Monitoring Bacterial Water Quality for Application to Watershed and Nearshore Fate and Transport Model Development

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Introduction

In order to protect public health, the amount of bacteria at Great Lakes beaches is monitored throughout the swimming season (typically late May through early September). This monitoring is routinely carried out by local county health departments but, due to the limitations of analysis methods, test results cannot be obtained in a timely manner and beach closures and advisories are commonly based on day-old bacterial monitoring results. The need to advance predictive ability and move beyond the current closure protocol is essential to protecting human health. Scientific and management communities alike are increasingly interested in linking watershed and nearshore processes in order to predict the fate and transport of pollutants, including bacteria, for application in decision support tools.

Unfortunately, traditional monitoring programs designed for beach management are not sufficiently informative to understanding the spatio-temporal variability of water quality at scales relevant to process modeling. During the ice free periods of 2012, 2013, and 2014 we carried out an increasingly intensive monitoring program specifically designed to support the development of a linked watershed-hydrodynamics modeling framework simulating the impacts of the Clinton River on the nearshore bacterial water quality in Lake St. Clair.

Although our project has focused on a single study site, the proximity of major tributaries to Great Lakes beaches makes this modeling framework potentially relevant to hundreds of world class freshwater beaches in this region (figure 1).

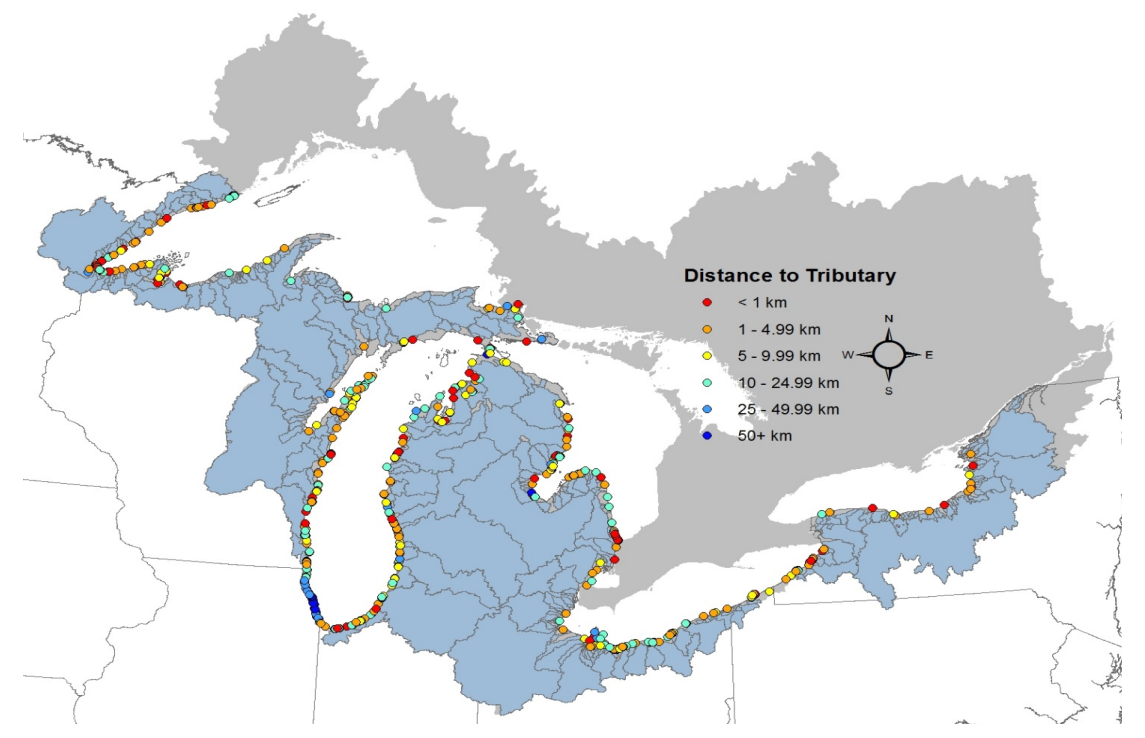

Figure 1: Great Lakes swimming beaches in the United States colored by their distance to the nearest major tributary.

Study Site

Located between Lakes Huron and Erie, Lake St. Clair is the smallest lake within the Laurentian Great Lakes system (figure 2B,C) and one of the most densely utilized lakes for recreational purposes.

The Clinton River watershed encompasses 1965km^2 of southeast Michigan draining via 2 outlets, the natural channel and a constructed spillway, to Lake St. Clair (figure 2D). Our sampling area includes the downstream reach of the Clinton River and 19.7km of Lake St. Clair shoreline including 2 popular public swimming beaches.

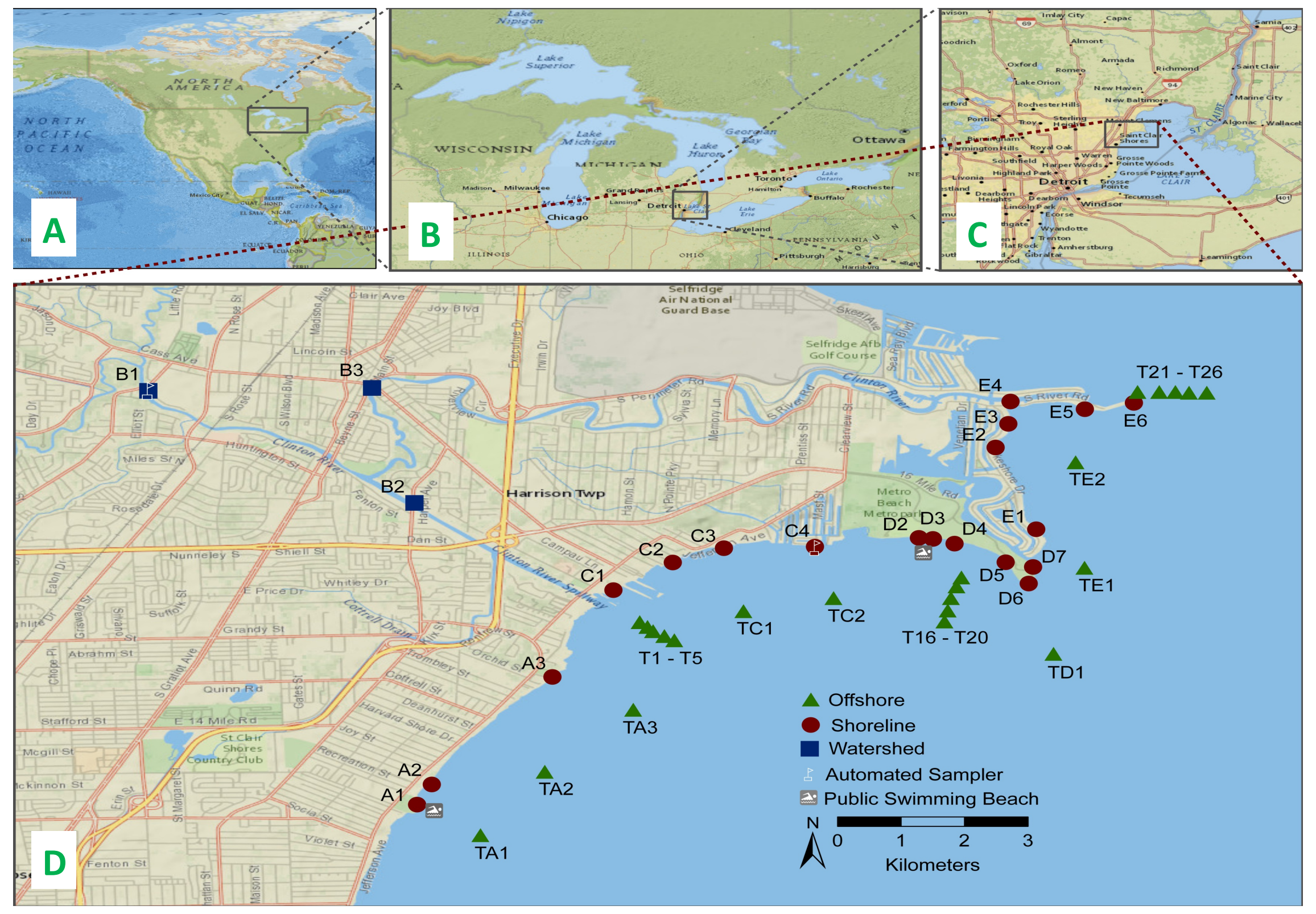

Figure 2: **A)** Geographical context for the Laurentian Great Lakes within North America. **B)** Location of Lake St. Clair within the Great lakes system **C)** Extent of study site in the Clinton River watershed and Lake St. Clair **D)** Map of offshore, shoreline, and watershed sampling sites. Public swimming beaches are also indicated.

Monitoring Program Design

Watershed Monitoring

Watershed monitoring provides observed data for the calibration and verification of the watershed hydrology model. This data is also used to increase our understanding of water quality variability over the hydrograph and how to most appropriately scale daily modeled loading output from the watershed model to hourly load input to the hydrodynamics model.

Three sampling sites were established in the lower Clinton River; 1 site upstream of where the spillway splits from the natural channel and 2 sites downstream of this split – one in each channel (figure 2D). Grab samples were collected weekly from all 3 sites for 3 years during ice free periods totaling 176 samples. In addition to grab samples, 6 multi-hour sets of sub-hourly samples were collected at site B1 in 2013. In 2014 an automated sampling station was established at site B1 in order to collect samples at high temporal frequency (hourly) during high-flow, rainfall events during the summer and early fall. Hourly samples were also collected at this location during baseflow conditions in 2014.

Shoreline Monitoring

Shoreline monitoring data is used for hydrodynamic model calibration and verification. It also helps inform how to scale load to hydrodynamic model particles.

Routine shoreline monitoring was conducted at 19 locations and constitutes the core of our monitoring program (figure 2D). In accordance with regulatory guidelines, grab samples were collected from approximately 35cm below the water surface at approximately 1 meter depth. Samples were collected, typically weekly, between June 2012 and October 2014 totaling 938. In additional to weekly samples, 13 sets of sub-hourly samples were collected from sites C2, D4, and D3 during the summer of 2013 (figure 2D).

Offshore Monitoring

Like other types of sampling, offshore monitoring provides observed values for model output comparison. The unique value of offshore data is that it allows for comparison of model accuracy near the model boundaries, that is the shoreline and nearshore zone where we are most interested in, against where the model is already known to be well resolved (offshore).

During the 2013 field season samples were collected along offshore transects perpendicular to the shore (figure 2D). These samples were collected monthly. In 2014, offshore monitoring expanded to include additional sampling transects parallel to the shore running the length of our study area (figure 2D). Sampling frequency was also increased to 1-2 times monthly. A total of 171 offshore samples have been collected.

Spatial Variability

Observed *E. coli* varied spatially in the nearshore environment (figures 3 and 4). Sampling sites located nearest to each other did not always exhibit the most similar *E. coli* concentrations. The magnitude of variability differed between sites but remained relatively the same at each site annually (figure 3).

Temporal Shoreline Variability

Variation in *E. coli* concentration was observed on sub-hourly (figure 5), daily (figure 4), weekly (figure 3) , and annual (figure 3) time steps. The magnitude of variability depends on the site and the period of sampling (figures 3, 4, and 5). Daily and sub-hourly variability on a single day is also important to acknowledge when the concentration is at or near the decision threshold. Due to this inherent variability, a management decision made according to common practice, could be different depending on precisely when the sample was collected (figures 4 and 5).

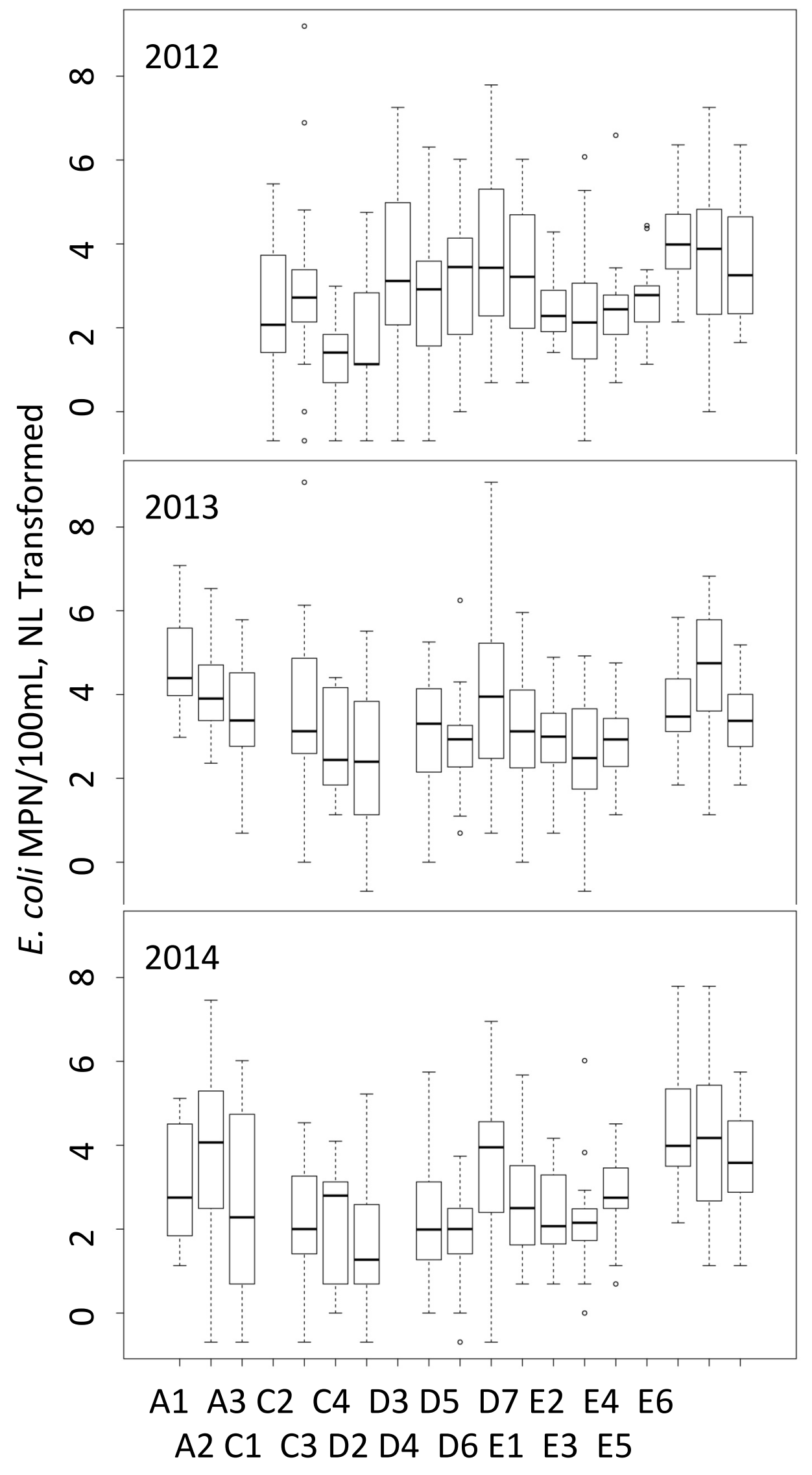

Figure 3: Variability of *E. coli* at shoreline sampling sites in 2012, 2013, and 2014. Sites are arranged along the x-axis in the same order which they are ordered along the shoreline southwest to northeast. Individual boxplots represent the weekly variability.

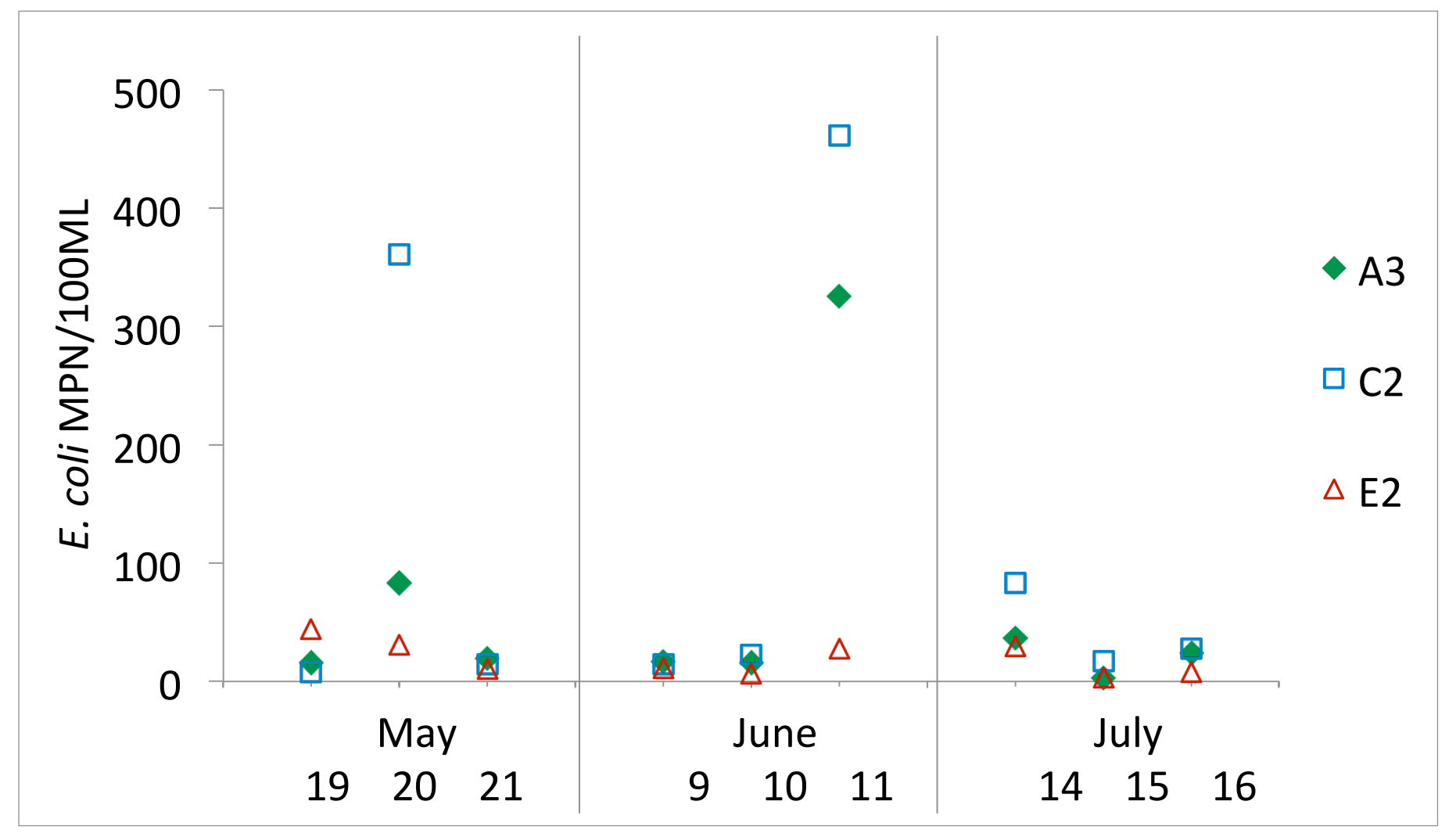

Figure 4: Daily observed *E. coli* concentrations at selected shoreline sites during three 2014 events.

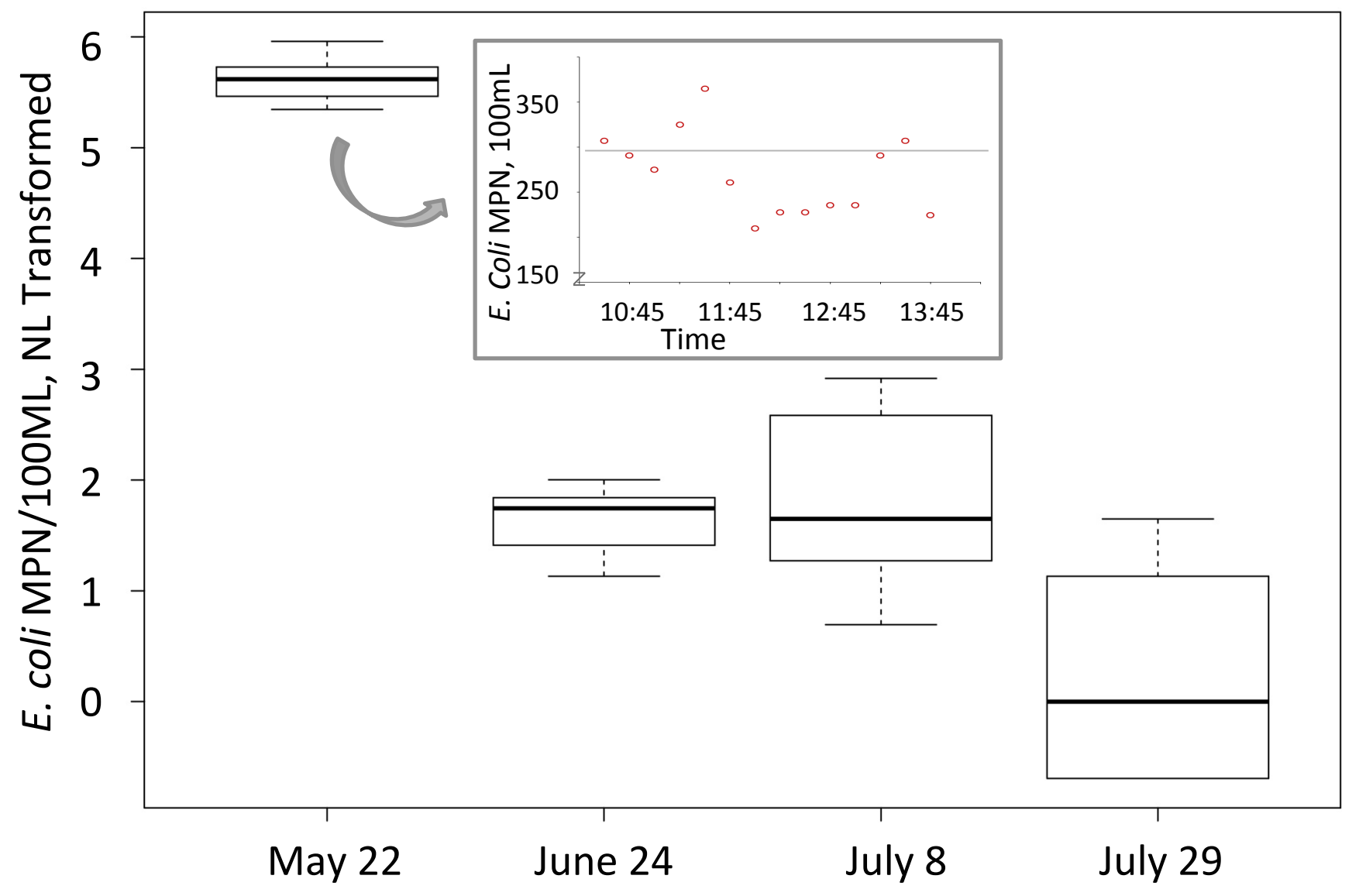

Figure 5: *E. coli* variability in sub-hourly sampling at Site C2 on select 2013 dates. Subset plot shows observed sub-hourly results on May 22, 2013. Horizontal gray reference line indicates threshold value at which a beach is closed.

Sub-hourly Watershed Variability

During baseflow, little variability in *E. coli* was observed in the river. When we observe discharge response to a rainfall event however, we observe *E. coli* concentration rising with discharge but lingering well after discharge has returned to baseflow (figure 6). This unmatched pattern in rainfall response is important to understanding the distribution of *E. coli* load over the hydrograph. Furthermore, turbidity, which is often used as a rapid indicator for *E. coli,* does exhibit a response similar to discharge but does not match that of *E. coli* concentrations (figure 6).

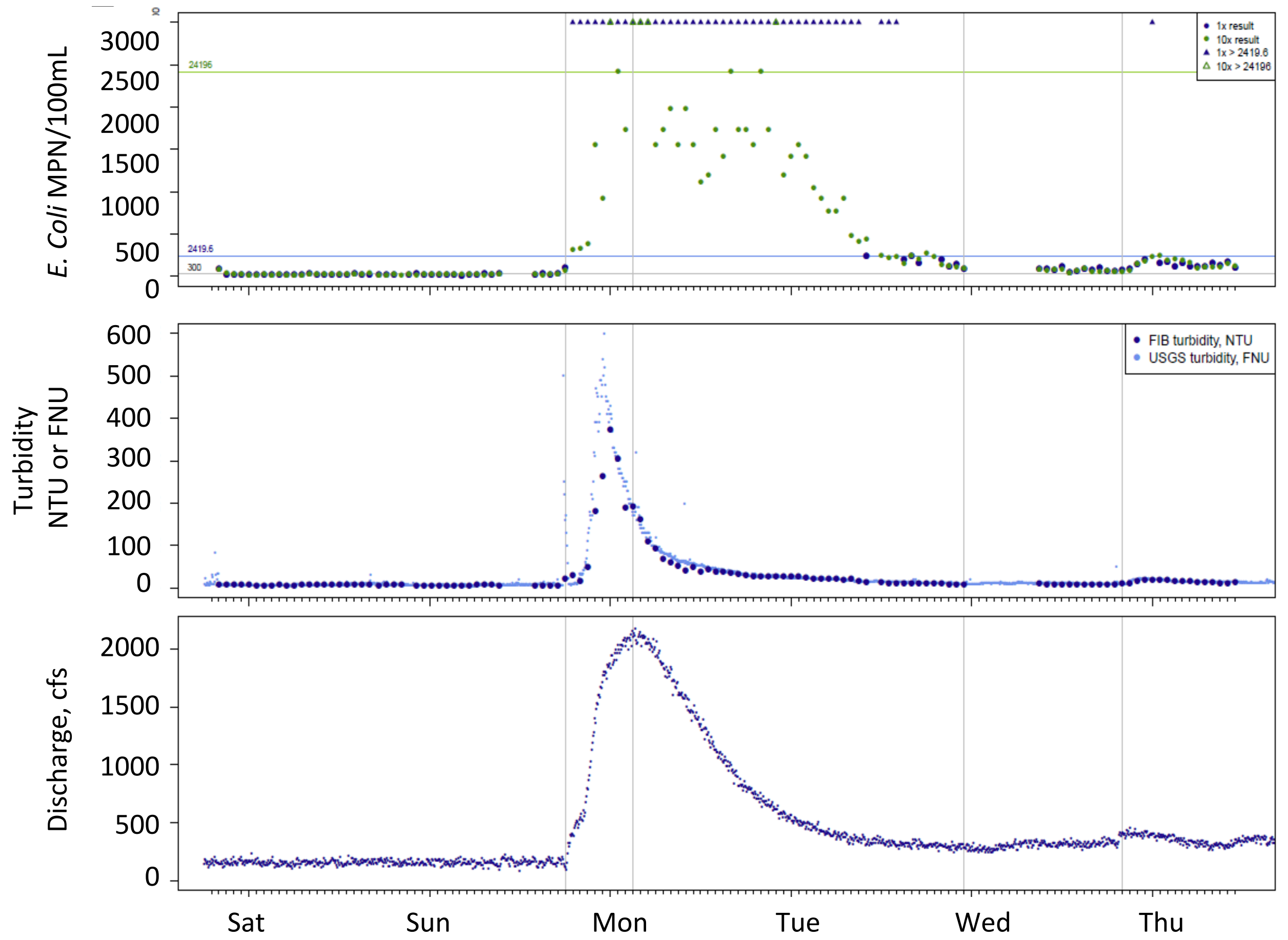

Figure 6: Observation of *E. coli,* turbidity, and river discharge immediately preceding and throughout a July 2014 rainfall event. From left to right, light gray vertical lines indicate the beginning of the initial rainfall response, the peak of river discharge, return to baseflow conditions, and the slight response from a secondary rainfall event. River discharge and turbidity (FNU) was obtained from the USGS National Water Information System[2].

Correlations between observed *E. coli* and indicators of river influence

We observed that each sampling site has a different relationship to the presence of river tracer as well as flow and load influences from the river on nearshore water quality (figure 7). Because there may be unmodeled sources of *E. coli*, such as waterfowl defecation, contributing to the nearshore water quality as well, these simple correlations help us identify the general relationship between *E. coli* and river influence at any given site. For example, at site A1 we observe a negative correlation to all tracers, flow, and load measurements. In contrast, site D3 expresses all positive correlations with these factors. At other sites we observed little to no correlations (E6), or a mix of positive and negative correlations (C1) (figure 7).

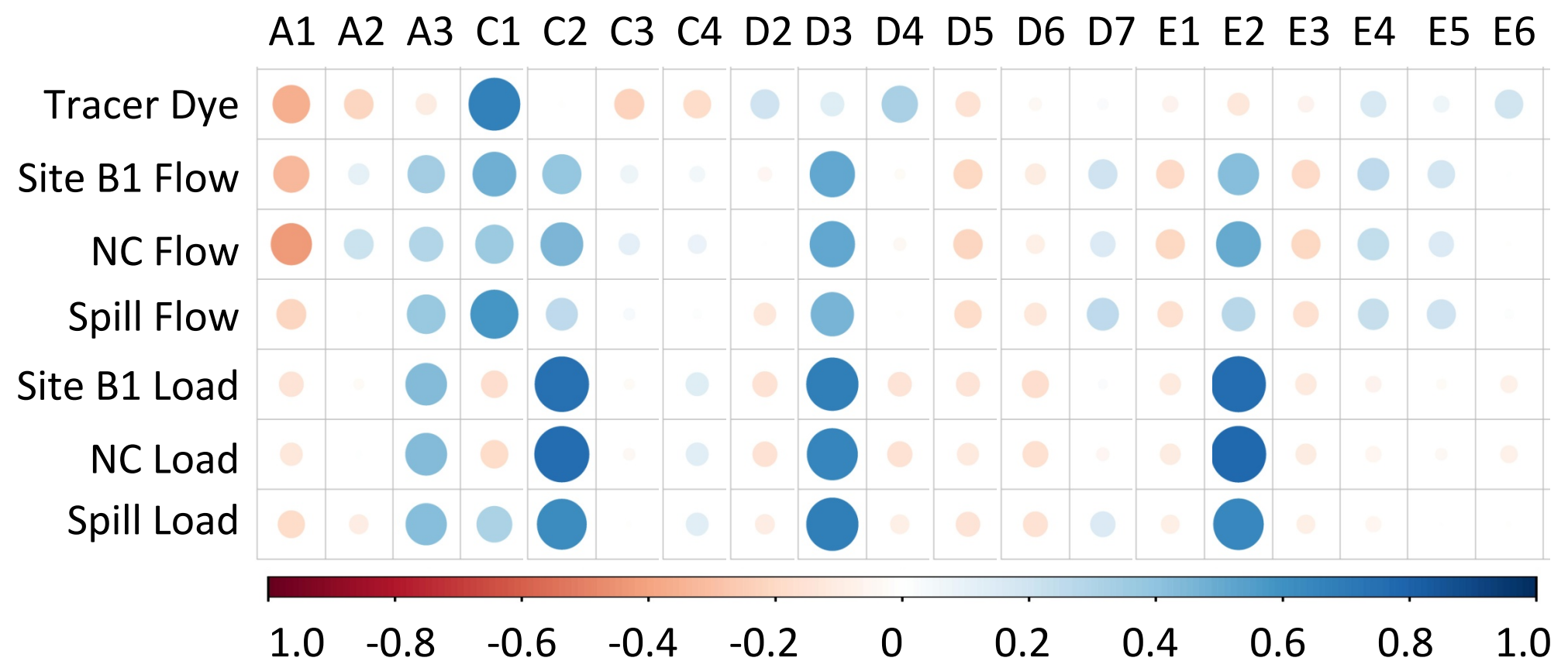

Figure 7: Visual display of correlations between *E. coli* and indicators of river influence. Dots are scaled by both color and size. Larger dots indicate stronger correlations, smaller dots weaker correlations. Darkening shades of red represent increasingly negative correlations while darkening shades of blue indicate increasingly positive correlations. 'Tracer dye' is the modeled ratio of river to lake water concentration produced by the hydrodynamics model[1]. Modeled flow and modeled load correlations are made with *E. coli* in the spillway channel (spill), in the most downstream reach of the natural channel (nc), and upstream of the spillway/natural split at site B1. Please see poster B13F-0250 for more information about the hydrodynamics and loading models.

Conclusions

- Monitoring to inform knowledge of in situ *E. coli* spatial variability indicates that modeling frameworks must be resolvable to the scale of meters.
- Monitoring at multiple temporal scales provides a basis for determining the most appropriate interval water quality models should operate at in order to be most useful as decision-support tools.
- A high temporal understanding of how the pollutant load is distributed over the hydrograph is critical in order to be able translate daily modeled washoff (hydrologic model) into hourly load input for a hydrodynamic-particle model.
- We expect the hydrodynamic model to perform best at locations where there are strong relationships, positive or negative, between observed *E. coli* and indicators of river influence.

References

[1] Anderson, E. J., D. J. Schwab, and G.A. Lang. Real-time hydraulic and hydrodynamic model of the St. Clair River, Lake St. Clair, Detroit River system. Journal of Hydraulic Engineering. August 2010: 507-518 (2010).

[2] USGS National Water Information System: Web Interface, "USGS 04165500 Clinton River at Moravian Drive at Mt. Clemens, MI" http://waterdata.usgs.gov/usa/nwis/uv?04165500

Acknowledgements

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