Predicting the risk of illegal activity and evaluating law enforcement interventions in the western Serengeti

Kristen Denninger Snyder1,2 | Philemon B. Mneney2 | George Wittemyer1

1Department of Fish, Wildlife and Conservation Biology, Colorado State University, Fort Collins, Colorado
2Grumeti Fund, Mugumu, Tanzania

Correspondence
Kristen Denninger Snyder, Department of Fish, Wildlife and Conservation Biology, Colorado State University, 1474 Campus Delivery, Fort Collins, CO 80523.
Email: kdsnyder@rams.colostate.edu

Present address
Philemon B. Mneney, GIZ Tanzania, Natural Resource Management Program, P.O. Box 1, Loliondo, Ngorongoro, Arusha, Tanzania.

Funding information
Grumeti Fund; Monfort Professorship at Colorado State University

Abstract
Illegal activity within protected areas is a primary driver of species decline and threatens conservation efforts. In the western corridor of the Serengeti Ecosystem of northern Tanzania, the Grumeti and Ikorongo Game Reserves and Ikona Wildlife Management Area provide an important buffer between permanent settlements and Serengeti National Park, while simultaneously maintaining critical wildlife habitat. Understanding the spatial distribution and environmental drivers of illegal activity is critical to optimize biodiversity protection efforts in this important ecosystem. We examined a rare dataset containing detailed records of reserve game scout patrol effort and occurrences of illegal activity between 2013 and 2016. We used presence only data to construct predictive models of five categories of illegal activity. We derived spatial predictions of the likelihood of different activities and identified the environmental variables predictive of risk for each activity. The highest risk areas were located along reserve edges, further from roads and scout camps, suggesting avoidance of enforcement presence. Activities associated with wildlife offtake were the most widely distributed in the study area and extended into the national park. Permanent scout camps were more effective deterrents of all illegal activities than observation posts, but their limited spatial influence demonstrated additional enforcement strategies are required.

Keywords
Africa, bushmeat, predictive modeling, protected areas, risk assessment, snare

1 | INTRODUCTION

The illegal extraction of natural resources is a threat to biodiversity globally, causing negative biological, ecological, economic, and social impacts and acting as a primary threat to the maintenance of protected areas (Chape, Harrison, Spalding, & Lysenko, 2005; Gavin, Solomon, & Blank, 2010). In ecological terms, illegal resource use contributes to declines in diversity at all scales and alterations to ecosystem services; economic and social impacts are felt via the reduction or loss of access or profits to users that operate within legal contexts (Gavin et al., 2010) and may be linked to political destabilization, causing threats to personal security (Wyler & Sheikh, 2008). Increasing human pressures on protected areas, driven in part by human population growth, will make securing protected areas and their biological resources more difficult (Jones et al., 2019). As such, developing strategies to effectively deter the illegal extractions of natural resources is an immediate priority.
A suite of approaches is required in order to reduce the prevalence of illegal activities. These include the diversification of livelihoods, increasing the direct benefits and reducing the costs that communities derive from living in close proximity to protected areas and wildlife, reducing demand in consumer markets, and strengthening disincentives for illegal behavior (Biggs et al., 2017; Challenger & MacMillan, 2014). While law enforcement is only one component of broader management strategies, it is a critical tool utilized by protected area managers to deter illegal activity (Hilborn et al., 2006; Keane, Jones, Edwards-Jones, & Milner-Gulland, 2008). In many areas, protected area managers are tasked with safeguarding reserves far greater in size than they have resources to adequately monitor and protect, and underfunding limits management effectiveness (Brunger, Gullison, Rice, & Da Fonseca, 2001; Juffe-Bignoli et al., 2014; Plumptre et al., 2014; Watson, Dudley, Segan, & Hockings, 2014). In order to better meet management objectives and maximize the efficiency with which limited resources are utilized, development and application of approaches to increase the efficacy of protection and monitoring are needed.

Identifying priority areas for intervention in order to reduce illegal activity is a key approach for optimizing protected area management. In many areas this is a challenging task because spatially explicit information on illegal activity is not available. Where collected, analyses of law enforcement interventions that assess the spatial and temporal correlates of illegal activities (e.g., landscape features) can facilitate predictions of risk across landscapes, including unsampled areas (for recent examples, see Critchlow et al., 2015, 2017; Plumptre et al., 2014). Additionally, such information can serve to investigate the spatial or temporal influence of different law enforcement tactics.

The western corridor of the Serengeti is part of an extensive network of protected areas known as the Greater Serengeti Ecosystem (GSE). This area protects key wildlife habitat, but also contains the highest density human population adjacent to Serengeti National Park (SNP; Tanzania National Bureau of Statistics [NBS], 2012), and is speculated to pose the greatest threat to the integrity of the ecosystem (Kaltenborn & Nyahongo, 2005; Knapp, 2012; Metzger, Sinclair, Hilborn, Hopcraft, & Mduma, 2010; Thirgood et al., 2004). Previous research on illegal activity in this area has emphasized illegal hunting, including estimating offtake of wildlife populations (Campbell & Hofer, 1995; Dublin et al., 1990; Mduma, Hilborn, & Sinclair, 1998; Rentsch & Packer, 2015) species preferences (Holmern, Mkama, Muya, & Røskaft, 2006; Ndibalema & Songorwa, 2008), and motivations or characteristics of those engaged in the hunting or consumption of bushmeat (Fischer, Naima, Lowassa, Randall, & Rentsch, 2014; Hofer, Campbell, East, & Huish, 2000; Kaltenborn & Nyahongo, 2005; Knapp, 2007, 2012; Loibooki, Hofer, Campbell, & East, 2002; Moro et al., 2013; Nuno, Bunnefeld, Naima, & Milner-Gulland, 2013; Nyahongo, Holmern, Kaltenborn, & Røskaft, 2009; Nyaki, Gray, Lepczyk, Skibins, & Rentsch, 2014). Poaching and the consumption of bushmeat is widespread, has contributed to substantial declines in wildlife populations in the GSE, and is recognized as a major threat to this ecosystem (Dublin et al., 1990; Loibooki et al., 2002; Metzger et al., 2010; Rentsch & Packer, 2015). While tree-felling for charcoal production and livestock grazing are broadly recognized as threats to protected areas, the prevalence of these activities has received less attention in this region (Brandon, 1998; Caro & Davenport, 2016).

Few studies have examined law enforcement efforts within the GSE, most likely because this data is difficult to obtain. Existing work found that increased anti-poaching effort within SNP was associated with declines in poaching activity (Hilborn et al., 2006) and that increased rates of detections of illegal activity by village game scouts in the western Serengeti corresponded with the arrival of migratory herbivores (Holmern, Muya, & Røskaft, 2007). More detailed assessments of the effectiveness of law enforcement interventions in deterring illegal activity (e.g., effective distances from camps or observation posts) are absent in the literature from this region, and uncommon more widely (Plumptre et al., 2014).

Here, we build upon this work by analyzing law enforcement data to construct predictive models of illegal activity in the western Serengeti. We evaluate five types of illegal activity common to the study area, and contrast the environmental drivers, identify the areas of highest risk, and assess the total extent of each. In addition, we assess the influence of permanent scout camps and observation posts in deterring illegal activity and how model generated inference can serve to focus management interventions, including both law enforcement and community outreach. This study exemplifies the utility of data-driven assessments to understand the spatial distribution of illegal activities, and how this information can be used to inform the allocation of limited resources in support of conservation objectives within protected areas.

2 | MATERIALS AND METHODS

2.1 | Study area

The study area covers 1,947 km² of the western corridor of the GSE in northern Tanzania (1°50’–2°12’S, 33°57’–34°59’E). The area is comprised of a number of protected areas with varying legal designations (Figure 1). The Grumeti and Ikorongo Game Reserves (IGGR) are a managed concession area where permitted hunting is allowed but
extremely limited. The Sasakwa Concession is an area within the game reserve designated for tourism development. The Ikona Wildlife Management Area (IWMA) is comprised of two blocks zoned for photographic tourism and permitted hunting; Robanda village is located within the photographic zone. Village managed limited use areas allow specific activities, primarily livestock grazing, but no permanent settlements, farming activities, or hunting. SNP is adjacent to the primary study area and allows photographic tourism, but all resource extraction is illegal. Permanent settlements are established immediately along the reserve boundary, particularly adjacent to Ikorongo Game Reserve. This region contains extensive wilderness, Pleistocene levels of wildlife abundance, and is considered a key landscape for conservation (European Commission, 2016). The reserve complex is inhabited by a number of threatened species, including elephant (*Loxodonta africana*), lion (*Panthera leo*), wild dog (*Lycaon pictus*), cheetah (*Acinonyx jubatus*), and leopard (*Panthera pardus*), hosts large populations of herbivores, and preserves an important corridor for the seasonal migration of wildebeest (*Connochaetes taurinus*), zebra (*Equus quagga*), and gazelle (*Eudorcas thomsoni*; *Nanger granti*). The western corridor also serves as an important buffer between the core habitat of SNP and permanent settlements, insulating the park from the effects of human activity and the threat of encroachment. This region is challenged by the highest human population density adjacent to the national park (NBS, 2012) and this area is speculated to pose the greatest threat to the integrity of the ecosystem (Kaltenborn & Nyahongo, 2005; Knapp, 2012; Thirgood et al., 2004). The dominant vegetation cover in the western half of the study area is grassland and scattered shrubland, and seasonal flooding is common due to the prevalence of flat, low-lying terrain with vertisols. The eastern half of the study area is dominated by bushland and woodland, with steeper, more variable topography.

The people living in the Mara Region come from a variety of ethnic backgrounds but are primarily of Bantu descent. Subsistence agriculture (farming and raising livestock) is the most important source of income in both Bunda and Serengeti Districts. Nearly all households engage in farming, while around three-quarters of households raise livestock (Grumeti Fund [GF], 2016; NBS, 2012). Agricultural losses due to damage by wildlife imposes a significant burden on those living in close proximity to the protected area (Denninger Snyder, Mneney, Benjamin, Mkilindi, & Mbise, 2019; GF, 2016; Walpole et al., 2004). The consumption and selling of bushmeat is frequently used to supplement household food supplies as well as income, and can be more profitable than other economic ventures (Knapp, 2012; Rentsch & Damon, 2013).

### 2.2 Data compilation

We analyzed patrol data collected during the period 2013–2016 provided by the law enforcement division of the
GF, which manages the landscape in coordination with the Tanzania Wildlife Authority, the WMA management team, and district and government officials. Two types of law enforcement interventions are used to monitor the area for signs of illegal activity. Eleven permanent scout camps serve as bases for patrolling operations. Eleven permanent observation posts situated on vantage points are manned 24 hr a day, and sightings are relayed to scout teams to direct patrols. Scout teams are comprised of full-time staff from the surrounding communities. GF law enforcement relies on ingrained protocols paired with regular oversight to maintain reliable and accurate data collection. During patrols, scouts use GPS tracks to record their path and the location and type of illegal activity events that they encounter. Patrol tracks are compiled on a weekly basis and maintained in a long-term database.

We examined records for the five most common types of illegal activity events—active hunting, bushmeat possession, livestock grazing, snaring, and tree felling for charcoal production. Only records containing GPS coordinates and an incident description were included. Snare records were limited to cases where placed snares were removed, excluding incidents where people were found to be moving through the reserve carrying snares, so as to focus on the location of the illegal activity rather than the transit to those locations.

### 2.3 Model development

We used MaxEnt, a statistical learning technique that can be used to model environmental suitability across a geographic extent (Elith et al., 2011). Widely used in species distribution modeling (for recent examples, see Berthon, Esperon-Rodriguez, Beaumont, Carnegie, & Leishman, 2018; Clemente et al., 2019; Coxen, Frey, Carleton, & Collins, 2017; Zhang, Yao, Meng, & Tao, 2018), we applied this approach to examine the spatial distribution of the risk of illegal activity rather than the transit to those locations.

We used the free MaxEnt software (version 3.4.1) and R packages “dismo” (version 1.1-4) and ENMeval (version 0.3.0) to tune, construct, and evaluate all models (Hijmans, Phillips, Leathwick, & Elith, 2017; Muscarella et al., 2014, 2017; Phillips, Dudík, & Schapire, 2015). We constructed separate models for each form of illegal activity. Multiple environmental layers were used to assess landscape characteristics related to illegal activities, including elevation, slope, land cover, distances to rivers, roads, scout camps, observation posts, and villages, and the type of protected area (Table 1). In combination, these factors are expected to influence accessibility, the threat of detection by law enforcement, and the local suitability for different activities. Pairwise evaluation of all environmental variables indicated that multicollinearity was not expected to be problematic ($\max r = .4$).

For each activity, we executed MaxEnt across a range of settings and used evaluation metrics to identify optimal model settings for regularization multipliers and feature-class combinations (Muscarella et al., 2014). We selected settings that minimized ΔAICc scores; in cases where competing models were produced (ΔAICc < 2), area under the receiver operator curve (AUC) was used to decide between alternatives (Supporting information, Data S1). The number of background points was increased from 10,000 (default) to 250,000 due to the high resolution of the environmental data in order to prevent truncation of the response curves due to insufficient sampling of background conditions (Guevara, Gerstner, Kass, & Anderson, 2018).

Spatial biases in sampling (in this case, patrol) effort can result in models that are overfit to environmental biases and lead to overestimates of model performance (Boria, Olson, Goodman, & Anderson, 2014; Fourcade, Engler, Rödder, & Secondi, 2014; Phillips et al., 2009). We sampled background points according to known scout patrol effort, therefore subjecting the background localities to the same bias as the occurrence records, which has been demonstrated as an efficacious approach to correct for sampling bias (Syfert, Smith, & Coomes, 2013). We determined patrol effort by calculating the line density of patrol tracks across the study area and normalizing the output to range from 0 to 1 to represent the probability that an area was patrolled. Selection of random background points was weighted according to patrol probability. Patrol tracks were compiled and analyzed using ArcMap 10.3.

Clustered sampling is a separate issue that can violate statistical assumptions of independent sampling (Phillips, Anderson, Dudík, Schapire, & Blair, 2017). We used Moran’s I and visual assessments of correlograms to evaluate spatial autocorrelation within model residuals (expected value of occurrence records minus predicted value). When all occurrence records were used spatial autocorrelation was present in model residuals. We applied spatial thinning where the minimum distance between occurrence records was set to the distance at which spatial autocorrelation was no longer present in model residuals (bushmeat possession and livestock grazing—2.5 km) or to the maximum distance.
possible as determined by the number of occurrence records (active hunting—2.5 km, snaring—3 km). In the latter case the effects of spatial autocorrelation were not completely removed but were greatly reduced. Spatial thinning was not applied to tree-felling due to the low number of presence records.

### 2.4 Model evaluation

*K*-fold cross-validation was used to evaluate each model. Random partitioning of testing and training bins can artificially inflate model performance metrics and lead to overfitting due to spatial autocorrelation between calibration and evaluation localities (Radosavljevic & Anderson, 2014). To address this, spatial rules can be used to partition testing and training data (Muscarella et al., 2014). We partitioned occurrence and background points into four testing and training sets using a “masked geographically structured” approach as implemented by the “checkerboard2” method in the ENMeval package (Muscarella et al., 2014; Radosavljevic & Anderson, 2014). In the model of tree-felling leave one out (jackknife) cross-validation was applied, as is recommended for sample sizes of less than 25 (Pearson, Raxworthy, Nakamura, & Townsend Peterson, 2007). Full models were constructed using the complete data sets. Area under the receiver operator curve (AUC), the true skill statistic (TSS), and Schoener’s *D* statistic were used to evaluate cross-validated model performance (Allouche, Tsoar, & Kadmon, 2006; Warren, Glor, & Turelli, 2008).

### 2.5 Risk assessment

The complete data sets were used to construct full models and to predict the risk of each type of illegal activity across the study area. We mapped the predicted presence–absence of each activity using the 10th percentile training presence to determine suitability thresholds; this approach was selected because minimizing false-negative predictions (mistakenly predicting areas where illegal activity is absent) is of primary concern in this conservation application (Norris, 2014; Pearson et al., 2007). The resulting maps were used to examine each activity’s total extent, degree of incursion into SNP, and inform the selection of activities posing the greatest risk to this ecosystem. To determine the influence of existing law enforcement tactics on recorded illegal activities, we assessed response curves for the risk of each activity relative to other activities.
to distance from scout camps and observation posts. We used the distance at which the response curve distinguished between the presence and absence of an activity to define the threshold distance from (a) scout camps and (b) observation posts that each type of illegal activity was deterred under average environmental conditions (all other environmental variables are held constant at their mean).

3 | RESULTS

The complete dataset contained 611 detection of illegal events, thinned to 221 for model development. Records were comprised of active hunting \((n = 57)\), bushmeat transportation/possession \((n = 45)\), tree-felling for charcoal production \((n = 18)\), passive hunting (snaring) \((n = 50)\), and livestock grazing \((n = 51)\). Overall, detections tended to be recorded within 1.5 km of roads and between 2 and 6 km of scout camps (Supporting information). All models performed better than random chance \((\text{AUC} > 0.5, \text{TSS} > 0)\). Models of bushmeat possession and grazing were the highest performing when considering agreement across all metrics (Table 2). Snaring was the worst performing model \((\text{AUC test} = 0.59, \text{TSS} = 0.27)\). Resulting models were unlikely to be overfit, as evidenced by the small differences between testing and training AUC scores (Table 2). High Schoener’s \(D\) scores (>0.9 for all models) indicate that overall, predictions were robust.

The importance of each environmental covariate, as measured by percent contribution, was variable across activities, but some general trends were apparent (Figure 2). The risk of each form of illegal activity increased with increasing proximity to settlements, and distance to village tended to be a top predictive covariate across illegal activities. The influence of distance to village was greatest for livestock grazing, followed by snaring and tree-felling. Risk increased further from scout camps across all activities. The effect of scout camps was most pronounced on active hunting, the transportation and possession of bushmeat, and tree-felling. The risk of all activities increased in areas with higher densities of woody vegetation. The influence of slope and distance from observation points tended to be weak across all activities.

The influence of management type, roads, rivers, and elevation was more variable. Management designation was highly influential for bushmeat possession, active hunting, and tree felling. Bushmeat possession was most likely to occur on village land, active hunting in the national park and village land, and tree-felling in game reserves. Proximity to roads had the greatest negative effect on the presence of active hunting, while the risk of bushmeat possession was lowest at moderate distances from roads. Activities related to wildlife offtake tended to occur in close proximity to rivers. Lower elevation areas of the reserve were at decreased risk for bushmeat transit and tree-felling.

For all activities, high-risk areas extend into protected areas (Figure 3). However, the total predicted extent varied by activity; illegal livestock grazing was the most spatially restricted activity, while hunting was the most widespread (Table 2). In areas where the IGGR and IWMA provide a sufficient buffer between permanent settlements and SNP, livestock grazing and tree felling were excluded from SNP. Notably, all hunting-related activities extend into the SNP; based on total extent and incursion into the core area of the ecosystem, these activities pose the greatest threat to conservation.

### Table 2

| Activity             | \(n^a\) | FC\(^b\) | RM\(^c\) | AUC\(_{\text{TRAIN}}^d\) | Mean AUC\(_{\text{TEST}}^e\) | AUC\(_{\text{FULL}}^f\) | Sens\(^g\) | Spec\(^h\) | TSS\(^i\) | \(D^j\) | \(\%\)^k | Occl\(^l\) |
|----------------------|--------|---------|---------|----------------|----------------|----------------|---------|---------|-------|-------|--------|---------|
| Active hunting       | 57     | L       | 3.5     | 0.72          | 0.68           | 0.72           | 0.68    | 0.68    | 0.36  | 0.93  | 0.46   | 71      |
| Bushmeat possession  | 45     | LQHP    | 3.5     | 0.80          | 0.73           | 0.80           | 0.78    | 0.64    | 0.43  | 0.90  | 0.36   | 65      |
| Grazing              | 51     | LQH     | 3       | 0.79          | 0.73           | 0.79           | 0.70    | 0.74    | 0.44  | 0.92  | 0.40   | 41      |
| Snaring              | 50     | LQH     | 3.5     | 0.69          | 0.59           | 0.69           | 0.53    | 0.74    | 0.27  | 0.93  | 0.47   | 66      |
| Tree-felling         | 18     | L       | 1.5     | 0.87          | 0.81           | 0.87           | 0.44    | 0.81    | 0.25  | 0.93  | 0.28   | 46      |

Abbreviation: TSS, true skill statistic.

\(^a\) The number of presence records used for each activity.

\(^b\) The feature-classes used.

\(^c\) The regularization multiplier used.

\(^d\) Average AUC score for the training datasets of the cross-validated models.

\(^e\) Average AUC score for the test datasets of the cross-validated models.

\(^f\) The AUC score for the complete model.

\(^g\) Average test sensitivity (maxSSS) for the cross-validated models.

\(^h\) Average test specificity (maxSSS) for the cross-validated models.

\(^i\) Average test TSS scores of the cross-validated models.

\(^j\) The similarity of resulting predictions from the cross-validated models, as given by Schoener’s \(D\) statistic.

\(^k\) Threshold value to distinguish presence and absence.

\(^l\) The predicted extent (“presence”) as a percentage of the total study area.
The derived response curves for each illegal activity illustrated the differentiated effects of scout camps and observation posts in deterring illegal activity (Figure 4). Across all activities, the risk of occurrence increases with increasing distance from scout camps. The risk of grazing and snaring increased at greater distances from observation posts. As defined by the threshold value distinguishing presence–absence under average model conditions, we observed that scout camps effectively prevent active hunting, bushmeat transit, and tree-felling within 0.25, 1.5, and 4 km of camps, respectively. Although the risk of snaring and grazing did decrease in closer proximity to camps, both activities were predicted to be present within any distance of camps. Observation posts were observed to have the greatest deterrent effect on livestock grazing and snaring, but all activities were predicted to occur within any distance of observation posts.

4 | DISCUSSION

Illegal activities threaten protected areas globally, and the size of protected areas and budget limitations mean that efficient application of management actions to impede such activities and their impacts is critical. The approach presented here is a broadly applicable technique for harnessing predictive modeling to understand the spatial distribution of illegal activity and its relation to management efforts.
However, appropriate data collection and analysis is fundamental when utilizing such an approach to avoid mis-specification that can lead to erroneous conclusions. As was demonstrated in the Greater Virunga Landscape (Plumptre et al., 2014), patrol effort was unevenly distributed. We found that effort was highly biased towards the presence of scout camps and roads and detections of illegal activity tended to be greatest within relative proximity to these features. Consequently, bias correction and the spatial filtering of clustered occurrence records were both required. The latter presents a particular challenge for this application; in order to sufficiently filter occurrence records so as to completely remove the effects of spatial autocorrelation, this approach is best suited to larger extents, highly variable terrain, or cases where extra effort is undertaken to sample widely and systematically.

We found that the distribution of risk varied by type of activity. Similar to results in other systems showing an inverse influence of travel distance on illegal behavior (Albers, 2010; Kimanzi, Sanderson, Rushton, & Mugo, 2015; Plumptre et al., 2014; Wato, Wahungu, & Okello, 2006), we found that distance from the reserve edge was an important factor that influences the risk of all activities. This effect was most pronounced for livestock grazing, which was most common along reserve edges and the most spatially restricted activity. Similar patterns have been demonstrated in Uganda (Critchlow et al., 2015), however, in the rest of the GSE livestock incursions occur much deeper into protected areas. Livestock paths extend up to 7 km into Maswa Game Reserve and bomas are established up to 10 km within Loliondo Game Controlled Area (Veldhuis et al., 2019). The study area contains the highest density of livestock of regions adjacent to GSE, and yet livestock incursions...
appear to pose less of a threat here than elsewhere in the GSE (Veldhuis et al., 2019). The relatively reduced impacts in the western Serengeti may be attributable to increased law enforcement presence in this area.
While the risk of wildlife offtake was positively associated with proximity to the reserve edge, the avoidance of enforcement was also highly influential. Our results show that the presence of game reserves and WMA insulated the core area of SNP from the effects of livestock grazing and tree felling, but activities related to wildlife offtake extended into the national park. The narrow extent of the western side of Grumeti GR and the location of Robanda Village deep within the WMA are two areas associated with illegal activity in the national park, indicating proximity to settlements was related to vulnerability within the national park. Results also indicate that people are willing to travel deep into the protected area in order to obtain bushmeat. Active hunting and the movement of bushmeat occurs deep within the reserve and into the national park. Illegal hunters avoid detection at the cost of increased travel distance by engaging in illegal behavior in locations where patrol effort per unit area was relatively low. We suspect the effort to avoid detection was related to penalties incurred if caught. Historically, penalties for illegal hunting in this area were low relative to the financial benefits and did not present a significant deterrent to bushmeat poachers (Bitanyi, Nesje, Kusiluka, Chenyambuga, & Kaltenborn, 2012; Knapp, 2012). However, penalties for illegal hunting are greater on average than those incurred for nonwildlife related offenses like livestock grazing, and recent judicial system trends of imposing harsher sentences may provide increased incentives to avoid detection (W. Gold, personal communication, April 24, 2019).

While debates are ongoing about the benefits and costs of militarized conservation (Duffy, St John, Büscher, & Brockington, 2015), we found that law enforcement was an important component of a broader strategy to prevent illegal resource extraction. Permanent scout camps deterred most illegal activity, although their effect was highly localized. Plumptre et al. (2014) found a similar effect in the Greater Virunga Landscape where illegal activity was reduced in areas close to permanent camps, but this effect deteriorated with increasing distance. Results indicated that observation posts are a less effective strategy than permanent camps. In the western Serengeti, observation posts did not deter active hunting, bushmeat transportation, or tree-felling and snaring and livestock grazing were predicted to occur in close proximity to posts.

The strategic placement of permanent camps in areas of high conservation value can be an effective protection strategy, but due to budget limitations, it is unlikely that permanent camps can be used in isolation to effectively patrol and protect entire reserves; supplementary approaches are needed. Similarly, our results suggest observation posts may deter certain illegal activities, namely illegal grazing. In areas where activities related to wildlife offtake are of greatest concern, alternative or supplementary law enforcement strategies may be a more optimal use of resources. Effectively patrolling all of a given landscape at a high enough frequency to deter illegal activities is unlikely to be financially feasible, but managers can utilize spatially explicit information on the distribution of threats to direct additional, or reallocate existing, resources to better deter illegal activity (Plumptre et al., 2014). Supplementary options include advanced planning of patrol routes using GIS to ensure broader coverage and to target high-risk areas, increasing the frequency of patrols, hiring additional scouts in order to cover more ground, utilizing mobile patrol units and temporary camps to spend more time patrolling in remote areas, and planning for the construction of new, or relocations of existing, permanent camps in identified gap areas of high conservation value. Rentsch and Damon (2013) suggested that increased enforcement may present the most effective way to reduce illegal hunting in the Serengeti Ecosystem by reducing supply, increasing bushmeat prices, and increasing consumption of alternative protein sources. In order for law enforcement to reduce the prevalence of illegal activity, multiple approaches are likely to be required and interventions must be implemented with a thorough understanding of their limitations.

As demonstrated by the persistence of illegal activity in a region with well-equipped anti-poaching teams, law enforcement is not a stand-alone solution and complementary approaches that target the drivers of harvest and consumption of illegally obtained resources are required. Spatial predictions of risk of illegal activity can be used not only to enhance law enforcement efforts, but to develop complementary strategies in support of management objectives. Illegal activities were most likely to occur within a few kilometers of settlements. Predictive outputs can serve to identify those communities most likely engaged in illegal resource extraction in order to develop targeted community outreach programs.

A number of complimentary approaches have been proposed and include reducing the prices of alternative proteins like fish and beef (Rentsch & Damon, 2013), designing outreach programs that address cultural preferences and increase benefit sharing, and reducing the costs of living with wildlife (Biggs et al., 2017; Challender & MacMillan, 2014). Economic development programs may reduce income shortfalls that encourage illegal behavior on the production side (Knapp, 2012; Loibooki et al., 2002), but increases in household income have previously been associated with the increased consumption of illicitly obtained resources, such as bushmeat (Brashares, Golden, Weinbaum, Barrett, & Okello, 2011; Rentsch & Damon, 2013). The linkages between complimentary economic, outreach, and law enforcement approaches and illegal behaviors is difficult to disentangle, but assessing their intersection could greatly advance our understanding of which suite of approaches are most likely to incentivize compliance in support of conservation objectives in various contexts.
As pressures on protected areas continue to increase, managers and stakeholders are in dire need of tools to maximize the use of limited resources in support of conservation objectives. We found that law enforcement interventions had a limiting effect on the spatial extent of illegal activity, but patrol effort was highly biased and the associated deterrent effect was limited to within 4 km of permanent posts. Spatially explicit outputs and local expertise can be used with careful planning to develop supplementary approaches that more effectively allocate law enforcement effort towards the areas of greatest risk and illegal activities of highest priority. Although law enforcement is a critical component of protected area management it is not a stand-alone solution; complementary approaches that target the drivers of production and consumption of illegally obtained resources are also required.

ACKNOWLEDGMENTS

We thank Tanzania Wildlife Research Institute (TAWIRI) and Tanzania Commission for Science and Technology (COSTECH) for research permissions. We are grateful for funding provided by the Grumeti Fund for the completion of this work, and the Research & Monitoring and Law Enforcement divisions for their careful collection and maintenance of the data that provided the basis for this work. We acknowledge Pete Goodman for his efforts in implementing the data collection and maintenance protocols, and Wesley Gold for insight into patrolling and data recording procedures. We thank Robert Hijmans for and two anonymous reviewers for their constructive comments on an earlier version of this manuscript.

CONFLICT OF INTEREST

The authors have no conflicts of interest to declare.

AUTHOR CONTRIBUTIONS

K.D.S. and G.W. conceived the research concept and methodology; P.M. collected and maintained the data; K.D.S. analyzed the data; K.D.S. and G.W. led the writing of the manuscript. All authors provided critical feedback and contributions on the manuscript drafts and gave final approval for publication.

DATA ACCESSIBILITY

The law enforcement datasets (including location of scout camps and observation posts) analyzed in this study are not publicly available due to the sensitive nature of the information, but are available from the corresponding author on reasonable request and with the permission of the Grumeti Fund.

ETHICS STATEMENT

The authors obtained all necessary research permissions within Tanzania under permits issued by the Tanzania Wildlife Research Institute (TAWIRI) and Tanzania Commission for Science and Technology (COSTECH).

ORCID

Kristen Denninger Snyder https://orcid.org/0000-0002-6833-2314

REFERENCES

Albers, H. J. (2010). Spatial modeling of extraction and enforcement in developing country protected areas. Resource and Energy Economics, 32(2), 165–179.

Allouche, O., Tsoar, A., & Kadmon, R. (2006). Assessing the accuracy of species distribution models: Prevalence, kappa and the true skill statistic (TSS). Journal of Applied Ecology, 43, 1223–1232.

Berthon, K., Esperon-Rodriguez, M., Beaumont, L. J., Carnegie, A. J., & Leishman, M. R. (2018). Assessment and prioritisation of plant species at risk from myrtle rust (Austropeucinia psidii) under current and future climates in Australia. Biological Conservation, 218, 154–162.

Biggs, D., Cooney, R., Roe, D., Dublin, H. T., Allan, J. R., Challender, D. W., & Skinner, D. (2017). Developing a theory of change for a community-based response to illegal wildlife trade. Conservation Biology, 31(1), 5–12.

Bitanyi, S., Nesje, M., Kusiluka, L. J., Chenyambuga, S. W., & Kaltenborn, B. P. (2012). Awareness and perceptions of local people about wildlife hunting in western Serengeti communities. Tropical Conservation Science, 5(2), 208–224.

Boria, R. A., Olson, L. E., Goodman, S. M., & Anderson, R. P. (2014). Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. Ecological Modelling, 275, 73–77.

Brandon, K. (1998). Perils to parks: The social context to threats. In K. Brandon, K. H. Redford, & S. E. Sanderson (Eds.), Parks in peril: People, politics, and protected areas. Washington, DC: Island Press.

Bruner, A. G., Gullison, R. E., Rice, R. E., & Da Fonseca, G. A. (2001). Effectiveness of parks in protecting tropical biodiversity. Science, 291(5501), 125–128.

Campbell, K., & Hofer, H. (1995). People and wildlife: Spatial dynamics and zones of interaction. In A. R. E. Sinclair & P. Arce (Eds.), Serengeti II dynamics, management, and conservation of an ecosystem (pp. 534–570). Chicago, IL: The University of Chicago Press.

Caro, T., & Davenport, T. R. B. (2016). Wildlife and wildlife management in Tanzania. Conservation Biology, 30(4), 716–723.

Challender, D. W., & MacMillan, D. C. (2014). Poaching is more than an enforcement problem. Conservation Letters, 7(5), 484–494.

Chape, S., Harrison, J., Spalding, M., & Lysenko, I. (2005). Measuring the extent and effectiveness of protected areas as an indicator for meeting global biodiversity targets. Philosophical Transactions of the Royal Society B: Biological Sciences, 360(1454), 443–455.
Clemente, P., Calvache, M., Antunes, P., Santos, R., Cerdeira, J. O., & Martins, M. J. (2019). Combining social media photographs and species distribution models to map cultural ecosystem services: The case of a Natural Park in Portugal. *Ecological Indicators*, 96, 59–68.

Coxen, C. L., Frey, J. K., Carleton, S. A., & Collins, D. P. (2017). Species distribution models for a migratory bird based on citizen science and satellite tracking data. *Global Ecology and Conservation*, 11, 298–311.

Crichtlow, R., Plumptre, A. J., Alidria, B., Nsbuga, M., Driciur, M., Rwetsiba, A., … Beale, C. M. (2017). Improving law-enforcement effectiveness and efficiency in protected areas using ranger-collected monitoring data. *Conservation Letters*, 10(5), 572–580.

Crichtlow, R., Plumptre, A. J., Driciur, M., Rwetsiba, A., Stokes, E. J., Tumwesigye, C., … Beale, C. M. (2015). Spatiotemporal trends of illegal activities from ranger-collected data in a Ugandan national park. *Conservation Biology*, 29(5), 1458–1470.

Denning Snyder, K., Menney, P., Benjamin, B., Mikilindi, P., & Mbise, N. (2019). Seasonal and spatial vulnerability of agricultural damage by elephants in the western Serengeti, Tanzania. *Oryx*. https://doi.org/10.1017/S0030605318001382

Dublin, H. T., Sinclair, A. R. E., Boutin, S., Anderson, E., Jago, M., & Arcese, P. (1990). Does competition regulate ungulate populations? Further evidence from Serengeti, Tanzania. *Oecologia*, 82, 283–288.

Duffy, R., St John, F. A., Büscher, B., & Brockington, D. A. N. (2015). The militarization of anti-poaching: Undermining long term goals? *Environmental Conservation*, 42(4), 345–348.

Elith, J., & Leathwick, J. R. (2009). Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology Evolution and Systematics*, 40, 677–697.

Elith, J., Phillips, S. J., Hastie, T., Dudik, M., Chee, Y. E., & Yates, C. J. (2011). A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions*, 17(1), 43–57.

European Commission (2016). Larger than elephants: Inputs for an EU strategic approach to wildlife conservation in Africa—Regional analysis. In *Directorate General for International Cooperation and Development*. Luxembourg: Publications Office of the European Union.

Fischer, A., Naiman, L. C., Lowassa, A., Randall, D., & Rentsch, D. (2014). Explanatory factors for household involvement in illegal bushmeat hunting around Serengeti, Tanzania. *Journal for Nature Conservation*, 22(6), 491–496.

Fourcade, Y., Engler, J. O., Rödder, D., & Secondi, J. (2014). Mapping species distributions with MAXENT using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. *PLoS One*, 9(5), e97122.

Gavin, M. C., Solomon, J. N., & Blank, S. G. (2010). Measuring and monitoring illegal use of natural resources. *Conservation Biology*, 24(1), 89–100.

Gruneti Fund. (2016). *Community outreach needs assessment report*. Mara Region, Tanzania: Author.

Guevara, L., Gerstner, B. E., Kass, J. M., & Anderson, R. P. (2018). Toward ecologically realistic predictions of species distributions: A cross-time example from tropical montane cloud forests. *Global Change Biology*, 24(4), 1511–1522.

Hijmans, R. J., Phillips, S., Leathwick, J., & Elith, J. (2017). Package “dismo,” version 1.1-4. Retrieved from http://cran.r-project.org/web/packages/dismo/index.html

Hilborn, R., Arcese, P., Borner, M., Hando, J., Hopcraft, G., Loibooki, M., … Sinclair, A. R. (2006). Effective enforcement in a conservation area. *Science*, 314(5803), 1266–1266.

Hofer, H., Campbell, K. L., East, M. L., & Huish, S. A. (2000). Modeling the spatial distribution of the economic costs and benefits of illegal game meat hunting in the Serengeti. *Natural Resource Modeling*, 13(1), 151–177.

Holmern, T., Mkama, S., Muya, J., & Røskaft, E. (2006). Intraspecific prey choice of bushmeat hunters outside the Serengeti National Park, Tanzania: A preliminary analysis. *African Zoology*, 41(1), 81–87.

Holmern, T., Muya, J., & Røskaft, E. (2007). Local law enforcement and illegal bushmeat hunting outside the Serengeti National Park, Tanzania. *Environmental Conservation*, 34(1), 55–63.

Jones, K. R., Venter, O., Fuller, R. A., Allan, J. R., Maxwell, S. L., Negret, P. J., & Watson, J. E. M. (2019). One-third of global protected land is under intense human pressure. *Science*, 360, 788–791.

Jufie-Bignol, D., Burgess, N. D., Belle, E. M. S., de Lima, M. G., Duguignet, M., Bertzky, B., … & Wicander, S. (2014). *Protected planet report 2014: Tracking progress towards global targets for protected areas*.

Kaltenborn, B. P., & Nyahongo, J. W. (2005). The nature of hunting around the Western corridor of Serengeti National Park, Tanzania. *European Journal of Wildlife Research*, 51, 213–222.

Keane, A., Jones, J. P., Edwards-Jones, G., & Milner-Gulland, E. J. (2008). The sleeping policeman: Understanding issues of enforcement and compliance in conservation. *Animal Conservation*, 11(2), 75–82.

Kimanzi, J. K., Sanderson, R. A., Rushton, S. P., & Mugo, M. J. (2015). Spatial distribution of snares in Ruma National Park, Kenya, with implications for management of the roan antelope Hippotragus equinus langheli and other wildlife. *Oryx*, 49(2), 295–302.

Knapp, E. J. (2007). Who poaches? Household economies of illegal hunters in western Serengeti, Tanzania. *Human Dimensions of Wildlife*, 12(3), 195–196.

Knapp, E. J. (2012). Why poaching pays: A summary of risks and benefits illegal hunters face in Western Serengeti, Tanzania. *Tropical Conservation Science*, 5(4), 434–445.

Loibooki, M., Hofer, H., Campbell, K. L. I., & East, M. (2002). Bushmeat hunting by communities adjacent to Serengeti National Park, Tanzania: The importance of livestock ownership and alternative sources of protein and income. *Environmental Conservation*, 29, 391–398.

Mduma, S. A. R., Hilborn, R., & Sinclair, A. R. E. (1998). Limits to exploitation of Serengeti wildebeest and implications for its management. In D. M. Newbury, H. H. T. Prins, & P. Brown (Eds.), *Dynamics of tropical communities* (pp. 243–265). Oxford, England: Blackwell Science.

Merow, C., Smith, M. J., & Silander, J. A. (2013). A practical guide to MaxEnt for modeling species’ distributions: What it does, and why inputs and settings matter. *Ecography*, 36, 1058–1069.

Metzger, K. L., Sinclair, A. R. E., Hilborn, R., Hopcraft, J. G. C., & Mduma, S. A. (2010). Evaluating the protection of wildlife in parks: The case of African buffalo in Serengeti. *Biodiversity and Conservation*, 19(12), 3431–3444.

Moró, M., Fischer, A., Czajkowski, M., Brennan, D., Lowassa, A., Naiman, L. C., & Hanley, N. (2013). An investigation using the choice experiment method into options for reducing illegal bushmeat hunting in western Serengeti. *Conservation Letters*, 6(1), 37–45.

Muscarella, R., Galante, P. J., Soley-Guardia, M., Boria, R. A., Kass, J. M., Uriarte, M., & Anderson, R. P. (2014). ENMeval: An R package for conducting spatially independent evaluations and
estimating optimal model complexity for MAXENT ecological niche models. *Methods in Ecology and Evolution*, 5, 1198–1205.

Muscarella, R., Galante, P. J., Soley-Guardia, M., Boria, R. A., Kass, J. M., Uriarte, M., & Anderson, R. P. (2017). Package “ENMeval,” version 0.3.0. Retrieved from https://cran.r-project.org/web/packages/ENMeval/index.html

Ndibalema, V. G., & Songorwa, A. N. (2008). Illegal meat hunting in Serengeti: Dynamics in consumption and preferences. *African Journal of Ecology*, 46(3), 311–319.

Norris, D. (2014). Model thresholds are more important than presence location type: Understanding the distribution of lowland tapir (*Tapirus terrestris*) in a continuous Atlantic forest of Southeast Brazil. *Tropical Conservation Science*, 7(3), 529–547.

Nuno, A., Bunnefeld, N., Naima, L. C., & Milner-Gulland, E. J. (2013). Drivers of illegal bushmeat hunting in the Serengeti. *Conservation Biology*, 27(6), 1355–1365.

Nyabongo, J. W., Holmern, T., Kaltenborn, B. P., & Roskaft, E. (2009). Spatial and temporal variation in meat and fish consumption among people in the western Serengeti, Tanzania: The importance of migratory herbivores. *Oryx*, 43(2), 258–266.

Nyaki, A., Gray, S. A., Lepczyk, C. A., Skibins, J. C., & Rentsch, D. (2014). Local-scale dynamics and local drivers of bushmeat trade. *Conservation Biology*, 28(5), 1403–1414.

Pearson, R. G., Raxworthy, C. J., Nakamura, M., & Townsend Peterson, A. (2007). Predicting species distributions from small numbers of occurrence records: A test case using cryptic geckos in Madagascar. *Journal of Biogeography*, 34(1), 102–117.

Phillips, S. J., Anderson, R. P., Dudík, M., Schapire, R. E., & Blair, M. E. (2017). Opening the black box: An open-source release of Maxent. *Ecography*, 40(7), 887–893.

Phillips, S. J., Dudík, M., Elith, J., Graham, C. H., Lehmann, A., Leathwick, J., & Ferrier, S. (2009). Sample selection bias and presence-only distribution models: Implications for overfitting and pseudo-absence data. *Ecological Applications*, 19(1), 181–197.

Phillips, S. J., Dudík, M., & Schapire, R. E. (2015). *Maxent software for modeling species niches and distributions (version 3.4.3)* [Internet]. Retrieved from http://biodiversityinformatics.amnh.org/open_source/maxent/

Plumptre, A. J., Fuller, R. A., Rwetsiba, A., Wanyama, F., Kujirakwinja, D., Driciru, M., … Possingham, H. P. (2014). Efficiently targeting resources to deter illegal activities in protected areas. *Journal of Applied Ecology*, 51(3), 714–725.

Radosavljevic, A., & Anderson, R. P. (2014). Making better Maxent models of species distributions: Complexity, overfitting and evaluation. *Journal of Biogeography*, 41(4), 629–643.

Rentsch, D., & Damon, A. (2013). Prices, poaching, and protein alternatives: An analysis of bushmeat consumption around Serengeti National Park, Tanzania. *Ecological Economics*, 91, 1–9.

Rentsch, D., & Packer, C. (2015). The effect of bushmeat consumption on migratory wildlife in the Serengeti Ecosystem, Tanzania. *Oryx*, 49(2), 287–294.

Syfert, M. M., Smith, M. J., & Coomes, D. A. (2013). The effects of sampling bias and model complexity on the predictive performance of MaxEnt species distribution models. *PLoS One*, 8(2), e55158.

Tanzania National Bureau of Statistics. (2012). *Census Info Tanzania, Sensa 2012*. Retrieved from http://dataforall.org/dashboard/tanzania/

Thirgood, S., Mosser, A., Tham, S., Hopcroft, G., Mwangomoe, E., Mlengeya, T., … Borner, M. (2004). Can parks protect migratory ungulates? The case of the Serengeti wildebeest. *Animal Conservation*, 7, 113–120.

Veldhuis, M. P., Ritchie, M. E., Ogutu, J. O., Morrison, T. A., Beale, C. M., Estes, A. B., … Wargute, P. W. (2019). Cross-boundary human impacts compromise the Serengeti-Mara ecosystem. *Science*, 363(6434), 1424–1428.

Walpole, M., Ndoinyo, Y., Kibasa, R., Masanja, C., Somba, M., & Sungura, B. (2004). *An assessment of human-elephant conflict in the Western Serengeti*. Tanzania: Wildlife Division, TANAPA, FZS. Retrieved from www.tnrf.org/files/E-INFO-FZS-WD-TANA_PA-An_Assessment_of_Human-Elephant_Conflict_in_the_Western_Serengeti_Walpole_et_al_2004.pdf

Warren, D. L., Glor, R. E., & Turelli, M. (2008). Environmental niche equivalency versus conservatism: Quantitative approaches to niche evolution. *Evolution*, 62(11), 2868–2883.

Wato, Y. A., Wahungu, G. M., & Okello, M. M. (2006). Correlates of wildlife snaring patterns in tsavo west national park, Kenya. *Biological Conservation*, 132(4), 500–509.

Watson, J. E., Dudley, N., Segan, D. B., & Hockings, M. (2014). The performance and potential of protected areas. *Nature*, 513(7525), 67–73.

Wyles, L. S., & Sheikh, P. A. (2008). *International illegal trade in wildlife: Threats and U.S. policy*. Damascus, MD: Congressional Research Service Report for Congress Order Code RL3.

Zhang, K., Yao, L., Meng, J., & Tao, J. (2018). Maxent modeling for predicting the potential geographical distribution of two peony species under climate change. *Science of the Total Environment*, 634, 1326–1334.

**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Denninger Snyder K, Mneeny PB, Wittemyer G. Predicting the risk of illegal activity and evaluating law enforcement interventions in the western Serengeti. *Conservation Science and Practice*. 2019;1:e81. [https://doi.org/10.1111/csp2.81]