Master Thesis (GEO4-2321)

Testing an innovative method to map human-wildlife interactions

Examining the potential of a new smart sensor tool to aid ‘digital conservation’ in a rewilding context

Martijn Wessels, 6924913, m.wessels2@students.uu.nl

Sustainable Development - ECE

Supervisor: Dr. Ine Dorresteijn

Co-supervisor: Dr. Joris Cromsigt

2nd reader: Dr. Martin Wassen

Word count: 8872

Acknowledgements

I would like to thank Dr. Ine Dorresteijn for her continuous guidance and help during this thesis period and its sometimes rough periods, as well as helping me out in the field. Furthermore I would like to thank Dr. Joris Cromsigt for his help with setting up the research. Other thanks go out for Tim van Dam (SmartParks) for providing the sensor and phones to conduct testing, together with his help ensuring data collection and processing went as smooth as possible. I must also thank Esther Rodriguez from PWN for her help regarding the Kraansvlak itself. Final thanks to ranger Imreël van der Sloot for ensuring my safety in the area while out conducting tests by guiding me through the area on my first day and giving me pointers on how to behave in close vicinity to the animals and how to read their behaviour.

Summary

An ecological conservation and restoration method that has received an increased interest in the past decade is rewilding. This activity is a type of conservation effort that aims at restoring natural processes and wilderness areas, besides protecting them. Activities within rewilding include increasing connectivity and protecting or (re)introducing keystone species. Trophic rewilding introduces species that restore top-down trophic interactions and associated trophic cascade promoting self-regulation biodiverse ecosystems. The Kraansvlak area in the Kennemerduinen National Park has started a rewilding project by reintroducing European bison. Visitors are free to visit the area with the bison, causing human-wildlife interactions. In Europe, human-wildlife interactions, especially two-way interactions, have rarely been studied. This research aims to explore the potential of a newly developed smart tracking sensor as a 'digital conservation' tool to aid in mapping human-wildlife interactions. Done through a unique use of contact-tracing, Bluetooth and Wi-Fi signals from phones are used in combination with the tracking of the animals to map interactions. As this is a new technology, this is still unknown territory. This research explores the amount of signal measurements the sensor is capable of, the signal strength, as well as the maximum distance from which it can report. It was found that habitat plays a main role in the functioning of the sensor, having a significant effect on all three functions explored. Finally these results are discussed in the context of rewilding.

Keywords: Rewilding, human-wildlife interactions, contact-tracing, digital conservation

Table of contents

Introduction

Rewilding as a form of ecological conservation and restoration received increased interest in the past decade. Rewilding activities are a type of conservation efforts which aim at restoring natural processes and wilderness areas, as well as protecting them. This includes activities such as providing connectivity between these areas and protecting or reintroducing apex predators and keystone species (Schepers & Jepston, 2016). Within Europe, recently there have been many initiatives to reuse and repurpose abandoned (agricultural) land (Ceausu et al., 2015). An initiative to reshape these lands is through trophic rewilding, introducing species that restore top-down trophic interactions and associated trophic cascades. These in turn promote self-regulating biodiverse ecosystems (Bakker & Svenning, 2018; Keulartz, 2018). Torres et al. (2018) state that overcoming challenges regarding monitoring and reporting rewilding projects will improve the practical implementation of rewilding, maximizing its conservation and restoration outcomes. However there are no good tools do so as of yet.

Monitoring rewilding projects is especially important in a densely populated continent like Europe due to newfound interactions between humans and wildlife, so called human-wildlife interactions. These interactions will occur more often and this could eventually lead to a high degree of land-sharing if everything goes well (Linnell et al., 2015; Linnell & Kaltenborn, 2019). Human-wildlife interactions can be classified as positive and negative, however most literature focusses on conflicts (White & Ward, 2011). Mapping interactions is necessary as humans and wildlife need to find ways to coexist together (Carter & Linnell, 2016; Linnell & Kaltenborn, 2019). European research has studied human–wildlife, but much is unknown about two way interactions, where both parties see a related effect, between humans and wildlife (Johansson et al., 2016). However it is important to understand these relationships as they are identified as a key leverage point for sustainability transitions (Abson et al., 2017). Most research that is done between human-wildlife interactions has been through direct observation focusing on either humans or animals (Treves et al, 2006). With new technological innovations it could also be possible to gather data through indirect observations, focusing on both parties involved (Marion et al., 2020).

Using new technological innovations to aid ecological conservation has been dubbed 'digital conservation' by Van der Wal & Arts (2015). Under this new term fall all kinds of digital innovations regarding nature conservation such as camera traps, GPS-collars and more recently metal detectors that can identify poaching threats (Martin, 2019). Another one of these innovations is an animal tracking collar using LoRaWAN (Long Range Wide Area Network) technology, that has a sensor that can measure Bluetooth and Wi-Fi signals (Feltrin et al., 2018). Throughout this research, this will be referred to as the 'smart sensor'. Since many people carry smartphones these days, this innovation can provide valuable new information to aid in mapping human-wildlife interactions. The smart sensor can measure these signals for an extended period of time, continuously collecting data. The smart sensor is using a form of contact-tracing as a way to monitor and map human-wildlife interactions. Currently contact-tracing is only used in public health scenarios, such as the Dutch 'CoronaMelder' app and other coronavirus applications (Cho et al., 2020). Through new ways of contact-tracing, data between human-wildlife interactions can be measured, such as frequency and interaction distance. This research will help testing the first smart sensor using contact-tracing in a unique way, helping to map human-wildlife interactions. This new type of digital conservation has high potential to provide valuable information for adaptive wildlife management worldwide.

As this smart sensor is newly developed, there is a need for data, making testing necessary. In the Netherlands, multiple rewilding projects have started. One of these projects focuses on the reintroduction of European bison in the Netherlands. The Kraansvlak is one area which saw bison reintroduction. PWN (Puur Water Natuur), who manage the Kraansvlak, has started a collaboration with Utrecht University and SmartParks. SmartParks develops animal tracking collars using the LoRaWAN network, and has collared animals in the Kraansvlak. For this research, I focussed on the collar for the European bison.

As nature varies greatly, this innovation should be tested in multiple environments, and the Kraansvlak contains a variety of habitats. The functionality of the smart sensor can be tested in habitats such as flat plains, dunes and forest. Therefore sensor performance can be tested within different habitats, and LoRaWAN network coverage can be examined throughout the whole area. This makes the Kraansvlak area a perfect location for a pilot study. The aim of this research is:

"Examining the potential of a new smart contact-tracing sensor to be used as a 'digital conservation' tool in the context of rewilding."

The feasibility of implementing this sensor depends on the quality of measurements. Key information to examine is: correct measurement of signals in its proximity, signal strength, and maximum distance of the sensor. It is essential that the sensor measures all signals that are there be measured. It is important that all signals are picked up. Furthermore signal strength of the sensor needs to be established. Weak signals are at risk of not being picked up, leading to incorrect data. With incorrect data, adaptive wildlife management strategies could turn out ineffective. For example, misunderstandings in distance related human-wildlife interactions can lead to an unsuccessful strategy (Miller & Freimund, 2018). Finally it is important to find out the sensor's maximum distance. Due to humans interacting with wild animals, a safe distance needs to be kept at all times. Nonetheless the smart sensor needs to have a reasonable range limit in order to provide useful and sufficient data. Thus a balance must be found between the usefulness of the data measured by the sensor, and the wellbeing of animal and human.

In order to find out of this new sensor can be useful in the future, three sub questions are established that will be discussed in the context of rewilding:

- *How well does the new sensor measure signals between the three different Kraansvlak habitats and between both Bluetooth and Wi-Fi?*
- *How strong are the picked up signals and does this differ between the habitats and between Bluetooth and Wi-Fi?*
- *How far away can the sensor pick up both types of signals and is this feasible regarding the Kraansvlak animal policies?*

Theory

Rewilding

Rewilding is used in ecological restoration as a method where the emphasis is on humans stepping back and leaving an area to nature, in contrary to more active forms of natural resource management (Pettorelli et al., 2019). Rewilding efforts can aim to create ecosystems requiring passive management, as successful long term rewilding projects can need little ongoing human attention. Rewilding efforts are made in the Netherlands, such as reintroducing large grazers like the European bison. European megafauna have always played a role in maintaining open landscapes

(Peirera & Navarro, 2015). That is, before humans brought most of them to extinction and replaced this megafauna by domesticated grazers (Johnson, 2009; Helmer et al., 2015).

Large herbivores are keystone species in many forest and grassland areas. These animals shape the structure, species diversity and functioning of ecosystems (Hale & Kropowski, 2018). The European bison is one of those keystone species (Kowalczyk et al., 2011). Herbivores have an obvious effect on soil and vegetation in the form of grazing and the consumption of herbage (Harrison & Bardgett, 2008). Trophic rewilding has the potential for positive effects on biodiversity, for example by creating within-habitat heterogeneity. Therefore it could help mitigate the biodiversity crisis, but data to test this is very limited (Bakker & Svenning, 2018). Research has shown that the amount of plant species seeds bison disperse is almost double from those dispersed by cattle and horses (Jaroszewicz & Pirożnikow, 2008). Within the Kraansvlak, the bison is also the first species in the area that actively includes tree bark in its diet (Kowalczyk et al., 2011). Thus rewilding the Kraansvlak with bison leads to a change in vegetation cover (Valdés-Correcher et al., 2018).

Human-wildlife interactions

Human-wildlife interactions can have both positive and negative effects. According to the WWF (2020), negative human-wildlife interactions relate to: "any interaction between humans and wildlife that results in negative impacts of human social, economic or cultural life, on the conservation of wildlife populations, or on the environment". These interactions are often called human–wildlife conflict (Madden, 2004). In many regions these conflicts have intensified over recent decades as a result of human population growth and the transformation of land use. Unfortunately, in recent times the disconnect between humans and nature has been growing more strongly (Beery & Wolf-Watz, 2014). Seeing how more people are currently recreating in, and thus encroaching, nature, combined with a growing population and increasing rewilding projects, parts of Europe will see an increase in human-wildlife interactions (Kabisch & Haase, 2011; Jepson & Schepers, 2016). Better understanding of two-way human-wildlife interactions can help shift the paradigm for adaptive wildlife management (Gigliotti et al., 2009; Andrews, 2018).

Negative human-wildlife interactions are a serious global threat to sustainable development (Nyhus, 2016; König et al., 2020). Generally, consequences of these interactions include: crop destruction, reduced farm productivity, competition for land and water, livestock predation, damage to infrastructure, and increased risk of disease transmission among wildlife and livestock (Nyhus, 2016). In the Kraansvlak, conflicts can lead to potential behavioral change of animals, as well as hazardous interactions (Haidt et al., 2018). Because of the disconnect between humans and nature, some people have wrong perceptions of animals, wrongly perceiving danger. Conversely, animals might get more conditioned to humans with frequent exposure (Conover, 2001; Dickman, 2010). However they could also become more aggressive. This has been observed in human-wildlife interactions with bison in Poland (Haidt et al., 2018). There are knowledge gaps here as there are still things unknown about human-bison interactions in Europe, due to the fact the European bison was extinct in the wild up until recently. Most studies regarding bison done are in forests in Eastern Europe. However the bison in Kraansvlak live in a more open environment mixed with forest, dunes and grasslands which is thought to be more true to their origin (Kerley et al., 2012). Thus this sensor should be tested in different habitats.

Positive interactions are also happening. By reintroducing previously extinct animals, public interest can be gained, creating potential for wildlife-tourism (Koninx, 2019). Unfortunately some benefits of human-wildlife interactions are difficult to quantify because outcomes can be intangible, nevertheless, their impact may be substantial (Soulsbury & White, 2016). One of these benefits could be increased mental health. Dallimer et al (2014), have researched the willingness to pay of people to see an increase in nature, in relation to the well-being of people. They found that an increase in nature often leads to increased well-being. This is exemplified in the current COVID-19 pandemic. More people are out in nature due to limiting options as a result of lockdowns, with social distancing still being possible outside (Karl et al, 2020). Since the pandemic started, there's been an increase in people participating in activities as running, bird spotting and hiking in nature (Grima et al.,2020; Morse et al., 2020). When the connectedness between humans and nature improves, it can minimize negative human-wildlife interactions, and boost positive interactions (Meadows, 1999; Treves & Santiago-Ávila 2020).

Digital conservation

In the last two decades, the World Wide Web and associated developments have shaped old and created new modes of business, management, communication and governance. These developments have led to naming the current era the Digital Age (Orton-Johnson & Prior, 2013). However, developments in the Digital Age have received relatively little attention from researchers focusing on environmental management in general and nature conservation in particular. The shaping of the Internet of Things (IoT) has created potential for new conservation methods, such as digital conservation. IoT relates to the interconnection between everyday objects (Xia et al., 2016). Many new technological innovations regarding the IoT fall under this new umbrella term of 'digital conservation' (Arts et al., 2015). Besides new smart sensors, an example of the possibilities to aid conservation is the use of digital games for biodiversity conservation such as MyConservationPark or eBird. This 'serious gaming' can be used to get people more acquainted with ecological conservation. This new technology can create strong incentives for learning and behavior change (Sandbrook et al, 2015).

Figure 1: The five key dimensions of digital conservation (Arts et al., 2015)

In Figure 1 the five key dimensions of digital conservation are seen as established by Arts et al (2015). In the Kraansvlak case study a smart senor is tested that, when implemented, will span all five dimensions. The sensor provides data on nature, the animal behavior in different habitats. Data on people is provided by measuring frequency and location where humans and wildlife interact. When certain habits of humans and wildlife are found, this data can be integrated into the communication and experience dimension, together with participatory governance in the form of adaptive management strategies and policy. This is especially important since the management of human-wildlife can become political, providing a challenge for governance (Treves et al, 2017). Collar data is used on websites such as wisent.nl where people can find the location of the Kraansvlak wisents. Other implementations can be aiding forest rangers to measure crowdedness in an area and people getting too close to animals.

These new internet-enabled tracking collars for animals need to be designed with a multiple year lifespan in order to minimize interference with the animals. These collars are deployed in ultra-remote areas, and in order to preserve battery power the device only powers on when it is required. GSM or cellular technology is widely deployed where connectivity is available, however GSM is also highly energy intensive (Sirotek & Hart, 2019). Devices either have a large battery or are only powered on when required. LoRaWAN is a new technology powering the Internet of Things connectivity, and is very energy efficient (Feltrin et al, 2018). This technology is beginning to be deployed in remote areas due to their ease of deployment and incredibly long range (Al Balushi et al, 2019). The advantages of these technologies for an animal tracking collar are that the device form size can be minimized and the battery life extended greatly (Panicker et al, 2019). As this tool can aid conservation in a new way, these technologies require testing in order to see if they are fit to aid ecological conservation purposes.

Contact-tracing

In public health, contact-tracing is the process of identification of persons who may been in touch with an infected person (the "contacts") and subsequent collection of information about these contacts. The goals of contact-tracing are:

- Interrupting ongoing transmission and reducing infection spread
- Alerting contacts to infection possibility, and offering preventive services or prophylactic care
- Offering diagnosis and treatment to infected people
- With treatable infections, helping to prevent reinfection
- Learning about the epidemiology of a disease in a particular population

A new method of contact tracing is through the use of smartphones. Due to all kinds of technological advancements, smartphones can now provide proximity information useful for contact tracing using GPS, Bluetooth or Wi-Fi signals. One of the recent uses of contact-tracing is done through "Corona Apps". These apps are relying on Bluetooth Low Energy (BLE) wireless radio signals for proximity information. These new tools would warn people that they had been in contact with people that are potentially infected by COVID-19. However, this method of mapping/tracing is only used for health purposes, but can be adapted to aid ecological conservation. Examples could be the use of a 'smart' app to warn rangers when parks get too crowded, or animals and humans are in too close vicinity of each other allowing for ranger intervention. It can also provide insightful information on locations where humans and wildlife have most interactions. There is also potential to analyze animal movement in relation to human-people interactions, which can lead to recommendations for adaptive wildlife management or certain policy changes (Frank et al., 2019). The only current application of contact tracing with animals is done by tracing back sources of infectious disease (Elbakidze, 2007; Rorres et al, 2018). However this animal tracing is done without the use of the newest technologies. Using contact tracing in the context of rewilding is a new technology of which the potential needs to be explored. Important is that the smart sensor does not invade people's privacy. Any details which can be used to invade privacy such as the MAC-address will be hashed, meaning it will be encrypted and inaccessible.

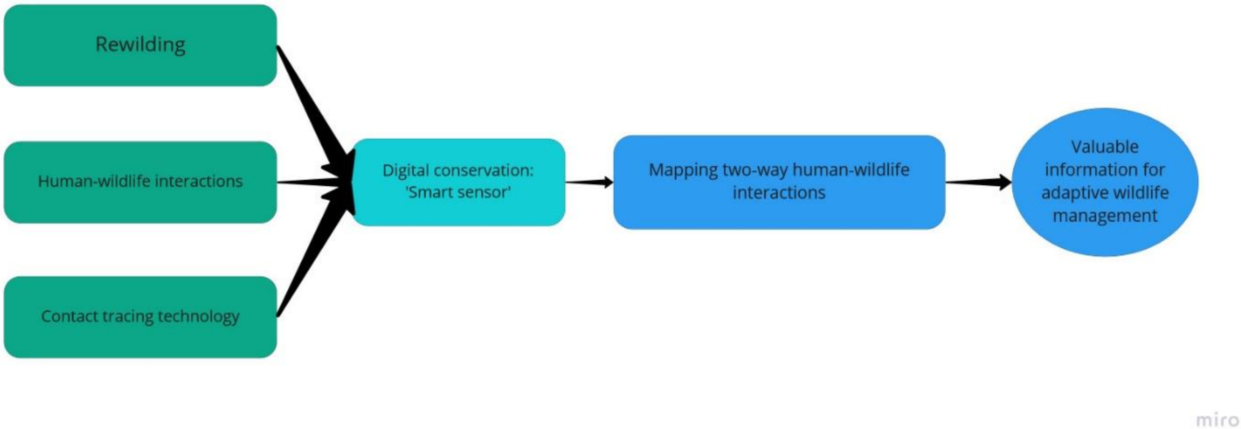


Figure 2: Conceptual framework showing integration of concepts in this research

In Figure 2, a conceptual model can be seen showing how different concepts are brought together in this research. The three concepts of rewilding, human-wildlife interactions and contact-tracing technology provide new innovations regarding digital conservation in the form of a smart sensor. This smart sensor aids in mapping two-way human-wildlife interactions not studied before. This mapping provides valuable information for adaptive wildlife management and future research.

Methods

Case study area

The European bison (*Bison bonasus*), also known as the wisent, is a European species of bison. It is the heaviest wild land animal in Europe. During the early years of the 20th century bison were hunted to extinction in the wild. To this day, it remains absent from most of its historical range (Krasińska & Krasiński, 2014). This range spans the Netherlands, and the wisent has been reintroduced in the Kraansvlak area in the Netherlands. The Kraansvlak is an area the size of 300ha in the Zuid-Kennemerland National Park, established in 1995. This area is a large conservation area with a dune ecosystem located close to the North Sea, doubling as a water-winning region for human consumption. PWN, among other stakeholders involved, have released the first three wisents in 2007 in the Kraansvlak in order to aid in restoring the ecosystem by trophic rewilding. This group has since grown to approximately 20 individuals. The bison have been released in an area that is only accessible for humans between September and March, following a special walking route. A bison viewpoint is accessible year round. Most European bison studied live mainly in forests, not in a dune landscape like Kraansvlak (Kowalczyk et al., 2011). This makes the Kraansvlak an interesting case study location acquiring new data.

Site selection

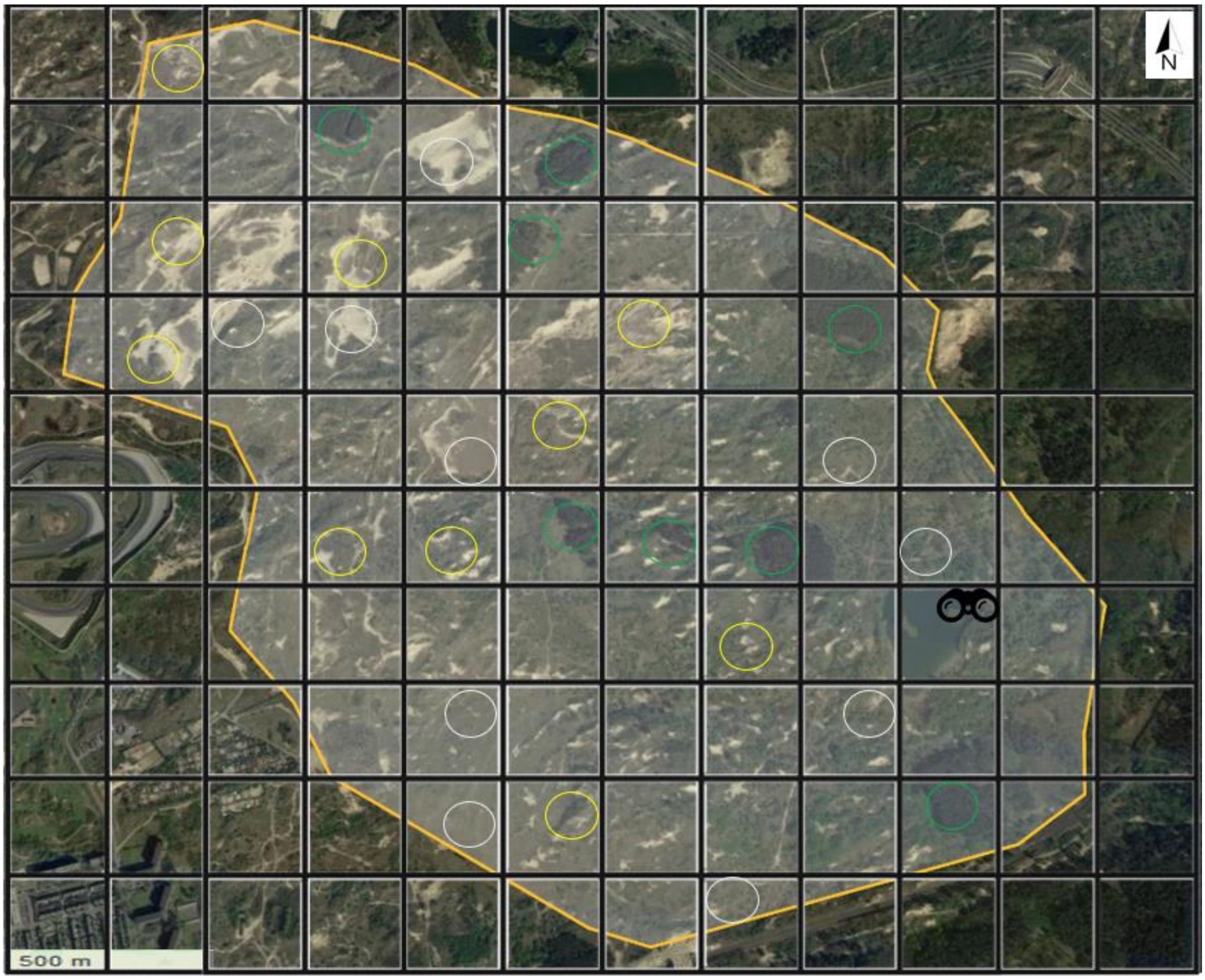


Figure 3: Selected sample sites for smart sensor testing in different Kraansvlak habitats (green = forest, yellow = dunes, grey = plains) and the bison viewpoint)

Figure 3 shows the Kraansvlak area. Indications for sample site locations were based on satellite images. A grid of 250m by 250m squares was placed over the area. To make sure that each site was independent, only one sample site per square was taken. In order to make sure every sample site location was the correct land use, the exact sample site locations were established in the field. In this research we aimed for 5-10 sample sites of each respective habitat (forest, plains, dunes). Every selected location spans over 100m in length, indicated by the circle, and locations are scattered throughout the Kraansvlak. This length is the assumed range of the smart sensor, established for testing purposes. The reasoning for this explained in the experimental design below. Locations were scattered throughout the area to test if the sensor strength remained steady throughout the entire area. The final sample site was located at the bison viewpoint. This helped to gather data in a more real life setting as visitors can freely walk in and out of the sensor's range when set up at the viewpoint. Testing in multiple habitats was necessary as tuning the sensor to a single habitat can lead to potentially inconsistent measurements in other habitats. Every habitat sample site was visited twice, in order to acquire sufficient data. This has provided 20 datasets per habitat, 60 in total. The bison viewpoint was visited during two weekends in summertime for a timeperiod of six hours per visit.

Experimental design

The experiment will conduct of two sampling strategies. The first strategy is collecting data in the three habitat types from a wisent GPS-collar with the new smart sensor, placed on a tripod with a height of approximately 1m on the locations as shown in Figure 3. The second strategy was setting up the sensor at the bison viewpoint, in order to test the sensor in a more real life scenario with people moving in and out of the range. As the current policy in the Kraansvlak area is a requested distance between people and the animals of 50m, the author has argued for a testing distance of double the requested distance. This way it can be tested if the sensor could measure people following the guidelines, as well as people not following them, or the animals moving closer to them. However as this is a new technology, the exact range of the smart sensor could still change depending on technological developments. Furthermore, to aid in testing speed, scan intervals were set as short as possible. By shortening this time, more tests could be done on a daily basis.

For every sample site in the first strategy, using GPS positioning, a straight line of 100 meter will be laid out. Before the start, the experimenter checks the MAC-address of the phones, to ensure that the data is only from the phones used. Then, the experimenter carrying the used phone(s) will walk from outside of the range, starting at 100m from the sensor, all the way to the sensor. The experimenter will stop three times among this line, for the duration of the scan interval. Stops will be done at 75m, 50m and 25m distance from the sensor, creating four distance groups. These distances are selected with regards to the current animal policy in the Kraansvlak as previously mentioned. These stops allow for the sensor to pick up the signal at a fixed position. Stops will be marked along the line with a small flag or ribbon. The stops are visualized by the cross (x) in Figure 4. The smartphone type used for this experiment are the Samsung A02s (Android).

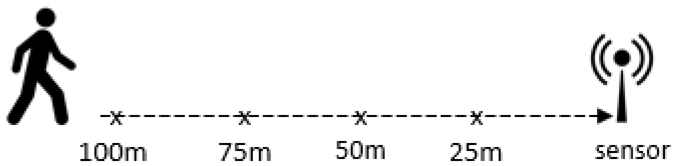


Figure 4: Schematic overview of the experimental design

Sub-question 1: Signal measurement

For sub-question one, we tested if the sensor correctly measured available phone signals. The smart sensor in the GPS collar measures Wi-Fi and Bluetooth signals sent from phones. In each sample site, a GPS collar with the built-in smart sensor will be placed on a tripod at roughly 1m height, as if it were a collared bison. The test was repeated three more times adding extra phones each time. The increasing number of phones went from one phone to two, four and six. This was done to mimic a busy day or group of people in the Kraansvlak in order to see if the sensor remained accurate with multiple signals. The signals measured by the sensor were sent to a SmartParks database from where they could be analyzed. In total, the sensor had the potential to pick up 52 signals each test for both

Wi-Fi and Bluetooth. Four times per test-run a signal was sent, times the amount of phones used (1, 2, 4, 6), which equals to 4+8+16+24 = 52 signals to be picked up by the sensor. Besides doing this experiment, data was collected by placing the smart sensor at the bison viewpoint. It was placed on four different days in the weekend, for a period of 6 hours with an observant nearby. The observer will manually count all people and checks this against the number reported from the sensor. Said observer will also ask visitors at the viewpoint if they are carrying smartphones, as it is futile to count people when they are not carrying one.

Sub-question 2: Signal strength

In order to measure signal accuracy, we use the Received Signal Strength Indicator (RSSI) of the sensor. This is a value that is represented in dBm, which is a unit of level used to indicate that a power level is expressed in decibels (dB) with reference to one milliwatt (mW). The RSSI value runs from -100 dBm to 0, meaning that a value closer to 0 is perceived as a strong signal whereas a value close to -100 is a weak signal. The RSSI will be compared for every habitat, together with the distance and the number of phones used to see if any of these three influenced the measured RSSI.

Sub-question 3: Maximum distance

The final sub-question relates to the maximum distance of the sensor. The maximum distance the sensor can pick up a signal needs to be established. We do this for all three habitats, in order to see if there are differences or if the maximum distance is the same. This will be done by starting a test at 75m from the sensor. Then in steps per 10m, a scan will be done. The scan will be done until the signal (RSSI) is lost. Following this, a scan will be done at the last signal picked up as well as 5m after the position, in order to check for potential inaccuracy. Afterwards we can make an estimation of the maximum distance, providing a maximum distance ± 5m.

Data analysis

The data gathered from the sensor is sent to a database from SmartParks. Here all data is instantly grouped together by timestamp in a table, which can then be converted into a csv or excel file. First a data validation check is made whereby incomplete data will be removed. When the dataset is complete and valid, an analysis is made using SPSS. With this analytical program we can check for statistical significance in the results of the dataset.

To start off a descriptive analysis will be conducted regarding the data of the three different sub-questions. The descriptive analysis is performed using the 'Compare Means' options in SPSS. Here we can put the mean, maximum, minimum, standard deviation, standard error and N together in a table to provide a clear overview.

After this descriptive analysis, a test of normality will be done. This is done in order to select the correct test to statistically analyze the data. The test of normality is done by plotting a histogram of all measurements together with the normality curve. When this curve is similar to the values shown in the histogram, a distribution can be considered normal.

Signal measurements:

For signal measurements we use the mean signal count per habitat and per signal. After seeing the data was not normally distributed, a Mann-Whitney test was conducted to test the differences between the two signals. The explanatory variable in this case is signal type, the response variable the is signal count. To compare the three different habitats, a Kruskal-Wallis test was conducted. Here the explanatory variable is habitat, the response variable is the signal count. Following this, the three habitats were compared against each other through three more Mann-Whitney tests, where a Bonferroni correction is applied. To correct this one must divide the alpha by number of tests. In the case of the habitats the new alpha will be 0.05/3 = 0.0167.

Signal strength:

Similar to signal measurements, the data again was not normally distributed. Thus we used a Kruskal-Wallis test to test for difference between the RSSI of Bluetooth and Wi-Fi, as well as testing if there was significant difference between phones used and distance from the sensor. Comparing these also led to multiple Mann-Whitney tests where applicable, and a Bonferroni correction was in place. Distance and phones used consist of four groups, thus the correction leaves an alpha of 0.05/4 = 0.0125. The explanatory variables for this test are habitat, distance in meter and number of phones, the response variable is RSSI.

Maximum distance:

After the normality test it was found that maximum RSSI was non normally distributed so another Kruskal-Wallis test was used where habitat type was the explanatory variable and maximum RSSI the response variable. The maximum distance was normally distributed, so a one-way ANOVA was used to check for significant difference. Here the response variable is maximum distance and the explanatory variable is habitat type. When a difference was found, a post hoc Tukey test was conducted.

Viewpoint measurement analysis:

This bison viewpoint data will be more of a descriptive analysis, rather than a statistical one. Here the mean RSSI is compared, together with the number of unique signals, as well as total signals measured. Analyzing the unique signals provides us with a percentage of accurate reports per signal type.

Results

Signal measurement

The minimum amount of phone signals found in a test was 20, and the maximum was 46 (Table 1). On average, 33 signals were picked up by the smart sensor. In total, the means between Bluetooth and Wi-Fi signals differed only by two, Bluetooth having a mean count of 32, Wi-Fi having 34 as seen in Appendix A. Nonetheless there were bigger differences in mean counts between the habitats. Dunes saw a mean count of 38 Wi-Fi signals compared to 24 Bluetooth signals. Forests saw a mean count of 27 Wi-Fi signals and 43 Bluetooth signals, while plains saw a mean count of 32 for both Wi-Fi and Bluetooth signals.

Table 1: Descriptive statistic of the total signal count

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
Signal count	180	33,13	6,386	20	46

When a test of normality is done, and a histogram plus normality curve is made, it can be seen that both the Wi-Fi count and the Bluetooth count as seen in Figure 5 and 6 are not normally distributed.

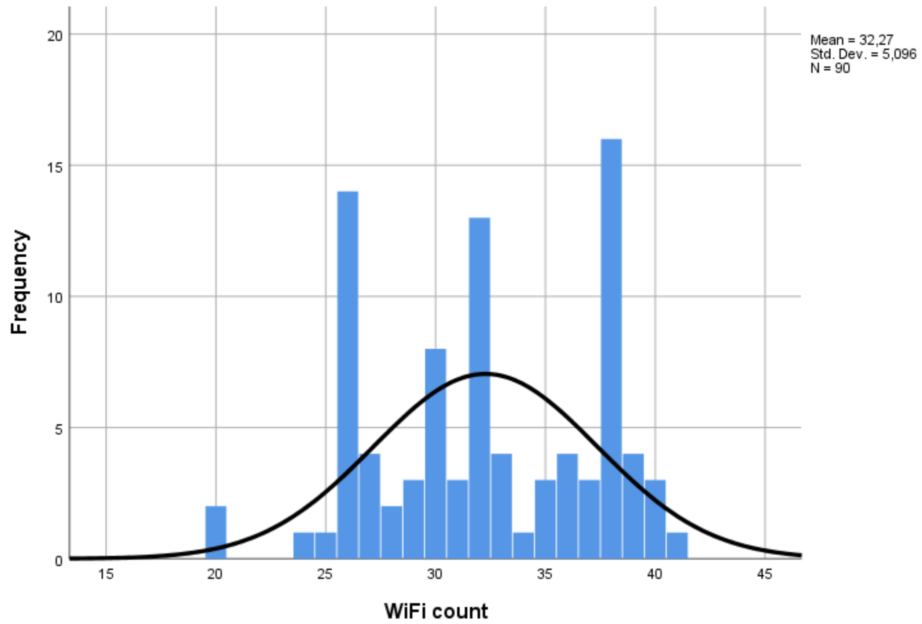


Figure 5: normality plot of the Wi-Fi count

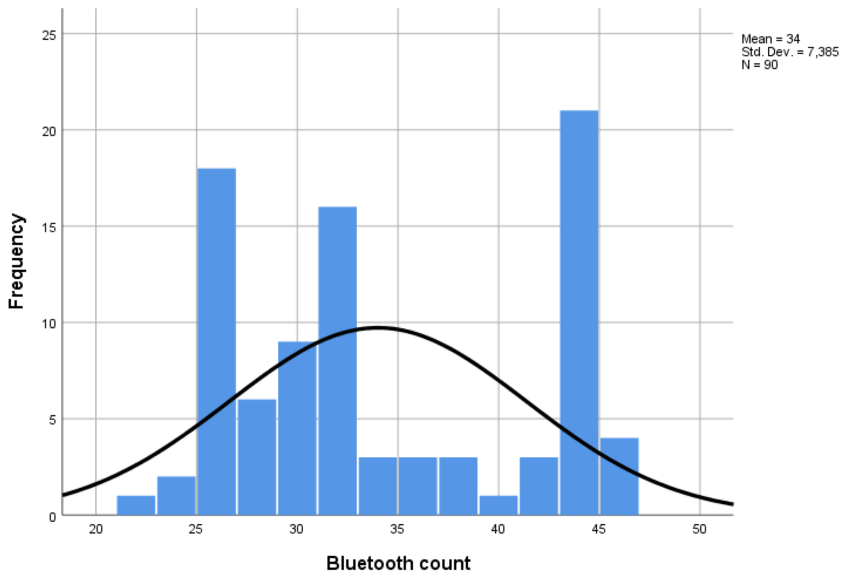


Figure 6: normality plot of the Bluetooth count

In order to test significance a Mann-Whitney test was ran in order to find out if Bluetooth and Wi-Fi signal type counts statistically differ. In order for the difference to be significant, the p-value should be below 0.05. As seen in Table 2**,** there is a p-value of 0.293, thus $p > 0.05$, and thus there is no significant difference in counts between signal types (for U = 3684, Z=-1.052 and p = 0.293).

Table 2; Mann-Whitney test for signal counts

Test Statistics[a]

	Signal count
Mann-Whitney U	3684,000
Wilcoxon W	7779,000
Z	-1,052
Asymp. Sig. (2-tailed)	,293

a. Grouping Variable: Signal type

To compare habitat type we used the Kruskal-Wallis test as visualized in Table 3**.** . As seen**,** there is a p-value of 0.206, thus $p > 0.05$, and thus there is no general significant difference in counts between the habitat types (for H = 3,163 and p = 0.206).

Table 3: Kruskal-Wallis test for habitat type & signal count

Test Statistics[a,b]

	Signal count
Kruskal-Wallis H	3,163
df	2
Asymp. Sig.	,206

a. Kruskal Wallis Test

b. Grouping Variable: Habitat_type

However, when we conduct a post hoc test by testing all habitat types against each other in a Mann-Whitney test, we find other results. Tables 4 & 5 below show no significant difference between the plains & dunes and plains & forest habitats due to their p-values of 0.935 and 0.735. But the test between forest & dunes gives a p-value of 0.012. Keeping the Bonferroni correction in mind, a value of $p < 0.0167$ is required to be significant. It can be seen in Table 6 that $p < 0.012$ so there is in fact a significant difference between the habitat types dunes and forest with regards to signal count.

Table 4: Mann-Whitney test for habitats Dunes & Plains

Test Statistics[a]

	Signal count
Mann-Whitney U	1784,500
Wilcoxon W	3614,500
Z	-,082
Asymp. Sig. (2-tailed)	,935

a. Grouping Variable: Habitat_type (Dunes & Plains)

Table 5: Mann-Whitney test for habitats Forest & Plains

Test Statistics[a]

	Signal count
Mann-Whitney U	1736,000
Wilcoxon W	3566,000
Z	-,339
Asymp. Sig. (2-tailed)	,735

a. Grouping Variable: Habitat_type (Forest & Plains)

Table 6: Mann-Whitney test for habitats Forest & Dunes

Test Statistics[a]

	Signal count
Mann-Whitney U	1324,000
Wilcoxon W	3154,000
Z	-2,525
Asymp. Sig. (2-tailed)	,012

a. Grouping Variable: Habitat_type (Forest & Dunes)

The mean counts per signal type are found in Appendix A and visualized in Figure 7. At first glance, the habitat type plains has the most balanced signal measure count. However of the possible 52 signals, only 32-33 are measured which equals 61-63% of the total signal count possible. Wi-Fi counts score better in the dunes habitat, whereas Bluetooth scores better in forests with a count of 37 (71%) and 43 (83%) respectively. In all three areas of the Kraansvlak there is a relatively similar overall percentage of signals that are measured. When looking at the standard errors, in the dunes and plains habitat the sensor performs better with Wi-Fi signals and in the forest habitat it performs better with Bluetooth.

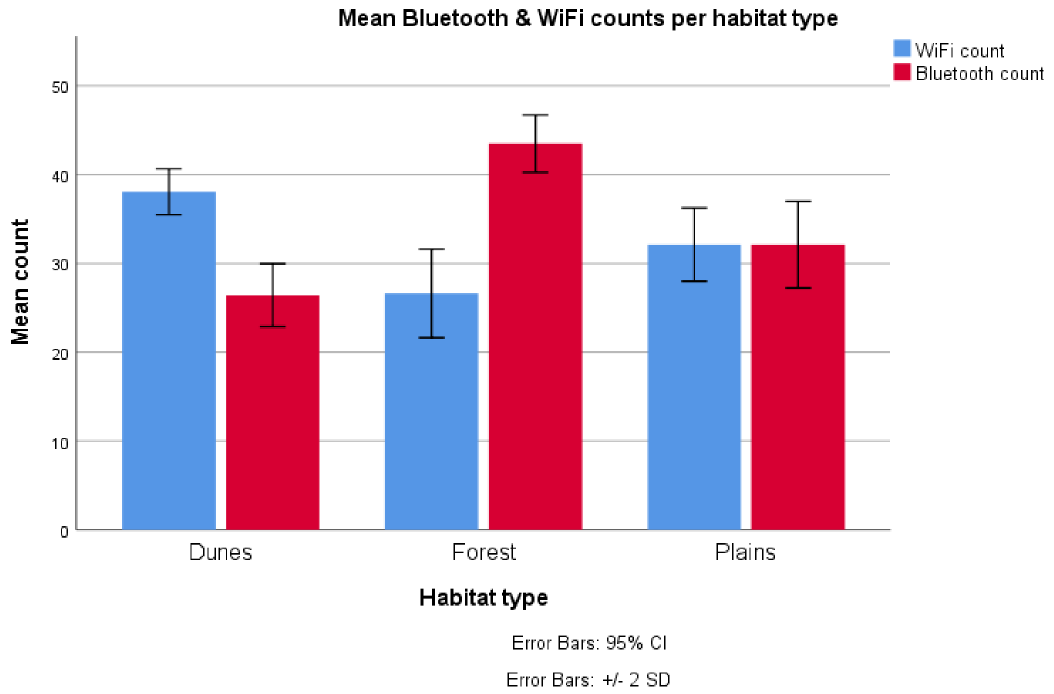


Figure 7: Mean Bluetooth & WiFi counts per habitat type

Finally, to answer sub-question 1: *How well does the new sensor measure signals between the three different Kraansvlak habitats?* We can say that the current sensor picks up at least more than half of all Wi-Fi and Bluetooth signals sent by phones. In the habitat types plains, forest and dunes the percentage of signals measured is 62.5%, 66.3% and 60.6%. This is a promising start for the new technology. With technology only becoming more advanced, the signal count is sure to increase even further.

Signal strength:

When we look at the descriptives as seen in Appendix B, we find a mean RSSI of -76 dBm for Wi-Fi and -79 dBm for Bluetooth. The minimum RSSI for Bluetooth and Wi-Fi are very similar with -94 dBm and -95 dBm respectively, but the maximum RSSI is more different with -40 dBm and -15 dBm respectively. Between habitats the minimum RSSI is roughly the same everywhere (-93 to -95 dBm), however the maximum differs, this is especially the case for Wi-Fi. When you look at the Bluetooth maximum this ranges between -40 and -44 dBm, but for Wi-Fi this is -15 to -29 dBm.

After conducting the normality test (histogram with normal curve) we see that both Bluetooth and Wi-Fi RSSI is also not normally distributed (Appendix B). Therefore we conduct the Kruskal-Wallis test. First this was conducted for distance to the sensor (Table 7), then for number of phones (Table 8), and finally for habitat types (Table 9). It can be seen that for distance ($p = 0.465$ & $p = 0.571$) and number of phones ($p = 0.3$ & $p = 0.69$) there are no significant differences between these grouping variables for both signal types. For habitat there is a significant difference for $p = 0.10$ and $p = 0.026$ between both Bluetooth and Wi-Fi signals.

Table 7: Kruskal-Wallis test for signal RSSI grouped by distance (m)

Test Statistics[a,b]

	WiFi RSSI	BT RSSI
Kruskal-Wallis H	2,555	2,006
df	3	3
Asymp. Sig.	,465	,571

a. Kruskal Wallis Test

b. Grouping Variable: distance (m)

Table 8: Kruskal-Wallis test for signal RSSI grouped by number of phones

Test Statistics[a,b]

	WiFi RSSI	BT RSSI
Kruskal-Wallis H	3,665	1,467
df	3	3
Asymp. Sig.	,300	,690

a. Kruskal Wallis Test

b. Grouping Variable: number of phones

Table 9: Kruskal-Wallis test for signal RSSI grouped by habitat types

Test Statistics[a,b]

	WiFi RSSI	BT RSSI
Kruskal-Wallis H	9,134	7,289
df	2	2
Asymp. Sig.	,010	,026

a. Kruskal Wallis Test

b. Grouping Variable: Habitat_types

In order to test which habitats significantly differ three Mann-Whitney tests were conducted. Once again taking into account the Bonferroni correction to divide the alpha by three. When looking at the results (Tables 10-12) we see no significant difference for either Bluetooth or Wi-Fi between forest and plains ($p = 0.989$ & $p = 0.711$), nor for Bluetooth between dunes and forest ($p = 0.057$). We do see a significant difference for Wi-Fi between dunes and forest ($p=0.007$), and for both Bluetooth and Wi-fi between dunes and plains ($p = 0.006$ & $p = 0.011$).

Table 10: Mann-Whitney test for RSSI between Dunes and Forest

Test Statistics[a]

	BT RSSI	WiFi RSSI
Mann-Whitney U	46747,500	44943,500
Wilcoxon W	98107,500	96303,500
Z	-1,906	-2,676
Asymp. Sig. (2-tailed)	,057	,007

a. Grouping Variable: Habitat_types (Dunes & Forest)

Table 11: Mann-Whitney test for RSSI between Dunes and Plains

Test Statistics[a]

	BT RSSI	WiFi RSSI
Mann-Whitney U	44783,500	45280,500
Wilcoxon W	96143,500	96640,500
Z	-2,746	-2,532
Asymp. Sig. (2-tailed)	,006	,011

a. Grouping Variable: Habitat_types (Dunes & Plains)

Table 12: Mann-Whitney test for RSSI between Forest and Plains

Test Statistics[a]

	BT RSSI	WiFi RSSI
Mann-Whitney U	51168,500	50335,000
Wilcoxon W	102528,500	101695,000
Z	-,013	-,370
Asymp. Sig. (2-tailed)	,989	,711

a. Grouping Variable: Habitat_types (Forest & Plains)

When the mean RSSI of Bluetooth and Wi-Fi signals are plotted per habitat you get Figure 9. This is the only variable that was proven to have significant difference. It can be seen that the mean RSSI for both Bluetooth and Wi-Fi between each habitat is roughly similar, however the large error bars due to the large standard deviation needs to be noted. What can be seen is that the error bars for Wi-Fi RSSI span a much larger area than the error bars for Bluetooth RSSI. This suggests that Bluetooth signals, albeit slightly weaker, are slightly more consistent in their strength than Wi-Fi signals

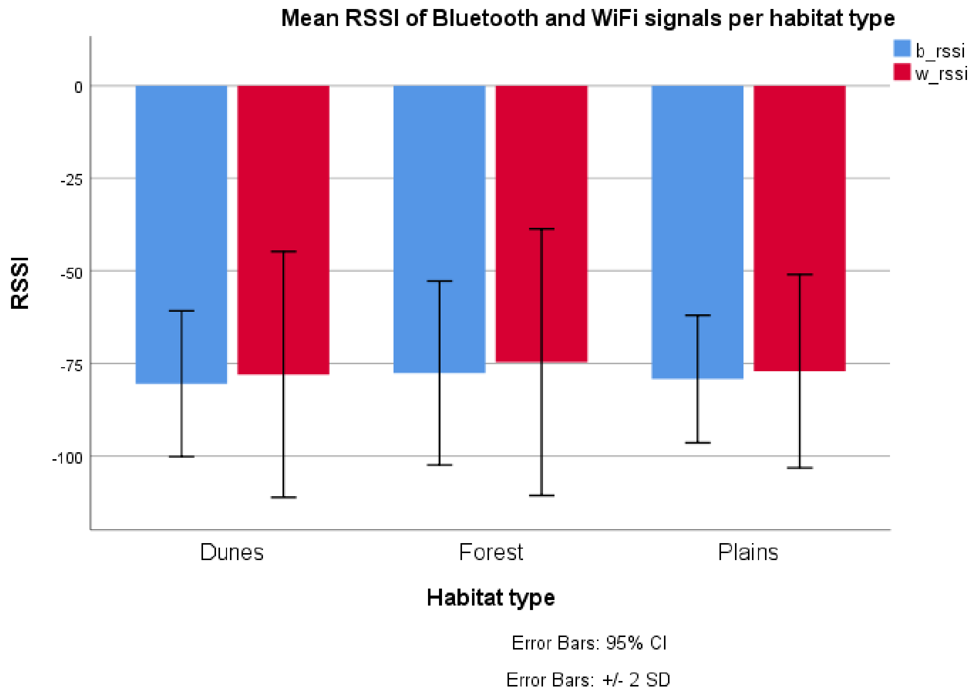


Figure 8: Mean RSSI of Bluetooth and Wi-Fi signals per habitat type

Coming back to the second sub-question: *How strong are the picked up signals and does this differ between the habitats?* We can say that the mean RSSI of a Bluetooth signal is slightly weaker than a Wi-Fi signal. However it is important to note the rather large standard deviations, and their differences between the habitats.

Maximum distance

After testing was concluded the maximum registered RSSI found was -95 dBm, whereas the mean maximum RSSI found was -94 dBm. The maximum distance found was ±100m, with a mean maximum distance of 96m. The largest maximum distance found was ± 100m in plains, and ± 95m in both dunes and forest. The mean max RSSI in the three different habitats were -93 dBm, -94 dBm and -95 dBm for dunes, forest and plains respectively.

The normality plots can be found in Appendix C, which has shown that maximum RSSI was not normally distributed, while maximum distance was normally distributed. Thus a Kruskal-Wallis test was conducted for maximum RSSI (Table 13) , while a One-Way ANOVA was conducted for maximum distance (Table 14). The Kruskal-Wallis test found a p-value of 0.236 which means there is no statistical significant different between the habitats for maximum RSSI. The ANOVA has shown a statistical significant difference between habitats for maximum distance ($p = 0.000$). After conducting a post hoc Tukey-test, it was found that there were no significant difference in maximum distance between forest and dunes ($p = 1.000$), while there is a significant difference between both plains and forest as well as plains dunes ($p = 0.000$).

Table 13: Kruskal-Wallis test for Max RSSI grouped by habitat types

Test Statistics[a,b]

	Max RSSI
Kruskal-Wallis H	2,887
df	2
Asymp. Sig.	,236

a. Kruskal Wallis Test

b. Grouping Variable: Habitat_types

Table 14: One-Way ANOVA for Max Distance (m)

ANOVA

Max Distance ±(m)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	201,667	2	100,833	60,500	,000
Within Groups	45,000	27	1,667		
Total	246,667	29			

Table 15: Post hoc Tukey-test comparing different habitats with depending variable Max Distance (m)

Multiple Comparisons

Dependent Variable: Max Distance ±(m)

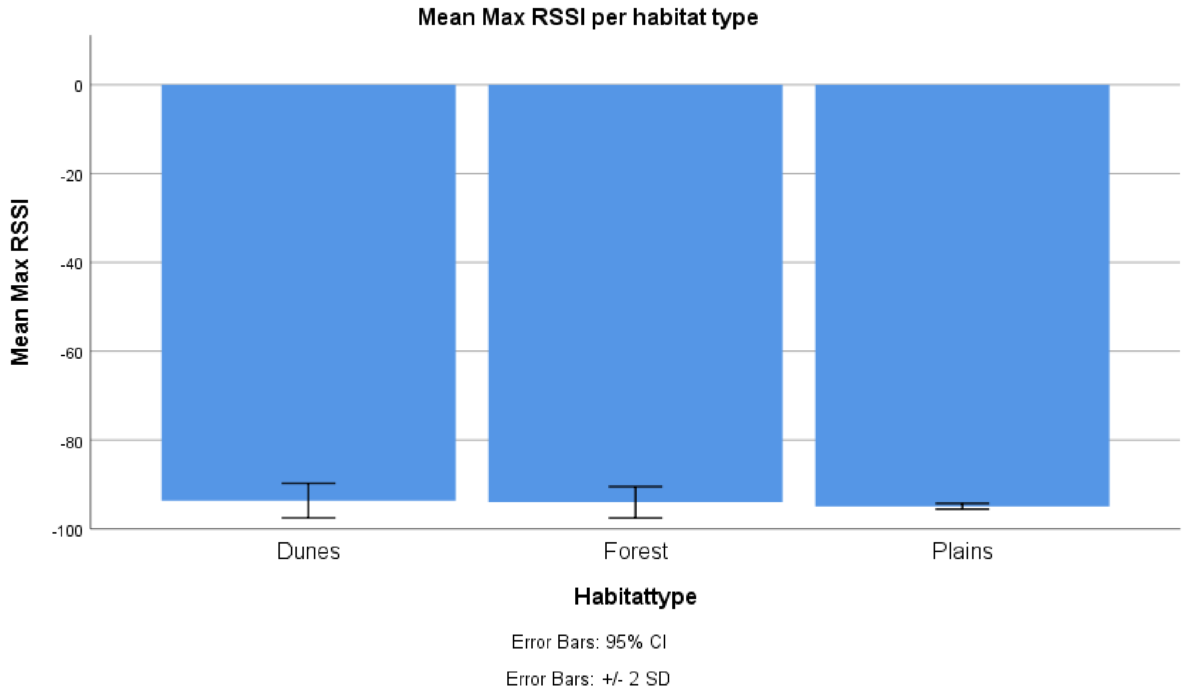
Tukey HSD

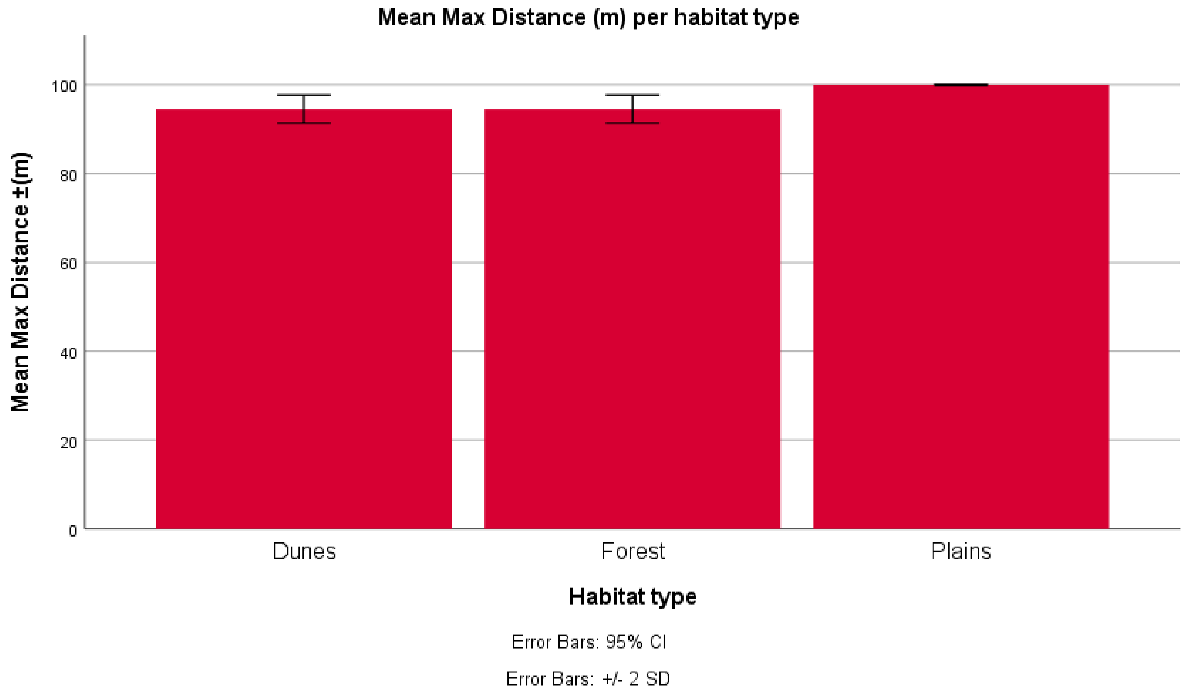
(I) habitat type	(J) habitat type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Dunes	Forest	,000	,577	1,000	-1,43	1,43
	Plains	-5,500*	,577	,000	-6,93	-4,07
Forest	Dunes	,000	,577	1,000	-1,43	1,43
	Plains	-5,500*	,577	,000	-6,93	-4,07
Plains	Dunes	5,500*	,577	,000	4,07	6,93
	Forest	5,500*	,577	,000	4,07	6,93

*. The mean difference is significant at the 0.05 level.

In Figure 10 we can see the mean max RSSI and distance per habitat types, it is clearly visible here that plains have a very tiny error bar for both variables, which indicates their maximum values are pretty accurate compared to dunes and forest, and were probably the actual maximum values.

Figure 10: Observations of Max RSSI and Max Distance a signal is measured





This leads us to answering the question: *How far away can the sensor pick up signals and is this feasible regarding animal policies?* It has become clear that the maximum distance the smart sensor can currently report is between 95 and 100m. However, this is not reported 100% of the times as there are occasions where a signal is lost on a shorter distance.

Bison viewpoint

During the observations at the bison viewpoint, the author has manually counted 95 people carrying phones. The sensor had picked up a total of 73 individual Wi-Fi signals, and reported a total of 99 signals, as some phones sent multiple signals to the sensor. For Bluetooth the sensor picked up all 95 individual signals, and reported a total of 219 signals. This means that the sensor picked up 76.8% of all independent Wi-Fi signal sources, and 100% of the Bluetooth signal sources (Table 16). When comparing the RSSI means and standard deviations of the bison viewpoint (Table 17) and the three habitat types we can see that these have similar values, giving the assumption that this test has proven that the smart sensor also works in a real life, less controlled scenario where multiple people freely walk in and out of range.

Table 16: Signal measurement at bison viewpoint

Signal type	Individual signals	Total signals	Percentage reported
Bluetooth	95	219	100%
Wi-Fi	73	99	76.8%

Table 17: Descriptive statistics for RSSI at bison viewpoint

Report

	WiFi RSSI	BT RSSI
Mean	-80,03	-81,05
Std. Deviation	10,763	16,104
Std. Error of Mean	,385	,529
Maximum	-42	-7
Minimum	-94	-95

Discussion

Examining the potential of this new smart sensor, we found that this first version of the smart sensor already measures over 60% of all signals emitted by smartphones, which indicates it could provide very useful information regarding two-way mapping of human-wildlife interactions. Furthermore we tested the signal strength at different distances, providing us with an overall mean RSSI of -75 to -79 dBm throughout all three habitats. While this is not the strongest RSSI, signals still get picked up regardless of what habitat the bison would reside in. In addition we established the maximum distance by means of maximum -dBm, showing a distance of roughly 100m. In the case of the Kraansvlak bison, this means that when people keep their safe distance of at least 50m, their signals can still be picked up by the sensor and used for mapping interactions. Finally we tested the smart sensor in a less controlled, real life scenario. Here we found that the sensor reports a large amount of signals and measures the vast majority of people coming within range.

Interesting to note is the large size difference between Wi-Fi and Bluetooth signals measured. The author has made the assumption here that this is largely affected by the CoronaMelder app that a majority of people encompasses all ages and genders have downloaded on their phones (Bente et al, 2021). As previously mentioned this is a contact-tracing app that scans for Bluetooth signals and then alarms you when you have been in contact with someone who tested positive. As the pandemic is still going on, many people have the app installed, leading to believe that this might be the cause of more Bluetooth signals being picked up. This test has proven that the smart sensor also works in a real life, less controlled scenario where multiple people freely walk in and out of range.

There is much unknown about the stress on animals caused by human visitor pressures. Klich et al., (2021) have found that European bison in a Polish zoos have little to no stress hormone level increase when visitor pressure increases. Mason (2010) argues that stress response to human pressures is species dependent, and Hill & Broom (2009) go even further arguing that individual animal traits are of great importance . However this research is mainly conducted on animals in captivity, and those are not wild animals. The wild bison in the Kraansvlak might respond differently, thus this new sensor can provide valuable information. The reported distance between humans and the bison from the sensor can be used in combination with their tracking system in order to see how bison move depending on whether or not humans are in the near vicinity. Kaczmarek-Okrój et al., (2016) established that the bison is sensitive to high environmental temperatures, so this in turn could also affect how they respond to human pressure.

Chan & Saqib (2021) argue that privacy concerns can explain unwillingness to download current COVID-19 apps that use contact tracing. This use of contact tracing is slightly different than the one used in the new smart sensor. In those apps you are able to receive messages when you have been in close contact with someone. This smart sensor only logs the fact that there is a signal near. The MAC-address of the signal is then hashed in the database, so there is no trace back to the person whose phone the signal belongs to. All that remains is the fact that a person has been near the sensor. Lu et al. (2021) have done research on preferences between human and digital contact tracing, and what type of information people would be willing to share. They found that a majority their respondents have little issues with providing their location information, paving the way for contact tracing to be used to map human-wildlife interactions, as the only data necessary to do so is their location.

Wall et al. (2014) have argued for real time wildlife monitoring since a few years now technology is becoming more and more advanced. One of their suggestions was geofencing, used to protect both animals and croplands. With this, one could monitor movement rate, proximity to croplands and possible immobility. Doing so, this places this technology also in the corner of digital conservation. This new smart sensor continues regarding this technological advancement as now two-way interactions are also possible to be mapped. More and more research is done regarding positive interactions between humans and wildlife. Rode et al. (2021) have expanded to positive interactions between humans and carnivores. Positives from these human-wildlife interactions could lead to benefits from game population control by large carnivores and wildlife tourism and commercial activities. Other benefits could include regional and product marketing, cultural heritage and identity, social cohesion, and important regarding rewilding, educational and research benefits.

Future research should focus on developing the sensor to improve the RSSI and amount of signals measured. Potential new locations should also be considered. For example a test with animals that are not in a confined, relatively small, area. Examples could be deer or the wolf in the Veluwe National Park. More urban animals could also be considered, such as foxes who frequent cities more and more (Scholz, 2021). As one of the activities of rewilding is reintroducing apex predators, it is not quite clear how useful a max reporting distance of only 100m can be, seeing how higher human population density negatively affects apex predator distribution (Morato et al, 2018).

The mapping of these two-way interactions between humans and wildlife will increase knowledge, and with more knowledge humans can find better ways to coexist with animals. In order for both parties to benefit from these interactions, human adaptation strategies are key (Killion et al., 2021). Killion et al. (2021) argue that humans lack a good understanding of how different social and ecological factors contribute to outcomes that can be beneficial to both parties. Limiting our opportunities to address local issues and scale up successful conservation actions. They state that active guarding is one of the strategies that generate cobenefits. The new smart sensor tested in this research can play an important role in developing new strategies to generate benefits for humans and wildlife. Other research has also suggested that rewilding can be more profitable than agri-environmental nature management (Schou et al, 2021). Furthermore rewilding areas with the right species can increase biodiversity and species richness (Dvorský et al, 2021). This could in turn lead to more wildlife tourism as previously mentioned, giving more opportunities for the new smart sensor to be used to help map human-wildlife interactions. As Elliott (2021) mentions, ecotourism is the preferred form of tourism to support the initiative of rewilding, however one must be wary of contradictions that could hamper the aims of rewilding such as greenwashing.

Regarding the Kraansvlak's current animal policies this distance is more than enough. The current policy is a distance of at least 50m from the bison. Therefore visitors coming to look for bison can still be measured on a more than safe enough distance, leaving the bison unbothered. Not only on the walking trail will this help map interactions, 100m is also a large enough distance to measure visitors at the bison viewpoint. Here the bison are fenced off from humans, and in turn might come closer than they would meeting them along the walking trail. This also brings potential for future purposes, as the smart sensor might report a change in the bison's movement behaviour when people are at a further distance. This in turn could lead to potential policy revisions.

This research, being a pilot study, naturally had certain limitations. Even though the sensor was standardized for current smartphones, to be entirely sure it works for all types of phones extra controlled experiments could be conducted with different types of phones. Another limitation could be the fact that smartphones might stop scanning and emitting signals after a certain amount of time not finding any source. T. van Dam (personal communication, June 15, 2021) from SmartParks has suggested that since the experiments were conducted in a remote area of a national park, after roughly 10 minutes phones might stop emitting signals if they don't find any sources to potentially connect to (such as Wi-Fi networks or Bluetooth devices), or when they go in 'sleep mode'. While this is something that we tested after by turning phones on always on, it could prove very valuable to look into this further. When people are out in nature, one could assume they aren't always on their phone as being out in nature relieves some of the stress of modern day life (Coyne, 2014). Thus there is a chance their phones are in sleep mode. Another limitation could be the reliance on a new technological development for accurate data. Since this is the first time something like this has been done, there are very little reference points. One more limitation could be the use of GPS counter on a smartphone to establish testing distances, there could be some inaccuracy in the data this way. A limitation for future purposes could be that currently it is still needed for SmartParks to deploy a certain amount of gateways for the smart sensor to pick up signals. Even though more and more gateways are deployed, it doesn't just work everywhere, yet.

Conclusion

The aim of this research was: *Examining the potential of a new smart contact-tracing sensor to be used as a new 'digital conservation' tool in the context of rewilding.* In order to examine this we had established three sub-questions to help aid in this examination. To achieve answering these sub-questions we tested the signal measurement, signal strength and maximum distance in the Kraansvlak, an area in the Kennemerduinen National Park that features three types of habitat (plains, forests and dunes). This location was chosen as the designated 'first user' of the sensor is the European bison that lives in this area, making it a great case study location. The results of the tests were to a certain extent very promising. Over half of all signals were picked up by the smart sensor. Both Bluetooth and Wi-Fi turned out to have similar RSSI, albeit with a large standard deviation, and the maximum distance was around 100m, which is more than enough distance to ensure visitor and bison safety. Furthermore the real setting where visitors walked in and out of the sensor proved valuable information, showing that it worked as intended, with similar RSSI values as in the controlled experiments. This provides hopeful potential to test the sensor around the neck of actual bison. This research has shown that there is potential for the sensor to encompass all five key dimensions of 'digital conservation'. The sensor gets data on nature such as bison movement through its LoRaWAN network, and data on people due to the measurement of phone signals. This data provision is being worked on by SmartParks who keep developing tools for data integration and analysis. Together with PWN, the participatory governance player they can suggest policy changes where necessary, as well as improving communication and experience. There are many pointers towards the potential of the smart sensor to become one of the go-to tools to aid in rewilding and nature conservation purposes. Nonetheless, this cannot be achieved without further research. More technical advancements can lead to a better performing sensor regarding signal measurements, increased RSSI and maximum distance. This can only be achieved if more testing is done, and more importantly if this is tested in a real scenario and not just a controlled experiment. With more research, this tool has potential to become a valuable way to passively map human-wildlife interactions.

References

Abson, D. J., Fischer, J., Leventon, J., Newig, J., Schomerus, T., Vilsmaier, U., & Lang, D. J. (2017). Leverage points for sustainability transformation. *Ambio*, *46*(1), 30-39.

Al Balushi, T., Al Hosni, A., Omar, H. A. T. B., & Al Abri, D. (2019, July). A LoRaWAN-based Camel Crossing Alert and Tracking System. In *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)* (Vol. 1, pp. 1035-1040). IEEE.

Andrews, N. (2018). How cognitive frames about nature may affect felt sense of nature connectedness. *Ecopsychology*, *10*(1), 61-71.

Arts, K., van der Wal, R. & Adams, W.M. Digital technology and the conservation of nature. *Ambio* **44,** 661–673 (2015). https://doi.org/10.1007/s13280-015-0705-1

Bakker, E. S., & Svenning, J. C. (2018). Trophic rewilding: impact on ecosystems under global change.

Beery, T. H., & Wolf-Watz, D. (2014). Nature to place: Rethinking the environmental connectedness perspective. *Journal of Environmental Psychology*, *40*, 198-205.

Bente, B. E., van't Klooster, J. W., Slijkhuis, P. J. H., Berkemeier, L., Schreijer, M. A., van Gend, J. E., ... & van Gemert-Pijnen, L. J (2021). The Dutch COVID-19 Contact Tracing App (the CoronaMelder): Usability Study. *JMIR formative research*, *5*(3), e27882.

Carter, N. H., & Linnell, J. D. (2016). Co-adaptation is key to coexisting with large carnivores. *Trends in Ecology & Evolution*, *31*(8), 575-578.

Ceaușu, S., Hofmann, M., Navarro, L. M., Carver, S., Verburg, P. H., & Pereira, H. M. (2015). Mapping opportunities and challenges for rewilding in Europe. *Conservation Biology*, *29*(4), 1017-1027.

Cho, H., Ippolito, D., & Yu, Y. W. (2020). Contact tracing mobile apps for COVID-19: Privacy considerations and related trade-offs. *arXiv preprint arXiv:2003.11511*.

Conover, M. R. (2001). *Resolving human-wildlife conflicts: the science of wildlife damage management*. CRC press.

Coyne, R. (2014). Nature vs. smartphones. *Interactions*, *21*(5), 24-31.

Cromsigt, J. P., Te Beest, M., Kerley, G. I., Landman, M., le Roux, E., & Smith, F. A. (2018). Trophic rewilding as a climate change mitigation strategy?. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1761), 20170440.

Dallimer, M., Tinch, D., Hanley, N., Irvine, K. N., Rouquette, J. R., Warren, P. H., & Armsworth, P. R. (2014). Quantifying preferences for the natural world using monetary and nonmonetary assessments of value. *Conservation Biology*, *28*(2), 404-413.

Dickman, A. J. (2010). Complexities of conflict: the importance of considering social factors for effectively resolving human–wildlife conflict. *Animal conservation*, *13*(5), 458-466.

Dvorský, M., Mudrák, O., Doležal, J., & Jirků, M. (2021). Rewilding With Large Herbivores Helped Increase Plant Species Richness in Dry Grasslands.

Elbakidze, L. (2007). Economic benefits of animal tracing in the cattle production sector. *Journal of Agricultural and Resource Economics*, 169-180.

Elliot, N. L. Ecotourism and Rewilding Europe. In *Routledge Handbook of Ecotourism* (pp. 344-356). Routledge.

Feltrin, L., Buratti, C., Vinciarelli, E., De Bonis, R., & Verdone, R. (2018). LoRaWAN: Evaluation of link-and system-level performance. *IEEE Internet of Things Journal*, *5*(3), 2249-2258.

Frank, B., Glikman, J. A., & Marchini, S. (Eds.). (2019). *Human–wildlife interactions: turning conflict into coexistence* (Vol. 23). Cambridge University Press.

Gigliotti, L. M., Shroufe, D. L., & Gurtin, S. (2009). The changing culture of wildlife management. *Wildlife and Society: The Science of Human Dimensions. Island Press: Washington, DC*, 75-89.

Grima, N., Corcoran, W., Hill-James, C., Langton, B., Sommer, H., & Fisher, B. (2020). The importance of urban natural areas and urban ecosystem services during the COVID-19 pandemic. *Plos one*, *15*(12), e0243344.

Haidt, A., Kamiński, T., Borowik, T., & Kowalczyk, R. (2018). Human and the beast—Flight and aggressive responses of European bison to human disturbance. *PloS one*, *13*(8), e0200635.

Hale, S. L., & Koprowski, J. L. (2018). Ecosystem-level effects of keystone species reintroduction: a literature review. *Restoration Ecology*, *26*(3), 439-445.

Harrison, K. A., & Bardgett, R. D. (2008). Impacts of grazing and browsing by large herbivores on soils and soil biological properties. In *The ecology of browsing and grazing* (pp. 201-216). Springer, Berlin, Heidelberg.

Helmer, W., Saavedra, D., Sylvén, M., & Schepers, F. (2015). Rewilding Europe: a new strategy for an old continent. In *Rewilding European Landscapes* (pp. 171-190). Springer, Cham.

Hill, S. P., & Broom, D. M. (2009). Measuring zoo animal welfare: theory and practice. *Zoo Biology: Published in affiliation with the American Zoo and Aquarium Association*, *28*(6), 531-544.

Jaroszewicz, B., & Pirożnikow, E. (2008). Diversity of plant species eaten and dispersed by the European bison Bison bonasus in Białowieża Forest. *European bison conservation Newsletter*, *1*, 14-29.

Jepson, P. R., & Schepers, F. (2016). Making space for rewilding: creating an enabling policy enviornment.

Johansson, M., Dressel, S., Kvastegård, E., Ericsson, G., Fischer, A., Kaltenborn, B. P., & Sandström, C. (2016). Describing human–wildlife interaction from a European perspective. *Human Dimensions of Wildlife*, *21*(2), 158-168.

Johnson, C. N. (2009). Ecological consequences of Late Quaternary extinctions of megafauna. *Proceedings of the Royal Society B: Biological Sciences*, *276*(1667), 2509-2519.

Kabisch, N., & Haase, D. (2011). Diversifying European agglomerations: evidence of urban population trends for the 21st century. *Population, space and place*, *17*(3), 236-253.

Kaczmarek-Okrój, M., Bruczyńska, M., Wojciechowska, M., Klich, D., Głowacz, K., Gajewska, K., & Olech, W. (2016). Rules of capture and transport of wisents from Poland to other European countries. *European Bison Conservation Newsletter*, *9*, 71-86.

Karl, S., Barthel, S., Colding, J., Macassa, G., & Giusti, M. (2020). Urban nature as a source of resilience during social distancing amidst the coronavirus pandemic. *OSF preprints*.

Killion, A. K., Ramirez, J. M., & Carter, N. H. (2021). Human adaptation strategies are key to cobenefits in human–wildlife systems. *Conservation Letters*, *14*(2), e12769.

Kerley, G. I., Kowalczyk, R., & Cromsigt, J. P. (2012). Conservation implications of the refugee species concept and the European bison: king of the forest or refugee in a marginal habitat?. *Ecography*, *35*(6), 519-529.

Keulartz, J. (2018). Rewilding. In *Oxford Research Encyclopedia of Environmental Science*.

Klich, D., Łopucki, R., Gałązka, M., Ścibior, A., Gołębiowska, D., Brzezińska, R., ... & Olech, W. (2021). Stress hormone level and the welfare of captive European bison (Bison bonasus): the effects of visitor pressure and the social structure of herds. *Acta Veterinaria Scandinavica*, *63*(1), 1-12.

König, H. J., Kiffner, C., Kramer-Schadt, S., Fürst, C., Keuling, O., & Ford, A. T. (2020). Human–wildlife coexistence in a changing world. *Conservation Biology*, *34*(4), 786-794.

Koninx, F. (2019). Ecotourism and rewilding: the case of Swedish Lapland. *Journal of Ecotourism*, *18*(4), 332-347.

Kowalczyk, R., Taberlet, P., Coissac, E., Valentini, A., Miquel, C., Kamiński, T., & Wójcik, J. M. (2011). Influence of management practices on large herbivore diet—Case of European bison in Białowieża Primeval Forest (Poland). *Forest Ecology and Management*, *261*(4), 821-828.

Krasińska, M., & Krasiński, Z. (2013). *European bison: the nature monograph*. Springer Science & Business Media.

Linnell, J. D., Kaczensky, P., Wotschikowsky, U., Lescureux, N., & Boitani, L. (2015). Framing the relationship between people and nature in the context of European conservation. *Conservation Biology*, *29*(4), 978-985.

Linnell, J. D., & Kaltenborn, B. P. (2019). Institutions for achieving human wildlife coexistence: the case of large herbivores and large carnivores in Europe. *Human–Wildlife Interactions: Turning Conflict into Coexistence*, *23*, 288.

Lu, X., L. Reynolds, T., Jo, E., Hong, H., Page, X., Chen, Y., & A. Epstein, D. (2021, May). Comparing Perspectives Around Human and Technology Support for Contact Tracing. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1-15).

Madden, F. (2004). Creating coexistence between humans and wildlife: global perspectives on local efforts to address human–wildlife conflict. *Human dimensions of wildlife*, *9*(4), 247-257.

Marion, S., Davies, A., Demšar, U., Irvine, R. J., Stephens, P. A., & Long, J. (2020). A systematic review of methods for studying the impacts of outdoor recreation on terrestrial wildlife. *Global ecology and conservation*, *22*, e00917.

Martin, B. (2019). Technology to the Rescue. In *Survival or Extinction?* (pp. 319-330). Springer, Cham.

Mason, G. J. (2010). Species differences in responses to captivity: stress, welfare and the comparative method. *Trends in ecology & evolution*, *25*(12), 713-721.

Meadows, D. H. (1999). Leverage points: Places to intervene in a system.

Miller, Z. D., & Freimund, W. (2018). Using visual-based social norm methods to understand distance-related human–wildlife interactions. *Human Dimensions of Wildlife*, *23*(2), 176-186.

Morato, R. G., Connette, G. M., Stabach, J. A., De Paula, R. C., Ferraz, K. M. P. M., Kantek, D. L. Z., ... & Leimgruber, P. (2018). Resource selection in an apex predator and variation in response to local landscape characteristics. *Biological Conservation*, *228*, 233-240.

Morse, J. W., Gladkikh, T. M., Hackenburg, D. M., & Gould, R. K. (2020). COVID-19 and human-nature relationships: Vermonters' activities in nature and associated nonmaterial values during the pandemic. *PloS one*, *15*(12), e0243697.

Nyhus, P. J. (2016). Human–wildlife conflict and coexistence. *Annual Review of Environment and Resources*, *41*, 143-171.

Orton-Johnson, K., & Prior, N. (Eds.). (2013). *Digital sociology: Critical perspectives*. Springer.

Panicker, J. G., Azman, M., & Kashyap, R. (2019, February). A LoRa wireless mesh network for wide-area animal tracking. In *2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)* (pp. 1-5). IEEE.

Pereira, H. M., & Navarro, L. M. (2015). *Rewilding european landscapes* (p. 227). Springer Nature.

Pettorelli, N., Durant, S. M., & Du Toit, J. T. (Eds.). (2019). *Rewilding*. Cambridge University Press.

Rode, J., Flinzberger, L., Karutz, R., Berghöfer, A., & Schröter-Schlaack, C. (2021). Why so negative? Exploring the socio-economic impacts of large carnivores from a European perspective. *Biological Conservation*, *255*, 108918.

Rorres, C., Romano, M., Miller, J. A., Mossey, J. M., Grubesic, T. H., Zellner, D. E., & Smith, G. (2018). Contact tracing for the control of infectious disease epidemics: Chronic Wasting Disease in deer farms. *Epidemics*, *23*, 71-75.

Sandbrook, C., Adams, W. M., & Monteferri, B. (2015). Digital games and biodiversity conservation. *Conservation Letters*, *8*(2), 118-124.

Schepers, F., & Jepson, P. (2016). Rewilding in a European context. *International Journal of Wilderness*, *22*(2), 25-30.

Scholz, C. (2021). *The ecology of red foxes (vulpes vulpes) in anthropogenic landscapes* (Doctoral dissertation).

Schou, J. S., Bladt, J., Ejrnæs, R., Thomsen, M. N., Vedel, S. E., & Fløjgaard, C. (2021). Economic assessment of rewilding versus agri-environmental nature management. *Ambio*, *50*(5), 1047-1057.

Sirotek, A., & Hart, J. (2019). Possibilities of monitoring cattle via GSM and A-GPS.

Soulsbury, C. D., & White, P. C. (2016). Human–wildlife interactions in urban areas: a review of conflicts, benefits and opportunities. *Wildlife research*, *42*(7), 541-553.

Torres, A., Fernández, N., Zu Ermgassen, S., Helmer, W., Revilla, E., Saavedra, D., & Pereira, H. M. (2018). Measuring rewilding progress. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1761), 20170433.

Treves, A., Wallace, R. B., Naughton-Treves, L., & Morales, A. (2006). Co-managing human–wildlife conflicts: a review. *Human Dimensions of Wildlife*, *11*(6), 383-396.

Treves, A., Chapron, G., López-Bao, J. V., Shoemaker, C., Goeckner, A. R., & Bruskotter, J. T. (2017). Predators and the public trust. *Biological Reviews*, *92*(1), 248-270.

Treves, A., & Santiago-Ávila, F. J. (2020). Myths and assumptions about human-wildlife conflict and coexistence. *Conservation Biology*, *34*(4), 811-818.

Valdés-Correcher, E., Rodriguez, E., Kemp, Y. J., Wassen, M. J., & Cromsigt, J. P. (2018). Comparing the impact of a grazing regime with European bison versus one with free-ranging cattle on coastal dune vegetation in the Netherlands. *Mammal research*, *63*(4), 455-466.

Van der Wal, R., & Arts, K. (2015). Digital conservation: An introduction. *Ambio*, *44*(4), 517-521.

Vaz, A. S., Moreno-Llorca, R. A., Gonçalves, J. F., Vicente, J. R., Méndez, P. F., Revilla, E., & Alcaraz-Segura, D. (2020). Digital conservation in biosphere reserves: Earth observations, social media, and nature's cultural contributions to people. *Conservation Letters*, *13*(3), e12704.

Wall, J., Wittemyer, G., Klinkenberg, B., & Douglas-Hamilton, I. (2014). Novel opportunities for wildlife conservation and research with real-time monitoring. *Ecological Applications*, *24*(4), 593-601.

White, P. C., & Ward, A. I. (2011). Interdisciplinary approaches for the management of existing and emerging human–wildlife conflicts. *Wildlife Research*, *37*(8), 623-629.

WWF (2020), from:
https://wwf.panda.org/discover/our_focus/wildlife_practice/problems/human_animal_conflict/

Xia, F., Yang, L. T., Wang, L., & Vinel, A. (2012). Internet of things. *International journal of communication systems*, *25*(9), 1101.

Appendix

A: Signal measurements

Table 18: Descriptive statistics of WiFi and Bluetooth counts per habitat

Report

habitat type		WiFi count	Bluetooth count
Dunes	Mean	38,07	26,43
	N	30	30
	Std. Deviation	1,285	1,775
	Std. Error of Mean	,235	,324
	Minimum	35	22
	Maximum	41	31
Forest	Mean	26,63	43,47
	N	30	30
	Std. Deviation	2,484	1,613
	Std. Error of Mean	,454	,295

	Minimum	20	38
	Maximum	30	46
Plains	Mean	32,10	32,10
	N	30	30
	Std. Deviation	2,057	2,440
	Std. Error of Mean	,376	,446
	Minimum	27	26
	Maximum	37	38
Total	Mean	32,27	34,00
	N	90	90
	Std. Deviation	5,096	7,385
	Std. Error of Mean	,537	,778
	Minimum	20	22
	Maximum	41	46

B: Signal strength

Table 19: descriptive statistics for RSSI

Report

habitat		BT RSSI	WiFi RSSI
Dunes	Mean	-80,49	-78,01
	N	320	320
	Std. Deviation	9,861	16,585
	Std. Error of Mean	,551	,927
	Minimum	-93	-95
	Maximum	-44	-17
Forest	Mean	-77,63	-74,69
	N	320	320
	Std. Deviation	12,424	18,013
	Std. Error of Mean	,695	1,007
	Minimum	-93	-95
	Maximum	-40	-15
Plains	Mean	-79,26	-77,11
	N	320	320
	Std. Deviation	8,605	13,071
	Std. Error of Mean	,481	,731
	Minimum	-94	-95
	Maximum	-44	-29
Total	Mean	-79,12	-76,60
	N	960	960

	Std. Deviation	10,474	16,069
	Std. Error of Mean	,338	,519
	Minimum	-94	-95
	Maximum	-40	-15

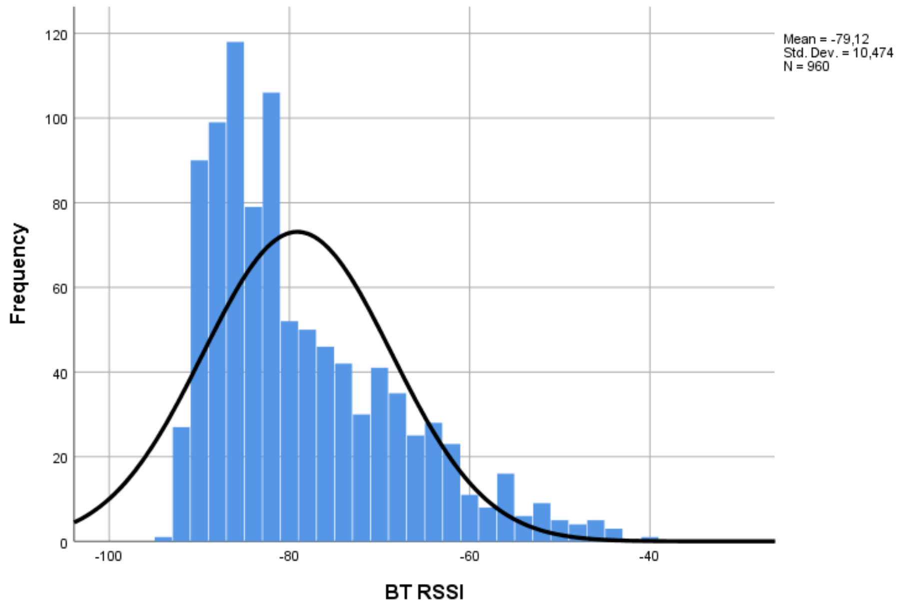


Figure 11: Normality plot for Bluetooth RSSI

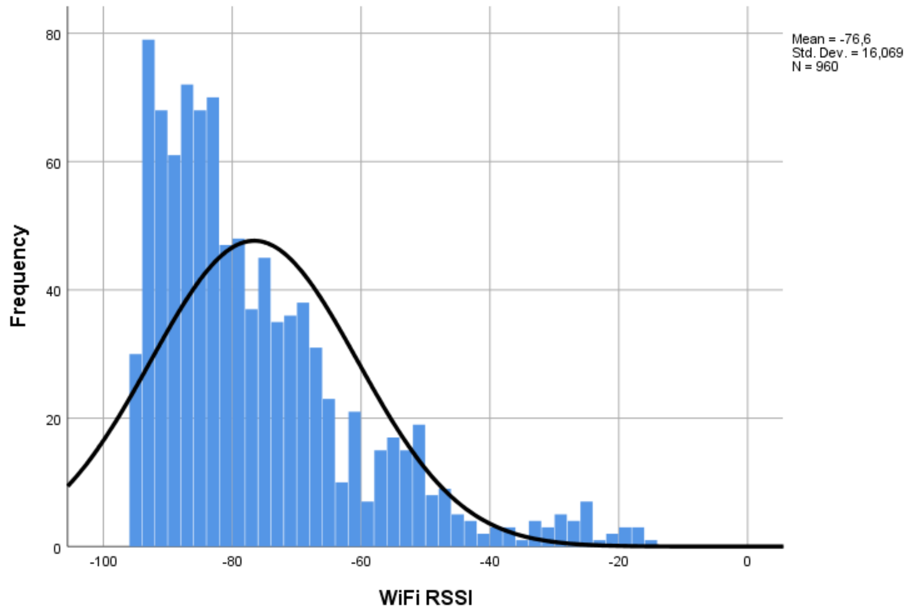


Figure 12: Normality plot for Wi-Fi RSSI

Table 10: RSSI averages per distance for Wi-Fi and Bluetooth

RSSI averages per distance

distance (m)		BT RSSI	WiFi RSSI
25	Mean	-78,47	-75,21
	N	240	240
	Std. Deviation	10,793	15,358
50	Mean	-78,60	-75,35
	N	240	240
	Std. Deviation	10,734	16,550
75	Mean	-79,43	-77,24
	N	240	240
	Std. Deviation	10,482	16,622
100	Mean	-79,51	-77,92
	N	240	240
	Std. Deviation	10,906	15,743
Total	Mean	-79,00	-76,43
	N	960	960
	Std. Deviation	10,729	16,069

C: Maximum distance

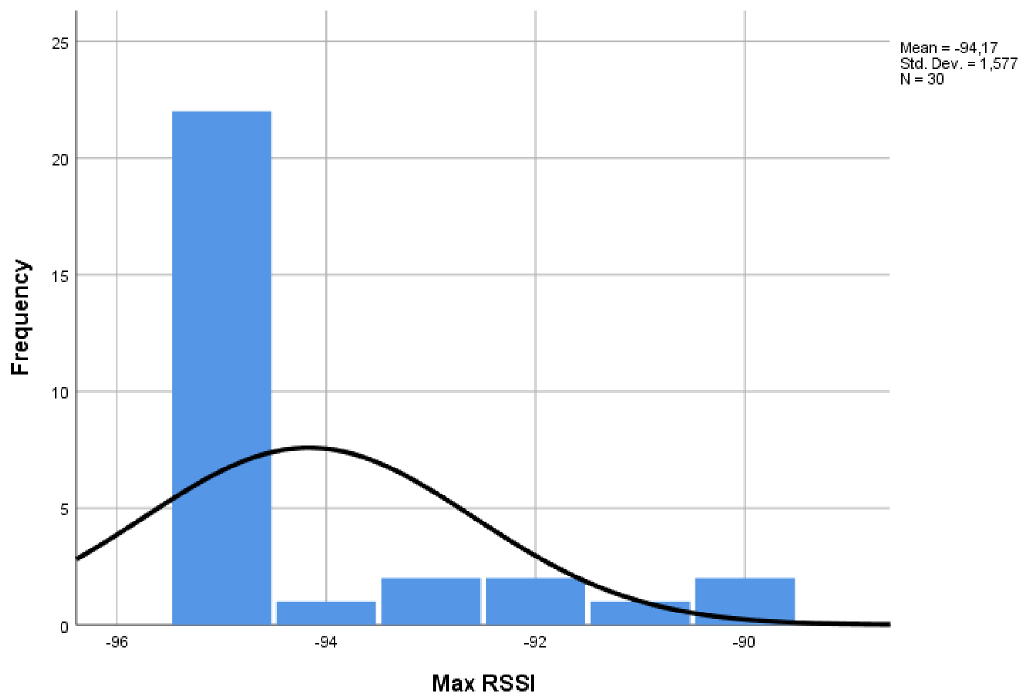


Figure 13: Normality plot for Max RSSI

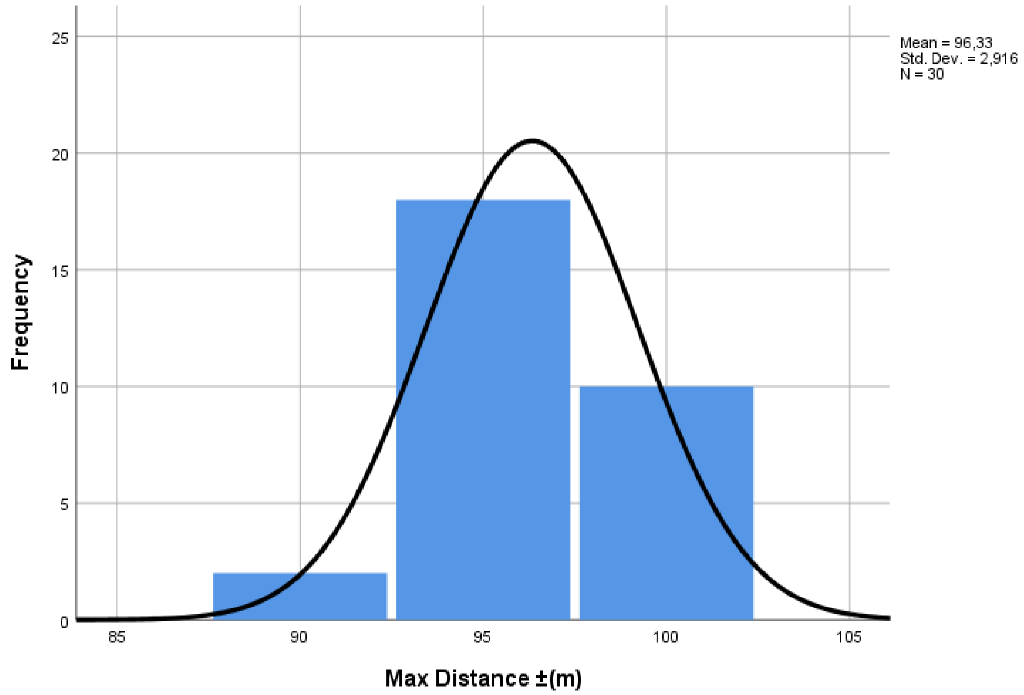


Figure 14: Normality plot for Max Distance (m)

Table 201: Descriptive statistics for max distance and RSSI

Report

Habitat		Max RSSI	Max Distance ±(m)
Dunes	Mean	-93,60	94,50
	N	10	10
	Std. Deviation	1,955	1,581
Forest	Mean	-94,00	94,50
	N	10	10
	Std. Deviation	1,764	1,581
Plains	Mean	-94,90	100,00
	N	10	10
	Std. Deviation	,316	,000
Total	Mean	-94,17	96,33
	N	30	30
	Std. Deviation	1,577	2,916

Table 22: Descriptive statistics for max distance per habitat type

Descriptive Statistics

Dependent Variable: Max Distance ±(m)

Habitattype	Mean	Std. Deviation	N
Dunes	94,50	1,581	10
Forest	94,50	1,581	10
Plains	100,00	,000	10
Total	96,33	2,916	30