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Evaluating and Mitigating End-to-End Human Impacts to U.S. Marine Systems

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Evaluating and Mitigating End-to-End Human Impacts to U.S. Marine Systems

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Environmental Science and Management

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Abstract

The oceans face increasing pressure from human activities. Land-based activities drive the runoff of pollutants into coastal waters where they can disturb or destroy natural habitat, while ocean-based activities can lead to the unsustainable extraction of marine resources, add additional pollutants, and disrupt biodiversity and ecosystem function. Yet, stewarding marine spaces intentionally can increase ecosystem function while deepening our understanding of these complex systems. Using a mix of spatial modeling and causal inference, the following dissertation, in three chapters, describes and presents solutions to improve stewardship of marine environments in the United States (US), considering our relationship with oceans from end to end. My first chapter describes and applies a novel tool to better understand the distribution of pollution from human activities, the second chapter proposes a strategy to mitigate the impacts of coastal nutrient pollution, and finally, my third chapter reveals key insights from our most intimate and foundational relationship with the ocean, our consumption of seafood. Each of these chapters is the product of long running, multi-disciplinary collaborations.

In the US, nitrate loading into marine environments has been relatively constant at a high input level over the past 20 years, while phosphate loading has continued to increase. In some places, excess nutrients drive cascading ecosystem changes, in others, despite significant additional nutrient loads, ecosystems are better able to absorb these impacts. In my first chapter, alongside collaborators, I identify pollution “hotspots” in continental US coastal waters where anthropogenic nutrient loading is high compared to natural nutrients in order to

help drive water quality management. We adapted generalized plume models for river and sewage to model the dispersal of anthropogenic nutrients into marine environments, we then combine model outputs with atmospheric N deposition, overlaying these with nutrient data from published sources (annual totals (kg/yr), 0.2 degree raster cell). We find nutrient pollution hotspots concentrated in the Northeast, US and in the Gulf of Mexico, however, some high-nutrient settings, like Southern California, have significant nutrient pollution in localized settings. This work contributes a novel application of generalized plume models that efficiently analyzes the transport and distribution of nutrient pollution at regional and national scales.

Given the severity of coastal nutrient loading, my second chapter explores a potential solution: strategic placement of seaweed aquaculture. Seaweed is capable of removing large quantities of nitrogen and phosphorus from coastal ecosystems, yet seaweed has gained little traction for its potential role in targeted nutrient assimilation. Marine nutrient pollution is increasing around the world, contributing to expanding eutrophic conditions and co-occurring with other stressors that impact the state and stability of aquatic ecosystems. In the US, climate change, legacy nitrogen, and nonpoint source pollution make it increasingly difficult to curb growing eutrophication and the associated effects, such as hypoxia (dissolved oxygen < 2 mgL^{-1}). Employing a synthetic semi-quantitative approach, we use the Gulf of Mexico as a case study – a US priority area for aquaculture with substantial nutrient pollution and one of the largest hypoxic zones on the planet – to assess the potential for native seaweed aquaculture to augment upstream pollution control with downstream nutrient assimilation. Results from this analysis suggest that given growing market demand, new product pathways, and nutrient pollution markets, seaweed aquaculture may be a feasible tool for nutrient assimilation that could subsidize, if not pay for itself.

Finally, my third chapter explores the impact of consumption on marine resources. Shifts in food access due to the COVID-19 pandemic were heterogeneous, offering a unique chance to differentiate the effects of restaurants, public assistance programs, and consumer attitudes on purchasing behavior. We use California's novel tiered COVID-19 restriction system, which imposed top-down county-level economic restrictions dependent on caseloads and testing rates, as a natural experiment to untether the effects of changing seafood access. We deployed a longitudinal survey (N=464) to capture seafood consumption patterns for the same population of Californians three times between August 2020 and August 2021. To casually identify marginal shifts in consumption behavior due to changing seafood access (i.e., food service restrictions and county-level factors) we use two-way fixed effects models. In parallel, we assess relationships between consumption at the species-level using network analyses. Nuanced purchasing behaviors, such as purchases of specific species (e.g. shrimp, salmon, and local species) and products (e.g. canned, fresh) became more entrenched given disruptions to access. Diversity of seafood consumption, however, remained unchanged from pandemic disruptions, shifting instead in response to individual attitudes. We find a personal relationship with seafood is the most pervasive driver of seafood consumption.

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Chapter 1: Nutrient Pollution Hotspots in US Waters

This chapter was created in partnership with Gabriel de la Rosa with significant guidance along the way from collaborators.

1.1 Introduction

Oceans are under increasing pressure from in-water and on-land human activities (Halpern et al. 2019). For the latter, nutrient and chemical run-off and direct wastewater inputs link coastal marine systems to terrestrial human activities and can act as important or dominant stressors in coastal ecosystems (Vitousek et al. 1997, Halpern et al. 2009, Malone & Newton 2020, Tuholske et al. 2021). Anthropogenic inputs of nitrogen (N) and phosphorus (P) to coastal ecosystems via river discharge is the primary cause of eutrophication and consequent ecosystem degradation in coastal ecosystems worldwide (Rabalais et al., 2009, 2010; Paerl et al., 2014). Between 2003 and 2013, global deposition of organic chemical and nutrient pollution into marine environments increased ca. 65% (Halpern et al. 2019). Previous studies have shown these anthropogenically driven increases in N availability caused by atmospheric deposition, riverine and outfall input have switched extensive areas from being N-limited to P-limited (Kim et al. 2011). Despite the large uncertainty in its magnitude, the anthropogenic reactive N flux to the ocean is of the same order as that of biological N fixation [60 to 200 Tg N year−1 (Dutkiewicz et al. 2012, Großkopf et al. 2012)].

Depending on a system's capacity, anthropogenic nutrient loading into global oceans can culminate in harmful algal blooms, low dissolved oxygen conditions, fish kills, habitat degradation and loss, reduced biodiversity, and altered food web dynamics (Laffoley et al. 2019; Rabalais et al. 2009; Lemly et al. 2019). Since the 1960s, an estimated 245,000 km^2 of oceans have been considered dead zones, triggered by excessive input of reactive N and P (Diaz & Rosenberg 2008). Nutrient and chemical pollution can also amplify risks from climate change and other anthropogenic stressors through synergistic interactions (He & Silliman 2019, Harley et al. 2006, Tuholske et al. 2021). The severity of impacts from nutrient loading are best determined by the relative load compared to natural ocean nutrients; the same raw amount of pollutant may have dramatically different effects in the high nutrient waters of southern California than in the low nutrient Gulf of Mexico. While location matters, nutrient loading is highly dependent on temporal factors as well, including seasonality and weather which may alter a system's ability to absorb excess nutrients. For example, storm events, which can drive substantial anthropogenic nutrients into coastal waters, can create localized impacts during lower-nutrient seasons or in discrete locations with lower natural nutrients (Warrick et al., 2005; Anderson et al., 2008). For example, storm events in nutrient-rich southern California have spurred HABs in southern California (Anderson et al., 2008). However, only the largest watersheds have high resolution data that can monitor and predict nutrient loading into coastal waters at a fine spatial and temporal scale.

There are three major sources of N and P pollution to coastal waters: rivers, sewage, and atmospheric deposition. Rivers are the primary interface between terrestrial and marine environments, driving many physical, biological, and geochemical processes in coastal and shelf sea areas (Dagg et al., 2004). During the course of the twentieth century, the primary cause of coastal eutrophication and consequent ecosystem degradation was due to increases in anthropogenic inputs of N and P via river discharge (Rabalais et al., 2009; Paerl et al., 2014). Across the US, more than two out of five river and stream miles have levels of nutrients that are too high for healthy aquatic ecosystems (58% of river and stream miles had excessive P, while 43% have excess N) (US EPA, 2020). The number of coastal and estuarine ecosystems with hypoxia have approximately doubled each decade since the 1960s (Diaz & Rosenberg 2008).

Second, marine outfalls, which discharge industrial and municipal waste into the ocean, contribute the largest source of anthropogenic P and a substantial source of N to coastal waters globally (Seitzinger et al., 2010; Tuholske et al. 2021). The US has areas of large N input from wastewater compared to watershed size (Tuholske et al. 2021). While the Clean Water Act and related environmental policies in the 1970s improved coastal water quality through the regulation of industrial and municipal effluent among other things, recent efforts to reduce the occurrence of nutrient pollution more generally appear to have plateaued (Byrnes et al. 2002). Stymied improvements have made the US home to some of the world's most significant contemporary water quality issues including the Gulf of Mexico Dead Zone (the 7th largest N watershed in the World (Tuholske et al. 2021)), toxic algal blooms off Florida's west coast, and eutrophication of the Chesapeake and Long Island Sound (Shortle et al. 2020).

Third, a significant amount of N also falls on the ocean through atmospheric N deposition, almost completely anthropogenic in origin (e.g. Kim et al. 2011). Bioavailable forms of N (NO_x and NH_y) are made broadly available through various human activities, especially due to the combustion of fossil fuels by internal combustion engines, and industrial activities, including electricity production (Fowler et al. 2013). Deposition is particularly important in driving nutrient inputs to offshore environments (Jickells et al. 2017). These additional nutrient inputs have the potential to modify oceanic, and even global, biogeochemical systems (Jickells et al. 2017).

Nutrient dispersal models tend to sit at one extreme of a spectrum of data and analytical intensity. On one end, analyses rely on long term, high-resolution observational data which, in practice, is not available for most of the world, and consequently are primarily available for the largest watersheds, and are often not extended into coastal waters (Tuholske et al. 2021). On the other end of the spectrum, diffusive modeling techniques are often used, particularly for global analyses when bespoke models are unavailable, in which simple Gaussian or logarithmic dispersal kernels use predictive variables to project material spread into marine environments. For example, Tuholske et al. 2021 mapped global sewage inputs globally by projecting N and fecal indicator organisms from sewage and river pourpoints. The effluent was propagated into coastal waters, based on population data, protein intake, and fertilizer application rates in a grid using a plume model based on a logarithmic decay function.

While considerable variability is found in the hydrodynamics of coastal river plumes, they commonly exhibit self-similar scaling relationships that include relatively uniform sizes and shapes along most coastal margins (Warrick & Fong, 2004). Outfall plumes are similar to river plumes in that they consist of a volume of water entering the ocean over a given time. However, outfalls have key differences from rivers including their effluent density, design of outfall, which may include multiple effluent release points, and depth of the pour point. While river plumes can be monitored through satellite imagery, outfalls frequently let out at depth, and thus outfall plumes are often monitored through field data collection and data intensive, site specific modeling. In the absence of data availability and modeling, the spread of materials from river and sewage plumes into coastal environments can be generalized, allowing for improved understanding of nutrient dispersal in marine environments at relatively fine spatial scales.

We adapt generalized, two-dimensional plume models which can determine the transport of materials from riverine and marine outfall areas at finer resolution than diffusive modeling to spatially quantify and map anthropogenic nutrient deposition relative to baseline marine N and P. Specifically, we employ Warrick and Farnsworth's (2017) river plume model, and adapt it to predict outfall plume dispersal. Although this is a simplified model of nutrient dispersion, it can be applied across a wide range of geographical locations without extensive oceanographic data. We apply these models in conjunction with atmospheric N to determine likely "nutrient hotspots" in the United States (US), which we define as areas of relatively high nutrient pollution (N, P) (annual totals of N and P in 0.2 degree raster cells). We report results across 3 US regions – Northeast, Gulf of Mexico, and Southern California.

1.2 Methods

River plumes

The spatial extent of river plumes loosely follows a self-scaling relationship with the size of the upstream watershed (Warrick & Farnsworth, 2017). This relationship holds relatively constant across a wide range of watershed sizes and geographic locations (Warrick & Farnsworth, 2017). As a result, plume extent for a given river can be estimated using the equation from Warrick & Farnsworth (2017):

$$P_r = c * A\ \beta$$

(Eq. 1)

where P_r is the size of the river plume, c is a plume size factor that is dependent on the relative magnitude of river discharge under consideration, A is the upstream watershed area and β is constant scaling factor. For our analysis, we use $c = 0.5$, a plume size scaling factor for moderate flows, and $\beta = 0.65$ (Warrick & Farnsworth, 2017; Warrick & Fong, 2004).

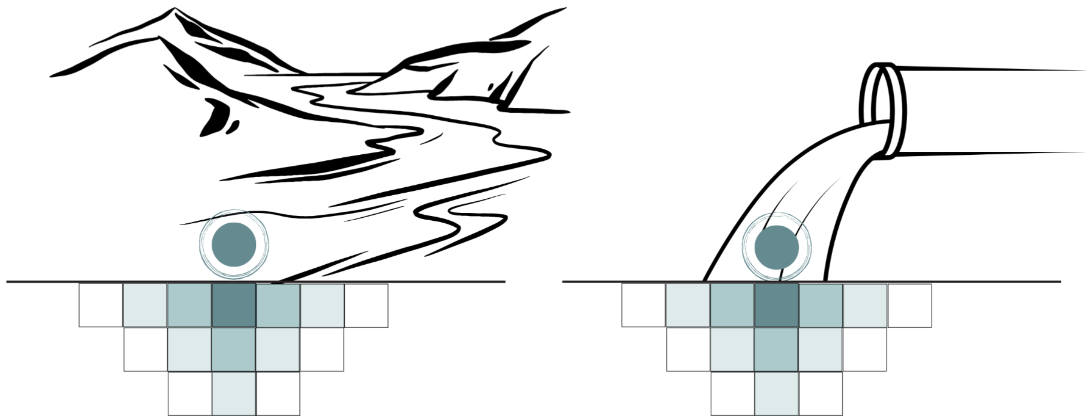


Figure 1*: Conceptual representation of plume model and materials distribution across spatial cells. A) River plume size is based on watershed area, river discharge, and constant scaling factor for river flow. B) Outfall plume size is based on relationship for river plumes, and adapted to outfall flow rate. Line: river/outfall and ocean interface. Circle: pourpoint location. Darker cells are more concentrated in materials than lighter cells.*

We assume river plumes disperse directly from the pourpoint, the location where surface water 'pours' into the ocean. Plumes are expanded iteratively into an ocean raster using a four-neighbor rule in which each raster is expanded in the four orthogonal directions until the total area of plumed cells exceeds the predicted plume size in the plume area calculated in Equation 1 (**Figure 1**).

This approach to modeling river plumes allows drivers to wrap around headlands and islands, but does not account for nearshore advection that acts to push suspended particles in particular directions.

To determine the plume area for all rivers that output to the ocean in the continental US, we combined spatial stream locations from NHDPlus (National Hydrography Dataset Plus) data and regional USGS SPARROW (SPAtially Referenced Regression On Watershed attributes) models, which estimate streamflow, N, P, and suspended sediments in stream reaches for the entire US (NHDPlus, USGS 2019). We filtered the combined dataset to only include terminal reaches, the ultimate stream segment before a water body. To only include reaches that outlet to marine environments, as opposed to those that outlet to lakes, we selected reaches within 2km of the marine coastline. We apply the river plume model across the continental US on all streams and rivers that reach marine environments.

Pollutants are most concentrated nearest to the pour point and become increasingly dilute towards the edge of a plume (Mertes et al. 1998). Operating on a 0.2 by 0.2 degree grid (~$22km^2$), our plume model fills neighboring cells one at a time until the total area of the plumed cells exceeds the calculated area of the plume. To simulate dilution in an outward gradient, we first divide the total mass of the nutrient by the number of expansions our model takes to achieve the plume area, so that each expansion contains the same total amount of nutrient. Then, we distribute the nutrient evenly to all the cells contained in the expansion: one in the first, three in the second, and so on (**Figure 1**).

Outfall plumes

As part of the Clean Water Act, National Pollutant Discharge Elimination System (NPDES) permits are required for any point source discharge, including industrial and wastewater treatment plant outfalls, to waters of the US. All outfall flow rates, N and P quantities are reported by permit location.

We took a generalized approach to calculating outfall plumes by estimating their extent based on their flow rate (cubic feet per second; CFS) by adapting the scaling relationship from Equation 1 (Warrick and Farnsworth 2017). Assuming a linear relationship between plume size and flow rate, we then found the plume size factor for outfalls (estimate of flow rate, c) as well as the constant scaling rate (intercept, β). To relate flow rate of outfalls to outfall plume area, we used a modified version of the relationship between plume area and flow rate for rivers:

$$P_o = c * F + \beta$$

(Eq. 2)

where P_o is the outfall plume area, $c=0.015$ is the plume size factor, that is dependent on F, the outfall daily average flow rate, and $\beta=7.48$ is the constant scaling rate. We then apply the same plume model as for river nutrients, where plumes are expanded via a four-neighbor rule until the area of the plume exceeds the calculated plume area (**Figure 1**).

Flow rates (CFS) are derived from the US Hypoxia Task Force Nutrient Model, which includes all point sources (EPA 2020). At the time of our analysis, public outfall data did not include pour point, only the site of the EPA NPDES permit, which is typically at the center of a sewage facility. Thus, we had to estimate pour point location, which varies substantially.

Nutrient Pollution "Hotspots"

We define nutrient pollution hotspots as areas, in 0.2 degree raster cells, of areas with three or more orders of magnitude higher nutrient pollution (annual kg N, P) from rivers, outfalls and deposition compared to baseline nutrient values.

We sourced average nutrient concentrations (kg/yr) in either river or outfall effluent from regional SPARROW models or US Environmental Protection Agency (EPA) NPDES permit reports, respectively. Each of the five regional SPARROW models, Midwest, Northeast, Pacific, Southeast, and Southwest, has slightly different parameters (see Supplementary Information). SPARROW models differentiate between natural and anthropogenic nutrients, to understand the relative contribution we parsed anthropogenic nutrients for each stream reach included in our plume model. Anthropogenic nutrients sources vary by region, but broadly include wastewater, septic effluent, urban and agricultural nonpoint sources such as fertilizer and manure (see SI for complete list by region). Outfall and atmospheric nutrient concentrations were assumed to be entirely anthropogenic in origin.

To represent anthropogenic atmospheric N in US coastal waters, we added N deposition data from NASA ORNL DAAC (Dentener 2006) to our cell specific riverine and outfall based nitrogen loading estimates.

To find the relative contribution from anthropogenic nutrient sources compared to nutrient data, including both natural and anthropogenic sources, from Bio-ORACLE, the load from each cell was calculated by dividing the plumed anthropogenic pollution in each cell by the projected non-anthropogenic concentration of either nitrate or phosphate in each cell using open source datasets available through Bio-ORACLE for average nitrate and phosphate levels (v. 2.1, Bio-Oracle).

Bio-ORACLE data often do not include cells immediately adjacent to coastlines, where the bulk of nutrient loading occurs. To estimate nutrient concentrations in these areas, we interpolated Bio-ORACLE data into these cells using a K-Nearest Neighbor, a supervised classification algorithm where each data point is classified according to its closest data point neighbors (Zamri et al. 2022). We used Euclidean distance to find the best similar data to the group.

We report results across 3 US regions – Northeast, Gulf of Mexico, and Southern California based on hotspots driven by individual sources of anthropogenic nutrient pollution (river plumes, sewage outfalls, atmospheric N deposition).

Uncertainty

In using a generalized plume model and public datasets, there is some uncertainty in our results. We use Bio-ORACLE data, which does not differentiate between naturally occurring nutrients and anthropogenic. Here, we are able to assess the relative load from rivers, outfalls and deposition and compare that to general data of nutrients in a given area. Second, we use a plume size scaling factor for moderate flows. However, plumes from smaller rivers exhibit more energetic temporal variability in response to external forcing, and thus are more variable than larger river plumes (Osadchiev & Zavialov 2020). Third, river plumes typically skew directions based on the Coriolis effect. To apply these generalized models at finer spatial scales, additional plume types should be developed dependent on the dominant plume direction of a given region (Warrick & Farnsworth, 2017).

Finally, outfall pourpoint locations vary substantially. For example, in the Santa Monica Bay, one sewage outfall is 1.6 km offshore while the other is 8 km offshore (Otim et al. 2018). While the generalized plume, in and of itself is effective in some contexts, we could not place most plumes at their pourpoint location. Depth of the outfall was also not available for inclusion at the time of analysis. Outfall plumes are placed at a wide variety of depths in the water column, thus, their plumes are subject to a wide variance of hydrodynamic conditions. However, depending on stratification, vertical mixing can be negligible in some settings (Hunt et al. 2010).

We validate our findings by comparing our results to published literature covering US coastal water quality.

Map Development

Maps were developed using the raster (v. 3.6-3, Hijmans 2003), sf (v. 1.0-1.4,Pebesma & Bivand 2023), rnaturalearth (v. 0.3.3, Massicotte & South 2023), and terra packages (v. 1.6-17, Hijmans et al. 2023) in R Studio version R 4.3.1

1.3 Results & Discussion

1.3.1 Plumes

Our analysis included 73,742 stream and river reaches, with an average plume size of 11 km^2 (median 1.2 km^2, max: 6,505 km^2), and 326 N outfalls delivering an average of 64,886 kg of N (median: 628 kg, max: 10.9 million kg), and 330 P outfalls, delivering an average of 4,485 kg P (median: 2.7 kg, max: 42,338 kg), with an average plume size 3.87 km^2 (median: 7.49 km^2, max: 12.5 km^2) (**Figure 2, b, d**). Rivers have higher annual discharges than outfalls typically do: many rivers deliver more than 10,000 kg N per ~22 km^2 (0.2 by 0.2 raster), while outfalls typically deliver an order of magnitude less (**Figure 2**).

Outfall permit locations are distributed across the US but are heavily concentrated in the Northeast and have less density in the Northwest. Permits releasing N via outfalls were distributed more evenly than permits to release P via outfalls, but generally, both roughly correspond to population density. Of note, there is higher concentration of N outfalls in the northeast, fewer P outfalls in Washington and Oregon and many in the Gulf of Mexico (SI Fig 1A).

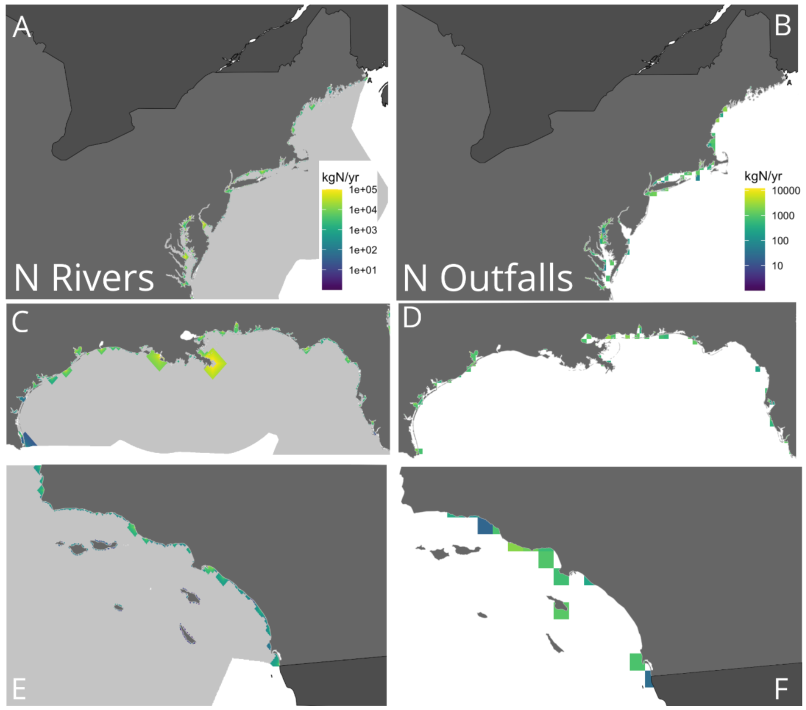


Figure 2: *Nitrogen from anthropogenic sources using generalized plume models: A) riverine N outputs in the Northeast, B) public N outfalls in the Northeast, C) riverine N outputs in the Gulf of Mexico B) public N outfalls in the Gulf of Mexico, D) riverine N outputs in the Southern California Bight, F) public outfall N outputs in the Southern California Bight*

1.3.2 Nutrient Pollution Hotspots Across the US

Areas with the most substantial differences between anthropogenic and naturally occurring nutrients are primarily from rivers, except in the Northeast where differences are commonly driven by industrial discharges and sewage outfalls. Unlike rivers and outfalls which have more localized impacts, deposition of N drives nutrient pollution to all parts of the US ocean (**Figure 3**). Areas within the Long Island Sound, northern Gulf of Mexico, and Santa Monica nearshore environment have larger contributions from anthropogenic nutrients than from naturally occurring N and P (**Figure 4**). The Northeast and Gulf of Mexico have higher anthropogenic nutrient loading at broad scales (**Figure 5**). The Southern California Bight, a

692-kilometer-long stretch of curved coastline that runs along the west coast of the United States and Mexico, from Point Conception in California to Punta Colonet in Baja California, has localized, discrete areas of relatively high nutrient pollution driven by rivers and by several large outfalls.

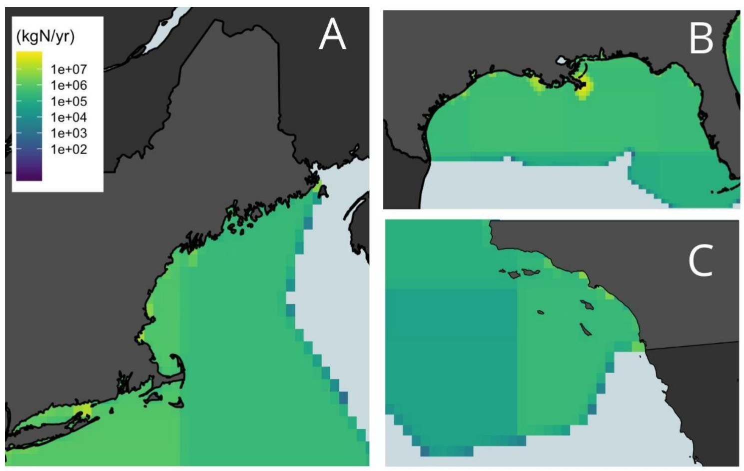


Figure 3: *Anthropogenic Nitrogen from riverine, sewage and atmospheric deposition (kg/yr) (yellow to purple). a) Northeast US from Canadian border to Hudson Bay, New York, b) Gulf of Mexico, c) Southern California Bight, from Point Conception to Mexican-US border*

Outfalls in the Northeast drive relatively high nutrient hotspots, most notably in the Long Island Sound, New York and Massachusetts Bay, Massachusetts (**Figure 3A**). Outfalls in the Long Island Sound contribute more than 110,000 kg of N per year, more than 12% of the historical nutrient budget of the Sound (pre-colonial nitrogen: 899,020 kg (NYSDEC 2000)). Massachusetts Bay has the largest outfall in the US. These hotspots in the Northeast are known to be amongst the 20 most concentrated N by watershed areas in the world, driven in part by sewage (Tuholske et al. 2021). Nutrient loading to the Northeastern Atlantic coast of the US is one of the highest on Earth and has elevated acid deposition influenced by NOx emissions and transformations (Boesch 2002; Howarth 2008; Sickles and Shadwick, 2015).

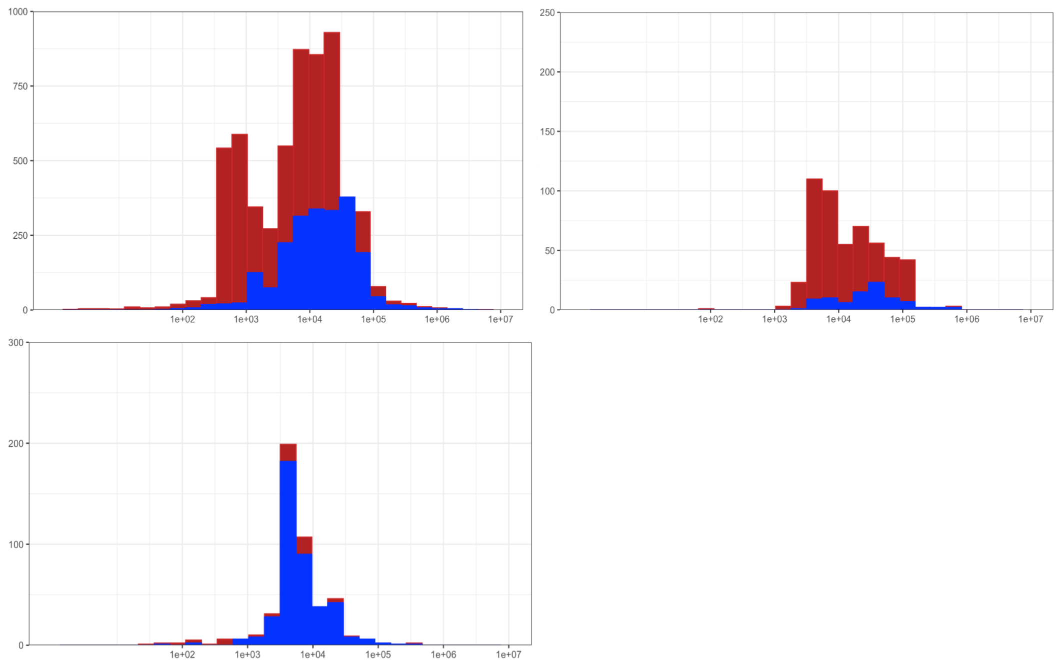


Figure 4*: Nutrient loading per area: blue: anthropogenic nutrients, red: total nutrient data. x axis: Nitrogen input per 0.2 by 0.2 raster cell, y axis: frequency. Top left: U.S. EEZ, Top right: Southern California, Button left: Northeast.*

Nutrients to the Gulf of Mexico are dominated by the Mississippi River, delivering extremely high levels of nitrate that spreads over the Louisiana continental shelf (plume size of >2 million km^2). We find higher levels of anthropogenic nutrients than naturally occurring nutrients in the most concentrated areas of the Mississippi River plume, corroborating contemporary understandings of the Gulf. Previous studies have found that agriculture contributes the largest source of N and P delivered to the Gulf via rivers and outfalls, 71% and 80%, respectively (Porter et al. 2015). The Gulf has low natural phosphate levels, yet receives a fair amount of P via rivers and outfalls (see SI Fig 2). Animal manure is the largest source of P, leaching into rivers and streams, while ~24% of N and 12% of P come from urban and atmospheric sources (e.g. wastewater treatment effluent, septic systems, and emissions from power plants) (Porter et al. 2015).

The Southern California Bight has relatively low anthropogenic nutrients compared to natural nutrients given its placement on the eastern boundary of the North Pacific Gyre and its high rates of wind driven upwelling. Our findings mirror this (**Figure 4**). However, in localized settings anthropogenic nutrients can impact ecosystem functioning even in high nutrient environments (Howard et al. 2014). Estuaries, for example, along the West Coast suffer from annual or persistent water quality issues spurred by high inputs of N and P, including high chlorophyll levels, macroalgal and epiphyte abundance problems, low dissolved oxygen concentrations, loss of submerged vegetation, and HABs (Howarth et al. 2002).

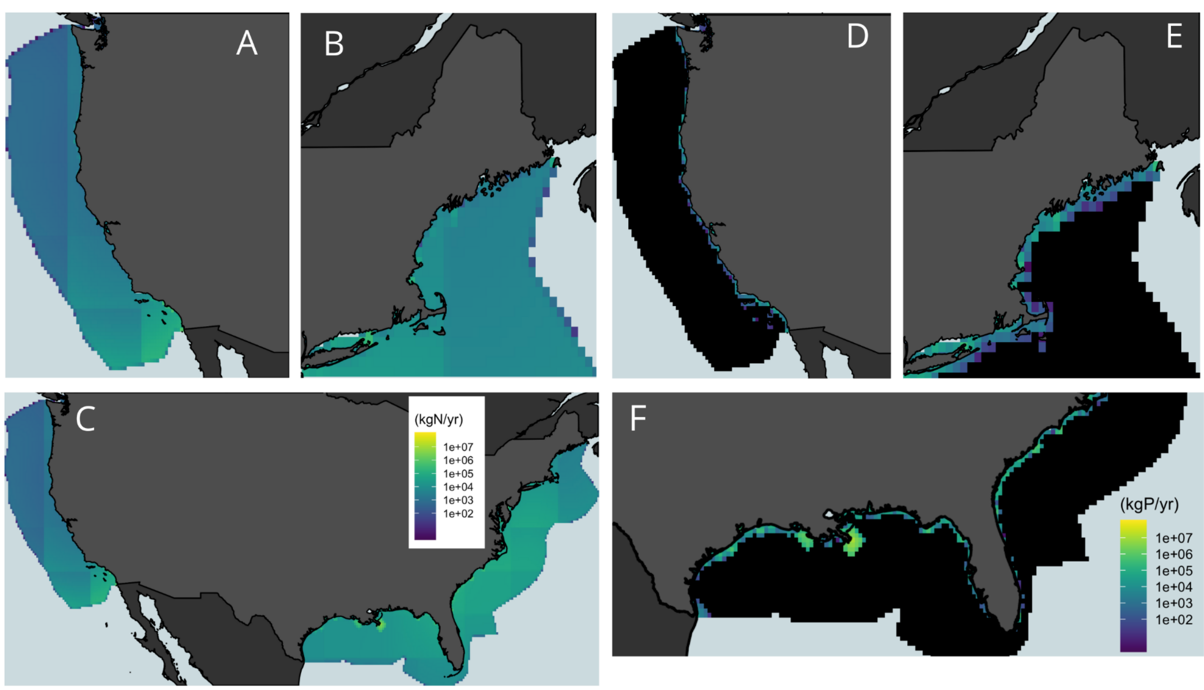


Figure 5: *Anthropogenic N and P as compared to naturally occuring N and P in kg/year (yellow:high, purple: lower): (a-c) N: a) West Coast, from Canadian to Mexican US borders, b) Northeast, from Maine to Hudson Bay, c) US EEZ, (d-f) P: d) Pacific Coast, from Point Conception to Mexican-US border, e) Northeast US from Canadian border to Hudson Bay, New York, f) Gulf and Southern Atlantic Coasts*

Rivers are known to be the dominant source of coastal pollution in Southern California (Warrick et al. 2004). We find that key areas in Southern California, specifically Ventura, Los Angeles, Long Beach, and San Diego have high levels of nutrient pollution due to river and outfall locations (**Figure 2**). Ventura is less than a tenth of the population of San Diego, and 2.5% the population of Los Angeles, yet because of the Santa Clara and Ventura rivers, which flow through substantial agricultural lands, it has one of the highest levels of nutrient pollution in the region. The Santa Clara River in particular releases large anthropogenic nutrient inputs to the eastern edge of the Southern California Bight where the western edge is typically where the most upwelling occurs. Further, storm events typically occur asynchronously to seasonal upwelling. Here, despite high levels of upwelling, anthropogenic nutrients can drive ecosystem changes.

Southern California has some of the largest sewage outfalls in the country, which rival the nutrient delivery of major rivers in the region. In Santa Monica Bay, home to two of the five largest outfall plumes in the US, outfall plume areas are between 112 km^2 and 129 km^2, contributing a collective 21.6 million kg of N per year. These outfall plumes are close in size to the largest rivers in the region. Despite this being an area of upwelling, harmful algal blooms in this region have likely been spurred by anthropogenic nutrient inputs (Anderson et al., 2008). Previous studies have found Los Angeles's outfalls into the Santa Monica Bay, a 50-mile stretch of coastline, have demonstrated impacts from marine outfalls, including impact on benthic communities and immune impairment in vertebrate species from organic contaminants (Otim et al. 2018; Greenstein et al. 2003, Sawyna et al. 2017).

1.4 Conclusion

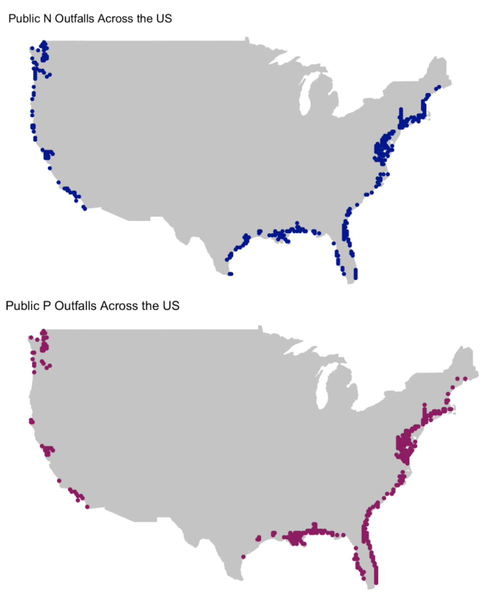
We contribute a novel application of generalized plume models to efficiently analyze the transport and distribution of nutrient pollution relative to naturally occurring nutrients at regional and national scales. We find nutrient pollution hotspots concentrated in the Northeast and in the Gulf of Mexico, areas with relatively low naturally occurring nutrients. However, significant nutrient pollution areas are also identified in localized, high natural nutrient settings driven by both rivers and outfalls (e.g. Southern California).

Our analysis is not without limitations. First, we assess major sources of N and P to coastal ecosystems, but we do not consider other important sources of nutrient pollution. In particular, we do not include groundwater inputs, which can leach substantial quantities of N (Basu et. al. 2022), or deposition of P, which has recently been found to be a critical driver of marine P cycling (Duhamel et al. 2021). At the time of analysis, we did not have access to data for this use. Our hotspots analysis is therefore relatively conservative in that areas identified as having outsized anthropogenic nutrient inputs likely have higher nutrient pollution concentrations than reported here. Second, our analysis is limited to annual averages, however, anthropogenic nutrients have increased potential to drive ecosystem impacts during specific time periods. However, monthly data is available and is an ideal next step.

We see several critical next steps: 1) develop nutrient hotspots analyses with higher temporal resolution to capture intra annual variability and major storm events, 2) develop vertically integrated maps to consider nutrient pollution across a depth gradient within the marine environment, and 3) build additional generalized plume model types that consider additional parameters such as employing plume scaling factors for small and large flows, the outfall position (e.g. depth), local hydrodynamics (e.g. dominant direction of river plume due to the Coriolis Effect).

1.5 Supplemental Information

SI Figure 1: *NPDES Public Outfall Permit Locations. Top: Nitrogen, Bottom: Phosphorus.*



Creating layers for pluming:

River Plume: Nutrient Pollution

This workflow combines the NHDPlus national dataset (stream reach spatial locations) with nitrogen/phosphorous that enters the ocean, as predicted by SPARROW models.

There are 5 regional sparrow models: Midwest, Northeast, Pacific, Southeast, and Southwest. They predict nitrogen/phosphorous loads in streams based on slightly different parameters for each region. Stars indicate anthropogenic source:

Midwest:

Nitrogen

- *wastewater treatment plants **
- *farm fertilizer**
- *manure**
- *atmospheric deposition*
- *urban land**
- *nitrogen fixing crops*

Phosphorus

- *wastewater treatment plants **
- *farm fertilizer**
- *manure**
- *natural sources*
- *urban land**

Northeast:

Nitrogen

- *Wastewater treatment plants**
- *Septic system effluent**
- *Fertilizer**
- *Crop fixation*
- *Manure**
- *Deposition*
- *Urban nonpoint sources**

Phosphorus

- *Wastewater treatment plants**
- *Fertilizer**
- *Manure**
- *Urban nonpoint sources**
- *Mineral erosion*

Pacific:

Nitrogen

- *Scrub and grassland*
- *Atmospheric deposition*
- *Urban land**

- *Spring discharge*
- *Red alder trees*
- *Fertilizer and manure**
- *Wastewater treatment plants**

Phosphorus

- *Channel sources*
- *Weathering of geologic material*
- *Spring discharge*
- *Urban land**
- *Grazing cattle manure**
- *Fertilizer and livestock**
- *Wastewater treatment plants**

Southeast:

Nitrogen

- *Wastewater treatment plants**
- *Farm fertilizer**
- *Manure**
- *Deposition*
- *Urban land**

Phosphorus

- *Natural sources*
- *Manure**
- *Wastewater treatment plants**
- *Farm fertilizer**
- *Mining facility discharge**
- *Urban land**
- *Mined areas**

Southwest:

Nitrogen

- *Deposition*
- *Wastewater treatment plants**
- *Farm fertilizer**
- *Manure**
- *Developed Land**

Phosphorus

- *Channel streams*
- *Developed land**
- *Farm Fertilizer**
- *Natural Sources*
- *Manure**

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Chapter 2: A case for seaweed aquaculture inclusion in U.S. nutrient pollution management

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2.1 Introduction

Deposition of organic chemical and nutrient pollution into the marine environment increased ca. 65% between 2003–2013 globally (Halpern et al. 2019), contributing to over-enrichment, or eutrophication. Eutrophication occurs when nutrients– particularly nitrogen (N) and phosphorus (P) from runoff or aerial deposition – stimulate the growth of algae and drive cascading environmental effects (Breitburg et al. 2018; Laffoley et al. 2019). Enhanced nutrient levels can stimulate the growth and subsequent decay of micro- and macroalgae (Nixon & Buckley 2004), contributing to severe ecosystem impacts, such as noxious and harmful algal blooms, reduced water quality, and low dissolved oxygen (hypoxic/anoxic) conditions (i.e., “dead zones”) (Laffoley et al. 2019; Rabalais et al. 2009). These coastal algal blooms are increasing in frequency, intensity, and scale, with a greater number of toxic species, more fisheries affected, and higher associated financial costs (Heisler et al. 2008). Non-toxic algal blooms, generally composed of *Ulva* or *Sargassum* (Smetacek & Zingone 2013), are also negatively impacting tourism, recreation, aquaculture, and artisanal fisheries

(Smetacek & Zingone 2013). For example, during the 2008 Beijing Summer Olympic Games, an *Ulva* bloom event in Qingdao required 30 million USD for seaweed removal to clear the sailing venue and resulted in ~123 million USD in aquaculture losses (Ye et al. 2011). While no global assessment has estimated the monetary cost of eutrophication (Smtacek & Zingone 2013), individual macroalgae bloom events have cost millions (USD) in removal (Heisler et al. 2008; Smetacek & Zingone 2013; Ye et al. 2011).

Despite promising techniques and tools, current approaches for controlling nutrient pollution are proving insufficient and costly. Pollution control primarily regulates point source pollutants, because they often contribute > 50% of the N and P mass reaching rivers in urban areas (Carpenter, et al. 1998; Preston et al. 2011). Point source control regulations (e.g., limits, fines) are designed to keep pollutant levels below local safety thresholds. However, not all pollutants in wastewater can be removed before treated water is released into the environment (Savage 2011), leading to the accumulation of pollutants at the regional scale. Nonpoint source pollution, including loose soil and excess fertilizer from farms, city streets, and feedlots, is particularly challenging to regulate due to its highly dispersed nature. In typically nutrient-limited water bodies, the resulting nutrient loading can have severe impacts on long-term ecosystem functioning (Rabotyagov et al. 2014). For the U.S. Gulf of Mexico (GoM), the inundation of nonpoint pollutants has led to one of the largest annual marine hypoxic zones on the planet (Rabotyagov et al. 2014). Management systems in the U.S. are insufficiently designed to address the full extent of this growing nonpoint source pollution problem (Rabotyagov et al. 2014), motivating further exploration of including nutrient assimilation in downstream environments.

A natural bio-extractant, seaweed, alongside shellfish, is one of the few available tools for removing nutrient pollution once it has entered waterways. As primary producers, seaweeds remove inorganic nutrients – including N, P, and carbon – from water to fuel growth (Xiao et al. 2017). When seaweeds are harvested, inorganic nutrients are effectively removed from systems. Additionally, seaweeds oxygenate the water column, providing potential refugia from hypoxia and declining oxygen levels (Duarte et al. 2017), and may be able to partially displace nuisance algae blooms (Heisler et al. 2017). Cultivating seaweeds could draw down available nutrients, thereby limiting resources for unchecked growth of wild, nuisance algae, and potentially curbing algal blooms, which rely on exogenous nutrients to be sustained (Heisler et al. 2017).

This paper explores the potential of seaweed aquaculture for nutrient pollution assimilation, using the GoM as a case study. To assess the spatial and economic feasibility of using native seaweed aquaculture, the Hypoxia Task Force (HTF) Goals of reducing N and P pollution 20% by 2025 are used as a benchmark, and financing opportunities including product pathways and water quality trading (WQT) programs are explored. These findings are timely given broadening support for aquaculture in national and state level agriculture and marine policy (e.g., the AQUAA Act (H.R. 6191), Executive Order 13921 on Promoting American

Seafood Competitiveness and Economic Growth, NOAA's efforts to cite Aquaculture Opportunity Areas) (AQUAA Act 2020; NOAA 2020; NOAA Fisheries 2020).

2.2 The Gulf of Mexico as a case for seaweed nutrient assimilation

The GoM exemplifies the challenges associated with eutrophication management: pollution sources can be diffuse and thus hard to regulate across multiple jurisdictions. More than 800 sub-watersheds across 32 states deliver nutrients into the GoM (AQUAA Act 2020). Since low oxygen conditions were first documented in the GoM in 1974, they have persisted, with the areal extent of the hypoxic zone generally increasing each year (Nutrient Task Force 2001; NRC 2012). In 2019, the GoM experienced one of the western hemisphere's largest dead zones on record. Estimated at 18,005 km^2, the dead zone was slightly smaller than the land area of New Jersey (NOAA 2019). The GoM contributes $2 trillion each year to the US gross domestic product (GDP) through ecosystem goods and services, including the production of 14% of the U.S. seafood catch (NOAA 2017). It is also home to half of the nation's coastal wetlands (Dahl 2009). Hypoxia in the GoM, which can cause die-offs and altered migration patterns for numerous marine species, therefore has broad implications for local livelihoods and ecosystem health (Rabotyagov et al. 2014).

The Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, later to become the HTF, composed of federal and state agencies and the National Tribal Water Council, was established in 2001 to develop an action plan to reduce hypoxia in the GoM and to protect inland waters. The HTF outlined and updated two primary goals: reduce the size of the dead zone to 5,000 km^2 and reduce N and P loading by 20% from initial baselines (Hypoxia Task Force 2019). Despite broad stakeholder engagement and supportive policies, federal-state interagency efforts have had limited progress in curbing nutrient pollution. The HTF has since pushed the target year for nutrient load reductions to 2025 and hypoxic areal reductions to 2035 (Hypoxia Task Force 2019). Yet, due to a variety of factors, including capacity and regulatory limitations (NRC 2012), nitrate loading over the past 20 years has been relatively constant, while phosphate loading has continued to increase (Nutrient Task Force 2015). In May 2019, P loads were 49% above the long-term average due to heavier than normal rains (NOAA 2019). Agricultural nonpoint source pollution is responsible for a large majority of nutrient inputs (NRC 2012). Additionally, recent modeling efforts suggest that legacy N, stored in groundwater and other storage areas is a substantial pollution source (Van Meter et al. 2018; Johnson & Sets 2019).

Growing support for aquaculture at the federal and state level in the GoM provides the opportunity to assess the feasibility for seaweed cultivation to address the growing pollution challenge facing the Gulf. For example, Executive Order (E.O.) 1392, signed in June 2020, designated the federal waters of the GoM as one of the first two regions to host future Aquaculture Opportunity Areas (AOA) (NOAA Fisheries 2020). At the same time, several Gulf states have recently expanded their aquaculture industries, including permitting commercial shellfish aquaculture in Texas state waters for the first time (H.B 1300), and the first finfish pilot project proposal in federal waters off the coast of Florida (Murphy 2017).

While Gulf states have an active intertidal and land-based shellfish aquaculture industry, seaweed aquaculture has been slower to develop. In 2018, Gulf states produced 10% of U.S. mollusks by value in intertidal waters and on land in tanks and ponds (USDA 2017). At the time of writing, Gulf seaweed aquaculture operations were limited to two small-scale pilot farms sponsored by the Department of Energy (DOE) off the coast of Texas and Florida (DOE 2017). Limited cultivation is not for lack of suitability. In fact, there are several native seaweed species that would grow well across the region (DOE 2017), and the Gulf's AOA designation was supported by the availability of spatial analysis data and industry interest (NOAA Fisheries 2020). In order to assess seaweed aquaculture's potential to meet HTF 2025 goals – specifically, to reduce nutrient loading by 20%, equivalent to 313,600 t N and 27,460 t P (Nutrient Task Force 2015) – we conducted an assessment of suitable area for cultivation and calculated potential N and P removal by seaweed farm installations relative to HTF goals (Fig. 1, Table S1).

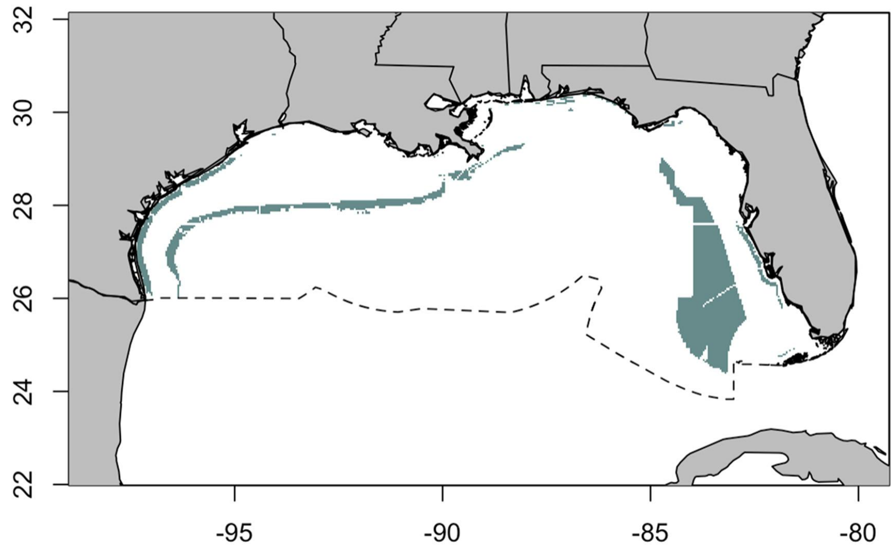

Figure 1. *Suitable area for native seaweed cultivation (green shading) in U.S. Gulf of Mexico waters. Suitability was constrained by major marine activities and biotic factors. Dotted line shows EEZ extent within the Gulf.*

The GoM is a crowded marine space, containing shipping lanes, oil wells, marine protected areas, and military zones. As a first step towards assessing the nutrient assimilation potential of seaweed cultivation, available suitable area was determined for cultivation by compiling open-source spatial data layers on these existing human uses as well as abiotic constraints on three native seaweed species in consideration for future cultivation: *Eucheuma* spp., *Gracilaria tikvahiae*, *and Sargassum* spp. (DOE 2017; Kim 2017) (Fig. 1). In particular, suitability of each candidate species was assessed using temperature, salinity, N:P ratio and depth (various sources; see Table SI). Combining human-use spatial data layers and areas abiotically unsuitable for cultivation, remaining feasible seaweed cultivation area was determined (Fig. 1, Table SII). To note, while *Sargassum* is known to be a pest species in the Caribbean Sea and Middle Atlantic (Wang et al. 2019), it is being grown off the coast of Texas in a pilot project funded by the DOE and thus is included in this analysis (USDA 2017).

In total, > 63,000 km^2 was found to be suitable and potentially available, equivalent to 8.9% of the U.S. GoM EEZ (707,832 km^2 (Sea Around Us)). To reach the HTF N reduction target, less than 2% of U.S. GoM EEZ would be required for cultivation of any of the three species, producing up to 12.5 mmt (dry weight (dw)) (Table 1). However, because P content varies significantly among species, achieving the HTF P reduction target will require between 0.11% and 8.43% of the U.S. GoM EEZ depending on the species cultivated.

Species	Dry Weight	Required Production (mt)	Area Farmed (km^2)	Portion of U.S. GoM EEZ (%)
***Eucheuma* spp.**	0.96% N	32,666,667	10,289	1.45%
	1.08% P	2,542,593	801	0.11%
Gracilaria tikvahiae	3.9% N	8,041,026	7236	0.99%
	0.04% P	6,865,000	59,696	8.43%
***Sargassum* spp.**	2.5% N	12,544,000	12,544	1.77%
	0.3% P	9,153,333	9153	1.29%

Table 1: *Projected production and spatial requirements of farming seaweed (dw) to meet HTF 2025 N and P reduction targets (313,600 mt N, 27,460 mt P) for three candidate seaweed species,* Gracilaria tikvahiae*,* Sargassum spp. *and* Eucheuma spp.

2.3 Diversifying funding through product pathways and water quality trading

Nutrient management interventions for large watersheds typically take years to implement and require substantial investment (Brietburg et al. 2019). Worldwide, approximately $164 billion is spent on water and wastewater treatments annually, with $27 billion spent in the U.S. alone (Goldman Sachs 2008). Despite these large investments in nutrient management, coastal waters across the globe continue to experience significant and growing nutrient loading. The costs of inadequate solutions, both to the receiving ocean ecosystems and the industries that depend on them, are likely far higher than those of effective solutions (e.g. (Goldman Sachs 2008)). This section outlines market opportunities for seaweed aquaculture to become a relatively cost effective, even potentially revenue generating, intervention for remediating global nutrient pollution.

Globally seaweeds have had limited market demand outside of Asia (globally valued over $6 billion (Ferdouse et al. 2018)). However, aquaculture production is projected to double in the next decade due to increased international demand for food, pharmaceutical products, and new product pathways such as biofuels, bioplastics, and textiles (Kim et al. 2019). Novel product pathways are likewise receiving growing support. Since 2017, the DOE has released ~$22 million in funding to accelerate the development of seaweed as a renewable feedstock for biofuel and energy applications (DOE 2016). Seaweeds farmed in areas ideal for nutrient assimilation, i.e., sites with high anthropogenic nutrient input, may have more constrained end product use (i.e., prohibited use for human or livestock consumption) due to the type and concentration of heavy metals (Allied Market Research 2018; EPA 2015). However, even where co-contaminants occur, a diverse set of product pathways may exist, including biofuels, bioplastics, hydrocolloids, fertilizers, building materials, and agars (Allied Market Research 2018).

Additionally, the nutrient assimilation service seaweed aquaculture provides could potentially provide a financing opportunity through WQT programs. WQT programs operate at the watershed level and can include a variety of pollutants, including but not limited to: water temperature, trace metals, N, and P. The promise of these programs is substantial and have subsequently received bipartisan support (BenDor et al. 2021). However, only half of current markets are operational and the establishment of new markets has declined since 2013 (BenDor et al. 2021). Given the U.S. Environmental Protection Agency's recently renewed interest in pursuing WQT programs as a means to meet environmental standards, there may be increased development and greater activity within these markets in coming years (EPA 2019).

The seaweed aquaculture industry is a potentially ideal trading partner for WQT programs. Because seaweeds provide a nutrient offsetting service, sources with high pollution control costs may be incentivized to purchase offsets from seaweed farming operations. This logic is already being applied to the shellfish aquaculture industry, where the first ever trade between a polluter and a shellfish operation were formalized in a WQT market in May 2020 (Chesapeake Bay Bulletin 2020).

Assuming that aquaculture could be similarly formalized as a trading partner in WQT programs in the Gulf, the financing potential of these trades can be assessed as a function of the credit price and the volume of the treated (i.e., assimilated) nutrient. Nutrient credit prices in WQT markets are currently dependent on context and differ with the watershed, market structure, and cost of alternative remediation options. Observed nutrient credit prices vary widely from \$0.09/kg of pollutant up to \$2834/kg (VNCEA 2020; Woodward 2003). Consequently, the cost for WQT markets to finance seaweed aquaculture is estimated as the credit price needed to entirely offset the costs of production – i.e., the "break-even price" – using published production cost values for *Eucheuma spp, Gracilaria tikvahiae* and *Sargassum spp*. Two values were considered in order to bound results: 1) the DOE's target production costs of their seaweed funding program, 80 USD mt/dw) (DOE MARINER 2017) and 2) an average price of industrial-scale, commercially grown seaweed globally, 670 USD mt/dw (see Supplementary information) (Forster & Radulovich 2015; Valderrama et al. 2013; Camus et al. 2019). To entirely offset the costs of production through WQT markets, *Eucheuma* spp. would require a N credit price between \$8.33 and \$69.79, *Gracilaria tikvahiae* \$2.05–\$17.17 per kg, and *Sargassum* spp. \$3.20–\$26.80 per kg (Table 2, Table SIII).

Type of Reduction	Price Range (USD/kg N removed)
***Eucheuma* spp.**	8.33–69.79
Gracilaria tikvahiae	2.05–17.17
***Sargassum* spp.**	3.2–26.80
Wetland	1–81
Drainage water management	3.46–1130
Buffers	4.72–373.44
Cover crops w/erosion controls	6.7–643
Erosion controls	7.12–1039
Nutrient management w/erosion controls	7.92–716
Drainage water management w/erosion controls	8.84–785
Cover crops	10.58–707

Table 2: *The potential costs (USD/kg N mitigated) of alternative nutrient mitigation strategies. Seaweed price range based on DOE's target cost (80 USD mt/dw) (lower bound) and average commercial seaweed farming costs (670 USD mt/dw)(upper bound)*

Water quality managers in the GoM watershed have a variety of alternative remediation strategies available, including nutrient management, drainage water management, erosion controls, cover crops, buffers, and expansion of wetlands (Marshall et al. 2018). These strategies are estimated to cost between USD 1–1790/kg N removed, depending on the location and mitigation technique chosen (Marshall et al. 2018). Therefore, the estimated breakeven nutrient credit prices for seaweed aquaculture are at least on par with the costs of alternative strategies available to managers in the GoM. This outcome highlights the attractiveness of using WQT markets to finance seaweed aquaculture in addition to generating revenue from the sale of seaweed biomass, especially if the cost of seaweed production is reduced. Seaweed cultivation may have additional financing pathways through alternative environmental markets, including carbon offsetting markets, for which seaweeds have garnered significant attention and funding, but those opportunities were not assessed here (e.g. Evans 2020; Pitchbook 2020).

2.4 Key considerations

Introducing seaweed aquaculture to coastal ecosystems requires significant siting considerations, both to maximize nutrient assimilation services as well as to avoid conflict with coastal communities and existing marine industries. While supportive U.S. policies at both the state and federal level are emerging (e.g., DOE "Mariner Program", NOAA AOA, E.O. 13921), social license for aquaculture development may be difficult to achieve (Froehlich et al. 2017).

Seaweed's nutrient assimilation capacity changes significantly across species and environmental conditions (e.g., season, temperature, water clarity, etc. (Kim et al. 2019)). There is general agreement that both N and P need to be controlled in aquatic ecosystems (Marshall et al. 2018), and configuring seaweed aquaculture for nutrient assimilation will require location, temporal, and species-specific policies and design. While there are many ecosystem services that seaweed aquaculture can provide, there are also externalities. Just as farmed seaweeds can be used to reduce eutrophication, they can also divert nutrients away from wild food webs (Grebe et al. 2019). Further, deploying farm infrastructure in the water alters local hydrodynamics and increases the potential for entanglements and the spread of pest species (Campbell et al. 2020; Liu et al. 2013). Species with opportunistic biological attributes, such as sargassum and Ulva, could be grown more safely with sterile strains (Loureiro et al. 2015). More generally, impacts can be minimized through informed siting, farming at lower densities, and rigorous monitoring (Liu et al. 2013; Froehlich et al. 2019). Marine spatial planning is also necessary to maximize nutrient assimilation services while avoiding potential environmental impacts and conflict with existing industries.

This study was not exhaustive in its assessment of siting considerations. Aquaculture expansion in U.S. waters may be limited by other marine activities not included here (e.g. artificial reefs) (NOAA Fisheries 2020). Any recommendation for expanded seaweed cultivation to draw down nutrient loading would require a spatial management plan that determines the area required to meet reduction targets. Because marine and offshore aquaculture is generally negatively perceived by the public (Froehlich et al. 2017), communication with, and public support from communities is essential to receive social license to operate (Krause et al. 2020; Kim et al. 2019).

2.5 Conclusion

Within the U.S. GoM there is substantial suitable area for seaweed aquaculture to augment upstream pollution control with downstream nutrient assimilation to achieve HTF 2025 N and P reduction goals. Compared to terrestrial-based methods of nutrient pollution control, seaweed aquaculture could be more cost effective and potentially revenue generating. An increasingly favorable policy and regulatory environment in tandem with growing market demand and social acceptance makes seaweed aquaculture a promising tool for nutrient pollution remediation, with the potential to alter the course of nutrient pollution in the GoM and around the world. However, to minimize externalities and realize seaweed aquaculture's nutrient assimilation potential, localized development of management practices, continual and rigorous monitoring programs, identification and development of candidate species, and the expansion of effective pollution markets will be required. Use of seaweed aquaculture for nutrient assimilation has significant conservation potential, offering a cost-effective tool for mitigating one of the most pressing anthropogenic impacts on the ocean.

2.6 Supplemental Information

SI Figure 1 We developed the map using QGIS Desktop 3.4.10. Area required for seaweed aquaculture to meet the Hypoxia Action Plan Nutrient reduction goals was calculated using the equation:

$$Aquaculture\ area\ = \frac{Nutrient\ content\ to\ decrease}{\left[(Seaweed\ DW\ \%\ nutrient)*\left(Average\ DW\ yield\ for\ seaweed\ species\ (\frac{mt}{ha}/yr\right)\right]}$$

We found the area required to remove nitrogen (N) and phosphorous (P) by taking an average of dry weight (DW) content of *Eucheuma* and *Sargassum* from published studies (Table S1).

	Eucheuma		***Sargassum***	
Nitrogen	Zheng (2018)	0.46%	Kim et al. (2017)	4.00%
	Kim et al. (2017)	1.7%		
	Freile-Pelegrín et al. (2006)	0.71%		
	Averaged Content	1.08%	Averaged Content	4.00%

Phosphorus	Doty et al. (1987)	0.04% & 0.03%	Hwarng et al. (2004)	Range of values
	Chopin et al. (1990)	0.14%		
	Zheng (2018)	4.10%		
	Averaged Content	0.96%	Averaged Content	0.2%

Table SI: Field studies of *Eucheuma spp.* and *Sargassum spp.* and their reported nitrogen and phosphorus dry weight content.

To reach the HATF nutrient reduction targets, 313,600 t N and 27,460 t P, less than 1% of the Gulf would be required for cultivation. Farming *Sargassum* for nutrient remediation purposes would require 0.07% for N or 0.13% for P of the Gulf of Mexico (1142 km2 or 2001 km2, respectively) to meet HATF targets. Since *Eucheuma* generally has lower N but higher P content, it would require 0.35% for N and 0.01% for P of the Gulf of Mexico (5603 km2 or 131 km2, respectively). By annual volume (dry weight), farming *Eucheuma* for N reduction in accordance with the HATF would require the production of 669,756 mt of seaweed, equivalent to just 4% of China's (the world's largest seaweed producer) current seaweed production. Meeting P reduction targets would require cultivating the equivalent to 98% of current Chinese production (13.9 million t (32)).

Species	Dry Weight %	Reference	Area farmed (km^2)	% Gulf of Mexico	Dry Weight (t)
Eucheuma spp.	See Table SI, N	Freile-Pelegrín et al. (2006); Kim et al. (2017); Zheng (2018)	5603.20	0.35%	28,509,090
	See Table SI, P	Doty et al. (1987); Chopin et al. (1990); Zheng (2018)	131.63	0.01%	669,756
Sargassum spp.	4.00% N	Kim et al. (2017)	1142.86	0.07%	7,840,000
	0.20 % P	Hwarng et al. (2004)	2001.46	0.13%	13,730,000

Table SII: Area required and projected production of farming seaweed to meet Hypoxia Action Plan N and P reduction targets for two candidate seaweed species, *Eucheuma spp.* and *Sargassum spp*.

To visualize water quality impact to the Gulf of Mexico, we used the extent of the 2019 dead zone adapted from N.N. Rabalais, Louisiana State University & Louisiana Universities Marine Consortium; R.E. Turner, Louisiana State University. Funding source: NOAA https://gulfhypoxia.net/research/shelfwide-cruise/?y=2019.

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Chapter 3: Pandemic Era Disruptions Further Entrenched Seafood Purchasing Behaviors

This chapter is in preparation for submission to a peer-reviewed journal with authorship as follows: Phoebe Racine, Micheal Weir, Ashley Bae, Elliott Matthews, Darcy Bradley, Steven Gaines, Matto Mildenberger

3.1 Main

Food systems' growing dependence on consolidated, highly traded commodities, while efficient and cheap, can create fragile supply chains. The United States (US) is a top five seafood exporter and is one of the world's largest seafood importers: 62-65% of US seafood is imported (Gephart et al. 2019), increasingly dominated by a limited set of commodity species – shrimp, salmon and tuna – which can be more easily distributed, marketed, and sold through restaurants (31%) and grocery stores where the vast majority (56%) of seafood is purchased (Gephart et al. 2019; Love et al. 2020). Compounding the food service sector's reliance on commodity species are the dietary preferences of US consumers, who typically purchase only familiar species and products (Witkin et al. 2015). This dependence on a limited set of commodities may leave the US seafood sector vulnerable to supply chain shocks (Cotrell et al. 2019, Stoll et al. 2020).

The COVID-19 pandemic disrupted consumer seafood access by stalling seafood exports and imports, limiting points of consumer purchasing, and changing economic realities of individuals. We use California's novel tiered COVID-19 restriction system as a natural experiment to untether the diverse effects of changing seafood access during the pandemic. California's unique tiered system placed its counties in varying stages of economic openness in response to COVID case loads and positive COVID test rates (CA.gov). This variation in policy across the state allows us to better understand individual level seafood consumption patterns, given shocks to the point of sale, regularity of shopping trips, and purchasing power.

As part of the tiered system, California's food service sector, the largest of any state (76,200 operations in 2018, National Restaurant Association), was under stop and go orders between March 2020 and June 2021. Restaurants, where two-thirds of seafood expenditures occur in the US (Love et al. 2020), were either closed entirely to dine-in business or were under imposed capacity limits. Restaurant closures and restrictions (hereafter, "closures") provided a unique chance to isolate the effect of restaurants on seafood consumption patterns.

Publicly-funded assistance programs, including food assistance, unemployment benefits, and economic impact payments, were broadly expanded at both the state and federal level. Perhaps most substantially, CARES Act funding expanded both who could receive unemployment payments and the amount received, which California supplemented, amounting to a $767 unemployment supplement per week from late March 2020 to September 2021 (CA EDD). California lost nearly 2.8 million jobs due to the pandemic, with a peak unemployment rate of 16% in April 2020, resulting in $133.8 billion in federal unemployment funding to Californians from 2020-2023 (CA EDD; DOL). This brought substantial, and varied, additional individual-level funding into California counties, with some inland, rural, and agricultural counties facing unemployment rates higher than 25% (versus 4.2% pre-pandemic (BLS)). This temporary and dramatic shift in purchasing power provided an opportunity to better isolate the impacts of assistance programs from consumer attitudes.

The pandemic had a heterogenous impact on the seafood sector, which included price collapses of major seafood markets (Amos et al. 2022), reduced production (e.g. FAO Globefish 2021 (1st issue); FAO Globefish 2021 (3rd issue)), stalled trade (Gephart et al. 2020), and boons in sales in some retail environments. However, retailers sold more fresh, frozen and canned seafood and local and alternative supply chains expanded (IRI and 210 Analytics; Garnett et al., 2020; Love et al., 2020, Stoll et al. 2021). How these external factors will affect long term purchasing behaviors is less understood. Dietary habits can serve as a proxy for purchasing behaviors and provide a nuanced understanding of consumer choices (Love et al. 2020). Given the commoditization of a limited set of species, US seafood consumers have settled into particular consumption patterns that vary by species, region, and retail outlet. For example, most shrimp in the US is purchased through food services, while most salmon is purchased for at-home consumption (Love et al. 2020).

California has some of the highest seafood consumption in the country (by total volume), dominated by similar species (e.g. shrimp, salmon, tuna) to the rest of the US (Love et al.

2020, **Figure 5**). However, California has the highest fresh and lowest frozen seafood sales of any state (Love et al. 2022). These products are on opposite price scales, with fresh seafood being sold at a higher price point and with a wider array of species available. Knowing that "old habits are hard to break," particularly for seafood consumption (Witkin, Dissanayke, and McClenachan 2015; Scholderer and Trondsen, 2008), tracking changes in consumer choices in response to an external supply shock allows for insight into how seafood access differentially shapes seafood consumption patterns.

In this effort, we distributed a survey among a panel (N=464) of seafood consumers across California from August 2020 to August 2021 in six month intervals to collect data on preferences, attitudes, and seafood purchase behaviors across the pre-, during, and post-food service sector restrictions and varying levels of economic assistance. We recruited the panel approximating a cross section of California using Facebook Quota Sampling (**Figure 3**). Our survey took an average of 13 minutes and consisted of up to 40 dynamic questions.

Dietary recall data, in combination with county-level pandemic restriction measures and unemployment data, provide a unique opportunity to identify the causal effects of food service restrictions and level of economic assistance on quantity, makeup, and diversity of seafood consumed before and during the pandemic. We use a two-way fixed effects model to identify marginal shifts in consumption behavior as a function of food service restrictions and county-level factors. In parallel, we investigate consumption patterns using network analyses to understand what species are most commonly consumed together and their shifting relationships through the pandemic. This approach offers a causal understanding of the effects of seafood access on nuanced *individual* purchasing behavior, which has received limited attention relative to aggregate consumption patterns.

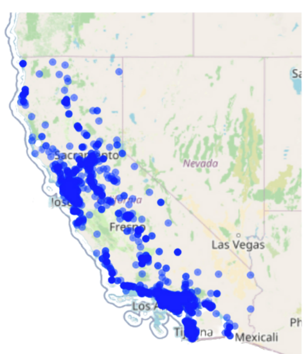
3.2 Methods

To explain shifts in seafood consumption due to changes in seafood access, we developed a one year panel with sample periods every six months tracking seafood consumption across California from July 2020 to August 2021. We assess relationships between species using network analysis, explore demographic drivers of seafood consumption using linear regression, and employ two way fixed effects models to causally explain the effect of pandemic policies and shifting attitudes towards seafood on seafood consumption. To account for the diversity of seafood species survey respondents consumed, we used three measures of diversity: species richness, Shannon Index and Simpson's Diversity Index.

Recruitment using Facebook Quota Sampling

We recruited survey participants using Facebook quota sampling (Zhang et al. 2020) in July-August 2020 (August 2020: 1,634, February 2021: 653, August 2021: 618, complete panel: 464). Convenience sampling methods that do not set demographic quotas can produce non-representative samples. To get a general sample of California seafood consumers, participants were recruited via Facebook ads targeted at individuals who, according to Facebook's algorithms, live throughout California and fall within 4 demographic variables: age, sex, race, and quadrant of California (*see appendix X*). We dropped any population group that represented less than 1% of the total population (based on ACS 5 Yr). Strata over 1% of the population with a combination of four location groups, two genders, four racial groups, and three age groups, generated 33 possible strata. We resampled on educational attainment and by location as our sample underrepresented those who did not have higher education degrees. We generated an additional eight strata, two educational groups, and two geographic areas: inland and coastal counties. We oversampled for rural areas given the importance of county level COVID-19 policies.

Survey participants skewed more female, wealthier, more educated, and more Democrat than the California population. Survey participants (survey round 1), were from 53 of the 58 California counties (**Figure 3**).



Variable	Sample	California Pop
Mean Age (years)	43	37.3
% Women	66%	50.3%
% White	70%	71%
Households making less than $25k	>10%	15.5%
% Democrat	65%	46.1%
% Urban (>500 people/mi2)	80.3%	94%

Figure 3*: Left: August 2020 survey responses (n=1,634) compared to California's population. Right: Table of survey (Round 1) sample compared to California population across key demographic indicators*

Survey Instrument

The survey instrument was developed using Qualtrics. It included 40 dynamic questions and took a mean time of 13 minutes (Qualtrics, Provo, UT). Questions included seafood history, seafood consumption (reflection on previous 4 weeks, including seafood meals, species, and volume of species), where seafood was purchased (reflection on previous 4 weeks, including following questions on restaurant purchases), concern for catching and spreading COVID-19, financial wellbeing, an experimental question to capture bias reporting number of seafood species consumed, and demographics including political ideology (see SI Appendix II).

Data

We used publicly available data by county to match COVID-19 related restrictions on the day a respondent took the survey (Yale), weekly average COVID-19 caseloads per 10,000 (CHHS), monthly average unemployment rate (EDD) and temperature and total rainfall in a given month (NOAA via Augusta Chronicle).

We group several sets of species for analyses: nori, ogo, kombu, and wakame into “seaweeds”; whitefish, cod, halibut, catfish and fish into “whitefishes”, and halibut, rockfish, white seabass, spiny lobster, and Dungeness crab into local species. We cannot verify if the species in origin is local, however, these are the most common set of local species to California that we measured (Get Hooked).

Data Processing

We account for outliers by winsorizing specific variables at the 95th percentile: total seafood purchases, total volume, species richness, number of species cooked at home for the first time, and Shannon Diversity Index. Simpson’s Diversity Index was winsorized at 10%.

To account for missing data, we used multiple imputation using Fully Conditional Specification implemented by the MICE algorithm (described in VanBuuren and Groothuis-Oudshoorn (2011)). We used multiple imputation for variables with less than 10% missingness (see SI Table 3). For continuous data we used predictive mean matching, binary data were imputed via logistic regression, unordered categorical data were imputed using polytomous logistic regression and ordered categorical data were imputed using a proportional odds model.

Our measure of concern for catching and spreading COVID-19 was developed reflecting the current understanding of how the disease was caught and spread. However, over time this question had less relevance to current understanding, and thus by August 2021, 33% of survey participants (n=208) skipped the question. We did not impute this question, but have included concern of catching and spreading COVID-19 in the two way fixed effects models. Two way fixed effects models listwise delete any rows with missing data. We find that those who answered the COVID concern question had better financial wellbeing and were older, but responses to seafood consumption questions were not significant (see SI Appendix II).

In winsorizing outliers, power was lost in most cases, however, after winsorizing outliers, restaurant closures had a significant effect on seafood purchases, whereas before, restaurant closures were moderately significant (SI Appendix III & SI Table 8, 19). Minimal changes occurred in incorporating imputed data, in some cases power was lost, for example when using non-imputed data, restaurant closures had a significant effect on volume of seafood consumed.

Diversity Indices

We employ two diversity indices, the Shannon Diversity Index (H), which is used to capture proportional abundance of species, and the Simpson's Diversity Index (D), which measures the probability that two individuals randomly selected from a sample will belong to the same species. The Shannon Index assumes all species are represented in a sample and that they are randomly sampled. It is an information statistic that accounts for species richness more than Simpson's Diversity Index, and it gives more weight to less common species. Simpson's Diversity Index gives more weight to abundant species in a sample. The addition of rare species to a sample causes only small changes in Simpson's Diversity Index value. We use both these as measures of seafood consumption diversity, then include them in fixed effects models as dependent variables to assess what drove shifts in proportional and relative abundance of species over time. We use the vegan package (v. 2.6-4, Oksanen, J. 2022). Simpson's Index and Shannon Index both have increasing diversity with higher numbers.

Shannon Diversity Index

$$H = -\Sigma pi * \ln(pi)$$

Where Σ is the sum of *pi,* the proportion of the entire community made up of species i, multiplied by the natural log (*ln*)

Simpson's Diversity Index

$$D = \Sigma(n/ N)^2$$

Where n is the total number of organisms of a particular species and N is the total number of organisms of all species.

Network Analyses

We use network analyses to help define what diversity means in this context and to describe relationships between species. Network analysis is a set of integrated techniques to depict relations among actors and to analyze the relationship structures that emerge from the recurrence of these relations. Network analysis visualizes the relationship between species that were consumed by the same person over the past month (**Figure 1**). We combine functions from the igraph (v. 1.3.5) (Csardi & Nepusz (2006)), the ggraph (v. 2.1.0) (Pedersen T (2022)), and the tidygraph (v. 1.2.2) (Pedersen T (2023)) packages.

Two Way Fixed Effects Models with Standard Errors by Clustered by County

We used a two way fixed-effects regression approach that estimated the effects of county level pandemic policies and attitudes towards seafood on seafood consumption for the same individuals, *i*, at different time points, *t*, using the package fixest (v. 0.11.1) (Bergé 2018).

Two way fixed effects controls for demographics and other stable factors that may influence an individual's seafood purchasing and consumption and controls for secular changes in the economic environment that have the same effect on all units.

$$Y_{it}=\alpha_i+\gamma_t+\beta X_{it}+\varepsilon_i$$

Y = seafood purchasing/consumption (e.g. kg of species, Shannon Diversity Index, Species richness)
X= time-varying independent variables:
County level: restaurant restrictions, unemployment rate, average monthly temperature, average monthly rainfall,
Individual level: COVID risk tolerance, financial wellbeing, attitudes towards seafood (feeling that seafood is "too expensive", ability to judge the quality of seafood, comfort cooking seafood)
i = survey participant
t = 3 time points: Aug 2020, Feb 2021, Aug 2021
B= coefficient
α & γ = unit and time fixed effects
ε= error term

At the county level, we included restaurant restrictions, unemployment rate (month), COVID cases per 100,000 (daily, on the day the survey participant took the survey) and weather, including average monthly temperature and total precipitation. We included individual COVID risk tolerance, financial wellbeing and individual attitudes towards seafood to account for individual response to shocks. Outcomes variables include: where and how many seafood purchases were made, number of species eaten per month, volume of species eaten per month, Shannon and Simpson's diversity indices, species cooked at home for the first time, and attitudes towards seafood.

We cluster standard errors by counties to account for correlation within county level variables (e.g. restaurant closures and COVID case loads).

Attitudes towards COVID-19 were not an important predictor in the two way fixed effects models, but it was very important to control for given wide ranging individual behavior and attitudes towards COVID-19. Similar, financial wellbeing did impact purchasing of some products, but was otherwise not a critical predictor but served as an important control.

3.3 Results & Discussion

3.3.1 Descriptive Statistics

On average, survey respondents purchased seafood a little more than once a week, reported eating seafood once a week, and consumed a median of 1.63 kg (mean: 2.3 kg) of seafood per person per month. Our findings are largely consistent with seafood consumption studies using dietary recall data, though survey respondents here likely consumed seafood more frequently and at higher volumes than the general population. Survey respondents recalled eating 5 species per month on average, and a mean Shannon Diversity Index of 1.47 and Simpson's Diversity Index of 0.71 (**SI Figure 4**), which indicate a moderately high degree of diversity/heterogeneity for these indices (Ortiz-Burgos 2016; Guajardo, 2015). There was an initial spike in cooking a new species at home for the first time in August 2020 (22.5%). In each subsequent survey, more than 18% of respondents reported cooking a new species at home.

Our results for species most commonly eaten and eaten in the highest volume are similar to those from the National Health and Nutrition Examination Survey (NHANES) (2007-2016) by the Center for Disease Control. Salmon, shrimp, and tuna remained the most popular species through the survey time period; around half of survey respondents reported eating shrimp and salmon. Alaska pollock, "fish" and clams are also within both top 10 lists (Love et al. 2020, Table 4).

Those making more than $50,000/yr. eat more seafood (see SI App. IV), this is consistent with prior studies that found income level to be one of the most important drivers of seafood consumption, with lower income levels associated with less seafood consumption (Love et al. 2022; Love et al. 2020). Consumption of some species (e.g. seaweeds) fall deeply along ethnic lines.

3.3.2 Seafood Consumption Networks

We use network analysis to visualize the number of species consumed, the relative abundance of species (size and darkness of circle "nodes") and the relationships between species (size and darkness of lines "edges") consumed by the same person over the previous month. Species with darker and larger edges between them co-occur more frequently. Through the course of the survey time period, shrimp, salmon and tuna have the highest degree centrality, the measurement of direct connection of a node with its neighbors. Shrimp, salmon and tuna are consistently the most commonly eaten and the most frequently eaten among other species. Some species have distinct consumption patterns and relationships, for example, catfish has little connection to crab, and sole has little connection to sardines. In August 2020 (N = 1,634), 62 species or species groups were reported with >70,000 connections among them (**Figure 1, see SI App. V**) and "fish" had a near average number of occurrences yet had the highest closeness, the degree to which a node is near to all other nodes in a network, given that it was most typically eaten by people who also ate other species. In February 2021, there were fewer connections per person, salmon overtook shrimp in popularity and nori was more widely consumed (**Figure 1**). By August 2021, there were fewer survey participants yet there were more connections between species (**Figure 1**). This was likely due to survey participants with higher seafood consumption disproportionately remaining in the survey. We control for individual preferences using fixed effects models.

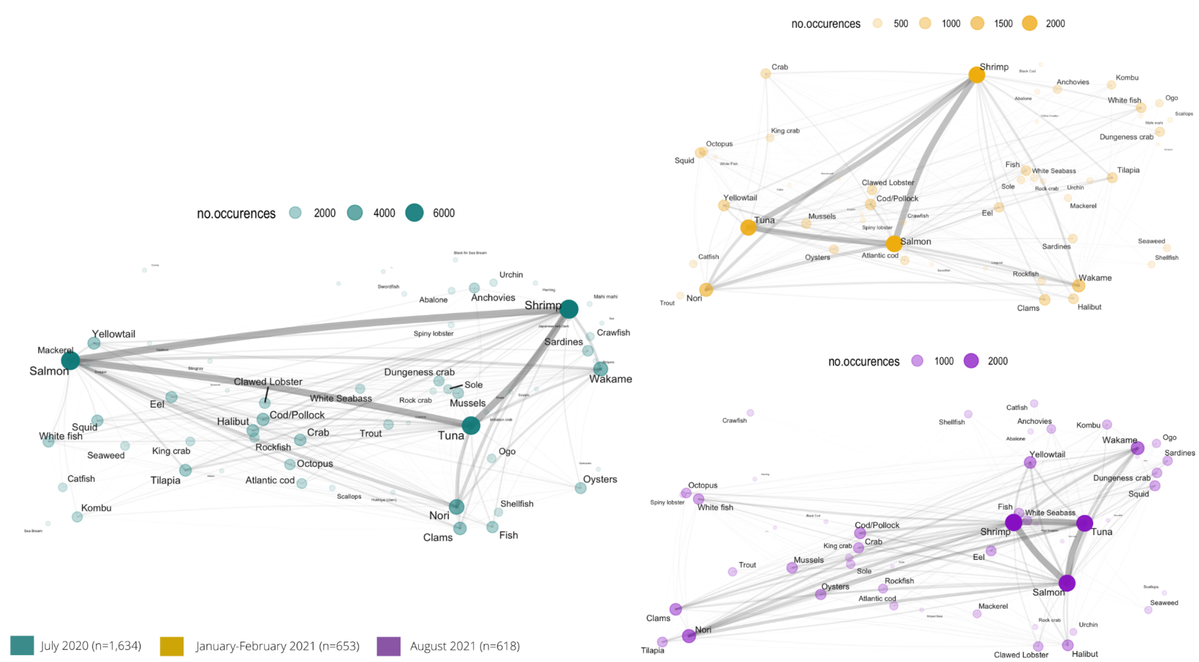


Figure 1: *Network analyses showing relationship between species the same individuals consumed within the previous 4 weeks, larger nodes (circles) indicate species has more occurrences, larger edges (lines) indicate a stronger relationship between species, each color corresponds to a survey time period.*

3.3.3 Shifts in Seafood Access Disrupted Seafood Consumption

Pandemic disruptions spurred dramatic shifts in seafood purchases and for the most part deepened existing purchasing trends of seafood species and products.

We found that restaurant closures and partial closures resulted in 12% fewer seafood purchasing trips (N=0.7 (SE = 0.2) fewer seafood purchases per month), a 47% decrease in restaurant purchases (compared to average purchases per month, N=0.9 (SE=0.3)), and shifted consumption of specific species and specific seafood products (**Figure 2**). Shrimp and salmon consumption had opposite responses to restaurant closures. The amount of shrimp consumed per month declined by 32% (= more than a serving; 4.96 oz, SE = 1.1 oz) (serving: 4 oz. (USDA)), while salmon saw a 40% boost (= more than 1.5 servings; 6.3 oz. (SE= 1.5 oz)) (**Figure 2B**). These differences are consistent with shrimp and salmon consumption patterns: an outsized share of shrimp is eaten at restaurants, while 70% of salmon is consumed at home (Love et al. 2020). By contrast, the effects of restaurant closures on tuna were heterogeneous. Tuna is a category containing several very popular species which result in very different products. Most tuna is sold canned, however, a growing portion of tuna is sold fresh through food service (Love et al. 2022; Supermarket Perimeter). Restaurant purchases drove down consumption of tuna, however, in times and places with higher COVID-19 cases, more tuna was consumed. Similarly, in times and places with higher caseloads, more grocery purchases were made.

We found more shelf stable products were purchased by those who consider seafood price ("too expensive") and found a moderate boost to canned seafood sales caused by restaurant closures (**SI Figure 4**). This reflects findings from previous studies which found that canned (of which 75% is tuna) and shelf stable seafood is typically purchased more in recessions and in times of inflation (Love et al. 2022, Seafood Source). Restaurant closures also led to an increase in frozen and live seafood purchases, potentially due to the survey period's overlap with Lunar New Year (Thapa et al. 2015).

Higher COVID-19 cases resulted in less grocery store purchases, less purchases from alternative seafood sources (i.e. direct, Farmer's Markets, Community Supported Fisheries (CSF), less seaweed (i.e. nori, wakame, ogo, kombu) consumed and more tuna (spp.). For every additional 100 COVID-19 cases per 100,000, there were 1.2 (SE = 0.05) fewer grocery store purchases (**Figure 2**), 1.4 fewer alternative seafood purchases, 7.9 oz (SE = 0.38 oz) more tuna purchased, and 5.8 oz (SE = 0.27) less seaweed consumed. Concern for catching and spreading COVID-19 resulted in more grocery store purchases and fewer restaurant purchases.

There was substantial variation among counties in the amount of individual stimulus funding (e.g. August 2020, range by county: minimum: 6.5%, maximum: 23.8%). Counties with higher funding had: a higher quantity of seafood purchases, more seafood eaten by volume, and more local species consumed. Similarly, higher unemployment had a moderate positive effect on seafood purchases from delis (i.e., ready-made food counters) as well as fresh seafood products. To note, better financial wellbeing led to more fresh seafood purchases, which have a significant price premium compared to other seafood products (Love et al. 2022). This reflects findings that CARES Act payments reduced food insecurity by 35% (Raifman et al. 2021). Similarly, unemployment benefits expansion in combination with an increase in food assistance benefits in California may have played a role in reducing food insecurity through the pandemic (Molitor et al. 2021). Unemployment rate had a moderate negative effect on frozen seafood product purchases, deepening California's trend of consuming the least frozen seafood per capita of any state (Love et al. 2022).

3.3.4 Personal Relationship with Seafood is the Most Pervasive Driver of Seafood Consumption

Shifts in seafood access due to the pandemic did not affect diversity of consumption. However, attitudes towards seafood did (**SI Figure 4**). For example, comfort in cooking seafood led to 16% more species consumed. Diversity of seafood consumption is not well characterized, although multiple studies have found North American seafood consumers purchase a limited number of species (Witkin, Dissanayke, & McClenachan 2015). However, diversity of consumption is a sign of increased economic security and wellbeing (Godfray 2011).

Some measures of seafood consumption were changed due to shifts in seafood access, however, attitudes towards seafood were consistently important across almost all measures of consumption. Comfort in cooking seafood significantly influenced seafood purchases overall, with 0.9 (SE=0.29) more purchases (16% increase from mean seafood purchasing) made per month, and more purchases from grocery stores and alternative seafood sources. Those who are comfortable cooking consumed 5 more servings of seafood (21 ounces (SE = 4.2 oz)). Comfort in cooking seafood additionally resulted in more consumption of most species, except seaweeds, and more seafood product purchases of all kinds, except deli and take-out (i.e. purchased from restaurants to take away).

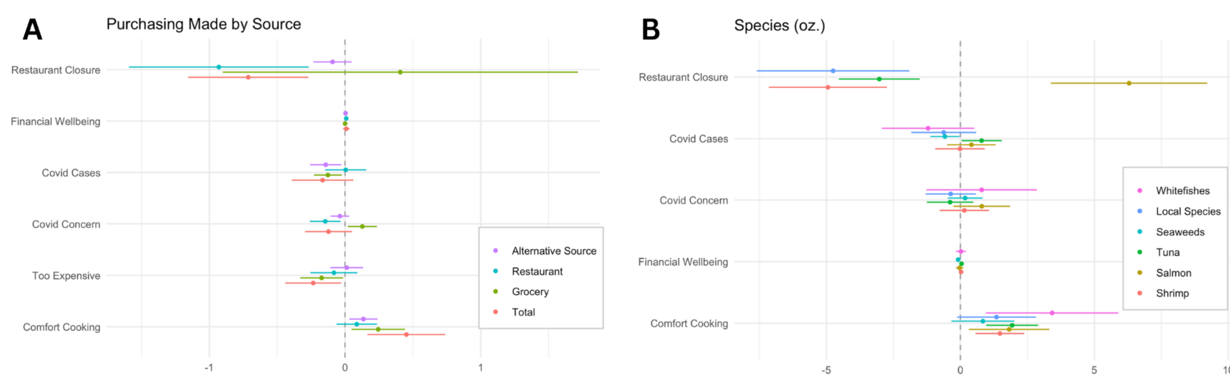


Figure 2*: Coefficient plots of two way fixed effects models (August 2020-August 2021) with COVID-19 related predictors and attitudes towards seafood, circles are estimates and lines span 95% confidence intervals. A) Purchasing of Seafood Products, B) Species consumed (lbs.). Predictors: Restaurant Closures (0: open, 1: closed), Financial Wellbeing (score between 0-100), Covid Cases (cases per 10,000), Covid Concern (0-3 scale: not concerned to most concerned), Too Expensive: measure of viewing seafood as "too expensive" 0: no, 1: not sure, 2: yes, Comfort Cooking: 0: no, 1: not sure, 2: yes.*

Viewing seafood as "too expensive" influenced how often someone ate seafood (**SI Table 4**). Conversely, financial wellbeing did not have a substantial impact on seafood consumption and only significantly impacted some seafood product purchases. Financial wellbeing and viewing seafood as "too expensive" both impacted purchases of specific seafood products: more canned and frozen seafood was purchased by people who view seafood as "too expensive", while more fresh seafood purchases were made by those with better financial wellbeing (**Figure SI 6**). This falls in line with seafood price and findings from previous studies: fresh seafood has higher price premiums over frozen and canned seafood products, and fresh seafood sales generally increase with household incomes (Love et al. 2022).

3.4 Conclusion

Our results demonstrate that constraints on seafood access by the COVID-19 pandemic shifted consumption in key ways, by changing where and what seafood was purchased. However, even in the face of a global pandemic, the portfolio of the top consumed species experienced little change. Nuanced purchasing behaviors, such as purchases of specific species and products were further entrenched by pandemic-era disruptions to seafood access. Diversity of seafood consumption remained unchanged from restaurant closures and unemployment rate, shifting instead in response to individual attitudes. While this provides stability to a commodity driven sector, it contrasts with recommendations emerging from nutrition studies that call for seafood consumption diversification via incorporation of local, seasonal, and lower trophic level species and highlights the importance of seafood education and literacy campaigns in achieving this goal (e.g. Willett et al. 2019). Previous studies have found that while there are barriers to diversification of species consumed, consumer preferences may be malleable, suggesting a long-term potential to shift demand provided consumer education occurs (Witkin Dissanayke, & McClenachan 2015). We find that many consumers do engage with a diverse set of seafood species (**Figure 1**), which could broaden given increased seafood exposure and education.

A personal relationship with seafood emerged as the most common and sometimes critical driver of seafood consumption. Those who already felt comfortable with cooking seafood, or were able to judge seafood freshness, continued their relationship with seafood and sometimes increased their seafood consumption. Attitudes towards eating seafood is well documented to be positively correlated with seafood consumption frequency (Carlucci et al. 2015, e.g. Birch & Lawley 2012), and some studies have found attitudes towards seafood are the most important predictor of seafood consumption (Carlucci et al. 2015, e.g. Verbeke & Vackier 2005). Comfort in cooking seafood and ability to judge seafood freshness resulted in higher seafood purchasing and higher seafood consumption across most species and products and was a critical driver of diversity of seafood consumption. Given time, resources, and seafood education, people have the potential to eat in a way that is more reflective of dietary guidelines and federal goals to develop stronger domestic markets (NOAA 2023). Seafood education campaigns have been effective in driving increased seafood consumption (Greiger, Miller, Cobiac 2012), and previous studies have found that increased seafood literacy correlates with more robust domestic seafood markets (Cusa et al. 2021). To increase and diversify seafood diets, as well as to develop regional and local markets, seafood education programs should receive additional attention.

Our study had some limitations. First, we did not include a measure of seafood prices. Inflation increased 5.3% from August 2020 to August 2021 which impacted purchasing overall, driving declines in fresh and frozen seafood sales and driving up purchases of shelf stable seafood (BLS; Seafood Source). However, county-level food sector inflation data were not available at the time of publication. Second, we adapted questions on financial wellbeing from the Consumer Finance Bureau, however, we did not include their full set of questions. This would have been useful to compare more meaningfully to other studies and more accurately use the Consumer Finance Bureau score. Third, by not including a question in the survey about employment status, we could not directly measure the effect of unemployment related CARES Act payments on seafood consumption.

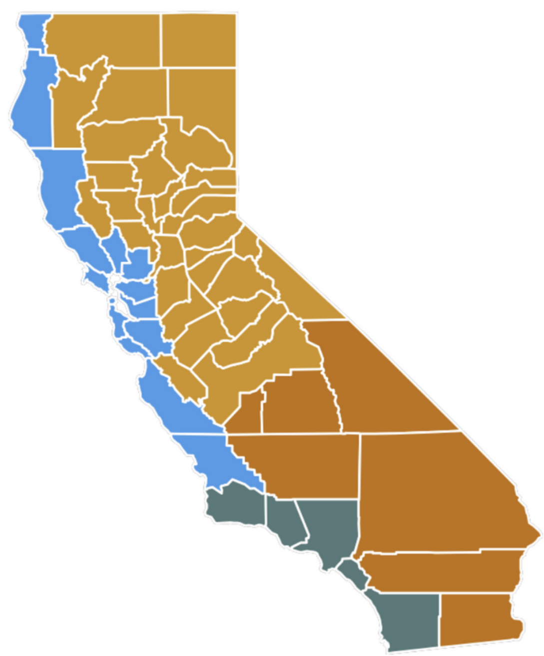
Finally, we used a combined measure for alternative seafood markets, which are by nature, very diverse supply chains. We grouped Farmer's Markets, direct seafood purchases from fishers and farmers, and Community Supported Fisheries together and found that COVID-19 cases had a negative effect on purchases from alternative seafood markets. Prior studies saw a boost in direct seafood sales and CSFs during the pandemic (Stoll et al. 2020), but our study was not designed to capture changes in these markets individually. Given the diverse ways alternative seafood supply chains reach consumers (e.g., mail, in person market, home delivery), findings here are not fully conclusive and future research should be undertaken to understand the long term effects on local and alternative supply chains, which are critical for domestic market development.

Ultimately, disruptions to seafood access caused by the COVID-19 pandemic have produced dramatic shifts across key aspects of seafood consumption, notably, shifts in seafood access resulted in further entrenchment of nuanced purchasing behavior. However, the pandemic did not conclusively cause seafood consumption consolidation or expansion.

3.5 Supplemental Information

Appendix I: Facebook Quota Sampling

Using methods developed by Zhang et al. 2018, we used quota sampling to recruit respondents using Facebook advertisements to approximate population-level public opinion. Zhang et al. had two primary findings, 1) their results from the Facebook-sampled survey are similar to those from a high-quality, commonly used online panel survey, and 2) results from the Facebook-sampled survey approximate results from the American Community Survey (ACS) for a set of validation questions (Zhang et al. 2018). Facebook quota sampling is radically less expensive than survey services, which pay participants, has similar quality, and has some notable strengths. First, this approach allows quota sampling on conditional strata (Zhang et al. 2018). Second, individuals who decide to take a survey on Facebook have buy-in, and thus are more likely to continue participation in future surveys and are likely motivated to fill out the survey well. As for cost, Facebook recruitment was one-eighth of the price of administering a singular survey and allowed for free follow-up.



SI Figure 1: Map of four advertising target areas across California

In order to secure a diverse sample given a constrained advertisement budget, we employed quota sampling to target demographic subgroups, or strata. Convenience sampling methods that do not set demographic quotas can produce non-representative samples. To get a general sample of California seafood consumers, participants were recruited via Facebook ads targeted at individuals who, according to Facebook's algorithms, live throughout California and fall within 4 demographic variables: age, sex, race, and quadrant of California (SI Table 1). We dropped any population group that represented less than 1% of the total population (ACS 5 Yr). Strata over 1% of the population with a combination of four location groups , two genders, four racial groups, and three age groups, generated 33 possible strata. Later, we resampled on educational attainment and by location as our sample underrepresented those with some high school and highschool educations. We generated a total of 8 strata, two educational groups, and two geographic areas: inland and coastal counties.

SI TABLE 1: *Demographic Characteristics Used to Generate Strata*

Demographic Categories	**Subgroups**
Four areas of California	North Coast, Inland North, South Coast, Inland South
Gender	female, male
Race	Asian American, Black, Hispanic/Latinx, White & Other
Age Group	18-34, 35-64, 65+
Educational Attainment	No high school diploma or GED, High school

Quadrants of California were divided by those bordering the coast and those that had no coastline, and then roughly by population (SI Figure 1). Age group was based on ACS 5 Yr, race was broken down according to Facebook's "Multicultural Affinities." "Multicultural Affinities" is meant to designate a user's "affinity" with racial and ethnic groups, rather than assign them to groups reflecting their actual race or ethnic background (Hitlin & Raine 2019).

Sampling ran July 20th- August 19th 2020. Each California area (four total) was targeted with an ad that is specific to that quadrant (SI Figure 1). Ads were identical save for the highlighted area on the map and specification of location, "coastal" or "inland". We used metadata to track which ad brought individual survey takers in.

Limitations & Assumptions

Zhang et al. 2018

Active Facebook users, and those more likely to click on ads, skew older (Guess 2022). Those who participate in a UC study are likely to have higher educational attainment. Facebook users who do not understand English – who are also more likely to be born outside the U.S. – cannot participate in the survey. Using Facebook's ad platform has limitations for research reproducibility as Facebook continually updates their ad platform. At the time Zhang et al. 2018 was published, advertisers could target ads based on race. In a court ruling, this was deemed discriminatory. Facebook changed their race categories to "multicultural affinities." Three weeks into our first sample period, August 11, 2020, Facebook removed "multicultural affinities" (Facebook 2020), as this was seen largely as a way to target based on race.

Facebook quota sampling rests on two major assumptions, as outlined by Zhang et al. 2018. First, it assumes that conditional on strata and observed respondent characteristics, responses of those who took the survey would be the same as those who did not take the survey. Zhang et al. results were similar to both an online survey as well as ACS (Zhang et al. 2018). We have managed this assumption by monitoring responses to our Facebook ads as well as weighting responses following (“Weighting” section). The second assumption asserts that conditional on strata and observable characteristics, each person in California has a non-zero probability of taking the survey. However, while not every adult in California has Facebook, is it a reasonable way of reaching a large portion of the population (223 Million U.S. users (Clement 2019)) compared to competitors such as Amazon’s Mechanical Turk or survey companies like Qualtrics.

Sample

Facebook ads proved to pull in survey respondents with geographic and age accuracy. However, similar to past studies multicultural affinity was highly inaccurate as was educational attainment (Hiltin & Rainie 2019, Gelauf et al. 2020).

We had a total of 2,238 responses, and used responses that were over 85% filled out. Those that filled out more than 85% provided their ethnicity, 1.5% of the 1,634 responses did not include financial or educational attainment. 85% of all full responses provided email addresses for follow up.

Appendix II: Survey Development and Survey Instrument

Respondents who click on the Facebook ad found themselves on a splash page that explains the research and consent based information. The first two questions are screeners, only consenting adults (>18 years old) and those in California may complete the study. The survey instrument took an average of 13 minutes, was dynamic, and had a total of 40 questions. Questions included: seafood consumption of species, product type, regularity, history, and source, fear of COVID-19 transmission, demographics including financial well being and political ideology. We included an experimental question, randomly administered, that assessed the perception of the number of species an individual consumes. Questions regarding individuals' feelings around seafood were adapted from Hicks et al. 2008, political ideology questions were adapted from Hiroyasu et al. 2019, and financial questions were adapted from Consumer Financial Protection Bureau 2015’s survey. Remaining questions were developed by Phoebe Racine and collaborators. The survey was pre-tested in three rounds.

Survey Instrument

Consent Statement & Screener Q1-2

This survey is part of a research study run by Phoebe Racine and Dr. Matto Mildenberger, University of California Santa Barbara, and Ashley Bae at the University of California Santa Cruz. The purpose of the research is to better understand the COVID-19 pandemic's long term effects on California's seafood supply chain. This research is intended to help recovery efforts for California's seafood sector. By seafood, we mean edible products, from fresh or salt water, including fish, shellfish, and seaweed.

In this survey, we'll ask you a series of questions about how and when you eat seafood. Participation involves answering simple survey questions and it should take 8-15 minutes to complete. Please note that you cannot go back pages and you can only enter the survey once. Should you choose to provide your email address at the end of the survey, you be will be entered to win one of three $100 gift cards of your choice. Your participation is voluntary and you can stop at any time. All responses will be anonymous and confidential. For questions about this research project, please email Phoebe Racine at pracine@bren.ucsb.edu or the UCSB Office of Research at warren@research.ucsb.edu.

If you are at least 18 years old and consent to take part in the study, please select "I Agree" to begin the survey. If not, please select "I Do Not Agree".

- ○ I agree
- ○ I do not agree

What state do you currently live in?

- ○ California
- ○ Other

Seafood Screener Q3-5

How do you feel about seafood?

	Agree	Not Sure	Disagree
It is easy to judge the freshness of seafood.	◯	◯	◯
Seafood is too expensive.	◯	◯	◯
I don't eat fish, shellfish, or seaweeds.	◯	◯	◯
Seafood is too cheap.	◯	◯	◯
I feel comfortable preparing seafood at home.	◯	◯	◯

When do you first remember regularly eating seafood?

◯ Birth-10 years old
◯ 11-20 years old
◯ 21-30 years old
◯ 31-40 years old
◯ 41-60 years old
◯ 61 or older
◯ I've never eaten seafood regularly

How many times in the last four weeks did you eat seafood (fish, shellfish, seaweed, etc.)?

◯ More than 2 times a week
◯ Once a week
◯ Twice
◯ Once
◯ I did not any eat seafood during this time
◯ I do not eat seafood

Experiment Q A

By weight, 86% of U.S. seafood consumption is made up of 10 species. How many seafood species would you estimate you eat in a given month?

Number of species (slider bar from 0-30)

Experiment Q B

By weight, 70% of U.S. seafood consumption is made up of just five species: shrimp, salmon, canned tuna, tilapia, and Alaska pollock. How many seafood species would you estimate you eat in a given month?

Number of species (slider bar from 0-30)

Seafood Consumption Q6-22

Please select which seafood products you purchased or ate in the last four weeks

	2+ times a week	Once per week	A few times	Once	Never
Prepared: restaurant (e.g. sushi, poke bowls, fish and chips, grilled fish)	○	○	○	○	○
Prepared: deli at grocery store	○	○	○	○	○
Canned (e.g. tuna, salmon, sardines)	○	○	○	○	○
Unfrozen (including fresh or previously frozen)	○	○	○	○	○
Frozen (e.g. fish sticks, frozen tuna or salmon, other products from frozen section)	○	○	○	○	○
Live (e.g. urchin, oysters, lobster)	○	○	○	○	○

Over the last four weeks, what types of seafood dishes have you ordered for take-out or dining in at a restaurant?

	Fish (e.g. salmon, cod) Take-in	Dine-out	Not Applicable	Shellfish (e.g. shrimp, clams) Take-in	Dine-out	Not Applicable	Seaweed Take-in	Dine-out	Not Applicable
Raw / Uncooked	☐	☐	☐	☐	☐	☐	☐	☐	☐
Soup	☐	☐	☐	☐	☐	☐	☐	☐	☐
Fried	☐	☐	☐	☐	☐	☐	☐	☐	☐
Steamed	☐	☐	☐	☐	☐	☐	☐	☐	☐
Baked	☐	☐	☐	☐	☐	☐	☐	☐	☐
Grilled	☐	☐	☐	☐	☐	☐	☐	☐	☐
Other / Unknown	☐	☐	☐	☐	☐	☐	☐	☐	☐

Please select which type of fish you purchased or ate in the last 4 weeks. (check all that apply)

- ☐ Salmon
- ☐ Trout
- ☐ Tuna
- ☐ Alaska pollock/Alaskan cod
- ☐ Atlantic cod
- ☐ Tilapia
- ☐ Catfish
- ☐ Pangasius/Basa (catfish)
- ☐ Halibut
- ☐ Rockfish
- ☐ Sole
- ☐ White Seabass
- ☐ White fish (unknown type)
- ☐ Yellowtail
- ☐ Mackerel
- ☐ Anchovies
- ☐ Sardines
- ☐ Unagi / Eel
- ☐ Other / Unknown fish
- ☐ None

Please select which type shellfish (crustacean or mollusk) you purchased or ate in the last 4 weeks. (check all that apply)

- Shrimp / Prawn
- Clams
- Mussels
- Oysters
- Dungeness crab
- Rock crab
- King crab
- Crab (unknown type)
- Spiny lobster
- Lobster (American, clawed)
- Crawfish
- Squid
- Uni / Urchin
- Abalone
- Octopus
- Other / Unknown shellfish
- None

Please select which type of seaweed you purchased or ate in the last 4 weeks. (check all that apply)

- ☐ Wakame (e.g. seaweed salad, miso soup)
- ☐ Nori (e.g. seaweed snacks)
- ☐ Kombu (e.g. dashi)
- ☐ Ogo (e.g. red seaweed in poke)
- ☐ Other / Unknown seaweed
- ☐ None

To the best of your ability, in the last 4 weeks, how much of each species did you purchase or eat? The slider is in pounds (lbs.).

each species selected by a respondent appears with a unique slider bar

In the last 4 weeks, please check which species you prepared at home for the first time.

each species selected by a respondent appears with a check box next to it

If you selected "other/unknown," what species did you eat or purchase that was not included?

In the last 4 weeks, where did you get seafood? (Select all that apply)

	2+ times a week	Once a week	A few times	Once	Never / Not Applicable
Restaurant	○	○	○	○	○
Grocery store	○	○	○	○	○
Community Supported Fishery (CSF) (subscription based seafood delivery service)	○	○	○	○	○
Farmer's or Fishermen's Market	○	○	○	○	○
Direct delivery from fishermen/farmer	○	○	○	○	○
Fished or farmed for myself/my family	○	○	○	○	○
Other	○	○	○	○	○

Please elaborate on what dishes you have ordered from restaurants.

Are you a current member of a Community Supported Fishery? A Community Supported Fishery sells locally sourced seafood, usually as part of a weekly or monthly subscription. Examples included Get Hooked and Real Good Fish.

○ Yes
○ No

If yes, what Community Supported Fishery are you a member of?

Please list the other locations you get seafood.

Fear of Transmission Q23-26

What factors into your concern of COVID-19 transmission through food? (check all that apply)

- ☐ Where I purchase food
- ☐ How the food is prepared (raw, live, fried, etc.)
  Who prepares the food (myself, a restaurant, grocery store, etc.)
- ☐ I am not concerned about transmission through food

Currently, how much do you fear transmission of COVID-19 through food?

- ○ Very worried, I will not eat certain foods because of it
- ○ Moderately worried, I will not eat some foods because of it
- ○ I consider transmission through food, but it doesn't change how or where I eat
- ○ Not at all

Currently, how much do you fear transmission of COVID-19 through seafood?

- ○ Very worried, I will not eat certain seafood because of it
- ○ Moderately worried, I will not eat some seafood because of it
- ○ I consider transmission through seafood, but it doesn't change how or where I eat
- ○ Not at all

What type of **seafood** gives you most concern of COVID-19 transmission? (select all that apply)

- ☐ Prepared: restaurant
- ☐ Prepared: deli at grocery store
- ☐ Canned (e.g. tuna, salmon, sardines)
- ☐ Frozen (e.g. fish sticks, frozen tuna or salmon, other products from frozen section)
- ☐ Fresh (including previously frozen)
- ☐ Live (e.g. urchin, oysters, lobster)
- ☐ Other; please explain

Demographic & Political Ideology Q27-37

Demographic questions help us better understand who consumes seafood. Next, we will ask a few questions to better understand what drives the results of our survey.

What is your zipcode?

[ ]

What is your gender?

- Male
- Female
- Non-binary
- Prefer not to say

Including yourself, how many people are part of your household?

- Adults (18 or older) [ ]
- Children (10-17) [ ]
- Young Children (0-9) [ ]

Are you responsible for your household grocery shopping?

- ○ Always
- ○ Most of the time
- ○ Rarely
- ○ Never

How old are you?

[ ]

How do you identify? (select all that apply)

- ☐ American Indian or Alaska Native
- ☐ Asian or Asian American
- ☐ Black or African American
- ☐ Hispanic or Latinx
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ White
- ☐ Other

What is the highest level of formal education you have completed?

- ○ Some high school, no diploma
- ○ High school (high school diploma or equivalent, including GED)
- ○ College-level courses without degree
- ○ Technical or Associate degree (Two year)
- ○ Bachelor's degree (Four year)
- ○ Master's degree
- ○ Doctoral degree (PhD)
- ○ Professional degree (JD, MD)

Which of the following ranges best describes your 2019 household income before taxes.

- ○ Less than $25,750
- ○ $25,751 - $38,625
- ○ $38,626 - $51,500
- ○ $51,501 - $64,375
- ○ $64,375 - $77,250
- ○ $77,251 - $124,999
- ○ $125,000 - $199,999
- ○ $200,000 - $299,999
- ○ $300,000 - $399,999
- ○ $400,000 or more

How well does this statement describe you or your situation?

	Completely	Very well	Somewhat	Very little	Not at all
I could handle a major unexpected expense	○	○	○	○	○
I am securing my financial future	○	○	○	○	○
Because of my money situation, I feel like I will never have the things I want in life	○	○	○	○	○
I can enjoy life because of the way I'm managing my money	○	○	○	○	○
I am just getting by financially	○	○	○	○	○
I am concerned that the money I have or will save won't last	○	○	○	○	○

Generally speaking, do you consider yourself a Republican, a Democrat, an Independent, or something else?

○ Democrat

○ Republican

○ Independent

○ Other; please specify

Where would you place yourself on this scale?

- Extremely liberal
- Liberal
- Somewhat liberal
- Moderate; middle of the road
- Somewhat conservative
- Conservative
- Extremely conservative
- I haven't thought about it much

Reflection and Volunteer Information Q38-40

As part of our study, we are seeking responses to this same survey after 6 months and 1 year out from the release of the first survey. With each round of surveys, there will be several randomly drawn $100 gift cards (gift card of your choice from TangoCard). Would you be willing to complete this survey in the future? If yes, please provide an email address that we can use to contact you. Note: Your email address will not be shared with anyone, will only be used to communicate about subsequent surveys, and will be deleted from all records at the end of the research period. Providing your email address at this time does not obligate you to future participation.

- Email Address here:
- Nope!

If you would like information from the study, including publications and reports, please enter your email below.

Is there anything else you'd like to add about how COVID-19 has changed how you purchase, cook, and eat seafood? You may also include any other comments or feedback about the survey here.

Appendix III: Data and Sample

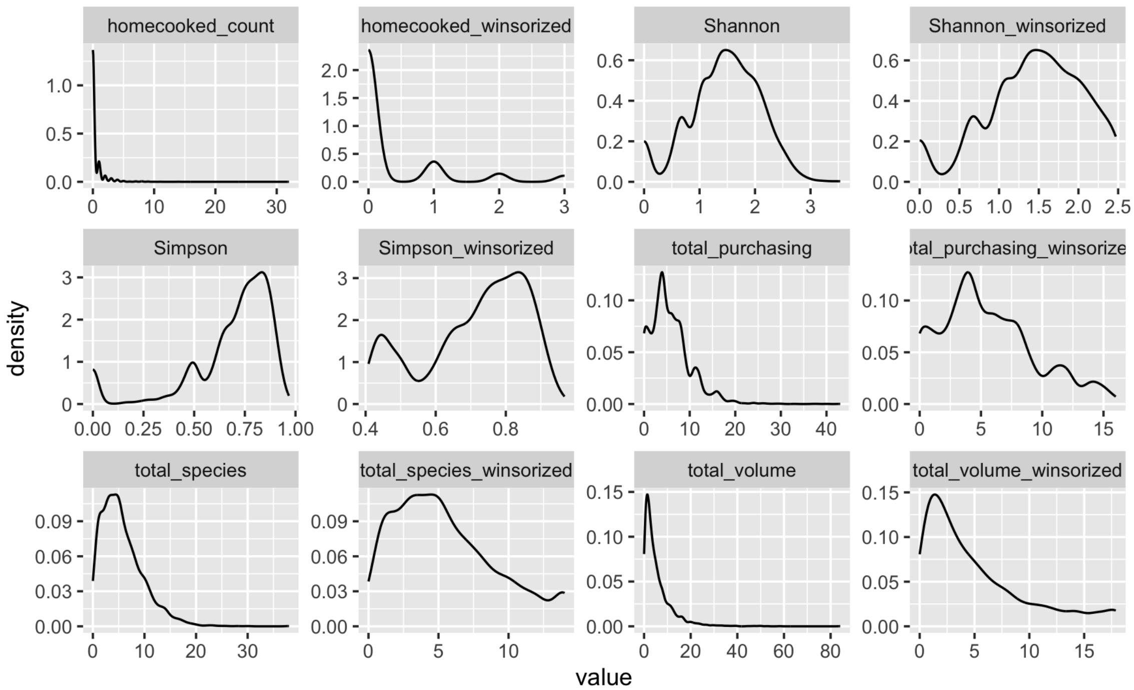
Sample

People who took all three surveys (n=464) vs full dataset

- comparing those in panel to those not in panel, those who took all three survey rounds had significantly higher financial wellbeing, 1.6 pts higher
- variability in full panel w/ financial wellbeing increasing through survey
- for those w/only all 3 surveys - very little variability in financial wellbeing
- Total species: not a lot of variance in time pts
- Total volume: not a ton of variation

Outliers

We followed the advice of Kwak and Kim 2017 to prepare data for analysis and handle outliers. For our purpose, we winsorized specific variables that had hard to believe outliers. In this practice, you cut off data in some distance from the mean, and fill in with outliers with the cut off value. In our case, we cut off total seafood purchases, total volume, number of species, number of species cooked at home for the first time, and Shannon index at 95th percentile and Simpson Index, which is left skewed, at 10% (5% was still 0).



SI FIGURE 2*: Raw data vs. winsorized data by variable*

To note about our data: many variables were on a likert scale of some kind, but the variables above are from adding together multiple questions. Total species comes from all the species someone clicked on. Total volume comes from all the volume reported for individual species: they had slider bars of pounds that could go up to 5 lbs each. Total purchasing was calculated by adding all places they reported purchasing from.

How did this change results? Lost some power, a couple results gained a little power

- *Simpson Index*: before winsorizing rain was moderately significant, now its not, freshness was moderately significant, now it's significant
- *Richness:* before winsorization, financial wellbeing was moderately significant, covid concern *was not* moderately significant
- *Total Volume*: restaurant order was moderately significant as was freshness
- *Homecooked*: freshness was moderately significant
- *Total seafood purchases*: outliers had caused covid concern & unemployment to be moderately significant, while restaurant closures were only moderate significant and now it's significant

Comparing raw data to imputed/winsorized final dataset (*see Appendix VI for regression outputs*):

- Richness - due to winsorization: financial wellbeing had been moderately significant,
- Simpson - due to winsorization: rain had been moderately significant (also due to outliers), comfort was not significant, freshness has been moderate
- Shannon - due to imputation: rain had been significant (now moderate),
- Total volume - due to imputation: restaurant orders had been significant, unemployment rate had been moderately significant.
- Home cooked - imputed: Unemployment rate had been significant, rain had been moderately significant, comfort cooking had been significant
- Meals: too expensive had been moderately significant

Imputed Missing Data

- Model 1: age, gender, race_Q, education, income, seafood feelings, products, sourcing, total volume
- Model 2: species specific volume
- Model 3: create separate model for demographics and merge those in to other datasets: not important for fixed effects models
- Model 4: reflection- cons_freq, sourcing: not critical to fixed effects models

***SI TABLE 2*:** Missingness by variable and use in imputation model

Variable	Percent Missing	Variables used to specify
Seafood Consumption		
Volume consumed per species	5.3% Round 1: 6% Several species: spiny lobster, ogo, sole, crawfish, fish, rockcrab have more than 10% (highest is 21%)	Model 2
Total volume of seafood	>4% (n=188)	Model 1
Richness (no. species)	>2% (n=52)	
Number of seafood meals "cons_freq"	3% (n=137)	Model 1
Total seafood purchases	>1% (n=1)	Model 1
Homecooked (no. of species cooked at home for the first time)	5.6% (n=163)	Model 1
Seafood products	*All products*: 13% NA in round 1, 11.7% NA in round 2, 12.8% NA in round 3 *By product:* Canned: 14.6% Frozen: 16% Live: 4% Deli: 7.7% Takeout: 16% Unfrozen: 18.7%	Model 1
Where seafood was purchased from ("sources")	*All products in 5 time pts:* 4.3% NA *By source:* Other: 14% Fishing: 6.8% Direct: 7% Farmers Market: 6.4% Restaurant: 3% Grocery: 1.5%	Model 1
Attitudes towards seafood		

Too expensive (Viewing seafood as “too expensive”)	>1% (n=13)	Model 1
Too cheap (Viewing seafood as “too cheap”)	>1% (n=18)	Model 1
Comfort cooking	>1% (n=11)	Model 1
“Freshness” (Being able to judge seafood freshness)	>1% (n=6)	Model 1
County Information		
Weather/Unemployment rate /cases/restaurant orders/urban	n=3, due to non-matching zipcodes	
Demographic		
Financial wellbeing score	n=156, round 1: 109, round 2:23, round 3: 25	
Income	n=81 people (round 1), 4.9%	
County	n=3, due to non-matching zipcodes	
Gender	17 prefer not to say and 1 is NA	
Age	n=43	

See two way fixed effects results with imputed and non-imputed data in Appendix VI.

Covid Concern - Missing vs Not Missing Data

Using linear regression we compared data from those who fully filled out questions about a respondent’s concern of catching and spreading COVID-19.

Demographics

- urban: not significantly different
- area of state: south coast (Southern California) more likely to skip question
- men: less likely to skip
- age: as folks get older significantly less likely to skip
- financial wellbeing: those with higher financial wellbeing less likely to skip
- respondents with doctorate less likely to skip

- respondents with highschool education moderately more likely

Purchasing, Meals, Attitudes

- purchases: not significantly different
- meals: inverse
- comfort/too expensive/too cheap: not significantly different

Diversity Measures

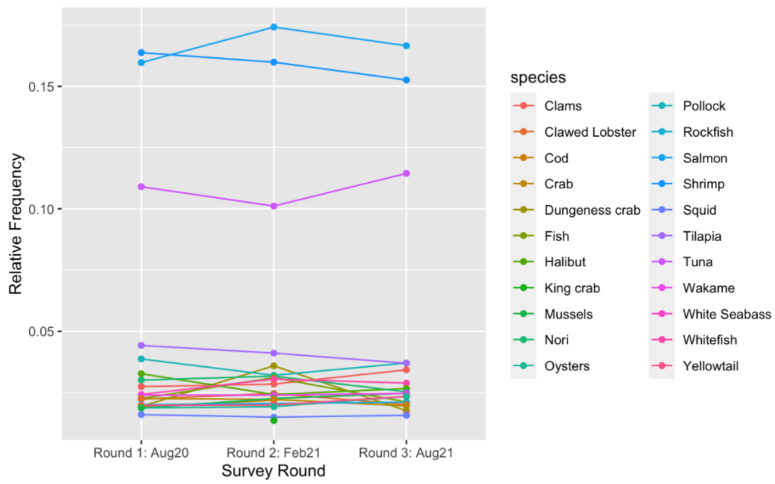
- species richness: not significantly different
- shannon: not significantly different
- simpson: not significantly different

Sources

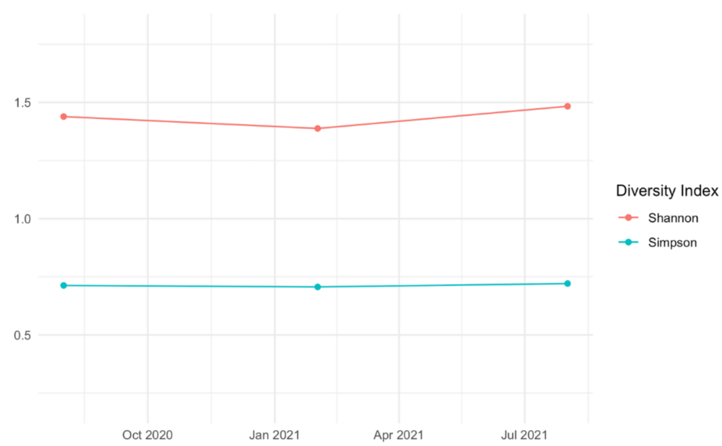
- grocery & restaurant purchases not significantly different

Appendix IV: Descriptive Statistics on Seafood Consumption

Respondents likely over- estimated the volume of seafood they ate. While Californians eat some of the highest volumes of seafood per capita, our survey respondents estimated eating three times the national average (US per capita consumption: 19.2 lbs.; Fiorillo 2021). Still, these estimates are useful in order to understand the overarching impact from shifts in seafood access and attitudes towards seafood. Consistent with previous studies, we found that older people eat more seafood and people with better financial wellbeing eat more seafood (e.g. Govzman et al. 2020).



SI FIGURE 3*: Relative frequency of species consumption from July 2020-August 2021*



SI FIGURE 4*: Shannon and Simpson Diversity Indices through time*

Appendix V: Network Analyses

These network analyses reflect most commonly eaten species, and species with most relationships.

August 2020, Round 1

- 62 species or species groups with 70,082 connection points between them from 1,634 people eating over 4 weeks
- Shrimp, salmon and tuna are the most commonly eaten species and have substantial relationships between them

Most popular species combinations:

- 830 (half) people ate shrimp and salmon
- 799 people ate shrimp and tuna
- 780 people ate salmon and tuna
- 407 people ate salmon and nori
- after the 3 top species (shrimp, salmon, tuna) the next most common pairings were with nori or wakame
- There are clusters of species eaten together and some that are more likely to be eaten together. For instance, eel (156 people ate both eel and salmon) had no relationship with 21 out of 62 species

Degree Centrality:

- shrimp, salmon and tuna are not only the most commonly eaten but they are the most frequently eaten among other species
- Species that were less commonly eaten (e.g. once or twice) have higher degrees if they were eaten by someone who ate a lot of other species (e.g. black fin sea bream was only eaten once but has a degree of 30), the lowest degrees possible then were for rare species only eaten by one person
- lowest degrees: sturgeon, perch, barramundi, milkfish

Betweenness:

- Betweenness centrality, which is defined as the number of geodesic paths (shortest paths) that go through a given node. “Nodes with high betweenness might be influential in a network if, for example, they capture the most amount of information flowing through the network because the information tends to flow through them." (Shizuka 2019)
- Extremely low betweeness (0): Abalone, Haddock, Herring, Barramundi, Black fin Sea Bream, Hokkigai (clam), Covina, Spiny lobster, Crawfish, Imitation crab, Opakapaka, Scallops, Stingray, Milkfish, Stripers, Japanese red clam, Sea Bream, Opa, Shark
- Highest betweeness: Shrimp (347), Salmon (330), Fish (312), Mussels (312), Tuna (269), Nori (121)

Closeness (least number of steps to get to another species)

- "fish" has a near average amount of occurrences yet has the highest closeness

February 2021: Round 2

- 50 species, 653 survey responses

- There are 35% of the amount of edges/connections compared to Round 1 (25,202)
- The big 3: shrimp, salmon, and tuna remain both the most common and with the most edges

Species combinations:

- shrimp and salmon had the most pairings again (n=334, again around half of survey respondents)
- tuna & salmon (n=301)
- tuna & shrimp (n=290)
- salmon & nori (n=183)
- shrimp & nori (n=172)
- plenty of species had no relationship (abalone & anchovies,black cod, barramundi, catfish, crawfish, Dungeness crab, etc.)
- rarer/less commonly eaten species had fewer relationships

Degree Centrality

- *S*almon had a higher degree of centrality (n=4,970)
- Shrimp was the next highest(4,946),
- Sturgeon again has the smallest degree centralization (n=12)

Closeness

- "Fish", "salmon" and "Shrimp" had the highest closeness - this is similar to August 2020 (Round 1)

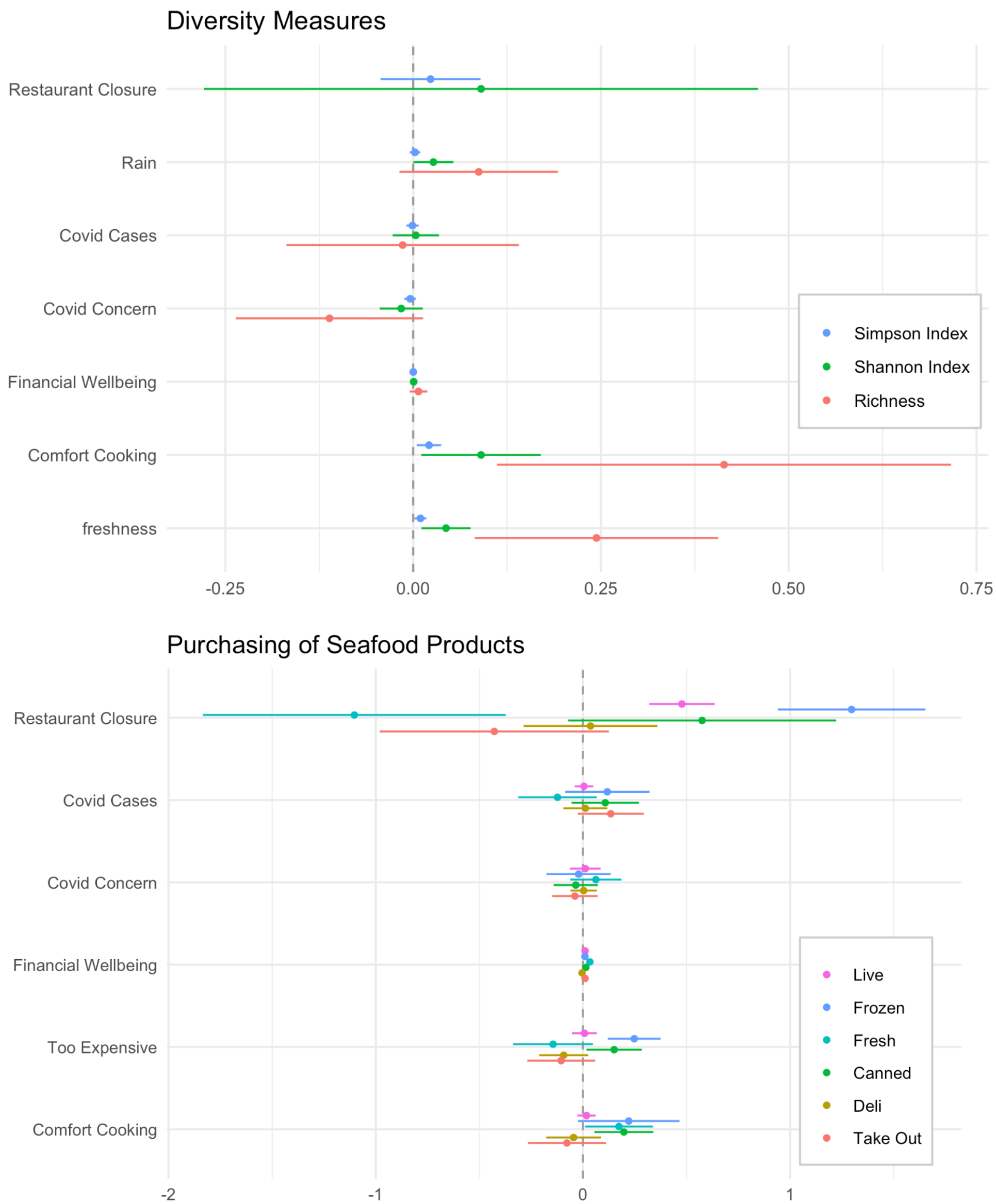
August 2021 Round 3

- 49 species were eaten in August 2021 by 618 people
- more connections were had by fewer people (30,172) compared to 25k in February 2021
- Shrimp has the highest degree centrality again (n=5,658) (salmon: 5,352)
- Shrimp, Salmon and Tuna remain the most commonly eaten with the most connections
- Tuna had the most closeness

Appendix VI: Two Way Fixed Effects Results

Seasonality & Weather

Seasonality impacted consumption of specific species, purchases of specific seafood products, and moderately impacted seafood consumption diversity. Times and places with more rain resulted in more diverse consumption overall (moderate, this could also be explained, in part, by the survey time period overlap with Lunar New Year), more tuna consumed and less whitefish, and fewer purchases of seafood products from the deli. Meanwhile, higher temperatures resulted in more seaweeds and local seafood species consumed and more purchases of seafood products from the deli.



SI FIGURE 4: *Coefficient plots of two way fixed effects models (August 2020-August 2021) with COVID-19 related predictors and attitudes towards seafood. A) Purchasing of Seafood Products, B) Species consumed (lbs.). Predictors: Restaurant Closures (0: open, 1: closed), Financial Wellbeing (score between 0-100), Covid Cases (cases per 10,000), Covid Concern (0-3 scale: not concerned to most concerned), Too Expensive: measure of viewing seafood as "too expensive" 0: no, 1: not sure, 2: yes, Comfort Cooking: 0: no, 1: not sure, 2: yes, Freshness: Ability to judge seafood freshness 0: no, 1: not sure, 2: yes.*

Regression Table Variable Information

- "**Under restaurant order**": binary, whether restaurant restrictions were in place in that county at the time of the survey (0 restaurant restriction in place at time of survey: 1 no restrictions in place at time of survey)
- "**Financial.wellbeing.score**": a score between 0 and 100 that measures financial wellbeing, higher indicates better financial wellbeing
- "**covid concern**": We gave a scaled concern of COVID 0-3 for each of the 3 questions. 0 means they are not concerned about COVID-19 transmission through food consumption or procurement. 3 is very concerned.
- "**Avg_temp_month**": Average monthly temperature at the county level (Farenheight)
- "**Percipitation_month_total**": Average precipitation at the county level (inches)
- "**unemployment rate**": monthly unemployment rate by county
- "**covid.cases.1**": by county on day of the survey, 1 case per 100,000, multiplied by 0.1
- "**seafood expensive**": We asked whether someone views seafood as too expensive. 0: seafood is too expensive, 1: maybe, 2: seafood is not too expensive
- "**Freshness**": We asked whether someone can judge the freshness of seafood. 0: cannot judge freshness of seafood, 1: maybe, 2: can judge the freshness of seafood
- "**comfort cooking**": We asked whether people are comfortable cooking seafood. 0 - not comfortable cooking seafood, 1 - maybe comfortable, 2 - comfortable cooking seafood

SI TABLE 3**:** Two way fixed effects result across diversity measures: richness (no. of species), Shannon Index and Simpon Index

	Richness	Shannon Index	Simpson Index
under_restaurant_order	-0.756	0.090	0.023
	(0.700)	(0.188)	(0.034)
financial.wellbeing.score	0.007	0.001	0.000
	(0.006)	(0.002)	(0.000)
covid.concern	-0.111+	-0.016	-0.004
	(0.064)	(0.015)	(0.004)
avg_temp_month	0.010	0.001	0.000
	(0.018)	(0.003)	(0.001)
percipitation_month_total	0.087	0.027+	0.002
	(0.054)	(0.014)	(0.004)
unemployment_rate	1.360	-0.578	-0.068
	(3.443)	(0.762)	(0.181)
covid.cases.1	-0.014	0.004	-0.001
	(0.079)	(0.016)	(0.004)
seafood_expensive	0.067	0.012	0.003
	(0.105)	(0.020)	(0.005)
freshness	0.244**	0.044*	0.010*
	(0.083)	(0.017)	(0.004)
comfort_cooking	0.414**	0.090*	0.021*
	(0.154)	(0.041)	(0.008)
:————————	———:	————:	————:
Num.Obs.	2694	2444	2444
R2	0.894	0.864	0.844
R2 Adj.	0.727	0.649	0.596
R2 Within	0.020	0.020	0.015
R2 Within Adj.	0.011	0.010	0.005
AIC	11808.9	2690.4	-3990.5
BIC	21506.5	11380.9	4700.0
RMSE	1.18	0.23	0.06
Std.Errors	by: county	by: county	by: county
FE: ID	X	X	X
FE: survey_round	X	X	X

Note: ^^ + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

***SI TABLE* 4:** Two way fixed effects result including number of seafood meals, total volume of seafood consumed and number of species someone cooked at home for the first time in a 4 week period

	Seafood Meals	Volume (lbs.)	Home Cooked
under_restaurant_order	-1.188	-0.822	-0.041
	(1.330)	(0.588)	(0.110)
log(financial.wellbeing.score)	0.657	-0.062	-0.098
	(0.597)	(0.554)	(0.165)
covid.concern	-0.021	0.112	-0.008
	(0.059)	(0.095)	(0.029)
avg_temp_month	-0.004	0.012	0.005
	(0.018)	(0.013)	(0.005)
percipitation_month_total	-0.009	0.051	0.016
	(0.070)	(0.097)	(0.028)
unemployment_rate	2.572	7.324*	-0.683
	(3.389)	(3.132)	(1.176)
covid.cases.1	0.022	0.047	-0.011
	(0.101)	(0.089)	(0.018)
seafood_expensive	-0.159*	0.073	-0.035
	(0.076)	(0.163)	(0.037)
freshness	0.156	0.148	0.033
	(0.110)	(0.119)	(0.033)
comfort_cooking	0.231+	0.660***	0.053
	(0.117)	(0.136)	(0.032)
:———————————-	————–:	————–:	————:
Num.Obs.	2694	2694	2694
R2	0.839	0.877	0.730
R2 Adj.	0.587	0.684	0.307
R2 Within	0.015	0.019	0.006
R2 Within Adj.	0.006	0.009	-0.004
AIC	11267.8	13623.3	5773.8
BIC	20965.4	23320.9	15471.3
RMSE	1.06	1.65	0.38
Std.Errors	by: county	by: county	by: county

***SI TABLE* 5:** Two way fixed effects result including total seafood purchases in a 4 week period, and purchases of seafood from different retail outlets

	Total Seafood Purchases	Grocery Purchases	Restaurant Purchases	Alternative Source Purchases
under_restaurant_order	-0.713**	0.407	-0.930**	-0.092
	(0.226)	(0.668)	(0.338)	(0.072)
financial.wellbeing.score	0.009	0.000	0.009	0.004
	(0.012)	(0.006)	(0.007)	(0.006)
covid.concern	-0.122	0.127*	-0.146*	-0.038
	(0.088)	(0.055)	(0.058)	(0.035)
avg_temp_month	-0.008	-0.008	0.002	0.009
	(0.018)	(0.014)	(0.013)	(0.011)
percipitation_month_total	0.040	0.125*	-0.027	-0.063
	(0.068)	(0.048)	(0.048)	(0.049)
unemployment_rate	5.869+	4.534	2.203	2.907
	(2.935)	(2.749)	(2.082)	(2.566)
covid.cases.1	-0.165	-0.126*	0.005	-0.143*
	(0.116)	(0.052)	(0.077)	(0.059)
seafood_expensive	-0.235*	-0.173*	-0.082	0.012
	(0.105)	(0.080)	(0.088)	(0.061)
freshness	0.088	-0.039	0.059	0.073
	(0.107)	(0.083)	(0.075)	(0.107)
comfort_cooking	0.452**	0.244*	0.086	0.135*
	(0.147)	(0.100)	(0.076)	(0.053)
:—————————	—————————:	——————:	————————:	——————————:
Num.Obs.	2694	2694	2694	2694
R2	0.859	0.833	0.815	0.784
R2 Adj.	0.638	0.573	0.526	0.446
R2 Within	0.018	0.020	0.012	0.010
R2 Within Adj.	0.009	0.011	0.002	0.001
AIC	13114.8	10990.0	10584.4	9811.6
BIC	22812.4	20687.6	20282.0	19509.2
RMSE	1.50	1.01	0.94	0.81
Std.Errors	by: county	by: county	by: county	by: county
FE: ID	X	X	X	X
FE: survey_round	X	X	X	X

Note: ^^ + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

***SI TABLE* 6:** Two way fixed effects results of purchasing of seafood products in a 4 week period

	Take_out	Deli	Canned	Unfrozen	Frozen	Live
under_restaurant_order	-0.428	0.037	0.575+	-1.103**	1.297***	0.478***
	(0.282)	(0.165)	(0.330)	(0.373)	(0.182)	(0.081)
financial.wellbeing.score	0.010	-0.004	0.014**	0.034***	0.010	0.010+
	(0.008)	(0.005)	(0.005)	(0.008)	(0.008)	(0.005)
covid.concern	-0.039	0.003	-0.034	0.062	-0.021	0.011
	(0.056)	(0.032)	(0.054)	(0.063)	(0.079)	(0.038)
avg_temp_month	-0.010	0.015*	0.004	-0.032+	-0.016	-0.002
	(0.016)	(0.006)	(0.013)	(0.018)	(0.013)	(0.006)
percipitation_month_total	-0.086	-0.064*	-0.001	0.040	0.038	0.030+
	(0.065)	(0.027)	(0.044)	(0.075)	(0.091)	(0.017)
unemployment_rate	-2.794	3.038+	2.955	6.185+	-5.166+	1.183
	(3.320)	(1.595)	(2.478)	(3.379)	(2.705)	(1.245)
covid.cases.1	0.134	0.012	0.108	-0.123	0.118	0.005
	(0.081)	(0.054)	(0.083)	(0.097)	(0.104)	(0.023)
seafood_expensive	-0.105	-0.093	0.151*	-0.144	0.248***	0.008
	(0.083)	(0.060)	(0.068)	(0.098)	(0.065)	(0.030)
freshness	0.083	0.023	0.065	0.041	0.047	0.073+
	(0.084)	(0.046)	(0.067)	(0.079)	(0.105)	(0.040)
comfort_cooking	-0.077	-0.045	0.198**	0.174*	0.221+	0.017
	(0.096)	(0.068)	(0.073)	(0.084)	(0.125)	(0.022)
:————————	———:	———:	———:	———:	———:	———:
Num.Obs.	2694	2694	2694	2694	2694	2694
R2	0.793	0.726	0.809	0.806	0.780	0.803
R2 Adj.	0.470	0.296	0.510	0.503	0.436	0.494
R2 Within	0.010	0.009	0.015	0.032	0.018	0.016
R2 Within Adj.	0.000	-0.001	0.006	0.023	0.009	0.007
AIC	10973.4	8394.6	10671.0	11092.5	11240.6	6387.8
BIC	20671.0	18092.2	20368.6	20790.1	20938.2	16085.4
RMSE	1.01	0.62	0.95	1.03	1.06	0.43
Std.Errors	by: county	by: county	by: county	by: county	by: county	by: county
FE: ID	X	X	X	X	X	X
FE: survey_round	X	X	X	X	X	X

Note: ^^ + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Comparing Winsorized and Non Winsorized Data

SI TABLE 7: *Two way fixed effects results comparing diversity measures that have been winsorized and those that have not*

	Richness	Richness Non Winsor	Shannon Non Winsor	Shannon Index	Simpson Non Winsor	Simpson Index
under_restaurant_order	-0.756	-1.011	0.085	0.090	0.108	0.023
	(0.700)	(0.777)	(0.190)	(0.188)	(0.079)	(0.034)
financial.wellbeing.score	0.007	0.012+	0.001	0.001	0.000	0.000
	(0.006)	(0.006)	(0.002)	(0.002)	(0.001)	(0.000)
covid.concern	-0.111+	-0.096	-0.015	-0.016	-0.006	-0.004
	(0.064)	(0.067)	(0.015)	(0.015)	(0.006)	(0.004)
avg_temp_month	0.010	0.010	0.002	0.001	0.001	0.000
	(0.018)	(0.021)	(0.003)	(0.003)	(0.001)	(0.001)
percipitation_month_total	0.087	0.082	0.025+	0.027+	0.011+	0.002
	(0.054)	(0.068)	(0.014)	(0.014)	(0.006)	(0.004)
unemployment_rate	1.360	5.176	-0.242	-0.578	-0.409	-0.068
	(3.443)	(4.038)	(0.797)	(0.762)	(0.307)	(0.181)
covid.cases.1	-0.014	-0.072	-0.001	0.004	0.004	-0.001
	(0.079)	(0.077)	(0.016)	(0.016)	(0.007)	(0.004)
seafood_expensive	0.067	0.037	0.010	0.012	0.001	0.003
	(0.105)	(0.132)	(0.022)	(0.020)	(0.008)	(0.005)
freshness	0.244**	0.313**	0.048**	0.044*	0.011+	0.010*
	(0.083)	(0.104)	(0.017)	(0.017)	(0.006)	(0.004)
comfort_cooking	0.414**	0.459**	0.094*	0.090*	0.028	0.021*
	(0.154)	(0.155)	(0.040)	(0.041)	(0.017)	(0.008)
:———————	———:	——————:	——————:	—————:	——————:	—————:
Num.Obs.	2694	2694	2444	2444	2444	2444
R2	0.894	0.893	0.866	0.864	0.824	0.844
R2 Adj.	0.727	0.726	0.655	0.649	0.546	0.596
R2 Within	0.020	0.022	0.020	0.020	0.016	0.015
R2 Within Adj.	0.011	0.013	0.010	0.010	0.005	0.005
AIC	11808.9	12432.2	2797.4	2690.4	-1723.9	-3990.5
BIC	21506.5	22129.8	11487.9	11380.9	6966.6	4700.0
RMSE	1.18	1.32	0.23	0.23	0.09	0.06
Std.Errors	by: county	by: county	by: county	by: county	by: county	by: county
FE: ID	X	X	X	X	X	X
FE: survey_round	X	X	X	X	X	X

SI TABLE 8: *Two way fixed effects results comparing several measures of seafood consumption (number of seafood meals consumed in a month: "seafood meals", total volume of seafood meals consumed, number of species cooked at home for the first time: "home cooked") that have been winsorized and those that have not*

	Seafood Meals	Volume (lbs.)	Volume Non Winsor	Home Cooked	Home Cooked Non Winsor
under_restaurant_order	-1.188	-0.822	-1.297+	-0.041	0.092
	(1.330)	(0.588)	(0.713)	(0.110)	(0.271)
log(financial.wellbeing.score)	0.657	-0.062	0.152	-0.098	-0.011
	(0.597)	(0.554)	(0.621)	(0.165)	(0.267)
covid.concern	-0.021	0.112	0.115	-0.008	-0.037
	(0.059)	(0.095)	(0.110)	(0.029)	(0.048)
avg_temp_month	-0.004	0.012	0.032	0.005	0.011
	(0.018)	(0.013)	(0.021)	(0.005)	(0.008)
percipitation_month_total	-0.009	0.051	0.104	0.016	0.041
	(0.070)	(0.097)	(0.117)	(0.028)	(0.053)
unemployment_rate	2.572	7.324*	10.142*	-0.683	-1.826
	(3.389)	(3.132)	(4.488)	(1.176)	(2.079)
covid.cases.1	0.022	0.047	-0.198	-0.011	-0.015
	(0.101)	(0.089)	(0.120)	(0.018)	(0.030)
seafood_expensive	-0.159*	0.073	0.096	-0.035	-0.027
	(0.076)	(0.163)	(0.233)	(0.037)	(0.054)
freshness	0.156	0.148	0.256+	0.033	0.093+
	(0.110)	(0.119)	(0.130)	(0.033)	(0.054)
comfort_cooking	0.231+	0.660***	0.836***	0.053	0.056
	(0.117)	(0.136)	(0.192)	(0.032)	(0.040)
:———————————-	—————:	—————:	———————:	————:	————————:
Num.Obs.	2694	2694	2694	2694	2694
R2	0.839	0.877	0.876	0.730	0.762
R2 Adj.	0.587	0.684	0.683	0.307	0.389
R2 Within	0.015	0.019	0.018	0.006	0.007
R2 Within Adj.	0.006	0.009	0.008	-0.004	-0.002
AIC	11267.8	13623.3	15276.1	5773.8	8392.2
BIC	20965.4	23320.9	24973.7	15471.3	18089.8
RMSE	1.06	1.65	2.24	0.38	0.62
Std.Errors	by: county	by: county	by: county	by: county	by: county
FE: ID	X	X	X	X	X
FE: survey_round	X	X	X	X	X

Note: ^^ + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Comparing Imputed and Non-Imputed Data

SI TABLE 9: *Two way fixed effects results comparing several measures of seafood consumption (number of seafood meals consumed in a month: "seafood meals", total volume of seafood meals consumed, number of species cooked at home for the first time: "home cooked") that have had data imputed and and those that left data missing ("Non-Imputed")*

	Seafood Meals	Seafood Meals Non-Imputed	Volume	Volume Non-Imputed	Home Cooked	Home Cooked Non-Imputed
under_restaurant_order	-1.188	-1.230	-0.822	-1.172*	-0.041	0.067
	(1.330)	(1.344)	(0.588)	(0.457)	(0.110)	(0.309)
log(financial.wellbeing.score)	0.657	0.507	-0.062	0.552	-0.098	-0.194
	(0.597)	(0.649)	(0.554)	(0.744)	(0.165)	(0.230)
covid.concern	-0.021	-0.030	0.112	0.153	-0.008	-0.058
	(0.059)	(0.058)	(0.095)	(0.111)	(0.029)	(0.053)
avg_temp_month	-0.004	-0.004	0.012	0.031	0.005	0.001
	(0.018)	(0.019)	(0.013)	(0.024)	(0.005)	(0.008)
percipitation_month_total	-0.009	-0.043	0.051	0.090	0.016	0.086+
	(0.070)	(0.052)	(0.097)	(0.134)	(0.028)	(0.049)
unemployment_rate	2.572	2.467	7.324*	9.191+	-0.683	-4.293*
	(3.389)	(2.826)	(3.132)	(5.460)	(1.176)	(2.043)
covid.cases	0.002	0.002	0.005	-0.009	-0.001	-0.001
	(0.010)	(0.010)	(0.009)	(0.012)	(0.002)	(0.003)
seafood_expensive	-0.159*	-0.149+	0.073	0.163	-0.035	-0.022
	(0.076)	(0.086)	(0.163)	(0.204)	(0.037)	(0.056)
freshness	0.156	0.154	0.148	0.130	0.033	0.051
	(0.110)	(0.112)	(0.119)	(0.122)	(0.033)	(0.051)
comfort_cooking	0.231+	0.213+	0.660***	0.849***	0.053	0.110**
	(0.117)	(0.126)	(0.136)	(0.199)	(0.032)	(0.038)
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Num.Obs.	2694	2524	2694	2526	2694	2222
R2	0.839	0.837	0.877	0.879	0.730	0.793
R2 Adj.	0.587	0.589	0.684	0.694	0.307	0.456
R2 Within	0.015	0.014	0.019	0.018	0.006	0.013
R2 Within Adj.	0.006	0.004	0.009	0.008	-0.004	0.001
AIC	11267.8	10568.2	13623.3	14122.0	5773.8	6764.6
BIC	20965.4	19464.5	23320.9	23019.4	15471.3	14610.5
RMSE	1.06	1.07	1.65	2.17	0.38	0.60
Std.Errors	by: county	by: county	by: county	by: county	by: county	by: county
FE: ID	X	X	X	X	X	X
FE: survey_round	X	X	X	X	X	X

Note: ^^ + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

SI TABLE 10: *Two way fixed effects results comparing seafood consumption diversity measures (richness: number of species, Shannon Index, and Simpson Index) that have had data imputed and and those that left data missing ("Non-Imputed")*

	Richness	Richness Non-Imputed	Shannon Index	Shannon Non-Imputed	Simpson Index	Simpson Non-Imputed
under_restaurant_order	-0.756	-1.040	0.090	0.066	0.023	0.108
	(0.700)	(0.755)	(0.188)	(0.195)	(0.034)	(0.079)
financial.wellbeing.score	0.007	0.012+	0.001	0.002	0.000	0.000
	(0.006)	(0.007)	(0.002)	(0.002)	(0.000)	(0.001)
covid.concern	-0.111+	-0.122+	-0.016	-0.023	-0.004	-0.006
	(0.064)	(0.065)	(0.015)	(0.014)	(0.004)	(0.006)
avg_temp_month	0.010	0.010	0.001	0.001	0.000	0.001
	(0.018)	(0.021)	(0.003)	(0.004)	(0.001)	(0.001)
percipitation_month_total	0.087	0.057	0.027+	0.032*	0.002	0.011+
	(0.054)	(0.071)	(0.014)	(0.013)	(0.004)	(0.006)
unemployment_rate	1.360	3.225	-0.578	-1.311	-0.068	-0.409
	(3.443)	(4.333)	(0.762)	(0.901)	(0.181)	(0.307)
covid.cases	-0.001	-0.005	0.000	0.002	0.000	0.000
	(0.008)	(0.008)	(0.002)	(0.002)	(0.000)	(0.001)
seafood_expensive	0.067	0.025	0.012	0.017	0.003	0.001
	(0.105)	(0.133)	(0.020)	(0.022)	(0.005)	(0.008)
freshness	0.244**	0.280*	0.044*	0.041*	0.010*	0.011+
	(0.083)	(0.110)	(0.017)	(0.019)	(0.004)	(0.006)
comfort_cooking	0.414**	0.427**	0.090*	0.091**	0.021*	0.028
	(0.154)	(0.149)	(0.041)	(0.033)	(0.008)	(0.017)
:————————–	———–:	——————–:	————–:	——————–:	————–:	——————–:
Num.Obs.	2694	2526	2444	2262	2444	2444
R2	0.894	0.890	0.864	0.865	0.844	0.824
R2 Adj.	0.727	0.723	0.649	0.656	0.596	0.546
R2 Within	0.020	0.019	0.020	0.023	0.015	0.016
R2 Within Adj.	0.011	0.010	0.010	0.012	0.005	0.005
AIC	11808.9	11706.2	2690.4	2568.7	-3990.5	-1723.9
BIC	21506.5	20603.7	11380.9	10433.5	4700.0	6966.6
RMSE	1.18	1.34	0.23	0.23	0.06	0.09
Std.Errors	by: county	by: county	by: county	by: county	by: county	by: county
FE: ID	X	X	X	X	X	X
FE: survey_round	X	X	X	X	X	X

Note: ^^ + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

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