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Individual level spatial-temporal modelling of exposure potential of livestock in the Cove Wash watershed, Arizona

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Abstract

Personal exposure studies suffer from uncertainty issues, largely stemming from individual behavior uncertainties. Built on spatial-temporal exposure analysis and methods, this study proposed a novel approach to spatial-temporal modeling that incorporated behavior classifications taking into account uncertainties, to estimate individual livestock exposure potential. The new approach was applied in a community-based research project with a Tribal community in the southwest United States. The community project examined the geospatial and temporal grazing patterns of domesticated livestock in a watershed containing 52 abandoned uranium mines (AUMs). Thus, the study aimed to 1) classify Global Positioning System (GPS) data from livestock into three behavior subgroups - grazing, traveling or resting; 2) calculate the daily cumulative exposure potential for livestock; 3) assess the performance of the computational method with and without behavior classifications. Using Lotek Litetrack GPS collars, we collected data at a 20-minute-interval for 2 flocks of sheep and goats during the spring and summer of 2019. Analysis and modeling of GPS data demonstrated no significant difference in individual cumulative exposure potential within each flock when animal behaviors with probability/uncertainties were considered. However, when daily cumulative exposure potential was calculated without consideration of animal behavior or probability/uncertainties, significant differences among animals within a herd were observed, which does not match animal grazing behaviors reported by livestock owners. These results suggest that the proposed method of including behavior subgroups with probability/uncertainties more closely resembled the observed grazing behaviors reported by livestock owners. Results from the research may be used for future intervention and policy-making on remediation efforts in communities where grazing livestock

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may encounter environmental contaminants. This research also demonstrates a novel robust geographic information system (GIS)-based framework to estimate cumulative exposure potential to environmental contaminants and provides critical information to address community questions on livestock exposure to AUMs.

Keywords

GPS; domesticated livestock; fuzzy logic; behavior patterns; cumulative exposure; time geography; GIS; parallel computing

1. Introduction

Uranium mining began on the Navajo Nation, USA, in February 1944 and peaked between the late 1950s and 1970s [1]. It was not until the mid-1980s that the demand of uranium ore declined, and mining activities ended on the Navajo Nation [2]. Although uranium mining projects ceased, the effects of uranium extraction did not, as uranium and other metals, metalloids, and radionuclides continued to enter the environment and food chain for animals and humans [3, 4]. According to a report by United States Environmental Protection Agency (EPA), after the mining industries cease extraction activities on the Navajo Nation more than 500 mine sites were left abandoned. Fifty-two of these abandoned uranium mine (AUM) sites are situated within the Cove Wash watershed, a Navajo community located in northeastern Arizona. Residents of the Cove Chapter are concerned about human exposures to metal mixtures from the presence of nearby AUMs as well as the health of their livestock.

For AUM sites, the chemical toxicity of uranium and other elements constitute the primary environmental health hazard [5]. Uranium, radon, and arsenic, which are byproducts of the uranium mining process, are hazardous to human health. In different regions, researchers have found that the chemical content near abandoned uranium mines is generally high for these elements [6–10]. Previous occupational exposure research indicates that radon inhalation from underground uranium mining is associated with cancer in the lung, bone, and skin [11–14]. People living in an area close to AUMs may also experience adverse pregnancy outcomes due to AUM contaminant exposure, which is an active area of research for the Navajo Birth Cohort Study (NBCS) [15].

Exposure to contaminants from AUMs may be via respiratory, oral, and dermal routes [16]. In general, more soluble compounds are less toxic to the lungs but more toxic to the respiratory system due to easier absorption from the lungs into the blood and transportation to distal organs [17]. The oral toxicity of uranium compounds has been evaluated in several animal species following exposure in drinking water or via grazing [18, 19]. Soil and water contaminated by AUMs are integrated into arable land via numerous environmental pathways and absorbed by perennial pasture plants present on lands that may be used for cropping, grazing, or hunting. Thus, consuming meat from grazing animals may also be a significant heavy metal and radionuclide exposure source [20–23]. Dermal exposure is related to exposure time, the total area of skin that is exposed, and other physical and physiological conditions [24]. Despite this potential complexity, the chemical toxicity of metals is the primary concern in extant exposure studies [25]. Thus, this paper is mainly focused on respiratory and oral exposure. In light of these findings and long-standing community concerns about AUMs, Cove community members requested a study investigating the accumulation of uranium in animal tissue. As a response, this study employed a community-driven approach, leveraging geospatial technology to estimate the cumulative environmental exposure potential for livestock grazing in the Cove Wash watershed.

Geographic information systems (GIS) technology provides powerful tools for assessing potential exposures from AUMs among livestock. Tobler's first law of geography has revealed a relationship in the spatial dimension – all things are related, but near things are more strongly related than distant ones [26]. With this law, researchers could analyze potential exposure to AUMs in different geographic areas using location-based methods. Simple location-based methods could be point-in-polygon, buffering, and other distance functions [27–30]. Additionally, there are other methods such as kriging, inverse distance weighting (IDW), regression mapping, etc. to interpolate an exposure map with limited data [31–33]. However, these methods are limited so GIS-based multi-criteria models (GIS-MCDA), and land-use regression models have been developed and applied to exposure studies [34–36].

There exists a growing body of literature integrating GPS data, environmental data, and traditional GIS approaches for livestock exposure assessments [37–39]. However, these GIS methods are limited since they consider spatial dimensions only and do not address temporal dimensions when applied to livestock studies. As a consequence, the computed exposure estimates may be less accurate. Moreover, existing approaches suffer from uncertainty issues, which usually result from inaccurate or misclassified GPS data or stochastic animal behaviors [40]. Given the environmental risk map, shown in Figure 1, the total exposure would be the sum of the environmental risk values along a pathway (e.g., $E1=R1+R2+R3$, where E is the total exposure of an individual and R is environmental exposure risk value at a given location), when only the spatial dimension is considered. However, in a real-world scenario, travel speed differs, and the time spent at different locations might vary. This would result in a higher cumulative exposure if the individual livestock spends a longer time inside an area with higher exposure potential, and vice versa (e.g., $E2=R1+(T2-T1)*R2+(T4-T3)*R3$, where T is time at a location). Thus, the total exposure could be different for the same route when considering the temporal dimension of livestock behavior.

Behaviors have been studied by geographers in many ways. Hägerstrand applied the lifeline concept in demography to study population movement across space, which then matured into the concept of time geography [41]. With the advocacy of Hägerstrand and the Lunde School under his leadership, time geography was introduced [42, 43]. Other research evaluated human behaviors and accessibility to a certain facility (e.g., grocery store, gym, etc.) [44–46]. Behavior information is critical for personal exposure assessment [16]. The present manuscript considers behavior patterns because different behaviors are related to different exposure rates, which might further influence the exposure estimates (e.g., $E3=W1*R1+W2*(T2-T1)*R2+W3*(T4-T3)*R3$, where Wi represents the weight of different behavior patterns based on their relative contribution to potential exposure). However, none of the above scenarios consider underlying uncertainties in exposure, including but not limited to: GPS positional accuracy, temporal uncertainty, and livestock behavior uncertainty; all of which need to be considered for an accurate representation and assessment of exposure [47].

Early attempts to track animals and record their behaviors were *in situ* observations. Other methods relied on human observation of natural (e.g., color patterns) or artificial features (e.g., colored collar or tag) to identify individual animals. Problems inherent in these methods include observer fatigue and associated error, study area accuracy and physical limitations, other external factors, and observer proximity effects on animals [48]. It has historically been challenging to discern an individual livestock from a herd based on its natural features (such as color patterns, height, or special spot). Therefore, new methods have been developed to address the above issues, including attaching a physical marker, marking the target animal with stable isotopes, radio tracing. However, disadvantages still exist in such methods, which is the trade-off between accuracy and observer proximity effects [49, 50].

Modern GPS collars record animal locations at high temporal frequencies, allowing for detection of animal behavior patterns and interactions between animals and the environment [51]. Previous studies have overlaid animal locations with land use types to find out frequencies of interaction with different places [48]. For example, if GPS locational points are clustered at two places, of which one is already known to be fenced in and the other is known to be a pasture, it can be inferred how much time animals spend in resting, grazing and other behavior patterns. Thus, the major livestock behaviors can be specified as: grazing, traveling, and resting. We assume, therefore, that when livestock are grazing, possible exposure routes might involve respiratory, oral, and dermal exposure; when resting, exposure routes might only include oral and respiratory exposure; and when traveling the routes might also contain oral and respiratory exposure. Therefore, it is important to obtain accurate livestock behavior patterns.

It is a challenging task to completely reproduce the past behaviors of livestock animals at a certain place. Livestock owners may lead a herd to a grazing area from 9:00 AM to 12:00 PM and record the grazing time every day, but an individual livestock may not continually graze during that period. Instead, an individual livestock might spend some time idling or resting. This means that livestock behaviors based on GPS data might involve a number of uncertainties that could be addressed using fuzzy logic. Fuzzy logic is a form of multivalued logic, the output of which can be any real number between 0 and 1, which means the genre of a target is neither A nor B; instead, it can be partially A and partially B at the same time. The key is how much the target belongs to A and how much it belongs to B. Given two sets – input 1 and input 2, fuzzy logic adapts the membership of each input value, for which the membership function is calculated first, followed by predefined fuzzy rules, and classified as an output according to a fuzzy classification. The membership itself represents the likelihood of a certain characteristic [53, 54].

The primary research objective of the study is 1) to develop a new approach for spatial-temporal modeling that incorporates automatic livestock behavior classifications accounting for uncertainties; 2) to calculate the daily cumulative exposure potential for livestock and 3) to assess the performance of the proposed method when compared with previous approaches without behavior classifications or probability/uncertainties. To answer these questions, we classified livestock behavior patterns, estimated the cumulative environmental exposure risk for each individual livestock with and without behavior patterns or probability/uncertainties, and compared the results. The implication of this study is two folds: on the one hand, the proposed method has the potential to produce more accurate exposure analysis results and therefore could have a widespread use in exposure studies; on the other hand, results from this study will help answer questions in a larger ongoing community-based research study on potential human health risks from consuming meat and organs of livestock grazing in the Cove Wash watershed and can therefore inform interventions and remediation efforts to address community environmental health concerns.

2. Data and Methods

2.1. Overview of this research

The workflow of this paper is shown in Figure 2. We first collected data with GPS collars to obtain locational and other relevant information of individual livestock at a 20-minute interval. Invalid records were removed as discussed in section 2.3.

Using valid records, we developed a fuzzy inference system to classify livestock behaviors using Matlab (Version R2020a). We first created the fuzzy rules and defined the thresholds of membership functions. Afterwards, we derived probabilities of three behavior patterns: grazing, resting and traveling. Details are discussed in section II-D. Potential exposure risk was based on a previously generated environmental risk map covering the Navajo Nation [24], we uploaded data with behavior and probability information to the high-performance computers at the University of New Mexico Center for Advanced Research Computing (CARC) with parallel computing capacities to calculate the cumulative environmental exposure (discussed in sections II-E and II-F).

2.2. Study area

The Cove Chapter of the Navajo Nation, with 420 residents (2010 U.S. Census), is situated in the foothills of the Chuska mountain range, tucked away in the Carrizo and Lukachukai mountains in northeastern Arizona. The Cove Wash watershed is in the Northern Agency of the Navajo Nation at the intersection of Utah, Arizona and New Mexico (Figure 3). The watershed contains approximately 52 miles of tributaries and receives about 12 – 16 inches of precipitation annually. The Cove Wash is an ephemeral stream, which is important when considering how uranium is deposited after rain events. There are 523 AUMs on Navajo Nation – 52 of which are located in Cove.

With permission and partnership from livestock owners in the Cove community and Dine College, we attached Lotek GPS collars to livestock (4 sheep and 4 goats) to collect information on location, elevation, and ambient temperature at a 20-minute interval. The battery life of the collars could support tracking for up to 1 year. Depending on the flock, tracking time was between 10 days to four months, which was fully determined by livestock owners.

2.3. Data Preprocessing

Some positional records were invalid due to the complex terrain in the watershed blocking signal transmission between satellites and GPS devices or even reflecting the signals before they are received by the devices (an example of collected GPS data is provided in Appendix, Table 5.)

Data were cleaned to remove records that failed to meet the following criteria: 1) duration less than 70 seconds; 2) valid latitude and longitude coordinates within the study area; 3) four or more GPS satellites used to record positional information; and 4) elevation greater than 800 meters. The duration field reflects the time the GPS receiver takes to connect with all satellites (the maximum time is set by the manufacturer to be 70s). Normally, it takes less than 70 seconds for the device to connect to satellites. Larger durations indicate that the device has failed to connect to any satellites and subsequently times out. The satellite field shows how many satellites are connected and used when calculating coordinates. At least four satellites are needed to estimate the 3D position. Thus, GPS data with three or fewer satellites were considered to be invalid. Because the lowest elevation of Cove is over 1000 meters, GPS data with altitude below 800 meters were also considered invalid.

2.4. Behavior patterns classification

The present workflow uses fuzzy logic to classify different behavior patterns and the corresponding possibility of each from the GPS data. Fuzzy logic enables inference while allowing for potential alternatives. In this paper, the input variables used for fuzzy classification were speed and the distance to a livestock owner's house. The speed, calculated using the coordinates and the time stamp, represents the average speed that an individual livestock travels within a 20-min time interval. Membership 1, speed, was used to specify whether the speed is high or low. With a higher value, the chance of moving around or traveling to other places was higher, while the chance of staying at one spot for grazing was lower, and vice versa. Membership 2, status (active or inactive), was used to specify whether distance to the house is large or small. Small distances were considered as "inactive zones", where the animals are most likely inside a corral. Conversely, large distances were considered to be "active zones", where the animals were shepherded outside to graze. The fuzzy rules are shown in Table 1.

The membership functions of speed and status are shown in Figure 4. The blue curve in Figure 4a shows the fuzzy membership function of low speed, while the red curve represents that of high speed. The thresholds of speed were confirmed with points geolocated inside the fence and along the road. After conversations with livestock owners, it was clear that the animals were held behind the corral from 00:00 am to 4:00 am next morning, during which point the average recorded speed was 0.787 meters per minute. When livestock were traveling from the corral to a grazing area, the average speed was 30.12 meters per minute. Thus, those two values were set as the speed thresholds for high and low values. The blue curve in Figure 4b depicts the membership function of inactive status, while the red curve represents that of active status. The average recorded distance is 82.58 meters when the sheep and goats are held inside the fence, but the average distance is 477.6 meters when they are out from 9:00 am to 11:00 am. Thus, 82.58m and 477.6m were set as the distance

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thresholds for inactive and active status. With these rules applied, a fuzzy membership score was computed for each valid GPS location.

2.5. Cumulative potential exposure

Fuzzy logic is used to derive the degree of occurrence of each behavior pattern. Even if the probability of one behavior is higher than the other two behavior patterns, the possibilities of the other two behaviors resulting from the classification method should be retained.

The potential environmental exposure of a certain behavior sequence was estimated based on the equation adapted from previous research [36] as below:

$$E_j = \int_{t1}^{t2} \int_{l1}^{l2} W_i R(t,\ l) dl dt \tag{1}$$

where W_i represents the weight of the behavior i based on the relative importance of each behavior pathway in producing the final exposure potential, and R represents the modeled potential for environmental exposure – a dimensionless value – at location l and time t. The corresponding uncertainty of the behavior sequence introduced by livestock behavior classification is quantified into probability:

$$P_j = \prod P_B \tag{2}$$

where P_B is the probability of certain livestock behavior derived from fuzzy logic. The uncertainty introduced by modeled potential for environmental exposure is quantified through Monte Carlo Simulation of criteria weights. The cumulative exposure potential was calculated as:

$$C_r = \sum_{j1}^{jn} E_j P_j \tag{3}$$

For example, if one animal travels in the time sequence from point A to B and then to C, the corresponding locational exposure level is R_1 at location A, R_2 at location B and R_3 at location C. The exposure map is derived from a GIS-MCDA model that considered multiple physical, environmental, and meteorological inputs, such as proximity to AUM, wind direction, topographic wind exposure, and landform [34]. For example, locations in close proximity to or downwind of an AUM might have a higher environmental exposure potential when compared with locations upwind or far away. More details about this map could be found elsewhere.

As discussed, an animal may be exposed to environmental toxicants through respiratory, oral intake, and dermal pathways [27]. Because the livestock owners in Cove are generally aware of risks associated with AUMs, they tend to avoid or otherwise limit time spent in areas close to AUMs. Also, the skin generally protects deeper tissues from harmful chemicals associated with AUMs [10]. In all, dermal exposure is likely negligible compared to respiratory and oral pathways. However, the mechanisms of respiratory and oral exposures involve the whole-body system, and it remains difficult to quantify the relative influence of each pathway. Thus, this study assumed that respiratory and oral exposure are equally influential. Livestock owners fed their animals hay grown outside Cove and regulated water from their homes when the animals were corralled. From 8 AM to 8 PM, the exposure pathway will be primarily respiratory while resting. The exposure pathway will include both oral intaking and respiratory while grazing. While travelling, the primary exposure pathway is respiratory but with a higher breathing rate. Hence, we assigned the weight of grazing as 2, the weight of resting as 1, and the weight of traveling as 2, considering the relative contribution of each behavior to exposure.

In theory, the results should have 27 combinations because the animal may graze or rest in all these three places. A demo is shown in Table 2. Then the daily cumulative environmental exposure risk would be $E = \quad C_1 * P_1 + C_2 * P_2 + \cdots + C_{26} * P_{26} + C_{27} * P_{27}$.

2.6. Parallel computing strategy

The Lotek GPS collars were programmed to collect data every 20 minutes, resulting in 3 GPS points per hour and 72 points per day for each animal prior to data cleaning. We tracked two flocks, A and B, in 2019. We collected 1-month of data for Flock A and 4-months of data for Flock B. The collection periods were determined by livestock owners. In total, there were approximately 2000 points for Flock A and 8000 points for Flock B. Thus, if we were to use one final number to represent the cumulative environmental exposure for an individual livestock, the calculation completeness would be 3^{2000} for Flock A and 3^{8000} for Flock B. This amount of computational task was impossible based on current computing capacity. The exponential increase of calculations as input points increase is referred to as the NP-hardness problem [51]. Decreasing the number of selected points is a typical way to overcome such problem. Thus, we converted the above analysis to daily scale. However, even at the daily scale, computing the cumulative exposure potential has 3^{72} calculation completeness, which was still impossible for any current computing recourses. Conversations with livestock owners informed our approach to this computation challenge. We knew that the livestock were corralled daily after 8:00 PM and were not let out until 8:00 AM the next day. Thus, this study only focused on time from 8:00 AM to 8:00 PM. Still, the time completeness of 3^{36} was too large. We decided to use one out of three GPS points (within every hour) to represent the hourly status of one individual livestock. After reducing the input data, the time completeness was 3^{12} per day. However, personal computers are unable to support the full load of such calculation task for a long time, due to restrictions of the power supply system and cooling system and the daily use demand. Data processing was in turn conducted at the University of New Mexico Center for Advanced Research Computing (CARC) where the Python codes to calculate daily cumulative exposure was uploaded into a high-performance computer with 40 parallel cores, each with 8 nodes. The total computing time was 4 days.

3. Results

After data cleaning, more than 90% records were retained. The total number of original GPS data points before data preprocessing, and the number of invalid and valid points for each individual livestock can be found in the Appendix Table 6 GPS points from livestock A715 along with lines used to connect the previous point and the latter point based on their time stamps are in Appendix Figure 10.

To protect livestock owners' privacy, locational information of the livestock is presented with a 500-meter buffer (Figure 5). Flock A spent most time in two places, the livestock corral downstream in the lower reaches of the watershed and a summertime grazing area higher in the watershed. They were kept inside the corral before July 8th, and then were held in the summer camp until July 19th. Generally, the flock only spent one or two hours in proximity to AUMs while they were traveling from the downstream corral to summer camp.

For Flock B, most locations were far from AUMs. A few paths intersected with 250m/500m buffers of the AUMs. In fact, only 0.44% of the data points were within 500m of an AUM and only 0.03% of the points were within 250m. As the distance from AUMs increases from 0m to 100m, elevated concentrations of toxic metals (e.g. radon, uranium, lead etc.) in the soil and the atmosphere decrease significantly and eventually reach background levels as distance increases [58, 59]. Therefore, the 100m buffer to AUMs is considered to be relatively high-risk; a 100m to 250m buffer is considered to be relatively medium-risk, and a 250m to 500m buffer is relatively low-risk.

For livestock in Flock A, distance to AUMs varied from 486 to 1321 meters and the average distance was 707 meters. For livestock in Flock B, distance to AUMs varied from 125 to 1930 meters and the average distance was 1086 meters Appendix Figure 11 displays a histogram of the livestock's distances to AUMs. In general, most of the GPS points were in the area 500m away from AUMs, where previous investigations indicated lower concentration of metals in soil and air [58, 59].

The daily cumulative exposure potential values for individual animals in Flock A are shown in Figure 6a, ranging between 2.1 to 2.6. A higher value means that the livestock has a relatively higher exposure potential to waste from AUMs. The exposure values of the three individual livestock A715, A716 and A719 increased slightly from July 8th to July 13th, while exposure of another individual livestock A719 decreased first from July 8th to July 10th then increased to its highest value on July 11th. Two of the target livestock – A716 and A720 – had an increase from July 14th to July 15th. Estimated exposure of all four livestock decreased to their lowest on July 16th and increased again thereafter. An analysis of variance (ANOVA) test suggests no significant difference in daily exposure potential value for livestock in Flock A (p-value = 0.79 when July 19 was included. p-value = 0.82 when July 19 was excluded).

The daily cumulative exposure potential results of Flock B are shown in Figure 6b. For one animal (B715), the cumulative exposure potential could not be calculated for six days due to insufficient points after filtering. In terms of temporal pattern, Flock B had a higher exposure in August and mid-September, with exposure values higher than 2.5. Lower exposure values occur in October with values lower than 2. In general, the cumulative exposure potential decreased from August to October and followed a similar trend. An ANOVA suggests no significant difference in daily exposure potential values for Flock B (p-vale = 0.68).

After the fuzzy logic analysis, each GPS point was assigned three variables, each representing the fuzzy membership of grazing, resting, and traveling (Appendix Table 7 gives a sample result). Based on these three fuzzy memberships, a kriging interpolation method was used to generate a map showing areas where the flocks graze, rest, and travel (Figure 7a).

Because Flock A was kept behind the fence by the livestock owner before July 8th, only GPS points around the Summer camp were used to generate the map. For Flock A, all 4 livestock shared similar area when they were grazing, resting or traveling. Those 4 animals had relatively high probability of grazing in the north, west, and south portions of the study area. On the contrary, they only had relatively high resting probability to the west, and tend to have a high probability of traveling in the south.

After adding up the fuzzy membership of each behavior, we derived the total membership of resting, grazing, and traveling for each animal, with which the frequency of each behavior is calculated (Appendix Table 8 details the frequency of each individual's behaviors). For each animal from Flock A, the resting frequency was around 63%, the grazing frequency was around 31%, and the traveling frequency was around 6%. Although the grazing area was larger than the resting area (Figure 7a), the frequency of grazing was smaller than resting. The flock did not only rest when they were kept inside the fence from 8 pm to 8 am next morning, but also took some rest when they were at grazing time. Thus, it is reasonable that the resting frequency was larger than 50%.

Similar to Flock A, the 4 livestock from Flock B also shared similar area when they were grazing, resting or traveling (Figure 7b). On the north-west side to the centroid point, they demonstrated a high probability of resting. On the west and south side, they demonstrated a high probability of grazing. These 4 animals were more likely to travel in the north-east of the study area.

For each animal from Flock B, the resting frequency was around 68%, the grazing frequency was around 28%, and the traveling frequency was around 4% (detailed frequency of Flock B's behaviors is shown in Appendix Table 9). Similar to Flock A, the resting behavior also had the highest frequency. The behavior frequency was not significantly different among the animals from Flock B. However, the resting frequency increased by around 7% in October, and the frequency of grazing and traveling decreased as well. Because the weight of resting is the lowest, this helps explain the decreasing pattern of daily cumulative exposure potential in Figure 6b.

When comparing daily exposure potential results between two flocks, Flock A (median value is 2.3) has an overall higher exposure potential when compared with Flock B (median value is 2.1). However, the frequency of resting of Flock A was smaller than that of Flock B, which could explain the results. Additionally, Flock A has lower variations in daily exposure than Flock B. These results, however, need to be corroborated by animal tissue and biomonitoring analysis results.

In order to demonstrate the robustness of the methods framework used in the research, two methods comparisons were conducted: a) comparison between the present method and those without considering behavior patterns; and b) comparison between the present method and those without considering probability.

3.1. Comparison between the present method and those without considering behavior patterns

As discussed in the methods section, the daily cumulative exposure potential is the weighted sum of the environmental contamination risk value of each possible behavior pattern sequence (Table 2). However, if we do not account for behavior patterns, the cumulative exposure potential would be the sum of the environmental contamination risk value along the travel route, which would be R1 + R2 + R3 (E1 in Figure 1). Results of the daily cumulative exposure potential for Flock A and B calculated with no behavior pattern included is presented in Figure 8.

Flock B, we only considered three animals due to missing data for one animal. After conversations with the livestock owner, we were aware that the flock tended to stay together when they were outside of livestock owner's corral. As such, we can assume that all animals in the flock occupied the same general place when grazing, resting, or traveling. Thus, the environmental exposure potential value of those three individual livestock was likely to be similar based on GPS data. Also, they were likely to share similar behavior patterns. A comparison of Figure 6 and Figure 8 indicates that results from the current method used in this study demonstrate more consistent patterns of environmental cumulative exposure potential within the same flock (p-value > 0.05 for both flocks, ANOVA test), while model results without behaviors included show significantly different patterns of environmental cumulative exposure potential (p-value of Flock B < 0.01, p-value of Flock A < 0.05, ANOVA test). Therefore, these results suggest that the present method framework results in more robust results that are closer to the expectation that livestock daily environmental cumulative exposure potential is similar within the flock (Figure 7).

3.2. Comparison between the present method and those without considering probability/ uncertainty

In this case, we only considered the dominant behavior defined as the behavior with the highest probability among all behaviors. Through this experiment, we intended to verify the usefulness of applying fuzzy memberships in the calculation [55, 63]. Using only the dominant behavior to calculate the daily cumulative exposure following the equation: $C_r = \sum_1^n W_i R(t, l)$, where Wi represents the weight of the dominant behavior i. As shown in Figure 1, the calculation of E_3 is based on this method. In this method, only 1 behavior at each location is considered, rather than 27 combinations of behavior sequences as shown in Table 2. Results from this method for Flock A and Flock B are presented in Figure 9.

As shown in Figure 9, the daily cumulative exposure potential demonstrates a similar pattern within flocks. However, this method was based on the principle that a dominant behavior was given a probability of 100% - a crisp rather than fuzzy output for each location, which fails to consider uncertainties in behavior classification. In fact, determining the dominant behavior was challenging in some scenarios. For example, there were records whose fuzzy membership of resting and traveling were similarly low (e.g., row 8 in Appendix Table

7). There were also circumstances when the other behaviors were not small enough to be ignored even though one behavior probability was the highest (e.g., row 7 in Appendix Table 7).

The statistical comparison between the current method and those without considering probability/uncertainty revealed that daily cumulative exposure potential estimated without probability/uncertainty for individual livestock within the same flock was more likely to be significantly different from each other than the current method, based on the p-values (Appendix Table 10). This could further indicate that the exposure results generated from the current method are closer to reality.

A closer comparison among Figure 6 and Figure 9 reveals that the daily cumulative environmental exposure potential among the Flock B had higher variance if probability of all behaviors were considered. For example, the environmental exposure potential for B716, B720 and B80295 on August 12th are 2.28, 2.06 and 2.53 in Figure 9 (without probability/uncertainty) respectively. However, when we considered behaviors, the corresponding values are 2.57, 2.51 and 2.56 (Figure 6b). From 12 selected points on that day, we found that for 5 1-hour periods, at least one animal's behavior could not be conclusively determined by the highest value of three fuzzy memberships because their differences were not significant enough to justify the omission of other behaviors. For example, from 9:00 to 10:00 (second row in Table 3), the fuzzy membership of grazing of these three animals was around 0.5 which could not be simply overlooked even though the traveling probability was higher. In such case, the potential of other behaviors should not be overlooked.

Table 4 lists the frequency of how many behavior probabilities are 0.5 larger than the rest. For two flocks, around 67% of GPS points had a resting probability 0.5 larger than that of grazing and traveling. Around 17% of points had grazing probability 0.5 larger than the other two. Only about 1% of points traveling behavior had higher fuzzy membership. In total, there were 85.7% points, among which the fuzzy membership of one behavior pattern was 0.5 larger than the other two behaviors. We still had 14.3% points with undetermined dominant behavior. We conclude that although the method considering probability/uncertainty was less computationally intensive, the proposed method is extensible to more real-world scenarios, especially when a dominant behavior cannot be determined.

4. Discussion

This research is situated at the intersection of time geography, GIS/GPS methods, parallel computing, and environmental exposure assessments. We examined the geospatial and temporal behavior patterns of domesticated livestock and modeled potential cumulative exposure to AUM waste at the individual animal level with corresponding uncertainty. A total of 8 animals (4 sheep and 4 goats) were fitted with GPS collars. Due to the terrain and canopy effects, some GPS data points were considered invalid. We intended to quantify the cumulative exposure risk as a sum of the product of probability of classified livestock behavior and environmental contamination for every GPS point location. However, the GPS data for one livestock animal was too large for a single linear calculation, which would generate one single number representing the total cumulative exposure potential for that animal during the whole recording period. Thus, this research employed parallel computing to calculate daily cumulative exposure potential to AUMs and AUM waste, which significantly lowered the number of GPS points for the aforementioned calculation. Yet, the calculation task was still impossible for a personal computer to complete. To overcome the N-P problem, we shifted our research focus to the time window from 8:00 AM to 8:00 PM when the animals might be grazing, and we selected only one GPS point every hour to represent the behavior pattern for that hour. Fuzzy rules were then applied to categorize the behavior patterns of animals, i.e., grazing or resting, and the possibilities of corresponding behaviors.

According to the results, the daily cumulative exposure potential of Flock A ranges from 2.1 to 2.6, the average value was approximately 2.3. Cumulative exposure, in this case, is dimensionless. However, there is not enough evidence to conclude that there are significant differences in the potential exposure among the four individuals. For Flock B, the daily cumulative exposure potential varied from 1.8 to 2.8. The average value was approximately 2.1. Not only do behavior patterns affect an animal's exposure potential, but the environmental contamination value at each GPS location also impacts the results. We adopted an environmental exposure potential model of this study area from a previous study [24]. However, grazing behaviors certainly have a higher impact on the final results since two exposure routes were considered and higher weight was assigned compared to other behaviors. These results similarly need to be corroborated by animal tissue and biomonitoring analysis results.

The cumulative exposure potential estimates proposed in this paper were built on widely adopted human exposure risk assessment models. There is little research that applies similar approaches on livestock exposure estimates. We adapted previous methods used for human environmental exposure assessment to livestock study and enhanced the methods by introducing a fuzzy logic-based behavior classification to mitigate uncertainties. A comparison of the proposed methods with previous approaches on probability-based risk assessments reveal that our approach is more robust for individual-level livestock exposure potential modeling using GPS data. Other methods that do not account for behaviors or behavior probability/uncertainties resulted in significantly different daily cumulative environmental exposure potential, which does not fit with the assumption that these animals tended to stay in one group. Additionally, another contribution of this study is that it is a GIS-based study informed largely by Native American culture and community involvement.

5. Limitations of the research

Due to the uncontrollable environmental influences, the GPS device performance, recent computing abilities, etc., this research has several limitations.

First, this research used a filtering strategy to solve the N-P problem, which was discussed in the methodology section. However, the filtering method employed could potentially misrepresent all GPS data during a given hour. Additionally, the recording interval of the GPS devices were set to be 20 minutes, which meant that we only had 3 points at most for every hour. However, when all 3 GPS records from one hour period were invalid, we used the previous hour or the next hour to search for a point to represent the current hour (less than 5% of data were under this scenario). Another possible solution offered here is that in the deficiency of high-performance computing resources, one could significantly decrease the number of selected GPS points by only including represented points to increase the computational efficiency.

The second limitation is related to animal behavior patterns. We initially intended to use 4 behavior patterns – grazing, resting, traveling, and drinking – to calculate the cumulative exposure potential, but this would raise the calculation up to 4^n times (n is the points number we selected). Oral exposure would also be separated into two subgroups – drinking and eating. To decrease the burden of the computing and cover as much time in a day as possible, we used the three most representative behavior patterns of livestock – grazing, resting, and traveling. Additionally, we only used 2 factors for fuzzy membership behavior classification because our classification was partially informed by livestock owners. For grazing behavior classification, the general grazing area was known. The general pattern of traveling and resting were also known. Therefore, factors such as terrain, sunlight, and vegetation were less important or have little relevance in the classification. Future studies might consider integrating accelerometer or activity sensor to better predict animal behaviors [60, 61]. Moreover, we did not conduct a formal assessment of the accuracy of behavior pattern classification because ground truthing at a fine spatial-temporal scale was not feasible. On the other hand, this study employs fuzzy logic, which has an advantage of addressing classification uncertainties through generating probabilities. We worked together with livestock owners to review the general patterns of behaviors after classification, which agreed with their understanding. In fact, information and knowledge about livestock behaviors through communication with livestock owners were used in the classification process. Nevertheless, future studies should collect point to point ground truthing data using different technologies (e.g., GoPro camera) to verify results.

Third, this research set weights of grazing, resting and traveling as 2:1:2, respectively, when estimating the cumulative exposure potential based on assumptions that the oral exposure and respiratory exposure were equally accumulated inside livestock’s body and the respiratory exposure while traveling is twice that of grazing and resting. More biological research is needed to verify and determine the relative importance of exposure between grazing and resting.

Fourth, the current study does not have a control set of livestock from uncontaminated places for the whole study duration. Therefore, it was not possible to compare our results against that from any control flock. Results from this study could have been influenced by prior long-term exposure as well as due to a lack of data prior to collaring.

Lastly, results from this study will need to be verified by animal tissue and organ sample analysis. As a collaborative research project, results from this study will be compared with levels of heavy metals detected in tissue and organs of individual livestock analyzed by our research partners. Nevertheless, this geospatial research provides a useful and reliable methodological framework for livestock exposure assessments in geographic areas with environmental contamination to understand and address environmental health questions.

6. Implication for future study

This is the first study combining time geography, GIS, and behavior pattern classification to create a new workflow to estimate livestock cumulative exposure potential. Results from this study can be further used to guide livestock owners to optimize grazing or pasturing to reduce potential exposure. The workflow presented here could potentially be adapted or extended to other areas of Navajo Nation and other geographic regions with multiple types of environmental contamination. This study has potential to inform research about animal exposure to the environment.

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APPENDIX

Table 5.

GPS data sample

GMT Time	Lat	Lon	Alt (meter)	Duration (second)	Temp (°C)	DOP	Satellites
6/24/2019 4:42:12 PM	0	0	0	2	24.5	0	0
6/24/2019 5:01:10 PM	0	0	0	70	29.5	0	0
6/24/2019 5:20:27 PM	35.09131	-106.617	1556.96	41	27	1.6	5
6/24/2019 5:40:28 PM	35.09127	-106.617	1542.07	27	25.5	1.6	5

Notes. GMT – Greenwich Mean Time; Lat – Latitude; Lon – Longitude; Alt – Altitude; Duration – the time it takes to connect to satellite; Temp – temperature; DOP – dilution of precision; Satellites – number of connected satellites

Table 6.

Basic information of datasets

Livestock	Total Points Collected	Duration = 70s	Number of Satellites < 4	Altitude < 800 m	Number of Valid Points
A715	2122	147 (6.93%)	81 (3.82%)	70 (3.30%)	1961 (92.41%)
A716	2091	181 (8.66%)	86 (4.11%)	80 (3.83%)	1902 (90.96%)
A719	2137	150 (7.02%)	73 (3.42%)	66 (3.09%)	1978 (92.56%)
A720	2098	204 (9.72%)	100 (4.77%)	86 (4.10%)	1878 (85.44%)
B715	7572	1201 (15.86%)	592 (7.82%)	610 (8.06%)	6214 (82.06%)
B716	8143	330 (4.05%)	116 (1.42%)	120 (1.47%)	7767 (95.38%)
B720	8085	453 (5.60%)	189 (2.34%)	187 (2.31%)	7561 (93.52%)
B80295	7957	650 (8.17%)	297 (3.73%)	279 (3.51%)	7204 (90.54%)

Table 7.

Sample result of fuzzy logic for behavior classification

FID	Local Time	FM_G	FM_R	FM_T
0	7/25/2019 15:40	0.3	1	0
1	7/25/2019 16:00	0.3	1	0
2	7/25/2019 16:21	0.3	1	0
3	7/25/2019 16:40	0.3	1	0
4	7/25/2019 17:00	0.3	1	0
5	7/25/2019 18:20	0.96591	0.329212	0.290145
6	7/25/2019 18:40	0.907084	0.260179	0.392916
7	7/25/2019 19:00	0.855618	0.238122	0.444382
8	7/25/2019 19:20	0.025429	0.359334	0.274571
…	…	…	…	…

Notes. FM_G – fuzzy membership of grazing; FM_R – fuzzy membership of resting; FM_T – fuzzy membership of traveling

Table 8.

Frequency of resting, grazing, and traveling of Flock A

	A715	A716	A719	A720	All individual
Resting	63.31%	62.85%	63.08%	62.90%	63.04%
Grazing	30.51%	31.00%	30.61%	30.79%	30.72%
Traveling	6.18%	6.15%	6.32%	6.32%	6.24%

Table 9.

Frequency of resting, grazing, and traveling of Flock B

		B715	B716	B720	B80295	All individual
Resting	All Months	67.06%	68.52%	68.47%	67.76%	68.00%
Grazing		28.18%	27.28%	27.32%	27.71%	27.60%
Traveling		4.76%	4.20%	4.20%	4.53%	4.40%
Resting	Aug	64.61%	65.81%	66.37%	64.93%	65.47%
Grazing		28.99%	28.27%	27.94%	28.72%	28.45%
Traveling		6.40%	5.92%	5.70%	6.35%	6.07%
Resting	Sep	64.44%	66.62%	65.79%	65.32%	65.59%
Grazing		30.12%	28.70%	29.18%	29.49%	29.34%
Traveling		5.44%	4.68%	5.03%	5.19%	5.07%
Resting	Oct	72.39%	73.15%	73.22%	73.10%	72.99%
Grazing		25.29%	24.87%	24.88%	24.90%	24.97%
Traveling		2.32%	1.98%	1.90%	2.00%	2.03%

Table 10.

T-test of daily cumulative exposure potential of Flock B comparison of the current method with those not considering probability/uncertainty

P-value	B716		B720		B80295	
	Current method	without probability/ uncertainty	Current method	without probability/ uncertainty	Current method	without probability/ uncertainty
B716			0.559	9.7×10^{-4}	0.044	6.2×10^{-5}
B720	0.559	9.7×10^{-4}			0.145	0.175
B80295	0.044	6.2×10^{-5}	0.145	0.175		

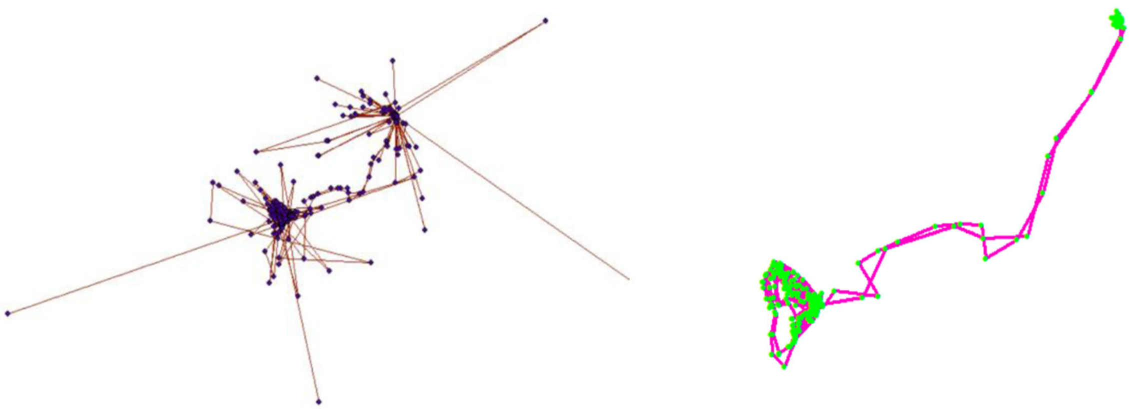

Figure 10.
Points before and after the data preprocessing. (Note: Base map is excluded to protect livestock owner's privacy).

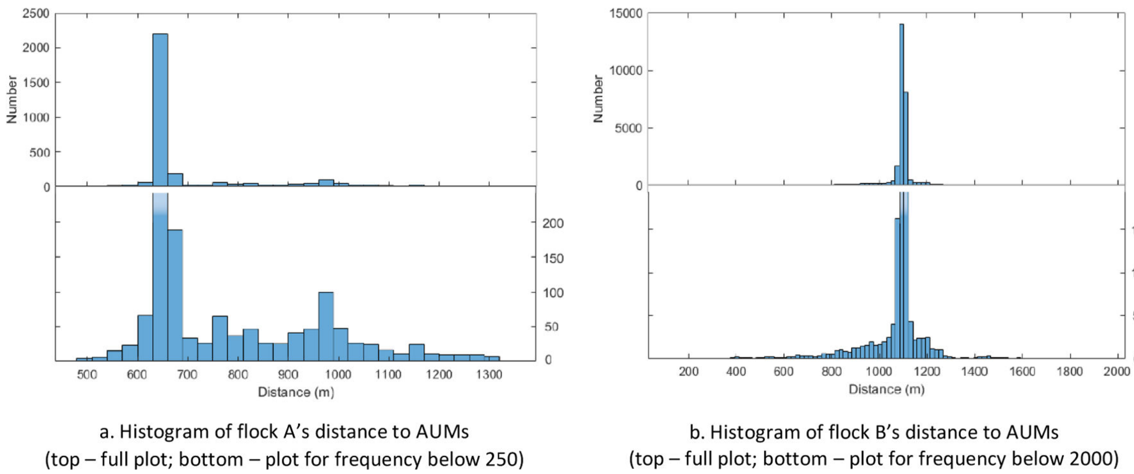

Figure 11.
Histograms of livestock distance to AUMs

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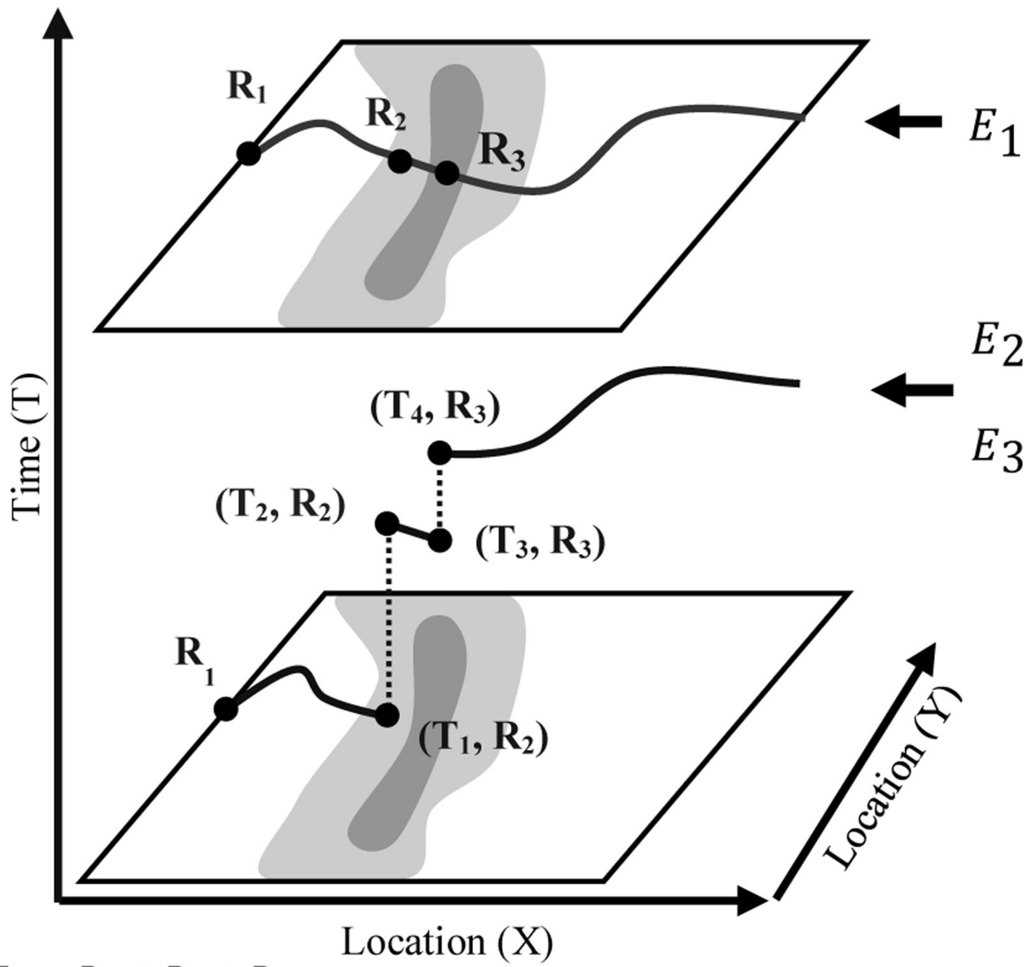


$$E_1 = R_1 + R_2 + R_3$$

$$E_2 = R_1 + (T_2 - T_1) * R_2 + (T_4 - T_3) * R_3$$

$$E_3 = W_1 * R_1 + W_2 * (T_2 - T_1) * R_2 + W_3 * (T_4 - T_3) * R_3$$

Figure 1.

Exposure assessment in spatial-temporal dimension (Example equations are listed to demonstrate exposure assessment approaches under different scenarios)

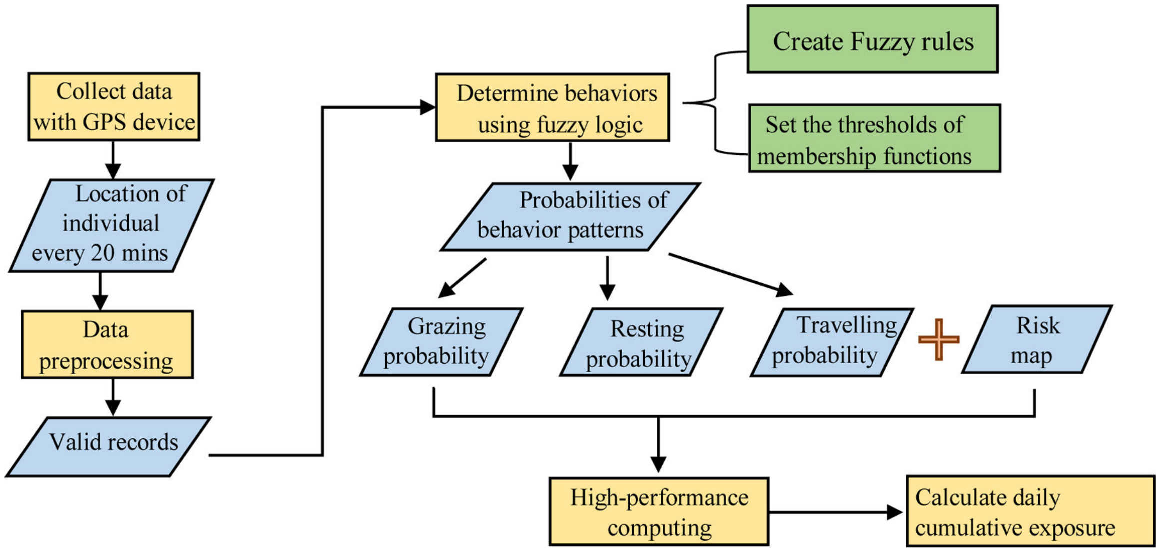


Figure 2.

Research workflow including data collection, cleaning and analysis

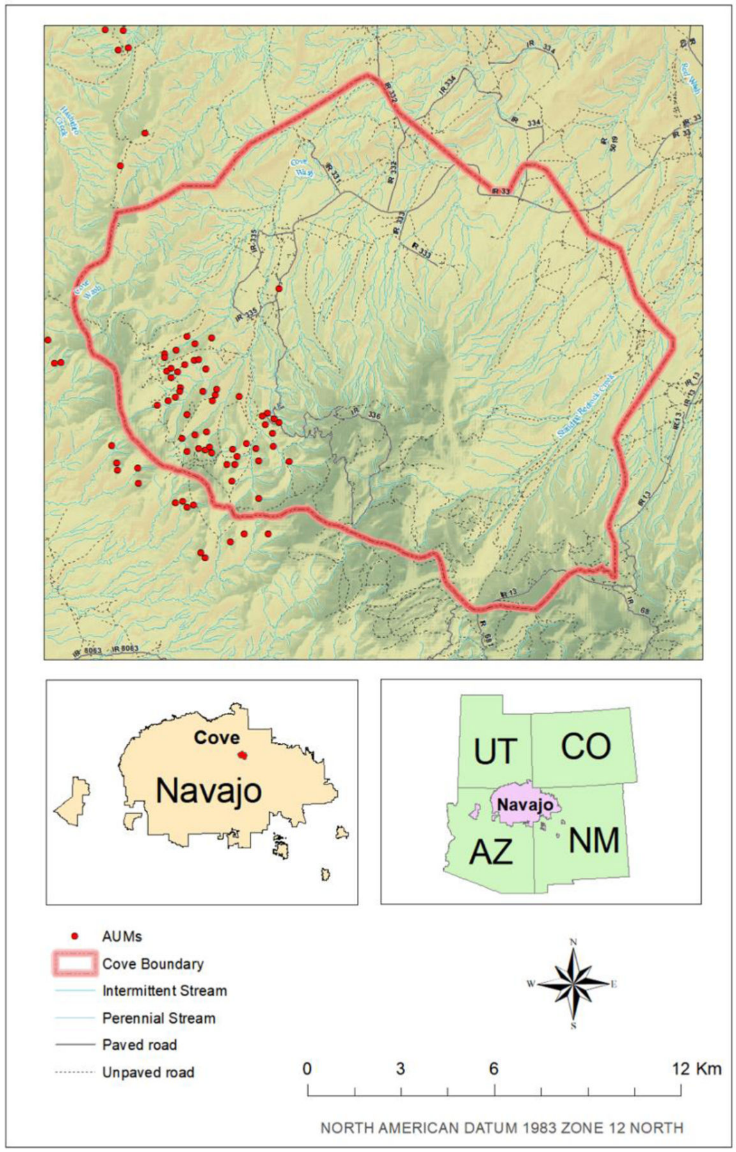


Figure 3.
Distribution of AUMs in Cove

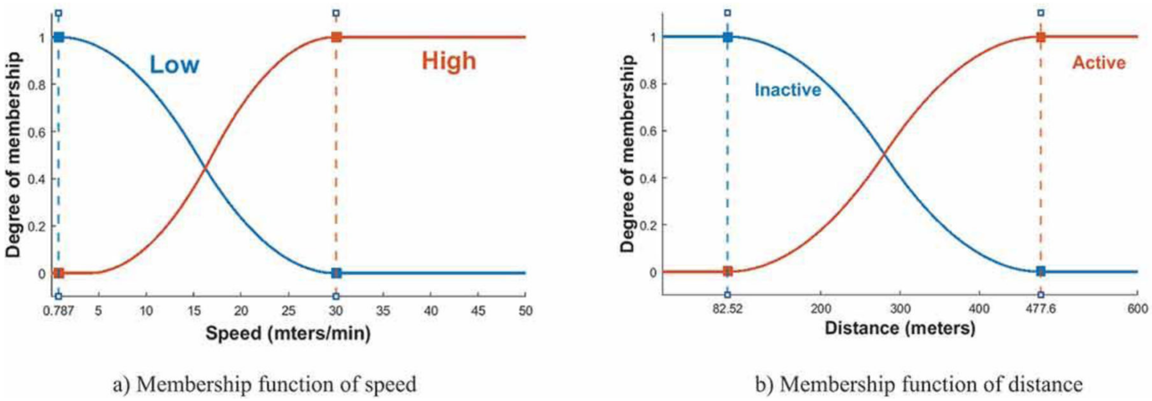


Figure 4.

Membership functions

a) The blue curve shows the fuzzy membership function of low speed, while the red curve represents that of high speed.

b) The blue curve shows the fuzzy membership function of inactive status, while the red curve represents that of active status.

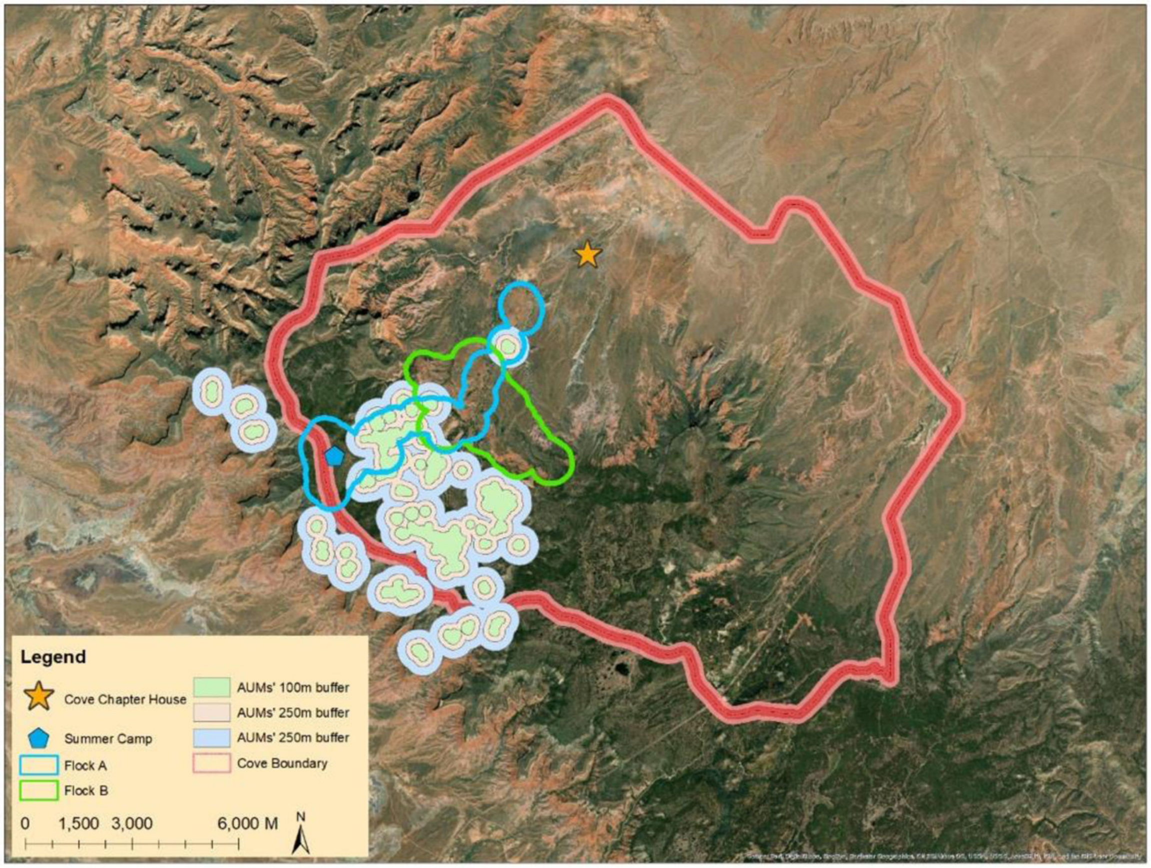
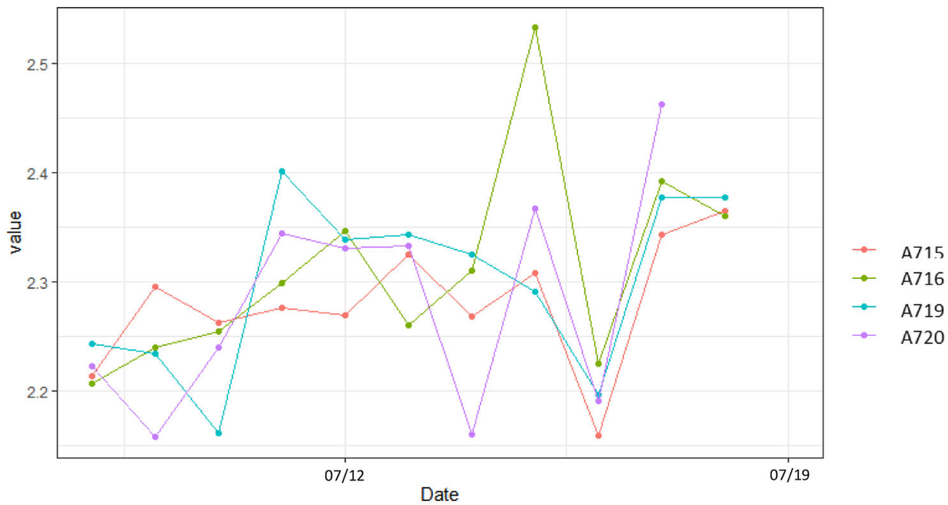
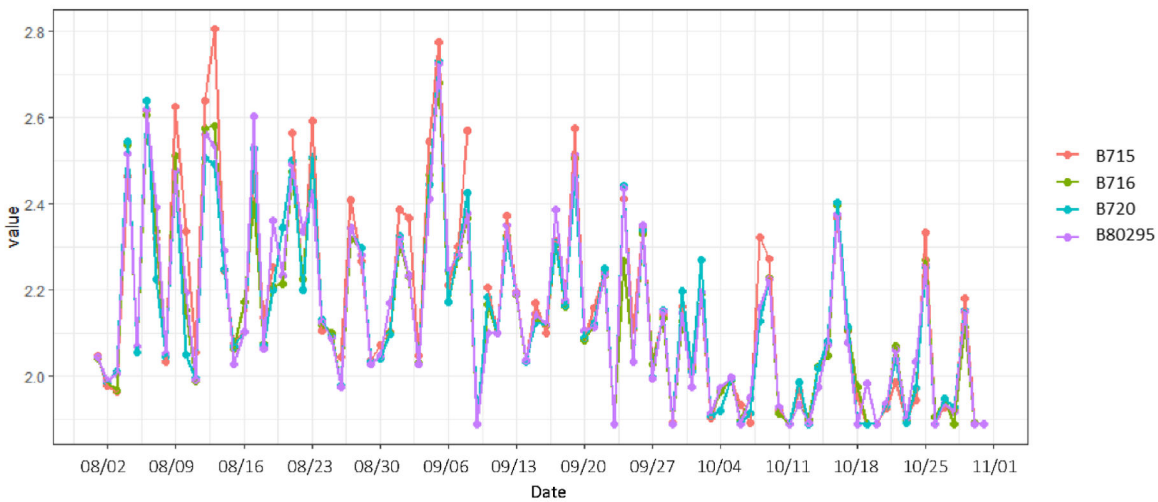


Figure 5.
Livestock location and proximity to AUMs



a. Daily exposure of Flock A



b. Daily exposure of Flock B

Figure 6.
Daily exposure of Flock A and Flock B

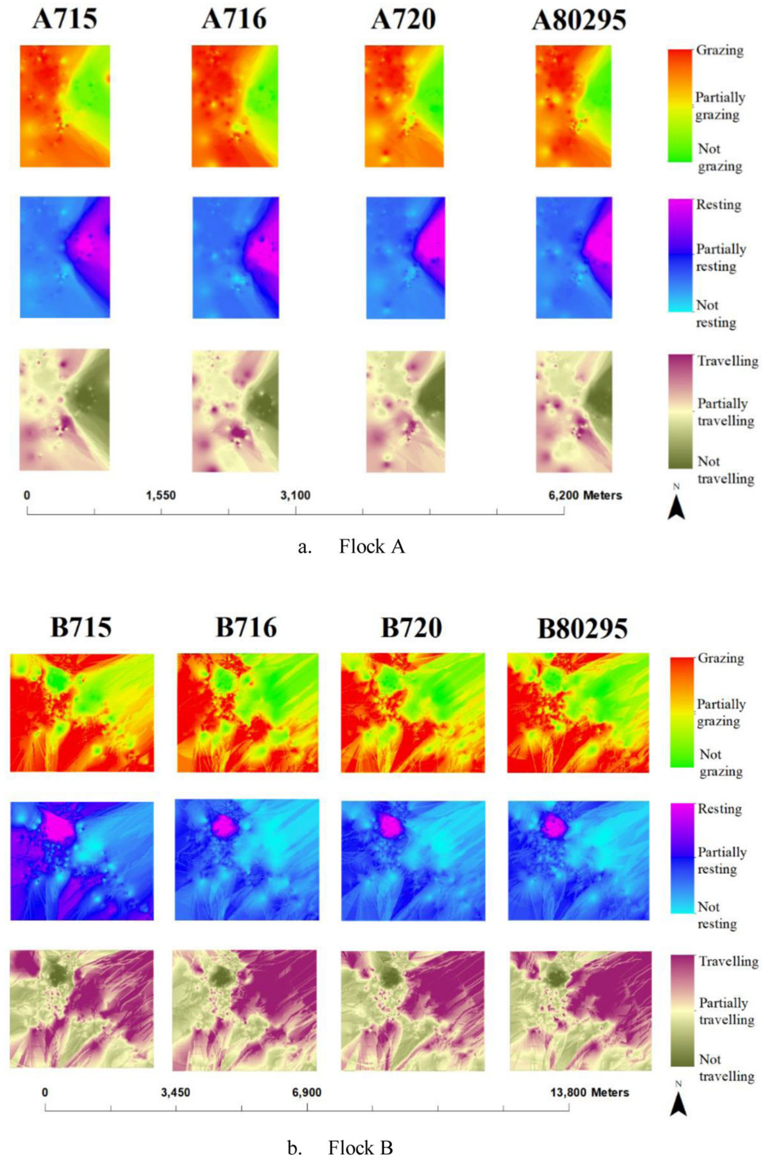


Figure 7.

Geographic distribution of area associated with grazing, resting, and traveling for Flock A and Flock B

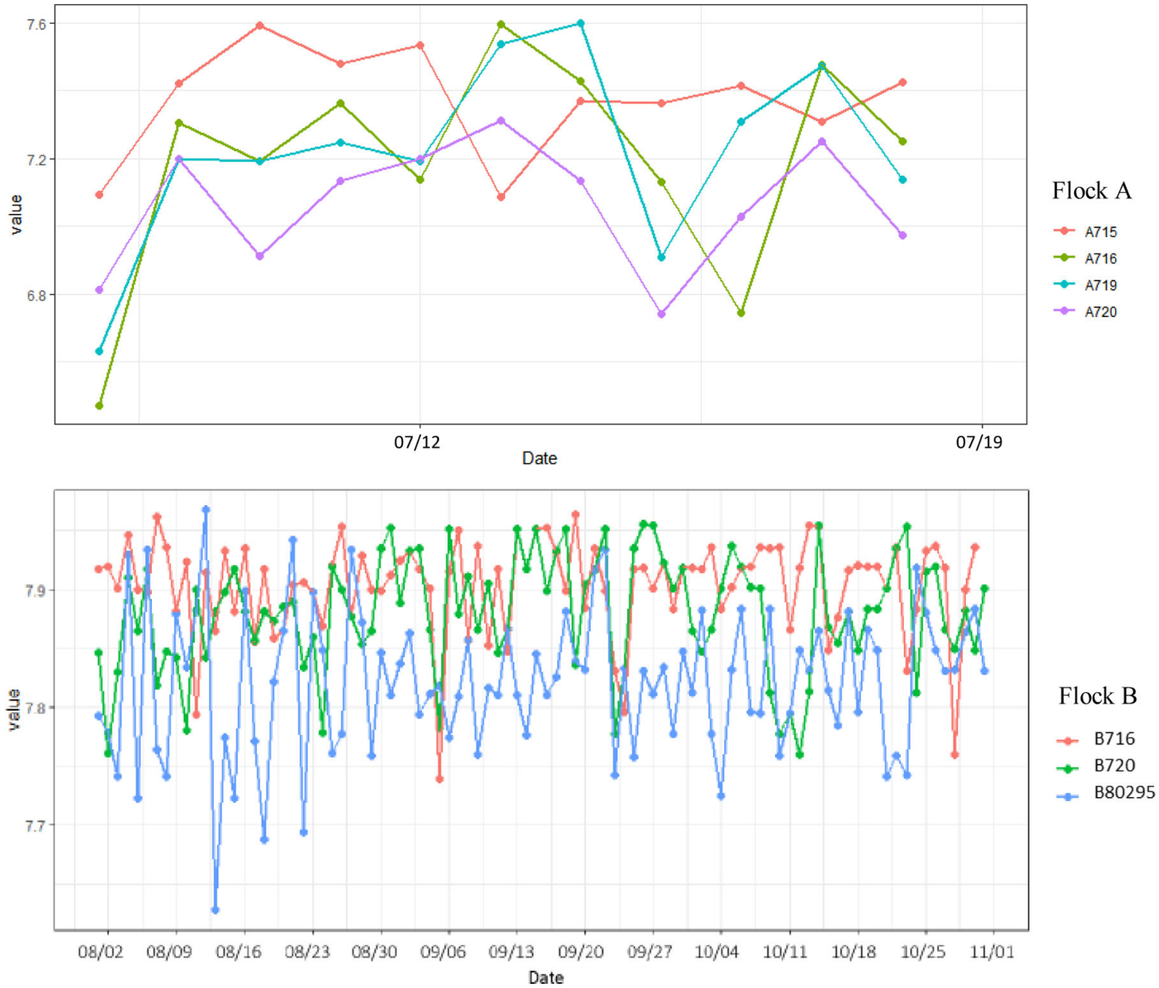


Figure 8.

Daily exposure without considering behavior patterns

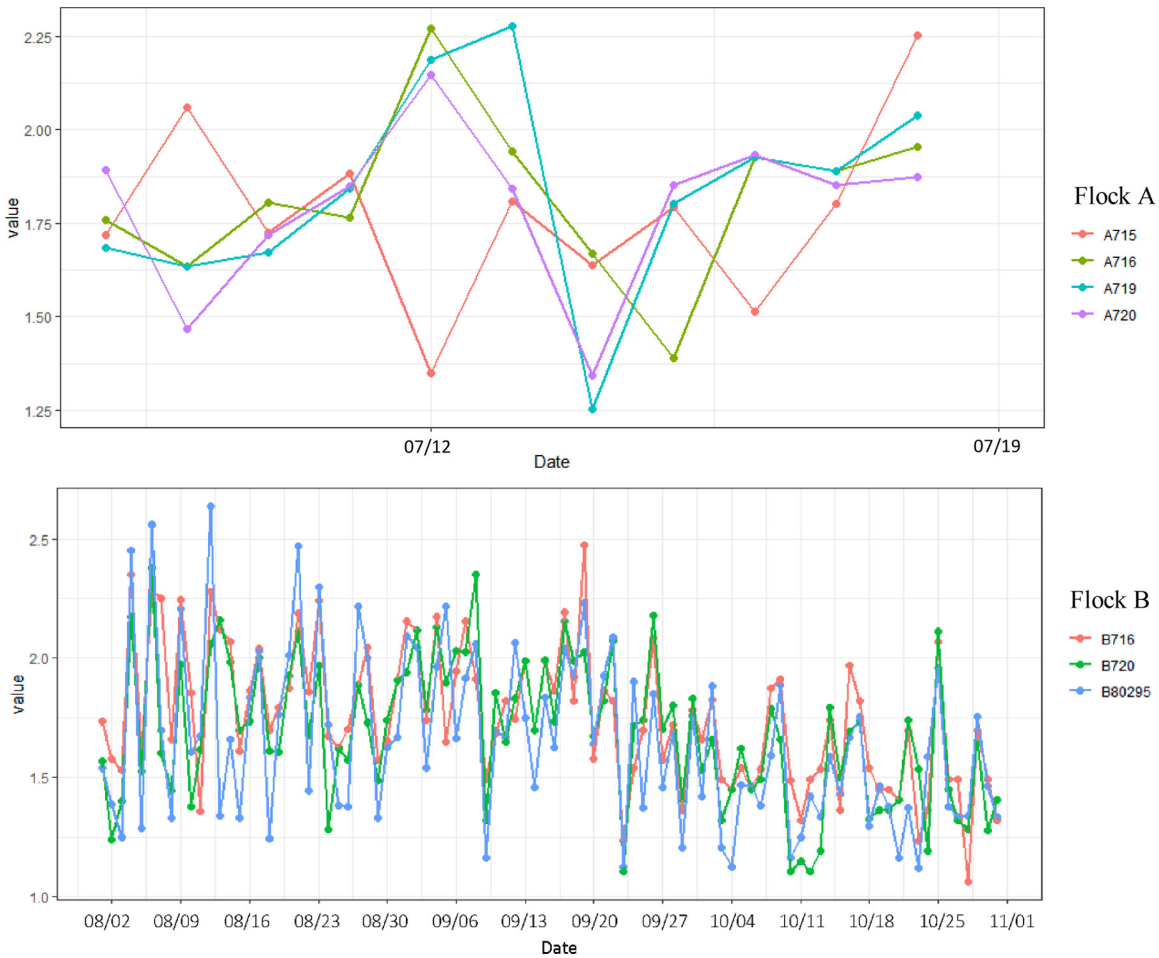


Figure 9.

Daily exposure considering behavior patterns but without probability/uncertainty

Table 1.

Fuzzy rules

Fuzzy Rules	Speed: High		Speed: Low	
	Behavior	**Membership**	**Behavior**	**Membership**
Status: Inactive	Grazing	Low	Grazing	Low
	Resting	Mid	Resting	High
	Traveling	High	Traveling	Low
Status: Active	Grazing	Mid	Grazing	High
	Resting	Low	Resting	Mid
	Traveling	High	Traveling	Mid

Table 2.

Calculation of cumulative risk and probability

Behavior combination (G: grazing; R: resting; T: traveling)	Risk $(W_G = 2;\ W_R = 1;\ W_T = 2)$	Corresponding possibility
GGG	$C_1 = 2R_1 + 2R_2 + 2R_3$	$P_1 = PG_A * PG_B * PG_C$
GGR	$C_2 = 2R_1 + 2R_2 + 1R_3$	$P_2 = PG_A * PG_B * PR_C$
GGT	$C_3 = 2R_1 + 2R_2 + 2R_3$	$P_3 = PG_A * \mathrm{PG}_B * P\mathrm{T}_C$
.	.	.
.	.	.
.	.	.
RRG	$C_{25} = 1R_1 + 1R_2 + 2R_3$	$P_{25} = PR_A * PR_B * PG_C$
RRR	$C_{26} = 1R_1 + 1R_2 + 1R_3$	$P_{26} = PR_A * PR_B * PR_C$
RRT	$C_{27} = 1R_1 + 1R_2 + 2R_3$	$P_{27} = PR_A * PR_B * P\mathrm{T}_C$

Table 3.

Fuzzy membership of Flock B on August 12th

B716				B720				B80295			
time	**FM_G**	**FM_R**	**FM_T**	**time**	**FM_G**	**FM_R**	**FM_T**	**time**	**FM_G**	**FM_R**	**FM_T**
8:20	0.30	1.00	0.00	8:20	0.30	1.00	0.00	8:20	0.30	1.00	0.00
9:40	0.51	0.09	0.79	9:40	0.45	0.06	0.85	9:41	0.56	0.11	0.74
10:20	1.00	0.30	0.30	10:20	0.97	0.29	0.33	10:20	0.97	0.29	0.33
11:20	1.00	0.30	0.30	11:20	1.00	0.30	0.30	11:20	1.00	0.30	0.30
12:20	1.00	0.30	0.30	12:21	1.00	0.30	0.30	12:20	1.00	0.30	0.30
13:41	0.74	0.19	0.56	13:20	0.99	0.29	0.31	13:20	0.98	0.29	0.32
14:20	0.02	0.34	0.28	15:00	0.24	0.86	0.06	14:21	0.01	0.32	0.29
15:20	0.30	1.00	0.00	15:20	0.30	1.00	0.00	15:20	0.30	1.00	0.00
16:20	0.30	1.00	0.00	16:20	0.30	1.00	0.00	16:20	0.30	1.00	0.00
17:20	0.30	1.00	0.00	17:20	0.30	1.00	0.00	17:20	0.30	1.00	0.00
18:20	0.59	0.12	0.71	18:20	0.65	0.15	0.65	18:20	0.55	0.11	0.75
19:20	0.53	0.13	0.71	19:20	0.48	0.11	0.76	19:20	0.52	0.11	0.76

Notes:

1). FM_G – fuzzy membership of grazing; FM_R – fuzzy membership of resting; FM_T – fuzzy membership of traveling.

2). Two points of B716 were selected on 9:40 and 13:41because points on 9:20 and 13:20 were missing.

Table 4.

Frequency of dominant behavior

	A715	A716	A719	A720	B716	B720	B80295	All individual
Resting	47.68%	47.66%	49.73%	46.96%	72.23%	71.47%	67.53%	67.27%
Grazing	25.34%	28.93%	26.78%	25.97%	14.00%	14.79%	17.17%	16.91%
Traveling	0.54%	0.55%	0.55%	0.55%	1.38%	1.64%	2.10%	1.52%
Total	73.57%	77.13%	77.05%	73.48%	87.61%	87.91%	86.81%	85.70%

Notes:

1) The dominant behavior was determined with the following condition:

grazing: FM_G > (FM_R + 0.5 and FM_T +0.5)

resting: FM_R > (FM_G + 0.5 and FM_T +0.5)

traveling: FM_T > (FM_G + 0.5 and FM_R +0.5)

2) FM_G – fuzzy membership of grazing; FM_R – fuzzy membership of resting; FM_T – fuzzy membership of traveling.