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Article

Leveraging statistical models to improve preseason forecasting and in-season management of a recreational fishery

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ABSTRACT

Objective: Effective management of recreational fisheries requires accurate forecasting of future harvests and real-time monitoring. Traditional methods that rely on historical catch data can be unreliable, particularly when regulatory changes alter angler behavior. This study aimed to develop and test statistical models to improve predictions of Gulf of Mexico Gag *Mycteroperca microlepis* harvests for both preseason planning and in-season monitoring.

Methods: We developed a statistical modeling framework to forecast Gag harvests and compared its performance to that of traditional historical average-based methods. Model accuracy was evaluated for both cumulative preseason projections and in-season monitoring. Additionally, we assessed the framework's ability to account for effort compression in shorter seasons.

Results: Our best-fitting model outperformed traditional methods in both preseason and in-season forecasts. The model also demonstrated higher accuracy in recent years, particularly for shorter seasons in which effort compression was apparent. Two key advantages of our framework are (1) the ability to account for changes in angler behavior as a result of effort compression and (2) the ability to quantify the probability of exceeding harvest quotas, providing managers with a tool to evaluate trade-offs between season duration and conservation objectives.

Conclusions: This study highlights the value of statistical modeling for improving fisheries management. By offering more accurate harvest predictions and explicit estimates of the probability of exceeding quotas, our approach provides a flexible tool to support decision making, particularly for vulnerable, highly targeted stocks.

KEYWORDS: effort compression, fishing season, Gag, Gulf of Mexico, in-season monitoring, season projections

LAY SUMMARY

Effective fisheries management needs accurate harvest forecasts. Traditional methods using historical data can be unreliable, especially with regulatory changes. Our model improved Gulf of Mexico Gag harvest predictions, helping managers to balance season length and conservation goals.

INTRODUCTION

One of the primary management strategies in recreational fisheries is the use of temporal harvest restrictions to reduce fishing pressure. Annual fishing quotas, determined in large part by stock assessments, are used to help establish the duration of the fishing season (Methot et al., 2014). The actual duration of the recreational fishing season is based on projections of when the quota will be exceeded. Therefore, the accuracy of these projections, along with in-season monitoring as the season progresses, is crucial to minimize the risk of overfishing and ensure sustainable fisheries.

Both preseason and in-season harvest projections are typically estimated using historical, temporally indexed harvest information from previous years (Carruthers et al., 2014).

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Recreational fishing season closure dates are often established before the season begins, thus providing private anglers and for-hire businesses with a clear expectation of the total season duration. This approach relies on projections for when the recreational quota will be met before any harvest data from the present year are available (Farmer & Froeschke, 2015; Farmer et al., 2020). However, temporally indexed recreational harvest estimates are seldom available on the timelines required for in-season management (Carter et al., 2015; National Academies of Sciences, Engineering, and Medicine, 2021). Due to the substantial number of participants in many recreational fisheries, recreational harvest is often estimated using sampling data from dockside interviews and mail surveys of effort, followed by survey-based extrapolation methods (Marine Recreational Information Program [MRIP], 2023; National Academies of Sciences, Engineering, and Medicine, 2021). The time required to implement this methodology, especially the mail survey, results in estimate reporting lags of up to several months after sampling. Consequently, managers are often forced to rely on limited in-season and past harvest information to formulate and update harvest forecasts as the season progresses.

Unfortunately, past harvest data can be an unreliable predictor of future harvest rates when regulations change (Carter et al., 2015). Angler behaviors, including decisions about whether to fish and which species to target, are heavily influenced by fishing regulations (Farmer et al., 2020; Hyman et al., 2024). Anglers often focus on popular species that are currently open for harvest and may concentrate their efforts on a particular species if its season is shortened (Abbott et al., 2018; Trudeau et al., 2022). When harvests exceed projections based on past estimates, managers may need to implement post hoc accountability measures, such as reducing the quota for the subsequent year (i.e., a payback; Methot et al., 2014). Participants in the recreational fishery may perceive these measures as punitive, despite their adherence to regulations, potentially leading to decreased future compliance and undermining management integrity (Cowan, 2011; Cowan et al., 2011). Therefore, techniques that bridge the gap between harvest data availability and real-time management needs are valuable tools for ensuring sustainable fisheries and promoting recreational angler satisfaction.

Modeling frameworks that leverage relationships between readily available social, environmental, and management variables and harvest have demonstrable success in improving the accuracy of both preseason projection and in-season monitoring estimates. For example, a suite of sophisticated modeling approaches has been applied to reliably forecast landings from a broad range of species, including Gulf of Mexico (hereafter, “Gulf”) Vermilion Snapper *Rhomboplites aurorubens* and Gray Snapper *Lutjanus griseus* (Farmer & Froeschke, 2015), Gulf Red Snapper *Lutjanus campechanus* (Farmer et al., 2020), Atlantic Menhaden *Brevoortia tyrannus* (Hanson et al., 2006), giant Pacific octopus *Enteroctopus dofleini* (Nagano & Yamamura, 2023), and Indian Oil Sardine *Sardinella longiceps* (Holmes et al., 2021). Such methods can be used to set season durations (Farmer et al., 2020) or to “nowcast” in-season catch rates (Carter et al., 2015) using combinations of fishing regulations, socioeconomic factors, weather conditions, and Internet search traffic. In fact, these modeling approaches can represent considerable improvements over more typical projections that are primarily based on past harvest data (Carter et al., 2015).

The accuracy gap between harvest projections based on statistical models and those derived from traditional methods may be most pronounced during stock rebuilding periods, when recreational quotas are low and seasons are significantly shortened. Managers typically reduce season durations to alleviate fishing pressure on vulnerable stocks. However, anglers may respond by intensifying their effort within the limited fishing window, leading to increased harvest rates (Abbott et al., 2018; Farmer et al., 2020). This phenomenon, known as “effort compression,” has been widely documented in the recreational fishery for Gulf Red Snapper (e.g., Farmer et al., 2020; Hyman et al., 2024; Powers & Anson, 2016, 2018; Topping et al., 2019), where federal season reductions from 194 d in 2005 to just 9 d in 2014 resulted in exponentially higher catch rates for both private and for-hire sectors (see Figure 4 in Farmer et al., 2020). Effort compression is most pronounced during the shortest seasons, typically when a stock is overexploited. Consequently, failing to account for this behavior can lead to substantial harvest overages precisely when the stock is most vulnerable. While traditional projections based on historical harvest averages cannot inherently account for these behavioral shifts, statistical modeling approaches can explicitly incorporate season duration effects (Farmer et al., 2020; Hyman et al., 2024), theoretically leading to more accurate forecasts and improved management outcomes. However, such frameworks have rarely been applied in management settings (Farmer et al., 2020).

In this study, we applied a regression framework to forecast harvest for the recreational sector component of the Gulf Gag *Mycteroperca microlepis* stock. Gag are highly targeted by recreational anglers in the Gulf (Hyman et al., 2024), and the Gag fishery is currently in a rebuilding plan (Gulf of Mexico Fishery Management Council [GMFMC], 2023). Recreational CPUE has declined in recent years (Southeast Data, Assessment, and Review [SEDAR], 2021), and stock status is currently considered impaired (i.e., overfishing is occurring and the stock is overfished; GMFMC, 2023; SEDAR, 2021; Southeast Fisheries Science Center, 2023). In response, the GMFMC reduced the recreational Gag annual catch limit (ACL) by 80% and reduced the season duration from 214 d in 2022 to 49 d in 2023 (GMFMC, 2023) and 15 d in 2024 (National Marine Fisheries Service [NMFS], 2024). Projections of season duration based on harvest rates from previous years underestimated harvest in the substantially shorter season, and the ACL was exceeded in 2023 (GMFMC, 2023; NMFS, 2024) and with preliminary 2024 estimates, suggesting the occurrence of intensified fishing effort within the shortened time frame. Consequently, more precise projection methodologies that (1) incorporate changes in harvest rates driven by temporal restrictions (i.e., effort compression) and environmental conditions and (2) quantify the risk of exceeding the harvest quota could enhance future fisheries management decisions. We developed a set of statistical models to generate monthly estimates of harvest rates (pounds per day open [1 lb = 0.45 kg]) using management, socioeconomic, environmental, and seasonal predictors. We also demonstrate that this framework may be used to generate preseason forecasts and in-season updates of when a hypothetical quota will be met.

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METHODS

Data sources

We compiled recreational Gag harvest data from the for-hire sector from the NMFS MRIP For-Hire Survey (FHS) combined with data from the Angler Point Access Intercept Survey (APAIS) and private recreational data from the Florida Fish and Wildlife Conservation Commission's State Reef Fish Survey (SRFS). This approach aligns with the data sources currently used for Gag management, as both the GMFMC and National Oceanic and Atmospheric Administration (NOAA)–NMFS monitor recreational Gag landings by using SRFS and FHS/APAIS data.

Since 2023, the annual recreational Gag quota has been determined based on the most recent stock assessment (SEDAR, 2021) in conjunction with a stock rebuilding framework (GMFMC, 2023), both of which fundamentally rely on recreational landings from the private fleet (represented by the SRFS) and the for-hire fleet (represented by the FHS). Aggregated monthly landings from these surveys are used to monitor quota attainment. We applied similar aggregation methods to construct our predictive models, with two exceptions. First, although MRIP collects data from shore-based anglers and includes shore harvest in the recreational quota, we excluded shore mode from our analysis due to its historically negligible contribution to Gag landings and the high uncertainty in its estimates (NMFS, Fisheries Statistics Division, personal communication). Second, our analysis focused on the west coast of Florida only (excluding the Florida Keys) rather than the Gulf as a whole, as more than 98% of all Gulf Gag landings have occurred in Florida since 2011 (GMFMC, 2023; NMFS, Fisheries Statistics Division, personal communication).

The SRFS was established in 2015 (originally named the "Gulf Reef Fish Survey") to improve harvest estimates for offshore species that are less frequently targeted and caught. The survey focuses on reef-associated species, including Gag, Red Grouper *Epinephelus morio*, Gray Triggerfish *Balistes capriscus*, Red Snapper, Vermilion Snapper, Greater Amberjack *Seriola dumerili*, Hogfish *Lachnolaimus maximus*, Mutton Snapper *Lutjanus analis*, and Yellowtail Snapper *Ocyurus chrysurus*. The SRFS estimates CPUE using a combination of data collected on these reef-associated species from the APAIS and data collected from SRFS intercepts, which are conducted at public boat ramps, where offshore fishermen are more commonly encountered. The SRFS mail survey is sent to a stratified random sample of anglers with the free State Reef Fish Angler (SRFA) designation on their Florida saltwater license, asking them to report their fishing activity over the past month.

The combination of increased dockside sampling at offshore access points, a larger sample size, and a more targeted mail survey frame allows the SRFS to produce more precise harvest estimates for reef fish compared to the MRIP survey, which has a broader scope of all saltwater fish species.

The FHS (NOAA MRIP) estimates recreational catch and effort for charter fishing trips in U.S. waters. This survey targets federally permitted for-hire vessels, including charter boats and head boats, which operate with licensed captains and provide fishing opportunities for recreational anglers. Catch and effort estimates are derived from a combination of APAIS dockside interviews, electronic logbooks, and randomly assigned telephone surveys, which are used to calculate total catch for the sector.

Both SRFS and FHS use dockside sampling to collect catch-per-trip data. In these interviews, trained samplers record details from anglers about their completed fishing trips, including the number and species of fish caught, the size of landed fish, and fishing effort (e.g., hours fished). These catch data are then combined with effort estimates from the mail or telephone surveys to calculate total harvest. Statistical methods are applied to account for sampling variability and potential reporting biases, thus ensuring robust estimates for fisheries management. To standardize harvest rates from the SRFS and FHS in Florida, we aggregated monthly Gag harvest estimates across months with varying open seasons. We then divided each monthly estimate by the number of days open to fishing to calculate daily harvest rates. To avoid division by zero in months when harvest was closed, we added one additional day to the denominator. This transformation improved model convergence and substantially enhanced overall prediction accuracy. However, dividing total harvest across out-of-season months resulted in artificially elevated monthly harvest "rates" for May and June 2024—months with minimal actual harvest. These values were exaggerated when expressed as a rate because no days were open to harvest. When we transformed the estimates back to total monthly harvest (our primary variable of interest), the relative deviations between predicted and observed values were greatly reduced. As a result, we deemed the transformation appropriate, as it yielded estimates that accurately reflected observed monthly harvest totals.

Predictors considered

We considered multiple regulatory, socioeconomic, and environmental predictors to model patterns in recreational Gag harvest rates (Table 1). Fundamentally, we expected Gag harvest rates to be positively related to whether a month was open to Gag harvest, as anglers would presumably target Gag when the season is open (Hyman et al., 2025). However, Gag temporal regulations along the Gulf coast of Florida are complex and have historically differed spatially, requiring careful consideration of how to translate these regulations into relevant predictors. From 2012 to 2022, a four-county special season for Gag in Florida applied to Franklin, Wakulla, Jefferson, and Taylor counties, occurring when the regular state and federal waters were closed. During this period, state waters in these counties were opened for recreational Gag harvest from April 1 through June 1 or June 30, depending on the year (Hyman et al., 2024). This special season allowed for local adjustments to manage the species effectively and support angling opportunities. For all Gulf state and federal waters, Gag harvest was generally open from June 1 to December 31. To account for spatial differences in Gag temporal restrictions, we created three predictors denoting whether the four-county season was open (denoted $\mathrm{Special}_{\mathrm{Gag}}$), the season for the remainder of Gulf state and federal waters was open (denoted $\mathrm{Full}_{\mathrm{Gag}}$), or neither season was open (denoted $\mathrm{Closed}_{\mathrm{Gag}}$).

These predictors were included as dummy variables in the mean component of the model (see the *Analysis* section below), conditioned on observing a nonzero harvest rate. The $\mathrm{Closed}_{\mathrm{Gag}}$ variable therefore was specified as the reference intercept and represented the expected nonzero harvest rate when the season was closed. In contrast, the $\mathrm{Full}_{\mathrm{Gag}}$ and $\mathrm{Special}_{\mathrm{Gag}}$ variables were specified as dummy indicators in reference to this baseline

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Table 1. Symbology and descriptions of each predictor considered in Florida State Reef Fish Survey (SRFS) Gag harvest models. Abbreviations are as follows: FWC = Florida Fish and Wildlife Conservation Commission, MRIP = Marine Recreational Information Program, and RS = Red Snapper.

Variable	Description	Data source and references
$\text{Closed}_{\text{Gag}}$	Gag harvest rate when the season is closed to fishing, taken to be the reference intercept	FWC
$\text{Special}_{\text{Gag}}$	Binary variable denoting whether the four-county "special" Gag season is open	FWC
Full_{Gag}	Binary variable denoting whether the Gag season is open statewide	FWC
Open_{Gag}	Binary variable denoting whether the Gag season is open at all	FWC
$\text{Season}_{\text{Gag}}$	Natural logarithm of the recreational Gag season duration in Florida	FWC
ln Past	Natural logarithm of the index of abundance taken as the average Gag harvest in a given month based on the most recent 3 years in which that month has been open	MRIP and SRFS
Days_{RS}	Fraction of days in a month that were open to Red Snapper harvest	FWC
$\sin_{12}$	Annual sine term	$\sin_{12,t} = \sin(2\pi \cdot t/12)$, where t is a given month
$\cos_{12}$	Annual cosine term	$\cos_{12,t} = \cos(2\pi \cdot t/12)$
$\sin_{6}$	Semi-annual sine term	$\sin_{6,t} = \sin(2\pi \cdot t/6)$
$\cos_{6}$	Semi-annual cosine term	$\cos_{6,t} = \cos(2\pi \cdot t/6)$
Year	Number of years since the start of the time series (2015)	
License	Number of active SRFS fishing licenses in a given month	FWC
Unfishable	Fraction of unfishable days in a month	Global Surface Summary of the Day weather data from the U.S. National Centers for Environmental Information (Sparks et al., 2017)
Fuel	Florida mean gasoline price (adjusted for inflation using 2024 U.S. dollars)	U.S. Energy Information Administration

when either season type was open. Furthermore, for the hurdle component of our regression model, we introduced a fourth binary variable, Open_{Gag}, which indicated whether either season was open. Here, the intercept of the hurdle denoted the probability of observing a Gag harvest rate of zero when the season was closed, while Open_{Gag} denoted the change in the probability of observing a zero Gag harvest rate when either the full season or the four-county season was open. This was based on the expectation that the probability of observing zero Gag harvested per day would depend on whether Gag harvest anywhere was permitted during that period. Hence, the management variables in the model reflected two distinct processes: (1) given whether any type of season was open, the probability of observing a nonzero harvest rate; and (2) conditional on a nonzero harvest rate, the expected harvest rate under each season type (closed, open in both state and federal waters, or open only in the special four-county area).

For highly targeted species, anglers often compensate for shorter fishing seasons by increasing the number of trips taken during the open season, a phenomenon known as effort compression (Powers & Anson, 2016, 2018; Topping et al., 2019; Trudeau et al., 2022). As a result, recreational harvest does not necessarily decline linearly with shorter seasons. To account for this nonlinearity, we included the duration of the Gag season (for both federal and statewide waters) as a predictor of harvest rate. Building on the logic presented by Hyman et al. (2024), we used the natural logarithm of season duration as a predictor. This approach reflects the principle that changes in season duration have a greater relative impact on harvest rates when the season is short. In contrast, as the season lengthens, the marginal impact of additional days diminishes, as longer seasons often exceed the practical number of fishing opportunities that most anglers can realistically pursue.

To arrive at preseason and in-season projections, NOAA's Southeast Regional Office (SERO) commonly uses an averaging approach in which the projected harvest for a specific month is calculated using the average harvest rate—both SRFS and FHS combined, divided by the number of days open to harvest—observed during the same month over the three most recent years when that month was open to harvest. As part of SERO's averaging approach, the harvest rate is assumed to be zero when the recreation season is closed. Although this method attempts to account for seasonal trends and variability, the accuracy of this approach is predicated on an assertion that past conditions underlying fishing conditions have remained unchanged—a strong assumption that does not always hold (Carter et al., 2015). To compare this approach to more complex modeling frameworks, we included this historical average (denoted as "Past") as a predictor in all models. The simplest tested model predicted harvest based only on this predictor and our Gag temporal regulation predictors. However, for the years 2015, 2016, and 2017, SRFS data were not available to calculate this 3-year average since the survey began in 2015. To obtain 3-year averages for these years, we supplemented SRFS data with private recreational data from the APAIS that were weighted by the MRIP Fishing Effort Survey and calibrated to be consistent with SRFS units using established methodology (Cross et al., 2020; Ramsay et al., 2024). Finally, the four-county special season introduced complexities into the estimation process, as harvest rates during a month open only to these four counties differed from rates when all of Florida's Gulf coast waters were open. To address this, we adjusted the 3-year averaging method. Specifically, if a given month–year t was open solely to the four-county season, we based the average on harvest rate data from the same month in the three most recent years when only the four-county season was active. Conversely, if the month–year t was open to all state

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and federal waters, the average was derived from the three most recent years in which the entire Gulf coast was open to recreational harvest of Gag. This adjustment ensured that projections accounted for the distinct harvesting patterns associated with spatial variations in the Gag season.

The Red Snapper is arguably the reef fish species most highly targeted by anglers in the Gulf; consequently, Red Snapper temporal regulations can affect other species within the wider reef fish complex. Recent evidence suggests that the status of the recreational Red Snapper season (open or closed) significantly impacts both recreational fishing effort overall and Gag harvest specifically (Hyman et al., 2024, 2025). This effect is likely driven by the Red Snapper's popularity and the shared tendency of Red Snapper and Gag to aggregate around structured reef habitats. To account for this dynamic, we included the proportion of time for which Red Snapper harvest was permitted in a given month as a predictor in our models.

Seasonality influences both angler behavior and Gag vulnerability to harvest. Recreational angler effort fluctuates throughout the year, often driven by environmental conditions, social events, and other external factors (Farmer & Froeschke, 2015; Farmer et al., 2020; Hyman et al., 2024; Trudeau et al., 2022). Additionally, seasonal movements associated with Gag life history, such as spawning migrations and habitat use, can alter the susceptibility of Gag to fishing pressure (Grüss et al., 2017; Heyman et al., 2019; Lowerre-Barbieri et al., 2020). To capture these seasonal dynamics, regression models can incorporate harmonic terms, such as sine and cosine functions, which account for periodic variations on annual or semi-annual cycles (e.g., Hyman et al., 2024; Trudeau et al., 2022). In our models, we included four harmonic terms: sine and cosine functions oscillating at 12-month (annual) and 6-month (semi-annual) frequencies, enabling a more precise representation of seasonal effects.

We included an annual trend as a predictor of Gag harvest rates. The inclusion of an annual trend in recreational fishing harvest models accounts for long-term changes, such as improved catch efficiency from advancements in technology and gear (e.g., Detmer et al., 2020; Marchal et al., 2007; Selgrath et al., 2018) as well as shifts in angler behavior and environmental conditions. These trends help to distinguish overarching patterns from short-term fluctuations, thereby enhancing model accuracy.

Recreational fishing activity is often influenced by weather conditions, with anglers less likely to fish during inclement weather (Farmer et al., 2020). To evaluate this relationship, we used the GSODR package in R to generate daily weather summaries along the Gulf coast of Florida for each day and month between 2015 and 2024 (Sparks et al., 2017). Weather data were extracted from all available U.S. National Centers for Environmental Information stations that were located within 30 km of the Gulf coast and operating within the study period. A total of 37 stations met these criteria. We defined days with average wind speeds exceeding 7.5 m/s as "unfishable" (Farmer et al., 2020). For each month, we calculated the proportion of unfishable days, denoted as the variable "Unfishable." These weather patterns did not appear to be trending over time in this time series. The Unfishable metric was included as a covariate in our analyses to account for the impact of adverse weather on recreational fishing effort and harvest.

Finally, we considered two socioeconomic variables—the number of Florida state reef fish license holders and annual fuel prices—as predictors of Gag harvest. Beginning in 2015, Florida required the Gulf Reef Fish Angler (GRFA) designation (later adapted to the SRFA designation) for licensed recreational fishermen to target select fish within the broader multispecies reef fish complex. We hypothesized that the number of anglers with the GRFA or SRFA designation in each month may be related to fishing effort targeted towards reef fish and, by extension, Gag harvest. Moreover, as fuel prices may affect anglers' decisions to fish and/or the length of fishing trips, we considered monthly fuel prices, adjusted for inflation, as an economic predictor. Notably, both socioeconomic predictors considered here generally increased throughout the time series.

Analysis

Monthly recreational Gag harvest rates (landings per day open) were analyzed using a hurdle gamma (HG) generalized linear model. This model has a probability mass function specified separately for zero and a probability density function for nonzero (positive) outcomes. The conditional density function for the HG probability distribution is used to describe the distributional forms:

$$\mathrm{HG}\left(y|\alpha,\,\phi,\,\theta\right)=\begin{cases}\theta, & y=0\\ (1-\theta)\,\mathrm{Gamma}\left(y|\alpha,\,\phi\right), & y>0,\end{cases} \tag{1}$$

where θ is the probability of observing a zero and $\mathrm{Gamma}(y|\alpha, \phi)$ is the gamma probability density function for the Gag harvest rate with inverse-scale and shape parameters α and ϕ. Notably, these parameters can be re-expressed in terms of the mean (μ) and variance (σ^2). We therefore employed a distributional regression approach whereby we modeled the mean and variance directly. Consequently, the harvest rate for Gag is expressed as

$$y_t \sim \mathrm{HG}\left(\alpha_t,\phi_t,\theta_t\right), \tag{2}$$

$$\alpha_t=\frac{\mu_t}{\sigma_t^2},$$

$$\phi_t=\frac{\mu_t^2}{\sigma_t^2},$$

$$\mu_t=\exp\left(\beta_0+\sum_{i=1}^{I}x_{t,i}\beta_i\right),$$

$$\sigma_t^2=\exp\left(\rho_0+\sum_{j=1}^{J}z_{t,j}\rho_j\right),$$

$$\theta_t=\frac{1}{1+\exp\left(\lambda_0+\sum_{l=1}^{L}k_{t,l}\lambda_l\right)},$$

$$\beta,\rho,\lambda\sim \mathrm{N}(0,4),$$

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where y_t denotes the weight of Gag harvested per day open in the tth month–year. Meanwhile, μ_t and σ_t^2 denote the mean and variance, respectively, of the gamma distribution conditioned on $y_t > 0$, and θ_t denotes the binomial probability of observing zero Gag caught in month–year t. We use x, z, and k to refer to predictors included in modeling μ_t, σ_t^2, and θ_t, respectively. Similarly, coefficients corresponding to μ_t, σ_t^2, and θ_t are denoted β, ρ, and λ, respectively. Both μ_t and σ_t^2 are related to their predictors and associated coefficients through a log-link function, whereas θ_t is related to its predictors and associated coefficients through a logit-link function. All regression coefficients were assigned relatively uninformative, normally distributed priors with a mean of zero and a variance of 16.

The Stan probabilistic programming language for Bayesian modeling (Gelman et al., 2015), accessed via R (R Core Team, 2024), was used to fit all models. Each model involved four parallel Markov chains with 5,000 iterations for warm-up and another 5,000 iterations for posterior sampling, yielding 20,000 total draws for inference. Covariates were deemed significant if their 80% CIs excluded zero (Chen et al., 2021; Kruschke, 2021; van de Schoot et al., 2021). All graphics were produced using the ggplot2 package in R (Wickham, 2016).

Model selection

We constructed five candidate models to predict Gulf Gag harvest rates. For all models, we employed the same predictors to estimate the hurdle and variance components and examined the predictive performance of differing mean structures (Table 2). For our simplest model (g_1), we considered Gag temporal regulations and the average historical Gag harvest as predictors of mean Gag harvest for the current year. This model was designed to emulate the methodology currently employed to predict harvest while also considering historic subtleties associated with Gag temporal regulations across the Gulf coast of Florida. Our second model, g_2, expanded on model g_1 to include season duration, an annual trend, seasonal harmonic terms, and Red Snapper temporal regulations. Model g_3 expanded on model g_2 to include social and economic variables, including the number of state reef fish license holders in each month as well as the average cost of fuel, adjusted for inflation. Conversely, model g_4 expanded on model g_2 to include a weather variable, namely the fraction of each month not considered fishable. Finally, model g_5 served as our "global" model, which included all predictors considered. For all models, the hurdle component was specified only as a function of the binary Open_{Gag} predictor, whereas the variance component was specified as a function of annual and semi-annual harmonic terms. We employed the estimated log-pointwise predictive density (ELPD) and corresponding Δ_{ELPD} values to assess the predictive performance of each model within our set of statistical models g_i (Vehtari et al., 2017). The ELPD values are commonly used to evaluate out-of-sample predictive accuracy, while Δ_{ELPD} values represent the difference between the ELPD of a given model and that of the best-performing model in the set. The ELPD and Δ_{ELPD} values were estimated using the approximate leave-one-out information criterion (Gelman et al., 2015; Vehtari et al., 2017), with the calculations performed through the loo package (Vehtari et al., 2022).

When two models showed similar Δ_{ELPD} values (i.e., ≤4; Sivula et al., 2020), the simpler model was selected based on the principle of parsimony.

Cross validation

We employed extensive cross validation (CV) to assess the predictive power of our best-performing statistical model. We considered two CV exercises, block CV and one-step-ahead performance (1-SAP) CV, to separately assess the suitability of our model for preseason and in-season projections, respectively. For our block CV exercise, we refitted the model to truncated data sets eight times—each with 1 year withheld—and subsequently compared predictions derived from our models to withheld observed response variables for all months in the withheld year. Because managers would only have information from previous years when making preseason projections, this CV method was a reasonable approach to assessing model preseason posterior prediction accuracy. In contrast, nowcasting entails making in-season projections for the current time step based on previous information both from the current year and previous years (Carter et al., 2015). As a result, for 1-SAP CV for each year, we subsequently refitted the model 11 times (once for each month). For each refit, we included months 1 to m in our training set and then compared posterior predictive distributions to observed data in month $m + 1$.

For each posterior scan (s) of 1,000 used, monthly harvest rates were converted to total harvest by multiplying the predicted rates by the number of days for which the month was open to harvest. In addition, for block CV, we then calculated the cumulative harvest for month m as the sum of harvest estimates across months $(1, \ldots, m)$ using posterior predictive scans derived from the HG distribution. To evaluate the practical utility of our approach, posterior predictions of both individual monthly harvest (using 1-SAP CV) and cumulative harvest (using block CV) were then compared to withheld data. This comparison assessed out-of-sample performance and demonstrated the applicability of our projections in real-world management scenarios.

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Table 2. Fixed-effects formulas for the mean structure of the five candidate Gag harvest models considered. All models had identical fixed-effects formulas for modeling the shape and hurdle parameters. Abbreviations for predictors are defined in Table 1.

Model	Formula
g_1	$\text{Closed}_{\text{Gag}} + \text{Special}_{\text{Gag}} + \text{Full}_{\text{Gag}} + \ln \text{Past}$
g_2	$\text{Closed}_{\text{Gag}} + \text{Special}_{\text{Gag}} + \text{Full}_{\text{Gag}} + \ln \text{Past} + \text{Season}_{\text{Gag}} + \sin_{12} + \cos_{12} + \sin_6 + \cos_6 + \text{Year} + \text{Days}_{\text{RS}}$
g_3	$\text{Closed}_{\text{Gag}} + \text{Special}_{\text{Gag}} + \text{Full}_{\text{Gag}} + \ln \text{Past} + \text{Season}_{\text{Gag}} + \sin_{12} + \cos_{12} + \sin_6 + \cos_6 + \text{Year} + \text{Days}_{\text{RS}} + \text{License} + \text{Fuel}$
g_4	$\text{Closed}_{\text{Gag}} + \text{Special}_{\text{Gag}} + \text{Full}_{\text{Gag}} + \ln \text{Past} + \text{Season}_{\text{Gag}} + \sin_{12} + \cos_{12} + \sin_6 + \cos_6 + \text{Year} + \text{Days}_{\text{RS}} + \text{Unfishable}$
g_5	$\text{Closed}_{\text{Gag}} + \text{Special}_{\text{Gag}} + \text{Full}_{\text{Gag}} + \ln \text{Past} + \text{Season}_{\text{Gag}} + \sin_{12} + \cos_{12} + \sin_6 + \cos_6 + \text{Year} + \text{Days}_{\text{RS}} + \text{License} + \text{Fuel} + \text{Unfishable}$

Comparison to current methods

We evaluated the predictive performance of our model, both in-sample and out of sample, against estimates derived using historical average harvest. To mirror current prediction methods, we multiplied the historical average harvest rate by the number of days that were open to Gag harvest in the current month to estimate monthly harvest values. These estimates were compared to those from our model under three scenarios: (1) fitted to the full data set, (2) fitted to data sets with individual years withheld (block CV), and (3) fitted to data sets with individual months withheld (1-SAP CV), alongside observed data. For block CV, we applied our preseason cumulative estimation procedures to the historical average harvest rates to enable direct comparisons with our modeling approach. Comparative predictive performance was assessed based on the root mean square error (RMSE) of each estimate (from our model [i.e., the median posterior predictive] or historical average harvest) relative to observed harvest values.

2025 projection

After establishing the posterior predictive accuracy of our models, we conducted simulations to predict a hypothetical 2025 Gag season duration using 1,000 posterior scans from our best-fitting model. To begin, we calculated the adjusted annual catch target (ACT) for 2025 by accounting for the 2024 overage penalty, which was defined as the amount of Gag harvested in 2024 (249,000 lb) that exceeded the 2024 ACL (163,000 lb) using preliminary estimates. This overage was subtracted from the 2025 ACT (319,000 lb) specified in the rebuilding plan (U.S. Office of the Federal Register, 2025 [see Table 2 to Paragraph (d)(2)(i)]; GMFMC, 2023; NMFS, 2024):

$$\begin{aligned}\text{2024 Penalty} &= \text{2024 ACL} - \text{2024 Harvest}\\ &= 163{,}000\ \text{lb} - 249{,}000\ \text{lb} = -86{,}000\ \text{lb},\end{aligned}$$

$$\begin{aligned}\text{2025 ACT} &= \text{2025 Unadjusted ACT} + \text{2024 Penalty}\\ &= 319{,}000\ \text{lb} - 86{,}000\ \text{lb} = 233{,}000\ \text{lb}.\end{aligned}$$

To develop our simulations, we constructed a design matrix in which all predictors (except for Gag temporal regulations and seasonal variables) were fixed at their 2024 values. We began by setting the season duration d to 1 d, with a starting date of September 1. Months without any days open to harvest were assigned the "Closed" temporal regulation treatment, whereas months with days open were assigned the "Full" treatment. Using our best-fitting model, we simulated posterior predictive distributions of monthly harvest rates for 2025 across 1,000 posterior scans (s). For each scan, monthly harvest rates were multiplied by the number of days open to harvest within the corresponding month to derive posterior predictions of monthly harvest. To estimate total harvest for each scan, we summed harvest estimates across all months. The process was repeated iteratively, incrementing the season duration d by 1 d at a time until d was equal to 121, which corresponded to the maximum possible season duration ending December 31. For each season duration ($d = 1, \ldots, 121$), we calculated the median and 80% posterior predictive interval of total harvest. Additionally, for each season duration, we estimated the probability that the ACT would be met or exceeded as the proportion of posterior predictive scans in which the total harvest met or exceeded the ACT. Finally, we compared these projections to those using the historic average harvest rate for September.

RESULTS

Model selection and diagnostics

The best-fitting model was g_2, which described mean Gag harvest as a function of Gag temporal regulations, past harvest, seasonal terms, an annual trend, and Red Snapper temporal regulations. Although models g_3, g_4, and g_5 demonstrated similar predictive performance, with Δ_{ELPD} values of 4 or less (Table 3), model g_2 was the simplest among the four. Consequently, we selected model g_2 for inference, adhering to the principle of parsimony. Notably, the posterior distributions of the additional coefficients introduced in models g_3, g_4, and g_5—beyond those included in model g_2—all had 80% CIs that included zero, providing further evidence that these additional predictors did not improve predictive performance (Table S1 [see online Supplementary Material]). Importantly, the ELPD score for model g_2 was substantially higher than that of model g_1, indicating that incorporating additional predictors beyond Gag temporal regulations and past harvest significantly enhanced predictive power. Hereafter, all inferences are based on model g_2.

Time series plots comparing observed and predicted values, along with posterior predictive checks, indicated that model g_2 provided a good fit to the observed data. Correlations between posterior distributions among differing management predictors were low (i.e., $R^2 \ll 0.1$), and correlations among continuous predictors were moderate ($R^2 \leq 0.5$), suggesting that all model coefficients were identifiable. The posterior predictive median and 80% CI monthly estimates aligned closely with in-sample estimates of monthly Gag harvest rates (Figure 1A). As a notable exception, the model underestimated two harvest rate values in 2024 when the season was closed. These apparently large deviations were

Table 3. Model selection results from five Bayesian hurdle gamma regression models (g_i) predicting recreational Gag harvest. Models are presented in order of predictive power based on collected data. Values for the selected model (g_2) are presented in bold italics. Abbreviations are as follows: LOO = approximate leave-one-out information criterion; ELPD_{LOO} = estimated log-pointwise predictive density calculated from the LOO; Δ_{ELPD} = relative difference between the ELPD of any model and the best model in the set; and SE Δ_{ELPD} = standard error for the pairwise differences in ELPD between the best model and any given model.

Model	LOO	ELPD_{LOO}	Δ_{ELPD}	SE Δ_{ELPD}
g_2	***1,448.61***	***−724.31***	***0.00***	***0.00***
g_4	1,450.83	−725.42	−1.11	0.73
g_3	1,454.08	−727.04	−2.73	1.22
g_5	1,455.08	−727.54	−3.23	1.50
g_1	1,490.43	−745.21	−20.91	6.92

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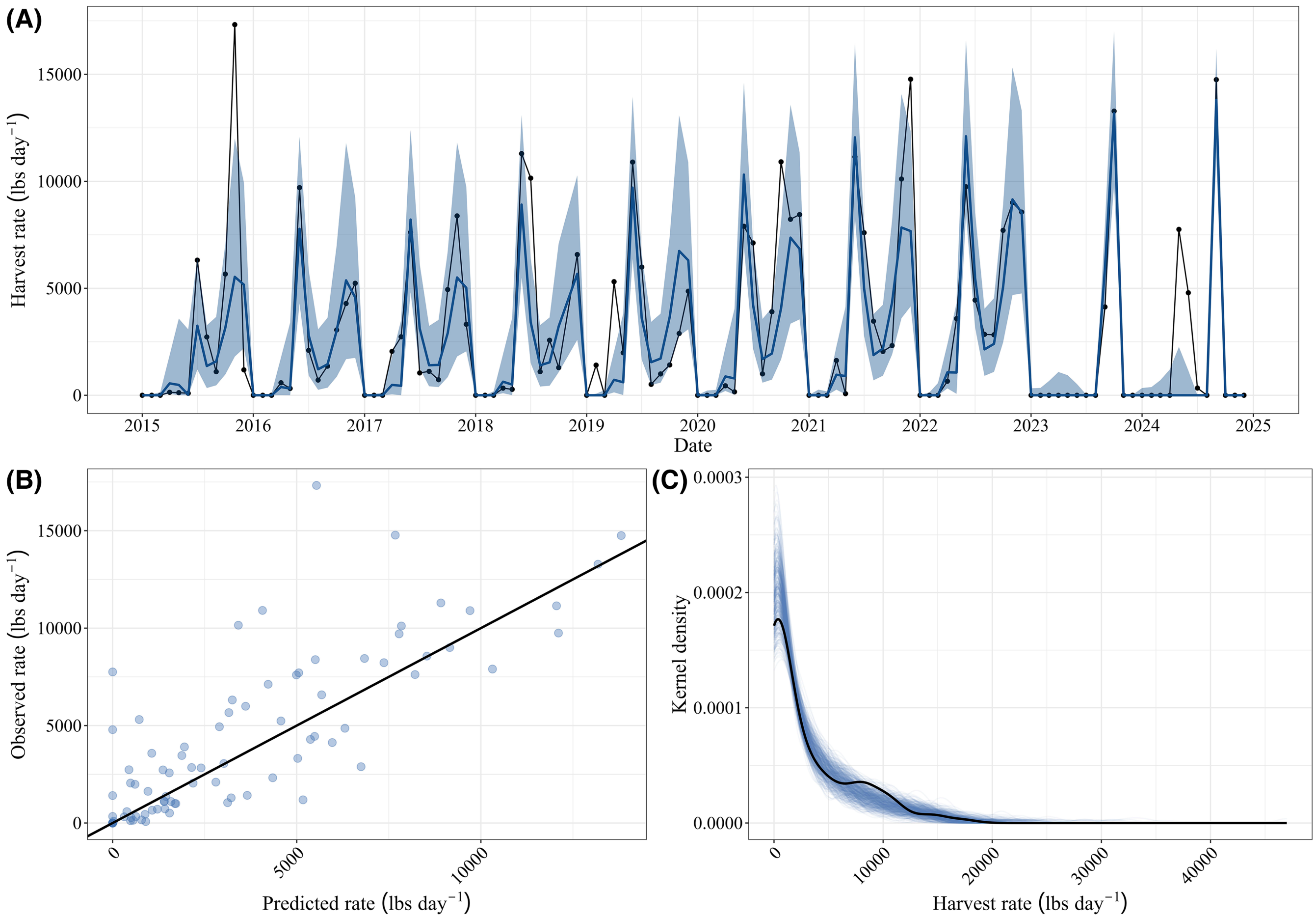

Figure 1. Model fit and diagnostic plots for the best-fitting model (g_2): (A) observed (black) and expected (blue) monthly Gag harvest rates (bands denote upper and lower 80% posterior predictive intervals; points shaded black denote observations); (B) scatterplot of median predicted versus observed Gag harvest rates, with the 1:1 line (black) superimposed; and (C) comparison of the empirical distribution of observed Gag harvest rate (black) to the distributions of 500 scans from the posterior predictive distribution (blue). Two discrepancies between model fit and observed harvest rate in May and June of 2024 are an artifact of dividing total monthly harvest in these out-of-season months by 1, resulting in an inflated harvest rate in these months. When converted to total monthly harvest (Figure 3A), these values remain the same (~5,000 and 7,500 lb [1 lb = 0.45 kg]), while all harvest rates in open months are multiplied by the number of days open plus 1 (80,000–400,000 lb). This causes the discrepancies to become substantially reduced in Figure 3A.

an artifact of dividing the total harvest in closed months by 1. Consequently, the model did not fit well to these values because it treated these out-of-season records as noise. Moreover, because these positive harvest values were insignificant when estimating total monthly harvest instead of the monthly harvest rate, these discrepancies were no longer apparent with total harvest. Additionally, diagnostic scatterplots of median predicted versus observed Gag harvest rates and comparisons of empirical distributions to posterior predictive distributions derived from model g_2 demonstrated satisfactory model performance (Figure 1B, C).

Predictors of monthly Gag harvest rates

Gag temporal regulations, the season duration, the annual trend, and seasonal harmonic terms all significantly explained variation in mean (nonzero) recreational Gag harvest rates (Table 4). Conditioned on a positive outcome and relative to a closed season, months when Gag harvest was open to the entire Florida Gulf coast (Full_{Gag}) resulted in higher harvest rates, while months that were open only for the four-county season ($\text{Special}_{\text{Gag}}$) resulted in lower harvest rates. The duration of the Gag season had a clear negative effect on harvest rates such that the harvest rate was lower during longer Gag seasons (Figure 2). The annual trend was positive and significant, indicating that after other predictors were accounted for, Gag harvest rates appeared to be increasing over time. Notably, after accounting for the effects of other predictors, past harvest did not significantly explain residual variation in Gag harvest rates.

The hurdle parameter θ was strongly and negatively impacted by whether Gag were open to harvest (either in the four-county region or across the Gulf coast of Florida). When the season was completely closed to Gag harvest, the probability of observing zero Gag harvested in a given month was 0.90 (80% CI = 0.84–0.95). However, this probability decreased to nearly zero when Gag were open to harvest. Meanwhile, both sinusoidal harmonic terms significantly influenced σ^2, suggesting that model uncertainty varied seasonally.

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Table 4. Posterior summary statistics (median and 80% CIs) for coefficient estimates for predictors in the mean (μ), hurdle (θ), and variance (σ^2) components of the best-fitting Gag harvest model (g_2). Coefficient terms with asterisks denote 80% CIs that excluded zero. Abbreviations for predictors are defined in Table 1.

Component	Predictor (coefficient)	10%	50%	90%
μ	$\text{Closed}_{\text{Gag}}{}^{*}$ (β_0)	8.28	9.64	10.92
	$\text{Special}_{\text{Gag}}{}^{*}$ (β_1)	−1.85	−1.31	−0.62
	$\text{Full}_{\text{Gag}}{}^{*}$ (β_2)	0.5	0.84	1.24
	$\text{Season}_{\text{Gag}}{}^{*}$ (β_3)	−0.64	−0.53	−0.39
	ln Past (β_4)	−0.09	0.04	0.18
	$\text{sin}_{12}{}^{*}$ (β_5)	0.1	0.37	0.6
	$\text{sin}_{6}{}^{*}$ (β_6)	−0.85	−0.64	−0.47
	cos_{12} (β_7)	−0.14	0.08	0.28
	$\text{cos}_{6}{}^{*}$ (β_8)	−0.38	−0.23	−0.06
	Year* (β_9)	0.05	0.08	0.11
	Days_{RS} (β_{10})	−0.13	0.18	0.48
θ	–* (λ_0)	1.64	2.23	2.91
	$\text{Open}_{\text{Gag}}{}^{*}$ (λ_1)	−10.5	−7.89	−6.16
σ^2	–* (ρ_0)	14.19	14.47	14.78
	$\text{sin}_{12}{}^{*}$ (ρ_1)	−1.48	−1.11	−0.74
	$\text{sin}_{6}{}^{*}$ (ρ_2)	−2.1	−1.65	−1.16
	$\text{cos}_{12}{}^{*}$ (ρ_3)	−1.05	−0.6	−0.1
	cos_{6} (ρ_4)	−0.37	−0.02	0.33

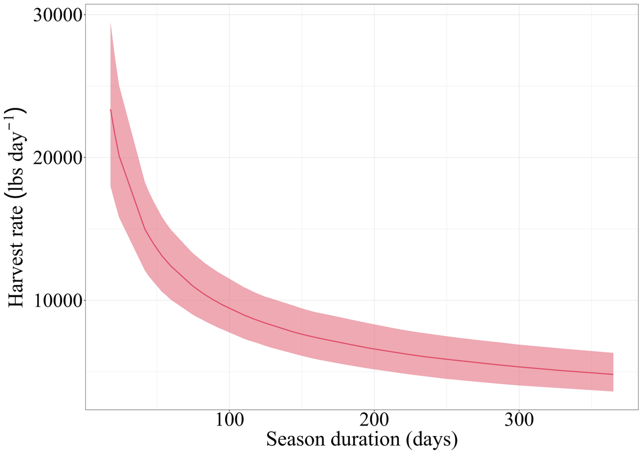

Figure 2. Conditional effects plot depicting the conditional expectation of the Gag harvest rate (1 lb = 0.45 kg) as a function of Gag season duration. Colored lines and bands denote median and nominal 80% Bayesian conditional prediction intervals derived from posterior predictive distributions, with all other coefficients fixed at September 2024 values (i.e., the final month in the data set that was open to harvest).

Comparison to historical average harvest

Comparisons of monthly harvest estimates derived from the in-sample fit of model g_2 with monthly harvest estimates derived using the historical average harvest demonstrated the superior performance of model g_2 (Figure 3). The R^2 value between the model g_2 posterior predictive median estimates and observed harvest was 0.75 (Figure 3C), compared to 0.54 using historical average harvest (Figure 3D). In addition, the RMSE between observed harvest and median estimates derived from model g_2 was 79,000 lb, compared to 105,000 lb (i.e., a 25% improvement). Notably, for the years 2023 and 2024, the RMSE from model g_2 was 57% lower (40,000 vs. 93,000 lb) and 92% lower (15,000 vs. 188,000 lb) than the RMSE from historical average harvest.

Cross validation

Cross validation suggested that our best-fitting model was statistically robust and reliably predicted withheld values. In addition, the model's median estimates outperformed the historical average harvest both for individual months and for cumulative preseason projections. For 1-SAP CV, 83% of withheld values were captured within 80% posterior predictive intervals among all values (Figure 4). The average RMSE between the median prediction using 1-SAP CV and withheld values for individual months was 54,000 lb, compared to an average RMSE of 66,000 lb when using predictions derived from historical average harvest (i.e., an 18% decrease in RMSE when switching from historical harvest to model g_2; Table 5).

For block CV, across all withheld blocks (years), 78% of cumulative values were captured within the 80% posterior predictive interval (Figure 4). For block CV, the average RMSE between the model's median prediction for cumulative harvest and withheld values was 98,000 lb (Table 5). In contrast, the average RMSE between cumulative estimates using historical average harvest and observed harvest was 144,000 lb (i.e., a 32% average decrease in RMSE when shifting from current methods to model g_2). Notably, for each month, the average RMSE of cumulative estimates was consistently equal to or lower than the corresponding RMSE from average values estimated using historical average harvest.

Projections

Our simulations indicated that the hypothetical 2025 Gag ACT of 233,000 lb would likely be exceeded within approximately 12 d, with an 80% CI ranging from less than 1 to 21 d (Figure 5A). In contrast, a projection using average historical harvests would have resulted in a 29-d season. Simulations indicated a 20% probability of exceeding the ACT even with a 1-d season, reflecting the substantial uncertainty in harvest rate estimates during extremely short seasons (Figure 5B). Meanwhile, the probability that harvest would exceed the ACT approached 100% after 39 d. Simulations indicated that the ACT would be exceeded by 1,800 lb on day 13 (1 d after the median projection), 58,000 lb on day 20 (the upper 80% confidence level), and 223,000 lb on day 39.

DISCUSSION

Effective management of recreational fisheries relies on accurate forecasting of future harvests. In this study, we developed models to improve the prediction of Gag harvests for both preseason and in-season management. Our results demonstrated that the best-fitting model enhanced forecasting accuracy, reducing cumulative preseason projection errors by an average of over 32% and in-season errors by almost 20% compared to currently used methods across all years. More recently, comparisons of observed harvest to estimates using in-sample model fits and historical harvest indicated that

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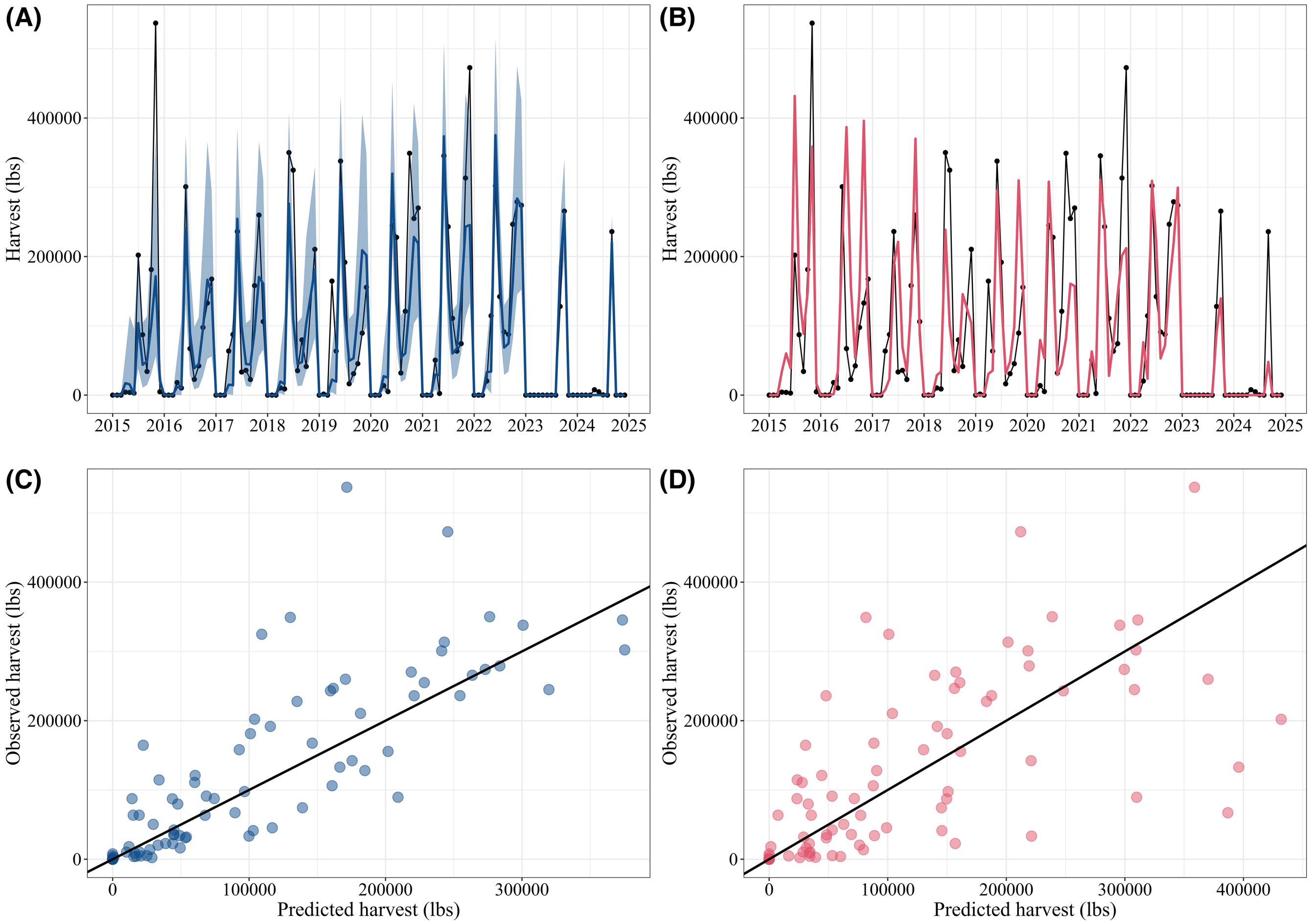

Figure 3. Comparison of in-sample predictive performance between monthly Gag total harvest estimates (1 lb = 0.45 kg) derived from model g_2 and historical average harvest. (A) Observed (black) and expected (blue) monthly Gag harvests using model g_2 are shown. Total monthly harvest is taken as the product of the monthly harvest rate and the number of days for which the month was open to harvest plus 1. Bands denote upper and lower 80% posterior predictive intervals. Points shaded black denote observations. (B) Observed (black) and expected (red) monthly Gag harvests using historical average harvest are depicted. (C) Scatterplot of median predicted versus observed Gag harvest using model g_2 is shown, with the 1:1 line (black) superimposed. (D) Scatterplot of median predicted versus observed Gag harvest using historical average harvest is shown, with the 1:1 line superimposed.

historical harvest estimates substantially underestimated the observed values in 2023 and 2024 by 57% and 92%, respectively, suggesting that our statistical models are particularly better suited to predicting harvest following rapid restrictions of recreational seasons. Therefore, the ability of this framework to account for angler behavioral responses to reductions in season duration represents a notable improvement in management outcomes. These findings complement previous work highlighting the potential of statistical modeling approaches in setting initial season durations and monitoring harvest as the season progresses (Carter et al., 2015; Compaire et al., 2024; Farmer & Froeschke, 2015; Farmer et al., 2020; Hanson et al., 2006).

A second improvement of the proposed framework is its ability to explicitly quantify the probability of exceeding the harvest quota for any given season duration. As more information becomes available over time, the predictive performance of this framework and similar approaches is expected to improve, further increasing its value for fisheries management.

Predictors of Gag harvest

Our results yielded insights into potential drivers of Gag harvest. Gag temporal regulations, seasonal terms, and an annual trend all significantly explained variation in Gag harvest rates, whereas past harvest, Red Snapper management regulations, the number of GRFA/SRFA license holders, fuel, and the fraction of unfishable days in a month did not. The significant influence of Gag temporal regulations on Gag harvest is unsurprising, as the choice to target a given fish species is dependent on whether that species is legally permitted to be harvested. Moreover, Gag harvest rates were generally much higher when the season was open to all Florida counties along the Gulf than when the season was only open for the four-county miniature season in Franklin, Wakulla, Jefferson, and Taylor counties. This was expected, as the underlying population of these four counties—and, by extension, the population of licensed anglers—is a small fraction of all Florida counties along the Gulf. Furthermore, the significant influences of two out of the four harmonic terms in our model were consistent with expectations and previous work, as both recreational angler and Gag

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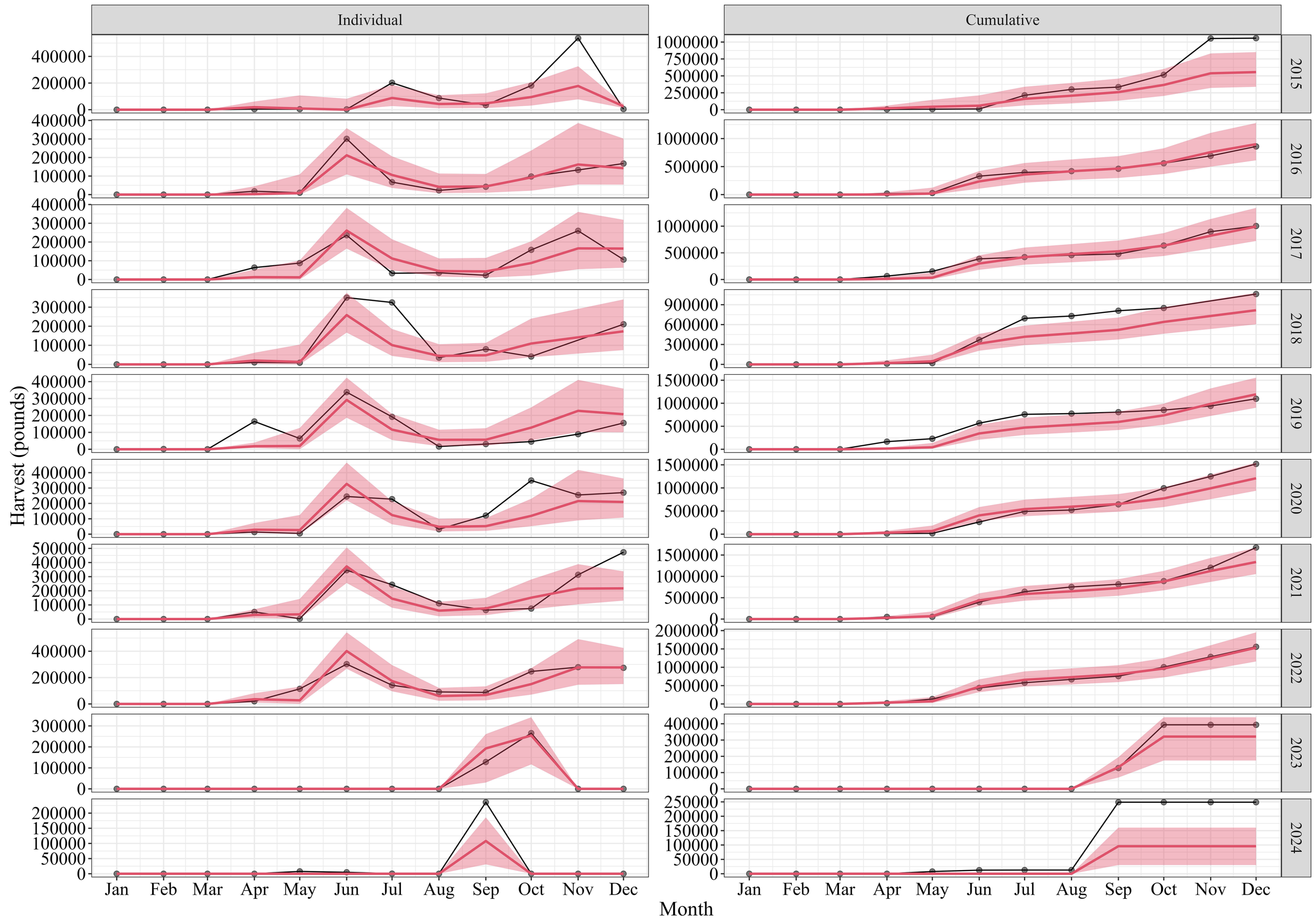

Figure 4. Individual monthly and cumulative cross-validation results for the best-fitting model of Gag harvest (g_2). Model posterior predictive intervals for each year are derived from refitted versions of model g_2 on truncated data sets with that year withheld (i.e., out of sample). Black points denote observed harvest, the red line denotes the expected Gag harvest, and the bands denote upper and lower 80% posterior predictive intervals. Left panels show individual monthly values estimated using one-step-ahead performance cross validation. Right panels depict cumulative preseason values estimated using block cross validation. Note that each *y*-axis is plot-specific; 1 lb = 0.45 kg

Table 5. Comparisons of average root mean square error (lb) between individual and cumulative monthly Gag harvest values (1 lb = 0.45 kg) across all years from our best-fitting model using block cross validation (Block) or one-step-ahead performance cross validation (1-SAP) and historical harvest (Historic). Values are rounded to the nearest thousand pounds.

	Individual		**Cumulative**	
Month	**1-SAP**	**Historic**	**Block**	**Historic**
Jan	0	0	0	0
Feb	0	0	0	0
Mar	0	0	0	0
Apr	51,000	55,000	52,000	55,000
May	41,000	45,000	76,000	81,000
Jun	60,000	58,000	98,000	116,000
Jul	98,000	150,000	131,000	185,000
Aug	28,600	55,000	125,000	213,000
Sep	54,000	71,000	130,000	236,000
Oct	96,000	110,000	125,000	240,000
Nov	136,000	142,000	205,000	287,000
Dec	86,000	102,000	236,000	315,000
Average	54,000	66,000	98,000	144,000

behavior vary seasonally (Compaire et al., 2024; Farmer & Froeschke, 2015; Hyman et al., 2024, 2025; Lowerre-Barbieri et al., 2020). Finally, the significant and positive annual trend may be related to increases in gear efficiency and changes in fishing effort directed at this species (e.g., Detmer et al., 2020; Marchal et al., 2007; Selgrath et al., 2018).

A key finding of this study is the pronounced effort compression observed in the Gulf Gag recreational fishery. Whereas previous research did not identify a relationship between Gag season duration and recreational reef fishing effort (e.g., Hyman et al., 2024), our model revealed a strongly negative effect on Gag harvest rates, which increased nonlinearly as season duration decreased. As noted by Hyman et al. (2024), a lack of contrast in season duration previously may have limited the detection of this effect. The recreational Gag fishing seasons have only recently been significantly shortened, with the 2023 and 2024 seasons being the shortest on record. This is supported by our block CV results: When 2024 data were included in model training, the model accurately predicted effort compression and correctly estimated the withheld Gag harvest rates for 2023 (Figure 4). However, when 2024 data

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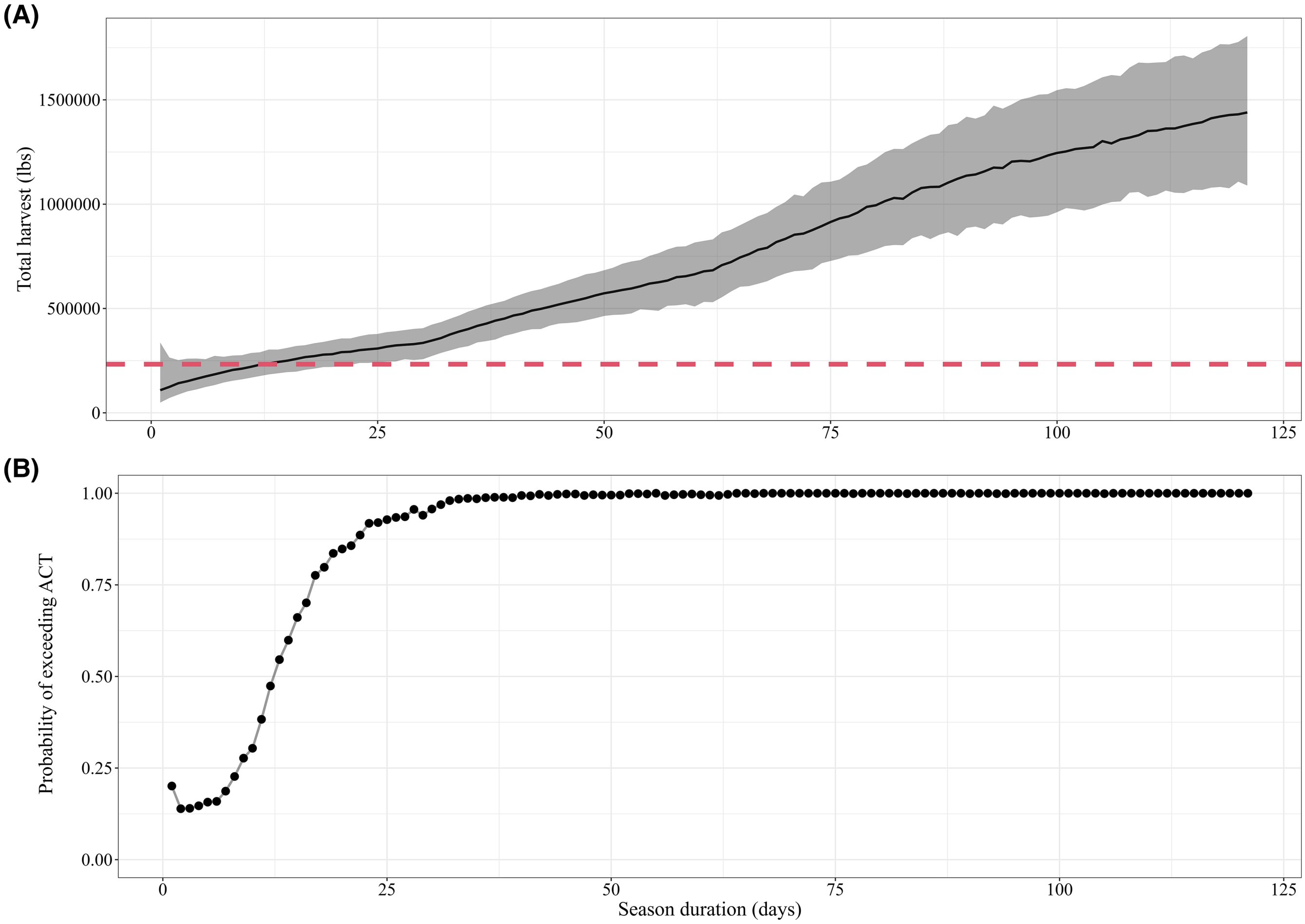

Figure 5. Season duration projections for a 2025 Gag season given a hypothetical annual catch target (ACT). (A) Counterfactual plot depicting the total harvest of Gag as a function of season duration for seasons ranging from 1 to 121 d is shown. The black line denotes the median total harvest estimate (1 lb = 0.45 kg) for each season duration, while the gray band denotes the 80% CI. The red dashed line denotes a hypothetical 2025 ACT of 233,000 lb. (B) Plot depicting the probability that the hypothetical ACT would be exceeded for each possible season duration is presented.

were excluded from the training data set, the model underestimated harvest rates for 2024, suggesting that the compression effect was underrepresented. Although similar effort compression in response to shortened seasons has been documented for Gulf Red Snapper (e.g., Farmer et al., 2020; Powers & Anson, 2016 , 2018; Topping et al., 2019), this study provides the first evidence of such effects in another important Gulf fishery. Given these findings, we recommend assessing harvest data for other vulnerable and highly targeted species with recently shortened seasons for evidence of effort compression, thus providing the ability to better manage harvest quotas and minimize overfishing risks.

Somewhat surprisingly, several predictors that were hypothesized to influence Gag harvest rates had no discernible effect. First, after we accounted for other predictors, past monthly harvest averages did not significantly predict future Gag harvest. Historical harvest data integrate influences such as angler effort, seasonal patterns, and Gag abundance or availability. However, since many of these factors were explicitly addressed through other predictors in our model, the lack of significance suggests that the information captured by past harvest averages may already have been explained, rendering it redundant as a standalone variable. Similarly, we did not observe a positive relationship between Gag harvest rates and Red Snapper temporal regulations despite prior studies suggesting such an effect (Hyman et al., 2025). A possible explanation for this discrepancy lies in the difference in spatial scale: Whereas previous research divided Florida's Gulf coast into multiple regions, our study aggregated data from the entire Florida Gulf coast to align with the management approach for the Gulf Gag stock. Since the impact of Red Snapper temporal regulations in earlier studies was region specific, it is likely that aggregating the regions in our analysis obscured this effect.

Predictive performance

Despite utilizing relatively few predictors, our model represents a significant improvement in predictive performance compared to current methods. Cumulative projections of Gag harvest, which are valuable for setting season durations before the season has started, were on average 32% more accurate than current methods (mean difference in RMSE of 46,000 lb). Given that the accuracy of future cumulative harvest estimates at the end of the season is crucial for accurately projecting season closure dates (e.g., Farmer et al., 2020), our modeling framework offers

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significant advantages for determining Gag season durations. Future Gag seasons are expected to be more variable than those observed in the past decade due to the current rebuilding plan. As our model appears particularly more accurate than currently employed methods when seasons are highly restricted, it may be especially useful when stock size is low. Moreover, as season durations become more variable, the model's predictive capacity will improve, benefiting from increased predictor contrast—an advantage not shared by historically used prediction methods. Monthly harvest predictions from the 1-SAP CV model also demonstrated significantly greater accuracy compared to the current methodology. This advancement holds critical implications for in-season management, during which reporting delays, at present, often exceed 45 d (Carter et al., 2015; MRIP, 2023). Improved forecasting and nowcasting of harvest levels enable managers to refine projections of when seasonal quotas will be reached, thereby minimizing the risk of quota overages and the associated penalties to future allocations.

One of the most significant advantages of the proposed framework over current methods is its ability to explicitly quantify the risk associated with management action. As demonstrated in our 2025 simulation, this approach facilitates the estimation of both the probability of exceeding a specified harvest quota and the expected magnitude of any overage for each potential season duration. This risk–duration trade-off provides managers with a valuable tool to balance the benefits of longer seasons against the potential costs to stock health. Such precautionary, probabilistic approaches are particularly critical when managing vulnerable stocks with low biomass, for which mismanagement can result in severe consequences, such as forced season closures in subsequent years or even stock collapse (Shertzer et al., 2010; Wilberg et al., 2019).

Future work

While our modeling approach improves upon existing methodologies, future applications could enhance it in several key ways. First, our framework did not account for the observation error that is inherent in the monthly estimates of Gag harvest. Although an earlier modeling attempt included these errors, we were unable to achieve model convergence. Incorporating observation error in future models could improve inference on influential predictors and enhance the accuracy of model predictions. Second, to simplify the modeling framework, we aggregated for-hire (FHS) and private recreational (SRFS) Gag harvest data into a single monthly harvest rate estimate. This approach facilitated prediction, but it may have constrained our ability to draw fleet-specific inferences. Future efforts should consider fleet-specific modeling strategies to identify fleet-specific drivers, particularly as more SRFS private recreational data become available. Third, as mentioned in the *Methods* section, we excluded the shore mode from our analyses due to its relatively small contribution to Gag landings and the high uncertainty associated with its estimates. However, NOAA SERO includes shore mode in its monitoring of the recreational Gag quota, alongside the for-hire and private modes (now represented using SRFS). Therefore, future modeling efforts that incorporate all three modes may improve the accuracy of harvest projections. Finally, the relatively small sample size of our data set may have limited the detection of effects from influential predictors, such as fuel prices or numbers of reef fish licenses. Consequently, as more data become available, statistically subtle influences of these variables may become more discernible. However, both fuel prices and license numbers are influenced by dynamic economic conditions and regulatory changes to reef fisheries, making them difficult to project with confidence. This complicates their utility in forecasting future harvest, as doing so would require reliable predictions of these covariates themselves. Nonetheless, including such variables in future models may still be valuable—not necessarily for their direct predictive power but because their inclusion could help to account for variance or interactions with other covariates that are more reliably forecasted. This could, in turn, improve overall model performance. We therefore recommend applying similar modeling frameworks to larger data sets or expanded predictor sets to improve accuracy and more robustly assess the relationships between harvest rates and explanatory variables.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *North American Journal of Fisheries Management* online.

DATA AVAILABILITY

All data and code will be made available upon request.

ETHICS STATEMENT

This research did not involve laboratory experiments or direct handling of live animals. All data used in this study were obtained through publicly available data sets.

FUNDING

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CONFLICTS OF INTEREST

No conflict of interest is declared.

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