Assessing resistance to recovery in oyster populations – inferences from inadequate monitoring programs

*Introduction* - Eastern oyster populations in the northern Gulf of Mexico are depressed from historic levels for reasons that are poorly understood. Since 2010, the states of Florida, Alabama, Mississippi, Louisiana, and Texas have all declared state or federal level oyster fishery disasters citing reasons including prolonged drought, intense rain events, or freshwater releases from water management structures (refs) and Florida has engaged in litigation at the US Supreme Court level over oyster population collapse in Apalachicola Bay (ref). Several of these states have implemented fishery closures in response to depressed status of oyster stocks (i.e., Mobile Bay in Alabama, Apalachicola Bay in Florida) but only one of these stocks (Mobile Bay) has reopened to harvest with Apalachicola scheduled to re-open in 2025. Oyster populations in the Gulf of Mexico were also damaged by the sinking of the *Deepwater Horizon* and subsequent oil spill (Deepwater Horizon Natural Resources Damage Assessment Trustees, 2016) which created substantial funding opportunities (more than $199M US) for oyster restoration in the Gulf of Mexico exceeding the annual value of oyster landings (Pine et al. 2022).

Many proposed, ongoing, recent, and historical oyster restoration efforts focus on the addition of various materials for oyster spat (larvae) to settle and grow. Adding this material to substrate is an effort to promote a positive oyster shell budget (harvest removes shell stock, Pine et al. 2015). This is done by providing material from outside of the system of management interest to replace degraded (but natively created), displaced (from culling during harvest) or removed (from harvest) cultch to mimic natural oyster cultch; a complex matrix of living and dead material where oyster larvae settle and grow. These restoration efforts are an attempt to shift oyster reefs from an observed low but resilient state to a more desired productive state (Pine et al. 2022) through restoration actions.

We used opportunistic sampling from ongoing and recently completed efforts to shift oyster populations from undesired to desired states through restoration and fishery closure projects in estuaries in the northern Gulf of Mexico. Many of the large restoration programs that are currently funding these efforts are long-term (10-year) projects, but information as learning is needed over shorter time scales to inform other proposed restoration and management projects in similar systems. This is an issue of both temporal and spatial scale (Pine et al. 2022). To facilitate learning under an adaptive management framework as programmatically adopted by these funders, these restoration efforts should be assessed in-progress, and if necessary, corrective changes made to improve the likelihood of the restoration objective of shifting the oyster population from an undesired low-level, to a more desired level. This desired state can vary by location, and type of oyster bar (intertidal vs. subtidal), and management goals. But in general, the desired expectation motivating these restoration efforts are to provide and promote both ecosystem services and create opportunities for oyster harvest through fishery recovery.

Site description – We assessed trends in oyster populations in three estuaries in the Florida panhandle that currently have ongoing or recently completed oyster restoration projects. Pensacola Bay (Figure 1) in northwest Florida (Santa Rosa and Escambia counties) is the fourth largest estuary in Florida with a surface area of approximately 126,000 total acres. Reported oyster landings, trips, and CPUE for Pensacola Bay in recent decades have declined (Figure 2) since the current mandatory TRIP ticket program was implemented in 198X. The East Bay (Figure 1) arm of St. Andrew Bay, near Panama City, Florida (Okaloosa and Walton Counties) is one region of St. Andrew Bay which has a total surface area of approximately XYZ acres. Reported oyster landings and trips for East Bay are not available, but for the counties comprising St. Andrew Bay oyster trips and landings in recent decades have declined and harvest in recent years is near zero (Figure 2). Apalachicola Bay is a large estuary in Franklin County which historically supported the largest oyster fishery in Florida before collapsing in fall of 2012 (Pine et al. 2015) and was closed to commercial harvest in December 2020 through December 2025 by the Florida Fish and Wildlife Conservation Commission.

Management actions – Cultch material was deposited in each bay in phases by individual state management agencies (Florida Department of Environmental Protection, DEP; Florida Fish and Wildlife Conservation Commission, FWC; Florida Department of Agriculture and Consumer Services, FDACS) as part of three different projects funded to the State of Florida with funds made available following the *Deepwater Horizon* oil spill. In Pensacola Bay approximately 20,103 cubic yards of limerock aggregate were distributed at 17 different sites at an approximate density of 228 cubic yards per acre (FDACS 2016a) during September and October 2016. In St. Andrews Bay approximately 17,000 cubic yards of crushed granite was distributed on nine different oyster reefs at a density of about 200 cubic yards per acre (FDACS 2016b) in June 2016. In Apalachicola Bay four different restoration projects with similar objectives and methodologies occurred during this time. In the first (NRDA), approximately 24,840 cubic cards of fossil shell material was deployed on 16 different sites at an average cultch density of 200 cubic yards per acre. In the second project (FDEP), approximately 95,500 cubic yards of limerock aggregate was deployed as part of an FDEP project on fourteen different oyster reef sites. Average density of cultch material was 300 cubic yards per acre. The third project (FWC) deployed 9600 cubic yards of shell material in sites 2-acres in size at densities of 100, 200, 300, or 400 cubic yards per acre. The fourth project deployed XYZ (FWC NFWF 2) deployed XYZ cubic yards of limestone at a density of ABC at Z different stations. Across all studies the actual area and density of cultch material deployed varied due to construction challenges and storm events that occurred during the study.

Table 1. Summary of deployment date, location, and project description.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Year | Bay | Project name | Agency | Material | Amount (yds3 by convention) | Sites | Average material density (yds3 per acre by convention |
| Fall 2016 | Pensacola | NRDA 4044 | DEP | Limestone | 20,103 | 17 | 228 |
| June 2016 | St. Andrews | NRDA 4044 | DEP | Crushed granite | 17,000 | 9 | 200 |
|  | Apalachicola | NRDA 4044 | DEP | Quarried shell | 24,870 | 16 | 200 |
|  | Apalachicola | GEBF 5007 | DEP | Limerock aggregate | 95,500 | 14 | 300 |
|  | Apalachicola | NFWF-1 | FWC | Quarried shell | 9,600 |  | 100,200,300,400 |
|  | Apalachicola | NFWF-2021 | FWC | Limerock aggregate |  |  |  |

*Methods*

Fisheries dependent data – We summarized commercial fisheries landings data for each of the three bays from Florida Fish and Wildlife Conservation Commission public database. For each bay we summed the landings and trips by county surrounding the bay, and the calculated catch-per-unit effort (CPUE) as annual landings/annual trips.

Reef construction – Reef construction methods across studies were similar and were designed to minimize costs and maximize amount of material deployed. Sites were selected for cultch placement based on local knowledge of historic or extant reef locations. Cultch material was deployed on site from barges by washing material from barge deck using high pressure hoses at a prescribed density.

Field collections – Similar methods were followed for all projects to estimate live oyster counts and mass of cultch material based on methods used in Florida since the 1980’s (FWC 2021 <https://myfwc.com/media/27745/oimmp-v2-ch11.pdf>) where divers haphazardly place ¼-m2 (0.5-m on each side) quadrats at selected sites and remove all oysters and cultch material to a “wrist deep” depth and place material in bags. Once bags are returned to the vessel, they are either processed on site or returned to the lab where counts of live and dead oysters, measurements of shell height, weight of cultch material, and other metrics depending on study were recorded.

Data Analyses – We followed methods for analyzing oyster count data described in Moore et al. (2020) modified based on how data were collected in the field. Briefly, we summed counts of live oysters at each restoration site and period into three size classes, spat (<26-mm shell height), sublegal (locally termed “seed” oyster; 26-75-mm shell height), and legal to harvest (>76-mm shell height). For some studies, counts were totaled in this way in the field and for other studies total counts (all sizes) were converted to counts per size class by calculating the proportion of oysters within each size class from concurrent oyster shell height samples to the sample of total oysters. We then assessed the distribution the count data follow by examining the ratio between the count mean and variance at each site (variance always exceeded mean). We used generalized linear models (GLMs; Bolker et al. 2009) with a negative binomial distribution to assess how oyster counts (dependent variable) vary over period (a time variable of equal length used to combine sampling months into winter [November-April] or summer [May-October]) and we used site as a random effect (to account for correlation among samples at each site). We assumed that the total oyster counts per site would be related to the number of quadrats collected at each site, so we included the number of quadrats as an offset of effort (log link function; Zuur et al. 2009, 2013). By using effort as an offset in this way we change the model from modeling counts, to modeling a rate measured as the count/quadrat as the response variable. Because the quadrats were the same size across study, the area sampled only changed as a function of the number of quadrats. Using counts and accounting for effort, as opposed to converting the counts to CPUE based on density sampled has two main advantages in our experience (1) maintains the response as an integer allowing the use of a negative binomial distribution (which we have observed oyster count data follow; Moore et al. 2020) and (2) fitted values and confidence intervals do not contain negative values (Zuur et al. 2009). We fit models to the data that included time (period), location (as a random effect), and then used the best fitting model (informed by AIC value and visual assessments of model fit to data) to predict oyster counts by period and location using the glmm.TMB (Brooks et al. 2017) and ggeffects packages (Lüdecke 2018) in R (R Core Team 2021). For Apalachicola Bay only, we assessed whether the number of days Apalachicola River discharge (the primary source of freshwater input to Apalachicola Bay) was below 12,000 CFS (by convention) measured at the Jim Woodruff gage (USGS 02358000) influenced counts of oyster spat. The 12,000 CFS convention has been identified as a reference point at different gage locations in Apalachicola River (Fisch and Pine 2016). This reference point is important because at discharge levels of about 12,000 CFS the adjacent floodplain becomes inundated (Light et al. 1998, Fisch and Pine 2016) although the exact point of inundation may have changed over time due to river bed degradation (S. Leitman, personal communication). Regardless, we use the number of days per Period river discharge was < 12,000 as an indicator of low freshwater inputs.

Because the oyster restoration projects had different starting points in time and cultch materials (Table 1), we summed the weight of cultch collected by divers by Bay, material, site, and period. We then used a similar generalized linear model framework as the live oyster count data to assess patterns in cultch material persistence across projects.

We examined river discharge for a small number of rivers entering each bay as a proxy for salinity and nutrient inputs by plotting the percent deviation in river discharge (CFS by convention) from the period of instrument record by month and year beginning in 2005. We began the time series about 10 years prior to restoration efforts to capture antecedent river discharge conditions prior to restoration beginning. Pensacola Bay has two rivers that enter the bay (Escambia and Blackwater rivers) and we used data from USGS gauge 02375500 from the Escambia River because this is the larger (by discharge) of the two river systems. St. Andrews Bay is unusual in that it has no major freshwater inputs (Crowe et al. 2008) thus no summary of freshwater inputs was made. For Apalachicola Bay we summarized river discharge information from USGS gauge 02358000 (Apalachicola at Chattahoochee). Data and all code used for analyses is available from the following Git repository ABCDEF.

*Results*

Trends in fisheries dependent data

Trends in fisheries dependent data from FWC since the implementation of the mandatory commercial fishery reporting requirements in 1985 show the Apalachicola Bay commercial fishery was several orders of magnitude larger (trips and landings) than Pensacola and St. Andrews bays combined (Figure 2). Apalachicola trips and landings increased sharply during the early 2000’s peaking in 2012 when the fishery collapsed, and subsequently closed in December 2020 with a scheduled reopening in 2025. All three bays show a common pattern of upticks in trips and landings in the mid-1980’s and again in the 2005-2010 period. Since 2010 trips and landings have declined in all three bays with extremely low levels of commercial fishing since 2015 when regional oyster restoration programs began.

Trends in oyster counts across Apalachicola, Pensacola, and St. Andrews Bays across reefs following restoration

The dispersion parameter using the binom2 family formulation of a negative binomial distribution was <1 for all models suggesting extreme overdispersion (example for spat Figure 3). We hypothesized that trends in oyster counts may vary over similarly over time (Period), Bay (Pensacola, St. Andrews, and Apalachicola Bay) or trends in oyster counts may be different among Bays (Period\*Bay) over time and created mathematical models to represent these hypotheses (Table X). For each model we considered site within the Bay as a random effect and used the log of the number of quadrats as an offset to control for differences in sampling effort over time and in each bay. Because our interest is in how counts of oyster spat change over time (as a restoration effort to shift the system from an undesired to desired state) we were most interested in the Period \* Bay interactive model including Period as a continuous covariate. This is because this model provides insight into (1) whether restoration triggered a response in oyster counts over time and (2) if this response was consistent among the three bays. From an AIC perspective, Bay \* Period model had the lowest value (delta AIC between lowest AIC and model with second lowest AIC = 3.3; Table X). For this model, over time, Apalachicola Bay live spat counts declined (beta = -0.17, SE beta = 0.04, p<0.0001), but Pensacola was relatively constant but with much higher uncertainty (beta = 0.07, SE beta = 0.15, p=0.10) as was St. Andrews (beta = 0.25, SE beta = 0.20, p=0.03) each showing a positive trend (positive slope) over time. This trend is uncertain (high standard error on beta terms) and the value is low suggesting an increase of about 1 oyster spat per quadrat for each time period (example back transformation exp0.25=1.3). This contrasts with Apalachicola Bay which was declining at about 0.8 live oysters per quadrat per period (exp-0.18 = 0.8). Predicted mean live oyster spat counts (95% CI) for the last period of the time series (period 14) from a single ¼-m2 quadrat are Apalachicola = 6.7 (4.4 - 10.0), Pensacola = 15.3 (1.5 - 160.8), and St. Andrews = 570.5 (33.0 – 9864.0) with only St. Andrews having a predicted (and highly uncertain) increase since the beginning of the time series (Figure 4).

Fitting the same Bay \* Period model to counts of seed or legal sized oysters revealed a similar pattern as seen in live oyster spat – observed and predicted declines in seed oysters over time in Apalachicola Bay, relatively constant values in Pensacola Bay, and increasing, but highly uncertain trends in St. Andrews Bay. St. Andrews Bay was the only system to have at least one live oyster per quadrat predicted (1.6 live legal oysters [0.41 – 6.20 95% CI]) whereas the other bays were predicted to have less than one live legal oyster per quadrat (Apalachicola 0.65, [0.31 – 1.38]; Pensacola 0.14, [0.04 – 0.50]).

A detailed analysis Apalachicola Bay oyster spat response to restoration measured by counts from rock and shell cultch from multiple studies

Analyzing available data and understanding Apalachicola oyster response to restoration actions is complicated because of variability in the design and monitoring programs used as part of ongoing restoration efforts. In Apalachicola Bay multiple restoration materials (limestone or quarried shell) have been used since 2015 and these materials have been placed in the bay at a variety of densities (Table 1). Because of construction challenges, some sites may have received both limestone and shell. Monitoring efforts to track oyster population response have been similar across studies, but the timing of monitoring post-construction has varied from monitoring beginning within weeks of cultch material being deposited, to monitoring not beginning for 1-2 years following cutch placement because of Covid-19 related delays in completing field efforts. Observed counts of oyster spat by research study highlight these challenges where the number of spat have ranged from 0 to more than 80,000 per 1/4-m2 depending on study and time (Figure 5) suggesting that these data are highly over dispersed, but over time oyster counts across study trend closer to zero (Figure 5).

We combined oyster count data from various surveys and standardized site names. We then fit GLM models to these data to describe the number of oysters of each size class over time (Period) with site as a random effect and the log of the number of quadrats as an offset. Results from this model found Period was significant (beta = -0.17, SE = 0.04, p < 0.001) suggesting that over time for each period and across study and cultch material used, and density of cultch material deployed, counts of oyster spat did not respond positively to restoration action. Predicted number of oyster spat per ¼-m2 transect (95%) in Period 14 was 7.1 (4.8 – 10.6) much lower than in Period 1 (102.2, 58.6 – 178.3; Figure 6). We fit the same model as above but included an additional parameter describing the number of days river discharge was below 12,000 CFS in the model. Both Period (beta = -0.21, SE = 0.04, p < 0.001) and the low days term are important in the model with the terms for low days ((beta = -0.006, SE = 0.003, p = 0.07) suggesting that for each day increase in the number of days discharge is below 12,000 CFS the number of oyster spat declines slightly (exp-0.006) by about 1 oyster spat per ¼-m2 quadrat. The same model, but a one Period lag on the number days discharge was below 12,000 CFS (as a measure of potential influence of antecedent flow conditions), suggested that the number of low days in the prior period did not influence the number of live spat in the current period (p = 0.27).

An examination of the different projects, which were deployed in different periods and monitoring begin in different periods, does not provide clear patterns into how counts of oyster spat change over time. We fit a GLM model that included period and Project (four different projects, three using rock and 1 using shell) to the observed counts of oyster spat per quadrat. Comparisons of the performance of project in producing oyster spat are difficult because of variations in the timing of when the monitoring began on each project. As an example, for one project monitoring did not begin until nearly two years following construction, and if the response of cultch to restoration is different two years following restoration than immediately after restoration, then this would not be clear. To create a comparative framework across studies we predicted the number of oyster spat per ¼-m2 in period 14, the last period of monitoring. In this comparison three studies would have completed their construction efforts 3-5 years prior (NFWF-1, NRDA 4044, NRDA 5007) and FWC-2021 would be < 2 years since construction. If time since construction were a major influence, then the predicted values for each study in the common period should differ. For the single project that used shell cultch (NFWF-1), we predict in Period 14 about 26.2 (95% CI 8.6 - 79.4) live oyster spat per ¼-m2 quadrat. For the projects that used rock cultch the predicted number of live oyster spat per ¼-m2 quadrat vary. For project NRDA 4044 mean predicted number of live spat = 3.5 (1.7 - 7.1), project NRDA 5007 mean predicted = 15.4 (8.3 – 28.3), and project FWC-2021 mean predicted = 7.0 (4.5 - 10.9). An interesting result is that the most recent (existing fewest number of years) constructed reef project FWC-2021 had predicted counts between the two older constructed reef projects, all with rock substrate. Project NFWF-1, the only project which used shell as cultch, had significantly higher initial (soon after restoration) observed live oyster spat counts by a factor of more than 100x than any of the other projects. The extreme dispersion observed for this project (Figure 5, observed counts) resulted in poor model fit.

Total cultch weights for Apalachicola Bay were made integers by rounding to nearest whole kilogram. Data were then subset for each project and calculations of mean and variance by project suggested the data were over dispersed (variance > mean). We then fit similar GLM models as described for oyster count data to the cultch biomass. To create a comparative framework across substrates we predicted the number of oyster spat per ¼-m2 in period 14, the last period of monitoring. Because Apalachicola was the only bay where rock and shell were used, we focused analyses to compare substrates on this bay only. From an AIC perspective, models that included Period + Substrate or models that examined the interaction between Period\*Substrate (both with log(number of transects) as an offset to control for effort) were not distinguishable (delta AIC between top models = 1.5). From a management perspective the interaction term is of interest to help understand how the biomass of either rock or shell changes over time. For rock substrate, the change in biomass over time was significant (beta = -0.08, SE = 0.03, p = 0.01) but the change was not significant for shell (beta = -0.05, SE = 0.04, p = 0.5). However, what is more important than the statistical significance is how the material persisted over time – the slope is negative for both substrates indicating declines over time. The predicted biomass of rock per ¼-m2 quadrat changed over time (Figure 7) from about 5.07 kg per ¼-m2 quadrat (95% CI 2.5 – 10.2) in Period 2 to about 2.0 kg per ¼-m2 quadrat (1.4 – 2.9) whereas the biomass of shell changed from about 1.7 kg per ¼-m2 quadrat (1.1 – 2.7) to about 0.93 (0.6 – 1.5). Because shell is less dense than rock, the differences in biomass per quadrat are not surprising - these results suggest a decline of about 60% biomass for the shell material by the end of period 13 and about 45% of the rock material. A critical point is that these are measures of biomass, not area, and oyster spat settle on area. However, if we assume a proportional loss in area to what is loss in biomass then shell biomass and likely areas degraded at a faster rate than rock material. Finally, we assessed the relationships among the biomass of cultch and number of live oyster spat from each quadrat. We graphically examined the relationship between the mean weight of cultch per quadrat and mean number of spat per quadrat for each project in Apalachicola Bay and found no clear pattern (Figure 8). This is important because it suggests that for a given biomass of cultch or across a range in cultch biomass, the number of mean spat can vary widely.

River discharge as a proxy for salinity and nutrient patterns

Apalachicola River discharge deviated significantly (i.e., 50-100% below period of record) for three or more months in 2006, 2007, 2008 with extreme drought in 2011 (9 of 12 months), 2012 (12 of 12 months), 2016 (6 of 12 months), and 2017 (4 of 12 months). Escambia River discharge patterns were generally similar reflecting the regional effects of drought (Figure 9). Regional river discharge patterns in 2019-2021 generally been average to above average for most months (Figure 9).

*Discussion*

Colden work

Then Smith et al con bio, make sure to look at the supplemental material counts and size structure

https://conbio.onlinelibrary.wiley.com/doi/full/10.1111/conl.12883#.Yk2Ifr4k7kc.twitter

##

Cognitive dissonance?

We tend to simplify complex problems so we can understand them, then we try and solve the simplified problem. This can backfire for wicked problems.

https://twitter.com/emollick/status/1509016407643762689/photo/2

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###This will be a really great map of the panhandle with the FL inset

Figure 1. Pensacola, St. Andrews, and Apalachicola bays…

A picture containing scatter chart

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Figure 2. Publicly available fisheries dependent data from the Florida Fish and Wildlife Conservation commission (<https://myfwc.com/research/saltwater/fishstats/commercial-fisheries/landings-in-florida/>). Each row represents a different bay (Apalachicola top row, Pensacola middle row, St. Andrews bottom row) and each column represents a different metric with the commercial trips in the first column, middle column as CPUE (catch-per-unit-effort), and last column as the landings (by convention in pounds). Note the y-axis are different on most panels by row because of the large differences in observations for each Bay.

Chart, scatter chart

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Figure 3. Period of time (x-axis) and spat CPUE (y-axis) per quadrat in each of the three study systems (Apalachicola, Pensacola, St. Andrews bays). Even number Periods are winter (November-April) beginning in 2015 while odd number Periods are summer (May-October) beginning in 2016.

Chart, histogram

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Figure 4. Predicted count of live spat (y-axis) by period of time (x-axis) for a single ¼ m2 quadrat from each of the three study systems (Apalachicola, Pensacola, St. Andrews). The black line is the best predicted values for each period and the grey ribbon represent the 95% confidence intervals around this line of best fit. Even number Periods are winter (November-April) beginning in 2015 while odd number Periods are summer (May-October) beginning in 2016. Predictions are made for a single quadrat because of the large differences in the average number of quadrats completed in each Bay. Predicting for a single quadrat allows for comparisons of the predicted count, for a standardized unit of effort in each Bay, as a measure of abundance and population trajectory over time. Note the large differences in the y-axis for each plot.

Chart, scatter chart

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Figure 5 Version 1. Live oyster spat CPUE (y-axis, counts per ¼ m2 quadrat) from each study over time (Period, x-axis). Each panel is a different study completed by DEP or FWC. Even number Periods are winter (November-April) beginning in 2015 while odd number Periods are summer (May-October) beginning in 2016. The NFWF\_1 study uses shell cultch and the other studies use rock cultch.

Chart, scatter chart

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Figure 5 Version 2. Total live oyster spat (y-axis) from each study over time (Period, x-axis). This figure will probably go away because it isn’t standardized, but it is just an example of what the different projects are counting in Apalachicola. Even number Periods are winter (November-April) beginning in 2015 while odd number Periods are summer (May-October) beginning in 2016.

Chart, scatter chart

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Figure 6 Preamble. This is an example plot to demonstrate fit of the nbGLM from TMB. These data (dots on the plot) are the sum of the rounded weights of cultch from the NFWF\_1 study. The model in R is written as Roundwt ~ Period + offset(log(Num\_quads) and is fit to a subset of the data which is only the NFWF\_1 study. This is just a simple approach of sub-setting the data compared to fitting the interactive model, but both will fit and the values are nearly identical. I did both approaches to explore model performance. The predicted value (solid black line) is the predicted total (sum) rounded weight of cultch for an average number of quadrats (150) predicted for every period. The ribbon is the 95% confidence interval around the predicted value. The y-axis is large because this is the amount of material that would come from 150 quadrats. This plot is just inserted to demonstrate visually the performance of the nbGLM using TMB predicted values compared to the data. This same type of model will be used for live spat counts and cultch biomass.

Chart, histogram

Description automatically generated

Figure 6 Preamble. This is an example plot to demonstrate fit of the nbGLM from TMB. The model in R is written as Sum\_spat ~ Period \* Project + offset(log(Num\_quads), which is an interactive model allowing for a unique slope for each Project across periods. These data (dots on the plot) are the total number of live spat for each period and site from the NFWF\_1 study. The predicted value (solid black line) is the predicted rounded weight of cultch for an average number of quadrats (150) predicted for every period. The ribbon is the 95% confidence interval around the predicted value. The y-axis is large because this is the amount of material that would come from 150 quadrats. This plot is just inserted to demonstrate visually the performance of the nbGLM using TMB predicted values compared to the data. This same type of model will be used for live spat counts and cultch biomass.

Graphical user interface, chart, histogram

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Figure 6. These are the predicted live oyster count for a single ¼ m2 quadrat predicted using a nbGLM model in R generally written as Sum\_spat ~ Period \* Project + offset(log(Num\_quads), which is an interactive model allowing for a unique slope for each Project across periods. The predicted value (solid black line) is the predicted number of live spat for a single quadrat for every period. The ribbon is the 95% confidence interval around the predicted value. All studies had more than one quadrat sampled, and no study sampled in all periods. I have predicted over all periods and for a single quadrat to demonstrate the difference in predicted number of live oyster spat for a common level of sampling effort (a single quadrat) to demonstrate both the variability in predicted counts and population trajectory over time as a representation of live oyster spat trends for each study. This utility of this plot is up for discussion.

Graphical user interface

Description automatically generated

Figure 7. Predicted change in cultch biomass from the four different studies in Apalachicola. The model in R is written as Roundwt ~ Period + offset(log(Num\_quads) and is fit individually to subsets of the data which represent the different studies. The predicted value (solid black line) is the predicted total (sum) rounded weight of cultch for a single quadrat for every period summed across sites. The ribbon is the 95% confidence interval around the predicted value. All studies had more than one quadrat sampled, and no study sampled in all periods. Predictions are only made for the periods that were sampled. The utility of this plot is up for discussion.

Chart, histogram

Description automatically generated

Alternate Figure 7. Predicted change in cultch biomass from a single study (NFWF 2021) in Apalachicola. The model in R is written as Roundwt ~ Period + offset(log(Num\_quads) and is fit individually to data from a single study. The predicted value (solid black line) is the predicted total (sum) rounded weight of cultch for a single quadrat for every period summed across sites. The ribbon is the 95% confidence interval around the predicted value. I can force the prediction and plotting for periods that were not sampled (as above, no sampling for FWC 2021 in Periods 2-11. But I don’t like predicting over a period of time when there are no data. The utility of this plot is up for discussion.

![Chart, scatter chart

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Figure 8

A screenshot of a computer

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Figure 9

Graphical user interface, chart, application

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this is the

new.tmb2 <- glmmTMB(Sum\_spat ~ Period \* Project + offset(log(Num\_quads)), data = new.dat2, family="nbinom2") #converge

and monitoring efforts. at a variety of densities. Additionall

Apalachicola has received multiple restoration projects using different materials (rock or shell) and materials at different densities

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We first tested to see if there was a response from any restoration over time by project. If so then what is unique about that project and does this benefit persist?

This section may draw in material from the short report produced earlier too.

##now go into other R code for detailed Apalachicola analyses