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

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Abstract

Marine Protected Areas (MPAs) are effective resource management and conservation measures, but their success is often hindered by non-compliant activities such as poaching. Understanding the risk factors and spatial patterns of poaching is therefore crucial for efficient law enforcement. Here, we conducted explanatory and predictive modelling of poaching from recreational fishers within no-take zones of Australia's Great Barrier Reef Marine Park (GBRMP) using Boosted Regression Trees (BRT). Combining patrol effort data, observed distribution of reported incidents, and spatially-explicit environmental and human risk factors, we modeled the occurrence probability of poaching incidents and mapped poaching risk at fine-scale. Our results: (i) show that fishing attractiveness, accessibility and fishing capacity play a major role in shaping the spatial patterns of poaching; (ii) revealed key interactions among these risk factors as well as tipping points beyond which poaching risk increased or decreased markedly; and (iii) highlight gaps in patrol effort that could be filled for improved resource allocation. The approach developed through this study provide a novel way to quantify the relative influence of multiple interacting factors in shaping poaching risk, and hold promises for replication across a broad range of marine or terrestrial settings.

1. Introduction

Marine Protected Areas (MPAs) are widely promoted as a tool for natural resource management and conservation (Lubchenco and Grorud-Colvert, 2015). While various elements of MPA design and implementation are essential (Claudet et al., 2008; Gill et al., 2017; Green et al., 2015; Jupiter and Egli, 2011), the effectiveness of an MPA is also reliant on its users' compliance with regulations. Yet, ensuring compliance remains a persistent problem, and numerous non-compliant activities (e.g. harvest, waste disposal, dampening, or illegal infrastructure development) continue to occur within many MPAs worldwide. Of these, illegal fishing in MPAs (i.e. poaching) is particularly prevalent, and can render MPAs ineffective (Campbell et al., 2012; Guidetti et al., 2008; Harasti et al., 2019; Samoilys et al., 2007) and erode trust in management (Di Franco et al., 2016).

As with all regulatory frameworks, individual reasons for not complying with rules vary between negligent, opportunistic and intentional offending. To be effective, compliance management should address each level of offending through appropriate strategies including, education, engagement and enforcement, respectively (Ivec and Braithwaite, 2015). Enforcement is often the most expensive management activity in MPAs; due to vessel, personnel and legal costs. Strategic allocation of resources by targeting patrols to locations and times at which poaching is most likely to occur is sensible and necessary. This is particularly critical in large scale MPAs where whole of area cannot practically be patrolled continually due to sheer size.

The present study draws on a growing body of evidence about wildlife crime. These studies demonstrate that various forms of wildlife crime tend to be concentrated in space (Brill and Raemaekers, 2009; Kurland et al., 2018a; Maingi et al., 2012) and time (Critchlow et al., 2015; Diogo et al., 2016), as well as on target species (Kurland et al., 2018b; Pires, 2015) and among offenders (Stevenson et al., 2012; Weekers et al., 2019). In line with the 'law of crime concentration' (Weisburd, 2015), these findings suggest that far from being a random activity, poaching across a broad range of contexts represents a highly structured activity defined by the convergence of willing offenders and vulnerable targets at suitable places (Moreto and Pires, 2018). 'Poaching hotspots' are formed when these points of convergence are repeated over time, revealing an underlying opportunity structure which supports the specific type of illegal activity.

Poaching hotspots tend to share a set of common characteristics, or risk factors. In coastal and marine environments, they include the target species' availability and attractiveness, accessibility (e.g. travel costs and travel time), opportunism (e.g. near the boundaries of MPAs), guardianship effectiveness, and the perceived likelihood and consequence of getting caught (Arias et al., 2016; Arias and Sutton, 2013; Bergseth et al., 2017; Weekers et al., 2019; Weekers and Zahnow, 2019). Surveillance activities are more effective when adequately and sustainably funded and staffed, and targeted to the right places at the right times (Critchlow et al., 2016, 2015; Jachmann, 2008; Petrossian, 2015).

Determining patterns of poaching is nonetheless challenging and often context-specific. Approaches assessing poaching hotspots based on raw patterns of incidents reported by patrols are useful tools to identify primary spatial trends (Arias et al., 2016; Brill and Raemaekers, 2009; Diogo et al., 2016; Haines et al., 2012). These logically cover areas that are routinely surveyed. Thus, failure to account for spatiotemporal variation in surveillance effort runs the risk of systematically over- or underestimating non-compliant activities (Keane et al., 2008; Plumptre et al., 2014). Other approaches have been proposed to explicitly account for detection biases (Critchlow et al., 2016, 2015), but they tend to rely on assumptions that may not necessarily hold in marine systems, such as the form of the relationship between predictors and incident occurrence. They also do not account for interactions between risk factors. These limitations represent a bottleneck for understanding how the potentially complex interactions between various risk factors determine poaching risk in MPAs, and thus for improving compliance patrol efficiency.

Here, we apply Boosted Regression Trees (BRT) to assess recreational fisher poaching risk within Australia's Great Barrier Reef Marine Park (GBRMP) between 2015-2019. We use spatially-explicit environmental and human predictors combined with patrol-collected incident and monitoring data commonly available across various settings to (1) quantify the relative influence of various risk factors in shaping poaching risk; (2) identify the main interactions and critical tipping points; (3) predict poaching risk in 44 no-take zones and quantify prediction uncertainty; and (4) identify potential gaps in patrol surveillance effort.

2. Methods

2.1 Study site

The Cairns Management Region (CMR) is located within Australia's Great Barrier Reef Marine Park (GBRMP) (Fig. 1). It is broadly bounded by Lizard Island in the North and Mission Beach in the South. The current GBRMP zoning plan was established in 2003 and came into force on July 2004 with the aim to protect the Reef's values and improve its resilience to a range of threats and pressures, including climate change. It consists of various types of multiple-use areas (GBRMPA, 2018). We focused here on Marine National Park (Green) Zones, a key zone type for the managing authority's resilience-based strategy (GBRMPA, 2018). Marine National Park (Green) Zones are 'no-take/regulated access' areas (Horta e Costa et al., 2016) where all extractive activities like fishing or collecting are prohibited (from now on, we refer to Marine National Park (Green) Zones as no-take zones). No-take zones represent about a third of the GBRMP total area (11.7% of the CMR, that is ~8,300 km^2), are located between 5 and 127 km from the nearest town (Supporting Information), and thus require extensive surveillance effort.

Management and enforcement efforts are focused on activities presenting the highest risks to the Reef. Due to their ecological (e.g. removal of biomass, coral damage via anchors, coral disease from discarded fishing line) and social impacts (e.g. affecting the legitimacy of zoning plan), illegal fishing and poaching represent a 'very high risk' to the GBRMP's values (GBRMPA, 2019). Poaching by recreational fishers in no-take zones is the most common form of offence in the GBRMP (GBRMPA, 2018), and a number of studies have suggested that such activity may be occurring significantly more frequently than previously thought (Bergseth et al., 2017; Castro-Sanguino et al., 2017; Davis et al., 2004). Improving recreational fishing compliance with the zoning plan thus represents a significant priority for GBRMPA to achieve its broader resilience-based strategy.

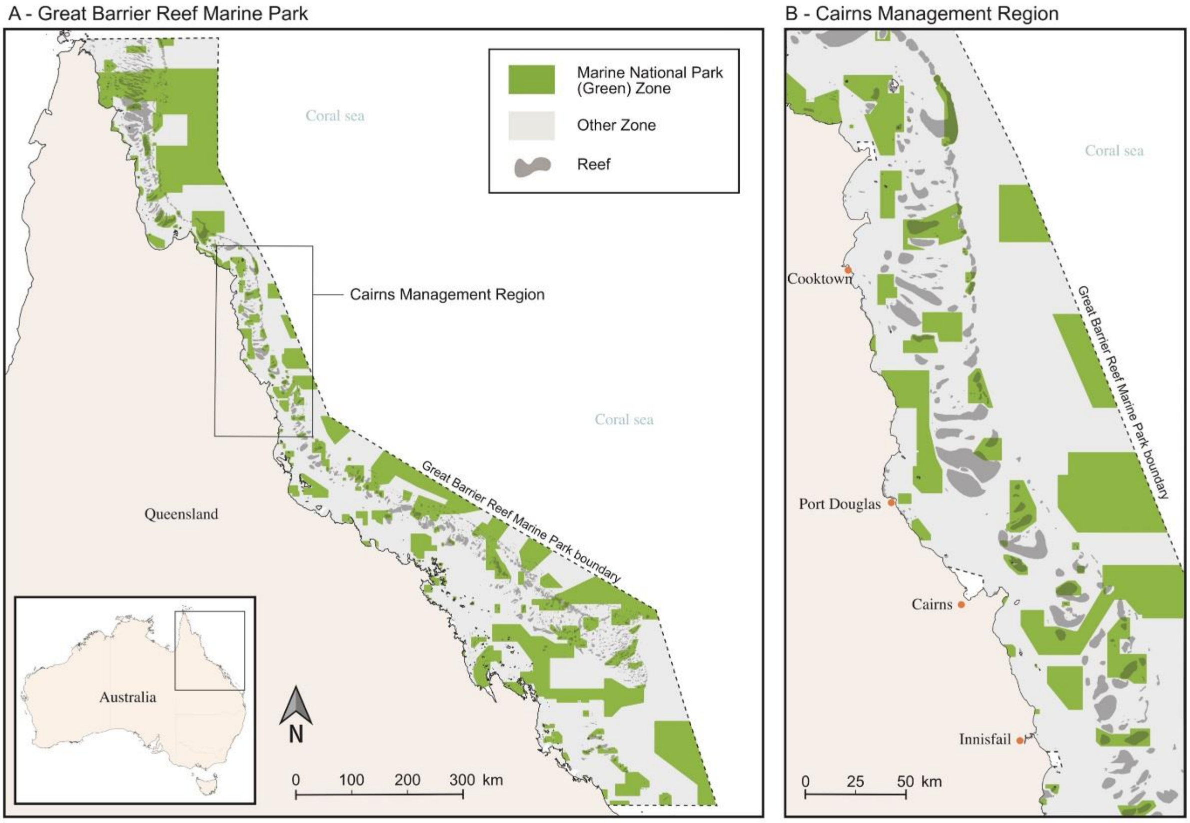

Figure 1: Location of the Cairns Management Region (CMR) within the Great Barrier Reef Marine Park, Australia.

2.2 Incidents' presence and pseudo-absence

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

Presence records (i.e. occurrence of poaching incidents) were obtained from the Field Management Compliance Unit (FMCU) at the Great Barrier Reef Marine Park Authority (GBRMPA). The data includes all reported incidents of illegal recreational fishing in CMR's no-take zones for the period January 2015 to March 2019 (n=221; Supporting Information). It represents reliable records at GPS recorded resolution, with heterogeneous detectability due to heterogeneous monitoring effort across the study area. To account for this, we assigned a weight to presence points based on monitoring effort, on the basis that incidents detected in highly monitored areas had lower weight than incidents detected in areas that are monitored more rarely (see Supporting Information).

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

2.3 Predictors of poaching risk

To predict the probability of incident occurrence, we considered ten spatially-explicit variables relating to environmental and human dimensions and expected to influence poaching by recreational fishers (Table 1). Distance-related predictors (i.e. *accessibility*, *facilities*, *islands*, *reefs*, and *boundary*) were derived from the most up-to-date data available on each of the elements' locations using the cost distance tool in ESRI's ArcGIS 10.5. Bathymetry data (*depth*) was obtained from the DeepReef database (https://www.deepreef.org/bathymetry/65-3dgbr-bathy.html). *Slope* and *aspect* were derived from the bathymetry model, using the 'Slope' and 'Aspect' tools in QGIS, respectively. *Coral* was modeled as the sum of the surrounding living coral patches, described as the number of 15x15m cells dominated by a coral taxon within a 1 km radius around each focal cell on the basis of the *Benthic cover type map for Reef Top* areas of the Cairns Management Region (GBRF, 2019). Finally, *fishing capacity*, defined as the overall ability of the recreational fishery to extract resources in a 50 km radius, was modeled by summing the number of motorized recreational boats (all size classes) registered within a 50 km radius around each cell.

Table 1 | Description and justification of variables used to predict poaching risk in no-take zones of the Cairns Management Region (CMR).

Name	Description	Rationale	Range (unit)
Accessibility	Distance to the nearest boat ramp access point	Determines ease and cost to access a given area from access nodes. Also has safety implications	0-107 (km)
Aspect	Compass direction that a slope faces (E:90°; S: 180°; W:260°; N:0°=360°)	Influences exposure to particular wind and current conditions	0-360 (°)
Coral	Number of coral-dominated cells within a 1 km radius	Specifically describes coral-related habitats	0-656 (no)
Depth	Distance from the surface to the sea bottom	Shapes fish composition and biomass and determines anchoring length	-150 - -0.6 (m)
Facilities	Distance to the nearest pontoon or mooring	Public infrastructures can provide safety and facilitate access to high use sites	0-53 (km)
Fishing capacity	Number of motorized recreational boats registered within a 50 km radius	Provides a proxy of the number of potential fishers in a given area	2.6-197.2 (n)
Islands	Distance to the nearest island	Land masses provide shelter and a potential access node	0-53.3 (km)
Reefs	Distance to the nearest reef	Specifically describes reef habitats	0-19.6 (m)
Slope	Incline of the sea bottom	Topography influences fish composition and biomass	0-63.6 (°)
Boundary	Distance from the nearest boundary	Poachers may fish in close proximity to no-take zone boundaries so as to be able to reduce their perceived risk of detection by patrols	0-6.8 (m)

All these predictor variables were generated at a spatial resolution of 50m and showed a Pearson correlation coefficient lower than |0.51| and a Variance Inflation Factor (VIF) lower than 1.6. Using this set of predictors, we were able to capture some previously unexplored potential risk factors in the GBRMP, although we acknowledge that poaching risk can have other dimensions such as individual determinants inherent among offenders, the weather, and/or the time of the day/week/year (Arias and Sutton, 2013; Bergseth et al., 2017; Bergseth and Roscher, 2018; Oyanedel et al., 2018; Weekers et al., 2019; Weekers and Zahnow, 2019) that we were not able to incorporate here. Hence, our predictive model provides a static picture of poaching risk, and assumes that other potential drivers are evenly distributed throughout the study area.

2.4 Building a predictive model of poaching risk

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

We calculated the median relative influence of the nine remaining predictor variables and 95% confidence intervals from 1,000 bootstrap replicates of the original dataset. Based on the same bootstrap replicates, we obtained partial dependency plots with 95% confidence intervals to visualize the relationships between the most influential predictor variables and the response (occurrence probability), while keeping all other predictors constant. We also quantified the relative interaction strength and significance between predictor variables using 500 bootstrap replicates (Pinsky and Byler, 2015). Maps of poaching risk (i.e. predicted probability of incident occurrence) were generated from the optimal BRT model's projections over the whole study area at each 50m x 50m cell with a continuous scale 0-1 for each bootstrap replicate, allowing the median poaching risk to be mapped as well as the 2.5% and 97.5% quantiles. Detailed methods used for model building and bootstrapping are provided in Supplementary Information.

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

3. Results

Almost 75% of the variability of incident occurrence was described by four predictors (Fig. 2). *Fishing capacity* was the most important predictor variable, accounting for 25.7% of the explained variability in incident occurrence. *depth*, *accessibility*, and *slope* explained a broadly similar portion of the variability in incident occurrence, ranging between 17.8% and 14.3%. *Boundary*, *islands*, and *facilities* had smaller contributions to the model prediction (7.1% each). *Reefs* and *aspect* explained little variability of incident occurrence.

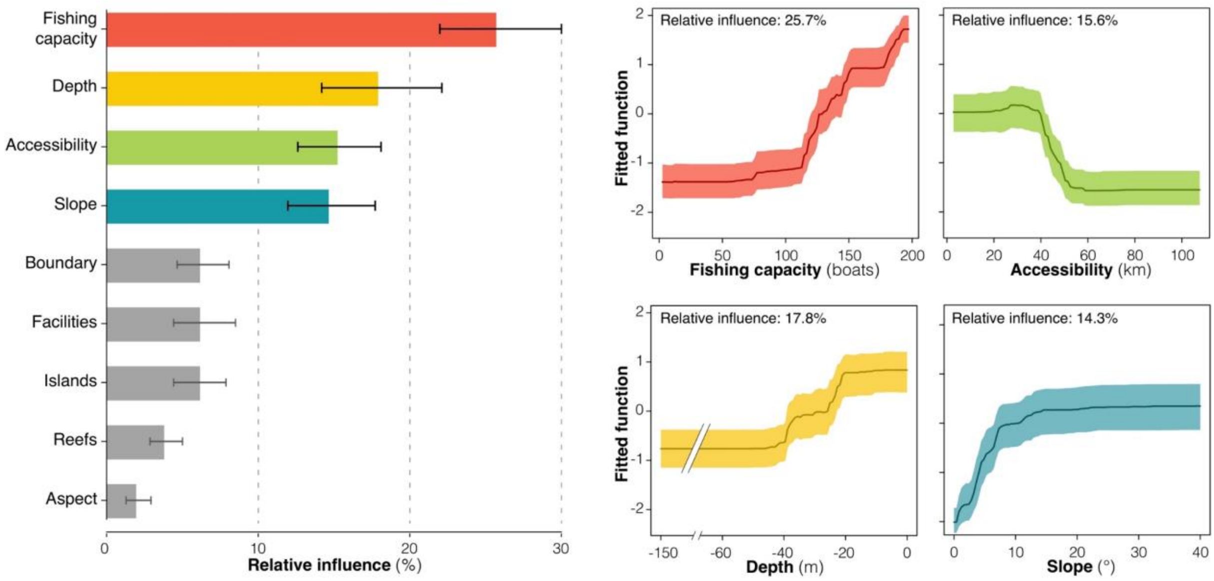

Figure 2: Predictors of poaching risk in no-take zones. The left panel shows the relative influence (and 95% confidence intervals) of the predictor variables. The right panel shows partial dependency plots and 95% confidence intervals for the four most influential variables. The graphs show the effect of a given predictor on the probability of incident occurrence while holding all other predictor variables constant at their mean. Note that sum of variables' relative influence does not equal 100 because estimates were obtained from bootstrapping.

Fitted function remained low at low levels of *fishing capacity* (25.7% relative influence) and then steadily increased from 100 boats per 50 km radius onwards (Fig. 2). Similar patterns were observed for *depth* (17.8%), with initially low levels of poaching likelihood (low fitted function) below -40m increasing until reaching a plateau around -20m depth. *Accessibility* was the third most important predictor of poaching occurrence (15.6%), with a negative sigmoid relationship displaying a threshold around 45 km from the nearest boat ramp. Fitted function for *Slope* (14.3%) displayed a positive asymptotic relationship that reached a plateau around

15° angle. Other less significant predictors with negative relationships were distance to: *boundary* (7.1%), *islands* (7.1%), and *reefs* (4.6%).

The analysis of interaction strength between predictor variables highlighted strong interactions, especially for *fishing capacity*. The four strongest pairwise interactions were *fishing capacity* x *accessibility* (71.51; p-value<0.001), *fishing capacity* x *depth* (36.9; p-value<0.001), *slope* x *accessibility* (14.1; p-value<0.001) and *fishing capacity* x *slope* (9.9; p-value<0.01). Occurrence probability for incidents was higher in areas characterized by higher *fishing capacity*, shallower depths, shorter distances to boat ramps (i.e. *accessibility*), and steeper sea bottom (Figs. 2-3).

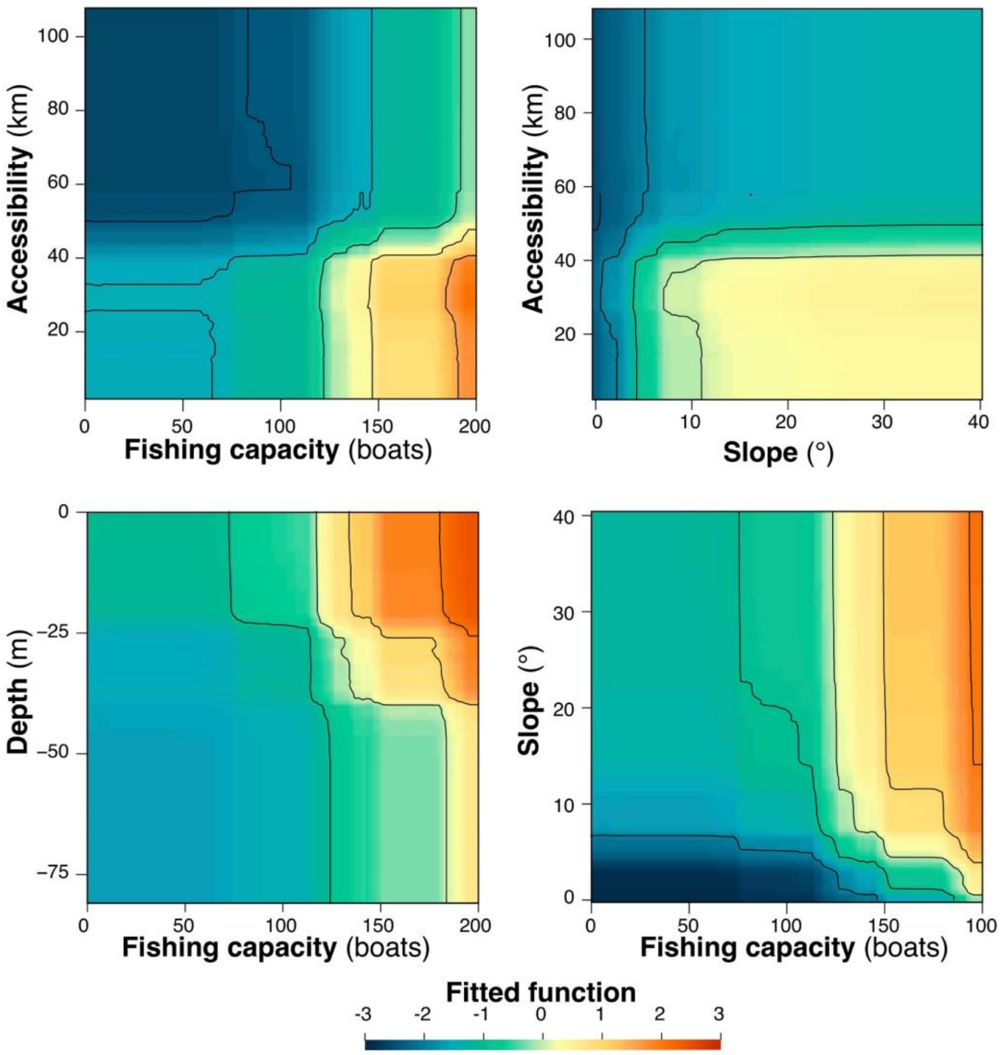

Figure 3: Pairwise interaction plots of the four strongest interactions between variables predicting poaching risk in no-take zones. Each panel indicates the median fitted function calculated on 1,000 bootstrap replicates. All interactions were significant. See Supporting Information for uncertainty surrounding these estimates.

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

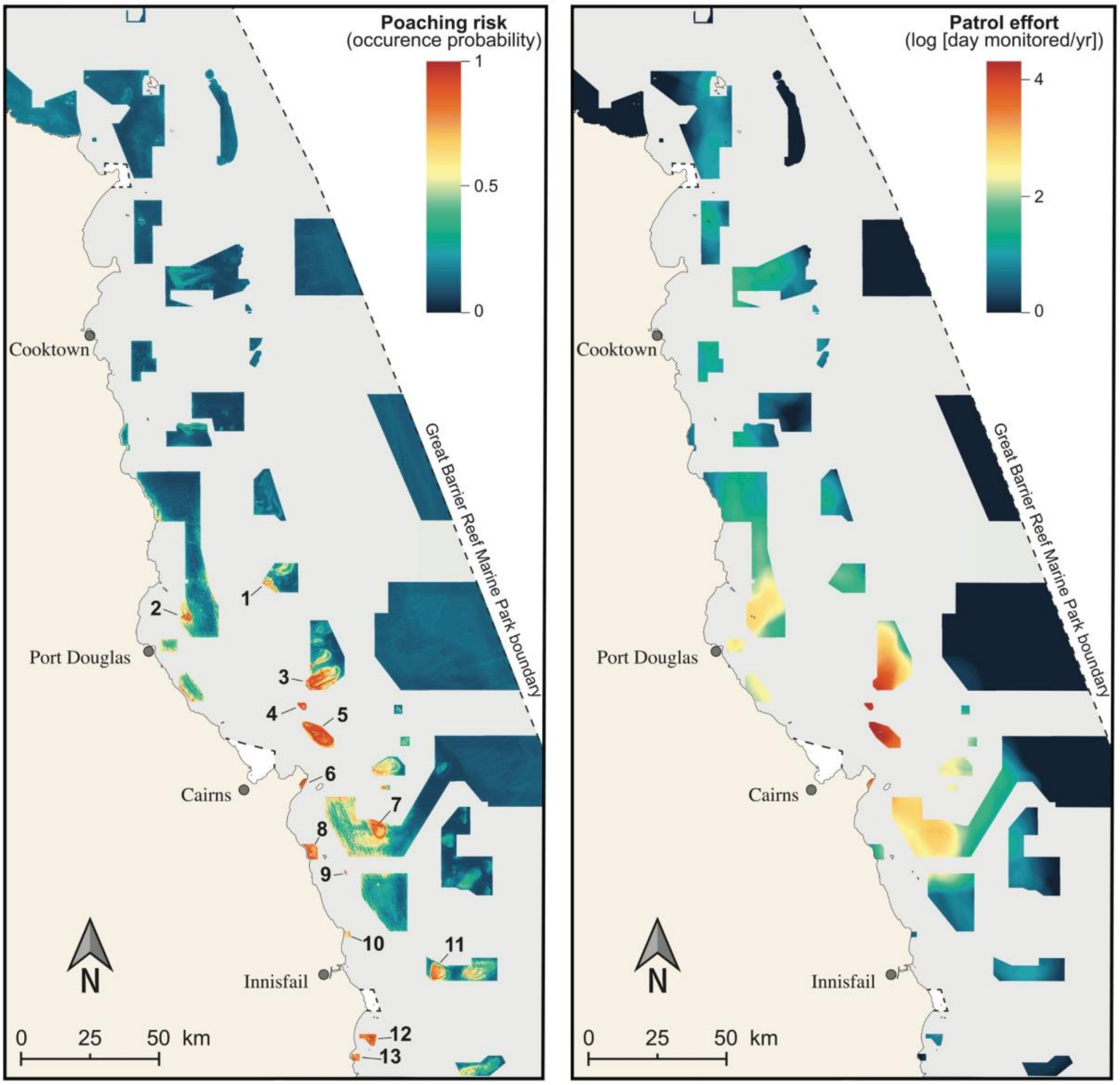

Figure 4: Poaching risk within the no-take zones of the Cairns Management Region of the Great Barrier Reef Marine Park, and associated level of patrol monitoring effort. Numbers indicate predicted poaching hotspots within no-take zones: 1- Tongue Reef; 2-Low Isles Reef; 3-Michaelmas Reef; 4-Upolu Reef; 5-Green Island Reef; 6-Wide Bay; 7-Scott Reef; 8-MNP-17-1070; 9-Normanby-Mabel Reef; 10-MNP-17-1066; 11-Feather Reef; 12-Sisters-Stephens Reef; 13-Gardens Beach. See Supporting Information for uncertainty surrounding poaching risk estimates.

Patrol effort was skewed towards a few no-take zones around Cairns and, to a lower extent, Port Douglas (Fig. 4). Of the 44 no-take zones located within the CMR, four accounted for 75% of the total patrol activity conducted between 2015 and 2019 (Supporting Information). This concentration of patrol effort partially matched with the spatial distribution of poaching risk (Fig. 5). While the highest levels of patrol effort were found in the three major poaching hotspots (yellow in Fig. 5), other areas with comparable levels of poaching risk received much less monitoring. These areas, which may represent enforcement gaps, were mostly located in the south of the CMR (maroon in Fig. 5). Areas predicted to be exposed to low poaching risk tended to be monitored less (blue in Fig. 5).

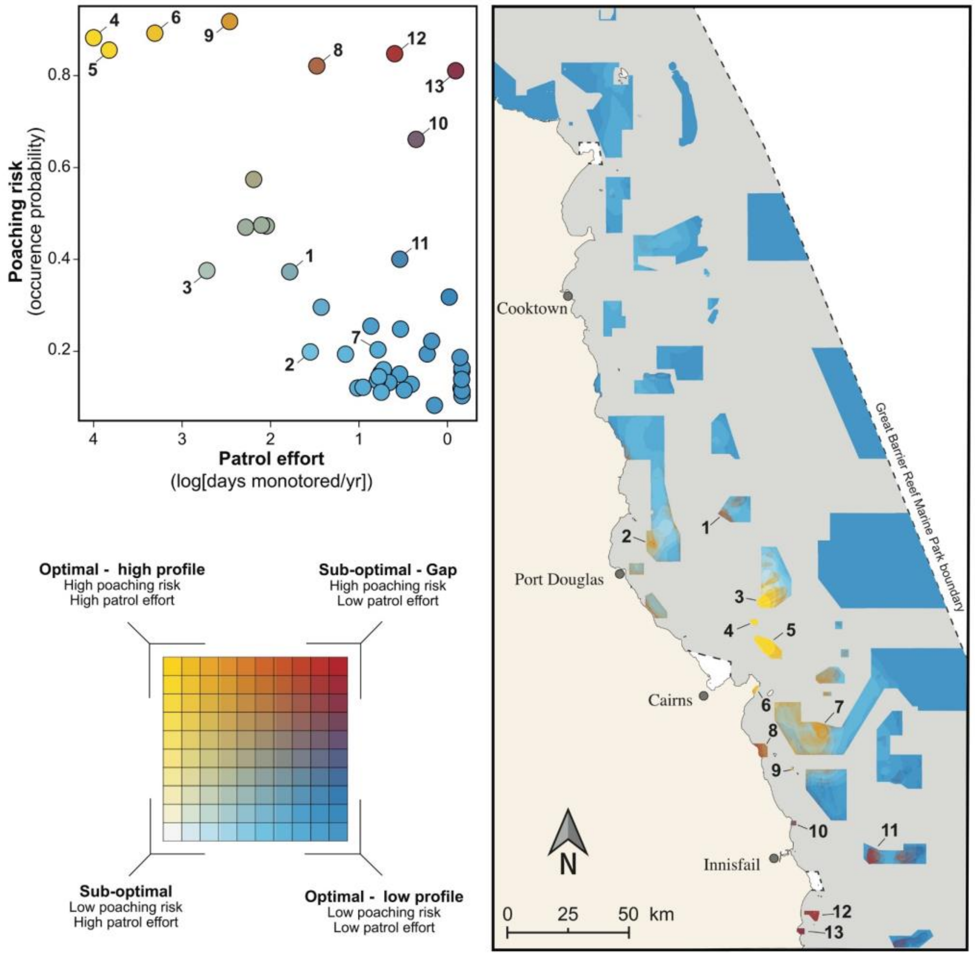

Figure 5: Congruence and mismatch between patrol effort and poaching risk. Bi-plot represent no-take zones' averages. Areas in yellow and blue respectively indicate where patrol distribution matches with poaching risk. Areas in greatest risk of poaching exposure with low surveillance effort are shown in maroon. Numbers indicate the poaching hotspots shown in Fig. 4: 1- Tongue Reef; 2-Low Isles Reef; 3-Michaelmas Reef; 4-Upolu Reef; 5-Green Island Reef; 6-Wide Bay; 7-Scott Reef; 8-MNP-17-1070; 9-Normanby-Mabel Reef; 10-MNP-17-1066; 11-Feather Reef; 12-Sisters-Stephens Reef; 13-Gardens Beach.

4. Discussion

Identifying the underlying drivers of poaching and understanding how they interact and structure poaching risk offer great value to managers seeking to strategically prioritize the distribution and allocation of limited resources. This study presents the first attempt at quantifying the relative influence of, and interaction between multiple risk factors of recreational poaching in a large Marine Protected Area (MPA) using commonly available patrol-collected data and spatial predictors. It offers novel insights that can inform management strategies and planning, via a new predictive approach that can potentially be applied to other marine and terrestrial settings.

Four predictors; *fishing capacity*, *depth*, *accessibility* and *slope*, dominate in explaining poaching risk. Our analysis confirms the assumption that poaching hotspots are characterized by substantial *fishing capacity;* however, our model identifies a threshold (i.e. about 100 boats within a 50 km radius; Fig. 2) beyond which poaching risk increases markedly. Similarly, poaching hotspots were predicted by the model at depths shallower than 40 m, short(er) distances to the nearest boat ramp of 0 to 45 km and in areas of complex topography, defined by a steep(er) sea bottom (Figs. 2-3). Overall, these findings emphasize the value of these simple yet critical features in the assessment of a no-take zone's likelihood to be exposed to poaching, and provide insights into the mechanisms by which they can interact.

Our results highlight the important role of benthic topography (described by *depth* and *slope*) in driving poaching risk. In coral reefs, areas with high slope and low depth –where poaching risk is the highest– typically reflect reef slopes and edges, which often harbor higher target fish abundance and biomass. Thus, these two variables can broadly define environmental bounds of "attractiveness" to recreational poachers, and may also represent places offering easier and safer anchorage to fishers. This attractiveness is affected by *accessibility*, the cost of travelling, in time and/or monetary value, across the intervening sea which remains a major constraining factor (Maire et al., 2016). It is worth noting that the tipping point beyond which poaching risk diminishes significantly (around 45 km from the nearest boat ramp) remains substantially higher in the GBRMP than in other places (Daw, 2008; Daw et al., 2011; Metcalfe et al., 2017). Such long travel distances might reflect the unique characteristics of this case study, including the large size of the zoning plan (GBRMPA, 2018) as well as the relative wealth of Australians and the investment by recreational fishers in faster and more sea-worthy vessels as fishing platforms (CRC, 2018, 2017).

Poaching risk was better predicted when drivers related to fishers' spatial preference (i.e. *accessibility* and attractiveness) interacted with *fishing capacity* (Fig. 3). The combined effects of attractiveness (*depth* and *slope*), *accessibility* and *fishing capacity* in driving fishing pressure generally (Castro-Sanguino et al., 2017; Daw, 2008; Harborne et al., 2018; Metcalfe et al., 2017; Thiault et al., 2017), and poaching risk specifically (Diogo et al., 2016; Weekers and Zahnow, 2019) have been shown elsewhere.

The critical roles of *fishing capacity* (determined by the number and location of registered recreational boats) and *accessibility* (determined by the number and location of boat ramps) indicate potential benefits associated with increased integration of new and updated data, for example, in coordination with the Queensland Department of Transport and Main Roads (TMR). Although the number of boats registered cannot be capped, TMR registration data, regulatory conditions, and planning schemes (e.g. for development and maintenance of recreational access points) represent potentially valuable points of opportunity around which to foster collaborative monitoring and management.

This approach will enhance resilience-based management of the Great Barrier Reef through the provision of prioritization guidance for compliance activities. Our findings indicate that patrolling effort only partially matches with the identified spatial patterns of our modelled poaching risk. Designing more cost-effective enforcement strategies may require redistributing partly patrol effort where enforcement gaps are likely to occur (i.e. higher poaching risk and lower patrol effort). Our model suggests that no-take zones that may benefit from increased effort are often adjacent to shore, indicating that land-based compliance officers might be deployed in these areas. Systematic resource allocation methods (e.g. MARXAN software or *prioritizer* R package) could also be used in future to optimize deployment of patrols (Plumptre et al., 2014).

This study provides a nuanced understanding of the interactions between various risk factors related to recreational poaching in the GBRMP. This allows reliable and accurate prediction of poaching risk to determine where to allocate enforcement patrols. The relatively low sample size, however, means that we were not able to incorporate the temporal dimension and identify when such patrols should be deployed. Future applications based on a higher number of incidence data collected over a longer period of time would provide more generalizable and dynamic predictions. For instance, understanding weather effects would enable better prediction of poacher behavior on a day-to-day basis (Critchlow et al., 2015) while longer temporal changes could help determining the deterrence effects of patrols (Dobson et al., 2018). Likewise, we acknowledge that while our model treats poachers as a homogeneous group, poaching intention, severity and behavior may vary from one individual to another depending on gear, values and other individual factors. Future studies should aim to refine predictive models by differentiating spatial patterns across disparate groups, and by accounting for other potentially influential variables (e.g. weather, seasonality, time of day). Combined, these insights will aid patrol strategy decisions and improve patrol ability to inhibit poaching opportunities (via targeted enforcement presence), which will in turn provide spillover benefits into surrounding areas (Eng Leong, 2014; Johnson et al., 2014).

Beyond the immediate compliance optimization benefits, this approach offers managers the opportunity to consider poaching risk along with other relevant elements such as additional ecosystem threats, resilience potential and sociocultural and economic values which, together, will enhance managers’ capacity to implement strategic resilience-based management.

Supporting Information

Additional details on the spatial information on no-take zones (Appendix S1) describing methods used to weight presence/pseudo-absence data (Appendix S2), fine-tune BRT parameters and the bootstrapping procedure (Appendix S3), along with additional results on model uncertainty (Appendix S4) and patrol effort (Appendix S5) are available online.

Acknowledgments

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Literature Cited

Arias, A., Pressey, R.L., Jones, R.E., Alvarez-Romero, J.G., Cinner, J.E., 2016. Optimizing enforcement and compliance in offshore marine protected areas: a case study from Cocos Island, Costa Rica. Oryx 50, 18–26. doi:10.1017/S0030605314000337

Arias, A., Sutton, S.G., 2013. Understanding Recreational Fishers’ Compliance with No-take Zones in the Great Barrier Reef Marine Park. Ecol. Soc. 18, art18. doi:10.5751/ES-05872-180418

Bergseth, B.J., Roscher, M., 2018. Discerning the culture of compliance through recreational fisher's perceptions of poaching. Mar. Policy 89, 132–141. doi:10.1016/j.marpol.2017.12.022

Bergseth, B.J., Williamson, D.H., Russ, G.R., Sutton, S.G., Cinner, J.E., 2017. A social-ecological approach to assessing and managing poaching by recreational fishers. Front. Ecol. Environ. 15, 67–73. doi:10.1002/fee.1457

Brill, G., Raemaekers, S., 2009. A decade of illegal fishing in Table Mountain National Park (2000–2009): trends in the illicit harvest of abalone Haliotis midae and West Coast rock lobster Jasus lalandii. African J. Mar. Sci. Publ. 35, 491–500. doi:10.2989/1814232X.2013.850443

Campbell, S.J., Hoey, A.S., Maynard, J., Kartawijaya, T., Cinner, J., Graham, N. a J., Baird, A.H., 2012. Weak Compliance Undermines the Success of No-Take Zones in a Large

Government-Controlled Marine Protected Area. PLoS One 7, e50074. doi:10.1371/journal.pone.0050074

Castro-Sanguino, C., Bozec, Y., Dempsey, A., Samaniego, B.R., Lubarsky, K., Andrews, S., Komyakova, V., Ortiz, J.C., Robbins, W.D., Renaud, P.G., Mumby, P.J., 2017. Detecting conservation benefits of marine reserves on remote reefs of the northern GBR. PLoS One 12, e0186146. doi:10.1371/journal.pone.0186146

Cerasoli, F., Iannella, M., D'Alessandro, P., Biondi, M., 2017. Comparing pseudo-absences generation techniques in Boosted Regression Trees models for conservation purposes: A case study on amphibians in a protected area. PLoS One 12, e0187589. doi:10.1371/journal.pone.0187589

Claudet, J., Osenberg, C.W., Benedetti-Cecchi, L., Domenici, P., García-Charton, J.-A., Pérez-Ruzafa, Á., Badalamenti, F., Bayle-Sempere, J., Brito, A., Bulleri, F., Culioli, J.-M., Dimech, M., Falcón, J.M., Guala, I., Milazzo, M., Sánchez-Meca, J., Somerfield, P.J., Stobart, B., Vandeperre, F., Valle, C., Planes, S., 2008. Marine reserves: size and age do matter. Ecol. Lett. 11, 481–489. doi:10.1111/j.1461-0248.2008.01166.x

CRC, 2018. Cairns Recreational Fishing Strategy 2018-2022.

CRC, 2017. Queensland Recreational Boating Facilities Demand Forecasting Study 2017 - Cairns Regional Council Assessment.

Critchlow, R., Andira, B., Box, P.O., Driciru, M., Box, P.O., Rwetsiba, A., Box, P.O., Wanyama, F., Box, P.O., Beale, C.M., 2016. Improving law enforcement effectiveness and efficiency in protected areas using ranger- collected monitoring data. Conserv. Lett. 10, 572–580. doi:10.1111/conl.12288.This

Critchlow, R., Plumptre, A.J., Driciru, M., Rwetsiba, A., Stokes, E.J., Tumwesigye, C., Wanyama, F., Beale, C.M., 2015. Spatiotemporal trends of illegal activities from ranger-collected data in a Ugandan national park. Conserv. Biol. 29, 1458–1470. doi:10.1111/cobi.12538

Davis, K.L.F., Russ, G.R., Williamson, D.H., Evans, R.D., 2004. Surveillance and poaching on inshore reefs of the Great Barrier Reef Marine Park. Coast. Manag. 32, 373–387.

doi:10.1080/08920750490487223

Daw, T.M., 2008. Spatial distribution of effort by artisanal fishers: Exploring economic factors affecting the lobster fisheries of the Corn Islands, Nicaragua. Fish. Res. 90, 17–25. doi:10.1016/j.fishres.2007.09.027

Daw, T.M., Maina, J., Cinner, J.E., Robinson, J., Collaborators, K., Gerry, C., Abunge, C., Thoya, P., Abernethy, K., Cedras, M., Mwaura, J., Ndegwa, S., 2011. The spatial behaviour of artisanal fishers: Implications for fisheries management and development (Fishers in Space) 1–79.

Di Franco, A., Thiriet, P., Di Carlo, G., Dimitriadis, C., Francour, P., Gutiérrez, N.L., Jeudy de Grissac, A., Koutsoubas, D., Milazzo, M., Otero, M. del M., Piante, C., Plass-Johnson, J., Sainz-Trapaga, S., Santarossa, L., Tudela, S., Guidetti, P., 2016. Five key attributes can increase marine protected areas performance for small-scale fisheries management. Sci. Rep. 6, 38135. doi:10.1038/srep38135

Diogo, H., Gil Pereira, J., Schmiing, M., 2016. Catch me if you can: Non-compliance of limpet protection in the Azores. Mar. Policy 63, 92–99. doi:10.1016/j.marpol.2015.10.007

Dobson, A.D.M., Keane, A., Beale, C.M., Ibbett, H., 2018. Detecting deterrence from patrol data 33, 665–675. doi:10.1111/cobi.13222

Elith, J., Leathwick, J.R., Hastie, T., 2008. A working guide to boosted regression trees. J. Anim. Ecol. 77, 802–813. doi:10.1111/j.1365-2656.2008.01390.x

Eng Leong, C., 2014. A Review of Research on Crime Displacement Theory. Int. J. Bus. Econ. Res. 3, 22. doi:10.11648/j.ijber.s.2014030601.14

GBRF, 2019. Delivering a reef resilience plan for the Cairns management area: Habitat Mapping. Townsville.

GBRMPA, 2019. Great Barrier Reef Outlook Report 2019, Great Barrier Reef Marine Park Authority. Townsville.

GBRMPA, 2018. Annual Report 2017-2018, Great Barrier Reef Marine Park Authority. Townsville.

Gill, D.A., Mascia, M.B., Ahmadia, G.N., Glew, L., Lester, S.E., Barnes, M., Craigie, I., Darling, E.S., Free, C.M., Geldmann, J., Holst, S., Jensen, O.P., White, A.T., Basurto, X., Coad, L., Gates, R.D., Guannel, G., Mumby, P.J., Thomas, H., Whitmee, S., Woodley, S., Fox, H.E., 2017. Capacity shortfalls hinder the performance of marine protected areas globally. Nature 543, 665–669. doi:10.1038/nature21708

Green, A.L., Maypa, A.P., Almany, G.R., Rhodes, K.L., Weeks, R., Abesamis, R. a., Gleason, M.G., Mumby, P.J., White, A.T., 2015. Larval dispersal and movement patterns of coral reef fishes, and implications for marine reserve network design. Biol. Rev. 90, 1215–1247. doi:10.1111/brv.12155

Guidetti, P., Milazzo, M., Bussotti, S., Molinari, A., Murenu, M., Pais, A., Spanò, N., Balzano, R., Agardy, T., Boero, F., Carrada, G., Cattaneo-Vietti, R., Cau, A., Chemello, R., Greco, S., Manganaro, A., Notarbartolo di Sciara, G., Russo, G.F., Tunesi, L., 2008. Italian marine reserve effectiveness: Does enforcement matter? Biol. Conserv. 141, 699–709. doi:10.1016/j.biocon.2007.12.013

Haines, A.M., Elledge, D., Wilsing, L.K., Grabe, M., Barske, M.D., Burke, N., Webb, S.L., 2012. Spatially explicit analysis of poaching activity as a conservation management tool. Wildl. Soc. Bull. 36, 685–692. doi:10.1002/wsb.194

Harasti, D., Davis, T.R., Jordan, A., Erskine, L., Moltschaniwskyj, N., 2019. Illegal recreational fishing causes a decline in a fishery targeted species (Snapper: Chrysophrys auratus) within a remote no-take marine protected area. PLoS One 14, e0209926. doi:10.1371/journal.pone.0209926

Harborne, A.R., Green, A.L., Peterson, N.A., Beger, M., Golbuu, Y., Houk, P., Spalding, M.D., Taylor, B.M., Terk, E., Treml, E.A., Victor, S., Vigliola, L., Williams, I.D., Wolff, N.H., zu Ermgassen, P.S.E., Mumby, P.J., 2018. Modelling and mapping regional-scale patterns of fishing impact and fish stocks to support coral-reef management in Micronesia. Divers. Distrib. 24, 1729–1743. doi:10.1111/ddi.12814

Hijmans, R.J., Phillips, S., Leathwick, J., Elith, J., 2016. dismo: Species Distribution Modeling.

Horta e Costa, B., Claudet, J., Franco, G., Erzini, K., Caro, A., Gonçalves, E.J., 2016. A regulation-based classification system for Marine Protected Areas (MPAs). Mar. Policy 72, 192–198. doi:10.1016/j.marpol.2016.06.021

Ivec, M., Braithwaite, V., 2015. Applications of responsive regulatory theory in Australia and overseas: Update. RegNet Occas. Pap. 23.

Jachmann, H., 2008. Monitoring law-enforcement performance in nine protected areas in Ghana. Biol. Conserv. 141, 89–99. doi:10.1016/j.biocon.2007.09.012

Johnson, S.D., Guerette, R.T., Bowers, K., 2014. Crime displacement: what we know, what we don't know, and what it means for crime reduction. J. Exp. Criminol. 10, 549–571. doi:10.1007/s11292-014-9209-4

Jupiter, S.D., Egli, D.P., 2011. Ecosystem-Based Management in Fiji: Successes and Challenges after Five Years of Implementation. J. Mar. Biol. 2011, 1–14. doi:10.1155/2011/940765

Keane, A., Jones, J.P.G., Edwards-Jones, G., Milner-Gulland, E.J., 2008. The sleeping policeman: understanding issues of enforcement and compliance in conservation. Anim. Conserv. 11, 75–82. doi:10.1111/j.1469-1795.2008.00170.x

Kurland, J., Pires, S.F., Marteache, N., 2018a. The spatial pattern of redwood burl poaching and implications for prevention. For. Policy Econ. 94, 46–54. doi:10.1016/j.forpol.2018.06.009

Kurland, J., Pires, S.F., Marteache, N., 2018b. Forest Policy and Economics The spatial pattern of redwood burl poaching and implications for prevention. For. Policy Econ. 94, 46–54. doi:10.1016/j.forpol.2018.06.009

Lubchenco, J., Grorud-Colvert, K., 2015. Making waves: The science and politics of ocean protection. Science (80-.). 350, 382–383. doi:10.1126/science.aad5443

Maingi, J.K., Mukeka, J.M., Kyale, D.M., Muasya, R.M., 2012. Spatiotemporal patterns of elephant poaching in south-eastern Kenya. Wildl. Res. 39, 234. doi:10.1071/WR11017

Maire, E., Cinner, J., Velez, L., Huchery, C., Mora, C., Dagata, S., Vigliola, L., Wantiez, L., Kulbicki, M., Mouillot, D., 2016. How accessible are coral reefs to people? A global assessment based on travel time. Ecol. Lett. 19, 351–360. doi:10.1111/ele.12577

Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R.K., Thuiller, W., 2009. Evaluation of consensus methods in predictive species distribution modelling. Divers. Distrib. 15, 59–69. doi:10.1111/j.1472-4642.2008.00491.x

Metcalfe, K., Collins, T., Abernethy, K.E., Boumba, R., Dengui, J.-C., Miyalou, R., Parnell, R.J., Plummer, K.E., Russell, D.J.F., Safou, G.K., Tilley, D., Turner, R.A., VanLeeuwe, H., Witt, M.J., Godley, B.J., 2017. Addressing Uncertainty in Marine Resource Management; Combining Community Engagement and Tracking Technology to Characterize Human Behavior. Conserv. Lett. 10, 459–468. doi:10.1111/conl.12293

Moreto, W.D., Pires, S.F., 2018. Wildlife crime: An environmental criminology and crime science perspective. Carolina Academic Press.

Oyanedel, R., Keim, A., Castilla, J.C., Gelcich, S., 2018. Illegal fishing and territorial user rights in Chile. Conserv. Biol. 32, 619–627. doi:10.1111/cobi.13048

Petrossian, G.A., 2015. Preventing illegal, unreported and unregulated (IUU) fishing: a situational approach. Biol. Conserv. 189, 39–48. doi:10.1016/j.biocon.2014.09.005

Pinsky, M.L., Byler, D., 2015. Fishing, fast growth and climate variability increase the risk of collapse. Proc. R. Soc. B Biol. Sci. 282, 1–9. doi:10.1098/rspb.2015.1053

Pires, S.F., 2015. A CRAVED Analysis of Multiple Illicit Parrot Markets in Peru and Bolivia. Eur. J. Crim. Policy Res. 21, 321–336. doi:10.1007/s10610-014-9264-4

Plumptre, A.J., Fuller, R.A., Rwetsiba, A., Wanyama, F., Kujirakwinja, D., Driciru, M., Nangendo, G., Watson, J.E.M., Possingham, H.P., 2014. Efficiently targeting resources to deter illegal activities in protected areas. J. Appl. Ecol. 51, 714–725. doi:10.1111/1365-2664.12227

R Core Team, 2017. R: A language and environment for statistical computing. R Found. Stat. Comput.

Samoilys, M.A., Martin-smith, K.M., Giles, B.G., Cabrera, B., Anticamara, J.A., Brunio, E.O., Vincent, A.C.J., 2007. Effectiveness of five small Philippines' coral reef reserves for fish populations depends on site-specific factors, particularly enforcement history. Biol. Conserv. 136, 584–601. doi:10.1016/j.biocon.2007.01.003

Stevenson, M.D., Rossmo, D.K., Knell, R.J., Le Comber, S.C., 2012. Geographic profiling as a novel spatial tool for targeting the control of invasive species. Ecography (Cop.). 35, 704–715. doi:10.1111/j.1600-0587.2011.07292.x

Thiault, L., Collin, A., Chlous, F., Gelcich, S., Claudet, J., 2017. Combining participatory and socioeconomic approaches to map fishing effort in small-scale fisheries. PLoS One 12, e0176862. doi:10.1371/journal.pone.0176862

Weekers, D.P., Zahnow, R., 2019. Risky facilities: Analysis of illegal recreational fishing in the Great Barrier Reef Marine Park, Australia. Aust. N. Z. J. Criminol. 52, 368–389. doi:10.1177/0004865818804021

Weekers, D.P., Zahnow, R., Mazerolle, L., 2019. Conservation Criminology: Modelling Offender Target Selection for Illegal Fishing in Marine Protected Areas. Br. J. Criminol. 59, 1455–1477. doi:10.1093/bjc/azz020

Weisburd, D., 2015. The law of crime concentration and the criminology of place. Criminology 53, 133–157. doi:10.1111/1745-9125.12070