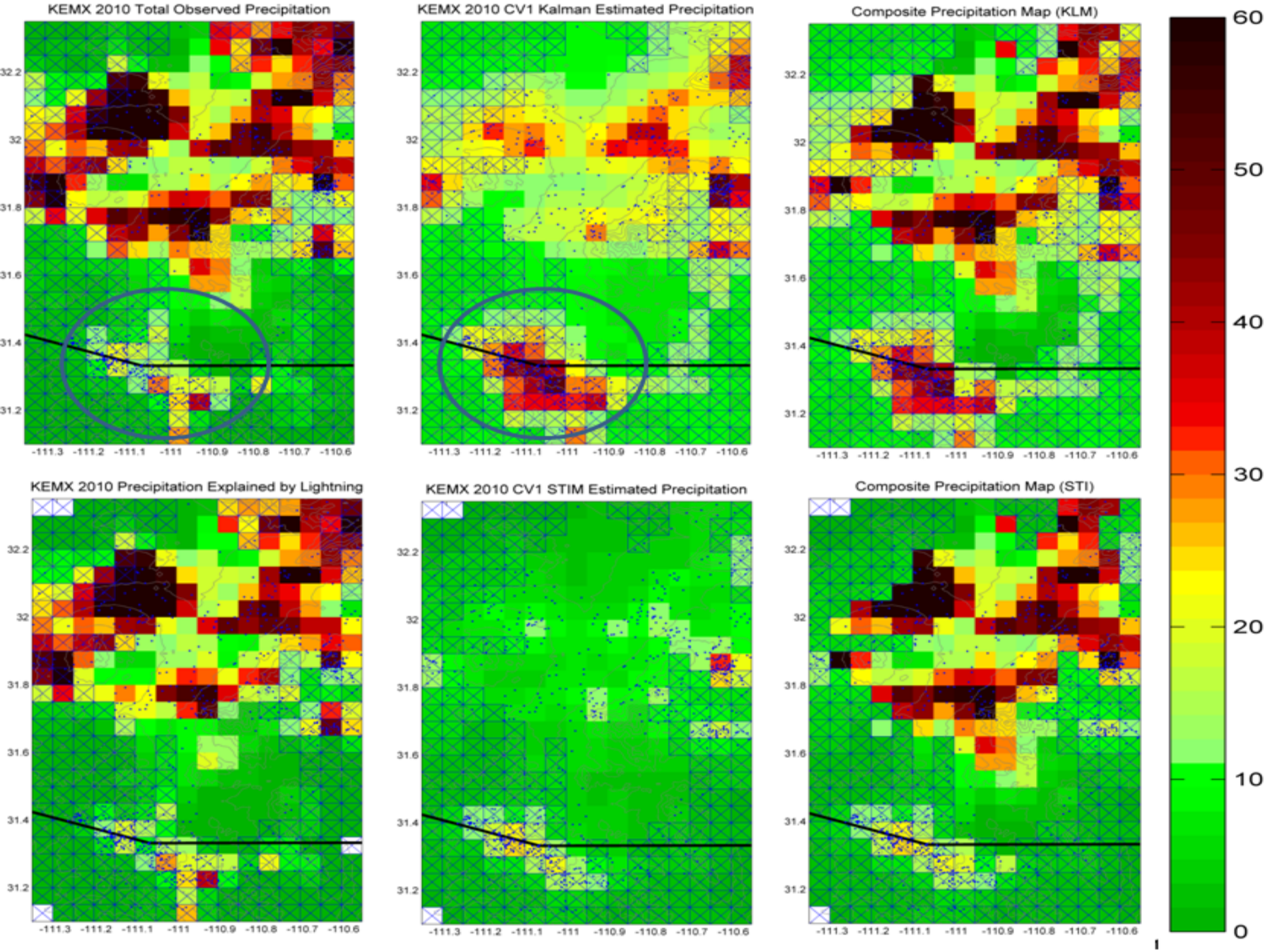
- A Kalman filter approach is applied to the STI model in order to track these changes.



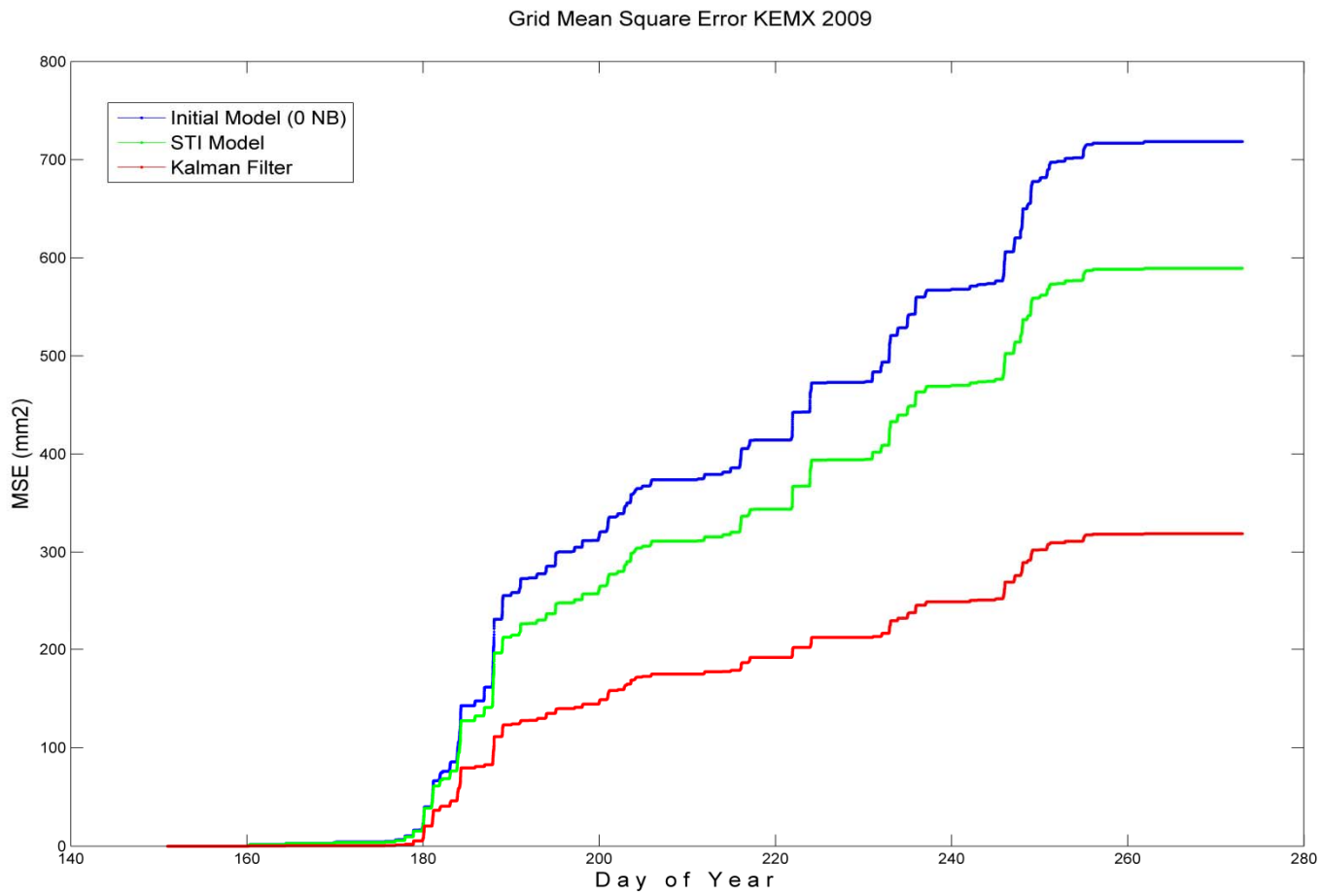
2009 Accumulated Precipitation



Tucson Event


KEMX 2010 Total Observed Precipitation
KEMX 2010 CV1 Kalman Estimated Precipitation
Composite Precipitation Map (KLM)
KEMX 2010 Precipitation Explained by Lightning
KEMX 2010 CV1 STIM Estimated Precipitation
Composite Precipitation Map (STI)
32.2
32
31.8
31.6
31.4
31.2
-111.3 -111.2 -111.1 -111 -110.9 -110.8 -110.7 -110.6
60
50
40
30
20
10
0

Benefits of the proposed models



Conclusions

- This work demonstrated that Lightning can be used to estimate precipitation over poor sensor coverage areas as several time resolutions.
- A 2-parameter linear model can work for 8 km and hourly or larger time periods (one hour to seasonal) but not for higher time and space resolutions (5 km and less than an hour)
- The STI model is a reasonable alternative for LPR at higher spatio-temporal resolutions
- The dynamic model showed that the STI retrievals are improved by tracking the LPR in time.

Future Work

- A greater number of years are needed to estimate the baseline climatology for the STI Model, as well as the definition of a representative geographical extension.
- The parameters in the Gaussian convolution, esp. the standard deviation, should be explored to verify that these are the optimal parameters to have higher correlations and PEL.
- Additionally to the Kalman filter, a further step is to build an algorithm that tracks specific storms within a spatial domain and obtain a set of parameters per each convective event and time step.
- The presented methods point to the incorporation of a lightning-based QPE in an integrated multi-sensor product, and be potentially used to develop a lightning augmented QPE.
- The developed QPE methodologies may be of great benefit in countries with limited radar or rain gauge networks that experience convective events in complex terrain
- It is possible to use the parameters of the Kalman method to quantify the LPR as a function of storm life and location.

Thank you
Any questions?

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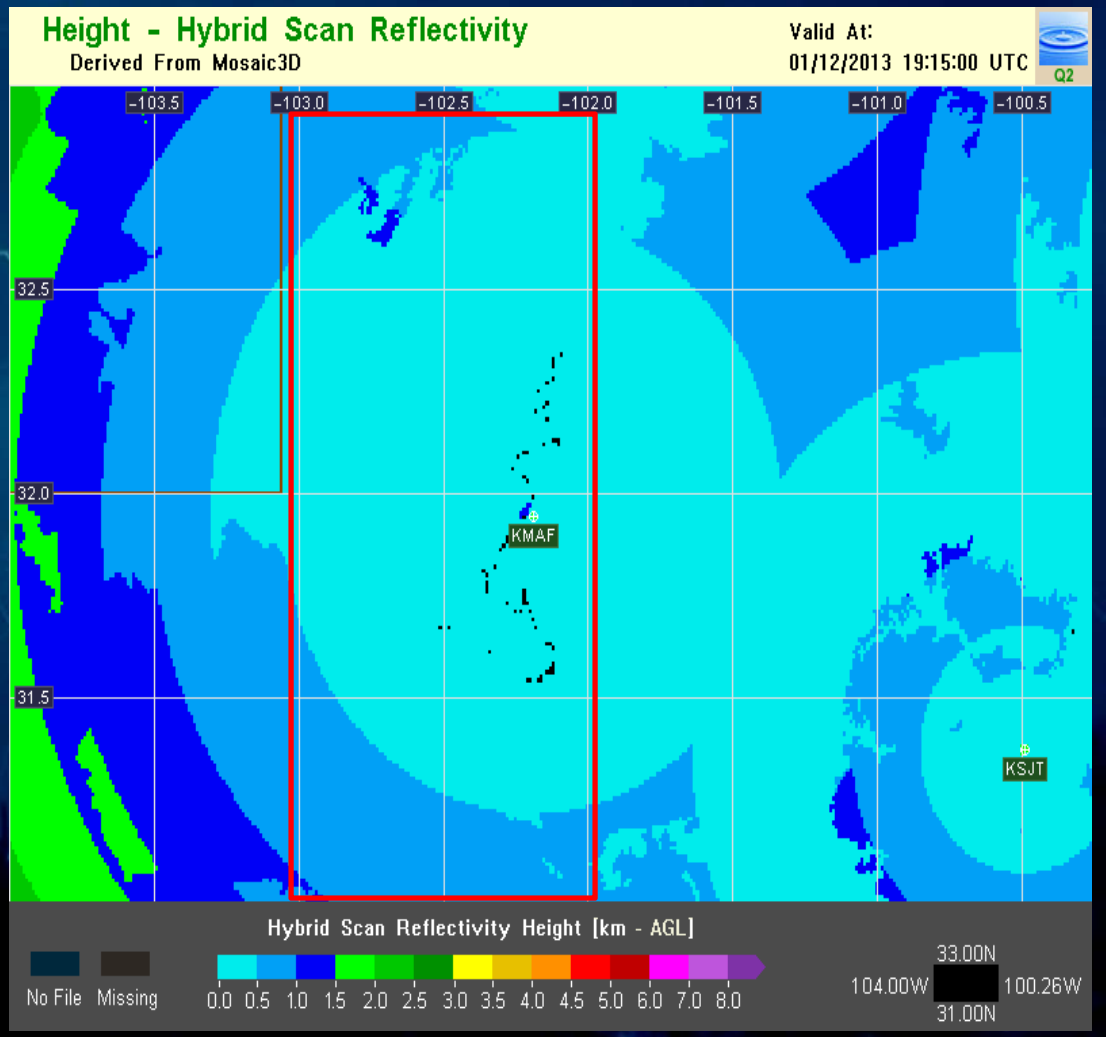
Denial Analysis Domain

- **The KMAF radar area was considered for the denial analysis.**
- **In this domain, the whole region has hybrid scan coverage of 1 km or better.**
- **We create an artificial coverage map**
- **Hence, we can compare estimated precipitation with observed precipitation.**

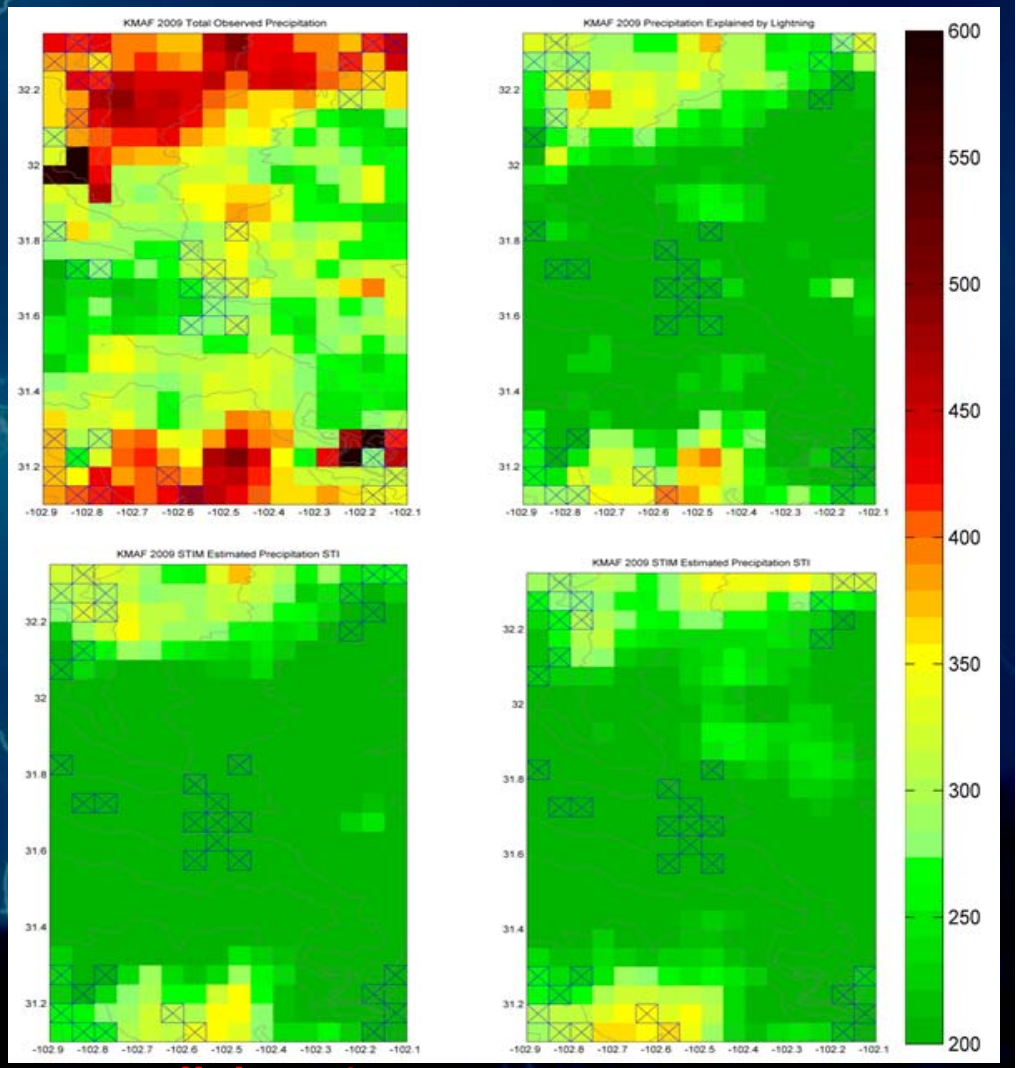


Denial Analysis Results

- We chose an artificial arbitrary coverage mask (blue squares)
- We ran the STI and the dynamic model to retrieve ltg-derived precipitation for the two conditions:
  - all domains considered
  - Only grids without blue sqs.

- We compared the total accumulated seasonal estimated precipitation that resulted from the two coverage cases for both models (static and dynamic).

Pobs PEL

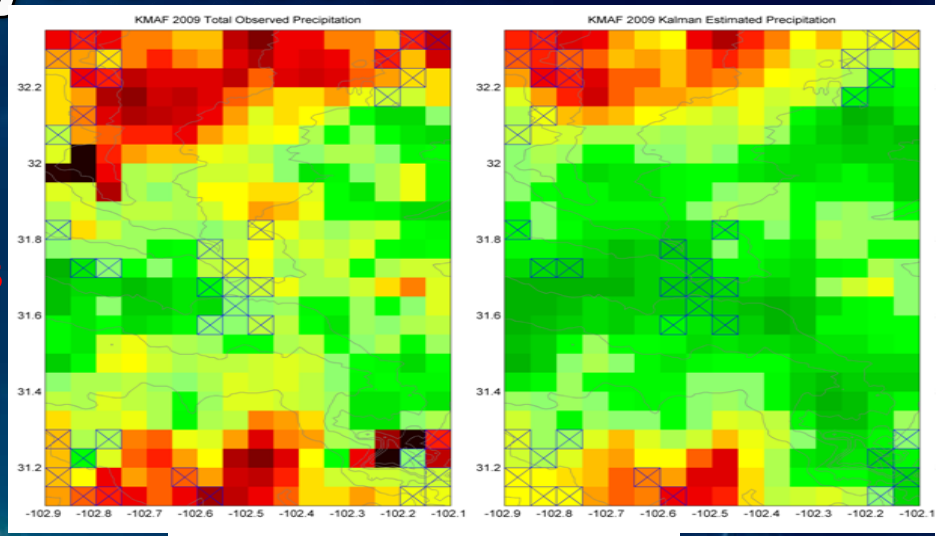


STI all domain STI denial domain

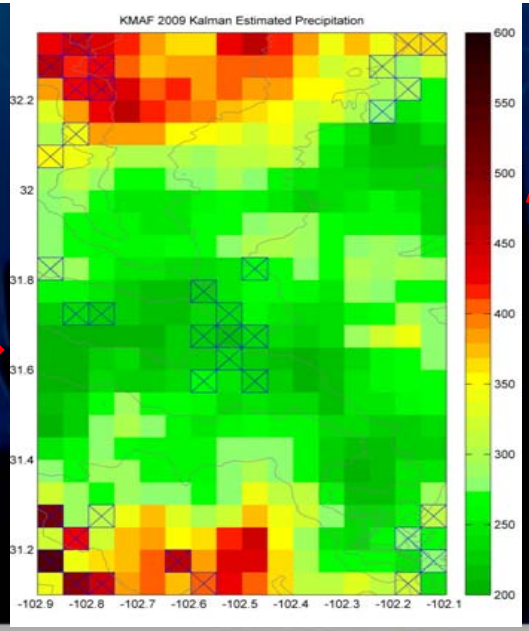
Denial Analysis Results

- It is clear that the Kalman retrieval improves the spatial distribution of precipitation with regards to the STI Model.
- The estimated precipitation for the two coverage cases are very similar for the STI model and the Kalman filter.
- Those grids that show strong disagreement with the estimation were events with high precipitation and very few lightning events.
- Next we will see what happened in time.

Pobs

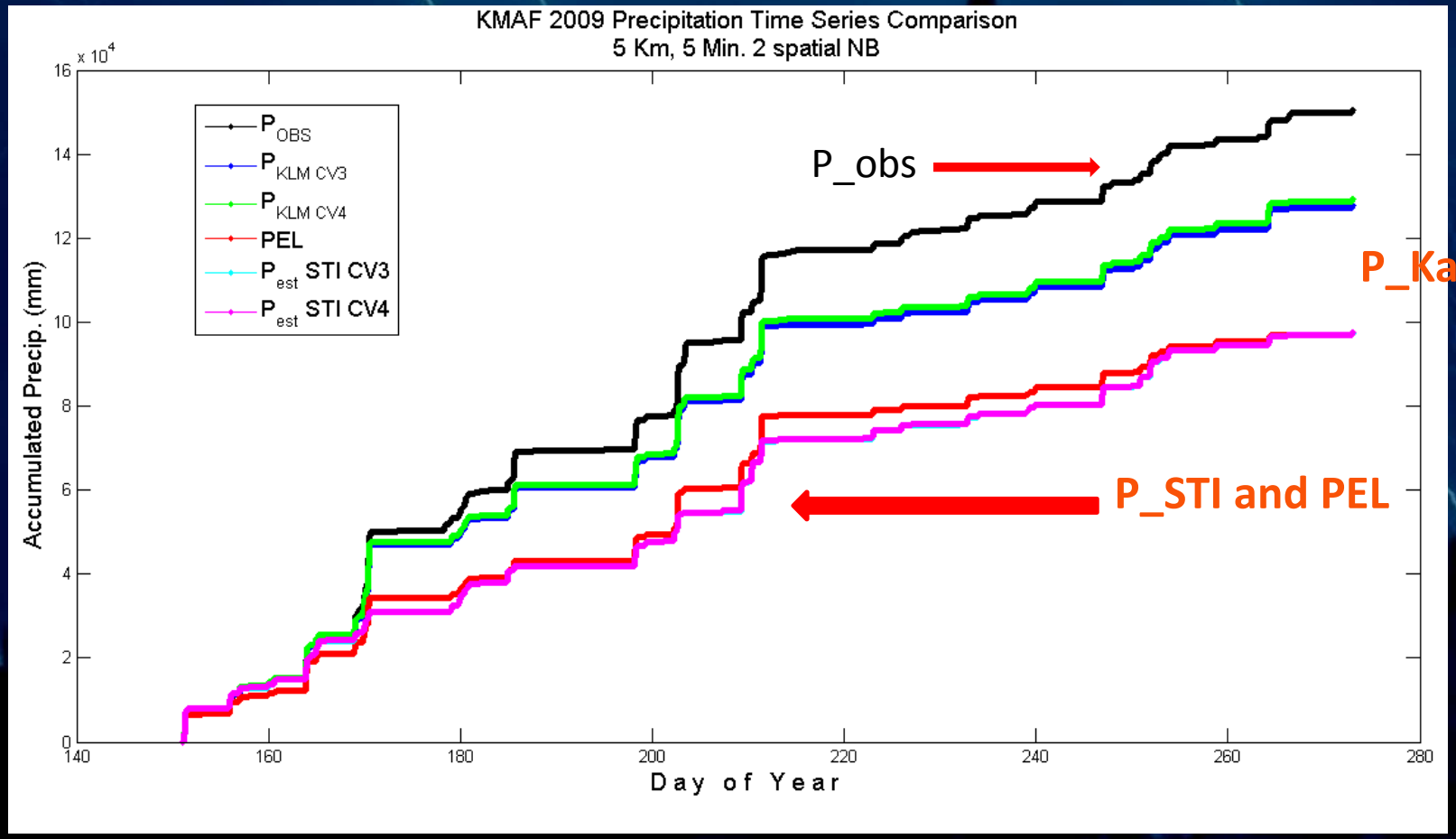


Pest
Denial
domain



Pest
All domain

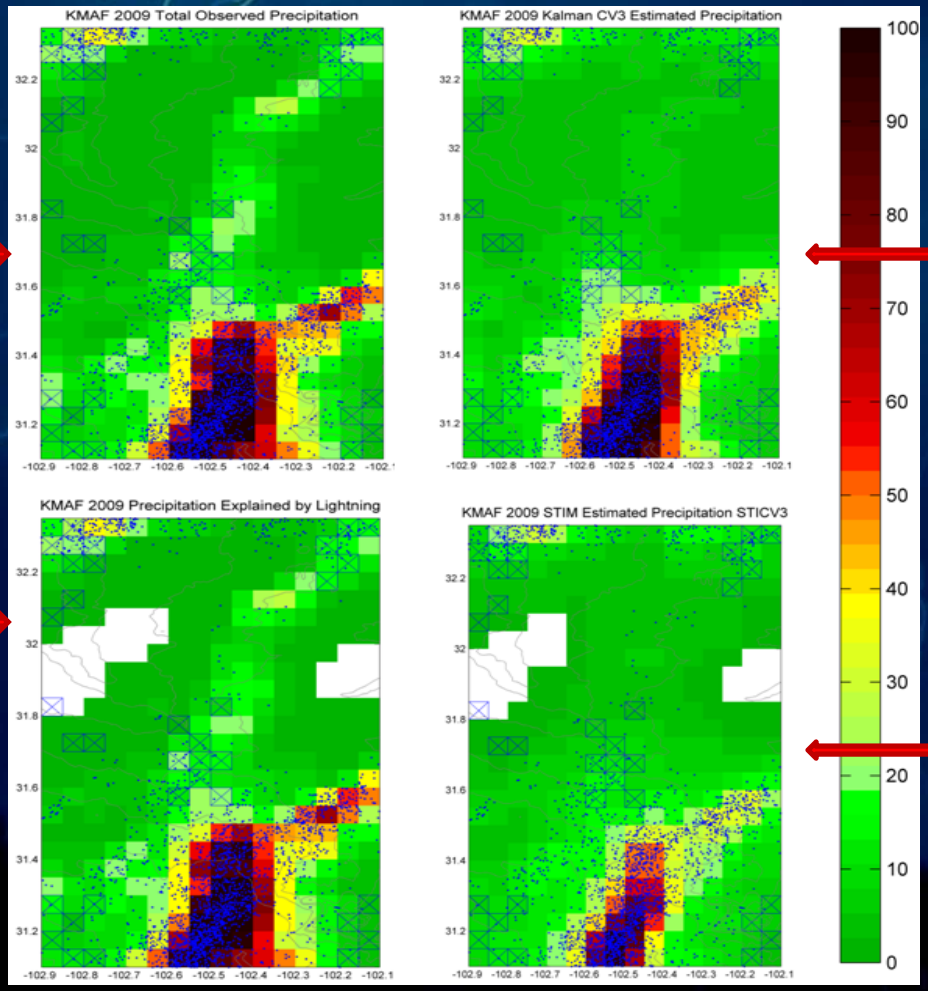
Time comparison



West Texas Event

Pobs

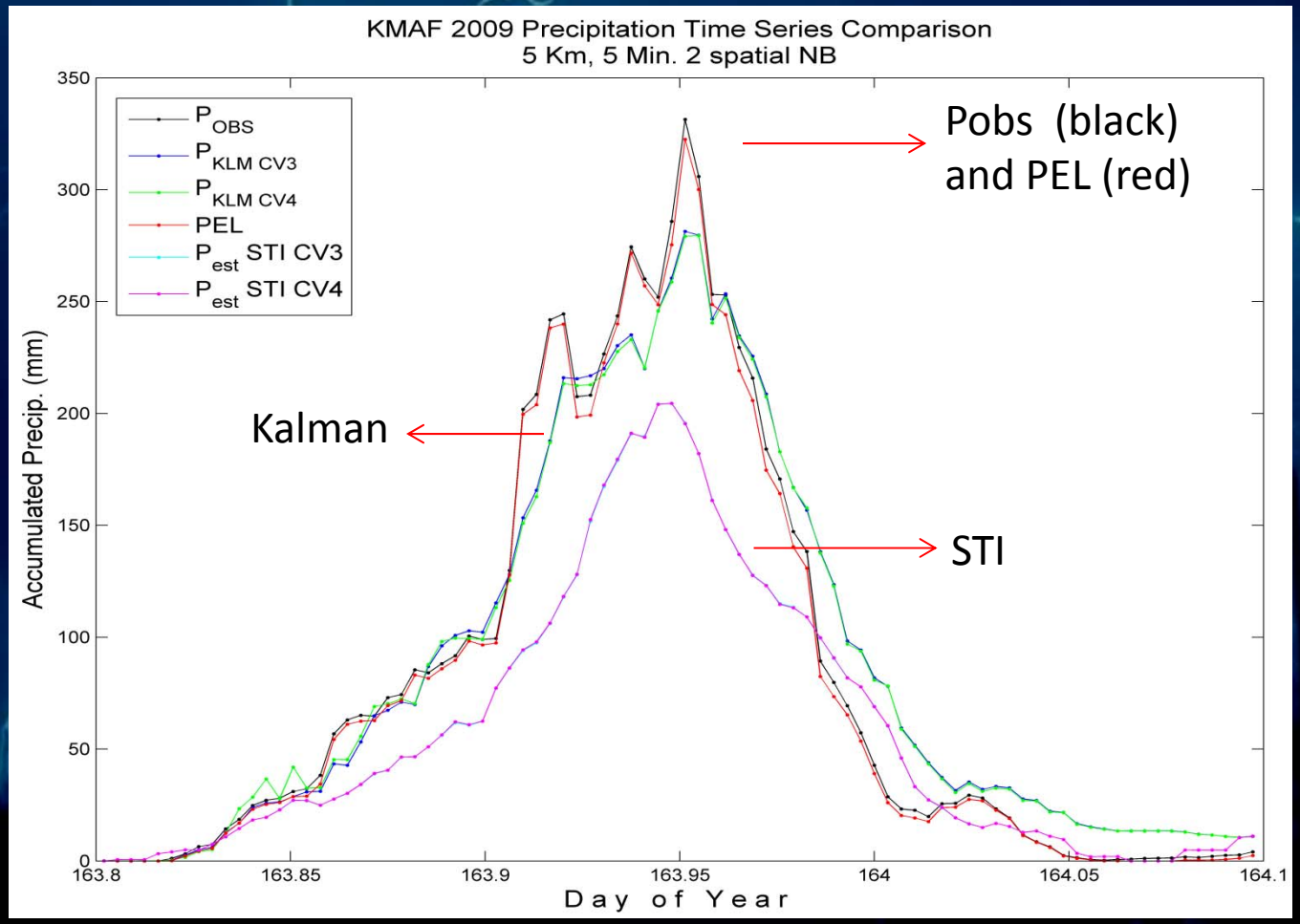
PEL



P Kalman all domain

P STI all domain

Time evaluation, Texas Event



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Kalman Algorithm

$$\square(t+1)=\square(t)+W(t)$$

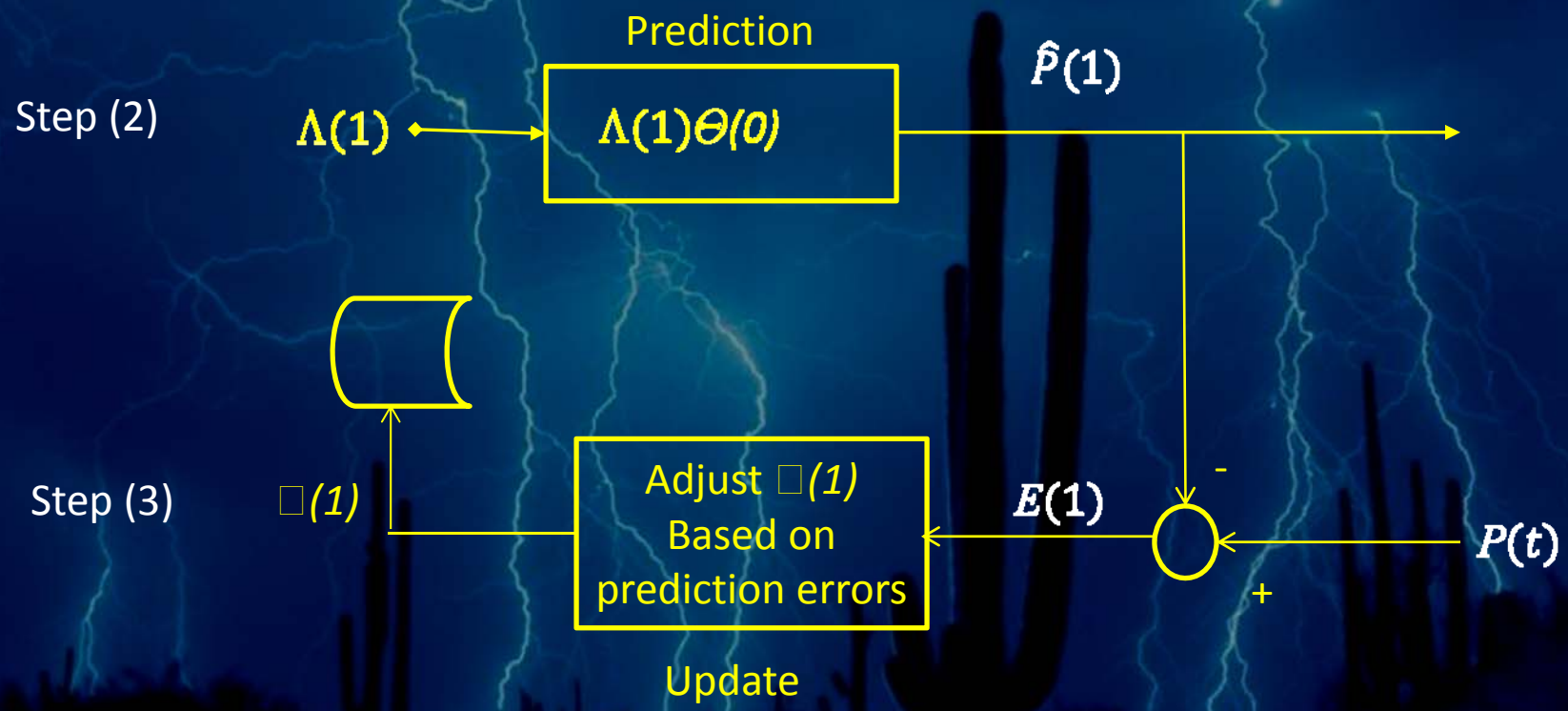
$$\Theta(0)=\Theta_{STI}$$

Prediction

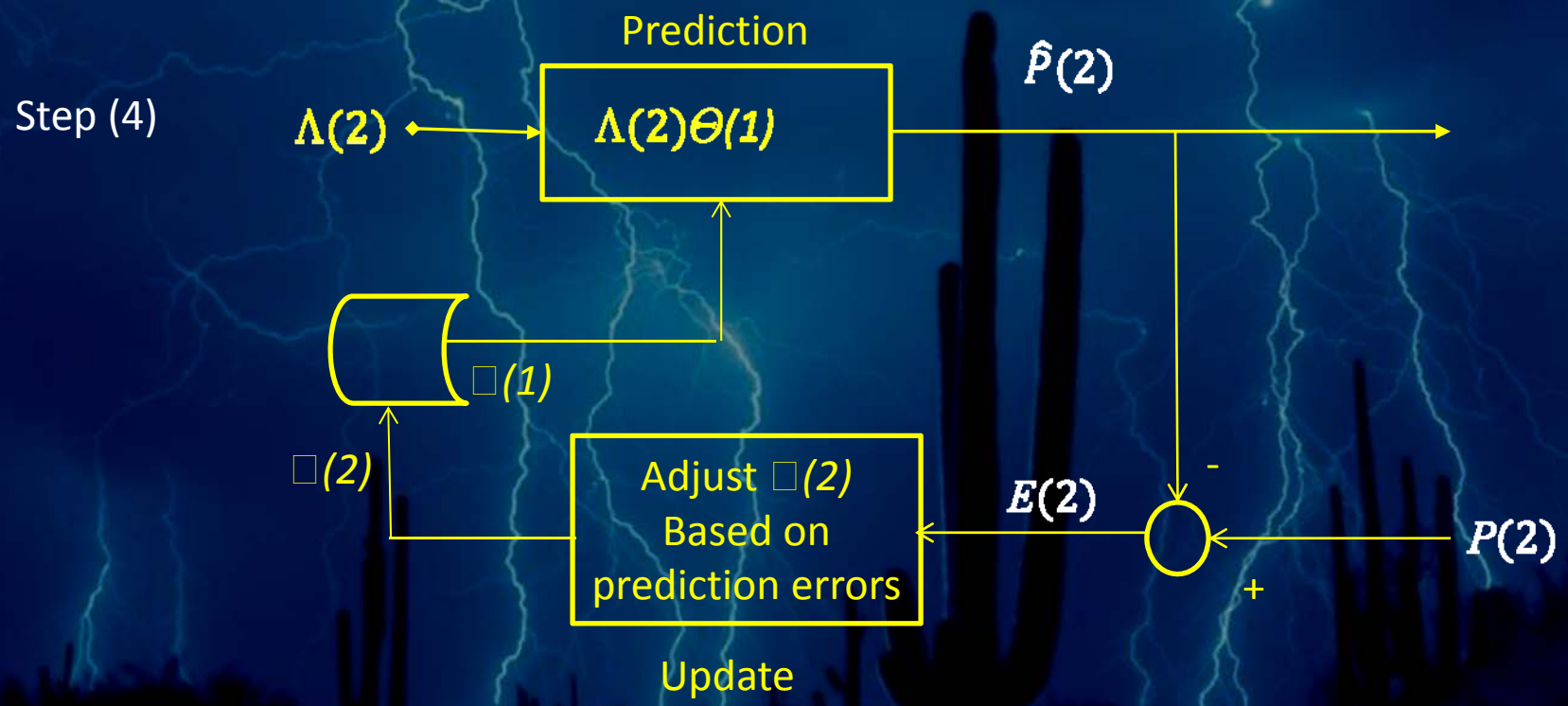
Step (1)

$\Lambda(1)$ ⟷ $\boxed{\Lambda(1)\Theta(0)}$ $\longrightarrow \hat{P}(1)$

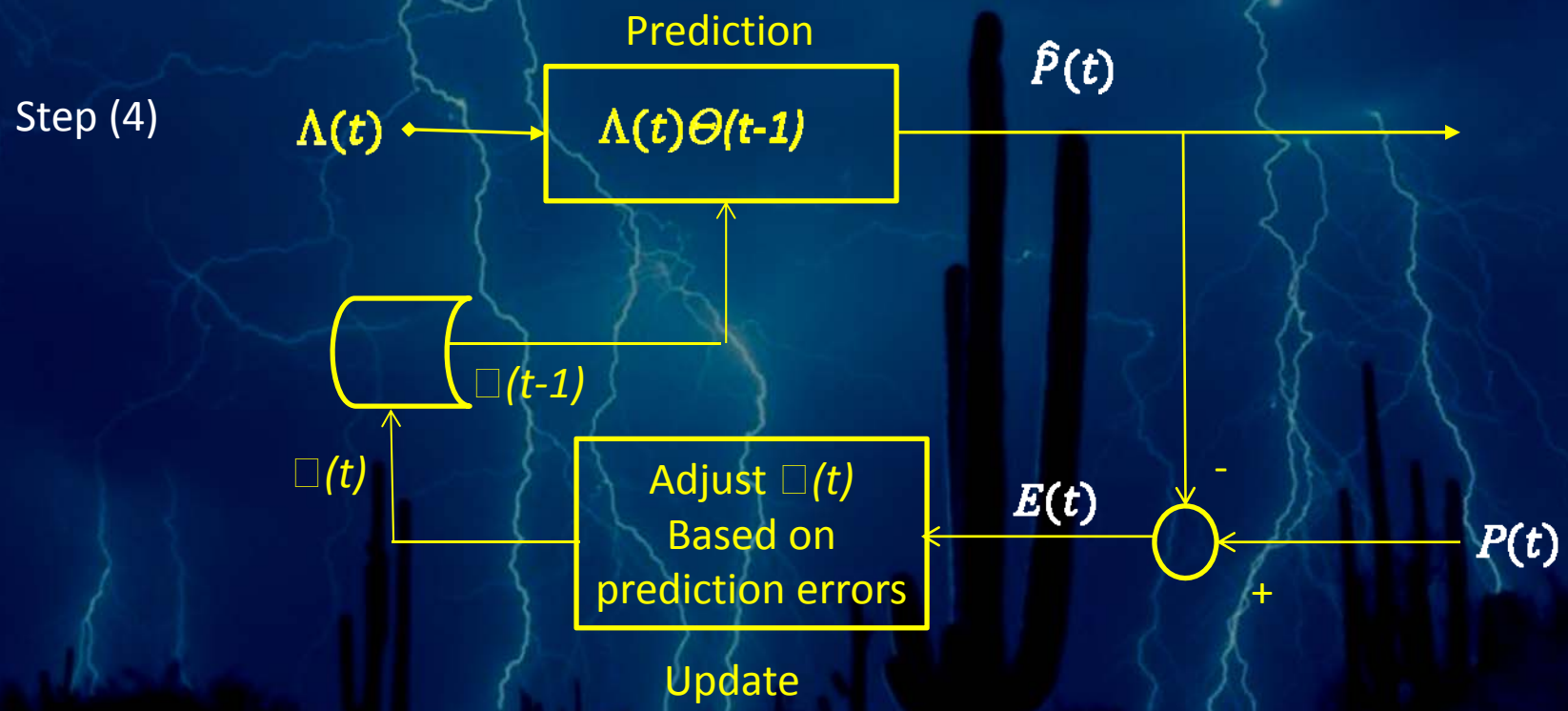
Kalman Algorithm



Kalman Algorithm



Kalman Algorithm



Kalman Equations

The Kalman filter is then used to estimate de values of $\Theta(t)$ from the dynamical discrete system

$$\Theta(t+1) = \Theta(t) + W(t), \tag{A.7}$$

where $W(t)$ is a parameter estimation error, modeled as a Gaussian random variable with zero mean and a covariance matrix Q. Using the STI formulation to estimate the precipitation in the covered grids, the Kalman filter algorithm is applied as follows:

1. $A'(t) = \Lambda(t) \cdot A(t-1) \cdot \Lambda^T(t) + Q$
2. $E(t) = Y(t) - H \cdot \Lambda(t) \cdot \theta(t-1)$

   The Kalman gain is given as:

3. $K(t) = A'(t) \cdot (H \cdot \Lambda(t))^T (H \cdot \Lambda(t) \cdot A'(t) \cdot (H \cdot \Lambda(t))^T + R)^{-1}$
4. $\hat{\theta}(t) = \hat{\theta}(t-1) + K(t) \cdot E(t)$
5. $A(t) = (I - K(t) \cdot H \cdot \Lambda(t))A'(t)$
6. $\hat{P}(t) = \Lambda(t) \cdot \hat{\theta}(t)$