Highlights

An Agent-Based Model of Elephant Crop Raid Dynamics in the Periyar-Agasthyamalai Complex, India

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- Developed a new ABM with parameters tuned using relocation data and validated with field data
- Emergent conflict patterns are governed by starvation in the forest, thermoregulation needs and aggression
- Crop habituation emerges as a driver for crop raids even in seasons with food abundance
- Thermoregulation emerges as a counter-intuitive factor for reducing conflict in dry/hot months

An Agent-Based Model of Elephant Crop Raid Dynamics in the Periyar-Agasthyamalai Complex, India

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ABSTRACT

Human-wildlife conflict poses significant challenges to conservation efforts around the world and requires innovative solutions for effective management. We developed an agent-based model to simulate complex interactions between humans and Asian elephants in the Periyar-Agasthyamalai complex of the Western Ghats in Kerala, India. Incorporating factors such as crop habituation, thermoregulation needs, and aggression models, this framework enables the evaluation of various experimental scenarios to quantify elephant behaviors and the resulting conflict situations. The ODD protocol, the various cognition models and environmental factors are provided in detail. We simulate different scenarios of food availability to analyze the behavior of elephant agents and assess the influence of environmental factors on space use and emergent conflict patterns. Validation is performed using field data from the region, and elephant movement parameters are tuned using relocation data. Through extensive experimentation, we show that wet months consistently exhibit increased conflict. Furthermore, the experiments reveal that thermoregulation requirements act as a crucial driver of elephant space use, which subsequently influences crop raid patterns. Our findings show how starvation drives wildlife toward crop damage, while crop habituation further exacerbates raid patterns, particularly in regions with limited forest food resources. This agent-based model offers valuable information to develop an intelligent decision support system for wildlife management and decision making.

1. Introduction

Communities residing in the forest fringe areas face a significant challenge: human-wildlife conflict. This problem is exacerbated by the degradation of habitats and the competition for resources such as space, food, and water [1]. The human burden of the conflict is mainly on marginalized communities that live close to the fringe. These conflicts result in human casualties, crop and livestock losses, and property damage [2]. In addition to direct costs, there are also hidden or indirect costs, such as food insecurity, financial insecurity, disruption of daily life, fear, anxiety, and additional expenses associated with the implementation of mitigation strategies [3, 2]. Wildlife are impacted by challenges from lack of food to threats to their long-term survival [4].

The main computational models for studying the human-wildlife conflict problem are the Equation-Based Model (EBM), the Game-Theoretic Model (GTM), and the Agent-Based Model (ABM) [5]. EBMs are generally used for a broad understanding using simplifying assumptions (e.g., predator-prey models [6, 7]). GTMs such as green security games have been applied in the conservation domain to mitigate poaching and learn the ranger strategy [8, 9]. GTMs are also very useful as a second level of decision-making when combined with EBMs or ABMs. ABMs are a versatile modeling framework that offers more flexibility in representing and capturing the heterogeneity of complex systems compared to EBMs [5, 10]. This is particularly relevant for modeling individual-level differences, social structures, and individual and group decision-making. Problems such as human-wildlife conflict, ecosystem resilience, and species resilience to bounce back and stabilize the population from a severely deprecated state can be well characterized and represented in an ABM rather than an EBM. ABMs are well suited to model human-wildlife conflict as its drivers exhibit a wide spatio-temporal variability. The drivers of interactions and conflicts could be external or environmental, as well as internal or behavioral. External drivers include, among others, habitat loss, forest fragmentation, unavailability of food and other resources, proximity to agricultural crops, and competition for resources due to population growth [11, 12]. Internal drivers refer to the behavioral states of the entities involved, for example, the habituation and risk-taking ability of wildlife, the tolerance and cultural perceptions of people towards wildlife, and law enforcement [13, 14, 15]. The temporal patterns of these interactions depend on factors such as the level of human disturbance and seasonality [16, 17]. Additionally, not every interaction between humans and wildlife becomes a conflict. These site-specific drivers of the human-wildlife interaction can be well modeled and characterized by ABMs. ABMs can act

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as a virtual laboratory to experiment and analyze critical interactions in space and time [10].

The present paper develops and applies an ABM to simulate and examine the conflict between humans and elephants in regions where human settlements and crop cultivation are located on the forest fringe. Human-elephant conflict arises when the needs or interests of humans and elephants clash, resulting in antagonistic interactions and challenges in their co-existence. Conflict may arise due to competition for resources such as food, water, and space; and natural or anthropogenic causes could trigger competition. Incompatibility in needs or interests can have negative consequences for either of the parties involved. The conflict does not necessarily imply hostility on the part of either humans or elephants, but instead denotes a scenario wherein their co-existence becomes challenging. In the present work, we focus only on crop damage and infrastructure damage incidents as conflict scenarios.

ABMs have been used extensively to study the problem of human-wildlife conflict [18, 19, 20, 14, 15]. For the human-elephant conflict problem, a predictive model was developed to study the variation in the demographic rates of elephant populations arising from spatio-temporal changes in vegetation [21]. Food availability was approximated by the median value of the Normalized Difference Vegetation Index (NDVI) in the ABM. Although this model captures the variation in available demographic data, the approximation of the entire study landscape with a uniform food value fails to capture the fine-grained behavioral mechanisms of the environment and elephant behavior. A proof-of-concept poaching mitigation strategy model was developed using ABMs in a virtual protected park where multiple poaching and law enforcement strategies were tested [5]. This work demonstrated the utility of ABMs as a useful management support tool in complex scenarios. ABMs have been used to study the anthropogenic and non-anthropogenic determinants of human-elephant interactions under resource scarcity in the Bunda district, Serengeti National Park, Tanzania [10]. An ABM with an integrated dynamic vegetation model was used to assess the impact of climate change on the distribution of elephants in Kruger National Park, South Africa ([22]). The space used by African Savannah elephants based on the availability of critical resources such as food, water, and shade was modeled using a spatially-explicit ABM [23]. This model explored different movement characteristics such as daily net and diel displacements (the total daily distance traveled), home range sizes, and distance from permanent water sources, and concluded that the availability and distribution of water have a major influence on the space use characteristics of African elephants. Using data from Gorongosa National Park, Mozambique, a combinatorial optimization approach was used with an ABM to identify elephant movement patterns and explore space use [24].

However, no previous research has been conducted on the use of ABMs for the behavioral modeling of Asian elephants (*Elephas maximus*) and their interactions with humans on the forest fringe characterized by human settlements and crop cultivation. The objective of the present paper is to develop a generalized ABM to simulate and study human-elephant conflict by taking crop raiding incidents in Seethathode, Kerala, India as a case study.

The elephant agent enters crop farms only in the event of food or water scarcity in the model implemented by [10]. However, this factor is not the only driver and other drivers could result in the movement of elephants into human settlement areas. For example, crop habituation could be a possible reason for the patterns of crop raid activity typically observed on fringes such as Seethathode [16, 25, 26, 17]. Thus, although food may be available in the forest, elephants engage in crop raiding activity due to their preference for the cultivated crops on the fringe. Crucially, the behavioral aspects of elephants, such as aggression and the ability to take risks, play an important role in these raids. The seasonal fruiting pattern and the daily human activity patterns also play important roles in crop raiding activities in Seethathode and similar areas [27, 28, 29, 30, 31, 32]. For example, elephants prefer to raid crops at night when human disturbance is minimal. In the present work, we develop a more comprehensive conflict model that includes these additional factors.

In what follows, in Sect. 2, we describe the field data and the development of the ABM following the standard Overview, Design concepts, Details (ODD) protocol [33, 34, 35, 36]. Next, the experimental setup (Sect. 3), results (Sect. 4) and discussion (Sect. 5) are provided.

2. Materials and methods

2.1. Study area

We focus on Seethathode village in Kerala, India, to develop our ABM. The study area (red box in Fig. 1 (a)) is part of the Periyar – Agasthyamalai landscape of the Western Ghats (green box in Fig. 1 (a)), which consists of two mountain ranges: the Periyar Hills and the Agasthyamalai Hills. The Western Ghats are a range of mountains that run for approximately 1,600 km parallel to India's western coastline, stretching from Gujarat in the north to Kerala in the south. The topography of the Periyar - Agasthyamalai landscape has a wide range of elevations, spanning from approximately 100 to 1800 m above sea level. The Periyar Hills and the Agasthyamalai Hills are separated by the Shencottah Gap, through which the National Highway 744 and a railway line run. This area has numerous human settlements and commercial plantations that lead to fragmentation of the elephant habitats between the Periyar and Agasthyamali forest complexes.

The study area is a square region located between latitudes 9.177^oN and 9.471^oN and longitudes 76.848^oE and 77.146^oE (Fig. 1 (b)). This area was selected to include the forest fringe, the human settlement zone with reported incidents of elephant attacks, and the considerable forest landscape surrounding it. This area is located within the

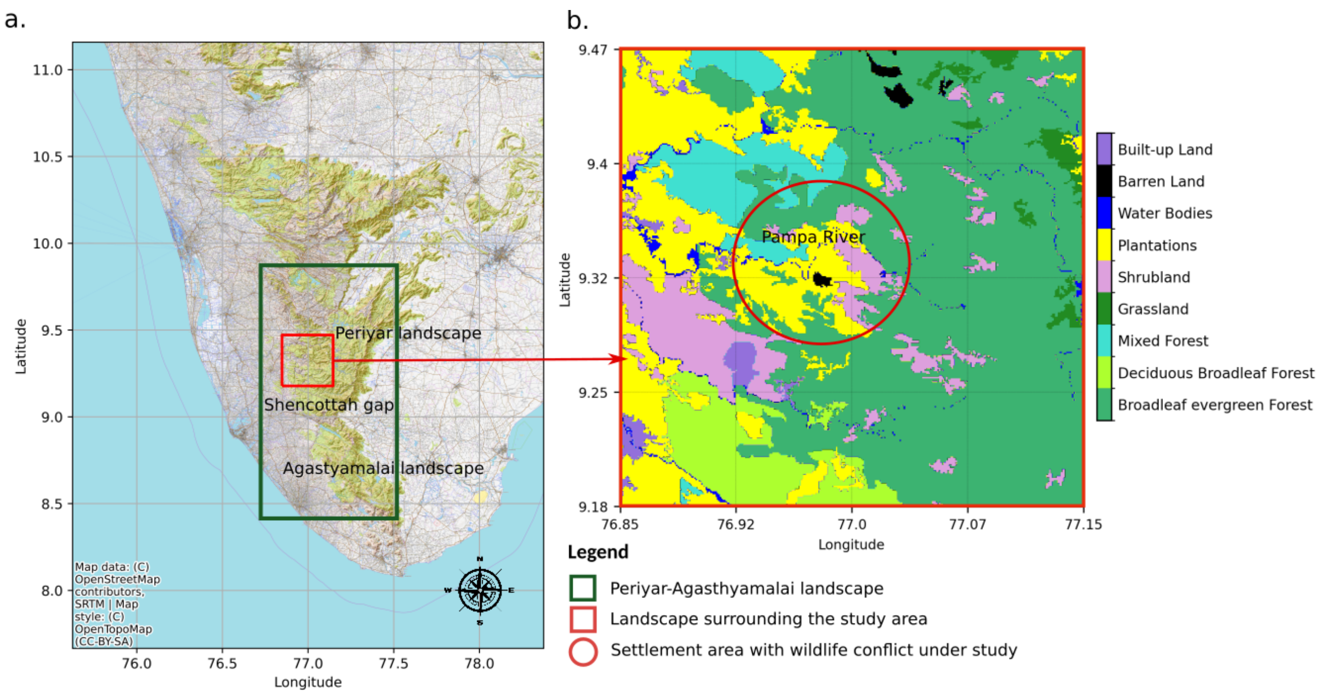

Figure 1: (a) Location of the study area within the Periyar-Agasthyamalai landscape in the southern Western Ghats range. (b) Map of detailed Land Use and Land Cover (LULC) of the study area's landscape.

Ranni Forest Division in the Pathanamthitta district of Kerala (India), which is part of the biodiversity corridor that connects two large protected area complexes to the north and south.

Broadleaf forests and plantations are the main land use categories in the study region. Other categories such as grasslands, water bodies, barren land, shrublands, mixed forests, and built-up land occupy only a small portion of the study landscape. Crop cultivation and human settlements are concentrated in areas designated as plantations (Fig. 2 (a)). Human activities are concentrated in the valleys, resulting in a higher population density in these lowland areas. As the elevation increases along steep mountain slopes, human activity gradually decreases. The terrain (Fig. 2 (b)) poses inherent challenges to movement due to its steep slopes and rugged topography. Humans and elephants traverse the hilly terrain, mainly using relatively flatter and more accessible routes in the valleys or passes for their movement (Fig. 2 (c)).

The agriculture in the region is mainly rubber cultivation, with various fruit crops such as plantain, jackfruit, and mango scattered throughout. The climate seasons are the southwest monsoon (June to September), the northeast monsoon (October to January) and a dry season (February to May). The region experiences heavy rain during monsoons. The Pampa River flows through the region and is a source of fresh water, especially during the dry season.

2.2. Field survey and data collection

The proximity of the plantation area to the forest has led to consistent crop raids by various species of wildlife, such as wild boar, monkeys, and deer, which present recurring concerns. The primary mode of data acquisition involved conducting structured interviews through in-person visits to residential households. During these interviews, the research team collected information on conflicts. At the same time, the GPS coordinates were meticulously recorded, providing precise geospatial references for each surveyed location. Different attributes such as land use types, crops grown, and conflict animals encountered were also collected during the study. The total number of sampling locations was 481, of which 386 faced some competition with wildlife. The data provided relate to conflict incidents that occurred before and during 2010. However, no specific timestamp is available for when these conflicts occurred. Additionally, the data collected were biased due to limitations such as the limited number of interviews conducted and the reluctance of individuals to disclose sensitive information. However, it was widely acknowledged that conflict, as a recurring issue, can potentially disrupt daily life.

Data obtained from the questionnaire survey indicate that opinions on fencing as a strategy to mitigate human-wildlife conflict are varied. Among the respondents, 32% reported using different types of fencing (such as barbed, electric or trench), but only 22% considered it a viable solution overall. It is important to mention that only 12% of the participants who used fencing expressed their support for its wider implementation, indicating possible limitations

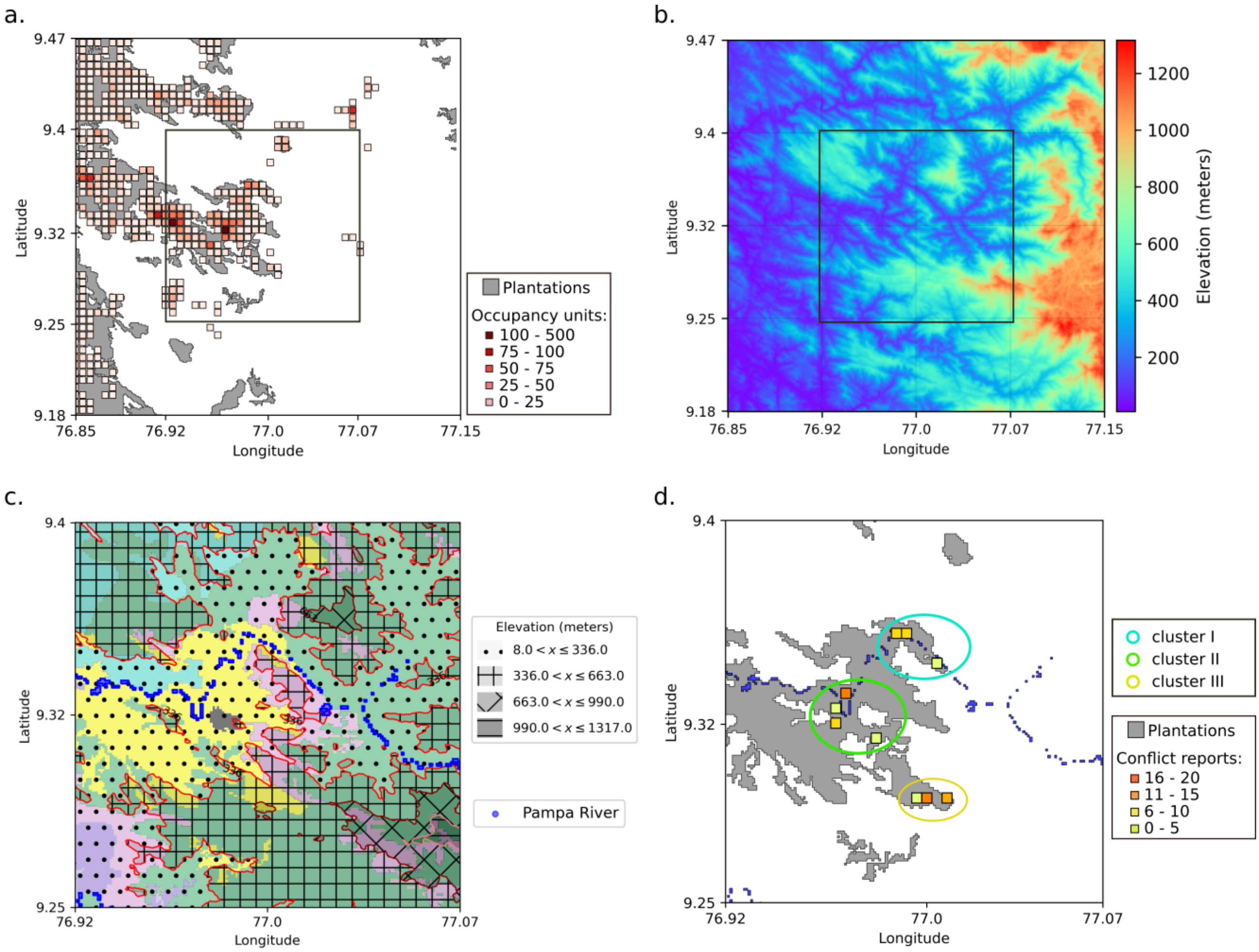

Figure 2: (a) Occupancy/building unit density within the study area. Each cell represents an area of 0.5 km^2. where buildings are present. Buildings are concentrated in areas classified as plantations. (b) The Digital Elevation Model (DEM) of the study area. (c) The elevation contour plot against the LULC map. The Pampa River flowing through is highlighted. The most accessible pathways for elephants are the low-lying regions that connect to plantations and human settlements (elevation: $8.0 < x \leq 336.0$). (d) Identified clusters of human-elephant conflict based on reported incidents. Panels (c) and (d) refer to the square-marked regions in the remaining panels, which specifically highlight the disputed settlement area.

on its efficacy. This highlights the need to explore alternative approaches beyond conventional fencing interventions. The survey also revealed a range of suggested solutions, including non-violent deterrents like using tin sheets to scare animals. Additionally, respondents called for government intervention, community participation, and even extreme measures such as culling of wildlife. Crop raiding was identified as the primary concern among people who reported conflict, followed by concerns about monkey incursions and attacks on domestic animals.

Although conflicts reported by other animal species exhibit a more uniform distribution along the forest fringe, the collected data reveal three distinct clusters of human-elephant conflict concentrated within specific regions of the study area (Fig. 2 (d)). Identification of clusters within the conflict data reported was performed using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN). DBSCAN classifies data points into clusters based on their proximity and density, effectively distinguishing dense regions as clusters while labeling isolated points as noise. The ability of this algorithm to handle varying cluster shapes and sizes makes it well suited for the analysis of conflict data characterized by complex spatial patterns. These identified clusters are used as a baseline for the validation and calibration of our agent-based model. Other conflict statistics extracted from the data were also used for model calibration [see Sect. 2.4].

2.3. Model description

The model description follows the standard Overview, Design concepts, Details (ODD) protocol for ABMs [33, 34, 35, 36]. The model has been implemented using Mesa(v 1.1.1) [37], the ABM framework in Python(v 3.9.13).

2.3.1. Purpose and patterns

Purpose The model is developed as a computational tool to study the spatio-temporal aspects of the human-elephant conflict problem in the forest fringe areas characterized by human settlement and crop cultivation. Specifically, the model is intended to provide insight into how the different drivers of conflict (both behavioral and environmental) on a microscale replicate different patterns of conflict scenarios on a macroscale. The high-level purpose of the model is to serve as an intelligent decision support system to predict how the conflict situation changes with respect to different mitigation measures and changing environments.

Patterns The usefulness of the model was evaluated on the basis of the reproducibility of the following patterns.

1. Emergent space-use pattern of the elephant that is governed by the elephant's cognition model, resource availability in the environment, and the behavioral response of the elephant to the available resources.
2. Emergent crop raid and infrastructure damage incidents that are governed by the distribution of agents, characteristics of the environment, the availability of resources, and models of cognition.

2.3.2. Entities, state variables and scales

Entities Primarily, there are two types of entity present in the model: the elephant agent and the environment (discretized into landscape cells).

Elephant agents Two distinct social structures are found within the populations of Asian elephants, namely matriarchal herds and solitary bulls. The matriarchal herd consists of adult females, and subadult and juvenile males and females. Subadult males disperse from the group after puberty and are mainly grouped as solitary bulls. There are also associations between these groups, which depend on the season, resource availability, competition for food and mates, etc. [38, 39, 40]. Pubertal and adult male elephants were found to take more risks compared to female-led matriarchal herds [41]. Although the pattern of crop raiding varied from place to place, male elephants exhibited more aggression in terms of the frequency of crop raid incidents and per capita damage [41, 42, 43, 44]. The present study focused solely on individual bulls due to their higher propensity to take risks and their greater potential for damage. However, the ideas presented in the modeling of bull elephants could be extended to incorporate matriarchal herds by varying the cognition parameters and modeling the association between individuals in the group, which will be carried out in a future study.

Environment The focus of the study was the examination of spatial characteristics and conflict patterns. Thus, the ABM was designed to be spatially explicit. The environment, which is two-dimensional, is discretized into landscape cells. The movement decision of elephants in each landscape cell is influenced by the landscape characteristics captured by the following attributes.

1. *Elevation-matrix*: This attribute captures the elevation value above sea level in meters in each landscape cell of the study area. It is obtained from a Digital Elevation Model (DEM).
2. *Slope-matrix*: This attribute captures the gradient of each landscape cell in the study area. Since the movement decisions of the elephant agents are dictated by the slope of the landscape, a DEM is used to infer the gradient and make appropriate movement choices.
3. *Land-use-matrix*: This attribute captures the land use class of each landscape cell of the study area. It is obtained from the Land Use Land Cover (LULC) map. This information is used by different sub-models of the ABM to represent the heterogeneity within the landscape. There are 19 different classifications for land use: Deciduous Broadleaf Forest, Cropland, Built-up Land, Mixed Forest, Shrubland, Barren Land, Fallow Land, Wasteland, Water Bodies, Plantations, Aquaculture, Mangrove Forest, Salt Pan, Grassland, Evergreen Broadleaf Forest, Deciduous Needleleaf Forest, Permanent Wetlands, Snow and Ice, and Evergreen Needleleaf Forest. Of these, the study area has only 9 land use classes (Fig. 1 (b)).
4. *Food-matrix*: This attribute captures the amount of food available to the elephant agents in each landscape cell of the study area. This information is used by elephant agents to make foraging and movement choices to satisfy their dietary requirements. The *food-matrix* is updated if the elephant agent consumes food while present in that cell.
5. *Water-matrix*: This attribute captures the amount of water available in each landscape cell of the study area. This information is used by elephant agents to satisfy their thermoregulation requirements. Each cell is a binary value that indicates whether or not a water source is present in the cell. Unlike the *food-matrix*, it is assumed that the quantity of water does not decrease with its consumption by an elephant agent.
6. *Proximity-maps*: This attribute captures how close each landscape cell is to a particular category of land use. Specifically, three different proximity maps are used: proximity to plantations, forests (Deciduous Broadleaf Forest, Mixed Forest and Broadleaf Evergreen Forest), and water sources. The magnitude of each cell of the matrix represents the proximity to that type of land use. These three maps are used in the decision-making process of the agent cognition model.
7. *Agricultural-plot-matrix*: This attribute captures the presence or absence of agricultural plots in the landscape cells. This information is used with a probability of damage to assess conflict scenarios.
8. *Building-matrix*: This attribute captures the presence or absence of buildings in the landscape cell. This

information is used with a probability of damage to assess conflict scenarios.

9. *Temperature-matrix*: This attribute captures the spatio-temporal changes in the temperature values of each landscape cell in the study area. This information is a crucial component in the decision-making process of our model and is utilized in multiple submodels of the agent behavior and environmental interactions.

State variables

Table 1 lists the 29 state variables of the elephant agent, and Table 2 lists the 9 state variables of the environment used to characterize the entities in the model. The state variables *fitness* and *aggression*, and the behavioral state *thermoregulation* are defined below.

The *fitness* of the elephant agent is directly related to its energy stores and its ability to survive. In the simulation, the agent's *fitness* is measured on a scale of 0 to 1. A *fitness* value of 0 indicates death, while a value of 1 indicates maximum health.

The *aggression* level of the elephant agent serves as an indicator of its willingness to take risks and venture into plantations for crop raiding. This metric measures the probability that the agent chooses riskier cells near plantations on a scale of 0 to 1, either when there is a shortage of food in the forest or when it has adapted to crops and there is an abundant food supply in croplands.

Thermoregulation in elephants: Mammals like elephants have less surface area available for heat dissipation due to their larger body size. Therefore, thermal stress and thermoregulation play a very important role in elephant ecology, especially in areas of high ambient temperatures [45, 46, 47]. Thermoregulation refers to the requirement of elephants to maintain their core body temperature at a constant level at all environmental temperatures. In our ABM, thermoregulation actions of shade seeking/resting and moving towards or visiting a water source are considered.

Scales

1. **Spatial scale**: The simulation was carried out on a landscape area of 1100 km^2, discretized into cells of 30×30 m. This spatial scale was chosen to accurately capture the scales at which elephants might make movement decisions [23].
2. **Temporal scale**: The temporal scale of the simulation was set at 5 minutes to match the spatial scale choice. This fine resolution also helps capture interactions with human agents (not included in the present study). Furthermore, movement data were available at this resolution to calibrate our movement model.

2.3.3. Process overview and scheduling

The process scheduling was reached through an iterative modeling process involving expert opinion, an extensive literature survey including academic publications and newspaper articles, and the rationality and understanding of the modelers. The drivers of conflict could be multiple. We attempted to build a comprehensive model that accommodates the multiple drivers of conflict and tested the model against the various patterns expected under the given ecological and psychological conditions. The most challenging part of the model development was approximating the elephant agents' cognition and determining the most important processes within its decision-making scheme. The elephant agents' process scheduling was finalized to be of the following order after a thorough study involving conceptual as well as experimental analysis:

1. Set the food goal for the agent according to its body weight at the beginning of the day. If the previous day's food goal was not satisfied or the elephant did not visit a water source, update its fitness accordingly.
2. If the elephant agent senses a danger to its life, handling this situation becomes the priority (*escape-mode*. If there is no danger to life, then the elephant agent proceeds with its activity (*foraging*, *thermoregulation* or *random-walk* mode).
3. If the elephant agent moves into a plantation or building cell, it inflicts some damage based on the corresponding damage probabilities.
4. The elephant agent consumes food and drinks water if it encounters a food or water cell.

Furthermore, the four different activity modes (*escape-mode*, *thermoregulation*, *foraging* and *random-walk*) and the corresponding subprocesses were designed to confirm with the patterns and observations reported by the sources mentioned above and validated through experimental analysis and is assumed to be the best approximation the modellers could arrive at keeping in mind the model complexity and computational cost.

Table 3 lists the 6 processes in the ABM and Fig. 3 shows the schedule of these processes. Of these, the 'activate agents' process triggers the processes associated with the elephant agent. Table 4 lists the 21 processes in the elephant cognition model, and Fig. 4 shows the scheduling of these processes.

2.3.4. Design concepts

Basic principles

The following are the general concepts used in model design:

1. The elephant agent's movement pattern and space use reflect the mountainous terrain of the study area. Specifically, slope and natural barriers that restrict movement are taken into account. The movement is either in an *exploratory* or *encamped* state as reported in the literature.
2. The optimal foraging theory is used to satisfy the daily dietary requirements and corresponding movement choices. Changes in elephant behavior with the changing external environment (food abundance and scarcity scenarios) are also considered.

Table 1
The elephant agent's state variables

Parameter	Description	Type	Range	Unit
unique-ID	Unique identifier of the agent, special name containing numeric and non-numeric characters (static)	string		
age	Age of the elephant (dynamic)	integer	15 to 60	Years
body-weight	Body weight of the elephant (dynamic)	float	3250 to 4000	kg
daily-dry-matter-intake	Daily dry matter dietary requirement of the elephant (dynamic)	float	48.75 - 76	kg
knowledge-from-fringe	The distance from the forest fringe where the elephant knows food availability (static)	float	0 - undefined	meter
percent-memory-elephant	The percentage of landscape cells known to the elephant in terms of food and water availability at the start of the simulation (static)	float	0 - 100	percentage
(current-lon, current-lat)	Current location of the elephant (dynamic)	tuple of floats	Extent of the simulation area	Longitude and Latitude in WGS84*
(next-lon, next-lat)	Location to which the elephant moves next (dynamic)	tuple of floats	Extent of the simulation area	Longitude and Latitude in WGS84*
mode	Current mode or behavioral state of the elephant (dynamic)	string	*random-walk* / *foraging* / *thermoregulation* / *escape-mode*	
p_t	Thermoregulation probability (dynamic)	float	0 - 1	
thermoregulation-threshold	Temperature value above which the elephant engages in *thermoregulation* mode (static)	float	0 - 1	
radius-food-search	Radius within which the elephant searches for food in its *memory-matrix* (static)	float	0 - undefined	meter
radius-water-search	Radius within which the elephant searches for water in its *memory-matrix* (static)	float	0 - undefined	meter
radius-forest-search	Radius within which agent remembers the forest boundary, to escape in case of conflict with humans (static)	float	0 - undefined	meter
fitness	Fitness of the elephant (dynamic)	float	0 - 1	
aggression	Aggression of the elephant (dynamic)	float	0 - 1	
movement-fitness-deprecation	Movement cost; the factor by which *fitness* decreases at each time step (static)	float	0 - 1	
fitness-increment-when-eats-food	Factor by which the *fitness* value increment when the agent consumes food (static)	float	0 - 1	
fitness-increment-when-thermoregulates	Factor by which the *fitness* value increment when the agent thermoregulates when in *thermoregulation* mode (static)	float	0 - 1	
fitness-threshold	*Fitness* value below which the elephant only engages in *foraging* mode (static)	float	0 - 1	
terrain-radius	Parameter in terrain cost function (static)	float	0 - undefined	meter
tolerance	Parameter in terrain cost function (static)	float	0 - undefined	
num-days-water-source-visit	Number of days elapsed since last visited a water source (dynamic)	integer	0 - undefined	Days
num-days-food-deprivation	Number of days elapsed since the daily dietary requirement was satisfied (dynamic)	integer	0 - undefined	Days
prob-crop-damage	Probability with which the agent damages crop when entered an agricultural cell (static)	float	0 - 1	
prob-infrastructure-damage	Probability with which the agent damages infrastructure when entering a building cell (static)	float	0 - 1	
danger-to-life	If the elephant perceives a danger to its life (dynamic)	boolean	True/False	
disturbance-tolerance	If the elephant agent is used to foraging in the presence of humans (static)	boolean	True/False	
food-habituation	If the elephant agent prefers to consume agricultural crops (static)	boolean	True/False	

[*] WGS84: World Geodetic System 1984

Table 2
The attributes of the landscape cells

Parameter	Description	Type	Range	Unit
Elevation-matrix	Digital Elevation Model of the study area (static)	array of floats	0 - undefined	meter
Slope-matrix	Slope map of the study area (static)	array of floats	0 - undefined	degrees
Land-use-matrix	Land Use Land Cover map of the study area (static)	array of integers	0 - 18	categorical
Food-matrix	Food availability matrix within the landscape (dynamic)	array of floats	0 - 100	kilograms
Water-matrix	Water availability matrix within the landscape (static)	array of integers	0 - 1	categorical
Proximity-maps	Proximity of the current cell to a particular category of land use cell (static)	array of floats	0 - undefined	meter
Agricultural-plot-matrix	Presence/absence of the agricultural plot within a landscape cell (static)	array of integers	0 - 1	categorical
Building-matrix	Presence/absence of the buildings within a landscape cell (static)	array of integers	0 - 1	categorical
Temperature-matrix	Hourly temperature within the study area (dynamic)	array of floats	0 - undefined	degree Celsius

Table 3
The process overview of the model

Process	Description
1. Initialize environment	The process that initializes different landscape attributes
2. Initialize elephant agents	The process associated with initialization and distribution of the elephant agents within the landscape
3. Update *Food-matrix*	The process that updates the landscape *Food-matrix*
4. Update *Temperature-matrix*	The process that updates the landscape *Temperature-matrix*
5. Update *human-disturbance*	The process that updates human disturbance/human-activity within the landscape
6. Activate agents	The process that determines the order in which the agents are activated

3. Elephants thermoregulate when the ambient temperature increases.
4. The effect of human disturbance on the elephant agent's movement and space use is considered.
5. The spatial memory attributes of elephants reported in the literature are captured in their decision-making.

To achieve the above basic principles, the model relies on the following underlying assumptions and conceptual theories.

Movement modeling of elephants: Several studies have shown two distinct states, viz. *exploratory* and *encamped* in elephant relocation data. Elephants have been observed to exhibit increased exploratory behavior in corridors and increased encamped movements near rivers during the dry season [48]. A study of the turning angles of elephant paths revealed two distinct movement states, *(i)* high tortuosity paths with frequent turns and *(ii)* straight line paths with minimal turning [49]. Thus, two-state Hidden Markov Models (HMMs) with *exploratory* and *encamped* states have emerged as an appropriate choice for modeling elephant movement [50]. This model is used in our ABM.

Thermoregulation in elephants: Elephants, as large mammals, have a limited surface area for heat dissipation, making thermoregulation crucial for their survival, especially in hot environments [45, 46, 47]. Studies have shown that elephants thermoregulate by adjusting their movement choices based on ambient temperature and landscape characteristics [45]. The core body temperature of elephants fluctuates throughout the day, gradually increasing until late in the evening and decreasing at night [51]. Their behavior also adapts to heat stress, with elephants seeking shade, increasing water-related activities, and resting more [52]. The availability of resources also influences the movement of elephants and the use of space [53, 54]. Seasonal changes in vegetation productivity affect its spatial distribution, and elephants depend more on water sources during dry seasons [55]. Water availability significantly affects movement patterns, and elephants in Kruger National Park exhibit shorter and faster movements towards water during warmer periods [47]. In areas with limited water, such as the Tsavo Conservation Area, elephants showed directional movement toward water sources, females rarely strayed far, and males traveled longer distances during dry seasons [56]. Feeding behavior also adapts to ambient temperature, with elephants showing bimodal peaks in activity during cooler mornings and evenings and resting more during the hot midday period [57]. These studies highlight the crucial role of thermoregulation in elephant decision-making. Thus, we include these factors in our ABM.

Effect of human disturbance on elephants: Numerous studies have documented the effects of human disturbance on elephants, highlighting its influence on their physiology, activity patterns, and behavior. Elephants exposed to human

Table 4
The process overview of the elephant agents

	Process	Description
1.	Movement model	Determines how the *next-step* for the agent to move is sampled
2.	Update *danger-to-life*	Updates whether the agent perceives a threat to its life
3.	Behavioral state switching	Chooses a behavioral mode based on the internal state of the agent as well as external factors.
4.	Feasible movement direction	Chooses a feasible direction for the agent to move depending on the movement cost in different directions
5.	*random-walk* mode	Decision-making process when the agent chooses to walk randomly in the landscape
6.	*foraging* mode	Decision-making process when the agent is in the foraging mode and moving toward a food target
7.	*thermoregulation* mode	Decision-making process when the agent is in the *thermoregulation* mode
8.	*escape-mode*	Decision making process of escaping to the forest in case of danger to life
9.	*target* to eat food	Decision making process of choosing a food source target
10.	*target* to thermoregulate	Decision making process of choosing a thermoregulation target
11.	*target* for escape	Decision making process of choosing a forest cell to escape to in case of danger to life
12.	Eat food	The process that determines how the agent consumes food from the landscape
13.	Update *fitness*	Includes all mechanisms by which the fitness of the agent is updated
14.	Crop and infrastructure damage	Decision making scheme of inflicting damage to crops and property
15.	Death	The process that determines if the agent is alive or dead
16.	Update *age*	The process that updates the *age* of the agent
17.	Update *body-weight*	The process that updates the *body-weight* of the agent
18.	Update *daily-dry-matter-intake*	The process that updates the *daily-dry-matter-intake* of the agent
19.	Update *memory-matrix*	The process that updates the *memory-matrix* of the agent
20.	Update *num-days-water-source-visit*	The process that updates the *num-days-water-source-visit* of the agent
21.	Update *num-days-food-deprivation*	The process that updates the *num-days-food-deprivation* of the agent

activity exhibited elevated concentrations of cortisol and estradiol, indicating elevated stress levels [58]. Elephant activity was significantly lower in areas with high human disturbances, and elephants shifted their movement to the night when the presence of humans was minimal [32]. In landscapes such as the Western Ghats, the presence of elephants was negatively affected by human interference, including competition for resources, habitat degradation, and hunting [30]. This factor also affects the spatial distribution of elephants, their movement patterns, vigilance, foraging behavior, and social interactions at the population and individual levels [27, 28, 29, 31]. Together, these studies underscore the considerable effects of human disturbance on elephants, highlighting the need to take this factor into account in our ABM.

***Memory-matrix* of elephants**: Studies indicate that elephants use their exceptional olfactory senses to identify water sources [56, 59] and food availability [60, 61, 62]. Furthermore, elephants have excellent memory, which allows them to retain knowledge of the landscape and food availability over time. Therefore, our ABM contains submodels to simulate realistic elephant foraging patterns that leverage both sensory perception and spatial memory. Specifically, we use a *memory-matrix* to capture the elephant's memory of these sources. Complete knowledge of water is assumed, while a *percent-memory-elephant* state variable that adaptively changes during foraging is used to capture the percentage of landscape cells with food known to the elephant.

Emergence The emergent space use pattern of the elephant agents and the emergent crop raid and infrastructure damage incidents were investigated.

Adaptation The elephant agent's movement decision and behavioral state switching have been modeled to adapt to changing internal state and external environment via simple empirical rules and probabilistic models. The goal of adaptation is to improve *fitness* through direct and indirect *fitness* maximization objectives.

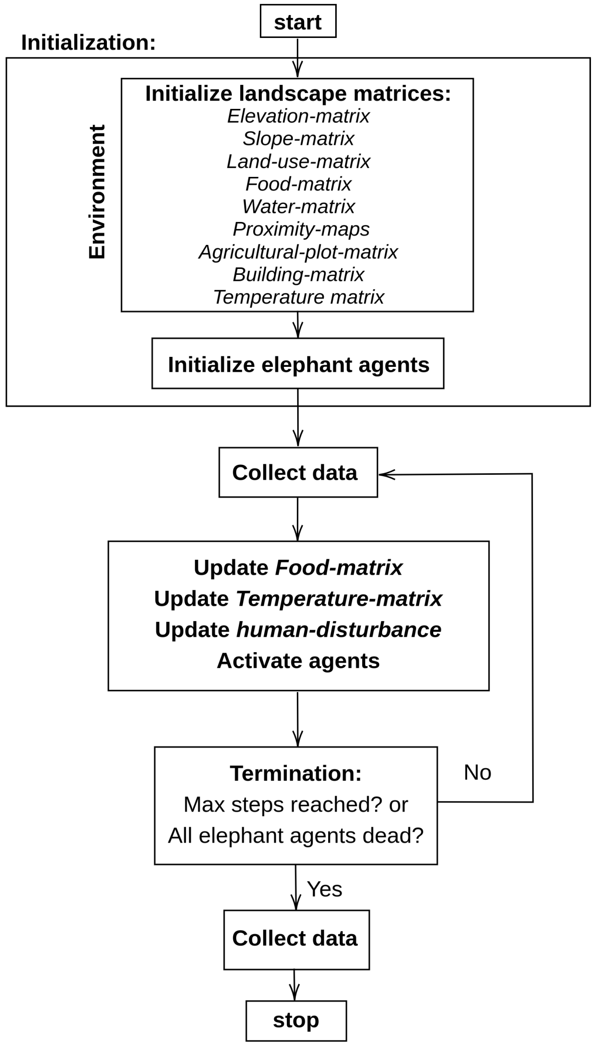

Figure 3: A summary of the model schedule and the process updates.

Objectives The primary objective of the elephant agent is to meet its daily nutritional and thermoregulation requirements while taking into account the cost of movement across different terrains.

Learning, Prediction Learning agents and prediction of future conditions were not implemented in the present model.

Sensing The elephant agents can sense the elevation of the surrounding landscape and know the food and water availability within the simulation area to some extent through their memory matrices, the land use classification types, and the spatio-temporal temperature changes within the study area. Elephant agents can also assess the level of human activities on the fringe to make choices about the temporal aspects of crop raiding depending on their risk profile.

Interaction Currently, only one bull elephant agent is considered. Thus, there are no interactions between multiple agents.

Stochasticity Submodels for elephant movement, choice of feasible movement direction, behavioral state switching, target to eat food, thermoregulate and escape, and food consumption are all partially modeled as stochastic processes (Sect. 2.3.7). The input environmental variables are not considered stochastic and their climatological values are used in the simulation.

Collectives There are no collectives in this model.

Observation The following data are collected at each time step of the ABM simulation: crop damage incidents, infrastructure damage incidents, number of elephant deaths, location (*current-lon, current-lat*), *fitness*, *mode*, *num-days-water-source-visit*, and *num-days-food-deprivation* of the elephant agents.

2.3.5. Initialization

All ABM simulations start with the same initial location for the bull elephant. This location is in a carefully chosen broadleaf evergreen forest cell, 7 km from the croplands and 600 m above sea level. The selection of this point was made because a spatial distribution study [63] found that elephant dung counts were predominantly recorded in evergreen forests in the altitude ranges of 600 and 1200 m, with a presence within 300 to 1300 m.

In all experiments, 40-year-old elephant agents with a body weight of 4000 kg were used. This elephant agent needs to consume 68 kg of food per day to meet its daily dietary requirement. The initial behavioral state of the elephant agent was randomly chosen from one of the *random-walk* and *foraging* modes. It was assumed that the elephant agents had met their dietary requirement (*num-days-food-deprivation* = 0) and visited a water source (*num-days-water-source-visit* = 0) at the start of the simulation. The *fitness* of all agents is initialized to their maximum value of 1. The state variable *aggression* was initialized according to the experiment conducted.

The value of the *knowledge-from-fringe* variable was set to 1500 m, and the *memory-matrix* of the elephant agent was initialized accordingly. This decision was made based on the following reasoning. It was assumed that the elephant agent knew the availability of food within the cells of its *memory-matrix*. The patterns of crop raid incidents vary depending on the environmental and behavioral characteristics of the elephant groups involved, as observed at different locations. For example, in a study conducted in a similar landscape in South India, crop raiding incidents were most common within 2 km from the forest boundary, with occasional incidents even reported beyond 5 km [16]. Another study on human-elephant conflict patterns found that crop raid incidents typically occurred within an average distance of 1.54 km from daytime elephant refuges [64]. However, there have also been reports of incidents where

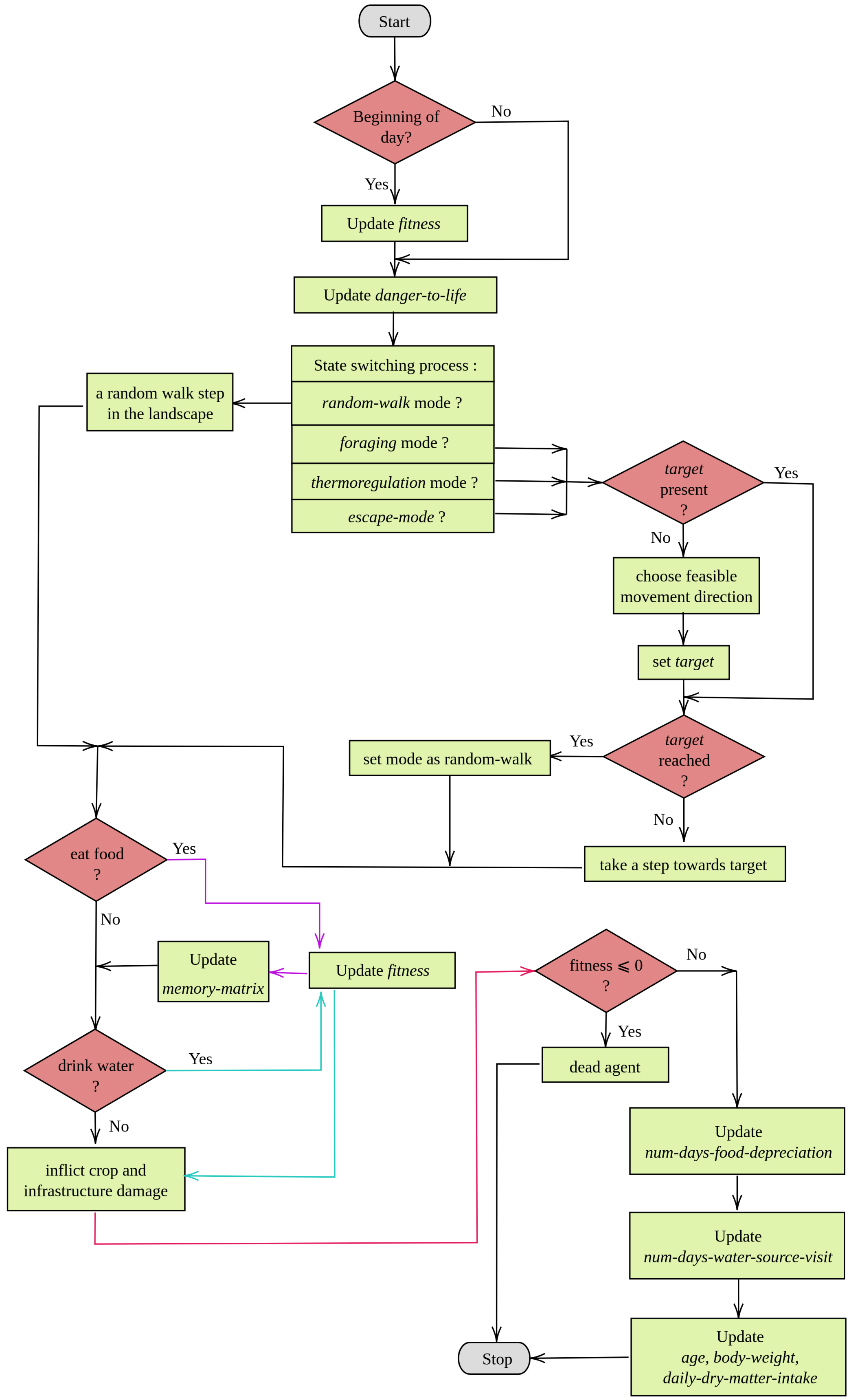

Figure 4: The flow chart of the decision-making process of the elephant agent at each time step.

the extent of damage per farm increased with increasing distance from the protected area boundary [65]. Based on the data collected from the questionnaire, conflict reports were recorded at a distance of 1500 *m* from the fringe. Therefore, the *knowledge-from-fringe* variable was set to this value.

The remaining state variables were set to their initial values through a meticulous calibration process using movement data (Sect. 2.4).

2.3.6. Input

The model development used data obtained from different external sources. The data were used as is or slightly adjusted to conform to the necessary data format to accurately represent the various attributes of the model.

The *elevation-matrix* and *slope-matrix* were created using data from a DEM of the study area, obtained from the Shuttle Radar Topography Mission (SRTM) data repository [66]. This data was available at our required resolution of 30 *m* and thus used directly.

The 2005 LULC data for India derived from Landsat, available at 100 *m* resolution were used [67]. The *Land-use-matrix* is created from these LULC data. The data was downscaled to our required spatial resolution of 30 *m* using GIS Software [68].

The *water-matrix* was also obtained from the downscaled LULC data at 30 *m* resolution. In all of our experiments, it was assumed that water is exclusively accessible in rivers and serves as the main water source for elephants. Each landscape cell is a binary value that indicates whether or not the water source is present within the cell. The impact of the existence of other water sources such as waterholes and ponds is excluded in the present study and may be considered in the future.

We considered Broadleaf Evergreen, Deciduous Broadleaf and Mixed Forests as one category of forest land. The *proximity-maps* with respect to plantations, forests and water sources were also derived from the downscaled LULC using QGIS.

Agricultural land use data for the study area were collected in the questionnaire (Sect. 2.2), identifying seven categories: home gardens with varying percentages of rubber trees (0%, 0-25%, 25-50%, 50-75%, 75-100%, 100%), and a None category. Data on the presence of different fruiting crops such as plantain, jackfruit, and mango were collected in the questionnaire. These data were used to initialize the *agricultural-plot-matrix* by extrapolating its statistics to encompass the entire cropland within the simulation limits. Given that elephants prefer fruiting crops found in home gardens, these gardens were designated as agricultural plots because the purpose of the ABM was to study the pattern of crop damage. The rubber trees in these gardens were assumed to be fully grown and therefore less susceptible to damage by elephants, as they are taller than the level of the elephant trunk.

The *building-matrix* was constructed from a population density map at 30 *m* resolution obtained from Facebook's Data for Good program [69]. Since this map was created by an image analysis of buildings, we constructed the *building-matrix* by identifying cells that had some population and designating it as a cell with a building.

The spatio-temporal temperature data was collected from the WorldClim data website [CRU-TS 4.06 [70]]. Additional information on the processing and its application within the model is provided in Sect. 2.4.4.

The *food-matrix* was constructed for different experimental setups and is detailed in Sect. 3.

2.3.7. Sub-models

The sub-models associated with the 6 processes in Table. 3 are as follows.

Initialize environment
This process sets up the state attributes of the environment by considering the day, month, and year specified at the beginning of the simulation.

Initialize elephant agents
The elephant agent is initialized as described in Sect. 2.3.5.

Update food-matrix
The *food-matrix* is updated whenever the elephant agent consumes food. The corresponding food value is decremented from the landscape cell in the *food-matrix*.

Update temperature-matrix
The *temperature-matrix* is updated every hour of simulation time using the temperature data collected.

Update human-disturbance
To account for the observed nocturnal crop raiding patterns within the study area, this study implemented a time-dependent human disturbance factor. This factor was set to exceed the elephant agents' *disturbance-tolerance* between 7 a.m. and 7 p.m., simulating increased human activity during the day. The factor was set at zero at night (7 p.m. to 7 p.m.), reflecting the reduced activity of humans. This approach aimed to capture the influence of human activity on elephant movement patterns specifically within the context of observed crop raiding behavior.

Activate agents
This process activates the agents in the ABM and triggers the corresponding decision-making process of the agents at each time step, depending on its state variables and the attributes of the environment. When the elephant agent is activated, the following sub-models associated with the 21 processes in Table. 4 are used.

Movement model
At every discrete time step, the movement model takes the elephant agent from the *current-lon, current-lat* to the *next-lon, next-lat* using a *step-length* and *turning-angle*. Two distinct movement patterns are considered in the ABM: *(i) exploratory* movement towards a destination and *(ii) encamped* movement within the landscape. The *exploratory*

is characterized by longer *step length*s with fewer turns. On the other hand, *encamped* movement is characterized by shorter *step-length*s and more turns. A Hidden Markov Model (HMM) is used to define the movement models and is calibrated with relocation data (Sect. 2.4.1). The *step-length* is modeled as a Gamma random variable in both patterns. The *turning-angle* is modeled as a von Mises random variable in the *encamped* movement model, and as a uniform random variable in the *exploratory* movement model.

The algorithm 1 describes the procedure by which the elephant agents move in each discrete time step during a *exploratory* walk movement. The target of this walk is either a food source, a water source or a forest cell, determined by the state switching process (Fig. 4). Once the target cell is identified, the *heading* of the agent is directed toward the target with an added uniform noise sampled from $U(-15°, +15°)$. The step lengths are sampled from the gamma distribution identified from the fit of the HMM model.

The algorithm 2 describes the procedure for the motion of the agent during *encamped* movement. The *step-length* and *turning-angle* are sampled and motion is executed.

Update danger-to-life

The elephant agent perceives danger to its life when *human-disturbance* is greater than the agent's *disturbance-tolerance* when it is in a plantation cell. In this condition, the agent's *danger-to-life* state is set to True.

Algorithm 1 *Exploratory* movement model

$step\text{-}length = gamma\ (\mu = 0.0398, \sigma = 0.0378)$
$heading = arctan2(target - (current\text{-}lon, current\text{-}lat))$
$theta = U(-15°, +15°)$
$\mathrm{dx} = step\text{-}length \times \sin(heading + theta)$
$\mathrm{dy} = step\text{-}length \times \cos(heading + theta)$
$next\text{-}lon = \mathrm{dx} + current\text{-}lon$
$next\text{-}lat = \mathrm{dy} + current\text{-}lat$

Algorithm 2 *Encamped* movement model

$step\text{-}length = gamma(\mu = 0.0040, \sigma = 0.0034)$
$turning\text{-}angle = vonMises(\mu = -3.0232, \kappa = 0.3336)$
$heading = prev\text{-}heading + turning\text{-}angle$
$\mathrm{dx} = step\text{-}length \times \sin(heading)$
$\mathrm{dy} = step\text{-}length \times \cos(heading)$
$next\text{-}lon = \mathrm{dx} + current\text{-}lon$
$next\text{-}lat = \mathrm{dy} + current\text{-}lat$

Behavioural state switching

Algorithm 3 describes the mode or behavioral state switching procedure. The elephant agent is modeled to exist in one of four different behavioral states: *random-walk*, *foraging*, *thermoregulation*, and *escape-mode*. If the elephant agent perceives a danger to its life, it switches to *escape-mode*. If there is no danger to its life, the elephant agent engages in either *random-walk* or *foraging* or *thermoregulation* mode. The probability of state switching between the modes *random-walk* (p_{11}) or *foraging* (p_{22}) was determined from the HMM movement model (Table 5). If the agent's *fitness* is very low (less than a set *fitness-threshold*), it only operates in *foraging* mode. The agent switches to *thermoregulation* mode when the ambient landscape cell temperature rises above its *thermoregulation-threshold*. If the agent is walking toward a target, it is said to have reached the target when the distance between its current location and the target location is less than half the spatial scale of the landscape cell. If the agent reaches its target location, it switches to *random-walk* mode.

Algorithm 3 State switching

```
if danger-to-life == True then
    mode = escape-mode
else
    if ambient-temperature > thermoregulation-threshold then
        mode = thermoregulation
    else if fitness < fitness-threshold then
        mode = foraging
    else
        num ~ Uniform(0, 1)
        if mode = random-walk then
            if num < p11 then
                mode = random-walk
            else
                mode = foraging
            end if
        else if mode = foraging then
            if num < p22 then
                mode = foraging
            else
                mode = random-walk
            end if
        end if
    end if
end if
```

Feasible movement direction

We consider eight discrete directions, viz. north, south, east, west, north-east, north-west, south-east, and south-west for the movement of the elephant agent. However, in a given landscape cell, all eight directions are not feasible for movement, as the motion of the elephants is constrained by the gradient of the landscape. A movement cost is defined to help the agent select a feasible direction. First, a *filter* matrix is used to select landscape cells in each of these directions (Fig. 6 (c)). Then, the movement cost is calculated as the sum of the slope values of landscape cells that are greater than 30° along these directions. A feasible direction is selected such that the movement cost is less than a set *tolerance* along these directions. If there are several feasible directions, then one among these is chosen randomly with equal probability.

random-walk mode
In the *random-walk* mode, the agent executes Algorithm 2 to move to the *next-step*. However, if the *next-step* falls within a plantation cell, the agent chooses to move only if there is no danger to its life. Else, it stays in the current cell itself and the simulation proceeds to the next time step.

thermoregulation mode
In the *thermoregulation* mode, a thermoregulation *target* is chosen as either a landscape cell within *radius-forest-search* whose temperature is less than the agent's *thermoregulation-threshold* or a landscape cell within *radius-water-search* with its proximity closer to a water source. If no such landscape cell is available, the agent chooses a forest cell within *radius-forest-search* as the thermoregulation *target*. The agent moves towards the chosen thermoregulation *target* using the exploratory movement model.

foraging mode
In *foraging* mode, the agent moves towards a food source using the *exploratory* movement model. If the *target* is a plantation cell, the *human-disturbance* level must be less than the *disturbance-tolerance* for activating exploratory walk. Else, the *escape-mode* is activated.

escape-mode
In escape mode, the agent chooses a target to escape and moves towards this target using the *exploratory* movement model.

target to eat food
The food target is selected from the agent's *memory-matrix* within the *radius-food-search* in the feasible movement direction. If the agent is not food-habituated, then it randomly picks up a food target. On the other hand, if the agent is food-habituated and has not been able to satisfy its dietary requirements for more than a *threshold-num-days* (set as three in the present ABM) or if there is *food-abundance* as measured by food in croplands more than 50% the food in the forest, it chooses a *target* closer to the croplands. If the agent is food-habituated and has been able to satisfy its dietary requirements, it chooses a *target* randomly from the *memory-matrix*. Else, a random cell is selected from within the search radius in the feasible movement direction.

target to thermoregulate
A thermoregulation *target* is chosen as a landscape cell within *radius-forest-search* whose temperature is less than the agent's *thermoregulation-threshold* or a landscape cell within *radius-water-search* with its proximity closer to a water source. If no such landscape cell is available, the agent chooses a forest cell within *radius-forest-search*.

target for escape
The *target* for escape is a forest cell, randomly picked from among the landscape cells within a distance of *radius-forest-search* from the agent's current location. If there are no forest cells available within the search radius, the agent moves to a cell that is closer to the forest than its current cell within the search radius. To make this decision, the agent uses the landscape attribute *proximity-to-forest*.

Eat food
The elephant agent consumes food if food is available within its current landscape cell. To be more realistic, it is assumed that the maximum food value in the landscape cell is not available to the elephant for consumption, a uniformly sampled food value between 0 and the maximum food value in the cell is available. When the food is consumed, the corresponding value of the food in the *memory-matrix* and the landscape cell is decreased. The *fitness* value of the agent increases with food consumption.

Update fitness
The fitness of the agent is updated in the following cases:

1. When the elephant agent eats food, the *fitness* increases by *fitness-increment-when-eats-food*.
2. When the elephant agent thermoregulates in *thermoregulation* mode, the *fitness* increases by *fitness-increment-when-thermoregulates*.
3. The *fitness* decreases at each time step by *movement-fitness-deprecation*.

The *movement-fitness-deprecation* is decreased from *fitness* at each time step, while *fitness-increment-when-eats-food* and *fitness-increment-when-thermoregulates* is updated at the end of every day.

Crop and infrastructure damage
In case an elephant agent is within a cell with buildings or agricultural plots, damage is incurred using the corresponding damage probabilities, *prob-infrastructure-damage* and *prob-crop-damage*.

Death
The elephant agent is declared dead if its *fitness* drops to zero.

Update age
The *age* of the elephant agent is incremented by 1 year, every time the simulation completes a year. This is used to account for the growth of elephants.

Update body-weight
The *body-weight* of the elephant agent is updated whenever its age is updated. The von Bertalanffy function is to update the body weight of the elephant agents corresponding to the increase in *age* (Sect. 2.4.4).

Update daily-dry-matter-intake
The *daily-dry-matter-intake* of the elephant agent is updated whenever its *age* and *body-weight* is updated. The *daily-dry-matter-intake* is updated as 1.7% of the *body-weight* of the agent.

Update memory-matrix
The *memory-matrix* is updated whenever the elephant agent

consumes food. The corresponding food value is decremented in memory.

Update num-days-water-source-visit
The *num-days-water-source-visit* is incremented by 1, for every day the agent is unable to visit a water source. If the agent visits a water source, *num-days-water-source-visit* is set to zero.

Update num-days-food-deprivation
The *num-days-food-deprivation* is incremented by 1, for every day the agent's food consumption was less than *daily-dry-matter-intake*. If the agent has been able to satisfy its *daily-dry-matter-intake*, then *num-days-food-deprivation* is set to zero.

2.4. Calibration of the model parameters and state variables

The model calibration and the determination of the initial conditions of the agents' state variables were carried out using a five-step approach as follows.

2.4.1. Identifying correlated random walk parameters by fitting a two-state Hidden Markov model to relocation data

Relocation data on elephant movement were obtained from the study *Elephants Java FZG MPIAB DAMN* (ID - 56232621; accessed on 3 May 2022) from *movebank.org*. These data consisted of geolocations with timestamps, documenting the movement of an adult female elephant in Jambi, Indonesia, during the period from March 2015 to December 2015 at a 5-minute interval. This information was used to calibrate the model parameters so that the elephant agent's movement statistics matched with the relocation data. Although the geographical locations were completely different, our objective was to identify the parameters of the stochastic movement sub-model that could be used in our ABM. The elephant agent movement model takes steps in discrete time, with each step defined by a *step-length* and a *turning-angle*. As mentioned in Sect. 2.3.7, two movement patterns were considered: *exploratory* walk and the *encamped* walk (Fig. 5 (a)). The *step-length* and *turning-angle* distributions were identified by fitting a two-state Hidden Markov Model (HMM) with *exploratory* and *encamped* states. The best-fit distributions for the *step-length* and *turning-angle* were determined using the Akaike Information Criteria (AIC) from a set of possible candidate distributions (Gamma, exponential and Weibull for *step-length*, and von Mises and wrapped Cauchy for *turning-angle* distribution). Table 5 shows the best parameters. The gamma distribution was identified as the best fit for *step-length* (Fig. 5 (c)), and the von Mises distribution was identified as the best fit for *turning-angle* (Fig. 5 (d)). The above analysis was performed using *moveHMM*, an R package designed for animal movement modeling using hidden Markov models.

Table 5
The parameters of the fitted two-state HMM

movement statistic	parameter	value	unit
State transition probability	p_{11}	0.8775	
	p_{12}	0.1225	
	p_{22}	0.9096	
	p_{21}	0.0904	
step-length: *encamped*	mean	0.0040	km
	standard deviation	0.0034	km
step-length: *exploratory*	mean	0.0398	km
	standard deviation	0.0378	km
turning-angle: *encamped*	mean	-3.0232	radians
	concentration	0.3336	
turning-angle: *exploratory*	mean	-0.0366	radians
	concentration	1.5202	

2.4.2. Genetic algorithm to identify parameters in the ABM

Since the detailed movement data for Seethathode elephants, such as monthly area usage and daily travel distances were unavailable, we used the relocation data from Jambi, Indonesia to calibrate four parameters/state-variables of the ABM: *prob-food-forest*, *max-food-value-forest*, *percent-memory-elephant* and *radius-food-search*. The parameters *prob-food-forest* and *max-food-value-forest* capture the spatial distribution and quantity of food resources within the forest. The state variables *percent-memory-elephant* and *radius-food-search* is used by the elephant agent in making foraging decisions. Changing these parameters leads to different space use patterns. Thus, an inverse problem was set up to identify the calibrated parameters that lead to the same space use patterns as in the relocation data.

Three specific spatial patterns were used as the objective functions for the calibration task: monthly space use measured by the minimum convex polygon, the total daily distance traveled (diel displacement) and the daily net distance (distance between the first and last locations each day). A multi-objective genetic algorithm called Non-dominated Sorting Genetic Algorithm (NSGA) - II was used for the calibration. The cost function was set in such a way that it penalized simulations that fell outside the confidence interval of the movement data. To simplify the calibration process, *thermoregulation-threshold* was set above the ambient temperature so that the elephant agent only participates in foraging and the forest-related ABM parameters could be calibrated for food availability. As the landscape in Jambi was flat, a relatively flat elevation matrix was used during this calibration step. The ABM was further modified

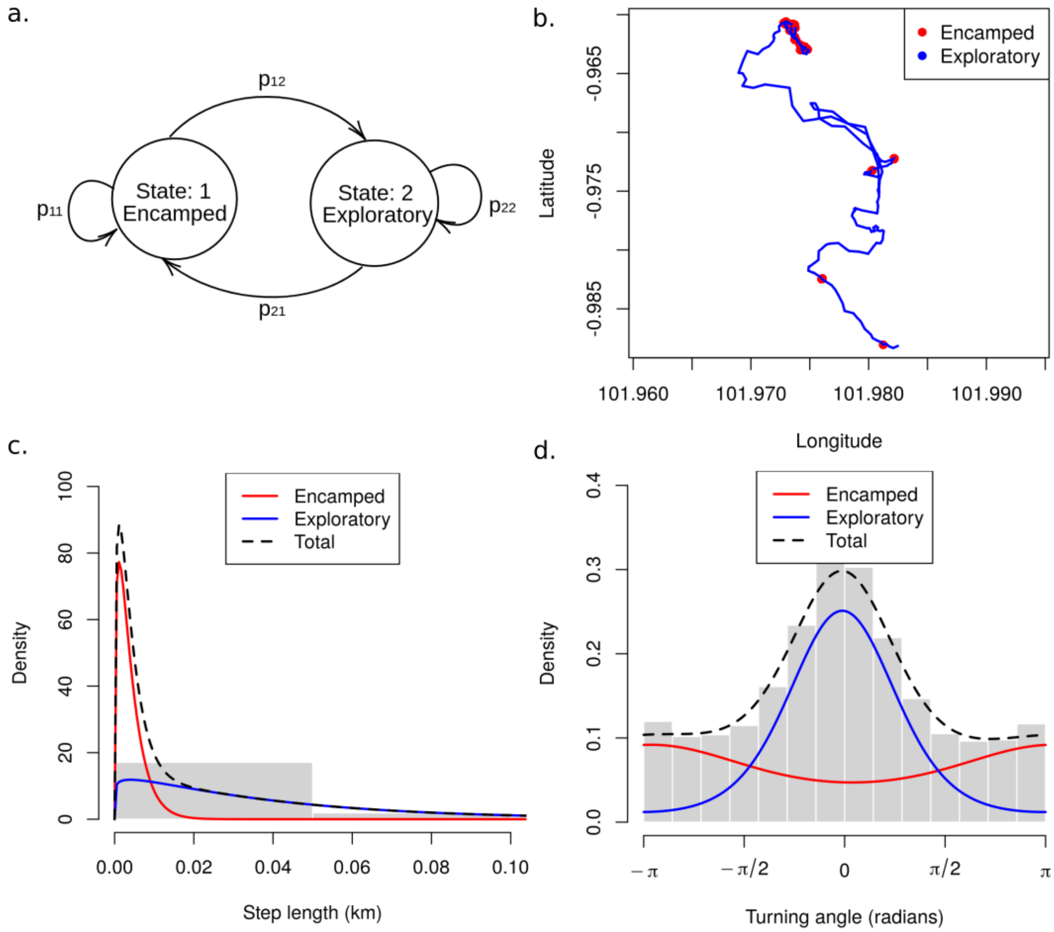

Figure 5: (a) Two-state hidden markov model used to fit relocation data. p_{ij} represents the state-transition probabilities where i, j are the current and next states. (b) A trajectory sequence from the relocation data showing the fitted states: *exploratory* states in blue and *encamped* states in red. (c) Fitted Gamma distributions to the step lengths. (d) Fitted von Mises distributions to the turning angles. The histogram depicting the corresponding statistics of the relocation data is shown in gray in panels (c) and (d).

and adapted to incorporate movement in hilly terrains in Sect. 2.4.3.

The genetic algorithm returned a pareto-optimal solution, where no alternative solution can improve one objective without compromising another. The process of selecting the final set of calibrated parameters from the pareto-optimal solution involved a critical assessment of the practical implications and feasibility of each parameter choice, with the aim of ensuring that the selected parameters align with the overall objectives and constraints of the optimization problem. The final values chosen for the parameter *prob-food-forest* is 0.1 and *max-food-value-forest* is 40 kg. The calibrated values of the elephant agent's state-variables are given in Table 6.

2.4.3. Cost of movement to traverse the slopes

A feasible movement direction submodel (Sect. 2.3.7) was required since the relocation data was obtained from a relatively flat terrain and our study area was in a hilly terrain. The primary difference in the decision-making of elephant agents in these two simulation environments lies in the number of candidates for the next feasible movement direction. In the case of a flat terrain, there are a greater number of options for the possible direction of movement compared to a hilly terrain. Thus, a restrictive movement cost was introduced to identify the next feasible movement direction.

The parameter *terrain-radius* in the movement cost function was set as the calibrated *radius-food-search* (Sect. 2.4.2). This was done to ensure that all the movement targets remain within the same spatial extent of the agent's current location in the elephant agent's every decision making. The parameter *tolerance* was adjusted by exploratory analysis to ensure that the elephant agents traverse slopes greater than 30° in not more than 1% of the simulated trajectories. The inclusion of this concession was intended to avoid overly restrictive limitations and to acknowledge inherent unpredictability in the decision-making process to align with the realities of the real world.

Interestingly, the addition of slope-based movement cost resulted in similar metrics of minimum convex polygon space usage, diel displacement, and net displacement as the movement data for a time frame of 30 days. This further justifies our use of Jambi data to tune the ABM in Seethatode.

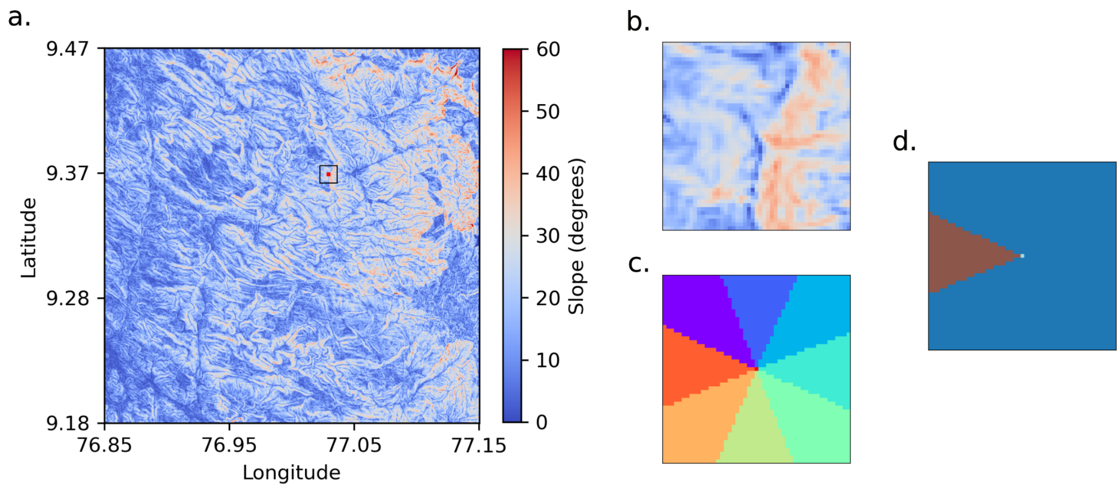

Figure 6: (a) The slope map of the simulation area with the red square highlighting the location of the elephant agent. The black square represents the *terrain-radius* within which movement decisions are made. (b) The slope map within the *terrain-radius* extent of the elephant agent (slope map within the black square in (a)). (c) The *filter* to choose landscape cells along the cardinal and ordinal directions. (d) The feasible direction of movement selected according to the slope constraint is shown in brown.

2.4.4. Literature-based initialization and parameterization

The following parameters and state variables were calibrated or initialized using an extensive literature survey.

Body weight and age of elephant agents: The von Bertalanffy functions have been extensively used to model the growth of vertebrates in size (height, length, weight; [41]). The general form of the equation is

$$S_t = S_x(1 - exp(-K(t - t_0))^M \,, \tag{1}$$

where, S_t is the size at age t, S_x is the asymptotic size, K is the catabolism coefficient (constant), t is the age of the animal in years, t_0 is the theoretical age at which the animal would have zero size, and K is the power of the function.

This equation is assumed to be cubic for the growth of body weight ($M = 3$). We use the parameters of eq. 1 as determined from captive Asian elephants [41]: $M = 3, K = 0.149, t_0 = -3.16, S_x = 4000$. In all experiments, we used a 40-year-old bull elephant. Thus, its weight according to Eq. 1 is 4000 kg.

Daily dry matter intake of the elephant agents: The daily dry matter intake of wild Asian elephants was estimated to be 1.5% to 1.9% of body weight [71]. In all experiments, we used the mean value of 1.7% of body weight as the daily dietary requirement of the elephant agents (68 kg/day).

Spatio-Temporal thermoregulation probability: In this study, spatio-temporal temperature data were collected from the WorldClim data website [CRU-TS 4.06 [70]]. In particular, maximum and minimum monthly temperature data were collected at a spatial resolution of 2.5 minutes for the corresponding simulation year. Since we are interested in the daily movements of elephants, the minimum and maximum climatological temperature was used with the empirical daily temperature curve to obtain hourly temperature data for the simulation time period (This was done using *chillR* in R). The *prediction_coefficient* needed in the empirical temperature curve was used from the nearest weather station closest to the study area (Thiruvananthapuram).

Given a threshold for thermoregulation, the probability of thermoregulation was calculated from the hourly temperature using the following formula [23]:

$$p_t = \frac{1}{1 + \exp(state \times [T_{current} - T_{threshold}]} \tag{2}$$

where, p_t is the *thermoregulation-probability*, *state* may be -0.2 or -0.1, highlighting the difference in sensitivity to environmental temperatures between family groups with and without calves, $T_{current}$ is the temperature of the agent's landscape cell, and $T_{threshold}$ is the temperature threshold for thermoregulation. The state was set as -0.1 for *solitary bulls* and -0.2 for *matriarchal herds*. If the *thermoregulation-probability* (p_t) was greater than 0.5 in its current landscape cell, the elephant agent would engage in thermoregulation. In the experiments, two *thermoregulation-thresholds* of 28° and 32° were chosen so that the elephant agent thermoregulates in all seasons at threshold 28° and only during the dry/hot season at the threshold 32°.

2.4.5. Other assumptions used in the calibration of the model

Based on the data collected from the questionnaire (Sect. 2.2), conflict reports were recorded at a distance of 1500 m from the fringe. Therefore, the *knowledge-from-fringe* variable was set to 1500 m.

It is assumed that the elephant agent will die in 10 days if it does not meet its food and thermoregulation needs.

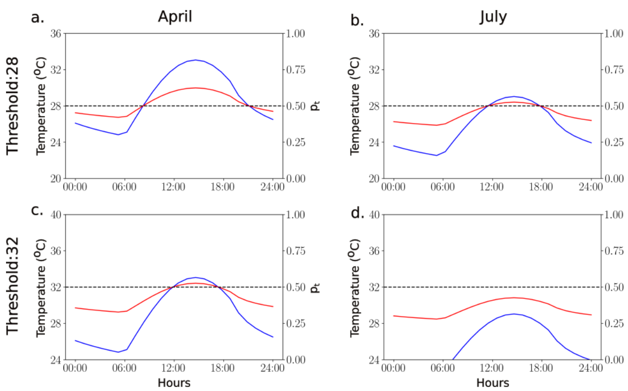

Figure 7: The figure illustrates the daily temperature variation (blue line) in the landscape cell at the center of the simulation area and the corresponding probability of thermoregulation (p_t) (red line) for a dry month (April) and a wet month (July) of the year. The horizontal line represents $T_{threshold}$. The temperature is shown in degrees Celsius on the left y-axis shows temperature ($°C$) and the right y-axis shows the probability of thermoregulation.

This would mean that each day *fitness* decreases by a factor of 0.1. The simulation runs at a temporal resolution of 5 minutes and each day comprises 288 time steps. Therefore, in each time step, *fitness* is reduced by a factor of 0.000347. This energy expended must be restored by eating food and maintaining a stable body temperature by thermoregulation. However, thermoregulation demands fluctuate throughout the seasons. As a result, depleted *fitness* must be increased daily by the values of *fitness-increment-when-thermoregulates* and *fitness-increment-when-eats-food*, proportionate to the number of time steps the agent spends in thermoregulation in a day.

Let a be the total number of thermoregulation time steps in a day; x be the total food consumed by the elephant agent in a day (kg); y be the total number of time steps that the agent actually thermoregulated in a day.

The value of the parameter *radius-water-search* was set to be equal to the value of *radius-food-search* for replicating spatial patterns of the collected movement data.

$$\textit{fitness-increment-when-eats-food} = \frac{1}{10} \times \frac{288 - a}{288} \times \frac{\max(x, \textit{daily-dry-matter-intake})}{\textit{daily-dry-matter-intake}} \quad (3)$$

$$\textit{fitness-increment-when-thermoregulates} = \frac{1}{10} \times \frac{a}{288} \times \frac{y}{a} \quad (4)$$

Here, $\frac{1}{10}$ represents the proportion of daily *fitness* loss, $\frac{288-a}{288}$ represents the proportion of the day not thermoregulating (available for eating), $\frac{max(x, daily-dry-matter-intake)}{daily-dry-matter-intake}$ incentivizes eating more than the daily requirement. If the elephant eats more than *daily-dry-matter-intake*, it receives the full benefit. Otherwise, the benefit scales proportionally to the amount eaten. $\frac{a}{288}$ represents the proportion of the day spent thermoregulating, and $\frac{y}{a}$ represents the efficiency of thermoregulation. If y is equal to a (perfect efficiency), full benefit is received. Otherwise, the benefit scales proportionally to the actual time spent thermoregulating.

The *movement-fitness-deprecation* is decreased from *fitness* at each time step, while *fitness-increment-when-eats-food* and *fitness-increment-when-thermoregulates* is updated at the end of every day.

fitness-threshold was set such that the elephant agent focuses on foraging if the energy falls below 40% of its maximum value.

3. Experimental setup

We conducted several experiments to explore the spatio-temporal space use patterns of elephant agents along three major axes: food availability conditions, elephant aggression levels and thermoregulation thresholds. 2010 was chosen for the experiments because field data on conflicts were available during this year. All experiments start on the first day of a month and end on the last day of that month. The calibrated state variables and model parameters are used for the experiments. In all experiments, one bull elephant agent with the same initial location (Sect. 2.3.5) is used. For each month, 192 simulations are performed to obtain trajectories, food consumption, crop raiding incidents, building damage incidents, movement and space use statistics.

Effect of food availability : In the first experiment, the movements and spatial utilization patterns of elephants were investigated under varying food availability conditions. Throughout the experiments, the food distribution remained constant with no changes over time, such as growth or decay.

The *food-matrix* is the main input used by the elephant agent in the ABM for making movement choices for food consumption. This matrix captures two important factors: the spatial distribution and the quantity of food resources. Only forest cells and plantation cells have food. The presence of food in every forest cell (or plantation cell) is assumed to be an Independent and Identically Distributed (IID) binomial random variable with a probability *forest-food-percent* (or *cropland-food-percent*). If a cell has food, then the amount of food available in that cell is a uniform random variable between 0 and *forest-max-food-value* (or *cropland-max-food-value*).

We used five different scenarios of scarce to abundant food availability named S1, S2, S3, S4, and S5 with *forest-max-food-value* values of 5, 10, 15, 20, and 25 kg, respectively. For S1 to S5, *forest-food-percent* was set to the calibrated *prob-food-forest* (Sect. 2.4.2). The parameters *cropland-food-percent* and *cropland-max-food-value* were selected so that there is a greater chance for elephant agents to satisfy their daily dietary needs during a crop-raiding event. A crop-raiding event typically occurs at night when human activity is minimal. The event starts when an elephant agent enters a plantation cell in search of food and ends

Table 6
Summary of the calibrated state variables of the elephant agent.

Parameter	Value	Assumptions	Paper Sect.	Supporting references
age	40 years	The experiments involved adult solitary male elephant	2.4.5	
body-weight	4000 kg		2.4.4	von Bertalanffy function for the body weight of male elephants [41]
daily-dry-matter-intake	68 kg	1.7% of body weight	2.4.4	1.5% to 1.9% of body weight [71]
knowledge-from-fringe	1500 m	Parameterized using collected field data	2.4.5	Records of damage incidents within a buffer zone close to the fringe [16, 64]
percent-memory-elephant	0.375	Replicating spatial patterns of collected movement data	2.4.2	
p_t		$1/[1+\exp(state \times (t_{current} - t_{threshold})]$	2.4.4	probability of thermoregulation given a threshold temperature [23]
thermoregulation-threshold ($T_{threshold}$)	$28°C$,$32°C$	Thresholds chosen so that the elephant agent thermoregulates in all seasons and only during dry season	2.4.5	
radius-food-search	750 m	Replicating spatial patterns of collected movement data	2.4.2	
radius-water-search	750 m	Replicating spatial patterns of collected movement data	2.4.5	
radius-forest-search	1500 m	Knowledge of forest from fringe if close to the fringe	2.4.5	Due to conflict, elephants are forced to venture deeper into human settlements, thus facing challenges in their ability to retreat back to forests [72]
movement-fitness-deprecation	0.000347	If the elephant agent cannot meet its thermoregulation or food requirements, it will die in 10 days	2.4.5	
fitness-increment-when-eats-food		$[(288 - a) \times [\max(x,$ *daily-dry-matter-intake*$)]]/(288\times$ *daily-dry-matter-intake*$)$	2.4.5	
fitness-increment-when-thermoregulates		$\frac{1}{10} \times \frac{a}{288} \times \frac{y}{a}$	2.4.5	
fitness-threshold	0.4	Focus on *foraging* if the energy falls below 40% of its maximum value	2.4.5	
terrain-radius	750 m	same as the radius of search of the food and water source	2.4.3	
tolerance	100		2.4.3	

when the agent returns to the forest in the morning. As the food quality in plantation cells is superior to that found in forests, we have assumed that the agents can meet their daily nutritional requirements in a single episode of crop raiding. To achieve this, we set *cropland-food-percent*=0.3 and *cropland-max-food-value*=100 kg, both higher than the corresponding values of *forest-food-percent* and *forest-max-food-value*. Table 7 provides information on the average availability of food within the forest for different parameterizations of *forest-max-food-value*. In all experiments, food availability within croplands was 0.526 ton/km^2 with *cropland-max-food-value* set to 100 kg.

The summary of the values of the above four parameters is given in the table 7.

Table 7
Parameter values related to food consumption. S1-S5 are scenarios used in the experiments.

Parameter	Values	Unit
forest-food-percent	0.1	
cropland-food-percent	0.3	
cropland-max-food-value	100	kg
forest-max-food-value	S1:5, S2:10, S3:15, S4:20, S5:25	kg
food within forest	S1:0.10, S2:0.25, S3:0.35, S4:0.45, S5:0.60	ton/km^2

Effect of aggression :

To examine the impact of various levels of aggression on space use and movement patterns, we experiment with four different aggression values (0.2, 0.4, 0.6, 0.8). Aggression levels represent the likelihood of selecting cells close to plantation cells when making foraging decisions. Note that foraging decisions are made in situations of limited food availability in the forest or in crop habituation.

Effect of thermoregulation threshold. Whenever the diurnal temperature of the agent's landscape cell increases beyond the thermoregulation temperature threshold, the agent has to thermoregulate by taking one of the thermoregulatory actions. Since we did not know the exact temperature threshold for thermoregulation for different groups of elephants within this particular study area, we explored two different thresholds (28° and 32° Celsius) of thermoregulation. These two thresholds were chosen so that the elephant agent thermoregulates in all seasons at the threshold 28° and only during the dry season at the threshold 32°.

Number of ABM simulations. Overall, 5 (food scenarios) × 4 (aggression levels) × 2 (thermoregulation thresholds) = 40 scenarios are simulated for each of the 12 months. In each month, 192 trajectories are obtained. Therefore, a total of 40×12×192 = 92,160 ABM simulations have been completed. Mesa software is used to implement ABM. 192 trajectories are chosen as we use four CPU nodes each with 48 cores, giving a total of 192 cores being used for the simulation. All trajectories start with identical initial conditions, and the stochasticity in the submodels lead to a multitude of possible paths that are analyzed to obtain the movement patterns.

4. Results

4.1. Model validation: Comparison of activity, space usage, and conflict patterns with literature

Model validation is done by qualitative and quantitative comparison with patterns observed in the literature. Table 8 identifies the patterns in the literature that emerge successfully in the ABM model. Fig. 8 shows the Minimum Convex Polygon (MCP) and the Kernel Density Estimate (KDE) of a simulated trajectory. The MCP area is measured to be 77.65 km^2. The fitted KDE contours of different levels of space use are also shown. The area occupied by 100% space use covers an area of 57.82 km^2, while 90% space use corresponds to 36.68 km^2. We see a good match of these numbers with the literature. In addition, there is a good match with the conflict data collected from the field.

4.2. Seasonal effect on daily activity budget of elephant agents

We analyze the patterns in the daily average time spent by the elephant agent in each of the *thermoregulation*, *random-walk*, and *foraging* modes across the different months (Fig. 9). The first observation is that when the thermoregulation threshold $T_{threshold} = 28°C$, the agent spends time in all three modes in all months; however, when $T_{threshold} = 32°C$, the agent enters the *thremoregulation* mode only in February, March, April, and May, which is the hot/dry season. A series of chi-square tests was performed to identify pairs of months with a statistically significant difference ($\alpha = 0.05$) in the distribution of the daily average time budget in the three modes. We found that the differences in the daily time budget of the agent states were statistically significant between the dry and wet months ($p < 0.05$) for

Table 8
Patterns present in the relevant literature, and those produced by the model.

Patterns present in the literature	Patterns reproduced by the ABM
Activity budgets	
An inverse relationship was observed between increasing temperatures and feeding activity, while a direct relationship was found between resting and increasing temperatures [57].	With increasing temperatures, the elephant agent rests near a water source or within the forest shade.
Space usage	
During the dry season, elephants congregated in river habitats, while they dispersed during the wet season [73].	The dry season leads to congregations in river valleys, while the dispersion patterns during the wet season are influenced by the availability of food in forested areas and plantations (see Fig. 11).
The spatial usage measured by the MCP was 35 km^2 in the dry season and 50 km^2 in the wet season [74].	The area utilization, determined by the MCP and KDE, exhibits comparable values (see Fig. 8).
The elephants exhibited a shuttling movement pattern when visiting water sources [47].	The model replicated the shuttling behaviors of the elephants with respect to water source visit (see Fig. 10).
Elephants tended to be close to water sources during the warmer parts of the day and spent more time at water sources during the dry season than during the wet season [47].	The model replicated similar patterns of space use diurnally and during the wet and dry months (see Fig. 10).
Conflict patterns	
Approximately 60% of the damage occurred close to the edges of the forest, within a distance of no more than 50 m from the boundary [25].	The conflict incidents were located mainly in close proximity to the forest-plantation boundary (see Fig. 11).

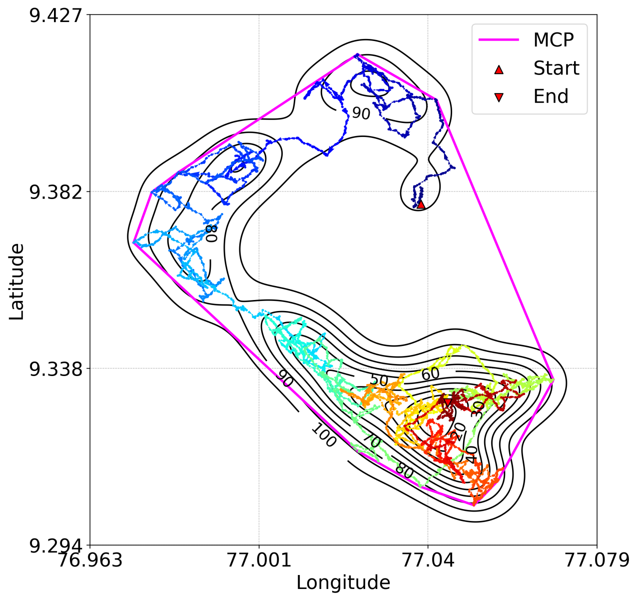

Figure 8: A simulated 30-day elephant trajectory with MCP and KDE shown.

all aggression levels at both $T_{threshold}$s. Chi-square tests were also performed to see if aggression levels and food availability within the forest resulted in differences in the distribution of the daily time budget. The results indicated that there are no statistically significant differences ($p < 0.05$).

4.3. Emergent space use patterns of the elephant agent

Fig. 10 shows a simulated trajectory sequence of an elephant agent in a dry month over eight days, demonstrating various dynamics and mechanisms that govern the elephant's movement through the landscape. Fig. 10(a) shows the entire simulation area, highlighting plantations in yellow and water bodies in blue. The red box shown in Fig. 10(a) highlights the zoomed area shown in Fig. 10(b). Fig. 10(b) presents a sequence of the elephant's movements, distinguished by daytime in black and nighttime in pink. Scatter points along the trajectory represent the elephant's behavioral mode at each hourly interval. These points represent three distinct states: *thermoregulation*, *random-walk*, and *foraging*, indicating how the behavior of the elephant changes throughout the day. The trajectory reveals various movement dynamics, including visits to water bodies and plantations, foraging, and crop-raiding, as well as landscape navigation based on slope and elevation. Importantly, the trajectory demonstrates recurrent crop raiding events (episode:1 and episode:2 in Fig. 10), both occurring at night. The trajectory sequence also highlights the shuttling movement of the simulated elephant agents with respect to the water sources when in *thermoregulation* mode (events marked as 'water source visit').

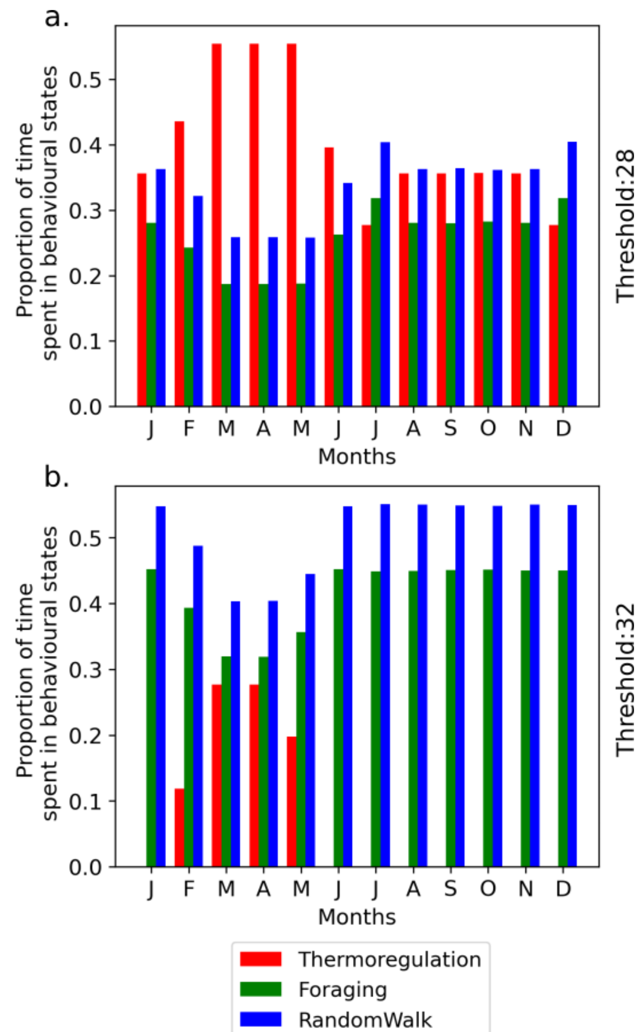

Figure 9: The agent's daily time budget across various behavioral states for different months of the year. (a) $T_{threshold}$: 28°C (b) $T_{threshold}$: 32°C.

The primary objective of the elephant agent in the ABM is to maximize its *fitness*, a dynamic measure influenced by various factors. Movement in the landscape incurs an energy cost that reduces *fitness*. On the contrary, eating food replenishes *fitness*. Furthermore, *thermoregulation* by resting or visiting a water source during thermoregulation periods further increases the agent's *fitness*. This intricate interplay between movement, resource acquisition, and thermoregulatory needs ultimately guides the agent's decision-making and shapes its potential paths, offering valuable insights into elephant movement patterns.

Fig. 11 shows the influence of varying levels of aggression, thermoregulation threshold, and food availability within the forest on the spatial distribution of elephants in the wet and dry months. The plots incorporate all simulated elephant trajectories to capture the inherent variability and uncertainty in the predictions of the elephant path. Dark red regions represent areas of high elephant density, whereas

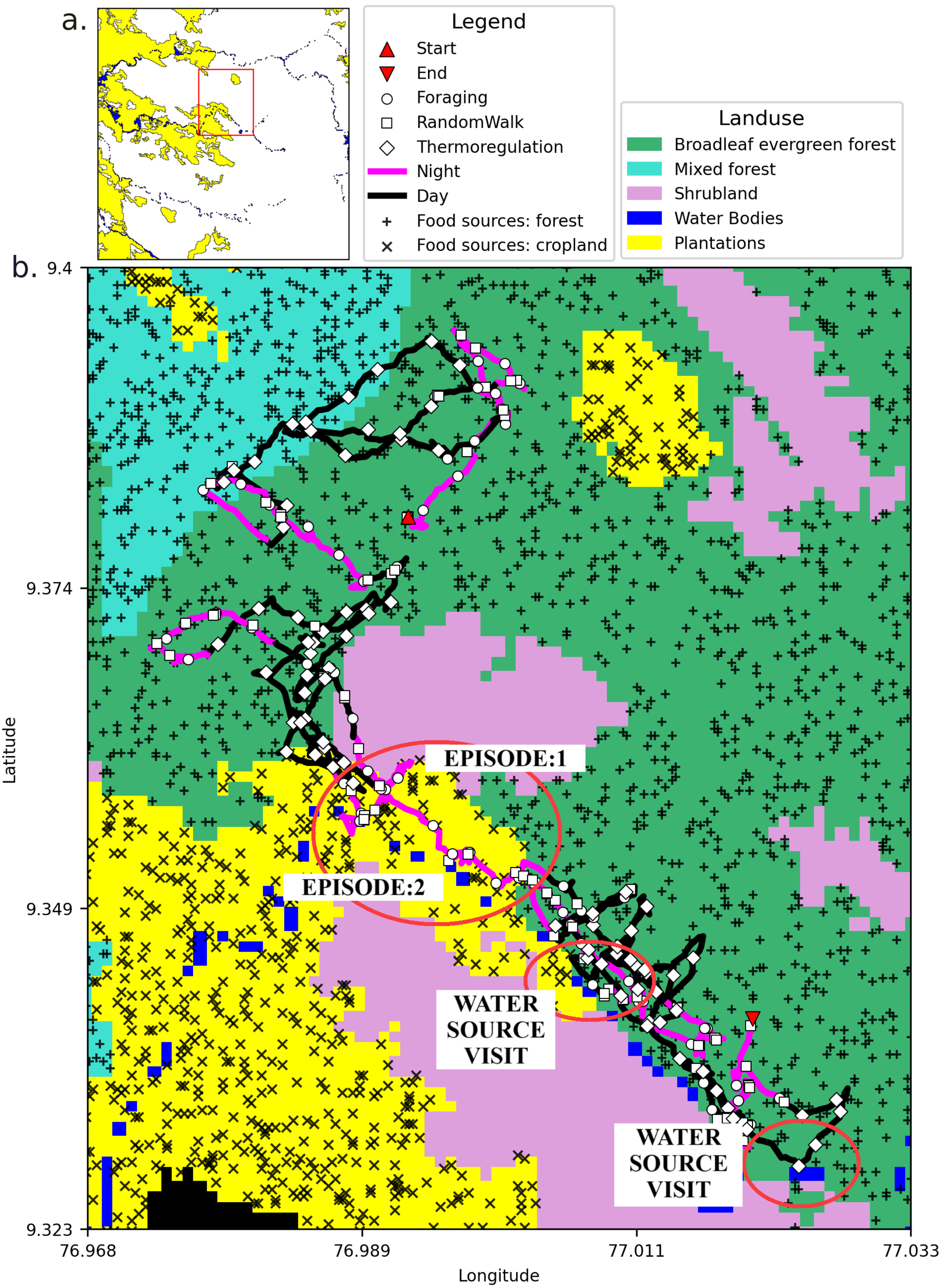

Figure 10: A simulated elephant trajectory sequence highlighting the activity during the day and night.

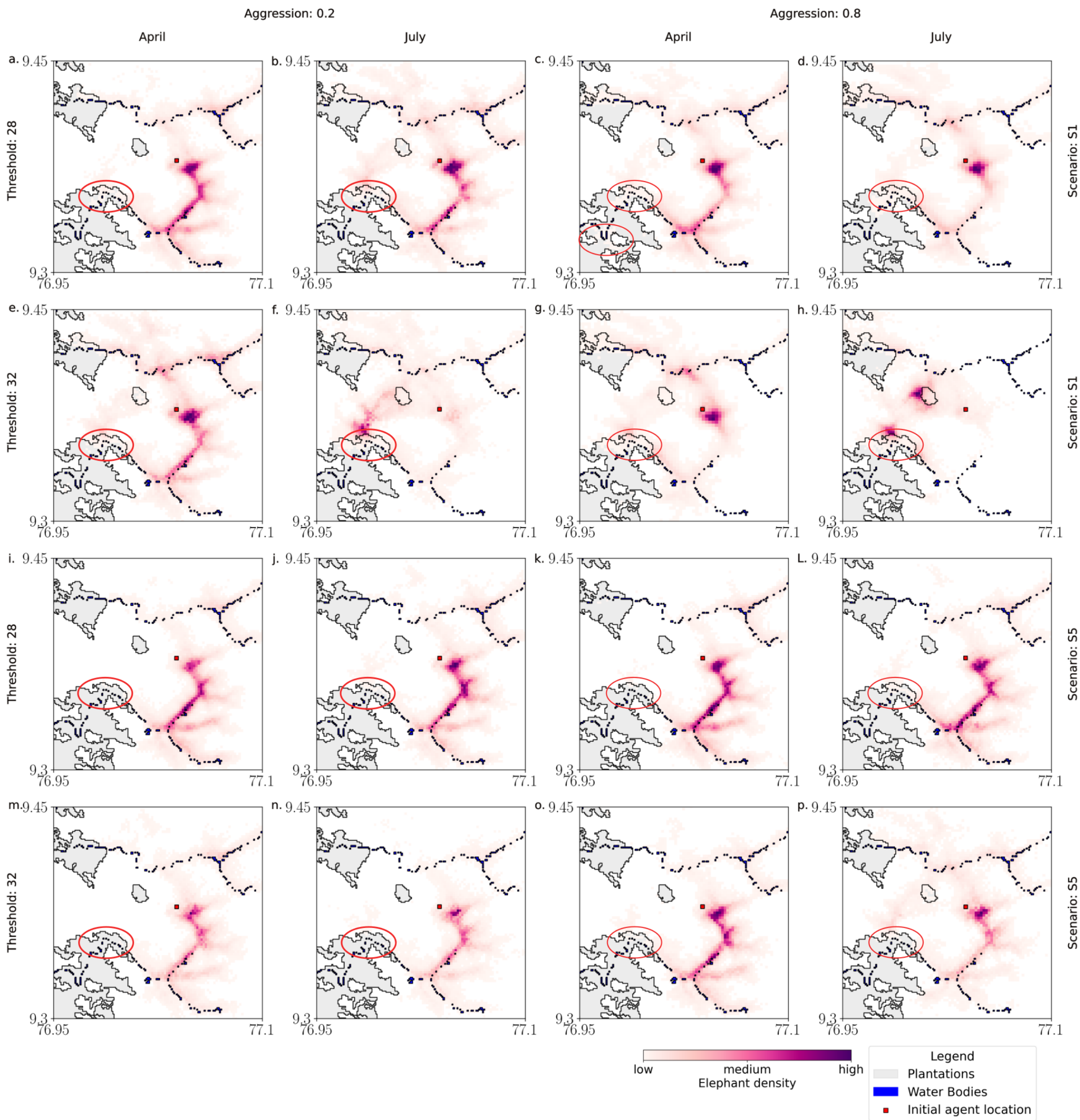

Figure 11: The summary of the spatial distribution of the agents at the two thermoregulation thresholds, two extreme aggression levels and two extreme food availability scenarios. Water sources and croplands are shown in the background.

light red areas indicate lower densities under simulated conditions. The spatial distribution of the elephant agents is superimposed relative to the water sources and croplands within the study area. The areas of reported human-elephant conflicts (Sect. 2.2, Cluster I, II and III in Fig. 2) are marked in a red oval.

The simulations revealed that crop raiding incidents in cluster I occurred in all experimental setups, with variations based on the availability of food in the forest, levels of aggression, and thermoregulation thresholds. Incidents in cluster II were only observed during the dry months with the highest level of aggression and a thermoregulation $T_{threshold}$ of 28°C. This suggests that elephants ventured deeper into croplands (cluster II) when: *(i)* they needed to expend a greater portion of their daily time (over 50%) for thermoregulation, *(ii)* they exhibited high aggression, and *(iii)* there was severe scarcity of food within the forest. The combined effects of demands for thermoregulation, aggression, and the potential scarcity of food in the forest probably drove these excursions. Furthermore, the presence of water, in conjunction with food, may have impacted their migration to these areas, which has the potential to satisfy both of these requirements. However, only aggressive elephants reached these areas, probably due to their increased tolerance to the risk of venturing deeper into the croplands. This analysis uncovers an intricate interaction between food availability, seasonal fluctuations, and aggression to influence elephant behavior in crop raiding. Finally, no incidents were observed in cluster III during any simulation. The reason for this could be the terrain and the fact that our simulations used only a single agent starting from the same location. In future work, more agents and longer simulations could be conducted to identify the factors that lead to conflicts in cluster III.

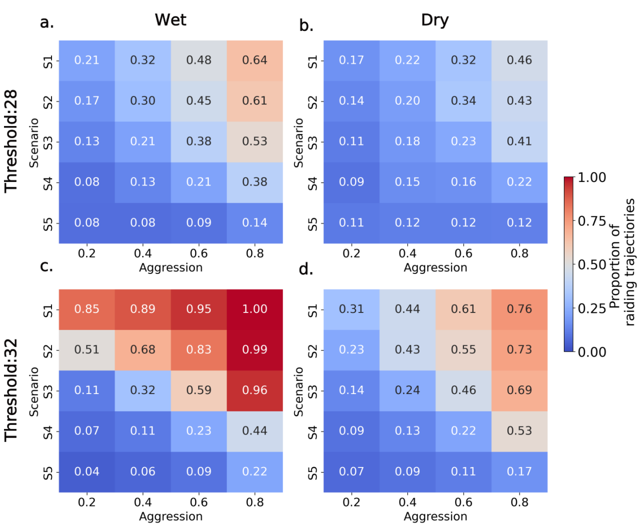

Figure 12: The variation in the proportion of the simulated elephant trajectories that exhibit crop-raiding behavior with aggression, forest food availability and thermoregulation. This proportion can be viewed as the probability of conflict.

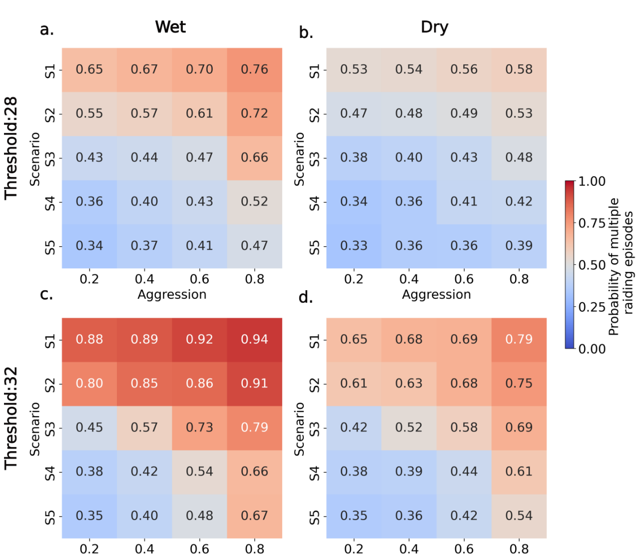

Figure 13: The likelihood of making multiple returns to the plantations by the crop-raiding elephant agents.

4.4. Human-elephant conflict: Crop raid patterns

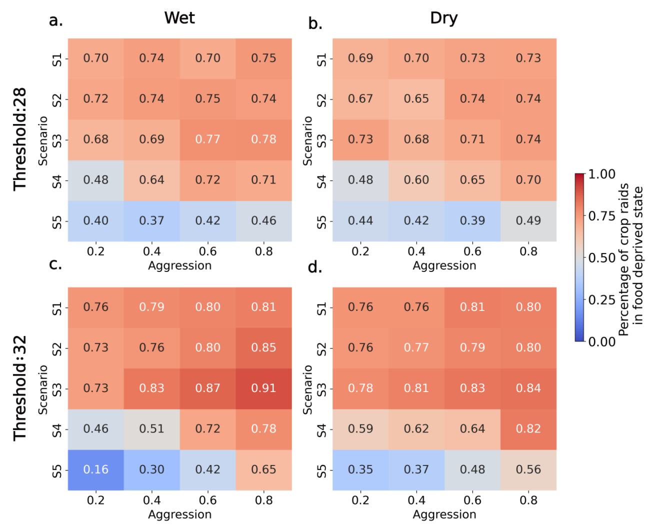

Figure 14: The proportion of crop raid episodes in which elephants are in a food-deprived state.

As the elephant agent's initial position in each simulation is located within the forest region, the evolution of the trajectories is based on diverse combinations of agent states and environmental factors. In particular, not all simulated trajectories lead to crop-raiding incidents; rather, only a subset of trajectories traverse mountainous valleys to reach croplands for raiding activities. The significance of these simulations lies in identifying scenarios where crop raiding is prevalent, thus indicating increased human-elephant conflicts within the study region. The proportion of trajectories that reach croplands could be used to calculate the probability of crop raids, with higher proportions suggesting greater risk (Fig. 12). Specifically, we define scenarios where more than 80% of the simulated trajectories engage in crop raids as the most critical for human-elephant conflicts. Fig. 12 (c) reveals the situations that are the most critical.

A combination of three factors leads to at least 80% of crop raiding trajectories: (i) agents are not in *thermoregulation* mode, (ii) food availability is scarce in the forest, and (iii) aggression is high. The first factor is observed during the wet months and higher thermoregulation thresholds ($T_{threshold}$=32°C), during which the agents allocate their daily activity budget solely to *random-walk*, and *foraging* modes, thereby allowing them to venture into the cropland. The second and third factors are simulated by changing food availability (S1-S3 scenarios) and aggression levels. When food is very scarce (Scenario S1), all aggression levels makes the situation most critical for human-elephant conflicts. When more food was available in the forest (scenario S2), only higher aggression levels (0.6 and 0.8) resulted in critical situations. With even more food availability (scenario S3), only the highest aggression level (0.8) resulted in a critical situation. Intutively, we expect agents to engage in crop raids when food availability in the forest is limited. However, the impact of additional factors, such as the need

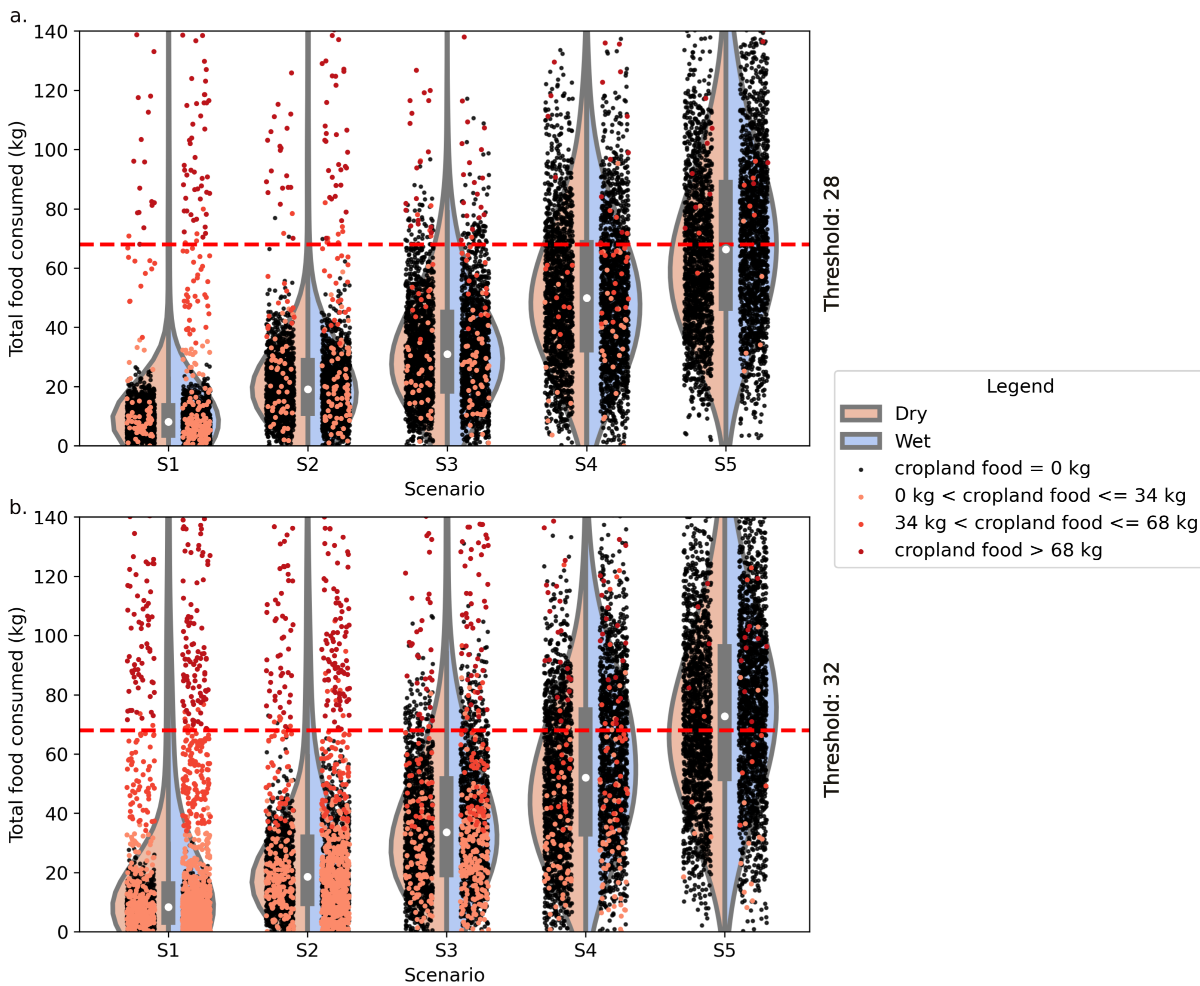

Figure 15: The daily food consumption of the elephant agents under various scenarios. The distribution is obtained considering samples of an equal number of days (5000 days) from the simulated trajectories for the wet and dry months.

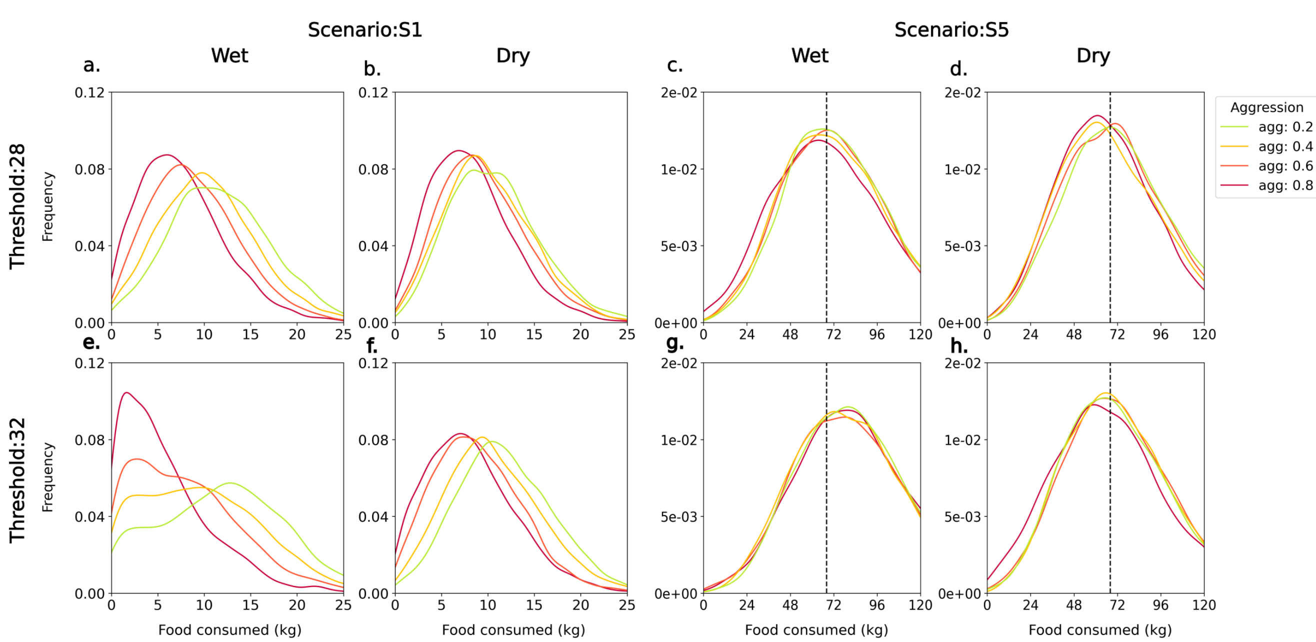

Figure 16: The probability distribution of food consumption from the forest with varying aggression factors.

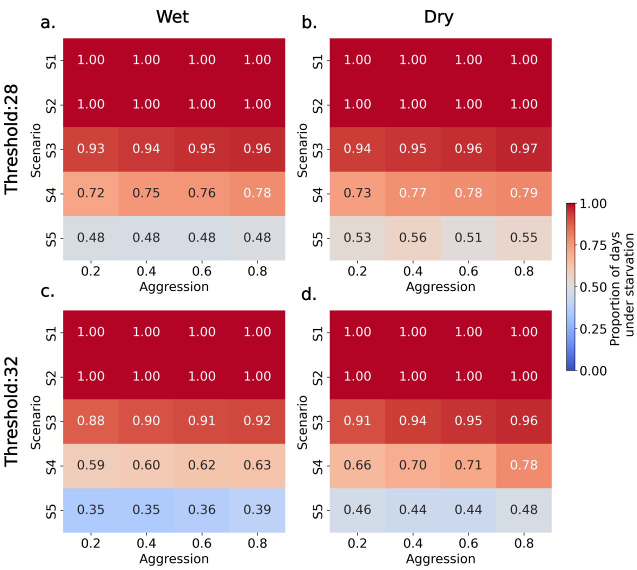

Figure 17: The likelihood of starvation considering all simulated daily trajectories and only food consumed from the forest.

for thermoregulation and aggressive behavior in crop raiding was unclear. Our study and the above synthesis provide an understanding of how these variables interact. Our simulations reveal a more intricate relationship between these factors.

One of the most challenging concerns is the recurrence of raids exhibited as multiple visits by the same crop raiding elephants. Fig. 13 shows the probability of making multiple returns to plantations by crop raiding elephant agents. As expected, the likelihood of individuals returning to plantations increases with the level of aggression and under conditions of food scarcity. However, the agent's recurrent visit to the plantations is also influenced by the need to thermoregulate. Figs. 12 and 13 illustrate the trade-off between *thermoregulation* and *foraging* in order to optimize overall fitness under varying circumstances.

When elephant agents cannot meet their dietary requirements within the forest, they move towards croplands to engage in crop raiding. Furthermore, elephants can still participate in crop raids even after meeting their dietary needs within the forest if they are habituated to consume fruiting crops. The proportion of crop raid episodes in which elephants are in a food-deprived state is given in Fig. 14. The remaining episodes are crop raid incidents where elephants have become habituated to crops.

To investigate how agents meet their dietary requirements within the forest, we examined food consumption in various scenarios of food availability within the forest. Fig. 15 illustrates the daily total food consumption (from forests and croplands) of elephant agents during dry and wet months in various scenarios for the lowest aggression level (0.2). With 192 trajectories per month, there are 1536 simulated trajectories for wet months (8 months total) and 768 for dry months (4 months total). For comparative analysis, we sampled an equal number of days (5000 days) from the simulated trajectories for the wet and dry months to generate Fig. 15. The horizontal dotted red line in Fig. 15 represents the threshold of 68 kg, which corresponds to the daily dietary requirement of the elephant agents within the simulations. The agents met their daily dietary needs when food consumption exceeded this threshold. On the other hand, if consumption falls below this threshold, the agent has not consumed enough food and is considered to be in a state of starvation.

We also investigated daily food consumption by elephant agents only from the forest at various levels of aggression and in different scenarios of forest food availability, for dry and wet months. Fig. 16 shows the probability density of food consumption only from the forest. Furthermore, we computed the probability of starvation, representing the probability of consuming less than the agent's dietary requirement of 68 kg. This probability is calculated as the area under the probability density curve to the left of the 68 kg threshold (Fig. 16). The probability of starvation when eating food only from the forest is presented in Fig. 17. As aggression levels increase, foraging efficiency in forests decreases, as agents are forced to prioritize movement toward croplands for raiding. This compromise results in suboptimal foraging within forests, especially in scenarios of food scarcity (Scenario: S1-S4), as seen in Fig. 16 (a), (b), (e), and (f). In scenarios of high food availability (Scenario: S5), the influence of aggression is less significant, and there is no discernible variance in food consumption with different levels of aggression (Fig. 16 (c), (d), (e), and (h)).

5. Discussion and Conclusion

Numerous conflicts occur between humans and elephants in the peripheries of forests in the Western Ghats. For example, the Chinnakanal and Santhanpara regions in the Idukki district of Kerala, India, often experience problems with wild elephants [75, 76, 77]. Two of the most well-known tuskers from this area, infamous for raiding and encroaching on residential areas, are named Arikomban and Chakkakomban. Arikomban, known for his frequent raids of rice stores, was sedated, captured, and moved to Periyar Wildlife Reserve in Kerala and then to Kalakkad Mundanthurai Tiger Reserve in Tamil Nadu after multiple efforts by forest authorities to prevent his intrusions [78]. Chakkakomban, known for his love of jackfruit, persistently causes problems for farmers, causing many to transition to different crops or to harvest jackfruits prematurely to minimize losses [77]. Although considerable debate persists on the underlying causes of conflict, some attribute it to food scarcity within forests [77], forest fragmentation [79], and food habituation [75].

Previous studies using ABMs have explored food or resource scarcity [10] as the primary driver of conflict. It is common to believe that crop raids occur during times of food scarcity, such as during the dry months. However, recent studies in South India have revealed a surprising pattern in which vulnerability to crop raids increases during the wet months [80, 81, 82]. The key takeaway from these studies is that the conditioning of elephants toward crops is an important driver of conflict. Furthermore, a recent survey on human-elephant conflict in Wayanad district in Kerala, India revealed the changing aggression behavior in elephants, with 97% of the respondents reporting increased elephant aggression [82]. In particular, all participants agreed that elephants previously exhibited avoidance behaviors in response to human deterrents, such as torches, firecrackers, and drums, which are no longer effective. Their findings suggested that further research is needed to examine and create targeted approaches to address the behavioral and cognitive aspects of elephants.

Previous research has investigated how climatic variables, such as precipitation and water availability, affect the spatial behavior of elephant populations [73]. It was identified that among all climatic factors, the availability of water, including its direct access to consumption and its influence on vegetation, plays the most crucial role in shaping the seasonal cycles of elephants. Elephants were seen to gather in high density near river valleys during the dry months and then disperse across their habitats during the wet months. Our model reproduced similar trends in both dry and wet seasons and examined how these, along with other variables, could influence conflict patterns. In our investigation, Conflict Cluster II emerged solely under one of the experimental conditions, and the availability of water was identified as a key factor in its emergence. However, the impact of thermoregulation on elephant behavior patterns and its consequent effect on crop raiding incidents has not been extensively investigated in prior studies, along with variables such as crop habituation and aggression.

The weather patterns and topography of the Wayanad forest range are similar to those of Seethathode, as both are located in the Western Ghats. Both areas experience a southwest monsoon from June to September and a northeast monsoon from November to December. During the southwest monsoon, there is heavy rainfall, while the period from February to May is characterized by dry conditions. However, the main difference between the two areas is the dominant crop cultivation. In Wayanad, coffee and paddy are the main crops, while Seethathode is dominated by rubber cultivation. The Wayanad region exhibits two distinct seasonal peaks in human-elephant conflict: the monsoon season (June-September) coinciding with jackfruit ripening and the paddy harvest period (October-December). The reported conflict arises when there is an abundance of high-quality forest forage during the monsoon season. This suggests that food scarcity is not the primary reason why elephants are attracted to croplands. Instead, they are drawn mainly to croplands due to the presence of mature jackfruit trees and paddy. In addition, heavy monsoon rains pose challenges to effective crop guarding, potentially increasing the risk of crop raiding during this time. These observations suggest that seasonal resource availability and human activity patterns play a crucial role in shaping human-elephant conflict dynamics within the region.

Another separate study conducted in Karnataka's Kodagu district, which shares similar climatic conditions with the Wayanad and Seethathode regions, revealed similar conflict patterns with increased activity during the monsoon and postmonsoon seasons [80]. Perennial crops such as bananas, coconuts, and arecanuts, which carry fruits throughout the year, have been reported to be vulnerable to raids during the monsoon and post-monsoon seasons, even when there is abundant forage available within the forests. This study highlights the need for more studies at finer spatial scales to understand the influence of rainfall on the patterns of crop raiding exhibited by elephants.

To effectively address human-wildlife conflict, it is crucial to have a comprehensive understanding of the root causes and to go beyond generic solutions that may not be suitable for every situation. The problem of moving beyond one-size-fits-all solutions is addressed in a study conducted in Nagarahole National Park [81]. Although generic solutions such as the creation of water holes or the cultivation of feed can be suggested, the effectiveness of these solutions is questioned in the study mentioned above, as the habituation of the crop by elephants emerges as the main driver. In addition, the efficiency of physical barriers, such as electric fences, depends on careful maintenance and surveillance, emphasizing the importance of evaluating each situation individually rather than making general recommendations.

Understanding the dynamics driving elephant space use is crucial for developing effective strategies to mitigate human-elephant conflicts and ensure co-existence. Our ABM is the first to incorporate the interaction between food scarcity, habituation, and aggression levels to study the emergent movement patterns of elephants. This tool can be used to provide qualitative and quantitative data to analyze "what if" scenarios for mitigation, as suggested in the recent survey [82].

5.1. Limitation

The limitation of the ABM model used in the present work is that migratory and long-term mobility patterns of elephants are not included. Each simulation captures only short-term behaviors, focusing on the movement dynamics of elephants when they are in close proximity to the plantations. Further, only one agent is currently used. However, we note that the ABM is capable of handling matriarchal herds and the tool can be used off-the-shelf for such simulations.

5.2. Future Directions

The ABM developed in the present work can be used to further explore the intricacies of human-elephant conflict. A key study would be to investigate the impact of water availability on space use and emerging conflict scenarios. Furthermore, the model can be used to explore the model's potential to serve as an effective tool for forecasting the possible evolution of human-elephant conflict in a changing climate. The present model uses rule-based cognition submodels, but more sophisticated machine learning techniques could be used to develop submodels with more capabilities. For example, sequential learning models could allow agents to learn from past experiences and adapt their strategies, while reinforcement learning could help uncover the best foraging and raiding strategies in simulated settings. Furthermore, human-elephant conflict represents a multifaceted competition for resources, and employing a game-theoretic framework provides a promising approach to exploring solutions. These future research directions ultimately aim to develop intelligent decision support tools that identify practical and satisficing solutions to ensure the well-being of humans and elephants.

A. Convergence analysis

In order to ensure convergence in simulations, it is necessary to assess the variance in the model's output [83]. This is particularly important in experiments that rely on simulations, such as agent-based models, where statistical averages derived from a limited number of repetitions need to be considered. However, the computational cost limits the number of simulation repetitions that can be performed without compromising the accuracy of the model. To determine the appropriate number of repetitions for each simulation, the Lorscheid method was used, which compares the convergence in mean and variance of the model's output. This method utilizes the coefficient of variation, which is the ratio of the standard deviation (σ) of a sample to its mean (μ) (Equation 5).

$$CV = \frac{\sigma}{\mu} \tag{5}$$

Here, μ is the mean sample and σ is the standard deviation sample.

This metric was selected because it does not assume a normal distribution for the output. The minimum number of repetitions is determined using a threshold ϵ, which represents the number of repetitions after which the difference in the coefficient of variation remains within the range of ϵ [84]. As the number of repetitions increases, the difference between the mean and variance of the sample and population metrics decreases, increasing the likelihood that they will become similar. To determine the minimum sample size required for an accurate assessment of variance in multivariate data, experiments were conducted on multiple outputs and sample sizes. The smallest sample size (*nmin*) was identified as the point at which the estimated difference in the coefficient of variation for any result does not deviate significantly from its value.

The elephant agent's trajectories displayed a significant amount of variability. The model outputs used for the convergence analysis were the MCP and 95% KDE measurements of the elephant agents' space utilization. The 95% KDE provided an estimate of the core area usage, while the MCP indicated the dispersion of the trajectories from the initial location. Random initialization was chosen to configure the model. The outputs were compared using 500 different model parameterizations and four values of ϵ (0.025, 0.05, 0.075, and 0.1) (see Fig. 18 (a)). Some model parameterizations required more iterations to achieve convergence due to the uncertainty in the trajectory evolution. The values of *nmin* for each ϵ value are summarized in Table 9.

Additionally, the convergence in the spatial arrangement of agents' paths was also assessed by calculating the Kullback-Leibler (KL) divergence in the 2D probability distribution of the agents. Similar to the previous configuration, 500 distinct random parameterizations were taken into account, and various thresholds were employed to determine the convergence (refer to Fig. 18 (b)).

Based on the findings of the two convergence studies, a value of 192 was selected as the minimum number of iterations (*nmin*) for subsequent experiments. The compute nodes in the *parampravega* system have 48 cores, and a total of 4 nodes were utilized in each experimental run. It was determined that the chosen *nmin* value of 192 successfully achieved the required convergence in all subsequent experiments and analyzes.

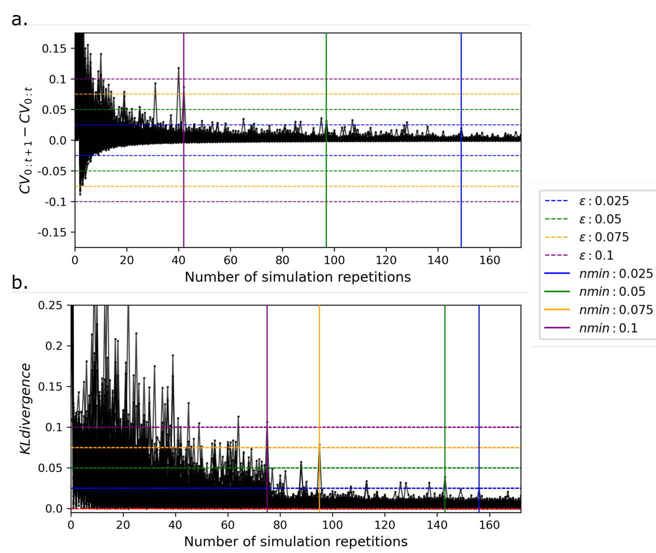

Figure 18: (a) The variation in the coefficient of variation as the number of simulation repeats increases. The model outputs being analyzed are the estimated space usage using the Minimum Convex Polygon and the 95% Kernel Density Estimate. (b) The KL divergence of the 2D agent distribution as the number of simulation repeats increases. Both plots represent 500 different random model parameterizations. The horizontal lines represent the threshold levels, while the vertical lines indicate the simulation repeats at which the change remains within the threshold.

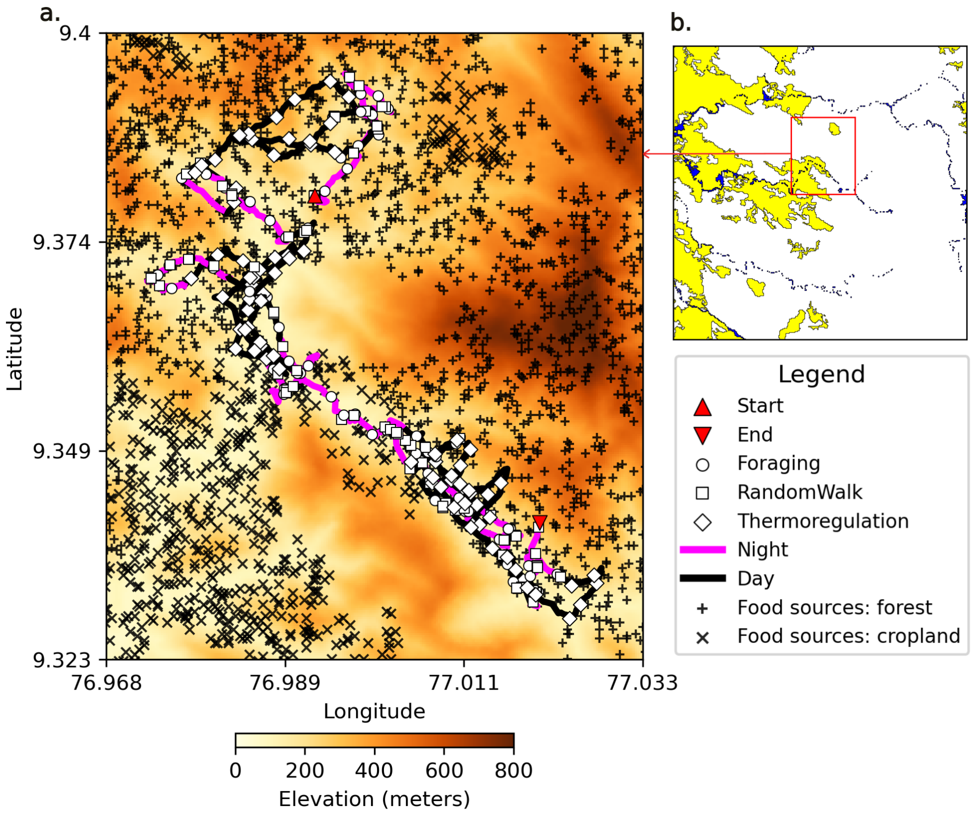

Figure 19: (a) A simulated elephant trajectory sequence that highlights the activity during the day and night shown against the DEM. The figure illustrates how elephant agents navigate mountainous terrain using valleys and flatter regions. (b) The simulation extent is displayed, with the zoomed in region in part (a) highlighted by the red box. Note that the trajectory sequence shown is the same as in Fig. 10.

Table 9
The minimum number of repeats for convergence

ϵ	*nmin* (estimated using CV)	*nmin* (estimated using KL divergence)
0.1	42	75
0.075	42	95
0.05	94	143
0.025	149	156

B. Model verification: movement of elephants taking into account the topography and slope

This section verifies the movement model of elephant agents across a mountainous terrain. Fig. 19 shows a sample trajectory sequence, highlighting the movement patterns of the elephant agents during the day and night against the DEM of the study area. The figure shows how agents navigate through valleys and flatter regions to traverse the mountainous landscape.

CRediT authorship contribution statement

Purathekandy Anjali: Conceptualization, Methodology, Software, Formal analysis, Investigation, Visualization, Writing - Original Draft. **Meera Anna Oommen:** Data Curation, Validation. **Martin Wikelski:** Data Curation. **Deepak N Subramani:** Conceptualization, Methodology, Supervision, Writing - Review and Editing.

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