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Individual Exposure potential Assessment for Livestock Based on Spatial-Temporal Analysis of GPS Data and Behavior Patterns Classification in Cove Wash Watershed, Arizona

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by

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ABSTRACT

This community-based research project examined the geospatial and temporal grazing patterns of domesticated livestock to model individual-level exposure potential to abandoned uranium mine (AUM) waste in an Tribal community in the southwest United States. Lotek Litetrack Global Positioning System (GPS) collars collected data at a 20-minute-interval for 2 flocks of sheep and goats during the Spring and Summer of 2019. Depending on the flock and individual animals, tracking time ranges from 10 days to four months. This research developed a GIS-based exposure potential framework that built on existing methodologies in time geography, GIS, and exposure mapping. The aims were to: 1) classify GPS data from livestock into into three behavior subgroups - grazing, traveling or resting; 2) estimate the potential environmental exposure for each animal, informed by behavior classifications, using GIS-modeling and parallel computing methods; and 3) quantify the uncertainty in both livestock behavior classification and modeled exposure potential. Results demonstrated no significant difference in individual

cumulative exposure potential within each flock when behaviors were considered. When daily cumulative exposure potential was calculated without consideration of animal behavior significant differences among animals within a herd were observed, which does not reflect animal grazing behaviors reported by livestock owners. This suggests that the proposed method more closely resembled hypothesized exposure potentials for animals within each flock – livestock within the same flock share similar cumulative potential environmental exposures, based on observation and livestock owner's accounts. Therefore, this research demonstrated a reliable and robust GIS-based framework to estimate cumulative exposure potential to environmental contaminants. This research advances GIS-based research methods for spatial-temporal GPS analysis in conjunction with environmental health and provides critical information to address community questions on livestock exposure to AUMs. Results from the research may be used for future intervention and policy making on remediation efforts in communities where livestock grazing may encounter environmental contaminants.

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1. Introduction

1.1 Hard rock mining history in Cove

Abandoned hard rock mines are prevalent throughout the western United States. These abandoned mines have caused public health concerns because they are known sources of deleterious environmental metals such as uranium, lead, cadmium, and arsenic. While many different types of ore were mined there remain more than 4,000 abandoned uranium mine sites (AUMs) throughout the western United States, many of which are proximal to indigenous communities. For example, it is reported that "mining companies blasted 4 million tons of uranium out of Navajo land between 1944 and 1986. The federal government was the primary buyer of the ore to make atomic weapons. As the Cold War threat petered out the companies left, abandoning more than 500 mines." (Laurel, 2016). On the Navajo Nation, there are 523 AUMs (Lewis et al., 2017), among which about 50 are located on Cove Wash watershed. The presence of AUMs in the Cove Wash Watershed has caused concerns about exposure to heavy metals and radiation from these sites. Local residents are not only worried about their own health but also their livestock's health because livestock remain a critical component of Navajo culture.

1.2 Health concern of AUM waste

Previous research has examined health outcomes and human exposure to AUM waste (Hund et al., 2015). Living in an area close to AUMs will increase the probability of getting cardiovascular disease, decrease the pregnancy among Navajo women, and affect the immune system, etc. (Harmon et al., 2017; Hoover et al., 2020; Erdei et al., 2019). Some studies used the chemical method (neutron activation analysis) to detect the concentration of uranium inside human body (Nozaki et al., 1970; Hernández et al., 2018, Saini et al. 2015) while other studies measured environmental concentrations in water, soil to determine how serious uranium exposure was for people living or working in the proximity of AUMs (Kurttio et al,. 2002; Fitzpatrick et al., 2007; Kheir et al., 2019).

Previous research also investigated dietary sources of uranium exposure, which suggested that 41% of uranium ingested by adults are delivered through beverages, 33% through vegetable and 26% from animal foodstuff (Anke et al., 2009). Living in the Cove, which is aggrieved by the historical reasons, residents are concerned about their health if they intake too much uranium through the animal foodstuff since they consume their livestock as a food source. Meanwhile, they are also concerned about the health of livestock because many people consider their livestock to be family members. To answer theses concerns, this research develops a workflow to measure the livestock individual's environmental exposure potential to AUMs.

1.3 Environmental exposure potential measurement

To measure exposure accurately among livestock, it is important to consider the risk rate of different behavior patterns (Lu et al., 2015). According to previous work, exposure pathways to uranium can be generally classified as respiratory exposure, oral exposure, and dermal exposure (Tannenbaum et al. 1948).

Earlier researchers followed animals to track their behaviors, which encountered problems like observer fatigue (Turner et al. 2000). To solve these problems, researchers recorded animals' locations using GPS tracker and classified their behaviors using location, time, and the environmental information (Handcock et al., 2009; Augustine et al., 2013; Wang et al., 2018). However, the above approaches suffered uncertainty issues, which is usually generated from the unknown geographic context or inaccuracy in GPS data (Brown 2004).

In previous studies about exposure to uranium for both human and animals, most work does not take individual activities and the time spent in contaminated areas into consideration. In recent years, scholars have integrated theories from time geography into individual behavior research to estimate the cumulative exposure. The cumulative exposure is an indicator describing the total exposure in a long period that the target gets from the contaminated source. It is related to the time that the target spends in one place and the risk value in that place. Space-time path is one of the approaches to visualize and help understand the total exposure (Lu et al., 2015). However, nobody has applied such method for livestock and also considered uncertainties when estimating exposure. To answer how much each individual livestock is exposed to AUM waste in the study area of Cove watershed, this thesis, at the intersection of time geography, GIS/GPS methods, parallel computing, and environmental exposure assessment, developed a GIS-based exposure assessment framework for livestock through examining the geospatial and temporal behavior patterns of domesticated livestock and modeling potential cumulative exposure to AUM waste at the individual animal level with corresponding uncertainty quantified.

1.4 Research goals

The objectives of this thesis were to: 1) examine and visualize the GPS data patterns based on environmental factors (e.g. topographic, landcover, distance to AUMs); 2) classify livestock behavior patterns using the fuzzy logic; and 3) estimate the cumulative exposure risk to AUMs for each animal with probabilities information in behavior pattern using high performance computing. The results from this study will help answer questions in a larger ongoing community-based research study on potential human health risk from consuming meat and organs from livestock grazing in the Cove Wash watershed and therefore inform interventions and remediation efforts to address community environmental health concerns.

2. Literature Review

2.1 Health effect from AUMs

Uranium is the heaviest metal in nature. It is silvery white with strong hardness, high density, extensibility, and radioactivity. The most common uranium isotopes found in the natural environment are: 234U (0.005%), 235U (0.720%) and 238U (99.274%). The uranium atom can produce fission reaction and release energy, which can be used in power generation, nuclear weapon manufacturing and other applications. At present, 22 uranium isotopic forms have been identified, which are mainly related to the operation of nuclear reactors or high-energy physical experiments (Katz et al., 1961). Due to the extremely important role that uranium plays in the nuclear reaction, uranium mining had come to the stage in the middle of 20^{th} century (Voyles, 2015).

The first mining project in Navajo Nation, USA began in February 1944. Oljato Mesa, part of Monument Valley, was mined from June to December 1944, which produced more than 4,000 pounds of uranium and nearly 6,000 pounds of vanadium (Eichstaedt, 1994). In 1948, the US Atomic Energy Commission (AEC) announced a price for all uranium ore mined in the United States (Holaday, 1969; Brugge and Goble, 2002). Also, as deposits had been discovered near Poison Canyon, Shiprock, Launa Pueblo, and other locations, more large companies were involved in the mining process including Kerr-McGee Oil Industries, Homestake

Mining Company, Phillips Petroleum Company, and the Anaconda Copper Company (Eichstaedt, 1994). Mining activities reached the peak between the late 1950s and the late 1970s. It was not until the mid-1980s that this craze gradually calmed down, when the demand of uranium ore declined, and those industries began to close (Fettus et al., 2012). Although uranium mining projects ceased, the effect of uranium extraction did not stop, as uranium and other chemical compositions continued to flow into the food chain to animals and humans. According to a report by United States Environmental Protection Agency (EPA), the mining projects extracted nearly 30 million tons of uranium ore on or near the Navajo Nation from 1944 to the 1986. After the mining industries left Navajo Nation and closed the mines, more than 500 mine sites were abandoned in the land, among which about 50 abandoned uranium mine (AUM) sites are within Cove Wash watershed, a small community of Navajo Nation located in northeastern Arizona.

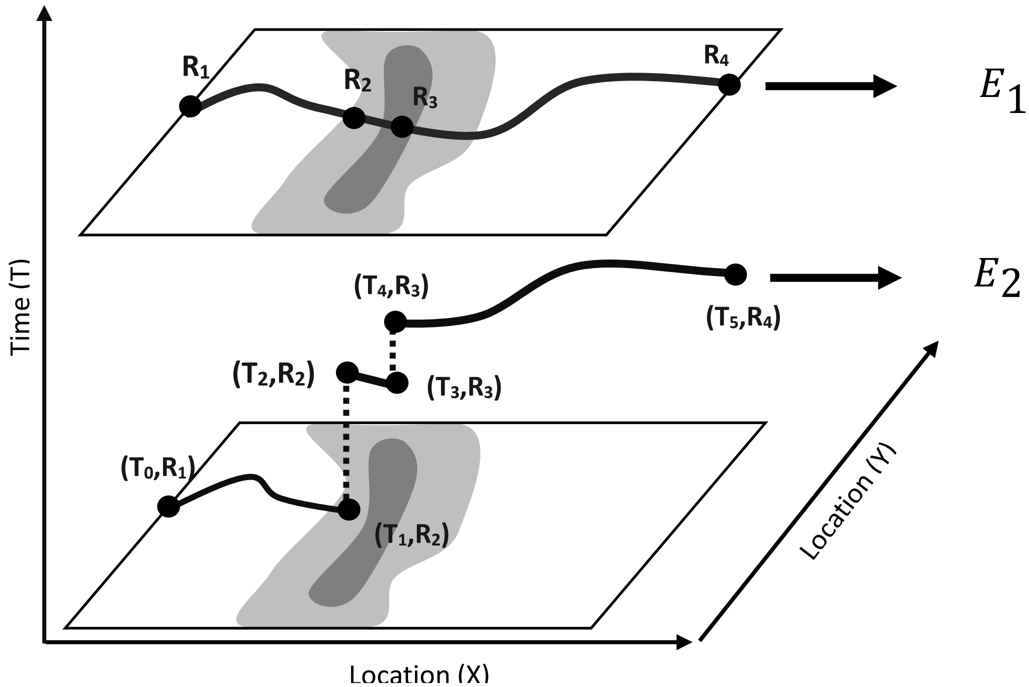
The health impacts of waste from AUMs comes from radiation and chemical exposures. Although natural uranium ore has certain radioactivity, the radiation level is very low due to the 4.5-billion-years half-life of the most common isotope. For AUM sites, the transport and accumulation uranium and other elements with chemical toxic effects constitute the primary environmental health hazard, while the radioactivity of uranium is a secondary concern (Meinrath et al., 2003).

The average adult body contains about 100 μg of uranium. Most of the uranium comes from ingestion of food (especially vegetables, cereals, and edible salt) and drinking water, which is about 1.5 μg per day. Metabolic processes result in the elimination of 90% of ingested uranium via excreta, while up to 2% is retained in organs and other tissues (Priest, 2001). The organ burdens of uranium include the skeleton principally with additional accumulation in muscle and soft tissue, lungs, kidney, liver, and heart. Previous research reported that uranium is toxic to these organs (Dang, 1995; Craft et al., 2004).

Rodrigues et al. demonstrated that the uranium accumulation phase in Wistar rats would transfer from anabolic to catabolic. And the incorporated uranium's radiation would increase the death rate of bone cells, which is harmful to skeleton (Rodrigues et al., 2013). In muscle and soft tissue of Wistar rats, there is no significant association between small-sized uranium pellets (2.0 x 1.0 mm) and tumor incidence, but large-scale uranium (2.5 x 2.5 mm) significantly increased local proliferative response and soft-tissue sarcoma (Hahn, 2002). As for humans, the chronic ingestion of uranium in drinking water significantly increased the urinary glucose, alkaline phosphatase, and β2-microglobulin in urine after 24 hours. Greater diastolic and systolic blood pressures are also related to uranium exposure and cumulative uranium intake (Zamora et al., 1998; Kurttio et al., 2006). Long-term exposure to uranium may increase the possibility of developing chronic kidney disease (Soderland et al., 2010; Semenova etal., 2020). In addition to uranium, radon and arsenic, which are generated along with the process of uranium mining, are also serious hazards to human health. In different regions, researchers have found that the radon and arsenic content near abandoned uranium mines is generally high (Vaupotić, 2001; Mudd, 2008; Fijałkowska, 2016; Hoover et al., 2017; Yazzie et al., 2020). There are sufficient research results demonstrating that uranium mining and AUMs are causes of multiple cancers, such as lung cancer, bone cancer, and skin cancer (Samet et al., 1984; Gottlieb and Husen, 1982; Hornung and Meinhardt, 1987; Mulloy et al., 2001). Living in an area close to AUMs may also influence pregnancy outcomes (Hoover, 2020), which is an active area of research through the Navajo Birth Cohort Study. In light of these findings Cove Community members requested a study investigating the accumulation of uranium in animal tissue. In response to this community concern, this study aimed to use geospatial technology to determine the cumulative environmental exposure potential of livestock that might graze in proximity to AUMs and waste.

2.2 Adapting time geography and behavior patterns for exposure potential assessment

Geography information system (GIS) provides powerful tools for assessing potential exposure to AUMs among the livestock. Tobler’s first law of geography has revealed relationship in the spatial dimension -- all things are related, but near things are more strongly related than distant ones (Tobler 1970). With this law, researchers could analyze potential exposure to AUMs in different geographic area with location-based methods. Simple location-based methods could be point-in-polygon, buffering, and other distance functions (Moolgavkar 2000; Barbone et al., 1995; Harrison et al., 1999; Jenelius et al., 2006). Additionally, there are other methods like Kriging, inverse distance weighting, regression mapping, etc. to create a exposure map with limited data (Zhan et al., 2018; Gong et al., 2014; Leelasakultum and Kim 2017). Other scholars have identified limitations in traditional methodologies and developed approaches to study exposure, like GIS-based multi-criteria model, land-use regression model, etc. (Lin et al., 2020; Ryan 2007; Lu and Fang 2015). However, all these methods were only based on spatial dimensions without considering temporal dimensions when applied to livestock study, which resulted in less accurate representation or assessment of exposure. Moreover, existing approaches suffered uncertainty issues, which is usually generated from the unknown geographic context, behaviors, or inaccuracy in GPS data (Brown 2004). As Figure 2.1 shows, an environmental risk map could be generated with one of the above methods. When only spatial dimension is considered, the total exposure along the livestock pathway could simply be the sum of the environmental risk values along the pathway (e.g. $E_1=R_1+R_2+R_3+R_4$, where E is the total exposure of a livestock and R is environmental risk value at a location). However, in the actual scenario, travel speed is different, and time spent at different locations might vary, resulting in a higher cumulative exposure if the individual livestock spends a longer time inside a higher-risk area, and vice versa (e.g. $E_2=R_1+(T_2-T_1)*R_2+(T_4-T_3)*R_3+R_4$, where T is time at a location). Thus, the total exposure could be different for the same route when time dimension is considered. To more accurately estimate potential exposure of livestock, it is necessary to apply time dimensions here which is an important concept in time geography. Also, livestock behavior patterns need to be considered into because different behavior patterns are associated with different exposure routes/rate which might further adapt the exposure estimates (e.g. $E_3=W_1*R_1+W_2*(T_2-T_1)*R_2+W_3*(T_4-T_3)*R_3+W_4*R_4$, where Wi represents the weight of different behavior patterns based on their relative contribution to exposure). However, none of the above scenarios considered underlying uncertainties in the exposure, including but not limited to, GPS locational accuracy, temporal uncertainty, and livestock behavior uncertainty. The uncertainties need to be considered for accurate representation and assessment of exposure (Kwan, et al., 2018).



$$E_1 = R_1 + R_2 + R_3 + R_4$$

$$E_2 = R_1 + (T_2 - T_1) * R_2 + (T_4 - T_3) * R_3 + R_4$$

$$E_3 = W_1 * R_1 + W_2 * (T_2 - T_1) * R_2 + W_3 * (T_4 - T_3) * R_3 + W_4 * R_4$$

Figure 2.1 The exposure assessment in spatial-temporal dimension

A Swedish geographer, Hägerstrand, applied the concept of lifeline in demography to study population movement with the spatial axes, which then became the concept of time geography (Hägerstraand, 1970). With the advocacy of Hägerstrand and the Lunde School under his leadership, time geography was introduced and popularized at the international scale (Pred, 1981; Raubal et al., 2004). Miller first developed a network-based space-time prism and accessibility algorithm in 1991(Miller, 1991). For the first time, Kwan used the geographical data of transportation network and urban facilities to realize accessibility measurement under the geospatial dimension (Kwan, 1998). Weber improved the algorithm and the simulation of human activities. According to him, it was believed that traffic congestion in the morning and evening rush hours and the opening time of urban facilities might become an important restriction on residents' activities (Weber, 2003). However, there was still a distance between activity simulation and real activity (Kim and Kwan, 2003). It is necessary to both identify the behaviors and measure the uncertainty. This thesis is taking behavior patterns into consideration, because different behavior patterns are related to different exposure rate ($E_3 = W_1 * R_1 + W_2 * (T_2 - T_1) * R_2 + W_3 * (T_4 - T_3) * R_3$, where W_i represents the weight of different behavior patterns). In this thesis, we focus on three behaviors: grazing, travelling, and resting. To identify weights of those three behaviors, we need to find out how those three behaviors affect exposure rate.

Exposure to AUMs could be specified as respiratory, oral, and dermal exposure (Brugge et al.,2005). In general, more soluble compounds are less toxic to the lungs but more toxic to the inhalation system due to easier absorption from the lungs into the blood and transportation to distal organs (Tannenbaum et al., 1948). The oral toxicity of uranium compounds has been evaluated in several animal species following exposure in drinking water or via grazing. Soil and water contaminated by AUMs are integrated into arable land or absorbed by perennial pasture plants, which may be used for cropping, grazing, and hunting. Thus, predators who ingest contaminated prey may also be affected by heavy metals and radionuclides (Gramss and Voigt, 2014; Anke et al., 2009; Zamora et al., 1998; Kurttio et al., 2006). The dermal exposure is related to the length of time of exposure, the size of the area that is exposed, and other physical and physiological conditions (Craft et al., 2004).

Because exposure routes are associated with different adverse health outcomes, it is necessary to distinguish behavior patterns, especially among grazing, resting, and travelling (Brugge et al.,2005). When livestock are grazing, possible exposure routes might involve respiratory, oral, and dermal exposure. When the individual is resting, exposure route might only include oral and respiratory exposure. When travelling the route might also contain oral and respiratory exposure.

Once those three different behavior patterns have been classified, methods from time-geography can be integrated to further analyze the potential accumulation risk of exposure to AUMs at each time. Previous work investigating the accumulation of uranium and other radioactive chemicals in animal tissue identified significantly higher concentrations in cattle from mining areas (Lapham, 1989). This work, however, did not account for animal movements throughout a contaminated area. In the Cove Wash Watershed, grazing animals may move throughout the watershed suggesting various exposure pathways with different duration and intensity. Not only the degree of environmental pollution, but also the accumulation of mine wastes in livestock are related to time each livestock spends, therefore it is very important to consider time dimension and methodology from time geography in this thesis.

2.3 Apply fuzzy logic to behavior pattern classification

The first attempt to track animals and record their behaviors is in situ investigation. Early methods relied on human observation of natural (color patterns) or artificial features (colored collar or tag) to identify the individual animal. Problems occurred in these methods, including observer fatigue and associated error, study area accuracy and physical limitations, external factors, and observer proximity effects on animals (Turner et al., 2000).

It was challenging to discern an individual livestock from a herd based on its natural features (like color patterns, height or special spot) (Rife et al., 2001). Therefore, new methods have been developed to address the above issues, including attaching a marker to an animal which had no or limited influences on animals to make animals recognizable. However, disadvantages still exist in such methods. For example, observer proximity effects would arise because animals would sense that there was an intruder to their habitat and would change their routine such as switching places for preying, migrating to other areas to build a new “home”, or being more vigilant to prepare for any emergency caused by the “intruder”. Strategies were developed to limit such observer proximity effects by decreasing the frequency of occurrence in the animal’s territory and by increasing the distance from the animals for minimum disturbance. This method, however, would impair the accuracy of results such as missing important behavior patterns due to a lower frequency of observation as well as more fatigue due to observing from a farther distance. Therefore, there is a trade-off between accuracy and observer proximity effects (Mech, 1983).

Global Position System (GPS) is one of the best solutions. GPS was initially designed for the military and users could obtain positions through earth-orbiting satellites. Because there are more than 24 satellites distributed in orbits where at least 5 satellites are reachable and generate/transmit signals from any area on the earth at any time, regardless of the influence of external factors such as terrain and weather, GPS can achieve global full-time accurate positioning. Due to these advantages in GPS, research has replaced the livestock markers discussed above with GPS collars.

A previous study developed different time intervals to record animal behaviors with GPS collars (Hull et al., 1960). It revealed that major behavior patterns — grazing, ruminating, and idling —observed animals to remain in a particular behavior pattern until the next time interval. It was noticed that there were highly significant differences in individual animal behavior patterns over a 24-hour period. According to previous research, the best interval to observe animal was 15 to 30 minutes. Normally, GPS devices can send and receive signals at an interval from every few seconds to every few hours, which suits the requirement for obtaining accurate data.

GPS collars have been used to record animal locations at high temporal frequency, which allows detecting animal behavior patterns and interactions between animals and the environment (Allan, 2013). Previous studies have overlain animal locations with land use types to find out frequencies of staying at different places (Turner, 2000). For example, animal GPS locational points are clustered at two places, of which one is already known as the fence and the other is known as a camp, then it can be concluded about how much time animals spend in resting, grazing and other behavior patterns.

Some researchers explored the concept of wireless sensor networks (Handcock et al., 2009; Xu, 2014). Wireless sensor networks are consisted of groups of devices which are distributed around a research area and can generate various variables as well as the correlation with nearby devices. This method can monitor animals' behavioral preferences, quantify social behavior, and integrate coordinates and environmental information to understand animal-landscape interactions.

GPS points can also be used to detect the home range of species. Home range identifies where the animals are, why they are there and where else they could be using methods such as kernel function, classification tree, etc. (Aarts et al., 2008; Augustine and Justine, 2013; Fleming et al., 2015). With long-time period data, home range generates animals' migration pattern and answers questions about where the origin is, where the destination is and the route between them. With short-time period data, the home range can classify active area into different regions such as resting, drinking, or eating area.

However, the behavior classifications based on the GPS points have a certain inaccuracy, since using GPS points cannot completely restore the scene. Thus, scholars adapt fuzzy logic to help identify different behavior patterns from locational points and quantify the uncertainty. Fuzzy logic is used to discern between types of classification – in this case it is behavioral. Fuzzy logic allows us to make inference while allowing for potential alternatives. Deterministic categorical counting requires that patterns be clearly classified into categories, just like sets in mathematics, without ambiguity. However, many things are often not accurately described, and sometimes do not need to be so precise. The correct division of things is either because problems can be accurately described, or because people can grasp the essence of fuzzy things to summarize. For computers, it is extremely difficult to design a computable way to describe things. Therefore, Zadeh, an American cybernetic expert, introduced the concept of fuzzy subset from the set theory and gave birth to fuzzy mathematics, which was introduced into the field of pattern recognition (Zadeh, 1965).

Models are used to simulate the real world, but they cannot completely reproduce the past events. Animal's behavior is not 100% sure at a certain place. Even if a pasture owner leads the herds to a grazing area from 9:00 AM to 12:00 AM and records the time every day, it does not mean that one individual livestock would keep eating grass during that period. Instead, the individual livestock may spend some time idling, hanging around or resting. Meaning, livestock behaviors based on GPS data might involve some uncertainties. Fuzzy logic, however, is a form of multivalued logic and the output can be any real number between 0 and 1, which means result can be partially true or partially false with probability information which could potentially address uncertainties. Therefore, the fuzzy logic, which can set rules to define each behavior's probability, is necessary in this research (Oren et al., 2003; Wan and Lin, 2016). This research will manipulate data collected from GPS collars with the fuzzy logic to generate behavior patterns and the corresponding possibility.

3. Data

3.1 Overview of this thesis research

Figure 3.1.1 shows the workflow of this research. We first collected data with GPS collars to obtain locational and other relevant information of individual livestock at a 20-minute time interval. Then we removed invalid records. Details are discussed in 3.3.

Using valid records, we ran a fuzzy logic analysis to classify livestock behaviors with probability information. To do that, we first created the fuzzy rules and then set the thresholds of membership functions. We derived probabilities of three behavior patterns: grazing, resting and travelling. Details are discussed in 3.4.

With a previously generated environmental risk surface (Lin et al. 2020), we uploaded data with behavior and probability information to the high-performance computers with parallel computing capacities (Center for Advanced Research Computing) to calculate the cumulative environmental exposure (discussed in 3.5 and 3.6).

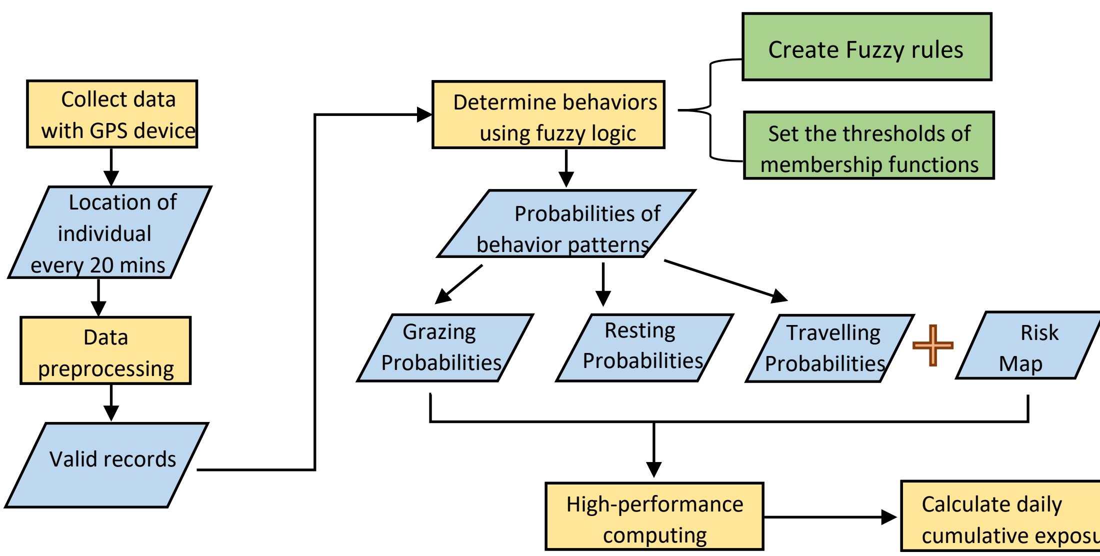


Figure 3.1.1 The workflow of this research

3.2 Study area

The Cove Chapter of the Navajo Nation, with 420 residents (2010 U.S. Census), was named for its remote location in the foothills of the Chuska mountain range, tucked away in the Carrizo and Lukachukai mountains in northeastern Arizona. Cove Wash watershed is in the Northern Agency of the Navajo Nation, which lays in the intersection of Utah, Arizona and New Mexico (Fig 3.2.1). The watershed contains approximately 52 miles of tributaries and receives 12 -16 inches of precipitation annually.

As mentioned in the Introduction section, there are 523 mines on Navajo Nation and 52 of them are located in Cove (Fig 3.2.2).

Location of Navajo Nation

Location of Cove

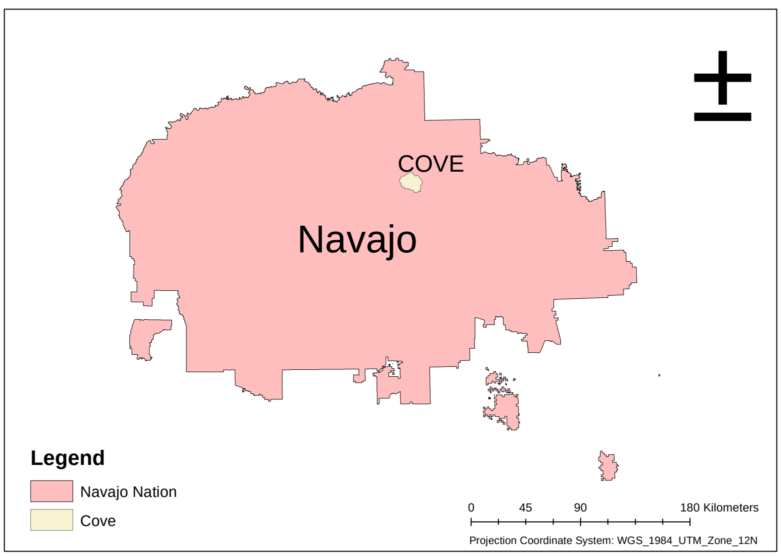


Figure 3.2.1 Location of Cove Chapter

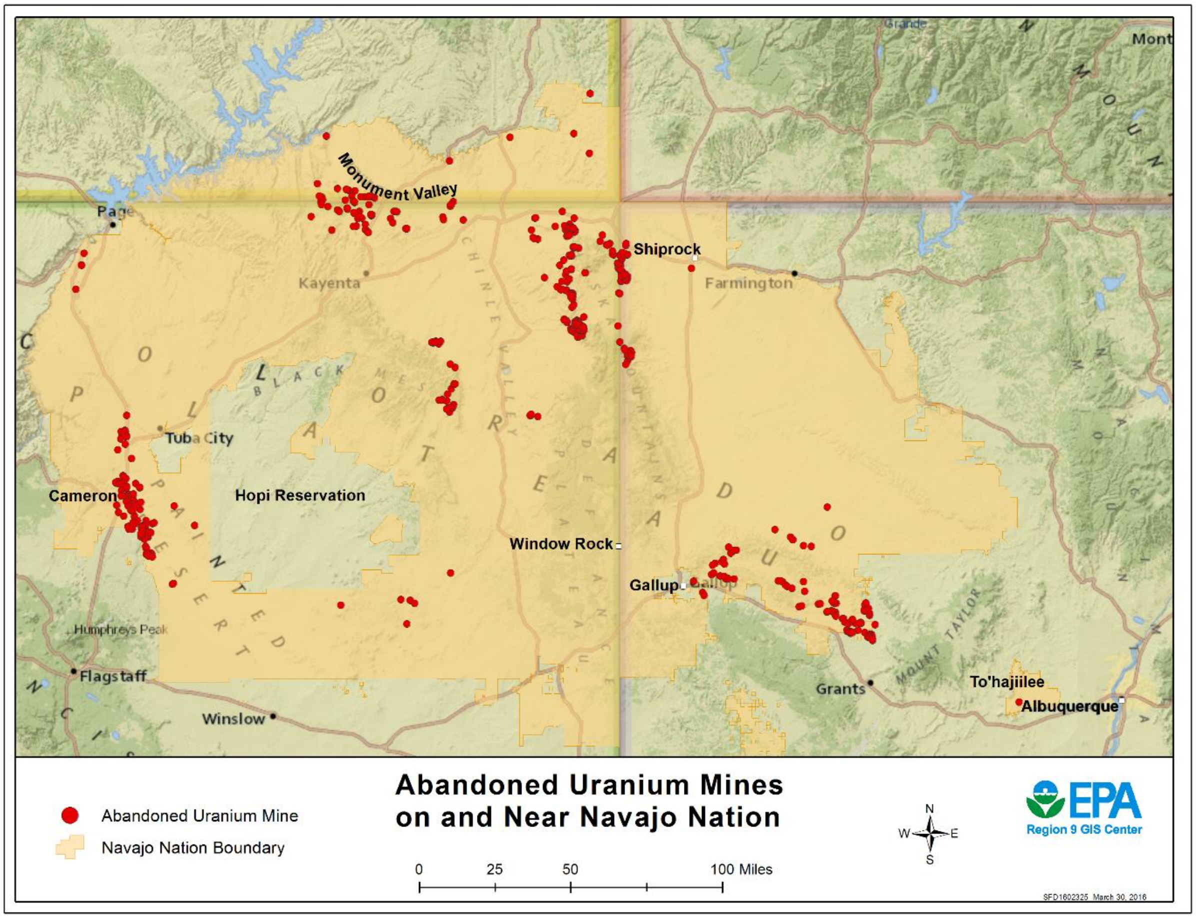


Figure 3.2.2 Abandoned uranium mines on Navajo Nation
Produced by EPA
https://www.epa.gov/navajo-nation-uranium-cleanup/abandoned-mines-cleanup

The US EPA had sent a team to conduct an aerial radiation and image survey of the abandoned Navajo uranium mines in the Cove Chapter. In December 2014, the team used a low-flying airplane to determine the potential radiation from old mines distributed around the Cove Chapter area. In June 2015, EPA and Dine College Environmental Institute collected soil, sediment and water samples across the Cove Wash Watershed to identify the extent of contamination around the land (Weston Solution Inc, 2014).

3.3 Data preprocessing

After we had a conversation with livestock owners in the Cove Community, in which we came out the most suitable plan of tracking animal and collecting data together, we had permissions and assistants from livestock owners to attach Lotek GPS collars to livestock (4 sheep and 4 goats) to collect information such as 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 as a community-based research.

Due to terrain effects, some positional coordinates records were invalid, which are far away from the true location. For example, tree canopy effect and buildings could result in inaccurate GPS records because they can block signal transmission between satellites and GPS devices or even reflect the signals before they are received by the devices. Therefore, it is necessary to remove inaccurate data points. Table 3.3.1 shows a sample GPS dataset for one goat. It contains Greenwich Mean Time (GMT Time), coordinates (Lat, Lon) and the information of environment (Alt, Temp) and satellites (Duration, DOP, and Sat).

Table 3.3.1 GPS data sample

GMT Time[a]	Lat[b]	Lon[b]	Alt[c] (meter)	Duration[d] (second)	Temp[e] (°C)	DOP[f]	Sat[g]
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

Note: [a]. "GMT Time" shows the Greenwich Mean Time when this device generates the coordinates.

[b]. "Lat, Lon" are latitude and longitude in decimal degrees.

[c]. "Alt" is the elevation with the unit of meter.

[d]. "Duration" is the time that the device spends to connect to all satellites with the unit of second.

[e]. "Temp" is the temperature with the unit of degrees in Celsius.

[f]. "DOP" is dilution of precision.

[g]. "Sat" shows how much satellites are connected with the device.

Table 3.3.2 gives the definition and unit of each field. The GMT time shows the Greenwich Mean Time when this device generates the coordinates, which is 6 hours earlier than local time of the study area. The coordinates are represented by latitude and longitude in decimal degrees. The units of elevation and temperature are meters and degrees in Celsius respectively. The duration field gives time the GPS device takes to get connected 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. If the duration reaches 70 seconds, it means that the device has a trouble of connecting to satellites. Thus, records with duration values of 70s are considered invalid. The DOP (Dilution of Precision) is a metric used to inform users about the accuracy of the coordinates, which is influenced by the position of connected satellites. Also, the GPS accuracy could be influenced by topography, canopy cover and other factors. With a smaller DOP value, the coordinates are likely more accurate and reliable. The “Sat” field shows how many satellites are connected and used when calculating coordinates.

Table 3.3.2 Fields' definitions

Field	Definition
GMT Time	Greenwich Mean Time
Temperature	The unit is °C
Altitude	Elevation. The unit is meters
Coordinate	Latitude & Longitude
Duration	The time it takes to connect to satellite in seconds
DOP	Dilution of precision
Sat	Number of connected satellites

In theory, at least 4 satellites are needed to estimate the 3D position. Thus, GPS data with 3 or fewer satellites number are considered invalid. Because the lowest elevation of Cove is over 1000 meters, GPS data with altitude below 800 meters are also considered invalid. After filtering out all invalid records, drifting points no longer existed in the map (Figure 3.3.3). To protect data privacy, Figure 3.3.3 only uses points of one sheep to represent the locations and uses the lines to connect those points.

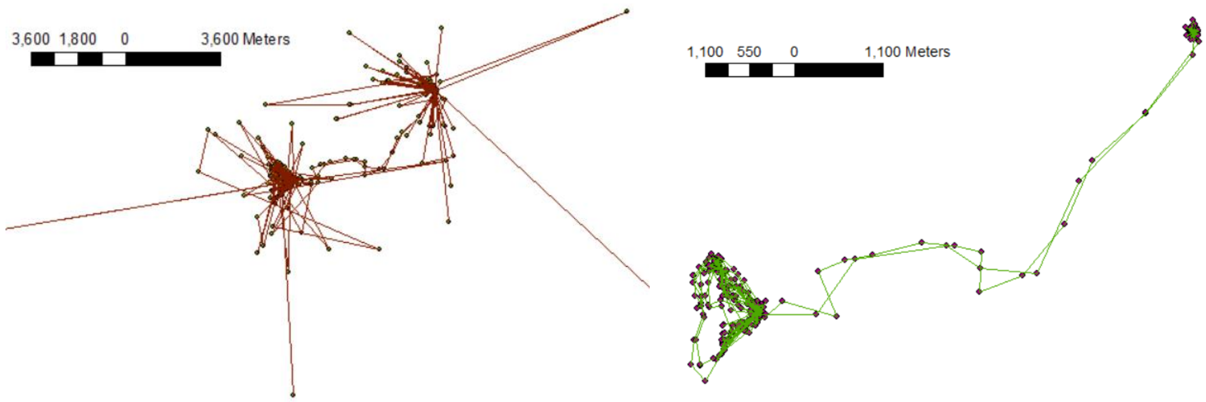


Figure3.3.2 Points before and after the data preprocessing

4. Methodology

4.1 Classify behavior pattern

As discussed in the literature review section, it is important to analyze animal behavior patterns because different patterns would have different effects on exposure to AUMs. For example, there are three animals at the same place at the same time. One of them is eating grass, one is drinking water and the other one is resting. In this case, the uranium intake is different for each livestock because the exposure route to AUM wastes is different. Inhalation would be the major route for the one that is resting. Oral intake is more significant for the ones that are grazing or drinking. Contamination in grass and water are different so that grazing and drinking would also contribute differently to the exposure.

This research, focusing on cumulative exposure potential to AUMs in livestock, requires both spatial and temporal information. Because GPS data did not directly provide behavior information or patterns, further analysis/classification on the GPS data was needed to reveal the patterns. We cannot guarantee that the automatic classification result is 100% correct unless we have tracked the animal from beginning to end, which is impossible. Fortunately, fuzzy logic can both discern individual behavior patterns and quantify the corresponding likelihood for a certain behavior. Therefore, we applied the fuzzy logic method to process GPS data and calculated the possibilities of three different behavior patterns for each GPS data point.

In fuzzy logic, the genre of a target is not either A or B, instead, it can be partially A and partially B in the same time. The key is how much possibility the target belongs to A and how much belongs to B. Figure 4.1.1 gives the brief process of how fuzzy logic works. Given two sets – input 1 and input 2, fuzzy logic adapts the membership of each one, which is calculated firstly with the membership function, to the fuzzy rules, then get the fuzzy classification as an output. The membership itself represent the likelihood of a certain characteristic.

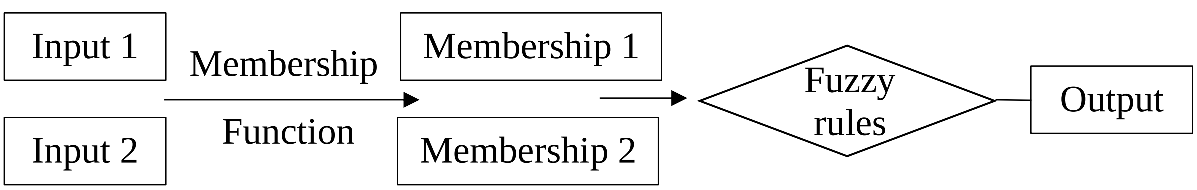


Figure 4.1.1 Fuzzy logic's workflow

In this research, the two inputs variables are velocity and the distance to livestock owner's house. The velocity, calculated from the coordinates and the time stamp, represents the average velocity that an individual livestock travels within a 20-min time interval. The membership 1 – speed – is used to specify whether the speed is high or low. With a higher value, the chance of moving around or travelling to other places is higher, while the chance of staying at one spot for grazing is lower, vice versa.

The membership 2 – status of active or inactive – is used to specify whether distance to the house is long or short. With a small distance, the membership 2 is considered to be "inactive zone", where the animals are held inside a corral. With a large distance, the membership 2 is considered to be "active zone", where the animals are shepherded outside to graze, drink or to do other things. The Fuzzy rules are shown in the Table 4.1.2.

Table 4.1.2 Fuzzy rules

Pattern probability	**Speed: High**		**Speed: Low**	
Status: Inactive	Grazing	Low	Grazing	Low
	Resting	Mid	Resting	High
	Travelling	High	Travelling	Low
Status: Active	Grazing	Mid	Grazing	High
	Resting	Low	Resting	Mid
	Travelling	High	Travelling	Mid

If speed is high and the animal is at inactive zone, the grazing possibility is low, the resting possibility is medium and the travelling possibility is high. If speed is low and the animal is at inactive zone, the grazing possibility is low, the resting possibility is high and the travelling possibility is low. If speed is high and the animal is at active zone, the grazing possibility is medium, the resting possibility is low and the travelling possibility is high. If speed is low and the animal is at active zone, the grazing possibility is high, the resting possibility is medium and the travelling possibility is medium.

The membership functions of speed and status are shown in Figure 4.1.3 and Figure 4.1.4. The thresholds of speed were confirmed with points recoded inside the fence and along the road. After conversations with livestock owners, it was clear that the animals were held inside the fence from 12:00 pm to 4:00 am next morning. When the livestock were held inside the corral, the average speed was 0.787 meters per minute. When the livestock were travelling from the home to the camping area, the average speed was 30.12 meters per minute. Thus, those two values were set to be the threshold of the speed. Also, the average distance to the house 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, 82.58 and 477.6 were set to be the threshold of the inactive and active status.

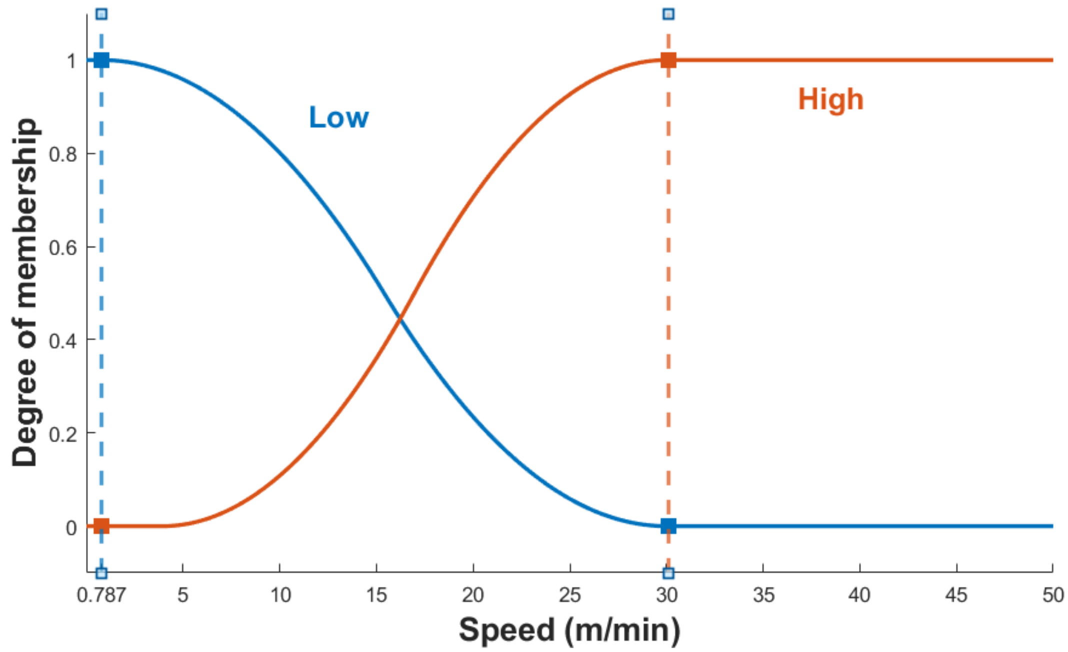


Figure 4.1.3 Membership function of speed

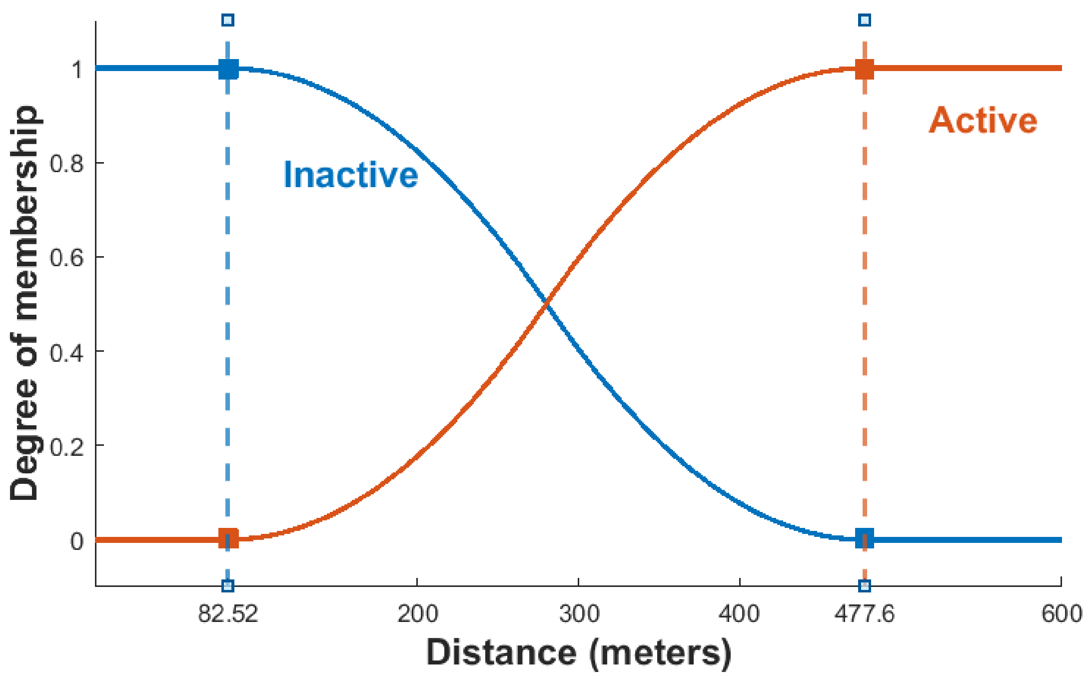


Figure 4.1.4 Membership function of status

4.2 Cumulative exposure

With fuzzy logic, we could derive the degree of occurrence of each behavior pattern. Even if the probability of grazing is higher than the other two behavior patterns, we cannot deny the possibility of grazing or resting resulted from the automatic classification method. As long as one behavior pattern doesn't take over 90% of the total probability, we cannot ignore the other behavior patterns.

The cumulative environmental exposure risk was estimated based on the formula below:

$$C_r = \int_{t_1}^{t_2} \int_{l1}^{l2} W_i R(t, l)\, dl\, dt \qquad (1)$$

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 at location l and time t. This equation is adapted from a previous research (Lu and Fang 2015). The uncertainty introduced by livestock behavior classification is quantified into probability:

$$P = \prod \int P_B \qquad (2)$$

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.

For example, Figure 4.2.1 shows the animal movement in the time sequence traveling from A to B and then to C. The exposure level, derived from previous work (Lin et al. 2020), is R1 at location A, R2 at location B and R3 at location C. The exposure map used multi-criteria model to take wind-index, topography, soil sample, etc. into consideration.

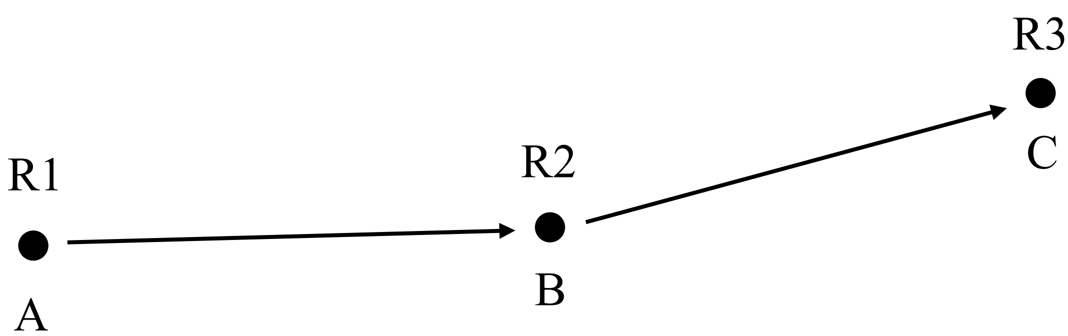


Figure 4.2.1 Animal's movement

As discussed in the literature review section, an animal may be exposed through respiratory intake, oral intake, and dermal exposure (Brugge et al.,2005). Since the pasture owners were aware of the risk of AUMs, they would avoid getting close to AUM area and not spend too much time staying there. Also, the skin generally protects deeper tissues from those harmful chemicals from AUMs (Yazzie, 2017). In all, dermal exposure is negligible compared to respiratory exposure and oral exposures. However, the mechanism of respiratory and oral exposures involves the whole-body system of living creatures. It is difficult to tell the relative importance of those two pathways with limited research on it. To simplify the process, this study assumed that the respiratory and oral exposure were equally important in exposure. For example, when an individual livestock is grazing, it will be exposed to AUMs from both oral and respiratory exposure. When it is resting, the exposure pathway will be primarily respiratory since the food source was the hay grown that the owner purchased in the market and the water came from the portable water system. When it is travelling, the exposure pathway is respiratory but with a higher breathing rate. Hence, this research assigned the weight of grazing as 2, the weight of resting as 1, and the weight of travelling as 2 considering the contribution of each behavior to exposure.

The results should have 27 combination in theory because the animal may graze or rest in all these three places discussed in Figure 4.2.1. A demo is shown in Table 4.2.2. Then the daily cumulative environmental exposure risk would be $E = C_1 * P_1 + C_2 * P_2 + \cdots + C_{26} * P_{26} + C_{27} * P_{27}$.

Table 4.2.2 Calculation of cumulative risk and corresponding probability

Behavior combination (G: grazing; R: resting; T: travelling)	**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	$C_3 = 2R_1 + 2R_2 + 2R_3$	$P_3 = PG_A * \mathrm{PG}_B * \mathrm{PT}_C$
.	.	.
.	.	.
.	.	.
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	$C_{27} = 1R_1 + 1R_2 + 2R_3$	$P_{27} = PR_A * PR_B * \mathrm{PT}_C$

4.3 High-performance computing strategy

Theoretically, the Lotek GPS collars collected data every 20 minutes, so there were 3 points per hour and 72 points per day for each individual. We have tracked two flocks A and B in 2019. We have collected 1-month data for flock A and 4-month data for flock B determined by livestock owner as discussed in the methods section. In total, there were around 2000 points per animal for flock A and 8000 points per animal 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 32000 for flock A and 38000 for flock B. This amount of computational task was impossible based on current computing capacity. Thus, we converted the above analysis to daily scale. However, even at the daily scale, computing the cumulative exposure has 372 calculation completeness, which was still impossible for any current computing recourses. Meanwhile, we had a conversation with the livestock owners and knew that the livestock were kept inside the fence after 7:00 PM and were not going out until 8:00 AM the next day. Thus, this study only focused on time from 8:00 AM to 7:00 PM. Still, the calculation 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 (Figure 4.7). We used the time xx:40 as the first choice to avoid the complexity from the past hour and the following hour. Then the computational complexity was 3^{12} per day (Du and Ko 2011). This situation that the calculation times increase exponentially with the increasement of the number of points is called NP-hardness problem (Fortnow 2009). Decreasing the number of selected points has been a typical way to overcome such problem.

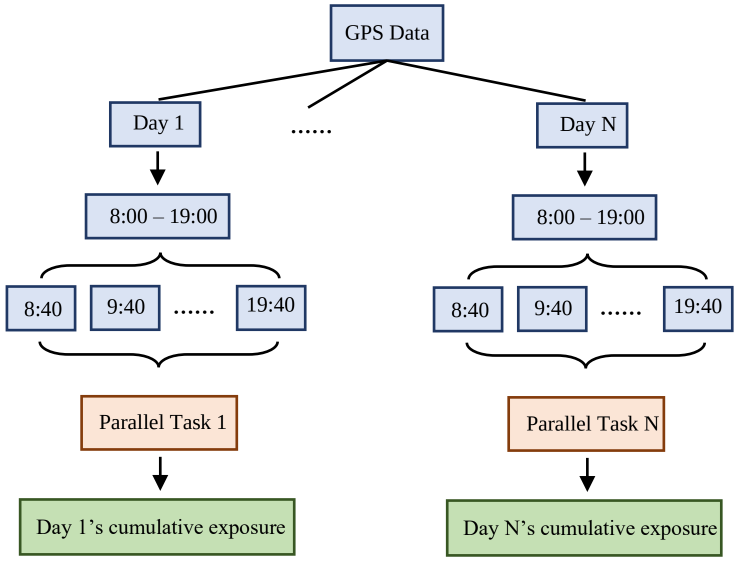


Figure 4.7 Workflow of data filtering

A personal computer usually has 4, 6 or 8 cores. The random-access memory (RAM) is usually 8, 16 or 32 GB. However, due to the power supply system and cooling system restrictions of personal computers, it is often unable to support the full load calculation for a long time, and daily use demand also reduces the full load calculation time, so it is difficult for the personal computer to complete the task. Thus, this data processing was conducted at the Center for Advanced Research Computing (CARC) through loading the code on the high-performance computers via parallel computing technologies. This paper generated results of the hourly behavior probabilities with the fuzzy logic package provided by Matlab in the local computer. Then inside Jupyter Notebook application, python codes calculating the daily cumulative exposure were uploaded on CARC machine –

Wheeler – with 40 cores (each core with 8 nodes) which provides parallel computing capacities to complete the task.

5. Results

Cove Wash Watershed is located in mountain area with high elevation, complex terrain and moderate vegetation coverage. As discussed in the methods section, the satellites signals were most likely to be blocked if the livestock happened to be under a tree or on a steep slope when the GPS device send/receive signals to/from the satellites, which caused inaccurate position of the point. Thus, records with invalid duration, number of satellites or altitude were removed in the data cleaning stage. Table 5.1 gives the numbers of total original GPS data points before data preprocessing, number of invalid and valid points for each livestock after cleaning. In sum, more than 90% records were valid in this study. Only livestock A720 and livestock B715 have less than 90% valid records. Around 60% of those invalid points lied in the time period from 8:00 AM to 7:00 PM, which was the study time of this research. However, this research only extracted one point among the three points to represent that hour (there are 3 points in one hour). If there was no point in hour, the author would look for the closest point in the previous hour and afterwards hour to represent it, which only accounted for 5.27% in the whole points.

Table 5.1 Basic Information of Data Sets

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%)

According to the National Land Cover Data, Cove Chapter contains 12 different land cover classes (Figure 5.2): open water, developed open space, developed low intensity, barren land, deciduous forest, evergreen forest, mixed forest, shrub and scrub, herbaceuous, wetlands and emergent herbaceuous wetlands. The majority of plants in Cove are trees (evergreen and deciduous) and shrubs. There are 50.98% of the area are covered with evergreen forest while 47.75% of the area are covered with shrub or scrub. The other land types only take less than 1.27% of the area. With different plants type, the canopy percentage varies from 0% to 64%. Where the plants are shrubs/scrubs, the canopy cover is near 0%, but the value will grow up to 64% where trees are more prominent (Figure 5.2).

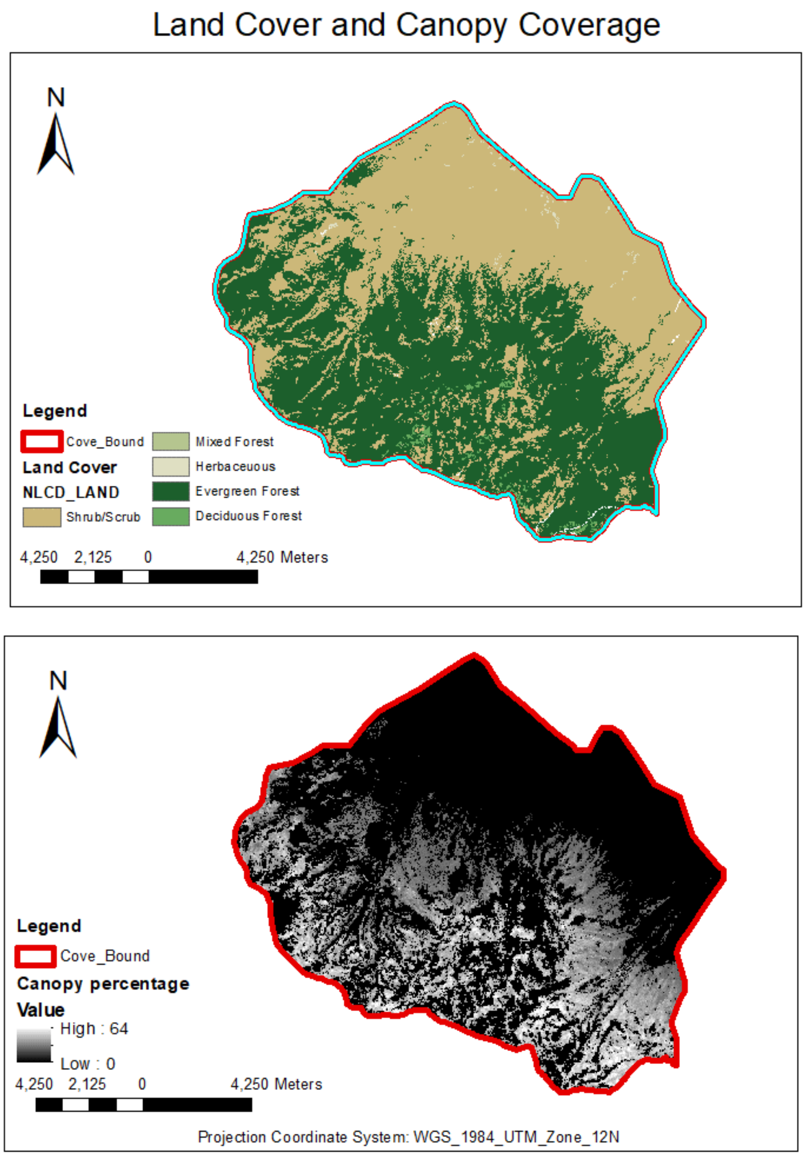


Figure 5.2 Land cover and canopy percentage in Cove

Topographic slope values were calculated using a digital elevation model (DEM) and results were used to calculate the percentage of visible sky. Visible sky is a metric used to measure potential GPS signal interference with satellites regarding the landforms blocking portions of the sky and impeding the communication between the GPS device and satellites. Most of the study area's surface is flat terrain; while in the southwestern portion of the study area the terrain becomes steeper. In general, the slope varies from 0° to 70°, and the average slope is 12°. If the slope is approaching 0 degree, all angle of the sky will be visible; with the slope being steeper, the sky is less visible. (Figure 5.3)

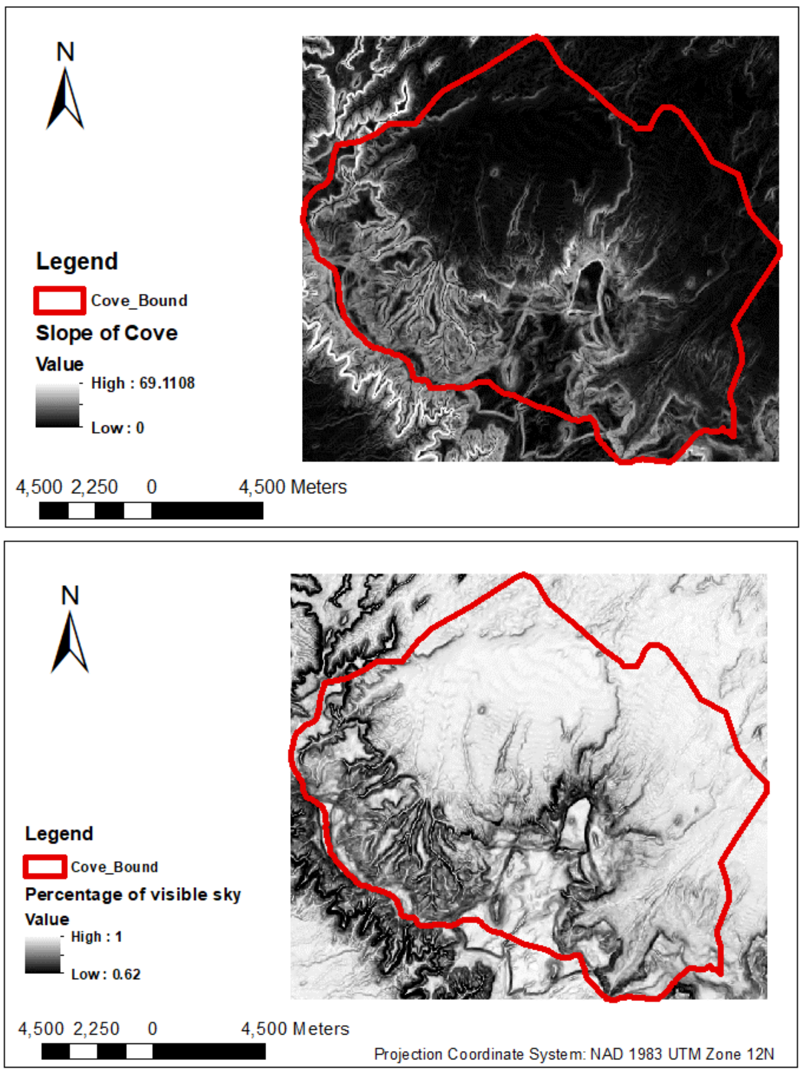


Figure 5.3 Slope and Visible Sky in Cove

To better understand whether the cleaned data sets are sufficient for the proposed analysis, this research did a further statistical analysis of the points against canopy coverage and visible sky based on the original data. The Cove Chapter was classified into 9 different habitats and terrain classes. Areas with canopy cover less than 10% were classified as open; canopy cover between 10 and 40% was classified as partial cover; and canopy cover exceeding 40% was classified as moderate cover. If more than 60% of the sky was visible from a location it was classified as unobstructed; if between 30 and 60% was visible the location was classified as partially obstructed; and if less than 30% of the sky was visible the location was classified as mostly obstructed. After data preprocessing, all records from two flocks based on terrain are completely unobstructed. The habitat classes of all records are mostly open, while only a few are partial covered, and few records are moderate covered (Table 5.4). Thus, we concluded that the valid data records were generated based on a well connection between the GPS device and the satellites.

Table 5.4 Visible Sky and Canopy Cover

Visible Sky & Canopy Coverage	B715	B716	B720	B80295	A715	A716	A719	A720
Unobstructed terrain (Visible sky > 60%)	100%	100%	100%	100%	100%	100%	100%	100%
Open habitat (Canopy < 10%)	97.46%	97.85%	97.98%	97.50%	99.59%	99.57%	99.59%	99.57%
Partial cover habitat (10% ≤ Canopy ≤ 40%)	2.25%	2.14%	2.04%	2.49%	0.3%	0.3%	0.4%	0.3%
Moderate cover habitat (Canopy > 40%)	0.03%	0.02%	0%	0.02%	0.1%	0.1%	0.05%	0.1%

To protect livestock owners' privacy, locational information of the livestock is presented with 500 meters buffer (Figure 5.5). For flock A, they spent most time in two places, the owners home and a summer camp in the mountains. They were kept inside the corral before July 8th, and then were held at the summer camp until July 19th. More specifically, they only spent one or two hours in proximity to AUMs while they were travelling from the farm to summer camp. For flock B, most locations were far away from AUMs. A few were intersected with 250m/500m buffers of the AUMs. In fact, only 0.44% of the data points were inside a 500m buffer of the AUMs, with 0.03% of the points inside the 250m buffer and none points inside the 100m buffer.

Livestock Location

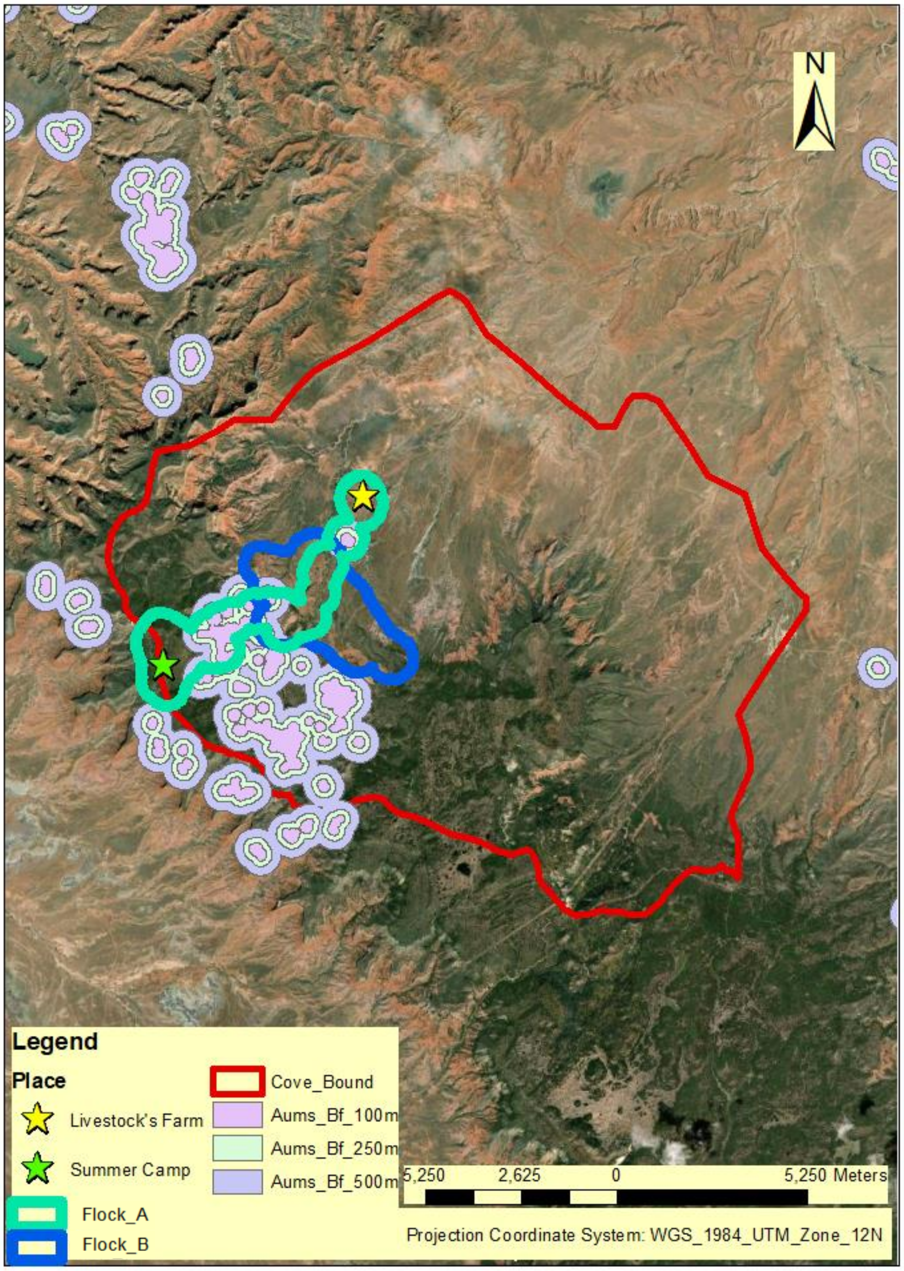


Figure 5.5 Livestock's Location and Proximity to AUMs

As mentioned in the Methods section, the general cumulative environmental exposure potential of each livestock over a long time period was impossible to be calculated due to the computing capability. Only daily exposure was generated from this study.

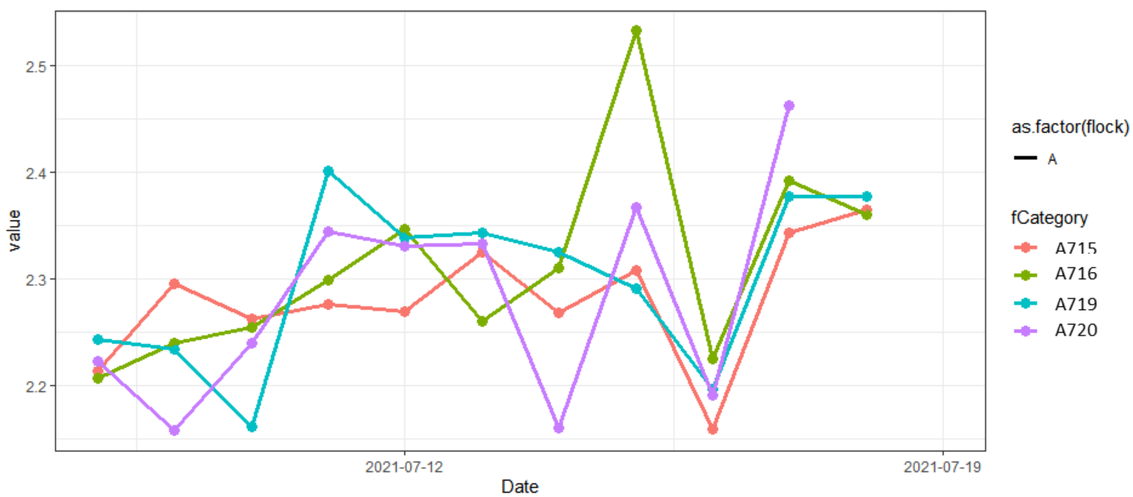


Figure 5.6 Daily Exposure potential of A's Livestock

The daily values for individual animals in flock A are shown in Figure 5.6. “as.facotor(flock)” indicated that this was the flock A. And fCategory distinguished different individual inside the flock A with different colors. The cumulative environmental exposure potential values range from 2.1 to 2.6. A higher value means that the livestock has a relatively higher exposure potential to AUMs and waste from AUMs. From July 8th to July 18th, Flock A were kept in the Summer camp which is in the upstream portion of the Watershed. The exposure values of the three individual livestock A715, A716 and A720 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.

Cumulative exposure potential results of Flock B are shown in Figure 5.7. For one livestock animal B715, 6 days of the cumulative exposure potential could not be calculated for Aug 5th, Aug 20th, Aug 25th, Sep 9th, Sep 23rd and Oct 14th due to insufficient points on these days.

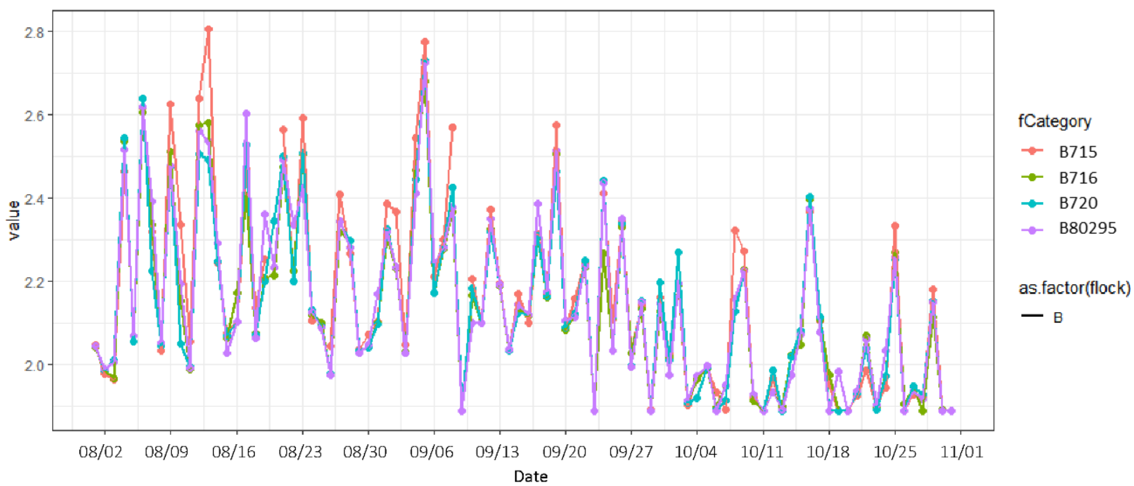


Figure 5.7 Daily Exposure of J's Livestock

In terms of temporal pattern, Flock B had a higher exposure on Aug 4th, Aug 6th, Aug 9th, Aug 12th, Aug 13th, Aug 17th, Aug 21st, Aug 23rd, Sep 5th and Sep 19th, with exposure values higher than 2.5. Lower exposure values occur in October with values lower than 2. In general, the cumulative exposure decreased from August to October and followed the similar trend.

Additional statistical analysis was conducted about the daily cumulative exposure among the two flocks. The results of Analysis of Variance (ANOVA) were used to test whether there were significant differences in daily cumulative exposure within or between flocks (Table 5.8 and Table 5.9). For flock A, because the p-value is 0.79 and it is greater than 0.05, it was concluded that no significant differences of daily cumulative exposure were observed among the four livestock within the flock . For flock B, the p-value is 0.68 which is also larger than 0.05. So, there was no significant differences of daily cumulative exposure within this flock either.

When comparing results between two flocks, flock A has an overall statistically significantly higher exposure potential when compared with flock B except for the month of August. However, 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.

Table5.8 ANOVA of Flock A

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
A715	11	25.08773	2.280703	0.003391
A716	11	25.4287	2.3117	0.00883
A719	11	25.28953	2.299048	0.006336
A720	10	22.81007	2.281007	0.010306

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.007344	3	0.002448	0.343046	0.79432	2.845068
Within Groups	0.278313	39	0.007136			
Total	0.285658	42				

Table 5.9 ANOVA of Flock B

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
B715	86	186.7362	2.171351	0.053534
B716	92	196.541	2.136315	0.039733
B720	92	196.7698	2.138802	0.041972
B80295	92	197.4158	2.145824	0.043076

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.067638	3	0.022546	0.507472	0.677362	2.629846
Within Groups	15.90537	358	0.044428			
Total	15.97301	361				

6. Discussion

This study is built on theory and methods in time geography and GIS to analyze livestock's daily cumulative environmental exposure potential to AUMs and elements found in AUM waste. We intended to quantify the cumulative exposure potential as a sum of the product of probability of livestock behavior and environmental contamination for every GPS point location. To overcome the N-P problem, we shrank our research focus to the time window from 8:00 AM to 7:00 PM when the animals might be out for grazing, and selected only one GPS point every hour to represent the behavior pattern for that hour. The 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 of flock A ranges from 2.1 to 2.6, the average value was approximately 2.3, which means more evidence was needed to confirm that there were significant differences in the potential exposure. For flock B, the daily cumulative exposure varied from 1.8 to 2.8. The average value was approximately 2.1. These results, however, need to be corroborated by animal tissue and biomonitoring analysis results.

As shown in Figure 4.2.1 in the methods section, the daily cumulative exposure is the weighted sum of the environmental contamination risk value of each possible behavior pattern sequence (Table 4.2.2). However, if we did not take the behavior patterns into consideration, the cumulative exposure would be the sum of the environmental contamination risk value along the travel route, which would be $R_1 + R_2 + R_3$ (see the methods section for detail). In order to demonstrate the robustness of the methods framework used in the thesis, another analysis based on the method without considering behavior patterns was conducted here. Results of the daily cumulative exposure for flock B is presented in Figure 6.1. Statistic results are shown in Table 6.2.

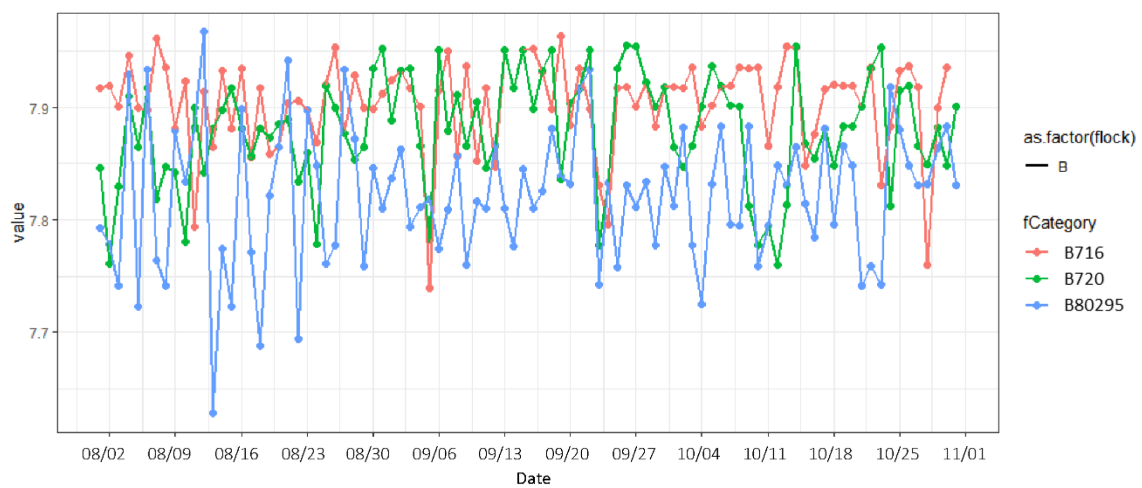


Figure 6.1 Daily cumulative exposure of flock B without considering behavior patterns

Table 6.2 ANOVA of Livestock B without considering behavior patterns

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
B716	91	719.2331	7.90366	0.001698
B720	92	724.9652	7.880056	0.002441
B80295	92	719.599	7.821729	0.003855

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.326032	2	0.163016	61.0947	1.22E-22	3.02897
Within Groups	0.725765	272	0.002668			
Total	1.051798	274				

We only considered three animals in the comparison due to missing data in 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 house. Since they stayed as a group, they shared the same place when they were grazing, resting, or travelling. Thus, the environmental contamination risk value of those three individual livestock was likely to be similar based on GPS data. Also, they were likely to share similar behavior patterns.

After the fuzzy logic analysis, a table was generated to present fuzzy membership results of each behavior pattern (Table 6.3), where the FM_G refers to the fuzzy membership of grazing, the FM_R refers to the fuzzy membership of resting and the FM_T refers to the fuzzy membership of travelling. Based on this table, kriging interpolation method was used to generate a map showing areas where these three individuals graze, rest, and travel (Figure 6.4). It is clear from the maps that these three individuals shared similar places of grazing, resting, and travelling. Thus, weights used associated with each behavior for each GPS data point in the calculation (1) was also similar among livestock in this flock.

Table 6.3 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
…	…	…	…	…

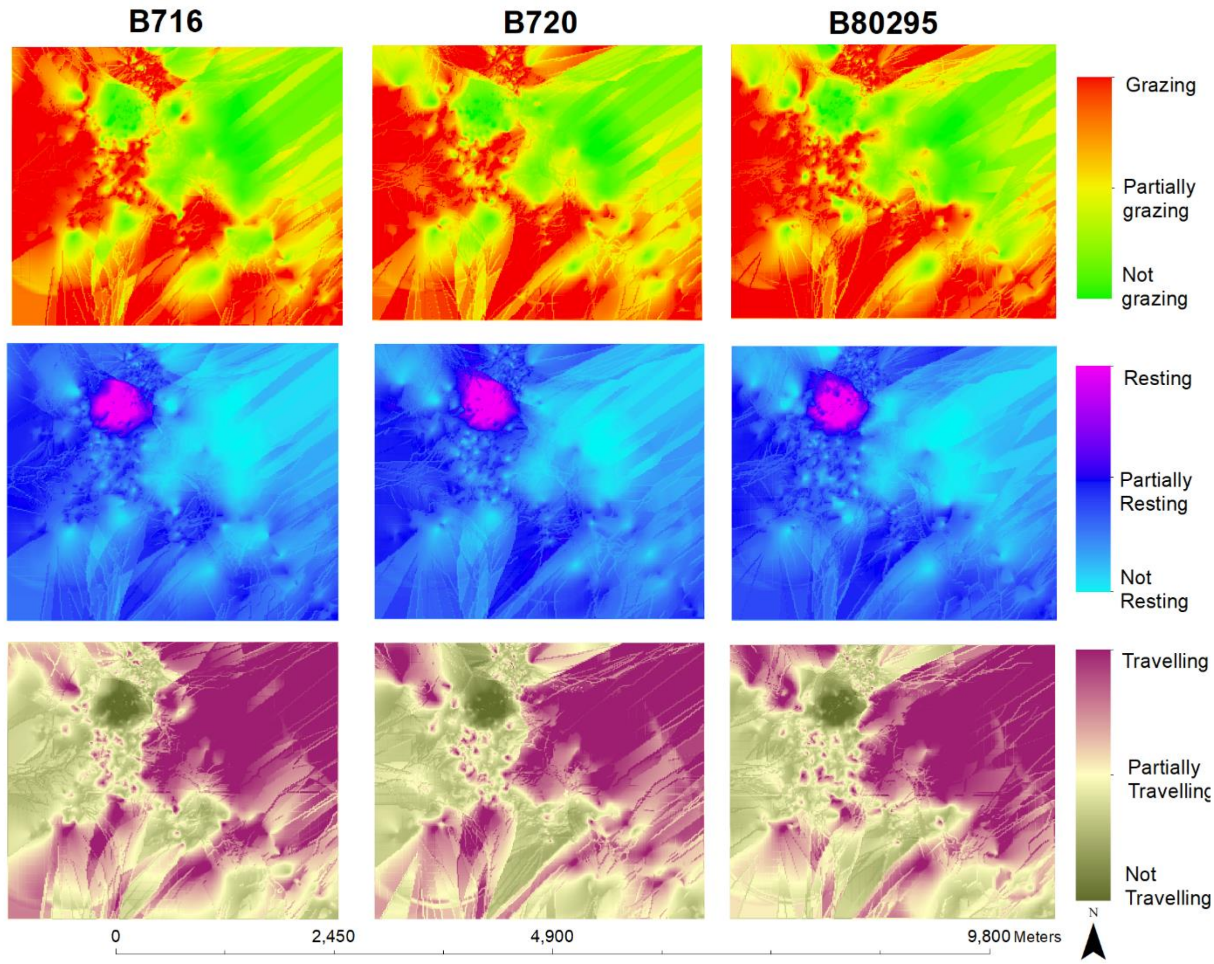


Figure 6.4 Geographic distribution of area associated with grazing, resting and travelling

Based on the above discussion as well as conversations with livestock owners, we could assume a ground truth that livestock daily environmental cumulative exposure potential is similar within the flock if effects like ages, weight, health conditions, or other biological characteristics (these factors would affect the travel speed and willingness to stay in the group of the individual) are ignored here. Based on this ground truth, a comparison between Figure 6.1 and Figure 5.8 indicated that results from current methods used in this study showed more similar patterns of environmental cumulative exposure within the same flock (p-value > 0.05, ANOVA test), while results from a prior method without behaviors included showed significantly different patterns of environmental cumulative exposure (p-value = 1.2×10^{-22}, ANOVA test). Therefore, the present methods framework resulted in more robust results that are closer to the expectation that livestock daily environmental cumulative exposure potential is similar within the flock, since they stayed as a group and shared the same place when they were grazing, resting, or travelling (Figure 6.4), while the previous method resulted in significantly different environmental cumulative exposure which could not explain the fact that these animals tended to stay in one group.

7. 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, this could raise another problem: Could selected GPS points fully represent all GPS data during that hour? Additional sensitivity analysis need to be conducted to assess the impact of the selected point per hour to the result.

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 had to switch to 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).

The second limitation is related to behavior pattern, we firstly intended to use 4 behavior patterns – eating, resting, travelling, and drinking – to calculate the cumulative exposure, but this would raise the calculation up to 4n times (n is the points number we selected). To decrease the burden of the computing and cover as much time in a day as possible, we used three most representative behavior patterns of livestock – grazing, resting, and travelling – among which eating and drinking are not separated from each other. Thus, the accuracy of the results might be reduced.

Third, this research set weights of grazing, resting and traveling as 2:1:2 when estimating the cumulative exposure based on an assumption that the oral exposure and respiratory exposure were equally accumulated inside livestock's body. And the quantifying of the ratio among these three behavior patterns need more biological research to verify.

Fourth, this research did not have a control set of livestock, from non-contaminated places for the whole studying period. Therefore, we could not compare our results against that from any control flock. We could not exclude any possible influence from prior exposing either due to a lack of data before collaring.

Lastly, results from this study will need to be verified by animal tissue and organ sample analysis. As a collaborative research project, results form this study will be compared with uranium level found in tissue and organ of individual livestock analyzed by our research partner. Nevertheless, this geospatial research provides a useful and reliable methods framework for livestock exposure assessment potential in geographic areas with environmental contamination to understand and address environmental health questions.

8. 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. Besides applied to the study area the workflow could potentially be adapted or extended to other areas of Navajo Nation and other geographic regions with other types of environmental contamination. This study has potential to guide researchers to study about living creature's exposure to the environment.

9. Reference

Aarts, G., MacKenzie, M., McConnell, B., Fedak, M., & Matthiopoulos, J. (2008). Estimating space-use and habitat preference from wildlife telemetry data. Ecography, 31(1), 140-160.

Allan, B. M., Arnould, J. P., Martin, J. K., & Ritchie, E. G. (2013). A cost-effective and informative method of GPS tracking wildlife. Wildlife Research, 40(5), 345-348.

Anke, M., Seeber, O., Müller, R., Schäfer, U., & Zerull, J. (2009). Uranium transfer in the food chain from soil to plants, animals and man. Geochemistry, 69, 75-90.

Augustine, D. J., & Derner, J. D. (2013). Assessing herbivore foraging behavior with GPS collars in a semiarid grassland. Sensors, 13(3), 3711-3723.

Barbone, F., Bovenzi, M., Cavallieri, F., & Stanta, G. (1995). Air pollution and lung cancer in Trieste, Italy. American Journal of Epidemiology, 141(12), 1161-1169.

Briggs, D. (2005). The role of GIS: coping with space (and time) in air pollution exposure assessment. Journal of Toxicology and Environmental Health, Part A, 68(13-14), 1243-1261.

Brown, J. D. (2004). Knowledge, uncertainty and physical geography: towards the development of methodologies for questioning belief. Transactions of the Institute of British Geographers, 29(3), 367-381.

Brugge, D., & Goble, R. (2002). The history of uranium mining and the Navajo people. American Journal of Public Health, 92(9), 1410-1419.

Brugge, D., & Buchner, V. (2011). Health effects of uranium: new research findings. Reviews on environmental health, 26(4), 231-249.

Brugge, D., deLemos, J. L., & Oldmixon, B. (2005). Exposure pathways and health effects associated with chemical and radiological toxicity of natural uranium: a review. Reviews on environmental health, 20(3), 177-194.

Craft, E. S., Abu-Qare, A. W., Flaherty, M. M., Garofolo, M. C., Rincavage, H. L., & Abou-Donia, M. B. (2004). Depleted and natural uranium: chemistry and toxicological effects. Journal of Toxicology and Environmental Health, Part B, 7(4), 297-317.

Dang, H. S., Pullat, V. R., & Sharma, R. C. (1995). Distribution of uranium in human organs of an urban Indian population and its relationship with clearance half-lives. Health physics, 68(3), 328-331.

Dearing, J. A., Battarbee, R. W., Dikau, R., Larocque, I., & Oldfield, F. (2006). Human–environment interactions: learning from the past.

Deevey, E. S. (1969). Coaxing history to conduct experiments. BioScience, 19(1), 40-43.

Du, D. Z., & Ko, K. I. (2011). Theory of computational complexity (Vol. 58). John Wiley & Sons.

Eichstaedt, P. H. (1994). If you poison us : uranium and native americans (1st ed.). Red Crane Books. INSERT-MISSING-URL.

English, P., Neutra, R., Scalf, R., Sullivan, M., Waller, L., & Zhu, L. (1999). Examining associations between childhood asthma and traffic flow using a geographic information system. Environmental health perspectives, 107(9), 761-767.

Erdei, E., Shuey, C., Pacheco, B., Cajero, M., Lewis, J., & Rubin, R. L. (2019). Elevated autoimmunity in residents living near abandoned uranium mine sites on the Navajo Nation. Journal of autoimmunity, 99, 15-23.

Fettus, G. H., & McKinzie, M. G. (2012). Nuclear Fuel's Dirty Beginnings. Natural Resources Defense Council.

Fijałkowska–Lichwa, L. (2016). Extremely high radon activity concentration in two adits of the abandoned uranium mine 'Podgórze'in Kowary (Sudety Mts., Poland). Journal of environmental radioactivity, 165, 13-23.

Fitzpatrick, M. L., Long, D. T., & Pijanowski, B. C. (2007). Exploring the effects of urban and agricultural land use on surface water chemistry, across a regional watershed, using multivariate statistics. Applied Geochemistry, 22(8), 1825-1840.

Fleming, C. H., Fagan, W. F., Mueller, T., Olson, K. A., Leimgruber, P., & Calabrese, J. M. (2015). Rigorous home range estimation with movement data: a new autocorrelated kernel density estimator. Ecology, 96(5), 1182-1188.

Fortnow, L. (2009). The status of the P versus NP problem. Communications of the ACM, 52(9), 78-86.

Gong, G., Mattevada, S., & O'Bryant, S. E. (2014). Comparison of the accuracy of kriging and IDW interpolations in estimating groundwater arsenic concentrations in Texas. Environmental research, 130, 59-69.

Gottlieb, L. S., & Husen, L. A. (1982). Lung cancer among Navajo uranium miners. Chest, 81(4), 449-452.

Gramss, G., & Voigt, K. D. (2014). Forage and rangeland plants from uranium mine soils: long-term hazard to herbivores and livestock?. Environmental geochemistry and health, 36(3), 441-452.

Hägerstraand, T. (1970). What about people in regional science?. Papers in regional science, 24(1), 7-24.

Hahn, F. F., Guilmette, R. A., & Hoover, M. D. (2002). Implanted depleted uranium fragments cause soft tissue sarcomas in the muscles of rats. Environmental Health Perspectives, 110(1), 51-59.

Handcock, R. N., Swain, D. L., Bishop-Hurley, G. J., Patison, K. P., Wark, T., Valencia, P., ... & O'Neill, C. J. (2009). Monitoring animal behaviour and environmental interactions using wireless sensor networks, GPS collars and satellite remote sensing. Sensors, 9(5), 3586-3603.

Harmon, M. E., Lewis, J., Miller, C., Hoover, J., Ali, A. M. S., Shuey, C., ... & Campen, M. J. (2017). Residential proximity to abandoned uranium mines and serum inflammatory potential in chronically exposed Navajo communities. Journal of exposure science & environmental epidemiology, 27(4), 365-371.

Harrison, R. M., Leung, P. L., Somervaille, L., Smith, R., & Gilman, E. (1999). Analysis of incidence of childhood cancer in the West Midlands of the United

Kingdom in relation to proximity to main roads and petrol stations. Occupational and Environmental Medicine, 56(11), 774-780.

Hernández Mendoza, H., Rios Lugo, M. J., & Romero Guzmán, E. T. (2018). Uranium isotopic analysis in human urine samples. In Proceedings of XI Regional Congress on Radiation and Nuclear Safety, Regional Congress of the International Radiation Protection Association (IRPA)).

Holaday, D. A. (1969). History of the exposure of miners to radon. Health Physics, 16(5), 547-552.

Hornung, R. W., & Meinhardt, T. J. (1987). Quantitative risk assessment of lung cancer in US uranium miners. Health Physics, 52(4), 417-430.

Hoover, J., Gonzales, M., Shuey, C., Barney, Y., & Lewis, J. (2017). Elevated arsenic and uranium concentrations in unregulated water sources on the Navajo Nation, USA. Exposure and Health, 9(2), 113-124.

Hoover, J. H., Erdei, E., Begay, D., Gonzales, M., Jarrett, J. M., Cheng, P. Y., ... & NBCS Study Team. (2020). Exposure to uranium and co-occurring metals among pregnant Navajo women. Environmental Research, 190, 109943.

Hull, J. L., Lofgreen, G. P., & Meyer, J. H. (1960). Continuous versus intermittent observations in behavior studies with grazing cattle. Journal of Animal Science, 19(4), 1204-1207.

Hund, L., Bedrick, E. J., Miller, C., Huerta, G., Nez, T., Ramone, S., ... & Lewis, J. (2015). A Bayesian framework for estimating disease risk due to exposure to uranium mine and mill waste on the Navajo Nation. Journal of the Royal Statistical Society. Series A (Statistics in Society), 1069-1091.

Jenelius, E., Petersen, T., & Mattsson, L. G. (2006). Importance and exposure in road network vulnerability analysis. Transportation Research Part A: Policy and Practice, 40(7), 537-560.

Katz, J. J., & Rabinowitch, E. (1961). The chemistry of uranium (Vol. 5). Рипол Классик.

Kheir, R. B., Greve, M., Greve, M., Peng, Y., & Shomar, B. (2019). A Comparative GIS tree-pollution analysis between arsenic, chromium, mercury, and uranium contents in soils of urban and industrial regions in Qatar. Euro-Mediterranean Journal for Environmental Integration, 4(1), 10.

Kim, H. M., & Kwan, M. P. (2003). Space-time accessibility measures: A geocomputational algorithm with a focus on the feasible opportunity set and possible activity duration. Journal of geographical Systems, 5(1), 71-91.

Kurttio, P., Auvinen, A., Salonen, L., Saha, H., Pekkanen, J., Mäkeläinen, I., ... & Komulainen, H. (2002). Renal effects of uranium in drinking water. Environmental health perspectives, 110(4), 337-342.

Kurttio, P., Harmoinen, A., Saha, H., Salonen, L., Karpas, Z., Komulainen, H., & Auvinen, A. (2006). Kidney toxicity of ingested uranium from drinking water. American journal of kidney diseases, 47(6), 972-982.

Kwan, M. P. (1998). Space‐time and integral measures of individual accessibility: a comparative analysis using a point‐based framework. Geographical analysis, 30(3), 191-216.

Kwan, M. P., & Schwanen, T. (2018). Context and uncertainty in Geography and GIScience: Advances in theory, method, and practice.

Laurel Morales. (2016). For the Navajo Nation, Uranium Mining's Deadly Legacy Lingers. National Public Radio. https://www.npr.org/sections/health-shots/2016/04/10/473547227/for-the-navajo-nation-uranium-minings-deadly-legacy-lingers

Lapham SC, Millard JB, Samet JM. Health implications of radionuclide levels in cattle raised near U mining and milling facilities in Ambrosia Lake, New Mexico. Health Phys. 1989 Mar;56(3):327-40. PubMed PMID:2917862.

Leelasakultum, K., & Kim Oanh, N. T. (2017). Mapping exposure to particulate pollution during severe haze episode using improved MODIS AOT-PM10 regression model with synoptic meteorology classification. GeoHealth, 1(4), 165-179.

Lewis, J., Hoover, J., & MacKenzie, D. (2017). Mining and environmental health disparities in Native American communities. Current Environmental Health Reports, 4(2), 130-141.

Lin, Y., Hoover, J., Beene, D., Erdei, E., & Liu, Z. (2020). Environmental risk mapping of potential abandoned uranium mine contamination on the Navajo Nation, USA, using a GIS-based multi-criteria decision analysis approach. Environmental Science and Pollution Research International.

Livingstone, A. E., Shaddick, G., Grundy, C., & Elliott, P. (1996). Do people living near inner city main roads have more asthma needing treatment? Case-control study. Bmj, 312(7032), 676-677.

Lu, Y., & Fang, T. B. (2015). Examining personal air pollution exposure, intake, and health danger zone using time geography and 3D geovisualization. ISPRS International Journal of Geo-Information, 4(1), 32-46.

Mech, L. D. (1983). Handbook of animal radio-tracking. U of Minnesota Press.

Meinrath, A., Schneider, P., & Meinrath, G. (2003). Uranium ores and depleted uranium in the environment, with a reference to uranium in the biosphere from the Erzgebirge/Sachsen, Germany. Journal of Environmental Radioactivity, 64(2-3), 175-193.

Miller, H. J. (1991). Modelling accessibility using space-time prism concepts within geographical information systems. International Journal of Geographical Information System, 5(3), 287-301.

Moolgavkar, S. H. (2000). Air pollution and daily mortality in three US counties. Environmental Health Perspectives, 108(8), 777-784.

Mudd, G. M. (2008). Radon releases from Australian uranium mining and milling projects: assessing the UNSCEAR approach. Journal of environmental radioactivity, 99(2), 288-315.

Mulloy, K. B., James, D. S., Mohs, K., & Kornfeld, M. (2001). Lung cancer in a nonsmoking underground uranium miner. Environmental Health Perspectives, 109(3), 305-309.

Newell, B., Crumley, C. L., Hassan, N., Lambin, E. F., Pahl-Wostl, C., Underdal, A., & Wasson, R. (2005). A conceptual template for integrative human–environment research. Global Environmental Change, 15(4), 299-307.

Nozaki, T., Ichikawa, M., Sasuga, T., & Inarida, M. (1970). Neutron activation analysis of uranium in human bone, drinking water and daily diet. Journal of radioanalytical chemistry, 6(1), 33-40.

Oren, T. I., & Ghasem-Aghaee, N. (2003, July). Personality representation processable in fuzzy logic for human behavior simulation. In Summer Computer Simulation Conference (pp. 11-18). Society for Computer Simulation International; 1998.

Priest, N. D. (2001). Toxicity of depleted uranium. The Lancet, 357(9252), 244-246.

Pred, A. (1981). Of paths and projects: Individual behavior and its societal context. Behavioral problems in geography revisited, 231-255.

Raubal, M., Miller, H. J., & Bridwell, S. (2004). User‐centred time geography for location‐based services. Geografiska Annaler: Series B, Human Geography, 86(4), 245-265.

Rife, J., & Rock, S. M. (2001, October). Visual tracking of jellyfish in situ. In Proceedings 2001 International Conference on Image Processing (Cat. No. 01CH37205) (Vol. 1, pp. 289-292). IEEE.

Rodrigues, G., Arruda-Neto, J. D. T., Pereira, R. M. R., Kleeb, S. R., Geraldo, L. P., Primi, M. C., ... & Semmler, R. (2013). Uranium deposition in bones of Wistar rats associated with skeleton development. Applied Radiation and Isotopes, 82, 105-110.

Ryan, P. H., & LeMasters, G. K. (2007). A review of land-use regression models for characterizing intraurban air pollution exposure. Inhalation toxicology, 19(sup1), 127-133.

Samet, J. M., Kutvirt, D. M., Waxweiler, R. J., & Key, C. R. (1984). Uranium mining and lung cancer in Navajo men. New England Journal of Medicine, 310(23), 1481-1484.

Saini, A. S., & Melo, J. S. (2015). Biosorption of uranium by human black hair. Journal of environmental radioactivity, 142, 29-35.

Semenova, Y., Pivina, L., Zhunussov, Y., Zhanaspayev, M., Chirumbolo, S., Muzdubayeva, Z., & Bjørklund, G. (2020). Radiation-related health hazards to uranium miners. Environmental Science and Pollution Research, 1-15.

Soderland, P., Lovekar, S., Weiner, D. E., Brooks, D. R., & Kaufman, J. S. (2010). Chronic kidney disease associated with environmental toxins and exposures. Advances in chronic kidney disease, 17(3), 254-264.

Tannenbaum, A., Silverstone, H., & Koziol, J. (1948). Tracer Studies on the Distribution and Excretion of Uranium in Mice, Rats, and Dogs. US Atomic Energy Commission, Technical Information Division.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. Economic geography, 46(sup1), 234-240.

Turner, L. W., Udal, M. C., Larson, B. T., & Shearer, S. A. (2000). Monitoring cattle behavior and pasture use with GPS and GIS. Canadian Journal of Animal Science, 80(3), 405-413.

Vaupotić, J. (2001). Radon and gamma-radiation measurements in schools on the territory of the abandoned uranium mine “Žirovski vrhl”. Journal of Radioanalytical and Nuclear Chemistry, 247(2), 291-295.

Voyles, T. B. (2015). Wastelanding: Legacies of uranium mining in Navajo country. U of Minnesota Press.

Wan, N., & Lin, G. (2016). Classifying human activity patterns from smartphone collected GPS data: A fuzzy classification and aggregation approach. Transactions in GIS, 20(6), 869-886.

Wang, J., Kwan, M. P., & Chai, Y. (2018). An innovative context-based crystal-growth activity space method for environmental exposure assessment: A study using GIS and GPS trajectory data collected in Chicago. International journal of environmental research and public health, 15(4), 703.

Weber, J. (2003). Individual accessibility and distance from major employment centers: An examination using space-time measures. Journal of geographical systems, 5(1), 51-70.

Weston Solutions, Inc. (2014) Mesa I, Mines 10-15-Abandoned Uranium Mine Site Reassessment Report. (EPA ID No.: NND983466772). https://www.epa.gov/sites/production/files/2016-10/documents/mesa_i_mines_final_reassessment_report_2014-01.pdf

Xu, G., Shen, W., & Wang, X. (2014). Applications of wireless sensor networks in marine environment monitoring: A survey. Sensors, 14(9), 16932-16954.

Yazzie, S. A. (2017). Assessing Indoor Radon Exposure on the Navajo Nation (Doctoral dissertation).

Yazzie, S. A., Davis, S., Seixas, N., & Yost, M. G. (2020). Assessing the Impact of Housing Features and Environmental Factors on Home Indoor Radon Concentration Levels on the Navajo Nation. International journal of environmental research and public health, 17(8), 2813.

Zadeh, L. A. (1965). Fuzzy sets. Information and control, 8(3), 338-353.

Zamora, M. L., Tracy, B. L., Zielinski, J. M., Meyerhof, D. P., & Moss, M. A. (1998). Chronic ingestion of uranium in drinking water: a study of kidney bioeffects in humans. Toxicological Sciences, 43(1), 68-77.

Zhan, Y., Luo, Y., Deng, X., Zhang, K., Zhang, M., Grieneisen, M. L., & Di, B. (2018). Satellite-based estimates of daily NO2 exposure in China using hybrid random forest and spatiotemporal kriging model. Environmental science & technology, 52(7), 4180-4189.