# Characterization of the for-hire fishery in the U.S. South Atlantic and regional policy implications

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ABSTRACT

Worldwide, recreational fisheries are of growing social and economic importance and recreational landings even exceed the commercial sector in some locations within the United States. However, there are continuing challenges to managing recreational fisheries, with respect to monitoring recreational participation and catch as well as satisfying a heterogeneous angler population and diverse management objectives. The southeastern U.S. is an epicenter for recreational fishing and is a transitional ecosystem, extending from subtropical Florida waters to the more temperate North Carolina ecosystems. Using participatory methods to gain insights from local knowledge, combined with data from standardized recreational monitoring programs and social media photos, we describe the dynamics of the for-hire fleet across the region with a particular emphasis on Dolphinfish (*Coryphaena hippurus*), a species of primary importance. We describe the landings composition, reliance of the fishery on different species based on their seasonal availability, and analyze how this varies across regions. Trends from a social media analysis are consistent with existing recreational monitoring programs and support the perspectives of fishermen gathered during a series of workshops. We show significant differences between landings characteristics in Florida versus North Carolina and Virginia, which underscores the need for subregional considerations when implementing management regulations across the jurisdictional scale. We also describe how our methods could be used to inform species landings associations and potential effort shifts, provide early warning signals for range shift or other changes in the fishery, and give insights relevant to innovation in recreational fisheries management.

## 1. Introduction

Recreational fisheries are of high economic and social importance and in some areas constitute the dominant source of fishing mortality [1,2]. The southeastern U.S. is considered a global epicenter for recreational fishing, due to the jurisdiction's proximity to diverse marine ecosystems ranging from tropical to temperate, its significant game-fish diversity, and overall ease of access to both ports and fishing grounds. The South Atlantic Fishery Management Council (SAFMC) jurisdiction extends from the Florida Keys to the North Carolina/Virginia border; on average, 76 % of the total landings are attributed to the recreational sector. In 2022, recreational anglers made a total of 71.8 million trips, and trip expenditures contributed $3.5 billion to the jurisdiction's economy [3]. Within the SAFMC jurisdiction, most of the recreational activity is focused in North Carolina and Florida's East Coast, where angler trips over the last decade have constituted 26 % and 55 % of the recreational effort, respectively [4].

Within North Carolina and Florida, Dolphinfish (*Coryphaena hippurus*) and to a lesser extent Wahoo (*Acanthocybium solanderi*) are popular species targeted by recreational anglers and constitute a significant portion of the for-hire sector landings. Dolphinfish are also known as "mahi-mahi" or simply "Dolphin" and we use the latter term as it is more commonly used in the fishery management realm in this jurisdiction. The two species are unique in that the SAFMC manages them in the

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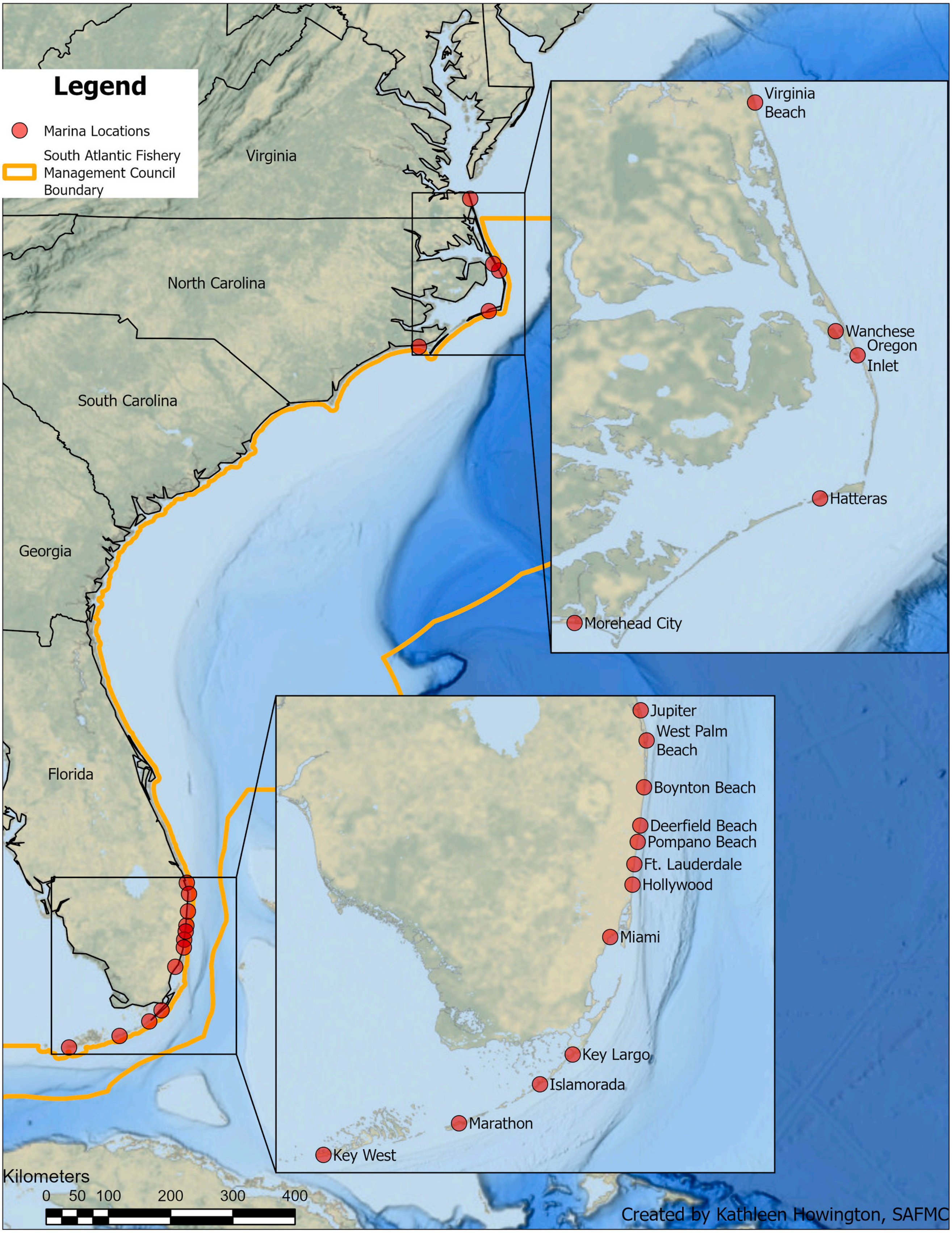


**Fig. 1.** Map of the study area showing the regions and subregions sampled. Note that the SAFMC jurisdictional boundary does not apply to all species; Dolphin and Wahoo are managed by the SAFMC across the entire eastern Atlantic coast.

Dolphin and Wahoo Fishery Management Plan that covers the entire U. S. Atlantic coast [5], and there is no international management of either species (such as International Commission for the Conservation of Atlantic Tunas) despite their extensive migratory range. Both of the species lack reliable indices of abundance for understanding stock trends, and no stock assessments are available with which to guide management advice. In recent years, there have been increasing concerns about the status of Dolphin, particularly from anglers in Florida [6].

Additionally, within the discussions surrounding amendments to this Fishery Management Plan, there have been repeated calls for the need to account for differences in the nature of the fisheries across the jurisdiction (e.g., Florida versus North Carolina). In response to these concerns, and given the paucity of data on these species with regard to overall abundance trends, definition of stock units, and total removals from some areas outside of the U.S. Atlantic Exclusive Economic Zone [7], NOAA Fisheries' Southeast Fisheries Science Center (SEFSC) and the SAFMC embarked on a participatory modeling effort to understand stakeholder perspectives and lend insights into the nature of the concerns [6]. The present study was carried out in an effort to test some of the hypotheses that emerged from this effort, primarily concerning the sentiments that there are major differences across the region that needed to be accounted for when implementing management measures.

Despite the importance of recreational fisheries from a cultural and management perspective, obtaining basic catch data and understanding patterns in resource usage can be challenging due to the spatiotemporal heterogeneity of the fleet and the existence of anglers fishing from multiple access points [8–10]. Non-conventional approaches and alternative data sources, such as digital applications and social media platforms, have gained attention among scientists as an alternative, cost-effective source of information for understanding angler behavior and preferences. The depiction of fishing successes through images is a long-standing tradition; fishing scenes appear in Roman mosaics dating back thousands of years [11], and from the early days of photography images have proliferated of anglers holding up trophy fish and of fishing charter clients surrounded by a layout of their day's catch. The recent rise of social media has facilitated sharing of such documentation and has led to an increasing interest in using these platforms for ecological monitoring [12,13], to improve the understanding of participants' behavior, practices and sentiments [14–16], and to evaluate the degree of participatory activity [17,18]. Social media can thus offer a pertinent source of information for examining people's activities in and attitudes towards the environment [19].

To date, little work has been done to compare and contrast in detail the catch composition and fishing practices of the charter fleet in the South Atlantic jurisdiction [20]. Modern recreational fisheries management, which must address an increasing number of anglers with diverse preferences and practices [21], could be increasingly fine-tuned with data collection programs that provide high-resolution sampling in space and time. Such a characterization is particularly useful for considering the impacts of regulations, which are often implemented on a jurisdictional scale, but can have different impacts at subjurisdictional levels. The purpose of this study was to characterize the species dependence of the for-hire fleet at fine spatial and temporal scales, using participatory methods, standardized recreational catch data collection and social media. Our goal was to understand how the fishery operates at these scales as well as the nature of differences between and within regions, in order to quantify differences in fishing operations across the jurisdiction and inform regional implications of management actions.

## 2. Methods

### *2.1. Participatory modeling workshops*

The intended research domain, which focused on areas of high Dolphin/Wahoo fishery activity as identified by the SAFMC and stakeholders with heavy involvement in the fishery, consisted of two separate areas within the SAFMC's jurisdiction: South Florida and the Florida Keys (from Key West to Jupiter, Florida), and North Carolina and Virginia (from Bird Island, NC to Wallops Island, VA; Fig. 1). These two areas are heretofore recognized as "regions," whereas smaller geographic areas or sites within the regions (e.g., towns or marinas) are referred to as "subregions." In 2020 and 2021, the SEFSC and SAFMC collaborated on a participatory modeling initiative to better understand the physical, biological, social, economic and institutional aspects of the Dolphin/Wahoo fishery with particular emphasis on these regions. During the workshops, SEFSC and SAFMC staff documented the perspectives of industry participants engaged in the fishery and built a conceptual model that represents the different internal and external factors affecting the fishery and how they interrelate. Representatives from the SAFMC and SEFSC traveled to three fishing communities in the North Carolina and Virginia region (Beaufort NC, Wanchese NC, and Virginia Beach VA) in March 2020 to carry out facilitated workshops with for-hire, private recreational, and commercial fishermen and local fish dealers and processors from those communities. In-person workshops were also planned for the South Florida and the Florida Keys region, but due to COVID-related travel restrictions a decision was made to move to a virtual format so that input from fishing industry members could be collected in a timely manner. One-on-one phone calls with 11 for-hire captains and private anglers were carried out between February and March 2021 (there is only a small commercial fishery for Dolphin and Wahoo in South Florida). A draft conceptual model for South Florida was then developed by the researchers using this interview information and reviewed and revised with the interviewees in a group webinar (see [6]). Insights gained from the participatory method are used to help interpret the findings from the analysis of recreational fishing surveys and social media data analyzed in the present study. During the in-person workshops, in addition to the participatory modeling we also asked participants to graph the dependence of their fishing operations across the annual cycle (Appendix A). For this study, we summarized data from all for-hire charter captains across all workshop sites within the NC/VA region; because we could not conduct in-person workshops in Florida we were not able to obtain this information from those participants. While the original focus of the workshops was on both Dolphin and Wahoo (due to the fact that they are managed under a shared management plan), Dolphin emerged as a species of primary importance and greater concern; thus, we devote additional focus on some aspects of this species.

### *2.2. Analysis of creel survey data and social media*

To gain an understanding of catch composition in the regions of study, we used data from NOAA Fisheries' Marine Recreational Information Program (MRIP), a standardized, peer-reviewed suite of recreational fishing surveys used to produce catch and effort estimates for quota monitoring and stock assessment in the United States. Within the MRIP suite we used a subset of charter trips from the Access-Point Angler Intercept Survey (APAIS), which collects catch data on individual fishing trips by intercepting anglers returning to shore at public sites ([22]; Appendix A). MRIP is a standardized survey suite that employs a complex statistical sampling design stratified across time, regions of the coast, and different fishing modes, which allows the intercept data to be scaled up by effort estimates to calculate total landings. As such a large-scale survey, it does not allow for repeated sampling at individual sites at high frequency (e.g. on a weekly basis) and is not intended for producing estimates of landings at high spatial and temporal scales ([23]). Because we were interested in uncovering fine-scale differences in angler preferences and fishing dynamics across our regions of focus, we additionally employed an analysis of social media data to gain insights into the behavior and preferences of the for-hire fleet. For the social media analysis, we compiled a list of marinas from each region where significant fishing activity geared toward Dolphin and Wahoo

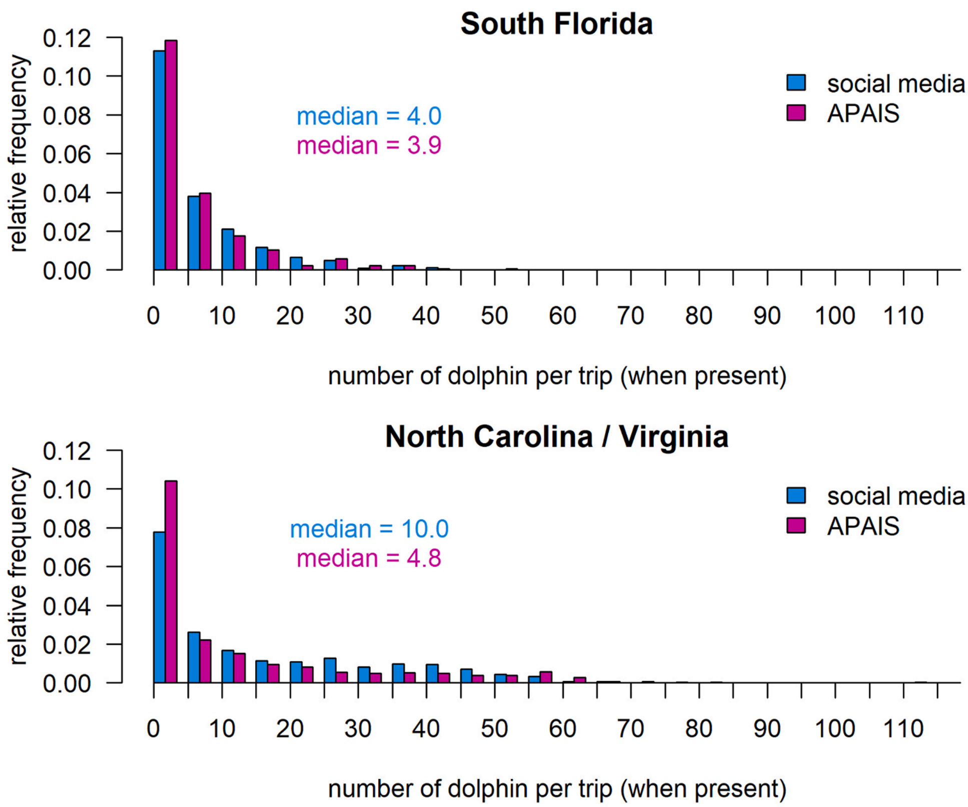


**Fig. 2.** Distribution of Dolphin landings per trip according to APAIS trip intercepts and social media count data, in South Florida (top) and NC/VA (bottom).

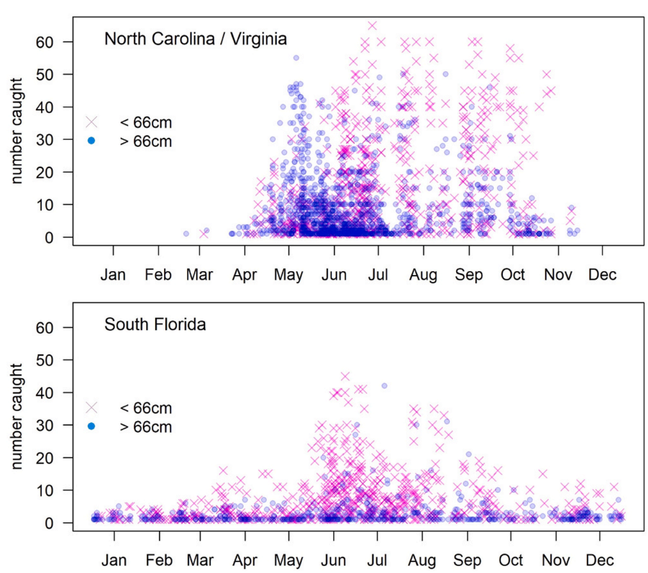


**Fig. 3.** Seasonal trends in abundance of gaffer sized (> approx. 66 cm) and bailer sized (approx. <66 cm) Dolphin for NC/VA (top) and South Florida (bottom), based on the social media data.

occurs, and collected photos posted on their webpages. Photos were then tabulated for species composition and frequency, providing a "trip intercept" database, similar to the APAIS survey (Appendix A).

### 2.3. Data visualization and statistical analyses

Descriptive plots of the seasonal trends in landings composition were generated by region (NC/VA versus South Florida), based on the raw social media photo counts. We performed an ordination analysis (nonmetric multidimensional scaling) on the combined social media data from both regions (NC/VA and South Florida), to quantify and visualize how landings composition varied with respect to subregion, region, season, and year. Analysis of similarity (ANOSIM) was then used to understand which factors (e.g, region, subregion, year, month) are responsible for the sources of variation in the landings composition. This analysis was carried out only on shared species among regions with occurrence rates of at least 1 %, and therefore it does not represent the full set of differences in fishing practices among regions and subregions, but rather the patterns in usage of the species targeted in both regions. Because the social media data (based on deck layout photos) will be biased toward species that are perceived to be most desirable, these analyses do not necessarily represent species' availability but rather the dependence of for-hire operations on the suite of species and how this varies over space and time. A hierarchical cluster analysis was used to visualize similarities within the landings composition data, and understand which species occurred most frequently together in a fishing trip. For the cluster analysis we wished to uncover the actual species associations and thus used the APAIS data set, which is unbiased and contains the full set of species targeted on each trip. Finally, we compared the species composition across data sets by summarizing both the APAIS and social media data at the same taxonomic resolution, across all years, and calculated the proportional contribution to the catch for each species or species group.

## 3. Results

### 3.1. APAIS and social media summary statistics

The number of APAIS angler trip interviews for the period 2017–2020 in the data subset we specified was 9,992 for NC/VA (including 49,153 total fish reported) and 2,150 for South Florida (including 7,753 total fish reported). In NC/VA, 138 species were identified but only 19 of these had occurrence rates > 1 %; in South

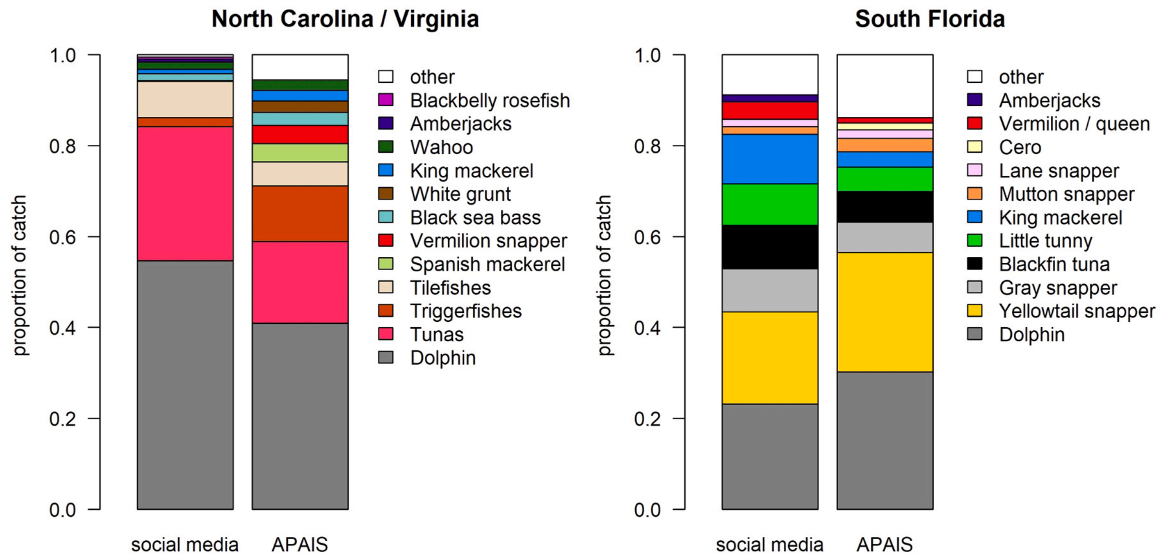


**Fig. 4.** Barplots of landings composition from social media analysis and Access-Point Angler Intercept Survey (APAIS) data set for the 10 species with highest landings from each data source. Plotted are the proportions of landings by species or species group, for each region and data source.

Florida there were 146 species, only 16 of which had occurrence rates > 1 %. A total of 1,864 photos from eight marinas were compiled from North Carolina and Virginia (NC/VA) and 2,007 photos from 14 marinas were compiled from South Florida; each of these photos is assumed to represent the landings of an individual fishing trip. A total of 38,965 individual fish were recorded from NC/VA and 20,044 from South Florida, including 20 species or species groups (11 of which had occurrence rates > 1 %) from NC/VA and 35 species (25 of which had occurrence rates >1 %) from South Florida. From the APAIS intercept data, 12 % of South Florida trips contained one or more Dolphin and 14 % of North Carolina/Virginia trips noted one or more Dolphin landed. From the social media counts, 40 % of South Florida photos contained at least one Dolphin, and in North Carolina/Virginia 60 % of photos contained one or more Dolphin.

### 3.2. Dolphin dynamics

The mean, median, and maximum number of Dolphin landed per trip (when present) are reported for each data source in Table 2 and distributions are shown in Fig. 2. According to social media counts in South Florida, large or "gaffer" Dolphin were caught in small numbers throughout the year, with slightly elevated abundance in the landings from June to October (Fig. 3). Small or "bailer" Dolphin became much more abundant in the landings from May to June, followed by a gradual decrease through October. In NC/VA, the patterns were substantially different; Dolphin were completely absent from December to March. A sudden increase in gaffer Dolphin abundance in the landings was observed from April to May, followed by a dip in June and July, a second maxima in September and then a rapid decline. Bailer Dolphin became highly abundant in the NC/VA landings starting in May and increasing through September, followed by a steep decline (Fig. 3).

### 3.3. Regional differences

Across regions and data sets, Dolphin was the single largest contributor to landings in terms of the overall species composition (Fig. 4). In NC/VA, Dolphin contributed 40.9 % of the landings by number according to APAIS and 54.7 % of the counts according to the social media data. In South Florida (SFL), Dolphin contributed to 30.2 % of the landings by number in the APAIS data and 23.1 % of the counts in social media data. While Dolphin are clearly a major contributor to for-hire landings in both regions, the similarities across regions were limited with regard to the rest of the species composition. In NC/VA, tuna species were the next major contributor, followed by triggerfishes (according to APAIS) and tilefishes (according to social media). In South Florida, the catch composition is more diverse and less dominated by a small suite of species. After Dolphin, Yellowtail snapper was a major contributor to landings, followed by Gray snapper, Blackfin tuna, and Little tunny in roughly equal amounts (all ~9 % of the landings according to social media and all ~6 % according to APAIS). King mackerel was also a major contributor according to the social media data and, to a lesser extent APAIS.

In South Florida, of the top ten species in each data set, all but one was shared; Amberjack landings were specific to the top ten species in the social media data and landings of Cero mackerel were specific to the top ten in APAIS landings. For NC/VA, there was less agreement between social media and APAIS, though the top ten species in either data set still had eight species in common. Amberjacks and Blackbelly rosefish were in the top ten contributors to landings in the social media data, whereas White grunt and Vermilion snapper were top ten contributors in the APAIS landings.

Ordination analysis was conducted on the suite of species occurring in both regions, with occurrence rates of at least 1 %. There were 13 species or species groups meeting this definition: Dolphin, tunas, King mackerel, snappers, Wahoo, amberjacks, tilefishes, groupers, barracuda, triggerfishes, Cobia, Spanish mackerel, and Blackbelly rosefish. Variation in landings composition of these species was analyzed and plotted with respect to region, subregion, year, and month (Fig. 5). Differences in landings composition between regions, subregions, and months were statistically significant ($p = 0.001$), whereas differences in landings between years were not seen ($p = 0.99$). Variation in landings composition was highest when considered in groupings by subregion; subregional variation was higher than variation by region. This indicates that there are some differences in landings composition that are driven by the availability of different species over time and space. However, at the subregional level, the target species appears to be a function of not only what is available at different times, but also as a result of the particular fishing practices and preferences unique to the different marinas and sites (which could also influence what photos are posted).

Cluster analyses based on presence-absence in the APAIS intercept data indicate which species are most frequently found together in the landings, by region (Fig. 6). Because the cluster analysis is based on the occurrence of species in the landings (not the total numbers), the results reflect which species tend to be associated on a trip, regardless of the

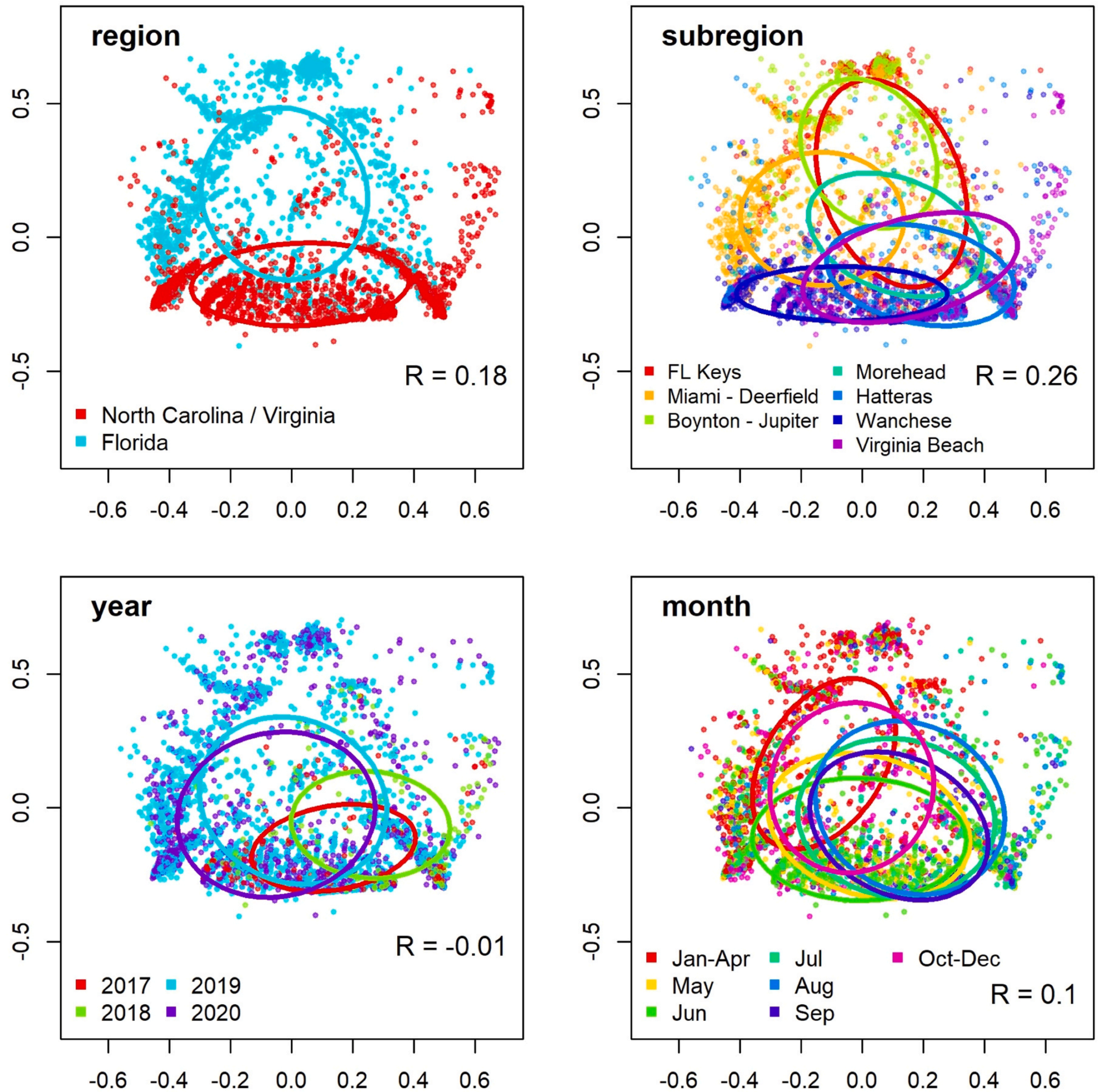


**Fig. 5.** Non-metric multidimensional scaling ordination plots of the social media landings composition data. Each dot represents landings from one photo; dots that appear more closely together are more similar in terms of species composition, and the ellipses represent the variation (+/- one standard deviation) in the data from each respective group. Axes are unitless and have no meaning other than to indicate relative distance between points. R values are reported from an analysis of similarity between groups, respectively, for the factor shown within each panel; higher values indicate more dissimilarity between groups.

number of each species that are caught. In NC/VA, there are three major clusters: 1) Dolphin, Wahoo, and tuna species, 2) mackerels, Great barracuda, and Little tunny, and 3) jacks and demersal species. In SFL, there are two distinct clusters, one containing reef-associated species as well as Yellow jack, Cero mackerel, Blue runner, and Spanish mackerel, and the other containing Dolphin, tunas, Almaco jack and Greater amberjack, and King mackerel. Where species are included in the cluster analysis across regions, they often are associated and paired similarly (e.g., King mackerel and Little tunny, Almaco jack and Greater amberjack). One notable difference in the clustering is that Spanish and King mackerel are closely associated in NC/VA, whereas they are not associated in SFL. In both SFL and NC/VA, Dolphin are caught in association with tuna species. In NC/VA, Dolphin are also associated with Wahoo; in SFL, however, Wahoo had an occurrence rate of only 0.8 % in the APAIS data and was therefore not included in the cluster analysis.

### 3.4. Multispecies seasonal dynamics

According to social media count data, in South Florida, the for-hire sector has less dependence on any single species throughout the calendar year than in NC/VA. Although Dolphin and Yellowtail snapper tend to dominate the landings throughout the year, contributing roughly one-third to one-half of the overall count, their contributions in terms of occurrence is less pronounced (Fig. 7). On the contrary, Dolphin and tuna species make up the vast majority of the landings in NC/VA, particularly in the spring, but also dominate in terms of their relative occurrence in the landings (Fig. 8). In South Florida, King mackerel, Blackfin tuna, Little tunny, and Yellowtail snapper have slightly elevated occurrences in the social media data during the spring season, when Dolphin appear to be scarcer. Wahoo are caught in very small numbers relative to the other species (most likely due to both their behavior and relative difficulty in catching); however, they are the eighth most frequently caught species in the social media counts, with elevated occurrence in both spring and fall.

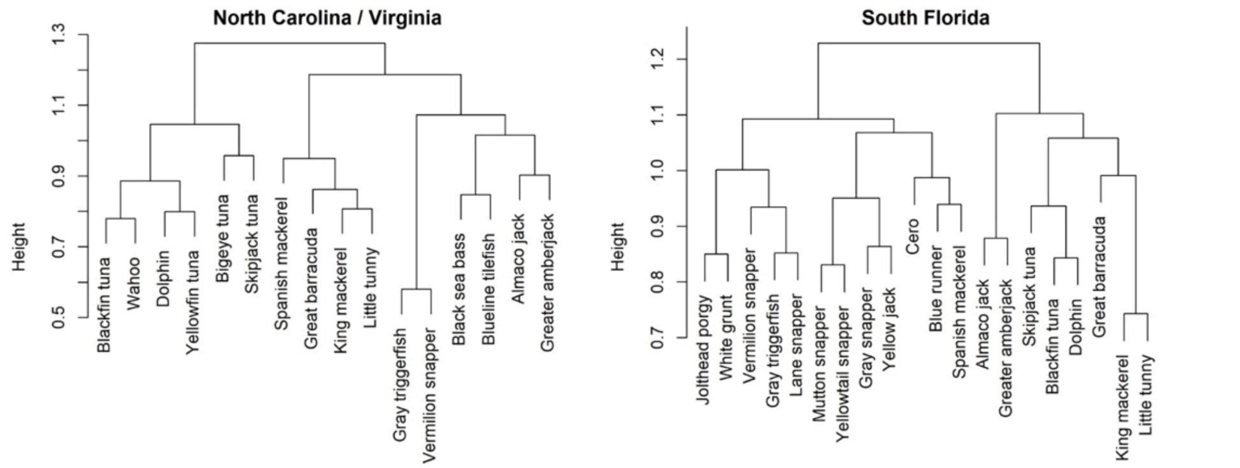


**Fig. 6.** Hierarchical clustering of APAIS trip intercept species presence/absence data, for NC/VA (left) and South Florida (right). The clusters indicate which species are most frequently found together in the landings, and can indicate where there may be synchrony in effort and/or discards.

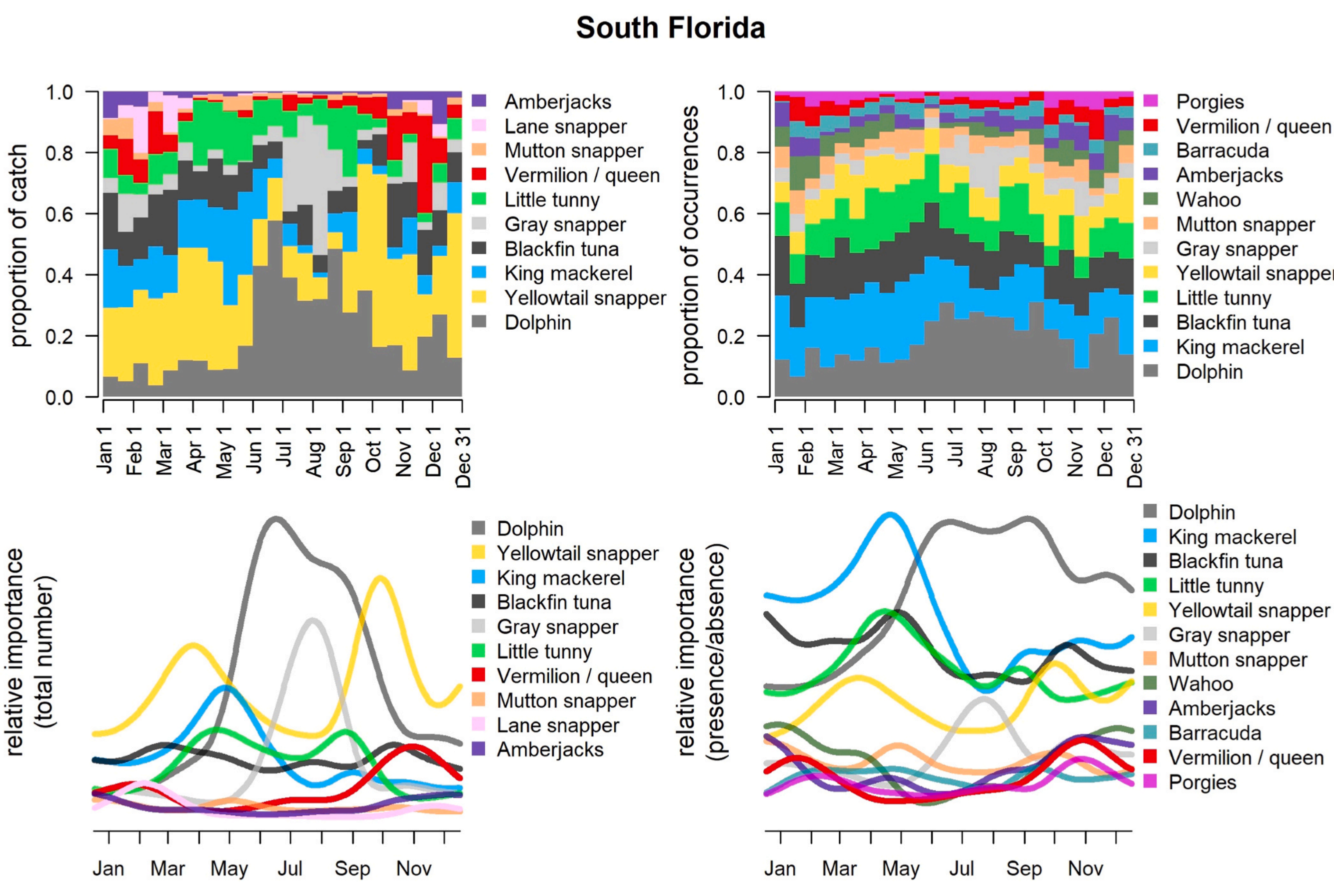


**Fig. 7.** Seasonal trends in South Florida landings composition based on social media data, with respect to total abundance in the landings (left panel) and occurrence in the landings (right panels). Data are presented as proportions of the total in twice-monthly bins (top) and as smoothed curves based on the raw data (bottom).

In NC/VA, tuna species are prominent in the landings, particularly at the beginning and end of the year, and in terms of proportion of occurrences tunas make up the highest proportion of the landings overall. Wahoo are seen in the landings throughout most of the year, with a peak in Oct - Nov. Because they are caught in smaller numbers, they are a relatively small proportion of the overall landings, but in terms of frequency of occurrence they are the third most common species, behind the tuna species group and Dolphin. Tilefishes are also relatively prominent in the landings, both in terms of number and occurrence, with a peak in August.

### *3.5. Corroboration with stakeholder input*

The primary findings and industry perspectives gleaned from the stakeholder workshops are summarized in McPherson et al. [6]. Of the major themes that emerged from the workshops, many related to the perceived need to account for regional differences in how the fishery operates. In particular, participants noted: 1) the considerable variation

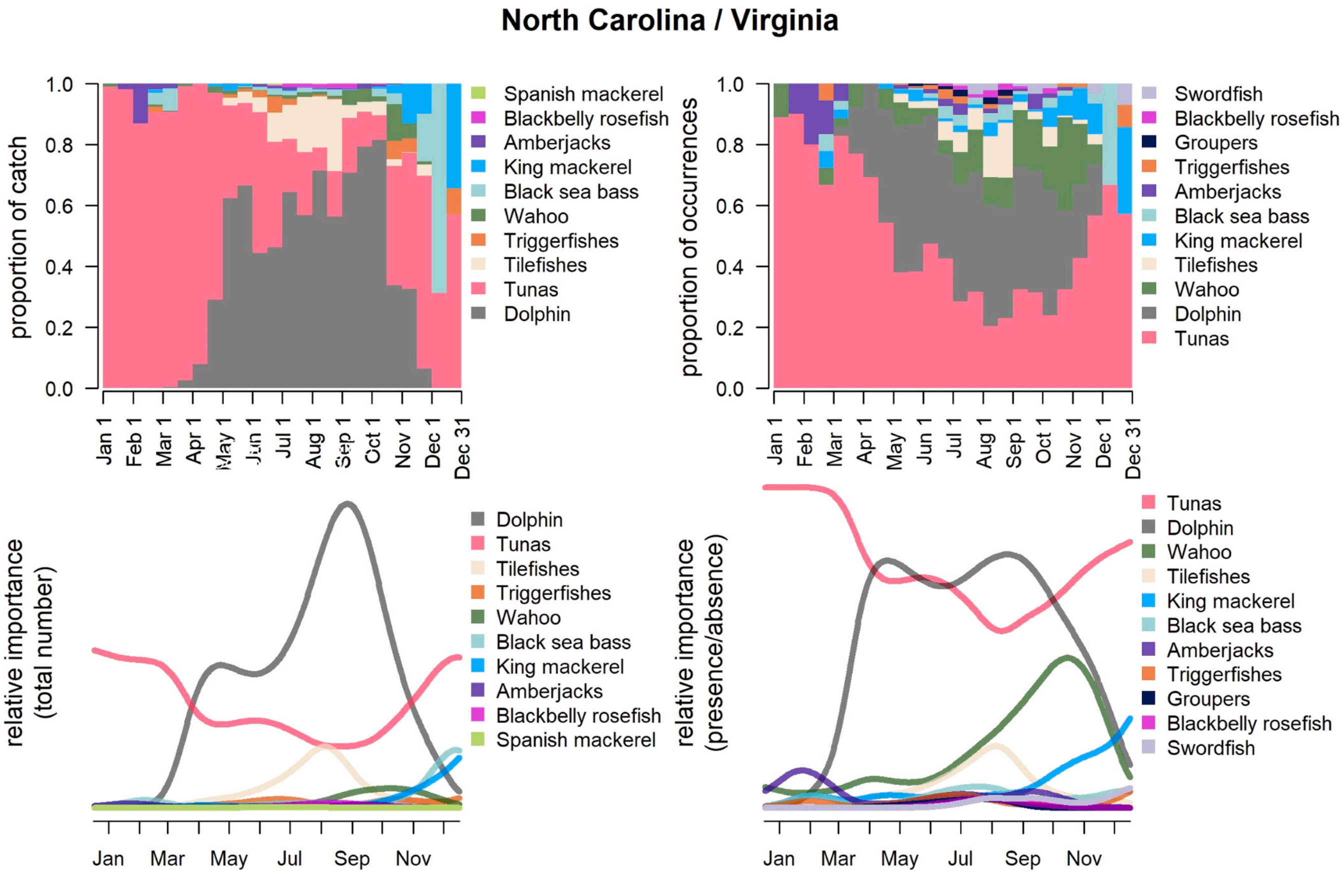


**Fig. 8.** Seasonal trends in North Carolina and Virginia landings composition based on social media data, with respect to total abundance in the landings (left panel) and occurrence in the landings (right panels). Data are presented as proportions of the total in twice-monthly bins (top) and as smoothed curves based on the raw data (bottom).

across the jurisdiction with respect to the role of different species in fishing portfolios, 2) seasonality in the availability of different Dolphin size classes and how this differed across the regions, 3) regional impacts of Dolphin bag limits on consumer satisfaction 4) sources of conflicts that differed at the regional and subregional levels, and 5) differences in the perceived impacts of regulations. Analysis of the recreational survey data and social media data allowed us to better understand the concerns raised by industry. For example, a major concern of Florida fishermen was the scarcity of large Dolphin in their area in recent years, and the social media analysis showed clearly that large Dolphin are caught much less frequently in South Florida than in NC/VA. Fishermen in NC/VA, and in particular Wanchese, mentioned the importance of an influx of gaffer Dolphin to their charter operations at the start of the year, and this influx could clearly be seen in the social media analysis as a peak in May - June. In some areas, particularly Virginia Beach, fishermen noted that demand is driven largely by the availability of tunas, with Dolphin filling in during part of the year, and this switch from tunas to Dolphin can clearly be seen in the social media results. Fishermen also noted that Wahoo was important in the "shoulder seasons" of spring and fall, when other major target species were in lesser abundance, and these peaks are also seen in the social media results (a large peak in October with a lesser peak in April). A major conclusion coming out of the workshops was that high variation in dependence on species can occur at very small scales, a finding that was validated by the multivariate analysis described above.

The seasonal trends in dependence on species that were drawn by participants within the NC/VA workshops matched closely with seasonal trends for that region as derived from the social media analysis. Not all of the trends could be compared because participants sometimes annotated their graphs at broader taxonomic groups (e.g., "snapper-grouper") or because fish that are heavily targeted are not landed (e.g., billfishes). However, for species that could be directly compared (e.g., Dolphin, Wahoo, tuna species, and King mackerel), trends from the social media analysis matched with workshop participants' descriptions of dependence on the species (Fig. 9). Both social media and participant graphs indicated an elevated dependence on Dolphin from April - September, although the stakeholder graphs indicated a narrower peak in high dependence in June. For Wahoo, both information sources indicated that the highest dependence on the species occurs in October, with a minor secondary peak in April. For tunas, both information sources indicated high dependence on tunas throughout the year, perhaps due to varying ability of different species within this complex, with a slight dip during the late summer. For King mackerel, both social media and participant graphs indicated that dependence on the species starts to increase rapidly in September and reaches a maximum at the end of the year.

## 4. Discussion

Recreational anglers – whether they are private anglers, or charter boat customers – represent a heterogeneous group, and the very existence of anglers motivated by different values and objectives presents a situation where there are inevitable competing objectives [21]. Despite the importance of recreational fisheries, there has been little innovation in policy to address such a situation [24]. The typical practice is to impose single regulations over entire management jurisdictions with heterogeneous populations; this leads to dissatisfaction and inefficient use of resources as it is impossible to satisfy diverse objectives simultaneously [21,25]. In the South Atlantic, the idea of regional

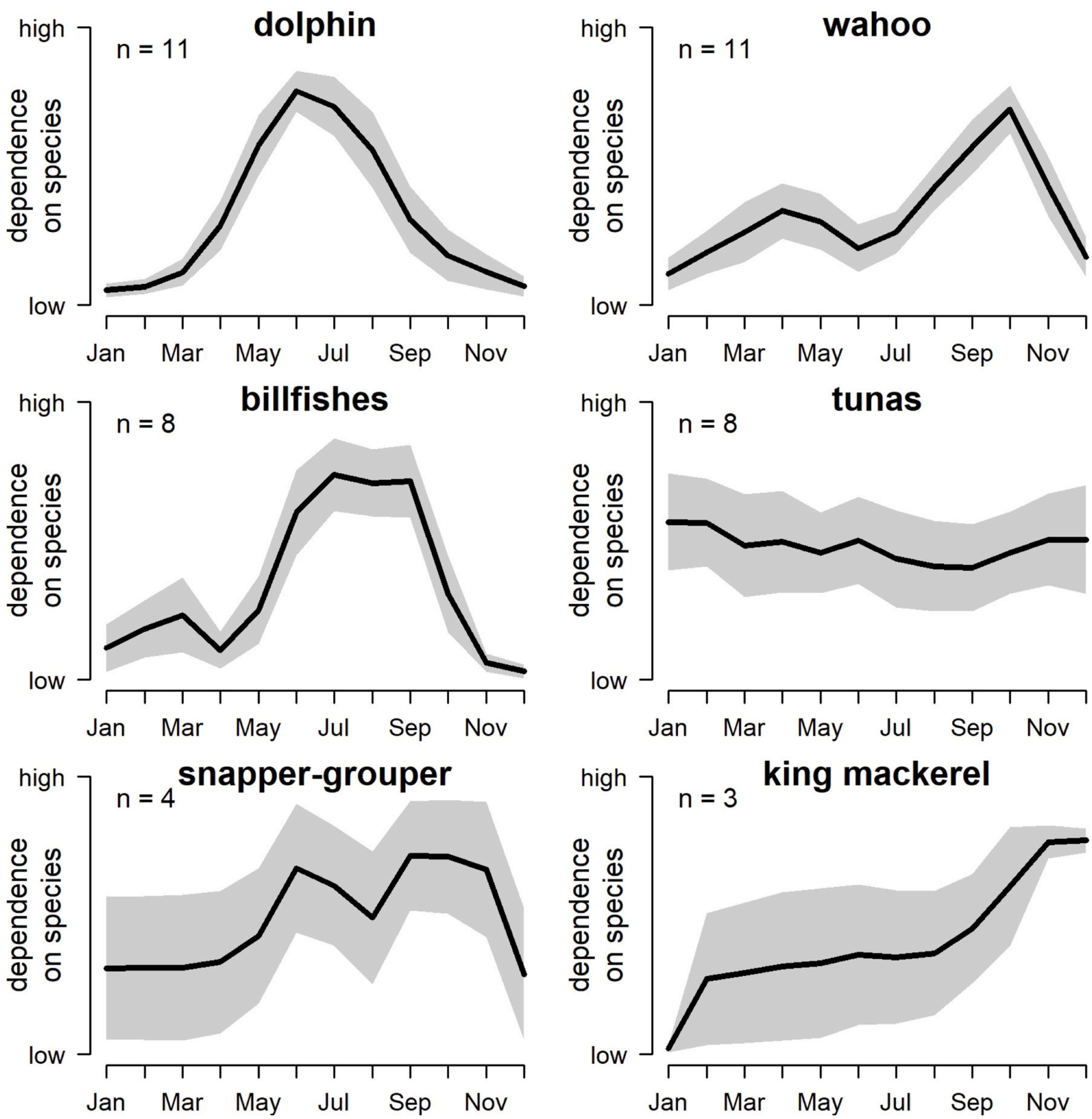


**Fig. 9.** Seasonal trends in species dependence based on averages across individual stakeholder graphs in NC/VA. Solid gray lines (with shading) are mean dependence values (+/- 1 S.E.). Values are unitless as they were scaled to the maximum dependence level for a given individual. Sample sizes refer to the number of individuals who graphed a given species (i.e., different individuals included different suites of species in their graphs).

management has come up frequently and was mentioned repeatedly in a Council-led visioning process for the snapper grouper fishery [26]. Our results show that even at subregional levels, there are substantial differences that management would want to consider because of possible differential impacts of regulations. For example, an unexpected closure of King mackerel toward the end of the year could be less disruptive for South Florida fishermen than NC/VA fishermen as they have heavier reliance on the species in November and December (though the overall economic impact to the fishery would depend on the relative size of the fishery in each area). Similarly, proposed bag limits would have differing impacts across the region depending on whether or not trips are meeting current limits.

Our approach can lend insights into issues that affect recreational fisheries management, particularly concerning impacts to the human system – considerations that are often required in fishery policy, but rarely quantitatively evaluated. A key aspect of the work is that it highlights the multispecies interactions at play, such as substitutes and possible effort shifts onto other species. For example, regulatory actions on any particular species would be expected to cause changes in effort or targeting for other species within a similar cluster. Bag limits or seasonal closures for Gray triggerfish might lead to substitution for Vermilion snapper in both NC/VA and South Florida, if fishermen sought to fill in their overall catches with species caught at the same time. Similarly, closures of either Black sea bass or Blueline tilefish in NC/VA would need to be aligned temporally to avoid regulatory discards of either species in this fleet. Conducting this kind of an analysis, which provides data with higher granularity at a local scale, on a regular basis (e.g. every five years), would potentially allow for quantification of temporal and latitudinal change in fisheries and provide insights into rates of change. Such an analysis could provide an early warning with regards to changes in the availability of species, shifts in species ranges, or the presence of invasive or rare species. The method could therefore be used to consider subregional or even community level dependence on certain species (seasonally or annually) and together with information on species shifts, help predict community response to changing environmental conditions (e.g., [27]). Overall, the ability to look at high resolution data in space and time provides insights for innovation in recreational fisheries management, and could help supplement data available through

**Table 1**
Scientific names of the species and species groups in the social media analysis.

| Species or Group | Species | Scientific Name |
|---|---|---|
| Dolphin | Dolphinfish | *Coryphaena hippurus* |
| Wahoo | Wahoo | *Acanthocybium solandri* |
| Tunas | Little tunny | *Euthynnus alletteratus* |
| | (Bonita) | *Thunnus atlanticus* |
| | Blackfin tuna | *Katsuwonus pelamis* |
| | Skipjack tuna | *Sarda sarda* |
| | Atlantic bonito | *Thunnus albacares* |
| | Yellowfin tuna | |
| Tilefishes | Blueline tilefish | *Caulolatilus microps* |
| | Golden tilefish | *Lopholatilus chamaeleonticeps* |
| Triggerfishes | Gray triggerfish | *Balistes capriscus* |
| | Ocean triggerfish | *Canthidermis sufflamen* |
| Amberjacks | Greater amberjack | *Seriola dumerili* |
| | Lesser amberjack | *Seriola fasciata* |
| | Almaco jack | *Seriola rivoliana* |
| | Banded rudderfish | *Seriola zonata* |
| Porgies | Knobbed porgy | *Calamus nodosus* |
| | Jolthead porgy | *Calamus bajonado* |
| Groupers (North Carolina/ Virginia) | Snowy grouper | *Epinephelus niveatus* |
| | Red grouper | *Epinephelus morio* |
| | Gag grouper | *Mycteroperca microlepis* |
| | Black grouper | *Mycteroperca bonaci* |
| | Scamp grouper | *Mycteroperca phenax* |
| Blue runner | | *Caranx crysos* |
| Cero mackerel | | *Scomberomorus regalis* |
| Spanish mackerel | | *Scomberomorus maculatus* |
| African pompano | | *Alectis ciliaris* |
| Tripletail | | *Lobotes surinamensis* |
| Black sea bass | | *Centropristis striata* |
| King mackerel | | *Scomberomorus cavalla* |
| Yellowtail snapper | | *Ocyurus chrysurus* |
| Rainbow runner | | *Elagatis bipinnulata* |
| Red grouper | | *Epinephelus morio* |
| Gray snapper | | *Lutjanus griseus* |
| Mutton snapper | | *Lutjanus analis* |
| Vermilion snapper | | *Rhomboplites aurorubens* |
| Cobia | | *Rachycentron canadum* |
| Black grouper | | *Mycteroperca bonaci* |
| Gag grouper | | *Mycteroperca microlepis* |
| Yellow jack | | *Carangoides bartholomaei* |
| Blackbelly rosefish | | *Helicolenus dactylopterus* |
| Snowy grouper | | *Epinephelus niveatus* |
| Barracuda | | *Sphyraena barracuda* |
| Silk snapper | | *Lutjanus vivanus* |
| Red snapper | | *Lutjanus campechanus* |
| Sailfish | | *Istiophorus albicans* |
| Lane snapper | | *Lutjanus synagris* |
| Bluefish | | *Pomatomus saltatrix* |
| Jack crevalle | | *Caranx hippos* |
| Cubera snapper | | *Lutjanus cyanopterus* |
| Ribbonfish | | *Trichiurus lepturus* |

**Table 2**
Mean, median and maximum number of Dolphin landed per trip when Dolphin was present, by region. APAIS intercept data include both observed and reported fish.

| | South Florida mean (median, maximum) | NC/VA mean (median, maximum) |
|---|---|---|
| APAIS | 6.8 (3.9, 52.0) | 14.1 (4.8, 118.8) |
| Social media | 7.5 (4.0, 45.0) | 16.8 (10.0, 70.0) |

other programs to better inform regional management discussions.

Information gleaned from the stakeholder workshops was consistent with social media analysis and standardized recreational monitoring data sources. For example, trends developed by extracting workshop participants' hand-drawn graphs matched closely with trends from the social media analysis, in terms of the specific months associated with peaks and troughs. Additionally, the workshop information put the observed trends in the wider context of the relevant drivers, pressures, and demands influencing charter operations. For example, some participants in NC/VA noted that the primary species motivating charter trips in their areas can be tunas, and that Dolphin are viewed as secondary species or as a good fallback when primary species are out of season or otherwise unavailable. Fishermen in North Carolina noted that declining availability of tunas (which are managed by NOAA Fisheries Highly Migratory Species) have contributed to increases in effort on Dolphin and Wahoo; our analyses of seasonal availability and dependence convey why this would likely occur. In South Florida, particularly mainland Florida, charter operations were sometimes described as being "opportunistic" in nature; i.e., target species were determined not so much by the expectations of the customer but driven by the conditions on the day of the trip and what was more easily caught. Our results show that local ecological knowledge, when collected systematically, can constitute a potentially robust source of information and give additional insights regarding angler behavior, which can be challenging to extract solely by analysis of landings data [28,29].

Currently in the U.S. Southeast, the primary method of recreational fisheries monitoring is the Marine Recreational Information Program (MRIP). The program is an effective method of surveying and monitoring recreational anglers at jurisdictional scales, but it is not intended to produce weekly or site level estimates of catch [23]. While our social media analysis is subject to possible biases due to the potential for non-representative sampling, it does allow for high-resolution data collection to facilitate understanding of fine-scale differences in how the fishery operates in space and time. Recently, the South Atlantic Fishery Management Council made a decision to move to electronic monitoring for the for-hire sector, which will greatly enhance the efficiency of data collection and provide much more high-resolution data. Effective electronic monitoring at high spatial and temporal scales would facilitate the types of analyses presented here, which would assist in understanding sub-regional differences in how the fisheries operate and better understand the differential impacts of management actions. Further analysis of social media data, alongside other monitoring programs, may additionally provide insights into angler preferences and help describe the particular attributes of a "good" fishing experience.

Other authors have similarly used data mining from social media to provide insights into the social dimension of recreational fishing, as well as harvesting patterns. For example, Monkman et al. [30] demonstrated that user knowledge retrieved by Google search engines can be used as a proxy indicator of coastal utilization in marine recreational fisheries. Sbragaglia et al. [31] displayed that YouTube can be a powerful tool to provide complementary data on controversial and data-poor aspects of recreational fisheries. Giglio et al. [32] demonstrated that data mining from social media can provide insights as an alternative approach into gathering data on recreational fisheries in understudied sites and indicate trends of targeted species and body sizes of fishes captured. Other studies have shown that online activity (e.g., activity on an online recreational fishing social network, internet searches) can be used to predict spatial and temporal distribution of fishing effort [18,33]. Our study adds to this growing body of literature that suggests that, while data mining of social media may not supplant traditional monitoring, the approach can provide valuable information on the patterns and dynamics of recreational fisheries.

Although we did not conduct a thorough, apples-to-apples comparison of the social media data with data from the standardized recreational survey methods, we found that the two data sources provided information that was generally consistent, with respect to some key trip characteristics such as the average number of Dolphin per trip and the proportional species composition. Given the wide proliferation of social media worldwide, more detailed comparisons may be warranted to allow for the use of social media in monitoring recreational fishing activity in regions where standardized monitoring programs are lacking. For example, in the U.S. Caribbean region, MRIP was discontinued after 2016 due to challenges with infrastructure following major hurricanes, and the extent and nature of recreational catches are currently unknown. The social media analysis is low cost in comparison to other sampling mechanisms; for the present study, photo compilation and data tabulation took a total effort of approximately ten person-days and yielded sample sizes that were comparable to the number of fishing intercept surveys over the same 4-year period. Following further validation, social media could thus be a valuable source of information on recreational fisheries in resource-limited regions that lack recreational monitoring.

Despite the value of information from the social media data, the analysis is subject to several limitations and caveats. Firstly, we were limited to the suite of charter businesses that regularly post their activities online, but recreational anglers that share their landings on social media sites are self-selecting, so they may not necessarily be representative of the overall fishing population [34]. In addition to comparison with other monitoring programs as in the present study, more attention to the descriptive text or captions associated with photos could be used to understand this potential bias, as could interviews with charter captains regarding their practices related to photo layouts of catch. Secondly, we assume that the dock layout photo is representative of the entire landings; but clearly species that are used as bait, or discarded, will be excluded from the count and would need to be monitored through other sampling programs. Excluded fish would also be species that are undesirable, discarded for regulatory reasons, or otherwise typically not harvested (e.g., billfishes). Thirdly, there can be a tendency for larger and more charismatic species to be displayed prominently in the photos, and other species may be left out or unintentionally cut out from the margins of the photo. In our analysis, this bias seemed to occur for tuna species in particular, and was more apparent in North Carolina and Virginia than in South Florida. Anglers who utilize social media may under-report small or non-target fishes (declaration bias), or trips where no fish are caught. Finally, the classification of Dolphin as "gaffers" and "bailers" could be unreliable as there was no way to quickly and easily calibrate the photos against any known length. In particular, the classification could be biased when Dolphin are displayed against anomalously large or small individuals of other species.

We found that there was high subregional variability in the landings composition, suggesting that landings are driven not only by local availability but also the specific fishing behaviors and targeting preferences that are common at the sites. Some of this subregional variability could be due to bias in the selection of photos that are posted online; species that are thought to be more popular or desirable to potential customers are more likely to be posted. To the extent that we conducted this analysis in order to understand regional preferences in for-hire fishing operations, these biases can also be informative because they reflect perceptions regarding landings composition trends that influence customer satisfaction. In South Florida, charter captains describe the nature of the operations as a "tourism fishery" with a for-hire industry frequented by a high diversity of clients, many of whom may have traveled to the region for non-fishing primary activities, and seek fishing opportunities without having any particular expectation regarding the catch [6]. On the other hand, charter captains in North Carolina and Virginia described charter operations as a "meat" fishery, and noted that many clients travel specifically to the area (which is generally less accessible than South Florida) for fishing activities, often by car, and are seeking larger quantities of fish to transport home [6]. These differences in the way that charter fisheries operate, and the types of clients they aim to attract, can explain why there could be more bias in the social media photos (as compared to APAIS) that are posted in North Carolina and Virginia versus South Florida.

## 5. Conclusions

Recently there has been an increasing push to recognize recreational fisheries as complex social-ecological systems, and manage them as such [35]. However, improved management and policy innovation necessitates an increased understanding of fine-scale usage patterns. As recreational fishing pressure increases, conflicts will only intensify and there will be increasing pressure to meet diverse angler objectives. Furthermore, the typical management response to offset effort increases has been to implement shorter seasons and smaller bag limits [36], but this causes regulatory discards to increase and can make it impossible to reduce fish mortality to target levels. Thus, refined understanding of species associations over space and time is critical to preventing such a scenario, and analyses such as those presented here illustrate the likely and potential behavioral aspects of a given fishing policy. Together with insights from workshops, this information gives us insight into how community dependence on species portfolios differs across space, the understanding of which is critical to help prepare for future predicted environmental conditions. Finally, our analysis lends insights into what constitutes a desirable fishing trip and how those attributes differ across regions, which can help to quantify the complexity behind the concept of "optimum yield" in a recreational fishery setting. There is growing appreciation of the recreational sector as composed of heterogeneous angler types with differing and competing objectives, and a realization that not all of these objectives can be simultaneously achieved under a homogeneous management system. Further analysis of recreational landings data at high spatial and temporal resolution could be conducted to help develop operational management objectives that vary across space and are considered more formally into management strategies and lead to policy innovations. Given the major management needs and knowledge gaps that exist in recreational fisheries worldwide, the utilization of social media for drawing insights is still valuable and underexplored.


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## CRediT authorship contribution statement

**Mandy Karnauskas:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Formal analysis, Conceptualization. **John Hadley:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Julia Byrd:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Matthew McPherson:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Anthony Mastitski:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.


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*Author disclaimer*

The scientific results and conclusions, as well as any views or opinions expressed herein, are those of the authors and do not necessarily reflect those of NOAA or the Department of Commerce.

## Appendix A. Description of data access and statistical methodology

### *5.1. Documenting perspectives during participatory workshops*

During the participatory modeling workshops, industry participants were handed a blank graph with an unlabeled horizontal and vertical axis, and were asked to label the graph with the months of the year on the x-axis and relative dependence (e.g., high, medium, low) on the y-axis. Participants then drew points, curves, or bars, representing their dependence on different species, with one color denoting each species. These graphs were scanned into electronic files; data points were extracted using the *digitize* package in R, by selecting the values above each month, such that for each individual graph there was a measure of species dependence for each species and month. These values of species dependence were scaled to a common relative unit by assigning the maximum value across all species and months to 10 and the minimum value to 0. This allowed us to calculate averages and standard errors for dependence on each species, across the individual graphs.

### *5.2. Access-point angler intercept survey*

In the Access-Point Angler Intercept Survey (APAIS), trained interviewers collect data on the number of harvested and released fish, take length and weight measurements of individual fishes, and collect an assortment of other details regarding the fishing trip. Trips report total catch (including fish not discarded but not brought to shore whole), discards, and observed harvest. We accessed the catch-level data for years 2017–2020 (accessed May 4, 2021) from the MRIP website (https://www.st.nmfs.noaa.gov/st1/recreational/MRIP_Survey_Data/) and subset the angler trips to include only charter trips and exclude inland fishing. For Florida, the subregion of the trip is specified in the database, and we subset trips for the two subregions approximately encompassing South Florida (specifically, Monroe County to Indian River County). For North Carolina and Virginia, subregions are not available at the county level and we used statewide estimates. For both regions, we excluded trips taken within three miles of shore, as the majority of trips targeting Dolphin and other pelagic species occur in waters > 3 mi [6]. We used the species count data for total harvest, which includes the observed harvest (fish that were caught, landed whole, and available for identification to species by the interviewer) as well as reported harvest (fish that were either discarded dead, or caught but not available for examination by the surveyor). Note that for private vessels or charter fishing trips it is challenging to separate catch by the individual angler, and in most cases, anglers will report grouped catch in the APAIS survey [23]. This sometimes requires an adjustment to be applied, such that when the group catches are weighted according to the sampling design, the landings are not overestimated. We therefore used the adjusted estimates in our calculations; note that these often result in fractional numbers of fish. To extrapolate to the total landings estimates, we multiplied the observed harvest (adjusted numbers) by the given survey design sampling weight, then totaled the landings by species across the four years of data before calculating the species composition in terms of their proportional contribution.

A hierarchical cluster analysis was used to visualize similarities within the landings composition data, and understand which species occurred most frequently together in a fishing trip. The hierarchical cluster analysis was performed on presence-absence data, such that the results indicate which species frequently appear in the landings together, regardless of the abundances with which they appear. The cluster analysis was carried out on a matrix of individual trip intercepts (which can be separated by an identification code in the APAIS database) by the species landed on that trip, and we used only species that have occurrence rates above 1 %. Because we are dealing with binary presence/absence data with a high percentage of zeros, we used the Jaccard index to calculate the distance matrix and clustering based on Ward's algorithm [37]. Analyses were carried out using the *stats* package in R version 4.4.1 [38].

### *5.3. Social media*

For the social media analysis, we first compiled a list of marinas from each region, where significant recreational fishing activity geared toward targeting Dolphin and Wahoo is known to occur. In addition to this list, recreational fishing groups (found on Facebook) were identified and examined. Within the page(s) of the social media groups, members inquire about the reputation of certain charter operations and their fishing practices. Members would comment on or "like" their preferred charter boats; the charters, which had the greater public preference, were selected to be studied with the assumption that these represented the most popular and frequented charter companies. There is the potential for bias in the selection of charters chosen for the analysis; however, we note that charters that are "preferred" frequently have a more consistent social media footprint. There is also the potential that anglers more engaged in fishing are more likely to comment or recommend businesses than the occasional angler that fishes on an occasional basis. However, these fishing groups have tens of thousands of members and would seem to be broadly representative of charter clientele in the region, as well as visitors from outside the region and from abroad.

Our search resulted in photo analysis from 14 marinas in South Florida and 8 marinas in North Carolina/Virginia. Photos were collected by visiting the respective charter's or marina's website domain or social media page. The social media presence in terms of the frequency of photo publications vary from charter to charter and the number of photos that were collected also differs between charters and marinas. In order to have a representative sample of charter landings over the full annual cycle, the timeframe of photos assembled was from January 1st 2019 to October 27th 2020 (the day photo collection was initiated). For those charters that posted with lower frequency (e.g., less than bi-weekly, approximately one-third of charters) we increased sample size by analyzing photos back to 2017. To eliminate the chances of a duplicative count, photos that were taken on board the vessel were not considered. Post-trip photos where the anglers display their landings on the deck in a layout fashion were chosen as these were thought to likely be the most representative of the total trip landings (e.g., Fig. A1). We acknowledge that there may be some bias stemming from the potential tendency to more frequently post what could be considered "successful" trips. However, we note that some companies posted photos on a daily basis and photo captions would sometimes discuss the severity of conditions or the mediocrity of catches, which suggests that less successful fishing trips were also posted. There was no filtering in the selection of photos; all within the period were counted and documented, regardless of landings.

Once the full suite of representative photos had been compiled, each photo was then examined for the species composition and frequency, and the full species composition was entered into a spreadsheet. We note that the photos do not represent any discarded fish, and hence may not represent the suite of species encountered during a trip, but rather the angler preference for the retained catch as restricted by any management measures (e.g. bag limits, seasonal closures). Fish were identified to the species level that was usually possible; amberjacks and tunas were assigned into their respective complexes due to identification difficulties from the low-quality photos. For Dolphin, we also tabulated the landings by size class and sex, to the best of our ability. Large Dolphin, colloquially referred to as "gaffers", we estimated to be > 24in, and smaller Dolphin, or "bailers", were < = 24 in. Based on literature research, male Dolphin develop a "bullhead" appearance by a maximum length of 600 mm [39,40]. Therefore, any Dolphin with a clear bullhead appearance was presumed to be at least two feet in length and could be used as an approximate reference for other fish in the photo. Photos were compiled and tabulated by a single individual. An independent quality check was carried out by a second individual by randomly selecting 5 % of the photos and checking the species counts and identification for accuracy.

Descriptive plots of the seasonal trends in landings composition relationships were generated by region (NC/VA versus South Florida). Because there was a high number of species appearing infrequently in the landings, descriptive analyses were limited to the top species in each region with regard to their total number within the landings and frequency of occurrence (i.e., the percentage of times that at least one individual of the species was found in the landings). Landings data were summarized with respect to the day of year in order to better visualize the seasonal trends. The landings composition was binned on a twice-monthly basis, and plotted in terms of percent of the total composition, and percent of total occurrence. A smoothing data function (the Nadaraya–Watson kernel regression estimate, using the *ksmooth* function in R) was applied to the raw data to produce curves approximating the seasonal representation of the species in the landings, which is also displayed in terms of raw numbers and occurrences.

Ordination analysis was performed on the combined data from both regions (NC/VA and South Florida), to quantify and visualize how landings composition varied with respect to region, season and year. Comparisons were also made of landing areas within each region to explore subregional variation. Prior to running the analysis, we identified all shared species among regions that had occurrence rates of at least 1 %; the ordination was conducted based on this subset of the data. We used non-metric multidimensional scaling (NMDS), a nonparametric method suited to the analysis of ecological data to represent similarities and dissimilarities in the landings data. To conduct the NMDS, pairwise dissimilarities (i.e., the differences in landings between each individual photo and all other photos) are first calculated; an algorithm then operates on these pairwise dissimilarity measures, seeking to represent the position of the objects (in this case the photos of landings) in a small number of dimensions. The NMDS outputs can be visualized graphically in space by placing objects (photos) according to their dissimilarity, such that photos with similar landings composition appear closely together in space. Analysis of similarity (ANOSIM) was then used to understand which factors (e.g, region, subregion, year, month) are responsible for the sources of variation in the landings composition. The ANOSIM is based on the same pairwise dissimilarity matrix described above, and statistically tests whether the similarities among groups are greater than the similarities within groups. We calculated dissimilarities using the Bray-Curtis measure, which is typically used for ecological count data, but we ran a sensitivity analysis with a suite of other distance measures and found that the overall results were not influenced by the choice of distance metric. We considered the impact of sample size on statistical power by randomly splitting the full data set into fourths and rerunning the NMDS analysis with the data subsets. All analyses were performed in R version 4.4.1 [38] and the multivariate analysis was carried out using package *vegan* [41].

To facilitate comparison across data sets, we summarized the total APAIS landings at the same taxonomic resolution as the social media photo counts; e.g., "Tunas" and "Tilefishes" were composed of multiple species summed according to the species lists given in Table 1. For simplicity in visualization, and because the vast majority of catch was composed of relatively few species or species groups, we limited the comparison to the top 10 species in the APAIS data set and the top 10 species in the social media photo counts. We calculated the proportion of the catch for these top 10 species, by data set and region, and then compared the proportions across data sets. As the dock layout photos from the social media analysis represent only the equivalent of the "observed harvest" portion of the catch, this comparison allows us to understand potential biases in the social media analysis. Because there is no effort estimate associated with the social media analysis, those counts could not be scaled similarly to reflect total landings across the region; this represents another source of potential bias.

**Figure A1.** Examples of post-trip photos, with landed fish displayed on the deck in a layout fashion, used in the social media analysis. Photo credits: Expert Fishing Charters of Jupiter, FL (left) and Pirate's Cove Marina of Manteo, NC (right).

## Data availability

Data will be made available on request.

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