Mapping Fishing Activities and Suitable Fishing Grounds Using Nighttime Satellite Images and Maximum Entropy Modelling

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Abstract: Fisheries surveys over broad spatial areas are crucial in defining and delineating appropriate fisheries management areas. Yet accurate mapping and tracking of fishing activities remain largely restricted to developed countries with sufficient resources to use Automated Identification Systems and Vessel Monitoring Systems. For most developing countries, the spatial extent and boundaries of fishing grounds are not completely known. We used satellite images at night to detect fishing grounds in the Philippines for fishing gears that use powerful lights to attract coastal pelagic fishes. We used nightly boat detection data, extracted by U.S. NOAA from the Visible Infrared Imaging Radiometer Suite, for the Philippines from 2012 to 2016, covering 1,713 nights, to examine spatio-temporal patterns of fishing activities in the country. Using density-based clustering, we identified 134 Core Fishing Areas (CFAs) ranging in size from 6 to 23,000 km^2 within the Philippines' Contiguous Maritime Zone. The CFAs had different seasonal patterns and range of intensities in total light output, possibly reflecting differences in multi-gear and multi-species signatures of fishing activities in each fishing ground. Using maximum entropy modeling, we identified bathymetry and chlorophyll as the main environmental predictors of spatial occurrence of these CFAs when analyzed together, highlighting the multi-gear nature of the CFAs. Applications of the model to specific CFAs identified different environmental drivers of fishing distribution, coinciding with known oceanographic associations for a CFA's dominant target species. This case study highlights nighttime satellite images as a useful source of spatial fishing effort information for data-deficient fisheries, especially in Southeast Asia.

Keywords: VIIRS; fisheries; maximum entropy; mapping

1. Introduction

Monitoring and mapping of fishing activities are critical components of planning and management for marine fisheries [1]. Fishing location data have been used to identify and delineate fishing grounds [2], improve stock assessments [1,3], estimate fishing effort [4], and evaluate the impact of exclusion interventions in redistributing maritime activities [5]. Properly applying spatial catch-per-unit-effort data as indices of fish population abundance trends also require information on changes in spatial distribution of fishing effort [6]. With the increased call to manage fisheries within an ecosystem context, understanding the spatial dimension of fisheries becomes more crucial, from identification of fisheries management units to the development of appropriate and efficient management actions [7–9].

Despite its importance, spatial information on fishing activities remains sparse in developing countries due to the large number of fishing vessels and the high costs associated with collecting these data. Southeast Asian countries, for example, have some of the highest fishing effort densities (in boat-meters per km^2) in the world [10], yet the majority of fishing vessels in this region do not have Automated Identification System (AIS) transceivers. A global mapping of fishing activities using AIS highlighted a clear and striking gap in fishing boat detections within the greater Southeast Asia [11]. Costs for setting up and maintaining vessel monitoring systems can be prohibitive, reaching in excess of U.S. $1 million to equip 1,000 vessels and more than U.S. $250,000 annually for maintenance [12]. With many developing countries having tens of thousands of fishing vessels, other complementary sources of spatial data for fisheries need to be explored.

Global nighttime satellite images offer an alternative source of spatial data for fisheries that use lights to attract shoaling fish [13–15]. The high intensity lights used by these fishing methods are identifiable from nighttime satellite images, which may then give important insights to fishing activities in data-poor areas. Maritime applications of nighttime satellite products include mapping light pollution in marine protected areas [16,17]; mapping offshore petroleum gas flares [18,19]; boat detection and tracking [20–22]; fish habitat suitability mapping [23,24]; estimating fishing effort and intensity for single species fisheries [23,25–27]; and mapping of current and predicted potential fishing areas / zones [24,28,29].

The quality and availability of nighttime satellite images have improved considerably, making it feasible to study fishing activities that use lights at night in greater detail. Compared to the nighttime satellites launched through the 40 year-old U.S. Defense Meteorological Satellite Program (DMSP), the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument on-board the newer Suomi National Polar-orbiting Partnership satellite captures nighttime lights at much finer resolutions of 742 x 742 meters (vs. 5 x 5km); detects an order of magnitude of dimmer lights ($\sim2 \times 10^{-11}$ Watts/cm^2/sr vs. $\sim5 \times 10^{-10}$ Watts/cm^2/sr); and has higher data quantization (14 bit vs. 6 bit) [30]. The increased quantization means that radiance values are stored as floating values with a much wider range than the 64 digital numbers available for DMSP-OLS, allowing for more precise measurements of light intensity.

Powerful lights are used extensively in Southeast Asia to attract schooling small pelagic fishes and squids, making them easier to enclose with nets and haul the catch or lure in with fish hooks. In the Philippines, the most common fishing gears using powerful lights are ring nets, purse seines, and boat-based lift nets (Table 1). In Indonesia, nighttime lights detected from the VIIRS Day/Night band matched with data from vessel monitoring systems for squid lift net and jigging and purse seine small pelagic fishing [31]. Weaker intensity lights are also used in association with fish aggregating devices for tuna [32] and in catching post-larval stages of small pelagic fishes using fine-meshed scoop nets [33].

Table 1. Major fishing gears utilizing lights to attract fishes in the Philippines [34]

Gear	Target species	Description of light use
Ring net	Small scad, sardine, mackerel	200-500 watt bulbs (4-8 bulbs/boat) FADs: 500 watt bulbs (2-4 bulbs/FAD) or pressurized gas lamps
Small pelagic purse seine	Scad, mackerel, sardines	Incandescent 1000 watts/bulb (10-12 bulbs/boat) Halogen 1000-5000 watts/bulb (6-10 bulbs/boat)
Tuna purse seine	Skipjack tuna	FADs are lighted by a dim light boat which has 2-4 pieces of 1,000 watt bulbs.
Bag net or fish lift net	Roundscad, Anchovies, Indian sardines	10-20 halogen lights (1000-5000 watts/bulb) Some use underwater metal halide lights Biggest found in Cavite, Quezon, Davao, and Zamboanga 19x1,000 watt bulbs or 2-8 units of high wattage metal halide bulbs (1,000-5,000 watts)
Commercial round haul seine	Anchovies Squids [35]	No details available on types of lighting used

We used data from the VIIRS satellite images to fill in crucial information gaps in the spatial distribution of light-assisted fishing activities in the Philippines. Our objectives in this study are to: (1) identify the Core Fishing Areas (CFA) based on the density of nighttime lights, (2) characterize the spatio-temporal patterns in nighttime light-assisted fishing activities for each core fishing area, and (3) produce fishing ground suitability maps based on the environmental conditions that distinguish core fishing areas from non-core fishing areas.

2. Materials and Methods

2.1. VIIRS Boat Detection Data

Nightly VIIRS Boat Detection (VBD) data from April 1, 2012 to December 31, 2016 were downloaded from the U.S. National Oceanic and Atmospheric Administration National Center for Environmental Information's Earth Observation Group's website (https://www.ngdc.noaa.gov/eog/viirs/download_phil_boat.html). Individual VBD records represent lit-up pixels in a VIIRS Day/Night Band image [21,31] for one night. The VBD data files contain information on geo-location of lit-up pixels, radiance value (in nanoWatts/cm²/sr), date and time the image was taken, quality flag, various thresholding values used to distinguish a potential fishing vessel light source versus others, and corresponding VIIRS Day/Night Band image filename. We extracted only VBD points with Quality Flags 1 (strong boat detection), 2 (weak boat detection), 3 (blurry boat detection), 8 (recurring lights), and 10 (weak and blurry lights), corresponding to radiance spikes that are more likely from marine vessel light sources.

Given the satellite's pole-to-pole orbit, some image granules can have zonal overlap especially in mid to higher latitudes with a 2 to 3-hour time difference. To avoid double counting of VBD for the same boat, we identified VBD from two overlapping granules that are 1 kilometer apart and randomly selected one of the two points to represent the vessel's location for that night.

Since most of the fishing gears that use lights (Table 1) are catching coastal pelagic fishes [36], we limited our analyses to VBD within the Philippines' 24-nautical mile contiguous zone [37].

2.2. Identification of Core Fishing Areas

While fishing activities can occur anywhere in the ocean, previous studies have shown that fishers tend to cluster highly at specific marine locations [38,39]. Initial inspection of VIIRS Boat Detection data revealed similar patterns in the Philippines. We thus defined these areas as Core

119 Fishing Areas (CFAs) or locations which are repeatedly visited and where there is dense fishing
120 activity.

121   We accounted for the visitation frequency by creating a standardized 700-meter resolution grid
122 and counting the number of years when VBD was detected in each grid cell. We only used the VBD
123 data within cells that had more than 1 year of VBD occurrence. This also removed a lot of widely
124 scattered lights. We then obtained the centroid coordinates of each cell with more than 1 year of VBD
125 data and ran a series of Hierarchical Density-Based Spatial Clustering of Applications with Noise
126 (HDBSCAN) [40] using different parameter combinations of "minimum cluster size" (i.e., 3 to 30)
127 and "minimum samples" (i.e., 3 to 35), resulting in 1,200 different clustering combinations. We
128 selected the clustering parameter combination that yielded the least number of points classified as
129 "noise" while maintaining reasonable clustering of known small pelagic fish (SPF) fishing areas (e.g.,
130 Northeastern Palawan round scad fishing grounds; Tayabas Bay fisheries; and Basilan strait sardine
131 fisheries). Concave hull polygons were estimated for each cluster of points using a Delaunay
132 Triangulation algorithm to visualize the clusters. Finally, using high resolution images from Google
133 Earth and shipping traffic data from https://www.marinetraffic.com/ as reference (Figure S1), we
134 developed a raster mask to removed polygons in areas with possible high occurrence of non-fishing
135 related shipping activities (e.g., around busy harbors, shipping lanes, and areas with mining activities
136 near the coast) since VBD points in these high-traffic areas could include a large number of non-
137 fishing vessels that turn on additional deck and navigational lights. This mask was also used for the
138 MaxEnt modeling of suitable fishing grounds based on annual VBD occurrence. Annual raster
139 overlays were done using R (v. 3.5.1, R Development Core Team) [41], while hierarchical density-
140 based spatial clustering of applications with noise [42] and concave hull estimations were ran using
141 Python 2.7 (www.python.org).

142 *2.3. Clustering CFAs based on monthly patterns and radiance values of VBDs*

143   Each CFA can be characterized by the composition of fishing gears operating in the area and the
144 seasonal patterns in fishing. Multiple light-assisted fishing gears (Table 1) most likely operate in each
145 fishing ground. Radiance values can be used as a relative measure of light source intensity with
146 higher radiance corresponding to brighter lights [43]. A narrow radiance range could imply
147 dominance of a single type of fishing gear while a wide range could mean that multiple gears are
148 operating in the area.   Seasonal patterns in fishing activities, on the other hand, could be defined by
149 the mean nightly VBD by month, averaged across years within each CFA.

150   For radiance values, we applied histogram-valued data analysis based on the L2 Wasserstein
151 metric between distributions on log-transformed radiance per CFA [44]. We limited this analysis to
152 VBD points within CFAs occurring during nights with less than 50% moon illumination and less than
153 50% cloud cover since both factors are known to affect recorded radiance beyond this percentage
154 [21,43] (Figure S2). Clustering was performed using the R Package "HistDAWass" [45]. For seasonal
155 patterns in fishing activities within each CFA, we used the mean nightly VBD by month, averaged
156 across years, and standardized the values between 0 and 1, corresponding to the minimum and
157 maximum mean nightly VBD count by month. CFAs were grouped based on hierarchical clustering
158 using Ward's linkage method [46].

159 *2.4. MaxEnt modeling to identify environmental covariates with CFAs*

160   We identified key environmental attributes that define Core Fishing Areas and used these
161 relationships to map out other areas in the Philippines that have similar environmental attributes.
162 Our main assumption is that environmental conditions can be used to partially predict the suitability
163 of a given area for catching small pelagic fishes using light-assisted fishing methods. The relative
164 abundance of target species plays a key role in the selection of fishing grounds by fishers. Spatial
165 distribution of small pelagic fishes has been known to correlate with various environmental attributes
166 that link with food availability and habitat suitability.

167   We applied MaxEnt version 3.4.1 [47], a machine learning algorithm based on the concept of
168 maximum entropy [48], to determine the environmental conditions that characterize Core Fishing

169 Areas and identify other areas in the country with similar suitable environmental conditions that
170 could also have high fish productivity.   Since the VIIRS satellite only takes one image per night and
171 small pelagic fishes are also caught using other gears that do not employ powerful lights, we
172 conservatively treated the VBD locations as presence-only data and randomly derived pseudo-
173 absences or background locations outside the CFAs. MaxEnt is one of the few models available that
174 can handle presence-only data and has been used extensively for species distribution modeling
175 [49,50].   It estimates the relative suitability of one place versus another by comparing conditional
176 density of covariates at presence sites with unconditional density of covariates across the study area
177 [51]. Probability of occurrences are returned which is relative to the "typical" conditions generated
178 from available presence points.
179   We applied MaxEnt at an aggregated 4 km resolution to match the resolution of remotely-sensed
180 environmental datasets used as predictors (Table 2). The model domain is the Philippines' 24 nautical
181 mile contiguous zone bounded from 4° to 22° North and from 116° to 128° East. "Presence" locations
182 were defined as the centroid coordinates of 4-km grid cells that had VBD data and were inside any
183 of the CFAs for the periods 2013 to 2016. VBD data for 2012 was incomplete (i.e., starting only in April
184 2012) so it was not used in the MaxEnt models. Background points (~10,000) were randomly selected
185 within the model domain. The default regularization parameter of 1 was used to minimize model
186 over-fitting. "Maximum iterations" was set at 500. The "auto feature" selection method was also used
187 to allow MaxEnt to determine the appropriate feature class (e.g., linear, quadratic, product, threshold,
188 or hinge) [51] for each environmental predictor.
189   We collated environmental covariates commonly associated with the distribution of small
190 pelagic fishes [52–55] (Table 2). Gridded bathymetry was downloaded from the General Bathymetric
191 Chart of the Oceans (GEBCO) website. Monthly netCDF files for the other environmental predictors
192 (i.e., chlorophyll-a and sea surface temperature from MODIS; sea surface salinity, mixed layer
193 thickness, and sea surface height from the HYCOM hydrodynamic model) were downloaded from
194 the NOAA Coast Watch's Environmental Research Division's Data Access Program archives for the
195 years 2013 to 2016. Climatological and annual means were calculated for each predictor across the 4
196 years. All raster layers were projected to a Behrmann's equal area projection at 4km resolution using
197 bilinear interpolation under the 'raster' package in R [56].

198   **Table 2.** Data used for the MaxEnt modeling of Core Fishing Areas.

Predictor	Original resolution	Units	Source
VIIRS Boat Detection	742m	--	NOAA Earth Observation Group (https://ngdc.noaa.gov/eog/viirs/download_boat.html)
Bathymetry	30 arc-sec	meters	GEBCO (https://www.gebco.net/data_and_products/ gridded_bathymetry_data/gebco_30_second_grid/)
Sea surface temperature	4km	°C	MODIS-AQUA from NOAA CoastWatch (https://coastwatch.pfeg.noaa.gov/erddap/index.html
Surface chlorophyll-a		mg/cm^3	
Sea surface salinity		psu	
Mixed layer thickness (at density change of 0.03kg/m^3)	1/12° (~9km)	meters	HYCOM + NCODA Global 1/12° Analysis (https://coastwatch.pfeg.noaa.gov/erddap/index.html)
Sea surface height		meters	

199 *2.5. MaxEnt Scenarios*

200   Using the biomod2 package in R [57], we ran three different sets of MaxEnt models and
201 scenarios: (a) climatology, (b) annual, and (c) specific CFAs (Table 3). For the climatology runs, we
202 generated time-series averaged rasters for all five dynamic predictors (i.e., except bathymetry) from
203 2013 to 2016. Under this set, models were run with and without bathymetry as a predictor and

204 accounting for possible effects of monsoons which have been known to affect small pelagic fish
205 production in the Philippines [58].
206   The exact location of fishing activities, even within the same CFA, often changes across years.
207 To account for annual variability of dynamic predictors on annual aggregated locations of VBD inside
208 CFAs, we developed annual MaxEnt models from 2013 to 2016, using respective annual VBD data
209 and annual averages for each predictor. Since the CFAs most likely differ in terms of the fishing fleet
210 composition and targeted fish species, we selected two CFAs for which the dominant target species
211 group is known and where most fishing gears that use lights are almost exclusively targeting these
212 species. These CFAs are (a) the round scad fishery in Northeastern Palawan island (CFA # 106 in
213 Figure 3) and (b) the sardine fisheries in the Sulu Archipelago (CFA # 70).
214   To identify other areas within the Philippines' 24 nautical mile contiguous zone with similar
215 environmental characteristics to delineated CFAs, we generated predicted CFA suitability maps for
216 all 10 MaxEnt models. Mean predicted suitability values per model was generated from suitability
217 maps produced in each of the cross-validation runs (n=10 per model). The resulting suitability
218 distributions were compared with the location of existing CFAs.

219   **Table 3.** MaxEnt models implemented

Model Name	Description
	A. Climatology
A1. Full	All VBD points within CFAs and mean climatology for all six environmental predictors
A2. Full – No Bathymetry	Bathymetry variable removed
A3. Northeast Monsoon (NEM)	Northeast monsoon model. VBD presence data limited to months within this monsoon period (i.e., November to April). Environmental predictors were averaged for Northeast monsoon months from 2013 to 2016.
A4. Southwest Monsoon (SWM)	Southwest monsoon model. VBD presence data limited to months within this monsoon period (i.e., May to October). Environmental predictors were averaged for Southwest monsoon months from 2013 to 2016.
	B. Annual
B1. 2013	All environmental predictors and VBD in CFAs for 2013
B2. 2014	All environmental predictors and VBD in CFAs for 2014
B3. 2015	All environmental predictors and VBD in CFAs for 2015
B4. 2016	All environmental predictors and VBD in CFAs for 2016
	C. CFAs
C1. Northeast Palawan	VBD in CFA # 106 (Northeast Palawan; Figure 3) and climatology of environmental predictors
C2. Sulu	VBD in CFA # 70 (Sulu; Figure 3) and climatology of environmental predictors

220 *2.6. Model Validation and Evaluation*

221   To test each MaxEnt model's predictive accuracy, we applied two repetitions of a 5-fold cross-
222 validation that splits the presence data into five subsets. For each run, four of the five subsets (i.e.,
223 80% of presence data) were aggregated and used to train the model, the remaining subset (i.e., 20%
224 of presence data) was used to evaluate how well the trained model can accurately predict these
225 occurrences [59]. Results were averaged across the repeated 5-fold cross-validation runs to predict

226 the current distribution of suitable fishing grounds for light-assisted fisheries within the Philippines'
227 24-nautical mile contiguous zone. Accuracy was measured for each cross-validation run using the
228 area under the curve of the receiver operating characteristic (AUC) and the true skill statistic (TSS)
229 [60–62]. AUC and TSS values range from 0 to 1. AUC values greater than 0.5 indicate that model
230 predictions are better than random predictions. TSS values greater than 0.4 indicate good models
231 [63].
232   We reported "variable importance" as a measure of the contribution of variables to the
233 discrimination of presence and pseudo-absence points. We also ran jackknife tests of environmental
234 importance (i.e., leave-one-out) which identifies improvements in model fit by adding or removing
235 each individual variable and measuring changes in training or testing data gain. Response curves
236 were generated and examined to derive the preferred range of environmental variables of potential
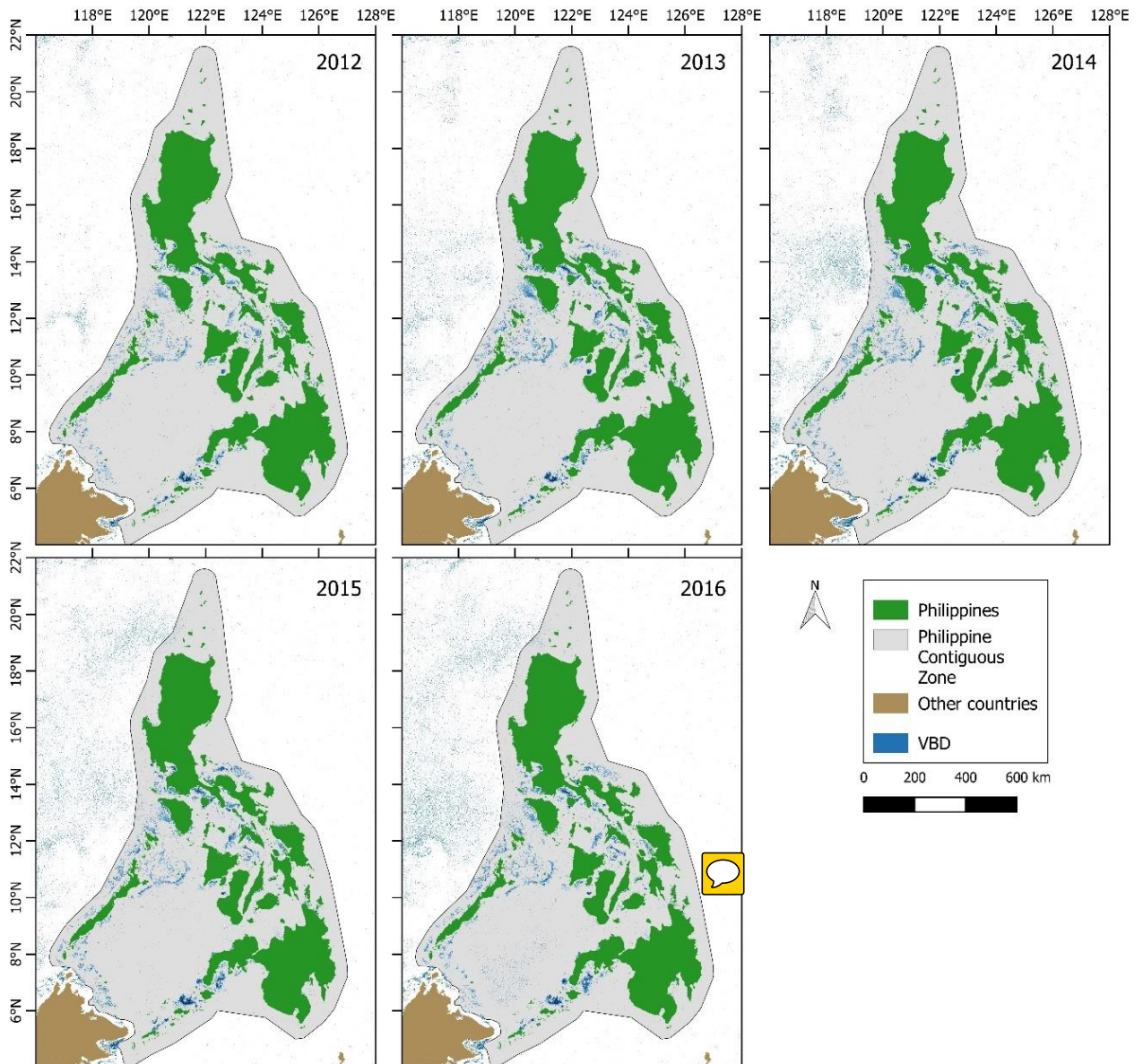237 fishing areas.

3. Results

239   VIIRS Boat Detection (VBD) locations within the Philippine's 24-nautical mile contiguous zone
240 are highly clustered with specific areas being frequently visited (Figure 1a). Spatial patterns are also
241 apparent in terms of mean radiance values with most VBD locations having radiance values greater
242 than 2.0 nanoW/cm²/sr (Figure 1b). VBD with less than 2.0 radiance values are clearly clustered
243 together in some areas. Across years, the spatial patterns of VBD aggregations within the Philippines
244 has not change greatly across the years from 2012 to 2016 (Figure 2).
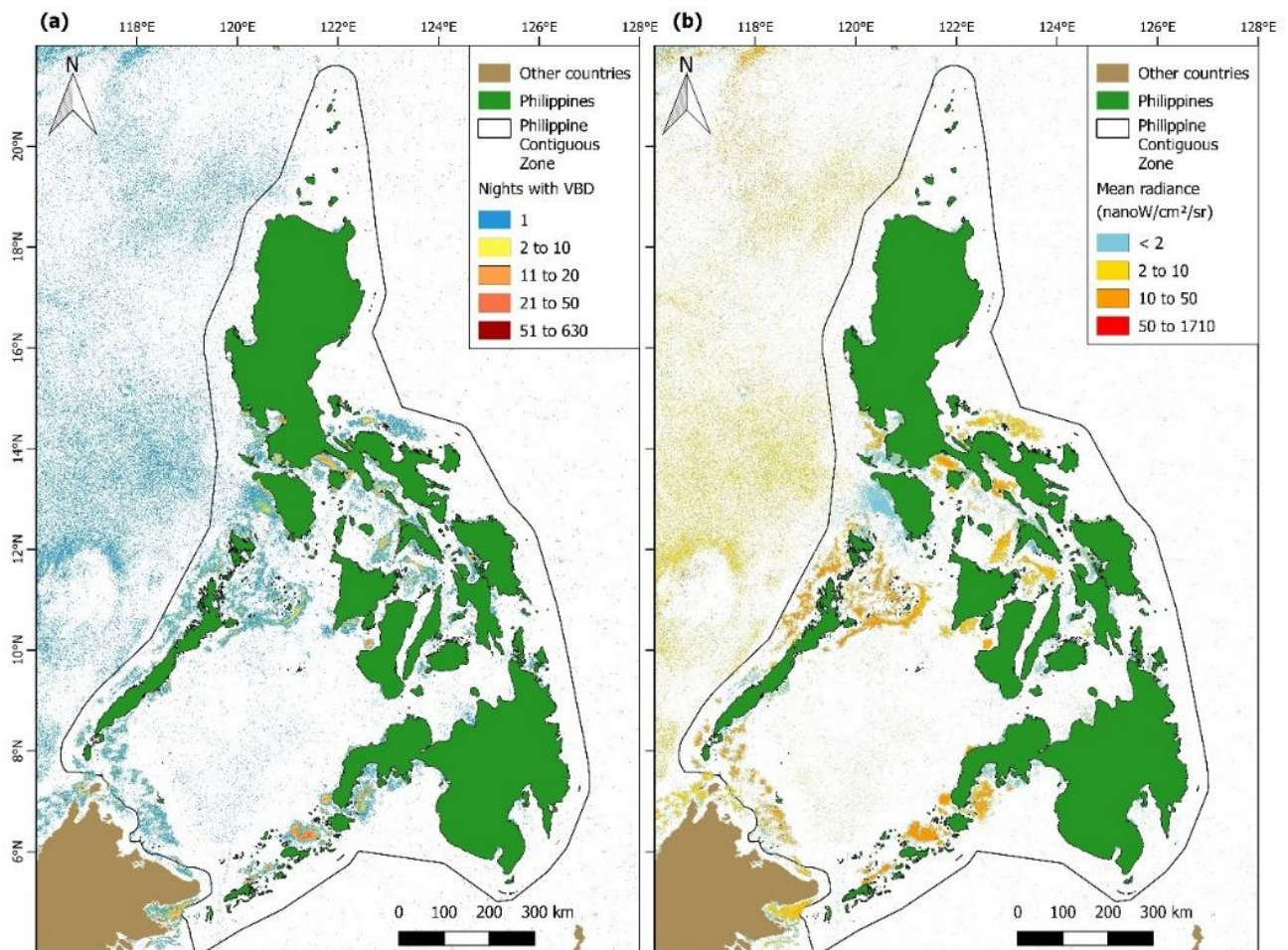
Figure 1. VIIRS Boat Detection (VBD) data from April 1, 2012 to December 31, 2016 aggregated on a
700m x 700m resolution grid showing (a) number of VBD detection per pixel over 1,713 nights and
(b) mean radiance value. The 24 nautical mile contiguous zone shapefile for the Philippines came from
Flanders Marine Institute's Marine Regions database [37].

Figure 2. Annual rasters of VIIRS Boat Detections (VBD) with 700m x 700m grid resolution.

3.1. Core Fishing Areas in the Philippines Maritime Contiguous Zone

A total of 694,793 VBD points was recorded within the Philippines' contiguous zone over 1,713 nights. Eighty-five percent (85%) of these data points were in cells that were visited for at least 2 years over the 5-year period (Figure 3).

We identified 134 Core Fishing Areas (CFA) for light-assisted fishing in the Philippines based on HDBSCAN results using a "minimum cluster size" of 4 and "minimum samples" value of 25 (Figure 3; S1). This HDBSCAN parameterization initially labelled 94% of the frequently visited VBD cell centroids into 160 clusters. We removed clusters that were (a) too small, (b) includes or are located near major ports / piers, and/or (c) located in major shipping lanes.

The 134 CFAs ranged in size from 5.6 km^2 to 23,215 km^2 with a mean size of 700 km^2. The maximum number of VBD for a given night was detected in March 3, 2014 with 1,124 lit-up pixels within the entire Philippines Contiguous Zone, 87% or 974 of these pixels were within CFAs. Per CFA, the maximum number of lights detected for a single night ranged from 2 to 227.
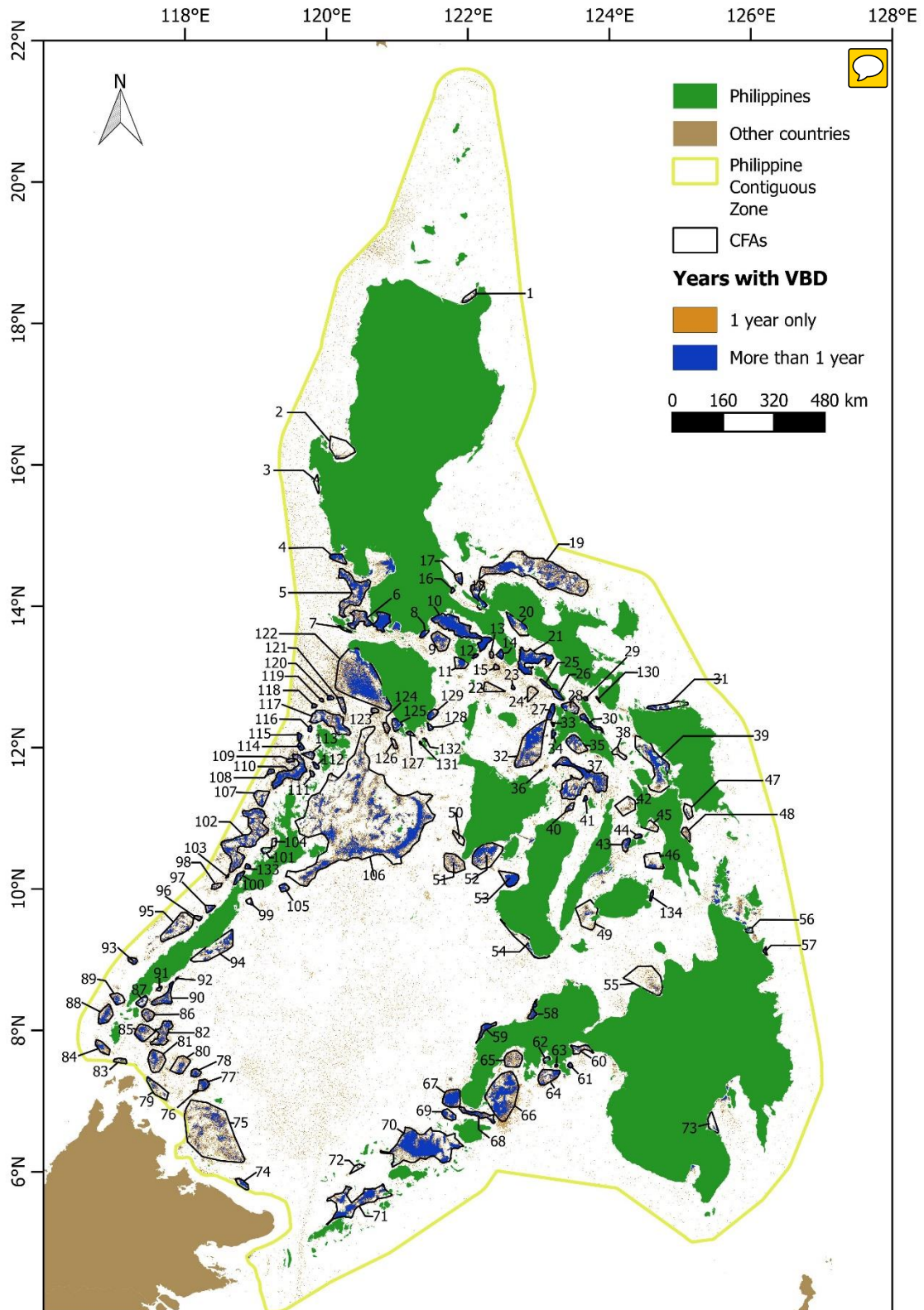
266

267 **Figure 3.** Core Fishing Areas (n=134) identified from HDBSCAN and after removing clusters in areas
268 that overlap with significant vessel traffic and close to major ports and piers, including mining jetties.
269 Details for each CFAs and corresponding names can be found in Table S1.

270

271　　　Seasonal patterns in fishing activity data varied per CFA (Figure 4; Figure S6-a). Cluster analyses
272　applied to averaged monthly VBDs showed two different groups based on the months when peak
273　fishing activity occur, generally corresponding with the monsoon months: (a) northeast monsoon
274　(November to April) and (b) southwest monsoon (May to October).
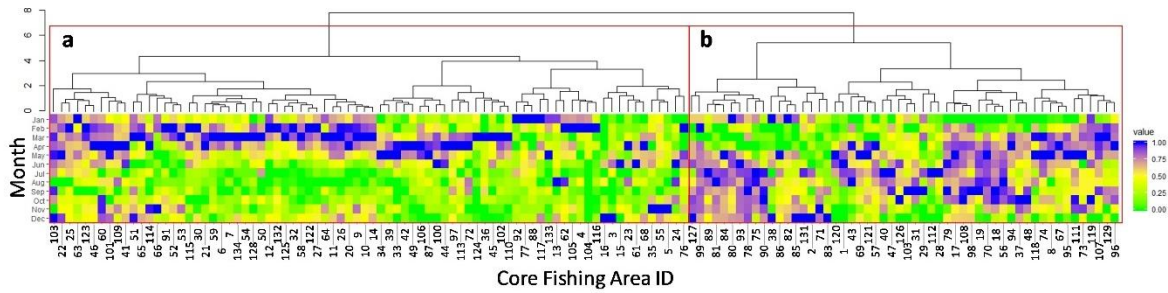
Figure 4. Hierarchical clustering of Core Fishing Areas based on scaled mean nightly VBD counts per
month using Ward's linkage method showing two groups based on months of peak fishing activity:
(a) southwest monsoon (May to October) and (b) northeast monsoon (November to April).

279　　　Mean radiance values per CFA ranged from 1 to 166 nanoWatts/cm²/sr (Figure 5; Table S1).
280　Hierarchical clustering on radiance distribution values per CFA identified two distinct groups (h
281　cutoff = 5): (a) low radiance values (group mean = 3.4 nanoWatts/cm²/sr) and (b) high radiance values
282　(group mean = 61.2 nanoWatts/cm²/sr; Figure 5; Figure S6-b).

283
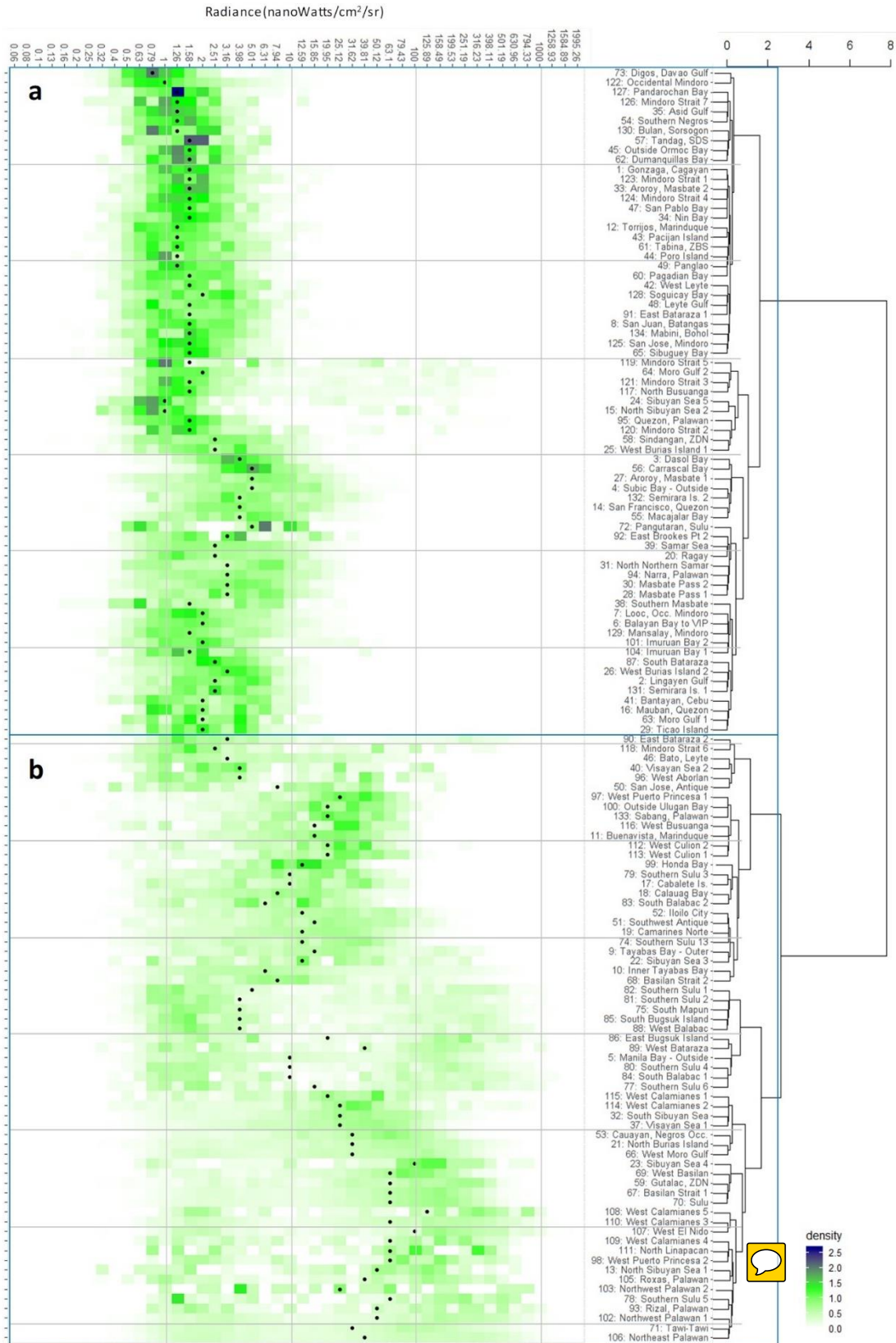
Figure 5. Hierarchical clustering of log-10 histograms of radiance values by CFA for nights with less than 50% moon illumination and cloud cover. Colors represent probability density of radiance bin per CFA. High-level groupings (around blue box) are based on spread of values with group (a) indicating high kurtosis, narrow range and low radiance values while group (b) are high radiance values with large spread and even some double peaks.

3.2. VBD and Environmental Variables

Mean sea surface temperature, chlorophyll-a, and bathymetry inside the CFAs differed from those outside (Figure 6). CFAs have mean depth ranging between 5 meters and 1480 meters, mean sea surface temperature between 28.5°C and 30.6°C, and mean surface chlorophyll-a values between 0.2 mg/m^3 and 2.2 mg/m^3. The difference between monsoons are apparent only in mean chlorophyll concentrations with the VBD points during the southwest monsoon located in areas with higher mean chlorophyll-a concentrations (0.75mg/m^3 for Southwest Monsoon vs. 0.43mg/m^3 for Northeast Monsoon; Welch Two Sample t-test p < 0.01).
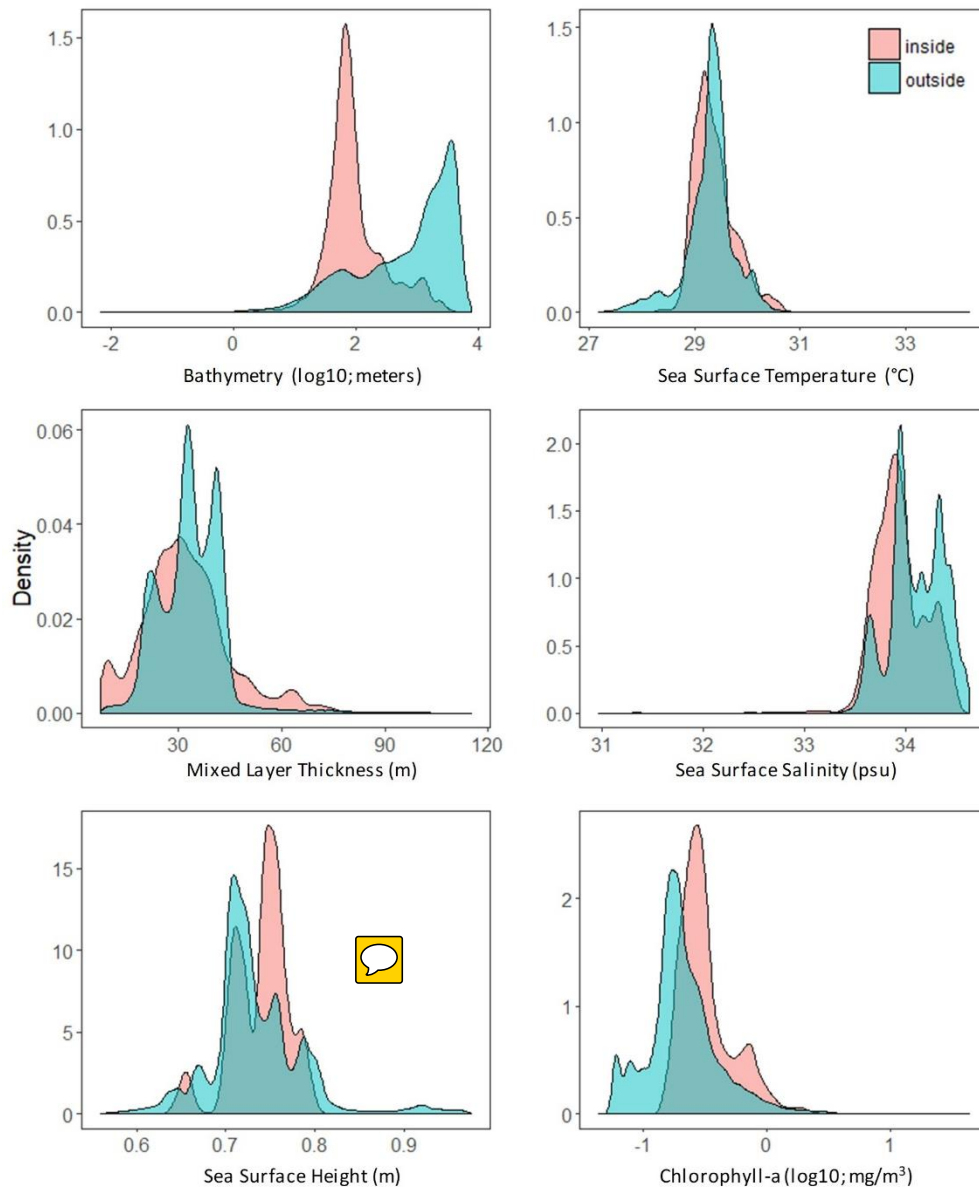
Figure 6. Density distribution of environmental predictors inside CFAs (red) versus outside (blue) within the Philippines' 24 nautical mile contiguous zone. Bathymetry and chlorophyll-a values log-10 transformed for clarity. Non-transformed values were used in the MaxEnt models.

All MaxEnt models performed better than random (i.e., AUC > 0.5 and TSS > 0.4; Table 4). Among all the models, the one without bathymetry had the lowest AUC and TSS scores. The full climatology, monsoonal, and annual models all had identical accuracy scores. The CFA-specific models performed very well, with very high AUC and TSS scores. However, this is to be expected given the restricted spatial extent of the VBD points used in these models.

308 **Table 4.** Model evaluation scores for the different MaxEnt models.

Model	AUC	TSS
Full Climatology	0.88	0.59
Full – no Bathymetry	0.86	0.55
Northeast Monsoon	0.87	0.58
Southwest Monsoon	0.88	0.59
2013	0.89	0.61
2014	0.88	0.60
2015	0.89	0.62
2016	0.88	0.59
Northeast Palawan	0.94	0.87
Sulu	0.93	0.87

309 Bathymetry ranked highest in variable importance among all non-CFA-specific models, with
310 permutation importance values ranging from 56% (2013) to 64% (Full model) (Figure 7). This was
311 followed by chlorophyll-a with permutation importance ranging from 14% (2016) to 24% (2013). In
312 the model without bathymetry, chlorophyll explained most of the difference between CFA and non-
313 CFA locations with a mean permutation importance of 55%. Jackknife tests also identified bathymetry
314 as the variable with the highest model training, testing, and AUC gain when used in isolation (i.e.,
315 most useful information by itself) and the greatest decline in gain when removed from the model
316 (i.e., contains most information that is not present in the other variables). Sea surface salinity ranked
317 third in terms of variable permutation importance, particularly in the monsoonal models. Sea surface
318 temperature and sea surface height varied in their contributions to the model but mostly at less than
319 10% importance. In contrast to this general pattern, the variables contributing to the CFA-specific
320 models were more even with bathymetry ranking lowest in importance for the round scad fishery in
321 Northeast Palawan (CFA # 106). In the Northeast Palawan model, sea surface salinity ranked highest
322 in importance (60%) followed by sea surface height (16%). In the Sulu CFA model, chlorophyll-a
323 ranked highest in permutation importance (34%) followed by bathymetry (28%), sea surface
324 temperature (17%), and sea surface salinity (10%).

325
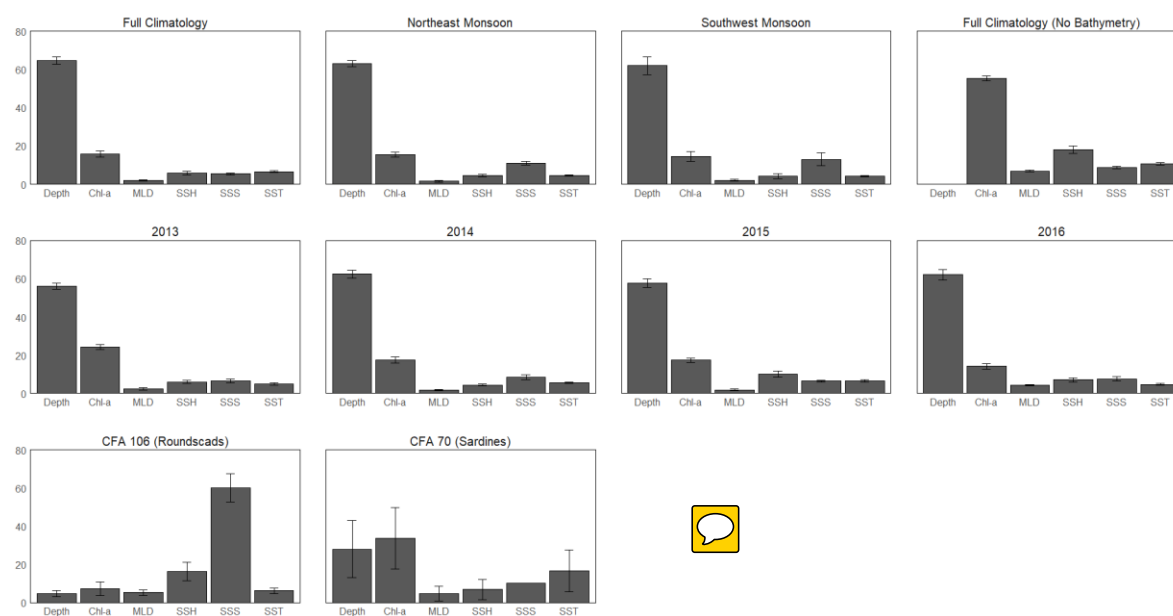
326 **Figure 7.** The relative contribution of different environmental predictors in determining the overall
327 fit of the MaxEnt models to the VBD presence data used (normalized to percentages). Values averaged
328 across two replicates of five-fold cross-validation runs of each MaxEnt model. Error bars are ± 1
329 standard deviation.

330   Model derived preferred ranges for the MaxEnt full climatology model are shown in Figure 8.
331 These response curves are marginal values showing the probability of occurrence of a site being a
332 Core Fishing Area with changing values of one variable while keeping all other variables at their
333 average sample value [64]. The logistic output or probability of occurrence increases with depth from
334 the shallowest depths up to around 100 meters then decrease rapidly to depths of 500 meters and
335 gradually declines further with depths deeper than 4000 meters. It peaked with chlorophyll-a values
336 between 0.3 and 2.0 mg/cm³. Frequently visited fishing sites also occurred more in areas with sea
337 surface temperatures between 28.6°C and 30.6°C. The effect of sea surface salinity, sea surface height,
338 and mixed layer thickness in discriminating CFA versus non-CFA areas was smaller compared to the
339 first three variables mentioned as indicated by the almost flat response across their entire range of
340 values.
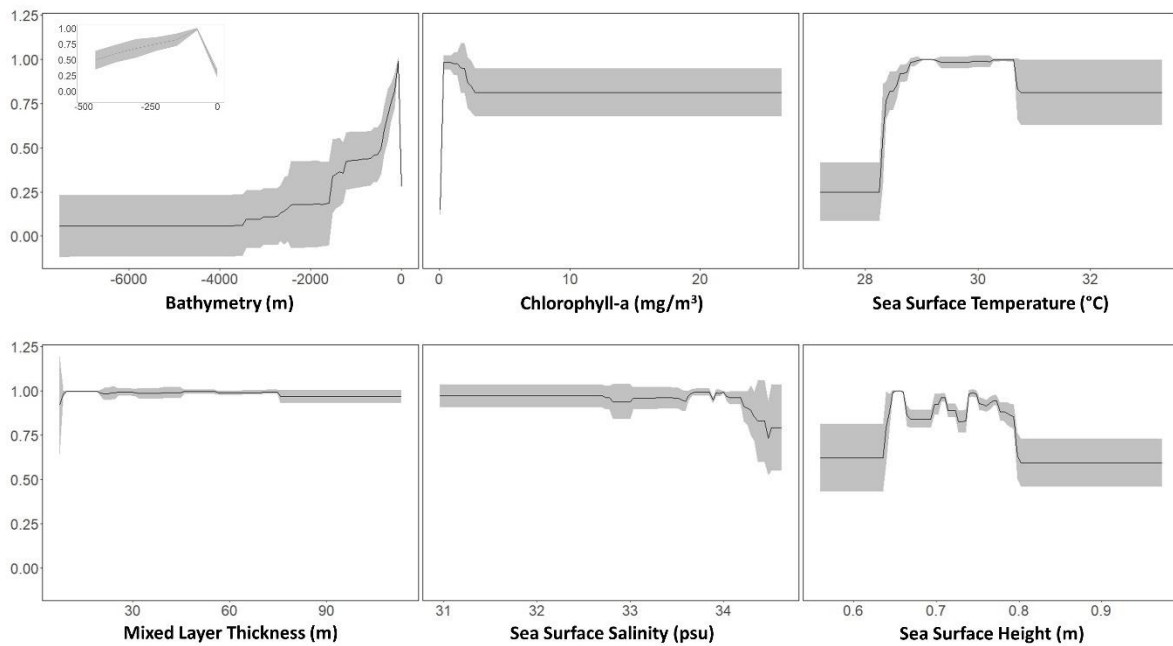
341

342   **Figure 8.** Response curves per environmental predictor for the Full Climatology MaxEnt model
343   showing how each environmental variable affects the MaxEnt logistic prediction. Black lines show
344   the mean response of the two replicate 5-fold cross-validation runs. Shading represents ± 1 standard
345   deviation. Inset: Response curve for bathymetry with x-axis minimum truncated to 500m depth.

346   The predicted suitability of marine areas for light-assisted fishing based on the climatology and
347 annual MaxEnt models are shown in Figure 9. Predicted suitable areas with environmental
348 conditions typical of the CFAs are found in shallow, nearshore areas around existing CFAs. Predicted
349 suitable areas do not vary greatly across monsoons and years. For the CFA-specific MaxEnt models,
350 we found highly constrained areas of high suitability (Figure 10). However, the predicted areas
351 correspond with other CFAs that were not included in the model (e.g., CFA # 77, 78, 80, 99, 94, 105,
352 and 107 for the Northeast Palawan round scad CFA and CFA # 53, 59, 69, and 73 for the Sulu sardine
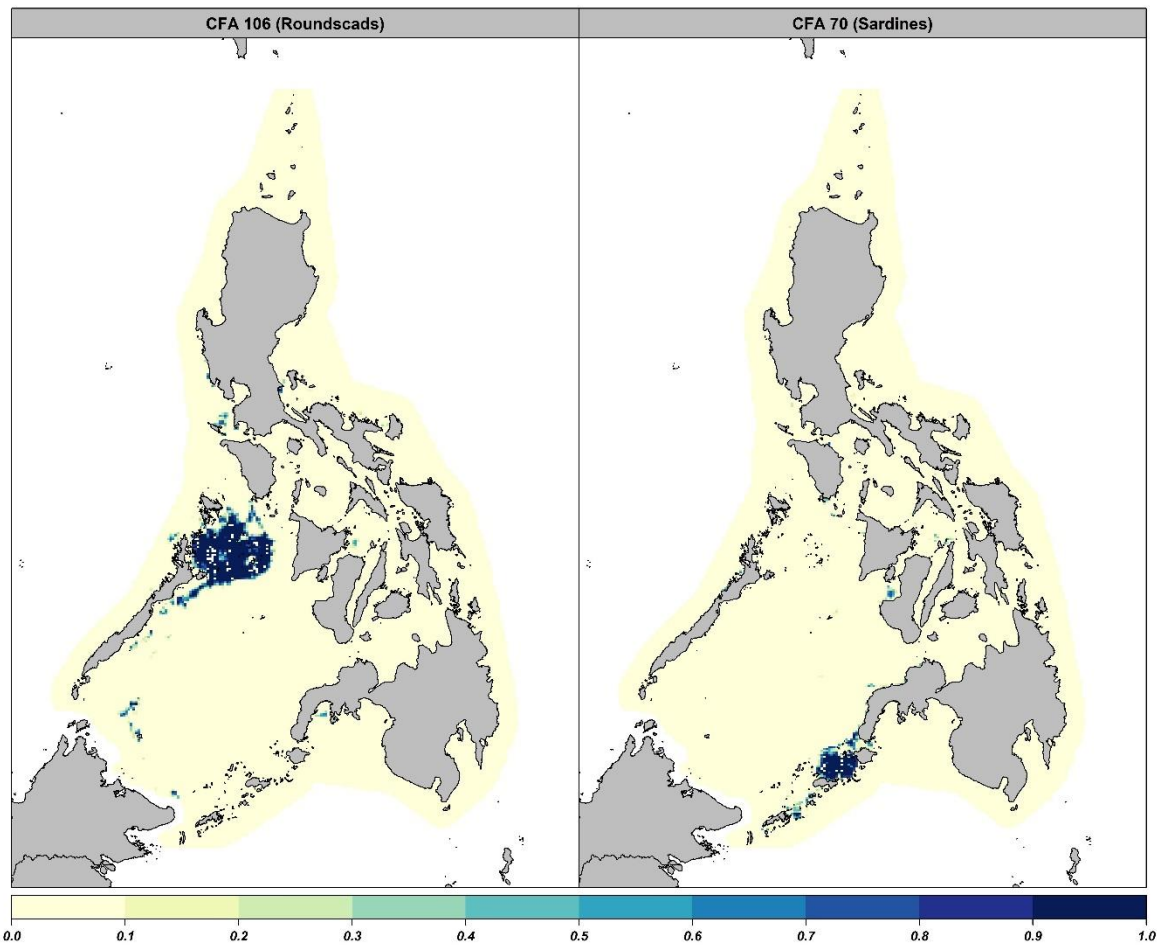353 CFA).
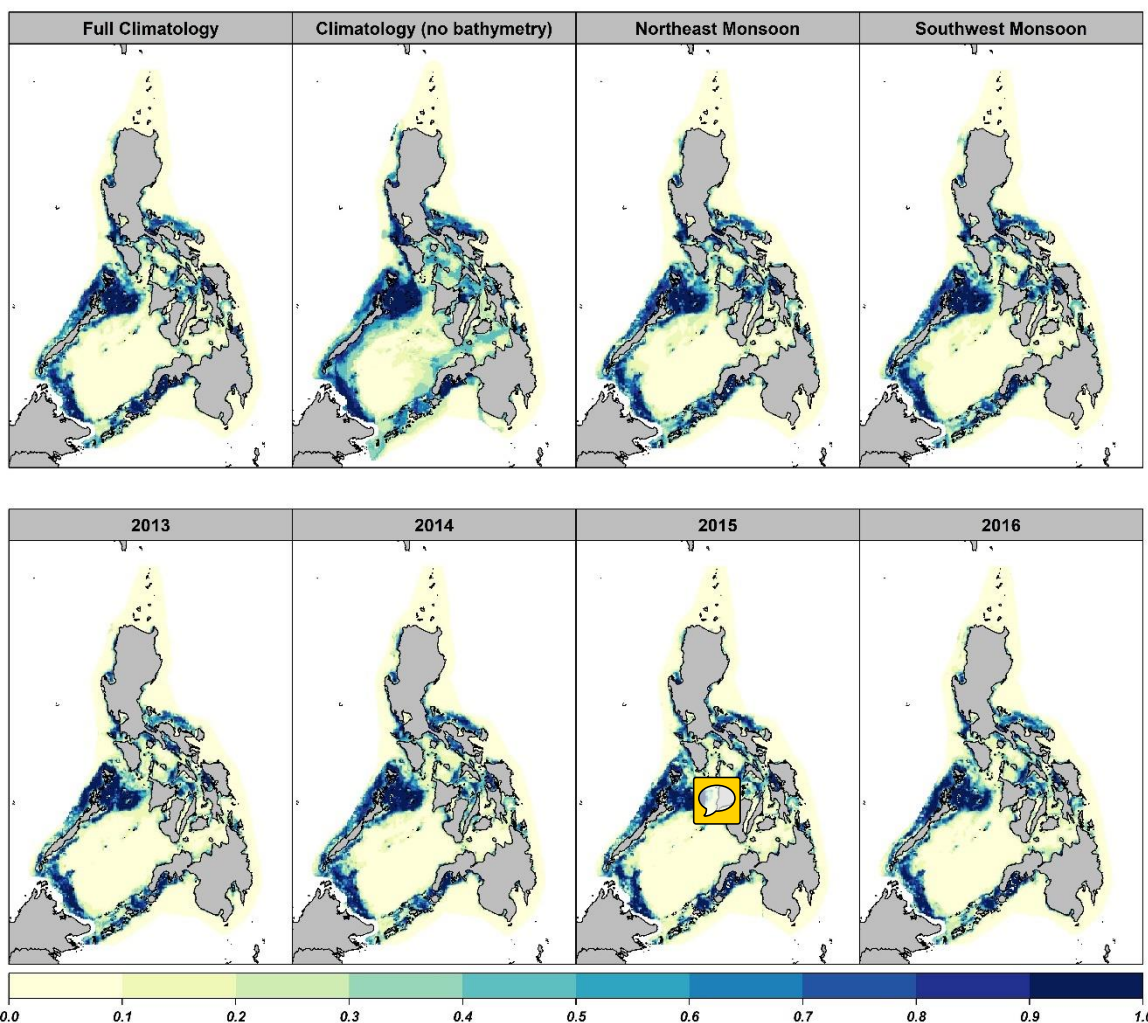
Figure 9. Predicted suitability maps for Core Fishing Areas for the different MaxEnt models developed using all VBD points inside the CFAs. Color scale represents degree of suitability relative to "typical" conditions found inside CFAs with 1 being highly suitable areas and 0 are unsuitable.

Figure 10. Predicted CFA suitability maps based on CFA # 106 (Northeast Palawan) and CFA # 70 (Sulu) representing predominantly round scad (*Decapterus sp.*) and sardine (*Sardinella lemuru*) fishing grounds, respectively. Color scale represents degree of suitability relative to "typical" conditions found inside CFAs with 1 being highly suitable areas and 0 are unsuitable.

4. Discussion

The VIIRS nighttime imaging capabilities significantly enhanced those of the DMSP satellites, particularly in terms of radiometric and spatial resolution, allowing for the nightly extraction of locations and radiance information of maritime lights [21,30]. We applied this freely accessible and novel dataset to identify, delineate, and characterize Core Fishing Areas (CFAs) and determine the suitability of other parts of Philippine coastal waters to light-assisted fisheries and their target species.

Many of the large CFAs identified are known primary fishing grounds for various coastal pelagic fishes. The Sulu CFA (#70) in Southern Mindanao is dominated by sardine purse seine fishing. It is one of the largest sources of the country's sardine (*Sardinella lemuru*) supply and has been subjected to seasonal fishery closures between November and March since 2011 due to concerns about overfishing and stock declines [65]. The Northeast Palawan CFA (#106) and those west of Palawan (e.g., CFAs # 102 to 117) are known round scad (*Decapterus macrosoma* and *Decapterus russelli*) fishing areas, also subjected to annual seasonal closure since 2015 [66]. Visayan Sea 1 (#37) and 2 (#40) CFAs are also part of a small pelagic fish seasonal closure established back in the 1970s primarily for to sardines (*Sardinella gibbosa*).

Bathymetry, chlorophyll-a, and sea surface temperature have all been cited as predictors of small pelagic fish spatial distribution in previous studies. Catches and fishing grounds for the Indian mackerel (*Rastrelliger kanagurta*) in Indonesia correlated significantly with chlorophyll-a and sea surface temperature [67]. Bottom depth and sea surface temperature explained variability in

382 European sardine (*Sardinella pilchardus*) presence in the Mediterranean Sea while bottom depth and
383 surface chlorophyll concentration predicted European anchovy (*Engraulis encrasicolus*) distribution
384 [68–70]. These three variables, along with salinity, are also used in mapping global distributions of
385 fish species through Aquamaps (www.aquamaps.org) [71,72]. These variables influence suitable
386 habitats for small pelagic fishes through zooplankton production and availability [73].
387   Bathymetry consistently ranked highest in discriminating between CFA and non-CFA sites,
388 accounting for the most variability not captured in the other variables. Chlorophyll accounted for
389 most of the variability in the MaxEnt model that excluded bathymetry indicating some correlation
390 between chlorophyll-a and bathymetry (Pearson's correlation r = 0.25; p < 0.01). Indeed, chlorophyll-
391 a tend to decline with increasing depth. However, zooming in on some of the CFAs show how VBD
392 data track, with surprising precision, bathymetry and depth contours using the 1-km resolution
393 GEBCO bathymetry data (Figure 11). Removing bathymetry as a predictor resulted in lower accuracy
394 model (AUC from 0.88 to 0.86 and TSS from 0.59 to 0.55; Table 4) and broader predicted areas of
395 suitability (Figure 9). Aggregating data at a 4km resolution removes these fine-scale spatial patterns
396 in nighttime lights and fishing sites. Finer resolution environmental data could explain more of the
397 variability in the distribution of nighttime lights in CFAs. Unfortunately, current available monthly
398 remote sensing data for chlorophyll and sea surface temperatures for this region are limited to a 4-
399 km resolution (i.e., MODIS images) while finer oceanographic models are not available for the entire
400 study area.
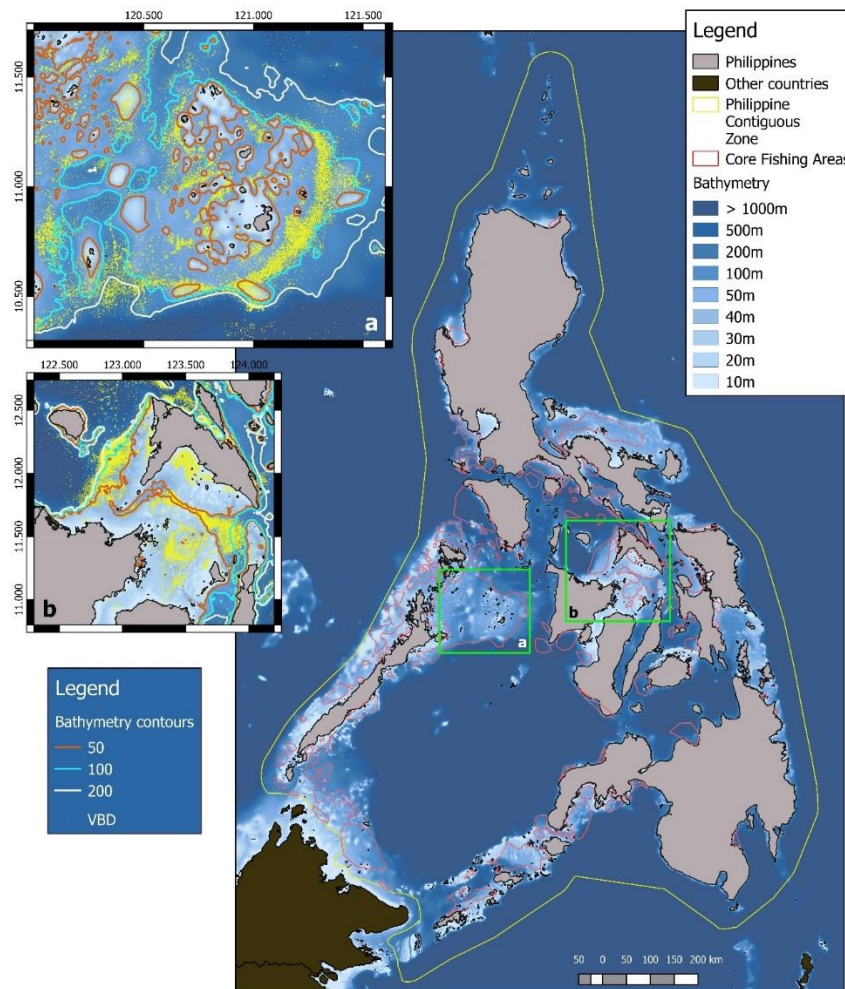
401

402 **Figure 11.** CFAs overlay on a bathymetry map of the Philippines showing most of the CFAs are
403 located in less than 200 meter depths. Inset maps show how VBD points align with depth contours
404 for (a) Northeast Palawan and (b) Visayan Sea.

405   The dominance of bathymetry in distinguishing CFA from non-CFA sites could be attributed to
406   (1) the depth preference of target species and (2) the multi-species nature of fisheries within CFAs. A
407   quick search in Fishbase (www.fishbase.org) on depth information for the dominant small pelagic
408   fishes caught in Philippines waters shows that commonly targeted small pelagic fishes by Philippine
409   fishing fleet are often found in depths of less than 200 meters [58]. In addition, CFAs most likely have
410   a large mix of different fishing gears that target various species of small pelagic fishes. Since different
411   species or species group tend to respond differently to water column characteristics (e.g., SST and
412   chlorophyll-a concentrations), the common denominator in their environmental preference becomes
413   bottom depth, a static variable which then gets captured as the main predictor of CFA versus non-
414   CFA sites. If the CFAs could be differentiated according to their dominant target species, the effect of
415   dynamic predictors in differentiating CFAs from non-CFAs for that particular species could be bigger
416   than bathymetry.

417   One of the main uses of the identified Core Fishing Areas and habitat suitability map in this
418   study is to delineate fisheries management areas as part of implementing Ecosystem Approaches to
419   Fisheries Management (EAFM) [8,9]. While we have provided here a way to identify frequently
420   visited fishing grounds and predict habitat suitability of non-fishing grounds based on nighttime
421   lights activity and environmental attributes, delineation of meaningful fisheries management unit as
422   part EAFM should be done in consultation with relevant stakeholders [2]. Some of the CFAs could
423   be grouped into larger fisheries management areas based on similarities in their target species and
424   fishing gears used. In the absence of actual fishing data available for each CFA, the seasonality of
425   fishing activities and the distribution of VBD radiance values could be used as a proxy for these
426   characteristics. For example, the northern Palawan CFAs (e.g., #102 to 117) can be grouped into one
427   FMA since they share the same seasonality in fishing activities (during northeast monsoon; Figure 4)
428   and radiance signature (Figure 5; see also Figure S6 for maps of the CFAs color-coded according to
429   cluster membership). The CFAs west of Mindoro island (#s 122 to 125) could also be considered as a
430   separate fisheries management area given their similarities in both seasonality of fishing activities
431   (during northeast monsoon) and radiance signature (mostly low radiance values). Of course, other
432   fishing activities and practices should also be considered in defining appropriate fisheries
433   management areas since the VBD only covers fishing vessels that use lights to attract fish. As Jennings
434   and Lee [2] stated, the ultimate delineation and definition of "fishing grounds" would be a societal
435   decision of choosing cut-offs and satisfying potential trade-offs in the use of limited marine space.

436   The VBD data could also provide important information on the levels of fishing effort over time.
437   The estimated number of fishing vessels using lights in the Philippines from the VBD data (~1,000) is
438   most likely an underestimate since the VIIRS instrument takes only one image per night and for most
439   nights, there is always a part of the country that is obscured by thick cloud cover. Summing up the
440   maximum nightly VBD per CFA for selected larger, well-separated CFAs (i.e., #s 19, 66, 70, 75, 106,
441   122) already results in 925 estimated light boats or fishing vessels with on-board lights. In
442   comparison, there are an estimated 6,371 commercial fishing vessels (i.e., 3 gross tons and heavier) in
443   the country as of 2007 [74]. Despite this potential underestimation of absolute fishing effort, the
444   quarterly pattern of nighttime fishing lights still tracks closely the national statistics of landed catches
445   of small pelagic fish (Figure S5). Monthly VBD data show a secondary peak between the 3rd and 4th
446   quarter of each year which is not captured in the quarterly landed catch data. This secondary peak in
447   the VBD data is most likely associated with the varying seasonal patterns of fishing activities among
448   CFAs with some CFAs' peak VBD counts occurring around this period (Figure 4). Subject to further
449   ground validation, the temporal trends in VBD data could be used as a proxy for relative fishing
450   effort at the national level for small pelagic fish catch, a key input for normalizing catch data.

451   *4.1. Limitations and future improvements*

452   In using the VBD data for fisheries studies, additional filtering is needed to ensure that most of
453   the data are fishing vessels. Although VBD use quality flags to identify non-vessel light sources in
454   the data, it has no flags to distinguish fishing from non-fishing vessels (e.g., cargo ships, tankers,
455   passenger ships, construction and mining-related temporary structures, among others). Navigation

456   routes are clearly seen from VBD overlays which correspond with known shipping lanes (e.g.,
457   between Mindoro and Panay Islands; Sabah, Malaysia and Tawi-Tawi, Philippines; Figure 3 and S4).
458   Major ports and mining areas also have high density aggregations of nighttime lights. It is possible
459   that many of these lights are also fishing vessels but without ground validation, we decided to
460   exclude them as Core Fishing Areas and in the MaxEnt modeling of suitable areas. Even though we
461   removed some of these potential CFAs, the fishing ground suitability map produced from MaxEnt
462   was still able to identify some of them as potential fishing grounds for small pelagic fishes based on
463   similarities in typical ocean conditions to most of the CFAs where lights are found (Figure 3; e.g.,
464   Northeast tip of Mindanao).

465   We ran the maximum entropy model under the assumption that areas where fishers often fish
466   (e.g., CFAs) are also areas of high relative abundance for the target species group, in this case, small
467   pelagic fishes, and that environmental factors can be used to predict habitat suitability [75]. At a
468   resolution of 742 meters, it is surprising that many of the cells where nighttime lights are found in
469   the last five years are revisited over the years. We hypothesized that environmental factors played a
470   large role in the spatial structure of the nighttime lights, particularly these frequently-visited and
471   high-density sites. However, other factors also influence fishers' decisions in selecting fishing
472   grounds such as projected fishing costs, estimated risk, and adherence to traditional fishing grounds
473   [76]. These are not captured in our model.

474   The utility of the VBD data in informing ecosystem approaches to fisheries management could
475   be enhanced by studies that can identify the relationships between radiance values and fishing
476   characteristics (e.g., fishing gear or strategy). This would help translate the VBD products from
477   remote sensing outputs to the more common fisheries metrics (e.g., number of vessels, fishing gears,
478   and/or species). Despite these limitations, having nightly information on distributions of light-
479   assisted fishing activities freely accessible and available to fisheries managers partially fills the crucial
480   spatial data gap for implementing ecosystem approaches to fisheries management.

5. Conclusions

482   Any marine resource management requires an understanding of the spatial and temporal
483   patterns of both resource use and target resources and the underlying processes. Yet collecting
484   information on spatial and temporal patterns of resource use at relevant scales for locally-adapted
485   action remains sparse especially in marine fisheries in developing countries. We used the VIIRS Boat
486   Detection data service from NOAA to identify high density fishing grounds and predict areas within
487   the Philippines's contiguous zone with similar environmental conditions in aid of implementing
488   ecosystem approaches to fisheries management. Nighttime lights are extensively detected in the
489   Philippine coastal waters. These lights spatially cluster and we have identified 134 distinct Core
490   Fishing Areas. Aggregating all boat detections inside CFAs, these areas are strongly distinguished
491   from non-CFA areas mainly by bathymetry, owing most probably to the multi-gear nature of fishing
492   and the varying fishing operation strategies employed within each CFA. In two of the largest CFAs
493   which we know are each targeting round scads and sardines, variable importance in the MaxEnt
494   models corresponded with environmental parameters previously known to be associated with these
495   species occurrence, highlighting the potential model improvement if the catch composition and
496   fishing fleets within each CFA can be characterized. In addition, using finer spatial resolution
497   environmental predictors could enhance model precision and differentiate suitable fishing areas even
498   within the same CFA.

499   The VIIRS Boat Detection data is provided freely and for public use. Its applications can be
500   further expanded by conducting ground-truthing and calibration studies to relate VBD radiance
501   values to common fishery statistics (e.g., number of vessels, types of vessels, comparative fishing
502   effort based on boat size, etc.). But even with the current dataset, having nightly coverage of fishing
503   activities, even if just a subset of the entire fishing sector, provides an invaluable data stream of
504   fishing effort for data-deficient fisheries, especially in Southeast Asia. Our results could also be used
505   as a basis for establishing fisheries management areas in the Philippines and our approach could be
506   applied to other countries that have high numbers of light-employing fishing vessels.

528

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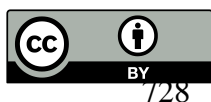
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