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Original Article

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Machine learning-based ensemble species distribution models to guide monitoring and survey design for offshore wind

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Abstract

(1) The rapid expansion of offshore wind energy raises concerns about potential impacts on marine wildlife, yet development often outpaces the capacity for ecological assessment. Data-limited species in offshore environments are particularly challenging to monitor, constraining the ability to evaluate potential risks and design evidence-based management strategies across large marine areas. (2) We present a novel, scalable framework based on ensemble machine learning methods, including shallow neural networks, to predict species distribution across extensive, data-limited marine systems. By combining multiple algorithms with high-resolution environmental predictors, the framework reduces model-specific bias, improves predictive reliability, and generates transparent, reproducible spatial predictions of species occurrence. This integrative approach demonstrates how heterogeneous and non-traditional data streams can be formally combined to inform applied ecological decisions. (3) We demonstrate the framework using Atlantic Sturgeon (*Acipenser oxyrinchus*), a long-lived, highly migratory species of conservation concern, by leveraging cooperative acoustic telemetry detections to predict distributions at ∼1 km² resolution across more than 620 000 km² of northwest Atlantic continental shelf waters. The approach explicitly accounts for dynamic habitat use and seasonal movements, providing a realistic representation of the species' spatial ecology in areas of limited observational coverage. (4) In the context of expanding offshore development and other emerging ocean uses, map outputs from these models function as ecological triage tools, providing early, defensible predictions to prioritize monitoring and help to allocate survey resources across areas of varying predicted risk. Importantly, the approach avoids the longstanding tendency to interpret data gaps as evidence of negligible risk, supporting precautionary and adaptive decision-making to better inform management under constrained conservation resources. (5) *Synthesis and applications*. The framework is modular and broadly transferable, applicable to other taxa, regions, and regulatory contexts, and readily accommodates new data as monitoring coverage grows. Embedding ensemble-based predictions within existing regulatory processes enhances transparency, defensibility, and ecological realism of offshore impact assessments. By linking predictive models directly to monitoring and management decisions, this approach supports adaptive, evidence-based stewardship of marine resources in an era of rapid offshore development, increasing human ocean use, and escalating conservation pressures.

Keywords Atlantic Sturgeon, ensemble species distribution models, machine learning, acoustic telemetry, offshore wind energy, marine spatial planning, conservation decision support

Introduction

The accelerated commercialization of offshore wind energy (OWE) has prompted significant concerns for marine wildlife (Akhtar et al. 2022). As global capacity of OWE is projected to increase rapidly in the coming decades (von Jouanne et al. 2025), there is an urgent need to develop and apply data-driven approaches capable of guiding management and conservation responses to commercial-scale development (Williams et al. 2024, Isaksson et al. 2025). However, despite major industry and policy investment in offshore renewable energy, the autecology of many species within prospective development areas remains poorly understood, and even basic ecological data on species occurrence and distribution needed to develop effective management and mitigation strategies are often lacking (Watson et al. 2024). Critical data gaps regarding the potential for spatiotemporal overlap between OWE and marine wildlife are further exacerbated by the logistical and financial challenges of monitoring cryptic and highly migratory populations across vast, heterogeneous marine environments. Because policy decisions often precede the availability of ecological data, practitioners are frequently required to rely on sparse, outdated, or uncertain information (Gill et al. 2024). Address-

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ing these limitations through targeted monitoring and integrative data analysis is essential to avoid regulatory mismatches as OWE development continues to outpace effective conservation measures (Boehlert and Gill 2010, Bailey et al. 2014).

In the United States (US), ambitious clean energy targets, together with favorable federal and state policies (e.g. offshore leasing programs and renewable energy incentives; Amaral 2024), have driven recent growth in the OWE market (Alola and Akadiri 2021, USDOE 2023). While the pace of development has fluctuated in response to broader policy and administrative priorities, candidate sites for OWE projects have been identified throughout the waters of the US Outer Continental Shelf (OCS), with active commercial leases and near-term operations primarily concentrated in the Northeast- and Mid-Atlantic OCS regions (Table S1, Supplemental Materials). As OWE projects already under contract or in construction across the US OCS continue to scale up to meet renewable energy demands, the evaluation of ecological effects across the entirety of these sites has become a necessarily complex undertaking. Although stressors to marine ecosystems and fauna are expected during all phases of OWE development (Bergström et al. 2014), the lack of scale-appropriate ecological data necessary to identify and mitigate potential resource conflicts, and the challenge of obtaining such data on a site-by-site basis across broad areas of poorly monitored marine habitat can impede robust impact assessment for both conservation and industry objectives, and may result in substantial delays in the consenting process (Boehlert and Gill 2010, Gill et al. 2024).

In this context, recent reviews have emphasized the importance of spatial and temporal considerations when evaluating the effects of OWE development on marine fauna (e.g. Galparsoro et al. 2022, Thomassen et al. 2025). While negative ecological and environmental impacts resulting from operational wind farms are putatively shaped by localized conditions (Bergström et al. 2014), continuing technological and engineering advancements (e.g. the deployment of larger turbines, floating platforms, and deeper-water installations), coupled with aggressive near-term goals, are expected to substantially expand the areal extent and geographic footprint of development (Beiter et al. 2022). As OWE arrays expand in size and density, the area of influence of individual projects may increasingly overlap, potentially generating cumulative or synergistic ecological effects. Yet, the evidence base needed to evaluate impacts across these broader and more complex spatial scales remains limited. Although some studies have provided valuable localized insights (e.g. Ingram et al. 2019), comprehensive efforts to assess ecological impacts have largely been eclipsed by the rapid expansion of OWE. Consequently, much of the available evidence remains fragmented and insufficiently robust to support extrapolation across regions or taxa, limiting its usefulness for timely statutory consultations or impact assessments. The ability to systematically collect and integrate ecological data across multiple scales is therefore critical to closing existing knowledge gaps, anticipating potential impacts, and supporting informed planning and decision-making across the OCS (Gill 2005, Gill et al. 2024, Watson et al. 2024).

Species distribution modeling (SDM) has emerged as an essential correlative-predictive approach and a critical tool for addressing ecological and management challenges associated with data-limited marine species and habitats (Robinson et al. 2017). SDM approaches enable researchers to link species occurrences with environmental predictors at ecologically relevant scales, providing actionable insights into patterns of biodiversity and informing a wide range of management applications. These models are particularly valuable for their high discriminatory performance and their ability to extrapolate species distributions across unsampled or novel environments (Martínez-Minaya et al. 2018, Qazi et al. 2022). While occupancy models (MacKenzie et al. 2002) offer a complementary framework that explicitly accounts for imperfect detection through structured repeated-survey designs, their application relies on key assumptions, including population closure within sampling periods and the availability of standardized repeat surveys, which are difficult to satisfy for highly migratory species across large marine extents, particularly where occurrence data are opportunistic. In contrast, SDMs are well suited to modeling species-environment relationships from presence-only occurrence data at broad spatial scales (Elith and Leathwick 2009), aligning with predictive objectives in spatial ecology. Furthermore, spatial products derived from SDMs, such as predictive spatial maps, are widely used in conservation planning and environmental impact assessments (Sofaer et al. 2019, Winship et al. 2020). As such, SDMs represent a versatile and increasingly indispensable tool for anticipating species responses to environmental change and guiding evidence-based decision-making across diverse ecological and management contexts.

The integration of machine learning methods, including shallow neural networks, into SDM frameworks has substantially enhanced model flexibility and predictive performance relative to traditional regression-based methods, which are often constrained by sample size requirements or assumptions of linearity (e.g. Lee et al. 2022, Vasconcelos et al. 2024). These advancements are now supported by increased data availability, broader data sharing, enhanced computational power, and algorithmic innovations, enabling machine learning methods to capture complex, nonlinear species–environment relationships across large and diverse datasets that were previously difficult or impossible to analyze. Ensemble modeling approaches further enhance predictive performance and reduce biases inherent in individual algorithms by combining outputs from multiple models into a consensus prediction (Araújo and New 2007, Marmion et al. 2009). Such approaches not only improve predictive reliability but also align with emerging principles of sustainable modeling, maximizing knowledge gain per unit of computational and data input while minimizing redundancy and ecological uncertainty (Bodner et al. 2020, Nijkamp et al. 2024, Ukoba et al. 2025). Despite the widespread use of SDMs in terrestrial and coastal systems, the application of machine learning-based ensemble species distribution modeling (ESDM) approaches at spatiotemporal scales required for offshore marine planning remains largely unexplored. Extending these methods to offshore environments represents a novel and potentially transformative step toward generating robust, spatially explicit insights that can directly inform conservation planning and resource management in increasingly exploited seascapes (Robinson et al. 2017).

To demonstrate the application of a machine learning-based ESDM framework for predicting species habitat extent across marine areas allocated for development under realistic, data-limited conditions, the Atlantic Sturgeon (*Acipenser oxyrinchus*, Acipenseridae) was used as a focal species. In the US, Atlantic Sturgeon are long-lived, anadromous fishes that undertake extensive marine migrations and may seasonally occupy areas of the Atlantic OCS currently designated for OWE development (e.g.

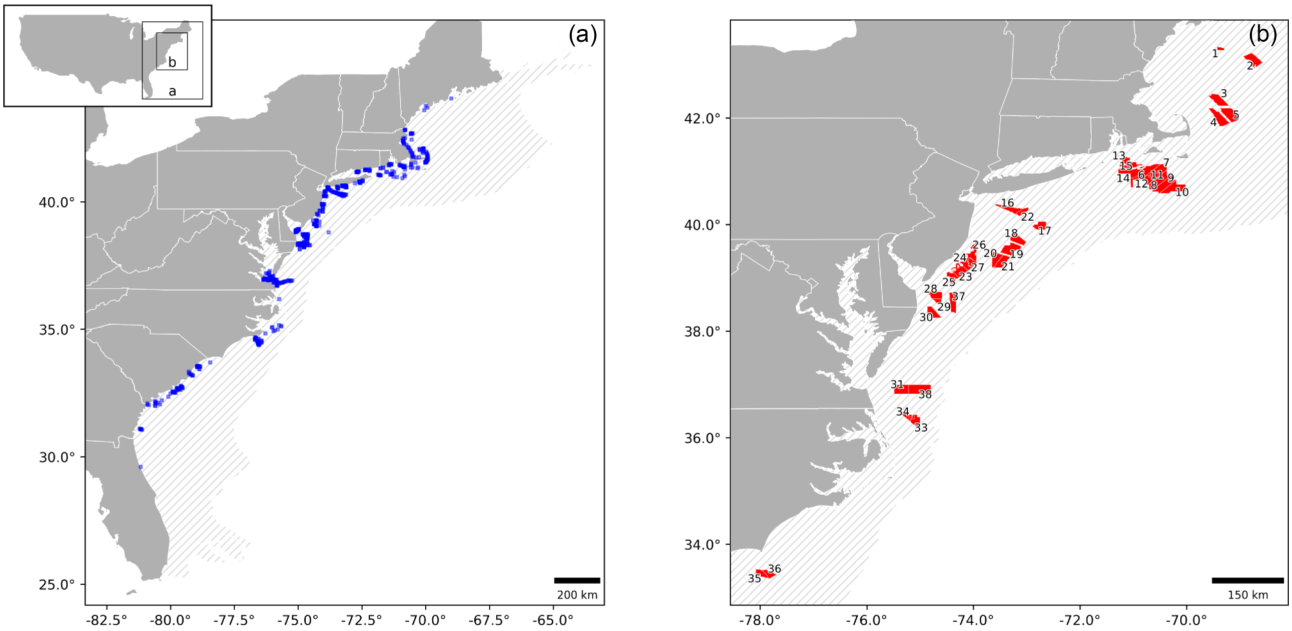

Figure 1 US Atlantic Outer Continental Shelf study site. (a) Unique Atlantic Sturgeon detections ($n = 845$, blue squares). (b) Planned offshore wind lease sites (red polygons, see Supplementary Table S1). Hatched area indicates the study site; inset shows US location.

Stein et al. 2004a, b, Dunton et al. 2010, Breece et al. 2017, Melnychuk et al. 2017, Ingram et al. 2019, Rothermel et al. 2020). The species is federally listed as distinct population segments (DPS) under the US Endangered Species Act (ESA) and is subject to coordinated management, with ongoing efforts focused on mitigating bycatch and protecting designated critical habitats. Despite these regulatory safeguards, substantial uncertainty remains regarding the species' marine distribution, migratory corridors, and potential exposure to offshore infrastructure. Evaluating spatial overlaps between Atlantic Sturgeon and OWE sites provides a basis for identifying areas of high risk, directing conservation and management efforts, and supporting compliance with statutory and regulatory requirements, including those established under federal endangered species and environmental review frameworks. However, research efforts have focused primarily on riverine and nearshore waters, and spatiotemporal habitat use throughout their marine range remains poorly understood (reviewed in Hilton et al. 2016). As a result, existing monitoring data rarely align with management-relevant spatial and temporal scales, potentially underestimating offshore habitat use and delaying timely management responses to ongoing or emerging threats.

The ESDM framework was applied to identify key patterns of Atlantic Sturgeon habitat use and management priorities. This integrative approach combines high-resolution telemetry data, publicly available environmental predictors, and AI-driven SDMs to provide a spatially explicit assessment of habitat use, offering actionable insights for fisheries management and offshore resource planning. Specifically, we aimed to (1) quantify regional habitat distribution across the US Atlantic OCS, (2) identify spatiotemporal habitat trends within areas allocated for offshore wind development, and (3) generate and validate ensemble prediction maps to directly inform site- and population-level management and conservation decisions. This represents the first application of an AI-based ESDM framework to an endangered species in offshore marine environments, advancing predictive ecology by providing a scalable, generalizable tool capable of generating robust, management-relevant predictions even from limited or heterogeneous datasets, and integrating predictive ecology into offshore infrastructure planning in data-poor, dynamic seascapes.

Materials and methods

Study region

Potential offshore habitats for Atlantic Sturgeon were delineated across the US Atlantic OCS, from the coastline to the shelf break, representing the theoretical range of marine occupancy in US waters based on literature review and biological opinion. This area (626 204 km^2; Fig. 1), representing the potential areal extent of offshore residency, was used as the clipping boundary for all subsequent spatial analyses, and included several large estuarine systems seasonally inhabited by Atlantic Sturgeon (Long Island Sound, New York Bay, Delaware Bay, and Chesapeake Bay).

Spatially referenced observations

Telemetry detections were compiled for Atlantic Sturgeon originally captured in coastal marine waters of the New York Bight (NYB) and acoustically tagged with internal transmitters ($n = 585$; Supplementary Table S2). Tag models and transmission characteristics varied across deployments, but transmitters were generally designed for multi-year tracking. All procedures were conducted in accordance with relevant guidelines and authorized by the National Marine Fisheries Service (NMFS; Endangered Species Permits 16 422 and 20 351), the New York State Department of Environmental Conservation (Endangered/Threatened Species Scientific License 336), and Stony Brook University's Institutional Animal Care and Use Committee (IRB-1022451–4). Acoustic telemetry detections providing spatial and temporal information on individually tagged Atlantic Sturgeon were collected between 2011 and 2021 through cooperative monitoring efforts, using receiver arrays deployed in the Atlantic OCS (Supplementary Table S3). Unique detection locations were aggregated by month across all years to generate monthly presence-only occurrence datasets and aligned to centroids of corresponding 0.01° raster cells within the Atlantic OCS study extent (~1 km^2 resolution). This aggregation reduces the potential influence of individual tag longevity and battery depletion on the spatial distribution of detections. Within raster cells for each month, duplicate detections were removed so that presence was recorded as a binary variable, rather than as counts.

Acoustic transmitters used in this study (V16; Innovasea Systems Inc., Canada) have manufacturer-reported battery lives of approximately 5–10 years, depending on transmission interval and tag configuration. To assess the potential influence of tag battery attrition on the temporal continuity of the dataset, we estimated the number of acoustically active transmitters in each year under three battery life scenarios: conservative (5-year), moderate (7-year), and liberal (10-year) assumptions. For each scenario, transmitters were assumed to remain active for the specified duration following deployment, after which they were removed from the active pool. Annual counts of active transmitters were calculated by summing all deployments remaining within their assumed battery life window (Supplementary Fig. S1). The continuous addition of new tagging cohorts throughout the monitoring period partially offset battery attrition, resulting in a dynamic pool of detectable individuals over time.

Environmental predictors

Potential explanatory variables were selected for biological relevance and availability across the full study period and extent. Only publicly available datasets were considered to maximize reproducibility and generalizability (see Supplementary Table S4). This approach also ensured that the modeling framework remains operationally scalable and applicable for management contexts, where reliance on consistently available data sources is essential. While additional ecologically relevant variables such as bottom temperature, dissolved oxygen, distance to natal river mouths, and chlorophyll-*a* concentration (as a proxy for primary productivity and prey availability) were considered to further refine predictions, their inclusion was constrained by limitations in spatial and temporal data availability and consistency across the study domain. The present framework therefore prioritizes widely available and operationally scalable data sources to ensure applicability for management and survey design, particularly for repeated or near-real-time prediction.

For variables with temporal variation, pooled monthly averages were computed over the study period. Multicollinearity among predictors was evaluated using correlation matrices and variance inflation factors (VIF; Chatterjee and Hadi 2006). Although VIF values were moderate, no strict thresholds were applied, and all variables were retained to preserve ecological interpretability and ensure consistency of predictors across months. The algorithms implemented are generally robust to multicollinearity in terms of predictive performance, although potential effects on variable importance are acknowledged.

The final suite of predictor variables was formatted as a raster stack in R (R Core Team 2024) using the "terra" package (Hijmans et al. 2026, Fig. 2). The stack was consistent in spatial extent and resolution (i.e. EPSG:4326; 0.01° raster cell size) and included: depth (m), gravel substrate (%), mud substrate (%), photoperiod (hours day^{-1}), precipitation (mm), sea surface salinity (SSS; practical salinity units, PSU), and sea surface temperature (SST; °C). Of the seven predictors, three were static across months (depth, gravel substrate, and mud substrate), whereas four varied temporally (photoperiod, precipitation, SSS, and SST). Accordingly, month-to-month variation in predictions reflects changes in the dynamic environmental conditions superimposed on a stable bathymetric and substrate framework.

Smart pseudoabsence generation

For Atlantic Sturgeon, as with other highly migratory and cryptic species, true absence data are difficult to obtain over large spatial scales because individuals move extensively and detection probability is variable. Because telemetry data record only detected locations and do not provide confirmed absences, they are treated as presence-only observations. To address this limitation and define the environmental domain for modeling, pseudo-absence points were generated to serve as background data (Phillips and Dudik 2008, Barbet-Massin et al. 2012).

An initial pool of 100 000 random background points was generated across the study extent for each month (Fig. 2). From these candidate points, pseudo-absences were selected using a two-step screening procedure designed to reduce spatial proximity bias and environmental overlap with presences. First, a disk filter was applied, creating a 50-km buffer around all known presences to exclude points immediately adjacent to observations and reduce the risk of false absences (McMahon et al. 2021, Ramirez-Reyes et al. 2021). Second, a surface range envelope (SRE) filter (e.g. Thuiller et al. 2009) was used to remove points within the 5th–95th percentile of environmental conditions observed at presences, retaining only candidate points outside this range (Barbet-Massin et al. 2012). This two-step procedure produced a filtered pool of pseudo-absences for each month that was both spatially and ecologically distinct from presences. From each monthly pool, 1000 pseudo-absences were randomly sampled to generate a final input dataset in which telemetry detections were coded as presences and pseudo-absences as absences.

To assess the sensitivity of model performance to pseudo-absence design, six alternative configurations were evaluated across all 12 months: four buffer distances (none, 25, 75, and 100 km), each with SRE applied; the original 50-km buffer without SRE; and a pure random background with neither buffer nor SRE filtering. Presence holdout points were kept fixed across all configurations to ensure comparability.

Data partitioning

The combined presence–pseudo-absence datasets were partitioned into two subsets: (i) 90% used for model development, with an 80/20 split for training and testing, and (ii) an independent 10% hold-out set reserved exclusively for external ensemble evaluation. Stratified sampling was used to preserve the proportion of presences and pseudo-absences in both subsets, minimizing potential bias in model evaluation. This is particularly important for species with low detection rates, such as Atlantic Sturgeon, to ensure that rare presence events are adequately represented in both training and evaluation datasets.

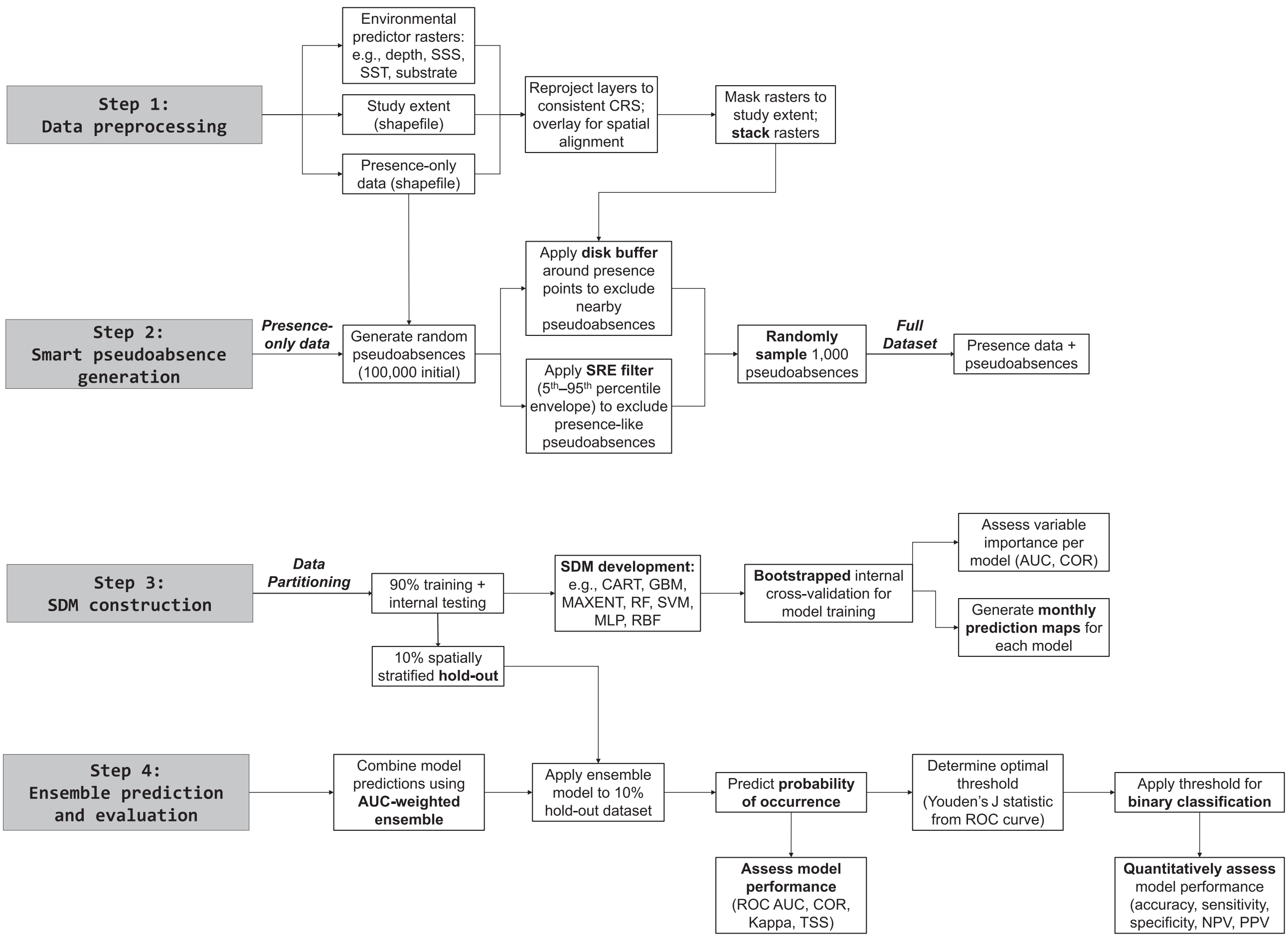

Figure 2 Workflow for predicting marine species distributions, including data preprocessing, pseudoabsence generation, monthly SDM construction, and ensemble prediction.

Fully independent external validation data of sufficient spatial and temporal resolution are rarely available in SDM studies (Robinson et al. 2011, Robinson et al. 2017), and this limitation applies here given the large study extent and restricted availability of independent occurrence data across the US Atlantic OCS. The stratified holdout approach therefore represents a practical and robust validation strategy under these constraints. To assess whether the random partitioning introduced spatial bias or inflated predictive performance, Moran's I and Geary's C were computed on ensemble model residuals at holdout locations for each month using a $k = 5$ nearest-neighbor spatial weights matrix (Fortin and Dale 2005). Residuals were defined as the difference between observed binary presence–absence values and ensemble-predicted probabilities. McNemar's test was used to evaluate asymmetry between false-positive and false-negative error rates (McNemar, 1947). Nearest-neighbor distances between holdout and training presence locations were also computed to characterize the spatial separation of the partitioned datasets.

Model development and evaluation

SDMs were developed in R (R Core Team 2024) using the "sdm" package (Naimi and Araújo 2016). Seven machine learning algorithms were employed: classification and regression trees (CART), gradient boosting machines (GBM), maximum entropy (MAXENT), multilayer perceptron (MLP), radial basis function networks (RBF), random forests (RF), and support vector machine models (SVMs). These methods combined machine learning techniques (i.e. CART, GBM, MAXENT, RF, SVM) with artificial neural networks (i.e. MLP, RBF), providing complementary approaches to capture both linear and nonlinear relationships between environmental predictors and Atlantic Sturgeon occurrences. Default hyperparameters were applied consistently across all algorithms to maintain comparability and generalizability across months and to avoid introducing model-specific optimization biases (see Supplementary Table S5).

For internal testing, 100 repeated bootstrap samples were drawn with replacement from the model development dataset. Within each bootstrap, 80% of the resampled data were used to train the model, and the remaining 20% were reserved for internal testing. This was repeated independently for all bootstrap iterations, resulting in 100 models per algorithm and a total of 700 models evaluated for each month (Barbet-Massin et al. 2012).

Individual model performance was evaluated on the independent holdout dataset and internal test subsets using a suite of complementary metrics, including the area under the receiver operating characteristic curve (AUC; Fielding and Bell 1997), true skill statistic (TSS; Allouche et al. 2006), Cohen's kappa (Cohen 1960), and the point biserial correlation (COR; Elith et al. 2006).

Metrics were summarized across bootstraps for each algorithm to provide means, standard deviations, and 95% confidence intervals. Higher AUC values indicated better discriminatory performance, whereas higher values of TSS and kappa indicate improved threshold-based classification performance.

Predictor influence

The relative influence of environmental predictors was quantified using a permutation-based approach (Thuiller et al. 2009). Predictor influence was assessed using two complementary metrics: AUC and COR. Changes in AUC following permutation quantified the reduction in model discriminatory performance attributable to each predictor, whereas the correlation between original and permuted predictions quantified changes in spatial agreement. Predictor influence was summarized as the mean across all bootstrap replicates for each month, encompassing seven modeling algorithms with 100 bootstrap iterations each (700 models per month in total). These measures reflect the contribution of each predictor to model performance and spatial prediction rather than evidence of causal ecological effects. Because some predictors exhibit moderate correlation, permutation-based importance may underestimate the contribution of correlated variables; results should therefore be interpreted as indicative of predictive contribution rather than independent ecological effects.

Ensemble predictions

Monthly ensembles integrating predictions from individual SDM algorithms were generated using the "sdm" package (Naimi and Araújo 2016). Ensemble predictions were computed as weighted means, with weights proportional to each model's AUC for the corresponding month. Only models with AUC > 0.8 were retained for final ensemble projections, following standard practice for filtering low-performing models within ESDM frameworks (e.g. Thuiller et al. 2019).

Ensemble performance was evaluated on the independent 10% hold-out set (Araújo et al. 2005). Predicted probabilities were extracted for all hold-out locations and compared with observed presence–absence data. Ensemble accuracy was assessed using AUC and confusion-matrix-based metrics, including sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). To convert ensemble predictions from continuous probabilities to binary presence–absence classifications, two complementary thresholds were applied. The first, a fixed cutoff of 0.5, provides a consistent benchmark across months and is widely used in SDM studies. The second, an optimal threshold derived from the receiver operating characteristic (ROC) curves using Youden's index (Youden 1950), maximizes the sum of sensitivity and specificity. This dual-threshold approach is widely recommended and provides a practical balance between interpretability and model realism, combining a standardized rule with a data-driven, performance-optimized criterion (Jiménez-Valverde and Lobo 2007, Liu et al. 2013).

To assess whether model performance was influenced by the number of presence points, correlations between monthly training sample size and holdout performance were tested using AUC and misclassification error. Non-parametric correlations (Spearman's ρ and Kendall's τ) and linear regressions were applied to evaluate whether months with more presence points systematically achieved higher predictive accuracy.

Results

Spatially referenced observations

A total of 585 Atlantic Sturgeon were included in this study (Supplementary Table S2). All fish were originally captured and tagged in riverine or coastal marine waters of the NYB between 2010 and 2020. Fork length (FL) measurements at capture of individual Atlantic Sturgeon ranged from 401 to 2050 mm, with a mean FL of 994.3 mm (SD $= 230.3$). All individuals were marine migrants at the time of detection, representing juvenile, subadult, and adult life stages. Accordingly, the dataset characterizes habitat use during the marine phase of the Atlantic Sturgeon life cycle, when individuals occupy shelf and nearshore habitats outside natal estuaries before returning to freshwater to spawn. While genetic data identifying river of origin or DPS assignment were not available, detections were assumed to primarily represent the ESA-endangered NYB DPS, which dominates captures in the tagging area and contributes most individuals detected in coastal and offshore habitats of the mid-Atlantic (Dunton et al. 2012).

Monitoring from 2011 to 2021 yielded 845 unique marine telemetry detection locations of these fish across acoustic receiver arrays deployed throughout the US Atlantic OCS study area (Fig. 2, Supplementary Fig. S3). The pooled monthly mean number of unique observations was 202.8 (SD $= 73.3$), with the highest number in December ($n = 348$) and the lowest in August ($n = 83$). Detection frequency was typically lower in late winter (January–February) and late summer (August–September), possibly reflecting reduced movement or receiver coverage. Detection locations correspond to receiver positions and are therefore constrained by receiver spacing and detection range. Previous studies using acoustic telemetry of Atlantic Sturgeon in coastal waters have assumed effective detection radii on the order of $\sim$600 m, with detection probabilities declining with distance and maximum detection ranges approaching $\sim$1400 m under favorable conditions (e.g. Ingram et al. 2019). As such, the effective spatial resolution of detections is coarser than that of the environmental predictor grid and reflects the structure of the monitoring array rather than precise animal locations. Individual receiver deployment coordinates were not available across all contributing organizations for the full study period, particularly for receivers without detections, precluding the inclusion of a spatially explicit receiver coverage map or direct quantification of monitoring effort across the study domain.

Spatial diagnostics indicated statistically significant positive autocorrelation in ensemble residuals across all 12 months (Moran's I $= 0.222$–0.673, all P-values < 0.0001; Geary's C $= 0.375$–0.874, all P-values ≤ 0.034; Supplementary Table S6; Fig. S1). However, median nearest-neighbor distances between holdout and training presence locations were consistently small, ranging from 0.02 to 2.53 km (mean $\pm$ SD: 1.46 $\pm$ 2.14 km across months; Supplementary Table S6). These distances are broadly consistent with the effective detection range of acoustic receivers ($\sim$600–1400 m), suggesting that spatial dependence occurs at the scale of the monitoring array. McNemar's test was non-significant for all months (*P*-values = 0.248–1.000), indicating balanced classification errors with no systematic directional bias.

SDM evaluation

Independent holdout AUC comparisons were used to assess relative discriminatory performance across algorithms, whereas threshold-dependent metrics are reported for the final ensemble model. Comparisons on the independent holdout dataset showed consistently high predictive performance across months (Table 1), with AUC values ranging from 0.936 to 1.000. RF, CART, GBM, MAXENT, and MLP generally achieved near-perfect discrimination in most months, while SVM and especially RBF showed slightly lower but still strong performance overall. No single algorithm consistently outperformed the others across all months, indicating that multiple modeling approaches captured similar underlying patterns in the data.

Internal test results showed a similar pattern (Supplementary Table S6). Across the internal test set, mean monthly AUC values ranged from 0.927 to 1.000, TSS from 0.773 to 0.990, and kappa from 0.582 to 0.980, indicating moderate to excellent predictive performance. RF generally showed the highest and most stable performance, whereas RBF was more variable, particularly in early and late months. CART, GBM, MAXENT, MLP, and SVM also performed well across most months. Together, the holdout and internal test results indicate that individual algorithms performed consistently well, supporting the use of a multi-algorithm ensemble framework as a robust basis for final spatial prediction.

Removing the SRE filter had no significant effect on Cohen's kappa (0.907 ± 0.056 vs. 0.909 ± 0.040; Wilcoxon $P = 0.969$), sensitivity (0.875 ± 0.079 vs. 0.887 ± 0.048; $P = 0.563$), or specificity (0.994 ± 0.011 vs. 0.994 ± 0.008; $P = 0.932$), indicating that the SRE filter did not artificially inflate classification performance. A statistically significant but negligible difference in AUC was observed (0.999 ± 0.002 vs. 0.993 ± 0.007; $P = 0.009$; $\Delta = 0.006$), indicating that model discrimination reflects genuine ecological signal rather than artifacts of pseudo-absence design.

Across the four buffer distances tested (all with SRE), a performance plateau was evident from 50 km onward. The 25 km buffer produced significantly lower kappa and sensitivity than the 75 km and 100 km configurations ($P \leq 0.036$), whereas the 50 km, 75 km, and 100 km buffers did not differ significantly across any metric (all $P \geq 0.108$), confirming the original 50 km design as an appropriate and parsimonious choice. Configurations without any spatial buffer produced the lowest performance across all scenarios (kappa = 0.815–0.859; Supplementary Table S8), further supporting the ecological rationale for spatial restriction of background points.

Predictor influence

Analysis of predictor influence identified depth, SST, SSS, and photoperiod as the most influential variables, though their relative importance varied seasonally (Fig. 3). Depth was consistently among the top predictors, while SST was most influential in August and photoperiod dominated in influence during September and October. AUC-based influence reflected contributions to model discrimination, whereas COR-based influence captured effects on the spatial structure of predictions. In some months, a predictor could

Table 1. Predictive performance of individual algorithms on the independent holdout dataset across months, expressed as area under the receiver operating characteristic curve with 95% confidence intervals.

Month	CART	GBM	MAXENT	MLP	RF	SVM	RBF
January	0.986 [0.968–1.000]	0.983 [0.963–1.000]	0.995 [0.986–1.000]	0.991 [0.980–1.000]	0.981 [0.960–1.000]	0.997 [0.991–1.000]	0.985 [0.967–1.000]
February	1.000 [1.000–1.000]	1.000 [1.000–1.000]	1.000 [1.000–1.000]	1.000 [1.000–1.000]	0.998 [0.991–1.000]	1.000 [1.000–1.000]	1.000 [1.000–1.000]
March	0.995 [0.987–1.000]	0.995 [0.987–1.000]	0.992 [0.982–1.000]	0.992 [0.983–1.000]	0.972 [0.949–0.994]	0.999 [0.997–1.000]	0.984 [0.967–1.000]
April	0.997 [0.991–1.000]	0.999 [0.996–1.000]	0.994 [0.984–1.000]	0.983 [0.960–1.000]	0.965 [0.930–1.000]	0.999 [0.998–1.000]	0.985 [0.968–1.000]
May	0.997 [0.991–1.000]	0.997 [0.991–1.000]	1.000 [1.000–1.000]	0.999 [0.998–1.000]	0.964 [0.928–0.999]	1.000 [1.000–1.000]	0.986 [0.969–1.000]
June	1.000 [1.000–1.000]	1.000 [1.000–1.000]	0.990 [0.972–1.000]	0.995 [0.985–1.000]	0.971 [0.944–0.999]	1.000 [1.000–1.000]	0.984 [0.964–1.000]
July	0.964 [0.893–1.000]	0.979 [0.951–1.000]	0.999 [0.998–1.000]	1.000 [1.000–1.000]	0.991 [0.979–1.000]	1.000 [1.000–1.000]	1.000 [1.000–1.000]
August	1.000 [1.000–1.000]	0.998 [0.994–1.000]	0.997 [0.992–1.000]	0.998 [0.993–1.000]	0.976 [0.953–1.000]	1.000 [1.000–1.000]	0.991 [0.977–1.000]
September	1.000 [0.999–1.000]	0.999 [0.996–1.000]	1.000 [1.000–1.000]	0.995 [0.986–1.000]	0.988 [0.975–1.000]	1.000 [1.000–1.000]	0.991 [0.976–1.000]
October	0.995 [0.986–1.000]	0.997 [0.992–1.000]	0.997 [0.992–1.000]	0.997 [0.992–1.000]	0.989 [0.973–1.000]	1.000 [1.000–1.000]	0.995 [0.987–1.000]
November	0.999 [0.997–1.000]	0.998 [0.995–1.000]	1.000 [1.000–1.000]	1.000 [1.000–1.000]	0.988 [0.971–1.000]	1.000 [1.000–1.000]	0.997 [0.991–1.000]
December	1.000 [1.000–1.000]	1.000 [1.000–1.000]	1.000 [1.000–1.000]	1.000 [1.000–1.000]	0.936 [0.877–0.995]	1.000 [1.000–1.000]	0.970 [0.937–1.000]

CART = classification and regression trees; GBM = gradient boosting machines; MAXENT = maximum entropy; MLP = multilayer perceptron; RBF = radial basis function networks; RF = random forests; SVM = support vector machines.

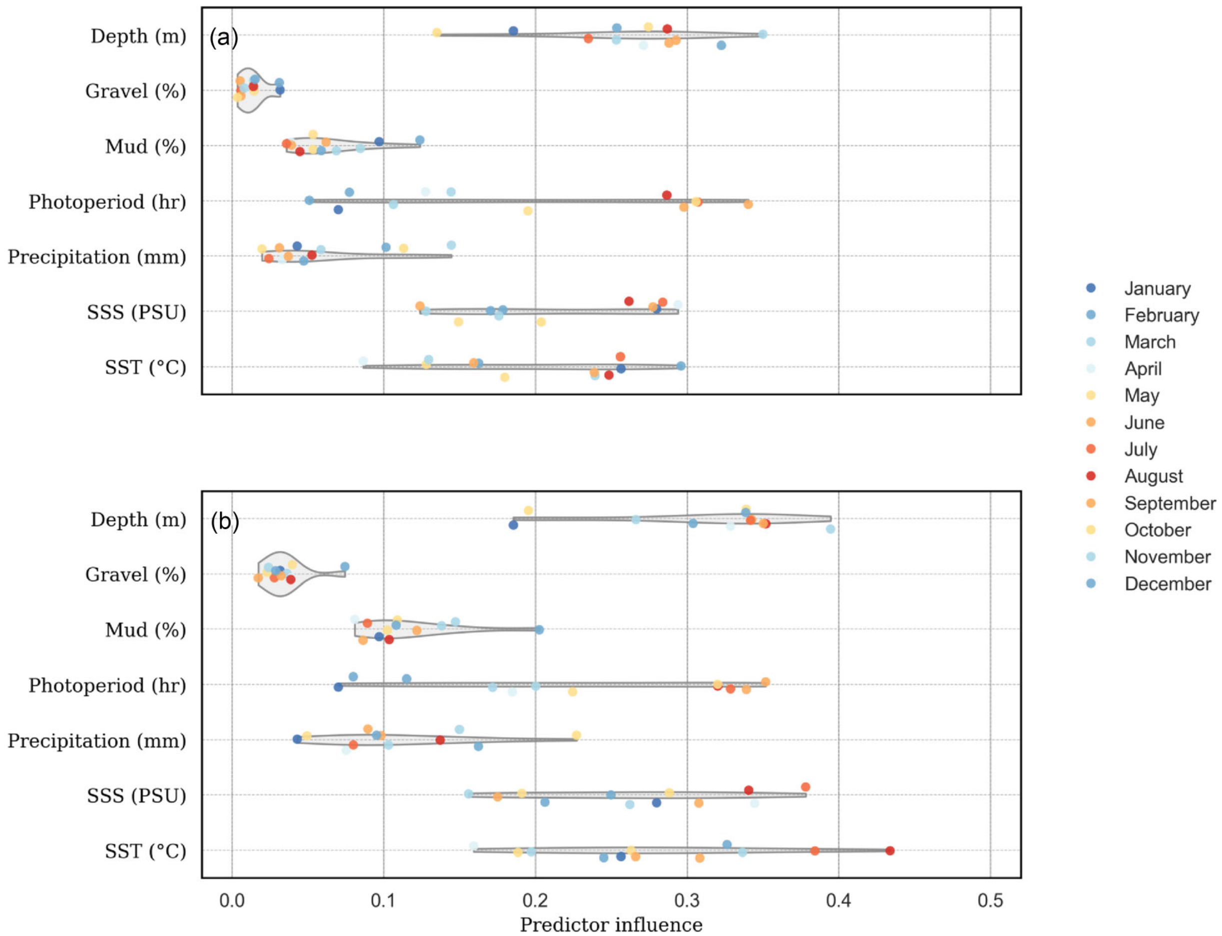

Figure 3 Violin plots of monthly predictor influence on Atlantic Sturgeon SDMs (700 runs/month). AUC shows contribution to discrimination; 1 − COR shows contribution to spatial structure. Width indicates value density; colored points are monthly means. Higher values indicate stronger influence. SSS = sea surface salinity; SST = sea surface temperature.

have moderate AUC influence but high COR influence, indicating that it strongly shaped the spatial pattern of predictions without greatly affecting overall discrimination (e.g. SSS in April). Conversely, variables such as SST in August had high AUC influence and correspondingly high COR influence, indicating both strong discrimination and spatial effects. Gravel and mud fractions, used as proxies for benthic substrate composition and associated prey availability, exhibited comparatively lower influence across all months in both metrics. This likely reflects limitations in the spatial resolution of substrate data, as prey distributions are not always well predicted by sediment type. Nonetheless, substrate characteristics can serve as coarse indicators of food availability, as sturgeon often forage in unconsolidated sediments where infaunal prey such as polychaetes and bivalves are most abundant (Johnson et al. 1997; McClean et al. 2013) . Precipitation similarly showed low influence, likely because its effects on nearshore conditions are indirect and spatially diffuse at the marine scale considered here. While precipitation can influence freshwater discharge and coastal salinity gradients, these processes are more directly captured by SSS in the models, reducing precipitation's apparent predictive power. These patterns align with known ecological constraints on Atlantic Sturgeon habitat use, including thermal preferences, seasonal photoperiod cues, and depth-related distribution patterns, consistent with observed seasonal and spatial movements in nearshore waters (e.g. Melnychuk et al. 2017, Ingram et al. 2019).

Ensemble predictions

All seven individual algorithms were independently run for each month and met the inclusion criterion (Supplementary Table S7). Mean ensemble AUC values ranged from 0.993 to 1.000 (mean = 0.998 ± 0.003), with narrow confidence intervals (≤0.01), indicating stable discrimination across months (Table 2). TSS values ranged from 0.714 to 1.000, and kappa ranged from 0.792 to 1.000, reflecting good to excellent agreement between observed and predicted occurrences. Overall classification accuracy exceeded 0.95 for all months, while sensitivity (≥0.714) and specificity (≥0.95) were consistently high, with positive and negative predictive values generally above 0.90. Evaluating ensemble predictions at optimal monthly thresholds (Supplementary Table S9) confirmed these patterns, with TSS ranging from 0.969 to 1.000, kappa from 0.889 to 1.000, and accuracy consistently ≥0.975.

Monthly ensemble maps revealed distinct seasonal shifts in predicted Atlantic Sturgeon occurrence across the study site (Fig. 4, Supplementary Figs S2–S13). From November through March, predicted occurrences expanded into southern and offshore habitats, whereas during June through August, distributions con-

Table 2. Holdout evaluation of ensemble SDMs showing mean performance metrics.

Month	AUC [95% CI]	TSS	Kappa	Accuracy [95% CI]	Sensitivity [95% CI]	Specificity [95% CI]	PPV [95% CI]	NPV [95% CI]
January	0.9994 [0.9979–1.0000]	0.889	0.931	0.983 [0.941–0.998]	0.889 [0.672–0.969]	1.000 [0.963–1.000]	1.000 [0.806–1.000]	0.981 [0.932–0.995]
February	0.9994 [0.9978–1.0000]	0.882	0.928	0.983 [0.941–0.998]	0.882 [0.657–0.967]	1.000 [0.964–1.000]	1.000 [0.796–1.000]	0.981 [0.933–0.995]
March	0.9966 [0.9911–1.0000]	0.921	0.885	0.967 [0.919–0.991]	0.950 [0.764–0.991]	0.971 [0.918–0.990]	0.864 [0.667–0.953]	0.990 [0.946–0.998]
April	0.9927 [0.9820–1.0000]	0.767	0.792	0.959 [0.907–0.987]	0.786 [0.524–0.924]	0.981 [0.935–0.995]	0.846 [0.578–0.957]	0.972 [0.922–0.991]
May	0.9996 [0.9985–1.0000]	0.920	0.949	0.984 [0.945–0.998]	0.920 [0.750–0.978]	1.000 [0.964–1.000]	1.000 [0.857–1.000]	0.981 [0.934–0.995]
June	1.0000 [1.0000–1.0000]	0.824	0.890	0.976 [0.931–0.995]	0.824 [0.590–0.938]	1.000 [0.966–1.000]	1.000 [0.785–1.000]	0.973 [0.924–0.991]
July	0.9990 [0.9964–1.0000]	0.900	0.943	0.991 [0.953–1.000]	0.900 [0.596–0.982]	1.000 [0.965–1.000]	1.000 [0.701–1.000]	0.991 [0.948–0.998]
August	1.0000 [1.0000–1.0000]	1.000	1.000	1.000 [0.967–1.000]	1.000 [0.510–1.000]	1.000 [0.965–1.000]	1.000 [0.510–1.000]	1.000 [0.965–1.000]
September	1.0000 [1.0000–1.0000]	0.714	0.824	0.982 [0.937–0.998]	0.714 [0.359–0.918]	1.000 [0.965–1.000]	1.000 [0.566–1.000]	0.981 [0.934–0.995]
October	0.9992 [0.9970–1.0000]	1.000	0.900	0.983 [0.940–0.998]	0.833 [0.552–0.953]	1.000 [0.965–1.000]	1.000 [0.722–1.000]	0.981 [0.934–0.995]
November	0.9987 [0.9955–1.0000]	0.857	0.914	0.984 [0.942–0.998]	0.857 [0.601–0.960]	1.000 [0.966–1.000]	1.000 [0.758–1.000]	0.982 [0.936–0.995]
December	0.9986 [0.9662–1.0000]	0.927	0.927	0.970 [0.926–0.992]	0.947 [0.827–0.985]	0.979 [0.928–0.994]	0.947 [0.827–0.985]	0.979 [0.928–0.994]

AUC = area under the ROC curve; CI = confidence interval; TSS = true skill statistic; Kappa = Cohen's kappa; PPV = positive predictive value; NPV = negative predictive value.

tracted toward nearshore areas centered on putative aggregation sites and NYB spawning rivers. Transitional distributions during April–May and September–October suggested migratory movements between these seasonal ranges.

Ensemble accuracy was further evaluated using the independent 10% hold-out dataset, providing an unbiased assessment of model generality. Performance remained high across all metrics, with mean AUC > 0.9 and balanced confusion-matrix statistics confirming strong generalization beyond the training data (Table 2). Correlations between monthly sample size and hold-out predictive accuracy (Table 3) revealed no significant association (AUC: Spearman: $\rho = -0.19$, $P = 0.55$; Kendall: $\tau = -0.14$, $P = 0.53$; misclassification error: Spearman: $\rho = 0.25$, $P = 0.44$; Kendall: $\tau = 0.17$, $P = 0.45$), and linear regressions confirmed the absence of a significant trend (AUC: $\beta \approx 0.0000$, $R^2 = 0.003$, $P = 0.86$; misclassification error: $\beta \approx 0.0001$, $R^2 = 0.16$, $P = 0.20$) indicating that models trained with more presence points did not achieve systematically higher predictive performance. These results suggest that predictive accuracy was robust across months with varying telemetry sampling effort, supporting the reliability of model predictions regardless of sample size differences.

Continuous ensemble outputs were converted to binary presence–absence classifications using two complementary thresholds. A fixed cut-off of 0.5 provided a consistent and easily interpretable reference across months, while optimal thresholds derived from ROC curves maximized the sum of sensitivity and specificity, minimizing both false presences and absences. Optimal monthly thresholds ranged from 0.30 to 0.44 (mean $= 0.37 \pm 0.05$; Supplementary Tables S7, S8), reflecting the low prevalence of detections and the conservative nature of the ensemble predictions. Performance under both thresholding approaches was evaluated to assess sensitivity of classification outcomes, with optimal thresholds generally yielding higher overall accuracy and better balance between sensitivity and specificity (Supplementary Table S10). Applying both thresholds allows direct comparison between conventional and optimized classifications and supports management interpretations under differing conservation or development risk tolerances (Fig. 5).

Overlap with OWE development areas varied seasonally. Predicted sturgeon occurrence within and adjacent to OWE lease sites increased during winter months as offshore habitat suitability expanded (Figs 5, 6). The 1-km^2 scale used for ensemble outputs provided high-resolution spatial predictions with sufficient detail that support both regional-scale analyses (e.g. NYB wind lease areas; see Fig. 5) and site-level assessments (e.g. South Fork Wind Farm and Revolution Wind projects; Fig. 6).

Ensemble vs. single-model comparison

All models demonstrated high predictive performance on the independent holdout data (AUC > 0.92; Table 1). Performance was broadly comparable across algorithms, with no single model consistently outperforming the others across all months. The ensemble approach performed consistently among the top-performing models while reducing reliance on any individual algorithm, supporting its use as a robust framework for spatial prediction. A Friedman test indicated overall differences among models ($P <$

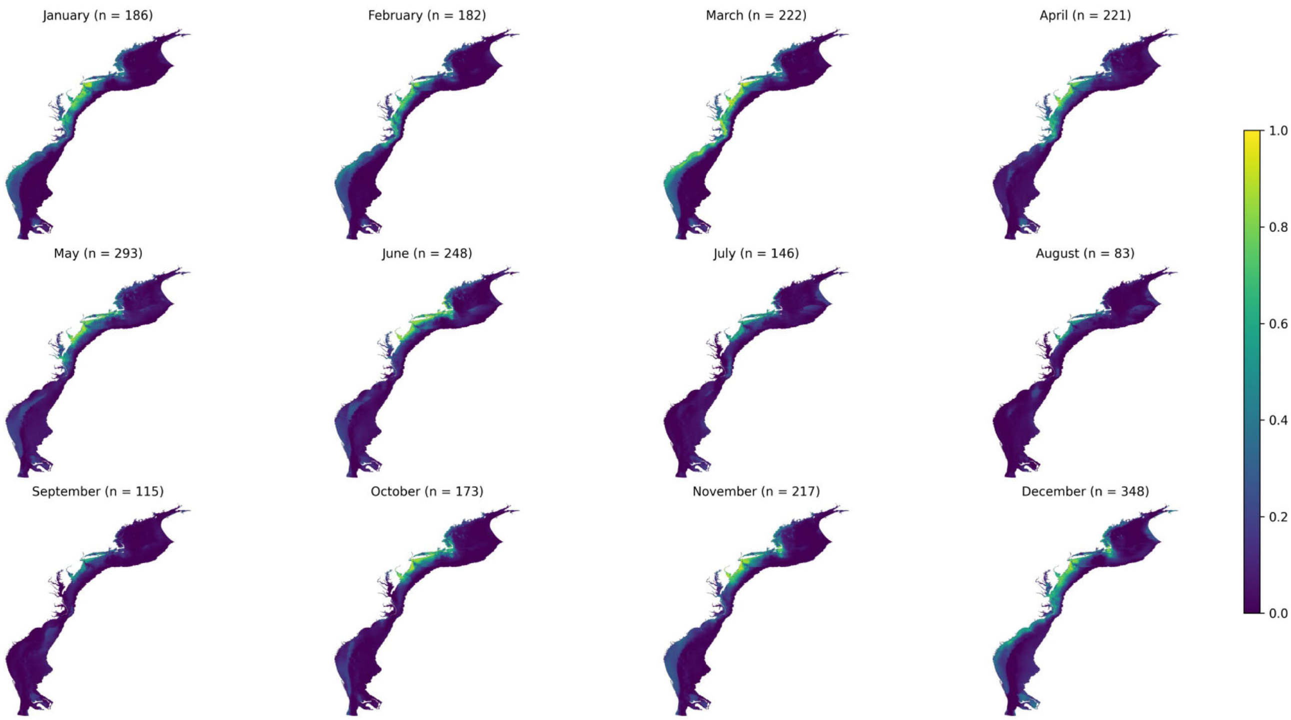

Figure 4 Monthly ensemble SDM maps of Atlantic Sturgeon occurrence across the US Atlantic OCS (1-km resolution). Color intensity indicates predicted probability (0–1); monthly detection counts shown.

Table 3. Correlation and regression analyses of monthly training sample size (n) on holdout performance of Atlantic Sturgeon ensemble SDMs Spearman's ρ and Kendall's τ = non-parametric correlations; β = regression slope; R^2 = variance explained.

Method	Test	Statistic	R^2/P
Spearman	ME $\sim n$	$\rho = 0.25$	$P = 0.44$
Spearman	AUC $\sim n$	$\rho = -0.19$	$P = 0.55$
Kendall	ME $\sim n$	$\tau = 0.17$	$P = 0.45$
Kendall	AUC $\sim n$	$\tau = -0.14$	$P = 0.53$
Linear regression	ME $\sim n$	$\beta = 1.00 \times 10^{-4}$	$R^2 = 0.157, P = 0.20$
Linear regression	AUC $\sim n$	$\beta = 0.00$	$R^2 = 0.003, P = 0.86$

No significant relationships were found, indicating predictive accuracy was robust to sample size variation.

0.001), but pairwise comparisons showed that most differences were not statistically significant after correction, with the exception of lower performance in the RBF model (Supplementary Table S11).

Inter-algorithm agreement was generally high, with low spatial variability across most of the study area (mean SD = 0.06–0.14). A substantial proportion of the domain exhibited strong agreement among models, with 65%–82% of grid cells showing SD < 0.10 across most months (Supplementary Table S12). Agreement was particularly high during late summer and early autumn, whereas higher variability was observed during transitional periods such as March, likely reflecting increased environmental heterogeneity and model sensitivity. These patterns demonstrate that the ensemble approach reduces the influence of individual model variability and stabilizes spatial predictions, particularly in periods of increased ecological complexity, highlighting areas where ensemble-based predictions are especially informative.

Discussion

This study presents a novel and scalable framework for mapping species occurrence across broad, data-limited marine systems by integrating machine learning algorithms within an ensemble species distribution modeling architecture. The accelerating expansion of OWE and other large-scale ocean uses underscores the need for structured, transparent frameworks to support ecological risk assessment and mitigation. The proposed approach enhances predictive performance by efficiently combining sparse occurrence records with high-resolution, publicly available environmental data.

Results from this case study demonstrate the framework's practical application, illustrating how ensemble SDMs can generate reliable predictive maps for rare or data-limited species and establish baseline spatial and temporal distribution criteria essential for assessing impacts throughout OWE development. More

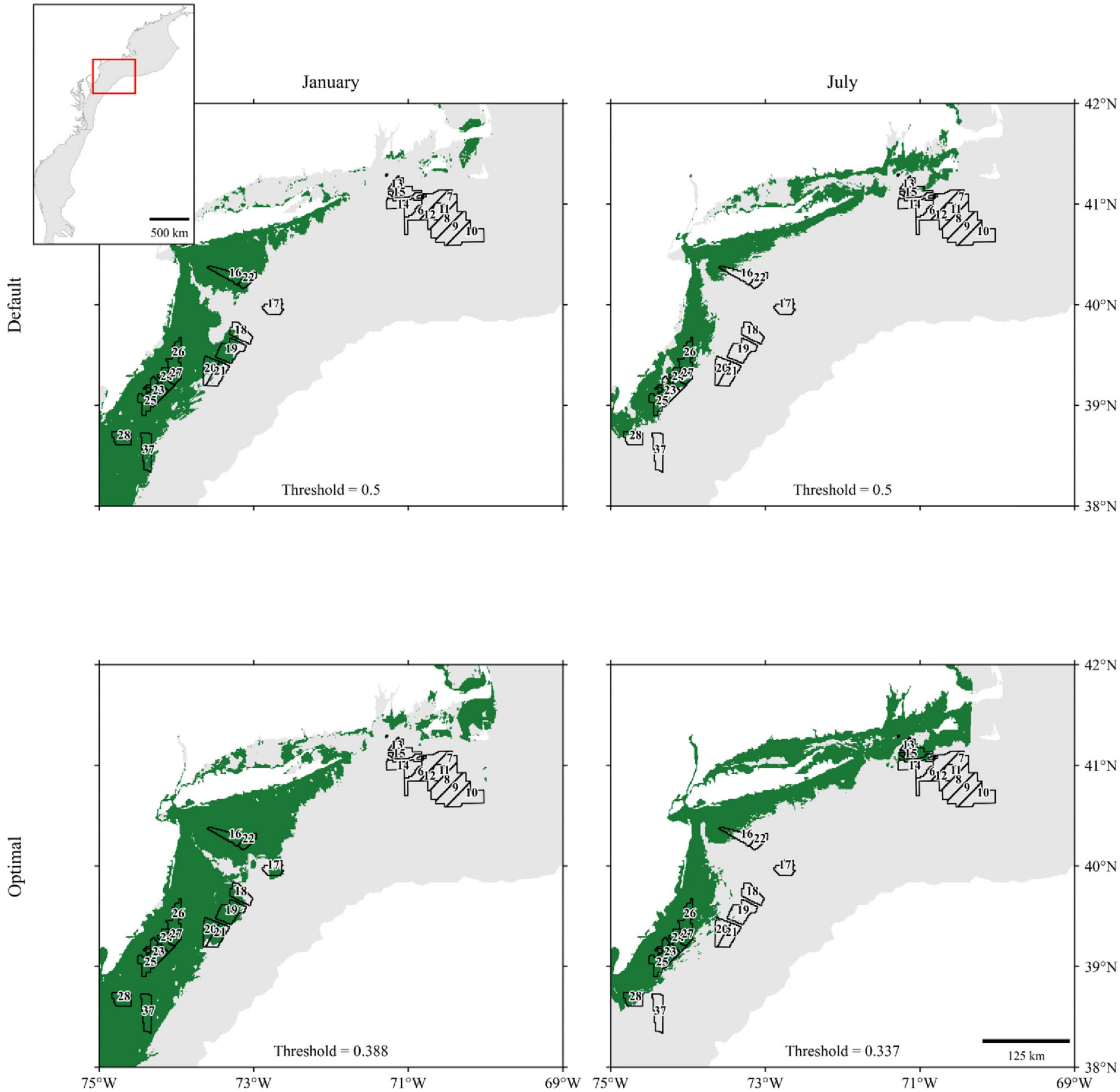

Figure 5 Binary presence–absence predictions for Atlantic Sturgeon in New York Bight offshore wind lease areas (1-km resolution). January and July shown; top panels use a 0.5 threshold, bottom panels use optimal Youden-index threshold. Green = presence, gray = absence; black outlines = lease boundaries (see Supplementary Table S1). Inset shows US Atlantic OCS location.

broadly, the framework functions as a flexible decision-support tool for evaluating species–environment relationships and identifying potential areas of interaction among marine industries, including fisheries, shipping, and coastal infrastructure. Scalable ensemble map products, when intersected with spatial layers of human activity, provide a practical basis for prioritizing monitoring, guiding conservation triage, and allocating management resources toward regions or periods of highest ecological sensitivity.

Many key environmental and spatial predictors are shared across taxa and ecosystems, which enhances model transferability and provides a foundation for streamlined ensemble map generation with only minor adjustments to input data. Incorporating expert knowledge into predictor selection and model validation can further improve transferability and ecological realism, especially in data-limited contexts (Synes and Osborne 2011, Qiao et al. 2019). This scalability enables rapid updates as datasets evolve and promotes consistency in management decisions across jurisdictions. Such flexibility is increasingly valuable given the expanding availability of high-quality, spatially referenced occurrence data from telemetry tagging programs (e.g. Block et al. 2016, Abescis et al. 2018), as well as research surveys, museum collections, and citizen science initiatives. While biases in these data are inevitable (Boakes et al. 2010), established protocols can ensure data suitability (Boria et al. 2014, Fourcade et al. 2014, Gaul et al. 2020).

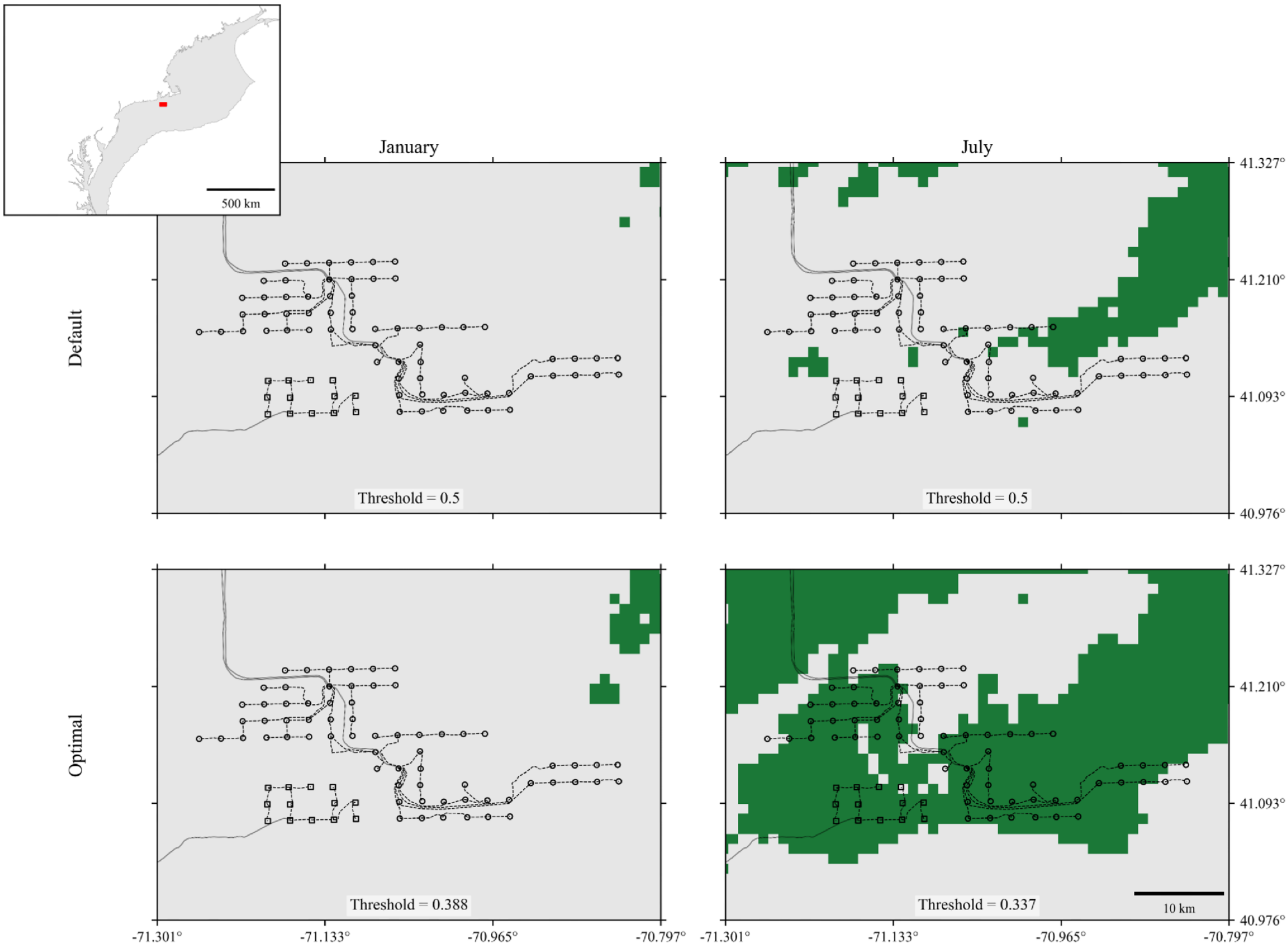

Figure 6 Site-specific binary presence–absence predictions for Atlantic Sturgeon at South Fork (OCS-A 0517) and Revolution Wind (OCS-A 0486) farms (1-km resolution). Operational foundations = open squares; planned foundations = open circles; transmission cables = solid (active) or dashed (proposed). January and July shown; top panels = 0.5 threshold, bottom = optimal Youden-index threshold. Green = presence, gray = absence; inset shows northern US Atlantic OCS.

The application of this framework to Atlantic Sturgeon illustrates the choices that must be made when balancing data availability, ecological realism, and management relevance. Telemetry detections and environmental covariates used here represent the best available data to predict Atlantic Sturgeon distribution in offshore waters. Despite inherent limitations, these data provide a far more robust and transparent foundation for impact evaluation than the qualitative or *ad hoc* assumptions often used to inform environmental assessments. Importantly, the integration of these quantitative, ensemble-based predictions within existing regulatory processes (e.g. NEPA environmental assessment [CEQ 2024]; ESA Section 7 consultation [NMFS 2021], and BOEM risk evaluation frameworks [BOEM 2023]) would help ensure that impact determinations are informed by the best available science. By grounding decisions in reproducible, data-driven models rather than subjective or inconsistent interpretations, this approach advances the transparency, defensibility, and ecological integrity of management decisions across the rapidly developing offshore domain.

The present case study primarily reflects detections of Atlantic Sturgeon from the NYB DPS, including fish originating from the Hudson and Delaware rivers, which dominate aggregations in the modeled region (Dunton et al. 2012, Wirgin et al. 2015). Consequently, these predictions may underrepresent habitat use by other populations. Nevertheless, they provide the most robust, defensible basis currently available for evaluating risk across the US OCS. Future development of population-specific SDMs, informed by spatially referenced observations of known-origin individuals, would further refine predictions and enable joint or stacked model frameworks to quantify population overlap and regionalized threats.

The strong performance of the algorithms in this case study highlights their utility for SDM applications in data-limited marine systems. Random forest (RF) models generally showed the highest and most stable performance, consistent with their ensemble structure, in which multiple decision trees are aggregated to improve predictive robustness and reduce overfitting (Breiman 2001). RF models are well suited for data-limited systems like Atlantic Sturgeon telemetry datasets, performing reliably across uneven sample sizes and heterogeneous environments (e.g. Mi et al. 2017, Butler and Sanderson 2022). However, reliance on a single algorithm may bias predictions toward its specific strengths, such as capturing nonlinear relationships, while potentially underrepresenting rare occurrences or fine-scale spatial patterns. Single-model approaches may also over- or under-emphasize certain environmental predictors and fail to capture uncertainty present across alternative model structures. By combining multiple algorithms into a weighted ensemble, these model-specific biases can be mitigated, producing predictions that are more robust, generalizable, and reflective of uncertainty across methods. This interpretation is supported by comparative evaluation across algorithms, which showed consistently high predictive performance on the independent holdout data, with no single model consistently outperforming the others across months.

The absence of a significant relationship between model performance and the number of training presence points indicates that predictive accuracy for Atlantic Sturgeon habitat use was not influenced by telemetry sample size or uneven spatial coverage. This suggests that variation in the number of tagged individuals or detection effort across months did not bias SDM outcomes, and that the ensemble modeling framework effectively captured species–environment relationships even in months with fewer presence records. Although months with more presence points might have been expected to produce slightly more stable parameter estimates, the consistent holdout AUC values across months indicate that model accuracy was largely driven by environmental predictor quality and algorithmic robustness rather than by sample size alone. This finding aligns with previous studies showing that once a minimum threshold of occurrences is met, additional presence records confer diminishing gains in predictive performance (Wisz et al. 2008, VanDerWal et al. 2009). Despite the limited influence of sample size on accuracy, larger datasets remain valuable for improving representation across environmental gradients, reducing spatial or temporal bias, and supporting more reliable estimates of uncertainty and model transferability. For Atlantic Sturgeon, expanding telemetry coverage could enhance the characterization of seasonal habitat shifts, particularly in under-sampled months or regions, and allow finer-resolution mapping of key predictors such as depth, sea surface temperature, and photoperiod.

Nevertheless, several sources of uncertainty must be acknowledged. Although our results indicate that predictive accuracy was not strongly dependent on the number of presence records, temporal and spatial sampling biases inherent in opportunistic telemetry detections remain important sources of uncertainty. Spatial diagnostics indicated statistically significant residual autocorrelation at holdout locations across all months (i.e. Moran's I and Geary's C), consistent with concerns associated with random data partitioning in spatially structured datasets (Roberts et al. 2017). However, the small median nearest-neighbor distances between holdout and training presence locations (0.02–2.53 km) indicate that this autocorrelation operates at the scale of acoustic receiver detection ranges (∼600–1400 m). As such, the observed spatial dependence reflects the effective sampling footprint of the monitoring array rather than an artifact of the partitioning strategy and therefore does not necessarily imply inflated model performance. While spatially structured cross-validation approaches (e.g. spatial blocking; Roberts et al. 2017) would provide a useful refinement, their application is currently constrained by limited monthly sample sizes relative to the large spatial extent of the study domain.

The spatial resolution and coverage of environmental predictors, as well as variation among predictions from individual algorithms, contribute additional uncertainty to estimates of habitat suitability. For example, areas predicted to be of low suitability may partly reflect limited receiver coverage rather than true ecological absence. However, explicitly including monitoring effort as a model covariate risks conflating habitat suitability with receiver placement (O'Toole et al. 2021, Baker et al. 2024). Developing robust approaches to account for sampling effort in passive acoustic telemetry data remains an active methodological challenge and represents an important priority for future work. Such limitations are common in large-scale marine SDM applications, where both sampling effort and environmental data availability are often uneven across space and time. Although these constraints may introduce uncertainty into monthly predictions, the high inter-algorithm agreement and limited sensitivity to pseudo-absence configuration observed here suggest that broad spatial patterns are robust. At the same time, these limitations highlight areas where targeted monitoring, improved environmental data resolution, or expanded tagging coverage could most effectively enhance model reliability.

In addition, temporal pooling of detections implicitly assumes stable species–environment relationships over the study period. Future work should explicitly evaluate temporal stationarity as longer time series and more consistent receiver coverage become available. Despite this limitation, the seasonal distribution patterns predicted here, including offshore and southward expansion in winter and nearshore contraction in summer, are broadly consistent with independent studies using pop-up satellite archival tagging (Erickson et al. 2011), multi-state mark–recapture telemetry (Melnychuk et al. 2017), and comparative migration analyses (Rothermel et al. 2020). Similar patterns have also been reported from complementary telemetry observations in the New York Bight (Ingram et al. 2019), providing qualitative ecological support for the model predictions.

Modeling efforts used a relatively small number of environmental predictors ($n = 7$) to fit SDMs with high accuracy, illustrating that carefully selected, ecologically relevant variables can capture key patterns of species occurrence even in data-limited systems, consistent with the principle of model parsimony. The strong predictive influence of these environmental factors suggests that broad-scale, seasonal shifts in Atlantic Sturgeon occurrence in offshore development sites are closely associated with spatial and temporal variation in abiotic conditions. Seasonal changes in predicted occurrence should therefore be interpreted as the result of temporally varying hydrographic and light-related conditions acting on a stable underlying bathymetric and substrate framework, providing a tractable basis for spatial prediction in applied management contexts. Because predictor importance was quantified using permutation-based measures of contribution to model performance, these results should be interpreted as identifying variables that improved prediction rather than demonstrating causal ecological mechanisms. Monthly shifts in predictor rank are therefore most appropriately viewed as changes in predictive association that are consistent with known environmental gradients on influencing habitat use and migratory behavior (e.g. Ingram et al. 2019).

From an ecological perspective, the patterns identified by the models are consistent with established understanding of Atlantic Sturgeon movement and habitat use. Atlantic Sturgeon undertake extensive coastal migrations, ostensibly to exploit favorable clinal gradients and temporally predictable foraging habitat (Gross et al. 1988, Dingle and Drake 2007). Observed preferential distribution in shallow, nearshore marine waters above sand or mud substrates may reflect areas of higher prey availability or foraging opportunity (e.g. Stein et al. 2004a, Johnson et al. 1997), although a clear linkage between foraging behavior and resource use in marine environments remains unresolved. Photoperiod and water temperature are recognized as key drivers of migration in other sturgeon species (e.g. Cech and Doroshov 2004, Papoulious et al. 2011) and may similarly act as seasonal cues associated with predictable movements of Atlantic Sturgeon between nearshore and offshore habitats (Ingram et al. 2019).

While the selected predictors captured key broad-scale environmental gradients and resulted in high predictive performance, additional variables such as bottom temperature, dissolved oxygen, distance to natal river mouths, and chlorophyll-*a* may further refine predictions. These variables are ecologically relevant for Atlantic Sturgeon, particularly in relation to benthic habitat use, hypoxic stress, and migratory behavior (e.g. Secor and Niklitschek 2001). However, the inclusion of such predictors was constrained by limitations in spatial and temporal data availability and consistency across the study domain. The present framework was therefore designed to prioritize widely available, operationally scalable data sources, ensuring applicability for management and survey design, particularly for near-real-time or repeated forecasting applications. Future work could explore the integration of these additional predictors to enhance ecological interpretation and fine-scale predictive accuracy.

High-resolution occurrence maps of Atlantic Sturgeon generated from monthly SDM ensembles demonstrated an increase in spatial overlap at wind energy sites during certain months and seasons, with distribution biased toward shallow, nearshore regions during the summer months and expanding latitudinally into deeper offshore habitat during the winter. These trends were largely consistent with observations of Atlantic Sturgeon in marine waters from previous studies (e.g. Erickson et al. 2011, Ingram et al. 2019, Rothermel et al. 2020) and provide further indication that the potential negative impacts of wind energy development can be largely mitigated by enacting spatial and temporal considerations during periods of increased incidence.

While shifts in seasonal distribution are readily discerned from coastwide maps, regional-scale options are necessary to support regulatory decision-making and project-level planning within specific jurisdictions (e.g. the NYB; see Fig. 5). At this resolution, predictions can be viewed simultaneously across multiple adjacent lease areas, enabling managers and developers to quickly identify where patterns of potential Atlantic Sturgeon occurrence converge, diverge, or extend across project boundaries. This multi-site perspective supports coordinated, basin-level planning by informing cumulative-effects evaluations, guiding alignment of mitigation measures across neighboring projects, and highlighting areas where biological constraints may arise prior to site-specific surveys. By integrating these regional outputs into planning workflows, stakeholders can optimize the timing and location of monitoring and construction activities, anticipate regulatory concerns, and make proactive, science-based decisions that reduce both ecological risk and project uncertainty.

Similarly, site-specific maps can inform management plans and policy settings across all phases of an individual project's development. For example, retrospective predictions at the South Fork Wind Farm (OCS-A 0517; Supplementary Table S1) and the adjacent Revolution Wind project (OCS-A 0486; Supplementary Table S1), located in marine waters off Massachusetts and Rhode Island, illustrate how ESDM outputs can be overlaid directly onto vector layers representing turbined foundations and associated transmission routes to evaluate potential areas of biological overlap (Fig. 6). The South Fork Wind Farm array and the larger Revolution Wind array both intersect predicted Atlantic Sturgeon habitat to varying degrees, with January and July maps indicating moderate seasonal overlap within the South Fork array and more extensive overlap across the Revolution Wind footprint.

Although the South Fork Wind Farm has been operational at commercial scale since December 2023, spatially explicit predictions of Atlantic Sturgeon occurrence were not available during statutory consultations to inform key planning decisions. This gap illustrates the potential value of ESDM outputs for informing site-specific planning decisions beyond foundation siting. Given the limited empirical data on the effects of electromagnetic fields associated with subsea power transmission (Hutchison et al. 2020, Bäckström and Warden 2023), early access to such spatially explicit predictions would have been especially valuable, enabling the identification of cable routes that align with ecological considerations across management boundaries. Such predictions can support the development of monitoring requirements or construction-avoidance windows and provide forward-looking guidance to assess ecological risks and prioritize mitigation and management actions, even for species with limited empirical data.

Although much of the current discourse has centered on the potential ecological effects of offshore wind development, empirical data describing where and when species overlap with development areas remain limited for many taxa of conservation and commercial importance. The predicted occurrence of Atlantic Sturgeon in offshore waters of the Atlantic OCS underscores the need for reliable, high-resolution distribution maps to guide marine spatial planning and conservation decision-making. By integrating standardized ensemble approaches with flexible data-handling procedures, the modeling framework accommodates varying data densities, spatial scales, and ecological complexities. This adaptability makes it suitable not only for highly migratory fishes such as Atlantic Sturgeon, but also for other wide-ranging or data-limited taxa of concern, including marine mammals (e.g. Becker et al. 2019) seabirds (e.g. Lewison et al. 2013), commercially important fishes (e.g. Goethel et al. 2019), and sensitive benthic organisms (e.g. Bowden et al. 2021).

Importantly, key parameters such as the exclusion buffer applied during pseudo-absence generation and the suitability envelope used to constrain environmental predictions can be tuned to balance conservatism and sample availability (Phillips et al. 2009). Larger buffers and narrower envelopes reduce potential spatial and environmental overlap between presence and absence data, thereby minimizing autocorrelation and extrapolation risk. Conversely, less conservative settings may be justified when sample sizes are limited or when fine-scale environmental variability is ecologically meaningful. This flexibility helps ensure that model design remains both ecologically defensible and operationally scalable, reinforcing the broader applicability of the framework to species distribution modeling and marine spatial planning under diverse data and management conditions.

The modeling framework adopted in this study was selected to prioritize predictive performance and scalability for spatial decision support in data-limited offshore environments. While alternative approaches such as Bayesian hierarchical SDMs offer important advantages in uncertainty quantification and ecological interpretability, the ensemble machine learning approach used here is well suited to capturing complex nonlinear relationships and interactions among environmental predictors without requiring *a* *priori* specification of functional forms (Cutler et al. 2007, Elith et al. 2008). The integration of multiple algorithms within a weighted ensemble further reduces model-specific bias and improves predictive robustness (Araújo and New 2007, Marmion et al. 2009), while maintaining the computational efficiency required to generate repeated monthly predictions across large spatial domains. Future work could explore the use of conditional random forests as a refinement for variable importance estimation under correlated predictor settings (Strobl et al. 2007, Strobl et al. 2008), as well as hierarchical or hybrid modeling frameworks to complement the present approach and provide additional ecological insight in support of spatial planning and management.

Conclusions

This study demonstrates that machine learning-based ensemble species distribution models can yield robust, ecologically meaningful predictions even in data-limited marine systems. By integrating multiple machine-learning algorithms within a single ensemble framework, the approach produces spatially explicit predictions that are interpretable at management-relevant scales. These outputs provide a rigorous basis for informing offshore wind impact assessment, monitoring design, and mitigation planning within marine spatial planning contexts.

Understanding spatiotemporal patterns of marine habitat use is fundamental to designing effective monitoring programs, assessing exposure risk, and prioritizing mitigation for species of conservation concern. By linking Atlantic Sturgeon occurrence to environmental drivers across monthly timescales, our results clarify when and where overlap with offshore development is most likely to occur. This enables consistent, decision-relevant spatial predictions that can be compared across regions, seasons, and development footprints, addressing a key limitation of current offshore impact assessments.

Importantly, robust predictions were achieved despite sparse and uneven data, a pervasive constraint in marine systems. By demonstrating how such data can still support meaningful spatial inference, this study provides a scalable and ecologically grounded basis for integrating species distribution modeling into applied conservation and regulatory decision-making in rapidly developing offshore environments.

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Supplementary material

Supplementary material is available at *ICES Journal of Marine Science* online.

Conflicts of interest

None declared.

Funding

None declared.

Data availability

Code used to develop species distribution models, ensemble predictions, and conduct associated analyses is available at: https://github.com/lbutler2405/Atlantic_Sturgeon_SDMs. Due to conservation considerations and existing data-sharing agreements, individual tag-level detection data are not publicly archived but may be made available upon reasonable request to the corresponding author.

References

Abecasis D, Steckenreuter A, Reubens J *et al.* A review of acoustic telemetry in Europe and the need for a regional aquatic telemetry network. *Anim Biotelemetry* 2018;**6**:12. https://doi.org/10.1186/s40317-018-0156-0

Akhtar N, Geyer B, Schrum C. Impacts of accelerating deployment of offshore windfarms on near-surface climate. *Sci Rep* 2022;**12**:18307. https://doi.org/10.1038/s41598-022-22868-9

Allouche O, Tsoar A, Kadmon R. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *J Appl Ecol* 2006;**43**:1223–32. https://doi.org/10.1111/j.1365-2664.2006.01214.x

Alola AA, Akadiri SS. Clean energy development in the United States amidst augmented socioeconomic aspects and country-specific policies. *Renew Energy* 2021;**169**:221–30. https://doi.org/10.1016/j.renene.2021.01.022

Amaral TD. Offshore wind financial incentive programs. *J Maritime Law Commerce* 2024;**52**:3. Available at: https://docs.rwu.edu/law_ma_jmlc/vol52/iss3/3

Araújo MB, New M. Ensemble forecasting of species distributions. *Trends Ecol Evol* 2007;**22**:42–7. https://doi.org/10.1016/j.tree.2006.09.010

Araújo MB, Pearson RG, Thuiller W *et al.* Validation of species-climate impact models under climate change. *Glob Chang Biol* 2005;**11**:1504–13. https://doi.org/10.1111/j.1365-2486.2005.01000.x

Backstrom JT, Warden NM. Optimizing offshore wind export cable routing using GIS-based environmental heat maps. *Wind Energy Sci Discuss* 2023;**9**:1105–21. https://doi.org/10.5194/wes-2023-146

Bailey H, Brookes KL, Thompson PM. Assessing environmental impacts of offshore wind farms: lessons learned and recommendations for the future. *Aquat Biosyst* 2014;**10**:8. https://doi.org/10.1186/2046-9063-10-8

Baker DJ, Maclean IMD, Gaston KJ. Effective strategies for correcting spatial sampling bias in species distribution models without independent test data. *Divers Distrib* 2024;**30**:e13802. https://doi.org/10.1111/ddi.13802

Barbet-Massin M, Jiguet F, Albert CH *et al.* Selecting pseudo-absences for species distribution models: how, where and how many? *Methods Ecol Evol* 2012;**3**:327–38. https://doi.org/10.1111/j.2041-210X.2011.00172.x

Becker EA, Forney KA, Redfern JV *et al.* Predicting cetacean abundance and distribution in a changing climate. *Divers Distrib* 2019;**25**:626–43. https://doi.org/10.1111/ddi.12867

Beiter P, Rand JT, Seel J *et al.* Expert perspectives on the wind plant of the future. *Wind Energy* 2022;**25**:1363–78. https://doi.org/10.1002/we.2735

Bergström L, Kautsky L, Malm T *et al.* Effects of offshore wind farms on marine wildlife—a generalize impact assessment. *Environ Res Lett* 2014;**9**:034012. https://doi.org/10.1088/1748-9326/9/3/034012

Block BA, Holbrook CM, Simmons SE *et al.* Toward a national animal telemetry network for aquatic observations in the United States. *Anim Biotelemetry* 2016;**4**:6. https://doi.org/10.1186/s40317-015-0092-1

Boakes EH, McGowan PJK, Fuller RA *et al.* Distorted views of biodiversity: spatial and temporal bias in species occurrence data. *PLoS Biol* 2010;**8**:e1000385. https://doi.org/10.1371/journal.pbio.1000385

Bodner K, Fortin M-J, Molnár PK. Making predictive modeling ART: accurate, reliable, and transparent. *Ecosphere* 2020;**11**:e03160. https://doi.org/10.1002/ecs2.3160

Boehlert GW, Gill AB. Environmental and ecological effects of ocean renewable energy development: a current synthesis. *Oceanography* 2010;**23**:68–81. https://doi.org/10.5670/oceanog.2010.46

BOEM (Bureau of Ocean Energy Management). Renewable energy modernization rule—draft environmental impact statement and risk evaluation framework. US Department of the Interior. 2023. Available from: https://www.regulations.gov/document/BOEM–2023–0005–0001. Date accessed 15 January 2024.

Boria RA, Olson LE, Goodman SM *et al.* Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. *Ecol Model* 2014;**275**:73–7. https://doi.org/10.1016/j.ecolmodel.2013.12.012

Bowden DA, Anderson OF, Rowden AA *et al.* Assessing habitat suitability models for the deep sea: is our ability to predict the distributions of seafloor fauna improving? *Front Mar Sci* 2021;**8**:632389. https://doi.org/10.3389/fmars.2021.632389

Breece MW, Fox DA, Haulsee DE *et al.* Satellite driven distribution models of endangered Atlantic Sturgeon occurrence in the mid-Atlantic Bight. *ICES J Mar Sci* 2017;**75**:562–71. https://doi.org/10.1093/icesjms/fsx187

Breiman L. Random forests. *Mach Learn* 2001;**45**:5–32. https://doi.org/10.1023/A:1010933404324

Butler L, Sanderson RA. National-scale predictions of plant assemblages via community distribution models: leveraging published data to guide future surveys. *J Appl Ecol* 2022;**59**:1559–71. https://doi.org/10.1111/1365-2664.14166

Cech JJ, Doroshov SI. Environmental requirements, preferences, and tolerance limits of North American sturgeons. In: LeBreton GTO, Beamish FWH, McKinley RS (eds). *Sturgeons and Paddlefish of North America. Fish & Fisheries Series*. Vol. **27**. Springer, Dordrecht, 2004. https://doi.org/10.1007/1-4020-2833-4_4

CEQ (Council on Environmental Quality). *NEPA: implementing regulations desk reference.* Washington, DC: U.S. Executive Office of the President. 2024. Available at: https://ceq.doe.gov/docs/laws-regulations/NEPA-Implementing-Regulations-Desk-Reference-2024.pdf. Date accessed 15 October 2024.

Chatterjee S, Hadi AS. *Regression Analysis by Example*. NJ: John Wiley and Sons, 2006. https://doi.org/10.1002/0470055464

Cohen J. A coefficient agreement for nominal scales. *Educ Psychol Meas* 1960;**20**:37–46. https://doi.org/10.1177/001316446000200104

Cutler DR, Edwards Jr TC, Beard KH *et al.* Random forests for classification in ecology. *Ecology* 2007;**88**:2783–92. https://doi.org/10.1890/07-0539.1

Dingle H, Drake VA. What is migration? *Bioscience* 2007;**57**:113–21. https://doi.org/10.1641/B570206

Dunton KJ, Chapman D, Jordaan A *et al.* Genetic mixed-stock analysis of Atlantic sturgeon *Acipenser oxyrinchus oxyrinchus* in a heavily exploited marine habitat indicates the need for routine genetic monitoring. *J Fish Biol* 2012;**80**:207–17. https://doi.org/10.1111/j.1095-8649.2011.03151.x

Dunton KJ, Jordaan A, McKown KA *et al.* Abundance and distribution of Atlantic Sturgeon (*Acipenser oxyrinchus*) within the Northwest Atlantic Ocean, determined from five fishery-independent surveys. *Fish Bull* 2010;**108**:450–65. Available at: https://spo.nmfs.noaa.gov/content/abundance-and-distribution-atlantic-sturgeon-acipenser-oxyrinchus-within-northwest-atlantic

Elith J, Graham CH, Anderson RP *et al.* Novel methods improve prediction of species' distributions from occurrence data. *Ecography* 2006;**29**:129–51. https://doi.org/10.1111/j.2006.0906-7590.04596.x

Elith J, Leathwick JR. Species distribution models: ecological explanation and prediction across space and time. *Annu Rev Ecol Evol Syst* 2009;**40**:677–97. https://doi.org/10.1146/annurev.ecolsys.110308.120159

Elith J, Leathwick JR, Hastie T. A working guide to boosted regression trees. *J Anim Ecol* 2008;**77**:802–13. https://doi.org/10.1111/j.1365-2656.2008.01390.x

Erickson DL, Kahnle A, Millard MJ *et al.* Use of pop-up satellite archival tags to identify oceanic-migratory patterns for adult

Atlantic Sturgeon, *Acipenser oxyrinchus oxyrinchus* Mitchell, 1815. *J Appl Ichthyol* 2011;**27**:356–65. https://doi.org/10.1111/j.1439-0426.2011.01690.x

Fielding AH, Bell JF. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environ Conserv* 1997;**24**:38–49. https://doi.org/10.1017/S0376892997000088

Fortin M-J, Dale MRT. *Spatial Analysis: A Guide for Ecologists*. Cambridge:Cambridge University Press, 2005. https://doi.org/10.1017/CBO9780511542039

Fourcade Y, Engler JO, Rödder D *et al.* Mapping species distributions with MAXENT using a geographically biased sample of presence data: a performance assessment of methods for correcting sampling bias. *PLoS One* 2014;**9**:e97122. https://doi.org/10.1371/journal.pone.0097122

Galparsoro I, Menchaca I, Garmendia JM *et al.* Reviewing the ecological impacts of offshore wind farms. *npj Ocean Sustain* 2022;**1**:1. https://doi.org/10.1038/s44183-022-00003-5

Gaul G, Sadykova D, White HJ *et al.* Data quantity is more important than its spatial bias for predictive species distribution modeling. *PeerJ* 2020;**8**:e10411. https://doi.org/10.7717/peerj.10411

Gill AB. Offshore renewable energy: ecological implications of generating electricity in the coastal zone. *J Appl Ecol* 2005;**42**:605–15. https://doi.org/10.1111/j.1365-2664.2005.01060.x

Gill AB, Bremner J, Vanstaen K *et al.* Limited evidence base for determining impacts (or not) of offshore wind energy developments on commercial fish species. *Fish Fish* 2024;**26**:155–70. https://doi.org/10.1111/faf.12871

Goethel DR *et al.*. Incorporating spatial dynamics into stock assessments of data-limited fisheries. *ICES J Mar Sci* 2019;**76**:2134–45.

Gross MR, Coleman RM, McDowall RM. Aquatic productivity and the evolution of diadromous fish migration. *Science* 1988;**239**:1291–3. https://doi.org/10.1126/science.239.4845.1291

Hijmans R, Brown A, Barbosa M. terra: Spatial Data Analysis. R package version 1.9-14. 2026. https://github.com/rspatial/terra. Date accessed 1 January 2026.

Hilton EJ, Kynard B, Balazik MT *et al.* Review of the biology, fisheries, and conservation status of the Atlantic Sturgeon, (*Acipenser oxyrinchus oxyrinchus* Mitchill, 1815). *Appl Ichthyol* 2016;**32**:30–66. https://doi.org/10.1111/jai.13242

Hutchison ZL, Secor DH, Gill AB. The interaction between resource species and electromagnetic fields associated with electricity production by offshore wind farms. *Oceanography* 2020;**33**:96–107. https://doi.org/10.5670/oceanog.2020.409

Ingram EC, Cerrato RM, Dunton KJ *et al.* Endangered Atlantic Sturgeon in the New York Wind Energy Area: implications of future development in an offshore wind energy site. *Sci Rep* 2019;**9**:12432. https://doi.org/10.1038/s41598-019-48818-6

Isaksson N, Scott BE, Hunt GL *et al.* A paradigm for understanding whole ecosystem effects of offshore wind farms in shelf seas. *ICES J Mar Sci* 2025;**82**:fsad194. https://doi.org/10.1093/icesjms/fsad194

Jiménez-Valverde A, Lobo JM. Threshold criteria for conversion of probability of species presence to either–or presence–absence. *Acta Oecologica* 2007;**31**:361–9. https://doi.org/10.1016/j.actao.2007.02.001

Johnson JH, Dropkin DS, Warkentine BE *et al.* Food habits of Atlantic Sturgeon off the central New Jersey coast. *Transac Am Fish Soc* 1997;**126**:166–70. https://doi.org/10.1577/1548-8659(1997)126⟨0166:FHOASO⟩2.3.CO;2

Lee W-H, Song J-W, Yoon S-H *et al.* Spatial evaluation of machine learning-based species distribution models for prediction of invasive ant species distribution. *Appl Sci* 2022;**12**:10260. https://doi.org/10.3390/app122010260

Lewison RL, Crowder LB, Wallace BP *et al.* Global patterns of marine mammal, seabird, and sea turtle bycatch reveal taxa-specific and cumulative megafauna hotspots. *Proc Natl Acad Sci* 2013;**111**:5271–6. https://doi.org/10.1073/pnas.131896011

Liu C, White M, Newell G. Selecting thresholds for the prediction of species occurrence with presence-only data. *Biogeography* 2013;**40**:778–89. https://doi.org/10.1111/jbi.12058

MacKenzie DI, Nichols JD, Lachman GB *et al.* Estimating site occupancy rates when detection probabilities are less than one. *Ecology* 2002;**83**:2248–55. https://doi.org/10.1890/0012-9658(2002)083[2248:ESORWD]2.0.CO;2

Marmion M, Parviainen M, Luoto M *et al.* Evaluation of consensus methods in predictive species distribution modeling. *Divers Distrib* 2009;**15**:59–69. https://doi.org/10.1111/j.1472-4642.2008.00491.x

Martínez-Minaya J, Cameletti M, Conesa D *et al.* Species distribution modeling: a statistical review with focus in spatio-temporal issues. *Stoch Environ Res Risk Assess* 2018;**32**:3227–44. https://doi.org/10.1007/s00477-018-1548-7

McClean MF . Dadswell MJ, Stokesbury MJW, Feeding ecology of Atlantic sturgeon, Acipenser oxyrinchus oxyrinchus Mitchill, 1815 on the infauna of intertidal mudflats of Minas Basin, Bay of Fundy. *Journal of Applied Ichthyology*, 2013;**29**:503–509.

McMahon DE, Urza AK, Brown JL *et al.* Modeling species distributions and environmental suitability highlights risk of plant invasions in western United States. *Divers Distrib* 2021;**27**:710–28. https://doi.org/10.1111/ddi.13232

McNemar Q . Note on the sampling error of the difference between correlated proportions or percentages. *Psychometrika*, 1947;**12**:153–157.

Melnychuk MC, Dunton KJ, Jordaan A *et al.* Informing conservation strategies for the endangered Atlantic Sturgeon using acoustic telemetry and multi-state mark–recapture models. *J Appl Ecol* 2017;**54**:914–25. https://doi.org/10.1111/1365-2664.12799

Mi C, Huettmann F, Guo Y *et al.* Why choose Random Forest to predict rare species distribution with few samples in large undersampled areas? Three Asian crane species models provide supporting evidence. *PeerJ* 2017;**5**:e2849. https://doi.org/10.7717/peerj.2849

Naimi B, Araújo MB. sdm: a reproducible and extensible R platform for species distribution modeling. *Ecography* 2016;**39**:368–75. https://doi.org/10.1111/ecog.01881

Nijkamp N, Sallou J, van der Heijden N *et al.* Green AI in action: strategic model selection for ensembles in production. In: *Proceedings of the 1st ACM International Conference on AI-Powered Software, AIware 2024*. New York, NY: Association for Computing Machinery, 2024,50–8. https://doi.org/10.1145/3664646.3664763

NMFS (National Marine Fisheries Service). *Offshore wind site assessment and site characterization activities programmatic consultation (Revision 1)*. US Department of Commerce, National Oceanic and Atmospheric Administration. 2021. Available at: https://media.fisheries.noaa.gov/2021-12/OSW-surveys-NLAA-programmatic-rev-1-2021-09-30-508-.pdf. Date accessed 15 July 2024.

O'Toole M, Queiroz N, Humphries NE *et al.* Quantifying effects of tracking data bias on species distribution models. *Methods Ecol Evol* 2021;**12**:170–81. https://doi.org/10.1111/2041-210X.13507

Papoulious DM, DeLonay AJ, Annis ML *et al.* Characterization of environmental cues for initiation of reproductive cycling and spawning in shovelnose sturgeon *Scaphirhynchus platorynchus* in the Lower Missouri River, USA. *J Appl Ecol* 2011;**27**:335–42. https://doi.org/10.1111/j.1439-0426.2010.01657.x

Phillips SJ, Dudík M. Modeling of species distributions with MaxEnt: new extensions and a comprehensive evaluation. *Ecography* 2008;**31**:161–75. https://doi.org/10.1111/j.0906-7590.2008.5203.x

Phillips SJ, Dudík M, Elith J *et al.* Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. *Ecol Appl* 2009;**19**:181–97. https://doi.org/10.1890/07-2153.1

Qazi AW, Saqib Z, Zaman-ul-Haq M. Trends in species distribution modeling in context of rare and endemic plants: a systematic review. *Ecol Process* 2022;**11**:40. https://doi.org/10.1186/s13717-022-00384-y

Qiao H, Feng X, Escobar LE *et al.* An evaluation of transferability of ecological niche models. *Ecography* 2019;**42**:521–34. https://doi.org/10.1111/ecog.03986

R Core Team. *R: A language and environment for statistical computing*. Vienna:R Foundation for Statistical Computing. 2024. Available at: https://www.R-project.org/. Date accessed 15 July 2025.

Ramirez-Reyes C, Nazeri M, Street G *et al.* Embracing ensemble species distribution models to inform at-risk species status assessments. *J Fish Wildl Manag* 2021;**12**:98–111. https://doi.org/10.3996/JFWM-20-072

Roberts DR, Bahn V, Ciuti S *et al.* Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography* 2017;**40**:913–29. https://doi.org/10.1111/ecog.02881

Robinson NM, Elith J, Hobday AJ *et al.* Pushing the limits in marine species distribution modelling: lessons from the land present challenges and opportunities. *Glob Ecol Biogeogr* 2011;**20** pp.789–802. https://doi.org/10.1111/j.1466-8238.2010.00636.x

Robinson NM, Nelson WA, Costello MJ *et al.* A systematic review of marine-based species distribution models (SDMs) with recommendations for best practice. *Front Mar Sci* 2017;**4**:421. https://doi.org/10.3389/fmars.2017.00421

Rothermel ER, Balazik MT, Best JE *et al.* Comparative migration ecology of striped bass and Atlantic Sturgeon in the US Southern mid-Atlantic bight flyway. *PLoS One* 2020;**15**:e0234442. https://doi.org/10.1371/journal.pone.0234442

Secor DH, Niklitschek EJ. Sensitivity of sturgeons to environmental hypoxia: a review of physiological and ecological evidence. In: *Fish Physiology, Toxicology, and Water Quality: Proceedings of the Sixth International Symposium*, La Paz, Mexico, 22–26 January 2001, 61–78. Ed. by Thurston RV. UMCES Contribution No. 3518-CBL. 2001.

Sofaer HR, Jarnevich CS, Pearse IS *et al.* Development and delivery of species distribution models to inform decision-making. *Bioscience* 2019;**69**:544–57. https://doi.org/10.1093/biosci/biz045

Stein AB, Friedland KD, Sutherland M. Atlantic Sturgeon marine distribution and habitat use along the Northeastern Coast of the United States. *Transac Am Fish Soc* 2004a;**133**:527–37. https://doi.org/10.1577/T02-151.1

Stein AB, Friedland KD, Sutherland M. Atlantic Sturgeon marine bycatch and mortality on the continental shelf of the Northeast United States. *N Am J Fish Manag* 2004b;**24**:171–83. https://doi.org/10.1577/M02-123

Strobl C, Boulesteix A-L, Zeileis A. Bias in random forest variable importance measures: illustrations, sources and a solution. *BMC Bioinf* 2007;**8**:25. https://doi.org/10.1186/1471-2105-8-25

Strobl C, Kneib T, Augustin T *et al.* Conditional variable importance for random forests. *BMC Bioinf* 2008;**9**:307. https://doi.org/10.1186/1471-2105-9-307

Synes NW, Osborne EJ. Choice of predictor variables as a source of uncertainty in continental-scale species distribution modeling under climate change. *Glob Ecol Biogeogr* 2011;**20**:904–14. https://doi.org/10.1111/j.1466-8238.2010.00635.x

Thomassen JA, Brown EJ, Henriksen O *et al.* Case-dependent impacts of offshore wind farms on ecosystems: a systematic review and meta-analysis. *Ocean Coast Manage* 2025;**270**:107853. https://doi.org/10.1016/j.ocecoaman.2025.107853

Thuiller W, Guéguen M, Renaud J *et al.* Uncertainty in ensembles of global biodiversity scenarios. *Nat Commun* 2019;**10**:1446. https://doi.org/10.1038/s41467-019-09519-w

Thuiller W, Lafourcade B, Engler R *et al.* BIOMOD—a platform for ensemble forecasting of species distribution. *Ecography* 2009;**32**:369–73. https://doi.org/10.1111/j.1600-0587.2008.05742.x

Ukoba K, Onisuru OR, Jen T-C *et al.* Predictive modeling of climate change impacts using Artificial Intelligence: a review for equitable governance and sustainable outcome. *Environ Sci Pollut Res* 2025;**32**:10705–24. https://doi.org/10.1007/s11356-025-36356-w

USDOE (United States Department of Energy). *US Offshore Wind Market Report: 2023 edn*. Washington, DC: US Department of Energy. 2023. Available at: https://www.energy.gov/sites/default/files/2023-09/doe-offshore-wind-market-report-2023-edition.pdf. . Date accessed 15 July 2024.

VanDerWal J, Shoo LP, Graham C *et al.* Selecting pseudo-absence data for presence-only distribution modeling: how far should you stray from what you know? *Ecol Model* 2009;**220**:589–94. https://doi.org/10.1016/j.ecolmodel.2008.11.010

Vasconcelos RN, Cantillo-Pérez T, Franca Rocha WJS *et al.* Advances and challenges in species ecological niche modeling: a mixed review. *Earth* 2024;**5**:963–89. https://doi.org/10.3390/earth5040050

von Jouanne A, Agamloh E, Yokochi A. A review of offshore renewable energy for advancing the clean energy transition. *Energies* 2025;**18**:4798. https://doi.org/10.3390/en18184798

Watson SCL, Somerfield PJ, Lemasson AJ *et al.* The global impact of offshore wind farms on ecosystem services. *Ocean Coast Manage* 2024;**249**:107023. https://doi.org/10.1016/j.ocecoaman.2024.107023

Williams KA, Gulka J, Cook ASCP *et al.* A framework for studying the effects of offshore wind energy development on birds and bats in the Eastern United States. *Front Mar Sci* 2024;**11**:1274052. https://doi.org/10.3389/fmars.2024.1274052

Winship AJ, Thorson JT, Clarke ME *et al.* Good practices for species distribution modeling of deep-sea corals and sponges for resource management: data collection, analysis, validation, and communication. *Front Mar Sci* 2020;**7**:303. https://doi.org/10.3389/fmars.2020.00303

Wirgin I, Breece MW, Fox DA *et al.* Origin of Atlantic Sturgeon collected off the Delaware coast during spring months. *N Am J Fish Manag* 2015;**35**:20–30. https://doi.org/10.1080/02755947.2014.963751

Wisz MS, Hijmans RJ, Li J *et al.* Effects of samples size on the performance of species distribution models. *Divers Distrib* 2008;**14**:763–73. https://doi.org/10.1111/j.1472-4642.2008.00482.x

Youden WJ. Index for rating diagnostic tests. *Cancer* 1950;**3**:32–5. https://doi.org/10.1002/1097-0142(1950)3:1⟨32::AID-CNCR2820030106⟩3.0.CO;2-3

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