

A Bayesian Hierarchical Spatio-Temporal Ratio-Estimator Approach to Model Phosphorus Loading in Six Ohio Watersheds: the Importance of Accounting for Inter-Annual and Inter-Basin Variabilities

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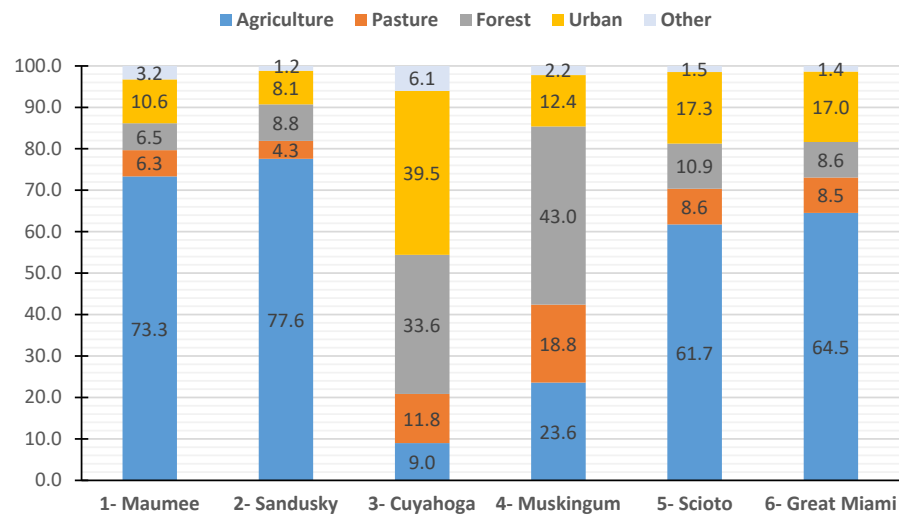
Nutrient loading and the problem of load estimation

- Accurately estimating riverine nutrient loads is a critical step towards mitigating and managing eutrophication-based water quality impairments
- Load estimation is hindered by the sporadic and infrequent monitoring of nutrient concentrations
 - Flow is continuously measured but concentrations are sparsely measured
- Several modelling approaches proposed to estimate pollutant loads
 - Most suffer from biases and/or from their limited abilities to transparently quantify uncertainties

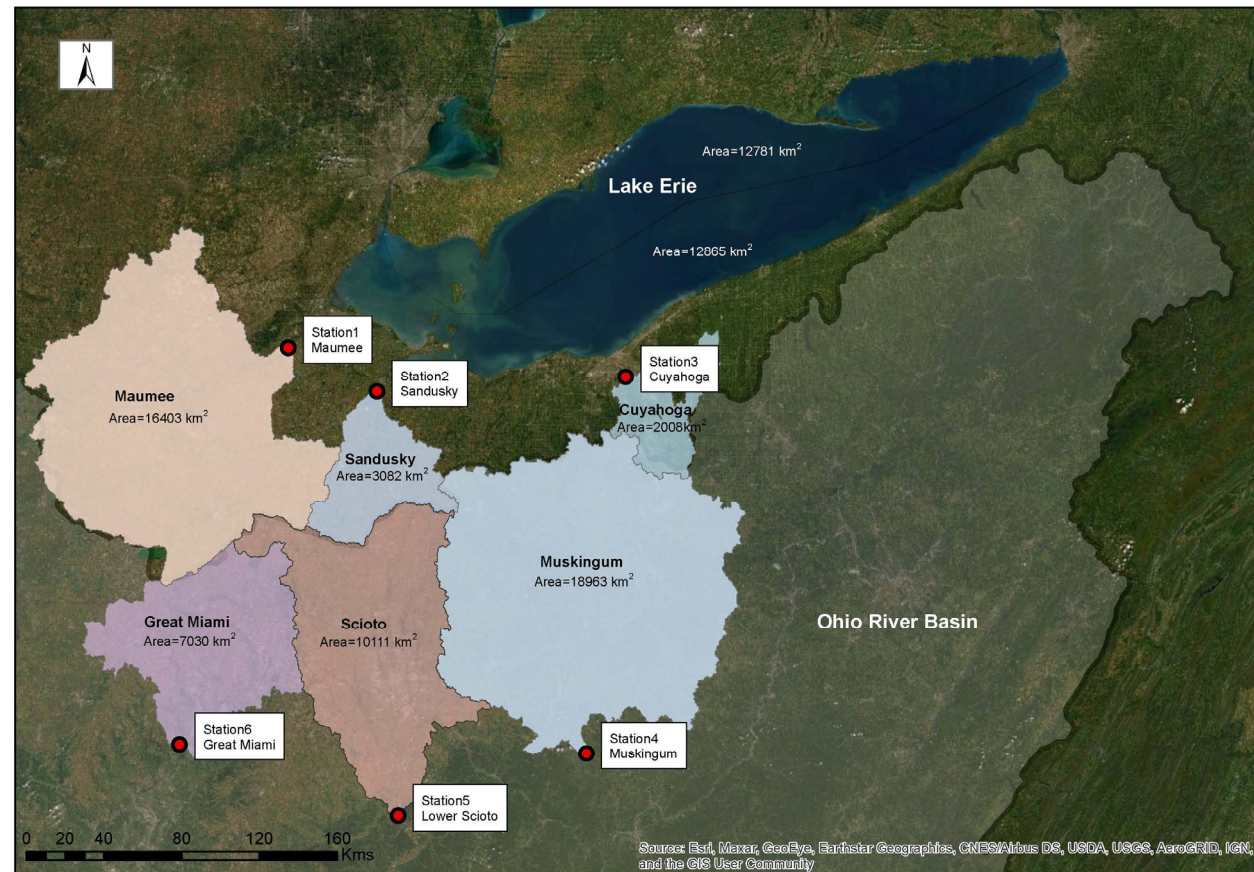
Study area

- Six watersheds pouring into the Lake Erie and Ohio River basin
 - Water quality and flow data continuously collected between 2005 and 2020 → opportunity to calculate the actual “true loads”
 - Varying landuse-landcover coverage

The Percent Coverage by LULC for the Six Watersheds



Station Number	Station Name	Drainage
1	Maumee	Lake Erie
2	Sandusky	Lake Erie
3	Cuyahoga	Lake Erie
4	Muskingum	Ohio River
5	Lower Scioto	Ohio River
6	Great Miami	Ohio River



Model development

- Developed a **Spatio-temporal Bayesian hierarchical ratio-estimator** model to predict the annual total phosphorus loads between 2005 and 2020 for the six intensively monitored watersheds
 - Ability to compare between the “True Loads” and the “Predicted Loads”
 - Can we accurately predict the “True load” if we had 6 or even 4 measurements of concentration per month?
 - Hierarchy allows for:
 - Pooling the data from multiple watersheds
 - Accounting for the impacts of LULC on inter-station variability in phosphorus load estimates (Space)
 - Accounting for the impacts of annual climatic variability on inter-annual variability in phosphorus load estimates (Time)
 - Model expands on the work done by Cha et al, 2010 on Saginaw River

$$\begin{aligned}L_{ijk} &= \beta_{jk} * Q_{ijk} + \varepsilon_{ijk} * (Q_{ijk})^{1/2} \\ \varepsilon_{ijk} &\sim N_o(0, \sigma^2) \\ \beta_{jk} &= \bar{\beta} + \Delta_{S_k} + \Delta_{Y_{jk}} \\ \Delta_{S_k} &= Space_k * \delta_S \\ \Delta_{Y_{jk}} &= Temporal_{jk} * \delta_Y\end{aligned}$$

Where: i is the day of the year, j is the year, and k is the station/watershed

Q is the daily measured flow; $\bar{\beta}$ is the spatio-temporally-averaged effective concentration; Δ_{S_k} and $\Delta_{Y_{jk}}$ are the spatial and temporal changes in the effective concentrations

$Space_k$ is a spatial predictor at the watershed level; $Temporal_{jk}$ is the temporal predictor at watershed k for year j

δ_S is the slope on the higher-level spatial predictor and δ_Y is the slope on the higher-level temporal predictor

Model comparison

Model predictions will be compared with load predictions calculated by:

1. Four Averaging Approaches:

Load estimation method using different averaging techniques of concentration and/or flow data

Method 1	Method 2	Method 3	Method 4
$L_1 = \left(\sum_{i=1}^n \frac{C_i}{n} \right) \times \left(\sum_{i=1}^n \frac{Q_i}{n} \right)$ <p>~ average concentration multiplied by average flow when concentration was measured.</p>	$L_2 = K_2 \left(\sum_{i=1}^n \frac{C_i \times Q_i}{n} \right)$ <p>~ average load when concentration was measured.</p>	$L_3 = K_3 \bar{Q}_r \left(\sum_{i=1}^n \frac{C_i}{n} \right)$ <p>~ \bar{Q}_r is the mean flow for the period of interest from a continuous flow record</p>	$L_4 = \frac{K_4 \sum_{i=1}^n (C_i \times Q_i)}{\sum_{i=1}^n Q_i} \bar{Q}_r$ <p>~ \bar{Q}_r is the mean flow for the period of interest from a continuous flow record.</p>

2. Bayesian Complete Pooling Approach:

One ratio-estimator model for the whole dataset → ignores variation across watersheds and years

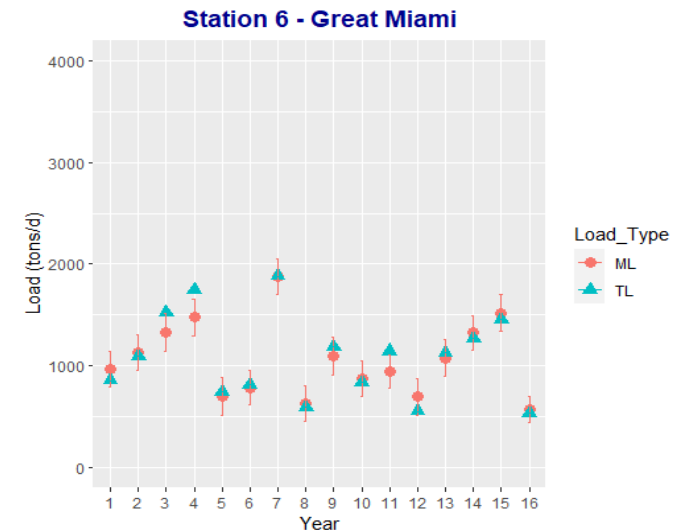
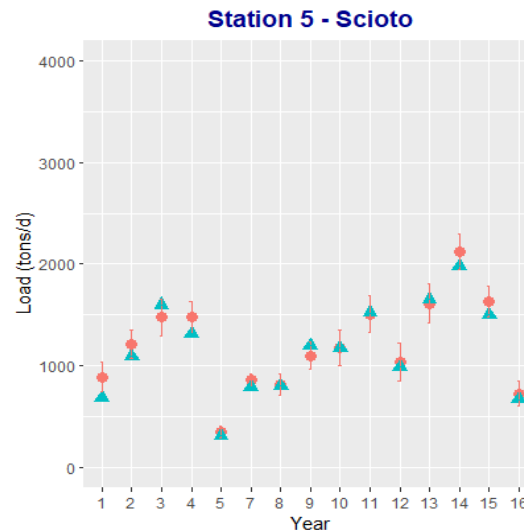
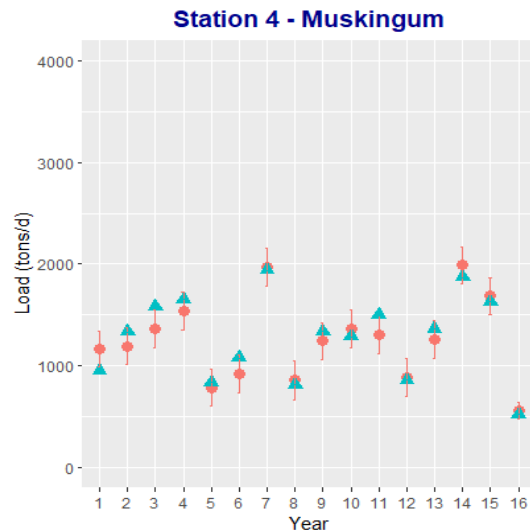
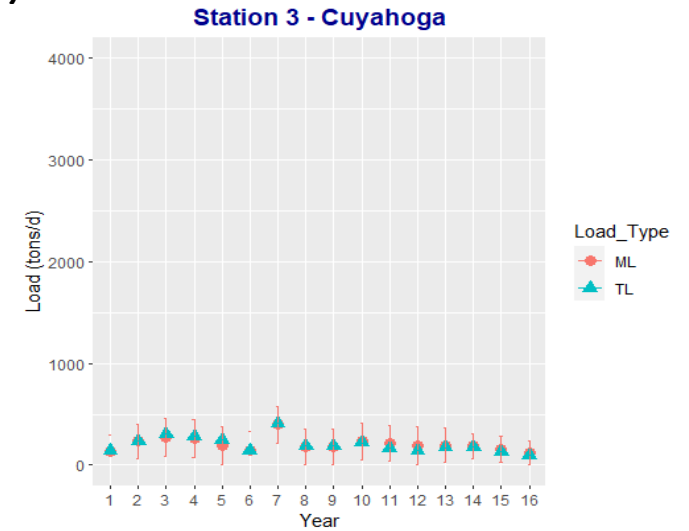
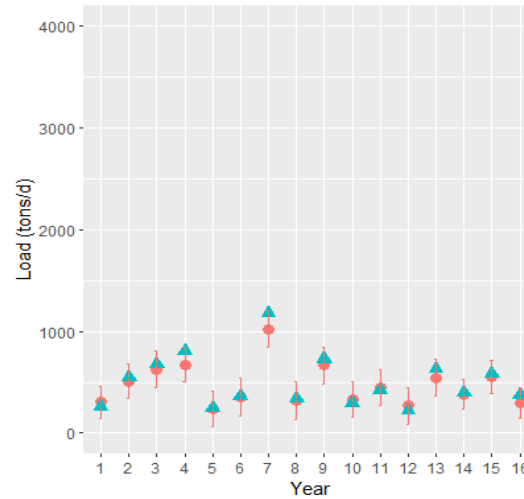
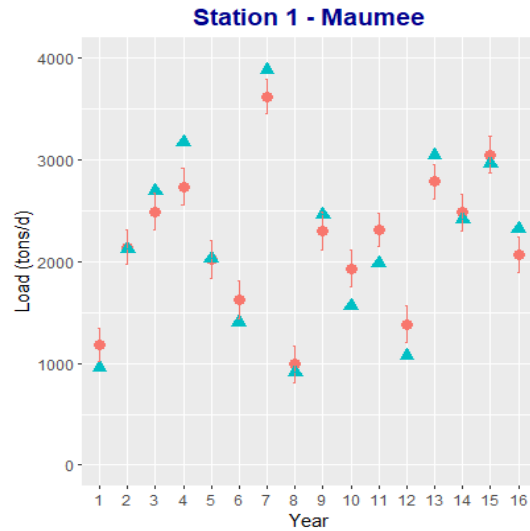
3. Bayesian No-pooling Approach:

One model for each station-year combination → no sharing of information across different stations and years

Results

How good are the model predictions vs the “True Loads”?

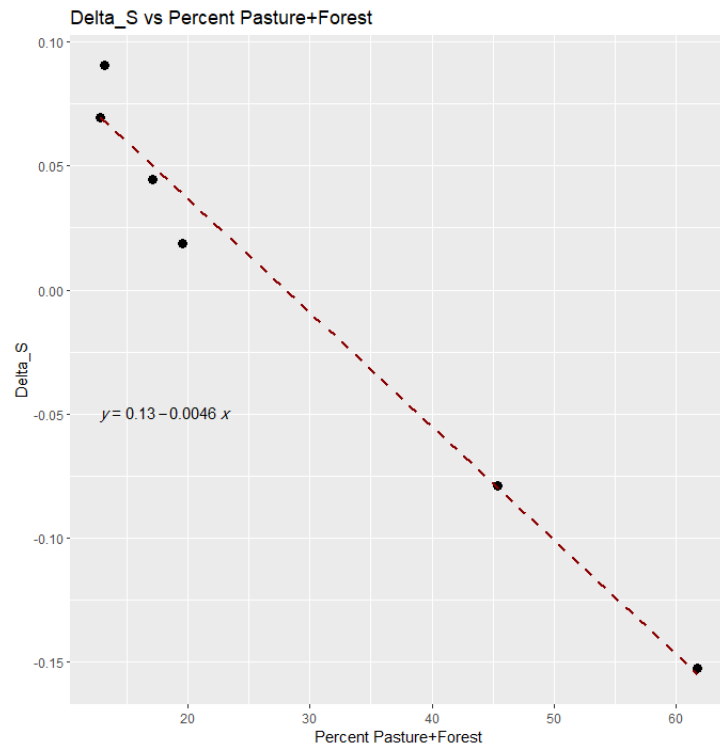
Model Load vs True Load (tons/day)



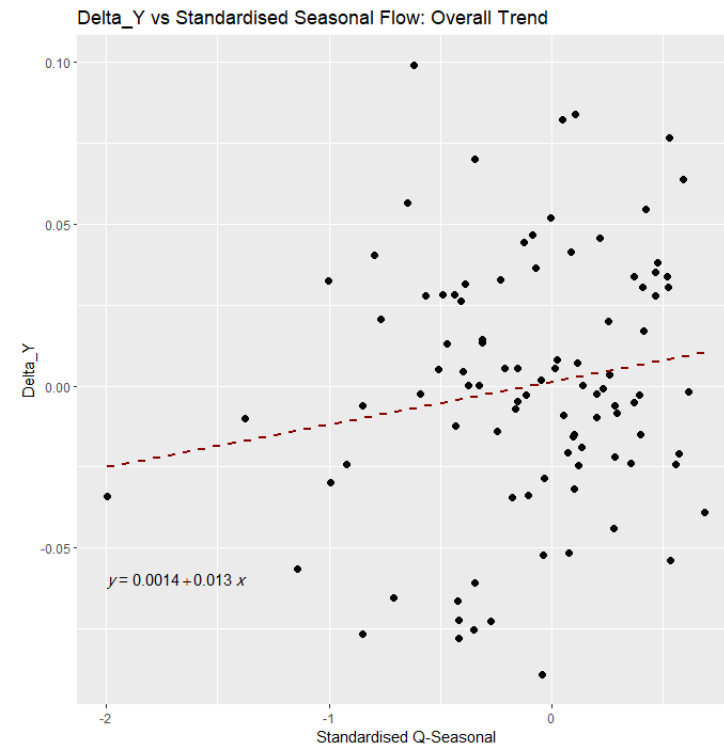
Was the Spatio-temporal Hierarchy necessary?

- The proposed hierarchical model structure strongly supports accounting for “watershed- level” spatial variability; moderately supports accounting for the interannual variability in flow (growing season flows)

Higher % of natural areas (pasture + forest) →
lower effective TP concentration for watershed



Higher seasonal flows → higher the effective TP
concentration for watershed
Importance of non-point sources



How good are the predictions vs other models?

- Hierarchical Bayesian model outperformed the averaging and the completely pooled and non-pooled models

	Our Model	% Difference Between True and Predicted Loads Across All Watersheds					
		Averaging Methods				Complete Pooling	No- Pooling
		Method1	Method2	Method3	Method4		
Average	1.7%	-11.5%	14.8%	-9.3%	17.4%	71.9%	-79.7%
Maximum	36.8%	214.9%	272.5%	188.8%	181.2%	550.6%	-65.9%
Minimum	-21.6%	-67.9%	-41.4%	-60.4%	-16.3%	-89.4%	-84.7%
Median	0.6%	-16.3%	6.6%	-15.8%	7.2%	44.0%	-80.1%

- Assuming that Bayesian model had a spatial hierarchy was equally good
 - Median difference in loads across the watersheds was 0.8% instead of 0.6%
 - Total loads vary between -18% and 52% from the true load
- Assuming that Bayesian model had a temporal hierarchy was significantly worse
 - Median difference in loads across the watersheds was 1.78% instead of 0.6%
 - Total loads ranged between -20% and 39% from the true load

Model Validation

Model performance using data from two “NEW” stations: Portage River and Chikasaw River

Portage River:

The load estimates from the proposed model

- Between -6% and 37% from the true loads
- Median difference of 6.5%

%Pasture+%Forest = 17.5%

Average Annual Seasonal Flow = 161,195,879 cmd

	Our Model	Complete Pooling
Average	12.55%	-19.24%
Maximum	37.74%	2.06%
Minimum	-6.36%	-36.95%
Median	6.44%	-24.32%

Chikasaw River:

The load estimates from the final proposed model

- Vary between -57% and 25% from the true loads
- Median difference of -27%

%Pasture+%Forest = 11.7%

Average Annual Seasonal Flow = 6,348,875 cmd

	Our Model	Complete Pooling
Average	-27.25%	-46.44%
Maximum	25.01%	9.44%
Minimum	-57.24%	-70.46%
Median	-27.25%	-48.89%

Conclusions

- Final model predictions of total annual load were on average 1.7% different from the true load
- The model proved to be robust and was validated by calculating the total loads for two additional stations along Portage River and Chikasaw River
 - Predicted total loads for the two new stations were around 6.5% and -27% different than the true load respectively
- Model performance remained adequate even when sampling was reduced to 3 samples per month
 - Total estimated annual loads were 3.94% different from the true loads
- The integration of higher-level spatial predictors successfully captured inter-station variabilities in phosphorus loading
 - Model shows that non-point sources are significant predictors of total phosphorus:
 - The flow-weighted effective nutrient concentration decreased with natural areas (it also increased with agricultural areas)
- Accounting for annual climatic variability helped explain temporal changes in the flow-weighted effective nutrient concentrations among the six watersheds
 - Higher flows during the growing season → higher effective concentrations (non-point sources)
- Spatial effects are more important to account for as compared to inter-annual temporal variability