Asiatic cheetah behavioral estimation from telemetry data using Bayesian statistics

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March 15, 2017

Keywords: *State-space model, Bayesian, animal movement, GIS, Remote sensing, Asiatic cheetah, Iran*

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Abstract

In this paper we study the movement behavior of Asiatic cheetah *Acinonyx jubatus venaticus*, a highly endangered cat found in Iran. At first, we fitted the differenced correlated random walk model to the data to estimate the probability of the behavior of the animal in two distinctive states. The moving state can be interpreted as the state when the animal had higher mobility and the resting state in which the animal had small step movements and constantly changes its direction. We considered a movement and observation model; we used the observation model to model the error associated with the GPS sensors. We employed the Bayesian framework for the model fitting in which the Markov Chain Monte Carlo (MCMC) simulation enabled us to estimate as many parameters found in the posterior distribution. The movement track was collected spanning four and a half months in 2007; probably, the cheetah was predated by a leopard after that period. The animal was monitored in Bafq area, a region in the central Iran with an arid environment. Plotting the animal track symbolized by the two behavioral modes revealed that the cheetah had more mobility between four clusters of resting phases. Applying the kmean clustering to the cheetahs resting locations, revealed that the cheetah had more mobility between eight clusters of resting phases. One speculation was that, these resting clusters were associated with the highest likelihood of prey concentration as cheetahs major preys, wild sheep, and goat, reside in these regions.

1 Introduction

The study of the movement in general and animal movement in specific has faced an enormous uplift in the recent years (Hussey et al., 2015; Kays et al., 2015). A huge body of research is devoted to understanding the behavior of animals in relation to their surrounding environment (Ahearn et al., 2016; Kays et al., 2015; Hazen et al., 2013; Raymond et al., 2015; Wakefield et al., 2011). However pure animal telemetry data lacks behavioral context, yet stochastic statistical approaches could be employed to infer some of this context (Bestley et al., 2013; Forester et al., 2007; Worton, 1989). Behavioral switching models and segment the path into distinct behavioral states; they model the movement process as either a correlated random walk (CRW) (Ahearn et al., 2016; Bestley et al., 2013; Jonsen, 2016; Worton, 1989), where the track is characterized by step-length and turn-angle distributions, or Markov process (Joo et al., 2013; Langrock et al., 2012; Patterson et al., 2009; Worton, 1989) and its derivative models where states are discrete. Markov oriented models are commonly useful for GPS location data with negligible location errors while CRW derived models accompanied by the Bayesian statistics and Markov chain Monte Carlo simulation (Worton, 1989) are better suited for Argos telemetry data with huge positional errors. Due to the generality of latter, it could also be employed to GPS data, i.e. as a mean for comparing the two approaches and the validation of the results from hidden Markov chains approach.

The Asiatic cheetah (*Acinonyx jubatus venaticus*) once found in Afghanistan, Turkmenistan, the Arabian Peninsula, Syria and Iran is the member of the family Felidae in the world (UNDP, 2010; Farhadinia, 2004), on the verge of extinction. Asiatic cheetahs are highly vulnerable to extinction, mainly due to causalities interceded by herder persecution, poaching and road collisions as well as prey and habitat loss. Some efforts have been made to address these threats, but range expansion in recent years is a result of greater survey effort, rather than population recovery (Farhadinia et al., 2017). In the last 20 years, Iran has been the last habitat for the Asiatic cheetah, although there have been frequent reports of cheetahs presence across the border in Pakistan (Farhadinia, 2004). Numerous studies (Farhadinia et al., 2016; Mohammadi and Kaboli, 2016) have reported that the Asiatic cheetah lives in small quantities ranging between 50 to 70 in Iran. Cheetahs being known for the speed and agility, have a large home range connecting sparse reserves through corridors (Farhadinia et al., 2013, 2016). Although traveling hundreds of kilometers is not difficult for them, the reason behind this effort is the shortage of prey density, loss of habitat, and the presence of competitors in the reserves. Despite the significant value of the Asiatic cheetah conservation, very few studies have been carried out on its movement data from GPS collars. Long range movement behavior of the Asiatic cheetah was discovered using camera traps and image matching of the spots on the body of the animal (Farhadinia et al., 2016). The only study on the radio telemetry of this rare species reported various research objectives on the analysis of its movements (Hunter et al., 2007), yet no subsequent quantitative study has been carried out on Asiatic cheetah movement data.

Estimating behavioral states and associated movement parameters of individual animals is potentially important for two reasons. First, it can be used for behavioral analysis of the animal and to understand when and where the animal tends to move and when to rest in energetics and time budgeting applications. Second it potentially can help to link the animal behavior to environmental correlates. This approach may be the most direct way that movements of individuals can be scaled up to better understand their population dynamics (Morales et al., 2010; Jonsen, 2016). However, In this study we had access to the movement tracks of two cheetahs, but only one was used in all analysis; two cheetahs were part of a coalition, thus they moved almost similarly. We fitted the first differenced correlated random walk (Jonsen et al., 2016) to the movement tracks of Asiatic cheetah to infer some of its context. We then linked cheetah's behavioral phases with the time of day to see when the cheetah tends to be moving during the course of the day. We also computed the resting spatial clusters of the animal to see where are the most favorable locations to the animal. The flow of study is demonstrated in the Figure 1.

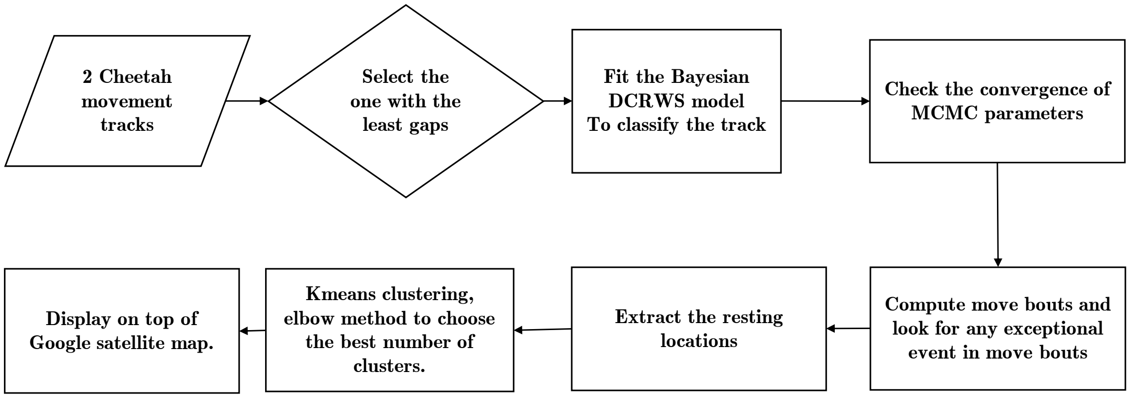

Figure 1: Flow of the analysis. **DCRWS:** Differenced correlated random walk with switching. **MCMC:** Markov chain Monte Carlo sampling.

2 Materials and Methods

The Asiatic cheetah study was conducted in the Bafq protected area in central Iran, one of five protected areas identified by CACP (2016) as the most important areas for cheetahs. Bafq is a barren area of land characterized by desert, with scarce rainfall, high temperature and degraded landscapes (Amiraslani and Dragovich, 2011). Animals, especially cheetahs, living in the Bafq desert, need adaptations to survive in this harsh environment. The Bafq desert is surrounded by human infrastructure such as cities, villages and highways which make the situation for the cheetah dispersal more difficual. The transportation networks surrounding the protected areas degrade natural habitats and contribute to a higher risk of mortality through roadkill. A large number (7 out of 50-70) of Asiatic cheetahs have been lost due to vehicle collisions in the region over the last decades (Mohammadi and Kaboli, 2016).

2.1 Movement track

The telemetry data under analysis is the one represented in Hunter et al. (2007) in a limited fashion. Two cheetahs were captured in the 885 km^2 area of Bafq protected area, Yazd Province. The monitoring started from February 27 to July 13 in 2007 and lasted for 136 days, when the cheetah body found dead, killed by another competitor likely a Persian leopard. The other cheetah was simultaneously captured in the same region to collect it's tracking data. Although both Cheetahs were part of a coalition and they moved almost together (Table 1).

Table 1: Summary of temporal characteristics of the telemetry data.

	Temporal Scale			**# of Observations**			
Animal	From	To	Days	8 hours	16 hours	24 hours	% of Gaps
Cheetah 1	2/27/2007	7/13/2007	136.7	358	26	-	7%
Cheetah 2	2/26/2007	7/6/2007	130	358	13	2	4.50%

Almost any radio telemetry solution exhibits gaps in the data. Gaps are more apparent in the sea animals where the animal is needed to come to the surface of water to capture a location fix. Animal-borne GPS sensors are not exception and they exhibit missing points either. The presence of any barrier between the

GPS satellites and the sensor is the main reason for missing points in location data. In our data, the cheetah may have been under a rock, tree, or a shrub, although trees are very scarce in the arid environment of Bafq. The particles in the polluted atmosphere and sometimes cloudy weather could also inhibit GPS signals from passing through the air. In our data as presented in the Table 1, 4.5-7% of the data was missing during the observation and the gaps were mainly one-step (16 h) and very few two-step gaps (24 h) were present. Gaps should be treated properly in the model fitting process since we have utilized the discrete time hidden Markov model where states are discrete. This can be dealt in various ways: 1) interpolating the consecutive points in time using linear regression, 2) splitting the movement path at big gaps i.e. two steps gap (24h) in our data, 3) using continuous time movement models that spontaneously handle missing values, and 4) subsampling the data. We employed the first approach to avoid further complexity and loss of data. The second approach was not viable because splitting the movement path leads to too short movement path while hidden Markov models perform well with at least 300 observations (Patterson et al., 2009; Langrock et al., 2012).

The spatial accuracy of GPS location data are usually high and the errors–roughly 5-10 meters–are negligible in the model fitting compared with the Argos data where location errors must be taken into account in the modeling framework explicitly (Jonsen et al., 2005; Jonsen, 2016). The cheetahs were fitted with GPS collars (Vectronics, Germany) with a timed CR-2A drop-off unit (Telonics, Arizona) that automatically removes the collar.

2.2 Analysis Methods

2.2.1 First differenced correlated random walk

We modeled the movement as a compound CRW that can be decomposed into two or more discrete behavioral states (Figure 2). We considered just two states: a moving state consisting of relatively fast and more directionally persistent movement (also known as moving state), and a resting state consisting of relatively slow movement with frequent course reversals, also known as the encamped state. In addition, fitting a 3 states model didn't improve the model and the sampling from the posterior distribution did not converge. The model was a first-differenced CRW including stochastic switches between behavioral states, where the states were defined as unique combinations of two movement parameters: the mean turn angle θ_{b_t} and the move persistence γ_{b_t}. The subscript b_t denotes the behavioral state at time t, where b = 1 (moving state) and b = 2 (resting state).

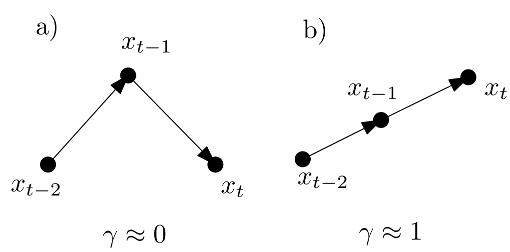

Figure 2: **a)** when γ is close to zero (resting mode), we have less auto-correlation in direction and speed. **b)** As the γ approaches 1, i.e. in moving mode, the auto-correlation in direction and speed increases.

This non-hierarchical model is described elsewhere (Jonsen, 2016; Jonsen et al., 2005), but has the general form:

$$x_t = x_{t-1} + \gamma_{b_t} T(x_{t-1} - x_{t-2}) + N(0, \Sigma)$$

where x_t and x_{t-1} are the unobserved true locations of an animal at times t and $t-1$. T is a matrix describing the mean turn angle, θ_{b_t}, between displacements $x_t - x_{t-1}$ and $x_{t-1} - x_{t-2}$:

$$T = \begin{pmatrix} \cos\theta_{b_t} & -\sin\theta_{b_t} \\ \sin\theta_{b_t} & \cos\theta_{b_t} \end{pmatrix}$$

and Σ is a variance-covariance matrix specifying the magnitude of stochasticity in the 2-dimensional movements:

$$\Sigma = \begin{pmatrix} \sigma_x^2 & \rho\sigma_x\sigma_y \\ \rho\sigma_x\sigma_y & \sigma_y^2 \end{pmatrix}$$

Switching between behavioral states is governed by a Markov chain with fixed transitional probabilities:

$$\Pr(b_t = i | b_{t-1} = j) = \alpha_{ji}$$

where α_{ji} is the probability of switching from behavioral state j at time $t-1$ to behavioral state i at time t. In a 2-state context the α_{ji}s are elements of a 2×2 transition matrix:

$$\alpha = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} = \begin{pmatrix} a_{11} & 1 - a_{11} \\ a_{21} & 1 - a_{21} \end{pmatrix}$$

where a_{11} and a_{22} are the probabilities of remaining in the moving and resting states, respectively. a_{12} and a_{21} are the probabilities of switching from the moving to the resting state and from the resting to the moving state, respectively. These transitions can be estimated assuming a first-order Markov categorical distribution. In practice, only a_{11} and a_{21} need to be estimated as the rows of matrix α sum to 1. Location uncertainty is accounted for via the observation model. It is assumed that the location uncertainty follows a bi-variate normal distribution, which is typical of GPS data :

$$y_t = x_t + N(0, \Omega)$$

where y_t is the observed location at time t and Ω is a variance-covariance matrix specifying the magnitude of uncertainty in the observed locations.

we used R (R Core Team, 2017) package (Jonsen et al., 2016) to fit the DCRWS to the movement data.

2.2.2 Markov chain monte carlo

The state-space differenced correlated random walk with switching (DCRWS), was fitted to the dataset using 2 chains of 250000 MCMC samples; the first 100000 samples were discarded as a burn-in and the remaining

150000 were thinned out to 3000 samples by retaining only every 50^{th} sample to reduce autocorrelation. Estimation of parameters were based on these final 3000 samples. For each estimated parameter, convergence and absence of autocorrelation were checked, and we also applied the convergence diagnostic of Gelman and Rubin (Gelman and Rubin, 1992). The model fitting was done using the R package BSAM (Jonsen et al., 2016) under the R 3.3.2 (R Core Team, 2017) with the Markov Chain Monte Carlo (MCMC) sampler of JAGS (Plummer et al. (2016), Figure 4).

We used the 0.55 threshold and classified the track into two discrete phases (Figure 4), i.e. the moving and resting phases.

2.2.3 Behavioral bout summary

Having used the DCRWS to distinguish between resting and moving behaviors, we broke the cheetahs movement track into 'bouts' (i.e., continuous blocks of time that the animal stayed in a single behavior) to calculate total displacement, beeline, duration, and daily speed in each behavioral phase. We then used the exploratory analysis tools, such as boxplot and scatterplot to find any significant observation.

2.2.4 Resting clusters

We have extracted the part of the track that the animal was in resting mode and applied the K-Means clustering. The K-Means clustering requires the number of clusters to be prespecified. However, we wanted to find an optimal number of clusters, thus we employed the elbow method to find best number of clusters (Ketchen and Shook, 1996). The elbow method looks at the percentage of variance explained as a function of the number of clusters: One should choose a number of clusters so that adding another cluster doesn't give much better modeling of the data. Finally, we superimposed the resting locations on top of Google Satellite imagery to add context to it (Figure 5) and to visually explore these resting locations.

2.2.5 Time of day and behavior

The GPS capturing intervals were fixed at 8 hours and the locations timestamps were at 00:00 , 08:00, 16:00. We computed the contingency table of time of day and behavioral classes, in order to find when the cheetah tended to rest or move. Figure 3 shows that the cheetah was more in the moving mode from 00:00 to 16:00, however the frequencies of being in each mode were roughly equal in the evening, i.e. from 16:00 to 00:00. We also ran a Chi-square statistical test on the contingency table to check whether they were independent.

3 Results

Using the 0.55 threshold, the DCRWS classified the movements into two clear states (Figure 4). The resting state had near zero step lengths and a nearly uniform turning angle distribution. The movement state was characterized by gamma step length mean 0.39 (se=0.09) and standard deviation of 0.3 (se=0.07) and more clustered turning angles (von-Mises clustering concentration 0.97 (se=0.23)

The K-Means clustering with the elbow method grouped the resting locations to 8 groups Figure 5. The ratio of between sum of squares to the total sum of squares was 97.4%. Visual inspection of the resting locations on top of satellite imagery showed that they were associated with the mid range elevations.

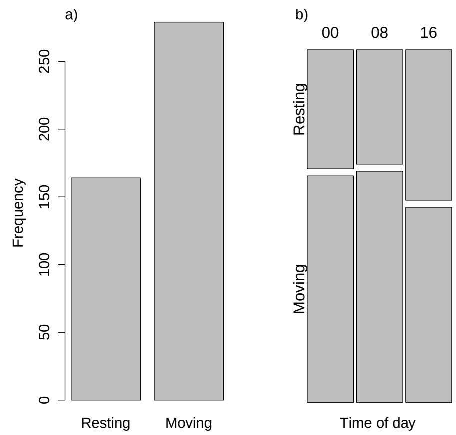

Figure 3: **a)** The cheetah was more in the moving mode rather than the resting mode; this could be due to the harsh situation in the arid environment of Bafq desert and the pursuit of prey by the cheetah. **b)** The frequency of being in each behavioral state indicated that the cheetah tended to be in moving phase from 00:00 to 16:00, although the frequencies of being in both movement phases are roughly equal in the evening (16:00 to 00:00). The Chi-square goodness of fit test was not significant.

we also found one extreme observation (excluded from the above summaries) during which the cheetah continuously moved 130.1 km for a duration of 352 h (14 days), ultimately returning to a location close to its starting location (beeline 3.5 km) with a daily speed of 8.9 (km/day) (Figure 6).

We found no significant difference in the probability of being in either state across time of day (00:00, 8:00, 16:00) (Chi-squared = 4.0657, df = 2, p-value = 0.1310, Figure 3).

4 Discussion

In this paper we examined the movement track of a Asiatic cheetah, a rare cat, hardly found in fragmented habitat of Iran deserts. We used the framework of first differenced correlated random walk to estimate the probability of the animal being in the moving mode. We then classified the track based on a predefined threshold (0.55) into two distinctive behavioral mode, also known as resting and moving modes.

Asiatic cheetah is a very agile and mobile animal. It tends to walk hundreds of kilometers to find a suitable habitat. The data at hand, was for a relatively short period of time (4.5 months), however the cheetah still showed significant mobility. This was evident from the classification of the track of the cheetah into two distinctive behaviors; the cheetah was more in moving state Figure 3a. The central region of Iran, Bafq, has a very harsh and arid environment. The cheetah's mobility could be related to this situation, which forces the animal to move, in order to find food and water. The steps that the cheetah took to find a convenient location for resting was important, however the locations where the animal selected for resting, were of interest.

In a very exceptional event, the cheetah entered into moving phase for straight 14.5 days and traveled 130 km within the same reserve. A detailed examination of this move bout showed that the cheetah was commuting between 3 hotspots multiple times in the north-west and central parts of its home-range, likely looking for

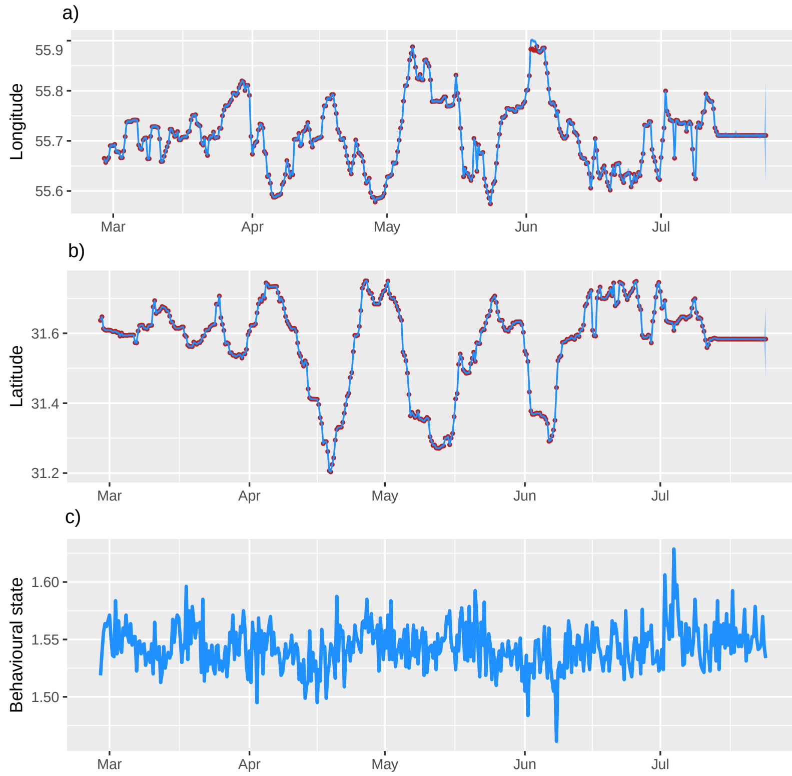

Figure 4: **a,b)** The longitude and latitude profiles could be used as a mean to visually inspect the changes in the both direction to check whether the animal is moving or resting; a useful plot to compare with the estimated behaviours from the DCRWS framework. **c)** For each location, DCRWS assigns the probability that the cheetah was in a resting (probability close to 1) or moving (probability close to 2) behavioral state according to its speed and turning angle.

hunt, though without any success. This is another evidence of an unsuitable habitat for cheetah, and the shortage of sufficient prey (Figure 6).

We also superimposed the classified track on the satellite imagery to add context to the cheetah's movement and superficially showed that the resting clusters of the cheetah locations were associated with the mid-range elevation habitat. This indeed should be examined more carefully using other statistical approaches such as logistic regression. The habitat features of the identified 8 resting clusters in this study should be explored to see why the cheetah is attracted to these locations (Figure 5).

We computed the frequency of the animal, being in each state. The results verified that the cheetah was more in moving state and this could be due to the harsh environment of Bafq deserts and the lack of prey and water in this area. We then computed the contingency table of the time of day and behavioral states, to find when the animal tended to rest or move. The results showed that the cheetah preferred to move and search for it's prey from 00:00 to 16:00. However, the behavioral pattern in the evening (00:00 - 16:00) was not distinguishable

The next step to this analysis is to link the estimated behaviors to environmental data and find the significant drivers of the movement and individual behavior. The attachment of environmental variables, such as temperature, elevation, and human infrastructure could be either done by using the Env-Data Dodge et al.

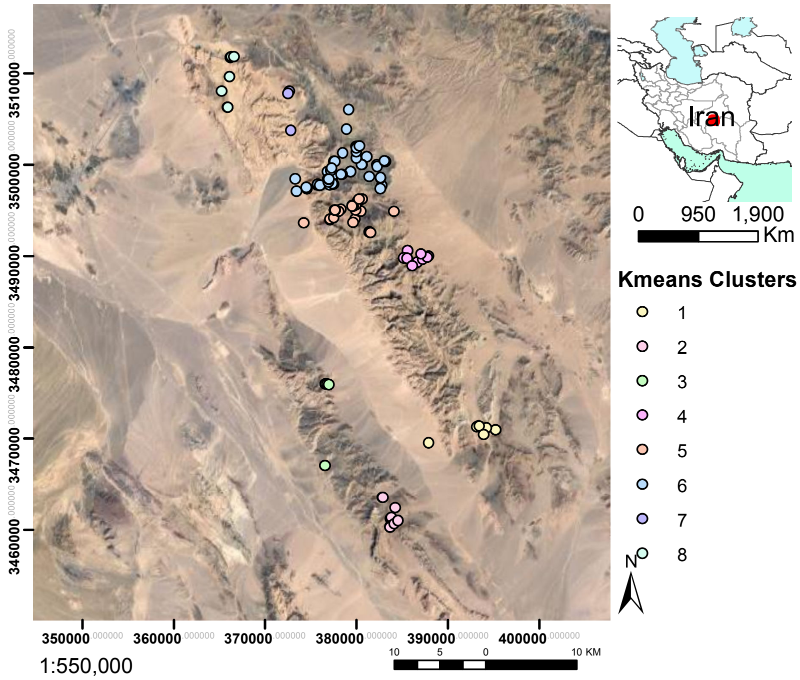

Figure 5: The estimated resting clusters, using K-Means clustering, superimposed on top of Google satellite imagery.

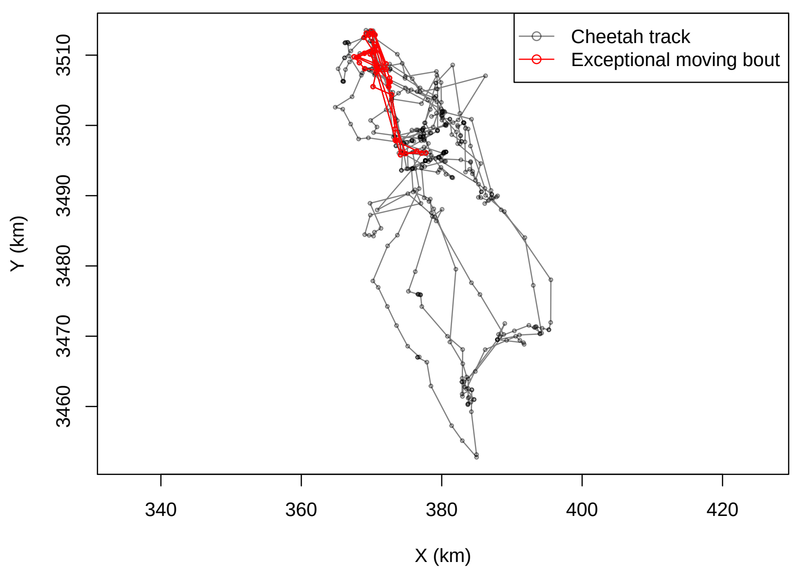

Figure 6: In a very exceptional event, the cheetah entered into moving phase for straight 14.5 days and traveled 130 km within the same reserve.

(2013) or manually downloading and extracting the environmental data from remote sensing products. For an animal like cheetah, with relatively small scale movement, the latter would be a more reasonable approach, because the resolutions of the remote sensing products that the Env-Data uses are coarse. Incorporating context into the behaviors which were estimated in this research, opens a whole new avenue to the analysis of the cheetah movement.

5 Acknowledgements

We thank United Nations Development Programme (UNDP) and Iran department of environment (DOE) for the funding of the project data; conservation of Asiatic cheetah project (CACP) for coordination; Wildlife Conservation Society (WCS) for the technology and expertise for the data collection. Specifically we acknowledge Mr. Houman Jokar and Mr. Javad Najafi from CACP, for their cooperation and insightful comments on the Asiatic cheetah ecology.

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A Appendix

A.0.1 JAGS Diagnostics plots

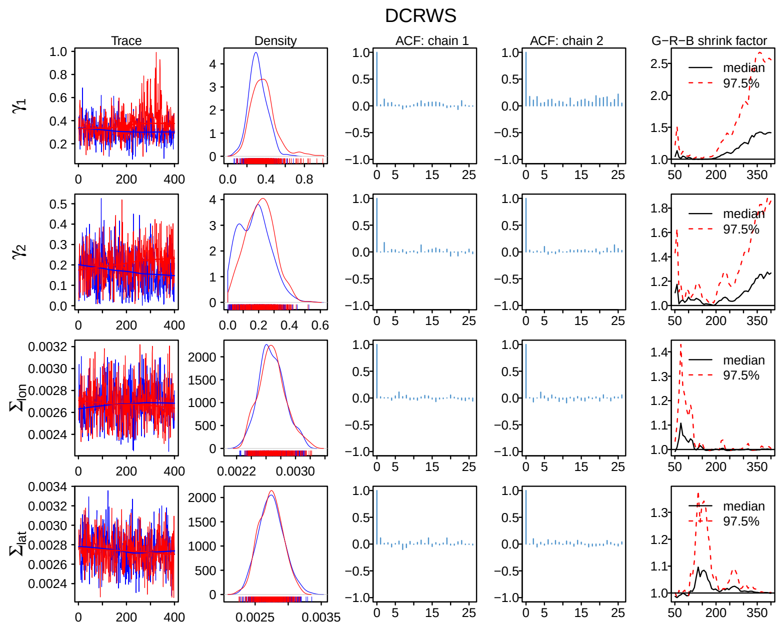

Figure 7: The diagnostics plots of the estimated paramters of the DCRWS model.