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ARTICLE

Fish Species of Greatest Conservation Need in Wadeable Iowa Streams: Current Status and Effectiveness of Aquatic Gap Program Distribution Models

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Abstract

Effective conservation of fish species of greatest conservation need (SGCN) requires an understanding of species–habitat relationships and distributional trends. Thus, modeling the distribution of fish species across large spatial scales may be a valuable tool for conservation planning. Our goals were to evaluate the status of 10 fish SGCN in wadeable Iowa streams and to test the effectiveness of Iowa Aquatic Gap Analysis Project (IAGAP) species distribution models. We sampled fish assemblages from 86 wadeable stream segments in the Mississippi River drainage of Iowa during 2009 and 2010 to provide contemporary, independent fish species presence–absence data. The frequencies of occurrence in stream segments where species were historically documented varied from 0.0% for redfin shiner *Lythrurus umbratilis* to 100.0% for American brook lamprey *Lampetra appendix*, with a mean of 53.0%, suggesting that the status of Iowa fish SGCN is highly variable. Cohen's kappa values and other model performance measures were calculated by comparing field-collected presence–absence data with IAGAP model–predicted presences and absences for 12 fish SGCN. Kappa values varied from 0.00 to 0.50, with a mean of 0.15. The models only predicted the occurrences of banded darter *Etheostoma zonale*, southern redbelly dace *Phoxinus erythrogaster*, and longnose dace *Rhinichthys cataractae* more accurately than would be expected by chance. Overall, the accuracy of the twelve models was low, with a mean correct classification rate of 58.3%. Poor model performance probably reflects the difficulties associated with modeling the distribution of rare species and the inability of the large-scale habitat variables used in IAGAP models to explain the variation in fish species occurrences. Our results highlight the importance of quantifying the confidence in species distribution model predictions with an independent data set and the need for long-term monitoring to better understand the distributional trends and habitat associations of fish SGCN.

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Freshwater systems are among Earth's most ecologically important, yet imperiled ecosystems (Dudgeon et al. 2006). The factors contributing to their imperilment include water pollution, flow alteration, physical habitat degradation, and introductions of nonnative species (Allan and Flecker 1993; Dudgeon et al. 2006). Consequently, many freshwater species are vulnerable to extinction (Richter et al. 1997; Jelks et al. 2008). For example, 700 North American freshwater and diadromous fish taxa have been identified as endangered, threatened, or vulnerable (Jelks et al. 2008). Additionally, 61 fish taxa have been identified as extinct in North America (Jelks et al. 2008), and Ricciardi and Rasmussen (1999) have suggested that freshwater species extinctions will continue at a rate five times faster than for terrestrial species. One approach to improving the status of freshwater species is protecting and enhancing critical habitats. Thus, understanding the distributions and habitat requirements of imperiled fish species is necessary for ensuring the success of conservation efforts.

Species distribution models are an important tool for addressing many natural resources issues and are commonly used to describe species–habitat relationships, identify suitable habitats for species reintroductions, prioritize areas for monitoring and conservation efforts, and forecast the effects of land use changes and habitat alterations (Olden and Jackson 2002; Guisan and Thuiller 2005; Lyons et al. 2010). As habitat loss and degradation continue to threaten fish biodiversity in North America (Miller et al. 1989; Richter et al. 1997; Jelks et al. 2008), species distribution models are playing an increasingly important role in fisheries conservation and management (Wall et al. 2004; Dauwalter and Rahel 2008; Hayer et al. 2008). However, modeling the distributions of fish species is challenging because their occurrences are influenced by a combination of abiotic and biotic factors acting at multiple spatial scales (Poff 1997; Marsh-Matthews and Matthews 2000; Jackson et al. 2001). The influence of landscape features (e.g., elevation, catchment size, surface geology, and land cover) on aquatic ecosystems and stream fish assemblages is well documented (Richards et al. 1996; Allan 2004; Hughes et al. 2006), and modeling species occurrences with large-scale variables is attractive because such variables are easily measured and mapped with geographical information systems (GIS). Similarly, the influence of instream habitat characteristics on stream fauna is well studied (Gorman and Karr 1978; Fischer and Paukert 2008; Rowe et al. 2009a). Thus, identifying the influence of processes acting at different spatial scales on fish species distributions is a common goal of fisheries ecologists (Wang et al. 2003; Gido et al. 2006; Ruiz and Peterson 2007).

Accurate species distribution models are an important tool for fisheries managers, but inaccurate models are of questionable value and may even misguide management decisions. All errors decrease the potential value of species distribution models, but omission errors (i.e., false absences) have the greatest consequence because they may lead to overlooking important conservation areas. Therefore, models must be assessed for accuracy to gauge the confidence one may place in their predictions and to identify their limitations for users. Various techniques are available for model validation, but the most robust approach is to use data independent of the data used to estimate the model parameters (Olden et al. 2002; Vaughan and Ormerod 2005). Proper model validation quantifies confidence in a model's ability to accurately predict species occurrences and tests model generality.

In Iowa, anthropogenic alterations of the landscape have many direct and indirect effects on aquatic ecosystems. For example, 72% of Iowa's landscape has been converted to row crop agriculture (USDA 2009), and many streams have been channelized, wetlands have been drained (e.g., drainage tiling), and riparian habitats have been altered. As a result, stream habitat conditions have been degraded and biodiversity has declined (Bulkley 1975; Menzel 1981; Wilton 2004). Consequently, 68 native fish species have been identified as species of greatest conservation need (SGCN; Zohrer 2005). Protecting and enhancing existing habitats that benefit fish SGCN, developing new habitats for them, and improving their status through broadly applied conservation efforts are priorities in Iowa (Zohrer 2005). Achieving these goals requires an understanding of distributions, abundances, and habitat associations of SGCN. Unfortunately, the monitoring of nongame fish species is limited and the status and habitat requirements of many Iowa fish SGCN are poorly understood.

As part of the U.S. Geological Survey's National Gap Analysis Program (USGS 2011), the Iowa Aquatic Gap Analysis Project (IAGAP) attempted to identify "gaps" in the distributions of Iowa fish species and streams under some form of protection due to public ownership (Loan-Wilsey et al. 2005). As a component of the IAGAP, fish species distributions were modeled using large-scale, GIS-measured variables. Only 3.6% of Iowa's stream length is on public land. Thus, IAGAP models may serve as a valuable tool for identifying critical habitats for fish SGCN and locations where conservation efforts and land acquisitions will provide the greatest benefit. However, the effectiveness of IAGAP models needs to be validated with an independent data set before these models are used for conservation planning. Additionally, the status of fish SGCN warrants further evaluation to aid in the prioritization of conservation efforts among species. The objectives of this study were (1) to evaluate the status of fish SGCN by comparing historical and contemporary fish assemblage surveys and (2) to test the effectiveness of IAGAP models in predicting the occurrence of fish SGCN in wadeable Iowa streams.

METHODS

Aquatic gap database and distribution models.—As part of the IAGAP, existing fish assemblage survey data were compiled and used to develop distribution models for fish species in Iowa's streams and rivers (Loan-Wilsey et al. 2005). Fish assemblage data were obtained from published literature, agency reports,

TABLE 1. Large-scale habitat variables used in decision tree analyses to create the Iowa Aquatic Gap Analysis Project (IAGAP) fish species distribution models (Loan-Wilsey et al. 2005).

IAGAP variable	Description
DlinkR	Nine categories describing the Shreve D-link number of the segment (D-link is the Shreve link number of the downstream segment).
LinkR	Eight categories describing the Shreve link number of the segment, excluding the Mississippi and Missouri rivers.
Dsize_Code	Five categories describing the size of the downstream segment.
Flow	Three categories differentiating among streams with permanent, intermittent, and unknown flows.
GradRchR	Ten categories describing the stream reach gradient.
GradSegR	Ten categories describing the stream segment gradient.
Max_ElevR	Eight categories describing the elevation at the upstream end of the segment.
Min_ElevR	Eight categories describing the elevation at the downstream end of the segment.
Sdiscr_2C	Two categories describing the size discrepancy with the downstream segment.
Sdiscr_5	Five categories describing the size discrepancy with the downstream segment.
Sdiscr_11C	Eleven categories describing the size discrepancy with the downstream segment.
Soiltext	Seventeen categories describing the surface soil texture.
Ssize_Code	Five categories describing the size of the segment.
Strahler	Strahler stream order of the segment.
Subregion	Two categories differentiating between the Central Plains and Eastern Broadleaf Forest subregions.
Temp_Code	Two categories differentiating between coolwater and warmwater streams.

museum collections, Iowa Department of Natural Resources reports and field notes, statewide biological survey databases, graduate theses and dissertations, and unpublished field notes (Loan-Wilsey et al. 2005). The IAGAP database was completed in 2005 and contains 10,993 fish assemblage samples collected from 2,969 unique U.S. Geological Survey National Hydrography Dataset stream segments between 1884 and 2002.

Following the approach of Sowa et al. (2004), Loan-Wilsey et al. (2005) created distribution models for 106 fish species using decision tree analyses. AnswerTree 3.1 statistical software (SPSS 2001) and the exhaustive chi-square automatic interaction detector algorithm were used to develop decision tree models based on fish species presence–absence data in the IAGAP database. The data for all fish assemblage samples were spatially linked to National Hydrography Dataset stream segments, and IAGAP models predicted the presence or absence of fish species at the same stream segment scale. Sixteen GIS-measured habitat variables characterizing flow, stream size, downstream segment size, gradient, elevation, soil texture, subregion, and temperature were spatially linked to each stream segment and used as predictor variables in the decision tree analyses (Table 1). Loan-Wilsey et al. (2005) used methods similar to those of Sowa et al. (2004) to construct and "prune" each decision tree. To prevent overfitting of the models, a maximum of seven levels was allowed in the decision trees. However, models never reached the maximum number of levels. The minimum number of collections allowed in "parent" nodes (i.e., nodes that were split) was set at 10% of the total number of collection records in the input data set, and the minimum number of collections in "child" nodes (i.e., nodes resulting from the splitting of the parent nodes) was set to one. The alpha level for splitting and merging was 0.05, and a Bonferroni adjustment was used to correct the alpha levels for multiple comparisons. The constructed decision tree models were further pruned to correct for overfitting by removing branches and terminal nodes. A "relative 50% approach," used to prune decision tree models in other Aquatic GAP projects, was used to identify which nodes to include in each species' final model (e.g., Sowa et al. 2004; Hayer et al. 2008). The product of each species model was a dendrogram with a set of mutually exclusive decision rules identifying the predictor variables (i.e., habitat variables) associated with the species' presence or absence. Decision tree models were reconstructed in a GIS-compatible code and applied to each species' historical geographic distribution at the 8-digit hydrologic unit code scale. This enabled prediction of a species' presence or absence in every stream segment within its historical distribution.

Sample site and species selection.—Sample sites and species were selected to enable the evaluation of species status and IAGAP model performance for the maximum number of fish SGCN. Three categories of wadeable (i.e., 2nd–5th-order) stream segments within each species' distribution were identified; these included (1) previously sampled stream segments in which the species was documented to be present (documented) within the last 50 years (i.e., since 1958), (2) stream segments that had not previously been sampled in which the species was predicted to be present (predicted) by the IAGAP model, and (3) stream segments that had not previously been sampled in which the species was not predicted to be present (not predicted). Documented stream segments were selected to evaluate the status of species, and predicted and not-predicted

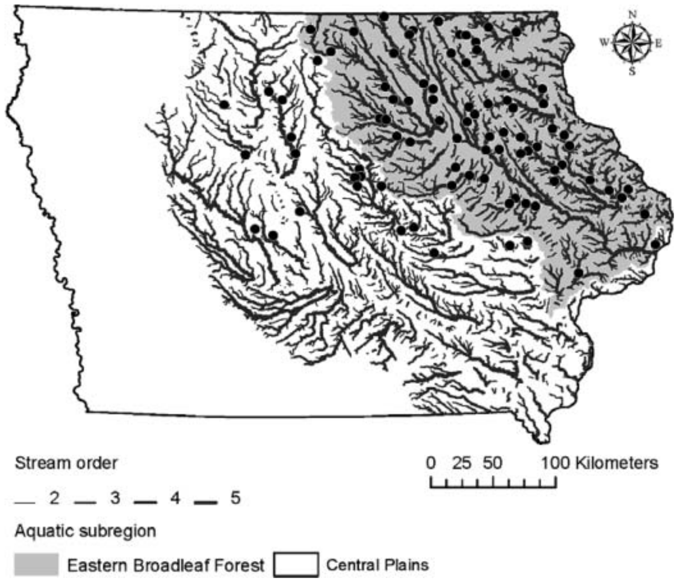

FIGURE 1. Locations of the 86 wadeable (2nd–5th-order) stream segments sampled in the Mississippi River drainage of Iowa during spring and summer (May–August) 2009 and 2010.

stream segments were selected to provide an independent data set for IAGAP model validation. The distributions of the three stream segment categories for all SGCN fish were overlaid, and 12 species were selected to optimize sampling efficiency: banded darter *Etheostoma zonale*, Mississippi silvery minnow *Hybognathus nuchalis*, American brook lamprey *Lampetra appendix*, redfin shiner *Lythrurus umbratilis*, Ozark minnow *Notropis nubilus*, slender madtom *Noturus exilis*, tadpole madtom *Noturus gyrinus*, logperch *Percina caprodes*, blackside darter *Percina maculata*, slenderhead darter *Percina phoxocephala*, southern redbelly dace *Phoxinus erythrogaster*, and longnose dace *Rhinichthys cataractae*.

Fish sampling.—Fish assemblages were sampled from 86 wadeable stream segments in the Mississippi River drainage of Iowa during the spring and summer (May–August) of 2009 and 2010 (Figure 1). Twenty-one stream segments were sampled from the Central Plains aquatic subregion and 65 stream segments from the Eastern Broadleaf Forest (EBF) aquatic subregion. Aquatic subregions are regions with unique geological characteristics, climate conditions, and riverine assemblages (Sowa et al. 2004). They are similar to the ecoregion provinces defined by Bailey (1995), but their boundaries were delineated by the Missouri Resource Assessment Partnership (University of Missouri, Columbia) to align with drainage divides. The Central Plains aquatic subregion is characterized by thick loess deposits over flat to gently sloping terrain with wide stream valleys. Many Central Plains streams were historically dominated by fine silt and sand substrates, and sediment input has been exacerbated by the conversion of native prairie to cropland. The EBF subregion of Iowa has also been altered for agricultural use but is geologically more diverse than the Central Plains subregion. The EBF contains the Paleozoic Plateau ecoregion, which was less impacted by glaciation than other Iowa ecoregions and is characterized by high topographic relief, rocky outcroppings, and dense forests (Griffith et al. 1994).

Sample reaches within stream segments were 300–400 m in length and visually divided into macrohabitat units identified as riffles, pools, runs, or off-channel units. When feasible, sample reaches were selected to encompass as many different macrohabitat units as possible and be greater than 100 m from a major artificial structure (e.g., a bridge or low-head dam). All fish sampling occurred during base-flow conditions to minimize the sampling inefficiencies associated with high flow, depth, and turbidity. Fish assemblages were sampled in each macrohabitat separately using single-pass upstream electrofishing with a pulsed-DC electrofishing unit (Simonson and Lyons 1995). When feasible, a generator-powered, barge-mounted VVP-15B (Smith-Root, Inc., Vancouver, Washington) electrofishing unit was used. However, if stream reaches were too shallow or inaccessible, a battery-powered backpack LR-20 (Smith-Root) electrofishing unit was used. For both backpack and barge-mounted electrofishing, three netters used 6.34-mm-mesh dip nets to collect fish. An effort was made to sample all available habitat types in each macrohabitat, and extra effort was directed toward structures likely to contain fish (e.g., woody debris, undercut banks, and boulders). Voltage output was adjusted to maximize efficiency and reduce incidental mortality in each sample reach. Fish were collected in each macrohabitat, examined for external abnormalities, identified, counted, and released. Up to five voucher specimens of each fish SGCN per sample reach were preserved in a 10% formalin solution. Fish that could not be identified in the field were also preserved and transported to the laboratory for identification.

Status evaluation.—Fish species presence–absence data collected from documented stream segments were used to evaluate the status of fish SGCN. Specifically, the frequency of occurrence of each selected species in the documented stream segments was used as an index of its status. If a species was frequently collected from stream segments in which it was previously documented, we hypothesized that the species' distribution was stable. If a species was not frequently collected in stream segments in which it was previously documented, we hypothesized that the species' distribution was declining. Similar comparisons of contemporary fish assemblage survey data with historical survey data have been used to evaluate the distributional trends of warmwater fishes elsewhere (Patton et al. 1998; Piller et al. 2004).

If a species' detection probability is less than 1.0, omission errors may occur (i.e., the species is present but not collected; MacKenzie et al. 2002; Tyre et al. 2003; Gu and Swihart 2004). Thus, the species may be incorrectly classified as absent, resulting in the false conclusion that the species' distribution is declining. In other words, if a species was not collected in a stream segment, it could be because the species was truly absent or because the species was present and simply not collected.

Therefore, we were cautious in our interpretations of species status because a frequency of occurrence less than 100% in documented stream segments may be due to a declining distribution, imperfect detection, or a combination of these factors.

Model validation.—Iowa Aquatic Gap Analysis Project distribution models were evaluated for each of the 12 selected species using presence–absence data collected from predicted and not-predicted stream segments within each species' historical distribution. Confusion matrices were created for each species by comparing model-predicted presences and absences with surveyed presences and absences (Fielding and Bell 1997). The status of each species in each stream segment was classified as a true presence (i.e., the species was both predicted to be present and was collected), a false presence (the species was predicted to be present but was not collected), a false absence (the species was not predicted to be present but was collected), or a true absence (the species was not predicted to be present and was not collected). Confusion matrices were used to calculate several accuracy measures for each species distribution model.

The primary statistic used to evaluate model performance was Cohen's kappa (κ), which is an index of the correct classification of events (i.e., presence or absence) relative to what would be expected by random chance (Cohen 1960). Kappa values of zero or less indicate model performance no better than random chance, whereas those of one indicate perfect model performance. Landis and Koch (1977) arbitrarily characterized kappa values of 0.0–0.2 as indicating "slight" performance, those of 0.2–0.4 as indicating "fair" performance, those of 0.4–0.6 as indicating "moderate" performance, those of 0.6–0.8 as indicating "substantial" performance, and those of 0.8–1.0 as indicating "almost perfect" performance. Cohen's kappa is commonly used in the medical and remote sensing fields (Congalton 1991; Manel et al. 2001) and has been extensively used to evaluate species presence–absence models (Collingham et al. 2000; Olden and Jackson 2001; Rushton et al. 2004; Hayer et al. 2008). Kappa may be overly sensitive to species prevalence (McPherson et al. 2004; Vaughan and Ormerod 2005); however, Manel et al. (2001) found kappa to be a robust indicator of model performance that was negligibly influenced by species prevalence. The standard error, significance, and 95% confidence interval of a kappa value can easily be calculated and used to test the null hypothesis that the value is equal to zero (Titus et al. 1984).

In addition, model sensitivity, specificity, and correct classification rates were calculated from confusion matrices to evaluate model performance (Fielding and Bell 1997). Sensitivity is the proportion of observed presences correctly predicted, and specificity is the proportion of observed absences correctly predicted. Low values of sensitivity and specificity correspond to higher omission and commission errors, respectively. Correct classification rates represent the percentage of presences and absences predicted correctly. Sensitivity, specificity, and correct classification rates provide insight into model performance but are highly influenced by species prevalence and must be interpreted with caution (Manel et al. 2001). For example, Manel et al. (2001) found that sensitivity increased and specificity decreased with increasing species prevalence.

Even when independent data are used to evaluate the accuracy of a species distribution model, the interpretation of model accuracy may be influenced by the species' distributional trends, prevalence, and detection probability (Manel et al. 2001; Gu and Swihart 2004; McPherson et al. 2004). For instance, the IAGAP models were developed with historical (1884–2002) data, and poor model performance may reflect declines in species' distributions rather than model inadequacies. In other words, the models may accurately predict the historical distributions of fish species but overestimate the contemporary distributions owing to declines in those distributions. Furthermore, if the detection probability of a species is less than one, the frequency of occurrence of the species may be underestimated due to omission errors. Therefore, as an additional analysis, the IAGAP models were evaluated by comparing the relative differences in the frequency of occurrence of each species in the three stream segment categories (documented, predicted, and not predicted). Comparing the relative difference between the frequency of occurrence in predicted and documented stream segments provides insight to those interested in maximizing the likelihood of finding each species. Similarly, comparing the relative difference between the frequency of occurrence in predicted and not-predicted stream segments provides insight to those who hope to use IAGAP models to increase the likelihood of finding species in stream segments that have not previously been sampled. If detection probabilities and distributional trends are consistent across stream segment categories, the potential biases are negligible and the relative differences in the frequency of occurrence of each species can be identified. Fisher's exact test was used to test the null hypothesis that each species' occurrence did not differ significantly ($\alpha > 0.05$) among stream segment categories (Fleiss 1981). All analyses were performed using the R program (R Development Core Team 2009).

RESULTS

The number of stream segments sampled in the documented category for the 12 selected species varied from 1 for Mississippi silvery minnow and logperch to 21 for blackside darters (Table 2). Thus, the status of the Mississippi silvery minnow and logperch were not evaluated due to an insufficient sample size in this stream segment category. The frequencies of occurrence in the documented stream segments for the remaining 10 species varied from 0.0% for redfin shiners to 100.0% for American brook lampreys, with a mean of 53.0% (SE = 10.4; Figure 2). Frequencies of occurrence greater than 80.0% in the documented stream segments suggest that the current distributions of banded darters, American brook lampreys, and southern redbelly dace are similar to the historical distributions. Similarly, Ozark minnow and longnose dace were collected in 66.7% and 73.3% of the documented stream segments, suggesting that these species have relatively stable distributions.

TABLE 2. Number of wadeable Iowa stream segments sampled in each stream segment category for 12 fish species of greatest conservation need during spring and summer 2009 and 2010. Stream segment categories were identified using the Iowa Aquatic Gap Analysis Project database and species distribution models (Loan-Wilsey et al. 2005).

	Stream segment category		
Species	Documented	Predicted	Not predicted
Banded darter	14	8	31
Mississippi silvery minnow	1	11	20
American brook lamprey	6	16	10
Redfin shiner	13	24	16
Ozark minnow	15	18	14
Slender madtom	5	7	8
Tadpole madtom	12	23	12
Logperch	1	11	11
Blackside darter	21	20	20
Slenderhead darter	12	14	26
Southern redbelly dace	17	18	21
Longnose dace	9	6	19

In contrast, as strong evidence of declining distributions, redfin shiners, slender madtoms, tadpole madtoms, blackside darters, and slenderhead darters were collected in 40.0% or fewer of the stream segments in which they were previously documented.

Fish species distribution models were evaluated with accuracy metrics calculated from confusion matrices for all 12 selected species. The number of stream segments sampled for each species varied from 6 to 26 in the predicted stream segments and from 8 to 31 in the not-predicted stream segments (Table 2). Overall correct classification rates varied from 0.34 for the tadpole madtom model to 0.84 for the longnose dace model (Table 3). Kappa values varied from 0.00 to 0.50, with a mean of 0.15 (SE = 0.05), and were only significantly greater than zero for the banded darter (0.42; $P = 0.02$), southern redbelly dace (0.34; $P = 0.02$), and longnose dace (0.50; $P = 0.04$) models. Model specificity (i.e., the proportion of absences that were correctly predicted) varied from 0.34 for the tadpole madtom model to 0.90 for the banded darter model and was greatest for models with kappa values significantly greater than zero. Model sensitivity (i.e., the proportion of presences that were correctly predicted) was greatest for redfin shiners and slenderhead darters, both of which were only collected from one stream segment. For IAGAP models that performed significantly better than random chance (i.e., $\kappa \geq 0.0$, $P \leq 0.05$), model specificity was always greater than model sensitivity. Thus, the three significant models were able to predict species' absences with more accuracy than species' presences.

Model performance was further evaluated by comparing the frequencies of occurrence among the stream segment categories for all 12 species. Frequency of occurrence was significantly greater in stream segments in which the species was previously documented than in segments in which it was predicted for American brook lampreys, Ozark minnow, and tadpole madtoms (Figure 2). Thus, the probability of finding these species was greatest in stream segments where they had previously been documented. There were no significant differences between the frequencies of occurrence in documented stream segments and predicted stream segments for the remaining nine species. Furthermore, the frequencies of occurrence in the predicted stream segments did not differ significantly from those in the not-predicted stream segments for 10 of the 12 species. These results suggest that the IAGAP models failed to differentiate between stream segments in which the species were present and those in which they were absent for a majority of the species. However, the models were able to effectively predict the occurrences of banded darters and longnose dace, which were collected in a significantly greater proportion of predicted stream segments than not-predicted stream segments.

The relationship between species status and IAGAP model performance suggests that the models performed best for species that exhibited stable distributions (Figure 3). Redfin shiners, slender madtoms, tadpole madtoms, blackside darters, and slenderhead darters exhibited apparent declines in distribution, and their IAGAP models did not perform significantly better than chance. On the other hand, southern redbelly dace, banded darters, and longnose dace exhibited stable distributions and their models had fair to moderate performance. However, this trend did not hold true for Ozark minnow and American brook lampreys. Both of these species exhibited stable distributions, but their IAGAP models did not predict their occurrence more accurately than would be expected by random chance. Thus, the poor performance of some IAGAP models may be attributed to declining species distributions, but other factors are responsible for the poor performance of other models.

DISCUSSION

Understanding the status of imperiled species is vital to prioritization of conservation efforts. However, reactionary efforts to conserve species that have exhibited substantial declines are often less successful and more costly than efforts to conserve species whose population declines are detected prior to the point of endangerment (Tear et al. 1993; Jennings 2000). Thus, monitoring species and identifying declines before they become irreversible is important for conservation success. The results of our study suggest that the status of fish SGCN in Iowa streams is highly variable. Three of 10 species were collected in over 80.0% of the stream segments in which they had previously been documented, whereas half of the species were collected in less than 40.0% of such stream segments. The most extreme decline in distribution was detected for the redfin shiner, which was not collected in any of the 13 stream segments in which it was previously documented. Between these extremes, Ozark

TABLE 3. Model performance measures for 12 Iowa Aquatic Gap Analysis Project fish species distribution models. Abbreviations are as follows: CCR = the correct classification rate, κ = Cohen's kappa statistic. The *P*-values pertain to the null hypothesis that κ equals zero.

Species	*n*	Prevalence	True presence	False presence	True absence	False absence	Sensitivity	Specificity	CCR	κ (SE)	*P*-value
Longnose dace	25	0.16	3	3	18	1	0.75	0.86	0.84	0.50 (0.21)	0.04
Banded darter	39	0.26	5	3	26	5	0.50	0.90	0.79	0.42 (0.17)	0.02
Southern redbelly dace	39	0.54	13	5	13	8	0.62	0.72	0.67	0.34 (0.15)	0.02
Blackside darter	40	0.28	7	13	16	4	0.64	0.55	0.58	0.15 (0.14)	0.17
American brook lamprey	26	0.19	4	12	9	1	0.80	0.43	0.50	0.12 (0.12)	0.23
Ozark minnow	32	0.13	3	15	13	1	0.75	0.46	0.50	0.09 (0.10)	0.30
Slenderhead darter	40	0.03	1	13	26	0	1.00	0.67	0.68	0.09 (0.07)	0.33
Redfin shiner	40	0.03	1	23	16	0	1.00	0.41	0.43	0.03 (0.03)	0.40
Slender madtom	15	0.00	0	7	8	0		0.53	0.53	0.00 (NA)	
Mississippi silvery minnow	31	0.00	0	11	20	0		0.65	0.65	0.00 (NA)	
Tadpole madtom	35	0.00	0	23	12	0		0.34	0.34	0.00 (0.00)	
Logperch	22	0.00	0	11	11	0		0.50	0.50	0.00 (0.00)	

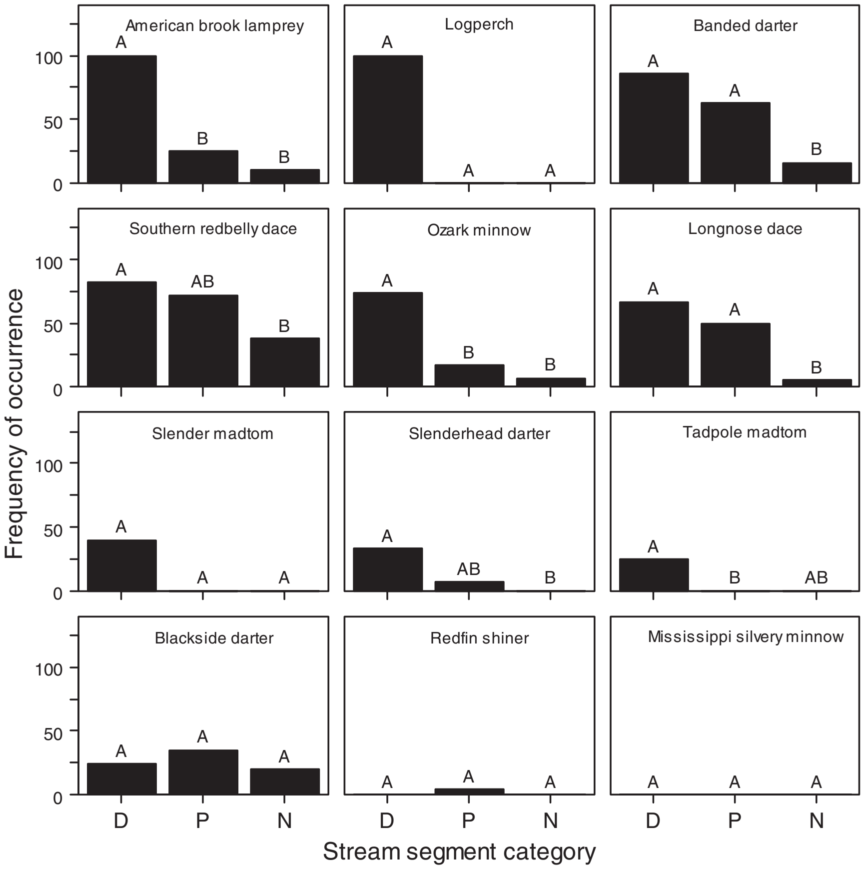

FIGURE 2. Frequencies of occurrence for 12 fish species of greatest conservation need in three stream segment categories: those in which the species was previously documented (D), those in which it was predicted to be present (P), and those in which it was not predicted to be present (N). Fish were sampled from 86 stream segments in the Mississippi River drainage of Iowa during spring and summer 2009 and 2010. Different letters above the bars indicate significant differences (Fisher's exact test; $\alpha = 0.05$).

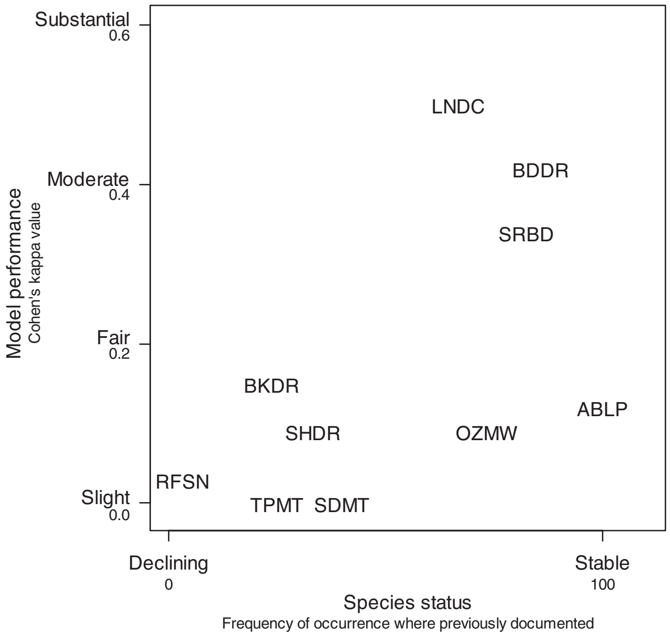

FIGURE 3. Relationship between Iowa Aquatic Gap Analysis Project species distribution model performance and the status of 10 fish species of greatest conservation need in wadeable Iowa streams. Species codes are as follows: BDDR = banded darter, ABLP = American brook lamprey, RFSN = redfin shiner, OZMW = Ozark minnow, SDMT = slender madtom, TPMT = tadpole madtom, BKDR = blackside darter, SHDR = slenderhead darter, SRBD = southern redbelly dace, and LNDC = longnose dace.

minnow and longnose dace were collected in 66.7% and 73.3% of the documented stream segments. Although the declines in the distributions of these two species are less substantial than those of other species, subtle declines may be early indicators of impending imperilment.

The historical distributions of species with high (≥60.0%) frequencies of occurrence in documented stream segments were noticeably different from those of species with low frequencies (≤40.0%) of occurrence. Species with historical distributions that were entirely or mostly confined to the EBF subregion exhibited relatively stable distributions. For example, American brook lampreys, Ozark minnow, and longnose dace all have distributions that were mostly confined to this subregion (Harlan and Speaker 1969), and all occurred in more than 65.0% of the documented stream segments. Similarly, southern redbelly dace were historically most common in the EBF subregion (Harlan and Speaker 1969) and in this study they were prevalent in wadeable streams throughout the EBF and collected in 82.4% of the documented stream segments. Species with historical distributions extending well beyond the EBF subregion exhibited greater declines. For example, blackside darters, slenderhead darters, and redfin shiners were historically found throughout the Mississippi River drainage of Iowa. Our results suggest that the distributions of all three species have declined. Similarly, tadpole madtoms and slender madtoms were historically found throughout much of the Mississippi River drainage and, corroborating the findings of Sindt et al. (2011), we also found declining distributions for both species. These differences in the distributional trends of fish SGCN may be attributed to differences in the geological characteristics (Griffith et al. 1994), habitat conditions, and agricultural intensities within their distributions. Although agriculture is pervasive across Iowa, its intensity varies by ecoregion (Heitke et al. 2006). Heitke et al. (2006) and others (e.g., Wilton 2004) identified a gradient of increasing ecological integrity and more favorable habitat running from the southwestern part of the state to the northeastern part. This is consistent with the stable distributions that we detected for fish species with distributions largely constrained to the EBF subregion of northeastern Iowa.

Agricultural practices degrade aquatic habitats and fish assemblages in many regions (Karr et al. 1985; Waters 1995; Roth et al. 1996; Wang et al. 1997), including Iowa (Wilton 2004; Heitke et al. 2006; Rowe et al. 2009a, 2009b). Increased sedimentation is a consequence of agricultural practices (Waters 1995; Walser and Bart 1999) that results in decreases in habitat complexity and fish diversity (specifically, the abundance of benthic insectivores; Berkman and Rabeni 1987; Walser and Bart 1999; Quist et al. 2003; Heitke et al. 2006). Slender madtoms, blackside darters, and slenderhead darters are all benthic insectivores that are intolerant of siltation, and intensive agricultural throughout their distributions in Iowa may be a leading cause of their declines. Lyons (1996) attributed the decline of slender madtoms in Wisconsin to agricultural practices and other anthropogenic habitat alterations.

In this study, we evaluated the effectiveness of IAGAP species distribution models for predicting the occurrences of 12 fish SGCN species in wadeable Iowa streams and assessed their value as potential conservation planning tools. Typically, the accuracy of species distribution models is evaluated with the same data that were used to estimate the model parameters and with simple measures of accuracy that fail to account for species prevalence (e.g., correct classification rates; Fielding and Bell 1997; Manel et al. 2001). However, the results of this study and others (e.g., Fielding and Bell 1997; Manel et al. 2001; Olden et al. 2002; Vaughan and Ormerod 2005) identify the risks associated with such approaches and emphasize the need for more robust techniques. We evaluated the accuracy of IAGAP model predictions against an independent data set and used Cohen's kappa value as a robust measure of model accuracy that is less influenced by species prevalence than are correct classification rates (Manel et al. 2001; Olden et al. 2002). Our results revealed that IAGAP models only predicted the occurrences of banded darters, southern redbelly dace, and longnose dace better than would be expected by chance.

Testing species distribution models against independent data is an important step in model validation because models are usually intended to be used with new data. Other studies have reported results similar to ours when testing fish species distribution models with independent data (Porter et al. 2000; Rashleigh et al. 2005). For instance, Porter et al. (2000) developed models that accurately predicted the presences and absences of 13 fish species in the Blackwater River drainage of British Columbia, but model performance was greatly reduced when they were applied to data from a distant drainage. In the mid-Atlantic Highlands region of the eastern USA, Rashleigh et al. (2005) found that species distribution model performance decreased when models were applied to an independent data set, with only 9 of 13 models performing better than chance. The correct classification rates of IAGAP models could be interpreted as satisfactory if other accuracy measures are ignored. For example, the slenderhead darter model correctly classified 68% of the presences and absences of that species; however, the model did not perform significantly better than would be expected by chance. By assessing model sensitivity and specificity, we were able to further assess model limitations and the potential risks of using IAGAP models to identify priority conservation areas. For example, low model sensitivity may lead to the oversight of areas with suitable habitat and conservation importance. Our results revealed that model specificity was greater than model sensitivity for all three significant ($\kappa > 0.0$; $P \leq 0.05$) species distribution models, indicating that they were better at predicting species absences than presences. Thus, users relying solely on these models are more likely to overlook important conservation areas than expend valuable resources to conserve unsuitable habitats.

Determining the cause of errors in species distribution models can help with the interpretation of model predictions and improve the accuracy of future models. Fielding and Bell (1997) identified two categories of prediction error for species distribution models: algorithmic errors and biotic errors. Algorithmic errors are associated with the limitations imposed by data gathering and statistical analyses. Many recent studies have focused on identifying the most appropriate statistical methods for modeling species distributions in an attempt to minimize one potential source of error (Olden and Jackson 2002; Oakes et al. 2005; Steen et al. 2006). Thus, in an attempt to reduce errors, IAGAP models were developed with a robust statistical method (i.e., a classification regression tree; Olden and Jackson 2002; Oakes et al. 2005; Steen et al. 2006) and a very large data set (10,993 fish assemblage samples). However, many fish SGCN are rare, and distribution models for rare species are particularly prone to algorithmic errors. By definition, these species are uncommon, and thus obtaining adequate data for developing and validating the models is difficult. Even when present, rare species may be difficult to detect because of their low abundance or cryptic behaviors (Gu and Swihart 2004). Thus, distribution models for rare species are likely to exhibit high rates of omission error, underestimate distributions, and misrepresent habitat associations (Tyre et al. 2003; Gu and Swihart 2004). Our results were consistent and showed that model performance tended to be low for rarer species.

The accuracy of the IAGAP models may also be influenced by the distributional trends of fish species. Of the nine species distribution models that failed to perform better than random chance, five exhibited substantial declines in distribution (≥60%). Since the IAGAP models were developed with historical (1884–2002) data, they may be more useful for hindcasting the historical distributions of species than accurately predicting their present-day occurrences. Similarly, Steen et al. (2008) suggested that distribution models for rare and declining fish species may be useful for predicting potential distributions even if they do not accurately predict contemporary occurrences. We found that the overall performance of the redfin shiner and slenderhead darter models was poor but that model sensitivity was high (1.00). Thus, these models may be useful for identifying suitable habitats where the species once persisted, even though they fail to accurately predict current distributions. Future research could compare IAGAP model performance in undisturbed and disturbed stream sites to better understand how it is influenced by the anthropogenic alterations that have occurred since the initial data collections.

Biotic model errors occur when models fail to include ecologically relevant processes as explanatory variables (Fielding and Bell 1997). Selecting the appropriate explanatory variables is challenging because the occurrence of fish species is influenced by a variety of abiotic and biotic factors operating at multiple spatial scales (Poff 1997; Marsh-Matthews and Matthews 2000; Jackson et al. 2001) and the most influential factors vary by species and system (Pont et al. 2005; Monti and Legendre 2009). Thus, the poor IAGAP model performance may reflect the inability of large-scale habitat variables to explain substantial variation in the occurrences of fish SGCN. However, determining whether the IAGAP models failed to accurately predict the occurrences of redfin shiners, slender madtoms, tadpole madtoms, blackside darters, and slenderhead darters as a result of biotic model errors is difficult because model performance may have been influenced by declines in these species' distributions. In contrast, American brook lampreys and Ozark minnow did not exhibit substantial declines in distribution and the failure of the IAGAP models to accurately predict their occurrence may be at least partly attributed to biotic model errors.

Large-scale variables are appealing for modeling species distributions because they are readily obtained from existing spatial databases and have been used to accurately predict the distribution of fish species elsewhere (e.g., Oakes et al. 2005; Gido et al. 2006; Steen et al. 2008). For example, Oakes et al. (2005) showed that landscape variables were effective for predicting the occurrence of a large number of fish species in a Great Plains river basin. Wall et al. (2004) similarly used large-scale variables to identify suitable habitats for and guide the conservation of the federally endangered Topeka shiner *Notropis topeka*. Some studies have even reported greater success in modeling fish species distributions and densities with large-scale variables than with smaller-scale habitat features (Leftwich et al. 1997; Creque et al. 2005). For example, Creque et al. (2005) found that GIS-measured variables explained more of the variation in the density of five Michigan stream fish species than local site–scale variables. Similarly, Leftwich et al. (1997) reported that models created with regional variables (i.e., elevation and stream order) correctly predicted the presence and absence of tangerine darters *Percina aurantiaca* more accurately than models created with local (e.g., width and depth) variables.

Compared with similar fish species distribution models created with GIS-derived variables and classification regression tree approaches, the IAGAP models performed relatively poorly. In Michigan, Steen et al. (2008) developed 93 stream fish species distribution models with an average correct classification rate of 72% when applied to an independent data set. Similarly, Lyons et al. (2010) developed models for 50 Wisconsin fish species that averaged 77% accuracy when validated. However, the GIS-derived variables used by Steen et al. (2008) and Lyons et al. (2010) had greater precision than the variables used in the IAGAP models. Most of the variables used to create the IAGAP models were categorical with as few as two categories (e.g., cool or warm stream temperature), while Steen et al. (2008) and Lyons et al. (2010) used mostly continuous variables (e.g., water temperature, air temperature, flow, and gradient). Additionally, their models included a variety of large-scale variables that were not included in the IAGAP models. For example, Steen et al. (2008) and Lyons et al. (2010) found that land use variables were important for predicting the distribution of many fish species. Thus, increasing variable precision and including more large-scale variables would probably improve the accuracy of the IAGAP models.

Although large-scale variables may be effective for predicting the distribution of some fish species, habitat variables measured at other spatial scales may be more effective for others. For example, Pont et al. (2005) showed that the relative influence of regional- and local-scale habitat variables on fish species occurrence is species specific. In Iowa, Rowe et al. (2009a, 2009b) suggested that local-scale habitat features explain substantial variation in stream fish assemblages and that the influence of landscape features is primarily indirect, operating through their direct influence on habitat. Variables characterizing instream habitat conditions may be more effective than large-scale variables for modeling the distribution of Iowa's stream fish SGCN. Wang et al. (2003) supported this premise by showing that reach-scale variables explained more of the variation in fish assemblages than riparian- or watershed-scale variables in minimally disturbed Midwestern watersheds. Ultimately, species distribution models that include habitat variables measured at multiple spatial scales are likely to have the greatest predictive power and interpretive value (Rabeni and Sowa 1996; Leftwich et al. 1997; Quist et al. 2005). For example, Quist et al. (2005) used large-scale abiotic, local-scale abiotic, and local-scale biotic factors within a hierarchical faunal filter framework to predict the occurrences of warmwater stream fishes in Wyoming and provide insight into the scale at which these factors constrained species occurrence. Thus, future efforts should be directed toward understanding the relationships between Iowa fish SGCN and habitat features measured at other spatial scales, such as instream habitat descriptors, that can be assessed concurrently with fish assemblages (Sindt 2011).

As a direct result of this study, the distributional trends of 10 Iowa fish SGCN were identified. Unfortunately, the status of many of Iowa's 68 fish SGCN remains poorly understood, and until the distributions and habitat associations of these fish are better known conservation efforts for them will have limited success. Although the IAGAP models performed poorly for species with declining distributions and accurately for some species with stable distributions, this trend did not hold true for all species. Thus, the poor IAGAP model performance probably reflects the difficulties associated with modeling the distribution of rare and declining species, along with those of incorporating the most ecologically relevant explanatory variables in species distribution models. Nonetheless, the IAGAP models may serve as a useful tool for identifying watersheds and streams with the greatest potential to provide suitable habitats for target species; even so, field sampling should be used to supplement and validate model predictions. Our results highlight the importance of quantifying the accuracy of species distribution models and the need for long-term monitoring efforts to provide insight into the distributional trends and habitat associations of fish species. Improving upon the ability to predict the occurrence of fish species will require further studies of the habitat associations of species at multiple spatial scales.

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