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# Unravelling drivers of activity patterns of crop raiding animals in the Surinamese Rainforest



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## *Abstract*

Human-wildlife conflict (HWC) presents a significant challenge in many regions, especially in the Global South, where subsistence farming often leads to clashes with wildlife. This study investigates the intricate dynamics between crop-raiding animals, specifically ocelots (*Leopardus pardalis*) and red-rumped agoutis (*Dasyprocta leporina*), and various environmental and anthropogenic factors in the Surinamese rainforest. Utilizing camera trap data, I examined the spatiotemporal activity patterns of these species, comparing their behaviours in forest and crop field settings. My findings reveal significant differences in agouti activity patterns between these habitats, with increased morning activity in crop fields. This adaptation suggests a strategic response to human presence, optimizing foraging efficiency while minimizing interaction. Additionally, the presence of predators such as ocelots and humans influence agouti activity, though not to a statistically significant extent. Predator-prey dynamics, assessed through avoidance-attraction ratios, indicated that predator presence alters agouti behaviour, but not sufficiently to confirm the risk allocation hypothesis. I also explored the impacts of temperature, rainfall, and human disturbance on agouti behaviour, finding a notable non-linear relationship between temperature and activity times. The GLM analysis reveals that while the intercept is significant, indicating a meaningful baseline relative abundance of agoutis, the standardized environmental predictors (temperature, anthropogenic disturbance, predator presence, and rainfall) are not significant, suggesting these factors do not strongly influence relative abundance in this dataset. Despite the comprehensive approach, the study highlights the need for further research with larger sample sizes and detailed environmental data. By promoting habitat conditions that support natural behaviours and reducing human-wildlife conflicts, these strategies can enhance coexistence and contribute to the sustainable management of agricultural landscapes. The results underscore the importance of developing tailored conservation strategies that consider species adaptability and promote coexistence between humans and wildlife.

## *Introduction*

The phenomenon commonly referred to as human-wildlife conflict (HWC) delineates the complex interplay between human populations and wildlife, characterized by a delicate equilibrium that influences both ecological systems and human societies. This research endeavours to contribute to our understanding of HWC by examining the nuanced interplay between environmental and anthropogenic factors that shape the activity patterns of crop-raiding animals, offering insights crucial for the development of effective and sustainable conservation strategies. Many communities, particularly in rural areas, rely on subsistence or small-scale farming (Distefano, 2005). Hence, the global south is disproportionately affected by human-wildlife conflicts due to their reliance on primary sector produce. At the heart of this complex dynamic lies the challenge posed by crop-raiding animals, whose interactions with cultivated landscapes evoke a myriad of socio-economic and ecological consequences. Crop raiding, defined as the action or result of wild animals damaging standing crops by feeding or trampling them (Hill, 2018), affects already precarious livelihoods through decreased yields and increased labour to protect crops (Abrahams et al., 2018). Despite these behaviour patterns, agoutis continue to forage in natural habitats, while ocelots primarily rely on hunting for prey. Crop raiding research is heavily centred around primates and elephants (Alemayehu & Tekalign, 2022; Campbell-Smith et al., 2010; Chiyo et al., 2005; Naughton-Treves et al., 1998; Tiller et al., 2021; Tweheyo et al., 2005), focusing mainly on their temporal patterns and prevalence. There is a substantial lack of knowledge on the environmental variables known to affect activity patterns. Identifying and quantifying the relationship between environmental factors and crop-raiding patterns provides insights into the ecological interactions between wildlife and their habitats. This knowledge will contribute to a better understanding of human-wildlife interactions.

Activity patterns describe the active hours of an animal and are a component of its behaviour, which can be inferred from the presence of an animal at a particular location in time and space (Bridges & Noss, 2011). As the majority of species are not cathemeral, meaning they are not adapted to be equally active at any time of the day, changes in their daily activity patterns can have adverse effects on their ability to move around in their environment, locate food, identify mates, and avoid predators (Mendes et al., 2020). Furthermore, activity levels of a species reflect the compromise between acquiring energy and avoiding predation (Suselbeek et al., 2014), key elements of an animal's fitness. The implications of species altering their activity patterns across temporal scales have discernible effects across all trophic levels and ecological functioning (Lewis et al., 2021). Research on the activity patterns of crop-raiding species in the Surinamese rainforest lacks comprehensive studies on temporal dynamics, including variations throughout the day and seasons. Moreover, there is currently no literature documenting crop raiding or activity patterns of small and medium-bodied animals based in Suriname.

Studying the predatory factors influencing the behaviour of animals is essential for comprehending their contribution to ecological balance (Carter et al., 2015; Dorresteijn et al., 2015; Shamoan et al., 2018). Predators exert pressure on crop raiders, influencing their spatial and temporal distribution (Swinkels et al., 2023), which in turn affects their impact on agricultural lands. Knowledge of predatorial factors can help identify whether predators are tracking prey or whether prey are avoiding predators. Parsons et al. (2016) discuss how wildlife can alter their behaviour to avoid humans and

dogs at certain times, aiming to minimize encounters and potential conflicts. Although there is literature documenting the relationship between ocelots and agoutis, the specific mechanisms (i.e., prey tracking or predator avoidance) are not well understood.

Animals are adapting to anthropogenic landscapes by gradually altering their diel activities, foraging at different times and spaces when they deem it less risky. Most risk-avoidance behaviours, such as spatial and temporal avoidance, have severe trade-offs between foraging efficiency and risk reduction (Suselbeek et al., 2014). Mounting evidence from camera-trap studies suggests that anthropogenic changes to landscapes and communities, including land-use alterations, human activities, hunting, and predator control, significantly impact species' activity patterns (Gaynor et al., 2018). Additionally, the introduction of invasive competitors or predators can further disrupt these patterns, influencing competitive and predatory interactions by altering temporal niche partitioning (Frey et al., 2017a). By analysing the local human disturbances, we can identify the principal factors and determine their effect on activity patterns.

The strong dichotomy between seasons in tropical rainforests characterizes the annual fluctuations in food availability. Ni et al. (2015) explored how gibbon activity patterns were influenced by food availability. During periods of abundant food, such as fruiting seasons, gibbons exhibited increased activity levels. However, research is limited on how cultivated food availability influences the activity patterns of wildlife species. The consequences of animals becoming overly dependent on human-provided food may disrupt natural ecological processes and lead to population declines or other ecological imbalances. Furthermore, the landscape of fear theory suggests there is an inextricable relationship between food acquisition and avoiding predation with activity patterns (Laundre et al., 2010); however, it goes beyond the scope of this project to investigate these relationships.

This research aims to elucidate the factors influencing the activity patterns of crop-raiding animals in the Surinamese rainforest, with a particular focus on the interplay between environmental and anthropogenic influences. The presence of crop-raiding species such as ocelots (*Leopardus pardalis*) and red-rumped agoutis (*Dasyprocta leporina*) presents significant challenges for both farmers and conservationists in this region. Understanding the dynamics of these interactions is crucial for developing effective and sustainable conservation strategies that mitigate human-wildlife conflict and promote coexistence. By addressing existing knowledge gaps, this study will enhance our comprehension of human-wildlife interactions and provide valuable insights for policy and management practices in areas impacted by crop raiding.

### *Research gap*

Despite the importance of studying wildlife behaviour in agricultural landscapes, gaps remain in our understanding of how predators, anthropogenic disturbance, and seasonal variations influence the activity patterns of crop raiding animals. More specifically, few studies have explicitly tested how interacting biotic and abiotic variables influence species' activity of crop raiders (Frey et al., 2017b). I intend to address this by examining the differences in activity patterns between forest and crop field settings, explore the impact of predators on agouti behaviour, and assess how anthropogenic disturbances and seasonality affect their movements. Although ocelots and agoutis are considered common in the region they inhabit, they can still be considered at risk due to the rate of landcover change and habitat destruction. Today, accurate and detailed information, scientific research and stakeholder commitment are key to the development of appropriate and sustainable strategies for both resolving human-wildlife problems and conserving different ecosystems and their wildlife inhabitants (Distefano, 2005).

### *Research objectives*

By delving into the intricate relationship between humans and wildlife in Suriname, this research has the potential to yield insights applicable to broader conservation strategies and sustainable cohabitation efforts globally. The benefit of this research being studied at community level allows for tailored results to aid livelihoods of the Niuew Aurora population. This research falls under that Sustainable Development Goals of number 11: *Sustainable Cities and Communities* whereby resources are managed to facilitate human and wildlife coexistence and number 15: *Life on Land* through conservation of species and maintenance of ecologically diverse regions.

The aim of this research is to gain an in-depth understanding of activity patterns in agoutis and ocelots on a spatiotemporal scale and identify which variables are significantly related to their daily activity patterns using camera trap detection methods. The results will be used to infer relationships between associated predatory and environmental factors as these medium-sized animals navigate cultivated and wild landscapes. The results can be applied to the development of appropriate species-based conflict mitigation strategies, such as raising local awareness, which requires a firm understanding of the underlying patterns of conflict (Campbell-Smith et al., 2010). Based on my research objectives, I formulated three research questions to thoroughly address the research gap.

### *Research questions*

#### **1. How do activity patterns of agoutis differ between forest and crop field settings?**

The first research question identifies the activity patterns of agoutis as they interact with both cultivated and wild landscapes, as Distefano (2005) highlights, there are variations in responses that are often species specific. Researching activity patterns across various habitat types helps identify areas of high activity used by crop raiding animals.

#### **2. How do human and non-human predators influence activity patterns?**

The activity patterns of agoutis was measured and compared in areas of high and low (human and non-human) predator presence to assess their affect. Additionally, Avoidance-Attraction Ratios (AAR), were measured between ocelot and agoutis (Parsons et al., 2016). This includes the interval between predator and prey detections, as well as the interval between prey and predator detections, was compared to consecutive prey detections to ascertain whether prey species were avoiding areas previously occupied by predators or if the presence of prey was attracting predators to these areas.

#### **3. How do environmental factors, such as anthropogenic disturbance and seasonality, influence spatial-temporal patterns?**

Lastly, to investigate the effects of environmental factors, the Anthropogenic Disturbance Index (ADI) was used to quantify human disturbance (Halmy, 2019). To measure seasonality, rainfall and temperature are used as a metrics of food availability to understand how it affects the spatial-temporal patterns of agoutis. The spatial aspect was measured using a GLM with relative abundance as the explanatory variability and all other measured factors as response variables.

### *Hypothesis*

I have based these hypotheses off the literature available and ordered them according to the aforementioned research questions.

1. Activity patterns of agoutis will differ in crop fields due to high human presence with agoutis exhibiting more nocturnal activity in crop fields due to higher human presence during the day. According to Ewart et al. (2024) & Kataria (2023) agouti's will alter their behaviour patterns in response to human disturbance.
2. Agoutis will exhibit different activity patterns in areas with high predator presence compared to areas with low predator presence, showing peaks in activity during times when predator activity is minimal.
3. Extreme weather conditions will lead to increased nocturnal activity in agoutis. In terms of spatial patterns, I hypothesise that the relative abundance of species will be lower in areas experiencing high levels of anthropogenic disturbance and predator presence compared to areas with minimal human impact and predatorial influence.



# Theoretical framework

In this theoretical framework chapter, I discuss the relevant concepts to contextualise the theory on which this research is based. Foremost, I discuss the activity patterns of agoutis and ocelots, then I discuss the influence of predators on activity patterns and I explore how anthropogenic disturbance and seasonality can affect the activity behaviour of the species.

## *Activity patterns*

Studying the activity patterns of animals is fundamental to advancing our understanding of their behaviour, ecology, and interactions with humans. They often vary seasonally, corresponding with food availability and climatic conditions, providing insights into the foraging behaviour of crop-raiding species. Agoutis are mostly documented as a diurnal species in literature, with bimodal peaks in the morning and afternoon (Ferregueti et al., 2018; Magalhães & Srbek-Araujo, 2019). Magalhães & Srbek-Araujo's (2019) paper highlights the plasticity in the activity patterns of agoutis resulting from their sensitivity to their environment and other abiotic variables, human disturbance and seasonality. They have adapted their diel cycles to minimise interaction with predators and as Kataria (2023) revealed, sites further away from human settlement displayed consistently more agouti activity and changes in activity patterns compared to near sites. Suselbeek et al. (2014) described this as the risk allocation hypothesis, where species assess trade-offs between areas based on their perceived risk of the area, which is measured in the first research question. Ocelots are typically nocturnal or active at dusk and dawn (Blake et al., 2016; Dillon & Kelly, 2008; Kolowski & Alonso, 2010; Porfirio et al., 2016), however, lunar cycles can also alter their night time activity (Di Bitetti et al., 2006; Pratas-Santiago et al., 2016). Less information is known regarding the activity patterns and habitat preferences due to their secretive habits, natural low population densities and large home ranges (Trolle and Kéry., 2003; Porfirio et al., 2016).

There has been a global increase in nocturnality of wildlife in human dominated environments demonstrating how effective the behavioural plasticity of animals is (Gaynor et al., 2018). Mendes et al. (2020) describes in great detail the causes and effects of temporal avoidance as a risk avoidance behaviour, whereby the activity patterns of prey shift from diel activity to nocturnal activity becoming active in a safer part of the day. Their study revealed a 47% change in the activity period of forest dwelling animals as a result of human disturbance, thereby confirming the landscape of fear theory. Spatial ecology is used to traditionally inform land planning policies but the introduction of new technologies can account for temporal interactions, revolutionising how zoning is implemented. Mendes et al. (2020) suggests diurnal "temporal zoning," a strategy similar to spatial zoning, may be used to limit some human activities during times of the day when animals of conservation interest are most active or when the risk of unfavourable human-wildlife interactions is greatest. Nocturnal behaviour is risky behaviour as their predators are hunting during these times. Prey species foraging at night indicates resource availability is low and they willing to accept the risk involved. This low food availability is also a push factor for crop raiding, worsening the perpetuating cycle of human wildlife issues.

Many studies focus on a singular habitat or fail to differentiate between habitats when researching wildlife activity patterns. Spatial-temporal scales of activity patterns are widely documented, with numerous studies observing crop-raiding patterns, particularly noting trends in elephant and primate species (Chiyo et al., 2005; Krief et al., 2014; Naughton-Treves et al., 1998; Tiller et al., 2021; Tweheyo et al., 2005). The relative abundance of species across a grid highlights their spatial distribution and offers critical insights into population dynamics and ecosystem health. This measure reveals species interactions with each other and their environment, providing a nuanced understanding of species-environment interactions and illustrating how species utilize resources and respond to habitat changes (Teixeira-Santos et al., 2020). Tiller et al. (2021) noted that typically diurnal elephants will crop raid at night to avoid human contact, a risk-avoidant behaviour seen in many species (Hill, 2018). Mendes et al. (2020) identified species such as Azara's agouti, nine-banded armadillo, ocelots, collared peccary, and white-lipped peccary in Brazil's Atlantic Forest, which shifted towards nocturnality in response to human disturbance. This trend towards increased nocturnality has significant consequences for the fitness of these species, impacting their ability to contribute genes to future generations (IPBES, 2019).

### *Predator prey relationships*

To comprehensively understand the relationship between predation and activity patterns, it is crucial to acknowledge that a substantial portion of animal behaviour is dedicated to obtaining food (Suselbeek et al., 2014). The process of foraging leaves prey vulnerable to predation, as landscape dynamics are known to predators. Therefore, prey can alter their daily activity patterns to avoid interaction with predators. Temporal partitioning refers to this process occurring over a specific timescale. Given the significant impact of predators, it is important to discern whether activity patterns are primarily influenced by anthropogenic factors or if they are also a response to predatory pressures. Understanding this distinction is crucial for accurately interpreting the drivers behind animal behaviour. The ocelot is the main predator of the red rumped agouti in Suriname (Kataria, 2023). Ocelots act as a predator and a prey within the food web, highlighting their key role within the ecosystem (Di Bitetti et al., 2006). They are preyed on by jaguars and pumas and predate on rodents, snakes and young peccaries and deer. According to Porfirio et al. (2016) study on ocelots in the Brazilian Pantanal, their main prey are the Brazilian rabbit (*Sylvilagus brasiliensis*), Azara's agouti (*Dasyprocta azarae*), and Paraguayan punaré (*Thrichomys pachyurus*). As a meso-carnivore and opportunistic predator, ocelots will prey on many small animals they encounter (Di Bitetti et al., 2006). Agoutis are prey species; they contribute greatly to the environment by burrowing in the ground which aids in soil aeration and nutrient cycling. They have also been noted for their role in seed dispersal (Mittelman et al., 2020, 2021).

Furthermore, the significance of prey tracking should not go unaddressed. Swinkels et al. (2023) discovered that the duration from when a prey animal was sighted at a location exceeded chance expectations when an ocelot had passed, and conversely, the duration until an ocelot was sighted at a location fell significantly short of chance expectations following prey passage. To further this, they made a crucial observation regarding the repeated use of locations by predators, that became zones of spatial avoidance with reduced prey activity. Ross et al. (2013) found that there was significant shift in prey activity patterns in various areas with different levels of predation. In terms of prey energy expenditure budget, they can save substantial efforts by foraging when and where areas less predators are present. Prey have developed various forms of anti-predator behaviour that becomes apparent

when observing the activity patterns. Species continuously alter their behaviour as they adapt to new conditions within their environment, therefore, favouring those more flexible in their behaviours.

### *Anthropogenic disturbance*

The twenty first century has seen a substantial decline in global biodiversity that can be attributed to both direct and indirect impacts of human-induced disturbances (IPBES, 2019). The consequences of anthropogenic pressures are seen globally and felt by every organism, as they adapt their livelihoods to new landscapes. In the global south, competition between rural settlements and wild animals over natural resources is more intense as rural human populations typically incur higher associated costs with their land (Distefano, 2005). The geography of Suriname facilitates this intricate interplay between humans and wildlife's that unfolds across shared landscapes. Villages are small and sparsely scattered throughout dense forestry, illuminating complex dynamics of coexistence and interaction between diverse species. The gradual encroachment of human settlement into forested areas causes mass habitat loss (Hooper et al., 2012). Given humans' substantial capacity for land alteration through the use of large machinery, the behavioural responses of animals are expected to be more pronounced. Humans pose the most significant threat to animals as a predator whether it is intentional or not, as all human activities can cause fear within animals (Gaynor et al., 2018). Humans pose direct and indirect threats to prey when interacting with their environment. Direct threats include hunting, habitat destruction, pollution, and climate change, while indirect threats encompass habitat fragmentation, noise, and disturbance (Cruz et al., 2018; Ewart et al., 2024; Halmy, 2019; Suraci et al., 2021). Prey exhibit risk-induced trait responses, such as altering habitat use or modifying foraging behaviour, in response to the presence of predators (Kelleher et al., 2021). These changes in foraging behaviour due to perceived risk depend on both the composition of the predator community and the environmental context (Gálvez & Hernández, 2022). This is partly due to prey responding to individual cues, rather than a holistic assessment of threats (Orrock et al., 2004). All of these responses typically result in changes in morphology, physiology and behaviour, therefore a change in activity patterns is likely.

Edge effects, whereby a micro-ecosystem forms at the boundary of two habitats, are evident in all neotropical forests and are a result of highly fragmented agro-mosaic landscapes altering the structure of the forest (Tabarelli et al., 2008). Practices of deforestation and farming carried out by locals, typically on a small scale for their subsistence lifestyle, that creates the fragmented landscape. However, the altered land disrupts foraging pathways taken by animals as they complete their daily activities and potentially limiting their access to resources. These processes have indirect repercussions for humans that are not often correlated at the local level. The heterogenous landscape where humans are the apex predator, has led to species adapting their activity patterns on spatial and temporal scales to minimise human contact (Ewart et al., 2024). The fragmented landscapes with pockets of cultivated food are improving the efficiency of foraging for species. Crop raiders have learned how to take advantage of these landscapes by foraging in crop fields whereby food availability is abundant in space and time (Strum, 1994). This method conserves energy for species and prevents foraging in areas where natural habitats have been degraded or fragmented.

It is safer for prey to overestimate the risk of predation and reduce foraging effectiveness than it is to underestimate it and risk dying from predation (Mendes et al., 2020). The landscape of fear has a significant impact on how a species behaves, with the majority of animals adopting risk-avoidance

strategies in areas perceived as dangerous (Laundre et al., 2010). Spatial-temporal avoidance can be employed at various scales depending on the species and environment. However, there are important trade-offs, as reducing human interaction does not necessarily ensure foraging effectiveness and danger reduction (Mendes et al., 2020). This is in line with the risk allocation hypothesis, the theory that suggests that species concentrate their foraging activities during times of day associated with lower risk (Suselbeek et al., 2014). Ocelots are known to be sensitive to anthropogenic disturbance as they have relatively small home ranges for a predator, thereby indicating their reliance on an undisturbed habitat (Dillon & Kelly, 2008; Kolowski & Alonso, 2010). Oppositely, agoutis have been described as relatively resilient animals (Kataria, 2023), hence their capability to inhabit areas close to human settlement. According to Ewart et al. (2024), agoutis shift their activity patterns towards nocturnal hours in non-protected areas of forest, thereby confirming the significant effect of landscape alteration.

### *Seasonality*

As we observe the escalating weather patterns annually attributable to climate change, it is imperative to acknowledge the resultant impact on species behaviour. Suriname experienced an extreme flooding event in 2023, followed by a prolonged dry season with exceptionally high temperatures, causing a significant loss of crops. The pronounced contrast between seasons stresses the landscapes, exacerbated by climate change and can result in disruption of nutrient cycling and habitat loss (Sheldon, 2019). Moreover, the scarcity of wild food becomes more pronounced, enhancing the appeal of crop raiding. The wet season in Suriname coincides with crop harvesting and provides abundant access to water, facilitating food and water acquisition for species. In contrast, the dry season brings drought, where food availability is low and waterways dry up. This limits the opportunities and resources available, increasing intra and inter specific species competition, which can alter activity behaviour. Hofmann et al. (2016) revealed the activity patterns of peccaries in the Brazilian Pantanal showed a notable correlation with air temperature across all measured parameters, and the species markedly decreased their activity when the air temperature surpassed 35 °C. The combined indirect effect of reduced food availability and the direct effect of extreme weather are likely to influence activity patterns.

### Conceptual framework

This visualisation of the conceptual framework, figure 1, displays the relationships between the variables. Predation risk directly influences habitat type and vice versa as the risk differs depending on environment and different habitats may facilitate predation more so than others. Environmental factors also directly affect predation risk via extreme weather events inhibiting predation and increased anthropogenic presence deterring predators. Additionally, environmental factors directly affect crop raiding behaviour through reduced food availability. Predation risk and activity patterns both affect each other risk of predation drives changes in activity patterns which can then in turn further increase predation risk. Habitat type influences activity patterns as some habitats are deemed too risky to enter during some time frames. Finally, environmental factors affect activity patterns from avoiding human interaction and weathers patterns disturbing foraging times.

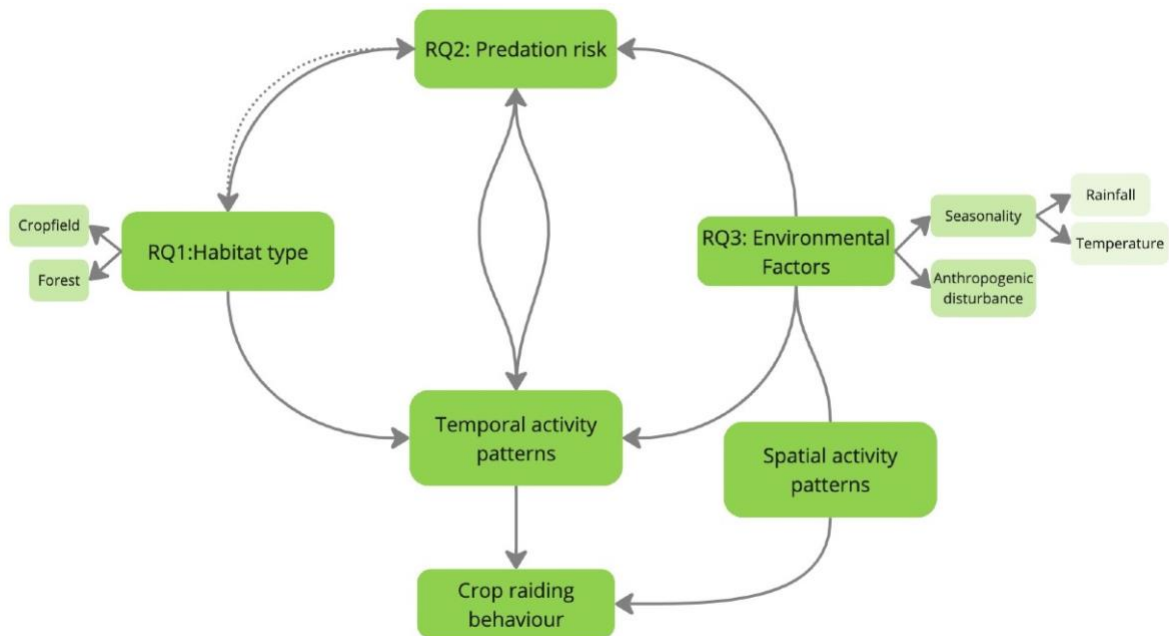


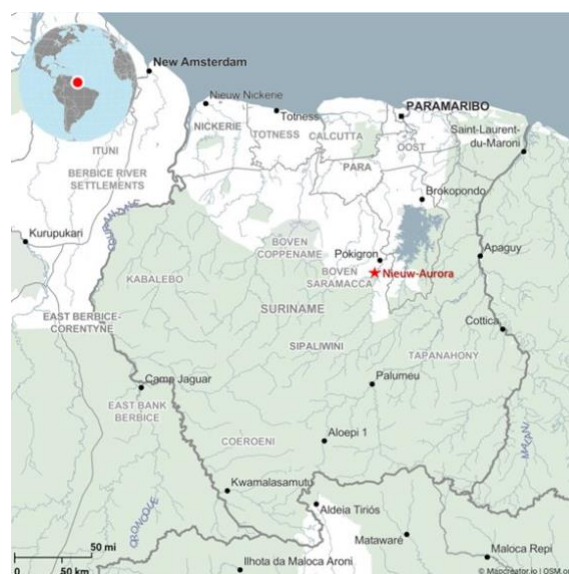
Figure 1: Schematic of research project designed by author.

# Methodology

## Study area

Suriname is located in the north-eastern corner of South America (map 1). The country has 93% tropical rainforest according to the Government of Suriname (2018); containing a wealth of biodiversity (Neugarten et al., 2020). The interior of Suriname is mostly tropical rainforest ecosystem, that is seasonally flooded in the wet season (Latawiec et al., 2014). For an extensive period, the national economy has been primarily influenced by primary and extractive industries, which heavily relies on intensive commercial timber and mineral extraction activities, encompassing bauxite and gold mining (Sieber et al., 2021). While there are logging activities within the region, the study area is not directly affected by these processes. This unique setting offers a dynamic platform to explore the multifaceted ways in which humans and wildlife interact,

This research project was carried out in a village called Nieuw Aurora on the Suriname River. Nieuw Aurora, situated in the heart of the Surinamese forest, contributes to a fragmented matrix of human habitats surrounded by wildlife and complex ecosystems, fostering a diverse array of flora and fauna. Antich-Homar et al. (2022) calculated the annual rainfall level in central Suriname as 1851 mm/year and the annual temperature as 27.6°C with a 4°C daily fluctuation. The rainy season, spanning from April to August, brings heavy precipitation and frequent thunderstorms, leading to overflowing rivers, lush vegetation, and high humidity. Conversely, the dry season, from September to March, saw significantly reduced rainfall, with occasional sporadic showers towards the end. As climate change worsens, these seasons became less predictable and more extreme, affecting ecosystem dynamics and therefore animal behaviour and activity. According to Distefano (2005), the main animals in South America responsible for crop damage are the Brazilian tapir (*Tapirus terrestris*), tayra (*Eira barbara*) and capybara (*Hydrochaeris hydrochaeris*); less harmful, but very frequent visitors are the collared peccary (*Tayassu tajacu*), paca (*Agouti paca*) and brown agouti (*Dasyprocta variegata*). The forest is a non-protected secondary forest, with many human-made paths throughout, used for access to crop fields and hunting. The population of approximately 3,000 traces its origins to the Dutch colonial era, during which slaves were transported from Africa.



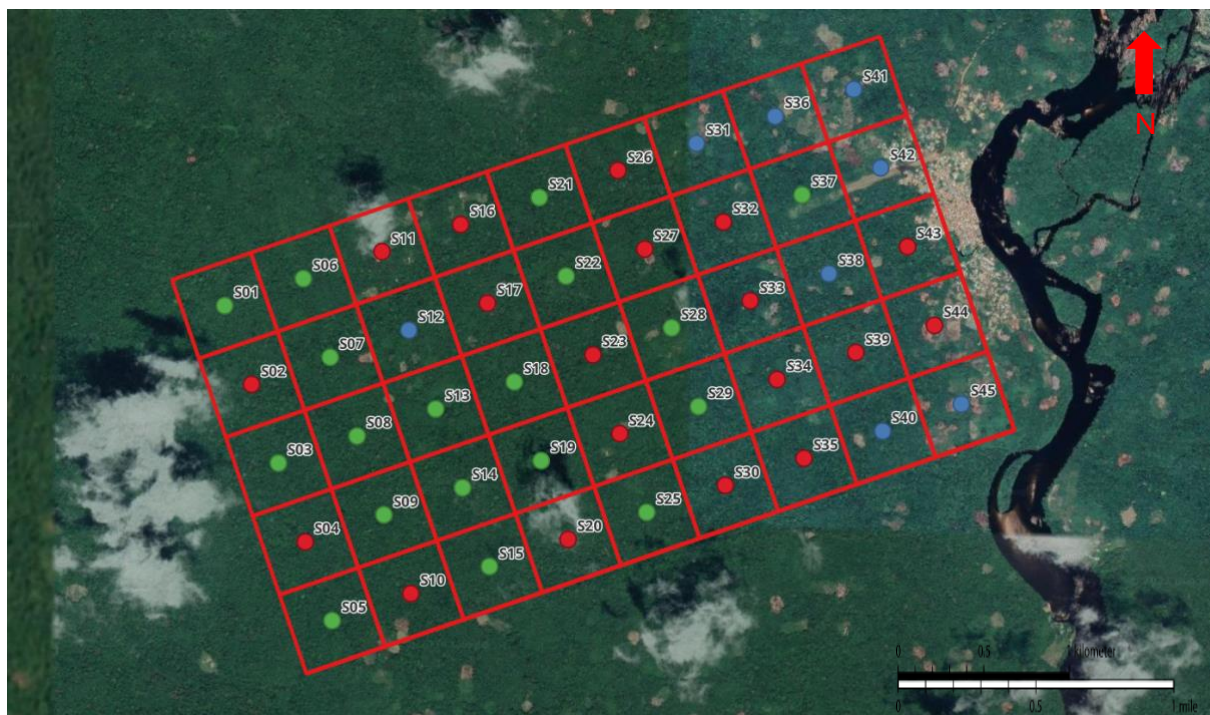
Map 1: Map of Suriname, highlighting the location of Nieuw Aurora.

### *Study design and data collection*

Camera traps are used in this study to reveal the drivers of activity patterns of crop raiding animals on a spatiotemporal scale. A systematic grid structure was designed to facilitate a random sampling approach to capturing animals on the camera. Moreover, a rectangular grid structure is commonly favoured due to its symmetrical, orthogonal coordinate system, which aligns well with the prevalent use of raster data in Geographic Information Systems (Birch et al., 2007). This grid size was selected to capture any gradient in human activity from the village towards the forest's interior. It was determined based on the dimensions of the area of interest from satellite pictures and field observations.

There were 45 grid cells spaced 500 meters apart, in a 5x9 larger grid system. The dimensions of the grid were 2500x4500 meters, with the short edge adjacent to the village, as visible in figure 2. In order to avoid a sampling bias, each cell is 250,000 square meters, which is larger than the agouti home range of 15,600–24,500 square meters for males and 13,400–19,700 square meters for females (Aliaga-Rossel et al., 2008). The ocelot's home range is larger, with an average of 26,000,000 square meters (Dillon & Kelly, 2008). Home range is a concept first described by Burt (1943), as the area covered by an individual during routine activities like foraging, mating, and caring for offspring.

The grid began in the village area and crop fields for 1.5 kilometres and a further 3 kilometres into the forest (map 2). The grid had 17 grid cells in the forest and 8 crop fields with a camera in each, as visible in figure 2 (Knippers, 2022), due to a limited number of cameras. Each station was classified as either crop fields or forest by determining the ecosystem that had over 50% cover in the grid cell. After processing, there were 12 stations with sufficient detection between agoutis, ocelots and humans. In the forested areas, the vegetation 4 metres in front of the camera lens was cleared for an unobstructed view.



*Map 3: Set up of grid structure displaying green centroids as grids with cameras present, red centroids where there were no cameras and blue where there was crop fields with cameras. Credit: Ronja Knippers.*

The camera traps were deployed from the 28<sup>th</sup> March 2023 to the 27<sup>th</sup> of October 2023. In October the cameras were serviced, however many had broken or were displaying faults, resulting in an average working time of 126.6 days per camera, with exact dates in appendix (2). Wet and dry season in Suriname were included, as well as the fruiting season, when foraging is at its maximum.

The camera trap model in use is the Browning Spec Ops Elite HP4, set to a medium picture quality (2-3MB). The camera traps have fast trigger speed and are highly sensitive, taking bursts of three pictures 0.3 seconds apart with one second between each burst. The lens of the camera is located 40 cm above the ground and orientated north between the angle 90° and 270°, to reduce potential glare from sunlight. There were halved flowerpots used as rain shields placed above each camera.

Data collection in the field entailed following the camera trap protocol (appendix 6) whereby a series of checklists are completed to ensure camera traps are functioning correctly. Firstly, the battery level was checked and replaced if necessary. Next, the SD card's memory space was checked and also replaced if there was less than 50% space remaining. Lastly, the camera position was altered if it has been disturbed and a final check to see if it is working correctly. SD memory cards and old batteries were stored in a box and brought back to camp.

#### *Data processing*

The pictures were uploaded to the Timelapse2 annotating software (Version 2.2.3.6). The species name and group size, date and time were recorded per picture. Empty pictures were discounted and pictures containing humans were counted then deleted. Timelapse2 create an excel spreadsheet output with every detection, which I then further processed to remove multiple entries that result from species loitering in front of the camera.

Pictures were then organised by location, timestamp and by species in Excel sheets. Agoutis were separated by station; however, ocelots and humans were grouped together because of insufficient detections. By insufficient detections, I refer to the significantly lower number of observations compared to agoutis, rendering a fair comparison infeasible. To prevent pseudo-replication of detections, a new detection of an animal is considered valid if it occurs at least one hour after the previous detection. Therefore, multiple detections of the same species within one hour are recorded as a single event. For this study, the presence of an animal was determined based on the timestamp of the last camera trap detection where the entire animal was visible in the frame. This approach aligns with the standard practice for medium-sized mammals, as recommended by Sollmann (2018) and supported by the majority of relevant literature. I categorized agouti detections by station to identify where most of the species are present, determined by the number of detections per station per day.

Initially, I measured the activity patterns of ocelots and humans for the entire grid rather than individually per station. Ocelots and humans cover larger areas per day due to their home range. Agoutis have significantly smaller home ranges compared to ocelots, which typically have larger spatial requirements as predators. Despite this, the abundance of agoutis is reflected in its position within the trophic levels, significantly outweighing the ocelot. Understanding the positionality of these species within their ecosystems is essential for describing their relationship.



## *Data analysis*

### RQ1: Agouti activity patterns in forest and crop fields

To examine the differences in activity patterns of agoutis between forest and crop field habitats, I measured their presence and time of presence in both environments. Given that agoutis are a prolific crop-raiding species, it is essential to determine how this behaviour influences their activity patterns. I employed the R package *Overlap*, developed by Ridout and Linkie (2009), for this analysis. Initially, I converted the times of activity detection into radians and used kernel density functions to plot them on a 24-hour scale, following the methodology of Ewart et al. (2024).

First, I plotted activity patterns individually per station to identify any irregular patterning or outliers. Second, I plotted activity patterns of agoutis per habitat type to assess whether agouti activity patterns differed between forest and crop field habitats. By plotting the activity patterns of both habitats together, I assessed whether there were significant differences in peak activity times. To statistically evaluate whether activity patterns differed between habitat types, I conducted a Wilcoxon Signed-Rank Test in R, treating it as a paired sample t-test to compare the activity patterns of agoutis, similar to the approach used in previous studies. The *W* statistic in the Wilcoxon signed-rank test is a measure used to compare paired data (I.C.A. & Ejuh, 2012). The overlap coefficient, ranging from 0 to 1 (where 0 indicates no overlap and 1 indicates complete overlap), indicates the degree of similarity between the two activity patterns (Ridout & Linkie, 2009).

### RQ2: Influence of predator presence on agouti activity patterns

To address the second research question, I conducted two analyses. First, I combined the data for ocelots and humans due to the insufficient data available for each species individually, making it challenging to analyse their separate influences on agoutis. Following this, I investigated the predator-prey dynamics by measuring the avoidance attraction ratios.

To analyse the impact of predators on the activity patterns of agoutis, I categorized the camera stations into those with predator presence and those without. I then separated the data into stations with predator presence and stations without predator presence. Following a similar approach to analysing habitat type differences, I plotted the time-activity graphs for agoutis at stations with predator presence and those without. Using the same methods described previously, I plotted the time-activity patterns, calculated the degree of overlap, and tested for significant differences between the activity patterns in these two contexts.

Avoidance-Attraction Ratios (AAR), hypothesized by Parsons et al. (2016), tests the rate at which prey avoided a particular location following the passage of a predator using the time series of detections from the camera. The interval time between predator and prey visits to the same station was measured to investigate the predatory influence on the activity patterns of prey. In this study, two time intervals, *T*<sub>1</sub> and *T*<sub>2</sub>, are defined: *T*<sub>1</sub> represents the time from the initial detection of an agouti to the subsequent detection of a predator, while *T*<sub>2</sub> represents the time from that first predator detection to the subsequent agouti detection. Even if multiple predators pass before the next agouti detection, *T*<sub>2</sub> is still measured from the first predator encounter. *T*<sub>4</sub>, the sum of *T*<sub>1</sub> and *T*<sub>2</sub>, indicates the time between

successive agouti detections with a predator detection between them, while T3 represents the time between successive agouti detections without a predator between them.

The attraction ratio ( $T2/T1$ ) and avoidance ratio ( $T4/T3$ ) were computed to quantify these behaviours. Wilcoxon signed-rank tests were performed to compare the attraction and avoidance ratios, as well as to test the differences between T2 and T1, and T3 and T4, to determine statistical significance. The paired nature of the test accounted for the fact that each ratio was calculated for the same locations or situations. The test results, indicated by the test statistic V and p-value, revealed whether there was a statistically significant difference between the attraction and avoidance ratios. A significant difference would suggest distinct prey behaviours in response to immediate and persistent predator presence, while no significant difference would indicate similar behaviours in these contexts.

### RQ3: Environmental and Anthropogenic factors on Spatial-temporal Patterns

For the third question, I firstly calculated and examined the variables individually to gain a comprehensive understanding of the data before constructing the regression models. This approach involved calculating descriptive statistics and visualizing each variable to identify patterns, outliers, and potential relationships. For the temperature and agouti detection time data, I plotted scatter plots and explored the distributions, which revealed possible non-linear relationships. Similarly, for the rainfall and detection time data, individual analysis helped in understanding the variability and distribution of rainfall values across different detection times. Additionally, I used the anthropogenic disturbance model to calculate the spatial gradient of human disturbance in the forest, providing further insights into the potential impact of human activities on the variables being studied. These preliminary steps were crucial in informing the choice of model and ensuring the accuracy and reliability of the subsequent regression analysis. By first visualizing and understanding the data individually, I was able to construct more appropriate and effective regression models that better captured the underlying patterns and relationships in the data.

## Anthropogenic disturbance model

The anthropogenic disturbance index was computed for all the station located in the forest that had presence of agoutis. The crop field camera stations were withheld because of crop fields being an indicator.

### *Variables*

The anthropogenic disturbance index (ADI), designed by Halmy et al. (2019), was the metric used to quantify human disturbance at each camera station in the grid. The model uses principal component analysis (PCA) to summarize the values of disturbance based on a set of indicators at each station. This value is then inserted into Halmy's equation (equation 1), where  $a_i$  represents the PC1 (first principal component) score for plot  $i$ ,  $a_{min}$  represents the minimum of the PC1 scores, and  $a_{max}$  represents the maximum of the PC1 scores.

$$ADI = 1 - \left( \frac{(a_i - a_{min})}{(a_{min} - a_{max})} \right)$$

*Equation 1: Anthropogenic disturbance index equation by Halmy et al. (2019).*

I adapted the indicators to reflect the environment and ecosystem in Niuew Aurora. I based them of personal observational notes, satellite data and literature related to measuring anthropogenic disturbance. Linear distances and buffer zones were measured using *high-resolution satellite data* on ArcGIS. Euclidean measurements were taken in Web Mercator map projection in ArcGIS Pro. Due to agouti's small home range, the distance to various different indicators, table 1, may have large effects on the species time activity patterns. Including a 200m buffer zone around the stations to assess crop fields was to account for stations further distances from other indicators. Road density is typically used as a disturbance indicator, however, there are no paved road in the region. As Kataria (2023) highlighted, despite disturbance in agouti's habitats, they can continue to thrive in reduced spaces. The values for the indicators were scaled and shifted to ensure all values were positive. The data was obtained using the ArcGIS

Indicator	Disturbance Characteristic	Justification
Distance to airstrip	Landuse change and noise will deter species from this area (Doherty et al., 2021).	The airstrip is a large piece of landed exposed land, planted with a monoculture grass, visible in figure 1 (from S42 to S37). It protrudes roughly 600m from the village into the forest. The effects of this airstrip on species may include heightened sense of fear due to proximity of open space and seldomly there is noise from aircraft.
Distance to village	Landuse change and high human presence will deter species from these areas (Doherty et al., 2021).	The village is an anthropogenic landscape, where the majority of tree have been removed. Houses are densely clustered together. There are a few streetlights situated throughout the village. Animals are typically shot if they roam into the village. These factors combined have resulted in a landscape of fear surrounding the village.
Proportion of crop fields in 200m buffer zone	Habitat modification can disrupt pathways taken by species (Kataria, 2023).	Crop fields are scattered around the stations, with higher density closer to the village. However, some are located further into the forest. Crop fields are hotspots for crop raiders.
Average number of human detections per operational day	Human presence causes agoutis to alter their foraging times (Kataria, 2023).	As there is no available data on paths within the jungle, the relative abundance will reveal which stations have high human traffic.

Table 1: The explanation of the indicators for the ADI, each with a justification of their use.

### Analysis

I assessed the principal component for each station to determine the most influential variable, identifying the highest weighted anthropogenic contributors. The PCA conducted on the disturbance indicators (distance to airstrip, distance to village, proportion of crop fields, and average number of humans) revealed that the first principal component (PC1) accounts for 83.8% of the total variance, indicating it captures the majority of the data's variability. The second principal component (PC2) adds an additional 12%, bringing the cumulative variance explained to 95.84%. The third (PC3) and fourth (PC4) components contribute minimally, with 4.05% and 0.1% respectively, indicating minimal returns in additional components. The variables contributing most to PC1 include distance to airstrip (0.525) and distance to village (0.508), while proportion of crop fields (-0.506) and average number of humans (-0.458) contribute negatively.

Using PC1, the ADI was calculated for each station, standardizing the disturbance levels across different stations. The ADI values range from 0.467 to 1, with higher values indicating greater disturbance. For instance, station 5 exhibits the highest ADI of 1, suggesting the highest level of disturbance, while station 28 has the lowest ADI of 0.47. The results were returned inverted despite ensuring there was a positive correlation between disturbance and the indicators. Therefore, this may have been a results of insufficient variables, as Halmy (2019) used a total of six, compared my use of four.

## *Seasonality*

Seasonality in the Surinamese rainforest follows a typical tropical pattern, marked by distinct wet and dry seasons. Therefore, I used the variables temperature and rainfall as indicators for seasonality. The camera trap device recorded the surrounding air temperature at the time the picture was taken.

### Rainfall

I was unable to obtain location specific rainfall data for Niuew Aurora. Instead, I utilized monthly precipitation data from Dondr.s, located in the centre of Suriname. Due to the unavailability of data from 2023, I used data from the years 2018 and 2019, as these were El Niño years, similar to 2023. I calculated the average monthly precipitation for these years and plotted this against the activity patterns of agouti to examine the potential relationship between rainfall and agouti activity. The spearman rank correlation test was used to identify whether there was a relationship present between the monthly rainfall data and the time activity patterns of agoutis.

### Temperature

The temperature ranged between 21°C and 33°C, with a mean of 25.44°C. This aligns with the average daily temperature in the coastal region is 27.6 °C, with an average daily fluctuation of 4 °C. The interior region exhibits a similar pattern but with even less annual variation in average temperatures (Antich-Homar, Hess, Solaun, Alleng, & Flores, 2022). The analysis aimed to determine the relationship between temperature and activity time for Agoutis using a polynomial regression model. Using the ggplot2 and Broom libraries in R, I transformed the Time variable to a 24-hour cycle. I then fitted a polynomial regression model of degree 3 to capture the non-linear relationship between Time and Temperature. The model's performance was evaluated by calculating the Root Mean Squared Error (RMSE) and R-squared values, which were found to be 1.2466 and 0.5061, respectively. These values indicate that the model explains approximately 50.61% of the variability in temperature, with an average prediction error of 1.2466°C. Finally, I visualized the data and the polynomial fit using ggplot2, confirming the non-linear trend in the relationship.

### Factors Affecting Spatial Patterns of Agoutis

To analyse all of the factors influencing agouti detections together, I employed a Generalised Linear Model (GLM). To add the spatial element to the analysis, I utilized the relative abundance of detections rather than just the raw detection counts. Relative abundance considers the proportion of detections in relation to the total number of observations, allowing for a more accurate representation of detection frequency across different locations. Pearce & Ferrier (2001) emphasize that modelling relative abundance, rather than just presence or absence, provides a more nuanced understanding of species distributions, which is crucial for effective conservation planning. Pearce & Ferrier (2001) studied environmental variables such as temperature, rainfall, and predator presence and highlighted how crucial they are for predicting the relative abundance of species. I preceded to standardise the predictor variables (Temperature, ADI, Rainfall, and Predator presence) using the scale function to ensure comparability and to aid in model convergence. Following this, I assessed the correlation matrix of the standardized predictors to check for multicollinearity, with no high correlations detected (i.e.,

all correlations were below the threshold of 0.8) calculated the Variance Inflation Factor using the `vif()` function in `r` from the `CAR` package (Fox et al., 2001).

The VIF values in table 2 below suggested that multicollinearity is not a significant issue in this dataset.

Temp	ADI	Rainfall	Predator
1.35783	1.615277	1.369151	1.184238

Table 2: Variance inflated factors for each variable in the `glmm`.

The correlation matrix, table 3, shows that there are some moderate correlations between pairs of variables, such as `Temp_s` and `ADI_s`, `Temp_s` and `rainfall_s`, and `ADI_s` and `predator`, but none of these correlations are extremely high (i.e., above 0.7 or 0.8), which further supports the lack of severe multicollinearity.

	Temp	ADI_s	Rainfall	Predator
Temp	1	-0.4296168	0.3597870	0.1485480
ADI	-0.4296168	1	-0.249791	-0.5011708
Rainfall	0.3597870	-0.2497912	1	0.2101437
Predator	0.1485480	-0.5011708	0.2101437	1

Table 3: Correlation matrix displaying the correlation coefficients for the variables in the `glmm`

Therefore, the combination of low VIF values and the moderate correlations between predictors indicates that multicollinearity is not a significant concern, allowing for reliable interpretation of the regression coefficients in the GLM analysis.

I proceeded to fit a generalized linear model (GLM) with Gaussian family to predict the relative abundance of the species, using the standardized predictors. The initial model indicated some heteroscedasticity, leading me to fit a weighted glm to address this. This approach assigns weights to each observation based on the variance of their residuals, reducing the influence of data points with higher variance. Specifically, I fitted the GLM using the `weights` argument in `R`, derived from the inverse of the squared residuals of an initial model. This method stabilizes the variance and improves the reliability of coefficient estimates. The weighted model showed a better fit, as indicated by a lower AIC and improved residual deviance. Predicted values from the model were plotted against observed values to visualize model performance using `ggplot2`. Finally, I used the `allEffects` function, from the `effects` package, to plot the effects of each predictor on the response variable, providing a comprehensive view of the relationships between predictors and relative abundance. This methodological approach ensures a robust and reliable analysis, accounting for multicollinearity, non-linearity, and outliers.

## Results

In this section, I present my findings on agouti activity patterns and their interactions with environmental factors in forest and crop-field habitats. I compared agouti activity in these habitats, revealing significant differences, and examined predator influence, finding potential trends but no statistically significant impact. I explored predator-prey dynamics to understand the influence of predator presence on agouti movements. Additionally, I assessed correlations between anthropogenic disturbance, temperature, and rainfall on agouti detection times and relative abundance. My analysis showed a significant non-linear relationship with temperature, while disturbance and rainfall had no significant effects. My generalized linear model indicated minimal and non-significant effects of predictors on agouti abundance.

In total there were 570 detections of agoutis, humans and ocelots between 21 stations out of the 26 station with cameras, see appendix. Agoutis had the most detections ( $n=511$ ) with an average of 39.3 detections per station ( $SD= 34.765$ ,  $min=0$ ,  $max= 160$ ). Humans and ocelots had an average of 1.35 and 1.11 ( $SD= 1.468$  &  $3.754$ ) respectively per station.

### *RQ1: Agouti activity patterns in forest and crop-field*

Both patterns exhibit bimodal characteristics (figure 2), featuring a prominent peak in the morning followed by a decline in activity during midday. Notably, in crop fields, activity peaks in the morning hours but maintains a relatively higher level during the midday period compared to the forest. Conversely, in forested areas, the initial peak in activity is less pronounced, with a subsequent decline during midday, albeit activity levels nearly matching those of the morning peak by evening.

The analysis of agoutis' activity patterns in a forest and crop field revealed significant differences. The overlap coefficient is 0.820147, indicating substantial overlap in the activity patterns between the two habitats. However, the Wilcoxon signed-rank test yields the results, ( $W=28550$  &  $p\text{-value}=0.02204$ ), suggesting that the differences in activity patterns between the forest and crop field are statistically significant. These results support the initial part of my hypothesis, indicating that the agoutis' activity patterns vary depending on the habitat. However, instead of shifting towards nocturnality, the change manifests as an altered diurnal activity pattern.

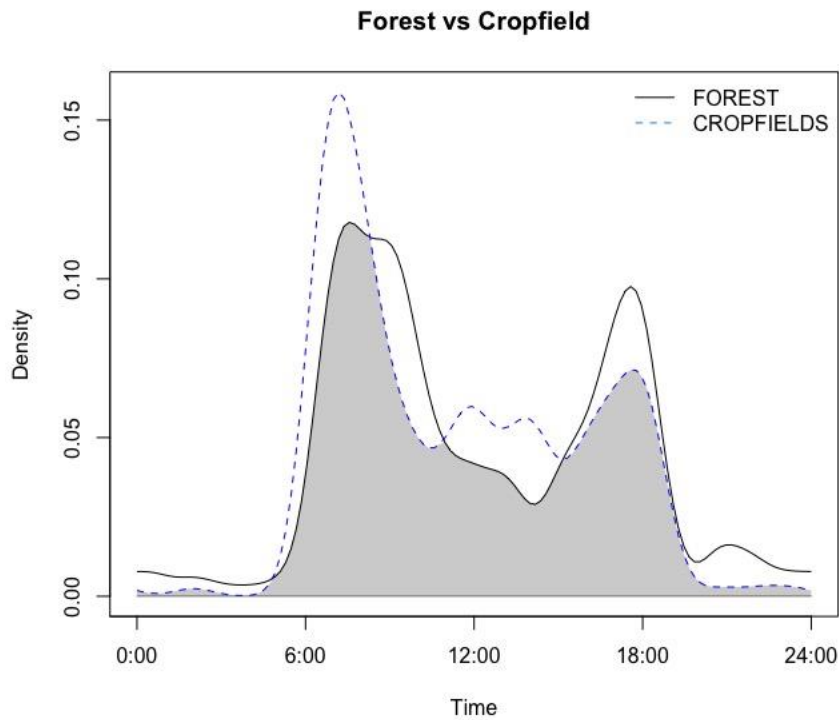


Figure 2: This overlap plot reveals the number of agouti detection plotted on a 24hr timescale. There were 273 detections of agoutis in the forest and 237 detections of agoutis in the crop fields.

#### RQ2: Predatorial influence of agouti activity patterns

The second question addressed the influence of predator on agouti activity patterns. Ocelot and human activity patterns were combined to wholly assess the effect of predators. The Wilcoxon test results ( $W = 1460$ ,  $p\text{-value} = 0.082$ ) suggest that there is no statistically significant difference in the overlap of agouti patterns between areas with and without predators. However, the  $p\text{-value}$  is below 0.1 indicates a potential trend that warrants further investigation. Additionally, the overlap coefficient of 0.7495181 suggests a moderate degree of overlap between the agouti patterns in the two areas. This value indicates similarity in the pattern distributions, implying that the presence of predators does not drastically alter the agouti pattern overlap. However, the  $p\text{-value}$  being slightly above the threshold might warrant further investigation for activity patterns of agoutis.

Figure 3 illustrates that in the presence of predators, agoutis exhibit distinct peaks in activity, with the highest peak occurring around early morning and another smaller peak in the late afternoon. In contrast, in areas without predators, agoutis display a more evenly distributed activity pattern throughout the day, with a noticeable peak in the morning. The results align with my hypothesis in that prey species adjust their activity patterns in areas of low predator activity, although the changes are not significant.



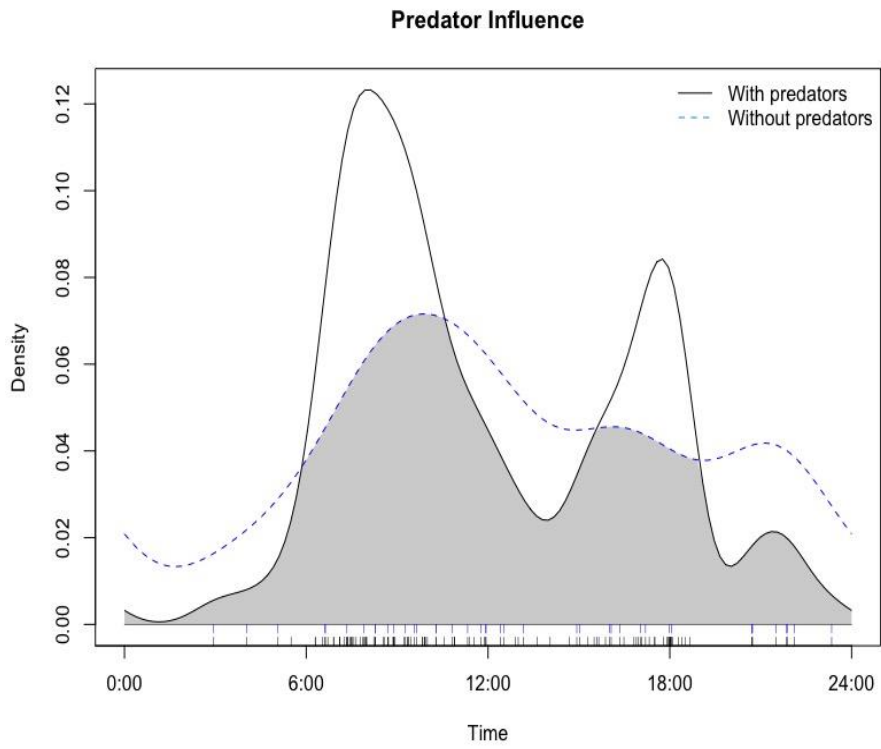


Figure 3: Overlap graph displaying agouti density at stations with () and without () predator presence.

## Predator prey dynamics

In examining predator-prey interactions, the analysis of two key time intervals aimed to understand the influence of predator presence on agouti movement patterns. A Wilcoxon signed-rank test ( $p$ -value = 0.875) was performed to compare the attraction ( $T2/T1$ ) and avoidance ratios ( $T3/T4$ ), which are defined as the time intervals between successive prey detections with and without predator presence, respectively. Since the  $p$ -value exceeds the common significance thresholds of 0.05 and 0.01, the null hypothesis cannot be rejected. This indicates that there is no statistically significant difference between the attraction ratio and the avoidance ratio. Therefore, the analysis does not provide sufficient evidence to suggest that the prey's attraction behaviour (time between successive detections with a predator present) significantly differs from their avoidance behaviour (time between successive detections without a predator present). Additionally, another Wilcoxon signed-rank test ( $p$ -value = 0.4258) was conducted to compare the time intervals between successive prey detections with a predator present ( $T2$ ) and without a predator present ( $T1$ ). Similar to the previous test, the  $p$ -value indicates no statistically significant difference between these time intervals. Thus, the analysis does not support the hypothesis that the time interval between successive prey detections differs based on predator presence. The bar chart (figure 4) illustrating these intervals shows that  $T3$  is longer than  $T4$ . However, the  $p$ -value of 0.875 suggests no statistically significant difference between the time intervals of successive prey detections without a predator ( $T3$ ) and with a predator ( $T4$ ). This finding suggests that the presence of predators does not significantly influence agouti behaviour in terms of detection frequency (intervals) when predators are nearby.

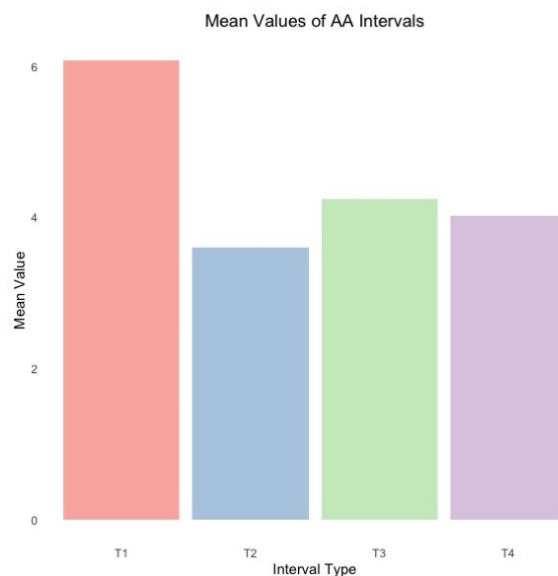


Figure 4: Bar chart displaying the mean of each avoidance-attraction interval times.

### *Q3: Anthropogenic and environmental variables on agouti spatial-temporal patterns*

#### Human disturbance gradient

The ADI results (appendix 1), display a gradient in anthropogenic disturbance, with the station at the furthest points on the grid having the largest values. Additionally, the stations at the periphery of the grid have larger values due to their closer distance from the airstrip and village, as these indicators had the most significant effect in the PCA test. The PCA test highlights that the airstrip and village proximity are major contributors to anthropogenic disturbance, overshadowing other potential factors. This suggests that human activities associated with these areas, such as habitation and related infrastructure, have a pronounced impact on the surrounding environment. The gradient in ADI values underscores the spatial variation in human influence, with the more interior and peripheral stations experiencing the highest levels of disturbance.

#### Impact of rainfall and temperature on activity patterns of agoutis

The Spearman's rank correlation test conducted to examine the relationship between agouti detection times and monthly rainfall values resulted in a Spearman's rho of 0.0157548 with a p-value of 0.7955. This very weak positive correlation coefficient, close to zero, indicates no relationship between the two variables. Moreover, the high p-value suggests that the observed correlation is not statistically significant, implying that the relationship is likely due to random chance. Therefore, based on this analysis, monthly rainfall does not appear to have a significant impact on agouti detection times, and other factors not captured by the rainfall my data are likely influencing agouti activity patterns. This result contradicts my hypothesis, as rainfall appears to not affect the activity patterns of agoutis.

The analysis of the polynomial regression model reveals significant insights into the relationship between temperature and Agouti detection times. The model was found to be highly significant, with all polynomial terms (first, second, and third order) showing p-values less than 0.001, indicating strong evidence against the null hypothesis of no effect. The model explained approximately 50.61% of the variability in temperature ( $R^2 = 0.5061$ ), with a Root Mean Squared Error (RMSE) of 1.2466, suggesting a reasonable fit. The residual analysis confirmed the appropriateness of the model, with residuals showing no apparent patterns and adhering to the assumptions of normality and homoscedasticity. These results indicate a significant and complex non-linear relationship between temperature and Agouti detection times, with the polynomial regression model effectively capturing the observed variations. In figure 5, the blue curved trend line reveals that as detection time progresses (from about 0.2 to 0.5 radians), there is a notable increase in temperature, reaching peaks of around 28°C. This suggests that during this mid-range of detection times, agoutis are more active at higher temperatures. Initially, as detection time increases, temperature also rises slightly, followed by a more significant increase, peaking before decreasing again towards higher detection times. These results counter the hypothesis I proposed, whereby agoutis would reduce their activity during the hot hours of the days. Instead the agoutis might be more frequently detected during certain temperature ranges, possibly due to their behavioural adaptations or ecological preferences.

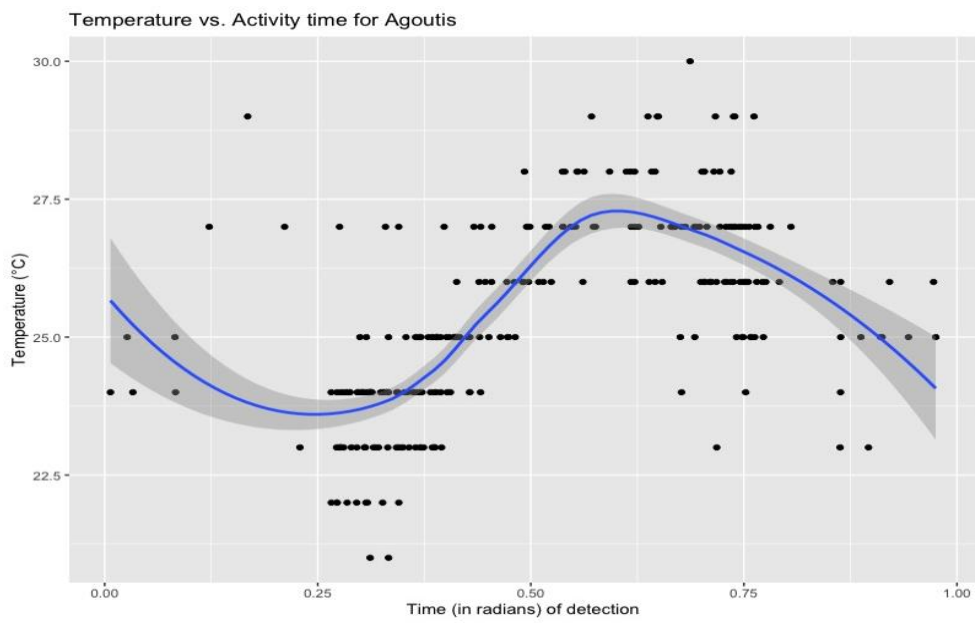


Figure 5: Scatter plot of temperature and detection times of agoutis with curved trend line

## Environmental and anthropogenic variables effect on spatial patterns of agoutis

Agoutis play a vital role in tropical forest ecosystems and their activity patterns and population dynamics are influenced by a variety of environmental factors, including temperature, anthropogenic disturbance, predator presence, and rainfall. The generalised linear model (GLM) results indicate the relationship between the relative abundance of agoutis and the standardized predictors (Temperature, ADI, Predator presence, and Rainfall). The GLM used for predicting relative abundance based on temperature (Temp\_s), anthropogenic disturbance index (ADI\_s), predator presence (predator\_s), and rainfall (rainfall\_s) shows several key findings. The intercept is significant indicating a meaningful baseline relative abundance when all predictors are at their mean values. However, the individual predictors are not significant, see table 4 below. This suggests that these environmental factors do not have a strong influence on relative abundance in this dataset. The lack of significant predictors implies that the variance in relative abundance is not well explained by these environmental variables. The weighted model's residual deviance is 8.636 on 7 degrees of freedom, with an AIC of 20.04, suggesting a better fit than the null model. Despite the improved fit, compared to non-weighted GLM, most predictors remain non-significant, with only the intercept showing strong significance. The marginal significance of temperature suggests it may influence relative abundance; however, further investigation with additional data is necessary to confirm this effect.

Table 4: Weighted glm results, with \*\* indicating strong evidence against the null hypothesis

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	0.52653	0.1492	3.529	0.00961 **
Temp_s	-0.16853	0.08681	-1.941	0.09334
ADI_s	-0.01424	0.19974	-0.071	0.94517
predator_s	0.1427	0.13961	1.022	0.34074
rainfall_s	-0.09567	0.12598	-0.759	0.4724

The effect plots, figure 6, for the generalized linear model examining the influence of temperature, anthropogenic disturbance index, predator presence, and rainfall on relative abundance reveal minimal and non-significant effects for all predictors. The slight negative trends in temperature and rainfall indicate that as these variables increase, relative abundance slightly decreases, while the slight positive trend in predator presence suggests a minor increase in relative abundance. The anthropogenic disturbance index also shows a minor negative effect. However, the wide confidence intervals for all predictors suggest low confidence in these effects, indicating that none of the environmental variables significantly influence relative abundance in this dataset. The results do not support my hypothesis, as they indicate that the relative abundance of agoutis is not significantly influenced by anthropogenic disturbance, predator presence, temperature, or rainfall, contrary to the expectation that these factors would reduce relative abundance in areas with high human impact and predatorial influence.

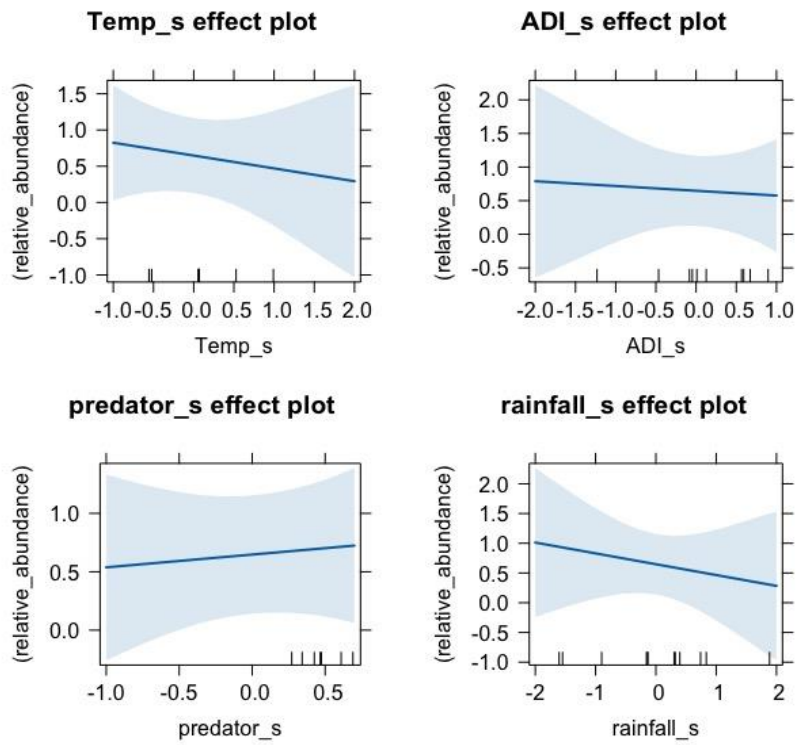


Figure 6: Four effect plots displaying the relationship between explanatory and response variables from the GLM.

# Discussion

This research investigated spatial-temporal patterns of crop-raiding animals, specifically ocelots and agoutis, aiming to unravel the intricate drivers behind their behaviours. By examining both environmental and anthropogenic factors, the study sought to provide a comprehensive understanding of these patterns, which is crucial for developing effective conservation strategies. The following discussion synthesizes the study's findings, highlighting the key influences on the activity patterns of these crop raiders and their implications for sustainable human-wildlife coexistence. Understanding activity patterns is critical as they reflect the animals' strategies to balance energy acquisition and predation avoidance (Suselbeek et al., 2014). This section summarises and discusses the main results, in chronological order of the research questions. While the findings of this research are limited, there are several key takeaways that offer valuable insights into the behaviour of crop-raiding animals like ocelots and agoutis.

## *Differences in Agouti Activity Patterns Between Forest and Crop Fields*

This research identified significant differences in agoutis' activity patterns between forest and crop fields, with higher morning activity in crop fields and increased evening activity in forests. Kataria (2023) observed that agoutis adjust their foraging behaviour in response to human presence, reducing foraging during peak human activity times to avoid interactions. This pattern could be attributed to decreased human presence in crop fields during the early hours of the day. As one of the most damaging crop raiders, agoutis are drawn to anthropogenic food sources, which alters their spatial distribution and influences their temporal activity (Abrahams et al., 2018). They exploit times when human presence in crop fields is low to optimize their crop raiding, potentially explaining the initial peak in the early morning and the small peak at midday (lunchtime) when they typically return to their burrows (Ferregueti et al., 2018; Suselbeek et al., 2014). In areas with higher food abundance, such as crop fields, agoutis demonstrate an even more pronounced avoidance of high-risk periods, thus their increased density in the early mornings before humans enter (Suselbeek et al., 2014). Therefore, the agoutis' temporal activity patterns reflect an adaptive strategy to maximize food intake while minimizing risk. The bimodal peak is characteristic of agouti activity patterns (Ferregueti et al., 2018; Suselbeek et al., 2014). These morning and evening peaks are visible in all forest stations (appendix []). According to Ferregueti et al. (2018), agoutis are most active shortly after sunrise and just before sunset, possibly to avoid the midday heat. This pattern is consistent with the need to balance energy expenditure and predator avoidance, particularly in the dense and competitive environment of tropical rainforests.

## *Adaptive Behaviour of Agoutis in Response to Predator Risk*

The second question aimed to investigate the impact of predator presence on the activity patterns of agoutis. In the presence of predators, agoutis exhibited distinct peaks in activity, with a prominent peak in the early morning and a secondary peak in the late afternoon. However, in the absence of predators, agoutis do not exhibit the traditional bimodal peak, insinuating that this pattern is a direct response to predator activity. Research on the agouti and ocelot relationship suggests that agoutis reduce their activity during sunrise and sunset, the peak activity times of ocelots (Suselbeek, 2014). However, this study portrays a different scenario, where agoutis remain active during these times in the presence of predators and reduce their activity in predator-free areas. Suselbeek (2014) noted that

this observation was particularly true during times of high food abundance; however, this study does not differentiate between times of high and low food abundance. Interestingly, in predator-free areas, agouti activity is more evenly distributed throughout the day, with a noticeable morning peak, indicating that the absence of predators allows for a less constrained foraging schedule. Therefore, this research cannot confirm nor deny the risk allocation hypothesis, which predicts that prey animals will concentrate their foraging activity during times of relatively low predation risk. These findings suggest that while agoutis do adjust their activity patterns in response to predator presence, the adjustments are not drastic enough to create a statistically significant difference in overall pattern overlap. However, the trend indicated by the p-value and the distinct peaks observed in the presence of predators highlight the need for further investigation. These results challenge the current narrative in the literature that agoutis adjust their activity patterns primarily to minimize predation risk. Suselbeek (2014) found that agoutis are less active during periods of high predator activity, specifically from sunset to sunrise when the risk from ocelots is highest. Gálvez and Hernández's (2022) study further revealed that agoutis exhibited lower seed dispersal and pilferage rates in areas with a high density of ocelots, indicating a reduction in overall activity in regions with higher predation risk. This adaptation suggests that agoutis focus their activities in safer locations to avoid predators. The absence of strong morning and evening peaks in agouti activity in the absence of predators could potentially be explained by their reduced vigilance, where they feel more comfortable remaining out of their burrows for longer periods. This aligns with concepts from the landscape and ecology of fear, which examine how the time and energy diverted to avoiding predators can reduce fitness and reproductive output (Clinchy et al., 2013; Landré et al., 2010). Prey may invest less in mating displays or parental care if they need to remain vigilant against predators. Additionally, high-risk perception can increase the production of stress hormones, reduce feeding efficiency, and severely affect reproductive success (Orrock et al., 2004). These symptoms can significantly impact survival rates, leading to substantial reductions in population numbers.

#### *Analysis of Predator-Prey Tracking Times and Behavioural Adjustments*

The avoidance-attraction ratios reveal predator-prey dynamics and how behaviour is modified in response to each other. The T2/T1 ratio indicates both predator attraction and prey avoidance, while T4/T3 reflects solely prey avoidance. These ratios help understand prey behaviour post-predator passage versus persistent presence, providing insights into habitat use and movement patterns. Randler and Kalb's (2020) study show that nocturnal and diurnal rodents adjust their activity patterns and vigilance to avoid predators, with environmental cues playing a significant role. Despite insignificant results from avoidance-attraction ratios, the predator-prey tracking times (T1 & T2) show differences in predator-prey following behaviours (Figure 4), aligning with Swinkels et al.'s (2022) findings on temporal overlap between ocelots and their prey, particularly during dawn and dusk. This synchronization suggests predators adjust activity to coincide with prey. The T4 & T3 analysis illustrates that predator presence influences prey behaviour, with more frequent detections (shorter intervals) when predators are nearby. However, statistical tests indicate that predator presence does not significantly alter prey detection intervals, suggesting prey may become more active or cautious near predators. This could be due to agoutis becoming more active or moving more cautiously when predators are present, resulting in shorter intervals between detections. Conversely, in the absence of predators, agoutis might move more freely and less frequently, leading to longer intervals between



successive detections. This pattern highlights the strong impact of predator presence on prey activity and spatial dynamics (Swinkels et al., 2022).

### *Influences of Anthropogenic Disturbance and Environmental Variables on Agouti Activity Patterns*

This study identified a gradient of anthropogenic disturbance decreasing with distance into the forest, showing higher human impact near forest edges. Ewart et al. (2024) noted behavioural changes in 5 out of 6 mammals in response to disturbances in non-protected areas, emphasizing the significance of edge effects. However, the statistical test revealed no significant relationship between time activity patterns and ADI results. Contrarily, Norris et al. (2008) found that agoutis' occurrence is not significantly influenced by the distance from the forest edge, likely due to their small home ranges and generalist diet, allowing them to tolerate changes near edges. To underscore the behavioural plasticity of agoutis, Kataria (2023) observed significantly more agoutis near human settlements. Rodrigues et al. (2023) suggest that in fragmented forest areas, humans may inadvertently protect prey species from predators, creating a "human shield" effect. This indicates that human activities, especially in areas with low forest integrity, can significantly alter wildlife interactions and spatial patterns. Although this extends beyond the current research scope, it offers valuable insights due to similar environmental characteristics, such as human-altered landscapes and the agoutis' lack of response to human presence. There was a strong correlation between temperature and agouti activity, with higher activity levels observed at moderate temperatures. Magalhães and Srbek-Araujo (2019) discuss the influence of temperature on the circadian rhythms of agoutis, noting that environmental temperature impacts their energy levels, thereby moderating their activity patterns. Additionally, while no significant relationship was found between rainfall and activity in this study, this result may stem from insufficient or inadequate data, rather than the absence of an effect. Previous research by Maestri and Marinho (2014) indicated that rainfall significantly increased rodent activity in neotropical forests. They concluded that increased movement during rainy periods likely results from immediate adverse effects of rain, such as wet fur and potential destruction of shelters, prompting rodents to seek new shelters or resources. Thus, rainfall should not be dismissed as a potential influencer of activity patterns due to limitations within this study.

### *Assessing the Influence of Environmental Variables on Agouti Abundance*

The GLM analysis intended to identify relationships between agouti abundance and environmental variables. The marginal significance of temperature ( $p = 0.09334$ ) suggests a potential influence on relative abundance, though not definitive. Effect plots revealed minimal and non-significant effects for all predictors, with slight negative trends in temperature and rainfall, and a minor positive trend in predator presence. In Pearce & Ferrier's (2001) findings, they revealed slight negative trends between both temperature and rainfall with agouti abundance, and a minor positive trend for predator presence, though none of these effects were statistically significant. They also encountered wide confidence intervals indicating considerable uncertainty, suggesting that the true impacts of these variables could vary. Hence, while these environmental variables—temperature, rainfall, and predator presence [and human disturbance for this study]—might intuitively seem influential, the current evidence, including the marginal significance and wide confidence intervals observed by Pearce & Ferrier (2001), indicates that their impacts on species abundance are not definitively established.

### *Limitations*

This research approach, which analysed various factors together, presents several challenges. Firstly, relying on external sources for rainfall data compromises the coherence of the results, as this source may be not specific to the study environment. Measuring the activity patterns of animals, which are highly specific to their environment, against generalized data like rainfall can affect the significance of the findings. The limited dataset also hindered the study's depth, with broken camera traps interfering with spatial data collection, further constraining the research. The presence of outliers and a broad spread of data points reflect the limitations of the GLM in capturing true variability. The use of a more robust glm could have revealed the information of the spatial aspect, highlighting which station are more sensitive to environmental variables and in turn how this affects the relative abundance of species. Additional research with larger sample sizes, more comprehensive data collection, and consideration of other factors—such as food availability, canopy density, habitat structure, moonlight, and inter-species interactions—is necessary to better understand the dynamics influencing the relative abundance of agoutis across landscapes. The sample size and data variability could affect the power of statistical tests, potentially masking subtle behavioural differences. Unaccounted environmental factors and specific characteristics of predator-prey interactions in the study area may have influenced the results. Therefore, expanding the study to include additional behavioural metrics and larger sample sizes could provide deeper insights into these dynamics. A longer study period would allow for the evaluation of changes over time, providing more robust data on the activity patterns of the animals.

### *Future Research & Ecological Implications*

This research primarily found that agoutis exhibit different activity patterns across various habitats, particularly in crop fields, demonstrating how animals adjust their behaviours to minimize anthropogenic interactions. This finding warrants further investigation to understand how other crop-raiding animals similarly alter their activity patterns. Additionally, future research should consider species that do not engage in crop raiding, as their responses to anthropogenic disturbances might differ significantly. The consequences of these behavioural adjustments for both agoutis and people are multifaceted. For agoutis, modifying activity patterns can help avoid human encounters, reducing the risk of conflict or harm. However, these changes might also affect their natural behaviours and stress levels, potentially impacting their overall health and reproductive success. For people, understanding these behavioural adjustments can inform better management and mitigation strategies to reduce crop damage and promote coexistence. Despite this study's limitations, it underscores the critical need for comprehensive investigations into the factors influencing the activity patterns of these animals. Future studies should aim to utilize larger sample sizes and ensure detailed measurement of environmental variables to draw more robust conclusions. By understanding the specific environmental and anthropogenic factors affecting agouti behaviour, conservationists can develop targeted strategies to mitigate human-wildlife conflicts, such as crop raiding. Effective management plans should account for the adaptability of species like agoutis, promoting habitat conditions that support their natural behaviours while reducing human-wildlife conflicts.

Edelblutte et al. (2023) discuss the integration of animal agency into wildlife conservation and management (WCM). This perspective challenges traditional WCM practices that often view animals through a lens of rigid behaviours and idealized wildness, neglecting the complexity of human-animal

relationships. By acknowledging animals' individuality, social learning, and capacity for culture, conservation strategies can become more adaptive and inclusive. The ultimate goal is to foster sustainable coexistence, ensuring the conservation of wildlife populations alongside human agricultural practices, nurturing healthy human-wildlife relationships. Future research should explore specific behaviours and environmental factors influencing these patterns, considering additional variables such as food availability, habitat structure, and inter-species interactions. This deeper understanding could offer more comprehensive insights into the adaptive strategies of agoutis in response to predation risk. Moreover, Suraci et al. (2021) found that only 33% of mammal species studied exhibited reduced occurrence and activity in response to increased human presence, while 58% were positively associated with increasing levels of human disturbance. These results highlight the nuanced and varied responses of wildlife to human activities, underscoring the importance of species-specific studies to understand the full spectrum of wildlife responses to environmental changes.

## Conclusion

This research delved into agouti activity patterns to understand complex behavioural drivers. Significant differences were found between forested areas and crop fields, with increased activity in crop fields during midday due to reduced human presence. Agoutis' bimodal activity pattern, characterized by morning and evening peaks, reflects their need to balance energy expenditure and predator avoidance. Targeted conservation strategies should account for species adaptability, promoting habitat conditions that support natural behaviours while mitigating human-wildlife conflicts. This approach is essential for nurturing healthy human-wildlife relationships and conserving wildlife populations alongside agricultural practices.

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# Appendix

## Appendix 1

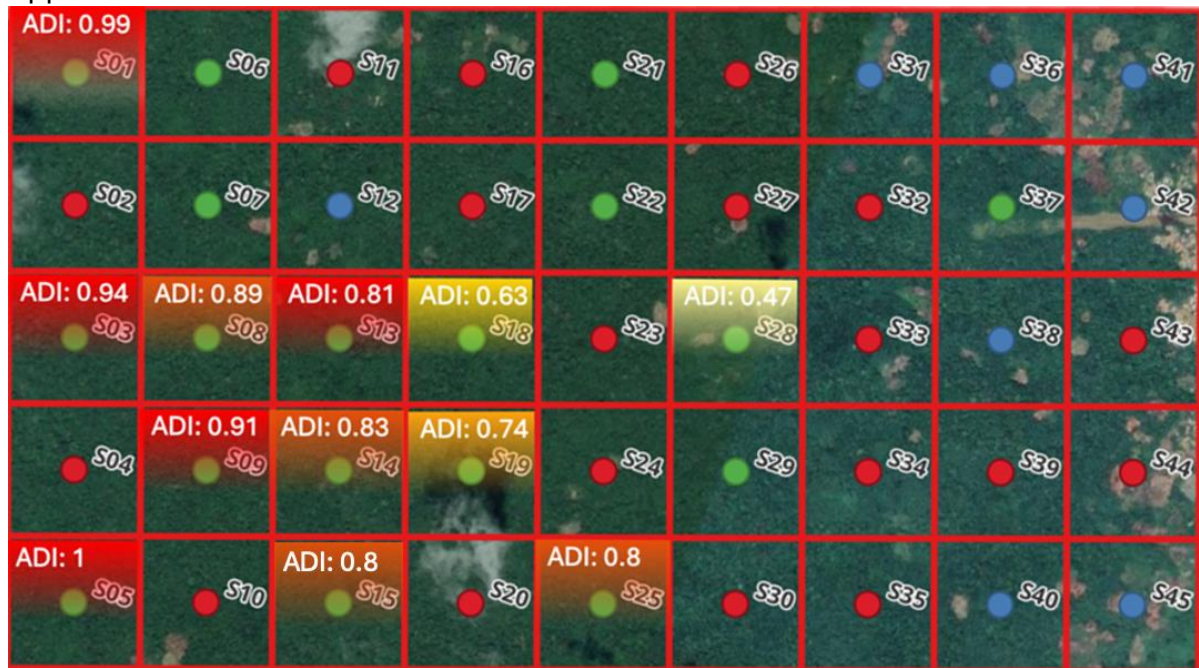


Figure 7: ADI results printed on the grid cell where it was calculated, with gradient in colour displaying gradient in human disturbance.

## Appendix 2

Table 5: Agouti, ocelot and human detection per station and habitat

Habitat	Station	Agouti	Ocelot	Human
forest	nas01	9	1	0
forest	nas02	na	na	na
forest	nas03	34	0	3
forest	nas04	na	na	na
forest	nas05	24	1	0
forest	nas06	4	0	0
forest	nas07	na	na	na
forest	nas08	69	3	0
forest	nas09	32	5	0
forest	nas10	na	na	na
forest	nas11	na	na	na
cropfield	nas12	17		0
forest	nas13	13	1	0
forest	nas14	37	4	0
forest	nas15	11	0	0
forest	nas16	na	na	na
forest	nas17	na	na	na
forest	nas18	12	2	1
forest	nas19	18	0	0
forest	nas20	na	na	na
forest	nas21	na	na	na
forest	nas22	na	na	na
forest	nas23	na	na	na
forest	nas24	na	na	na
forest	nas25	3	0	0
forest	nas26	na	na	na
forest	nas27	na	na	na
forest	nas28	15	0	1
forest	nas29	na	na	na
forest	nas30	na	na	na
forest	nas31	1	2	5
forest	nas32	na	na	na
forest	nas33	na	na	na
forest	nas34	na	na	na
forest	nas35	na	na	na
cropfield	nas36	20	1	16
cropfield	nas37	160	0	0
cropfield	nas38	na	na	na
cropfield	nas39	na	na	na
cropfield	nas40	na	na	na
cropfield	nas41	na	na	na
cropfield	nas42	39	0	0
cropfield	nas43	na	na	na
cropfield	nas44	1	0	0
cropfield	nas45	3	0	0
avg		522	1.07142857	1.53333333
SD		34.765	1.468	3.754

Appendix 3

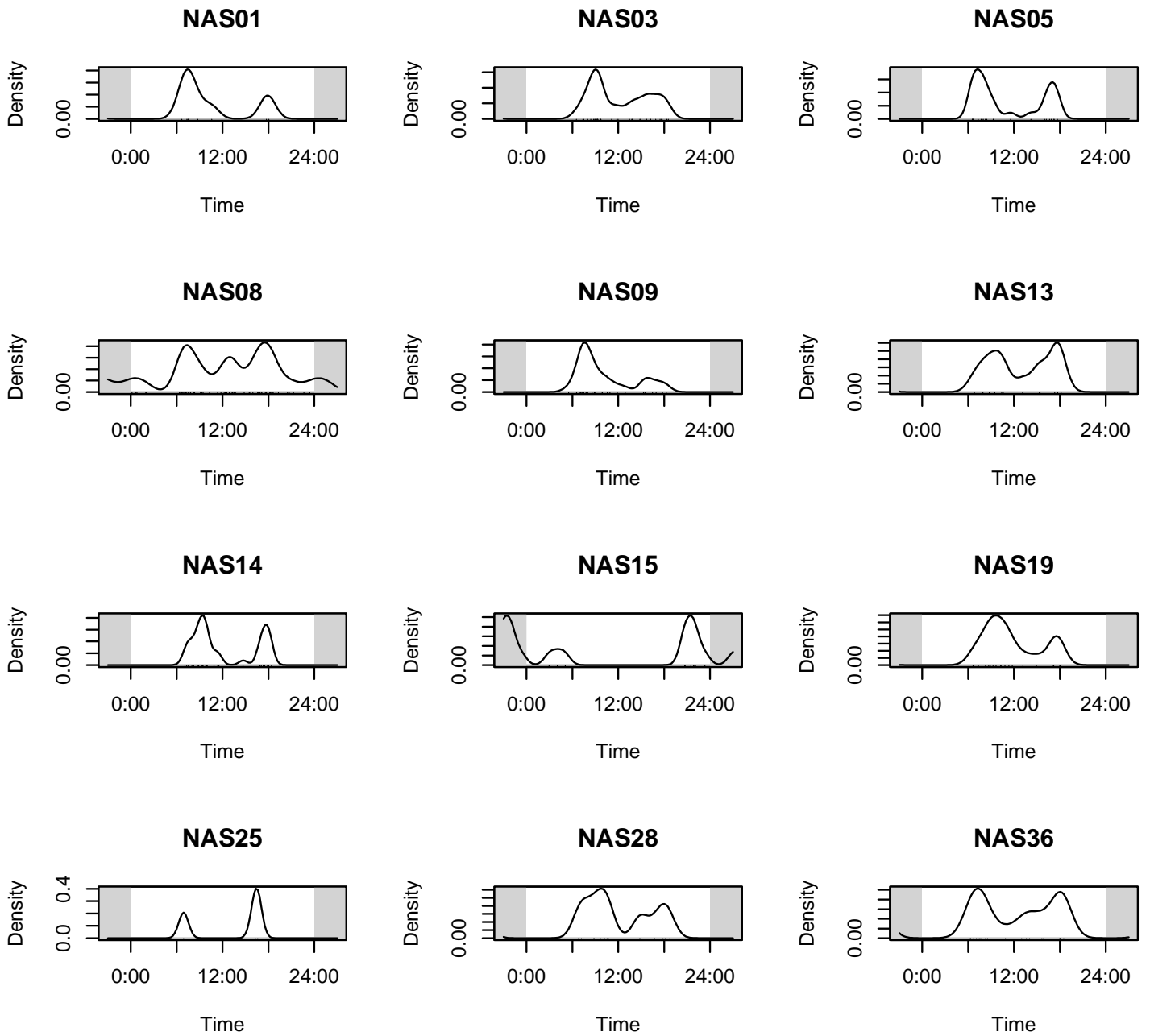


Figure 8: Activity patterns of agoutis for each station

## Appendix 4

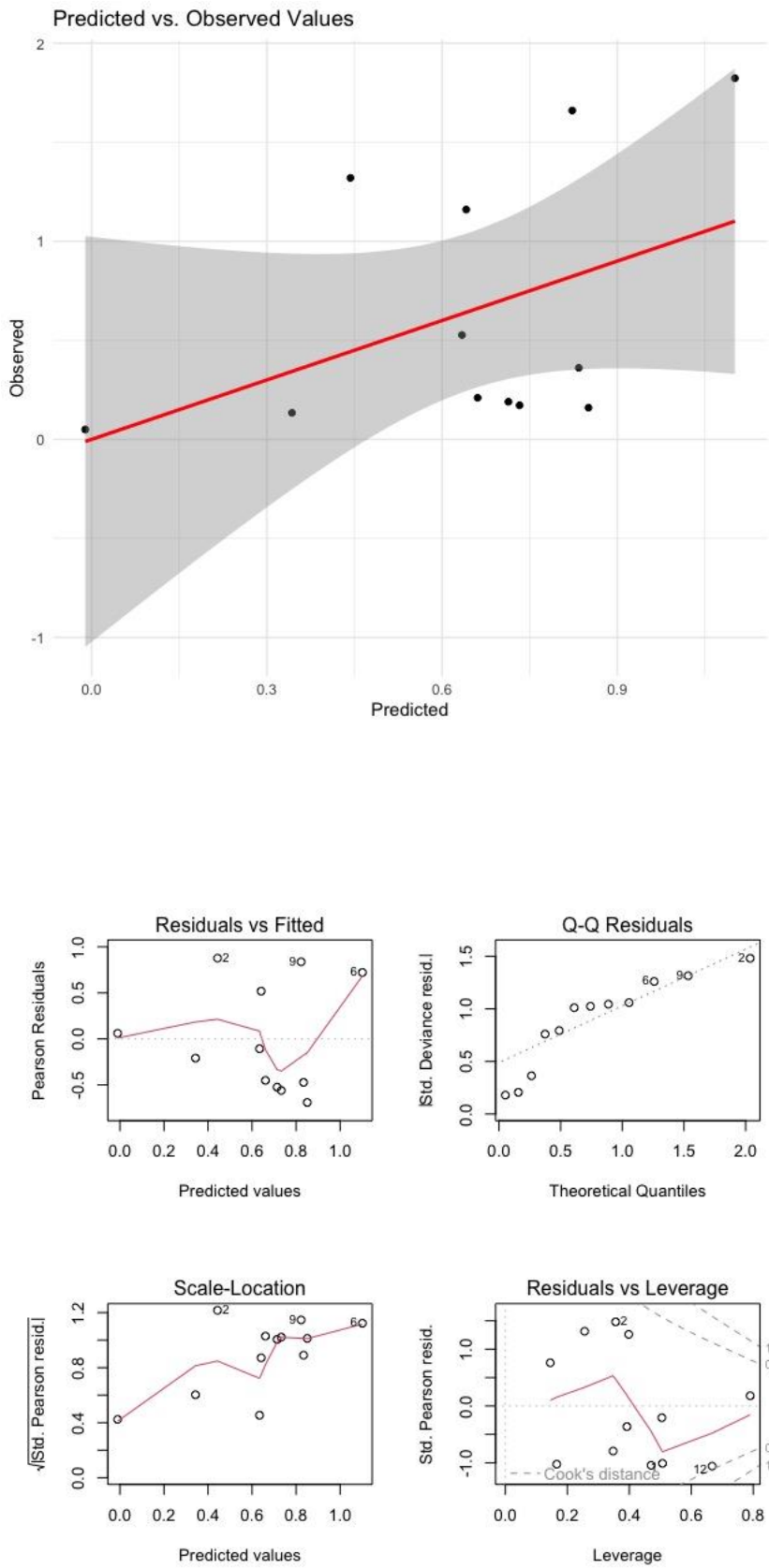


Figure 9: Predicted vs observed values in upper graph and diagnostic plots in lower plots, both from GLM

## Appendix 5

Code:

### Agouti and human overlap plots

```
library(overlap)

# time to radians
timeRad1 <- human_data$Time * 2 * pi
timeRad2 <- a_NAS01$Time * 2 * pi
timeRad3 <- a_NAS03$Time * 2 * pi
timeRad4 <- a_NAS05$Time * 2 * pi
timeRad5 <- a_NAS08$Time * 2 * pi
timeRad6 <- a_NAS09$Time * 2 * pi
timeRad7 <- a_NAS13$Time * 2 * pi
timeRad8 <- a_NAS14$Time * 2 * pi
timeRad9 <- a_NAS15$Time * 2 * pi
timeRad11 <- a_NAS18$Time * 2 * pi
timeRad12 <- a_NAS28$Time * 2 * pi
timeRad13 <- a_NAS36$Time * 2 * pi
timeRad14 <- ocelot_data$Time * 2 * pi

legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')
par(mfrow = c(4, 3), mar = c(3, 2, 2, 2))

### Agouti

#NAS01
NAS01 <- timeRad2[a_NAS01$station == "NAS01_" & a_NAS01$common_name == 'Agouti']
min(length(NAS01), length(Human))
tigmactest <- overlapEst(Human, NAS01, type="Dhat4")
tigmactest
overlapPlot(NAS01, Human, main="NAS01", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS03
NAS03 <- timeRad3[a_NAS03$station == "NAS03_" & a_NAS03$common_name == 'Agouti']
min(length(NAS03), length(Human))
tigmactest <- overlapEst(Human, NAS03, type="Dhat4")
tigmactest
overlapPlot(NAS03, Human, main="NAS03", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS05
NAS05 <- timeRad4[a_NAS05$station == "NAS05_" & a_NAS05$common_name == 'Agouti']
min(length(NAS05), length(Human))
tigmactest <- overlapEst(Human, NAS05, type="Dhat4")
tigmactest
overlapPlot(NAS05, Human, main="NAS05", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS08
NAS08 <- timeRad5[a_NAS08$station == "NAS08_" & a_NAS08$common_name == 'Agouti']
min(length(NAS08), length(Human))
tigmactest <- overlapEst(Human, NAS08, type="Dhat4")
tigmactest
overlapPlot(NAS08, Human, main="NAS08", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS09
NAS09 <- timeRad6[a_NAS09$station == "NAS09" & a_NAS09$common_name == 'Agouti']
min(length(NAS09), length(Human))
```

```

tigmac2est <- overlapEst(Human, NAS09, type="Dhat4")
tigmac2est
overlapPlot(NAS09, Human, main="NAS09", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS13
NAS13 <- timeRad7[a_NAS13$station == "NAS13" & a_NAS13$common_name == 'Agouti']
min(length(NAS13), length(Human))
tigmac2est <- overlapEst(Human, NAS13, type="Dhat4")
tigmac2est
overlapPlot(NAS13, Human, main="NAS13", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS14
NAS14 <- timeRad8[a_NAS14$station == "NAS14_" & a_NAS14$common_name == 'Agouti']
min(length(NAS14), length(Human))
tigmac2est <- overlapEst(Human, NAS14, type="Dhat4")
tigmac2est
overlapPlot(NAS14, Human, main="NAS14", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS15
NAS15 <- timeRad9[a_NAS15$station == "NAS15_" & a_NAS15$common_name == 'Agouti']
min(length(NAS15), length(Human))
tigmac2est <- overlapEst(Human, NAS15, type="Dhat4")
tigmac2est
overlapPlot(NAS15, Human, main="NAS15", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS18
NAS18 <- timeRad11[a_NAS18$station == "NAS18_" & a_NAS18$common_name == 'Agouti']

min(length(NAS18), length(Human))
tigmac2est <- overlapEst(Human, NAS18, type="Dhat4")
tigmac2est
overlapPlot(NAS18, Human, main="NAS18", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS19
NAS19 <- timeRad10[a_NAS19$station == "NAS19_" & a_NAS19$common_name == 'Agouti']
min(length(NAS19), length(Human))
tigmac2est <- overlapEst(Human, NAS19, type="Dhat4")
tigmac2est
overlapPlot(NAS19, Human, main="NAS19", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS28
NAS28 <- timeRad12[a_NAS28$station == "NAS28_" & a_NAS28$common_name == 'Agouti']
min(length(NAS28), length(Human))
tigmac2est <- overlapEst(Human, NAS28, type="Dhat4")
tigmac2est
overlapPlot(NAS28, Human, main="NAS28", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

#NAS36
NAS36 <- timeRad13[a_NAS36$station == "NAS36_" & a_NAS36$common_name == 'Agouti']
min(length(NAS36), length(Human))
tigmac2est <- overlapEst(Human, NAS36, type="Dhat4")
tigmac2est
overlapPlot(NAS36, Human, main="NAS36", rug= TRUE)
#legend('topright', c("Agoutis & Humans"), lty=c(1,2), col=c(1,4), bty='n')

pdf(file = "h&a.pdf")

```

```

dev.off()
agouti and ocelot overlap plots
par(mfrow = c(4, 3), mar = c(3, 2, 2, 2))
ocelot <- timeRad14[ocelot_data$Station == 'NAS01_' & ocelot_data$common_name == 'Ocelot']

### Agouti

#NAS01
NAS01 <- timeRad2[a_NAS01$station == "NAS01_" & a_NAS01$common_name == 'Agouti']
min(length(NAS01), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS01, type="Dhat4")
tigmactest
overlapPlot(NAS01, ocelot, main="NAS01", rug= TRUE)

#NAS03
NAS03 <- timeRad3[a_NAS03$station == "NAS03_" & a_NAS03$common_name == 'Agouti']
min(length(NAS03), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS03, type="Dhat4")
tigmactest
overlapPlot(NAS03, ocelot, main="NAS03", rug= TRUE)

#NAS05
NAS05 <- timeRad4[a_NAS05$Station == "NAS05_" & a_NAS05$common_name == 'Agouti']
min(length(NAS05), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS05, type="Dhat4")
tigmactest
overlapPlot(NAS05, ocelot, main="NAS05", rug= TRUE)

#NAS08
NAS08 <- timeRad5[a_NAS08$station == "NAS08_" & a_NAS08$common_name == 'Agouti']
min(length(NAS08), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS08, type="Dhat4")
tigmactest
overlapPlot(NAS08, ocelot, main="NAS08", rug= TRUE)

#NAS09
NAS09 <- timeRad6[a_NAS09$station == "NAS09_" & a_NAS09$common_name == 'Agouti']
min(length(NAS09), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS09, type="Dhat4")
tigmactest
overlapPlot(NAS09, ocelot, main="NAS09", rug= TRUE)

#NAS13
NAS13 <- timeRad7[a_NAS13$station == "NAS13_" & a_NAS13$common_name == 'Agouti']
min(length(NAS13), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS13, type="Dhat4")
tigmactest
overlapPlot(NAS13, ocelot, main="NAS13", rug= TRUE)

#NAS14
NAS14 <- timeRad8[a_NAS14$station == "NAS14_" & a_NAS14$common_name == 'Agouti']
min(length(NAS14), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS14, type="Dhat4")
tigmactest
overlapPlot(NAS14, ocelot, main="NAS14", rug= TRUE)

#NAS15
NAS15 <- timeRad9[a_NAS15$station == "NAS15_" & a_NAS15$common_name == 'Agouti']
min(length(NAS15), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS15, type="Dhat4")
tigmactest
overlapPlot(NAS15, ocelot, main="NAS15", rug= TRUE)

```



```
#NAS18
NAS18 <- timeRad11[a_NAS18$station == "NAS18_" & a_NAS18$common_name == 'Agouti']
min(length(NAS18), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS18, type="Dhat4")
tigmactest
overlapPlot(NAS18, ocelot, main="NAS18", rug= TRUE)
```

```
#NAS19
NAS19 <- timeRad10[a_NAS19$station == "NAS19_" & a_NAS19$common_name == 'Agouti']
min(length(NAS19), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS19, type="Dhat4")
tigmactest
overlapPlot(NAS19, ocelot, main="NAS19", rug= TRUE)
```

```
#NAS28
NAS28 <- timeRad12[a_NAS28$station == "NAS28_" & a_NAS28$common_name == 'Agouti']
min(length(NAS28), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS28, type="Dhat4")
tigmactest
overlapPlot(NAS28, ocelot, main="NAS28", rug= TRUE)
```

```
#NAS36
NAS36 <- timeRad13[a_NAS36$station == "NAS36_" & a_NAS36$common_name == 'Agouti']
min(length(NAS36), length(ocelot))
tigmactest <- overlapEst(ocelot, NAS36, type="Dhat4")
tigmactest
overlapPlot(NAS36, ocelot, main="NAS36", rug= TRUE)
```

#### predator graphs

```
timeRad11 <- agouti_solo$Time * 2 * pi
without_predators <- timeRad11[agouti_solo$common_name == 'Agouti']
densityPlot(without_predators, rug= TRUE, main="Agoutis without predators", ylim=c(0, 0.2))
legend("topright", c("Agoutis"), lty=c(1,2), col=c(1,4), bty='n')
```

#### ## with & without predators graphs

```
tigmactest <- overlapEst(with_predators, without_predators, type="Dhat4")
tigmactest
overlapPlot(with_predators, without_predators, main="Predator Influence", rug= TRUE, xlab="Time", ylab="Density")
legend("topright", c("With predators","Without predators"), lty=c(1,2), col=c(1,4), bty='n')
```

#### ## comparison test

```
wilcox_test_results <- wilcox.test(Time ~ set, data = agouti_predator_data)
print(wilcox_test_results)
```

#### habitat graphs

```
F1 <- timeRad21[FOREST$common_name == 'Agouti']
C1 <- timeRad22[CROPFIELDS$common_name == 'Agouti']
min(length(C1), length(F1))
tigmactest <- overlapEst(F1, C1, type="Dhat4")
tigmactest
overlapPlot(F1, C1, main="Forest vs Cropfield", xlab="Time", ylab="Density")
legend("topright", c("FOREST","CROPFIELDS"), lty=c(1,2), col=c(1,4), bty='n')
```

#### ## comparison test

```
wilcox_test_results <- wilcox.test(Time ~ set, data = agouti_data_all)
print(wilcox_test_results)
```

```

## avoidance attractions ratios ##
library(ggplot2)
library(reshape2)
library(dplyr)

data <- overlap_values
T1 <- data$T1
T2 <- data$T2
T3 <- data$T3
T4 <- data$T4

# Calculate the ratios
data$attraction <- data$T2 / data$T1
data$avoidance <- data$T4 / data$T3

wilcox_test_result <- wilcox.test(data$attraction, data$avoidance, paired = TRUE)
print(wilcox_test_result)

####

wilcox_test_result <- wilcox.test(data$T2, data$T1, paired = TRUE)
print(wilcox_test_result)

####

wilcox_test_result <- wilcox.test(data$T3, data$T4, paired = TRUE)
print(wilcox_test_result)

T3_value <- data$T1
T4_value <- data$T4

values <- c(T3_value, T4_value)
interval_type <- c("T3", "T4")

# Create the bar plot
barplot( height = values,
         names.arg = interval_type,
         main = "Successive prey interactions and predator-prey interactions",
         xlab = "Interval Type",
         ylab = "Time Interval",
         xlim = c(0,1),
         col = "lightblue",
         border = "blue")

### plotting means
mean(T1)
mean(T2)
mean(T3, na.rm = TRUE)
mean(T4, na.rm = TRUE)

means <- c(6.08, 3.6, 4.24, 4.02)
groups <- c("T1", "T2", "T3", "T4")

# Create a data frame for ggplot2
df <- data.frame(Group = groups, Mean = means)

# Create the bar plot using ggplot2
myplot <- ggplot(df, aes(x = Group, y = Mean, fill = Group)) +
  geom_bar(stat = "identity") +
  labs(title = "Mean Values of AA Intervals", x = "Interval Type", y = "Mean Value") +
  theme_minimal() + theme(plot.title = element_text(hjust = 0.5)) +
  scale_fill_brewer(palette = "Pastel1")

```

```
myplot+ theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank(),
  panel.background = element_blank())
```

### ##ADI ##

```
disturbance <- ADI$ADI
timeRad20 <- ADI$Time
```

```
cor_test_result <- cor.test(timeRad20, disturbance)
print(cor_test_result)
```

### ## temperature ##

```
library(ggplot2)
library(broom)
```

```
timeRad20 <- agouti_data_1$Time * 2 * pi
```

```
Agouti <- timeRad20[agouti_data_1$common_name == 'Agouti']
data <- data.frame(Agouti)
```

```
Temp <- timeRad20[agouti_data_1$Temp]
```

```
model <- lm(Temp ~ poly(Time, 3), data = agouti_data_1)
```

```
summary(model)
```

```
agouti_data_1$predicted <- predict(model, agouti_data_1)
```

```
# Calculate RMSE and R-squared
rmse <- sqrt(mean((agouti_data_1$Temp - agouti_data_1$predicted)^2))
r_squared <- summary(model)$r.squared
```

```
print(paste("RMSE:", rmse))
print(paste("R-squared:", r_squared))
```

```
# Plot the results
```

```
ggplot(agouti_data_1, aes(x = Time, y = Temp)) +
  geom_point(color = 'black') +
  geom_line(aes(y = predicted), color = 'blue', size = 1) +
  labs(title = "Temperature vs. Activity time for Agoutis",
    x = "Time (in radians)",
    y = "Temperature (°C)") +
  theme_minimal()
```

### ## rainfall ##

```
##### correlation test
```

```
correlation_test <- cor.test(timeRad20, rainfall_measurements, method = "spearman")
```

```
# Print the results
print(correlation_test)
```

### ## linear model ##

```
library(dplyr)
library(lme4)
library(ggplot2)
library(car)
library(effects)
library(sjPlot)
library(MASS)
library(sandwich)
library(lmtest)
```

```

glmm$Temp_s <- scale(glmm$temp)
glmm$ADI_s <- scale(glmm$ADI)
glmm$rainfall_s <- scale(glmm$rainfall)
glmm$predator_s <- scale(glmm$predator)

##### correlations
cor_matrix <- cor(glmm[, c("Temp_s", "ADI_s", "rainfall_s", "predator_s")])
print(cor_matrix)
# No high correlations (e.g., above 0.8 or below -0.8) suggest no severe multicollinearity among predictors.
# All predictors can be included in the model

##### generalised mixed model

model_glm <- glm(relative_abundance ~ Temp_s + ADI_s + predator_s + rainfall_s,
                data = glmm, family = gaussian)
summary(model_glm)
# best fit based on the lowest AIC and residual deviance, even though none of the predictors are significant.
##### variance inflated factor <5, therefore proceed
vif(model_glm)

par(mfrow = c(2, 2))
plot(model_glm)
# some heteroskidaity, gls wont work (insufficient unique data points)

#Calculate robust standard errors
robust_se <- vcovHC(model_glm, type = "HC3")
coefTest(model, robust_se)

# weighted glm
weights <- 1 / (residuals(model_glm)^2)
model_wls <- glm(relative_abundance ~ Temp_s + ADI_s + predator_s + rainfall_s, family = gaussian, weights =
weights, data = glmm)
summary(model_wls)

##### plotting predictions
glmm$predicted <- predict(model_wls, type = "response")

ggplot(glmm, aes(x = predicted, y = relative_abundance)) +
  geom_point() +
  geom_smooth(method = "lm", col = "red") +
  labs(x = "Predicted", y = "Observed", title = "Predicted vs. Observed Values") +
  theme_minimal()

##### plotting effects
# Plot the effect of env_factor1
effect_plot <- allEffects(model_glm)

# Plot all effects
plot(effect_plot)

```

## Appendix 6

### PROTOCOL CAMERAVALEN CONTROLEREN

Er hangen **34 camera's** in Nieuw-Aurora. De camera's die in het bos hangen (**18 in totaal**) moeten in de week van **12-18 juni** gecontroleerd worden om de batterijen te vervangen en te kijken of de SD kaarten vervangen moeten worden. De camera's die in de kostgronden hangen (**16 in totaal**) moeten **gecontroleerd worden tijdens het maandelijks opnemen van de plots op de kostgronden**. Alle dagen waarop dit moet gebeuren staan onderaan dit document.

De coördinaten en locatie van alle cameravallen staan in deze tabel:

<b>Cameraval nummer</b>	<b>Coördinaten en stations</b>	<b>Locatie: kostgrond of bos</b>
1	W055°25.424' N04°22.546' (NA S21 C01)	Bos
3	W055°25.509' N04°21.942' (NA S18 C03)	Bos
5	W055°26.451' N04°22.185' (NA S01 C05)	Bos
6	W055°26.105' N04°22.102' (NA S07 C06)	Bos
7	W055°24.926' N04°21.867' (NA S29 C07)	Bos
8	W055°24.997' N04°22.106' (NA S28 C08)	Bos
9	W055°26.273' N04°21.679' (NA S03 C09)	Bos
10	W055°26.017' N04°21.767' (NA S08 C10)	Bos
11	W055°25.770' N04°21.851' (NA S13 C11)	Bos
12	W055°26.101' N04°21.170' (NA S05 C12)	Bos
13	W055°25.938' N04°21.511' (NA S09 C13)	Bos
14	W055°25.681' N04°21.608' (NA S14 C14)	Bos
15	W055°25.421' N04°21.688' (NA S19 C15)	Bos
16	W055°25.351' N04°21.351' (NA S15 C16)	Bos
17	W055°25.085' N04°21.522' (NA S25 C17)	Bos
18	W055°24.577' N04°22.551' (NA S37 C18)	Bos
19	W055°25.349' N04°22.278' (NA S22 C19)	Bos
20	W055°24.405' N04°22.657'	Kostgrond

	(NA S42 C20)		
21	W055°24.396' (NA S42 C21)	N04°22.665'	Kostgrond
22	W055°24.116' (NA S44 C22)	N04°22.090'	Kostgrond
23	W055°24.117' (NA S44 C23)	N04°22.070'	Kostgrond
24	W055°24.106' (NA S45 C24)	N04°21.831'	Kostgrond
25	W055°24.122' (NA S45 C25)	N04°21.815'	Kostgrond
26	W055°24.634' (NA S36 C26)	N04°22.835'	Kostgrond
27	W055°24.646' (NA S36 C27)	N04°22.809'	Kostgrond
28	W055°24.207' (NA S41 C28)	N04°23.060'	Kostgrond
29	W055°24.218' (NA S41 C29)	N04°23.095'	Kostgrond
30	W055°24.842' (NA S31 C30)	N04°22.704'	Kostgrond
31	W055°24.861' (NA S31 C31)	N04°22.695'	Kostgrond
32	W055°25.799' (NA S12 C32)	N04°22.086'	Kostgrond
33	W055°25.799' (NA S12 C33)	N04°22.075'	Kostgrond
34	W055°24.465' (NA S38 C34)	N04°22.314'	Kostgrond
35	W055°24.449' (NA S38 C35)	N04°22.303'	Kostgrond
36	W055°26.195'	N04°22.282' (NA S06 C36)	Bos

Op de datum dat de camera's gecontroleerd moeten worden krijg je een herinnering van Ronja Knippers.

Neem de volgende spullen mee het veld in:

- **Sleutels van de sloten (er zijn 5 verschillende, neem van elke één mee voor de zekerheid)**
- **Doos met volle batterijen** (oplaad instructies onderaan het document)
- **Doos voor lege batterijen**
- **Doosje met lege SD kaarten**
- **Doosje voor volle SD kaarten** (!!! Zorg dat lege en volle batterijen en SD kaarten gescheiden blijven !!!)
- **Clipboard en schrift**

- Leeg camera val invulformulier
- Twee potloden
- Gum
- Zwarte stift
- GPS
- Kalibratiestok
- Duimstok (2 meter)
- Houwer
- Stappenplan
- Telefoon voor foto's of om Ronja te bellen

Zoek in de GPS de waypoint op dat hoort bij de camera. Voor camera 1 is dit "NA S21 C01". Ga naar de aangegeven coördinaten. **Volg het volgende stappenplan**. Het is belangrijk om heel **nauwkeurig** te kijken, te lezen en te schrijven. Snap je iets niet? Neem contact op met Ronja.

1. Vul je **naam** in op een nieuw invulformulier.
2. Vul de **datum en tijd** in op het invulformulier.
3. Kijk op de **GPS** wat de **coördinaten** zijn van de camera waar je bijstaat en vul die in op dezelfde rij van het invulformulier. **RAAK DE CAMERA NOG NIET AAN!**
4. Gebruik de **kalibratiestok** om de camera te **kalibreren voordat je hem aanraakt**. Begin 1m voor de camera. **Zorg ervoor dat de stok recht staat** en dat je voldoende tijd (**10 seconden**, niet te snel tellen!) stilstaat zodra je goed staat. **Houd je opgestoken duim in het beeld** zodra de stok goed recht staat en **beweeg met je been** om de camera af te laten gaan. Doe dit **25 keer op verschillende afstanden in het zicht van de camera**.

Dit moet voor alle bos camera's en de lage camera's in de kostgronden. **NIET** voor de hoge camera's in de kostgronden!

5. Open het deurtje van de camera en druk één keer goed op de '**mode**' knop. Het scherm van de camera moet nu aangaan. Gaat de camera niet aan? Dan zijn de batterijen leeg en de SD kaart vol. Vul het **camera nummer** in wat op de binnenkant staat in een **nieuwe rij van het invulformulier**.
6. Linksonder in het scherm kan je het **percentage batterij** aflezen. **Schrijf het batterij niveau op** in de kolom "**Hoeveelheid batterij**" in dezelfde rij van het invulformulier.
7. Als het batterij niveau **lager is dan 50%** (of precies 50%) moeten de batterijen **wel allemaal vervangen** worden. Als het batterij niveau **hoger is dan 50%** moeten de batterijen **niet vervangen** worden. Schrijf **JA of NEE** in de kolom "**Batterijen vervangen?**" om aan te geven of de batterijen vervangen moeten worden.

8. Rechtsonder in het scherm kan je het aantal **gemaakte foto's** aflezen. Hoeveel foto's zijn er tot nu toe gemaakt? **Schrijf het aantal foto's op** in de kolom "**Hoeveelheid foto's**" in dezelfde rij van het invulformulier.
9. Kijk in de onderstaande tabel of de SD kaart vervangen moet worden of niet. **Schrijf JA of NEE** in de kolom "SD kaart vervangen?".

Soort SD kaart	Huidige hoeveelheid foto's (links)	Vervangen ja of nee?
32 GB (bos)	Meer dan 23000	<b>JA</b>
32 GB (bos)	Minder dan 23000	<b>NEE</b>
64 GB (kostgrond)	Meer dan 46000	<b>JA</b>
64 GB (kostgrond)	Minder dan 46000	<b>NEE</b>

10. Zet de camera **UIT** door de schuifknopje naar beneden te drukken zodat deze bij "**off**" staat. Zet een **kruisje in de kolom "Uitzetten"**.
11. Als de SD kaart vervangen moet worden, pak dan de oranje bak voor de **gebruikte** SD kaarten. **Klik de SD kaart uit de onderkant van de camera.** Zorg dat deze droog blijft, **leg hem NIET op de grond.** Leg de SD kaart in de oranje bak voor gebruikte SD kaarten. Pak de paarse bak met de nieuwe SD kaarten. Camera's in het **bos moeten een 32 GB** SD kaart krijgen. Camera's in de **kostgronden moeten een 64 GB** SD kaart krijgen. Pak een lege SD kaart uit het paarse doosje. Stop deze in de camera met de oneven kant naar boven en de tekst naar voren.
12. Als de batterijen vervangen moeten worden, pak dan de doos voor de **gebruikte batterijen** met daarin de lege doosjes. **Klik op de "Eject" knop** om de batterijen bak te openen. Trek **zacht** aan de batterijen bak totdat deze eruit komt. Houd de andere hand eronder zodat de batterijen er niet uit vallen. Stop de batterijen terug in de lege hoesjes (4 per hoesje) en doe ze in de doos voor lege batterijen. Laat ze **niet nat** worden! Leg de batterijen nooit op de grond.  
Pak nu de doos met de **nieuwe batterijen**. Haal 8 batterijen uit de doosjes en stop ze in de batterijhouder. **Let goed op dat de + en – op de goede plek zitten.**
13. Als de camera is verschoven, bijvoorbeeld doordat er stokjes weggehaald zijn of het slot los gemaakt moest worden, zorg er dan voor dat hij zo precies mogelijk terug wordt gehangen in dezelfde positie als voorheen. Knoop ook de strap en het slot weer vast als je ze los hebt gehaald.
14. Zet de camera **AAN** door de schuifknop naar boven te drukken zodat deze bij "**on**" staat. Zet een **kruisje in de kolom "Aanzetten"**. De batterij moet nu op 100% staan en er moeten 0 foto's op staan. Klik elke paar seconden twee keer op "mode" zodat de camera niet begint met foto's maken!
15. Controleer of de camera **goed gepositioneerd** staat door de 2m **duimstok** uit te klappen en in een rechte lijn voor de lens van de camera te leggen. Steek de



houwer op 2 meter van de camera in de grond. De hele houwer moet te zien zijn op het scherm van de camera met een klein stukje grond eronder. Is de camera verschoven of anders opgehangen. Maak dan een foto en stuur deze naar Ronja met de locatie, cameranummer en datum erbij.

16. Schrijf met de zwarte stift **een briefje** in het schrift met de naam van de **camera locatie** zoals aangegeven in de gps (bijvoorbeeld NA S21 C01), de **datum en de tijd**.
17. Maak een paar **foto's van het briefje** en controleer of er **leesbare** tussen zitten. Doe dit door op de 'mode' knop te drukken. Selecteer vervolgens 'playback' door er op te gaan staan en op de 'E' knop te drukken. Gebruik het knopje links naast de 'E' knop om de gemaakte foto's te bekijken. Druk vervolgens weer op mode en ga terug naar de 'home screen'.
18. Als je zeker weet dat je de camera niet meer aan hoeft te raken zorg dan dat deze **aan staat en doe het deurtje dicht. Het is extreem belangrijk dat de camera aan staat! Controleer dit goed!**
19. **Kalibreer** de camera opnieuw voordat je weggaat zoals beschreven in stap 4.

Dit moet voor alle bos camera's en de lage camera's in de kostgronden. NIET voor de hoge camera's in de kostgronden!

20. Zet een **kruisje in het vak "Handelingen"** als je alle nodige handelingen uitgevoerd hebt.
21. Heb je iets gezien dat niet klopt, wat je niet snapt of wat je opvalt? **Schrijf kort in vakje "Opmerkingen" en stuur een bericht met foto naar Ronja.**
22. Ga door naar de volgende cameraval met behulp van de GPS. **Begin weer bij stap 2 van het stappenplan.**
23. Zorg dat alle cameravallen die op de planning staan bezocht worden. Ronja zal op de dagen dat er gemeten moet worden een bericht sturen als herinnering.

### **Batterijen opladen**

Als de batterijen van camera's zijn vervangen dan moeten de lege batterijen zo spoedig mogelijk worden opgeladen. Gebruik hiervoor de oplader die is achtergelaten. Er kunnen 16 batterijen tegelijkertijd opgeladen worden. Dit duurt enkele uren. Volg de volgende stappen:

1. Pak de **oplader** en de bak met **lege batterijen**.
2. Haal de **lege batterijen** uit de bak en doe ze één voor één **in de oplader. Zorg ervoor dat de + en – aan de goede kant zitten.**

3. **Controleer** of alle batterijen **goed in de oplader** zitten; soms moeten ze nog een keer aangedrukt worden.
4. Doe de oplader in het stopcontact. De twee **schermpjes** op de oplader worden **blauw** verlicht als de batterijen worden opgeladen.
5. **Controleer nogmaals** of de batterijen goed in de oplader zitten door **op de schermpjes te kijken** of de hoeveelheid batterijen die opgeladen wordt overeenkomt met het aantal batterijen dat in de oplader zit.
6. De **schermpjes** van de oplader worden **grijs** als de **batterijen volledig opgeladen zijn**. Als de batterijen vol zijn haal je de stekker uit het stopcontact, de batterijen uit de oplader, en **doe je ze in de doos voor volle batterijen**. Stop batterijen altijd weer in de witte kartonnen doosjes. Berg de batterijen en de oplader vervolgens goed op en zorg dat ze niet vochtig of nat kunnen worden.