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EXPLORING ANIMAL MOVEMENT BEHAVIOR WITH SWITCHING STATE SPACE MODELS

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Abstract

Understanding animal movement is pivotal in addressing population dynamics. Bayesian statistical techniques have been concentrated in literature to study intricate animal movement, by adapting their analytically manageable likelihoods. With the utilization of Hidden Markov Models (HMMs), the study examines animal tracking data of one elk and highlights step lengths and turning angles across two states. Data is obtained from the work of Morales et al. (2004), titled "Extracting more out of relocation data: building movement models as mixtures of random walks." Collected using tracking systems, the data indicates elk position (longitude and latitude), and the animal's proximity to water sources along its movement paths. To effectively analyze step length and turning angles on HMMs, Gamma and Von Mises distributions and employed respectively. Results indicate a difference in step length between states 1 and 2, with longer steps observed in state 2 than in state 1. In turning angles, state 1 showcases a uniform distribution, signifying *undirected movement in comparison to State 2 which showcases directed movement. The study concludes that movement in state 1 is indicative of foraging, while state 2 signifies traveling between habitat patches and wandering movements, and that the elk grazes closer to water and forages away from water.*

1. Introduction

Recent research in the analysis of animal movement has primarily focused on comprehending intricate processes such as inter and intra-specific interactions, population dynamics, and spatial behavioral patterns. This line of investigation has been particularly concentrated on the dissection of movement patterns into discrete behavioral modalities, each governed by a distinct set of parameters. Bayesian statistical techniques have gained notable prominence in the study of these modalities, largely due to their utility in conducting inference through analytically manageable likelihoods within models.

Numerous methodologies have been employed for the examination of animal tracking data. This paper places specific emphasis on one such approach—Hidden Markov Models (HMMs). This statistical framework belongs to the family of latent variable models, wherein an observed process is contingent on an unobserved discrete latent state process, commonly referred to as the "hidden" state process. This latent process is governed by a Markovian dynamic. HMMs have garnered considerable appeal due to their amalgamation of modeling flexibility, lucid interpretability, and computational feasibility. The primary objective underlying the utilization of HMMs in movement modeling is the decomposition of movement processes into distinct underlying states. This aligns with the prevailing understanding that a significant proportion of animal locomotion can be attributed to transitions between fundamental behavioral modes (McClintock et al., 2012; Langrock et al., 2012; Jonsen et al., 2005).

We choose to focus our work to be centered on the modeling of elk movement data, which is characterized by positional attributes (latitude and longitude) as well as distance from water sources. We chose to look at a particular dataset from the literature, specified in the work by Morales et al. (2004), titled "Extracting more out of relocation data: building movement models as mixtures of random walks." The authors applied their analysis to relocation data acquired from a GPS-collared elk released in east-central Ohio. Their investigation identified two discernible phases of movement behavior: an "encamped" state marked by short step lengths and pronounced turning angles, and an "exploratory" state characterized by elongated step lengths and more subtle turning angles. The study further revealed that the elk predominantly assume the encamped state within open habitats, comprising agricultural fields and open forested areas. On the other hand, the exploratory state demonstrated no specific habitat association.

In the context of this study, we analyze the same elk dataset, albeit through the lens of HMMs.

The discrete latent states within the HMMs framework are harnessed to symbolize distinct behavioral states exhibited by the elk. The fundamental attributes of step lengths and turning angles within this elk dataset are subjected to modeling using a range of HMM variants. These encompass models featuring two and three states, both with and without the incorporation of a covariate (i.e., the distance to water). To effectively model the emissions related to step lengths and turning angles, the Gamma and Von Mises distributions are employed, respectively. The Gamma distribution involves shape and rate parameters, rendering it suitable for distances, while the Von Mises distribution is aptly suited for circular data, rendering it suitable for the quantification of turning angles. The computational processing of the data, HMMs training, and results visualization were facilitated through the use of the R package (Michelot et al., 2016).

2. Methods and Results

Model 1 and Model 2 are 2-state HMMs with model 1 having no covariate and model 2 having a covariate of distance to water as shown in Figure 1 below.

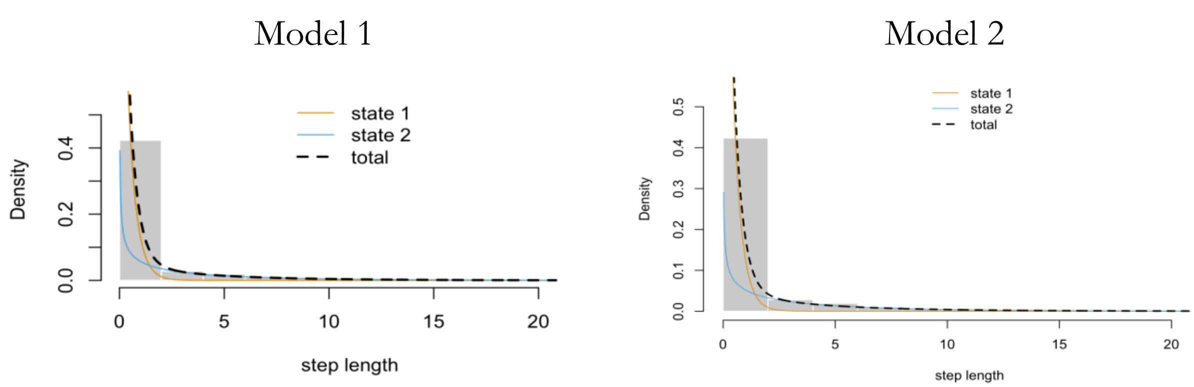

Figure 1

As observed by the distribution curves in Figure 1 for models 1 and 2, the distribution of step lengths for state 1 consists of mostly shorter steps, whereas state 2 includes longer steps.

State 1 has a greater probability for shorter steps and state 2 has a greater probability for longer steps. There was no significant interpretable difference between models 1 and 2.

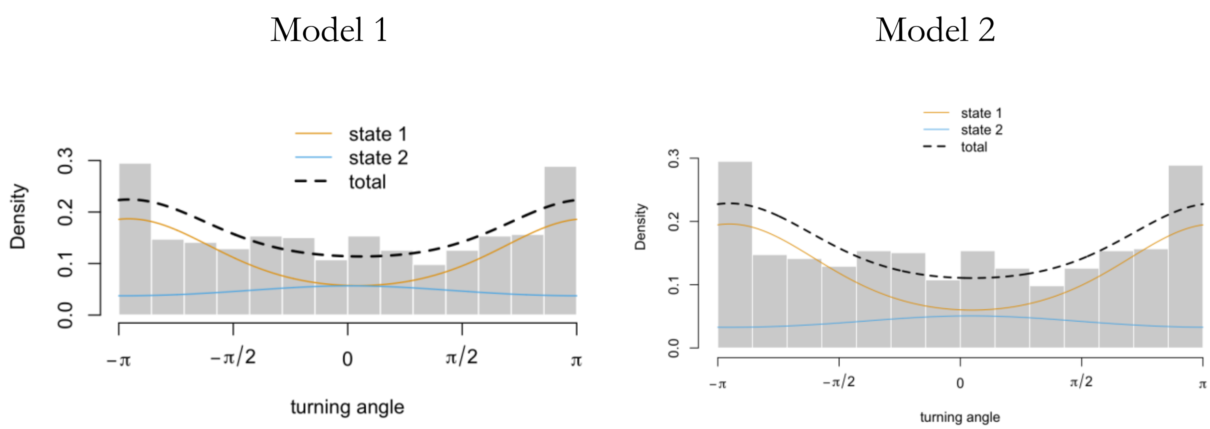

Figure 2

From Figure 2, State 1 peaks at pi and negative pi, which is a uniform distribution of turning angles, signifying undirected movement. On the contrary, state 2 peaks at 0, signifying directed movement. There doesn’t appear to be a significant interpretable difference between models 1 and 2.

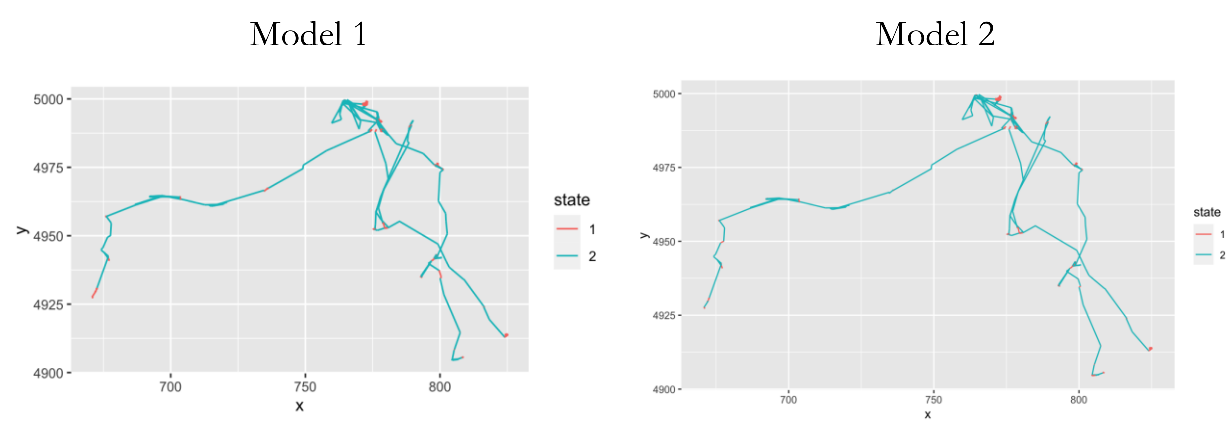

Figure 3

Graphs in Figure 3 depict deterministically decoded movement of the elks as latent states, with state 1 showcasing shorter step lengths and state 2 having longer step lengths, as previously shown.

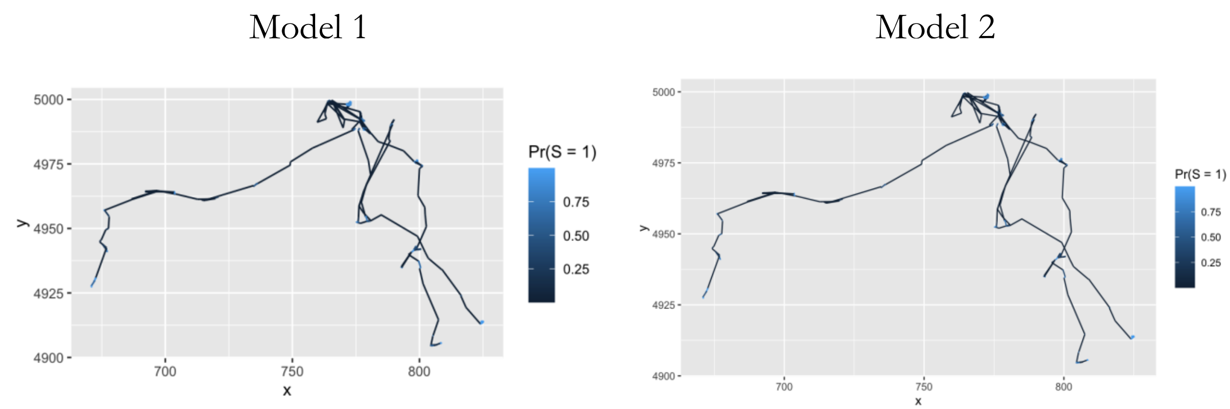

Figure 4

Graphs in Figure 4 indicate that the elk movement is probabilistically belonging to a latent state. As previously shown, shorter step lengths are more likely to belong to state 1.

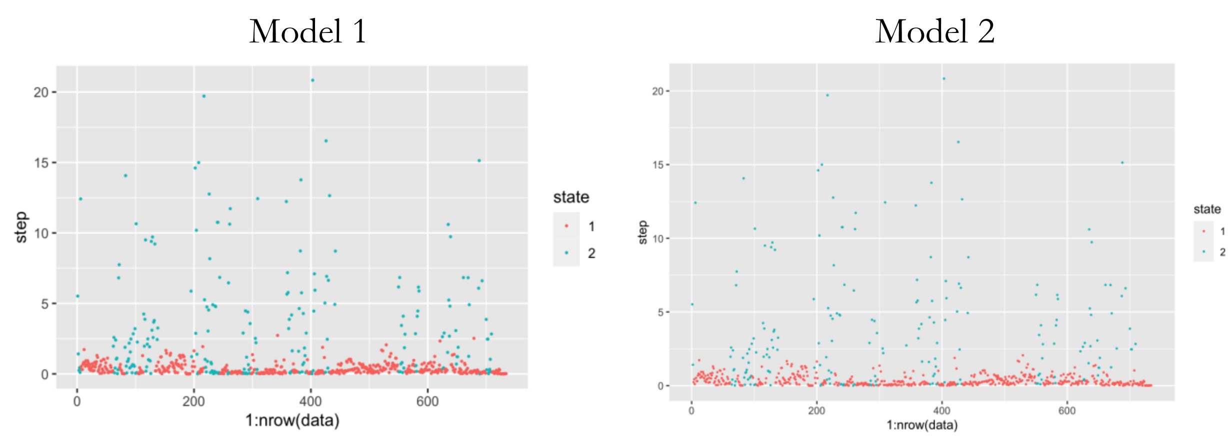

Figure 5

Figure 5 includes scatter plots showing the distribution of movement by step length. State 1 has small step lengths and uniform turn angles, i.e. undirected movement which can be associated with foraging and state 2 has greater step lengths and turning angles near zero, i.e. directed movement which can be associated with traveling between habitat patches and more wandering movements.

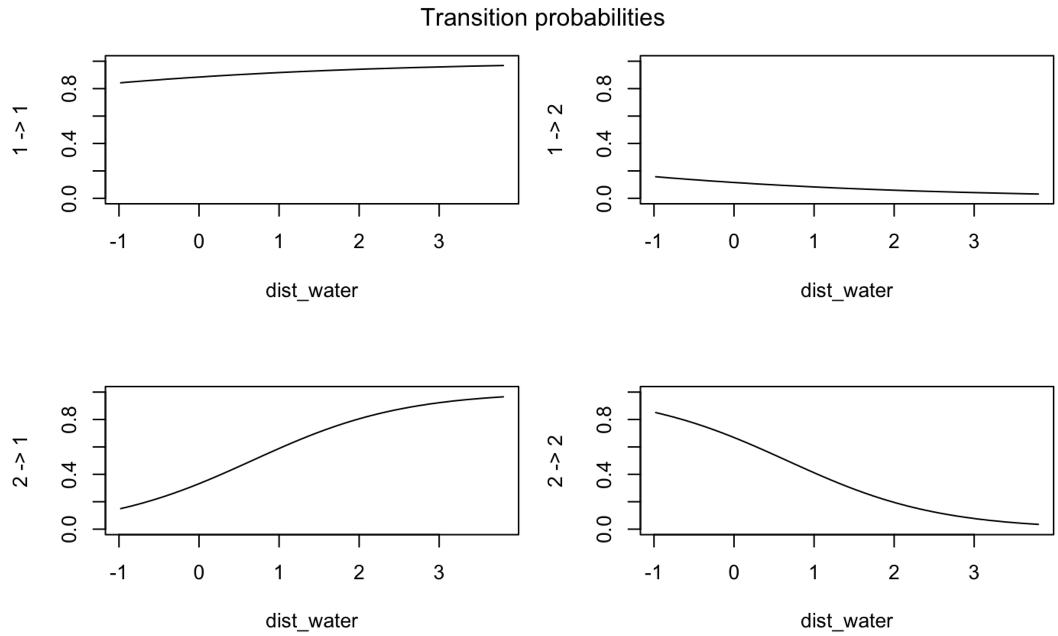

Figure 6

Figure 6 shows that there is a higher probability of transitioning from state 2 to 1 when away from water and a high probability of staying in state 2 when near water, that is when the distance to water is shorter. Based on the description of the animals associated with each state, it can be concluded that the elks forage further away from water and graze closer to water.

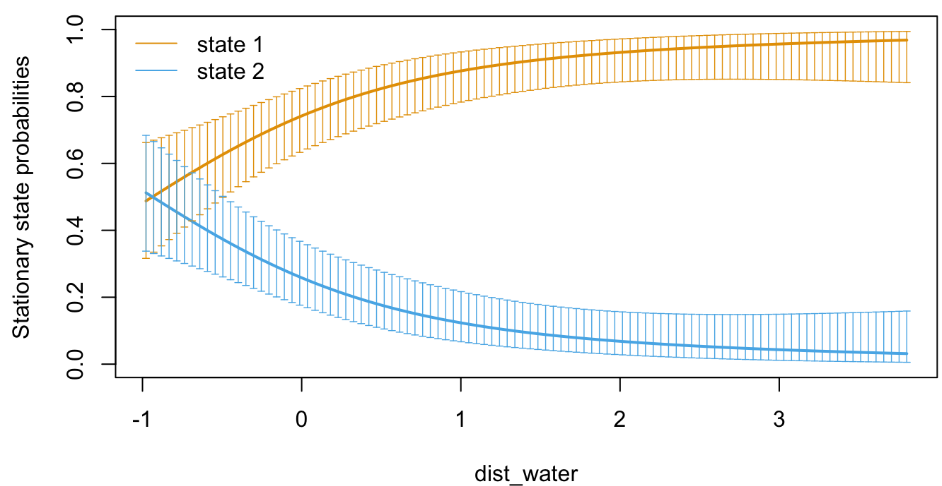

Figure 7

Figure 7 shows that foraging for state 1 occurs farther away from water and that traveling in habitat patches occurs closer to water.

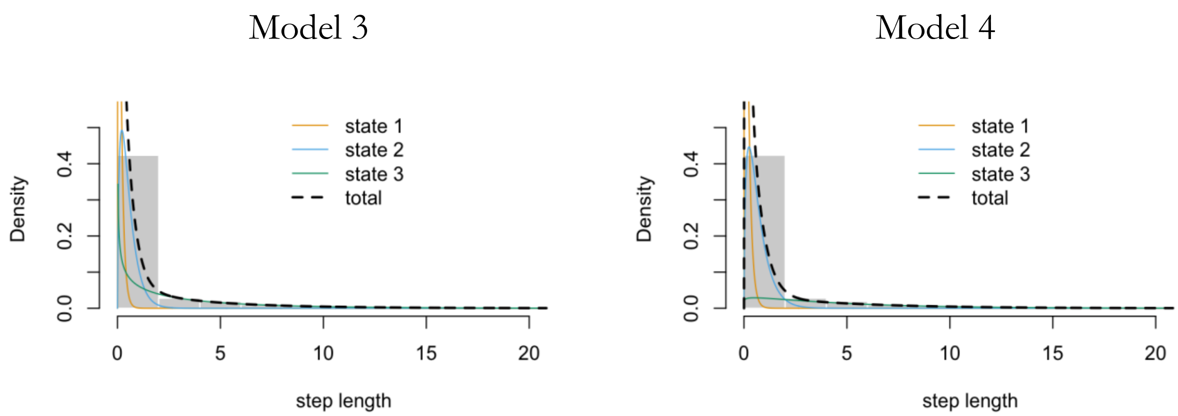

Figure 8

In Figure 8, three discrete states were used for the HMMs. From the distribution curves, state 3 has a significant peak in Model 3 but not in Model 4. This shows that the state is less likely to consist of short steps with the inclusion of the covariate. State 1 indicates very short step lengths, state 2 a bit larger step lengths, with state 3 having the considerably largest step lengths.

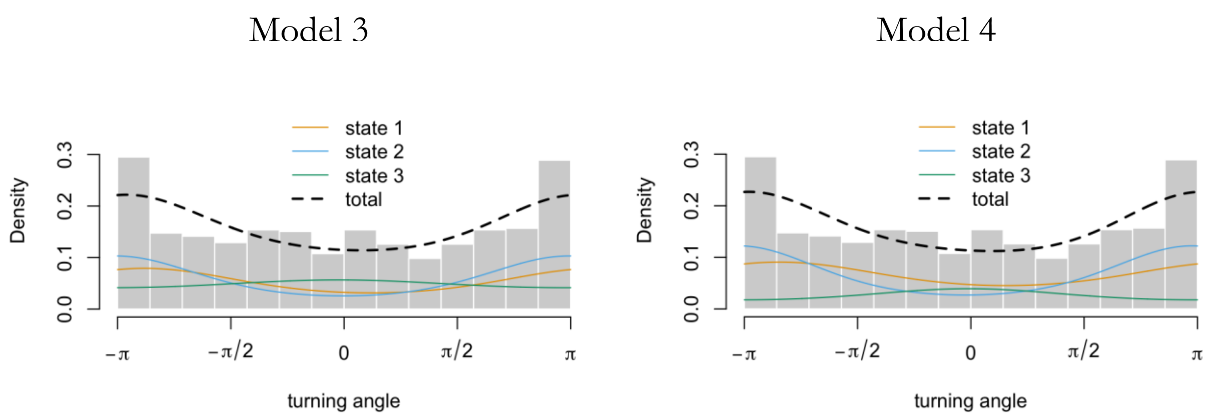

Figure 9

In Figure 9, states 1 and 2 indicate more undirected movement with peaks at pi and negative pi in both models. However, state 3 correlates to directed movement, peaking at 0. The probability of directed movement is relatively greater in Model 3

Model 3 Model 4

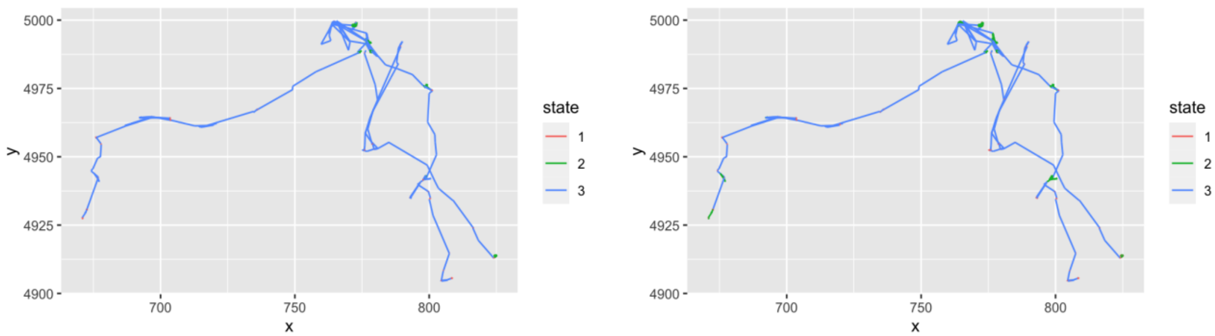

Figure 10

As seen in Figure 10, the graphs that depict the elk movement as latent states, state 3 correlates with significantly longer steps compared to states 1 and 2.

Model 3 Model 4

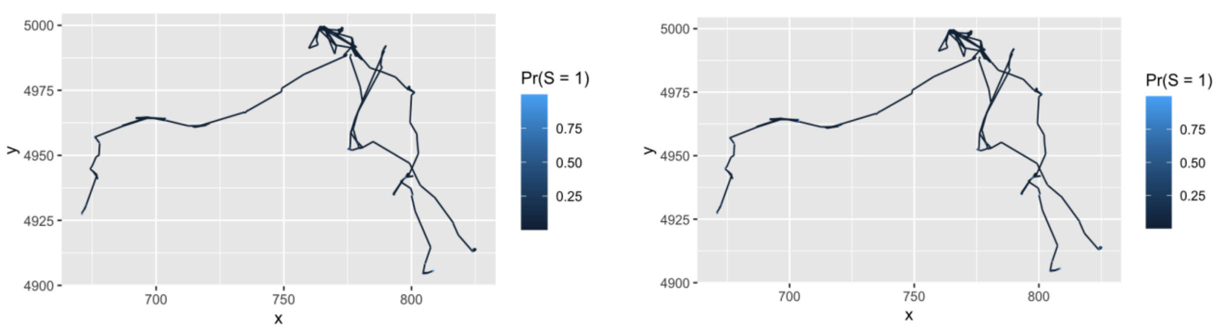

Figure 11

In Figure 11, the graphs indicate that each movement of the elk is probabilistically belonging to a latent state. As previously shown, shorter step lengths are more likely to belong to state 1.

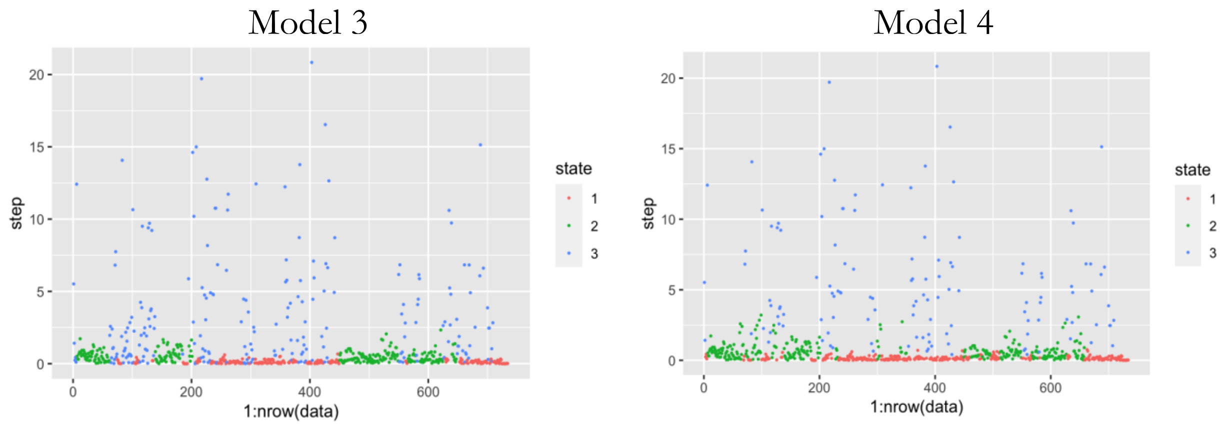

Figure 12

The distribution of movement by step length in Figure 12 shows the correlation of states 1 and 2 with shorter steps and state 3 with varying ranges of step lengths but typically longer.

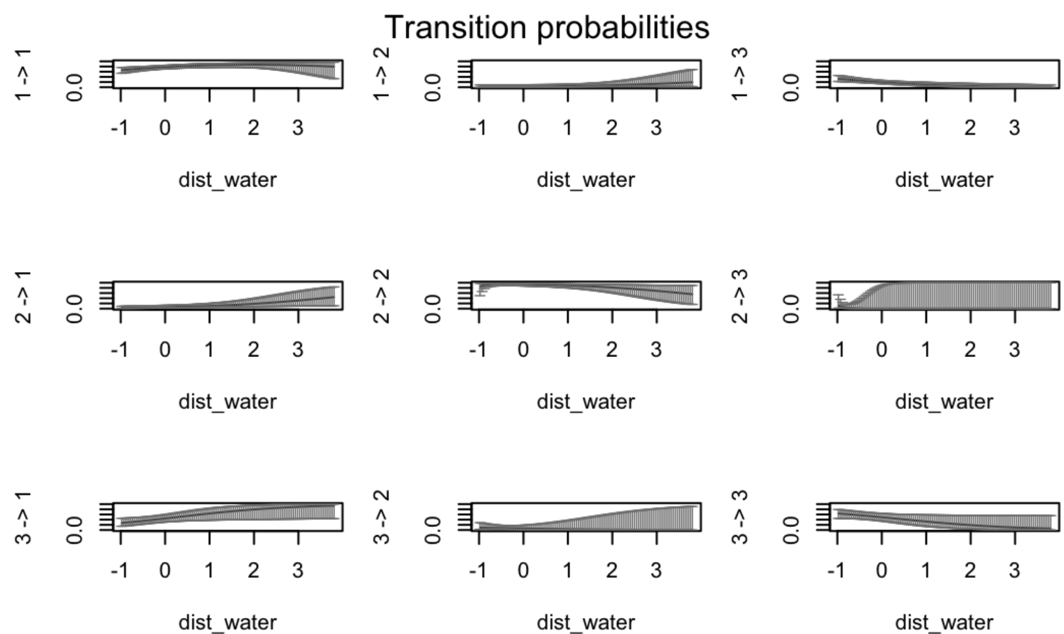

Figure 13

There is a higher probability of transitioning from states 1 to 3 when closer to water, a high probability of staying in states 2 and 3 when near water, and a high probability of transitioning from state 2 and state 3 to state 1 when away from water as shown in Figure 13. Based on the description of the animals associated with each state, it can be concluded the elks forage further away from water and graze closer to water.

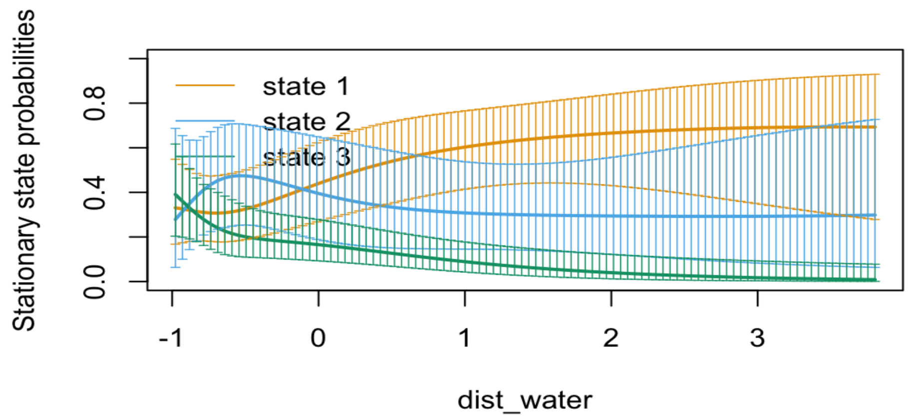

Figure 14

The plot in Figure 14 shows that state 1 occurs farthest away from water, state 3 is closest to water, and state 2 is further away from water but not as far as state 1.

To compare the four models, the Akaike information criterion or AIC was used, which is an estimator of prediction error that assesses the quality of statistical models for the same set of data. The AIC estimates the quality of a model relative to other models in a collection allowing us to select models and understand which model is better suited to the data. Since AIC shows the prediction error, the lower the AIC the better fit the model is.

Table 1

Model	AIC
mod4	3655.750
mod3	3667.443
mod2	3799.493
mod1	3811.949

As seen in Table 1 above, since model 4 and model 2 are respectively better than model 3 and model 1, it can be concluded that including a covariate helps with the performance of the model on the data. Since models 4 and 3 are better than models 2 and 1, using an HMM with 3 states to segment the data more accurately describes the data than an HMM with only 2 states.

3. Discussion

The classification of the elk's movement behavior, as delineated by Morales et al., was affirmed by this study, segregating it into two distinct modalities by leveraging the discrete states inferred from Hidden Markov Models (HMMs). The analysis highlights the presence of a mode characterized by diminutive step lengths and non-directed movement, which may be attributed to foraging activities. Conversely, another mode is characterized by extensive step lengths and purposeful movement, likely indicative of travel between habitat patches and more extensive roaming behaviors.

Within the framework of a conventional HMM, adherence to a Markov process is observed within the transition function, thereby engendering a dependence of the discrete latent state at each temporal instance upon the preceding time point. Consequently, the dwell-time distribution within states conforms to a geometric decay pattern. To enhance model flexibility, the incorporation of semi-Markov state processes introduces the construct of a Hidden Semi-Markov Model (HSMM). The HSMM explicitly models the temporal duration an animal remains within a behavioral state, thereby transcending the limitations imposed by the geometric decay assumption within standard HMMs. The extension to HSMMs is particularly advantageous within ecological time series analyses, as it engenders greater realism and potential improvements in model fitting. Furthermore, it furnishes invaluable insights into the dynamics of behavioral transitions, a fact that conventional HMMs are incapable of furnishing.

Nevertheless, it is imperative to acknowledge the inherent limitations associated with HMMs. Primarily, the employed HMM approach operates within a discretized temporal framework, rendering it suitable solely for regularly spaced observations. When dealing with varying time intervals between successive observations, the assumption of uniform state transition probabilities and state-dependent distributions becomes untenable. For scenarios encompassing irregularly spaced observations over time, alternative models such as continuous-time Hidden Markov Models, the Ornstein-Uhlenbeck process (Blackwell, 2003), or a continuous-time correlated random walk (CRW) (Johnson et al., 2008) offer more appropriate alternatives. While these models afford enhanced independence between behavior scales and observation scales, they entail heightened complexity and methodological challenges. Additionally, it is noteworthy that HMMs are best suited for time series characterized by negligible observational error. While some level of random error in observations can be accommodated, any substantial introduction of such errors precipitates technical complications.

Notwithstanding these limitations, the utility of HMMs in the analysis of animal movement remains profound. Many ecological investigations yield observations acquired at fixed intervals. As technological advancements progressively mitigate measurement errors, the adoption of HMMs is poised to surge not only within ecology but across diverse disciplines. The mathematical elegance and computational manageability inherent to HMMs augur well for their sustained relevance in the foreseeable future.

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