



# Air Force Research Laboratory



***Integrity ★ Service ★ Excellence***

## Generation of AE9/AP9 Runtime Tables

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# Outline



- **List of Runtime Tables**
- **Runtime Process**
- **Flow chart of statistical processes**
- **Example of gap filling with templates**
- **Example results for one bin**
- **Correlations**



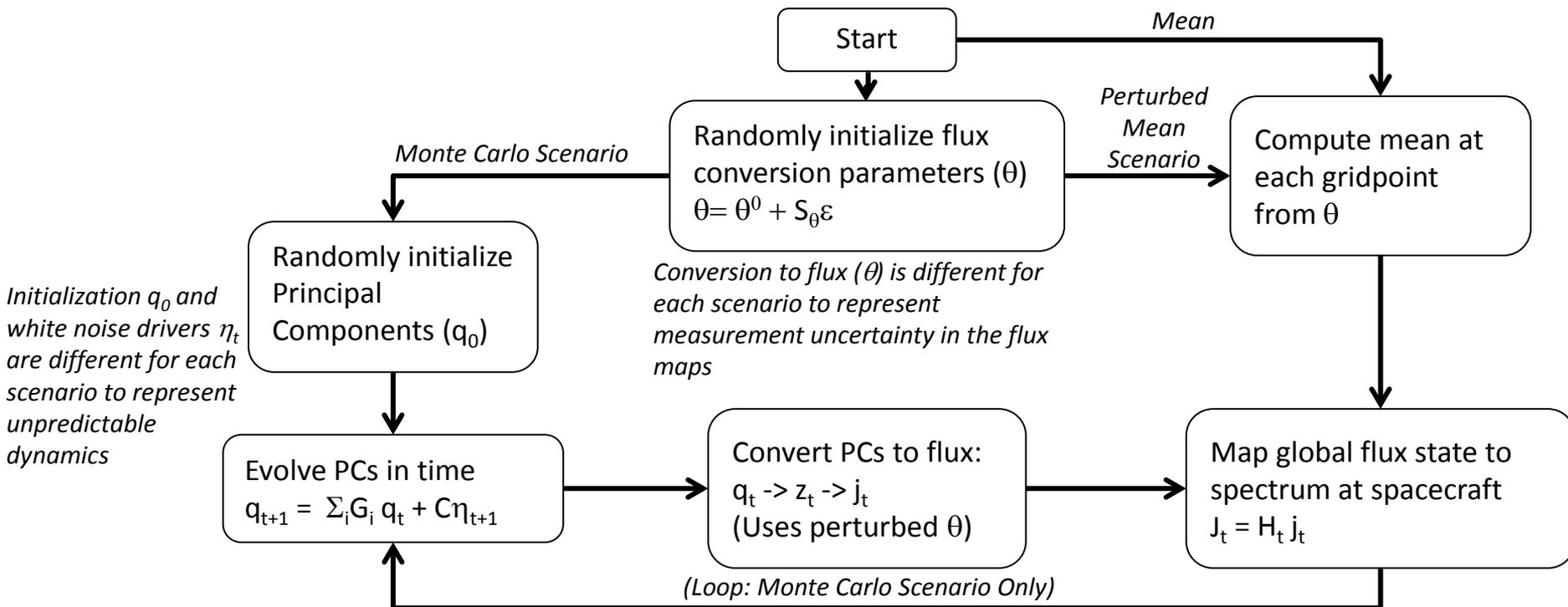
# Runtime Tables



Quantity	Symbol	Size	Purpose
Parameter map	$\theta(E,K,\Phi)$	$\sim 50,000 \times 2$	Represents transformed 50 <sup>th</sup> and 95 <sup>th</sup> percentile flux on coordinate grid (weather variation) $\theta_1 = \ln(50\% \text{ Flux})$ , $\theta_2 = \ln[(95\% \text{ Flux}) - (50\% \text{ Flux})]$
Parameter Perturbation Transform	$S_\theta(E,K,\Phi)$	$\sim 50,000 \times 2 \times \sim 10$	Represents error covariance matrix for $\theta$ (measurement errors). $S_\theta S_\theta^T$ is the error covariance matrix for $\theta$ .
Principal Component Matrix	$Q(E,K,\Phi)$	$\sim 50,000 \times 10$	Represents principal components ( $q$ ) of spatial variation (spatial correlation). $QQ^T$ is the spatial covariance matrix for normalized flux ( $z$ ).
Time Evolution Matrix	$G$ 's	$\sim 10 \times 10 \times 5$	Represents persistence of principal components (temporal correlation)
Noise Conditioning Matrix	$C$	$\sim 10 \times 10$	Allocates white noise driver to principal components (Monte Carlo dynamics)
Marginal Distribution Type	N/A	N/A	Weibull (electrons) or Lognormal (protons) used for converting 50 <sup>th</sup> and 95 <sup>th</sup> percentiles into mean or other percentiles



# Runtime Process



*Initialization  $q_0$  and white noise drivers  $\eta_t$  are different for each scenario to represent unpredictable dynamics*

*Conversion to flux ( $\theta$ ) is different for each scenario to represent measurement uncertainty in the flux maps*

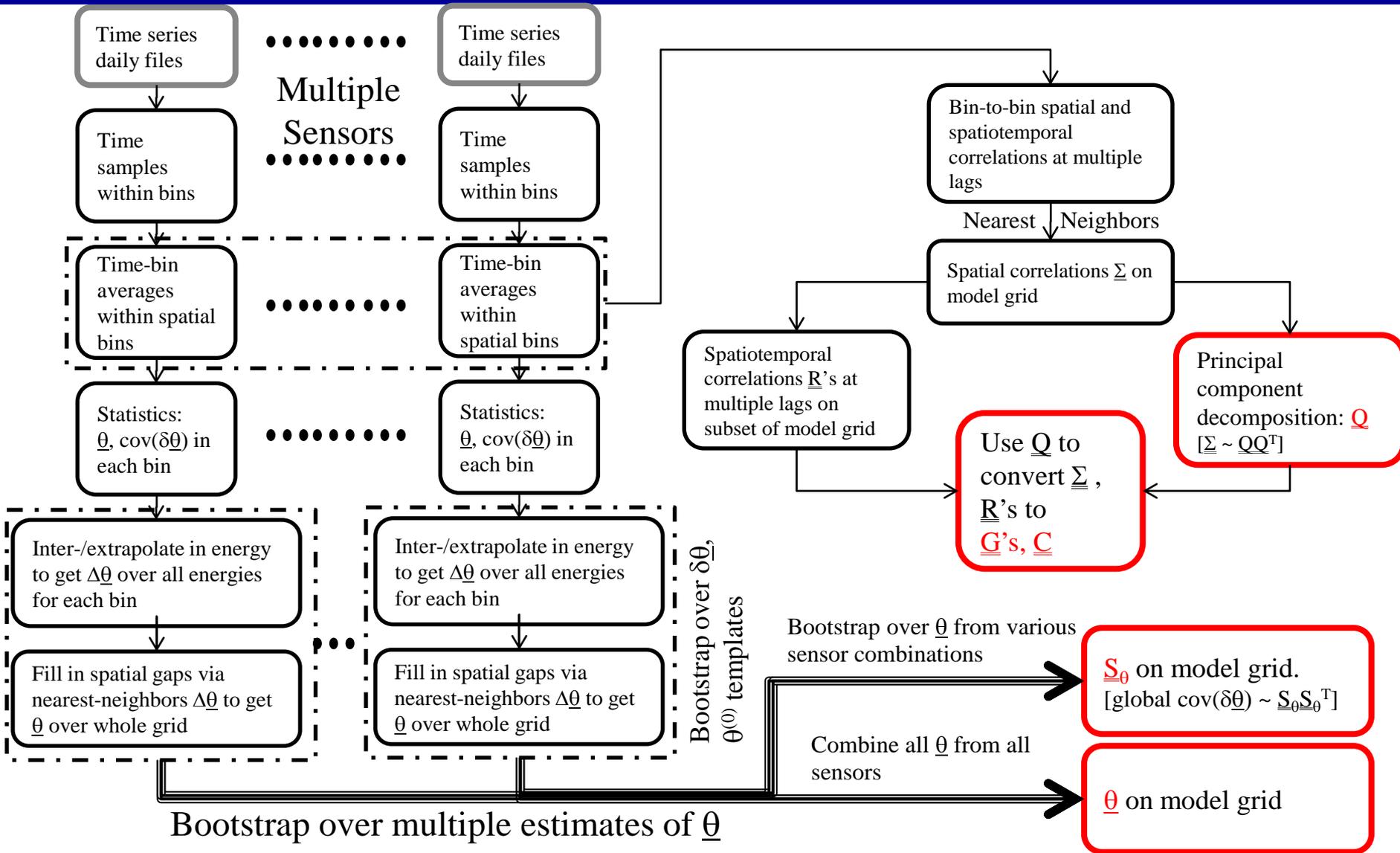
*G, C, and the parameters of the conversion from PCs to flux are derived from statistical properties of empirical data and physics-based simulations*

*The measurement matrix H is derived from the location of the spacecraft and the energies/angles of interest*

To obtain percentiles and confidence intervals for a given mission, one runs many Monte Carlo or Perturbed Mean scenarios and post-processes the flux time series to compute statistics on the estimated radiation effects across scenarios.

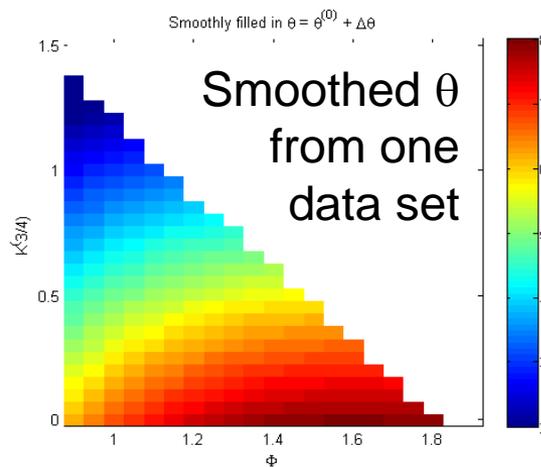
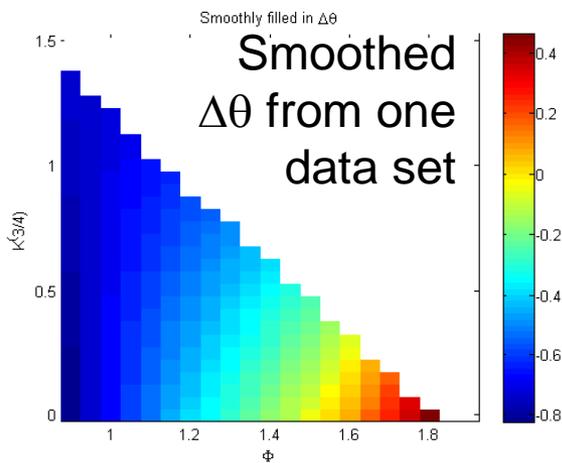
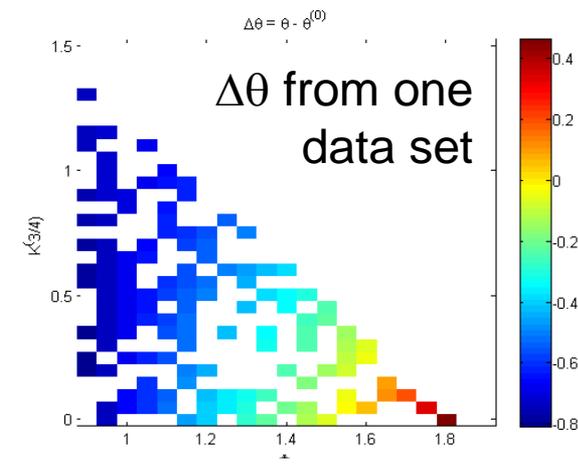
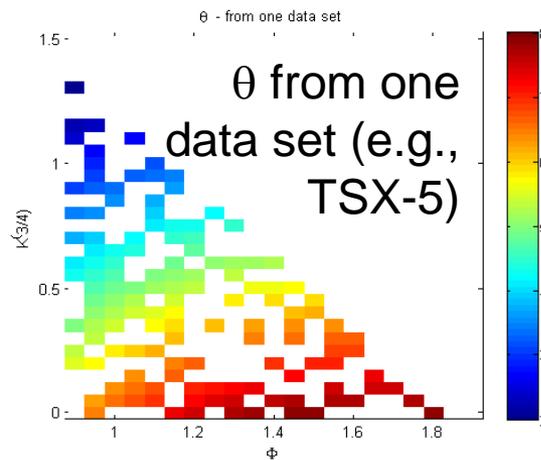
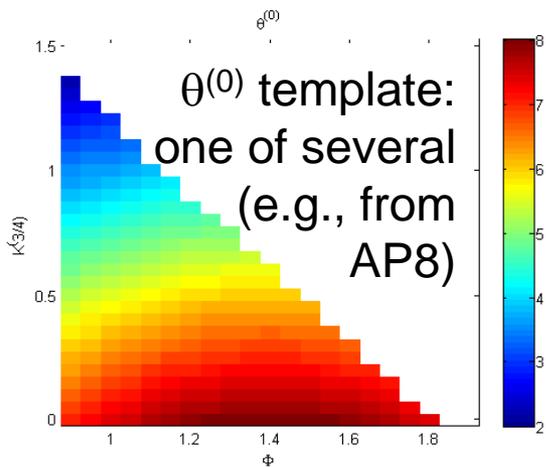


# Generating the Runtime Tables





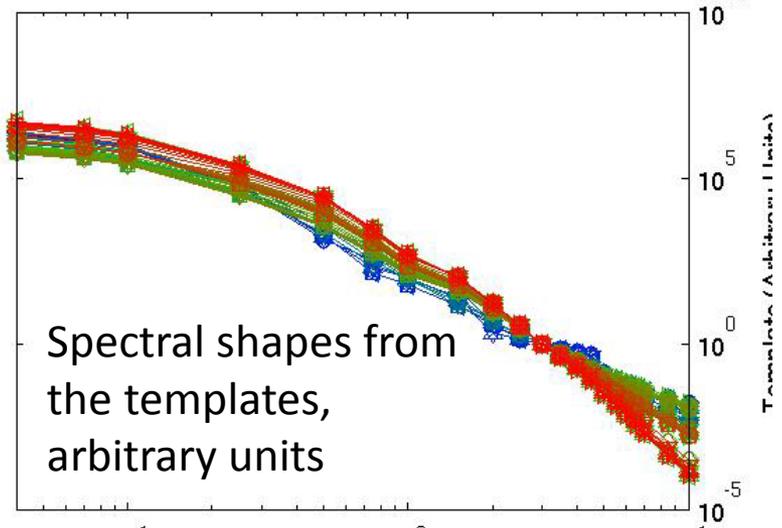
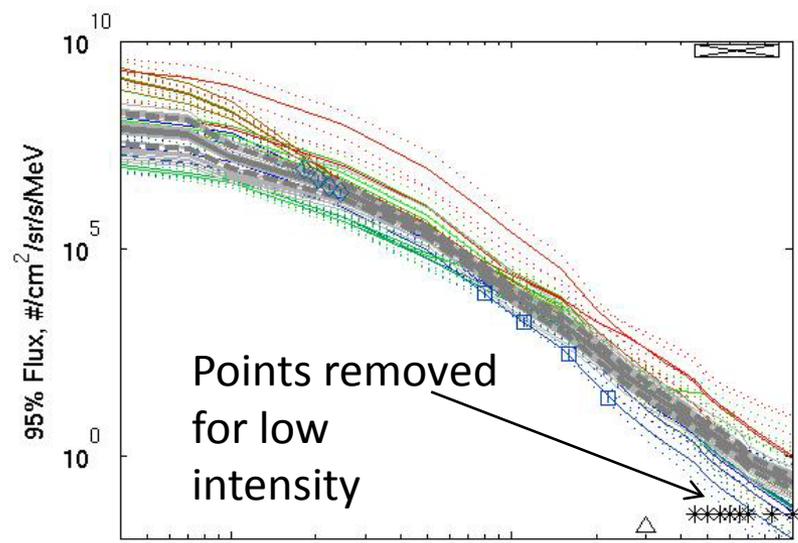
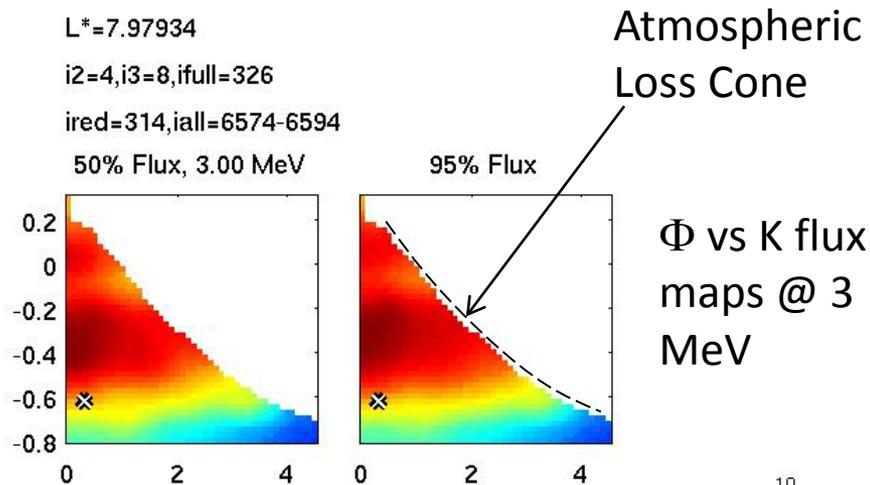
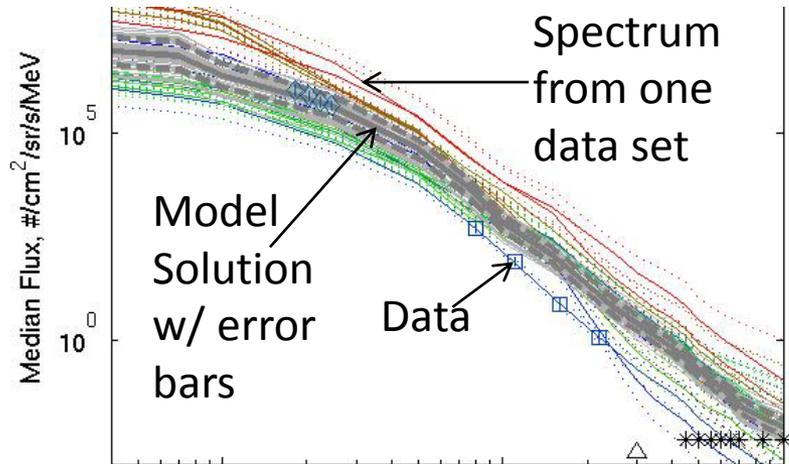
# Illustration of Building a Whole Flux Map from One Data Set



- The  $\Delta\theta$  smoothing/filling algorithm is a nearest-neighbors average
- For each combination of template and sensor data set we make several filled-in flux maps
- We bootstrap over templates, errors in  $\theta$  ( $\delta\theta$ ) and combinations of data sets to estimate the error in the filled-in flux map
- We combine these filled-in flux maps over all sensors to get a best estimate flux map and its errors ( $\underline{S}_\theta$ )



# Spectra in One Bin, AE9





# Correlations (1)



- **Correlations in fluxes and in model/data errors have a significant impact on any results obtained from the model**
- **Correlations are very hard to measure and quantify**
- **The use of templates allows us to address correlated errors (e.g., some particular sensor is a little higher than the others in some regions of space). These correlated errors end up in  $\underline{S}_\theta$ .**
- **The use of principal components ( $\underline{Q}$ ) allows us to address spatial correlations in the fluxes. However, the principal components are derived from an empirical estimate of spatial correlations**



# Correlations (2)



- Empirical flux correlations are sparse (rarely do we have two satellites in any given pair of grid points)
- Empirical correlations can be artificially large due to sample size limitations
- We would like to explore obtaining spatial correlations from long-term simulations, especially data assimilative ones (reanalyses)
- This would also allow us to obtain better spatiotemporal correlations for the monte carlo dynamics (G's, C)
  - e.g., solar rotation, semiannual, and, someday, solar cycle timescales
  - AP9: 1, 4, 26, 52 weeks
  - AE9: 1, 7, 14, 27, 183, 365 days



# Questions & Discussion

