Testing watershed properties as candidate predictors of long-term average streamflow

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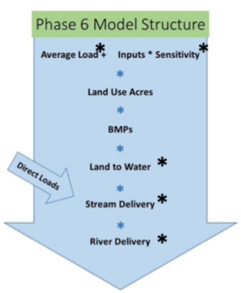
Modeling Workgroup Quarterly Review
7/6/2021

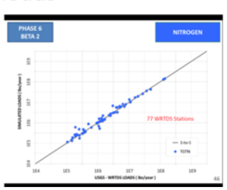
CalCAST Hydrology Model Development

- Average annual streamflow *(Q)* is the difference of Rainfall and Actual Evapotranspiration *(AET),* where *AET* can be estimated from Potential Evapotranspiration *(PET)* and/or other watershed properties.



$$Q = \sum_{\substack{upstream \\ geography}} Precipitation - PET \times f_{LU} \cancel{\times Fn(watershed\ properties})$$

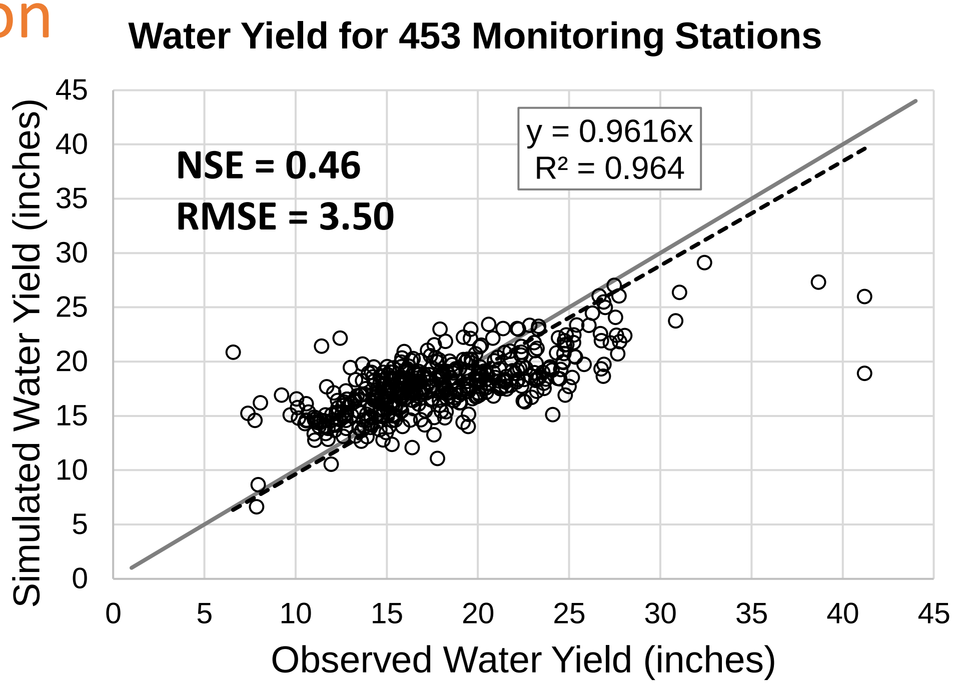
Calibration of meta-parameters to spatial loads



$$e.g., Fn(watershed\ properties) = a + f_w \times Wetness + f_s \times Slope$$

Results (CalCAST Hydrology – an initial, simplified prototype)

After Calibration



$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(pred_i - obs_i)^2}{\sum_{i=1}^{n}(obs_i - \overline{obs})^2}$$

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}\frac{(obs_i - pred_i)^2}{n}}$$

Tests with different initial parameters, objective functions, etc. were conducted.

Stats summary

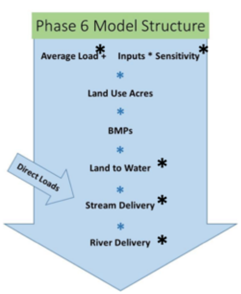
84% of all station within ±25%

89% of ≥ 50cfs P6 stations

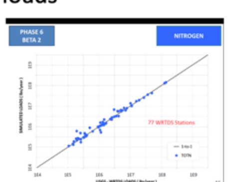
77% of new stations

Goal: Test candidate watershed properties for potential inclusion in CalCAST to improve average annual streamflow prediction

Broader goal: transition from P6 hydrology calibration largely based on adjusting PET by county to calibration based on mechanistically plausible / management-relevant properties (land use, watershed characteristics, climate…)



Calibration of meta-parameters to spatial loads



$$Q = \sum_{\substack{upstream \\ geography}} Precipitation - PET \times f_{LU} \times \boldsymbol{Fn(watershed\ properties)}$$

$$\boldsymbol{e.g., Fn(watershed\ properties) = a + f_w \times Wetness + f_s \times Slope}$$

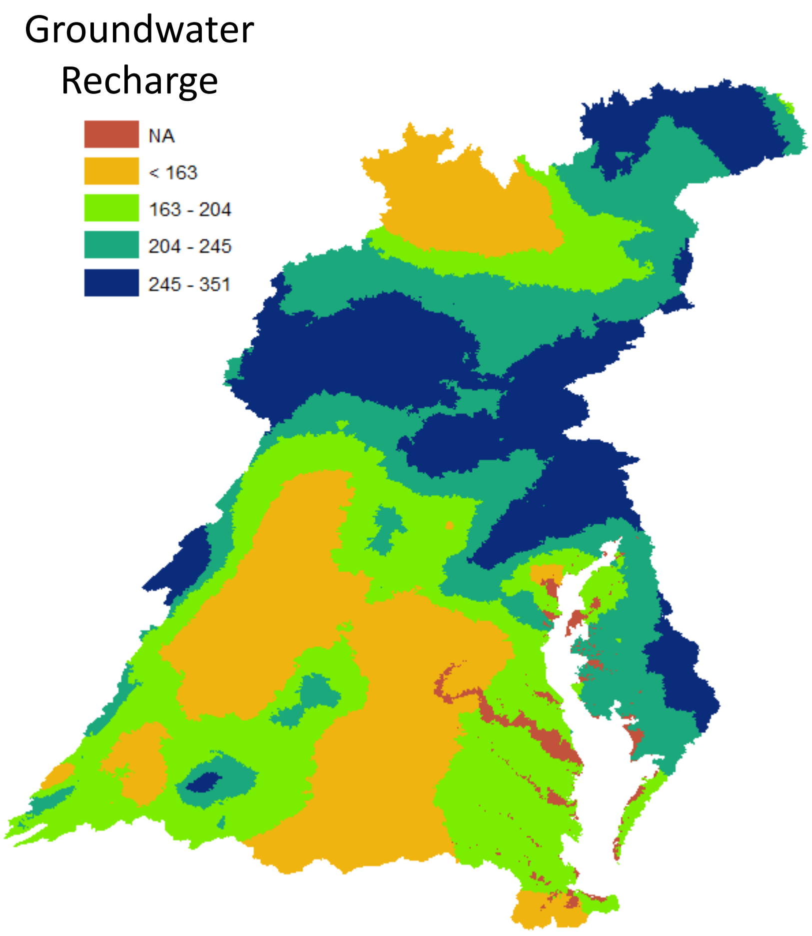
Candidate predictors of streamflow

Climate (long-term average)
Air Temperature
Percent of precipitation as snow

Geology
Bedrock permeability classes
Hunt geology
Principal aquifers and rock types (USGS, 2003)
Olson geology types (Olson, 2014)
Soller surficial materials (Soller et al., 2009)
Generalized lithologic classes (Anning & Ator, 2017)
Dominant geology type (Reed & Bush, 2001)

Topography
Catchment mean slope
Catchment mean elevation
Stream mean slope
Stream length/Catchment Area

Land use
% of 12 land use classes (crop, forest, impervious, etc..)

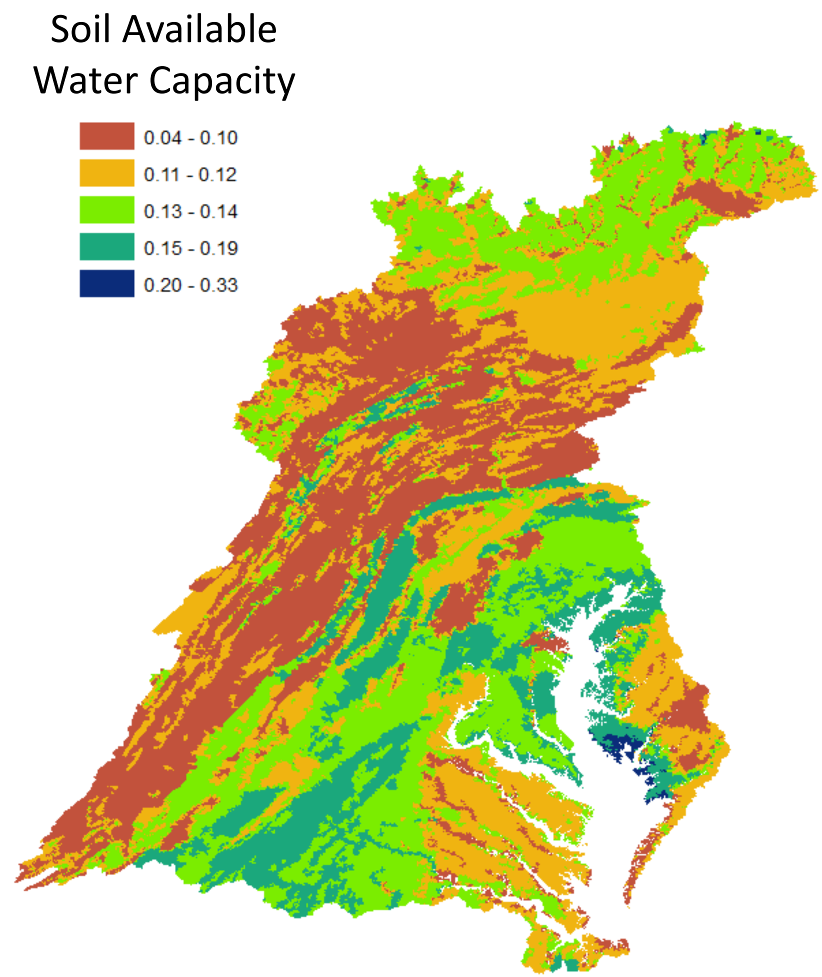


Wieczorek and Schwarz, 2018. https://doi.org/10.5066/F7765D7V

Candidate predictors of streamflow

Hydrology
Base Flow Index
Contact time
RUSLE R factor
Groundwater recharge
Saturation overland flow as % of streamflow
Topographic Wetness Index
Depth to water table
Infiltration-excess overland flow as % of streamflow
Enhanced vegetation index

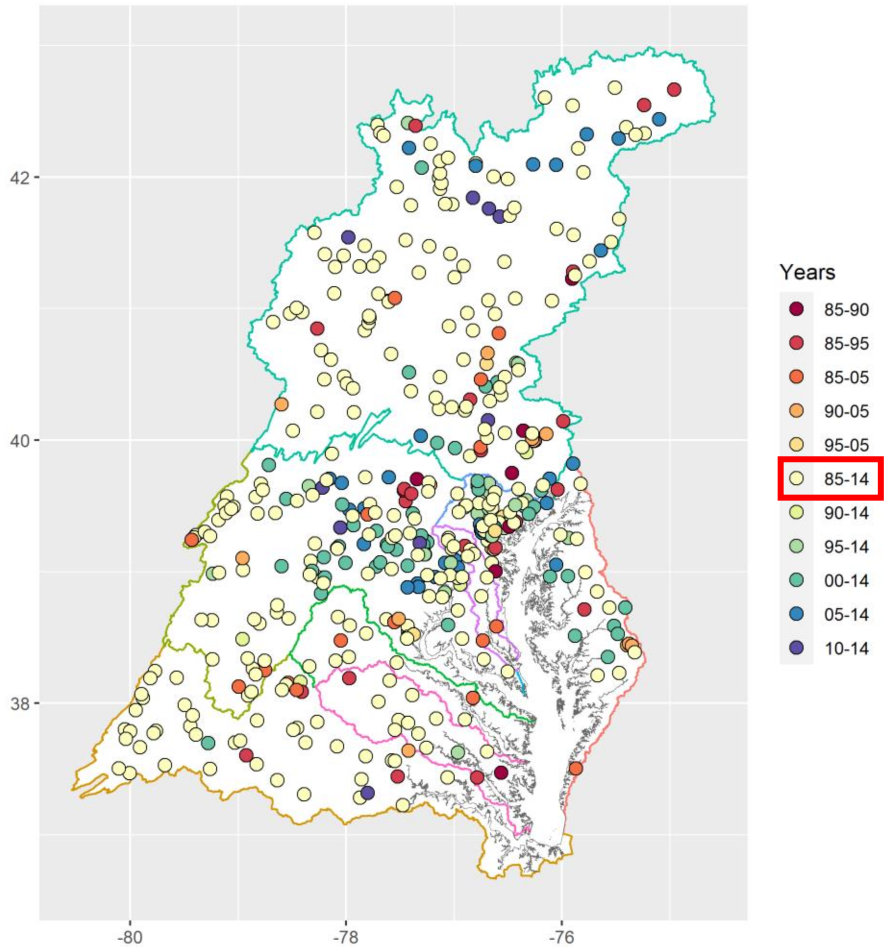
Soil
Texture (% clay, sand, silt)
Hydrologic groups
Permeability
Moisture storage
Available water capacity
Percent organic material
Rock depth

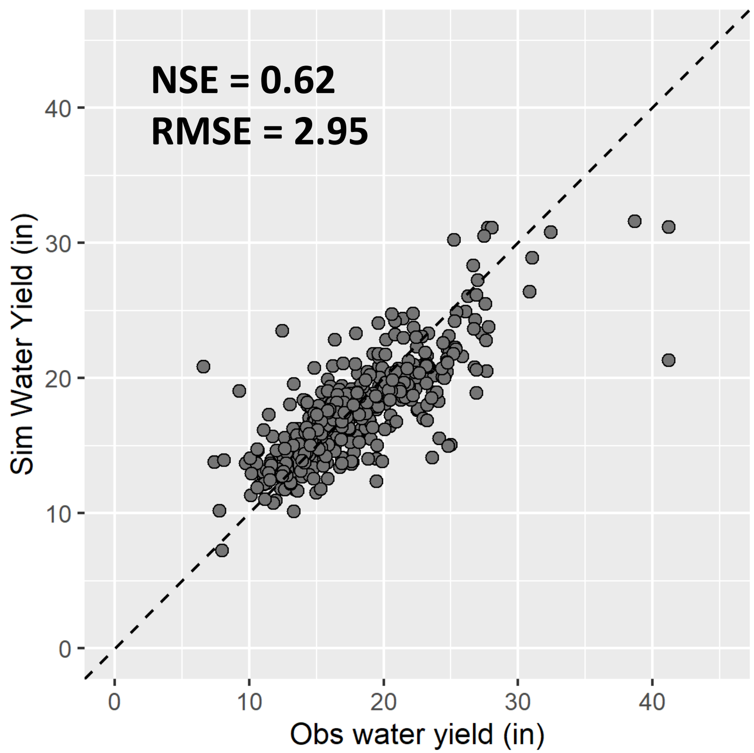


Wieczorek and Schwarz, 2018. https://doi.org/10.5066/F7765D7V

Candidate predictors of streamflow

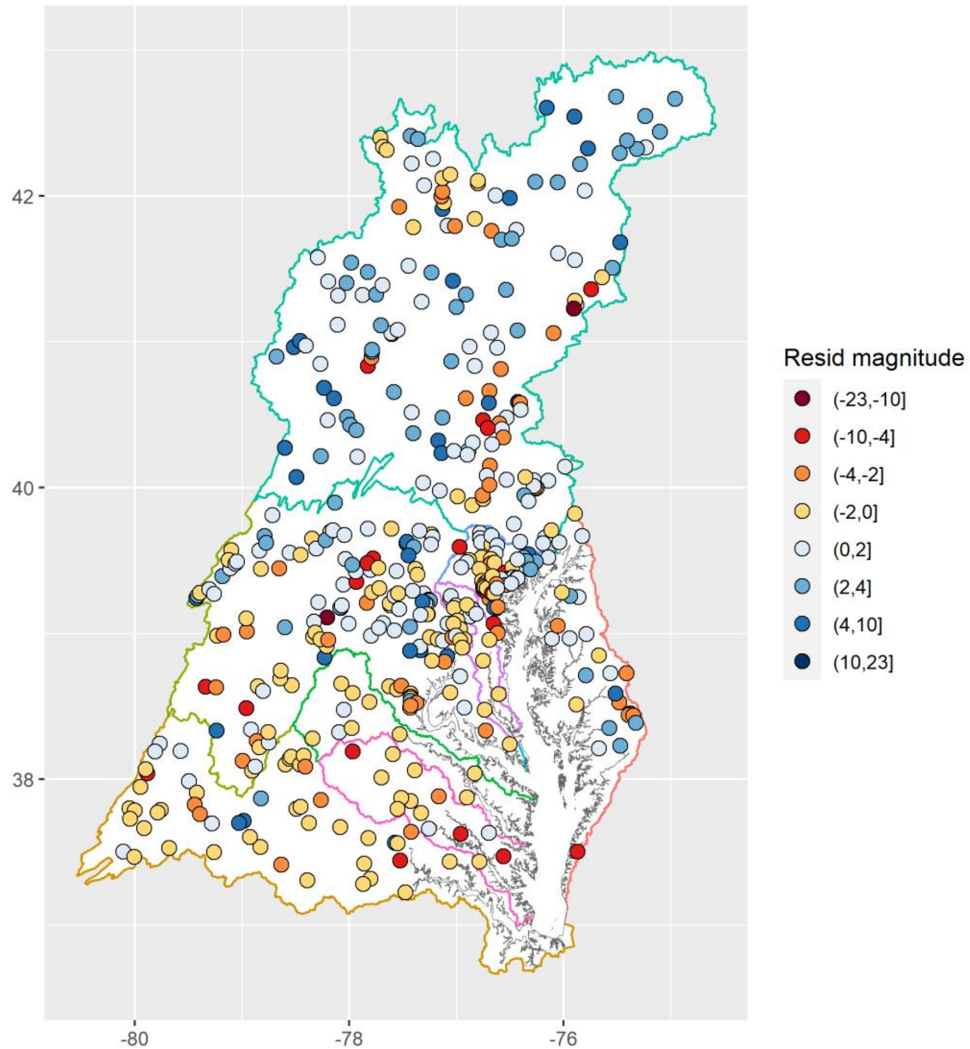
First step: Stations have different periods of record. We matched PCP and PET inputs to years of record at each station (we previously used 1991-2000 at all stations just to get the code working)





Candidate predictors of streamflow

Second step: analysis of residuals (OBS – SIM) to look for patterns that may point to missing predictors

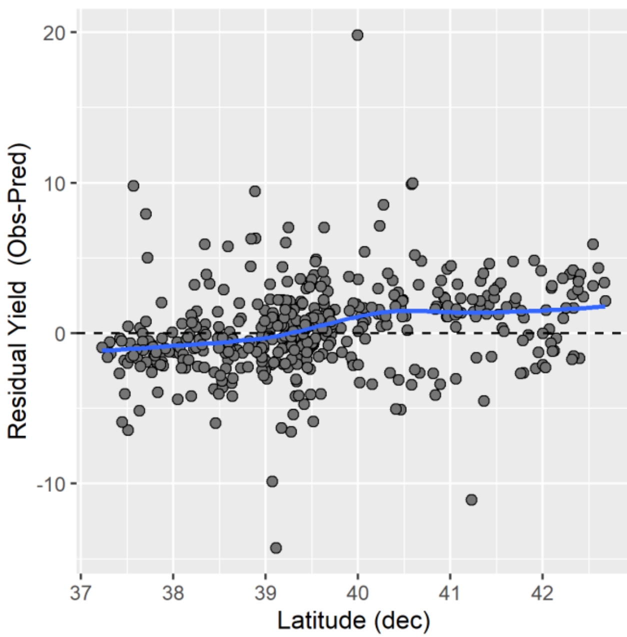


Tendency to underpredict (blue shades) streamflow in upper portion of watershed and overpredict in lower portion (red shades)

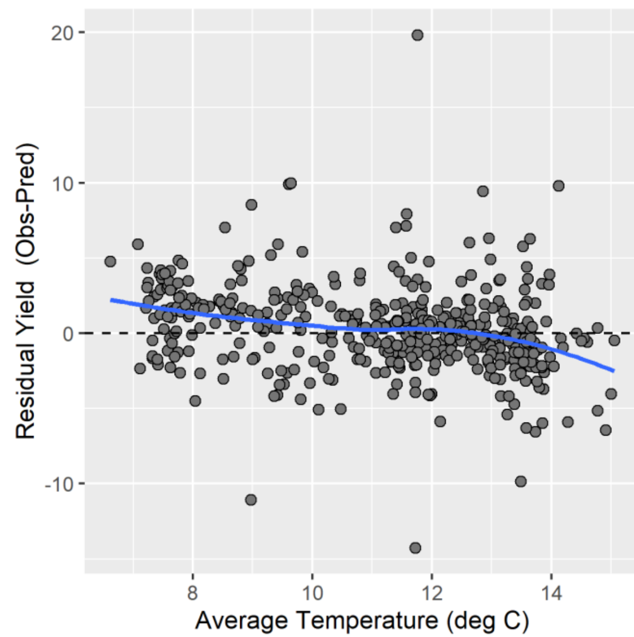
Candidate predictors of streamflow

Second step: analysis of residuals (OBS – SIM) to look for patterns that may point to missing predictors

Residuals vs. latitude



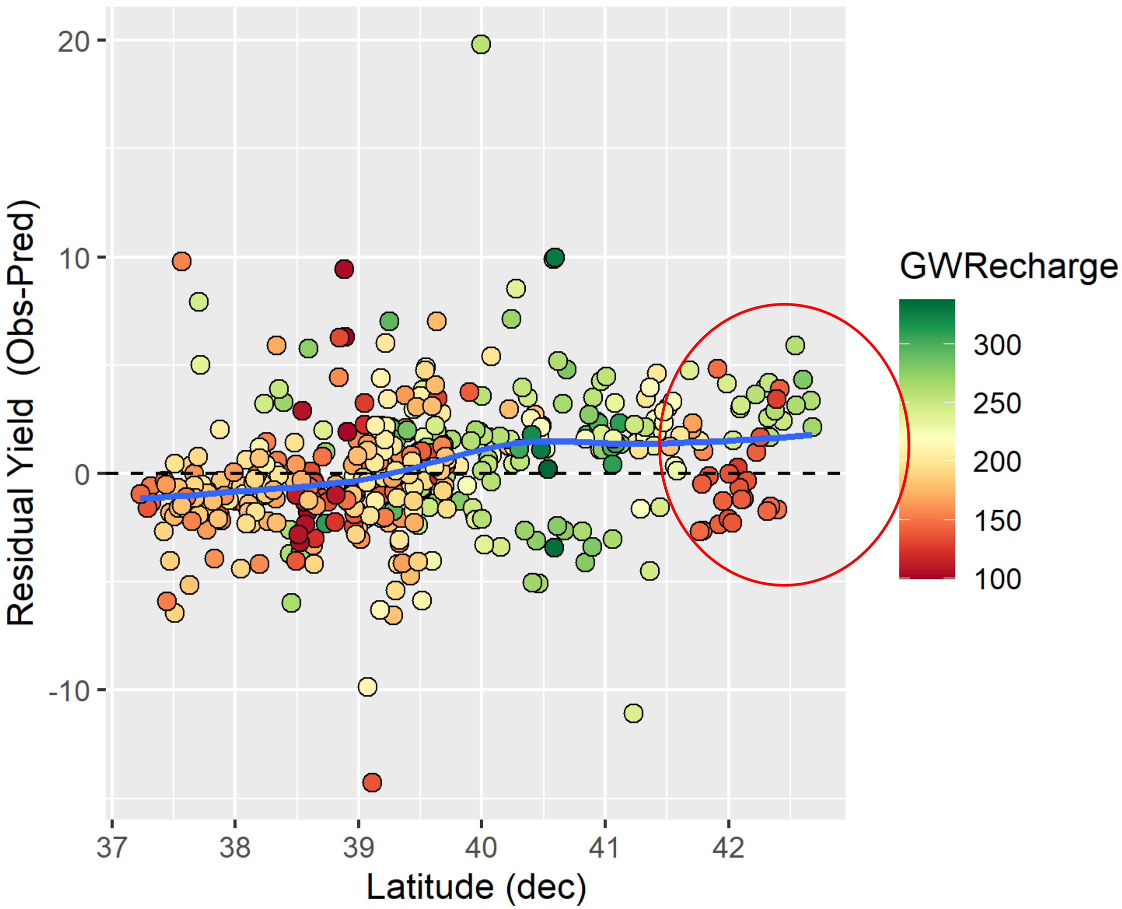
Residuals vs. temperature



Inclusion of a variable like latitude or temperature may help remove this north-south spatial pattern in residuals

Candidate predictors of streamflow

Second step: analysis of residuals (OBS – SIM) to look for patterns that may point to missing predictors

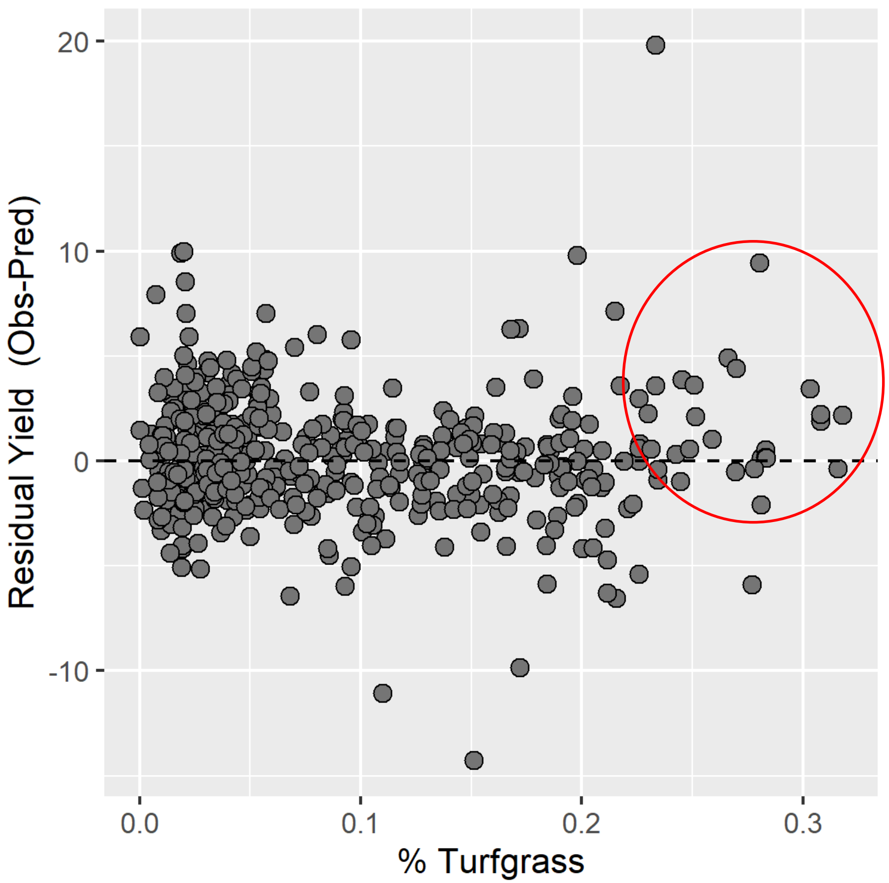


In upper portion of watershed, some tendency to overpredict in low gw recharge area and underpredict in high gw discharge area

Inclusion of an interaction term between latitude and gw recharge may help capture this pattern

Candidate predictors of streamflow

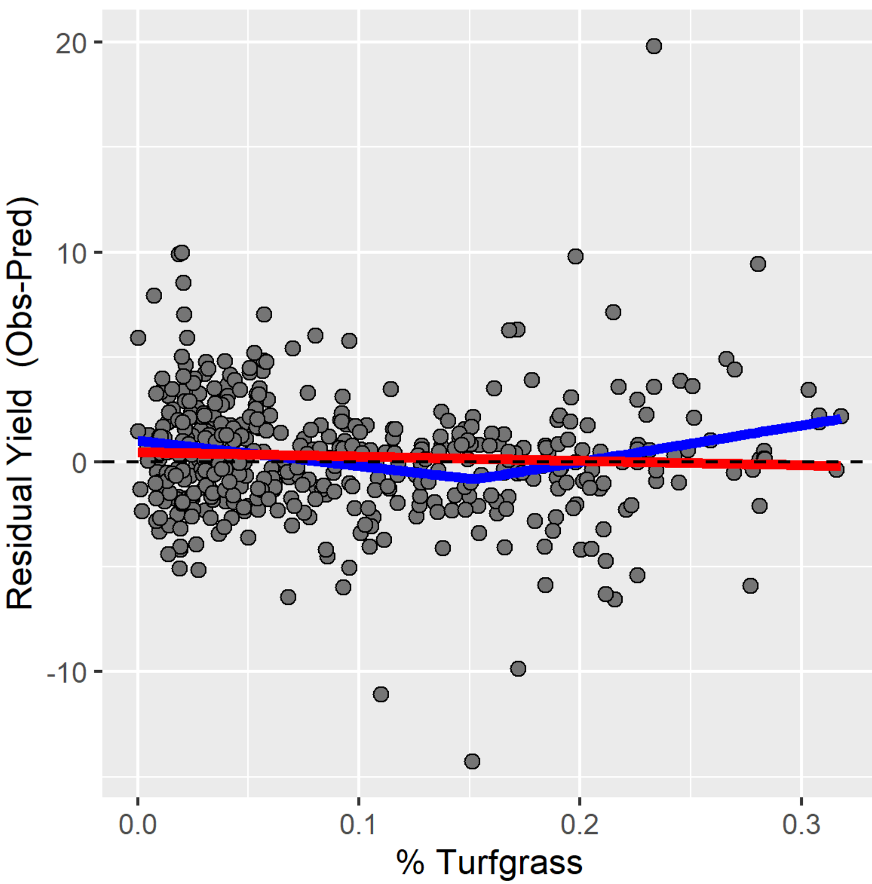
Second step: analysis of residuals (OBS – SIM) to look for patterns that may point to missing predictors



Some tendency to underpredict at very high levels of % Turfgrass (high % of turfgrass tend to co-occur with high % of impervious surfaces)

Candidate predictors of streamflow

Second step: analysis of residuals (OBS – SIM) to look for patterns that may point to missing predictors

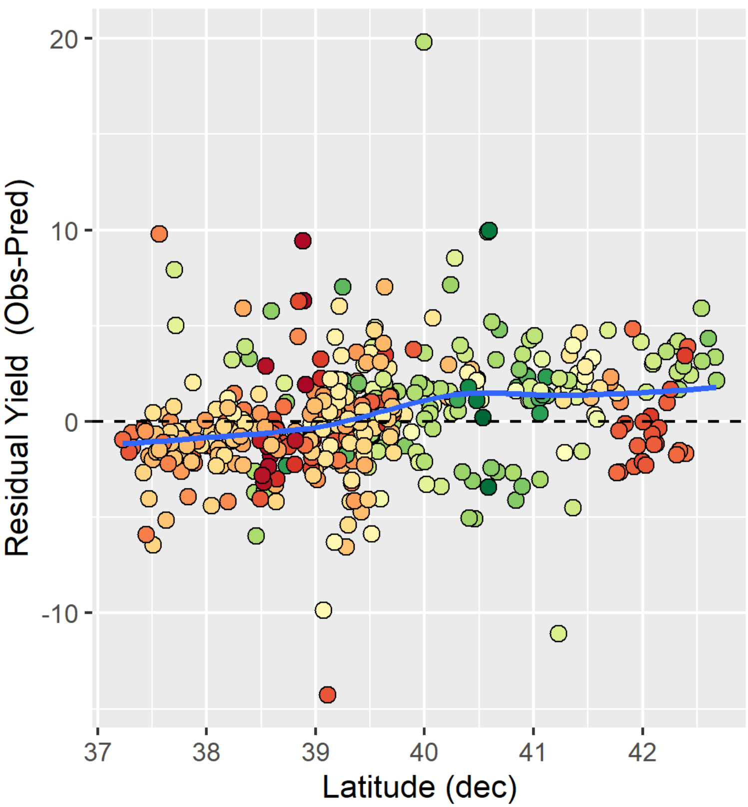


A piecewise regression (**blue line**) better captures this apparent non-linear pattern than a simple linear regression (**red line**).

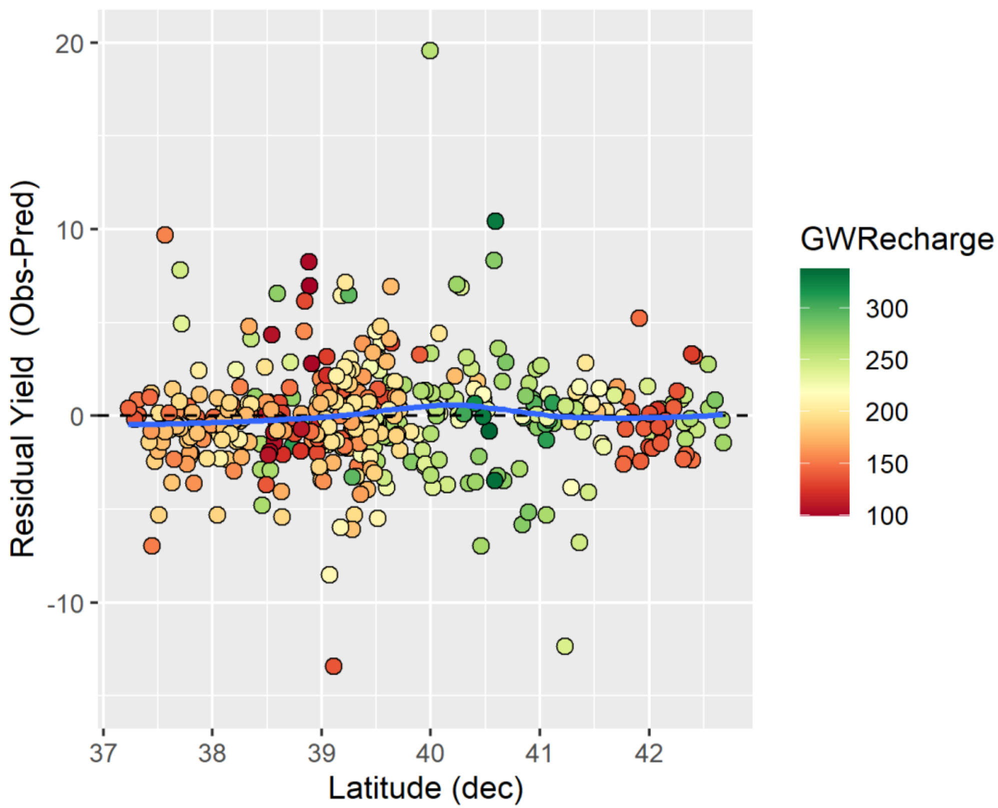
Inclusion of %Turfgrass as a piecewise regression term in the model may help capture this pattern

Candidate predictors of streamflow

$$Q = \sum_{\substack{upstream\\geography}} Precipitation - PET \times f_{LU}$$



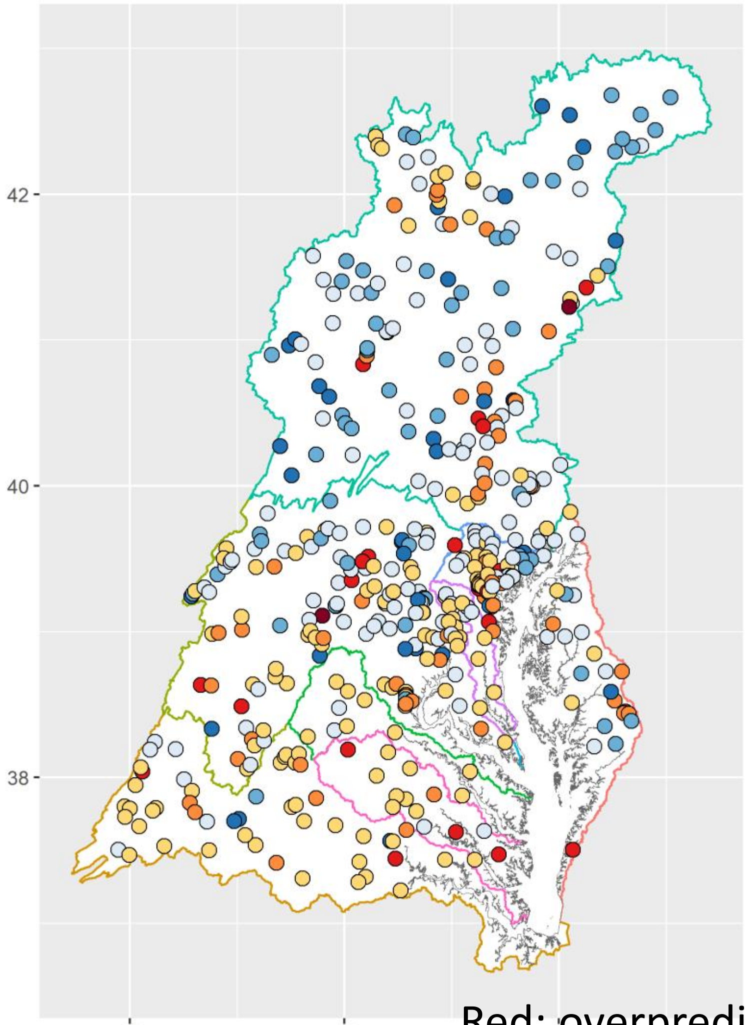
$$Q = \sum_{\substack{upstream\\geography}} Precipitation - PET \times f_{LU} \times (\boldsymbol{T, GWRECH, TURFG})$$



Substantially decreased overprediction at low latitudes and underprediction at high latitudes/high gw recharge.

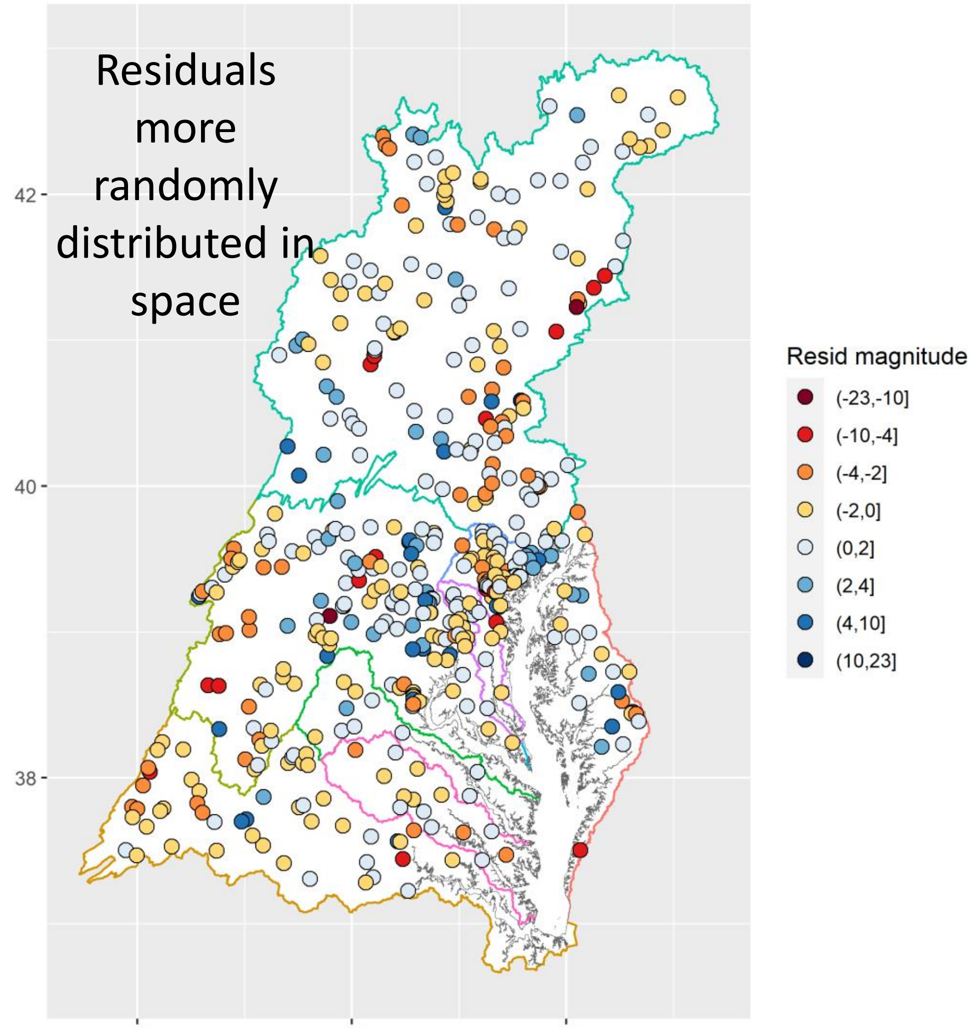
Candidate predictors of streamflow

$$Q = \sum_{\substack{upstream\\geography}} Precipitation - PET \times f_{LU}$$



$$Q = \sum_{\substack{upstream\\geography}} Precipitation - PET \times f_{LU} \times (\boldsymbol{T, GWRECH, TURFG})$$

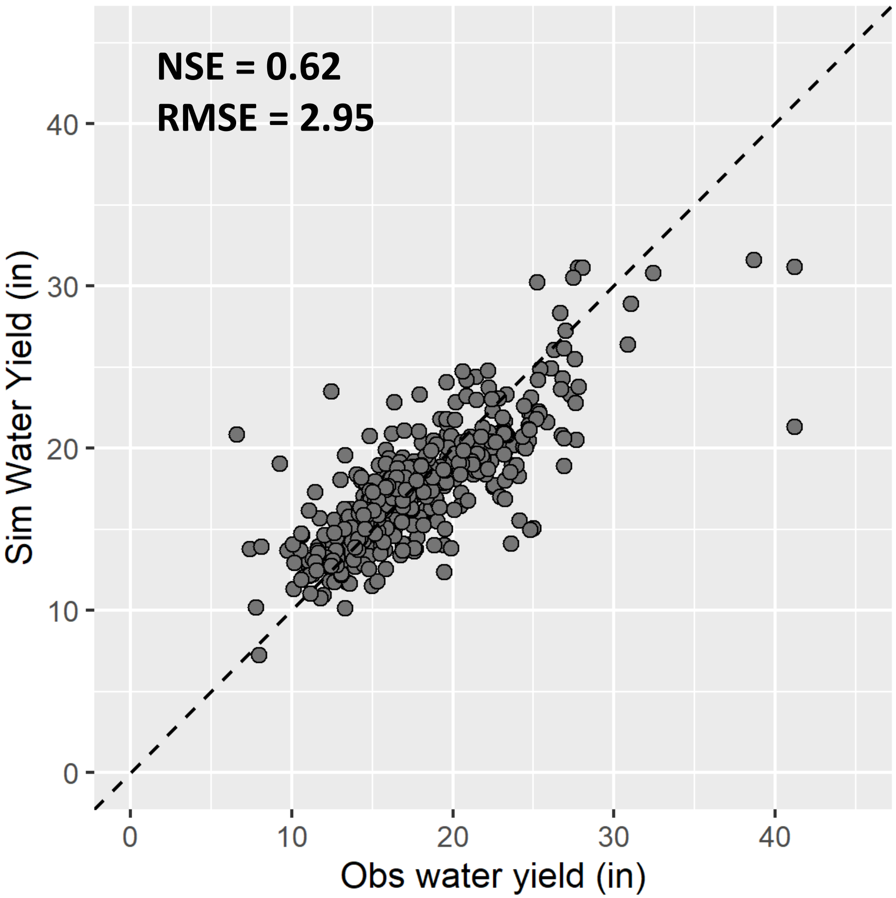
Residuals more randomly distributed in space



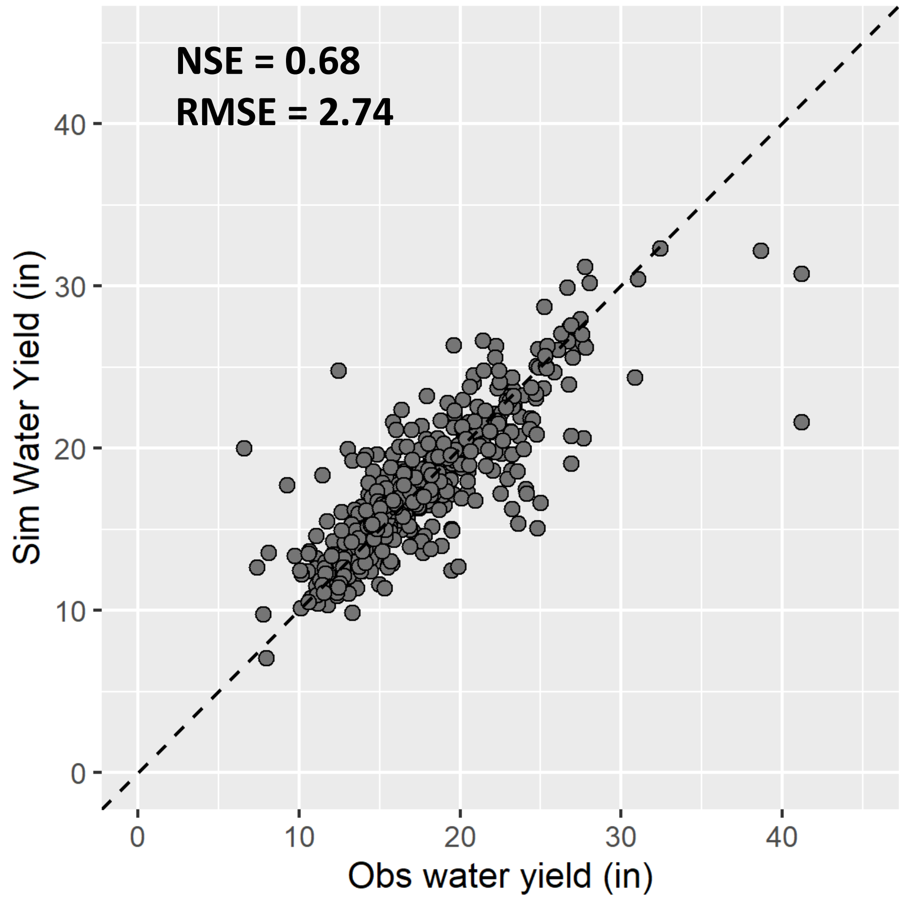
Red: overpredict

Candidate predictors of streamflow

$$Q = \sum_{\substack{upstream \\ geography}} Precipitation - PET \times f_{LU}$$

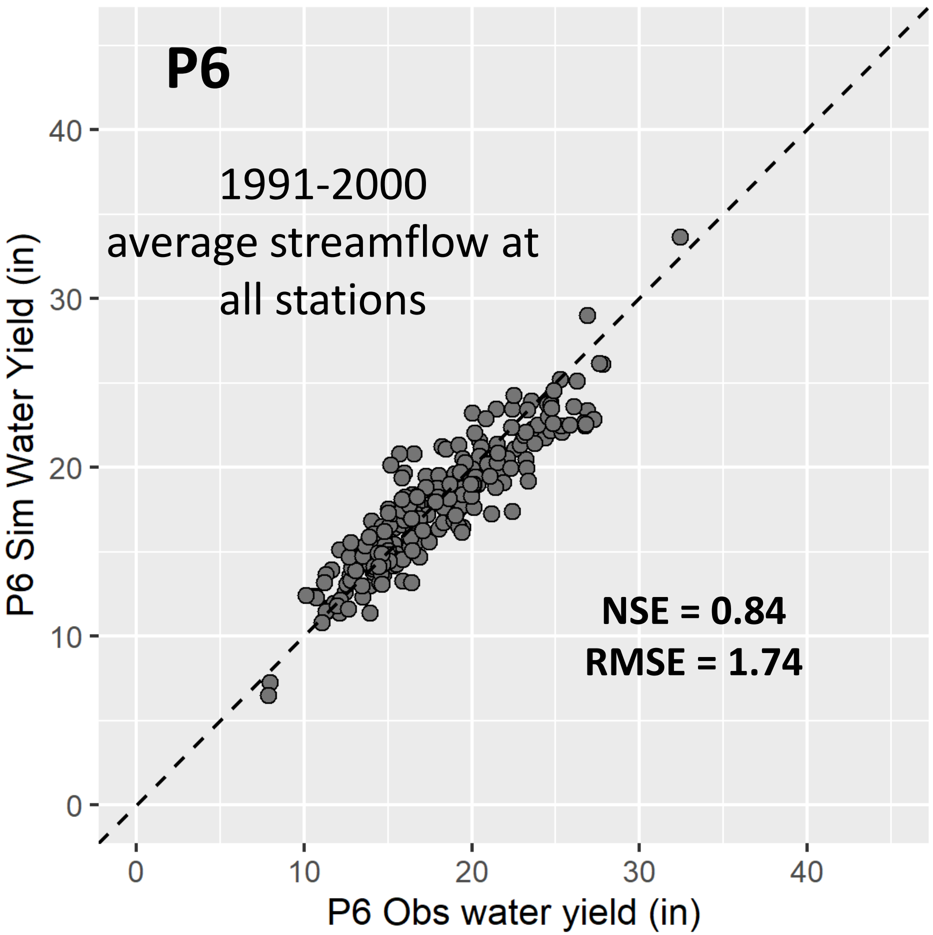


$$Q = \sum_{\substack{upstream \\ geography}} Precipitation - PET \times f_{LU} \times (T, GWRECH, TURFG)$$

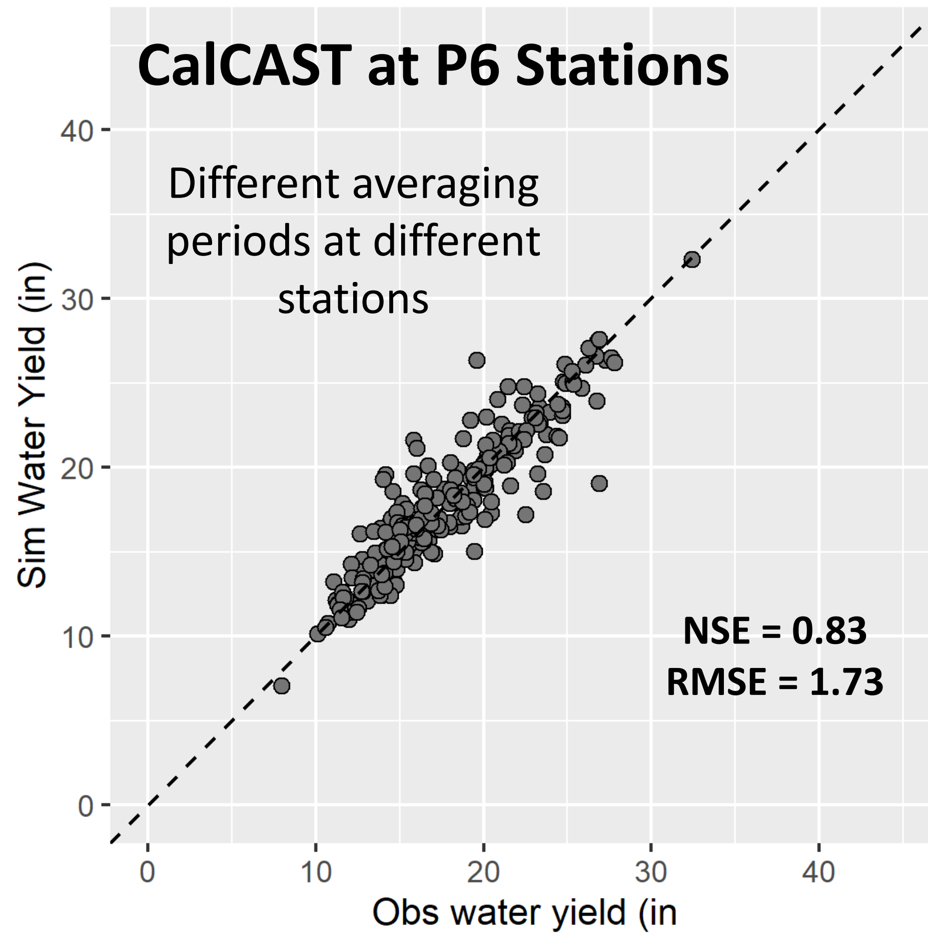


Candidate predictors of streamflow

Comparison with P6 hydrology



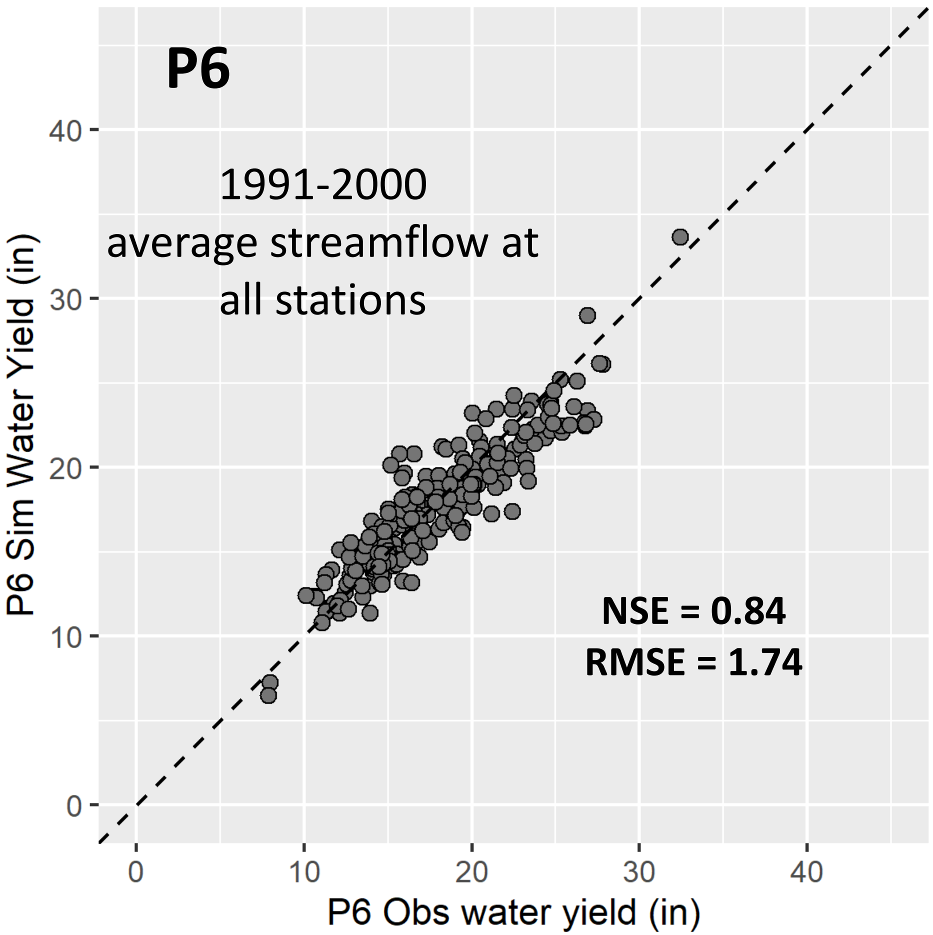
Calibration based on varying PET coefficient by county

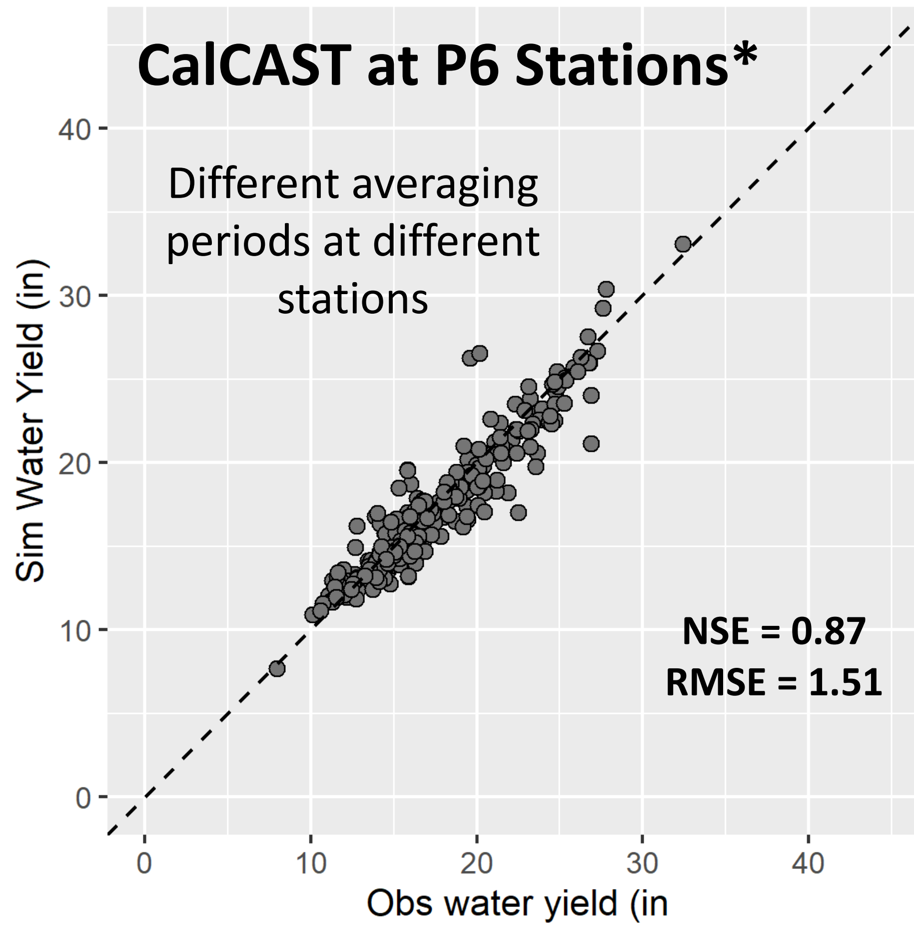


Calibration based on mechanistically meaningful watershed properties

Candidate predictors of streamflow

Comparison with P6 hydrology

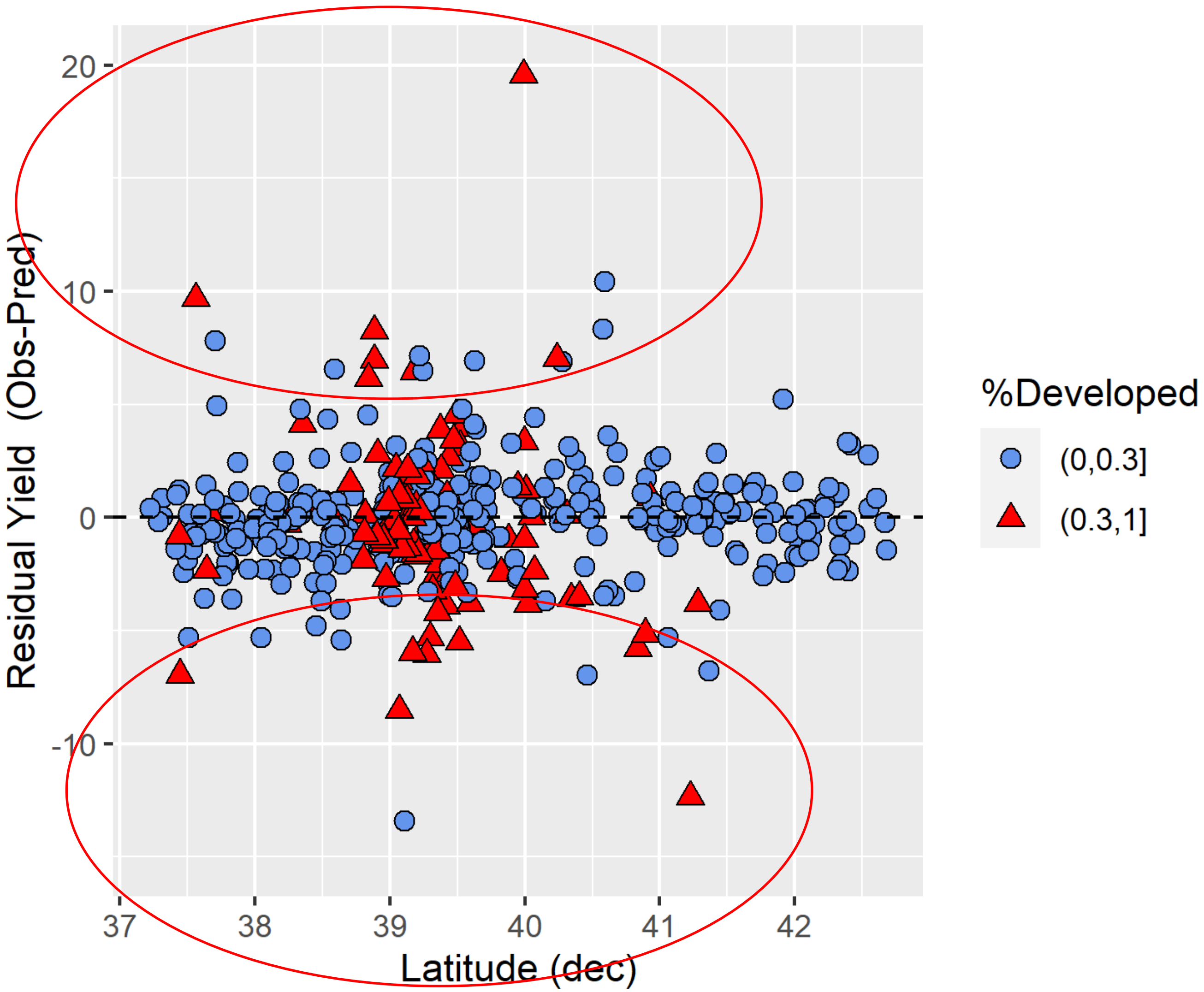




*Replacing **PCP** and **PET** inputs with **RUNOFF** predicted by relatively simple water balance model (Wolock & McCabe, 2018)

Candidate predictors of streamflow

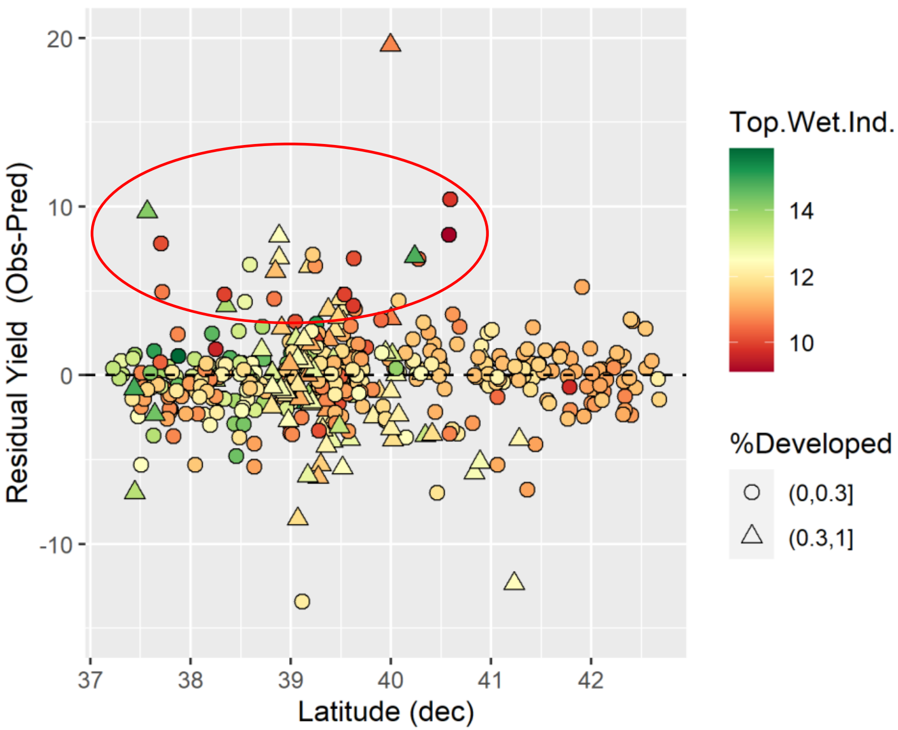
Room for improvement

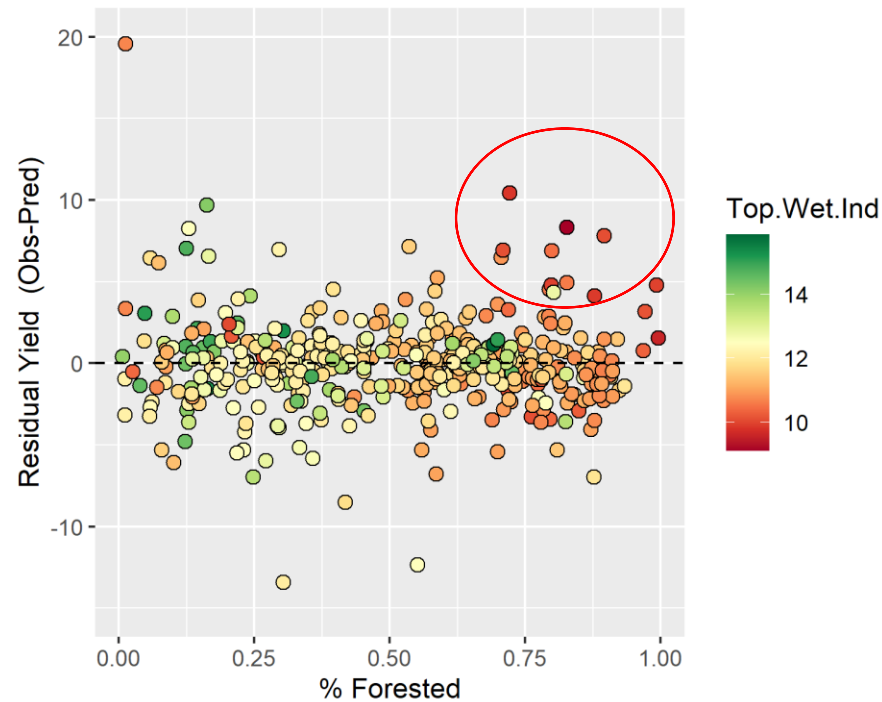


Several of the stations where the model performs the worst have relatively high % developed land (triangles)

Candidate predictors of streamflow

Room for improvement



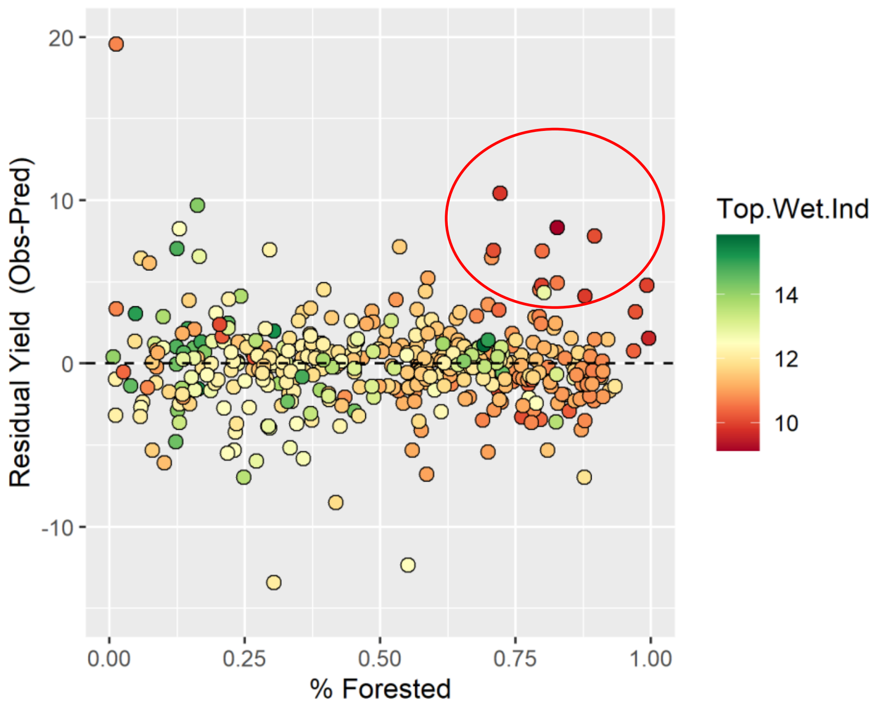


Several of the stations where the model performs the worst (of those with low % developed) exhibit some of the largest % forested land and some of the lowest Topographic Wetness Index values

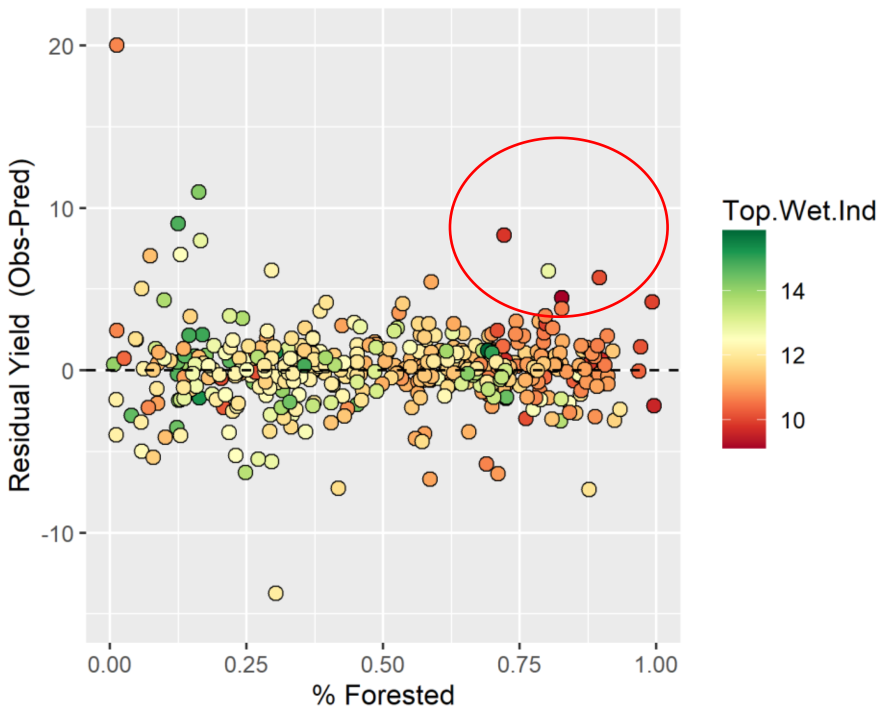
Candidate predictors of streamflow

Room for improvement

$$Q = \sum_{\substack{upstream\\geography}} Precipitation - PET \times f_{LU} \times (\boldsymbol{T, GWRECH, TURFG})$$



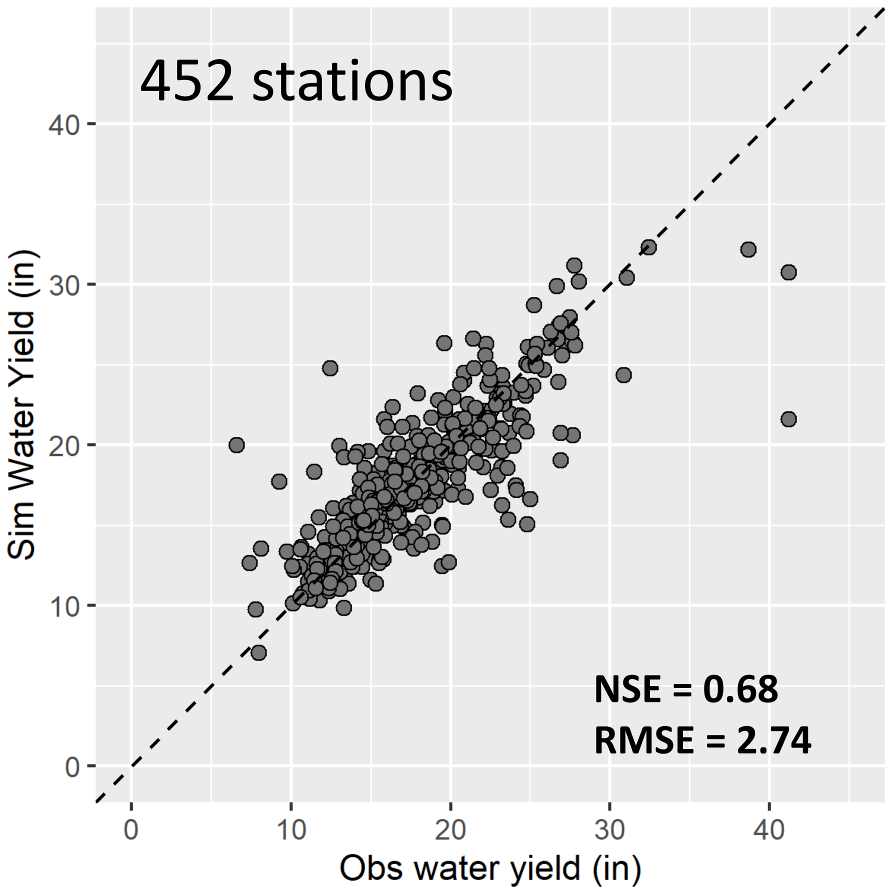
$$Q = \sum_{\substack{upstream\\geography}} RUNOFF * \times f_{LU} \times (\boldsymbol{T, GWRECH, TURFG})$$

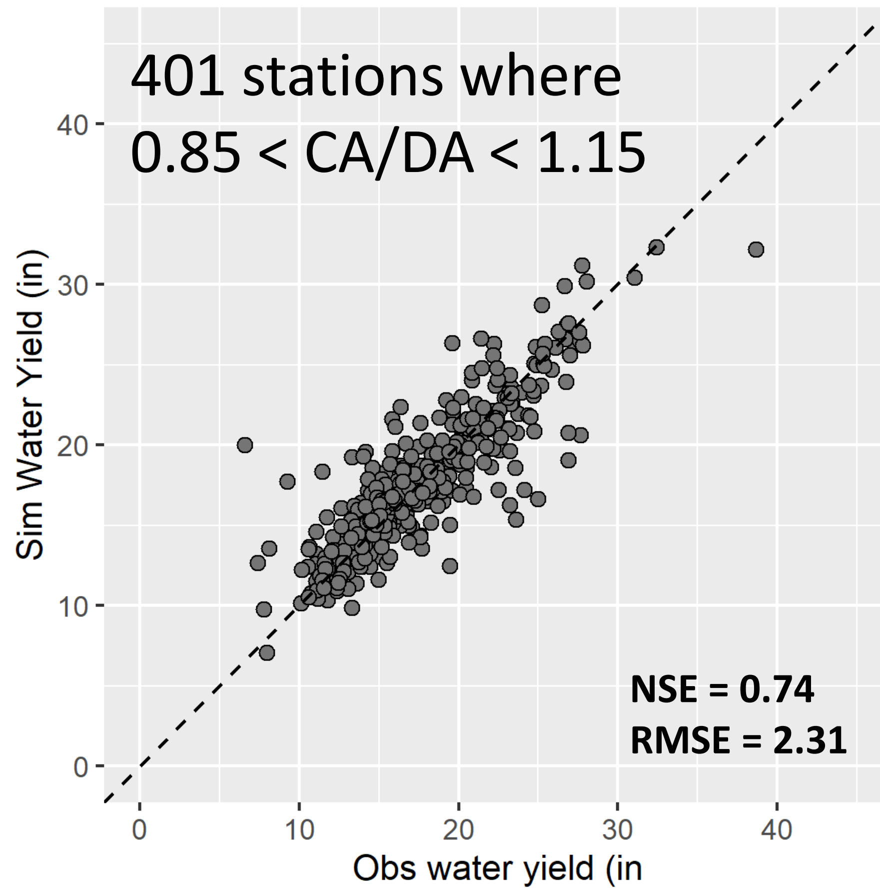


*Replacing **PCP** and **PET** inputs with **RUNOFF** predicted by relatively simple water balance model (Wolock & McCabe, 2018)

Candidate predictors of streamflow

Room for improvement





CA: station`s catchment area estimated as sum of all upstream NHDPlus catchments
DA: station`s upstream drainage area provided by USGS

Conclusions

We will continue to explore candidate predictors that may help base hydrology calibration on mechanistically plausible / management-relevant properties of the watershed

Most likely a hybrid calibration approach will be needed (combination of relevant watershed properties and P6-like approach)

Comparison of Modeled and Monitored Nutrient Trends

Isabella Bertani, Gopal Bhatt, Gary Shenk, and the Factors Team

Modeling Workgroup Quarterly Review 7/6/2021

Comparing modeled and monitored nutrient trends

Management Question

- TMDL: Implement the practices by 2025 that will eventually lead to meeting water quality standards
- CAST prediction: What is the long-term load resulting from a given state of the watershed (land use, point sources, management actions, etc)
- WRTDS- flow normalized loads: based on a moving relationship between flow and concentration, how do loads change over time if annual flow is the same
- Science question: How do we use monitoring data to validate the predictions of CAST

Recap from April Quarterly

Comparing modeled and monitored nutrient trends

Two major objectives:

- Help understand and communicate where and why monitoring data and CAST do not match and how those differences can be reconciled

- Inform future refinements of the watershed model

Recap from April Quarterly

Comparing modeled and monitored nutrient trends

CAST vs WRTDS_FN is not an "apples-to-apples" comparison

CAST and WRTDS Differences

- Unrealistic expectations
  - Implementation amount
  - BMP effects
- Lag times
  - Implementation / maturation of BMPs
  - Groundwater
  - Soil equilibration
- Insufficient Monitoring –
  - Quantified as uncertainty in WRTDS trends
- Competing effects
  - Conowingo
  - Climate change
  - Weather cycle effects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REVIEWS AND ANALYSES

Factors driving nutrient trends in streams of the Chesapeake Bay watershed

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Assigned to Associate Editor Yongshan Wan.

Abstract
Despite decades of effort toward reducing nitrogen and phosphorus flux to Chesapeake Bay, water-quality and ecological responses in surface waters have been mixed. Recent research, however, provides useful insight into multiple factors complicating the understanding of nutrient trends in bay tributaries, which we review in this paper, as we approach a 2025 total maximum daily load (TMDL) management deadline. Improvements in water quality in many streams are attributable to management actions that reduced point sources and atmospheric nitrogen deposition and to changes in climate. Nutrient reductions expected from management actions, however, have not been fully realized in watershed streams. Nitrogen from urban nonpoint sources has declined, although water-quality responses to urbanization in individual streams vary depending on predevelopment land use. Evolving agriculture, the largest watershed source of nutrients, has likely contributed to local nutrient trends but has not affected substantial changes in flux to the bay. Changing average nitrogen yields from farmland underlain by carbonate rocks, however, may suggest future trends in other areas under similar management, climatic, or other influences, although drivers of these changes remain unclear. Regardless of upstream trends, phosphorus flux to the bay from its largest tributary has increased due to sediment infill in the Conowingo Reservoir. In general, recent research emphasizes the utility of input reductions over attempts to manage nutrient fate and transport at limiting nutrients in surface waters. Ongoing research opportunities include evaluating effects of climate change and conservation practices over time and space and developing tools to disentangle and evaluate multiple influences on regional water quality.

1 | INTRODUCTION

Recent efforts toward reducing nutrient flux to Chesapeake Bay from its watershed have been insufficient to meet water-quality and ecological standards in the bay (Chesapeake Bay Program, 2018a; Kleinman et al., 2019; Linker,

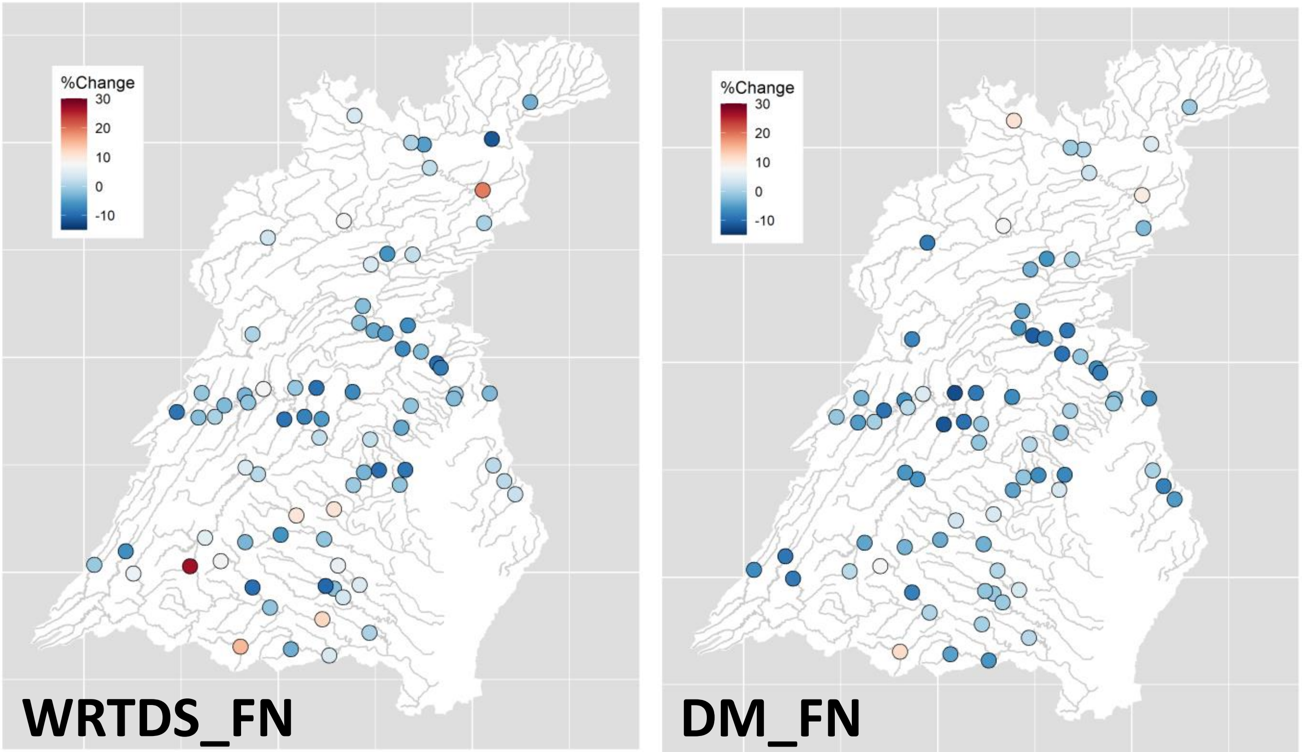
Abbreviations: SPARROW, SPAtially Referenced Regressions On Watershed attributes; TMDL, total maximum daily load.

Recap from April Quarterly

Dynamic watershed model (DM): same inputs as CAST but accounts for (gw) lag times, varying hydrology (and flow-normalization effect on it), non-stationary watershed response to changing conditions

- Explore patterns in differences between WRTDS_FN and DM_FN trends as a function of "unrealistic expectations"

TN – % Change over last 5 years (2009-2013)



- Land Use
- Nutrient inputs
- BMP type/level
- Watershed characteristics
- Time period
- …

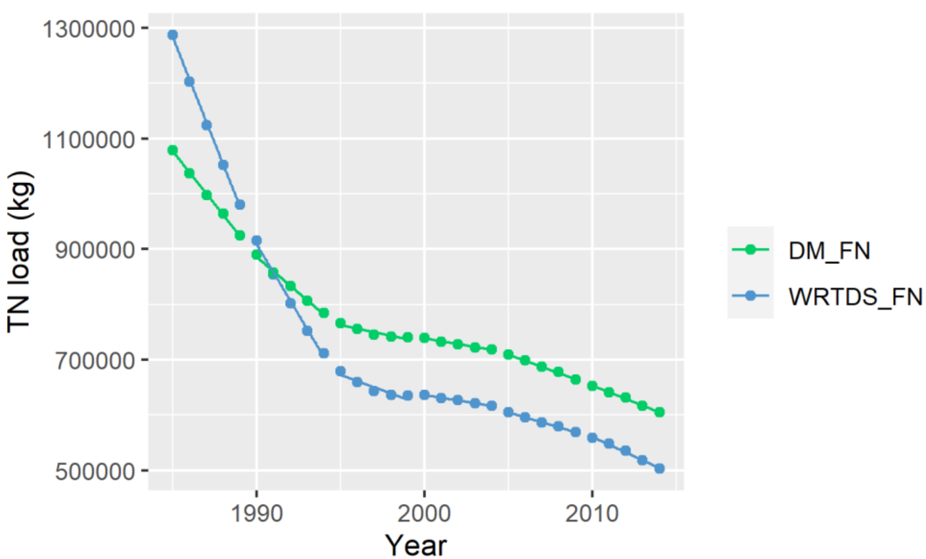
Recap from April Quarterly

Example of exploratory analysis

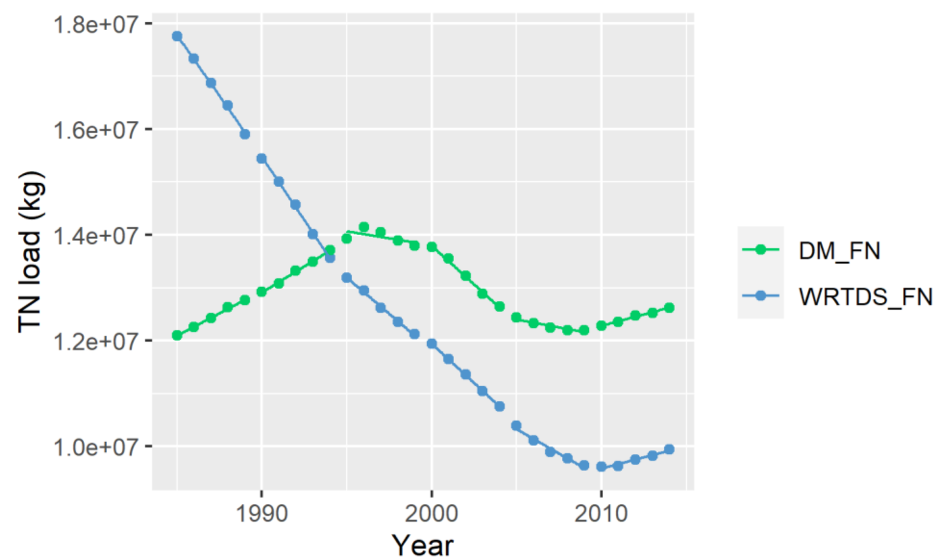
Q: where and when are trends in WRTDS_FN and DM_FN most similar/different? Why is that?

Example response variable: Slope of WRTDS_FN vs. DM_FN for consecutive 5-year periods (85-89, 90-94, 95-99, 00-04, 05-09,10-14)

Patuxent River near Bowie, MD

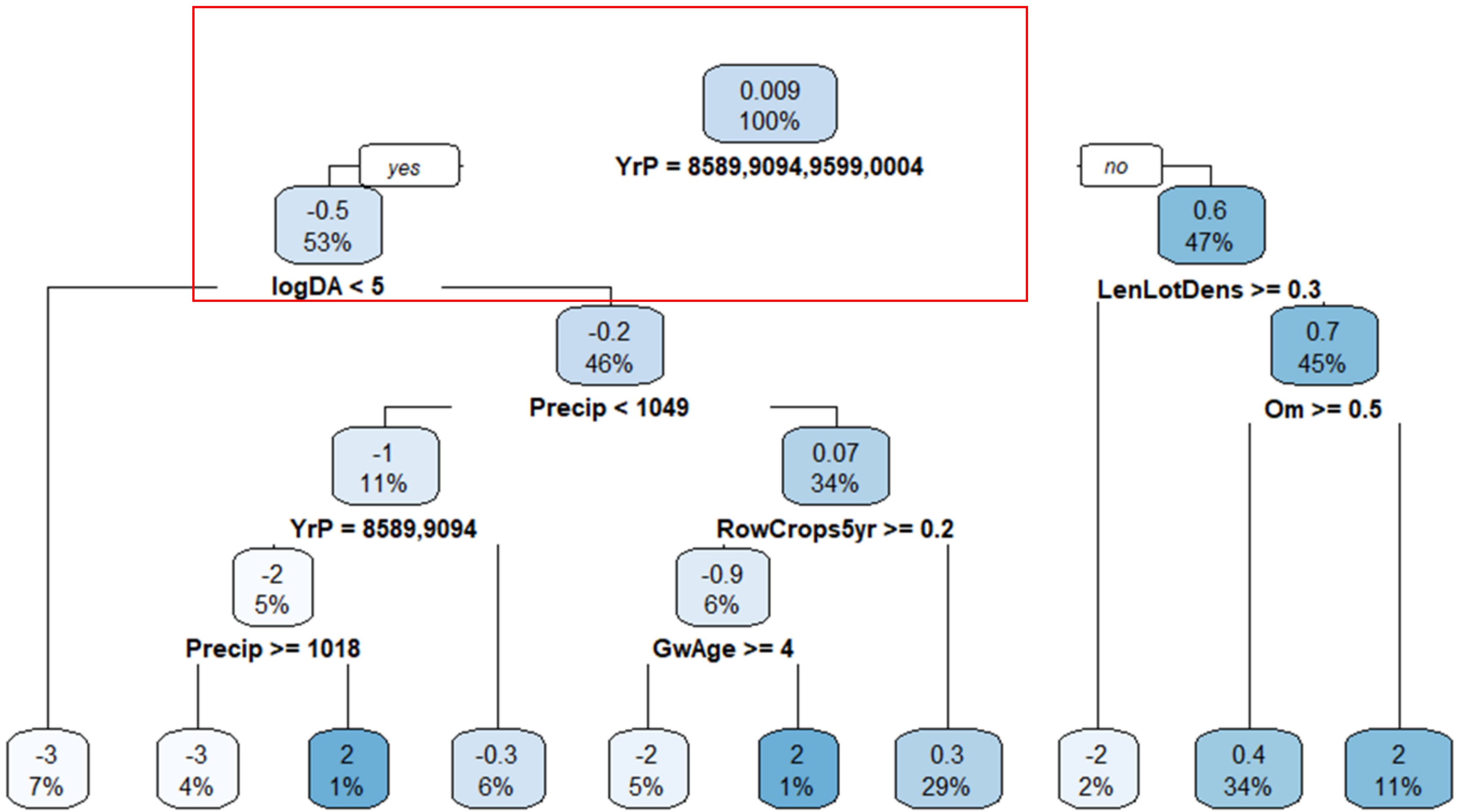


Susquehanna River at Towanda, PA



Recap from April Quarterly

Example of exploratory analysis

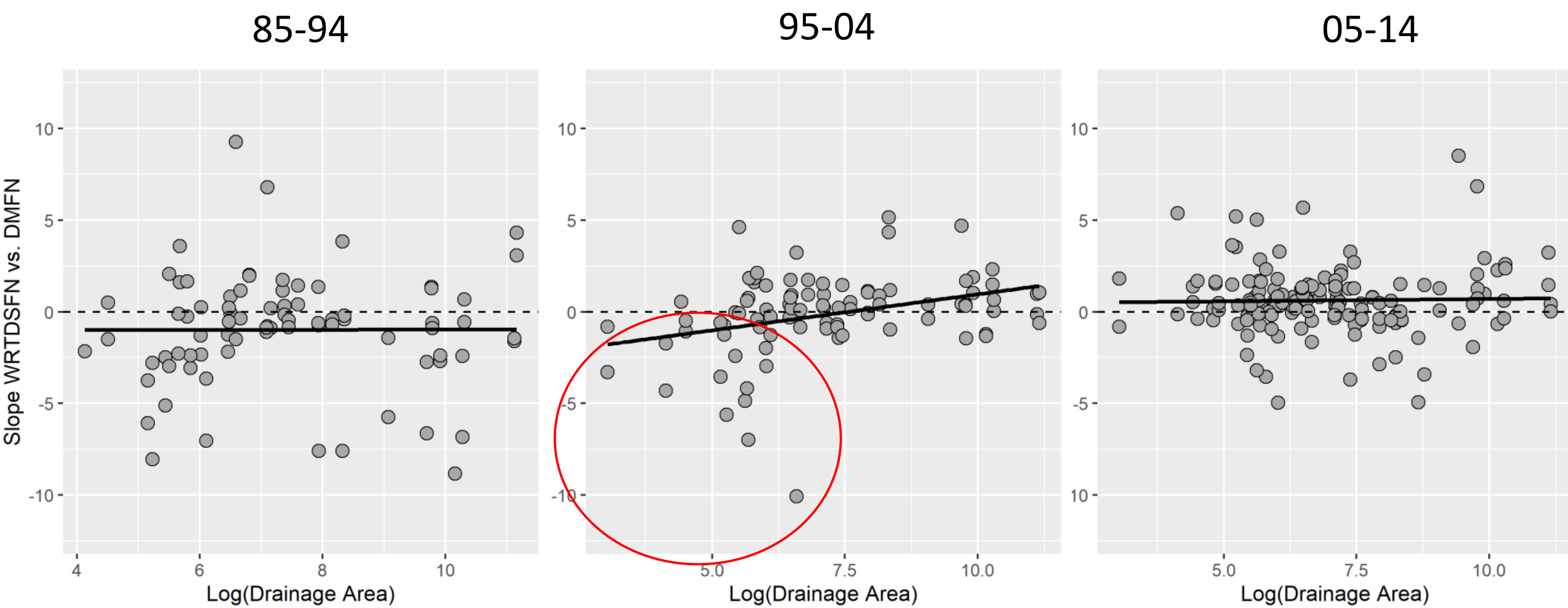


***YrP** = 5-year time period (85-89, 90-94, 95-99, 00-04, 05-09,10-14)

***logDA** = log(Station Drainage Area)

Recap from April Quarterly

Slope of WRTDS_FN vs. DM_FN and Drainage Area



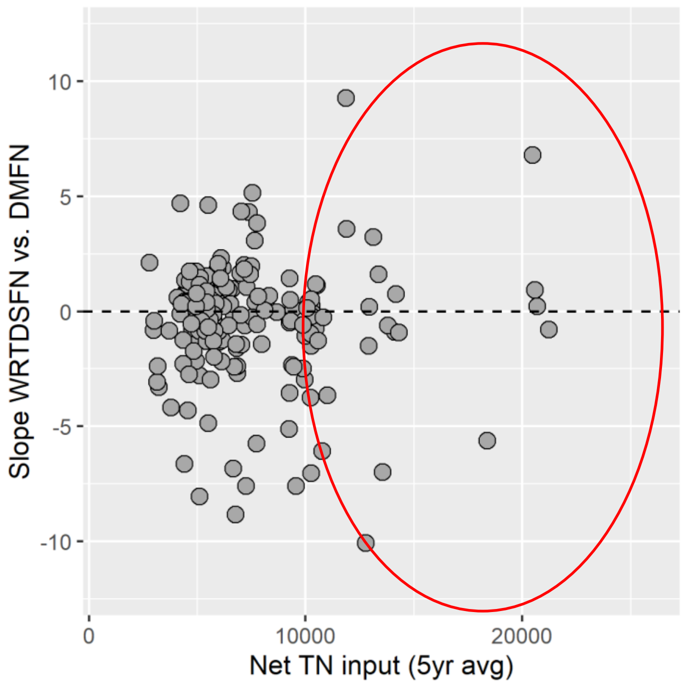
Larger scatter compared to other periods – strongest disagreement between WRTDS and DM

Stations with smaller drainage areas show strongest disagreement

The same is not true in later years

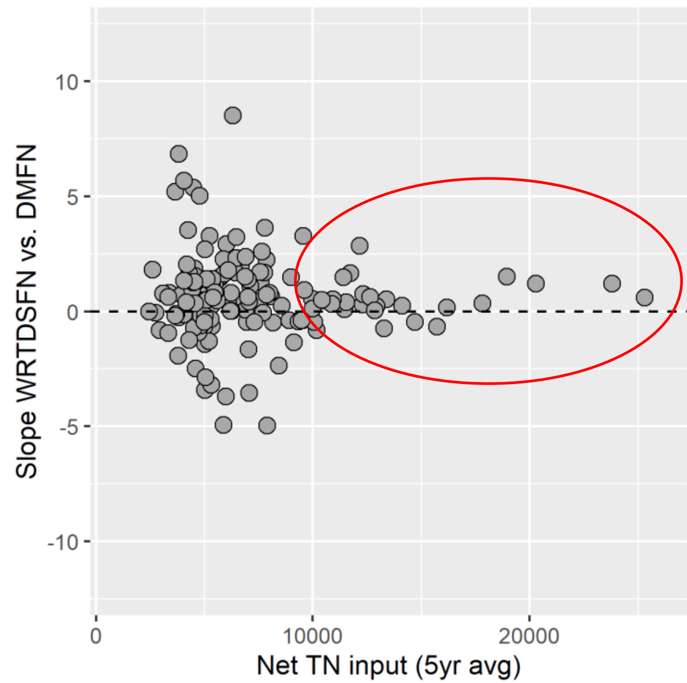
Slope of WRTDS_FN vs. DM_FN and TN inputs

85-04



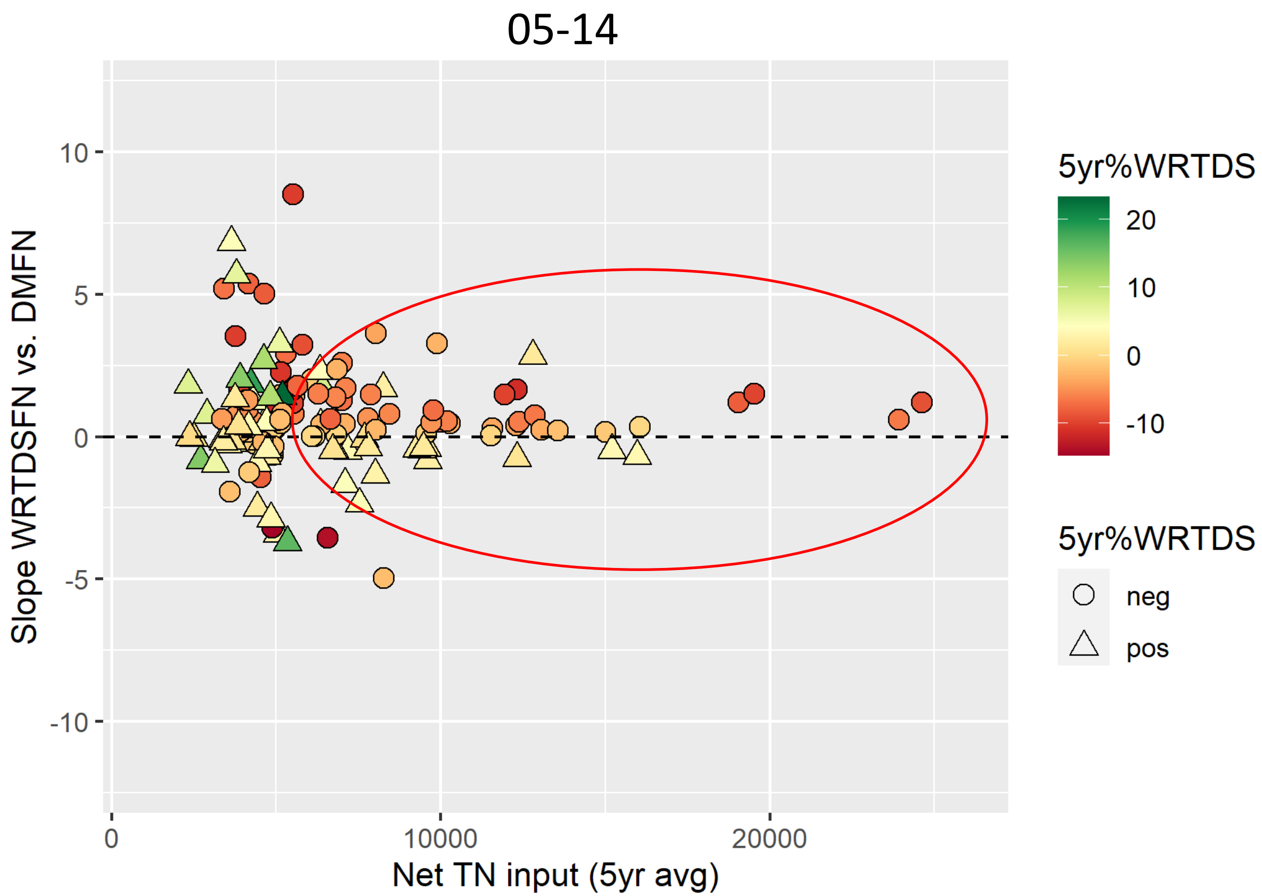
Stations with larger inputs do not show better agreement in earlier years

05-14



Better agreement (slopes closer to 1) at stations with larger inputs in later years

Slope of WRTDS_FN vs. DM_FN and TN inputs



At stations with larger inputs, stations where DM and WRTDS show opposite trends (slope < 0) tend to be those that show an increase in WRTDSFN (triangles) in later years

Summary

DM_FN and WRTDS_FN exhibit the largest disagreement at stations with smaller drainage area in the middle of the period of record, but the same is not true in earlier and later years

In later years, DM_FN and WRTDS_FN exhibit good agreement at stations with high TN inputs and where WRTDS_FN exhibits a negative trend. At stations with high TN loads where WRTDS_FN exhibits a positive trend in later years, DM_FN has opposite trend

In later years, most disagreement at stations with low TN inputs, working on understanding why