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Understanding site selection of illegal border crossings into a fenced protected area: a rational choice approach

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Abstract

This study investigates illegal border crossings by rhino poachers into a fenced reserve in South Africa, comparing journeys to and after crime using a rational choice approach. Using various regression models, our analysis indicates poachers prefer to enter and exit the reserve near high rhino densities, while high road densities outside the reserve increase the odds of an illegal entry. The results also show that half of the incursions occurred at a single location, leading us to describe the special circumstances of this outlier. The study lays a foundation for understanding the location choices poachers make and presents a methodology that can be replicated in other reserves.

Keywords: Wildlife crime, Illegal border crossings, Rational choice, Crime journeys, Rhino poaching

Introduction

Rhino poaching in South Africa

Wildlife conservationists and criminologists have conducted a substantial amount of research on the rhino-poaching crisis in South Africa and on the illegal wildlife trade (Ayling 2013; Haas and Ferreira 2015; Hill 2015; Mulero-Pázmány et al. 2014; Warchol and Kapla 2012). Rhino poaching has surged in response to increases in black market prices for horn (Milliken et al. 2009). South Africa plays an important role in rhino conservation because it holds about 82% of the total rhino population in Africa (Emslie 2012). Most of these rhinos live within protected, often fenced reserves.

Studies on the spatial–temporal distributions of poached animals provided insight in poachers' target selection (Haines et al. 2012). However, this is only one stage of the rhino poaching crime script (Fig. 1). Crime scripts are a useful method to obtain a structured understanding of all stages within the crime commission process (Cornish 1994). The illegal border crossing into a fenced protected area is first offense in the rhino poaching crime script that rangers can detect and report. Poachers need to decide on where to cross the border before they can start hunting. After a certain amount of time inside a reserve, they make a decision on where to exit the area. Understanding the sequence of actions that are involved in rhino poaching is important for law enforcement to identify possible risk locations inside the reserve.

Explaining illegal border crossings: a rational choice perspective

The spatial–temporal behavior of offenders is often explained from a variety of approaches like the rational choice perspective (RCP) (Cornish and Clarke 1986), routine activity theory (Cohen and Felson 1979), and crime pattern theory (Brantingham and Brantingham 2008). In the case of target selection, offenders first select an area within which to offend and then select a specific target (Bernasco and Nieuwbeerta 2005; Cornish and Clarke 1986). RCP has been applied to explain crime events in urban areas (Bernasco and Nieuwbeerta 2005; Gottschalk 2016; Vandeviver et al. 2015), but can also be used to explain crime in nature reserves, including wildlife poaching (Hill et al. 2014).

This study aims to understand the rhino poachers' spatial preferences for illegal border crossings in a partially fenced nature reserve in South Africa. It addresses the

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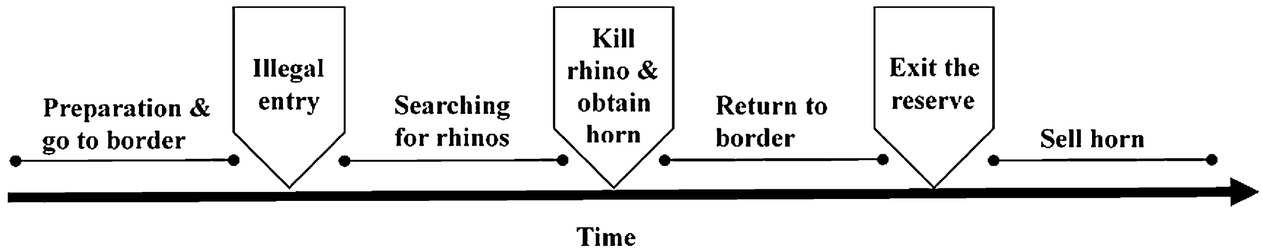

Fig. 1 The rhino poaching crime script and its seven stages in sequential order

question what environmental attributes makes a location attractive for rhino poachers to cross? This research provides a framework for studying illegal crossings. The study expands the application of crime theory into new areas of wildlife crime and provides information relevant to wildlife practitioners.

Theoretical framework and hypotheses

RCP assumes offenders are goal-oriented and make rational decisions structured by the social environment and situational circumstances (Cornish and Clarke 1986). This means that environmental characteristics make it more or less rewarding, costly, and risky for poachers to commit crime. We assume that poachers want to avoid detection while simultaneously maximizing their chances to obtain rhino horn (Eloff and Lemieux 2014).

Poacher crime journeys

Before presenting hypotheses, it is important to discuss how border site attractiveness differ between entry and exit sites. This distinction is related to what is called the 'journey to crime' and the 'journey after crime' (Brantingham and Brantingham 1981). For this paper, the journey to crime involves the travel to where poachers enter the reserve and their hunt inside the reserve to a rhino kill site or abandonment point. The journey after crime is travel from a rhino kill site or abandonment point back to the border where poachers select an exit site. Previous research on crime journeys indicates that the offender's travel is local in nature and described by a distance decay function (Lu 2003; Rossmo 2000; Tonkin et al. 2010). Studies on the journey after crime are rare because it is difficult to collect accurate data on where and how offenders may have travelled during or after they commit a crime (Synnott et al. 2016).

Reverting back to RCP, offenders face greater risk in the journey after crime, compared to the journey to crime. To illustrate, the punishment of getting caught with a rhino horn is much higher, a fine up to 10 million ZAR (approximately US$660,000 in June 2016) or imprisonment of up to 10 years, whereas getting caught with a firearm only is punishable by a few weeks of imprisonment (De Wet 2014). Hence, poachers may select different border sites based on whether they are trying to break in or escape from the reserve.

Increase rewards

Theory suggests offenders select targets that yield the highest rewards. Hübschle (2016) found that 1 kg of rhino horn sells for approximately US$25,000 to $65,000 on Vietnamese black markets, although poachers likely sell the horn below optimum prices to secure immediate income (Milliken and Shaw 2012). Poachers are paid approximately US$1750 to US$6500 for 1 kg of rhino horn (Haas and Ferreira 2016; Smith 2015). Rhinos are the most valuable species to poach in South Africa which is why individuals target these animals over other species. Rhinos are not evenly distributed over the landscape, with higher densities found in habitats more suitable to the species (Emslie 2012). This should impact the spatial decisions poachers make.

Hypothesis 1 The closer the border site is to areas with high rhino densities, the more likely it is selected by a poacher to enter the fenced reserve.

Minimize risk

Offenders select sites that minimize their risk of detection. Rangers are responsible for protecting wildlife from poachers. Poachers can reduce the risk of apprehension by rangers by spending little time inside the reserve. This may be especially true for successful poachers as they want to escape the reserve quickly after obtaining rhino horn. Thus, rhino densities form an important part of a poacher's risk consideration.

Hypothesis 2a The closer the border site is to high rhino densities, the more likely it is selected by a poacher to exit the fenced reserve.

Rangers are not the only capable guardians; informal guardians can also prevent a criminal act from happening (Brown and Altman 1982; Hollis-Peel et al. 2011). In this study's context this includes private landowners and tourist operators, who are capable of reporting suspicious activity. Tourist operators make a living off the wildlife inside the reserve and have an incentive to report anything suspicious. A poacher would therefore avoid areas around tourist lodges. Private homes and tourist facilities inside the reserve house these guardians, which leads to Hypothesis 2b.

Hypothesis 2b A border site without buildings present inside the fenced reserve is more likely to be selected by a poacher to enter or exit.

Minimize effort

Theory suggests offenders select sites that require minimal effort. Here, we look at the communication between offender and co-offenders. Wildlife poachers in South Africa often work in groups of two to three individuals (Kruger National Park 2016; Michler 2008; Ramsay 2014). Evidence suggests that one poacher drops off the others and stays behind to pick them up later (Mulero-Pázmány et al. 2014; Snitch 2014; Spicer 2014). Communication via mobile phones facilitates the ability to organize a rendezvous efficiently but network coverage is a limiting factor. Therefore, offenders may select exit sites with usable mobile phone signal to make contact with co-offenders.

Hypothesis 3a A border site with usable phone signal is more likely to be selected by a poacher to exit the fenced nature reserve.

Site accessibility also reduces effort (Clare et al. 2009). For example, property crimes are most likely to occur on accessible streets within a road network and have higher levels of traffic (Frith et al. 2017). A high density of roads outside the reserve may lead to more illegal crossings because these areas provide easier access. Ease of access facilitates easier drop-off by their co-offenders, but also allows them to escape faster after exiting the reserve.

Hypothesis 3b The higher the road density outside the reserve, the more likely a border site is selected by a poacher to enter or exit the fenced reserve.

Navigation

Based on experiences in the field, we formulated a fourth criterion: navigation. Navigating through a reserve is challenging because no road markers exist for orientation. Poachers may overcome this by using large landmarks as a navigational guide. Landmarks can serve either as beacons at a target location or mark paths along the way (Foo et al. 2005). Examples of landmarks that poachers may use are power lines, radio towers, or tall factory chimneys.

Hypothesis 4 The closer the border site is to large landmarks, the more likely it is selected by a poacher to enter or exit the fenced reserve.

Methods

Study area

We conducted this study in a partially fenced private nature reserve in the North-Eastern part of South Africa. The border connected to another reserve is unfenced. Given the sensitive nature of rhino security information (Chapman and Grafton 2008), we present no information that identifies the study area or the border crossing sites. The reserve consists of nine smaller management sections, each with a warden coordinating anti-poaching measures. Seven sections are responsible for patrolling the reserve's border and monitor 9–24% of the total outer borders. While no information was available on the spatial distribution of patrols during the study period, the teams cover most of their borders on a daily basis.

Data collection and preparation

Illegal border crossings data

The reserve's ranger teams documented 110 illegal border crossings between 2011 and 2016. Rangers report illegal crossings while on patrol along the border. They classified each crossing as an entry or exit based on the detected signs around the site, for example direction of footprints or cuts in the fence. When possible, the team tries to follow the tracks to see where they lead and if they can find any more evidence, for example snares or an animal carcass. If any evidence near the crossing location suggests that the poacher was not a rhino poacher, for example camp fires or snares, then these data entries were removed from our dataset. It is important to note that not all poachers were successful in killing a rhino. Our dataset included crossings from successful and unsuccessful poachers. The reserve is divided into a grid where each grid cell is 1.02 km by 1.1 km ($0.01° \times 0.01°$). Each cell has a unique reference number. The rangers recorded all border crossings using this grid reference system (see Fig. 2) and therefore, we carried out the analyses on this level as well. The fenced border goes through 90 grid cells and hence this was the population size of the study.

Environmental variables

The reserve provided data on rhino distributions, tourist lodges, private homes, roads, and landmarks. We measured mobile phone signal during a field survey in June–July 2016. Table 1 describes the environmental variables.

We used the yearly animal count surveys conducted in the reserve for the rhino density distribution. The count surveys are conducted every September and in a systematic way that covers the whole reserve; aggregated rhino counts from 2011 to 2016 were used. Rhino densities showed some minor fluctuations between the years, but overall they were quite stable. A common way to estimate

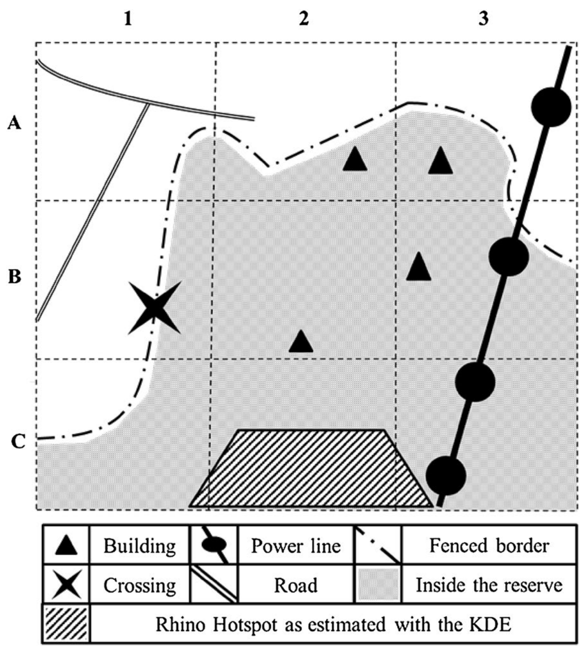

Fig. 2 Abstract representation of the study area with a 3 × 3 reference grid plotted on top (dotted lines)

a species' spatial distribution is by using a kernel density estimate (KDE). This produces a 'hotspot' map showing the spatial variation in rhino density across the study area. A KDE-value of at least twice the standard deviation above the mean was classified as a rhino density hotspot (Hart and Zandbergen 2014). Next, we divided the reserve's border into points with a 10-m interval and calculated the distance from each of these points to the nearest rhino density hotspot. Finally, we averaged all the points along the border within the same 1.02 km by 1.1 km grid cell to calculate the average distance to the nearest rhino hotspot. We used these measurements for the descriptive statistics. For the analysis, we took the natural logarithm and multiplied this by −1 so that high values indicate areas near high rhino densities. We refer to this variable as 'proximity to rhino' in the analysis.

The 10-m interval points were used to calculated the distance to the nearest large landmark. We choose power lines to act as navigational landmarks. The power lines crossing the border are visible at large distances from inside and outside the reserve. This would help poachers navigating through the reserve. We averaged distances for each border cell to estimate the average distance to the nearest power line.

We scored the variable 'buildings' as 1 if they were present within a border grid cell and 0 if they were not. We measured the variable 'roads outside' as the total road length outside the reserve divided by the area outside the reserve within the grid cell (see Fig. 2).

We measured mobile phone signal for two major network providers in South Africa. The mobile application 'GSM Field Test' continuously recorded the Received Signal Strength Indication (RSSI) (Kozyukov 2014). The values range between −50 and −150 dBm with higher values indicating a stronger signal. We took a reading every 10 m along the border and averaged the measurements per grid cell for each network provider. Next, we used the highest value to determine if there was any usable signal in that cell. As a general rule, values between −110 and −50 dBm have a usable signal, while values lower than −110 dBm were considered to be unusable (Mammen 2015). Finally, we scored the variable as 1 if the average signal along the border was above −110 dBm, and 0 if it was lower, i.e. no signal.

Descriptive statistics

Rangers reported 110 illegal crossings across 24 border cells (Table 2). Out of those 24 border cells, 16 cells were found to have one or more illegal entries, and 17 cells were found to have one or more exits. We found some overlap as 9 border cells contained both an entry and exit

Table 1 Overview of the explanatory variables used in this study

	Variable	Measure	Rationale	Hypothesis
1	Distance to rhino	Average distance (km) to nearest rhino hotspot	Reward	More illegal border entries in areas near high rhino densities
2a	Distance to rhino	Average distance (km) to nearest rhino hotspot	Minimal risk	More illegal border exits in areas near high rhino densities
2b	Buildings	1 = Buildings present 0 = No buildings	Minimal risk	Fewer illegal border crossings where buildings are present
3a	Phone signal	1 = Usable signal 0 = No or unusable signal	Minimal effort	More border exits in areas with a usable phone signal
3b	Roads outside	km road/km^2	Minimal effort	More illegal border crossings in areas with high road densities outside the reserve
4	Distance to power lines	Average distance (km) to nearest power line	Navigation	More illegal border crossings in areas near power lines

Table 2 Frequency table for the number of illegal border crossings between 2011 and 2016

Number of illegal crossings	Frequency
0	66
1	11
2	4
3	2
4	4
5	1
9	1
55	1

sites. Most border cells used by poachers contained only one illegal crossing. However, one particular cell contained half of all the illegal crossings (n = 55). Although statistically an outlier, we did not exclude this data point but discuss it as an important case-study. We describe this further in our analytic strategy.

Descriptive statistics show the variation between the border cells with and without illegal crossings (Tables 3, 4). The distance to nearest rhino density was lower for border cells with illegal crossings, entries, and exits compared to cells without illegal crossings (Table 3).

The average for road density outside the reserve was similar across the border cells with the highest density observed for cells with illegal entries and the lowest for cells with illegal exits (Table 3). On average, border cells with illegal crossings, entries, and exits were closer to power lines compared to cells without crossings (Table 3).

Buildings were present in 54% of border cells with illegal crossings, while 41% of the cells without crossing contained buildings (Table 4). Phone signal was present in almost all border cells with crossings, entries, and exits (Table 4).

Analytic strategy

Crime analysis of outlier

The descriptive statistics showed that one border cell contained half of all the documented illegal crossings. Statistically, the high number of illegal crossings in a single cell is an outlier (Table 2). In general, researchers deal with outliers by either removing them from the analysis or by transforming the dependent variable. However, except when outliers are linked to a mistake in the study design, it is never appropriate to remove them from the analysis (Altman and Krzywinski 2016). From a crime analysis perspective, outliers like these are important to study because this allows us to break down a larger phenomenon into a specific problem on a local level (Clarke and Eck 2005; Poyner 1986). This enables law enforcement to use their resources more effectively. A successful intervention strategy aimed at outlier locations, disrupts crime opportunities and likely displaces poachers to other, sub-optimal areas. Therefore, rangers need to know where poachers are likely displaced to.

We examined this outlier in more detail to identify what caused the high number of illegal crossings. A general model based on the RCP would help us in explaining the overall distribution of illegal crossings. We built general models using logistic regression models and a quasi-Poisson distribution to explain illegal crossings by rhino

Table 3 Comparison of the descriptive statistics of the continuous variables for all border cells

Variable (unit)	Grid cells with illegal border crossings				Grid cells with illegal border entries				Grid cells with illegal border exits				Grid cells with no illegal border crossings			
	M	SD	Min	Max	M	SD	Min	Max	M	SD	Min	Max	M	SD	Min	Max
Distance to rhino (km)	5.54	2.99	2.02	10.47	5.68	2.87	2.18	10.47	5.30	3.15	2.02	10.47	7.48	2.55	2.01	12.33
Roads outside (km/km^2)	4.07	3.50	0	14.75	4.93	3.87	0.70	14.75	3.55	2.73	0	10.38	4.17	2.71	0	12.09
Distance to power line (km)	1.41	1.82	0.13	7.97	1.68	2.18	0.13	7.97	1.41	1.80	0.25	7.97	2.26	1.86	0	7.91

Table 4 Frequency table for the binary variables used in this study

Variable	Grid cells with illegal border crossings	Grid cells with illegal border entries	Grid cells with illegal border exits	Grid cells without illegal border crossings
Buildings	13	10	9	27
No buildings	11	6	8	39
Phone signal	22	14	16	57
No phone signal	2	2	1	9

poachers. The logistic regression models compare border cells with illegal crossings to the cells without crossings. By doing this, the outlier does not influence the results more than other border cells with illegal crossings. We also compared the counts to see how the outlier influence our results when it was included and excluded. The logistic regression and quasi-Poisson models are described below.

Logistic regression models using penalized maximum likelihood estimation

Logistic regression models are used for a dichotomous dependent variable. However, logistic regression modelling using a standard maximum likelihood estimation tends to be unreliable for small sample sizes (Pearce and Ferrier 2000; Scott Long 1997). We considered the sample size of 90 border cells to be too small and therefore used a penalized maximum likelihood estimation. This method results in approximately unbiased estimates of coefficients even with small sample sizes and separation issues (Allison 2008; Firth 1993; Heinze and Schemper 2002). We built three separate models; the first model used all border crossing data by pooling both entry sites and exit sites, the second one used all entry crossings, and the third one used all exit crossings. Border length (in km) was included as an offset-term to account for unequal border length across the grid cells (see Fig. 2). We used the *logistf*-package (Heinze et al. 2013) in R (R Core Team 2016) to estimate the models. The profile likelihood was used for the confidence intervals and P-values estimation to ensure consistency (Cole et al. 2014; Zorn 2005).

Quasi-Poisson models

This dataset contained a low number of border cells with at least one illegal crossing. Most border cells contained no illegal crossings, resulting in a relatively large number of zeros (Table 2). The negative binominal distribution is appropriate for analyzing count data with excess zeros. Most wildlife crime datasets are characterized by a low sample mean, which causes the low mean problem (LMP). The LMP in a negative binomial distribution affects the dispersion parameter estimation (Lord 2006), especially when combined with small sample sizes (Zhang et al. 2007). Therefore, we used a quasi-Poisson model to correct the standard errors for overdispersion. It estimates a dispersion parameter, which is a multiplicative factor allowing the variance to be larger or smaller than the mean. We examined the effect of the outlier by estimating two models; the first used all illegal crossings, and a second excluded the outlier. Border length (in km) was included as an offset-term as well (see Fig. 2). We used R to estimate the quasi-Poisson models (R Core Team 2016).

Diagnostics and robustness checks

A crucial element in the KDE is the bandwidth parameter selection, but there is no general consensus on how to set these (Hart and Zandbergen 2014). We used five different approaches: average distance to K nearest neighbors, where K is the square root of the number of observations (Devroye et al. 2013), cross validated bandwidth selection (Diggle 2003), the reference bandwidth (Calenge 2006), the method described by Vanek (2016), and a bandwidth used by the reserve based on visual assessments. The estimated bandwidths ranged from 1298 to 3861 m. The five bandwidths for estimating rhino hotspots were used in the models separately, but did not affect the results. In the end, we used a bandwidth of 1298 m using the method described by Vanek (2016). This model had the lowest Akaike Information Criterion compared to the other models using different bandwidth estimators (Burnham and Anderson 2003).

We examined the data to see if it suffered from issues of multi-collinearity. The generalized Variance Inflation Factors (VIF) were estimated using the *car*-package (Fox and Weisberg 2011) and we found no variables with a VIF-value higher than 2.5. Using the Durbin–Watson test, we found that autocorrelation did not affect the residuals. The Moran's I test from the *spdep*-package (Bivand et al. 2013; Bivand and Piras 2015) detected no spatial autocorrelation in the residuals. For this test, we defined neighbors as those cells that touch each other along the border.

Results

Explaining the high number of illegal crossings in a single border cell

We found that 55 illegal crossings were documented in a single border cell; 27 entries and 28 exits. The nearest rhino hotspot was approximately 3.09 km from this location. Buildings and usable phone signal were present in the border cell as well. The outside road density was 5.68 km/km^2, the distance to nearest power line was 0.25 km. However, the main difference between this border cell and the other cells was the presence of a bridge over a large river. This is the only bridge in this area that crosses the river and is accessible by people from the outside. Furthermore, the location where the bridge crosses the river into the reserve is unfenced. This provides poachers an easier access point to and from the reserve, because at all other areas they need to cross the fence. In the following sections, we show the results of analyzing the overall distribution of illegal crossings.

Logistic regression models

The logistic regression model using all illegal crossings showed that 'proximity to rhino' was the only statistically significant predictor (Table 5). The likelihood of an illegal crossing was higher for border cells in close proximity to high rhino densities compared to cells further away; a one-unit increase in proximity to rhino increases the odds of an illegal crossing by a factor of 4.91. This finding is in line with the study's hypothesis. The other variables were not found to be statistically significant with regards to illegal crossings.

The logistic regression model using only illegal entries showed that the variables 'proximity to rhino' and 'outside roads' were statistically significant predictors (Table 6). A one-unit increase in proximity to rhino increases the odds of an illegal border entry by a factor of 3.41. A one-unit increase in outside road density increases the odds of an illegal entry by a factor of 1.28. Both findings were in line with the study's hypotheses. There was no statistically significant relationship between the other variables and illegal entries.

The logistic regression model using only illegal exits found that the variable 'proximity to rhino' was a statistically significant predictor (Table 7). A one-unit increase in proximity to rhino increases the odds of an illegal border exit by a factor of 5.15. This finding was in line with the study's hypothesis. There was no statistically significant relationship between the other variables and illegal exits.

Quasi-Poisson models

The quasi-Poisson model using all illegal crossing data, including the outlier, found no statistically significant effect for the predictor variables. This was related to the dispersion parameter, which the model estimated to be 49.26. This means that the standard errors in this model are $\sqrt{49.26} \approx 7$ times larger. When we excluded the outlier from the analysis, the model showed that proximity to rhino was the only statistically significant predictor variable (Table 8). The dispersion parameter was 3.22, suggesting that the outlier influenced the results. The closer the border cell was located to a rhino hotspot, the higher the number of illegal crossings. A one-unit increase in proximity to rhino increases the expected number of illegal crossing by a factor of 3.44.

Table 6 Logistic regression model using penalized MLE using all illegal entry crossings

Variable	Odds ratio	95% conf. interval		χ^2
Proximity to rhino	3.41*	1.08	11.37	4.40
Buildings	2.60	0.82	9.10	2.64
Roads outside	1.28*	1.03	1.62	5.05
Distance to power lines	0.84	0.54	1.18	0.88

*P < .05

Discussion

Outlier case study: bridge

This study found that half of all illegal crossings occurred in a single border cell. This cell was different from the other border cells because it contains a bridge over a large river. Just as the reserve's fence is a barrier for poachers, the river can also be regarded in this way; Clare et al. (2009) found that large water bodies inhibit offender movements. The river in the reserve is a significant barrier and dangerous to cross. The bridge allows poachers to safely cross the river and gives them easier access to the reserve because this is an unfenced section. Parts of the river dry up during the dry season, making it easier to cross it at other places. Although we did not test how seasonality influenced the number of illegal crossings, poachers used the unfenced bridge consistently between 2011 and 2016. Hence, it is attractive for poachers to enter and exit the reserve, because it is a well-known and consistent opportunity to cross the river.

The high number of crossings could also be partly a reporting issue. Patrols do tend to visit areas in which they expect poaching is most likely to occur (Gavin et al. 2010). Their understanding of the spatial distribution of poaching often comes from past experiences and patrol observations. Unfortunately, ranger patrol routes were not recorded during our study period. Based on

Table 5 Logistic regression model using penalized MLE using both entry and exit crossings

Variable	Odds ratio	95% conf. interval		χ^2
Proximity to rhino	4.91**	1.78	14.92	9.59
Buildings	1.46	0.52	4.13	0.52
Phone signal	1.97	0.43	12.89	0.71
Roads outside	1.12	0.92	1.40	1.42
Distance to power lines	0.74	0.47	1.04	0.09

**P < .01

Table 7 Logistic regression model using penalized MLE using all illegal exit crossings

Variable	Odds ratio	95% conf. interval		χ^2
Proximity to rhino	5.15**	1.72	17.03	8.73
Buildings	1.17	0.38	3.66	0.08
Phone signal	2.46	0.46	25.77	1.00
Roads outside	1.00	0.79	1.25	0.00
Distance to power lines	0.83	0.50	1.21	0.86

**P < .01

Table 8 Quasi-Poisson model using entry and exit crossings without the outlier of 55 illegal crossings

Variable	Incidence rate ratio	95% conf. interval	
Proximity to rhino	3.44*	1.33	8.92
Buildings	1.24	0.46	3.42
Phone signal	1.13	0.32	6.68
Roads outside	1.04	0.85	1.25
Distance to power lines	0.77	0.48	1.11

*P < .05

our communication with the reserve's management, we do not believe there were substantial large differences in patrol effort between the bridge border cell and other border cells with crossings.

Potential solutions derived from situational crime prevention techniques

The unfenced bridge has the potential to become less attractive poachers by applying situational crime prevention techniques (Cornish and Clarke 2003). The most straightforward option is to fence off the bridge and increase the risks through formal surveillance. Ranger patrols can achieve this by physically monitoring the bridge or with technology such as security cameras. An alternative is to turn the bridge into an access control gate. The people working or living inside the reserve can still use the bridge in this way. However, both solutions still require a response team to follow-up on poacher detections or staff to be posted at the control gate, emphasizing the need for human personnel to increase risks effectively. The reserve's management was keen on the idea of a permanent team to guard the bridge and protocols have been put in place to better secure this area.

Risk and reward: proximity to rhino density

Proximity to high rhino densities came up as a significant predictor in all logistic regression models and in the quasi-Poisson model with the outlier excluded. By entering and exiting near high rhino densities, poachers minimize the time spent in inside the reserve. This would reduce the chances of encountering a patrolling ranger team, and hence reducing the poachers' risk of apprehension. This could be especially true for the journey after crime of successful poachers as they want to escape the reserve as quickly as possible after obtaining rhino horn. By choosing these sites, they increase the chance of encountering a rhino, and in turn increase the chance of obtaining high rewards.

While the finding is in line with Hypothesis 2a, it raises another question: "How do poachers know the locations of high rhino densities?" One explanation is that the poachers are experienced hunters who can read rhino activity signs to guide them to the nearest rhino. Poachers may also learn through previous experiences, since there were no major fluctuations in the spatial distribution of high rhino densities. Another, more worrisome, explanation is that somebody familiar with the reserve is involved in poaching by providing information to the poachers (Macleod 2012). Levels of corruption have been increasing in South Africa (Stone 2006) and it is likely to play a role in rhino poaching too. Future studies using arrest information and interviews might provide more insight as to how poachers plan their illegal crossing and uncover more about their target selection and the potential role of corrupt rangers or residents.

Minimal risk: presence of buildings

The results showed no support for Hypothesis 2b. Presence of buildings was not found to be a significant predictor for illegal crossings. This variable was used as a proxy measure for guardianship, assuming poachers would avoid areas with private homes and tourist lodges. The other guardians, rangers, might still influence the poacher's target selection. We did not study the effect of patrols because no such data were available before 2016. However, the reserve established updated data collection protocols, including GPS tracking of ranger movements. These data provide opportunities to update our analysis in future studies.

Least effort: roads outside the reserve and phone signal

Regarding effort, our results only found support for Hypothesis 3a. Outside roads had a statistically significant effect in the illegal entries model, while phone signal had no statistically significant effect. Roads facilitate movement to areas that would have otherwise been inaccessible or require more effort. Other studies found similar results and showed that the distance to roads was a strong predictor for levels of poaching (Blake et al. 2007), and that poachers use roads to penetrate into a national park (Blom et al. 2005). Outside roads can also facilitate drop-offs (Mulero-Pázmány et al. 2014; Snitch 2014; Spicer 2014). This suggests that poachers select entry sites that require minimal effort. This effect was not found for exit sites. A possible explanation is that a poacher has more time when deciding where to enter the fenced reserve, and can also decide not to enter at all, for example if he spots patrolling rangers. During the journey after crime, a poacher wants to exit quickly. Whether or not the exit site has good accessibility is less important. Even if poachers are unsuccessful, they probably have less control over where and when they exit the reserve, because this is dependent on their search inside the reserve.

Phone signal was not found to be a significant predictor for illegal exits. We measured phone signal in 2016 only, and applied this for all illegal crossings in previous years. It is most likely that phone coverage improved during our study period. We may have overestimated the phone signal distribution as a result. The reserve's updated data collection protocols now include phone signal measurements. In the future, it would be possible to study in more detail if and how phone signal influences the poacher's target selection.

Navigation: distance to power lines

We did not find any evidence that poachers were using power lines to navigate where they enter and exit the reserve. Power lines or other landmarks may still play a role during a hunt; however, it appeared not to be important for illegal entries or exits. Should information about poacher movements become available, it would be easier to study how the poachers navigate and whether such landmarks play any role.

Limitations

To study crime location choice, it is necessary to use spatial data, such as crimes reported to police by victims or bystanders. Spatial analyses of wildlife crimes are more difficult because animals cannot report crime. This 'silent victim' problem means quantifying true levels of crime is challenging (Lemieux 2014). Using patrol data to analyze crime location choice can be misleading because ranger patrols are biased towards certain areas (Gavin et al. 2010); they focus on areas where they expect the highest returns. Patrol teams are responsible for large areas, but often lack the resources to cover it on a regular basis. This results in an incomplete knowledge of crime levels and distributions, also known as the 'dark figure' (Biderman and Reiss 1967).

Overcoming these difficulties to study the poacher location choices is no easy task. However, fenced protected areas offer a unique opportunity to study specific stages of a poaching event. If a poacher wants to poach inside a fenced area, they have to find a way to enter it, and, after a certain amount of time, find a way to exit it. Regular fence patrols increase the probability of obtaining information on illegal crossings. We could not account for the spatial and temporal distribution of patrol effort because no such data were available before 2016. However, the reserve established updated data collection protocols, including GPS tracking of ranger movements. Future studies will be able to take patrol effort into account.

Another limitation of this study was the small sample size. This is explained by the reserve's size together with the relatively large grid cell sizes, but also because poaching is a rare event. It was not possible to determine the exact location of where poachers crossed the border because the illegal crossings were recorded at the grid-level. With the updated data collection protocols, crossings are now recorded at the exact location with GPS-coordinates.

Future research

This study's methodology could be replicated for other protected areas with similar data. Future research might focus poacher movements and what environmental features influence their spatial decisions. These data can be collected when GPS-tracked rangers follow the exact trail the poachers used. Dense vegetation was not included in our study, but likely influences poacher movements on the micro-level. The location of rivers may also help to explain the entry and exit locations of poachers on the micro-level, and it should be able to identify them by analyzing remote satellite imagery. In our study we neglected temporal elements that may influence poacher decision-making, but these should be studied in more detail to understand if spatial patterns are related to seasonal or monthly cycles. Arrest data and interviews would give more insight into how poachers plan their illegal crossing and uncover more about their modus operandi. Such detailed studies are useful for law enforcement to help with patrol planning.

Conclusion

This study contributes towards understanding illegal border crossings by rhino poachers into a fenced reserve in South Africa and can help law enforcement to identify risk locations. The descriptive results show that half of the observed crossings occurred at a single location, leading us to describe the special circumstances of this outlier. Next, we analyzed the poacher's target selection in general. By breaking a poacher's trip into a journey to crime, and a journey after crime, it was possible to determine the similarities and differences between the two. Poachers go for the nearest way out of the reserve, by choosing exit sites near high rhino densities. The entry sites are also near high rhino densities, suggesting that poachers try to minimize time spent inside the reserve and have knowledge on rhino locations. Furthermore, poachers select sites with high road density outside the reserve. Roads outside the reserve facilitate the journey-to-crime by providing easier access to the reserve. The reward and risk aspects of the rational choice framework were found to be most strongly related to the rhino poacher's spatial preference for illegal border crossings.

Effort was also found to be a significant predictor but not as strong as the reward and risk aspects, and only for entries.

Abbreviations
RCP: rational choice perspective; KDE: kernel density estimate; RSSI: received signal strength indication; LMP: low mean problem; VIF: variance inflation factors.

Authors' contributions
NvD and AML carried out the fieldwork. The design of the methodology was lead by NvD, with help from SR and AML. NvD was the lead writer of this paper, carrying out the necessary literature review and performing data cleaning. NvD drafted the manuscript, after which AML and SR commented and made suggestions. NvD addressed the reviewers comments, after which AML and SR did some minor editing. All authors read and approved the final manuscript.

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The authors declare that they have no competing interests.

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Given the sensitive nature of rhino security information, the authors cannot share the used dataset.

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