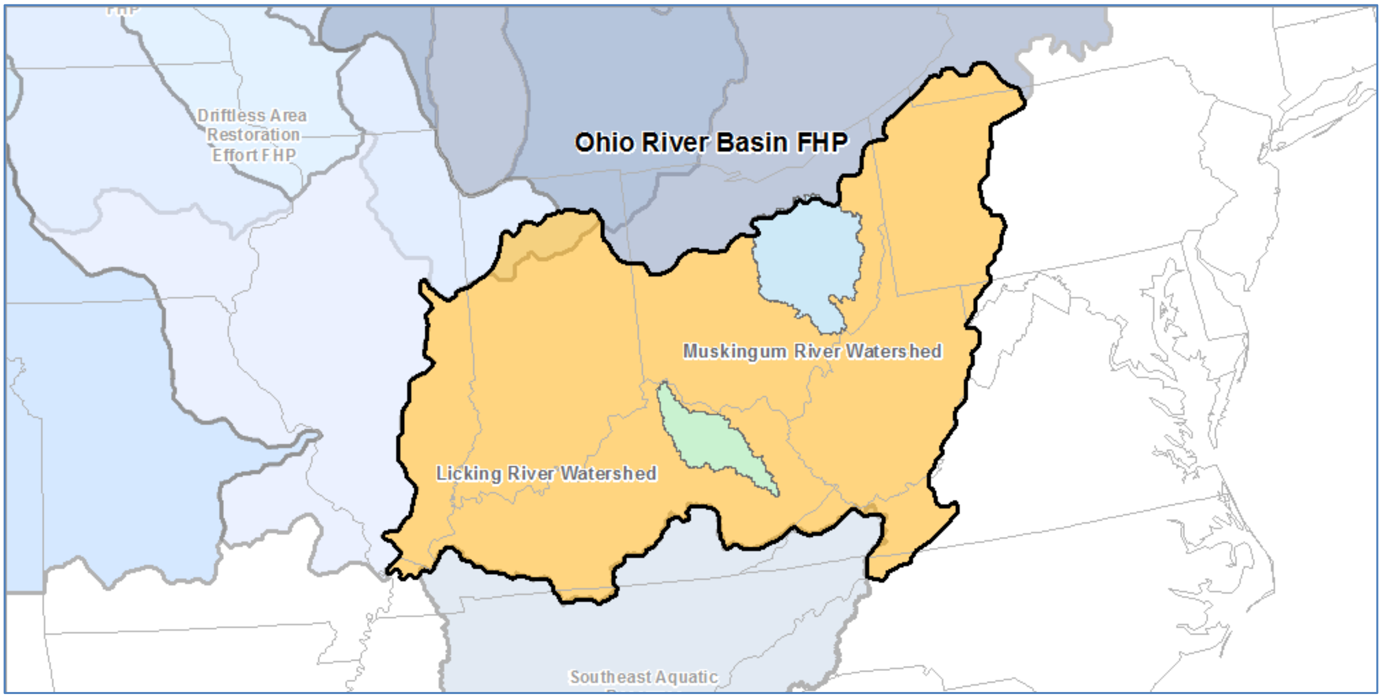
Ohio River Basin Fish Habitat Partnership Habitat Modeling Results

Ohio River Basin Watershed Models

Model Summaries
2/21/2014

Licking River (KY) watershed: Predicted Macroinvertebrate Bioassessment Index (MBI) score

Muskingum River (OH) watershed: Predicted Fish Index of Biotic Integrity (IBI) score



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ABBREVIATIONS

BRT	boosted regression tree
ASI	anthropogenic stress index
HQI	natural habitat quality index
CV	cross-validation
DS	Downstream Strategies
FHP	Fish Habitat Partnership
GIS	geographic information systems
GLB	Great Lakes Basin
NHD	National Hydrography Dataset
NPDES	National Pollutant Discharge Elimination System
ROC	receiver operating characteristic
USFWS	United States Fish and Wildlife Service

1. INTRODUCTION

1.1 Document outline

This report provides a summary of the key outcomes resulting from models developed by DS for use in assessing aquatic habitats for the Midwest Fish Habitat Partnerships. The appendices provide additional maps, charts, and metadata useful for evaluating the results of the models.

This document is divided into four major sections. This section, Section 1, summarizes the project goals, structure, and methodology. Sections 2 and 3 summarize the model input and results for each of the three response variables. Section 4 summarizes some of the limitations to this modeling effort, and outlines suggestions for future similar works.

The following are included for each model's results summary.

- Subsection one, *Modeling inputs*, discusses details of the predictor and response variables used in the analyses.
- Subsection two, *Modeling process*, covers the basic details and outcomes of the statistical modeling process using BRTs, including information on model certainty. Variable influence and functional relationships between predictor and response variables are included under corresponding headings as well.
- Subsection three, *Post-modeling*, contains information resulting from the post-modeling process, including information on the top stressors and natural habitat variables and their role in the calculation of the final indices.
- Subsection four, *Mapped results*, contains maps for visualizing conditions at the 1:100k catchment scale and includes maps of expected current probability of presence, stress, and natural quality; it also provides examples of how the two post-modeling indices (i.e., HQI and ASI) can be combined to inform restoration priorities and how those priorities can be visualized in a spatially explicit manner.

1.2 Project background

Fishery and aquatic scientists often assess habitats to understand the distribution, status, stressors, and relative abundance of aquatic resources. Due to the spatial nature of aquatic habitats and the increasing scope of management needs, traditional analytical assessment methods are often limited in their ability to address complex and dynamic aquatic systems. Advancements in the geographic information systems (GIS) field and related technologies have enabled scientists and managers to more effectively collate, archive, display, analyze, and model spatial and temporal data. For example, spatially explicit habitat assessment models allow for a more robust interpretation of many terrestrial and aquatic datasets, including physical and biological monitoring data, habitat diversity, watershed characteristics, and socioeconomic parameters.

Downstream Strategies (DS) was contracted by the United States Fish and Wildlife Service (USFWS) to create a spatially explicit data analysis and modeling system for assessing fish habitat condition for several individual Fish Habitat Partnerships (FHP) across the Midwest and Great Plains based on a range of metrics. These analyses provided data and tools for specific aquatic species for each FHP, and were constructed at the scale of the individual FHP or at a region-wide scale. These results were useful, but the models covering large extents led to the identification of broad-scale regional variables as indicators of stress and habitat quality. DS then performed an analysis of scale that indicated that driving variables for the same aquatic response changed markedly depending on the scale (extent) that the model was built, and indicated that more localized models would be more effective at pinpointing localized stressors. This project built upon the knowledge gained and framework designed during the individual FHP-scale modeling efforts and provided more localized estimates of aquatic health. Additionally, for this analysis, an updated methodology was developed for assigning stress and determining natural quality of aquatic habitats

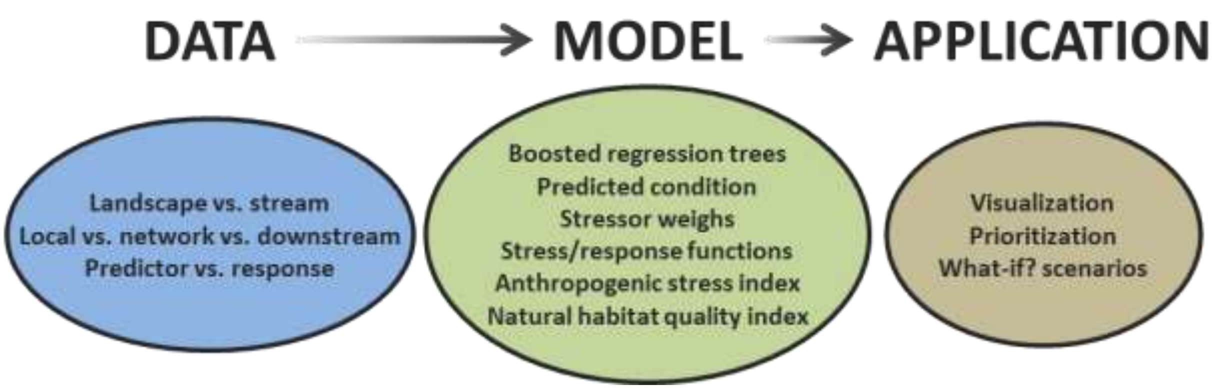
Generally, the models, analyses, and data produced as a result of this project are intended to enable a unique, broad, and spatially explicit understanding of the links between natural habitat conditions, human influences on aquatic habitats, and aquatic health. Specifically, the outcomes can be utilized to conduct fish habitat condition assessments based on a range of stakeholder-specified metrics and modeling endpoints to help determine natural drivers of aquatic conditions, as well as major stressors for the selected watersheds within the Ohio River Basin. The ultimate goal is to improve understanding of how local processes influence stream conditions in the region and to provide additional knowledge, data, and tools to help prioritize and drive conservation action throughout the study area.

1.3 Overview of the assessment process

1.3.1 *Modeling*

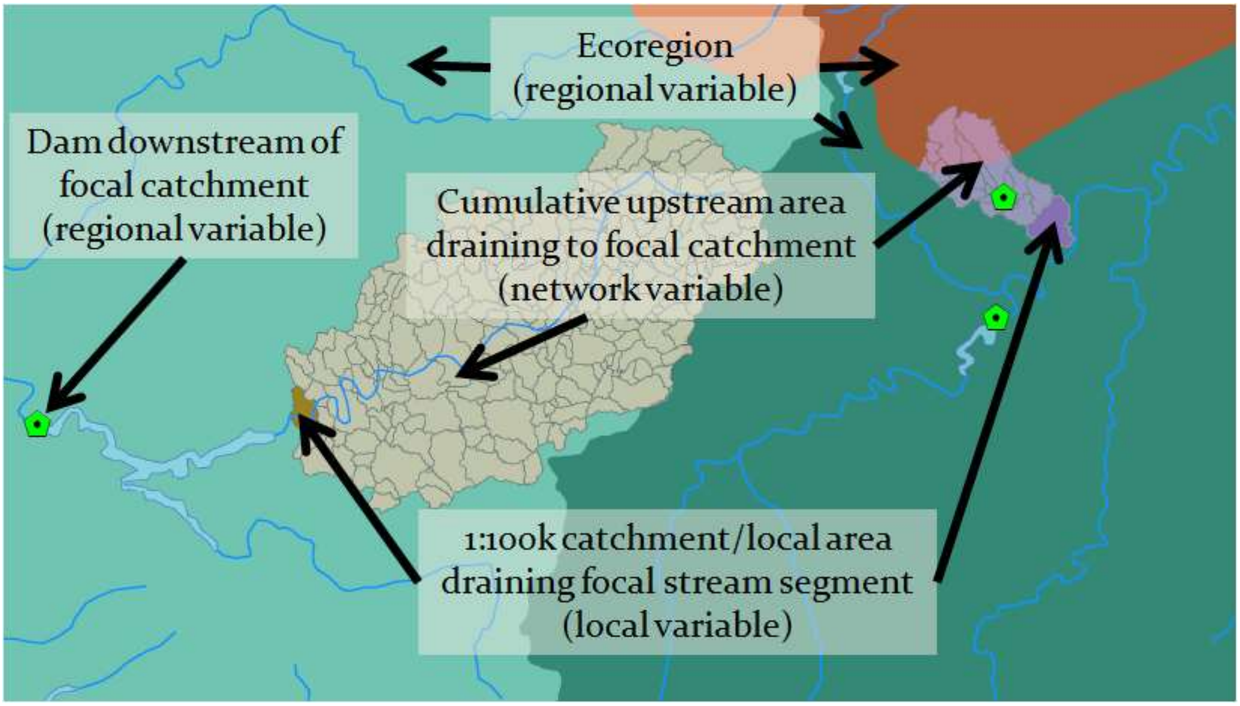
A diagram of the general assessment process is outlined in Figure 1. DS received landscape and aquatic data specified and provided by the individual FHPs to develop models and tools for visualizing expected current and potential future conditions and prioritizing management actions.

Figure 1: Diagram of the habitat assessment process



The data provided by FHPs for use in the modeling process can be broken down into two categories: response variables and predictor variables. There were two response variables used in this assessment: Licking watershed MBI and Muskingum watershed IBI scores. Each response variable represented a separate model. The predictor variables are typically measures of land use or land cover derived from GIS, such as percent impervious surface area or road crossing density. Although the response variable is always measured at the same local scale (e.g., individual sample site on a stream), the predictor variables are compiled at multiple scales (Figure 2), including the local scale (e.g., single 1:100k National Hydrography Dataset (NHD) stream catchment), the network scale (e.g., all upstream catchments and the local catchment), or the regional scale (e.g., ecoregion).

Figure 2: Diagram and examples of different scales of data used for predictor variables



For this assessment nearly all of the predictor and response data necessary was already held by DS from prior individual FHP assessments across the Midwest. This data was simply clipped to the selected watershed boundaries. The final list of potential predictor variables is shown below in Table 1.

Table 1: Predictor variables

Variable description	Source	Variable Type
Network drainage area	NHD+	Natural
Minimum catchment elevation	NHD+	Natural
Slope of catchment flowline	NHD+	Natural
Mean annual precipitation	NHD+	Natural
Mean annual air temperature	NHD+	Natural
Mean annual baseflow index	USGS	Natural
Mean annual recharge rate	USGS	Natural
Bedrock geology	USGS	Natural
Surficial Geology	USGS	Natural
Soil hydrologic group	STATSGO	Natural
Landcover classification	NLCD 2006	Varies
Riparian agriculture	NLCD 2006	Anthropogenic
Riparian development	NLCD2006	Anthropogenic
Nutrient inputs	USGS	Anthropogenic
Wetlands	NWI/GAP	Anthropogenic
Impervious surface data	NLCD 2006	Anthropogenic
Surface mine area (Licking River only)	OSM, KOMSL, KYDR	Anthropogenic
Groundwater use rate	USGS	Anthropogenic
Surface water use rate	USGS	Anthropogenic
Population density	NOAA	Anthropogenic

Road/stream crossing density	TIGER	Anthropogenic
Road density	TIGER	Anthropogenic
Dam density	National Inventory of Dams	Anthropogenic
Active mine density	USGS	Anthropogenic
Toxic release inventory site density	USEPA	Anthropogenic
NPDES permit density	USEPA	Anthropogenic
Superfund site density	USEPA	Anthropogenic

The process then employs a statistical modeling approach, called boosted regression trees (BRT), to relate the instream response variable to the landscape-based predictor variables. BRT models combine decision trees (i.e. classification and regression trees [CART]) and boosting methodologies, which result in better cross-validated models than other methods (Elith et al., 2006[i]), including CART. Decision trees are advantageous because (1) they can incorporate any type of predictor data (binary, numeric, categorical); (2) model outcomes are unaffected by differing scales of predictors; (3) irrelevant predictors are rarely selected; (4) they are insensitive to outliers and non-normalized data; (5) they can accommodate missing predictor data; and (6) they can automatically handle interactions between predictors (Elith et al., 2008). The boosting algorithm used by BRT improves upon the accuracy of a basic CART approach by following the idea that averaging many rough models offers efficiency over finding a single prediction rule that is highly accurate (Elith et al., 2008[ii]).

This process results in a series of quantitative outcomes, including predictions of expected current conditions to all catchments in the FHP (on the scale of the response), measures of the accuracy of those predictions, a quantification of each predictor variable's relative influence on the predictions (i.e., variable importance), and a series of plots illustrating the modeled functional relationship between each predictor and the response (e.g., plot of impervious area vs. presence-absence). The predictions of current conditions are created by extrapolating the BRT model to each catchment within the modeling area. The units of the predicted current condition for this assessment are predicted index scores for each catchment. These current conditions are useful for assessments of suitable habitats and mapping the distributions of the index scores.

Predictive accuracy is quantified using an internal cross-validation (CV) method (Elith et al., 2008). The method consists of randomly splitting the input dataset into ten equally-sized subsets, developing a BRT model on a single subset and testing its performance on the remaining nine, and then repeating that process for the remaining nine subsets. Thus, the accuracy measures, such as the CV receiver operating characteristic (ROC) score (for presence-absence responses) or the CV correlation coefficient, are actually averages of ten separate ROC or correlation measurements. A standard error for the ten estimates is also given. CV measures are designed to estimate how well the model will perform using independent data.

1.3.2 *Post modeling*

Characterizing anthropogenic stress and natural habitat quality of aquatic habitats is a useful and necessary process for helping land and fisheries managers identify place-based conservation and restoration strategies. For each model, a post-modeling process was used to characterize anthropogenic stress and natural habitat quality for all catchments within the study area. Stress and natural habitat quality indices and metrics were identified and calculated based on BRT model outputs, and details of those calculations are below.

Once developed, these indices of stress and habitat quality can be used to generate and visualize restoration and protection priorities by analyzing how stress reduction or habitat improvement can increase the predicted index score. For example, areas of high natural quality and low stress could represent protection priorities, whereas areas of high natural quality and high stress may represent restoration priorities.

Anthropogenic stress

Stress indices are critical for evaluating anthropogenic landscape drivers that structure aquatic responses. Managers can use stress indices and metrics to assess how anthropogenic processes are impacting aquatic responses and can utilize this information to cite restoration projects in order to maximize efficiency. Individual stressors were identified by examining BRT model outputs, both the variable influence table and the functional relationship between predictor variables and response variables. Any predictor variable significantly affected by anthropogenic disturbance was included as a potential stressor. Stressors were not utilized for calculation of stress in the model when the functional relationship between a potential stressor and the response variable was not indicative of a mechanistic relationship.

Individual stress metrics were calculated by determining the increase in predicted index score for each catchment when stress for that predictor variable was hypothetically removed. A new predictor variable dataset was produced to calculate each individual stressor metric. The new predictor dataset contained the same values as the original predictor dataset except for a single anthropogenic variable for which a stress metric was calculated. For this variable, the values were all hypothetically set to reflect "no stress." This provided a hypothetical baseline that represented the removal of all stress from that predictor variable. The existing BRT model was then applied to the new hypothetical landscape data to provide an extrapolation of the current model assuming zero stress for that stressor. The difference between the current predicted index score and the predicted index score under this "no stress" situation indicated the change that could be attributable to stress. This process was repeated for each stressor to generate individual metrics of stress. Higher stress values indicated a larger change in predicted index score after removing stress, and lower stress values indicated that the catchment was relatively unaffected by removing stress (Table 2).

For each catchment, the individual stress metrics (e.g. agriculture stress, impervious surface stress, etc) were then summed to produce an overall stress metric, the anthropogenic stress index (ASI). The generalized formula for calculating individual stress metrics and ASI is as follows:

$$\textit{individual stress metric} = \textit{predicted index score}_{\textit{no stress}} - \textit{predicted index score}_{\textit{current}}$$

$$\textit{anthropogenic stress index (ASI)} = \textit{individual stress metric 1} + \textit{individual stress metric 2} + \ldots.$$

Table 2: Example of stress calculations

Comid	Current Condition Predictions	Stressor 1 Predictions	Stressor 1 Metric	Stressor 2 Predictions	Stressor 2 Metric	Anthro. Stress Index (ASI)
Catchment ID	**Predictions using current landscape data**	**Predictions when stressor 1 removed**	**(Stressor 1 pred – Current Pred)**	**Predictions when stressor 2 removed**	**(Stressor 2 pred – Current Pred)**	**Stressor 1 Metric + Stressor 2 Metric**
1234567	20	24	4	20	0	4
1234568	30	42	12	33	3	15
1234569	48	49	1	48	0	1

Natural habitat quality

Natural habitat quality metrics provide critical baseline information on the optimal potential condition of a catchment. We defined natural quality as the maximum predicted index score under a zero-stress situation; essentially, the highest attainable condition in the catchment. These metrics allow managers to further classify each catchment and target specific land-based conservation or restoration actions.

The natural habitat quality index (HQI) was calculated directly from the BRT output. Metrics for 'natural' predictor variables were calculated using a different approach than the stressor calculations detailed above. Individual natural quality metrics were not seen as useful since individual habitat variables were not considered practical management targets (e.g., elevation is a relatively fixed value) and therefore were not used in the calculation of HQI. A single hypothetical 'no stress' dataset was created where all stressors were removed. The existing BRT model was then applied to this hypothetical predictor dataset, and the resulting predicted index score indicated the maximum condition attainable by removing all stress. The index score calculated by the BRT model for this hypothetical 'no stress' dataset is the HQI and this value indicates the maximum condition expected in each catchment.

$$\textit{natural habitat quality index (HQI)} = \textit{predicted index score}_{\textit{all stressors removed}}$$

1.3.3 *Assessment Summary*

These methods provide current predictions of index scores, ASI scores, and HQI scores for both models. Metrics and indices were generated at the 1:100k NHD catchment scale and then mapped in GIS.

2. LICKING RIVER WATERSHED (KY) MBI

2.1 Modeling inputs

DS coordinated with ORBFHP scientists to model the predicted index score for the Kentucky Macroinvertebrate Bioassessment Index (MBI) across the Licking River watershed. The MBI was developed to provide a statewide biotic integrity index of stream health by utilizing data from macroinvertebrate communities (Pond et al. 2003). The MBI creates a continuous index of potential scores from 0-100, and also defined thresholds for general classifications of streams. For this report, all mapping of MBI scores will be done using the following classification scheme, which utilizes the threshold recommendations for wadeable streams in the "Bluegrass" region of Kentucky, which covers the majority of the Licking River watershed we are modeling here.

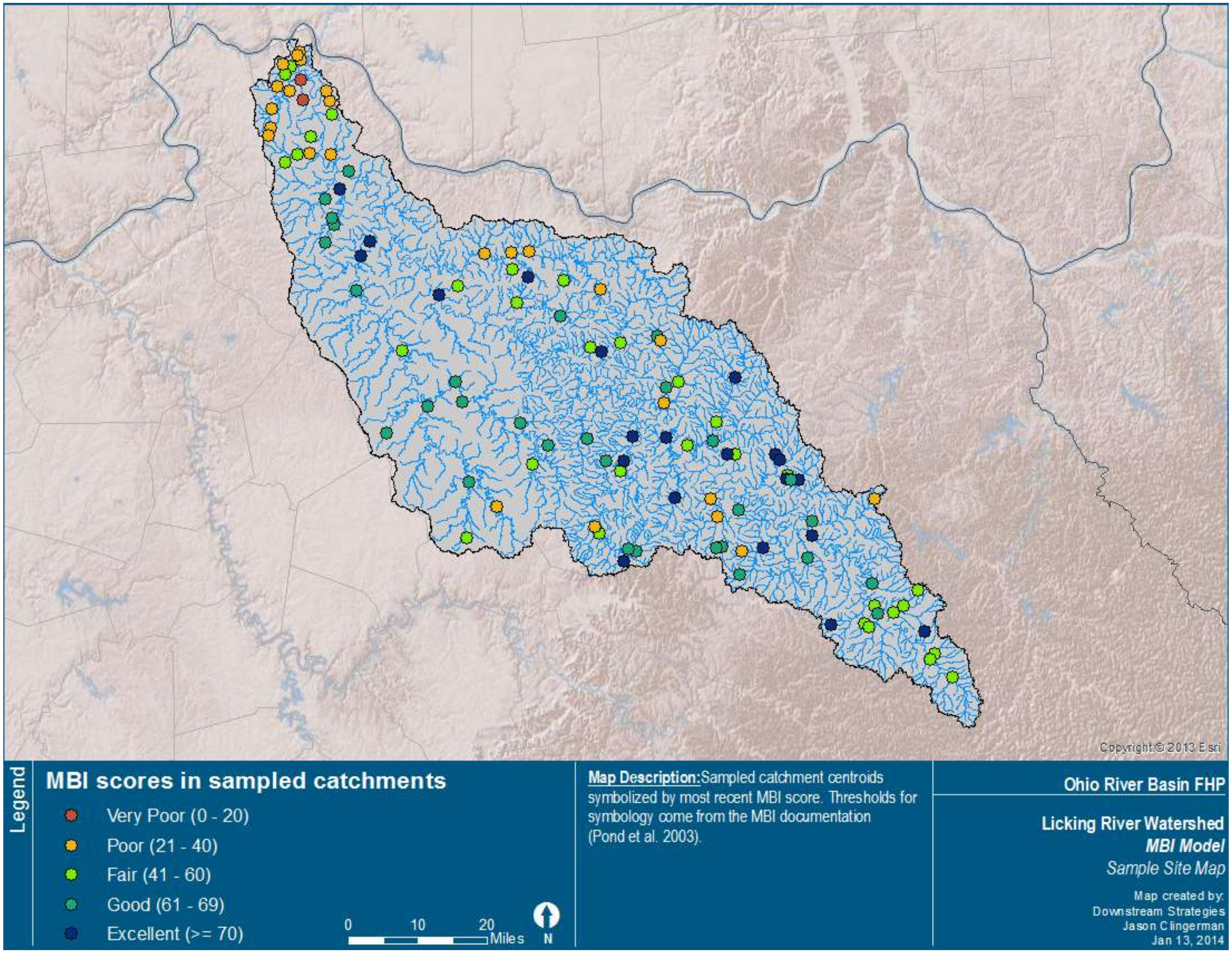
Table 3. MBI stream rating thresholds

Stream rating	MBI Score
Excellent	≥ 70
Good	61-69
Fair	41-60
Poor	21-40
Very Poor	0-20

ORBFHP provided DS with data collected in streams over a time frame spanning from 1999 to 2011 which was comprised of 109 observations. Figure 3 maps all of the sampling sites that were used to construct the model and outlines the Licking River watershed boundary. Model outputs were applied to all 1:100k catchments within the Licking River watershed.

DS cooperated with ORBFHP scientists to arrive at a list of landscape-based habitat variables used to predict aquatic responses throughout the region. These variables were also used to characterize habitat quality and anthropogenic stress. Building on the science team's input, DS compiled a list of 93 predictors for evaluation. Preliminary exploratory models were then run to identify variable predictive performance and statistical redundancy. From that list, 76 variables were removed due to statistical redundancy ($r > 0.6$), logical redundancy, or poor predictive performance (relative influence < 1.0 in preliminary model run). This resulted in a final list of 17 predictor variables for the BRT model and assessment. See Appendix A for a full data dictionary.

Figure 3: MBI sample sites and Licking River watershed



2.2 Modeling process

2.2.1 *Predictive performance*

The final selected model was comprised of 1,600 trees. The model had a CV correlation statistic of 0.521±0.093.

2.2.2 *Variable influence*

The BRT output includes a list of the predictor variables used in the model ordered and scored by their relative importance. The relative importance values are based on the number of times a variable is selected for splitting, weighted by the squared improvement to the model as a result of each split, and averaged over all trees (Friedman and Meulman, 2003). The relative influence score is scaled so that the sum of the scores for all variables is 100, where higher numbers indicate greater influence. The relative influence table for the MBI model is shown below in Table 4.

Table 4: Relative influence of all variables in the final MBI model

Variable code	Variable description	Relative influence
BFI_MEANC	Network mean baseflow index	17.579
WATER_GWC	Network groundwater use	10.758
WATER_SWC	Network surface water use	9.423
GRASSPC	Network grassland land cover	8.041
ROADCR_DEN	Local road crossing density	7.820
IMP06C	Network impervious surface cover	7.708
WETLANDPC	Network wetland land cover	6.360
ROADCRC_DEN	Network road crossing density	5.642
CUMDRAINAG	Network drainage area	4.786
RIP_AGC	Network riparian agriculture density	4.623
AG_PC	Network agriculture land cover	3.587
BROCK7PC	Network shale bedrock geology	3.180
SOIL2PC	Network soil hydrologic group B	2.790
RIP_DEVC	Network riparian development	2.359
BROCK5PC	Network sand/gravel bedrock geology	2.027
SURF3PC	Network alluvium surficial geology	1.726
TEMP	Mean annual air temperature	1.591

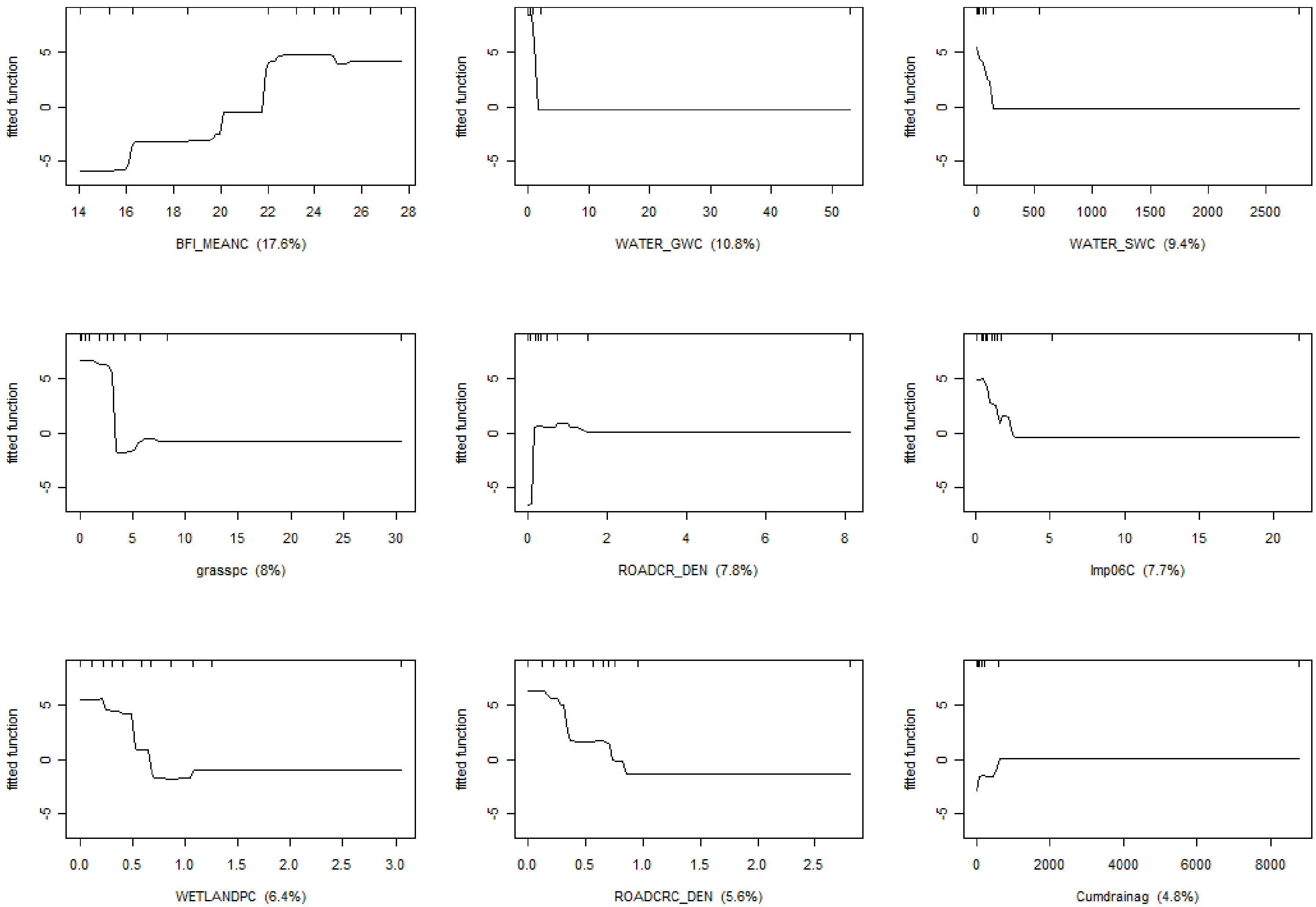
Note: Individual variables are highlighted according to whether they were determined to be anthropogenic (grey shading) or natural (no shading).

2.2.3 *Variable functions*

The BRT output also contains quantitative information on partial dependence functions that can be plotted to visualize the effect of each individual predictor variable on the response after accounting for all other variables in the model. Similar to the interpretation of traditional regression coefficients, the function plots are not always a perfect representation of the relationship for each variable, particularly if interactions are strong or predictors are strongly correlated. However, they do provide a useful and objective basis for interpretation (Friedman, 2001; Friedman and Meulman, 2003).

These plots show the trend of the response variable (y-axis) as the predictor variable (x-axis) changes. The response variable is transformed (usually to the logit scale) so that the magnitude of trends for each predictor variable's function plot can be accurately compared. The dash marks at the top of each function represent the deciles of the data used to build the model. The function plots for the nine most influential variables in the MBI model (Table 4) are illustrated in Figure 4. The plots for all variables are shown in Appendix B.

Figure 4: Functional responses of the dependent variable to individual predictors of MBI



Note: Only the top nine predictors, based on relative influence (shown in parentheses; see Appendix A for descriptions of variable codes), are shown here. See Appendix B for plots of remaining predictor variables.

2.3 Post-modeling

2.3.1 *Stress and natural quality*

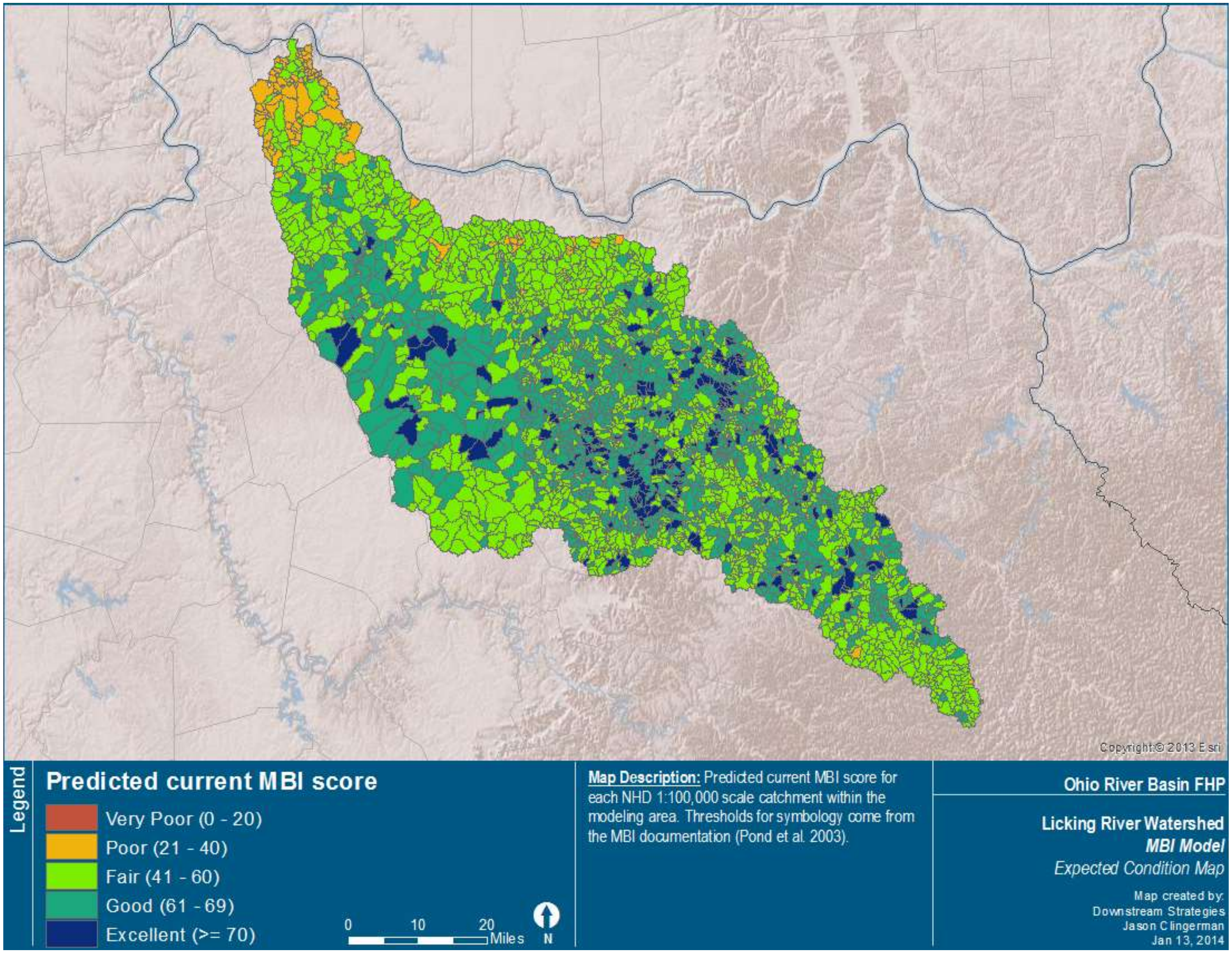
The variable importance table and partial dependence functions of the final BRT model were used to assess the potential stressors for the MBI model. Within the model, there were ten variables considered anthropogenic in nature (Table 4). After reviewing the functional relationships of these potential stressors, four stressors were removed from ASI calculations. These variables (‘ROADCR_DEN’, ‘WETLAND_PC’, ‘RIP_AGC’, and ‘AGPC’) had function plots that were unintuitive: their relationships to the response likely captured some sort of spatial variation in the model rather than a mechanistic relationship with the response. The remaining stressors were used to calculate ASI for the MBI model. Section 1.3.2 details how ASI and HQI were calculated for each model.

2.4 Mapped results

2.4.1 *Expected current conditions*

MBI scores were calculated for all 1:100k stream catchments in the study area using the BRT model. The predicted scores ranged from 19.86 to 79.63. The mean predicted score across the region was 57.60. Of the total 3,719 catchments, about 5% (189 catchments) had a predicted MBI score greater than 70 (excellent rating), and about 37% (1,377 catchments) had a predicted MBI score in the ‘good’ range (61-69) These results are mapped in Figure 5.

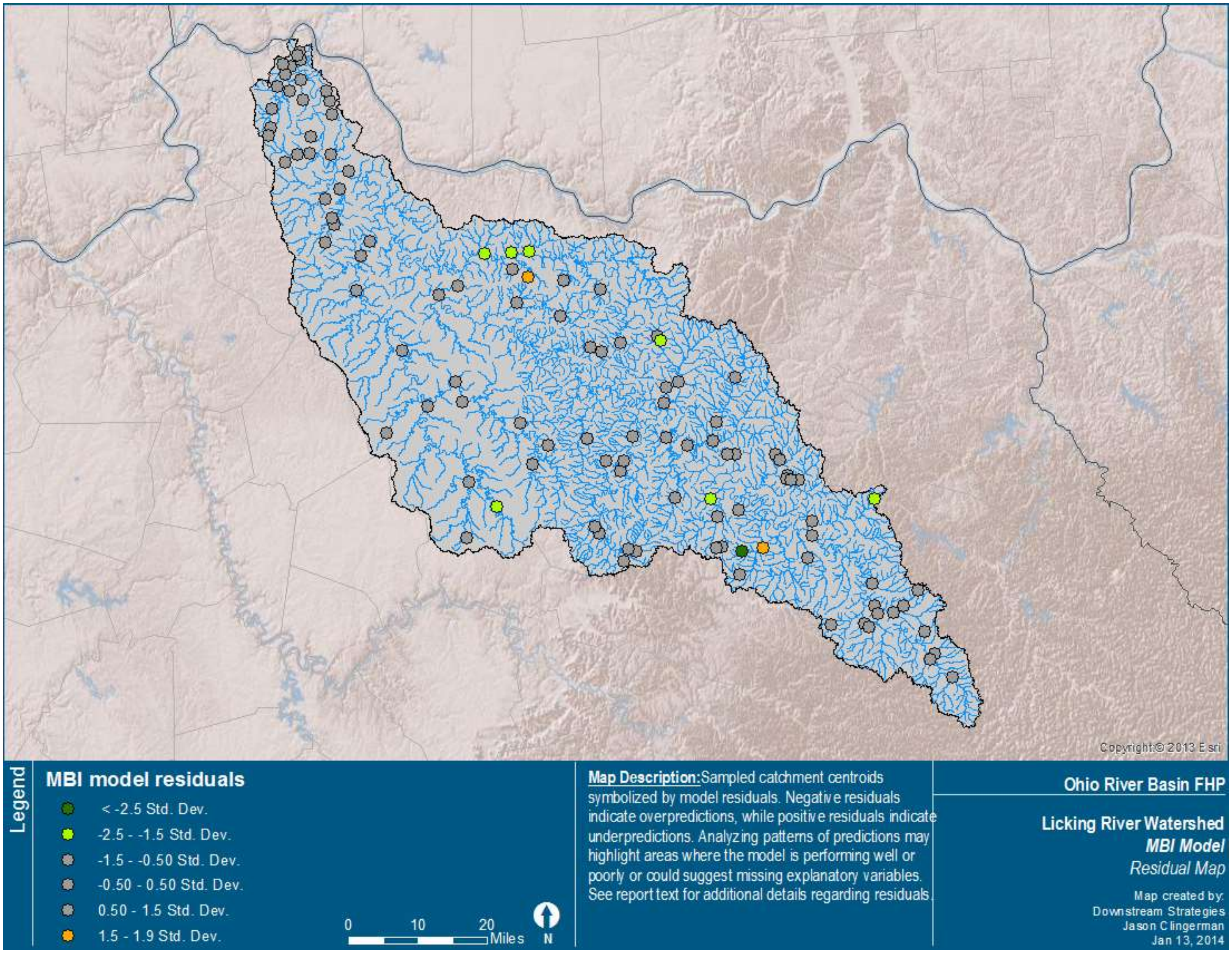
Figure 5: Expected coldwater guild distribution



2.4.2 *Spatial variability in predictive performance*

Analyzing patterns of omission and commission may highlight regions where the model is performing well or poorly or could suggest missing explanatory variables. To assess omission and commission, residuals were calculated by the BRT model. The residuals are a measure of the difference in the measured and modeled values (measured value *minus* modeled value). Negative residuals indicate overpredictions (predicting higher values than are true), while positive residuals indicate underpredictions (predicting lower values than are true). Figure 6 shows the distribution of model residuals per sampling site.

Figure 6: Distribution of MBI model residuals by sampling site



2.4.3 *Indices of stress and natural quality*

Maps of HQI and ASI illustrate the spatial distribution of natural habitat potential (i.e., HQI score) and anthropogenic stress (i.e., ASI score) throughout the modeled region. HQI and ASI scores are mapped in Figure 7 and Figure 8, respectively. The variables contributing toward the calculation of ASI are mapped in Figure 9 through Figure 14. See Sections 1.3.2 and 2.3 for more details on HQI and ASI calculation. For HQI, higher values indicate higher natural quality, while higher values for ASI indicate higher levels of anthropogenic stress.

Figure 7: Natural habitat quality index for MBI

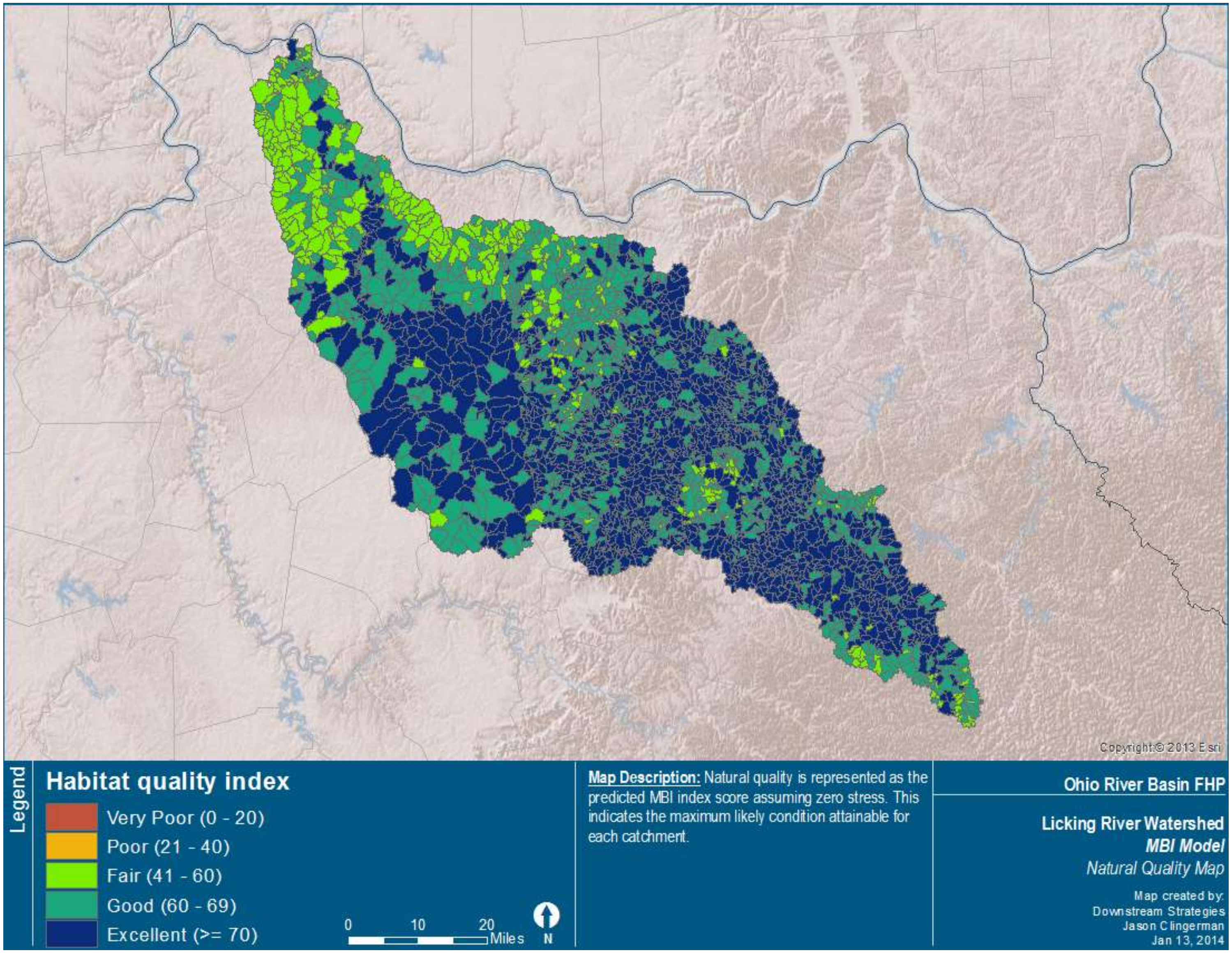


Figure 8: Anthropogenic stress index for MBI

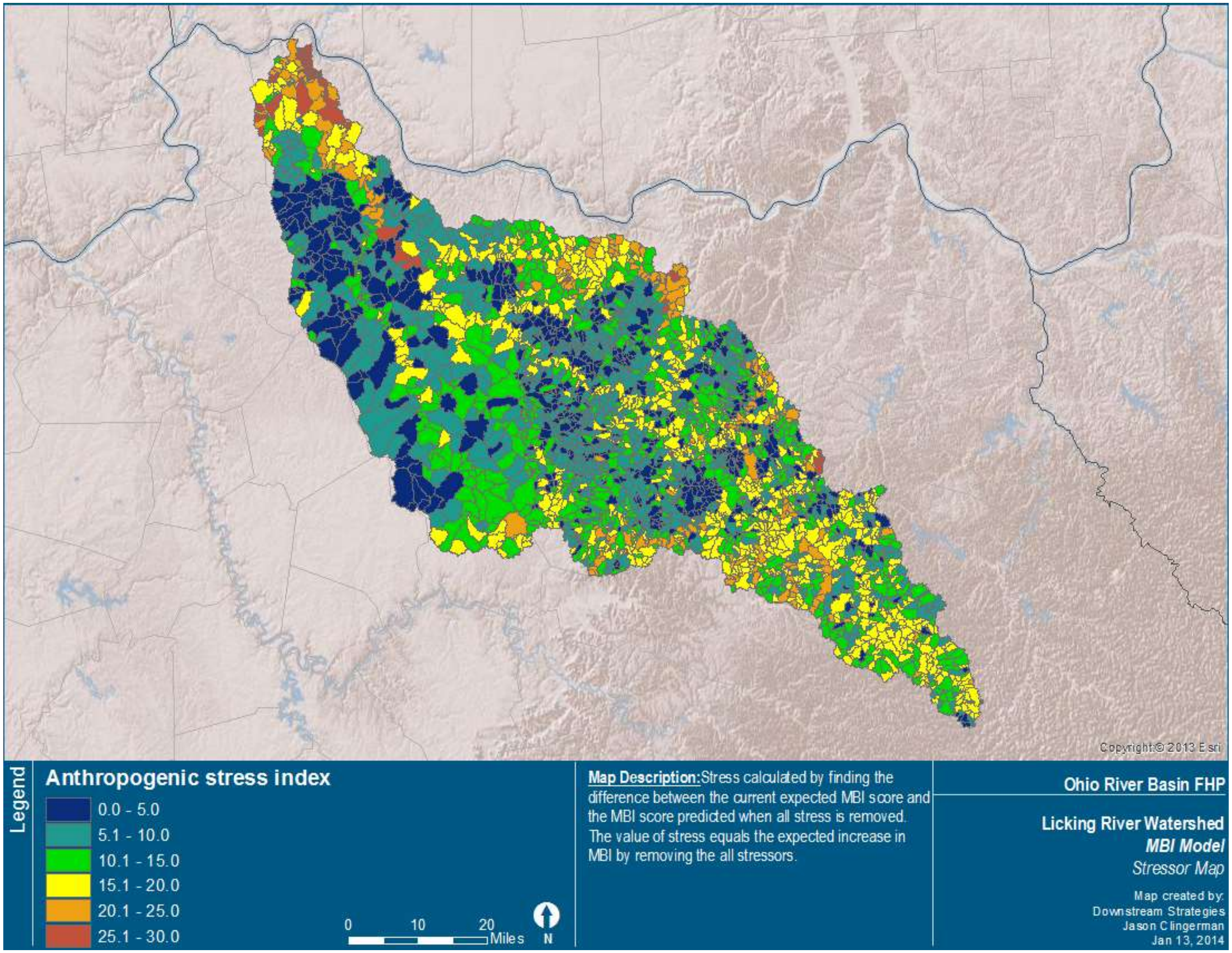


Figure 9: Groundwater use stressor metric for MBI

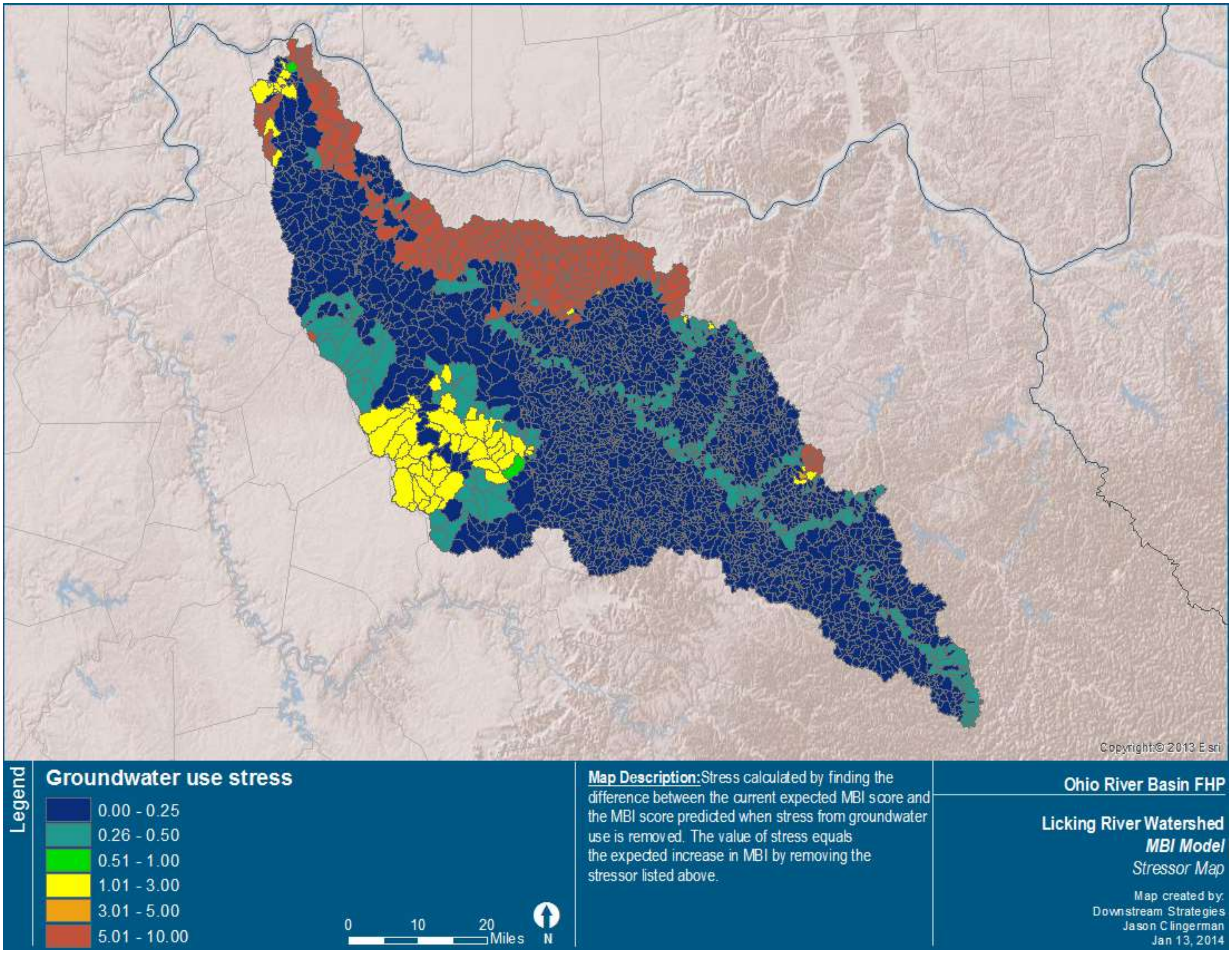


Figure 10: Surface water use stressor metric for MBI

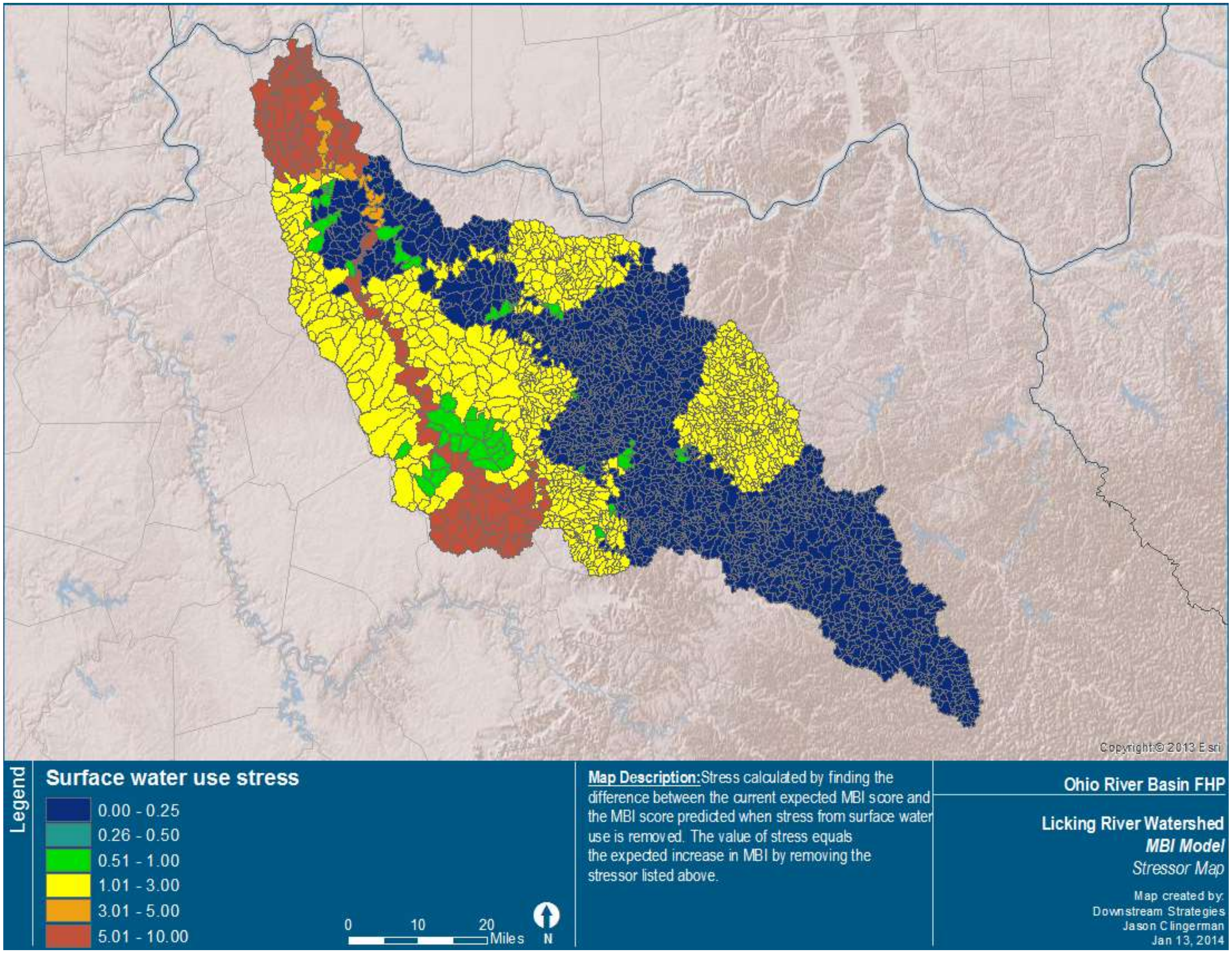


Figure 11: Grassland stressor metric for MBI

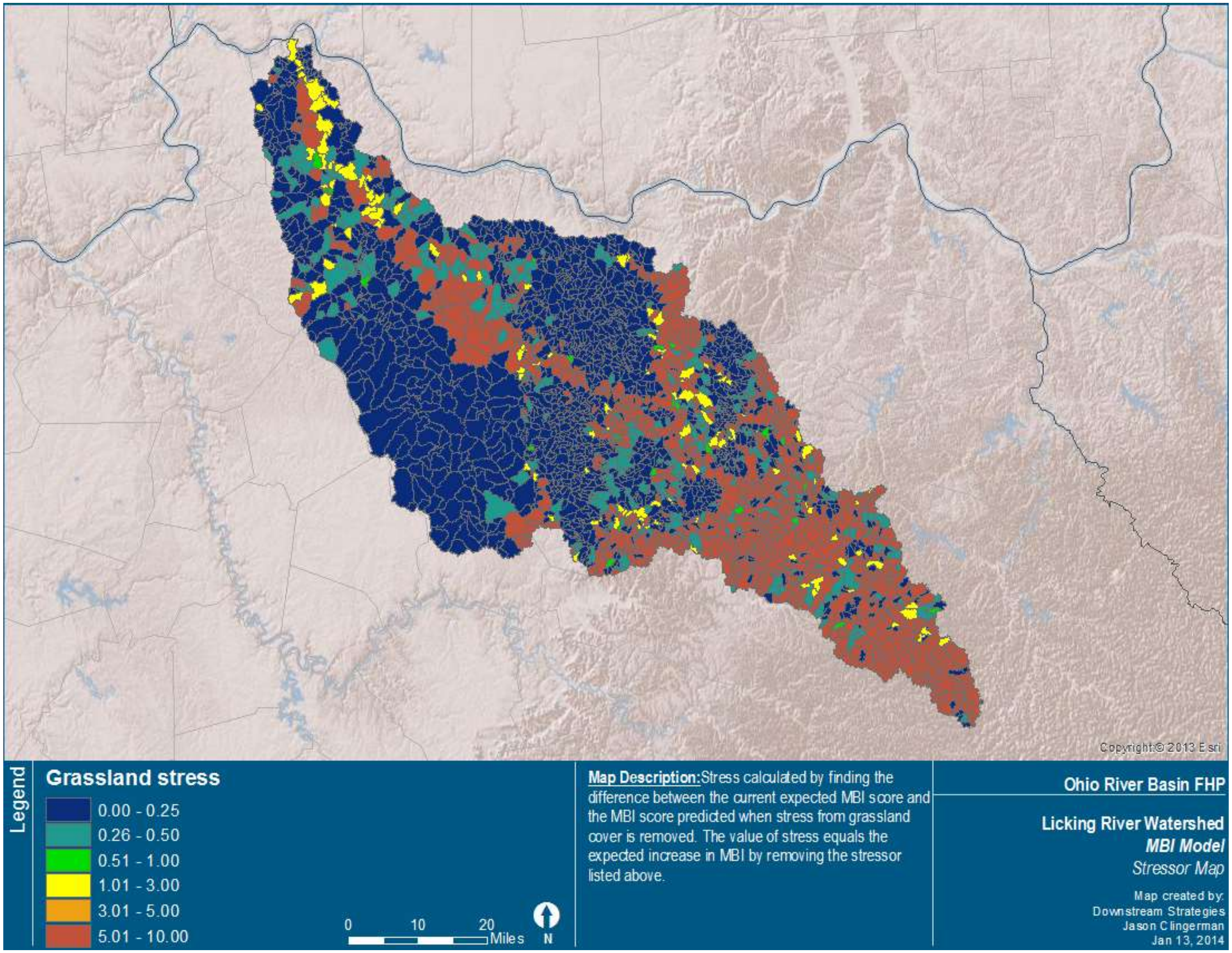


Figure 12: Impervious surface stressor metric for MBI

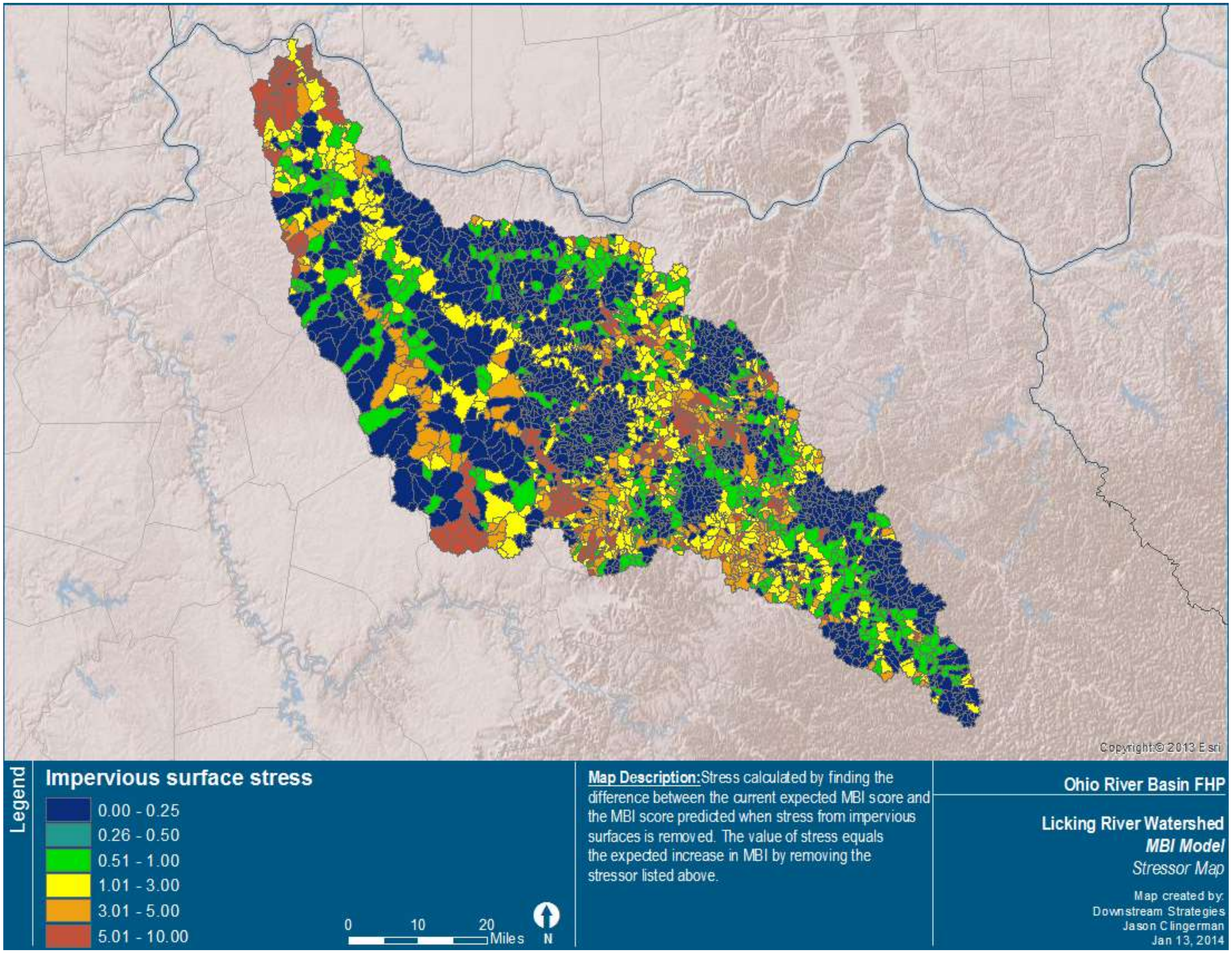


Figure 13: Road crossing stressor metric for MBI

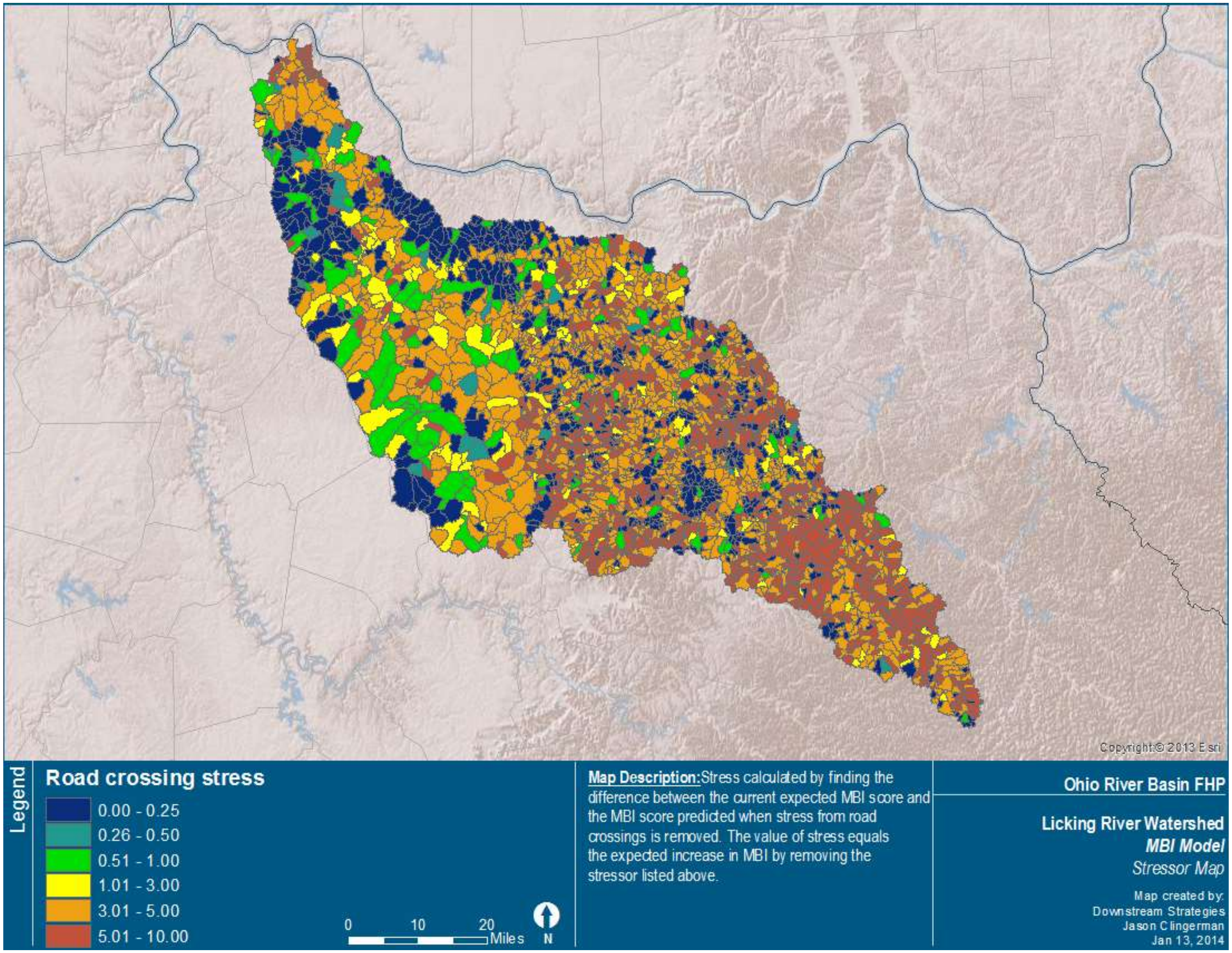
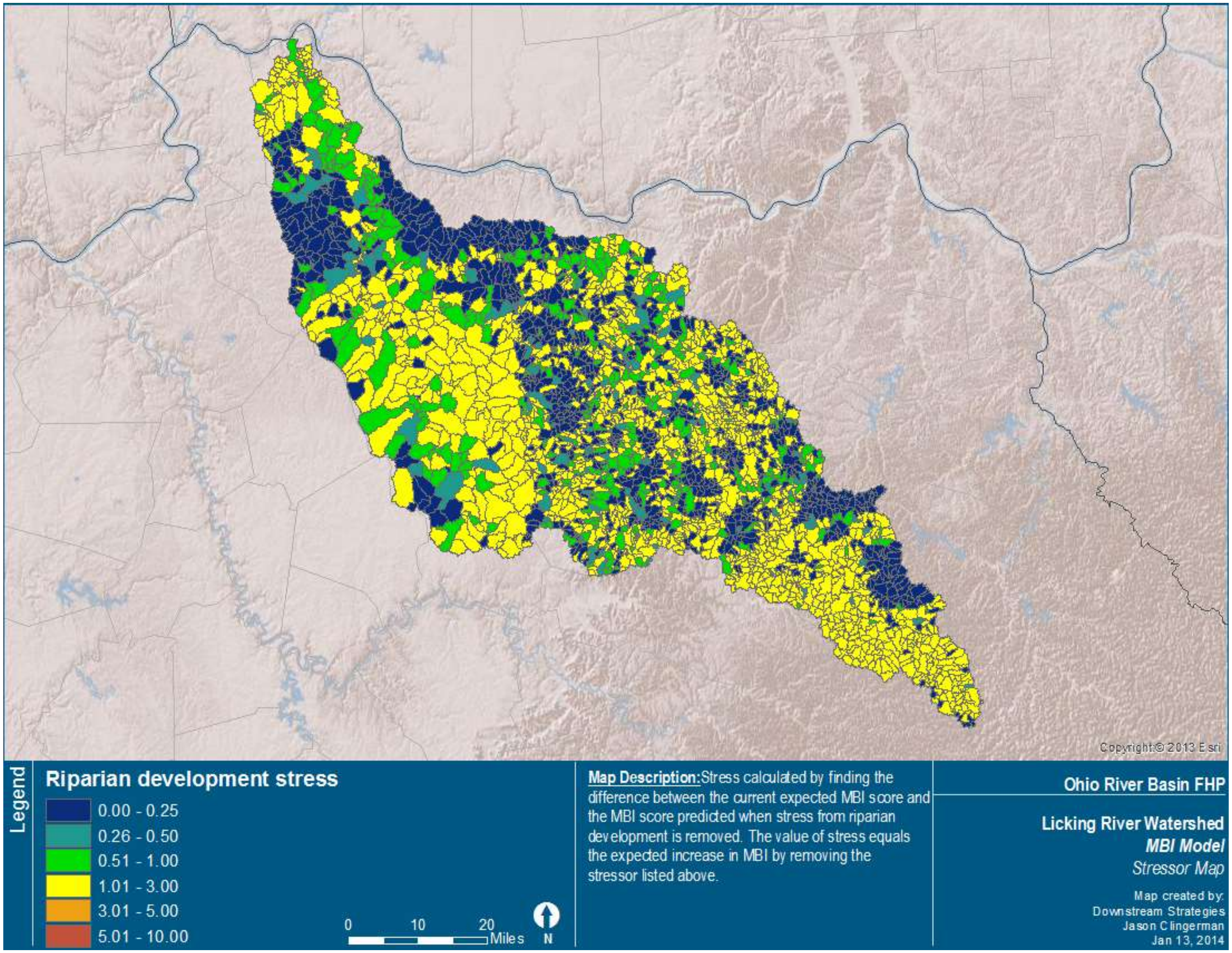


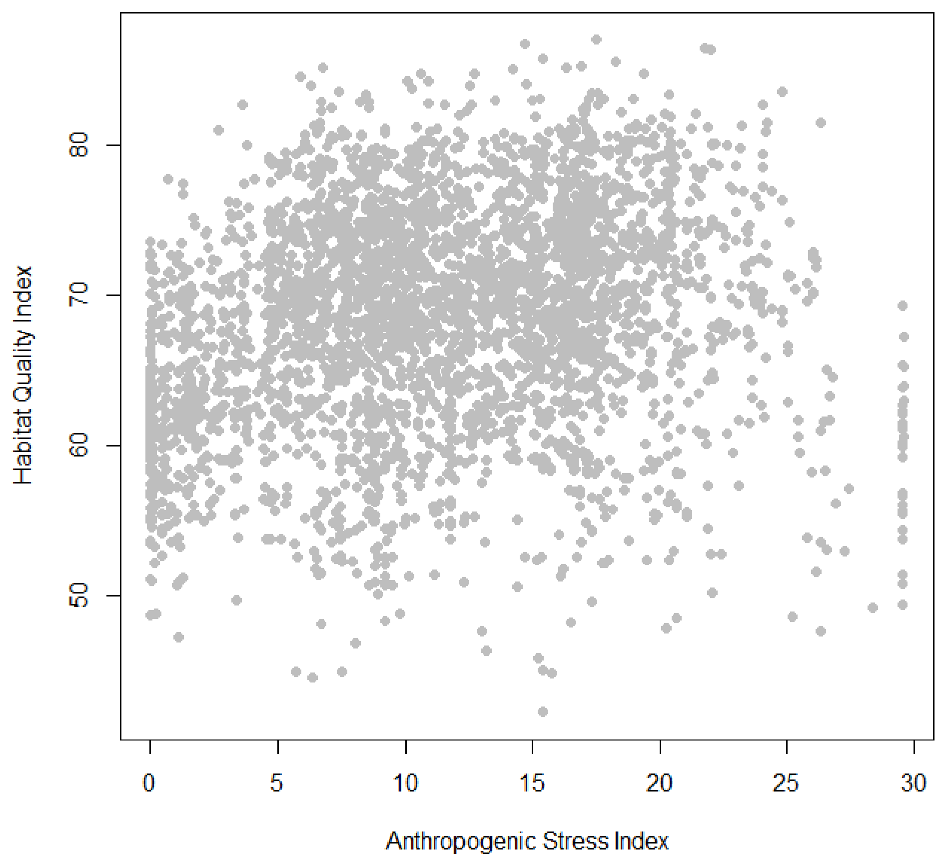
Figure 14: Riparian developed land stressor metric for MBI



2.4.4 *Restoration and protection priorities*

A plot of HQI versus ASI values for all catchments in the study area can be used as a reference to define HQI and ASI thresholds when evaluating restoration and protection priorities (Figure 15). Restoration priorities could be areas in the upper right hand corner of the plot below, where stress is high, but natural quality is also high. Along the same lines, catchments falling in the upper left hand corner of this plot where stress is low and natural quality is high may be the highest priorities for protection. This information is presented to explain the functionality of querying catchments based on these attributes to identify areas that meet user-defined criteria to guide conservation, protection, and restoration planning.

Figure 15: Coldwater guild HQI versus ASI values for all catchments



3. MUSKINGUM RIVER WATERSHED (OH) IBI

3.1 Modeling inputs

DS coordinated with ORBFHP scientists to model the predicted index score for the Ohio Fish Index of Biotic Integrity (IBI) across the Muskingum River watershed. The IBI was developed to provide a statewide biotic integrity index of stream health by utilizing data from fish communities (Ohio Environmental Protection Agency (OHEPA). 1987). The IBI creates an index of potential scores from 0-60. IBI scores are used to assign a narrative evaluation of a streams ecological condition (OHEPA. 2013) and are also used as biocritera to assess if streams meet water quality standards for designated uses (OHEPA 1989), as summarized in Table 5 for the "Western Allegheny Plateau" region of Ohio which covers the Muskingum River watershed modeled for this assessment. For this report, all mapping of IBI scores will be done using the classification scheme in Table 6, which utilizes the narrative ranges and biocriteria recommendations.

Table 5. OHEPA narrative evaluations and biocriteria levels for OHEPA water quality use designations

Narrative evaluation	Water quality use designation	IBI Score
Exceptional	EWH	50 – 60
Very good	EWH non-significant departure	46 – 49
Good	WWH	44 – 45
Marginally good	WWH non-significant departure	40 – 43
Fair		28 – 39
Poor	MWH-C / MWH-A	24 – 27
Poor		18 – 23
Very poor		12 – 17

Note: EWH = exceptional warmwater habitat, WWH = warmwater habitat, MWH-A = modified warmwater habitat, mine affected, MWH-C = modified warmwater habitat, channel modified

Table 6. Classification scheme used for mapping symbology throughout this report

Narrative evaluation	Water use designation	IBI Score
Exceptional	EWH	50 – 60
Very good/Good	WWH	44 – 49
Marginally good		40 – 43
Fair		28 – 39
Poor	MWH-C /MWH-A	24 – 27
Poor/Very poor		0 – 23

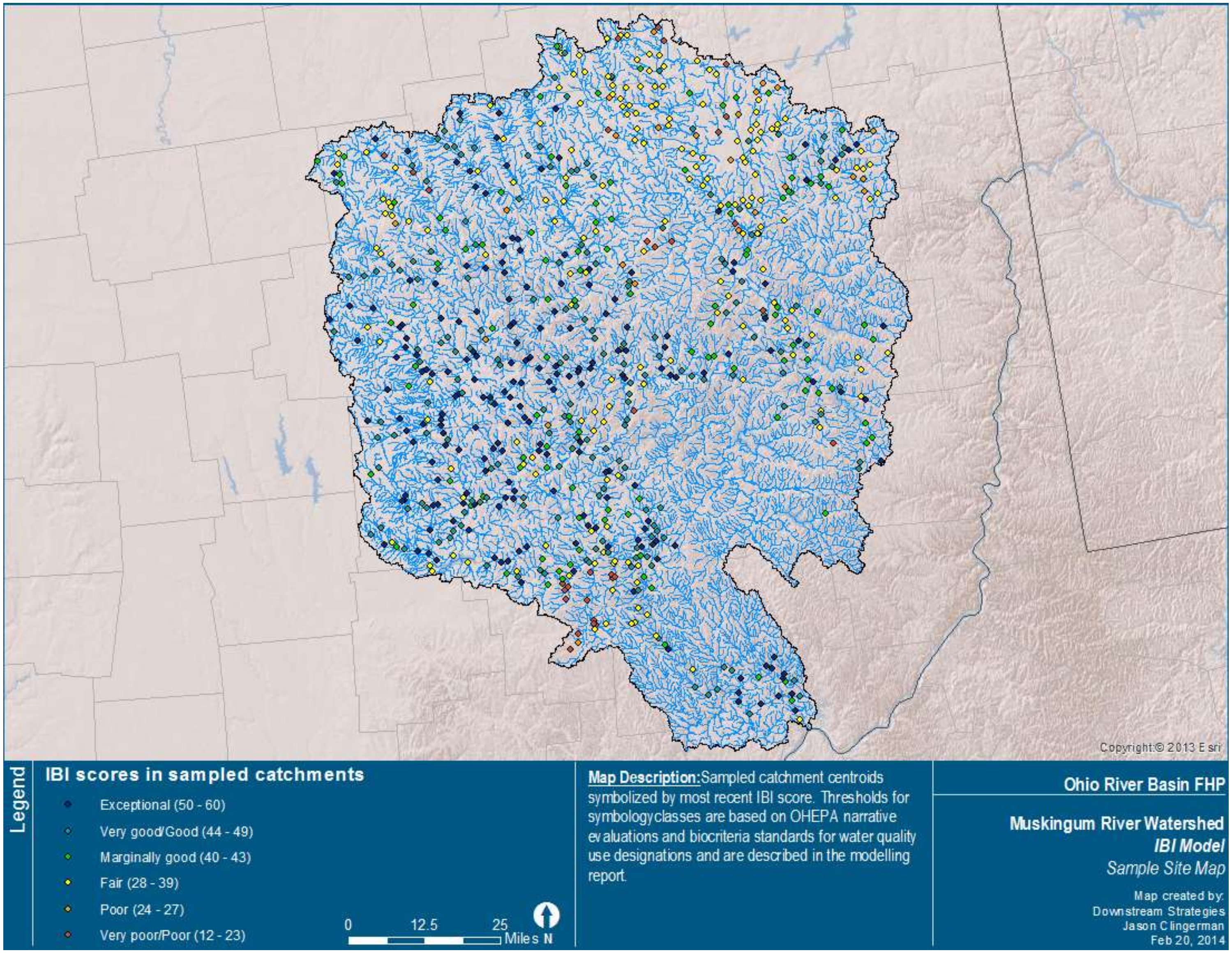
Note: EWH = exceptional warmwater habitat, WWH = warmwater habitat, MWH-A = modified warmwater habitat, mine affected, MWH-C = modified warmwater habitat, channel modified

ORBFHP provided DS with data collected in streams over a time frame spanning from 2003 to 2012 which was comprised of 724 observations. Figure 16 maps all of the sampling sites that were used to construct the model and outlines the Licking River watershed boundary. Model outputs were applied to all 1:100k catchments within the Licking River watershed.

DS cooperated with ORBFHP scientists to arrive at a list of landscape-based habitat variables used to predict aquatic responses throughout the region. These variables were also used to characterize habitat quality and anthropogenic stress. Building on the science team's input DS compiled a list of 91 predictors for evaluation.

Preliminary exploratory models were then run to identify variable predictive performance and statistical redundancy. From that list, 73 variables were removed due to statistical redundancy ($r > 0.6$), logical redundancy, or poor predictive performance (relative influence < 1.0 in preliminary model run). This resulted in a final list of 18 predictor variables for the BRT model and assessment. See Appendix A for a full data dictionary.

Figure 16: IBI modeling area and sampling sites



3.2 Modeling process

3.2.1 *Predictive performance*

The final selected model was comprised of 2,700 trees. The model had a CV correlation statistic of 0.520±0.034.

3.2.2 *Variable influence*

The BRT output includes a list of the predictor variables used in the model ordered and scored by their relative importance. The relative importance values are based on the number of times a variable is selected for splitting, weighted by the squared improvement to the model as a result of each split, and averaged over all trees (Friedman and Meulman, 2003). The relative influence score is scaled so that the sum of the scores for all variables is 100, where higher numbers indicate greater influence. The relative influence table for the IBI guild model is shown below in Table 7.

Table 7: Relative influence of all variables in the final IBI model

Variable code	Variable description	Relative influence
PRECIP	Mean annual precipitation	12.62
AGPC	Network agriculture land cover	12.53
GRASSPC	Network grassland cover	12.53
BFI_MEANC	Network mean baseflow	11.14
WETLANDPC	Network wetland land cover	7.70
CUMDRAINAG	Network drainage area	6.68
PASTPC	Network pasture land cover	4.30
IMP06C	Network impervious surface cover	4.07
BROCK6PC	Network sandstone bedrock geology	4.00
CATTLEC	Network cattle density	3.97
TEMP	Mean annual air temperature	3.62
FORP	Local forest land cover	3.47
SOIL2PC	Network soil hydrologic group 2	3.43
ROADCR_DEN	Local road crossing density	2.32
GRASSP	Local grassland cover	2.18
CROPSP	Local crop landcover	2.16
ROADCRC_DEN	Network road crossing density	1.92
RIP_AG	Local riparian agriculture land cover	1.66

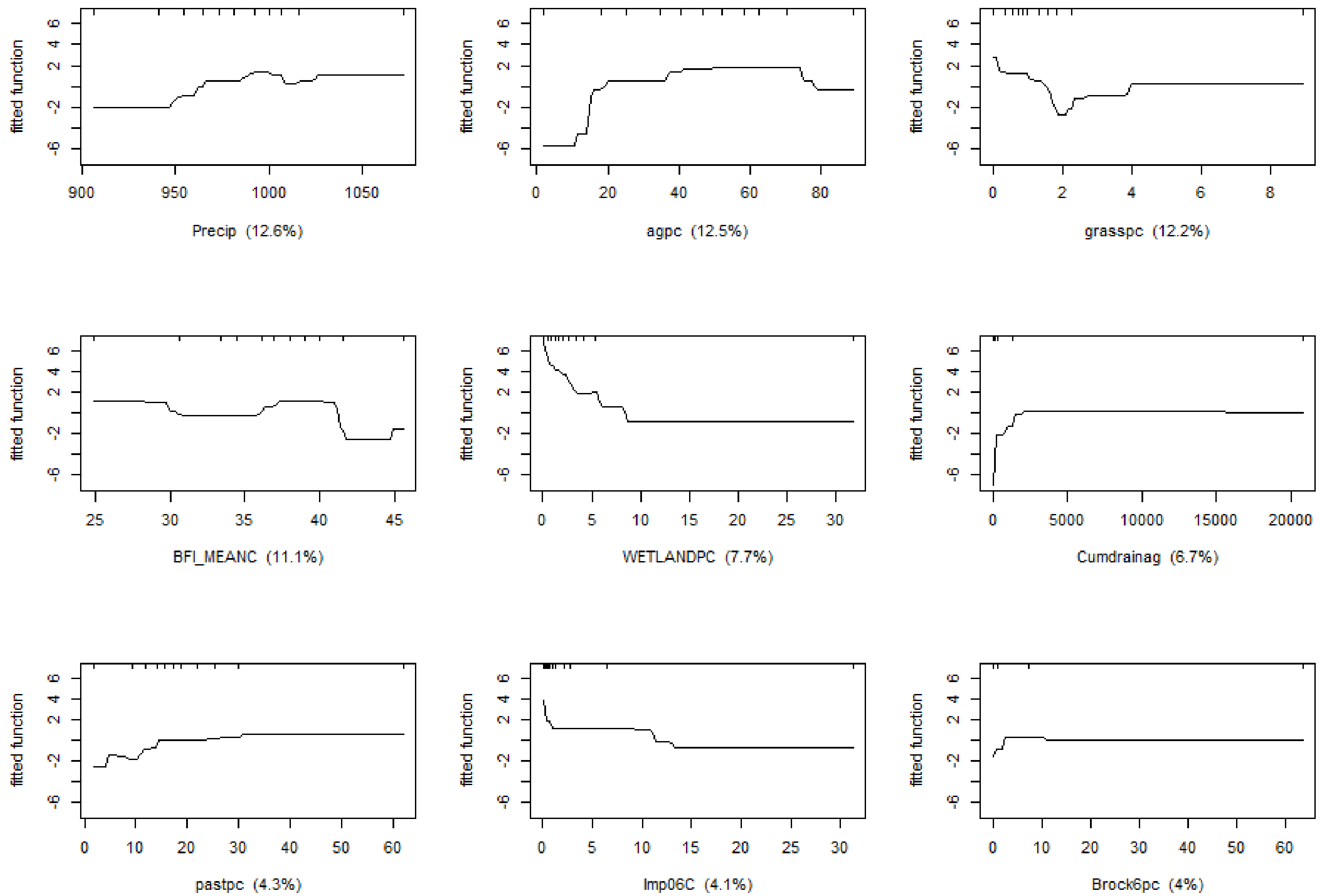
Note: Individual variables are highlighted according to whether they were determined to be anthropogenic (grey shading) or natural (no shading).

3.2.3 *Variable functions*

The BRT output also contains quantitative information on partial dependence functions that can be plotted to visualize the effect of each individual predictor variable on the response after accounting for all other variables in the model. Similar to the interpretation of traditional regression coefficients, the function plots are not always a perfect representation of the relationship for each variable, particularly if interactions are strong or predictors are strongly correlated. However, they do provide a useful and objective basis for interpretation (Friedman, 2001; Friedman and Meulman, 2003).

These plots show the trend of the response variable (y-axis) as the predictor variable (x-axis) changes. The response variable is transformed (usually to the logit scale) so that the magnitude of trends for each predictor variable's function plot can be accurately compared. The dash marks at the top of each function represent the deciles of the data used to build the model. The function plots for the nine most influential variables in the IBI model (Table 7) are illustrated in Figure 17. The plots for all variables are shown in Appendix B.

Figure 17: Functional responses of the dependent variable to individual predictors of IBI



Note: Only the top nine predictors, based on relative influence (shown in parentheses; see Appendix A for descriptions of variable codes), are shown here. See Appendix B for plots of remaining predictor variables.

3.3 Post-modeling

3.3.1 *Stress and natural quality*

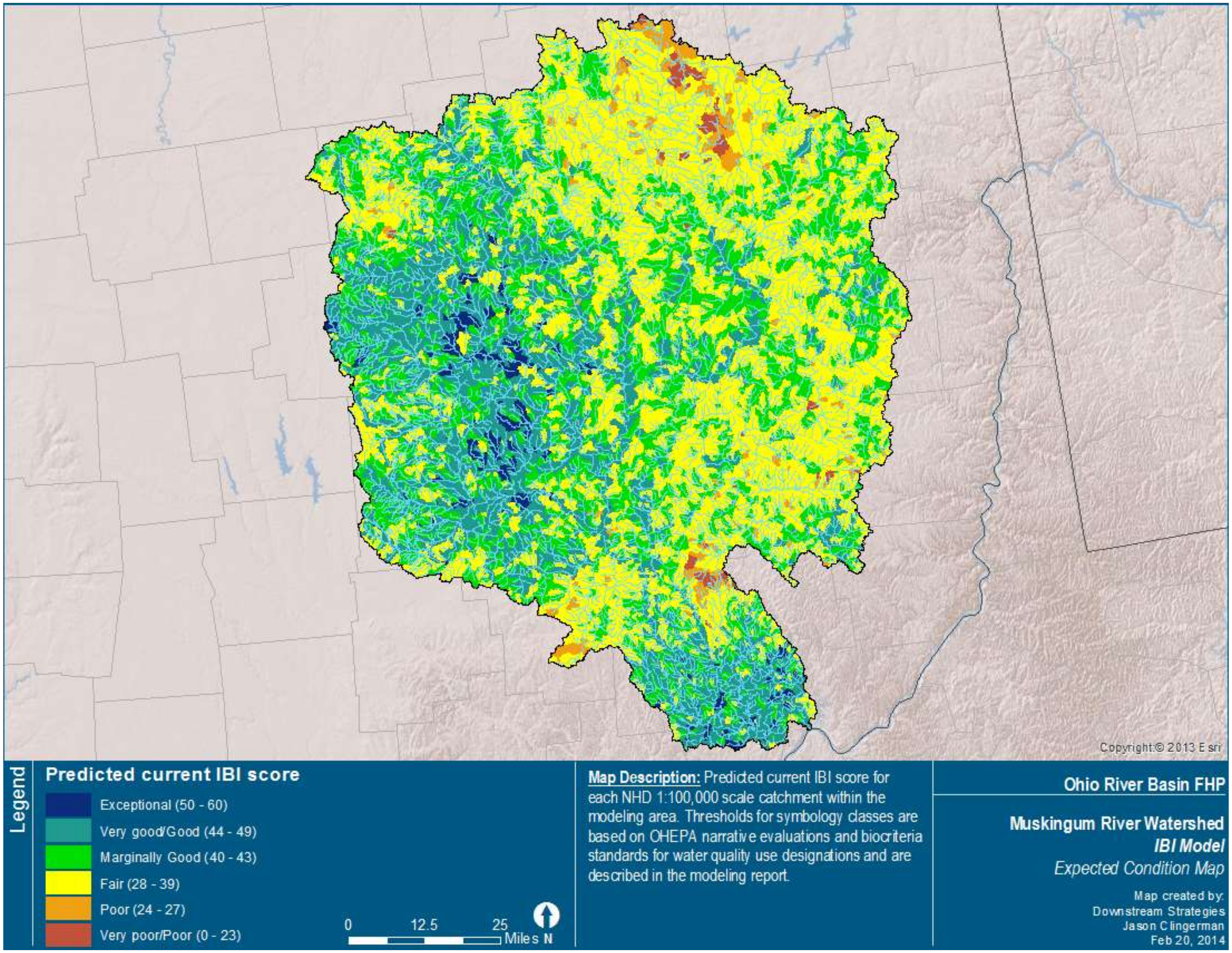
The variable importance table and partial dependence functions of the final BRT model were used to assess the potential stressors for the MBI model. Within the model, there were ten variables considered anthropogenic in nature (Table 7). After reviewing the functional relationships of these potential stressors, five stressors were removed from ASI calculations. These variables (‘AGPC’, ‘PASTPC’, ‘ROADCR_DEN’, ‘ROADCRC_DEN’, and ‘RIP_AG’) had function plots that were unintuitive: their relationships to the response likely captured some sort of spatial variation in the model rather than a mechanistic relationship with the response. The remaining stressors were used to calculate ASI for the MBI model. Section 1.3.2 details how ASI and HQI were calculated for each model.

3.4 Mapped Results

3.4.1 *Expected current conditions*

IBI score was calculated for all 1:100k stream catchments in the study area using the BRT model. The predicted IBI scores ranged from 14.6 to 54.4. The mean predicted IBI score was 39.2. Of the total 10,351 catchments, about 1.5% (155 catchments) had a predicted IBI greater than 50, which would correlate to OHEPA’s biocriteria for exceptional warmwater habitat (EWH). About 47% (4,837 catchments) had predicted scores between 40 and 50, which meet the biocriteria for warmwater habitat (WWH) or non-significant departure from WWH. Another 47% (4,878 catchments) were predicted to be in the “fair” category determined by OHEPA with scores of 28-40. Only 4.5% of the catchments in the watershed (481 catchments) were predicted to be in the “poor” or “very poor” categories. The predictions are mapped in Figure 18.

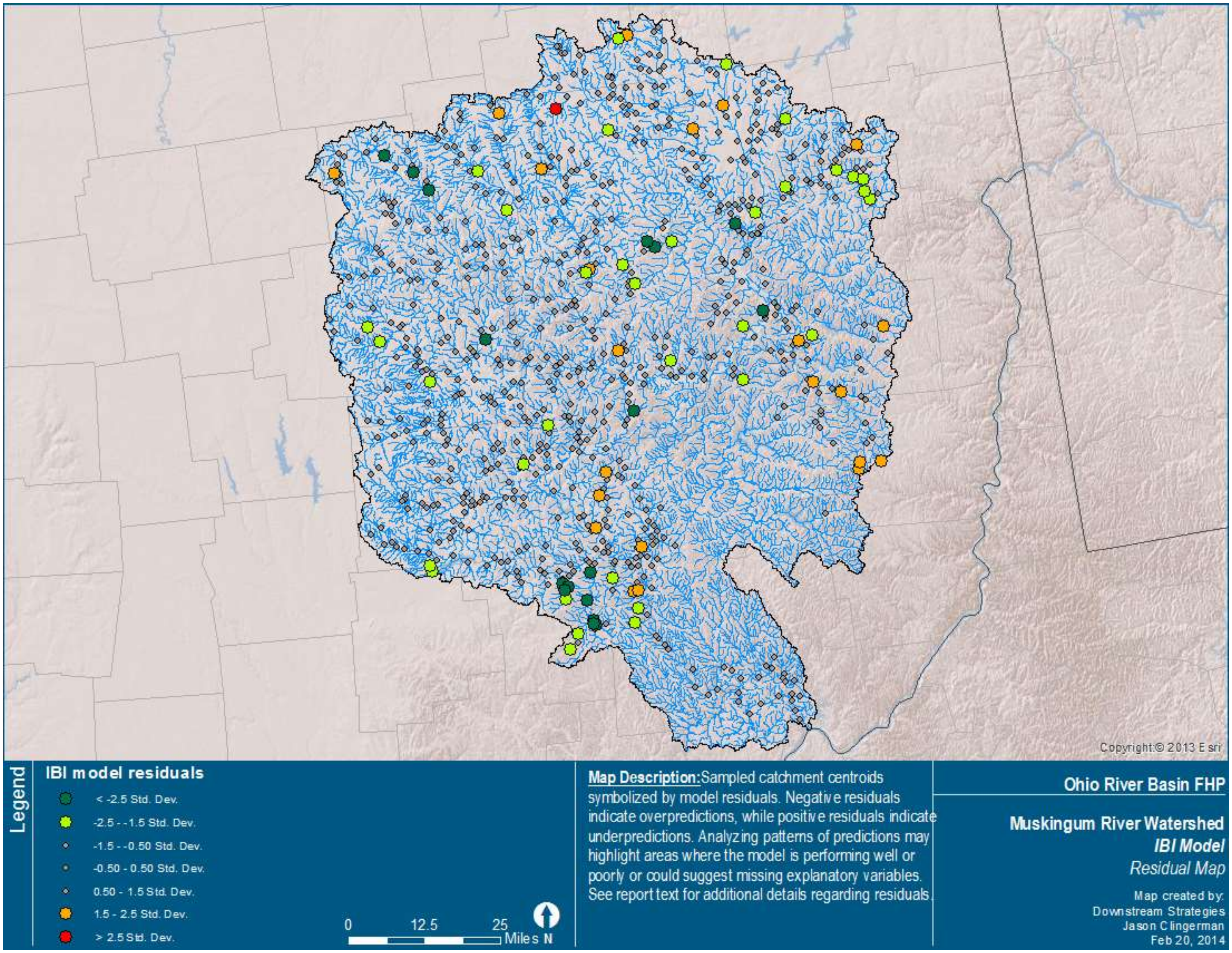
Figure 18: Expected IBI distribution



3.4.2 *Spatial variability in predictive performance*

Analyzing patterns of omission and commission may highlight regions where the model is performing well or poorly or could suggest missing explanatory variables. To assess omission and commission, residuals were calculated by the BRT model. The residuals are a measure of the difference in the measured and modeled values (measured value *minus* modeled value). Negative residuals indicate overpredictions (predicting higher values than are true), while positive residuals indicate underpredictions (predicting lower values than are true). Figure 19 shows the distribution of model residuals per sampling site.

Figure 19: Distribution of IBI model residuals by sampling site



3.4.3 *Indices of stress and natural quality*

Maps of HQI and ASI illustrate the spatial distribution of natural habitat potential (i.e., HQI score) and anthropogenic stress (i.e., ASI score) throughout the Midwest region. HQI and ASI scores are mapped in Figure 20 and Figure 21, respectively. The variables contributing toward the calculation of ASI are mapped in Figure 22 - Figure 26. HQI, ASI, and their metrics are all scaled on a 0-1 scale (see Sections 1.3.2 and 3.3 for more details on HQI and ASI calculation). For HQI, higher values indicate higher natural quality, while higher values for ASI indicate higher levels of anthropogenic stress.

Figure 20: Natural quality index for IBI

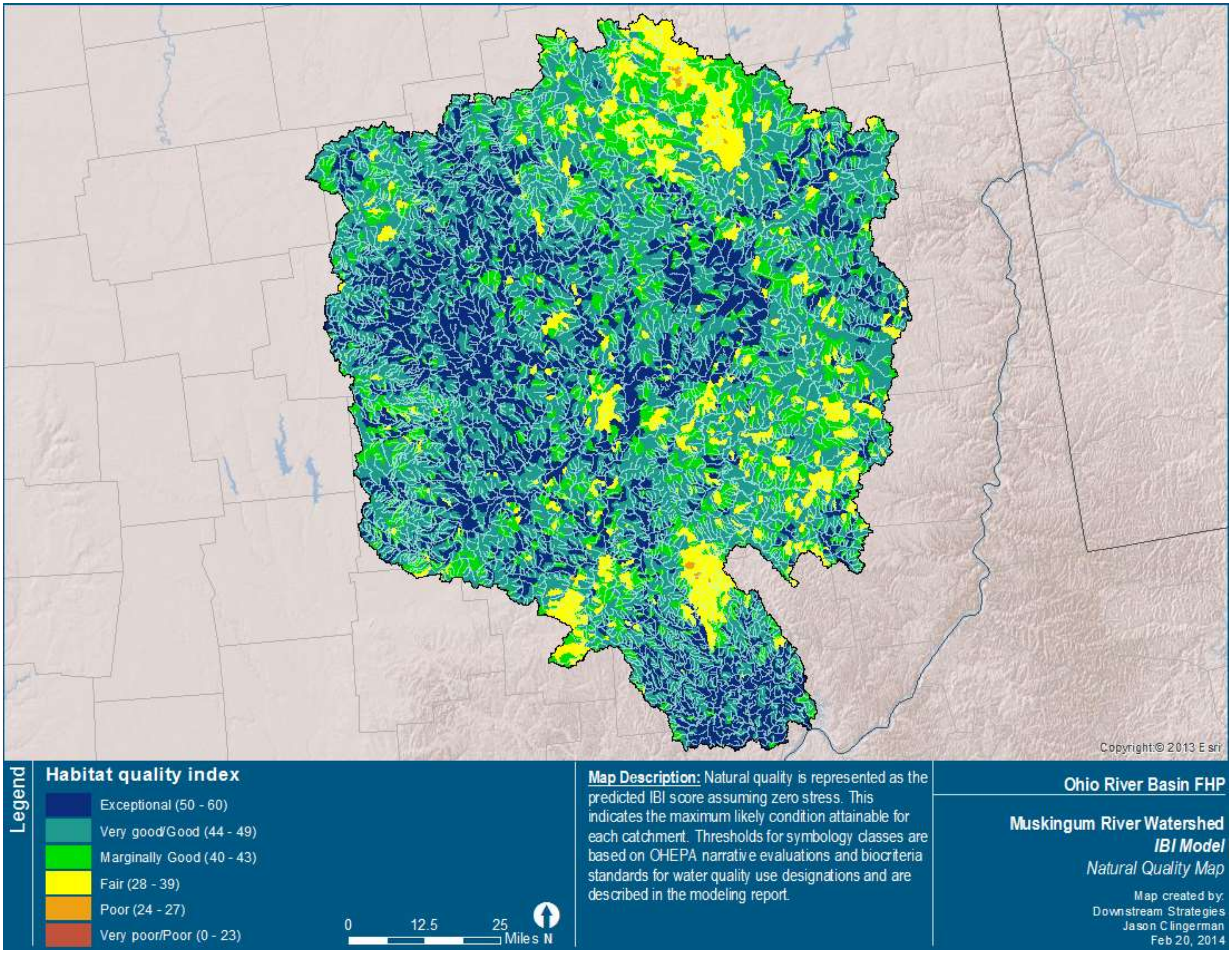


Figure 21: Anthropogenic stress index for IBI

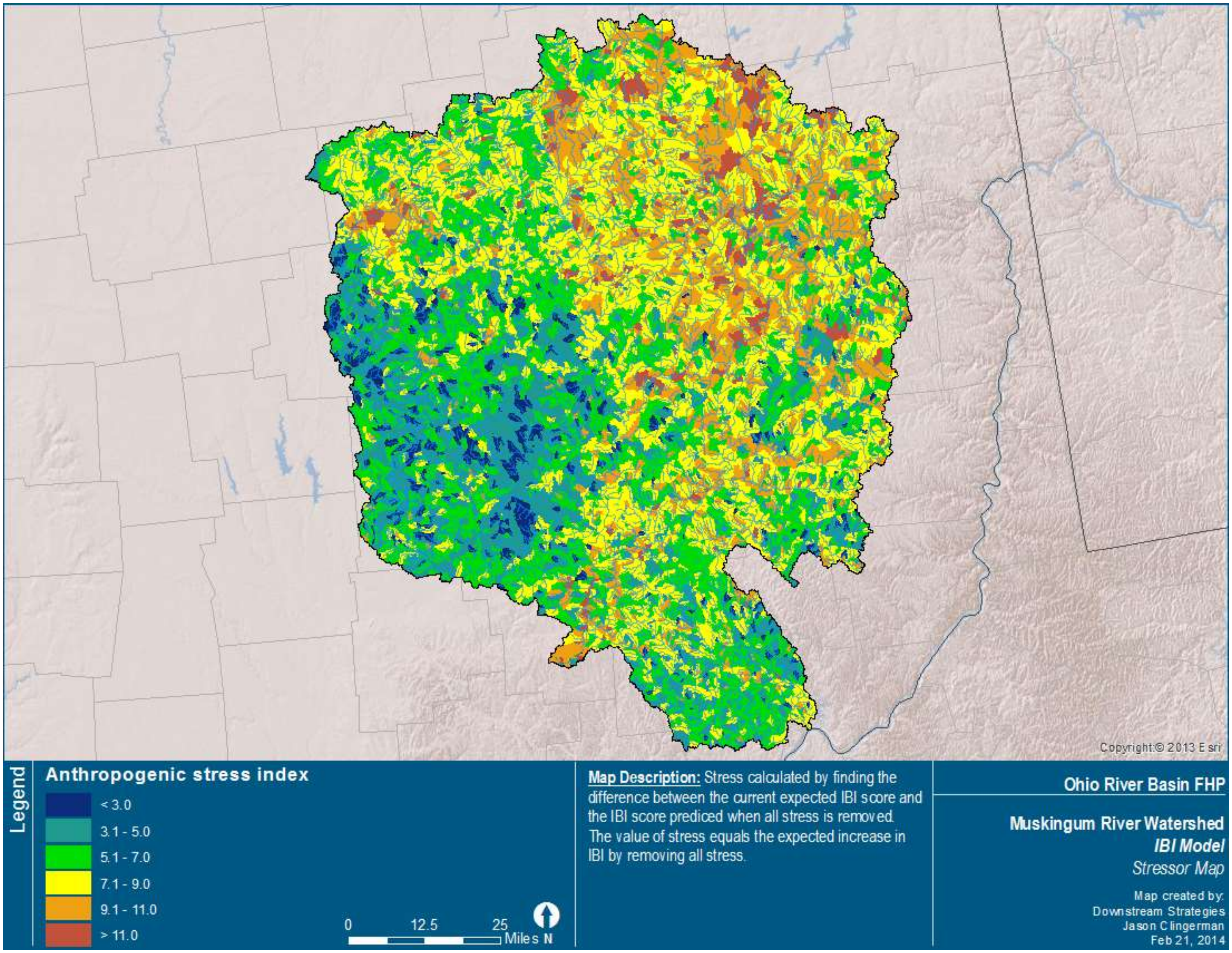


Figure 22: Network grassland stressor metric for IBI

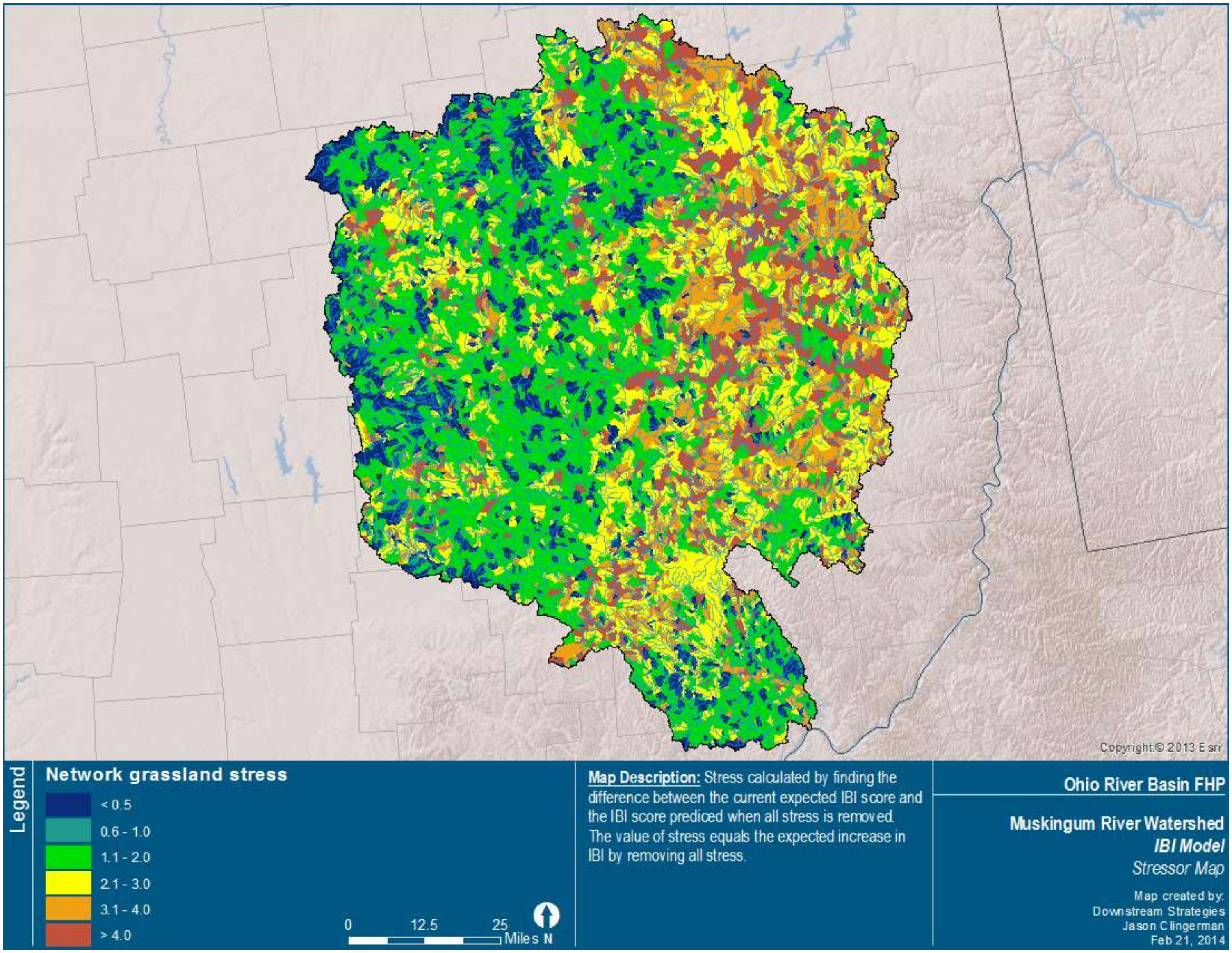


Figure 23: Network impervious surface stressor metric for IBI

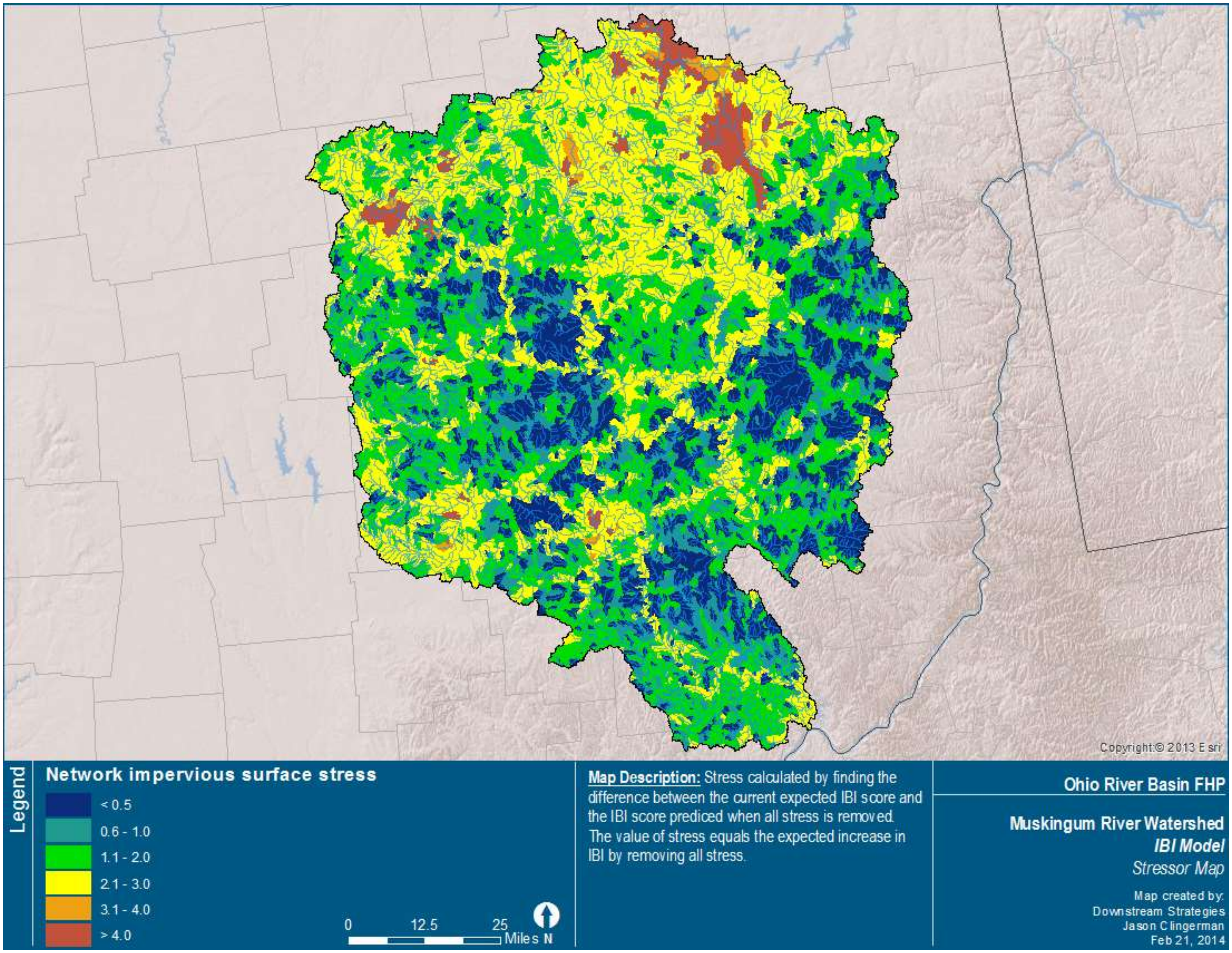


Figure 24: Cattle density stressor metric for IBI

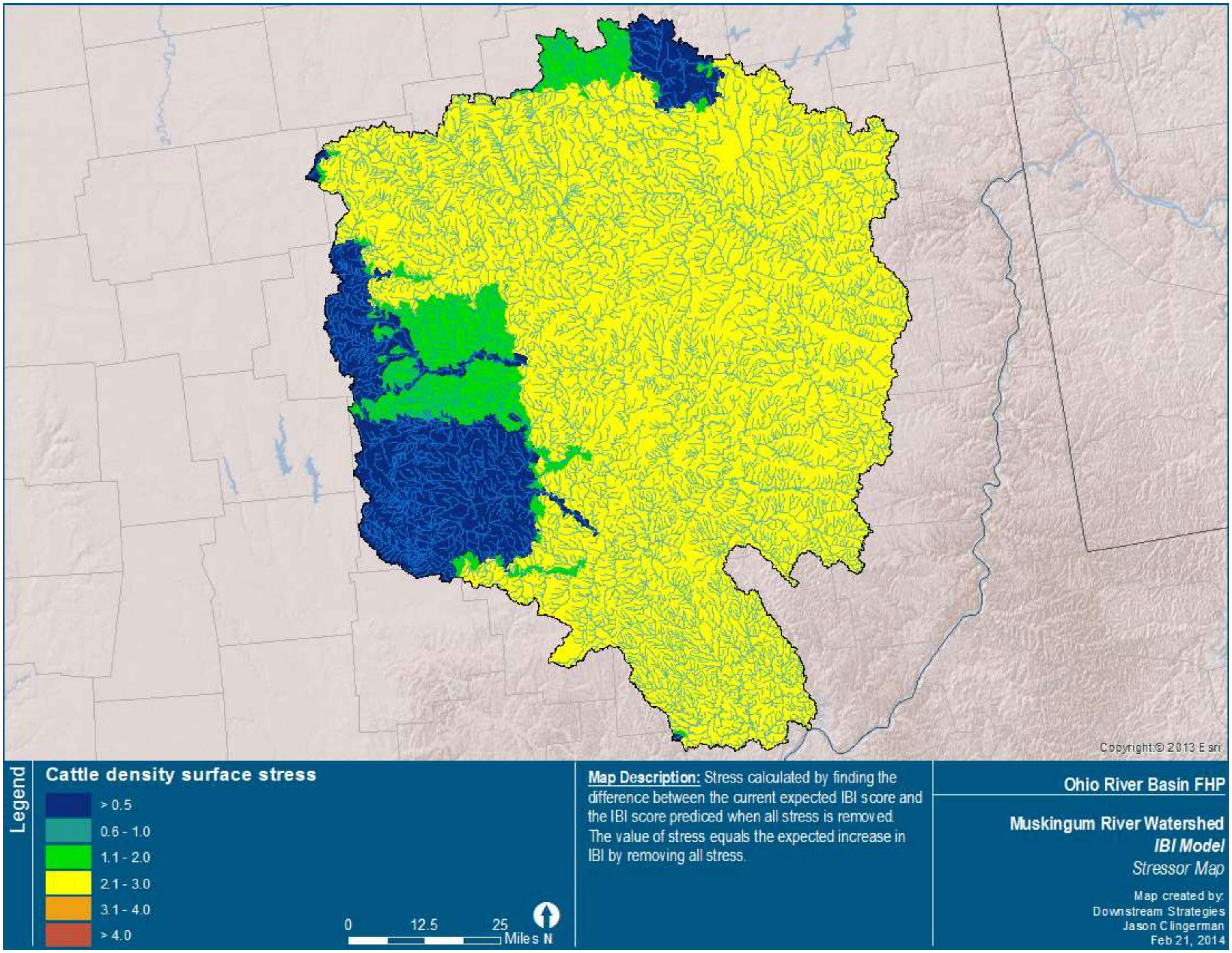


Figure 25: Local grassland stressor metric for IBI

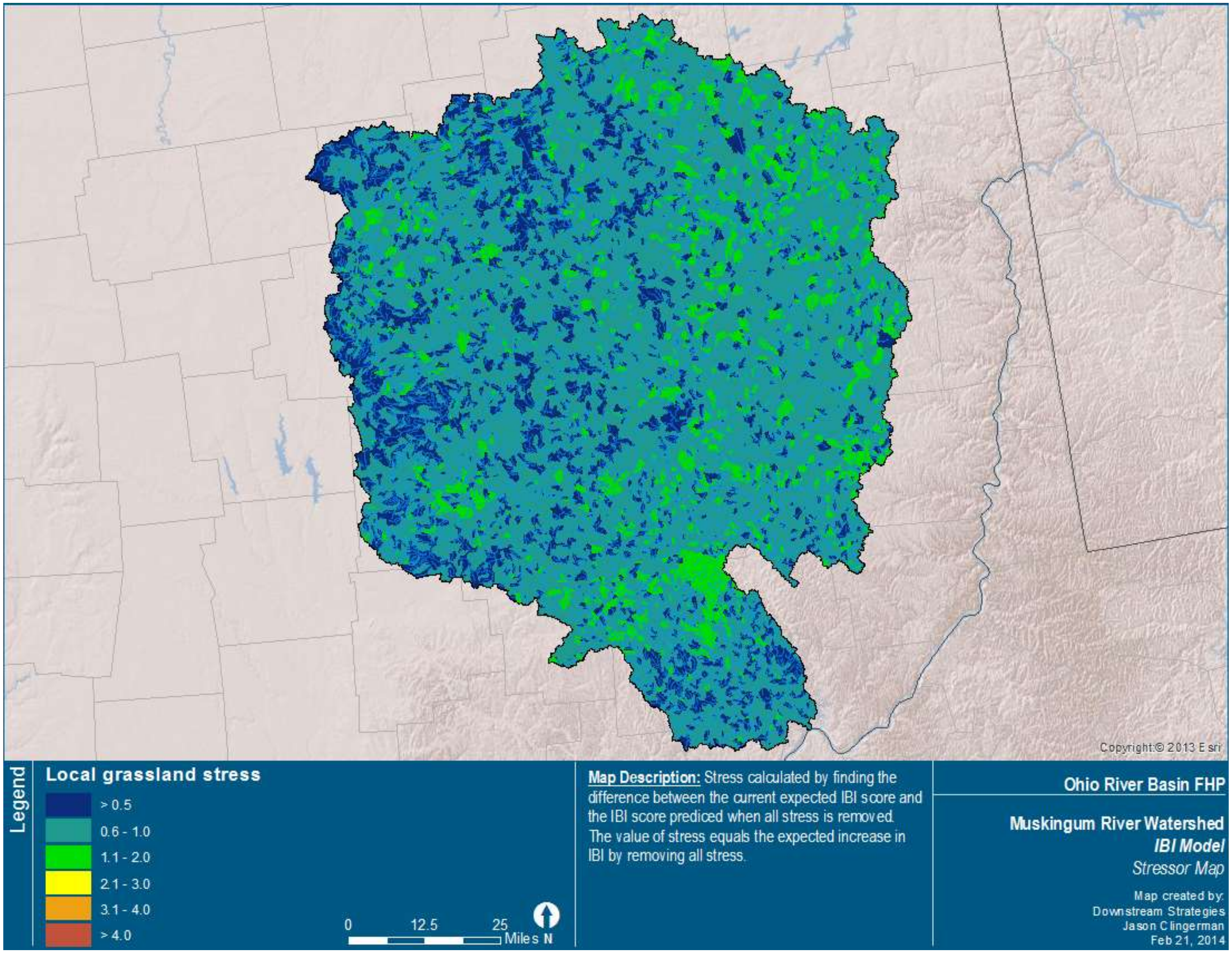
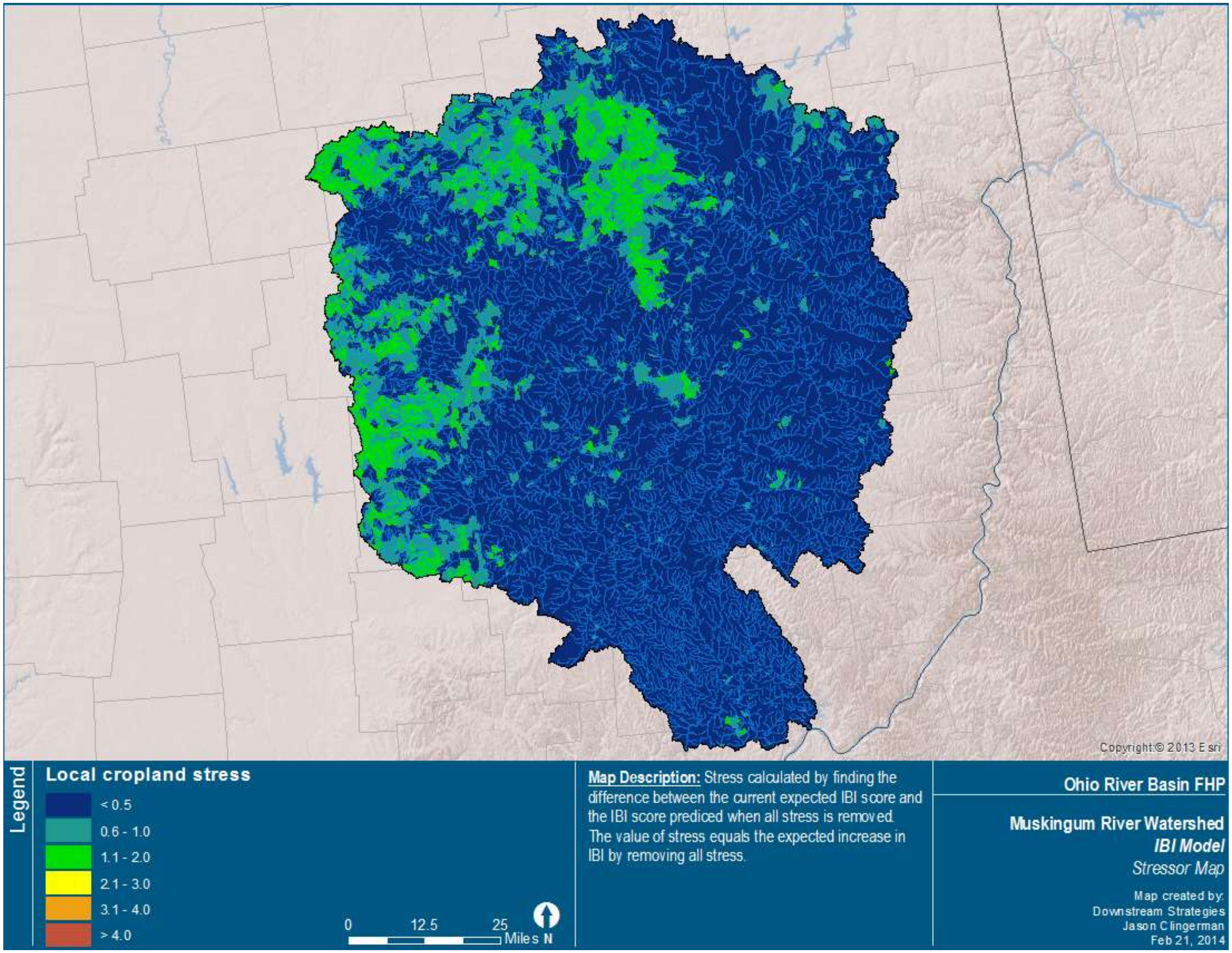


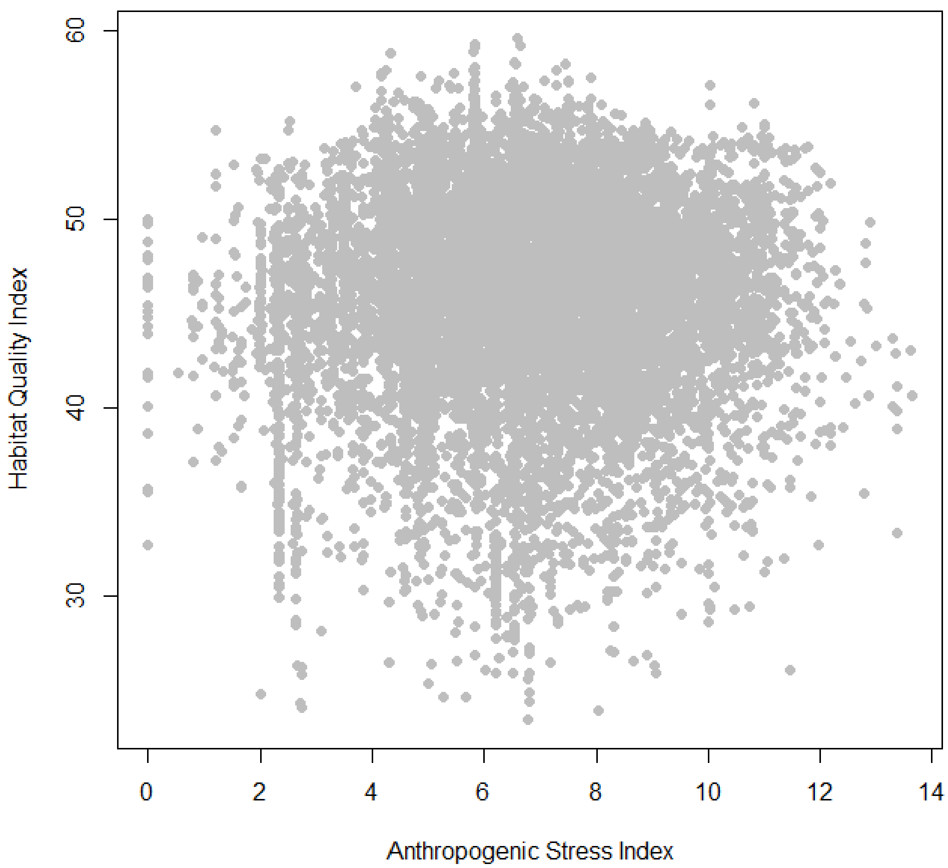
Figure 26: Local cropland stressor metric for IBI



3.4.4 *Restoration and protection priorities*

A plot of HQI versus ASI values for all catchments in the study area can be used as a reference to define HQI and ASI thresholds when evaluating restoration and protection priorities (Figure 27). Restoration priorities could be areas in the upper right hand corner of the plot below, where stress is high, but natural quality is also high. Along the same lines, catchments falling in the upper left hand corner of this plot where stress is low and natural quality is high may be the highest priorities for protection. This information is presented to explain the functionality of querying catchments based on these attributes to identify areas that meet user-defined criteria to guide conservation, protection, and restoration planning

Figure 27: HQI versus ASI values for all catchments for IBI



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4. LIMITATIONS AND SUGGESTIONS FOR FUTURE WORK

In general, while the estimates of index scores, HQI, and ASI generated through this assessment represent a useful and objective means for assessing aquatic habitat and prioritizing habitats for restoration or protection, there are some limitations that are important to consider. Results generated through the modeling process are ultimately limited by the quality of data used to generate them. In the future, the model can be improved by improving the resolution and precision of the data. For example, some county-level data were used as predictor variables although the data likely generalize conditions at the catchment scale. Although these variables—such as network surface water consumption—were limited in spatial resolution, they still had high relative influence in the BRT model and were important to retain for predictive performance. In the future, refinement of these county-level variables or inclusion of higher resolution surrogates could improve both the precision of the BRT model predictions and post-modeling indices.

A second limitation is that the data and maps represent only a snapshot in time. Therefore, the models may not represent conditions before or after the data were collected or created. For example, any habitat lost or gained due to increased impervious surface cover since the 2006 National Land Cover Database (NLCD) was not considered in this assessment. The amount of such changes would likely be minimal, but at this scale of study the differences could be important. Similarly, a portion of the uncertainty can be attributable to the temporal mismatches between the response data and landscape data, although we used the best available matching data to avoid this as much as possible, though improving the temporal match between those datasets for future work would be beneficial.

These models offered valuable insight into which landscape-level stressors and natural conditions were structuring aquatic responses across the modeled watersheds. Recent modeling efforts at the regional and FHP scale have indicated that smaller-scale models like these are likely necessary to pinpoint localized stressors. Please see the DS report “Analysis of scale on boosted regression tree fish habitat models” for a case study of how scale influences the importance of stressor variables. The case study was performed on presence-absence responses and showed improved predictive performance as the extent of the models was reduced. The responses modeled in this effort were likely subject to the improved predictive performance of a more localized model extent, but the cross-validated correlation score indicates these models are performing only moderately well. Some of this can likely be attributed to modeling a continuous response variable rather than a presence-absence response.

As with any modeling efforts, all of the variation in predicted measures can never be fully accounted for, and the same holds true for these assessments. Some unexplained variation could likely be explained by local habitat measures such as water quality (pH, alkalinity, instream temperature), physical habitat complexity, and substrate size are examples of local measures important to structuring aquatic communities. By including variables such as slope, geology, and land cover, some of these processes may be accounted for in our assessment, but still could not be directly quantified in this analysis given the scope and scale of the project. These variables were not directly used as predictor variables, although, when possible, surrogates were used to approximate variation in the model resulting from these processes. Nonetheless, exclusion of detailed local measures likely accounts for some uncertainty in the model results. Thus, the results from this analysis should be combined with local expert knowledge and additional field data to arrive at the most accurate representation of habitat conditions.

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Appendix A: DATA DICTIONARY

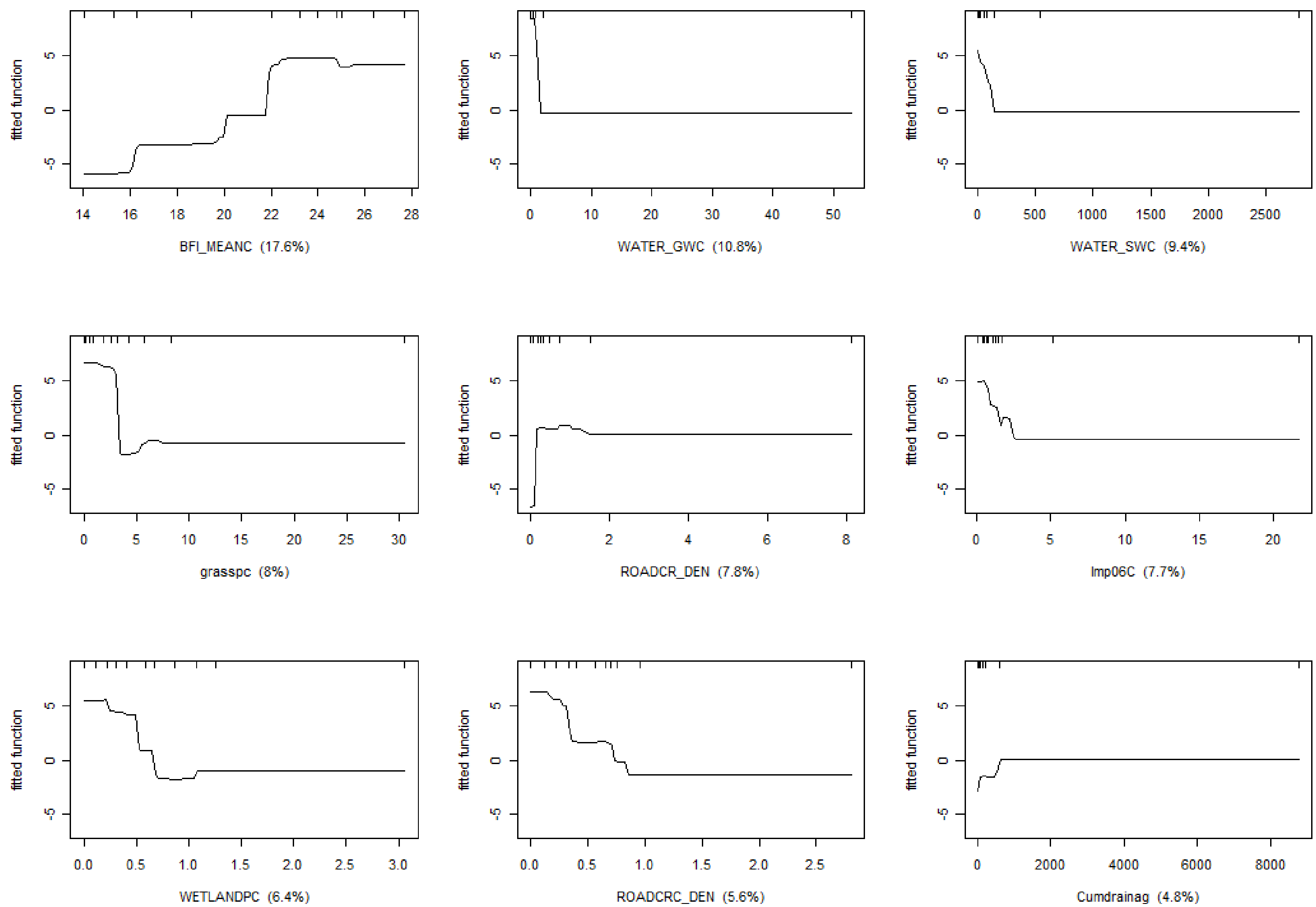
Field	Description	Source
Comid	catchment comid (unique identifier)	NHDPlus
Areasqkm	area of catchment, sq km	NHDPlus
Cumdrainag	Cumulative drainage area in square kilometers	NHDPlus
Minelevraw	Minimum elevation (unsmoothed) in meters	NHDPlus
Slope	Slope of flowline (cm/cm)	NHDPlus
Precip	Mean annual precipitation in mm	NHDPlus
Temp	Mean annual temperature in degrees centigrade * 10	NHDPlus
Imp06	mean percent impervious, catchment	NLCD 2006
Imp06C	mean percent impervious, cumulative	NLCD 2006
Brock1P	Catchment bedrock geology, percent Carbonate (LOCAL)	USGS (Reclassified by Letsinger)
Brock 2P	Catchment bedrock geology, percent Felsic (igneous) (LOCAL)	USGS (Reclassified by Letsinger)
Brock 3P	Catchment bedrock geology, percent Mafic (igneous) (LOCAL)	USGS (Reclassified by Letsinger)
Brock 4P	Catchment bedrock geology, percent Metamorphic (LOCAL)	USGS (Reclassified by Letsinger)
Brock 5P	Catchment bedrock geology, percent Sand and gravel (LOCAL)	USGS (Reclassified by Letsinger)
Brock 6P	Catchment bedrock geology, percent Sandstone (LOCAL)	USGS (Reclassified by Letsinger)
Brock 7P	Catchment bedrock geology, percent Shale (LOCAL)	USGS (Reclassified by Letsinger)
Brock 1PC	Network bedrock geology, percent Carbonate (CUMULATIVE)	USGS (Reclassified by Letsinger)
Brock 2PC	Network bedrock geology, percent Felsic (igneous) (CUMULATIVE)	USGS (Reclassified by Letsinger)
Brock 3PC	Network bedrock geology, percent Mafic (igneous) (CUMULATIVE)	USGS (Reclassified by Letsinger)
Brock 4PC	Network bedrock geology, percent Metamorphic (CUMULATIVE)	USGS (Reclassified by Letsinger)
Brock 5PC	Network bedrock geology, percent Sand and gravel (CUMULATIVE)	USGS (Reclassified by Letsinger)
Brock 6PC	Network bedrock geology, percent Sandstone (CUMULATIVE)	USGS (Reclassified by Letsinger)
Brock 7PC	Network bedrock geology, percent Shale (CUMULATIVE)	USGS (Reclassified by Letsinger)
Soil1p	Revised soil hydrologic group code 1 (A, A/D), area (%), catchment	STATSGO
Soil2p	Revised soil hydrologic group code 2 (B, B/D), area (%), catchment	STATSGO
Soil3p	Revised soil hydrologic group code 3 (C, C/D), area (%), catchment	STATSGO
Soil4p	Revised soil hydrologic group code 4 (D), area (%), catchment	STATSGO
Soil1pc	Revised soil hydrologic group code 1 (A, A/D), area (%),upstream cumulative	STATSGO

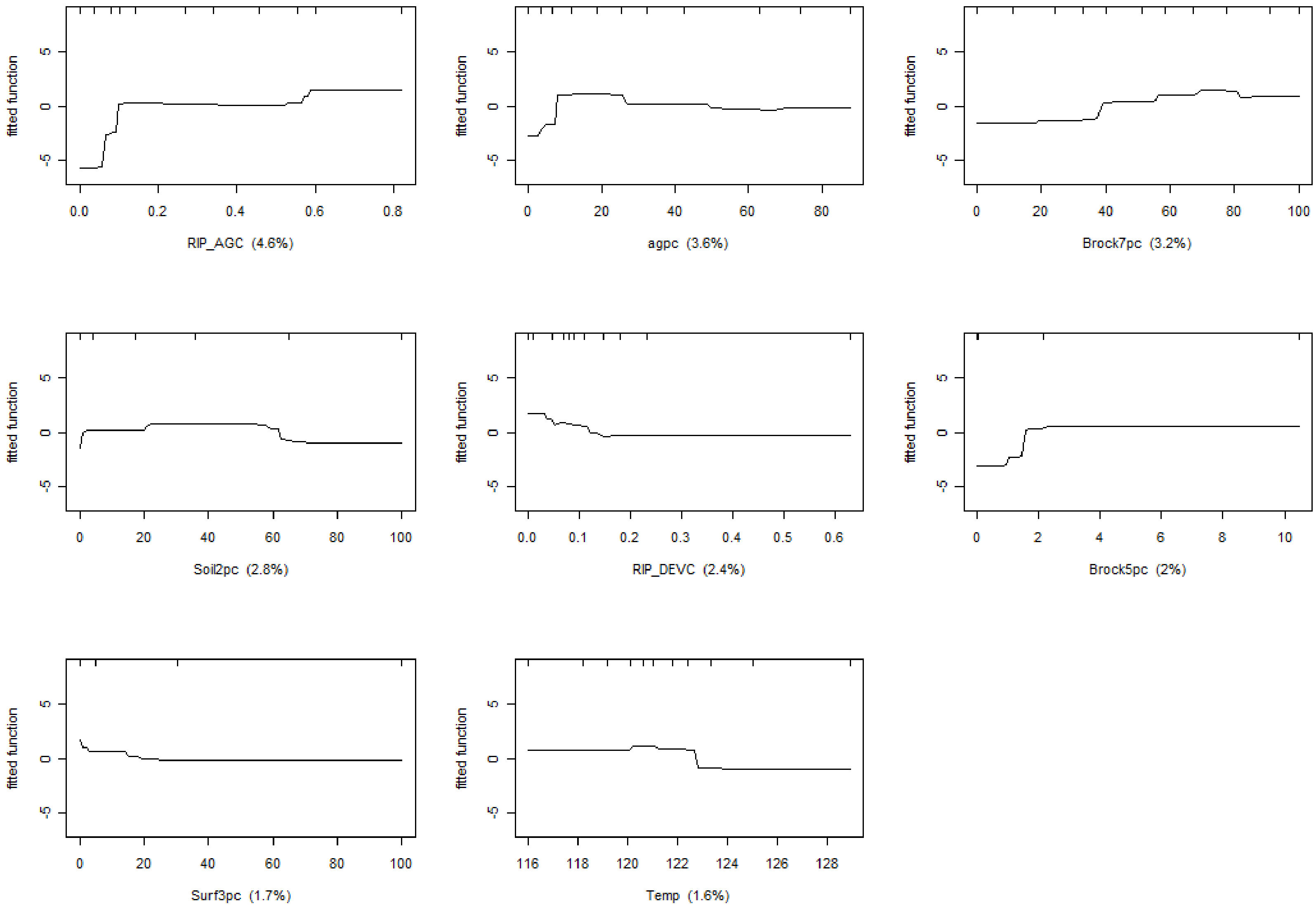
Soil2pc	Revised soil hydrologic group code 2 (B, B/D), area (%), upstream cumulative	STATSGO
Soil3pc	Revised soil hydrologic group code 3 (C, C/D), area (%),upstream cumulative	STATSGO
Soil4pc	Revised soil hydrologic group code 4 (D), area (%),upstream cumulative	STATSGO
Surf1p	Surficial geology, group code 1 (Till), area (%), catchment	USGS
Surf2p	Surficial geology, group code 2 (Outwash), area (%), catchment	USGS
Surf3p	Surficial geology, group code 3 (Alluvium), area (%), catchment	USGS
Surf4p	Surficial geology, group code 4 (Lacustrine), area (%), catchment	USGS
Surf5p	Surficial geology, group code 5 (Loess), area (%), catchment	USGS
Surf6p	Surficial geology, group code 6 (Residuum), area (%), catchment	USGS
Surf7p	Surficial geology, group code 7 (Clay), area (%), catchment	USGS
Surf8p	Surficial geology, group code 8 (Colluvium), area (%), catchment	USGS
Surf1pc	Surficial geology, group code 1 (Till), area (%),upstream cumulative	USGS
Surf2pc	Surficial geology, group code 2 (Outwash), area (%), upstream cumulative	USGS
Surf3pc	Surficial geology, group code 3 (Alluvium), area (%),upstream cumulative	USGS
Surf4pc	Surficial geology, group code 4 (Lacustrine), area (%),upstream cumulative	USGS
Surf5pc	Surficial geology, group code 5 (Loess), area (%),upstream cumulative	USGS
Surf6pc	Surficial geology, group code 6 (Residuum), area (%),upstream cumulative	USGS
Surf7pc	Surficial geology, group code 7 (Clay), area (%),upstream cumulative	USGS
Surf8pc	Surficial geology, group code 8 (Colluvium), area (%),upstream cumulative	USGS
DEV_P	NLCD 2006, % of developed land cover classes (0 to 100), (NLCD classes 22, 23, 24)	NLCD 2006
AG_P	NLCD 2006, % of agricultural land cover classes (0 to 100), (NLCD classes 81, 82)	NLCD 2006
FOR_P	NLCD 2006, % of forest land cover classes (0 to 100), (NLCD classes 41,42,43)	NLCD 2006
GRS_P	NLCD 2006, % of grassland cover classes (0 to 100), (NLCD classes 71)	NLCD 2006
DEV_PC	Network NLCD 2006, % of developed land cover classes (0 to 100), (NLCD classes 22, 23, 24)	NLCD 2006
AG_PC	Network NLCD 2006, % of developed land cover classes (0 to 100), (NLCD classes 81, 82)	NLCD 2006
FOR_PC	Network NLCD 2006, % of developed land cover classes (0 to 100), (NLCD classes 41,42,43)	NLCD 2006
GRS_PC	Network NLCD 2006, % of grassland cover classes (0 to 100), (NLCD class 71)	NLCD 2006
WETLANDP	Wetland area, percent of catchment's area (0 to 100%)	NWI and GAP wetlands
WETLANDPC	Network wetland area, percent of upstream contributing area (0 to 100%)	NWI and GAP wetlands
RIP_AG	Riparian zone in agriculture, percentage, catchment, (0-100), (NLCD classes 81, 82)	NLCD, FEMA
RIP_DEV	Riparian zone developed, percentage, catchment, (0-100), (NLCD classes 22, 23, 24)	NLCD, FEMA
RIP_AGC	Riparian zone in agriculture, percentage, upstream cumulative, (0-100), (NLCD classes 81, 82)	NLCD, FEMA
RIP_DEVC	Riparian zone developed, percentage, upstream cumulative, (0-100), (NLCD classes 22, 23, 24)	NLCD, FEMA
Mine_P	Surface mines, percentage, catchment, (0-100)	OSM, KOMSL, KYDR
Mine_PC	Surface mines, percentage, upstream cumulative, (0-100)	OSM, KOMSL, KYDR

N_KGDEN	Total estimated N inputs (kg/year), per sq km, catchment	USGS
P_KGDEN	Total estimated P inputs (kg/kear), per sq km, catchment	USGS
N_KGDENC	Total estimated N inputs (kg/year), per sq km, upstream cumulative	USGS
P_KGDENC	Total estimated P inputs (kg/kear), per sq km, upstream cumulative	USGS
BFI_mean	Mean baseflow index (catchment)	USGS
BFI_meanc	Mean baseflow index (network)	USGS
Water_gw	LOCAL: USGS National Atlas of the US: Ground Water Use by COUNTY 2000: Millions gallons per day/km2	NFHAP
Water_sw	LOCAL: USGS National Atlas of the US: Surface Water Use by COUNTY 2000: Millions gallons per day/km2	NFHAP
Cattle	LOCAL: Agricultural Census 2002, 1:2M scale, INTEGER: average number of cattle/acre farmland	NFHAP
Popdens	LOCAL: US Population Density 2000, NOAA, scale 1km, #/km2	NFHAP
Roadcr	LOCAL: Census 2000 TIGER Roads, 1:100K scale, road crossings identified by INTERSECT, with points generated, #/km2	NFHAP
Roadlen	LOCAL: Census 2000 TIGER Roads, 1:100K scale, units not given - m/km2	NFHAP
Dams	LOCAL: National Inventory of Dams, 2002-2004, #/km2	NFHAP
Mines	LOCAL: USGS Active Mines and Mineral Processing Plants, 2003, #/km2	NFHAP
Tri	LOCAL: USEPA, 2007: #/km2 Toxics Release Inventory Program sites	NFHAP
Npdes	LOCAL: USEPA, 2007: #/km2 National Pollutant Discharge Elimination System sites	NFHAP
Cerc	LOCAL: USEPA, 2007: #/km2 Compensation and Liability Information System sites	NFHAP
Water_gwc	NETWORK: USGS National Atlas of the US: Ground Water Use by COUNTY 2000: Millions gallons per day/km2	NFHAP
Water_swc	NETWORK: USGS National Atlas of the US: Surface Water Use by COUNTY 2000: Millions gallons per day/km2	NFHAP
Cattlec	NETWORK: Agricultural Census 2002, 1:2M scale, INTEGER: average number of cattle/acre farmland	NFHAP
Popdensc	NETWORK: US Population Density 2000, NOAA, scale 1km, #/km2	NFHAP
Roadcrc	NETWORK: Census 2000 TIGER Roads, 1:100K scale, road crossings identified by INTERSECT, #/km2	NFHAP
Roadlenc	NETWORK: Census 2000 TIGER Roads, 1:100K scale, units not given - m/km2	NFHAP
Damsc	NETWORK: National Inventory of Dams, 2002-2004, #/km2	NFHAP
Minesc	NETWORK: USGS Active Mines and Mineral Processing Plants, 2003, #/km2	NFHAP
Tric	NETWORK: USEPA, 2007: #/km2 Toxics Release Inventory Program sites	NFHAP
Npdesc	NETWORK: USEPA, 2007: #/km2 National Pollutant Discharge Elimination System sites	NFHAP
Cercc	NETWORK: USEPA, 2007: #/km2 Compensation and Liability Information System sites	NFHAP

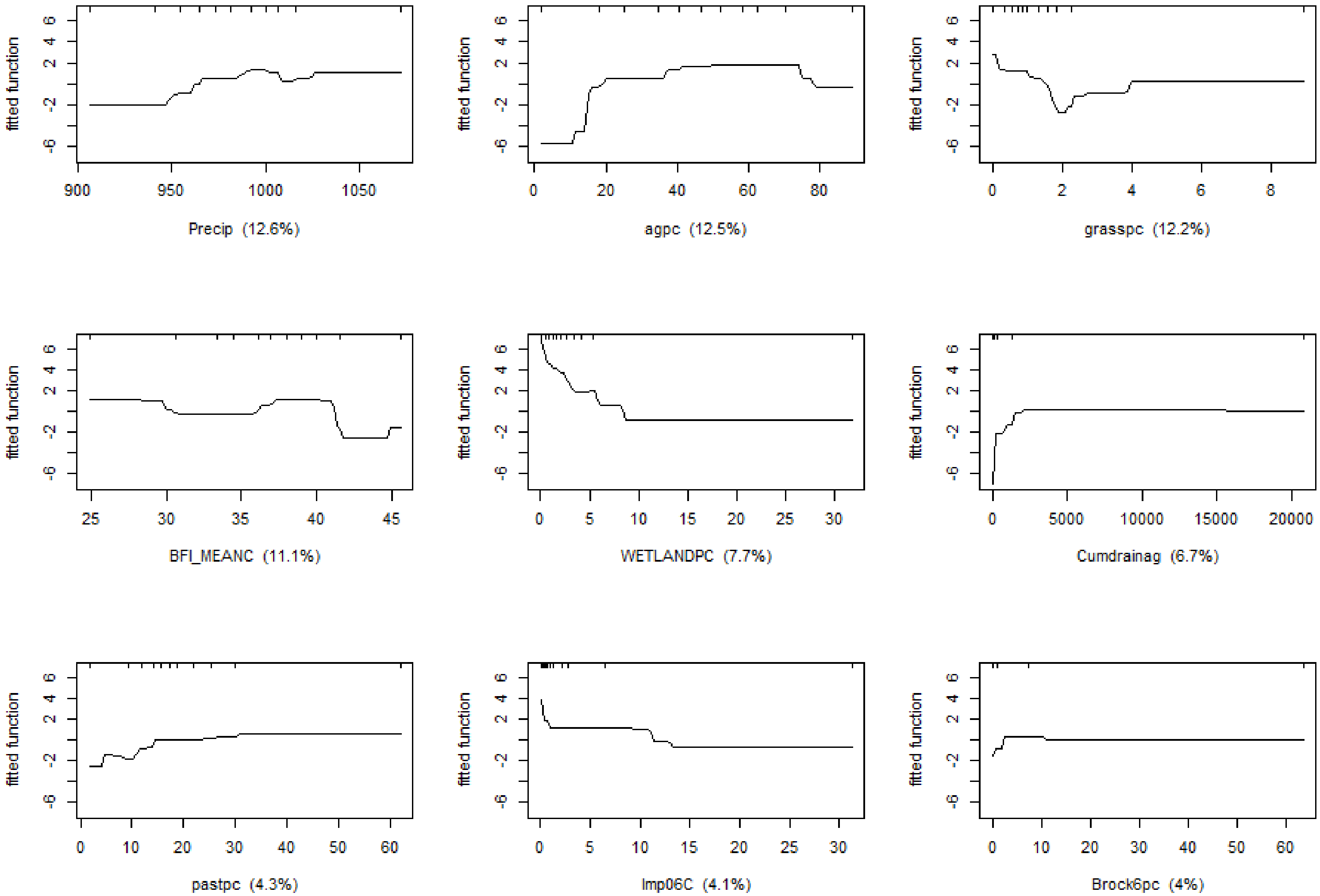
Appendix B: FUNCTIONAL RESPONSE PLOTS

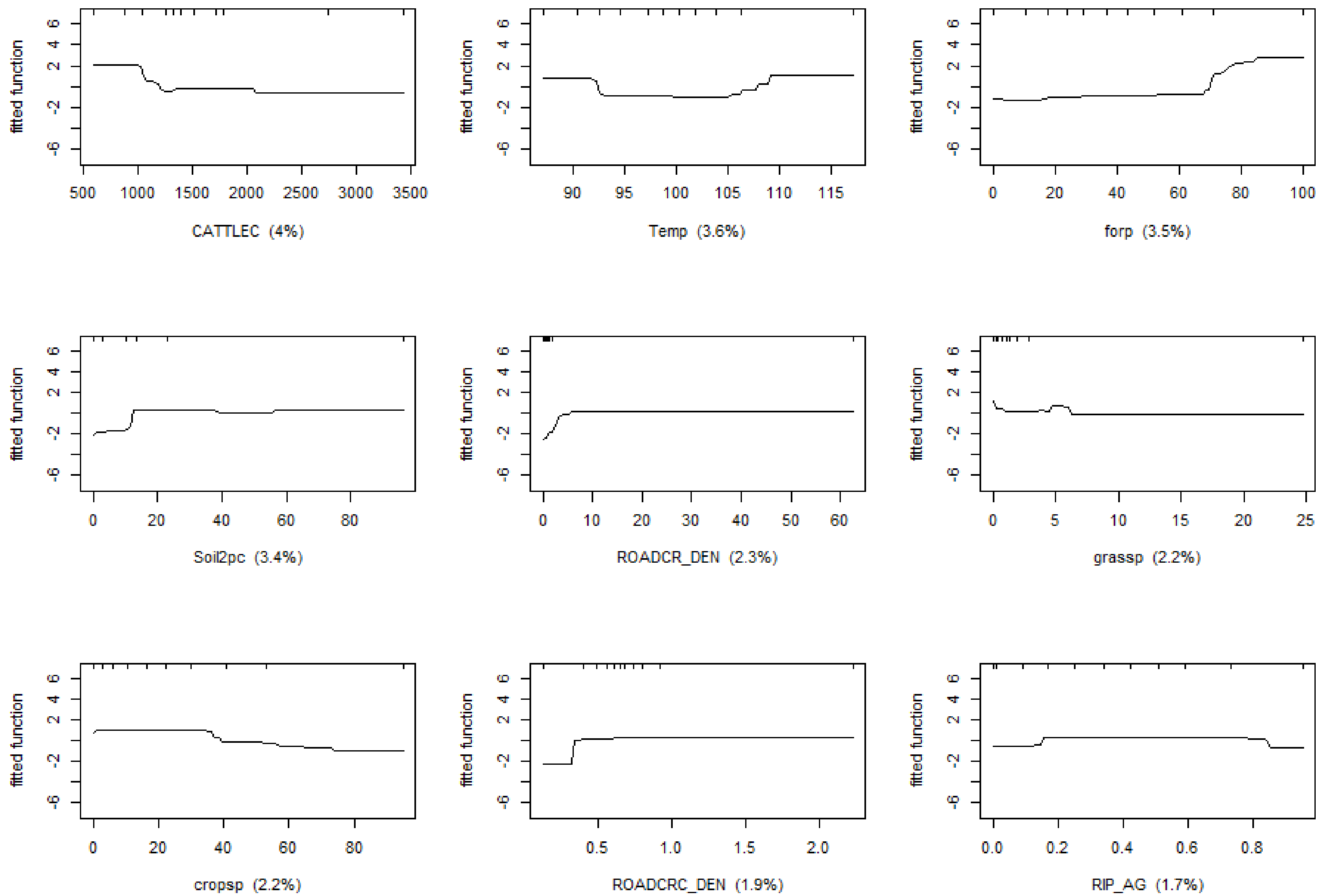
Licking River watershed MBI




fitted function
-5
0
5
0.0
0.2
0.4
0.6
0.8
RIP_AGC (4.6%)
0
20
40
60
80
agpc (3.6%)
0
20
40
60
80
100
Brock7pc (3.2%)
0
20
40
60
80
100
Soil2pc (2.8%)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
RIP_DEVC (2.4%)
0
2
4
6
8
10
Brock5pc (2%)
0
20
40
60
80
100
Surf3pc (1.7%)
116
118
120
122
124
126
128
Temp (1.6%)

Muskingum River watershed IBI




fitted function
CATTLEC (4%)
500 1000 1500 2000 2500 3000 3500
Temp (3.6%)
90 95 100 105 110 115
forp (3.5%)
0 20 40 60 80 100
Soil2pc (3.4%)
0 20 40 60 80
ROADCR_DEN (2.3%)
0 10 20 30 40 50 60
grassp (2.2%)
0 5 10 15 20 25
cropsp (2.2%)
0 20 40 60 80
ROADCRC_DEN (1.9%)
0.5 1.0 1.5 2.0
RIP_AG (1.7%)
0.0 0.2 0.4 0.6 0.8
-6 -2 2 4 6

[i] http://www2.research.att.com/~phillips/pdf/Elith_et_al_ecography.pdf

[ii] http://onlinelibrary.wiley.com/doi/10.1111/j.1365-2656.2008.01390.x/pdf