Linking Benthic Macroinvertebrate Metrics to Stream Hydrology using Functional Data Analysis

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ABSTRACT

The statistical relationship between a stream's flow regime and the ecological function it can support have typically relied on the use of both hydrologic and ecological metrics. Hydrologic metrics cannot fully encompass the key components of the flow regime: magnitude, frequency, duration, predictability, and flashiness. More advanced statistical techniques in the sub-branch of statistics known as "functional data analysis" exist that allow these key components to be used in a single model. A functional linear model was developed by relating hydrology to 117 benthic macroinvertebrate community samples. The model identified statistically significant relationships to stream flow over a 12-month time frame and the characteristics of the benthic macroinvertebrate community ($R^2 = 0.61$). Improvements could be made to the model, such as altering the time frame or adding in additional predictor variables; however, the model has been validated and can be used by ERM staff to help define the minimum flow regime (both quantity and timing of flow) necessary to maintain ecologically healthy streams under the influence of urban stressors.

INTRODUCTION

Urbanization, which can be represented by increasing impervious cover in a watershed, can impact the hydrology of streams by increasing the volume of stormwater that travels to the stream in a shorter time interval during a storm event. This alters the natural flow regime of the stream, for example, by increasing the peak flow during storm events and by reducing the persistence of baseflow due to entrenchment and reduced infiltration. It is an objective of the Environmental Resource Management (ERM) Division to restore baseflow quantity and quality to the maximum extent possible in urban streams and to preserve/restore the natural character in suburban/rural streams (City of Austin 2015). Restoring or preserving baseflow in streams entails mitigating urban stormwater runoff effects to the stream through methods that detain, retain, and infiltrate stormwater. This may redirect urban runoff to infiltration or to move more slowly to the stream following a rain event thereby extending its presence in baseflow. This results in a less altered, or more natural, flow regime in the stream. Thus, an idealistic objective of ERM is to restore or preserve the natural flow regime of Austin streams through managing the runoff of stormwater to the stream.

Unfortunately, the idealistic objective of restoring the natural flow regime in an urban stream is often infeasible and the term "to the maximum extent possible" in ERM's objectives lacks quantitative specificity. Thus, it is unknown how many resources should be expended to mitigate stormwater runoff within a watershed. ERM is undertaking a project called Objective Zero to develop S.M.A.R.T. objectives which are: Specific, Measurable, Achievable, Relevant, and Time-Specific (Herrington 2017). Developing such objectives for hydrology would allow ERM to set specific flow regime targets within a watershed.

Alterations in flow regime have been shown to alter the composition and function of aquatic ecosystems (Stanford and Ward 1979; Poff and Ward 1989; Dynesius and Nilsson 1994; Poff et al. 1997), and therefore it is necessary to maintain the natural flow regime of a stream to preserve the structure and function of healthy aquatic communities (Sparks 1992; Dynesius and Nilsson 1994; Hawley and Vietz 2016). ERM decided to evaluate flow regimes relevant to the integrity of aquatic ecosystems in Austin streams in order to answer the question: how much can the flow regime be altered in Austin streams before the aquatic community composition shifts? This is similar to the evaluation of an "environmental flow" defined by Texas State law. An environmental flow is the flow of water (both quantity and timing of flow) needed to maintain ecologically healthy streams and rivers, as well as bays and estuaries, while balancing human needs (Title 2, Texas Water Code, Section 11.002.16). In 2001, Senate Bill 2 directed the Texas Parks and Wildlife Department (TPWD), Texas Commission on Environmental Quality (TCEQ), and the Texas Water Development Board (TWDB) to establish and maintain a data collection program for instream flows. In addition, the agencies were to conduct studies to establish flow conditions necessary to support a "sound ecological environment". As a result, the Texas Instream Flows Program (TIFP) was created to conduct these studies; however, to date, very few areas of Texas have been addressed because the studies are complex and take many years to complete. However, more general research efforts have produced a body of knowledge for establishing relationships between aquatic communities and characteristics of the flow regime (Kennard et al. 2007; Stewart-Koster et al. 2011; Gido et al. 2013), with some emphasizing environmental flows in human-altered systems (Arthington et al. 2006; Poff et al. 2010; Poff and Zimmerman 2010). ERM has attempted to define an environmental flow for Austin streams in previous work (Scoggins 2000; Glick et al. 2010; Richter 2011).

Benthic macroinvertebrates and diatoms are collected by ERM to represent the aquatic communities in Austin streams. Evaluation of such communities can provide a sensitive measure of contamination or physical and structural degradation of aquatic habitats (Barbour et al. 1999). Community composition is transformed into univariate metrics which reflect aspects of the community structure and function such as intolerant taxa richness (Barbour et al. 1994). Scoggins (2000) demonstrated that hydrologic metrics proposed by Poff and Ward (1989) and Richter et al. (1996) could be related to biological community metrics. Hydrologic metrics are calculated by examining a hydrograph for a period of time and reducing the hydrograph to a single number. Typical hydrologic metrics include the mean flow or peak flow of the hydrograph. In 2010, ERM expanded upon this idea by forming a linear regression model relating various hydrologic metrics to biological metrics of benthic macroinvertebrates in the streams (Glick et al. 2010). Daily average flow data was used to construct the hydrographs which were used to calculate the hydrologic metrics. However, it was thought that the use of smaller time steps in the hydrograph could lead to a more accurate computation of hydrologic metrics. In 2011, ERM further refined the linear regression model between stream hydrology and the response of benthic macroinvertebrates by using hydrologic metrics computed based on stream flow data collected on 15-minute intervals (Richter 2011). Stream hydrology was again characterized using hydrologic metrics, which has often been an approach taken by researchers to describe components of a hydrograph (Olden and Poff 2003; Mathews and Richter 2007; Gao et al. 2009; Kennard et al. 2009).

Many years of using hydrologic metrics to relate hydrology to ecology has resulted in a greater ecological understanding of stream systems along with more informed programs to manage water resources (Richter et al. 2006; Olden et al. 2012). However, there are substantial problems associated with the use of hydrologic metrics. First, there is a large amount of data lost when translating a hydrograph down to a single numerical number such as the average flow or peak flow during a time period. The metrics are descriptors of some aspect of the hydrograph and not a depiction of the flow regime itself. There are five components to consider when attempting to characterize the flow regime of a stream: magnitude of flow, frequency (how often flow exceeds or is below a given magnitude), duration (how long flow exceeds or is below a given magnitude), predictability (regularity of occurrence of different flow events), and rate of change or “flashiness” (how quickly flow changes from one magnitude to another) (Poff and Ward 1989; Richter et al. 1996). One problem related to the loss of data is that a single metric can only describe one of these five components. A second problem is that two very different hydrographs can have the same or similar values for a set of calculated hydrologic metrics.

Another issue with the use of hydrologic metrics is that there are now hundreds of hydrologic metrics that have been developed and it is difficult to decide which metric to select (Olden and Poff 2003). In addition, many metrics are associated with a high level of statistical uncertainty (Kennard et al. 2009). This can make building a sound statistical model that determines an environmental flow difficult because models could be constructed of ecological response variables and potentially disparate hydrologic metrics (Arthington et al. 2006).

More advanced statistical approaches have been incorporated into the realm of hydrology to provide more meaningful hydrologic descriptors of a stream’s flow regime. Fourier and wavelet analysis are examples of quantitative analytical approaches which incorporate a more continuous perspective when attempting to describe a flow regime (Steel and Lange 2007; Sabo and Post 2008). These analytical approaches decompose a set of observed continuous or effectively continuous data into a set of mathematical functions which can be used in statistical analysis (Priestley 1981). Ramsay and Silverman are largely credited with solidifying functional data analysis as an official sub-branch of statistics in 1997, which provides the framework for incorporating the decomposition of functional data into statistical models such as a linear regression model (Ramsay and Silverman 2010). Functional data analysis has seen rapid development over the last 15 years and has reached a level of maturity to where the sub-branch is generally viewed as fundamental to the subject of statistics (Kokoszka and Reimherr 2017). The analysis in this paper uses the functional data analysis framework to build a functional linear model where benthic macroinvertebrate community metrics may be estimated from an entire hydrograph rather than a metric of the hydrograph which incorporates more of the flow regime into the estimate of the health of the aquatic ecosystem.

METHODS

<u>Functional Linear Model Background</u>

In statistics, data is typically analyzed as discrete points, meaning that each point of data has a single qualitative or quantitative value. If the value is quantitative this is known as a scalar quantity and only contains the magnitude of the data point. In a linear regression model, for example, one would take a set of independent scalar quantities and try to create an equation that would accurately predict a set of scalar response quantities using the following equation format:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

where Y_i is the i^{th} value of the response variable, β_0 is a constant intercept, X_i the i^{th} value of the predictor variable, β_1 is the regression coefficient describing the relationship between the response variable and the predictor variable, and ε_i is the residual of the i^{th} observation in the model. The goal of the analysis is to estimate β_0 and β_1 so that Y_i is estimated accurately by the equation. This is why the formation of metrics is important when attempting to analyze biological community or hydrologic data. If the complexity of the data set can be reduced to a single numerical value, then common statistical techniques can be used to analyze the data. In previous work done by ERM staff, a linear regression was developed using an Aquatic Life score scalar quantity to represent a biological community at a certain location in time as a response and different scalar hydrologic metrics as quantities used to predict the Aquatic Life score (Glick et al. 2010; Richter 2011).

Functional data analysis is a newer branch of statistics where data typically consist of continuous observations of a process over space or time that are derived from mathematical functions (Ramsay and Silverman 2002). In other words, functional data analysis arises when one of the variables in a data set can be naturally viewed as a smooth curve or function. Ecological data that fits this description includes continuous temperature readings, continuous dissolved oxygen readings, or stream discharge in the form of a hydrograph (e.g. Ainsworth et al. 2011). This continuous data is called functional data, which is where the branch of statistics derives its name. The simplest form of functional data is as follows:

$$x_n(t_{j,n}) \in \mathbb{R}, t_{j,n} \in [T_1, T_2], n = 1,2, \dots, N, j = 1, \dots, J_n$$

Or that N different curves, x_n, are observed on a common time interval [T_1, T_2]. The observed values of the curves are only known at specific points in time, $t_{j,n}$, which can be different for different curves. However, in functional data analysis one would study smooth curves of the form:

$$x_n(t): t \in [T_1, T_2], n = 1,2, \dots, N$$

for which the values of each curve, $x_n(t)$, exist at any point t in the common time interval [T_1, T_2]. This can be accomplished by expressing the functional data as a basis expansion:

$$x_n(t) \approx \sum_{k=1}^{K} c_{nk} B_k(t)\,, 1 \leq n \leq N$$

where B_k are some collection of basis functions, such as splines, wavelets, or sine and cosine functions. The idea is that functional data are observations from smooth curves that share some shape properties and can be approximated as linear combinations of some K basic shapes B_k. Then each curve, x_n, is represented by a column vector $c_n = [c_{n1}, c_{n2}, \dots, c_{nK}]$. Two common types of basis functions used to convert the observations to mathematical functions are Fourier basis functions and B-splines (Ramsay and Silverman 2010). Fourier series are the decomposition of a periodic series into the sum of sine and cosine waves which can be used to quantify the frequencies of periodic patterns in time series (Sabo and Post 2008). Examples might include daily temperature or dissolved oxygen fluctuations. B-spline curves consist of a series of joined polynomial functions which do not rely on periodic patterns in the data. Thus, using B-spline curves allows for more flexibility when quantifying functional data (Ramsay and Silverman 2010). Seasonality may exist in long-term hydrologic data due to local climatic factors such as rainfall patterns; however, periodic patterns may not exist when the time interval being considered is relatively short such as one year or shorter. Thus, using B-spline basis functions may be more appropriate to define the hydrograph as a functional predictor variable when time intervals are shorter than one year (e.g. Ainsworth et al. 2011).

Once a set of mathematical functions has been determined to describe each curve, x_n, it is important to consider what specific goas are to be achieved with those functions. Goals of performing analysis within the functional data analysis sub-branch of statistics include, but are not limited to, the desire to understand characteristics of the functional data itself, categorize functional data from different sample sources, or to use functional data to predict a response variable (either scalar or functional) (Kokoszka and Reimherr 2017). The goal of this analysis is to predict a benthic macroinvertebrate community metric (scalar quantity) from a stream hydrograph (functional data) through the development of a functional linear model (Ramsay and Silverman 2002; Müller and Stadtmüller 2005). The model would relate the community metric at a single point in time to the hydrograph over a specified time interval. Thus, hydrologic metrics are no longer used as predictor variables and instead the entire hydrograph takes their place.

The mathematical form of a simple functional linear model is that of an integral equation:

$$Y_n = \beta_0 + \int \beta_1(t) x_n(t) dt + \varepsilon_n, 1 \leq n \leq N$$

where Y_n is the n^{th} value of the response variable, β_0 is a constant intercept, $x_n(t)$ are the set of N curves derived from methods in the above paragraphs, $\beta_1(t)$ is the regression coefficient describing the relationship between the response variable and the predictor variable at time t, and ε_n is the residual of the n^{th} observation in the model. This is the general form of a scalar-on-function (scalar response with functional predictor variable) functional linear model. The goal of the analysis is to estimate β_0 and $\beta_1(t)$ such that Y_n can be predicted accurately by the equation. The simplest approach to the solution is to expand the function β_1 using basis functions as described above which results in:

$$\beta_1(t) = \sum_{m=1}^{M} a_m D_m(t)$$

where D_m are some set of basis functions and $\beta_1(t)$ will be approximated as a linear combination of M basic shapes D_m. The vector $a = [a_1, a_2, \ldots, a_M]^T$ is then estimated as $\hat{a} = (X^T X)^{-1} X^T Y$ where

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1M} \\ x_{21} & x_{22} & \cdots & x_{2M} \\ \vdots & \vdots & \vdots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{NM} \end{bmatrix}$$

and the estimate of $\beta_1(t)$ is

$$\widehat{\beta_1}(t) = \sum_{m=1}^{M} \hat{a}_m D_m(t)$$

The selection of basis functions D_m influences the shape of the solution along with the selection of M. A reasonable approach is to use the same basis functions chosen for the predictor variable and to experiment with several selections of M (Kokoszka and Reimherr 2017).

Data Collection

Benthic Macroinvertebrates

Benthic macroinvertebrate data has been collected by ERM staff since 1994 and involves the identification and enumeration of aquatic invertebrate taxa present at a given site representing designated reaches on a two- or three-year rotating schedule. Methodology for the collection of macroinvertebrate communities has primarily been three-surber composites in riffle habitat; however, kick-nets have been used when baseflow is lacking. Protocols may be found in the ERM Standard Operating Procedures Manual (ERM 2019). For each sample collected, ERM staff computes 22 univariate metrics that help describe the structural and functional attributes of the biological communities. Each year, nine of these biological metrics are combined to calculate a Bug Sub-Index score, which is used as a part of the Environmental Integrity Index (EII) total score that represents the overall aquatic health of a site. The subset of biological metrics used in the Bug Sub-Index includes: number of taxon, percent dominance (top 3 taxa), Hilsenhoff Biotic Index, number of Ephemeroptera taxa, number of EPT taxa, number of intolerant taxa, percent of total as Chironomidae, percent of total as EPT, and percent of total as predators (Barbour et al. 1999; TCEQ 2005).

In addition to the nine standard metrics that are calculated as a part of the EII, four additional metrics were designed by ERM staff that were intended to reflect a regionally specific condition of flow permanence (or lack thereof). The four additional metrics calculated for use in this analysis were: percent of Ephemeroptera as Baetidae, percent of total as long-lived taxa (defined as dobsonflies and dragonflies), percent of total as short-lived taxa (defined as belonging to the families Chironomidae, Culicidae, Ceratopogonidae, or the genus Fallceon), and percent of total as Hemiptera (personal communication Todd Jackson). These additional benthic metrics along with the Bug Sub-Index were selected to be response variables in separate functional linear models. Metrics were calculated using a script developed in SAS version 9.4.

Flow Hydrographs
In order to use functional data analysis to create a predictive model of benthic macroinvertebrate communities from a flow regime, rich data sets of flow readings are needed from flow gages near sites where benthic macroinvertebrate communities have been sampled. WPD has a long-standing contract with the United States Geological Survey (USGS) in which WPD pays the USGS to operate and maintain flow gages in Austin, Texas. Following data quality checks performed by the USGS, the WPD uploads the records into a Hydstra database. In addition, WPD has a storm monitoring team which assembles, operates, and maintains additional flow gages in Austin. Data collected at storm monitoring sites are verified and validated by WPD staff and then archived in the Hydstra database. WPD biologists speculate that a flow regime one year prior to a benthic macroinvertebrate sample collection event was a reasonable time interval to use as a predictive variable because the majority of benthic macroinvertebrates in the Austin area are univoltine or multivoltine (personal communication Todd Jackson). Macroinvertebrate data has been collected in Austin streams since 1994, thus, the average daily flow from each gage collected between 1993 and 2017 was pulled from the Hydstra database.

Site Selection
Sites for which benthic macroinvertebrate data was available near flow gages were selected for this study to enable comparison of the biologic data to the hydrologic data. When a direct match was not available, a representative site (upstream or downstream) was selected such that the hydrology would be similar to the flow gage (Table 1). Sites were not used in the analysis if a hydrologically comparable site was unavailable. Sites include a mixture of perennial/intermittent streams, small/large drainage areas (715 to 207,310 acres), and varying levels of impervious cover in each site's watershed (7 to 46%).

The date was recorded for each macroinvertebrate sampling event and the daily average flow of the associated flow gage for exactly one year prior to that date was used as the predictor variable for that data point. Macroinvertebrate data at a given site was typically collected once every three years through 2008 and then once every two years starting in 2009. The year of each macroinvertebrate sampling event associated with a site and flow gage is listed in Table 1.

Roughly 10% of the samples were not used in the training data set, or the data used to develop the model, but were instead used to validate the model. This means that after the functional linear model was created from the training data set, hydrology from the validation data set was run through the model and new Bug SubIndex scores were predicted for these data points. Observed Bug SubIndex values were compared to the predicted values to determine if the model developed can accurately predict values from data outside of the training data set. The validation data set included any samples collected prior to 2000 or any samples that were thought to be outliers. Outliers were included in the validation data because no formal outlier analysis was done to classify them as such. They were classified as outliers by the analyst's best professional judgement based on precipitation data from Austin-Bergstrom International Airport each year and comparing the precipitation to the hydrology of a site in each year. A year of hydrology data which was different from hydrology at the same site in other years where precipitation was similar was classified as an outlier. It was still of interest to examine the predicted model results for these samples to determine if the model could accurately predict Bug SubIndex scores, in case the judgement of the analyst was incorrect regarding the hydrology of these samples.

Table 1: Flow gages and associated benthic macroinvertebrate sample location with sample year for sites in which flow data was available. Underlined and red samples were not used in the development of the model but were instead used in a validation data set.

Gage ID	Flow Gage Location	Biological Sample Location	Years Sampled
USGS Flow Gages			
08155240	Barton Ck @ Lost Ck. Blvd.	51-Barton Ck DS of Lost Creek Blvd	'06, '09, '11, '13, '15
08155200	Barton Ck @ State Hwy 71	48-Barton Ck @ Hwy 71 DS of Little Barton	'96, '03, '06, '09, '11, '13, '15
08155400	Barton Ck above Barton Springs	879-Barton Ck Between Dams US of Pool	'00, '03, '09, '11, '13, '15
8158810	Bear Ck below FM 1826	1534-Bear Ck DS of Bear Creek Pass	'04
		4112-Bear Ck @ Bear Creek Pass	'07, '10, '12, '14
08158819	Bear Ck nr Brodie Lane nr Manchaca	3935-Bear Ck @ Escondido	'07
08157700	Blunn Ck near Little Stacy Park	180-Blunn Ck @ Riverside Drive	'00, '03, '06, '09, '11, '13, '15
08158050	Boggy Ck @ US Hwy 183	493-North Boggy Ck @ Delwau Lane	'00
08158030	Boggy Ck at Manor Rd at Austin	2754-North Boggy Ck @ Manor Rd	'09, '11, '13, '15
08158035	Boggy Ck at Webberville Rd	837-North Boggy Ck @ Nile Street	'09, '11, '13, '15
08154700	Bull Ck @ Loop 360	350-Bull Ck @ Loop 360 First Crossing	'96, '01, '04, '10, '12, '14
08157600	East Bouldin Ck @ South 1st St.	119-East Bouldin Ck @ Elizabeth St	'00, '03, '06, '09, '11
08105886	Lake Ck @ Lake Creek Parkway	1100-Lake Ck DS of Meadowheath Drive	'12, '14
08158380	Little Walnut Ck at Georgian Dr	3860-Little Walnut Ck @ Georgian Dr	'09, '11, '13, '15
08158827	Onion Ck at Twin Creeks Rd nr Manchaca	236-Onion Ck @ Twin Creeks Road	'07, '10, '12
08159000	Onion Ck @ US Hwy 183	255-Onion Ck @ McKinney Falls ds Lower Falls	'01, '04, '07, '10, '12, '14
08158700	Onion Ck near Driftwood	612-Onion Ck near Driftwood (Hwy 150)	'98, '04, '07, '10, '12, '14
08156800	Shoal Ck @ 12th St.	122-Shoal Ck US of 1st St	'95, '96, '00, '03, '06, '09, '11, '13, '15
08158840	Slaughter Ck @ FM 1826	623-Slaughter Ck @ FM 1826	'07, '10, '12, '14
08157500	Waller Ck @ 23rd St.	624-Waller Ck US of 23rd Street	'00, '03, '06, '09, '11, '13, '15
08156910	Waller Ck at Koenig Ln	780-Waller Ck @ 51st Street	'09, '11, '15
08158600	Walnut Ck @ Webberville Rd.	503-Walnut Ck Upstream of Freescale	'00, '03, '06, '09, '13, '15
08155541	West Bouldin Ck at Oltorf Rd	3854-West Bouldin Ck @ Oltorf Street	'09, '11, '13, '15
City of Austin Watershed Protection Flow Gages			
FBU	Bear Ck @ FM 1826	600-Bear Ck @ FM 1826 (South Fork)	'98, '01
FTB	Fort Branch	898-Fort Branch Ck @ Single Shot Circle	'11, '15
WRE1192	Gilleland Ck @ FM973	1192-Gilleland Ck @ FM 973	'02, '05, '08, '09, '11
LBA	Little Bear Ck above Recharge	3374-Little Bear @ Ashmun Property	'10, '12, '14

Data Analysis

Functional Linear Model

The functional linear model was developed in R 3.5.2 (R Core Team 2018) using the RStudio IDE (RStudio Team 2016) and the *fda* (*v2.4.8*; Ramsay et al. 2018) and the *fda.usc* (*v2.0.1*; Febrero-Bande and Oviedo de la Fuente 2012) packages. Flow data was log transformed following suggestions from Stewart-Koster et al. (2014) and Ainsworth et al. (2011) to reduce skewness in the predictor variables and facilitate regression coefficient estimation. The transformed data was used to create a functional data object, or a continuous interpolated line (e.g., Figure 1A). The first and second derivatives of flow were calculated from the functional data object (e.g., Figure 1B-1C), and the absolute value of each derivative was computed for use in the linear model.

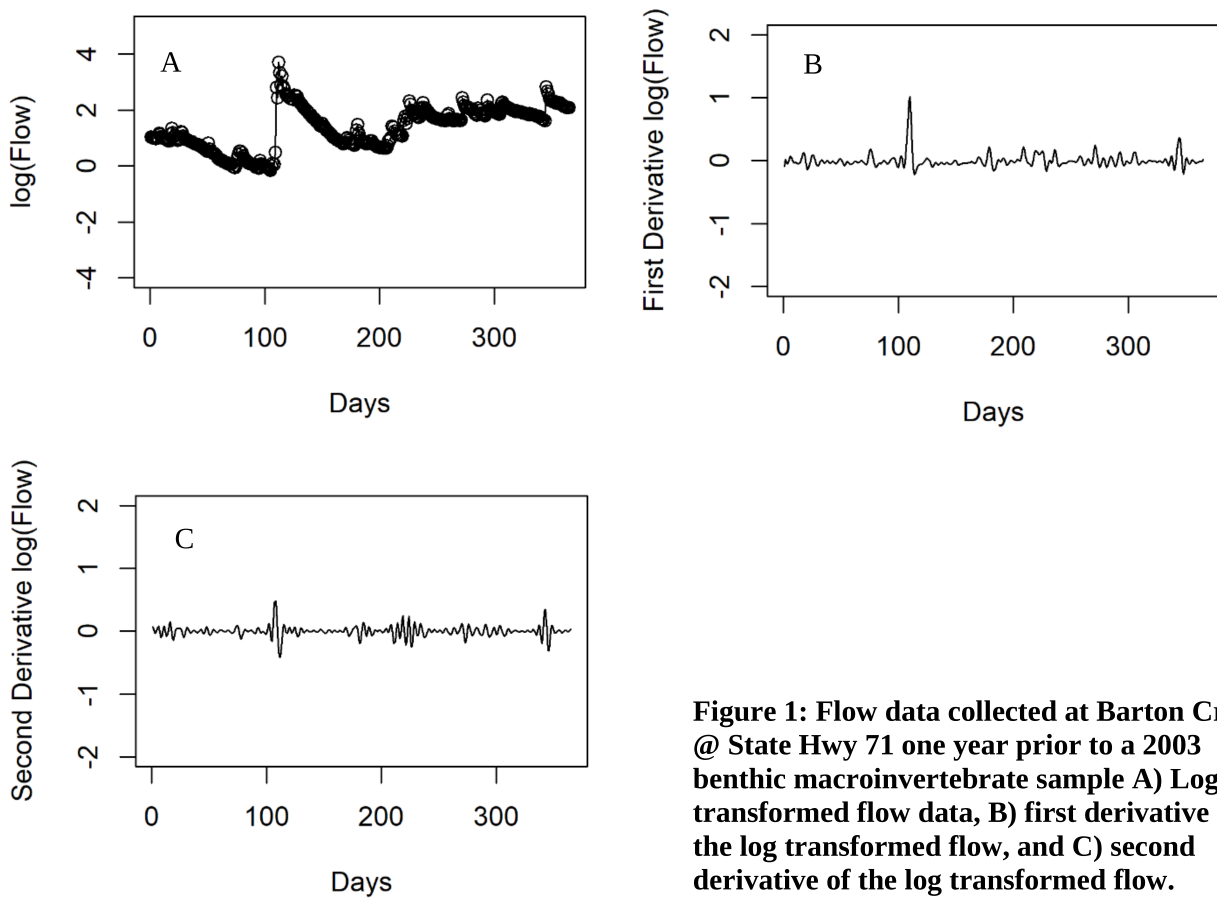

Figure 1: Flow data collected at Barton Creek @ State Hwy 71 one year prior to a 2003 benthic macroinvertebrate sample A) Log transformed flow data, B) first derivative of the log transformed flow, and C) second derivative of the log transformed flow.

While the creation of the functional data object creates a continuous line, it does not create a smooth function from which to perform statistical analyses. Thus, basis expansion was then done to create a set of basis functions for the flow data, first derivative, and second derivative. B-splines were used as basis functions for all three covariates and the number of functions used was set to 150, in order for the linear combination of the basis functions to closely mimic the daily average flow following suggestions from Ainsworth et al. (2011) and Stewart-Koster et al. (2014). An example of the combined basis functions can be seen in Figure 2. Notice that the function produced by the basis functions (Figure 2A) is very similar to the observed data (Figure 2B) but on occasions when the daily average flow spikes and rapidly decreases, the function is dampened and does not quite reach the level of flow seen in the observed data.

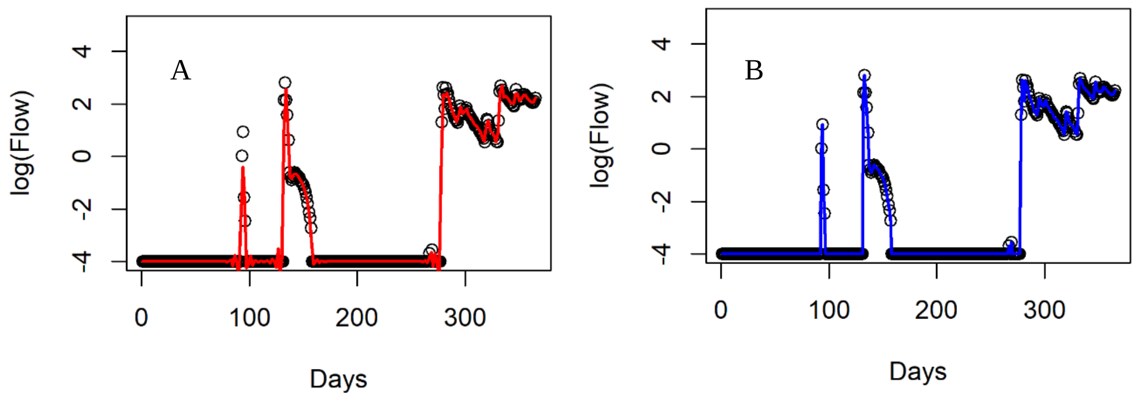

Figure 2: A) Function created through basis expansion of flow data observations in Barton Ck above Barton Springs one year prior to a benthic macroinvertebrate sample collected in 2000 to be used in statistical analysis and B) functional data object connecting each data point for the same flow data.

The below formulas were used to estimate the regression coefficients β_1, β_2, and β_3 for the functional covariates of daily average flow, first derivative of the flow (xd), and second derivative of the flow (x2d), respectively.

$$Bug\ SubIndex_n = \beta_0 + \int \beta_1(t) Flow_n(t)\, dt + \varepsilon_n$$

$$Bug\ SubIndex_n = \beta_0 + \int \beta_1(t)\, Flow_n(t) dt + \int \beta_2(t)\, xd_n(t) dt + \varepsilon_n$$

$$Bug\ SubIndex_n = \beta_0 + \int \beta_1(t)\, Flow_n(t) dt + \int \beta_2(t)\, xd_n(t) dt + \int \beta_3(t) x2d_n(t) dt + \varepsilon_n$$

The first equation was developed to determine if the log transformed daily average flow could be used to predict the Bug SubIndex while the second and third were developed to determine if the first and second derivatives of the flow increased the predictability of the model. Similar models were intended to be run for the following community metrics: percent of Ephemeroptera as Baetidae, percent of total as long-lived taxa (defined as belonging to the Order Megaloptera or the Suborder Anisoptera), percent of total as short-lived taxa (defined as belonging to the Families Chironomidae, Culicidae, Ceratopogonidae, or the Genus Fallceon), and percent of total as Hemiptera.

Recall that the solutions for β_1, β_2, and β_3 involved basis expansion and that the number of basis functions used in the expansion can influence regression coefficients. Thus, multiple runs of the above equations were performed using various numbers of basis functions for β_1, β_2, and β_3. When the number of basis functions are chosen, the data set of flow is cut into equal interval parts. If it is desired to make each basis function represent a week of flow data then the number of basis functions is set to 52 since there are 52 weeks in a year. The initial number of basis functions chosen for each regression coefficient was 26, which corresponds to a two-week time interval as suggested by Ainsworth et al. (2011) and Stewart-Koster et al. (2014). The maximum number of basis functions that could be used in the model before mathematical instability was detected was 40, so this was chosen as the maximum number of basis functions used for analysis. The number of basis functions used was decreased to 17 (~three week intervals), 13 (~four week intervals), 10 (~five week intervals), 8 (~six week intervals), 7 (~7 week intervals), 6 (~8.5 week intervals), and 5 (~10 week intervals) which was the minimum number of basis functions allowable in the model before reaching mathematical instability on the lower range. Regression coefficients and R^2 values were computed for each iteration of the model using the *fregre.lm()* function in RStudio.

The developed model was then validated by running hydrology data from the data points marked as validation data in Table 1 through the model using the *predict()* function in RStudio. Predicted metrics were then compared to the observed metrics to determine if the model could accurately predict benthic macroinvertebrate community metrics outside of the training data set (the data used to develop the model).

RESULTS

The only results discussed in this report are those from the functional linear model using the EII Bug SubIndex as a response with both daily average flow and the first derivative as functional predictors. This is because the functional linear model using the EII Bug SubIndex as a response with only daily average flow as the functional predictor explained substantially less variability than when the first derivative was added as a predictor and thus does not predict the EII Bug SubIndex as well. The other benthic macroinvertebrate metrics that were designed by ERM biologists that were calculated are summarized below in Figure 3 The percent of Ephemeroptera as Baetidae, percent of long-lived taxa, and percent as Hemiptera metrics did not possess the range of data needed to develop a sound linear model for prediction. An important note is that long-lived taxa (dobsonflies and dragonflies) and Hemiptera were absent in almost all of the macroinvertebrate samples. The percent of total as short-lived taxa metric did span a large enough range to develop a functional linear model (Figure 3); however, the model that was produced was not significant, had a low R^2 value, and did not predict values well outside of the training data set. Thus, these four metrics will not be discussed further.

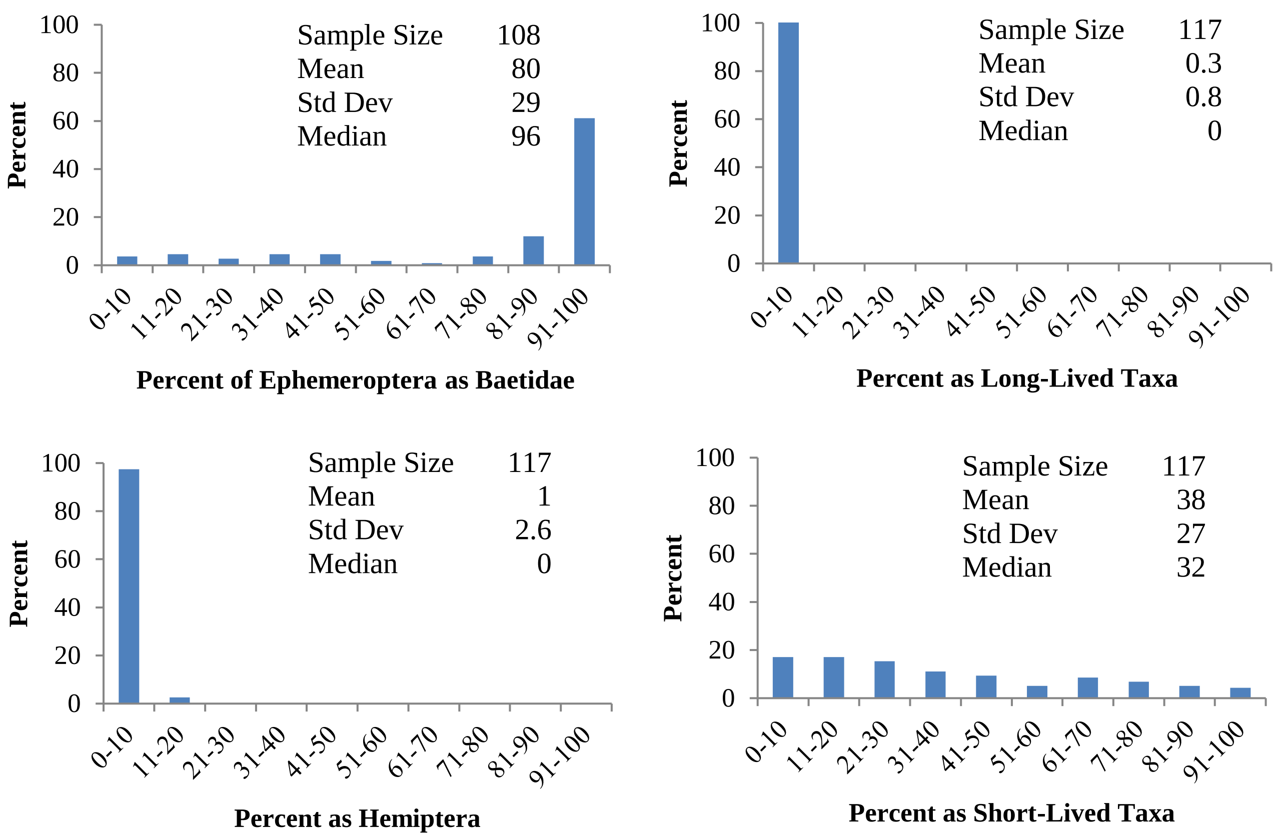

Figure 3: Histograms and summary statistics for percent of Ephemeroptera as Baetidae (upper left), percent of total as long-lived taxa (upper right), percent of total as Hemiptera (lower left), and percent of total as short-lived taxa (lower right). The sample size is smaller for percent of Ephemeroptera as Baetidae because there were no Ephemeroptera in nine of the samples.

Multiple models were developed using both average daily flow and the first derivative of the flow as functional predictors with a varying number of basis functions for the regressor coefficients, β_1 and β_2. Each model developed was significant ($p < 0.05$) and fit the data relatively well (Table 2). When the number of basis functions for the daily average flow was increased from 5 to 17 there was not a noticeable difference in the R^2 values; however, when the number of basis functions increased to 26 there was a noticeable increase in the R^2. Which means that substantially more variation in the data can be explained using 26 basis functions when compared to anything lower that was tested. Another substantial jump in the R^2 value can be seen when the number of basis functions increased to 40.

When the regressor coefficient for the first derivative changed from a constant over time to being allowed to vary over time (i.e. any of the models where number of basis functions were set), the R^2 value always increased substantially. This indicates that the derivative should be a functional regressor as the influence of the derivative on the Bug SubIndex changes over the one-year time interval. Very little change is noted in the R^2 values when the number of basis functions changed from 5 to 10 for the first derivative; however, substantial increases occurred when the number of basis functions was set to 13, 17, and 40 (Table 2).

Table 2: R^2 values for each iteration of the functional linear model using the Bug SubIndex as a response and both the average daily flow and derivative of flow as functional predictors. The iterations were done to vary the number of basis functions used to expand the regression coefficients for each predictor. The number of basis functions ranged from 5 to 40 for each predictor with an extra model run with the coefficient set to a constant for the derivative. As the R^2 values increase, predicted Bug SubIndex values will match observed Bug SubIndex scores within the model more accurately (lighter to darker shading). These models also become more complex with the darker shading and can lead to overfitting (low predictability of Bug SubIndex scores from new flow data). The model with the highest R^2 value (highlighted in black) and the model that is used to make inferences (highlighted in blue) are discussed in the paragraphs below.

Predictor		First Derivative of the Flow										
	No. of basis functions	Constant	5	6	7	8	9	10	13	17	26	40
Daily Avg. Flow	5	0.56	0.59	0.60	0.61	0.60	0.60	0.60	0.62	0.64	0.65	0.73
	6	0.57	0.60	0.61	0.61	0.60	0.60	0.60	0.63	0.64	0.65	0.73
	7	0.57	0.60	0.61	0.61	0.60	0.60	0.61	0.63	0.64	0.65	0.72
	8	0.57	0.60	0.61	0.61	0.60	0.60	0.61	0.63	0.64	0.64	0.72
	9	0.57	0.60	0.61	0.60	0.60	0.59	0.60	0.62	0.63	0.63	0.71
	10	0.57	0.59	0.60	0.60	0.59	0.59	0.59	0.62	0.63	0.63	0.71
	13	0.56	0.59	0.61	0.62	0.61	0.60	0.61	0.64	0.65	0.64	0.74
	17	0.57	0.59	0.62	0.63	0.62	0.62	0.63	0.65	0.67	0.68	0.77
	26	0.63	0.63	0.66	0.66	0.67	0.67	0.67	0.69	0.70	0.69	0.78
	40	0.69	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.75	0.76	0.81

It would stand to reason that the appropriate model for future use is the functional linear model with 40 basis functions for each functional predictor as the R^2 value was the highest for this model ($R^2 = 0.81$). However, very little can be said about the flows relationship to the Bug SubIndex upon examining the estimated β_1 and β_2 over the one-year time interval from this model (Figure 4) because the function is overly complicated. In addition, using this model to predict a Bug SubIndex using data outside of the training data set led to many incorrect predictions. The Bug SubIndex ranges from 0 to 100 and some predicted values were negative while others were approximately 150. This indicated that this particular model was likely overfit and should not be selected for further discussion.

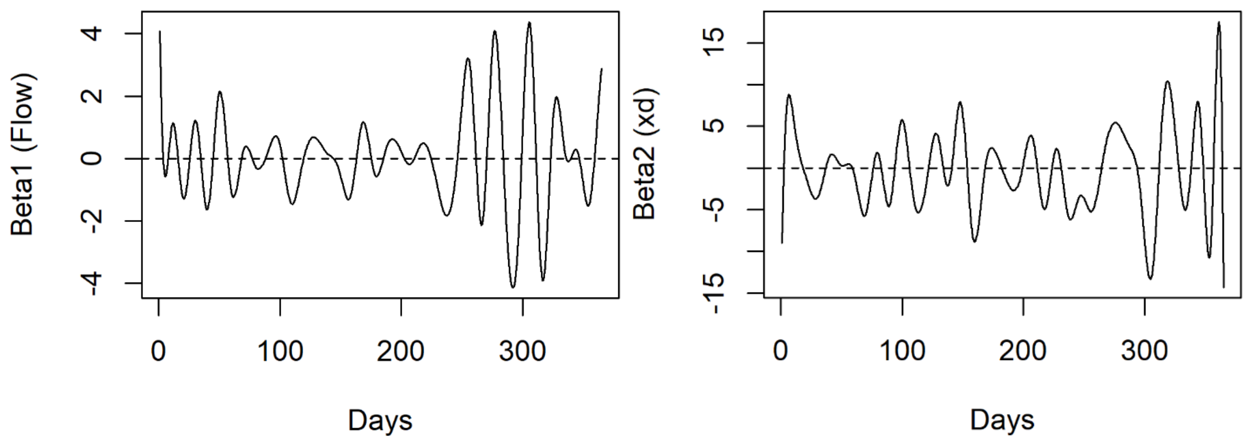

Figure 4: Estimates of the functional regression coefficients for average daily flow, β_1 (left), and the first derivative of flow, β_2 (right), using 40 basis functions for each functional regressor. Little inference can be made about the relationship of hydrology to the benthic macroinvertebrate community because the number of basis functions is too high.

It is very difficult to make a reasonable inference between the relationship of hydrology and benthic macroinvertebrate communities until you reduce the number of basis functions to below 10 for each functional predictor. In addition, it is a best practice to limit the complexity of a model unless substantially more can be explained by adding complexity to the model. In this case, adding complexity means increasing the number of basis functions. If this practice were to be followed the model using six basis functions for each functional predictor would be selected to discuss further ($R^2 = 0.61$, Table 2). However, as discussed in Ainsworth et al. (2011) and Stewart-Koster et al. (2014), the selection of the number of basis functions can alter your model interpretations. Thus, the coefficient estimates for every model with the number of basis functions ranging from five to ten were visually examined to see if the model interpretations would be different. While the interpretations were not thought to be different between the different models, the model using five basis functions for the average daily flow and seven basis functions for the first derivative was thought give the best interpretation of the relationship between hydrology and the benthic macroinvertebrate community.

The regression coefficient for the average daily flow starts out positive and then drops to a negative value around day 50. The negative trend continues until around 150 days where the value switches back to a positive number and increases until day 365 (Figure 5), which is the day of the benthic macroinvertebrate sample. Many of the macroinvertebrate samples are taken in May or June every year, so day zero would typically relate to May/June directly after the sample is taken. Day 50 would be associated with a July/August time frame, day 150 with September/October, and day 300 with March/April. According to the model, having flow in the stream from May/June to July/August and from September/October to May/June will cause the Bug SubIndex value to increase but having flow in the stream from July/August to September/October will cause the Bug SubIndex to decrease. Speculation on a reason for these results is provided in the discussion section. The derivative of the flow is related to how much change is experienced in the average daily flow on a day-to-day basis. If there is a large increase or decrease in the average daily flow from the previous day, the derivative will be large. The model indicates that from May or June when the benthic macroinvertebrate sample is taken to approximately late February or early March, large changes either positive or negative in flow will decrease the Bug SubIndex value. However, large changes in the daily average flow rate will increase the Bug SubIndex if they occur from March to early May (Figure 5).

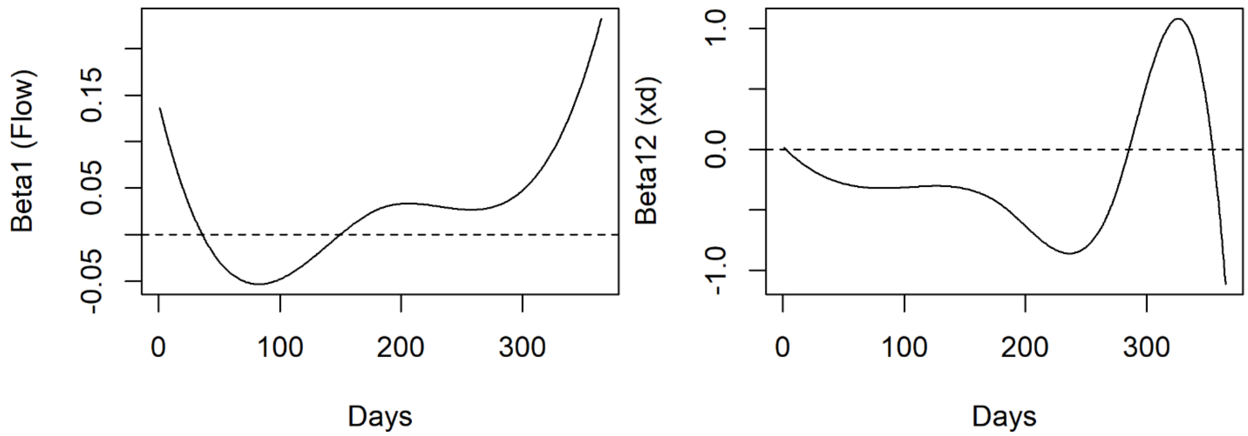

Figure 5: Estimates of the functional regression coefficients for average daily flow, β_1 (left), and the first derivative of flow, β_2 (right), using five basis functions for average flow coefficient and seven basis functions for the derivative coefficient. The Bug SubIndex will improve substantially when there is more flow in the stream approx. 60 days prior to the sample based on β_1. Large increases or decreases in flow from day to day throughout the one-year time interval result in worse Bug SubIndex values with the exception of approx. 60 day prior to the sample which are related to increases in the Bug SubIndex based on β_2.

Residuals indicate how much difference there is between a predicted Bug SubIndex and the observed Bug SubIndex. A valid model should not contain any patterns in the residuals. The overall dispersal of the residuals looks to have a slight upward trending pattern but does not make the model invalid (Figure 6). Plots of the predicted Bug SubIndex against the observed Bug SubIndex show this relationship in an easier to understand manner (Figure 7). The plots indicate that the model slightly underestimates the Bug SubIndex at the lower end of the Bug SubIndex and overestimates the Bug SubIndex at the higher end. The range of the residuals is more concerning. It is not uncommon for the model to predict a Bug SubIndex which is 20 points away from the observed value. For reference, the EII Bug SubIndex is broken into eight categories, with a range of 12.5 each, which designates the qualitative health of the benthic macroinvertebrate community. This ranges from poor (0 to 12.5) to excellent (87.6 to 100). Dotted lines are provided in the residual plot and the predicted vs observed plot to display when the model predicted a Bug SubIndex score more than one category away from the observed Bug SubIndex (Figures 6 and 7).

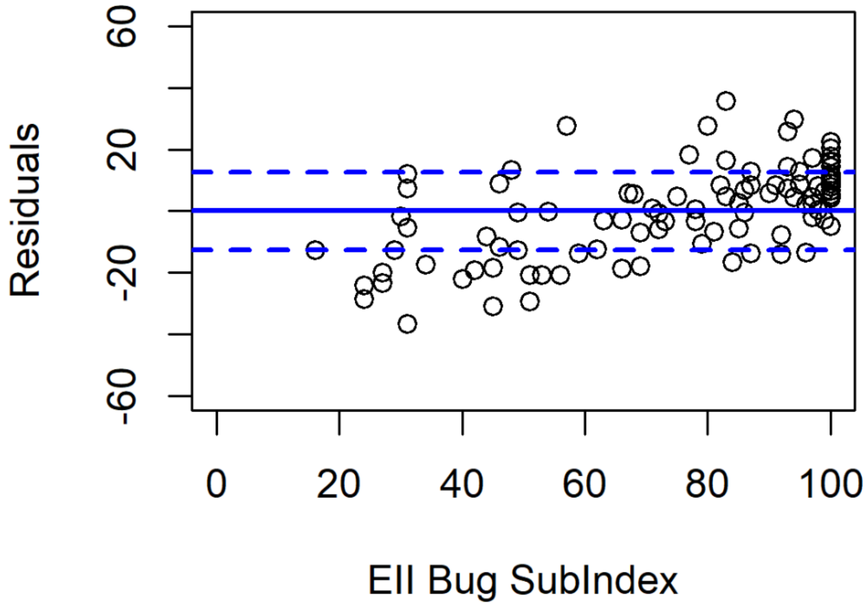

Figure 6: Residual plot for the functional linear model using average daily flow and the derivative of the flow as functional predictors. A valid model should produce a residual plot with points scattered randomly about zero. Residual plots show a slight pattern with lower residuals at lower EII Bug SubIndex scores. Dotted lines provide reference to when the difference between predicted values and observed values was > 12.5 (range of an EII scoring category).

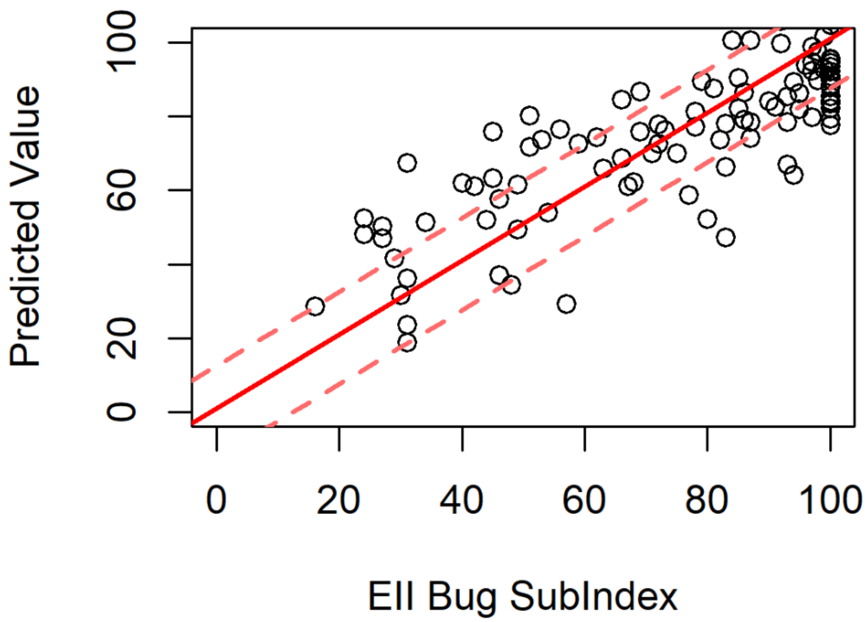

Figure 7: Predicted vs observed Bug SubIndex values for the functional linear model using average daily flow and the derivative of the flow as functional predictors. The model tends to slightly underpredict at lower Bug SubIndex values and overpredict at high Bug SubIndex. The solid red line provides a reference for when the predicted value would match the observed value perfectly and the dotted red lines provide reference to when the difference between predicted values and observed values was > 12.5 (range of an EII scoring category).

About two-thirds of the Bug SubIndex values were predicted well from the validation data set (Figure 8). The remaining one-third was substantially incorrect. These inaccurately predicted values were not always considered "outliers" though, because some could be rationally explained. For example, the most inaccurately predicted sample was collected from Shoal Creek at 12th Street in 1995 and was not considered an outlier. The hydrograph showed the hydrology to be highly flashy with large changes in daily average flow and little to no flow in the stream outside of rain events. The model predicted a low Bug SubIndex value but the actual value that year was quite high at 78. The sample was taken during the month of June along with all biological samples collected for EII during 1995. Many of the metrics calculated for the Shoal Creek at 12th bug community in 1995 were similar to sites which ERM staff would consider reference or minimally disturbed. The Bug SubIndex is normalized on a score of 0 to 100 each year, so for years in which reference sites reflected poor bug communities then Bug SubIndex scores would be elevated at nonreference sites. This appears to be the case for this 1995 sample. In 1996, reference site locations had substantial increases in certain metrics (e.g., TCEQ Quantitative Aquatic Life Use) while the Shoal Creek at 12th community did not respond in kind and the Bug SubIndex for the Shoal Creek site in 1996 was calculated as 30. This is a flaw of the current model due to the normalization of the Bug SubIndex. Performing the analysis on non-normalized metrics may improve predictive performance. However, it should also be noted that it is possible that some of variability in score could be related to field staff and site-specific collection differences.

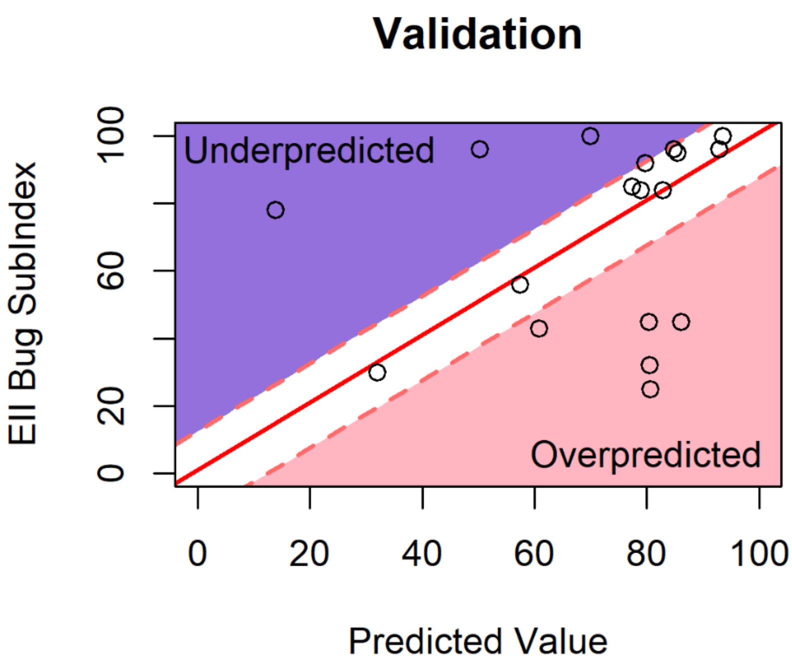

Figure 8: Predicted values of the Bug SubIndex versus Bug SubIndex values calculated from bug samples. These samples were not used to create the model but instead new flow data was inserted into the created model to investigate how well the model can predict EII Bug SubIndex values from new flow data. Perfect predictions would fall along the diagonal line. Four samples were predicted extremely well, six more samples fit closely, and eight samples were predicted poorly (> 12.5 points away from the actual score). Four samples were underpredicted (purple region) and five samples were overpredicted (pink region).

Another sample that was underpredicted was taken from Little Bear Creek upstream of the Recharge Zone (flow at LBA gage; biology sample at Little Bear @ Ashmun Property) in 2014. The hydrograph showed that the site was mostly dry throughout the year with some flow in the stream for about two to three weeks prior to the sample being taken so the model predicted a lower value for the Bug SubIndex while the actual value was 96. This is an example of a site where due to minimal development upstream, the water quality should support a high integrity bug community. When such conditions exist, it may not take a long, sustained period of flowing water in the creek to support high community integrity if there are perennial pools for refugia. Under low flow/good water quality conditions, the aquatic community may be spatially concentrated resulting in samples with high diversity which would be dispersed when a flow event came, elevating the Bug SubIndex score. While the flow data during this time period at Little Bear Creek upstream of the Recharge Zone showed zero flow, it is important to remember that the gage used to collect the data may have a difficult time measuring very low flows and it is possible that low flows were occurring in the creek that the gage would not register. This can also happen on a highly localized scale below large pools where alluvial material can store and seep baseflow downstream for an isolated reach while there may not be any flow upstream or downstream.

Five samples were overpredicted: West Bouldin Creek at Oltorf in 2011, Barton Creek above Barton Springs in 2000, East Bouldin Creek at South First Street in 2009 and 2011, and Waller Creek at 23rd Street in 2006. There is no inherently noticeable difference in the flow data for West Bouldin Creek at Oltorf in 2011 when compared to flow data at this site in other years, so there is no reason the authors can remark on for this prediction being overestimated by 17 approximately. However, this value of 17 is comparable to the residuals from the model (Figure 6) which indicates that the overestimation is within the model's predictive capability. The Barton Creek sample was likely predicted to be high because the hydrograph showed continuous flow in the creek for at least three months prior to the sample; however, the rest of the year the site had little to no flow with no upstream perennial pools for refugia. Hydrographs for the site in East Bouldin prior to 2009 showed this location to be very flashy with little to no flow in the stream the majority of the time. The hydrographs in 2009 and 2011 showed continuous flow in the stream with no large changes in the daily average flow. A similar hydrograph was shown for Waller Creek at 23rd Street in 2006. Based on the continuous flow conditions from the collected data, the model predicted higher values for the Bug SubIndex. There is no evidence that would lead the authors to believe that hydrology would have shifted from a historically flashy flow regime to a more natural flow regime at these sites and the continuation of low observed Bug SubIndex scores tends to confirm this notion. Thus, the flow data collected at these gages is suspected to be inaccurate.

DISCUSSION

The functional linear model developed during this analysis successfully quantified the relationship between a benthic macroinvertebrate community metric (the EII Bug SubIndex) and the respective flow regime; however, there are some major concerns regarding the use of the model to predict an EII Bug SubIndex score solely from flow. Using the hydrograph as a functional predictor in the model allows for the inclusion of four of the key components that characterize a flow regime: magnitude, frequency, duration, and predictability of stream flow. The fifth key component, flashiness, is represented by the first derivative of the daily average flow functional predictor. Thus, functional linear models are an approach to quantifying relationships between hydrology and the ecological communities that live within the streams that enables a more comprehensive characterization of the flow regime to be captured in the model.

Results of the model confirmed a seemingly intuitive assertion that having continuous flow in the stream throughout most of the year would positively impact the benthic macroinvertebrate communities in Austin streams. However, the model suggested a brief window between July/August through September/October when having flow in the stream appears to negatively impact the macroinvertebrate communities. This negative relationship is perplexing because one would assume that perennial flow in the stream would always cause an increase in the Bug SubIndex; however, late July through August are typically hot and dry in Austin when the streams experience cessation of flow. One hypothesis that might explain this is that local taxa have evolved to deal with these low flow conditions and streams with abnormally persistent baseflows during these months may negatively impact the integrity of the community. For example, a "normal" community structure may include drought-specialists that could be inhibited from completing phases necessary to their life cycle and are subsequently further disrupted/displaced by dominance of generalists that would otherwise be out-competed in this harsh environment. A second hypothesis is that the presence of baseflow in streams that would normally go dry may indicate presence/dominance of urban water leakage that is not ideal for sensitive species such as infiltration of municipal potable water (from irrigation or leaks) or wastewater (from leaks or re-use).

In accordance with Staff biologists' expectations, the model substantiated that flashiness of a hydrograph typically has a negative impact on benthic macroinvertebrate communities, presumably due to scour/extreme disturbance of habitat. However, surprisingly, the model appears to indicate that there is a significant positive effect due to flashiness occurring during late March/April and possibly through May. Over the past 20 years, the Austin area typically experiences two wet seasons in a year, one spanning late March to June and a second spanning September through November (NOAA's National Online Weather Data). The model may therefore just be revealing that the "natural" weather patterns in the Spring do not degrade community integrity because they evolved to cope with this condition. It is interesting that the model suggested that large changes in flow during the months of September and October would negatively impact the Bug SubIndex since these months would also experience large storm events due to natural weather patterns. However, there are significant differences between Spring and Fall rainfall. Spring storms are typically a regular series of dwindling cold fronts with brief but violent lines of thunderstorms. Fall storms typically result from banks of tropical moisture residuals from Gulf cyclonic depressions. Additionally, the rain events during the Fall may result in less runoff due to dry soils and empty creeks muting the effect on hydrographs and may not affect the biological community in creeks that have gone dry in the summer. Further inspection of historical flow at individual gages could be done to address this question. It should also be noted flashiness occurring from November to January might negatively impact the Bug SubIndex more so than at other times of the year. More investigation would need to be done to determine if that is a real phenomenon.

The use of a functional linear model is a novel and improved approach, but it does not alleviate all of the problems inherent in finding a reliable relationship between hydrology and aquatic communities. The selection of the time interval of the hydrograph can potentially influence the results of the analysis (Ainsworth et al. 2011) and the use of the one-year flow regime prior to a benthic macroinvertebrate sample used in this model may not be the ideal time interval. ERM biologists indicate that voltinism (the recurrence interval of reproduction) varies within macroinvertebrate communities in our region which is relevant to the potential effects of flow persistence and time interval employed in a model. Some short-lived, rapidly reproducing species (such as mosquitoes) are multivoltine (two or more generations per year), others (such as many mayflies) are univoltine (one generation per year) and long-lived species (such as dobsonflies) are semivoltine (generation time is longer than one year). Multivoltine organisms would not require long durations of sustained flow to prosper, nor might they be affected by flashiness. In fact, intermittent flow and flashy streams may even favor these species. Thus, models with shorter flow regimes could be used to predict the effects of hydrology on these organisms but these effects should still be present when using a one-year flow regime model. In contrast, semivoltine organisms (such as dobsonflies and some large dragonflies) require long durations of reliable inundation in order to prosper at a location. These organisms likely require a model with longer time intervals for a flow regime (i.e., 2 or 3 years of flow data prior to a sample) and data regarding presence of pool refugia. It is interesting to note that very few semivoltine taxa were present in the samples analyzed for this report. Thus, a better predictive model maybe built using a shorter time interval.

Knowledge about a site's historical flow regime should be incorporated into the model in order for the model to make more accurate predictions. The validation samples for East Bouldin Creek at South First Street in 2009 and 2011, and Waller Creek at 23rd Street in 2006 contained annual hydrographs which the model predicted could support a high integrity macroinvertebrate community. Upon examining the available historical hydrology at these locations, the validation sample hydrographs were quite different than the historical hydrographs. Historical hydrographs contained much less baseflow and had a high degree of flashiness. Thus, the current year of hydrology data at a site is insufficient to predict the EII Bug SubIndex score. Underlying conditions at a site or within a watershed along with the established benthic community at the site location may not allow for immediate positive response in the community metrics due to a single year of continuous flow. This could be incorporated into the model by looking at multiple years of flow data or possibly incorporating a site specific prior EII Bug SubIndex score into the model.

The developed model might also benefit from the addition of more predictor variables such as a scalar predictor representing the suitability of habitat for macroinvertebrates (i.e., pool refugia for prolonged inundation, available substrate or woody debris to mitigate hydraulic disturbance) or the water quality at the site location. The wide range of the residuals in the model suggest that hydrology is not the only key component impacting the macroinvertebrate community. In addition, the validation samples collected at Little Bear Creek upstream of the Recharge Zone in 2014 and Barton Creek above Barton Springs in 2000 showed that relying solely on the average daily flow one year prior to the collection of a sample could lead to dramatically incorrect predictions of the EII Bug SubIndex. Including other predictor variables might increase the model R^2 value and allow the model to better predict the Bug SubIndex; however, the additional predictors should be well thought out with the inclusion of expert staff biologists and theoretical modelers.

Finally, it was noted during this analysis that the EII Bug SubIndex may change by upwards of a value of 20 even within years where the hydrographs associated with that sample location are very similar. This led to very wide residuals in this model and is one of the reasons that the functional linear model predictions cannot be more reliable. The above suggestions may increase the reliability of the model but there seems to be something more inherently wrong with using the EII Bug SubIndex as the response variable. The validation sample collected for Shoal Creek at 12th Street in 1995, discussed above, revealed that the act of normalizing the EII Bug SubIndex each year compromises the development of a reliable model. Computing a non-normalized metric or further evaluating the benthic community composition using community analyses should be done on these data prior to further development of a hydrology model in order to develop an appropriate response variable to represent the benthic community integrity.

CONCLUSION

The development of the functional linear model was a good first step into the development of determining “environmental flows” for Austin streams. The model can provide ERM staff with a substantiated estimate for the flow regime that can be expected to support a given Bug SubIndex value. As noted above, this estimate may be too variable to produce an accurate estimate of the Bug SubIndex. The functional linear model should be refined by first developing a response variable which better characterizes the benthic macroinvertebrate communities than does the current EII Bug SubIndex. Next, an appropriate time interval of flow should be selected for the refined functional linear model. The time interval should be appropriate for the newly selected response variable. Finally, the functional linear model should be updated with additional variables that attempt to characterize site specific habitat suitability, water chemistry, and prior benthic macroinvertebrate community integrity. If the refined model can better predict the integrity of the benthic community then staff would then need to define a threshold in the newly defined community response that would be necessary to maintain “ecologically healthy” streams in Austin. This may be general, or it may be that different locations (watershed size or ecoregion) would have different thresholds for what is needed to maintain ecological health.

Staff within ERM are currently working to develop and calibrate watershed models for Austin which can predict the flow regime at any location within a watershed. The watershed models will combine various land use changes and placement of mitigation techniques to determine instream hydrology. The functional linear model developed as a part of this analysis could be coupled with these watershed models to determine how the altered flow regime would impact the aquatic community. Thus, in nonurban streams, scenarios with increasing theoretical impervious cover in a watershed model could define the threshold at which the aquatic community composition is altered to determine the flow regime of water (both quantity and timing of flow) needed to maintain the ecological health of that stream. For urban streams in which the flow has already been altered and the aquatic community has likely already shifted in composition, scenarios could be run to estimate how much of the ecological health of the stream might be restored in a quantitative manner. ERM could estimate how much each structural control installed to mitigate stormwater runoff would impact the aquatic community and thus have a sound decision-making process for prioritizing resources.

It would be best to refine the functional linear model prior to coupling it to the watershed models; however, ERM has not identified a more suitable quantitative tool to translate hydrology to the biological community and the ability to quantify hydrological impacts to Austin's streams and biological community is needed. It is a current objective of ERM to increase each stream in Austin to an EII score of "good" or better. It stands to reason that an initial threshold needed to maintain ecologically healthy streams in Austin would be to reach a "good" or better Bug SubIndex value. This could be achieved if the functional linear model can be refined or a more suitable quantitative tool developed that can more reliably predict the biological integrity of Austin's streams.

RECOMMENDATIONS

- ERM biologists and modeling staff should work to refine the functional linear model in the following manner: define a more appropriate response to biological communities than the Bug SubIndex to be used in the model, refine the time interval needed in the model, and introduce additional predictor variables into the model (i.e., habitat suitability, water chemistry, prior biological community integrity).
- Modeling staff should begin coupling watershed model output with the functional linear model to further validate the functional linear model. If the functional linear model can be further validated, the modelers should determine what impact watershed scenarios may have benthic macroinvertebrate communities based on the functional linear model results.
- If the functional linear model cannot be further validated, then the modelers should pause for the results of a refined model to be developed as described in the first recommendation or the development of a separate but more reliable quantitative tool.
- ERM biologists should try to define a new variable that represents the benthic macroinvertebrate community which is not normalized and can better characterize the system than does the Bug SubIndex. Once identified a threshold should be developed for this new variable, above which the biological community could be considered to represent an ecologically healthy stream system.

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