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Ecological Limits of Hydrologic Alteration in Wisconsin Streams

Revised Report
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Report Summary

Title: Ecological Limits of Hydrologic Alteration in Wisconsin Streams

Project ID:

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Period of Contract: October 1, 2011 – June 30, 2013

Background/Need: Groundwater withdrawal can significantly affect the flow regime of streams and rivers, but it is difficult to predict how hydrologic changes affect stream biological communities. Models that relate flow alteration to biological response are needed to assess whether proposed high-capacity wells will have a significant adverse impact on surface water resources.

Objectives:

1. Delineate high-resolution watershed boundaries and assemble a database of stream and watershed characteristics for Wisconsin's 1:24,000-scale hydrography.
2. Develop hydrologic models that relate climate and landscape characteristics to temporal and spatial variation in stream flows across Wisconsin.
3. Develop statistical models that relate modeled hydrologic indicators to the measured occurrence and abundance of fish species in Wisconsin streams.
4. Develop a process for using fish-flow relationships to determine whether flow alterations will have a significant adverse impact on surface water resources.

Methods:

1. Watersheds were delineated for each feature in Wisconsin's 1:24,000-scale hydrography using a 10 m resolution digital elevation model. Several hundred characteristics for watersheds, riparian zones, and stream channels were derived from existing GIS datasets, including land cover, geology, topography, climate, and stream connectivity.
2. Empirical stream flow models were developed for 23 flow metrics, including mean Jun-Sep flow; 5, 10, 25, 50, 75, 90, and 95% annual exceedance flows, and 10, 50, and 90% exceedance flows for three seasonal (spring, summer, fall) and two monthly (April, August) periods. The models are mixed effects linear models, include weather and watershed characteristics as predictors, and were fit to USGS gage data from 1980-2011.
3. Species distribution models were developed for 79 stream fish species using random forest models. The models predict the probability of occurrence of each species based on watershed, riparian, and channel characteristics, including several stream flow and water temperature metrics.

4. Generalized additive models were used to predict the response of each species to changes in median August flow yield and mean July water temperature. A separate physically-based model was developed to estimate the water temperature change that would result from a given change in flow. These functions were incorporated into a spreadsheet template that will allow managers to predict the effects of flow alterations on stream fishes.

Results and Discussion:

1. Weather, watershed characteristics, and their interactions were all important predictors for most of the stream flow metrics. Patterns in precipitation influenced most flow metrics out to 2-4 years prior to the flow monitoring period. Agricultural land cover and artificial drainage have complex effects on stream flows that depend on precipitation. The standard errors of flow predictions vary by stream size, with small streams (e.g., 10 cfs) having larger errors (~40%) and large rivers (e.g., 1000 cfs) having smaller errors (~15%).
2. Stream size (represented by watershed area) is the most important variable driving distributions of the 79 modeled fish species, followed by water temperature, climate, stream flow, land cover, topography, and geology. Species models were moderately to highly accurate, with a mean of 85% (range: 67-98%) correct prediction when assessed with cross-validation. The partial dependence plots for August median flow yield and July mean temperature for each species were generally consistent with other evidence of habitat preferences, and were highly variable among species. The most sensitive species are trout, sculpin, and lampreys because they are sensitive to both flow and temperature. Many small stream species (e.g., dace, stickleback, mudminnow) appear to be relatively tolerant of low flows, but are sensitive to temperature, so flow reductions may cause a stream to exceed thermal limits before flow itself becomes limiting.

Conclusions/Implications/Recommendations: The models developed by this study will allow managers to predict the effects of flow alterations on stream fishes. This framework provides a consistent method for evaluating potential flow alterations to balance extractive water uses with ecological requirements. The question of what constitutes a significant adverse impact will be addressed in a separate policy document being developed by the Wisconsin Department of Natural Resources (WDNR).

Related Publications:

Menuz, D.R., A.S. Ruesch, and M.W. Diebel. 2013. 1:24K Hydrography Attribution Metadata.
Ruesch, A.S., D.R. Menuz, and M.W. Diebel. 2013. 1:24K Hydrography Creation Toolset.

Key Words: groundwater-surface water interaction, stream flow, fish distributions

Funding: Wisconsin Department of Natural Resources, Bureau of Drinking Water and Groundwater

Final Report: A final report containing more detailed information on this project is available for loan from Wisconsin's Water Library, University of Wisconsin-Madison, 1975 Willow Drive, Madison, Wisconsin 53706 (608) 262-3069.

Introduction

It is widely recognized that stream flow regime is a primary determinant of aquatic and riparian ecological structure and function (Poff et al. 2010). Water use, landscape modification, and climate change can all modify flow regimes, but there are few tools available to predict the effects of these changes on ecological conditions. Scientifically-based water management requires methods for assessing the tradeoffs between alteration of natural water flow patterns and consequent changes in ecological health. These relationships can serve as the foundation of social and political processes for balancing the benefits of water use and landscape modification with those that derive from healthy, functioning ecosystems. In addition, they can help design management strategies that are robust to potential climate changes.

The Ecological Limits of Hydrologic Alteration (ELOHA) framework provides an approach for determining *environmental flows* – the quantity, timing, and quality of water flows required to sustain freshwater ecosystems and the human livelihoods and well-being that depend on these ecosystems (Arthington et al. 2006, Poff et al. 2010). ELOHA is designed to be applied at regional scales in cases where site-specific studies cannot be performed for all streams in a region. ELOHA synthesizes existing hydrologic and ecological databases from many streams in a region to generate *flow alteration-ecological response relationships* that can then be used to simulate the ecological effects of various human activities that alter stream flows. For example, Michigan is using this approach to support review of groundwater withdrawal permit applications (Hamilton and Seelbach 2011). ELOHA frameworks may be used in many stages of decision making, including broad discussions of issues, long-range planning, land use zoning, public land acquisition, and permit review.

From a technical perspective, an ELOHA framework is composed of hydrologic and ecological models. The hydrologic models relate metrics of climate, natural landscape characteristics, and human activities to temporal and spatial variation in stream flows. The ecological models relate hydrologic and other stream characteristics to one or more ecological characteristics, such as fish species composition. When linked, these models can not only be used to simulate how various human activities, such as groundwater withdrawal, will affect stream flows, but how those changes in flow will be manifested in ecological characteristics. In other words, how much change in flow can a stream tolerate before an unacceptable ecological impact occurs?

This report describes hydrologic and ecological models that are designed to be integrated into a first generation ELOHA framework for Wisconsin streams. The models were developed by the Wisconsin Department of Natural Resources (WDNR) Bureau of Science Services and the US Geological Survey's (USGS) Wisconsin Water Science Center. The first step in this process was to develop a geographic information systems (GIS) database of stream and watershed characteristics for Wisconsin's high resolution hydrography. These characteristics were used as predictors in both the hydrologic and ecological models. The ecological models use fish species composition as a surrogate for overall biological integrity. Because they are at the top of the food chain, fish reflect the overall health of the aquatic environment, and are also valued by society for food and recreation. Hydrologic models were designed to predict stream flow metrics that influence fish species distributions, including measures of low and high flows at annual, seasonal, and selected monthly time scales. These models include several indicators of human activities, including land cover, impervious surface, agricultural drainage, precipitation, and temperature. A simple stream temperature model was also developed to predict how changes in flow would influence water temperature, which also has a strong influence on fish species distributions. To help decision makers, these models are integrated in a spreadsheet template which may be used to develop stream-specific curves describing fish community response to flow alterations.

Methods

Stream characteristic database

Landscape characteristics, such as watershed land cover composition, have strong influences on streams (Hughes et al. 2006). When organized into a GIS database, these variables can serve as the foundation of models that predict other stream characteristics, such as flow regime and biological community composition. In the last decade, the USGS Aquatic Gap Program (GAP) and other cooperating projects developed a GIS framework for collecting, managing, and analyzing multiscale landscape variables across the Great Lakes Basin states, including Wisconsin (Brenden et al. 2006). The GAP database contains hundreds of variables for each feature in the 1:100,000 scale National Hydrography Database (NHD) in Wisconsin. However, because the WDNR uses its own 1:24,000 scale hydrography database as the base layer for all surface water data, it was necessary to create a comparable database for this higher resolution hydrography. We based the selection of variables (Table 1), definitions of spatial scales (Figure 1), and other aspects of database design on the GAP database. A detailed description of the creation and contents of this database are provided in a separate report (Menuz et al. 2013). All of the GIS processing steps used to delineate watersheds and calculate variables were developed as Python scripts, which makes it relatively easy to develop new variables or apply the entire process in other locations. A detailed description of these tools, formatted as a tutorial, is provided in a separate report (Ruesch et al. 2013). The hydrography characteristic database is being incorporated into WDNR's Surface Water Data Viewer (<http://dnrmaps.wi.gov/sl/?Viewer=SWDV>) and is available for download and public use at: ftp://dnrftp01.wi.gov/geodata/hydro_va_24k/.

Stream flow models

Empirical stream flow models were developed for 23 flow metrics, including mean Jun-Sep flow; 5, 10, 25, 50, 75, 90, and 95% annual exceedance flows, and 10, 50, and 90% exceedance flows for three seasonal (spring, summer, fall) and two monthly (April, August) periods. These flow metrics were chosen to encompass the range of flows that fish regularly encounter, and therefore should influence species distributions more than rarely-occurring low (e.g., Q7,10) or high (10-year recurrence flood) flows.

Discharge data were downloaded from the USGS National Water Information System

(NWIS) database (USGS 2001) for all Wisconsin stream gages with at least 1 year of daily discharge data collected between 1981 and 2011. Sites where impoundments comprised more than 10% of the watershed area were excluded. At each site, exceedance flows for each time period were calculated for each year in which discharge was recorded for at least 90% of the days in that period.

Weather variables that were expected to influence stream flow were calculated from DayMet (<http://daymet.ornl.gov/>) grids. For each stream feature, the watershed-average daily maximum (T_{\max}) and minimum (T_{\min}) temperature and precipitation (P) were calculated and used for all further calculations. Daily “effective precipitation” was estimated as precipitation minus snowpack accumulation (precipitation that occurs when average daily temperature $< 0^{\circ}\text{C}$) plus snowmelt (estimated from day of year and average daily temperature using a simplified version of SNOW-17, Anderson 2006). Potential evapotranspiration was estimated from T_{\max} , T_{\min} , and the latitude of the watershed centroid using the Hargreaves method (Hargreaves and Somani 1985). For each site/period, effective precipitation was summarized over seven time frames: the period of discharge data and a series of time periods prior to the period of discharge data: 1-3, 4-6, 7-9, 10-12, 13-24, and 25-48 months. Potential evapotranspiration was summarized as the average over the period of discharge data.

In addition to weather, several watershed characteristics were included as covariates in the flow models, including watershed area and slope, agricultural land cover and drainage, and adjusted soil permeability (Table 2). Adjusted soil permeability was calculated as soil permeability from STATSGO soils multiplied by the proportion of pervious land cover. Agricultural drainage was estimated as the intersection of agricultural land cover and poorly or very poorly drained SSURGO soils. Land cover variables and the impervious cover component of adjusted soil permeability (Table 2) for each site-year combination were derived from the closest in time of three satellite-derived datasets: WISCLAND 1992, and National Land Cover Dataset 2001 and 2006. Watershed area and slope were assumed to be constant over time at a site. Variables were transformed (square root or log) to approximate normality if necessary and then converted to z-scores by subtracting the mean and dividing by the standard deviation.

Mixed effects models were fit using the lmer function in the lme4 package in R. In addition to the fixed effects of the weather and watershed characteristics described above and in Table 2, the models include a random effect of gage ID to account for correlated errors among

multiple observations (years) at the same gage. Variables and interactions were selected for inclusion in the models based on their effect on a standard metric of model parsimony (Akaiki's Information Criterion) and based on the consistency of their coefficients with theoretical expectations. Two variables which were evaluated but not included in the final model were groundwater withdrawal depth (more details in discussion) and the percentage of the watershed that is internally drained (i.e., in closed depressions). Exploratory model selection indicated minor differences among models in which variables were significant predictors, so a common model structure was used for all response variables. The model formula is:

$$\log Q \sim (1 | \text{site}) + \text{shedL} + \text{plag1} + \text{plag4} + \text{plag7} + \text{plag10} + \text{plag13} + \text{plag25} + \text{pmean} * (\text{pet} + \text{adjPermS} + \text{slopeL} + \text{ag} + \text{drainedS}) + \text{pet} * (\text{waterL} + \text{wetland}) + \text{adjPermS} * \text{slopeL}$$

Flow predictions were made for USGS water years 1984-2010, and are also reported as the geometric mean of these annual predictions. The accuracy of flow predictions was assessed with coefficient of determination (R^2), root mean square error (RMSE), and 90% prediction intervals. For all flow metrics, residual variance in predictions was highest at low predicted discharges and decreased linearly (on a log scale) as predicted discharge increased. Therefore, the standard deviation of predictions was estimated with quantile regression relating $\log(\text{flow})$ to the 0.68 quantile of the absolute value of residuals. This regression can then be used to estimate variable-width prediction intervals across the range of predicted flows. Gages with fewer than 10 years of flow record were not included in the estimates of geometric mean prediction intervals because errors were generally higher at gages with short periods of record.

In addition to the predictions for this “current” period, pre-settlement stream flows were simulated by setting agricultural and impervious surface variables to zero and estimating historic wetland percent from “Original Vegetation Cover of Wisconsin” (WDNR 1990).

Fish species distribution models

In this ELOHA analysis, fish species distribution models serve two main purposes. First, they predict which species are most likely to occur in any given stream. Second, they can be used to simulate how a change in any of the model variables, such as August median flow yield, would affect the suitability of that stream for each of its predicted resident species.

Fish data

Distribution models were developed to predict the presence/absence of the 79 stream fishes that were present in at least 10 of the 762 surveys used to develop the models. The surveys were conducted by single-pass electrofishing during the summers of 1996-2011 by WDNR staff. The particular surveys used for model development were selected to cover a wide range of environmental conditions, without over-representing any single stream type (e.g., trout streams) or area of the state. In wadeable streams <3 m wide, a backpack electrofisher was used for a length of 100 m. In wadeable streams >3 m wide, a tow-barge electrofisher with three handheld anodes was used for a length of 400 m or 35 times the mean channel width, whichever was shorter. In non-wadeable rivers, a boat-mounted, fixed-anode boom electrofisher was used for a length of 1620 m. In all sizes of stream, an attempt was made to capture all fishes observed.

Environmental variables

The variables used to predict fish species distributions were assembled from the stream characteristic database described earlier, and from modeled stream flow and stream temperature metrics (Table 3). Rather than include all 23 modeled stream flow metrics, we selected five that span the range of flow magnitude and season and have previously been shown to influence fish species distributions (Zorn et al. 2002, Steen et al. 2008, 2010, Lyons et al. 2010) in the upper Midwest. Two of these metrics represent baseflow conditions that typically occur in the summer: the annual 90% flow is used by the USGS as a “baseflow index” (Holmstrom 1981) and the August 50% exceedance flow is used as the “index flow” in Michigan’s groundwater withdrawal assessment tool (Hamilton and Seelbach 2011). The August 90% exceedance flow is a measure of summer low flow. The annual 50% exceedance flow, or median annual flow represents typical flow conditions. The April 10% exceedance flow is a measure of the high flow during a period when spawning activities (e.g., migration, nest construction) for many fishes may be influenced by stream flow. To separate the effects of stream size from flow, all flow metrics were expressed as flow yields by dividing discharge by drainage area.

Stream water temperatures were estimated from an artificial neural network (ANN) model of measured daily water temperatures linked with geology, topography, climate, and land cover variables. This model was described in more detail in Roehl et al. (2006), Stewart et al.

(2006) and Lyons et al. (2009). For the fish models, daily water temperature predictions for the summers of 1990-2008 were summarized into three metrics: June–August mean, July mean, and maximum daily temperature. The accuracy of these predicted summary statistics, assessed with independent data, is approximately $\pm 1^{\circ}\text{C}$.

Statistical models

Random forest (RF) models were used to predict species distributions. RFs are constructed from large groups of classification trees, which place observations (in this case observations of presence or absence of a fish species) into groups by sequentially splitting the full dataset based on values of predictor variables (Breiman 2001). Each tree in a RF is constructed from a random subset of the data and a random subset of the predictors. Accuracies and error rates are computed for each observation using only the trees that did not include that observation, and then averaged over all observations. The prediction for a species at a site is a probability of occurrence, which is simply the fraction of trees that classify the species as present.

RF models for each of the 79 species were fit using the randomForest package in R. All models were composed of 500 trees. Classification accuracy in RF models tends to be biased toward the dominant class, which for most species is absence. In an effort to balance classification accuracy between presence and absence, particularly for relatively rare species, the number of presences and absences in each tree were initially set as the number of absences in the full dataset. However, because many of these models still had relatively poor presence classification skill (<60%), we reduced the number of observations, if necessary, until the correct presence rate was within 20% of the correct absence rate. For a few species (e.g., redbelt dace, Iowa darter), despite relatively high and balanced correct classification rates, preliminary models were clearly over-predicting their distributional extent. In those cases, the number of observations in each tree was adjusted to balance the competing objectives of high classification rates and correct distributional extent.

The final model for each species was used to predict its probability of occurrence in all streams in the WDNR hydrography database. A probability cutoff of 0.5 was used to distinguish presence from absence. Using this approach, the predicted fish community composition for any stream in Wisconsin is the group of species that are more likely than not to occur there.

Effect of flow alteration on fish

The RF models developed for Wisconsin stream fishes can predict the presence/absence of most species with high accuracy (average 85% correct). However, because many of the predictor variables in these models are inter-correlated, it is not possible to describe the independent effects of these variables on fish species. For example, it would be useful to be able to predict the response of brook trout to changes in stream baseflow, but there are several variables in the RF model for brook trout that either directly or indirectly represent baseflow, so the partial dependence plots for these variables almost always underestimate the magnitude of their effects, and sometimes mischaracterize the shapes of the relationships.

To address this shortcoming, generalized additive models (GAMs) were developed for each species that only include the variables that are known to be dominant influences on stream fish distributions. The models were fit using the gam function in the mgcv package in R. The variables include mean July water temperature, and either median August discharge or the combination of watershed area and median August flow yield. The variables included in each species model were those that produced the most parsimonious model as measured by AIC and generally had p-values <0.05. All variables were fitted as smooth functions with the number of degrees of freedom that minimized overall model AIC and created unimodal functions.

The GAMs and the plotted functions in Appendix 5 replace the RF partial dependence plots in the version of this report dated February 10, 2014 for the purpose of predicting the response of stream fishes to changes in flow and temperature. The RF models are still the best choice for predicting the probability of occurrence of stream fishes under current conditions. The fish response curve spreadsheet tool combines the GAM and RF models using the following equation:

$$PXR = 1/(1+EXP(-(LN(P0R/(1- P0R))+LN(PXG/(1- PXG))-LN(P0G/(1-P0G))))))$$

Where:

PXR is probability of occurrence from the RF model with X% flow reduction

P0R is probability of occurrence from the RF model with no flow reduction

PXG is probability of occurrence from the GAM with X% flow reduction

P0G is probability of occurrence from the GAM with no flow reduction

Effect of flow on temperature

Baseflow reductions increase stream temperature during periods when air temperature is warmer than water temperature (i.e., summer) because the reduced water depth and velocity increase the rate of heat exchange with atmosphere and the time available for radiative heating. We used an approach similar to the one used by Michigan (Zorn et al. 2008) to estimate the change in July mean temperature that would result from a given reduction in August median flow yield (July and August flow and temperature conditions were assumed to be equivalent and were used interchangeably). The model works as follows. The water temperature in a stream segment after some flow reduction (T_{W2}) is:

$$T_{W2} = T_E + (T_{W1} - T_E) \times e^{-kt}$$

where T_E is the equilibrium temperature ($^{\circ}\text{C}$), T_{W1} is the stream temperature before the flow reduction ($^{\circ}\text{C}$), t is the change in the travel time (h) of water through the segment due to the flow reduction, and $k = 0.0085/d$, where d is water depth (m). T_E is estimated as mean July air temperature + 3°C , which approximates the highest observed July mean stream temperatures observed across Wisconsin (22°C in the far north to 25°C in the far south). The parameters d and t are estimated by solving Manning's equation for normal depth in a rectangular channel, knowing gradient (estimated from the 10 m resolution National Elevation Dataset), channel width (hydraulic geometry equations in Bartrons et al. 2013) and discharge (August median flow from this study), and assuming roughness is 0.04. For headwater streams, T_{W1} is the predicted July mean temperature from the ANN model. As an illustrative example, if the flow were reduced by 50% in a stream with an initial depth of 10 cm and a gradient of 0.5%, starting at 18°C with an equilibrium temperature of 24°C , the stream temperature will increase by 0.17°C in the first kilometer. This may not appear to be a large effect, but if flow reductions manifest over long distances, the accumulated heating may be significant (Nuhfer and Baker 2004). In our model, the warming that occurs in a segment is propagated downstream as follows. If segment C is downstream of segments A and B, both of which have experienced warming, the new starting temperature (T_{W1}) for segment C is calculated as the weighted average of the T_{W2} values for segments A and B and the original T_{W1} for segment C, where the weights are proportional to the contribution of each segment to the discharge in segment C.

Results

Stream flow models

Model structure

The three main variable types – weather, watershed characteristics, and their interactions – were all important predictors for most of the stream flow metrics (Appendix 2). As expected, all 23 flow metrics were lower when potential evapotranspiration was higher and were higher when effective precipitation in at least some of the time periods was higher. Precipitation during the flow monitoring period had the strongest effect on all metrics except August 50% and 90% exceedance flows, which were more strongly related to precipitation during the three months prior to the flow period. Lagged precipitation effects were detectable in most flow metrics, including some high flows such as April 10% exceedance flow, out to 2-4 years prior to the flow monitoring period.

Watershed characteristics had more variable influences on the range of flow metrics. For example, soil permeability and slope were both positively correlated with low flow metrics and negatively correlated with high flow metrics. Agricultural land cover was associated with lower values of most flow metrics, but particularly metrics of high flow (e.g., 10% exceedance in all periods). Agricultural drainage, wetland, and open water all had relatively weak effects on most flow metrics on their own, but were stronger in their interactions with weather variables. For example, agricultural drainage only increases flows during wet periods, and wetland has a much greater negative influence on flows during periods with high potential evapotranspiration. Soil permeability and slope have strong interactions with precipitation; variability in precipitation has a much stronger influence on most flow metrics where permeability and slope are low.

Model accuracy

In log space, the models all have very good fit, with R^2 values from 0.93-0.98 between predicted and observed geometric mean flows (Appendix 2). The root mean square error of predictions ranges from 26-63% among models. In general, higher flows (e.g., 10% exceedance) were predicted more accurately as percentages of their observed values than were lower flows. Similarly, flows in larger streams were predicted more accurately than flows in smaller streams. For example, the standard error of a summer mean flow prediction is 40% for a small stream with a predicted flow of 10 cfs, but only 14% for a large river with a predicted flow of 1000 cfs

(Table 4). As expected, flow predictions for individual years were less accurate than their long-term geometric means (Table 4).

Fish species distribution models

Watershed area is by far the most important variable driving distributions of the 79 modeled fish species; it is the single most important variable for 45 of the 79 species (Appendix 3). The three water temperature metrics are the next most important variables, followed by median annual flow yield, stream gradient, and proximity to the nearest medium-sized river. Among the remaining variables, climate and stream flow metrics were most important, followed by land cover, topography, and geology.

The fish species distribution models range from moderately to highly accurate. Because accuracy estimates are derived from a procedure similar to cross validation, they should be considered accurate estimates of how well the models will perform at new sites. Overall model accuracy and specificity (correct absence) both ranged from 67% (black bullhead) to 98% (river carpsucker), with a mean of 85% (Table 5). Model sensitivity (correct presence) ranged from 50% (Iowa darter) to 100% (river shiner and blue sucker), with a mean of 82% (Table 5). Maps of predicted distributions for each species are presented in Appendix 4.

The shapes of partial dependence plots for August median flow yield and July mean temperature varied substantially among species (Appendix 5), and are generally consistent with other information on habitat preferences (summarized in Lyons et al. 2009).

Discussion

Stream flow models

The stream flow models developed in this study build on previous models (Seelbach et al. 2011) that only included watershed characteristics by adding weather variables and several interactions between watershed characteristics and weather. By including weather variables, we were able to use stream flow data from gages with short periods of record (as little as one year), which resulted in models that reflect a broader range of stream sizes and locations in the state. The strong interactions between watershed characteristics and weather variables indicate that streams vary in their response to weather variability, and therefore may respond differently to climate change.

Most of the variables in the flow models have coefficients that are easily interpretable and consistent with theory and previous studies (e.g., Seelbach et al. 2011). However, the influence of agriculture on stream flows appears to be complex. For example, the coefficient on agricultural land cover is negative or insignificant in all the models, which implies that streams in agricultural watersheds have lower flows. However, most of the models also have a significant interaction between precipitation and agriculture and between precipitation and agricultural drainage. Specifically, agriculture reduces all of the annual flow metrics, but the reductions are primarily during dry years. During wet years, agriculture increases the moderate to low flow metrics. Agricultural drainage increases high flows, and has little effect on low flows during wet periods, but decreases low flows during dry periods.

Contrary to our expectations, high capacity well withdrawal rate (volume/watershed area) was not a significant predictor of any of the stream flow metrics. This finding does not mean that groundwater does not influence surface water. Instead, it probably reflects the fact that few gaged streams have significant groundwater withdrawals in their watersheds, as a fraction of the overall water budget of the watershed. Also, some of the highest groundwater withdrawal rates are from deep aquifers, which may not have significant interactions with surface waters, at least over the time span that they have been operating. In short, the dataset and the methods we used were not well suited to detecting the effects of groundwater withdrawals on surface waters.

Fish species distribution models

The 79 fish species distribution models developed in this study are the latest generation

of a series of models developed over the last decade for Wisconsin and neighboring states (Zorn et al. 2002, Steen et al. 2008, Diebel et al. 2010, Lyons et al. 2010). The improvements made in this generation include addition of new predictor variables describing connectivity and stream flow, use of a more robust statistical approach, and application to the highest resolution stream hydrography used by resource managers in Wisconsin. In addition to ecological flows analyses, these models will be used for a variety of applications, including simulations of land cover and climate change effects on stream fish distributions.

For the ecological flows analyses, the models perform two distinct functions. First, they may be used to predict the baseline fish community of any stream. This fish community does not reflect a pristine (e.g., pre-European settlement) status, but rather the community that would be expected given broad patterns in natural factors (topography, geology) and current land use. The models do not account for highly local human impacts, such as barnyards, channel alterations, or flow alterations caused by dams, diversions, or groundwater withdrawals. The baseline fish community represents the set of species whose sensitivity to flow reductions will determine the ecological limits of hydrologic alteration in any given stream. Second, the partial dependence plots for flow and temperature (Appendix 5) derived from the fish distribution models describe the expected response by each species to changes in those variables. As such, these plots are the key result of this project.

The species distribution models were designed to balance the objectives of predicting presence and absence of each species. Thus, while the models correctly predict both the presence and absence of the average species ~85% of the time, this still means that almost all streams are predicted to have substantially higher species richness than they actually do. An example illustrates how this pattern arises. Mud Creek actually has 10 species, of which 8 are correctly predicted to be present by the models. This performance is probably acceptable for most purposes. Of the 69 species that are actually absent, 15% (model error rate), or 10 of those species are predicted to be present in Mud Creek. The predicted species richness is therefore about double (18 vs. 10) the actual species richness. This outcome is an inevitable side effect of developing models that have reasonably high ability to predict species presence. Model users should keep this in mind when interpreting predictions. For example, when refining the baseline fish community for a stream with ancillary data (e.g., surveys, known biogeographical limits), it would generally be more appropriate to exclude a species that has a higher probability of

occurrence (>0.5) but whose actual occurrence is unlikely than to include a species that has a lower probability of occurrence (<0.5) but is believed (but not documented) to be present.

The variety of shapes of the partial dependence plots (Appendix 5) indicates that Wisconsin fishes are highly variable in their sensitivity to flow and temperature. Most of the species that require high flow yields also mainly live in larger rivers, almost all of which have high flow yields. This correlation makes it difficult to determine if these species actually require high flow yields or are just associated with them because of their preference for other aspects of large rivers, such as low gradient or access to backwater habitats. Fortunately, large rivers are probably the least vulnerable stream type to flow alteration by groundwater withdrawal. Among smaller stream species, relatively few require high flow yields (trout, sculpin, lampreys), while many can tolerate low flow yields if other characteristics are suitable. Many of the species that can tolerate low flow yields are coolwater species (Lyons et al. 2009), so flow reductions may cause a stream to exceed thermal limits before flow itself becomes limiting.

Comparison with Michigan's approach

As mentioned earlier, this approach to assessing the ecological effects of stream flow alterations is similar to and was largely based upon a method being used in Michigan (Zorn et al. 2008, Hamilton and Seelbach 2011). While there are several minor differences between the methods, two major differences are discussed here. The first difference is in how the relationships between flow and temperature and fish species were evaluated. In Michigan's approach, the optimal values of August median flow yield and July mean temperature for each species were estimated as the mean values of those variables at sites that had the top 20% of observed abundance of that species. Similarly, the *tolerance for change* in flow or temperature was based on the variance of those variables at sites with the top 20% of observed abundance. This approach assumes that abundance for any given species is distributed normally around optimal values of flow and temperature. We decided not to use this approach in Wisconsin for two reasons. First, for almost all species, we did not observe strong relationships between abundance and modeled flow or temperature. This finding may have been the result of variation in other stream characteristics that were more important or that obscured these relationships. In contrast, there were strong relationships between flow and temperature and the occurrence (presence/absence) of most species in the random forest models that also included several other

variables (Table 3). Second, based on the partial dependence plots from the generalized additive models, the relationships between flow and temperature and the occurrence of most species do not follow normal distributions (Appendix 5). In contrast, most of the plots approximated linear or threshold relationships. In many cases, the consequence of using a normal distribution to describe a threshold relationship would be to underestimate the sensitivity of that species to flow or temperature changes.

The second major difference is related to the specificity of the expected fish response to flow alterations among streams. Michigan created fish response curves for 11 stream types (defined by size and temperature), where each curve was the average of the curves for ~20 streams in that class. They chose this approach because fish communities are generally similar within a stream type, and because the average curves should be less sensitive to errors in predicted species composition than stream-specific curves. We chose to create stream-specific curves because our species distribution models provide relatively precise predictions of species composition in any given stream and because, particularly in coolwater streams, there is a lot of variability in species composition driven by factors such as gradient, land cover, and biogeographical limits. We recognize that errors in predicted species composition could lead to unrealistic fish response curves, so we encourage use of survey data when available to identify the resident fish community.

In addition to these differences, whether the allowable flow reductions from our approach are similar to Michigan's regulatory thresholds (Hamilton and Seelbach 2011) depends on policy decisions about what constitutes a "significant adverse environmental impact". These decisions will be addressed in a separate policy document that is being developed by WDNR.

Conclusions

The stream flow and fish distribution models developed through this study provide tools for predicting the biological effects of reductions in summer low flows in Wisconsin streams. The stream flow models use weather and watershed characteristics to predict 23 flow metrics at annual, seasonal, and monthly time scales. These models are potentially useful for many applications, including simulating the effects of land cover and climate change on stream flows, estimating hydraulic geometry (width, depth, velocity) of streams, and estimating water residence time of lakes and reservoirs. The flow metrics and hundreds of other stream and watershed characteristics are being incorporated into WDNR's Surface Water Data Viewer (<http://dnrmaps.wi.gov/sl/?Viewer=SWDV>) and are available for download and public use at: ftp://dnrftp01.wi.gov/geodata/hydro_va_24k/. The fish distribution models predict the occurrence of 79 stream fishes across Wisconsin based on stream flow, temperature, and several other GIS-derived stream and watershed characteristics. These models can be used to predict the resident fish community of any stream in Wisconsin and to simulate the effects of flow and temperature alterations on each species. This framework provides a consistent method for evaluating potential flow alterations to balance extractive water uses with ecological requirements. The question of what constitutes a significant adverse impact will be addressed in a separate policy document that is being developed by WDNR.

Table 1. Characteristics of hydrographic features were calculated at five spatial scales: stream channel (C), incremental watershed (W), cumulative watershed (WT), incremental riparian (R), and cumulative riparian (RT).

Characteristic	C	R	RT	W	WT
Area		X	X	X	X
Surficial geology types	X	X	X	X	X
Bedrock geology types and depth	X	X	X	X	X
Soil permeability				X	X
Slope				X	X
Sinks (% internally drained area)				X	X
Groundwater flow velocity (Darcy)				X	X
Land cover (NLCD 1992, 2001, 2006; pre-settlement; projected 2020, 30, 40, 50)		X	X	X	X
Climate (annual precipitation; annual, growing season, and July temperature)				X	X
High capacity well withdrawal rate (annual 1981-2010)				X	X
Stream gradient	X				
Aquatic patch size (area and length bounded by dams)	X				
Connectivity and distance to large rivers, lakes, and Great Lakes	X				

Table 2. Flow model predictor variables.

Variable Name	Units	Description
shedL	km ²	Total upstream watershed area
adjPermS	in/hr	Soil permeability from STATSGO soils multiplied by the proportion of pervious land cover
slopeL	%	Average land slope from 10 m NED
ag	%	Sum of pasture/hay and cultivated crops
drainedS	%	Agricultural drainage estimated as the intersection of agricultural land cover and poorly or very poorly drained SSURGO soils
waterL	%	Open water
wetland	%	Sum of woody wetlands and emergent herbaceous wetlands
pmean, plag1, plag4, etc.	mm/day	Effective precipitation (details in methods)
pet	mm/day	Potential evapotranspiration (details in methods)

Table 3. Fish model variables.

Variable Name	Definition
Stream size	
WT_AREA	Watershed area (km ²) upstream of reach
Water temperature	
TEMP_MAX	Average maximum daily mean water temperature (°C)
TEMP_JULX	Average daily mean water temperature (°C) for July
TEMP_JJAX	Average daily mean water temperature (°C) for summer (June, July, August)
Channel characteristics	
GRADIENT	Gradient (m/km) of channel
SINUOUS	Sinuosity of channel
Stream flow	
Q10_APR	10% exceedance (high) flow yield (ft ³ /s/mi ²) in April
Q50_ANN	50% exceedance (median) flow yield (ft ³ /s/mi ²) for entire year
Q90_ANN	90% exceedance (low) flow yield (ft ³ /s/mi ²) for entire year
Q50_AUG	50% exceedance (low) flow yield (ft ³ /s/mi ²) in August
Q90_AUG	90% exceedance (very low) flow yield (ft ³ /s/mi ²) in August
Connectivity	
GL_DIST	Distance downstream to Great Lake
LAKE_SM_DIST	Distance to nearest lake >=500 acres within 50 km in any direction
LAKE_MD_DIST	Distance to nearest lake >=50 and <500 acres within 50 km in any direction
LAKE_LG_DIST	Distance to nearest lake >=5 and <50 acres within 50 km in any direction
RIVER_MD_DIST	Distance downstream to nearest river with at least 100 km ² watershed area
RIVER_LG_DIST	Distance downstream to nearest river with at least 1000 km ² watershed area
SUBNET_LK_AR	Sum of lake area in connected sub-network
SUBNET_ST_LEN	Sum of stream length in connected sub-network
Valley form, soil permeability, and groundwater potential	
R_DARCY	Mean Darcy value (groundwater potential) for adjacent riparian area
RT_DARCY	Mean Darcy value (groundwater potential) for upstream riparian areas
W_DARCY	Mean Darcy value (groundwater potential) for adjacent watershed
WT_DARCY	Mean Darcy value (groundwater potential) for upstream watershed
R_PERM	Mean soil permeability (in/hr X 100) in adjacent riparian area
RT_PERM	Mean soil permeability (in/hr X 100) in upstream riparian areas
W_PERM	Mean soil permeability (in/hr X 100) in adjacent watershed
WT_PERM	Mean soil permeability (in/hr X 100) in upstream watershed

Variable Name	Definition
R_SLOPE	Mean slope (percent) of adjacent riparian area
RT_SLOPE	Mean slope (percent) of upstream riparian areas
W_SLOPE	Mean slope (percent) of adjacent watershed
WT_SLOPE	Mean slope (percent) of upstream watershed
Adjacent riparian land cover	
R_AGRIC	Percent agriculture (all categories combined) in adjacent riparian area
R_FORST	Percent forest (all categories combined) in adjacent riparian area
R_GRASS	Percent grassland (all categories combined) in adjacent riparian area
R_URBAN	Percent urban (all categories combined) in adjacent riparian area
R_WATER	Percent open water (all categories combined) in adjacent riparian area
R_WETLD	Percent wetland (all categories combined) in adjacent riparian area
Upstream riparian land cover	
RT_AGRIC	Percent agriculture (all categories combined) in upstream riparian areas
RT_FORST	Percent forest (all categories combined) in upstream riparian areas
RT_GRASS	Percent grassland (all categories combined) in upstream riparian areas
RT_URBAN	Percent urban (all categories combined) in upstream riparian areas
RT_WATER	Percent open water (all categories combined) in upstream riparian areas
RT_WETLD	Percent wetland (all categories combined) in upstream riparian areas
Adjacent watershed land cover	
W_AGRIC	Percent agriculture (all categories combined) in adjacent watershed
W_FORST	Percent forest (all categories combined) in adjacent watershed
W_GRASS	Percent grassland (all categories combined) in adjacent watershed
W_URBAN	Percent urban (all categories combined) in adjacent watershed
W_WATER	Percent open water (all categories combined) in adjacent watershed
W_WETLD	Percent wetland (all categories combined) in adjacent watershed
Upstream watershed land cover	
WT_AGRIC	Percent agriculture (all categories combined) in upstream watershed
WT_FORST	Percent forest (all categories combined) in upstream watershed
WT_GRASS	Percent grassland (all categories combined) in upstream watershed
WT_URBAN	Percent urban (all categories combined) in upstream watershed
WT_WATER	Percent open water (all categories combined) in upstream watershed
WT_WETLD	Percent wetland (all categories combined) in upstream watershed
Surficial and bedrock geology in upstream watershed	
WT_BR_SAND	Percent sandstone bedrock in upstream watershed

Variable Name	Definition
WT_BR_SHAL	Percent shale bedrock in upstream watershed
WT_BR_CARB	Percent carbonate bedrock in upstream watershed
WT_BR_META	Percent metamorphic bedrock in upstream watershed
WT_BR_IGNS	Percent igneous bedrock in upstream watershed
WT_SG_FINE	Percent fine textured surficial geology in upstream watershed
WT_SG_MED	Percent medium textured surficial geology in upstream watershed
WT_SG_CORSE	Percent coarse textured surficial geology in upstream watershed
Climate (1961-2000)	
W_PRCP_ANN	Mean annual precipitation (mm) in adjacent watershed
W_TEMP_ANN	Mean annual temperature (°C) in adjacent watershed
W_TEMP_GS	Mean growing season (Apr-Oct) temperature (°C) in adjacent watershed
W_TEMP_JULY	Mean July temperature (°C) in adjacent watershed
WT_PRCP_ANN	Mean annual precipitation (mm) in upstream watershed
WT_TEMP_ANN	Mean annual temperature (°C) in upstream watershed
WT_TEMP_GS	Mean growing season (Apr-Oct) temperature (°C) in upstream watershed
WT_TEMP_JULY	Mean July temperature (°C) in upstream watershed

Table 4. 90% prediction intervals for stream flow models. Type *mean* is the geometric mean of predictions for the period of record at gages with >10 years of record. Intercept and slope define the regression relating the residual standard deviation with the predicted discharge in log space. Lower and upper values for each example predicted discharge are 90% prediction intervals in real space.

		Predicted Discharge (cfs)			1		10		100		1000	
Type	Period	Metric	Intercept	Slope	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
mean	WRT	mean	0.438	-0.044	0.49	2.06	5.7	17.4	68	147	801	1248
year	WRT	mean	0.687	-0.059	0.32	3.10	4.0	24.7	51	198	633	1579
mean	WY	5%	0.384	-0.036	0.53	1.88	6.1	16.4	70	143	799	1251
year	WY	5%	0.489	-0.030	0.45	2.23	5.0	19.9	56	177	632	1582
mean	WY	10%	0.378	-0.036	0.54	1.86	6.2	16.2	71	142	808	1237
year	WY	10%	0.513	-0.039	0.43	2.32	5.0	20.1	58	173	669	1494
mean	WY	25%	0.334	-0.034	0.58	1.73	6.6	15.2	75	134	852	1173
year	WY	25%	0.537	-0.048	0.41	2.42	5.0	20.2	59	168	712	1404
mean	WY	50%	0.519	-0.060	0.43	2.35	5.4	18.7	67	149	846	1182
year	WY	50%	0.629	-0.066	0.36	2.82	4.6	21.9	59	171	753	1329
mean	WY	75%	0.744	-0.094	0.29	3.40	4.2	23.8	60	166	858	1165
year	WY	75%	0.737	-0.082	0.30	3.36	4.1	24.6	55	180	758	1320
mean	WY	90%	0.701	-0.083	0.32	3.17	4.3	23.1	59	169	811	1233
year	WY	90%	0.793	-0.088	0.27	3.68	3.8	26.5	53	190	734	1363
mean	WY	95%	0.811	-0.101	0.26	3.79	3.9	25.9	57	177	830	1205
year	WY	95%	0.854	-0.097	0.25	4.08	3.5	28.2	51	196	738	1356
mean	spring	10%	0.477	-0.044	0.46	2.19	5.4	18.5	64	157	754	1326
year	spring	10%	0.536	-0.029	0.41	2.41	4.6	21.6	52	194	576	1738
mean	spring	50%	0.332	-0.032	0.58	1.73	6.5	15.3	74	136	829	1206
year	spring	50%	0.574	-0.047	0.39	2.57	4.7	21.5	56	180	667	1500
mean	spring	90%	0.606	-0.062	0.37	2.71	4.7	21.4	59	169	746	1340
year	spring	90%	0.727	-0.067	0.30	3.31	3.9	25.6	50	198	651	1537
mean	summer	10%	0.432	-0.038	0.49	2.04	5.7	17.6	66	152	759	1318
year	summer	10%	0.704	-0.043	0.31	3.18	3.7	27.1	43	230	512	1955
mean	summer	50%	0.621	-0.073	0.36	2.78	4.7	21.1	63	160	826	1211
year	summer	50%	0.780	-0.080	0.28	3.61	3.8	26.7	51	197	687	1455
mean	summer	90%	0.902	-0.109	0.23	4.41	3.4	29.2	52	193	780	1282
year	summer	90%	0.893	-0.098	0.23	4.34	3.3	29.9	49	206	705	1419
mean	fall	10%	0.576	-0.060	0.39	2.58	4.9	20.5	61	163	771	1297
year	fall	10%	0.732	-0.059	0.30	3.33	3.7	26.7	47	214	584	1713
mean	fall	50%	0.627	-0.076	0.36	2.80	4.8	21.1	63	158	843	1186
year	fall	50%	0.790	-0.082	0.27	3.67	3.7	26.9	51	197	691	1447
mean	fall	90%	0.779	-0.100	0.28	3.60	4.1	24.7	59	169	861	1161
year	fall	90%	0.966	-0.108	0.20	4.90	3.1	32.5	46	216	696	1437
mean	April	10%	0.630	-0.057	0.35	2.82	4.4	22.8	54	184	674	1483
year	April	10%	0.609	-0.023	0.37	2.72	4.0	25.0	44	229	475	2105
mean	April	50%	0.489	-0.045	0.45	2.24	5.3	18.8	63	159	748	1336
year	April	50%	0.604	-0.035	0.37	2.70	4.2	23.7	48	207	550	1818
mean	April	90%	0.484	-0.041	0.45	2.22	5.3	19.0	61	163	715	1398
year	April	90%	0.633	-0.039	0.35	2.83	4.1	24.4	47	211	551	1816
mean	August	10%	0.580	-0.061	0.38	2.60	4.8	20.6	61	164	769	1300
year	August	10%	0.843	-0.065	0.25	4.00	3.2	31.2	41	244	526	1903
mean	August	50%	0.743	-0.086	0.29	3.39	4.1	24.5	57	177	783	1276
year	August	50%	0.885	-0.089	0.23	4.29	3.3	30.7	46	219	638	1567
mean	August	90%	0.754	-0.087	0.29	3.46	4.0	24.8	56	178	780	1282
year	August	90%	0.951	-0.104	0.21	4.78	3.1	32.2	46	218	681	1467

Table 5. Fish species distribution model summary statistics. Prevalence is the percentage of the 762 fish surveys where the species was present.

Species	Prevalence	Correct Classification Rate		
		All	Absence	Presence
Coldwater Species				
mottled sculpin	21%	80%	80%	80%
brown trout	15%	79%	79%	77%
brook trout	15%	81%	82%	76%
rainbow trout	3%	88%	88%	71%
Coolwater Species				
white sucker	58%	80%	74%	85%
creek chub	51%	77%	77%	76%
central mudminnow	40%	81%	81%	82%
johnny darter	39%	77%	79%	74%
brook stickleback	34%	76%	76%	76%
blacknose dace	28%	77%	78%	73%
longnose dace	17%	85%	85%	84%
walleye	16%	92%	92%	90%
northern hog sucker	15%	86%	86%	85%
yellow perch	14%	81%	82%	78%
northern pike	13%	76%	77%	71%
northern redbelly dace	12%	86%	88%	72%
pearl dace	11%	86%	87%	71%
brassy minnow	7%	77%	78%	66%
blacknose shiner	6%	83%	83%	83%
burbot	5%	85%	85%	82%
finescale dace	5%	89%	89%	87%
redside dace	4%	91%	92%	75%
northern brook lamprey	3%	86%	86%	90%
American brook lamprey	3%	83%	83%	78%
muskellunge	2%	90%	90%	91%
Warmwater Species				
common shiner	36%	79%	80%	78%
smallmouth bass	26%	89%	89%	88%
shorthead redhorse	23%	92%	92%	91%
fathead minnow	23%	76%	77%	74%
common carp	23%	91%	91%	90%
bluntnose minnow	23%	76%	76%	76%
hornyhead chub	23%	82%	83%	81%
bluegill	22%	75%	75%	74%
green sunfish	21%	81%	82%	80%
rock bass	19%	82%	81%	84%
logperch	18%	81%	82%	80%
spotfin shiner	17%	89%	89%	89%

Species	Prevalence	Correct Classification Rate		
		All	Absence	Presence
fantail darter	17%	81%	81%	81%
blackside darter	15%	83%	83%	85%
golden redhorse	14%	86%	85%	89%
black bullhead	13%	67%	68%	66%
central stoneroller	13%	80%	81%	75%
emerald shiner	12%	97%	97%	97%
pumpkinseed	11%	76%	77%	69%
largemouth bass	11%	69%	69%	70%
silver redhorse	10%	90%	89%	92%
channel catfish	9%	89%	89%	84%
sand shiner	9%	86%	86%	82%
black crappie	9%	75%	74%	75%
quillback	9%	94%	94%	96%
yellow bullhead	9%	79%	79%	77%
golden shiner	8%	72%	73%	67%
southern redbelly dace	8%	87%	88%	78%
stonecat	8%	86%	86%	84%
freshwater drum	8%	92%	92%	92%
largescale stoneroller	7%	78%	79%	74%
sauger	6%	95%	95%	95%
rosyface shiner	6%	86%	86%	87%
bigmouth shiner	6%	75%	75%	71%
river carpsucker	6%	98%	98%	97%
blue sucker	5%	98%	98%	100%
gizzard shad	5%	91%	91%	91%
banded darter	5%	85%	85%	84%
rainbow darter	5%	86%	86%	81%
smallmouth buffalo	5%	96%	96%	97%
highfin carpsucker	4%	96%	96%	96%
iowa darter	4%	83%	84%	50%
white bass	4%	93%	93%	91%
longnose gar	4%	97%	97%	91%
river shiner	4%	97%	96%	100%
greater redhorse	3%	87%	87%	85%
mooneye	3%	94%	94%	90%
bullhead minnow	3%	93%	93%	89%
bowfin	3%	83%	83%	82%
suckermouth minnow	2%	93%	94%	80%
slenderhead darter	2%	74%	74%	71%
grass pickerel	2%	87%	87%	75%
tadpole madtom	2%	80%	80%	67%
river redhorse	1%	87%	87%	86%

Figure 1. Illustration of spatial scales of characteristics of an example stream segment, shown as thick line in panel a (channel (a), incremental riparian (b), cumulative riparian (c), incremental watershed (d), cumulative watershed (e)) (adapted from Brenden et al. 2006).

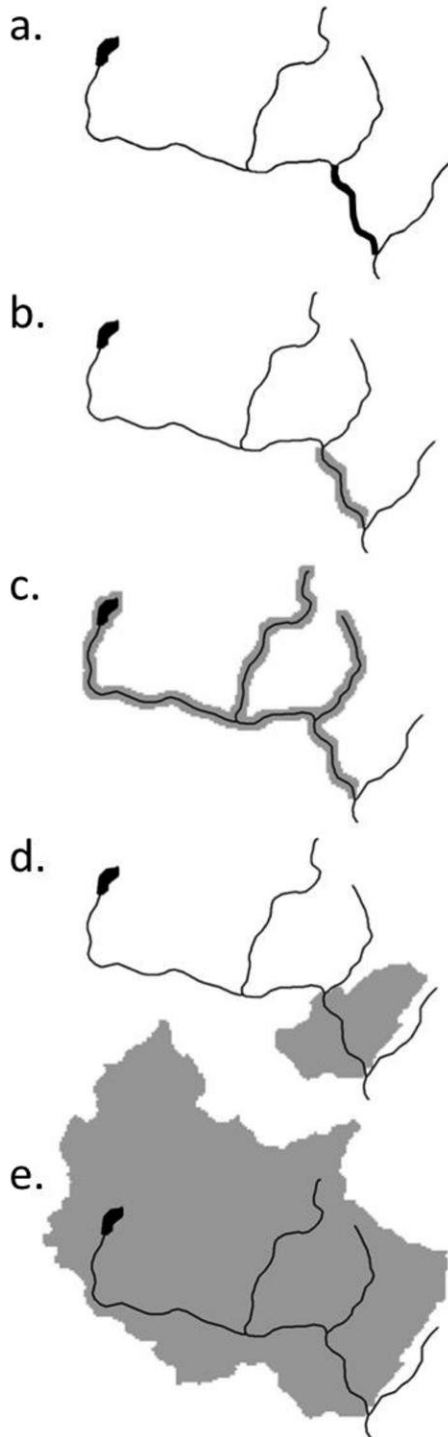
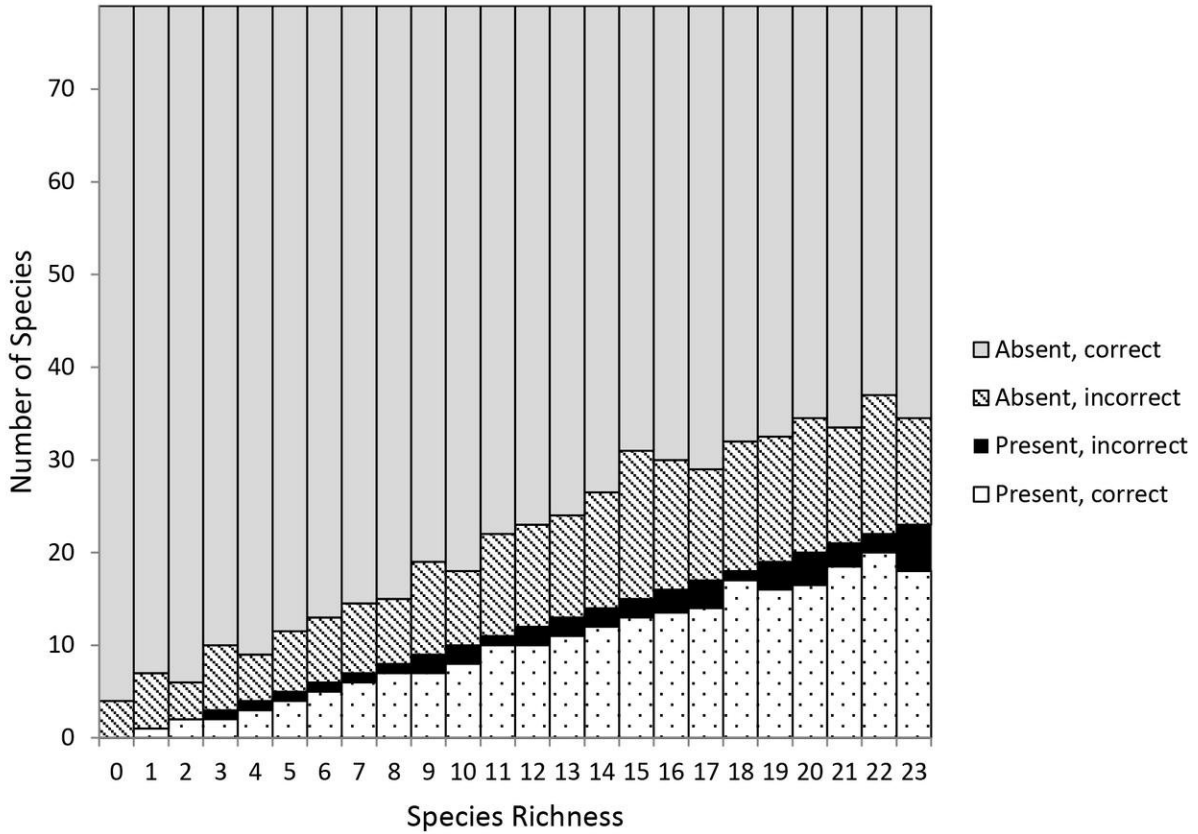


Figure 2. Model performance at predicting identity of entire fish community across a range of observed species richness. For each value of observed species richness on the horizontal axis, classification values are the medians of all sites with that richness.



List of Appendices

Appendix 1. Instructions for using fish response curve spreadsheet template (in development).

Appendix 2. Flow model summary table. Model fit statistics are presented for all sites, and sites with ≥ 5 and ≥ 10 years of record. For each model/parameter, Est is the coefficient estimate and t is the T-statistic. RMSE is root mean square error.

Appendix 3. Influence scores for variables in fish models (Gini purity normalized to range from 0 (no influence) to 1 (most important) for each species).

Appendix 4. Maps of predicted distributions for 79 Wisconsin stream fishes. Points are the 762 fish surveys used in model development. This appendix is not included in the WRI version of this report because it is a large file (320 MB).

Appendix 5. Partial dependence plots for statistically significant variables in generalized additive models of 79 Wisconsin stream fishes.

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Appendix 2 - Flow model coefficients and accuracy

Period		April						August					
Metric		10%		50%		90%		10%		50%		90%	
R ² (all sites)		0.960		0.961		0.943		0.945		0.919		0.894	
R ² (>=5 years)		0.974		0.974		0.976		0.967		0.957		0.937	
R ² (>=10 years)		0.970		0.971		0.972		0.967		0.955		0.934	
RMSE (all sites)		0.478		0.488		0.578		0.563		0.712		0.819	
RMSE (>=5 years)		0.372		0.378		0.362		0.395		0.485		0.607	
RMSE (>=10 years)		0.368		0.372		0.364		0.364		0.468		0.584	
<25% error (all sites)		54%		58%		51%		45%		43%		42%	
<50% error (all sites)		72%		76%		74%		69%		63%		57%	
<100% error (all sites)		88%		89%		87%		85%		80%		74%	
<25% error (>=5 years)		66%		68%		64%		56%		52%		46%	
<50% error (>=5 years)		80%		83%		82%		78%		73%		67%	
<100% error (>=5 years)		92%		91%		94%		91%		86%		82%	
<25% error (>=10 years)		67%		71%		65%		63%		58%		51%	
<50% error (>=10 years)		78%		83%		81%		83%		79%		71%	
<100% error (>=10 years)		92%		91%		93%		92%		87%		85%	
		Est	t	Est	t	Est	t	Est	t	Est	t	Est	t
Intercept		5.83	179.6	5.16	140.4	4.74	138.5	4.70	139.2	4.09	90.2	3.78	74.0
shedL		2.16	69.7	2.21	64.4	2.17	66.9	2.11	63.5	2.17	51.0	2.13	43.6
weather	pet	-0.05	-5.2	-0.08	-9.3	-0.09	-9.8	-0.03	-2.1	-0.08	-6.9	-0.09	-7.6
	pmean	0.48	54.1	0.38	46.6	0.26	30.6	0.53	43.4	0.27	27.4	0.11	11.9
	plag1	0.17	20.8	0.17	21.9	0.18	21.9	0.38	34.4	0.33	37.0	0.31	36.6
	plag4	0.13	16.0	0.13	17.6	0.13	16.0	0.09	8.5	0.09	11.1	0.09	12.0
	plag7	0.07	8.6	0.10	12.5	0.12	14.7	-0.01	-0.8	0.01	1.3	0.05	4.8
	plag10	0.09	12.4	0.05	7.9	0.05	6.6	0.12	10.9	0.10	12.2	0.10	11.9
	plag13	0.03	4.5	0.05	6.6	0.03	4.7	0.02	1.6	0.04	4.6	0.06	6.9
	plag25	0.09	10.6	0.06	8.5	0.05	5.8	0.05	4.1	0.09	10.5	0.08	10.0
watershed	adjPermS	-0.18	-5.2	-0.01	-0.3	0.06	1.7	-0.04	-1.0	0.17	3.6	0.25	4.9
	slopeL	-0.21	-6.2	-0.07	-1.9	0.04	1.2	0.01	0.1	0.17	3.8	0.25	4.8
	ag	-0.26	-7.0	-0.05	-1.4	-0.03	-0.8	-0.31	-7.2	-0.10	-2.1	-0.09	-1.7
	drainedS	0.12	4.0	0.02	0.6	0.03	1.0	0.03	0.9	-0.10	-2.9	-0.07	-2.0
	waterL	-0.03	-1.2	0.04	1.5	0.02	0.8	0.01	0.2	0.04	1.2	0.02	0.8
	wetland	0.08	3.1	0.12	4.8	0.12	4.8	-0.04	-1.2	0.01	0.2	-0.01	-0.3
interactions	pmean:pet	0.02	2.5	-0.01	-1.4	-0.01	-1.3	-0.03	-2.1	-0.05	-3.6	0.00	-0.1
	pmean:adjPermS	-0.10	-13.2	-0.06	-9.1	-0.03	-4.4	-0.16	-14.3	-0.08	-8.4	-0.04	-4.7
	pmean:slopeL	-0.09	-9.7	-0.10	-11.6	-0.08	-8.6	-0.10	-9.9	-0.07	-7.8	-0.04	-5.7
	adjPermS:slopeL	0.05	1.8	0.02	0.6	-0.02	-0.6	-0.04	-1.1	-0.08	-2.1	-0.16	-3.3
	pmean:ag	0.00	0.4	0.02	1.5	0.05	4.4	-0.08	-6.3	-0.06	-5.5	-0.03	-3.0
	pmean:drainedS	-0.01	-0.8	0.01	0.5	0.02	1.3	0.07	5.0	0.04	3.5	0.00	0.5
	pet:waterL	0.01	1.5	0.01	0.9	-0.01	-1.1	0.00	0.0	-0.01	-1.0	-0.01	-1.4
	pet:wetland	0.00	-0.3	0.00	0.6	0.00	0.3	-0.04	-2.8	-0.03	-2.3	-0.02	-1.6

Appendix 2 - Flow model coefficients and accuracy

Period		Spring						Summer					
Metric		10%		50%		90%		10%		50%		90%	
R ² (all sites)		0.967		0.965		0.916		0.959		0.935		0.900	
R ² (>=5 years)		0.980		0.980		0.970		0.975		0.965		0.938	
R ² (>=10 years)		0.978		0.978		0.967		0.979		0.961		0.930	
RMSE (all sites)		0.422		0.441		0.695		0.475		0.618		0.789	
RMSE (>=5 years)		0.311		0.321		0.395		0.346		0.429		0.600	
RMSE (>=10 years)		0.307		0.308		0.386		0.287		0.427		0.606	
<25% error (all sites)		54%		66%		52%		54%		49%		40%	
<50% error (all sites)		77%		80%		71%		74%		71%		60%	
<100% error (all sites)		90%		91%		85%		90%		84%		75%	
<25% error (>=5 years)		69%		75%		63%		63%		60%		46%	
<50% error (>=5 years)		87%		87%		79%		87%		79%		71%	
<100% error (>=5 years)		94%		95%		92%		96%		88%		84%	
<25% error (>=10 years)		72%		79%		65%		70%		67%		49%	
<50% error (>=10 years)		87%		87%		79%		89%		82%		75%	
<100% error (>=10 years)		94%		95%		91%		97%		88%		85%	
		Est	t	Est	t	Est	t	Est	t	Est	t	Est	t
Intercept		5.89	202.5	5.02	168.6	4.33	110.0	5.20	190.2	4.30	111.9	3.78	76.1
shedL		2.14	75.5	2.13	74.1	2.10	55.1	2.11	76.9	2.14	59.4	2.12	44.8
weather	pet	-0.06	-9.5	-0.08	-13.3	-0.06	-7.6	-0.17	-14.4	-0.18	-19.0	-0.15	-16.2
	pmean	0.31	49.8	0.22	38.6	0.16	21.3	0.40	42.1	0.29	38.8	0.24	31.7
	plag1	0.09	10.6	0.10	13.6	0.13	12.4	0.23	24.0	0.19	25.3	0.16	20.7
	plag4	0.11	19.2	0.11	22.5	0.09	13.1	0.11	8.3	0.11	10.3	0.10	9.6
	plag7	0.05	8.2	0.12	22.2	0.11	15.2	0.05	5.8	0.07	10.4	0.09	12.6
	plag10	0.03	5.5	0.04	8.3	0.07	10.2	0.04	4.3	0.05	7.6	0.07	10.4
	plag13	0.00	0.9	0.03	6.5	0.04	5.8	-0.03	-3.6	0.01	1.4	0.04	5.0
	plag25	0.04	6.3	0.00	0.9	0.02	2.7	0.07	7.5	0.08	11.1	0.08	10.8
watershed	adjPermS	-0.21	-7.1	-0.03	-0.8	0.09	2.2	-0.09	-3.1	0.13	3.4	0.26	5.4
	slopeL	-0.23	-7.3	-0.04	-1.4	0.16	3.9	-0.09	-3.0	0.18	4.8	0.27	5.5
	ag	-0.19	-6.0	-0.10	-3.1	-0.17	-4.1	-0.27	-7.5	-0.11	-2.6	-0.10	-2.1
	drainedS	0.02	1.0	-0.02	-1.1	0.07	2.2	0.12	4.0	-0.01	-0.5	-0.05	-1.6
	waterL	-0.02	-0.9	0.03	1.5	0.03	1.2	0.02	0.8	0.06	2.3	0.01	0.5
	wetland	0.01	0.7	0.07	3.5	0.05	2.0	-0.04	-1.5	-0.04	-1.7	-0.05	-1.9
interactions	pmean:pet	-0.03	-5.4	-0.02	-3.5	0.00	0.3	-0.02	-2.7	-0.07	-9.5	-0.06	-8.7
	pmean:adjPermS	-0.05	-8.9	-0.03	-5.8	-0.03	-4.3	-0.11	-11.5	-0.05	-7.3	-0.02	-2.9
	pmean:slopeL	-0.04	-6.5	-0.04	-7.1	-0.04	-4.9	-0.09	-9.2	-0.10	-13.9	-0.09	-11.9
	adjPermS:slopeL	0.08	2.7	-0.01	-0.4	-0.07	-1.8	-0.02	-0.8	-0.05	-1.5	-0.15	-3.1
	pmean:ag	0.01	1.1	0.02	2.6	0.03	3.4	0.01	0.9	0.01	1.2	0.03	3.3
	pmean:drainedS	-0.01	-0.7	0.01	1.3	0.03	2.9	0.07	5.2	0.06	6.2	0.04	3.5
	pet:waterL	0.00	0.4	0.00	-0.2	-0.04	-4.1	-0.02	-1.4	-0.02	-2.3	-0.01	-0.7
	pet:wetland	-0.01	-1.5	0.00	-0.2	0.02	2.3	-0.04	-3.3	-0.02	-2.1	-0.02	-2.4

Appendix 2 - Flow model coefficients and accuracy

Period		Fall						Annual					
Metric		10%		50%		90%		5%		10%		25%	
R ² (all sites)		0.954		0.939		0.877		0.976		0.973		0.968	
R ² (>=5 years)		0.971		0.964		0.933		0.983		0.983		0.981	
R ² (>=10 years)		0.977		0.962		0.924		0.983		0.983		0.981	
RMSE (all sites)		0.517		0.607		0.903		0.355		0.382		0.419	
RMSE (>=5 years)		0.382		0.444		0.632		0.281		0.286		0.313	
RMSE (>=10 years)		0.313		0.436		0.630		0.257		0.260		0.287	
<25% error (all sites)		52%		48%		40%		65%		66%		63%	
<50% error (all sites)		75%		68%		61%		81%		83%		82%	
<100% error (all sites)		87%		84%		78%		93%		93%		92%	
<25% error (>=5 years)		60%		59%		48%		76%		77%		72%	
<50% error (>=5 years)		81%		77%		69%		88%		90%		88%	
<100% error (>=5 years)		93%		91%		85%		95%		95%		94%	
<25% error (>=10 years)		65%		66%		52%		80%		80%		77%	
<50% error (>=10 years)		85%		81%		73%		88%		90%		89%	
<100% error (>=10 years)		95%		90%		87%		95%		95%		95%	
		Est	t	Est	t	Est	t	Est	t	Est	t	Est	t
Intercept		5.01	156.2	4.32	117.0	3.83	73.4	5.88	252.5	5.53	220.0	4.97	169.6
shedL		2.11	66.1	2.10	58.2	2.11	42.3	2.08	91.1	2.10	86.5	2.13	75.5
weather	pet	-0.12	-7.9	-0.11	-7.9	-0.13	-7.7	-0.11	-15.5	-0.11	-16.9	-0.10	-13.3
	pmean	0.44	51.1	0.26	33.2	0.15	16.6	0.26	52.7	0.25	53.6	0.22	43.7
	plag1	0.25	29.5	0.26	33.6	0.31	35.4	0.09	18.8	0.10	21.8	0.11	22.9
	plag4	0.07	8.2	0.11	14.6	0.12	13.3	0.06	13.2	0.07	16.8	0.08	17.6
	plag7	0.01	1.1	0.06	4.9	0.03	2.4	0.00	0.5	0.01	1.1	0.02	4.6
	plag10	0.06	6.4	0.09	10.5	0.08	8.6	0.01	2.7	0.01	2.7	0.01	2.3
	plag13	0.04	4.8	0.04	5.7	0.06	6.5	0.02	4.9	0.04	8.2	0.04	9.2
	plag25	0.05	5.6	0.05	6.4	0.03	3.2	0.01	2.2	0.00	1.0	0.02	3.2
watershed	adjPermS	-0.05	-1.6	0.17	4.6	0.27	5.1	-0.24	-10.1	-0.16	-6.4	0.00	0.0
	slopeL	-0.04	-1.3	0.17	4.6	0.29	5.5	-0.19	-8.0	-0.15	-5.6	-0.03	-0.9
	ag	-0.18	-4.7	-0.05	-1.1	0.00	0.1	-0.16	-6.3	-0.11	-4.3	-0.07	-2.4
	drainedS	-0.05	-1.6	-0.04	-1.4	-0.05	-1.4	0.05	2.9	0.01	0.6	-0.04	-1.7
	waterL	-0.02	-0.6	0.04	1.6	0.03	0.9	0.00	0.3	0.04	2.2	0.05	2.7
	wetland	0.02	0.8	0.06	2.1	-0.01	-0.4	0.03	1.6	0.03	1.8	0.02	0.9
interactions	pmean:pet	-0.10	-9.0	-0.04	-3.9	-0.03	-2.2	-0.05	-8.8	-0.04	-8.8	-0.05	-8.9
	pmean:adjPermS	-0.12	-14.0	-0.06	-8.1	-0.05	-5.1	-0.05	-10.3	-0.04	-10.0	-0.04	-8.2
	pmean:slopeL	-0.10	-11.0	-0.07	-8.6	-0.04	-4.1	-0.02	-4.0	-0.03	-6.0	-0.04	-7.3
	adjPermS:slopeL	-0.01	-0.2	-0.11	-2.9	-0.16	-3.3	0.09	3.8	0.06	2.5	-0.01	-0.3
	pmean:ag	0.00	0.1	-0.02	-1.9	0.01	0.5	0.03	4.9	0.04	6.0	0.04	5.8
	pmean:drainedS	0.03	2.6	0.03	2.1	-0.01	-0.7	0.02	2.5	0.02	3.5	0.03	4.0
	pet:waterL	0.04	3.2	0.00	0.0	0.00	0.1	0.02	2.8	0.02	2.9	0.01	1.9
	pet:wetland	-0.02	-1.6	0.01	0.5	0.01	0.5	-0.03	-3.7	-0.04	-5.1	-0.02	-2.8

Appendix 2 - Flow model coefficients and accuracy

Period		Annual								Jun-Sep	
Metric		50%		75%		90%		95%		mean	
R ² (all sites)		0.936		0.907		0.936		0.918		0.957	
R ² (>=5 years)		0.971		0.953		0.953		0.942		0.975	
R ² (>=10 years)		0.970		0.945		0.951		0.937		0.979	
RMSE (all sites)		0.608		0.768		0.634		0.726		0.480	
RMSE (>=5 years)		0.391		0.522		0.532		0.600		0.341	
RMSE (>=10 years)		0.374		0.536		0.517		0.582		0.291	
<25% error (all sites)		56%		49%		48%		42%		55%	
<50% error (all sites)		77%		66%		62%		61%		77%	
<100% error (all sites)		87%		80%		80%		77%		90%	
<25% error (>=5 years)		63%		60%		51%		44%		61%	
<50% error (>=5 years)		83%		75%		68%		68%		85%	
<100% error (>=5 years)		91%		88%		86%		84%		94%	
<25% error (>=10 years)		68%		64%		56%		49%		70%	
<50% error (>=10 years)		85%		78%		73%		75%		88%	
<100% error (>=10 years)		91%		88%		86%		84%		96%	
		Est	t	Est	t	Est	t	Est	t	Est	t
weather	Intercept	4.45	121.0	4.05	85.7	3.78	84.2	3.62	73.7	4.67	168.2
	shedL	2.14	61.5	2.16	48.5	2.14	49.9	2.14	46.1	2.09	77.1
	pet	-0.09	-12.7	-0.13	-14.9	-0.14	-15.0	-0.14	-14.1	-0.18	-18.2
	pmean	0.19	38.8	0.18	29.1	0.19	28.3	0.19	27.5	0.34	42.0
	plag1	0.11	23.9	0.13	21.7	0.12	19.3	0.12	18.5	0.20	24.0
	plag4	0.09	19.2	0.09	16.9	0.10	16.1	0.10	16.0	0.10	9.6
	plag7	0.05	10.2	0.07	10.8	0.07	10.1	0.07	9.7	0.04	5.0
	plag10	0.02	4.6	0.02	3.8	0.02	2.4	0.01	1.9	0.02	2.8
	plag13	0.04	8.9	0.05	8.4	0.06	8.9	0.06	9.1	-0.02	-2.3
plag25	0.03	7.1	0.05	8.6	0.06	9.2	0.06	8.6	0.07	9.1	
watershed	adjPermS	0.12	3.5	0.16	3.6	0.25	5.8	0.28	6.0	-0.04	-1.2
	slopeL	0.12	3.2	0.27	5.8	0.35	7.7	0.39	7.9	0.01	0.3
	ag	-0.06	-2.0	-0.07	-1.8	-0.09	-2.0	-0.08	-1.7	-0.20	-6.0
	drainedS	-0.07	-3.4	-0.02	-0.6	-0.05	-1.8	-0.05	-1.8	0.03	1.2
	waterL	0.04	2.4	0.06	2.6	0.05	2.1	0.03	1.3	0.04	1.9
	wetland	0.01	0.5	0.01	0.6	-0.02	-0.8	-0.03	-1.1	-0.08	-3.1
interactions	pmean:pet	-0.05	-8.8	-0.02	-3.1	-0.01	-0.7	-0.01	-1.3	0.01	0.7
	pmean:adjPermS	-0.04	-8.9	-0.02	-3.9	-0.02	-2.5	-0.01	-2.1	-0.09	-11.3
	pmean:slopeL	-0.05	-9.9	-0.05	-8.3	-0.06	-7.7	-0.06	-7.9	-0.09	-10.7
	adjPermS:slopeL	-0.07	-2.1	-0.14	-3.2	-0.17	-4.0	-0.19	-4.1	-0.05	-2.0
	pmean:ag	0.04	5.9	0.02	2.6	0.01	1.4	0.02	1.9	0.01	0.8
	pmean:drainedS	0.02	3.1	0.04	4.5	0.04	4.3	0.04	3.8	0.05	4.1
	pet:waterL	0.00	0.3	-0.03	-3.3	-0.03	-2.7	-0.02	-1.8	0.01	0.6
	pet:wetland	-0.02	-2.3	-0.01	-1.1	-0.02	-2.2	-0.03	-2.4	-0.04	-3.7

Appendix 3 - Fish model variable influence scores

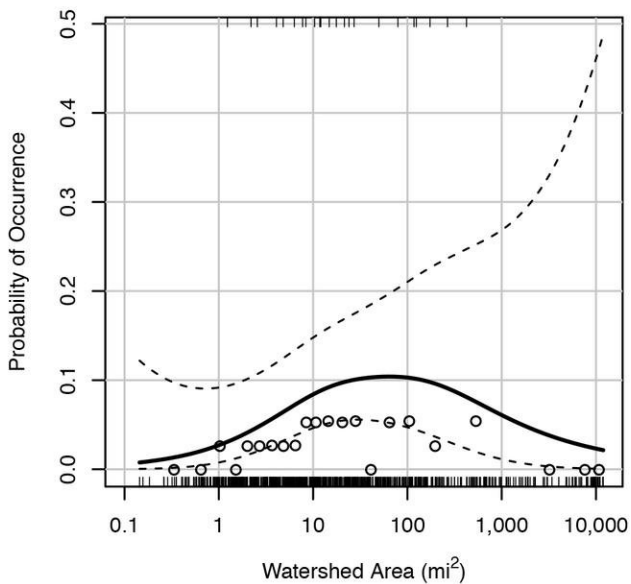
	sucker- mouth minnow	tadpole matdom	walleye	white bass	white sucker	yellow bullhead	yellow perch
Stream Size							
WT_AREA	0.28	1.00	1.00	0.84	1.00	1.00	0.81
Temperature							
TEMP_MAX	0.14	0.70	0.38	0.75	0.34	0.26	0.65
TEMP_JULX	0.15	0.45	0.21	1.00	0.28	0.41	0.60
TEMP_JJAX	0.19	0.34	0.22	0.79	0.28	0.39	0.64
Stream Flow							
Q50_ANN	0.30	0.45	0.72	0.61	0.25	0.21	0.53
Q90_ANN	0.12	0.28	0.20	0.13	0.15	0.19	0.19
Q10_APR	0.20	0.38	0.07	0.15	0.25	0.33	0.27
Q50_AUG	0.16	0.28	0.35	0.13	0.20	0.21	0.24
Q90_AUG	0.12	0.21	0.11	0.06	0.15	0.12	0.19
Connectivity							
GL_DIST	0.00	0.01	0.01	0.00	0.02	0.02	0.02
LAKE_SM_DIST	0.02	0.32	0.03	0.05	0.11	0.07	0.16
LAKE_MD_DIST	0.05	0.16	0.06	0.02	0.09	0.08	0.22
LAKE_LG_DIST	0.04	0.08	0.01	0.01	0.08	0.08	0.10
RIVER_MD_DIST	0.16	0.50	0.32	0.11	0.14	0.15	0.24
RIVER_LG_DIST	0.02	0.58	0.53	0.51	0.09	0.13	0.06
SUBNET_ST_LEN	0.11	0.54	0.05	0.15	0.29	0.46	0.27
SUBNET_LK_AR	0.06	0.43	0.03	0.22	0.27	0.15	0.13
Soils/Slope							
GRADIENT	0.21	0.84	0.22	0.81	0.50	0.28	0.37
SINUOUS	0.07	0.23	0.05	0.16	0.40	0.14	0.19
R_PERM	0.10	0.37	0.11	0.07	0.10	0.12	0.63
R_SLOPE	0.09	0.64	0.05	0.08	0.22	0.18	0.13
R_DARCY	0.05	0.27	0.09	0.07	0.15	0.18	0.22
RT_PERM	0.31	0.25	0.11	0.15	0.12	0.13	0.75
RT_SLOPE	0.31	0.44	0.03	0.03	0.17	0.33	0.24
RT_DARCY	0.21	0.36	0.08	0.05	0.13	0.19	0.17
W_PERM	0.20	0.45	0.05	0.08	0.11	0.12	0.64
W_SLOPE	0.28	0.76	0.04	0.05	0.18	0.14	0.20
W_DARCY	0.09	0.22	0.04	0.03	0.17	0.15	0.14
WT_PERM	0.32	0.29	0.09	0.40	0.15	0.15	0.53
WT_SLOPE	0.13	0.31	0.04	0.02	0.16	0.25	0.35
WT_DARCY	0.19	0.29	0.05	0.03	0.16	0.16	0.17
Land Cover							
R_AGRIC	0.26	0.37	0.02	0.02	0.09	0.09	0.18
R_FORST	0.07	0.42	0.04	0.17	0.12	0.13	0.18
R_GRASS	0.01	0.06	0.02	0.02	0.06	0.03	0.05
R_URBAN	0.36	0.26	0.04	0.01	0.13	0.11	0.15
R_WATER	0.04	0.25	0.33	0.37	0.10	0.14	0.08
R_WETLD	0.08	0.24	0.04	0.13	0.15	0.11	0.21
RT_AGRIC	0.80	0.44	0.03	0.09	0.18	0.12	0.23
RT_FORST	0.41	0.25	0.07	0.04	0.14	0.26	0.19
RT_GRASS	0.13	0.40	0.04	0.05	0.23	0.39	0.23
RT_URBAN	0.12	0.38	0.04	0.03	0.15	0.15	0.25
RT_WATER	0.03	0.60	0.23	0.11	0.15	0.56	0.94
RT_WETLD	0.23	0.45	0.09	0.07	0.14	0.19	0.49
W_AGRIC	0.08	0.31	0.03	0.02	0.15	0.12	0.13
W_FORST	0.06	0.12	0.03	0.08	0.13	0.20	0.21
W_GRASS	0.03	0.50	0.02	0.02	0.10	0.09	0.11
W_URBAN	0.14	0.64	0.04	0.03	0.14	0.25	0.21
W_WATER	0.02	0.15	0.43	0.53	0.13	0.10	0.17
W_WETLD	0.23	0.29	0.05	0.20	0.21	0.10	0.16
WT_AGRIC	0.87	0.38	0.04	0.11	0.17	0.14	0.22
WT_FORST	0.58	0.14	0.05	0.06	0.13	0.18	0.15
WT_GRASS	0.09	0.41	0.03	0.17	0.23	0.23	0.20
WT_URBAN	0.17	0.46	0.04	0.04	0.13	0.33	0.17
WT_WATER	0.06	0.71	0.49	0.31	0.27	0.49	1.00
WT_WETLD	0.32	0.38	0.08	0.20	0.15	0.19	0.48
Geology							
WT_BR_SAND	0.08	0.26	0.04	0.08	0.09	0.17	0.08
WT_BR_SHAL	0.03	0.14	0.02	0.09	0.07	0.09	0.05
WT_BR_CARB	0.50	0.19	0.05	0.02	0.04	0.17	0.04
WT_BR_META	0.01	0.30	0.07	0.09	0.04	0.09	0.06
WT_BR_IGNS	0.00	0.09	0.07	0.21	0.05	0.06	0.11
WT_SG_FINE	0.04	0.10	0.01	0.08	0.07	0.10	0.07
WT_SG_MED	0.01	0.06	0.02	0.23	0.05	0.08	0.06
WT_SG_CORS	0.12	0.37	0.05	0.06	0.08	0.11	0.19
Climate							
W_PRCP_ANN	0.45	0.56	0.02	0.05	0.11	0.16	0.38
W_TEMP_ANN	0.68	0.25	0.03	0.05	0.11	0.20	0.19
W_TEMP_GS	0.98	0.30	0.03	0.06	0.11	0.20	0.21
W_TEMP_JULY	0.93	0.36	0.04	0.06	0.12	0.22	0.25
WT_PRCP_ANN	0.51	0.32	0.05	0.05	0.12	0.17	0.21
WT_TEMP_ANN	0.73	0.31	0.05	0.05	0.11	0.38	0.22
WT_TEMP_GS	1.00	0.41	0.03	0.06	0.10	0.33	0.20
WT_TEMP_JULY	0.60	0.49	0.05	0.07	0.11	0.28	0.24

Appendix 5. Partial dependence plots for statistically significant variables in generalized additive models of 79 Wisconsin stream fishes.

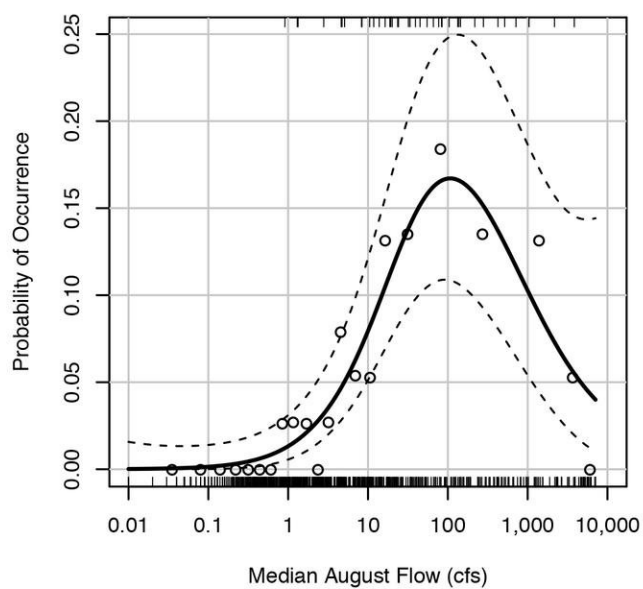
Plots were created to illustrate the relationship between each variable and the probability of occurrence of each species. The mean (solid line) and 95% confidence interval (dashed lines) around each function were calculated with the *predict.gam* function in *mgcv*. The data used to illustrate the relationship between one variable and one species were the full range of the focal variable in the observation dataset and the mean values of the other variables where the species was present in the observation dataset. For example, the relationship between mean July water temperature and the occurrence of brook trout was predicted from a vector of temperature (14-26°C) with watershed area and median August flow yield held at their means where brook trout were present (9.5 mi² and 0.35 cfs/mi²). The resulting plot shows the effect of temperature on brook trout while controlling for the effects of watershed area and flow yield.

The “rugs” of tick marks on the bottom and top of the plots show the individual values of the predictor variable where the species was absent and present, respectively. The points on the plots are the fraction of observations in bins of the predictor variable where the species was present. In most plots, the line of the fitted function follows the pattern of the points. In plots where the line is offset vertically from the points, the mean values of the non-focal variables where the species is present are significantly different than the mean values of those variables in the entire observation dataset. For example, in the plot of the effect of flow yield on brown trout, the line is higher than the points because the line shows the effect of flow yield when watershed area and temperature are optimal for brown trout and the points include many streams where these variables are not suitable. In some cases, the line is a completely different shape than the pattern of points, which indicates that one or more non-focal variables have a stronger effect on the species and are also correlated with the focal variable. For example, the pattern of points on the plot of flow yield for common carp suggests that carp prefer streams with high flow yield. However, flow yield is positively correlated with watershed area in the observation dataset and after controlling for the effect of watershed area, carp appear to actually prefer streams with lower flow yield.

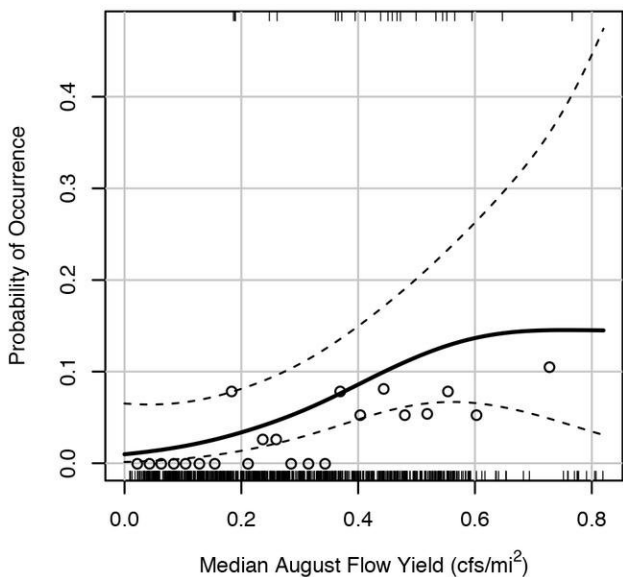
American brook lamprey



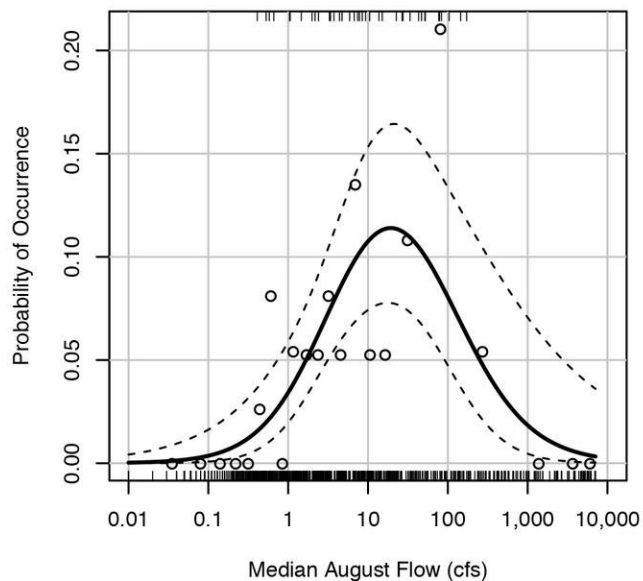
banded darter



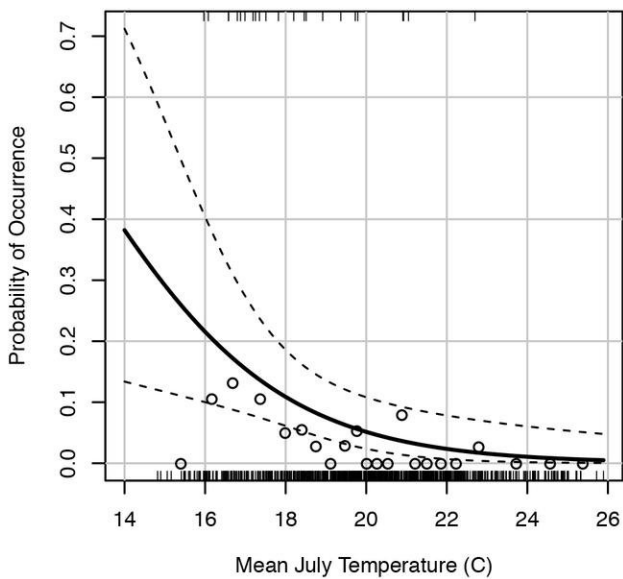
American brook lamprey



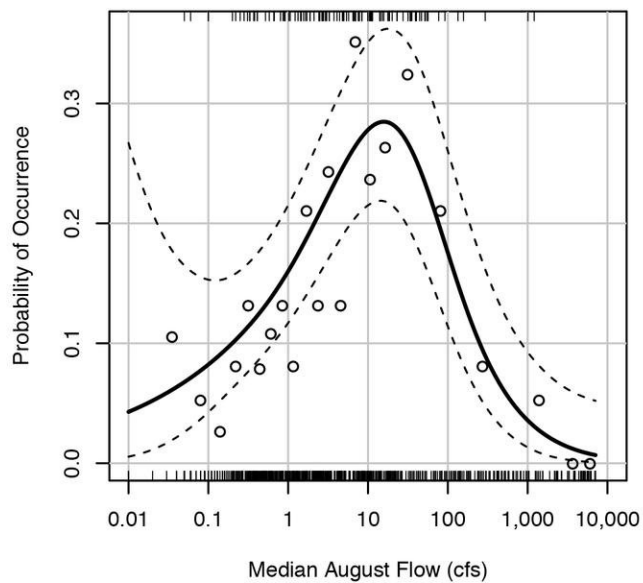
bigmouth shiner



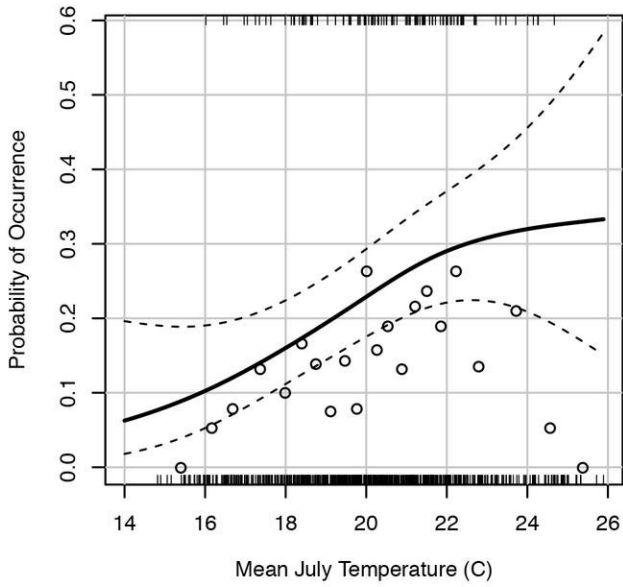
American brook lamprey



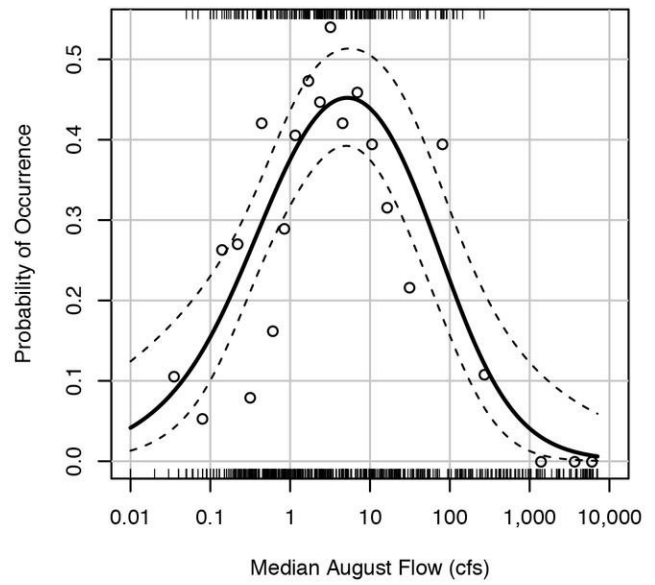
black bullhead



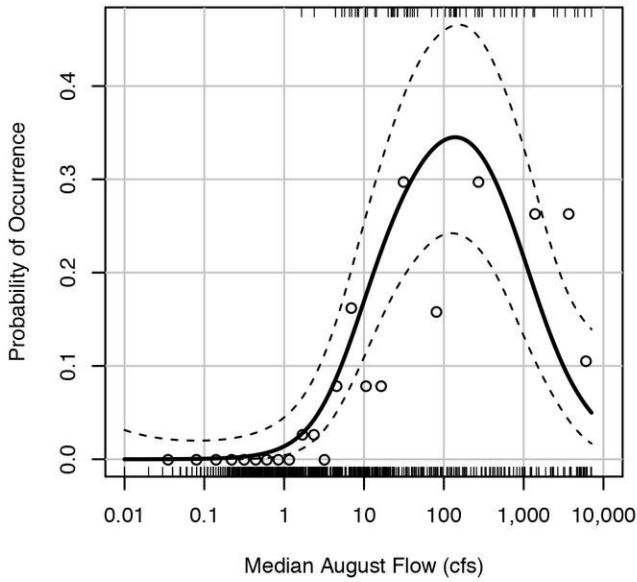
black bullhead



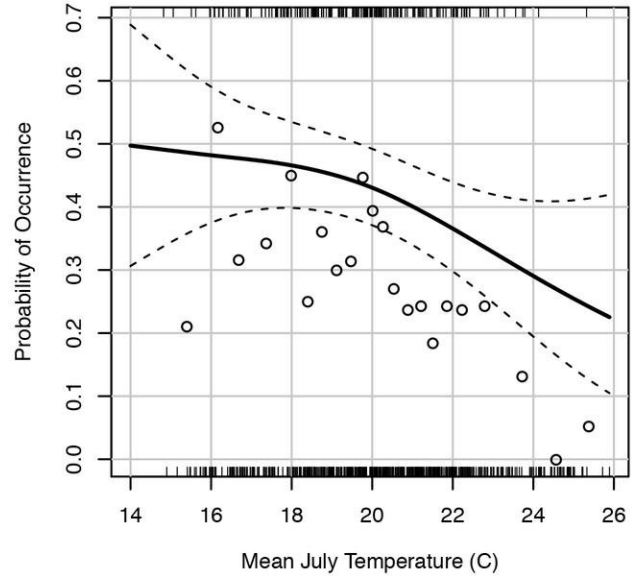
blacknose dace



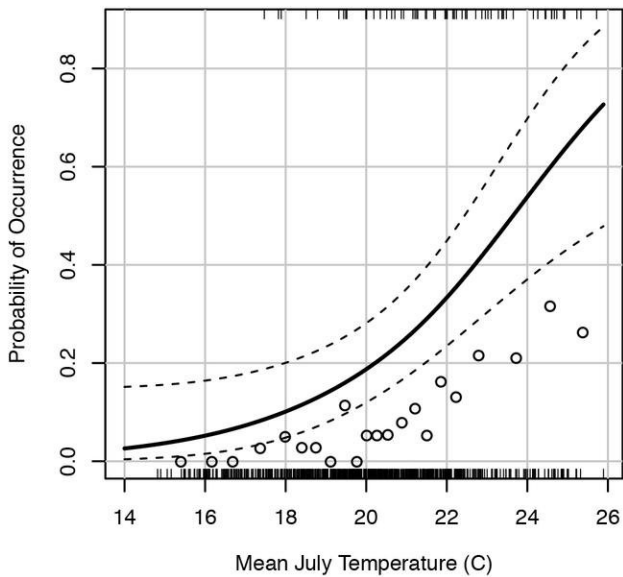
black crappie



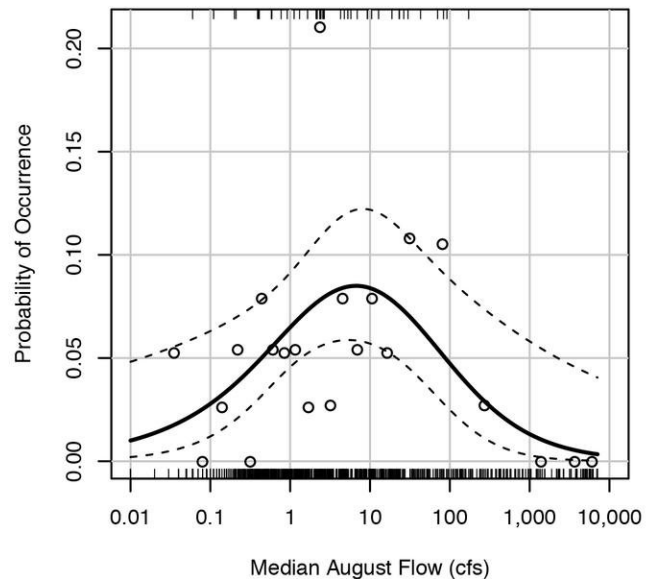
blacknose dace



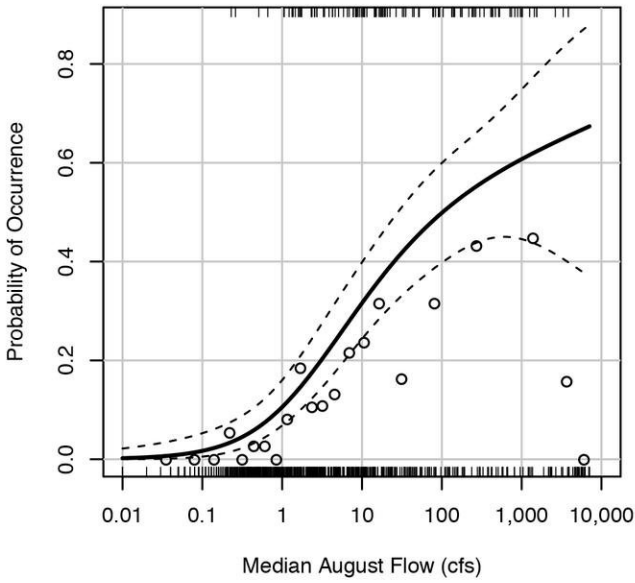
black crappie



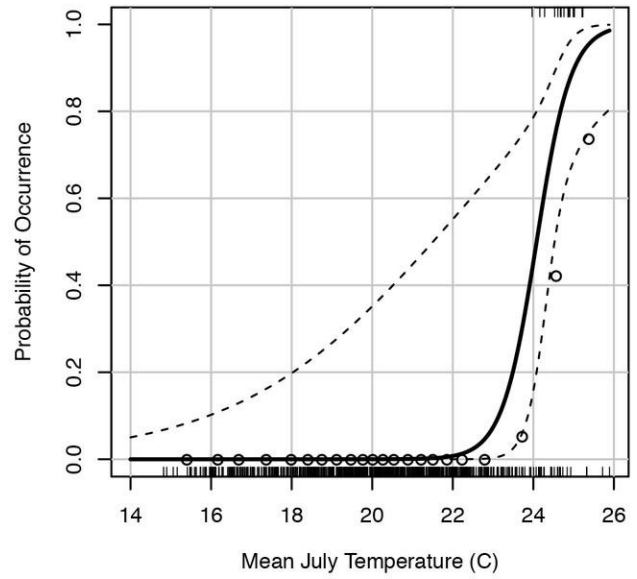
blacknose shiner



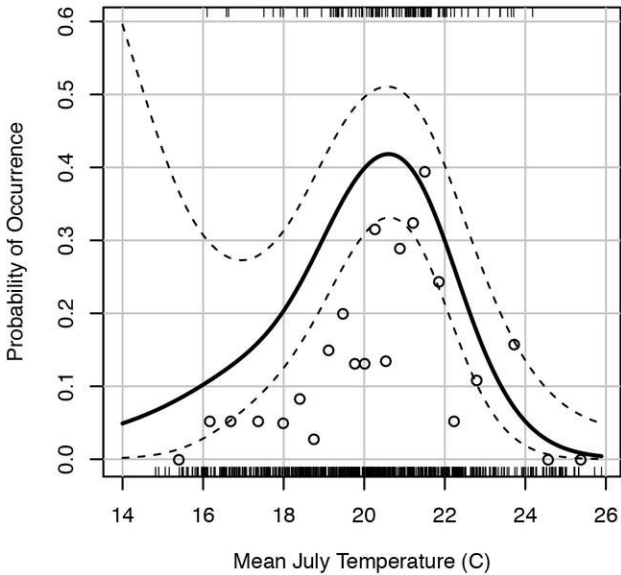
blackside darter



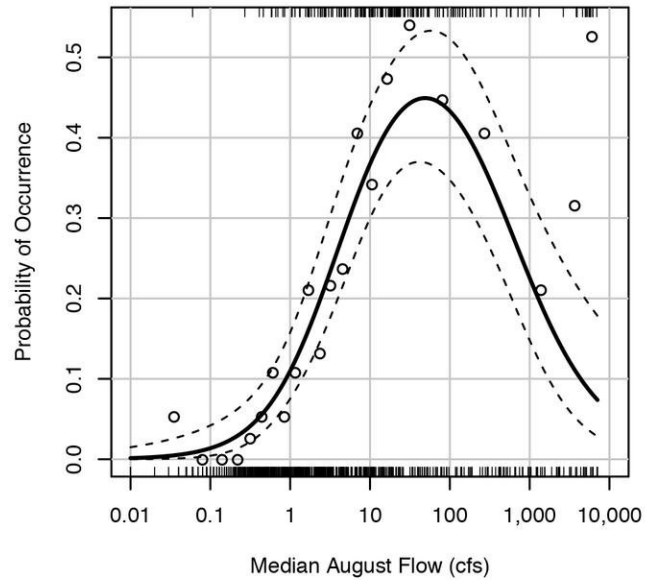
blue sucker



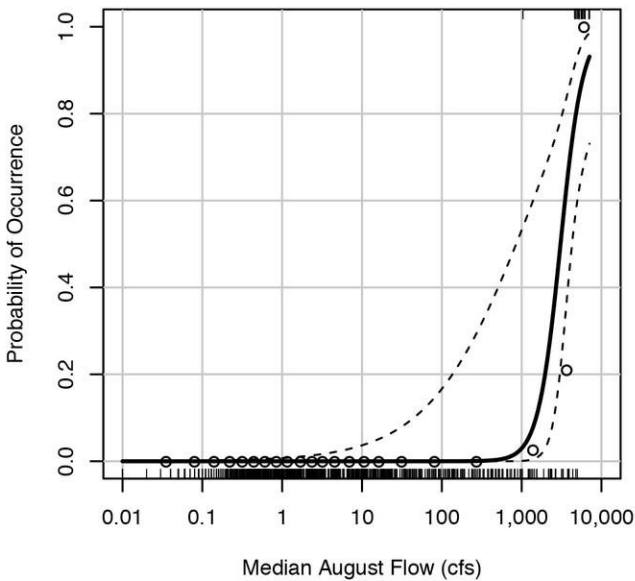
blackside darter



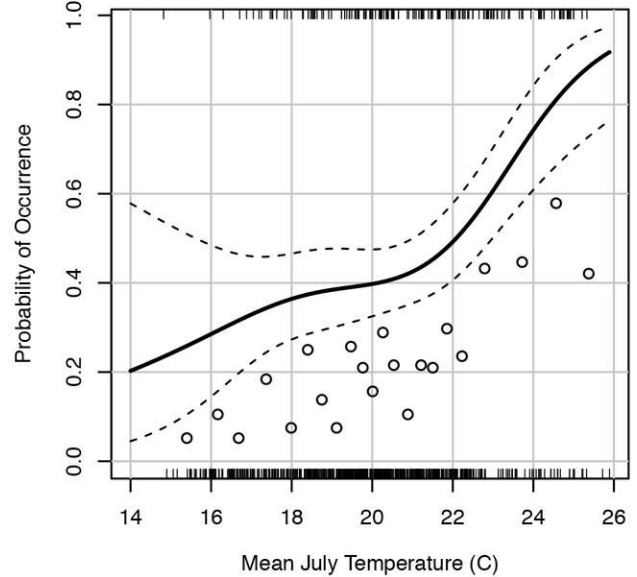
bluegill



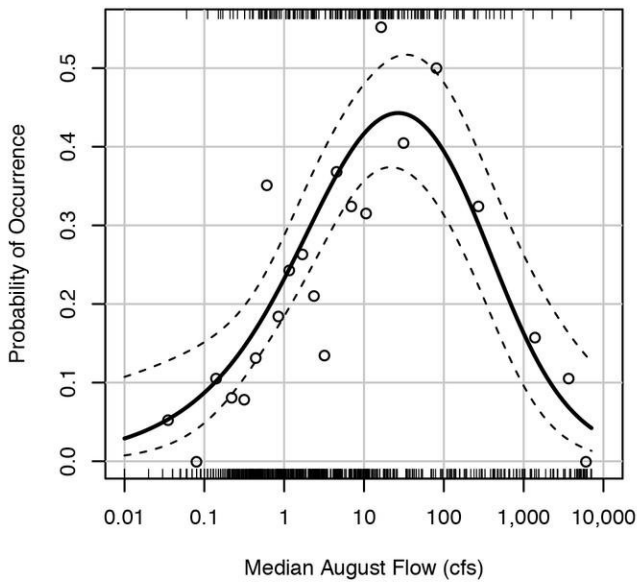
blue sucker



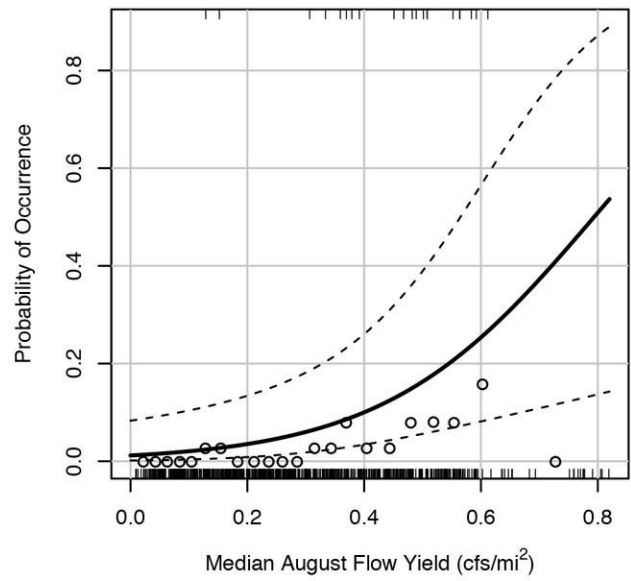
bluegill



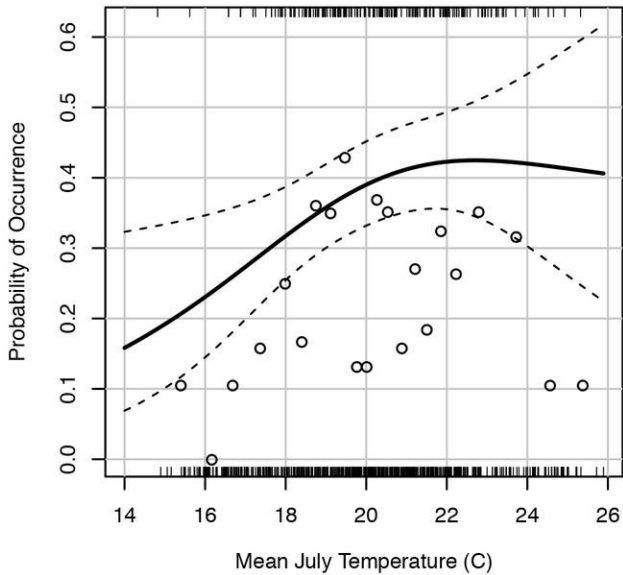
bluntnose minnow



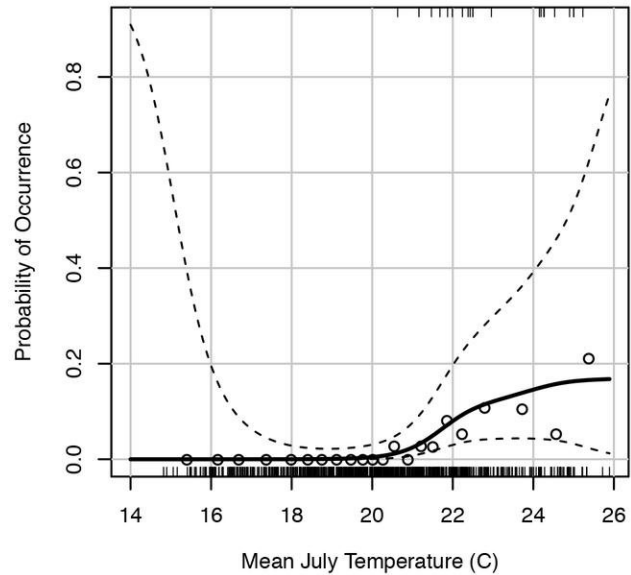
bowfin



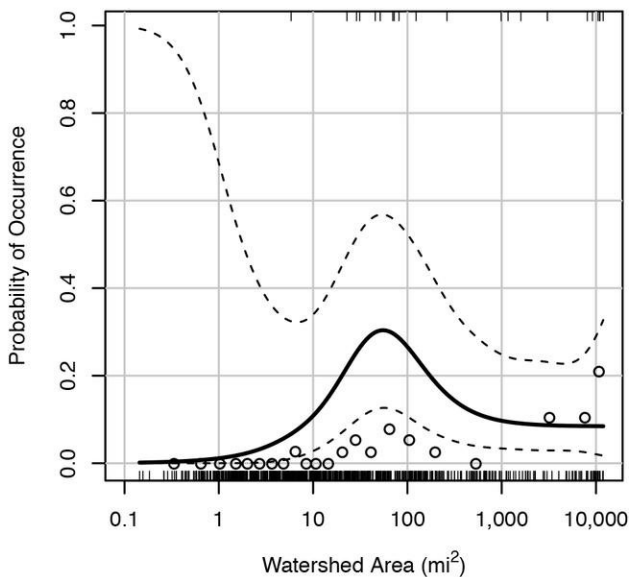
bluntnose minnow



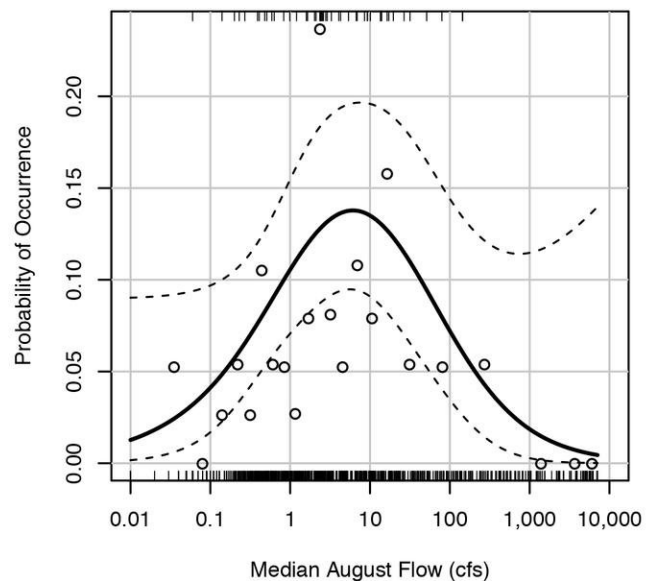
bowfin



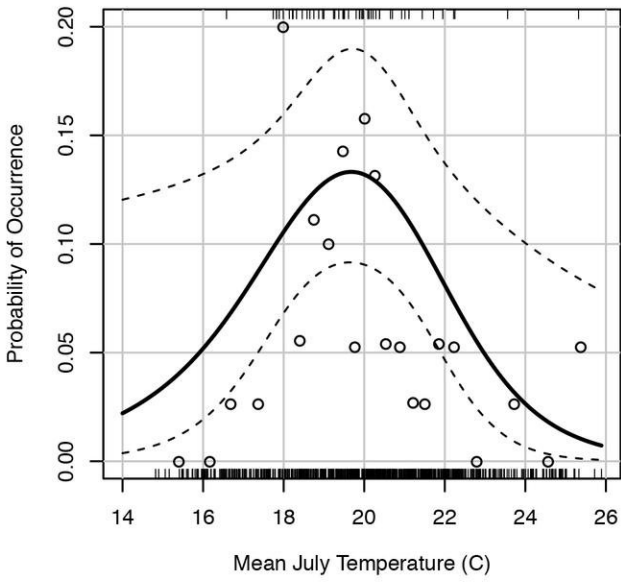
bowfin



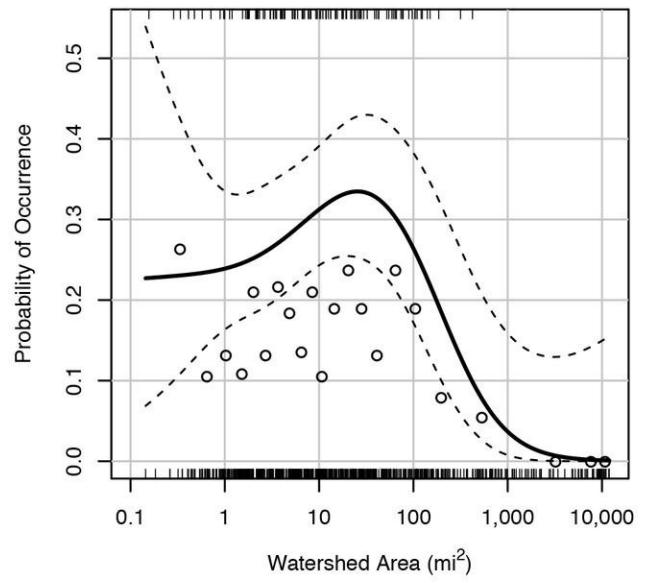
brassy minnow



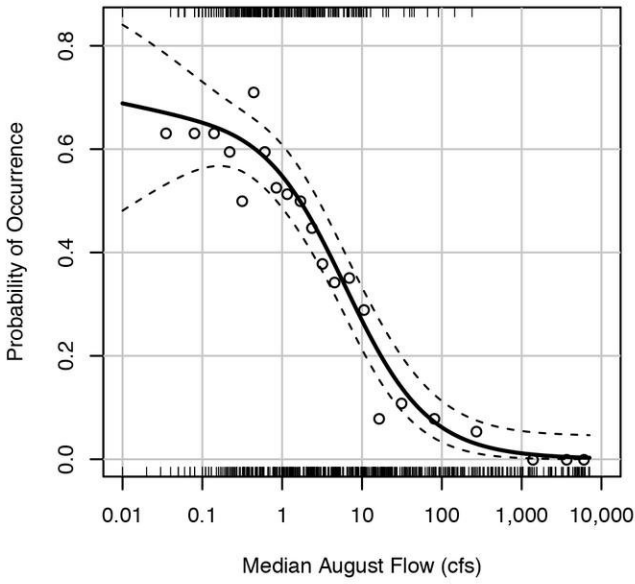
brassy minnow



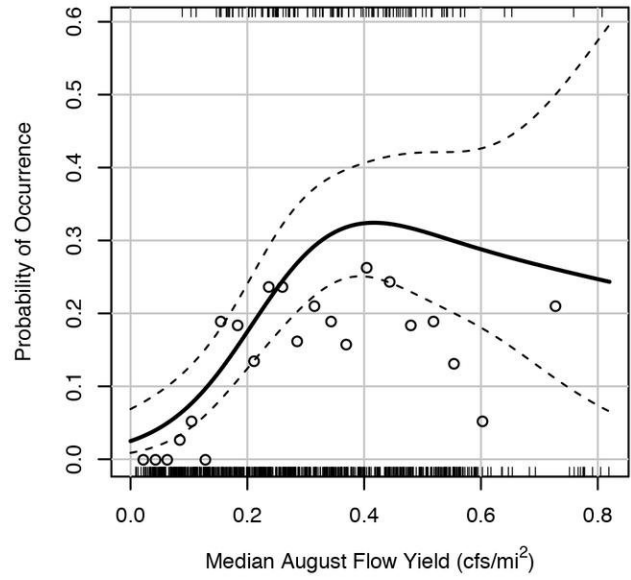
brook trout



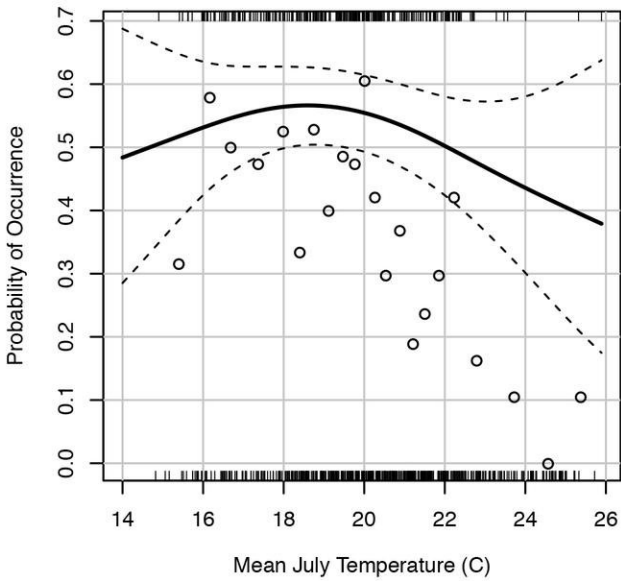
brook stickleback



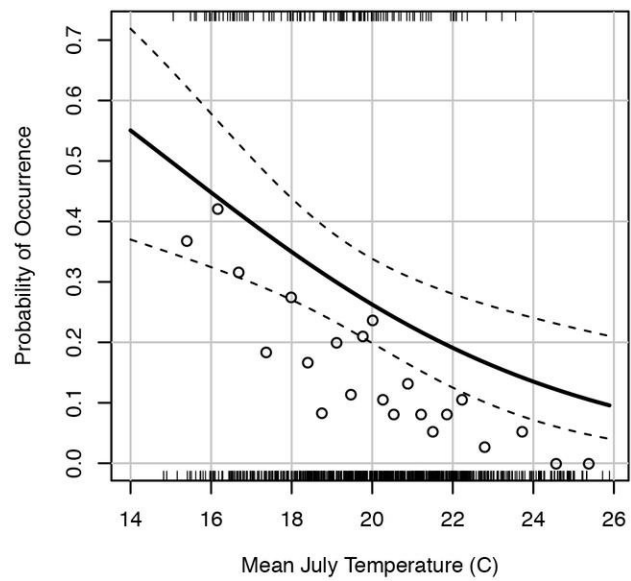
brook trout



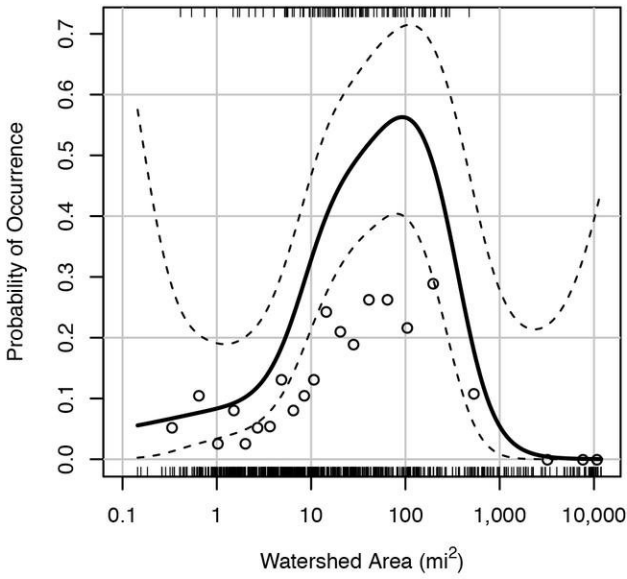
brook stickleback



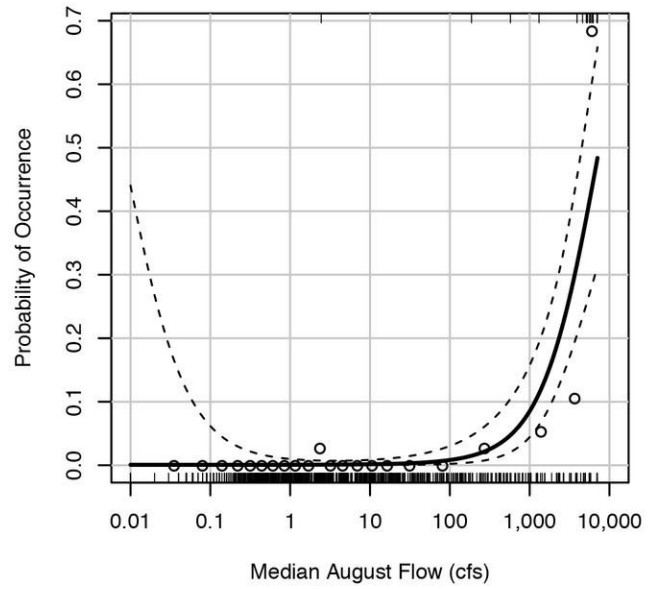
brook trout



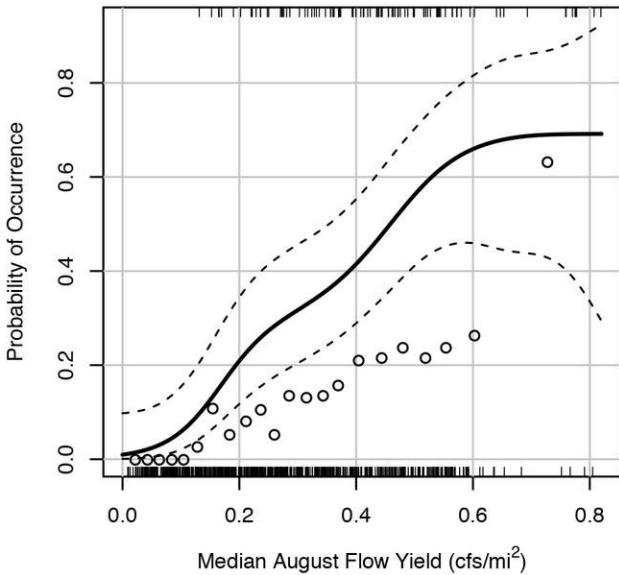
brown trout



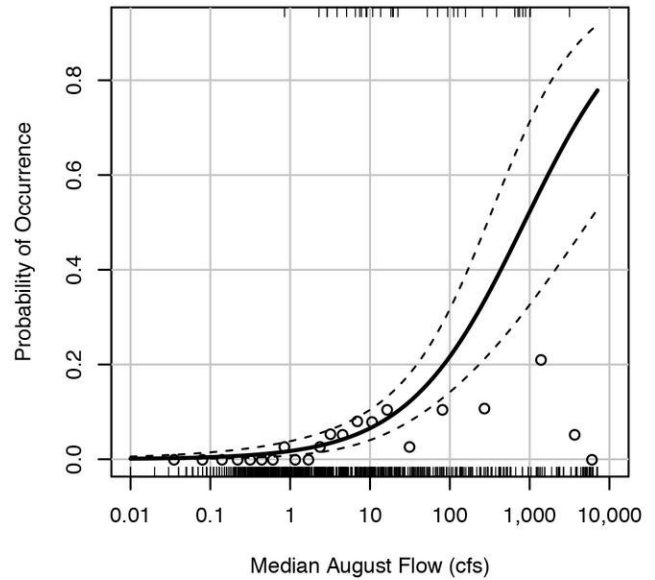
bullhead minnow



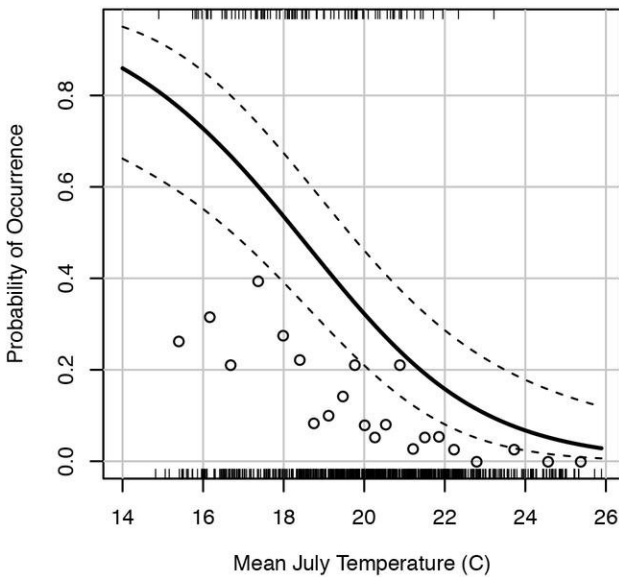
brown trout



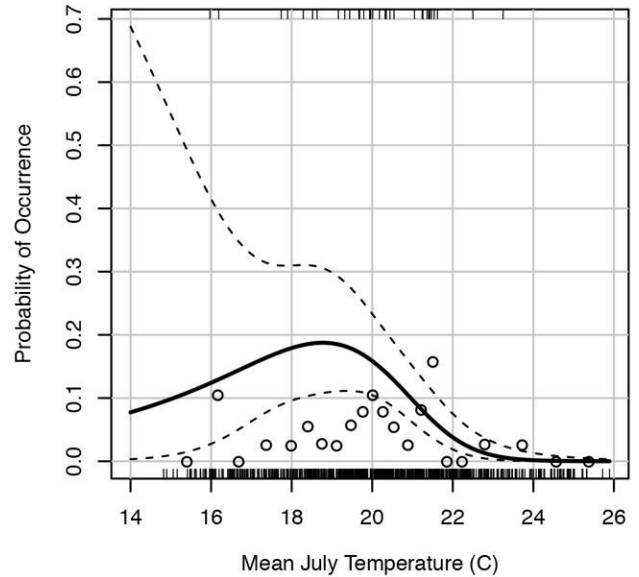
burbot

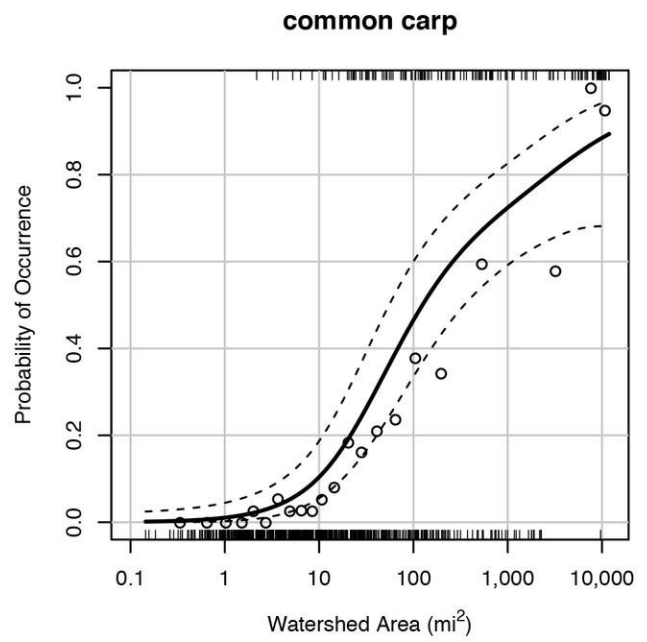
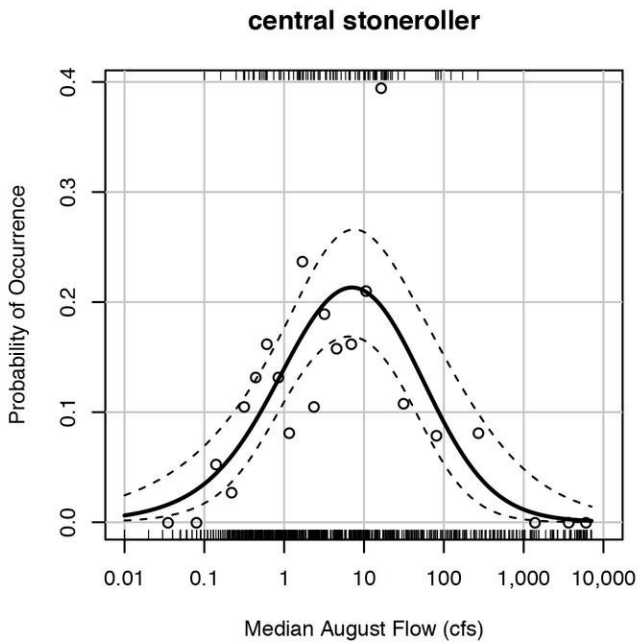
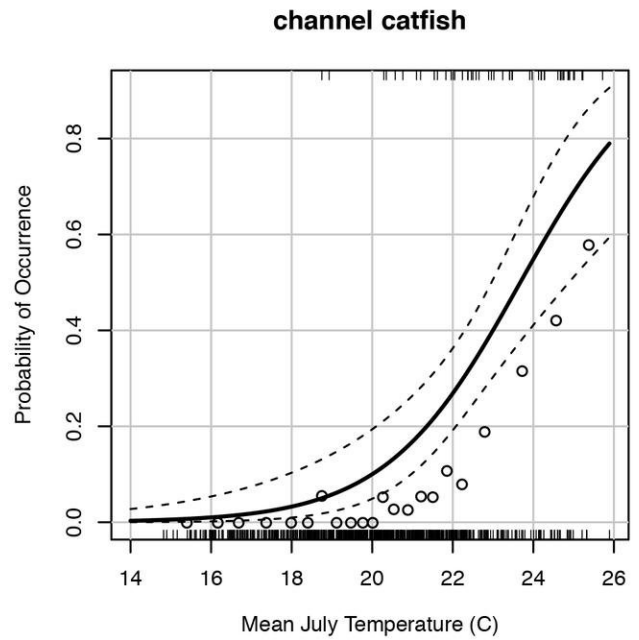
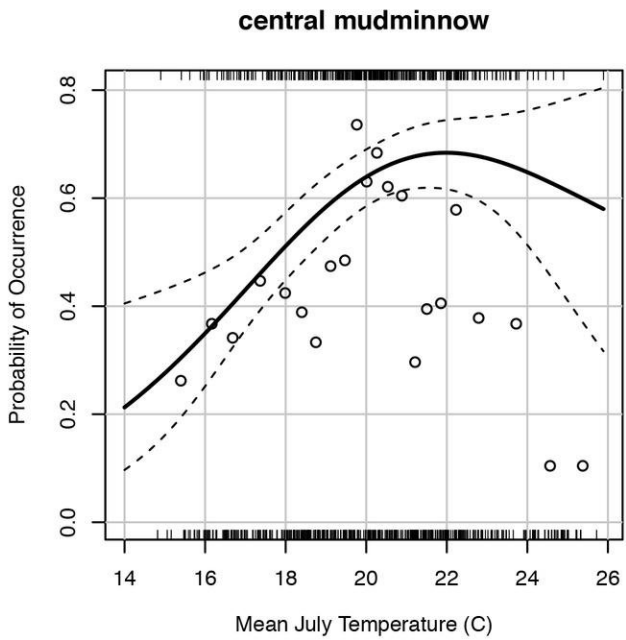
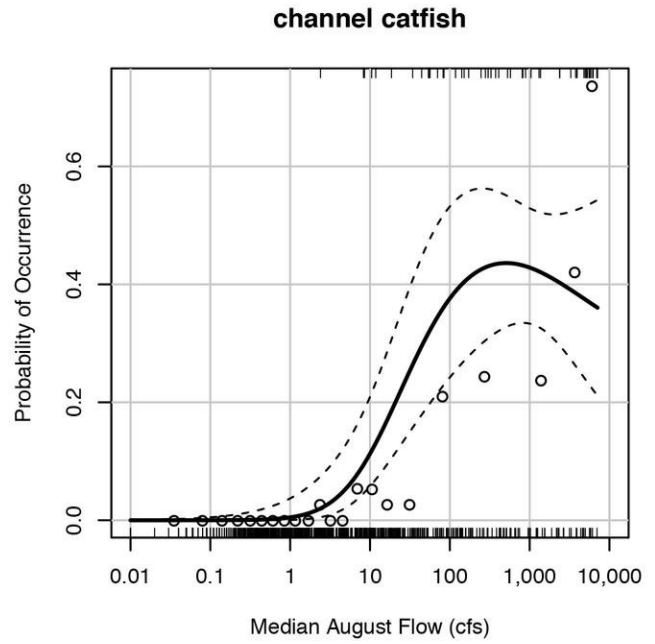
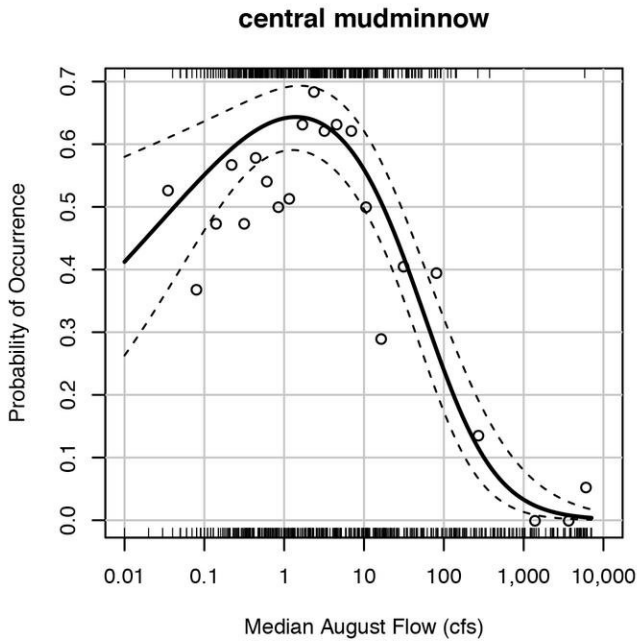


brown trout



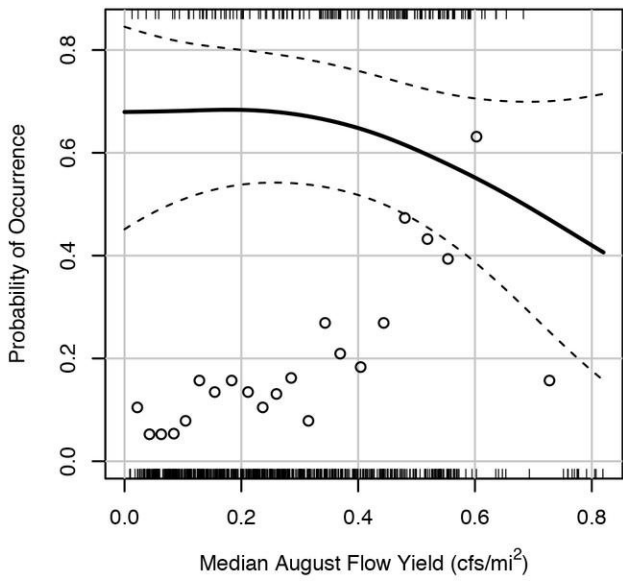
burbot



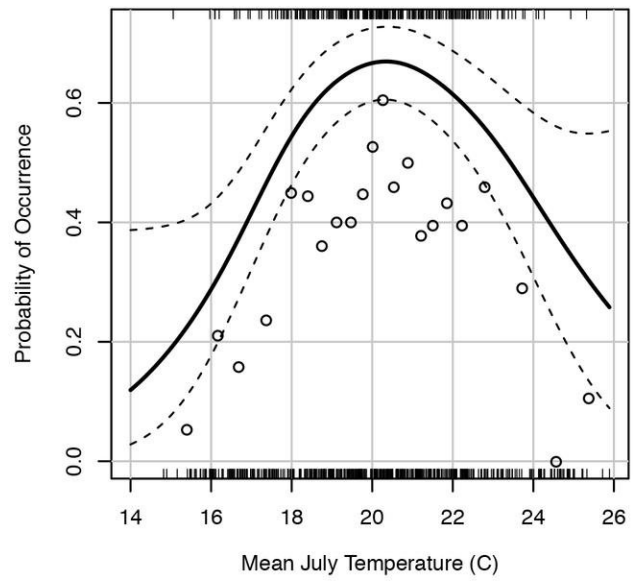


Appendix 5 - Partial dependence plots

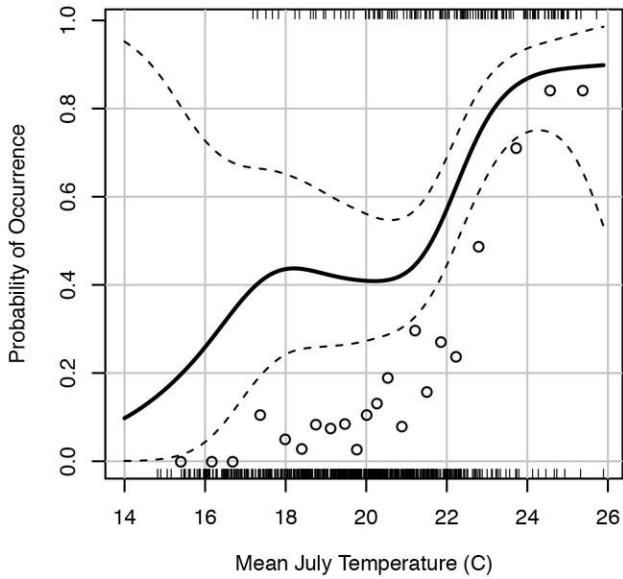
common carp



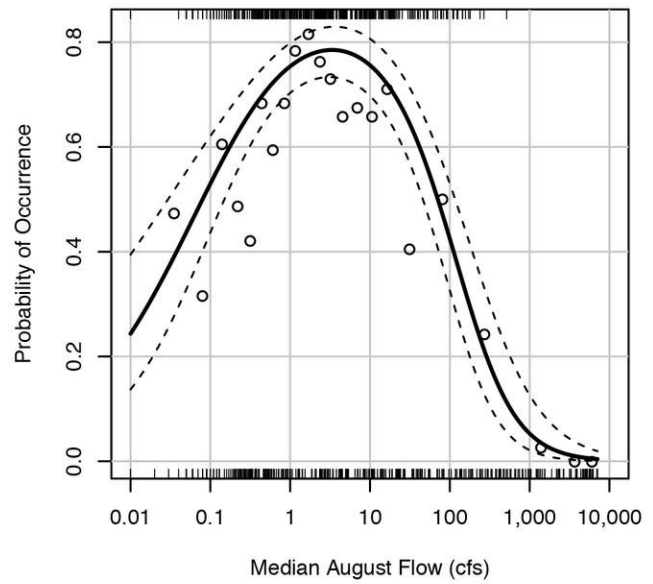
common shiner



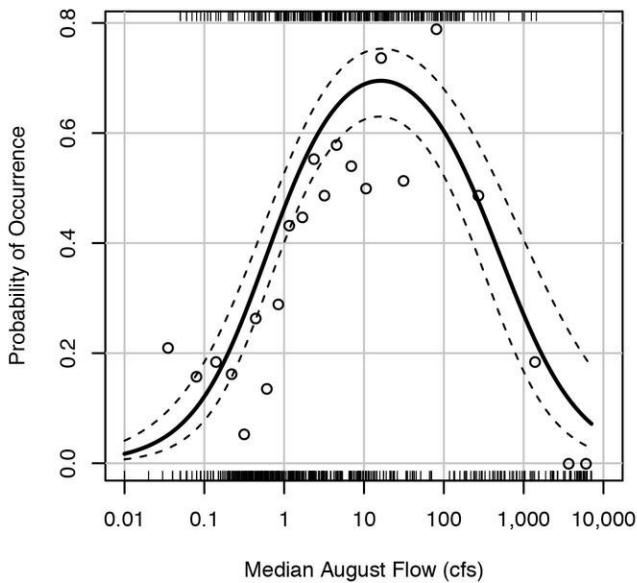
common carp



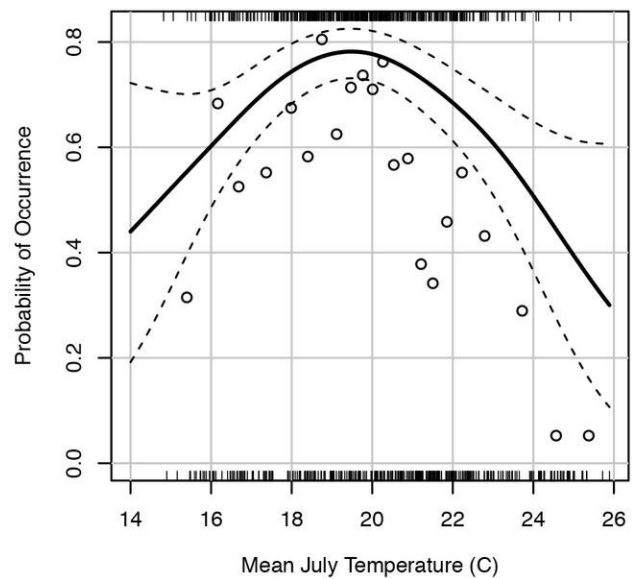
creek chub



common shiner

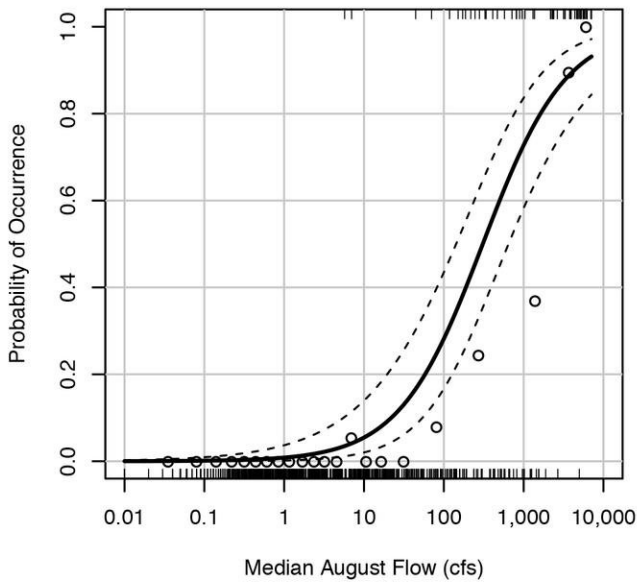


creek chub

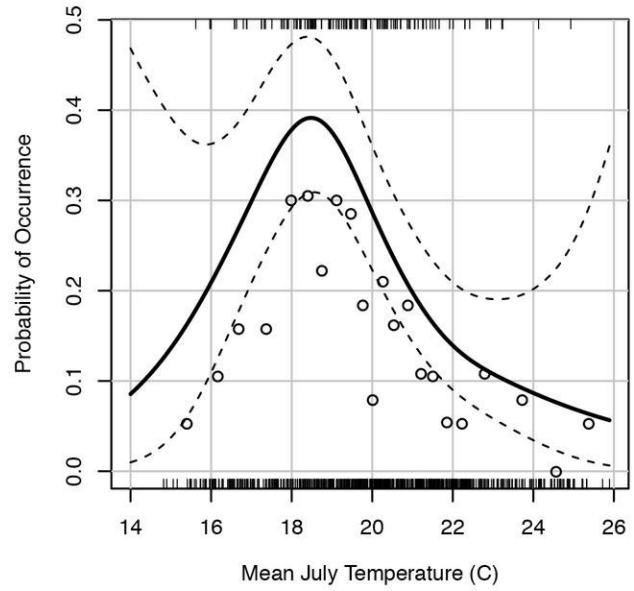


Appendix 5 - Partial dependence plots

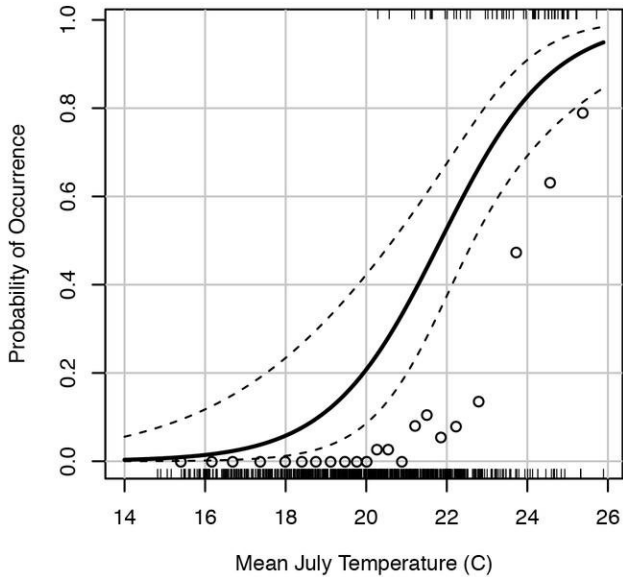
emerald shiner



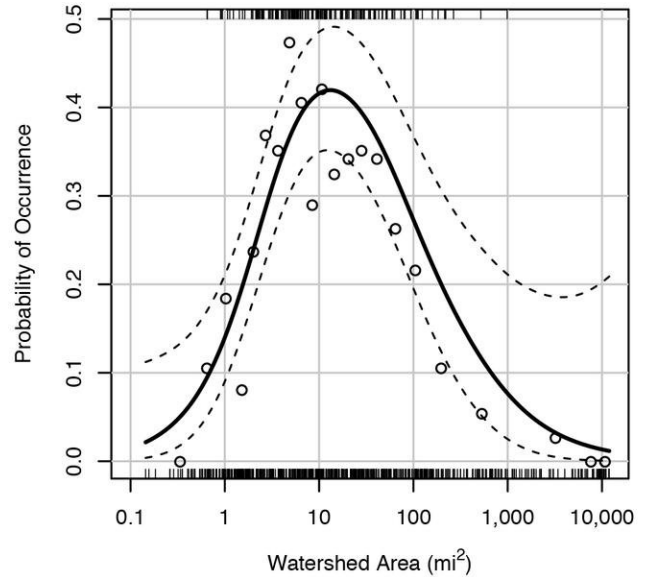
fantail darter



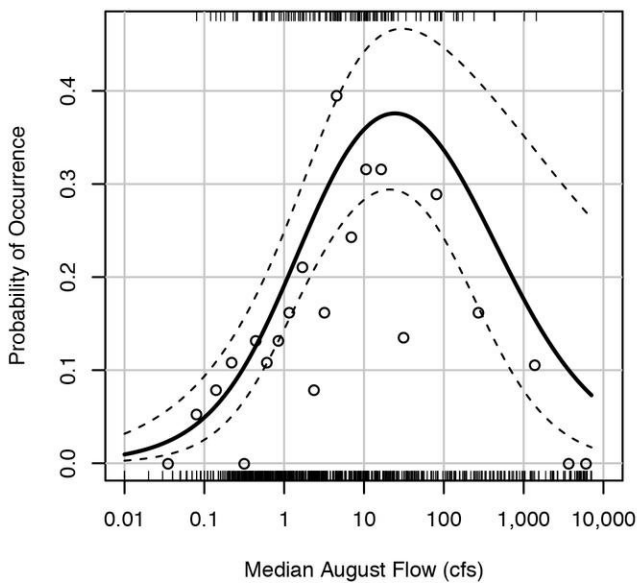
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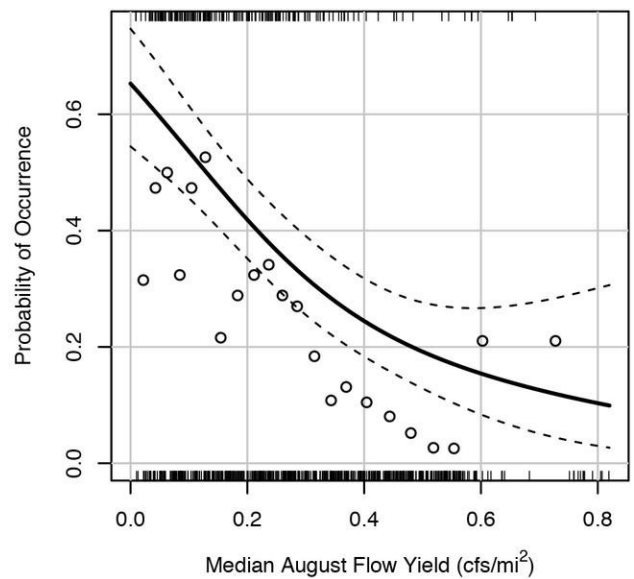
fathead minnow



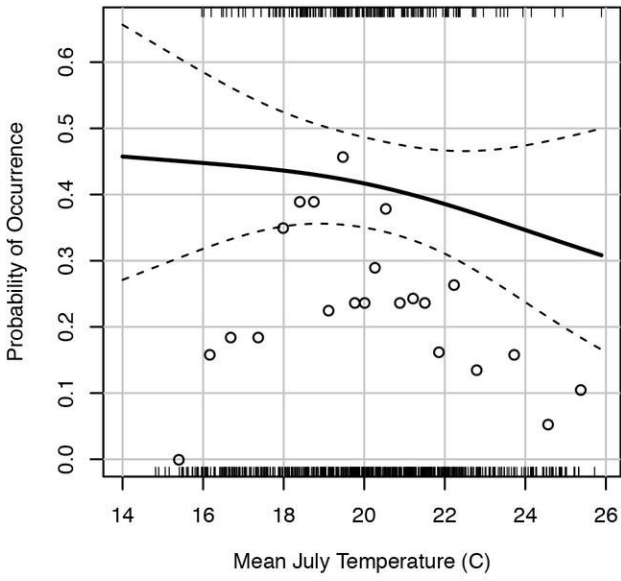
fantail darter



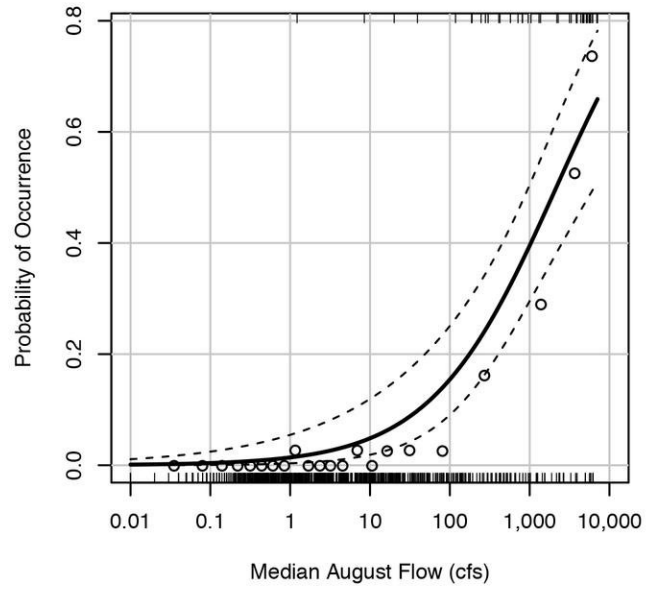
fathead minnow



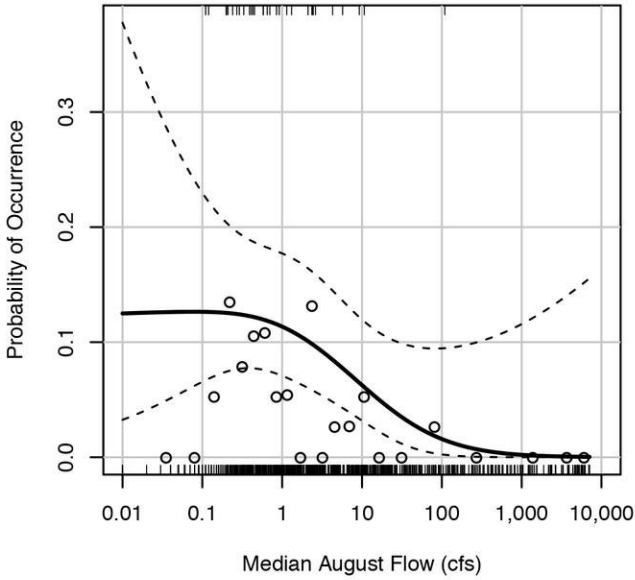
fathead minnow



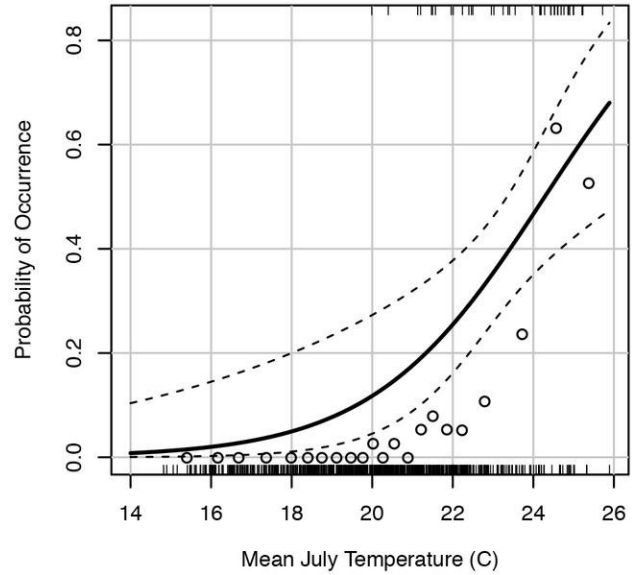
freshwater drum



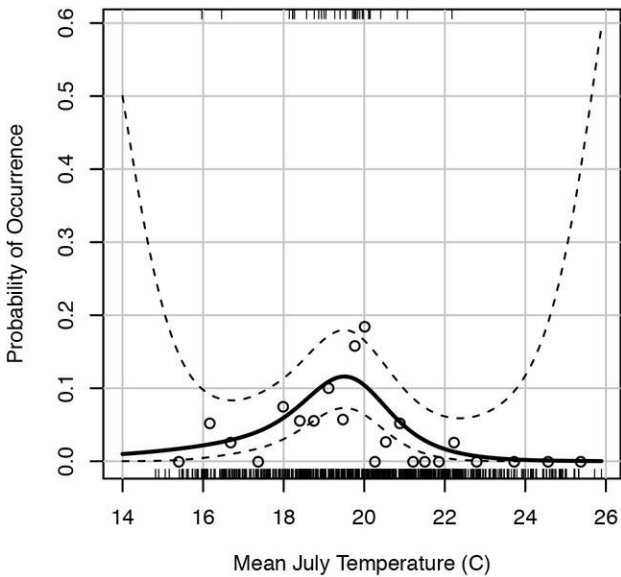
finescale dace



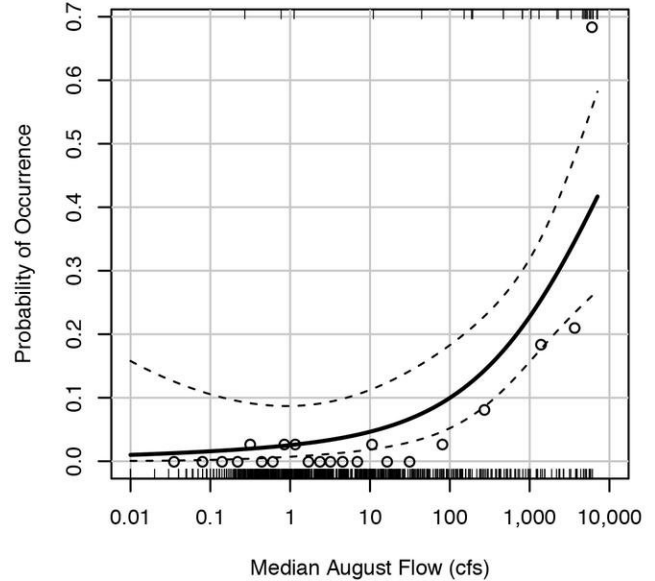
freshwater drum



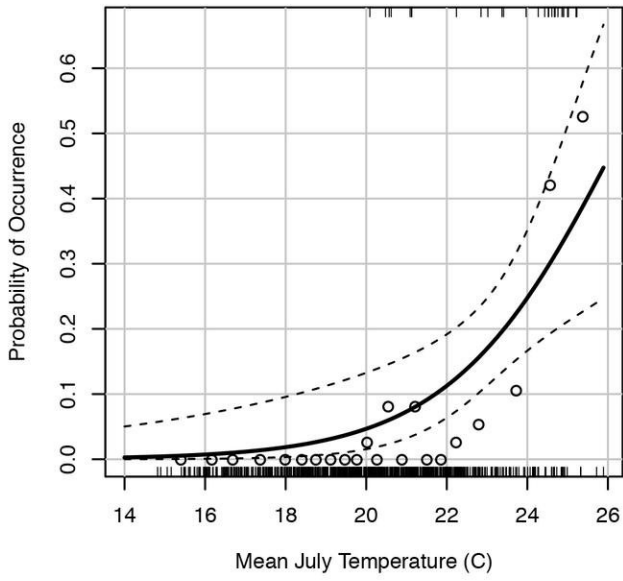
finescale dace



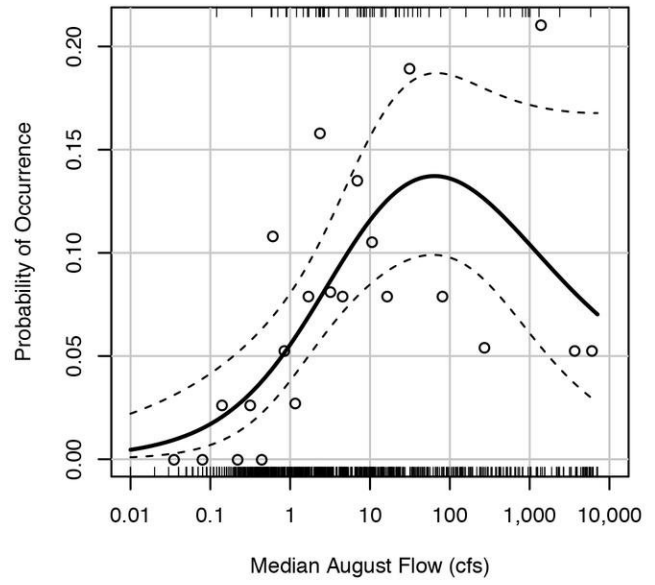
gizzard shad



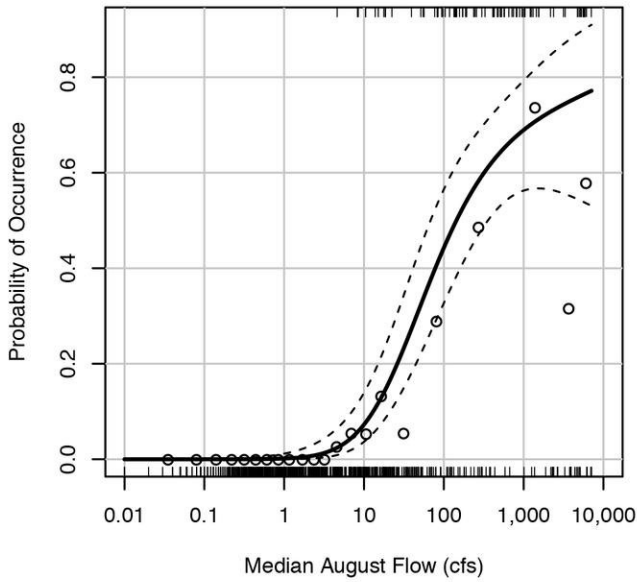
gizzard shad



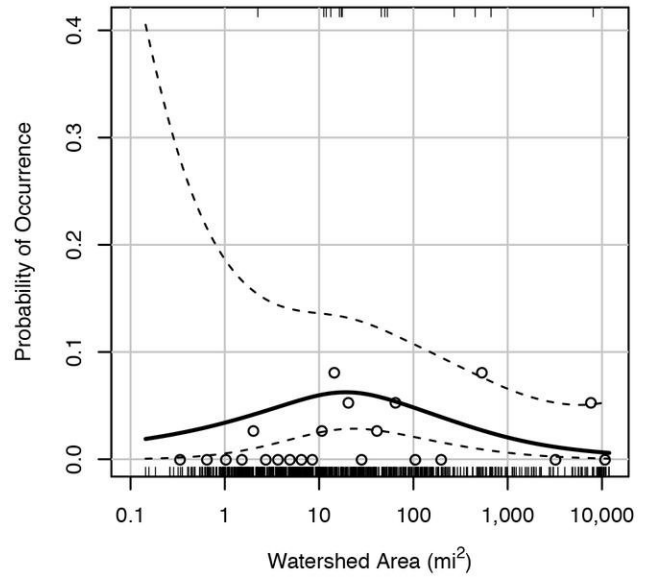
golden shiner



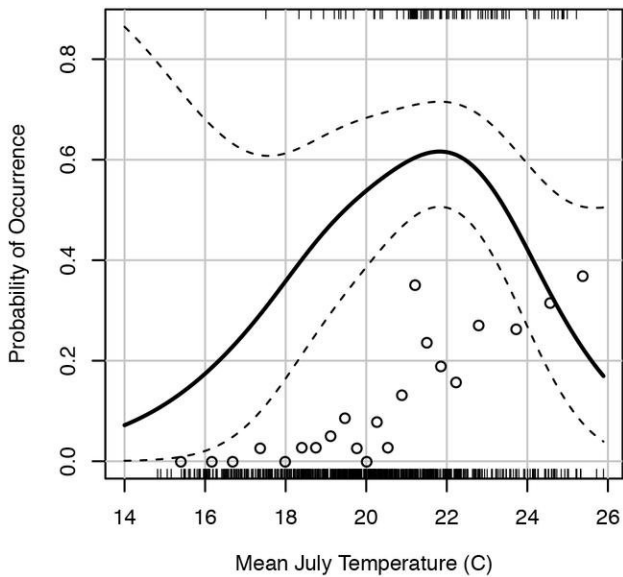
golden redhorse



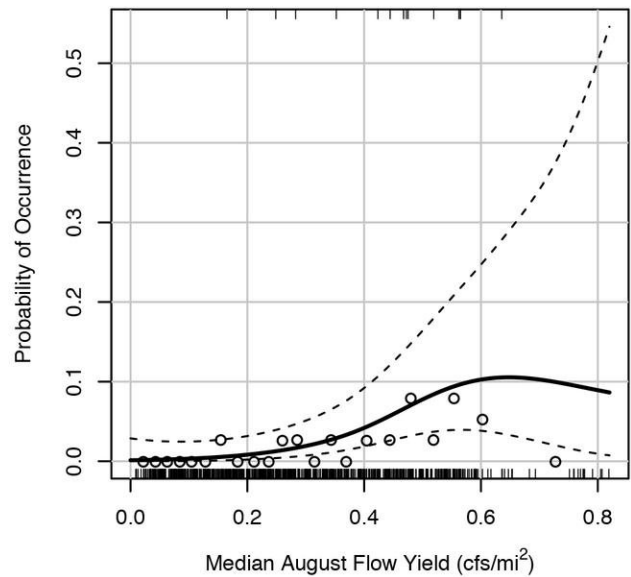
grass pickerel



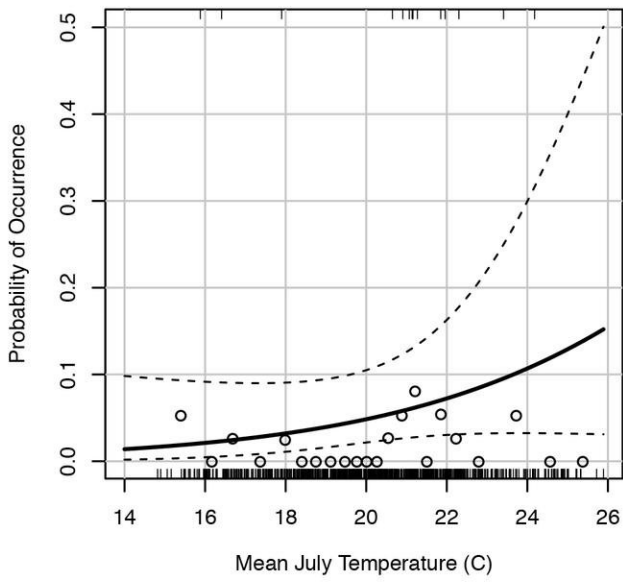
golden redhorse



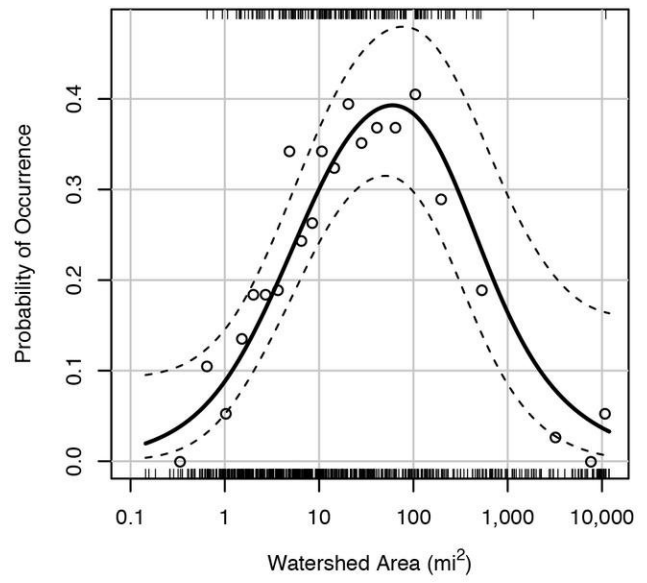
grass pickerel



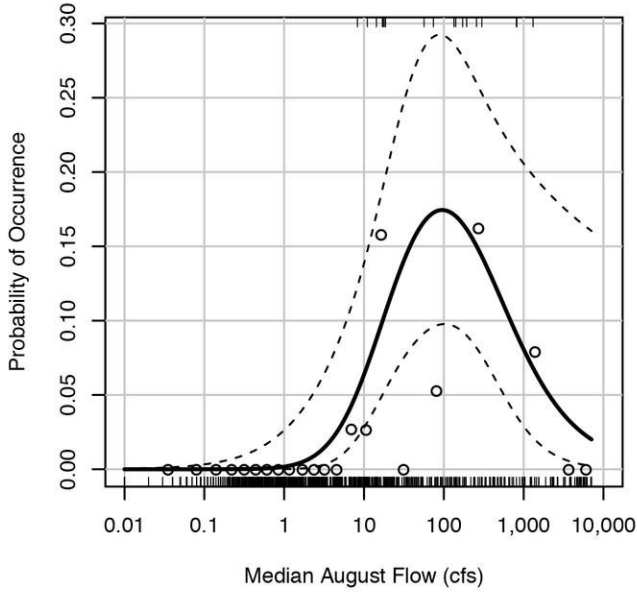
grass pickerel



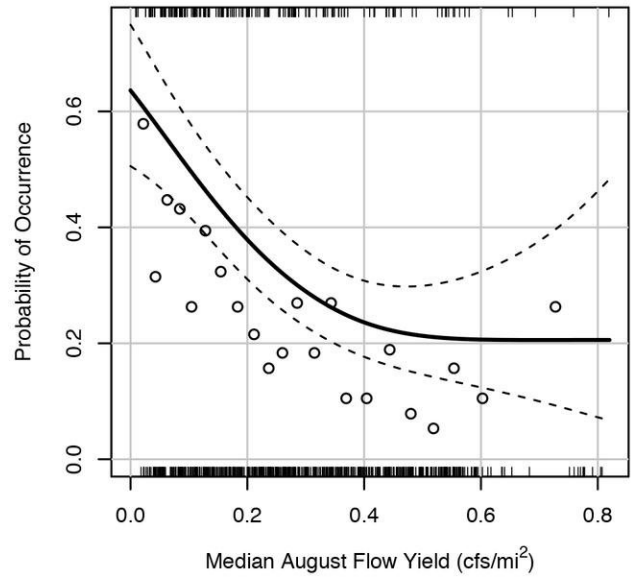
green sunfish



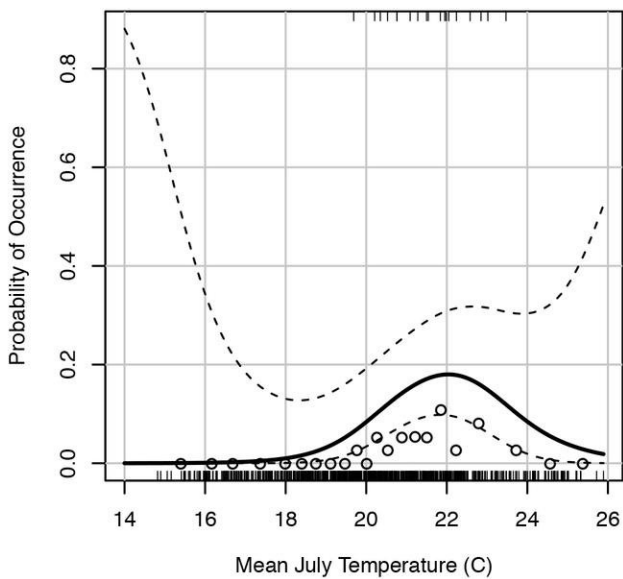
greater redhorse



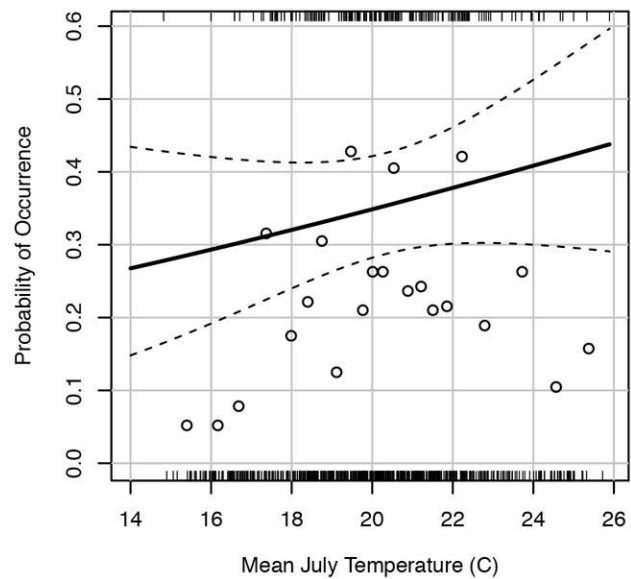
green sunfish



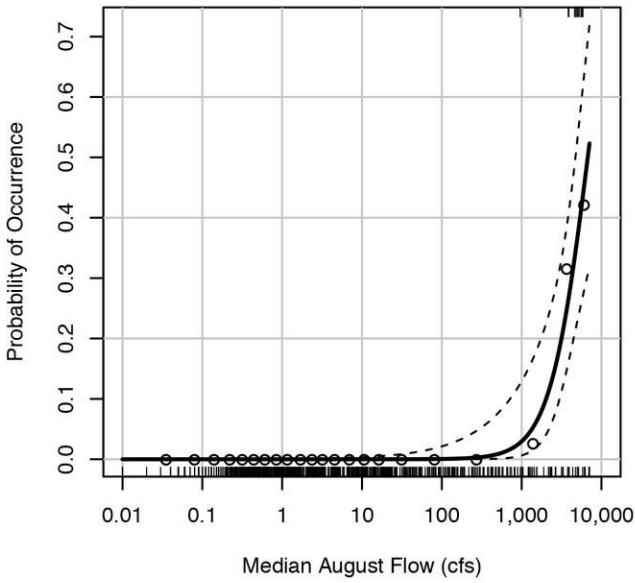
greater redhorse



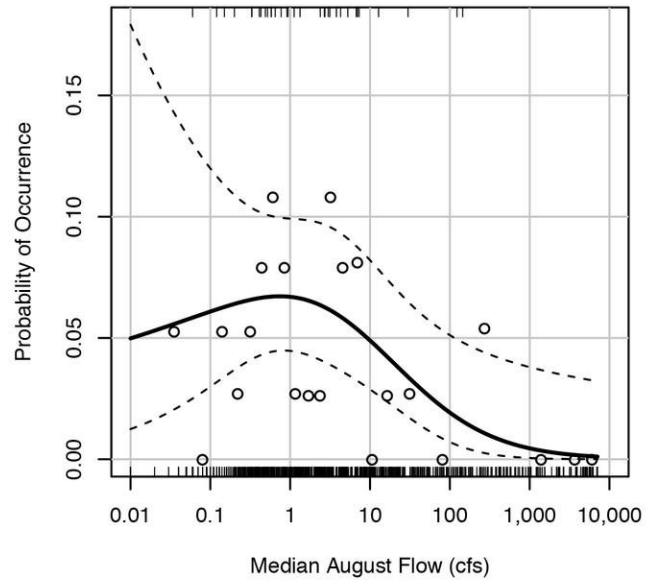
green sunfish



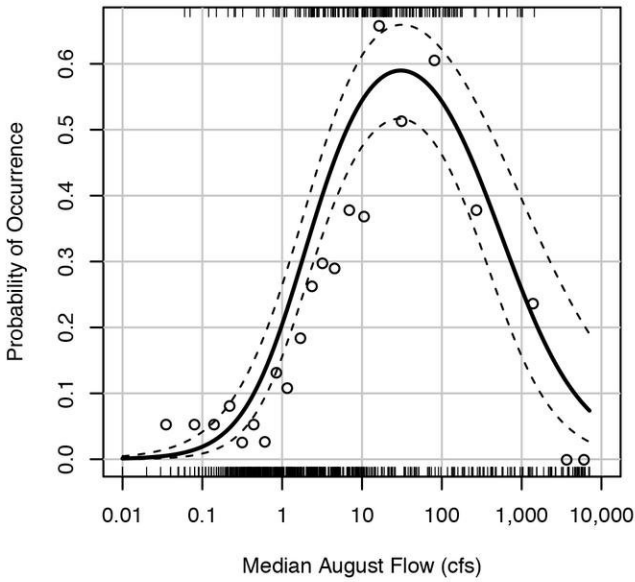
highfin carpsucker



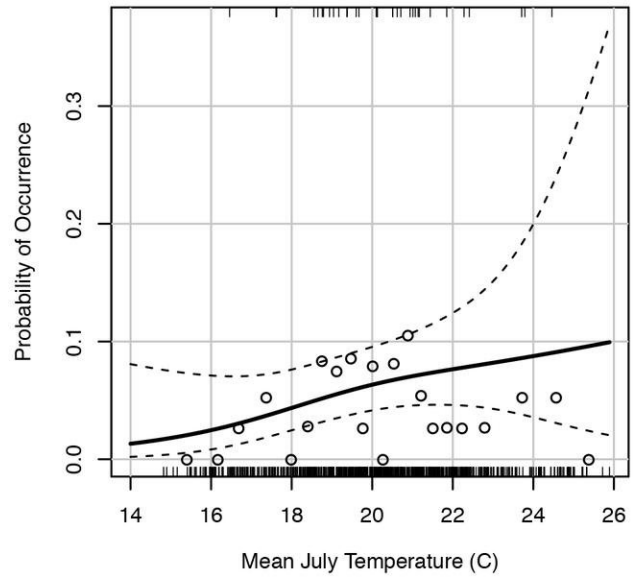
lowa darter



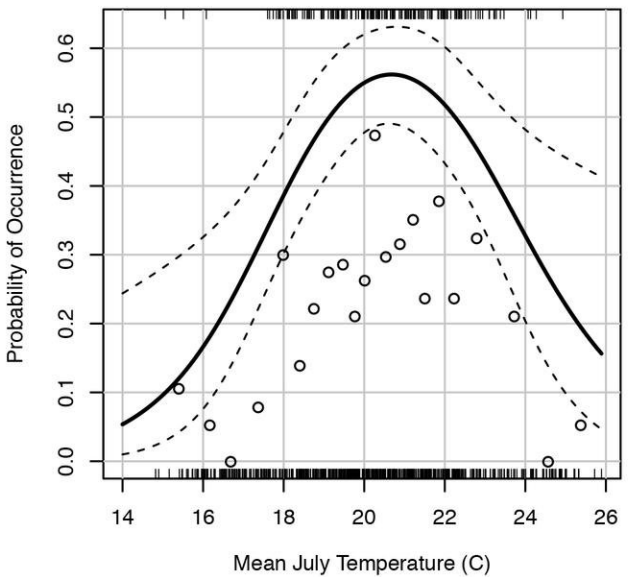
hornyhead chub



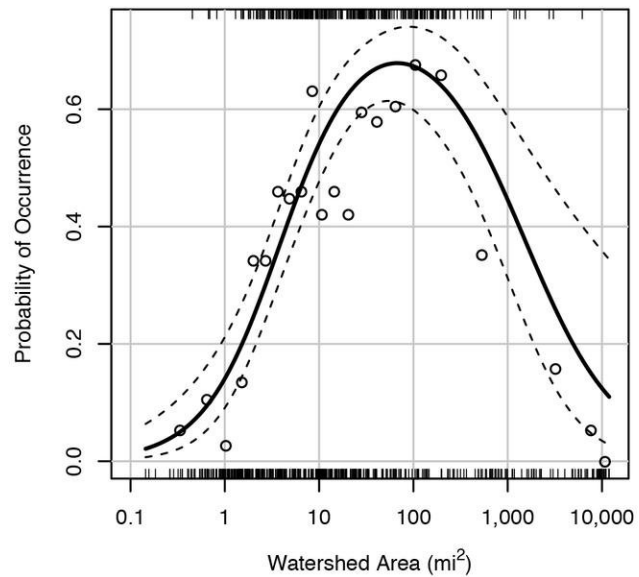
lowa darter



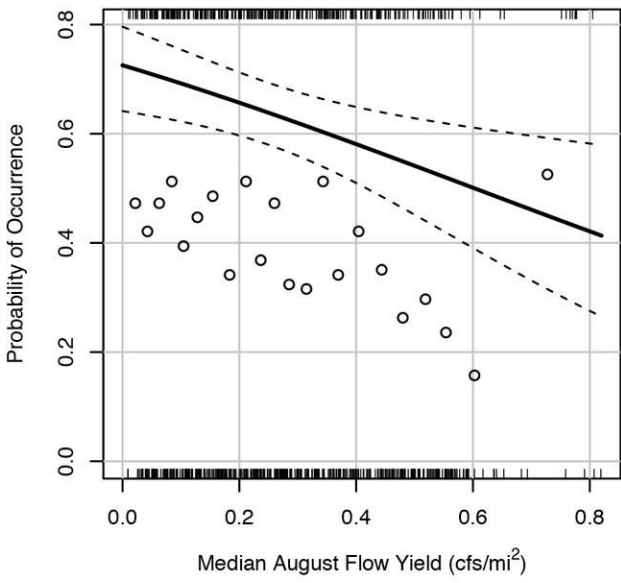
hornyhead chub



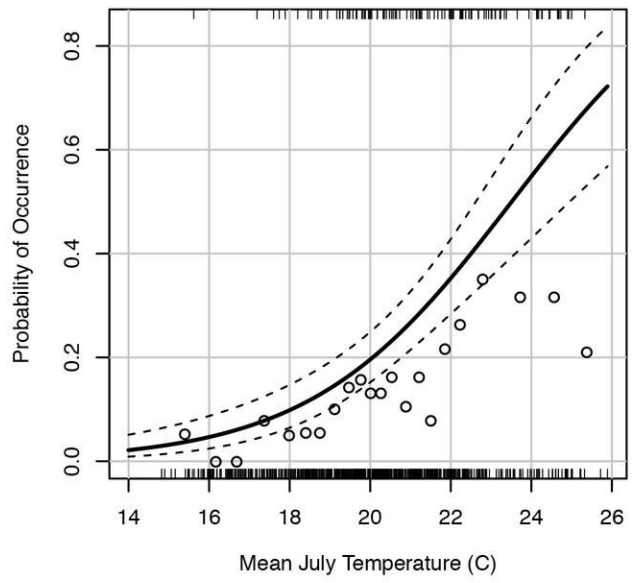
johnny darter



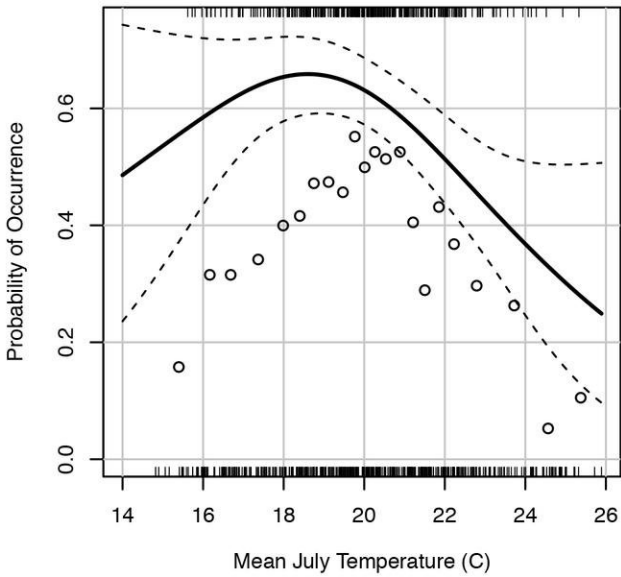
johnny darter



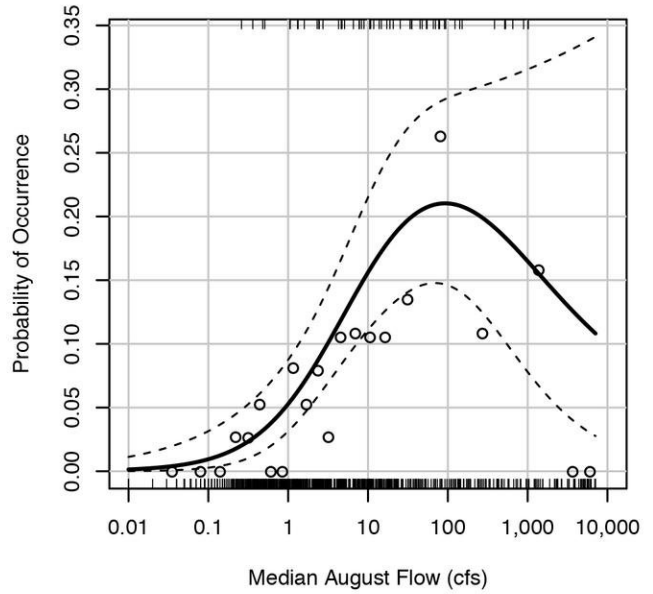
largemouth bass



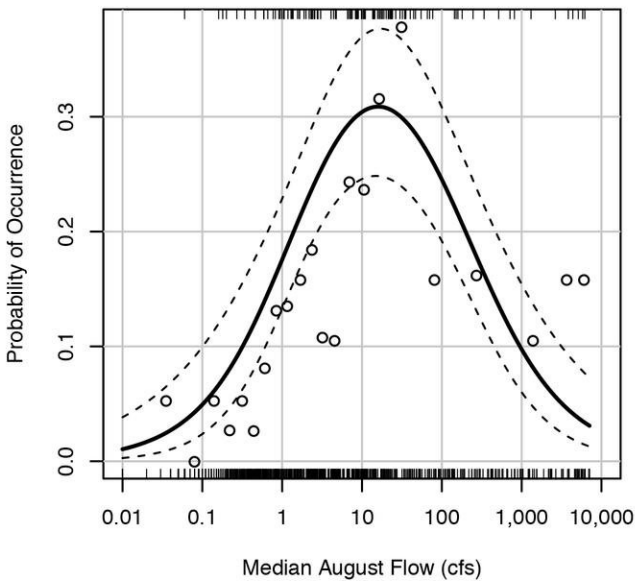
johnny darter



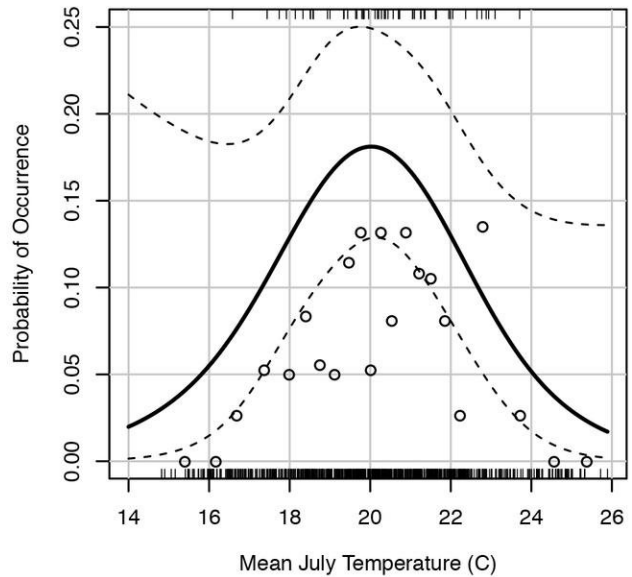
largescale stoneroller



largemouth bass

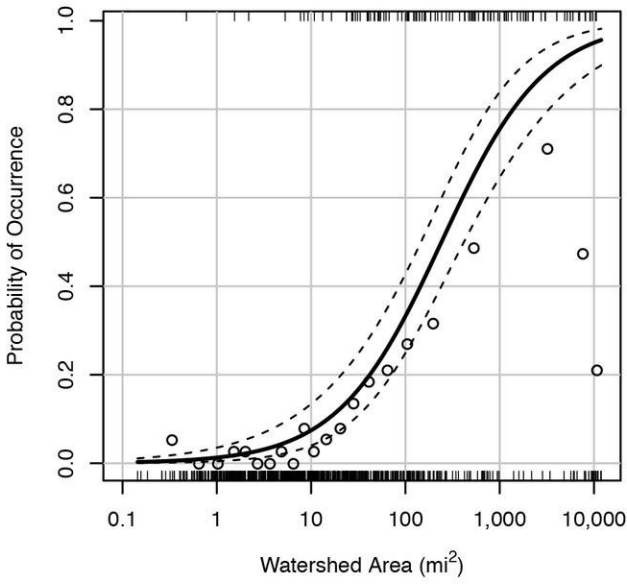


largescale stoneroller

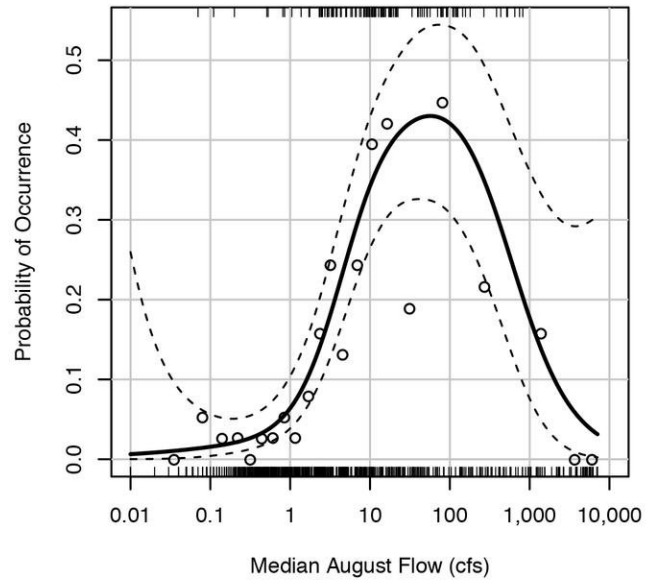


Appendix 5 - Partial dependence plots

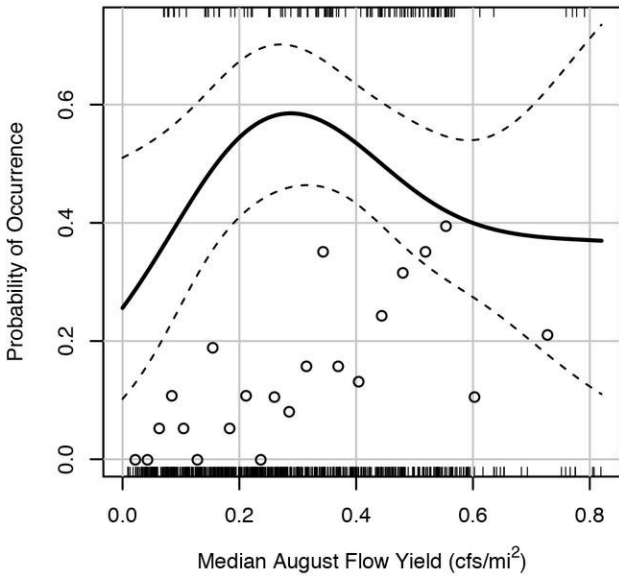
logperch



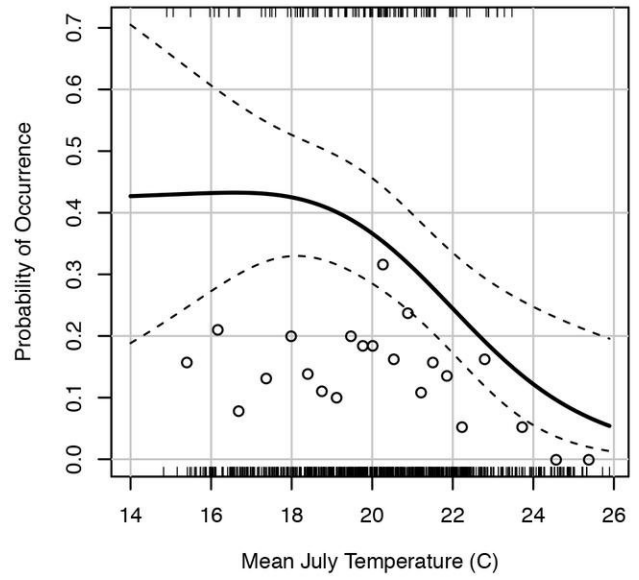
longnose dace



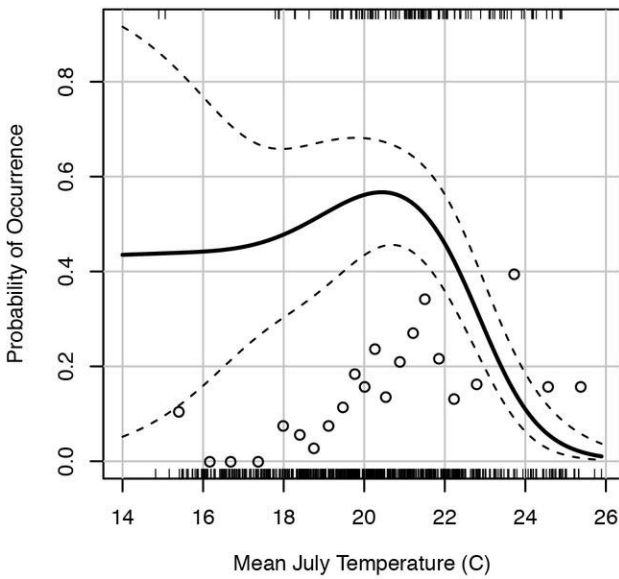
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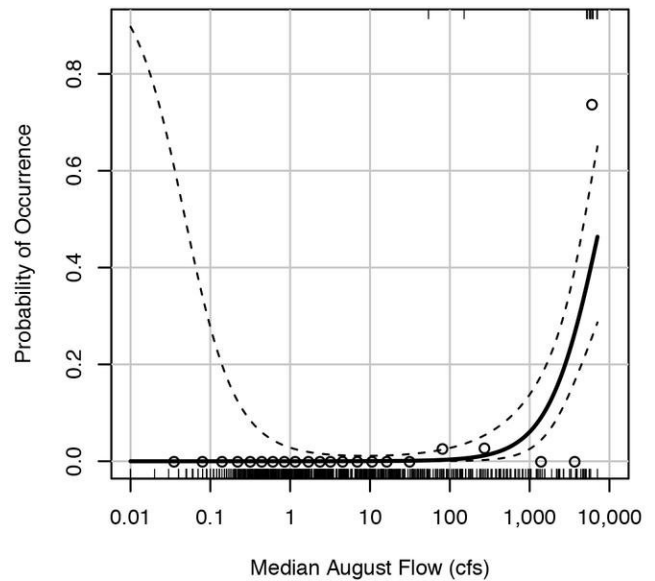
longnose dace



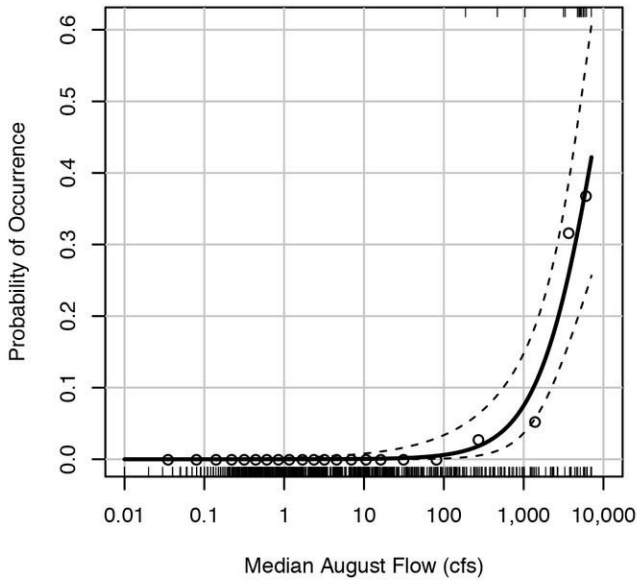
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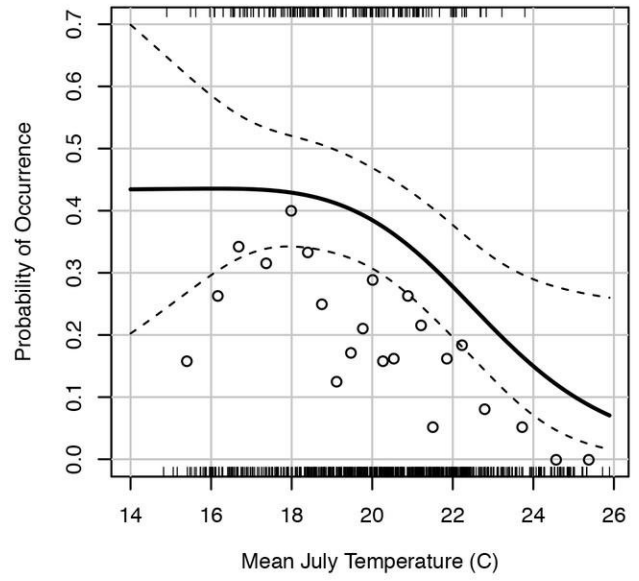
longnose gar



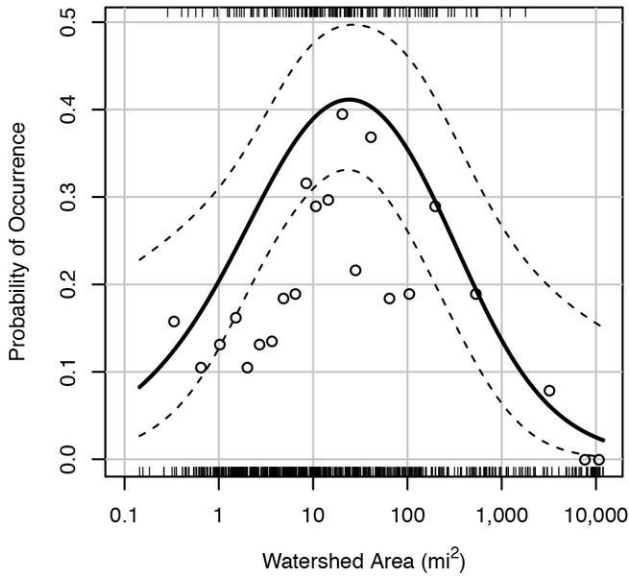
mooneye



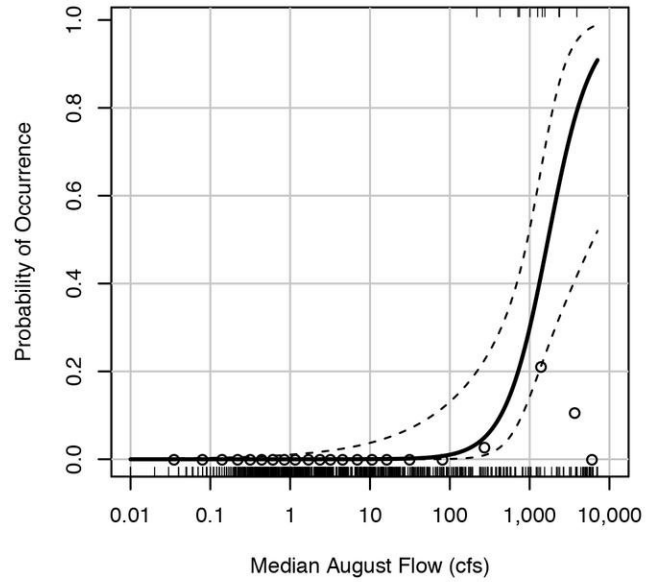
mottled sculpin



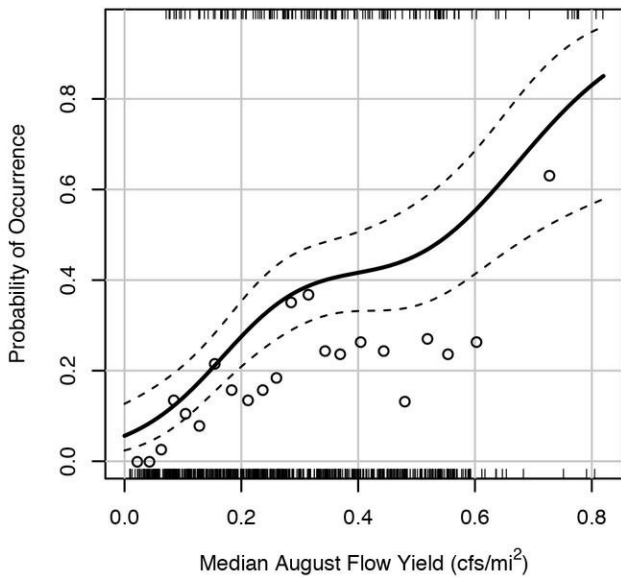
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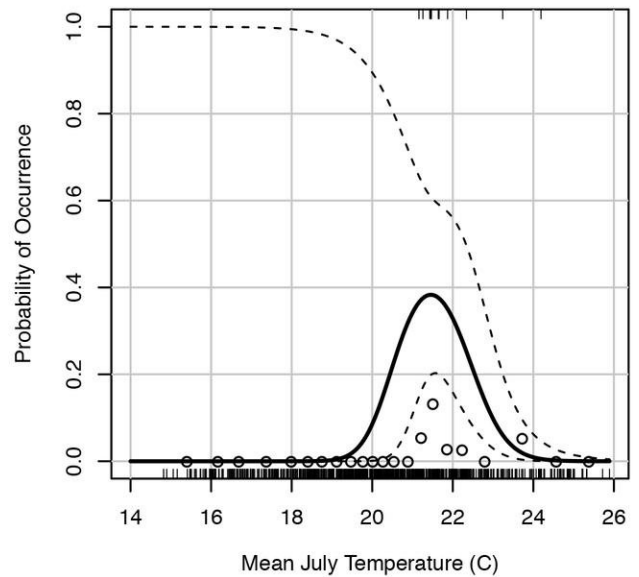
muskellunge



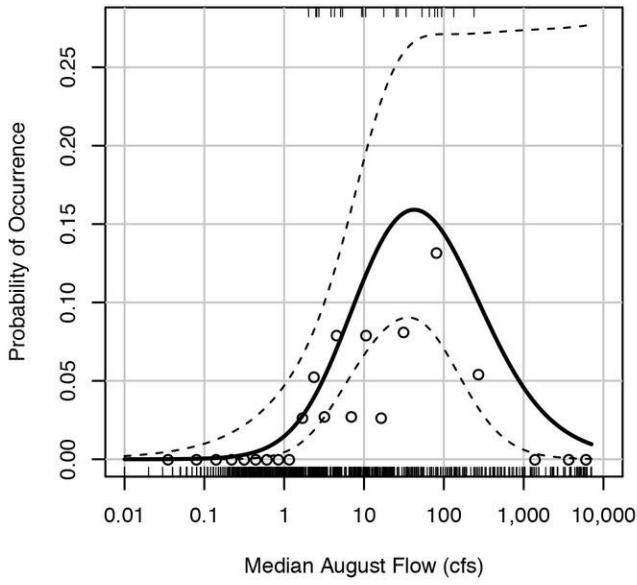
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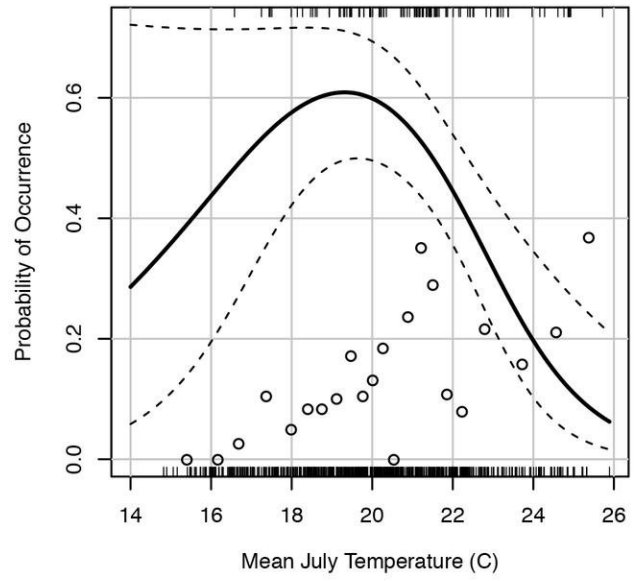
muskellunge



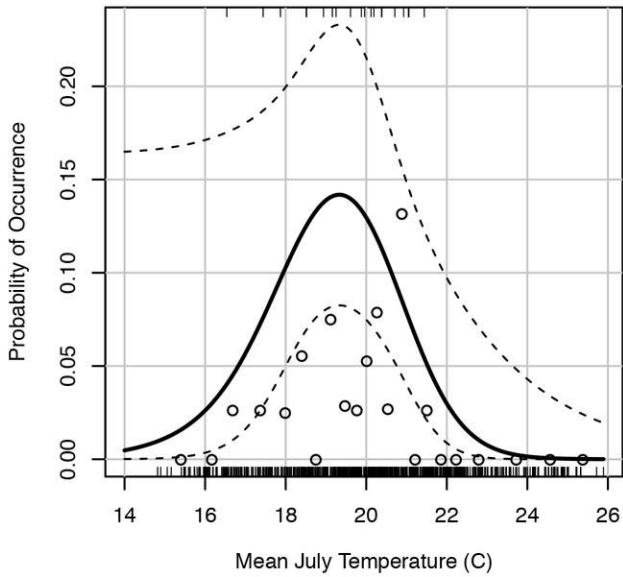
northern brook lamprey



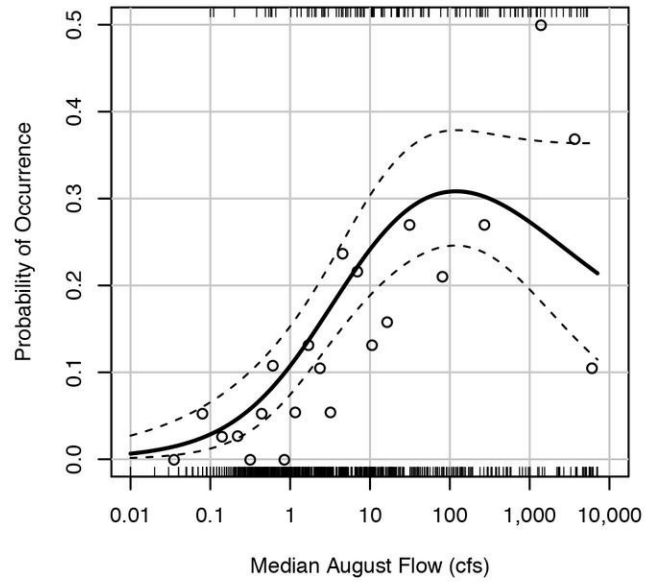
northern hog sucker



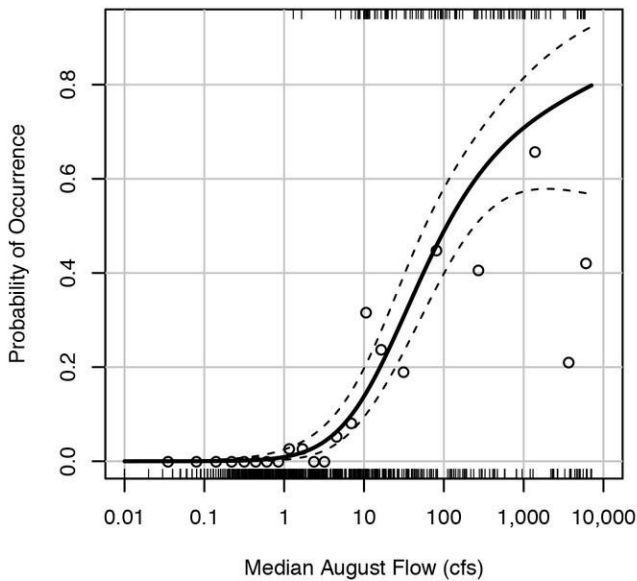
northern brook lamprey



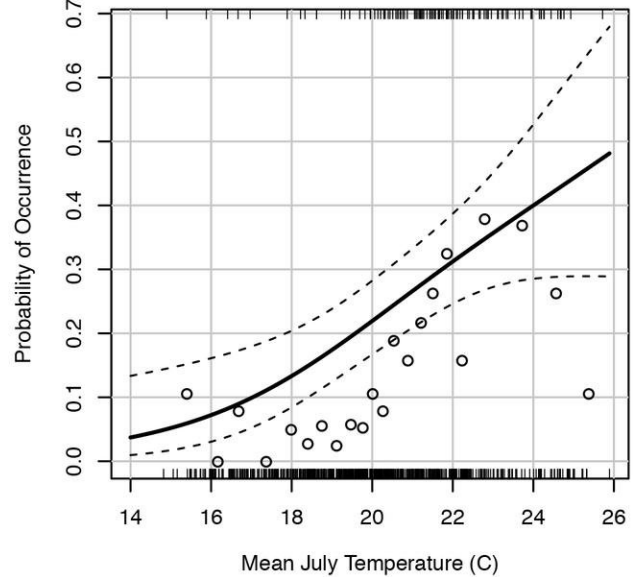
northern pike



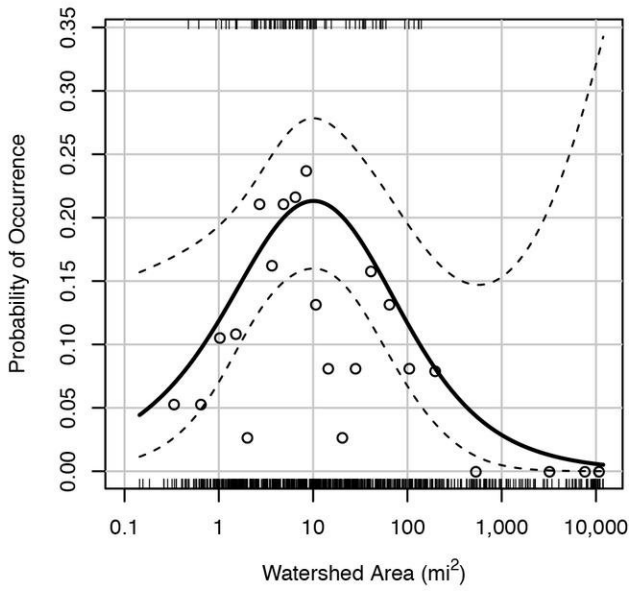
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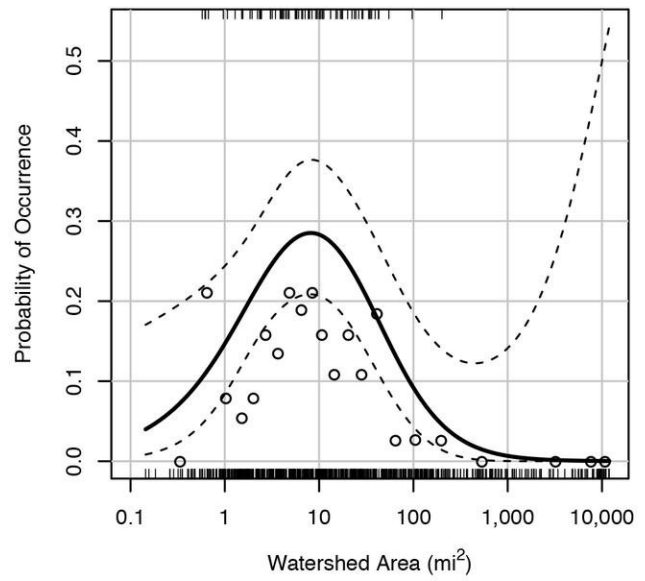
northern pike



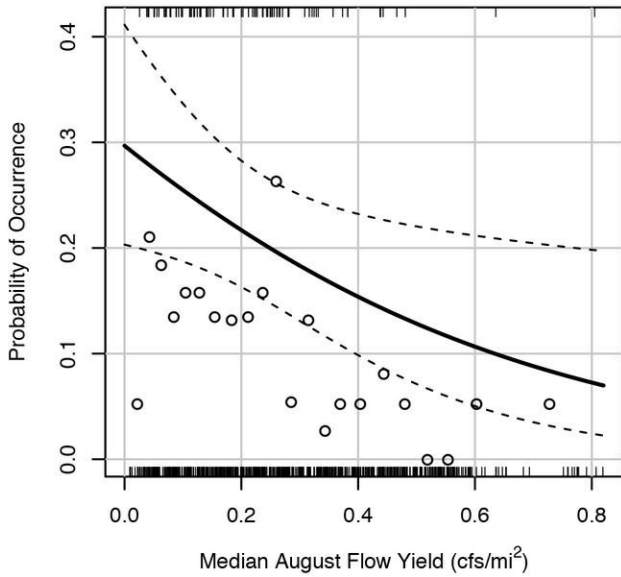
northern redbelly dace



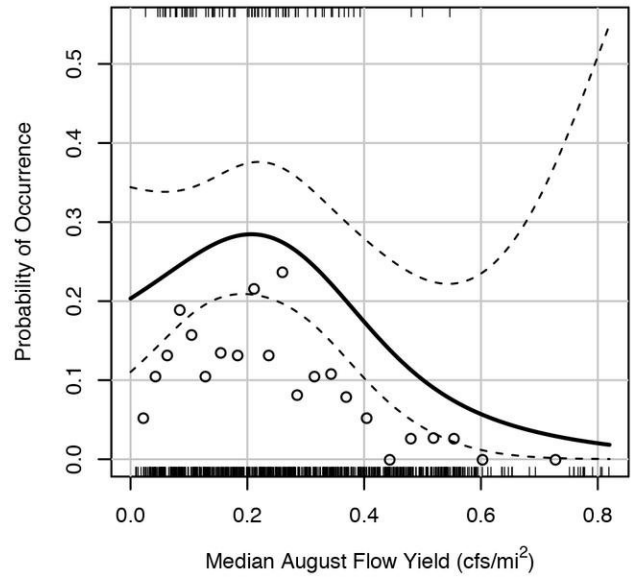
pearl dace



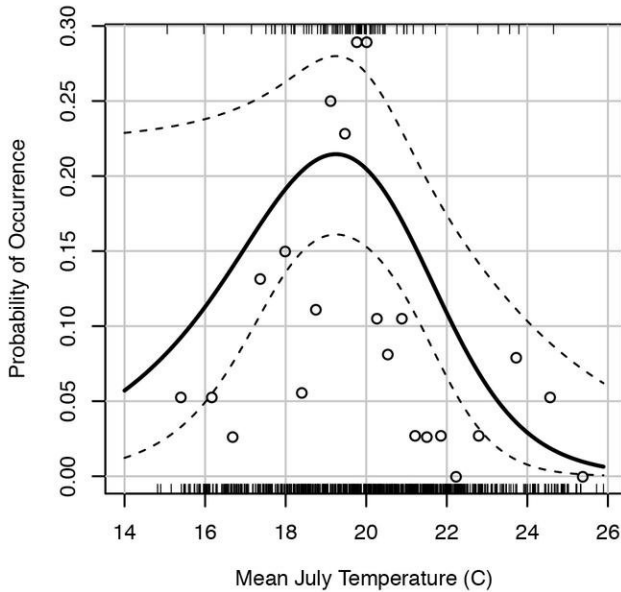
northern redbelly dace



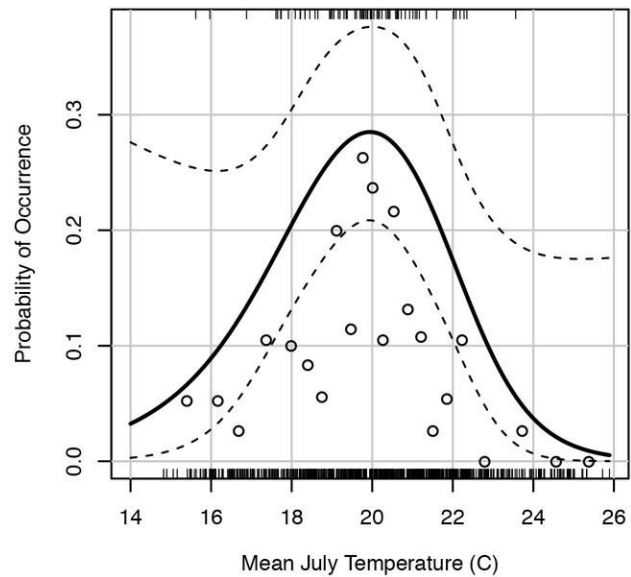
pearl dace



northern redbelly dace

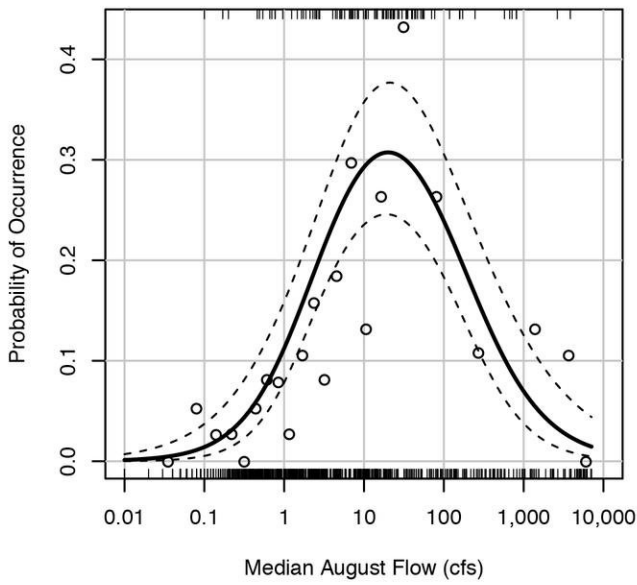


pearl dace

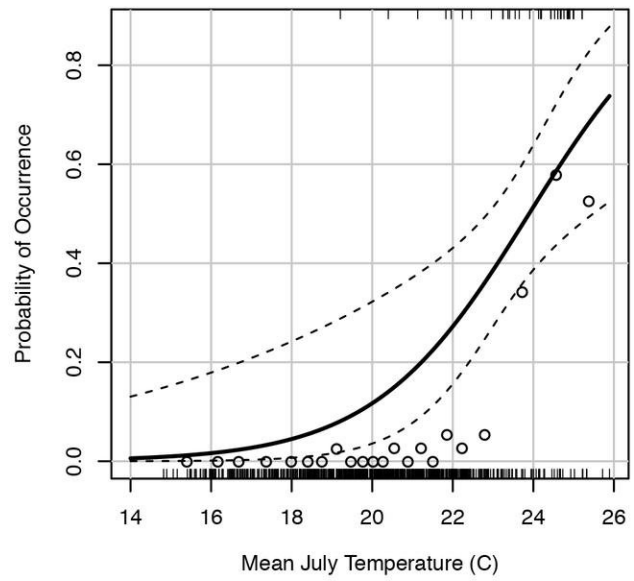


Appendix 5 - Partial dependence plots

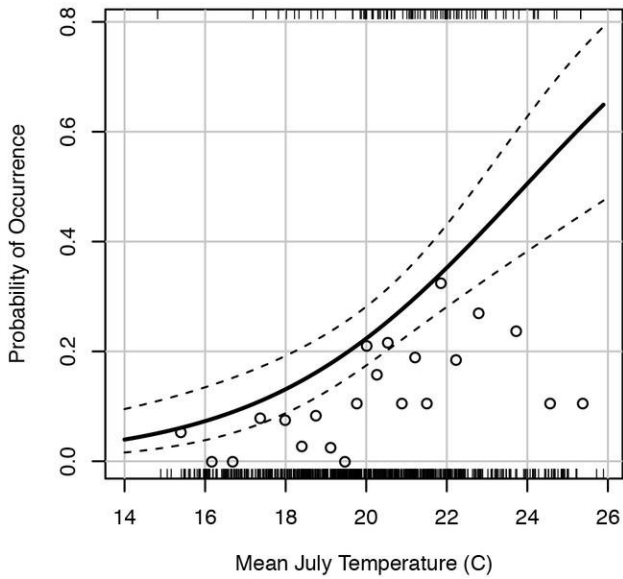
pumpkinseed



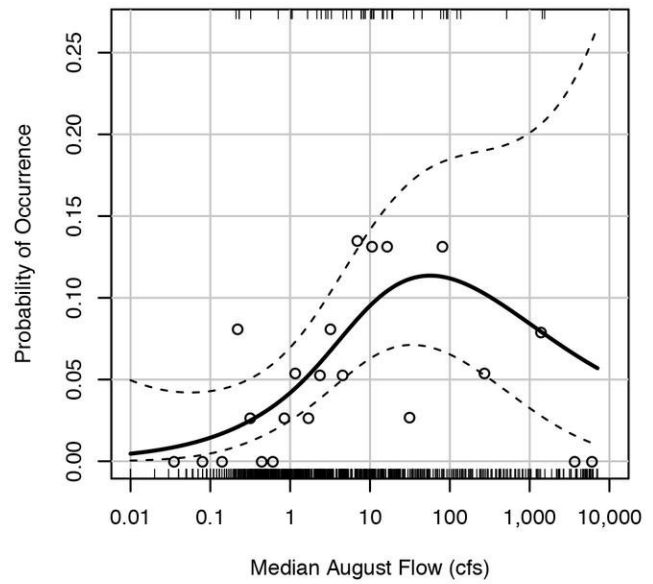
quillback



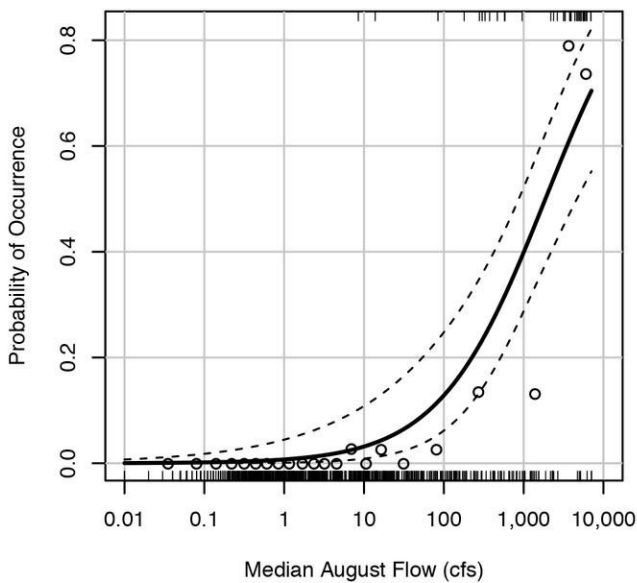
pumpkinseed



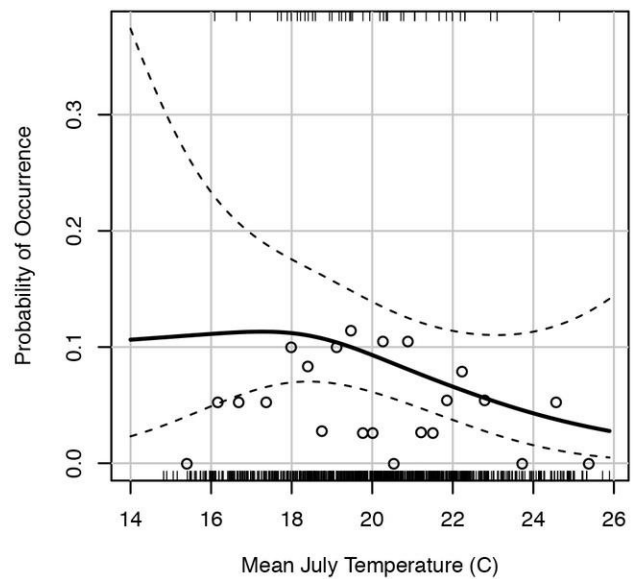
rainbow darter



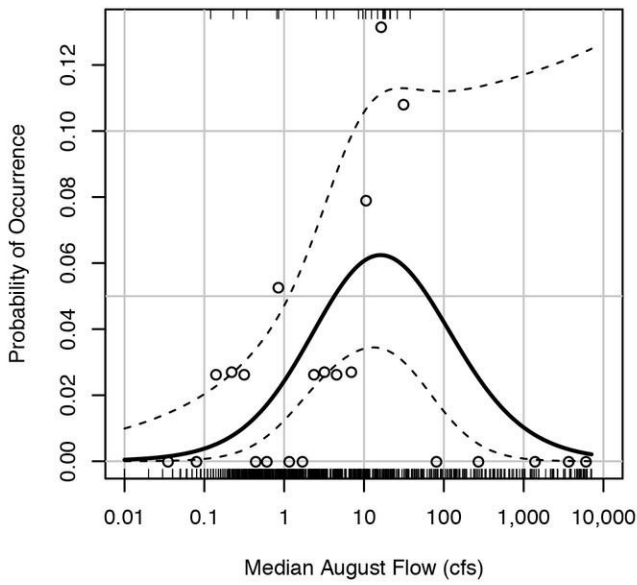
quillback



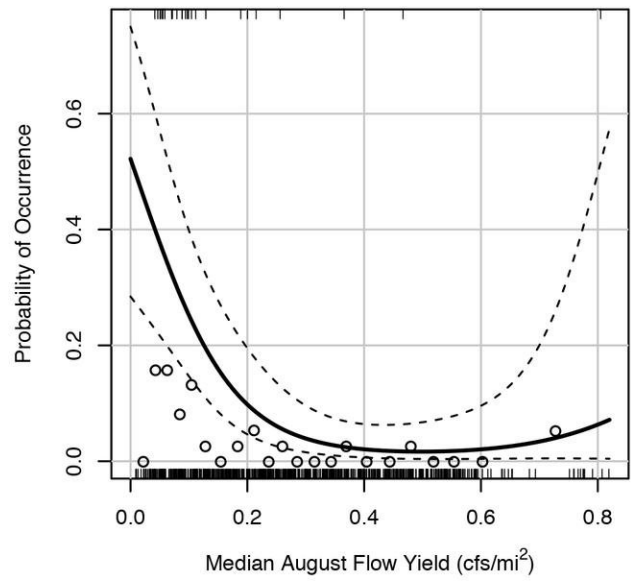
rainbow darter



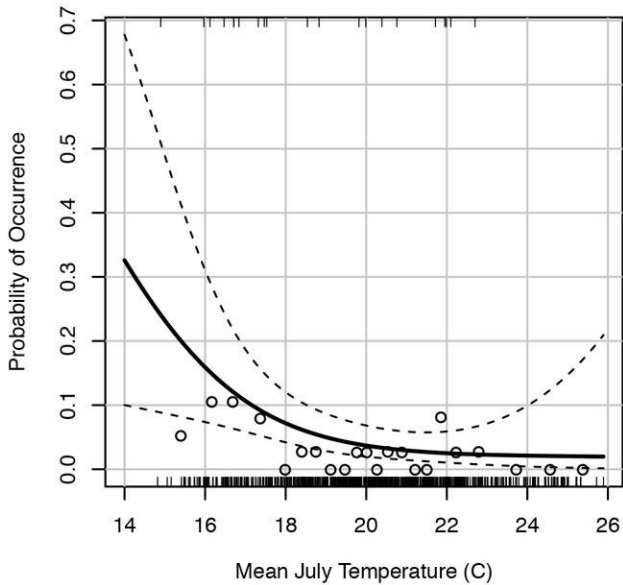
rainbow trout



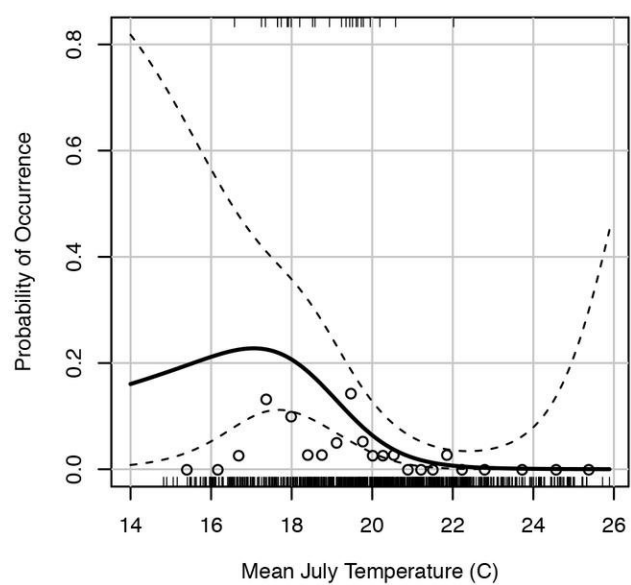
reidside dace



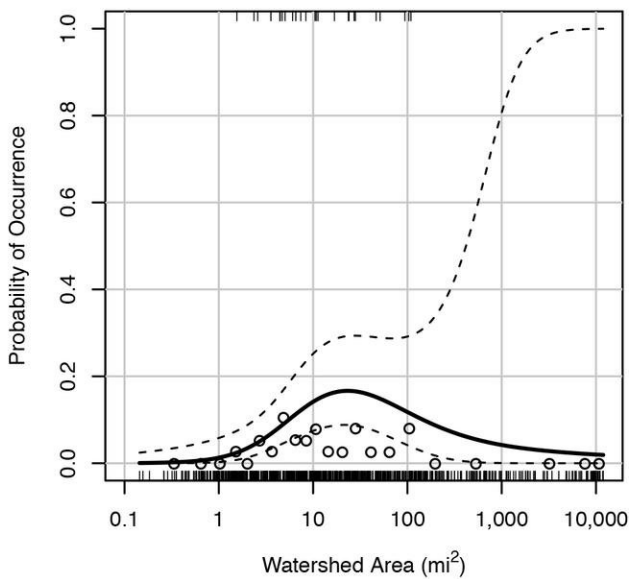
rainbow trout



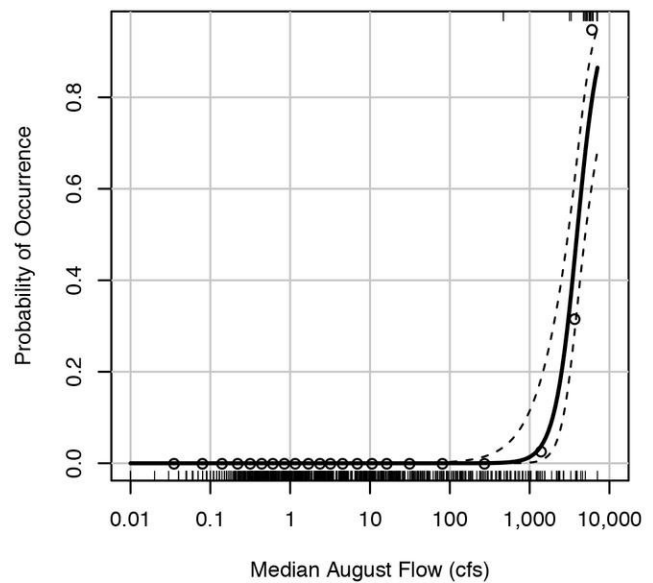
reidside dace



reidside dace

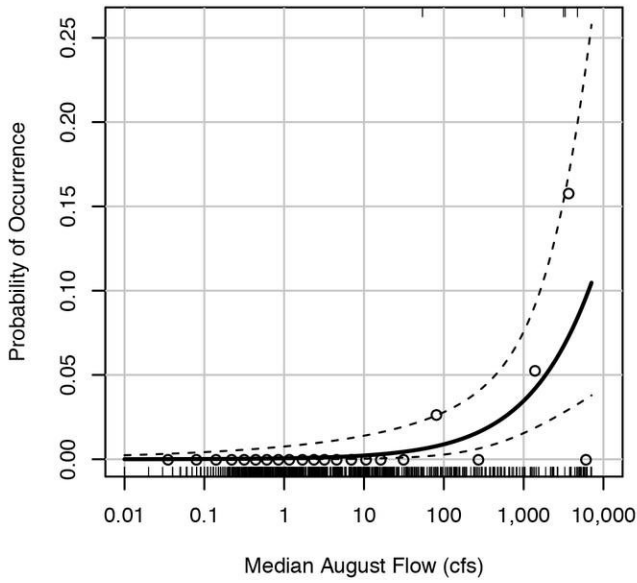


river carsucker

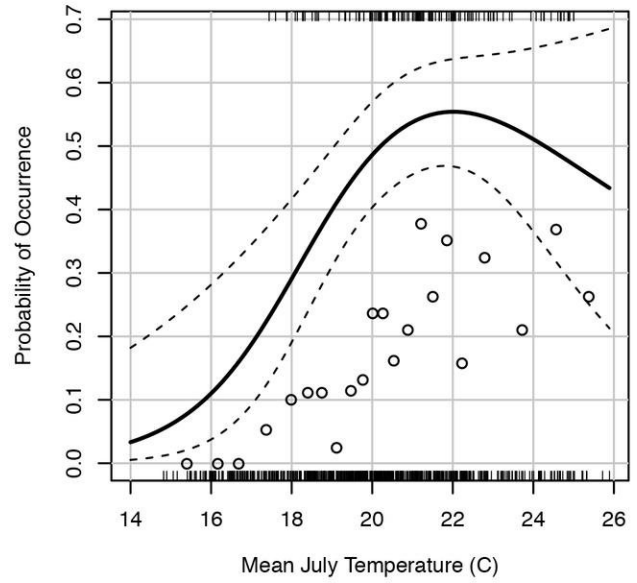


Appendix 5 - Partial dependence plots

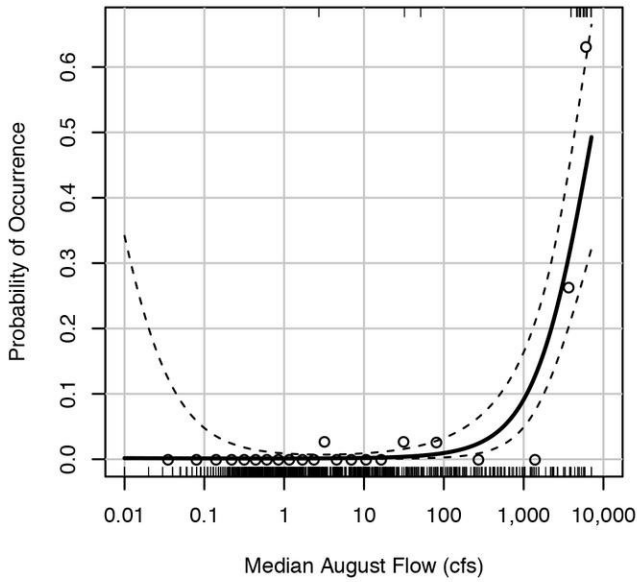
river redhorse



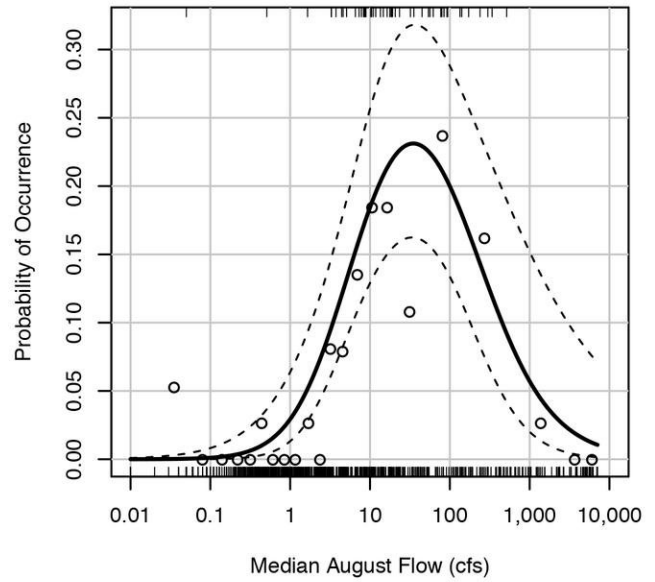
rock bass



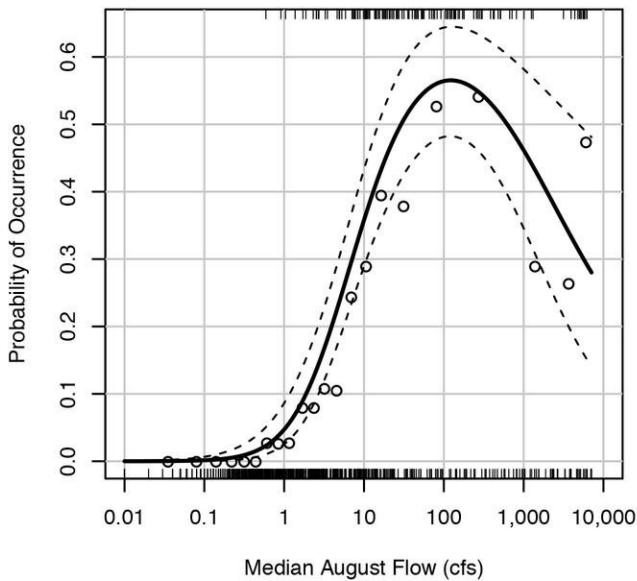
river shiner



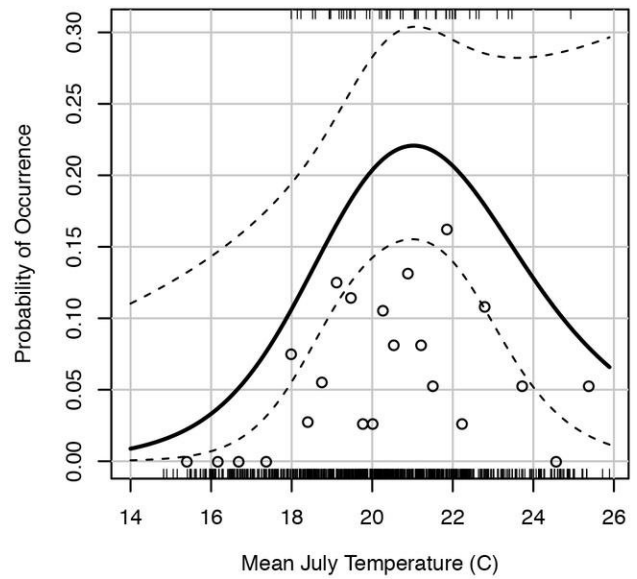
rosyface shiner



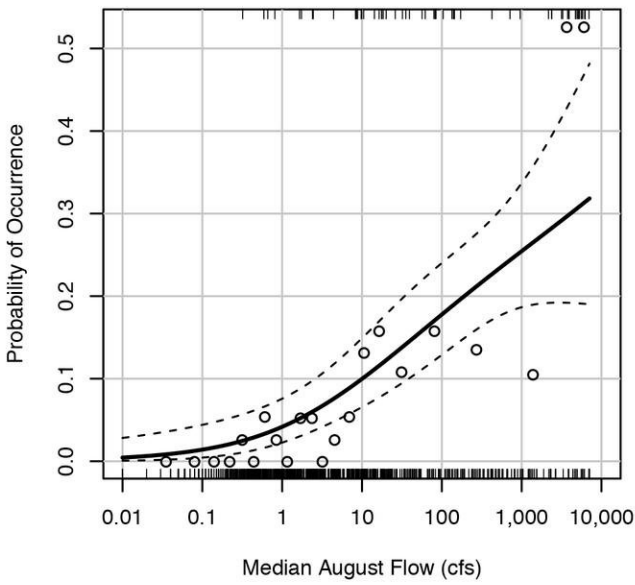
rock bass



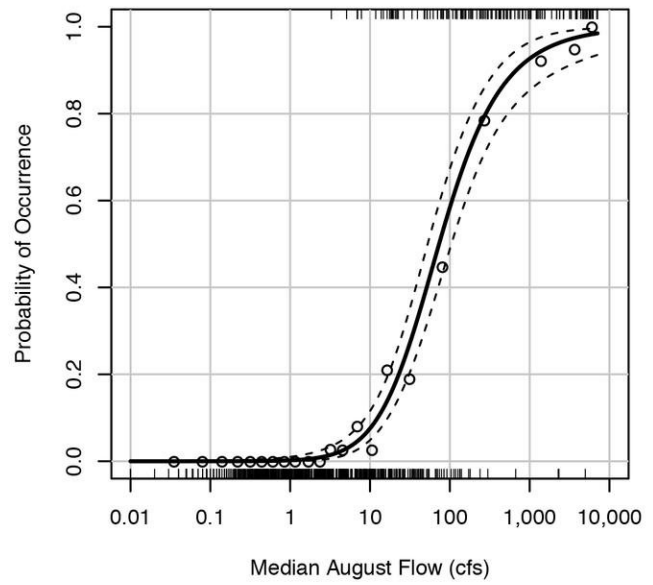
rosyface shiner



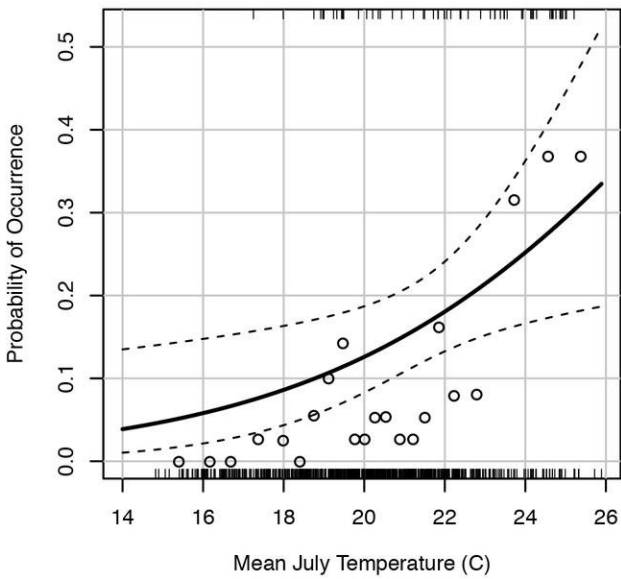
sand shiner



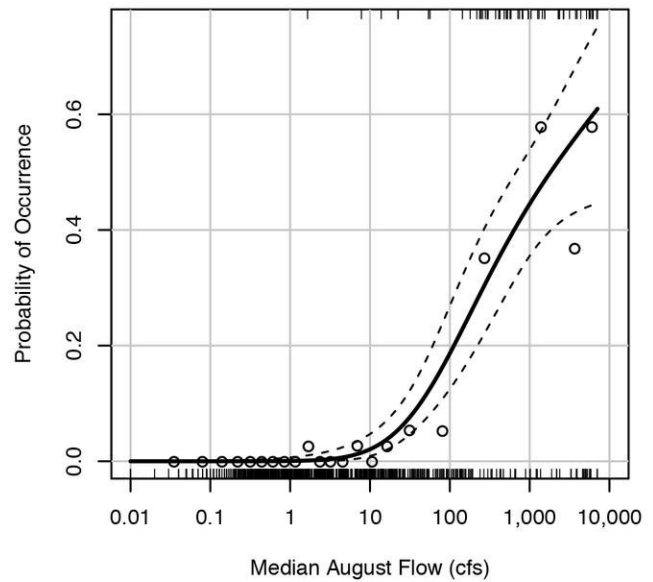
shorthead redhorse



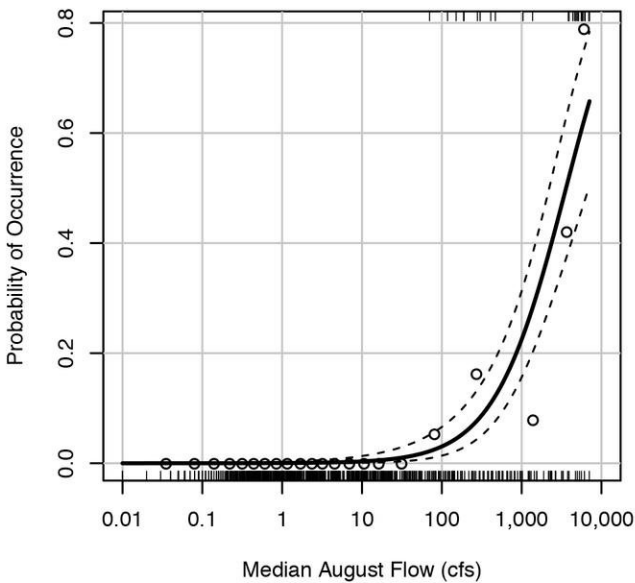
sand shiner



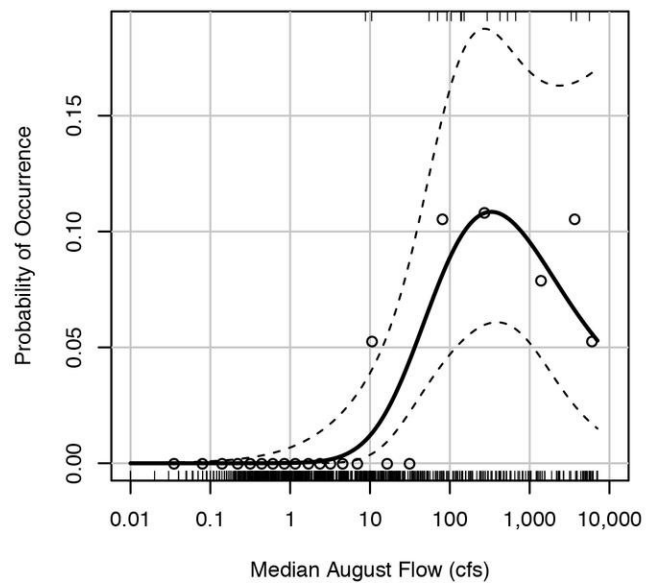
silver redhorse



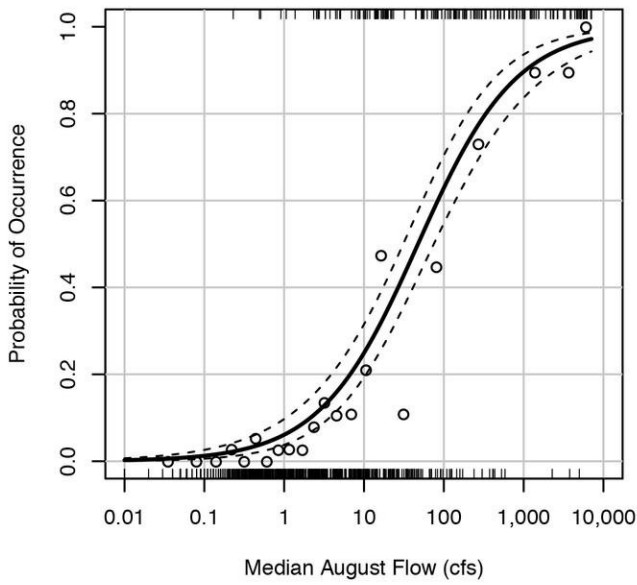
sauger



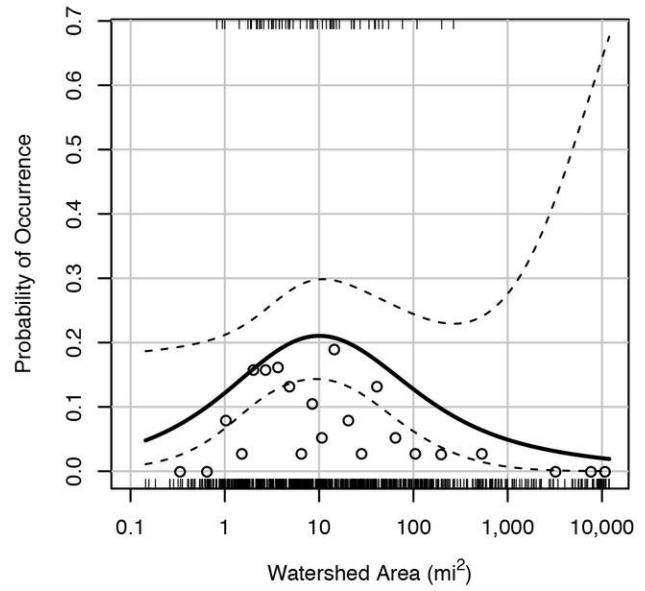
slenderhead darter



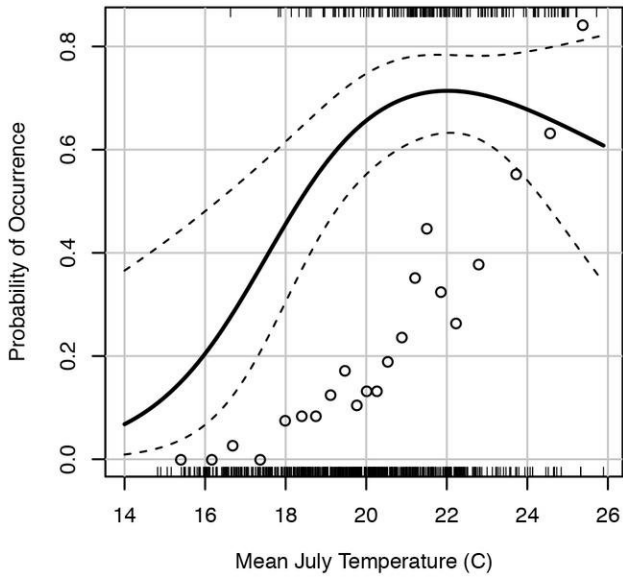
smallmouth bass



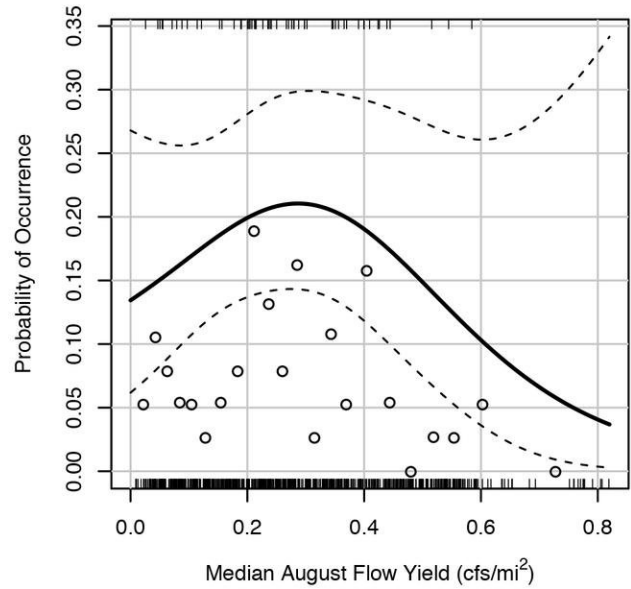
southern redbelly dace



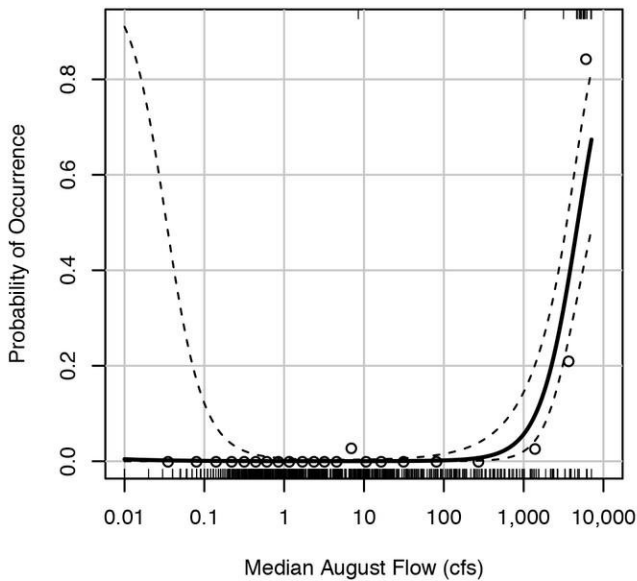
smallmouth bass



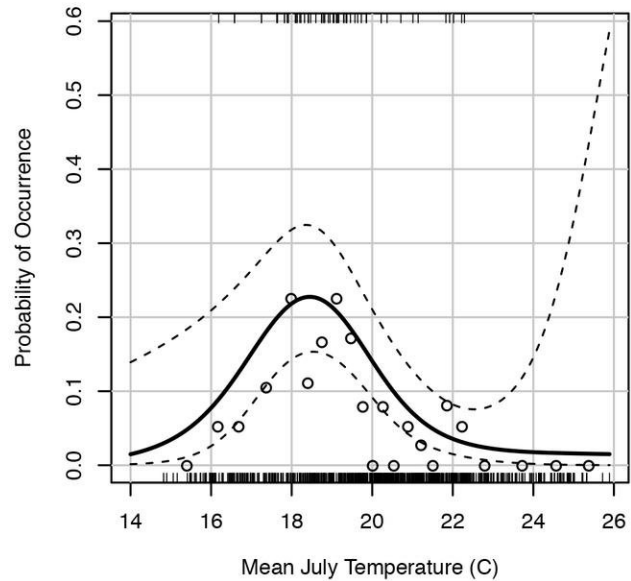
southern redbelly dace



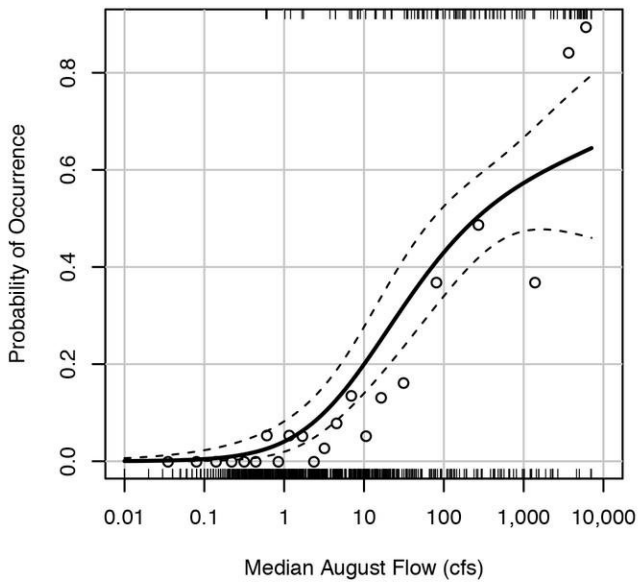
smallmouth buffalo



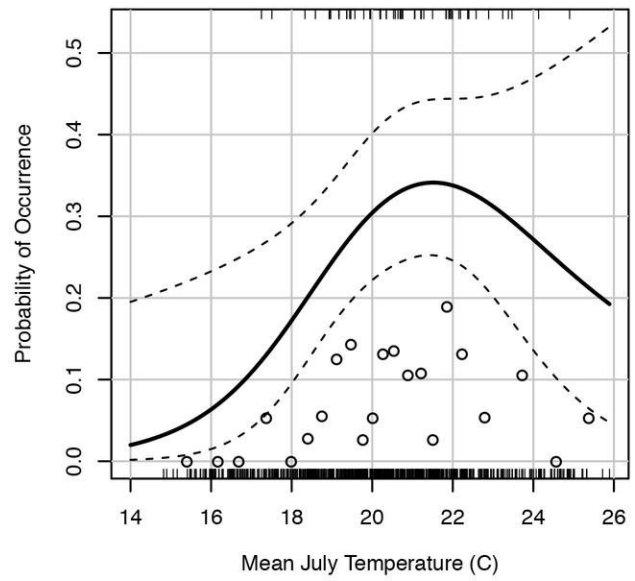
southern redbelly dace



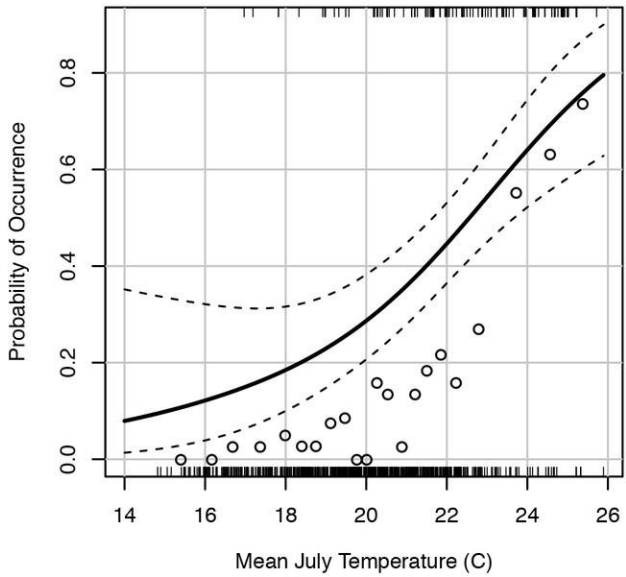
spotfin shiner



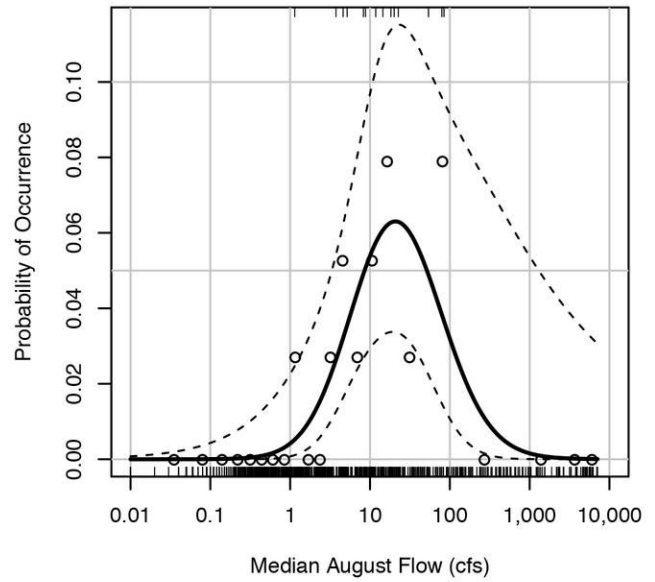
stonecat



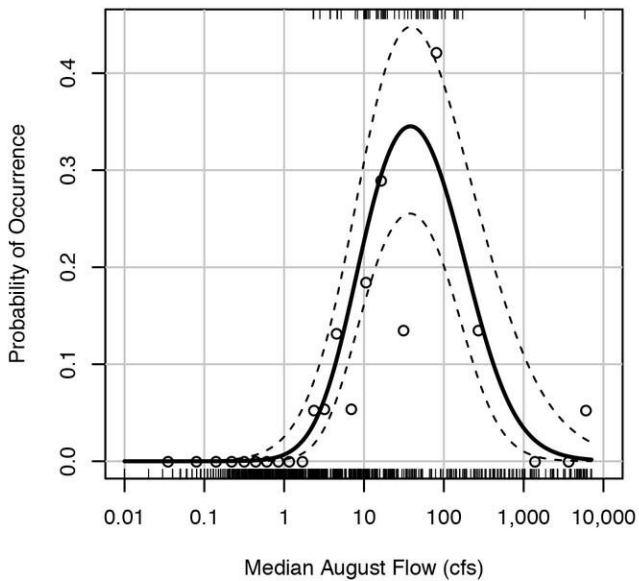
spotfin shiner



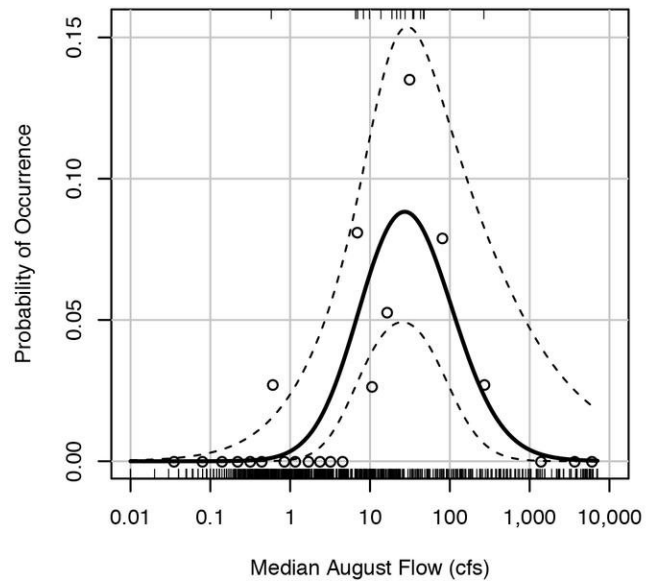
suckermouth minnow



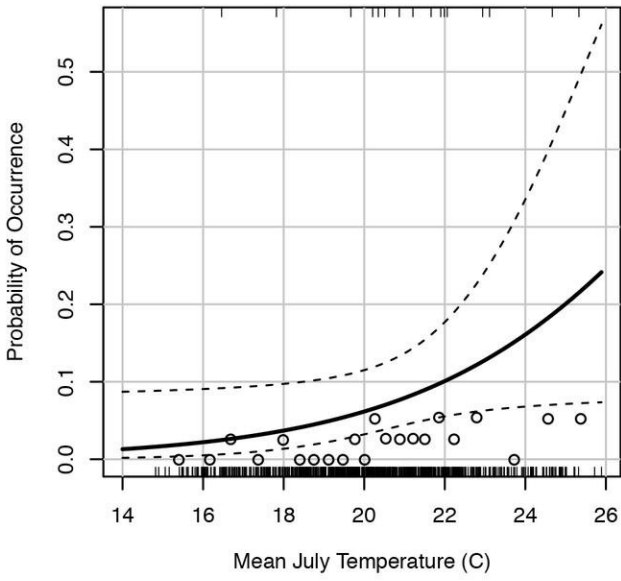
stonecat



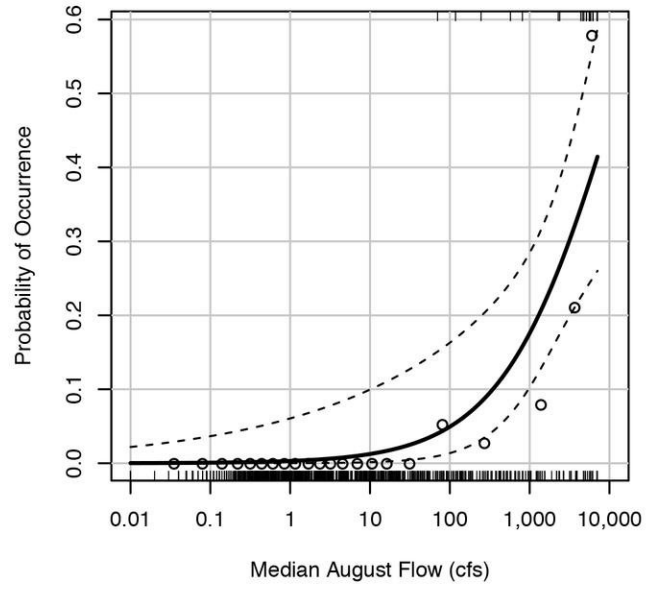
tadpole madtom



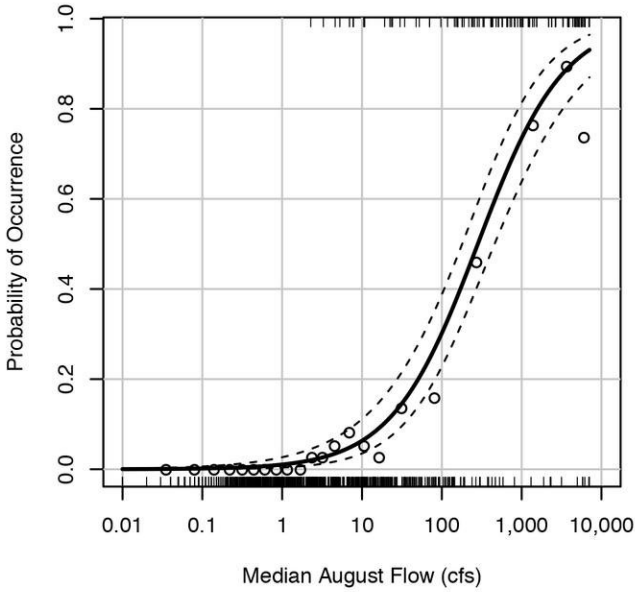
tadpole madtom



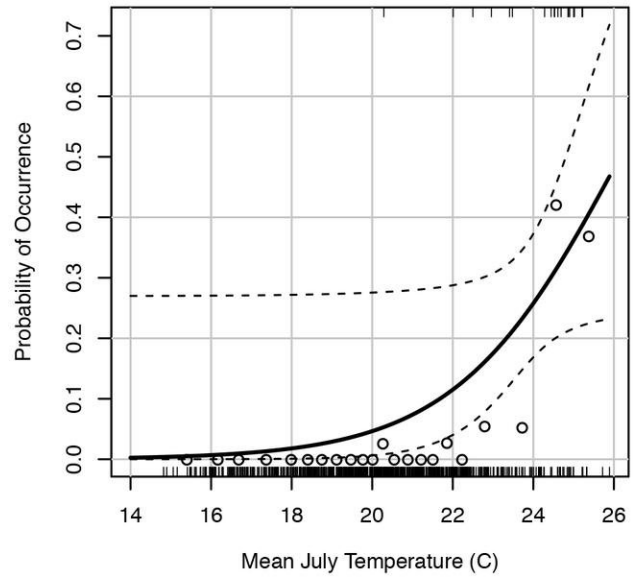
white bass



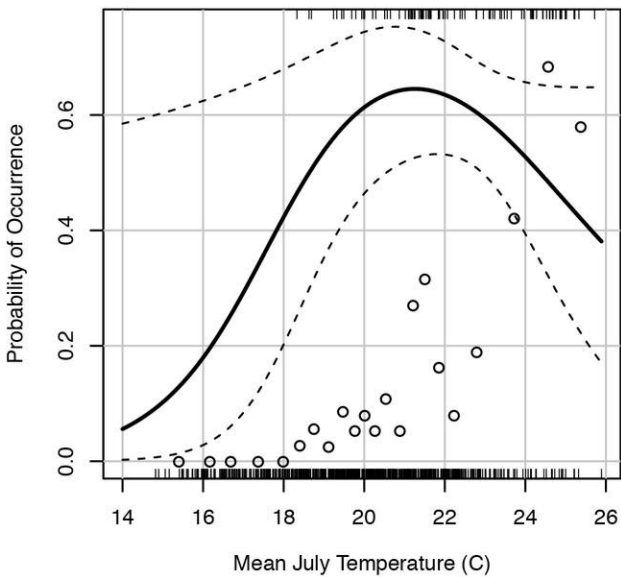
walleye



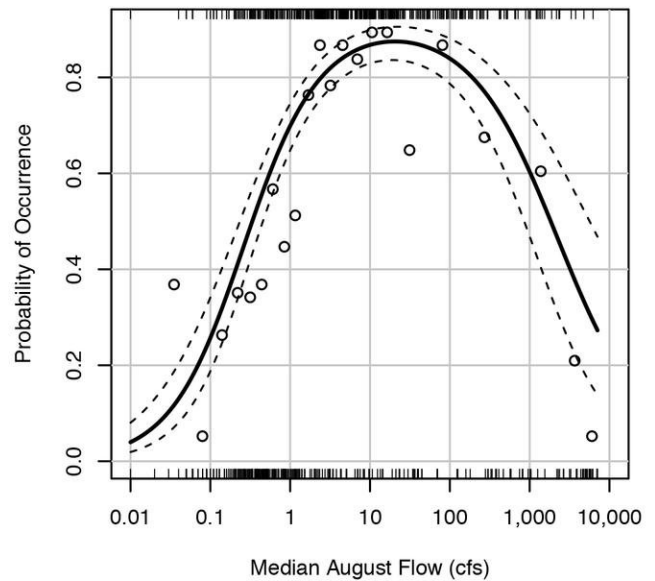
white bass



walleye

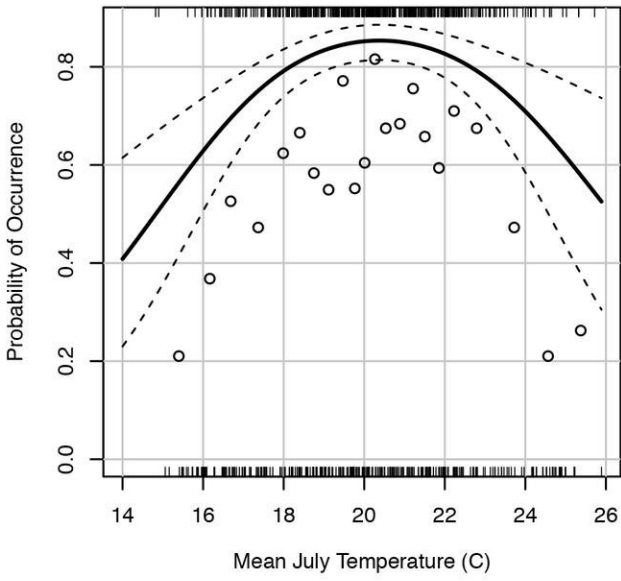


white sucker

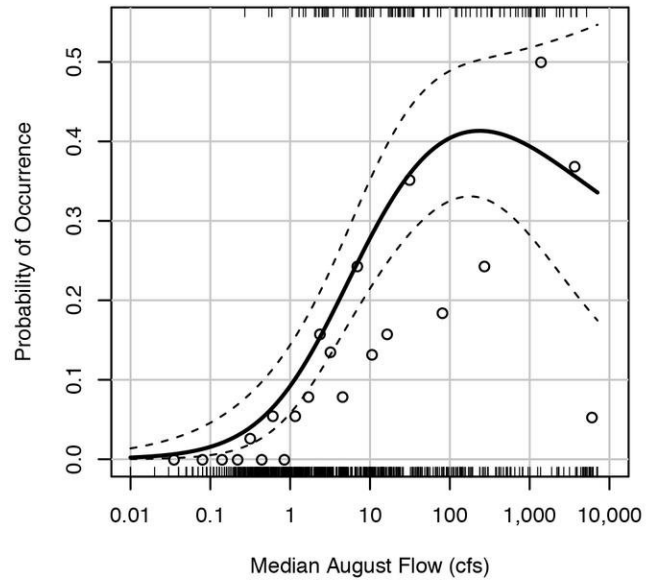


Appendix 5 - Partial dependence plots

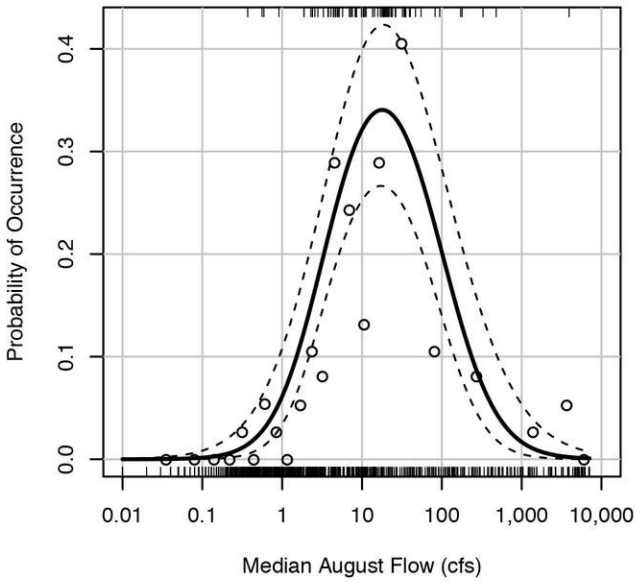
white sucker



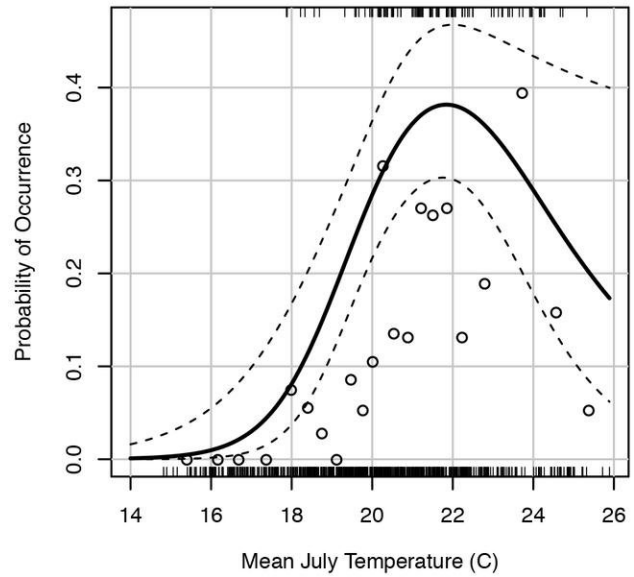
yellow perch



yellow bullhead



yellow perch



yellow bullhead

