RESEARCH ARTICLE

Integrating human behavior and snake ecology with agent-based models to predict snakebite in high risk landscapes

Eyal Goldstein1,*, Joseph J. Erinjery1,2, Gerardo Martin3,4, Anuradhani Kasturiratne5, Dileepa Senajith Ediriweera6, Hithanadura Janaka de Silva7, Peter Diggle8,9, David Griffith Laloo10, Kris A. Murray3,4,11, Takuya Iwamura1,12*

1 School of Zoology, Department of Life Sciences, Tel Aviv University, Tel Aviv, Israel, 2 Department of Zoology, Kannur University, Kannur, India, 3 MRC Centre for Global Infectious Disease Analysis, Department of Infectious Disease Epidemiology, School of Public Health, Imperial College London, London, United Kingdom, 4 Grantham Institute—Climate Change and Environment, Imperial College London, London, United Kingdom, 5 Department of Public Health, Faculty of Medicine, University of Kelaniya, Kelaniya, Sri Lanka, 6 Health Data Science Unit, Faculty of Medicine, University of Kelaniya, Kelaniya, Sri Lanka, 7 Department of Medicine, Faculty of Medicine, University of Kelaniya, Ragama, Sri Lanka, 8 CHICAS, Lancaster University Medical School, Lancaster, United Kingdom, 9 Johns Hopkins Bloomberg School of Public Health, Baltimore, Maryland, United States of America, 10 Liverpool School of Tropical Medicine, Liverpool, United Kingdom, 11 MRC Unit the Gambia at London School of Hygiene and Tropical Medicine, Atlantic boulevard, Fajara, The Gambia, 12 Department of Forest Ecosystems and Society, College of Forestry, Oregon State University, Corvallis, Oregon, United States of America

* pogoyoly@gmail.com (EG); takuya.iwamura@oregonstate.edu (TI)

Abstract

Snakebite causes more than 1.8 million envenoming cases annually and is a major cause of death in the tropics especially for poor farmers. While both social and ecological factors influence the chance encounter between snakes and people, the spatio-temporal processes underlying snakebites remain poorly explored. Previous research has focused on statistical correlates between snakebites and ecological, sociological, or environmental factors, but the human and snake behavioral patterns that drive the spatio-temporal process have not yet been integrated into a single model. Here we use a bottom-up simulation approach using agent-based modelling (ABM) parameterized with datasets from Sri Lanka, a snakebite hotspot, to characterise the mechanisms of snakebite and identify risk factors. Spatio-temporal dynamics of snakebite risks are examined through the model incorporating six snake species and three farmer types (rice, tea, and rubber). We find that snakebites are mainly climatically driven, but the risks also depend on farmer types due to working schedules as well as species present in landscapes. Snake species are differentiated by both distribution and by habitat preference, and farmers are differentiated by working patterns that are climatically driven, and the combination of these factors leads to unique encounter rates for different landcover types as well as locations. Validation using epidemiological studies demonstrated that our model can explain observed patterns, including temporal patterns of snakebite incidence, and relative contribution of bites by each snake species. Our predictions can be used to generate hypotheses and
inform future studies and decision makers. Additionally, our model is transferable to other locations with high snakebite burden as well.

**Author summary**

Snakebite is a neglected tropical disease affecting millions, and a major cause of death of agricultural workers in the tropics. In this research, the authors have developed a simulation model that includes data for agricultural activity across the days and seasons, as well as snake behavioral patterns, and the times and locations humans and snakes meet. Using this model, they predicted observed seasonal snakebite patterns in Sri Lanka, and they successfully showed how these patterns vary between different agricultural activities, including seasonal rice cultivation, and rubber and tea harvests. The findings arising from this study demonstrate that different combinations of human and snake activity, including species and farming practice differences, are likely to generate differences in snakebite patterns across locations. This model could be applied to analyze and predict snakebite in tropical regions around the globe to help mitigate the problem.

**Introduction**

Globally, five million people are bitten by snakes every year, resulting in approximately 94,000 deaths out of 1.8 million envenoming cases, and up to 400,000 morbidities [1,2]. Most of this burden occurs in the tropics of south east Asia and Sub Saharan Africa [2]. Despite its impacts, snakebite is still considered a neglected tropical disease that is concentrated among the poorest of the poor [2,3], and this may have contributed to the lack of funding and scientific research on snakebite relative to other disease of similar or lesser burden [3–5]. In 2017 snakebite was formally identified a neglected tropical disease by the World Health Organization [3], which prompted the scientific community to increase efforts for combating this disease, including the development of a global snake bite strategy and roadmap [6].

Several past studies have hypothesized on the importance of overlap between snake and human activities as a cause of snakebite patterns (e.g. [7–9]). However, previous research on snakebite has relied heavily on correlative models, that statistically relate bite data (e.g., from hospital admissions) to a range of social and, less often, environmental variables to identify key risk factors [10]. Such studies include those which incorporate climatic factors such as precipitation, humidity, and mean temperature [4,11–13], social factors including human population density, poverty, and farming activities [4,12,14–17], and ecological factors such as snake activity or distribution information [11,14,18,19]. For example, Yañez-arenas et al., (2016) [19] show a correlation between snake distributions and bites, and Akani et al., (2013) [14] matched patterns of snake activity with agricultural activity of local farmers across different months to reveal correlation with snakebite occurrences. However, no studies have yet taken a mechanistic socio-ecological approach that integrates both human and snake distributions and behaviors to investigate the ways in which snakebite epidemiology is simultaneously shaped by ecology, climate, and landscape characteristics.

Agent based modelling (ABM) is a bottom up approach for modeling complex and adaptive systems. ABMs are comprised of collections of individuals (agents) that are programmed to display behavioral traits, while their interactions with each other generate phenomena at a higher level [20–23]. ABM is used both for representing the internal dynamics of complex
systems, and discovering emergent patterns that may be found in those systems [24,25]. Spatially explicit social-ecological dynamics are increasingly modelled using an ABM approach (e.g.: [22,26,27]), such as those involving land use and land cover change [26,28,29]. ABM has also been used for modelling ecological epidemiology, including zoonotic disease transmission across landscapes (e.g.: [30]), mosquito behavior in models for malaria transmission [31], rabies transmission among foxes [32], and the spread of foot and mouth disease [33]. With snakebite sharing many socio-ecological characteristics with zoonotic diseases [10], ABM is an ideal and novel approach to investigate the epidemiology of snakebite from a mechanistic perspective (see Fig 1).

Sri Lanka is a global snakebite hotspot [2]. It has been estimated that nationally there are more than 80,000 snakebites a year, 30,000 of which involve envenoming. Due to high quality health systems, only around 400 of these result in deaths annually [12]. Nevertheless, morbidity is considerable and the total annual economic burden on households of snakebite envenoming in Sri Lanka amounts to almost $4 million, while it costs the public health system around $10 million per year [34]. Sri Lanka is home to over a hundred snake species, as well as nine medically important land snake species, including: Daboia russelii, Naja naja, Bungarus caeruleus, Bungarus ceylonicus, Echis carinatus, Hypnale hypnale, [35]. Many of these species also contribute to an extensive burden in neighboring regions in South Asia [36]. Previous studies have shown that the frequency of snakebites in Sri Lanka is spatially correlated with climatic, geographic, and socio-economic factors, such as ethnicity, age, occupation, and income [12], with bites occurring seasonally (primarily in the months of November-December, March-May and August) [7]. Snakebite incidence is broadly congruent with the geographical patterns of snake species occurrence across the island [37].

In this study, we integrate socio-ecological factors associated with snakebites in Sri Lanka into a single model by constructing an ABM simulation based on detailed datasets of snake

![Fig 1. Modeling approach: Our model simulates daily and seasonal cycles. A day is represented as 24 time steps. 1. Farmer agent: Farmer agent has its own daily/seasonal activity schedule according to farmer types (rice, tea, rubber). It owns its piece of crop land. Farmer agent commutes from its home location to its field. It moves inside of her crop area. 2. Snake activity layer: Snake activity level is determined by the snake species, crop types (habitat types) and precipitation. Snake species determines its distribution probability, habitat preferences, daily/seasonal activity schedule and attack rate. 3. Precipitation cycle: Precipitation affects snake activity and farmer's activity.](https://doi.org/10.1371/journal.pntd.0009047.g001)
distributions, snake behaviors, landscape characteristics, and farmers’ behavioral patterns. Sri Lanka provides an ideal case study for modeling snakebite mechanisms in this way, as not only is it a global hotspot of snakebite, it also provides highly reliable snakebite incidence data and has a high volume of accumulated medical research from which the model can be developed and validated [7,12,35,37]. We developed a spatially explicit ABM to analyze the spatio-temporal overlap between the different medically important snake species and farmers of different crops in Sri Lanka, and integrated climate and landcover as drivers of human-snake interaction across different affected landscapes, in order to create a predictive model that can inform both future research as well as decision makers.

Materials and methods

Ethics statement

Our research has been reviewed by the ethics review committee of the faculty of medicine, University of Kelaniya, Kelaniya, Sri Lanka 11600, reference number p/22512/2018. Our study included permission of written consent by all participants who were interviewed during the field work.

Agent based modeling. Agent based modelling (ABM) is a bottom up approach for modeling complex and adaptive systems using autonomous agents, that explain macro level phenomenon [20–23]. ABM is used both for studying complexity that is not easily reducible to differential equations, and discovering emergent patterns and phenomenon found in those systems, as well as study the internal dynamics of these system [24,25]. ABM has been extensively used in different fields of study for modeling complex phenomenon, such as social, political, and economical science [24]. There are now multiple programs used for ABM, including NetLogo [38], Repast [39], as well as the SpaDES package in R [40]. Recently, spatially explicit social-ecological dynamics are increasingly modelled using an Agent-based modeling approach (e.g.:[22,26,27,41]). It is commonly used for modelling social behavior including modeling land use and land cover change [26,28,29], as well as zoonotic disease transmission across landscapes (e.g.: [30]).

We used Netlogo [38] to develop a spatially explicit model that represents the dynamics of snakebites among farmers (S1 Fig). The model simulates real landscapes in the Study Area, each of which is represented by a 2x2 km study location comprised of a matrix of 10x10m grid cells. We simulated 17 study locations in total.

For the design and analysis of our model we used pattern oriented modelling (POM) [42,43]. This approach emphasizes use of multiple patterns at different hierarchical scales for calibration and validation in order to reduce uncertainty in model structure and parameters. This approach allows us to examine not only large scale phenomena (such as macro level epidemiological observations), but also probe the dynamics and intricacies of the mechanism(s) that may be hidden or unobservable by just examining the different patterns individually.

The pattern oriented modelling protocol is comprised of four steps [42]: 1) aggregate known biological data regarding a system and use it to construct a model that is related to a hypothesis and is theoretically capable of reproducing previously observed patterns; 2) determine the parameter values of the system; 3) compare systematically between the independently observed data and those patterns predicted by the model, which may involve iteratively improving the model by removing certain parameters or choosing combinations of parameters that are more plausible or better represent observed patterns; and 4) look for secondary predictions in the model, which are different from the original patterns to which the model was compared during the third step of the process.
For each one of the locations studied, the model uses a range of input data to simulate the movement and interactions of different ‘agents’ among cells for a fixed duration. We used a discrete time series comprised of both months and hours. Each month is condensed to 24 timesteps which are representative of individual hours of the daytime, and the simulation is performed across the 12 months of the year, comprising of 288 timesteps in total. Parameters and variables in the simulation are recorded and updated both hourly and monthly, depending on the agent (snake seasonal activity and farmers’ working schedules update at the beginning of each month; snake daily activity is updated at the beginning of each hour).

There are two types of agents in the model: farmers and snakes. Farmers are able to work in multiple land cover classes, depending on seasonal needs (see ‘Recording Farmer Characteristics’ below). Farmers have a state variable of working schedule, which includes the land cover type they should be farming, time of day they begin to work, and the number of hours they will spend working in that land cover class. Using the work schedule, the farmers move between the land cover they are farming and their home.

Each snake agent is characterized by a set of ecological and behavioral traits, including: species, daily activity, habitat preference, aggressiveness, and seasonal activeness. Each species is given a set of probabilities for movement between land cover classes depending on the land association factor (see “Snake distribution and behaviour” below) and number of patches for each land cover class (see “Remote sensing dataset” below).

The influence of the environment on agent activity is represented by climatic variables (precipitation and number of non-rainy days (see “Climate dataset” below)).

**Study area and spatial data.** We focused our modelling effort on the district of Ratnapura in the wet zone of Sri Lanka, which is characterized by high precipitation (see Fig 2). This district has a great diversity of crop types, including tea, rubber, coconut, as well as rice cultivation albeit practiced here on a smaller scale in comparison to other zones of Sri Lanka due to topographic conditions [44–46]. Within the district, we focused our research on four different divisions (Eheliyagoda, Balangoda, Kalawana, and Embilipitiya) that represented the variation in crop types within the district, and at each division level we ran simulations on between 4–5 locations, with 17 locations in total (see Fig 3).

![Fig 2. Ecoregions of Sri Lanka [47]. Annual precipitation of the Ratnapura district (Bioclim variable 12; [48]). The four different divisions (Eheliyagoda—northwest, Kalawana—southwest, Balangoda—northeast, and Embilipitiya—southeast) used in analyses are marked. The Ratnapura district borders on the highlands in the center of the country, the dry zone in the south east, and is part of the wet zone in its center and west.](https://doi.org/10.1371/journal.pntd.0009047.g002)
Landcover - The main attribute of each cell in the model is its landcover type (Rice, Tea, Forest, Rubber, Home). We used Sentinel-2 remotely sensed images from 2017 to produce vegetation type classification maps (Tile T44NMN and relative orbit numbers R119 & R076), which were chosen based on quality of images and percentage of cloud cover. Tiles were downloaded from the USGS earth explorer portal and were processed using the SNAP program and the Sen2cor plugin [49]. After removing cloud cover, the tiles were merged into a single tile before classification.

We classified the images into five different landcover types giving importance to major crop types and vegetation in the district: forest, rubber, tea, paddy, and water bodies, with a resolution of 10 x 10m (Fig 3). The classification was made using two different supervised classification algorithms: support vector machine (SVM) and maximum likelihood (ML), with 100 training polygons for each land cover type. We used spectra from 4 different bands and NDVI index for classification (band number 2 –Blue, band number 3 –green, band number 4 –red, and band number 8 –near-infra red), with band numbers 4 and 8 used for calculation of the NDVI index. We obtained an overall accuracy of 83.2% and kappa coefficient of 0.68 for the SVM classification and an accuracy rate of 80.7% and kappa coefficient of 0.66 for the ML classification (see accuracy assessment in S1 Table). The classification was later supplemented with a home class, where homes were randomly assigned in each study location in proportion to the population, with a fixed population size of 200 farmers for each simulation.

Climate - We used monthly precipitation (mm) from the climate research unit dataset [50] downscaled to a resolution of 1km$^2$, using the Delta method [48,51]. For each one of the locations modelled, we extracted the raster values and used them in our model as integer values for each month. In addition, we estimated the number of non-rainy days per month from past literature [52].

Human agent characteristics. Farmer activity - The characteristics and behavior of farmers in the study area (see above) was first characterized via a community survey conducted during two weeks in July 2019. We visited four different divisions in the district of Ratnapura, and in each one we interviewed 10 farmers (40 in total) of different crops: with 22 engaged in rice farming, 22 in tea farming, and 10 in rubber (some farmers tend multiple crops). Each farmer was asked to answer a set of questions related to work schedules, including: planting season, harvest season, hour of starting work, hour of finishing work, seasonal rotation of
crops, as well as size of plot. We also asked farmers about previous encounters with snakes, including location, and season when snakes were encountered. Our final farming dataset included a list of parameters that defined the farming behavior in the model (see Table 1). Based on the results of the survey, we allowed farmer agents in the model to have the option of moving among up to three different landcover types, and to choose between different working schedules on each landcover type. To take into account the seasonal variation of labour requirements according to the various cropping cycles, we first developed a labor index:

\[ I_{ij} = \frac{247 \times F_{ij}}{30 \times D_{ij}} \]

where \( I_{ij} \) is the labor index for landcover \( i \) during month \( j \) for 1 square kilometer of that landcover, \( F_{ij} \) is the number of farmers needed at landcover \( i \) during month \( j \) for the size of landcover owned by a specific farmer, \( A_i \) is the size of landcover \( i \) in acres, and \( D_{ij} \) is the number of days per month that land cover \( i \) is farmed during month \( j \), and 247 is used to convert acres (the measurement farmers used when answering the questionnaire) into square kilometers.

A mean value of \( I_{ij} \) was calculated using the different index values obtained by the farmers and was distributed between the months according to the working schedule described by the farmers in the interviews. For the rubber landcover the index was calculated for a single day, and then multiplied by the estimated number of non-rainy days that occur in that specific month, since rubber farmers cannot work in the rain due to technical limitations of rubber harvesting methods.

In the model, the probability of each farmer attending each landcover type is then calculated at the beginning of each month:

\[ W_{ij} = \frac{S_i \times I_{ij}}{W_{max}} \times P \]

where \( W_{ij} \) is the number of farmers that are going to work in month \( i \) in landcover type \( j \), \( S_i \) is the size of landcover type \( j \) in a simulation, \( I_{ij} \) is the labor index for month \( i \) and landcover \( j \) (from Eq 1), \( W_{max} \) is the maximum value of \( W \) possible for the location being simulated, and \( P \) is the farmer population size of the location being simulated. Once a farmer is assigned a certain landcover for month \( i \), they will only work on that specific landcover during that month.

## Table 1. A complete list of parameters used in the model for all agent types.

Each of the parameters is either an input for the snake behavior submodel, farmer behavior submodel, or a global variable (climate and landcover).

| Model   | Parameter                          | Value                  | Source                     |
|---------|------------------------------------|------------------------|----------------------------|
| Farmers | Farmer type                        | Rice, Rubber, Tea      | Field work                 |
| Farmers | Land type work index               | 0–110                  | Field work                 |
| Farmers | Starting hour                      | 4-9AM                  | Field work                 |
| Farmers | Number of hours worked             | 4–14                   | Field work                 |
| Farmers | Percentage of population working as farmers | 30–70%                | Government reports [53]    |
| Snake   | Point process models               | 0–3'10^-8              | Calculated from snake data (S1 Data) |
| Snake   | Seasonal activity probability      | 0–1                    | Literature [54–56]        |
| Snake   | Daily activity patterns            | 0–5                    | Literature [57]           |
| Snake   | Aggressiveness                     | 1–10                   | Local herpetologists’ questionnaire |
| Snake   | Land association factor            | 0–2.429                | Calculated from snake data (S2 Table) |
| Land cover | Type of land cover               | Rice, Tea, Rubber, Forest, Water, Home | Remote sensing          |
| Climate | Mean monthly precipitation         | 21–1054                | Climate Research Unit     |
| Climate | Number of rainy days               | 10–25                  | Literature [52]           |

[https://doi.org/10.1371/journal.pntd.0009047.t001](https://doi.org/10.1371/journal.pntd.0009047.t001)
The farmers are then assigned a random number from a uniform distribution composed of the possible number of hours farmers work in the field for that specific landcover, based on what was reported by the farmers interviewed during the field work (S3 Table). For the starting hour, the farmers choose a random value out of a normal distribution composed of the possible starting hours for that specific landcover, based on what was reported by the farmers during the field work (S4 Table).

**Snake agent characteristics. Distribution and abundance** - We used Poisson Point Process Models (PPMs) to represent potential abundance of snakes for each species. We interpreted these models as representing the relative carrying capacity and a proxy for potential abundance for each species in each one of the locations modelled in our simulation. In order to calibrate our model’s snake population size, we used previous research in which the species *Hypnale hypnale* was systematically surveyed to estimate the number of individuals per square kilometer of forest habitat [58]. This provided a link between PPM outputs and measured snake abundance in forest landscapes, which we then applied to other species and habitat types according to relative model weights following a habitat preference analysis (see below). This method resulted in abundance estimates up to 900 individuals per species per 2x2km tile (= up to 225 snakes per species per km$^2$).

**Habitat preferences** - Preference of landscape for each snake species was defined by a land association factor, calculated using the data points that were used to create the species distribution models. Using chi-square tests, the likelihood of a snake species being found on a specific land cover versus the probability that it would be found there at random was calculated (see S2 Table).

**Activity and behavior** - We incorporated several different measures of snake activity and behavior into the model, including seasonal activity patterns, daily behavioural habits, movement preferences among available habitats, and aggressiveness.

In the model, we assumed that there are a fixed number of snakes for each species present on a tile based on the PPM maps and population size estimate. Changes in activity levels throughout the year were defined according to observed seasonal activity in the tropics [54–56], and according to observations made on *Hypnale* spp [58]. At each monthly update a certain percentage of the snakes from each species becomes active according to the level of precipitation measured (see section 4), as calculated by:

$$A_i = \frac{P_i}{P_{\text{max}}}$$

where $A_i$ is the activity factor for month $i$, and $P_i$ is the precipitation level for month $i$, and $P_{\text{max}}$ is the max level of precipitation for the region.

The snake daily activity is determined probabilistically according to the snake activity patterns, with each species being pre-defined as either diurnal, nocturnal, crepuscular, or cathemeral [57]. A probability distribution was designed for each of the different daily activity patterns by identifying hours of sunrise and sunset, and setting the distributions in relation to those hours. All snakes were defined to have a baseline probability of 0.1 (10% chance) for being active even in hours when they are biologically defined as inactive, e.g. nocturnal snakes during daytime, in order to capture the full scope of encounter probability as described by epidemiological surveys (see below).

The probability of snakes moving to a specific landcover type is calculated using the amount of landcover type available and the attraction of the snake to that specific landcover type (see S2 Table for the land association factor). The probability of each species moving to any type of
landcover type was defined by a transition rule as:

$$M_{ij} = \frac{P_j L_{ij}}{P_j L_{i1} + P_n L_{in}}$$  \hspace{1cm} (4)$$

where $M_{ij}$ is the probability of an individual of snake species $i$ to move to land cover type $j$, $P_j$ is the number of cells of land cover $j$, and $L_{ij}$ is the landcover association factor between snake species $i$ and landcover $j$. After calculating the transition rule, a random number is drawn to decide what landcover the snake will move to.

**Snakebites.** Agents are tracked within the model locations and their encounters (occurring in the same grid cell at the same time) are recorded as snakebites under the following conditions. The probability of a snakebite occurring during an encounter is calculated by taking into account the varying propensities of each species to attack during an encounter. We incorporated aggressiveness by way of an aggressiveness index, which is a ranking of between 1–10 ($1 = $docile, 10 = very aggressive) as determined by local herpetologists (Table 2). The probability of a snakebite occurring is therefore calculated as:

$$P_i = \frac{A_i}{A_{max}}$$  \hspace{1cm} (5)$$

where $P_i$ is the probability of snake species $i$ causing a snakebite when there is a human-snake interaction, $A_i$ is the aggressiveness index for snake $i$, and $A_{max}$ is the maximal value for aggressiveness. When humans and snakes meet on the same cell, a random number is drawn between 0–1, and if it is smaller than the value obtained from the calculation then a snakebite occurs. This function is designed in order to assign a threshold for bites according to each snakes aggressiveness level, with the assumption that combining the aggressiveness along with the human-snake overlap would provide a good measure for snakebites occurring.

**Model evaluation.** We evaluated our model in two different ways: hypothesis testing (verification) and validation. For validation we used the “multiple patterns” methodology in order to check for consistency between the model and the observed data. This was done to make sure we were not overfitting the model, and to make sure it represented the general dynamics of the system [43,59]. For the hypothesis testing we examined the process representation to make sure our model represented both the micro and macro level phenomena correctly, and that the system properly represented the dynamics and mechanism(s) that it is supposed to be representing. For validation we used the model formulations that were chosen during model selection. In addition, for the variables that were tested during the sensitivity analysis we chose variable values that were parameterized using the analysis output in order to make sure the

| Species               | Common name          | Aggressiveness | Daily activity   | Zonation       |
|-----------------------|----------------------|----------------|------------------|----------------|
| Daboiia russelli      | Russell’s viper      | 8              | Nocturnal        | Terrestrial    |
| Echis carinatus       | Saw scaled viper     | 10             | Cathemeral       | Terrestrial    |
| Hypnale hypnale       | Hump nosed viper     | 10             | Nocturnal        | Semi-arboreal  |
| Hypnale zara          | Hump nosed viper     | 10             | Nocturnal        | Semi-arboreal  |
| Hypnale napa          | Hump nosed viper     | 10             | Nocturnal        | Semi-arboreal  |
| Bungarus caeruleus    | Common krait         | 2              | Nocturnal        | Terrestrial    |
| Bungarus ceylonicus   | Ceylon Krait         | 1              | Nocturnal        | Terrestrial    |
| Naja naja             | Cobra                | 5              | Cathemeral/ Crepuscular | Semi-aquatic |

https://doi.org/10.1371/journal.pntd.0009047.t002
values were above a threshold that allowed emergent patterns to appear in our system. For the full description of model selection and sensitivity analysis see S1 Appendix.

**Validation.** For external validation we chose multiple patterns on which there was already research conducted in Sri Lanka, such as temporal patterns of snakebites [7], the relative risk of snakebite between locations [12], and biting snake species composition among bite victims as inferred from hospital records [37]. This was done in accordance with the POM protocol [43], which suggests that multiple patterns be assessed and the fit between the model predictions and these patterns evaluated (as opposed to comparing results to a single statistic or a single pattern). This is supposed to prevent overfitting of the model to an expected output, or falsely representing the model by using only one output parameter, and to make sure that the model can represent the dynamics of the system that it is attempting to represent.

**Hypothesis testing**

We checked for consistency of process representation, following the spatial and temporal patterns of the snake and farmer agents, and snakebites. We did this for the distribution of snakebites across both the months of the year and across the hours of the day. We then checked when peak snakebites were occurring and their relationship to the movement patterns of the agents. This allowed us to make sure that the system was properly representing both the micro level (agents’ movements) and the macro level (snakebite distribution) and the relationship between them.

**Hypothesis generation**

The POM protocol also suggests looking for secondary predictions that emerge from the model and using them later for further validation if observations become available, and if not then using them to prompt further research in the field [42]. We checked for the following secondary predictions: monthly and daily patterns by snake species, by division, and by landcover types.

**Results**

**Validation**

Overall, the model performed well in differentiating between high and low risk locations. The results are based on simulation runs for 45 different locations across the entire district of Ratnapura, with high and low defined as above or below the median snakebite risk for all locations simulated. Predictions of the ABM showed a significant difference in prediction between locations where snakebite risk was above the median of all locations simulated and those where snakebite risk was below the median using Welch two sample t-test ($t = -5.539$, $df = 39.20$, p-value < 0.001) (S2 Fig).

The model also effectively predicted the relative contribution of different species to overall snakebite patterns as derived from hospital surveys [37], both in divisions 1–3 (Eheliyagoda, Balangoda, and Kalawana) which were located in the wet zone, and divisions 4 (Emptilipitiya) which was located in the intermediate zone (Table 3 and Fig 4). The simulation contribution of cobras was overestimated in our model in all locations, and the contribution of Russell’s viper and hump nosed viper against entire snakebites were underestimated in the intermediate zone. Additionally, in contrast to the hospital survey our model did not include non-venomous species, so an over estimation is to be expected to a certain extent.

The model was also successful in predicting the temporal patterns of snakebite in Sri Lanka reported previously. Snakebite has been reported as having three peaks in general throughout
the year (November–December, March–May, August), although there are regional variations [7]. The ABM predicted the possibility of different main peaks of snakebites through the year, including a large peak in March-May (Balangoda, Eyeliyagoda, Kalanawa, Embilipitiya), a second peak around August (Balangoda, Kalanawa), and a third peak in November-December (Balangoda, Eyeliyagoda, Kalanawa, Embilipitiya) (Fig 5).

### Hypothesis testing

The model performed well in representing the micro level (agent movement) and its relation to the macro level (snakebite distribution), with a clear pattern of spatial-temporal overlap between snakes and farmers as the cause of snakebites (Fig 6). The highest frequency of snakebite during the year occurred when both farmers and snakes were present and active on the different landcover types, although bite frequency differed among landcover types. On tea plantations, snakebites are simulated to follow snake activity closely as the activity level of farmers is highly consistent throughout the year (Fig 6A–6D). Since the level of snake activity is defined by the amount of precipitation, the snakebites patterns follow seasonal rainfall

**Table 3. The average predicted proportion of bites from different snake species across four different locations.**

The first three divisions (Balangoda, Eheliyagoda, Kalawana) belong to the wet zone of Sri Lanka, while the fourth region (Embilipitiya) belongs to the intermediate zone of Sri Lanka.

| Wet zone (1–3) | Model prediction | Hospital data |
|---------------|------------------|---------------|
| Hump nosed viper | 51–57% | 65% |
| Russell’s viper | 21–24% | 25% |
| Cobra | 23–26% | 3% |
| Non-venomous species | 5% | |

| Intermediate zone (4) | Model prediction | Hospital data |
|-----------------------|------------------|---------------|
| Russell’s viper | 39% | 50% |
| Hump nosed viper | 16% | 30% |
| Common Krait | 10% | 10% |
| Cobra | 33% | 5% |
| Non-venomous species | 5% | |

https://doi.org/10.1371/journal.pntd.0009047.t003

![Fig 4. The average predicted proportion of bites from different snake species across four different locations.](https://doi.org/10.1371/journal.pntd.0009047.g004)
For rice paddies, snakebite peaks occur at different time periods—either in April-May (peak snake activity), in August (peak farmer activity), or November (a combination of both) (Fig 6B–6E). This reflects seasonal variability of rice farmers’ behaviors, which have a different activity peak from snakes (Fig 6B–6E). On rubber plantations, snakebites are a mixture of both snake and farmer activity as well, with the highest peak in bites occurring when snakes are most active in April-June (Fig 6C–6F).

Distinct patterns of spatio-temporal overlaps on the daily level are also evident. For the tea landcover, peak activity tends to follow a bimodal pattern with peaks occurring in both late afternoon and early morning (S3A Fig). This pattern reflects the working pattern of tea farmers that tend to start working early during the day, but also follow long working hours, which results in farmers meeting snakes both when snakes are active early morning, and when snakes are active during late afternoon. For the rice landcover, snakebites have the highest probability of occurring during late afternoon when farmers and snakes have high overlap, but may also occur in the early morning during peak activity months (S3B Fig). This pattern reflects the
working pattern of rice farmers that tend to start later during the day, but work for long hours, there for increasing the chances of encounter while snakes are active later in the day. For rubber, snakebites have the highest probability of occurring during the early hours of the morning (S3C Fig). This pattern reflects the working pattern of rubber farmers that tend to start working early in the day when snakes are active, but also have short working hours, so a second snakebite peak later in the day does not occur.

Hypothesis generation

A secondary prediction of our model was that the monthly burden of snakebites varies across locations, (Fig 7). Our model predicted that in drier locations the peak in bites occurs earlier in the year during February-April, whereas wetter locations tend to have a higher peak in bites during the month of May (Fig 7). The different patterns cannot be traced to a single factor but is likely caused by a combined effect of land cover and climatic differences, and the interaction between snakes, farmers, and their environment within these locations (see S4, S5, S6, S7 and S8 Figs). This prediction also suggests that there may be significant temporal differences in snakebites between the wet, dry, and intermediate zones in Sri Lanka.

Another secondary prediction from our model estimates that the monthly distribution of snakebites varied between species, with a different pattern for each species (Fig 7). These different patterns are not caused by snake activity alone, but by a combination of snake habitat preference, snake activity, and the seasonal patterns of farmers on different landcover types.

Discussion

Snakebite affects poor and rural populations that are exposed to venomous snakes, yet few studies have attempted to decompose spatial and temporal patterns and predict risk on the basis of social-ecological causative mechanisms. Here we develop a mechanistic model to examine snakebite dynamics by simulating snake-human encounters in rural agricultural communities using an agent-based model (ABM). Our simulation represents the farmer-snake interactions that are driving snakebite patterns in Sri Lanka, a bite hotspot country within the highly affected South Asian region. While it has been previously shown that snakebites can have strong spatial and temporal patterns [12,37], and different studies have explored these patterns on local scales [60,61], our model provides a unique mechanistic perspective regarding the emergence of these patterns from basic ecological principals regarding species

Fig 7. Secondary predictions A) the yearly distribution of snakebites for different divisions. Each division showed a distinct pattern of snakebite, with the largest peak of the year varying between March and May. B) The yearly distribution of snakebites for different species. Each species showed different snakebite peaks through the year, with the largest peak occurring between February and May.

https://doi.org/10.1371/journal.pntd.0009047.g007
interactions on a more local scale. Results showed that the model performed well in simulating snakebite occurrences across spatial and temporal scales, including daily and seasonal patterns, biting species assemblages, and bite incidence variation among locations (Figs 4, 5, 6 and S2–S8).

The results suggest that the risks of snakebite depend on factors influencing the behaviors of both farmers and snakes, including landcover, precipitation, and the interaction between humans and snakes (Figs 6 and 7). Our model also concurs with previous research showing that seasonal precipitation patterns dictate patterns of snakebites by influencing the activities of both snakes and farmers (Fig 6) [4,12]. We further discovered that different crop types result in distinct work schedule in relation to daily human activities and rainy seasons, greatly altering overall risk profiles of snakebites for each crop (Fig 6E, 6F and 6G). Additionally, the composition of snake species is different among various crop types (S8 Fig), leading to complex social-ecological interactions that in turn contribute to snakebite risk [14].

Our model suggests greater resolution on the composition of species delivering bites is essential in order to better resolve snakebite risks in future (Fig 4). Previous research has supported the idea that following the ecology and behavior of each species would give a better understanding of both the mechanism driving bite patterns for individual snake species [18], and for different types of landcover (e.g.: [62]). Our model provides a mechanistic explanation for the ways snake ecology and human behavior combine to result in species specific snakebite patterns. For example, in our study system, although two species (Russell’s vipers and Hump nosed vipers) show similar seasonal activity patterns, a stronger preference for rice paddies for one of the species (Russell’s vipers) and a stronger preference for rubber plantations in the other species (Hump nosed vipers) results in very different temporal patterns of encounter.

Understanding the overall pattern of snakebite therefore requires understanding of the specific ecology of each species (Fig 7B).

Such differences in an example of why predicted snakebite patterns vary considerably between locations, since spatial heterogeneity of farmer types and snake species create fine scale differences in encounter risk, a prediction which concurs with previous research [12,13,37,63]. In our study, this difference between locations was in practice caused by a combination of factors, including different distributions of key landcover types and climatic conditions, which in turn affect either snakes or farmers or both. For example, the division of Embilipitiya, which is located in the intermediate climatic zone of Sri Lanka, had a less suitable environment for Hump-nosed vipers and a high concentration of rice paddies, resulting in a snakebite pattern different, including overall risk, temporal patterns of risk and biting species composition, to those found in the sites in the wet zones (Figs 4, 5 and 7).

Our study clearly showed that the spatio-temporal synchronicity in both snake and farmer behaviors is the key to understand the snakebite patterns in the Ratnapura district in Sri Lanka (Figs 6 and S3). In particular, multiple climatic profiles within the district may result complex snake-farmer associations evident from the snakebites patterns as well as the composition of responsible snake species (Figs 4, 5 and 7). While our study shows a strong implication of social-ecological dynamisms of snakebites in dry and wet-dry climate zones in Sri Lanka, other studies have already invoked similar mechanisms to explain observed patterns of risk in rural communities outside of Sri Lanka (e.g.: [14,17]). Considering the ease of re-parameterizing simulation models to generate baseline snakebite risk predictions on any spatial and temporal scale, our model has strong potential for applications in other areas across the tropics. For example, locations outside of Sri Lanka that include some of the same venomous snake species have shown yearly temporal distributions of snakebites that contrast with those observed inside of Sri Lanka [16,17,64], which provides a strong avenue for hypothesis generation and testing of the model in different systems. Outside of Sri Lanka, other studies have similarly
reported land-use specific risks (e.g. rubber in Liberia and rice in the Philippines) [65,66]. Transferring the model to these regions could shed further light on the combinations of factors that underpin different snakebite patterns among different locations, again a potentially fruitful avenue for hypothesis generation or validation.

While our model represented some of the most important snake behavior factors relevant to snakebite, there are other elements that we did not address, primarily due to data limitations. These include reproduction phenology and its association with climate [4], seasonal variability in landcover preferences [58], or feeding habits and species-specific feeding strategies. For example, it is known that reproductive behavior can increase the chances of encountering snakes [67,68], and integrating this behavior into the model may improve predictions. Additionally, differences between feeding strategies such as active hunting (e.g. *Naja naja*) and ambush (e.g. *Hypnale hypnale* & *Daboia russellii*) may lead to different encounter outcomes, and integrating these traits may reduce the overestimation of cobra bites in comparison to other snake species and improve our predictions for the Ratnapura district. Similarly, we have not captured all the behavioral traits of farmers, such as differences in farming practices between small and large plantations, seasonal crop rotations [69], and additional crop types (e.g., small gardens, cinnamon, banana, coconut) [45], adaptive characteristics that represent farmers’ planning strategies over multiple years, or specific behaviors relating to snakebite epidemiology, such as health seeking behavior or the use of protective measures (e.g., boots) [70]. Additionally, we did not integrate the distance between homes and fields due to limitations of our modeling framework, even though it has been known to be an important factor for snakebite occurrence. Nevertheless, our model has demonstrated the importance of integrating both human and snake behavior into a single model and has shown that integrating even a few essential characteristics can have strong explanatory value for predicting patterns of snakebite.

Snakebite is an ongoing concern in Sri Lanka, and across southern Asia and much of the tropical and subtropical developing world. The World Health Organization has launched a strategic plan to reduce snakebite injuries and mortality by 50% by the year 2030, yet it has been suggested that one of the key barriers to preventing snakebite is the lack of good quality research to help direct effort [36]. Here we explored fine scale spatially explicit predictions by developing a novel mechanistic model to explain snakebite risks based on snake behaviors (e.g. snake activities and distributions) and farmer behaviors (e.g. work schedules for different landcover types). Our approach is based on clear, general mechanisms and strong socio-ecological theory and is therefore highly transferrable to other systems, where the risks of snakebite are similarly associated with occupational characteristics, environmental conditions and snake ecological traits [8,17,19,71–73]. Our model, once implemented with local datasets, can examine the local socio-ecological drivers of snakebites and predict spatial and temporal snakebite patterns, as well as generating hypotheses and testing the efficacy of policy intervention. With snakebite burden in Sri Lanka expected to increase under climate change [7] our findings carry important implications for future snakebite prevention in the study sites where it was developed. The insights gained in this study will help to focus future efforts to collect relevant data and resolve key mechanisms underlying snakebite risk, which should help advance management planning and the direction of scarce management resources.

**Supporting information**

S1 Fig. Model outline. A. model outlines B. model structure. (DOCX)
S2 Fig. Model output of mean snakebite risk for locations with high and low snakebite occurrence.
(DOCX)

S3 Fig. The daily spatial temporal overlap of farmers and snakes for rice farmers. A. Rice farmers B. Tea farmers C. Rubber farmers.
(DOCX)

S4 Fig. Daily distribution of snakebite by division.
(DOCX)

S5 Fig. Daily distribution of snakebite by landcover type.
(DOCX)

S6 Fig. Daily distribution of snakebite by snake specie.
(DOCX)

S7 Fig. Yearly distribution of snakebite by landcover type.
(DOCX)

S8 Fig. Percent of snakebite by snake specie.
(DOCX)

S1 Table. Classification assessment. A. Support vector machine B. Maximum likelihood.
(DOCX)

S2 Table. Land association factor.
(DOCX)

S3 Table. Farmers working hours.
(DOCX)

S4 Table. Farmers starting hours.
(DOCX)

S1 Data. PPM at different locations.
(XLSX)

S1 Appendix. Technical evaluation. A. Model selection B. Sensitivity analysis C. Results.
(DOCX)

Acknowledgments
We are grateful to Ruchira Somaweera for curation of snake occurrence data, and to Udaya Wimalasiri for assistance during the field work.

Author Contributions
Conceptualization: Eyal Goldstein, Kris A. Murray, Takuya Iwamura.

Data curation: Eyal Goldstein, Joseph J. Erinjery, Gerardo Martin, Anuradhani Kasturiratne, Dileepa Senajith Ediriweera, Hithanadura Janaka de Silva, Takuya Iwamura.

Formal analysis: Eyal Goldstein, Takuya Iwamura.

Funding acquisition: Hithanadura Janaka de Silva, Peter Diggle, David Griffith Laloo, Kris A. Murray, Takuya Iwamura.
Investigation: Eyal Goldstein, Joseph J. Erinjery, Gerardo Martin, Kris A. Murray, Takuya Iwamura.

Methodology: Eyal Goldstein, Kris A. Murray, Takuya Iwamura.

Project administration: David Griffith Lalloo, Kris A. Murray, Takuya Iwamura.

Software: Eyal Goldstein, Takuya Iwamura.

Supervision: Joseph J. Erinjery, Kris A. Murray, Takuya Iwamura.

Validation: Eyal Goldstein, Joseph J. Erinjery, Takuya Iwamura.

Writing – original draft: Eyal Goldstein, Takuya Iwamura.

Writing – review & editing: Joseph J. Erinjery, Gerardo Martin, Anuradhani Kasturiratne, Dileepa Senajith Ediriweera, Hithanadura Janaka de Silva, Peter Diggle, David Griffith Lalloo, Kris A. Murray, Takuya Iwamura.

References

1. Gutierrez J. M., Williams D., Fan H. W., & Warrell DA. Snakebite envenoming from a global perspective: Towards an integrated approach. Toxicon. 2010; 56: 1223–1235. https://doi.org/10.1016/j.toxicon.2009.11.020 PMID: 19951718

2. Kasturiratne A., Wickremasinghe A.R., de Silva N., Gunawardena N.K., Pathmeswaran A., Premaratna R., Savioi L. LDG and de SHJ. The global burden of snakebite: A literature analysis and modelling based on regional estimates of envenoming and deaths. PLoS Med. 2008; 5: 1591–1604. https://doi.org/10.1371/journal.pmed.0050218 PMID: 18986210

3. Chippaux J. Snakebite envenomation turns again into a neglected tropical disease! J Venom Anim Toxins Incl Trop Dis. 2017; 23: 38. https://doi.org/10.1186/s40409-017-0127-6 PMID: 28804495

4. Chaves LF, Chuang T, Sasa M, Gutiérrez JM. Snakebites are associated with poverty, weather fluctuations, and El Niño. Sci Adv. 2015; 1.

5. Harrison RA, Hargreaves A, Wagstaff SC, Faragher B, Lalloo DG. Snake envenoming: A disease of poverty. PLoS Negl Trop Dis. 2009; 3. https://doi.org/10.1371/journal.pntd.0000569 PMID: 20027216

6. World Health Organization. Snakebite envenoming: A strategy for prevention and control. 2019.

7. Ediriweera DS, Diggle PJ, Kasturiratne A, Pathmeswaran A, Gunawardena NK, Jayamanne SF, et al. Evaluating temporal patterns of snakebite in Sri Lanka: The potential for higher snakebite burdens with climate change. Int J Epidemiol. 2018; 47: 2049–2058. https://doi.org/10.1093/ije/dyy188 PMID: 30215727

8. Rahman R, Faiz MA, Selim S, Rahman B, Bashir A, Jones A, et al. Annual Incidence of Snake Bite in Rural Bangladesh. PLoS Negl Trop Dis. 2010; 4: 1–6. https://doi.org/10.1371/journal.pntd.0000860 PMID: 21049056

9. Stock RP, Massougbodi A, Alagón A, Chippaux JP. Bringing antivenoms to sub-Saharan Africa. Nat Biotechnol. 2007; 25: 173–177. https://doi.org/10.1038/nbt0207-173 PMID: 17267747

10. Murray K.A., Martin G and Ti. Focus on snake ecology to fight snakebite. Lancet. 2020; 395: e14. https://doi.org/10.1016/S0140-6736(19)32510-3 PMID: 31982076

11. Angarita-Gerlein D, Bravo-Vega CA, Cruz C, Forero-Munoz N.R., Navas-Zuloaga M.G., Umana-Caro JD. Snakebite Dynamics in Colombia: Effects of Precipitation Seasonality on Incidence. Ires. 2017; 2017: 1–4. Available: https://mcmse.asu.edu/RES

12. Ediriweera DS, Kasturiratne A, Pathmeswaran A, Gunawardena NK, Wijayawickrama BA, Jayamanne SF, et al. Mapping the Risk of Snakebite in Sri Lanka—A National Survey with Geospatial Analysis. PLoS Negl Trop Dis. 2016; 10: 1–14. https://doi.org/10.1371/journal.pntd.0004813 PMID: 27391023

13. Hansson E, Sasa M, Mattisson K, Robles A, Gutiérrez JM. Using Geographical Information Systems to Identify Populations in Need of Improved Accessibility to Antivenom Treatment for Snakebite Envenoming in Costa Rica. PLoS Negl Trop Dis. 2013; 7. https://doi.org/10.1371/journal.pntd.0002009 PMID: 23383352

14. Akani GC, Ebere N, Franco D, Eniang EA, Petrozzi F, Politano E, et al. Correlation between annual activity patterns of venomous snakes and rural people in the Niger Delta, southern Nigeria. J Venom Anim Toxins Incl Trop Dis. 2013; 19: 1–8. https://doi.org/10.1186/1789-9199-19-1 PMID: 23849430
15. Hansson E, Cuadra S, Oudin A, Jong K De, Stroh E, Tore K. Mapping Snakebite Epidemiology in Nicaragua—Pitfalls and Possible Solutions. PLoS Negl Trop Dis. 2010;4. https://doi.org/10.1371/journal.pntd.0000896 PMID: 21124884

16. Mohapatra B., Warrell D.A., Suraweera W., Bhatia P., Dhingra N., Jotkar R.M., Rodriguez P.S., Mishra K., Whitaker R., Jha P. Snakebite Mortality in India: A Nationally Representative Mortality Survey. PLoS Negl Trop Dis. 2011; 5: 1–8. https://doi.org/10.1371/journal.pntd.0001018 PMID: 21532748

17. Sharma SK, Koimala S, Dahal G, Sah C. Clinico-epidemiological features of snakebite: a study from Eastern Nepal. Trop Doct. 2004; 34: 20–22. https://doi.org/10.1177/004947550403400108 PMID: 14959965

18. Yañez-Arenas C., Peterson A. T., Mokondoko P., Rojas-Soto O., & Martínez-Meyer E. The Use of Ecological Niche Modeling to Infer Potential Risk Areas of Snakbeite in the Mexican State of Veracruz. PLoS One. 2014; 9. https://doi.org/10.1371/journal.pone.0100957 PMID: 24963989

19. Yañez-arenas C, Peterson AT, Rodriguez-medina K, Barve N. Mapping current and future potential snakebite risk in the new world. Clim Change. 2016; 134: 697–711. https://doi.org/10.1007/s10584-015-1544-6

20. Brown DG, Riolo R, Robinson DT, North M, Rand W. Spatial process and data models: Toward integration of agent-based models and GIS. 2005; 25–47. https://doi.org/10.1007/s10109-005-0148-5

21. Filatova T, Verburg PH, Cassandra D, Ann C. Environmental Modelling & Software Spatial agent-based models for socio-ecological systems: Challenges and prospects q. Environ Model Softw. 2013; 45: 1–7. https://doi.org/10.1016/j.envsoft.2013.03.017

22. Parker DC, Manson SM, Janssen MA, Hoffmann MJ, Deadman P. Multi-agent systems for the simulation of land-use and land-cover change: A review. Ann Assoc Am Geogr. 2003; 93: 314–337. https://doi.org/10.1111/1467-8306.9302004

23. Wilensky U. and Rand W. An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo. MIT Press; 2015.

24. Bonabeau E. Agent-based modeling: Methods and techniques for simulating human systems. 2002; 99. https://doi.org/10.1073/pnas.082080899 PMID: 12011407

25. Epstein J.M. and Axtell R. Growing artificial societies: social science from the bottom up. Brookings Institution Press; 1996.

26. Deadman P, Robinson D, Moran E, Brondizio E. Colonist household decisionmaking and land-use change in the Amazon Rainforest: An agent-based simulation. Environ Plan B Plan Des. 2004; 31: 693–709. https://doi.org/10.1068/b3098

27. Iwamura T, Lambin EF, Silvius KM, Luzar JB, Fragoso JMV. Agent-based modeling of hunting and subsistence agriculture on indigenous lands: Understanding interactions between social and ecological systems. Environ Model Softw. 2014; 58: 109–127. https://doi.org/10.1016/j.envsoft.2014.03.008

28. An L, Liu J, Ouyang Z, Linderman M, Zhou S, Zhang H. Simulating demographic and socioeconomic processes on household level and implications for giant panda habitats. Ecol Modell. 2001; 140: 31–49. https://doi.org/10.1016/S0304-3800(01)00267-8

29. Evans TP, Kelley H. Multi-scale analysis of a household level agent-based model of landcover change. J Environ Manage. 2004; 72: 57–72. https://doi.org/10.1016/j.jenvman.2004.02.008 PMID: 15246574

30. Lambin EF, Tran A, Vanwambek e SO, Linard C, Soti V. Pathogenic landscapes: Interactions between land, people, disease vectors, and their animal hosts. Int J Health Geogr. 2010; 9: 1–13. https://doi.org/10.1186/1476-072X-9-1 PMID: 20082711

31. Almeida SJ de Martins Ferreira RP, Eiras ÁE Obermayr RP, Geier M. Multi-agent modeling and simulation of an Aedes aegypti mosquito population. Environ Model Softw. 2010; 25: 1490–1507. https://doi.org/10.1016/j.envsoft.2010.04.021

32. Thulke HH, Grimm V, Müller MS, Staubach C, Tischendorf L, Wissel C, et al. From pattern to practice: A scaling-down strategy for spatially explicit modelling illustrated by the spread and control of rabies. Ecol Modell. 1999; 117: 179–202. https://doi.org/10.1016/S0304-3800(98)00198-7

33. Dion E, Lambin EF. Scenarios of transmission risk of foot-and-mouth with climatic, social and landscape changes in southern Africa. Appl Geogr. 2012; 35: 32–42. https://doi.org/10.1016/j.apgeog.2012.05.001

34. Kasturiratne A., Pathmeswaran A., Wickremasinghe A.R., Jayamann e S.F., Dawson A., Isbister G.K., de Silva H.J., de Silva D, de Silva HJ, Laloo D. The socio-economic burden of snakebite in Sri Lanka. PLoS Negl Trop Dis. 2017; 11: 1–9. https://doi.org/10.1371/journal.pntd.0005647 PMID: 28683119

35. De Silva A, Ranasinghe L. Epidemiology of snake-bite in Sri Lanka: a review. hCeylon Med J. 1983; 28: 144. PMID: 6386199
36. Ralph R. The timing is right to end snakebite deaths in south Asia. bmj. 2019; 364: k5317. https://doi.org/10.1136/bmj.k5317 PMID: 30670457
37. Kasturiratne A, Pathmeswaran A, M.M.D. F, Laloo DG, Brooker S, Silva HJ De. Estimates of disease burden due to land-snake bite in Sri Lankan hospitals. Southeast Asian J Trop Med Public Health. 2005; 36: 733–740. Available: http://www.embase.com/search/results?subaction=viewrecord&from=export&id=L41316804 PMID: 16124448
38. Wilensky U. NetLogo. Evanston, IL: Center for connected learning and computer-based modeling, Northwestern University. 1999.
39. Macal CM, North MJ. Agent-based modeling and simulation. Proc 2009 Winter Simul Conf. 2009; 86–98. https://doi.org/10.1109/WSC.2009.5429318
40. Rs Team. Rstudio. RStudio: Integrated Development for R. RStudio; 2020. Available: http://www.rstudio.com/.
41. Liu J., Dietz T., Carpenter S.R., Alberti M., Moran E., Peli A.N., Deadman P., Krazt T., Lubchenco J. and Ostrom E. Complexity of coupled human and natural systems. Science (80-). 2007; 317: 1513–1517. https://doi.org/10.1126/science.1144004 PMID: 17872436
42. Wiegand T, Jeltsch F, Hanski I, Grimm V. Using pattern-oriented modeling for revealing hidden information: a key for reconciling ecological theory and application. Oikos. 2003; 100: 209–222.
43. Grimm V, Revilla E, Berger U, Jeltsch F, Mooij WM, Railsback SF, et al. Complex Systems: Lessons from Ecology. Science (80-). 2005; 310: 987–991. https://doi.org/10.1126/science.1116681 PMID: 16284171
44. Department of census and statistic Sri Lanka. Detail information on Tea in Sri Lanka. 2005.
45. Ministry of Plantation Industries Sri Lanka. Statistical Information on Plantation Crops. 2013.
46. Supphriah R, Yoshino M. Some agroclimatological aspects of rice production in Sri Lanka. Geogr Rev Jpn. 1986; 59: 137–153.
47. Olson D. M., Dinerstein E., Wikramanayake E. D., Burgess N. D., Powell G. V. N., Underwood E. C., D’Amico J. A., Itoua I., Strand H. E., Morrison J. C., Loucks C. J., Allnutt T. F., Ricketts T. H., Kura Y., Lamoreux J. F., Wettengel W. W., KR. Terrestrial ecoregions of the world: a new map of life on Earth. Bioscience. 2001; 53: 933–938.
48. Hijmans RJ, Cameron SE, Parra JL, Jones G, Jarvis A. Very high resolution interpolated climate surfaces for global land areas. Int J Climatol A J R Meteorol Soc. 2005; 25: 1965–1978. https://doi.org/10.1002/joc.1276
49. Zuhlke M., Fomferra N., Brockmann C., Peters M., Veci L., Malik J., & Regner P. SNAP (sentinel application platform) and the ESA sentinel 3 toolbox. Sentin Sci Work. 2015;V ol. 734.
50. Harris I., Jones P.D., Osborn T.J. and Lister DH. Updated high-resolution grids of monthly climatic observations—the CRU TS3.10 Dataset. Int J Climatol. 2014; 34: 623–642.
51. Mosier TM, Hill F, Sharp K V. 30-Arcsec ond monthly climate surfaces with global land coverage. Int J Climatol. 2014; 34: 2175–2188. https://doi.org/10.1002/joc.3829
52. Domroes M, Ranatunge E. A statistical approach towards a regionalization of daily rainfall in Sri Lanka. Int J Climatol. 1993; 13: 741–754. https://doi.org/10.1002/joc.3370130704
53. Department of Census and statistics. Census of agriculture 2002, sri lanka. 2002.
54. Rocha CFD, Bergallo HG, Vera y Conde CF, Bittencourt EB, Santos H de C. Richness, abundance, and mass in snake assemblages from two Atlantic Rainforest sites (Ilha do Cardoso, São Paulo) with differences in environmental productivity. Biota Neotrop. 2008; 8: 119–120. https://doi.org/10.1590/s1676-06032008000300011
55. Rahman. Monsoon does matter. annual activity patterns in a snake. Herp J 23(4). 2013;23 : 203–208.
56. Franca, Frederico Gustavo Rodrigues and V da SB. Diversity, activity patterns, and habitat use of the snake fauna of Chapada dos Veadeiros National Park in Central Brazil. Biota Neotrop. 2013; 13: 74–84.
57. de Silva A. Colour guide to the snakes of Sri Lanka. R & A. Portishead, UK: R & A Publishing Ltd.; 1990. https://doi.org/10.1001/0041-0101(91)90090-e
58. Sawant NS, Jadhav TD, Shyama SK. Distribution and abundance of pit vipers (Reptilia: Viperidae) along the Western Ghats of Goa, India. J Threat Taxa. 2013; 2: 1199–1204. https://doi.org/10.11609/jott.o2489.1199–204
59. Grimm V, Railsback SF. Pattern-oriented modelling: A “multi-scope” for predictive systems ecology. Philos Trans R Soc B Biol Sci. 2012; 367: 298–310. https://doi.org/10.1098/rstb.2011.0180 PMID: 22144392
60. De Silva A. Snakebites in Anuradhapura district. The Snake. 1981; 13: 117–130.
61. Farooqui JM, Mukherjee BB, Manjhi SNM, Farooqui AAJ, Datir S. Incidence of fatal snake bite in Loni, Maharashtra: An autopsy based retrospective study (2004–2014). J Forensic Leg Med. 2016; 39: 61–64. https://doi.org/10.1016/j.jflm.2016.01.013 PMID: 26854851

62. Kularatne SAM, Silva A, Weerakoon K, Maduwage K. Revisiting Russell’s Viper (Daboia russelii) Bite in Sri Lanka: Is Abdominal Pain an Early Feature of Systemic Envenoming? PLoS One. 2014; 9: 1–8. https://doi.org/10.1371/journal.pone.0090198 PMID: 24587278

63. Molesworth AM, Harrison R, Theakston RDG, Laloo DG. Geographic information system mapping of snakebite incidence in northern Ghana and Nigeria using environmental indicators: A preliminary study. Trans R Soc Trop Med Hyg. 2003; 97: 188–192. https://doi.org/10.1016/s0035-9203 (03)90115-5 PMID: 14584375

64. Kumar S. Clinical and epidemiologic profile and predictors of outcome of poisonous snake bites—an analysis of 1, 500 cases from a tertiary care center in. Int J Gen Med. 2018; 11: 209–216. https://doi.org/10.2147/IJGM.S136153 PMID: 29692202

65. Stahel E. Epidemiological aspects of snake bites on a Liberian rubber plantation. Acta Trop. 1980; 37: 367–374. PMID: 6110326

66. Watt G., Padre L., Tuazon M. L., & Hayes CG. Bites by the Philippine Cobra (Naja naja philippinensis): an Important Cause of Death among Rice Farmers. Am J Trop Med Hyg. 1987; 37: 636–639. https://doi.org/10.4269/ajtmh.1987.37.636 PMID: 3688317

67. Sawant NS, Jadhav TD, Shyama SK. Habitat suitability, threats and conservation strategies of Hump-nosed Pit Viper Hypnale hypnale Merrem (Reptilia: Viperidae) found in Western Ghats, Goa, India. J Threat Taxa. 2013; 2: 1261–1267. https://doi.org/10.11609/jott.o2490.1261–7

68. Bauwens D, Claus K. Intermittent reproduction, mortality patterns and lifetime breeding frequency of females in a population of the adder (Vipera berus). PeerJ. 2019;2019. https://doi.org/10.7717/peerj.6912 PMID: 31119090

69. Food and Agriculture Organization of the United: regional office for Asia and The Pacific. Crop diversification in the Asia-Pacific region. 2001.

70. Silva A., Marikar F., Murugananthan A. and Agampodi S. Awareness and perceptions on prevention, first aid and treatment of snakebites among Sri Lankan farmers: a knowledge practice mismatch ? J Occup Med Toxicol. 2014; 9: 20. https://doi.org/10.1186/1745-6673-9-20 PMID: 24847375

71. Albuquerque HN, Fernandes A, Albuquerque ICS. Snakebites in Paraíba, Brazil. J Venom Anim Toxins Incl Trop Dis. 2005; 11: 242–251. https://doi.org/10.1590/s1678-919920050000300003

72. Inamdar IF, Aswar NR, Ubaidulla M, Dalvi SD. Snakebite: Admissions at a tertiary health care centre in. S Afr Med J. 2010; 100: 456–458. https://doi.org/10.7196/samj.3865 PMID: 20822595

73. Zacarias D, Loyola R. Climate change impacts on the distribution of venomous snakes and snakebite risk in Mozambique. Clim Change. 2019; 152: 195–207. https://doi.org/10.1007/s10584-018-2338-4