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FEATURE

Mexican Small-Scale Fisheries Reveal New Insights into Low-Carbon Seafood and “Climate-Friendly” Fisheries Management

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Fishing at sunset. Photo credit: Octavio Aburto/Mares Mexicanos

As a society, we are confronted with the question of how best to feed an expanding human population, and some have pointed to seafood as a “climate-friendly” option. To date, the contributions of small-scale fisheries (SSFs) have been largely excluded from studies on food footprint. Here, we calculated the Emission Intensity profiles for seven seafood types generated by Mexican SSFs. Based on these results—which indicate that there exist several low-carbon SSFs in Northwestern Mexico—we provide a coarse approximation for the total carbon footprint of Mexico’s motorized small-scale fleet. Finally, we scrutinize the utility of non-fuel data (such as GPS data) in predicting fuel consumption/carbon emissions across SSFs. To our knowledge, this is the first life-cycle assessment to compare multiple seafood products generated by Mexican SSFs, and the first published link between tracking data and carbon accounting for SSFs specifically. We discuss how these results, in combination with insights gained from monitoring efforts in Northwestern Mexico, might be used to inform and incentivize “climate-friendly” fisheries management. While carbon footprint represents just one component of sustainability, this article serves as a helpful case study for those preoccupied with carbon accounting and fishers sustainability in traditionally data-limited scenarios.

INTRODUCTION

Social–ecological functioning on our planet faces radical disruption due to anthropogenic climate change (IPCC 2018; IPBES 2019), with nature, Indigenous peoples, and low-income communities projected to bear severe climate injustices (IPCC 2018; IPBES 2019; Whyte 2019). Simultaneously, we are confronted with the question of how best to feed an expanding human population on a planet where increasing climate instability already threatens food security (IPCC 2018; FAO 2019). Some studies point to seafood as a source of “climate-friendly” protein (Hilborn et al. 2018)—that is, protein which has a negative, neutral, or low carbon footprint—while others are less conclusive (Nijdam et al. 2012).

Of the research that provides estimates for carbon dioxide (CO₂) or CO₂-equivalent (CO₂e) emissions associated with food, only a handful report information about seafood landed in small-scale fisheries (SSFs; Kelleher and Mills 2012; Alder et al. 2018). This underrepresentation of SSFs in the footprint literature is remarkable, given their contributions to the global food system. Worldwide, SSFs provide about one-half of all seafood landed for direct consumption, directly employ over 40 million people, and support many more millions in the post-production sector (Kelleher and Mills 2012; Alder et al. 2018). Their exclusion from the footprint literature is primarily attributed to lack of data (e.g., Hilborn et al. 2018; Parker et al. 2018), and because it can be difficult to make “generalizable” conclusions about them (Smith and Basurto 2019). Further, we speculate that emissions from SSFs are understudied due to the incorrect assumption that SSFs are too small to substantively contribute to food security (see Too Big to Ignore; Chuenpagdee 2019).

Here, we explore the carbon footprints associated with seafood from Mexico’s SSFs, based on over 4,900 catch records reported by fishers (Mascareñas-Osorio et al. 2020). We provide Emission Intensity estimates per kilogram of wet weight and kilogram of protein, followed by a coarse approximation for the carbon footprint produced by the country’s motorized (marine) small-scale fleet (defined as boats <12 m; FAO 2003, 2019). Finally, we demonstrate that GPS data can be used to predict the fuel footprint of SSF activities as a proxy for carbon emissions. To the best of our knowledge, this is the first carbon assessment of SSF products in Mexico, and the first published link between geospatial tracking data and carbon accounting in SSFs specifically. We conclude with a discussion about how this information might be leveraged to inform climate-friendly fisheries management in Mexico and beyond.

METHODS

Collecting GPS, Fuel Use, and Landings Data

Scientists with the Gulf of California Marine Program (GCMP) have worked collaboratively with small-scale fishers for over a decade to collect fisheries data from eight communities along the Baja California peninsula and around the Gulf of California, Mexico (Figure 1). This fisheries monitoring program employs portable GPS tracking devices to populate an SSF database with thousands of fishing tracks (> 25,000). Many of these tracks are appended with catch data reported by fishers. Approximately 4,900 of these records were single-species trips with information about geospatial movement, catch, and fuel consumption, collected from the years 2013–2018; these records represent the universe of data we used as our primary sample (Figure 2). The GCMP dataset (Mascareñas-Osorio et al. 2020) is assumed



Figure 1. A map showing the eight different communities in which we work and have collected samples from. (Map of Baja California Peninsula courtesy of Wikimedia commons, available: <http://bit.ly/3uZ6keZ>)

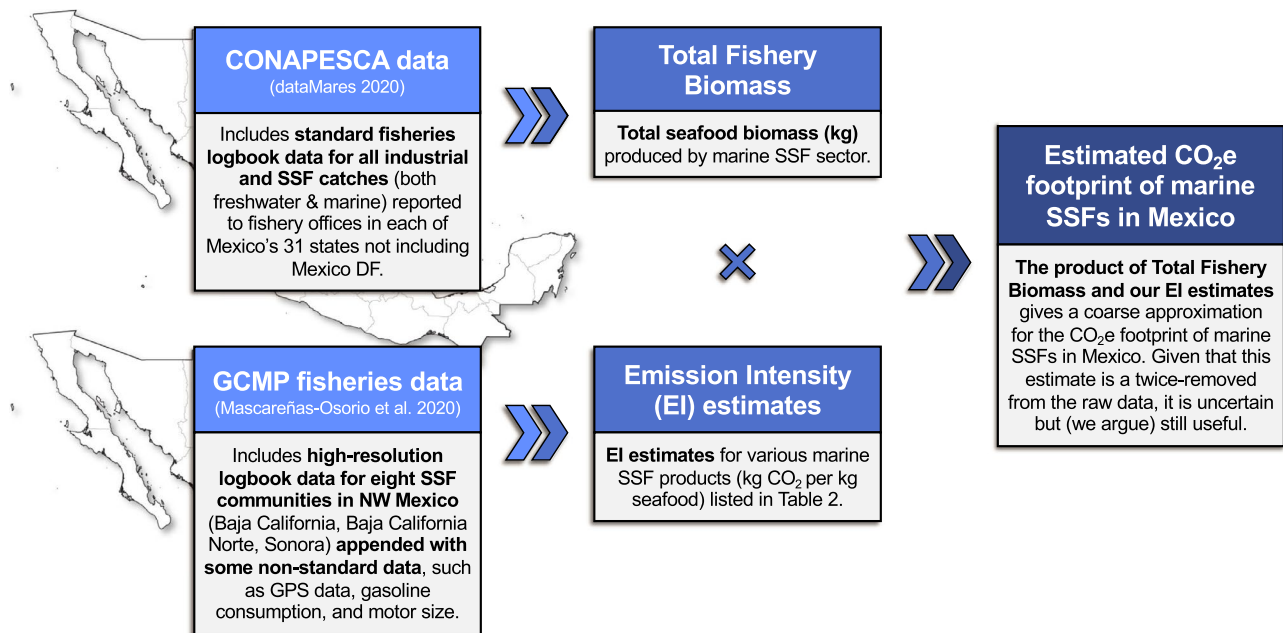


Figure 2. Shows the flow of data used throughout our analyses. Here, SSF = small-scale fisheries, GCMP = Gulf of California Marine Program, and CONAPESCA = Comisión Nacional de Acuacultura y Pesca.

to be representative of SSFs in Mexico (see Supplemental Material) and is available by request at dataMares.ucsd.edu.

Classing Organisms

In both the data set we collected (Mascareñas-Osorio et al. 2020), and in a supporting data set provided by Mexico's Comisión Nacional de Acuacultura y Pesca (CONAPESCA; dataMares 2020; Figure 2), taxa are reported to lowest taxonomic level possible. We grouped each taxa into 1 of 11 organismal classes: (1) small pelagic fishes (<30 cm), (2) large pelagic fishes (> 30 cm), (3) residential demersal fishes, (4) non-residential demersal fishes, (5) demersal molluscs, (6) non-shrimp crustaceans, (7) shrimp/prawns (hereafter shrimp), (8) cephalopods, (9) echinoderms, (10) primary producers, or (11) other.

In most cases, the class to which an organism was assigned was obvious and indisputable. However, some of the demersal fishes were difficult to class, given the diversity of life-history strategies these fish do, or could theoretically, employ. For some demersal fishes, their behavior and natural history are not well known. Here, “resident” refers to demersal fishes with high site fidelity and/or those consistently associated with complex substrate or biogenic structure (e.g., reefs, kelp forests, seagrass meadows, or mangroves). These fishes do not frequently traverse pelagic waters. We assigned resident versus non-resident status to demersal fishes based on: (1) known life history; (2) a preponderance of evidence one way or another, plus consensus among authors using FishBase (<https://www.fishbase.se/>; Froese and Pauly 2020) as well as other publicly available sources; or, as a last resort, (3) the known life history of the species' congener or family member. To give two examples of how this worked, a study by TinHan et al. (2014) found that, of individuals sampled, 50% of Leopard Grouper *Mycteroperca rosacea* showed high site fidelity, versus only 25% of Yellow Snapper *Lutjanus argentiventris*; we classified these fish as resident and non-resident species, respectively.

The CONAPESCA data included records pertaining to 527 distinct taxa spanning all 11 classes, 462 of which we included in this analysis. The remaining 65 taxa (which comprised 7.0% of landed biomass) were identified as (11) other and omitted from our analysis; this catch-all category consisted of freshwater species, unidentified bycatch, unspecified organisms, and a small number of cnidarians. Within the data we collected (Mascareñas-Osorio et al. 2020), 39 taxa were observed (Table 1), representing classes (1)–(7) and 32 genera. Of all landed biomass reported to CONAPESCA (dataMares 2020), 28.6% of biomass was derived from these genera specifically.

Calculating Emission Intensity Estimates for Different Types of Seafood

An Emission Intensity (EI) estimate tells us the emission rate of CO₂e, or the global warming potential per kilogram of product. These estimates are useful for comparing carbon footprint between foods and allow us to approximate the total emissions generated by a fishing fleet, using landings data alone (see Figure 2). Very often, EI estimates refer to the live/wet weight of product, but can also refer to butchered/filleted weight (Nijdam et al. 2012). We calculated EI estimates for each class of organism based on samples of seafood *wet weight* and fuel consumption (Mascareñas-Osorio et al. 2020). To encourage comparison between our EI estimates and those previously published, we applied estimation methods approximately consistent with Parker et al. (2018), with some minor caveats outlined below.

Out of 5,295 trips complete with gasoline data, less than 8% were flagged as multi-species trips. Thus, to avoid the numerous uncertainties associated with portioning fuel consumption among multiple species (Vázquez-Rowe et al. 2012), we only considered single-species trips ($n_{\text{single-species trips}} = 4,939$ samples). Unlike Parker et al. (2018), whose EI estimates are global but largely informed by industrial fleets powered by marine diesel,

Table 1. Lists the 39 taxa represented by the samples we collected in Northwestern Mexico (Mascareñas-Osorio et al. 2020), grouped by class.

Small pelagic fish (< 30 cm)	Non-resident demersal fish
Clupeidae spp.	<i>Cynoscion othonopterus</i>
<i>Sardinops sagax</i>	<i>Cynoscion</i> spp.
	<i>Gnathanodon speciosus</i>
Large pelagic fish (> 30 cm)	<i>Lutjanus peru</i>
<i>Atractoscion nobilis</i>	<i>Lutjanus</i> spp.
<i>Isurus oxyrinchus</i>	<i>Micropogonias megalops</i>
<i>Mobula thurstoni</i>	<i>Mulloidichthys dentatus</i>
<i>Mustelus californicus</i>	<i>Paralichthys californicus</i>
<i>Prionace glauca</i>	<i>Stereolepis gigas</i>
<i>Rhinoptera steindachneri</i>	
<i>Scomberomorus concolor</i>	Demersal molluscs
<i>Seriola lalandi</i>	<i>Chione californiensis</i>
unspecified sharks	<i>Hexaplex</i> spp.
	<i>Panopea generosa</i>
	<i>P. globosa</i>
Resident demersal fish	Non-shrimp crustaceans
<i>Balistes polylepis</i>	<i>Callinectes bellicosus</i>
<i>Caulolatilus princeps</i>	<i>Panulirus interruptus</i>
<i>Epinephelus labriformis</i>	
<i>Hyporthodus niphobles</i>	
<i>Mugil</i> spp.	
<i>Mycteroperca jordani</i>	Shrimp
<i>M. rosacea</i>	<i>Farfantepenaeus californiensis</i>
<i>Paralabrax maculatofasciatus</i>	<i>Litopenaeus stylirostris</i>
<i>P. nebulifer</i>	
<i>Paranthias colonus</i>	
<i>Sphaeroides annulatus</i>	

we calculated emissions borne from the combustion of gasoline (used by Mexican SSFs). We assumed a fuel-to-emissions conversion of 2.8 kg CO₂e/L of gasoline, accounting for the direct (2.3 kg CO₂e/L; Natural Resources Canada 2014) and indirect (0.5 kg CO₂e/L; DEFRA 2011) emissions associated with combustion and upstream production. We assumed that non-fuel emissions directly associated with fishing contributed an additional 10% to total fishing emissions (supported by Gulbrandsen 2012), accounting for CO₂e sources like the production/consumption of ice. All data analysis was performed using R version 4.0.3, and graphs were generated using ggplot2.

To obtain EI estimates for each class of organism, we first generated EI estimates for individual trips by multiplying reported fuel consumption (L) by a factor of 3.11 CO₂e/L and dividing by the wet weight of catch (kg) reported for each entry. To limit the influence of outliers, we applied a 95% winsorization to all EI estimates (R DescTools package), except for small-pelagic fishes where $n = 7$. Using this data set, we produced mean EI estimates for classes (1)–(7) and bootstrapped a 95% confidence interval for each (R boot package). Due to lack of data, we were unable to generate EI estimates for classes (8) cephalopods, (9) echinoderms, and (10) primary producers, which are fished throughout Mexico and account for 22.7% total landed biomass reported to CONAPESCA (dataMares 2020).

Comparing to Other Types of Animal Protein

To contextualize our results for seafood landed by SSFs, versus other sources of protein, we provide an approximation for CO₂e emissions per kilogram of protein, derived from each class of organism (Table 2), employing methods approximately consistent with Nijdam et al. (2012) and Parker et al. (2018). We assumed protein content was equal to 20% of total edible catch (Nijdam et al. 2012; Parker et al. 2018), which we approximated as 40% of landed biomass (Nijdam et al. 2012; Parker et al. 2018), unless the catch was marked as prepared in some way. For example, about half of all entries were reported as having been “gutted,” “des-shelled,” “beheaded,” or otherwise butchered. We treated these landings as *de facto* edible catch, while all other records were assumed to report unprocessed wet weight. Following this transformation, we multiplied the CO₂e estimate for edible catch by a factor of 0.2 to obtain kg CO₂e/kg protein. As was the case for our EI estimates, we winsorized estimates for CO₂e per kilogram of protein at the 95% level (grouped by class, sans small pelagics).

Unlike Parker et al. (2018)—though consistent with other “cradle-to-gate” life-cycle assessments (Vázquez-Rowe et al. 2012)—we assumed that the downstream emissions associated with processing and distribution of these products were equal to zero, primarily because the value chains of Mexican SSF products are non-uniform and poorly resolved. Thus, the estimates for EI per kilogram of protein reported here are conservative and may not reflect a 100% assessment of life-cycle emissions, but close to it. (Note that, when approximating the CO₂e emissions per kg of edible protein, Parker et al. [2018] added an additional 0.5 kg per landed kg of seafood. If we were to apply this extra source of emissions to our calculations, our estimates for emissions per kg of protein would increase by ~16%.)

Estimating Carbon Footprint of Mexico's Marine SSFs

To calculate the carbon footprint for marine SSFs in Mexico, we utilized our EI estimates in combination with SSF data reported in the country's 17 coastal states (Figure 2; dataMares 2020). We grouped records for SSF catch by class (total biomass, kg), and then multiplied these observations by the best available estimate for EI. For classes (1)–(7), we used the EI estimates produced directly by our analysis, and for classes (8)–(10) we supplied a “best guess” estimate.

For (8) cephalopods, we assumed that the EI was equal to that of the global estimate reported by Parker et al. (2018) of 2.8 kg CO₂e/kg. For (9) echinoderms and (10) primary producers, providing a best guess estimate was not so straightforward, since very little published data on their footprint exists. What data does exist is not readily applicable to SSF production in Mexico. For example, Purcell et al. (2018) estimate an EI of 3.5 kg CO₂/kg of fresh sea cucumber in Fiji, however, differences in habitat, fisher behavior, use of boats, and fleet size between sea cucumber fishing in Fiji and Mexico are notable. Similarly, we identified a handful of studies estimating the carbon footprint associated with industrially farmed plant products (e.g., Nijdam et al. 2012) and algae farmed for biofuel (Quinn and Davis 2015), which we did not feel were applicable to SSFs in Mexico. Thus, for classes (9) and (10), we supplied the most conservative EI estimate produced by our own data (which, as we report below, is that of demersal molluscs).

Table 2. Lists Emission Intensity (EI) estimates and protein footprint estimates for each class of organism, with 95% confidence intervals listed beneath each estimate; whether or not the EI estimate for that particular type of seafood is better than the global EI estimate generated by Parker et al. (2018), and comparable to vegan protein (Nijdam et al. 2012). Finally, the boxplot shows the distribution of EI estimates, among and within classes, where: the x-axis is $\log_{10}(\text{EI})$, the mean is marked by a blue diamond, and individual EI estimates that fell outside of the first and fourth interquartile range appear as individual black points. (Seafood icons courtesy of IAN/UMCES Symbol and Image Libraries, available: ian.umces.edu/imagelibrary/; image authors: Tracey, Saxby, Saxby, Tracey, Chen-ery, Tracey)

#	Class	sample size	Emission Intensity (EI)		EI per kg protein (kg CO ₂ e kg ⁻¹ protein)	Better than global EI estimate? ¹	Comprable to vegan protein footprint? ²	Distribution of EI observations assorted by class	
			bootstrap iterations	95% CI (Low, High)				x-axis = log ₁₀ (EI)	Class
(1)			Small pelagics (< 30 cm)						
		7		3.84	48.05	no	no		
		1000		(1.78, 6.36)	(23.98, 83.55)				
(2)			Large pelagics (> 30 cm)				yes		
		521		1.03	12.93	yes	yes		
		3000		(0.96, 1.12)	(12.01, 13.96)				
(3)			Resident demersal fish				yes		
		596		1.49	18.58	yes	no		
		3000		(1.41, 1.58)	(17.56, 19.72)				
(4)			Non-resident demersal fish				yes		
		348		1.20	15.06	yes	yes		
		3000		(1.03, 1.43)	(12.76, 17.91)				
(5)			Demersal Molluscs				yes		
		187		0.87	10.89	yes	yes		
		3000		(0.78, 0.99)	(9.63, 12.23)				
(6)			Crustaceans (non-shrimp)				yes		
		1290		2.73	34.12	yes	no		
		6000		(2.74, 2.96)	(34.24, 36.95)				
(7)			Shrimp				no		
		1985		72.73	909.18	no	no		
		6000		(63.80, 82.42)	(793.6, 1032.1)				

NOTE: EI estimates are not reported for (8) Cephalopods, (9) Echinoderms, or (10) Primary Producers due to lack of data. However, these classes of organisms are fished throughout Mexico and accounted for in our subsequent analysis.

¹EI estimates for the global fleet (including small-scale and industrial vessels) are reported by Parker et al. (2018).

²Comparable to the carbon footprint associated with a 100% plant based protein (i.e., legumes, 100% vegetal meat substitutes) reported by Nijdam et al. (2012), that is: 4–17 kg CO₂e/kg protein.

We ran our calculation for the total carbon footprint of Mexican SSFs three separate times: (1) using the mean EI estimates supplied by our data and best guesses, as well as the (2) high and (3) low EI estimates predicted by each 95% confidence interval. This allowed us to report the estimate for total carbon footprint in addition to a low–high “range” for that estimate, which we list in parenthetical notation as such: [*main estimate*] (low–high estimate). This low–high estimate was propagated throughout subsequent calculations and reported throughout the text as appropriate.

Estimating Footprint Using GPS Data

As a proxy for carbon emissions, we decided to test the utility of non-fuel data in predicting SSF fuel consumption over individual trips and a 100-member sample of trips (i.e., a small fishing fleet). Using the lme4 package in R, we generated three multiple linear regression models, each one more saturated than the last. In our first model (Y_1), we performed a multiple linear regression where fuel consumption was predicted by (i) the total distance travelled (continuous) and (ii) hours spent on the water (continuous), such that $Y_1 = \beta_1 x_1 + \beta_2 x_2 + e_1$. Our second model (Y_2) was similar to Y_1 with the additional predictor variable of (iii) class of organism fished (categorical), such that $Y_2 = Y_1 + \beta_3 x_3 + e_2$. Then, using only fuel records appended with information about the vessel’s motor size (which reduced our sample to $n_{\text{motor sample}} = 915$, excluding $n_{\text{small-pelagics}} = 1$), we performed a third multiple linear regression (Y_3), including (iv) motor size/horsepower (categorical), such that $Y_3 = Y_2 + \beta_4 x_4 + e_3$.

We scrutinized the predictive ability of all three models (Y_1 , Y_2 , and Y_3) when applied to a small fishing fleet using a Monte-Carlo Cross-Validation technique (Xu and Goodacre 2018), which calculated the percent error borne from the difference between predicted and observed fuel consumption over 100 fishing trips, bootstrapped/iterated 1,000 times, such that $n_{\text{trips}} = 100$ and $n_{\text{bootstrap iterations}} = 1,000$. Twenty-five percent of all available data was used to train the model(s) and generate predicted values, while the remaining 75% of the data points were retained. By iterating this process 1,000 times, we were able to generate the mean of, and range for, percent error borne from each model, providing a coarse picture as to how well each model might perform in the “real world.”

RESULTS

EI Estimates for Popular Seafoods in Mexico

EI estimates including 95% confidence intervals for each class of organism are reported in Table 2 and vary between classes and within trips. For example, shrimp—which have long been the target of environmentally hazardous fishing (Cisneros-Mata 2010; Aburto-Oropeza et al. 2017b)—contribute over 83 times as many carbon emissions per kilogram of catch than do demersal molluscs (EI = 72.73 versus 0.87 kg CO₂e/kg). Large-pelagic and non-resident demersal fishes contribute low- to moderate-carbon catches (EI = 1.03 and 1.20 kg CO₂e/kg, respectively), while resident demersal fishes have a slightly higher carbon footprint (EI = 1.49 kg CO₂e/kg).

Closer scrutiny of the data reveals that non-shrimp crustaceans, such as crabs and lobsters, contribute far fewer emissions per kilogram than do shrimp (EI = 2.73 versus 72.73 kg CO₂e/kg), likely explained by gear type used to fish them (see Table 3). For example, crabs and lobsters are landed using stationary traps, which are lightweight and easy to collect relative

to other types of gear. In contrast, shrimp are landed using trawls or large gillnets, which carry tremendous mass as they drag across the sea floor. Lending credence to this hypothesis are the results from previous studies (e.g., Kelleher and Mills 2012; Parker et al. 2018), and the observation that, on average, small-scale vessels fitted with “eco-friendly” trawls (*changos*) use 3–26 times less gas per kilogram of unprocessed shrimp than do vessels fitted with traditional trawl nets and large gillnets. Specifically, the EI estimates associated with shrimp landed using eco-friendly trawls is 6.19 kg CO₂e/kg ($n_{\text{records}} = 586$) versus 165.28 kg CO₂e/kg for traditional trawls ($n_{\text{records}} = 859$) and 21.29 kg CO₂e/kg for large gillnets ($n_{\text{records}} = 256$). Point estimates presented here are based on non-winsorized EI values. The decision to winsorize or not changes the point estimates but not the interpretation of our results. Given these discrepancies, we speculate that SSF vessels are particularly fuel-inefficient when it comes to towing heavy equipment (Gulbrandsen 2012).

When we partitioned the data by gear type, we still observed considerable variance across EI estimates for shrimp. A wide range in shrimp EI estimates is driven by high volatility in catch, where some trips were very successful (max = 272.58 kg beheaded), and others were not at all (min < 1 kg beheaded). We observed a similar pattern for the other classes of organisms, where trips with a low catch drove up the average EI, and trips with high catch drove down the average EI. This suggests that one way to lessen emissions associated with seafood is to improve the health of fishery stocks and increase the catch-per-unit effort (Kelleher and Mills 2012).

Certain Seafoods from SSFs Offer Low-Carbon Protein

Some of the seafood landed by SSFs in Mexico offer low-carbon harvests of animal protein (Table 2), consistent with the footprint of a vegetarian or vegan diet, and are potentially climate-friendly (Table 3). Although an exhaustive comparison between proteins is beyond the scope of this paper, previous studies support the following conclusions from our data:

- (1) Protein from demersal molluscs, large pelagic fish, and non-resident demersal fish has a low carbon footprint, comparable to protein from vegan meat substitutes (Nijdam et al. 2012; Hilborn et al. 2018; Parker et al. 2018).
- (2) Protein from resident demersal fish and non-shrimp crustaceans is about as carbon-intensive as protein from eggs, milk, and poultry (Nijdam et al. 2012; Hilborn et al. 2018; Parker et al. 2018).
- (3) Protein from small pelagic fish landed by SSFs may be carbon-intensive, similar to pork. However, this estimate is highly uncertain due to our small sample size, and is inconsistent with literature surrounding other small pelagic fisheries (Avadí et al. 2014; Hilborn et al. 2018; Parker et al. 2018).
- (4) Protein from shrimp is carbon-intensive, on par with protein from ruminant herbivores like cows and sheep (Nijdam et al. 2012; Hilborn et al. 2018; Parker et al. 2018).

The Carbon Footprint of Mexico’s Small-Scale Fleet

Using the latest available catch records reported to CONAPESCA (dataMares 2020), in combination with our EI results (Table 2), we estimate that the carbon footprint for Mexico’s SSFs was 3.35 million metric tons of CO₂e in 2014 (with a low–high estimate of: 2.96–3.86 million metric tons). Since there exist ~74,000 small-scale motorized vessels in Mexico (Alder et al. 2018), we estimate that the mean

Table 3. Characteristics of each small-scale fishery (SSF) beyond Emission Intensity (EI) estimates, including relevant measures of economic and ecosystem impacts. (Seafood icons courtesy of IAN/UMCES Symbol and Image Libraries [available: ian.umces.edu/imagelibrary/]; image authors: Tracey, Saxby, Saxby, Tracey, Saxby, Saxby, Saxby, Tracey)

#	Class	Emission Intensity (EI)		Ratio of ex-vessel revenue : biomass ²		Typical trophic level		Commonly-used gear	
		(kg CO ₂ e kg ⁻¹ live wt)	EI per ex-vessel peso ¹ (kg CO ₂ e peso ⁻¹)	higher- vs. lower-revenue landings	8.7 : 1	common role in the food web	% of trips using gear X		
(1)	 Small pelagics (< 30 cm)	3.84	1.082	lower-revenue landings	8.7 : 1	Low often primary consumers	NA*	*sample too small to generalize: hook & line (n = 4), cast net (n = 3)	
(2)	 Large pelagics (>30 cm)	1.03	0.086	lower-revenue landings	11.4 : 1	High generally apex predators	Gillnets	82% gillnets; 13% trawls	
(3)	 Resident demersal fish	1.49	0.078		21.8 : 1	Medium - High many meso predators	Mixed	35% traps; 26% trawls; 20% gillnet; 18% hook & line	
(4)	 Non-resident demersal fish	1.20	0.108		17.7 : 1	Medium - High many meso predators	Gillnets	86% gillnets; 10% hook & line	
(5)	 Demersal Molluscs	0.87	0.007	lower-revenue landings	11.0 : 1	Low often primary consumers	Hookah	100% hookah	
(6)	 Crustaceans (non-shrimp)	2.73	0.072		27.5 : 1	Low - Medium some secondary consumers	Traps	100% traps	
(7)	 Shrimp	72.73	0.671	higher-revenue landings	49.5 : 1	Low - Medium some secondary consumers	Trawls	79% trawls; 21% gillnets	

¹Values based on individual records of fuel consumption and ex-vessel sales from communities in Northwest Mexico (Mascareñas-Ororio et al. 2020).

²Ratio of total ex-vessel revenue (pesos) to total landed biomass (kg), based on records from marine SSFs throughout all of Mexico in the year 2014 (dataMares 2020).

annual emissions per vessel is 45.3 metric tons of CO₂e (low–high estimate: 40.0–52.2 metric tons) or ~ 14,597 L gas/year (low–high estimate: 12,909–16,825 L gas/year). Uncertainties associated with this result are discussed in Supplemental Material, however, our estimate appears consistent with findings by Martínez-Cordero and Sanchez-Zazueta (2017), who report median CO₂ reductions in Mexico’s SSF fleet resulting from a motor replacement program (not including non-fuel emissions).

Our estimate for fuel use among Mexican SSFs suggests that, relative to other *motorized* SSF fleets, the average SSF vessel in Mexico is “middle of the road” to high in terms of its carbon footprint. For example, compare the average footprint of a small-scale vessel in Mexico (~14,597 L gas/year) to: 1,349 L/male fisher/year for the sea cucumber fishery of Vanua Balavu-Fiji (a sparsely motorized fishery; Purcell et al. 2018); 2,963–15,416 L/vessel/year for the Peruvian Anchoveta *Engraulis ringens* fishery (degrees of motorization; Avadí et al. 2014); and an average 15,000 L/vessel/year among eight SSFs in the European Union (fully motorized; Guyader et al. 2013).

Evidence that Tracking Technologies May Enable Footprint Estimation

We performed three multiple linear regressions (Y_1 , Y_2 , and Y_3), where fuel was predicted by an increasing number of variables: (i) the total distance travelled (continuous), (ii) hours spent on the water (continuous), (iii) class of organism fished (categorical), and (iv) motor size (categorical).

Our simplest model (Y_1) was significant ($F(2, 4931) = 552.8$, $p < < < 0.05$), but only explained 18% of the variance in our data ($R^2_{adj} = 0.18$); both predictor variables (i) and (ii) were significant ($p < < < 0.05$). Our second regression equation (Y_2) included the third predictor variable (iii) class of organism fished, and was significant ($F(8, 4925) = 859.8$, $p < < < 0.05$), explaining 58% of the variance in our data ($R^2_{adj} = 0.58$); all Y_2 predictor variables were significant ($p < < < 0.05$), except for small-pelagic fishes. Finally, our third multiple linear regression (Y_3), which was applied to a smaller subset of the data containing information about vessel motor size ($n_{\text{motor sample}} = 915$), was significant ($F(10, 904) = 407.1$, $p < < < 0.05$), and explained 82% of the variance in our data ($R^2_{adj} = 0.82$); and all Y_3 predictor variables (i)–(v) were significant ($p < 0.01$). This makes sense given that Y_3 is more saturated than Y_2 , and Y_2 more saturated than Y_1 , at the expense of model parsimony.

Using a Monte-Carlo Cross-Validation method (Xu and Goodacre 2018) to test the utility of our regression models in predicting real-world outcomes (where $n_{\text{trips}} = 100$ and $n_{\text{bootstrap iterations}} = 1,000$), Y_1 predicted the observed fuel footprint of a 100-member fleet with a mean percent error of -0.2% (95% CI: $-0.5, 0.1$), and a range of -16.4% to 15.3% error. Y_2 had a mean percent error of -0.02% (95% CI: $-0.2, 0.2$), with a range of -10.6% to 11.0% error. And, Y_3 had a percent error of -0.2% (95% CI: $-0.4, 0.0$), with a range of -11.5% to 11.5% error. In all cases, percent error is close to normally distributed around zero, and dissipates as n_{trips} increases.

A visual assessment of model output suggests that models Y_1 and Y_2 do not accurately predict individual trips with unusually high fuel consumption (Figure 3A), but perform reasonably well over a small fleet (Figure 3B). Since model Y_3 was applied to a smaller and more “normal” subset of the data, it is unknown how Y_3 would predict fuel consumption for trips or fleets with unusually high values.

Cumulatively, these results suggest that in a real world application of models Y_1 through Y_3 , Y_2 would most accurately predict the fuel footprint of a small fleet (Figure 3B), closely rivaled by Y_3 , then Y_1 . This is interesting in that one might expect Y_3 to have more predictive power than Y_2 , given that Y_3 explains a larger amount of variance observed among individual fishing trips. While this may be an artifact of disparate sample size, it still hints at a useful takeaway: while information about motor size is useful, even without it, a large sample size makes it such that Y_2 performs reasonably well at predicting fuel consumption over several trips. Even Y_1 , which only contains information about (i) total distance travelled and (ii) hours spent on the water, performs moderately well at predicting fuel consumption over a small fleet, suggesting that footprint estimation may be possible based on GPS data alone.

DISCUSSION

Our results provide a baseline understanding for scientists and fishery managers who seek to incorporate carbon footprint into their calculus surrounding SSFs and carbon management. Additionally, they indicate that SSFs in Mexico contribute substantially to food security (FAO 2003, 2019; Kelleher and Mills 2012) with relatively low carbon impacts. Yet, carbon footprint represents only one dimension of fisheries sustainability to be aware of, and characteristics for each SSF class (summarized in Table 3) lend valuable context to our understanding of what it means for a fishery to be truly climate-friendly. For example, meso and apex predators are known to play an important role in structuring healthy and resilient marine ecosystems (Estes et al. 2011), which, in turn, support carbon sequestration and regulation of Earth’s climate (e.g., Atwood et al. 2015). Thus, intense fishing of large pelagic and non-resident demersal fishes may negatively impact carbon reductions overall, despite their apparently low EIs.

To help incentivize climate-friendly fishing, managers might employ various strategies, such as communications campaigns (Merayo et al. 2019), support for cooperative fisheries management (Hilborn 2004; Cota-Nieto et al. 2018), and direct financial transfers to fishers and their communities as they transition away from high-carbon fishing (Cisneros-Montemayor et al. 2016; Merayo et al. 2019). Managers might also consider removing “harmful” subsidies, which artificially decrease the price of fuel, as these tend to encourage unsustainable fishing practices (Sumaila and Pauly 2007; Sumaila et al. 2010; Merayo et al. 2019; Cisneros-Montemayor et al. 2020).

On the supply side of fisheries production, fuel subsidies disincentivize fuel consciousness among existing fishers and lower the barrier to entry for new fishers, contributing to fleet overcapacity (Sumaila et al. 2010; Merayo et al. 2019). While on the demand side, cheap fuel leads to distortions in seafood prices (Sumaila et al. 2010; Merayo et al. 2019), obscuring the costs of harvest and undermining consumers’ propensity to select for low-carbon seafood products. Such subsidies give rise to a socially inefficient outcome, where fisheries are more vulnerable to overexploitation (Sumaila et al. 2010; Merayo et al. 2019; Cisneros-Montemayor et al. 2020), and likely increase fishery emissions on net.

At the same time, it is important to understand that these harmful subsidies disproportionately fall to industrial fisheries (Cisneros-Montemayor et al. 2020), and holistic SSF management must account for the various

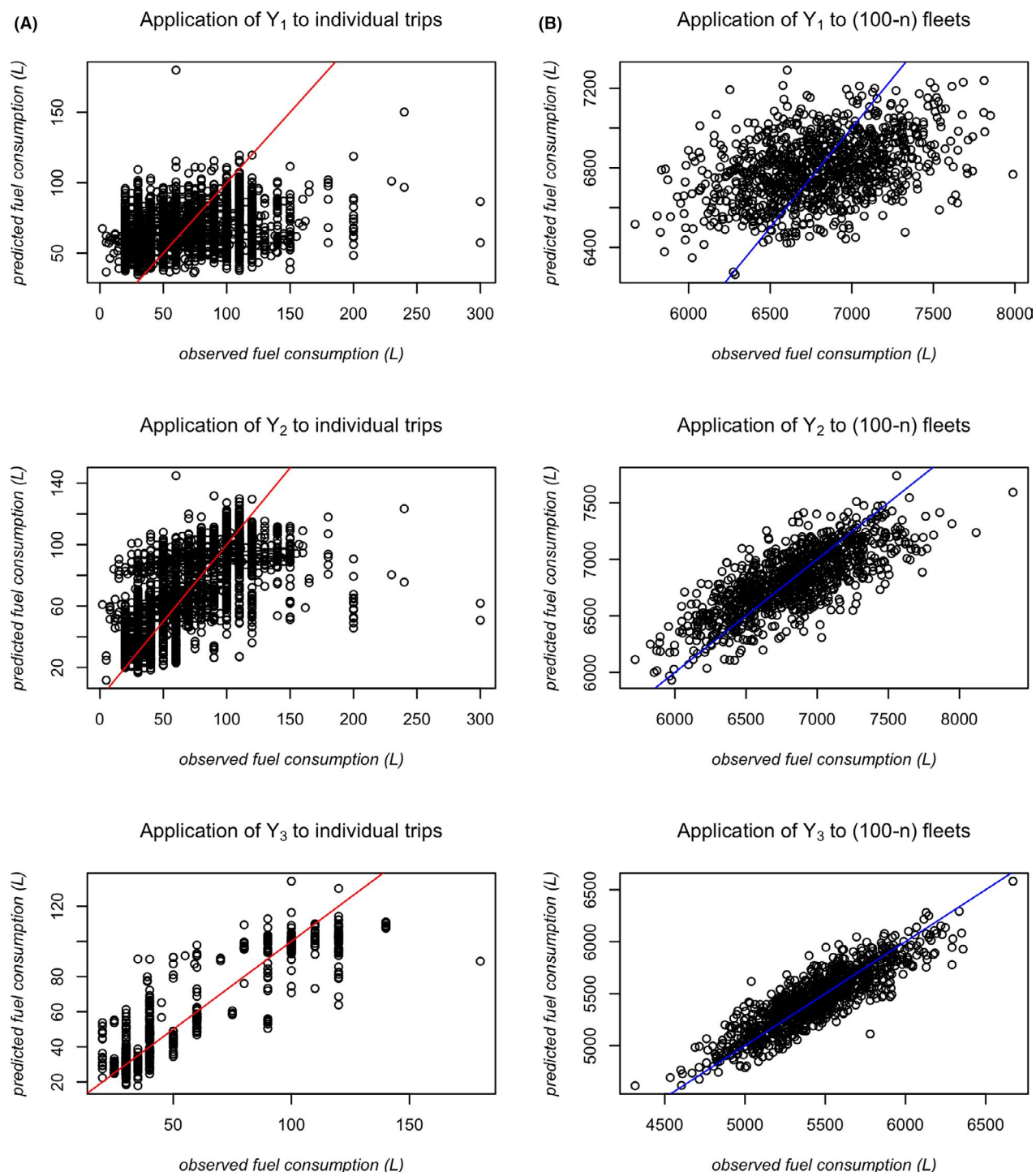


Figure 3. Graphs depicting goodness-of-fit results for multiple linear regression models Y_1 , Y_2 , and Y_3 , when applied to individual trips (A) and small (100-member) fleets (B). Accordingly, in graphs on the left, each point indicates the fuel consumption for an individual fishing trip. In graphs on the right, each point indicates the total fuel consumption for 100-member “fleet,” randomly sampled from the wider universe of data (described in “Estimating Footprint Using GPS Data”). Respectively, red and blue lines indicate a perfect 1:1 relationship between the observed and predicted values generated by each multiple regression when applied to individual trips and 100-member fleets, such that points clustered close to the red/blue line indicate a good model fit, and points far from the red/blue line indicate a poor model fit.

socio-economic benefits conferred by a particular subsidy or style of fishing. Our results suggest that shrimp landed by SSFs in Northwestern Mexico, for example, carry a high carbon footprint per kilogram of protein, but a much lower

carbon footprint per peso (Table 3). Thus, policies designed to promote climate-friendly fishing need be considered on a case-by-case basis and in the wider context of fisheries “sustainability.”

To monitor and address uncertainties between our estimates for fishing emissions and our carbon reality, emergent technologies may provide new and improved information. As evidenced by our results, tracking devices may enable SSF carbon accounting with relatively little adaptation to tracking/monitoring efforts already underway. For example, in an effort to curb illegal, unreported, and underreported fishing, geopositioning technologies such as Automatic Identification Systems and Vessel Monitoring Systems have become commonplace within the world's industrial fishing fleet. These technologies produce massive amounts of automated and semi-automated data, which can be readily utilized by scientists and managers alike through platforms such as the Global Fishing Watch (<https://globalfishingwatch.org>). We reason that the Global Fishing Watch (and platforms like it) may be able to provide estimates for fishery emissions in nearly real time and at a relatively low cost, based on ground-truthing studies such as ours, plus subsequent modifications to its machine learning algorithms.

Fisheries tracking data has proven valuable for reasons beyond surveillance, in both industrial (Kroodsma et al. 2018) and small-scale settings (e.g., Metcalfe et al. 2016; Cardiec et al. 2020), though fishers' feelings towards tracking technologies are generally mixed. Some are suspicious that tracking data will lead to management decisions that penalize participants who fish honestly, while others benefit from access to geospatial information. Among SSFs, GPS data has been demonstrated to enhance cooperative fisheries management (Metcalfe et al. 2016; Cardiec et al. 2020), observance of Marine Protected Areas (Cardiec et al. 2020), and compensation for area closures (Aburto-Oropeza et al. 2017b).

Fishers' willingness to help with monitoring and management increases when they are included in leadership and decision making (Hilborn 2004; Cota-Nieto et al. 2018; Alder et al. 2018). In our experience, fishers' local ecological knowledge not only provides better context for program design, implementation, and data analysis, fishers are well equipped to identify and communicate issues particular to their community and the resources they fish (e.g., Aburto-Oropeza et al. 2017a, 2017b). Furthermore, establishing trust and equity among stakeholders has been identified as integral to sustainable transformation and restoration of ecosystems, fisheries, and human communities (Bennett et al. 2019; Whyte 2019; Merayo et al. 2019). Therefore, administrators of novel tracking platforms should strive to include fishers as both participants and leaders in program development and implementation.

Our findings demonstrate that there exist several low-carbon SSFs in Northwestern Mexico, and that it may well be possible to monitor and improve upon climate-friendly fishing in the region. The methods described here may prove useful for studies in other countries, in data-limited scenarios, and for monitoring programs already underway. Ideally, this work will serve as stepping stone for novel research in SSF science and contribute to our understanding of sustainable seafood production in a rapidly changing world.

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DATA AVAILABILITY STATEMENT

The primary data sources used herein (Mascareñas-Osorio et al. 2020; dataMares 2020) are available by request at dataMares.org. Individuals who are interested in specific details of the analysis should carefully review the Methods section or contact the corresponding author.

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SUPPORTING INFORMATION

Additional supplemental material may be found online in the Supporting Information section at the end of the article.
Supplementary Material [AFS](#)