Spatial Analysis of Mean Annual Maxima for Precipitation Frequency Estimation

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Developing MAM grids in-house

Benefits of an in-house capability:

- Provides an **efficient and iterative process** for responding to expert analysis and public feedback
- Provides a **mechanism for continuing improvement** of MAM analysis through innovation and process modernization
- Provides a **long-term solution** for gridded MAM analysis
- The resulting MAM grids will likely show **improved accuracy** over previous methods

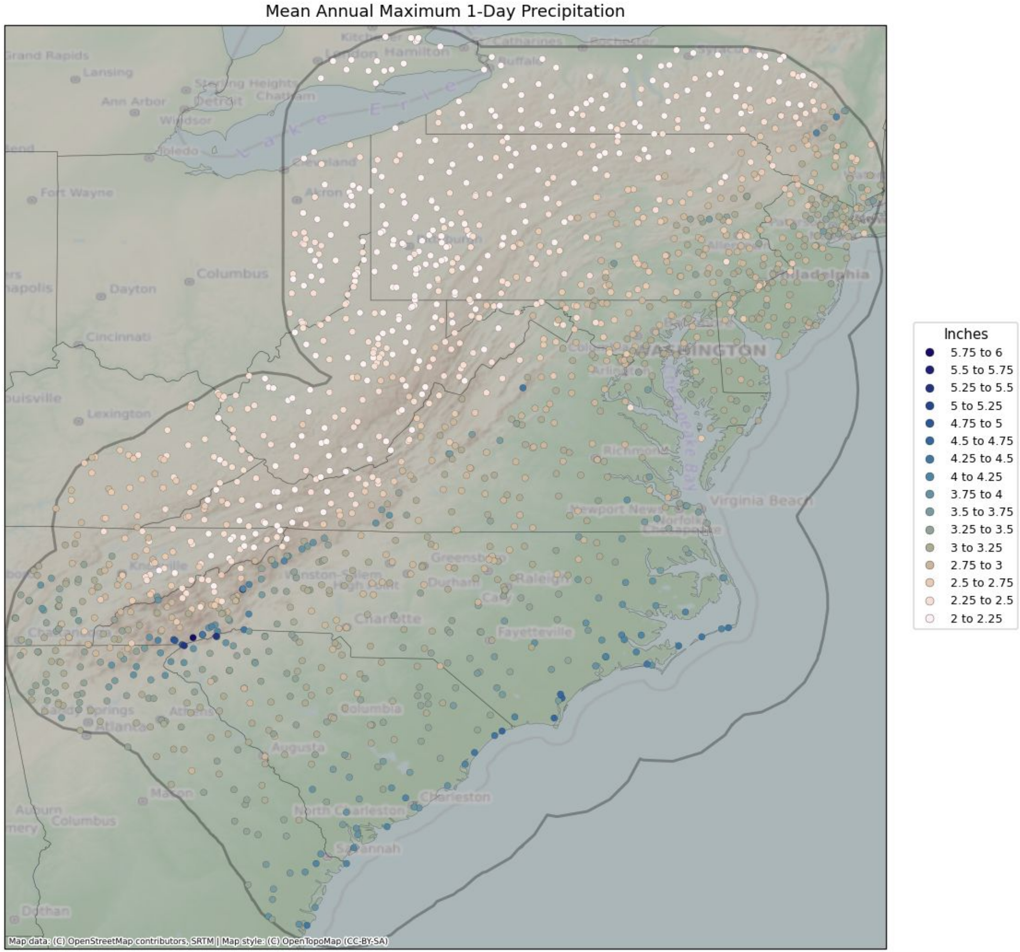
Summary of the method:

- **Data**
  - **At-station MAM** from annual maximum series (AMS) data
  - Gridded (raster) **spatial covariates**
- **Regions**
  - **Atlas 14** Volumes 12 (Interior Northwest) and 13 (East Coast)
  - **Atlas 15** (CONUS, oCONUS)
- **Techniques**
  - **Stepwise multiple linear regression**
  - **Ordinary kriging**
- **Evaluation**
  - **Leave-one-out cross validation (LOOCV)**

Background/1st guess

Covariates (independent variables):

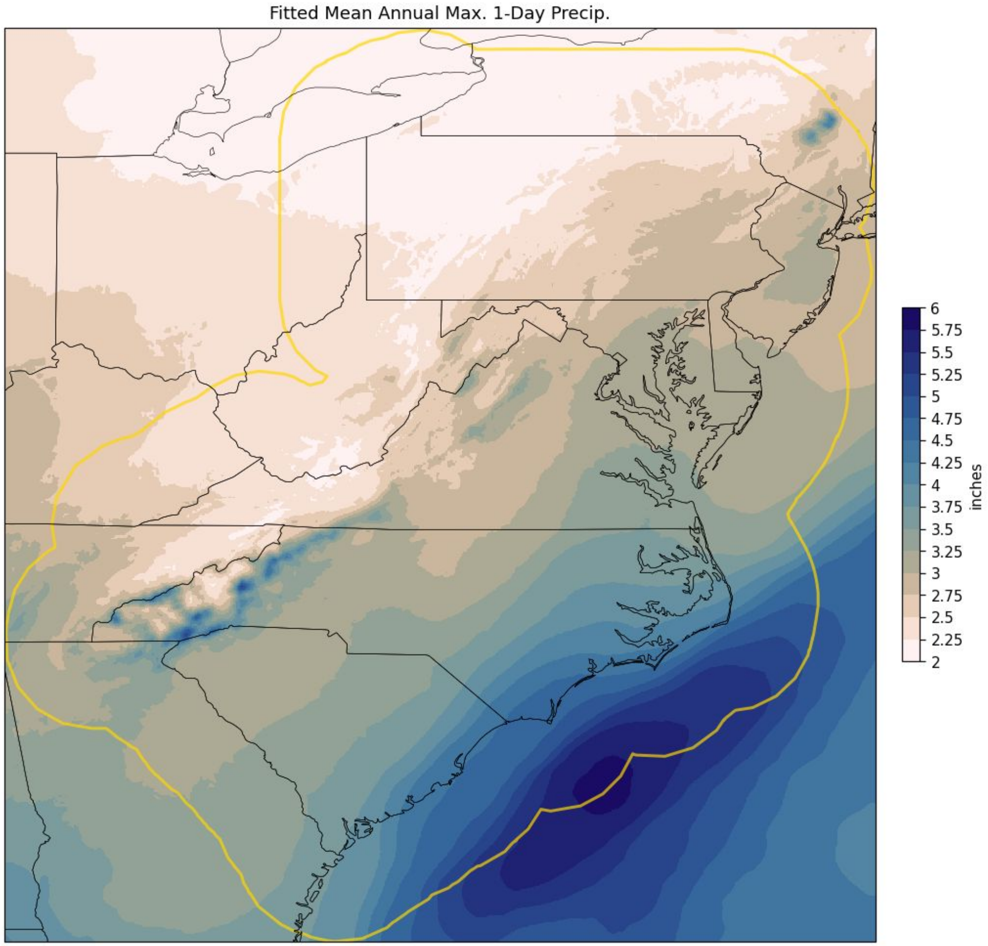
1. **Primary static**
   (e.g., elevation, distance to coast)
2. **Secondary static**
   (e.g., height above local terrain, TPI)
3. **Climatological**
   (e.g., PRISM mean annual precipitation, CONUS404 MAM)



Background/1st guess

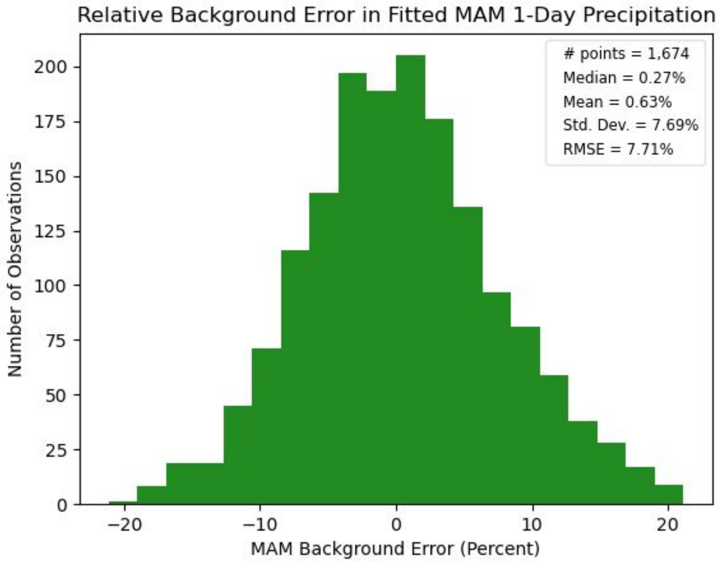
Stepwise multiple linear regression with backward elimination:

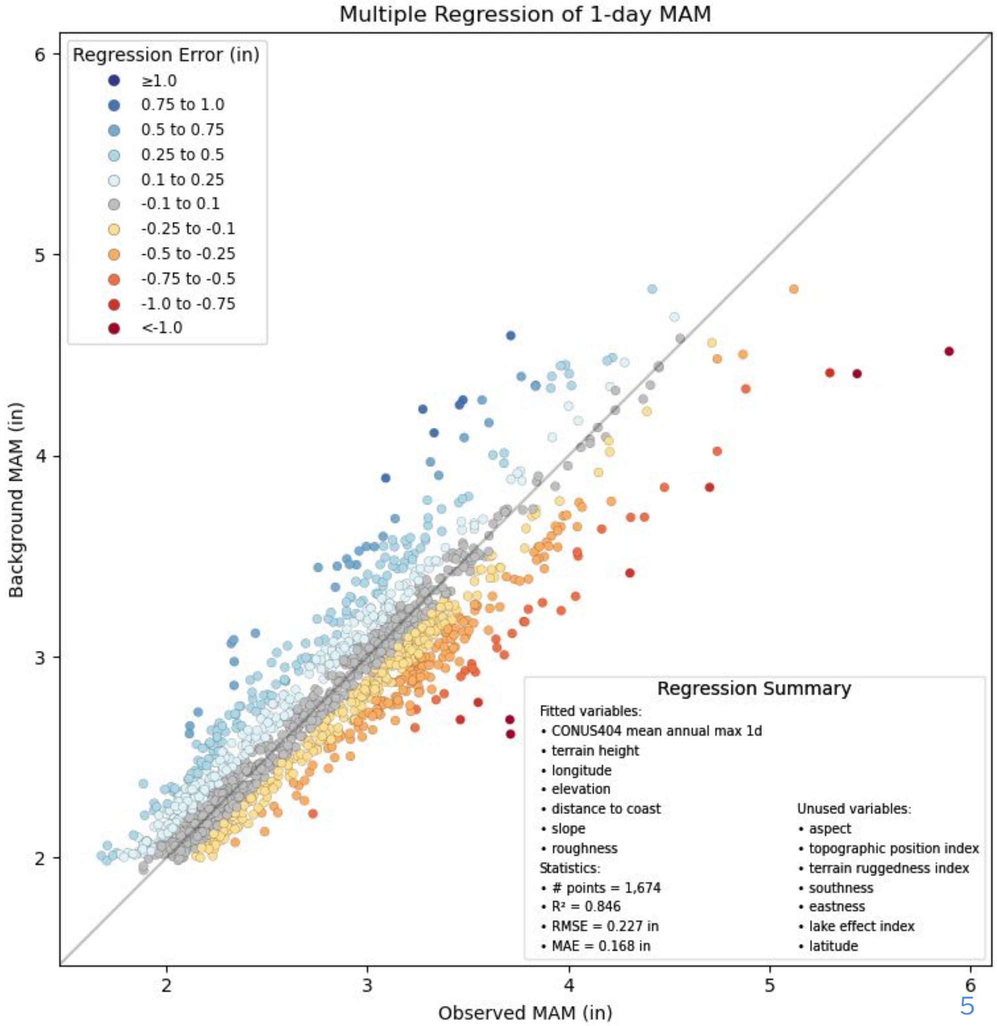
1. Combination of ≤8 covariates with highest adjusted R^2 and condition number ≤ 20 is selected
2. Covariates with p-values ≥0.05 are removed iteratively
3. Covariates having variance inflation factor (VIF) >7.0 are removed iteratively



Background/1st guess

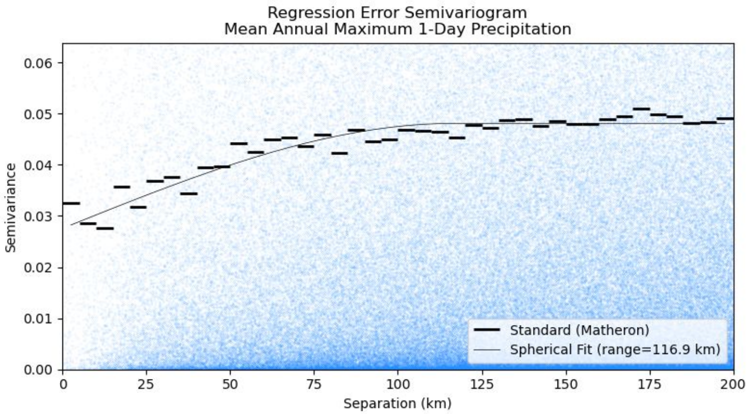
- 7 of 14 covariates selected
- R^2 = 0.85
- RMSE = 0.28 in.; relative = 7.7%

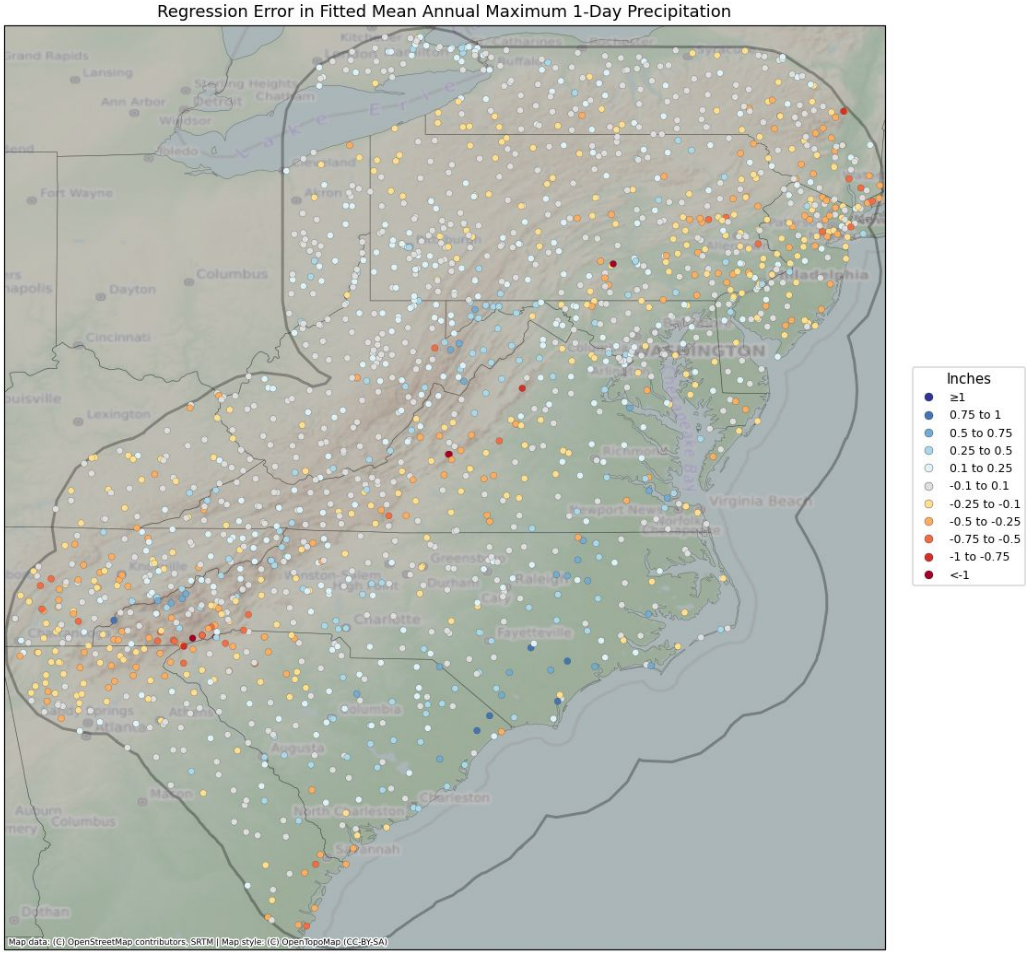




Kriging adjustment

Ordinary kriging interpolates errors in the background estimate using a spherical variogram model.





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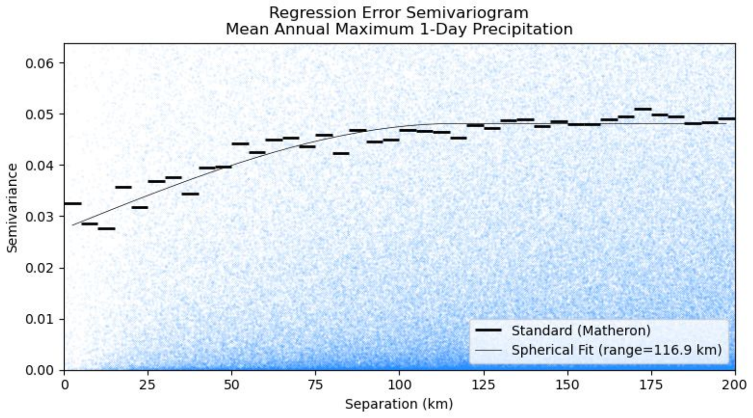

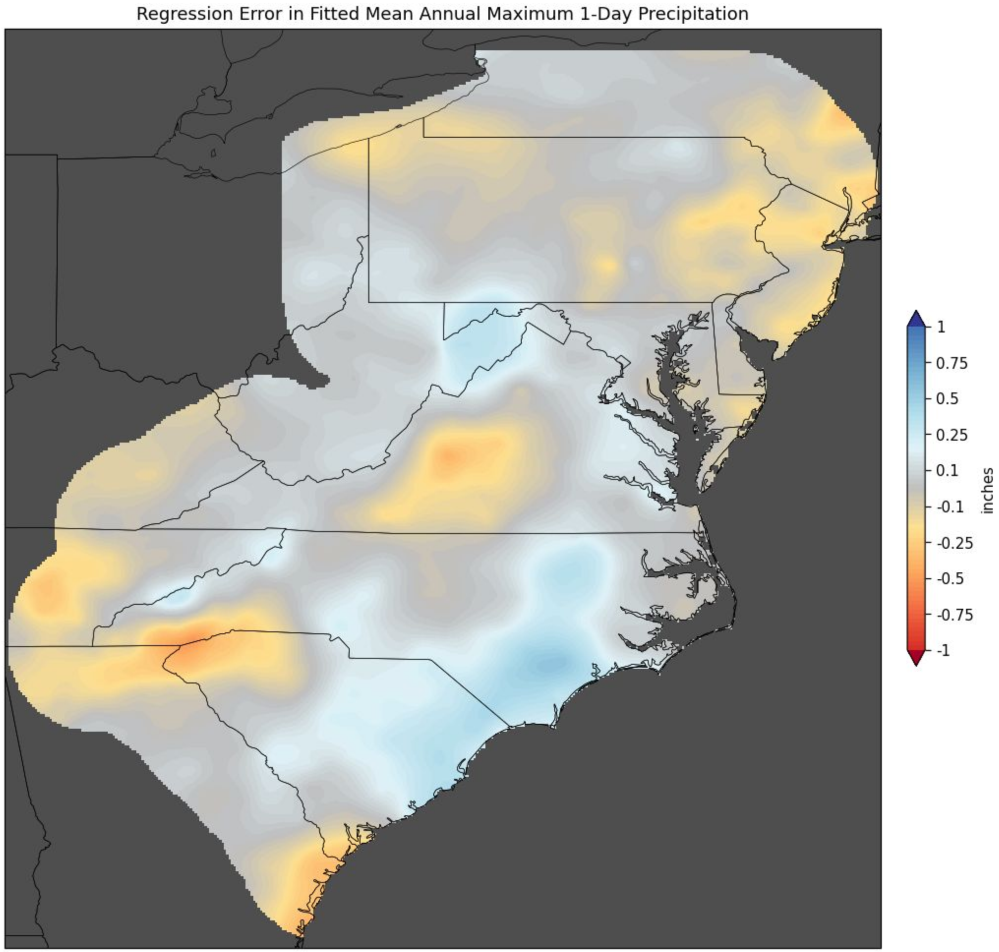

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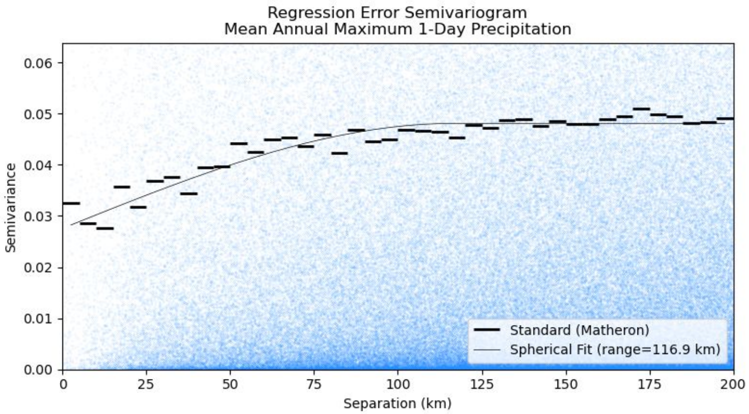

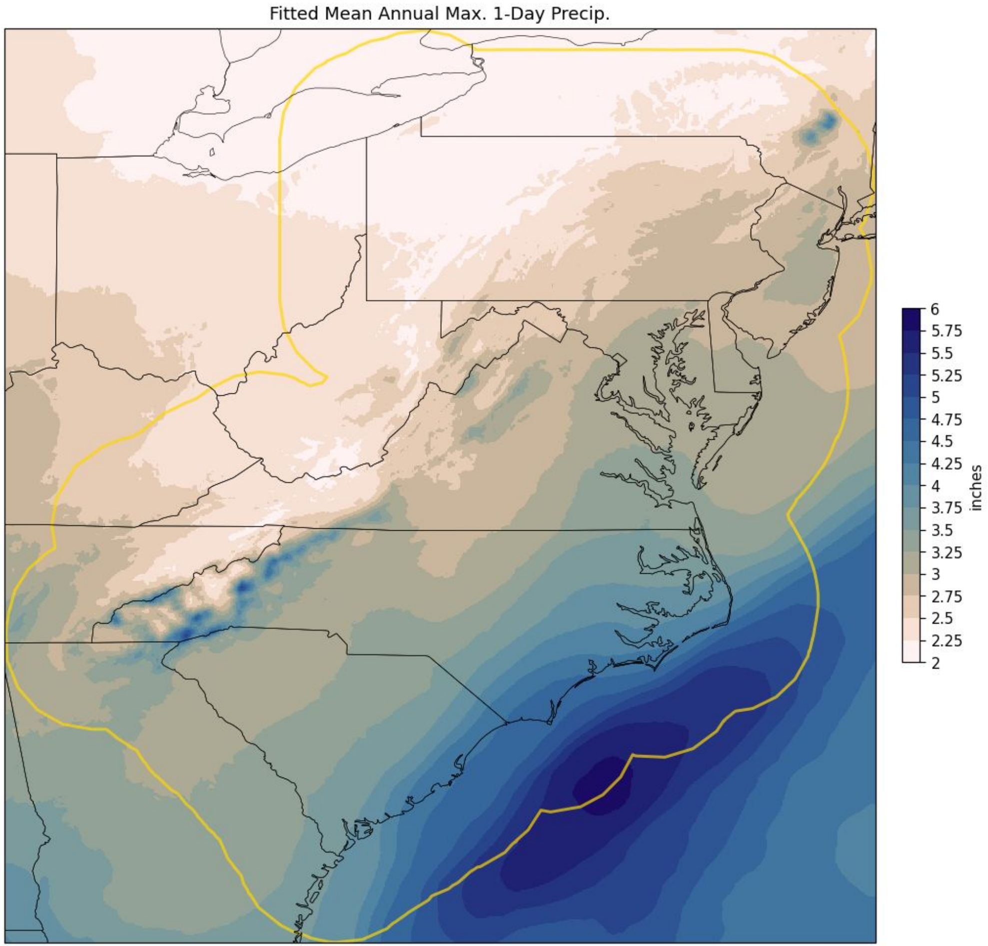

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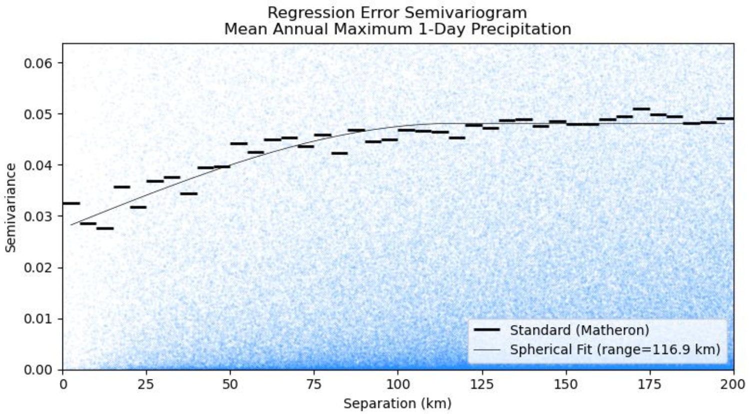
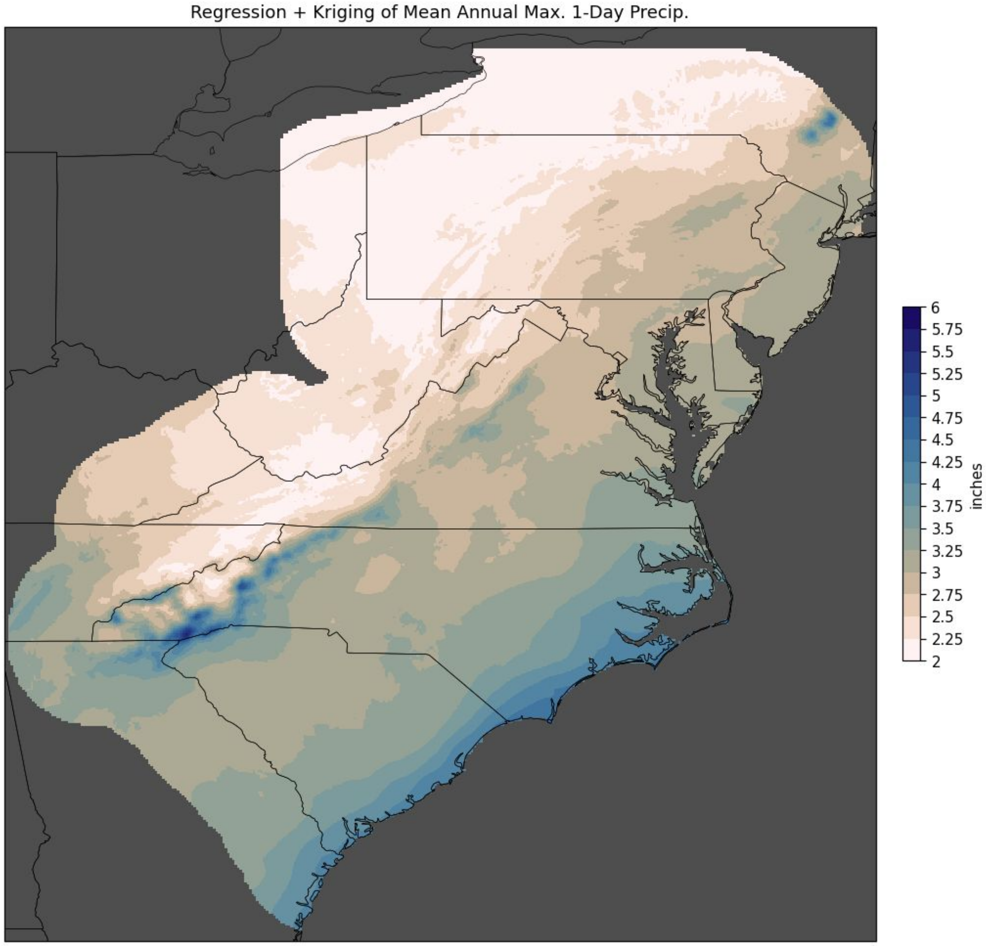
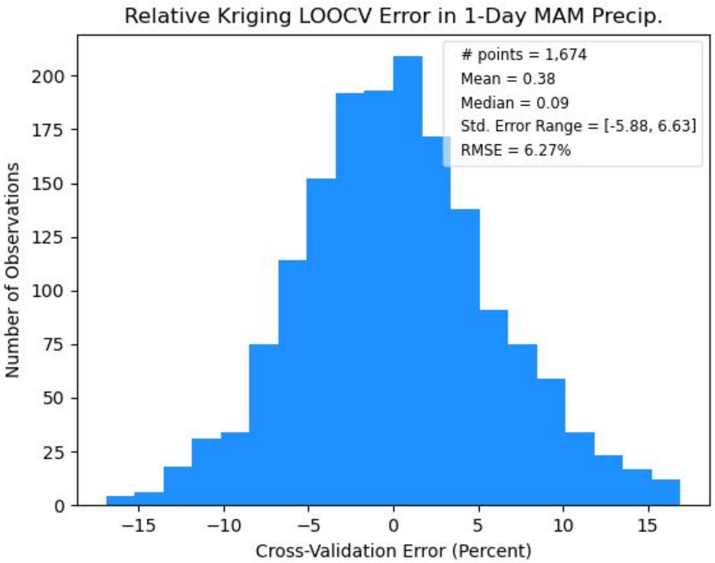
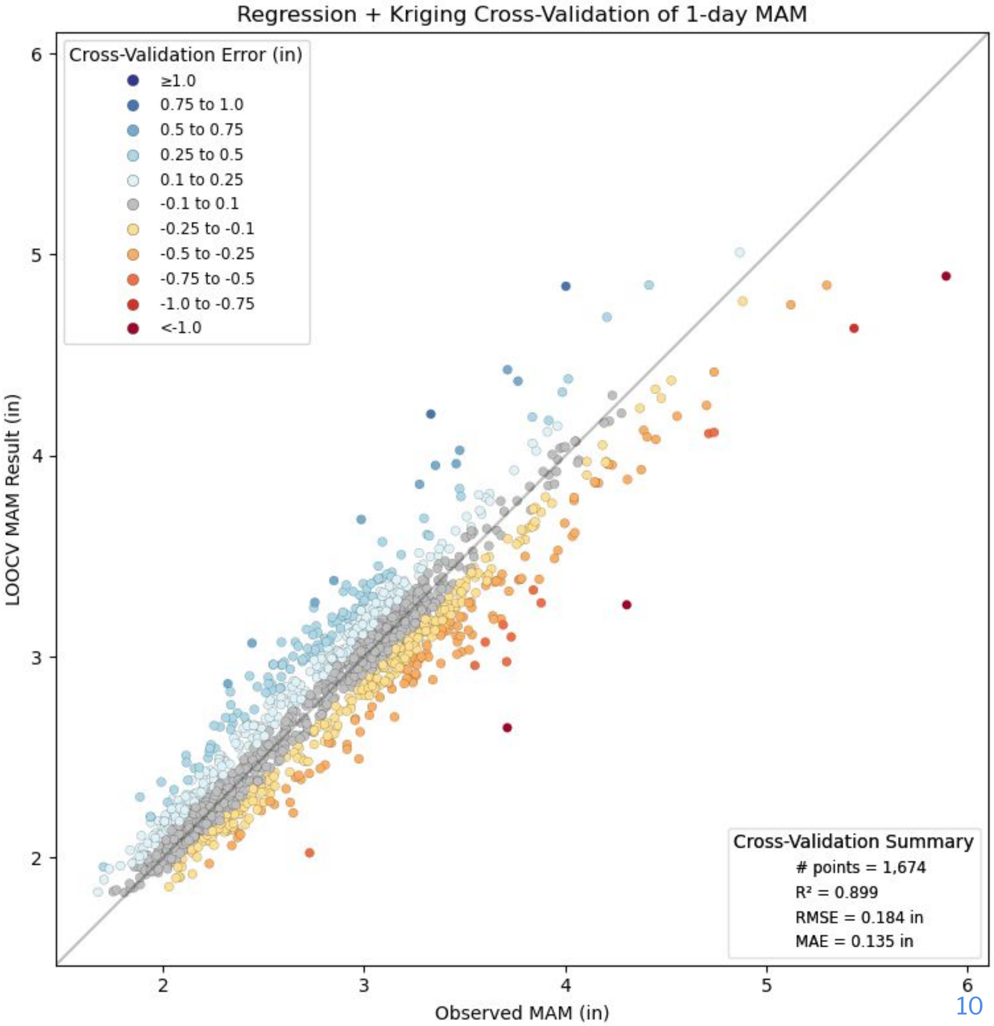




Kriging adjustment

- Leave-one-out cross validation (LOOCV) analysis
  - $R^2 = 0.90$
  - RMSE = 0.18 in.; relative = 6.3%



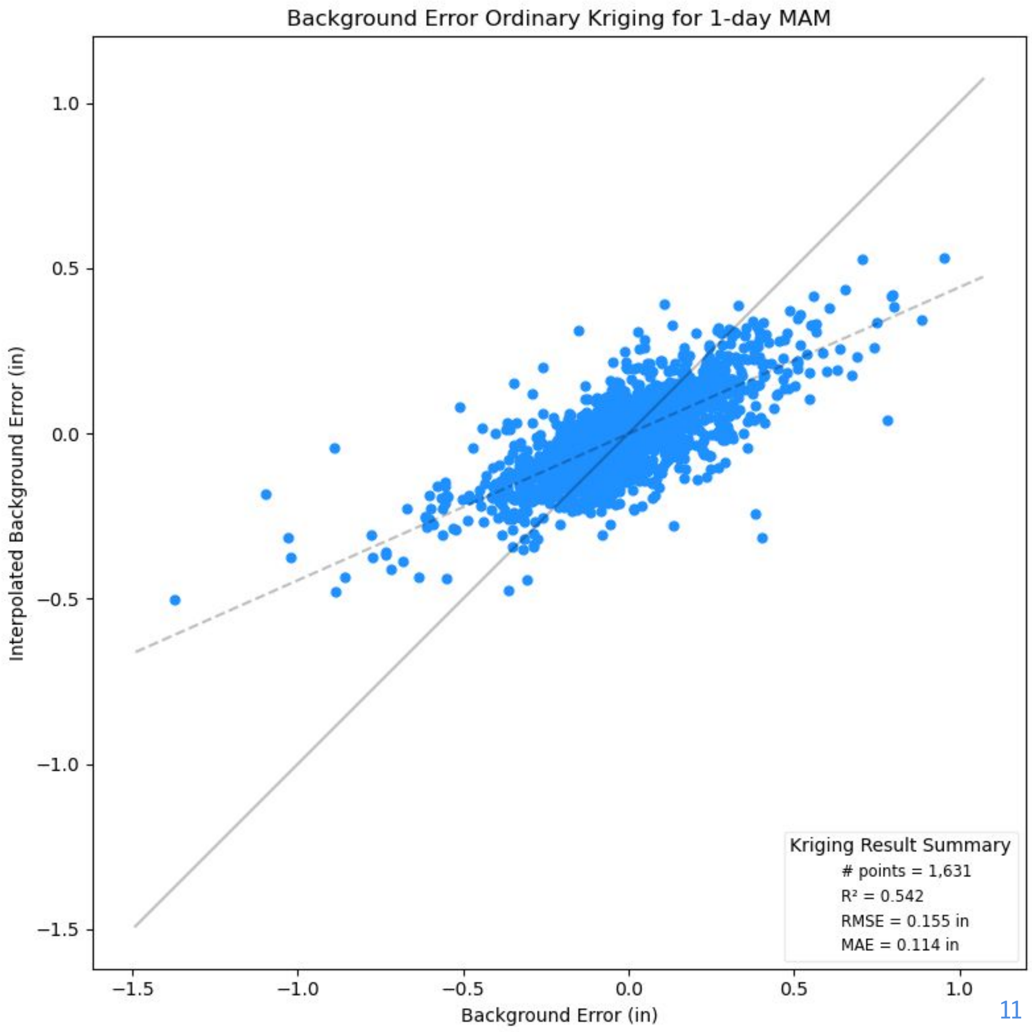


Kriging adjustment

Ordinary kriging tends to undershoot point values.

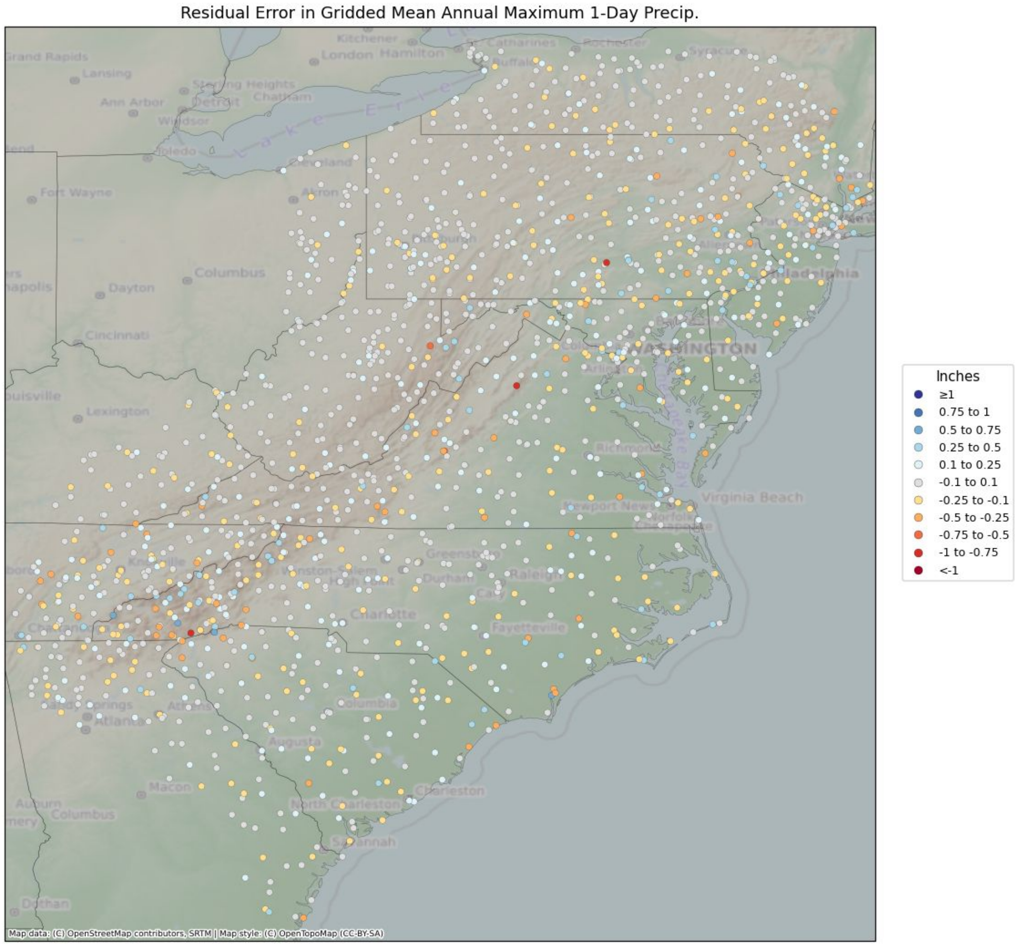
- Kriging seeks to **minimize error variance**, not squared error.
- This tendency to undershoot is related to the **nugget effect**, which leads to "smooth" kriging results.

For **engineering applications** it is important for grid values to be consistent with corresponding at-station MAM values.



Final adjustment

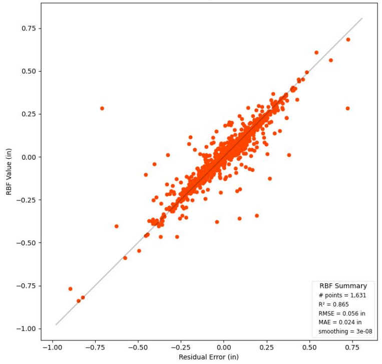
- Requirements call for a step to **reduce residual errors**
- Currently testing **radial basis function (RBF) interpolation**



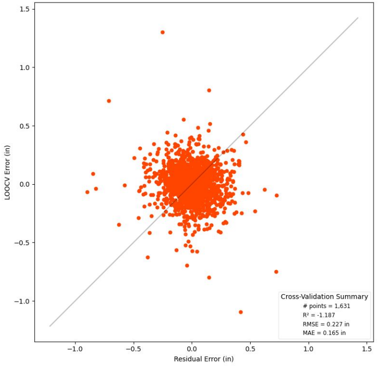
Final adjustment

- Requirements call for a step to **reduce residual errors**
- Currently testing **radial basis function (RBF) interpolation**
  - Matches grid to station values
  - No skill at remote locations

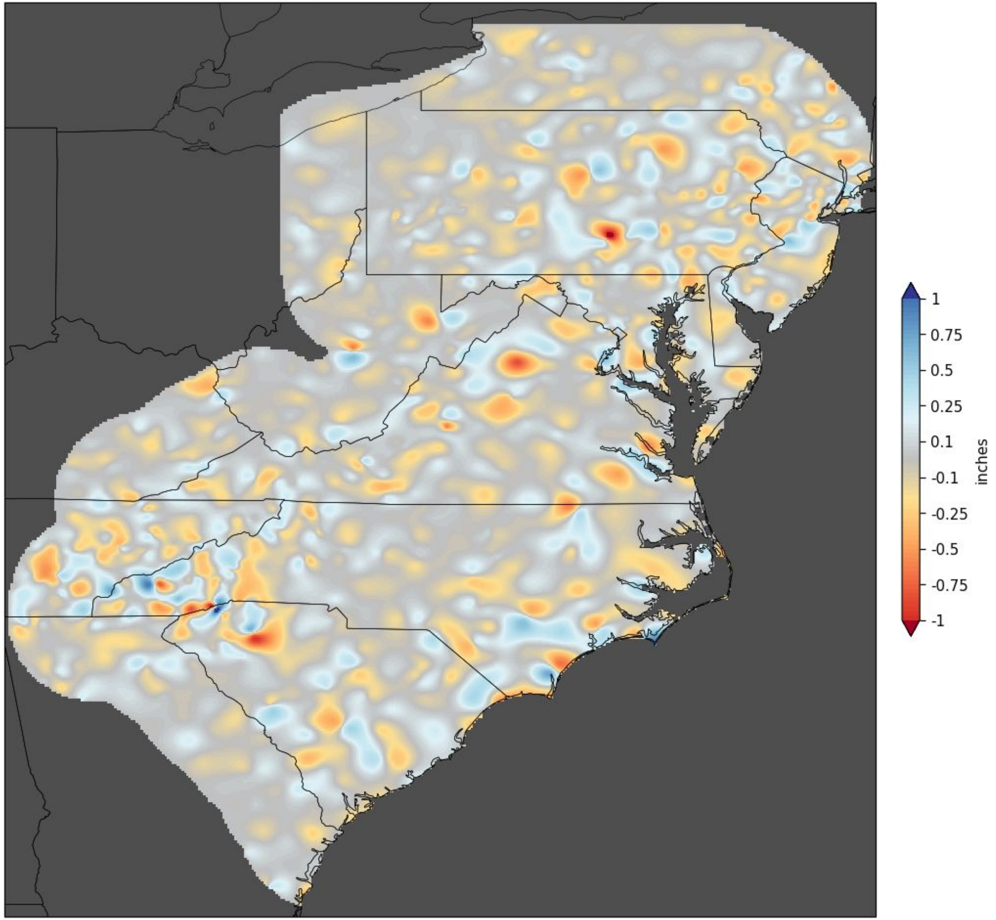
Residual 1-day MAM Error,
RBF Interpolation



Residual 1-day MAM Error,
RBF Cross-Validation



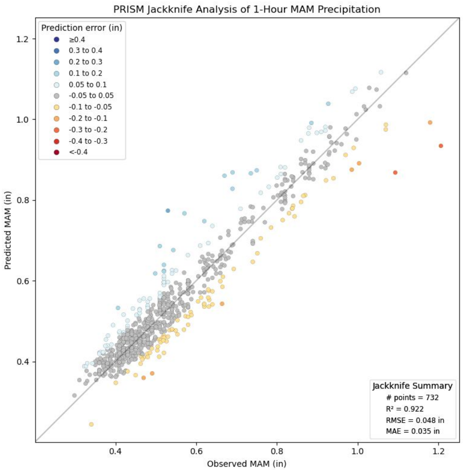
Residual Error in Regression + Kriging Estimate of 1-Day MAM Precip.



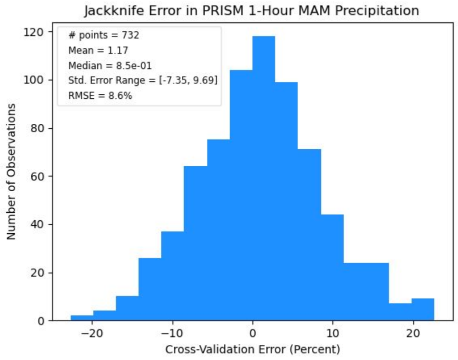
Comparison with PRISM

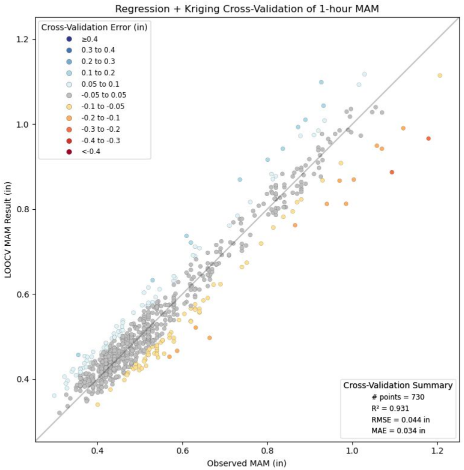
- Final Atlas 14, Volume 12 MAM result for 1-hour duration
- Same observation data
- Both use LOOCV analysis

LOOCV statistic	PRISM	OWP
R^2	0.921	0.931
RMSE	8.60%	8.05%
MAE	6.48%	6.36%

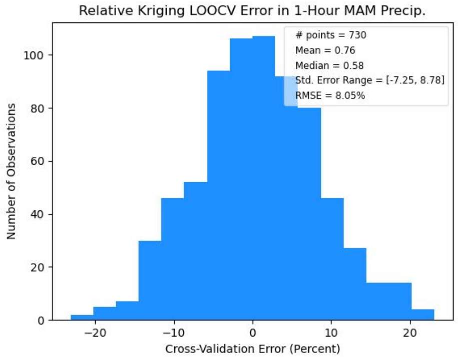


PRISM



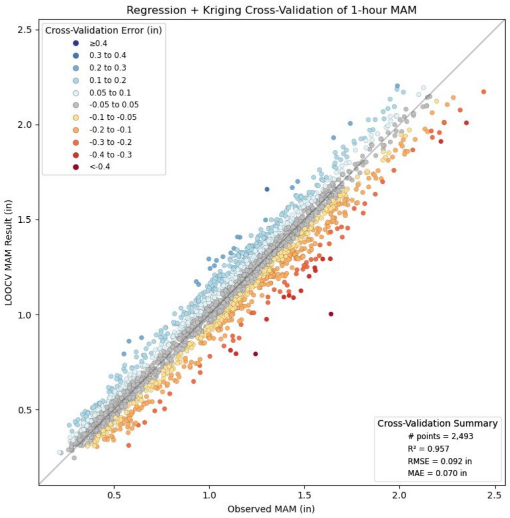


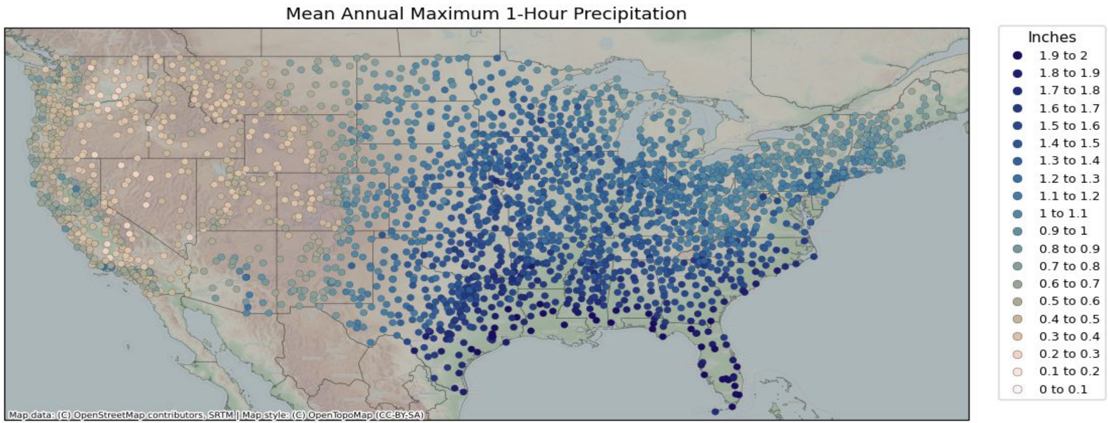
OWP

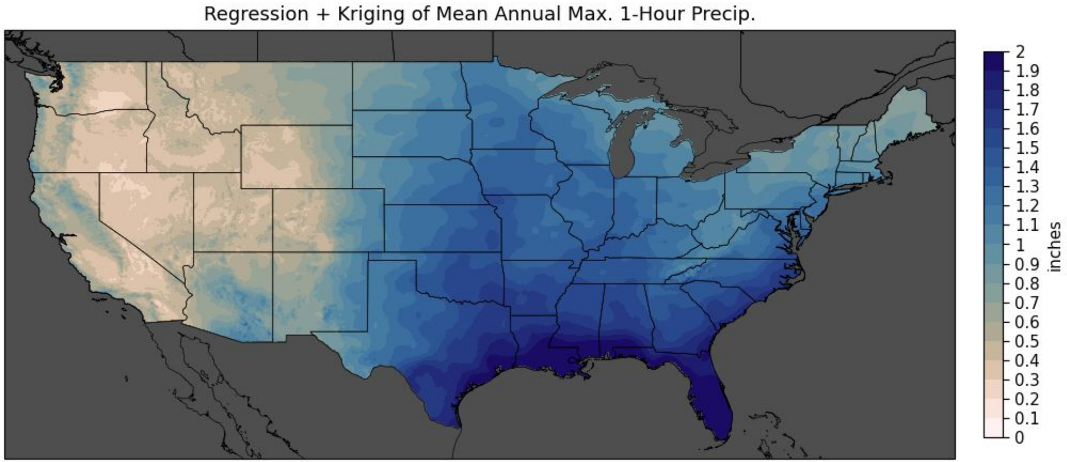


CONUS domain

- 1-hour MAM estimate
- LOOCV R^2 = 0.96
- LOOCV RMSE = 0.092 in.; relative = 10.1%







Conclusions

- Performance metrics are similar to those calculated for the PRISM-based analysis.
- Residual error adjustment following the kriging step may have limited skill.
- The quantity and quality of observation data will improve throughout the course of Atlas 14 (Volume 13) and Atlas 15 development.
- Further covariate development is planned; we expect this to improve regression accuracy.

Risks, Issues, and Next Steps

- Many open source modules (e.g., `pykrige`, `scipy.interpolate`) use Cartesian search/sort and distance metrics. We have adapted these for the (non-Cartesian) Earth's surface.
- Regression analysis over large, inhomogeneous domains (e.g., CONUS) benefits from the large quantity of observation data, but regional accuracy can be negatively affected.
- Weighted least squares is needed, using at minimum MAM standard deviation and possibly a cluster weighting component.
- Cross validation of the entire process will be performed after a method for the final adjustment is fully established.

Thank You!

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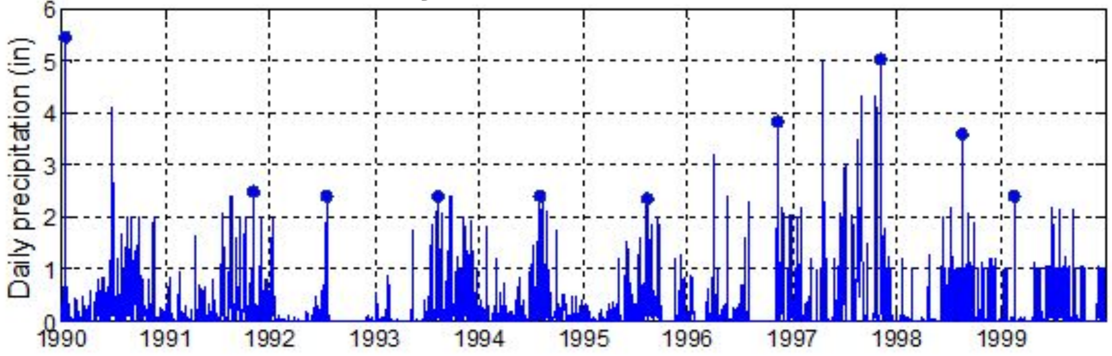
Mean Annual Maximum (MAM) Precipitation

- For Atlas Volumes ≤12 (L-moments based), station MAM represents the **first parameter** (`lambda1`) of the probability distribution function.
- ~~For future Volumes, station MAM is a **covariate** in the fitting of GEV parameters.~~
- At-station MAM values are **interpolated** to a grid (raster) to provide MAM values at ungauged locations.

1- Day Time Series Data

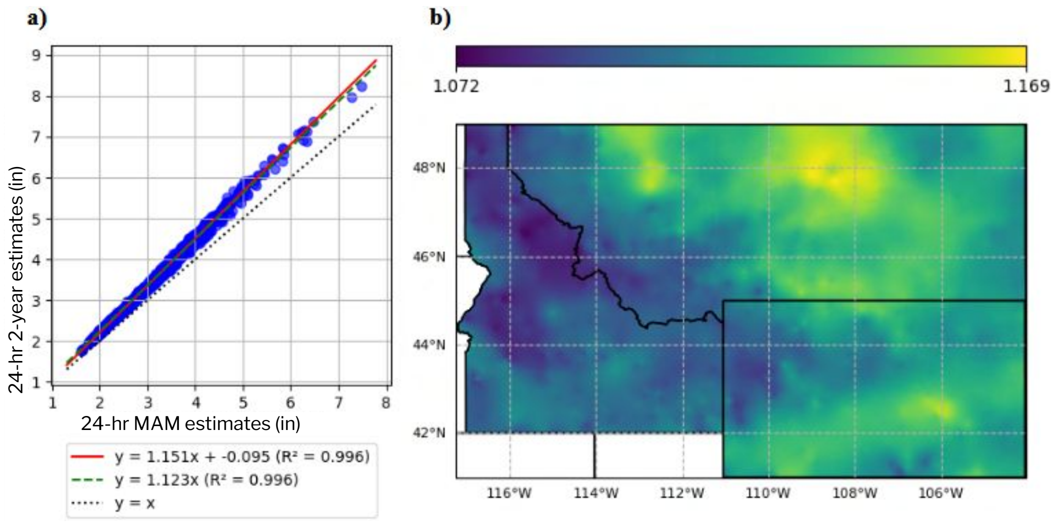


Annual Maxima

Year	Annual 1-day Maxima (in)
1990	5.5
1991	2.5
…	…
1998	3.7
1999	2.3
Average (MAM)	**3.1**

Mean Annual Maximum (MAM) Precipitation

Gridded (raster) MAM precipitation serves as the basis for deriving gridded precipitation frequency estimates at different frequencies and durations.



Conceptual illustration of how gridded precipitation frequency estimates are derived from MAM grids.

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  - Atlas 15 (CONUS, oCONUS)
- **Techniques**
  - Stepwise multiple linear regression
  - Ordinary kriging
- **Evaluation**
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