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Geography limits island small-scale fishery production

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Interacting social and ecological processes shape productivity and sustainability of island small-scale fisheries (SSF). Understanding limits to productivity through historical catches help frame future expectations and management strategies, but SSF are dispersed and unaccounted, so long-term standardized data are largely absent for such analyses. We analysed 40 years of trade statistics of a SSF product that enter international markets (sea cucumber) from 14 Pacific Island Countries and Territories (PICT) against response variables to test predictors of fishery production: (i) scale, (ii) productivity and (iii) socio-economics. Combined production in PICT peaked over 20 years ago, driven by exploitation trends in Melanesia that accounted for 90% of all production since 1971. The size of island fisheries (as measured by total exports), and the duration and magnitude of fishery booms were most influenced by ungovernable environmental variables, in particular land area. The large and high islands of Melanesia sustained larger booms over longer periods than atoll nations. We hypothesize that land area is a proxy for land-based nutrient availability and habitat diversity, and therefore the productivity of the shallow water areas where SSF are operating. PICT need to tailor management based on the intrinsic productivity of shallow inshore habitats: harvests from atoll nations will need to be smaller per unit area than at the high islands. Particularly countries with low productivity fisheries must consider the crucial economic “safety nets” that export SSF make up for dispersed island populations and incorporate them into broader development and island resilience strategies.

KEYWORDS
beche-de-mer, governance, invertebrate, management, markets, trepang

1 INTRODUCTION

Managing ecosystem use is an exercise in uncertainty (Carpenter, Brock, Folke, van Nes, & Sheffer, 2015; Folke, 2006; Polasky, Carpenter, Folke, & Keefer, 2011; Schindler & Hilborn, 2015). In tropical small-scale fisheries (SSF), outcomes may be determined by a multitude of factors other than fishery management (Brewer et al., 2012; Cinner et al., 2016). For example, environmental factors may drive patterns of resource abundance and diversity (e.g., Bellchambers, Meeuwig, Evans, & Legendre, 2011; Cariglia et al., 2013; Gove et al., 2013; McClanahan, 2015; Van Wensberge et al., 2016; Williams et al., 2015). Even where rules are in place, human pressures such as market drivers and livelihood requirements often override management (e.g., Cinner et al., 2009; Sulu et al., 2015). Understanding how social and ecological processes interact to shape productivity and sustainability of SSF systems remains a scientific frontier.

The role of SSF in economic growth and human well-being is recognized in contemporary development strategy (e.g. MSG, 2015), and SSF
are increasingly seen as important in mainstream development as an irreplaceable source of nutrition and income (Eriksson et al., 2017; Mills et al., 2017) and the multiple dimensions of human well-being (Cohen et al., 2016; Lawless et al., 2017; Purcell, Crona, Lalavanua, & Eriksson, 2017). For small island nations, SSF play a crucial role in development and in ambitions to achieve the Sustainable Development Goals. The operations and structures that make up SSF across coastal environments are diverse and complex (Jentoft 2007; Mills et al., 2011), and the catch is often consumed locally with trade dispersed and unaccounted (Sulu et al., 2015).

Many tropical SSF have failed to match governance and management institutions to the life histories of species and the dynamics of fishing, particularly in those fisheries targeting spatially structured, sedentary species (Anderson, Flemming, Watson, & Lotze, 2011; Jul-Larsen, Kolding, Overå, Raakjær Nielsen, & van Zwieten, 2003; Orensanz et al., 2005; Uthicke, Welch, & Benzie, 2004). Fisheries under weak governance exploiting species with such life histories are vulnerable to boom-bust patterns of exploitation. In some, catches are so valuable on global markets that their exploitation is more akin to the mining of diamonds and other "lootable" resources (Berkes et al., 2016; Lawless et al., 2017; Purcell, Crona, Lalavanua, & Eriksson, 2017), and so expose fishing communities to inequitable trade (Purcell, Polidoro, Hamel, Gamboa, & Mercier, 2014; Purcell et al., 2013).

Given the dispersed nature of SSF, local time-series information on exploitation or data from fishery dependent or independent surveys is rarely available (e.g., Pinca et al., 2010). As a result, there is limited potential to obtain large-scale standardized data from which to analyse SSF production trends against other explanatory variables. However, long-term trade data are available from certain species sourced from SSF that enter more formal trade for international markets. Whilst the value of catch and trade data as an indicator of resource status is debatable (Hilborn & Branch, 2013; Pauly, 2013), for data-poor fisheries, trade statistics provide an opportunity to characterize and evaluate factors influencing exploitation trajectories under differing island circumstances to inform and refine management approaches. Trade statistics are becoming a valuable source of information in the pursuit of understanding patterns of wildlife exploitation, conservation concerns and to support sustainability institutions (e.g., Crona et al., 2016; Eriksson & Clarke, 2015; Moran & Kanemoto, 2017; Watson, Nichols, Lam, & Sumaila, 2017).

In this study, we analyse a large 40-year Pacific Island regional data set of sea cucumber trade statistics to explore the influence of environmental and social characteristics on SSF production profiles. Despite more than a century of exploitation in the Pacific region (Conand, 1989), sea cucumber resources were still considered to have potential for further growth and development in the 1970–1980s (Adams, 1992; Kriz, 1994; Sant, 1995). Today, this situation is difficult to comprehend: most Pacific Island countries and territories (PICT) have exhausted their stocks and closed fisheries in an attempt to reverse declines (Pakoa & Bertram, 2013; Purcell et al., 2013; Purcell, Polidoro et al., 2014). Traditional tenure systems and modern centralized governance models have struggled to stabilize and maintain trade (Friedman, Eriksson, Tardy, & Pakoa, 2011). Failure to manage these harvests results in fishers forgoing one of the few opportunities they have to receive a cash income from local products (Christensen, 2011), and countries losing valuable foreign income. Depletion of coastal resources also has the potential to negatively impact the natural function of shallow water coastal ecosystems (Michio et al., 2003; Purcell, Conand, Uthicke, & Byrne, 2016).

Export volumes of sea cucumber are generally recorded by national customs agencies because some countries collect revenue on export licences or trade tariffs or regulate the fishery through export quotas, or as the only means to generate some information from an otherwise dispersed fishery (Barclay et al., 2016). These trade statistics have been used to summarize broad trends (e.g., Kinch, Purcell, Uthicke, & Friedman, 2008; Pakoa, 2013; Purcell, Gossuin, & Agudo, 2009) and to gauge the value of fisheries in the Melanesian subregion (Carleton, Hambrey, Govan, Medley, & Kinch, 2013). Here, we analyse these trade statistics against a range of explanatory variables to explain patterns of productivity and sustainability in island SSF, and to help identify production limits and management guidelines.

2 | METHODS

2.1 | Data sources and treatment

Trade data from 14 PICT (Figure 1) were compiled from published sources, national fisheries and trade agencies, and from records collated by staff of the Pacific Community (SPC) (Table S1). National records and management plans were used to determine when closures were in place and these records were supplemented with information from interviews with national fisheries officials, as appropriate.

The data comprised total annual exports of beche-de-mer (dried sea cucumbers) for the period 1971–2013. Unless otherwise specified, all measures of weight in this study refer to dry weight in tonnes (t). For some countries, adjustments of data were necessary due to varying product types and presence of a domestic market. For example, French Polynesia exports both dry and frozen products. This product pair does not have established conversion factors; a conversion factor of 0.2 was used to standardize frozen exports to dry weight for a mixed species compliment (Eriksson & Clarke, 2015). Fisheries for domestic trade and consumption exist in Fiji, Palau and Samoa. Reported domestic catches from Fiji (Pakoa, 2014a) and Palau (Pakoa, 2014b) were converted from wet weight to dried using a conversion factor of 0.1 (wet to dry weight) for a mixed species composition using the recovery ratios described in Skewes et al. (2004). These records were combined with reported export dry weight to provide an overall picture of national fishery production.

In Samoa, a small domestic fishery targets a limited number of species (e.g., Bohadschia vitiensis, Holothuria hilla, Stichopus monotuberculatus) that are sliced and stored in bottles and traded at markets and road sides (Kinch et al., 2008). This multispecies product cannot readily be converted to dried weight and so these records were omitted from analyses.

Export trends over time were analysed by subregion (i.e., Melanesia, Polynesia and Micronesia) using a loess model, which is a useful method when no theoretical model exists and data have a simple deterministic structure (e.g., export statistics; Cleveland, 1979).
The loess curve was fitted with a window of 75% of the data. All data were analysed using R 3.1.0 (R Development Core Team, 2014).

2.2 | National sea cucumber production profiles

Total exports (t dry weight) were used to create national profiles of production. From these profiles, metrics were derived to characterize national fisheries for further analyses (Table 1). Given the erratic production history of sea cucumber fisheries (Anderson et al., 2011), we were particularly interested in volatility in catches (booms and busts in production). First, sums of country exports were accumulated as a measure of fishery size (“Exports”). Then, the coefficient of variance (“CV”) for export data was calculated as a measure of overall variability in trade for each country.

The upper confidence limit (Mean + 1.96 × Standard Error) of national export data was calculated as a fishery-specific reference point to create further metrics from the export profiles. The number of years national exports were above this upper limit was used as a measure of fishery’s ability to sustain very high catches (“boom duration”). The ratio of the peak export and this upper limit was calculated as a relative measure of the magnitude of the boom (“peak boom”). Whilst related, these metrics describe different attributes of fishery production.

2.3 | Explanatory variables of production profiles

We hypothesized sea cucumber fishery production was a function of (i) the areal extent of fishable habitat, (ii) the productivity of fishing grounds and (iii) the human dimensions of the fishery. To evaluate whether the environmental and social characteristics of the 14 PICT help explain the dynamics of production profiles (i.e., Export, CV, boom duration and peak boom), a range of potential explanatory variables were collated within each of the three categories for each country (Table S2). These variables are summarized in Table 2 and further described below.

2.3.1 | Fishery scale variables

1. The shallow water area (0–30 m) within country Exclusive Economic Zones (EEZ) was calculated in ArcGIS from the SeaWIFS bathymetric layer created by NASA as a measure of the extent of fishable habitat. We did not exclude protected areas. The region has many undocumented and irregularly protected marine areas under local ownership. There are also more permanent protected areas with no-take rules under uncertain management efficacy, of which most are oceanic. For example, the large Phoenix Island Protected Area in Kiribati is mostly deep sea;

2. The number of commercial species recorded in each country was taken from the PROCFish survey report by SPC (Pinca et al., 2010) as a measure of available target species;

3. We used the great circle distance between the longitude of capital cities of PICT and the Coral Triangle (nominally the city of Sorong in West Papua) as a measure of distance from the Coral Triangle. The Coral Triangle is a broad swath of tropical reef habitat in South-East Asia and the western Pacific Ocean, known as a global epicentre of marine biodiversity and productivity (Green, Petersen, Cross, & MacLeod, 2008). Longitude and distance were extracted from the world.cities database within the world.maps package in R. The great circle distance between each capital city and Sorong was calculated using the fossil package in R.

2.3.2 | Fishery productivity variables

1. Land area within a 25 km inward swathe from coastline was calculated using ArcGIS as a measure of land-based nutrient influx. The justification for considering an area 25 km inwards from the coastline as a proxy for land influence was based on...
a hypothesized decreasing influence on the fishery from inland areas beyond that point, and to down weight the contribution of the very large landmass of Papua New Guinea;

2. Coastline length (km) was summarized for each country from the CIA World Factbook (CIA, 2013);

3. Reef area within a 150 and 300 km swathe of coastline was calculated to indicate countries contiguous reef habitat as a measure of isolation at two spatial levels. Sea cucumbers suffer disproportionately from alee effects when their densities decline in fished areas (Bell, Purcell, & Nash, 2008). We theorized that larger more connected reef systems would likely hold more refuge areas for potential spawning stock and support more sustained production than isolated small-scale reef systems. The swathes of 150 and 300 km were selected to reflect what relatively little we know from recruitment dynamics, which suggests gamete dispersal distances could reach 100s of kilometres, as published for similar invertebrates (Kinlan & Gaines, 2003).

4. Latitude at capital city was extracted from the world.cities database in world.maps package in R and great circle distance for each capital city to the equator calculated using the fossil package in R, as a measure of temperature and irradiance influencing productivity.

### 2.3.3 Socio-economic variables

1. The total population of each country was divided by the shallow water area as a measure of population pressure on available fishing grounds. For PNG, which has a high inland population compared to other PICT, the coastal population within a 5-km inland swathe was used;

2. The average Human Development Index (HDI) for available years between 1980 and 2013 was calculated from UNDP (2014), as a measure of national standard of living. For French Polynesia, Kiribati, Marshall Islands, Tuvalu and Wallis and Futuna, which were not included in UNDP (2014), single measurements of HDI were taken from Hastings (2009);

3. The per capita fish consumption was taken from the SPC National Minimum Development Indicator Database v2.0 (www.spc.int/nmdi/; accessed 4 May 2017) as a surrogate measure of reliance on coastal fisheries.

All GIS data processing and area calculations were carried out using the ESRI ArcGIS Desktop version 10.0. The SeaWiFS shallow bathymetry data initially in pgm format (http://netpbm.sourceforge.net/doc/pgm.html; accessed 4 May 2017) were converted and rescaled into a table with “latitude,” “longitude” and “depth” values and then interpolated using the “Point to Raster” function in the ArcGIS Geoprocessing Toolbox.

### 2.4 Model development

We adopted a “full subsets model selection” approach, in which models were compared using Akaike information criterion for small sample sizes (AICc), and AICc weight (\(\omega_i\)) values (Burnham & Anderson, 2002). To ensure the resulting models remained ecologically interpretable and to avoid overfitting with our relatively small sample size (14 PICT), we only fitted models with up to two predictor variables in a single model. Collinear models (predictors correlated by >|0.30|, following Graham, 2003) were not included in the model set.

All models were fitted using generalized additive models (GAM), via the gam function from the mgcv package in R (Wood, 2006). GAM was adopted rather than linear or nonlinear parametric multiple regression to allow for possible nonlinear effects of predictors on the

**TABLE 1** Metrics calculated from each country export data for further analyses

<table>
<thead>
<tr>
<th>Metric</th>
<th>Definition</th>
<th>Measure</th>
<th>Inference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exports</td>
<td>Total weight of all beche-de-mer exported</td>
<td>Scale of trade for fishery</td>
<td>Size of fishery</td>
</tr>
<tr>
<td>Coefficient of variance (CV)</td>
<td>Ratio of the SD of exports to mean export weight</td>
<td>Standardized measure of variability of trade</td>
<td>Stability of fishery over time</td>
</tr>
<tr>
<td>Upper limit of confidence interval (ULCI)</td>
<td>Mean annual export weight + (1.96 × SE)</td>
<td>Fishery-specific reference point for elevated levels of trade within variation descriptor described as “normal”</td>
<td>Upper limit of average trade within “normal” variation of trade data set</td>
</tr>
<tr>
<td>Boom duration</td>
<td>The number of years that exports were larger than the ULCI.</td>
<td>Standardized characterization of fisheries tendency for “non-normal” years of elevated trade</td>
<td>Standardized measure of duration of fishery boom periods</td>
</tr>
<tr>
<td>Peak boom</td>
<td>Peak export divided by ULCI</td>
<td>Standardized characterization of the level of fisheries boom, against background fishery reference point for elevated trade</td>
<td>Standardized measure of fishery peak relative to overall production</td>
</tr>
</tbody>
</table>
response variable, without the necessity to define the functional form. Smooth terms were fitted using a cubic spline basis (Wood, 2006) and by limiting the argument $k$ to a maximum value of 4 to avoid overfitting and ensure monotonic relationships given our small sample size.

We examined model assumptions (homogeneity of variance and normality in the distribution of residuals) using residual plots and found these assumptions were adequately met following a square root transformation of export, boom duration and peak boom. No transformations were made to CV. For the predictor variables, coastline was square root-transformed, and population density, shallow water area, land area and reef area within 150 and 300 km were log-transformed to improve the spread of data across their range. All models with an AICc weight greater than 0.1 were considered. To determine the relative importance each variable across the whole model set, we summed the $\omega_i$ values for all models containing each variable. The higher the combined weights for an explanatory variable, the more important it was for the analysis (Burnham & Anderson, 2002).

For summed variable weights to be meaningful, it is necessary to have the same number of models containing each variable (Burnham & Anderson, 2002). As this was not the case because collinear models were removed, we calculated averaged variable weights (average $\omega_i$) by dividing each weight ($\omega_i$) by the total number of models containing each variable or class of variables, respectively, and rescaled these to zero (variable with the lowest summed weight) and one (variable with the highest summed weight). We explored the impact of including spatial autocorrelation structures within the GAM model fits, with little impact on the results.

### 2.5 | Standardized metric of export and fishing intensity

Export data were standardized for number of years of exploitation and shallow water area, to generate a standardized export metric relative to time of fishing and fishing ground area for each country. This metric
was developed for two reasons: (i) evaluate fishing intensity for each country in the data set and (ii) to inform guidelines for production.

3 | RESULTS

3.1 | Regional and subregional sea cucumber production

Since 1971, the region has recorded exports of over 32,000 t of beche-de-mer. Annual sea cucumber production from the region peaked in 1992 at 2,043 t. Melanesian countries (i.e., PNG, Solomon Islands, Vanuatu, Fiji and New Caledonia) exported considerably more sea cucumbers than countries from Polynesia or Micronesia (Figure 2). Exports from Melanesia fell sharply from 2010, after fisheries moratoria in PNG, Vanuatu and Solomon Islands. In contrast, Polynesia and Micronesia have more recently increased exports after reopening fisheries, notably in Tonga (Polynesia), in Palau and Marshall Islands (Micronesia).

3.2 | National sea cucumber production profiles

Total exports of sea cucumbers were greatest from PNG (10,963 t), followed by Fiji (8,719 t), Solomon Islands (6,081 t) and New Caledonia (2,257 t; Figure 3). The peak exports relative to upper CI limit (peak boom) in these countries were relatively low (2.0–2.8) reflecting more sustained production, except for Solomon Islands that had a peak at 3.7 times the upper CI limit. PNG’s sea cucumber fishery exported product above its upper CI limit for 18 of 39 years (1971–2009), the most sustained and stable high-level of production in the region. In contrast, countries that produced less tended to have concentrated periods of production that were not sustained. For example, Tuvalu and Federated States of Micronesia had large but short-lived peaks in production relative to other years (peaks at 9.2 and 6.3 times their upper CI limit, respectively).

For all four response variables examined, models with high weight ($\omega_i > 0.1$) generally included land area, either alone (for boom duration, peak boom) or with population density (for export, boom duration), distance to the centre of biodiversity (for export and CV) or distance to the equator (for export and boom duration) also included (Table 3). The size of fishery (export) also had relatively high weight for a model with shallow water area, and HDI ($R^2 = 0.67$, $\omega_i = 0.1$, Table 3). Predictably, total exports were higher in countries with larger fishing grounds, as measured by shallow water area, and were negatively influenced by the level of economy and market infrastructure (HDI). Relative variable importance for the best fitting models for each response variable is presented in Figure 4a–d.

Land area had a clear positive influence on total national export (Figure 5a). The standardized measure of variability in national exports (CV) was negatively influenced by land area, meaning that less land area meant more erratic export profiles (Figure 5b). The model also included distance to the centre of biodiversity, although this appeared largely driven by high CV in Palau, and low CV in Kiribati. Countries with larger land area experienced more prolonged booms in exports than countries with small land area (Figure 5c). Similarly, countries with smaller land area tended to have relatively bigger peak booms than those with larger land area (Figure 5d).

3.3 | Standardized metric of export and fishing intensity

Tonga exported about 41 kg year$^{-1}$ km$^{-2}$ shallow water, the second highest corresponding value was for Samoa at 39 kg year$^{-1}$ km$^{-2}$ (Figure 6). These two Polynesian countries, both having high islands, exhibited far higher fishing intensity relative to fishing ground than any other country. Few years of open fishing contribute to driving up the intensity measure in both these countries. At the other end of the scale, Federated States of Micronesia exported 0.2 kg year$^{-1}$ km$^{-2}$. French Polynesia, Marshall Islands had a metric of 1 kg year$^{-1}$ km$^{-2}$. Notably, for PNG and Fiji, the two largest producers in the region, the metric was very different at 2.5 and 16 kg year$^{-1}$ km$^{-2}$, respectively.

4 | DISCUSSION

4.1 | Land area and fishery productivity

The scale of island fisheries and their production profiles varied markedly, and patterns were driven largely by un governable environmental factors. Globally, fishery boom and bust production patterns are well documented for resources under high market demand (Berkes et al., 2006; Anderson et al., 2011), but our analyses show that a country’s boom duration and its peak boom varied predictably with its land area. The area of shallow water (fishing ground area) proved less influential on fishery production dynamics. Our calculation of shallow water area is an imperfect measure of habitats and ecological processes that drive patterns of resource abundance and diversity (e.g., Bellchambers et al., 2011; Cariglia et al., 2013; Eriksson, Byrne, & de la Torre-Castro, 2013). Better refined national level measures of coastal key habitats (e.g., seagrass, mangrove) could not be obtained.
FIGURE 3  Dried sea cucumber (beche-de-mer) exports from 14 Pacific Island Countries and Territories in vertically descending order of total exports. Horizontal line is export upper confidence interval limit. Area above upper confidence interval limit is shaded (boom duration). The figure on top of the peak export is the maximum export divided with the upper confidence interval limit, as a measure of export topography (peak boom). Red shaded areas on the x-axes are periods of export moratoria. For Federated States of Micronesia, the shaded area represents the closure in Yap state. Solomon Islands closed its fishery again in 2014. Kiribati and Tonga closed their fisheries in 2015 [Colour figure can be viewed at wileyonlinelibrary.com]
We theorize that land area is foremost a proxy for productivity of coastal waters and habitat complexity, because island geology-type and geography dictates nutrient input through terrestrial sources and oceanography (Littler, Littler, & Titlyanov, 1991; McClanahan, 2015; Williams et al., 2015). For example, land-based nutrient influx influences algae biomass and the density of echinoderms (Birkeland, 1982; Mora, 2008; Uthicke, Schaffelke, & Byrne, 2009). Land area can also be translated to a measure of coastal morphology and a habitat proxy for level of coastline complexity influencing species presence and distribution (Chefaoui, 2014). The inference we take from these analyses is that stocks in high-island countries and territories with large landmass are more able to absorb fishing pressure than in low lying atolls because these are more nutrient rich and complex interconnected environments that have a greater capacity to support diverse and productive sea cucumber fisheries.

It is well documented that human drivers influence the state of coral reefs (Cinner et al., 2009; Jouffray et al., 2015) and, in trying to elucidate better the influence of human pressures, our assessment spanned a range of potential human drivers. Higher human populations tend to have a negative effect on reef fisheries (Brewer, Cinner, Green, & Pressey, 2012; Stallings, 2009; Williams et al., 2015), and such effects have been detected at relatively coarse measures, such as national population density (Mora, 2008). Together with land area, population density, which varied from 6 to 316 people per km$^2$ of shallow water area (<30 m depth) in Palau and Samoa, respectively, had a significant but weak influence on export volumes in the best fitting model assessments.

**TABLE 3** Generalized additive model (GAM) fits for all best models (with >0.1 model weight) for the predictor variables influencing four catch metrics. Shown are the included model parameters (all best models), model size (number of included predictors), $R^2$, AIC, BIC and Akaike weights ($\omega$).

<table>
<thead>
<tr>
<th>Response variable</th>
<th>Best model</th>
<th>Model size</th>
<th>$R^2$</th>
<th>AIC</th>
<th>BIC</th>
<th>$\omega$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Export</td>
<td>Land area + Population density</td>
<td>2</td>
<td>0.82</td>
<td>112.3</td>
<td>116.2</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>Land area + Distance to COB</td>
<td>2</td>
<td>0.75</td>
<td>113.2</td>
<td>117.0</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>Land area + Distance to equator</td>
<td>2</td>
<td>0.76</td>
<td>113.4</td>
<td>117.3</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>Shallow water area + HDI</td>
<td>2</td>
<td>0.67</td>
<td>114.2</td>
<td>118.1</td>
<td>0.10</td>
</tr>
<tr>
<td>CV</td>
<td>Land area + Distance to COB</td>
<td>2</td>
<td>0.82</td>
<td>33.4</td>
<td>37.2</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td>Land area</td>
<td>1</td>
<td>0.58</td>
<td>36.2</td>
<td>38.7</td>
<td>0.14</td>
</tr>
<tr>
<td>Boom duration</td>
<td>Land area</td>
<td>1</td>
<td>0.93</td>
<td>18.1</td>
<td>20.7</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>Land area + Population density</td>
<td>2</td>
<td>0.96</td>
<td>21.1</td>
<td>24.9</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>Land area + Distance to equator</td>
<td>2</td>
<td>0.96</td>
<td>21.8</td>
<td>25.7</td>
<td>0.10</td>
</tr>
<tr>
<td>Peak boom</td>
<td>Land area</td>
<td>1</td>
<td>0.63</td>
<td>14.6</td>
<td>17.2</td>
<td>0.64</td>
</tr>
</tbody>
</table>

**FIGURE 4** Relative variable importance for the four response variables modelled in this study according to the full subsets generalized additive model analysis (see Panels a-d). Variable importance was calculated as the sum of the Akaike weight values ($\omega$) for all models containing each variable of interest, divided by the total number of models in which that variable occurs, and rescaled to zero and one (one being the variable of most importance). Variables with full dots are those included in the best fitting model, and variables with open circles are those not part of best fitting model. Variables are ordered according to the three categories modelled in this study: (i) fishery scale, (ii) fishery productivity and (iii) socio-economic (see Table 2).
We hypothesized that the measure of isolation chosen in our model (reef area within 150 km or 300 km) would signal that countries and territories with less contiguous reef area would exhibit shorter peak duration and larger peak booms. For example, Richmond (1997) reported that only two individuals of one edible species of sea cucumber were found 50 years after large sea cucumber exports were made from isolated atolls in Federated States of Micronesia in the late 1930s. However, our proxy of isolation did not influence results in our models. Some effect of biogeography can be interpreted as variability of exports (response variable CV) increased with distance from the centre of biodiversity in the Coral Triangle. However, the inferences from these variables are limited because the data we have are incomplete for being able to explain processes at smaller scales. For example, our analyses operated at the country level using amalgamated annual exports, and these measures are probably too broad for gauging patterns that may occur at more ecologically relevant island or reef scales (e.g., Bellchambers et al., 2011; Cariglia et al., 2013; Eriksson et al., 2013; Feary et al., 2014; Van Wynsberge et al., 2016), for which more refined proxies and response variables are required.

4.2 Production limits and reference points

The conclusion that historical catches of sea cucumber in most PICT have been too high is self-evident and widely reported (e.g., Anderson et al., 2011; Friedman et al., 2011; Pakoa & Bertram, 2013; Purcell et al., 2013). Trade statistics provide increasingly valuable information for evaluating trade flows and gauging globalized impacts (e.g., Eriksson & Clarke, 2015; Moran & Kanemoto, 2017; Watson et al.,...
For fisheries that can be managed by regulating trade, such as SSF that predominantly supply international markets, such data can also be used to develop management guidelines by helping to estimate production and provide evidence for catch limits. However, the national sea cucumber export statistics used in this assessment lacked detail on species composition, fishing area or effort. Consequently, our analysis does not provide a sufficiently strong basis for delivering a “rule of thumb” exploitation level (see for example McClanahan’s (2015) proposed 600 kg/ha threshold for reef fish). Nevertheless, annual total catches and catches per unit area (fishing intensity) provide limit reference points of sorts; it is safe to conclude that they have been too high and that catch levels needed to rebuild stocks will need to be considerably less than the historical estimates of fishing intensity given in this study.

The strong influence of land area on production profiles suggests that fisheries have been exploited to the environmental productivity limits in most PICT. We found that Fiji has extracted far more sea cucumber per year and shallow water area than PNG (16 kg year\(^{-1}\) km\(^{-2}\) compared to 2.5 kg year\(^{-1}\) km\(^{-2}\)), inferring that there may be differences in shallow water productivity in regards sea cucumber stock responses between the two biggest producers in the region. However, such comparisons are made complicated by the influence of fishing patterns (e.g., accessibility and effort). Across the Pacific, the conditions for operating productive fisheries vary significantly and harvests from atoll nations of Polynesia and Micronesia will need to be targeted at lower levels per unit area than in the high islands that predominate in Melanesia, where our results suggests conditions are more favourable for productive fisheries. Governing systems of SSF will need to tailor their management approaches based on these intrinsic conditions.

Historical patterns in booms and busts in the export of sea cucumbers may offer a clue in how to rethink fisheries in the region. Melanesian countries that have shown high historical levels of fishery productivity might reasonably aspire to developing sustainable fisheries with annual harvests reflecting best available information on catch limits. Annual export quotas at levels below the limit of the confidence interval calculated from historical exports are a place to start (below horizontal lines in Figure 3) once stocks have been rebuilt. Evaluating and adjusting conservative exports below this measure will help identify rates of exploitation that might be trialled to sustain production over longer periods than past booms and busts.

In contrast, history suggests that lower productivity fisheries in Polynesian and Micronesian countries, particularly in the atoll nations, cannot extend beyond very small annual harvests. As an alternative strategy particularly suitable in these countries, sea cucumber stocks may perhaps more usefully be framed as national resources to be used only irregularly during periods of special requirements—rather than as a reliable component of a fishing livelihood. For example, giving access to protected stocks has provided rapid injection of cash for rebuilding community economies and livelihoods after severe natural hazards (Eriksson et al., 2017). When protected, high-value export species from SSF can form crucial economic “safety nets” for dispersed island populations. Future SSF policy and management plans may consider this unique feature of these species when incorporating SSF into broader development and island resilience strategies.

Thus far, fisheries agencies have mostly relied on export regulation to reduce fishing effort. Regulating trade through national export quotas will continue to have a role to play in managing production (Barclay et al., 2016; Carleton et al., 2013), and the findings in our study help guide development of future production limits once stocks under moratorium recover. Additionally, innovations in value-adding (Porcell, 2014) and local scale management, such as those developed in Vanuatu (Léopold et al., 2013) or PNG (Hair, Foale, Kinch, Yaman, & Southgate, 2016) that focus on adaptability and the minimum requirements for sustainability (Cochrane, Andrew, & Parma, 2011), will also continue to be a priority.

5 | CONCLUSIONS

Our fishery metrics and related model outputs contribute to a growing body of literature that seeks to use wildlife trade statistics to augment management of data-poor production systems and establish impacts from larger scale trade patterns. Fishery trade data provide limited resolution to evaluate processes associated with exploitation. Similarly, explanatory variables at a fishery and country level provide only a large-scale definition of predictors. Nevertheless, our analysis documents combined modern production of sea cucumber in SSF from the region and provides insights into dynamics associated with varying island contexts across a large oceanic region.

It is clear that “not all fisheries are equal” in how they responded to fishing and management. The retrospective analysis of trade statistics help balance expectations of what islands can produce in the future with respect to their intrinsic natural attributes and help identify limit reference points for island SSF. Instituting fishery closures has been used as effective way to drastically reduce pressure to ensure long term sustainability of these fisheries. Next, governing systems must adhere to the lessons from historical booms and busts if SSF in the Pacific region are to fulfil their promise in contributing to food security and national development: high-value export species from SSF can form crucial economic “safety nets” for dispersed island populations.

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**SUPPORTING INFORMATION**

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