The Effect of Environmental Conditions on Macroinvertebrate Communities

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Abstract

There has been increased biodiversity loss throughout the world resulting from human activity. This is particularly true for aquatic ecosystems that suffer from habitat modification and pollution. Aquatic macroinvertebrate communities are sensitive to such changes in their environments. While past studies have shown that a variety of environmental variables can negatively affect community structure of macroinvertebrates, these have not been clearly identified. Here, we are interested in how differences in environmental conditions will affect the richness and evenness of macroinvertebrate communities. Using macroinvertebrate data from the National Ecological Observatory Network, we assessed the effects of pH, conductance of water, and riparian cover on these two measures of community diversity. Although our results were insignificant, we found positive trends for pH and riparian cover on richness, and a negative trend for conductance. Similarly, we found negative trends for all three variables with community evenness. While our results did not have sufficient power, they suggest that macroinvertebrates may indeed suffer negative consequences from drastic changes to their ecosystems. Future studies should aim to clearly identify these trends and their magnitude in order to aid in conservation efforts.

Introduction

In the past century, we have seen an increase in extinction rates globally, with a potential trigger being accelerated anthropogenic activity and land use. There is evidence suggesting that we are entering the sixth mass extinction, and will lose over 75% of our current estimated biodiversity (Barnosky et al. 2011). Thus, in order to predict the possible outcomes of human activity and prevent further damage to biodiversity, we must identify and investigate the contributing factors. One of the most significant human impacts on the ecosystem is modification of both land and aquatic regions. While significant policies have been introduced towards the protection of terrestrial ecosystems, coastal and freshwater systems have often been overlooked. This is of particular concern as many aquatic organisms are sensitive to changes in local environmental conditions.

Macroinvertebrates are one of the most studied groups of organisms when trying to assess human impact on aquatic environments. They are ubiquitous in all water bodies around the world and are a fundamental link in the food web between plants and fish. Moreover, the early life stage of macroinvertebrates, defined as "macrobenthos", play an essential role in our understanding of ecological relationships in aquatic ecosystems. All of these make macroinvertebrates a particularly important feature of aquatic ecosystems (Hauer and Resh 2017). The macroinvertebrate community index (MCI) has often been used as an indicator of water body quality around the world (Clapcott et al. 2017). In recent years, with the need to understand the effects of human activity, aquatic ecosystems have been receiving increasing attention. As a result, macroinvertebrates, usually at the community level, have been studied quite extensively, with most research focusing on the effects of different environmental factors on their health. These environmental factors range from land use and pollution to seasonality and water quality (Grönroos and Heino 2012, Burger et al. 2018). A study conducted by Rawi et al. (2014) investigated the effect of hydrological and physio-chemical factors on macroinvertebrate diversity in tropical forest streams. They found that environmental indicators such as pH, dissolved ions (oxygen and nitrogen), and habitat quality measures (e.g., canopy cover) contribute to the modification of macroinvertebrate structure in the local streams (Rawi et al. 2014).

The conductance of water is not only a measure of the concentration of ions in the water, but it has also been identified as a contributing factor to macrobenthic community structure for both species richness and community variation (Boehme et al. 2016, Drover et al. 2019). A study by Drover et al. (2019) suggested that although dominant species may respond differently to elevated specific conductance (SC), richness is strongly negatively related to SC and is particularly robust to changes in seasonality. This reflects the negative impact of high salinity on macroinvertebrate communities. On the other hand, a paper by Boehme et al. (2016) proposed that variation within macroinvertebrate communities and their response to elevated SC is influenced by seasons.

One significant factor that was included in most of the aquatic community studies is pH. A few decades ago, a study by Kullberg (1992) assessed 20 streams with varying pH values and suggested that there is a positive relationship between pH and macrobenthic species richness. Yet, they also proposed that there is a pH threshold beyond which species richness plateaus. Studies conducted by Courtney and Clements (1998) suggested that macroinvertebrates have different sensitivity to changes in pH. A notable example is mayflies, which are particularly vulnerable to acidic pH; as a consequence, their abundances have been decreasing significantly in acidic waters of Rocky Mountains streams.

In 2012, Seger et al. suggested that with increased riparian cover, the relative abundance, taxon richness, dissolved oxygen, and Shannon diversity index increased as well. Another study found that reduced riparian cover is related to a change in the community structure in macroinvertebrates, though richness remained unaffected (Moraes et al. 2014).

A study conducted on beta diversity of macroinvertebrates in tropical streams found that pH and latitude are reliable indicators of beta diversity, while habitat degradation and longitude are not (Al-Shami et al. 2013). However, another study on forest structure found that young and nutrient demanding forest structures have a positive effect on macroinvertebrate diversity (Jonsson et al. 2017). This suggests that conservation of riparian cover may be particularly important. Although it is suggested that agriculture can negatively affect aquatic environments through pesticide runoff into local freshwater sources, the effect of physical land cover conversion on the macroinvertebrate community still needs to be investigated (Macchi et al. 2018).

In this study, we will investigate the effects of changing environmental conditions on macroinvertebrate communities. We chose the macroinvertebrate dataset available from the open data portal of the National Ecological Observatory Network (NEON). This data was collected from a variety of aquatic bodies that spread through the United States and with samples taken along the benthos of streams ("Macroinvertebrate collection" - NEON data). In addition to the macroinvertebrates data, we will also use data on the following environmental variables: conductance, pH, anthropogenic land use, and riparian cover.

There are many conflicting views on how the variables listed above affect macroinvertebrate communities and a lack of studies conducted through the North America aquatic ecosystems. Thus, we will use these variables to answer our broad research question of how changes in different environmental variables shape macroinvertebrate communities. We predict that pH should positively impact species richness, since acidic pH was found to reduce the abundance of some macroinvertebrate species. Moreover, we predict that conductance should negatively impact species richness since high salinity stresses macroinvertebrates. Finally, we predict that riparian cover will positively impact species richness, since riparian vegetation can trap runoff from agricultural fields and provide more food sources for macroinvertebrates. Since each species within macroinvertebrate communities may have different sensitivities to these three variables, we predict that they may impact evenness in different directions and magnitudes.

Methods

Data Description

The data used in this analysis comprised of multiple open data sets from the National Ecological Observatory Network (NEON). These data sets were collected in a variety of states in the USA for three main water body types: rivers, lakes, and streams. Observations for conductance (to measure ion quantity) and pH (to measure water acidity) were sourced from the "Water Quality" dataset; the percentage of riparian cover metric was found in the "Riparian Vegetation % Cover" dataset; land use data was found in the "Riparian Composition and Structure" dataset; finally, taxonomic information was from the "Macroinvertebrate Collection".

<u>Water Quality Dataset</u>

Sampling of water quality took place in various months of the year, with the spring, summer, and fall months selected for this analysis, since winter months were included very infrequently. The data included various water quality metrics with conductance and pH being selected. These metrics were collected using YSI.EXO pH and conductance probes. The data set further contained information about longitude, latitude, site and date.

Riparian Dataset

The "Riparian Vegetation % Cover" dataset was used to find percent riparian cover. This information was collected once a year in May during the peak period of riparian vegetation growth. This dataset contained riparian percent cover that was collected along various points of the stream, longitude and latitude information, date, elevation and total density. The "Riparian Composition and Structure" dataset was used to assess the amount of land use in each area. Land use information was assessed once a year during the peak growth of riparian vegetation. This dataset contained information about the presence or absence of agriculture, buildings, roads, laws, agriculture and industry. It further contained longitude and latitude information, date, site, bank soil information, and elevation.

Macroinvertebrate Dataset

Sampling of macroinvertebrate communities took place three times a year: spring, summer, and fall, where family, order, genera, and species identities were collected. Longitude, latitude, aquatic site type, total counts, and sample percentage were also included. Species were sampled using various net scraping techniques.

Data Analysis

We isolated all freshwater stream sites, then narrowed the number of sites down to 14 after excluding a site with insufficient taxonomic and environmental data (TECR). The sites used were: BIGC, BLDE, CARI, COMO, KING, LECO, MART, MAYF, MCDI, MCRA, POSE, PRIN, REDB, and WLOU (Figure 7); the full location names can be found on the NEON data portal. For each of these sites, we extracted multiple data sets for our analyses. Information on species name was inadequate for taxonomic data, so we instead used the genus name in classifications of richness and evenness. These data were categorized based on year and season they were collected, as well as longitude and latitude information. Data was also filtered for measurement or inputting error; most notably, pH data had values outside the range of 0-14pH and conductance had two values over 10,000 mS/cm. After the preliminary data explorations, linear models, richness and evenness calculations, the data were amalgamated into a final large set to run structural equations models.

Before determining the effects of pH and conductance on genera diversity, we investigated the relationship between these environmental variables and local site conditions. Both variables were analysed using an optimized linear mixed effect model structure. Assumptions such as normal distribution, heteroscedasticity, and independence of residuals were tested. Since the conductance data violated these assumptions, we used a log-transformation. The fit of various models, each with a unique structure of random or fixed effect variables, were compared using the Akaike Information Criterion corrected for small sample sizes (AICc). The significant predictor variables of these models were used to structure the structural equation models used to predict evenness and richness.

Spatial autocorrelation of both pH and conductance were evaluated using Moran's I. Only conductance was significantly spatially autocorrelated, and this relationship was visualized using semivariograms. This non-independence was accounted for by fitting five autoregressive correlation structures, and selecting the one with the lowest AICc value. Note that in order to fit these structures to the data, the longitude and latitude coordinates had to be slightly jittered, as they were identical for samples occurring at the same site over successive months or years.

The percentage of riparian canopy cover, measured at various points along the stream transect with a densiometer, was used to quantify the amount of riparian vegetation. Various land use types were ranked in terms of presence or absence. Presence and absence scores were converted into 1 and 0, respectively, and values were summed to determine the fraction of a particular type of land use at each site of a given year. Land use types of interest included industry, agriculture, buildings, lawns and parks, and roads. The correlation between the percentage of riparian cover and land use types was analysed to determine if any relationships exist.

SEM Assumption Testing

Assessing the relationship between the three environmental predictor variables (pH, conductance, and % riparian cover) and community richness and evenness required the use of structural equation models. These were used to account for any correlations between the predictor variables, and for the potential indirect effects of seasonality and site. Constructing the structural equation model first required checking for its assumptions. Firstly, all outliers found in the predictor variables were identified and removed. Following this, the assumptions of normal distribution of these variables were evaluated using histograms. A scatter plot of each predictor variable versus the two dependent variables were then produced and a linear regression was fit to meet the linearity assumption of a structural equation model.

Construction of the SEM

Following the testing of the model assumptions and the construction of linear models to test significant effects on our predictor variables, a structural equation model was constructed for both richness and evenness. The correlations between the predictor variables were justified as following: since a pH is a measure of hydrogen ions in the water, it is possible to it may inadvertently contribute to increased conductivity. Moreover, a study by Schoonover et al. (2005) found that increased riparian cover can act as a buffer to agricultural runoff. As such, increased riparian cover may then be correlated with conductance and pH. Since we assumed all of our predictor variables would equally affect these two diversity measures, the two SEMs for richness and evenness were identical in structure.

Results

Linear mixed effects models for pH and conductance

Figure 1 visualizes the spread of pH values across seasons and site ID. The final model, which had the lowest overall AICc value, included both season and site ID as predictor variables, where the random effect was month nested in year (Table 3a). This indicates that the pH value in a given stream is determined by both season and site. This later informed our structural equation models, where season and site had a causal effect on pH. Spatial autocorrelation of pH values was calculated using Moran's I, however the P-value was insignificant (Table 1). This indicates that sites closer to one another do not share more similar pH values.

The same process was used to predict conductance. The large differences in spread of conductance for each site is visualized in Figure 2. Only site ID as a fixed effect and year as a random effect best fit the model (Table 4a); therefore, with the data available, only site is a relevant predictor for the value of conductance. As a result, in our structural equation models for evenness and richness, conductance is only dependant on site. However, the P-value of Moran's I for conductance was highly significant, indicating that the values are spatially autocorrelated (Table 1).

Correlations between land use and riparian cover

The correlation coefficient, r, is very low between each land use type and amount of riparian cover (Table 2). We could not definitively state that nearby anthropogenic land use changes are affecting the amount of riparian vegetation, an important metric for stream quality (Chua et al. 2019). This is likely due to clustering of land use values at zero (Figure 3). The lack of variation of values for increased levels of anthropogenic disturbance made it impossible to draw conclusions on the impacts on riparian cover, water quality, and diversity metrics.

SEM Results

Following the results of the linear models the predictor variables, and conclusions on correlation drawn from the literature, the structure for the richness and evenness SEMs was established (Figure 4). This structure was chosen because site was found to have a significant effect on both pH and conductance, while seasonality only had an effect on pH. Moreover, correlation was found between all 3 predictor variables, and as a result correlation arrows were drawn between them.

The results for the SEM run for richness are summarized in Table 5. The relationship between pH and richness is positive as initially predicted by our hypothesis (Table 5; Figure 5). However, this relationship was statistically insignificant (P= 0.720), and so we could not definitively conclude that richness increases as pH increases towards a value of 7. As conductance increased, species richness decreased which further matched our initial predictions (Table 5; Figure 5). However, again, this relationship was not significant ($P= 0.726$). Finally, there was a statistically insignificant increase in richness as riparian cover increased which followed with our initial hypothesis (Table 5; Figure 5). Significant interactions were found between site and pH and site and conductance ($P= 0.035$; $P=0.001$) which follows with the previous results we found in our mixed linear models (Table 3a; Table 4a). Moreover, two of the correlations that were expected under our hypotheses (pH and conductance, and canopy cover and conductance) were also statistically significant ($P= 0.008$; $P=0.034$)**.**

The results for the SEM run for evenness are summarized in Table 6. All 3 predictor variables (pH, conductance, riparian cover) had a negative effect on species evenness (Table 6; Figure 6). While these results were statistically insignificant, this follows with our initial predictions ($P= 0.539$; $P=0.449$; $P=0.195$).

Discussion

Understanding how environmental factors affect communities of species is becoming significantly more important as humans are increasingly changing the environment away from the evolutionary environment of communities.

The effects of each of the variables are largely consistent with our predictions. As pH decreases due to acidification, only the acid tolerant species would be able to persist, decreasing richness and evenness (Camargo, 1994). The reduction of riparian cover, which is one of the most common changes to occur due to human land use, was shown to decrease richness due to the loss of habitat and shelter (Valente-Neto et al. 2015). The measure of evenness in this case depends largely on how much the dominant species depend on woody debris. Our collection of sites are in diverse biomes, meaning that the community composition is likely very diverse between sites. The minimal effect of evenness we see in the result could be due to the high variance in the community composition in the sites. This explanation is also likely true for the effect of conductance on evenness, as the sensitivity of the dominant or rare species to conductance will be variable between the sites (Drover et al. 2019). The conductance has a negative effect on richness, as predicted by existing evidence (Drover et al. 2019).

One of the main limitations of our result is that our analysis lacked power. We suspect that this contributed to the statistically insignificant P values of the variables of interest. Using "rules of thumb" for using sample size as a proxy for statistical power, our data is far below the 5:1 rule for the ratio of sample size and the number of parameters (Wolf et al. 2013, Bentler and Chou, 1987). Further analyses with more sampled data could help resolve this issue. Another caveat of our model is that the relationship between the diversity measures and the environmental variables were assumed to be linear (Rosseel et al. 2019). Theory suggests that diversity could follow a non-linear pattern along a pH gradient, as the range of tolerance of the species will overlap at intermediate pH values. However, with regard to pH, we are interested in the acidification of streams as a result of anthropogenic land use, which only looks at the change in pH in one direction. There is evidence showing that the relationship between acidification and macroinvertebrate diversity can be modeled linearly (Feeley et al. 2011). Despite these limitations, it has to be noted that our analyses propose a plausible structure for environmental variables to affect macroinvertebrate communities.

Our ultimate goal was to identify variables that influence macroinvertebrate diversity and their relative importance, and to identify sites where interventions and changing nearby land use patterns would benefit the macroinvertebrate communities. There is evidence for changing land use patterns affecting the macroinvertebrate diversity via changing the hydrological conditions (Jonsson et al. 2017). We were not able to find a significant relationship between land use and canopy cover in our analysis due to the limited number of sites with land use. Therefore, it does not mean that there is no relationship between anthropogenic land use and the environmental variables of interest. With interventions in mind, it is important to note that the estimates of the regression should not be compared to as an indicator for the relative importance of the effect of the variable. In other words, pH has the largest estimate for the regression of its effect on richness, but this does not mean that intervention strategies that target pH should be chosen. Because these variables are correlated, restoration strategies that can facilitate improvement in all of the variables should be considered.

Future research direction includes conducting the same analyses with more sites, especially sites with higher degrees of neighboring land use, which would allow us to incorporate land use into the model, instead of using site ID as a proxy for land use. Sampling more sites would also increase the statistical power, allowing for a more reliable assessment of the importance of the environmental variables.

Conclusion

Land use coupled with a changing climate is negatively affecting terrestrial and aquatic ecosystems. In this study we attempted to understand these effects on macroinvertebrate communities. Our study suggests that environmental factors like pH, conductance, and loss of riparian cover may affect community structure and richness in various ways. Future work is necessary to determine the magnitude of these effects in order to direct effective policy.

Figures

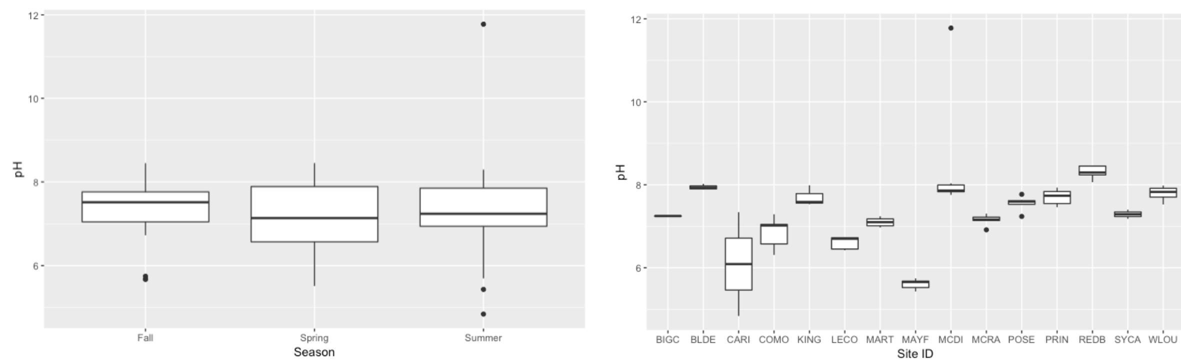

Figure 1. Spread of pH values across seasons (left panel) and sites (right panel). Season and site were included as fixed effect predictors for pH.

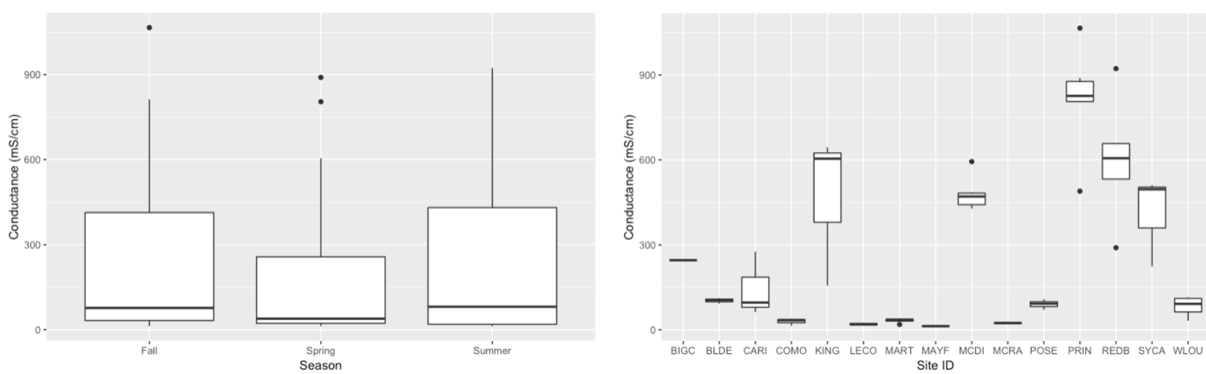

Figure 2. Spread of conductance values across seasons (left panel) and sites (right panel). Only site was included as a fixed effect predictor for conductance.

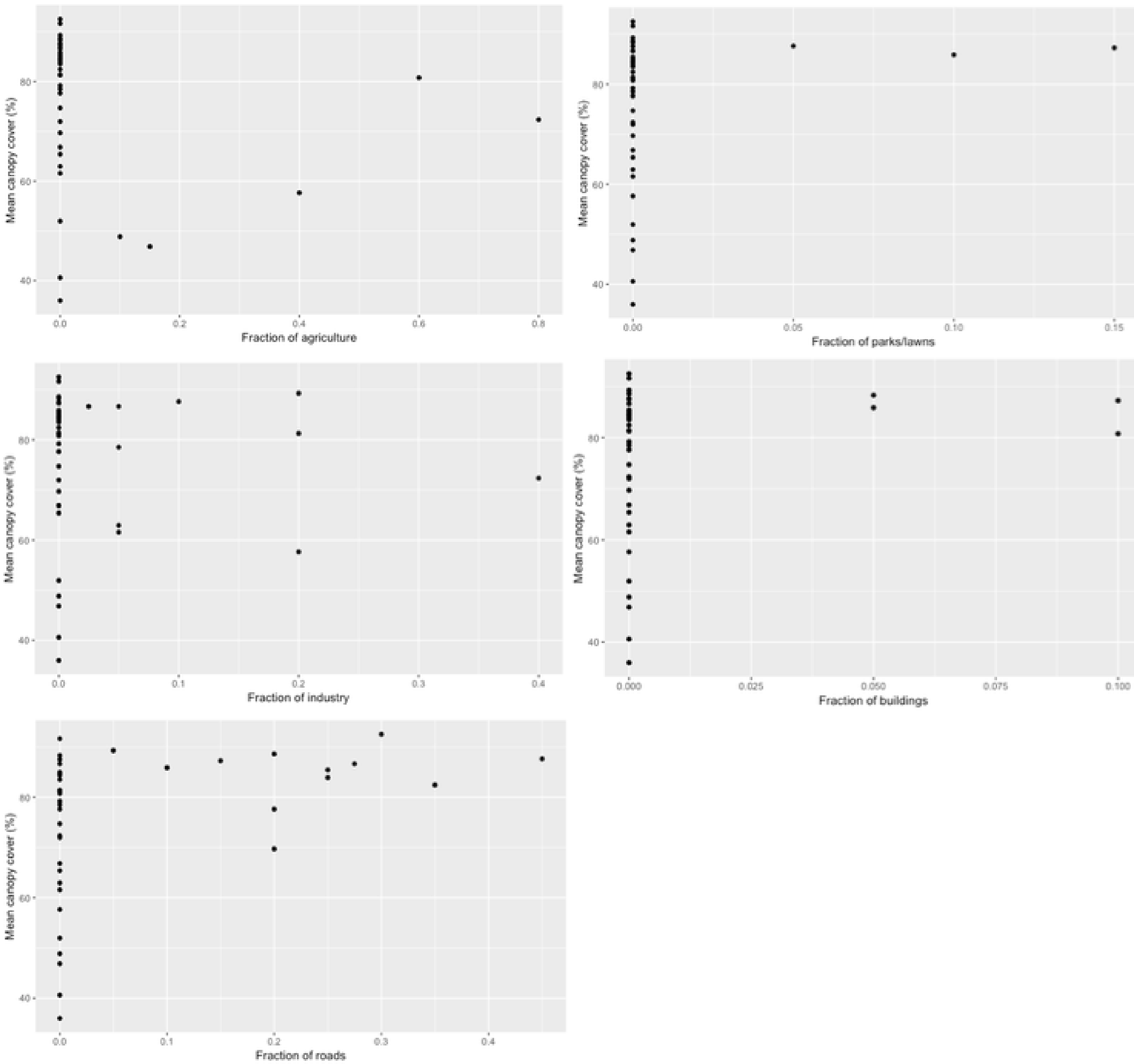

Figure 3. The fraction of each land use type (relative to undisturbed riparian zones) compared to the mean canopy cover. Each data point represents an observation for a specific year at a specific site.

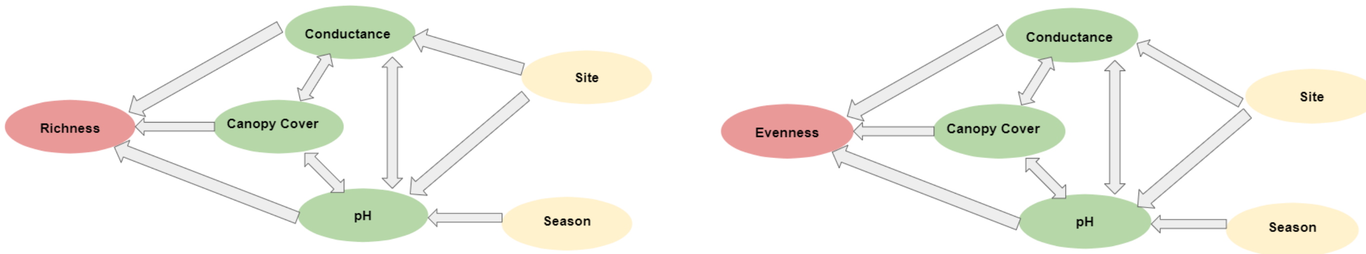

Figure 4. SEM structure for the effect of conductance, canopy cover, pH on richness (left panel), and on Evenness (right panel).

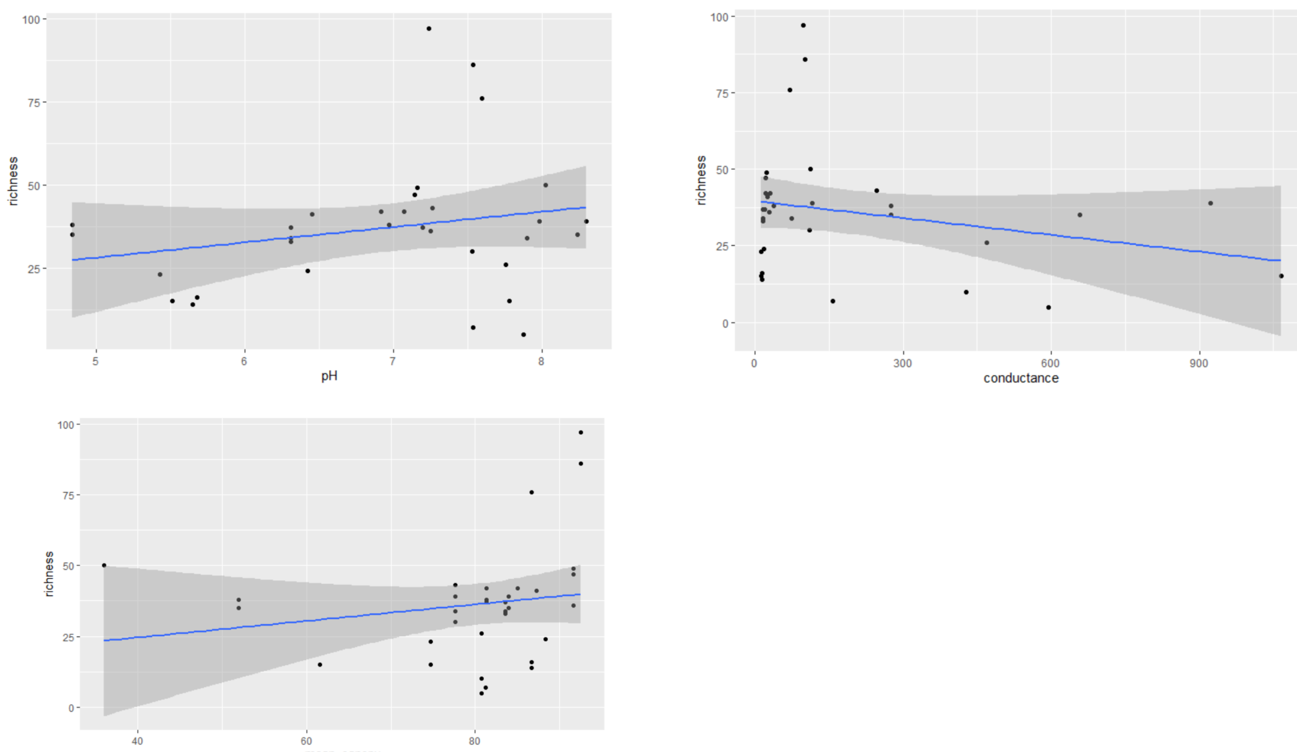

Figure 5. pH plotted versus richness for all sites (upper left panel, p-value= 0.720). Conductance plotted versus richness for all sites (upper right panel, p-value= 0.726). Riparian cover plotted versus richness for all sites (lower left panel, p-value= 0.197).

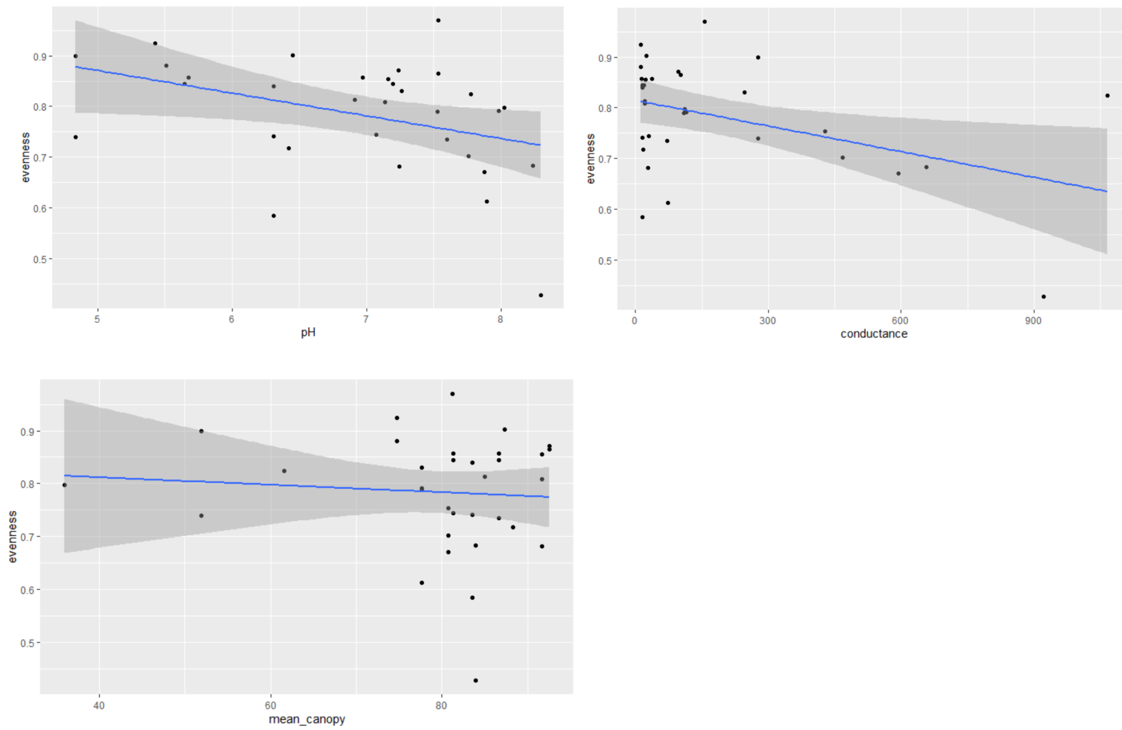

Figure 6. pH plotted versus evenness for all sites (upper left panel, p-value= 0.531). Conductance plotted versus evenness for all sites (upper right panel, p-value= 0.449). Riparian cover plotted versus evenness for all sites (lower left panel, p-value= 0.195).

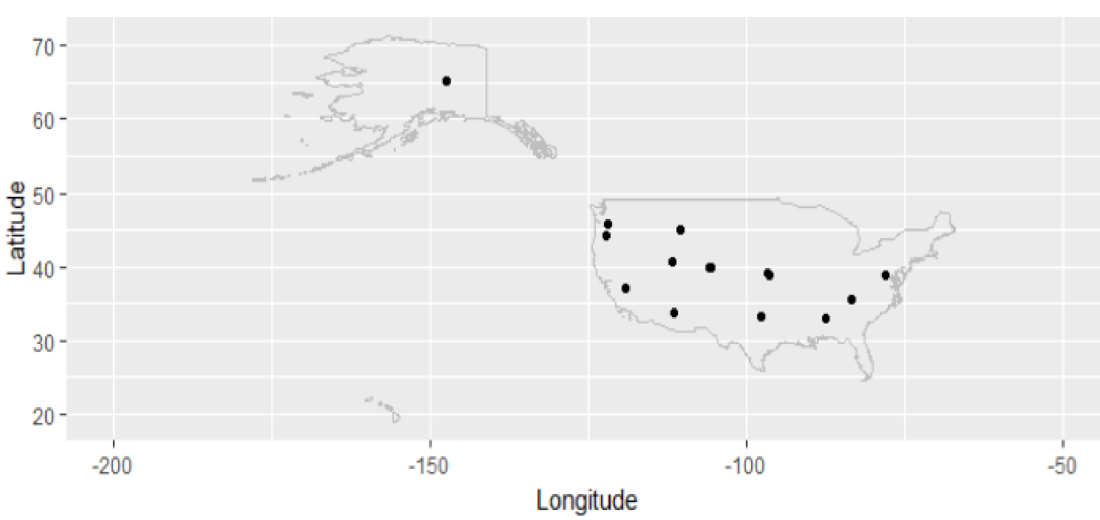

Figure 7. A map of the 14 different stream sites across the US: BIGC, BLDE, CARI, COMO, KING, LECO, MART, MAYF, MCDI, MCRA, POSE, PRIN, REDB, and WLOU

Tables

Table 1. Moran's I outputs to quantify spatial autocorrelation of pH and conductance. Values are rounded to the fourth decimal place.

Variable	*Observed*	*Expected*	*Standard deviation*	*P-value*
pH	0.0021	-0.0137	0.0296	0.5926
Conductance	0.1305	-0.0133	0.0303	2.0853 e-06

Table 2. The correlation between various land use types and mean amount of riparian cover at the site across all sampling years.

Land use type	*Correlation coefficient (r)*
Buildings	0.2046
Agriculture	-0.1449
Industry	-0.0054
Lawns/parks	0.2036
Roads	0.3690

Table 3a. Fit values for best linear mixed model predicting pH based on site and season.

Response variable	*Predictor variable*	*Sample size*	*AIC*	*R^2 marginal*	*R^2 conditional*
pH	Site (fixed)	74	145.5500	0.5279	0.9983
	Season (fixed)				
	Year (random)				
	Year:month (random)				

Table 3b. Values for each significant predictor for pH. Note that only significant values are included to keep the table brief.

Response variable	*Predictor variable*	*Estimate*	*Standard error*	*Df*	*t-value*	*p-value*
pH	Intercept	7.2141	0.4931	17.5451	14.630	2.88e-11
	Site BLDE	0.6699	0.0891	56.6729	7.519	4.48e-10
	Site CARI	-2.82195	0.14783	57.55749	-19.089	< 2e-16
	Site KING	0.3043	0.1049	56.7955	2.900	0.0053
	Site LECO	-0.6008	0.10688	56.67724	-5.621	6.03e-07
	Site MART	-0.24432	0.08910	56.67290	-2.742	0.00815
	Site MAYF	-1.56121	0.08546	56.67743	-18.269	< 2e-16
	Site MCDI	0.54311	0.10211	56.77617	5.319	1.84e-06
	Site POSE	0.39895	0.08546	56.67743	4.668	1.90e-05
	Site PRIN	0.39899	0.08546	56.67743	4.669	1.90e-05
	Site REDB	1.04980	0.08910	56.67290	11.783	< 2e-16
	Site WLOU	0.39694	0.11773	56.91612	3.372	0.00135

	Summer:BLDE	3.95896	0.16796	56.90612	23.571	< 2e-16
	Summer:COMO	-0.75360	0.12389	56.67828	-6.083	1.07e-07
	Summer:MCDI	3.98717	0.14345	56.80457	27.795	< 2e-16
	Summer:POSE	-0.31304	0.12389	56.67828	-2.527	0.01433
	Summer:REDB	-0.43674	0.14058	56.86534	-3.107	0.00295

Table 4a. Fit values for best linear mixed model predicting conductance based on site.

Response variable	*Predictor variable*	*Sample size*	*AIC*	*R^2 marginal*	*R^2 conditional*
pH	Site (fixed)	76	78.62158	0.9554	0.9554
	Year (random)				

Table 4b. Values for each significant predictor for conductance. Note that only significant values are included to keep the table brief.

Response variable	*Predictor variable*	*Estimate*	*Standard error*	*Df*	*t-value*	*p-value*
pH	Intercept	5.5053	0.3028	76	18.183	< 2e-16
	Site BLDE	-0.8712	0.3385	76	-2.574	0.012005
	Site CARI	-0.7295	0.3496	76	-2.087	0.040283

	Site COMO	-2.1761	0.3237	76	-6.723	2.91e-09
	Site LECO	-2.5110	0.3270	76	-7.678	4.53e-11
	Site MART	-2.0439	0.3270	76	-6.250	2.19e-08
	Site MAYF	-2.9232	0.3211	76	-9.103	8.49e-14
	Site MCDI	0.6634	0.3270	76	2.029	0.045999
	Site MCRA	-2.3292	0.3237	76	-7.196	3.74e-10
	Site POSE	-1.0091	0.3237	76	-3.118	0.002573
	Site PRIN	1.1747	0.3270	76	3.592	0.000580
	Site REDB	0.8290	0.3317	76	2.499	0.014595
	Site WLOU	-1.2021	0.3385	76	-3.551	0.000662

Table 5. Summary of the SEM ran for species richness including direct effects and correlations. Significant p-values are bolded. One tilda denotes a causal relationship, two tildas denote a correlation.

lhs	*op*	*rhs*	*Estimate*	*SE*	*P value*
Richness	~	pH	1.6394	4.5690	0.7197
Richness	~	Canopy cover	0.1618	0.4626	0.7265
Richness	~	conductance	-0.0196	0.0152	0.1968

Conductance	~	Site	34.7942	16.4983	**0.0349**
pH	~	Site	0.1509	0.04662	**0.0012**
pH	~	Season	-0.1059	0.2629	0.6872
Conductance	~~	pH	95.3252	36.4263	**0.0089**
Conductance	~~	Canopy cover	-1432.9400	677.6340	**0.0345**
pH	~~	Canopy cover	-0.3936	2.8843	0.8915

Table 6. Summary of the SEM ran for species evenness including direct effects and correlations. Significant p-values are bolded. One tilda denotes a causal relationship, two tildas denote a correlation.

lhs	*op*	*rhs*	*Estimate*	*SE*	*P value*
evenness	~	pH	-0.01157	0.018475	0.531112
evenness	~	Canopy cover	-0.00141	0.001863	0.448824
evenness	~	conductance	-1.62E-04	1.25E-04	0.194735
conductance	~	Site	34.79419	16.42094	**0.0341**
pH	~	Site	0.150948	0.046113	**0.001062**
pH	~	season	-0.10586	0.263594	0.687963
conductance	~~	pH	95.32527	36.57907	**0.00916**
conductance	~~	Canopy cover	-1432.94	668.9758	**0.032194**
pH	~~	Canopy cover	-0.39355	2.90248	0.892144

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