Response to TRP questions: Powers et al. "Greater Amberjack (*Seriola dumerili*) Abundance, Distribution, and Movement in U.S. Waters in the South Atlantic and Gulf of Mexico"

A. Context

Our original proposal was designed to be responsive to the requirements and, when possible, additional priorities listed in the RFP. Because page limitations prevented a detailed explanation of all of the aspects that we proposed, we are very pleased to have this opportunity to expand on those elements where the panel had questions and space limitations may have led to brevity regarding details. Key to evaluating our proposal is the clear requirement listed in the RFP (Program goal) that the abundance estimate be stratified by habitat type (artificial, natural, and uncharacterized bottom) and region. This is clearly indicated in our original hypotheses, which were chosen to reflect the overall priority of a habitat-based approach and the need to resolve issues associated with movement dynamics of GAJ. Further, the abundance estimate was to be separated into size or age bins. These requirements in the RFP were well-thought out by the Steering Committee and critical to the management application of project results, and in our opinion very appropriate for the goals of the study. The results of the Great Red Snapper Count demonstrated a high level of agreement between the abundance estimated by the SEDAR stock assessment and the GRSC abundance estimate for the exploited portion of the population associated with artificial and natural reefs. Disparities between the two estimates likely resides in the inclusion of the uncharacterized bottom habitat with previously unknown/expected high abundance over this habitat type. While this might or might not be the case for Greater Amberjack, we felt the need to explicitly incorporate all available habitats due to the limited understanding of the importance of these uncharacterized habitats for reef fishes as a whole and because inclusion of a habitat component gives far more information to managers. Further, much of the debate in the SSC was focused on how to manage a stock when most individuals are located in habitat(s) where Red Snapper are not easily exploited. Additionally, the increasing push for regional based management as well as the need to partition GAJ between two fisheries management councils (SAFMC and GMFMC) requires any abundance estimate to have regional structure. Finally, managers need the estimate separated into age (or size bins) to reconcile the estimate with current stock assessments and to inform managers on mortality patterns and spawning stock biomass.

In responding to the RFP, our PI team applied many of the valuable lessons learned from the Great Red Snapper count (need to ensure results by region and habitat type were additive, better characterization of uncertainty and variance, and greater compatibility with ongoing fisheries independent surveys conducted by NMFS and various states, and gear calibration). While we agree with the steering committee that the abundance estimate should be separable into habitat types and region, the review of the GRSC questioned whether the final estimate was truly additive because no one unifying gear was used across all regions and habitats. The GAJ RFP recognized that this is likely to be the case for this study as well. We address this question in three ways: (1) we adopt similar unified sampling gear through all regions (drop cameras and hydroacoustics), (2) because these two gear types may provide different estimates, we propose extensive calibration experiments between these two gears as well as other video based approaches we will use to augment these two gears (see responses to TRP questions 3, 5 and 6), and (3) we will utilize a modeling framework that can integrate both relative abundance estimates as well as absolute abundances. We have provided additional detail on our integrative modeling approach in Appendix A. In summary, this approach includes components for each habitat in each subregion (State), and separate effects are modeled for each gear type so that the results are additive across all habitats and subregions. This approach also allows for the propagation of uncertainty across all stages of modeling, and integration of gear calibration data in a variety of ways

A key element in developing our approach was the desire to create a legacy that would extend beyond the usefulness of a snapshot estimate of GAJ abundance. The proposed project will use an approach that is compatible with Reef Fish Video Surveys (RFVS) conducted in both the GoM and SA by NMFS and various state partners, and thus is directly responsive to the RFP's call to "leverage existing data sets and ongoing research efforts to augment data collection and cost effectiveness." We will incorporate extensive camera survey data from the Gulf Fishery Independent Survey of Habitat and Ecosystem Resources or G-FISHER Project (NOAA RESTORE, led by PI Switzer at FWC). This project is aimed at standardizing and expanding state and federal video surveys to create the most comprehensive database for Gulf reef fish and associated benthic habitat in the GoM. By integrating common approaches into our surveys, we will be able to take advantage of considerable ongoing data collection by state and federal agencies to dramatically increase the number of stations sampled. This will enhance our ability to effectively measure habitat, region, and state-specific estimates of GAJ abundance. Moreover, existing data from both NOAA's RFVS and G-FISHER camera surveys will be used to develop priors for Bayesian abundance models. Finally, an important outcome of our proposed project will be the development of calibrations among multiple camera and acoustic sampling technologies, including those currently in use in the GoM and SA. This will allow for scaling of data from ongoing surveys to absolute abundance in the future. Thus, rather than simply providing a one-time estimate of absolute abundance of GAJ, **a central goal of this project is to develop an approach and analysis framework that can be meaningfully applied to current and future RFVS surveys to monitor changes in the abundance of GAJ,** thereby improving our ability to manage stocks in the GoM and SA.

B. Specific Responses to questions

1. *The TRP asks the Grantors to reconsider the 2-year timeline and offer the proposers the option of designing a 3 or more year timeline. This will be especially valuable to achieve the three Phase research plan offered here.*

Because this question is addressed to the Grantor, the PI's ability to respond is limited. The RFP required that "Projects can be up to two years. Extensions may be granted, if necessary." The approach we outlined in our proposal was designed to meet this ambitious goal. The lack of Phase I funding (as was the case for the Great Red Snapper count) limited the specificity that could be provided in our experimental design in the proposal. However, the PI's feel that the proposal does provide enough detail on our phased approach to be evaluated by reviewers. The project PIs have extensive experience conducting these types of surveys and processing survey data under tight assessment deadlines, so we do not anticipate any issues with meeting our proposed timeline. Our understanding from Dr. Swann in his latest correspondence was this response an opportunity to clarify our proposal narrative and not an opportunity to redesign the proposed project. If the grant timeline is extended, it will allow more time between calibration experiments and field count studies.

2. *Does the fact that no early life history features will be examine negate the other positive features of the proposal? Since this proposal does not address early life history has the budget commensurately adjusted?*

Our resources are primarily allocated to respond to the program goal listed on page 2 of the RFP "Provide an agency-independent estimate of absolute abundance, distribution by habitat type and movement of age-1 and older greater amberjack in the U.S. waters of the SA and GoMEX regions." Nevertheless, we feel life history parameters are important and included several studies to better understand the life history of GAJ (habitat affinity and association, movement, migration, genetic connectivity, and age-growth relationships) that the PI's felt were necessary to achieve this goal. Budget limitations prevented inclusion of a component focused on early life history (< 1 year old). Because the program goal was explicit in its specification of age-1 and older, focusing on early life history stages was not viewed as a priority. Recent studies (e.g. F. Hernandez et al. NRDA and NOAA Restore grants) have focused on elucidating the role of sargassum in the early life history of GAJ and other economically important finfish species and have narrowed our knowledge gap of the early life history of these species. It should also be noted that our team includes PIs with extensive experience in early life history studies who have provided valuable contributions to closing this information gap. For example, PI's in our group have generated a 10-year time series on larval and juvenile fishes in the northern GoM, with carangids being the numerically dominant taxa in these collections. Nevertheless, early life history research was deemed low priority by Steering Committees/Advisory Panels in charge of developing both the previous red snapper RFP and current GAJ RFP. Consequently, the PI's do not understand how not including a specific study of early life history (< 1 yr old) "negate the positive features of a proposal" whose mandated goal is to estimate abundance of age-1 and older GAJ.

Regarding the budget part of the question, the PI's believe the budget is quite reasonable for the work proposed and it would compromise the rigor of other aspects of the proposal if an extensive early life history study was included. Considering the geographic extent of the GAJ study area is almost twice as large as that covered by the Great Red Snapper Count (GRSC) and we have proposed much more extensive calibration studies than the GRSC, the PI's have proposed a realistic budget based on their past experience.

3. *How does the PI plan to adequately address the calibration issue among gear types*?

The use of "calibration" studies when employing multiple sampling gears for direct estimates of absolute abundance of fishes involves two main considerations. First, inter-calibrating the various sampling approaches is necessary to evaluate the relative performance of each in estimating absolute (or relative) abundance. Second, calibration coefficients or correction factors need to be developed so that data from multiple sources and multiple habitat types can be integrated into what may be considered a population-wide estimate of absolute abundance. Our first approach to assembling an overall population estimate for GAJ using stratified random sampling will involve using, to the extent possible, absolute density estimates for various gears, and summing these over the habitat strata determined from the data and deriving appropriate variance estimates. As discussed in detail in Appendix A, the second approach to assembling an overall population estimate using Bayesian hierarchical modeling can either take estimated calibration coefficients as prior distributions in the Bayesian model or can use all of the calibration data as a level in the hierarchical framework and estimate the calibration coefficients internal to the model.

The intercalibration of various sampling gears presents a statistical and logistical challenge, but solvable, for several reasons. First, there are four quantitative sampling approaches to be deployed during the experiment, in addition to tagging and DNA-related studies which may produce independent population size estimates. The four *in situ* sampling gears are: (1) water column hydroacoustics (WCH), (2) towed video camera systems, (TVS) (3) baited (DCP-B) and unbaited (DCP-U) drop camera pods, and (4) remotely operated vehicles (ROV). Each of these approaches have associated assumptions and potential biases with respect to extrapolating observed abundances to actual densities. Briefly these biases include attraction or avoidance behaviors by GAJ to the sampling gear, sea-floor proximity interference, limited field of view and/or depth of view, and difficulties in estimating the effective area sampled by each gear so that observed abundances can be converted to counts per unit area. **The goal of calibration experiments with the four *in situ* samplers is to estimate the ratio of apparent densities to a standard observation (see section below), and thereby extrapolate actual densities over the sampling domain.**

The main null hypotheses to be tested in this phase of the project are:

$H_{0,1}$: There is no statistical difference in GAJ densities (numbers per unit area) between gears used in this project

$H_{0,2}$: Baited and unbaited DCPs do not differ in densities based on paired field trials.

We propose a series of intercalibration experiments to quantify the relative catchability of GAJ to the four gears and to relate estimated calibration coefficients to the absolute densities over the spatial domain of each experiment. Each calibration experiment will utilize all four sampling gears deployed in a variety of habitats either simultaneously or closely associated in time. For each gear the density estimates will be obtained. For example, WCH, towed and ROV video will each estimate the apparent numbers over volume or area sampled. In the case of the DCPs, the "maxN" (maximum numbers encountered in a sampled video frame) will be calculated (Ellis and DeMartini 1995). Using a regression framework, relative catchability of the various gears will be calculated. This will provide a series of calibration coefficients that can be used in the stratified random sampling estimation of abundance. Alternatively, the different gear-specific detection rates can be incorporated as priors in the Bayesian hierarchical models, or the calibration data themselves can be incorporated as a level in the hierarchical framework and calibration coefficients can be estimated internal to the models (see Appendix A).

The pair-wise comparisons between relative catchabilities among gears deployed will be assessed in a series of comparative fishing experiments conducted in three areas (North Carolina, Alabama/Florida, and Texas/Louisiana) prior (Fall 2021 and spring 2022) to the large scale-field sampling effort (late Spring-Summer). The PI's know of several potential areas where GAJ are abundant, the seafloor has been recently mapped (ensuring artificial reefs, natural hard bottom and uncharacterized bottom are present), and a network of hydrophones will be deployed (see later description of use of acoustic telemetry during calibration experiments). From these data we will develop relative calibrations (to a standard gear type) using general linear models.

Within these same areas, a separate set of experiments will test baited vs. unbaited DCPs to test hypotheses. The use of DCPs is particularly relevant to the current study because of the fact that two major, ongoing survey programs (State of Florida and NMFS) employ these gears (Campbell et al. 2015). The NMFS program samples over the entire USA portion of the Gulf of Mexico (Figure 1), while the state of Florida's program samples primarily on the West Florida Shelf. If the use of the baited DCPs can be calibrated to absolute biomass using appropriately derived experimental model coefficients, then the survey time series from historical data and those obtained in the future can be used to provide estimates of absolute abundance or biomass.

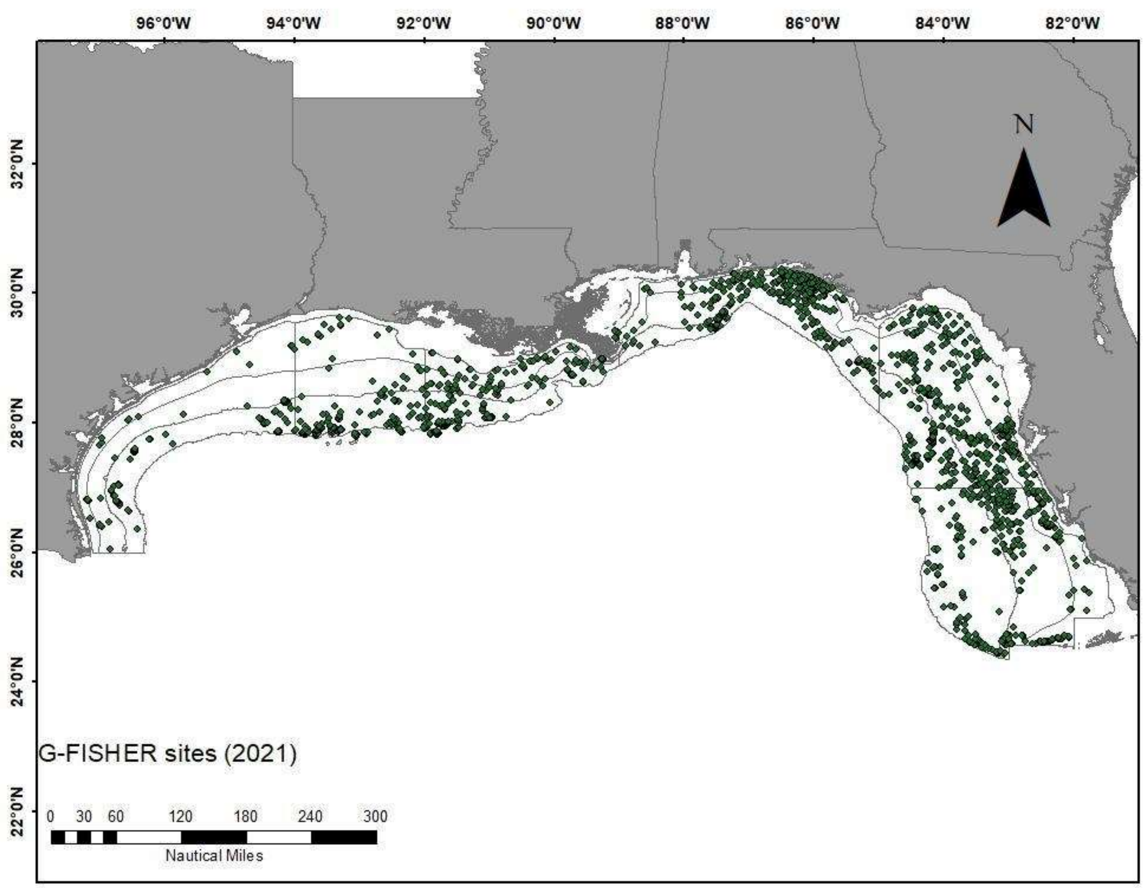

Figure 1. Map of sites to be sampled in 2021 by the Gulf Fishery Independent Survey of Habitat and Ecosystem Resources. This survey, which extends from 10 – 180 m, employs a stratified-

random design whereby sampling effort on natural and artificial reef features is allocated among various spatial and habitat strata. Although sites are randomly selected each year, this map provides a representative example of the typical spatial distribution of annual sampling effort.

For the baited vs. unbaited DCP calibrations, two critical issues are the range of attraction of the two gear configurations (over what area does the bait attract fish to the camera) and what is the difference in MaxN with and without bait? Addressing the second issue first, we propose to conduct paired evaluations of baited and unbaited traps nested within our Gulf and Atlantic-wide survey sampling scheme. For a selected number of the DCP drops we will pair both baited and unbaited systems. For habitats known to include amberjacks we will randomly select which treatment (baited vs. unbaited) to deploy first. The 20-minute deployment will be made, after which the second (baited or unbaited) DCP will be deployed within the same habitat type after waiting at least 30 minutes to allow any plume from the bait to disappear. The order of unbaited or baited will be randomized at each station. Further, for all of our stationary camera reads, we record the time of occurrence of MaxN. Consequently, we should be able to provide some anecdotal insight into whether GAJ might be more influenced by the survey instrument (MaxN early during our video read) or might be more influenced by bait (MaxN later during the read).

This exercise will generate about 100 paired observations of MaxN for baited vs. unbaited cameras. The hypothesis $H_{o,2}$ will be tested with a paired t-test. Additionally, the 100 data pairs will be used to fit several versions of linear and non-linear relative catchability models. For the linear model, the expected DCP-U catch at the i-th station ($C_{i,U}$) is given by: $E(C_{i,U}) = q_U\lambda_i = \mu_{i,U}$. where q_U is the survey catchability coefficient for the DCP-U and λ_i is the fish density at station i. Similarly the expected DCP-B catch is: $E(C_{i,A}) = q_B\,\lambda_i, = \gamma\mu_{,i,U}$·, where γ is the calibration coefficient for converting unbaited MaxN to baited MaxN catch units. The conversion coefficient is given by the ratio of the catchability coefficients for baited to unbaited DCPs, viz: $\gamma = q_B / q_U$. We will adopt the quasi-likelihood estimator defined by Pelletier (1998) for estimating the calibration coefficients. Under the assumption of a common underlying distribution and a quadratic mean-variance relationship, the conversion coefficient can be developed using a ratio estimator based on the sum of catches for each baited vs. unbaited DCP pair. We will estimate the standard error of the conversion coefficient using the bootstrap procedure recommended by Pelletier (1998) in which the selection for resampling is made on the paired observations.

In order to relate these calibration coefficients to absolute densities, a standard will need to be established. This standard will be achieved in two ways. The first, will use data obtained from the calibration experiments, the team will determine, as best as possible the absolute density in the areas where experiments occur. This may include several analytical approaches. For example, to a certain extent the towed video and acoustic-based estimates may be complementary vs. coincident (see Figure 2 below). In this case, the towed video can only "see" fishes at camera height and below, whereas the acoustics can "see" fish from the sea surface to the "dead zone" near bottom. In this case the best absolute estimate of amberjack total abundance may be the additive sum from both samplers, minus any overlaps in coverage. These judgements will be made during the analysis phase of the project. Once an absolute estimate density for the sampling domain is established (density per unit area), absolute calibrations using the coefficients as derived above will be calculated. A second independent method to estimate a standard will rely on the release of a known quantity of acoustically tagged GAJ within an array of hydrophones that will allow for accurate positioning of the tagged fish (i.e. VPS array). All acoustically tagged fish will have a prominent Floy tag so that visual observation an discern the ratio of tagged to untagged GAJ (See responses to Questions 5 and 6).

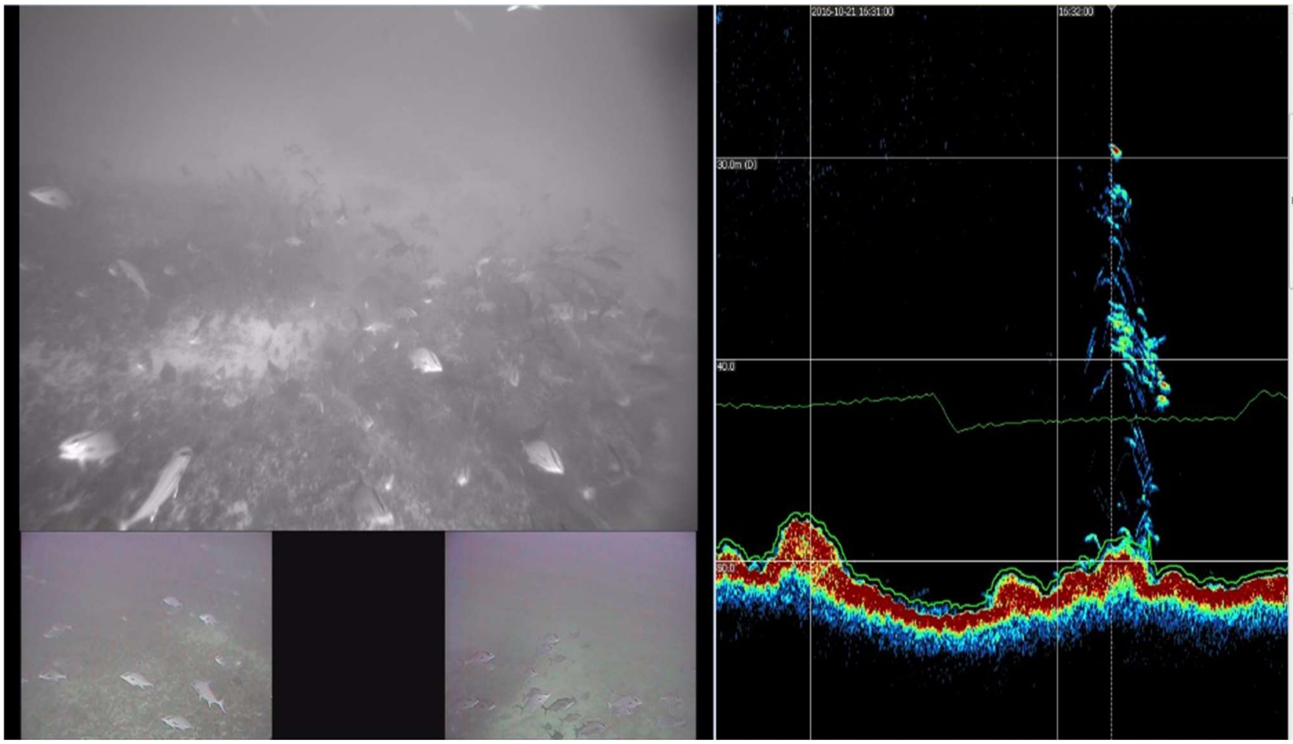

Figure 2. A side-by-side multi-video frame grab (left) from the C-BASS towed video system and echogram (right) showing the bathymetry and potential fish targets along the transect in The Elbow ridge feature. A school of GAJ (*Seriola dumerili*) were encountered along the transect and have an increased vertical distribution in the water column over relief features. Note, the upper green line on the echogram shows the approximate altitude path of the towed camera (Murawski 2020).

Prior to the calibration experiments (August- early September) the PI's will refine the approach to generate hydroacoustic-based estimates of density. Because towed/ship-based hydroacoustics are used in all regions, it is critical to initially develop a working model of the expected acoustic backscatter response attributable to targeted species. We will employ a combination of modalities with the acoustic data collection to take advantage of the power of broadband approaches to examine the 'acoustic fingerprint' of a fish yielding capacity to classify among species based on the spectral response (Figure 3). Thus, the initial work conducted prior to the calibration study will comprise an assessment of the acoustic properties of Amberjack as well as other Seriola species. This will include a high intensity localized effort in an area where Seriola species are abundant to derive in situ acoustic measures of broadband-width scattering properties paired with video data. Fish will be collected through angling and transported back to the lab to perform Computed-Tomography of the body parts and swimbladders to develop acoustic scattering models (following Boswell et al. 2020) to aid in the discrimination and classification based on acoustic data. By being able to better interpret the acoustic data in the water column, and building on existing acoustic models of dominant reef fish species, coupled with improvements in machine learning and artificial intelligence (Roa et al., In review), the potential to exploit spectral scattering properties is greatly improved (Gugele et al. 2021). By improving the efficacy for discriminating among species with acoustics, we will be able to quantitatively compare acoustically-derived density estimates with those from the optical approaches during the calibration experiments.

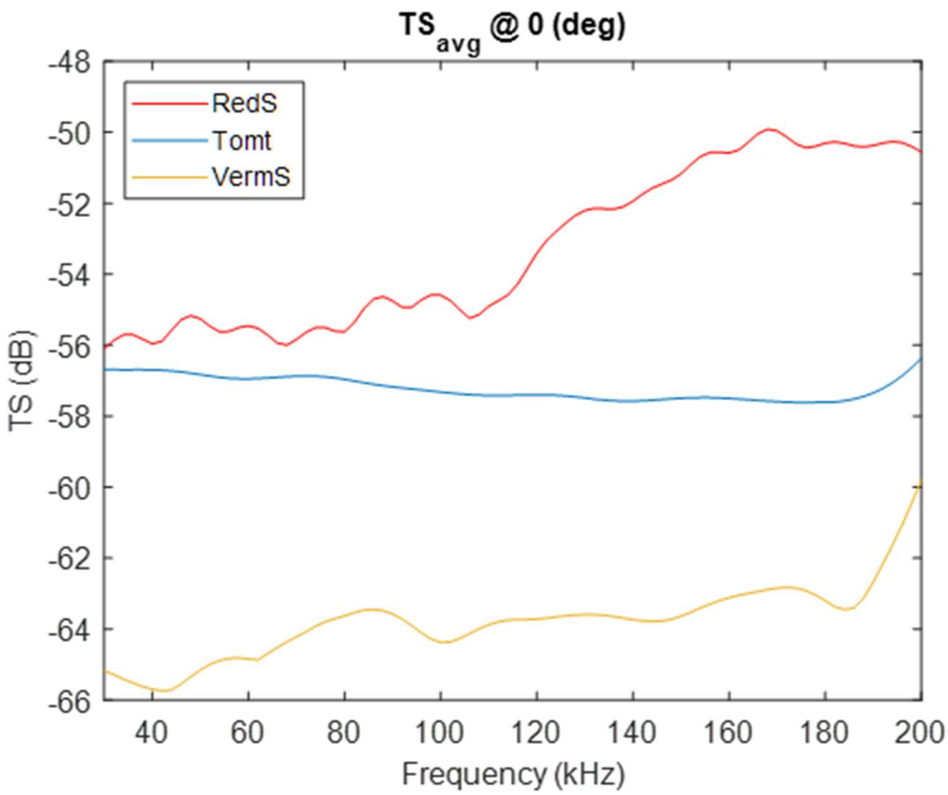

Figure 3. Averaged broadband backscatter (Target Strength, dB) from three dominant reef fish species (Red Snapper, Tomtate, Vermillion) in the Gulf of Mexico. Response indicates species specific backscatter response across bandwidth indicating potential for classification based on morphological properties. Boswell et al 2020. A similar frequency spectra based on acoustic models will be performed for GAJ and other *Seriola* spp.

As detailed in the original proposal, our phased approach is design to utilize the results of the calibration experiments in adopting our final sampling methodology. We have proposed all-hands PI meetings with the Steering committee at the end of each major phase. Analysis and interpretation of the calibration results will inform the field studies after the PIs and steering committee have had a chance to view all the data (from the calibration experiments as well as the synthesis results).

4. *While outreach to the public is essential, should the effort be more directed toward keeping the public informed of progress and results rather than to try to incorporate the untested and unverifiable information they are likely to provide?*

We agree that outreach to the public and broad dissemination of research outcomes are an essential component of this project. To that end, our proposal includes a clear plan to partner directly with the team funded through the Sea Grant Reef Fish Extension Program opportunity to ensure that the stakeholders are informed. Specifically, we will employ techniques that have proven successful in similar large-scale reef fish abundance estimates (Scyphers et al. 2021), including digital/print/social media products and stakeholder surveys. However, **it is important to recognize that these outreach and communication activities are not the same as engagement as defined and prioritized in the RFP.**

Specifically, the RFP states: "Engagement with fishermen should be included from the start of project and be an integral component of the proposal. It is possible to include funding in the budget to contract with commercial and for-hire fishermen to assist in identifying regional geographic areas and habitats where GAJ occur, which may assist with catching and tagging fish."

Rather than "untested and unverifiable," our proposed plan for engagement directly addresses the RFP by quantitatively measuring Local Ecological Knowledge (LEK) and integrating it in both study design and modeling through a Bayesian prior (see Appendix A). As clearly described in NOAA Ecosystem Lead Dr. Mandy Karnauskas' letter, LEK is highly valuable for broadening engagement and providing robust information possibly not available from traditional sources. Specifically, Dr Karnauskas states: "In my experience, the incorporation of local knowledge in scientific study is highly valuable for obtaining alternative perspectives that may not exist within the scientific community, and vetting some of the fundamental assumptions on which research results are based. Given this unique aspect of the proposed research, I have even more reason to suspect that the team will produce robust results that are accepted by stakeholders and integrated into management."

In addition to fishermen (commercial and recreational) involvement and outreach, The PI's also have included extensive plans to involve state and federal fisheries managers. Illustration of the broad engagement and support from stakeholders can be seen in the extensive letters of support/collaboration included in our original submission. Demonstration of this level of engagement is a hallmark of a competitive SeaGrant proposal.

5. *A major concern is calibration based on behavior and age distribution. Will amberjack be attracted or avoid a device? How do you identify the difference between similar species or the anticipated patchy distribution? Comparisons across sampling devices is not the same as ground*

truthing a local population. How do you calibrate estimates when we need to know the true abundance?

The PI's agree that this is a valid point and important point of consideration. Without question, understanding behavioral shifts by GAJ (i.e., horizontal movements, swimming speed, vertical position) is fundamental to estimating their abundance both within and across habitats using the proposed gears. Page limitations prevented the PI's from fully explaining all synergies among our objectives in the initial proposal. The acoustic telemetry and conventional tagging that we proposed to examine local (habitat), regional and among region movements and behavior (objective 4) also provides an opportunity to help elucidate gear biases and develop robust estimates of efficiency and equivalency of gear types (Objective 3, see response to TRP Q3).

Behavioral shifts (e.g., diel patterns, gear attraction/avoidance) that may influence abundance estimates will be investigated using transmitters equipped with accelerometer and pressure sensors that transmit 3D acceleration and depth data at select reefs and/or artificial structures (e.g., platforms, reefs). We will also utilize an acoustic positioning system (Vemco Positioning System, VPS) to further characterize fine-scale 3D positions (~1 m resolution by triangulation) and behavioral modification of GAJ to survey gears by releasing individuals and performing gear calibration trials on the natural banks and platforms equipped with VPS. PIs on this proposal have extensive experience using acoustic positioning systems to monitor habitat scale movement patterns for a variety of marine fish (Dance and Rooker 2015, Moulton et al. 2017, Bacheler et al. 2018, Rooker et al. 2018, Shertzer et al. 2020, Bacheler et al. 2021) and have previously applied this approach to successfully characterize fish behavior in response to scientific monitoring gears (e.g., baited traps, cameras) (Bacheler et al. 2018). We will take advantage of a unique opportunity to perform calibration trials on natural and artificial reefs in North Carolina, Alabama/Florida, and Texas/Louisiana that will have VPS installed by the end of 2021 by PIs of this study in collaboration with state and federal agencies. The VPS arrays do not require additional funds and funding already requested in our original proposal will cover the cost of acoustic tags. This will enhance our understanding of behavior features that may impact abundance measures from the different gear types being utilized. Deployment of VPS arrays and releasing many of the tagged fish within the area allows for both a known number of GAJ to be in an area (tagged and untagged GAJ can be discerned via video observation of prominent Floy tags) while doing calibration studies and for behavior of GAJ around stationary sampling gears to be recorded. VPS arrays deployed in three locations (e.g., North Carolina, Alabama/Florida, and Texas/Louisiana) will cover areas of approximately 0.5-1 km^2. Between 25-30 GAJ will be fitted with pressure sensor acoustic transmitters (Vemco, V16, 69kHz) and released within each VPS array.

In addition, fish tagged with conventional and acoustic tags within VPS arrays will allow us to estimate absolute abundance using a Lincoln-Peterson estimator at each VPS receiver array from estimates of (on any given day) the total number of tagged animals within the array (determined from entry and exit rates of telemetered animals) and counts (ratio) of tagged and untagged animals observed on cameras (Shertzer et al. 2020). Sites with VPS arrays can be sampled during calibration experiments (described above) to provide a standard (true) estimate of abundance independent from camera and acoustic gears to develop calibration coefficients for other sampling gears or identify a gear (or combination of gears) that provides a robust estimate of abundance without correction. This telemetry-based approach has recently been applied by PIs and NOAA partners on this proposal to estimate absolute abundance of reef fish at reef sites

6. *The will be multiple sampling devices used in same location, different locations, and varied seasons. How does one calibrate the different results over space and time: Which gears do you trust the most? How do you resolve many of the sampling issues and comparability from different methods when amberjack is distributed vertically in the water column? How do you resolve these issues?*

The RFP states “it is not expected that a single sampling method will be capable of providing one absolute abundance estimate in each habitat type.” Given the behavioral peculiarities of GAJ (e.g. distributed vertically in water column, attracted to sampling gear), the RFP recommended a multiple sampling gear approach that included camera arrays, ROVs, towed cameras, and hydroacoustics. We agree and have taken an approach that is aligned with the RFP, and view the variety of gear types as a positive when estimating GAJabundance. Two gears will be deployed region-wide (drop cameras, acoustics), and although not entirely synoptic, our surveys will be conducted in a somewhat focused seasonal window (April – September) that we believe involves limited broad-scale movement or migration. Although recent telemetry studies conducted by the PIs indicate that site fidelity is relatively high for GAJ during warmer months (Jackson et al. 2018), this assumption will be further tested within the telemetry component of the project and adjustments can be made, if needed. However, as the reviewer points out, having multiple gear types does require calibrations among sampling gears and those calibration studies are described above. While it is premature to identify a gear that we trust the most, our calibration experiments will include an estimate of absolute abundance from conventional and telemetry tags within a VPS array (see response to #5 above) that is less susceptible to the potential biases of camera (attraction) and hydroacoustic (species ID) gears. Moreover, the described tagging approach would provide an estimate of abundance for GAJ throughout the water column within the receiver array area that can serve as the “true” or standard estimate of abundance to calibrate other sampling gears.

While the issue of vertical distribution of GAJ will be addressed in the calibration study with abundance estimates from tagging data, we also describe in the response (Q3) above how two gears (hydroacoustics and towed camera) could be used in combination to estimate counts of GAJ throughout the water column. Furthermore, the use of depth coded tags in the VPS trials will provide us with 3D behavioral data that will allow us to examine and account for the potential effects of various sampling gears on vertical distribution of GAJ.

7. *The timeframe of the study does not permit an examination of the importance of seasonality as factor in the abundance estimates. How will this be addressed?*

Our plan does encompass at least one year to detect movement patterns among our acoustically and conventionally tagged GAJ and hence will provide information on seasonal movement. While additional years of data from these tagged fish would help determine seasonal movements (and these data will be a legacy of our project because the tags will be active for multiple years), we restrict our field work dedicated to an abundance estimate to a relatively narrow time period (late April through September) during the warmer months of the year. This should minimize the effect of seasonality on our abundance estimate. Additionally, the synthesis phase of our project will examine fisheries independent and dependent data that was collected throughout the calendar year and allow us to better understand seasonal movements and any changes in habitat associations.

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Appendix A: Elaboration of the Bayesian hierarchical modeling approach

The Technical Review Panel (TRP) did not specifically ask about the Bayesian modeling framework. However, there were questions raised by the reviewers under Weaknesses/Issues and under Recommendations. Calibration was identified by the TRP as a major concern. Because calibration enters into the Bayesian modeling framework, we address how calibration is handled in the Bayesian models, and thus we first address the reviewers' issues.

A summary of the Reviewers' Issues and the TRP Questions with respect to the statistical modeling is as follows:

- how anecdotal information will be included in the modelling (page 3, first and third bullets; page 4 fifth bullet and 5th bulleted Recommendation) – we address this below under Section (d) on Incorporating LEK into priors)
- lack of detail in the description of the Bayesian hierarchical modeling (page 3, fifth bullet; page 4, 2nd bulleted Recommendation; page 5, 4th bulleted Recommendation) – we address this below under Section (b) on Bayesian hierarchical/multilevel modeling – integrative approach
- how model selection (choosing among competing models) will be accomplished (page 4, 2nd bulleted recommendation) – we address this below under Section (c) on Evaluation of competing models and precision of final model
- how uncertainty in the final estimates will be estimated/evaluated (page 5, 2nd bulleted Recommendation) – we address this below under Section (c) on Evaluation of competing models and precision of final model
- The TRP was very concerned about gear calibration studies and treatment of calibration data (page 5, TRP Question 3, 5, 6). – we address this below under Sections (e.i) on Gear calibration results as priors and (e.ii) on Extending model hierarchy to incorporate gear calibration data.

a. The Bayesian inference paradigm

Bayesian inference employs current information about the parameters of interest in terms of a *prior* probability distribution that describes the strength of one's belief that a parameter takes on certain values. For example, experience might suggest that a particular sampling gear likely detects around 80% of what it encounters but it could be as low as 50% and as high as 110% (if some animals are counted twice). It represents the expert's opinion and uncertainty on the topic, prior to collecting new data. The idea is that enough actual data will be collected to resolve the uncertainty associated with a particular individual; this is done by blending the existing information with the new data into a *posterior* probability distribution through the formal Bayesian inference approach. "Making Bayesian inference" is to interpret the posterior distribution.

As the amount of data increases, the relevance of the prior information decreases. Because Bayesian inference employs pre-existing information or data as a "starting point" (hence, *prior information*) to the inference, even in the extreme case where only a single new data point ($n = 1$) is available, statistical inference for a single-parameter problem is still possible; though, the resulting inference in this case is only as reliable as the prior information.

Regardless of the number of parameters, as the amount of new data increases, the inference becomes more dominated by the new data, so that the influence of the prior information on the inference goes down to 0.

Thus, the influence of the prior information on the final result depends on two things: i) the size of the collected sample of new data, and ii) the width (uncertainty) of the prior distribution. In the above example of detectability, a triangular prior distribution ranging from 50% to 110% with peak at 80% will have more influence on the final result than one ranging from 30% to 110% with peak at 80% because the latter expresses less certainty about the value of the detectability parameter. It should be noted that there are standard diagnostic procedures to examine the appropriateness of a model including the specification of the prior distributions.

Bayesian inference can naturally augment (update) the existing inference by additionally incorporating new data. When the approach in Section (b.i) below is applied to the pre-existing synthesis data from Phase I of the project, the resulting inference (in the form of a joint posterior distribution) can be used as prior information (as a joint prior distribution) for modeling the new survey data from Phase II of the project.

The construction of prior distributions from local ecological knowledge (LEK) is discussed in Section (d).

b. Bayesian hierarchical/multilevel modeling — integrative approach

The Bayesian hierarchical framework provides a formal approach to simultaneously model relationships that are nested within other relationships and relationships that are crossed with other relationships. You can also have relationships that are both nested and crossed (as in the classic split plot design).

Each level of the model hierarchy expresses the level-specific response (e.g., observation at the top level) as a function of the level-specific covariate and level-specific random effects. In turn, the level-specific covariate and/or random effects can be expressed as the response in the next level.

Bayesian hierarchical modeling (BHM) "borrows information" across the entire model hierarchy. The integrative nature of BHM is such that *all* observed formal data, *all* prior information, and the *entire* model hierarchy as a whole are *simultaneously* utilized to make inference for any parameter and missing data point. Thus, BHM inference typically has much higher statistical power than non-hierarchical approaches. For example, the approach in Section (e.i) below involves fitting a simple standalone model, then feeding the results as priors into a separate BHM. Thus, it is expected to have less statistical power than the fully integrative approach in Section (e.ii) with a single BHM whose hierarchy requires many levels. The caveat is that the higher the model complexity (the more levels in the model hierarchy), the more computational time the inference requires, e.g., the fully integrative approach in Section (e.ii) may take weeks on a supercomputer to fit a single run of the model, even before any attempt of model refinement and refitting.

The above technical description is rather obtuse so we illustrate the concepts with an example below (Section (b.i)). There are, of course, numerous modeling decisions to be made depending on the nature and structure of the data, so we indicate areas that will have to be investigated once the survey data (Phase II data) have been collected. We note that there are choices for how to utilize the calibration data. They can be analyzed separately with the results used to formulate prior distributions for absolute and relative catchability – see Section (e.i) below. Alternatively, they can be added to the Bayesian model as another level in the hierarchy of model equations – see Section (e.ii) below.

b.i Illustration: One way to produce a map of GAJ densities across habitats from the Survey data (Phase II)

To illustrate the BHM framework for GAJ abundance, here we assume observations y_{ijk} of positive GAJ density will be taken in habitat type i at location j with gear type k using sampling effort E_{ijk}. These observations are assumed here to be already standardized to reflect absolute abundance (but see Section (e) for details of how calibration can be included in the model). The observations are associated with a vector of covariates $\mathbf{x}_{ijk}$; the covariate vector without reference to the gear type is denoted $\mathbf{x}_{ij}$. The density in habitat i at location j is p_{ij}, whereas the detectability parameter is π_{ijk} and, as used here, it depends on the density p_{ij} given that it is positive. Thus, the observation y_{ijk} is a Poisson random variable with mean $E_{ijk}\,\pi_{ijk}$, i.e., the expected observation is the product of the sampling effort and the detectability. This is the first level (observation level) of the hierarchy in the Bayesian model (see Figure A.1). It is important to again note that detectability depends on fish density, and this dependence is defined in the second level of the hierarchy.

In addition to the density, the detectability parameter also depends on the covariates and a spatial random effect (which is spatially autocorrelated with the random effects at nearby locations). Formally, this is modeled as: $\log(\pi_{ijk}) = \log(p_{ij}) + \boldsymbol{\beta}'\mathbf{x}_{ij} \ + \phi_{ijk}$, where $\boldsymbol{\beta}'\mathbf{x}_{ijk}$ is a linear combination of the covariates $\mathbf{x}_{ijk}$, and $\boldsymbol{\beta}$ represents a vector of regression coefficients, i.e., for p covariates $\boldsymbol{\beta}'\mathbf{x}_{ijk} = \beta_1 x_{1ijk} + \beta_2 x_{2ijk} + \ldots + \beta_p x_{pijk}$; ϕ_{ijk} is the (i, j, k)-th spatial random effect. This is the second level of the hierarchy.

In the third level of the hierarchy, $\log(p_{ij})$ is modeled as normally distributed with mean equal to a linear combination of the covariates, i.e., for p covariates the mean is $\alpha_1 x_{1i} \ + \alpha_2 x_{2ij} + \ldots + \alpha_p x_{pij}$. Again, in the current illustration, the model is applied to known GAJ habitat only. It is important to note that, if the project is funded, the full model will incorporate an additional component in Level 3 to reflect locations where GAJ are unobserved ($y = 0$) but cannot be ruled out as GAJ habitat. This additional component will involve occupancy modeling (e.g., MacKenzie et al., 2017), which can in turn involve zero-inflation modeling. Also in the third level, the value of the gear-specific covariate vector $\mathbf{x}_{ijk}$ is a function of the spatial coordinates, and the spatial effects are autocorrelated with mean 0.

The fourth level is similar to the equation in the third level for covariates, except here the covariates are non-gear-specific.

It can be seen in Figure A.1 that each of Levels 1–4 is nested in the previous level, hence, the *hierarchical structure* to the model. Finally, the fifth level is made up of prior distributions only, some of which are nested in Level 4 but others in Level 3, so that Level 5 is partially crossed with Level 3.

The symbols and model relationships are summarized below.

Symbols:

E_{ijk} = sampling effort in habitat type i at location j with gear type k (offset term, i.e., a covariate with known slope of 1)
y_{ijk} = (i, j, k)-th GAJ observation (of absolute density)
$\mathbf{x}_{ijk}$ = (i, j, k)-th covariate vector (including dummy variables for categorical predictors such as habitat type, jurisdiction, gear type, …)
$\mathbf{x}_{ij}$ = (i, j)-th non-gear-related covariate vector
(u_{ijk}, v_{ijk}) = (i, j, k)-th spatial coordinates
(u_{ij}, v_{ij}) = spatial coordinates for (i, j)-th location

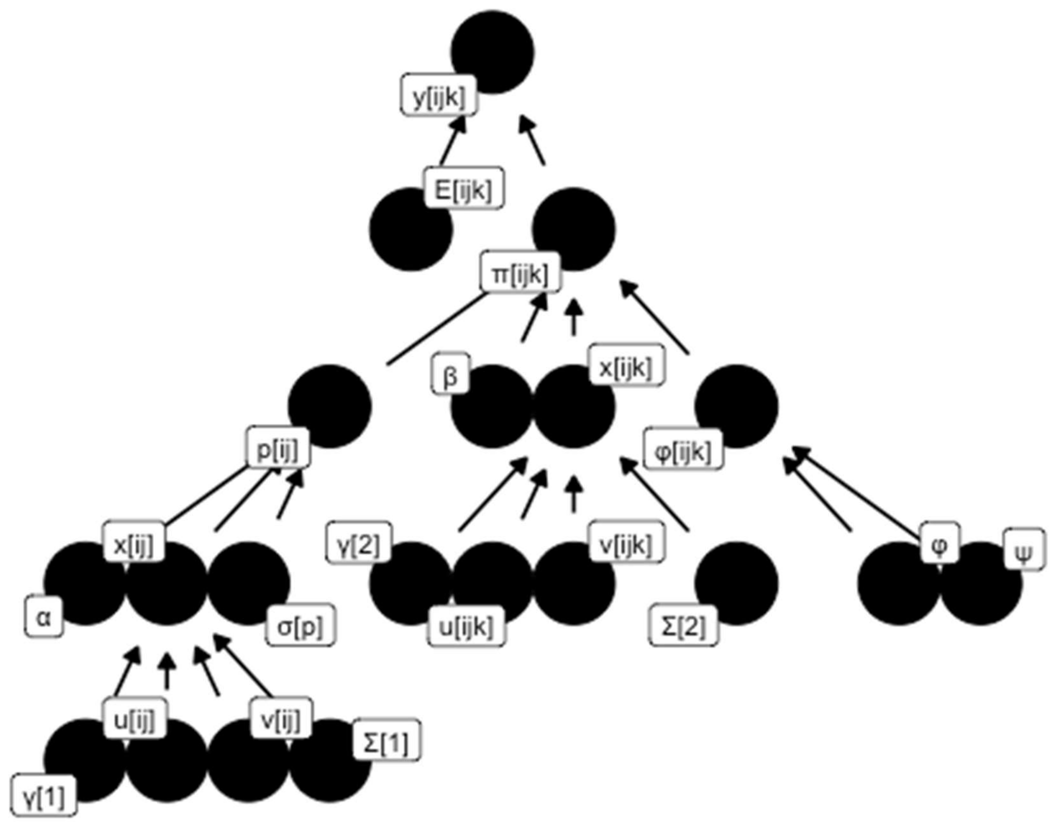
Model parameters:

p_{ij} = GAJ density in (i, j)-th location (to be mapped)
π_{ijk} = (i, j, k)-th GAJ "detectability" (depends on p_{ij})
ϕ_{ijk} = (i, j, k)-th spatial random effect (spatially autocorrelated)
$\boldsymbol{\alpha}$ = regression coefficient vector relating density p_{ij} to covariates $\mathbf{x}_{ij}$
$\boldsymbol{\beta}$ = regression coefficient vector relating detectability π_{ijk} to covariates $\mathbf{x}_{ijk}$
$\boldsymbol{\gamma}_1$ = regression coefficient vector relating covariate values $\mathbf{x}_{ij}$ to spatial coordinates (u_{ij}, v_{ij}); the form of the regression equation is specified by the function $\mathbf{f}_1$ (form to be determined by investigating possible choices)
$\boldsymbol{\gamma}_2$ = regression coefficient vector relating covariate values $\mathbf{x}_{ijk}$ to spatial coordinates (u_{ijk}, v_{ijk}); the form of the regression equation is specified by the function $\mathbf{f}_2$ (form to be determined by investigating possible choices)
$\sigma_p^2, \boldsymbol{\psi}, \boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2$ = (MV)N variance and covariance parameters

Model equations:

Level 1: $y_{ijk} \mid E_{ijk}, \pi_{ijk} \sim \text{Poisson}(E_{ijk}\pi_{ijk})$
Level 2: $\log \pi_{ijk} = \log p_{ij} + \boldsymbol{\beta}'\mathbf{x}_{ijk} + \phi_{ijk}$
Level 3: $\log p_{ij} \mid \boldsymbol{\alpha}, \mathbf{x}_{ij}, \sigma_p^2 \sim N(\boldsymbol{\alpha}'\mathbf{x}_{ij}, \sigma_p^2)$
$\mathbf{x}_{ijk} \mid \boldsymbol{\gamma}_2, u_{ijk}, v_{ijk}, \boldsymbol{\Sigma}_2 \sim \text{MVN}(\mathbf{f}_2(\boldsymbol{\gamma}_2, u_{ijk}, v_{ijk}), \boldsymbol{\Sigma}_2)$
$\boldsymbol{\phi} | \boldsymbol{\psi} \sim$ MVN with parameters that depend on $\boldsymbol{\phi}, \boldsymbol{\psi}$ to specify spatial autocorrelation structure
Level 4: $\mathbf{x}_{ij} \mid \boldsymbol{\gamma}_1, u_{ij}, v_{ij}, \boldsymbol{\Sigma}_1 \sim \text{MVN}(\mathbf{f}_1(\boldsymbol{\gamma}_1, u_{ij}, v_{ij}), \boldsymbol{\Sigma}_1)$
Level 5: prior distributions for all unknown model quantities

Figure A.1: Depiction of Levels 1–4 of the model hierarchy (an observation, node y[ijk], is at Level 0). The observation depends on the effort E[ijk] and the detectability p[ijk] specified in the first level. The detectability depends on the local abundance p[ij], the covariates x[ijk] whose influence depend on the regression coefficients b, and the spatial effects f[ijk] specified in the second level. Thus, the second level is nested within the first level. The local abundance p[ij] depends on the non-gear-related covariates x[ij] whose influence is determined by the regression coefficients a and variance s[p] at the third level; similarly, the effects of the covariates x[ijk] at the second level are determined by the geographic coordinates u and v and the regression coefficients g[2] and variance S[2] at the third stage, and the spatial random effect f[ijk] is determined by the other spatial random effects and their covariance y. The covariate effects x[ij] in the third level are determined by the spatial effects that are determined by the location coordinates u[ij] and v[ij] and the regression coefficients g[1] at the fourth level. It is seen that each level is nested within the level above.



Notes on the model:

- In the model above, the data (observations on GAJ) are calibrated before being entered into the Bayesian modeling. This makes sense as a starting point because it keeps the number of levels of hierarchy to a minimum. The prior distribution for the variance parameter σ_p^2 can be chosen to reflect the uncertainty in the calibration factor in the example above and in any preliminary model.

- Whether "location j" is to be modeled as a point in continuous space or as a grid cell is part of the statistical research to take place if the project is funded.
- Because spatial coordinates (u, v) are always observed, any missing x_{ijk} and/or y_{ijk} and/or x_{ij} in the model hierarchy can be imputed under the Bayesian framework. Importantly, this imputation allows the inference for density p_{ij} and detectability π_{ijk} at unsampled instances of (i, j, k).
- The formulation of Levels 3–4 (specifically, $\mathbf{f}_1, \mathbf{f}_2$, and the MVN mean and covariance for $\boldsymbol{\phi}|\boldsymbol{\psi}$) is part of the statistical research to take place if the project is funded.
  - In the main proposal, it is suggested that two types of spatial structure will be explored for Level 3: a conditional autoregressive (CAR, i.e., nearest neighbor) dependence and an exponential autocorrelation function of inverse-distance. For example, a CAR formulation such as in Chiu et al. (2013) would take each ϕ_{ijk} to be normally distributed with conditional expectation equal to a weighted average of all ϕ_{lmk}s for which (l, m) is an immediate neighbor of (i, j), and with a variance that depends on $\boldsymbol{\psi}$ but constrained to be inversely proportional to the number of immediate neighbors. Alternatively, an autocorrelation function of exponential decay such as in Kuh, Chiu and Westveld (2020) would take the joint distribution of ϕ_{ijk}s as multivariate normal with a 0 mean vector and a covariance matrix $\boldsymbol{\psi}$ whose entries are pairwise covariances, $\mathrm{Cov}(\phi_{ijk}, \phi_{lmk})$, each proportional to $e^{-d_{ijlm}}$ where d_{ijlm} is the distance between (i, j) and (l, m) such that the covariance drops off exponentially with increasing distance between points.
- The formulation of Level 5, especially the priors for $\boldsymbol{\alpha}$ and σ_p^2 based on LEK, and the priors for $\boldsymbol{\beta}$ based on gear calibration, is part of the statistical research to take place if the project is funded. See Sections (d) and (e) below for more details.

b.ii Producing a map of GAJ absolute abundances

Once the inference for GAJ densities is made, the inference and associated uncertainty estimates can be propagated to that for GAJ absolute abundances by scaling the densities according to (i, j, k)-specific areal coverage. This scaling is appropriate as long as the (i, j, k)s are defined such that the actual GAJ density within (i, j, k) is relatively homogeneous.

How to define the (i, j, k)s to ensure relative homogeneity of actual GAJ density within (i, j, k) is part of the research to take place if the project is funded.

c. Evaluation of competing models and precision of final model

First, it is important to understand that this project will estimate GAJ abundance using two separate approaches: classic sampling theory (stratified random sampling, double sampling, etc.) and hierarchical Bayesian modeling. The former is simple in concept and can provide precise results with corresponding standard errors if spatial and habitat strata can be defined that are relatively homogeneous (compared to unstratified sampling). The latter can potentially afford greater precision, provide spatially explicit estimates (maps) of abundance and associated uncertainty, and enable one to make inferences about the effects of environmental variables on GAJ occurrence and abundance. General agreement between the two approaches is a strong indicator of the reliability of the estimates from both approaches.

Specific to the Bayesian approach, there are a number of standard Bayesian model comparison metrics including Bayes factor, BIC, DIC, and WAIC — e.g., see Kuh, Chiu, Westveld (2020). We will use a variety of these metrics to compare competing model formulations. In addition, we can use out-of-sample cross-validation to assess the model's predictive power — e.g., see Hyman, Chiu, et al. (2021). This involves dividing the data into a training set and a test set; the fitted model based on the training dataset is then used to predict the values in the test set, and the discrepancy between the observed and predicted observations is evaluated. This gives a fair indication of the reliability of the model to predict observations not included in the data used to fit the model and thus provides an indication of the reliability of the model fitted to the full data set. When the test set consists of a single observation withheld at random, and the exercise is carried out repeatedly, this type of out-of-sample cross-validation forms the highly computationally intensive leave-one-out procedure, which may be impractical for a limited project timeline. Though, predictive power evaluations can be complemented with goodness-of-fit evaluations using less intensive in-sample posterior predictive checks — e.g., see Chiu et al. (2013).

d. Incorporating LEK into priors

LEK, i.e., anecdotal information from knowledgeable fishers, expert opinion, and non-quantitative reports of GAJ occurrence (e.g., from newspaper fishing reports), can be used to suggest specific sites where GAJ are likely to occur or to not occur, and to suggest habitat variables that are likely to influence GAJ occurrence and abundance. This information is treated as prior information (i.e., obtained prior to the project's sampling activities in Phase II).

In the absence of any LEK, the posterior distribution from the preliminary model fitted in Phase I of the project will be the Phase II prior distribution for all model parameters. For the subset of (i, j, k)s where LEK exists, this LEK can be incorporated into the (i, j, k)-specific prior:

1. Marginalize the joint prior to the LEK-specific (i, j, k)s.
2. Use the marginalized prior to derive distributions for p_{ij}s and π_{ijk}s.
3. Compare the derived distributions from Step 2 (e.g., location, spread, shape) to LEK. If necessary, modify the distributions from Step 2 to reflect LEK.
4. Derive new prior distributions for model parameters (e.g., $\boldsymbol{\alpha}, \boldsymbol{\beta}$) so that applying Step 2 to these new priors will lead to those distributions resulting from Step 3.

e. Use of calibration data

e.i Gear calibration results as priors

Standard gear calibration involves two steps. In the first step, the data from one gear is regressed on the data from another gear to obtain an equivalence factor. In the second step, the index obtained from the standardized observations is converted to an absolute fish density by determining the efficiency of the standardized gear. The inference (not necessarily Bayesian) for the calibration coefficients can be translated into priors for parameters such as $\boldsymbol{\alpha}, \boldsymbol{\beta}, \sigma_p^2$ in the example in Section (b.i) above. In particular, the prior for σ_p^2 can reflect extra uncertainty for p_{ij} due to calibration.

e.ii Extending model hierarchy to incorporate gear calibration data

In principle, the BHM hierarchy given in Section (b.i) can be augmented to directly incorporate the regression equations from Section (e.i) as additional levels to the model hierarchy. How to ensure this is feasible in a 2-year project timeline is part of the statistical research to take place if the project is funded.

References

References 1–4 illustrate the methods described in the text and also demonstrate the investigators' experience developing and using these methods.

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