

Harnessing Camera Trap Data to Understand Wildlife Dynamics at Water Sources: Effect of Predation Risk on Prey Behavior

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As water is a necessary resource for both predator and prey, overlaps at water sources are inevitable, and the resulting predation risk can strongly affect prey movement and behavior. Water availability has been largely affected by climate change and human activity, and a deeper understanding of such interactions can help with wildlife conservation. This study thus explores the potential large-scale patterns created by the effects of predation risk on prey presence and characteristics of prey visits to water sources, such as frequency, duration and herd size. Data was collected from non-invasive camera traps set up in five locations across central Kenya, each with two experimental groups, one with a water source and one without as a control. Through analyses performed using R, it has been shown that while the availability of water does have a large effect on prey presence and behavior, predation risk has a minimal effect, as both predator and prey presence increased together without a conclusive pattern of antipredator behavior.

Keywords: predation risk, antipredator behavior, predator-prey interactions, water availability, camera trap

I. INTRODUCTION

Studying wildlife interactions and its effects on predator and prey interactions is necessary to understanding the ever-changing ecological landscape. One factor that can drive such interactions is the shared need for access to water, as water sources can cause predator and prey overlap, acting as a natural environment for studying antipredator behavior (e.g., avoidance, group defense; Mortoja et al., 2018).

The availability of water has been heavily impacted by climate change through, for example, droughts, as well as human behavior, where activity such as irrigation and livestock use compete with natural wildlife for water (de Leeuw et al., 2001; Mehran et al., 2017); wildlife access to water sources is also necessary for maintaining water quality and cleanliness (Fox & Alexander, 2015). Thus, a deeper understanding of the movement and behavior of predators and prey revolving around water can help with conservation efforts and guide more environmentally friendly human settlement.

While some have studied the effects of water on predator and prey interactions (Verdeny-Vilalta & Moya-Laraño, 2014), few studies have experimentally manipulated water availability to study predation risk and antipredator behavior. To close this gap and better understand wildlife interactions, this study aims to investigate such antipredator behavior in natural settings, the savanna in central Kenya in this case. Using the data collected with the help of camera traps and citizen scientists, risk-taking behavior stemming

from overlaps at water sources can be measured through data analysis.

Since water sources spur increased predator activity and therefore risks (Verdeny-Vilalta & Moya-Laraño, 2014), it is hypothesised that antipredator behavior can be measured, where characteristics of prey visits can be compared to levels of risk incurred by the presence of predators (i.e., increased risk level means reduced prey presence, fewer prey visits, shorter prey visits and larger herd sizes for more protection). Survival will likely be valued over satisfying immediate thirst requirements, meaning sites without a water source would be less affected by predation risk.

II. EXPERIMENTAL METHODS

This study was conducted in three main steps: data collection, data processing and data analysis.

A. Data collection

Data was collected from five main locations across the Ol Pejeta Conservancy in Kenya with the help of camera traps. Each of the five main locations were further separated into two groups: filled pans and dry sites (see *Figure 1*). Camera traps, triggered by animal movement or heat up to 12 - 15 meters away, were set up throughout each location and ran for a total of 2 years (August 2016 - August 2018). These are non-invasive and have been proven to be a more effective way of capturing animal movement and of detecting a large range of species than other methods (e.g., live traps, radio-tracking; Wearn & Glover-Kapfer, 2019).

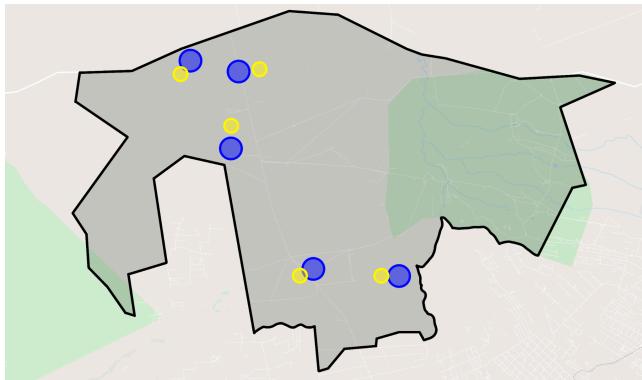


FIG. 1. Map of the Ol Pejeta Conservancy in Laikipia county, central Kenya (0.0043° S, 36.9637° E) with labelled experimental groups within the five main areas. Blue (filled pan) denotes a range centered around a water source, and yellow (dry site) denotes a range located at least 1 km away from any water source. (Original figure taken from Titcomb et al., 2021, recreated with Google Maps.)

Images taken by the camera traps were then uploaded to a citizen science website (Zooniverse), where volunteers helped with identifying animal species and counting the number of animals from each individual photograph. Each image was viewed by five citizen scientists to ensure accuracy. (See Titcomb et al., 2021 for more details.)

B. Data processing

The final dataset consisted of ‘triggers’ (movement that occurred within five minute windows) and information about each individual trigger. This included duration, animal count, animal species and date (year, month, day). Trigger duration was assumed to be at least five seconds, and animal count was calculated by averaging animal counts reported by citizen scientists. (See Titcomb et al., 2021 for more details.)

C. Data analysis

Based on the final dataset, three common species of prey, along with their respective predators, were chosen to be studied and are listed in *Table 1*. Using the data for these species, four characteristics of prey visits were studied: (1) presence of prey, (2) number of visits per day, (3) average visit duration and (4) average herd size.

(1) Presence of prey was a binary variable where ‘yes’ meant presence and ‘no’ meant absence at a particular risk level. As such, for remaining research questions, data were filtered to instances when prey were present.

(2) Number of visits per day (in units of animals/day) was defined as the total count of species from all the triggers from a consecutive 24 hour period.

(3) Average visit duration (in units of seconds) was defined as the average duration of all the triggers from a consecutive 24 hour period.

Prey Species	Predator Species
<i>Aepyceros melampus</i>	<i>Acinonyx jubatus, Canis mesomelas, Panthera leo, Panthera pardus, Papio anubis</i>
<i>Equus quagga</i>	<i>Acinonyx jubatus, Crocuta crocuta, Lycaon pictus, Panthera leo, Panthera pardus</i>
<i>Taurotragus oryx</i>	<i>Crocuta crocuta, Lycaon pictus, Panthera leo, Panthera pardus</i>

TABLE 1. Table of prey and predator species studied. Each row corresponds to one prey-predator pairing, where the main predators of each prey species have been identified for calculating risk level. Species chosen had relatively high levels of data collected. **Bolded** species are of conservation interest (near threatened or higher conservation status), and underlined species are impacted by diminishing access to or drastic changes in water sources due to causes such as increased competition with livestock or drought.

(Table generated with the help of Mpala Live!, 2021.)

(4) Average herd size (in units of animals) was defined as the average count from each individual trigger from a consecutive 24 hour period.

Each characteristic (x variable) was then plotted on a separate graph in relation to the risk level (y variable) of the particular day. Risk level (in units of animal*seconds) was calculated by multiplying the count of predators by the duration of predator visits for each trigger over a consecutive 24 hour period and summing these values up.

For all, diagnostics (e.g., for residuals and deviance values) were run and visualised to ensure model fit and accuracy using the DHARMA (v0.4.3; Hartig, 2021) package. All data analyses were performed using R 4.1.0 (R Core Team, 2021).

III. RESULTS

A. Presence v Risk Level (1)

The first column of *Figure 2* shows the relationship between presence of prey and risk level. Risk level had an insignificant effect on prey presence at dry sites for all species ($p = 0.579$); increasing the risk level by 1 animal*second increased only the likelihood by a species average of 0.00424%. Risk level had a positive effect at filled pans ($p < 0.001$); likelihood of prey presence increased by an average of 0.758%, which approximates to a roughly 179 times greater rate.

Across all species, prey were more likely to be present at filled pans, but the magnitude of the effect was variable. The average likelihood of presence over a 24 hour period regardless of risk level was 0.107%, 0.123% and 0.0146% for dry sites and 0.141%, 0.243% and 0.0459% for filled pans, for *A. melampus*, *E. quagga* and *T. oryx*, respectively.

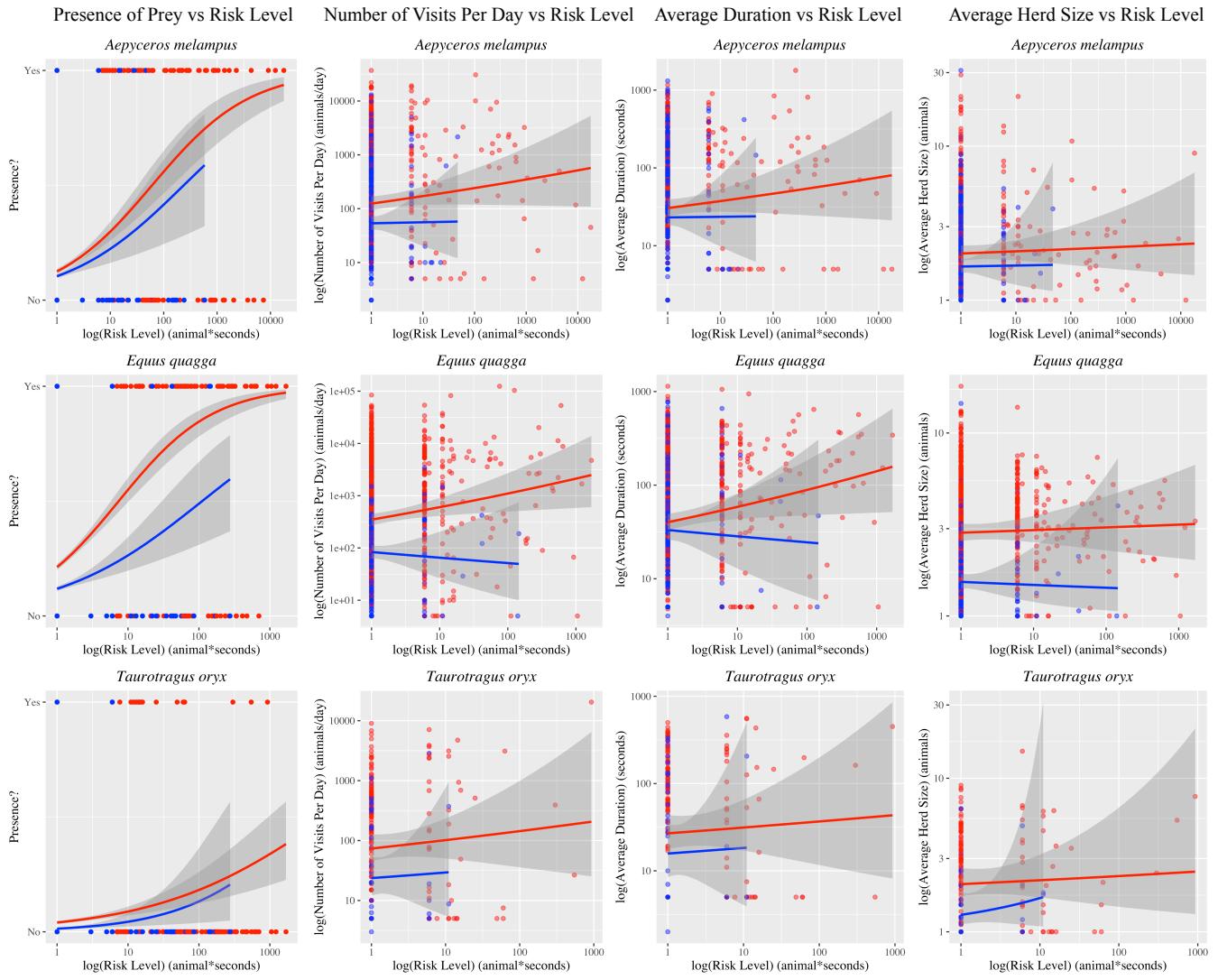


FIG. 2. Graphs of (1), (2), (3) and (4) compared to predation risk level, separated by species. Logarithm was used for all data (except presence) due to the heavily right-skewed data. (1) Graphs comparing presence of prey with risk level were fitted using a binomial logistic regression model, leading to a line describing the likelihood of finding prey based on different risk levels, due to binary choice of 'yes' or 'no'. (2), (3), (4) Graphs looking at the effect of risk level on different characteristics of prey visits were fitted using a negative binomial generalised linear model due to non-normal data. All graphs (and the best fit line for (1)) were generated using the ggplot2 package (v3.3.5; Wickham, 2021), and best fit lines for (2), (3) and (4) were generated with the MASS package (v7.3-54; Venables & Ripley, 2002).

B. Number of Visits Per Day v Risk Level (2)

While risk level had a variable trend of effect on number of visits per day at dry sites, it consistently had a positive effect at filled pans, as seen in the second column of *Figure 2*. On average across all species types, for every 1 animal*second increase in risk level, the number of visits per day increased by 0.259 animals/day at filled pans ($p < 0.001$) compared to the insignificant average of 0.00260 animals/day increase at dry sites ($p = 0.741$), an approximately 100 times greater rate at filled pans.

Prey also visited filled pans more frequently than dry sites throughout the day, regardless of risk levels and

species. Dry sites garnered an average of 450.41, 372.25 and 164.99 animals/day, while filled pans had an average of 1532.9, 3300.6 and 751.98 animals/day, for *A. melampus*, *E. quagga* and *T. oryx* respectively. This is a species-wide average of 5.61 times more visits per day to filled pans than dry sites, with the highest difference being 8.87 times for *E. quagga* and the lowest being 3.40 times for *A. melampus*.

C. Average Duration v Risk Level (3)

Average visit duration was insignificantly impacted by risk level in dry sites ($p = 0.810$) and only slightly in filled pans ($p = 0.0588$), as shown in the third column of *Figure*

2. For every 1 animal*second increase in risk level, average visit duration increased by 0.00192 seconds and 0.105 seconds for dry sites and filled pans respectively, an approximately 54 times greater rate of increase for filled pans.

When looking at the average visit duration regardless of risk level, the experimental group did play a larger factor. On average, visit durations were 87.40, 86.85 and 61.27 seconds at dry sites and 116.35, 108.59 and 92.23 seconds at filled pans, for *A. melampus*, *E. quagga* and *T. oryx*, respectively, meaning visit durations were approximately 1.3 times longer at filled pans.

D. Average Herd Size v Risk Level (4)

Risk level has shown an insignificant effect on the average herd size of prey visits at dry sites ($p = 0.686$) and a significant one at filled pans ($p < 0.001$), as seen in the fourth column of *Figure 2*. Dry sites averaged a 0.0828 animals increase in herd size per 1 animal*second increase in risk level across the three species while filled pans averaged a 0.516 animal increase, an approximately 6 times larger rate.

Effects of risk level were variable between species types in filled pans, with *E. quagga* having the highest rate of increase of 0.701 animals per animal*second ($p < 0.001$) and *A. melampus* having the lowest of 0.278 animal per animal*second ($p < 0.001$).

Across all risk levels, the average measured herd size (i.e., total count of animals divided by total count of herds) was consistently larger at filled pans compared to dry sites, regardless of species. This was a difference of 0.680 animals for *A. melampus* (2.07 animals at dry sites and 2.75 animals at filled pans); 1.72 animals for *E. quagga* (1.69 animals at dry sites and 3.41 animals at filled pans); and 1.13 animals for *T. oryx* (1.50 animals at dry sites and 2.64 animals at filled pans).

IV. CONCLUSIONS AND DISCUSSION

Compared to *A. melampus* and *T. oryx*, *E. quagga* had much more presence at filled pans than dry sites. This can be attributed to their heavy dependence on a constant source of water, preferring to stay near areas with water, which also explains the slightly downward trend for dry sites in *Figures 2*, where general increased animal activity did not convert into increased *E. quagga* activity.

Due to the limited amount of data available for days with high levels of risk, many graphs have large error bars, only providing an estimate for such types of days; this is especially true for *T. oryx*, which had the fewest camera trap triggers. The large error bars (in grey) are also likely due to the variable and oftentimes uncontrollable nature of wildlife behavior and movement.

A. Big Picture Takeaways

Data and analyses show that more predator presence has not led to measurable antipredator behavior, especially at filled pans; instead, it is associated with increased prey presence, more visits per day and longer visits. This is likely due to the general increase in activity surrounding water sources, as dry sites had lower predator and prey activity, depicted by the fewer points of high risk levels in blue and the lower likelihood of prey presence. Unlike the other characteristics of prey visits to water, average herd size did increase with predator presence; however, this is likely more indicative of the previously mentioned effect, where water had garnered increased presence in general, rather than that prey visited in larger herds for increased protection.

The lack of measured antipredator behavior could also be due to the opposite of the predicted effect. Instead, more prey activity has possibly led to more predator activity, as they view interactions at water sources as opportunities for food and crowd water sources at prey-heavy times.

A factor that did influence wildlife behavior is the presence of water sources, whose effect has been measurable throughout the different aspects investigated in this study. As such, it is necessary to preserve water sources, natural drivers of interactions and activity, for all species of wildlife, especially those that are heavily impacted by drought or competition with livestock for water. The populations of many of these species are also on the decline due to human activity or heavily impacted by climate change induced drought, further necessitating conservation efforts.

B. Future Studies

To better understand the diversity of animals in the wild, the range of species for predators and prey analysed could be widened, as only medium-sized land mammals found in the Kenyan savanna were chosen for this study. If possible, data on less common animals would also increase diversity.

A more small-scale approach could be taken as well to look at individual interactions, such as shortening time spans to less than a day or looking specifically at captured predator-prey interactions, as this study mainly sought to focus on bigger or more large-scale patterns for a more holistic approach to conservation.

Collecting more data in the future would also help to lower the large error bars and lessen variability, which can provide a more conclusive understanding of the effect of predation risk on antipredator behavior, especially at times with high predation risk and high prey presence.

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