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Abstract

The study of animal movement has gained impetus in recent years with improvements in telemetric technologies which enable high resolution tracking, providing researchers with a wealth of animal "big-data". Coupling such movement data with information about the environments in which the animal moves provides a rich data source that can be exploited to understand an animal's rationale for movement, which in turn can be used to extract "rules" that govern movement. The extraction of rules can be done using spatial, statistical and machine learning techniques. Once the rules replicating patterns and predictors of movement have been "discovered", they can be subsequently used to build simulation models (ABMs) to mimic in-silico the behaviours of both individuals and groups of animals. We use field data collected by tracking Red Colobus (*Procolobus rufomitratus*) monkey groups from Kibale National Park, combined with land cover and terrain information, to show how this might be achieved.

Keywords (separated by "-")

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Automated Extraction of Movement Rationales for Building Agent-Based Models: Example of a Red Colobus Monkey Group

AQ1

Raja Sengupta, Colin Chapman, Dipto Sarkar, and Sarah Bortolamiol

Abstract The study of animal movement has gained impetus in recent years with improvements in telemetric technologies which enable high resolution tracking, providing researchers with a wealth of animal "big-data". Coupling such movement data with information about the environments in which the animal moves provides a rich data source that can be exploited to understand an animal's rationale for movement, which in turn can be used to extract "rules" that govern movement. The extraction of rules can be done using spatial, statistical and machine learning techniques. Once the rules replicating patterns and predictors of movement have been "discovered", they can be subsequently used to build simulation models (ABMs) to mimic in-silico the behaviours of both individuals and groups of animals. We use field data collected by tracking Red Colobus (*Procolobus rufomitratus*) monkey groups from Kibale National Park, combined with land cover and terrain information, to show how this might be achieved.

AQ2

Keywords

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1 Introduction

Agent-Based Models (ABMs) have been used extensively to explore the impact of animal movement patterns across space and time and predict environmental outcomes. As an example, ABM simulations of red colobus (*Procolobus rufomitratus*) monkey groups in Kibale National Park, Uganda, suggested that fragmentation of landscapes combined with animal movement strategies allow for the emergence of hotspots for zoonotic diseases [1]. However, the movement rationale expressed in such ABMs have thus far been based on expert knowledge about the behaviour of the Red Colobus monkeys, which were subsequently converted to rules.

With the advent of tracking technologies such as GPS tags, there has been a concomitant rapid rise of animal movement studies generating an enormous volume of valuable tracking data [2]—an example of "big data". This provides a significant opportunity to utilize this widespread availability of movement data and extract the rationale behind the movements, and to convert these into agent-rules. Here, we propose that the availability of such large datasets with high spatial and temporal granularity (both animal and human) can be combined with other GIS data and methods for automated extractions of movement rules. Tested rationales could be preferred habitats, avoidance of high risk predator or disease areas, territorial defense, and social behaviour. This augments the expert's interpretation, which was traditionally based on field observations. Additionally, success in identifying the rationales for movement can be used for parameterization and for calibration of ABM model output [3–5].

2 Extracting Movement Rationales from Data

Over two decades ago, Rodgers & Anson [6] had prophetically suggested that "GPS-based animal-location systems will set a new standard for habitat-resource utilization studies of large animals over the next five to 10 years". This availability of high resolution movement data, particularly those collected via GPS telemetry (i.e., sequence of GPS locations), has given rise to the field of "movement ecology" [7]. Additionally, the Max Planck Institute of Ornithology has developed a free online database, Movebank (movebank.org) that allows researchers interested in animal movement to "manage, share, protect, analyze, and archive their data". Current studies range from estimating the home ranges of animals to understanding the space use and detailed movements of animals [8]. Furthermore, new methods have been developed to analyze the data to understand the unknown rules followed by the study animals [9, 10]. The broad goal of movement ecology is to study the processes that cause and influence movement in animals [11]. These processes are diverse, with suggestions that individual mechanisms such as spatial memory, internal time measures, communication, and reliance on co-specifics are all factors that underlie movement behaviour [12–15]. Additionally, to coordinate the nature and timing of their activities (including movement), interactions amongst individuals is necessary for most animals living in groups [16]. Since social hierarchies and predation risk varying among individuals and resulting in individual-specific strategies, this further complicates our understanding of movement dynamics.

In its most elementary stage, Nathan et al. [7] suggest that the movement of an individual organism occurs due to the interplay of four mechanistic components: its internal state, its motion capacity, its navigation capacity and external factors. Internal states are difficult to capture solely from "big data" at present. However, we propose that attempts can be made to extract rules about motion, navigation and external (environmental) factors. Motion and navigation, for example, manifest themselves as the direction, magnitude and periodicity of movement, all of which can be extracted from time-series location information [11, 17–19]. Recently, it has been suggested that there are common movement strategies across taxa (although such generalizations can be quickly disputed) [20, 21], further bolstering the argument that motion by itself can be quantified and extracted as rules. Moreover, information about navigation can be gleaned by studying external factors (e.g., land use-land cover, topography) to identify environmental reasons that drive movements (e.g. navigation is controlled by availability of food sources but limited to specific areas due to slope).

New spatial methods have focused on analyzing the relative periodicity and directionality of movement as an important and integral part of a broader framework of movement-related studies in GIScience [11, 17, 18]. Specifically, pattern and cluster methods can help identify similarity of movement behavior or locate places of repeat interaction or use [22]. Understanding these "episodal movements" are critical to capture repeat patterns in the behaviour of a moving point object [17, 23]. When integrated with distance, it can also provide information about similarity of movement patterns for a pair of moving objects.

Additionally, several applications have been coupled with spatial analysis methods to provide a better understanding of animal behaviours from an ecological perspective [24–26]. Very useful software packages have been built to exploit information from telemetry-based movement data combined with spatial (GIS-based) datasets (e.g., datasets on percent canopy cover, elevation, water bodies etc.). For example, Geospatial Modelling Environment [27] analyses animal movements considering the surrounding ecosystem, and allows these movements to be decomposed into component localized movements that can be correlated with environmental or habitat information. Such specialized open source software augment the analysis provided by traditional GIS methods. Importantly, they allow researchers to understand the movements in the context in which they are occurring (e.g., fragmented landscapes with or without corridors). The Environmental Data Automated Track Annotation System (EnvDATA) within Movebank is one such software that allows environmental data obtained from remotely sensed satellite information to be attached onto Movebank's data locations [11, 28]. This then facilitates a greater understanding by allowing the movement to be contextualized with respect to the environment in which it occurred.

3 An Example of Red Colobus (*Procolobus rufomitratus*) Monkey Group Movements in Kibale National Park, Uganda

To simplify movement rationale, we seek to consider three main drivers of movement patterns: (1) availability of food resources, (2) social factors (e.g., territoriality, mating opportunities), and (3) predation risk. Additionally, several external and observable factors (e.g., percent canopy cover, elevation, water bodies) can be considered while determining movement behavior. This allows predicting the percentage of the variation in movement patterns explained by each driver. Such variation can then be used to derive rules that may be pertinent to deciphering movements in a variety of contexts.

In order to demonstrate how automated rule extraction for ABM development could proceed, we analyze a 1.5 year snapshot (30 March, 2011–15 Sept, 2012) of a red colobus monkey group movement in Kibale National Park (KNP), Uganda (Fig. 1). The dataset includes sighting location co-ordinates by continuously following one group of red colobus monkeys living inside KNP on a daily basis. The GPS points were collected every 15 min by a research assistant located amidst

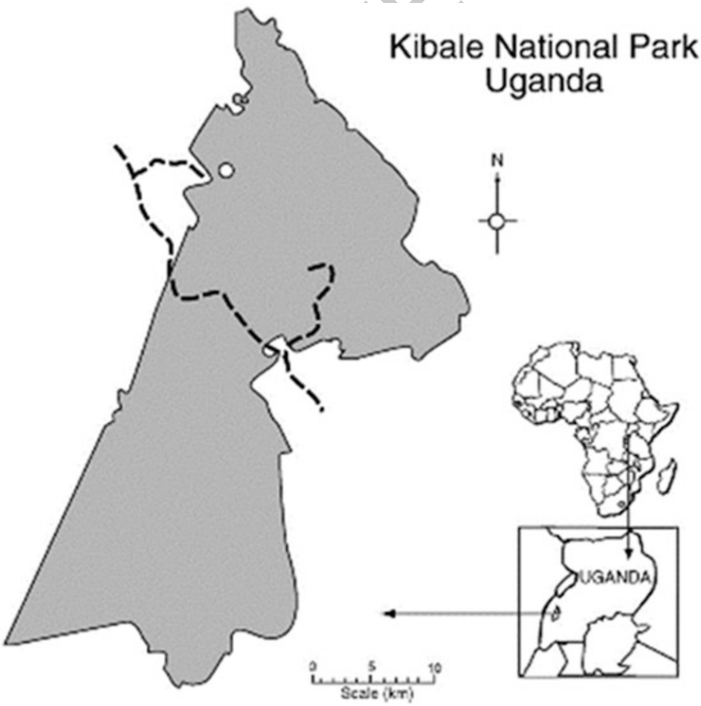

Fig. 1 Location of study area: Kibale National Park, Uganda

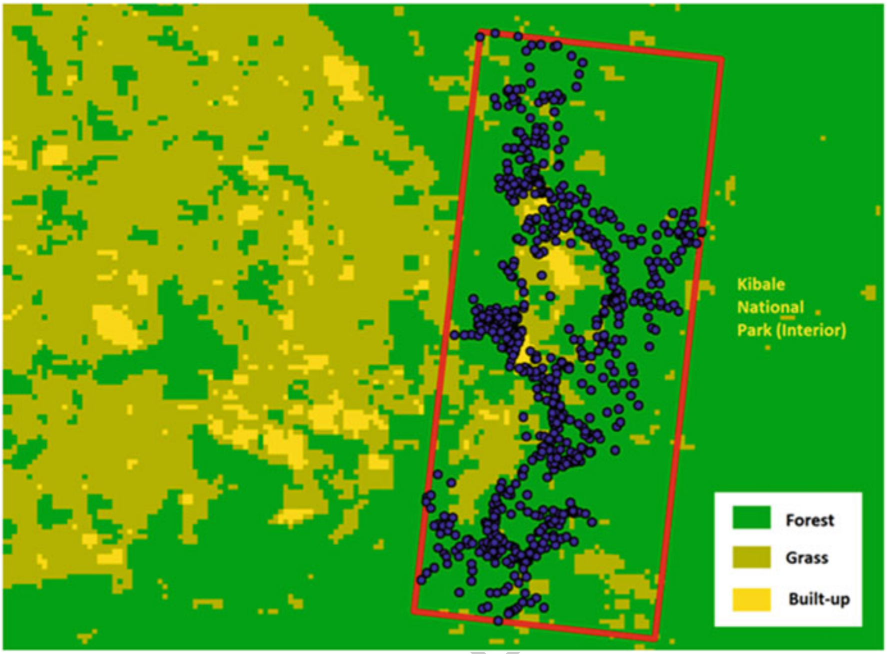

Fig. 2 Distribution of Red Colobus observations (girded by a Minimum Bounding Rectangle)

members of this group. A total of 743 observations were collected in this time period (Fig. 2), and all observations fall within an approximately 600 m × 1500 m bounding rectangle highlighted in red. Also red colobus are not territorial, they are relatively small size mammals and live in social groups that do not move in search of mates [29]. Further, this set of points were selected for analysis because of their relative continuity (i.e., lack of gaps in data collection), and because of the fact that no predation was observed during this period. This is important because predation can significantly alter movement characteristics in red colobus [30, 31]. Thus, all movement seen during this period is likely solely because of foraging strategies employed by the group.

To direct this work, movement rationales were broken down into two categories, one related to the movement itself, and the other to underlying environmental factors controlling movement. For the first category of "movement rules", characteristics of movement such as initiation, distance, and direction can be extracted from the analysis of big movement data and used to suggest an agent's probable motion. The second, "constraining rules" analyze if the new location proposed by "movement rules" is viable based on environmental factors. Hence, questions relating to the two categories can be specified as (Fig. 3):

Movement rules: How frequently does the group move? And once the group is in motion, how far and in which direction does it move?

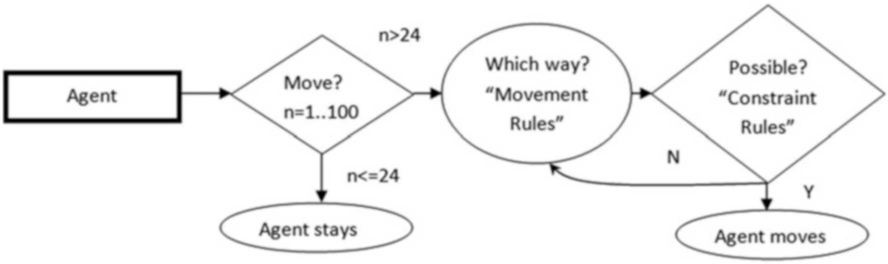

Fig. 3 Decision-making steps taking by an agent based on "movement" and "constraint" rules

Constraining Rules: What is the most common environmental factor (e.g., percent canopy cover, elevation, water bodies) that puts spatial bounds on the groups' observed location?

Movement Rules: How frequently and which way (distance, direction) does the group move?

During the period of observation (taken every 15 minutes), the group moved 76.03% of the time, and was consequently stationary the rest (23.97%) of the time. Overall, the group's movement was normally distributed (Fig. 4) with a mean of 29.5 m and a standard deviation of 27.86 m. However, there were longer transects up to 303 m during the observation period. These infrequent yet important longer movements show up in a detailed time series analysis of movement data [32], particularly via a spectral analysis where the periodogram shows a prominent seasonal trends every ten readings (Fig. 5). There was no observed correlation between frequency and distance of movement.

To convert these analyses into "movement rules" governing motion of agents (where the agent is the group), three components of any movement can be considered: initiation, distance and direction. Initiation, which is the start of a movement following a sedentary period, should be proportional to the time where movement was observed (76.03%). For this study, this can be controlled via a rule that depends on a random function, e.g., pick an integer between 0–100, and initiate movement if the random number exceeds 24 (Fig. 3). An additional rule can then randomly select the distance to move as a function of the mean and standard deviation of observed data (i.e., the normally distributed observations as seen in Fig. 4). It should also allow for longer transects to be included cyclically every ten time steps (and with some randomness of $\pm$1–2 time steps, as evidenced by the spectral analysis in Fig. 5). An analysis of the direction of movement did not yield any prominent trend for this dataset, i.e., there seems to be no specific preferences (Fig. 4). The direction of movement can therefore be randomly selected to be from 0 to 359°. Together, these rules specify the initiation, distance and direction of movement as a function of observed parameters.

Constraining Rules: What are the most common environmental factors (e.g., percent canopy cover, elevation, water bodies) that puts bounds on the groups' motion?

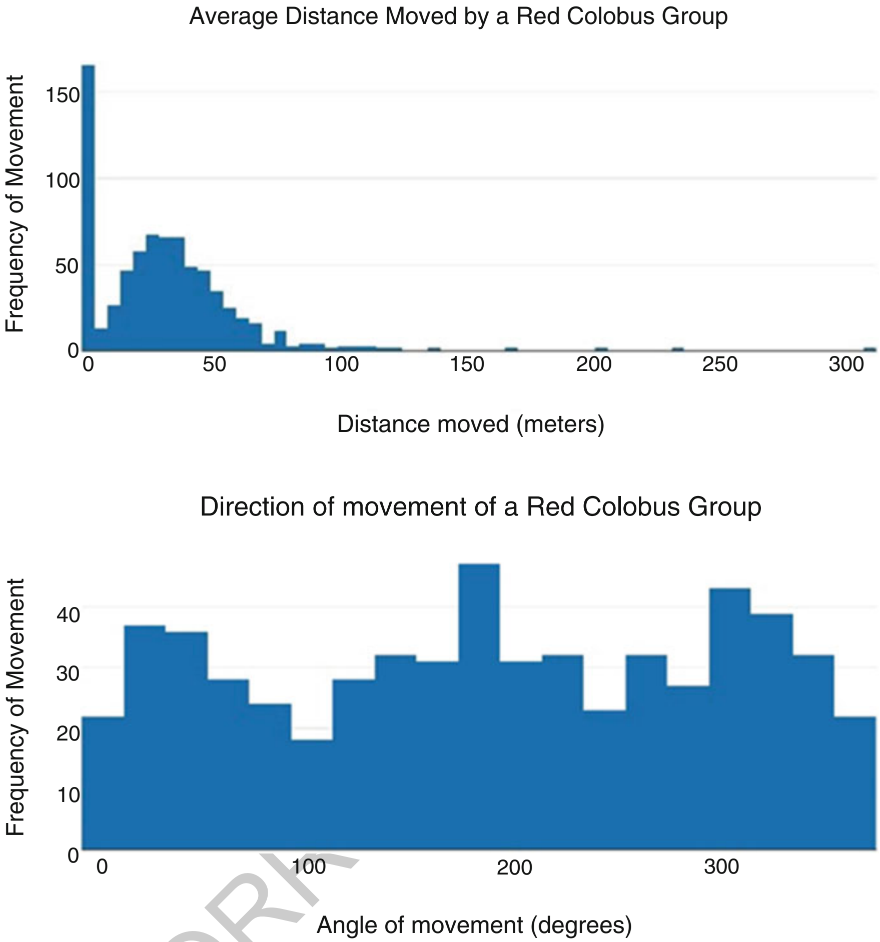

Fig. 4 Distribution of movement frequency of Red Colobus group

The "movement rules" derived by analyzing the data on when, how far, and in what direction the animals moved can readily be used to inform agents in an ABM. However, there is no check to see whether the move itself would be possible in a real-world setting. For example, movement rules may suggest a location far away from a forest edge as they do not consider land cover, but in the real-world the group may never move there due to safety concerns and other factors. Environmental factors such as availability of food and water resources, and other constraints such as elevation, often limit the exact movement strategies of most species, including the red colobus. We therefore propose a set of additional "constraining rules" that evaluate the appropriateness of the new location for the agent based on environmental characteristics (Fig. 3). These rules act as a check on the directional rules generated above, i.e., if the suggested "new" location for an agent group does

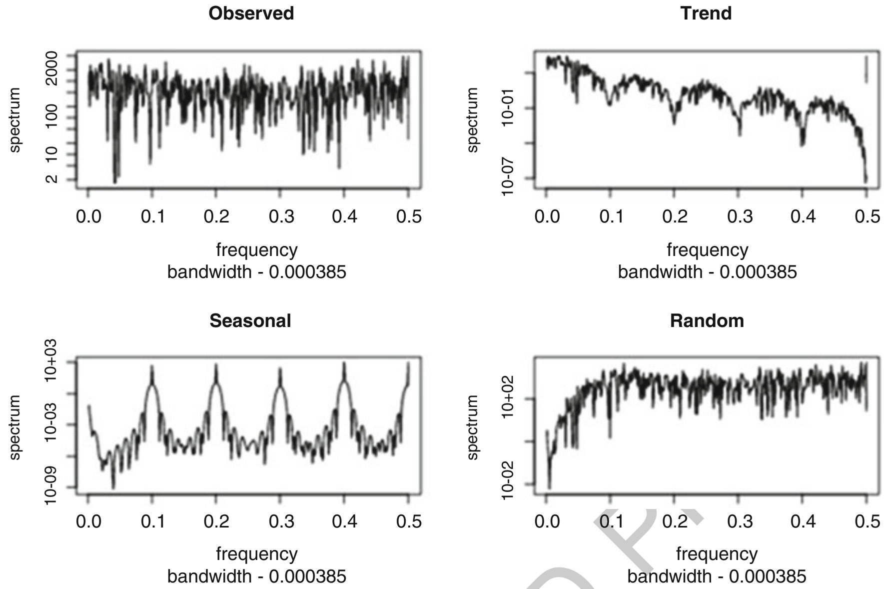

Fig. 5 Seasonality detected in the periodogram indicating pattern in movement trends [32]

not meet the criteria generated from analysis of environmental characteristics, then the agent is not allowed to move, but a new movement rule is generated. The agent is only allowed to move IF the new location proposed by movement rule meets the criteria of environmental factors, as specified below.

To evaluate the controls exerted by environmental factors, we selected a group of GIS-based layers guided by expert knowledge about common ecological constraints [33, 34] on the red colobus groups. These were analyzed using ArcGIS 10's Spatial Analyst functions [35]. Specifically, we utilized a land cover (LC) map (obtained from supervised classification of SPOT imagery; classified as Forest, Grass/Swamp and Built up areas) as well as a Digital Elevation Model (DEM of 90 m resolution, obtained from the SRTM Shuttle Radar mission) of the study area. Following analyses were conducted using the base information: (1) extract a raster layer indicating distance (in meters) away from open areas (i.e., Grass/Swamp and Built-up; as specified in the reclassified SPOT image); (2) derive slope in degrees from DEM using the "Slope" function; and (3) associate the values from these four raster layers (LC, DEM, distance raster, and slope) with the 743 point observation locations. The last step stores the extracted values of the four raster layers in four corresponding attribute fields for each of the 743 observation locations: LULCVAL with values 0-forest 1-grass/swamps, 2-built-up areas; DEMVAL; DISTVAL; and SLOPEVAL.

To test if there are indeed environmental controls on movements, a data mining software Weka 3.8 [36], and its M5 pruned model tree with default values, was utilized. The M5 is a decision tree classifier with linear regression functions at the

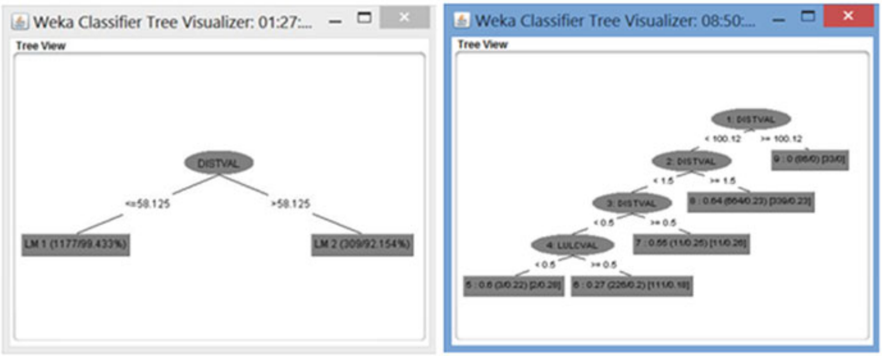

Fig. 6 (**a**, **b**) If the random points generated are restricted to the bounding rectangle in Fig. 2, distance from open areas (DISTVAL) <58.125 is the only variable controlling the location of observations. Comparing to a larger set of random points, the observed Red Colobus locations are <100.12 m from open areas, and always located in forested areas (LULCVAL of 0; LULCVAL <0.5)

leaves [37, 38]. If a presence/absence dataset is provided to it, it can generate a decision tree that "classifies" the presence/absence (dependent variable) as a function of the independent variables—which in turn are selected using linear regression at the leaf level. To run the classifier, an additional 743 random points were generated as "absence points" (using a "create random points" function) that serve as the null hypothesis. As with the 743 observation locations (now denoting "presence"), values from the four environmental layers (LC, DEM, distance and slope) were also associated with these newly generated random points. The dependent variable is now denoted by a 0 for random/absence and 1 for presence.

Initially, the "absence" points were randomly generated within the red bounding box, as this was assumed to be the region of occurrence for the Red Colobus group (Fig. 2). The resulting decision tree (shown in Fig. 6a) suggests that a distance of less than 58.125 meters from open areas (grass/swamps and built up; DISTVAL <58.125) is the only deciding factor in the location of the monkey group. The "constraining rule" therefore is that an agent (representing the Red Colobus group) is allowed to move to a new location only within 58.125 m of open areas. Else another movement rule has to be fired, specifying a new distance and direction of movement. However, this single constraint of within 58.125 m produced by Weka 3.8 may be a result of constraining the random points to within the bounding box, where most of the land cover is forest (87.3% of observed locations, and 83.9% of the randomly generated points fell on forested areas). Given the fact that the Red Colobus group is not really territorial [29], a larger area was subsequently considered.

The consideration of a larger area (Figs. 6b and 7) suggested a more complex picture, with a distance of <100.12 m from open areas being considered the threshold for locations visited by the monkey group (the randomly generated points,

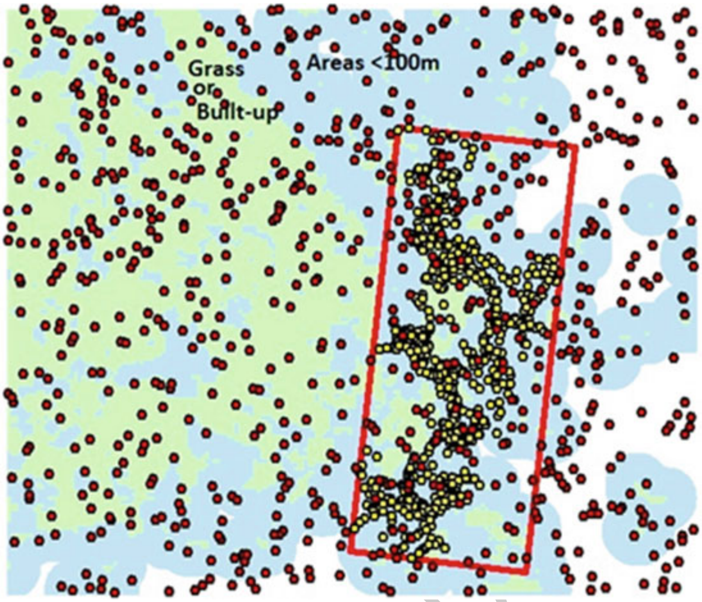

Fig. 7 The observed Red Colobus (*Procolobus rufomitratus*) (*yellow dots*) and random (*red dots*) locations superimposed on grass/built-up areas (*light green*), and areas <100 m (*light blue*) from them

on the other hand, were located at distances >100.12 m). Additionally, the actual Red Colobus observations were located inside forested areas (an LULCVAL of 0 indicates forests; with the decision tree suggesting that LULCVAL <0.5 indicates observed Red Colobus locations). This analysis indicates that any movement by the Red Colobus (*P. rufomitratus*) group must occur in forested areas that are within 100.12 m of grass and built-up areas, which are basically the forest edges (Fig. 7). The related constraining rules are therefore: allow the move (as specified by the highest value of 0.6 in Class 5; Fig. 6b) if the new location is less than 100.12 m from forest edge (DISTVAL <100.12) and is located on a land cover value of 0 (LULCVAL <0.5).

4 Future Possibilities

As the availability of "big data" collected at a high spatial and temporal resolution grows, it opens up options for its analysis with spatial, statistical, and data mining and learning techniques to develop and refine the rules governing movement in ABMs. Movebank, for example, included data from 2484 studies across 548 taxa, and from 303 million locations. This represents an enormous wealth of data on animal movement patterns across species, spatial and temporal scales, and landscapes. It also opens the door for detailed analysis of the patterns and rationale for movement across numerous species, functional groups, habitat, landscapes, disturbance regimes, etc. Specifically, it becomes possible to derive rules that control the initiation, motion and navigation of individual agents, as well as to place constraints on the plausibility of certain movements. The attempts herein to develop standard methodologies using statistics and machine learning to extract rules from observational data meshes well with concurrent work elsewhere to automatically extract movement rules, as well as calibrate motion in ABMs [3–5]. In the future, such automated extractions are expected to replace or augment the heuristic knowledge of experts regarding animal movement, which had hitherto been the standard method for deriving rules [1, 26, 39, 40]. As a consequence, the future of ABM model development and calibration may increasingly depend on the extracting of meaningful patterns from a significant source of movement data. We provide one way forward towards achieving this objective by developing automated methods of extracting movement behaviors as "movement" and "constraining" rules, and representing the agents movement as an interplay of these two sets of rules.

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