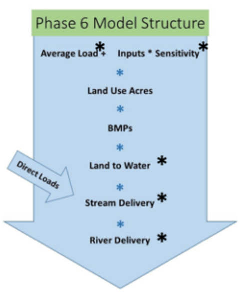
Testing watershed properties as candidate predictors of long-term average streamflow

Isabella Bertani, Gopal Bhatt, Gary Shenk

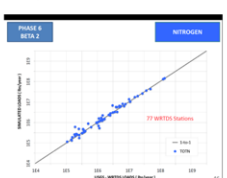
Modeling Workgroup Quarterly Review
10/05/2021

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.



Calibration of meta-parameters to spatial loads

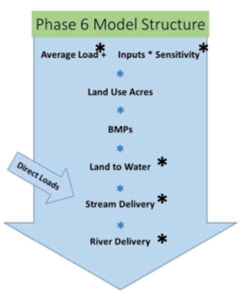


$$Q = \sum_{\substack{upstream \\ geography}} Precipitation - PET \times f_{LU} \cancel{\times Fn(watershed\ properties})$$

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

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

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



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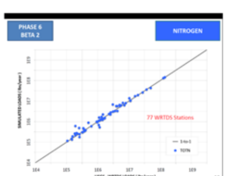


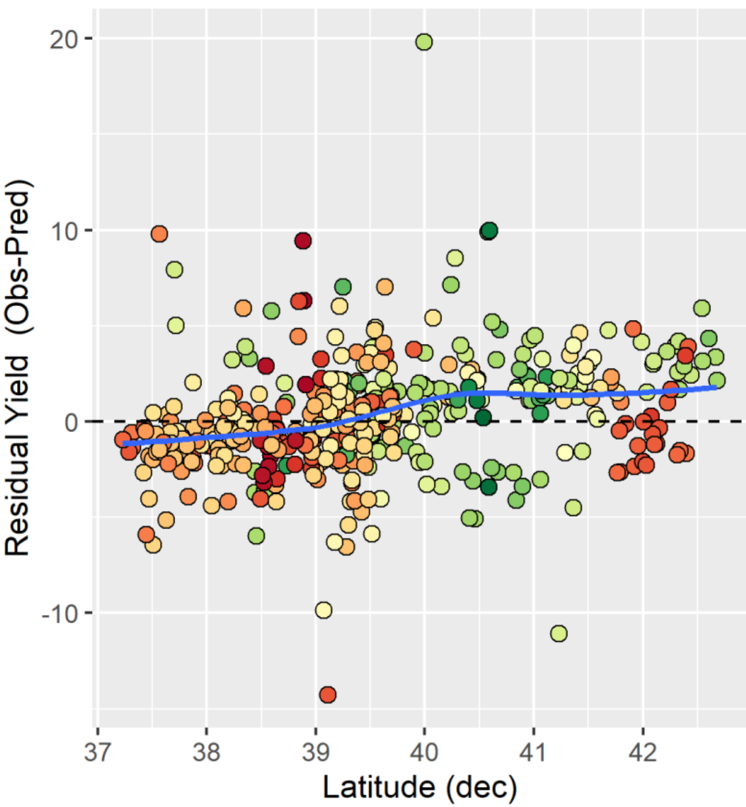
$$Q = \sum_{\substack{upstream \\ geography}} Precipitation - PET \times f_{LU} \times \boldsymbol{Fn(watershed\ properties)}$$

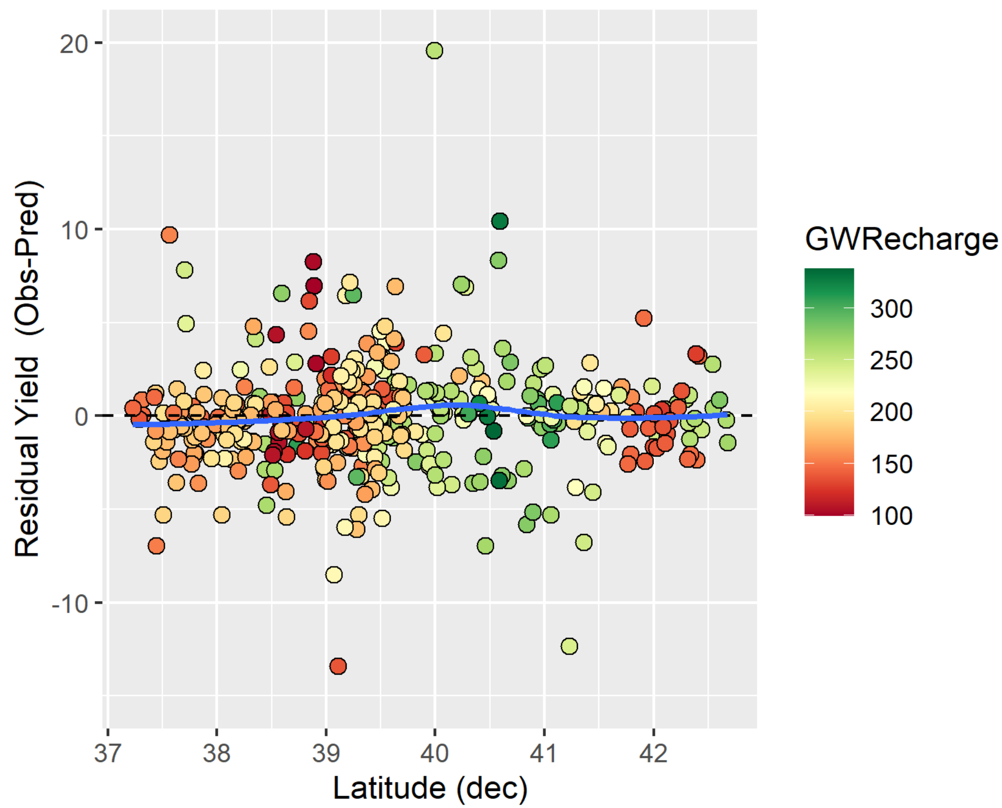
$$\boldsymbol{e.g., Fn(watershed\ properties) = a + f_w \times Wetness + f_s \times Slope}$$

Candidate predictors of streamflow

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

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





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

Candidate predictors of streamflow

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

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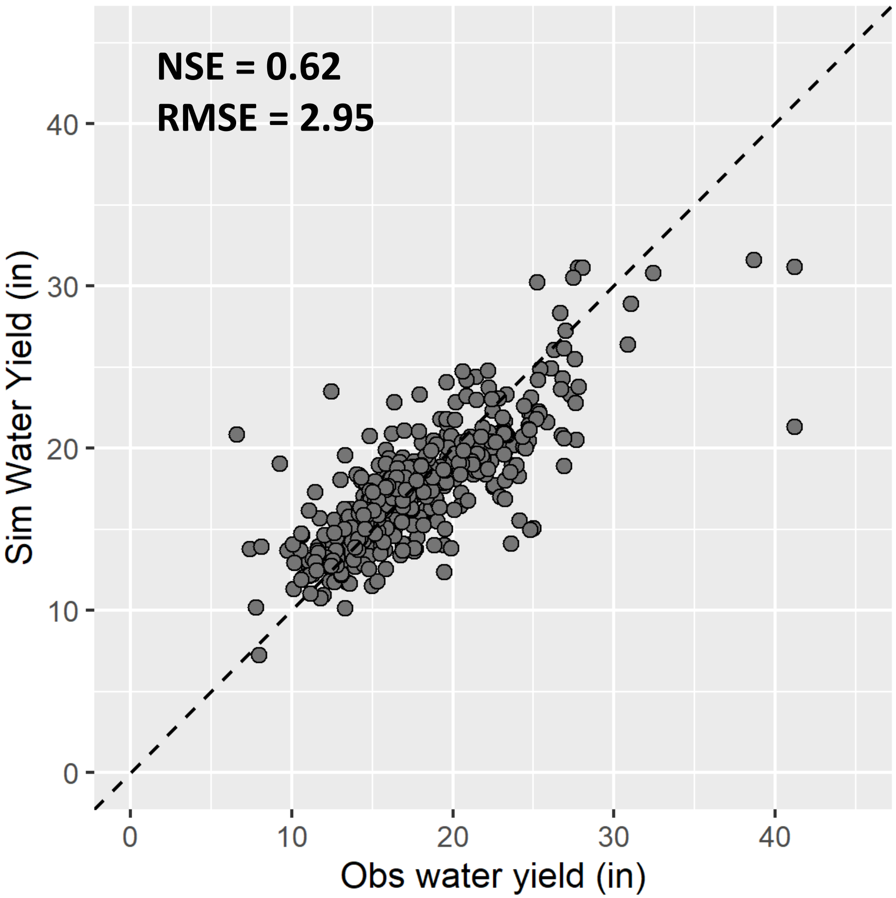
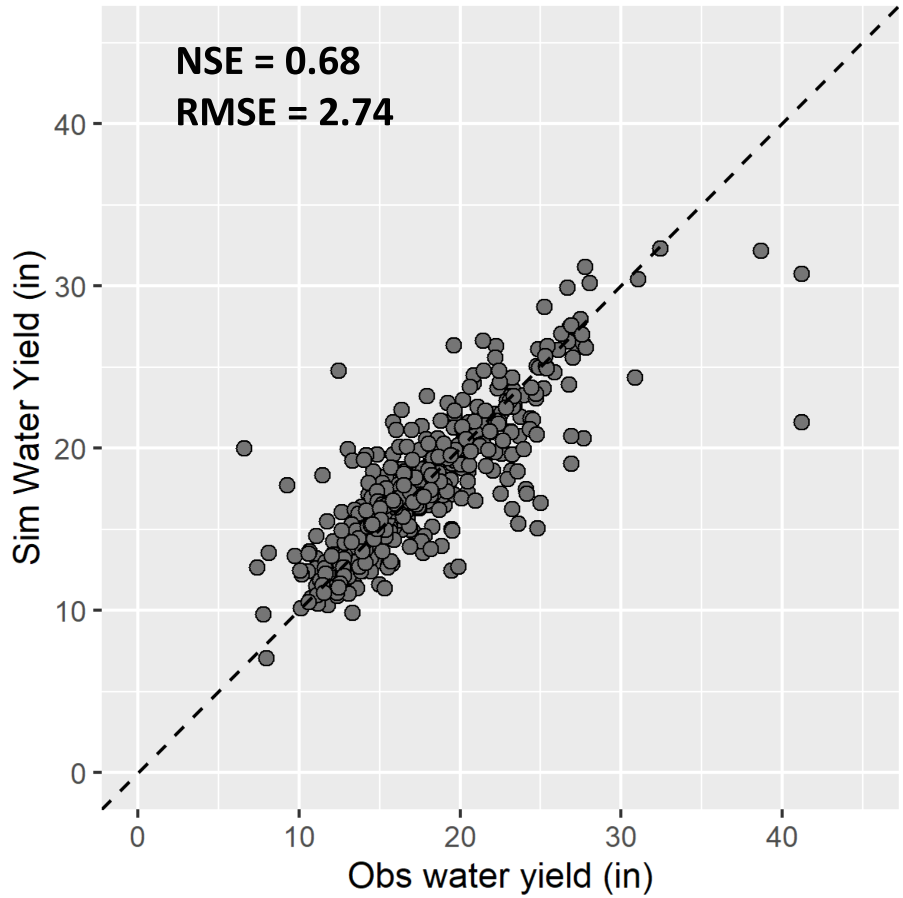
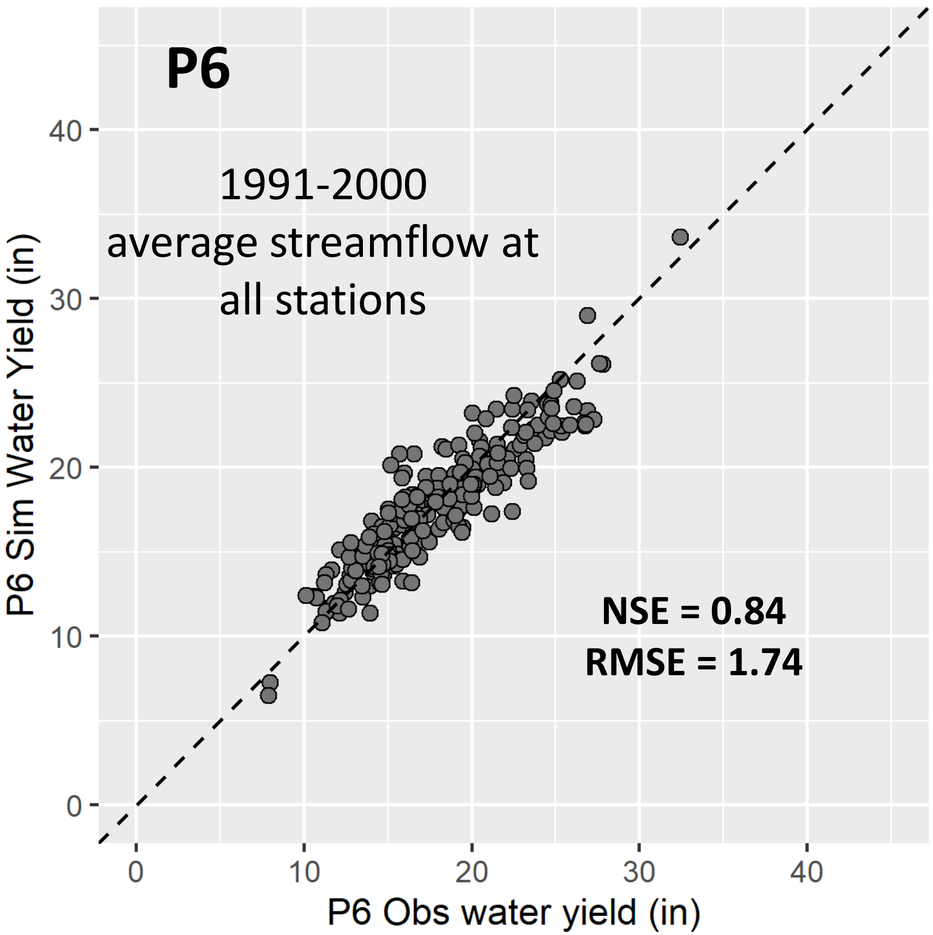


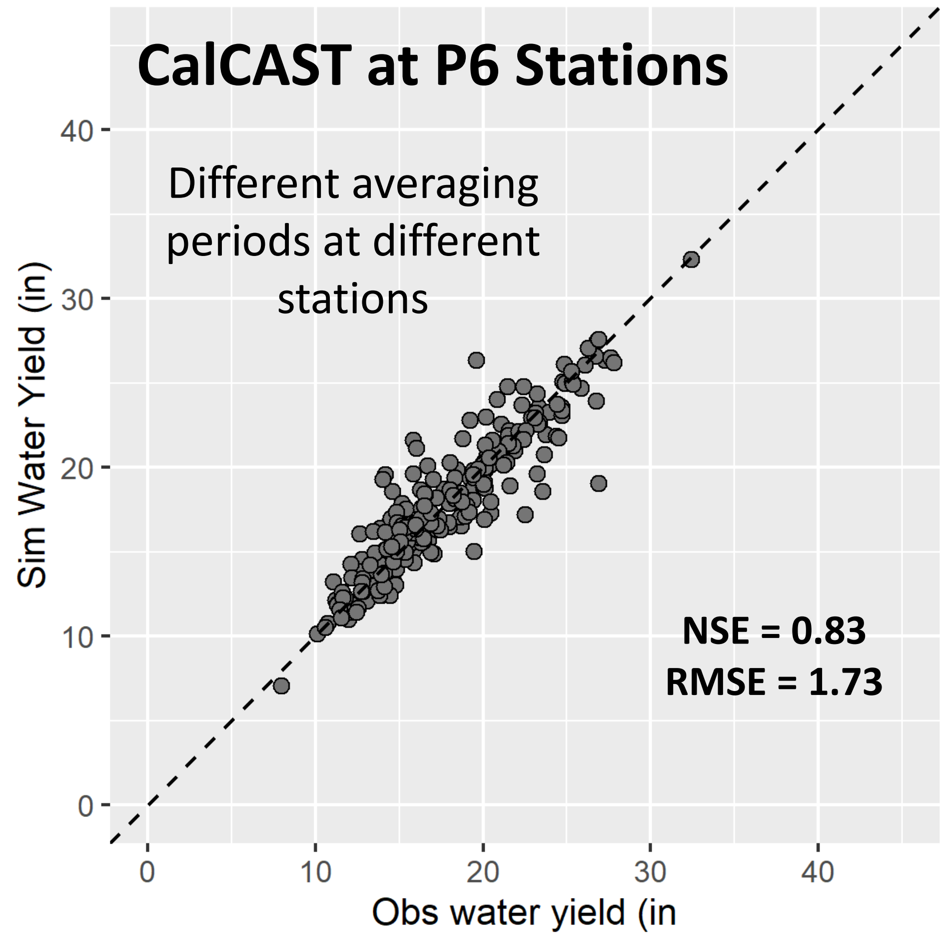


Candidate predictors of streamflow

Comparison with P6 hydrology



Calibration based on varying PET coefficient by county



Calibration based on mechanistically meaningful watershed properties

Withdrawals

Water withdrawals were available at the scale of P6 river segment

As an initial stopgap measure, withdrawals were «downscaled» to NHDPlus catchments by assigning all withdrawals within a P6 river segment to the same NHDPlus catchment

We went back to the original withdrawal datasets provided by the states to assign correct NHDPlus catchment based on lat/long information

Lat/long information available for: PA, VA, DE, DC, and NY

We assigned correct NHDPlus catchment to withdrawals in VA, DE, DC, NY, and PA (irrigation)

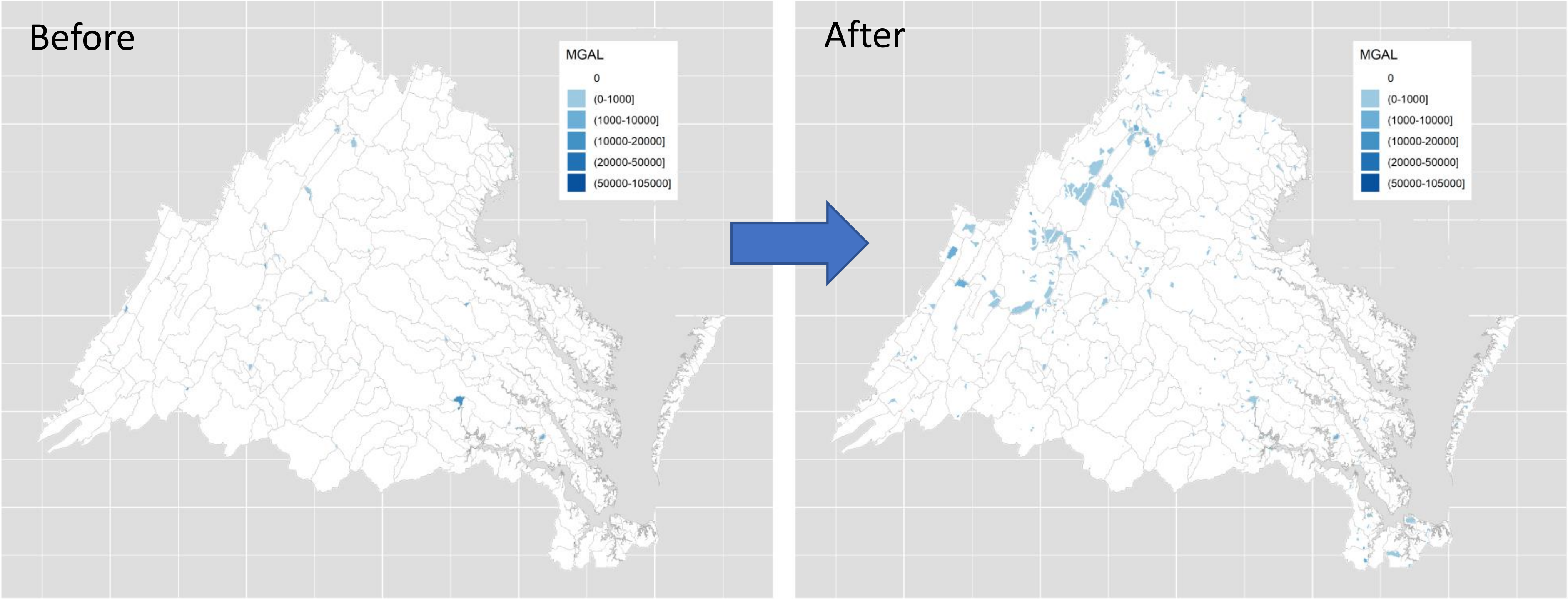
Withdrawals in PA (public supply), MD, and WV have not been updated yet, Alex plans to work on it next

Withdrawals

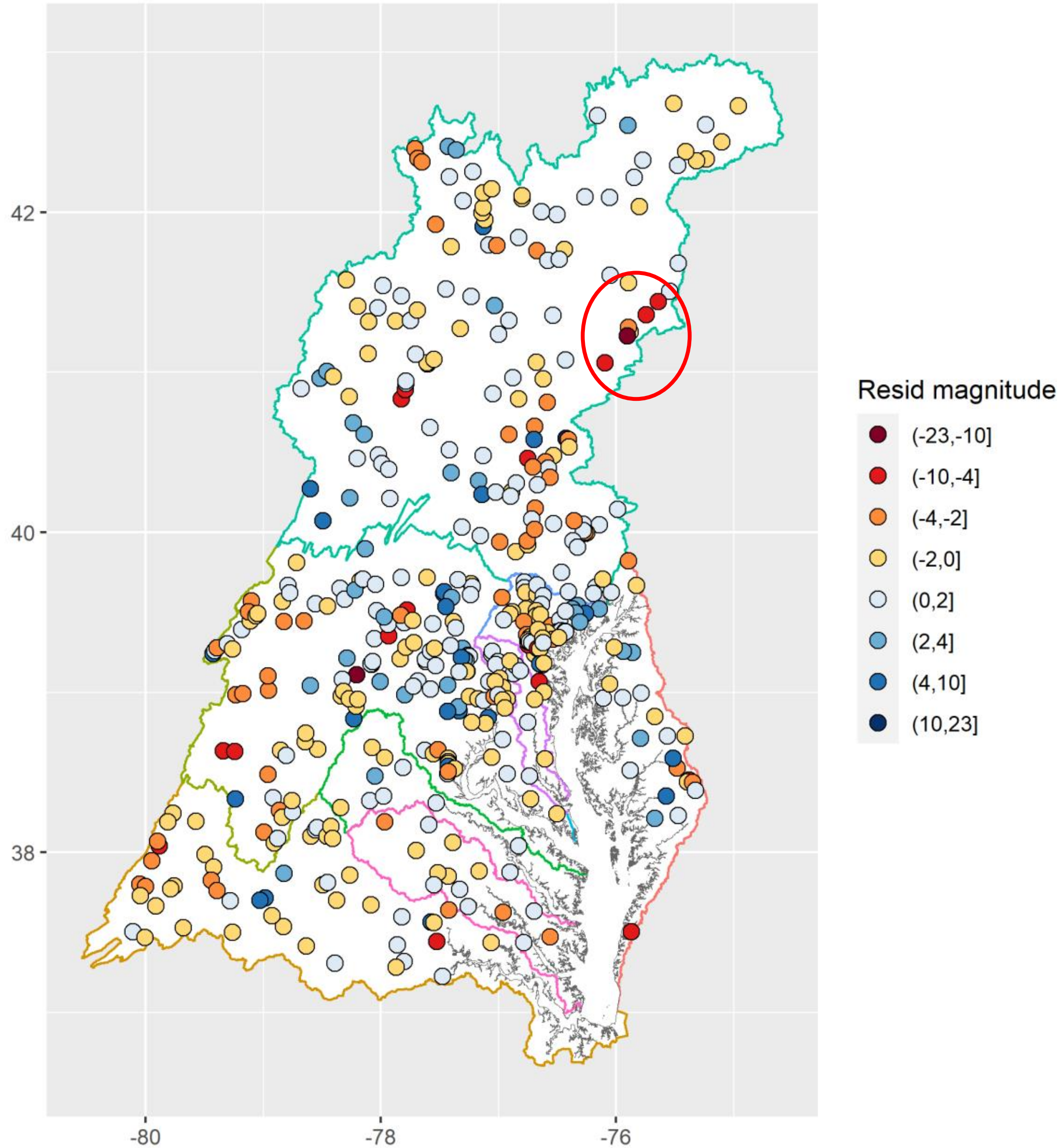
Example state: Virginia

Withdrawals assigned to NHDPlus catchments based on P6 river segments

Withdrawals assigned to NHDPlus catchments based on lat/long



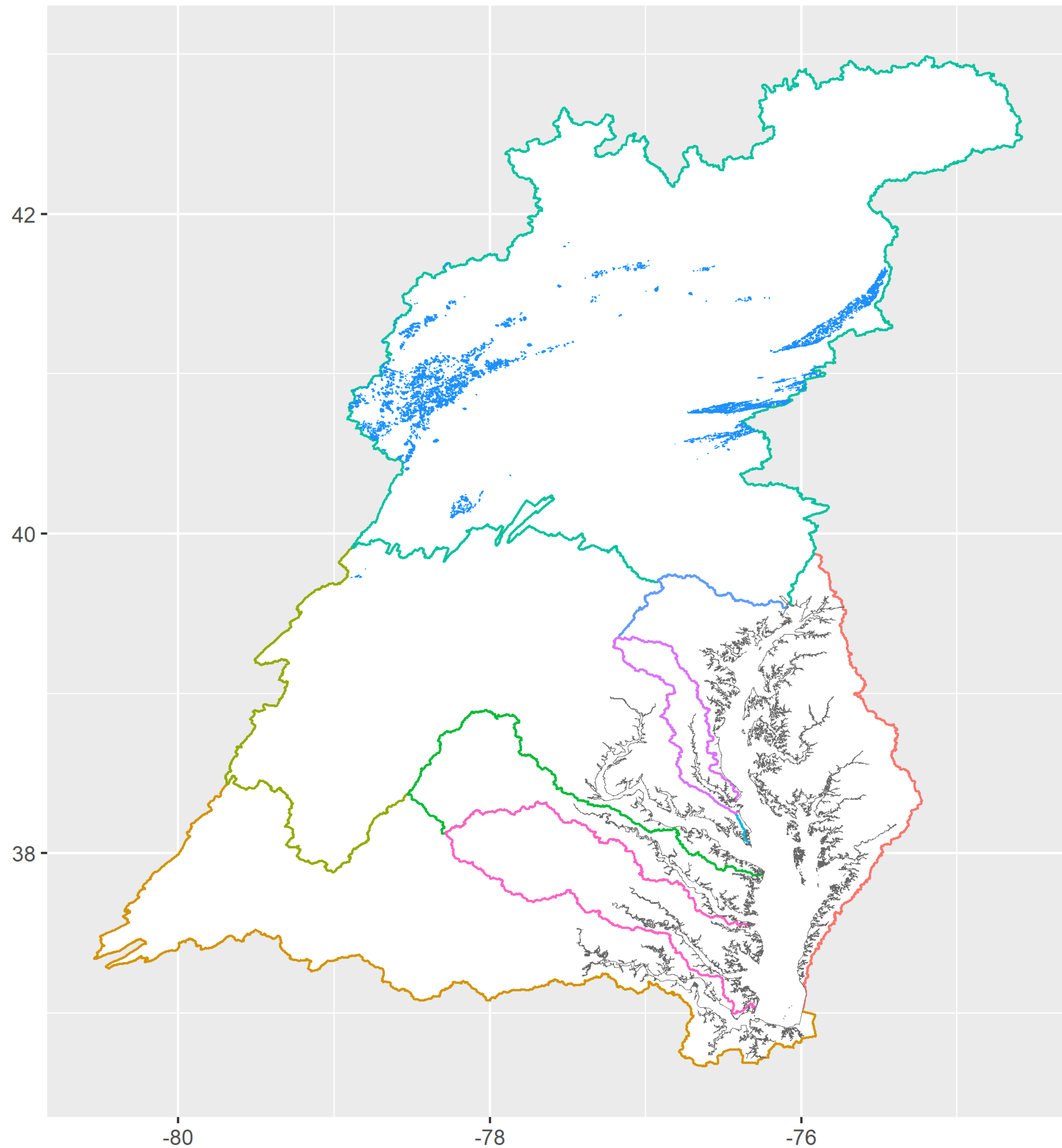
Abandoned coal mine land



Model largely overpredicts flow at a cluster of nearby stations in northeastern PA

We tested the inclusion of legacy coal mining extent in the model to assess whether it would help explain this pattern

Abandoned coal mine land

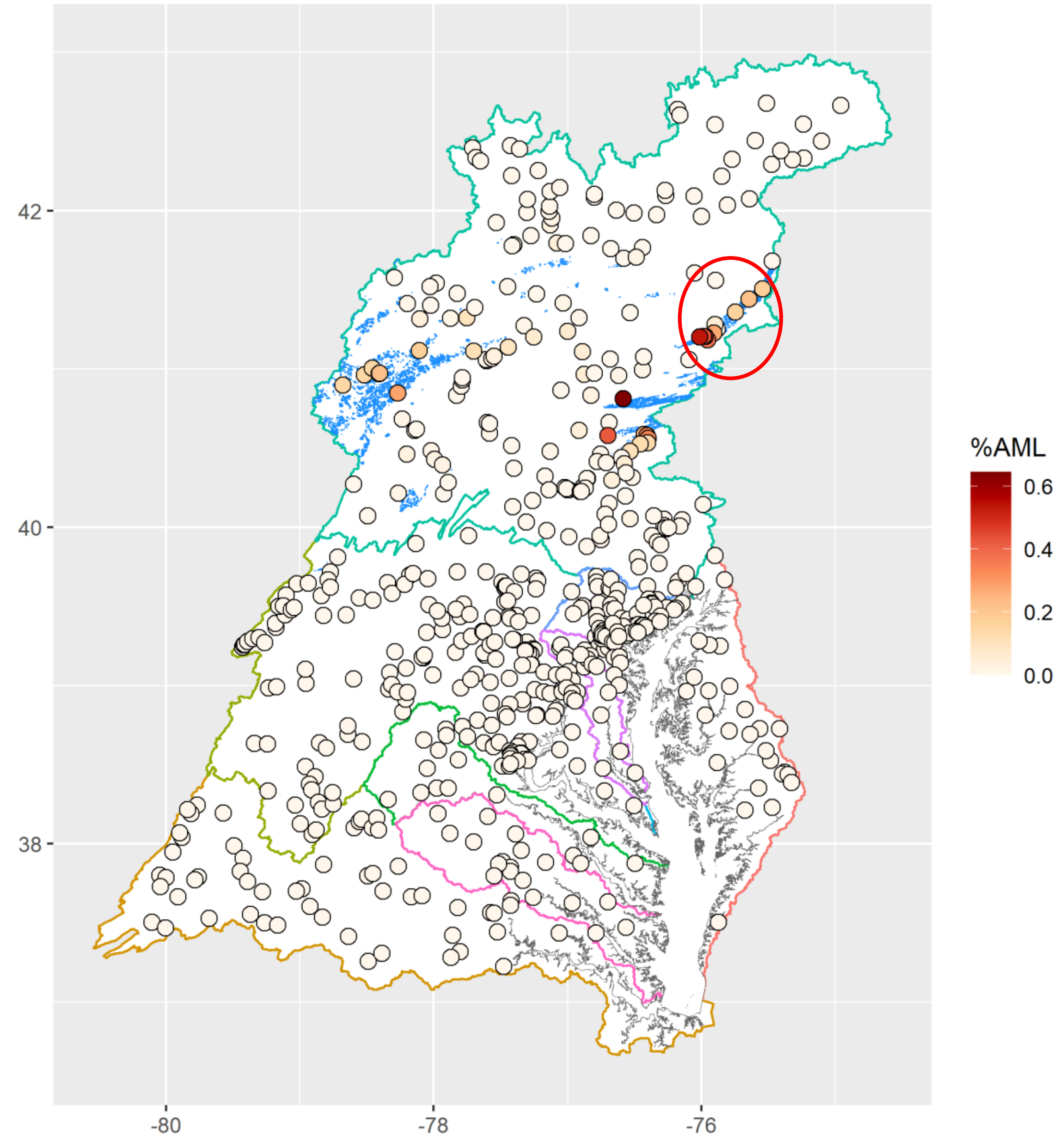


We obtained a dataset providing approximate location and extent of abandoned mine land areas from PA DEP

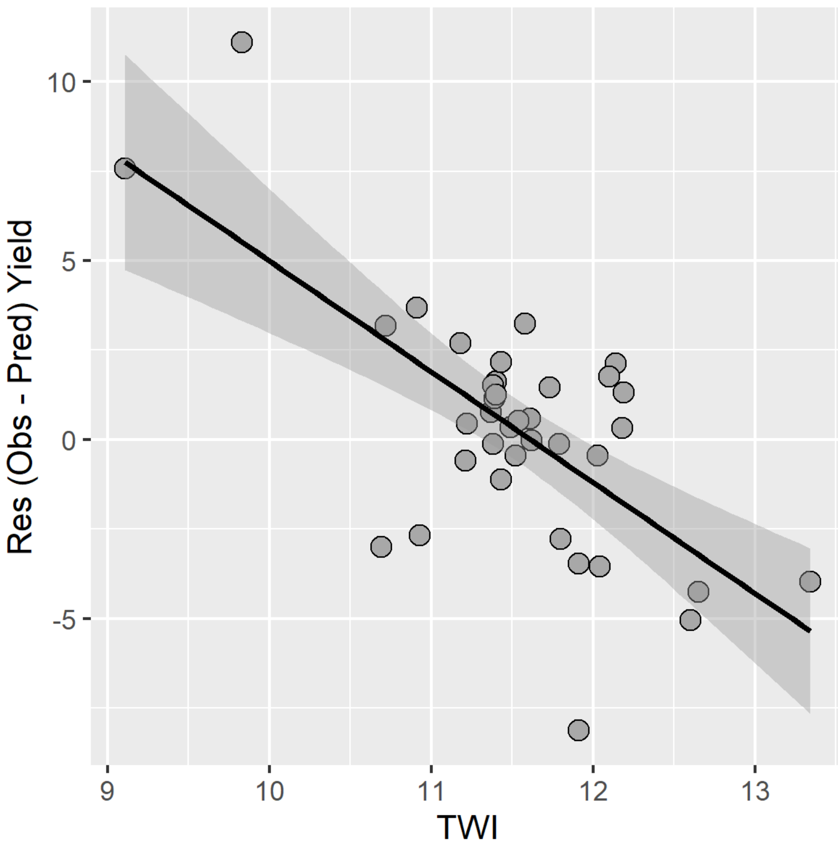
We estimated the fraction of each catchment's area affected by past coal mining

https://newdata-padep-1.opendata.arcgis.com/datasets/abandoned-mine-land-inventory-polygons/

Abandoned coal mine land



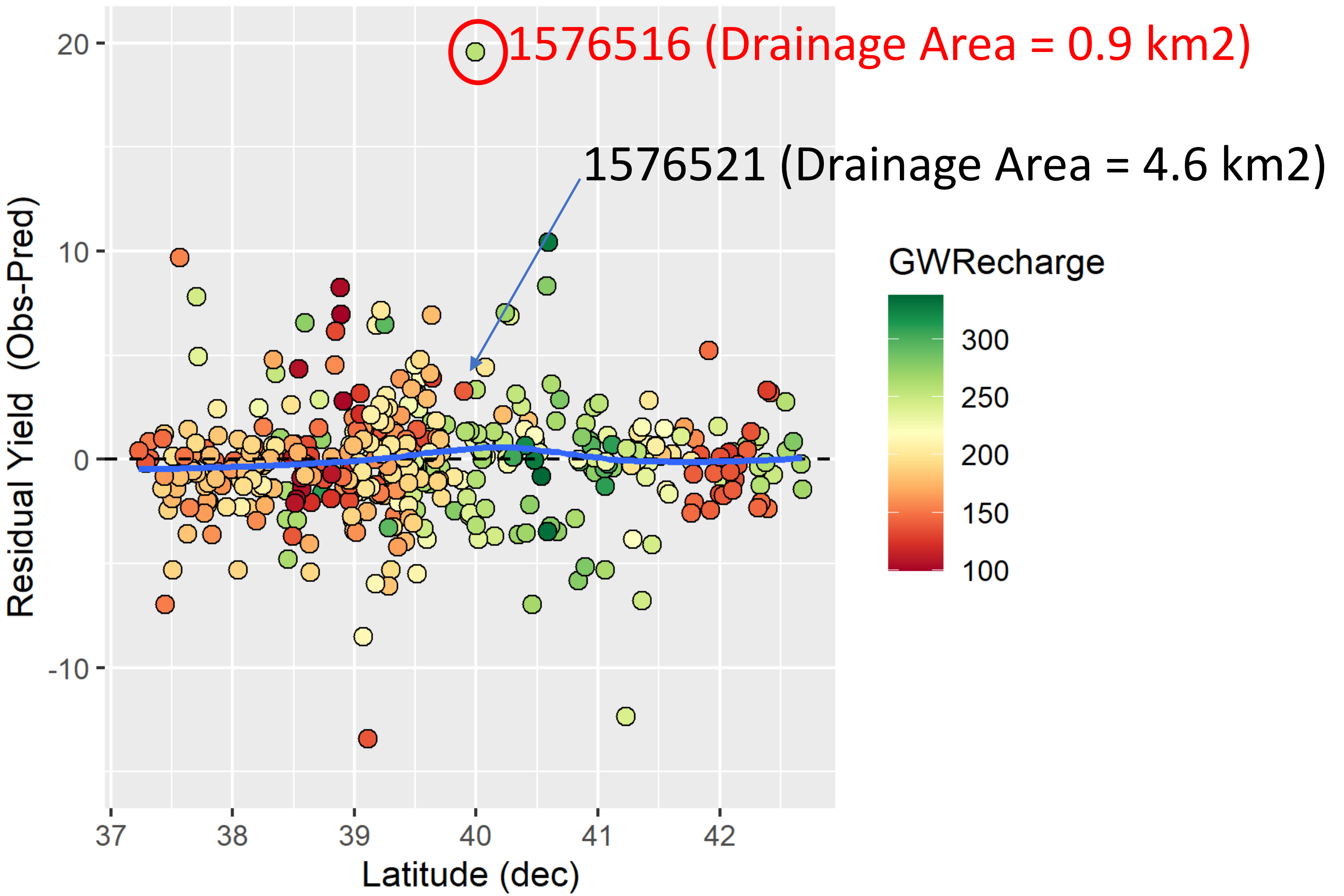
Topographic Wetness Index



We also tested the inclusion of an interaction term between TWI and LAT, given that residuals appear correlated with TWI in the upper portion of the watershed (~LAT>40)

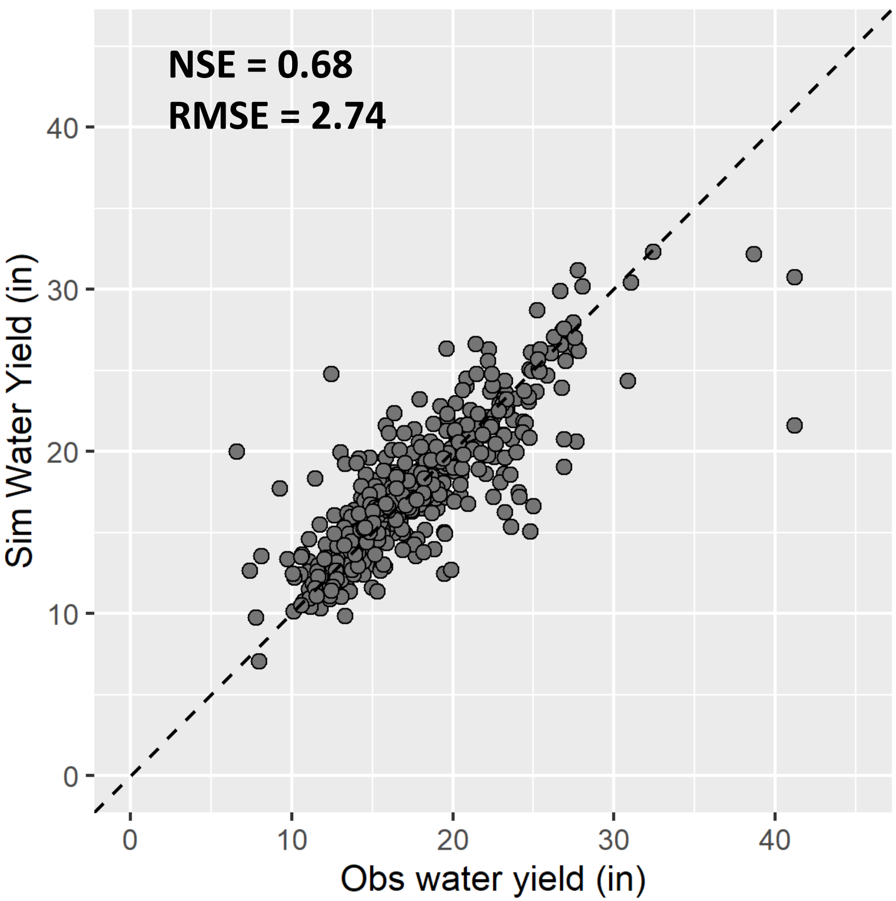
Removed station 1576516

Stations 1576516 and 1576521 are in the same NHDPlus catchment
(Catchment Area = 4.8 km2)



Candidate predictors of streamflow

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



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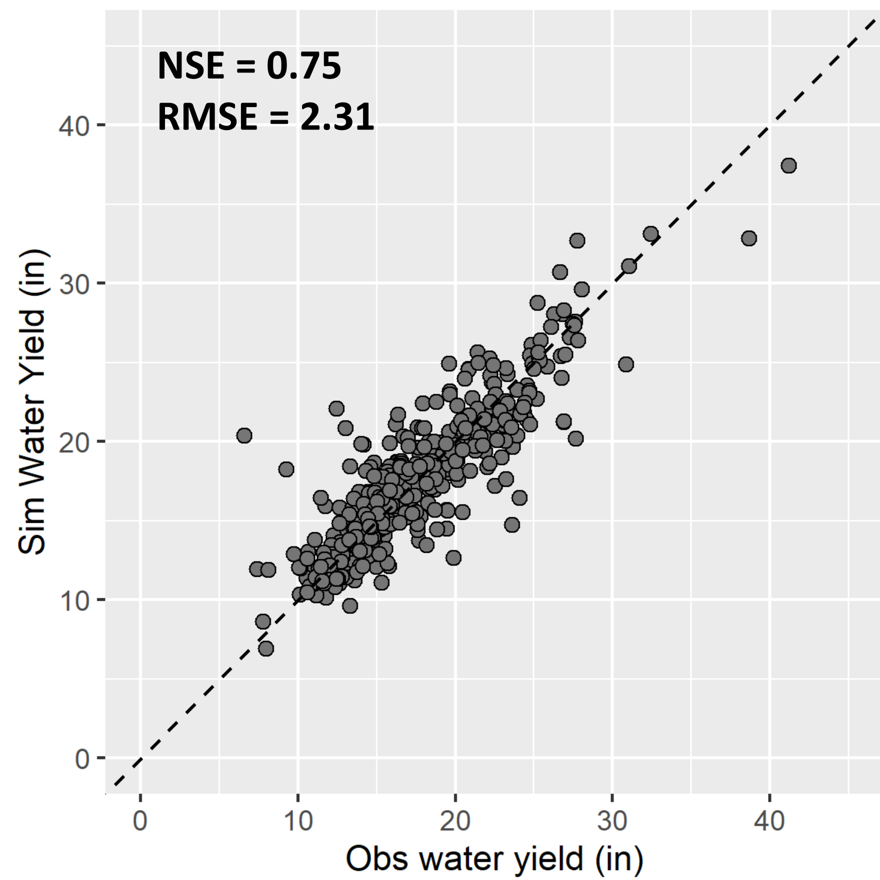

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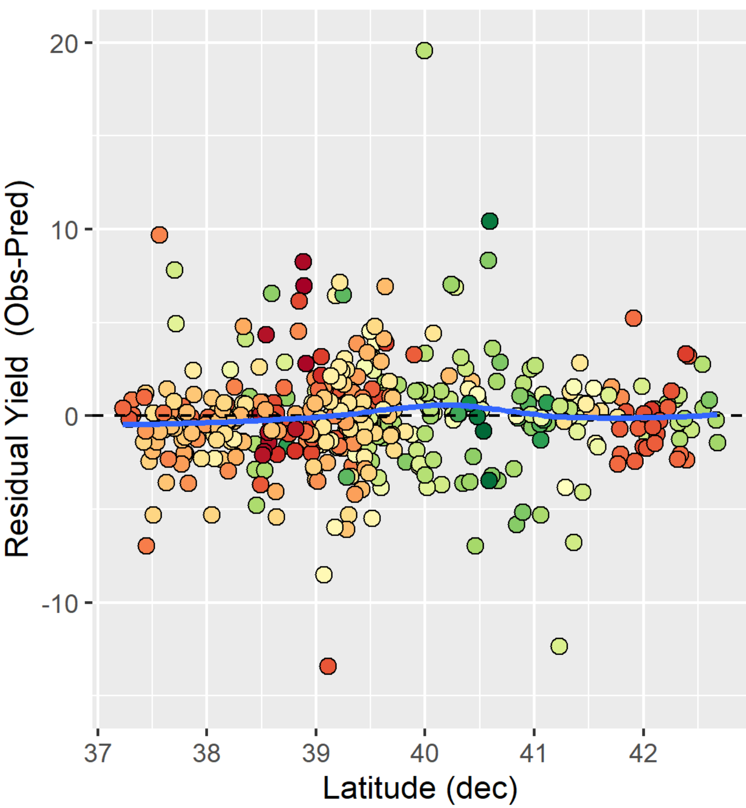
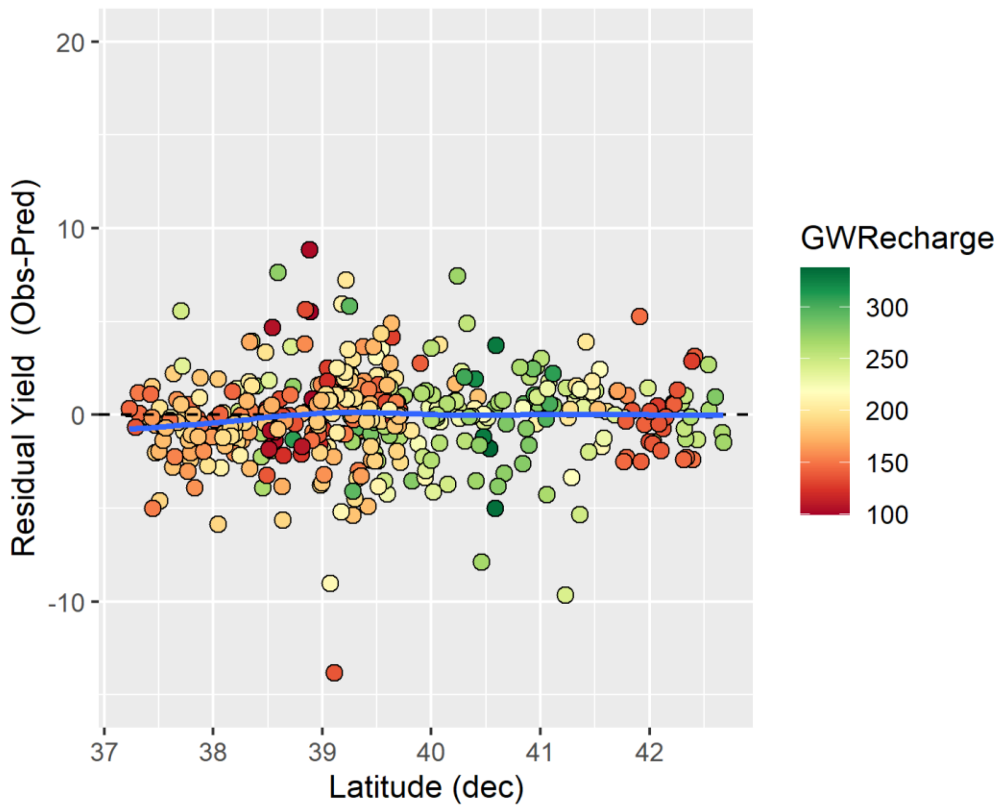
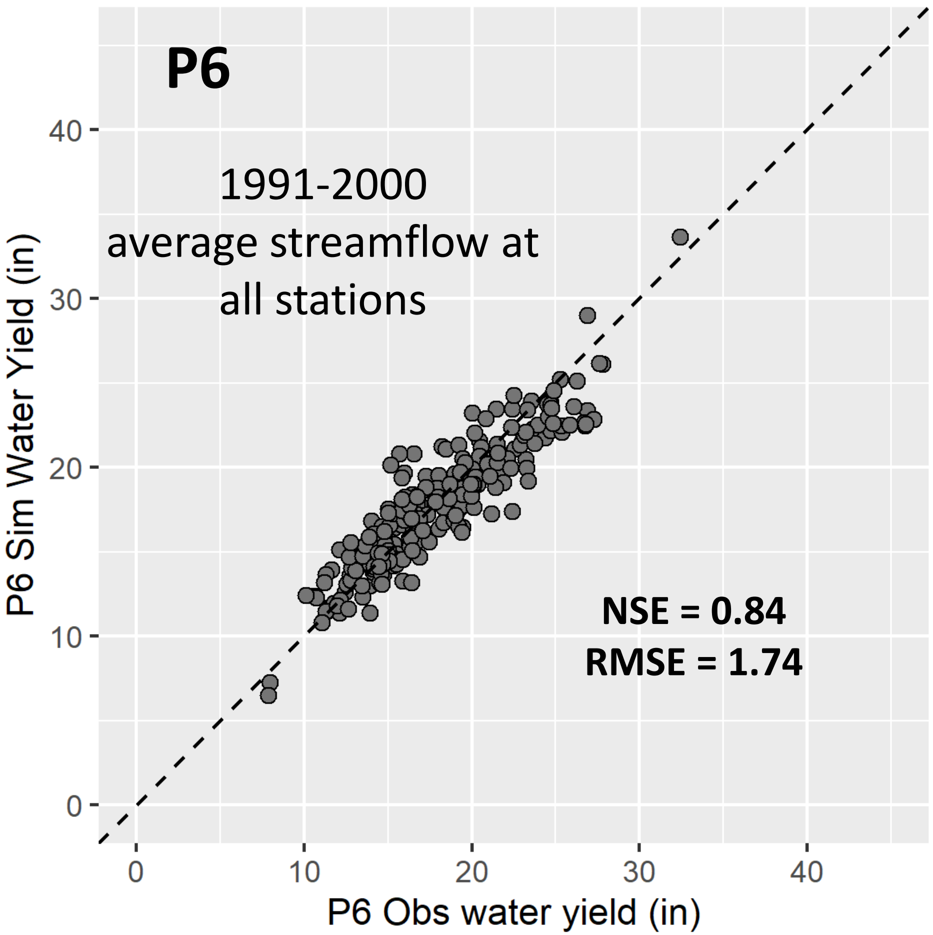




Candidate predictors of streamflow

Comparison with P6 hydrology



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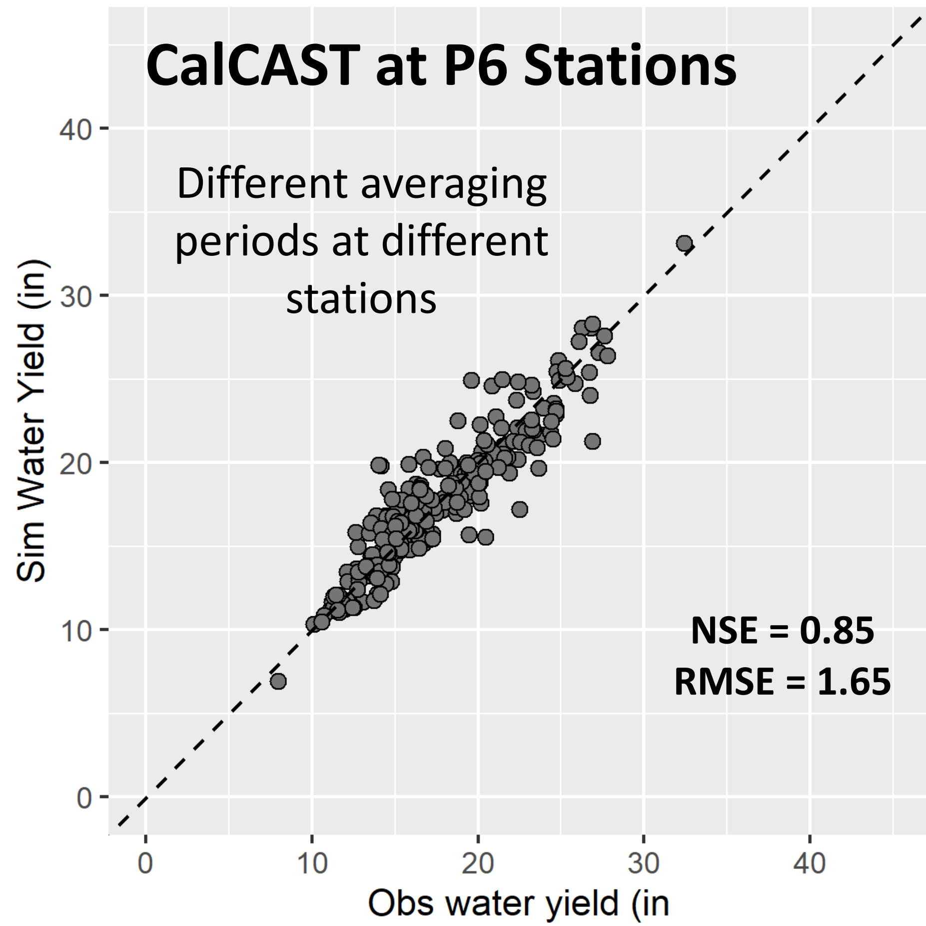


Calibration based on mechanistically meaningful watershed properties

Conclusions

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

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 5/10/2021

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

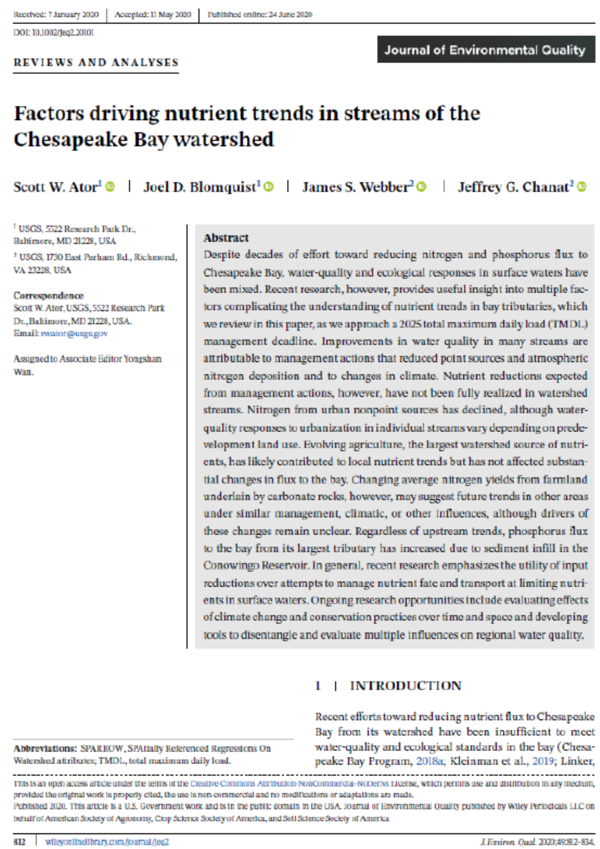
Recap from April Quarterly

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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Journal of Environmental Quality
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.

812 | wileyonlinelibrary.com/journal/jeq2 J. Environ. Qual. 2020;49:812–834.

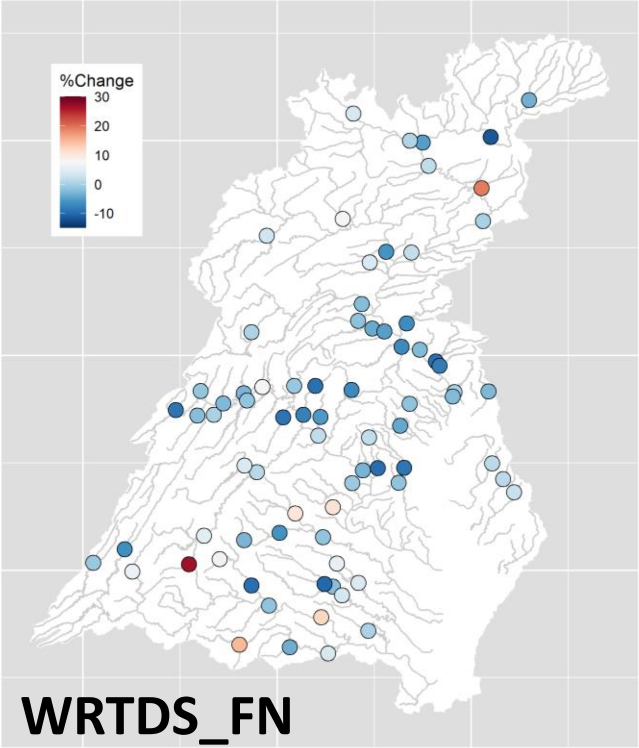
Recap from April Quarterly

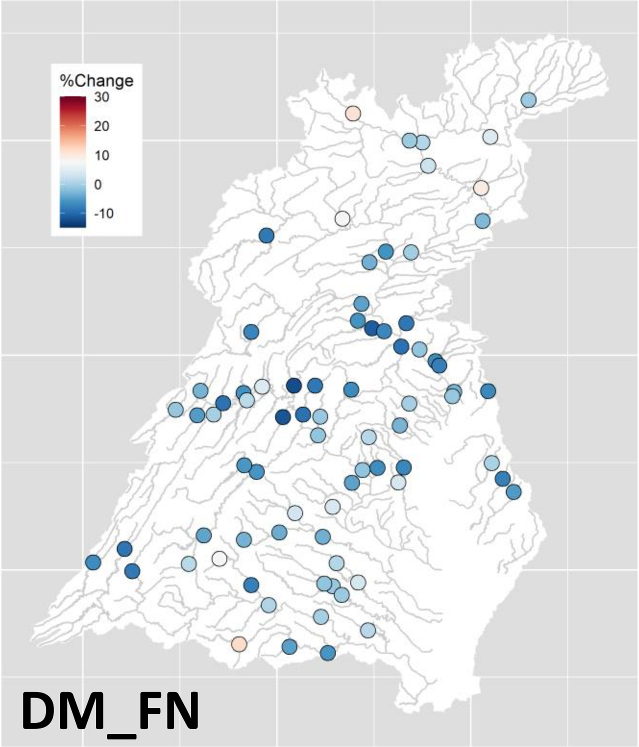
Dynamic watershed model (DM): same inputs as CAST but accounts for (gw) lag times, varying hydrology (and flow-normalization effect on it), non-stationary watershed response to changing conditions

- 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

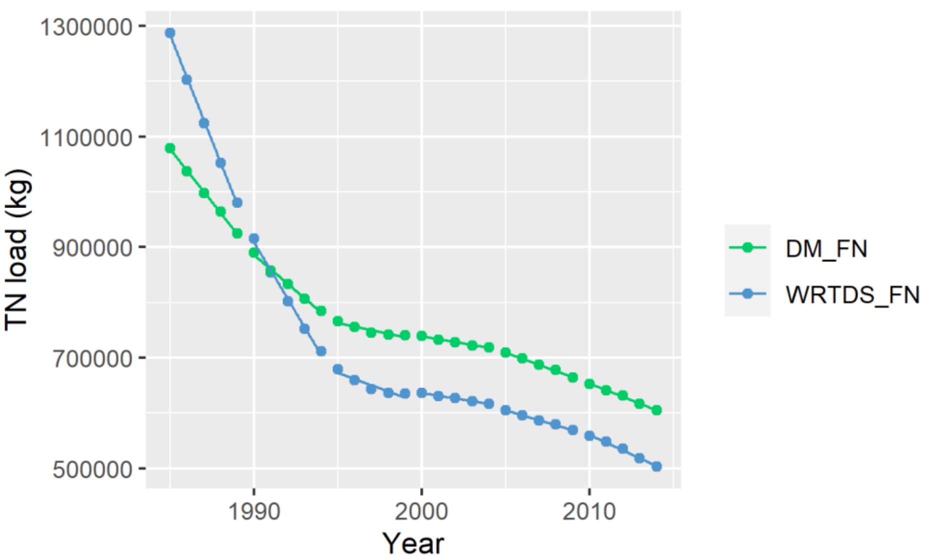
Q: where and when are trends in WRTDS_FN and DM_FN most similar/different? Why is that?

Response variable: Slope of WRTDS_FN vs. DM_FN for 10-year moving windows

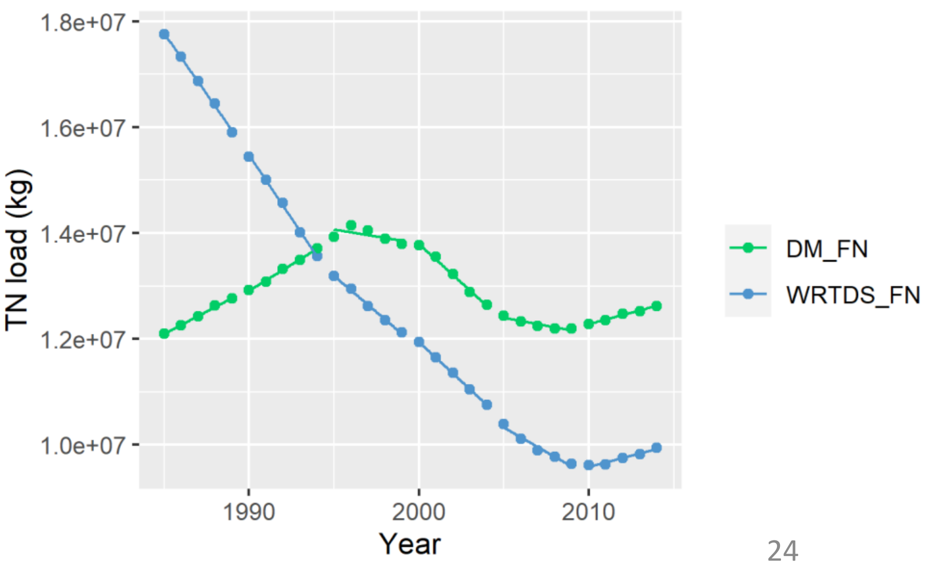
Qualitative response variable - 4 classes:

DMneg_WRneg
DMpos_WRpos
DMneg_WRpos
DMpos_WRneg

Patuxent River near Bowie, MD



Susquehanna River at Towanda, PA



Candidate predictors

Time-varying variables

- **Land Use**: % of each station`s catchment occupied by each of 9 load source groups (Impervious Developed, Pervious Developed, Forest, Pasture, Hay, Row Crops, Other Ag, Open Space, Feeding Space, Wetlands)
- **CAST BMP type/implementation level:** % acres/average pass-through factor of BMPs applied to each of 9 load source groups above each station
- **CAST Nutrient inputs**: fertilizer, manure, atm dep, etc.

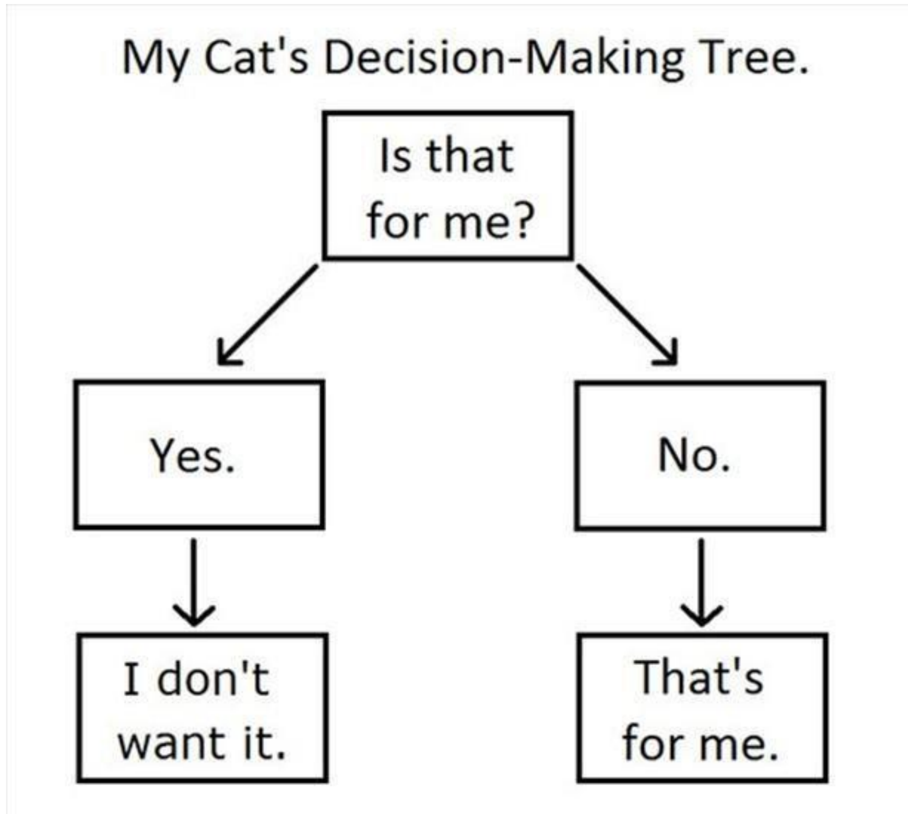
For each time-varying variable, consider different aggregations over time (e.g., average of previous 5 yrs, 10 yrs, 15 yrs, etc.)

Static variables that describe spatial variability in watershed characteristics

- Lithology
- Soil properties
- Groundwater age
- Density of ponds/reservoirs/dams
- ….

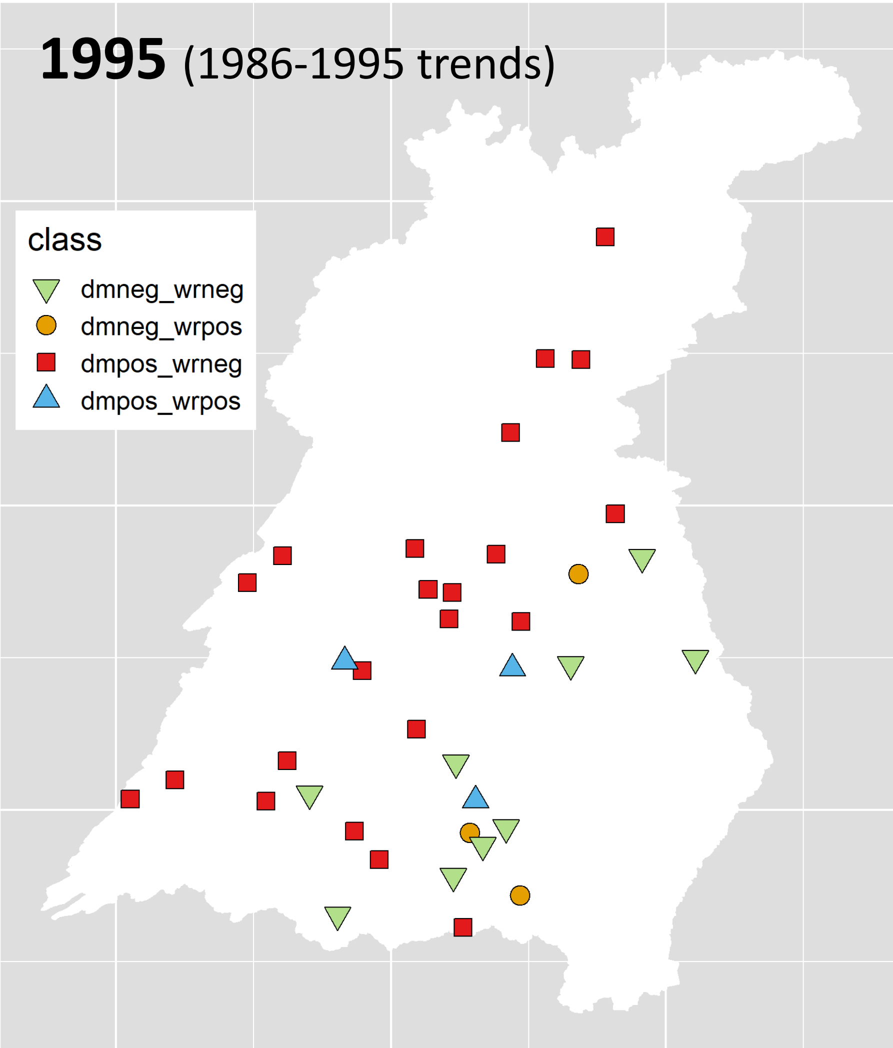
Classification tree analysis

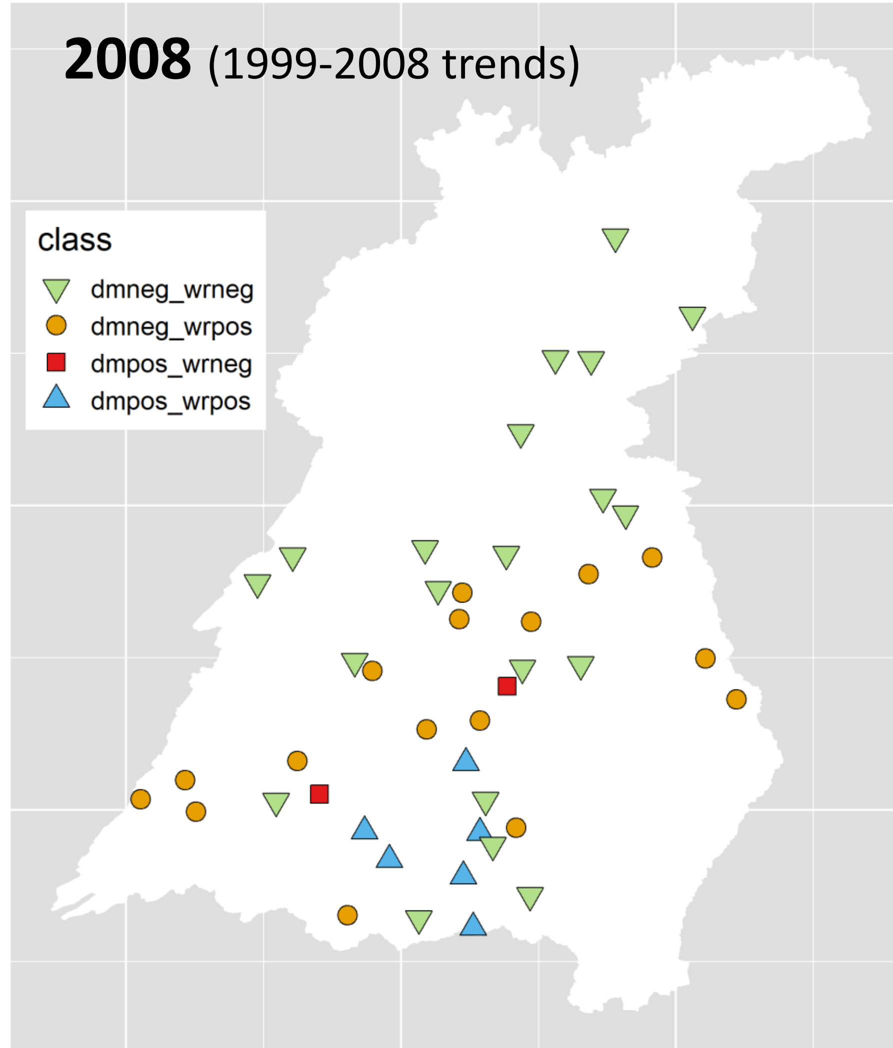
What candidate predictors best discriminate among the 4 classes that describe agreement between DM and WRTDS trends?



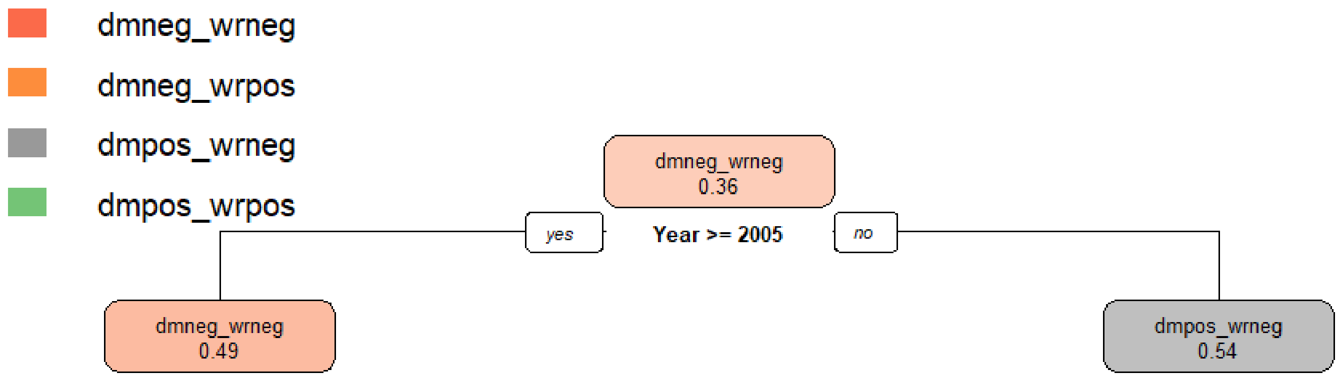
http://www.acheronanalytics.com/acheron-blog/brilliant-explanation-of-a-decision-tree-algorithms

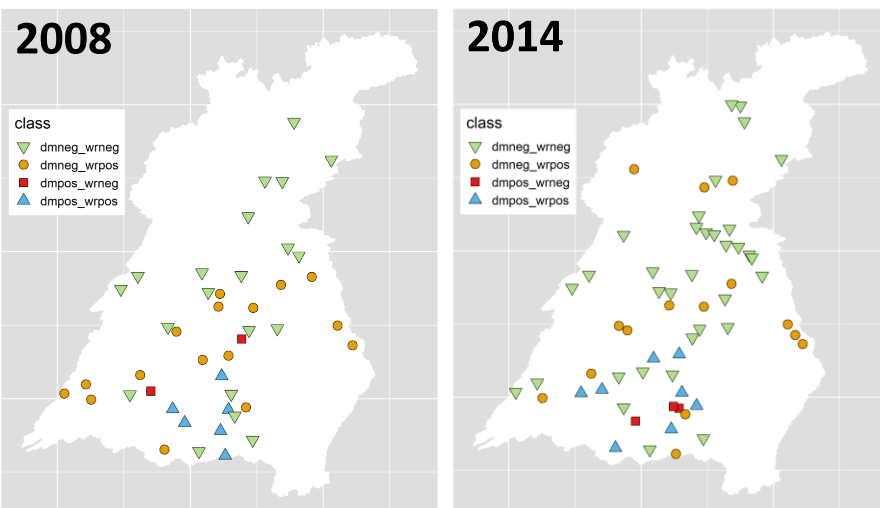
Examples of response variable

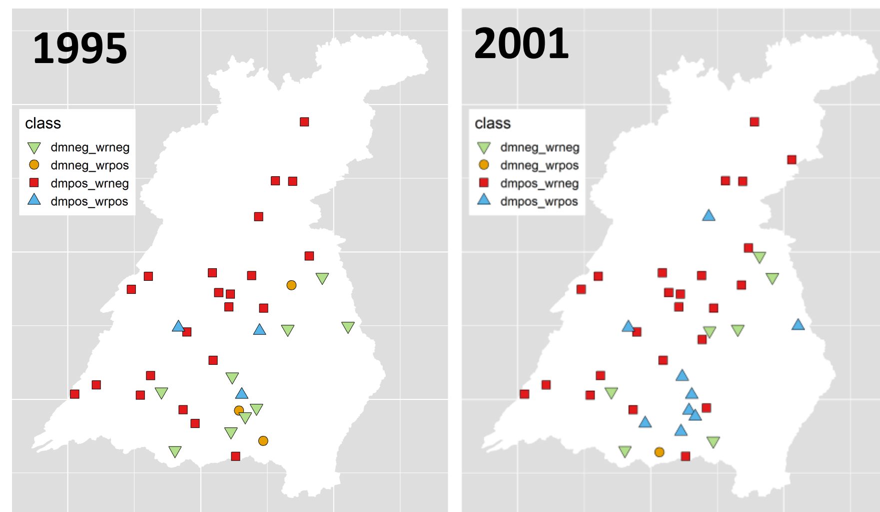




Classification Tree



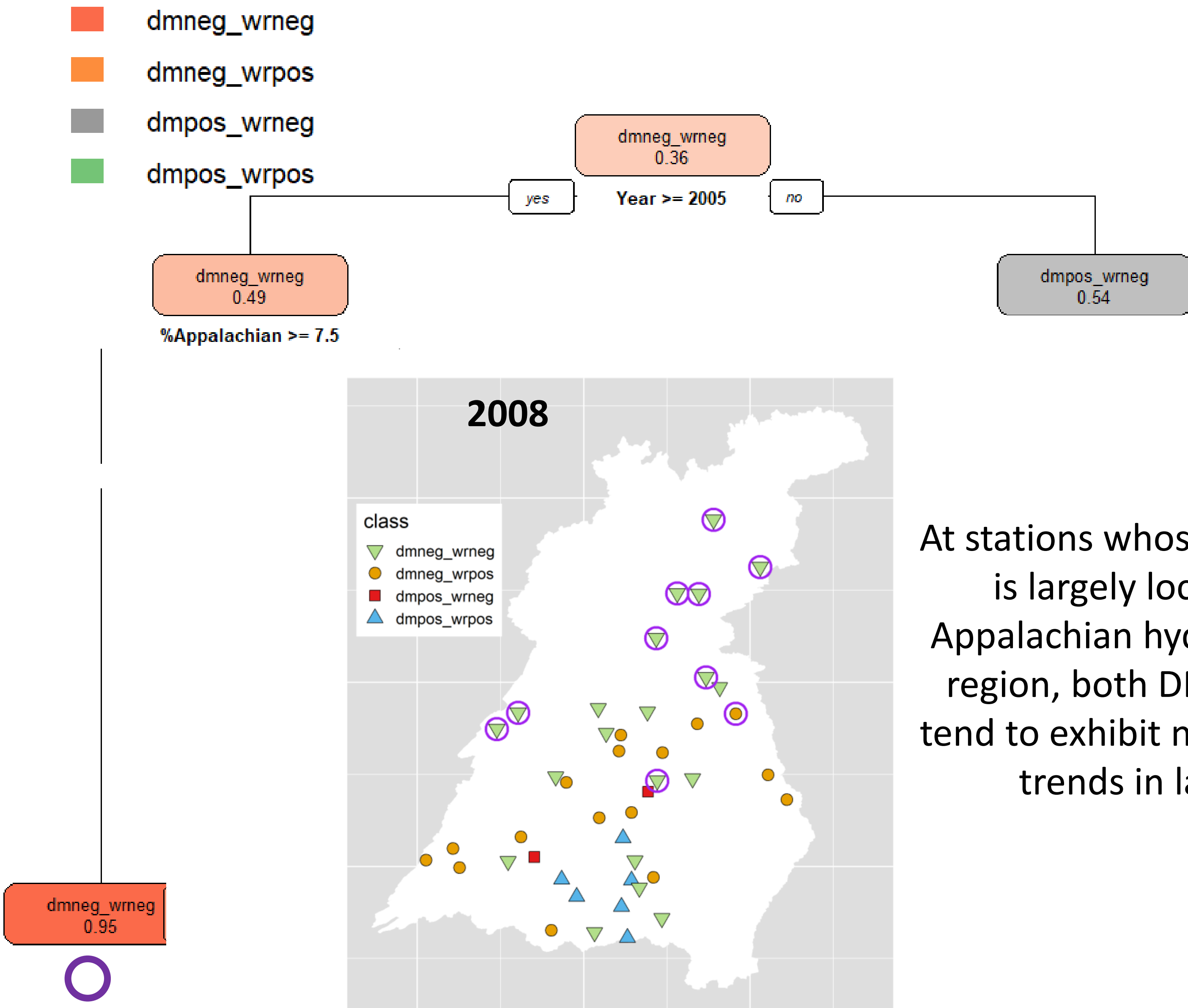




In later years: most frequent class is DMneg_WRneg

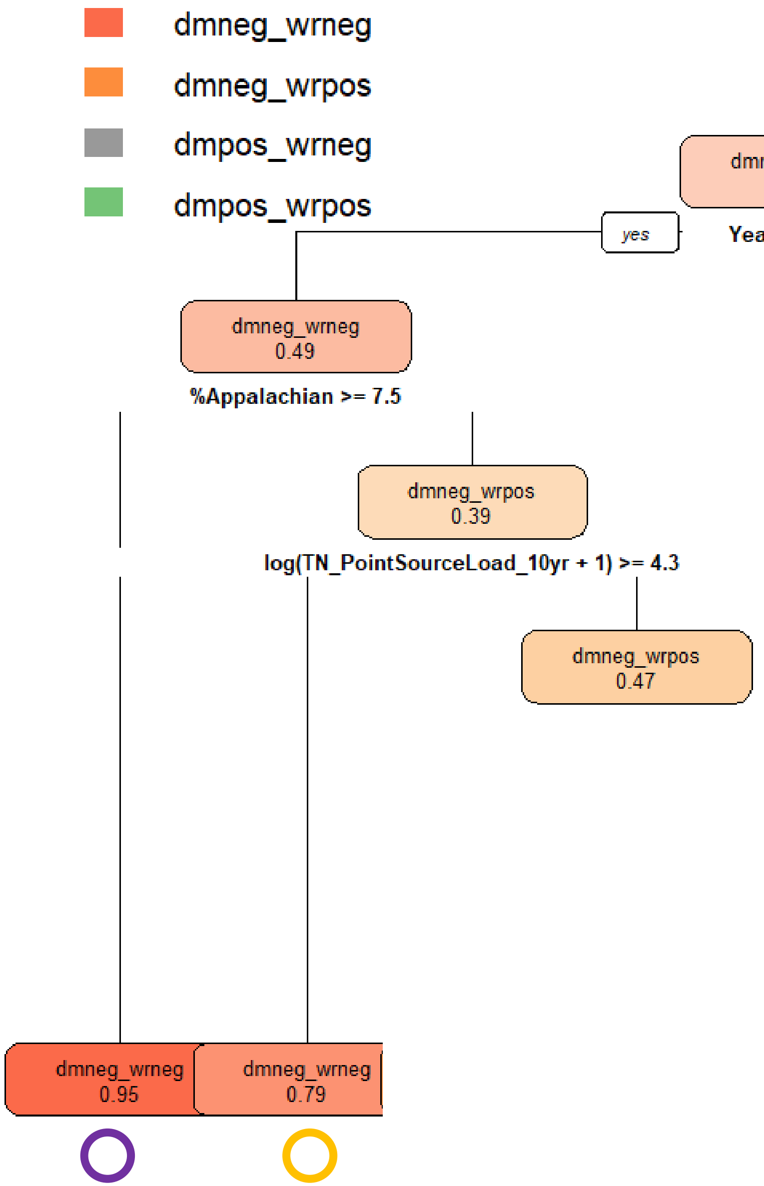
In earlier years: most frequent class is DMpos_WRneg

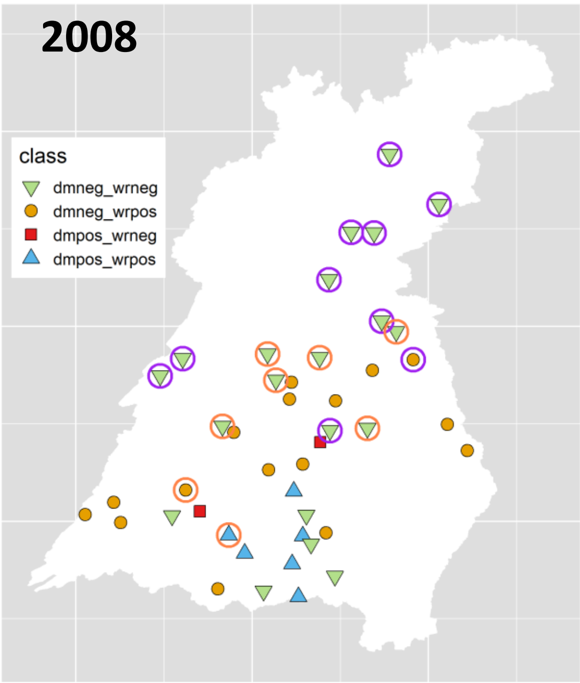
Classification Tree



At stations whose drainage area is largely located in the Appalachian hydrogeomorphic region, both DM and WRTDS tend to exhibit negative 10-year trends in later years

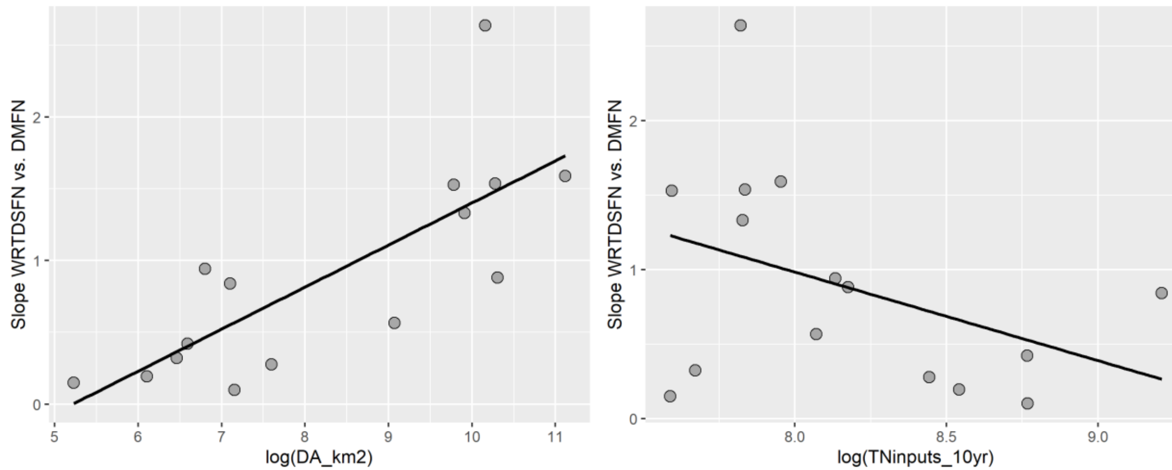
Classification Tree





At stations with larger amounts of point source loads, both DM and WRTDS tend to exhibit negative 10-year trends in later years

Classification Tree

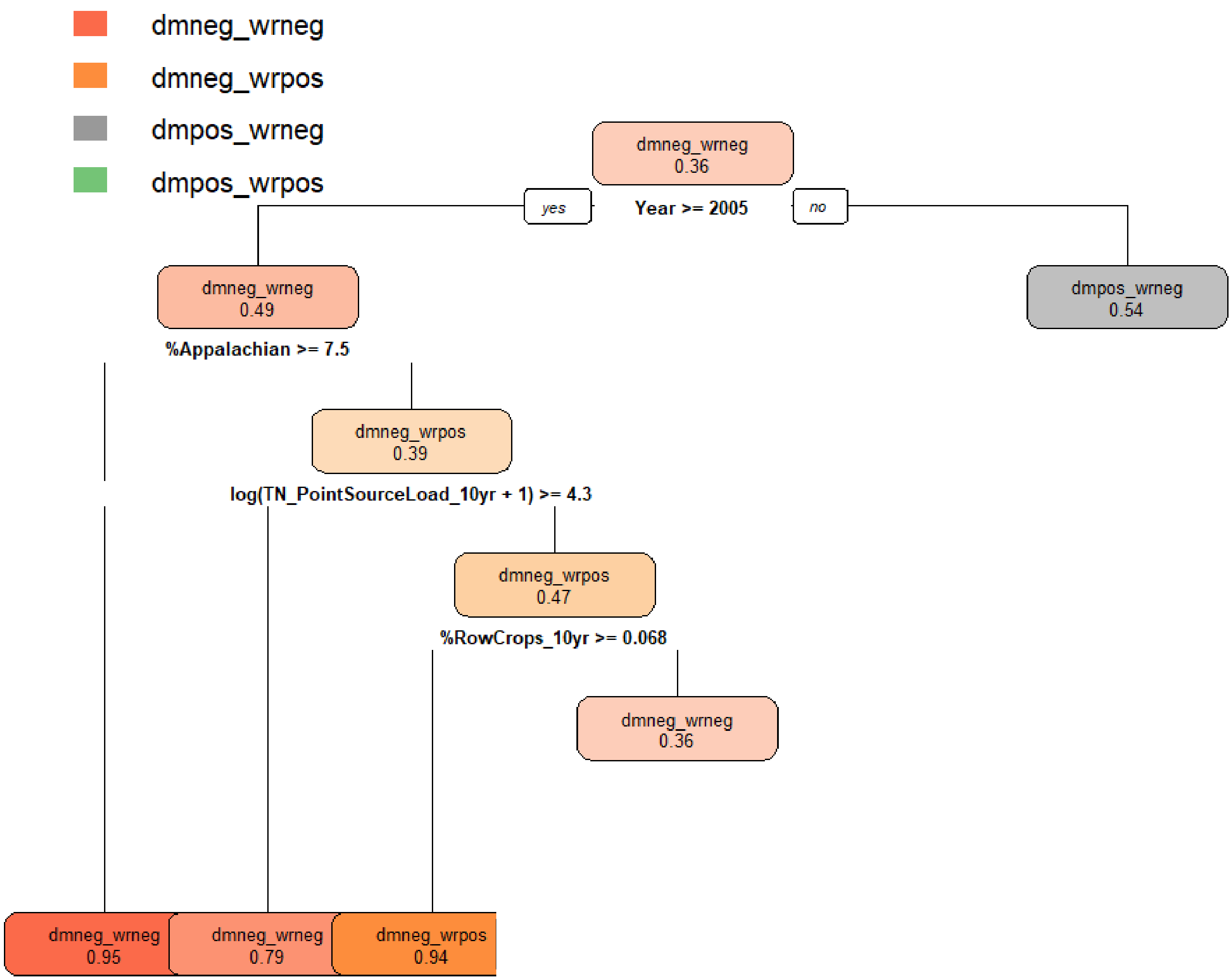


Within these two groups of stations:

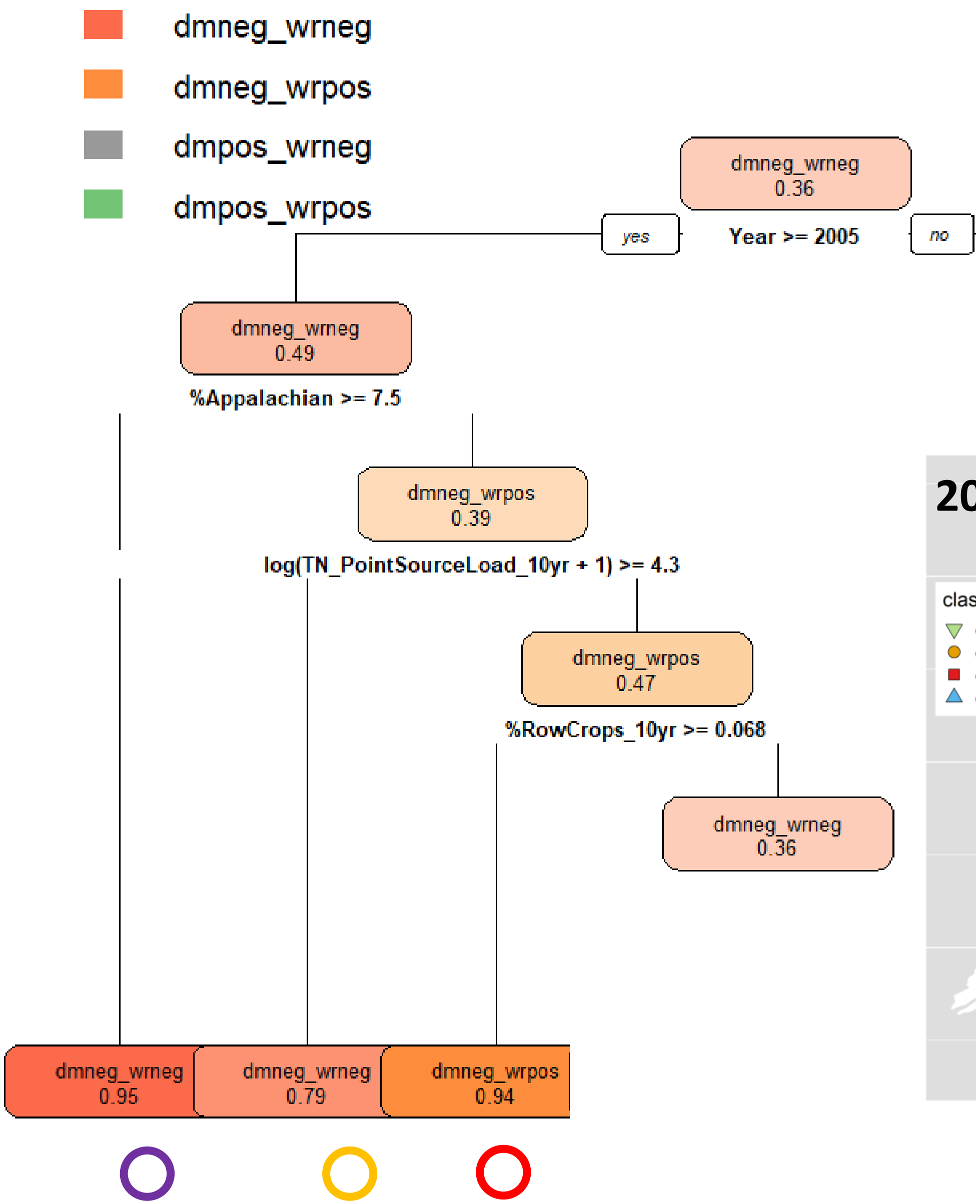
- at stations with relatively higher TN inputs and smaller drainage areas the slope of WRTDSFN vs. DMFN tends to be <1, i.e., DM decreases more than WRTDS

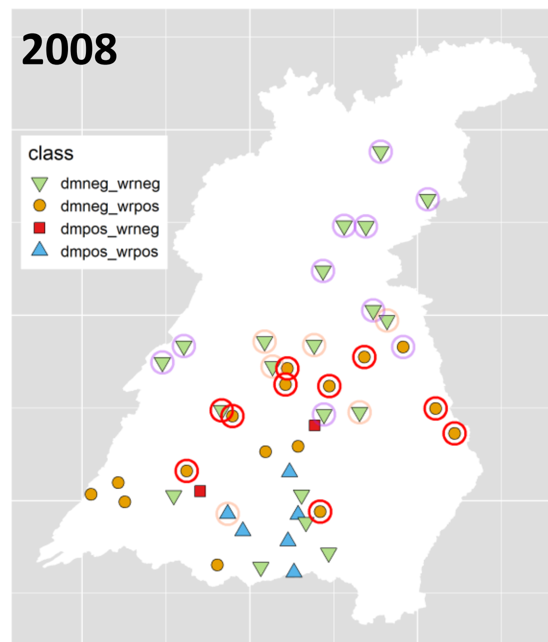
- at stations with relatively lower TN inputs and larger drainage areas the slope of WRTDSFN vs. DMFN tends to be >1, i.e., DM decreases less than WRTDS

Classification Tree



Classification Tree

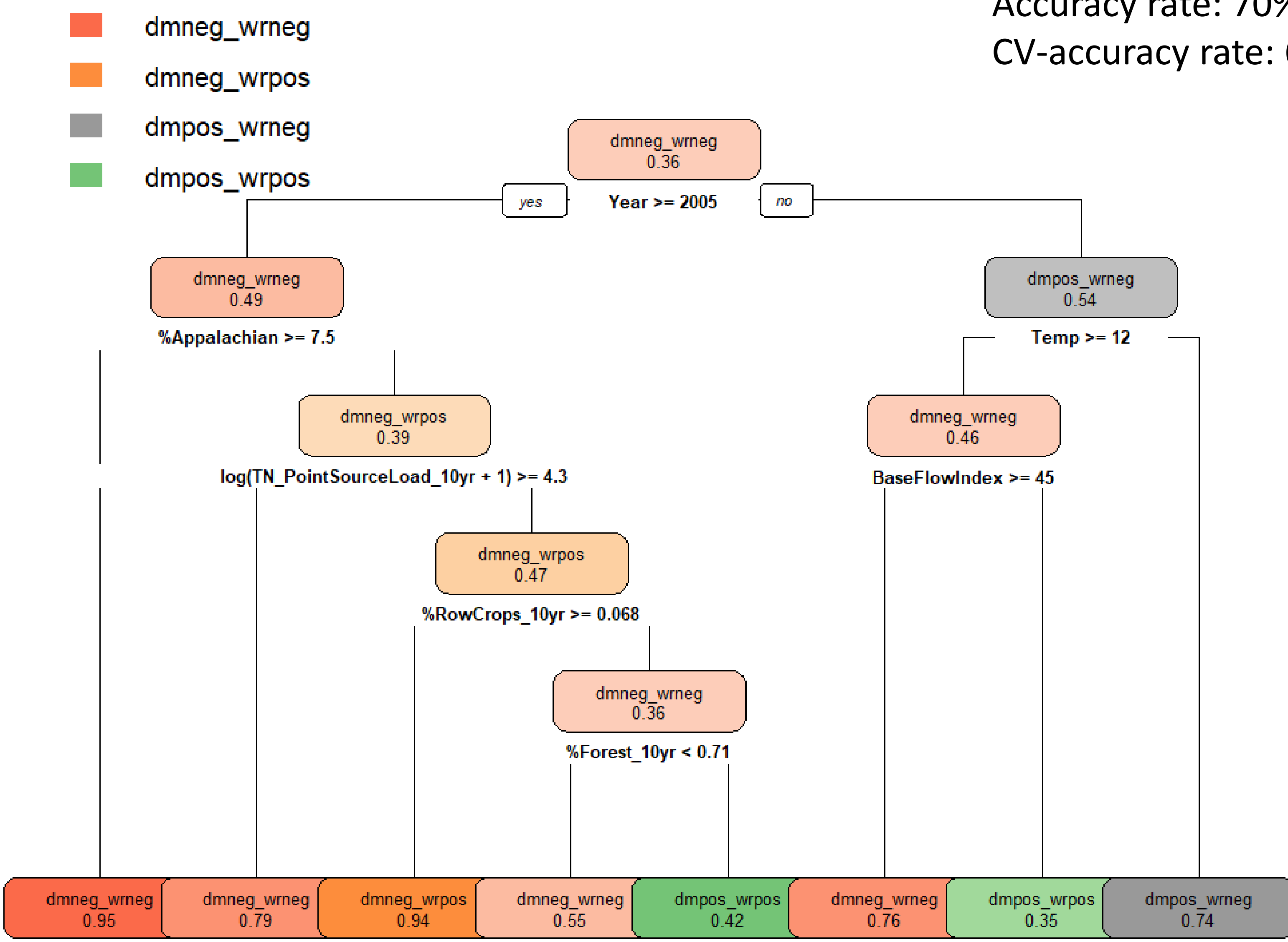




At stations with relatively lower amounts of point source loads and larger amounts of row crop land use, WRTDS tends to exhibit a positive trend while DM has a negative trend

Classification Tree

Accuracy rate: 70%
CV-accuracy rate: 60%



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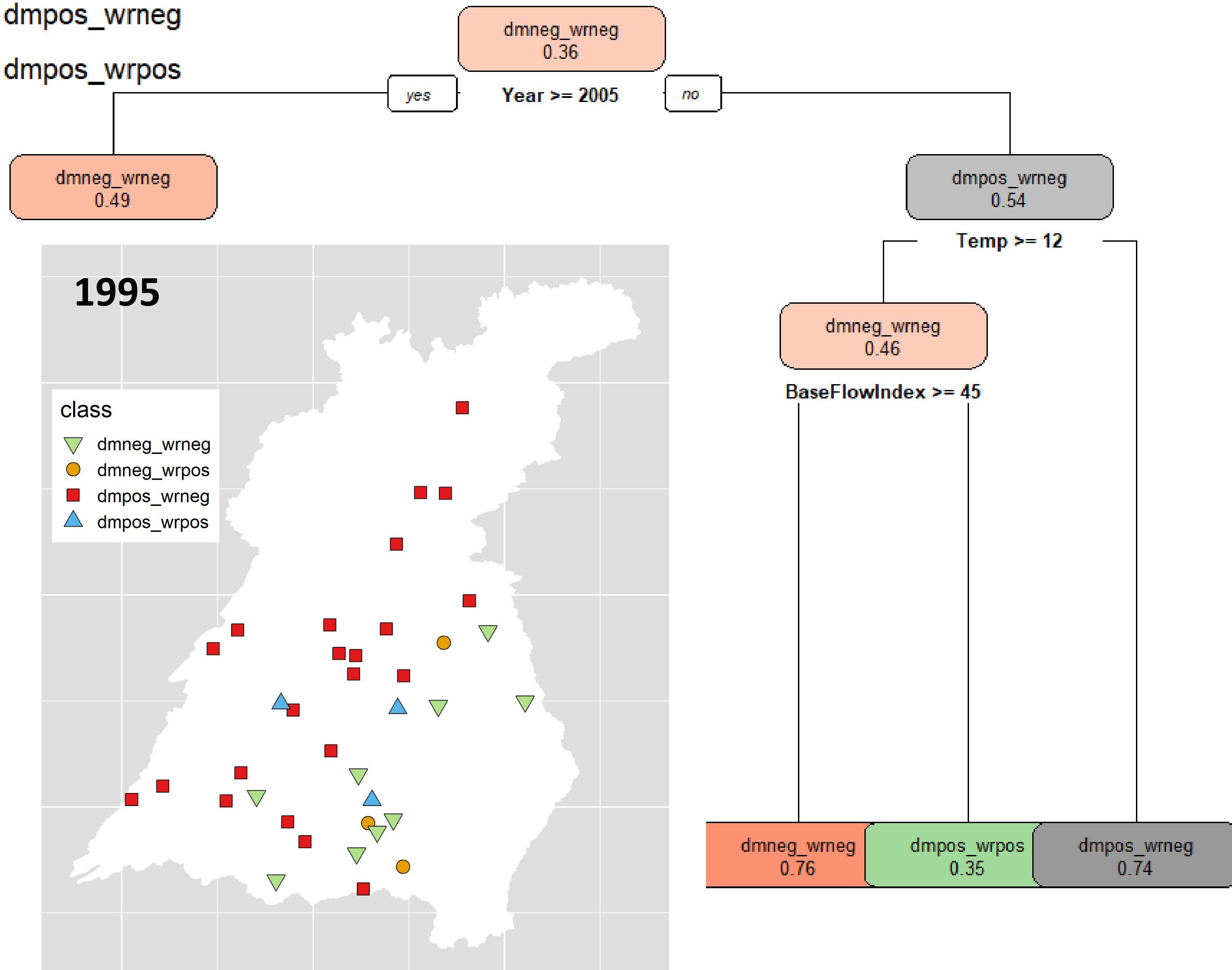

Summary

Classification tree analysis can help identify spatial and temporal signatures in level of agreement between DM and WRTDS

Next steps: use this information to narrow down candidate predictors for inclusion in a parametric model that explains differences in trends while also accounting for trend uncertainty (e.g., through EGRET CI)