SMU Data Science Review

Volume 5 | Number 1 Article 11

2021

Using Machine Learning Methods to Predict the Movement Trajectories of the Louisiana Black Bear

Daniel Clark
Southern Methodist University, danielclark@mail.smu.edu

David Shaw
Southern Methodist University, shawd@smu.edu

Armando Vela
Southern Methodist University, arvela@mail.smu.edu

Shane Weinstock
Southern Methodist University, sweinstock@mail.smu.edu

John Santerre
Southern Methodist University, john.santerre@gmail.com

See next page for additional authors

Using Machine Learning Methods to Predict the Movement Trajectories of the Louisiana Black Bear

Daniel Clark, Armando Vela, Shane Weinstock, David Shaw, Dr. John Santerre, Dr. Joseph D. Clark

Masters of Science in Data Science, Southern Methodist University,
Dallas, TX 75275 USA
WorldVentures Holdings, 5100 Tennyson Pkwy,
Plano, TX 75024 USA
[3] U.S. Geological Survey, Northern Rocky Mountains Science Center,
Knoxville, TN 37996 USA

Abstract.

1 Introduction

Human population and the accompanying infrastructure have negatively impacted the habitat and sustainability of many wildlife species around the globe. Historically, ranges for mammal species such as gray wolves (Canis lupus) and black bears (Ursus americanus) extended across most of the land space in North America. Today, their ranges are reduced, fragmented, and isolated. For example, the Louisiana black bear (U.a. luteolus) had a historical range that extended from south Texas, through all of Louisiana and to the eastern border of Mississippi. This included all Texas counties east of Cherokee, Anderson, Leon, and Robertson to Mississippi counties south of Washington, Humphreys, and Attala. Now, the Louisiana black bear subspecies is limited to four distinct areas all within the state of Louisiana. These include the St. Mary's Parish and Iberia Parish in south Louisiana, Point Coupee Parish in central Louisiana, Richard K. Yancey Wildlife Management Area and the northeastern Louisiana parishes of Tensas, Madison and West Caroll. Whereas bears may have been seen outside of these areas, their presence is not consistent enough to be considered an expansion of the current range (see Fig. 1) [1].

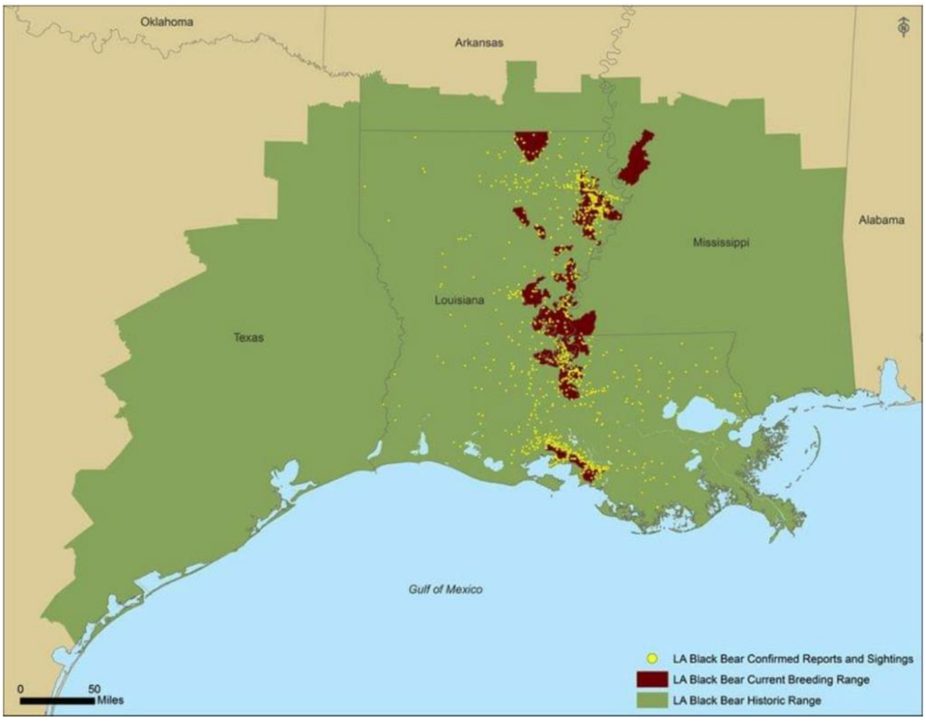


Fig 1. Louisiana black bear Historical and Current Range [1]

With the Louisiana black bear being isolated into smaller subpopulations, they are inherently more vulnerable to extinction due to environmental changes and chance fluctuations in recruitment or survival. Moreover, there is evidence of inbreeding because of the singularization within their subpopulations, a factor that may be more pervasive and insidious than previously realized [1]. For example, if small populations of bears are isolated with little crossbreeding for multiple generations, their alleles can become fixed to the respective populations which will reduce their ability to adaptively evolve, and maladaptive mutations may proliferate [2]. Moreover, inbreeding can occur, and these risks persist for this subspecies in Louisiana even though the Louisiana black bear was removed from the U.S. Endangered Species List in 2016. To ensure future population health, there needs to be a mechanism for gene exchange between bear subpopulations. The ability to predict movement behavior and potential pathways for interaction can provide conservationists with information for improving prospects for such interchange between subpopulations (e.g., habitat restoration, translocations). This provides benefits, not only to reduce the occurrence of maladaptive genets, but also to bolster failing populations through demographics with colonizing immigrant bears.

To evaluate movement behavior of the Louisiana black bear, a team of researchers from the University of Tennessee, Knoxville, and the US Geological Survey (UTK/USGS) anesthetized and equipped several young males and female bears with GPS radio collars from three subpopulations in the Upper and Lower Atchafalaya river basins and the Tensas River Basin in Louisiana. These radio collars were designed to obtain one radiolocation every two hours for a period of up to 18 months. Thirty-one bears (twenty-three males and eight females) were collared yielding over 36,000 GPS locations consisting of longitude and latitude coordinate data with time stamps reformatted into a series of "steps", each with a step length and a turning angle from the previous step. This observed location data was paired with random points (random step lengths and turning angles) and the UT/USGS team used conditional logistic regression to identify landscape features, previous movement direction, and then associated that data with the speed that would discriminate between steps chosen and not chosen (I.e., decision making [3]).

Though this approach is well established and provided useful information for the team's study, modern machine-learning methods have been under-utilized for predicting animal movement and has potential benefits over traditional statistical methods. For example, Wang (2018) discussed state space models, hidden Markov models, random forest models and support vector machines to infer and predict animal movement. The state space models have shown to be valuable in accounting for measurement error in GPS (Global Positioning System) to provide a more accurate estimation of an animal's position, while Markov models have shown to provide value to estimation of the probability of an animal switching between behavioral modes [24]. Wijeyakulasuriya (2020) explored Neural and Recurrent Neural Networks (RNN) to compare short term step selections with long term simulations of migratory seagull species [25].

The approach of this paper can be broken down into three distinct components. First, build a machine learning classifier that identifies the key combination of features that best inform the next step a bear will take along a trajectory based on previous locations and time of year. This helped to identify that distance to agriculture and natural land cover are the strongest predictors of a bear's behavior. Next, build a model Long Short-Term Memory (LSTM) process to model the probabilities associated with each step in each layer of a bear's journey and separate foraging, nesting, and resting behavior from migratory behavior. Finally, explore the impact of the specific environmental features on bear decision making and understand characteristics can create movement barriers.

By going through this process, a framework of probabilities can be developed for how a community of Louisiana black bears might respond to local stimuli in a given location and time of year. GME (Geospatial Model Environment) simulation tools are used to simulate the paths of a hypothetical bear populations at up to 100 random starting points over multiple years. This simulation provides insight into the forecasted movement patterns of black bears using the improved classification model in accordance with historical performance and given the spectrum of land survey information available. While it is impossible to completely understand what goes on inside an animal's mind, data science can effectively infer the patterns of behavior of the species which can help managers manipulate habitats to facilitate interchange which is critical to bear population sustainability.

This study aims to explore the significance of these geographical features, which serve to reduce the suitable environments for survival and can impact movement and behavior of bears. A series of bears were captured, and radio collared, their movements were recorded, and the movement behaviors were tested in supervised and unsupervised machine learning methods. As a result, this study found that there were significant factors through land features. Factors identified included the foraging behavior of the species and it was also observed as roadways restricted the movement of bears and exposed corridors in which they traveled. More specifically, environmental categories that included land categories defined as natural and agricultural landscapes were the greatest factors determining foraging and behavior.

When a habitat is lost, species reduced the range of which they would travel, promoting inbreeding within subpopulations of species. Increases in human populations, agriculture, and urban development were also observed to have influence in altering animal movements. A reduction in genetic fitness is defined as an "inbreeding depression" and it can play a major impact in the health of the overall bear population [2]. This study hypothesizes that historical step distances will play a significant role in the next step of the bear. To demonstrate how this technique could be used to better map various species and their movement routes and continue to encourage genetic diversity.

2 Literature Review

Several factors have been shown to affect black bear movement behaviors throughout its life. This includes proximity of food, habitat, humans, time of day, the sex of the bear, reproductive habits, and season. Male bears have shown to have larger home ranges and greater rates of movement than females, which is common among most mammal species. Additionally, food scarcity often triggers increased movements. Bears have been known to travel great distances to feed, guided by memory. This is particularly important in Autumn when bears store up food reserves for winter denning. Females who find food supplies in the Fall will use that energy for bearing and raising cubs, while Fall foods for males will increase their chances of siring cubs in the following year. Noyce and Garshelis [18] studied this behavior when they classified movements of 206 individual bears. They were comparing cases of bear forays (moves in which the bear returned) and dispersal (permanent departures of bears known to be in the study area). They found the males that did not die by age 2 or lost from the study all showed cases of dispersal, while only 1 female left her home range and never returned. Dispersal took place in all non-hibernating months.

Dispersal is an important concept because it allows for bear populations to grow without inbreeding and to habituate into uninhabited environments. Inbreeding in mammals is hypothesized that only one sex is required to disperse, and males are more likely to be the sex involved with dispersal. Bears tend to have overlapped home ranges with other bears and segregation is typically by mutual communication [26].

Looking deeper into bear movement behavior, researchers must factor the need for food into the decision making of bears and the direction they choose to move. Researchers typically must rely on surrogates for food like land cover data to uncover relationships between food and bear movement. Karelus, McCown, Scheick, van de Kerk, Bolker and Oli asked this question for black bears in 2017 when they investigated the movement patterns of 16 black bears in Florida [19]. They found that step lengths of males were longer than the step lengths of females, and both showed shortened step lengths during daytime. Bears moved more slowly near creeks, wetlands and marsh habitats which would suggest foraging behavior however, they moved quicker in urban areas. Roads were found to be a semipermeable barrier to bear movement, meaning male bears would more likely cross roadways than females, and larger roads were less likely to be crossed than small roads.

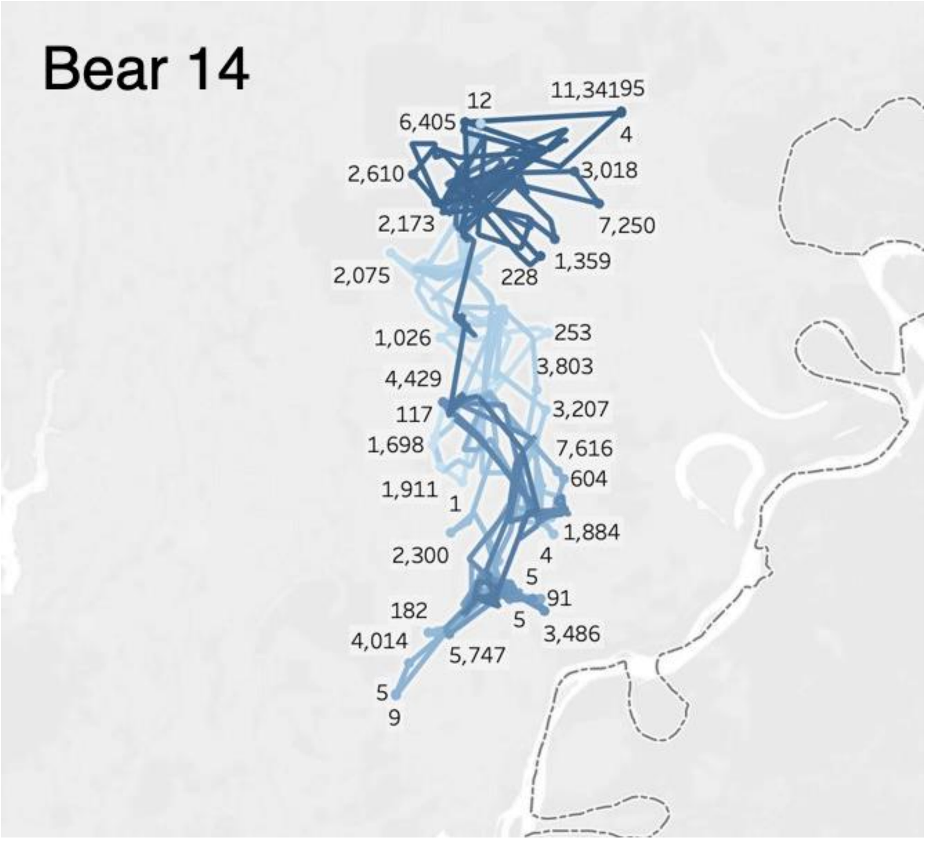
Black bears range across the North American continent but at-risk populations, such as the Louisiana black bear, can occur. The Louisiana black bear was listed as “threatened” under the United States Endangered Species Act on 7 January 1992 because of habitat destruction, overexploitation, and isolation [4]. Research was subsequently initiated beginning in 2006 to evaluate the population health of this subspecies. In 2016, the Louisiana black bear was removed from the U.S. Endangered Species List based on a Bayesian population viability analysis and evidence of genetic interchange. The study by Laufenberg, et. al. (2015) found that two populations were viable with persistence probabilities in the Tensas River Basin and Atchafalaya River Basin of over 95% during the next 100 years [27]. The study on movement modeling was a vital component of the evidence for recovery and is the key reference source to better evaluate how Louisiana black bears make use of their environment.

Radio telemetry is the most common technique for exploring wildlife-habitat relationships and the advent of global position system (GPS) radio collars in recent years has expanded that ability. GPS collars can gather location data that are more accurate, more frequent, and can be collected during any time of day or night compared with more traditional Very High Frequency (VHF) telemetry [28]. Although GPS collars have been a boon to wildlife research, they can present challenges. For example, GPS data sets can be extremely large, can require filtering to remove false or inaccurate locations, often have gaps in the time series, and typically are temporally autocorrelated. New analytical methods are needed to handle more complex data. These methods such as attention mechanism can help to memorize long source strings in a neural machine translating, recurrent neural networks such as a LSTM which is powerful for modeling timesteps of a sequence by encoding information in an internal state. Advances in analytical methods could provide deeper understanding of distinct trajectory patterns and decision making among animals [11].

With the additional capacity for data, there are several disadvantages which have been noted with GPS tracking devices (collars) that have limited previous step selection and movement trajectory studies. They are expensive, and thus studies have funding to support only a limited number of collars. The unintended effects of small samples sizes can affect the results and inferences, which are common with ecological studies [7]. Fortunately, there have been advancements that allow for the increase the samples and definition of data collected, which are discussed in depth later in this paper.

Once the radio collars are deployed, there are several insights that can be derived from the movement patterns of bears. Bears are not like birds in that they follow “round trip” movement patterns that cycle based on a seasonal trip in one direction and back to the original location (i.e., migration). However, they do occasionally exploit food resources that are outside their normal home ranges due to their acute sense of smell. This can take place in the late summer and fall and can range up to 200km (about half the length of New York State), as seen in Figure 2. This behavior is caused by what is known as hyperphagia, which is defined by extended foraging time and increased caloric consumption in bears [17]. Black bears also have excellent hearing, but poor vision, so loud and unfamiliar stimuli such as cars on a road is likely to scare them off easily. Male bears can also bite, claw, and rub trees, signs, and other objects to chemically communicate with other bears during breeding season [26].

The UTK/USGS team that performed the original radio collaring accounted for this ensuring that these factors were captured in the data set.


Bear 14
12
11,34195
6,405
4
2,610
3,018
2,173
7,250
1,359
2,075
228
253
1,026
3,803
4,429
3,207
117
1,698
7,616
604
1,911
1
1,884
2,300
4
5
91
182
5
3,486
4,014
5,747
5
9

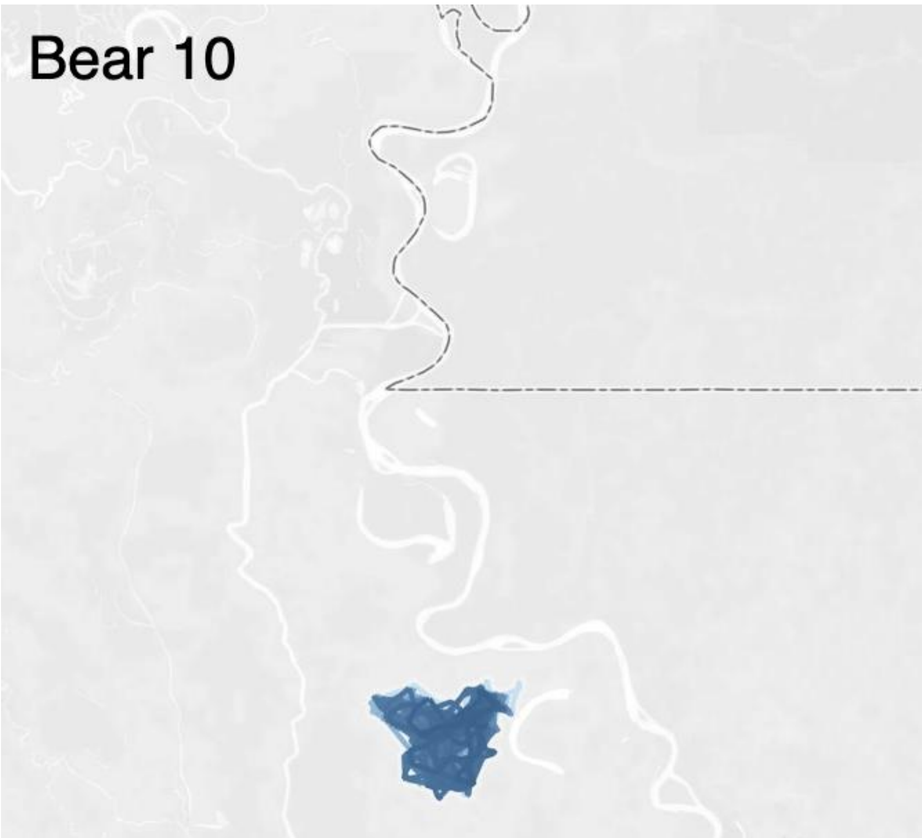


Fig. 2: Movement trajectory of Sample Bear 14 (male) and Sample Bear 10 (female), over span of 3 years. The numbers correspond to the order of the steps. One can see a wider range of movement for male bears compared to females.

2.1 Markov Chains

A Markov Chain process, or property is most easily defined as "the memory-less random process i.e., a sequence of a random state" [13]. This method has been used to compile sequential steps of a bear's movements in between the radio-collar reports by calculating a respective probability of a step considering all the features associated with the step. This allows the model to have a breakdown of direction probabilities based on the environmental features, time of day and sex of the bear doing the movement. Having this definition can expand upon the previous limitations of GPS reporting through such collars and allow greater insight into their movements. This could provide the proximity a bear or a species comes to a modeled attribute (i.e., a roadway, human population, water source, migration channel). By attaining this more granular data, there are new more powerful methods in Neural Networks (NN) which are designed to mimic the thought patterns of humans. It is through a specific NN tools that a “pattern prediction or a process of forecasting/prediction in space and in time at the points where there are no measurements” which can also substantiate some of the data lacking in previous studies [10]. These combined techniques can help fill the gaps and provide a deeper understanding of ecological behaviors.

A key piece of previous work involves the research of subpopulations of Louisiana black bears utilizing a step selection function to predict and understand key factors determining movement among bears. Step selection functions typically use conditional logistic regression to compare the step that a bear selected (a step consists of 2 sequential locations with a distance and a bearing) and a series of random steps generated from an empirical distributions of step lengths and turning angles. Conditional logistic regression is typically used to evaluate how landscape factors affect whether a step is chosen by an animal or not. The purpose of performing logistic regression was to allow the researchers to test correlations on all possible models against each variable left out, and their interactions. Clark et al. (2015), captured and radio collared thirty-one bears (twenty-three male and eight female bears) and followed their movements over a span of two years. Using spatial land survey data (e.g., land cover type, proximity to roads, agriculture, natural vegetation, and density of the land cover), they were able to estimate the probabilities that presumed what steps might be chosen by a bear. The probability of the step being selected by the bear increased as the distance to natural land cover decreased. Additionally, the steps tended to go in a forward direction and tended to avoid roadways. Random walks were then constructed based on the step selection function to assess how frequently bears may intersect other subpopulations of bears for presumed gene exchange. A correlated random walk of 4,000 hypothetical steps suggested some gene exchange for males but little for female bears. This suggested that males were likely to intersect and disperse to neighboring subpopulations if there was natural land cover, which fit prior notions of mating behavior. Females were much less likely to make this movement, so the health of the population relied on permanent residency of the sex within each region [3].

Overall, there is some research on machine learning to track animal movements. While previous research focused on drawing correlations between environmental stimuli and behaviors, the aim of this study is to apply modern machine learning tools with hopes of improving the predictive performance of the models which can offer improved tracking simulations. Additionally, the Louisiana Bear Research Project from Clark et al. (2015) did not delve into the classification of foraging and exploratory behavior and its relationship with the environment. Additionally, this paper aims to explore the relationship between bear migration and roadways and apply some of the methods used in previous black bear studies to understand how bears tend to traverse landscapes and identify specific locations where corridors can be built where bears would cross to interact with other subspecies to help support cross breeding.

There has been great exposure during this study surrounding the topic of data collection and utilization. The original research for this study was conducted by another group, but it required humane collection and utilization. Unfortunately, there is not much guidance around these topics. There is one document to refence, the Animal Welfare Act, although there is only one small section that pertains to research. This is section is under Title 7 Chapter 54 Section 2157. It states the various penalties carried upon the release or misuse of confidential information surrounding research facilities and their records, mostly pertaining to financial, but also to include statistical data. Although, there are very minimal guidelines for research facilities and their definitions within the document, there is still some consideration that needs to be lent to the data which has been utilized in this study.

With minimal guidance on how to conduct security and release of data pertaining to this study, all researchers involved should take additional precautions. This becomes more pertinent given the repercussions more so to the animals involved versus the participating researchers or interested parties. This study has been extremely cautious in the data that has been presented throughout our findings and ensures that the focus remains on the benefit of the animals without providing additional reason for harm.

With the final objective in our purview, it is pertinent that the study considers that the method of collecting these data is also humane. This paper discusses later how the collars operated in greater detail, but there was no harm, discomfort, or additional stress brought to the animals who were selected for participation. The collars did not interfere with the life of the animal, and this served a dual purpose as the study wanted to capture their movements in the most natural way possible to ensure the animal did not make new choices given the introduction of the collar itself. The collars were also collected from the environment based on their last location upon the expiration of the battery life on the collar itself, ensuring no additional environmental impact.

The question of why it is important to have confidentiality surrounding this studies data also became a curious topic. Although it seems that there is no direct threat to the animal given the collection and dispersion of this data, there absolutely could be. The animals at hand have already experienced the hardship of nearing extinction due to their rapid environmental changes, and although the study aims to counter future near extinction events, others may not have as great an interest in preserving this species. With that said, it becomes ever clearer that these animals could present opportunity for others. In the past, politics have used much more simple methods for personal and political gain through gerrymandering and vendetta campaigns. Studies such as this one help in identifying protected habitats which can influence roadways and other civilizational needs. In the wrong hands, these could be improperly placed or placed for gain opposed to the interests of the animals. Another large consideration with these data and similar data surrounding animals is the exposure of migration patterns and the general avenues of approach that the animal takes. This provides an extreme insight into the animal's habits which can then be predicted and allows for the most accurate data for poaching a particular species for financial and again personal gain.

There are many other scenarios not considered in this study to which this data could be abused, as these are only a few which the study considered during the development of these new methods. It is ever more important that data surrounding animals continues to be evaluated for external threats, especially as more and more becomes understood about the animals within the studies. Just as the study values the data surrounding human beings, those finding themselves utilizing data involving animals should always be thoughtful of what is best for the animal and the most humane or just application of said data, especially given the animal cannot decide for itself.

3 Methods

The study area encompassed the entire state of Louisiana, western Mississippi and small sectors of southern Arkansas and east Texas. Field data collection focused on the original three subpopulations in the Upper and Lower Atchafalaya river basins and the Tensas River Basin.

The radiolocation data came from both male and female bears. Young male bears were the primary target for the analysis because they are more prone to dispersal and long-distance travel, but a smaller sample of females were also collared. The radio collars lasted up to three years and a programmable release mechanism was used to detach the collars from the bears' neck just before the battery died. the GPS device was activated every 2-4 hours and a location was recorded. Those locations were periodically sent to a satellite for downloading, but locations were retrieved from the dropped collars as well.

From these raw location data, erroneous locations and those with poor precision were removed from the data set and the time series of locations were used to estimate step length and turning angle for each consecutive location. With the erroneous locations dropped, the step length readings were normalized with time to create a variable accounting for the rate of movement, rather than overall distance. Dayparts were also included at six-hour intervals as a variable to explore how time of day affects movement. Using Geographical Information System (GIS), the location of each bear was coupled with environmental data based on Landsat satellite data. The environmental data came from the National Land Cover Database (NCLD) with the 16-class land cover classification scheme simplified into five unique categories: forests natural, agriculture, water, roads. A data layer consisting of the Euclidian distance to the closest forest was added based on the hypothesis that bears would be more likely to select steps near or in a forest than otherwise. The density of these environmental categories was calculated with each step to account for the possibility that a bear could pass through multiple environment categories at once [3].

A study in 2000 conducted by White and associates found that rivers posed barriers to bear movement. They also found sex differences related to the likelihood of bear crossings [15] (as demonstrated in Fig. 3 with the 2006 bear data). With males represented in blue and females represented in red, females had movement trajectories that passed closer to water than their male counterparts, particularly in the springtime of the three-year study period. In the initial exploratory data analysis of the Clark et al. bear data, these factors were found to be consistent with previous findings, however it will also help to better understand what to expect from a species in each environment, improving future critical environment considerations. This could also assist in identifying and preserving emigration and immigration routes through GPS collar-generated data points [10].

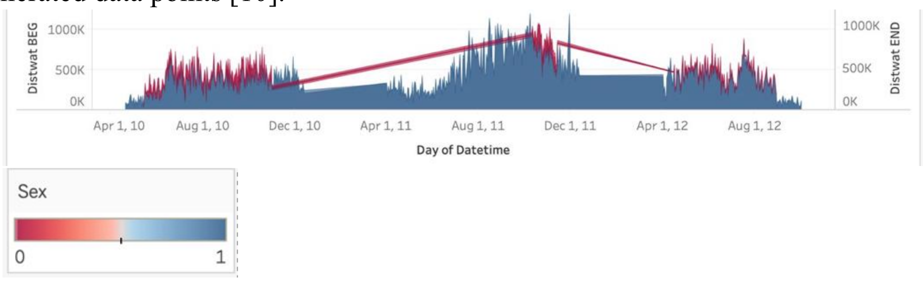


Fig 3. Relationship between bear location and water over time by sex.

3.1 Behavioral States

Another method for characterizing the movement of animals is the estimation of behavioral states. For example, an animal moving in a forward direction with large steps into novel areas might be consistent with an animal that is exploring its environment or dispersing whereas an animal with short, non-directed steps might represent an animal that is foraging or making routine movements within its home ranges. Theoretically, sequential locations classed into a foraging state might indicate that the bear's mindset is focused more on foraging for food, finding water resources or looking for shelter, rather than involved in exploratory or dispersal behaviors.

To measure this statistically, the male and female bear data from the Clark et al. (2015) study was combined, and a Boolean classification variable was created to classify instances where a bear is foraging and when a bear is exploring. This can be represented by constant straight-line paths consisting of steps relative to time above the median for each sex and turn angles <45 degrees. Based on the three years of data (with the hibernation period dropped from Jan – April), the exploratory state (blue) was more predominant in the spring and early summer and foraging behavior was more common in the late summer and fall (red, Fig. 4) via an exploratory analysis of the test data. The blue peaking sooner in the cycle indicates that the bears are walking in more of a foraging behavior in the early seasons from April through mid-summer. In the late fall, more consistent movement patterns (exploration, labeled with orange) are seen which is consistent with the notion that bears are focused on finding food in preparation for hibernation.

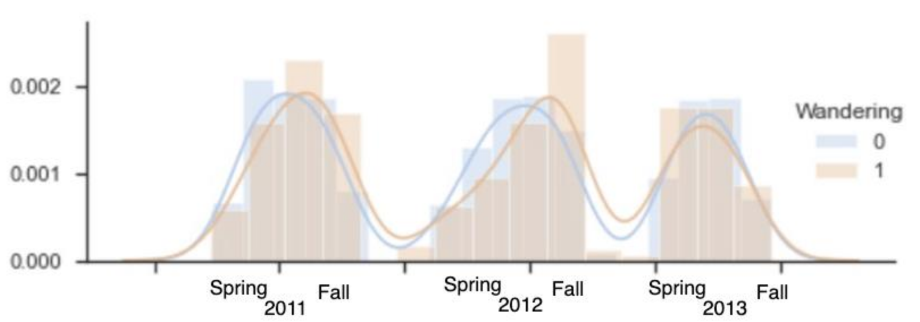


Fig 4. Date Time Distribution by Foraging Exploratory Behavior (blue represents exploratory behavior while orange represents foraging behavior)

Looking at the landscape variables, a classification algorithm and logistic mixed modeling with random effect was used to further explore how environmental covariates can affect step length and turning angles of bear movement trajectories. The additive effects of sex, season, distance to waterways, distance to agriculture, distance to roads, distance to natural, and distance to forests are used to inform the predictive ability for foraging behavior. A synthetic minority over sampling technique (SMOTE) was used to account for the minority instance of exploratory behavior to standardize the results and help balance the classification model. After setting up the model, the SMOTE method creates synthetic data like the existing training data to help ensure the two classifiers have equal weighting. This gave the model a much larger data set to work with as well which helped in better tuning the classifier.

A Python package (PyCaret) was used to aggregate 14 different algorithms scored on the metrics for precision, recall, F1 score, accuracy, and AUC to evaluate the classification and misclassification rate of the bears' foraging and exploratory behaviors. Once the top model was selected, hyperparameter tuning was set up to identify the optimized imputers, PCA (Principal Component Analysis), transformations, feature selections and interactions. Then once, the final classifier was selected, an analysis of feature importance can show which environmental landmarks influence foraging and exploratory behavior. This was done after the supervised machine learning model aggregates completed and the winning model was chosen. The values of a feature were permuted in the model with the model performance reevaluated, and the features which drive the highest accuracy are listed.

Within the PyCaret aggregate model, the tree-based methods included classifiers such as extreme gradient boosting (XGBoost), random forest, and support vector machine (SVM). The XGBoost algorithm is a modern advancement from the gradient boosted decision trees algorithm. This is an ensemble method in which a decision tree continues to be created then optimized by factoring in predicted residuals as the algorithm performs multiple iterations over the same dataset. Random forest is an ensemble decision tree method where N-number of trees are created to predict the target variable and based on the tally of those predictions determine the model's prediction. Lastly, the SVM algorithm attempts to identify a hyperplane that maximizes the support vector distance between a target variable. In simpler terms, a line would separate a 2D model whereas a plane separates a 3D model.

The metric used to determine model fit was the F1 score. F1 Score helps measure the model's accuracy by calculating a weighted average of the model's precision and recall scores. Note that the precision compares all true positive predictions vs all predicted positive results, whereas recall compares true positive predictions vs all actual positive results (Fig. 5).

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = \frac{\text{TP}}{\text{TP} + \frac{1}{2}(\text{FP} + \text{FN})}$$

Fig 5. Calculation of the F1 score, which is a function of precision * recall over precision + recall. TP references true positives which are the correctly predicted positives. FP references false positives which are incorrectly predicted positives. FN represents false negatives are incorrectly predicted negatives.

3.2 Deep Learning Methods

3.2.1 Long Short-Term Memory Networks

Time series analysis is a linear process where the model will evaluate the sum of the terms, most like linear regression. These types of models only permit communication or association between what is most near, or what is linear or can be fit to the model's underlying curve or line. To provide a different analysis, a nonlinear process can allow data points from early in a time series to "communicate" with data points in the time series during training of the model. Thus, the long-term dependencies that are key in time series analysis can be lost as a greater number of associations are found throughout the data in the nonlinear process. Traditional multi-layer perceptron neural networks tend to suffer from this "vanishing gradient" problem which inhibits its ability to learn [31]. Error signals will decrease exponentially as they are backpropagated through layers of the neural network so that layers closer to the input are not trained. If any long-term dependencies need to be preserved, such as in the case of time series data, the vanishing gradient is a real problem.

Long short-term memory networks (LSTM) were developed by Hochreiter et al. in 1997 to address this issue with long time lags [8]. An LSTM is comprised of a series of linear, self-connected *memory cells*, each of which is comprised of an input gate, a constant error carousel, and an output gate. The input and output gates serve to filter out unnecessary input data via an activation function, preventing input/output weight conflicts that can arise from a naïve constant error approach. The purpose of the constant error carousel is to ensure that learning is still conducted, but that the derivatives are always set to 1.

Modeling Louisiana black bear movement paths as a discrete time series of steps different parameters such as the distance to water, distance to land, or elevation were tracked over time using an LSTM architecture. In this way, the powerful connectivity of neural networks can be harvested without sacrificing the spatiotemporal dependencies inherent to a movement pattern.

Two LSTM analyses were used in our study. First, the network was used for a univariate time series analysis where the parameter of interest is the bear's distance to water. A network with 40 neurons and 20 training epochs, and a sliding time window of 30 was used for the analysis. In this architecture, each 30-time steps will predict the value of the next time step. Secondly, a classification model with covariates was used to best predict foraging vs exploratory behavior. A similar architecture was used with a sliding time window of 15. These results will be compared to the other classical machine learning techniques.

3.2.2 Attention Networks

While LSTM models proved powerful on initial conception, they are not well-suited to scale. Because of the inherently sequential nature of LSTM processing, where the hidden states depend on the outputs of the previous hidden states, parallelization is precluded. For learning long-term dependencies, the computation time of LSTM or RNN networks can be prohibitive.

To address this scaling problem, another technique emerged to attack sequence modeling problems: attention networks [30]. Conceptually, attention mechanisms look to find encodings of sequence vectors such that outputs are mapped to key features in the input vectors. The key features in the inputs would then be weighted appropriately such that they are more powerful predictors of the output than other less important features.

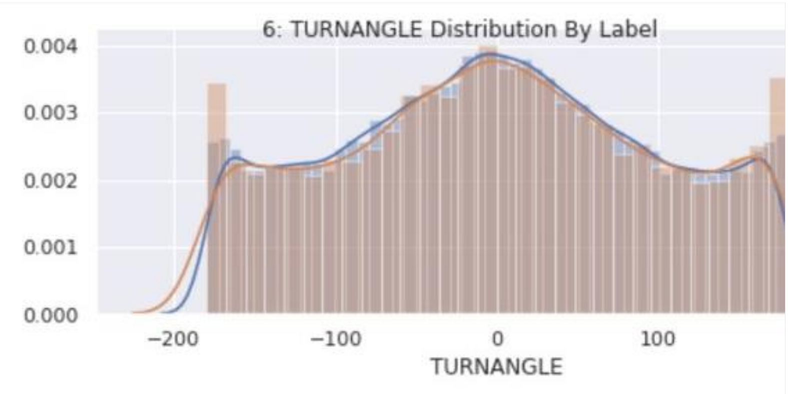
Attention models are derived from the standard encoder-decoder models commonly used to perform machine translation tasks. The main architecture of the encoder-decoder model consists of an encoder, which processes the input vectors into a context. The context is then sent to the decoder, which produces the outputs. The encoders and decoders are typically themselves RNNs and in the standard encoder-decoder structure, the last hidden layer of the encoder forms the basis of the context [29].

However, in an attention model, *all* hidden states are retained and passed to the context. To produce an output, the decoder will calculate a SoftMax score for each hidden layer, then multiply each hidden layer by the SoftMax score so that lower-score layers are "drowned out." In this way, "strong" features are weighted more powerfully in the model. Because the computation can be parallelized in this way and the model is no longer dependent on sequential processing, computation can be sped up a few orders of magnitude.

Although scaling is not a primary concern in analyzing black bear movement patterns, the power of both an attention approach and an LSTM approach can be compared.

4 Results

From April 2010 through October 2012, the thirty-one bears (twenty-three males, eight females) were collared generating 5,400 individual steps for females and 30,832 steps for males. The median step length was 610.7 meters and turn angle was –1.249 degrees. Turn angles tended to be straight (closer to 0 degrees turn angle) and step lengths were skewed, with most being skewed toward zero with few step lengths in excess 5,000 meters (Fig. 6). This would suggest there was a central tendency to bear movement, rather than a random uniform distribution. Meaning, a Louisiana black bear is more likely to move forward rather than right or left when traveling between step intervals.



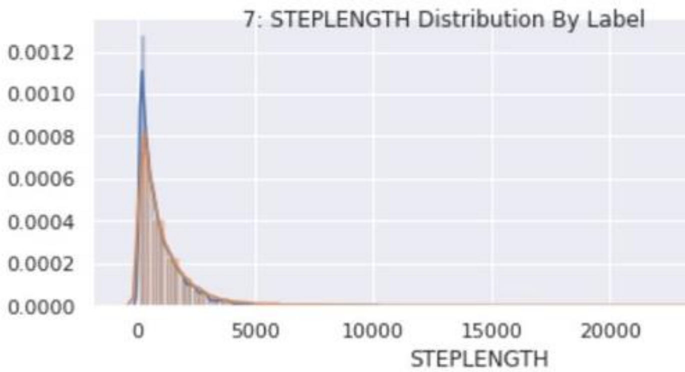
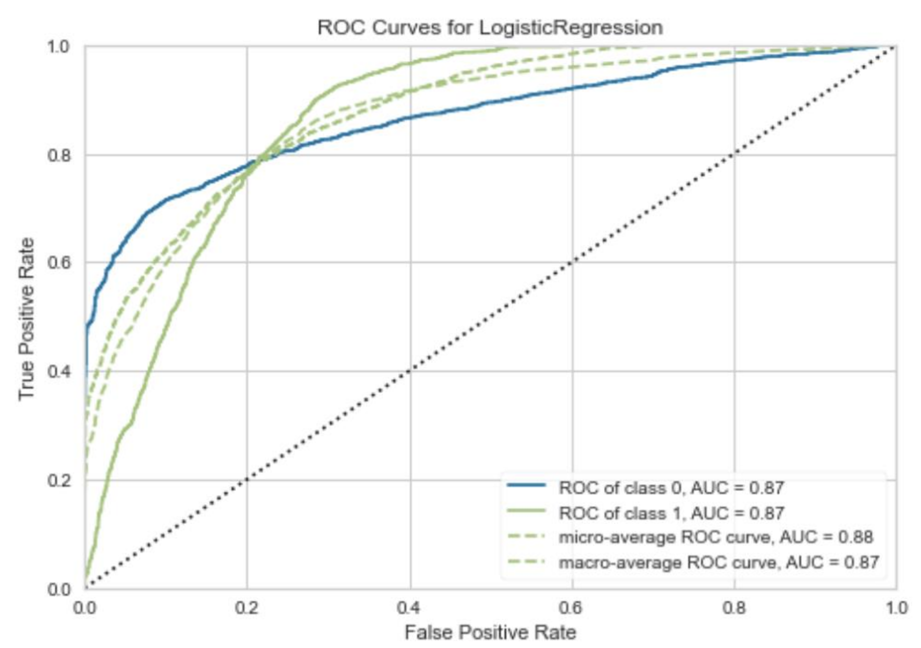


Fig. 6: Turn angle and step length distribution for the black bears in the study, 2011-2013, Louisiana. Note that step lengths above 10,000 and below 1 were omitted.

4.1 Foraging and Exploratory Classifier

After removing correlated variables and creating a 70-30 training and test set for the observations labeled as "Foraging" and "Exploratory" on both male and female steps across all land survey variables such as land cover, forest density, agriculture proximity, etc., a PyCaret model was able to correctly classify the response variables with an accuracy score of 0.78, an AUC score of 0.86, a Recall of 0.82, a Precision of 0.64, and an F1 score of 0.72 (Fig. 7). More specifically, the model correctly identified 1928 foraging steps and 917 Exploratory steps while misclassifying 366 Foraging Steps and 417 Exploratory steps. As the Foraging and Exploratory variables were balanced to 50-50%, then this balance suggests an accuracy rate of 87% and an F1 score of 71%.



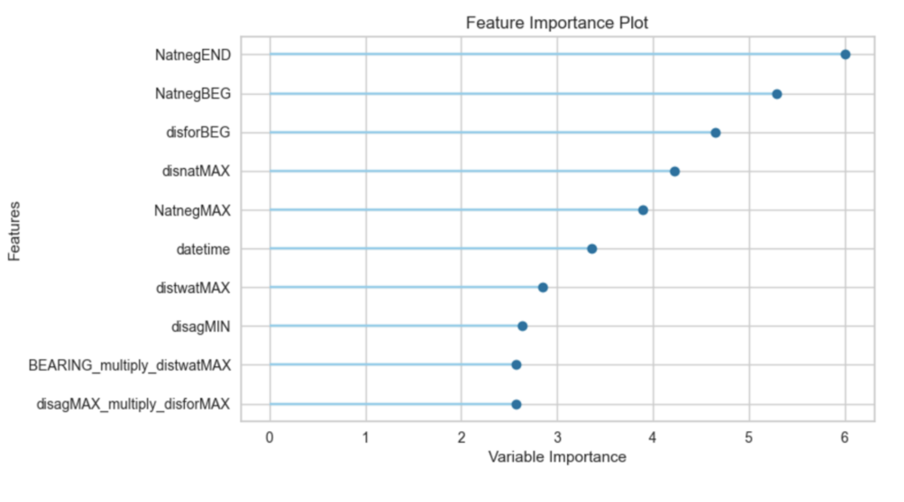


Figure 7: The ROC Curve of the Foraging/Exploratory Classifier Behavior with key features driving performance.

After balancing our classifier variables by utilizing the SMOTE method, our ROC curve shows a significant increase in classification ability using the environmental factors. Proximity to natural vegetation, forest, and agriculture max and min were the strongest forces for classifying foraging and exploratory behavior based on calculating feature importance with the winning CatBoost classifier. Additionally, datetime, distance to the water category, and the combination of distance from agriculture in relation to distance to forest were strong factors in predicting foraging behavior. Long steps were most prevalent in medium density forest and not as prevalent in high nor low density forests.

4.2 Deep Learning Methods

The first attempt with long-short term memory networks was a univariate time series forecast, attempting to model the time pattern of movement of each bear. The network track distance from water for a single bear as a parameter of interest. It then predicts the next value as a function of the last 30 values and produces the following plot (Fig. 8).

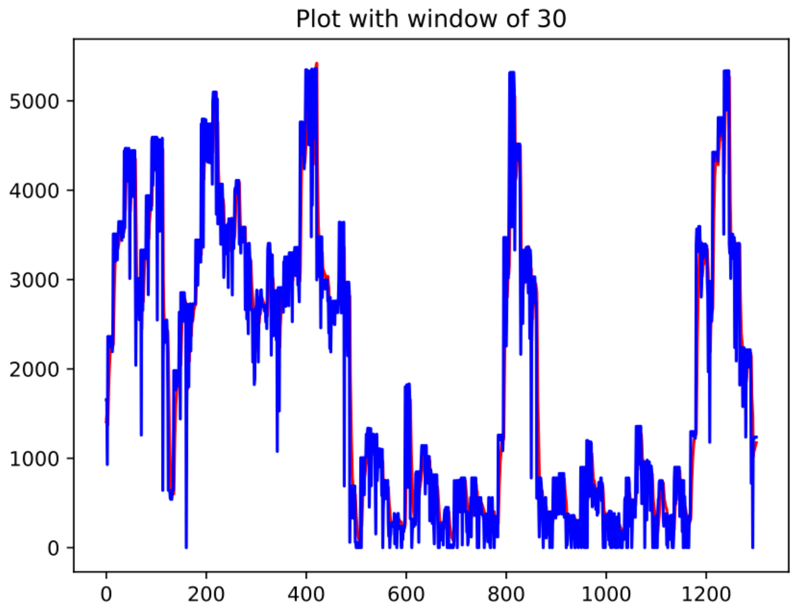


Fig 8. Plot of one bear's distance to water over time. Blue represents the observed behavior while red represents the predicted behavior.

The predicted behavior very closely matches the observed behavior with how closely the red line follows the path of the blue line throughout the chart, suggesting that the network does a decent job with short-term forecasting.

Classifying exploratory and foraging behavior can also be done with the deep learning methods discussed in section 3.2. To accomplish this, a single bear's observed movement pattern was held out as the validation set, and window the other bear's timesteps to create overlapping time windows. Then the model can then fit the LSTM or attention model sequentially over our overlapping sequences, using the holdout bear as the validation set. Both models are scored using mean squared error and use the "Adam" optimizer. Both models ran for up to 500 epochs, with early stopping set to end fitting when the loss bottomed out.

The size of the sliding time window over the dataset is an important parameter in the modeling strategy. Intuitively, longer windows provide more history to predicting the next step, while using shorter time windows means only recent history is used in forecasting. For this study, a sliding time window of 5 steps produced the most accurate predictions by our validation metrics.

The primary output scoring factors of interest are the accuracy and the area under the curve metric (AUC). The summary statistics are displayed below.

Model	Accuracy	AUC
LSTM	0.80	0.89
Attention	0.90	0.96

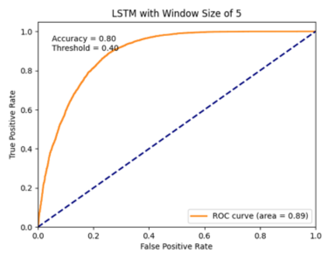
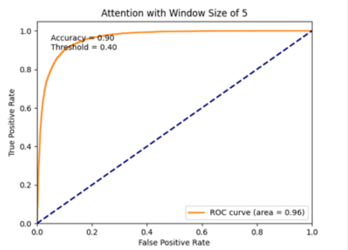
LSTM	Attention
	

Figure 9: LSTM and Attention ROC Curves

The two-receiver operating characteristic (ROC) curves show the performance of the classifier at different classification thresholds. If the threshold is raised, the model must be more certain to predict a positive class, and therefore more false negatives are expected. A good model will consistently outperform the baseline of a random guess at all thresholds (displayed in dashed blue). The reported AUC measure stands for area under the ROC curve, which is an aggregate measure of performance across all thresholds.

Both deep learning models outperform the tree-based Catboost and random forest algorithms based on AUC. In particular, the attention model produces strong predictive accuracy of both positive and negative class instances.

5 Discussion

Although relationships between the classifier variable for step length and turn angle and factors quantifying the agriculture, forest, and water were important, the factor with the greatest level of predictability was Euclidian distance to natural land cover. Although roads played a role in the individual bears' movement behavior, there was not a meaningful relationship that emerged between roads and deciphering between foraging/exploratory behavior.

The exclusive use of the landscape attributes associated with each step point will limit the overall ability to evaluate the cover of individual radiolocations.

Additionally, the specific features related to the environment have changed over the years and would not necessarily translate to a model today. However, the model used to predict the features most strongly associated with movement behaviors can be leveraged in future bear studies and locations (adjusting for location category names). Even in ten years, the environmental landscape has changed tremendously. However, mean location measures between steps proved to be less parsimonious than beginning and endpoint steps. Accounting for the changes in the environment and collecting new data on bears interacting with it, there could be some value to these methods for ongoing research related to bear behavior tracking. As radio collar technology improves, measurements will be taken more often which allows for stronger modeling performance.

The deep learning approaches discussed, both the LSTM and attention networks, should theoretically allow a more accurate capture of the wandering/exploratory behavior of the bears, with the tradeoff of lost interpretability from the standpoint of the importance of features included. This trend is manifested in the results, especially with the attention model. Strong improvements in the precision/recall metrics are observed compared to the tree-based algorithms. In this case, preserving the natural time dependencies in the dataset and using the power of deep learning can most accurately predict the future behavior of the bear. However, deep learning models are infamously opaque. The predictive power is derived from the thousands of interlinked equations in the hidden layers of the network, meaning that the “features” forming the final predictions are nigh indecipherable.

One expected process neither model captured was the bear’s migratory flight behavior. Although long periods of wandering behavior followed by long periods of foraging behavior were expected in the created labels, no such pattern emerged. A better labeling algorithm might produce some of the expected behavior and allow more precise classification. Additional experimentation with optimizers, epochs, and layers could also yield more accurate classification; comprehensive coverage of the hyperparameter grid for a neural net model was not feasible given the time constraints. However, the most promising direction of future improvements is likely to come from additional data collection. More precise encoding of each bear’s location in relation to the surrounding geography is most likely to increase any modeling approach’s classification power. For example, better mapping of the terrain features like hillsides, elevation, exact forestry locations, and trail paths can help narrow down the search space and provide more informed predictions of bear behavior. Domain knowledge and rule-based approaches can then be used to model future behavior, rather than depending on deep learning methods to hypothesize the terrain features.

Step Selection and movement behavior modeling has shown to have applications in other fields of animal behavior research using similar methods. Migratory animals such as birds, fish and mammals such as wildebeests, bats and reindeer could be tested and modeled using LSTM and tree-based methods. All that is needed is a clear methodology for differentiating between what could be classified as foraging behavior and exploratory behavior based on movement patterns. Studies are emerging using different methods for deciphering between foraging and exploratory behavior. These can be based on methods such as density of movements rather than individual movements. Additionally, factoring specific locations of berry patches or other known feeding spots can help to strengthen the criteria used for classification.

6 Conclusion

When the Louisiana black bear was placed on the endangered species list, the recovery plan required the establishment of a series of immigration corridors between the viable subpopulations of the Upper and Lower Atchafalaya and the Tensas river basins to keep the populations sustainable. The Clark, et al. (2015) study demonstrated some limited interchange of male bears between sub-populations, but not females. Furthermore, they concluded that the construction of corridors of natural land cover between sub-populations would be only marginally effective. Occasional male dispersals might maintain genetic diversity among subpopulations, but the most effective method would be to provide human assistance by physically translocating bears among the subpopulations.

This study was able to go further into the types of land cover that aides in long narrow pathways of bears, which is indicative of migration and immigration patterns, with hopes to predict instances of when they are exploring based on landscape characteristics. Coupling with the Clark, et al. (2015) research can better understand movement behaviors in real time and locations for relocation to better secure successful dispersal. The study's machine learning methods have been able to add an element of prediction to the model and determine which features are playing an active role in bear foraging and exploratory behavior.

The continued success of the Louisiana black bear recovery relies on the long-term protection of their habitat. While not all the land that bears covered during the study is under federal ownership, the policy can be implemented to ensure better habitat management within private lands. Incentives to landowners to sustain natural landcover that best accommodates bear movement will be essential for conservation planning and long-term population persistence.

Acknowledgments. Jacquelyn Cheun, PhD. – Professor; David Josephs – Collaborator.

References

1. "Louisiana Black Bear." Southeast Region of the U.S. Fish and Wildlife Service, U.S. Fish and Wildlife Service, www.fws.gov/southeast/wildlife/mammals/louisiana-black-bear/#:~:text=The%20louisiana%20black%20bear%20was%20removed%20from%20the%20endangered%20species. Accessed 12 Sept. 2020.
2. Keller, Lukas, and Donald Waller. "Inbreeding Effects in Wild Populations." TRENDS in Ecology & Evolution, vol. 17, no. 5, May 2002, pp. 230–241.
3. Clark, Joseph D., et al. "Connectivity among Subpopulations of Louisiana Black Bears as Estimated by a Step Selection Function." The Journal of Wildlife Management, vol. 79, no. 8, 28 Aug. 2015, pp. 1347–1360, 10.1002/jwmg.955. Accessed 13 Sept. 2020.
4. Boersen, Mark, et al. "Estimating Black Bear Population Density and Genetic Diversity at Tensas River, Louisiana Using Microsatellite DNA Markers." Wildlife Society Bulletin, vol. 31, no. 1, Apr. 2003, pp. 197–207. Jstor.org.
5. Bowker, Bob, and U.S. Fish and Wildlife Service. Region 4. Louisiana Black Bear, Ursus Americanus Luteolus: Recovery Plan. Jackson, Miss., U.S. Fish and Wildlife Service, Southeast Region, 1995.
6. Cunningham, Brian, et al. "Framework for Evaluation of Flash Flood Models in Wildfire-Prone Areas." SMU Data Science Review, vol. 1, no. 4, 2018, p. Article 9.
7. Hebblewhite, Mark, and Daniel T. Haydon. "Distinguishing Technology from Biology: A Critical Review of the Use of GPS Telemetry Data in Ecology." Philosophical Transactions of the Royal Society B: Biological Sciences, vol. 365, no. 1550, 27 July 2010, pp. 2303–2312, 10.1098/rstb.2010.0087. Accessed 30 Apr. 2020.
8. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-1780.
9. Kanevski, Mikhail, et al. Handbook of Theoretical and Quantitative Geography. University of Lausanne, Switzerland, Faculty of Geosciences and Environment, Jan. 2009, pp. 175–227.
10. Kirasich, Kaitlin, et al. "Random Forest vs Logistic Regression: Binary Classification for Heterogeneous Datasets." SMU (Southern Methodist University) Data Science Review, vol. 1, no. 3, 2018, p. Article 9.
11. Millgate, Kris. "GPS Collars Help Wildlife Researchers Answer Important Questions." Popular Science, Outdoor Life, 23 Mar. 2020, www.popsci.com/story/technology/things-researchers-learn-from-gps-collars/.
12. Nelson, Michael E., et al. "TRACKING OF WHITE-TAILED DEER MIGRATION BY GLOBAL POSITIONING SYSTEM." Journal of Mammalogy, vol. 85, no. 3, June 2004, pp. 505–510, academic.oup.com/jmammal/article/85/3/505/901275, 10.1644/bos-120. Accessed 6 Nov. 2019.
13. O'Donoghue, Brendan, et al. "The Uncertainty Bellman Equation and Exploration." International Conference on Machine Learning, July 2018, pp. 3836–3845.
14. Singh, Ayush. "Introduction to Reinforcement Learning: Markov-Decision Process." Medium, 23 Aug. 2020, towardsdatascience.com/introduction-to-reinforcement-learning-markov-decision-process-44c533ebf8da. Accessed 12 Sept. 2020.
15. Song, Xinyuan, et al. "Hidden Markov Latent Variable Models with Multivariate Longitudinal Data." Biometrics, vol. 73, no. 1, 5 May 2016, pp. 313–323, 10.1111/biom.12536. Accessed 5 July 2019.
16. White, Thomas H., et al. "Influence of Mississippi Alluvial Valley Rivers on Black Bear Movements and Dispersal: Implications for Louisiana Black Bear Recovery." Biological Conservation, vol. 95, no. 3, Oct. 2000, pp. 323–331, 10.1016/s0006-3207(00)00024-0. Accessed 12 Sept. 2020.

17. "Wildlife Monitoring, Wildlife Tracking | Satellite Imaging Corp." Satimagingcorp.Com, 2017, www.satimagingcorp.com/applications/environmental-impact-studies/wildlife-and-marine-conservation/wildlife-monitoring/
18. Karen, Noyce, and Garshelis David. "Seasonal Migrations of Black Bears (Ursus Americanus): Causes and Consequences." Behavioral Ecology and Sociobiology, vol. 65, no. 4, 16 Sept. 2010, pp. 823–835, citeseerx.ist.psu.edu/viewdoc/downloaded=10.1.1.1075.9484&rep=rep1&type=pdf#:~:text=Abstract%20American%20black%20bears%20frequently,to%20fatten%20themselves%20for%20hibernation.&text=Bears%20were%20least%20apt%20to,during%20a%20widespread%20food%20failure.
19. Karelus, Dana, et al. "Effects of Environmental Factors and Landscape Features on Movement Patterns of Florida Black Bears." Journal of Mammalogy, May 2017, pp. 1–16, 10.1093/jmammal/gyx066.
20. https://wiki.openstreetmap.org
21. Srivastava, Pranjal. "Essentials of Deep Learning: Introduction to Long Short Term Memory." Analytics Vidhya, 10 Dec. 2017, www.analyticsvidhya.com/blog/2017/12/fundamentals-of-deep-learning-introduction-to-lstm/.
22. Shi, X., Chen, Z., Wang, H., & Yeung, D. (n.d.). Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting. Retrieved from https://papers.nips.cc/paper/2015/file/07563a3fe3bbe7e3ba84431ad9d055af-Paper.pdf
23. Bouktif, S., Fiaz, A., Ouni, A., & Serhani, M. A. (n.d.). Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches. Retrieved from https://www.mdpi.com/1996-1073/11/7/1636/html
24. Wang, Guiming. "Machine Learning for Inferring Animal Behavior from Location and Movement Data." Ecological Informatics, vol. 49, Jan. 2019, pp. 69–76, 10.1016/j.ecoinf.2018.12.002. Accessed 20 Aug. 2019.
25. Wijeyakulasuriya, Dhanushi A., et al. "Machine Learning for Modeling Animal Movement." PLOS ONE, vol. 15, no. 7, 27 July 2020, p. e0235750, 10.1371/journal.pone.0235750. Accessed 30 Jan. 2021.
26. Clark, Joseph D., et al. BEARS of the WORLD: Ecology, Conservation and Management. S.L., Cambridge Univ Press Us, 2021, pp. 122–138.
27. Laufenberg, Jared S., et al. "Demographic Rates and Population Viability of Black Bears in Louisiana." Wildlife Monographs, vol. 194, no. 1, 15 June 2016, pp. 1–37, 10.1002/wmon.1018. Accessed 10 Nov. 2019.
28. Kochanny, Christopher O, et al. "Comparing Global Positioning System and Very High Frequency Telemetry Home Ranges of White-Tailed Deer." Journal of Wildlife Managment, vol. 73, no. 5, 1 July 2009, pp. 779–787, bioone.org/journals/arcJournal-of-Wildlife-Management/volume-73/issue-5/2008-394/Comparing-Global-Positioning-System-and-Very-High-Frequency-Telemetry-Home/10.2193/2008-394.short.
29. Muñoz, Eduardo. "A Guide to the Encoder-Decoder Model and the Attention Mechanism." Medium, 11 Feb. 2021, betterprogramming.pub/a-guide-on-the-encoder-decoder-model-and-the-attention-mechanism-401c836e2cdb. Accessed 27 Mar. 2021.
30. Vaswani, Ashish et al. "Attention is all you need", arXiv:1706.03762, 2017.
31. Hochreiter, Sepp. "The Vanishing Gradient Problem during Learning Recurrent Neural Nets and Problem Solutions." International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, vol. 06, no. 02, Apr. 1998, pp. 107–116, 10.1142/s0218488598000094.