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Master Thesis

Going Wild with Weather: Exploring the Viability of Wildlife Collars as Supplemental Temperature Data Sources

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Abstract

Obtaining fine-scale accurate temperature data can be a difficult prospect. Due to variances in environmental factors like topography and vegetation cover, stationary weather stations and satellites may fail to adequately represent the full range of temperatures across a landscape. Wildlife equipped with temperature recording GPS telemetry collars may be a valuable source for this fine-scale temperature data, but the factors influencing temperature differences between animal collars and air temperature must be determined to accurately record and model temperature. Likewise, choice of species would need to be evaluated for their suitability to serve as "mobile weather stations". Two commonly monitored terrestrial mammal species were selected to compare differences in temperature offset. Data collected from 15 roe deer *(Capreolus capreolus*) over 3 years and 11 brown bears (*Ursus arctos*) over 14 years equipped with temperature logging GPS telemetry collars were compared with corresponding historical temperature data from nearby weather stations. Data was analyzed using generalized linear mixed modeling (GLMM) to identify variables most impactful to temperature offsets, such as animal weight and wind speed. Results indicate that the temperatures obtained from roe deer equipped with GPS collars are highly correlated to the temperatures reported by nearby weather stations. With an average (mean ± 2SD) temperature difference of 7.69 ± 3.23 °C year-round (6.30 ± 3.02 °C in summer and 8.98 ± 2.85 °C in winter). When fitted to a predictive model roe deer collar measurements were able to successfully predict temperature of nearby weather stations R^2=0.83. It was discovered that body size and activity level were most impactful for accounting for temperature offsets. Brown bears showed greater temperature discrepancies with a difference of 14.58 ± 4.11 C° year-round (10.36 ± 3.87 °C in summer, and 17.0 ± 4.58 °C in winter, during their denning period). When modeled, brown bear collar measurements were less able to accurately predict nearby weather station temperature R^2=0.52. We demonstrate that wildlife telemetry collars have the capability to accurately gather fine-scale temperature data, but species selection plays a vital role as well as what variables are most important to account for temperature offsets. prior knowledge of key variables and species selection play a vital role in predicting temperature.

Key Words: *Capreolus capreolus*, fine-scale, micro-climate, telemetry collar, *Ursus arctos*, weather station

Contents

1. Introduction

As climate models become more sophisticated, researchers look for ways to measure fine-scale climate variables in historically unmonitored or remote places (Franklin et al., 2013; Rummukainen, 2010). Traditional meteorological data is obtained from stationary weather stations and an array of orbiting satellites (Mendelsohn et al., 2007). While these remain reliable sources of data, they are limited in their complete depiction of on-the-ground temperature ranges. Topographic features like canyons and tree canopy found in dense forests create distinct microclimates (Chen et al., 1999; De Frenne & Verheyen, 2016). Temperature recording devices on wildlife telemetry collars are a potential source of information to fill this data gap and better tailor climate and weather prediction models on a local scale. However, the choice of species serving as these 'mobile weather stations' may be important in the reliability of obtaining accurate and useful data. Differences in physiology, phenology, and life history traits such as metabolism, collar placement, and hibernation can cause drastic variation in recorded body temperature between shifting seasons and species. (Clarke & Rothery, 2008; Geiser, 2004; Heinrich, 1977)

Fine-scale temperature data have numerous applications in ecological studies. For instance, species distribution models (SDM) (Ford et al., 2013; Franklin et al., 2013), can be used to predict the change in a species distribution in the future under changing climate conditions (Elith et al., 2009). This type of data may also aid researchers and wildlife managers in determining thermal refuges or hotspots in landscapes, especially in relation to wildlife's response to intense weather events like heat waves (Alibright et al., 2011). On a smaller scale, habitats may possess features including changes in vegetation cover or topography overlooked by traditional temperature measuring methods (Ford et al., 2013). Retrieving this fine-scale data can be difficult and costly for researchers if they need to deploy temperature sensors and perform surveys in person. Wildlife already equipped with temperature sensors may offer a more feasible, dynamic, and cost-efficient data source.

Boreal and alpine systems face considerable shifts due to climate change caused by factors like alterations in snowpack, annual precipitation, and temperatures (Price et al., 2013; Gobiet et al., 2014; IPCC, 2023). These conditions can lead to a range of issues like wildfires, altered timber growth, crop failure, and animal fatalities, both wild and domestic. This creates challenges for forestry industries, wildlife managers, farmers, and landowners (Kasischke et al., 2012; Stocks, 1998; Venäläinen et al., 2022; Volney et al., 2020). Due to their mountainous nature, these ecosystems often have dense forests and highly varying topological features (Dirnböck et al., 2003). This makes recording accurate fine-scale temperature data difficult for the varied weather stations present in a landscape. Since weather stations are only able to measure the temperature in their immediate vicinity and are often too few in between, getting a complete coverage of the variability in landscape temperatures can be challenging (Martin et al., 2019).

In addition, satellites can be a useful tool in monitoring temperature and creating climate models. They are excellent in providing consistent data over large areas over long time spans. However, satellites are currently less accurate in determining true temperature conditions at a given point than a traditional weather station, as they measure the brightness of the atmosphere and then convert that to a temperature reading with accuracy hindered by topography and latitude (Climate NASA, 2023; Palmer et al., 2018). They also struggle with fine-scale temperature changes throughout a landscape and are unable to provide temperature readings in areas under dense vegetation canopy or anywhere else where direct visibility is hindered, such as under intense cloud cover or in deep ravines (Dubovik et al., 2021). Despite this, there are efforts to compensate for these challenges using modeling techniques (Kearney et al., 2020).

Over the last decade, GPS (Global Positioning System) telemetry collars have become more sophisticated, affordable, and available in wildlife research and management, and are starting to replace or complement older technology such as VHF (Very High Frequency) collars (Allan, 2013). These GPS collars allow researchers to track and record the location and movement of individuals and groups of animals over large distances and lengths of time, making them excellent sources of long-term data (Dussault et al., 1999; Habib et al., 2014; Johansson et al., 2016). Recent advances in GPS telemetry collars allow for additional data streams to be collected, including temperature data when collars are equipped with temperature sensors. This enables the recording of temperatures in the animals' immediate vicinity at regular intervals. These collar sensors can be used to establish the external temperature of a given animal, or to record air temperature adjacent to the collar (Whitford & Klimley, 2019; Weaver, 2021).

Such data has the potential to answer a variety of research questions related to physiological, ecological, and behavioral topics. In marine environments, wildlife has been used to gather environmental temperature data for years, but this method remains underutilized in terrestrial environments (Simmons et al., 2011; McMahon et al., 2021). A challenge to this use is the possibility that a collared animal's ambient body heat may influence the temperature readings. Body heat can influence temperature readings to a varying degree depending on multiple factors, such as body position, denning, collar position, activity level, or weather conditions. (Harlow et al., 2004). Previous studies have investigated the offsets between telemetry collar temperature sensors and air temperature (Messeri et al., 2019; Ericsson et al., 2015; Schwartz et al., 2009; Maier, 1996), and some have even attempted to reduce the effects of body temperature of sensors (Jiang et al., 2012). The different factors contributing to this offset, as well as how it varies between species, is not well known. The effects that differences in biology, behavior, and weather conditions play must be investigated further if wildlife telemetry collars are to be used to gather accurate temperature data.

This study investigates the viability of using wildlife telemetry collars equipped with temperature sensors for gathering accurate climate data by assessing the drivers of temperature offset between collars and nearby weather stations. Our goal is to establish what conditions should be accounted for when using terrestrial wildlife equipped with telemetry collars to gather useful air temperature measurements. We also investigate which species may be better suited to accurately predict air temperature. To do this we use data obtained from two commonly monitored wildlife species: brown bear (*Ursus arctos*) and roe deer (*Capreolus capreolus)* to determine how species selection may affect temperature offsets.

We hypothesize that knowing a collared animal's weight, as well as the wind speed of the area will be among the most impactful in explaining temperature differences between collar and true air temperature. Because animals with lower body weight generally produce more heat due to higher metabolic rates (MacNab, 1970), smaller individuals may produce a larger temperature difference between the collar’s recorded value and the actual air temperature. Higher wind speeds may move warmer ambient air away from collars, reducing the effect of the animal's body heat on the collar’s temperature sensor (Dematteo & Harlow, 1997; Messeri et al., 2019). Additionally, we hypothesize that roe deer are a more reliable source of accurate temperature data than brown bears. This is for several reasons, first, the greater variance in weight in brown bears throughout a year than roe deer (Pettorelli et al., 2002; Swenson et al., 2007). We theorize that wind will have a stronger effect of dissipating body heat around roe deer collar sensors due to differences in collar fit because of neck size and fur (Hennig et al., 2020; Morrant et al., 2022). Finally, the act of denning during winter in brown bears will make them less useful for year-round temperature monitoring (Schwartz et al., 2010). We believe that if certain biological traits and climatic conditions such as weight and wind speed are adequately considered, these collars could provide an additional source of accurate fine-scale temperature data.

2. Materials and Methods

2.1 Study Areas

The brown bear population in this study is primarily situated within Dalarna, Gävleborg, and Jämtland counties in Sweden (Fig. 1). This area is within the boreal forest biome (Östlund, 1997) and faces pressures from agriculture and timber harvesting (Angelstam, 2021). All recorded GPS locations ranged between latitudes 60.79° N and 64.27° N. The northern and western regions of the study area are characterized by the rugged terrain of the Scandinavian mountains, while the eastern and southern portions of the region include open plains, hills, and forested areas with numerous rivers and lakes (Kullman, 2004). This is a landscape that has widely separated weather stations, creating gaps in temperature monitoring (Friedly, 2009; Martin, 2019).

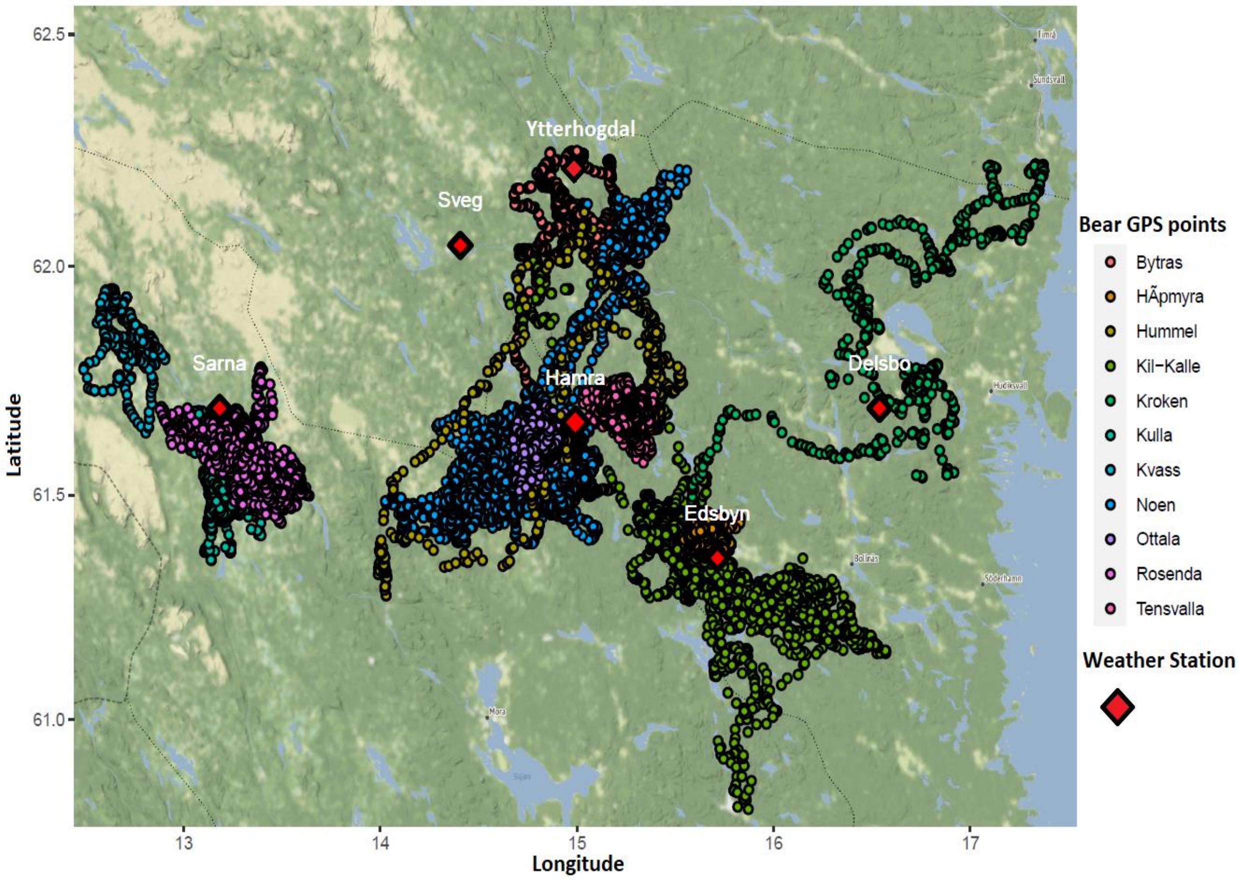

Figure 1: Brown Bear Study Area with movement of the 11 bears included in the study spanning from 8 April 2008 to 29 Sept. 2022

Table 1: Number of data points per closest weather station by bear. Showing which bears were closest to which station

Bear ID	Delsbo	Edsbyn	Hamra	Sarna	Sveg	Ytter
Bytras	0	0	108	0	53	1035
Hampyra	0	11589	0	0	0	0
Hummel	0	0	2928	67	16	136
Kil-Kalle	0	26812	111	0	89	25
Kroken	1291	77	0	0	0	0
Kulla	0	0	0	21686	0	0
Kvass	0	0	0	772	0	0
Noen	0	0	8622	3	0	1408
Ottala	0	0	11936	0	0	0
Rosenda	0	0	0	8447	0	0
Tensvalla	0	0	4761	0	0	0

Table 2:Mean, minimum, and maximum distance in kilometers bears were from their closest weather station during the study

Bear ID	Mean Distance (km)	Min. Distance(km)	Max. Distance(km)
Bytras	12.14	2.43	28.07
Hampyra	5.64	0.66	13.82
Hummel	22.87	4.35	66.62
Kil-Kalle	18.48	0.35	65.18
Kroken	33.26	2.27	75.86
Kulla	18.39	3.62	38.65
Kvass	31.26	18.90	43.21
Noen	22.84	2.77	55.84
Ottala	10.75	1.99	23.36
Rosenda	15.57	1.93	33.68
Tensvalla	13.24	3.87	22.85

The roe deer population is located in Canton Zürich, Switzerland. Their habitat is largely a mix of agricultural, suburban, and reserved forested areas, in this instance the Zurich Wilderness Park Sihlwald. Three locations surround the study area: Aeugst am Albis, Uetliberg, and Wädenswil and their respective weather stations were used in the analysis (MMAEU, UEB, WAE). This area is mountainous and is characterized by steep hills (Swiss Federal Statistical Office, 2012). Open farmland, suburban and forested areas may allow for a variety of thermal ranges as well (Shen et al., 2019).

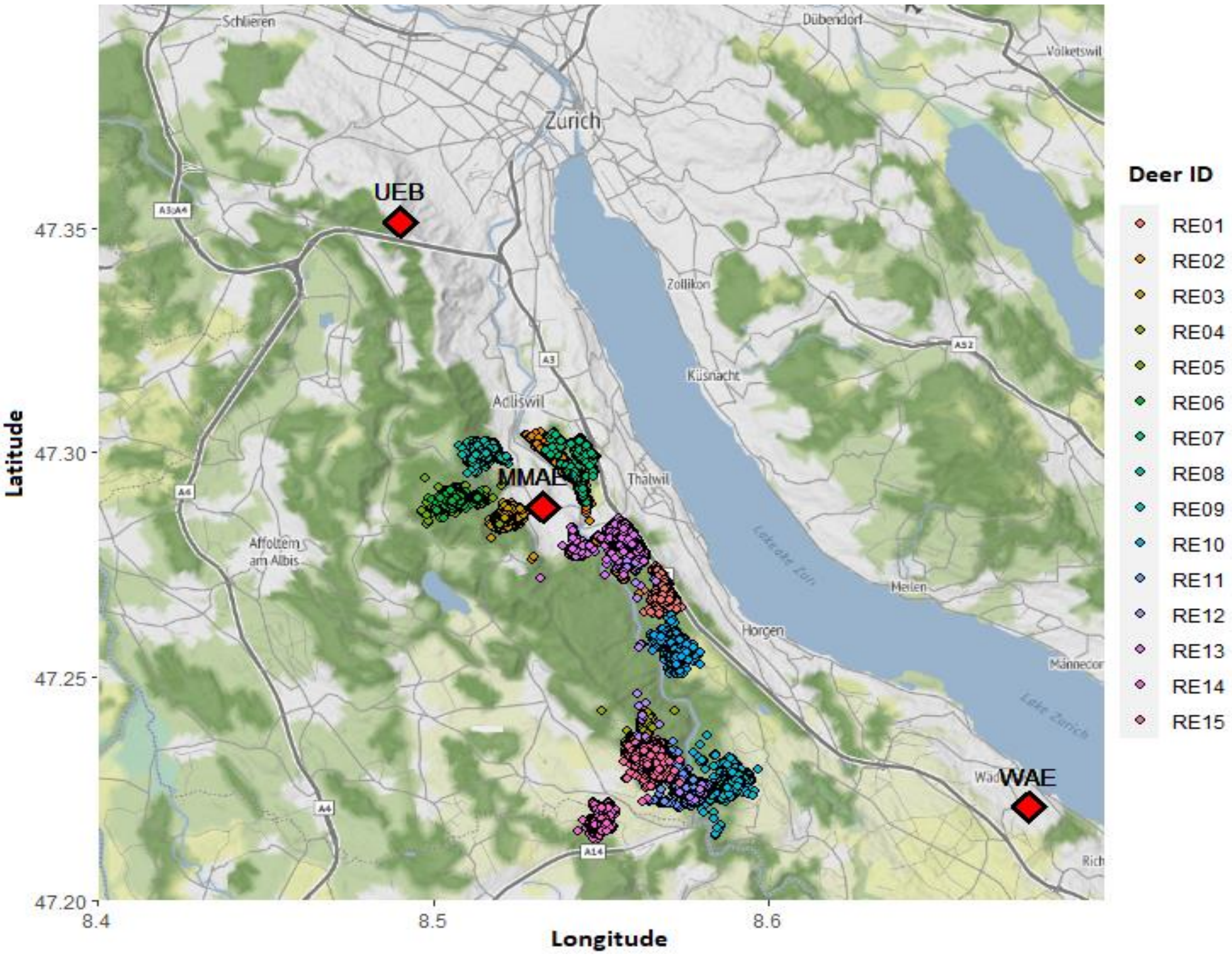

Figure 2: Roe deer study area with movement of the 15 deer included in the study spanning from 12 Sept. 2013 to 4 June. 2016

*Table 3: Mean, minimum, maximum distance in kilometer of each deer from their closest weather station throughout the study *All deer except RE09 & RE11 were closest to MMAEU*

Deer ID	Mean Distance (km)	Min. Distance (km)	Max. Distance (km)
RE01	3.39	2.26	4.36
RE02	1.12	0.89	4.84
RE03	0.82	0.44	1.39
RE04	6.32	5.22	6.86
RE05	2.02	1.05	2.73
RE06	1.97	1.35	2.48
RE07	1.52	0.90	1.90
RE08	1.91	1.32	2.43
RE09	8.08	6.71	9.02
RE10	4.69	3.94	5.28
RE11	7.80	6.50	8.13
RE12	2.09	1.56	8.06
RE13	1.86	0.81	2.65
RE14	7.92	6.17	8.34
RE15	6.74	6.22	7.50

2.2 Brown Bear and Swedish Weather Station Dataset

The brown bear dataset was provided by the Scandinavian brown bear research project as part of a long-term ecological study. A smaller subset of that data was obtained for use in this research project, consisting of 11 Scandinavian brown bears with 6 males and 5 females between 1 to 24 years old, all of which resided in the Dalarna, Gävleborg, and Jämtland counties in Sweden. These bears were selected due to having home ranges closest to active weather monitoring stations. Each animal was equipped with Vertex Plus telemetry collars that featured GPS, dual-axis motion sensors, VHF transmitters, Global System for mobile communication modem, and temperature loggers (Vectronic-aerospace, Berlin, Germany). The collars recorded positional data as well as temperature readings (°C) every hour.

As part of the ongoing research project involving these bears, various biometrics were recorded during collaring, such as each individual's weight. To explore the biological drivers of temperature difference between collar and weather station, these variables were included as in analysis (Table 4). The earliest data was recorded on 8 April 2008 and the last data obtained was on 29 September 2022, providing 14 years of monitoring. However, bears were captured and collared throughout the study period and provided data for differing lengths of time. The shortest monitoring period for an individual bear was only 2 months, while the longest period an individual was monitored was nearly 8 years. (Fig. 3)

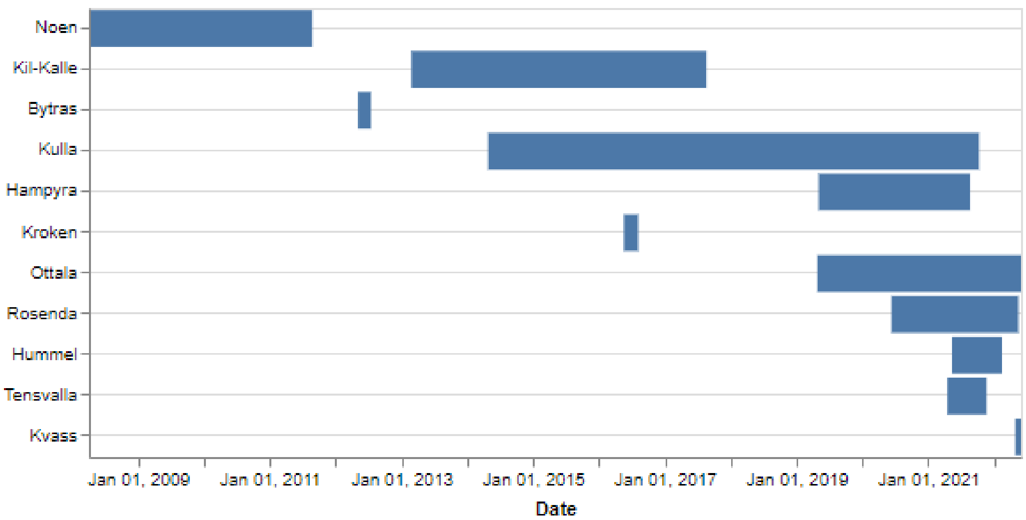

Figure 3: Gannt chart deplicting the duration each bear was recording data for the duration of the study

Swedish weather station data was provided by the Swedish Meteorological Service (SMHI) and is available for public use and download from their website: (https://www.smhi.se). Along with temperature, several metrological variables were chosen as potential drivers of temperature offsets (Table 4). Historical meteorological data was downloaded and then standardized to match the same time frame as our monitored bears. The weather stations Delsbo A, Edsbyn A, Hamra A, Sveg A, Särna A, and Ytterhogdal were the stations that geographically close with our selected bear population’s home ranges.

Table 4: List of variables included in analysis of brown bear collar temperature

Variable	Units	Type	Source
Distance	km	Continuous	Station-Bear collar
Elevation Difference	km	Continuous	Station-Bear collar
Temperature (Station)	°C	Continuous	Station
Precipitation Rate	mm(daily total)	Continuous	Station
Wind Speed	m/s	Continuous	Station
Wind direction	Degrees	Continuous	Station
Sex	M/F	Categorical	Bear collar
Weight	Kg	Continuous	Bear collar
Family Status	Solitary/cubs	Categorical	Bear collar
Age	Years	Continuous	Bear collar
Temperature (bear collar)	°C	Continuous	Bear collar
Time	00:00-24:00	Continuous	UTC Standard

2.3 Roe Deer and Swiss Weather Station Dataset

The roe deer dataset was provided through the Zurich University of Applied Science (ZHAW) by the Wildlife Management Research Group (WILMA). This dataset consists of 15 individual roe deer with 2 yearlings and 13 adults (6 males, 9 females). Each deer was equipped with the same model of GPS Plus telemetry collars, from Vectronic Aerospace. These collars provided positional data as well as temperature readings (°C) at a time interval of every 3 hours. As with the brown bear, various biometric data was recorded when each deer was collared. We selected a portion of these biometrics we thought would be drivers of temperature offset (Table 5). The available telemetry collar GPS and temperature data began on 12 September 2013 and went through until 4 June 2016, spanning 3 years. Not all collared individuals were monitored for the same amount of time throughout the study period (Fig. 4).

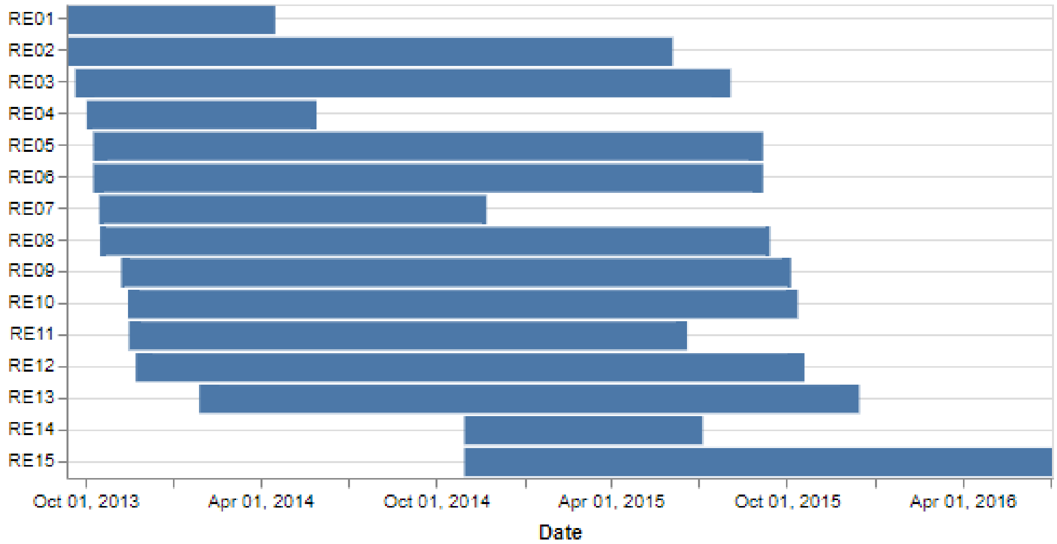

Figure 4: Gannt chart depicting the duration each deer was recording data for the duration of the study

Three weather stations considered to be geographically close to the roe deer study area were considered (MMAEU, UEB, WAE). The weather station data was provided through the Federal Office of Meteorology and Climatology MeteoSwiss, Switzerland and is available for public download through their website (https://www.meteoswiss.admin.ch). Historic meteorological data was downloaded and then matched to the same timeframe that the roe deer were monitored for.

Table 5: Variables used in analysis of roe deer collar temperature

Variable	Units	Type	Source
Distance	km	Continuous	Station-Deer
Elevation Difference	km	Continuous	Station-Deer
Temperature (Station)	°C	Continuous	Station
Precipitation Rate	mm	Continuous	Station
Wind Speed	m/s	Continuous	Station
Wind direction	0-360°	Continuous	Station
Temperature (Deer)	°C	Continuous	Station
Sex	M/F	Categorical	Deer
Weight	kg	Continuous	Deer
Hind leg length	cm	Categorical	Deer
Neck circumference	cm	Continuous	Deer
Chest circumference	cm	Continuous	Deer
Lower jaw length	cm	Continuous	Deer
Activity	m/day	Continuous	Deer
Time	00:00-24:00	Continuous	UTC Standard

Finally, the same model of telemetry collar the roe deer population was equipped with was placed onto the WAE weather station from January 18th to May 5th, 2023. This collar was intended to act as a control to determine if the temperature sensors of the collars are as sensitive as the weather station sensors, and to determine if there is an inherent temperature difference between the technologies. Unfortunately, logistical constraints prevented a similar treatment with the brown bear telemetry collars and any local weather stations.

2.4 Data Analysis

Data analysis was performed using the R programming language version 4.2 (R Core Team, 2021) with the package lme4 (Bates et al., 2023) along with base R functions being used for modeling. For a complete list of packages used in data manipulation, cleaning, and visualization see appendix.

In order to conduct a uniform analysis our telemetry collar datasets and weather station datasets were cleaned and formatted by ensuring there were no missing values, looking for aberrant values and ensuring matching coordinate systems by converting both to the Swiss Coordinates System EPSG2056 (https://epsg.io/2056/) for ease of comparison, as it was the system used in initial analysis. The telemetry collar data was then combined and matched with their corresponding counties' weather station data. Each species had differing data recording regimes which required aligning with the recording regime of their respective weather stations. The bear collars recorded every hour with some small variance, therefore each bear value that was within 5 minutes of the hour was rounded to its hour mark to match the more consistent weather station recording interval. The deer collar uploads were every 3 hours, which were then rounded in the same manner to match their respective Swiss weather stations.

The earliest date with a single bear telemetry collar recording (8 April 2008) was chosen as our start time. We then split each year into two periods; denning and non-denning, both to represent the differences in temperature during the warmer and colder periods of the year and to represent the hibernating/denning behavior of these bears. We define the non-denning season as 6 April to 29 October and the denning season as 30 October to 5 April. These dates were selected based on the median den entry and exit dates found in Evans et al. (2016).

As with our bear analysis, our start date for the deer analysis was determined by the earliest recorded values for our monitored deer population (12 September 2013). With uniform formatting as our bear dataset, deer collar data was then matched with their respective closest weather station. For sake of comparison, we also split the year by using the denning dates to analyze the differences in temperature offset in warmer and colder periods of the year and compare those differences to our bear analysis.

One of the initial parameters considered was the distance of the individual animal from their closest weather station. This was done using the coordinates of the respective weather stations in each study area and the GPS locations provided by the telemetry collars. Then calculating the distance to each GPS point and the coordinates of the closest weather station at the time. We calculated Euclidean distance, elevational difference (altitude), and absolute distance (elevational and Euclidean distance).

Euclidean distance was defined as:

$$d(P,Q) = \sqrt{(x2 - x1)^2 + (y2 - y1)^2}$$

And absolute distance defined as:

$$d(P,Q) = \sqrt{(x2 - x1)^2 + (y2 - y1)^2 + (z2 - z1)^2}$$

Where d(P,Q) is the Euclidean distance between two given points (P and Q). x_1,y_1,z_1 represent the coordinates of point P while x_2,y_2,z_2 represent the coordinates of point Q. Z in this instance representing elevation.

2.5 Modeling

Due to the discrepancy in the scale of values for some of our variables, all values except temperatures were normalized so that each variable is between a scale of 0 and 1, where 0 is the lowest recorded value possible and 1 is the highest. This was done so that a difference in scale did not result in some variables being favored over others when modeling. The closest weather station's temperature was the response variable in each model, with the various meteorological, biological, and geographical distance variables acting as our explanatory variables. Due to the size of each dataset, to account for repeated measurements a random effect (collar/animal ID) was used in model creation.

Using the parameters we expected to be impactful on temperature offsets (Table 4 & 5), a range of candidate Generalized Linear Mixed Models (GLMMs) were created that incorporated different combinations of our variables. This was done by calculating Akaike's information criterion (AIC) for each set of parameters. AIC was used as the primary criterion for model selection due to it being a commonly accepted tool for comparing and selecting models (Arnold, 2010). After calculating AIC for each potential model, those with 4 or less parameters were selected for our model testing with the goal of producing low AIC scores while including the fewest parameters. Reviewing our lists of models, we noted diminishing returns regarding lower AIC values when more than 4 parameters were used. (Fig. 6). Models with fewer variables were prioritized due to the penalization of overparameterization when using AIC (Bozdogan H., 1987), and in order to balance goodness of fit and model complexity.

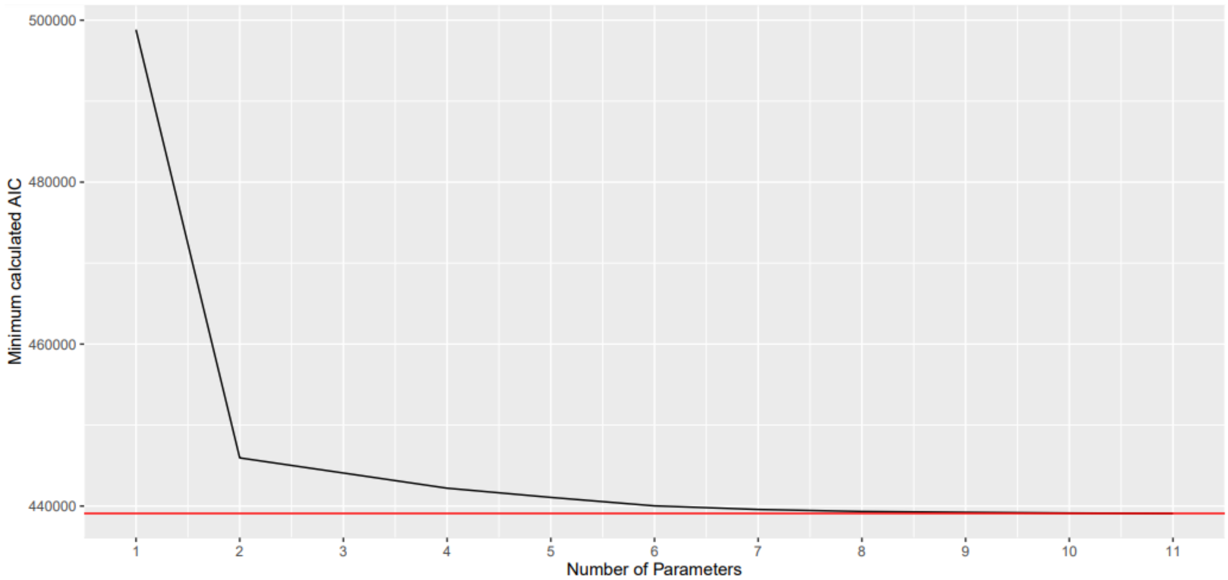

Figure 5: Plot depicting minimum AIC scores per model based on number of parameters used in model. Diminishing returns noted after 4 parameters used

We therefore primarily examined models using 2 to 4 parameters to focus on those explanatory variables that would be most important in accounting for temperature differences. A final feature selection was done based on our AIC score. We selected the best performing model out of those with 4 or less explanatory variables while maintaining the relative lowest AIC score. Predicted temp was calculated based on the model output and plotted against the recorded temperature of the nearest weather station.

We decided to create another set of GLMMs that excluded distance and elevational difference to determine how effective the temperature prediction could be without knowledge of the location of the closest weather station. Considering one of the goals of this study is to determine whether these GPS collars could be used as sources of data to supplement or even replace traditional weather stations, it is necessary to determine whether accurate temperature data can be obtained without any auxiliary information from local weather stations.

3. Results

3.1 Chosen Parameters

The recorded temperature of the telemetry collar was included in each model as it was understandably the strongest predictor of temperature offset. Weight, distance from weather stations, as well as elevation difference were most often included in our best performing models for brown bears (Table 6). Chest circumference, activity level, and time of day were most included in the best performing models for roe deer. (Table 7)

Table 6: List of best candidate brown bear collar temperature models based on AIC score with corrosponding ΔAIC compared to the highest rank model and each parameter used in said model

AIC	ΔAIC	Model Parameters Used in Brown Bear GLMMs
442206.5	0	Distance + Elevation Difference + Weight + Bear collar temp
442973.3	766.7	Elevation Difference + Time + Weight + Bear collar temp
442984	777.4	Distance + Time + Weight + Bear collar temp
443223.8	1017.2	Distance + Wind Speed + Weight + Bear collar temp
443240.2	1033.6	Elevation Difference + Wind Speed + Weight + Bear collar temp
443478.9	1272.3	Distance + Family Status + Weight + Bear collar temp
443479.5	1272.9	Distance + Wind Direction + Weight + Bear collar temp
443504.7	1298.1	Elevation Difference + Wind Direction + Weight + Bear collar temp
443675.9	1469.3	Distance + Sex + Weight + Bear collar temp
443699.3	1492.7	Elevation Difference + Weight + Age + Bear collar temp

Table 7: List of best candidate roe deer temperature models based on AIC score with corrosponding ΔAIC compared to the highest rank model and each parameter used in said model

AIC	ΔAIC	Model Parameters Used in Roe Deer GLMMs
336634.8	0	Activity + Hindleg Height + Chest Circumference + Deer Temp
337388.2	753.3	Activity + Jaw Height + Chest Circumference + Deer Temp
338061.5	1426.7	Elevation Difference + Activity + Chest Circumference + Deer Temp
338634	1999.2	Time + Activity + Chest Circumference + Deer Temp
338967.3	2332.51	Time + Hindleg Height + Chest Circumference + Deer Temp
339258.7	2623.9	Elevation Difference + Activity + Sex + Deer Temp
339587.3	2952.5	Time + Jaw Height + Chest Circumference + Deer Temp
339675.8	3041.0	Elevation Difference + Time + Chest Circumference + Deer Temp
339771.5	3136.7	Activity + Neck Circumference + Chest Circumference + Deer Temp
339816.9	3182.1	Activity + Sex + Chest Circumference + Deer Temp

3.2 Temperature Offsets

After analyzing brown bear collar temperatures by comparing them to their closest weather station, an average (mean ± 2SD) temperature difference of 14.58 ± 4.11 C° was found throughout the whole year. This difference is exacerbated during the colder denning period, with an average difference of 17.0 ± 4.58 °C. The difference during the warmer non-denning portion of the year was an average of 10.36 ± 3.87 °C.

Temp [°C]	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Collar Temp	15.8	16.7	15.5	15.5	18.5	22.1	23.1	23.4	22.6	20.1	16.4	15.6
Nearest Station Temp	-8.03	-2.12	-0.987	3	8.05	13.4	14.8	13.2	9.06	4.43	-0.244	-2.94
Temp Difference	23.8	19.9	16.5	12.5	10.4	8.76	8.23	10.1	13.6	15.7	16.7	18.8

Table 8: Mean temperatures for brown bears by month

Roe deer were analyzed in an identical fashion. They had an average (mean ± 2SD) temperature difference of 7.69 ± 3.23 °C year-round. During the colder part of the year and our bear denning season they had a higher average temperature difference of 8.98 ± 2.85 °C, while during the warmer part of the year they had an average difference of 6.30 ± 3.02 °C.

Temp [°C]	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Collar Temp	11.7	11.4	15.1	18.3	20.6	23.4	23.9	22.7	20.8	18.4	13	11.2
Nearest Station Temperature	2.01	1.67	6.53	10.1	12.7	17.7	19.5	17.7	14.8	11.8	4.98	2.36
Temp Difference	9.66	9.77	8.54	8.2	7.9	5.68	4.4	4.97	6.31	6.66	8.07	8.88

Table 9: Mean temperature for roe deer by month

3.3 Model Outputs

Based on our model selection, the best performing brown bear model (Table 6) to predict the temperature of the closest weather station contained the parameters distance, elevation difference, bear collar temperature, and bear weight ($Y = 0.93x - 1.3$, R^2=0.52, Fig. 7A). When the difference in location of the closest weather station was omitted, the next best performing model contained bear collar temperature, bear weight, wind speed and time of day ($Y = 0.92x + 0.39$, R^2=0.51, Fig. 7A).

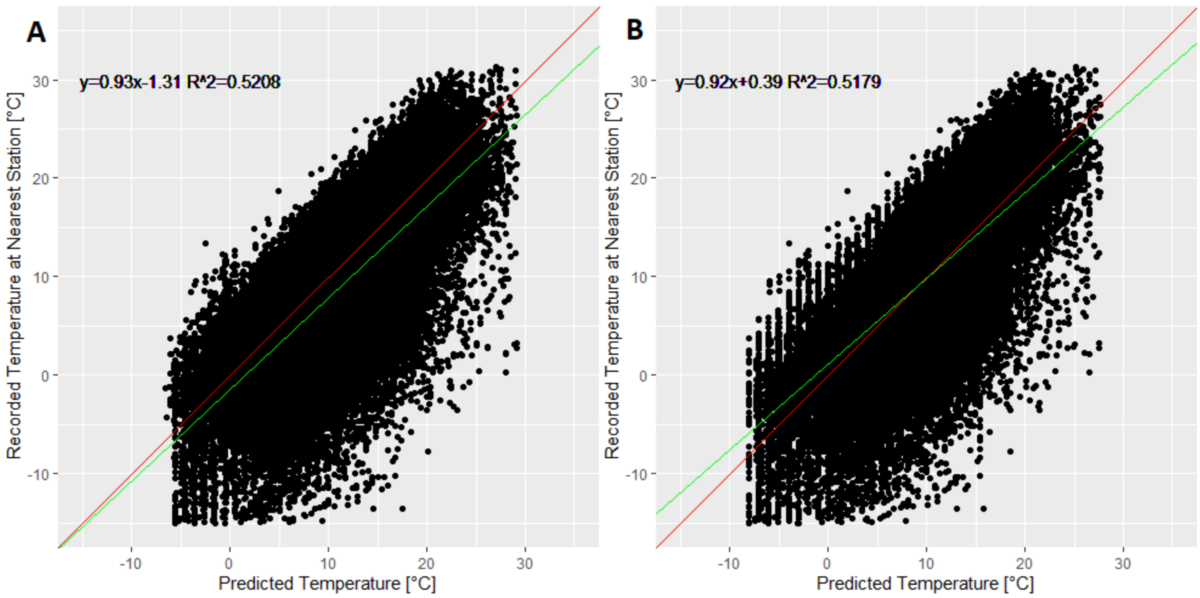

Figure 6: Plot of brown bear collar temp. model outputs. Y-Axis is the recorded temperature of the closest weather stations, X-axis is the models' predicted temp. Red line is Y=X, when model predicted temperature is the same as recorded weather station temp. Green line is the best fit line when comparing the model predicted temperature with the record temperature.

When it comes to our best performing roe deer model (R^2=0.83) chest circumference, activity level, hindleg height, and deer collar temperature were included as parameters (Y =

0.98x + 1.05, R^2=0.83, Fig. 8B). Considering two of the parameters that were most indictive of temperature difference in our brown bear collar models was distance and elevation difference we wanted to compare how those parameters would perform in our roe deer collar models with their smaller distance and elevation difference from the closest weather stations (Tables 2 & 3). That model including those two parameters, along with deer collar temperature, was less correlated with the weather station temperature (Y = 0.92x + 1.05, R^2=0.76, Fig. 8A).

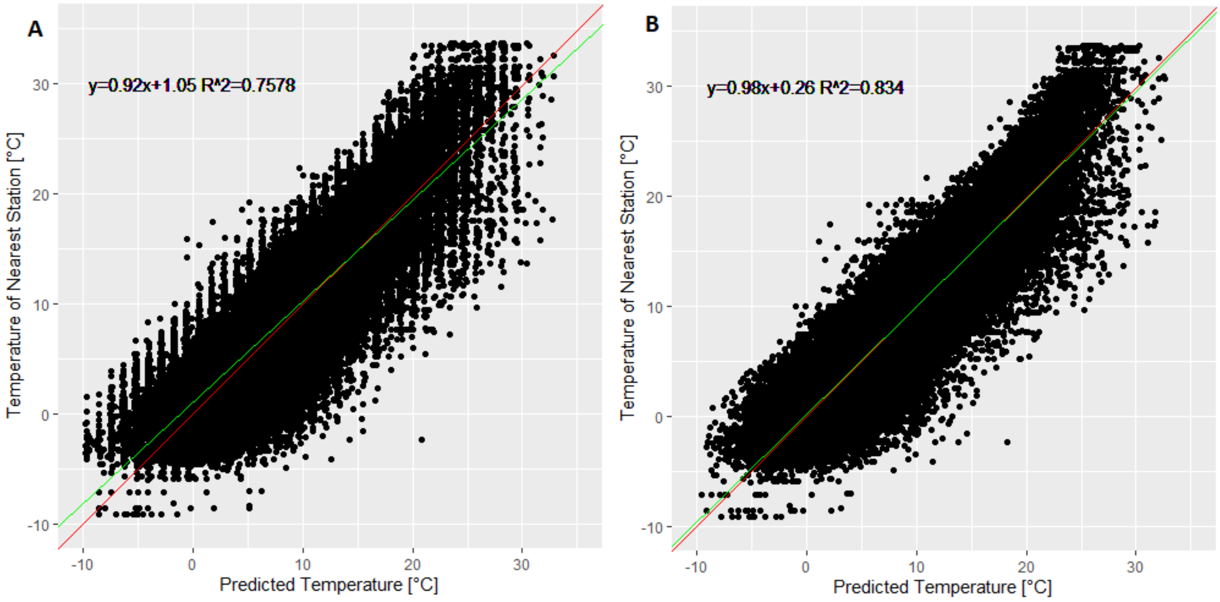

Figure 7: Plot of roe deer temp. model outputs. Y-Axis is the recorded temperature of the closest weather stations, X-axis is the models predicted temp. Red line is Y=X, when model predicted temperature is the same as recorded weather station temp. Green line is the best fit equation for model output.

3.4 Control Collar

Finally, the output of the collar that was placed on the WAE weather station to act as our control was analyzed to determine if the collar sensors had any systemic offset from the weather station's instruments. Initial analysis showed a considerable offset from the WAE weather station's temperature and was not strongly correlated to the stations temperature reading (Y =1.8x + 1.7, R^2=0.67, Fig.5A). Upon investigation, it appeared that the discrepancy was mostly limited to the brightest hours of the day (Fig. 5A). When non-peak daylight hours were analyzed, the correlation between the temperatures recorded by the weather station and the collar became much closer (Y = 0.97x + 0.38, R^2=0.96, Fig 5B). The collar was positioned in such a way that the electronic housing containing the temperature sensor was pointing straight up with the battery pack hanging below, putting the temperaure sensor in direct sunlight. This is most often how telemetry collars are worn in the field by wildlife (Vectronic Aerospace, n.d., 2022)

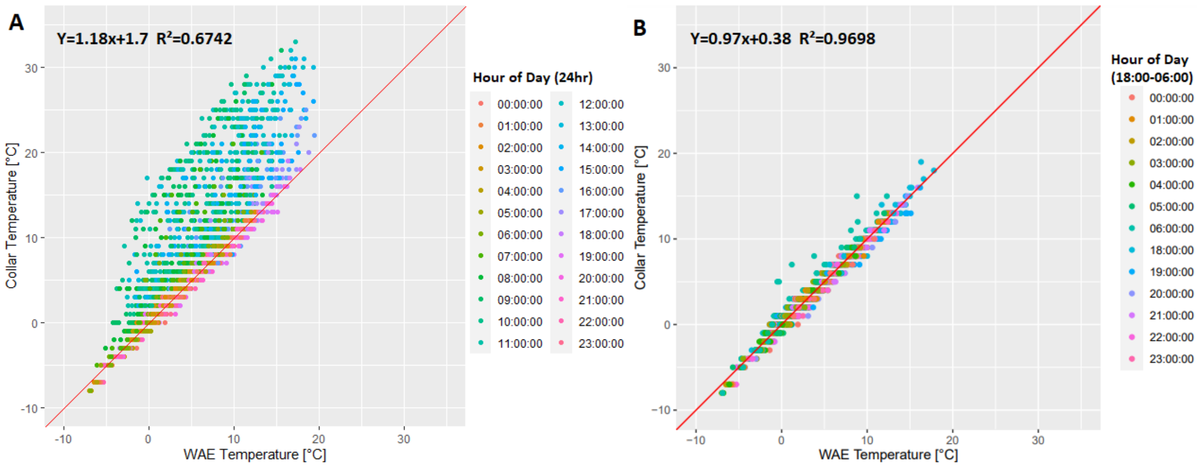

Figure 8A: Line plot showing temperature recordings of control collar compared to the average temperature of the WAE weather station (red line). 5B: Only showing values for collar recordings from 18:00 to 06:00 to show effect of daylight on temperature difference

4. Discussion

This study indicates that of our two test species, roe deer are more accurately able to model air temperature (Fig. 8). While our brown bear models are not strongly correlated to their closest weather station (Fig. 7) even when omitting winter denning periods. Roe deer also showed less temperature offsets compared to brown bears (Table 8&9). However, our deer population was spread over a much smaller area and stayed much closer to a single weather station, having an average (mean ± 2SD) distance of 3.89 ± 0.19 km. With an average distance of 18.6 ± 6.81 km away from their closest weather station, it is likely there were numerous instances where a bear collar was sampling different air temperature then what was being recorded at their closest weather station, especially considering the terrain of the area (Fig.1).

Regarding what variables are important factors to know beforehand when attempting to model ambient temperature with wildlife, part of our initial hypothesis appears correct. In both species cases it seems knowing the size of the individual is valuable. Weight was the primary measure of body size we had reference for brown bears and appeared in all our highest-ranking models (Table 6). However, for roe deer we had multiple measurements regarding body size. Chest circumference, hindleg length, and lower jaw length were included in our top models while weight was omitted (Table 7). It has been shown that chest circumference is a good predictor of weight in deer (Bundy et al. 1991). It may be that chest circumference is more correlated with surface area which would have a more direct impact on skin temperature and therefore affect the collar sensor more than weight alone (Porter & Gates 1969). We found it interesting that the previous body measurements were included more often in our better performing models than neck circumference. We had assumed that neck circumference would play a more prominent role as the temperature sensor is in more direction contact with the neck.

Our hypothesis that wind speed would be impactful in calculating temperature offset appears dependent on species. While wind speed, as well as wind direction, was included in some of the best performing models for our brown bear analysis, it was omitted from all our best performing roe deer models. Since the bear population was so much further on average from their weather stations than roe deer (Table 2 & 3), and given how impactful topography is on wind speed and direction (Helbig et al., 2017; Ravazzani et al., 2020) it is likely the bears were experiencing larger differences in wind speed as distance from station increase, especially in mountainous areas such as our study site. This may be due to physiological differences between these two species. Denser and longer fur require higher wind speeds to result in surface level heat loss (Tregear, 1965). As brown bears possess longer and denser coats than roe deer (Elgmork & Riiser, 1991; Bubenik, 1996), that may at least partially explain why wind speed was more impactful in explaining temperature differences for the bear population than deer.

Time of day was a parameter that appears in both species higher ranking models (Table 6 & 7). While not directly measured in this study, we suspect the importance of time of day is related to the amount of solar radiation the temperature sensor is exposed to. We can see from our control collar that temperature offsets are greatest during the portion of the day when the sun is highest (Fig. 5). Due to the position of the electronic housing of the collar, it is meant to sit on the back of the animal's neck (Vectronic Aerospace, n.d., 2022). This means it is directly exposed to solar radiation, which has been found to influence temperature readings in collars. (Messeri et al., 2019).

Species selection for use as accurate air temperature monitoring and to act as "mobile weather stations" is a complex topic in need of more research than this one study, but the initial hypothesis that deer may provide a better source of accurate temperature data appears true. We show that roe deer have less temperature differences to nearby weather stations year-round than brown bears (Table 8 & 9) and are able to more closely predict the temperature of those weather stations (Fig. 7 & 8). However, the discrepancies in the types of variables used in each species analysis and foremost, the difference in proximity to their respective weather stations (Table 2&3) make it difficult to give a concrete conclusion to that question.

Cervids, as a whole, may be useful in this role, as the average offset of our deer population was 7.69 ± 3.23 °C, which is close to the average temperature offset of 7.2 °C found in moose (*Alces alces*) to their closest weather station (Ericcson et al., 2015, results section). Temperature recordings from telemetry collars worn by red deer (*Cervus elaphus L.*) Messeri et al., 2015 were similarly able to successfully create predictive temperature models matching nearby weather stations.

However, the landscape and scope a researcher wants temperature data for may inform their decision on which species to use. Our deer had a small geographic range, which may have been in part due to their semi-urban environment, and it has been shown in previous studies that roe deer have limited sized home ranges (Tufto et al., 1996; Saïd, & Servanty, 2005). Our bears on the other hand had much wider ranges (Table 2&3), and as a species have much larger home ranges on average (Dahle & Swenson, 2003). This may mean that despite roe deer potentially offering more accurate temperature data, if a researcher wants data over a larger area, they may choose a species with a larger home range such moose.

4.1 Limitations

Before any concrete conclusions can be drawn from these results, multiple limitations in this study should be examined. Firstly, the discrepancies between the sample size and monitoring duration of our two species should be mentioned. The brown bear dataset was larger and consisted of measurements over the course of 14 years, whereas the deer dataset had a little over 3 years' worth of data. While monitoring, some individuals in both our bear and deer populations were only recording values for a short span in either particularly warm or cold months which could further skew analysis. The number of animals monitored was suboptimal as well. With only 11 bears and 15 deer, it would have been beneficial to have a larger number of individuals monitored.

Another element that may have provided interesting results is if monitored animals had internal bio-loggers that were able to record internal body temperature. The temperature offsets between bio-loggers and collars would have provided another measure of temperature in this study. However, research has shown that for some species, collar temperature is an accurate reflection of internal temperatures (Dausmann, 2005). Another variable that would have been informative is a measure of solar radiation. Previous studies have found it to be an important explanatory variable when investigating temperature offsets between telemetry collars and weather stations (Messeri et al., 2015). While time of day may have acted as proxy for such (Fig. 5) a direct measurement would have been ideal.

Since one objective was to determine how suitable wildlife may be to act as sources of reliable air temperature data, using an animal's closest weather station was only a proxy for true air temperature. There were no doubt instances where there was a difference in air temperature at the animal's location versus that of its closest weather station. Ideally if we could have somehow been able to record temperature at the animal's location but isolated from the animals body heat, at the same time as the collar it would have provided a better snapshot of the differences in true air temperature and that recorded by the collar.

4.2 Possible Implications and further research

We hope that the results of this study may inform and aid future researchers in a variety of research objectives. Knowing what variables affect temperature readings of telemetry collars may lead to developments in future collar temperature sensor designs to provide more precise measurements, whether the goal is more accurate wildlife body temperatures readings, or to mitigate body heat's effect to gather more precise air temperature (Jiang et al., 2012). Primarily, we hope that this study can offer insight into what metrics should be known about an individual animal and the environment they live in if they are to be used to gather air temperature data.

The application of using wildlife as proxies for weather stations may not be as useful in countries or areas with dense weather station networks, but for those areas that are lacking in that infrastructure it could provide a valuable source of temperature data in an otherwise under-monitored area. This may aid in constructing more precise species distribution maps, which will only become more important in the age of a changing climate. It could also help conservation efforts in monitoring temperature changes in sensitive habitats like rainforests.

While we have only looked at two possible species to act as sources of temperature data, numerous other species of wildlife are commonly monitored using telemetry collars and could be used to collect temperature data. Likewise, we only examined a handful of metrics to help explain temperature offset and more research is needed to have a fuller understanding of that relationship.

4.3 Conclusion

Our research objectives were multifaceted, with the goal of investigating if wildlife could be used to accurately record air temperature while aiming to identify the factors contributing to the offset between telemetry collars sensors and their closest weather station temperature. We hoped to shed light on the possibility of utilizing what we believed to be an overlooked source of temperature data. We showed that it is possible to accurately predict air temperature based on wildlife equipped with temperature sensors and what factors should be known beforehand to more accurately compensate for our two sample species.

This demonstrates how valuable non-traditional sources of data can be and may further encourage researchers to look for alternative routes to answer their questions. In a time with a rapidly changing climate, fine-scale temperature data will only become more valuable to a range of fields like ecology and meteorology. The potential for wildlife to serve as dynamic weather stations to help us better understand the climates they reside in is a fascinating possibility that we believe will be more commonplace as other researchers are made aware of the possibilities.

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Ethics Statement

Ethical review and approval were not required for this study.

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Appendix

R packages used in cleaning, data manipulation, analysis, and visualization:

dplyr (Wickham, 2022), lubridate (Grolemund & Wickham, 2011), ggplot2 (Wickham, 2011), ggpmisc (Pedro, 2016), ggridges (Wilke, 2023), ggmap (Kahle & Wickham, 2013), scales (Wickham, 2022), tidyverse (Wickham et al., 2019), candela (Kitware, 2016), sf (Pebesma & Bivand, 2021), (Bates et al., 2023), and RColorBrewer (Neuwirth, 2022), lme4 (Bates et al., 2023).