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Predicting poaching risk in marine protected areas for improved patrol efficiency Predicting poaching risk in marine protected areas

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1 **Cover Page**

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3 Predicting poaching risk in marine protected areas

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28 **Manuscript**

29 **Abstract**

30 Marine Protected Areas (MPAs) are effective resource management and conservation
31 measures, but their effectiveness is often hindered by non-compliant activities such as
32 poaching. Better predicting poaching risk and spatial patterns is crucial for efficient law
33 enforcement and to ensure MPAs are delivering the outcomes they were established for.
34 Here, we predicted poaching risk from recreational fishers within fully protected MPAs of
35 Australia's Great Barrier Reef Marine Park (GBRMP). Combining patrol effort data, observed
36 distribution of reported incidents, and geographically-referenced predictor variables, we
37 modeled the occurrence probability of poaching incidents using boosted regression trees
38 and mapped poaching risk at fine-scale. Our findings (i) reinforce the key role of fishing
39 attractiveness, accessibility and capacity in shaping the spatial patterns of illegal recreational
40 fishing; (ii) identify key interactions among XXX and tipping points beyond which poaching is
41 more likely to occur; and (iii) highlight gaps in patrol effort that could be filled for improved
42 resource allocation. The methods developed through this study provide a novel approach to
43 quantify the relative influence of multiple interacting factors in shaping poaching
44 occurrence, and hold promises for replication across a broad range of marine or terrestrial
45 settings.

46 **Introduction**

47 Marine Protected Areas (MPAs) are widely promoted as a tool for resource management
48 and conservation (REFs). While various elements of MPA design and implementation are
49 essential (Claudet et al. 2008; Jupiter & Egli 2011; Green et al. 2015; Gill et al. 2017), the
50 effectiveness of an MPA is ultimately reliant on its users' compliance with regulations. Yet,
51 ensuring compliance, or infringements, remains a persistent problem, and numerous non-
52 compliant activities (e.g. harvest, waste disposal, dampening, or illegal constructions)
53 continue to occur within many MPAs worldwide (REF?). Of these, illegal fishing inside MPAs
54 (i.e., poaching) is particularly prevalent, and can easily render MPAs ineffective (Samoilys et
55 al. 2007; Guidetti et al. 2008; Campbell et al. 2012) and erode trust in management (REF).

56 As with all regulatory frameworks, individual reasons for not complying with rules vary
57 between negligent, opportunistic and intentional offending. To be effective, compliance
58 management should address each level of offending through appropriate strategies
59 including, education, engagement and enforcement, respectively (Ivec & Braithwaite 2015).
60 Enforcement is often associated to resource-demanding management activities in MPAs (i.e.
61 due to vessel, personnel and legal costs), resources need to be strategically allocated by
62 effectively targeting patrols to locations and times at which poaching is more likely to be
63 prevalent. This is particularly critical in large MPAs .

64 It has recently been shown that wildlife crime tend to be concentrated in space (Brill &
65 Raemaekers 2009; Maingi et al. 2012; Arias et al. 2014), time (Diogo et al. 2016), on specific
66 ecosystem components (Pires 2015; Kurland et al. 2018) and were concerning a restricted
67 set of offenders (Weekers et al. 2019). Understanding what prevails/drives these patterns
68 can assist in the development of cost-effective surveillance strategies.

69 Surveillance activities are more effective when adequately and sustainably funded and
70 staffed, and targeted to the right places at the right times (Jachmann 2008; Critchlow et al.
71 2015, 2016; Petrossian 2015). In line with the 'law of crime concentration' (Weisburd 2015),
72 poaching is far from being a random activity. Poaching is a highly structured activity driven
73 by the convergence of willing offenders and vulnerable targets at suitable places (Moreto &
74 Pires 2018). 'Poaching hotspots' are formed when these points of convergence are repeated

75 over space and time, revealing an underlying opportunity structure for illegal activities.
76 Poaching hotspots tend to share a set of common characteristics, or risk factors (REF). In
77 coastal and marine environments, they include the harvest target availability and
78 attractiveness, accessibility (e.g. travel costs and travel time), opportunism (e.g. along MPA
79 boundaries), guardianship effectiveness, and the perceived likelihood and consequence of
80 getting caught (Arias et al. 2014; Bergseth et al. 2017; Weekers & Zahnow 2018; Weekers et
81 al. 2019).

82 Determining the relative importance of risk factors and patterns of poaching is nonetheless a
83 challenging and often context-specific tasks. While approaches assessing patterns of illegal
84 activities based on raw patterns of incidents reported by patrols are useful tools to identify
85 where crimes are occurring more frequently (Hilborn et al. 2006), they are typically biased
86 towards areas that are routinely surveyed. Failure to account for spatiotemporal variation in
87 surveillance effort runs the risk of systematically over- or underestimating non-compliant
88 activities (Keane & Jones 2008). Other approaches have been proposed to explicitly account
89 for detection biases (Critchlow et al. 2015, 2016), but they tend to rely on assumptions that
90 may not necessarily hold in marine systems (e.g. on the form of the relationship between
91 predictors and incident occurrence) and fail to account for interactions between risk factors.

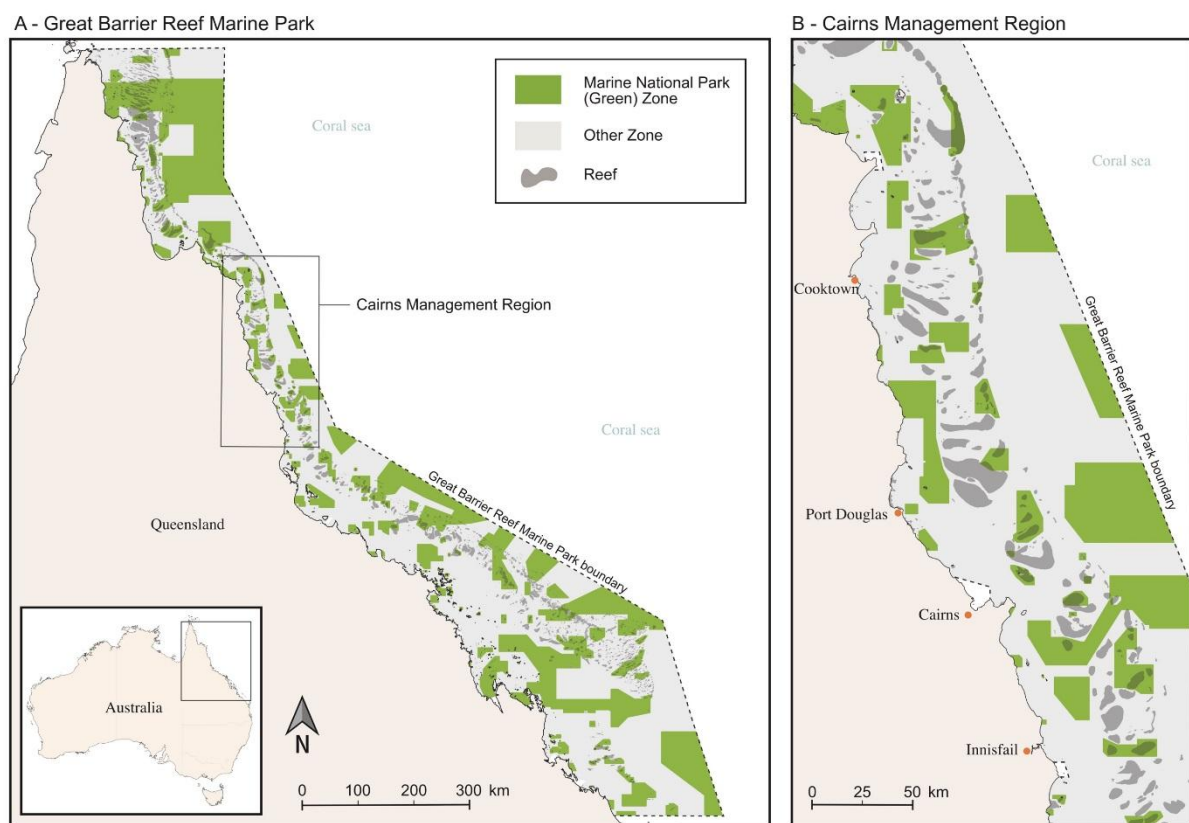
92 Here, we aim at improving patrol efficiency by better understanding and predicting how
93 [potentially complex] interactions among [various] risk factors shape poaching risk. We use
94 spatially-explicit environmental and human predictors combined with patrol-collected
95 incident and monitoring data commonly available across various settings to (1) quantify the
96 relative influence of various risk factors in shaping poaching risk; (2) identify main
97 interactions and critical tipping points; (3) predict poaching risk in 44 no-take MPAs within
98 Australia's Great Barrier Reef Marine Park (GBRMP); and (4) identify potential gaps in patrol
99 surveillance effort.

100 **Methods**

101 **Study site**

102 The Cairns Management Region (CMR) is located within Australia's Great Barrier Reef
103 Marine Park (GBRMP) (Fig. 1). The current zoning plan was established in 2003 and came

104 into force on 1 July 2004. It consists of various types of multiple-use areas, but we focused
105 here on Marine National Park (Green) Zones, a key zone type for the managing authority's
106 strategy (Great Barrier Reef Marine Park Authority 2018). Marine National Park (Green)
107 Zones are 'no-take/regulated access' areas (Horta e Costa et al. 2016) where all extractive
108 activities like fishing or collecting are not allowed. They fall within the broader type of Fully
109 Protected Areas (Horta e Costa et al. 2016) (from now on, we refer to Marine National Park
110 (Green) Zones as no-take zones). No-take zones represent about a third of the GBRMP total
111 area (11.7% of the CRM) and thus require extensive surveillance effort. The primary form of
112 offence in Australia's Great Barrier Reef Marine Park (GBRMP) is poaching by recreational
113 fishers in no-take zones (Great Barrier Reef Marine Park Authority 2018), and a number of
114 studies have suggested that such activity may be occurring significantly more frequently
115 than previously thought (Davis et al. 2004; Castro-sanguino et al. 2017; Bergseth et al. 2017).



116

117 **Figure 1:** Location of the Cairns Management Region (CMR) within the Great Barrier Reef Marine Park,
118 Australia.

119 **Incidents' presence and pseudo-absence**

120 Drawing on spatially explicit occupancy models increasingly used in the predictive ecological
121 community (Marmion et al. 2009), we modelled the spatial distribution of poaching risk
122 within the CMR's no-take zones using Boosted Regression Trees (BRT; Elith *et al.* (2008)
123 based on observed distribution of reported incidents as a function of geographically-
124 referenced predictor variables,. Gradient boosted regression tree approaches such as BRT
125 are increasingly used over statistical approaches for prediction because they better handle
126 interactions among predictor variables and non-linearity than regression-based approaches;
127 both of which were expected to emerge in our case. BRTs also can prevent overfitting by
128 providing regularization (Elith et al. 2008).

129 Presence records (i.e. occurrence of poaching incidents) were obtained from the Field
130 Management Compliance Unit (FMCU) at the Great Barrier Reef Marine Park Authority. The
131 data represents all reported incidents of illegal recreational fishing in CMR's no-take zones
132 for the period January 2015 to March 2019 (n=221, Fig. S1). About 95% of these happened
133 during daylight hours, between 7am and 7pm, reflecting effort data from the patrol vessel.
134 The presence data used in this study represents reliable records at GPS resolution, with
135 heterogeneous detectability due to heterogeneous monitoring effort across the study area.
136 To account for this, we assigned a weight to presence points based on monitoring effort, on
137 the basis that incidents detected in highly monitored areas had lower weight than incidents
138 detected in areas that are monitored more rarely (see Supporting Information).

139 In our case, confirmed absences of incidents (i.e. locations where poaching never occurred)
140 are more difficult to obtain due to the diffuse nature of offenders and the impracticability to
141 monitor the entire area constantly. Therefore, we created artificial absence data (herein
142 pseudo-absence) following guidelines from (Cerasoli et al. 2017). Specifically, we generated
143 the pseudo-absences using geographically stratified random selection (i.e. based on density
144 estimate of presences) so that the sum of the weights on the pseudo-absences (i.e.
145 proportional to monitoring effort) equals the sum of those on the presence points (i.e.
146 inverse of monitoring effort). This process yielded a total of 498 pseudo-absence points (Fig.
147 S1).

148 **Predictors of poaching risk**

149 We used a set of ten spatially-explicit predictors relating to environmental and human
 150 dimensions to predict the probability of incident occurrence (Table 1). Distance-related
 151 predictors (i.e. *Accessibility, Features, Islands, Reefs, and Boundary*) were derived from the
 152 most up-to-date data available on each elements' locations using the cost distance tool in
 153 ESRI's ArcGIS 10.5. Bathymetry data (*Depth*) was obtained from the DeepReef database
 154 (<https://www.deepreef.org/bathymetry/65-3dgb-bathy.html>). *Slope* and *Aspect* were
 155 derived from the bathymetry model, using the 'Slope' and 'Aspect' tools in QGIS,
 156 respectively. *Coral* was modeled as the sum of the surrounding living coral patches,
 157 described as the number of 15x15m cells dominated by a coral taxon within a 1km radius
 158 around each focal cell on the basis of the *Benthic cover type map for Reef Top* areas of the
 159 Cairns Management Area. Finally, *Fishing capacity*, defined as the overall ability of the
 160 recreational fishery to extract resources in a 50km radius, was modeled by summing the
 161 number of motorized recreational boats (all size classes) registered in postcodes located
 162 within a 50km radius around each cell.

163 **Table 1** | Predictors used to predict poaching in no-take zones of the Cairns Management Area.

Name	Description	Range (unit)
Accessibility	Distance to the nearest boat ramp access point	0-107 (km)
Aspect	Compass direction that a slope faces (E:90°; S: 180°; W:260°; N:0°=360°)	0-360 (°)
Coral	Number of coral-dominated patches within a 1km radius	0-656 (nb)
Depth	Distance from the surface to the sea bottom	-150 - -0.6 (m)
Features	Distance to the nearest pontoon or mooring	0-53 (km)
Fishing capacity	Number of motorized recreational boats registered within a 50km radius	2.6-197.2 (nb)
Islands	Distance to the nearest island	0-53.3 (km)
Reefs	Distance to the nearest dry reef	0-19.6 (m)
Slope	Incline of the sea bottom	0-63.6 (°)
Boundary	Distance from the nearest boundary	0-6.8 (m)

164

165 All these predictors were generated at a spatial resolution of 50m, and showed a Pearson
 166 correlation coefficient lower than |0.51| and a Variance Inflation Factor (VIF) lower than 1.6.
 167 Using this set of predictors, we were able to capture some previously unexplored potential
 168 risk factors in the GBRMP, although we acknowledge that poaching risk can have other
 169 dimensions such as individual determinants owned by offenders, weather, or time of the

170 day/week/year (Bergseth & Roscher 2017; Bergseth et al. 2017; Oyanedel et al. 2018;
171 Weekers & Zahnow 2018; Weekers et al. 2019) that we were not able to incorporate here.
172 Hence, our predictive model provides a static picture of poaching risk, and therefore
173 assumes that other potential drivers are held evenly distributed throughout the study area.

174 **Building a predictive model of poaching risk**

175 We fitted the BRT models with a weighted logistic regression for binary classification against
176 the ten predictors (Table 1) using the {dismo} package (Hijmans et al. 2016) in the R
177 statistical software version 3.4.0 (R Core Team 2017). This technique requires the
178 specification of three main parameters: the shrinkage parameter, limiting the contribution
179 of the single trees added to the model through the boosting algorithm (*tc*), the minimum
180 loss reduction required to make a split (*lr*), and the bag fraction (*bf*), proportion of data to be
181 selected at each step. In order to identify the best set of parameters, we implemented a
182 two-step tuning process that retained the set of parameters maximizing cross-validated Area
183 Under the Curve (AUC) (Supplementary Information). We also explored the possibility of
184 eliminating non-informative predictor variables to select the most parsimonious model,
185 which led to the exclusion of the variable *Coral*. The final model explained 61% of the cross-
186 validated variance and had an AUC score of 0.93, indicating strong explanatory and
187 predictive performance, respectively.

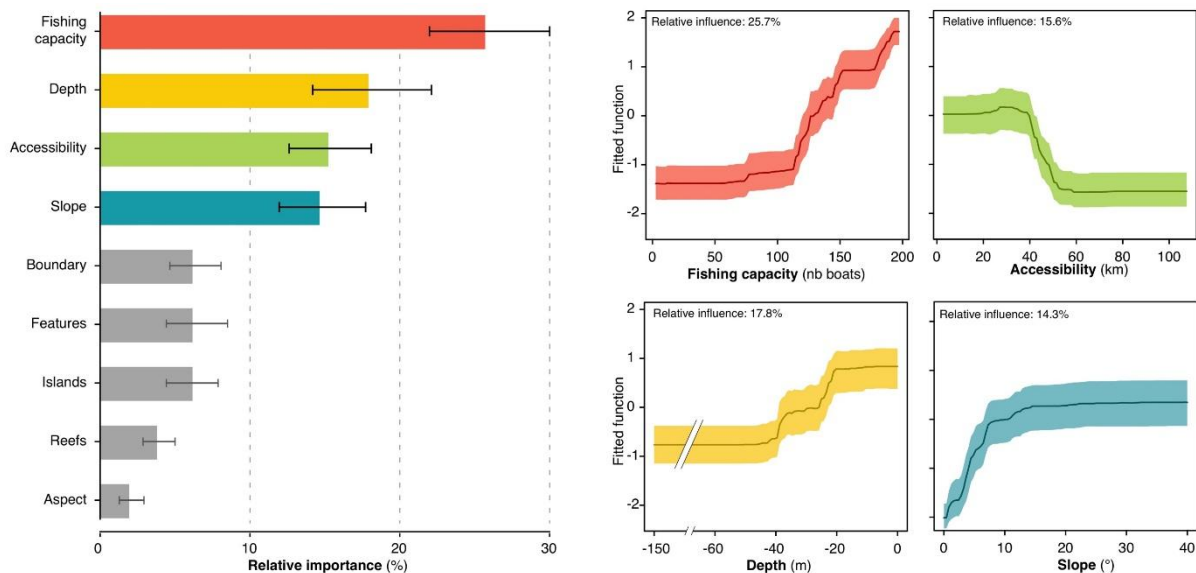
188 We quantified the relative interaction strength and significance between the nine remaining
189 predictor variables using 500 bootstrap resampling (Pinsky & Byler 2015).

190 We calculated the relative influence of the predictor 95% confidence intervals from 1,000
191 bootstrap replicates of the original dataset. Based on the same bootstrap replicates, we
192 obtained partial dependency plots with 95% confidence intervals to visualize the
193 relationships between the most influential predictor variables and the response (occurrence
194 probability), while keeping all other predictors constant. Maps of the predicted poaching risk
195 (i.e. probability of incident occurrence) were generated from the optimal BRT model's
196 projections over the whole study area at each 50m * 50m cell with a continuous scale 0-1 for
197 each bootstrap replicate, allowing the median predicted poaching risk +/- 95% confidence
198 interval to be mapped. Detailed methods used for model building and bootstrapping are
199 provided in Supplementary Information.

200 Because the model underlying this map accounts for heterogeneous detectability, we were
201 able to overlap the predicted poaching risk with patrol effort and identify potential spatial
202 mismatch. We visualized how predicted poaching risk with patrol effort overlap using a
203 bivariate choropleth map.

204 Results

205 Almost 75% of the spatio-temporal variability of incident occurrence was described by four
206 predictors (Fig. 2). *Fishing capacity* was the most important predictor variable, accounting
207 for 25.7% of the explained variability in incident occurrence. *Depth*, *Accessibility*, and *Slope*
208 explained a broadly similar portion of the variability in incident occurrence, ranging between
209 17.8% and 14.3%. *Boundary*, *Islands*, and *Features* had smaller contributions to the model
210 prediction (6.1% each). *Reefs* and *Aspect* explained little variability of incident occurrence(s).



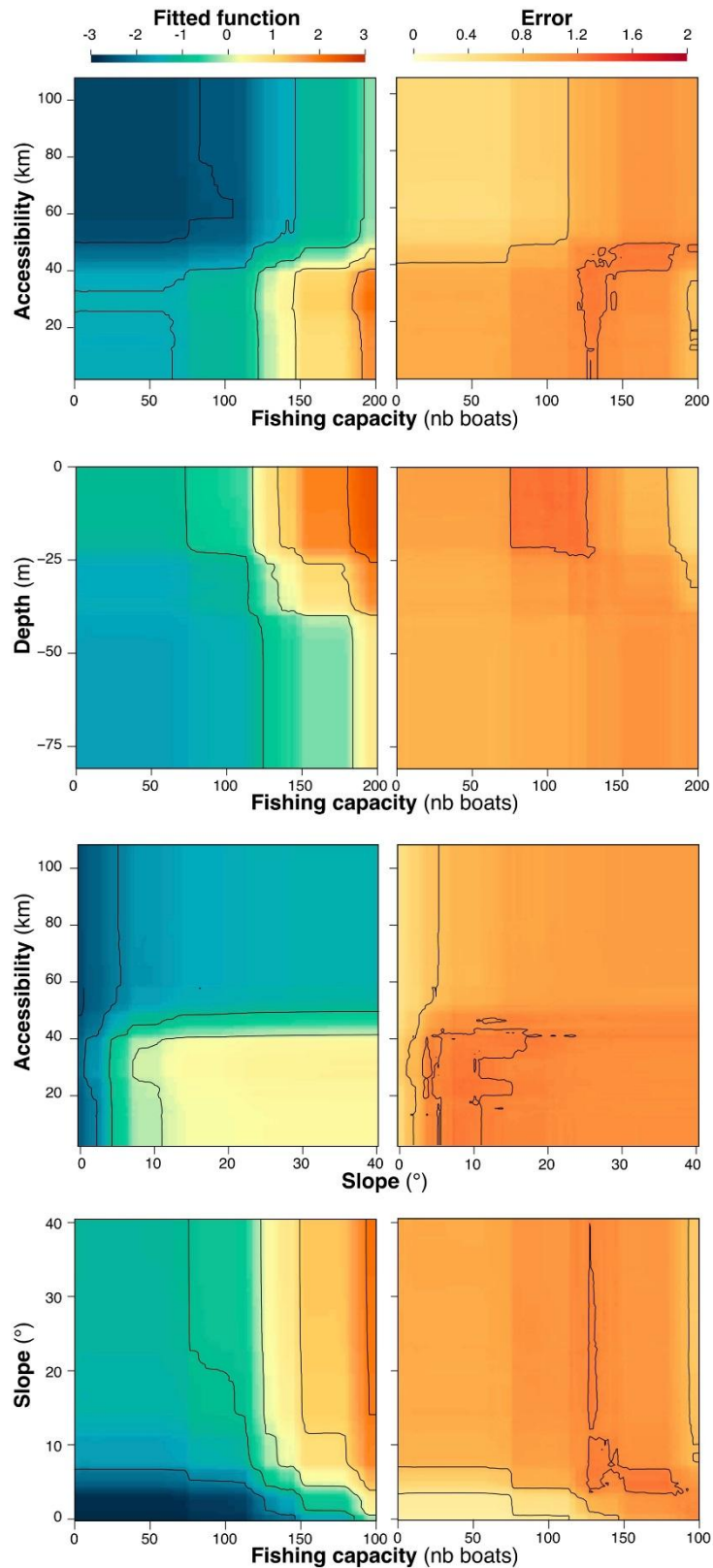
211

212 **Figure 2:** Predictors of recreational incident occurrence in no-take zones. The left panel shows the relative
213 influence (and 95% confidence intervals) of the predictor variables. The right panel shows partial dependency
214 plots with 95% confidence intervals for the four most influential variables. The graphs show the effect of a
215 given predictor on the probability of incident occurrence while holding all other predictor variables constant at
216 their mean.

217 The occurrence probability remained low at low levels of *Fishing capacity* (25.7% relative
218 influence) and then steadily increased from 100 boats per 50km radius onwards (Fig. 2).
219 Similar patterns were observed for *Depth* (17.8%), with initially low levels of poaching
220 likelihood below -40m increasing until reaching a plateau around -20m depth. *Accessibility*

221 was the third most important predictor of poaching occurrence (15.6%), with a negative
222 non-linear relationship displaying a threshold around 45km from the nearest boat ramp.
223 Fitted function for *Slope* (14.3%) displayed a positive asymptotic relationship that reached a
224 plateau around 15° angle. Other less significant predictors with negative relationships were
225 distance to: *Boundary* (6.1%), *Features* (6.1%), *Islands* (6.1%), and *Reefs* (3.6%).

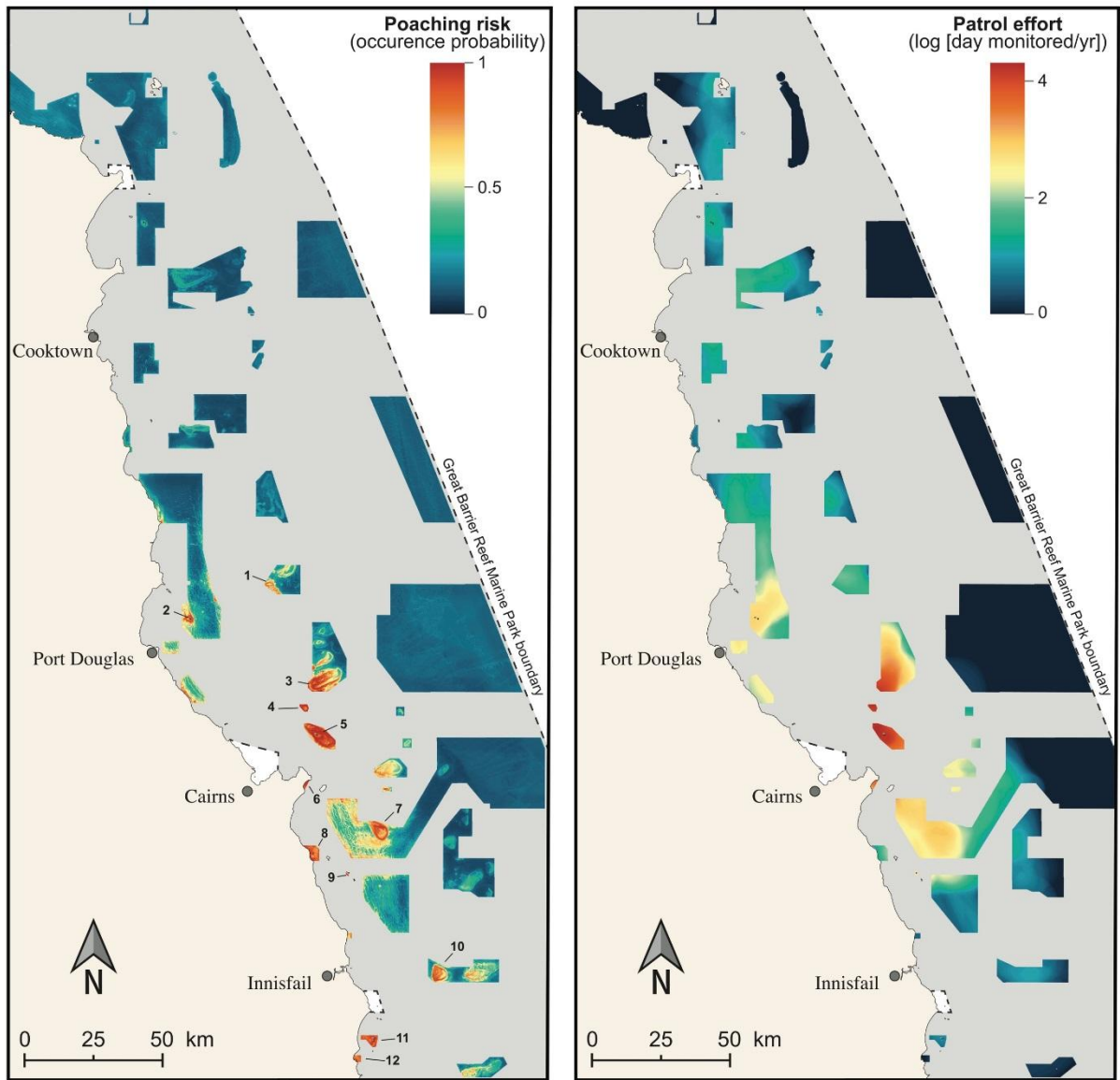
226 Models considering interactions between predictors performed better than simpler ones.
227 The four strongest pairwise interactions were *Fishing capacity* x *Accessibility* (71.51; p-
228 value<0.001), *Fishing capacity* x *Depth* (36.9; p-value<0.001), *Slope* x *Accessibility* (14.1; p-
229 value<0.001) and *Fishing capacity* x *Slope* (9.9; p-value<0.01). Occurrence probability for
230 incidents was higher in areas characterized by higher *Fishing capacity*, shallower *Depths*,
231 shorter distances to boat ramps (i.e. *Accessibility*), and steeper sea bottom (Figs. 2-3).



232

233 **Figure 3:** Pairwise interaction plots of the four strongest interactions between variables predicting poaching
 234 risk. The left panels indicate the median fitted function calculated on 1,000 bootstrap replicates. The right
 235 panel indicates error around this fitted function, measured as the difference between the 0.95 and 0.05
 236 quantiles calculated on the same bootstrap replicates. All interactions were significant ($p < 0.01$).

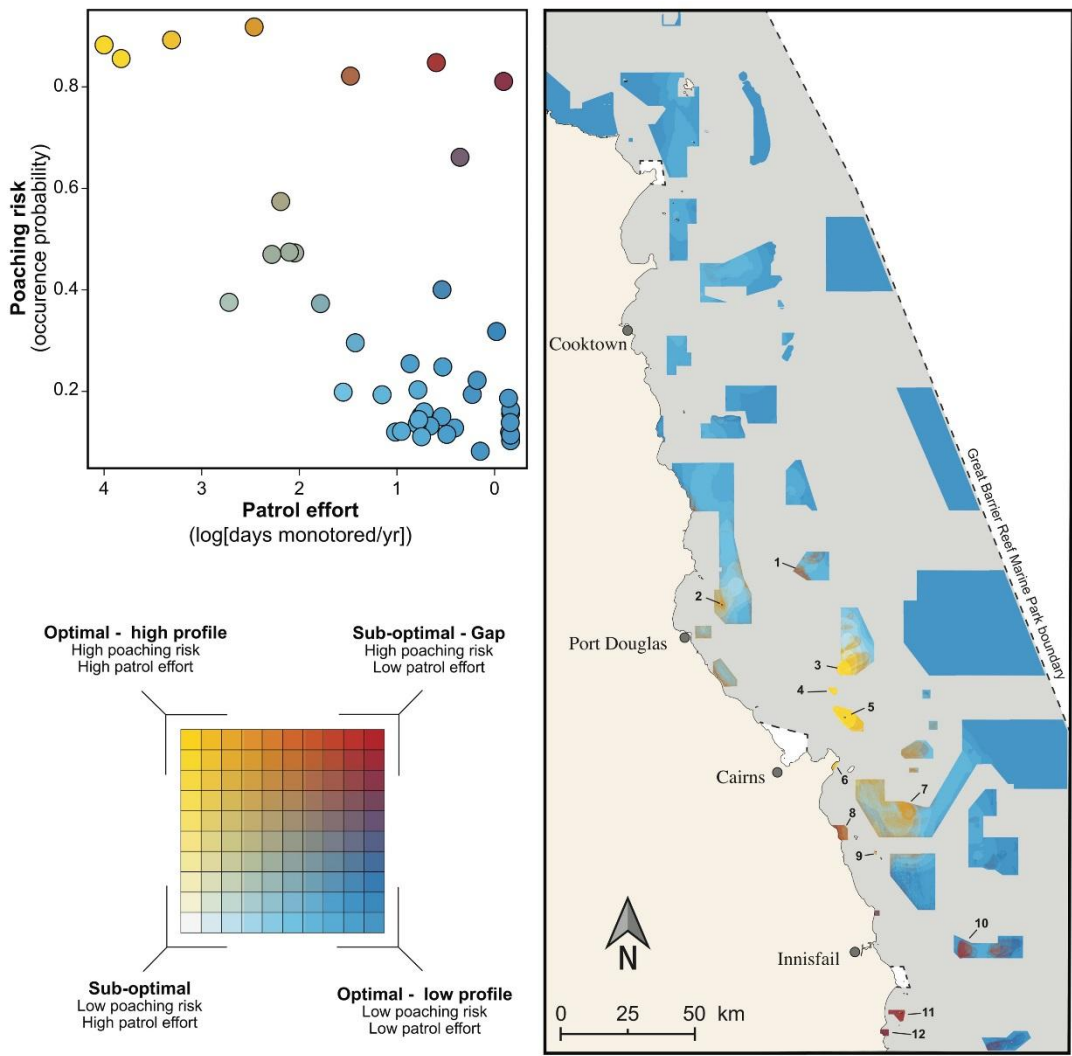
237 As a consequence of these interactions and thresholds, predicted poaching risk was highly
 238 heterogeneous across the study area (Fig. 4). Poaching risk was concentrated on inshore and
 239 mid-shelf reefs located near major towns (Port Douglas, Cairns and Innisfail). Conversely, no-
 240 take zones located far off-shore and in the north of the Cairns Management Region were
 241 exposed to lower levels of predicted poaching risk. Poaching hotspots include sites such as
 242 Low Isles Reef, Upolu Reef, Green Island Reef, Wide Bay, and Sisters-Stephens Reef (Fig. 4).



243

244 **Figure 4:** Predicted relative probability of incident occurrence within the no-take MPAs of the Cairns
 245 Management Region of the Great Barrier Reef Marine Park, and associated level of patrol monitoring effort.
 246 Numbers indicate poaching hotspots within no-take zones: 1- Tongue Reef; 2-Low Isles Reef; 3-Michaelmas
 247 Reef; 4-Upolu Reef; 5-Green Island Reef; 6-Wide Bay; 7-Scott Reef; 8-MNP-17-1070; 9-Normanby-Mabel Reef;
 248 10-Feather Reef; 11-Sisters-Stephens Reef; 12-Gardens Beach.

249 Patrol allocation was skewed towards a few MPAs around Cairns and, to a lower extent, Port
 250 Douglas (Fig. 4). Indeed, among the 44 MPAs located within the CRM, 75% of the total patrol
 251 monitoring conducted between 2015 and 2019 was allocated in only four of them (Fig. S2).
 252 This great heterogeneity of patrol effort partially matched with the spatial distribution of
 253 predicted poaching risk (Fig. 5). Indeed, while the highest levels of patrol effort were found
 254 in the three major poaching hotspots (yellow in Fig. 5), other areas with comparable levels of
 255 poaching risk received much less monitoring. Such areas, which may represent enforcement
 256 gaps, are mostly located in the south of the CMR (maroon in Fig. 5). Areas predicted to be
 257 exposed to low poaching risk tended to be monitored less (blue in Fig. 5).



258
 259 **Figure 5:** Congruence and mismatch between patrol effort and poaching risk. Bi-plot represent MPA averages.
 260 Areas in yellow and blue respectively indicate where patrol distribution matches with poaching risk. Areas in
 261 greatest risk of poaching exposure with low surveillance effort are shown in maroon; they correspond with

262 areas potentially requiring more patrolling given their predicted level of poaching risk. These include 1-Sisters-
263 Stephens Reef; 2-Gardens Beach; 3-Feather Reef; 8-MNP-17-1070.

264 **Discussion**

265 Identifying the underlying drivers of poaching and understanding how they interact to
266 structure poaching risk offer great value to managers for cost effective surveillance. This
267 study presents the first attempt at quantifying the relative importance of, and interaction
268 between multiple risk factors of recreational poaching in a large Marine Protected Area
269 (MPA) using commonly available patrol-collected data. As such, it offers novel insights that
270 can inform management strategies and planning, via a new predictive approach that can
271 potentially be applied to other settings.

272 The overwhelming influence of only four predictors (*Fishing capacity, Depth, Accessibility*
273 *and Slope*) in explaining poaching risk is striking. Our analysis confirms the assumption that
274 poaching ‘hotspots’ are characterized by substantial *Fishing capacity*; however, our model
275 identifies a threshold (i.e. >100 boats within a 50km radius; Fig. 2) beyond which poaching
276 risk increases markedly. Similarly, poaching ‘hotspots’ were predicted by the model at
277 depths shallower than 40m, short(er) distances to the nearest boat ramp (0 to 45km) and in
278 areas of complex topography, defined by steep(er) sea bottom (Figs. 2-3). Overall, these
279 findings emphasize the value of these simple yet critical features in the assessment of an
280 MPA’s likelihood to be exposed to poaching and provide insights into the mechanisms by
281 which they can interact.

282 Our results highlight the critical role of benthic topography (*Depth* and *Slope*) in driving
283 poaching risk. In coral reefs, areas with high slope and low depth –where poaching risk is the
284 highest– typically reflect reef slopes and edges, which often harbor higher target fish
285 abundance and biomass. This suggests that these two variables can be appealing to
286 recreational fishers and therefore may broadly define environmental bounds of
287 “attractiveness” to recreational poachers. Since travel time or cost remain constraining
288 factors (Maire et al. 2016), *Accessibility* proved also to be an important driver. Nevertheless,
289 it is worth noting that the tipping point beyond which poaching risk diminishes significantly
290 (around 45km from the nearest boat ramp) remains substantially higher in the GBRMP than
291 in other places globally (Daw 2008; Daw et al. 2011; Metcalfe et al. 2017). Such difference in

292 maximum travel distance might reflect the relative wealth of Australians and the investment
293 by recreational fishers in faster and more sea-worthy vessels as fishing platforms (CRC 2017,
294 2018).

295 Poaching risk was better predicted when drivers related to fishers' spatial preference (i.e.
296 accessibility and attractiveness) interacted with *Fishing capacity* (Fig. 3). The combined
297 effects of attractiveness, accessibility and fishing capacity in driving fishing pressure
298 generally (Daw 2008; Castro-sanguino et al. 2017; Thiault et al. 2017; Metcalfe et al. 2017;
299 Harborne et al. 2018), and poaching risk specifically (Diogo et al. 2016; Weekers & Zahnow
300 2018) have been showed elsewhere. However, the fact that poaching-specific predictors
301 (e.g. distance to the nearest boundary) are more marginal compared to fishing capacity
302 suggests that most incidents may be due to fishers' negligence rather than driven by
303 opportunistic or intentional motivations. This is particularly XXXX given the fishers' positive
304 perception of the current zoning (Sutton & Tobin 2009) and their negative attitude towards
305 poaching activities in general (Bergseth & Roscher 2017) XXXXX .

306 The critical roles of fishing capacity (determined by the number and location of registered
307 recreational boats) and accessibility (determined by the number and location of boat ramps)
308 indicate potential benefits associated with increased integration of new and updated data,
309 for example, in coordination with the Queensland Department of Transport and Main Roads
310 (TMR). Although the number of boats registered cannot be capped, TMR registration data,
311 regulatory conditions, and planning schemes (e.g. for development and maintenance of
312 recreational access points) represent potentially valuable points of opportunity around
313 which to foster collaborative monitoring and management. [It is also worth noting that the
314 main predictor of poaching risk in our case (i.e. *Fishing capacity*) is largely influenced by boat
315 ownership, which is in turn driven by the broader external economic context (e.g.
316 Queensland's resources boom and associated Fly-In-Fly-Out workforce patterns; Queensland
317 Government, 2015).]

318 Our findings provide the preliminary indication that the patrol strategies applied in this case
319 may have been sub-optimal, as patrolling effort only partially matches with the identified
320 spatial patterns of poaching risk. Designing more cost-effective enforcement strategies may
321 require redistributing partly patrol effort where enforcement gaps are likely to occur (i.e.

322 higher poaching risk and lower patrol effort). No-take MPAs that may benefit from increased
323 effort are often adjacent to shore. Thus, land-based compliance officers might be deployed
324 more frequently in these areas. Systematic resource allocation methods (e.g., Marxan) could
325 also be used to achieve an optimum deployment of patrol vessels, aiding the design of cost-
326 effective enforcement strategies (Plumptre et al. 2014).

327 The benefit of our approach provides a nuanced and precise understanding of the
328 interactions among various risk factors related to recreational poaching, allowing one to
329 reliably and accurately predict poaching risk and examine *where* patrols may be
330 preferentially allocated. The relatively low sample size, however, means that we were not
331 able to incorporate the temporal dimension and identify *when* such patrols should be
332 deployed. Future applications based on multiple times and long periods would provide more
333 dynamic predictions. Weather effects would for instance enable an improved contextual
334 understanding and help to better predict poacher behavior on a day-to-day basis (Critchlow
335 et al. 2015), while longer temporal changes could help determining the deterrence effects of
336 patrols (Dobson et al. 2018), both of which will aid patrol strategy decisions and improve
337 patrol efficiency as a whole. It also important to never forget to invest in all activities that
338 also help promote compliance, such as information or participation to decision-making.

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470 **Table**471 **Table 1** | Predictors used to predict poaching in Green Zones of the Cairns Management Area.

Name	Description	Range (unit)
Accessibility	Distance to the nearest boat ramp access point	0-107 (km)
Aspect	Compass direction that a slope faces (E:90°; S: 180°; W:260°; N:0°=360°)	0-360 (°)
Coral	Number of coral-dominated patches within a 1km radius	0-656 (nb)
Depth	Distance from the surface to the sea bottom	-150 - -0.6 (m)
Features	Distance to the nearest pontoon or mooring	0-53 (km)
Fishing capacity	Number of motorized recreational boats registered within a 50km radius	2.6-197.2 (nb)
Islands	Distance to the nearest island	0-53.3 (km)
Reefs	Distance to the nearest dry reef	0-19.6 (m)
Slope	Incline of the sea bottom	0-63.6 (°)
Boundary	Distance from the nearest boundary	0-6.8 (m)

472

473 **Figures**

474 **Figure 1:** Location of the Cairns Management Region (CMR) within the Great Barrier Reef Marine Park,
475 Australia.

476 **Figure 2:** Predictors of poaching risk in no-take zones according to the final BRT model. The top-left plot shows
477 the relative influence of the predictor variables used to model the occurrence of poaching incidents. The other
478 plots show partial dependency plots with 95% confidence intervals for the four most influential variables. The
479 graphs show the effect of a given predictor on the probability of incident occurrence while holding all other
480 predictor variables constant at their mean.

481 **Figure 3:** Pairwise interaction plots of the four strongest interactions between variables predicting poaching
482 risk. The left panels indicate the median fitted function calculated on 1,000 bootstrap replicates. The right
483 panel indicates error around this fitted function, measured as the difference between the 0.95 and 0.05
484 quantiles calculated on the same bootstrap replicates. All interactions were significant ($p < 0.01$).

485 **Figure 4:** Predicted relative probability of incident occurrence within the no-take MPAs of the Cairns
486 Management Region, and associated level of patrol monitoring effort. Numbers indicate poaching hotspots
487 within no-take zones: 1- Tongue Reef; 2-Low Isles Reef; 3-Michaelmas Reef; 4-Upolu Reef; 5-Green Island Reef;
488 6-Wide Bay; 7-Scott Reef; 8-MNP-17-1070; 9-Normanby-Mabel Reef; 10-Feather Reef; 11-Sisters-Stephens
489 Reef; 12-Gardens Beach.

490 **Figure 5:** Identifying potential mismatch between patrol effort and poaching risk. Bi-plot represent MPA
491 averages. Areas in yellow and blue respectively indicate where patrol distribution matches with poaching risk.
492 Areas in greatest risk of poaching exposure with low surveillance effort are shown in maroon; they correspond
493 with areas potentially requiring more patrolling given their predicted level of poaching risk. These include 1-
494 Sisters-Stephens Reef; 2-Gardens Beach; 3-Feather Reef; 8-MNP-17-1070.