


# Species distribution modeling and Native Fish Conservation Area prioritization to guide landscape-level conservation

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Cooperator Science Series # 180-2026

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This document (USGS IPDS #: IP-187938) was developed in conjunction with the U.S. Geological Survey, Texas Cooperative Fish and Wildlife Research Unit in collaboration with the funding partner, U.S. Fish and Wildlife Service.

**Recommended citation:**

Rogosch, J.S. 2026. Species distribution modeling and Native Fish Conservation Area prioritization to guide landscape-level conservation. U.S. Department of Interior, Fish and Wildlife Service, Cooperator Science Series FWS/CSS-180-2026, Washington, D.C. https://doi.org/10.3996/css90376900

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# Species distribution modeling and Native Fish Conservation Area prioritization to guide landscape-level conservation

Cooperative Report: Study Funded by U.S. Fish and Wildlife Service, Fish and Aquatic Conservation, and U.S. Geological Survey

March 2026

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# Executive Summary

Texas' freshwater ecosystems support one of the most diverse fish assemblages in North America, yet they face increasing pressures from land-use change, groundwater extraction, invasive species, impoundments, and climate-driven hydrologic shifts. To address these growing threats, Texas has adopted a landscape-scale conservation framework centered on Native Fish Conservation Areas (NFCAs), but effective implementation requires data-driven tools capable of predicting species distributions, identifying priority habitats, and assessing vulnerability. This project developed ensemble species distribution models for 76 native freshwater Species of Greatest Conservation Need (SGCN); identified areas of high SGCN richness and species most vulnerable to climate and land-use change; and created a standardized, transparent approach to species status assessment using geospatial data and life-history traits within the NatureServe methodology. Climate emerged as the dominant driver of fish distributions, followed by land cover, human infrastructure, and topography. Future projections suggest warmer temperatures, altered precipitation patterns, expanding development, and declining forest and wetland cover—changes likely to exacerbate drought severity and increase fragmentation, particularly in western basins. Ensemble model outputs indicated that 12% of SGCN fishes are vulnerable to expected 2040 conditions, with pelagic broadcast-spawning minnows and range-restricted species at greatest risk. Spatial patterns of richness strongly aligned with the existing NFCA network, though a few areas emerged as candidates for refinement pending expert review of the SGCN, local habitat conditions, and stakeholder values and existing conservation partnerships to sustain conservation actions where they are most likely to be successful. Species status assessments revealed that over one-third of evaluated taxa are imperiled, with many species showing evidence of range contraction or insufficient recent data to assess trends. Collectively, these results underscore the importance of integrating predictive modeling, life-history-based threat evaluation, and geospatial analyses to strengthen conservation prioritization. The products developed through this effort have been transferred to Texas Parks and Wildlife Department for incorporation into the 2025 State Wildlife Action Plan and will support ongoing conservation planning aimed at safeguarding Texas' native fish biodiversity under accelerating environmental change.

# Introduction

Freshwater ecosystems in Texas host one of the most diverse fish assemblages in North America but face escalating threats from land-use change, groundwater extraction, impoundments, invasive species, and climate-driven hydrologic change. Conserving these habitats and preserving native fish biodiversity requires the development of strategies to conserve intact communities rather than single-species approaches that are often ineffective (Abell et al. 2007). Managing freshwater ecosystems by considering whole watersheds maintains habitat diversity and the ecological processes required for healthy aquatic ecosystems (Williams et al. 2011). To this effect, Texas has adopted a landscape-scale conservation framework emphasizing Native Fish Conservation Areas (NFCAs), which are watershed-scale units designed to preserve ecological function and native fish communities (Birdsong et al. 2019). While this framework provides a spatial foundation for conservation, data-driven prioritization tools are needed to assess species vulnerability, and guide resource allocation. Effective conservation planning requires robust tools to predict species distributions, anticipate the impacts of future environmental change, and identify priority habitats for protection. Species distribution models (SDMs) provide a framework for relating species occurrences to environmental predictors, producing spatial predictions to unsurveyed areas (Elith & Leathwick, 2009). These models are widely used in ecology and conservation biology to forecast range shifts, guide survey efforts, and inform management actions.

Similarly, prioritizing fish species identified as species of greatest conservation need (SGCN) is essential to effectively direct limited conservation resources toward protecting freshwater biodiversity and preventing species declines (Master 1991). Approximately 40% of the native fishes in Texas require targeted conservation efforts, primarily due to human-induced threats (Hubbs et al. 2008). Given that financial and human resources are typically insufficient to implement conservation actions for all species, habitats, or locations simultaneously, setting clear and justified conservation priorities becomes critical (Pullin et al. 2013; Maire et al. 2017; Le Berre et al. 2019). Identifying conservation priorities based on species vulnerability and relative conservation needs thus provides a structured approach to guide targeted management actions and optimize resource use.

Thus, funds from the U.S. Fish and Wildlife Service Interagency Agreement were used to 1) develop SDMs to predict probability of species occurrences within and outside of NFCA network, especially for at-risk species (SGCN), 2) identify areas with high richness of SGCN species and species vulnerable to diminished distributions to inform candidate watersheds for protection or restoration, and 3) develop a more standardized approach to species ranking assessments using life-history traits and geospatial data applied to species status ranking of SGCN in Texas. Products from these objectives were used as inputs for the 2025 revision of the Texas State List of Threatened and Endangered Species and the State Wildlife Action Plan and provide insights on the conservation of species and priority conservation areas.

# Methods

## Study area

The study area included freshwater stream networks intersecting with the boundaries of Texas, spanning major river basins such as the Red River and Rio Grande as well as endemic Texas basins such as the Guadalupe, Trinity, Neches, and Sabine rivers. Texas encompasses highly variable climatic zones, from arid regions in the west to humid subtropical systems in the east, resulting in strong environmental gradients influencing species distributions. The development of SDMs encompassed the full breadth of river basins, however in developing species rankings, data were subset to the Texas political boundary to align with jurisdiction of natural resource management in the state.

## Fish data

The Fishes of Texas (FoTX) database (Hendrickson and Cohen 2022) collates species occurrence data based on records from a variety of sources, such as museum-vouchered specimens, state and federal agency datasets, literature reviews, citizen science, etc. While the dataset focuses on species that exist within Texas, it contains all possible occurrence data for those species, not limited to Texas but encompassing most of the southern central region of the United States. Our investigation focused on the 3 hydrographic regions that intersected with the state of Texas – the Arkansas-Red-White, Texas, and Rio Grande – identified with hydrologic unit codes (HUC) 11, 12 and 13 in the National Hydrography Dataset Plus version 2 dataset (NHDPlus v2, U.S. Geological Survey (USGS) 2022). FoTX is maintained by the University of Texas at Austin, whose team standardized, merged and checked those records for errors. Each record's coordinates are associated with an estimated uncertainty. The median uncertainty is 45 m. We decided to drop all entries that were either 1) recorded on the same date within 45 m of each other to remove possible duplicates or 2) entries associated with large coordinate uncertainty. We defined large as any uncertainty larger than the average size of a subwatershed (corresponding to HUC12 in the hydrologic database), which is the grain we chose for our SDMs. The average subwatershed surface in the conterminous U.S. is around 100 km². Thus, although there is a lot of variation in subwatershed shapes, we used 10 km as our uncertainty threshold. We converted species abundance data to presence/absence (i.e., occurrence) to account for gear efficiency and associated differences in catch per unit effort among sampling protocols. Species occurrence data were summarized as the total number of occurrences in each subwatershed. Finally, most large reservoirs were constructed in the Big Dam Era through the 1960s. Given those large structures affected flowing water habitats and species ranges in Texas, we decided to focus on species distributions since dam construction, resulting in a temporal extent between 1980 and 2022. Out of the 86 freshwater fish SGCN present in Texas, 82 had extant records within the spatial and temporal extent of our analysis. After applying the above filters, 76 species remained, across almost 34,000 occurrence records. These 76 species correspond directly with native and extant SGCN under current conservation and management of

Texas Parks and Wildlife Department (TPWD; Birdsong et al. 2020, TPWD 2023). The median number of records per species was 160, with an average of 400.

## Environmental data

To capture spatial drivers of variation in species assemblage composition, we chose variables that represented climate, landcover, human infrastructure, and topography. Given the scarcity of in-stream habitat and physicochemical measurements available, we identified variables that are publicly available and correlated with more local environmental variables affecting fish assemblages (e.g., air temperature instead of water temperature for thermal conditions; Paukert et al. 2020). Climate variables included historical averages (1971-2020) of precipitation, maximum quarterly summer (June, July, August) and minimum winter (December, January, February) air temperatures through the Climate Toolbox (°C; https://climatetoolbox.org). Land cover was evaluated by calculating the average proportion of urban, crop, or pasture land present in each subwatershed (HUC 12) from 1992 to 2005 (National Land Cover Database (NLCD); USGS 2022). We categorized the following types of land covers as combined values for predictors: developed (NLCD code 2), wetlands (NLCD codes 15 and 16), forests (NLCD codes 3, 8, 9 and 10) and agricultural land including crops and pastures (NLCD codes 13 and 14). When a category was composed of several NLCD codes, the value for that category, for any given catchment, is the sum area of all individual areas for those NLCD codes, within that catchment. That total value was then divided by total catchment area, so as to obtain a proportion of each of those land cover categories, within each catchment. We estimated the effects of human infrastructure in multiple ways. Specifically, we estimated dam storage volume, stream road-crossing density (number per square kilometer), and population density. Dam storage was obtained from the StreamCat dataset (Hill et al. 2018). In addition, we estimated the density of road-stream crossings (USGS Database of Stream Crossings, Wieferich 2022). Population density for each catchment is the average population density from census blocks it intersects, weighted by respective intersected area (Falcone 2016). Topographic variables included subwatershed elevation (m), subwatershed drainage area ($km^2$), mean annual discharge (ft3/s), stream segment length, stream order, and average stream segment slope, obtained from the NHDPlus v2 (USGS 2022). All variables were summarized for each subwatershed.

For predicting future changes in fish distributions, we similarly summarized projected climate and land use changes at the subwatershed level. We used climate scenario RCP8.5, which is a business as usual scenario commonly used for short-term, mid-century predictions also accessed through the Climate Toolbox. Additionally, climate change scenarios are based on human activity scenarios, which specifically model land uses changes. We used scenarios A1B for land use projections which represented a business as usual scenario with a globalized world with rapid economic growth and balanced emphasis across all energy sources (Sohl et al. 2018). The time horizon for the predictions was 2040. In addition, we wanted to estimate the rate of change in development, for which we calculated the difference between the projected and

contemporary developed land proportion, and human population growth. To estimate changes in human population density, we used estimates that urban population in Texas would go from 81% to 89% by 2040, while total population would also grow by 20% overall (Texas Demographic Center 2022). Thus, urban centers will experience a 32% population growth ([0.89*1.2]/0.81 = 1.32) while non-urban areas will experience a population shrinkage ([0.11*1.2]/0.19 = 0.69). Those rates were applied to all developed land within a catchment.

## Species distribution model

Given that the accuracy of SDMs is critical for guiding effective conservation priority decisions and for assessing assemblage changes under future climate and land cover scenarios, we used single-species ensemble modeling approach (Rose et al. 2016). Ensemble models have lower variance and more accuracy than single models because they reduce the sensitivity of predictions that may be due to a single model class (Araujo and New 2007). The models used to create an ensemble prediction probability included: generalized linear models (GLM), lasso and ridge regressions, generalized additive models (GAM), boosted regression trees (BRT), random forest (RF), down sampled random forest, maximum entropy (MaxEnt), multivariate adaptive regression splines (MARS), gradient boosting tree (XGBoost), and supported vector machine (SVM). Models were fit independently for each species using weighted occurrences, where the number of presences in each subwatershed provided the weight for calculating the predicted probability of species occurrence. Absence points were down-weighted to have a total (summed) weight equal to the total weight of the presences (Elith et al. 2006, Guisan et al. 2017). Models were trained using 80% of the dataset and k-fold cross validated (k = 5) using the remaining 20%.

Model diagnostics included output for area under curve of the receiving operator characteristics curve (ROC) and Precision Recall gain curve (PR-gain). ROC estimates the probability that given a random presence and absence pair, the model makes a correct classification, with values above 0.5 indicating better discrimination than random classification. Because the baseline for evaluating performance is fixed at 0.5, this allows comparison of models fitted to different species. The PR-gain focuses on positive predictive value; the proportion of presence predictions that are true species presences. Positive values indicate discrimination better than random, with PR-gain of 1 indicating perfect discrimination. This metric is useful for evaluating SDMs of rare species where the number of absences or pseudo-absences is much larger than presences (Sofaer et al. 2019, Valavi et al. 2022). As long as PR-gain values were positive, ROC values greater than 0.7 indicated reasonable discrimination of the model between presence and absence, and were therefore retained for the ensemble predicted probability (Pearce and Ferrier 2000).

As a threshold for determining species presence, a probability of 0.5 or greater was applied for final predictions and subsequent calculations of estimated species richness.

Additionally, occurrences were adjusted to mask model predictions to river basins (using Hydrologic Unit Code, HUC 6; NHDPlus v2) with contemporary occurrence records. Because SDMs are based on environmental similarity, masking was applied to reflect the geographical boundaries that prevent fish from moving between basins unassisted. Thus, if there are no observed contemporary occurrences in a given basin, all predicted values for those catchments within the basin are assigned a probability of zero (0). If species presence was observed, the predicted values from the model were retained.

For each model, predictors were ranked by how strong of a driver a variable was in the model. This varied individually by model, however, top drivers were all classified by predictor contribution to explain overall model variation. This was performed for each model and saved by species. The top three drivers were retained for each model, then re-categorized and counted as follows: precipitation and temperature variables count toward the "Climate" category, the proportion of developed, wetland, forest or agricultural areas within a catchment count toward the "Land Cover" category, dam storage volume, number of road crossings and population density variables count toward the "Human Infrastructure" category, and the catchment area, elevation, stream length, slope and stream order variables counted toward the "Topography" category. For a given species, we counted the number of times each of those 4 categories were represented within the top 3 drivers, summed up across all model runs for that species.

We also evaluated the patterns of vulnerability across species by comparing forecasted and contemporary species occurrences. For each species we calculated the change in the probability of occurrence for each subwatershed. Species with a decrease of 25% or greater were classified as vulnerable to the projected 2040 landscape conditions, as determined by predictors associated with the future climate and land cover scenarios.

## Species status ranking

We applied our species status ranking approach within the framework of the NatureServe conservation status assessment methodology. The methodology considers 10 potential core factors relevant to risk of extirpation/extinction grouped into three categories of rarity, threats, and trends (Master et al. 2012). At least two factors are needed to calculate a score, which is translated into a calculated rank of Critically Imperiled (S1), Imperiled (S2), Vulnerable (S3), Apparently Secure (S4), or Secure (S5) (Faber-Langendoen et al. 2012).

*Rarity*

To quantify the geographic distributions of SGCN freshwater fish species in Texas, the Geospatial Conservation Assessment Tool (GeoCAT) was used to calculate the extent of occurrence (EOO) and the area of occupancy (AOO) for each species (Bachman et al. 2011). Fishes of Texas (Hendrickson and Cohen 2022) occurrence data points were inputted into GeoCAT from a .CSV file containing latitude and longitude coordinates for all collection locations for each species. EOO is a measure of the geographic range size of the species and was calculated as the minimum convex polygon encompassing all known occurrence points. The

AOO is a measure of the area in which a species occurs and was estimated by overlaying a grid with a defined cell width of 1 km and counting the number of occupied grid cells. In addition, estimates of the number of occurrences (i.e., populations) for each species were calculated using ArcGIS Pro (Version 3.4.0). Occurrence points were overlaid onto Hydrologic Unit Code (HUC) 8 watershed boundaries obtained from the Watershed Boundary Dataset (USGS 2025). Each HUC8 where a species was detected counted as a distinct population, and the total number of occurrences was summed across all HUC8s for each species. These spatial metrics (EOO, AOO, and number of occurrences) provide quantitative measures of the distribution, occupancy, and population distribution of Texas SGCN fishes, which were incorporated into our conservation priority assessment.

*Trends*

The occurrence data from FoTX database was also applied to the species-specific assignment of long-term trends. The methods of the trend analysis generally follow previously described structure and process with some adjustments due to the large geographic scope and sample size of occurrence records in the FoTX database (Buckwalter et al. 2017, Cohen et al. 2018). Following, we note some of the key points and differences from the original methodology and updates that have been made and applied to the latest version of the database (known as Track 3; Hendrickson and Cohen 2022) by Dennis Wylie (University of Texas at Austin, Center for Computational Biology & Bioinformatics) in consultation with Adam Cohen and Dean Hendrickson (University of Texas, Fishes of Texas Project), which was input into NatureServe rank assessments. Due to the variability in records across species, a species-specific temporal binning system was used and constrained to the total range of each species within the state of Texas using only vouchered specimens in museum collections. This was done to increase consistency and reliability of trend estimates while accounting for the variable geographic distribution of species across the 18 major river basins. Trends in occurrence were computed as detections per HUC sampled (DPHS), using HUC10 as the spatial sampling unit. These binned occurrence trends were fit to all the potential model structures (Buckwalter et al. 2017). Trends were only computed for species with occurrences in 10 or more HUC10s, therefore geographically restricted species have all been classified with “unknown” trend. Additionally, when none of the model fits achieved an adjusted R-squared value greater than 0.05, the species trend was also classified as “unknown.” Generally, this occurred because either the trajectory was non-monotonic and/or there were very few temporal bins for fitting the trajectory. The other rating code value classifications of declines or increases were based on calculations using the top model or models in the best fit candidate set. The candidate models were determined based on Akaike weights and included all models in the 95% confidence set. The top models were those models with small evidence ratios compared to the best fit model and had less than 7 units of difference in AIC scores. Predicted change in DPHS over time were calculated for each of the competing top models. The predicted differences between the start and end of the species-specific occurrence records were typically in concordance, falling in the same NatureServe rating code value (e.g., all models predict decline of 10 – 30%, corresponding to rating value F). If

model predictions in the best fit models spanned across rating codes, we selected the code with agreement to the most models, and if there were ties, picked the rating value that erred toward a higher-ranking status.

*Threats*

Historically, the assignment of threats has relied heavily on expert opinion of one or a few individuals, which can lead to biased estimates of conservation status that may not reflect the true nature of their conservation need. To address this concern we developed a more standardized framework to assess threats based on broad fish life-history categories and environmental predictors from publicly available geospatial data. Fish life-history strategies were used as a unifying principle to assess threats. Fish life history strategies are closely linked to extinction vulnerability, as they reflect evolutionary trade-offs in reproduction, survival, and population growth (Reynolds et al. 2005). Fish species are commonly classified as equilibrium, periodic or opportunistic life history strategies (Winemiller and Rose 1992). Opportunistic strategists tend to be small-bodied, mature early, and produce many offspring with low survival rates, traits that help them thrive in highly variable or disturbed environments. Periodic strategists are typically large-bodied with delayed maturity and high fecundity, but their offspring experience low survival; they are adapted to predictable, seasonal environments where reproduction is timed with favorable conditions. Equilibrium strategists exhibit traits such as intermediate body size, late maturity, low fecundity, and high parental investment, resulting in higher offspring survival. These strategies represent evolutionary trade-offs that shape how species respond to environmental threats. Therefore, we use life-history categories and sub-categories to assign similar species to similar severity and timing of level one threat categories (Table 1). Descriptions of threat categories can be found in the NatureServe documentation (Master et al. 2012).

To characterize the scope of environmental threat categories associated with each species assessed in our study, we began by quantifying the percent composition of land cover types within each HUC8. Land cover data were obtained from the 2023 National Land Cover Database (NLCD; USGS 2024). By using ArcGIS Pro, the area occupied by each land cover category within each HUC8 was calculated. Species occurrence points were then spatially joined to the land cover dataset to extract land cover percentages for all HUC8s where each species was present. For each occupied HUC8, the percent cover of developed and agricultural land cover type was determined and summed across the NLCD sub-categories of these two types. Land cover percentages were then determined across the HUC8 occupied range for each species and incorporated into the “Residential and Commercial Development” and “Agriculture and Aquaculture” threat categories. Averaging land cover across occupied watersheds provides a useful index of the typical habitat conditions experienced by a fish species across its distribution.

The scope of the “Climate Change and Severe Weather” threat assessment was quantified by using observed drought intensity using data obtained from Climate Engine (Huntington et al. 2017), focusing on the Palmer Drought Severity Index (PDSI). Raster climate data were

processed in ArcGIS Pro to calculate the percentage of each HUC8's area that has experienced moderate drought or worse (moderate drought PDSI is a value of -1) within the last 15 years. This time frame includes two of the most recent and severe droughts in Texas 2011 and 2022 (TWDB 2022), making it particularly relevant to understanding hydrologic and associated physiological stress on fish. For each species, the drought-affected area was averaged across all HUC8s where the species was observed to produce a mean drought exposure metric.

Fish also face threats from anthropogenic hydrologic fragmentation from built infrastructure, therefore the densities of dams and road-stream crossings within the range of each species was calculated for threat categories of "Natural System Modifications" and "Transportation & Service Corridors", respectively. Dam location data were obtained from the National Aquatic Barrier Inventory (Southeast Aquatic Resources Partnership [SARP] 2024), and road-stream crossing data were acquired from the USGS Database of Stream Crossings in the United States (Wieferich 2022). Both datasets were processed in ArcGIS Pro by spatially counting the total number of dams and crossings within each HUC8 watershed occupied by a species and located within the political boundary of Texas. For each species, dam and crossing densities were then calculated as the total number divided by the cumulative area (km2) for all occupied HUC8s. The quantiles of the densities were subsequently used to assign to corresponding bins of small, restricted, large, or pervasive. These density metrics reflect the degree of anthropogenic fragmentation each species experiences across its distribution.

NatureServe defines threats to a species as factors that negatively affect the long-term viability of a species through impacts to survival, reproduction, or habitat quality and availability. Such threats encompass land use characteristics, pollution, development, to natural disasters (Table 2). For the assignment of severity and timing, threats were evaluated in the context of a SGCN species and its evolved life history strategy. For our analysis, we assigned each SGCN species as opportunistic, periodic, or equilibrium. Additionally, specific life history strategies (e.g., broadcast spawners) were considered. Each threat category was assessed in terms of its expected impact to a species with different life history strategies. Threats to a species were evaluated through a combination of factors, including the scope (geographic extent), severity (degree of impact), and timing (immediacy) of each threat. Scope is assessed on a 10-year timeframe for a species. Severity is assessed within the scope and covers 10 years or 3 generations of a species. Timing evaluates the immediacy of the threat to species. For a given species and life history strategy, each threat was individually evaluated. Selections for severity and timing were made using professional judgements or based on species profiles available on the FoTX database and supplemented with peer-reviewed scientific literature. Comments were added for justification to support process transparency and aid future reproducibility.

# Results and Discussion

## Species distribution models

Climate predictors were the main driver of predicted species occurrences followed by land cover, human infrastructure and topography (Figure 1). Under future business as usual climate scenario (RCP 8.5), average annual precipitation is expected to decrease by up to 20 mm, while minimum winter temperatures are expected to rise by up to 2°C, and maximum summer temperatures by up to 3° C. Projections of changes in precipitation regimes tend to be less certain than increasing temperature regimes, though increasing variability is expected to lead to more frequent and longer droughts in the western portion of the state and more intense flooding in central Texas drainages (Nielsen-Gammon et al. 2020). The main drivers of species occurrences were most often related to climate variables and likely reflects the wide geographic variability in climate across Texas and its importance as a large-scale environmental filter (Lynch et al. 2016). However, implications for potential changes in SGCN fish distributions in response to projected changes in temperature and precipitation regimes within river basins remain uncertain. Species that experience a wide range of climate conditions are hypothesized to be less sensitive to changes in temperature, which would indicate that fishes in Texas may have higher acclimation capacities and be resilient to climate change (Bozinovic et al. 2011). To date, the few studies that document distribution shifts in response to climate have observed an increase in the presence, abundance and distribution of species at mid-latitudes (40°N to 50°N; Alofs et al. 2014). By contrast, fishes in Texas experience a warmer climate at its more southern latitudes and thus fish may already be near their upper thermal limit. Additionally, the rise of temperatures and associated evapotranspiration and overall decline in magnitude of precipitation and increase in variability are likely to lead to more frequent and intense droughts especially in western Texas. Increasing droughts in the more arid western part of the state are likely to disproportionately affect pelagic broadcast spawning SGCN that are sensitive to fragmentation and drying river beds (Perkin et al. 2015). However, micro-geographic variation, such as the occurrence of thermal refuges, and phylogenetic relationships affect physiologic adaptations to climate and influence regional and species-specific responses (Comte and Olden 2017). Upper thermal tolerances and acclimation capacity of potentially competing native congeners or introduced non-native species may also affect the ultimate assemblage structure under future climate conditions within a river basin (Westhoff et al. 2021).

Under future land cover change business as usual scenario (A1B), forest and wetlands are expected to decrease while agriculture and developed land increase in Texas with concomitant human population growth (Figure 2). These land cover changes will likely have a larger impact under rising temperatures for the streams they buffer than they would if land conversion occurred in isolation. Freshwater ecosystems are highly sensitive to multiple-stressors as integrators of catchment and regional processes at the land-water interface (Jackson et al. 2016). Forest and wetland cover provides important regulating services to streams that reduce erosion, reduce

evaporation loss from surface waters, cool stream temperatures, and increase infiltration to buffer streams from pollutants in run-off. The loss of these land cover types due to development and growing density of human population centers impose an ongoing and increasing threat to freshwater biodiversity (Reid et al. 2019), especially given that any remaining riparian forest is less likely to mitigate the effects of pollution and stormwater runoff in urban areas (Roy et al. 2007). Together the cumulative effects of changing climate and land cover create stressors that increase the vulnerability of fish SGCN and may potentially increase the number of species of conservation need in Texas. Of the fishes currently classified as SGCN, 12% (9 species) are vulnerable to the combined effect of projected climate and land use change. Indeed, these vulnerable species include known or suspected broadcast spawning minnows that are sensitive to drought and fragmentation: *Hybognathus placitus, Notropis girardi,* and *Notropis megalops*. The other fishes predicted to have a loss of occurrence in at least 5% of currently occupied watersheds include range restricted species such as *Cyprinella proserpina, Dionda argentosa, Dionda diaboli, Dionda texanus, Etheostoma grahami,* and *Etheostoma radiosum.* These species are bound to specific river drainages and will not be able to escape climate change to higher latitudes, nor have redundant populations to withstand major conversions of land cover and growing human populations. The designation of NFCAs to prioritize habitat protection in areas with high ecological integrity and restoration or enhancement where ecological integrity may be improved will be essential to maintaining native fish biodiversity especially for SGCN potentially vulnerable to ongoing regional and global environmental change.

Areas with high richness or that contributed unique but perhaps geographically restricted species, had high congruence with NFCAs developed in 2012 (Figure 3). This reflects the strong focus on species complementarity that was taken into consideration for prioritizing fish biodiversity conservation areas in Texas (Leathwick et al. 2010, Birdsong et al. 2019). Thus, substantial refinements of native fish priority areas were not required. Based on richness and proportion of SGCN alone, there was some indication that particular reaches of priority watersheds could be reassessed for exclusion from or incorporation into the existing network. For example, there is an NFCA that covers the Davis mountains region that is not a hotspot on the map created from the ensemble species distribution model that could be considered for exclusion. By contrast the lower Nueces is not currently in the NFCA network, although it is indicated as a hotspot. Any refinements would need to be based on local expert knowledge of the species, river system, and stakeholder values and existing conservation partnerships to sustain conservation actions where they are most likely to be successful (Acreman et al. 2019). Taking the two example cases, the Davis Mountains will remain included in the NFCA network due to the last potentially remaining population of a federally listed species in Texas, *Gila pandora* (Rio Grande Chub and Rio Grande Sucker Conservation Team 2020). Similarly, despite the contemporary predicted SGCN richness, the Nueces River will remain a lower priority conservation opportunity area, given that it is highly impaired and would require substantial investments that may not be feasible given limited economic and human resources. Additionally, conservation opportunity areas in Texas must reflect both terrestrial and aquatic biodiversity and

significant habitats, determined by decision makers. Such decisions are often complex and require multiple lines of information, including the data and visualizations provided by the products developed with this project for freshwater fish SGCN. Spatial information on the distribution of fish SGCN were transferred to TPWD in February of 2025 and incorporated into the 2025 State Wildlife Action Plan (www.txswap.org), including area prioritization as part of the Texas Conservation Opportunity Area Viewer (https://experience.arcgis.com/experience/89e51b7822004bb88a2c40e75308848b/page/Web-Viewer). In addition, the species specific occurrence predictions have been incorporated into the open access FoTX database as of March 2026, which is a comprehensive online resource of species records, distributions and life-history profiles for Texas fish biodiversity (Hendrickson and Cohen 2022). Specifically, one may access the maps by going to the taxa web tab (https://fishesoftexas.org/taxa/) and toggling the habitat suitability layer in the map window of a species.

Species distribution models (SDMs) are widely used in freshwater fisheries science because they provide one of the few tractable approaches for relating species occurrence to environmental gradients and generating spatially explicit predictions across large and often sparsely sampled river networks, making them a foundational tool for basin-scale conservation and management applications (Huang & Frimpong, 2015; Yu et al., 2023). However, their predictive performance is frequently overestimated, as most applications rely on internal cross-validation and thus have been found to have limited transferability among river basins or over time (Huang & Frimpong 2016, Huang et al. 2016). These limitations are compounded by sensitivity to key processes that are particularly important in freshwater systems, including imperfect detection, and the dendritic structure of river networks, all of which can bias inference and reduce predictive realism (Wagner et al. 2020). Thus, the inference of the results of this study should remain bound by the state of Texas study area and consider that these broad scale SDMs will miss key local environmental variables including biotic interactions and fine-scale habitat variation that are also important determinants of fish species occurrence. Where available, current agency and research efforts can build on these state-wide SDMs for individual watersheds or subwatersheds by integrating local high-resolution independent fish and environmental datasets, such as adopting occupancy-based approaches that explicitly account for detection error when sampling effort and repeat monitoring data are available, and incorporating stream network structure and ecological processes through joint modeling frameworks to improve predictive reliability and applicability for management (Gimenez, 2024; Wagner et al., 2020).

## Species status ranking

Climate and land use are primary drivers of species distributions, as outlined above, and are also considered primary drivers of biodiversity loss (Reid et al. 2019). While land use is often considered in the development of threat indices and to prioritize habitats (Comte et al. 2022, Sievert et al. 2016), species conservation assessments rarely include this type of information

when designating species status (de Baan et al. 2013). Here, we quantified threat impacts and incorporated life history information to predict how a given species will likely respond to ecological threats. In doing so we created a methodology to improve the reproducibility and transparency for future researchers and practitioners in synergism with a framework developed for mussels of Texas (de Moulpied et al. 2024).

Seventy-two of the 76 species analyzed in our NatureServe conservation assessment had sufficient data for ranking, of those, 26 (34%) were ranked as critically imperiled (S1), 28 (37%) ranked imperiled (S2), and 18 (24%) ranked vulnerable (S3). Of these ranks, 35 species had no change in ranking from when they were last assessed, six species went down a rank (e.g., S2 to S3), 21 species went up one rank (e.g., S2 to S1) three species went up two ranks, indicating they were more vulnerable (Table 3). Additionally, seven previously unranked species were able to be ranked using our approach. Changes in ranks could be due to the implementation of this new ranking approach and updated occurrence and trend data associated with the latest version of the FoTX database. Due to the design of the species conservation status assessment, changes in ranks are most likely reflective of changes in distribution that are used as inputs to rarity and trends values in the NatureServe calculator. Specifically, these data are captured in metrics of total range extent, area of occupancy, number of occurrences, and long-term occurrence trends (Faber-Langendoen et al. 2012, Master et al. 2012). These factors are weighted as 0.7, whereas threats are weighted 0.3 in the calculation of the overall score. The weight of importance of these metrics have also been verified by the percentage of variation explained by previous ranking studies (de Moulpied et al. 2024, Perkin et al. 2021). Thus, the overall trend in increased ranks may be an indicator that there is substantial range contraction of species in Texas, likely due to the increasing threats imposed by land cover conversions and climate change. Species with increasingly narrow ranges are at higher risk of extinction due to catastrophic events. Therefore, species whose rank has increased with an indication of long-term declines or unknown may be good candidates for conservation prioritization. Those candidates include species from the pelagic broadcast spawning reproductive guild such as *Hybognathus placitus* and *Notropis girardi* and geographically restricted species such as *Etheostoma radiosum*. In total, 14 of the species were estimated to have long-term declines in occurrence using the trend analysis, and an additional 48 species did not have sufficient data to estimate trends in occurrence. However, further study of individual species and updated monitoring may be needed to verify whether these represent true declines in occurrence or potential information gaps in the past decade from which surveys submit specimen collections or other verified data to the FoTX database.

Initial rankings conducted by this project were transferred to TPWD in December of 2025, where they will undergo a review before they are incorporated into the Texas Natural Diversity Database (https://tpwd.texas.gov/huntwild/wild/wildlife_diversity/txndd/) and updated in the State Wildlife Action Plan (www.txswap.org), which functions as a living document with ongoing revisions.

## Conclusions

The conservation of at-risk species is a difficult task because of incomplete information. However the complement of approaches, SDMs and species ranking assessments, which incorporate species occurrence data and potential current and future threats as conducted in this work can serve as a framework to inform prioritizations. Importantly, assessing vulnerability through predicted species distributions under current and projected future conditions point to similar priority species as the contemporary range and threat assessment associated with NatureServe rankings. Specifically, species from the guild of pelagic broadcast spawners and species with limited geographic range were indicated as candidates for further research, monitoring, and conservation prioritization. Applying geographic information to the assessment of distribution change and conservation assessment provides a quantitative, and more transparent and reproducible approach to prioritizing areas and species for conservation and reduces the uncertainty and subjectivity in the assignment of conservation ranks.

## Acknowledgments

Dr. Diane LeBouille contributed to model development and analysis of species distribution models. Dr. Scott Collins and Owen George contributed to the methodological development and analysis of species ranking assessments.

## Funding information

Funding was provided by the U.S. Fish and Wildlife Service by Interagency Agreement, G21AC10841. The Texas Cooperative Fish and Wildlife Research Unit is sponsored jointly by the U.S. Geological Survey, Texas Parks and Wildlife Department, Texas Tech University, the Wildlife Management Institute, and the U.S. Fish and Wildlife Service. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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# Tables

Table 1. Life-history categorizations used to assign similar species threat categories.

| Main Life-history | Distinguished subcategory | Notes |
|---|---|---|
| Opportunistic | Darters | Require clear water with clean, rocky substrates |
| Opportunistic | Pelagic broadcast spawners | Require hundreds of kilometers of unfragmented stream |
| Periodic | Migratory | Require hundreds of kilometers of unfragmented stream |
| Periodic | Non-migratory | |
| Equilibrium | Bass/sunfish | Nest builders and guarders |

Table 2. Summary of the twelve NatureServe threat categories evaluated for each SGCN fish species, and examples of how Scope, Severity, and Timing are assigned across species. Scope was determined using areal calculations for occupied subbasins (USGS HUC 8s) by species.

| *Threat* | *Category* | *Scope* | *Scope Source Data* | *Severity* | *Timing* |
|---|---|---|---|---|---|
| *1* | Residential & commercial development | % developed land (total Developed Open Space, Low, Medium, and High Intensity) | National Land Cover Dataset (USGS 2024) | Based on life-history (e.g., serious for short-lived opportunistic species) | Low (i.e., long-term – threat not expected to increase in next 10 years) |
| *2* | Agriculture & aquaculture | % agricultural land (total Hay/Pasture and Cultivated Crops) | National Land Cover Dataset (USGS 2024) | Based on life-history (e.g., serious for short-lived opportunistic species) | Low (i.e., long-term) |
| *3* | Energy production & mining | Unknown | NA | Insignificant | Unknown (threat is generally from catastrophes) |
| *4* | Transportation & service corridors | Stream crossing density | Wieferich 2022 | Based on life-history (e.g., higher for migratory or pelagic broadcast) | High (i.e., continuing, given effect on dispersal) |
| *5* | Biological resource use | Small (unless recreational species) | NA | Species specific | Negligible (unless recreational) |
| *6* | Human intrusions & disturbance | Restricted | NA | Species specific | Negligible |
| *7* | Natural system modifications | Dam density | National Inventory of Dams (USACE 2020) | Based on life-history (e.g., higher for migratory or pelagic broadcast) | High (i.e., continuing, given effect on dispersal) |
| *8* | Invasive & other problematic species, genes & diseases | Small (unless problematic species is known) | Species specific | Species specific | Negligible to high (species specific) |
| *9* | Pollution | | | | |
| *10* | Geological events | Unknown | NA | Insignificant | Unknown (threat is generally from catastrophes) |
| *11* | Climate change & severe weather | % area in drought over the past 15 years | Climate Engine (2025) | Based on life-history (e.g., higher for opportunistic) | Moderate (could come back in short-term |
| *12* | Other options | Unknown | NA | Insignificant | Unknown |

Table 3. NatureServe conservation status rankings for fish species of greatest conservation need (SGCN) including updated 2025 proposed rankings, 2023 rankings used by Texas Parks and Wildlife department (ranging from S1: critically imperiled to S4: apparently secure; SNR indicates species not ranked due to data deficiency and SX indicates presumed extirpation), and NatureServe categorical assignment of long-term occurrence trends (e.g., U: unknown, G: stable, D: decline of 50-70%; Master et al. 2012).

| *Scientific name* | *Common name* | *2025 proposed rank* | *2023 rank* | *Long-term trend category* |
|---|---|---|---|---|
| *Agonostomus monticola* | mountain mullet | S2 | S2 | U: unknown |
| *Ammocrypta clara* | western sand darter | S2 | S3 | U: unknown |
| *Anguilla rostrata* | american eel | S3 | S4 | G: stable |
| *Atractosteus spatula* | alligator gar | S3 | S4 | G: stable |
| *Campostoma ornatum* | Mexican stoneroller | S2 | S1 | D: decline of 50 - 70% |
| *Campostoma spadiceum* | highland stoneroller | S1 | SNR | U: unknown |
| *Cycleptus elongatus* | blue sucker | S2 | S3 | G: stable |
| *Cyprinella lepida* | plateau shiner | S2 | S2 | U: unknown |
| *Cyprinella proserpina* | proserpine shiner | S3 | S2 | G: stable |
| *Cyprinodon bovinus* | Leon Springs pupfish | S1 | S1 | U: unknown |
| *Cyprinodon elegans* | Comanche Springs pupfish | S1 | S1 | U: unknown |
| *Cyprinodon eximius* | Conchos pupfish | S1 | S1 | U: unknown |
| *Cyprinodon pecosensis* | Pecos pupfish | S1 | S1 | G: stable |
| *Cyprinodon rubrofluviatilis* | Red River pupfish | S2 | S2 | G: stable |
| *Dionda argentosa* | manantial roundnose minnow | S2 | S2 | U: unknown |
| *Dionda diaboli* | Devils River minnow | S1 | S1 | U: unknown |
| *Dionda episcopa* | roundnose minnow | S2 | S1 | F: decline 10-30% |
| *Dionda flavipinnis* | Guadalupe roundnose minnow | S2 | SNR | G: stable |
| *Dionda nigrotaeniata* | Medina roundnose minnow | S1 | S1 | U: unknown |
| *Dionda serena* | Frio roundnose minnow | S2 | S2 | U: unknown |
| *Dionda texensis* | Nueces roundnose minnow | S3 | SNR | U: unknown |
| *Erimyzon claviformis* | western creek chubsucker | S3 | S2S3 | F: decline 10-30% |
| *Etheostoma fonticola* | fountain darter | S1 | S1 | U: unknown |
| *Etheostoma grahami* | Rio Grande darter | S3 | S2 | G: stable |
| *Etheostoma radiosum* | orangebelly darter | S1 | S3 | U: unknown |
| *Etheostoma thompsoni* | gumbo darter | S3 | SNR | G: stable |
| *Gambusia gaigei* | Big Bend gambusia | S1 | S1 | U: unknown |
| *Gambusia heterochir* | Clear Creek gambusia | S1 | S1 | U: unknown |

| *Scientific name* | *Common name* | *2025 proposed rank* | *2023 rank* | *Long-term trend category* |
|---|---|---|---|---|
| *Gambusia krumholzi* | spotfin gambusia | S1 | S1 | U: unknown |
| *Gambusia nobilis* | Pecos gambusia | S1 | S2 | U: unknown |
| *Gila pandora* | Rio Grande chub | S1 | S1 | U: unknown |
| *Hiodon alosoides* | goldeye | S2 | S3 | E: decline of 30 to 50% |
| *Hybognathus amarus* | Rio Grande silvery minnow | SX | SX | U: unknown |
| *Hybognathus nuchalis* | Mississippi silvery minnow | S3 | S4 | F: decline 10-30% |
| *Hybognathus placitus* | plains minnow | S2 | S4 | F: decline 10-30% |
| *Hybopsis amnis* | pallid shiner | S3 | S4 | F: decline 10-30% |
| *Ictalurus lupus* | headwater catfish | S2 | S1S2 | G: stable |
| *Macrhybopsis aestivalis* | speckled chub | S2 | S1S2 | G: stable |
| *Macrhybopsis australis* | prairie chub | S1 | S1 | U: unknown |
| *Macrhybopsis hyostoma* | shoal chub | S3 | SNR | G: stable |
| *Macrhybopsis marconis* | burrhead chub | S2 | SNR | G: stable |
| *Macrhybopsis storeriana* | silver chub | S2 | S3 | G: stable |
| *Macrhybopsis tetranema* | peppered chub | S1 | S1 | U: unknown |
| *Menidia clarkhubbsi* | Texas silverside | S3 | S3 | G: stable |
| *Micropterus treculii* | Guadalupe bass | S3 | S3 | U: unknown |
| *Minytrema melanops* | spotted sucker | S1 | S3 | U: unknown |
| *Moxostoma austrinum* | Mexican redhorse | S3 | S1 | U: unknown |
| *Notropis amabilis* | Texas shiner | S3 | S4 | G: stable |
| *Notropis atrocaudalis* | blackspot shiner | S3 | S3 | F: decline 10-30% |
| *Notropis bairdi* | Red River shiner | S2 | S3 | U: unknown |
| *Notropis blennius* | river shiner | S1 | S3 | U: unknown |
| *Notropis braytoni* | Tamaulipas shiner | S2 | S1S2 | G: stable |
| *Notropis buccula* | smalleye shiner | S2 | S1S2 | F: decline 10-30% |
| *Notropis chalybaeus* | ironcolor shiner | S2 | S3 | U: unknown |
| *Notropis chihuahua* | Chihuahua shiner | S1 | S2 | F: decline 10-30% |
| *Notropis girardi* | Arkansas River shiner | S1 | S2 | F: decline 10-30% |
| *Notropis jemezanus* | Rio Grande shiner | S2 | S1 | F: decline 10-30% |
| *Notropis maculatus* | taillight shiner | S1 | S1 | U: unknown |
| *Notropis megalops* | West Texas shiner | S2 | SNR | H: Increase of 10 - 25% |
| *Notropis oxyrhynchus* | sharpnose shiner | S2 | S1S2 | F: decline 10-30% |
| *Notropis potteri* | chub shiner | S2 | S2 | G: stable |
| *Notropis sabinae* | Sabine shiner | S2 | S3 | G: stable |
| *Notropis shumardi* | silverband shiner | S3 | S4 | G: stable |
| *Percina apristis* | Guadalupe darter | S2 | S2 | U: unknown |
| *Percina maculata* | blackside darter | S2 | S1 | F: decline 10-30% |
| *Percina shumardi* | river darter | S3 | S4 | U: unknown |

| *Scientific name* | *Common name* | *2025 proposed rank* | *2023 rank* | *Long-term trend category* |
|---|---|---|---|---|
| *Phenacobius mirabilis* | suckermouth minnow | S3 | S4 | U: unknown |
| *Platygobio gracilis* | flathead chub | S1 | S2 | U: unknown |
| *Polyodon spathula* | paddlefish | SU | S3 | U: unknown |
| *Prietella phreatophila* | Mexican blindcat | S1 | S1 | U: unknown |
| *Pteronotropis hubbsi* | bluehead shiner | S1 | S1 | U: unknown |
| *Rhinichthys cataractae* | longnose dace | S2 | S2 | U: unknown |
| *Satan eurystomus* | widemouth blindcat | S1 | S1 | U: unknown |
| *Scaphirhynchus platorynchus* | shovelnose sturgeon | SU | S2 | U: unknown |
| *Trogloglanis pattersoni* | toothless blindcat | S1 | S1 | U: unknown |

# Figures

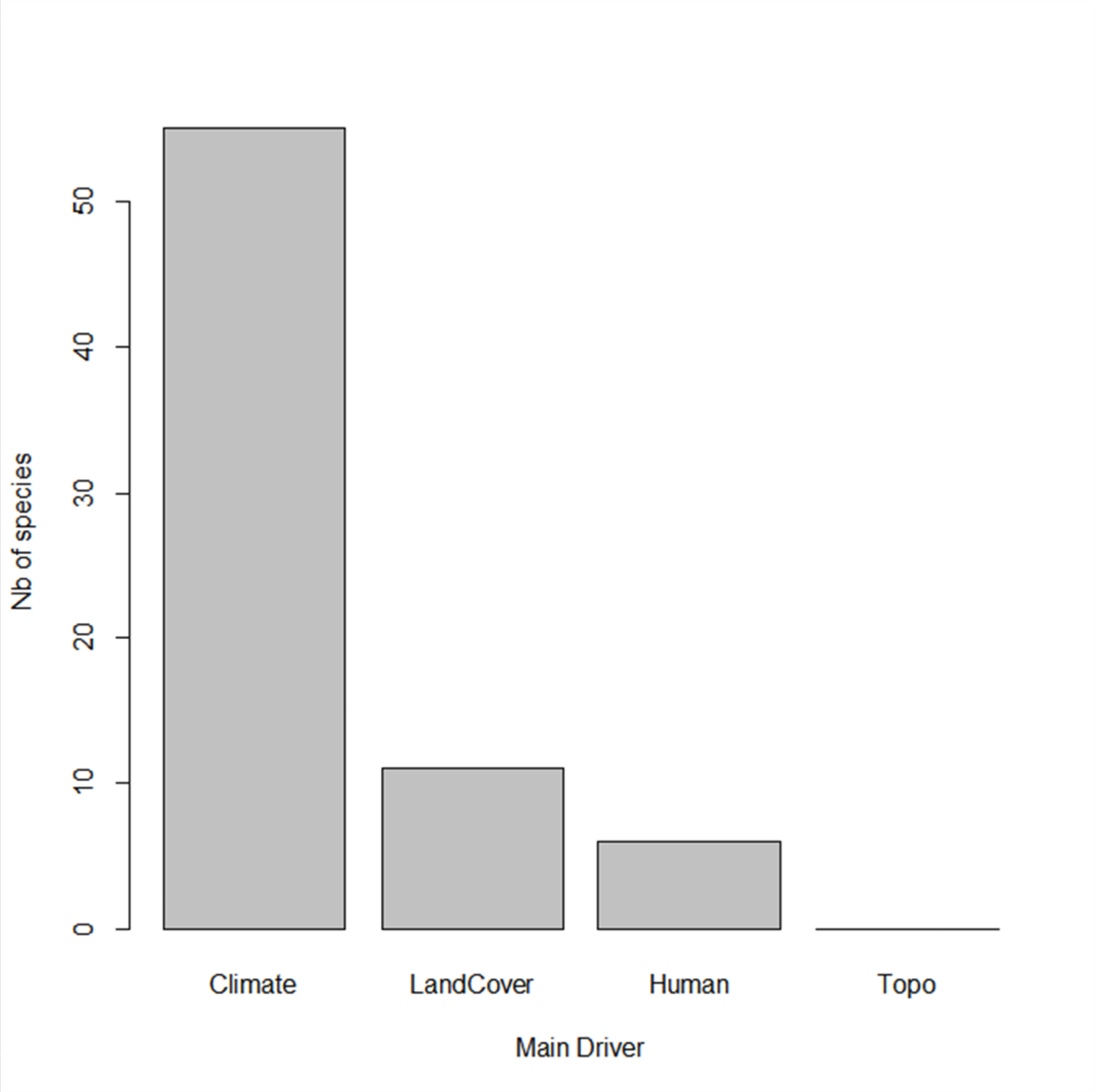



Figure 1. Frequency of main driver categories predicting species occurrences including climate (i.e., mean annual precipitation, maximum summer temperature, and minimum winter temperature), land cover (i.e., developed, agricultural, forest, and wetland area in subwatershed), human infrastructure (i.e., dam storage volume, number of road crossings, population density in subwatershed), and topography (i.e., elevation, stream order).

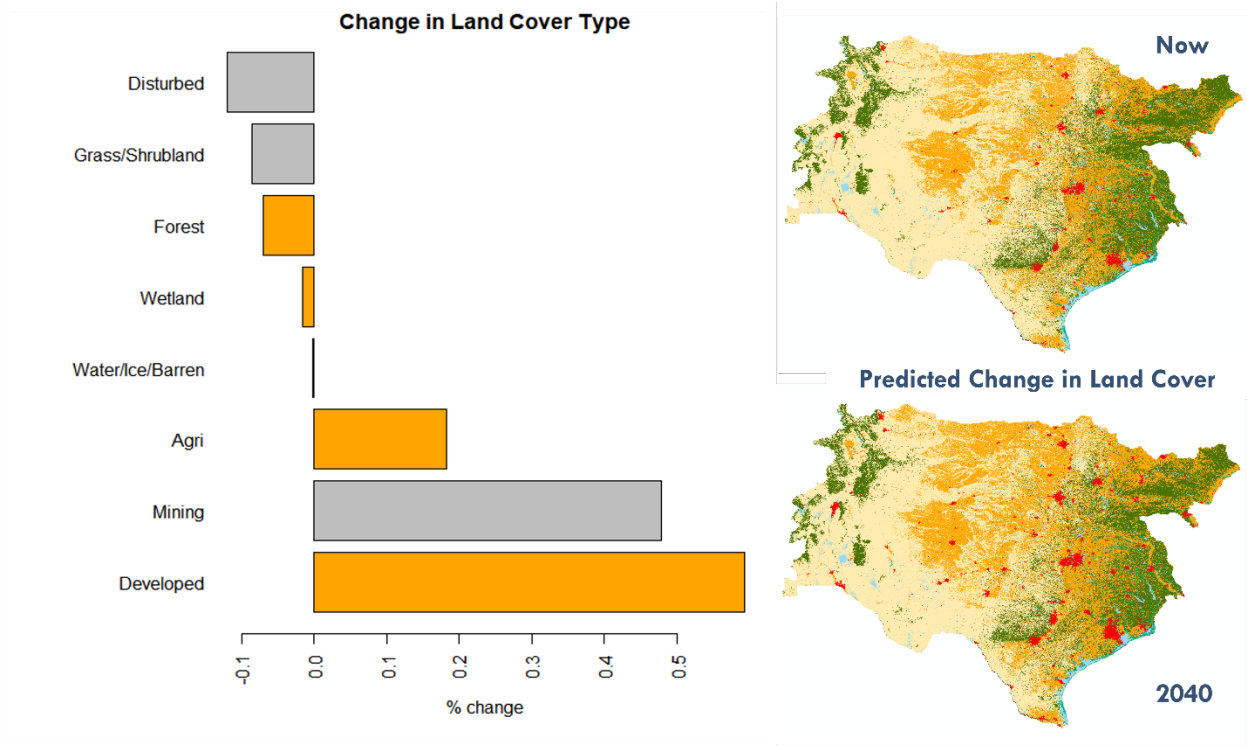



Figure 2. Predicted change in landcover under the A1B, business as usual, scenario. In the change in land cover bar chart, orange bars indicate predictors used in the species distribution modeling. On the land cover maps, red is developed, green is forest, orange is agriculture, blue is wetland cover, and beige is other land cover categories not evaluated as predictors in our species distribution modeling.

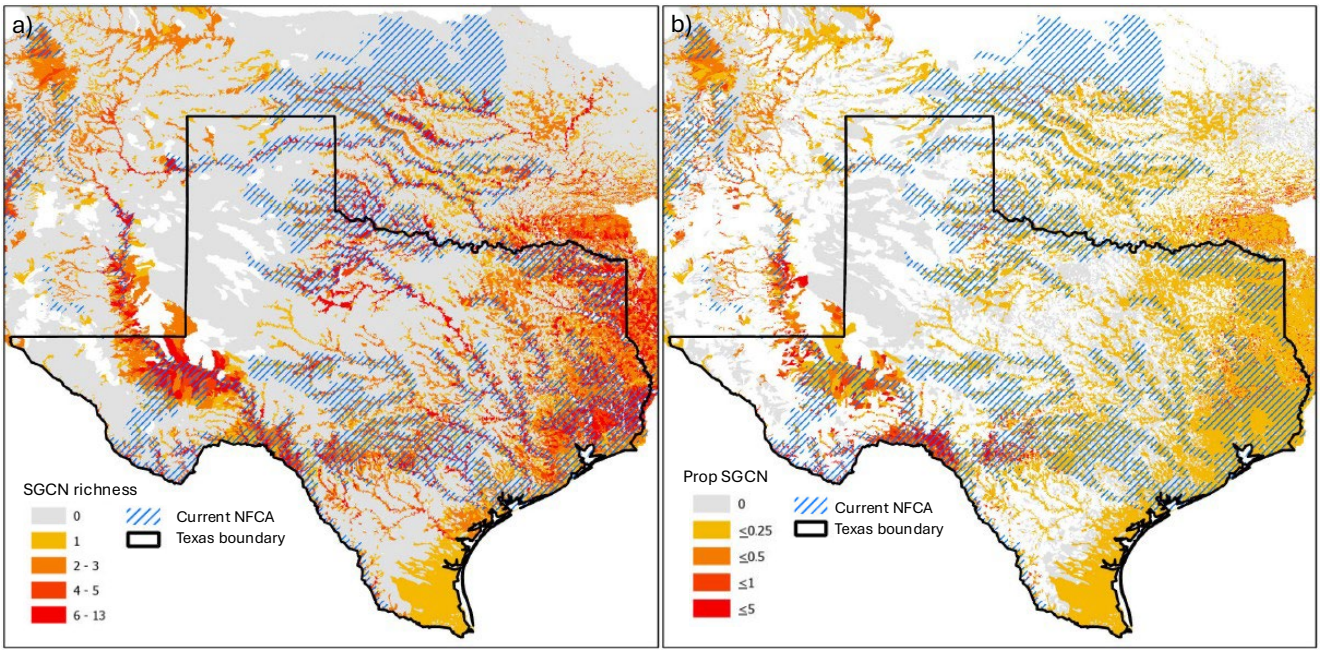



Figure 3. Patterns of a) fish SGCN richness and b) proportion of fish SGCN by catchment for all major river basins that intersect with Texas. SGCN diversity patterns derived from ensemble predictions of species distributions are overlayed by the current network of Native Fish Conservation Areas (NFCA). Proportion values greater than 1 indicate that only SGCN species were present.