

# A Gridded Precipitation and Temperature Observation Ensemble over the US (and Applications)

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# Outline

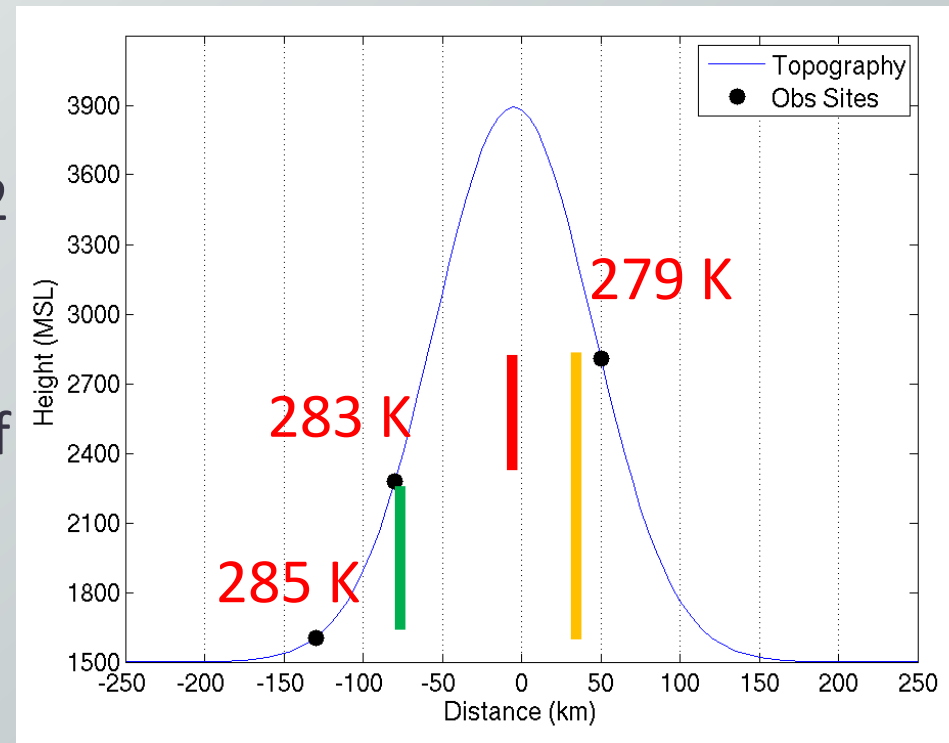
- Motivation
- Brief Methodology
- Results and Applications
  - Brief ensemble examples
  - Verification of RCM simulations
  - Intercomparison across the Western US
- Next Steps & Summary

# Motivation

- Gridded Datasets:
  - Transform sparse, irregularly spaced observations to continuous, gridded fields
    - Provides an estimate everywhere in space and time
    - Make comparisons to gridded model output easier
    - Allows for spatial verification techniques
    - Used for statistical downscaling, impact modeling
- Why continue to develop new gridded datasets?
  - Models continue to challenge observational capabilities
  - Incorporate new observing networks
  - Need to begin incorporating uncertainty more regularly
    - Observational and grid transformations introduce uncertainty
    - Understand and reduce uncertainty

# Example: Temperature

- Stations over a mountain
  - Temperature at 3 heights
  - 1600, 2300, 2800 m
  - Station estimated lapse rates: 2.5 K/km, 8 K/km, 5 K/km, 5.2 K/km (avg)
  - Climatology:  $\sim 6.5$  K/km
  - What is temperature at top of mountain (3800 m)?
  - Range: 271-276.5 K



# Methodology Overview

# Methodological Choices in Generating a Gridded Dataset

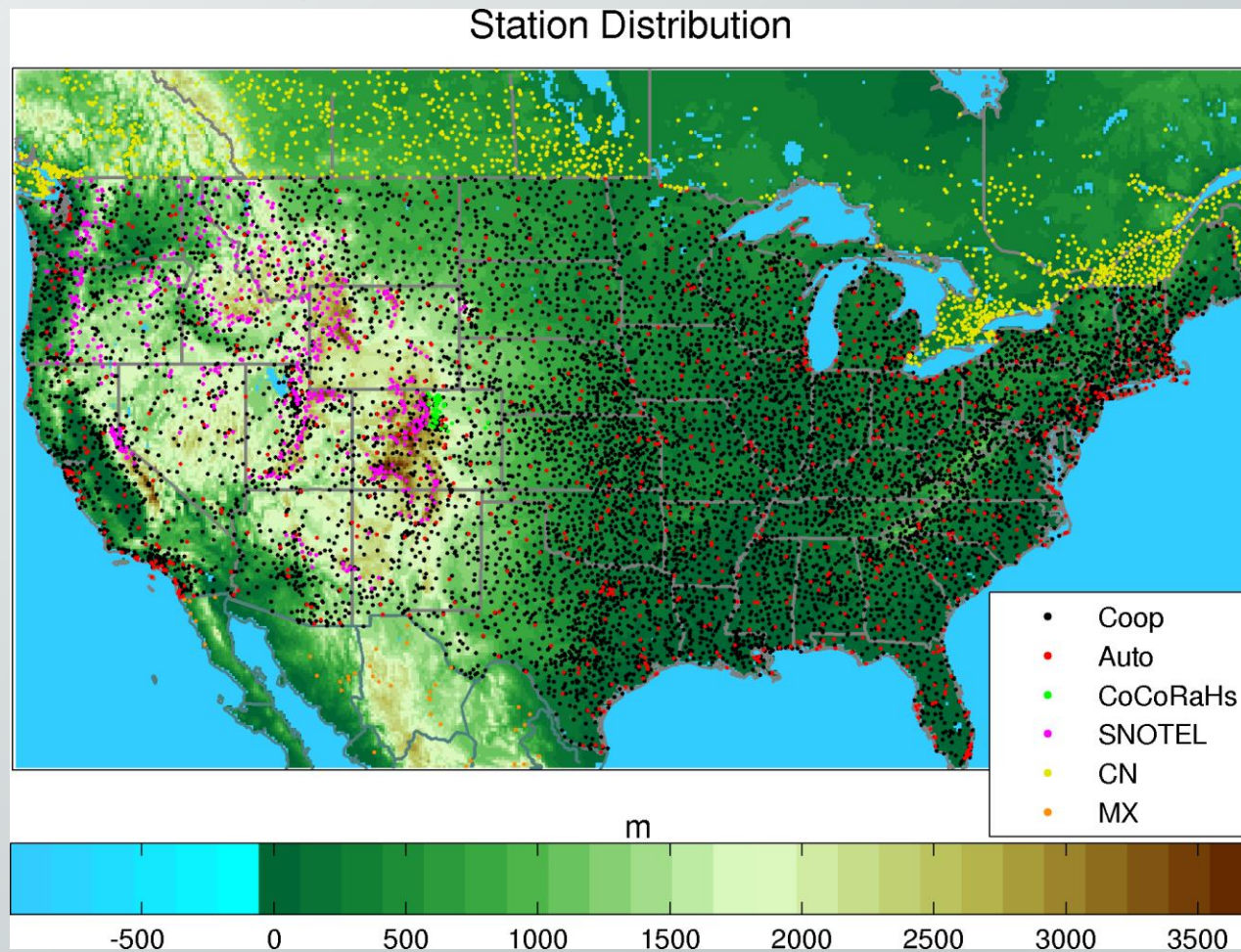
- Interpolation scheme
  - Inverse distance, kriging, etc.
- Data
  - Which station networks to include?
  - Missing data
    - Use serially complete (gap filled) station data or use only available observations?
- Others: Spatial resolution, time step and temporal disaggregation, precipitation occurrence prediction, lapse rates in complex topography
- These methodological choices may have a large impact
  - **Try to estimate uncertainty within a specific set of methodological choices**

# Ensemble Generation: Brief Methodology

- Transform station data to 12-km (1/8<sup>th</sup> degree) grid on daily time step for precipitation and temperature
  - 1980-2012 currently, will be updating to run through 2015 or 2016 soon
  - Newman et al. 2015, J. Hydrometeorology
- Use regression techniques to estimate occurrence, amount and uncertainty at each grid point
  - Location, elevation, terrain slope are predictors
  - Explicit prediction of occurrence
- Sample from these values and generate 100 realizations of gridded precipitation and temperature
  - Include estimates of spatial and temporal correlation

# Ensemble Generation: Input Data

- 12,000+ stations with serially complete data (used various missing data filling methods)
  - Precipitation, temperature or both

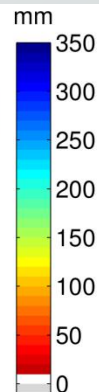
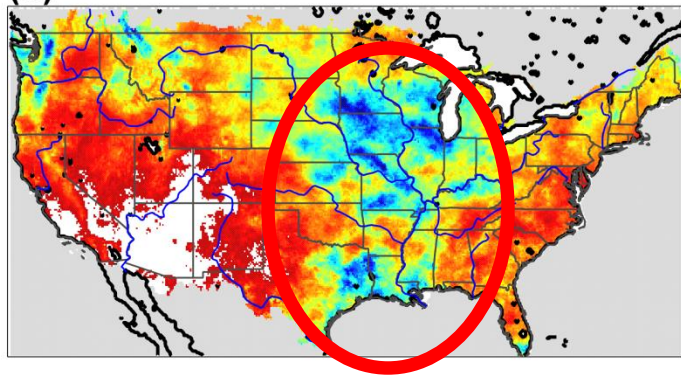




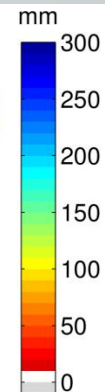
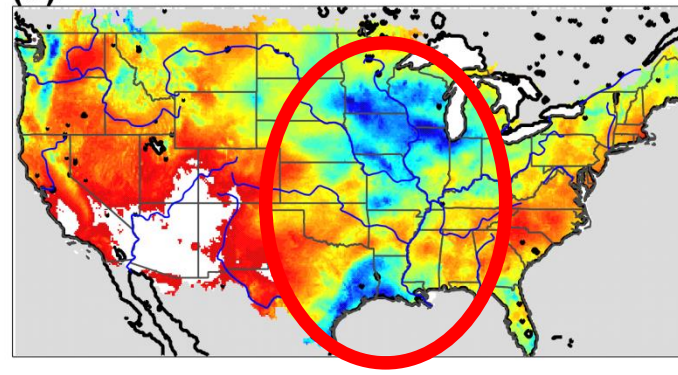
# Example Output

- Central US Flood of 1993
  - June 1993 total precipitation

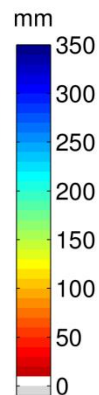
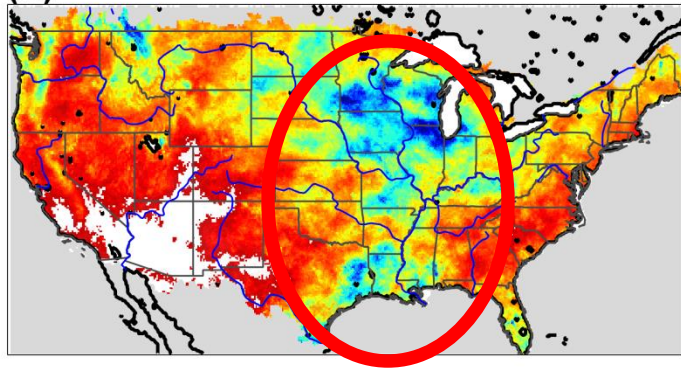
**(a)** 1993 June Precipitation, Ens Mem 011



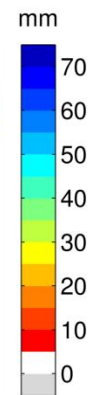
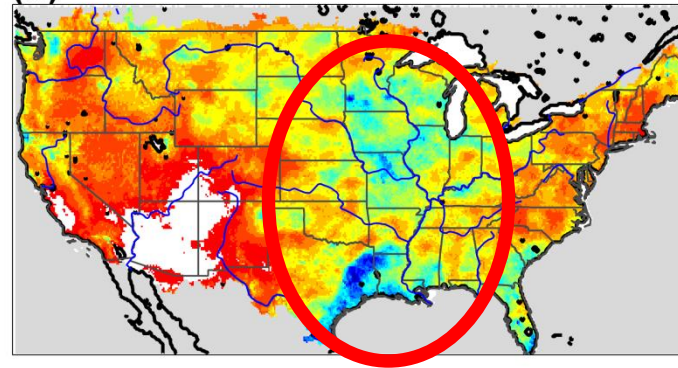
**(c)** 1993 June Precipitation, Ensemble Mean



**(b)** 1993 June Precipitation, Ens Mem 075

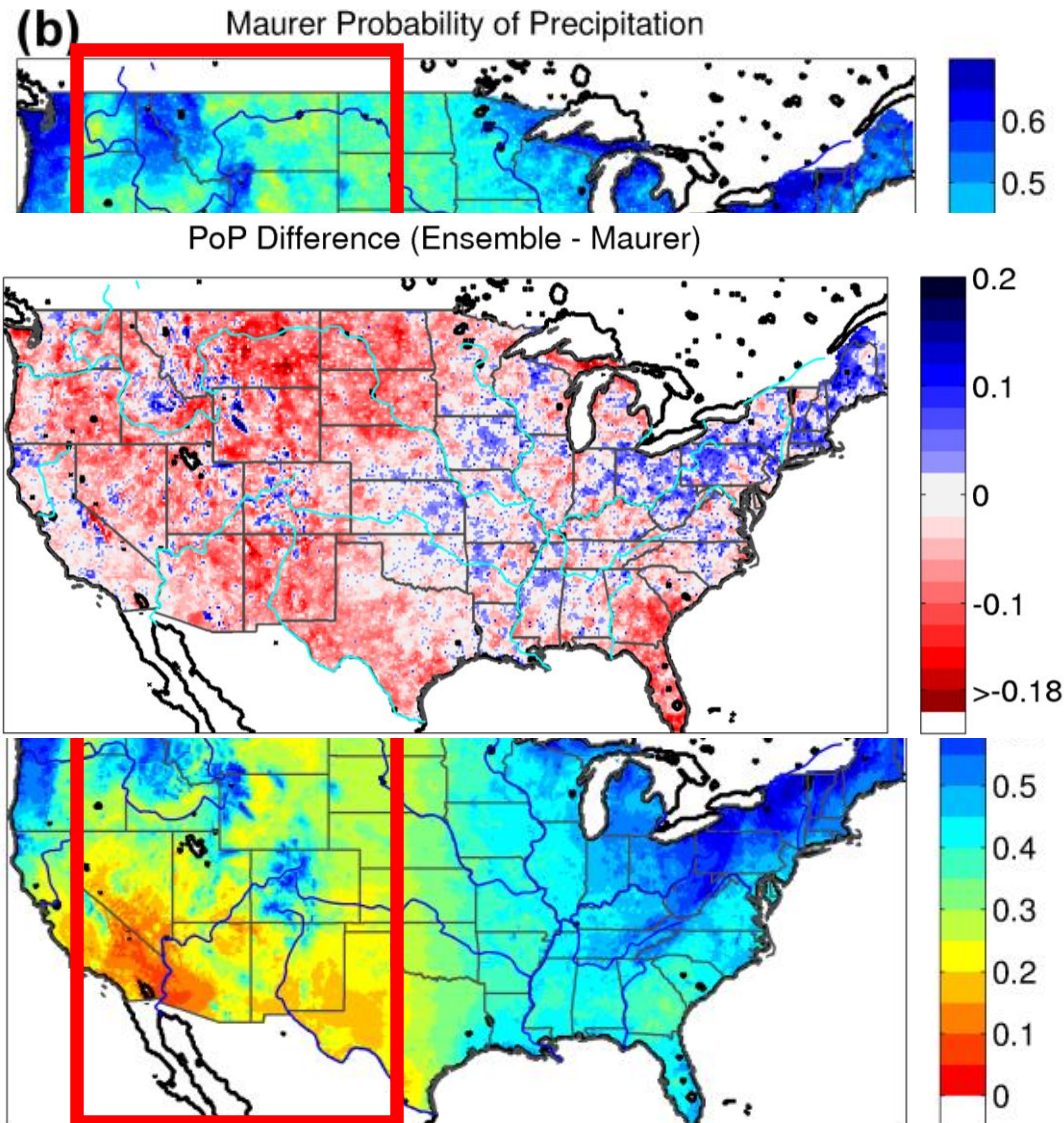


**(d)** 1993 June Precipitation, Ensemble Std Dev



# Probability of Precipitation (PoP)

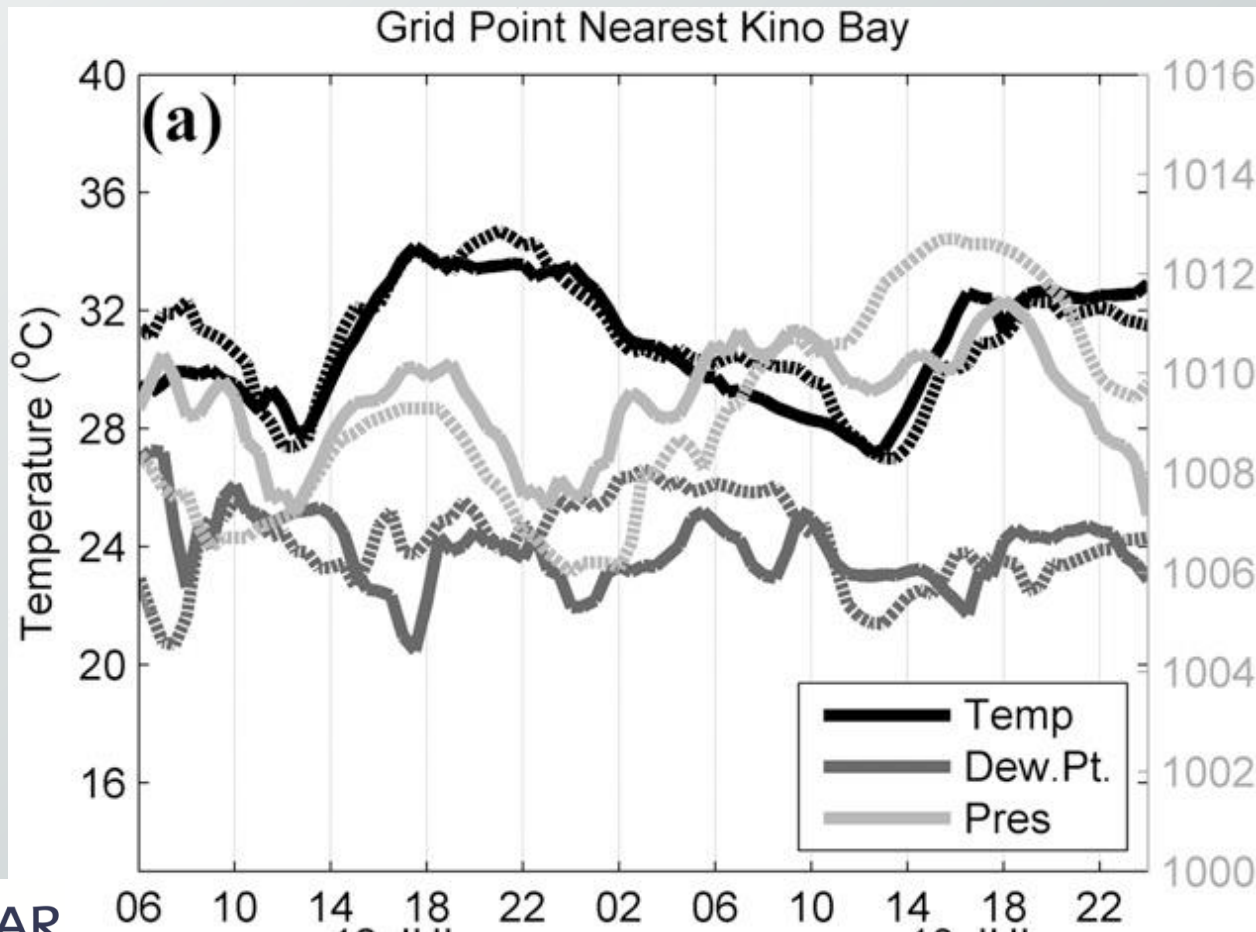
- Maurer et al. (2002)
  - Interpolation between observations increases precipitation occurrence
- Ensemble:
  - Explicit prediction of occurrence gives more realistic PoP
  - Generally reduces PoP
  - Data differences may be responsible for PoP increases



# Model Verification using Ensemble(s)

# Model Verification

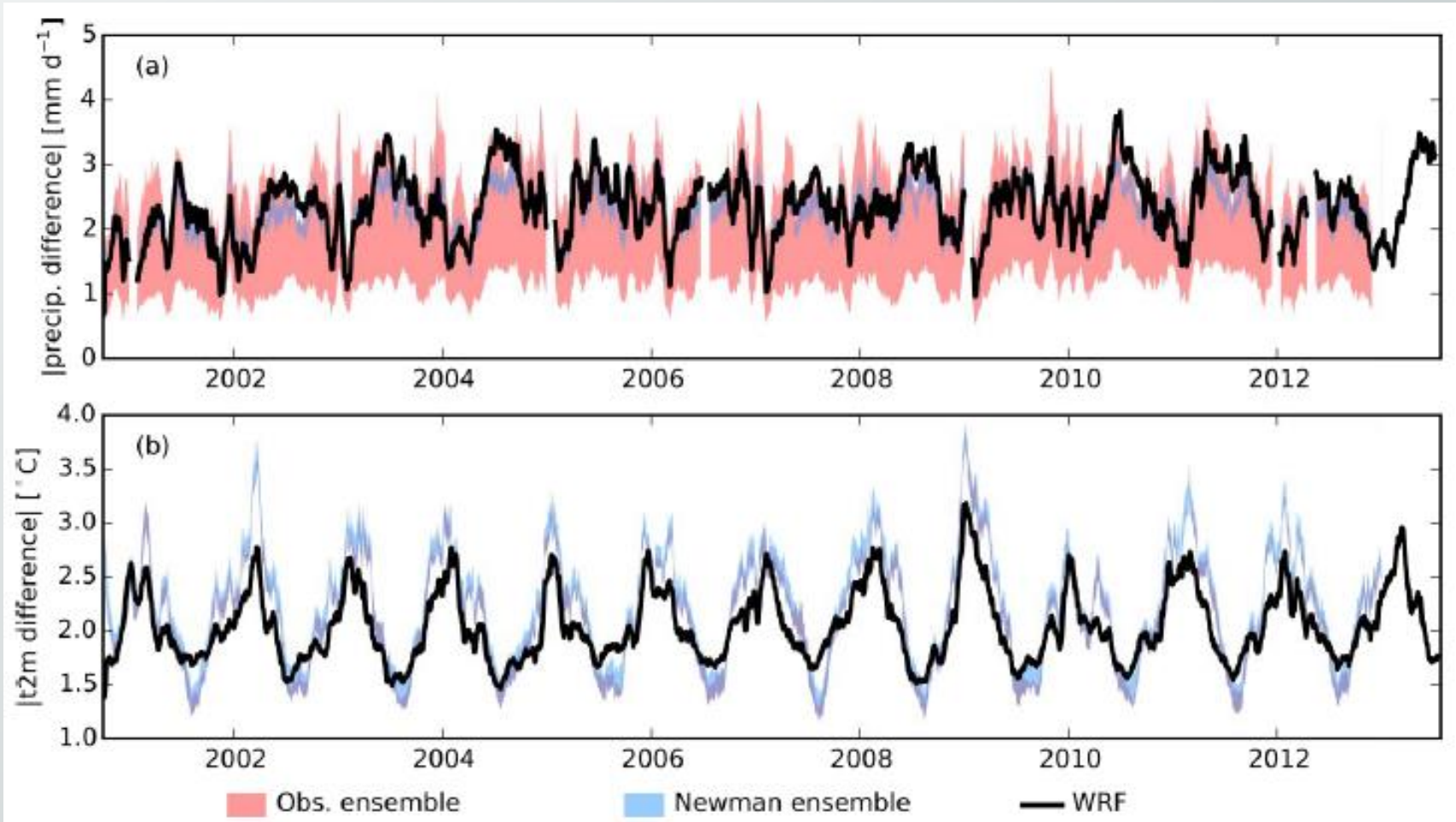
- Include observational uncertainty in model verification
  - Move past comparing “similar” lines or difference fields



Newman et al. (2012)

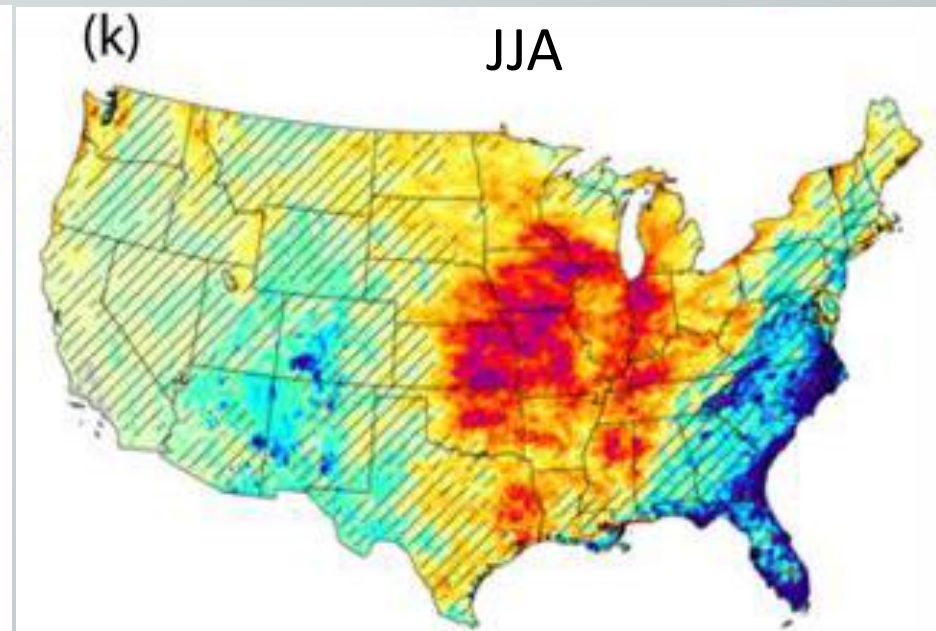
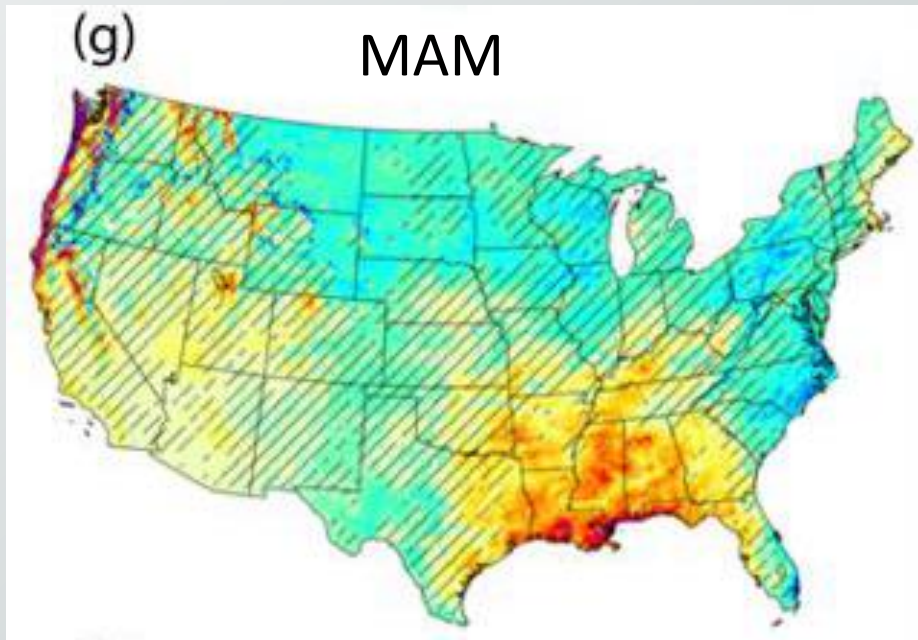
# Model Verification

- Include observational uncertainty in verification
  - Move past comparing “similar” lines or difference fields



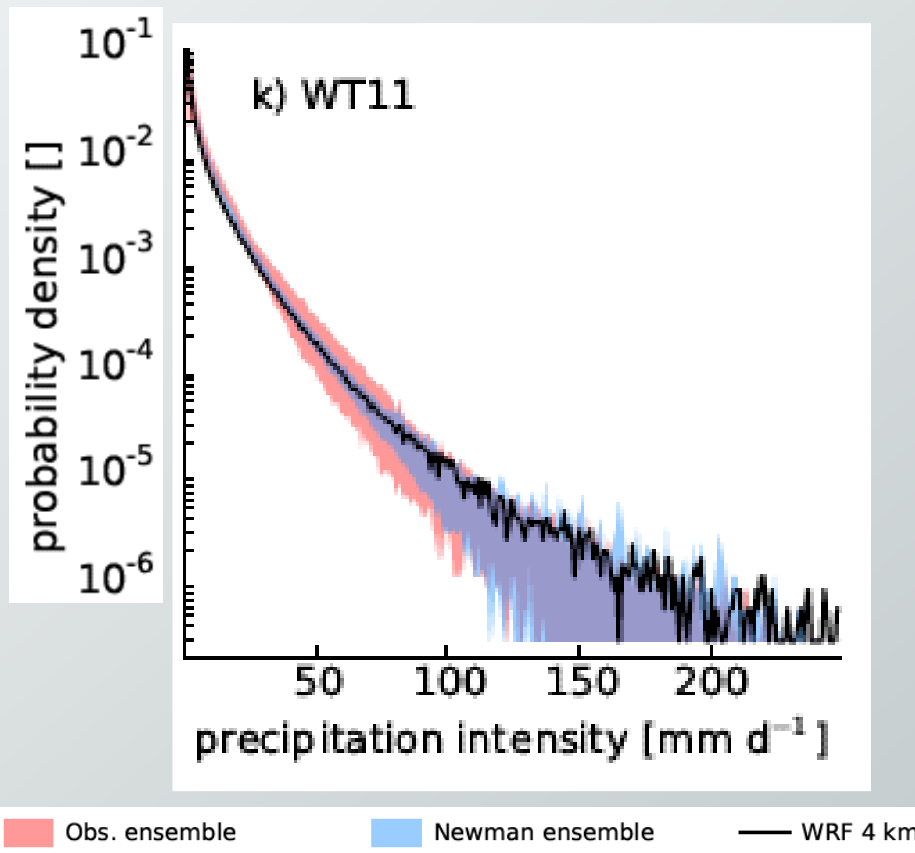
# Model Verification

- Include observational uncertainty in model verification
  - Incorporate some estimate of uncertainty and statistical tests whenever possible -> significant differences, focuses model improvement work
  - Is mountain over-prediction partially related to plains under-prediction? Overactive solenoid circulation(s)?



# Model Verification

- PDF of precipitation



- Frequency of occurrence of intensity is also uncertain
- Uncertainty of observations increases with decreasing frequency
- Use ensemble dataset – blue/purple shading
- Red shading includes other observational datasets (including remotely sensed)
- WRF represents PDF of precipitation well

# Comparisons Across Observational Products

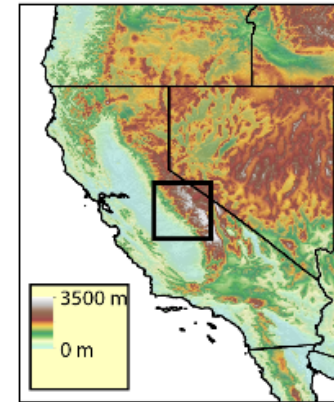
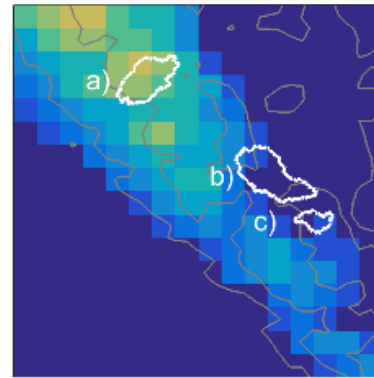
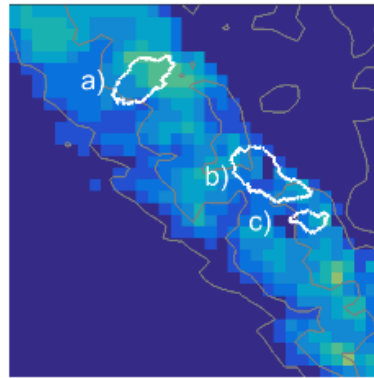
- How uncertain are our gridded observations in complex terrain in the Western US?
- Can we use ancillary observations (when available) to highlight areas needing improvement?
- Led by Brian Henn (Univ. of Washington)



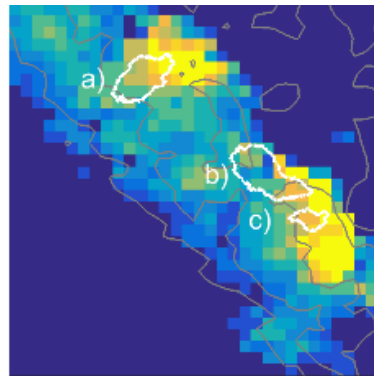
# Gridded Product Comparison: Example Year

- These products are have been considered “truth” for many studies

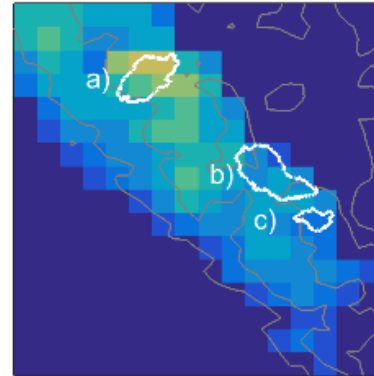
Hamlet et al. (2010) Newman et al. (2015)



Livneh et al. (2013)

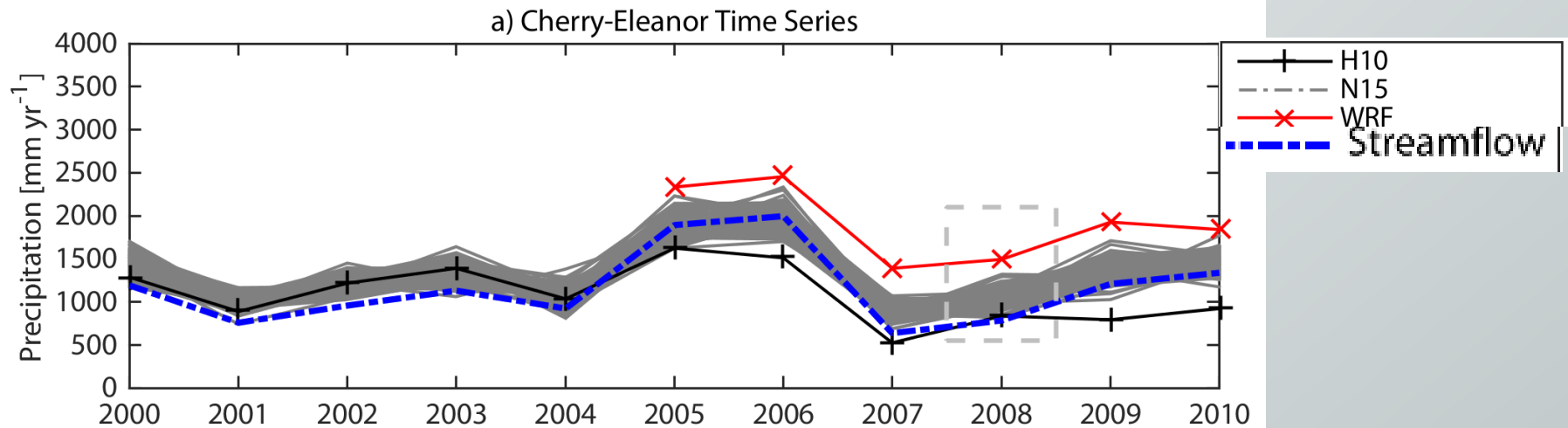


NLDAS-2



- Differences in water year 2005 precipitation over central Sierra Nevada (Henn et al. 2016a, J. Hydrology)

# Gridded Product Comparison: River Basins



- Water balance over long term:  $\text{Runoff} = P - ET$ 
  - Streamflow is as large as gridded estimated precipitation  $R = P$
  - No (or negative) evapotranspiration some years is **non-physical**
  - High-resolution WRF retrospective simulation **most realistic?**
  - Gauge network and current statistical methods to estimate orographic precipitation underestimate
    - Gauge undercatch is not accounted for in most products
    - Miss processes using statistical methods with sparse observations
      - Small scale mountain – flow interactions

# Next Steps

- Various development across time horizons
  - *In situ* only, data fusion with remote sensing, data fusion with WRF output
  - Near term (3-6 months):
    - Complete Alaska and Hawai'i ensemble for *in situ* coverage across all 50 states
  - Longer term/ongoing:
    - Increase resolution of CONUS product O(5 km)
    - Include remotely sensed observations (e.g. radar rainfall estimates)
    - Sub-daily 2002-present *in situ* and remotely sensed product
    - WRF – observation fusion product
      - E.g. WRF based precipitation and temperature information (e.g. lapse rates or direct WRF grid information)
      - Capture missed processes in *in situ* only products
    - Develop periodic updates to keep products near present time

# Summary

- First ensemble hydrometeorological dataset for CONUS (Newman et al. 2015, J. Hydrometeorology)
  - Available at: <http://dx.doi.org/10.5065/D6TH8JR2>
  - Estimate of uncertainty that varies in time and space; generated using a consistent methodology
- Model verification
  - Use ensemble directly, uncertainty information (e.g. satellite rainfall products), multiple “trusted” deterministic products
  - Allows for ensemble assessment of model-observation differences and statistical testing
  - More challenging and involved verification, but can lead to stronger conclusions
- Need to understand the observations used in an evaluation
  - Methodological differences between datasets give rise to large differences
    - In some specific locations, observations are still very uncertain