Illinois Natural History Survey

Final Report

Ecological Classification of Rivers for Environmental Assessment and Management:
Model Development and Risk Assessment

Ann Marie Holtrop, Leon C. Hinz Jr., and John Epifanio

Final Project Report

Submitted to:

Illinois Department of Natural Resources
One Natural Resources Way
Springfield, Illinois 62702

Illinois Natural History Survey
Division of Ecology and Conservation Science
1816 South Oak Street
Champaign, Illinois 61820

November 2006

Illinois Natural History Survey Technical Report 2006/12

Illinois Natural History Survey
Center for Aquatic Ecology and Conservation

(February 1, 2003 - September 30, 2006)

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ACKNOWLEDGMENTS

This project was funded through Illinois' State Wildlife Grant Program (T-2-P-01) and enhanced through collaboration with researchers at the USGS – Great Lakes Aquatic Gap Program, Illinois Environmental Protection Agency, Institute for Fisheries Research of the Michigan Department of Natural Resources, University of Michigan, Illinois Department of Natural Resources, and Wisconsin Department of Natural Resources. Paul Seelbach initiated this three state collaborative effort under a US EPA STAR Grant (R-83059601-0). We would also like to acknowledge several individuals that contributed substantially to the success of this project. Arthur Cooper (Institute for Fisheries Research) provided valuable assistance with the GIS components of the project, John Lyons (Wisconsin DNR) and Paul Steen (USGS) offered valued advice on the fish models, Beth Sparks-Jackson developed the macroinvertebrate models, and Brian Pijanowski (Purdue University) developed the land transformation models.

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INTRODUCTION

Hawkins et al. (1993) describe several purposes that a general classification of stream habitats should serve, including facilitating communication between researchers and managers. Although the scale of their classification (channel units) may differ from what we propose (stream reaches), their suggestions on the functionality of a classification are very relevant. Unlike our terrestrial colleagues who have described habitat types at various spatial scales with much clarity, stream ecologists lack standardized names for systems that are widely accepted. Until aquatic systems are uniformly described and named, it is difficult for researchers and managers to agree on the status of and preferred management options for various stream types. Hawkins et al. (1993) further suggest that the attributes used in the classification are at the appropriate spatial scale to the biota of interest and the defined stream types are ecologically meaningful to both researchers and managers. We recognize that aquatic biota are influenced by local features within the channel, but are also influenced by the surrounding landscape and the water moving through the channel from the upstream watershed. Therefore, we have developed a database of attributes at several spatial scales that includes the local channel, local riparian zone, and local catchment, as well as the entire upstream riparian zone and watershed for each stream reach. A description of the GIS-derived attributes can be found in Holtrop et al. (2005).

Various methods for classifying rivers exist and range from purely physical or biological classifications to combinations of both. Geomorphic classifications such as that proposed by Rosgen (1994) and the channel evolution model (Schumm et al. 1984) are widely used across the United States. The premise of these classifications is that channels develop in a set pattern and can be classified as to their current state. Although these developmental channel stages can be shown to be important, purely geomorphic classifications do not capture variations in key ecological factors such as chemistry, hydrology, and temperature that also strongly shape the aquatic biota. Further, purely biological classifications, such as the Biological Stream Characterization (BSC; Bertrand et al. 1996) developed for Illinois waters, do not take into account physiochemical habitat when rating streams. BSC ratings are assigned to a stream reach primarily based on the fish community sampled at the site. Given the limitations of each of these approaches Illinois resource managers need a tool that will integrate ecological, biological, and geomorphic factors in a way that allows aquatic systems to be described in a standardized fashion.

To build on these existing approaches, we proposed the development of a statewide database system consisting of physically and biologically attributed stream reaches that can be used for description and classification of Illinois streams. The objectives for this project are to: 1) build models to predict habitat and biota from mapped landscape and local variables, and 2) assess risk of Illinois streams to future land use change. These objectives correspond to jobs 2.4 and 4.4 respectively in T-2-P1.

Job 2.4. Location and condition of stream habitats.

The purpose of this job is to build statistical models for predicting riverine site habitats and biota from mapped landscape and local variables. Specifically, we created a series of models for flow, instream temperature, macroinvertebrates, and fish. The models described below are based on landscape-scale environmental variables that were derived from GIS data layers under Job 2.1 in T-3-P1 (see Holtrop et al. 2005 for more details). The models were then used to predict biological and habitat conditions for all river segments, including sampled and unsampled reaches.

Flow

Discharge was characterized using data from 70 U.S. Geological Survey stream gages scattered across Illinois. These gages were selected to minimize the influence of direct alteration by major diversions or seasonal regulation at dams. We summarized data from 1981-2000 to match the most recent land cover available and to be long enough to characterize natural inter-annual variation in discharge. Additional information associated with these catchments was derived from GIS data layers and used for model development and application (Figure 2.4a).

Multiple linear regression models were developed for a range of annual exceedence discharges (5%, 10%, 25%, 50%, 75%, 90%, and 95%). Potential predictors were proportions of surficial geology, landcover, and summary characteristics of the stream network (e.g., drainage area, link number, precipitation, slope) based on the catchment associated with the USGS gage data. Some variables were combinations of attributes such as the percentage of lakes and percent emergent wetlands combined into one ‘open and wet’ variable. Summarized discharge data and all potential predictors were checked for normality assumptions and transformed if necessary (generally natural logarithm or exponential).

Model development essentially followed an addition ($p<0.05$)/removal ($p<0.10$) stepwise regression procedure with initial development focused on the median flow. After each addition or removal, the predictive equation derived for the median flow model was reparameterized with high flow (Q_{10}) and with low flow (Q_{90}) data. If the most recent change did not result in a major decrease in the fit (adjusted R^2 and standard error) of these models, then the change was kept and development continued. When additional changes did not improve the fit of the models, then this combination of predictors was used to create a family of models for the additional exceedence flows (i.e., Q_5, Q_{10}, Q_{25}, Q_{75}, Q_{90}, Q_{95}). All models predict the natural log of the exceedence discharge in cubic meters per second and all predictors were retained in these models (values were converted to cubic feet per second for this report). Overall these models had good fits with high flows consistently predicted better than low flows (Table 2.4a).

Summaries from our georeferenced database system were applied to these hydrologic models for stream segments throughout the state. Modeled flows were added to the database system by attributing stream segments with the model output, thus allowing for a state-wide view of expected annual flows (Figures 2.4b-d). Less than two percent of all segments within Illinois were not able to be assessed with this method because the models did a poor job predicting discharge in small catchments with uniform surficial geology and/or landcover and in very large rivers.

Temperature

Records from 75 temperature loggers collected between 1999 and 2005 demonstrate a broad range of thermal conditions existing in Illinois streams (Figure 2.4e). These temperature summaries were used with landscape based GIS catchment summaries to develop multiple regression models that estimate water temperatures. Since thermal records were seldom longer than a single year at any of the sites, we focused on summer water temperatures. We used landcover and geology summary data from several scales as potential predictors. Summaries were acquired for each logger location and each stream reach throughout the state for the local watershed, total upstream watershed, local riparian buffer, and total upstream riparian buffer. Summarized temperature data and all potential predictors were checked for normality assumptions and transformed if necessary (e.g., arcsine, square root, natural logarithm, or exponential). Model development followed an addition/removal stepwise regression procedure similar to that used for modeling discharge (see above). Mean daily maximum and mean daily minimum water temperatures for the month of July were modeled separately from these data (Table 2.4b).

The developed models were applied within our statewide georeferenced database system as a preliminary assessment of the thermal conditions within Illinois streams. Mean daily July temperatures were then derived as the average of the daily maximum and minimum temperatures from these models (Figure 2.4f). Stream segments were given a thermal code based on the Minimum and Maximum July water temperatures from the model output. The vast majority (79%) of segments had characteristics of warmwater streams but cold-/cool-water segments comprised approximately 16% of the total number of coded segments statewide (Figure 2.4f). Roughly four percent of all segments within Illinois were not able to be assessed with this method because these models did a poor job predicting water temperatures in very large rivers and small and/or relatively uniform catchments.

Macroinvertebrates

Summaries of macroinvertebrate sample collections from 636 stations were obtained from the Illinois Environmental Protection Agency (IEPA) that cover a broad range of conditions occurring in wadeable streams throughout the state. These collections were made between 1982 and 1998 by IEPA biologists and approximate the time associated with the recent landcover in our database system. With the assistance of our collaborators in Michigan, multiple linear regression models were developed that relate summaries of the invertebrate assemblage to human-induced stressors (e.g., landcover) and natural causes/covariates (e.g., drainage area, geology, etc). Total catchment and riparian zone summaries were obtained for each station from our existing database and used to develop models for several invertebrate assemblage summaries (i.e., number of Ephemeroptera Taxa, number of Ephemeroptera + Plecoptera + Trichoptera (EPT) Taxa, and the Macroinvertebrate Biotic Index (MBI)).

Where necessary, independent variables were transformed to meet assumptions of normality. Predictors that had the highest correlations with the invertebrate metrics were added into the models first; subsequent variables were added only if they were significant ($p<0.05$) and they improved the model fit (r^2). Overall these models explained slightly more than one quarter of the statewide variation in these invertebrate assemblage summaries (Table 2.4c) and demonstrate the potential for using our statewide database system for analysis with macroinvertebrate collections. While the model fits are not spectacular, they are in the range of similar models developed in other parts of the Midwest (M. J. Wiley, University of Michigan, personnel communication).

IEPA modified its sampling protocol during the course of this study and developed a macroinvertebrate Index of Biotic Integrity to better meet their assessment needs and water-quality objectives (Tetra Tech, Inc. 2005). These changes increase the sensitivity of the MBI but also make our model results difficult to compare with current assessment practices since the sampling protocol differs. Therefore we did not apply the macroinvertebrate models developed in this study throughout the state. However, we expect to undertake the development of similar models once adequate samples collected with the revised methods are available, and will subsequently apply these results within our statewide system.

Fish

We obtained fish community data for this study from the Fisheries Analysis System (FAS) database, which contains hundreds of samples collected by IDNR - Office of Resource Conservation biologists. Some sites have been sampled multiple times throughout IDNR=s monitoring program, thus a sample comprises the fish community sampled at a site on a given day. A subset of samples within FAS have corresponding water quality and instream habitat data collected by the Illinois Environmental Protection Agency as part of a cooperative agreement between the two agencies. All samples used in this modeling effort were wadeable or semi-wadeable sites, and were sampled as part of basin surveys. Abundance data for fishes were obtained from single pass electrofishing surveys conducted during summers from 1990 - 2000 at 442 sites.

Initially, our dataset comprised 146 fish species, including 9 hybrids. Each site had 3 - 41 species. Similar to Zorn et al. (2002), we used cluster analysis to group fishes that shared similar abundance patterns. Prior to analysis, hybrid species, individuals that were identified to genus, and rare species (i.e., those that occurred at less than 2% of sites) were removed. Sites were grouped into fish assemblage categories based on flexible beta hierarchical clustering (beta = -0.25) of a Relative Sorensen distance matrix, carried out in PC-ORD (PC-ORD 1999). Cluster analysis was performed on abundance data, which was defined as catch per unit effort (CPUE). For this job, CPUE was defined as the natural log (catch of each species per 1000 ft of stream length sampled +1). Initial analysis suggested that two ubiquitous species, Bluntnose minnow (present at 89% sites) and Green sunfish (present at 83% of sites) influenced the assemblage clusters. Therefore, these two species were removed prior to final clustering.

We used classification and regression tree (CART) analysis (Salford Systems 2002) to predict the occurrence of fish assemblages (defined by cluster analysis) and six individual species in Illinois streams based on landscape-scale variables. Thirty-two landscape-scale environmental variables, which were derived from GIS data layers, were used as predictors (Table 2.4d). Presence/absence data were used to model six individual species. Hornyhead chub (*Nocomis biguttatus*), Smallmouth bass (*Micropterus dolomieu*), Striped shiner (*Luxilus chrysocephalus*), Creek chubsucker (*Erimyzon oblongus*), Longear sunfish (*Lepomis megalotis*), and Fantail darter (*Etheostoma flabellare*) were chosen because they represented four families, three fish assemblages defined through our cluster analysis, as well as different ranges and habitat preferences. Smallmouth bass is identified as a species in greatest need of conservation in Illinois' Wildlife Action Plan.

To assess the accuracy of CART models, we assessed the classification rate, which is the group membership predicted by the model compared to the actual group membership. For the individual species models we further described the level of misclassification into errors of commission, where the model predicted presence but absence is observed in the data, and omission, where absence is predicted but presence is observed.

Using the remaining 86 species, we identified seven clusters of fishes for continued analysis (Table 2.4f). A dendrogram from the cluster analysis is shown in Figure 2.4g. Group 1 includes a few generalist warm-water fish species, and many species that are affiliated with clear water and minimal human impacts. The species included in group 2 tend to be restricted to the Wabash/Ohio drainage, and half of the species are in family Percidae. Group 3 is the largest group and comprises 26 species that are relatively common in larger streams and rivers. Many species in the group prefer sand or gravel substrates. Species comprising group 4 either persist only in southern Illinois, or are most abundant in backwaters, low gradient, and well-vegetated streams. Group 5 comprises species that tend to prefer slower moving water, quiet pools, and larger creeks or rivers. We combined groups 6 and 7 into one group based on the species= affinities to clear, cool, faster-flowing water. The final group comprises two shiner species, which prefer large to very large rivers. Presumably this group would comprise more species if our analysis included non-wadeable streams, which would include other large river species.

We used CART analysis to predict the occurrence of fish assemblages that we defined by cluster analysis. Four of the original seven clusters lacked sufficient representation in the dataset for further analysis; thus only three assemblages (Group 1, 2, 5 in Table 2.4g) were modeled using CART (Table 2.4f). The resulting model was then used to predict one of the three fish assemblages for every stream arc in Illinois (Figure 2.4h). Overall, these predicted fish assemblages matched our expectations. As our dataset grows to include more examples of the rare assemblage types (i.e., the four we could not model due to inadequate sample size), we will revisit the development of an assemblage-level model for fish. We expect the output from a more refined assemblage model will be very valuable for guiding restoration and protection efforts of Illinois' fish species in greatest need of conservation.

In addition to modeling fish assemblages, we modeled the presence/absence of six individual fish species (Tables 2.4g – 2.4l). Models included three to eight variables, and all included latitude and at least one landcover predictor (Table 2.4m). At least half of the models also included geology (bedrock or surficial), size, and flow. The range of total misclassification for each model was acceptable and ranged from 17% - 27% (Table 2.4m). Errors of commission accounted for 75% of the misclassification errors for all species models. Each model was then applied to all stream arcs, and the results of the models are shown in Figures 2.4i – 2.4n.

In general, the individual species models predict similar trends to known presence and absence of the selected species. In some cases (e.g., Striped shiner [Figure 2.4i] and Longear sunfish [Figure 2.4j]), latitude and longitude were such strong predictors that models appear to be driven almost exclusively by those factors. Other models (e.g., Creek chubsucker [Figure 2.4l] and Fantail darter [Figure 2.4n]) clearly have a latitudinal component, but other variables weigh in to predict occurrence of species outside of the latitude/longitude boundaries. Overall, the model for Smallmouth bass appears to have the most overlap between known presence and absence and the model predictions (Figure 2.4k). In Illinois, Smallmouth have a limited distribution and have a strong preference for streams with rocky substrate, continuous flow, and cooler water; these habitats are not uniformly represented throughout the state. The individual species models suggest that our approach is useful for predicting species presence/absence, especially for species that have specific habitat requirements.

Job 4.4. Future risk assessment of Illinois= streams.

The purpose of this job is to develop a series of predictions for ecological attributes of river segments reflecting various scenarios of human disturbance. To do this, we linked output from a land transformation model to some of the models developed in Job 2.4. This linkage allows forecasting of riverine conditions as they relate to land use changes in specific river reaches. The future scenarios will help identify stream segments at risk for future impacts loss due to land use changes including urban development.

Land Transformation Model

Bryan Pijanowski, Ph.D., and his colleagues at Purdue University developed a Land Transformation Model (LTM) for Illinois that uses neural net logic to build a map of predicted land cover changes over time. A key component to building a land transformation model is having at least two landcover datasets for a given area that are consistently developed. Because Illinois' two recent landcover datasets (IDNR 1996 and USDA NASS et al. 2002) were developed with different methods, Dr. Pijanowski lacked the necessary land use change data to build the basic land transformation model. Therefore, he relied on other sources of data to create the base model. In the northern quarter of Illinois, he used change data collected by the Northeastern Illinois Planning Commission (NIPC). For the southern three quarters of Illinois, Dr. Pijanowski relied on central Indiana data. The NIPC and central Indiana data were used to determine the urban rates of growth in small towns and to identify what other landcover is being added or lost. Once these rates and factors were identified, they were applied to Illinois landcover data (IDNR 1996). The resulting LTM was applied statewide, and a series of maps reflecting potential future development scenarios was created (Figure 4.4a).

Risk Assessment

The risk assessment portion of this project proved more difficult than anticipated. Each time series modeled (i.e., 2005, 2010, 2015, 2020, 2025, and 2030) resulted in a new land cover map (Figure 4.4a). In order to rerun the models described in Job 2.4, proportions of each land cover type for each time series had to be attributed to each arc. Further, landcover had to be summarized at four spatial scales (i.e., local riparian zone, entire riparian zone, local watershed, and entire watershed). Given that there are approximately 55,000 stream arcs in Illinois, attributing six different time series of landcover at four spatial scales proved to be beyond our computer capability. Therefore we selected the Kaskaskia River basin as a pilot for the risk assessment portion of this project. Further, we limited our analysis to current landcover and model outputs from 2025, which corresponds to the timeframe of Illinois' Wildlife Action Plan.

Output from the LTM representing the 2025 development scenario was assigned to each arc, and then summarized into variables used in models described in Job 2.4.

Flow

Annual median discharge was attributed to more than 92% of the available arcs in the Kaskaskia River basin using the flow models developed in this project. Certain reaches with extremely small catchments and areas associated with reservoirs (i.e., Carlyle Lake and Lake Shelbyville) were not modeled successfully (Figure 4.4b). Discharge was also estimated by applying summaries from the 2025 LTM and attributed to the appropriate arc (Figure 4.4c). Comparisons between these modeled flows suggest that most stream reaches would experience only small changes in annual median flow characteristics under the conditions described with the 2025 LTM. The majority of segments (62.6%) had projected median discharges within 10% of those from the recent land cover with over forty percent (43.8%) of all modeled segments expected to have changes less than 5% under the 2025 projected land cover. However, a small fraction of stream segments show large percentage change in this analysis. These stream segments are primarily those with extremely low discharge where small changes in magnitude are described as large percentage change (Table 4.4a). This highlights a weakness in this form of analysis but also of flow models that were developed based on a regional dataset that under-represent catchments with small drainage areas and those with very low discharge. Our flow models have a tendency to overestimate low flows and underestimate high flows due to these factors and in part from the linear modeling techniques used in their development. Additional discharge data from small streams and the development of separate models for headwaters would greatly improve our statewide assessment of these important areas.

Temperature

Mean daily temperature for July was attributed to more than 95% of the available arcs in the Kaskaskia River basin using the temperature models developed in this project. Certain reaches with extremely small catchment areas and/or with relatively uniform surficial geology or land cover were unable to be modeled successfully. Similarly, areas associated with reservoirs (i.e., Carlyle Lake and Lake Shelbyville) were not modeled (Figure 4.4d). July stream temperatures were estimated by applying summaries from the 2025 LTM and attributed to the appropriate arc (Figure 4.4e). These results suggest that the Kaskaskia River contains a wide range of summer temperatures but that warmer waters flow through the majority of the basin. Modeled temperatures were similar between those derived from the recent land cover and the 2025 LTM with over half of the stream arcs (58.3%) differing within the resolution (< 0.1 C) of our temperature recorders (Table 4.4a). This analysis suggests that the majority of the Kaskaskia River basin will maintain similar summer water temperatures under conditions as described in the 2025 LTM. It must be kept in mind that altering temperatures even small amounts may impact stream biota if they are living near their thermal limits. This could be particularly important for coolwater species or those that live in the very warmest of streams. However, little is currently known about the distribution of streams with extreme summer thermal conditions within Illinois, especially coolwater areas, where these types of impacts may occur.

Fish

The fish assemblage model was rerun based on output from the land transformation model and the results were applied statewide (Figure 4.4e). Ninety-five percent of the stream arcs had the same fish assemblage predicted for current conditions as well as potential conditions in 2025. Approximately half of the arcs that showed a change between current conditions and those suggested in 2025 are associated with reservoirs (i.e., Carlyle Lake and Lake Shelbyville) where this model is not applicable. The majority of the remaining arcs (i.e., 96%) differing between current and 2025 conditions were predicted to change from group 5, which comprises species preferring slower moving water and quiet pools, to group 2, which comprises species of the Wabash/Ohio drainage or species in the family Percidae. Although only a small proportion of arcs showed a change in fish assemblages, the arcs that did change suggest the potential for alteration in land cover to effect local fish distribution.

Because our model for predicting fish assemblages is rather simplistic, we selected Longear sunfish as a test to see if individual species models might be more sensitive to future land use change. When the Longear sunfish model was run based on LTM output for 2025, no additional locations were predicted for species presence. However, if we ignore the stream arcs comprising Carlyle Lake and Lake Shelbyville, there are still a few stream reaches where Longear sunfish were predicted to occur in present conditions, but were predicted absent using the 2025 land cover scenario (Figure 4.4f). This analysis suggests that the land cover change associated with the 2025 LTM would lead to a loss of stream reaches with suitable conditions for Longear sunfish.

DISCUSSION

This project marks an important step toward developing a tool that simplifies the natural variability in stream systems. The flow, temperature, and fish models developed in this project have been applied and attributed to streams segments statewide. By providing expectations for stream habitat and fish communities in sampled and unsampled reaches throughout the state, the resulting database system will be a valuable tool for implementing Illinois' Wildlife Action Plan. For example, one of the actions identified in the stream's campaign of Illinois' Plan is to restore populations of imperilled and extirpated aquatic animals (State of Illinois 2005). To meet this objective, resource managers need to identify where suitable habitat persists, which may include groundwater fed streams, as well as those with cool summer water temperatures. Prior to the completion of this project, summer water temperatures and groundwater influence were unknown for most streams in Illinois. Additionally, many of the GIS attributes developed in Holtrop et al. (2005) and used in the models in this project provide the basis for identifying system-wide limiting factors such as connectivity.

Hydrologic modeling provides a tool for developing expectations for stream flow where data are lacking or for assessing potential alterations in flow associated with local changes in model parameters (e.g., land cover). Application of the models developed in this project suggests the existence of a wide range of annual flow conditions within the streams of Illinois. When applied to the Kaskaskia River basin and compared with the 2025 LTM, these models provide a spatial analysis of potential alterations in flow associated with changes in land cover. While many of the stream reaches show little change in flow character, certain areas appear to be vulnerable to large alterations in flow conditions if current development trends continue. These results may help develop guidance for flow standards and will provide insight into the contribution of land alteration to the modification of flow regimes especially as additional basins are assessed.

Our assessment of thermal conditions in Illinois streams provides a geospatial picture of the locations where summer temperatures may limit the distribution or success of many aquatic species, particularly those considered coolwater or those that require high dissolved oxygen concentrations. However, our temperature models are based only on summer water temperatures from a single year at each site and thus provide no information about interannual variability or nonsummer conditions. Longer thermal records that would allow the modeling of mean conditions that take into account annual variability should improve the fit of our temperature models and provide more accurate estimates of the thermal character of modeled streams. Long periods of cold temperature are another potential period of stress for stream organisms that are not addressed with these models but may have a strong influence on the distribution of aquatic species in Illinois streams. These limitations could easily be addressed by continuing to annually monitor water temperature at fixed stations and in a variety of different streams throughout the state. Redevelopment and improvement of temperature models as additional data become available would improve and expand the reliability of our assessment of Illinois stream temperatures.

Although the fish assemblage model presented in this report is simplistic, it presents a useful approach to classifying biotic communities in rivers. As more data become available, the models may be refined to identify locations of rarer community types, including coolwater and headwater fish assemblages. The individual species models, which are based on presence/absence data, provide one approach for identifying areas that can be conserved to sustain population of listed species, as well as identifying suitable habitats for species reintroductions.

The outputs for the models developed in this project along with the GIS attributes developed in Holtrop et al. (2005) provide the necessary data for developing a stream classification for Illinois. We intend to develop an approach for grouping stream arcs into larger stream reaches and then classify these reaches into stream types. An ecological classification of rivers as we propose will help Illinois resource managers identify high-quality examples of all river and stream communities, thereby helping to set restoration and management priorities. In this project, we attempted to document changes in flow, temperature, biota associated with altered land use. In general, our models did not detect numerous changes between current conditions and those of 2025. However the changes that were identified suggest areas that may be at risk by future land use change. As our models are refined, we should have increased ability to detect potential risks to biota in the future.

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Table 2.4a. Summary of hydrologic model family fit statistics. Landcover and surficial geology Variables are transformed proportions of the total upstream watershed. **Bold** are statistically significant (p<0.05).

Model	**Q05**	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**	**Q95**
R squared	98.6%	98.4%	98.0%	96.9%	93.9%	81.9%	75.6%
R squared (adjusted)	98.4%	98.2%	97.7%	96.6%	93.2%	79.8%	72.7%
Standard Error	0.197	0.2175	0.2551	0.3372	0.537	1.37	1.888
Degrees of Freedom	67	67	67	67	67	67	67
Variable	**prob**	**prob**	**prob**	**prob**	**prob**	**prob**	**prob**
Constant	**< 0.0001**	**< 0.0001**	0.0924	0.7583	0.6245	0.2167	0.8084
(Ln) Drainage Area	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**
(exp) Forested Wetland	**< 0.0001**	**0.0741**	**0.0006**	**< 0.0001**	**< 0.0001**	**0.0003**	**0.012**
(exp) Open and Wet	0.4399	0.157	**< 0.0001**	**< 0.0001**	**< 0.0001**	**0.0019**	**0.0045**
(exp) Fine Moraine	**0.0002**	0.5422	**0.0002**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**
(exp) Urban	0.7493	**0.0139**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**	**< 0.0001**
(exp) Coarse Moraine	0.34	**0.0769**	**0.0022**	**0.0044**	**0.0044**	**0.0343**	**0.0525**
(exp) Bedrock	**< 0.0001**	**0.019**	0.7737	**0.0082**	**< 0.0001**	**0.0055**	**0.0203**
(exp) Medium Moraine	**0.0032**	**0.0662**	0.5843	**0.026**	**< 0.0001**	**< 0.0001**	**< 0.0001**

Table 2.4b. Summary of temperature fit statistics and model predictor variables. Landcover and geology variables are transformed proportions of the total upstream watershed (WT_), local riparian (R_), total upstream riparian (RT_). **Bold** are statistically significant (p<0.05).

July mean daily Minimum	Fit	July mean daily Maximum	Fit
R squared	68.6%	R squared	55.5%
R squared (adjusted)	63.4%	R squared (adjusted)	48.2%
Standard Error	1.418	Standard Error	1.724
Degrees of Freedom	61	Degrees of Freedom	61
Variable	**prob**	**Variable**	**prob**
Constant	**< 0.0001**	Constant	**< 0.0001**
WT_Darcy	**< 0.0001**	WT_Darcy	**< 0.0001**
(asin) R_Shale	**0.0199**	(asin) R_Shale	**0.0009**
(asin) R_BD0 50	**0.0036**	(asin) R_BD0 50	**0.0027**
(asin) RT_Moraine	**< 0.0001**	(asin) RT_Moraine	**0.0004**
(sqrt) WT_Moraine	**0.0019**	(sqrt) WT_Moraine	**0.0207**
(ln) WT_Slope	**0.0012**	(ln) WT_Slope	**0.0001**
(ln) Link	**0.0012**	(ln) R_Soil_Permeability	**0.0068**
RT_Carbonate	0.0523	(ln) RT_Slope	**0.0006**
(asin) RT_Fine	**0.0475**	(ln) Link	**0.0152**
(sqrt) R_Slope	0.0896	(exp) R_Forest Total	**0.0092**

Table 2.4c. Multiple linear regression models developed for macroinvertebrate assemblages in Illinois streams. Models are in the general form Y = constant + $B_1 Ln(X_1+0.0001) + B_2 Ln(X_2+0.0001) + \ldots + B_n Ln(X_n+0.0001)$. All independent variables are catchment scale attributes, land use and geology are in percentages, drainage area in km^2, Air temp in °C, ecoregion code 1 = interior river valleys and hills, ecoregion code 2 = driftless area. [a]No transformation used on variable, [b]Square root transformation used on variable.

Dependent Variable	Independent variable	Coefficient	Coefficient standard error	Coefficient P-value	Model R^2	Model P-value
No. of E taxa	Constant	0.466	0.407	0.253	29.7	<0.001
(E count)	Drainage area	0.842	0.072	<0.001		
	Urban	-0.213	0.046	<0.001		
	Wetland	-0.795	0.102	<0.001		
	Forest	0.205	0.077	0.008		
	Q90/Q10 [b]	-3.844	1.335	0.004		
No. of EPT taxa	Constant	15.600	4.671	<0.001	27.4	<0.001
(EPT count)	Drainage Area	1.095	0.098	<0.001		
	Urban	-0.439	0.069	<0.001		
	Wetland	-0.650	0.132	<0.001		
	JL Air Temp Max[a]	-0.458	0.152	0.003		
Macroinvertebrate	Constant	6.029	0.114	<0.001	26.3	<0.001
Biotic Index	Drainage area	-0.183	0.021	<0.001		
(MBI)	Urban	0.094	0.013	<0.001		
	Forest	-0.113	0.022	<0.001		
	Q90/Q10 [b]	1.142	0.418	0.007		
	Ecoregion code 1[a]	0.675	0.071	<0.001		
	Ecoregion code 2[a]	0.657	0.211	0.002		

Table 2.4d. Landscape-scale environmental variables used in CART analysis. All variables are taken, calculated, or predicted from GIS data layers.

Variable Name	Definition
Connectivity	
DAM	Categorical variable which identifies the presence of a dam (1) versus not (0)
BIGRIVER	Categorical variable which identifies if the stream reach is connected to a large river, defined as
DLINK	Shreve stream order of downstream arc
Water Temperature	
MEANJULY	Maximum daily mean water temperature, based on model predictions
RANGEJULY	Greatest daily range in water temperature between June through August, based on model predictions
MEANCODE	Categorical variable for predicted mean July temperature
RANGECODE	Categorical variable for range July temperature
Channel Form	
SLOPE	Mean slope
SINUOSITY	Sinuosity of stream reach, the actual channel length/straight line
GRADIENT	Channel gradient, the change in elevation /channel length from start to finish
Flow	
Q_MAGNITUDE	50% exceedence flow, the median flow; as 50% of flows are higher and 50% of flows are lower
Q_VARIATION	10% exceedence flow divided by the 90% exceedence flow
Q50YIELD	50% exceedence flow/drainage area
Location	
LATITUDE	Latitude (decimal degrees, N)
LONGITUDE	Longitude (decimal degrees, W)
ECOREGION	Omernik's Level III ecoregions
Potential Groundwater Inputs	
R_DARCY	Average Darcy value, an index of potential groundwater movement with lower values indicating more groundwater potential, for an area 150 m wide, centered on channel
Land Use/Land Cover	
R_URBAN	% of riparian zone with urban land uses such as roads, residential,
R_AGR	% of riparian zone with agricultural land uses such as row crops, pasture, orchards, farm buildings, and feedlots
R_FOREST	% of riparian zone with forest land cover, excluding forested wetlands
WT_URBAN	% of entire watershed with urban land uses
WT_AGR	% of entire watershed with agricultural land uses

WT_FOREST	% of entire watershed with forest land cover

Bedrock and Surficial

W_BD0_50	% of watershed with bedrock at a depth of 50 ft or less
W_SHALE	% of watershed with shale bedrock
W_FINE	% of watershed with fine texture surficial geology
W_MEDIUM	% of watershed with medium texture surficial geology
W_COARSE	% of watershed with coarse texture surficial geology

Size

LINK	Shreve stream order
ORDER	Strahler stream order
DA_KM2	Drainage area of entire watershed, calculated in square kilometers

Table 2.4e. Fish species assemblages as defined by cluster analysis. Table is sorted by common name within each group.

	SPECIES CODE	COMMON NAME	SCIENTIFIC NAME	FAMILY
Group 1				
	BMS	Bigmouth shiner	Notropis dorsalis	Cyprinidae
	BLD	Blackside darter	Percina maculata	Percidae
	COS	Central stoneroller	Campostoma anomalum	Cyprinidae
	CRC	Creek chub	Semotilus atromaculatus	Cyprinidae
	GOR	Golden redhorse	Moxostoma erythrurum	Catostomidae
	HOC	Hornyhead chub	Nocomis biguttatus	Cyprinidae
	JOD	Johnny darter	Etheostoma nigrum	Percidae
	NHS	Northern hog sucker	Hypentelium nigricans	Catostomidae
	ORD	Orangethroat darter	Etheostoma spectabile	Percidae
	RES	Red shiner	Cyprinella lutrensis	Cyprinidae
	ROB	Rock bass	Ambloplites rupestris	Centrarchidae
	RYS	Rosyface shiner	Notropis rubellus	Cyprinidae
	SAS	Sand shiner	Notropis ludibundus	Cyprinidae
	SHR	Shorthead redhorse	Moxostoma macrolepidotum	Catostomidae
	SVR	Silver redhorse	Moxostoma anisurum	Catostomidae
	SMB	Smallmouth bass	Micropterus dolomieu	Centrarchidae
	STC	Stonecat	Noturus flavus	Ictaluridae
	STS	Striped shiner	Luxilus chrysocephalus	Cyprinidae
	SUM	Suckermouth minnow	Phenacobius mirabilis	Cyprinidae
	WHS	White sucker	Catostomus commersoni	Catostomidae
Group 2				
	BAD	Banded darter	Etheostoma zonale	Percidae
	BLR	Black redhorse	Moxostoma duquesnei	Catostomidae
	BRM	Brindled madtom	Noturus miurus	Ictaluridae
	DUD	Dusky darter	Percina sciera	Percidae
	ESD	Eastern sand darter	Etheostoma pellucidum	Percidae
	LOP	Logperch	Percina caprodes	Percidae
	RAD	Rainbow darter	Etheostoma caeruleum	Percidae
	SFS	Spotfin shiner	Cyprinella spiloptera	Cyprinidae
	SPB	Spotted bass	Micropterus punctulatus	Centrarchidae
	SDS	Spotted sucker	Minytrema melanops	Catostomidae
Group 3				
	BHC	Bighead carp	Aristichthys nobilis	Cyprinidae
	BLB	Black bullhead	Ameiurus melas	Ictaluridae
	BNS	Blacknose shiner	Notropis heterolepis	Cyprinidae
	CAP	Carp	Cyprinus carpio	Cyprinidae
	CCF	Channel catfish	Ictalurus punctatus	Ictaluridae
	CYM	Cypress minnow	Hybognathus hayi	Cyprinidae
	EMS	Emerald shiner	Notropis atherinoides	Cyprinidae
	FHM	Fathead minnow	Pimephales promelas	Cyprinidae
	FCF	Flathead catfish	Pylodictis olivaris	Ictaluridae

	FRD	Freshwater drum	Aplodinotus grunniens	Sciaenidae
	GZS	Gizzard shad	Dorosoma cepedianum	Clupeidae
	GOL	Goldeye	Hiodon alosoides	Hiodontidae
	GRC	Grass carp	Ctenopharyngodon idella	Cyprinidae
	HFC	Highfin carpsucker	Carpiodes velifer	Catostomidae
	LOG	Longnose gar	Lepisosteus osseus	Lepisosteidae
	NOP	Northern pike	Esox lucius	Esocidae
	ORS	Orangespotted sunfish	Lepomis humilis	Centrarchidae
	ULL	Quillback	Carpiodes cyprinus	Catostomidae
	RSF	Redear sunfish	Lepomis microlophus	Centrarchidae
	RVC	River carpsucker	Carpiodes carpio	Catostomidae
	SHD	Slenderhead darter	Percina phoxocephala	Percidae
	SAB	Smallmouth buffalo	Ictiobus bubalus	Catostomidae
	WAE	Walleye	Stizostedion vitreum	Percidae
	WES	Weed shiner	Notropis texanus	Cyprinidae
	WHB	White bass	Morone chrysops	Moronidae
	WHC	White crappie	Pomoxis annularis	Centrarchidae
Group 4				
	BAS	Banded sculpin	Cottus carolinae	Cottidae
	BKB	Black buffalo	Ictiobus niger	Catostomidae
	BLC	Black crappie	Pomoxis nigromaculatus	Centrarchidae
	BOW	Bowfin	Amia calva	Amiidae
	FLR	Flier	Centrarchus macropterus	Centrarchidae
	RBS	Ribbon shiner	Lythrurus fumeus	Cyprinidae
	STD	Stripetail darter	Etheostoma kennicotti	Percidae
	TPM	Tadpole madtom	Noturus gyrinus	Ictaluridae
Group 5				
	BST	Blackspotted topminnow	Fundulus olivaceus	Cypriodontidae
	BLT	Blackstripe topminnow	Fundulus notatus	Cypriodontidae
	BLG	Bluegill	Lepomis macrochirus	Centrarchidae
	BRS	Brook silverside	Labidesthes sicculus	Atherinidae
	CCS	Creek chubsucker	Erimyzon oblongus	Catostomidae
	GRP	Grass pickerel	Esox americanus	Esocidae
	LMB	Largemouth bass	Micropterus salmoides	Centrarchidae
	LOS	Longear sunfish	Lepomis megalotis	Centrarchidae
	MOF	Mosquitofish	Gambusia affinis	Poeciliidae
	PRP	Pirate perch	Aphredoderus sayanus	Percopsidae
	RDS	Redfin shiner	Lythrurus umbratilus	Cyprinidae
	SJM	Silverjaw minnow	Notropis buccatus	Cyprinidae
	SES	Steelcolor shiner	Cyprinella whipplei	Cyprinidae
	YEB	Yellow bullhead	Ameiurus natalis	Ictaluridae
Group 6				
	BKD	Blacknose dace	Rhinichthys atratulus	Cyprinidae
	CMS	Common shiner	Luxilius cornutus	Cyprinidae
	FAD	Fantail darter	Etheostoma flabellare	Percidae

	LSS	Largescale stoneroller	Campostoma oligolepis	Cyprinidae
Group 7				
	OZM	Ozark minnow	Notropis nubilus	Cyprinidae
	SRD	Southern redbelly dace	Phoxinus erythrogaster	Cyprinidae
Group 8				
	MMS	Mimic shiner	Notropis volucellus	Cyprinidae
	RVS	River shiner	Notropis blennius	Cyprinidae

Table 2.4f. Results of CART analysis of the fish assemblage cluster dataset. Four of the original seven clusters lacked sufficient representation in the dataset for CART analysis; thus only three assemblages were modeled using CART. The CART model is portrayed as a dichotomous key. For each leaf in the model, N indicates the number of sites within that leaf. Parentheses are used to identify the number of sites with each assemblage type in that leaf. The total misclassification rate for the model is 25%.

1a. ECOREGION $\leq$ 63.000 **Go to 2.**

  2a. GRADIENT $\leq$ 0.001 **Go to 3.**

    3a. QVARIATION $\leq$ 192.859 **Go to 4.**

      4a. WT_URBAN $\leq$ 1.495; N=37 (1=19, 2=1, 5=17)

      4b. WT_URBAN > 1.495; N=21 (1=17, 2=3, 5=1)

    3b. QVARIATION > 192.859; N=43 (1=38, 2=3, 5=2)

  2b. GRADIENT > 0.001; N=146 (1=139, 2=3, 5=4)

1b. ECOREGION **>** 63.000 **Go to 5.**

  5a. QANN50_CMS $\leq$ 0.287; N=111 (1=29, 2=78, 5=4)

  5b. QANN50_CMS > 0.287 **Go to 6.**

    6a. W_SHALE $\leq$ 87.555; N=30 (1=18, 2=2, 5=10)

    6b. W_SHALE > 87.555 **Go to 7.**

      7a. R_FOREST $\leq$ 20.460; N=7 (1=4, 2=1, 5=2)

      7b. R_FOREST > 20.460; N=35 (1=16, 2=18, 5=1)

Table 2.4g. Results of CART analysis of Striped shiner presence/absence dataset. The CART model is portrayed as a dichotomous key. For each leaf in the model, N indicates the number of sites within that leaf. Parentheses are used to identify the number of sites where the species is present or absence in that leaf. The total misclassification rate for the model is 19%.

1a. WT_FOREST $\leq$ 6.500 **Go to 2.**

- 2a. LATITUDE $\leq$ 41.500 **Go to 3.**

  - 3a. LONGITUDE $\leq$ -90.500; N=11 (0=9, 1=2)

  - 3b. LONGITUDE > -90.500; N=152 (0=24, 1=128)

- 2b. LATITUDE > 41.500 **Go to 4.**

  - 4a. WT_AGR $\leq$ 76.000; N=17 (0=17, 1=0)

  - 4b. WT_AGR > 76.000; N=18 (0=8, 1=10)

1b. WT_FOREST >6.500; N=243 (0=212, 1=31)

Table 2.4h. Results of CART analysis of Longear sunfish presence/absence dataset. The CART model is portrayed as a dichotomous key. For each leaf in the model, N indicates the number of sites within that leaf. Parentheses are used to identify the number of sites where the species is present or absence in that leaf. The total misclassification rate for the model is 17%.

1a. LONGITUDE ≤ -89.500; N=152 (0=136, 1=16)

1b. LONGITUDE > -89.500 **Go to 2.**

  2a. LATITUDE ≤ 41.500 **Go to 3.**

    3a. W_BDO_50 ≤ 1.500 **Go to 4.**

      4a. R_FOREST ≤ 67.000 **Go to 5.**

        5a. QANN50_YLD ≤ 0.003; N=37 (0=6, 1=31)

        5b. QANN50_YLD > 0.003 **Go to 6.**

          6a. LINK ≤ 40.500; N=29 (0=9, 1=20)

          6b. LINK > 40.500; N=11 (0=10, 1=1)

      4b. R_FOREST > 67.000; N=13 (0=10, 1=3)

    3b. W_BDO_50 > 1.500; N=162 (0=18, 1=144)

  2b. LATITUDE > 41.500; N=37 (0=37, 1=0)

Table 2.4i. Results of CART analysis of Smallmouth bass presence/absence dataset. The CART model is portrayed as a dichotomous key. For each leaf in the model, N indicates the number of sites within that leaf. Parentheses are used to identify the number of sites where the species is present or absence in that leaf. The total misclassification rate for the model is 26%.

1a. LATITUDE ≤ 39.500; N=166 (0=164, 1=2)

1b. LATITUDE > 39.500 **Go to 2.**

2a. DA_KM2 ≤ 73.000; N=44 (0=34, 1=10)

2b. DA_KM2 > 73.000 **Go to 3.**

3a. LATITUDE ≤ 40.500 **Go to 4.**

4a. QANN50_YLD ≤ 0.002; N=12 (0=11, 1=1)

4b. QANN50_YLD > 0.002 **Go to 5.**

5a. W_FINE ≤ 58.500 **Go to 6.**

6a. QANN50_YLD ≤ 0.003; N=12 (0=11, 1=1)

6b. QANN50_YLD > 0.003 **Go to 7.**

7a. WT_URBAN ≤ 7.000 **Go to 8.**

8a. WT_AGR ≤ 85.000; N=18 (0=4, 1=14)

8b. WT_AGR > 85.000; N=13 (0=11, 1=2)

7b. WT_URBAN > 7.000; N=6 (0=6, 1=0)

5b. W_FINE > 58.500; N=18 (0=5, 1=13)

3b. LATITUDE > 40.500; N=152 (0=48, 1=104)

Table 2.4j. Results of CART analysis of Creek chubsucker presence/absence dataset. The CART model is portrayed as a dichotomous key. For each leaf in the model, N indicates the number of sites within that leaf. Parentheses are used to identify the number of sites where the species is present or absence in that leaf. The total misclassification rate for the model is 20%.

1a. LATITUDE ≤ 39.500 **Go to 2.**

2a. LONGITUDE ≤ -89.500 **Go to 3.**

3a. WT_URBAN ≤ 0.500; N=6 (0=3, 1=3)

3b. WT_URBAN > 0.500; N=29 (0=29, 1=0)

2b. LONGITUDE > -89.500; N=131 (0=65, 1=66)

1b. LATITUDE > 39.500 **Go to 4.**

4a. W_FINE ≤ 99.500 **Go to 5.**

5a. QVARIATION ≤ 7020.190; N=257 (0=253, 1=4)

5b. QVARIATION > 7020.190; N=7 (0=3, 1=4)

4b. W_FINE > 99.500; N=11 (0=6, 1=5)

Table 2.4k. Results of CART analysis of Hornyhead chub presence/absence dataset. The CART model is portrayed as a dichotomous key. For each leaf in the model, N indicates the number of sites within that leaf. Parentheses are used to identify the number of sites where the species is present or absence in that leaf. The total misclassification rate for the model is 21%.

1a. LATITUDE ≤ 39.500; N=166 (0=164, 1=2)

1b. LATITUDE > 39.500 **Go to 2.**

2a. DA_KM2 ≤ 284.500; N=275 (0=90, 1=185)

2b. DA_KM2 > 284.500 **Go to 3.**

3a. R_AGR ≤ 5.500; N=15 (0=13, 1=2)

3b. R_ARG > 5.500; N=61 (0=30, 1=31)

Table 2.4l. Results of CART analysis of Fantail darter presence/absence dataset. The CART model is portrayed as a dichotomous key. For each leaf in the model, N indicates the number of sites within that leaf. Parentheses are used to identify the number of sites where the species is present or absence in that leaf. The total misclassification rate for the model is 29%.

1a. LATITUDE ≤ 39.500 **Go to 2.**

    2a. SLOPE ≤ 5.500; N=159 (0=157, 1=2)

    2b. SLOPE > 5.500; N=7 (0=4, 1=3)

1b. LATITUDE > 39.500 **Go to 3.**

    3a. QANN50_CMS ≤ 1.007 **Go to 4.**

        4a. R_AGR ≤ 39.000 **Go to 5.**

            5a. W_SHALE ≤ 84.000; N=58 (0=26, 1=32)

            5b. W_SHALE > 84.000 **Go to 6.**

                6a. LONGITUDE ≤ -89.500; N=39 (0=37, 1=2)

                6b. LONGITUDE > -89.500; N=60 (0=36, 1=24)

        4b. R_AGR > 39.000 **Go to 7.**

            7a. R_FOREST ≤ 0.500; N=10 (0=6, 1=4)

            7b. R_FOREST > 0.500; N=47 (0=45, 1=2)

    3b. QANN50_CMS > 1.007 **Go to 8.**

        8a. WT_FOREST ≤ 11.500; N=56 (0=55, 1=1)

        8b. WT_FOREST > 11.500; N=5 (0=2, 1=3)

Table 2.4m. Comparison of CART results for individual fish species based on presence/absence data. A misclassification of commission (COM) indicates that the model predicted the species to be present but it was actually absent, whereas omission (OM) indicates the models predicted the species to be absent but it was actually present. The predictor variables are listed in order of entry into the model; variables separated by a backslash entered at the same level but at different branches in the tree.

		% Misclassification			
Species	Sites Present	Total	COM	OM	Predictor Variables
Striped shiner	171	19	10	9	WT_FOREST, LATITUDE, LONGITUDE/WT_AGR
Longear sunfish	215	17	13	4	LONGITUDE, LATITUDE, W_BDO_50, R_FOREST, QANN50_YLD, LINK
Smallmouth bass	147	26	21	5	LATITUDE, DA_KM2, LATITUDE, QANN50_YLD, W_FINE, QANN50_YLD, WT_URBAN, WT_AGR
Creek Chubsucker	82	20	17	3	LATITUDE, LONGITUDE/W_FINE, WT_URBAN/QVARIATION
Hornyhead chub	187	21	15.6	5.7	LATITUDE, DA_KM2, R_AGR
Fantail darter	73	27	21	6	LATITUDE, SLOPE/ QANN50_CMS, R_AGR/ WT_FOREST, W_SHALE/ R_FOREST, LONGITUDE

Table 4.4a. Potential change in annual median discharge and mean July temperature based on model output from the LTM 2025 for the Kaskaskia River basin.

Model Assessed Median Discharge	**Percent change between models.**					
	< 1 %	**< 5 %**	**< 10 %**	**< 25 %**	**< 50 %**	**> 50 %**
% of stream segments	21.0	43.8	62.6	89.6	95.9	4.1

July Mean Daily (C)	**Magnitude of change between models.**				
	< 0.1	**< 0.5**	**< 1**	**< 1.5**	**> 1.5**
% of stream segments	58.3	97.7	99.8	100.0	0.0

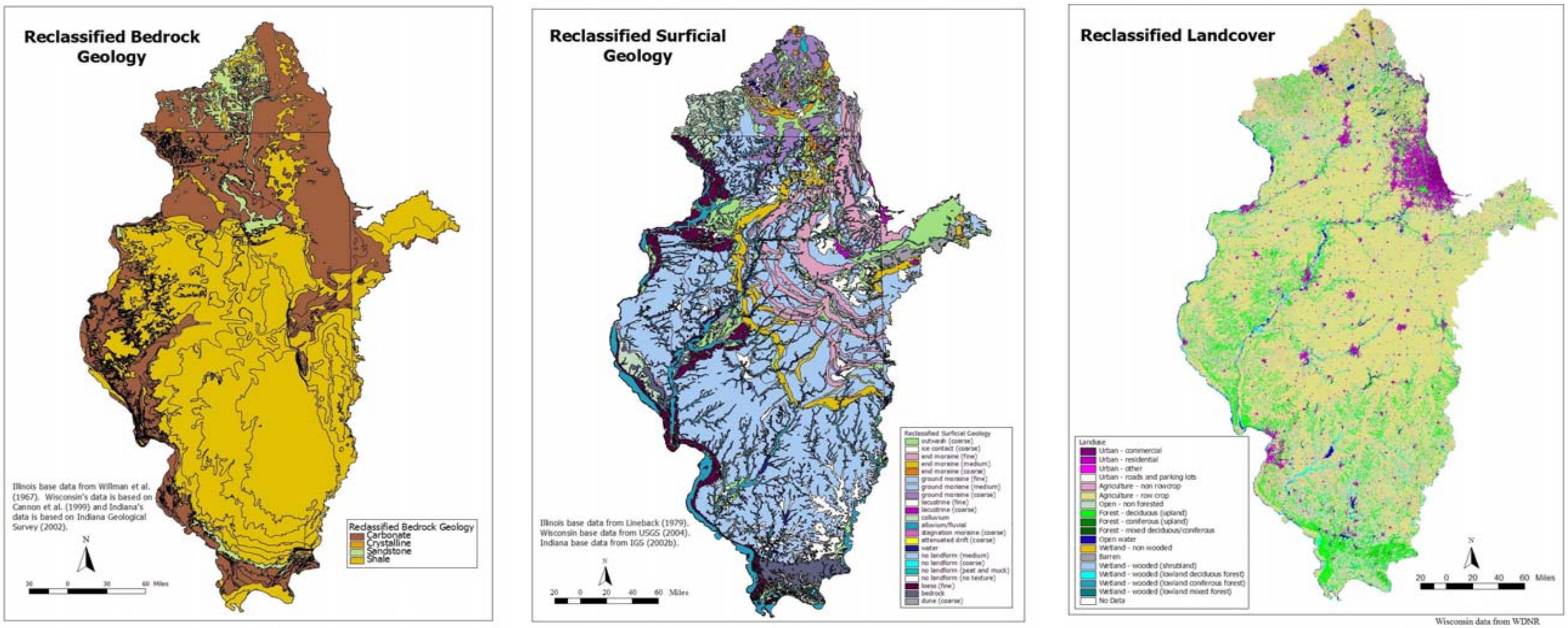

Figure 2.4a. Map-based summaries were derived from existing data and used to populate stream reaches using a GIS system. Summaries of bedrock geology, surficial geology, landcover, digital elevation, and meteorological data (e.g., air temperature, growing degree days, precipitation) were incorporated by attributing these data to individual stream reaches.

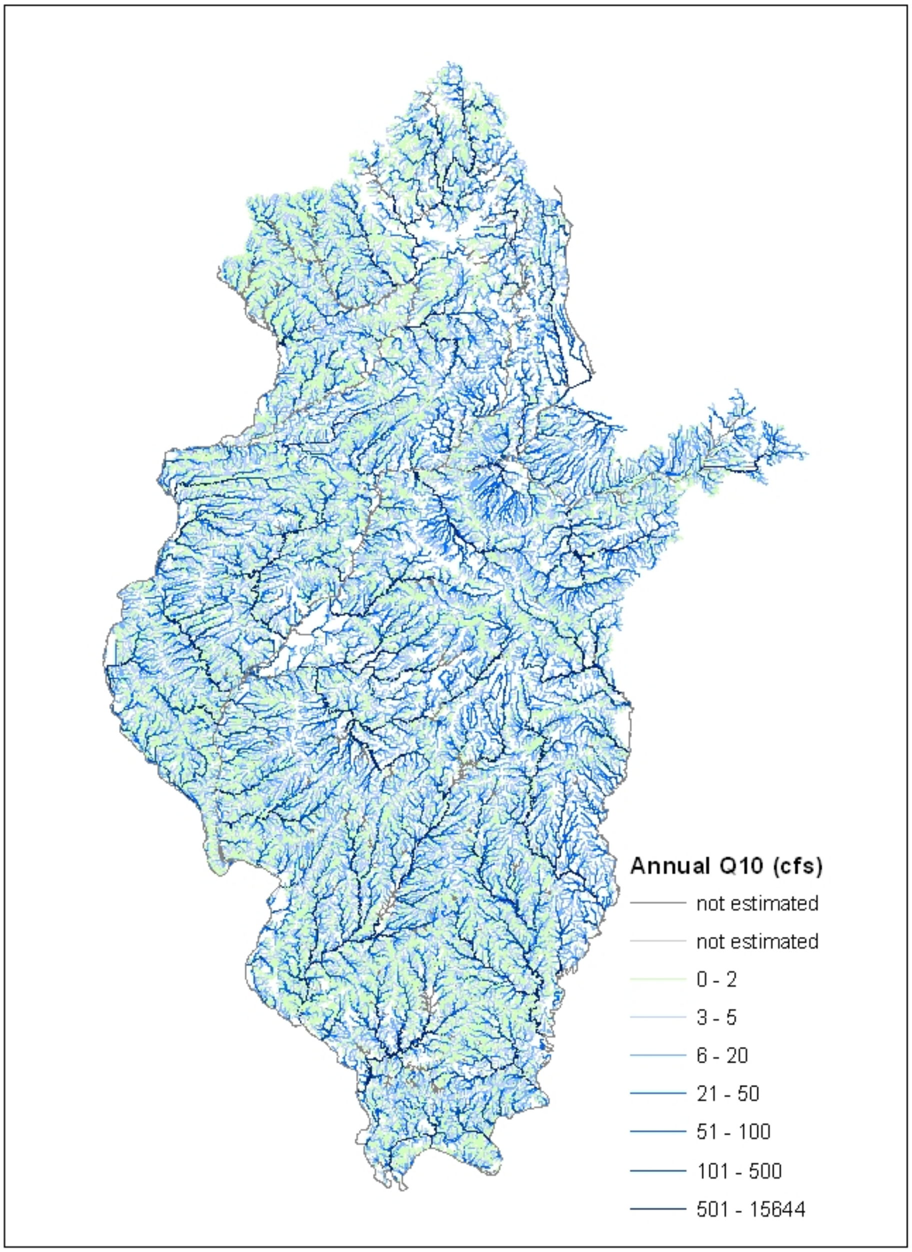

Figure 2.4b. Annual High Flow Discharge based on model output.

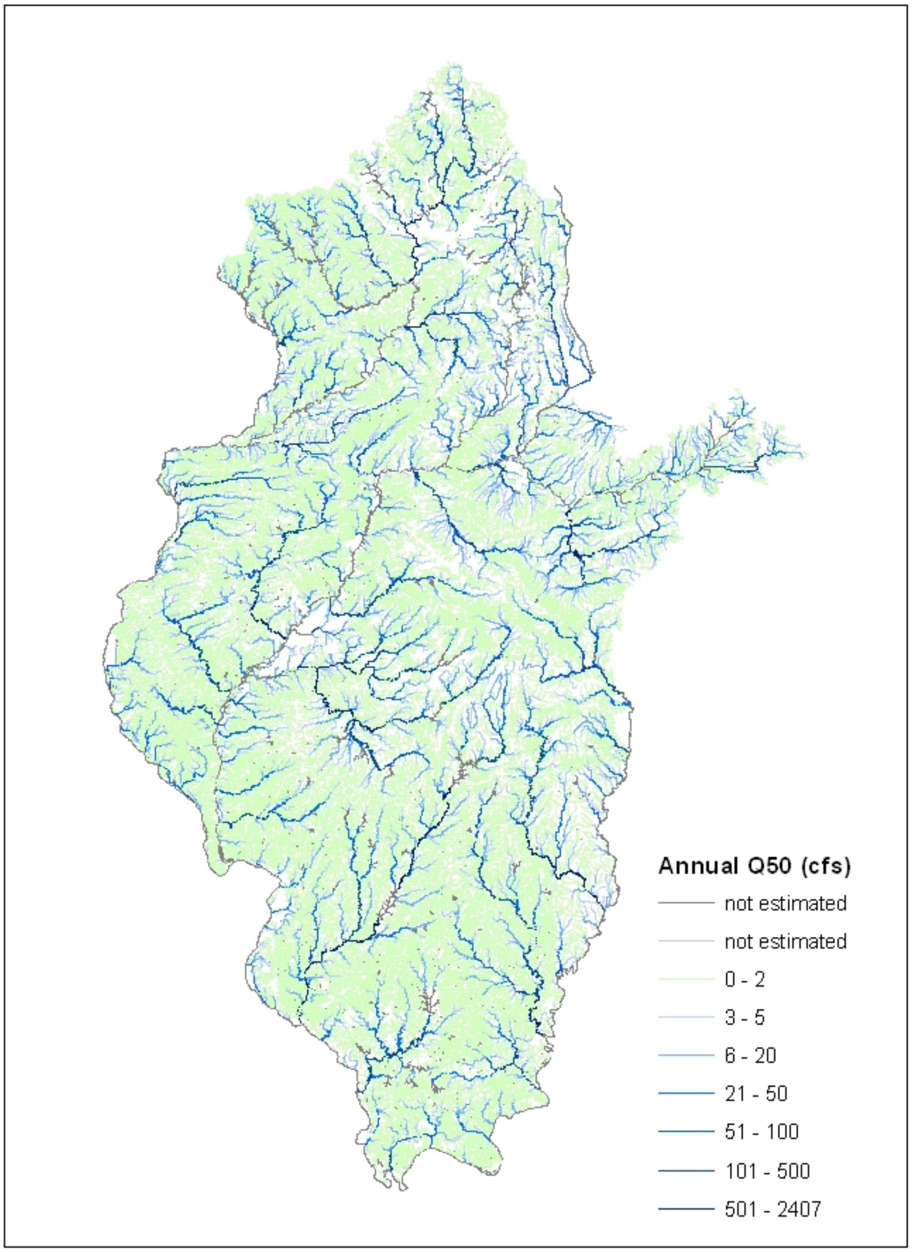

Figure 2.4c. Median Annual Discharge based on model output.

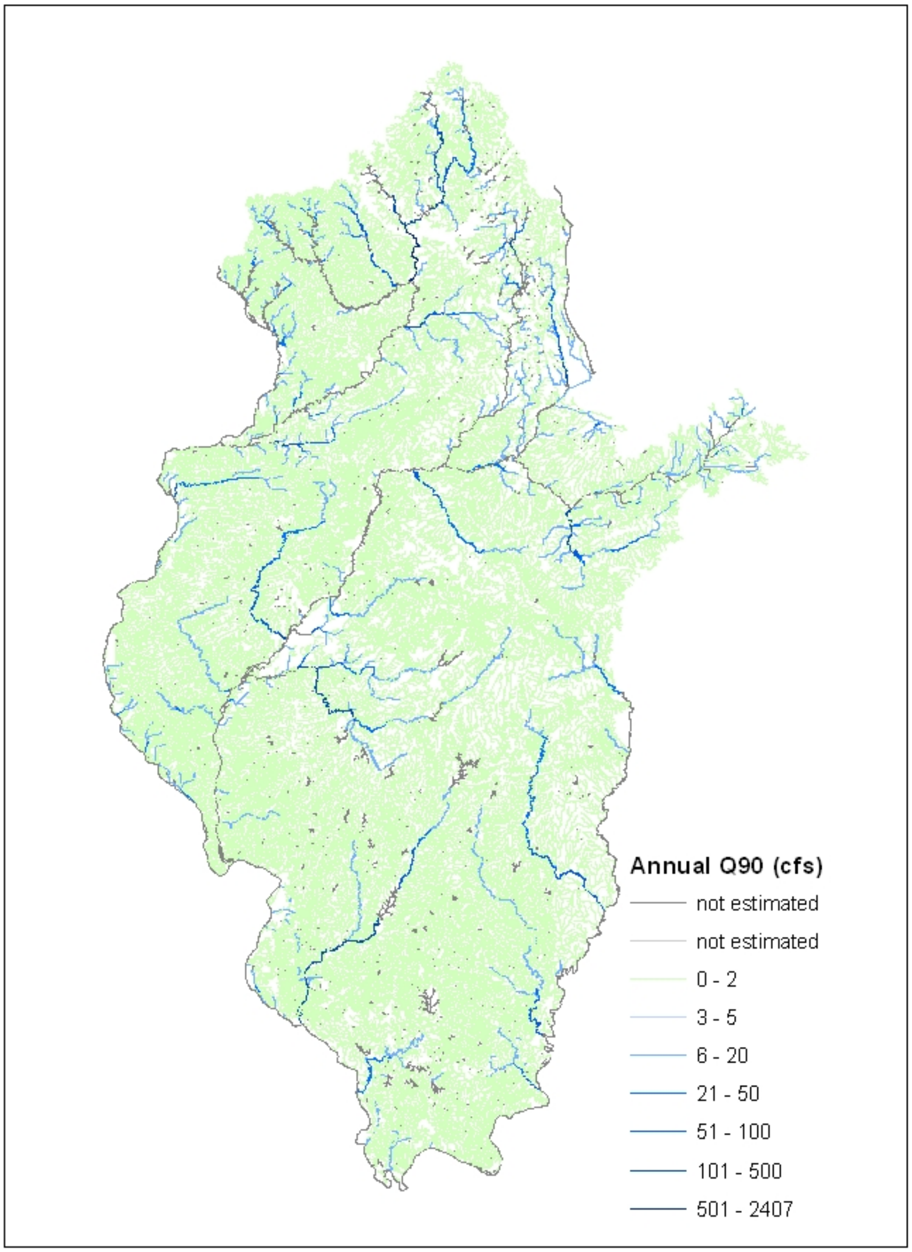

Figure 2.4d. Annual Low Flow Discharge based on model output.

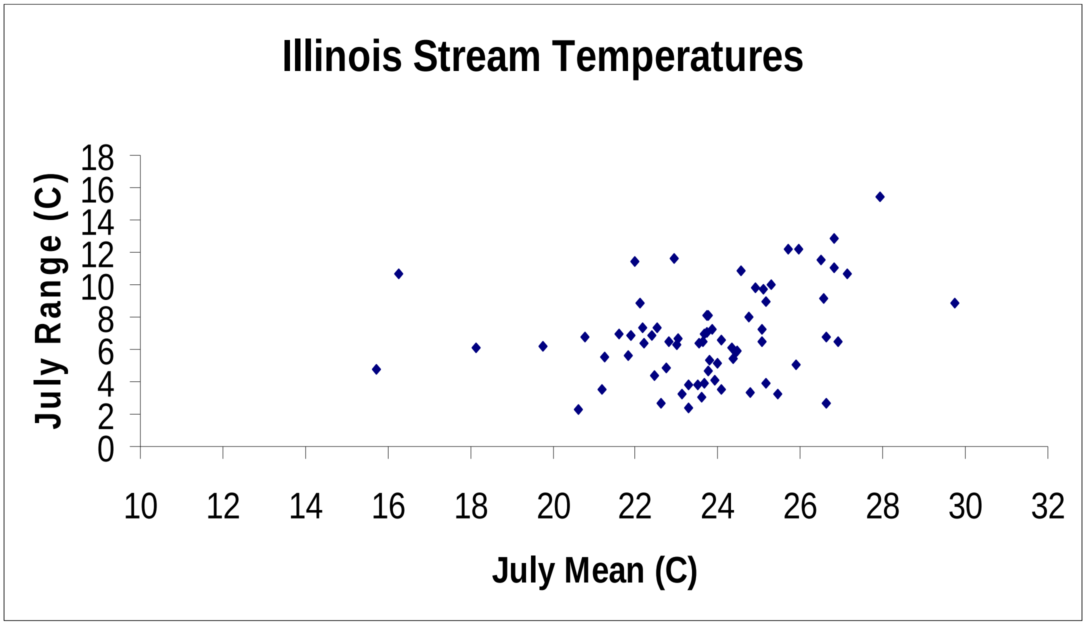

Figure 2.4e. Summer stream temperatures from loggers records collected 1999 – 2005 throughout Illinois. Each point provides a summary of an individual site that collectively illustrate the wide range of thermal conditions that exist within the wadeable streams of Illinois.

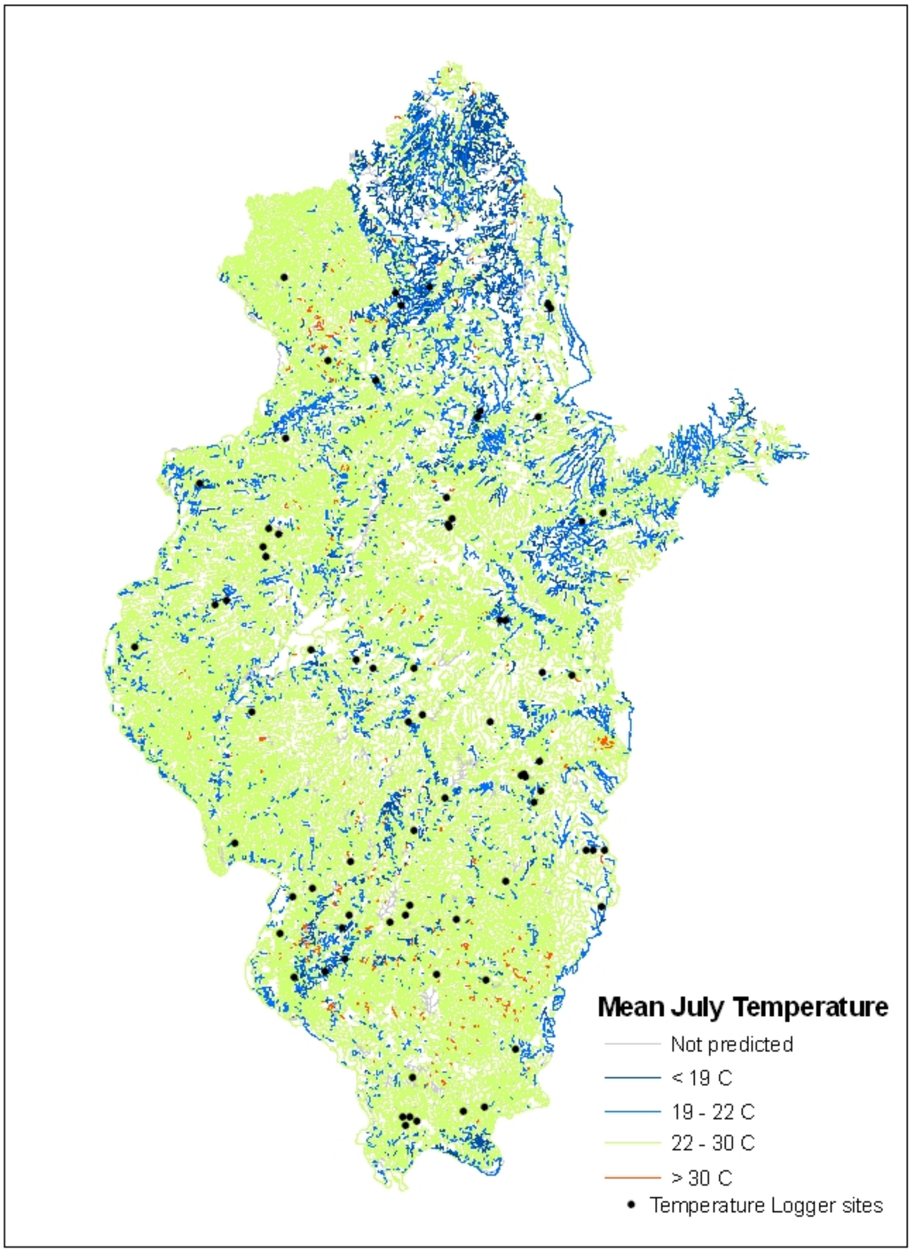

Figure 2.4f. Summer Stream Temperatures based on model output.

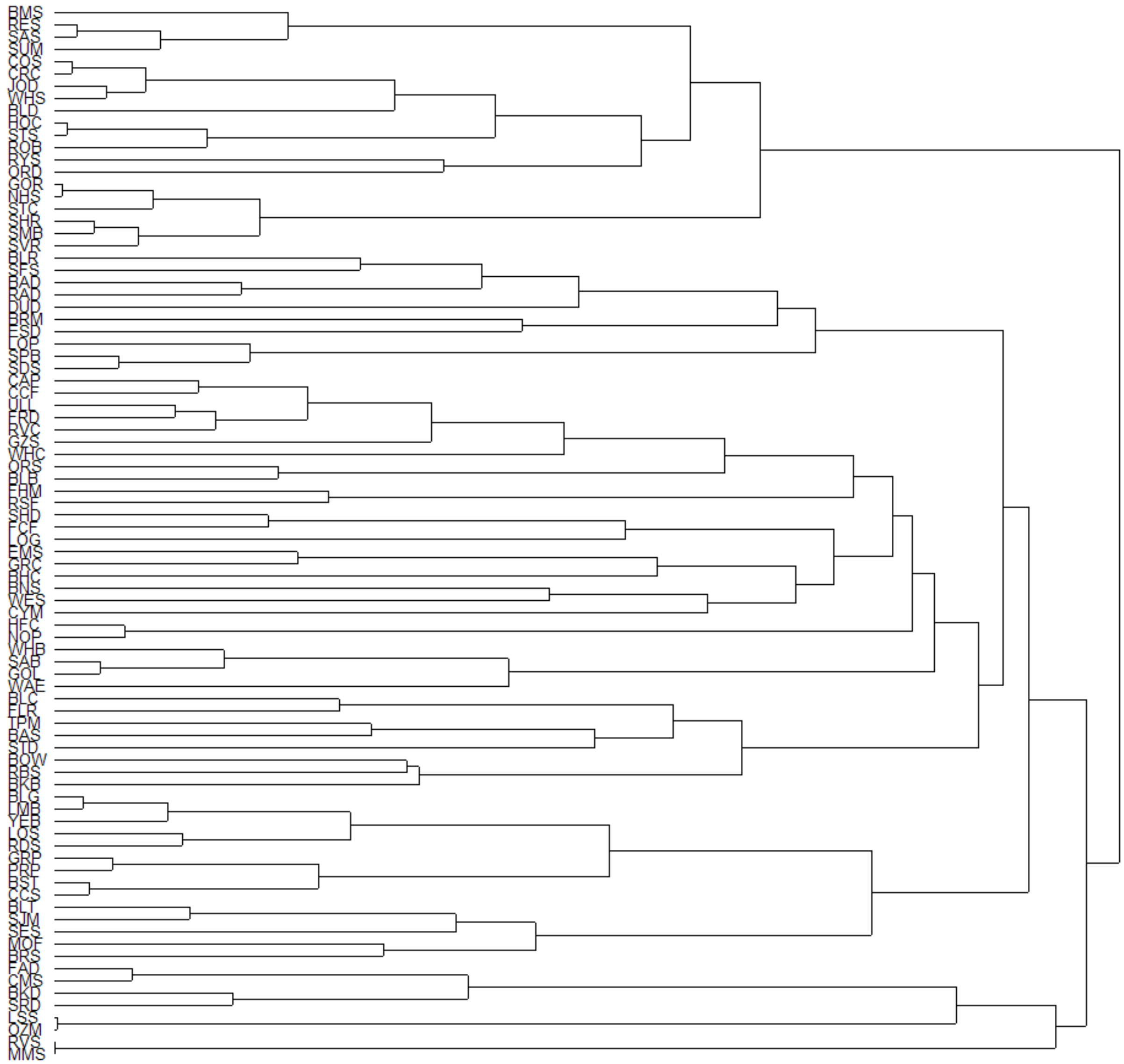

Figure 2.4g. Dendrogram resulting from cluster analysis carried out in PC-ORD.

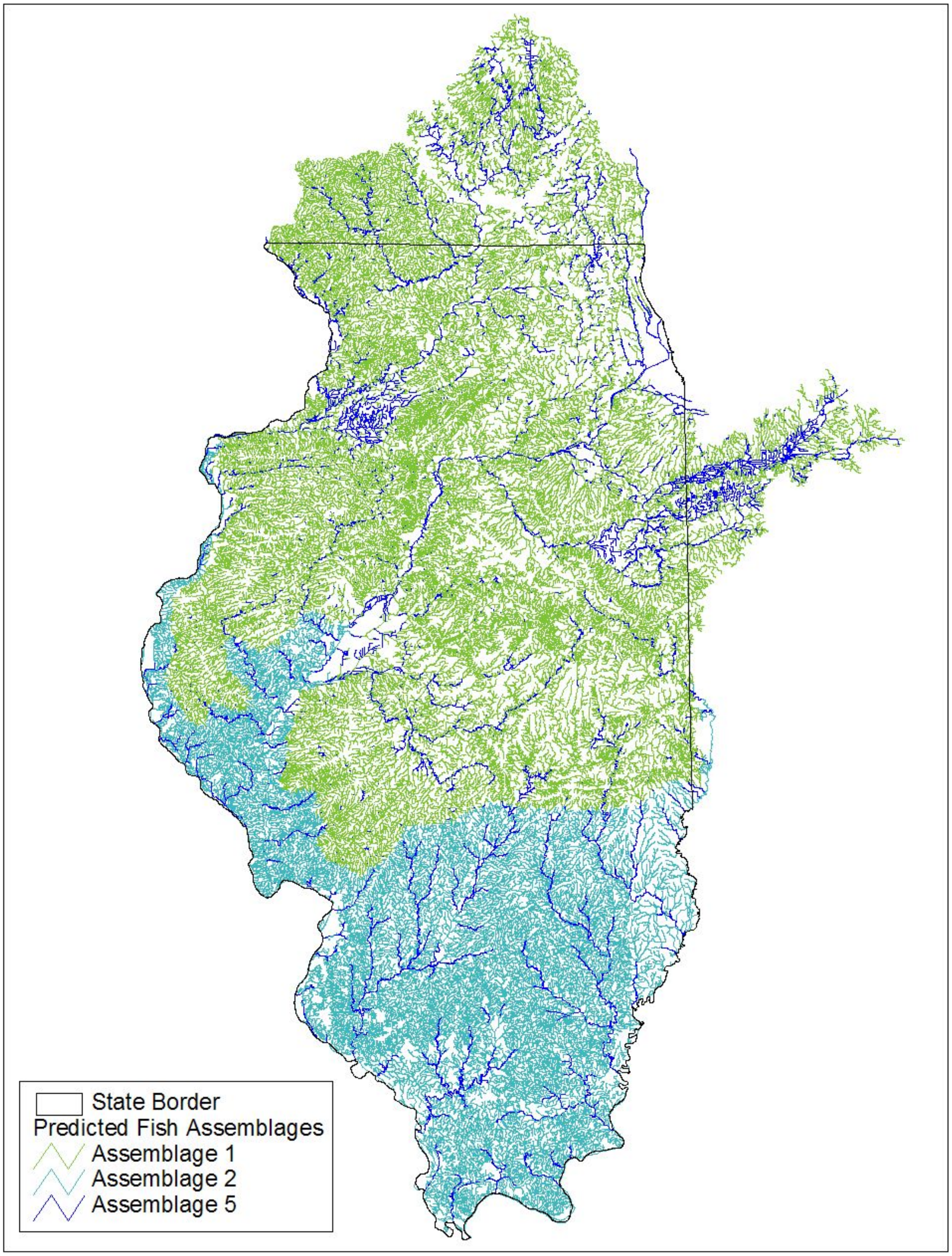

Figure 2.4h. Fish assemblages based on CART-derived model output. Only three assemblages, which are described in Table 2.4e, contained sufficient members for modeling.

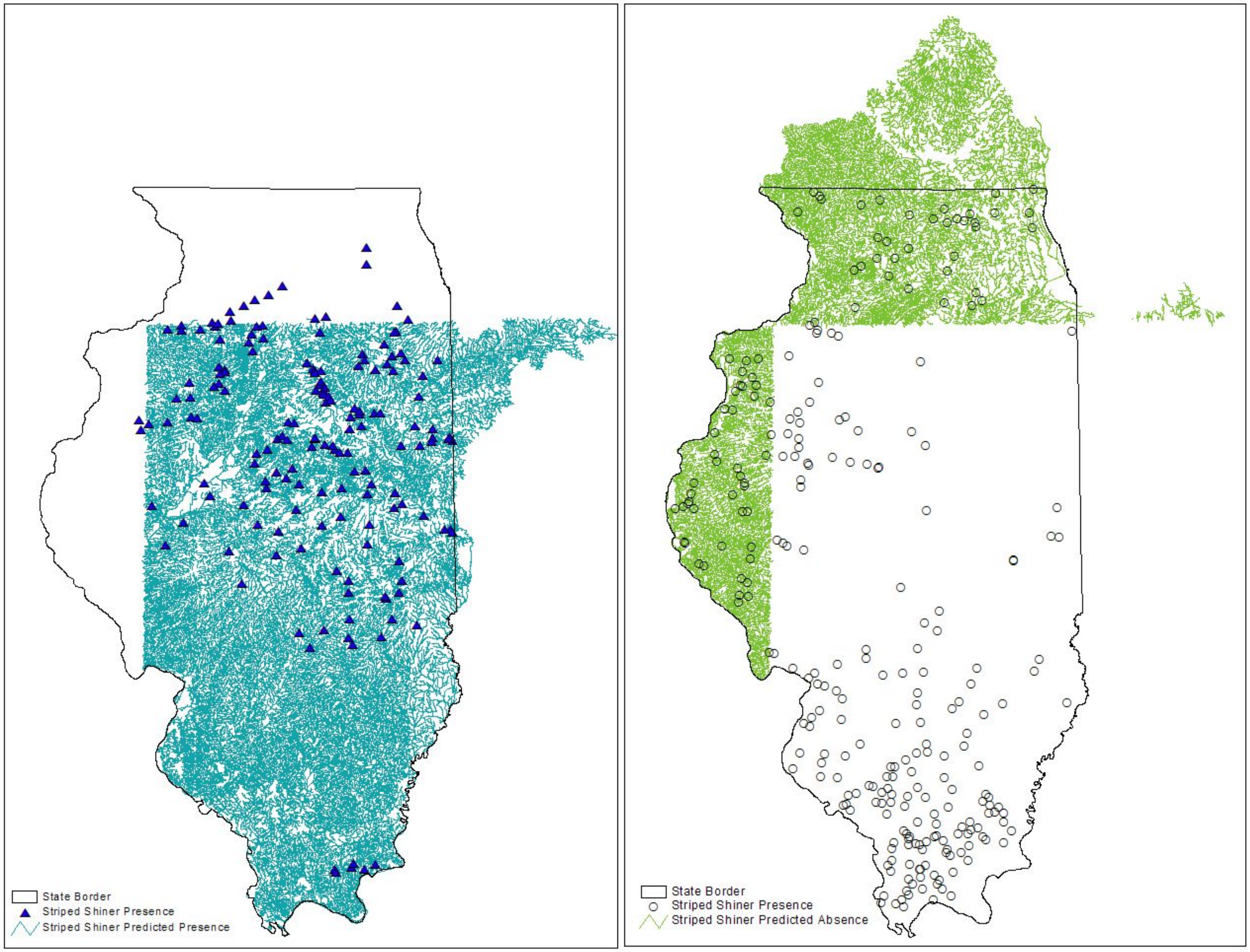

Figure 2.4i. Known presence and absence of Striped shiner compared to predicted presence and absence of the species.

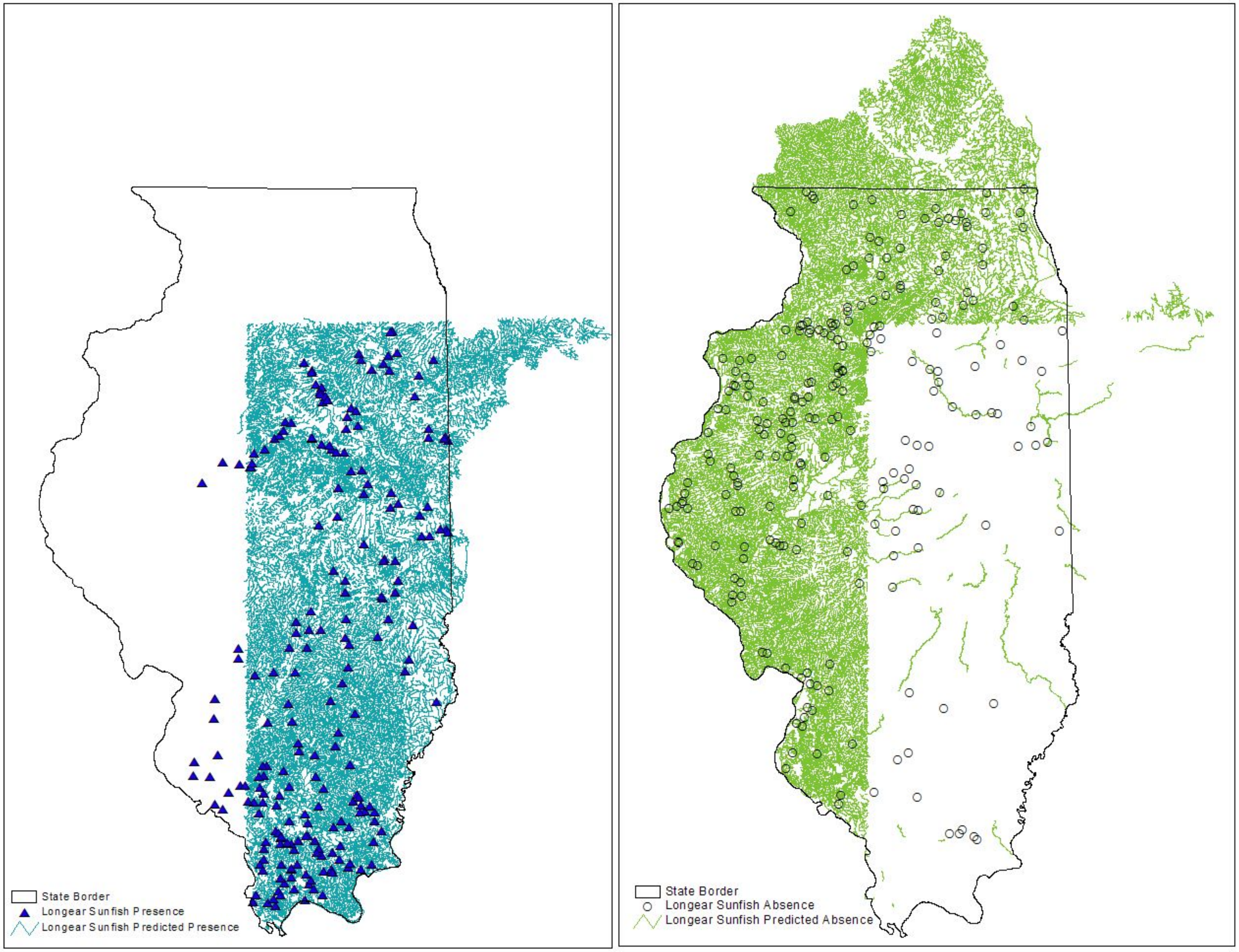

Figure 2.4j. Known presence and absence of Longear sunfish compared to predicted presence and absence of the species.

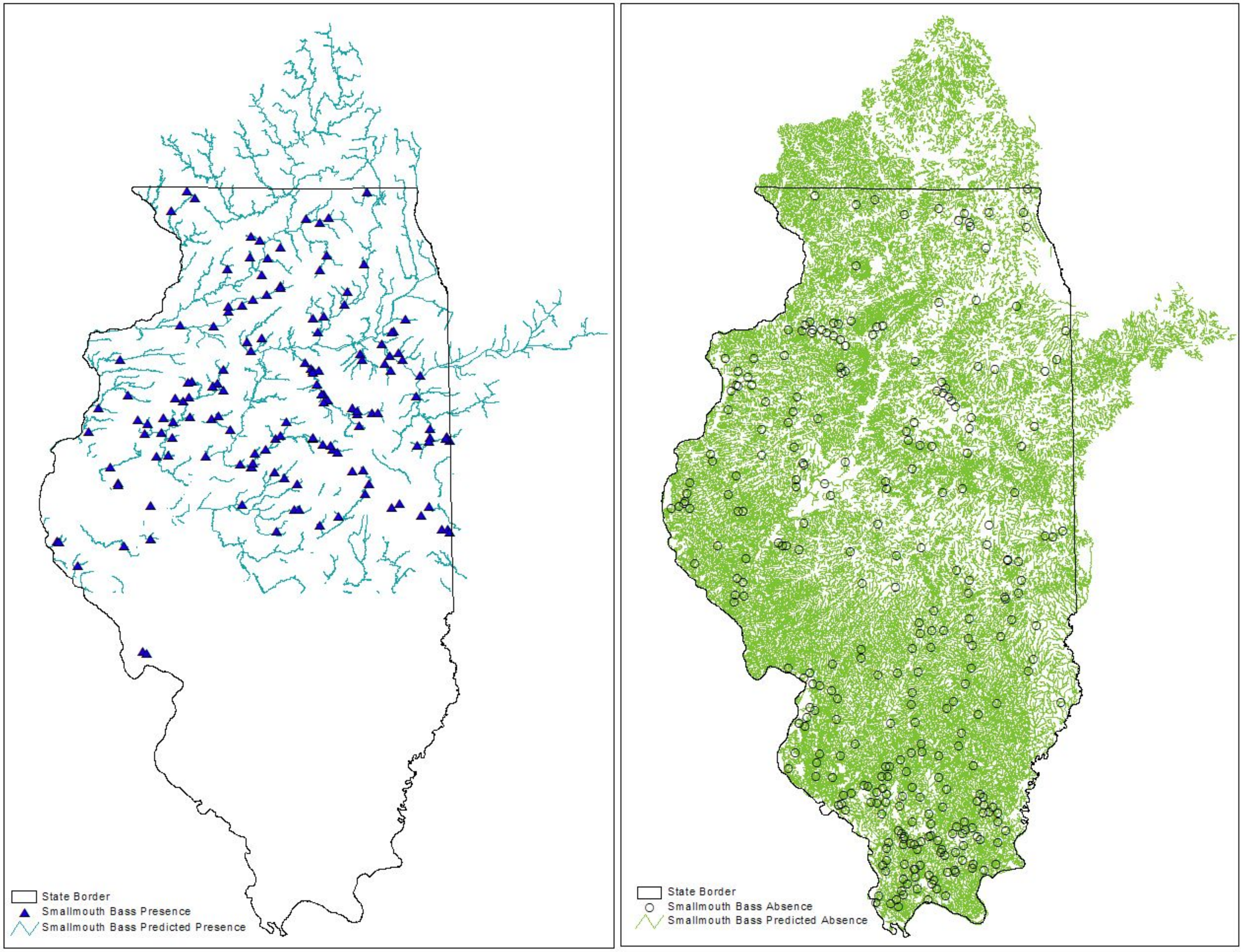

Figure 2.4k. Known presence and absence of Smallmouth bass compared to predicted presence and absence of the species.

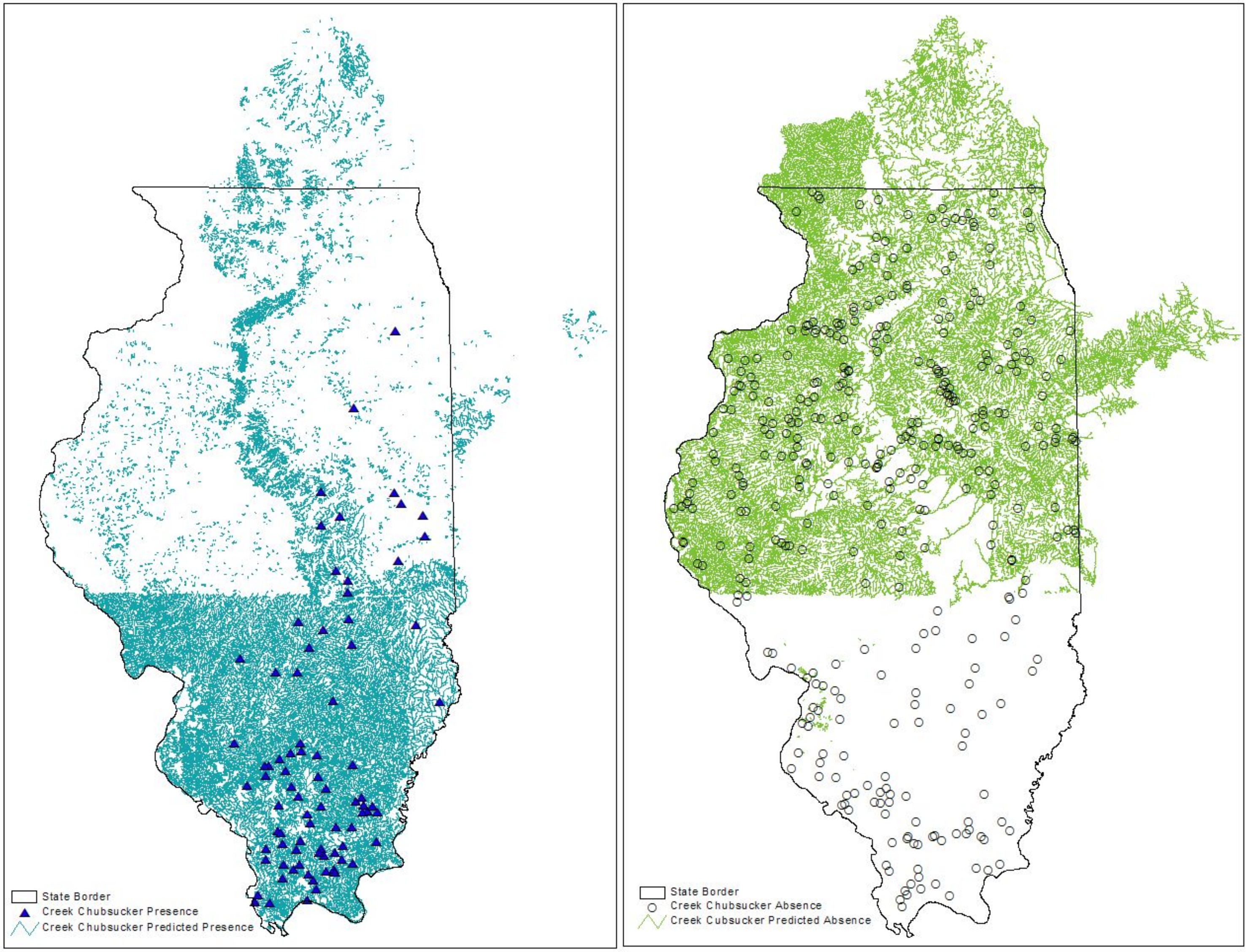

Figure 2.4l. Known presence and absence of Creek chubsucker compared to predicted presence and absence of the species.

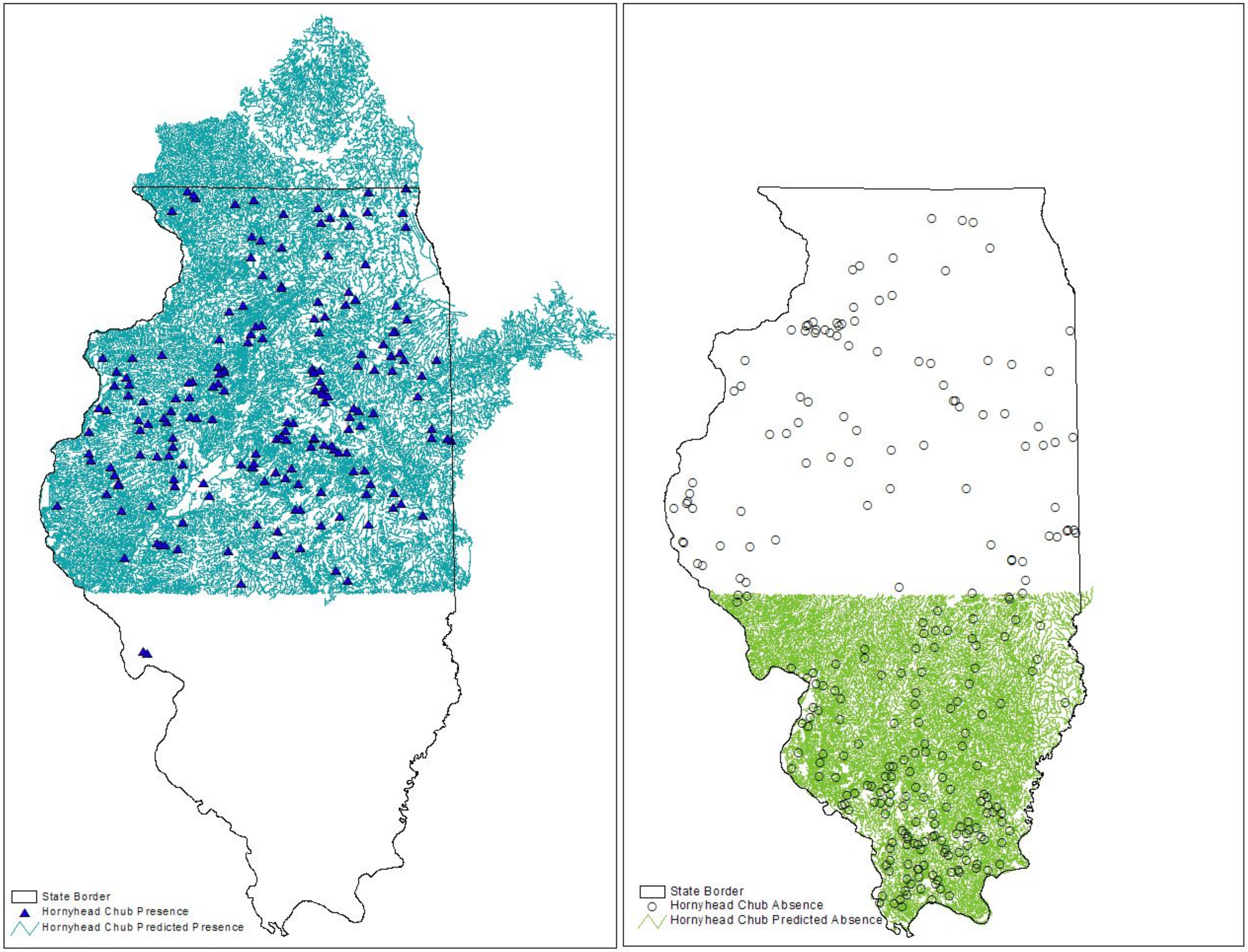

Figure 2.4m. Known presence and absence of Hornyhead chub compared to predicted presence and absence of the species.

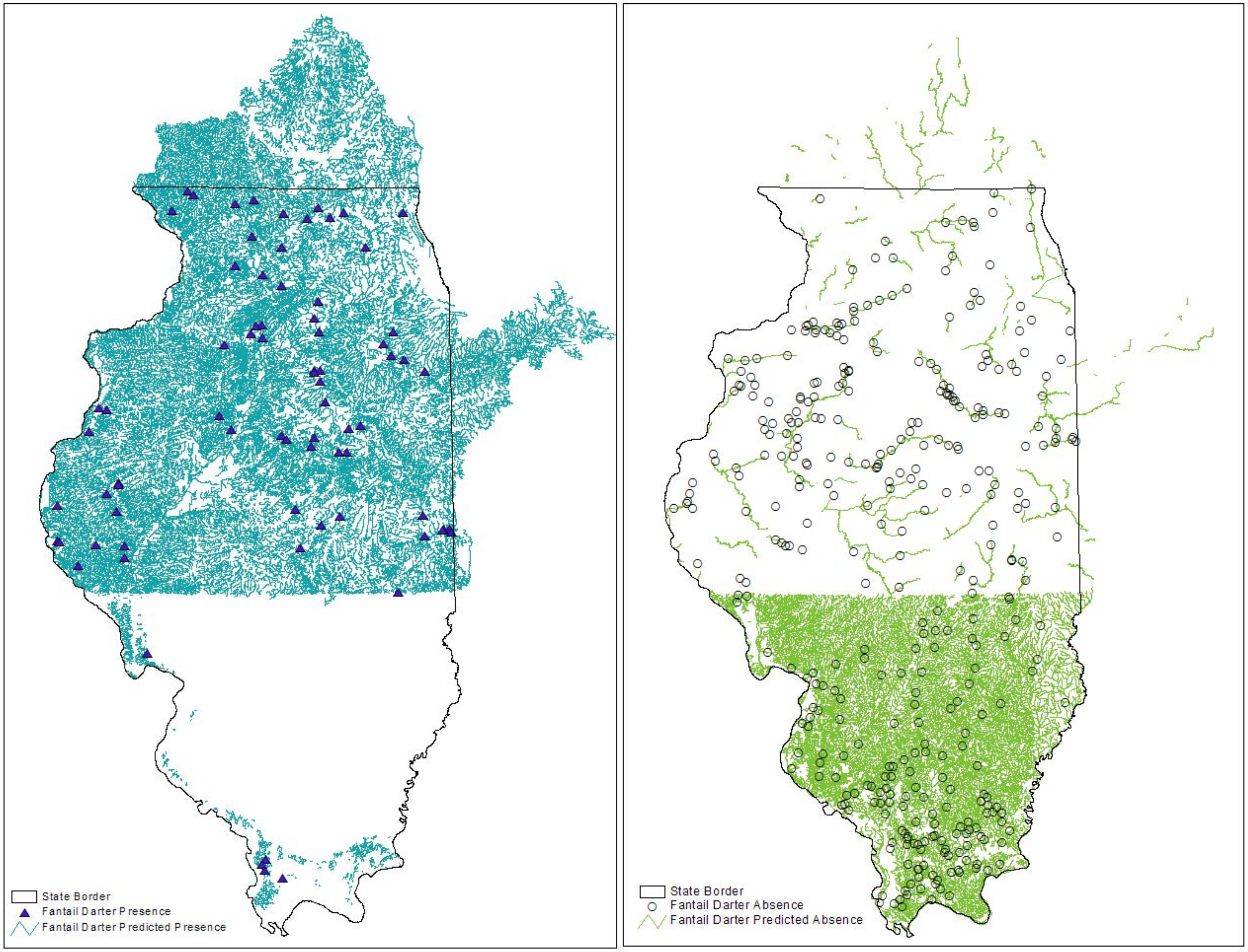

Figure 2.4n. Known presence and absence of Fantail darter compare to predicted presence and absence of the species.

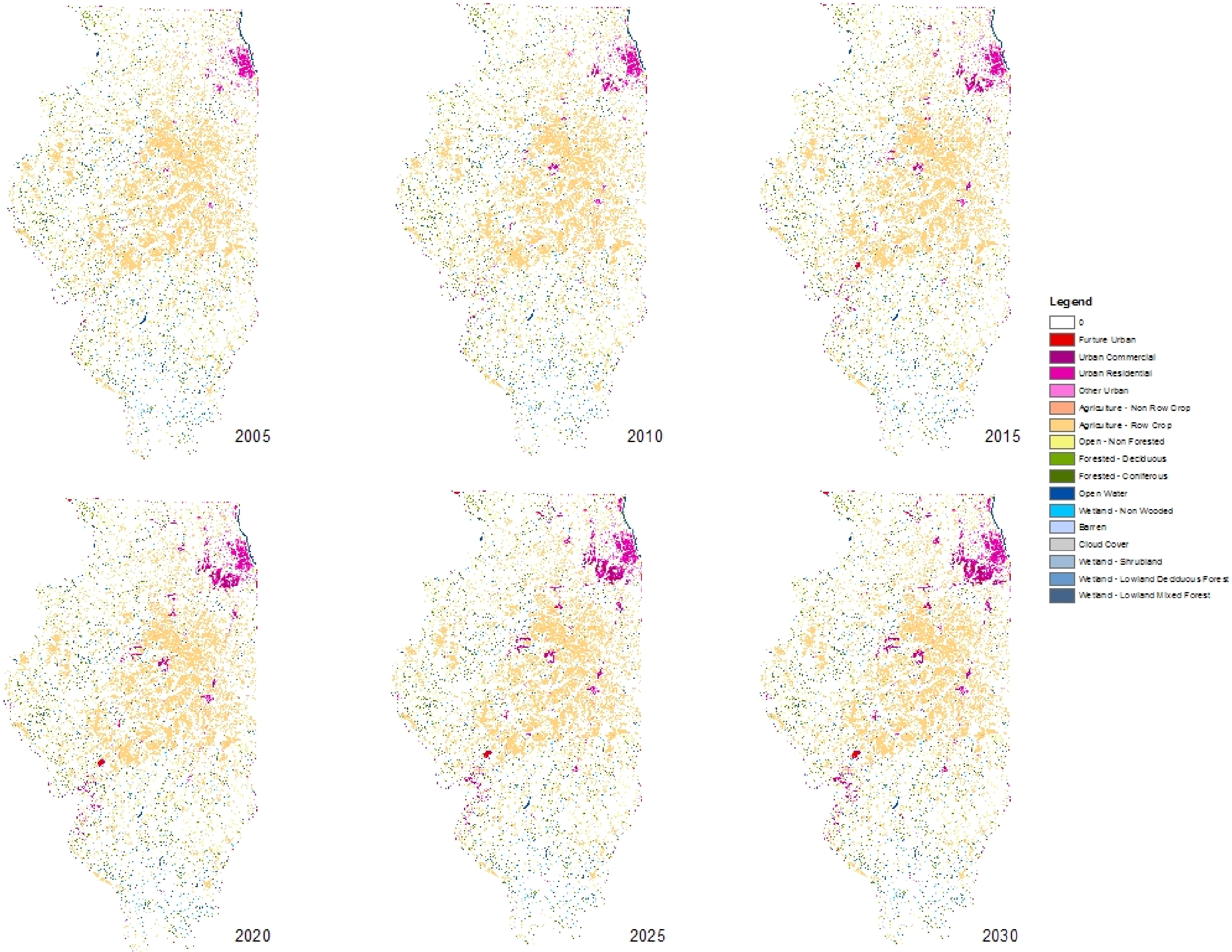

Figure 4.4a. Potential future scenarios based on a land transformation model developed by Bryan Pijanowski, Ph.D.

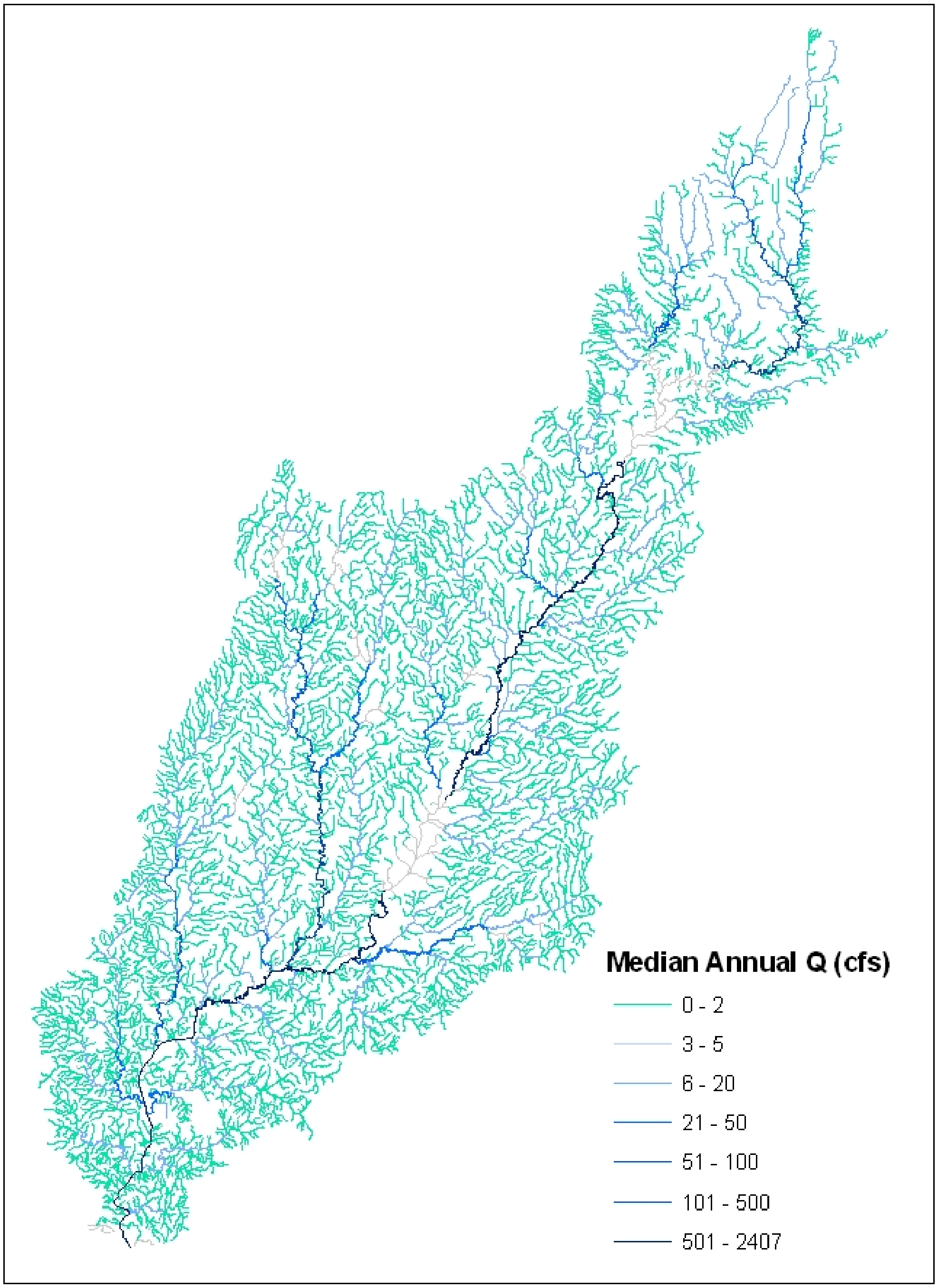

Figure 4.4b. Kaskaskia River median annual discharge estimates based on MLR output for recent landcover.

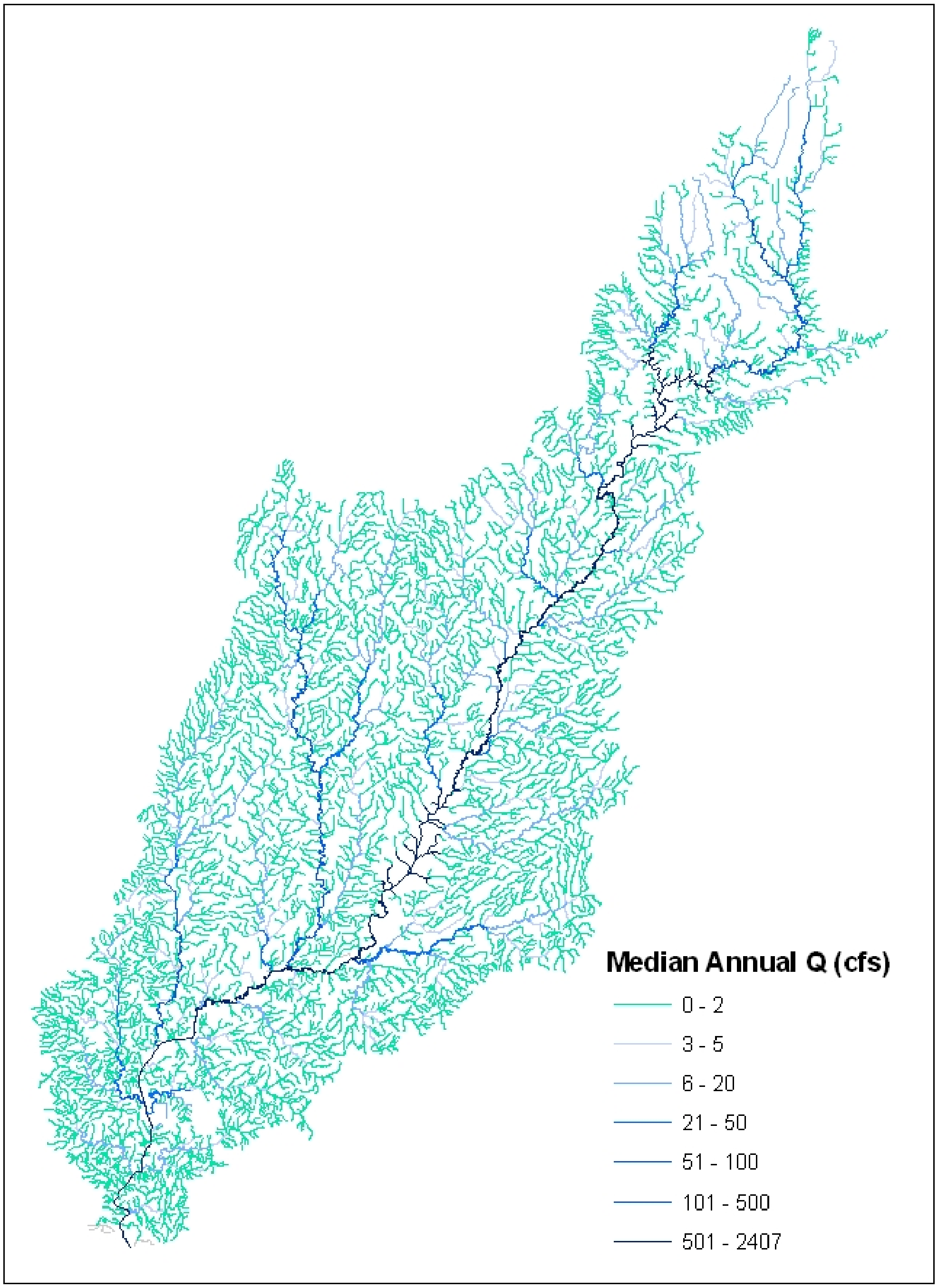

Figure 4.4c. Kaskaskia River median annual discharge estimates based on LTM output for 2025 Scenario.

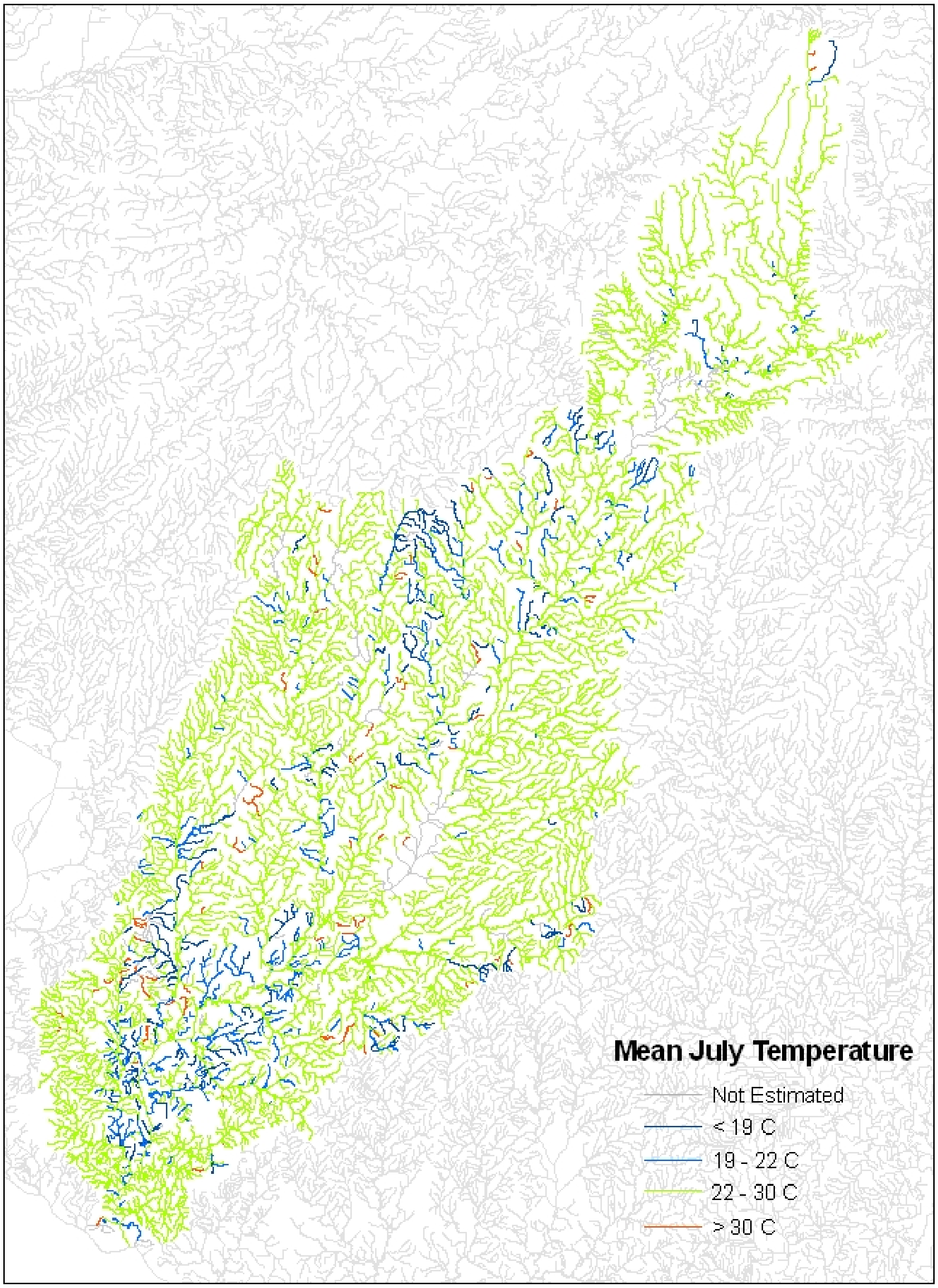

Figure 4.4d. Kaskaskia River summer stream temperature estimates based on MLR model output for recent landcover.

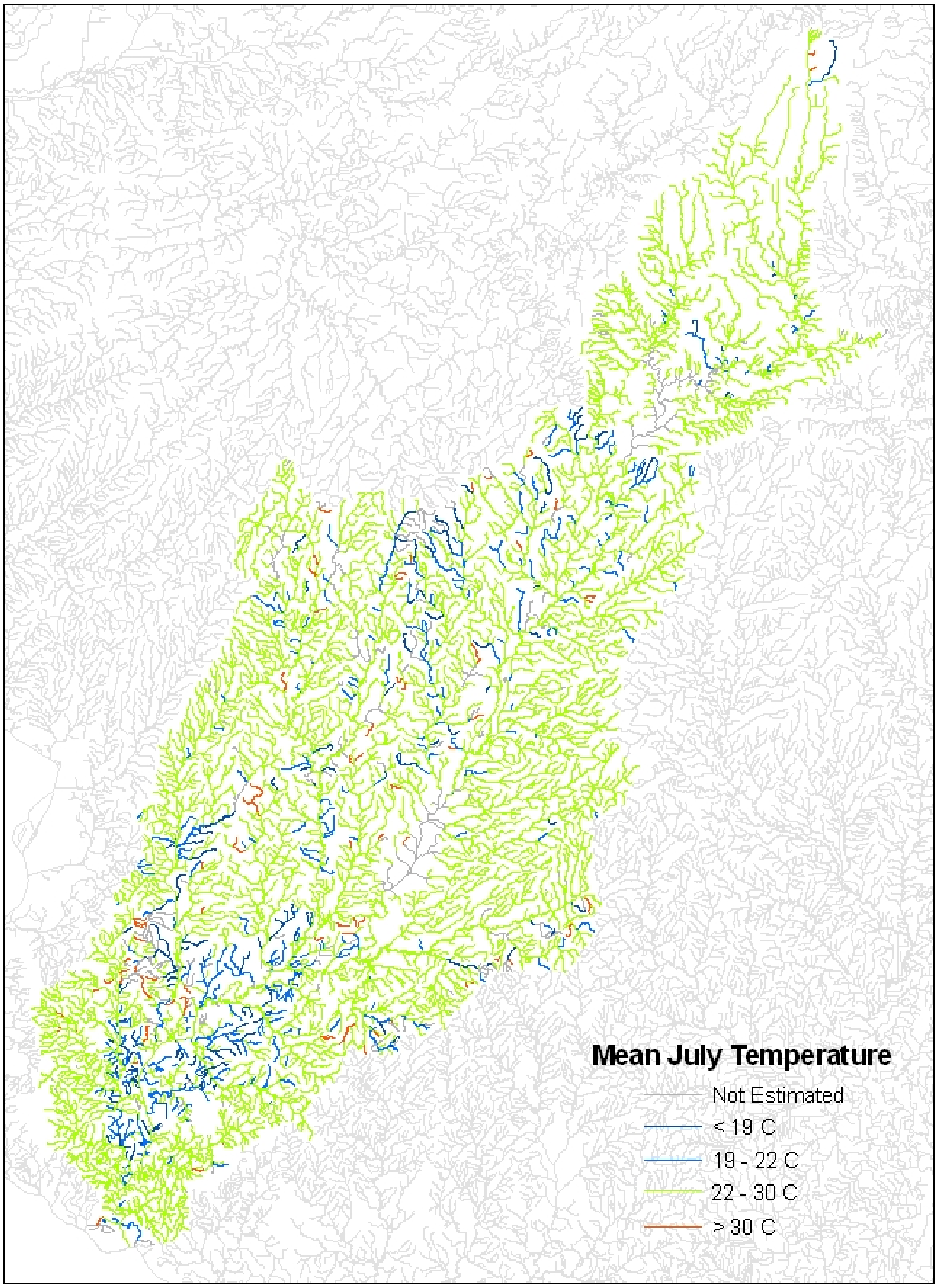

Figure 4.4e. Kaskaskia River summer stream temperature estimates based on LTM output for 2025 Scenario.

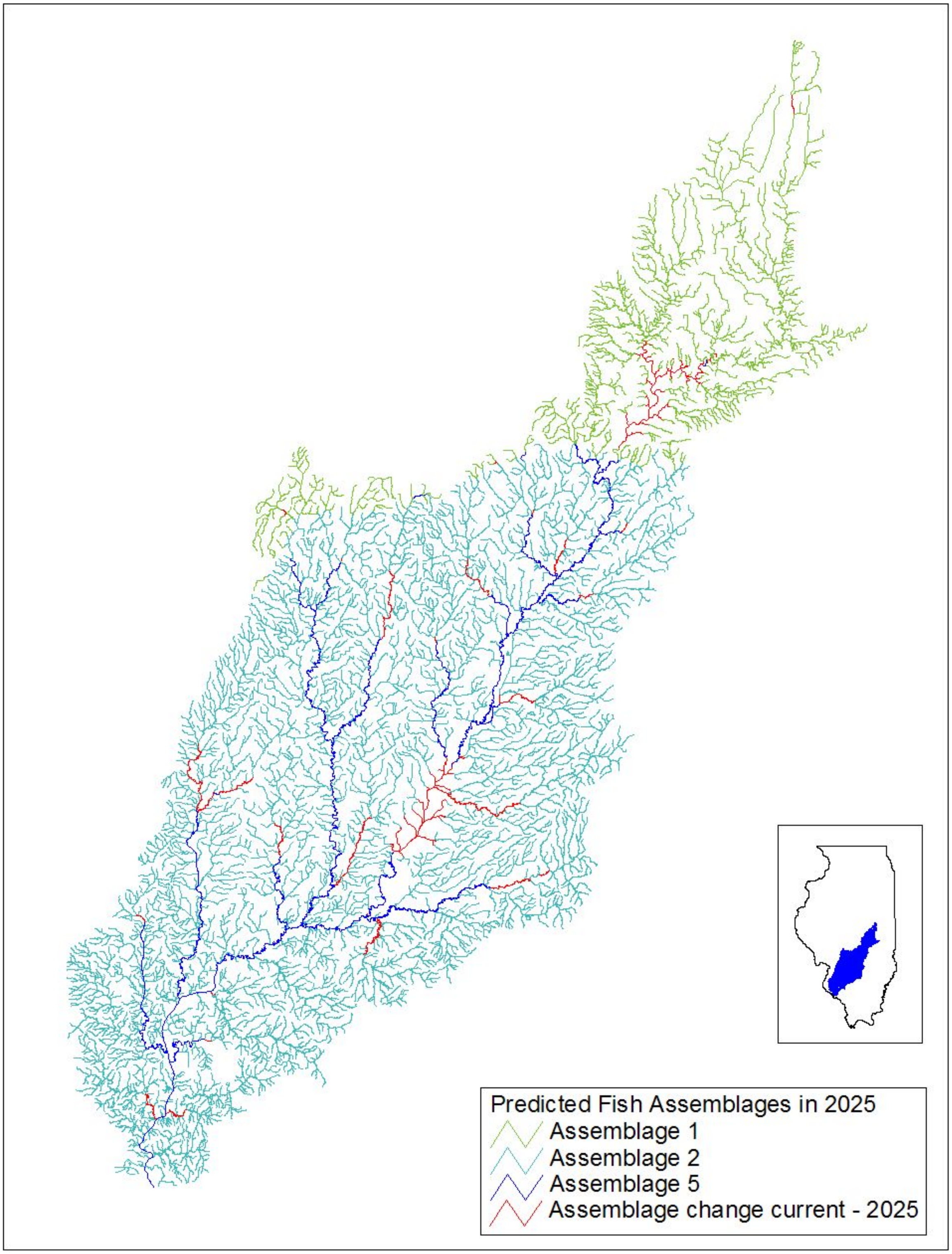

Figure 4.4f. Kaskaskia River fish assemblages based on LTM output.

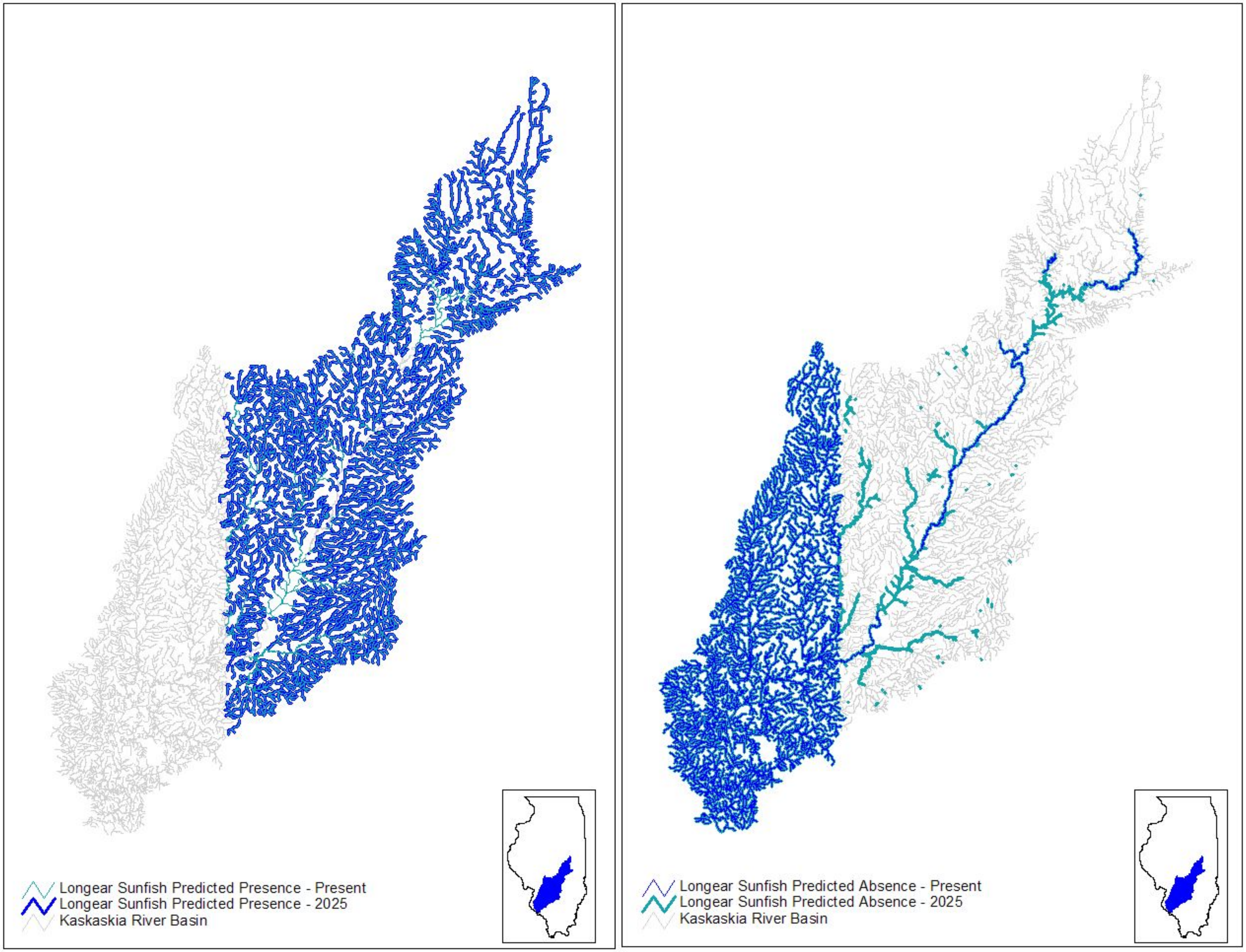

Figure 4.4g. Predicted occurrence of Longear sunfish based on LTM output.