The Impact of Improved Hydrogeological Representation through the Use of Airborne Electromagnetic Data on Reducing Model Forecast Uncertainty

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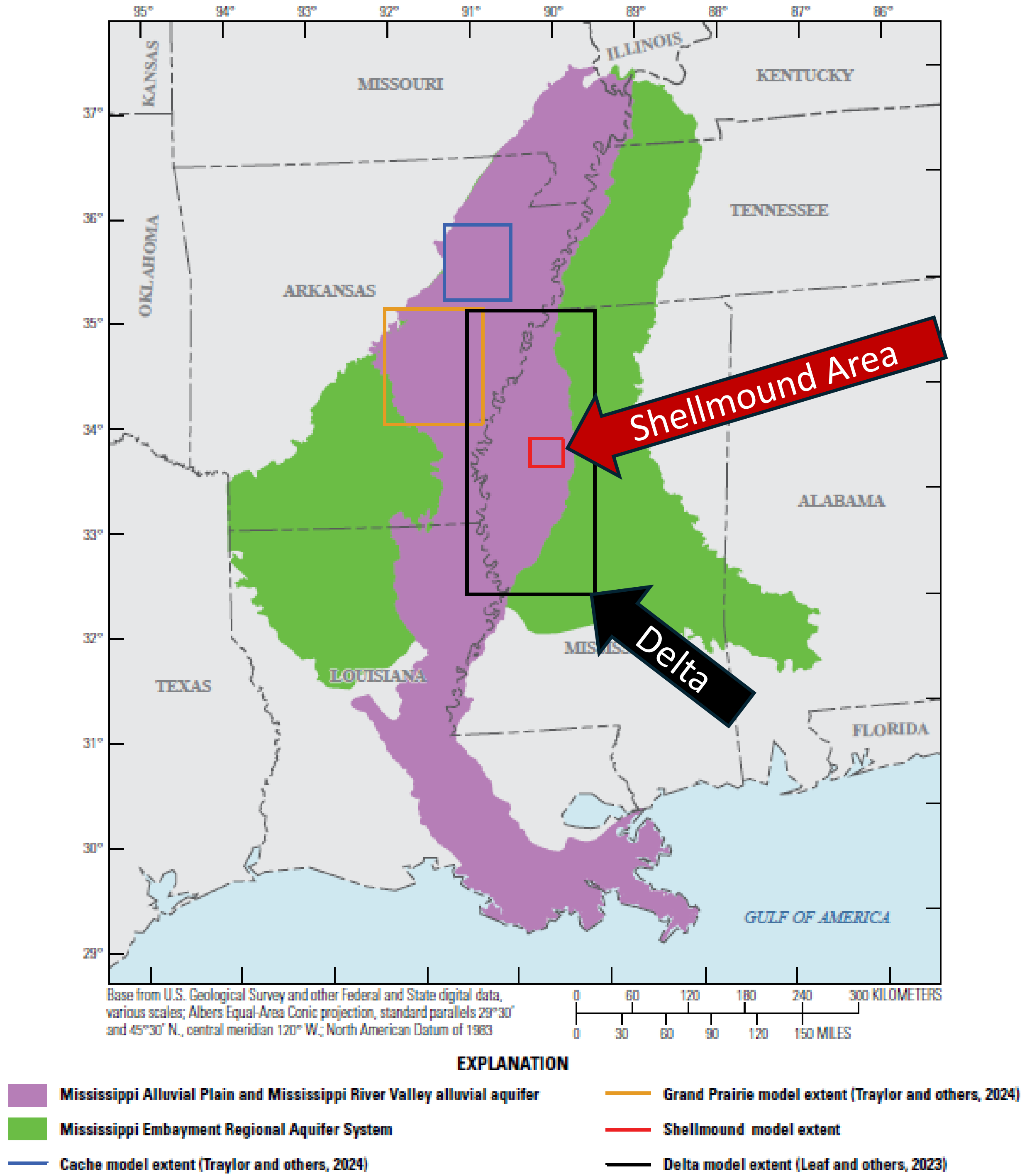
Project Overview

- Airborne Electromagnetic (AEM) and other geophysical methods are regularly used to inform groundwater model hydrogeology
- Geophysical data offer insights into the hydrogeologic structure of the subsurface, which allows for the construction of models that include more realistic heterogeneities; however, **does the incorporated information from AEM reduce the uncertainty of model forecasts?**
- We quantitatively assess the usefulness of AEM data in constraining model hydrogeology to represent observed hydraulic responses.
- To do this, we determined how different model parameters reduce uncertainty for two MODFLOW models created for the Shellmound, MS Groundwater Transfer and Injection Project (G-TIP)
  - One of which used AEM data to highly parameterize the model, and another that did not.

Site Location

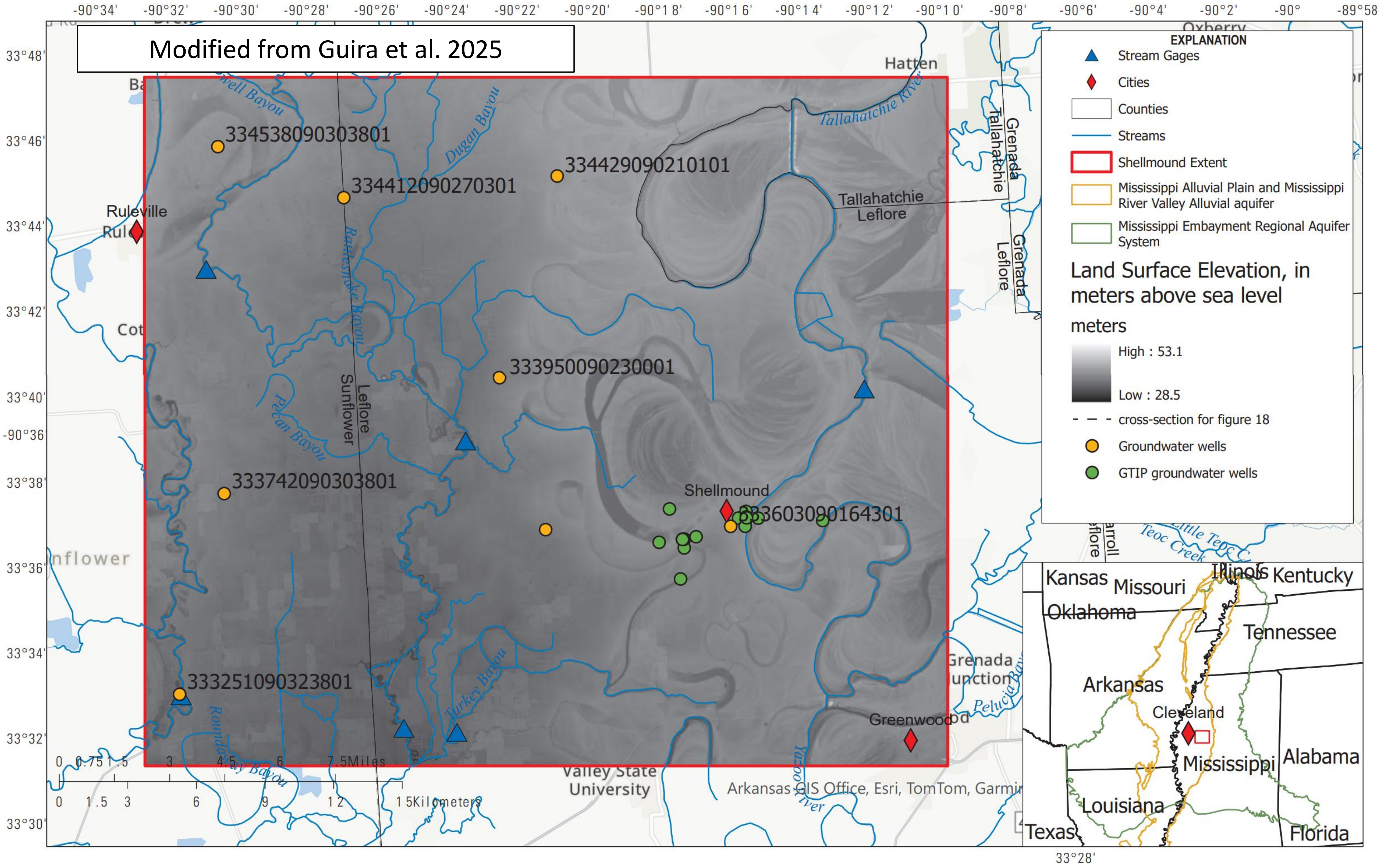
Background



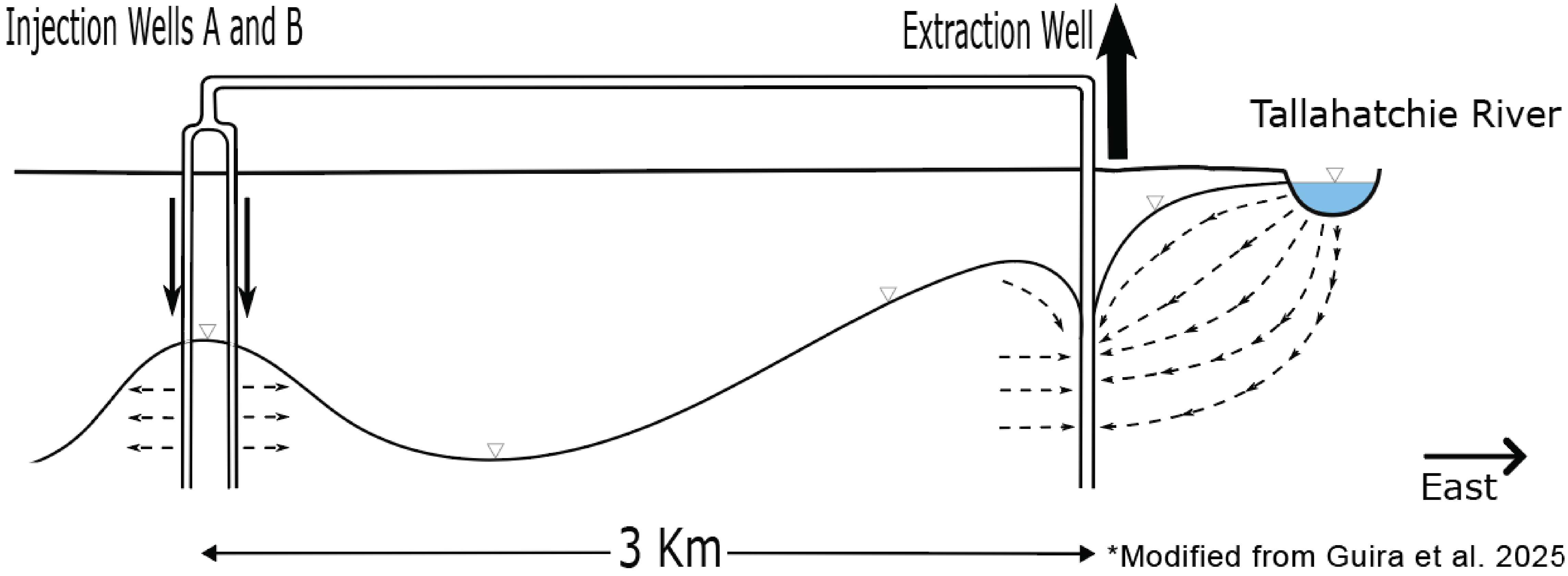
- Shellmound Groundwater Modeling Study (Guira et al. 2025)
  - Inset model of the Delta Model
- Models were created to predict outcomes of the Groundwater Transfer and Injection Pilot (G-TIP) project
- Created two groundwater models with varying discretization and parameterization

Modified from Guira et al. 2025

Site Location

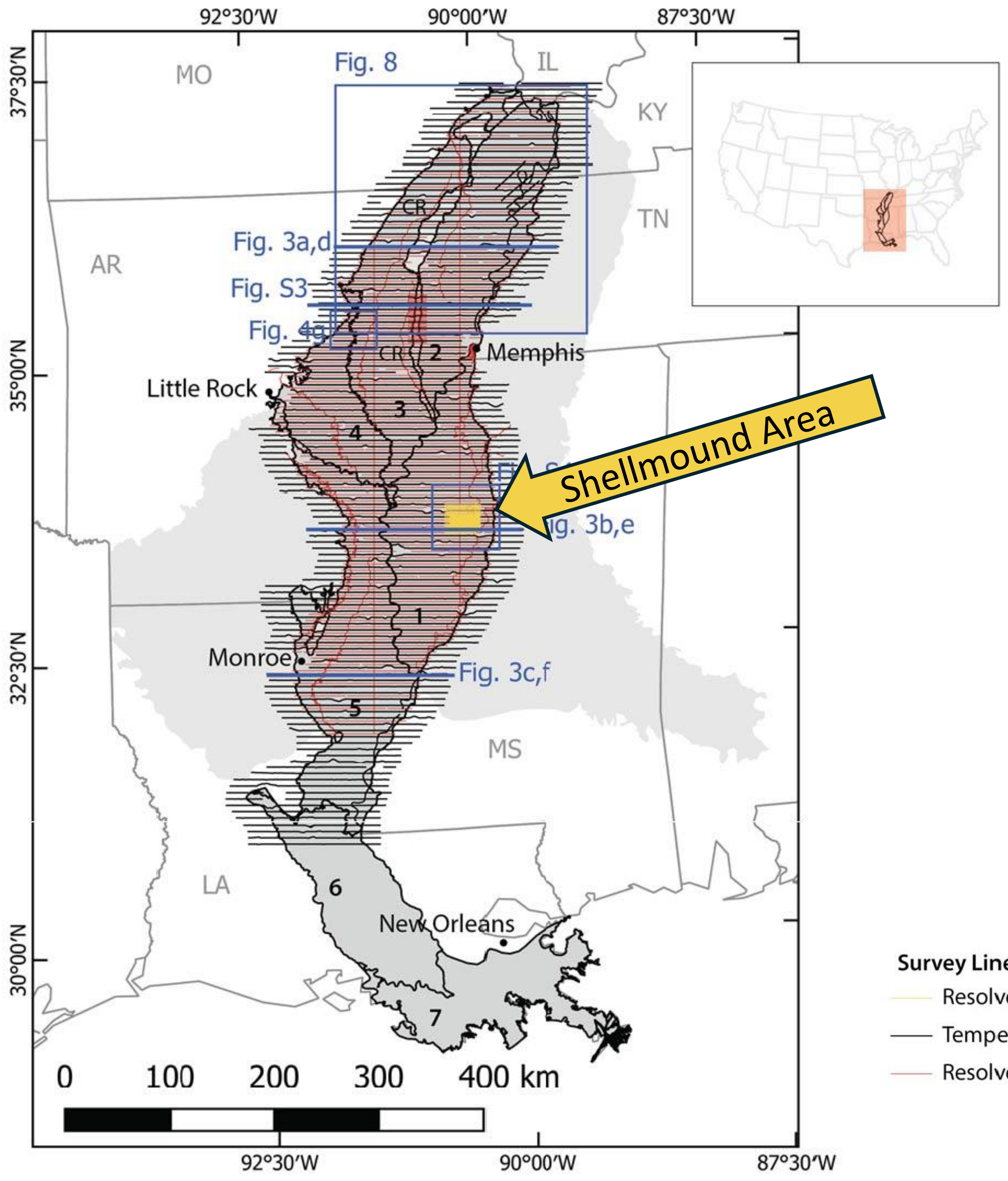


Groundwater Transfer and Injection Pilot (G-TIP)



*Modified from Guira et al. 2025

AEM Data Collection

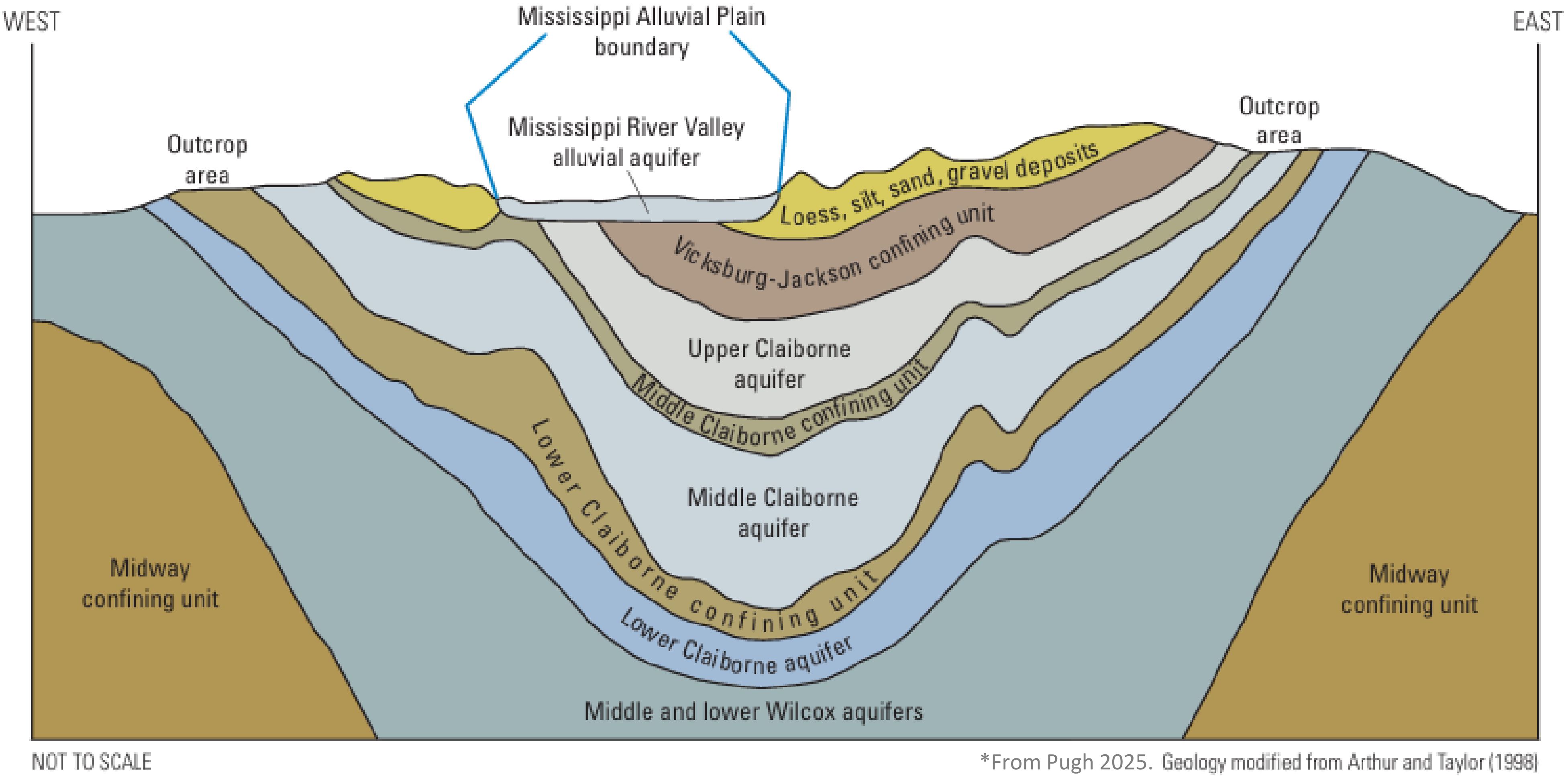


*Modified from Minsley et al. 2021

Background

- 43,000 flight-line-kilometers of AEM were flown as part of the update to the Mississippi Embayment Regional Aquifer Study (MERAS) (Minsley et al. 2021)
- Increased density of data in the Shellmound area (Minsley et al. 2021)
- Created several datasets, including facies classes based on resistivity, aquifer thickness, surficial connectivity, connectivity MRVA and subcropping Tertiary (Minsley et al. 2021)

Regional Hydrogeology



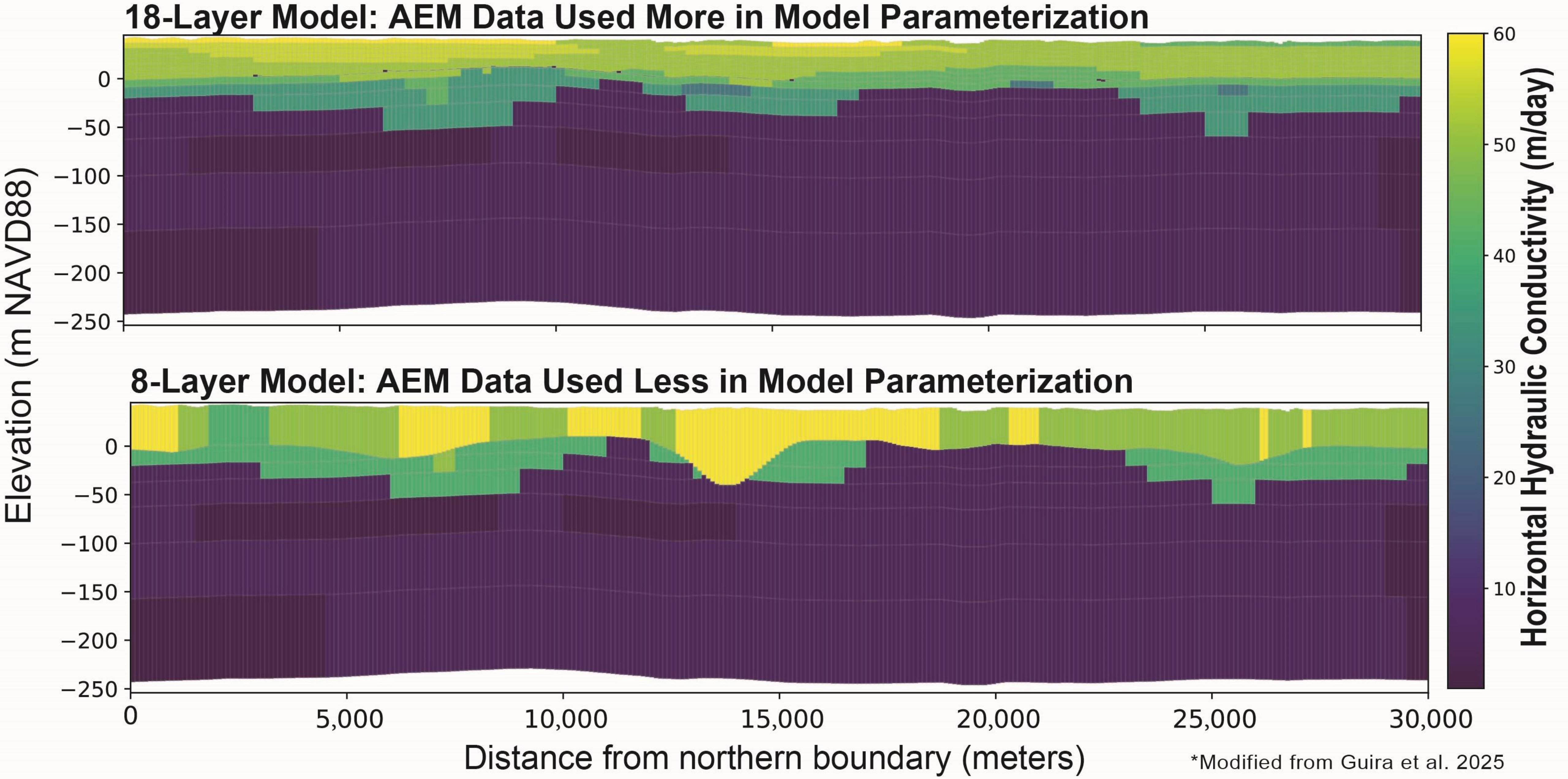
*From Pugh 2025. Geology modified from Arthur and Taylor (1998)

Hydrogeology & Model Structure

Time-stratigraphic unit			Group	Formation	Regional geohydrologic unit	18-Layer Model	8-Layer Model
Era	System	Series					
Cenozoic	Quaternary	Holocene	--	Alluvium, terrace, and loess deposits	Mississippi River Valley, Ouachita-Saline River, and Red River alluvial aquifers	1 to 8	1
		Pleistocene					
	Tertiary	Oligocene	Vicksburg	Vicksburg Formation	Vicksburg-Jackson confining unit	Missing in Shellmound	
		Eocene	Jackson	Jackson Formation			
			Claiborne	Cockfield Formation	Upper Claiborne aquifer	Missing in Shellmound	
				Cook Mountain Formation	Middle Claiborne confining unit	9 to 18*	2 to 8*
				Sparta Sand	Middle Claiborne aquifer		
				Zilpha Clay, Winona Sand, Tallahata, Formation	Lower Claiborne confining unit		
				Meridian Sand Member	Lower Claiborne aquifer		
			Wilcox	Undifferentiated	Upper, middle, and lower Wilcox aquifers		

Modified from Guira et al. 2025

Varying Discretization and Hydrologic Properties Between Models

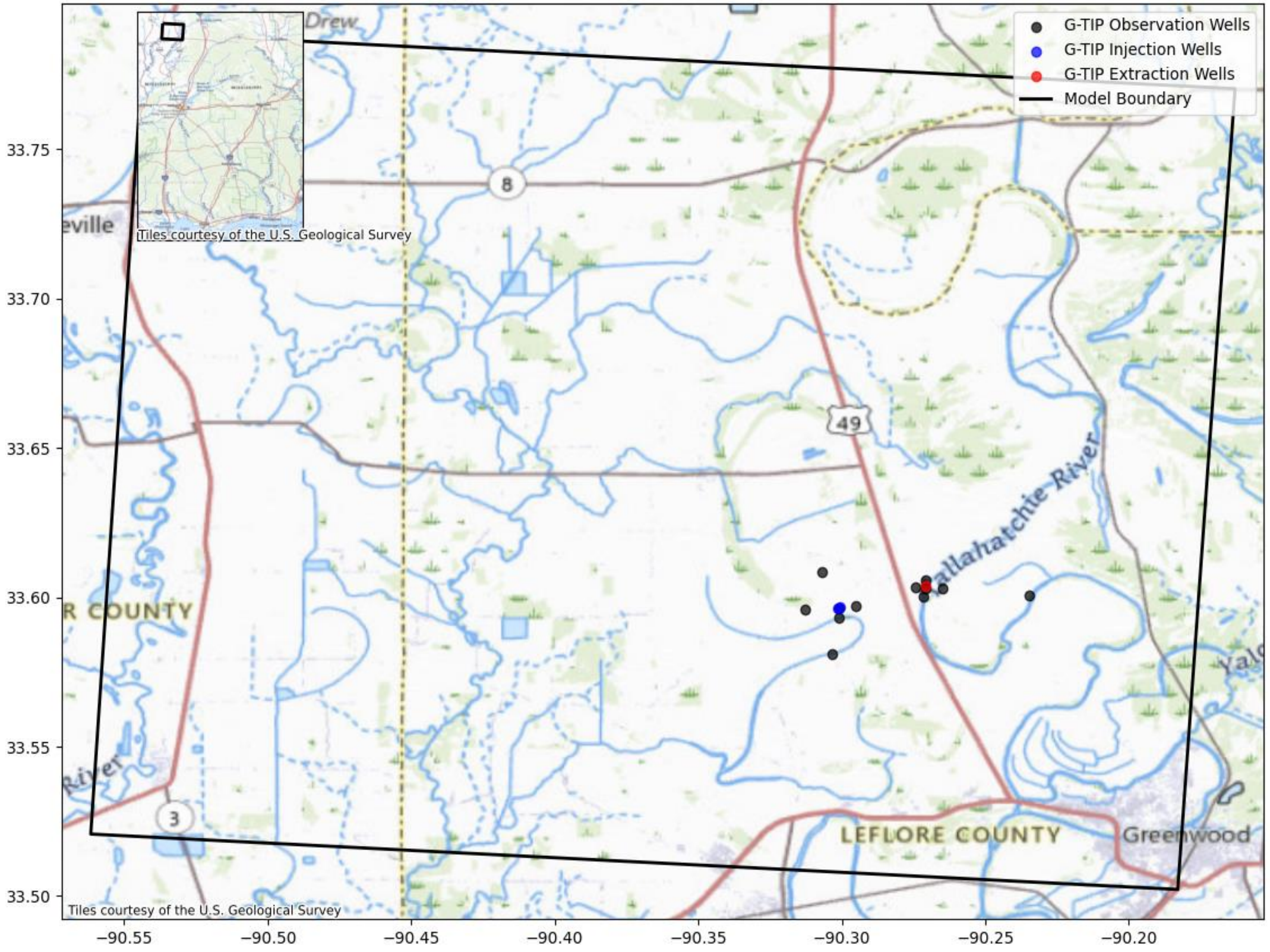


Methodology Overview

- Adjusted models to predict future G-TIP conditions
- Calculated and added G-TIP Composite Head forecasts as PEST++ observations for forecast variance reduction calculations
- Calculated flow path lengths using MODPATH and added those forecasts as PEST++ observations for forecast variance reduction calculations
- Spatially sorted parameters so the models would have the same parameter groups
- Calculated the Jacobian matrix with PESTPP-GLM
- Calculated the forecast variance reduction using the PyEmu Python libary

Model Forecasts

- G-TIP Wells Composite Head Forecasts
  - Mean head of wells surrounding extraction/injection wells
  - 1 forecast for every future stress period (141 forecasts)
  - Composite heads were added as zero-weight PEST observations
- Flow Path Length Forecasts
  - MODPATH was for future stress periods
  - Particles started at the Tallahatchie River and the injection well (1800 particles/forecasts)
  - Total path length was used as a PEST zero-weight observations



Mathematical Background

*From Fienen et al. 2025

Jacobian Matrix

$$\mathbf{J} = \frac{\partial z_i}{\partial \theta_j}$$

J: Jacobian sensitivity matrix
z_i: model observation i
θ : parameter j

Forecast Sensitivity

$$\mathbf{y} \triangleq \frac{\partial s}{\partial \boldsymbol{\theta}} \approx \frac{s(\boldsymbol{\theta} + \Delta\boldsymbol{\theta}) - s(\boldsymbol{\theta})}{\Delta\boldsymbol{\theta}}$$

y: forecast sensitivity
s: model forecast

Schur Complement

$$\overline{\boldsymbol{\Sigma}}_\theta = \boldsymbol{\Sigma}_\theta - \boldsymbol{\Sigma}_\theta \mathbf{J}^T \left[\mathbf{J}\boldsymbol{\Sigma}_\theta \mathbf{J}^T + \boldsymbol{\Sigma}_\epsilon\right]^{-1} \mathbf{J}\boldsymbol{\Sigma}_\theta$$

Σ_θ: prior covariance for the parameters
$\overline{\Sigma}_\theta$: posterior covariance for the parameters after updating with new observations
T: transpose

Mathematical Background

Prior Variance

$$\sigma_s^2 = \mathbf{y}^T \boldsymbol{\Sigma}_\theta \mathbf{y}$$

$\sigma_s{}^2$: prior variance of a forecast

Posterior Variance

$$\sigma_{s_{\theta_i}}^{2} = \mathbf{y}^T \overline{\boldsymbol{\Sigma}}_\theta \mathbf{y} = \mathbf{y}^T \boldsymbol{\Sigma}_\theta \mathbf{y} - \mathbf{y}^T \boldsymbol{\Sigma}_\theta \mathbf{J}^T \left[\mathbf{J} \boldsymbol{\Sigma}_\theta \mathbf{J}^T + \boldsymbol{\Sigma}_\epsilon\right]^{-1} \mathbf{J} \boldsymbol{\Sigma}_\theta \mathbf{y}$$

$\sigma_{s_{\theta_i}}{}^2$: posterior variance of a forecast parameter *i* known perfectly

Parameter Importance

$$\frac{\bar{\sigma}_s^2 - \bar{\sigma}_{s_{\theta_i}}^2}{\bar{\sigma}_s^2} \times 100 \text{ percent}$$

*From Fienen et al. 2025

Modeling Methods

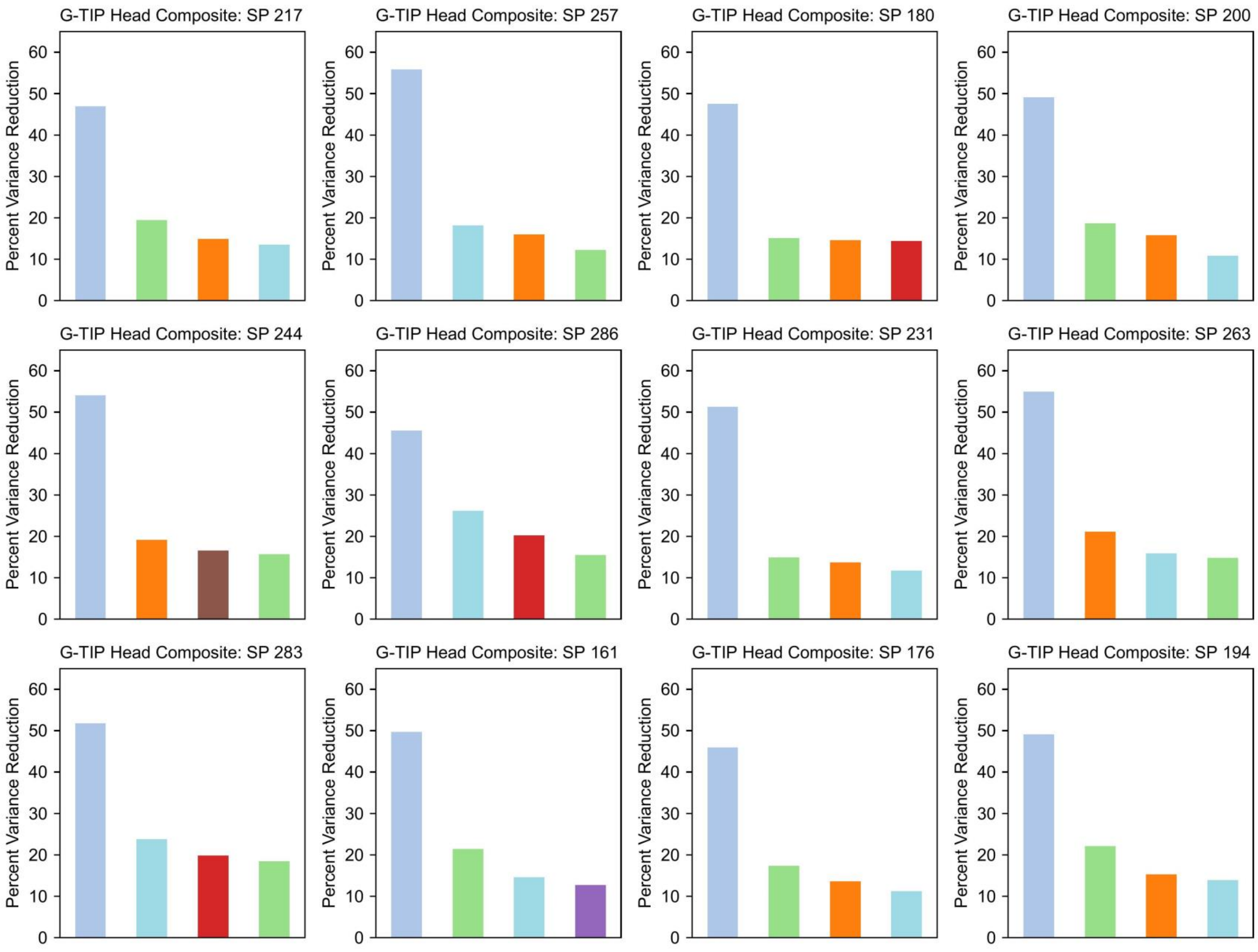
PyEmu

```
pst = pyemu.Pst(pst_file)

jco = pyemu.Jco.from_binary(jco_file)

obscov = pyemu.Cov.from_observation_data(pst)

wanted_forecast_names = [gtip_composite_1, flow_path_1]

sc = pyemu.Schur(pst=pst, jco=jco, obscov=obscov,
forecasts=wanted_forecast_names)

par_contrib = sc.get_par_group_contribution()
```

Results

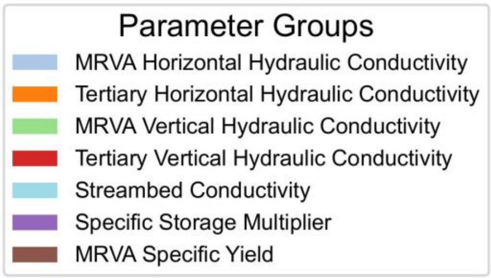
- Forecast uncertainty reduction for individual head composite forecasts;
- Overall trends for forecast uncertainty reduction for head composite forecasts;
- Forecast uncertainty reduction for individual flow path length forecasts;
- Overall trends for forecast uncertainty reduction for flow path length forecasts.

18-Layer Model - Head Composite Forecasts: Percent Variance Reduction

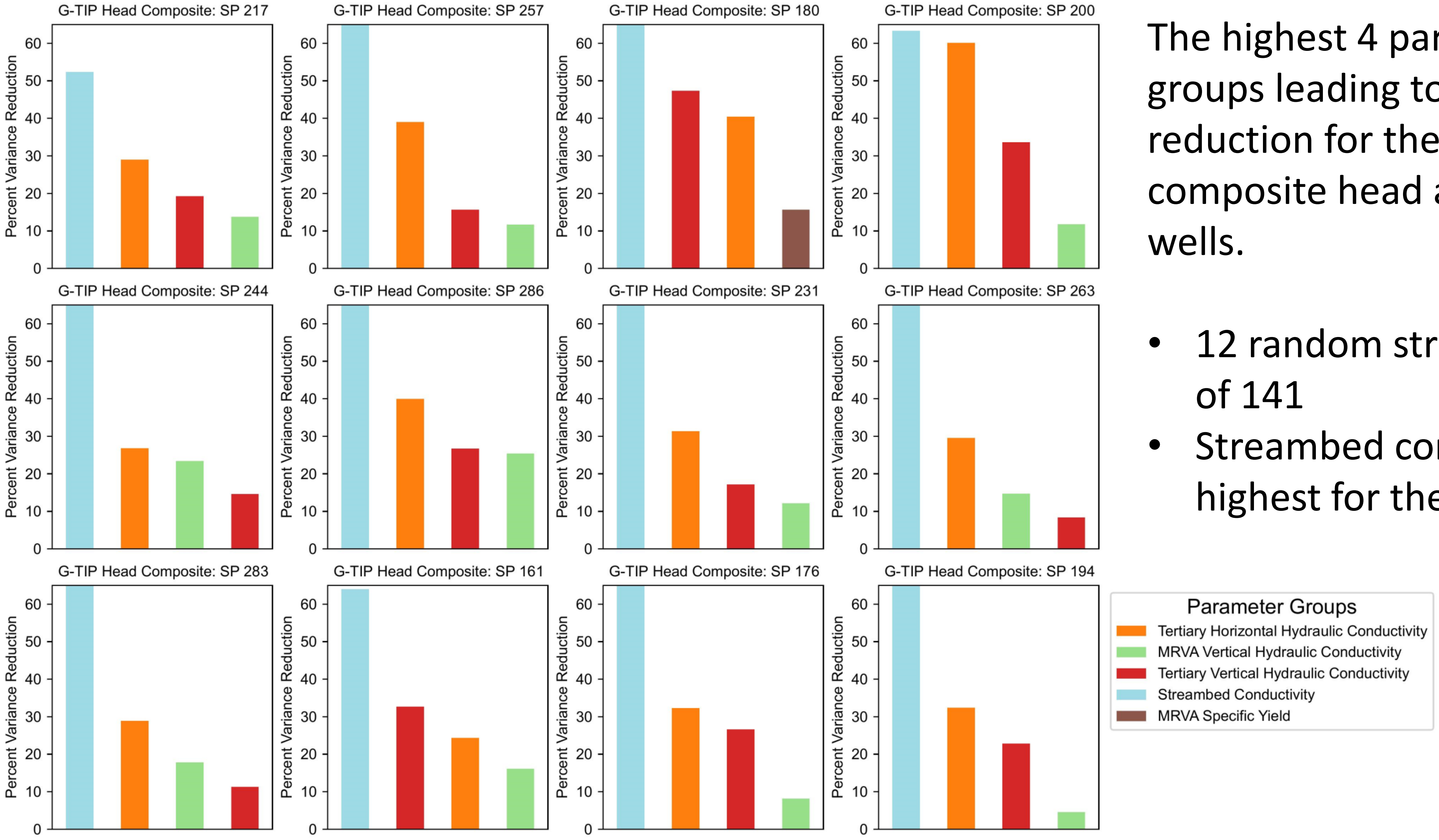


The highest 4 parameter groups leading to variance reduction for the mean composite head around G-TIP wells.

- 12 random stress periods of 141
- MRVA K_H always highest



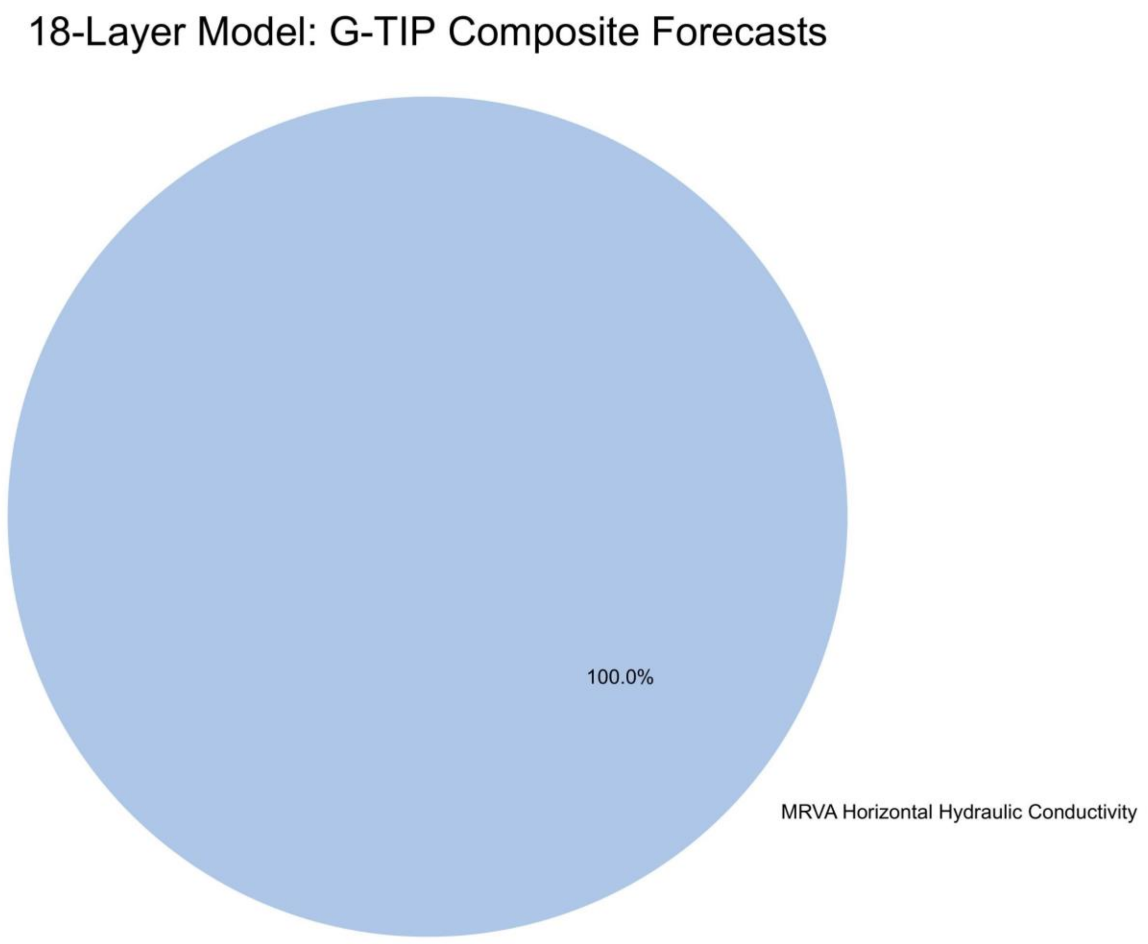
8-Layer Model - Head Composite Forecasts: Percent Variance Reduction

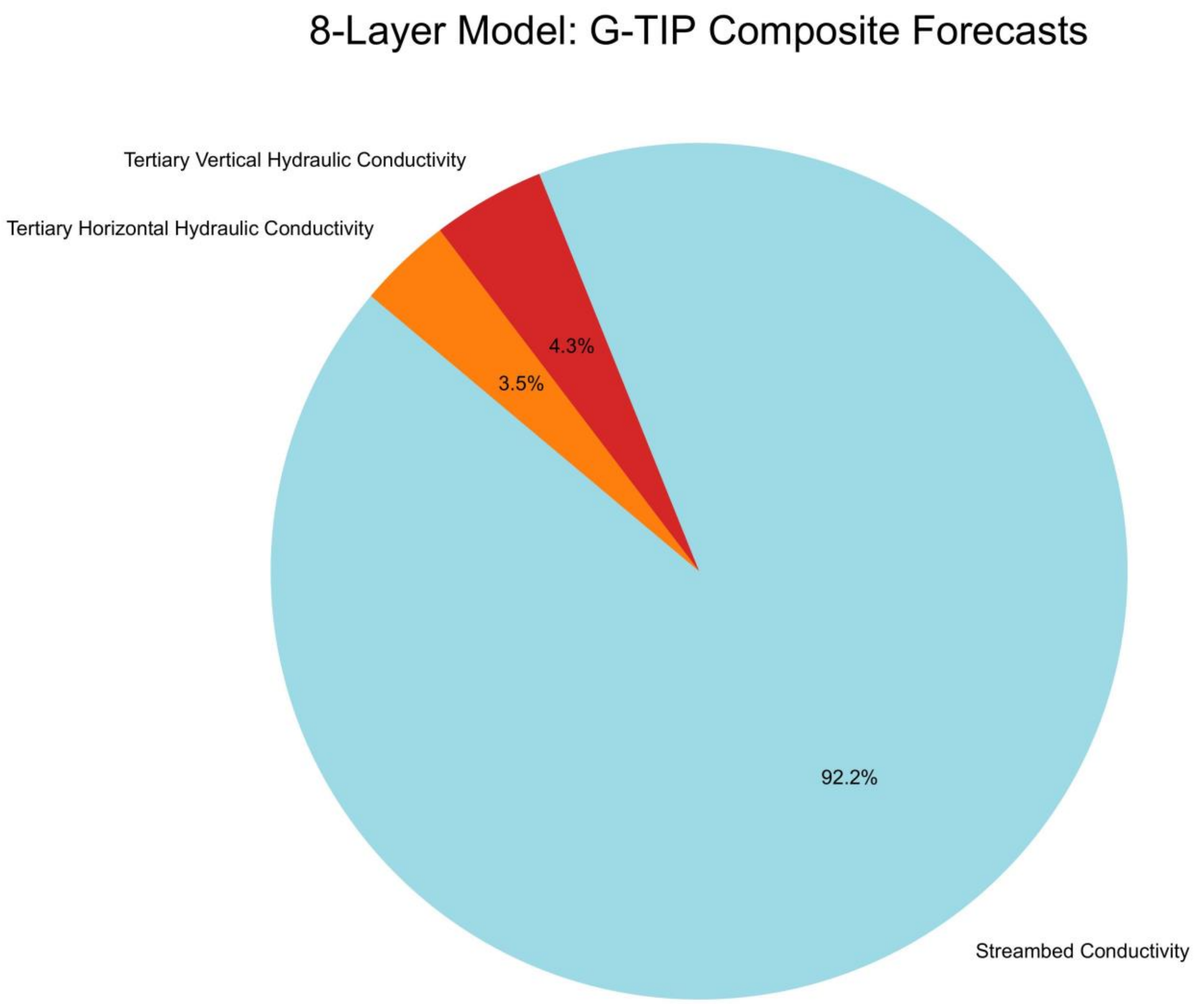


The highest 4 parameter groups leading to variance reduction for the mean composite head around G-TIP wells.

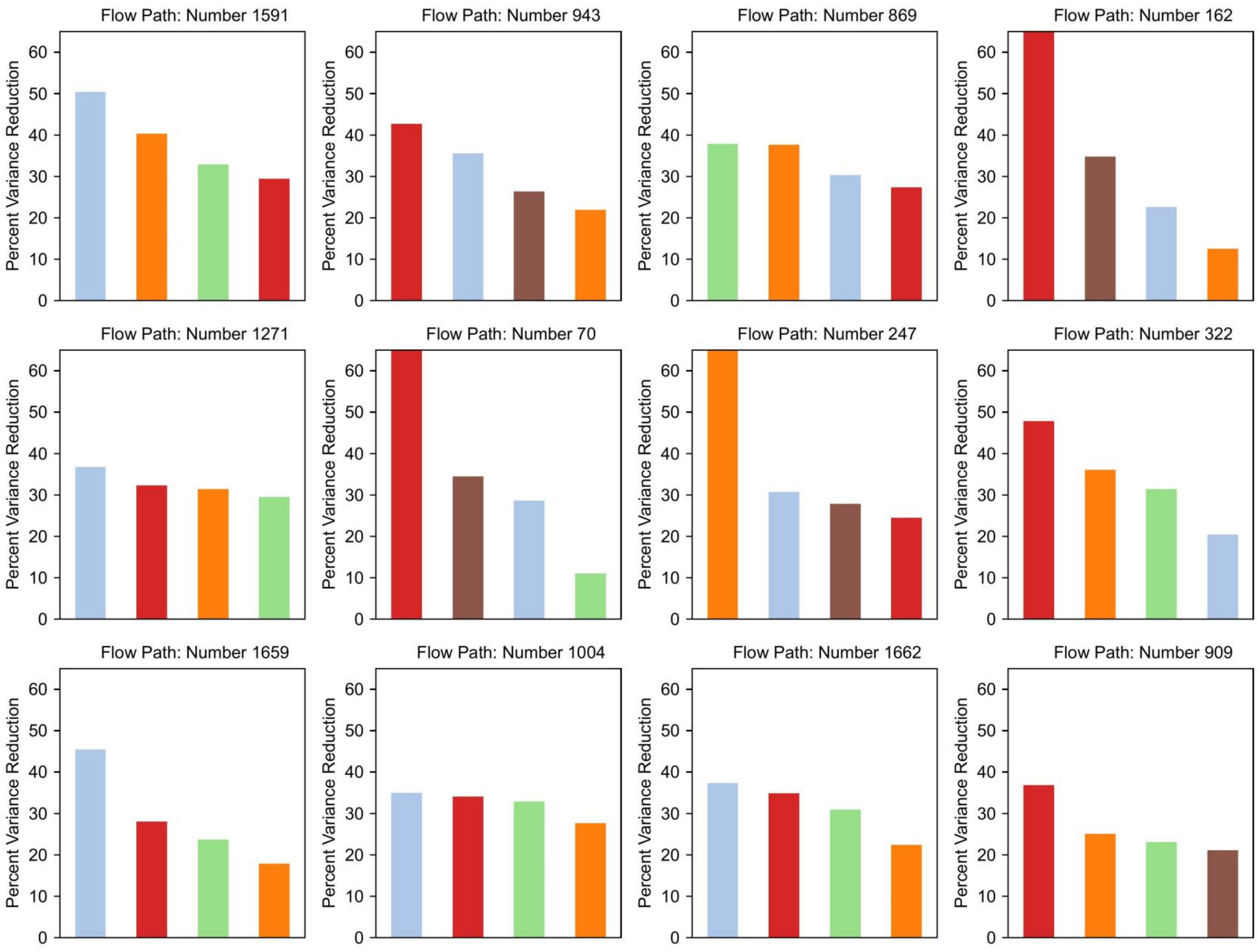
- 12 random stress periods of 141
- Streambed conductivity is highest for the sampling

Percent of Forecasts where Certain Parameter Group is the Most Important





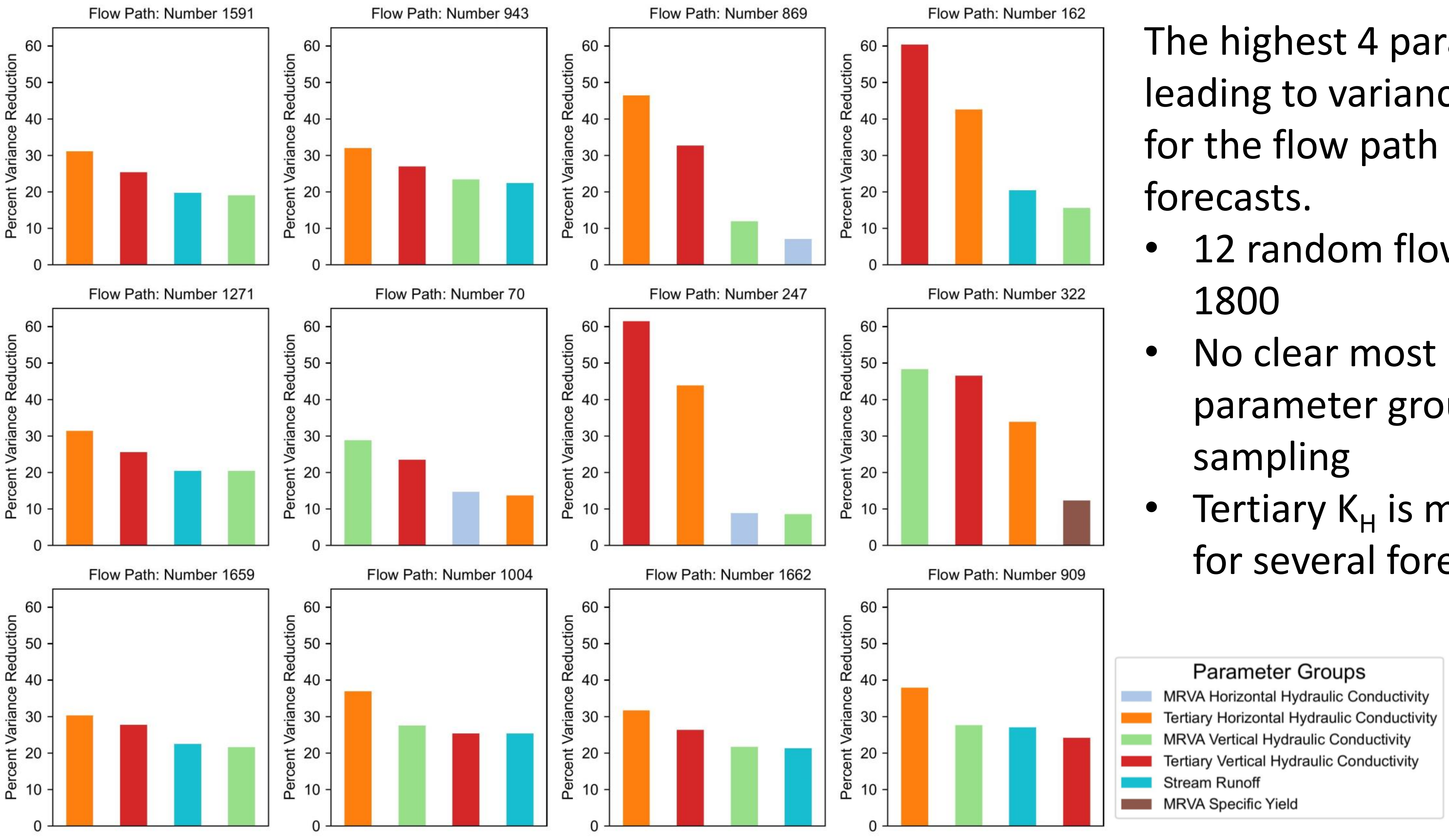
18-Layer Model - Flow Path Length Forecasts: Percent Variance Reduction



The highest 4 parameter groups leading to variance reduction for the flow path length forecasts.

- 12 random flow paths of 1800
- No clear most important parameter group from this sampling
- MRVA K_H is most important for several forecasts

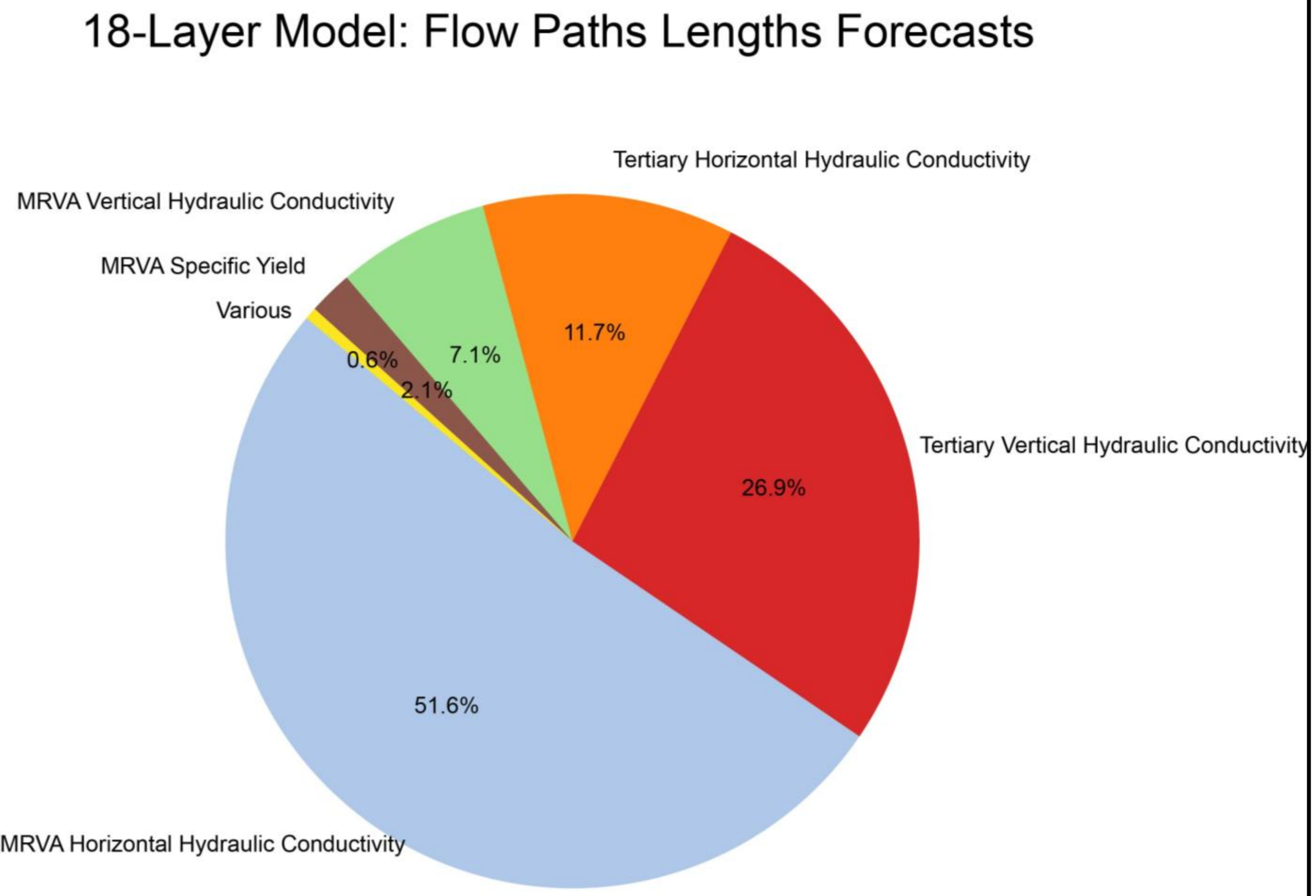
8-Layer Model - Flow Path Length Forecasts: Percent Variance Reduction

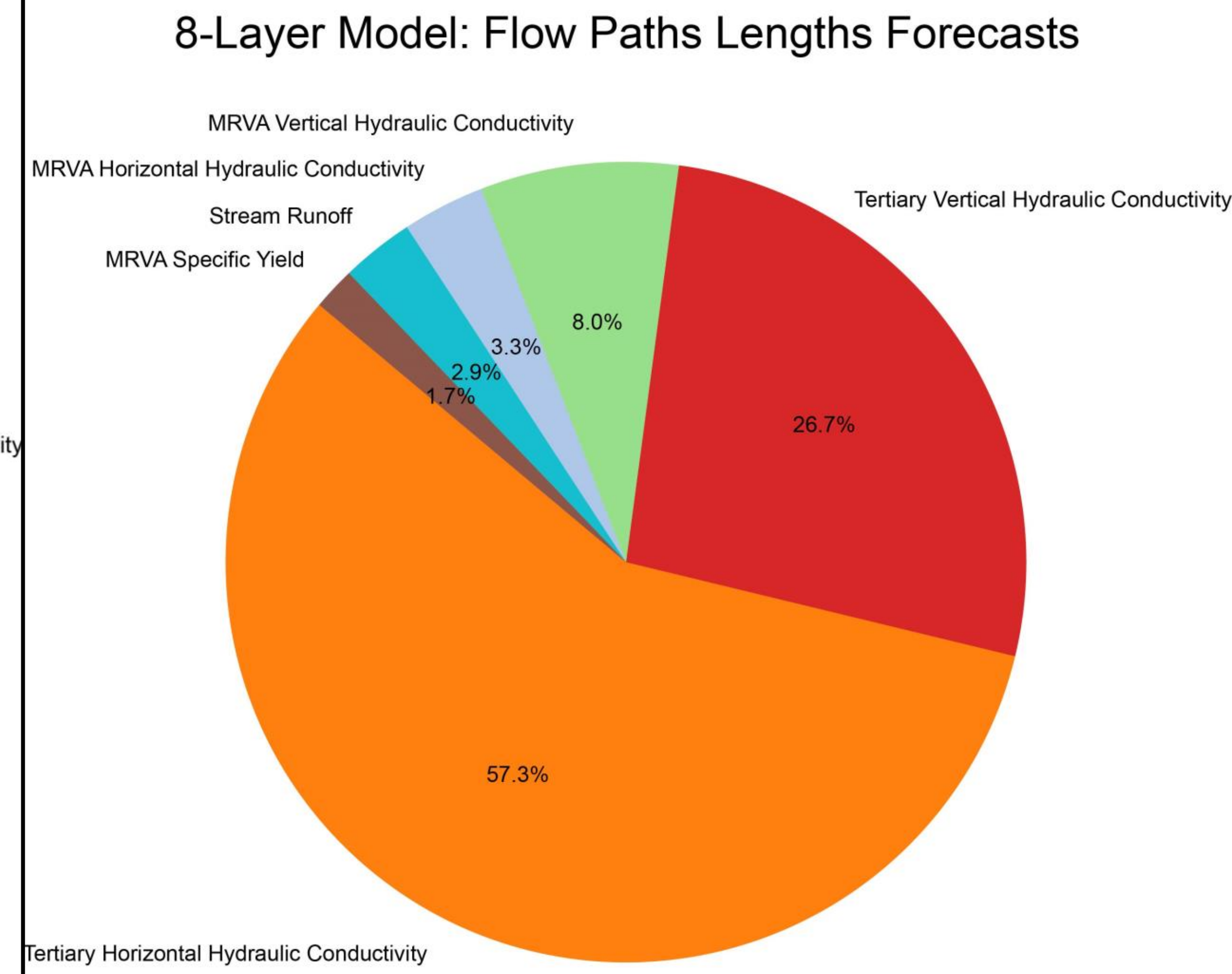


The highest 4 parameter groups leading to variance reduction for the flow path length forecasts.

- 12 random flow paths of 1800
- No clear most important parameter group from this sampling
- Tertiary K_H is most important for several forecasts

Percent of Forecasts where Certain Parameter Group is the Most Important





Summary and Conclusions

- 100% of composite head forecasts for the 18-layer model were most reliant on the MRVA Horizontal Hydraulic Conductivity parameter group.
    - The MRVA Horizontal Hydraulic Conductivity group was highly parameterized using AEM data.
    - Because a parameter group with incorporated AEM data was the most important for reducing uncertainty, the AEM was valuable for reducing model forecast uncertainty.
- 92% of composite head forecasts for the 8-layer model were most reliant on the streambed conductivity parameter group.
    - Since the AEM data was not utilized to introduce complexity in the model for calibration purposes, understanding streambed conductance proved to be more critical than knowing the hydraulic conductivity of the model layers.
- When AEM data is used for refining model hydrogeology, the parameters where AEM is used become more important for reducing model forecast uncertainty.

Summary and Conclusions

- **52%** of flow path forecasts for the 18-layer model were most reliant on the **MRVA Horizontal Hydraulic Conductivity** parameter group.
- **57%** of flow path forecasts for the 8-layer model were most reliant on the **Tertiary Horizontal Hydraulic Conductivity** parameter group.
- The MRVA Horizontal Hydraulic Conductivity parameter group was the most important parameter group for reducing forecast uncertainty for 52% of the flow paths in the 18-layer model, compared to 3% of the flow paths in the 8-layer model.
- When AEM data was used to increase the vertical discretization of the hydrogeology, the parameters that incorporated AEM data became more important in reducing model forecast uncertainty.

References

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