Comparison of Modeled and Monitored Nutrient Trends

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

Modeling Workgroup Quarterly Review 4/6/2021

Comparing modeled and monitored nutrient trends

Management Question

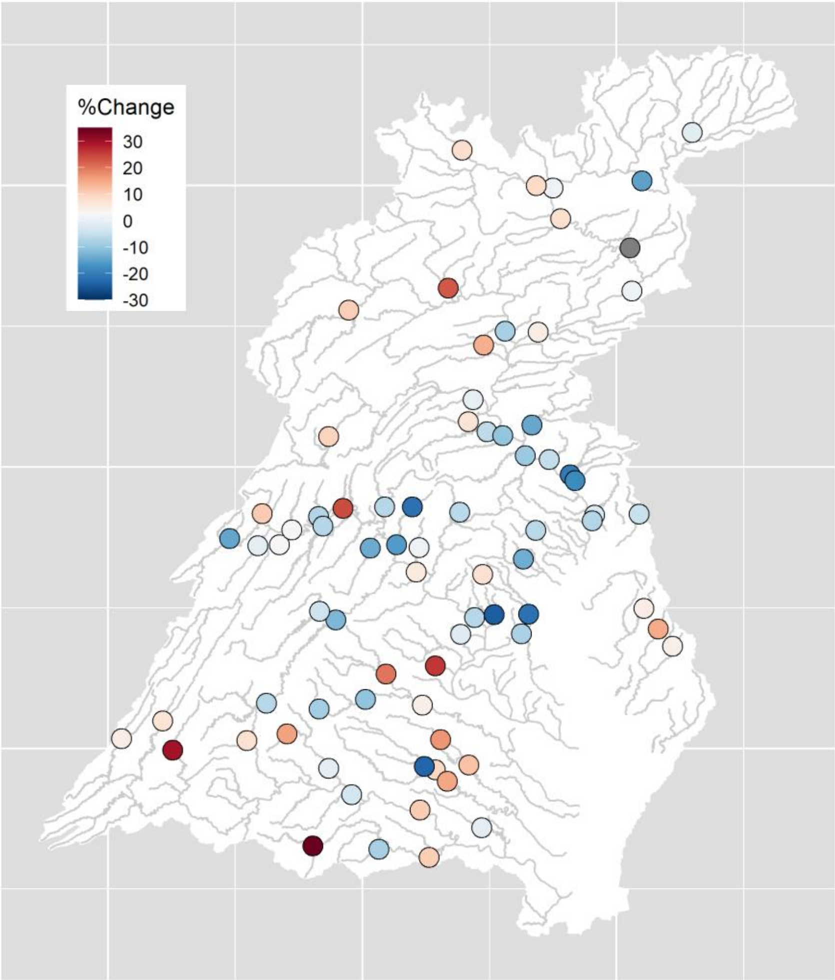
- TMDL: Implement the practices by 2025 that will eventually lead to meeting water quality standards
- CAST prediction: What is the long-term load resulting from a given state of the watershed (land use, point sources, management actions, etc)
- WRTDS- flow normalized loads: based on a moving relationship 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

Comparing modeled and monitored nutrient trends

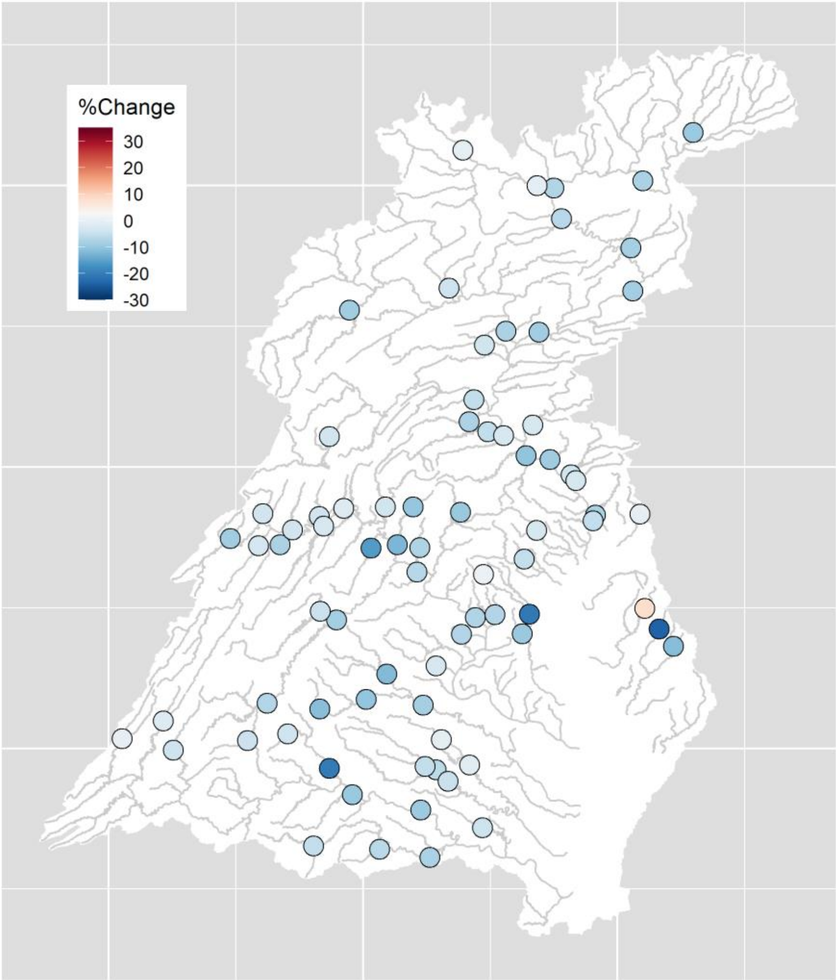
We started by looking at disagreement between CAST and WRTDS

TN – % Change over last 10 years

WRTDS FN



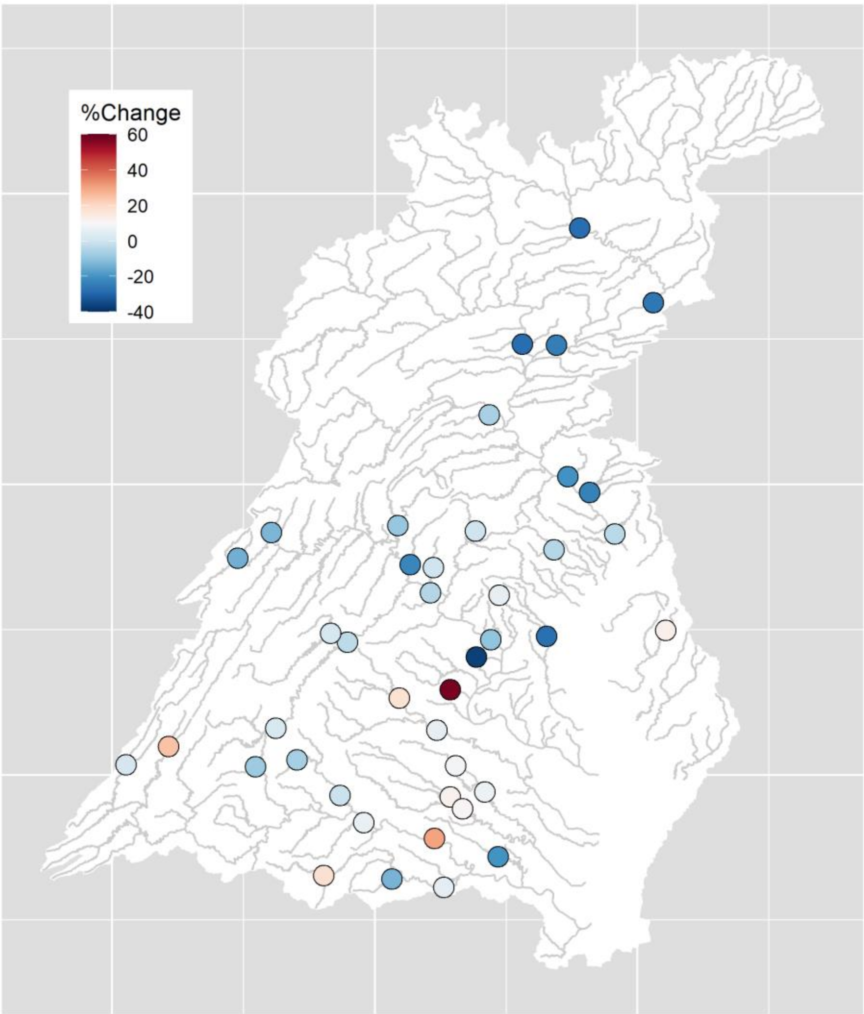
CAST



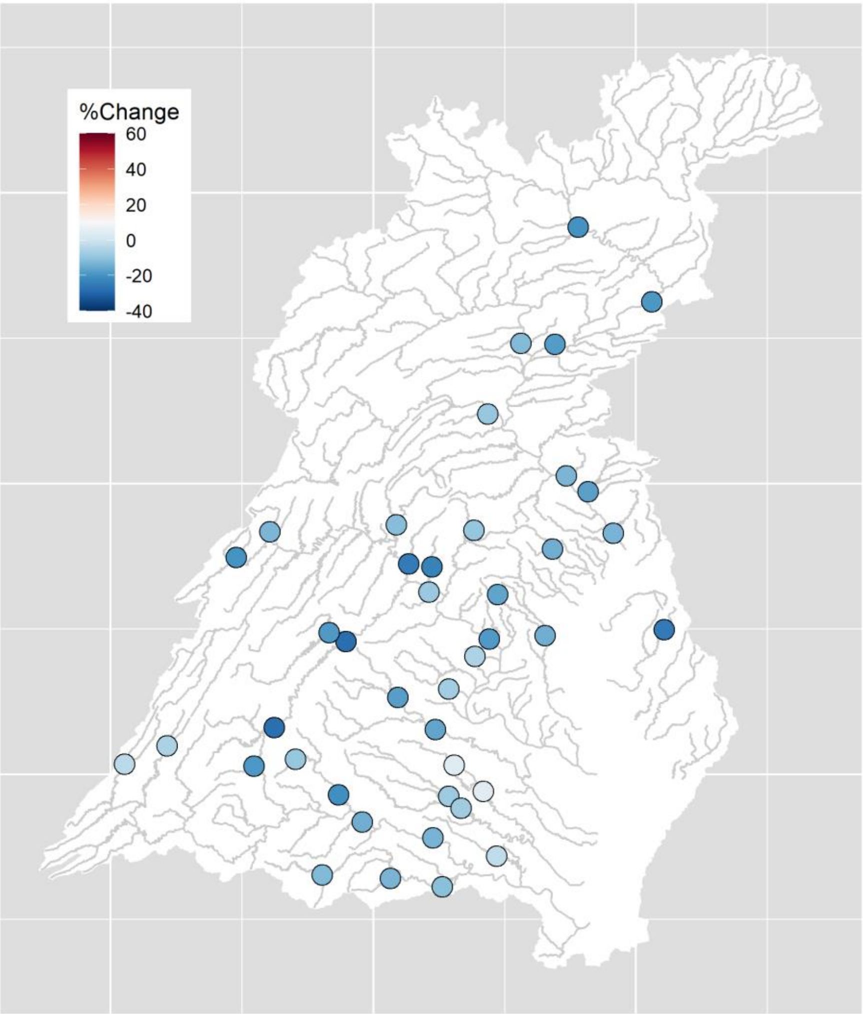
Comparing modeled and monitored nutrient trends

TN – % Change over last 20 years

WRTDS FN



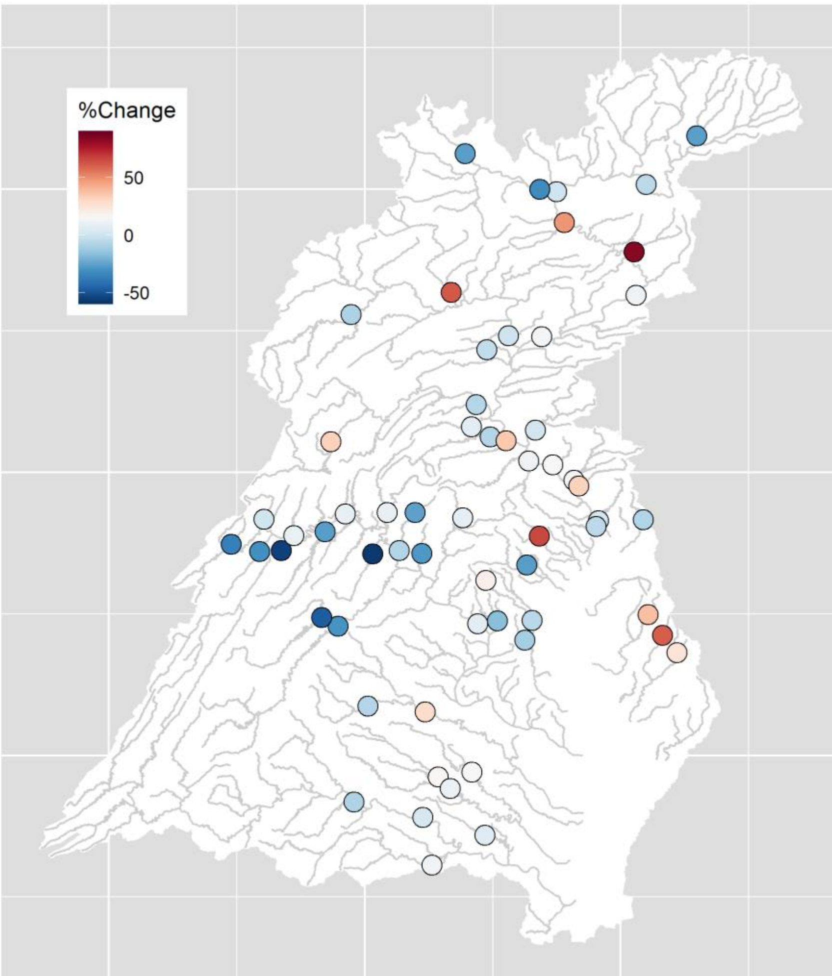
CAST



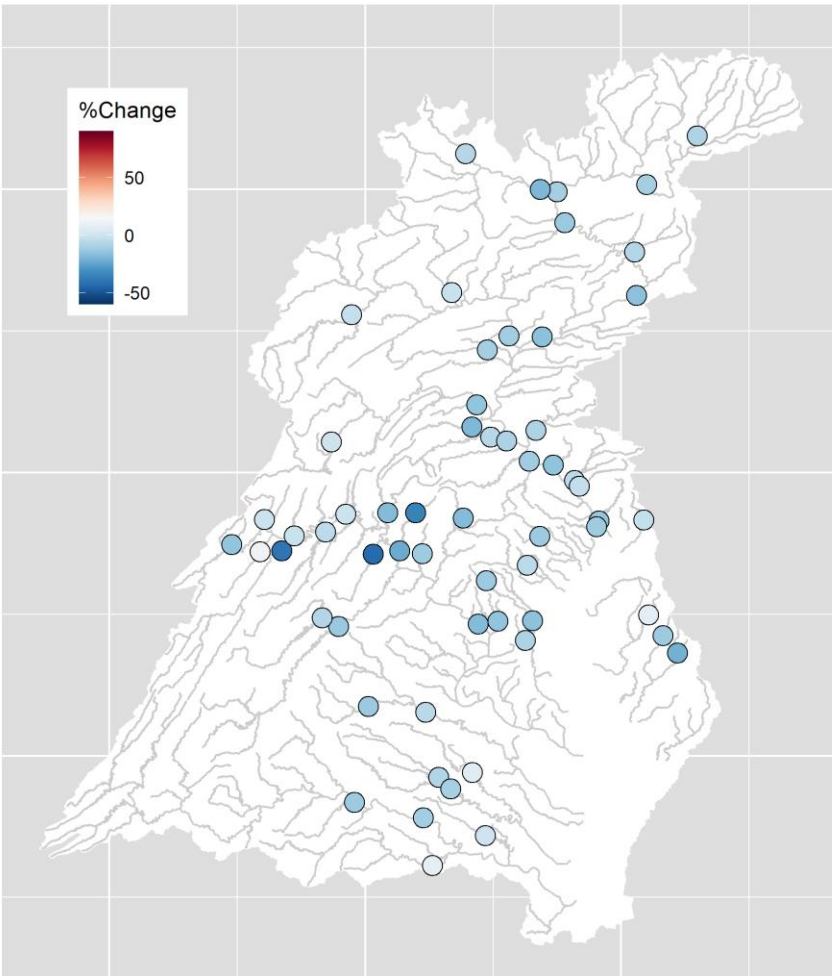
Comparing modeled and monitored nutrient trends

TP – % Change over last 10 years

WRTDS FN



CAST



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

Received: 7 January 2020 | Accepted: 11 May 2020 | Published online: 24 June 2020
DOI: 10.1002/jeq2.20101

Journal of Environmental Quality

REVIEWS AND ANALYSES

Factors driving nutrient trends in streams of the Chesapeake Bay watershed

Scott W. Ator[1] | Joel D. Blomquist[1] | James S. Webber[2] | Jeffrey G. Chanat[2]

[1] USGS, 5522 Research Park Dr., Baltimore, MD 21228, USA
[2] USGS, 1730 East Parham Rd., Richmond, VA 23228, USA

Correspondence
Scott W. Ator, USGS, 5522 Research Park Dr., Baltimore, MD 21228, USA.
Email: swator@usgs.gov

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.

Step 1

Create apples-to-apples comparison by accounting for differences due to:

1. Lag times

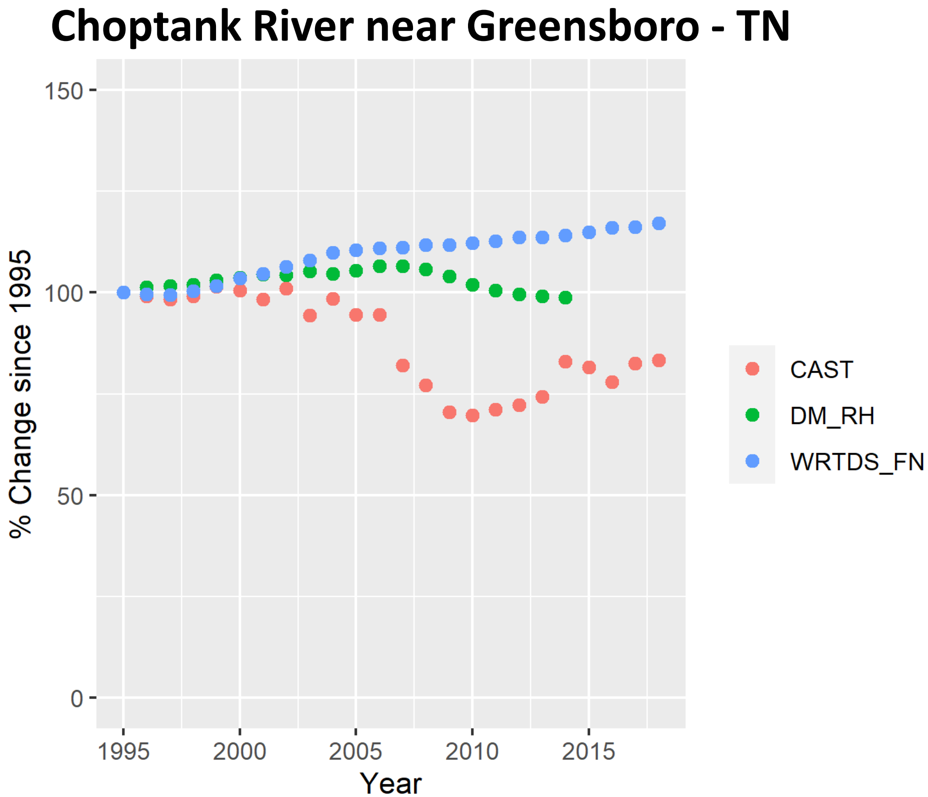
2. Insufficient monitoring

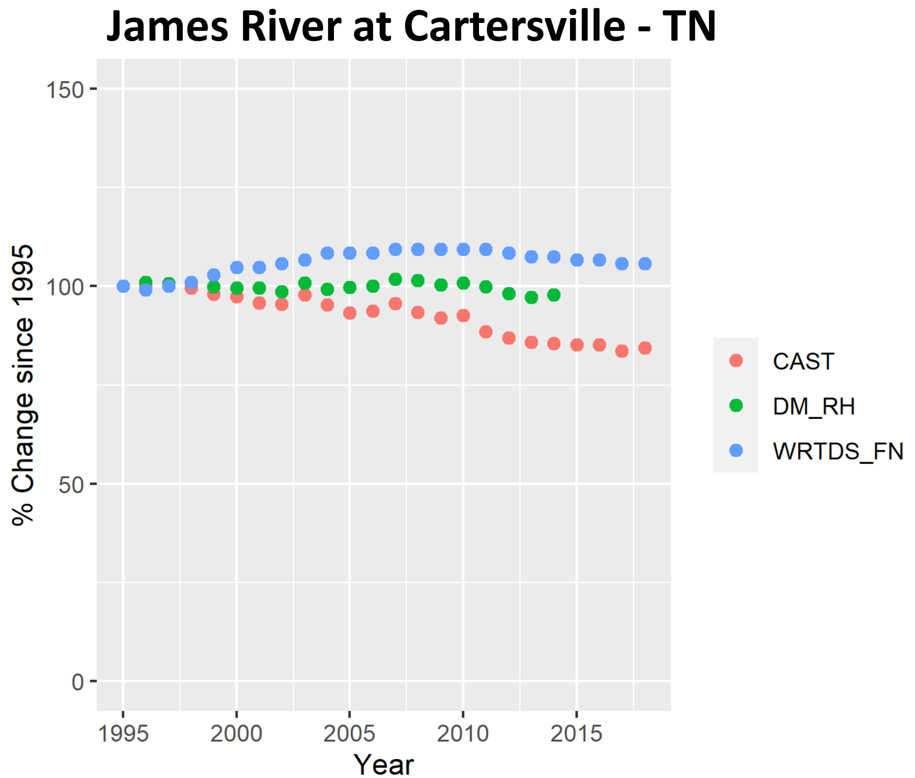
3. Competing effects

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

1. Quantify effects of lag times

- **CAST** – long term trends in management
- Dynamic Model; Always 1989 Weather (**DM_RH**) – Hourly simulation with the same inputs as CAST, Repeat 1989 weather for each year
- Lag times account for differences in shape. If CAST and the Dynamic Model were 'correct', the Dynamic Model would be the true flow normalized trend.

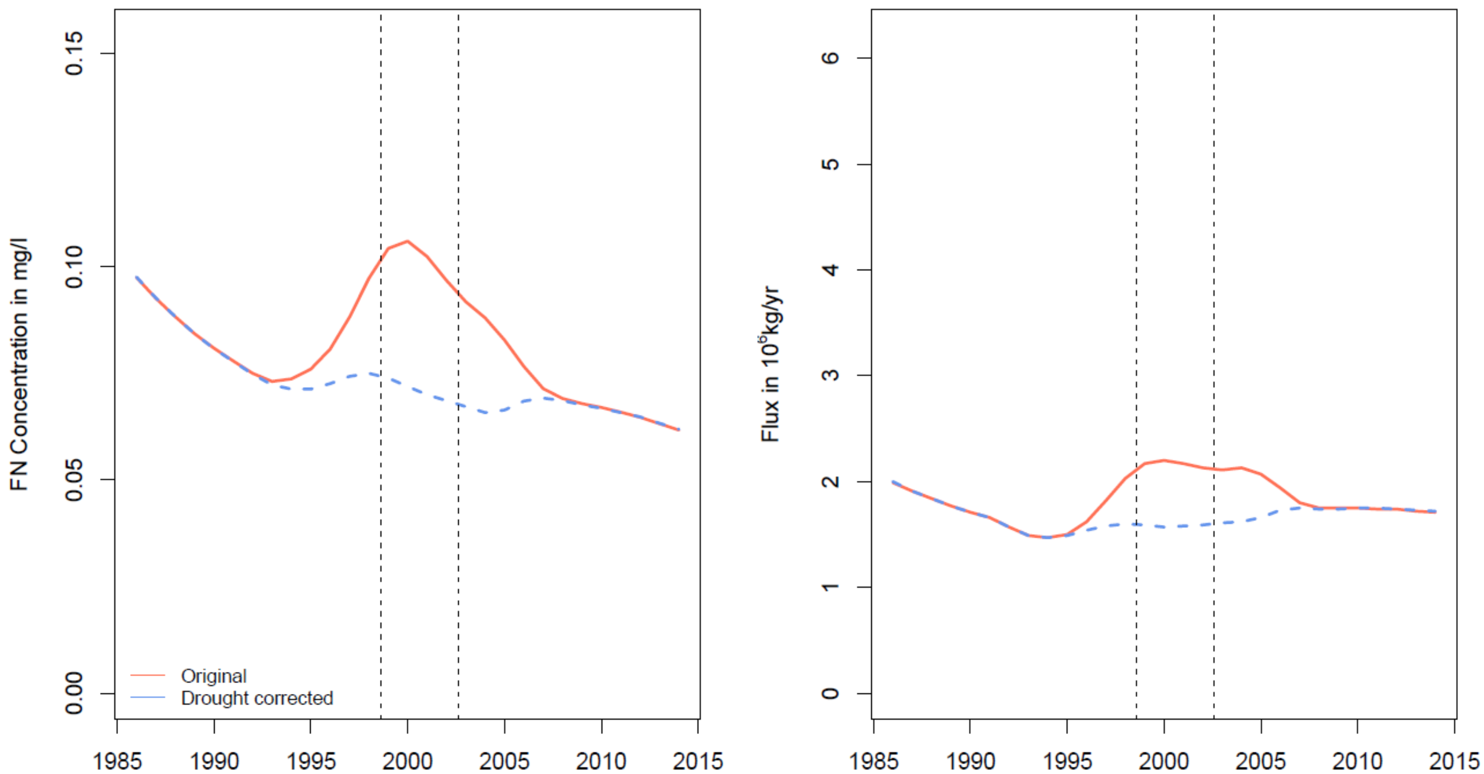




2. Quantify effects of competing effects

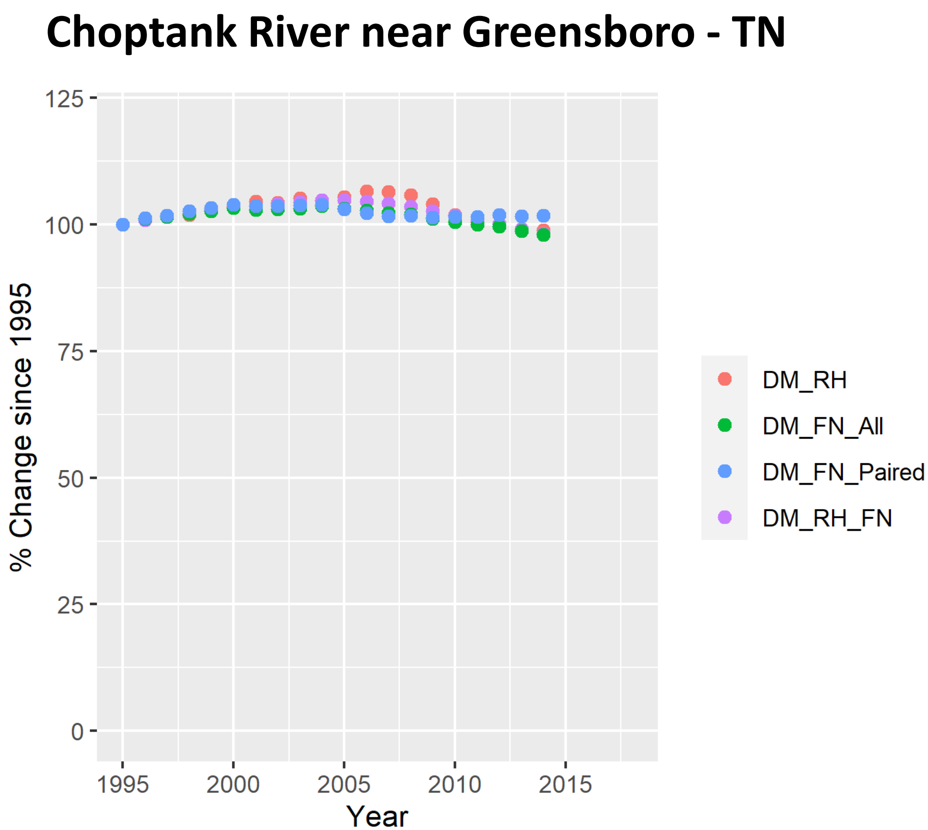
Example of "competing effect": Drought effect on TP

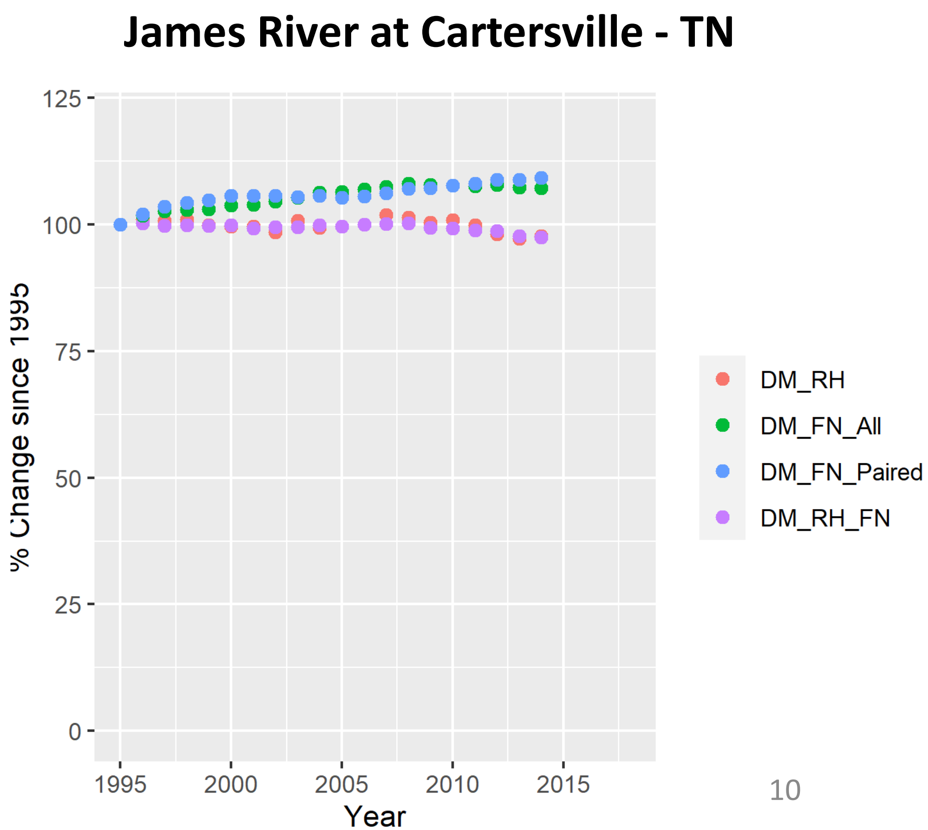
Potomac River at Chainbridge - TP



3. Quantify effects of WRTDS technique

- Dynamic Model; Always 1989 Weather; Flow normalized with WRTDS (**DM_RH_FN**)
- Dynamic Model; Real weather; Flow normalized with WRTDS; All Data (**DM_FN_ALL**)
- Dynamic Model; Real weather; Flow normalized with WRTDS; Paired Data (**DM_FN_Paired**)
- Assesses the ability of WRTDS to flow normalize given variable weather and sparse sampling



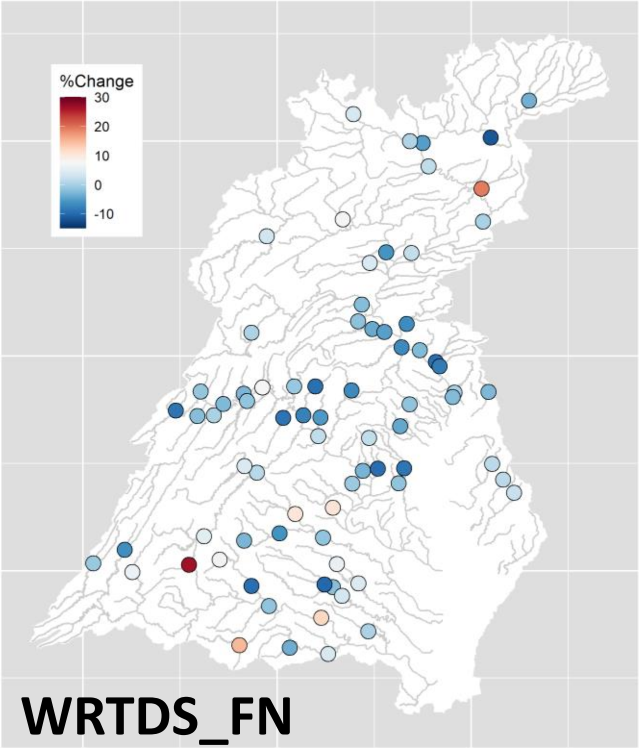


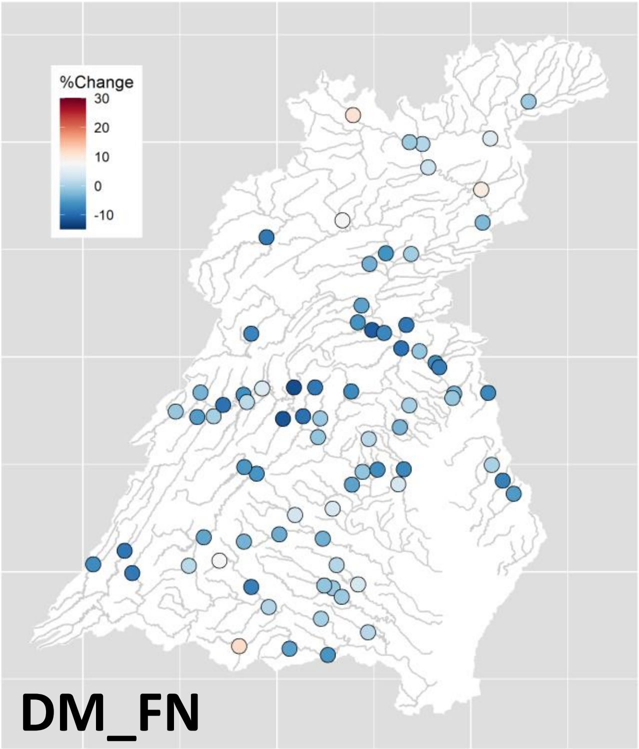
Step 2

- 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
- …





- Answering this question gives us information on where to focus efforts to improve watershed model

Gathering 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.)

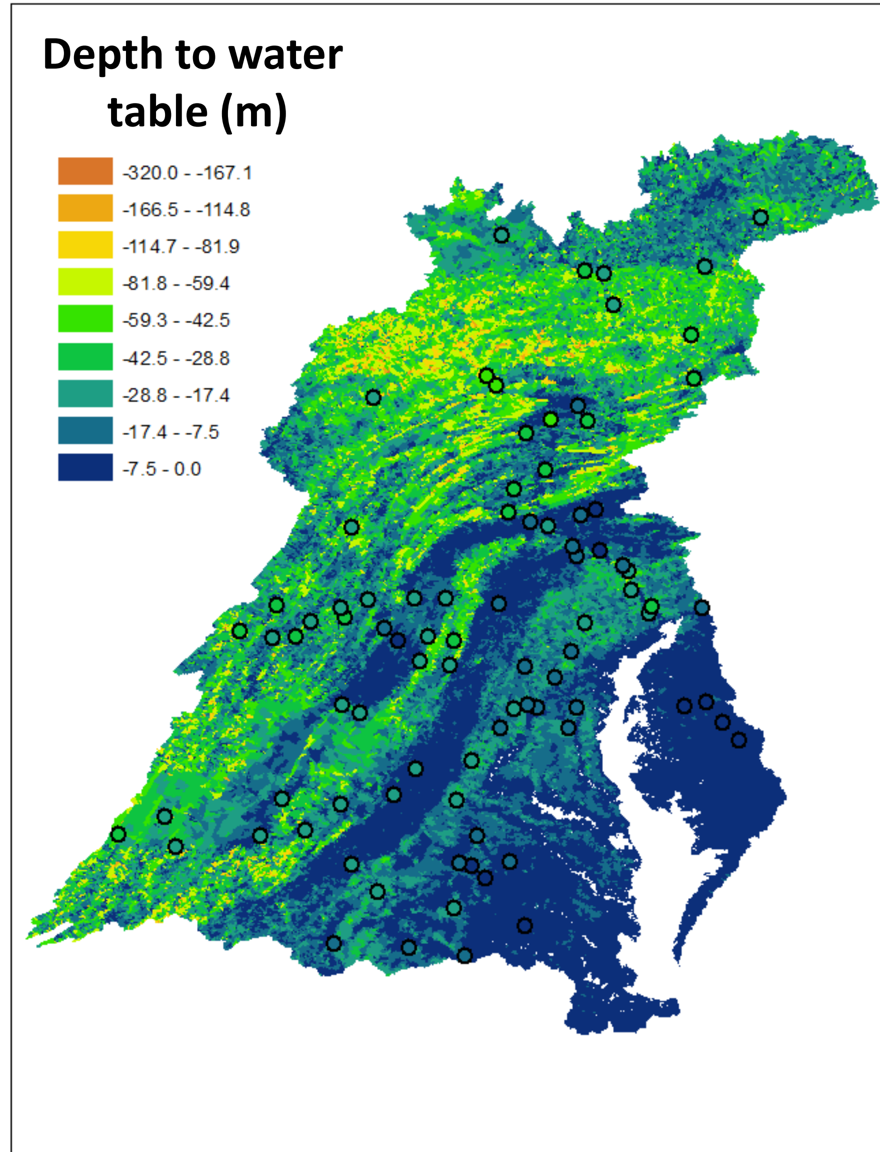
Static variables that describe spatial variability in watershed characteristics

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

Gathering candidate predictors

E2NHDPlusV2_us: Ancillary Hydrologic Attributes and Modified Routing for NHDPlus Version 2.1 Flowlines (Brakebill et al. 2020)

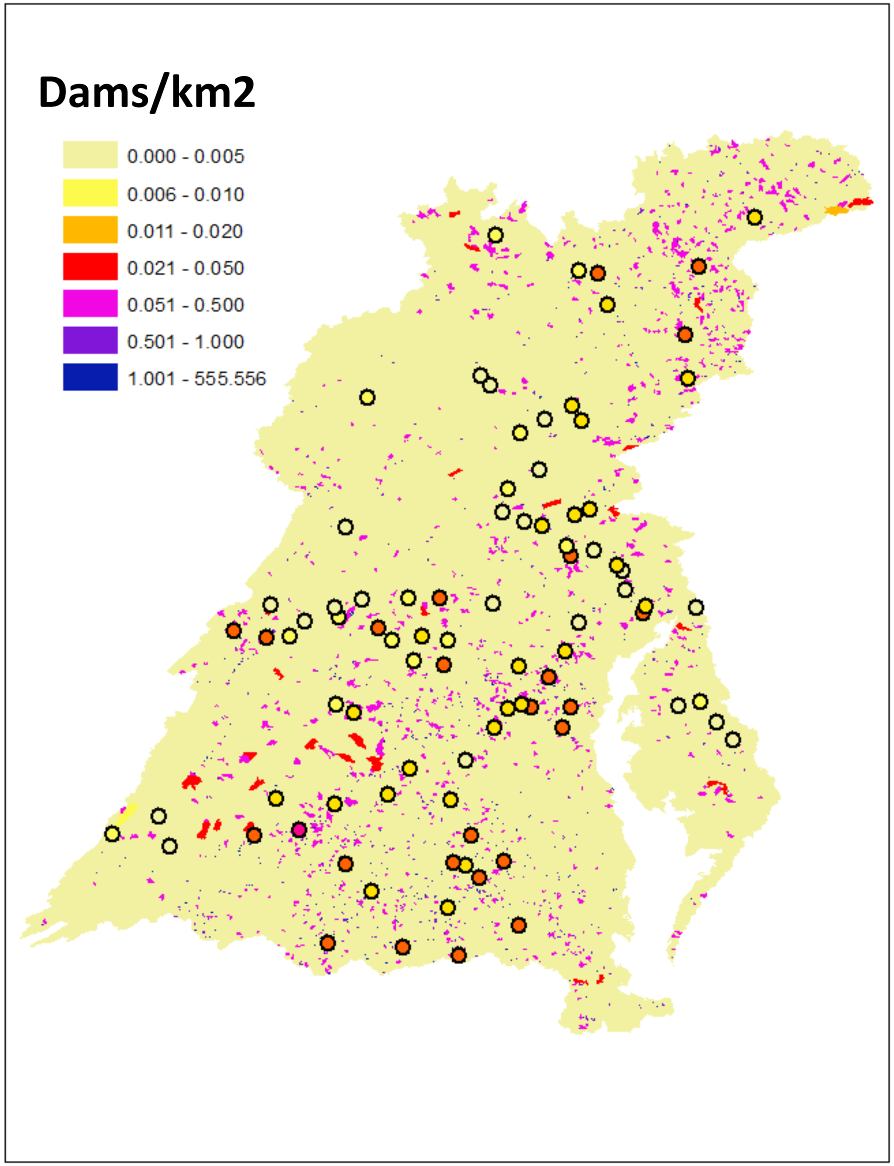
Elevation and slope
Addition/removal locations
Average annual flow, temp, pcp, PET
Average annual runoff
Bedrock permeability classes
Lithology
BFI
Topographic Wetness Index
Depth to water table
% of irrigated Ag
Dams
Soil properties from SSURGO/STATSGO



Gathering candidate predictors

The Stream-Catchment (StreamCat) dataset: a database of watershed metrics for the conterminous United States (Hill et al. 2016)

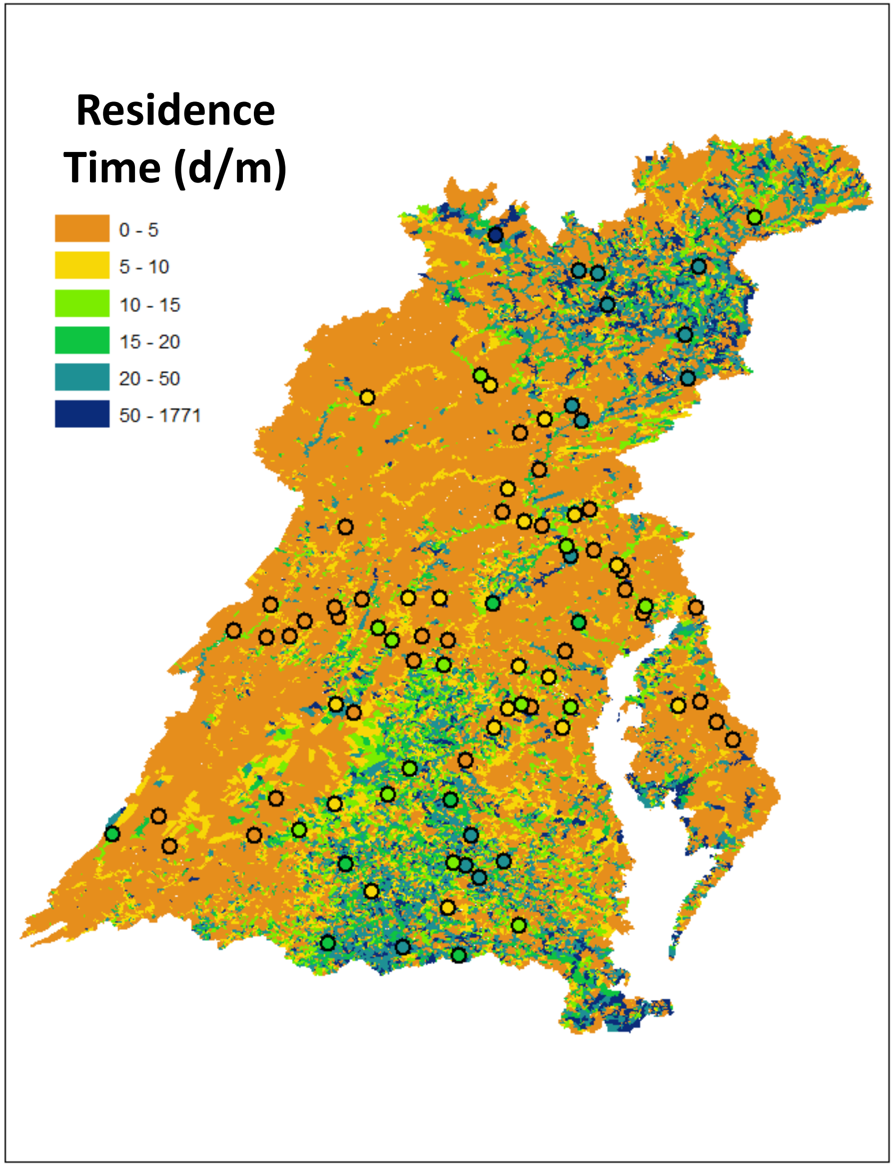
Number and volume of dams per unit area
Surface geology (e.g., Ca content)
Average lithological hydraulic conductivity
Average soil erodibility
Lithology types
Average annual pcp, temp, runoff



Gathering candidate predictors

NHD-RC: Extension of NHDPlus Version 2.1 with high-resolution river corridor attributes (Schmadel & Harvey, 2020)

Areal density of all lentic and lotic features
Areal density of lakes, reservoirs, small
ponds, managed small ponds
Residence time of all lotic and lentic features
Residence time of lakes, reservoirs, small
ponds, managed small ponds

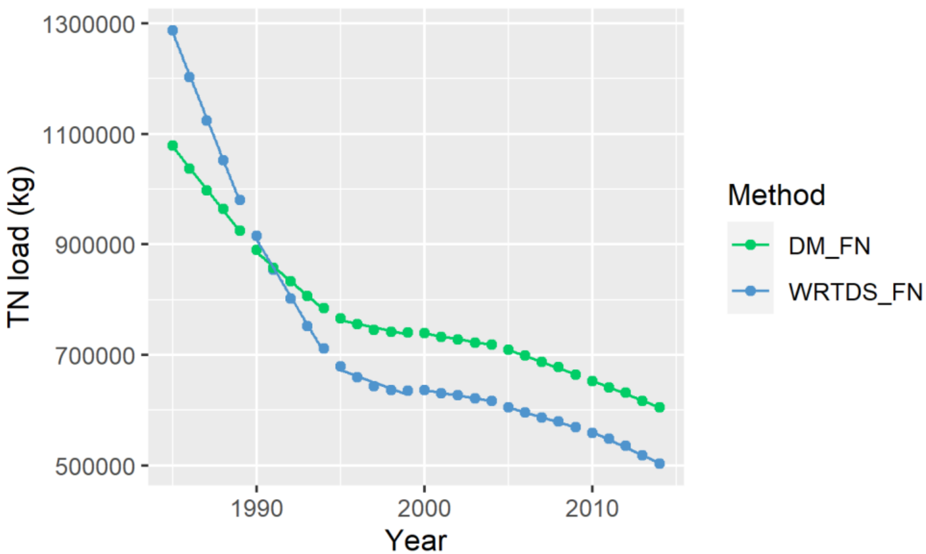


Example of exploratory analysis

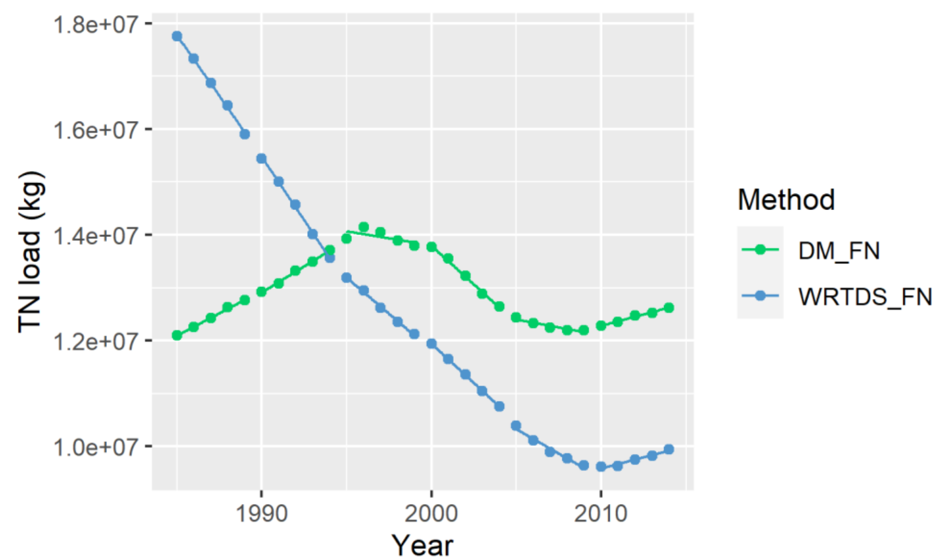
Q: where and when are trends in WRTDS_FN and DM_FN most similar/different? Why is that?

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



Gathering 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.)

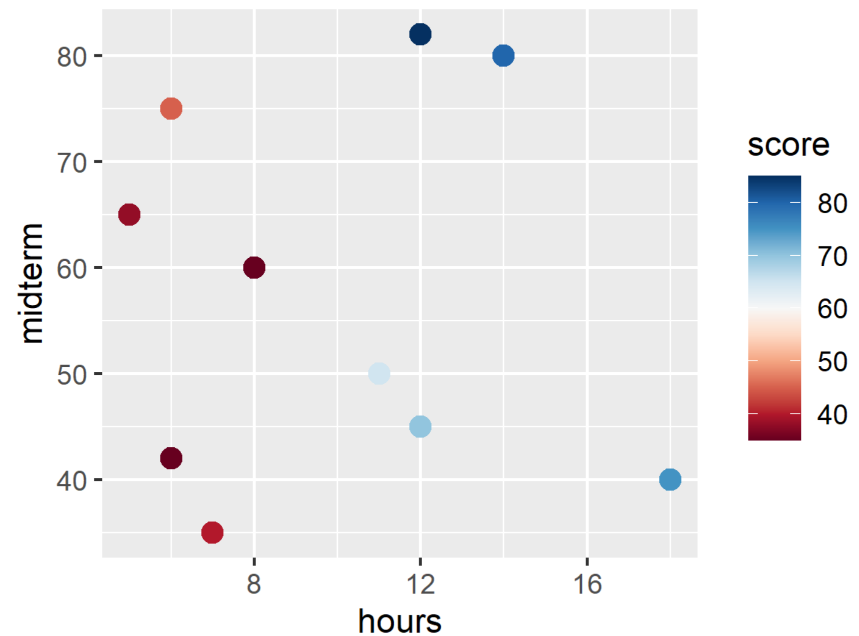
Static variables that describe spatial variability in watershed characteristics

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

Example of exploratory analysis: regression trees

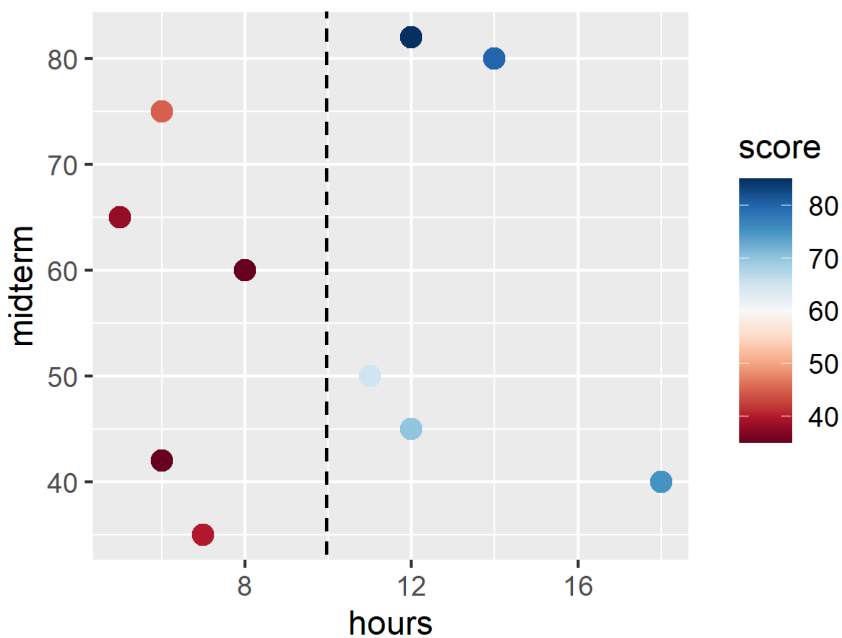
Can we predict a student`s Final Score (response variable) based on two predictors: Midterm Marks and Hours Spent Studying?

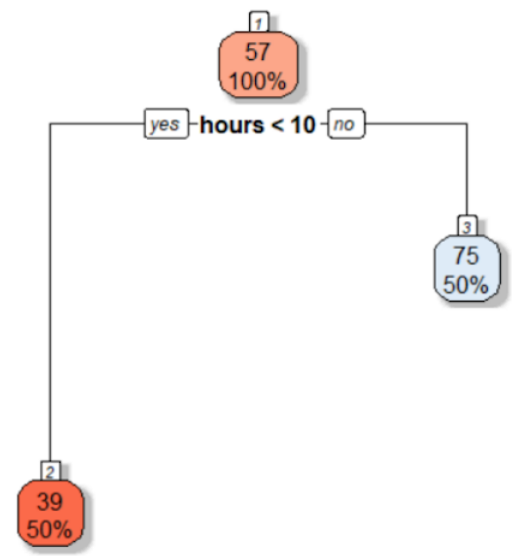
	score	hours	midterm
1	35	6	42
2	38	5	65
3	40	7	35
4	45	6	75
5	35	8	60
6	65	11	50
7	70	12	45
8	75	18	40
9	80	14	80
10	85	12	82



Example of exploratory analysis: regression trees

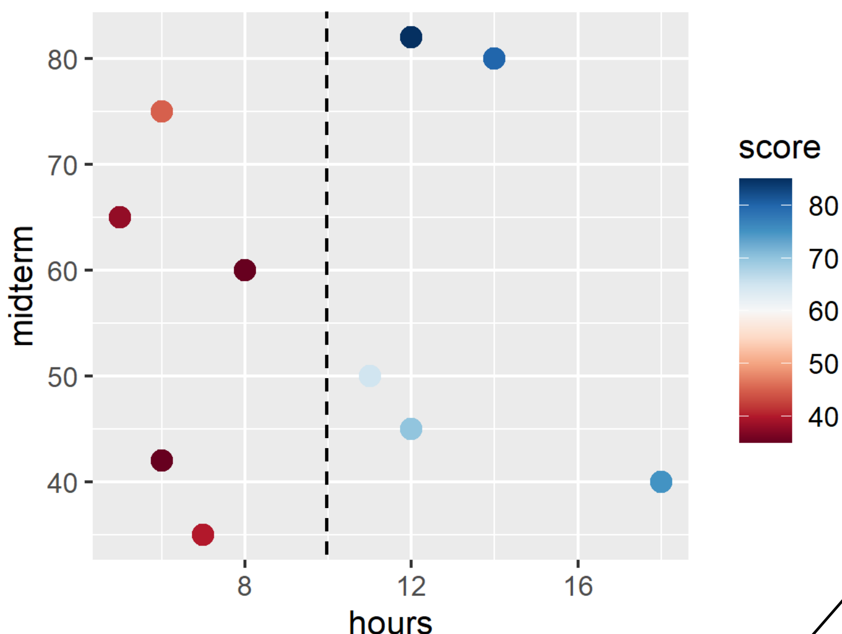
Can we predict a student`s Final Score (response variable) based on two predictors: Midterm Marks and Hours Spent Studying?

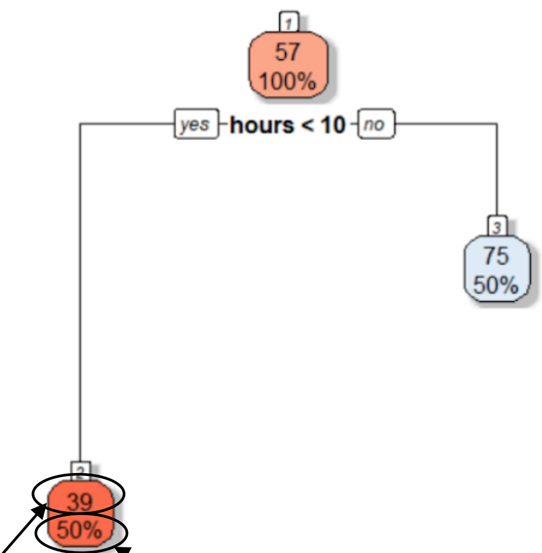




Example of exploratory analysis: regression trees

Can we predict a student`s Final Score (response variable) based on two predictors: Midterm Marks and Hours Spent Studying?



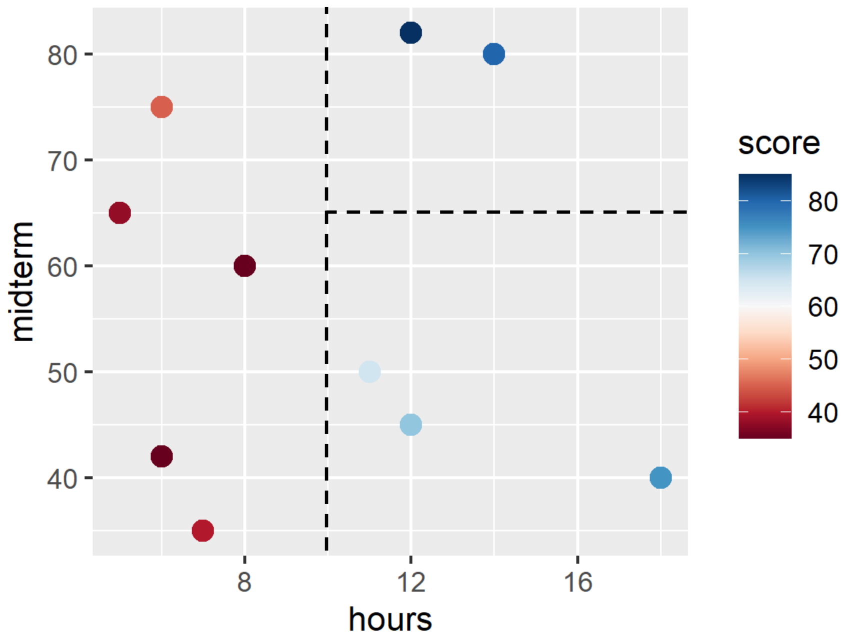


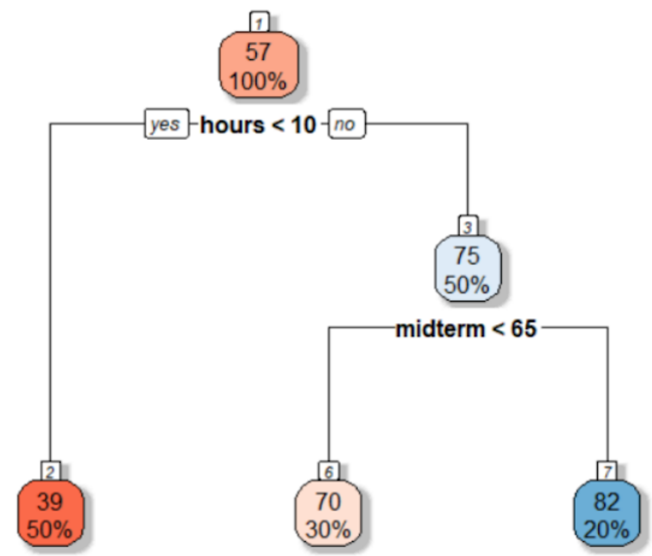
Mean value of the response variable (score) for this group

Fraction of the total number of data points that falls in a group

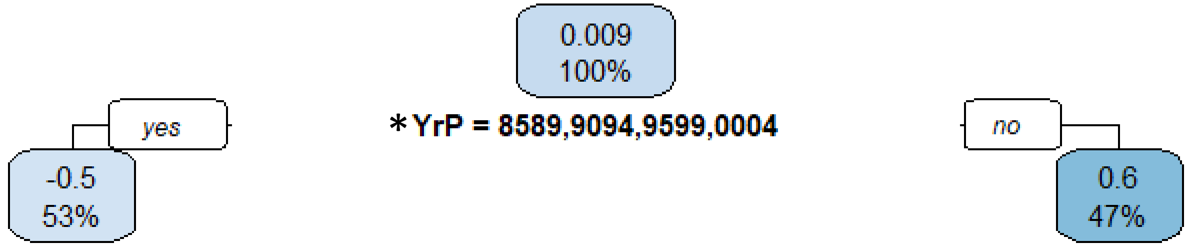
Example of exploratory analysis: regression trees

Can we predict a student`s Final Score (response variable) based on two predictors: Midterm Marks and Hours Spent Studying?



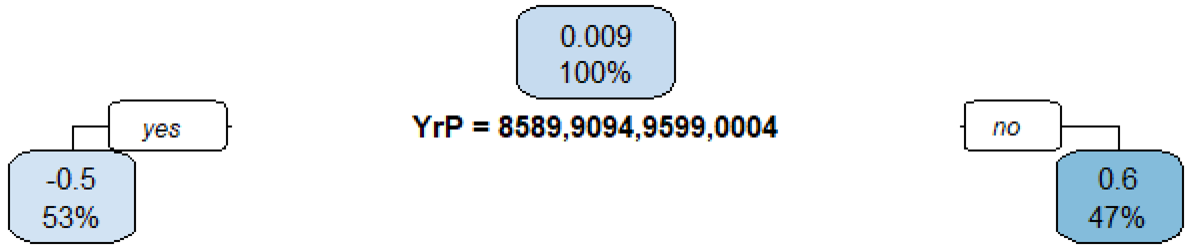


Example of exploratory analysis

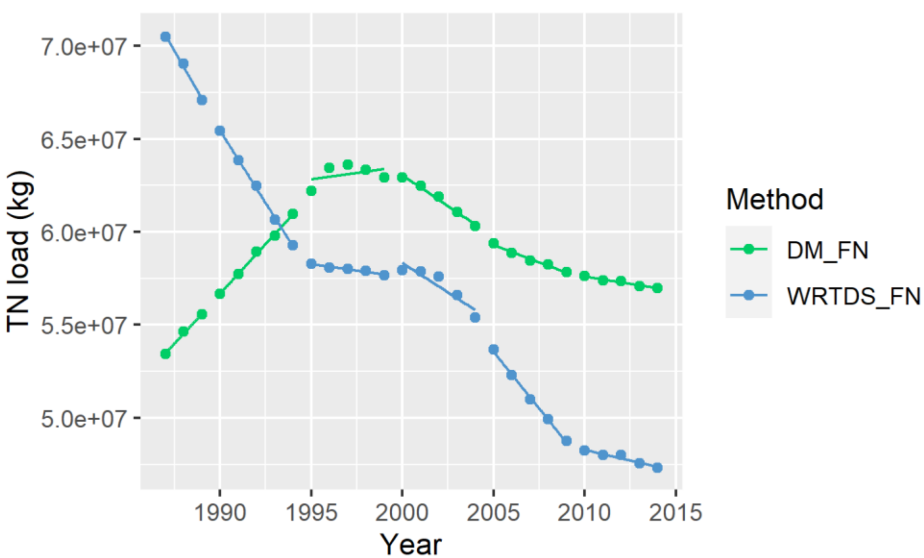


*YrP = 5-year time period (85-89, 90-94, 95-99, 00-04, 05-09,10-14)

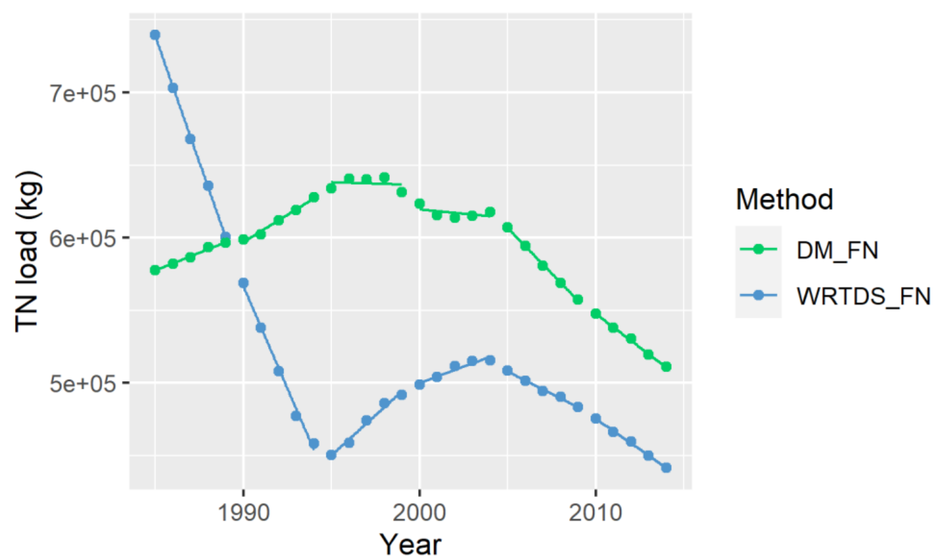
Example of exploratory analysis



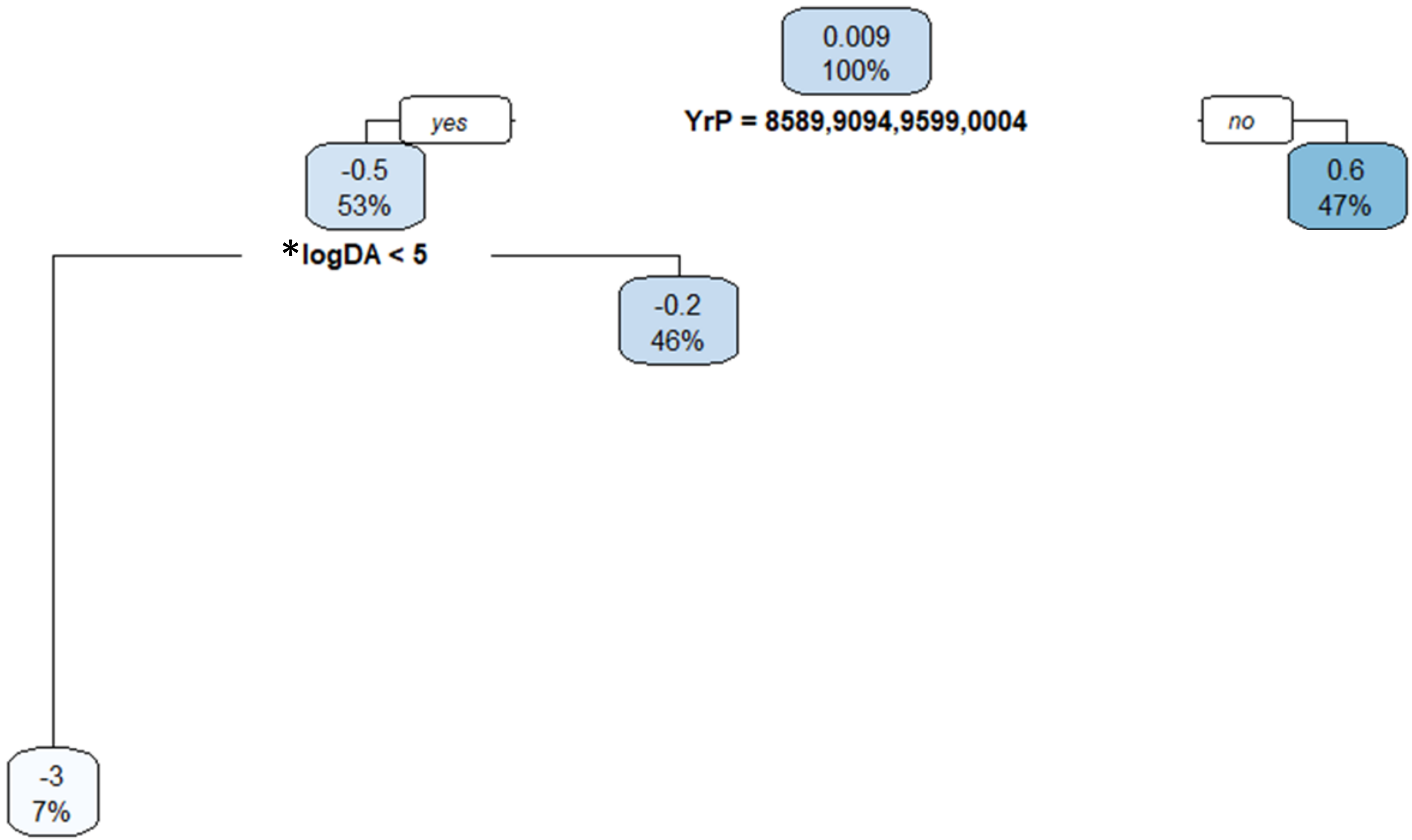
Susquehanna River at Marietta, PA



Monocacy River at Bridgeport, MD

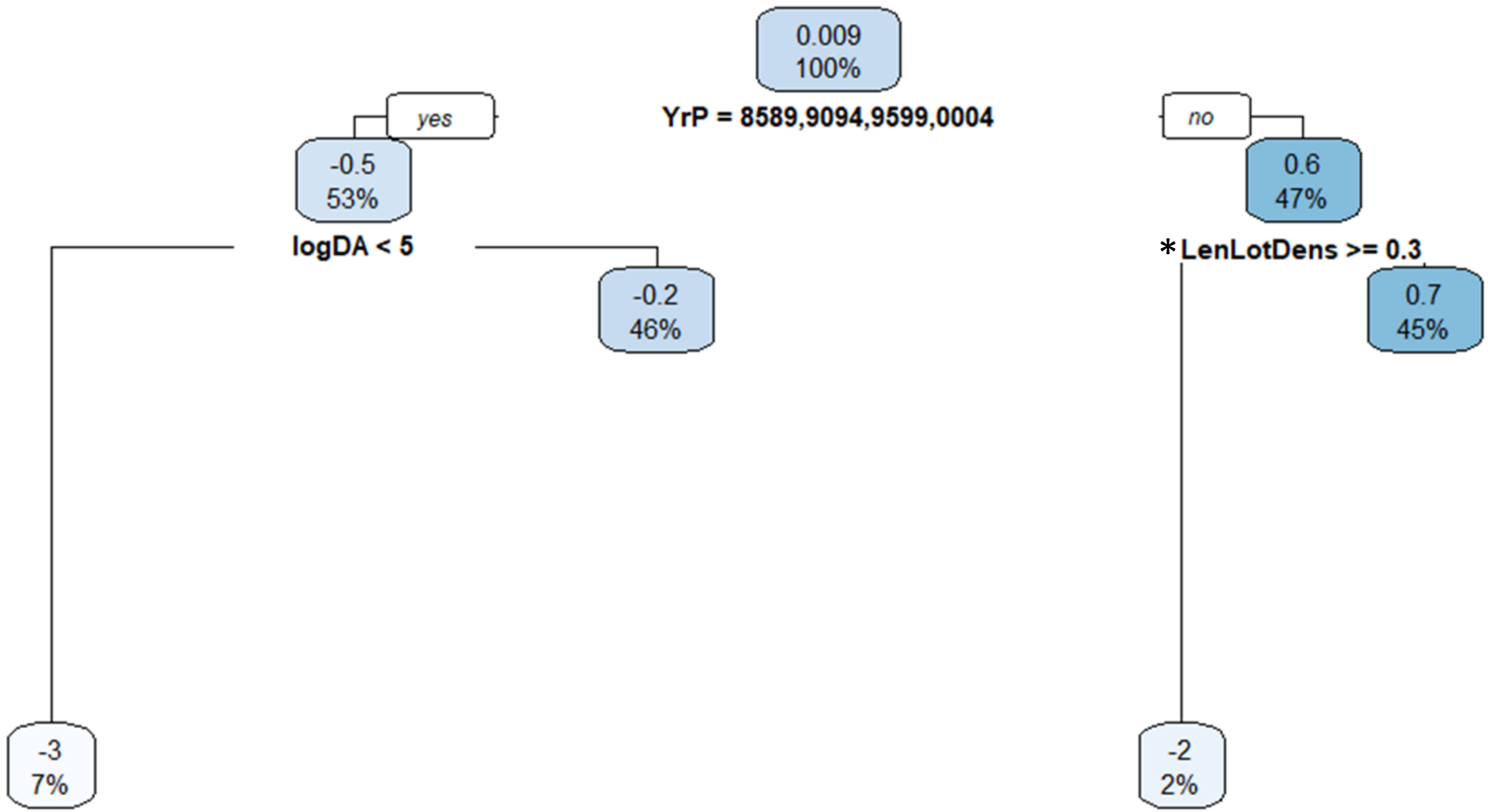


Example of exploratory analysis



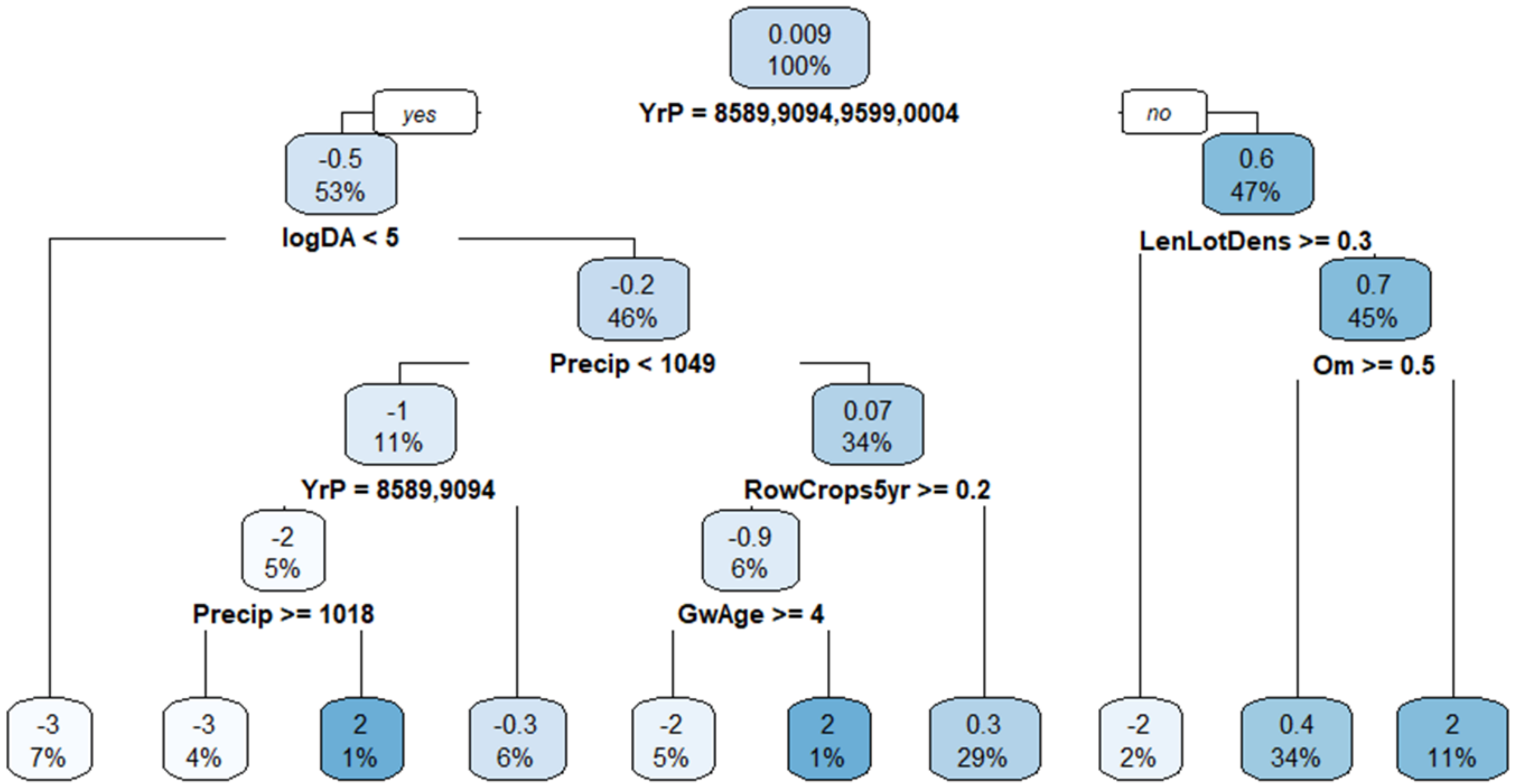
*logDA = log(Station Drainage Area)

Example of exploratory analysis



*LenLotDens = log(Areal density of upstream lentic and lotic features). Areal density is percent of accumulated water surface area per drainage area

Example of exploratory analysis



Next steps

- Expand and refine exploratory analysis, e.g.:
    - Consider different response variables
    - Address highly correlated predictors
    - Better tune regression tree algorithm
    - Explore regression tree expansions (RF, BRT) or other machine learning algorithms

- Use insight from exploratory analysis to inform building of a parametric statistical model that helps explains discrepancies between WRTDS and DM both in time and space